Using Machine Learning for Real-time Activity Recognition and Estimation of Energy Expenditure

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Submitted to the Program in Media Arts and Sciences, School of Architecture and Planning, in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy
at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2008

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Abstract

Obesity is now considered a global epidemic and is predicted to become the number one preventive health threat in the industrialized world. Presently, over 60% of the U.S. adult population is overweight and 30% is obese. This is of concern because obesity is linked to leading causes of death, such as heart and pulmonary diseases, stroke, and type 2 diabetes. The dramatic rise in obesity rates is attributed to an environment that provides easy access to high caloric food and drink and promotes low levels of physical activity. Unfortunately, many people have a poor understanding of their own daily energy (im)balance: the number of calories they consume from food compared with what they expend through physical activity. Accelerometers offer promise as an objective measure of physical activity. In prior work they have been used to estimate energy expenditure and activity type. This work further demonstrates how wireless accelerometers can be used for real-time automatic recognition of physical activity type, intensity, and duration and estimation of energy expenditure. The parameters of the algorithms such as type of classifier/regressor, feature set, window length, signal preprocessing, sensor set utilized and their placement on the human body are selected by performing a set of incremental experiments designed to identify sets of parameters that may balance system usability with robust, real-time performance in low processing power devices such as mobile phones. The algorithms implemented are evaluated using a dataset of examples of 52 activities collected from 20 participants at a gymnasium and a residential home. The algorithms presented here may ultimately allow for the development of mobile phone-based just-in-time interventions to increase self-awareness of physical activity patterns and increases in physical activity levels in real-time during free-living that scale to large populations.

KEYWORDS: Activity recognition, context awareness, energy expenditure, physical activity, wearable sensors, obesity, mobile phone, pattern recognition, machine learning, ubiquitous, pervasive, just-in-time.

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Acknowledgments

Stephen
I am grateful for the time and advice that you provided over the past six years. This thesis owes much of its contents to your ideas and guidance.

Kent
Thank you for offering me the opportunity to study at MIT and for guiding me through my learning process at the institution.

In the following paragraphs, I write the acknowledgements to the most important people in my life. Those who have loved, supported, and encouraged me unconditionally over the course of my life. I also dedicate the contents of this thesis to my sister Anaid Munguia Tapia. Since my heart does not know how to speak or write in English, the following paragraphs are written in Spanish, the native language of my heart.

Mi hermana Anaid
Hermana mia, estoy eternamente agradecido por tu amor y cariño incondicional. Tú has sido una verdadera inspiración para mi trabajo y me has enseñado que hay cosas más importantes que ser un buen estudiante o trabajador. Me has enseñado que la vida es más que triunfar económicamente o lograr un mejor estatus social. Gracias por tu paciencia durante todos esos años tan difíciles en los cuales no sabíamos porque las cosas estaban pasando y que era lo que finalmente Dios nos tenía preparado. Tambien quiero pedirte disculpas por permanecer tantos años alejado de ti cuando debí de estar a tu lado, cuidándote y haciendo tu condición mas pasadera. Espero y puedas comprender que lo hice por un mejor futuro económico para todos. Aunque la verdad, creo que tienes razón. Ningún título de ninguna institucion en el planeta, incluyendo MIT, me puede ahora regresar el tiempo que perdí a tu lado. Te amo hermana mia con todo mi corazón y espero tenerte cerca de mi en un futuro muy cercano.

Mi mamá Josefina y papá Leonardo
Gracias por enseñarme a soñar, a soñar en grande y sobre todo a protejer mis sueños de personas que piensa que son tan grandes que son imposibles de realizar. Me siento afortunado de haber sido su hijo, gracias por cuidarme y educarme con tanto amor. Madre, gracias por cuidar de mis hermanos cuando mas lo necesitaban y permitirme ir a estudiar a la capital en busca de mis sueños, cuando mi apoyo tanto económico como emocional hacían tanta falta en el hogar durante esos duros momentos de enfermedad y desolación. Gracias a su gran fortaleza y apoyo, el día de hoy puedo decir que me graduo como un doctor en filosofía del Instituto Tecnológico de Massachusetts.

Mi esposa Margarita
Amor mio, gracias por tu maravilloso amor, por ser mi compañera, mi fortaleza e inspiración. Gracias tambien por brindarme todo tu apoyo durante todos esos años que permanecimos separados de tal manera que el día de hoy pudiera cumplir mi sueño de terminar un doctorado en MIT. Espero poder cumplir con la promesa que hice ante Dios el día de nuestra boda: brindarte una vida llena de paz, dicha y felicidad. ¡Te amo!

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1 Introduction

Due to its dramatic increase over the past decades, obesity is now considered a global epidemic that may dramatically impact health in the industrialized world [1]. The prevalence of obesity from 1960 to 1994 in the U.S alone increased approximately 50% from 13.4% to 22.3%. At present, 65% of adult Americans aged 20 years and older are considered overweight (a body mass index [BMI] $\geq$ 25 kg/m^2) and 30% are considered obese (BMI $\geq$ 30 kg/m^2). Further, 16% of children and teenagers (age 6-19) are presently considered overweight and the percentages are rising [2].

If this trend in obesity continues and no action is taken, the majority of the U.S. adult population could be overweight within a few generations [3]. Extrapolating from existing data from the World Health Organization [1], approximately half (45-50%) of the U.S. adult population could be obese by year 2025. This is an alarming statistic because obesity is linked to leading causes of death in the U.S., such as heart and pulmonary diseases, stroke, and type 2 diabetes [2]. Obesity is also a risk factor for chronic conditions such as high blood cholesterol, hypertension, and osteoarthritis [4].

Obesity is a complex condition caused by the interaction of many factors such as such as genetic makeup, neuroendocrine disorders, emotions, and even secondary effects from medical treatments. The rise in obesity, however, is generally believed to result from a caloric imbalance. Most Americans have (1) high caloric intake due to easy access to foods and beverages with a high caloric content and (2) extremely low levels of physical activity relative to that caloric intake [5-7]. Increased calorie intake may have resulted from pervasive advertising and ubiquity of the fast food industry [8], easy access to energy-dense packaged foods such as snacks and soft beverages [9], and the expanding portion sizes of meals and food packages [10]. Advances in transportation and household appliances have also contributed by minimizing everyday physical activity and encouraging sedentary behaviors. Many leisure activities such as sports and outdoor activities have been increasingly replaced by sedentary behaviors such as television viewing, arcade videogame playing (particularly in children), and internet surfing [11, 12]. In fact, a study by Harris Interactive released in 2003 [13] found that Americans 13 years and older spend on average eight hours a day sitting and four hours a day watching TV, playing video games, or surfing the web.

Energy intake and energy expenditure are determined by the individual's daily behavior and, consequently, addressing behavior change has been an important focus of work in treating obesity. For example, clinical behavioral interventions attempt to modify behavior related to physical activity and diet by educating individuals about the benefits of daily exercise, healthier food choices, and portion sizes. These interventions have shown some level of success in reducing body mass index (BMI) and increasing physical activity levels in the short-term (e.g. [14]). Nevertheless, this success may primarily result from the network of health care professionals and researchers constantly monitoring each individual's behavior, making the interventions too costly to scale to the entire population. When people are left to manage their own weight, without the constant support of professionals, they struggle to maintain newly acquired healthy behaviors [15, 16]. In fact, ninety five percent of people who have lost weight during these interventions regain approximately one third of the lost weight during the following year and are usually back to their initial weight within three to five years [17]. Ultimately, if *cost-effective* long-term behavior change is required, individuals must initiate and sustain healthy habits related to physical activity and diet without continuous monitoring by health professionals.

Daily information about physical activity level, energy expenditure, and energy intake is central to weight control since energy balance is defined by the interaction between these variables [6, 12, 18]. Presently, many people have little or no idea how much daily meaningful physical activity they get and how that compares to the minimum standards suggested by medical professionals and their estimated caloric intake. Consequently, there is a need for tools that allow people to measure their physical activity intensity and intake over the course of a day to allow them to make informed decisions and perform energetic trade-offs (e.g. increase physical activity while overeating or reduce food consumption while sedentary). Moreover, tools that automatically inform individuals about how small changes in behavior (e.g. in non-exercise activity) could positively impact their daily energy expenditure might allow people to plan personalized modifications to daily routine that are more likely to be conducive to incremental adoption and subsequently sustained over long periods of time.

Unfortunately, existing technologies in the area of physical activity are mostly designed for those individuals who have already achieved a high level of physical fitness, such as athlete runners. For example, the Nike+iPod sport kit [19] allows individuals to track the speed, distance, pace and calories burned while running by slipping a motion sensor in the Nike+iPod ready shoe and snapping a wireless receiver unit into the iPod nano MP3 player. The Adidas+Polar training system [20], another recently introduced technology, integrates a heart rate monitor on a shirt, a stride sensor on a shoe, and a wristwatch computer to monitor work out zones based on heart rate, speed and distance data. These new portable technologies demonstrate the use of real-time biofeedback as a way to motivate behavior modification, since heart rate data and energy expenditure is used to maintain the work out at particular zones. Still, the challenge remains to come up with technologies that can be used by those who have difficulty maintaining a healthy weight and minimum levels of physical activity every day.

In summary, there is a need for weight maintenance technologies that (1) use automation so that they can scale well in cost to the majority of the population, (2) present information about physical activity levels, energy expenditure, and energy intake in real-time over the course of a day to help people to make more informed decisions related to physical activity and diet, (3) create opportunities for interventions that permit incremental changes that do not necessitate sudden and drastic modifications to daily routine, (4) teach individuals skills that will help them in maintaining their weight in the long term, and that (5) are inexpensive, easy to use and unobtrusive so that people are willing to use them longitudinally during free-living.

1.1 The Opportunity

As the popularity of portable handheld computers such as mobile phones increases and their cost decreases, opportunities for novel healthcare applications arise. Mobile phones are often carried with people nearly everywhere they go, and people generally keep them functioning and charged [21]. Consequently, they can be used to gather and deliver tailored health-related information continuously over long periods of time during free-living conditions.

One important area where mobile phones and wearable accelerometers can be applied in combination is in creating valid and reliable measures of physical activity and energy expenditure. Automatic detection of physical activity and/or energy expenditure would enable new types of health assessment and intervention tools that help people maintain their energy balance and stay physically fit and healthy. For example, mobile phones could be used to run algorithms that automatically recognize physical activities and estimate energy expenditure from body-worn accelerometers and display this information as behavioral feedback in real-time. Indeed, with the advent of accelerometer-enabled mobile phones (e.g. [22-25]), some applications such as mobile phone based pedometers and activity level monitors have started to emerge [25, 26].

Another powerful extension of mobile technology is to use it to deliver "just-in-time" interventions at the point of decision, for example, to encourage a positive behavior change [27, 28]. In this scenario, accelerometer-based mobile phones or mobile phones combined with wearable accelerometers distributed at strategic body segments can be used to detect activities of interest (e.g. *walking slowly*) and encourage increases in intensity levels (e.g. *brisk walking* over *walking slowly*). Obviously, for these types of applications to be possible, activity recognition algorithms running on mobile phones have to be capable of recognizing the intensity of physical activity.

A new area of research where mobile phones and wearable accelerometers might also be applied is non-exercise activity thermogenesis (NEAT) [29]. Recent results suggest that small changes to daily routine such as *walking upstairs* vs. *riding the elevator*, *sitting fidgeting feet* vs. *sitting* and *brisk walking* vs. *walking* can accumulate over the course of a day to meaningful amounts.

Mobile phones could also be used to acquire information related to food intake, body weight and body composition automatically and use it to provide useful estimates of energy balance over time. In fact, Some mobile phone based commercial applications such as MyFoodPhone [30] and Sensei [31] have already started to appear. These applications allow individuals to collect dietary information on phones and, if desired, receive useful feedback from dietitians. Unfortunately, better applications are still required that do not either rely on experts to manually analyze data or end-users to painstakingly enter information about what they eat using a phone.

1.2 Challenges of Estimating Energy Balance

Unfortunately, the accurate measurement of physical activity, energy expenditure, and energy intake is challenging and, at present, there is no technology that allows people to measure these variables comfortably, accurately, and continuously over the course of a day and obtain real-time feedback. Existing technologies capable of measuring these variables accurately that are used in research (e.g. diet and physical activity diaries, indirect calorimetry, doubly labeled water, and chemical analysis of duplicate food samples) impose a considerable degree of burden to the end user due to (1) the need of maintaining detailed daily records related to physical activity and diet or (2) the use of intrusive and expensive medical equipment available only at specialized laboratories. When methods more suitable for free-living conditions are used to estimate these variables (e.g. recall surveys, end of study interviews, and non-detailed diaries), they provide too coarse of an estimate to allow for useful consumer-based applications.

Motion sensors (accelerometers) are commonly used in exercise physiology research to measure physical activity quantitatively and estimate energy expenditure during free-living. A common method used during large scale medical research studies is to place a single accelerometer (e.g. Actigraph [32]) at the hip to obtain an estimate of physical activity level (e.g. *light*, *moderate*, *vigorous*) and energy expenditure due to overall body motion (e.g. ambulation). This method may perform poorly on some activities that involve primarily upper or lower body motion, which can be difficult to detect from a single accelerometer at the hip [33, 34]. Another disadvantage of this and another existing technologies (e.g. [33, 35, 36]) is that they do not provide any information about the type of activity being performed.

Recognizing activity type (e.g. *washing dishes* vs. *wiping a surface*) across individuals is challenging because individuals perform activities differently. Although there has been extensive research in the area, most algorithms implemented have been evaluated off-line and consequently, it is not clear if they are capable of real-time performance (e.g. [37-40]). Those few algorithms that recognize activities in real-time either recognize a limited set of activities involving mainly postures and ambulation (e.g. [41-44]) or are in a prototype research stage (e.g. [45, 46]). Furthermore, to the best of the author's knowledge, there are presently no technologies or algorithms available to automatically recognize the intensity of physical activity (e.g. *walking at 3mph* vs. *walking at 4mph*). As a result, the only available methods to capture to capture information about the intensity of physical activity are direct observation and physical activity diaries.

Estimation of energy expenditure presents some additional challenges over physical activity recognition. For example, energy expenditure needs to be estimated in a subject independent manner due to the unavailability of the necessary equipment to allow people to collect energy expenditure data about their activities during free-living. Furthermore, one of the main challenges in estimating energy expenditure is inter-individual variations since two individuals performing the same activity would present different energy expenditure measurements depending on their fitness level, age, and gender. Another challenge is that resistance or work load effort involved in activities such as *walking uphill* or *carrying a heavy box* are difficult to detect from accelerometers. Heart rate data, on the contrary, is able to detect these changes in physical effort, but it suffers from inter-individual variations due to different fitness levels of individuals and intra-individual variations due to emotional states, nicotine, and temperature among others [47-49].

There are still some questions in physical activity recognition and energy expenditure estimation research that prior work has partially addressed or not addressed at all. Some of these questions include: What features computed over the accelerometer data allow better recognition of activities and estimation of energy expenditure? What sliding window lengths (or epochs) provide the highest performance? Do multiple accelerometers at different body segments improve performance? How does the performance of relatively simple classifiers amenable for real-time performance compare to more complex state-of-the-art classification algorithms? Do non-linear regression techniques improve energy expenditure estimates significantly? Do activity dependent regression models improve energy expenditure estimation? Does the combination of accelerometer and heart rate data improve performance? What is the minimum number of accelerometers required to recognize activities and estimate energy expenditure? Where these accelerometers should be placed to maximize usage comfort and performance? The work presented in this thesis explores some possible answers to all of the above questions by performing a set of experiments to find a reasonable compromise that balances the various criteria required to create activity recognition and energy expenditure algorithms amenable for real-time performance in low processing power devices.

1.3 System Goals

The main goal of the work presented in this thesis is to demonstrate the viability of technology that can reliably detect information about activity type and intensity, and estimate energy expenditure from accelerometers in real-time. Such technology might eventually enable the development of a consumer-based energy expenditure meter that is easy to use, unobtrusive, inexpensive, always on and near the user, accurate, and that can be used longitudinally during free living conditions. Knowledge of physical activity and energy expenditure information in real-time over the course of a day could increase individuals' self-awareness and allow them to perform energetic trade-offs that might help in maintaining a healthy weight (e.g. exercise more when overeating or eating less when sedentary).

1.4 Experimental Goals

In this work, algorithms for automatic detection of physical activity type and intensity and energy expenditure estimation using multiple wireless accelerometers are evaluated on a dataset collected from 20 participants. The dataset consists on data collected at a gymnasium under relatively controlled laboratory conditions and at a residential home under less controlled free-living conditions. During the data collections, participants wore seven wireless accelerometers, a heart rate monitor, and a portable indirect calorimeter to collect data about motion patterns associated with activities, heart rate, and energy expenditure. This dataset is particularly challenging (for the algorithms implemented) since it consists on data collected for 52 different activities, 26 of which have different intensity levels and 18 of them which include examples of the unconstrained motion found in household activities. The parameters of the activity recognition and energy expenditure algorithms such as type of classifier/regressor, feature set, window length, sensor set utilized and their placement on the human body are selected by performing a set of incremental experiments. These experiments have the goal of identifying a set of parameters that could enable robust real-time performance. Once the parameters are selected, the activity recognition algorithm is evaluated on various sets of activities. First, the algorithm is evaluated over all the 52 activities contained in the dataset. Then, it is evaluated again over all activities but without differentiating among activities containing different intensity levels. Later, the algorithm is evaluated over activities involving postures and ambulation, and then over activities involving postures, ambulation and two MET intensity levels, and finally; the algorithm is evaluated by only recognizing postures. The results presented in each of the experiments are clustered according to five activity categories to better understand the performance of the algorithm: Postures, ambulation, exercise activities, resistance exercise activities, and household activities. To the best of the author knowledge, the dataset collected for this work is larger and more complex that other datasets used in activity recognition studies published to date.

This thesis explores the following:

- The development of algorithms that recognize physical activities and estimate energy expenditure from accelerometer data in real-time amenable for implementation in low-processing power devices such as mobile phones.
- The development of algorithms that recognize not only the physical activity type (e.g. *walking* vs. *cycling*) but also the intensity (e.g. *walking at 3mph* vs. *walking at 4mph*) of some activities.
- The development of a system that simultaneously recognizes activities and estimates energy expenditure from a set of three accelerometers worn at the hip, dominant wrist, and dominant foot.
- The exploration of the impact in performance of different signal processing techniques (e.g. band-pass filtering, data smoothing) and feature computation methods (e.g. feature computation per axis and per sensor) during activity recognition and estimation of energy expenditure.
- The examination of the impact in performance per activity of varying the sliding window length used during physical activity recognition and estimation of energy expenditure.
- The exploration of the subsets of features with highest performance (out of a set of 41 features) during the recognition of physical activities and estimation of energy expenditure.
- The study of the impact in performance achieved by incorporating heart rate data during physical activity recognition (e.g. to better recognize the intensity of activities) and estimation of energy expenditure.
- The exploration of the minimum set of sensors to utilize and their locations in the human body (out of a total set of seven) that maximize performance and usage comfort during recognition of physical activities and estimation of energy expenditure.
- The exploration of how well can different sets of activities be recognized in increasing order of complexity such as postures (4 activities), postures+ambulation (8), postures+ambulation+MET intensity (11), all activities with no intensities (31), and all 52 activities (including exercise and household activities and the garbage or unknown activity).
- The evaluation of activity recognition and energy expenditure estimation algorithms in a subject dependent and independent manner.
- The evaluation of the training data requirements for subject dependent recognition of activities.
- The comparison in performance between complex state-of-the-art classifiers/regressors and simpler classifiers/regressors amenable for real-time performance during the recognition of activities and estimation of energy expenditure.

- The real-time evaluation of the final version of the activity recognition algorithm implemented during a short study where individuals interactively provide the training data required to recognize 10 activities of their choice.
- The investigation of the performance achieved if activity dependent regression models are used to estimate energy expenditure.
- The exploration of the difference in performance between estimating energy expenditure using regression techniques and scoring of activities using the Compendium of Physical Activities.
- The development of a system to recognize activities and estimate energy expenditure that might enable mobile phone based interventions for obesity in the near future that are (1) scalable to large populations due to the use of readily available mobile phones and low-cost sensors, and (2) that can be used longitudinally during free-living conditions due to their ease-of-use and low burden.

1.5 Organization of Thesis

This thesis is organized as follows. Chapter 2 presents a usage scenario and extended examples of how the work developed in this thesis might be used in mobile phone energy measurement interventions. The chapter also describes the system components required to achieve such interventions and their desired characteristics. In Chapter 3, background in prior research and methods in the areas of physical activity recognition and energy expenditure estimation is introduced. Chapter 3 also highlights some of the research challenges and open questions in these areas and explains the existing technological limitations that have prevented the development of mobile phone physical activity detection and energy expenditure estimation interventions. Chapter 4 presents an overview of the system designed and implemented in this work, the research approach followed to collect the data to develop and evaluate the algorithms, and the incremental set of experiments designed to select the parameters of the algorithms presented. Chapter 5 starts by discussing how results are reported and analyzed for the activity recognition and energy expenditure estimation algorithms and continues by presenting the results obtained in each experiment designed to select the parameters of these algorithms. In addition, Chapter 5 presents the evaluation of the final version of each algorithm in full detail. Finally, Chapter 6 presents the main contributions of this work, a discussion of unresolved issues concerning long term deployment of the systems implemented, and some recommendations for future work.

2 The System Goal

As the popularity of portable handheld computers such as mobile phones increases and their cost decreases, novel healthcare opportunities arise. Mobile phones are often carried with people nearly everywhere they go [21] and people generally keep them functioning and charged. Consequently, they can be used to deliver and gather tailored health-related information in free-living situations. The work presented in this thesis attempts to take advantage of this opportunity by developing activity recognition and energy expenditure estimation algorithms that are amenable for real-time implementation in mobile phones. These algorithms, in combination with a small set of wireless accelerometers could allow the development of a consumer-based energy expenditure meter that is easy-to-use, unobtrusive, fun and that could be utilized longitudinally during free-living conditions. This section explains the different technology components required to achieve such scenario, and explores different alternatives to utilize the real-time information related to physical activity and energy expenditure during free-living.

2.1 Mobile Phone Energy Balance Interventions

Most interventions for obesity have relied on healthcare professionals (e.g. clinical behavioral interventions), required drastic modifications to daily routine (e.g. low calorie diets and exercise routines), or imposed a high level of burden on users (e.g. dietary records). Moreover, most technology currently available to asses physical activity is either only utilized by people who have already achieved a good level of physical fitness (e.g. iPod+Nike sport kit [19]) during short periods of time or by medical professionals during research studies (e.g. Actigraph [32]).

As a result, one of the main goals of this work is to provide a technical foundation on which others can develop mobile phone energy expenditure interventions that can be used longitudinally during free-living, that are inexpensive, and scalable to large populations because they do not rely on humans and because they utilize technologies readily available (mobile phones and wireless accelerometers).

2.1.1 Mobile Phone Energy Balance Interventions Wish List

The technical contributions of this work support the development of a real-time physical activity detection and energy expenditure device. This might enable interventions to be considered that take advantage of real-time physical activity type and intensity detection to achieve the following properties:

- *Presents real-time information at convenient times or at the point of decision.* The intervention might provide real-time information about physical activity type and intensity over the course of a day. Knowledge of physical activity type might make it possible to determine good times to present feedback (e.g., during bouts of physical activity).

- *Provides objective feedback.* People sometimes have difficulty judging if they have met guidelines for physical activity, such as 30 minutes of "brisk walking." An objective measure of energy expenditure or time spent in certain types of activities might help people make more informed decisions about how and when they get physical activity.
- *Provides tailored feedback.* By tracking physical activity type and intensity over long periods of time, interventions may then be able to present tailored feedback to motivate behavior change (e.g., today's activity is 10% less vigorous than yesterday's).
- *Permits incremental behavior change*. Real-time feedback about physical activity may enable new interventions focused on rewarding positive behaviors rather than only suggesting new behaviors that require drastic modifications to daily routine. Interventions may help people integrate more intensity into the activities they already do, rather than simply suggesting that people make radical changes to schedules that they feel they cannot achieve (e.g., going to the gym for 30 minutes a day).

2.1.2 Required Components

This section briefly discusses the system components required to implement mobile phone based interventions that utilize physical activity type, intensity, and energy expenditure information. The necessary system components are (1) an activity recognition system and (2) an energy expenditure estimation system. Here, it is assumed that the system is implemented on a mobile phone platform. In this work we demonstrate the technology is feasible for real-time performance on a PC but anticipate that real-time performance should be possible on emerging mobile phone technology as well. Implementation on a phone would permit real-time interventions based on automatically detected physical activity type and intensity.

2.1.2.1 Automatic Recognition of Physical Activities

The physical activity recognition system recognizes a variety of everyday postures, physical activities, household activities and common exercise routines from a small set of wearable accelerometers using pattern classification techniques. This systems needs to be capable of (1) real-time performance with short classification delays in mobile phones, (2) recognition of activity type (e.g. *walking* vs. *cycling*), intensity (e.g. *walking at 5mph* vs. *walking at 6mph*), duration (e.g. seconds, minutes, hours), and frequency (e.g. daily, weekly, etc), (3) recognition of activities in a subject independent manner or in a subject dependent manner but with small training data requirements (e.g. few minutes per activity). Finally, the algorithm should only utilize a small number of accelerometers that can be worn comfortably at strategic but convenient body locations. This maximizes ease of use during free-living.

This thesis will present an activity recognition algorithm that recognizes various sets of physical activities (up to 52) from just three triaxial accelerometers worn at the hip, dominant wrist, and dominant foot (on top of shoe laces). These sensors could be embedded in convenient easy-to-wear devices such as wristwatches, shoe pods or simply put inside the pocket in the case of the accelerometer at the hip. The algorithm was trained over data collected from 20 participants performing 52 activities at two locations: a gymnasium and an instrumented residential home. The algorithm is capable of real-time performance with short classification delays (5.6s) on existing laptop computers. The algorithm is also amenable for implementation in mobile phones due to its low computational requirements. Section 5.4 presents in-depth details on this physical activity recognition algorithm implemented.

2.1.2.2 Estimation of Energy Expenditure

The energy expenditure estimation system combines data collected from multiple wearable sensors (e.g. accelerometers or heart rate monitors) and user specific information, such as age, gender, weight, and height to generate estimates of energy expenditure (e.g. in METs or kcal/min) over the course of a day. The energy expenditure estimation system needs to be capable of (1) real-time performance with short estimation delays in mobile phones, (2) estimation of energy expenditure accurately for all types of activities, including activities with upper body, lower body, and overall body motion, and (3) estimation of energy expenditure in a subject independent manner, since the equipment required to collect energy expenditure data is expensive and unavailable to most people. Similarly the algorithm should provide the estimates from a small set of sensors strategically placed on the human body to maximize comfort and performance.

The energy expenditure estimation algorithm implemented in this work estimates energy expenditure by applying different models depending on the types of activities being performed by individuals. The activity dependent models were trained on data collected from 16 individuals (6hrs per individual) collected at a gym and at a residential home. The algorithm performs in real-time with short classification delays (5.6s) and is able to estimate energy expenditure for activities that have proven difficult in the past. These activities include upper body activities (e.g. *bicep curls* and *bench weight lifting*) and non-ambulatory lower body activities (e.g. *cycling*). This energy expenditure estimation algorithm also relies on the data collected by three wireless accelerometers placed at the hip, dominant wrist, and dominant foot. This was found to be the good sensor combination to capture upper body, lower body and overall body motion. As stated previously, these three sensors could be ultimately embedded in easy-to-wear devices such as wristwatches, shoe pods, and belt-clips.

Presently, existing techniques that produce the most accurate measurements of energy expenditure are either only suitable for laboratory due to the specialized equipment and expertise required (e.g. indirect calorimetry), used in small population studies due to their high cost (e.g. doubly labeled water), or do not provide continuous measurement with low user burden (e.g. activity diaries). The algorithm presented in this work allows the automatic estimation of energy expenditure and recognition of activity context during free-living from a small set of wearable accelerometers. This system improves on currently utilized accelerometer-based techniques by improving energy expenditure estimation for activities involving upper body and lower body activity and by also recognizing the activity type and intensity being performed.

2.1.3 Scenarios Exploiting Real-Time Feedback

This section explores how the technical results for physical activity type and intensity detection and energy expenditure estimation presented later in this thesis might be used in novel, real-time interventions.

Real-Time Personalized Behavioral Feedback Mobile-phone Screensaver

Personalized behavioral feedback related to physical activity and energy expenditure could be presented as background images or screen savers on mobile phones over the course of a day. In this way, users could have access to this information in real-time by simply staring at the phone for a couple of seconds, such as when answering a phone call or checking on the time. The main advantage of this approach is the low level of burden imposed on users since no action other than staring at the phone's screen is necessary to initiate the feedback. Another advantage is that users can choose to ignore this information if they are busy, so this intervention is unlikely to be perceived as intrusive or burdensome. The information presented might be helpful to facilitate self-regulation by allowing individuals to perform energetic trade-offs during the course of the day, and to encourage a positive behavior change.

End-of-day Behavioral Feedback Graphs

Another method that can be utilized to provide daily behavioral feedback related to physical activity and energy expenditure is to display end-of-day behavioral feedback graphs. These graphs could show the energy expended through non-exercise and exercise activity partitioned per activity performed. These graphs would have the objective of increasing individuals' understanding on how energy is spent while performing different activities over the course of a day. Some examples of end-of-day behavioral graphs are shown in Figure 2-1 and Figure 2-2.

Encouraging Increases in Non-exercise Physical Activity

A relatively new and promising area of research is non-exercise activity thermogenesis (NEAT). This are of research suggests that small behavior modifications to daily routine (e.g. *sitting fidgeting legs* vs. *sitting*, *standing* vs. *sitting*, and *brisk walking* vs. *walking slowly*). can sum up over the course of a day and boost overall energy expenditure and thus have a protective effect against weight gain [29, 50, 51]. This is because most of the energy expended everyday comes from non-exercise activity. Thus, if a mobile phone could recognize non-exercise activities and their associated energy expenditure, it could suggest small changes in daily routine that might impact daily energy expenditure positively. The main advantage of this type of intervention is that small behavioral modifications are likely to be not perceived as drastic changes but have the potential to help in controlling weight problems.

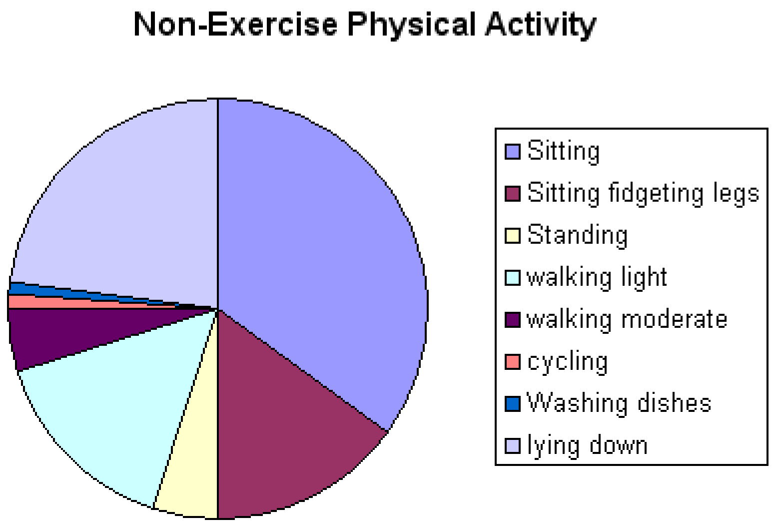


Figure 2-1: Non-exercise activity (NEAT) partitioned according to activity performed over the course of a day.

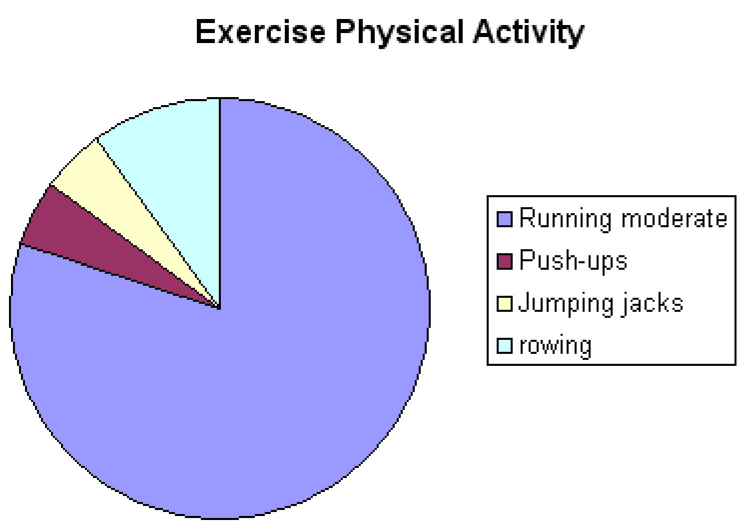


Figure 2-2: Daily exercise activity partitioned per activity performed. Graphs like this one could be presented at the end of the day to increase self-awareness related to physical activity of individuals.

Just-in-time Interventions to Increase Physical Activity Levels

Real-time information about activity type, intensity and duration might allow the development of just-in-time interventions to foster increases in physical activity levels. For example, a mobile phone capable of recognizing different intensities of *walking* (e.g. *walking* at 2, 3, and 4mph) could encourage someone already *walking* to either increase the *walking* speed or the duration of *walking* to boost overall energy expenditure. The phone could also provide positive behavioral feedback by present information about the extra number of calories burned by increasing activity intensity or duration.

2.1.3.1 Why These Interventions Have not Been Possible Before?

The types of interventions previously mentioned have not been possible yet due to hardware and algorithmic limitations. For example, some of the hardware limitations include unavailability of real-time data due to the lack of power efficient wireless communication protocols to receive/send data from multiple sensors simultaneously and continuously and inconvenient sensors form factor for longitudinal use. Some of the algorithmic or software limitations that have prevented real-time interventions like the ones described are: (1) *Coarse estimates* since most existing technologies to measure physical activity provide too coarse of an estimate to allow useful applications (e.g. pedometers and single accelerometers at the hip), (2) *Poor energy expenditure estimation performance over upper and lower body activity* such as when using a single accelerometer at the hip, (3) *Limited or no contextual information* since existing technologies available to measure physical activity provide limited or not contextual information about the type, intensity, and duration of the physical activities being performed. (4) *Lack of efficient algorithms that run in real-time on low-processing power devices*. Most algorithms available for recognizing activities and estimating energy expenditure have been implemented to run offline and have not been tested for real-time performance. Section 3.3 presents a detailed discussion on why these types of interventions have not been previously possible after a discussion of the advantages and disadvantages of existing technology to measure physical activity and estimate energy expenditure.

2.1.3.2 Ensuring Ease-Of-Use

Mobile phone based applications that recognize activities, estimate energy expenditure, and trigger interventions would have to be easy to use so that they are used longitudinally during free-living. Ensuring ease-of-use involves addressing factors such as usage comfort of the sensors, the number of sensors utilized and their location in the human body, training time requirements of the algorithms if subject dependent training is used, capability of real-time performance, real-time recognition delay, and invariance to small changes in sensor location and orientation during the installation process. Low training data requirements during subject dependent training is important because it determines the time end-users would have to spend providing examples of the activities to recognize. The longer this time, the more likely end-users will find this training procedure difficult to complete or annoying. Similarly, real-time performance during subject dependent training is particularly important since it would allow individuals to test the performance of the algorithms quickly so the procedure is not perceived as burdensome. Finally, invariance to small changes in sensor orientation and location during installation on the body is important since these will occur during free-living conditions and the algorithms have to be able to perform well despite these variations. Section 3.2.6 describes prior work addressing some factors involved in creating systems easy to use and describes how the work presented this thesis addresses them.

2.1.3.3 Gathering Person-Specific Training Data from End Users

Previous work in activity recognition (e.g. [38]) suggests that subject independent recognition of activities is significantly more difficult than subject dependent recognition of activities. As a result, activity recognition algorithms are likely to perform better if users provide examples of the activities to recognize. Thus, activity recognition algorithms using subject dependent training will require efficient and intuitive user interfaces that allow users to interactively train and test the algorithms. Furthermore, intuitive user interfaces would also be required to allow individuals to ‘fix’ the recognition algorithms when they do not function properly. This could be achieved by either requesting more training data for activities with low performance or by allowing end-user to modify the inner workings of the algorithms. Section 5.4.9.1 explains how training data requirements for subject dependent recognition of activities are evaluated in this work. Section 5.5 presents the evaluation of the user interface implemented in this work to train and test the activity recognition algorithms implemented in real-time.

2.2 Other applications

The algorithms implemented in this work to automatic recognize activities from sensor data can also be exploited by other context-aware applications in other domains. For example, they can be utilized in context sensitive reminders [52-56], context aware experience sampling for health research [57, 58], physical therapy or recovery [59, 60], sports training [60-63], personal health tracking [64-66], interactive games [67-69], autism research [70, 71], availability and interruptability prediction [72, 73], and automatic annotation of important events [73-76]. Thus, all these application areas would also benefit from activity recognition algorithms that can run in real-time in existing or future mobile phones.

3 Research Challenges and Prior Work

This section discusses prior work in the areas of activity recognition and energy expenditure estimation from wearable sensors such as accelerometers and heart rate monitors, highlighting the advantages and disadvantages of each approach and challenges that remain. Finally, the section states the assumptions in which the work presented in this thesis relies, and emphasizes the user interface challenges associated with creating mobile phone physical activity and energy expenditure interventions.

3.1 Assumptions

Mobile phones are carried with people nearly anywhere they go and their popularity is increasing among all socio-economic groups [21]. As a result, this work attempts to take advantage of this trend and develop some of the required technology to achieve mobile phone interventions that use physical activity type and intensity detection in the near future. One of the assumptions of this work is that the majority of mobile phones by year 2015 will have a CPU capable of running at a speed of least at 1GHz. This processing power could allow running activity recognition and energy expenditure algorithms like the ones presented in this work in a manner that is not too perceptible to end users (e.g. no apparent delays observed). It is also assumed that the accelerometers required by the system presented in this work to sense human motion could be embedded on devices already worn at convenient locations such as wrist watches, mobile phones, belt clips, and shoe pods. This would make the accelerometers easy and comfortable to wear continuously. Another assumption is that by year 2015, power efficient and standard wireless communication protocols (e.g. similar to WiBree [77] or ZigBee [78]) will exist that will allow the wireless wearable accelerometers to easily communicate with mobile phones.

3.2 Challenges for Each System Component

This subsection describes the research challenges and open questions in the areas of activity recognition and energy expenditure estimation. The subsection also discusses some of the most recent work in these areas from a hardware and algorithmic perspective.

3.2.1 Off-the-Shelf Devices to Recognize Physical Activity

One popular approach to the assessment of physical activity in free-living populations is ambulatory monitoring. Ambulatory monitoring can be classified as (1) the use of various types of motion sensors (e.g. pedometers and accelerometers [79, 80]), (2) the use physiological sensors such as heart rate (HR) [81, 82] and body temperature, and (3) the use of combinations of these (e.g. [48, 83, 84]).

Pedometers [85, 86] work by measuring the vertical motion generated at the hip by locomotion using a spring-suspended lever arm switch. They primarily assess locomotion or ambulatory activities by counting steps. However, pedometers only provide information about the number of steps performed and no information about upper body or non-ambulatory lower body activity.

Accelerometers assess physical activity by measuring the intensity of body segment, limb, or trunk acceleration that is proportional to muscular force. The intensity of motion measured is usually presented in the form of counts over a specific time period (or epoch) usually of 60 seconds that represent an estimate of the overall physical activity level. Unfortunately most commercially available activity monitors (accelerometers) either measure only rough physical activity levels (e.g. *light*, *moderate* and *vigorous*) or a small set activities (e.g. postures and ambulation). For example, the Actigraph activity monitor [32] is a uniaxial accelerometer normally mounted at the hip that provides activity counts at pre-defined time intervals (e.g. 60s) and that can be used to detect time spent in different activity levels (e.g. *light*, *moderate*, *vigorous*) using a variety of offline algorithms [87, 88]. Since this activity monitor is normally placed at the hip, it is best suited to measure physical activity involving overall body motion, such as ambulatory activities. A recently introduced algorithm by Crouter et al. [34] uses data from this device to recognize *sedentary*, *ambulatory* (e.g. *walking* and *running*) and *lifestyle* activities from raw activity counts and the coefficient of variation computed over 10s windows. Nevertheless, the algorithm runs offline and has difficulties detecting non-ambulatory lower body activity such as *cycling* mostly due to the difficulty of measuring non-ambulatory lower body activity using a single accelerometer at the hip as discussed by the authors.

Hearth rate (HR) monitors (e.g. [89]) are physiological sensors that can indirectly measure physical activity because heart rate (HR) is proportional to the intensity of movement and oxygen supplied to skeletal muscles [90]. Most heart rate monitors come in chest strap form factor and work by measuring the time intervals between peaks of the ECG signal (heart beats). Hear rate information can be utilized to measure time spent in different intensity levels (e.g. *light*, *moderate*, *vigorous*) using mostly subject specific regression equations (e.g. [91, 92]). Although heart rate monitors are adequate for short duration exercise sessions, their use and acceptance for prolonged periods of time is presently questionable because they are uncomfortable and their electrodes can cause skin irritation and dermatitis. Recently, Adidas, in collaboration with Polar, introduced a new chest-based heart rate monitor in a shirt form factor that may be more comfortable to wear than other existing chest strap monitors [93]. However, the technology is relatively expensive and is mainly targeted for people already physically fit such as runners and athletes.

One of the few commercially available device capable of recognizing activities such *ambulation*, *stationary biking*, *resting*, and *weight lifting* from several physiological sensors is the bodybugg armband [42, 94]. This device is worn at the dominant upper arm (biceps area) and uses a biaxial accelerometer and four additional sensors (skin temperature, galvanic skin response, heat flux, and ambient temperature) to recognize activities and estimate energy expenditure. To the best of the author's knowledge, only one published paper exists that evaluates the performance of the bodybugg at recognizing activities ([94]). In this technical report, the authors report recognition accuracies of

99.8% for ambulatory activities, 99.8% for stationary biking, 99.3% for resting, and 97.6% for bench weight lifting over 350 hours of data collected from several studies (number of participants not specified). The authors also point that the latest version of the proprietary algorithm (4.2) achieves accuracies of 90% for lying down and sleeping, 99.8% for road biking, and a total accuracy of 96.9%. The algorithms to detect activity are proprietary, and the web-based software available to end-users of the bodybugg system [95] only report contextual information for the following activities: *Lying down*, *sleeping*, and four MET intensity levels (*sedentary*, *moderate*, *vigorous*, and *very vigorous*). Finally, recent studies evaluating the performance of the device in estimating energy expenditure have found that the device significantly underestimate energy expenditure for lower body activities [96]. This is not surprising because the bodybugg is worn at the upper arm and consequently may not fully measure non-ambulatory lower body activity. This same limitation can be expected to impact any algorithm that attempts to use bodybugg data to detect specific lower body activities.

The Intelligent Device for Energy Expenditure (IDEEA) monitor [41] is another off-the-shelf device that, according to its creator, can detect postures (e.g. *lie*, *recline*, *sit*, *stand*, and *lean*), ambulatory activities (e.g. *walk*, *run*, *ascending*/*descending stairs*) and transitions between some activities [97]. Unfortunately, to the best of the author's knowledge, there is no independent validation of the performance of this device in recognizing activities. Moreover, the recognition algorithms are proprietary and cannot be re-used or improved upon. The device uses five biaxial accelerometers placed at the limbs and hip to recognize the activities of interest. In its current implementation, the device restricts the wearer's movements because wires are run from a data collection unit placed at the hip to each of the five accelerometers.

In summary, there are few off-the-shelf devices that allow the detection of physical activities, and those that are available detect only time spent at different physical activity levels or a limited set of postures and ambulatory activities. Only the IDEAA performs specific activity detection in real-time, but a cumbersome wired system is required.

3.2.2 Physical Activity Recognition Algorithms

Over the past couple of years, a wide variety of algorithms using supervised classifiers have been applied to the problem of recognizing physical activities from accelerometer data. The classifiers utilized in the algorithms have included generative classifiers such as dynamic and static Bayesian networks (e.g. [38, 39, 98, 99]), a variety of discriminative classifiers such nearest neighbors, decision trees, and support vector machines (e.g. [38, 40]), ensembles of classifiers (e.g. [37, 40]), and combinations of all of the above (e.g. [37]).

Among the most popular classifiers applied to the problem are dynamic Bayesian networks (DBNs). A DBN is formed when a static Bayesian network is 'unrolled' over several times slices (time intervals) and graphical dependencies are specified among them. These dependencies among consecutive time slices allow DBNs to capture first order temporal information of the problem at hand. DBNs also allow common sense knowledge of the problem to be encoded in the internal structure of the network by manually specifying the nodes and links of the network. For example, the work by Raj et al. [98, 99], handcrafted the internal structure of a DBNs to simultaneously recognize human activities from accelerometer data and location from GPS traces. Nevertheless, the results presented [98] indicate that the performance of the handcrafted DBN was no different from the performance of a hidden Markov Model (simpler DBN) learned automatically from the data and ignoring GPS traces for activity recognition. In addition, this approach is not scalable since it depends on experts coding common sense knowledge in the network structure that is likely to change depending on the activities to recognize. Due to the high computational complexity necessary to perform exact inference in DBNs, approximate inference algorithms such as particle filters [100] are often utilized [98, 99]. The number of particles used by this algorithm to perform inference can be adjusted depending on the processing power available on a particular device (e.g. in handheld devices); Nevertheless, its performance degrades as the number of particles is reduced.

Simpler DBNs such as hidden Markov models (HMMs) that have shown excellent performance in speech recognition applications have also been widely applied to classify activities from accelerometer data (e.g. [39, 45, 101-103]). The most common approach used is to train one HMM per activity to recognize using the Baum-Welch algorithm [104]. Once the models are trained, the classification is performed by choosing the model (HMM) that results in the highest log-likelihood over the observation sequence (sequence of feature vectors) as computed using the forward-backwards algorithm [104]. Even though this approach successfully incorporates intra-activity sequential information, its main disadvantage is its high computational requirements because one HMM per activity to recognize is required. Moreover, the forward-backwards algorithm has to be run as many times as there are activities (i.e., HMM models) to recognize so it is computationally expensive. Another disadvantage of this approach is that the number of internal hidden states needs to be specified a priori either using expert knowledge of the activities structure or learning it from training data using a cross-validation procedure.

Another approach to recognizing activities using HMMs is to use a single HMM where each internal state represents one of the activities to recognize [37]. In this approach, sequences of activities performed can be inferred online using the Viterbi algorithm [104] or particle filtering [100]. The main advantage of this approach is the incorporation of information about the transitions between activities (inter-activity sequential information) via the transition matrix of the system and the reduction of computational complexity (with respect to the use of one HMM per activity). One obvious disadvantage of this approach is that since only one hidden state is used to represent each activity, some internal temporal structure for each activity is lost (intra-activity sequential information).

Recent work has also attempted to recognize activities from accelerometer data applying a hybrid approach that combines discriminative and generative classifiers [37]. Discriminative classifiers differentiate among activities of interest by building a decision boundary or mathematical function that separates the features representing each class as much as possible with respect a given criterion. Generative classifiers on the other hand, first attempt to create a model that describes how the data for each activity is being generated before building a mathematical function to discriminate among the activities in the feature space. The combination of discriminative and generative classifiers is useful because discriminative classifiers are known to outperform generative classifiers in classification tasks [105], and generative approaches such as HMMs incorporate first order temporal information on how features or even activities transition over time.

Consequently, the approach improves discrimination among the activities of interest and performs temporal smoothing over the activity classifications. The results presented in the work by Lester et al. [37] show that overall accuracy was improved 4% with respect to the performance of the discriminative classifier alone (Adaboost combined with decision stumps). Unfortunately, this slightly higher performance comes at the expense of higher computational requirements, because the computational complexity of discriminative and generative classifiers is combined in this approach. Thus, for practical applications, it is questionable if the small improvement achieved in performance justifies the extra computation incurred by combining these two algorithms.

Other less computationally expensive Bayesian networks such as the naïve Bayesian classifier [106] have also been applied to detect activities from wearable accelerometers [38, 40, 45, 107, 108]. In the naïve Bayesian classifier, the class (or activity) node is the parent to all attribute nodes (or features) and thus, its main assumption is that all the attribute variables are conditionally independent given the class. It calculates the most probable class given the data (attributes) using Bayes rule. Despite its simplicity, this classifier has obtained excellent results with respect to more complex classifiers in realistic datasets [109-111], One disadvantage of simple Bayesian networks is that they do not capture temporal information automatically unless it is encoded in the features extracted. The main advantage is that naïve Bayesian classifiers are fast to train and also perform fast classifications in comparison with DBNs.

Decision tree (DT) classifiers such as the C4.5 algorithm [112] are among the most used to recognize activities from wearable accelerometers [38, 40, 45, 107, 113, 114]. This is because of the following reasons: (1) They learn classification rules that are believed to be easier to interpret than the ones learned by other methods such as neural networks (although for real-world problems, these rules can be quite complex and not trivial to interpret) (2) they incorporate information gain feature selection during the learning process that identifies the most discriminatory features to use, and (3) they perform fast classifications making them suitable for real-time implementation. A disadvantage of decision trees is that they tend to overfit the data if they are trained on small datasets and may not combine probabilistic evidence as well as other methods. Furthermore, decision trees are static classifiers that do not incorporate any temporal transition information of the modeled activities unless it is encoded in the features used.

When the activity recognition results presented in prior work are analyzed, it is found that their evaluation suffers from some limitations. For example, some pieces of work only use total classification accuracy as the performance measure and completely ignore the number of false positives generated by the algorithm as well as other important performance measures such as those discussed in Section 5.1. For instance, the work in [115] is among the few ones to quantify the number of false positives as number of insertions and substitutions over the recognized sequences of activities. Other prior work reports results on small datasets collected at laboratory settings from as few as five participants (e.g. [37, 40, 101, 103, 116]) or researchers themselves (e.g. [101, 103]), possibly introducing an unintentional bias towards simplification of how activities are performed. Most prior work only performs offline evaluation of the algorithms; exceptions are [41, 43, 45, 46, 59, 76, 117, 118]. There are also some important questions that have only been partially addressed in prior work. For example, what is a good compromise between classifier and feature set complexity to allow an acceptable level of real-time performance over a given set of activities? How the sliding window length impacts performance for different types of activities? What is the minimum set of sensors to use and where should they be worn to recognize a given set of activities? How sensor placement impacts performance for different activities? The answer to these questions strongly depends on the activities to recognize, so it is necessary to explore these questions over a large set of activities. Finally, no prior work to the best of the author's knowledge addressed the problem of recognizing the intensity of physical activity (e.g. *running* at 5mph vs. 6mph). The following paragraphs describe some few pieces of work that have explored some of the important questions raised in this paragraph.

The work by Bao and Intille [38] has been one of the few pieces of work to evaluate the activity recognition algorithms proposed on data collected for a relatively large set of 20 activities performed by 20 participants in non-laboratory settings during semi-naturalistic conditions. For each participant, an average of 90 minutes of data was collected. The authors report accuracies ranging from 85-95% for *ambulatory* activities, *postures*, and more complex activities such as *brushing teeth* and *folding laundry* using the C4.5 decision tree classifier. The same work also determined that user-independent recognition of twenty activities is possible from five biaxial accelerometers with an overall accuracy of 73%. The authors also perform experiments to determine the minimum number of accelerometers required to recognize the twenty activities of interest and find that it is possible to achieve an accuracy of ~81% just using two biaxial accelerometers located at the thigh and dominant wrist.

Identifying a minimal or reasonable number of sensors to recognize activities and their placement on the human body has been explored in at least three pieces of prior work [39, 45, 116]. The work by Kern et al. [116] analyzed 18.7 minutes of data collected for eight activities (*sit*, *stand*, *walk*, *upstairs*, *downstairs*, *handshake*, *writing* and *typing*) by one of the authors and found that sensors located at the dominant part of the body (e.g. right side for right handed people) are better at discriminating most of the eight activities. Similarly, the combination of a sensor at the hip and another at the ankle achieves the best performance in recognizing lower body activities. The work also found that during subject dependent training, single sensors at the lower body (e.g. hip, knee, and ankle) achieved similar performance so that they could potentially be used interchangeably to recognize lower body activities. When the performance of single sensors was analyzed in recognizing upper body motion, it was found that the single sensor with best performance was the one placed at the shoulder, and the best sensor combination was shoulder and wrist. The work by Blum [45] performed a similar analysis and found that just two accelerometers at the hip and dominant wrist are sufficient to recognize eight postures with an accuracy of 85% from a dataset consisting of 24 hours of data collected by the author. The work by Olguin Olguin [39] also performed an analysis of the number of sensors to use and their location using HMMs to recognize the following eight activities: *Sit-down*, *Run*, *Squat*, *Walk*, *Stand*, *Crawl*, *Lay down*, and *Hand movements.* Three accelerometers located at the hip, chest, and dominant wrist was used to recognize the activities. As expected the sensor combination with highest overall accuracy of 92% was the wrist+hip+chest sensor combination on data collected from three participants performing each activity three times. The results also indicate that the single accelerometer with best overall accuracy (62%) is the one at the chest. Adding another accelerometer either at the hip or dominant wrist improved overall accuracy to ~81%.

The work by Ravi et al. [40] explored the performance of different classifiers in recognizing activities such as decision tables, decision trees, support vector machines, nearest-neighbor, and naïve Bayes classifiers individually and in different meta-classifier configurations such as boosting, bagging, stacking, and plurality voting. The results presented were evaluated over data collected from two participants performing eight activities (*ambulatory activities*, *sit-ups*, *vacuuming* and *brushing teeth*) several times while wearing a single triaxial accelerometer at the pelvic region. In general, it was found that meta-classifiers outperformed base-level or single classifiers as expected. It was also found that boosted support vector machines (SVMs) achieve the highest overall accuracy of 73% followed by the naïve Bayesian classifier with an overall accuracy of 64% during subject independent evaluation. For subject dependent evaluation, the highest overall accuracy was obtained for plurality voting (99.6%) followed by Boosted SVMs (99.4%). The naïve Bayesian classifier also achieved a good overall accuracy of 98.9% during subject dependent training. By analyzing the difference between the performance of the naïve Bayes classifier and the Boosted SVMs of 9% for subject independent training and 0.5% for subject dependent training, the authors concluded that it was clear that meta-classification offers a significant improvement during subject independent evaluation.

The work by Huynh and Schiele [119] analyzed a the importance of five features and different window lengths (0.25-4s) to recognize six activities: *walking*, *standing*, *jogging*, *skipping*, *hopping*, and *riding a bus*. The data used to perform the experiments consisted on 200 minutes of data collected by two participants. The main finding of the paper, as expected intuitively, is that there is no single window length or feature that maximizes performance for all activities. Instead, the choice of window length and feature set to use depends on the activities to recognize. It was also found that one of the best features to use is the FFT coefficients, but that the coefficients to use depend on the activities being recognized. This is expected, since different activities are performed at different speeds and thus, are represented by different frequencies (FFT coefficients). The findings for the window length experiment performed in this work suggest that the best overall performance for all activities was obtained with window lengths between one and two seconds. This might be explained by the fact that the fundamental period of the activities explored in this work can be captured with these window lengths. It was also found that *standing* requires relatively short window lengths (e.g. 0.25 - 0.5s). Also, longer window lengths are required for activities with longer fundamental durations such as *skipping* and *hopping*.

The work presented in this thesis improves on prior work by exploring how various algorithmic and feature computation tradeoffs impact activity type recognition in a relatively large and complex dataset incorporating examples of 52 activities collected from 20 participants at two locations (gymnasium and home).

3.2.3 Existing Devices and Techniques to Measure Energy Expenditure

Real-time and reliable measurement of energy expenditure (EE) would create new health intervention opportunities, as described in Section 2.1.3. Presently, the methods that generate the most accurate measurement of energy expenditure are: (1) direct calorimetry, (2) indirect calorimetry [120], (3) doubly labeled water (DLW) [121], and (4) physical activity scoring using direct observation and the Compendium of Physical Activities [122]. Unfortunately, none of these methods can be applied to large-scale population studies because of their high cost, intrusiveness, complexity, and specialized resources and personnel required. For example, direct calorimetry estimates energy expenditure by directly measuring the heat released by living organisms at rest or during physical activity. Heat released from the body can be measured by confining subjects to a metabolic chamber equipped with specialized sensors. It can also be measured using infrared thermo sensitive cameras, but this technique is primarily employed in measuring EE in preterm infants [123]. Although direct calorimetry produces high quality estimates of EE, it is expensive, intrusive and difficult to perform since specialized equipment and personnel are required. Indirect calorimetry, also known as respirometry, estimates energy expenditure by measuring the volume of oxygen consumption (VO_2) and carbon dioxide production (VCO_2) in living organisms. The relationship between energy expenditure and oxygen uptake is linear because every cell in the human body requires oxygen to generate the energy required for cellular work (ATP). Indirect calorimetry is measured using either (1) closed respirometry or (2) open respirometry. In closed respirometry, O_2 uptake and CO_2 production are measured by placing the subject in a small sealed room (e.g. [124]). The main disadvantage of this method is its high cost and the confinement of the subject to a laboratory room that restricts and modifies his/her behavior. In open respirometry, O_2 uptake and CO_2 production are analyzed (after being collected using face masks or plastic canopies) using metabolic carts [125, 126] or portable indirect calorimeters (e.g. [125, 127]). The main disadvantage of open respirometry is that the equipment is expensive, uncomfortable, and obtrusive even when portable indirect calorimeters (e.g. [127, 128]) are used. Despite its disadvantages, indirect calorimetry is considered a reference method to measure EE and is one of the most widely used by the medical community.

The use of the doubly labeled water technique (DLW) is considered the 'gold-standard' in measuring total energy expenditure (TEE) in free living conditions because it does not interfere with individual's daily activities. This method consists of the oral administration of two stable isotopes (oxygen 18 (^{18}O) and deuterium (^2H)) to participants and the monitoring of their elimination rates from the body via urine samples. In this way, total carbon dioxide production can be determined and used to compute an estimate of total energy expenditure. Although the main advantage of this method is its non-intrusiveness, its main disadvantage is that it only provides an overall estimate of the total energy expenditure at the end of the measurement period (e.g. usually 7-18 days [47]) and no information about physical activity type, intensity, or duration. One important disadvantage of all the previously discussed techniques to estimate energy expenditure is that they provide no contextual information about the physical activities being performed. Knowledge of the physical activities performed by individuals and their associated intensities is important because it can be used to (1) improve the energy expenditure estimates, (2) to motivate behavior change, and (3) to better understand relationships between physical activity and behavior.

A method to estimate energy expenditure that provides rich contextual information about the activities performed is physical activity scoring using the Compendium of Physical Activities [122]. This technique involves recording the duration, intensity and frequency of physical activities and scoring these parameters by consulting the Compendium of Physical Activities [122]. The Compendium of Physical Activities contains the energy cost incurred in performing various activities and intensities in

METs. METs are defined as the number of calories expended by an individual while performing an activity in multiples of his/her resting metabolic rate (RMR). Thus, METs can be converted to calories by measuring or estimating and individual's RMR. Some limitations of this method in estimating energy expenditure are that (1) the energy expenditure values listed on the Compendium of Physical Activities only represent the average energy cost for the physical activities and the subject population explored in the Compendium of Physical Activities study, and (2) that other conditions on how the activity is performed such as terrain inclination and intensity levels not included in the Compendium of Physical Activities cannot be evaluated [47]. Furthermore, the accuracy of the energy estimate produced by this method strongly depends on the quality of the RMR estimate and the physical activity information collected. Despite these limitations, this method has been one of the most widely used in published medical research. The intensity, duration and frequency of physical activities can be best compiled through direct observation. Direct observation [129], considered the "gold standard" for assessment in medical and psychological research studying behavior in natural settings, does not suffer from selective recall if performed by trained observers. Direct observation techniques include a person following the subject and the use of continuous video, audio or sensor data recordings to acquire information related to the behaviors of interest in natural environments. Even though direct field observation can provide valuable qualitative and quantitative measures, it is costly, time-consuming, and disruptive. This technique also raises privacy concerns since researchers need to invade private settings such as the home.

Other less accurate methods that researchers have used to measure physical activity and energy expenditure in large subject population studies are: (1) self-reported information such as recall surveys, end of study interviews, and diaries, and (2) ambulatory monitoring using motion and/or physiological sensors. Recall surveys such as questionnaires (e.g. [130-133]) are widely used for assessment of behavior in naturalistic settings. However, this method is known to suffer from recall and selective reporting biases - users can often not remember what they did and/or do not report what they actually did. Furthermore, most questionnaires used in epidemiological studies don't provide detailed information on the type, intensity or duration of activities. End of study interviews consist of interviewing the participants at the conclusion of a study. Interviews have shown to be particularly effective for critiquing ideas or gathering information about the participants' tasks and activities if performed properly. Often however, participants know more than they say in a single or even several interviews [134], and will tend to have difficulty understanding and recalling how context impacts their behavior (i.e. exhibiting selective recall and selective reporting biases [135]). In fact, several studies have shown that is harder for participants to recall *moderate* or *light* activities than *vigorous* bouts of activities [136, 137]. While using diaries, participants write down what they do during the day either as they do it or at regular, finely-spaced intervals [138]. This method completely relies on the ability of participants to recall (from short and long term memory) the information relevant to the behaviors of interest. Diaries provide better data than questionnaires, recall surveys or end of study interviews but they are burdensome for the user and the quality of the data depends entirely on the participant's compliance. Recent improvements over paper diaries include web-based diaries, PDA-based diaries [139], and electronic experience sampling [140, 141]. These improved diaries are less susceptible to subject recall errors than other self-report feedback elicitation methods [135, 142]. Nonetheless, these also suffer from the disadvantages of self-report methods such as subject inconvenience, reporting bias, poor memory, and poor compliance [143]. The physical activity information collected using self-report can be converted to energy expenditure estimates by scoring the information using the Compendium of Physical Activities. Nevertheless, these EE estimates are usually coarse and less accurate than EE estimates computed from detailed physical activity information collected via direct observation.

One of the most popular methods to estimate energy expenditure in free-living populations is ambulatory monitoring using pedometers, accelerometers, and physiological sensors such as heart rate, body temperature, body flux, and galvanic skin response. Ambulatory monitoring offers some advantages over self-reported data such as reduced report bias and subject burden (when compared with diaries).

The number of steps measured using pedometers can be combined with demographic information (weight, height, age and gender) to produce rough estimates of energy expenditure due to ambulatory activity. Ambulatory activities such as walking account for a major proportion of daily energy expenditure [144], so pedometers are considered a good starting point for computing a daily energy expenditure estimate. One disadvantage of pedometers is that they are incapable of measuring energy expenditure due to stress effort in activities such as lifting heavy objects from the floor.

Similarly, the activity counts or acceleration values collected using accelerometers can be combined with demographic information and regression techniques [34, 47, 145-152] or physical models of the human body [153, 154] to produce energy expenditure estimates. The complexity of accelerometry to measure energy expenditure ranges from the use of single uniaxial accelerometers [35, 36, 155, 156], biaxial and triaxial accelerometers ([151, 157-161]), to the use of multiple biaxial or triaxial accelerometers [41, 49, 146, 148, 162, 163]. The previously discussed Actigraph activity monitor [32] is one of the most popular uniaxial accelerometers used to estimate energy expenditure in the medical community [34, 164, 165]. The only accelerometer-based device available off-the-shelf that measures energy expenditure using multiple accelerometers (five biaxial) is also the previously discussed IDEEA monitor [41]. As explained before, the system requires wires that restrict the wearer's physical movements and its current cost (~$4000) is prohibitive for large scale deployments. One disadvantage of accelerometers is that they cannot distinguish between the energy costs of performing activities involving different resistance levels or work loads such as *carrying* light vs. a heavy loads and *walking* downhill vs. uphill. Currently most accelerometers available off-the-shelf allow the collection of data in non-volatile memories from 1 to 42 days depending on the sampling rates used and are relatively accessible ranging from $70 to $400 dollars. However, no off-the-shelf accelerometers make the data available wirelessly for real-time processing. This is unfortunate because real-time data could allow the development of powerful interventions to increase energy expenditure in free-living. Table 3-1 presents a summary of the most popular ambulation monitoring devices used to estimate energy expenditure.

Heart rate information (e.g. beats-per-minute) can be converted to energy expenditure by generating subject dependent or independent regression equations between heart rate and volume of oxygen uptake (VO_2) as collected from laboratory experiments

Device	Sensors Used	Body locations	Storage Capacity (days)	Cost ($)
Pedometer Omron HJ-112 [85]	Spring-suspended lever arm switch	Waist	7	25
Pedometer Yamax Digiwalk CW-200 [86]	Spring-suspended lever arm switch	Waist, neck, ankle	0	20
Actigraph GT1M (previously CSA) [166]	Uniaxial accelerometer	Wrist, ankle or waist	42*	400-1500
Tri-trac (CT1 and RT3) [167]	Triaxial accelerometer	Waist	21	100-500
Actitrac, Digitrac and Biotrainer [157]	Actitrac and Biotrainer (biaxial), Digitrac (triaxial)	Wrist, ankle or waist	5-62	70
Actiwatch [168] (also ActiCal)	Uniaxial accelerometer and Light	Wrist, ankle or waist	11-44	1075
X-Max CalTrac [35]	Biaxial accelerometer	Waist	0	70-90
Tracmor [169]	Triaxial accelerometer	Wrist, ankle or waist	NA	NA
Actillume Actigraph [155]	Uniaxial accelerometer And light	Wrist, ankle or waist	NA	NA
Bodybugg armband [158]	Biaxial accelerometer + other sensors	Dominant upper arm	14	400-600
IDEEA [41]	Five biaxial accelerometers	Body segment, limb or hip.	2.5	4000

Table 3-1: Most popular ambulatory monitoring technologies available off-the-shelf to estimate energy expenditure and measure physical activity. NA stands for non applicable.

[32, 47, 170, 171]. The main challenges in using heart rate information to estimate energy expenditure are intra-individual and inter-individual variations in heart rate. For example, intra-individual variations in heart rate include changes in heart rate due to emotional states, nicotine, digestion, altitude and temperature [172]. Inter-individual variations in heart rate are mainly due to differences among individuals in fitness level, age, sex, and gender [173]. Heart rate also exhibits a delayed response to physical activity and remains altered once a physically demanding activity has finished. Finally heart monitors do not provide information about the type or frequency of physical activities (e.g. running at 6mph for 5min).

There have been several attempts to estimate energy expenditure by combining several sensor modalities [83, 96, 174, 175]. For instance, one of the few device of this kind available off-the-shelf to estimate energy expenditure during free-living is the previously discussed bodybugg armband [158]. The bodybugg combines information from its five sensors with proprietary algorithms to estimate energy expenditure. Even though energy expenditure comparisons between the bodybugg and indirect calorimetry have shown low error rates (10-15%), two recent validation studies suggest that the device's energy expenditure estimate may not be consistent across different types of activities [176, 177]. Furthermore, the energy expenditure algorithm used by the bodybugg Armband has been found to significantly underestimate lower body activity (e.g. *cycle ergometry*) and overestimate upper body activity (e.g. *arm ergometry*) [96]. This is because its location at the upper arm prevents it from detecting lower body motion generated by non-ambulatory activities. In late 2007, a new digital watch was introduced that allows the bodybugg system to display real-time information about energy interventions, the bodybugg system presently does not make the real-time data available to other applications nor does it use the data to enable physical activity interventions.

Method	Advantages	Disadvantages
Direct calorimetry	-Very accurate	-Expensive -Intrusive -Restricts daily activity -Requires specialized equipment and expertise.
Indirect Calorimetry	-Very accurate	-Expensive -Cumbersome to wear (portable versions) -Restrictive (room calorimetry) Requires specialized equipment and expertise.
Doubly labeled water	-Very accurate -Unobtrusive since does not interfere with subject's daily activities.	-Expensive ($1500 per person) -Only measures average TEE over periods of 1-3 weeks. -Requires specialized equipment and expertise.
Physical Activity Scoring Using the Compendium of Physical Activities	-Provides qualitative and quantitative information. -Provides contextually rich information (activity data) -Relatively low cost if self-reported information is used -Relatively easy to administer if self-report is used	-Expensive (direct observation) -Disruptive (direct observation) -Time consuming (direct observation) - Suffer from selective recall and reporting bias (self report) - Burdensome for subjects (if diaries or experience sampling is used) -Possible compliance problems (diaries and experience sampling)
Pedometry	-Small and easy to wear technology -Low cost and off the shelf availability.	-Crude EE estimates based on ambulatory activity. -Does not measure upper body activity or muscular contraction.
Accelerometry	-Small and easy to wear technology -Moderate cost and off the shelf availability. -Can provide contextual information	-Only measures motion of body segment they are attached to. -Do not measure EE related to muscle contraction, work load, or resistance effort -Conversion of acceleration counts to EE is challenging.
Heart rate monitors	-Moderate cost - Physiological parameter that provides intensity, frequency and duration information about physical activity. -Low burden for short data collections.	-HR varies within individuals due to factors other than physical activity such as emotional states, nicotine, temperature, etc. -HR varies across individuals due to differences in fitness level, age, gender, etc. -Compliance issues in longitudinal studies. -Not clear how to convert HR to EE in a subject independent manner

Table 3-2: Comparison of advantages and disadvantages of existing methods used to estimate energy expenditure.

In summary, the energy expenditure estimation methods using various forms of ambulatory monitoring previously reviewed all have their strengths and weaknesses, and while they are adequate for some purposes, none are satisfactory for accurately determining energy expenditure over weeks or months of a free-living population. As a result, this work explores how energy expenditure estimation can be improved to be more accurate and amenable for longitudinal use in free-living. This is achieved by investigating the following questions: (1) Which features computed over the accelerometer data provide better estimates? (2) What sliding window lengths (epochs) are better for estimating energy expenditure? (3) Do multiple accelerometers at different Body segments improve the estimates? (4) Do non-linear regression techniques improve the estimates significantly? (5) Do activity dependent regression models improve energy expenditure estimation? Finally this work also explores if the combination of acceleration and heart rate data improves the energy expenditure estimates.

3.2.4 Energy Expenditure Estimation Algorithms

There exists a large body of algorithmic approaches to estimate energy expenditure from accelerometer data. These approaches can be broadly classified in (1) those that use physical models of the human body, and (2) those that use regression algorithms. The algorithms that use physical models of the human body to estimate energy expenditure (e.g. [153, 154]) usually attempt to first estimate velocity or position information from accelerometer data by integrating the accelerometer signals. Unfortunately, this is a difficult task since errors in the acceleration signal accumulate rapidly over time due to the integration (summation) of values containing small amounts of error. Once velocity and/or position are known, these algorithms use kinetic motion and/or segmental body mass to estimate energy expenditure. Some algorithms such as [154] attempt to circumvent the problem of integrating the accelerometer signal to estimate velocity or position by learning the coefficients of the kinetic equations describing the human body motion directly from training data (acceleration and energy expenditure data). Although the use of physical models of the human body in the estimation of energy expenditure makes perfect sense, no prior work to the best of the author's knowledge has shown that this approach has considerable advantages over the use of regression algorithms.

Regression algorithms, on the contrary, estimate energy expenditure by directly mapping accelerometer data to energy expenditure using linear and/or non-linear models. In their simplest form, these algorithms attempt to estimate energy expenditure from a single accelerometer (usually an Actigraph [32]) placed at the hip using simple linear regression (e.g. [145-148]). Some prior work also uses multiple linear regression models to improve the estimates [149]. Estimating energy expenditure from an accelerometer at the hip using linear regression may not fully capture the complex relationship between acceleration and energy expenditure [34, 178]. As a result, some work has explored the idea of using non-linear regression models to estimate energy expenditure from a single accelerometer at the hip [34, 150, 151, 179]. Most prior work estimates energy expenditure over sliding windows (epochs) of one minute in length and uses only the number of acceleration counts (per minute) to estimate energy expenditure. However, some recent work suggests that the utilization of shorter window lengths might improve the estimates of energy expenditure [34, 180]. Other recent work [34, 152] also suggests that computing more complex features over the accelerometer signal such as the coefficient of variation, the inter-quartile interval, the power spectral density over particular frequencies, kurtosis, and skew can improve the estimates of energy expenditure by capturing motion information that would otherwise be lost if simple accelerometer counts are used to estimate energy expenditure.

Presently, the two state-of-the-art algorithms to estimate energy expenditure from a single accelerometer mounted at the hip are the work by Crouter et al. and Rothney [34, 152, 181]. The main idea behind the algorithm presented by Crouter et al. [34] is to classify activities into three categories before estimating energy expenditure: (1) *sedentary* activities, (2) ambulatory activities such as *walking* and *running*, and (3) *lifestyle* activities. Once the activities are recognized, different regression models are applied for each activity type to estimate energy expenditure. The algorithm recognizes sedentary activities by simply setting a threshold over the acceleration counts. Once they are recognized, they are assigned an energy expenditure equivalent of 1 MET. Ambulatory activities such as *walking* and *running* are differentiated from *lifestyle* activities by setting a threshold over the coefficient of variation (CV) as computed over 10s sliding windows. If *walking* and/or *running* are detected, a linear regression model is applied to estimate their energy expenditure; otherwise, an exponential regression model is applied to estimate the energy expenditure associated with *lifestyle* activities. The work by Rothney [152, 181] estimates energy expenditure by first computing features over the accelerometer signal such as the coefficient of variation, the inter-quartile interval, the power spectral density over particular frequencies, kurtosis, and skew and then uses these features to train an artificial neural network (non-linear regression model) to estimate energy expenditure. The artificial neural network is trained on nearly 24 hours of data collected from 102 participants which makes this work one of the most extensive with respect to amount of data used. This work also incorporates demographic data as features into the model (neural network) to compensate for inter-individual variations in energy expenditure. It is important to consider inter-individual variations because two individuals performing the same activity might generate similar acceleration signals but different energy expenditure signals due to differences in age, gender, height, weight and ethnicity. One clear disadvantage of these two methods to estimate energy expenditure is that they have difficulties capturing upper body and non-ambulatory lower body motion because of the use of a single accelerometer at the hip. For example, the work by Crouter et al. [34] completely excluded the *cycling* activity from analysis (even when data was collected for it) because the accelerometer at the hip did not produce any readings for this activity. Furthermore, the largest errors obtained in this work occurred for activities involving upper body motion such as *basketball*, *racquetball*, *vacuuming*, and *mowing the lawn*. The work Rothney [152, 181] did not present performance results per activity, so the performance over the *biking* activity cannot be determined. Other prior work also indicates that accelerometers mounted at the hip significantly underestimate lower body activities such as *cycling* and *sliding* [33].

There has also been some prior work attempting to combine the advantages of accelerometers and heart rate monitors in estimating energy expenditure [48, 83, 84, 174, 175, 182-186]. For example, the work by Strath et al. [83, 174] combined accelerometer and heart rate data by employing two different HR-EE regression equations depending on upper body or lower body activity. Upper body activity was detected using one accelerometer at the arm and lower body activity by an accelerometer at the leg. More recent work by Brage et al. [46, 175] takes advantage of the synchronization between heart rate and accelerometer data by applying a branched regression model technique to combine heart rate and accelerometer data. The branched modeling technique weights two different regression equations differently depending on the intensity of motion experienced by an accelerometer at the hip and the intensity of physical activity detected by the heart rate monitor. One equation models accelerometer data only and another heart rate data only. The work by Strath et al. and Brage et al. showed significant improvements over the isolated use of accelerometer or heart rate data. Section 5.6.1 will later summarize some of the most recent results obtained when estimating energy expenditure from accelerometers and heart rate monitors.

3.2.5 Exploiting Real-Time Physical Activity Feedback to Motivate Behavior Change

Existing technologies that provide automatic feedback related to physical fitness unobtrusively during free-living are mostly designed for those individuals who have already achieved a good level of physical fitness such as athlete runners. For example, the Nike+iPod sport kit [19] allow individuals to track the speed, distance, pace and calories burned while running by slipping a motion sensor in the Nike+iPod ready shoe and snapping a wireless receiver unit into the iPod nano MP3 player. Another recently introduced technology is the Adidas+Polar training system [20] that integrates a heart rate monitor on a shirt, a stride sensor on a shoe, and a wristwatch computer to monitor work out zones based on heart rate, speed and distance data. The utilization of these new portable technologies is a good example of real-time biofeedback as a way to motivate behavior modification since heart rate data and energy expenditure is used to maintain the work out at particular zones. Still, the challenge remains to come up with technologies that can be used by those who have difficulty maintaining healthy levels of physical activity every day.

Algorithms that automatically recognize activities and estimate energy expenditure using portable devices such as mobile phones offer the potential to provide longitudinal feedback related to physical activity and diet during free-living conditions. In its simplest form, feedback can be presented in the form of graphs showing how a person is getting meaningful physical activity. Mobile technologies that recognize activities or estimate energy expenditure could deliver "just-in-time" interventions at the point of decision [27, 28, 187]. For example, mobile devices could motivate increases in physical activity by detecting physical activities of interest (e.g. *walking*) and utilizing positive feedback combined with persuasive techniques [188] to encourage increases in activity levels (e.g. *walking at 4mph* vs. *walking at 3mph*.). Recent applications have started to explore this idea. The work by Bickmore et al. [189] developed an animated PDA-based advisor to motivate increases in physical activity over the course of a day. The authors are planning to extend this work by adding an accelerometer to provide positive feedback in real-time after a bout of *walking* or to encourage compliance when users have previously committed to exercise at a given date/time. One recently developed application exploring real-time feedback on mobile phones is UbiFit Garden [190]. In this work, a hip-worn accelerometer-based sensing device [44] is combined with a mobile phone to provide real-time feedback related physical activity performed over the course of a day. The feedback is graphically represented as a garden with flowers representing levels of physical activity and butterflies representing physical activity goals.

Another area in which real-time activity recognition and energy expenditure algorithms can be applied to provide valuable feedback to users in non-exercise activity thermogenesis (NEAT) [51, 191]. This relatively new area of research has attracted much interest because it suggests that small increments in non-exercise physical activity such as *standing*, *brisk walking*, *using stairs* and *fidgeting* can accumulate over the course of a day to boost overall energy expenditure. In fact, a recent study [192] demonstrated that the caloric difference between obese sedentary individuals and obese sedentary individuals increasing NEAT activity levels can be as high as 300kcal per day. Other studies also suggest that replacing TV watching by moderate non-exercise physical activity can lead to reductions in body weight [193, 194]. Activity recognition algorithms combined with energy expenditure algorithms might be used to provide detailed feedback about the number of calories burned per activity performed so that individuals can better understand how they expend their daily energy, and perhaps, plan increases in non-exercise activity that fit their daily routine.

Finally, another interesting application of real-time feedback is to combine it with fun games to make it more amenable to children and adults [6]. This approach attempts to replace the sedentary behaviors usually involved in playing video games with workout routines or small increases in overall body motion. For instance, Dance Dance revolution is a video game that takes advantage of these concepts to motivate physical activity while playing a videogame. As arrows move across the screen representing dance movements, the player steps on the corresponding arrows printed on a 3-foot-square metal mat that replaces the conventional game pad. The game has been so successful that has sold about 2.5 million copies, and by 2009 more than 750 public schools will begin using the video game to motivate physical activity among their students [195]. The new Nintendo Wii console [67] can be used in a similar way requiring users to perform arm-gestures to control the gaming interaction. Real-time sensing may create new opportunities for games that encourage NEAT during everyday activities such as television watching [196].

3.2.6 Ensuring Ease-Of-Use

Ensuring ease-of-use involves addressing factors such as comfort of the sensors, the number of sensors used and their location in the human body, training time requirements of the algorithm, capability of real-time recognition of activities, and real-time recognition delay. Wearability of sensors has received little attention in prior work because sensors have been mainly used during pilot research studies of relatively short duration. For example, most existing wireless accelerometers capable of broadcasting data in real-time (e.g. [44, 197, 198]) have cumbersome form factors and casings ill-suited for longitudinal use. Some existing off-the-shelf devices (e.g. [32, 36, 157]) have more convenient form factors, but they are incapable of making the data available in real-time. The system presented in this work uses wireless accelerometers (MITes [199]) that have smaller form factors than most existing accelerometers and suitable casing and battery life to allow continuous data collection over the course of a day during research studies.

Previous work making recommendations for the minimum number of sensors to use and their locations on the body has been performed the analysis over a limited set of activities and little data collected from one to three subjects [39, 45, 116]. The exception is the work in [38], which analyzes results over different combinations of sensors for 20 activities on data collected from 20 participants. This work continues to explore that question using a significantly larger dataset of 52 activities on data collected from 20 participants at two locations: a gymnasium and a home.

To the best of the author's knowledge, no prior work has explored the training data requirements of activity recognition algorithms because it has been assumed that subject independent recognition of activities will be possible one day. On the contrary, this work explores if it is possible to create subject-dependent activity recognition algorithms that require small amounts of training data and if the data required has the potential to be provided interactively. As a result, this work performs experiments to determine the minimum amount of training data required to recognize an activities reliably during subject dependent training.

Few accelerometer-based activity recognition algorithms presented in prior work have been tested in real-time. For example, the e-watch [43, 117] is one of the few research technologies with a convenient form factor capable of recognizing activities in real time. However, given its location and form factor (wristwatch), it can mainly recognize upper body activities and ambulatory activities involving overall body motion. Other research technologies capable of real-time performance use a single accelerometer at the hip to perform the inference (e.g. [59, 118]). As a result, they are constrained to recognize activities involving overall posture, and motion such as walking and running. The few real-time activity recognition systems that use several accelerometers to perform the recognition (e.g. [41, 45, 76]) recognize activities that have been fixed a priory, and thus the systems do not allow users to specify and train new activities to recognize. In fact, to the best of the author's knowledge, no prior work has presented a real-time system to recognize activities that allows users to specify and train the activities that they want to be recognized. The closest system is presented by Feldman et al. [46], but the activities targeted by the system are mainly upper body activities (hand gestures). Therefore, this work develops an activity recognition and energy expenditure estimation system that uses one or several accelerometers and evaluates the performance of the activity type recognition algorithm in real-time during a short study where participants train and test the recognition algorithms to recognize different activities of their interest themselves.

Finally, real-time classification delay is important to consider because the longer the user has to wait for a recognition result, the less likely it is that users will have the patience to train and test the performance of the algorithms in real-time. Similarly, longer recognition delays degrade the performance of other applications (e.g. interventions) that may use the recognition results and require high-precision prompting. This work includes an analysis of how the sliding window length impacts the recognition performance; a window length is selected that minimizes classification delay while maximizing performance.

3.3 Summary of Technological Limitations to Enable Real-Time PA Type and Intensity Detection

In summary, the combination of easy-to-use and easy-to-wear sensors and activity recognition and energy expenditure algorithms that can run in existing mobile phones would allow the development of interventions that (1) have the potential to scale to large populations due to the utilization of mobile phones and low-cost sensors that can be mass produced easily. (2) that are easy to use and impose minimum burden on the user, (3) that provide end-user value on a daily basis by presenting real-time information at the point of decision (related to physical activity and energy expenditure) that is usually unknown to individuals, so that people continue to use them for months or years with little effort, (4) that could potentially incorporate persuasive techniques to engage the user in his/her interactions with the system, and (5) that are fun, easy-to-use and engaging.

The types of interventions previously mentioned have not been developed yet due to hardware and algorithmic limitations. For example, some of the hardware limitations that have prevented these interventions are: (1) *Unavailability of real-time data*. Most existing accelerometers available to measure physical activity store the data in onboard memories and do not make the data available in real-time. The only few accelerometers that make the data available in real-time are relatively expensive technologies in a prototype stage such as [197, 198]. Making the data available in real-time is important because other applications can use it to trigger just-in-time interventions. (2) *Unavailability of technologies to receive data from multiple sensors simultaneously*. Most existing technologies that allow the collection of data from multiple accelerometers (e.g. [32]) rely in offline analysis of the data. This is because data is stored locally in the devices and thus, data has to be first downloaded from the multiple devices and synchronized offline. There are also few technologies that allow the simultaneous reception of data from several sensor types (e.g. accelerometers and heart rate monitors). This prevents real-time applications that use multiple data types in real-time. Naturally, if data cannot be received from multiple accelerometers and/or sensor types in real-time, applications that use this data cannot be implemented. (3) *Inconvenient form factors*. Existing accelerometers have inconvenient form factors to be used inconspicuously for prolonged periods of time.

Some of the algorithmic or software limitations that have prevented real-time interventions are: (1) *Coarse estimates*. Most existing technologies to measure physical activity provide too coarse of an estimate to allow useful applications. For example, pedometers [85] only provide rough estimations of ambulatory energy expenditure and single accelerometers at the hip have difficulties capturing upper body and non-ambulatory lower body motion. As a result, they usually underestimate energy expenditure during lifestyle activities [200]. (2) *Limited or no contextual information.* Technologies available to measure physical activity provide limited or not contextual information about the type, intensity, and duration of the physical activities being performed (e.g. Actigraph [32], and the bodybugg [42]). Contextual information about physical activities is important for educating the user about physical activity patterns, for motivating a positive behavior change, for estimation of energy expenditure, and for the development of powerful physical activity interventions that are triggered based on the activities being performed. (3) *Lack of efficient algorithms that run in real-time on low-processing power devices*. Most algorithms available for recognizing activities and estimating energy expenditure have been implemented to run offline and have not been tested for real-time performance. As a result, data has to be downloaded from the data collection devices before feedback related to physical activity and energy expenditure can be obtained. This is inconvenient for both end-users and researchers during large-scale longitudinal studies.

There are also some open questions that have prevented the development of real-time interventions related to physical activity. For example, the number of sensors and their placement in the human body required to recognize activities and to estimate energy expenditure is still unknown. Obviously, the answer to this question depends on the target activities, but there is no prior work that analyzes the answer to this question over a large set of activities. It is also not clear what computationally efficient algorithms achieve the best performance at recognizing activities and estimating and estimating energy expenditure and how their performance compare to more complex state-of-the-art algorithms. It is also unclear what set of features need to be computed to recognize activities and estimate energy expenditure efficiently and with good performance from accelerometer data. Finally, the impact of utilizing different sliding window lengths in recognizing activities and estimating energy expenditure has not being explored in full detail. The work presented in this thesis explores the answer to these questions by evaluating the recognition and energy expenditure estimation for a set of 52 activities and subsets of them.

4 Approach and Procedure

This section presents an overview of the design of the activity recognition and energy expenditure estimation systems presented in this work. The section also describes the research approach followed to collect the necessary data to develop and evaluate these algorithms

4.1 Overview of Research Approach

The procedure followed in this work to develop the activity recognition and energy expenditure algorithms consisted of three steps. (1) First, activity and energy expenditure data were collected from 20 participants at a gymnasium and residential home to develop train and test the algorithms. At the gymnasium, data about exercise related physical activity were collected under relatively controlled conditions because several stationary exercise machines are used to collect the data (e.g. cycling, rowing, and treadmill machines). During the home data collection, participants performed a variety of everyday household activities under more naturalistic conditions. (2) Once the data were collected, a set of systematic experiments was performed to determine a reasonable set of activity recognition and energy expenditure algorithm parameters that enable real-time performance. Some of these parameters include the classifier (or regression algorithm), the signal processing techniques, the sliding window length, and the feature set to use. Also, experiments were performed to determine the minimum set of sensors to use, sensor placement on the body, and the impact on performance when heart rate data were incorporated. The experiments were organized so that each incrementally answers a relevant question about the algorithm parameters, starting from the most restrictive parameters (e.g. classifier or regression algorithm, feature set) and moving to the least restrictive parameters (sensor modality, window length). (3) Finally, once all the parameters were selected by running offline experiments, the final activity recognition algorithm was implemented on a laptop computer and its real-time performance was evaluated in a small feasibility demonstration.

4.2 Overview of System Design

The system presented in this work consists of two mayor components: (1) A real-time physical activity recognition system, and (2) a real-time energy expenditure estimation system. Both systems recognize activities and estimate energy expenditure from data provided by several wireless accelerometers placed at different body locations. In some cases a heart rate monitor is also used. The physical activity recognition system recognizes a variety of everyday postures, exercise routines, and household activities. The energy expenditure estimation system converts overall body motion (acceleration) and heart rate into energy expenditure estimates (in METs) over the course of a day. The following sections describe the wearable sensors used and the data collection protocols followed to collect the necessary data to develop and evaluate the activity recognition and energy expenditure estimation algorithms.

4.2.1 Wearable Sensors

The wearable sensors used to collect the necessary data to develop and evaluate the activity recognition and energy expenditure algorithms were: (1) a wireless sensing platform called MIT environmental sensors (MITes) [199], and (2) some off-the-shelf sensors such as the MT1 Actigraph [32], the HJ-112 pedometer [201], the bodybugg armband [202], and the Cosmed K4b2 indirect calorimeter [203]. The following sections describe these sensors in more detail.

4.2.1.1 MIT Environmental Sensors (MITes)

The MIT environmental sensors (MITes) [199] were used to collect the accelerometer and heart rate data. The wireless accelerometers measure 3-axis acceleration in a range of ±2G with a 9-bit resolution. They are small (3.2x2.5x0.6cm), light (8.1g including battery), and easy to wear without constraining the wearer's movements. The battery life on a CR2032 battery is up to 31 hours. The MITes toolkit also includes a heart rate transceiver powered by a 9V battery that converts the beats per minute (BPM) data from a Polar wearable chest strap transmitter (WearLink) to the same format as the accelerometer data and forwards it to the same receiver used by the accelerometers in real-time. The wireless receiver included in this kit is small (see Figure 4-3), and can be easily attached to any USB port of a PC/Computer or mobile phone with USB host capabilities. The wireless link uses 16-Bit CRC error checking and consequently, the probability of data corruption due to noise is low. When CRC detects packet corruption, the packet is discarded. The raw data broadcasted by the MITes sensor nodes (accelerometers and heart rate transceiver) are time stamped after reception by the data collection software running on the laptop computer where the wireless receiver is attached. The sampling rate of the sensors depends on the number of sensors used per receiver (samplingRate=180Hz/numberOfSensors). As a result, during some data collection protocols followed in this work, two receivers are used (four sensors per receiver) to achieve a relatively high sampling rate of 45Hz when collecting data from seven accelerometers and a heart rate monitor. Figure 4-1a shows an image of the MITes wireless accelerometers and Figure 4-1b an image of the heart rate transceiver with corresponding 9V battery attached.

4.2.1.2 The MT1 Actigraph

The MT1 Actigraph accelerometer [32] is a small (3.8 x 3.7 x 1.8cm.) and lightweight (27g) uniaxial accelerometer that can measure accelerations in the range of 0.05–2 G sampled at 30Hz and band-limited between 0.25–2.5 Hz with a 12-bit resolution. This accelerometer and its previous version (the CSA activity monitor) are the commonly used for physical activity and energy expenditure studies. The MT1 Actigraph is shown in

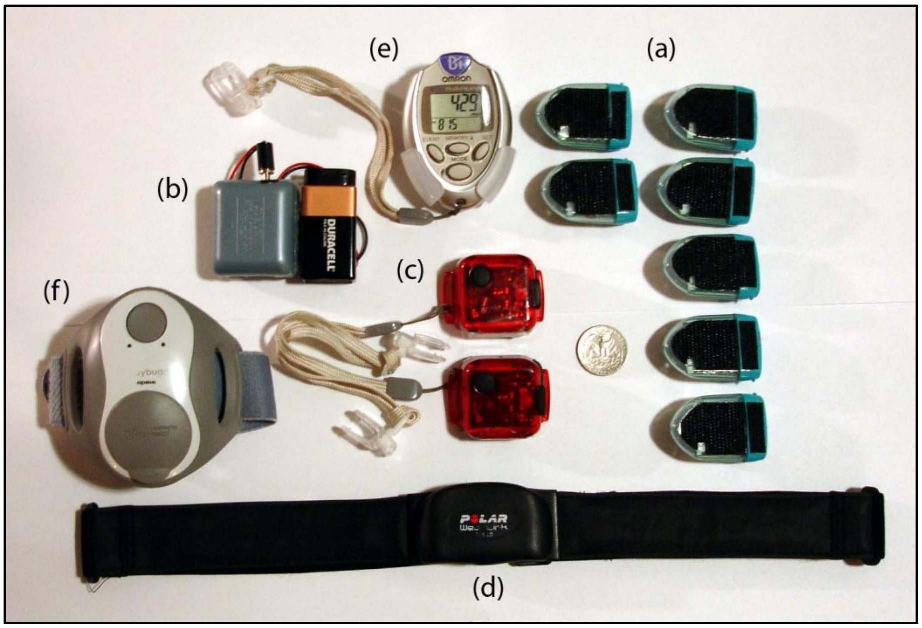


Figure 4-1: Wearable sensors used during the data collections. (a) Wireless accelerometers, (b) heart rate transceiver, (c) MT1 Actigraphs, (d) Polar WearLink chest strap heart rate monitor, (e) HJ-112 pedometer, and (f) the bodybugg armband.

Figure 4-1c. During the data collection protocols, participants wore either one Actigraph at the hip or two Actigraphs placed at the dominant wrist and dominant side of the hip. The Actigraphs were set to record data using one second epochs (1s windows), and they were synchronized immediately before the data collection with the computer collecting MITes data.

4.2.1.3 The Polar Chest Strap Heart Rate Monitor

The Polar WearLink chest strap heart rate monitor [204] was used during the data collections to measure participants' heart rate in beats-per-minute (BMP). This heart rate monitor has been found to be a valid instrument for measuring heart rate in several studies [205-207]. The Polar WearLink chest strap is shown in Figure 4-1d. Before utilizing the heart rate data collected using the WearLink chest strap, a 15s running average filter was applied to the data to minimize noisy readings.

4.2.1.4 The Cosmed K4b2 Indirect Calorimeter

The Cosmed K4b2 indirect calorimeter [125] is an apparatus that measures oxygen uptake (VO_2) and carbon dioxide (VCO_2) production by means of a face mask. VO_2 values (in ml/min) can be converted to resting metabolic equivalents (METs) by dividing by the subject body weight and 3.5 (One MET is equivalent to 3.5ml of VO_2 per kilogram per minute). The device weighs less than 1kg and is composed of a face mask, a data collection unit, and a rechargeable battery. Figure 4-4 shows an example of how participants wore the Cosmed K4b2 system. The data collection unit and battery pack were affixed to the participant's chest using a special harness consisting of adjustable belts. Before the data collection, the equipment was calibrated according to the manufacturer's specifications and synchronized with the time of the computer saving MITes data. Data were recorded in the unit's memory and later downloaded to a PC computer. The Cosmed device provides breath-by-breath data that are usually averaged over 30-60s intervals during energy expenditure research studies (e.g. [200]). In this work, a 15s running average filter was applied to minimize noisy readings. To account for the weight of the Cosmed K4b2 device and the other sensors used, 0.99Kg was added to the participant's weight in all MET calculations. The Cosmed K4b2 device has been found to be a valid and accurate device to measure energy expenditure in prior studies [200, 208, 209]. However, the quality of the measurements obtained strongly depends on the quality of the attachment of the face mask to participants.

Prior work utilizing the Cosmed K4b2 indirect calorimeter to measure energy expenditure has found standard deviations per activity ranging from 0.13 to 1.63MET. For example, the work by Bassett et al. [200] measured standard deviations per activity ranging from 0.31 to 1.58 MET for a set of 20 activities including household and exercise activities with moderate intensities. The work by Strath et al. [174] found standard deviations between 0.4 to 1.1MET over 14 lifestyle activities, and the work by Crouter et al. [34] standard deviations between 0.13 and 1.63MET for 18 exercise and lifestyle activates. The standard deviations obtained for the data collections performed in this work are discussed in Section 5.6.2.

4.3 Activity Recognition Algorithms

The process of recognizing activities from sensor data can be described in five steps: (1) signal processing, (2) signal or data segmentation, (3) feature computation, (4) classification, and (5) temporal smoothing. The first step is signal processing and, in the case of wireless sensor data, it usually includes band-pass filtering of the signals to eliminate undesirable noise and signal interpolation to fill out sensor values lost during wireless transmission. Depending on the sensors used, signal processing could also include signal calibration to compensate for slight sensor-to-sensor variations in output values due to hardware differences.

Signal segmentation refers to the process of grouping sensor values over time. This is necessary because features are computed not over single sensor values but over sequences of sensor values accumulated over time. Some common approaches to signal segmentation are the use of sliding windows, overlapping sliding windows, and signal spotting. The sliding windows technique consists on accumulating the sensor data over windows of specific length, where there is no time overlap between consecutive windows. Overlapping sliding windows, on the contrary, allow for some overlap between consecutive windows (e.g. 50%). Overlapping sliding windows are sometimes used because they are believed to minimize the edge conditions that arise when partitioning the data into independent sequential windows. Sliding windows and overlapping sliding windows have shown to be useful for analyzing periodic signals generated by repetitive motion such as *running* [37, 38, 40, 45, 103, 210, 211]. The length of the windows used in these two segmentation techniques can vary depending on the activity being recognized from less than one second to a minute or longer. The length of the window introduces a real-time recognition delay equivalent to the duration of the window. The longer the window duration is, the longer the real-time recognition delay will be. Signal spotting [115, 212, 213] is widely applied in gesture recognition where the goal is to identify the start and end times of rarely occurring movements of interest from a stream of non-relevant signals or movements. In a simple manner, signal spotting could be implemented by, for example, setting a threshold over the variance of the signals for a given window of time. This would allow the identification of 'chunks' of signal data where the amount of motion observed is significant.

Features must be computed from the segmented sensor data to capture important temporal and spatial relationships. How these features are computed impacts the performance of the pattern classification algorithms. In fact, the features extracted are as important as, if not more important than the classifiers used to obtain good performance. Examples of time and frequency domain features often extracted include variance, mean, correlations, energy, entropy, and FFT coefficients [37, 38, 40, 103, 210, 211], among others.

Once features are computed, pattern classification algorithms are employed to discriminate among the activities of interest. There exist a wide variety of generative and discriminative classification algorithms, with different computational requirements and discriminatory power. Discriminative classifiers differentiate among activities of interest by building a decision boundary or mathematical function that separates the features representing each class as much as possible with respect a given criterion. Generative classifiers on the other hand, first attempt to create a model that describes how the data for each activity is being generated before building a mathematical function to discriminate among the activities in the feature space. Some examples of generative classifiers include Bayesian networks (e.g. the naïve Bayes classifier [106]) and dynamic Bayesian networks (e.g. hidden Markov models [214]), and some examples of discriminative classifiers include boosting classifiers (e.g. Adaboost [215]), decision tree algorithms (e.g. C4.5 classifier [112]) and support vector machines [216].

The final and sometimes optional step in activity recognition consists on performing temporal smoothing. Since classifications are performed over small windows of data and usually those windows are each considered independently of the others, the classification results usually contain spurious classifications. For example, if *running* is performed over ten consecutive windows, a classifier might confuse *running* with *walking* for a small subset of these windows. The confusion indeed makes sense since both activities involve similar motion patterns; nevertheless, the fact that most of those 10 windows are classified as *running* suggests that the activity being performed is *running*. One reason for the generation of spurious classifications in the previous scenario is that temporal information about the activity being performed is not incorporated. In other words, the classifier does not know that instantaneously switching back and forth between *running* and *walking* is difficult and, for other activities, not even possible. One simple strategy to partially mitigate this problem has been the use of a majority filter. This filter consists on simply reporting the activity with most classifications (majority class) over the past *n* number of windows as the latest classification result. Another possible strategy is to incorporate information about the transition probability between activities. For example, it is more likely to transition from *sitting* to *standing* than from *sitting* to *walking*. In fact some algorithms such as hidden Markov models attempt to implicitly include this information.

The design goals for the activity recognition algorithm developed in this work in decreasing order of importance are (1) real-time performance, (2) recognition of physical activity type and intensity, (3) subject independent performance (if possible) or subject dependent performance with small training data requirements, (4) minimization of the number of sensors required to recognize activities while maintaining good performance, (5) placement of sensors in the most comfortable body locations, (6) as much invariance to small changes in the sensor placement on the human body as possible, and (7) small real-time classification delay. Section 5.4 presents a set of incremental experiments specially designed to explore the feasibility of the aforementioned design goals.

4.4 Energy Expenditure Estimation Algorithms

The standard procedure used to estimate energy expenditure from accelerometer data in prior work consists of the following steps: (1) collect accelerometer and energy expenditure data for a specific set of activities of interest by having *n* number of subjects wear an accelerometer (e.g. an Actigraph [32]) at the hip and an indirect calorimeter (e.g. the portable Cosmed K4b2 indirect calorimeter [125]. Another option is to place participants inside room indirect calorimeters (e.g. Vanderbilt indirect calorimetry room [124]) (2) Eliminate the portions of data where energy expenditure does not reach steady state by removing a portion of the data (e.g. 30-40%) at the beginning of each activity. (3) Partition the data collected into training data (usually 60-70% of total data) and test data (usually 30-40% of data). (4) Compute the absolute value of the acceleration signal and sum it sample by sample over one-minute windows (if not already computed by the activity monitor). This feature is usually referred as activity “counts” and represents the overall motion experienced by an accelerometer over a one minute interval. If the accelerometer used has multiple acceleration axes (e.g. if a biaxial or triaxial accelerometer is used), the summation is usually performed over all axis to produce a single value representing the overall motion experienced by the sensor in all directions. (5) Compute the mean value over the same one minute windows for the ground truth energy expenditure data collected using the indirect calorimeter (given in METs or Kcal/min). (3) Employ a regression algorithm to map activity counts to energy expenditure using the training data. (4) Test the performance of the regression algorithm by predicting energy expenditure over the test data using the model learned from the training data.

In summary, the standard procedure followed to estimate energy expenditure from accelerometer data is a simplified version of the procedure presented in the previous section to recognize activities. The main differences are the following: (1) regression algorithms such as multivariable linear regression are used instead of classification algorithms to predict energy expenditure, (2) the segmentation technique usually employed is non-overlapping sliding windows of 60s in length, and (3) in most prior work the only feature computed from the accelerometer data is number of activity counts. When multiple accelerometers are used, multivariable regression algorithms such as multivariable linear regression are employed to produce the mapping between acceleration and energy expenditure.

The design goals for the energy expenditure estimation algorithm presented in this work are the same as the goals presented in Section X for the activity type recognition algorithm. This work extends the standard procedure used estimate energy expenditure by exploring (1) if non-linear regression algorithms and activity dependent regression models improve energy expenditure estimates, (2) if shorter window lengths with shorter real-time estimation delays produce acceptable estimates, (3) if computing more complex features over the accelerometer data improve the estimates, and (4) if a minimum set of multiple sensors at strategic and comfortable body locations improve the estimates. One of the main goals is also to identify regression algorithms, window lengths, features, and accelerometers (number and placement) that produce an energy expenditure estimation algorithm amenable for real-time performance.

4.5 Interactive Training of Algorithms in Real-Time

Previous work on activity recognition (e.g. [38]) suggests that subject independent recognition of activities is more difficult than subject dependent recognition of activities. This means that a recognition algorithm performs better if all users provide examples of all the activities to recognize. Thus, it might be expected that some degree of subject dependent training will be necessary to recognize activities during free-living conditions reliably.

This work evaluates the activity recognition algorithms implemented using both -- subject dependent and independent training. The training data requirements during subject dependent training are also evaluated. This analysis is important because it gives an idea of the minimum amount of training data that users might have to provide to the recognition algorithms to achieve a reasonable performance. Finally, the activity recognition algorithm developed in this work is implemented and evaluated in real-time. This is achieved by having several participants interactively train and test the performance of the algorithm over activities specified by participants themselves. The main goal of this real-time evaluation is to determine how difficult it would be for end-users to interactively train and test the activity recognition algorithms in practice. The energy expenditure estimation algorithm, on the other hand, is evaluated primarily using subject independent training because of the unavailability of the specialized equipment (portable indirect calorimeter) required to collect the energy expenditure data during free-living. Nevertheless, once the final algorithm is presented, its performance is also evaluated during subject dependent training.

The main goal of the user interface of the application developed to test the performance of the activity recognition algorithms in real-time is to allow users to (1) type in the activities they want the activity recognition algorithm to recognize, (2) provide the required training data automatically by simply performing the activities of interest sequentially for a given period of time (e.g. 2 minutes), and (3) test the performance of the recognition algorithm immediately after the training process has finished. More details on this interactive application can be found in Section 5.5.

4.6 Data Collection

Three different datasets were used during the development of the activity recognition and energy expenditure estimation algorithms in this work. The first one, referred as the Boston Medical Center Protocol, was a small dataset consisting of 14 activities collected from two participants by researchers at the Boston Medical Center. This dataset was used to validate the energy expenditure data collected for developing the energy expenditure estimation algorithm in this work. The second dataset, referred as the Stanford and Boston University protocol, consists of data collected during two independent data collection sessions at those institutions where acceleration and heart rate data was collected from participants to develop the activity recognition algorithms. Finally, the third dataset referred as the MIT dataset, is the most extensive data set since accelerometer, heart rate, and energy expenditure data was collected from 20 participants at two locations (a gymnasium and residential home) for 52 different activities. The following sections discuss each of the data collection sessions in more detail. Researchers interested in using these datasets should contact the author or visit http://architecture.mit.edu/house_n/data

4.6.1 Boston Medical Center Protocol

This is a dataset consisting of 14 activities collected from two participants by researchers at the Boston Medical Center. The activities for which data was collected are shown in Appendix A10. This data was used to validate the energy expenditure data collected in the MIT protocol for the development of the energy expenditure estimation algorithm. This comparison was possible because the 14 activities contained in this protocol are a subset of the 52 activities contained in the MIT protocol. Section 5.6.2 presents the results of the validation study. The main difference between the Boston Medical Center protocol and the MIT protocol is that different indirect calorimeters were used during the data collections. The Boston Medical Center protocol used the Parvo Medics TrueOne 2400 metabolic measurement system [126], and the MIT protocol used the Cosmed K4b2 indirect calorimeter [125]. The number and placement of all other wearable sensors remained the same for both protocols. For more details on the placement of the other sensors refer to Section 4.6.3. Figure 4-2 shows an example of the data collection setup during the *cycling* activity for the Boston Medical Center protocol.

4.6.2 Stanford and Boston University Protocol

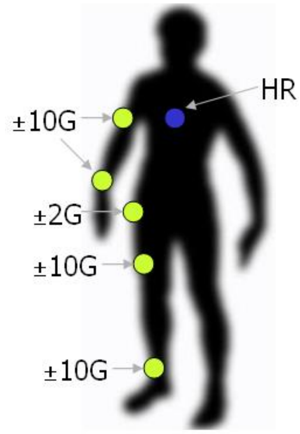
For this protocol, a total of 21 participants with ages ranging between 18 and 65 years old and with varying levels of physical fitness were recruited at two separate medical laboratories: (1) Stanford Medical School and (2) The Boston Medical Center. The participants were screened for any medical condition that would contraindicate moderate to vigorous intensity exercise using the Physical Activity Readiness Questionnaire (PAR-Q) [217] and the Stanford Brief Physical Activity Survey (SBAS) [133] before inclusion in the study.

Figure 4-2: Example of the data collection setup for the Boston Medical Center Protocol. The indirect calorimeter used was the Parvo Medics TrueOne 2400. Participant's face has been blurred to preserve anonymity.

During the data collections, researchers placed five accelerometers on each subject, with one at each of the following locations: top of the dominant wrist just behind the wrist joint, side of the dominant ankle just above the ankle joint, outside part of the dominant upper arm just below shoulder joint, on the upper part of the dominant thigh, and on the dominant hip. The wireless accelerometers were attached to subjects using cotton elastic sweat bands or non-restrictive adhesive bandages. All the accelerometers were ±10G except the accelerometer on the hip, which was ±2G. Prior work suggests that body extremities can reach ±12G in rare circumstances [218], but at the hip ±2G should be sufficient to avoid saturation. The heart rate monitor was worn on the chest. The location of each sensor is indicated in Figure 4-3. After the sensors were placed, each participant was asked to sit still and, after a stabilization period, resting HR was measured by measuring pulse for one minute. The participant's age-predicted maximum HR (MHR=220-age) was calculated. During the data collection, if the participant reached 85% of this value, participants were instructed to stop the activity being performed and take a two minute rest break. That activity was not attempted again.

A combined 21 participants each performed 30 gymnasium activities, with 12 and 9 datasets being collected from each site, respectively. The list of activities broken down by type and intensity differences is shown in Appendix A11. Each activity was performed for two minutes. The research assistant would wait until the participant had started the activity and appeared to be engaged confidently in the activity before indicating the activity was started using annotation software. In most of the gym activities, the gym equipment could be set at a particular speed and/or resistance level. For cycling or rowing, the "light," "moderate," and "hard" resistance settings were made by setting the speed (e.g., rpm) and then as the participant peddled or rowed, adjusting the resistance

(a)



(b)

Figure 4-3: Five triaxial wireless accelerometers, a polar chest strap heart rate monitor, a MITes heart rate transceiver with 9V battery attached, and a USB wireless receiver, and (b) Placement of the sensors on the body. Green dots indicate accelerometer locations and blue the heart rate monitor location.

Variable	**Men (*n* = 8)**	**Women (*n* = 12)**	**All Participants (*n* = 20)**
Age (yr)	27.8 ± 7.2 [22.0 - 42.0]	29.2 ± 6.4 [18.0 - 40.0]	28.6 ± 6.6 [18.0 - 42.0]
Body Mass (Kg)	85.1 ± 11.0 [73.2 - 103.8]	75.5 ± 17.3 [60.7 - 119.1]	79.3 ± 15.6 [60.7 - 119.1]
Height (m)	1.9 ± 0.0 [1.79 - 1.9]	1.7 ± 0.0 [1.54 - 1.82]	1.7 ± 0.1 [1.54 - 1.9]
Fat percent (%)	12.2 ± 4.6 [5.5 - 20.3]	30.7 ± 7.9 [19.8 - 52.3]	23.3 ± 11.4 [5.5 - 52.3]
Water percent (%)	58.9 ± 4.7 [50.0 - 65.5]	48.2 ± 4.9 [35.4 - 54.4]	52.7 ± 7.2 [35.4 - 65.5]
Bone mass (Kg)	3.6 ± 0.3 [3.2 - 4.0]	2.7 ± 0.5 [2.2 - 3.9]	3.0 ± 0.6 [2.2 - 4.0]

Table 4-1: Physical characteristics of the 20 study participants. Values are means (SD) with range shown in parenthesis. n is the number of subjects.

until the participant reported that they were in the desired intensity level.

The activities for this protocol were selected because (1) they are listed in the Compendium of Physical Activities [219], (2) because they include examples of upper, lower, and overall body motion, (3) and because these activities are of practical interest to the medical community because they are prescribed as part of weight management programs. From Appendix A11, we can observe that the activities with different intensity levels are *walking*, *cycling*, and *rowing*. For *walking*, intensity was varied by changing the treadmill speed (e.g. 2, 3, and 4 mph) and inclination (e.g. 4, 8, and 12 degrees). These walking speeds and inclinations were used for all participants. For *cycling*, the cycle speed (e.g. 60, 80, and 100rpm) and the cycle resistance level were set to settings that participants subjectively considered equivalent to light, moderate, and hard. Finally, for *rowing*, the rowing speed was maintained constant at 30 strokes per minute (spm) while the resistance was varied until reaching levels that participants considered light, moderate, and hard. The average duration of each activity was 1.9min except for *jumping jacks*, *sit-ups*, *push-ups*, and *bicep curls* that have an average duration of 0.87min. This is because these activities are physically demanding, and most participants were not able to perform them for at least 2min. The Stanford University dataset differs slightly from the Boston Medical Center dataset because due to lab constraints, data for the *move weight*, and *calisthenics* activities were not collected, and the *rowing* activity was replaced by the *arm ergometry* activity. Nevertheless, the Stanford University dataset still contains the same number of activities with different intensity levels as the Boston Medical Center dataset (*walking*, *cycling*, and *arm ergometry*). The activity recognition results utilizing the datasets collected at Stanford and Boston University are presented in the work by Munguia Tapia et al. (2007) [220].

4.6.3 MIT Protocol

For this data collection protocol, total of 20 participants with an age range between 18 and 42 years old and with varying levels of physical fitness were recruited at MIT. The participants were screened for any medical condition that would contraindicate moderate to vigorous intensity exercise using the Physical Activity Readiness Questionnaire (PAR-Q) [217] and the Stanford Brief Physical Activity Survey (SBAS) [133] before inclusion in the study. Each participant's age, gender, ethnicity, height, weight, and body composition parameters were recorded at the beginning of the study. Each participant's height was measured using a measuring tape and body weight and composition parameters using a Tanita Body Composition Scale Model BC-536 [221]. Table 4-1 shows the physical characteristics of the 20 participants included in the study.

The participants were asked to perform a script of physical activities at two locations while they wore a variety of sensors that measured body motion (acceleration), heart rate, and energy expenditure. One data collection session took place at MIT Zesiger Sports and Fitness Center and the other at a residential home called the PlaceLab [222]. Participants were expected to complete both data collection sessions, which lasted approximately three hours each.

During the data collections, participants wore seven wireless accelerometers [199], a chest strap heart rate monitor [199, 223], two Actigraph activity monitors [166], a HJ-122 pedometer [85], a bodybugg armband [158], and a K4b2 portable indirect calorimeter [125]. The wireless accelerometers and heart rate monitor collected data about participant's motion, and heart rate, and the portable indirect calorimeter 'ground truth' energy expenditure data. The wireless accelerometers were placed at the following locations: At the feet (on top of the shoe laces), wrists, hip (non-dominant side), dominant upper arm, and dominant thigh. The Actigraph monitors were placed at the dominant wrist, and at the dominant side of the hip. The bodybugg armband was placed at the dominant upper arm, near the bicep muscle, the pedometer at the hip, and the heart rate monitor on the chest. Accelerometers were held in place using cotton elastic sweat bands or non-restrictive adhesive bandages. The K4b2 Cosmed indirect calorimeter [125] was calibrated according to the manufacturer's specifications and affixed to the participant's chest using a special harness consisting of adjustable belts. The location of each sensor is shown in Figure 4-4.

The Actigraph is commonly used to estimate energy expenditure by the medical community in free-living and was used for comparison purposes. The bodybugg data was not utilized in this work due to the lack of access to expensive proprietary software ($5,000). The wireless accelerometers and heart rate transceiver used in this study are part of an existing wireless sensing platform called MIT environmental sensors or (MITes)[199]. All other sensors are available off-the-shelf [89, 125, 158, 166]. A member of our research group followed the participants to label (using the data collection laptop computer) the start and end times activities as they were performed.

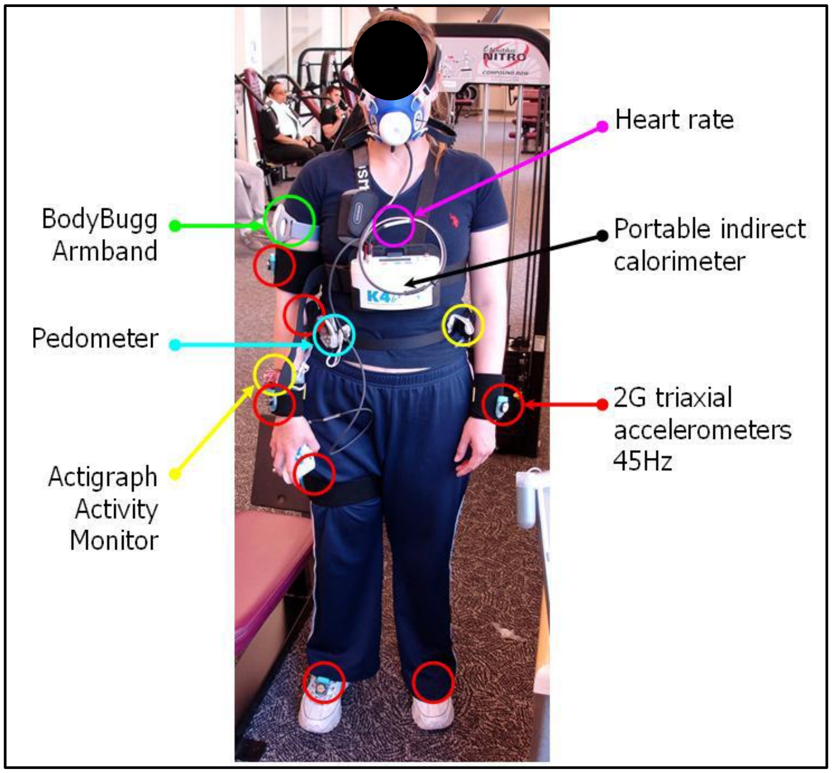


Figure 4-4: Example of how participants wore the sensors used during the data collections at the (a) gymnasium (shown here) and (b) home. Participant's face has been blurred to preserve anonymity.

During both data collection sessions, participants were asked to lie down for a period of five minutes once sensors were properly installed on the subject so that resting metabolic rate and resting heart rate could be measured. The participant's age-predicted maximum HR (MHR=220-age) was also calculated. During the experiment, if a participant reached 85% of this value, he or she was instructed to stop the activity being performed and take a 2 minute rest break. That activity was not attempted again.

After lying down for five minutes, subjects were asked to perform a script of activities depending on the location of the data collection. Appendix A12 presents the script of activities for the gymnasium and the home, respectively. Appendix A12 also presents a detailed list of the activities and a brief explanation of the data collection conditions for each activity. Each activity was performed for three to four minutes, except for physically demanding activities that were executed for as long as the subject's physical fitness allowed. A research assistant would wait until the participant had started the activity and appeared to be engaged confidently in the activity before indicating that the activity was started using the annotation software.

One important difference between this protocol and the Stanford and Boston University protocol is that this study does not define the intensity levels light, moderate, and hard depending on the subject's exertion perception. In other words, the intensity levels (speed of execution of activity, resistance level, or weight loads used) were set in advance and used for all subjects. The intent was to minimize inter-individual variations due to different fitness levels of individuals. Appendix A4 describes the speeds of execution, resistance level, and weight loads used for each activity involving different intensity levels.

Variable	Men (n = 7)	Women (n = 9)	All Participants (n = 16)
Age (yr)	25.71 ± 4.61 [22.0 - 35.0]	29.56 ± 7.16 [18.0 - 40.0]	27.88 ± 6.30 [18.0 - 40.0]
Body Mass (Kg)	84.30 ± 11.66 [73.2 – 103.8]	72.28 ± 12.05 [60.7 - 101.8]	77.54 ± 13.03 [60.7 - 103.8]
Height (m)	1.85 ± 0.04 [1.79 - 1.9]	1.67 ± 0.09 [1.54 - 1.82]	1.75 ± 0.12 [1.54 - 1.9]
Fat percent (%)	12.11 ± 4.99 [5.5 - 20.3]	28.14 ± 4.67 [19.8 - 34.2]	21.13 ± 9.44 [5.5 - 34.2]
Water percent (%)	59.11 ± 5.05 [50.0 - 65.5]	49.66 ± 2.88 [46.5 - 54.4]	54.07 ± 6.24 [46.5 - 65.5]
Bone mass (Kg)	3.56 ± 0.29 [3.2 – 4.0]	2.70 ± 0.56 [2.2 - 3.9]	3.10 ± 0.62 [2.2 - 4.0]

Table 4-2: Physical characteristics of the 16 participants included in the MIT energy expenditure datasets. Values are means ± SD with range shown in parenthesis and n is the number of subjects.

Finally, the set of activities contained in this protocol were included because they are common everyday activities or exercises for which data could be collected in the gym or home setting available, and because most of them are listed in the Compendium of Physical Activities [219]. Appendix A4 presents the amount of training data collected for each activity.

4.6.4 MIT Energy Expenditure Dataset

After visually inspecting all of the datasets collected during the MIT protocol, 13 data collection sessions with suspiciously low energy expenditure readings were identified. These low energy expenditure readings might indicate an improper attachment of the Cosmed K4b2 indirect calorimeter face mask during the data collection. Improper attachment of the face mask is known to produce low energy expenditure readings because air (VO_2 and VCO_2) escapes from the mask and, consequently, is not measured by the indirect calorimeter data collection unit. Some subjects did express at times that the face mask felt too tight, and as a result, it had to be loosened, increasing the likelihood of air leaks. In other cases, the face mask did not properly match the subject's face anatomy, even when the closest face mask size was selected from those available with the Cosmed K4b2 equipment.

In total, 13 sessions out of a total of 40 were removed from analysis. These sessions removed included data collections at the gymnasium, the residential home, or both. Appendix B17 presents a list of the data collection sessions included in the MIT energy expenditure dataset. A data collection session was eliminated if any of the activities performed (during the data collection), presented an energy expenditure value below ~40% of the values observed for other participants or with respect to the Compendium of Physical Activities. All sessions were removed before performing any of the experiments presented in this work. The new dataset created after eliminating the sessions with low readings is referred as the MIT energy expenditure dataset, and contains data for 16 different subjects. Table 4-2 presents the characteristics of the 16 subjects included in the MIT energy expenditure dataset. Appendix B16 presents the average energy expenditure (in METs and Kcal/min) and average heart rate per activity when non-steady state data is eliminated and when it is not.

5 Evaluation

This section presents a summary of the standard quantitative measures in which activity recognition and energy estimation algorithms are commonly evaluated. Useful evaluation measures that are important to consider but are usually neglected when evaluating the algorithms are discussed. The measures used to evaluate the algorithms developed in this work are introduced, and the section discusses why is it difficult to compare results obtained with different algorithms developed in previous work and what will be considered to be a "good" result in this thesis.

5.1 Reporting and Analyzing Activity Recognition Results

This section explains what performance measures will be used to evaluate the activity recognition algorithms developed in this work and why.

5.1.1 Standard Quantitative Measures

Activity recognition algorithms are often evaluated based on how well they recognize all the target activities of interest with respect to overall standard performance measures. Such measures might include accuracy, true positive rate, false positive rate, true negative rate, false negative rate, precision, recall, F-Measure, area under ROC curve, and some others recently introduced [224, 225]. Appendix A1 presents a brief description of some of these standard evaluation measures. However, even when improving the recognition over all of the activities of interest is important, overall improvements as represented by specific performance measures can be deceiving. For example, overall performance can increase even when the performance on some individual activities might, in fact, decrease. Furthermore, when improvements indeed occur over all or some activities without affecting performance on others, these improvements can be so small (e.g. 95.5% over 94.2% accuracy) that the increase in the complexity of the algorithm might not justify the improvement obtained. Consequently, it can be argued that *epsilon* improvements in overall performance do not necessarily represent significant improvements over results obtained with previously developed algorithms unless the new algorithms provide some other benefit, such as faster run-time or training performance or better interactive training potential.

The target domain dictates the relative importance of recognizing particular activities. For example, an algorithm might improve the recognition accuracy of *ascending stairs* which might allow better differentiation between *walking* and *ascending stairs*. This improved differentiation might be considered a strong result by exercise physiologists interested in estimating energy expenditure during free living given the significantly different energy expenditure costs associated with these activities.

Therefore, the algorithms developed in this work will be evaluated by (1) paying special attention to the individual performance on activities and classes of activities that are considered important for the medical community (e.g. cycling, ascending/descending stairs, postures, moderate intensity, among others) and (2) utilizing other important evaluation measures commonly neglected while evaluating results in previous work.

5.1.2 Neglected Performance Measures

The end goal of this work is to move towards a consumer-based system for helping people measure and motivate behavior changes. Therefore, factors beyond recognition accuracy must be considered. Additional dimensions along which algorithms can be evaluated are briefly explained below.

5.1.2.1 Complexity of the Activities to Recognize

Algorithms can be evaluated based on the complexity of the activities they recognize. The complexity of activities can vary depending on the number of activities, the types of activities, and the complexity of the training data collected for those activities (e.g. lab vs. free-living). It is extremely important to consider the complexity of the activities being studied when evaluating algorithms, because by carefully picking the number of activities, the types of activities, and the data collection method, excellent results can be obtained by many classification algorithms.

- *Number of activities to recognize*: Recognizing five activities is easier than recognizing twenty or fifty activities. As the number of activities increases, the classifier has to learn how to discriminate among a larger set of activities, which is usually harder. Discrimination is also harder if activities are "similar" to one another. In this work the recognition rate as compared to chance is listed when reporting all results.
- *Complexity of the types of activities to recognize*: Activities that are static in nature such as postures (e.g. *lying down* and *standing still*), are easier to recognize than activities that are periodic in nature such as *running* and *cycling*. Furthermore, activities that involve different intensity levels (e.g. *running at 4mph* vs. *running at 5mph*) are also harder to recognize because of their motion similarity and therefore similarity in the feature space. Likewise, activities involving highly unconstrained motions impacted by objects in the environment such as *cleaning* and *making the bed* are more difficult to recognize than periodic activities when only accelerometer data from limb motion is available.
- *Complexity of the training data collected for the activities*: Activities for which training and test data is collected in laboratory settings are usually easier to recognize than activities for which training and test data is collected during free-living conditions. Subjects will usually behave differently and in less constrained ways outside of formal laboratory settings. This work utilizes data collected for 52 activities at a gym during relatively controlled conditions (since exercise equipment such as a treadmill, cycling machine, etc was utilized) and from a residential home during less controlled conditions. It can be argued that this is a relatively complex dataset containing a large set of activities. However, direct observation was utilized during both data collections to acquire the labels of the activities being performed

by participants. Thus, the results presented in this thesis would require validation over datasets collected when direct observation is not utilized.

In this work, the performance of the activity recognition algorithms will be evaluated on different subsets of activities, ranging from relatively easy (postures in a gym) to difficult (cleaning activities collect in a home setting). First, a worse-case scenario of activity recognition complexity will be used when selecting the parameters of the recognition algorithm (e.g. classifier, window length, features, etc). This worse-case scenario consists of recognizing 52 different activities, 26 of which have different intensity levels and 18 of them include examples of the unconstrained motion found in household activities. Once the parameters are selected, the recognition performance of the algorithm will be evaluated on various groups of activities. First, the algorithm will be evaluated by only recognizing postures. Then, it will be evaluated on postures and ambulation, then on exercise activities with different intensity levels (periodic motion), and finally for household activities (unconstrained motion). The algorithm will also be evaluated when recognizing all the activities but without differentiating among activities containing different intensity levels. The datasets on which the algorithms are evaluated were collected in both (1) relatively controlled laboratory conditions and (2) less controlled free-living conditions. To the best of the author knowledge, the dataset collected for this work is larger and more complex that other datasets used in activity recognition studies published to date.

5.1.2.2 Training Data Requirements of an Algorithm

Algorithms can also be evaluated based on the type of training data available (e.g. subject dependent vs. independent) and the amount of training data that they require.

- *Subject independent recognition of activities*: Ideally, an activity recognition algorithm would be trained on a given subject population and then recognize activities accurately on unseen populations without requiring further person-specific training data. Unfortunately, previous work (e.g. [38]) strongly suggests that subject independent recognition of activities is difficult to achieve for diverse sets of activities due to the high variability in the way that individuals perform activities. Body type can also impact sensor readings (e.g., hip sensors at different angles of tilt due to body shape).
- *Amount of training data required for subject dependent recognition of activities*: In general, previous work on activity recognition suggests that algorithms will perform better with more person-specific training data. For many activities, providing this data can be time consuming and burdensome, so ideally training data requirements would be kept to a minimum. For example, an algorithm that takes only 1min to train might allow end-users to iteratively test and perhaps improve the recognition of poorly recognized activities by providing more training examples in-situ. Algorithms with long training times (e.g. several hours or days) might exhaust end-user's patience while subject dependent training is required.

This work will evaluate the performance of the algorithms developed using subject independent and subject dependent training. The differences in performance using both training methods will be reported overall and per activity. Moreover, the training data requirements for subject dependent training will also be evaluated by training the algorithms using different amounts of training data to determine the minimum amount required to obtain good recognition performance.

5.1.2.3 Sensor Data Requirements of the Algorithm

The number of sensors required to recognize activities, the types of sensors used, and their location on the human body can also dramatically impact algorithm performance:

- *Number of sensors required to recognize activities*: Algorithms that recognize activities from a small set of sensors are easier to use in real-world applications and have lower computational requirements (since fewer sensor signals need to be analyzed) than algorithms that use large sets of sensors. Fewer sensors usually mean the technology can be deployed more affordably.
- *Intrusiveness of the sensors required to recognize activities*: A recognition algorithm that requires sensors such as ECG or EMG monitors that must be inconveniently stuck on the body may be perceived as more difficult to use, more uncomfortable, and more of a burden than an algorithm that uses sensors such as accelerometers that can be easily and comfortably slipped on the body.
- *Location of the sensors required to recognize activities*: Sensors worn at socially accepted and comfortable locations on the body are more likely to be used for longer periods of time. Sensors that might be integrated into existing clothing or devices already worn (watches, shoes) and carried (phones) are preferable.

This thesis will evaluate tradeoffs between different types (e.g. accelerometers vs. heart rate monitors), numbers, and locations of sensors to determine sets of sensors to use that provide good recognition with minimal usability burden.

5.1.2.4 Usability Factors Imposed by an Algorithm

Some other usability factors in addition to usage comfort of the sensors and training time requirements of the algorithm are:

- *Real-time recognition of activities*: An algorithm capable of recognizing activities in real-time, particularly from hand-held devices such as mobile phones, would permit many new health interventions using just-in-time feedback to be created [28].
- *Real-time recognition delay (lag)*: Some real-time recognition algorithms introduce lag between activity occurrence and detection. Shorter recognition delays may allow for better point of decision interventions.

This work will analyze the usability factor imposed by the activity recognition algorithm carefully, since one of the main goals of this work is to develop an algorithm amenable for longitudinal use during free-living. First, it will be determined if reasonable recognition of activities can be obtained using classifiers suitable for real-time performance in low-processing power devices such as mobile phones. Secondly, it will be decided if subject independent recognition of activities is possible with reasonable performance. If not, the training data and training time requirements of the algorithm will be evaluated in a subject dependent manner. Experiments will also be conducted to find the minimum number of least intrusive sensors to wear and their more comfortable location on the human body.

5.1.3 Comparison Challenges

In general, it is difficult to compare the performance of newly developed algorithms with respect to the performance obtained by algorithms in previous work. This is because different pieces of work explore different types and numbers of activities, datasets are collected from different subject populations under different conditions (e.g. lab vs. non-lab), and the duration of the data collections is different (activity examples have different lengths).

For example, Table 5-1 presents the comparison of two state-of-the-art activity recognition algorithms: The work by Bao and Intille [38] and the work by Lester et al. [37]. The work by Bao and Intille is one of the first pieces of work to explore a relatively large set of activities (20) collected from a large number of subjects (20) during semi-naturalistic and controlled conditions. The algorithm presented recognizes activities from up to five accelerometers and is evaluated using subject dependent and subject independent training. Moreover, experiments are performed to determine the minimum set of sensors with best performance and their locations on the human body. One of the main finding is that an accuracy of 81% can be obtained for a complex set of activities (postures, ambulation, and household activities) using only two sensors located at the thigh and the wrist. The work also indicates that some activities are well recognized using subject independent training but others do appear to require subject dependent training. The work by Lester et al. explores the recognition of ten activities from eight sensor types located at the shoulder. The algorithm is evaluated on the data collected from two subjects during everyday naturalistic conditions. Their main finding is that using different sensor types at a single location can offset the need to place sensors at different locations, making the system easier to use and wear. The algorithm developed is a complex combination of discriminative classifiers (e.g. a modified version of AdaBoost) and generative classifiers (hidden Markov Models). The work obtains a final recognition accuracy of 95% while recognizing ten activities involving mainly postures and ambulation.

From Table 5-1, it can be seen that comparing these two activity recognition algorithms is a complex task. Some of the performance dimensions were not evaluated, the number of activities explored and their complexity is different, and the datasets were collected under different conditions. As a result, it is challenging to determine what a meaningful

Performance Dimension	Bao and Intille '04 ([38])	Lester et al. '05 ([37])
Overall performance	Yes (84% accuracy)	Yes (95% accuracy)
Performance per activity	Yes (True positive rate)	Yes (precision and recall)
Complexity of activities to recognize		
Number of activities	20	10
Complexity of activity type	Activities included Postures (static), ambulation (periodic), and household activities (unconstrained motion).	Activities included Postures (static) and ambulation (periodic)
Complexity of training/testing data	20 subjects, data collected under semi-naturalistic and controlled conditions, data collection boards did not restrict subject's movement. 33 hours of total data with an average of 2.6min of data per activity.	2 subjects, 12 hours of total data collected under naturalistic conditions. On average, one hour of data per activity.
Training data requirements		
Subject independent recognition	Yes	Yes
Subject dependent recognition	Yes	No
Amount of training data required	No	No
Sensor data requirements		
Number of sensors	Five biaxial accelerometers located at hip, wrist, arm, ankle and thigh	Eight sensors located on the shoulder: a triaxial accelerometer, microphone, IR/Visible light, high frequency light, barometric pressure, humidity, temperature and compass.
Intrusiveness of sensors	Yes (only unobtrusive sensors used)	Yes (only unobtrusive sensors used)
Location of sensors	Yes, accelerometers at thigh and wrist achieved best performance	No
Usability		
Comfort	Analysis performed to determine best sensor location but data collection boards are bulky and heavy.	Yes, only sensors at a single location (shoulder) are used. No analysis on multiple locations is performed though.
Training data requirements	No	No
Training time requirements	No	No
Real-time performance	No (offline analysis only)	No (offline analysis only)
Real-time classification delay	No (offline analysis only)	No (offline analysis only)
Interpretability of recognizer	No	No
Ability to fix errors	No	No
Cost	No	No

Table 5-1: Comparison of two state-of-the-art activity recognition algorithms along all the performance dimensions discussed in Sections 5.1.1 and 5.1.2. The comparison is difficult, and it is not clear what algorithm would perform better under similar conditions.

improvement is over these works when only considering one of the performance dimensions (e.g. overall accuracy).

5.1.4 Comparison Strategy in this Work

In this work, the activity recognition algorithms will be evaluated across all the performance dimensions discussed in Sections 5.1.1 and 5.1.2. The experiments performed will mostly be used to compare incrementally to previous results obtained in this work, particularly when selecting the parameters (e.g. classifier, window length, features) of the recognition algorithm. The goal is to converge on a functional system that is balanced in all dimensions as much as possible, where testing is done on a relatively large and complex set of activities relative to past work. Where possible, comparisons will be made against results presented in previous work by other authors, but they will be presented cautiously given how challenging this task is as explained in the previous section.

This work will utilize the following performance measures that can be computed from the confusion matrix to evaluate recognition algorithms: overall accuracy, true positive rate per activity, false positive rate per activity, F-Measure per activity, and the confusion matrix itself. These standard performance measures are briefly explained in Appendix A1. Furthermore, the results presented in each experiment will be clustered based on activity categories that are useful for interpreting the results. These categories are: (1) postures, (2) ambulation, (3) exercise activity, (4) resistance exercise activity, and (5) household activity. Appendix A2 explains what activities are considered under each clustering category. As stated in the previous sections, subject dependent and independent evaluation will be performed when necessary.

Based on the results obtained in previous work, this work will consider a good result to recognize the set of 52 activities contained in the MIT dataset with overall accuracies equal or greater than 80% in a subject dependent, or even better, independent manner. Another strong result would be to recognize the activities from only one or two sensors, with an overall decrease in accuracy of less than 5% and no significant decrease in performance per activity. Under the same conditions (number of activities, types of activities, number of subjects, number of sensors, evaluation criteria, etc), this work will also consider an overall performance improvement of 15% or greater as significant improvement over previous work provided that the complexity of the algorithms is comparable or even lower.

5.2 Reporting and Analyzing Energy Estimation Results

The same evaluation dimensions discussed in the previous section can also be used to evaluate the performance of energy expenditure estimation algorithms. However, there are four main differences with respect to evaluating activity recognition algorithms: (1) The performance measures used are different since energy estimation involves numeric prediction, (2) there is less agreement in the literature on which performance measures to use while reporting results, (3) results presented are more difficult to compare against one another since energy expenditure can be predicted as net energy or gross energy and reported in different units (e.g. Kcal/Min, METs), and (4) most previous work has been done on data collected at a laboratory from few activities (usually *walking* and *running* on a treadmill) under steady-state assumption of energy expenditure.

5.2.1 Standard Quantitative Measures

Energy expenditure estimation algorithms can be evaluated by comparing two numeric values: the ground truth energy expenditure values acquired usually from an indirect calorimeter and the predicted energy expenditure values estimated by the algorithm from the sensor data. In this scenario, errors can occur due to erroneous readings from the indirect calorimeter itself and the estimation errors performed by the algorithm. The errors produced by the estimation algorithm can be evaluated by computing the difference (error) between the calorimeter values and the predicted values according to a performance measure. However, there is little agreement as to which error measures to use to report results in the literature. For example, some of the most often used error measures are: root mean squared error (RMSE), standard error of the estimate (SEE), Pearl's correlation coefficient (r), squared Pearl's correlation coefficient (r^2), mean absolute error (MAE), maximum absolute error deviation (MAED), relative absolute error (RAE), root relative squared error (RRSE), percentage difference, difference in total energy expenditure, and mean error scores, among others. Often, scatter plots and Bland-Altman plots are also used to present the results. This makes comparison of existing and previous work difficult, as explained in the next section.

5.2.2 Neglected Measures

The same performance dimensions used to evaluate activity recognition algorithms can be used to evaluate energy expenditure estimation algorithms. However, one important difference with respect to activity recognition is that most previous work in estimating energy expenditure from wearable sensors has been performed over data collected at the laboratory from a limited set of activities. Algorithms in prior work have most often been trained and tested using data collected from treadmill activities such as *walking* and *running* at different speeds. The datasets may not reflect the variations found in other exercise or lifestyle activities. Consequently, it is no surprise that regression models trained only on these activities have been found to slightly overestimate the energy cost of *walking* and light activities and greatly underestimate the energy expenditure associated with moderate-intensity lifestyle activities [200]. There are few exceptions to this trend of training and testing algorithms on treadmill activities [34, 152]. In work by [34], models were trained over data collected for 18 activities from 20 subjects and in a work by [152], data was collected for 12 activities over nearly 24hours for 102 subjects.

Another potential limitation of previous work in energy expenditure estimation is that the regression models are usually trained assuming steady-state energy expenditure conditions. That is, researchers eliminate the periods of time in which energy expenditure is not in steady state before training and testing the algorithms. Steady-state is usually defined as a coefficient of variation (CV) of less or equal to 5 or 10% computed over windows of 1-5mins [47]. Another common practice is to ignore 30 to 40% of the data located at the beginning and/or end of each activity to eliminate non-steady state conditions. This may be problematic because energy expenditure might not reach steady-state conditions during free-living. Figure 5-1a shows real energy expenditure data collected from subject MIT-001 performing 32 activities at a gymnasium. It can be seen that energy expenditure reaches steady state at the end of most periodic activities such as *walking*, *running*, *cycling*, and *rowing*, but it never reaches steady state for some physically demanding activities such *ascending stairs* and calisthenics activities. Figure 5-1b shows the same energy expenditure data with non-steady state periods eliminated (30% of the beginning of each activity eliminated) and Figure 5-1c the same data concatenated. What is more, Figure 5-1c also shows the data corresponding to *walking* and *running* at different speeds highlighted in red, which would normally be the only data used to train and test energy expenditure estimation algorithms. Finally, Figure 5-1d shows the energy expenditure data collected over more naturalistic conditions while the same subject performs 19 activities in a real home for three hours. It can be clearly seen that energy expenditure almost never reaches the steady state condition.

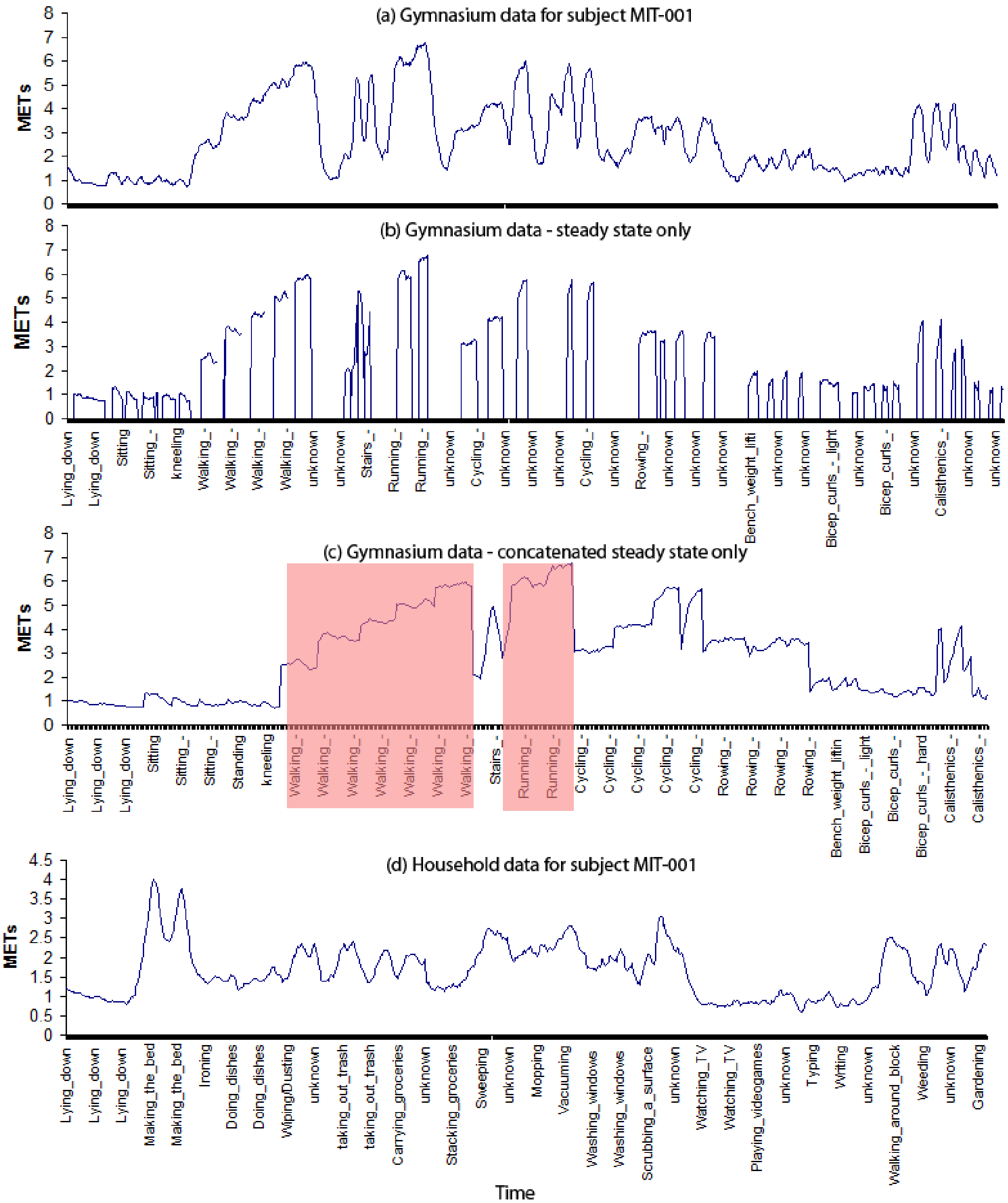


Figure 5-1: Energy expenditure data collected using the Cosmed K4b2 indirect calorimeter from subject MIT-001. (a) data collected at the gymnasium from 32 activities (b) same gym data with non-steady-state data eliminated and treadmill activities highlighted in red, (c) same data when non-steady-state data has been eliminated and the remaining data has been concatenated (note that in this plot, the time axis has a different scale than for plot a and b) and (d) energy expenditure data collected in a real home while performing 19 activities.

5.2.3 Comparison Challenges

Comparing the performance of energy expenditure estimation algorithms is even more difficult than comparing activity recognition results for three reasons: (1) There is less agreement in the literature on which performance measures to use while reporting results as explained in Section 5.2.1, (2) energy expenditure can be predicted as net energy or gross energy expenditure, and (3) the results can be reported in different units (e.g. Kcal/min, METs).

Energy expenditure can be estimated either as net energy expenditure or gross energy. gross energy expenditure is the total energy expended by the body at any given time and is composed of resting energy expenditure and kinetic energy expenditure (due to body motion). Net energy expenditure corresponds only to the kinetic energy or energy spent during actual motion. Thus, it can be estimated from gross energy by subtracting the resting metabolic rate (resting energy). Consequently, energy expenditure estimation algorithms that estimate net energy cannot be directly compared to algorithms that estimate gross energy expenditure easily unless resting metabolic rate is known. Another factor that complicates comparison across algorithms is that energy expenditure can be predicted and reported in different units. For example, most algorithms that include subject characteristics (e.g. gender, weight, and age) in their regression equations to compensate for variations across subjects report energy expenditure in Kcal/Min. Other algorithms try to reduce the impact of differences across subjects by predicting energy expenditure in units that are normalized with respect to one or some subject characteristics (e.g. weight) such as METs (35 ml of oxygen per kg per min). Conversion between values therefore requires knowledge of subject characteristics that are usually reported using summarization statistics over groups of subjects (e.g. means and standard deviations) in the literature.

Table 5-54 shows a summary of the most recent state-of-the-art work in energy expenditure estimation algorithms. From the results column in this table, it can be seen how difficult it is to compare results across different pieces of work. Some results are presented using different performance measures such as SEE, MAED, MAE, RMSE, r, r^2, and reported in different units such as METs, Kcal/min, and Kcal. Furthermore, some of these pieces of work do not provide the necessary data to convert among different units. Consequently, this work will primarily compare the results obtained by experimenting with different regression algorithms, feature sets, and sliding window lengths incrementally over the dataset collected for this work during the development of the final algorithm. When possible, results will be compared against results obtained in previous work, but this will be avoided as much as possible given the difficulty of doing so as explained in this section.

5.2.4 Comparison Strategy in this Work

In this work, the energy expenditure estimation algorithms will be evaluated across all the performance dimensions discussed in Sections 5.2.1 and 5.2.2. In addition, the following error measures will be used while evaluating the energy expenditure estimation algorithms: the root mean squared error or standard error of the estimate (RMSE or SEE), Pearl’s correlation coefficient (r), mean absolute error (MAE), and maximum absolute error deviation (MAED). Appendix B1 presents a brief description of each of these measures and the formulas for computing them. Special attention will be put in improving the energy expenditure estimation for some activities whose energy expenditure estimation has proven difficult in previous work and that are important for the medical community. Some examples of these activities include lower body activities such as *cycling* and *sitting fidgeting feet and legs*, and upper body activities such as *bicep curls*, *bench weight lifting*, *doing dishes*, *washing windows*, and *scrubbing surfaces*. The experiments are performed incrementally, where parameters are selected (e.g. regression algorithm, feature set, sliding window length) based on improvement over prior results on the same dataset. The goal of this systematic procedure is to converge on a system that is balanced in all dimensions.

This work will compare the performance of accelerometers and a Polar heart rate monitor to determine if one modality or the combined modalities provide the best performance. Recent work [152] suggests that energy expenditure estimation can be improved by (1) computing features over the raw accelerometer data and (2) utilizing non-linear regression models such as neural networks to perform the estimation. However, an open question is which of these two steps contributes the most to the improvement of energy expenditure estimation. Thus, this work will compute a large set of features over the accelerometer and heart rate data and evaluate the performance over subsets of those features using linear regression and non-linear regression algorithms. The work will also evaluate the performance of different subsets of accelerometers worn at different body locations to find a reasonable compromise set of sensors that enable good EE estimation without undue subject burden. Most previous work on energy expenditure estimation provides estimates over sliding windows of one minute. Intuitively, one might expect that better results and smaller real-time estimation delays can be obtained by utilizing smaller window lengths [34, 180]. As a result, this work will evaluate the impact of estimating energy expenditure over shorter windows of time to determine if they provide better performance and shorter estimation delays. State-of-the-art work in estimating energy expenditure [34, 96] also suggests that activity dependent regression models might be required to improve energy expenditure estimation. Therefore, this work will evaluate the performance of estimating energy expenditure by creating regression models that depend on the activity being performed. Section 5.6.1 will later explore some of the latest results obtained in recent work when accelerometer and heart rate data is utilized to estimate energy expenditure. The section will also discuss what might be considered a good result with respect to prior work.

5.3 Training Procedures and Assumptions

This section presents the training and testing procedures used to evaluate the performance of the activity recognition and energy expenditure algorithms in this work. The section also explains some of the assumptions made during the evaluation of the algorithms.

5.3.1 Subject Dependent Evaluation

One way to test algorithms on relatively small datasets of examples is using 10-fold stratified cross-validation [226]. For subject dependent evaluation, cross validation was performed over each subject's data and the results obtained were averaged over all the subjects. This training/testing technique gives an idea of how well the algorithm recognizes activities or estimate energy expenditure when subjects provide 2-4min of example data for each activity to train the algorithm. The use of 10-fold stratified cross-validation was chosen because previous work suggests that 10 is a reasonable number of folds to use to evaluate the performance classifiers and regression algorithms [226]. This technique is known as individual calibration (IC) in the medical literature.

5.3.2 Subject Independent Evaluation

Ideally, an algorithm that recognizes activities or estimates energy expenditure would not require training data from a particular individual; instead it would use a corpus of training data acquired in advance from other individuals. To evaluate if subject-independent training is possible, the algorithms were trained with the data of all the subjects but one and tested the performance on the left-out subject. This procedure was repeated for all the subjects and the results were averaged. This technique is also known as group calibration (GC) in the medical community.

5.3.3 The Addition of the Garbage or Unknown Class

It is a common practice in the activity recognition field to include an additional class called the *garbage, zero* or *unknown* class to the activities or classes of interest that contains all the periods of time with no associated labels during the data collection. The addition of this class is believed to provide a more realistic evaluation of the activity recognition algorithms because the classifier has to discriminate between the actual activities of interest and periods of time where the subject performs activities that are not relevant. In some cases, however, when the classes or activities of interest are mutually exclusive, the addition of the garbage class damages the classification performance because it can include examples of the activities of interest that were not labeled during the data collection. In this work, in an attempt to evaluate the algorithms in the most realistic conditions, the garbage class was added to many experiments even though the set of activities explored in this work is mutually exclusive.

5.3.4 Transitions Between Activities

Transitions between activities are particularly problematic when (1) utilizing heart rate data to recognize activities and (2) when estimating energy expenditure. The reason is that heart rate and energy expenditure are not stable during the beginning and end of activities. This is particularly true for physically demanding activities such as *ascending stairs* and performing *sit-ups,* where heart rate and energy expenditure keep increasing over time and steady-state conditions are almost never reached. Moreover, heart rate and energy expenditure can remain altered for relatively long periods of time once physically demanding activities have been finished. As a result, there is high variability in the features computed over heart rate data that might be difficult to model by the recognition algorithms. Similarly, *standing still* might exhibit different levels of energy expenditure depending if someone was previously *sitting* on a chair or *running* on a treadmill at 5mph. In this work, the accelerometer and heart rate data associated with non-steady-state energy expenditure were not eliminated during the training and testing of energy expenditure estimation algorithms in an effort to make the evaluation as realistic as possible.

5.3.5 Assumption Made During the Estimation of Energy Expenditure

This work makes the assumption that energy expenditure may not reach steady state for a particular activity. In other words, segments of data were ground truth energy expenditure did not reach steady state are not eliminated from the training data. This assumption is opposite and more realistic than the steady-state assumption normally made by the medical community while estimating energy expenditure. Using this assumption, the energy expenditure algorithms presented in this work are tested over worst case scenario conditions. Furthermore, if non-steady state data were to be eliminated, performance of the algorithms presented would most likely increase due to a reduction in the complexity of the data. The algorithms developed to estimate energy expenditure predict gross energy expenditure. This means that the algorithms developed produce energy expenditure estimates for sedentary activities involving no motion. That is, the energy expenditure algorithms estimate resting metabolic rate (energy expenditure values close to ~1MET) when no motion is observed for a given activity. Finally, energy expenditure is predicted in METs and not in Kcal/min or other unit of energy. This is because MET units reduce inter-individual variations by normalizing energy expenditure with respect to the weight of the participants.

5.4 Activity Recognition algorithm Experiments

In general, it is not possible to optimize all aspects (parameters) of an algorithm at once. Consequently, this section presents a set of systematic experiments to determine the classifier, signal processing techniques, sliding window length, and feature set to utilize in order to select a reasonable and practical set of parameters to achieve real-time performance. The section also presents experiments to determine the minimum set of sensors to use, the impact on recognition rates of adding heart rate monitoring, and where accelerometers they be worn on the human body to maximize usage comfort and performance. The experiments are organized so that each answers a relevant question about the algorithm parameters incrementally, starting from the most restrictive parameters (e.g. classifier, feature set) to the least restrictive parameters (sensor modality and location). In each case, decisions are made that will support both good recognition rates *and* real-time performance.

The experiments in general will be performed under a worse-case activity recognition scenario where the algorithm has to discriminate among the 51 activities contained in the MIT dataset. Furthermore, a *garbage* or *unknown* class is added containing all the unlabeled segments of data in the MIT dataset. The addition of this class is a common procedure in the activity recognition community and is mainly used to allow the classifier to distinguish between activities of interest and random activities that might be contained in a dataset or performed by the subject in real-life. However, the *unknown* class might contain examples of the activities of interest that were just not labeled during the data collection that might damage the classification performance. In the experiments presented in this section, the addition of the *unknown* class has the sole purpose of evaluating the recognition algorithms under worse-case scenario conditions. In summary, the experiments performed can be assumed to be worse-case activity recognition conditions due to the following facts: (1) The large number of activities (52) to recognize, (2) the inclusion of 26 activities with different intensity levels, (3) the inclusion of 18 household activities containing examples of unconstrained motion, (4) the inclusion of a garbage class (*unknown* activity) containing all the time periods with no associated activity labels, and (5) the attempt to recognize all activities in a subject independent manner (which is more challenging that recognizing activities in a subject dependent manner).

The results presented in this section will be also clustered under activity categories that are helpful while analyzing the results. These activity categories are: Postures, ambulation, exercise, resistance exercise, and household activities. All the activities explored in this work are assumed to be mutually exclusive.

Finally, all the experiments presented in this section utilize the following signal preprocessing and segmentation strategies:

5.4.1 Cubic Spline Interpolation

Since wireless accelerometer are used to collect the human motion information, acceleration samples (sensor values) can be lost during wireless transmission (from the sensing nodes on the body to the wireless receiver) due to environmental noise or body blocking of the signals (i.e. blocking of signal due to the high water content of the human body). Consequently, interpolation of the signal is required to fill out the missing sensor values (samples). This work utilizes cubic spline interpolation to fill out samples lost during wireless transmission when the number of total samples lost is less than 20% of the number of samples contained in a given window. If the number of samples lost is greater than 20%, the total window of data is discarded since there is not enough information to interpolate the signal reliably. The threshold of 20% was chosen after visualizing the results of interpolating the signal when different percentages of samples are lost. The signal quality after interpolation when 20% of the samples are lost is of reasonable quality. Larger thresholds tend to distort the signal shape and quality.

5.4.2 Band-pass and Low-pass Filtering of Accelerometer Signals

Once the accelerometer signals are interpolated, their information is separated into motion and posture information by applying a band-pass filter between the frequencies of

Band-Pass Chebyshev Type I IIR Filter Parameters	Value	Low-Pass Equiripple FIR Filter Parameters	Value
Sampling Frequency (Fs)	45	Sampling Frequency (Fs)	45
First Stopband Frequency	0.1	Filter Order	10
First Passband Frequency	0.2	Passband Frequency (Fpass)	1
Second Passband Frequency	18	Stopband Frequency (Fstop)	5
Second Stopband Frequency	20	Passband Weight (Wpass)	1
First Stopband Attenuation (dB)	60	Stopband Weight (Wstop)	1
Second Stopband Attenuation (dB)	80	Density factor (dens)	20
Passband Ripple (dB)	1		

Table 5-2: Parameters used in the design of the Band-Pass Chebyshev Type I infinite impulse response (IIR) Filter designed to filter the accelerometer signals between 0.1 and 20Hz and the equiripple low-pass finite impulse response filter (FIR) designed to filter the accelerometer signals below 1Hz. All frequency values are in Hz.

0.1 to 20Hz and a low-pass filter with a cutoff frequency of 1Hz respectively. Band-pass filtering the signal between 0.1 and 20Hz has to goals: (1) to eliminate the static acceleration or DC component of the signal that captures posture information about the orientation of the sensor with respect to ground (<0.1Hz) and (2) to eliminate the signal components generated by non-human motion and high frequency noise (>20Hz). Low-pass filtering at a cutoff frequency of 1Hz has the opposite purpose: To eliminate most of the signal generated by dynamic human motion and to preserve the information generated by static human motion or posture information. Again, this information is represented by the DC component of the accelerometer signal. The band-pass filter applied is a Chebyshev Type I infinite impulse response filter (IIR) designed using the CHEBY1 MATLAB [227] function and also re-implemented in Java. The low-pass filter applied is an equiripple finite impulse response filter (FIR) designed using the FIRPM function in MATLAB and re-implemented in Java. Table 5-2 shows the design parameters of the filters. The reason why motion and posture information are separated by applying these filters is that different types of features will be computed over these two signals to better capture the motion and posture information. Appendix A3 presents the list of features explored in this work and a brief explanation on how they are computed. The prefix "AC" in the features indicates they were computed over the band-pass filtered accelerometer signal and the prefix "DC" indicates that they were computed over the low-pass filtered accelerometer signal.

5.4.3 Non-overlapping Sliding Windows Segmentation

After the accelerometer signals have been interpolated and filtered, they are segmented into non-overlapping sliding windows. This segmentation consists in simply partitioning the acceleration signal into consecutive windows of fixed length. For most experiments, the window length used is 5.6s since it is the optimal window length found as explained in Section 5.4.6. The use of non-overlapping sliding windows was preferred over 50% overlapping windows, a common applied segmentation technique while recognizing activities from accelerometer data, because of its lower computational requirements since half of the classifications are required for real-time performance.

Classifier	Classifier Description	Parameters	Ref
Nearest Neighbor (NN)	A memory-based classifier with a non-linear decision boundary that classifies examples based on their similarity with the training data. New data points are classified by simply returning the class of the closest training point.	Nearest neighbors classifier with no distance weighing, the Euclidean distance as similarity function, and brute-force linear search of neighbors.	[228]
Naïve Bayesian (NB)	A generative probabilistic classifier with a linear decision boundary. Experimental testing has demonstrated that naive Bayes networks are surprisingly good classifiers on some problem domains, despite their strict independence assumptions between attributes and the class.	Naïve Bayes classifier using a one dimensional continuous Gaussian distribution (μ,σ) per feature per class. Prior distributions are learned from the data.	[229]
LogitBoost	A Boosting algorithm based on the log likelihood-loss and Newton optimization. LogitBoost is a statistical version of AdaBoost, of one of the most successful boosting algorithms, that has been found to perform better in more realistic and noisier datasets. LogitBoost produces more accurate classifiers from a sequence of base weak classifiers learned iteratively from reweighed versions of the original data. During each iteration, the weight of instances difficult to classify is increased. Consequently, weak classifiers learned later in the process focus their classification effort on examples that have been found difficult to classify in previous iterations.	LogitBoost with decision stumps (decision trees with two leaf nodes) as base classifiers, with 10 boosting iterations, shrinkage set to 1.0, a weight threshold of 100, likelihood threshold of -1.79E308 and no resampling.	[215]
C4.5	A state-of-the-art decision tree classifier with non-linear decision boundaries that are parallel to the features axis. The algorithm grows the decision tree one node at a time by selecting the best attribute to split on based on the information gain criterion. Once the tree is built, instances are classified by transversing the tree from the root to the corresponding leaf node that contains the example classification.	C4.5 decision tree classifier using pruning with a confidence (certainty) factor of 25% (0.25), subtree rising when pruning, minimum of two instances per leaf, and no Laplace smoothing on leaves.	[112]

Table 5-3: Brief description of the classifiers explored in this section, their parameters used during the experiments presented in this section and references to papers describing them in full detail.

5.4.4 Can Fast Run-Time Classifiers Produce Acceptable Performance?

This section explores if classifiers amenable for real-time performance due to their fast training and classification times can achieve similar results than other popular or state-of-the-art classifiers with longer training and classification times. The Weka toolkit [226] was used to compare the performance of the following classifiers: The nearest neighbor classifier (NN) [228], the Naïve Bayesian (NB) classifier [229], the LogitBoost classifier [215], and the C4.5 decision tree classifier [112]. The NN classifier was chosen because it is one of the oldest and most widely used algorithms in existence. The NB classifier because it is a probabilistic classifier that has been found to perform extremely well in a variety of realistic datasets despite its simplicity, the LogitBoost because it is a state-of-the-art boosting algorithm that has been found to outperform AdaBoost (leading boosting algorithm) in a variety of classification tasks, and the C4.5 classifier for being one of the most popular decision tree classifiers due to its fast classification, high performance, and the interpretability of the classification rules it generates. Table 5-3 presents a brief description of each of these classifiers and the values of their parameters used during the experiments.

The performance and computational requirements of the classifiers shown in Table 5-4 is tested under two extreme conditions: (1) a best-case scenario where a small set of features is needed to recognize the activities of interest, and (2) a worse-case scenario where a large set of features is required to recognize the activities. In the best case scenario, the classifiers were trained and tested using the *ACAbsArea* feature set computed over each of the three axis (x, y, and z) of the seven accelerometers giving a

	Feature Set	NN	NB	LogitBoost	C4.5
Total training time (Average time per instance)	ACAbsArea	0.03s (7.8ms)	0.8s (0.02ms)	457s (11.1ms)	54s (1.3ms)
Total classification time (Average time per instance)	ACAbsArea	24s (11.3ms)	1.3s (0.6ms)	0.09s (0.04ms)	0.14s (0.06ms)
Total training time (Average time per instance)	MaxAcceleration	0.8s (0.01ms)	58s (1.4ms)	33000s (816.7ms)	1662s (40.6ms)
Total classification time (Average time per instance)	MaxAcceleration	2823s (1319.0ms)	53s (25.1ms)	0.16s (0.07ms)	0.17s (0.08ms)

Table 5-4: The total training time and classification times (in seconds) required to train the classifiers using the data from subjects MIT-002 to MIT-020 (19 subjects) and classify the activity examples of subject MIT-001. The features used are the *ACAbsArea* (21) and *MaxAcceleration* (247) computed over sliding windows of 5.6s.

total of 21 features (Features used, such as *ACAbsAreas* are fully described in Appendix A3). In the worse-case scenario, the classifiers where evaluated by computing the following set of features per acceleration axis: *ACAbsArea, DCArea, ACTotalAbsArea, DCMean, ACAbsMean, DCTotalMean, ACTotalSVM, ACRange, ACSegmentalforce, ACTotalSegmentalForce, ACVar, ACAbsCV, ACEnergy, ACEntropy, ACFFTPeaks, ACDomFreqRatio, ACBandEnergy, ACModVigEnergy, ACLowEnergy, ACCorr, ACKur, ACSkew, ACMCR, ACQ1, ACQ2, ACQ3, ACIQR, and ACPitch.* This feature set is referred as the *MaxAcceleration* set and consists of a total of 247 features. Appendix A3 presents the description of each of these features and how to compute them.

Features are computed over sliding windows of 5.6s in length after interpolating and band-pass and low pass filtering the raw accelerometer signals as explained in Section 5.4.2. Section 5.4.6 will later explain why this window length is a good one to use. The classifiers are attempting to discriminate among the 52 activities contained in the MIT dataset (including the *unknown* class) in a subject dependent and independent manner. This allows to testing the performance and computational requirements of the classifiers in a worse-case activity recognition scenario, as explained in the introduction.

Since the main goal of this section is to identify the classifiers more amenable for real-time performance, the section starts by discussing the training and testing time requirements of the classifiers. Table 5-4 presents the training and classification times (in milliseconds) required by the classifiers when recognizing the 52 activities contained in the MIT dataset using *ACAbsArea* and the *MaxAccelerationSet* feature sets in a subject dependent and independent manner using a 1GHz Intel core microprocessor. The total training time shown is the time required to train the classifiers using the data from subjects MIT-002 to MIT-020 (19 subjects) and the total classification time is the time required to classify the activity examples of subject MIT-001. The average training and classification time per activity example is shown in parenthesis.

From Table 5-4, it can be seen that the NN classifier achieves the lowest training times since training only requires the computation of a matrix containing the distances among all training examples. The classification times for the NN classifier however, are the longest ones from all the classifiers explored because every single example to classify has to be compared against all the examples available in the training data. When computing the *MaxAcceleration,* the NN classifier requires a classification time of 1.3s that might be unacceptable in some activity recognition applications. What is more, in order to work, the NN classifier requires storing in memory all the training examples available (46,216 in the MIT dataset). This might be a limitation in handheld devices with limited RAM memory such as existing mobile phones. Clearly in its current implementation, the NN algorithm is not too amenable for real-time performance in small mobile devices. The NB classifier has the second fastest training times from all the classifiers since training involves only computing the sample means and standard deviations over each feature per class. Its classification times are midrange, since they are 52 times faster than the NN classifier but 335 times slower than the classification times of the LogitBoost and C4.5 classifiers when using the *MaxAcceleration* feature set. The classification model generated by the NB classifier requires to store in memory the parameters of a univariate Gaussian distribution for each of the features and for each of the classes. When using the *MaxAcceleration* feature set, the number of parameters is 25,688. Furthermore, classification of new examples using the NB classifier requires the evaluation of 12,844 Gaussian distributions, a task that might prove difficult to achieve in low-processing power devices. The LogitBoost and C4.5 decision tree classifiers exhibit the fastest classification times from all the classifiers explored. This is because classification involves only the evaluation of simple if-then rules generated by the decision stumps in the case of the LogitBoost classifier and the decision tree in the case of the C4.5 classifier. One important disadvantage of the LogitBoost over the C4.5 classifier is its extremely long training times. The LogitBoost classifier took 9.3hours to train while the C4.5 classifier only 27.7min when using the *MaxAcceleration* feature set. This is because training the LogitBoost classifier requires the training of weak classifiers (decision stumps) in repeated iterations (10 in this experiment) to create the final ensemble of classifiers. Long training times might be particularly unacceptable if subject dependent training is required to recognize activities, since end-users might not be able to test the performance of the classifier immediately after the system has been trained. It is important to remember that the training and testing times presented in this section for the *MaxAcceleration* feature set is a worse-case scenario where the largest and most complex feature set is utilized (all accelerometer-based features shown in Appendix A3). Training and testing times will obviously reduce as the number of features is reduced. Section 5.5 will later show that real time performance can be achieved by utilizing a subset of the most discriminant features contained in the *MaxAcceleration* set.

In summary, the two classifiers more amenable for real-time performance are (1) the C4.5 decision tree classifier and the (2) NB classifier. The C4.5 classifier is a good choice when classifying activities from low-processing power hand-held devices due to its fast classification times, mid-size classification models, and medium range training times. The NB classifier is a good option when low training times are particularly important and processing requirements are available to evaluate the Gaussian functions required by the algorithm in real-time. Now, it is necessary to compare the performance of the C4.5 and NB classifiers against those obtained by the NN and LogitBoost classifiers.

Table 5-5 and Table 5-6 present the performance of evaluating the classifiers using the *MaxAcceleration* feature set using subject dependent and independent training respectively over the MIT dataset. First, it can be seen that the performance of subject dependent training is considerably higher (~81-88%) than the performance obtained using subject independent training (~33-59%). The probability of random guessing in this scenario is 1.9% for 52 activities. The best overall performance in both cases is achieved using the LogitBoost classifier. This is because weak classifiers learned in the final iterations of boosting concentrate their classification efforts on instances that are difficult

Activity Category	NN	NB	LogitBoost	C4.5
All (accuracy)	82.5 ± 2.1	83.1 ± 2.1	88.2 ± 1.4	81.7 ± 1.5
Postures	91.9±6.3 (0.0±0.0)	89.2±6.8 (0.1±0.22)	95.1±4.7 (0.0±0.0)	92.2±5.8 (0.1±0.0)
Ambulation	88.4±8.4 (0.2±0.1)	93.8±6.3 (0.1±0.1)	88.9±7.3 (0.1±0.0)	84.4±9.1 (0.2±0.1)
Exercise	83.9±11.5 (0.2±0.1)	90.9±9.2 (0.1±0.1)	90.6±8.5 (0.0±0.0)	88.6±9.9 (0.15±0.1)
Resistance Exercise	78.5±13.8 (0.3±0.2)	88.7±10.0 (0.2±0.2)	87.0±9.6 (0.1±0.0)	84.8±10.7 (0.2±0.1)
Household	84.0±9.7 (0.4±0.3)	84.1±7.7 (0.5±0.4)	82.2±9.6 (0.1±0.1)	75.1±9.9 (0.4±0.2)
Unknown	70.55 ± 7.03 (3.7 ± 1.1)	63.53 ± 8.43 (3.5 ± 0.7)	86.89 ± 3.94 (7.71 ± 1.38)	74.81 ± 5.54 (7.63 ± 1.35)

Table 5-5: True positive rate and false positive rate (shown in parenthesis) clustered per activity category while classifying the 52 activities contained in the MIT dataset in a subject dependent manner. Classifiers were trained by computing the *MaxAcceleration* (247) feature set per accelerometer axis over sliding windows of 5.6s.

Activity Category	NN	NB	LogitBoost	C4.5
All (accuracy)	48.9 ± 5.1	33.9 ± 4.5	59.59 ± 4.43	49.4 ± 4.9
Postures	50.7±16.2 (0.3±0.2)	36.3±14.2 (1.6±0.7)	71.9±28.2 (0.2±0.3)	66.8±31.3 (0.2±0.3)
Ambulation	44.7±26.7 (0.7±0.6)	54.6±31.6 (1.2±1.1)	54.3±30.1 (0.7±0.7)	41.4±26.0 (0.8±0.8)
Exercise	44.5±24.8 (0.6±0.4)	48.2±29.8 (0.8±0.7)	51.8±31.5 (0.6±0.6)	39.8±33.6 (0.5±0.6)
Resistance Exercise	34.1±21.5 (0.7±0.5)	34.5±28.6 (1.1±0.9)	40.1±31.5 (0.8±0.8)	31.5±29.6 (0.8±0.7)
Household	45.3±19.6 (1.3±0.7)	32.1±18.8 (1.6±0.8)	49.7±25.2 (0.6±0.6)	37.9±24.4 (0.9±0.7)
Unknown	48.2 ± 5.6 (13.0 ± 4.0)	11.7 ± 5.3 (2.4 ± 2.8)	73.5 ± 5.2 (17.8 ± 7.2)	65.3 ± 6.6 (24.0 ± 7.2)

Table 5-6: True positive rate and false positive rate (shown in parenthesis) clustered per activity category while classifying the 52 activities contained in the MIT dataset in a subject independent manner. Classifiers were trained by computing the *MaxAcceleration* (247) feature set per axis over sliding windows of 5.6s.

to classify in previous iterations, giving the classifier and advantage when handling activity examples difficult to classify. The overall performance of NN, NB and C4.5 is quite comparable during subject dependent training (see Section 5.3.1 and 5.3.2 for a description of subject dependent vs. independent training procedures). One important difference of the NB classifier is that it tends to classify ambulation, exercise, resistance exercise and household activities slightly better than the other classifiers. However, its performance while classifying the unknown activity is the worst of all the classifiers during both, subject dependent and independent training. One explanation might be that the NB classifier is recognizing more unlabeled activity examples contained in the *unknown* class as real activities of interest that the other classifiers. This can be seen from the large number of false positives generated by the other classifiers for the unknown class, since they classify the other activities of interest as the *unknown* class. This can be a side effect of the large number of examples contained in the *unknown* class with respect to the number of examples contained in other classes (Appendix A4 shows the number of training examples available per class). The NB classifier might be able to recognize the activities of interest better with respect to the *unknown* class given the high probability seen by the evidence (features) for the other activities despite the high prior probability assigned to the *unknown* class. The other classifiers, on the contrary, decide to classify some of the examples of the activities of interest as belonging to the *unknown* class. The NB classifier also has more problems when recognizing postures as compared to the other classifiers. This is because it confuses most postures with the lying down posture given that this posture has a higher number of examples with respect to the other postures.

During subject independent training, the NB classifier also has a lower recognition rate for postures and for the *unknown* class with respect to the other classifiers for the same reasons previously explained. It also tends to recognize ambulation, exercise and resistance exercise slightly better than the C4.5 decision tree classifier. The overall performance of the C4.5 classifier is the second highest from all the classifiers and is comparable to the performance obtained with the NN classifier. Interestingly, the C4.5 classifier presents the largest false positive rate for the *unknown* class, reflecting the fact that it might be influenced by the large number of training examples available for this class. Finally, the lowest recognition performance from all the activity categories during subject independent training is obtained for resistance exercise activities. These activities are difficult to discriminate from accelerometer data since most of them do not involve changes in the motion patterns of the activity, but changes in the effort required to perform the activities. Interestingly, this low performance is not so obvious during subject dependent training for this category. It is possible that different subjects perform slight changes in the motion patterns of an activity when different resistance levels are used that the classifiers are able to successfully learn to discriminate among the activities.

In order to better understand the performance differences among classifiers, figures were generated to graphically highlight the per class performance across classifiers. Figures Figure 5-2 through Figure 5-5 show the performance per class for the classifiers while using subject dependent and independent training respectively. The figures show the performance per class as a grayscale image normalized with respect to the lowest and highest performance across all classifiers. For example, in Figure 5-2, the maximum true positive rate of 99.7% is represented by the color white and the minimum of 45.7% by the color black. With this coding scheme, areas of poor performance can be easily identified as dark (black) areas in the image.

Figure 5-2 shows the true positive rate per activity for all the classifiers as evaluated using subject dependent training. From the image it is easy to see that the classifier with best performance per class is the LogitBoost classifier (since it has lighter colors overall), followed by the NB classifier. As discussed previously, the NB classifier has difficulties recognizing the *unknown* class and outperforms the LogitBoost and C4.5 classifiers while recognizing household activities. One possible explanation for this behavior is that the Gaussian distributions used by the NB classifier to represent features are able to better learn distinctive motion patterns per subject such as the circular motion of hands while *scrubbing a surface*, or while *washing windows* that are not learned by the other classifiers due to the high motion variability in these activities.

Figure 5-3 shows the false positive rate per activity as a grayscale image for all the classifiers. Similarly, poor areas of performance are identified by dark areas. It can be seen that largest number of false positives (7.63%) is generated by the LogitBoost and C4.5 classifiers for the *unknown* class. Again, this is because some examples of real

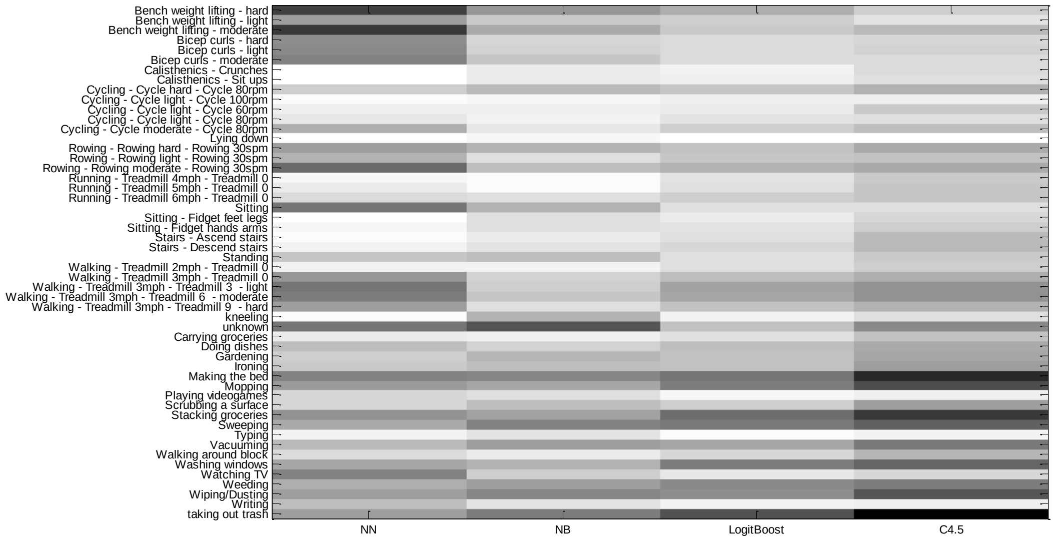


Figure 5-2: True positive rate per activity for all the classifiers using the *MaxAcceleration* feature set and subject dependent evaluation. The grayscale image is scaled so that the maximum true positive rate of 99.7% is represented by the color white and the minimum of 45.7% by the color black. In other words, poor areas of performance are shown in black.

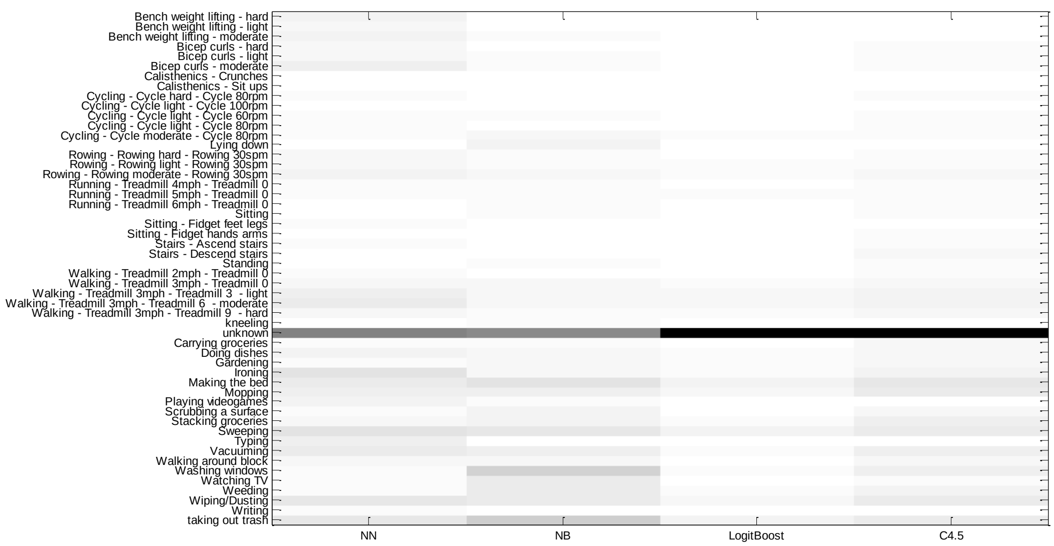


Figure 5-3: False positive rate per activity for all the classifiers using the *MaxAcceleration* feature set and subject dependent evaluation. The grayscale image is scaled so that the minimum false positive rate of 0% is represented by the color white and the maximum of 7.63% by the color black. In other words, poor areas of performance are shown in black.

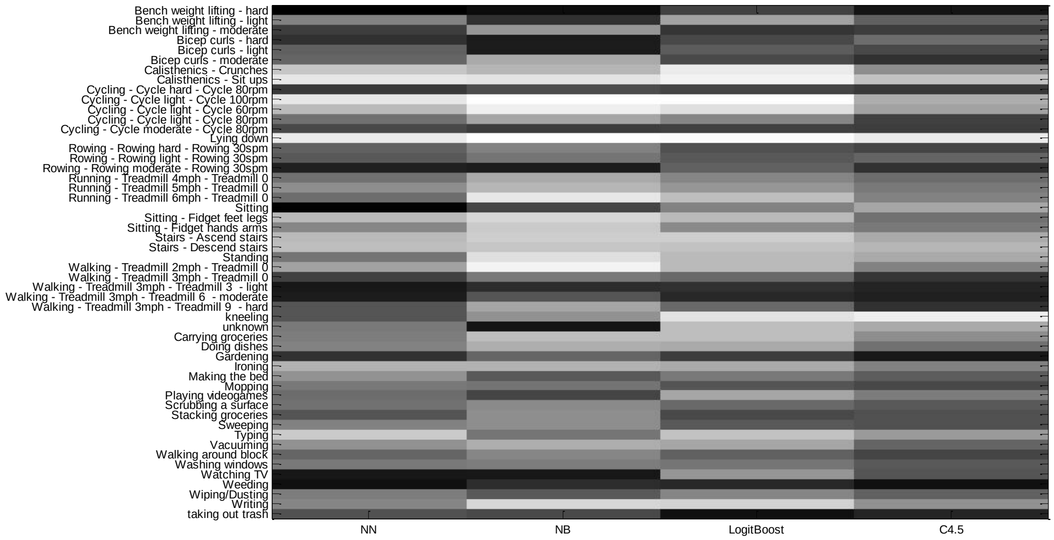


Figure 5-4: True positive rate per activity for all the classifiers using the *MaxAcceleration* feature set and subject independent evaluation. The grayscale image is scaled so that the maximum true positive rate of 96.7% is represented by the color white and the minimum of 4.5% by the color black. In other words, poor areas of performance are shown in black.

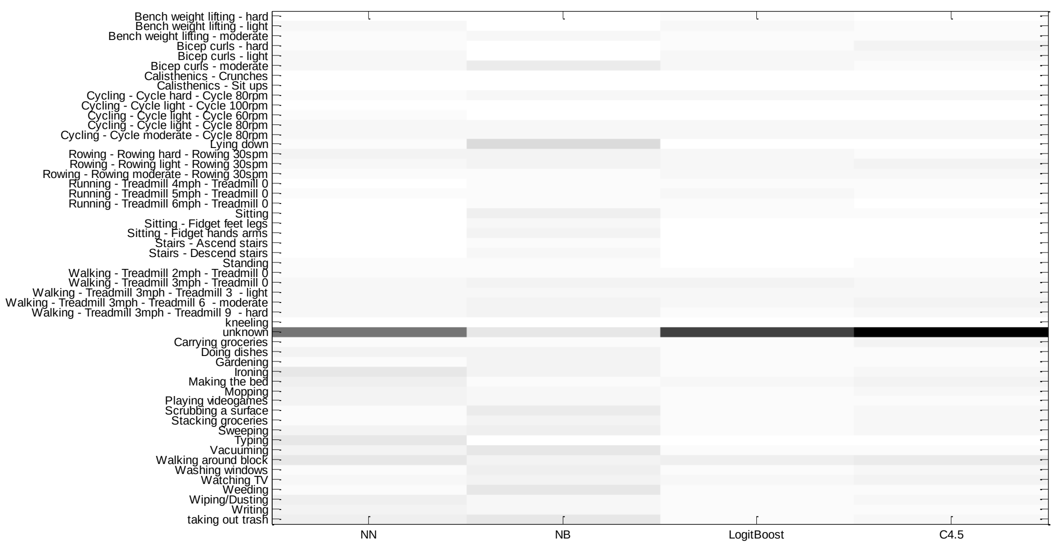


Figure 5-5: False positive rate per activity for all the classifiers using the *MaxAcceleration* feature set and subject independent evaluation. The grayscale image is scaled so that the minimum false positive rate of 0.01% is represented by the color white and the maximum of 24% by the color black. In other words, poor areas of performance are shown in black.

activities are classified as the *unknown* class. The *unknown* class contains examples of the other activities of interest that were just not labeled during the data collections. The C4.5 classifier also generates a larger number of false positives for household activities when compared to the NB classifier. However, the number of false positives for the NB classifier is concentrated in the *unknown* class. In general, the NN classifier presents a high number of false positives for resistance exercise activities such as *bench weight lifting* and *bicep curls*.

Figures Figure 5-4 and Figure 5-5 show the true positive rate and false positive rate per activity for all the classifiers using the *MaxAcceleration* feature set and subject independent evaluation. These figures highlight three main differences between the NB and the other classifiers: (1) the NB classifier tends to recognize some periodic activities such as *ascending stairs*, *descending stairs*, *walking* at 2mph, and *cycling* at 60 and 100rpm better than the other classifiers. This is also true for household activities including periodic motion such as *scrubbing a surface*, *stacking groceries*, *sweeping*, *vacuuming*, and *writing*. This is perhaps because the Gaussian distributions capture the periodicity of the motion across different subjects better than the non-linear decision boundaries used by the other classifiers. (2) In activities involving similar motion patterns but different resistance levels (e.g. light, moderate, hard), the classifier tends to classify better the activity with the medium resistance level (moderate). This is because activities with moderate intensity represent the average amount of motion for all the activity intensities. The other classifiers, on the contrary, learn to discriminate equally well among all the different intensity levels of the same activity. (3) Finally, the false positive rate in the NB classifier tends to be more uniformly distributed across all the activities. In contrast, the other classifiers tend to concentrate the number of false positives in a single class: the *unknown* class.

Since one of the main differences between the NB and the C4.5 classifiers seems to be the recognition performance over the *unknown* class, a new set of experiments was performed to compare these classifiers when the *unknown* class is left out. Table 5-7 shows the performance of these classifiers during subject dependent and independent training. The feature set used to train the classifiers was the *MaxAcceleration* set computed over windows of 5.6s in length. It can be seen that the overall performance of the NB classifier is slightly better during both subject dependent and independent training. During subject dependent training, the C4.5 classifier recognizes postures and exercise activities slightly better than the NB classifier. The NB classifier, on the other hand, classifies ambulation and household activities slightly better than the C4.5 classifier. During subject independent training, the same conditions are true except that now, the NB classifier also outperforms the C4.5 decision tree classifier during exercise and resistance exercise activities.

To better compare the performance of the NB and the C4.5 decision tree classifier, grayscale images comparing their performance per class were again generated. These images are shown in Figures Figure 5-6 through Figure 5-9. Figure 5-10 and Figure 5-11 show the confusion matrices for subject dependent and independent training using the *MaxAcceleration* feature set.

In general, as shown by figures Figure 5-6 and Figure 5-7, both classifiers have difficulties recognizing household activities during subject dependent training. For example, the classifiers confuse activities involving standing and walking such as *making the bed* and *taking out trash*. They also confuse activities involving standing and upper body motion such as *washing windows* and *wiping/dusting*. The classifiers also confuse activities involving walking and upper body motion such as *sweeping* and *mopping*. In summary, the NB classifier has more problems in recognizing *sweeping*, *wiping/dusting*,

	Subject Dependent		Subject Independent	
Activity Category	**NB**	**C4.5**	**NB**	**C4.5**
All (accuracy)	90.6 ± 1.8	89.4 ± 2.2	57.8 ± 4.4	53.3 ± 5.3
Postures	90.9±6.1 (0.1±0.1)	95.9±4.4 (0.1±0.1)	72.4±17.1 (1.0±0.5)	79.5±26.1 (0.3±0.4)
Ambulation	94.7±5.8 (0.1±0.1)	90.9±7.1 (0.2±0.1)	64.7±27.8 (0.9±1.0)	49.0±29.1 (1.2±1.1)
Exercise	91.9±8.9 (0.1±0.1)	93.2±7.6 (0.1±0.1)	53.9±27.0 (0.8±0.7)	49.6±32.4 (0.9±0.9)
Resistance Exercise	89.7±9.7 (0.2±0.2)	89.8±8.8 (0.2±0.2)	43.3±26.7 (1.0±0.8)	36.0±31.9 (1.3±1.1)
Household	86.2±7.5 (0.4±0.3)	82.9±8.4 (0.4±0.2)	49.7±23.2 (0.9±0.6)	50.4±24.5 (1.2±0.9)

Table 5-7: True positive rate and false positive rate (shown in parenthesis) clustered per activity category while classifying the 51 activities contained in the MIT dataset using the NB and C4.5 classifier without the *unknown* class. Classifiers were trained by computing the *MaxAcceleration* (247) feature set per axis over sliding windows of 5.6s.

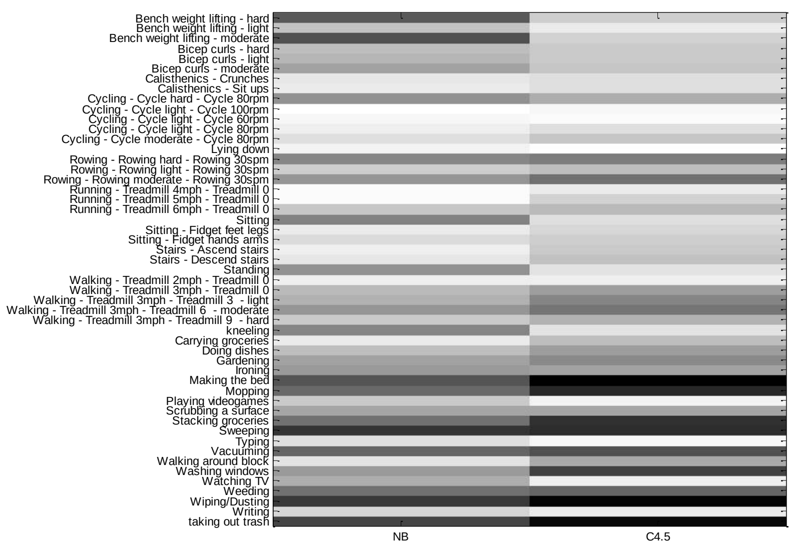


Figure 5-6: Comparison of true positive rate per activity for the NB and C4.5 Classifiers using the *MaxAccelerationSet1* without the *Unknown* Class evaluated using subject dependent training. The grayscale image is scaled so that the maximum true positive rate of 99.9% is represented by white and the minimum of 67.7% by black.

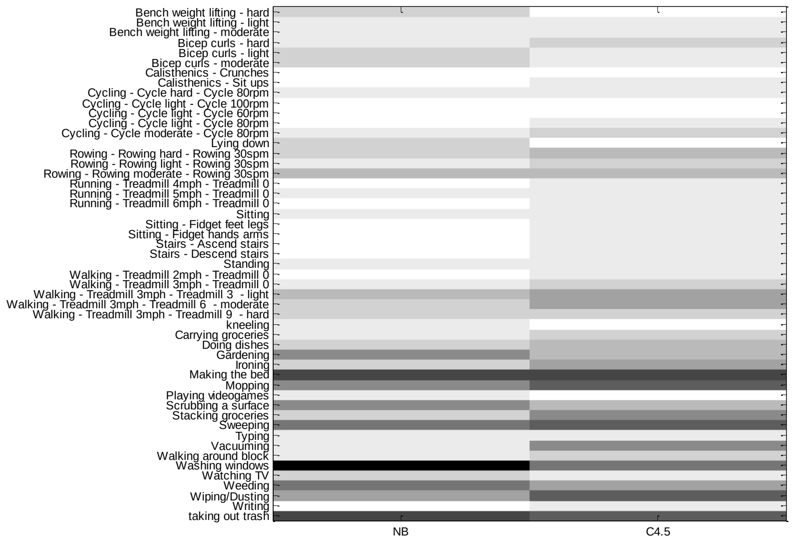


Figure 5-7: Comparison of false positive rate per activity for the NB and C4.5 Classifiers using the *MaxAccelerationSet1* without the *Unknown* Class evaluated using subject dependent training. The grayscale image is scaled so that the minimum false positive rate of 0.0% is represented by white and the maximum of 1.1% by black.

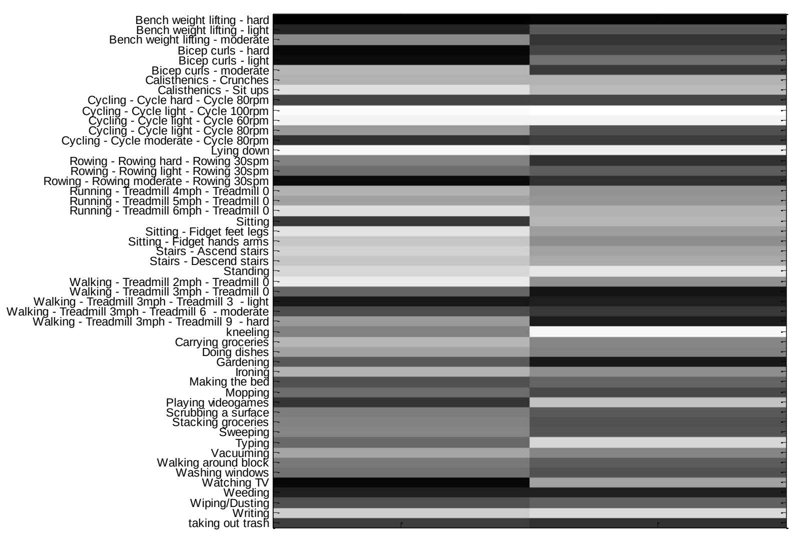


Figure 5-8: Comparison of true positive rate per activity for the NB and C4.5 Classifiers using the *MaxAccelerationSet1* without the *Unknown* Class evaluated using subject dependent training. The grayscale image is scaled so that the maximum true positive rate of 98.8% is represented by white and the minimum of 11.3% by black.

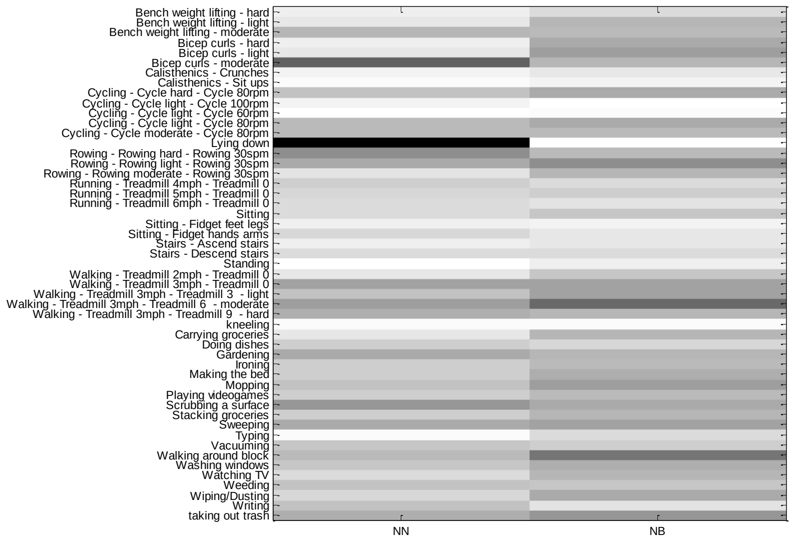
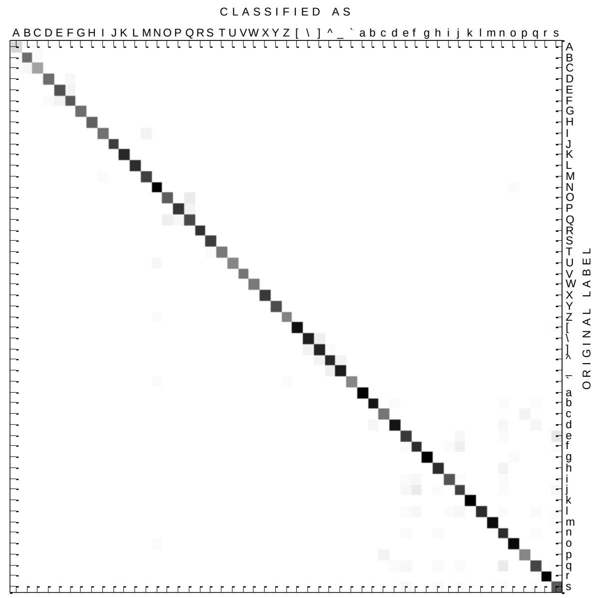


Figure 5-9: Comparison of false positive rate per activity for the NB and C4.5 Classifiers using the *MaxAccelerationSet1* without the *Unknown* Class evaluated using subject dependent training. The grayscale image is scaled so that the minimum false positive rate of 0.0% is represented by white and the maximum of 4.1% by black.

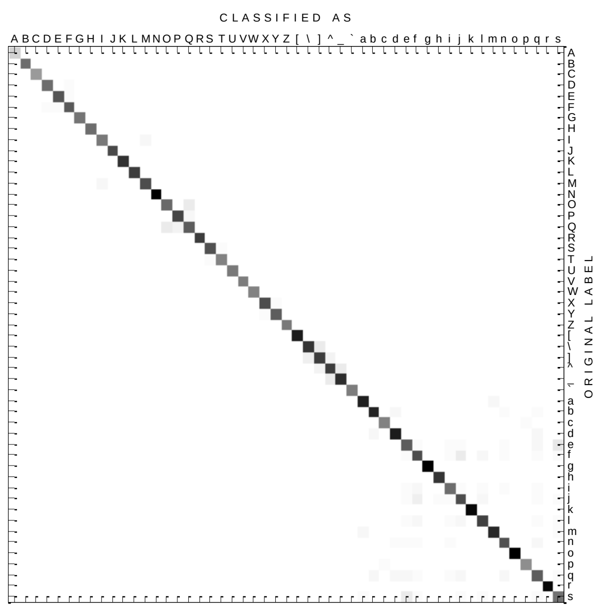
taking out trash, and *bench weight lifting* (hard and moderate). The C4.5 Classifier presents more difficulties recognizing *making the bed*, *wiping/dusting*, *taking out trash*, *moping* and *sweeping*. Figure 5-7 also shows that the number of false positives is more evenly distributed among all the classes that in the NB classifier. In the NB classifier, the number of false positives in concentrated in the *washing windows* activity.

During subject independent training, the performance of both classifiers as shown by Figure 5-8 is not easy to compare. Both classifiers are good at recognizing some sets of activities while bad at recognizing others. The NB classifier has more difficulties recognizing *bench weight lifting* light, *bicep curls* (light and hard), *rowing* moderate, and *watching TV* than the C4.5 classifier. At the same time, the C4.5 classifier has more difficulties recognizing *gardening*, and *walking* activities in general than the NB classifier. Figure 5-8 and Figure 5-9 show that the NB classifier is particularly bad at recognizing postures. For example, it confuses activities involving different postures such as *watching TV*, *playing video games*, *kneeling*, and *sitting* with *lying down*.

In summary, the overall performance of the NB classifier is slightly better during subject dependent (1.3%) and independent training (4.5%) than the one of the C4.5 classifier when the *unknown* class is not included. However, both classifiers have strengths and weaknesses. For example, the NB classifier seems is good at recognizing periodic activities but is bad at recognizing postures. The C4.5 classifier is good at recognizing postures, and its performance over activities with different intensity levels is more uniformly distributed than when using the NB classifier. When the *unknown* class is eliminated, the C4.5 classifier has a false positive rate per activity more evenly distributed across all activities than the NB classifier. When taking into account the classification time, the C4.5 classifier has an advantage since it can classify new examples 312 times faster than the NB classifier. The NB classifier, in contrast, can be



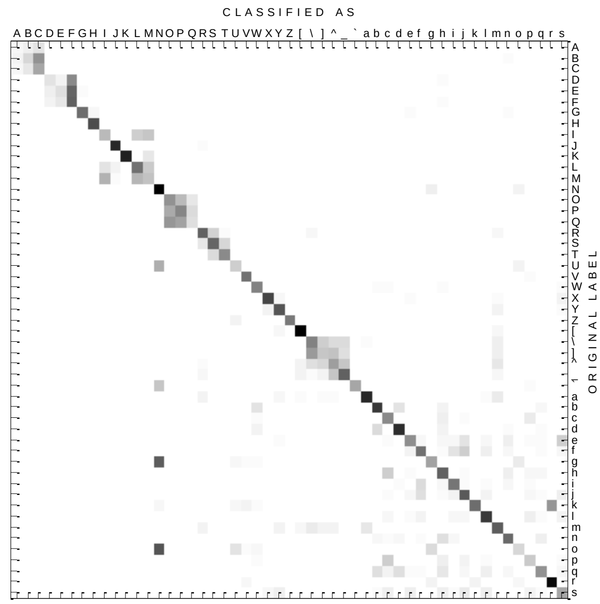
(a) NB Classifier



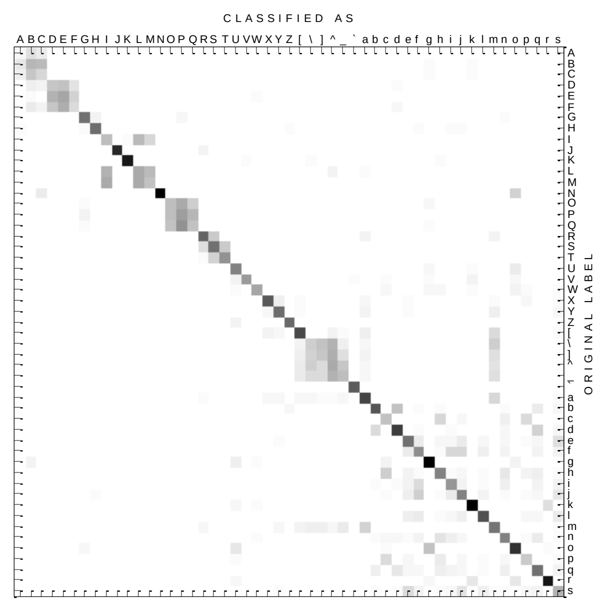
(b) C4.5 Classifier

```
A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[ -> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-
_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-
_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-
_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m ->
Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash
```

Figure 5-10: Confusion matrices for the NB and C4.5 classifier without the *unknown* class using subject dependent evaluation and the *MaxAcceleration* feature set.



(a) NB Classifier



(b) C4.5 Classifier

```
A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[ -> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-
_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-
_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-
_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m -> Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash
```

Figure 5-11: Confusion matrices for the NB and C4.5 classifier without the *unknown* class using subject independent evaluation and the *MaxAcceleration* feature set.

trained 28 times faster than the C4.5 classifier. Taking into account all the advantages and disadvantages of both classifiers, this work will utilize the C4.5 decision tree classifier as the final classification algorithm for the remainder of this thesis.

Lastly, the answer to the question posed by this section is yes. Fast run time classifiers such as the C 4.5 decision tree classifier and the NB classifier can achieve performances similar to the ones obtained by popular classifiers such as the NN classifier and state-of-the-art classifiers such as the LogitBoost Classifier. Upcoming sections will perform experiments to determine the set of parameters (e.g. feature set and window length) required to make the training process of the C4.5 classifier more amenable for real time performance without sacrificing recognition performance too much.

5.4.5 Can Features Computed Over Each Sensor Reduce Computational Requirements Without Sacrificing Performance?

In the previous section, as in most previous work, features were computed over each of the axis (*x*, *y*, and *z*) of the accelerometer signal. Nevertheless, computing features over each axis adds substantial computational load, particularly when complex features are computed over a large number of sensors. For example, if the FFT coefficients are being computed as features when using three triaxial accelerometers, the FFT algorithm would have to be run nine times (3 accelerometers times 3 axes) every time a new example has to be classified. As a result, it is worth exploring if it is possible to compute features per sensor and achieve similar performance as when computing features per axis. If this is in fact possible, at least a threefold improvement in computational performance would be obtained in the feature computation step. Further computational improvements would also be obtained during training and classification since fewer features are required.

Features can be computed per sensor by first summarizing the overall acceleration (motion) experienced by each sensor in all axes. This can be done by computing the sum of the acceleration over all axes (*x*, *y*, and *z*) sample by sample. Another technique is to compute the signal vector magnitude (SVM) over all axes. However, the SVM is computationally expensive since it requires the computation of square and root square operations. The formulas for the two techniques are shown in Table 5-8.

Sum	$Sum = x + y + z$
Signal Vector Magnitude	$SVM = \sqrt{x^2 + y^2 + z^2}$

Table 5-8: Two techniques used to summarize the acceleration (motion) experienced by a sensor: The sum over all acceleration axes (*x*, *y*, and *z*) and the signal vector magnitude.

In this section, the performance of computing features per sensor is evaluated by summarizing the motion experienced by each sensor using the sum operation. The experiments compare the performance of the NB and C4.5 classifiers when features are computed per axis and per sensor using the *MaxAcceleration* feature set over sliding windows of 5.6s. The classifiers are trying to recognize the 51 activities in the MIT dataset without including the *unknown* class. The *unknown* class was not added during these experiments to maximize the interpretability of the results per class. The experiments are evaluated using subject dependent and independent training.

	Subject Dependent Evaluation					
Activity Category	**NB Per Sensor**	**NB Per Axis**	**Change in Performance**	**C4.5 Per Sensor**	**C4.5 Per Axis**	**Change in Performance**
All (accuracy)	88.5 ± 3.6	90.6 ± 1.8	-2.16	87.3 ± 3.8	89.4 ± 2.2	-2.06
Postures	94.7±4.4 (0.0±0.1)	90.9±6.1 (0.1±0.1)	3.8 (-0.1)	96.5±3.9 (0.1±0.1)	95.9±4.4 (0.1±0.1)	0.6 (0)
Ambulation	91.8±6.3 (0.2±0.2)	94.7±5.8 (0.1±0.1)	-2.9 (0.1)	87.4±8.2 (0.4±0.2)	90.9±7.1 (0.2±0.1)	-3.5 (0.2)
Exercise	90.0±9.2 (0.2±0.2)	91.9±8.9 (0.1±0.1)	-1.9 (0.1)	91.9±7.6 (0.2±0.2)	93.2±7.6 (0.1±0.1)	-1.3 (0.1)
Resistance Exercise	85.9±10.9 (0.4±0.3)	89.7±9.7 (0.2±0.2)	-3.8 (0.2)	86.4±9.3 (0.3±0.2)	89.8±8.8 (0.2±0.2)	-3.4 (0.1)
Household	81.6±9.8 (0.6±0.4)	86.2±7.5 (0.4±0.3)	-4.6 (0.2)	80.0±9.8 (0.6±0.4)	82.9±8.4 (0.4±0.2)	-2.9 (0.2)

Table 5-9: True positive rate, false positive rate (shown in parenthesis) and change in performance while computing features per sensor and per axis clustered per activity category while classifying the 51 activities contained in the MIT dataset using the NB and C4.5 classifier without the *unknown* class. Classifiers were trained by computing the *MaxAccelerationSet1* (247 over sliding windows of 5.6s using subject dependent training.

	Subject Independent Evaluation					
Activity Category	**NB Per Sensor**	**NB Per Axis**	**Change in Performance**	**C4.5 Per Sensor**	**C4.5 Per Axis**	**Change in Performance**
All (accuracy)	47.6 ± 6.0	57.9 ± 4.4	-10.23	45.5 ± 7.7	53.3 ± 5.3	-7.88
Postures	42.7±22.0 (1.4±0.8)	72.4±17.1 (1.0±0.5)	-29.7 (0.4)	58.7±38.4 (0.7±1.0)	79.5±26.1 (0.3±0.4)	-20.8 (0.4)
Ambulation	47.8±34.8 (1.3±1.4)	64.7±27.8 (0.9±1.0)	-16.9 (0.4)	37.8±26.6 (1.4±1.6)	49.0±29.1 (1.2±1.1)	-11.2 (0.2)
Exercise	42.2±30.8 (1.1±1.1)	53.9±27.0 (0.8±0.7)	-11.7 (0.3)	39.1±28.5 (1.2±1.5)	49.6±32.4 (0.9±0.9)	-10.5 (0.3)
Resistance Exercise	30.9±27.5 (1.3±1.2)	43.3±26.7 (1.0±0.8)	-12.4 (0.3)	25.9±25.3 (1.6±1.8)	36.0±31.9 (1.3±1.1)	-10.1 (0.3)
Household	32.5±24.1 (1.2±1.0)	49.7±23.2 (0.9±0.6)	-17.2 (0.3)	32.3±26.8 (1.6±1.5)	50.4±24.5 (1.2±0.9)	-18.1 (0.4)

Table 5-10: True positive rate, false positive rate (shown in parenthesis) and change in performance while computing features per sensor and per axis clustered per activity category while classifying the 51 activities contained in the MIT dataset using the NB and C4.5 classifier without the *unknown* class. Classifiers were trained by computing the *MaxAccelerationSet1* (247 over sliding windows of 5.6s using subject independent training.

Table 5-9 presents a comparison of the performance of the NB and C4.5 classifiers while computing features per sensor and per axis using subject dependent training. It can be seen that the overall decrease in performance for both classifiers is very close and corresponds to a decrease of approximately 2%. The decrease in performance for the NB classifier is larger for household activities (-4.6%) and resistance exercise activities (-3.8%). One explanation for the performance decrease in resistance exercise activities is that subjects perform characteristic motions in several axes while struggling with different load or resistance levels. An interesting result is that the performance for postures increases when computing features per sensor for both classifiers during subject dependent training. It seems that computing features per axis while recognizing postures in a subject dependent manner introduces more variability in the features leading to a decrease in performance. Moreover, the smallest decrease in performance for both classifiers occurs for exercise activities. Exercise activities include activities with very characteristic periodic motions differentiated by the use of particular limbs such as *bicep*

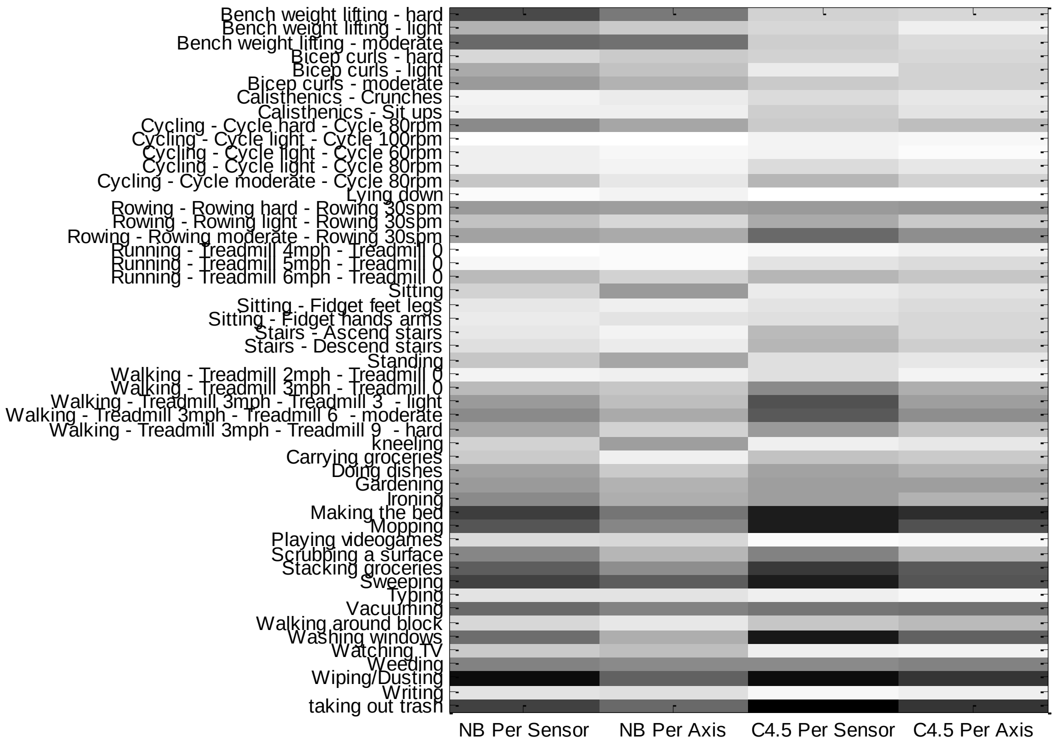


Figure 5-12: True positive rate per activity using the *MaxAcceleration* feature set computed per sensor and per axis and evaluated using subject dependent training with the NB and C4.5 classifiers. The grayscale image is scaled so that the maximum true positive rate of 100% is represented by white and the minimum of 60.3% by black. In other words, poor areas of performance are shown in black.

curls, *cycling*, *and calisthenics* activities (*crunches*, *sit-ups*) and ambulation (*walking* and *running*). Consequently, they can be well differentiated without analyzing the motion per axis.

Table 5-10 presents the performance while computing features per sensor and per axis for both classifiers using subject independent training. The overall decrease in performance of approximately 9% for both classifiers is larger than the decrease observed during subject dependent training. The decrease for the NB classifier is 10% and for the C4.5 classifier is 7.8% (slightly lower). In contrast to subject dependent training, it can be seen that a decrease in performance occurs for all the activity categories. The most dramatic decrease occurs for postures (29% for NB and 20% for C4.5) and household activities (17% for NB and 18% for C4.5). It can be concluded that analyzing motion per axis is more important during subject independent training since this extra information compensates for the high variability found in the performance of activities across subjects. The smallest decrease in performance occurs again for exercise activities because they are mainly discriminated by analyzing the motion of different body limbs moving at different speeds.

In an effort to better identify the differences per activity while computing features per sensor and per axis, images were generated to highlight the differences in performance

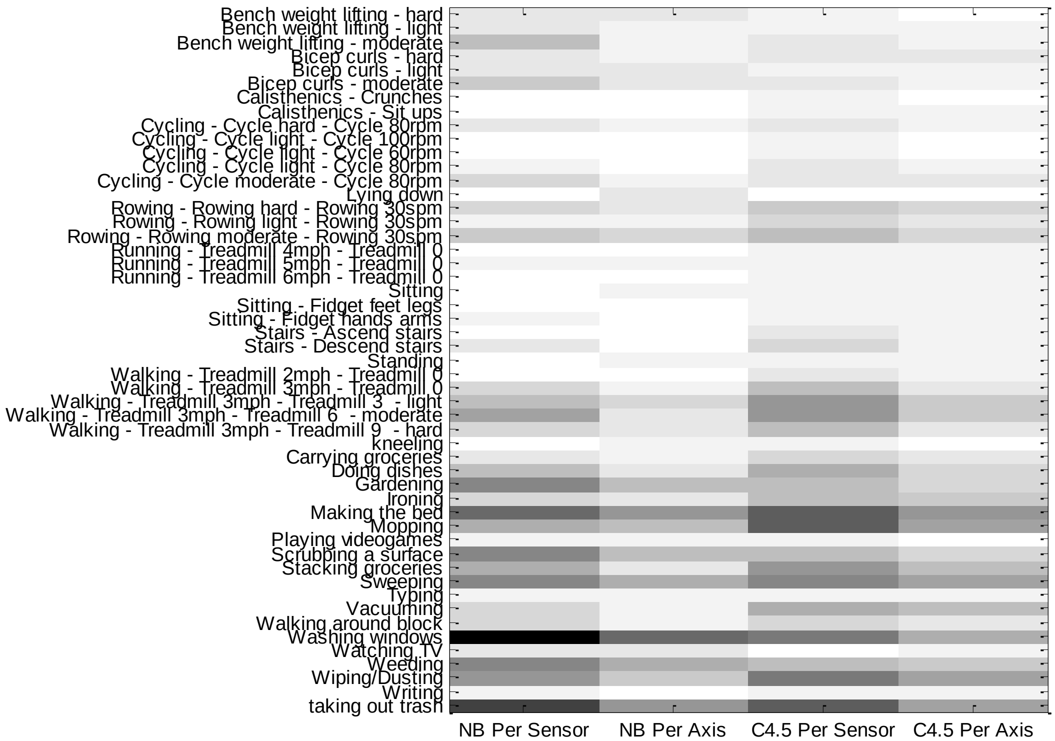


Figure 5-13: False positive rate per activity using the *MaxAcceleration* feature set computed per sensor and per axis and evaluated using subject dependent training with the NB and C4.5 classifiers. The grayscale image is scaled so that the minimum false positive rate of 0.0% is represented by white and the maximum of 1.9% by black. In other words, poor areas of performance are shown in black.

per activity. The images are grayscale images normalized so that the worse performance per activity is shown in black and the best performance per activity is shown in white.

Table 5-10 shows the true positive rate for both classifiers when features are computed per sensor and per axis using subject dependent training. One of the first differences one might notice is that both classifiers are having difficulties recognizing *wiping/dusting*. When inspecting the confusion matrices for the C4.5 classifier shown in Figure 5-16 and Figure 5-17, it can be seen that this activity is being confused with *ironing*, *doing dishes*, and *washing windows*. These are all activities involving the standing posture and upper body motion. The reason why the classifiers are even able to differentiate (to some extent) between these activities when motion is analyzed per sensor is the computation of features that capture posture information such as the *DCAreas* and *DCMeans* features (these features are explained in Appendix A3). For example, the classifiers are able to differentiate between *wiping/dusting* and *washing windows* due to the different posture of the dominant arm during the activities. Analyzing motion by axis helps in discriminating between these activities better as can be observed from Figure 5-12 and Figure 5-13. For the same reasons, the C4.5 classifier also confuses *washing windows* with *wiping/dusting* and *scrubbing a surface.* The activities least affected by not analyzing motion per axis are activities involving periodic motion and movement of distinctive limbs such as *cycling*, *calisthenics*, *walking* and *running*.

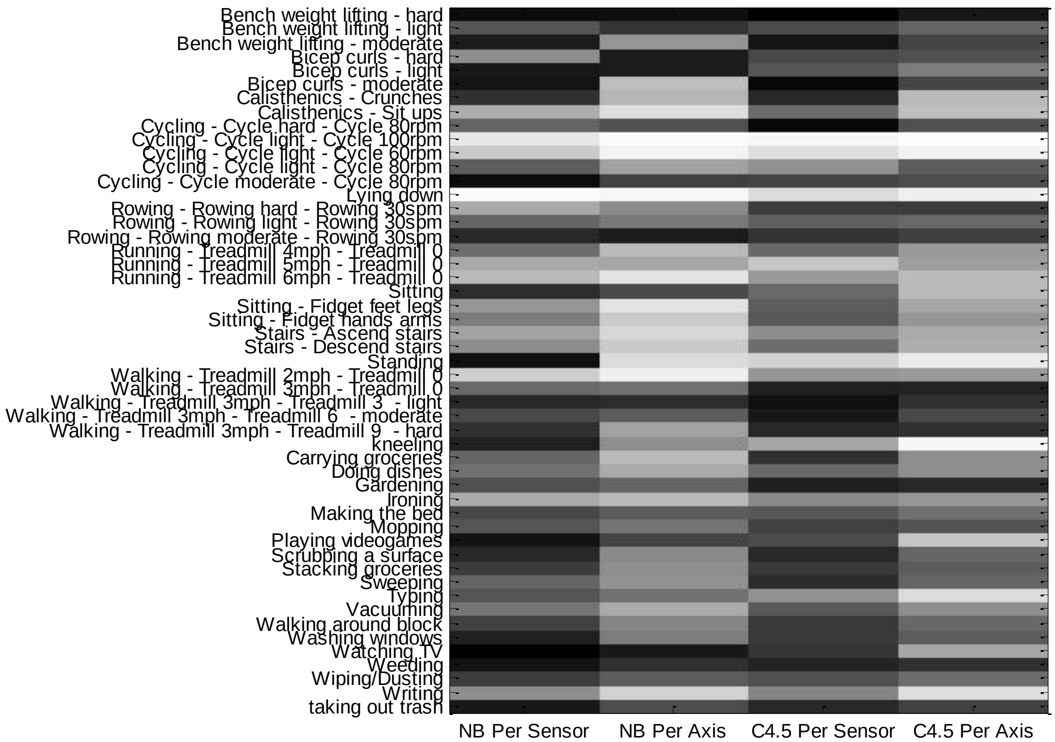


Figure 5-14: True positive rate per activity using the *MaxAcceleration* feature set computed per sensor and per axis and evaluated using subject independent training with the NB and C4.5 classifiers. The grayscale image is scaled so that the maximum true positive rate of 98.8% is represented by white and the minimum of 4.2% by black. In other words, poor areas of performance are shown in black.

Figure 5-13 presents the false positive rate per activity for both classifiers. According to the figure, the number of false positives for the NB classifier is concentrated in the *washing windows* activity since it is confused with other activities involving standing and upper body motion as previously explained. In general, it can be seen that analyzing motion per axis decreases the number of false positives per class.

Figure 5-14 and Figure 5-15 show the true positive and false positive rate per class when evaluating the classifiers in a subject independent manner. In general, the performance per class follows the same behavior as the one observed during subject dependent training. However, the performance of some activities involving different resistance levels such as *cycling*, *walking* (at different inclinations), and *bicep curl* is dramatically affected by not computing features per axis in both classifiers. As explained before, subjects might perform motions in different axis while struggling with different loads that might help in the discrimination between these activities. In addition, the performance on some activities with different postures such as standing, playing video games and weeding is also highly affected for the NB classifier. In the previous section, it was explained that the NB classifier has problems recognizing postures, and it seems that

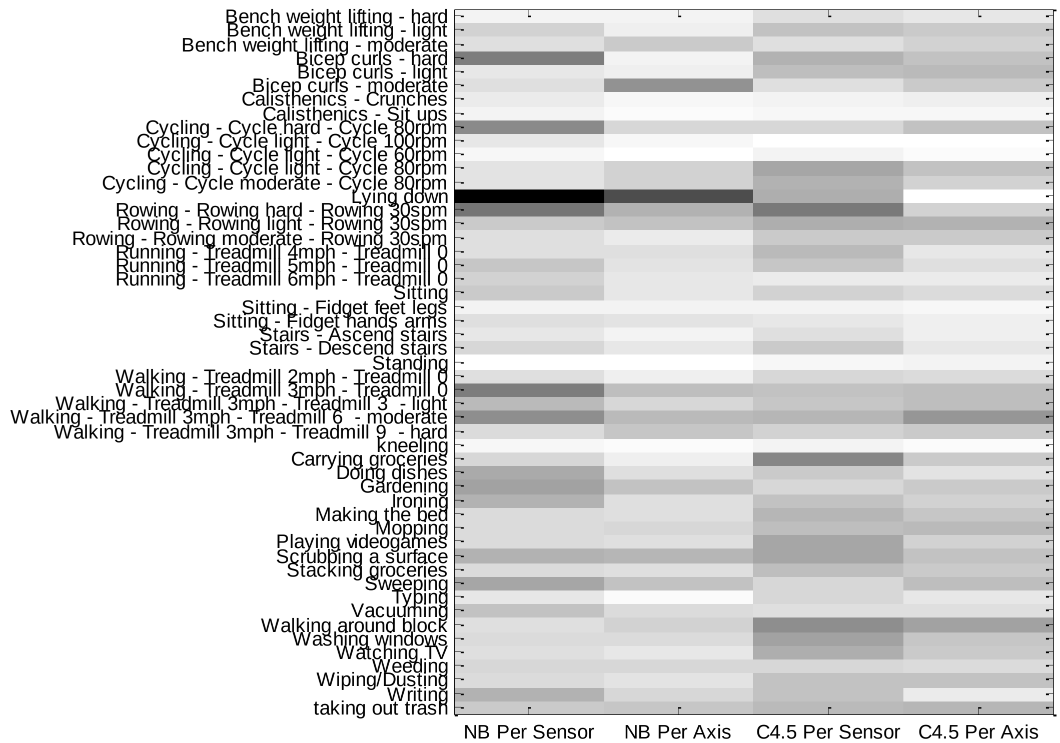
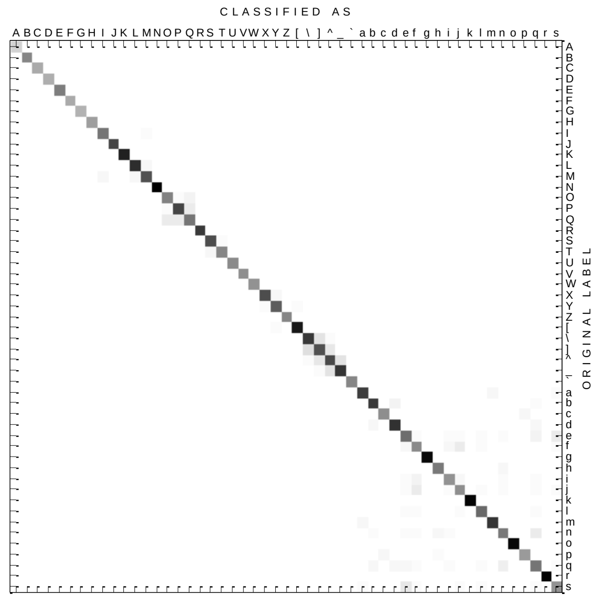


Figure 5-15: False positive rate per activity using the *MaxAcceleration* feature set computed per sensor and per axis and evaluated using subject dependent training with the NB and C4.5 classifiers. The grayscale image is scaled so that the minimum false positive rate of 0.0% is represented by white and the maximum of 5.9% by black. In other words, poor areas of performance are shown in black.

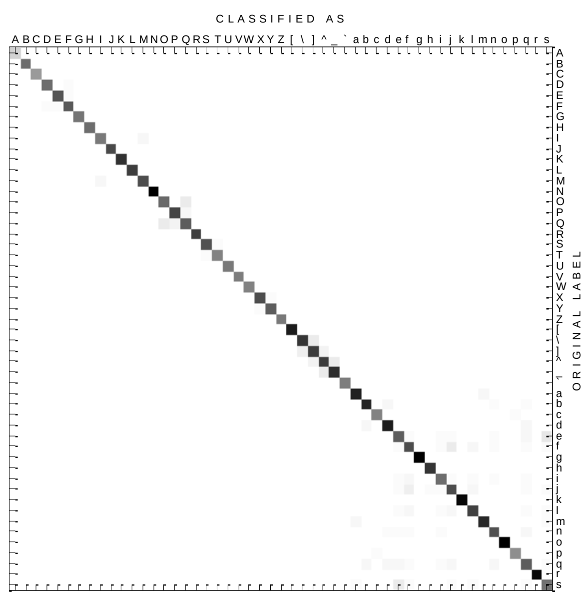
computing features per axis helps this classifier to better differentiate between activities involving different postures. When analyzing the confusion matrix for the C4.5 classifier during subject independent training (shown in Figure 5-17a), it can also be observed that this classifier is confusing activities involving different postures such as *watching TV*, *playing video games*, and *typing* when features are computed per sensor. Furthermore, it can also be seen that the C4.5 classifier also confuses *walking* at different speeds with *running*.

Finally, Figure 5-14 shows the true positive rate for both classifiers when subject independent training is used. Again, the true positive rate per class tends to be higher when features are computed per axis. It can also be seen that the C4.5 classifier has a false positive rate per class more evenly distributed across all activities and that the false positive rate for the NB classifier is higher for the activity *lying down*.

In summary, performance is affected less during subject dependent training than during subject independent training when features are computed per sensor. The decrease in performance with respect to feature computation per axis was ~2% for subject dependent training and ~9% for subject independent training. Using both training methods, the activities most affected where the ones involving similar postures (e.g. *watching TV* and *playing video games*), similar motion of limbs (e.g. *wiping/dusting* vs. *ironing*), and



(a) C4.5 Classifier Per Sensor



(b) C4.5 Classifier Per Axis

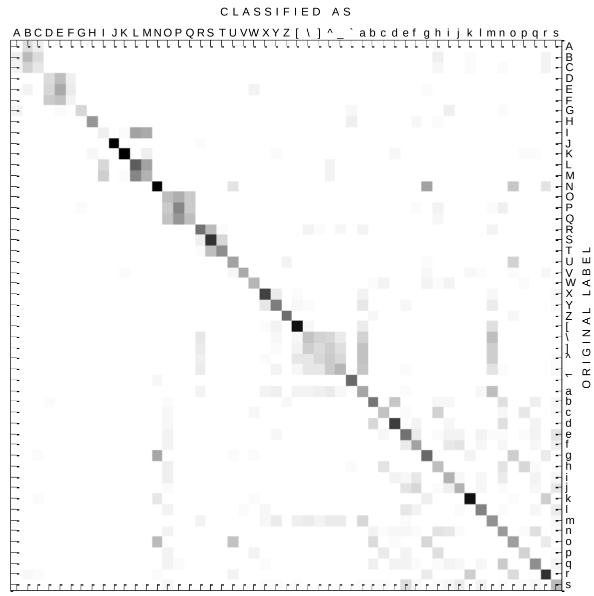
```
A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm

M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs

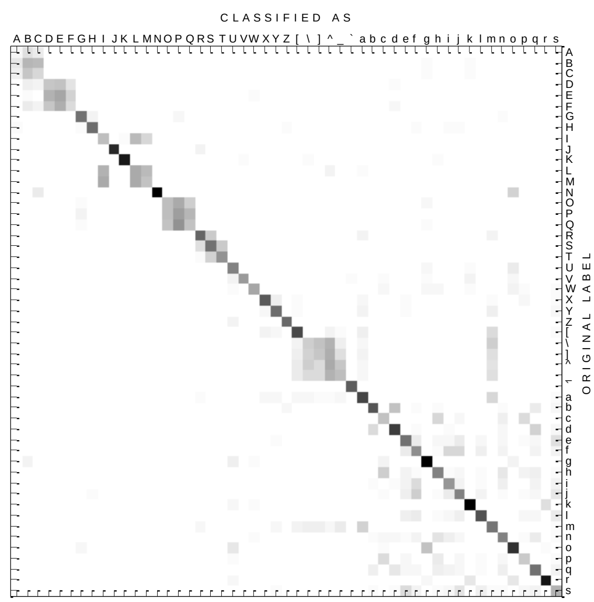
Z -> Standing
[ -> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-
_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-
_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-
_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping

g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m ->
Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash
```

Figure 5-16: Confusion matrices comparing the performance of the C4.5 classifier when the *MaxAcceleration* feature set is computed per sensor and per axis using subject dependent training.



(a) C4.5 Classifier Per Sensor



(b) C4.5 Classifier Per Axis

```
A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[ -> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-
_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-
_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-
_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m -> Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash
```

Figure 5-17: Confusion matrices comparing the performance of the C4.5 classifier when the *MaxAcceleration* feature set is computed per sensor and per axis using subject independent training.

activities involving different resistance levels (e.g. *bicep curls* moderate vs. hard). The activities least affected by feature computation per sensor were activities involving characteristic motion of a particular limb (e.g. *cycling* vs. *running*) or activities involving motion at different speeds (e.g. *running* at 5mph vs. 6mph). Consequently, feature computation per sensor can be used with only a 2% loss in recognition performance with subject dependent training, particularly when the activities of interest can be differentiated by the use of a particular limb, or motion at a particular speed without a considerable decrease in performance. From this point on, results will be presented utilizing feature computation per axis to better differentiate between the activities of interest and show the best possible performance during subject independent evaluation. While this is more computationally expensive, it might improve activity recognition performance in latter sections that analyze other parameters of the activity recognition algorithm. Finally, at three-fold increase in computational performance can be achieved by switching from feature computation per axis to feature computation per sensor at expense of some decrease in the performance for some activities if the amount of processing power is limited in some applications (e.g. in real-time applications implemented to run on mobile phones).

One possible criticism of the experiments performed in this section is that the analysis was performed using a large set of features (*MaxAcceleration* feature set). This might be a problem because the training and testing data might not be enough to reliably evaluate the difference in performance between feature computation per sensor and per axis. This is less of a problem for the C4.5 classifier since it performs feature selection during the training process and only utilizes the set of most discriminant features in the models generated. However, future work is required to analyze the difference between feature computation per sensor and per axis over subsets of accelerometer features to see if the results presented in this section hold when the number of features is decreased (at least for the naïve Bayes classifier).

5.4.6 What is the Optimal Sliding Window Length to Use?

Acceleration signals need to be broken down into windows of specific lengths so that features summarizing the mathematical properties of the signals can be computed. Selecting an appropriate sliding window length is a trade-off between the quality of some of the features computed and the real-time classification delay. The quality or resolution of some features such as the FFT transformation and the Pearson’s correlation coefficients strongly depend on the window length used. Usually, the longer the window length, the better these features can be estimated. On the other hand, the longer the window length, the longer the end-user of an activity recognition system has to wait for a recognition result. Another trade-off involved in selecting the window length is the ability to capture the motion patterns associated with the activities of interest. Long windows might introduce additional variability in the motion patterns observed for some highly unconstrained activities (e.g. household activities) while very short windows might not be able to capture the fundamental variability that characterizes a given activity (e.g. periodicity of motion during *walking* or *running*).

In this section, the most appropriate sliding window length is determined by measuring the performance of the C4.5 decision tree classifier over the two features whose quality is

Number of Samples	Time (s)
64	1.4
128	2.8
256	5.6
512	11.3
1024	22.7
2048	45.5
4098	91

Table 5-11: Window lengths explored while selecting the optimal window length to use for the activity recognition algorithm. The length is shown in number of acceleration samples and corresponding time in seconds, assuming a sampling rate of 45Hz.

most likely to vary with the window length: The FFT Peaks (*ACFFTPeaks*) and the Pearson's correlation coefficients (*ACCorr*). As a baseline, the performance is also computed utilizing the *ACAbsAreas* feature. The features will be first computed over window lengths ranging from 1.4 to 91 seconds (64 -2048 accelerometer samples) using feature computation per sensor, and later on a reduced set of window lengths using feature computation per axis. This procedure is followed to minimize the time and number of experiments to run. Window lengths shorter that 1.4s were not considered because they are intuitively too short to capture the repetitive motion patterns found in some periodic activities such as *walking* slowly at 2mph. Similarly, window lengths longer than 91s were not considered due to the extremely long real-time classification delay they introduce into the system.

The length of the sliding windows is constrained to be a power of two by the algorithms required to compute the Fourier and Wavelet transformations efficiently. Table 5-11 shows the windows lengths explored in this section in number of acceleration samples and corresponding time in seconds assuming a sampling rate of 45Hz. Figure 5-18 and Figure 5-19 present the true positive rate per activity category while evaluating the performance of the C4.5 decision tree classifier over different window lengths using the *ACAbsAreas* and *FFTCorr* feature set (*ACFFTPeaks* and *ACCorr* features) computed per sensor during subject dependent and independent training. Appendix A5 presents the same results in a tabular form.

The figures illustrate that during subject dependent training, the true positive rate for all activities reaches a maximum at a window length of 22.7s for the *ACAbsArea* feature and 5.6s for the *FFTCorr* feature set. After these maxima, the true positive rate for all the activities starts declining sharply. This is because increasing the window length reduces the number of activity examples available for training. For example, increasing the window length from 5.6s to 45s reduces the number of training examples per activity by a factor of 8. Since the MIT dataset contains between 1 and 4.5min of data for each activity, a window length of 45s reduces the number of training examples to be only between 1 and 6 per activity. In general, it can be observed that the performance for most activities increases as the window length increases. This makes sense since the quality or resolution of features such as the FFT and the correlation coefficients usually increases with increasing window lengths. The increase in performance when longer window lengths are used is more dramatic for household and ambulation activities when using the *ACAbsArea* feature and for household and resistance exercise activities while using the *FFTCorr* feature set. In fact, the performance over household activities keeps increasing even when the performance over all the activities has started decreasing for the *FFTCorr*

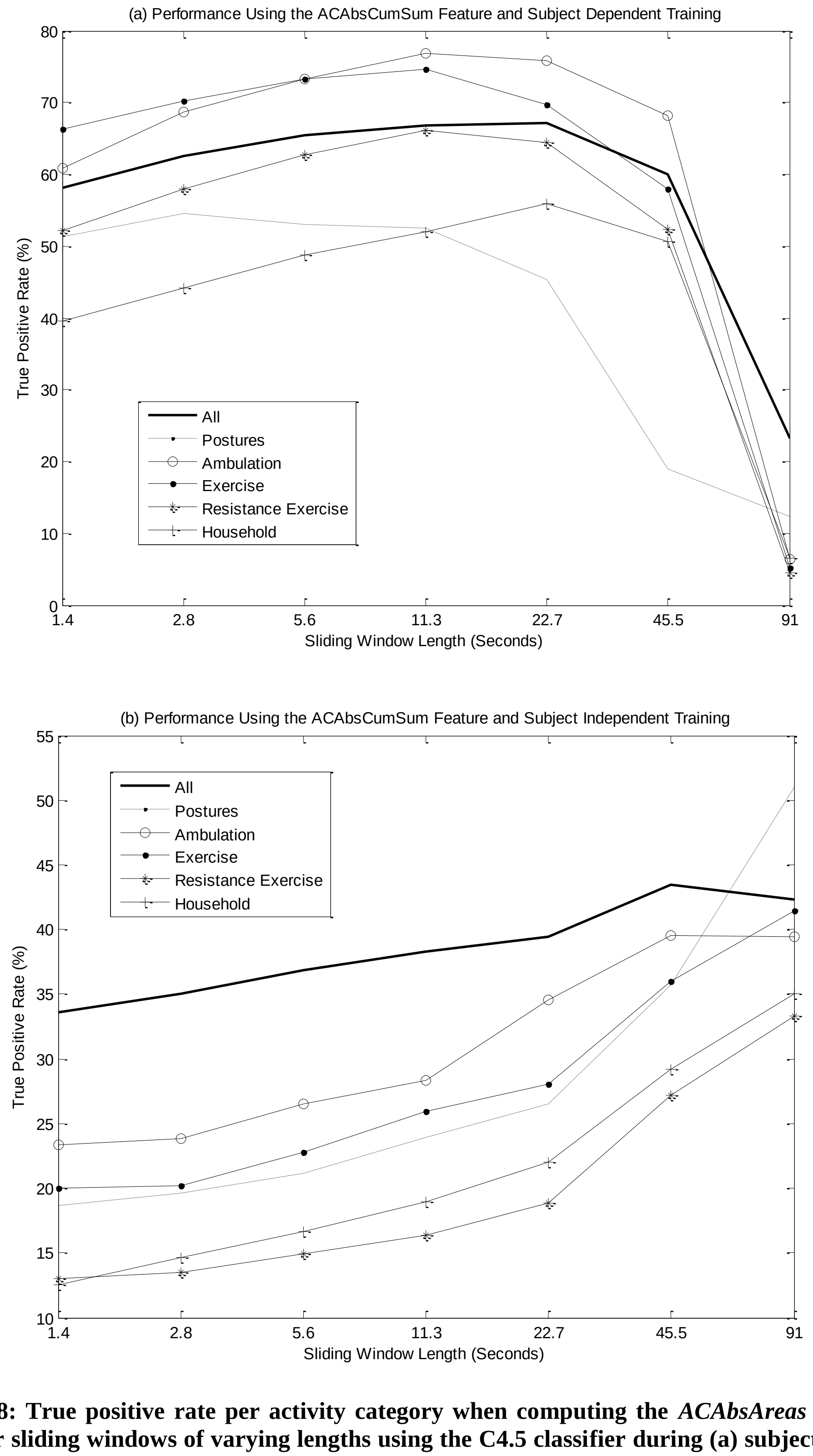


Figure 5-18: True positive rate per activity category when computing the *ACAbsAreas* feature per sensor over sliding windows of varying lengths using the C4.5 classifier during (a) subject dependent and (b) independent evaluation.

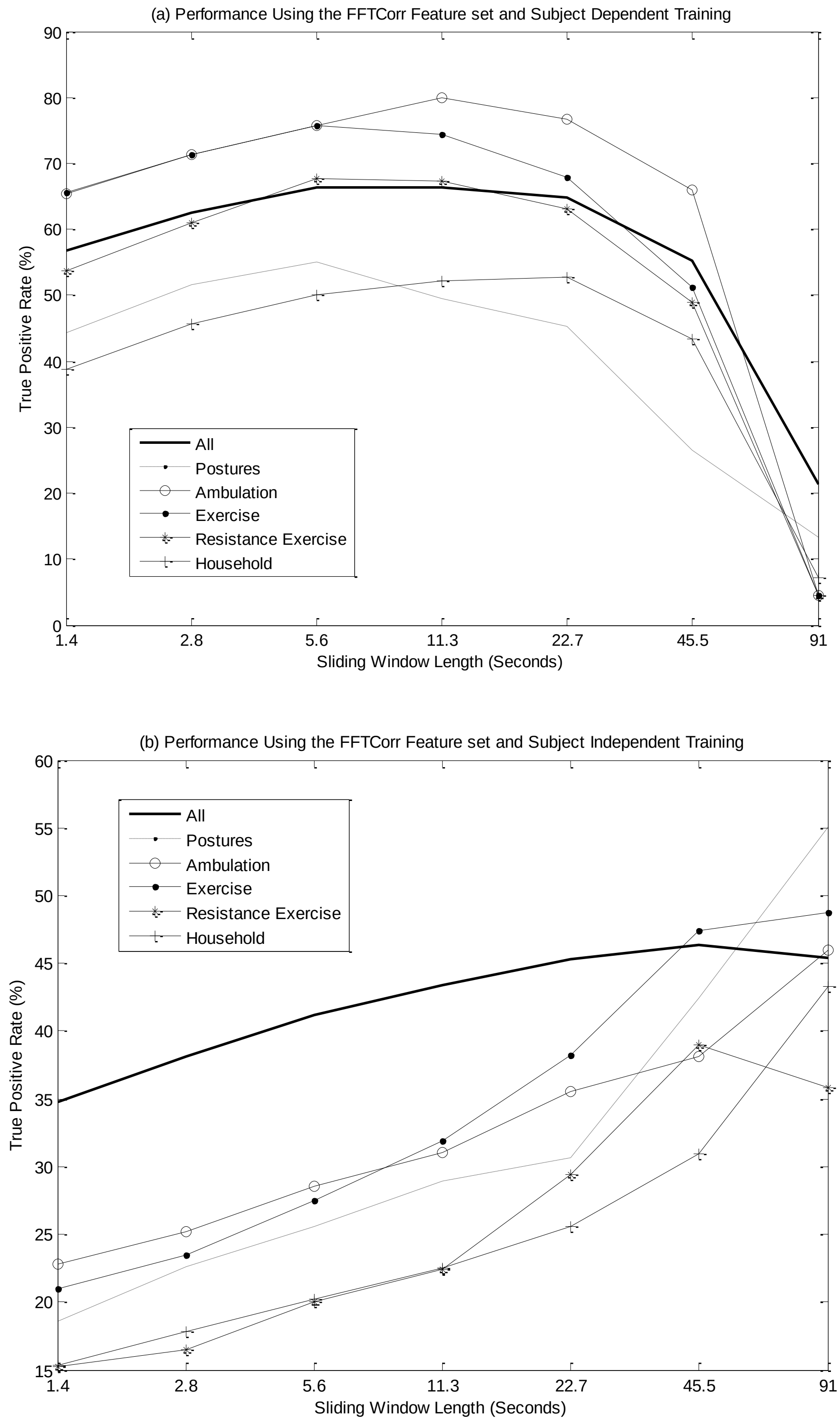


Figure 5-19: True positive rate per activity category when computing the *FFTCorr* feature set (*ACFFTPeaks* and *ACCorr* features) per sensor over sliding windows of varying lengths using the C4.5 classifier during (a) subject dependent and (b) independent evaluation.

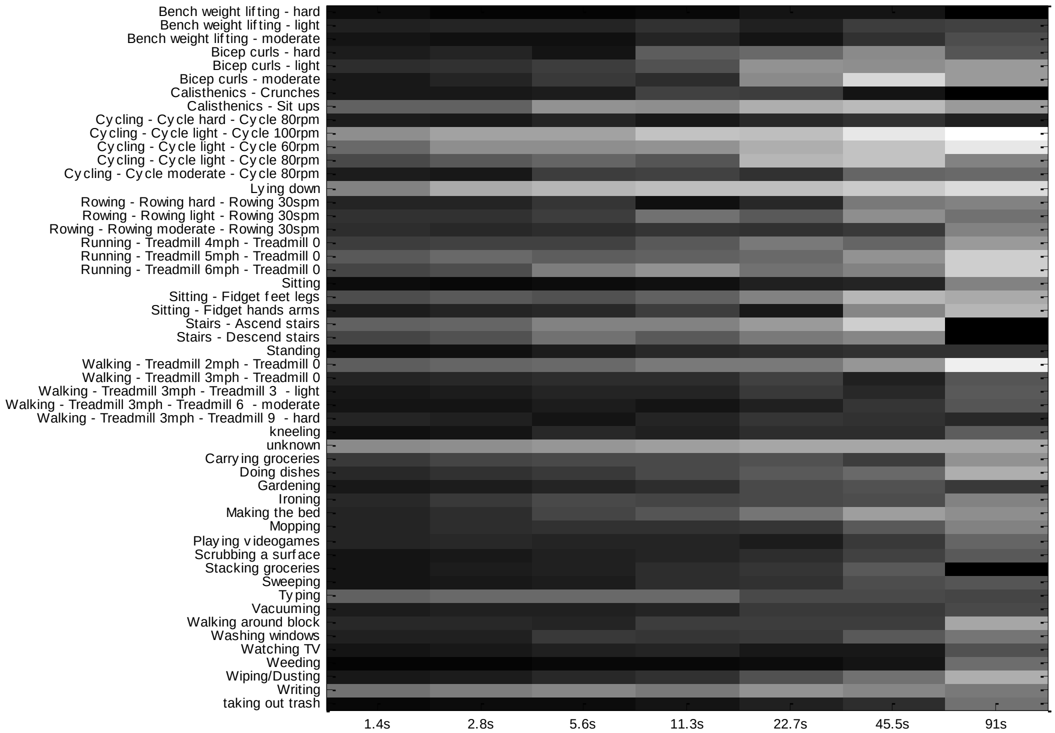


Figure 5-20: True positive rate per activity using the *FFTCorr* feature set computed per sensor and evaluated using subject independent training with the C4.5 classifier. The grayscale image is scaled so that the maximum true positive rate of 100% is represented by white and the minimum of 0% by black. In other words, poor areas of performance are shown in black.

feature set. This indicates, as one might expect, that longer window lengths (e.g. 22-45s) are necessary to capture the high motion variability found in household activities.

The only activity category whose performance does not increase with longer window lengths is postures. The performance over postures reaches a maximum at a window length of 2.8s when the *ACAbsArea* feature is used and at 5.6s when the *FFTCorr* feature set is used. This is because longer window lengths introduce more motion variability that can be thought as noise for the static nature of the posture information represented by the DC level or static component of acceleration signals.

During subject independent training, the performance over all activities increases with increasing window lengths until a window length of 44.5s is reached in both feature sets (*ACAbsArea* and *FFTCorr*). After a window length of 44.5s, the performance decreases for ambulatory activities when the *ACAbsArea* feature is used and for resistance exercise activities when the *FFTCorr* feature set is used. After inspecting the performance per activity, one of the major problems of using long window lengths was found: Poor performance over short duration activities. For example, physically demanding activities such as *bench weight lifting* and *bicep curls* (included in the resistance exercise category) were only performed for less than a minute. Consequently, during training, the C4.5 classifier has few or no training examples for some of these activities.

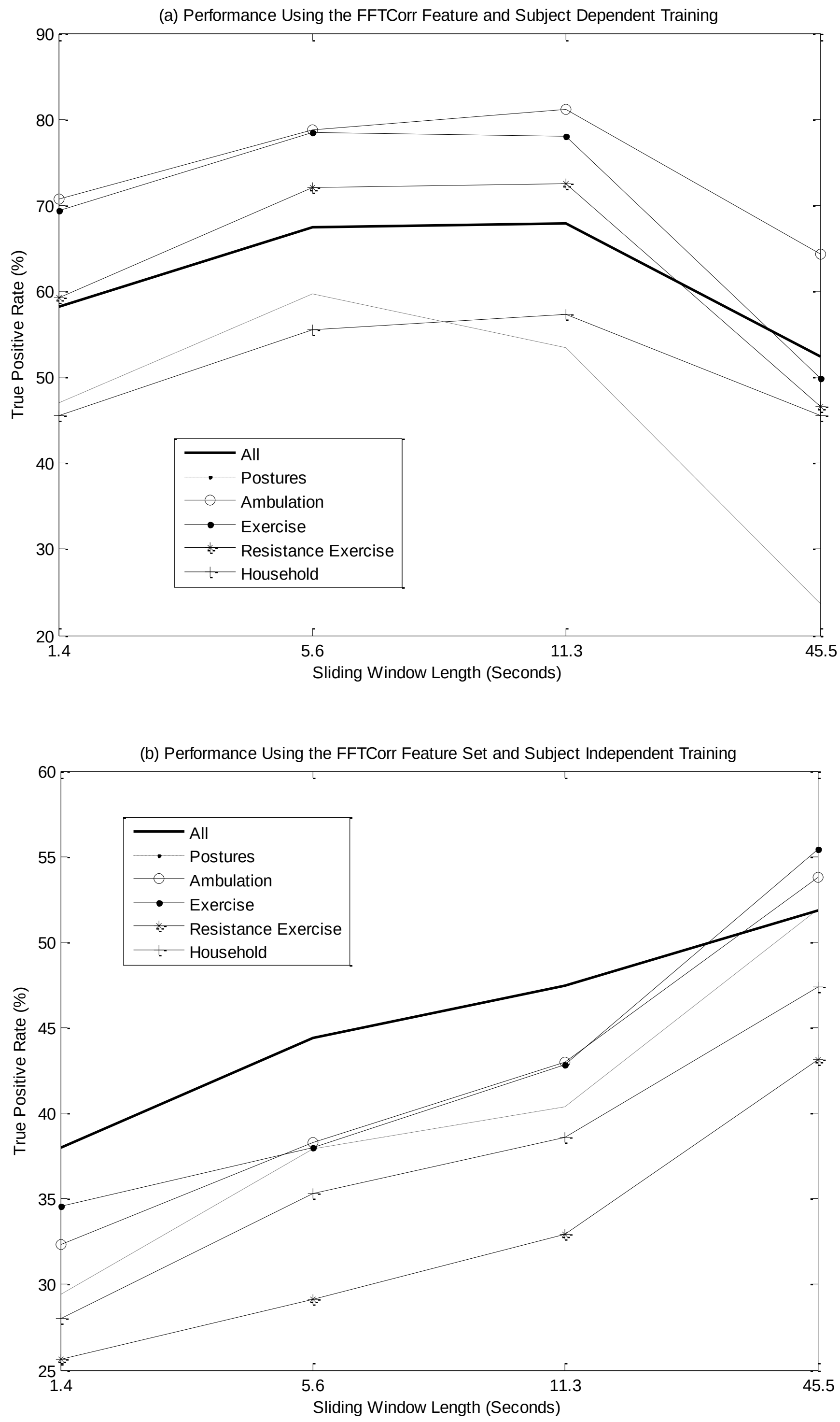


Figure 5-21: True positive rate per activity category when computing the *FFTCorr* feature set (*ACFFTPeaks* and *ACCorr* features) per axis over sliding windows of varying lengths using the C4.5 classifier during (a) subject dependent and (b) independent evaluation.

To better understand this problem, a grayscale image was created to highlight the difference in performance per class using the *FFTCorr* feature set and subject independent training.

The image (shown in Figure 5-20) presents the best true positive rate of 100% as white and the worse of 0% as black. This image also shows that the performance over short duration activities such as *ascending and descending stairs*, and physically demanding activities performed for short periods of time such as *crunches* and *sit-ups* gets progressively worse as the window length is increased. This limitation of long window lengths is of practical concern, since activities shorter than the window length will be most likely merged with activities of longer duration performed before or after the short duration activity or confused with other activities by the recognition algorithm. For example, *ascending stairs* for 20 seconds after having walked for three minutes will be most likely recognized as walking if sliding window lengths longer than 30 or 40s are used. Figure 5-20 also shows that the performance for some periodic activities such as *cycling*, *walking* and *running* gets progressively better with longer window lengths. As explained before, this is because their periodicity is better captured by the FFT transformation as its resolution increases with increasing window lengths. Finally, the reason why the performance for most activities (including postures) increases with increasing window lengths during subject independent evaluation is that differences in the way subjects performed the activities are smoothed out when longer windows of time are used, leading to an improved performance. The performance also increases because the number of training examples is decreased (to some extent although there are still enough training examples during subject independent evaluation) as longer window lengths are used, lowering the chances of misclassification. Unlike the subject dependent scenario, here, the performance for most activities keeps increasing, even after window lengths of 91s. This is because during subject independent training the data of all the subjects minus one is used for training and enough training data exists to train the algorithm using long window lengths. Figure 5-21 shows the true positive rate for different window lengths when the *FFTCorr* feature set is computed per axis and the performance is evaluated in a subject dependent and independent manner using the C4.5 classifier. From the figure, it is clear that feature computation per axis exhibits the same performance behavior observed for feature computation per sensor in Figure 5-18 and Figure 5-19. The figure also shows that during subject dependent training a window length of 5.6s represents the optimal choice for recognizing postures and near the optimal choice for overall performance. During subject independent training, the performance over all activities and activity categories also increases with increasing window lengths as observed before.

In conclusion, one of the main findings of this section is that the optimal window length to utilize depends on the activity being recognized. This finding is in agreement with prior work by [119] that also found that the best window length to utilize depends on the activity being recognized. However, utilizing one window length per activity is computationally expensive since all the features used need to be re-computed over every different window length utilized. Thus, this work will perform activity recognition using only a single window for all activities. After analyzing the performance of different window lengths during subject dependent and independent evaluation, it has been determined that the best single window length to use in this work is 5.6s. This is because the performance of this window length using the *ACAbsArea* and *FFTCorr* feature sets is either near optimal (*ACAbsArea*) or optimal (*FFTCorr*) during subject dependent training. Furthermore, this short window length allows optimal performance while recognizing postures during subject dependent evaluation. This short window of 5.6s length also allows the accurate recognition of short duration activities such as *bench weight lifting*, *bicep curls*, *ascending and descending stairs*, and intense calisthenics activities such as *crunches* and *sit-ups*. More importantly, the classification delay introduced by this window length is short enough to allow fast interventions at the point of decision that could be triggered almost as soon as the activity of interest is recognized. One obvious disadvantage of such short duration window is an expected lower performance on some household activities with high motion variability such as *making the bed*, *taking out trash*, *stacking groceries*, *gardening* and *weeding*. Intuitively, the high variability in motion presented by these activities would be better captured using long windows since these activities can be performed in different ways from day to day by the same individual and naturally by different individuals under different household layouts.

5.4.7 Which Features Provide the Most Discriminatory Information and Have the Lowest Computational Cost?

Features are computed over acceleration signals to capture specific motion characteristics (e.g. magnitude, periodicity, spectral content) that might allow better discrimination between the activities of interest. Nevertheless, it is important to carefully consider the type and the number of features used since some of them might not provide enough discriminant information and others might be too computationally expensive to achieve real-time performance.

Therefore, this section presents experiments to determine the subset of features (from the ones shown in Appendix A3) that discriminate better between the activities of interest and that have the lowest computational cost. This is performed by first ordering the features according to their importance (information they provide) using the information gain criterion. This technique is known as information gain feature selection and will be performed when computing features per sensor and per axis over windows of 5.6s in length (a good compromise window length as reported in section 5.4.3). These experiments are performed in a best case scenario where all the seven accelerometers are used for recognizing activities. Once subsets of potentially high discriminating features are found, their performance will be evaluated using the C4.5 decision tree classifier in a subject dependent and independent manner. As in previous experiments, the classifier attempts to discriminate between the 52 activities contained in the MIT dataset, including the *unknown* class. Finally, once the best feature subsets are identified their performance will be evaluated utilizing only some subsets of the sensors (accelerometers). This will help to identify the feature set that provides the most information when only few sensors are used to recognize activities.

A complete list of all the features explored in this section is shown in Appendix A3. These features consist on a superset of features used in previous work that have shown good performance as well as some new features not explored before. Table 5-12 presents a list of the features and a brief explanation of the information they attempt to capture. Features are computed after preprocessing the acceleration signals to better differentiate

Information captured by the features	Features
Measures of body posture	Mean (*DCMean*), mean over all axes or sensors (*DCTotalMean*), area under signal (*DCArea*), and mean distances between axes (*DCPostureDist*).
Measures of motion shape	Means over absolute value of signal (*ACAbsMean*), area under absolute value of signal (*ACAbsArea*), area under absolute value of signal summarizing overall motion (*ACTotalAbsArea*), mean of signal vector magnitudes over all samples (*ACTotalSVM*), entropy of the signal (*ACEntropy*), skewness of the signal (*ACSkew*), kurtosis of the signal (*ACKur*), and quartiles of the signal (*ACQ1*, *ACQ2*, *ACQ3*).
Measures of motion variation	Variance of the signal (*ACVar*), Coefficient of variation of the absolute value of the signal (*ACAbsCV*), inter-quartile range of signal (*ACIQR*), and range of the signal (*ACRange*).
Measures of motion spectral content	Fast Fourier transform coefficients (*ACFFTCoeff*), Fast Fourier Transform Peaks (*ACFFTPeaks*), and fast Wavelet transform coefficients (*FWTCoeff*).
Measures of motion energy	Total energy of signal (*ACEnergy*), energy between frequencies 0.3-3.5Hz (*ACBandEnergy*), energy between frequencies 0-0.7Hz (*ACLowEnergy*), energy between frequencies 0.71-10Hz (*ACModVigEnergy*), heart rate above resting heart rate (*HRAboveRest*), and heart rate scaled between resting heart rate and heart rate while running at 5mph on a treadmill (*ScaledHR*).
Measure of trend in physical activity	The slope of the regression line computed over the heart rate data (*HRTrend*)
Measures of motion periodicity	Pitch of the signal (*ACPitch*), ratio of energy in dominant frequency and energy in the other bands of the spectrum (*ACDomFreqRatio*), mean crossing rate of the signal (*ACMCR*).
Measures of motion similarity across body segments	Correlation coefficients among all accelerometer signals (*ACCorr*).
Measures of force employed per body segment	Segmental force computed by multiplying the sum over the absolute value of the accelerometer signal by the mass of the corresponding body segment (*ACSF*), sum of all the segmental force for all body segments (*ACTotalSF*).
Measures of subject characteristics	Gender, age, height, and weight.
Measure of subject fitness	Body mass index (*BMI*), fat percentage (*FatPercent*), heart rate reserve (*HRR*).

Table 5-12: Features explored in this work and the information they capture about motion or physical activity. A complete description of the features can be found in Appendix A3.

Information Gain Per Sensor		Information Gain Per Axis	
Feature (1-14)	**Feature(15-28)**	**Feature (1-14)**	**Feature (15-28)**
ACTotalSF (1)	ACModVigEnergy (7)	ACTotalAbsArea (1)	DCMean (21)
ACTotalAbsArea (1)	DCMean (7)	ACTotalSVM (1)	ACLowEnergy (21)
ACTotalSVM (1)	DCPostureDist (21)	ACAbsArea (21)	DCPostureDist (21)
ACSF (5)	ACMCR (7)	ACAbsMean (21)	ACModVigEnergy (21)
ACAbsArea (7)	ACLowEnergy (7)	ACIQR (21)	ACFFTPeaks (210)
ACAbsMean (7)	ACFFTPeaks (70)	ACQ3 (21)	ACDomFreqRatio (21)
ACIQR (7)	ACDomFreqRatio (7)	ACQ1 (21)	ACBandEnergy (21)
ACQ3 (7)	ACBandEnergy (7)	ACRange (21)	ACQ2 (21)
ACQ1 (7)	ACQ2 (7)	ACPitch (21)	ACEnergy (21)
DCTotalMean (1)	ACEnergy (7)	DCTotalMean (1)	ACAbsCV (21)
ACPitch (7)	ACAbsCV (7)	ACMCR (21)	ACKur (21)
ACRange (7)	ACKur (7)	ACEntropy (21)	ACCorr (210)
ACEntropy (7)	ACCorr (21)	ACVar (21)	ACSkew (21)
ACVar (7)	ACSkew (7)	DCArea (21)	
DCArea (7)			

Table 5-13: Acceleration features in decreasing order of importance according to the information gain criterion for (a) feature computation per sensor and (b) feature computation per axis. Features were computed over sliding windows of 5.6s over the MIT dataset. Feature 1 is the most important.

between motion information and posture information. The features intended to capture motion information are computed over the accelerometer signals after applying a band-pass filter between the frequencies of 0.1 and 20Hz. It has been shown in prior work that human acceleration has amplitudes below 12G and frequencies below 20Hz for most activities [218]. This preprocessing has two goals: (1) eliminate the DC or static component of the acceleration signal due to the orientation of the sensors with respect to ground (posture information) and (2) filter high frequency noise and motion not

Information captured by the features	Features
Measures of body posture	*DCTotalMean, DCArea, DCMean, and DCPostureDist*.
Measures of motion shape	*ACTotalAbsArea, ACTotalSVM, ACAbsArea, ACAbsMean, ACQ3, ACQ1, ACEntropy, ACQ2, ACKur*, and *ACSkew*.
Measures of motion variation	*ACIQR, ACRange, ACVar, and ACAbsCV,*
Measures of motion spectral content	*ACFFTPeaks*
Measures of motion energy	*ACLowEnergy or ACModVigEnergy, ACBandEnergy, and ACEnergy,*
Measures of motion periodicity	*ACPitch, ACMCR, and ACDomFreqRatio*.
Measures of motion similarity across body segments	*ACCorr*
Measures of force employed per body segment	*ACTotalSF and ACSF.*

Table 5-14: Features ordered in decreasing order of importance (from left to right) according to the information gain criterion clustered according to the information they capture from the accelerometer signals.

generated by the human body. The features intended to capture posture information are computed over the accelerometer signals after low-pass filtering them at a cut-off frequency of 1Hz. This has the purpose of eliminating most of the signal information due to body motion and preserving the information due to static acceleration or posture. Features that capture motion information start with the prefix "AC" and those that capture posture information start with the prefix "DC". Table 5-13 shows the acceleration features in decreasing order of importance according to the information gain criterion when features are computed over all the accelerometers per sensor and per axis respectively. The first thing to notice is that the ordering of the features in both tables is almost identical, suggesting that the importance of the features does not change significantly when features are computed per sensor and per axis. Overall, features that capture information about the motion of activities (starting with prefix "AC") are ranked with higher importance than features that capture information about the activity posture (starting with prefix "DC"). This is because most of the activities contained in the dataset are activities that can be differentiated just by analyzing their distinctive motion signatures. Furthermore, the top ranking features are the ones that capture information about the overall motion of the human body while performing an activity such as the *ACTotalSF*, *ACTotalAbsArea*, and *ACTotalSVM*. This is because these features are computed over signals that summarize the overall motion (acceleration) experienced by the human body while performing the activities of interest. The reason why the *ACTotalSF* feature is outperforming the *ACTotalAbsArea* feature is that the *ACTotalSF* feature multiplies the acceleration signal per body segment by the mass of the body segment, thus, including additional information as to which body segment is generating the motion. Interestingly, the tables also show that some of the most discriminant features such as the *ACSF*, *ACAbsArea*, and the *ACAbsMean* are some of the features with the lowest computational requirements. The column labeled as "Information Gain Per Axis" in Table 5-13 does not show the *ACTotalSF* and *ACSF* features because its computation does not depend on computing features per axis or per sensor by definition and where already shown in column "Information Gain Per Sensor" in Table 5-13.

After analyzing Table 5-13, the acceleration features where rearranged so that their importance is shown according to the information they capture. The rearranged features are shown in Table 5-14. In this table, the features are ordered according to their importance from the most important at the left to the least important at the right of the table. When generating Table 5-14, the ordering of the features importance matched

Features subsets	Evaluation	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
ACEnergy	Subject Dependent	41.9 ± 10.2	20.3±14.0 (1.3±0.5)	62.7±15.5 (0.8±0.4)	44.0±15.3 (1.0±0.4)	35.0±13.6 (1.2±0.4)	14.8±11.6 (1.3±0.6)
ACLowEnergy	Subject Dependent	38.8 ± 8.8	18.6±14.8 (1.5±0.7)	44.5±15.7 (1.1±0.4)	41.0±15.0 (0.9±0.4)	27.7±12.4 (1.1±0.5)	9.1±7.0 (1.2±0.6)
ACModVigEnergy	Subject Dependent	39.6 ± 9.4	19.2±14.2 (1.4±0.5)	47.0±13.7 (1.1±0.4)	44.9±15.1 (0.9±0.4)	31.7±12.9 (1.2±0.5)	9.7±7.2 (1.4±0.7)
ACBandEnergy	Subject Dependent	51.1 ± 7.9	35.7±17.1 (1.0±0.5)	56.0±15.9 (1.0±0.4)	57.7±17.9 (0.7±0.3)	42.5±17.4 (1.0±0.4)	27.1±13.8 (1.2±0.5)
ACEnergy	Subject Independent	27.9 ± 4.9	7.75±8.02 (1.25±0.51)	19.9±18.7 (1.2±0.9)	14.5±13.9 (0.8±0.5)	9.1±10.6 (0.9±0.5)	3.6±4.2 (0.8±0.4)
ACLowEnergy	Subject Independent	31.0 ± 5.6	12.80±8.43 (1.63±0.70)	15.7±12.5 (1.3±0.7)	14.4±11.4 (0.7±0.5)	9.1±8.7 (0.7±0.4)	1.6±2.2 (0.4±0.2)
ACModVigEnergy	Subject Independent	30.8 ± 4.8	9.7±8.16 (1.25±0.52)	20.9±17.0 (1.2±0.7)	20.8±15.1 (0.7±0.5)	12.1±10.6 (0.9±0.5)	3.1±3.5 (0.8±0.3)
ACBandEnergy	Subject Independent	34.1 ± 4.5	18.4±5.6 (1.00±0.4)	20.6±17.1 (1.2±0.72)	16.9±16.5 (0.7±0.5)	9.0±10.2 (0.8±0.5)	7.8±7.6 (0.8±0.4)

Table 5-15: Performance of the features that capture motion energy using the C4.5 classifier when features are computed per sensor over the MIT dataset evaluated in a subject dependent and independent manner.

perfectly for the two columns labeled as "Information Gain Per Sensor" and "Information Gain Per Axis" in Table 5-13 except for two of the features that capture the energy of motion: *ACLowEnergy* and *ACModVigEnergy*. The *ACModVigEnergy* shows higher ranking in column "Information Gain Per Sensor" but lower ranking in column "Information Gain Per Axis" with respect to the *ACLowEnergy* feature. Consequently, their importance cannot be disambiguated from these columns in Table 5-13. In order to disambiguate their importance, an experiment was run by measuring the performance of all the features that capture energy motion over the MIT dataset using the C4.5 classifier when features are computed per sensor using subject dependent and independent evaluation. The results are shown in Table 5-15. From the table, it can be seen that the most discriminant feature is the *ACBandEnergy*, followed by the *ACEnergy* or *ACLowEnergy*, and the *ACModVigEnergy*. Even when the ordering of importance for some of these features is not completely disambiguated by this experiment, one thing is clear: the best feature to use to capture the energy of motion is the *ACBandEnergy* feature. This is because this feature is computed over the frequencies in which the majority of human activity is believed to lie [218]. From Table 5-15, it can also be seen that the *ACLowEnergy* feature is good at discriminating sedentary or low energy activities such as postures while the *ACModVigEnergy* features is good at discriminating activities with higher motion energy such as ambulation and exercise activity, just as one might intuitively expect. One reason why the *ACLowEnergy* feature outperforms the *ACEnergy* and *ACModVigEnergy* features during subject independent evaluation is that this feature includes frequency zero or the DC component of the acceleration signal, thus, giving it an advantage over the other features while recognizing postures. However, this also makes the *ACLowEnergy* feature more dependent on the magnitude of the accelerometer signal. This dependency might be undesirable since the magnitude of the acceleration signal changes with slight variations in the way accelerometers (sensors) are worn.

Two features that were not included during the information gain feature selection experiment in Table 5-13 were the Fast Fourier transform coefficients (*ACFFTCoeff*) and

Features subsets (Feature size)	**Evaluation**	**All Activities**	**Postures**	**Ambulation**	**Exercise**	**Resistance Exercise**	**Household**
	Subject Dependent	55.1 ± 8.0	45.9±15.8 (0.9±0.4)	60.2±14.2 (0.7±0.3)	61.4±16.5 (0.6±0.2)	53.2±16.0 (0.8±0.3)	33.3±12.2 (1.4±0.6)
ACFFTPeaks (70)	Subject Dependent	65.5 ± 6.4	54.1±14.7 (0.7±0.3)	73.6±11.2 (0.6±0.2)	73.1±12.5 (0.4±0.2)	64.1±14.4 (0.6±0.3)	49.6±15.2 (1.0±0.4)
ACFWTCoeff (1785)	Subject Dependent	28.7 ± 6.4	24.0±9.3 (1.4±0.4)	17.6±9.7 (1.5±0.5)	23.7±12.1 (1.4±0.4)	17.3±8.9 (1.6±0.5)	11.4±6.5 (1.9±0.7)
ACFFTCoeff (889)	Subject Independent	36.8 ± 3.8	23.2±14.8 (0.9±0.4)	24.3±18.6 (1.0±0.7)	25.5±21.0 (0.7±0.5)	17.9±16.1 (0.9±0.6)	14.2±11.9 (1.2±0.5)
ACFFTPeaks (70)	Subject Independent	41.6 ± 4.3	27.2±19.6 (0.8±0.5)	28.2±22.7 (0.9±0.7)	28.2±24.3 (0.6±0.6)	20.1±18.4 (0.8±0.6)	19.8±16.6 (1.0±0.6)
ACFWTCoeff (1785)	Subject Independent	26.6 ± 3.5	17.1±10.0 (1.0±0.4)	14.9±11.0 (1.3±0.5)	16.7±14.4 (0.9±0.4)	11.6±10.4 (1.0±0.5)	6.9±5.9 (1.4±0.4)

Table 5-16: Performance of the features that capture the spectral content of motion computed per axis using the C4.5 classifier and evaluated in a subject dependent and independent manner.

Information captured by the features	**Features**
Measures of body posture	*DCArea, DCMean, DCPostureDist, and DCTotalMean, ,*
Measures of motion shape	*ACAbsArea, ACAbsMean, ACQ3, ACQ1, ACQ2, ACTotalAbsArea, ACTotalSF, ACTotalSVM A, ACEntropy, ACKur*, and *ACSkew*.
Measures of motion variation	*ACIQR, ACVar, ACRange, and ACAbsCV,*
Measures of motion spectral content	*ACFFTPeaks, ACFFTCoeff*, and *FWTCoeff*.
Measures of motion energy	*ACBandEnergy ACEnergy, ACLowEnergy, or ACModVigEnergy.*
Measures of motion periodicity	*ACPitch, ACMCR, and ACDomFreqRatio.*
Measures of motion similarity across body segments	*ACCorr*
Measures of force employed per body segment	*ACTotalSF and ACSF.*

Table 5-17: Final ordering of the features according to their importance (decreasing order of importance from left to right) according to all the experiments performed in this section.

the Fast Wavelet transform coefficients (*ACFWTCoeff*). These features were not included in the experiment to prevent their large vector sizes (889 and 1785 respectively) to interfere with the ordering of the results. Therefore, a new experiment was run to determine which of the features that capture the motion spectral content is more discriminating. This was achieved by measuring the performance of these features computed per sensor over the MIT dataset in a subject dependent and independent manner. The results in Table 5-16 shows that the most discriminating feature is the *ACFFTPeaks* during both subject dependent and independent training. It can also be observed that the order of importance of the *ACFFTCoeff* and the *ACFWTCoeff* features corresponds to their inverse ordering with respect to their sizes. This indicates that their performance is low because of their large size and not because of the information they provide. In fact, the *ACFFTPeaks* feature summarizes just some of the information contained in the *ACFFTCoeff* feature. It is thus, clear that the large amount of information contained in the *ACFFTCoeff* and the *ACFWTCoeff* features needs to be summarized to prevent poor performance when the number of features is large with respect to the amount of training data available. One way to achieve this is to utilize feature extraction techniques such as linear discriminant analysis (LDA) or principal component analysis (PCA) to reduce the size of the features. However, this will not be explored in this work due to the high computational requirements of these techniques.

Finally, in order to corroborate the ordering of importance of the remaining features in Table 5-14, their individual performance was tested over the MIT dataset using feature computation per sensor and subject independent evaluation. Appendix A6 presents the results obtained. The analysis shows that the order of importance for the features that capture the periodicity of motion (*ACPitch*, *ACMCR*, and *ACDomFreqRatio*) is the same as the one shown in Table 5-14. The ordering of the features that capture posture information also remains the same except for the *DCMean* and *DCArea* features. The experiment shows that the *DCMean* feature slightly outperforms the *DCArea* feature in capturing posture information (2% improvement). This is because the *DCArea* feature is more affected by motion than the *DCMean* feature. While the *DCArea* feature takes into account all the motion over a given window, the *DCMean* feature only computes the average value of the motion over the window, making it more robust to motion variability and noise. However, the *DCMean* feature is more computationally expensive than the *DCArea* feature since it requires the computation of averages. As a result, the order of importance of these features was not modified.

Finally, the appendix shows that the ordering for some of the features that capture information about the motion shape needs to be modified. Table 5-14 shows that the performance of features computed over signals summarizing the overall motion experienced by the whole body such the *ACTotalAbsArea* and the *ACTotalSVM* features have more importance than the same features computed over signals summarizing motion per sensor or axis such as the *ACAbsArea and ACAbsMean.* Appendix A6 on the contrary, shows that the *ACAbsArea and ACAbsMean* features are more informative. Intuitively, this makes sense since these features incorporate the additional information of which body segment is generating the motion. Consequently, the ordering of importance for these features will be reversed. Table 5-17 shows the final ordering of importance of all the accelerometer features explored in this work according to all the experiments performed in this section.

Once the order of importance of all the features with respect to the information they capture was determined, experiments were performed over different subsets of the most discriminant features of each category (information they capture) to determine the best performing ones. Five feature subsets were selected for presenting their results because one or more of the following reasons: Their performance was among the highest, they were fast to compute, they were more invariant to the magnitude of the acceleration signals, or because they could serve as a comparison baseline. These feature subsets were labeled as follows: (1) *All features*: This feature set includes all the features computed over the accelerometer data and serves as a baseline of the performance that can be achieved if all the features are used without regard to computational speed. (2) *Fast to compute*: This feature set includes the best performing features found over most categories that are fast to compute. (3) *Fast to compute reduced*: This set includes the two features that showed the best performance from all the features and were the easiest to compute. This set also serves as a baseline of the performance that can be obtained with the simplest possible features. (4) *Invariant total*: This set includes all the features that are more invariant to the magnitude of the acceleration signal. Invariance to the magnitude of the acceleration signal is important because it can change due to hardware differences among sensors or with differences in the positioning of the sensors on the body. (5) *Invariant reduced*: This feature set is a subset of the *Invariant total* feature set containing only the most discriminant features. The performance of these five feature

Features subsets	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
All Features: MaxAcceleration	80.6 ± 3.6	89.3±7.3 (0.1±0.1)	81.6±9.0 (0.3±0.1)	87.2±10.1 (0.2±0.1)	81.9±11.6 (0.3±0.1)	72.2±10.4 (0.5±0.3)
Fast to compute: ACAbsArea, DCArea, ACVar, ACRange, ACMCR	81.5 ± 3.5	91.8±6.9 (0.1±0.1)	81.1±9.8 (0.4±0.2)	87.5±9.4 (0.2±0.1)	82.1±11.2 (0.3±0.2)	74.1±10.5 (0.5±0.3)
Fast to compute reduced: ACAbsArea, DCArea,	82.2 ± 3.3	92.0±5.9 (0.1±0.1)	81.0±8.9 (0.4±0.2)	88.0±9.4 (0.2±0.1)	82.7±10.2 (0.3±0.2)	75.0±9.9 (0.5±0.3)
Invariant: total DCPostureDist, ACVar, ACBandEnergy, ACLowEnergy, ACModVigEnergy, ACEntropy, ACFFTPeaks, ACPitch, ACMCR and ACCorr	80.6 ± 3.8	89.4±8.2 (0.2±0.1)	81.5±9.4 (0.4±0.2)	87.3±10.0 (0.2±0.1)	82.0±11.3 (0.3±0.2)	71.8±11.3 (0.6±0.3)
Invariant reduced DCPostureDist, ACVar, ACBandEnergy, ACFFTPeaks,	80.7 ± 3.6	90.4±7.8 (0.2±0.1)	80.7±9.4 (0.4±0.2)	87.9±10.0 (0.2±0.1)	82.2±11.3 (0.3±0.2)	73.1±11.0 (0.5±0.3)

Table 5-18: Performance of the four best feature subsets found in this work while computing features per sensor and evaluating the results in a subject dependent manner.

Features subsets	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	*Household*
All Features: MaxAcceleration	44.8 ± 6.1	42.9±35.2 (0.4±0.5)	29.0±25.7 (0.9±1.0)	27.4±30.1 (0.6±0.7)	20.0±25.0 (0.8±0.8)	23.8±22.7 (0.9±0.7)
Fast to compute: ACAbsArea, DCArea, ACVar, ACRange, ACMCR	41.6 ± 6.5	41.6±33.3 (0.4±0.6)	24.4±24.4 (1.0±1.0)	23.7±28.1 (0.7±0.8)	16.9±22.2 (0.9±0.9)	21.8±23.3 (0.9±0.8)
Fast to compute reduced: ACAbsArea, DCArea,	40.1 ± 5.9	39.78±31.23 (0.49±0.60)	22.48±24.87 (1.02±1.14)	24.5±29.0 (0.7±0.8)	16.3±23.7 (0.9±1.0)	18.7±20.9 (0.9±0.8)
Invariant total DCPostureDist, ACVar, ACBandEnergy, ACLowEnergy, ACModVigEnergy, ACEntropy, ACFFTPeaks, ACPitch, ACMCR and ACCorr	43.9 ± 6.9	40.4±33.6 (0.4±0.5)	28.5±25.7 (1.0±0.9)	27.7±29.9 (0.7±0.7)	20.2±24.4 (0.9±0.8)	23.3±22.5 (1.0±0.8)
Invariant reduced DCPostureDist, ACVar, ACBandEnergy, ACFFTPeaks,	43.4 ± 5.8	38.7±35.6 (0.5±0.8)	28.3±26.0 (1.0±1.0)	28.6±30.8 (0.7±0.8)	20.6±25.5 (0.9±0.9)	23.5±23.6 (1.0±0.8)

Table 5-19: Performance of the four best feature subsets found in this work while computing features per sensor and evaluating the results in a subject independent manner.

Features subsets	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
All Features: MaxAcceleration	81.76 ± 1.57	92.2±5.9 (0.1±0.1)	84.4±9.2 (0.3±0.1)	88.7±9.9 (0.2±0.1)	84.8±10.8 (0.2±0.1)	75.2±10.0 (0.4±0.2)
Fast to compute: ACAbsArea, DCArea, ACVar, ACRange, ACMCR	82.61 ± 1.70	93.4±5.2 (0.1±0.1)	85.2±9.4 (0.3±0.1)	88.4±9.8 (0.2±0.1)	84.2±11.1 (0.2±0.1)	77.4±10.0 (0.4±0.2)
Fast to compute reduced: ACAbsArea, DCArea,	83.27 ± 1.64	94.0±5.1 (0.1±0.1)	86.1±8.0 (0.2±0.1)	89.4±8.6 (0.1±0.1)	85.6±9.6 (0.2±0.1)	77.7±9.3 (0.4±0.2)
Invariant: total DCPostureDist, ACVar, ACBandEnergy, ACLowEnergy, ACModVigEnergy, ACEntropy, ACFFTPeaks, ACPitch, ACMCR and ACCorr	80.45 ± 2.02	90.3±8.3 (0.1±0.1)	82.9±9.8 (0.3±0.1)	88.2±9.5 (0.2±0.1)	84.1±10.4 (0.2±0.1)	72.8±10.3 (0.5±0.2)
Invariant reduced DCPostureDist, ACVar, ACBandEnergy, ACFFTPeaks,	81.0 ± 1.9	93.1±6.0 (0.1±0.1)	82.4±10.4 (0.3±0.1)	88.8±9.7 (0.2±0.1)	84.0±10.8 (0.3±0.1)	74.3±10.5 (0.4±0.2)

Table 5-20: Performance of the four best feature subsets found in this work while computing features per axis and evaluating the results in a subject dependent manner.

Features subsets	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
All Features: MaxAcceleration	49.4 ± 4.9	66.9±31.4 (0.3±0.4)	41.4±26.0 (0.8±0.8)	39.8±33.7 (0.6±0.6)	31.5±29.7 (0.8±0.8)	37.9±24.4 (0.9±0.7)
Fast to compute: ACAbsArea, DCArea, ACVar, ACRange, ACMCR	48.2 ± 3.8	64.6±29.4 (0.3±0.4)	33.8±26.1 (0.9±0.8)	40.9±34.3 (0.7±0.7)	28.1±29.3 (0.9±0.9)	39.3±23.4 (0.9±0.6)
Fast to compute reduced: ACAbsArea, DCArea,	47.0 ± 4.7	60.0±32.5 (0.3±0.4)	35.2±27.3 (0.9±0.8)	41.9±35.1 (0.6±0.6)	29.9±30.3 (0.8±0.8)	36.1±24.0 (1.0±0.7)
Invariant: total DCPostureDist, ACVar, ACBandEnergy, ACLowEnergy, ACModVigEnergy, ACEntropy, ACFFTPeaks, ACPitch, ACMCR and ACCorr	47.3 ± 5.9	59.2±34.4 (0.4±0.5)	38.4±27.0 (0.8±0.8)	37.0±30.3 (0.6±0.6)	28.3±26.8 (0.8±0.7)	35.9±23.3 (0.9±0.6)
Invariant reduced DCPostureDist, ACVar, ACBandEnergy, ACFFTPeaks,	47.0 ± 4.1	54.5±34.0 (0.4±0.5)	38.4±26.1 (0.9±0.8)	38.4±31.9 (0.6±0.7)	29.4±28.2 (0.8±0.8)	37.2±23.4 (0.9±0.6)

Table 5-21: Performance of the four best feature subsets found in this work while computing features per axis and evaluating the results in a subject independent manner.

subsets using feature computation per sensor, per axis, subject dependent and independent evaluation is presented in Table 5-18 through Table 5-21.

Overall, Table 5-18 and Table 5-20 illustrate that the best performing feature sets for subject dependent training in decreasing order of performance are: *Fast to compute reduced*, *fast to compute*, *invariant reduced*, *invariant total*, and *all features*. It is surprising that features so easy to compute such as the *ACAbsArea* and the *DCArea* contained in the *Fast to compute reduced* set can achieve the best performance during subject dependent training. One explanation might be that subjects perform activities in such a distinctive manner that these simple features are enough to discriminate among all the activities of interest well enough. The performance per activity during subject dependent training (as shown in Appendix A6) is also consistently higher for *the fast to compute reduced* feature set than for the other feature sets except for few activities such as *callisthenic crunches*, *Cycling hard at 80rmp*, *running at 4mph*, *walking at 3mph (3 grade incline)*, and *vacuuming*. Nevertheless, the difference in performance on these activities with respect to the *all features* and *invariant total* feature sets ranges only from 2.0 to 5.3%.

The best performing feature sets during subject independent evaluation from Table 5-19 and Table 5-21 in decreasing order of performance are: *All features*, *invariant total*, *invariant reduced*, *fast to compute*, and *fast to compute reduced*. It is clear, thus, that for subject independent training more features are required to capture the high variability found in the way activities are performed from individual to individual. In this scenario, the overall decrease in performance obtained by using the *fast to compute* feature set with respect to the performance of the *all features* and *invariant reduced* feature sets is ~2% during both feature computation per sensor and per axis.

When the differences in performance are analyzed per activity during subject independent training, it is found that all the feature subsets explored have difficulties recognizing activities involving the same speed and type of motion but different resistance levels. These activities include *bench weight lifting* and *bicep curls* with different weight loads, *walking* at the same speed (3mph) but different inclination grades, and *rowing* at the same speed but with different resistance levels. This is expected, since the accelerometer signals look alike given that the activities are performed at the same speed and with a very similar motion patterns. Section 5.4.8 will later explore if this activities can be better discriminated by incorporating heart rate information. All the feature sets have also difficulties recognizing activities that were performed with high degree of variability from subject to subject such as *gardening*, *weeding*, and *taking out trash*. These activities are also difficult to discriminate because they include short periods of time where other activities being recognized are executed such as *walking*, *standing*, and *kneeling*.

When the performance per activity of the subsets is compared against the performance of the *all features* subset, it is found that they have different strengths and weaknesses. Figure 5-22 and Figure 5-23 show the differences in true positive and false positive rate per activity coded as a grayscale image. The grayscale images show the performance per activity scaled so that the best performance is shown in white and the worst performance is shown in black. In other words, poor areas of performance are shown as dark regions in the image. Again, it can be seen that the best performing feature subset is the *all features* set. When comparing the differences of the *fast to compute* and *invariant reduced* feature

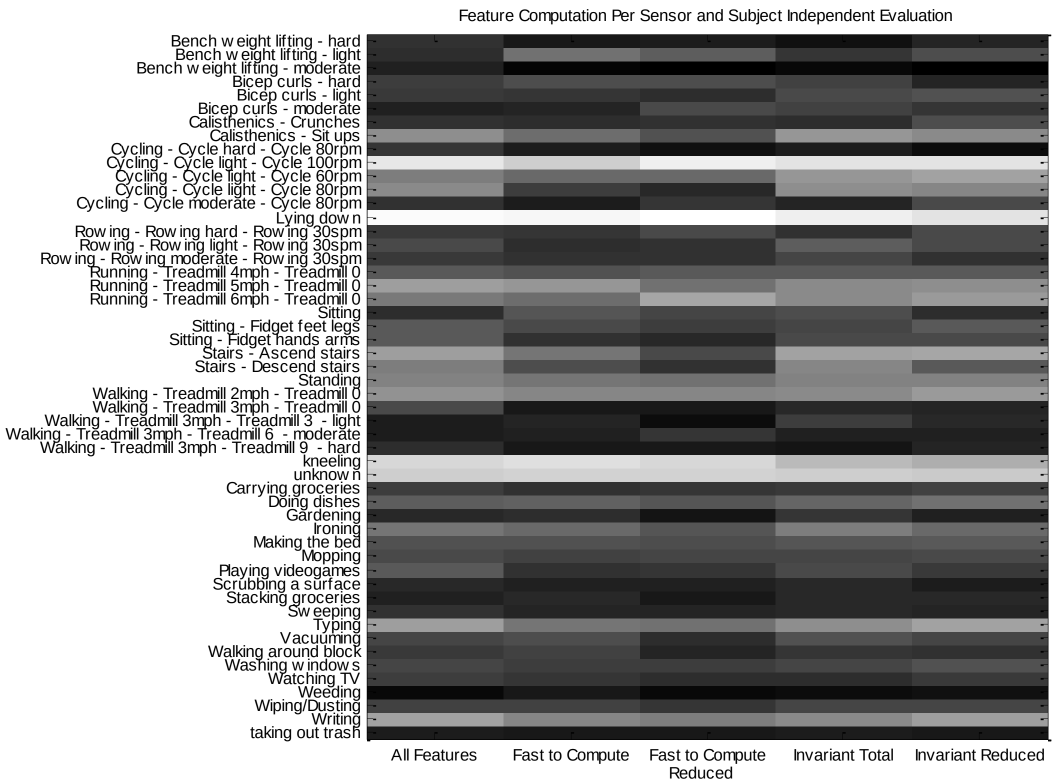


Figure 5-22: True Positive Rate per Activity when the different subsets of features are computed per sensor using the C4.5 decision tree classifier and subject independent evaluation. The grayscale image is scaled so that the maximum true positive rate of 79.1% is represented by white and the minimum of 1.3% by black. In other words, poor areas of performance are shown in black.

sets against the *all features* set it is found that the *invariant reduced* feature set has more problems recognizing activities involving different postures than the *fast to compute* feature set. These activities include *sitting*, *standing*, *kneeling*, *bench weight lifting*, *bicep curls*, and *rowing at 30spm*. On the contrary, the *fast to compute* feature set has more difficulties than the *invariant reduced* feature set in recognizing some activities involving periodic motion such as *carrying groceries*, *ascending and descending stairs*, *cycling at 80rmp*, *calisthenics sit-ups*, *rowing moderate at 30spm*, and *typing*. These differences in performance can be explained by the fact that the *fast to compute* feature set includes the *ACAbsArea* and *DCArea* features that capture posture information better than the *invariant reduced* feature set. Similarly the *invariant reduced* feature set includes the *ACFFTPeaks* feature that provides powerful information about the periodicity of activities, thus giving it an advantage over the *fast to compute* feature set. One might expect that a new feature set created by merging the *fast to compute* and *invariant reduced* feature sets would address the short comings of both feature sets. However, this new feature set would be more computationally expensive and not invariant to the magnitude of the acceleration signal.

To better understand the impact of utilizing fewer sensors to recognize activities on the feature sets, an experiment was performed using the *fast to compute* and *invariant reduced* feature sets to recognize activities using the C4.5 classifier over different subsets

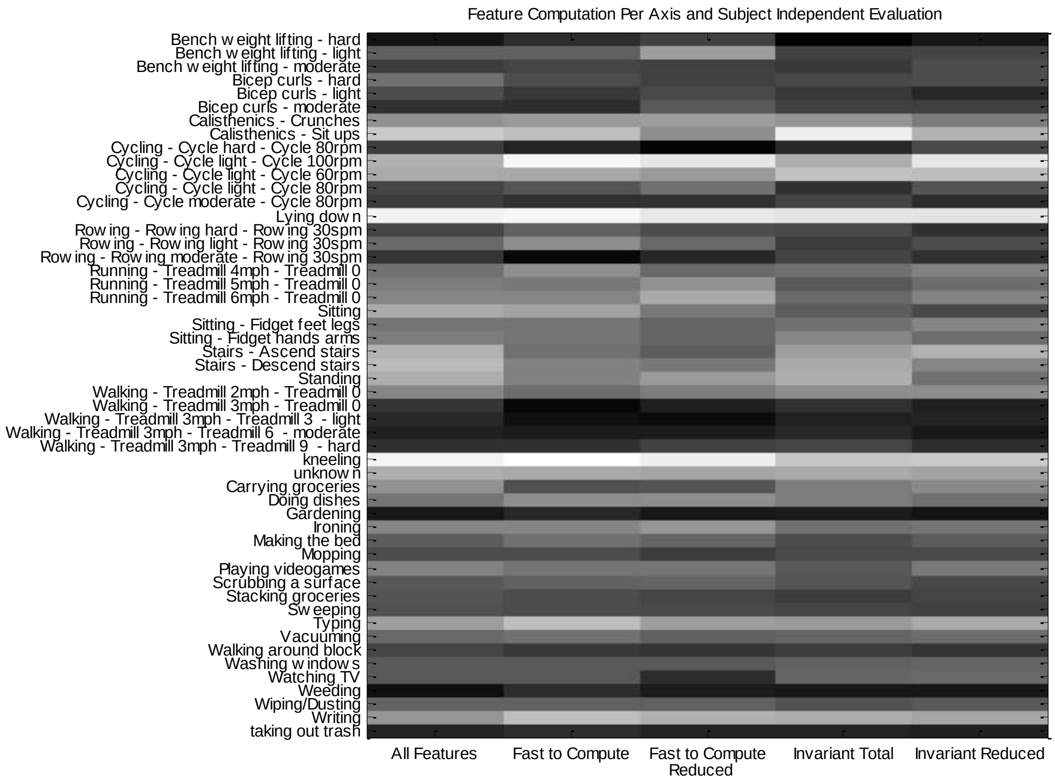


Figure 5-23: True Positive Rate per Activity when the different subsets of features are computed per axis using the C4.5 decision tree classifier and subject independent evaluation. The grayscale image is scaled so that the maximum true positive rate of 93.8% is represented by white and the minimum of 4.8% by black. In other words, poor areas of performance are shown in black.

of sensors. Table 5-22 and Table 5-23 present the performance of these two feature sets when recognizing activities using (1) three sensors worn at the dominant wrist, hip, and dominant foot, (2) a single sensor worn at the hip, (3) a single sensor worn at the dominant wrist, and (4) a single sensor worn at the dominant foot evaluated in a subject dependent and independent manner. From the tables, we can see that during subject dependent training, the *fast to compute* feature set achieves the best performance when all the sensors are used and when three sensors located at the wrist, hip and foot are used. Nevertheless, the *invariant reduced* feature set has a slightly higher performance than the *fast to compute* feature set when only one sensor is used to recognize activities. Overall, the performance of both feature sets during subject dependent training is very similar and both show approximately the same decrease in performance when the number of sensors is reduced. Therefore, it can be concluded from the results presented in this work that both feature sets achieve similar performance when recognizing activities in a subject dependent manner.

The same behavior is found during subject independent training. *The fast to compute* feature set performs well when at least one sensor per limb is used and *the invariant reduced* feature set outperforms considerably *the fast to compute* feature set when only one sensor is used. The difference in performance is higher (3 and 9%) when only one

Features subsets	Sensor subset	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
Invariant Reduced	All	80.5 ± 2.0	90.3±8.3 (0.1±0.1)	82.9±9.8 (0.3±0.1)	88.2±9.5 (0.2±0.1)	84.1±10.4 (0.2±0.1)	72.8±10.3 (0.5±0.2)
Fast to Compute	All	82.6 ± 1.7	93.4±5.2 (0.1±0.1)	85.2±9.4 (0.3±0.1)	88.4±9.8 (0.2±0.1)	84.2±11.1 (0.2±0.1)	77.4±10.0 (0.4±0.2)
Invariant Reduced	Hip DWrist DFoot	79.2 ± 2.6	91.6±7.7 (0.1±0.1)	81.6±9.1 (0.3±0.2)	85.9±11.7 (0.2±0.1)	80.8±12.4 (0.3±0.2)	74.0±10.1 (0.4±0.2)
Fast to Compute	Hip DWrist DFoot	80.4 ± 2.1	90.6±7.4 (0.1±0.1)	83.9±9.3 (0.3±0.1)	86.8±9.7 (0.2±0.1)	81.9±11.0 (0.3±0.2)	74.0±10.1 (0.4±0.2)
Invariant Reduced	Hip	73.5 ± 2.9	86.5±9.8 (0.2±0.1)	80.4±11.0 (0.3±0.2)	81.2±13.6 (0.3±0.2)	74.3±15.8 (0.4±0.2)	61.7±13.0 (0.6±0.2)
Fast to Compute	Hip	72.4 ± 2.7	87.8±9.3 (0.1±0.1)	80.3±11.8 (0.4±0.2)	80.3±13.9 (0.3±0.2)	73.3±14.8 (0.4±0.2)	58.8±13.3 (0.7±0.3)
Invariant Reduced	DWrist	65.2 ± 3.8	85.0±11.9 (0.2±0.1)	68.1±13.1 (0.5±0.2)	69.3±15.6 (0.4±0.2)	61.5±15.8 (0.6±0.2)	54.2±13.4 (0.7±0.3)
Fast to Compute	DWrist	67.0 ± 3.7	85.8±11.5 (0.2±0.1)	69.7±14.1 (0.5±0.2)	69.4±17.1 (0.4±0.2)	61.6±17.3 (0.5±0.3)	57.3±12.6 (0.7±0.3)
Invariant Reduced	DFoot	68.8 ± 3.8	88.2±12.1 (0.2±0.1)	68.1±11.5 (0.5±0.2)	78.1±14.0 (0.3±0.2)	67.1±16.8 (0.5±0.2)	56.9±15.4 (0.7±0.3)
Fast to Compute	DFoot	66.4 ± 3.5	91.0±8.4 (0.1±0.1)	65.3±12.0 (0.6±0.2)	77.4±14.5 (0.3±0.2)	64.5±15.8 (0.5±0.2)	51.9±14.6 (0.8±0.3)

Table 5-22: Performance of the two feature subsets with highest performance and lowest computational requirements when features are computed per axis and subject dependent evaluation is used. DWrist stands for dominant wrist and DFoot for dominant foot. The activities to recognize are the 52 activities contained in the MIT dataset including the *unknown* class.

Features subsets	Sensor subset	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
Invariant Reduced	All	47.3 ± 5.8	59.2±34.4 (0.4±0.5)	38.4±27.0 (0.8±0.8)	37.0±30.3 (0.6±0.6)	28.3±26.8 (0.8±0.7)	35.9±23.3 (0.9±0.6)
Fast to Compute	All	48.2 ± 3.8	64.6±29.4 (0.3±0.4)	33.8±26.1 (0.9±0.8)	40.9±34.3 (0.7±0.7)	28.1±29.3 (0.9±0.9)	39.3±23.4 (0.9±0.6)
Invariant Reduced	Hip DWrist DFoot	43.8 ± 5.4	50.1±33.2 (0.5±0.7)	33.6±25.7 (0.9±0.8)	33.6±29.7 (0.7±0.7)	27.2±27.0 (0.8±0.7)	34.7±23.0 (0.9±0.6)
Fast to Compute	Hip DWrist DFoot	44.3 ± 4.9	52.0±31.1 (0.3±0.4)	33.3±27.2 (0.9±0.9)	35.9±32.3 (0.6±0.6)	28.5±28.2 (0.8±0.8)	32.5±23.4 (1.0±0.7)
Invariant Reduced	Hip	36.1 ± 4.1	35.0±22.9 (0.8±0.7)	28.0±22.9 (1.0±0.8)	26.2±24.8 (0.7±0.6)	20.5±20.6 (0.8±0.7)	22.5±17.8 (1.2±0.6)
Fast to Compute	Hip	26.5 ± 5.5	19.1±18.5 (0.8±0.8)	20.8±22.8 (1.0±0.9)	17.4±19.7 (0.7±0.7)	10.1±14.7 (0.8±0.6)	11.7±14.2 (1.4±0.8)
Invariant Reduced	DWrist	36.9 ± 5.2	30.8±31.1 (0.8±0.8)	28.0±22.6 (1.0±0.9)	26.9±21.6 (0.7±0.5)	25.4±19.3 (0.8±0.5)	29.6±17.7 (1.1±0.7)
Fast to Compute	DWrist	35.1 ± 4.8	31.2±26.6 (0.8±0.7)	23.8±20.8 (1.0±0.8)	23.7±21.9 (0.7±0.6)	21.8±18.1 (0.9±0.6)	28.6±18.4 (1.1±0.7)
Invariant Reduced	DFoot	33.9 ± 3.6	41.1±27.4 (0.7±0.7)	26.3±18.6 (1.1±0.8)	28.1±22.1 (0.7±0.5)	20.5±18.7 (0.8±0.6)	17.2±13.4 (1.2±0.7)
Fast to Compute	DFoot	27.1 ± 4.1	29.7±20.1 (0.6±0.8)	24.9±20.2 (1.1±0.9)	23.7±18.9 (0.7±0.8)	14.1±16.5 (1.0±0.9)	7.2±8.9 (1.4±1.1)

Table 5-23: Performance of the two feature subsets with highest performance and lowest computational requirements when features are computed per axis and subject independent evaluation is used. DWrist stands for dominant wrist and DFoot for dominant foot. The activities to recognize are the 52 activities contained in the MIT dataset including the *unknown* class.

sensor is worn at the hip and at the dominant foot. The results indicate that the *invariant reduced* feature set has important advantages over the *fast to compute* feature set, particularly during subject independent training.

It can be concluded from the results presented in this section, that the best feature set to use is the *invariant reduced* feature set. Even when this feature set is more computationally expensive than the *fast to compute* feature set, it has important advantages such as invariance to the magnitude of the accelerometer signal and higher performance during subject independent training. If invariance to the magnitude of the accelerometer signal is not important and if activities are recognized in a subject dependent manner, the *fast to compute* feature set can be used to recognize activities with extremely low computational requirements. For the remaining of this thesis, the invariant reduced feature set will be used to recognize activities in future experiments.

5.4.8 Does the Incorporation of Heart Rate Data Improve Recognition of Activities?

Accelerometers are good at recognizing activities with different postures or distinctive motions of the body segments at particular speeds. However, they may not be well suited for recognizing activities that involve similar motion signatures but different resistance work or effort. Examples of some of these activities include *cycling at 80rmp* at different resistance levels, performing *bicep curls* with different weights at the same speed of motion, and *walking on a treadmill at 3mph* with different inclination grades. On the other hand, heart rate has a linear relationship with energy expenditure and can detect changes in effort or resistance load [47, 48, 81]. This section explores whether combining accelerometer and heart rate data improves the recognition of activities involving the same motion characteristics (e.g. speed) but different resistance work.

First, a baseline is obtained by recognizing activities utilizing only features computed from heart rate data. This also serves the purpose of identifying the most discriminant features based on heart rate. Later, the most discriminating heart rate features are incorporated to the best set of accelerometer-based features found in the previous sections. As in previous experiments, the activities to recognize are the 52 activities contained in the MIT dataset, including the *unknown* class.

In general, heart rate data from devices that are relatively convenient to wear for moderate periods of time such as the Polar chest strap tends to be noisy, particularly for activities with high degree of motion such as *running* on a treadmill at 5 or 6mph. This is because the quality of heart rate data depends on the good attachment of the heart rate monitor to the chest of the subject. The more the heart rate monitor moves, the noisier the heart rate data. Thus, in order to reduce the noise, a 15s running average filter is applied over the heart rate data before the segmentation and feature computation steps. This filter is applied over windows of 15s because it was found via informal testing to reduce noise considerably while minimizing the delay introduced in some activities with rapid changes in heart rate such as ascending and descending stairs. Heart rate data is then segmented by accumulating the data over sliding windows of specific lengths. When the accelerometer data is included, the heart rate window length extends from the end of the acceleration window backwards in time (see Figure 5-24). Accelerometer features are computed over windows of 5.6s (optimal window length found in Section 5.4.6), so the two types of features are being computing using different window lengths.

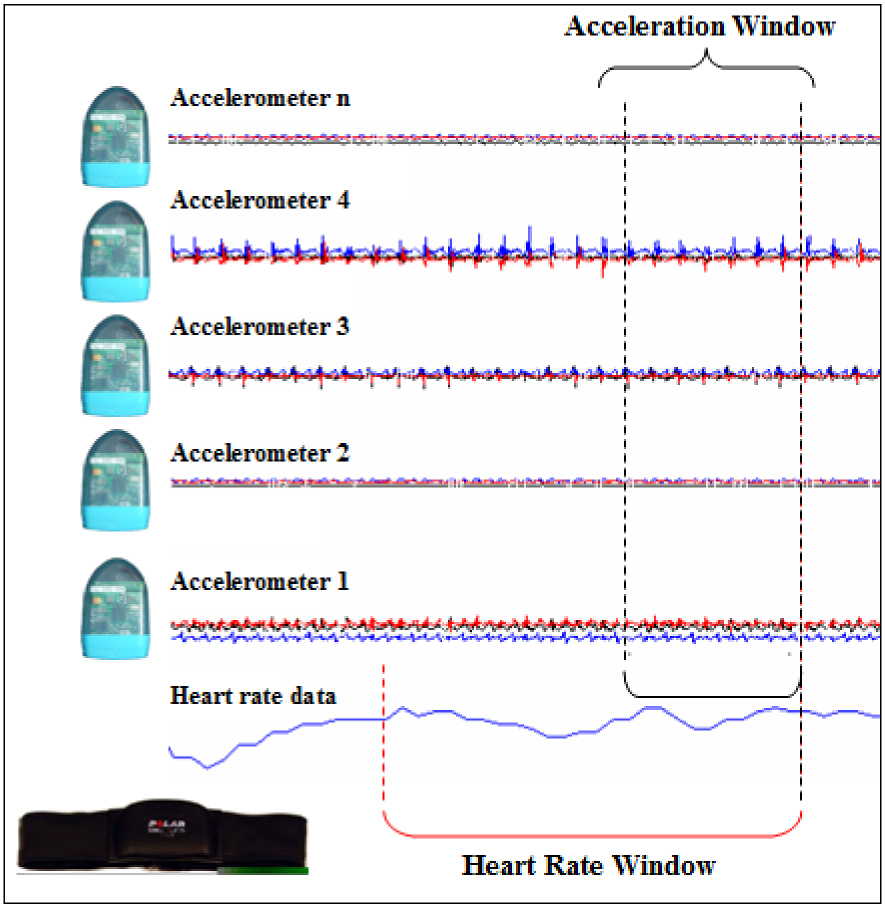


Figure 5-24: Graphic representation of the segmentation of heart rate and accelerometer data using the sliding window approach. Note that the windows for accelerometer and heart rate data are of different lengths and that the heart rate sliding window extends from the end of the end of the accelerometer window backwards in time.

Heart rate windows and their associated acceleration windows are discarded when no sensor values are available for heart rate over a given window. The results presented in this section are evaluated using subject dependent and independent training.

5.4.8.1 How Well can Activities be Recognized from Heart Rate Data?

This subsection has two goals: (1) to identify the heart rate features with highest discriminant power and (2) to establish a baseline as to how well can the activities of interest be recognized from heart rate data alone. The heart rate features explored in this section are: *HRMean*, *HRAboveRest*, *ScaledHR*, *HRVar*, and *HRTrend*. Appendix A3 provides an explanation of how these features are computed. These features attempt to capture either the level of physical effort associated with an activity (*HRMean*, *HRAboveRest, and ScaledHR*), its variability (*HRVar*), or tendency (*HRTrend*).

First, information gain feature selection was performed over the heart rate features. This sorts the features in order of importance according to the information they provide. The ordering of the features from most important to least important obtained from the procedure is as follows *ScaledHR*, *HRAboveRest*, *HRMean*, *HRTrend,* and *HRVar*. The three most important features *ScaledHR*, *HRAboveRest,* and *HRMean* capture the same information. However, the better performance of *ScaledHR* is expected since this feature normalizes the heart rate data of an individual to lie between resting heart rate (a value of zero for this feature) and the average heart rate value obtained while the subject runs on a treadmill at 5mph (a value of 1 for this feature). Using this normalization, two individuals with different fitness level performing the same activity could have different heart rate values but relative to their heart rate values at rest and while running at 5mph, they could be performing in the same intensity zone. Thus, this normalization helps to minimize the inter-individual variations in heart rate values due to differences in the fitness level. Ideally, this feature would normalize heart rate between resting heart (RHR) rate and maximal heart rate (MHR). Unfortunately, for this to be possible, a maximal physical exertion test would be required. These tests are inconvenient in practice because they require an exhaustive exercise session where the physical condition of the subject is push to the limit to measure heart rate during maximal exertion. Some individuals not physically fit or with other medical conditions might not even be able to perform such a test. Furthermore, these tests would be impractical to impose for a consumer-based mobile phone application – the ultimate goal. The least important features are *HRTrend* and *HRVar* (an experiment will later characterize how least important they are). These features capture the variability or tendency of the heart rate data. The *HRTrend* feature, in particular, tells if heart rate data is increasing (positive value for the feature), decreasing (negative value) or in steady state (near a value of zero) over time. This might be important information to capture because heart rate for some physically demanding activities such as *ascending stairs*, *crunches* and *sit-ups* constantly increases continuously as the activity is performed, possibly for the duration of the activity if a person is not very fit and the maximal exertion is not reached Consequently, when features such as *ScaledHR* are computed over these activities, they show high variability in their values that leads to a low recognition performance by the C4.5 classifier. One possible explanation for the low ranking of these features (*HRVar* and *HRTrend*) is that they were computed over a short duration window (5.6s). Later in this section, experiments will be performed to measure the impact of utilizing longer window lengths over these features.

To corroborate the ordering of importance found using information gain feature selection, the performance over individual features was tested using the C4.5 classifier during subject dependent and independent training. The results are illustrated in Table 5-24 and Table 5-25. The ordering during subject dependent training is the same as the one found during information gain feature selection. For subject independent training, the ordering with respect to overall performance is reversed for the *ScaledHR* and *HRAboveRest* features. However, when analyzing the result per activity category it can be seen that the *ScaledHR* feature is outperforming the *HRAboveRest* feature in most activity categories. The main difference in overall performance between these features is due to the performance over the *unknown* class. The *HRAboveRest* feature achieves a true positive rate of 88.0% for this class while the *ScaledHR* feature achieves only a true positive rate of 80.3%. When the true positive rate is analyzed per activity during subject dependent evaluation, it is found that the activities with highest performance are *lying down* (87-89%), *running at 5mph* (7-31%), and *running at 6mph* (12-29%).

Heart Rate Features (Number of features)	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
ScaledHR (1)	37.7 ± 7.0	27.4±17.4 (1.0±0.7)	26.6±20.5 (1.1±0.6)	30.3±22.7 (1.0±0.6)	24.5±18.8 (1.0±0.6)	16.3±14.0 (1.2±0.6)
HRAboveRest (1)	37.4 ± 7.4	26.8±18.1 (1.0±0.8)	27.2±20.8 (1.1±0.6)	29.9±22.5 (1.0±0.6)	24.5±18.8 (1.1±0.6)	16.2±14.4 (1.2±0.7)
HRMean (1)	37.4 ± 6.6	26.5±18.5 (1.0±0.6)	27.4±20.9 (1.1±0.6)	30.6±22.5 (1.0±0.6)	24.9±18.7 (1.10±0.6)	16.8±13.8 (1.2±0.7)
HRVar (1)	29.7 ± 8.5	6.8±9.1 (0.9±1.0)	1.4±2.8 (0.5±0.5)	6.5±9.3 (0.6±0.5)	5.9±8.7 (0.5±0.4)	2.0±3.6 (0.5±0.5)
HRTrend (1)	29.3 ± 8.3	4.9±5.9 (0.9±0.9)	1.9±3.3 (0.5±0.4)	6.3±8.6 (0.7±0.6)	6.2±8.3 (0.7±0.6)	1.7±2.9 (0.5±0.4)

Table 5-24: Performance of recognizing the 52 activities contained in the MIT dataset (including the *unknown* class) from heart rate features only over windows of 5.6s using the C4.5 decision tree classifier during subject dependent evaluation.

Heart Rate Features (Vector size)	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
ScaledHR (1)	30.0 ± 6.3	15.2±4.9 (0.9±0.8)	5.5±4.2 (0.4±0.4)	4.4±4.3 (0.5±0.5)	1.0±1.9 (0.4±0.3)	1.3±1.6 (0.4±0.2)
HRAboveRest (1)	31.4 ± 7.0	15.2±4.2 (0.8±0.8)	1.8±2.9 (0.2±0.2)	1.85±3.1 (0.3±0.2)	0.7±1.4 (0.2±0.1)	0.9±1.2 (0.2±0.1)
HRMean (1)	27.8 ± 7.3	4.2±3.2 (1.1±1.4)	1.7±3.0 (0.2±0.2)	1.6±2.7 (0.3±0.3)	0.6±1.1 (0.2±0.2)	0.6±1.4 (0.2±0.2)
HRVar (1)	29.9 ± 7.6	0.0±0.0 (0.0±0.0)	0.0±0.0 (0.0±0.0)	0.8±1.9 (0.0±0.0)	0.8±2.0 (0.0±0.0)	0.0±0.0 (0.0±0.0)
HRTrend (1)	29.8 ± 7.9	0.0±0.0 (0.0±0.0)	0.0±0.0 (0.0±0.0)	0.0±0.0 (0.0±0.0)	0.0±0.0 (0.0±0.0)	0.0±0.0 (0.0±0.0)

Table 5-25: Performance of recognizing the 52 activities contained in the MIT dataset (including the *unknown* class) from heart rate features only over windows of 5.6s using the C4.5 decision tree classifier during subject independent evaluation.

These activities are better discriminated because heart rate reaches steady state for a good proportion of the activity length and because they represent the extreme values that heart rate data can reach. The overall performance of the *HRVar* and *HRTrend* features during subject independent evaluation is deceiving. From Table 5-25, it can be seen that their performance for all activity categories is zero, while their overall performance is around 29%. This is because the *unknown* class, which is the class with largest number of examples (see Appendix A4), has a true positive rate of near 100% when both features are used. To prevent this from happening in the following experiments, the *unknown* class is no longer included for the remaining of this section.

Given that the main difference found between the *HRAboveRest* and *ScaledHR* feature is the performance over the *unknown* class, new experiments were run to better understand the performance per activity when this class is not included. Table 5-26 presents the new results obtained. The table shows that the performance using both features is very similar during subject dependent training. When the true positive rate is analyzed per class for both features, it is found that the best performance is achieved for *lying down* (87%), *cycling hard at 80rmp* (65%), *cycling light at 60rmp* (66.5%), *running at 5 and 6mph* (56-64%), and *walking* at different speeds and inclinations (47-55%). Again, this is because these activities include periods where the heart rate data reaches steady state and that the classifier utilizes to discriminate among the activities.

Features	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
ScaledHR Subject Dependent	38.4 ± 7.8	37.7±22.3 (1.5±1.0)	39.0±22.2 (1.7±0.8)	38.3±23.9 (1.4±0.8)	34.2±20.6 (1.6±0.9)	24.0±18.0 (2.0±1.1)
HRAboveRest Subject Dependent	38.0 ± 7.7	37.6±21.7 (1.5±1.0)	39.5±22.1 (1.7±0.8)	37.7±23.6 (1.4±0.8)	34.2±20.2 (1.6±0.9)	23.6±17.3 (2.1±1.1)
ScaledHR Subject Independent	13.8 ± 3.2	16.2±5.9 (1.7±1.2)	14.2±9.3 (2.3±1.3)	9.0±7.5 (1.6±1.0)	4.1±5.2 (1.7±0.8)	4.3±4.9 (1.7±0.9)
HRAboveRest Subject Independent	11.9 ± 3.32	17.5±7.0 (1.7±1.3)	5.7±7.4 (2.2±1.0)	4.8±7.2 (1.7±0.8)	3.8±5.4 (1.8±0.8)	4.3±5.0 (1.7±0.8)

Table 5-26: Performance of recognizing the 51 activities contained in the MIT dataset (without including the *unknown* class) in a subject independent manner using the C4.5 decision tree classifier trained over the *ScaledHR* and *HRAboveRest* features over a heart rate sliding window of 5.6s

The activities with poorest performance are those whose heart rate value keeps increasing as the activity is performed such as *ascending stairs* (2.9%) and *bench weight lifting hard* (8.7%). When the confusion matrix is analyzed for subject dependent training (shown in Appendix A7), it can be seen that there exists a high degree of confusion among household activities.

This is because heart rate has similar values for most of these activities and there is no single heart rate value characterizing each of the activities. Interestingly, the household activities better recognized were sedentary activities where the heart rate value reaches steady state such as *ironing* (36%), *playing video games* (34%), *typing* (30%), and *writing* (48%). The confusion matrix also shows that sedentary and ambulatory activities are being confused with household activities. This is because most household activities include short periods of time where postures and ambulatory activities are executed.

The results using subject independent evaluation show in Table 5-26, suggest that the *ScaledHR* feature has a slightly higher performance (~2%) than the *HRAboveRest* feature. This better performance is more apparent for ambulation an exercise activities where the true positive rate doubles for the *ScaledHR* feature. This can be explained by the fact that the *ScaledHR* feature helps in normalizing the heart rate signal so that differences in fitness level of individuals are minimized. The notable low performance during subject independent training with respect to subject dependent training is due mainly to the different fitness level of the individuals. Two individual performing the same activity, but with different fitness levels, would have heart rate readings with different values. Although the *ScaledHR* feature attempts to mitigate this problem, it is clear that new ways to compensate for this variation among individuals are required.

One way to mitigate the differences in the fitness level of individuals would be to include features that attempt to capture this information such as the body weight of an individual (*weight*) and the percentage of fat of an individual (*FatPercent*). Therefore, an experiment was run to determine if the addition of these features improves subject independent recognition of activities when heart rate data alone is used. Table 5-27 presents the results. The table also includes another feature that attempts to better describe the fitness level of an individual. This feature is labeled as *FitnessIndex* and is computed by dividing the number of steps by the average heart rate value (in beats-per-minute) of a subject while *running* on a treadmill at 5mph. This feature is an approximation to the fitness index suggested in [230]. The results show that comparing

Features	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
ScaledHR	13.8 ± 3.2	16.2±5.9 (1.7±1.2)	14.2±9.3 (2.3±1.3)	9.0±7.5 (1.6±1.0)	4.1±5.2 (1.7±0.8)	4.3±4.9 (1.7±0.9)
ScaledHR + Weight	12.9 ± 5.3	19.0±13.5 (2.6±2.7)	14.4±18.1 (3.0±2.9)	9.4±12.8 (2.1±1.9)	5.7±10.0 (2.2±1.9)	5.2±9.3 (2.6±2.3)
ScaledHR + FatPercent	12.0 ± 3.9	19.3±15.3 (2.7±3.0)	11.2±13.3 (2.7±2.6)	7.5±10.3 (2.1±2.2)	4.1±8.5 (2.2±2.1)	4.1±7.3 (2.5±2.1)
ScaledHR + FitnessIndex	13.8 ± 3.6	20.5±15.5 (2.6±2.5)	14.1±17.9 (2.8±2.4)	10.4±16.4 (2.0±1.9)	6.7±13.9 (2.2±1.9)	6.5±10.0 (2.5±2.1)

Table 5-27: Performance of combining features that attempt to describe the fitness level of an individual with heart rate features (*ScaledHR*) during subject independent evaluation using the C4.5 decision tree classifier. The target activities were the 51 activities contained in the MIT Dataset, without including the unknown class.

the difference in overall performance is again deceiving. For example, the overall performance for *ScaledHR+Weight* is lower than for the *ScaledHR* feature alone,
but the performance per activity category shows that the *ScaledHR+Weight* features have a slightly higher performance ranging from 1 to 4%. Cautious analysis of the performance per activity when the *Weight*, *FatPercent*, and *FitnessIndex* features are added to the *ScaledHR* feature (Tables can be found in Appendix A7) show that the addition of these features changes the distribution of the performance per activity little. As a result, there is no clear advantage of incorporating these features. One explanation why these features do not improve recognition of activities is that the number of subjects is relatively low (20) to capture the fitness differences across individuals.

Since the performance of heart rate features such as *ScaledHR*, *HRVar*, and *HRTrend* can vary depending on the window length used, an additional experiment was run to measure this effect. During this experiment, the heart rate window length was varied from 5.6s to 45.5s while the performance over these features was measured using the C4.5 decision tree classifier. Figure 5-25 presents the results obtained from the experiment for the *ScaledHR* feature. The results for the *HRVar* and *HRTrend* can be found in Appendix A7. During subject dependent training, Figure 5-25 shows that the window length with higher performance over all and per activity category is 5.6s. After this window length, the performance for all the activities and each activity category drops significantly. The main reason why performance decreases as the window length is increased is a reduction in the number of training examples available. Longer window lengths also introduce more variability in the heart rate data readings for some activities such as postures and thus, further decreases performance as seen in Figure 5-25a. During subject independent training, on the contrary, the performance per activity seems to improve as observed when increasing the window length for accelerometer-based features. This is because longer window lengths have a smoothing effect over the heart rate data that reduces inter-subject variability. The effect of increasing the window length for the *HRVar* and *HRTrend* features (as shown in Appendix A7) during subject dependent training has a similar effect as the one observed for the *ScaledHR* feature. The only difference is that for these features, a little improvement in performance (~1-2%) is observed for the ambulation, exercise, resistance exercise, and household activities at a window length of 11.3s. Nevertheless, the decrease in performance at this window length

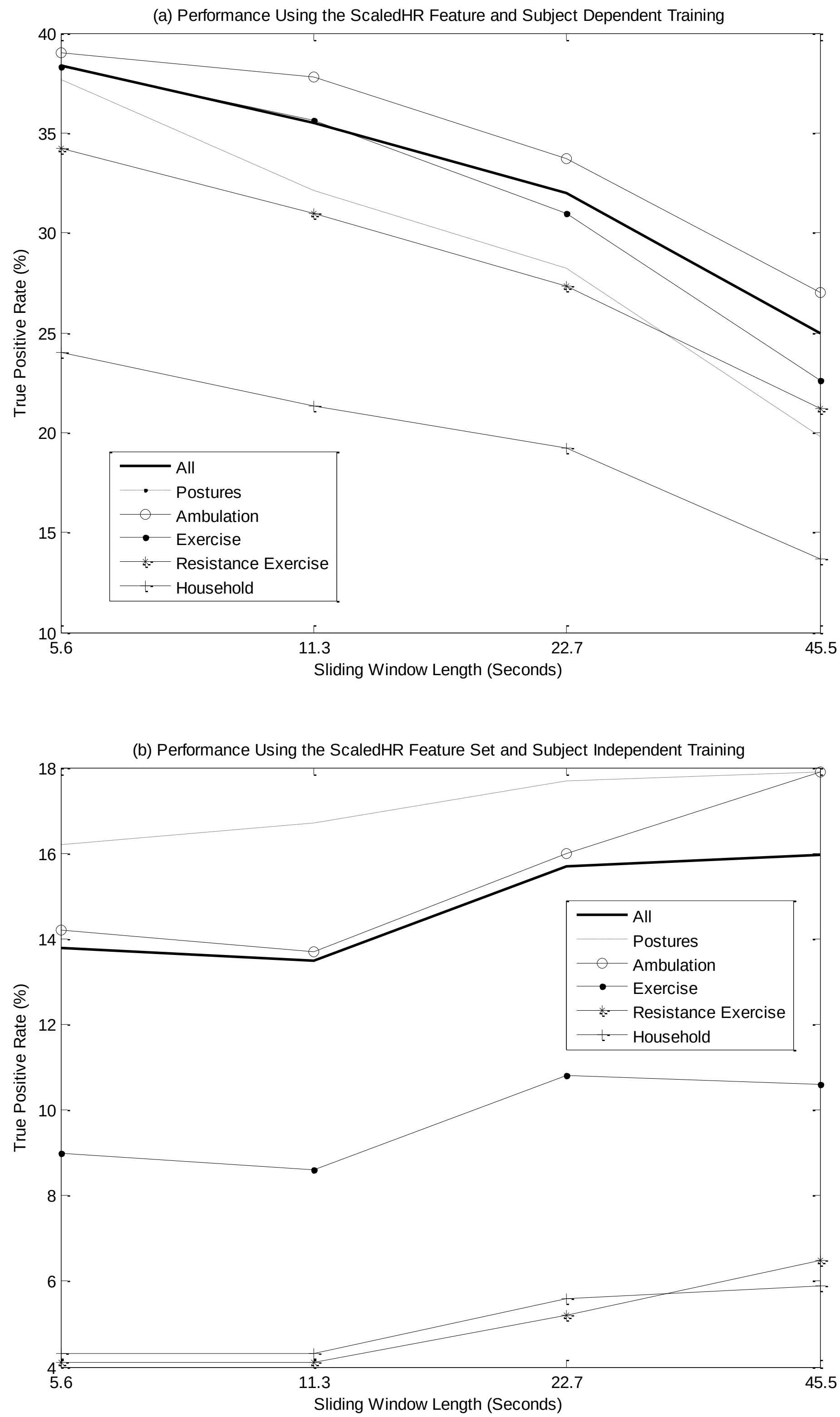


Figure 5-25: Performance of the *ScaledHR* feature computed over varying window lengths using the C4.5 classifier and evaluated using (a) subject dependent training and (b) subject independent training.

(11.3s) for postures is about 4.3%. For subject independent training, it is found that the performance using the *HRVar* and *HRTrend* features decreases as the window length increases. This is because the variability and trend of the heart rate data is less distinctive for each activity as the window length is increased since increasing window lengths have a smoothing effect on the data. In summary it can be concluded that the optimal window length to use for heart rate data is 5.6s. This window length has the highest performance during subject dependent training for the *ScaledHR* feature and is the optimal window length to use for the *HRVar* and *HRTrend* features. The performance during subject independent training improves for the *ScaledHR* feature as the window length increases, but the overall improvement obtained is only about 2% when increasing the window length from 5.6s to 45.5s.

Given the low performance obtained while recognizing activities from heart rate data alone, one might predict that combining heart rate with accelerometer data might not substantially improve recognition of activities unless the C4.5 classifier could learn to utilize it only to discriminate among activities involving different effort or resistance level. Although this option will be explored in the next section, another alternative is to force the C4.5 classifier to use heart rate data only to discriminate among these activities. This can be achieved by first classifying the activity type using accelerometer data, and then utilizing a classifier trained only on heart rate data to discriminate among the intensity levels of an activity. Consequently, to test this idea, we trained five independent classifiers utilizing the *ScaledHR* feature to discriminate among the different intensity levels of an activity in a subject independent manner. Table 5-28 presents the overall accuracy of each classifier and Appendix A7 presents the accuracies per activity. It can be seen that even just recognizing among the intensity level of few activities using heart rate data is difficult. The best accuracy achieved is 51% for the classifier that discriminates between the intensity levels of *bench weight lifting*, and the worse accuracy of 29% is for the *rowing at 30spm* classifier. The performance of the *rowing at 30spm* classifier is perhaps the worst because the resistance level of the rowing machine used during the data collection changes only slightly compared to the other machines used. Thus, heart rate readings do not change dramatically for the different intensity settings. In fact, the resistance of a rowing machine is mostly set by the pulling effort and expertise of each individual at the machine. It follows that even when this hierarchical approach is followed to incorporate heart rate data, the discrimination among intensity levels of an activity would still be poor for subject independent recognition. Again, the main problem is the diverse heart rate readings obtained for each activity due to differences in subjects' fitness. Another option would be to utilize subject dependent training to discriminate among the intensity levels of an activity, but this requires the subject to provide examples of the activities of interest. The main challenge then would be to come up with strategies to make the training process easy and amenable to end-users.

This section has shown that recognizing activities from heart rate data alone is difficult, particularly in a subject independent manner. Even when the best performing feature is used (*ScaledHR*), the best total accuracy obtained is 38.4 ± 7.8 for subject dependent training and 13.8 ± 3.2 for subject independent training. The main problem found so far is that the values of heart rate data are different for two individuals performing the same activity but with different fitness level and without requiring burdensome training

Intensity Activity Classifier	Intensities	Total Accuracy
Bicep Curls	Weight Load: Light (0.9Kg), moderate (2.2Kg), and hard (3.6Kg)	42.1 ± 10.8
Bench Weight Lifting	Weight Load: Light (0.9Kg), moderate (3.1Kg), and hard (7.7Kg)	51.3 ± 20.0
Cycling at 80rmp	Resistance level: Light (2), moderate(7), and hard (13)	41.0 ± 15.5
Rowing at 30spm	Resistance level: Light (2), moderate(5), and hard (8)	29.7 ± 11.2
Walking at 3mph	Treadmill inclination: 0, 3, 6, 9	43.2 ± 11.6

Table 5-28: Performance of five independent C4.5 classifiers trained utilizing the *ScaledHR* feature to discriminate among the different intensity levels of an activity. The *ScaledHR* feature was computed over windows of 5.6s in length.

procedures measuring maximal expenditure we have no mechanism to normalize them. After plotting misclassification histograms, it was also found that the errors were concentrated at the beginning and end of activities. This is because heart rate lags physical activity and remains altered once the activity has finished (errors at the end of activity or beginning of the next one). Furthermore, for vigorous activities of short duration such as *ascending stairs*, *crunches*, and *sit-ups*, heart rate constantly increases resulting in classification errors all across the activity. Finally, another problem with heart rate data while recognizing sedentary activities is that heart rate can also be altered by emotional states, stress, biological processes, and even smoking. This problem was not apparent in our dataset but it might be of potential concern in practice.

The poor performance obtained by recognizing activities from heart rate data alone in this section might be a consequence of the static nature of the classification approach followed, where no temporal information about the variability of heart rate over time is incorporated. More computationally expensive classification techniques such as hidden Markov models (HMMs) or dynamic Bayesian networks (DBNs) might improve the classification results obtained in this section by incorporating temporal information about how hear rate changes over time as activities change. This approach was not explored in this work due to its high computational requirements since one of the main goals of this work is to come up with classification strategies amenable for real-time performance in existing handheld devices.

5.4.8.2 How Well can Activities be Recognized by Combining Acceleration and Heart Rate Data?

In this section, the best performing heart rate feature found (*ScaledHR*) in the previous section is added to the best set of acceleration-based features (*invariant reduced* feature set) found in previous sections. Table 5-29 presents the results of combining both feature sets using the C4.5 classifier during subject dependent and independent evaluation. Both feature sets are computed over windows of 5.6s. The detailed results per activity can be found in Appendix A7.

Table 5-29 shows that the improvement in overall performance when the *ScaledHR* feature is incorporated is approximately 1.6% during both subject dependent and independent evaluation. When the performance per class is inspected for subject dependent training (shown in Appendix A7), it is found that the C4.5 classifier indeed learns to improve the performance of activities involving different levels of effort or

Features subsets	Evaluation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
Invariant Reduced	Subject Dependent	87.93 ± 2.08	96.9±4.1 (0.1±0.1)	88.8±8.4 (0.2±0.2)	92.6±7.7 (0.1±0.1)	88.0±9.5 (0.2±0.2)	80.6±9.0 (0.4±0.2)
Invariant Reduced + ScaledHR	Subject Dependent	89.49 ± 1.81	96.9±4.1 (0.1±0.1)	91.7±7.3 (0.2±0.1)	93.3±7.6 (0.1±0.1)	90.4±8.7 (0.2±0.2)	82.0±8.5 (0.4±0.2)
Invariant Reduced	Subject Independent	50.63 ± 5.18	77.0±24.0 (0.5±0.7)	46.6±27.1 (1.2±1.0)	46.6±31.6 (0.9±0.9)	34.1±29.9 (1.2±1.0)	43.8±25.6 (1.3±0.9)
Invariant Reduced + ScaledHR	Subject Independent	52.28 ± 5.84	76.2±24.6 (0.5±0.7)	51.8±28.8 (1.0±1.0)	46.4±31.5 (0.8±0.9)	36.6±31.4 (1.1±1.0)	43.7±25.8 (1.3±0.8)

Table 5-29: Performance of recognizing activities when the most discriminating accelerometer (invariant reduced feature set) and heart rate feature (*ScaledHR*) are computed per axis and fed to the C4.5 classifier to recognize the 51 activities contained in the MIT dataset without including the *unknown* class.

resistance load without changing the performance for the other activities. The performance improves for *cycling at 80rmp* hard and moderate (improvement between +1.6 and +4.5%), *Rowing at 30spm* light, moderate and hard (+1.9-2.9%), *walking at 3mph* on a treadmill at inclinations of 0, 3, 6, and 9 (+3.7-12.5%), *wiping/dusting* (+4.6%), and *taking out trash* (+3.2%). *stacking groceries* (+3%), *sweeping* (+2.3%), *Vacuuming* (+1.5%), The performance also increases for *washing windows*, *carrying groceries*, and *scrubbing a surface*, but the increase is less than +1%. During subject independent evaluation, the performance also increases between +2.4% and +28.7% for some activities such as *cycling at 80rmp* hard, *rowing at 30spm* moderate, *running at 5mph*, *walking* on a treadmill at different inclinations, and *taking out trash*. However, even when the improvement seems considerable for some activities (e.g. 28.7% for *walking at 3mph* with an inclination of 9), other activities such as *bicep curls* hard and moderate, *rowing at 30spm* hard, and *running at 6mph* suffer a decrease in performance as high as 8%. Therefore, the improvement achieved by incorporating heart rate data during subject independent training is less obvious than the one obtained for subject dependent training. The confusion matrices for the combination of the invariant reduced and *ScaledHR* features are shown in Appendix A7. From these matrices, it can be seen that most of the confusion during subject dependent training happens among household activities. In subject independent training, confusions are concentrated among household activities, and between ambulation and postures and household activities.

In conclusion, the overall improvements achieved while incorporating heart rate data during both, subject dependent and independent training is only 1.6%. The improvement is more obvious for subject dependent activities where the performance is increased between 1.6 and 12.5% for activities involving different levels of effort or resistance load. Nevertheless, the improvement obtained might not justify (1) the burden associated with wearing a heart rate monitor or (2) the need for personalized training. As a result, from this point on, this thesis will only utilize accelerometer-based features (*invariant reduced* feature set) to recognize the activities of interest.

Evaluation Method	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
Subject dependent without Unknown class Random guess: 1.96%	87.9 ± 2.0	96.9±4.1 (0.1±0.1)	88.8±8.4 (0.2±0.2)	92.6±7.7 (0.1±0.1)	88.0±9.5 (0.2±0.2)	80.6±9.0 (0.4±0.2)
Subject dependent with unknown class Random guess: 1.92%	81.0 ± 2.0	93.1±6.0 (0.1±0.1)	82.4±10.4 (0.3±0.1)	88.8±9.7 (0.2±0.1)	84.0±10.8 (0.3±0.1)	74.3±10.5 (0.4±0.2)
Subject independent without unknown class Random guess: 1.96%	50.6 ± 5.2	77.0±24.0 (0.5±0.7)	46.6±27.1 (1.2±1.0)	46.6±31.6 (0.9±0.9)	34.1±29.9 (1.2±1.0)	43.8±25.6 (1.3±0.9)
Subject independent with unknown class Random guess: 1.92%	47.0 ± 4.2	54.5±34.0 (0.4±0.5)	38.4±26.1 (0.9±0.8)	38.4±31.9 (0.6±0.7)	29.4±28.2 (0.8±0.8)	37.2±23.4 (0.9±0.6)

Table 5-30: True positive and false positive rate (shown in parenthesis) of the C4.5 classifier when recognizing the 51 activities contained in the MIT dataset either including or not including the *unknown* class. The feature set used is the *invariant reduced* computed per axis over windows of 5.6s in length over all the seven accelerometers. The accuracy of random guessing is 1.92% (for 52 activities) when the unknown class is included and 1.96% (for 51 activities) when it is not.

5.4.9 How Well Can All Activities Be Recognized Using the Selected Classifier, Window Length, Feature Set, and Signal Preprocessing Techniques?

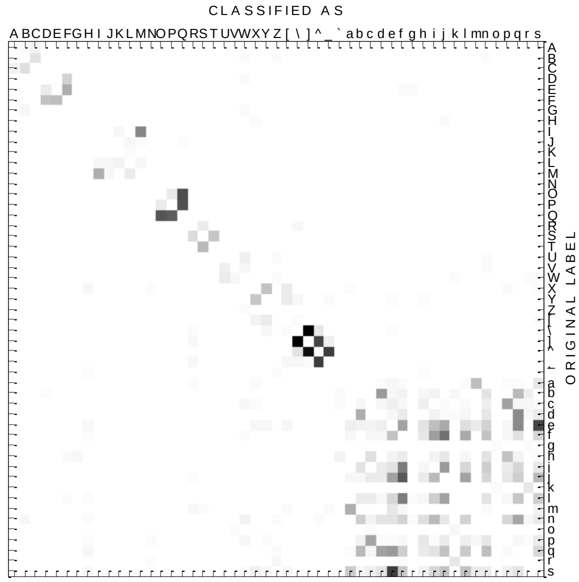
This section presents the performance of the final implementation of the activity recognition algorithm using the set of parameters incrementally selected in the previous sections. These parameters consist of the C4.5 decision tree classifier, the *invariant reduced* feature set (*ACVar*, *ACFFTPeaks*, *ACBandEnergy*, and *DCPostureDist*), feature computation per axis, and sliding windows of 5.6s in length.

First, the performance of the algorithm is evaluated over the 51 activities contained in the MIT dataset using subject dependent and independent training. The results are presented for both cases -- when the *unknown* class is included and when it is not. The inclusion of the *unknown* class is used to test the performance of the recognition algorithm under somewhat more realistic conditions where there are examples of untrained or ill-defined activities. Once these results are presented, the training data requirements for subject dependent training are evaluated by training the algorithm with decreasing amounts of data. Finally, an experiment is performed to determine a good number of accelerometers to use and their locations in the human body, considering both recognition performance and everyday convenience.

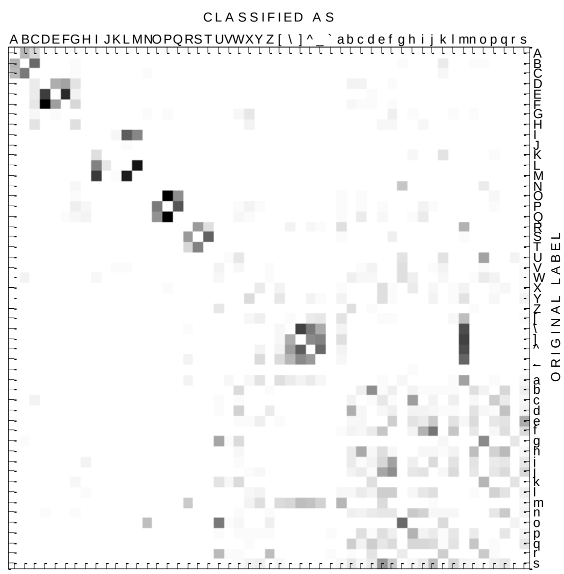
Table 5-30 presents the true positive and false positive rate obtained during subject dependent and independent training while the *unknown* class is included and when it is not. The table illustrates that the best performance overall (87.9%) and per activity category is obtained for subject dependent training when the *unknown* class is not used. When the *unknown* class is added, overall performance drops 7% for subject dependent training and 3.6% for subject independent training. This is expected, since the *unknown* class contains examples of the activities of interest that were just not labeled during the data collection. The *unknown* class may also contain examples of activities very similar to the target classes. The difference in performance of 34-37% between subject dependent and independent training is considerable. This reflects the higher difficulty of recognizing activities across individuals since each individual perform activities differently.

During subject dependent training, the best performance is obtained for postures and the worse performance is obtained for household activities. Postures are recognized well because the accelerometer signals they generate are static in nature (DC component of the signal), so there is not much variation to model. Moreover, the window length of 5.6s used is optimal for postures, as explained in Section 5.4.6. Obviously, variations in the posture signals increase when multiple individuals are considered thus decreasing performance between 20-39% during subject independent training. Household activities are the most difficult to recognize during subject dependent training because they involve a high degree of variation in the signal even when a single individual performs the activities. Some of these activities such as *wiping/dusting*, *making the bed*, *taking out trash*, and *stacking groceries* even involve multiple postures and ambulation modes that change based on how the person interacts with objects in the environment. Consequently they are confused with postures and ambulatory activities, as seen from the confusion matrices shown in Figure 5-26. Another reason why household activities are not well recognized is because they may require windows longer than 5.6s due to their high motion variability, and they may involve execution of sequences of events (e.g. standing, walking). Finally, from Table 5-30, it can be seen that the true positive rate for ambulation, exercise, and resistance exercise activities is very close, ranging from 82 to 92% during subject dependent training. During subject independent training, the performance for ambulation and exercise activities is also close (46% when the *unknown* class is used and 38% when it is not); however, the performance is worse for resistance exercise activities. This is due to a combination of two factors: (1) High variability in the way activities are performed across individuals and (2) the difficulty in recognizing activities with similar motion signatures (e.g. speed of execution) but different levels of resistance or work load from accelerometers.

When the performance per activity is evaluated from Appendix A8, it is found that the activities with lowest performance are resistance exercise activities such as *bench weight lifting* and *bicep curls* with different weights, *rowing at 30spm* and *cycling at 80rmp* at different resistance levels, *walking at 3mph* at different inclination grades, and some household activities such as *weeding*, *gardening*, *making the bed*, and *taking out trash*. As explained before, this is because accelerometers are not good at detecting changes in effort or resistance load, and because household activities are highly variable, even within an individual. Surprisingly, during subject dependent training, some resistance exercise activities such as *bench weight lifting* and *bicep curls* with different weights, and *cycling at 80rpm* at different resistance levels are recognized with high true positive rates ranging from 88.4 to 99.5%. Even activities such as *rowing at 30spm* at different resistance levels and *walking at 3mph* at different inclination grades are relatively well recognized with true positive rates ranging from 76 to 88.9%. This seems to indicate that changes in weight load, resistance level, or grade of inclination induce a change in the motion signature of the activity that is distinctive of each individual. For example, someone struggling with a heavier weight during *bicep curls* might unconsciously reduce the performance speed of the activity. This reduction in speed is detected by the accelerometers and captured by the features so that the classifier learns to differentiate among the different intensity levels of an activity. One important caveat here is that this



(a) Subject Dependent



(b) Subject Independent

```
A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[ -> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-
_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-
_Treadmill_6__-_moderate
_ -> Walking_-_Treadmill_3mph_-
_Treadmill_9__-_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m -> Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash
```

Figure 5-26: Confusion matrices for the C4.5 classifier when recognizing the 51 activities in the MIT dataset without including the *unknown* class during (a) subject dependent and (b) independent training. The feature set used is the *invariant reduced* computed per axis over windows of 5.6s in length. The maximum number of confusions per cell is 95 and 262 for subject dependent and independent training respectively.

slight reduction in motion patterns detected by the accelerometers could be different if sensors are worn with slight different variations in orientation and position from day to day. Therefore, future work should analyze the impact of slight variations in sensor placement and orientation on data collected over multiple days for the same person during subject dependent training.

Figure 5-26 presents the confusion matrices for subject dependent and independent training as a grayscale image scaled to highlight large number of classification confusions in black and low number of classification confusions in white. It can be seen that most confusions happen among household activities for both, subject dependent and independent training. In particular, activities involving postures and ambulation such as *taking out trash*, *making the bed*, *sweeping*, *vacuuming*, *mopping*, *wiping/dusting* are either confused among each other or with ambulatory activities. Ambulatory activities such as *carrying groceries*, *walking around block*, *walking at 2mph*, and *walking at 3mph* are also being confused among each other. Finally, activities involving similar posture and upper body motion such as *wiping/dusting*, *washing windows*, *ironing*, and *doing dishes* are also being confused, particularly during subject independent training.

5.4.9.1 How Much Training Data is Required During Subject Dependent Training?

The performance of subject dependent training is consistently and considerably better than subject independent training. These results strongly suggest that for activity recognition to be practical with a large number of diverse target activities such as those used here, some level of personalized training will be desirable. Thus, one of the main questions to answer is how much training data is required to achieve a reasonable performance while minimizing training time. This section explores this question by measuring the performance the final activity recognition algorithm implemented when varying amounts of training data are used.

For this experiment, the amount of data collected from each activity example provided by participants was partitioned in 75% training data and 25% testing data. The 25% of the data located at end of each activity example is utilized to test the performance of the recognition algorithm while 75% of the data at the beginning of each activity example is used to train the recognition algorithm. During the analysis, the performance of the recognition algorithm is measured when the 75% of the data located at the beginning of each activity is decreased from its original length of 100% to a final length of 10% in decrements of 20% and used to train the recognition algorithm. During this procedure, true positive rate is evaluated on the 25% of the data located at the end of each activity example. Figure 5-27 illustrates the procedure followed by representing how the data from an activity example is utilized to train and test the recognition algorithm during this analysis. This procedure was followed to keep the amount of testing data constant while the amounts of training data were varied.

Ideally, the amount of training data for each activity would be the same to perform a fair comparison among all activities. This is not the case during the analysis performed in this section since most activity examples have different lengths (as shown in Table 5-31).

	(Start)			Activity Example			(end)
	75%						25%
Experiment 1: 100% training data						100%	
Experiment 2: 80% training data					80%		
Experiment 3: 60% training data				60%			
Experiment 4: 40% training data			40%				
Experiment 5: 20% training data		20%					
Experiment 6: 10% training data	10%						

Figure 5-27: Graphical representation of the experiment performed to measure the performance of utilizing different amounts of training data during subject dependent training. The right side of the table represents the duration of an individual activity example performed by one of the participants. The start of the activity is represented by the (start) tag and the end by the (end) tag. The 25% of the data located at the end of the activity example (shown in blue) is used for testing the algorithm while the varying amounts of the 75% of the data at the start of the activity are used for training (shown in red). Unused segments of data per experiment are shown in white.

Percentage of training data used	Percentage of total activity length	Length of activity training examples in minutes			
		Lying down	Postures	Physically demanding activities	Rest of Activities
-	100%	5	2	1.5 - 2.0	3 - 3.5
100%	75%	3.7	1.5	1.1 – 1.5	2.2 – 2.6
80%	60%	3.0	1.2	0.9 – 1.2	1.8 – 2.1
60%	45%	2.2	0.9	0.6 – 0.9	1.3 - 1.5
40%	30%	1.5	0.6	0.4 – 0.6	0.9 - 1.0
20%	15%	0.7	0.3	0.2 – 0.3	0.4 - 0.5
10%	7.5%	0.3	0.15	0.1 – 0.15	0.2 - 0.3

Table 5-31: Percentage of training data used in comparison with the average total amount of data available per activity and corresponding duration (in minutes) of training data with respect to some activity categories.

activity Category	CV	100%	80%	60%	40%	20%	10%
All	87.9 ± 2.0	80.8 ± 3.4	76.2 ± 4.7	70.5 ± 4.7	63.7 ± 5.5	48.2 ± 4.8	34.4 ± 4.7
Postures	96.9±4.1 (0.1±0.1)	96.6±11.9 (0.2±0.3)	95.3±12.9 (0.3±0.4)	87.2±23.9 (0.4±0.6)	76.8±34.6 (0.7±1.1)	42.1±34.6 (1.5±1.2)	24.3±1.5 (2.7±1.1)
Ambulation	88.8±8.4 (0.2±0.2)	92.1±12.8 (0.3±0.4)	90.7±11.9 (0.2±0.3)	83.1±16.6 (0.4±0.5)	69.0±25.4 (0.7±0.7)	37.0±30.4 (0.9±0.9)	0.0±0.0 (0.0±0.0)
Exercise	92.6±7.7 (0.1±0.1)	84.2±20.4 (0.3±0.4)	80.8±24.4 (0.4±0.5)	75.9±25.3 (0.6±0.6)	67.8±29.8 (0.7±0.7)	56.2±31.3 (0.9±0.8)	47.7±33.5 (1.6±1.4)
Resistance Exercise	88.0±9.5 (0.2±0.2)	78.4±23.2 (0.4±0.5)	73.7±27.1 (0.6±0.6)	68.3±27.5 (0.8±0.7)	58.9±31.0 (0.9±0.8)	44.7±30.8 (1.2±1.0)	37.3±29.6 (1.8±1.4)
Household	80.6±9.0 (0.4±0.2)	73.1±21.1 (0.6±0.6	69.2±23.9 (0.8±0.8)	65.0±25.6 (0.9±0.9)	59.0±29.6 (1.0±0.9)	43.9±29.3 (1.5±1.4)	28.4±26.8 (1.9±1.5)

Table 5-32: True positive rate and false positive rate (shown in parenthesis) during subject dependent recognition of activities when varying amounts of training data are used. The target activities are the 51 activities contained in the MIT dataset without including the *unknown* class. CV stands for 10-fold stratified cross-validation. All seven accelerometers are utilized in this experiment.

One possible way to force the activity examples to have the same length would be to cut their length so it is the same as the one for the activity example with shortest duration. However, this procedure was not followed during this analysis because some physically demanding activities such as *bench weight lifting hard*, *cycling at 80rmp hard*, *running at 6mph*, *sit-ups*, and *crunches* have very short durations ranging from 20s to less than a minute. Reducing the duration of all activity examples to this short duration would make the analysis performed in this section difficult do to the unavailability of enough data. Another possibility could be to eliminate the short duration activities from the analysis

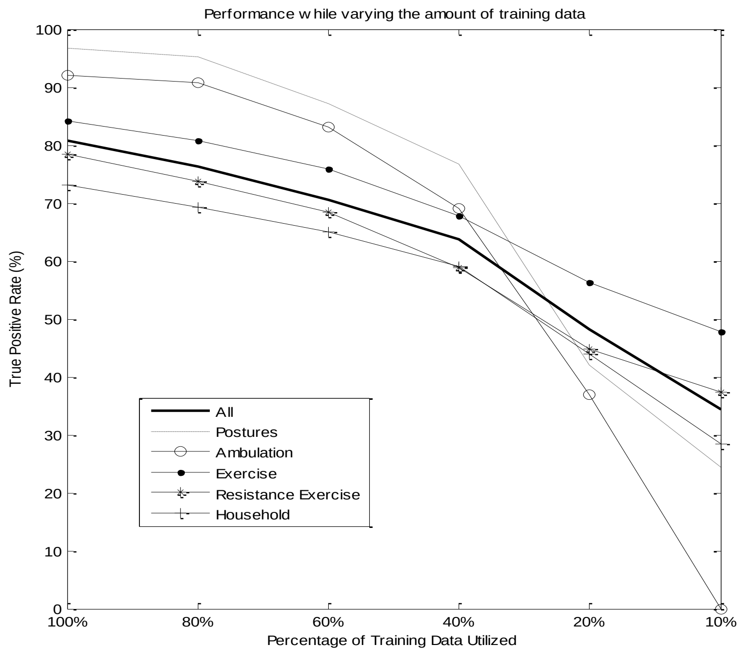


Figure 5-28: True positive rate during subject dependent recognition of activities when varying amounts of training data are used. The target activities are the 51 activities contained in the MIT dataset without including the *unknown* class. In this experiment, all seven accelerometers are utilized.

but this would prevent the presentation of results for these activities. Table 5-31 presents the average amount of training data available per activity in minute so that the results presented in this section can be better interpreted.

Appendix A4 presents the average amount of training data available per activity in the MIT energy expenditure dataset. Table 5-31 shows a summary of this information as well as the duration of each activity example as a function of the percentage of training data used. It can be seen that the total amount of data available for each activity is on average 5min for *lying down* since heart rate and resting metabolic rate were measured during this activity, 2min for the remaining the postures, 1.5-2.0min for some physically demanding activities such as *bench weight lifting hard*, *cycling at 80rmp hard*, *running at 6mph*, *sit-ups*, and *crunches* and 3.0-3.5min for all other activities. Data for some physically demanding activities such as *sit-ups*, *crunches*, and *bench weight lifting hard* were collected over several repetitions of the activity, thus, leading to multiple short duration examples (<1min in length). There are also three examples for the *ascending* and *descending stairs* activities per data collection (participant) because the length of the stairs from the ground floor to the 4thrd floor allowed only the collection of 1min of data continuously for these activities.

Table 5-32 and Figure 5-28 present the results of varying the amount of training data while recognizing the 51 activities contained in the MIT dataset when the *unknown* class is not included. Table 5-32 also shows the performance of 10-fold stratified cross-validation (CV) as a comparison baseline. The performance using CV is higher than when using 100% of the training data (75% of activity duration) because there is more training and testing data available during CV as observed in practice. From Table 5-32, we can observe that, as expected, overall performance and performance per activity category decreases as the amount of training data is decreased. The overall accuracy of 80% while using 100% of the training data suggests that reasonable recognition results can be achieved when just two and three minutes of data for most activities is provided. The activity categories with lower true positive rates are ambulation, resistance exercise, and exercise activity. The poorer performance over these activities is due to the difficulty involved in discriminating among the intensity levels of the activities from accelerometer data, as explained previously, and the smaller amounts of data available for physically demanding activities. The decrease in overall accuracy of only 4.6% when the percentage of training data is reduced from 100% to 80% suggests that the amount of training data can be as little as 2min per activity without significant decrease in performance. The true positive rate overall and per activity category starts decreasing sharply when only 40% of the training data is used. In this setting, there is about 1min of training data for most activities and approximately 0.5min of data for postures and physically demanding activities. Thus, with a window length of 5.6s, there are only between 5 and 10 training examples per activity. It is thus, expected to observe a sharp decrease in performance after this point since having less than 5 examples per activity to train a classifier seems unreasonable.

In conclusion, the experiment suggests that it is possible to provide only 2min of training data per activity and achieve an overall accuracy of 76% when discriminating between 51 activities, and true positive rates per activity category ranging from 69 to 95%. Nevertheless, it might be possible to obtain higher performance even with less training data if discrimination among the intensity levels of an activity is not required or if the number of activities to recognize is reduced. Section 5.5 will later evaluate the real-time performance of subject dependent recognition of activities during a short study where participants provide 2min of training data per activity to recognize.

5.4.9.2 What is a Good Compromise on the Number and Placement of Sensors to be Work for Recognition of Activities?

This section evaluates the performance of the activity recognition algorithm when different combinations of sensors (accelerometers) are used during subject dependent and independent training. The main objective is to determine a good compromise on the number and placement of sensors to use, balancing recognition performance with usage comfort and sensor cost.

Table 5-33 and Table 5-34 present the results obtained while recognizing the 51 activities in the MIT dataset (without the *unknown* class) using different combinations of accelerometers with the C4.5 classifier, the *invariant reduced* feature set computed per axis, and windows of 5.6s in length. The *unknown* class is not used during this analysis to prevent its large number of examples (with respect to the other activities) from altering the results obtained. Figure 5-29 and Figure 5-30 present the true positive rate as a grayscale image scaled so that the best true positive rate is shown in white and the worse is shown in black. In other words, the image highlights the difference in performance per activity category by showing good areas of performance in white and poor areas of performance in black. The prefix “D” in the sensor location label (e.g. DWrist) used in

Sensor Combination	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	87.9 ± 2.0	96.9±4.1 (0.1±0.1)	88.8±8.4 (0.2±0.2)	92.6±7.7 (0.1±0.1)	88.0±9.5 (0.2±0.2)	80.6±9.0 (0.4±0.2)
Hip + DWrist + DFoot	86.3 ± 1.6	96.6±4.2 (0.1±0.1)	87.8±8.5 (0.3±0.2)	90.5±8.4 (0.2±0.1)	85.4±9.9 (0.3±0.2)	79.0±9.7 (0.5±0.3)
Hip + DWrist	83.6 ± 2.3	95.7±4.3 (0.1±0.1)	86.5±9.2 (0.3±0.2)	86.3±12.9 (0.2±0.2)	81.6±13.2 (0.3±0.2)	75.4±10.4 (0.6±0.3)
Hip + DFoot	84.8 ± 2.3	96.6±3.8 (0.1±0.1)	87.1±8.4 (0.3±0.2)	90.4±8.3 (0.2±0.1)	84.4±10.9 (0.3±0.2)	76.0±11.1 (0.6±0.3)
DWrist + DThigh	81.6 ± 2.6	95.5±5.8 (0.1±0.1)	81.5±10.6 (0.4±0.2)	87.5±9.9 (0.2±0.2)	80.6±11.5 (0.4±0.2)	72.6±10.6 (0.6±0.3)
DWrist + DFoot	81.1 ± 2.1	95.8±4.1 (0.1±0.1)	79.9±9.6 (0.4±0.2)	86.9±10.5 (0.2±0.2)	78.2±13.1 (0.4±0.3)	73.6±10.7 (0.6±0.3)
Hip	80.5 ± 2.7	94.8±5.5 (0.1±0.1)	86.5±8.8 (0.3±0.2)	85.7±12.9 (0.2±0.2)	79.2±14.3 (0.4±0.3)	68.7±11.8 (0.7±0.3)
DWrist	70.7 ± 3.7	91.0±8.6 (0.1±0.1)	73.5±11.8 (0.6±0.3)	73.1±14.1 (0.5±0.3)	65.0±15.7 (0.7±0.3)	61.5±12.7 (0.9±0.3)
DFoot	74.8 ± 3.7	93.3±7.7 (0.1±0.1)	73.6±11.0 (0.6±0.3)	84.1±12.3 (0.3±0.2)	72.4±15.7 (0.5±0.3)	63.4±14.8 (0.8±0.4)
DUpperArm	74.4 ± 3.9	88.0±9.8 (0.2±0.2)	81.7±10.4 (0.4±0.2)	79.1±12.0 (0.4±0.2)	69.8±14.9 (0.6±0.3)	61.2±12.6 (0.9±0.3)
DThigh	74.6 ± 2.9	93.1±7.1 (0.1±0.1)	76.1±12.3 (0.5±0.3)	84.8±11.9 (0.3±0.2)	73.9±15.1 (0.5±0.3)	59.4±13.3 (0.9±0.4)

Table 5-33: Performance of the C4.5 classifier using the *invariant reduced* feature set computed per axis over windows of 5.6s in length using different subsets of accelerometers while recognizing the 51 activities contained in the MIT dataset in a subject dependent manner (without including the *unknown* class). The guessing accuracy is 1.96% for all the activity categories shown in the table.

Sensor Combination	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	50.6 ± 5.2	77.0±24.0 (0.5±0.7)	46.6±27.1 (1.2±1.0)	46.6±31.6 (0.9±0.9)	34.1±29.9 (1.2±1.0)	43.8±25.6 (1.3±0.9)
Hip + DWrist + DFoot	46.6 ± 7.5	66.9±32.3 (0.6±1.0)	39.6±27.3 (1.3±1.1)	39.2±31.1 (1.0±0.9)	30.9±28.6 (1.2±1.1)	42.9±24.0 (1.3±1.0)
Hip + DWrist	42.7 ± 5.9	46.1±34.3 (1.0±1.1)	37.9±27.3 (1.4±1.3)	35.4±27.1 (1.1±1.0)	29.1±23.7 (1.2±1.0)	42.9±23.5 (1.3±0.9)
Hip + DFoot	41.0 ± 6.5	57.5±33.6 (0.8±1.1)	35.6±28.3 (1.3±1.2)	39.1±31.7 (1.0±1.0)	28.5±29.2 (1.2±1.1)	32.4±22.5 (1.6±1.1)
DWrist + DThigh	46.5 ± 4.9	55.4±34.2 (0.8±0.9)	44.1±24.1 (1.2±0.9)	45.6±29.5 (0.8±0.8)	33.0±27.3 (1.1±0.9)	39.7±21.7 (1.4±0.9)
DWrist + DFoot	44.0 ± 7.3	62.8±29.5 (0.6±0.9)	37.9±25.0 (1.3±1.1)	36.5±28.1 (1.0±0.9)	30.4±24.9 (1.1±0.9)	40.1±23.4 (1.5±1.0)
Hip	36.2 ± 6.2	40.1±27.7 (1.0±1.0)	37.5±26.3 (1.4±1.1)	35.3±29.1 (1.0±1.0)	26.5±24.9 (1.2±1.0)	28.2±20.2 (1.7±0.9)
DWrist	36.6 ± 7.6	35.3±33.1 (1.0±1.0)	32.6±26.2 (1.3±1.1)	31.7±23.6 (1.1±0.8)	28.3±21.8 (1.2±0.8)	36.2±20.1 (1.5±1.0)
DFoot	33.0 ± 5.4	46.9±32.1 (1.1±1.4)	32.6±20.2 (1.4±1.1)	33.7±22.9 (1.1±0.9)	24.7±21.9 (1.2±0.9)	22.6±16.8 (1.7±1.0)
DUpperArm	37.2 ± 3.5	39.2±24.3 (1.0±0.9)	42.3±23.0 (1.3±1.0)	43.4±22.9 (0.9±0.9)	28.2±20.9 (1.2±1.0)	24.2±16.5 (1.8±0.9)
DThigh	29.0 ± 4.6	19.4±20.4 (1.4±1.3)	38.4±23.8 (1.3±0.9)	40.4±27.6 (1.0±1.1)	23.7±23.8 (1.3±1.2)	17.3±14.7 (2.0±1.3)

Table 5-34: Performance of the C4.5 classifier using the *invariant reduced* feature set computed per axis over windows of 5.6s in length using different subsets of accelerometers while recognizing the 51 activities contained in the MIT dataset in a subject independent manner (without including the *unknown* class). The guessing accuracy is 19.6% for all the activity categories shown in the table.

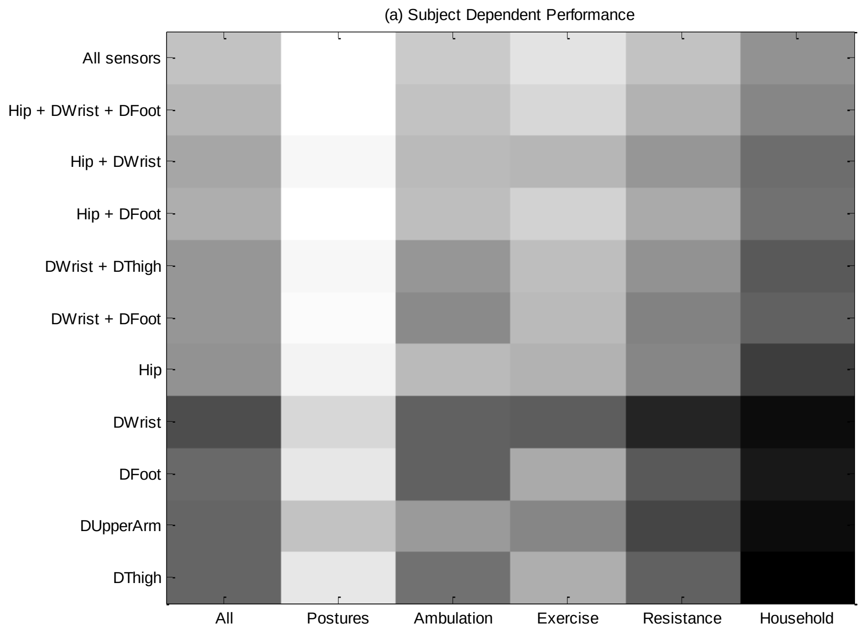


Figure 5-29: True Positive Rate per sensor combination using the C4.5 classifier when features are computed per axis over windows of 5.6s during subject dependent evaluation. The grayscale image is scaled so that the maximum true positive rate of 96.9% is represented by white and the minimum of 59.4% by black. In other words, poor areas of performance are shown in black.

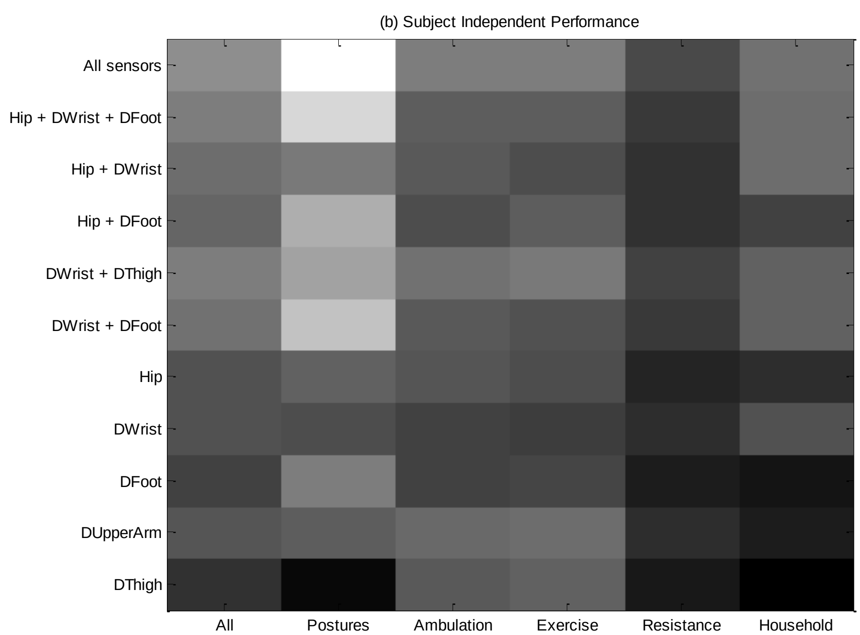


Figure 5-30: True Positive Rate per sensor combination using the C4.5 classifier when features are computed per axis over windows of 5.6s during subject independent evaluation. The grayscale image is scaled so that the maximum true positive rate of 77.0% is represented by white and the minimum of 17.3% by black. In other words, poor areas of performance are shown in black.

the tables and figures stands for "dominant" and implies that the sensor was worn at the dominant limb of the subject (e.g. right wrist if subject was right handed). Refer to Figure 4-4 for an image of the placement of sensor during the data collections.

The results show that the three sensor subsets with best performance (after the one using all the sensors) during subject dependent evaluation are the Hip+DWrist+DFoot, Hip+DWrist, and Hip+DFoot. For subject independent evaluation, the best three subsets are Hip+DWrist+DFoot, DWrist+DThigh, and DWrist+DFoot. Therefore, the Hip+DWrist+DFoot combination has the higher performance overall and per activity for both, subject dependent and independent training. The performance of this sensor combination drops only 1.6% during subject dependent training and 4% during subject independent training with respect to the performance obtained using all seven sensors. The fact that the Hip+DWrist+DFoot sensor combination achieves the best performance intuitively makes sense, since this sensor combination captures upper body motion (DWrist), lower body motion (DFoot), and overall body motion at the Hip. The other sensor combinations explored do not capture motion information at least in one the aforementioned locations (upper, lower or overall). When the Hip+DWrist+DFoot sensor combination is used, the activity categories that suffer the greatest decrease in performance (with respect to the all sensors combination) are ambulation (1-7%), exercise (2.1-7%) and resistance exercise (2.6-7.4%). The reason is that activities involving resistance or load effort such as *bench weight lifting*, *bicep curls*, *cycling at 80rpm* (different resistance levels), *walking at 3mph* (different inclinations), and *rowing at 30spm* (different resistance levels) are better recognized when more sensors are used. As explained in previous sections, changes in resistance or load induce changes in the motion signature of an activity (e.g. execution speed) that allow discrimination between the intensity levels. When the number of sensors is decreased, these slight differences in motion are more difficult to detect, leading to poorer performance on these activities. The performance per activity for the Hip+DWrist and Hip+DFoot sensor combinations was analyzed to determine why these combinations are the two second best performing ones during subject dependent training even when they do not measure both lower body or upper body motion (other than through the hip_. It was found that for the Hip+DWrist sensor combination, the performance over activities involving lower body motion such as *cycling*, *sitting fidgeting feet and legs*, *ascending* and *descending stairs* indeed decreases, particularly during subject independent training. However, during subject dependent training, the decrease in performance for these activities ranges only from 1% to 8%. It appears that during subject dependent training, the small changes induced in the acceleration signal at the hip while performing lower body activities are enough to allow good performance over these activities. For the Hip+DFoot sensor combination, it was found that the performance over activities involving upper body motion such as *bench weight lifting*, *doing dishes*, *playing video games*, *scrubbing a surface*, *typing*, *writing*, *washing windows*, *wiping* and *dusting* was also lower. Nevertheless, the performance on some activities also including upper body motion such as *ironing* and *sitting fidgeting hands and arms* did not change. Again, it appears that changes in the acceleration signal at the hip induced while performing upper body activities are enough to allow good performance over some of these activities.

During subject independent training, the two second best performing sensor combinations were DWrist+DThigh and DWrist+DFoot. Both sensor combinations place one sensor at the upper body and one sensor at the lower body. In particular, the performance of the DWrist+DThigh sensor combination is as good as the performance obtained for the Hip+DWrist+DFoot sensor combination (0.04% performance difference). The accelerometer located at the thigh (DThigh) provides more reliable information than the accelerometer located at the foot (DFoot) because it experiences less variation in the signal. The foot has a higher degree of motion (or freedom) than the thigh and consequently, produces more variable signals during ambulation, exercise, and resistance exercise.

Unfortunately, the thigh is a problematic location to wear a sensor on because the sensor can be easily knocked off during ambulation and because the attachment of a sensor at this body location is difficult. For example, if bandages are used, they tend to loosen up over time and slip from this body location. If other elastic materials are used, they need to be placed so tight that they might become uncomfortable to wear.

Finally, when the performance of single sensors is analyzed during subject dependent training, it is found that the sensors with best performance in decreasing order are Hip, DFoot, and DThigh. The sensor at the hip has a consistently higher performance per activity category than the DFoot and DThigh sensors. The performance per activity category for the DFoot and DThigh sensors is very similar. From Table 5-33, it can be observed that the activity category that suffers the largest decrease in performance when single sensors are used to recognize activities is household activities. This is an expected result, since household activities involve a high degree of variation in upper body and lower body motion during their execution. During subject independent training, the single sensors with higher performance in decreasing order of importance are DUpperArm, DWrist, and DHip. The difference in overall accuracy when using these sensors is less than 1% though. The single sensor at the hip has more problems recognizing resistance exercise activities than the DUpperArm sensor but it is slightly better at recognizing household activities. The DWrist sensor on the other hand, is better at recognizing household activities than the DUpperArm and Hip sensors. This is because most household activities involve some degree of upper body motion. Finally, a note of caution is required while interpreting the relatively good performance obtained during subject dependent evaluation of the single sensors placed at the Hip, DFoot, and DThigh. During the real-time study performed in Section 5.5, it was found that the performance over these sensors is not as good as the one implied by the results obtained during the experiments performed in this section. The results of the real-time evaluation indicate, as expected, that the sensor placed at the hip has difficulties recognizing activities involving upper body and non-ambulatory lower body activities. Similarly, the sensors at the dominant foot and thigh present difficulties recognizing upper body activities. Consequently, the good performance obtained for these sensors in this section might be a result of overfitting, even when stratified crossvalidation was utilized to evaluate their performance during subject dependent training.

In summary, it was found that the sensor combination Hip+ DWrist+DFoot obtains a performance close to the one obtained using all the seven sensors during subject dependent and independent evaluation. This sensor combination was also found to consistently outperform the other sensor combinations explored in this section. This is an intuitive result since this sensor combination captures upper, lower, and overall body motion. The two second best performing sensor combinations during subject dependent training were the ones placing a sensor at the hip and another one either at the upper body (Hip + DWrist) or lower body (Hip + DFoot). During subject independent training, the two second best performing sensor combinations were the ones placing one sensor at the upper body (DWrist) and another sensor at the lower body (e.g. DThigh or DFoot). Based on these experiments, for this set of activities, wearing three sensors located at the hip, dominant wrist, and dominant foot seems to provide a reasonable compromise between performance and ease-of-use. During free-living, the sensor at the wrist could be worn as a bracelet, the sensor at the hip as a clip on addition to the belt or pants, and the sensor at the foot as a shoe pod with clip on capabilities so it can be conveniently attached to the shoe laces. Furthermore, in the future, these sensors could be miniaturized and embedded in wristwatches, shoes, and perhaps, even in the elastic material surrounding the hip utilized in underwear (a convenient location for the hip sensor provided it is small enough to be comfortable to wear).

5.4.9.3 How Well Can All Activities be Recognized Without Differentiating Among Intensity Levels?

In the previous section, it was found that some of the activities presenting the lowest performance were activities involving different intensity levels, particularly when the intensity changes due to the use of different resistance levels or work loads. As a result, this section explores how well activities can be recognized without differentiating among the intensity levels of an activity. This is performed by merging all activities with different intensity levels into a single activity. For example, all the intensity levels for *cycling* at different speeds and resistance levels are merged into a single class called *cycling*. The same procedure is repeated for *walking*, *running*, *rowing*, *bench weight lifting*, *bicep curls*, and *sitting,* leaving a total of 31 activities to be recognized. This gives a guessing accuracy of 3.2% when the *unknown* class is not incorporated and 3.1% when it is. The column labeled as “All Activities with No Intensity” in Appendix A2 shows a detailed list of the activities whose intensity levels were merged. The activity recognition algorithm used uses the following parameters: the C4.5 classifier, the *invariant reduced* feature set, feature computation per axis, and a sliding window length of 5.6s.

Table 5-35 presents the performance obtained during subject dependent and independent training while the *unknown* class is included and when it is not. The highest performance overall and per class is again obtained during subject dependent training when the *unknown* class is not used. When the *unknown* class is incorporated, overall performance drops 8% for subject dependent training, and 12% for subject independent training. The decrease in performance during subject dependent training is similar to the one obtained while recognizing the intensity level of activities (7%). For subject independent training, however; the decrease in performance is three times greater than the one obtained when intensity levels are being recognized. Note that during these comparisons, decreases in performance are computed when the number of activities being recognized is the same (51 for the previous section and 31 for this section), so the difference in random guessing is not relevant. This is because the *unknown* class is being confused more with *walking* and *sitting* now that their intensity levels have been merged. During the *unknown* activity (segments of data not labeled during the data collection),

Evaluation Method	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
Subject dependent without Unknown class Random guessing: 3.2%	91.4 ± 1.6	97.3±2.9 (0.1±0.1)	94.4±4.8 (0.2±0.2)	97.9±2.9 (0.1±0.1)	92.4±4.8 (0.2±0.2)	79.5±9.1 (0.5±0.2)
Subject dependent with unknown class Random guessing: 3.1%	83.3 ± 1.9	93.9±5.0 (0.2±0.1)	87.5±7.2 (0.6±0.2)	94.2±4.7 (0.2±0.1)	87.3±6.6 (0.4±0.2)	73.1±10.4 (0.4±0.2)
Subject independent without unknown class Random guessing: 3.2%	72.0 ± 5.7	83.9±13.5 (0.6±0.8)	78.4±20.3 (0.8±0.7)	82.0±25.0 (0.4±0.7)	75.6±21.3 (0.8±0.9)	43.5±25.9 (1.2±0.9)
Subject independent with unknown class Random guessing: 3.1%	59.9 ± 6.6	60.4±33.5 (0.5±0.6)	63.1±24.9 (1.0±0.6)	67.6±30.6 (0.3±0.3)	65.2±25.1 (0.8±0.5)	34.8±24.0 (0.8±0.5)

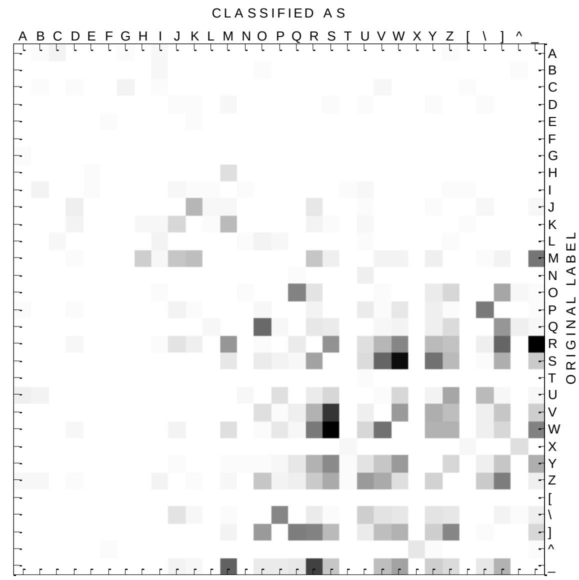
Table 5-35: True positive rate and false positive rate (shown in parenthesis) of the C4.5 classifier when recognizing 31 activities without intensity levels during subject dependent and independent evaluation. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length over all the seven accelerometers. The probability of random guessing for all activity categories presented in this table is 3.1% when the *unknown* class is used and 3.2% when it is not.

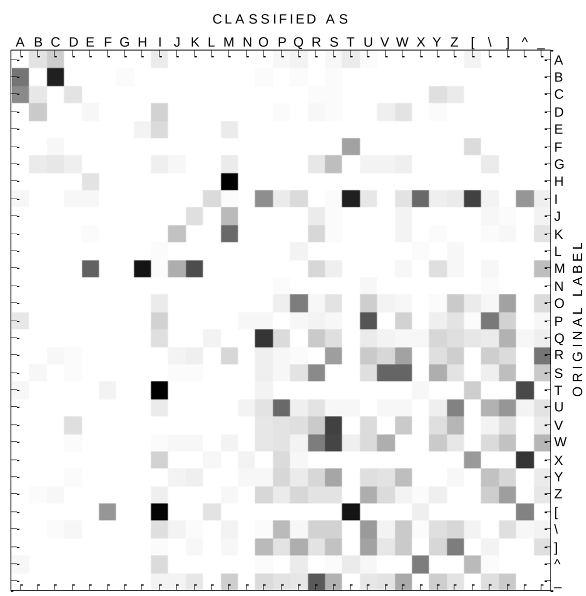
subjects were *standing* or *sitting* while resting, or *walking* while transitioning from one activity to another (e.g. transitioning from one exercise machine to another during the gym data collection or transitioning among rooms during the household data collection).

The improvement in performance of +21% obtained for subject independent training when the intensity levels of activities are not being recognized is substantial although this comparison is unfair since the probability of random guessing has increased from 1.96% to 3.2% now that intensity levels are not recognized. The improvement during subject dependent training; however, is only +3.5%. As explained in the previous section, this is because during subject dependent training, the recognition algorithm is able to differentiate well between the intensity levels of an activity because changes in resistance level or work load induce changes in the motion signature of activities that are detected by the accelerometers.

Table 5-29 shows the confusion matrices for subject dependent and independent training when the *unknown* class is not used. The grayscale images were normalized to highlight the activities being confused the most (shown in black), and the ones confused the least (shown in white). For subject dependent training, the activities confused the most are *sweeping* with *mopping*, since both include similar upper body motion and walking, and *making the bed* with *taking out trash*, since both include upper body motion and sequences of standing and walking. The confusion matrix for subject dependent training also shows that most of the confusions happen among household activities. As explained before, they involve high degree of variability in their motion and performance as well as sequences of standing and walking behaviors. Finally this confusion matrix also shows that *walking* is being slightly confused with *ascending* and *descending stairs*. This is expected due to the similarity of motion involved in these activities.

The confusion matrix for subject independent training shows that the activities being confused the most are activities with similar postures such as *sitting*, *watching TV*, and *playing video games*, and activities involving similar posture and upper body motion such as *writing*, *typing*, and *playing video games*. Moreover, *walking* is also being confused with *running* and with *descending stairs*. This is expected since they all involve similar motion patterns that can be confused, particularly during subject independent evaluation.





A -> Bench_weight_lifting
B -> Bicep_curls
C -> Calisthenics_-_Crunches
D -> Calisthenics_-_Sit_ups
E -> Cycling
F -> Lying_down
G -> Rowing
H -> Running
I -> Sitting
J -> Stairs_-_Ascend_stairs
K -> Stairs_-_Descend_stairs
L -> Standing
M -> Walking
N -> kneeling
O -> Doing_dishes
P -> Gardening
Q -> Ironing
R -> Making_the_bed
S -> Mopping
T -> Playing_videogames
U -> Scrubbing_a_surface
V -> Stacking_groceries
W -> Sweeping
X -> Typing
Y -> Vacuuming
Z -> Washing_windows
[-> Watching_TV
\ -> Weeding
] -> Wiping/Dusting
^ -> Writing
_ -> taking_out_trash

Figure 5-31: Confusion matrices for the C4.5 classifier when recognizing 31 activities without intensity levels and without the *unknown* class during (a) subject dependent and (b) independent evaluation. The feature set used is the invariant *reduced* feature set computed per axis over windows of 5.6s in length. The maximum number of errors in a given cell of a confusion matrix is 73 and 169 for subject dependent and independent training respectively.

Sensor Combination	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	91.4 ± 1.6	97.3±2.9 (0.1±0.1)	94.4±4.8 (0.2±0.2)	97.9±2.9 (0.1±0.1)	92.4±4.8 (0.2±0.2)	79.5±9.1 (0.5±0.2)
Hip + DWrist + DFoot	90.2 ± 1.6	97.6±3.1 (0.1±0.1)	92.4±6.3 (0.3±0.2)	97.3±2.9 (0.1±0.1)	91.3±5.6 (0.3±0.2)	77.1±10.4 (0.5±0.3)
Hip + DWrist	88.4 ± 2.2	97.0±4.2 (0.1±0.1)	90.7±6.1 (0.3±0.2)	96.9±3.3 (0.1±0.1)	89.2±5.2 (0.3±0.2)	73.1±10.7 (0.6±0.3)
Hip + DFoot	88.9 ± 1.9	97.2±3.2 (0.1±0.1)	92.2±5.9 (0.3±0.3)	97.4±3.2 (0.1±0.1)	90.3±6.4 (0.3±0.2)	73.8±11.6 (0.6±0.3)
DWrist + DThigh	87.8 ± 2.2	96.8±3.5 (0.1±0.1)	87.9±5.4 (0.4±0.2)	97.7±3.9 (0.1±0.1)	88.3±6.8 (0.3±0.2)	71.3±10.9 (0.7±0.3)
DWrist + DFoot	87.4 ± 2.1	96.8±3.3 (0.1±0.1)	85.4±6.4 (0.4±0.2)	96.5±3.8 (0.1±0.1)	88.4±6.9 (0.3±0.2)	71.2±11.7 (0.7±0.3)
Hip	85.9 ± 2.2	95.1±5.3 (0.1±0.1)	91.0±6.0 (0.4±0.2)	96.9±3.4 (0.1±0.1)	86.2±6.1 (0.4±0.3)	66.6±11.9 (0.7±0.3)
DWrist	80.4 ± 3.4	90.9±7.6 (0.2±0.2)	79.9±8.8 (0.8±0.4)	93.4±5.5 (0.3±0.2)	82.1±7.3 (0.7±0.3)	58.2±12.8 (0.9±0.4)
DFoot	83.4 ± 3.1	94.5±6.8 (0.1±0.1)	84.1±8.0 (0.5±0.3)	95.5±4.8 (0.2±0.2)	85.3±8.8 (0.4±0.3)	62.3±15.1 (0.9±0.4)
DUpperArm	82.6 ± 3.9	88.9±8.4 (0.3±0.2)	88.6±6.1 (0.4±0.2)	96.1±4.2 (0.2±0.2)	84.1±7.2 (0.5±0.3)	59.3±14.5 (0.9±0.4)
DThigh	82.9 ± 2.8	94.8±6.2 (0.2±0.2)	86.6±5.9 (0.4±0.2)	97.7±3.3 (0.1±0.1)	83.9±7.5 (0.4±0.2)	58.8±13.1 (0.9±0.4)

Table 5-36: Performance of the C4.5 classifier while recognizing 31 activities with no intensity levels and without the *unknown* class using different sensor combinations during subject dependent training. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length.

Sensor Combination	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	72.0 ± 5.7	83.9±13.5 (0.6±0.8)	78.4±20.3 (0.8±0.7)	82.0±25.0 (0.4±0.7)	75.6±21.3 (0.8±0.9)	43.5±25.9 (1.2±0.9)
Hip + DWrist + DFoot	67.6 ± 10.6	72.5±28.1 (1.0±1.5)	67.8±24.2 (1.3±1.3)	71.5±30.9 (0.5±0.7)	69.6±26.1 (0.9±0.8)	43.2±25.0 (1.3±1.0)
Hip + DWrist	64.5 ± 8.7	46.9±26.9 (1.3±1.2)	65.1±26.3 (1.3±1.1)	70.0±30.0 (0.8±1.3)	67.0±25.8 (1.2±1.1)	43.1±22.8 (1.3±0.9)
Hip + DFoot	61.0 ± 8.4	60.2±30.9 (1.3±1.5)	64.2±23.1 (1.3±1.1)	70.1±32.1 (0.5±0.7)	63.2±26.2 (1.1±1.0)	31.4±22.8 (1.6±1.3)
DWrist + DThigh	67.5 ± 5.7	63.4±29.8 (1.2±1.2)	72.2±19.7 (1.0±1.0)	77.3±27.7 (0.4±0.7)	70.4±21.0 (0.9±0.7)	39.5±22.2 (1.4±0.8)
DWrist + DFoot	65.5 ± 9.6	75.2±25.0 (1.0±1.2)	65.4±22.0 (1.3±1.1)	65.5±26.3 (0.6±1.0)	68.8±23.9 (1.0±0.9)	39.9±23.9 (1.4±0.9)
Hip	55.8 ± 9.3	41.9±23.4 (1.6±1.2)	64.9±25.2 (1.4±1.0)	62.1±30.9 (0.9±1.4)	58.0±27.7 (1.5±1.3)	27.2±18.9 (1.7±1.0)
DWrist	57.4 ± 10.4	44.1±32.6 (1.5±1.3)	57.1±24.6 (1.7±1.1)	65.3±29.0 (1.0±1.1)	62.8±24.9 (1.4±1.0)	34.9±18.9 (1.5±1.0)
DFoot	52.9 ± 6.4	54.7±32.0 (1.9±2.0)	57.5±21.0 (1.6±1.3)	55.3±24.2 (1.1±1.2)	57.4±24.3 (1.4±1.1)	21.5±17.5 (1.7±1.0)
DUpperArm	57.5 ± 4.3	40.4±20.8 (1.4±1.2)	79.9±20.2 (0.8±0.8)	72.3±28.5 (0.8±1.1)	63.9±20.9 (1.4±1.1)	22.9±16.6 (1.7±1.0)
DThigh	49.0 ± 5.9	28.0±23.6 (1.9±1.4)	68.1±20.1 (1.1±1.0)	65.5±27.7 (1.0±1.3)	52.8±19.4 (1.6±1.2)	16.2±13.8 (2.0±1.4)

Table 5-37: Performance of the C4.5 classifier while recognizing 31 activities with no intensity levels and without the *unknown* class using different sensor combinations during subject independent training. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length.

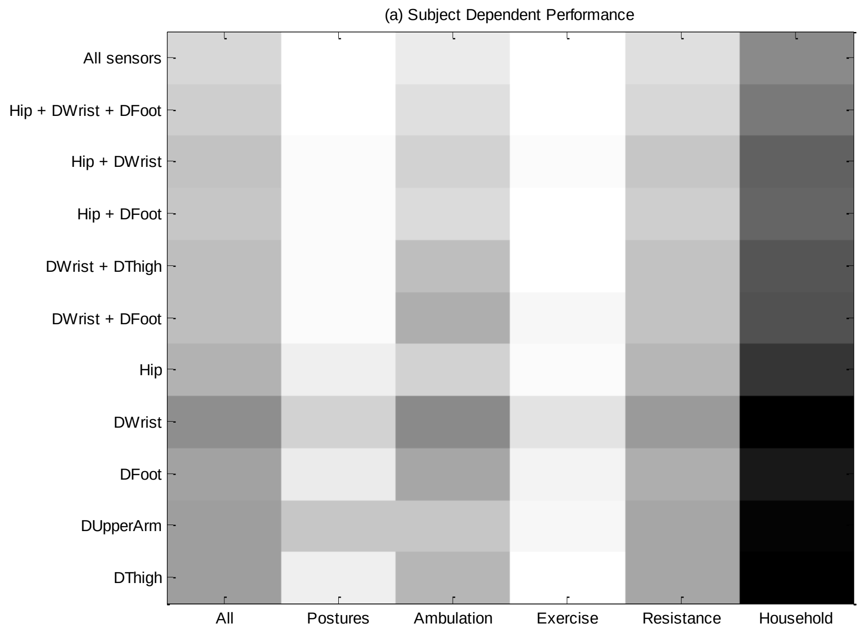


Figure 5-32: True Positive Rate per sensor combination using the C4.5 classifier when features are computed per axis over windows of 5.6s during subject dependent evaluation. The grayscale image is scaled so that the maximum true positive rate of 97.9% is represented by white and the minimum of 58.2% by black. In other words, poor areas of performance are shown in black.

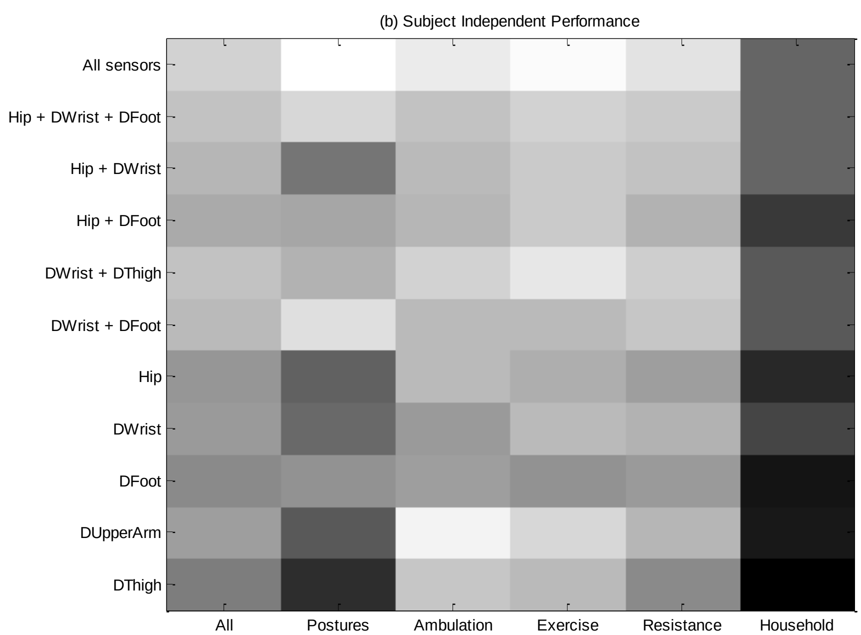


Figure 5-33: True Positive Rate per sensor combination using the C4.5 classifier when features are computed per axis over windows of 5.6s during subject independent evaluation. The grayscale image is scaled so that the maximum true positive rate of 83.9% is represented by white and the minimum of 16.2% by black. In other words, poor areas of performance are shown in black.

As in subject dependent training, most confusions also happen among household activities.

Figure 5-38 and Figure 5-39 present the true positive and false positive rate obtained when different combinations of sensors are used to recognize activities. As in the previous section, Figure 5-38 and Figure 5-39 present the true positive rate as a grayscale image, scaled to highlight the differences in performance. The best performance is shown in white while the worse performance is shown in black. From these tables and figures, it can be observed that the best performance overall and per class is obtained using the Hip+DWrist+DFoot sensor combination. The decrease in performance for this sensor combination with respect to the performance obtained using all the sensors is 1.2% for subject dependent training and 4.4% for subject independent training. Again, the performance decreases more for subject independent training because more sensors are required to capture inter-individual variations in the way activities are performed. The second best performing sensor combinations for subject dependent training are Hip+DWrist, and Hip+DFoot. These are the same sensor combinations with higher performance found in the previous section when the intensity level of activities was being discriminated. For subject independent training, the sensor combinations with higher performance are also the same: DWrist+DThigh, and DWrist+DFoot. The performance of the combination DWrist+DThigh is also very close to the performance obtained with the Hip+DWrist+DFoot sensor combination (0.1% difference). So far, it can be concluded that the best sensor combination for recognizing activities during subject dependent and independent training is Hip+DWrist+DFoot. Nonetheless, during subject independent training, the DWrist+DThigh sensor combination can be also used with a very little decrease in overall performance. The main difference between these sensor combinations is that the DWrist+DThigh sensor combination achieves a higher performance ranging from +0.8 to +4.4% for the ambulation, exercise, and resistance exercise activity categories. This can be explained by the fact that the DThigh sensor experiences less variability than the DFoot sensor while activities are performed. The Hip+DWrist+DFoot sensor combination on the other hand, is significantly better at recognizing postures (+9% better), and slightly better at recognizing household activities (+3.7% better). It seems that the sensor at the hip is responsible for the better performance over these activities.

When the performance of single sensors is analyzed from Figure 5-32 and Figure 5-33, it can be seen that again, the activities that the activities with lower performance are household activities. The single sensors with higher overall performance in decreasing order are Hip, DFoot, and DThigh during subject dependent training and DUpperArm, DWrist, and Hip during subject independent training. This is also the same ordering of sensors found in the previous section, when the intensity level of activities is being recognized. The relatively good single sensor performance of the sensor at the hip during subject dependent training is due to the fact that upper body and lower body activity induce small changes in the acceleration signal at this sensor that allow the recognition of some of these activities. The performance of the DUpperArm sensor during subject independent training can be explained by the fact that this sensor is able to sense upper body motion with less variability than the sensor at the wrist, and that it can also detect changes in posture almost as well as the sensor at the hip. The sensor at the hip has the advantage of recognizing household activities slightly better (4.3%) than the DUpperArm sensor because the overall body motion experienced in some activities *stacking groceries*, *gardening* and *weeding* is better detected at this body location. The DWrist sensor is also better than the DUpperArm sensor in recognizing household activities and postures during subject independent training.

In conclusion, when the intensity level of activities is not of interest, the activities in the MIT dataset can be recognized with an overall accuracy of 91.4% during subject dependent training and with an accuracy of 72% during subject independent training. The improvement in performance is higher (+21%) during subject independent training. The best sensor combination to use to recognize these activities is again the Hip+DWrist+DFoot combination. If a single sensor is to be used to recognize activities, its location depends on the activities of interest. For example, if ambulatory, exercise, or resistance exercise activities are to be recognized the best single sensor to utilize is the DUpperArm. If postures and household activities need to be recognized, the DWrist sensor seems to be the best one to utilize. Finally, the sensor that provides average performance over all activity categories is the sensor at the hip. These results need to be interpreted with caution, since the location of the sensors to use strongly depends on the activities being recognized. The relatively higher performance obtained for the DUpperArm and DWrist sensors with respect to the performance of the Hip sensor might be due to the fact that most activities contained in the MIT dataset involve upper body motion.

5.4.9.4 How Well Can Postures, Ambulation, and Two MET Intensity Categories be Recognized?

This section explores how well postures, ambulation, and two MET intensity categories can be recognized utilizing all and several sensor combinations during subject dependent and independent training. The activity recognition algorithm is the same as the one used in the previous sections and has the same parameters: the C4.5 classifier, the *invariant reduced* feature set, feature computation per axis, and a sliding window length of 5.6s. The activities explored in this section are 11 in total and consist of the following activities: *Lying down*, *standing*, *sitting*, *kneeling*, *walking* at 2mph and 3mph, *running* at 4, 5, and 6mph, and the *moderate* and *vigorous* MET intensity categories. Appendix A2 shows a detailed list of the activities that were merged into the *moderate* and *vigorous* intensity categories according to their associated number of METs from the Compendium of Physical Activities [122]. The random guessing probability for these activities is 9%. Exploring this set of activities and these two MET intensity categories (*moderate* and *vigorous*) makes sense from a medical point of view for the following reasons: (1) Most daily energy expenditure is spent in sedentary or light activities such as postures and ambulation. Consequently, if these activities are well recognized in a subject independent manner, better energy expenditure algorithms can be created that estimate energy depending on the activity being performed. Furthermore, if walking and running speeds are also recognized, one might expect further improvements in the estimation of energy expenditure. (2) When medical interventions are designed to foster an increase in physical activity levels, it is important to know if the target population is exercising at *moderate* or *vigorous* intensity levels. If they are, there may be no need for an

Evaluation Method	All	Postures	Ambulation	Moderate	Vigorous	Unknown
Subject dependent without unknown class Random guessing: 9%	96.5 ± 1.1	96.5±3.8 (0.1±0.1)	96.0±4.5 (0.1±0.1)	96.4±1.7 (2.4±1.2)	93.3±3.5 (1.3±0.6)	-
Subject dependent with unknown class Random guessing: 8.3%	89.5 ± 1.5	94.1±5.9 (0.1±0.1)	88.2±8.2 (0.3±0.1)	84.0±3.0 (3.8±0.8)	89.6±4.1 (1.3±0.4)	89.7 ± 2.1 (8.7 ± 1.7)
Subject independent without unknown class Random guessing: 9%	81.3 ± 4.7	91.3±9.3 (0.5±0.8)	64.4±33.6 (1.0±1.1)	86.8±5.4 (13.0±5.4)	66.0±15.4 (5.3±2.9)	-
Subject independent with unknown class Random guessing: 8.3%	70.8 ± 5.2	72.3±25.0 (0.4±0.5)	49.5±32.8 (0.7±0.7)	58.3±8.4 (8.0±1.9)	59.3±13.9 (2.6±0.8)	82.4 ± 3.3 (29.9 ± 7.7)

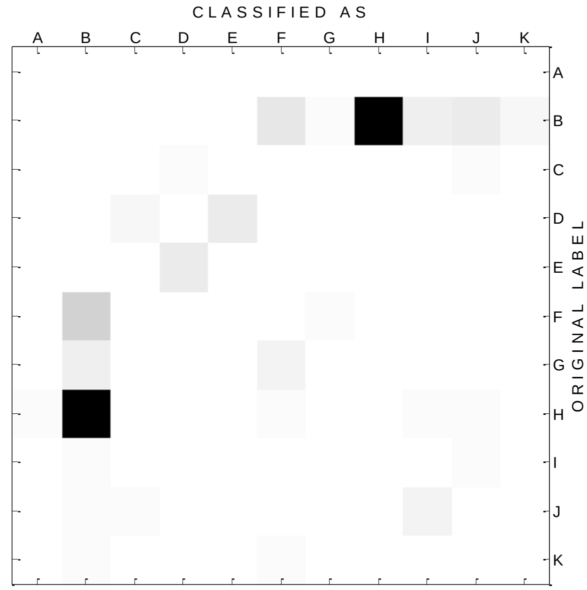
Table 5-38: Performance of the C4.5 classifier when recognizing postures, ambulation, and two MET intensity categories when the *unknown* class is included and when it is not. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length over all the seven accelerometers during. The probability of random guessing is 9% when the *unknown* class is not utilized and 8.3% when it is utilized.

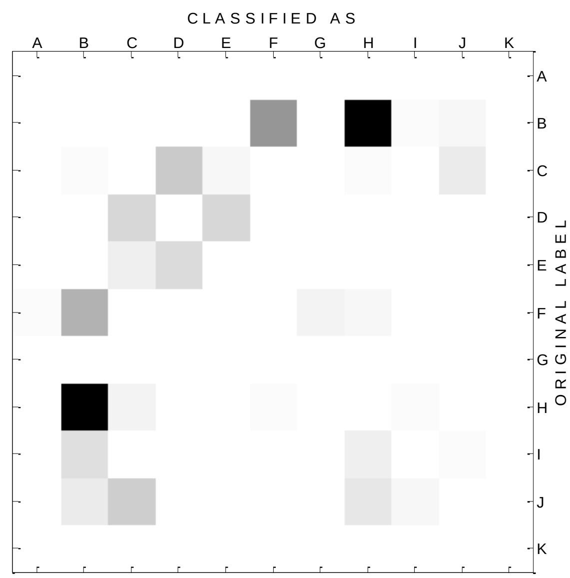
	Subject Dependent			Subject Independent		
Class	**TP Rate**	**FP Rate**	**F-Measure**	**TP Rate**	**FP Rate**	**F-Measure**
Lying down	99.9 ± 0.3	0.0 ± 0.0	99.7 ± 0.3	99.3 ± 1.3	0.1 ± 0.4	99.1 ± 1.9
Standing	93.3 ± 7.0	0.1 ± 0.1	94.5 ± 6.0	94.2 ± 12.1	0.2 ± 0.7	92.8 ± 13.6
Sitting	96.1 ± 3.9	0.2 ± 0.2	96.2 ± 3.2	73.7 ± 19.3	1.6 ± 1.8	73.3 ± 16.8
kneeling	96.6 ± 3.9	0.0 ± 0.1	97.3 ± 3.2	97.9 ± 4.4	0.1 ± 0.2	97.4 ± 5.1
Walking - Treadmill 2mph - Treadmill 0	97.8 ± 2.4	0.2 ± 0.1	96.4 ± 2.8	75.8 ± 34.2	0.3 ± 0.4	77.7 ± 29.5
Walking - Treadmill 3mph - Treadmill 0	99.0 ± 1.2	0.2 ± 0.1	98.9 ± 0.8	89.0 ± 23.3	0.7 ± 1.0	89.6 ± 20.5
Running - Treadmill 4mph - Treadmill 0	97.7 ± 2.3	0.1 ± 0.1	97.0 ± 2.6	53.0 ± 36.1	1.9 ± 2.3	47.9 ± 30.6
Running - Treadmill 5mph - Treadmill 0	94.7 ± 3.3	0.1 ± 0.1	94.9 ± 2.8	52.8 ± 34.1	1.4 ± 1.1	47.5 ± 26.2
Running - Treadmill 6mph - Treadmill 0	91.0 ± 13.2	0.1 ± 0.1	91.9 ± 10.2	51.3 ± 40.0	0.8 ± 0.9	45.0 ± 33.4
Moderate	96.4 ± 1.7	2.4 ± 1.2	96.4 ± 1.4	86.8 ± 5.4	13.0 ± 5.4	83.8 ± 3.6
Vigorous	93.3 ± 3.5	1.3 ± 0.6	93.8 ± 2.9	66.0 ± 15.4	5.3 ± 2.9	69.2 ± 10.7

Table 5-39: Performance per activity while recognizing postures, ambulation, and two MET intensity categories using the final implementation of the activity recognition algorithm. The algorithm consists of the C4.5 classifier using the *invariant reduced* feature set computed per axis over windows of 5.6s in length. The probability of random guessing is 9% for all activities shown in this table.

intervention. However, if they are not, it might be important to know what activities are being performed (e.g. postures, ambulation type and intensity) to plan the intervention according. An intervention might encourage the transition from sedentary activities to ambulatory or exercise activities, or an intervention might promote a person to increase in intensity of ambulatory activities during everyday living (e.g. encourage *walking* at 3mph over *walking* at 2mph).

Table 5-38 presents the results obtained during subject dependent and independent training while the *unknown* class is used and when it is not. Again, presenting results incorporating the *unknown* class has the sole purpose of testing the performance of the recognition algorithm in a worse-case difficulty scenario. The best performance of 96.5% is achieved, as expected, during subject dependent training when the *unknown* class is not used. It can be observed that the overall accuracy in recognizing the 11 activities explored is excellent during subject dependent training (96.5%) and reasonably good during subject independent training (81.3%). The performance when the *unknown* class is






```
A -> Lying_down                                  G -> Standing
B -> Moderate                                    H -> Vigorous
C -> Running_-_Treadmill_4mph_-_Treadmill_0_     I -> Walking_-_Treadmill_2mph_-_Treadmill_0_
D -> Running_-_Treadmill_5mph_-_Treadmill_0_     J -> Walking_-_Treadmill_3mph
E -> Running_-_Treadmill_6mph_-_Treadmill_0_     K -> kneeling
F -> Sitting
```

Figure 5-34: Confusion matrices for the C4.5 classifier when recognizing postures, ambulation, and two MET intensity categories when the unknown class is not included during (a) subject dependent and (b) independent evaluation. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length. The maximum number of errors in a given cell of a confusion matrix is 247 and 1330 for subject dependent and independent training respectively.

Sensor Combination	All	Postures	Ambulation	Moderate	Vigorous
All sensors	96.5 ± 1.1	96.5±3.8 (0.1±0.1)	96.0±4.5 (0.1±0.1)	96.4±1.7 (2.4±1.2)	93.3±3.5 (1.3±0.6)
Hip + DWrist + DFoot	95.3 ± 1.1	95.5±3.8 (0.1±0.2)	96.4±5.1 (0.1±0.1)	94.9±1.5 (3.3±0.8)	91.4±2.6 (1.9±0.7)
Hip + DWrist	94.9 ± 1.4	94.7±5.1 (0.1±0.2)	94.0±7.2 (0.2±0.1)	94.8±1.4 (3.5±1.4)	90.7±4.1 (2.1±0.8)
Hip + DFoot	95.8 ± 1.0	95.5±4.0 (0.1±0.2)	96.4±4.1 (0.1±0.1)	95.4±1.6 (2.7±0.7)	92.7±3.0 (1.7±0.7)
DWrist + DThigh	94.3 ± 1.4	95.6±4.1 (0.1±0.2)	92.7±5.9 (0.2±0.2)	94.4±1.7 (3.7±1.2)	89.6±4.7 (2.4±0.7)
DWrist + DFoot	93.8 ± 1.6	95.5±3.7 (0.1±0.1)	94.3±6.7 (0.2±0.1)	93.3±1.8 (4.3±1.5)	88.2±4.4 (2.7±0.8)
Hip	94.8 ± 1.5	92.7±5.5 (0.2±0.2)	95.1±5.2 (0.2±0.1)	94.4±1.6 (3.2±1.4)	91.4±4.0 (2.2±0.8)
DWrist	89.6 ± 3.0	91.3±7.6 (0.3±0.2)	87.9±10.8 (0.4±0.3)	89.4±3.3 (7.1±2.5)	82.4±6.7 (4.2±1.4)
DFoot	92.9 ± 2.2	94.1±7.4 (0.2±0.2)	93.5±4.6 (0.2±0.2)	92.5±2.3 (4.6±1.7)	86.6±5.1 (3.1±1.0)
DUpperArm	93.8 ± 1.8	91.0±6.9 (0.3±0.2)	95.6±3.9 (0.2±0.1)	93.3±1.8 (4.0±1.5)	89.7±4.2 (2.5±0.9)
DThigh	94.2 ± 1.3	95.2±4.8 (0.2±0.2)	93.0±5.7 (0.2±0.2)	93.7±1.7 (3.7±1.3)	90.7±3.8 (2.2±0.6)

Table 5-40: Subject dependent performance of the C4.5 classifier when recognizing postures and ambulation using the *invariant reduced* feature set computed per axis over windows of 5.6s in length using different subsets of accelerometers. The *unknown* class was not included in this experiment. The probability of random guessing is 9% for all activity categories shown in this table.

Sensor Combination	All	Postures	Ambulation	Moderate	Vigorous
All sensors	81.3 ± 4.7	91.3±9.3 (0.5±0.8)	64.4±33.6 (1.0±1.1)	86.8±5.4 (13.0±5.4)	66.0±15.4 (5.3±2.9)
Hip + DWrist + DFoot	76.2 ± 8.4	80.7±25.2 (0.7±0.9)	62.1±33.7 (1.3±1.2)	85.6±6.1 (15.7±6.1)	58.4±16.2 (7.5±5.6)
Hip + DWrist	72.5 ± 7.6	52.3±26.3 (1.4±1.8)	59.6±29.3 (1.5±1.5)	84.0±7.6 (14.4±4.8)	60.0±14.6 (8.8±7.4)
Hip + DFoot	72.9 ± 8.9	75.2±25.5 (1.3±1.4)	57.3±33.2 (1.5±1.6)	81.9±8.5 (15.9±7.2)	58.0±17.5 (7.0±3.3)
DWrist + DThigh	78.6 ± 5.3	69.7±28.3 (1.1±1.2)	72.9±25.2 (0.9±1.0)	83.2±7.5 (12.1±3.1)	67.2±11.4 (6.9±4.3)
DWrist + DFoot	74.5 ± 6.9	83.3±23.1 (0.7±1.0)	57.3±34.5 (1.6±1.8)	82.2±6.9 (15.7±4.4)	57.5±11.7 (7.4±2.6)
Hip	72.0 ± 7.4	51.0±24.7 (1.4±1.4)	60.7±30.2 (1.5±1.4)	82.8±7.9 (15.7±5.0)	57.6±12.6 (8.0±6.6)
DWrist	68.5 ± 6.6	52.6±28.4 (1.7±1.7)	48.5±29.3 (1.5±1.5)	81.3±4.6 (18.5±5.6)	55.2±10.6 (8.6±2.2)
DFoot	67.1 ± 9.1	67.7±30.2 (1.5±1.4)	50.1±32.2 (1.8±1.9)	79.8±8.1 (19.6±6.4)	45.8±15.8 (8.5±3.9)
DUpperArm	75.7 ± 4.0	55.0±22.8 (1.4±1.4)	71.7±26.7 (1.0±1.2)	83.3±6.6 (16.3±5.0)	63.8±11.3 (5.8±2.0)
DThigh	67.9 ± 7.4	40.8±30.4 (2.5±2.2)	69.6±28.2 (0.8±0.9)	73.4±9.3 (20.6±8.4)	69.1±13.6 (7.4±5.7)

Table 5-41: Subject independent performance of the C4.5 classifier when recognizing postures and ambulation using the *invariant reduced* feature set computed per axis over windows of 5.6s in length using different subsets of accelerometers. The *unknown* class was not included in this experiment. The *unknown* class was not included in this experiment. The probability of random guessing is 9% for all activity categories shown in this table.

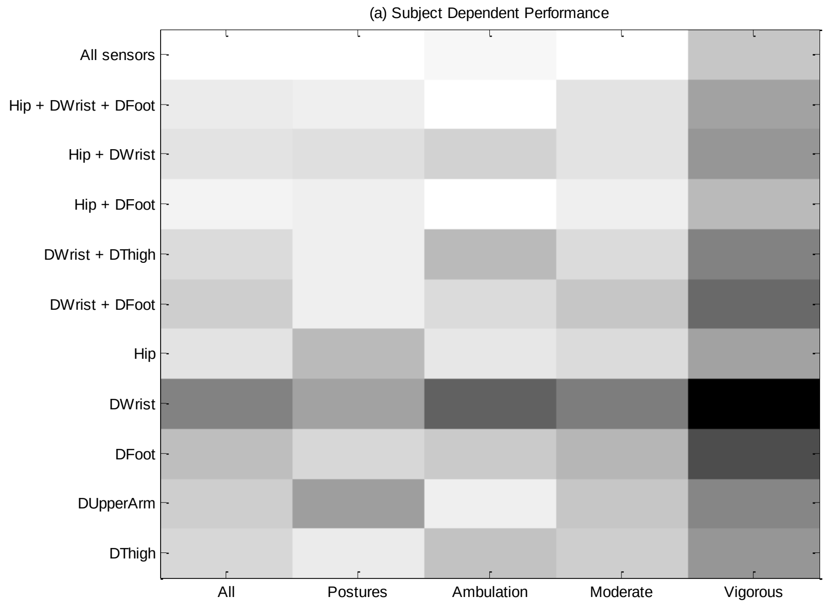


Figure 5-35: True positive rate per sensor combination while recognizing postures, ambulation, and two MET intensity categories using the C4.5 classifier when features are computed per axis over windows of 5.6s during subject dependent evaluation. The grayscale image is scaled so that the maximum true positive rate of 96.5% is represented by white and the minimum of 82.4% by black. In other words, poor areas of performance are shown in black.

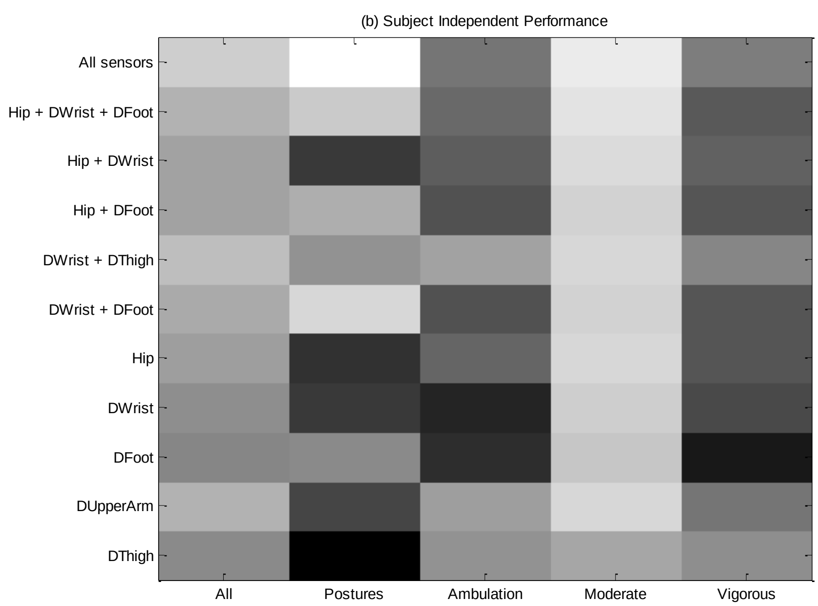


Figure 5-36: True Positive Rate per sensor combination while recognizing postures, ambulation, and two MET intensity levels using the C4.5 classifier when features are computed per axis over windows of 5.6s during subject independent evaluation. The grayscale image is scaled so that the maximum true positive rate of 91.3% is represented by white and the minimum of 40.8% by black. In other words, poor areas of performance are shown in black.

included drops between 7-10% because it contains unlabeled examples of *sitting*, *standing*, and *walking* at different speeds.

Table 5-39 presents the performance per activity and Figure 5-23 the confusion matrices for subject dependent and independent training. The confusion matrices are grayscale images scaled to highlight large number of confusions in black and low number of confusions in white. During subject dependent training, the true positive rate over postures, ambulation, and the moderate MET category is very similar (~96%). The activity category with lower performance is vigorous, with a performance of 93.6%. This is because the vigorous intensity category is being confused with the moderate intensity category during both subject dependent and independent evaluation as shown by the confusion matrices (Figure 5-34). This confusion happens because these intensity categories include activities with similar motion patterns such as *cycling*, *crunches* and *sit-ups* that were just partitioned due to their associated MET intensities into the *moderate* and *vigorous* MET intensity categories. Figure 5-23 also shows that there is a considerable degree of confusion between *lying down* and the *vigorous* MET intensity level. This is because the examples for the activities *crunches* and *sit-ups* were merged into the vigorous MET intensity level. These two activities include examples of lying down, particularly when participants rested for a couple of seconds between repetitions. When the performance per activity is inspected for subject dependent training, it can be seen that the lowest performance is obtained for running at 5mph (94.7%) and 6mph (91%), standing (93%), and the vigorous category (93%). The performance is relatively low for running at 6mph (91%) because most subjects only performed this activity for less than 2min due to its physical difficulty. Finally the confusion matrix (Figure 5-34) for subject dependent training also illustrates that sitting is being confused with the moderate intensity category. This is because some activities included in the moderate intensity category such as bench weight lifting and bicep curls are performed in a in a sitting position.

When the performance per activity is analyzed for subject independent training, it is found that the worse performance is obtained while discriminating among the intensity levels or speeds of running (TP rate between 51-53%) and for the vigorous intensity category (66%). Inspection of the confusion matrix (Figure 5-23) also reveals confusions among the different speeds of running, confusion between sitting and the moderate intensity category, and confusion between the moderate and vigorous categories for the same reasons explained before.

Finally, the performance of recognizing postures, ambulation, and the two MET intensity categories was evaluated when utilizing different sensor combinations. Table 5-40 and Table 5-41 present the results obtained. Figure 5-35 and Figure 5-36 also present the true positive rate as a grayscale image normalized to show the best performance in white and the worse performance in black. These tables and figures show that the three best performing sensor combinations for subject dependent training in decreasing order are Hip+DFoot, Hip+DWrist+DFoot, and DHip. This ordering is different from the one obtained in previous sections, and suggest that when the number of activities to recognize is decreased the number of sensors can also be decreased without significant decreases in performance. When comparing the results per activity category for the Hip+DFoot and for the Hip+DWrist+DFoot sensor combinations, it is found that their performance is very similar. It seems that the DWrist sensor becomes less useful when gymnasium and household activities with high energy upper body motion are merged into the moderate MET intensity category. The sensor at the hip detects this upper body motion indirectly well enough to allow discrimination, at least during subject dependent training. The fact that the Hip sensor is the third best performing sensor also suggests that this sensor captures lower body motion indirectly well enough to discriminate between the different intensity levels of walking and running. It is thus clear that the best single sensor to utilize while recognizing the set of activities explored in this section is the sensor at the hip. When the performance per activity for this sensor is compared against the performance of the Hip+DFoot sensor combination, it is found that it has a slightly lower performance for the postures (-2.8%) and ambulation (-1.3%) categories. In general, the change in performance obtained while evaluating different sensor combinations to recognizing activities is higher for subject independent training than for subject dependent training.

The three best performing sensor combinations found for subject independent training in decreasing order are DWrist+DThigh, Hip+DWrist+DFoot, and DUpperArm. The order is also different from the one obtained in previous sections. Now, the combination of a sensor at the dominant wrist and at the dominant thigh (DWrist+DThigh) slightly outperforms the combination Hip+DWrist+DFoot. This increased performance is distributed across the ambulation (+10%) and the *vigorous* MET intensity category (+8.8%). The Hip+DWrist+DFoot sensor combination; however, is better at recognizing postures (+10%). The best single sensor to utilize during subject independent training is the DUpperArm, followed by the Hip sensor, and the DWrist sensor. The DUpperArm sensor is better in recognizing ambulation and the vigorous intensity category that the sensor at the Hip. This is because it better recognizes the upper body activity found in these activities. The sensor at the hip (Hip) is better at recognizing ambulation than the sensor wrist (DWrist). This is because the sensor at the wrist experiences more variability in the accelerometer signals due to the higher degree of freedom of the wrist.

In summary, the best compromise sensor combination to use for detecting postures, ambulation, and the two MET intensity categories is still the Hip+DWrist+DFoot sensor combination. However, because the number of activities explored has been reduced or merged into the *moderate* and *vigorous* intensity categories, the number of sensors can be reduced. For example the Hip+DFoot or DHip sensor combinations can be used during subject dependent training and the DWrist+DThigh or DUpperArm combinations during subject independent training with little decrease in performance.

5.4.9.5 How Well can Postures and Ambulation be Recognized?

This section explores how well postures and ambulation with no intensity levels can be recognized from several combinations of accelerometers using the final implementation of the activity recognition algorithm. Thus, this experiment is performed by eliminating all the activities that are not postures or ambulation from the MIT dataset and by merging the different intensity levels of ambulatory activities such as *walking* and *running* into a single class. The column labeled as “Postures and Ambulation” in Appendix A2 shows what activities are considered in this experiment and what intensity levels of *walking* and *running* are being merged. The activities to recognize are the following eight activities:

Evaluation Method	All	Postures	Ambulation	Unknown
Subject dependent without Unknown class Random guessing: 12.4%	98.4 ± 0.8	98.9±1.9 (0.1±0.1)	95.4±3.9 (0.4±0.4)	-
Subject dependent with unknown class Random guessing: 11.1%	91.4 ± 1.7	93.8±5.1 (0.3±0.2)	87.9±5.4 (1.1±0.4)	89.9 ± 2.7 (7.1 ± 1.9)
Subject independent without unknown class Random guessing: 12.5%	92.9 ± 3.9	96.4±8.9 (0.3±0.9)	85.3±15.5 (2.1±2.2)	-
Subject independent with unknown class Random guessing: 11.1%	78.5 ± 8.8	71.8±22.7 (0.7±0.6)	68.4±24.2 (1.8±1.1)	87.4 ± 4.0 (24.2 ± 3.7)

Table 5-42: True positive and false positive rate (shown in parenthesis) for the C4.5 classifier while recognizing postures and ambulation without intensity levels during subject dependent and independent evaluation. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length over all the seven accelerometers. The random guess probability for all activities shown in this table is 12.4% when the unknown class is not included and 11.1% when it is included.

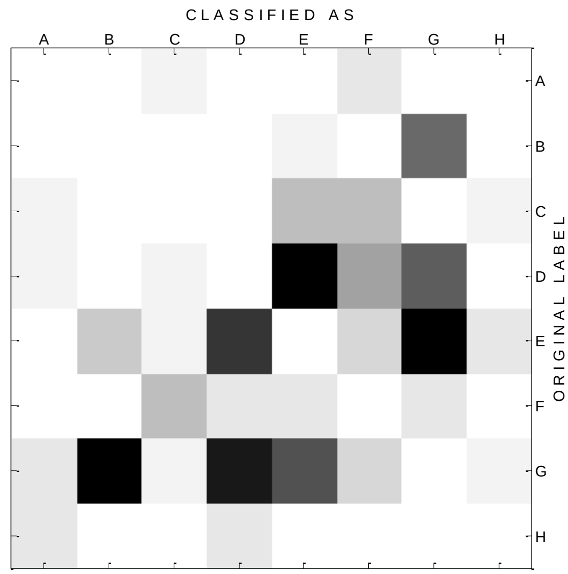
	Subject Dependent			Subject Independent		
Class	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Lying down	99.9 ± 0.3	0.1 ± 0.1	99.8 ± 0.3	100.0 ± 0.0	0.2 ± 0.9	99.6 ± 1.9
Standing	97.5 ± 3.9	0.2 ± 0.2	96.5 ± 3.7	96.3 ± 9.6	0.7 ± 2.3	92.7 ± 15.5
Sitting	99.0 ± 1.3	0.1 ± 0.1	99.2 ± 0.8	90.9 ± 21.7	0.3 ± 0.5	92.3 ± 19.3
kneeling	99.0 ± 2.0	0.0 ± 0.1	99.1 ± 1.6	98.4 ± 4.3	0.0 ± 0.1	98.6 ± 2.5
Walking	98.9 ± 0.9	0.7 ± 0.7	99.0 ± 0.8	93.2 ± 6.5	4.9 ± 3.5	93.3 ± 4.4
Running	99.2 ± 1.4	0.2 ± 0.2	98.8 ± 1.2	85.6 ± 23.7	1.6 ± 2.8	85.6 ± 22.5
Stairs - Ascend stairs	93.1 ± 5.1	0.3 ± 0.2	93.4 ± 3.9	94.4 ± 6.4	0.7 ± 0.9	91.5 ± 6.6
Stairs - Descend stairs	90.6 ± 8.4	0.4 ± 0.3	91.4 ± 6.8	68.0 ± 25.6	1.3 ± 1.5	68.5 ± 24.4

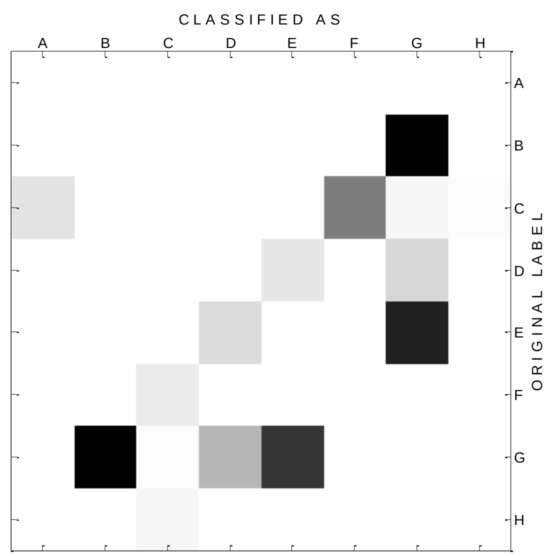
Table 5-43: Performance per activity obtained for the C4.5 classifier when recognizing postures and ambulation without intensity levels and without the *unknown* class during subject dependent and independent evaluation. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length over all seven accelerometers. The random guess probability for all activities shown in this table is 12.4%.

Lying down, *standing*, *sitting*, *kneeling*, *walking*, *running*, *ascending stairs*, and *descending stairs*. These eight activities produce a random guessing probability of 12.5%. The parameters used in the activity recognition algorithm are the C4.5 classifier, the *invariant reduced* feature set computed per axis, and a sliding window length of 5.6s.

Table 5-42 presents the true positive and false positive rate per activity category when the *unknown* class is included and when it is not. It is clear that the performance obtained while recognizing only postures and ambulation without intensity levels is excellent.
The best overall accuracy of 98% is obtained during subject dependent training when the unknown class is not used. The performance obtained during subject independent training is 92.9% when the *unknown* class is not used and 78.5% when it is used. This large decrease in performance (-14.4%) obtained when including the *unknown* class is due to the fact that the *unknown* class has unlabeled examples of *sitting*, *standing*, and *walking*.
As a result, when the *unknown* class is included, it is confused with these activities resulting in the decreased performance observed.

Table 5-43 shows the true positive rate, false positive rate, and F-Measure per activity during subject dependent and independent training when the *unknown* activity is not used. The performance per activity during subject dependent training is excellent, ranging






```
A -> Lying_down                              E -> Stairs_-_Descend_stairs
B -> Running                                 F -> Standing
C -> Sitting                                 G -> Walking
D -> Stairs_-_Ascend_stairs                  H -> kneeling
```

Figure 5-37: Confusion matrices for the C4.5 classifier when recognizing postures and ambulation without intensity levels and without considering the *unknown* class during subject dependent and independent evaluation. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length over all accelerometers. The maximum number of errors in a given cell of a confusion matrix is 26 and 168 for subject dependent and independent training respectively.

Sensor Combination	All	Postures	Ambulation
All sensors	98.4 ± 0.8	98.9±1.9 (0.1±0.1)	95.4±3.9 (0.4±0.4)
Hip + DWrist + DFoot	98.1 ± 1.1	98.8±2.4 (0.1±0.1)	94.5±4.9 (0.5±0.5)
Hip + DWrist	97.7 ± 1.0	98.2±2.8 (0.1±0.2)	93.0±5.0 (0.6±0.5)
Hip + DFoot	98.1 ± 1.1	98.6±2.7 (0.1±0.2)	94.3±5.4 (0.5±0.5)
DWrist + DThigh	97.0 ± 0.6	99.0±1.5 (0.1±0.1)	90.2±5.2 (0.8±0.5)
DWrist + DFoot	96.4 ± 1.4	97.5±2.9 (0.2±0.2)	88.1±6.1 (1.0±0.6)
Hip	97.36 ± 1.2	97.4±3.8 (0.1±0.2)	92.1±6.3 (0.7±0.5)
DWrist	94.3 ± 1.9	94.2±6.3 (0.3±0.4)	84.7±7.6 (1.5±0.8)
DFoot	95.6 ± 1.8	95.9±5.7 (0.3±0.3)	86.4±6.5 (1.1±0.7)
DUpperArm	96.0 ± 2.4	92.9±8.0 (0.4±0.4)	91.1±6.7 (0.9±0.8)
DThigh	96.6 ± 0.9	98.8±2.0 (0.1±0.2)	89.1±5.6 (0.9±0.5)

Table 5-44: Subject dependent performance over different combination of sensors for the C4.5 classifier when recognizing postures and ambulation without intensity levels and without the *unknown* class. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length. The random guess probability for all activities shown in this table is 12.5%.

Sensor Combination	All	Postures	Ambulation
All sensors	92.9 ± 3.9	96.4±8.9 (0.3±0.9)	85.3±15.5 (2.1±2.2)
Hip + DWrist + DFoot	86.5 ± 5.6	88.7±17.9 (1.0±1.7)	74.0±23.3 (3.5±3.5)
Hip + DWrist	81.9 ± 6.5	59.6±27.3 (2.5±3.8)	73.6±20.2 (3.2±2.4)
Hip + DFoot	83.6 ± 7.2	78.5±24.8 (1.6±2.0)	69.5±26.1 (3.7±3.6)
DWrist + DThigh	84.9 ± 9.4	73.4±32.2 (2.0±3.1)	76.8±18.5 (2.7±3.0)
DWrist + DFoot	85.5 ± 8.4	90.7±15.6 (1.0±1.8)	71.3±22.0 (3.7±3.7)
Hip	81.0 ± 5.9	55.5±29.1 (2.9±3.6)	73.5±20.8 (3.1±2.3)
DWrist	79.3 ± 8.4	58.5±28.4 (2.8±3.3)	73.0±19.1 (3.6±3.3)
DFoot	77.9 ± 10.6	75.7±27.0 (2.4±2.4)	66.8±23.6 (4.6±4.1)
DUpperArm	86.5 ± 4.3	60.8±20.9 (2.1±2.0)	85.9±15.7 (2.1±2.5)
DThigh	79.9 ± 9.4	68.4±31.7 (3.1±3.2)	72.3±18.8 (3.2±3.5)

Table 5-45: Subject independent performance over different combination of sensors for the C4.5 classifier when recognizing postures and ambulation without intensity levels and without the *unknown* class. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length. The random guess probability for all activities shown in this table is 12.5%.

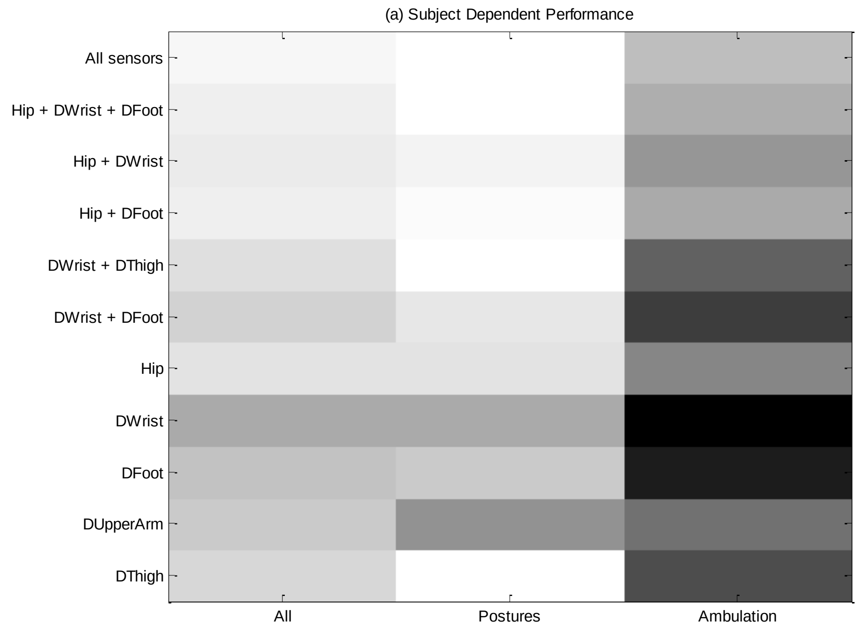


Figure 5-38: True Positive rate per sensor combination using the C4.5 classifier when features are computed per axis over windows of 5.6s during subject dependent evaluation. The grayscale image is scaled so that the maximum true positive rate of 99.0% is represented by white and the minimum of 84.7% by black. In other words, poor areas of performance are shown in black.

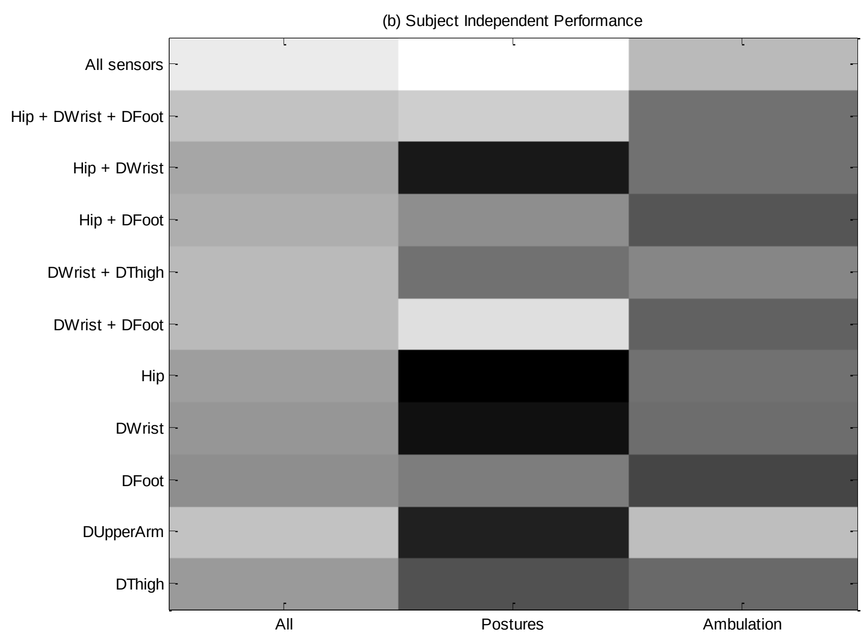


Figure 5-39: True Positive Rate per sensor combination using the C4.5 classifier when features are computed per axis over windows of 5.6s during subject independent evaluation. The grayscale image is scaled so that the maximum true positive rate of 96.4% is represented by white and the minimum of 55.5% by black. In other words, poor areas of performance are shown in black.

from 90 to 99.9%. The activity with lowest performance (90%) is *descending stairs* because it is being confused with *walking* and *ascending stairs* due to the motion similarity (see Figure 5-37). Other activities being confused during subject dependent evaluation are *walking* with *running, descending stairs* with *ascending stairs, and standing* with *sitting.*

During subject independent training, the true positive per class is higher than 93.2% for all the activities except for *running* (85.6%) and *descending stairs* (68%). *Running* and *descending stairs* also have a relatively large false positive rate of 1.6 and 1.4% respectively. This is because *running* is being confused with *walking,* and *descending stairs* is being confused with *walking* and *ascending stairs*. In fact, the *walking* activity has a false positive rate of 4.9% because this class is being predicted when the *running* and *descending stairs* activities are performed. Confusion among ambulatory activities is expected, particularly during subject independent training due to the motion similarity among the activities.

Table 5-44 and Table 5-45 present the true positive and false positive rate when different sensor combinations are used to recognize activities during subject dependent and independent training. Figure 5-38 and Figure 5-39 also illustrate the true positive rate as a grayscale image normalized to highlight good performance in white and poor performance in black. For subject dependent training, the sensor combinations with higher performance are Hip+DFoot, Hip+DWrist+DFoot, and Hip+DWrist. The combinations Hip+DFoot and Hip+DWrist+DFoot have the same overall accuracy of 98.1% and very similar performance per activity category. Again, one sensor at the hip and one sensor either at the upper or lower body achieves a performance similar to the one obtained using the Hip+DWrist+DFoot sensor combination. During subject dependent training, all the sensor combinations explored achieve an overall accuracy greater than 94.3%. When the performance of single sensors is analyzed during subject dependent training, the sensor that achieves the best overall accuracy is the sensor at the hip (97.3%), followed by the sensor at the thigh (96.6%), and the sensor at the dominant upper arm (96%). Consequently, the best single sensor to utilize during subject dependent training is the Hip sensor. The sensor at the thigh, achieves a slightly higher performance (+1.4%) than the one at the hip in recognizing postures.

During subject independent training, the sensor combinations with best performance are Hip+DWrist+DFoot, DUpperArm, and DWrist+DFoot. The combinations Hip+DWrist+DFoot, DUpperArm have the same overall accuracy but the Hip+DWrist+DFoot combination shows a higher performance for postures (+20%) while the DUpperArm sensor presents a higher performance for ambulation (+12%). Thus, the additional sensors allow better discrimination among postures. One possible explanation of why the DUpperArm sensor has a higher performance in recognizing ambulation is that it experiences less random variations during these activities than the sensors DWrist and DFoot. During the data collections, it was observed that sensors at the wrists and at the feet generally experience more variation in the accelerometer signals due to the higher degree of motion available at these body parts. For example, while sitting, subjects fidget the feet in random patterns. This was also observed during the bicep curls and bench weight lifting activities where subjects impatiently fidget feet while experiencing physically intense effort. The accelerometers at the wrists also experience a high degree of variability because hands are constantly in motion, particularly during unconstrained

Evaluation Method	All	Lying down	Standing	Sitting	Kneeling	Unknown
Subject dependent without unknown class Random guessing: 25%	99.3 ± 0.7	99.9 ± 0.2 (0.5 ± 0.8)	97.7 ± 3.2 (0.1±0.3)	98.6 ± 2.7 (0.3 ± 0.5)	98.6 ± 2.8 (0.1 ± 0.2)	-
Subject dependent with unknown class Random guessing: 20%	97.6 ± 0.9	99.5 ± 1.1 (0.4 ± 0.3)	83.4 ± 12.4 (0.5 ± 0.3)	86.6 ± 11.7 (0.5 ± 0.4	95.4 ± 5.7 (0.1 ± 0.2)	98.2 ± 0.7 (4.1 ± 2.5)
Subject independent without unknown class Random guessing: 25%	98.0 ± 4.9	100.0 ± 0.0 (1.4 ± 6.0)	98.1 ± 8.5 (0.8 ± 2.9)	95.9 ± 17.7 (0.9 ± 3.0)	100.0 ± 0.0 (0.0 ± 0.0)	-
Subject independent with unknown class Random guessing: 20%	93.4 ± 2.8	90.7 ± 18.4 (0.5 ± 1.0)	68.5 ± 24.8 (0.7 ± 0.6)	36.2 ± 40.2 (1.1 ± 1.0)	94.8 ± 7.6 (0.4 ± 1.4)	97.4 ± 1.8 (16.5 ± 10.2)

Table 5-46: True positive rate and false positive rate (shown in parenthesis) per activity for the C4.5 classifier when recognizing postures in a subject dependent and independent manner. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length over all seven accelerometers. The random guess probability is 25% when the *unknown* class is not included and 20% when it is included.

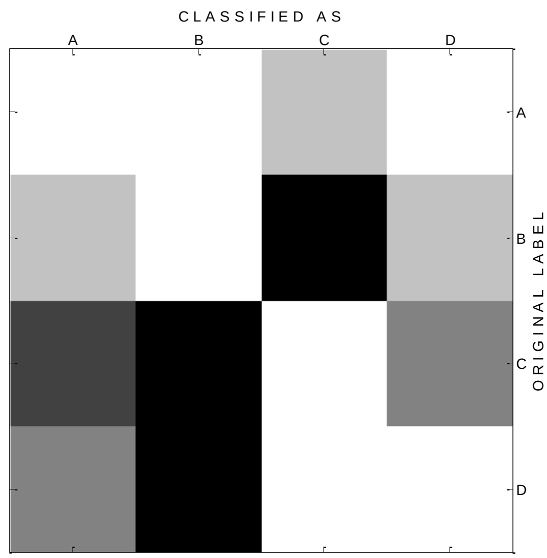
activities such as household cleaning. The relatively poor performance of these sensors can be seen from Figure 5-39 as dark areas for the ambulation category. The best single sensors to use to recognizing postures and ambulation in a subject independent manner are DUpperArm, Hip, and DThigh. The DUpperArm sensor is better for recognizing ambulation, while the DThigh sensor is better at recognizing postures. The sensor at the hip presents average performance (with respect to DUpperArm and DThigh) in recognizing postures and ambulation.

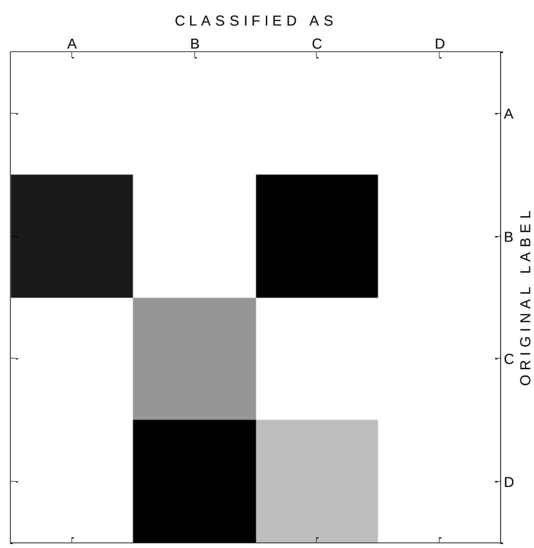
In conclusion, a good combination to use for recognizing postures and ambulation without intensity levels during subject dependent training is Hip+DWrist. The best single sensor is the Hip sensor. During subject independent training, the best sensor combination to use is either DWrist+DFoot or Hip+DWrist+DFoot. The single best sensor to use is sensor at the dominant upper arm (DUpperArm). Thus, when only postures and ambulation need to be recognized, two sensors are enough to achieve good discrimination performance among these activities.

5.4.9.6 How Well can Postures be Recognized?

This section explores how well can postures be recognized using the final implementation of the activity recognition algorithm while different combination of sensors are used. This is performed by eliminating all the activities that are not postures from the MIT dataset and by merging the activities *sitting fidgeting feet and legs* and *sitting fidgeting hands and arms* with the *sitting* activity. The column labeled as “Postures” in Appendix A2 shows the activities that were included in this experiment. The total number of activities to recognize is then four, giving a random guess probability of 25% when the unknown class is not included and 20% when it is included.

Table 5-46 presents the total accuracy, as well as the true positive and false positive rate per activity obtained from this experiment when the *unknown* class is included and when it is not. The overall accuracy obtained during subject dependent and independent training is excellent, ranging from 93 to 99%. Obviously, this is the result of the limited number of activities being recognized (4). The lowest performance is observed for



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A -> Lying_down                          C -> Standing
B -> Sitting                             D -> kneeling
```

Figure 5-40: Confusion matrices of the C4.5 classifier when recognizing postures without the *unknown* class during (a) subject dependent and (b) independent training. The feature set used is the *invariant reduced* feature set is computed per axis over windows of 5.6s in length over all the sensors. The maximum number of errors in a given cell of a confusion matrix is 5 and 19 for subject dependent and independent training respectively.

Sensor Combination	All	Lying down	Standing	Sitting	Kneeling
All sensors	99.3 ± 0.7	99.9 ± 0.2 (0.5 ± 0.8)	97.7 ± 3.2 (0.1±0.3)	98.6 ± 2.7 (0.3 ± 0.5)	98.6 ± 2.8 (0.1 ± 0.2)
Hip + DWrist + DFoot	99.1 ± 0.9	99.9 ± 0.4 (0.2 ± 0.6)	97.2 ± 3.8 (0.3 ± 0.5)	98.6 ± 3.1 (0.3 ± 0.5)	98.0 ± 2.9 (0.2 ± 0.3)
Hip + DWrist	98.8 ± 0.7	99.9 ± 0.3 (0.5 ± 0.8)	97.7 ± 3.5 (0.6 ± 0.7)	97.7 ± 2.9 (0.3 ± 0.5)	95.8 ± 4.6 (0.2 ± 0.4)
Hip + Foot	99.2 ± 0.8	99.9 ± 0.3 (0.3 ± 0.7)	97.41 ± 4.2 (0.3 ± 0.5)	98.8 ± 2.6 (0.3 ± 0.5)	98.0 ± 2.9 (0.0 ± 0.21)
DWrist + DThigh	98.9 ± 0.7	99.9 ± 0.2 (0.8 ± 0.9)	95.80 ± 4.6 (0.3 ± 0.3)	97.9 ± 2.3 (0.4 ± 0.4)	97.9 ± 2.4 (0.2 ± 0.4)
DWrist + DFoot	99.0 ± 0.7	99.9 ± 0.4 (1.0 ± 1.4)	97.27 ± 3.4 (0.2 ± 0.4)	98.6 ± 2.71 (0.2 ± 0.4)	97.1 ± 3.6 (0.1 ± 0.3)
Hip	98.6 ± 0.9	99.9 ± 0.3 (0.5 ± 0.8)	95.81 ± 4.9 (0.7 ± 0.6)	97.9 ± 2.9 (0.4 ± 0.5)	95.8 ± 4.6 (0.3 ± 0.6)
DWrist	97.7 ± 1.7	99.9 ± 0.2 (1.2 ± 1.2)	94.18 ± 7.2 (1.0 ± 1.3)	95.7 ± 5.1 (0.2 ± 0.5)	91.8 ± 8.9 (0.8 ± 0.9)
DFoot	98.0 ± 2.4	99.4 ± 1.6 (2.5 ± 3.9)	97.19 ± 5.3 (0.4 ± 0.7)	97.9 ± 4.4 (0.5 ± 0.8)	91.8 ± 12.0 (0.3 ± 1.0)
DUpperArm	96.7 ± 2.7	99.9 ± 0.2 (0.6 ± 0.8)	89.9 ± 10.1 (1.4 ± 1.7)	95.4 ± 7.8 (0.5 ± 0.9)	88.5 ± 10.6 (1.5 ± 1.3)
DThigh	99.0 ± 0.7	99.9 ± 0.2 (0.4 ± 0.7)	95.9 ± 4.8 (0.2 ± 0.3)	98.4 ± 2.2 (0.4 ± 0.4)	98.1 ± 2.4 (0.3 ± 0.5)

Table 5-47: True positive and false positive rate (shown in parenthesis) during subject dependent training for the C4.5 classifier when recognizing postures without the *unknown* class over different sensor combinations. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length.

Sensor Combination	All	Lying down	Standing	Sitting	Kneeling
All sensors	98.0 ± 4.9	100.0 ± 0.0 (1.4 ± 6.0)	98.1 ± 8.5 (0.8 ± 2.9)	95.9 ± 17.7 (0.9 ± 3.0)	100.0 ± 0.0 (0.0 ± 0.0)
Hip + DWrist + DFoot	90.6 ± 13.9	95.8 ± 12.3 (1.9 ± 7.4)	80.1 ± 35.9 (3.3 ± 5.9)	88.5 ± 30.1 (4.3 ± 6.4)	94.0 ± 22.9 (3.0 ± 8.4)
Hip + DWrist	79.4 ± 13.5	97.5 ± 11.0 (5.0 ± 22.4)	51.6 ± 40.5 (6.3 ± 6.3)	65.3 ± 43.2 (6.5 ± 14.8)	50.9 ± 45.4 (11.2 ± 5.8)
Hip + Foot	83.3 ± 13.9	95.0 ± 15.1 (1.6 ± 7.1)	64.3 ± 46.8 (9.1 ± 6.8)	59.8 ± 49.2 (9.8 ± 6.5)	100.0 ± 0.0 (3.9 ± 11.2)
DWrist + DThigh	82.1 ± 12.4	90.5 ± 17.0 (4.5 ± 11.1)	67.9 ± 37.9 (4.8 ± 5.5)	83.9 ± 32.0 (10.1 ± 13.7)	65.1 ± 32.4 (4.9 ± 5.1)
DWrist + DFoot	92.4 ± 10.5	97.1 ± 11.0 (1.9 ± 7.4)	86.7 ± 30.2 (3.7 ± 5.9)	84.9 ± 31.7 (2.7 ± 5.1)	94.0 ± 22.9 (1.9 ± 7.4)
Hip	71.4 ± 11.6	96.0 ± 12.2 (5.0 ± 22.4)	31.5 ± 35.9 (13.7 ± 10.2)	38.7 ± 40.9 (8.6 ± 8.0)	35.1 ± 38.9 (13.0 ± 10.7)
DWrist	66.9 ± 18.4	79.4 ± 23.4 (9.1 ± 20.7)	44.3 ± 34.4 (14.0 ± 14.9)	70.1 ± 37.8 (14.2 ± 16.2)	43.5 ± 37.2 (11.1 ± 11.5)
DFoot	75.9 ± 14.0	84.8 ± 23.4 (7.0 ± 10.7)	65.4 ± 43.04 (8.6 ± 6.9)	64.2 ± 46.3 (7.6 ± 6.6)	82.0 ± 27.0 (11.9 ± 17.0)
DUpperArm	75.4 ± 9.0	96.5 ± 11.4 (6.8 ± 17.1)	37.9 ± 31.4 (9.3 ± 9.9)	50.7 ± 38.3 (7.0 ± 8.0)	41.3 ± 23.9 (10.7 ± 7.3)
DThigh	69.3 ± 22.9	85.9 ± 22.6 (14.1 ± 12.6)	54.2 ± 37.9 (4.2 ± 5.6)	56.3 ± 37.3 (19.4 ± 26.0)	60.7 ± 39.7 (6.4 ± 4.8)

Table 5-48: True positive and false positive rate (shown in parenthesis) during subject independent training for the C4.5 classifier when recognizing postures without the *unknown* class over different sensor combinations. The feature set used is the *invariant reduced* feature set computed per axis over windows of 5.6s in length.

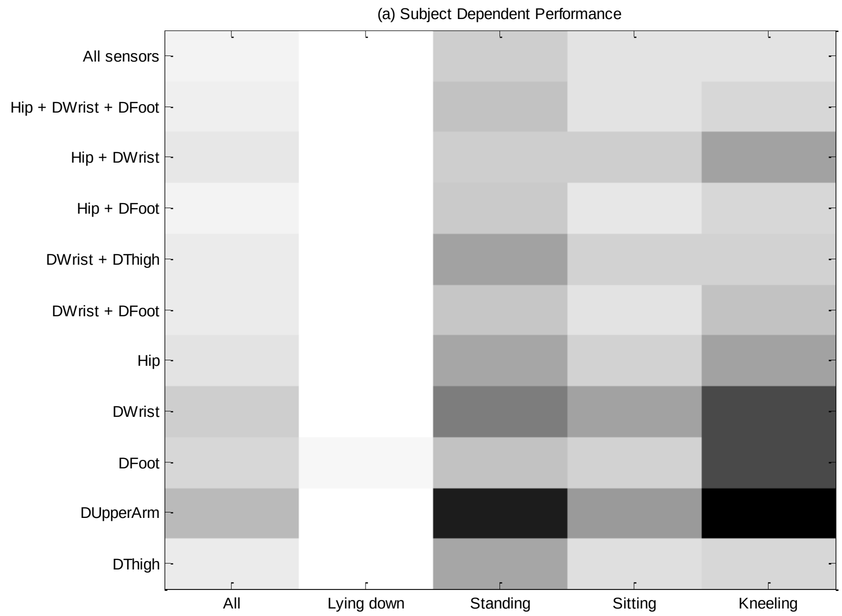


Figure 5-41: True positive rate per sensor combination during subject dependent evaluation using the C4.5 classifier when features are computed per axis over windows of 5.6s. The grayscale image is scaled so that the maximum true positive rate of 99.9% is represented by white and the minimum of 88.5% by black. In other words, poor areas of performance are shown in black.

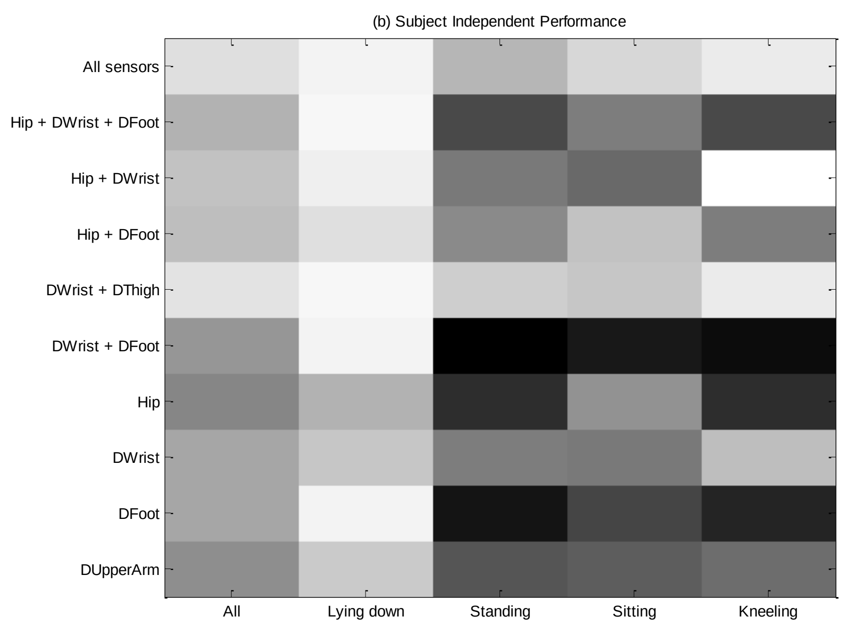


Figure 5-42: True positive rate per sensor combination during subject independent evaluation using the C4.5 classifier when features are computed per axis over windows of 5.6s. The grayscale image is scaled so that the maximum true positive rate of 100% is represented by white and the minimum of 31.5% by black. In other words, poor areas of performance are shown in black.

standing (97-98%) and *sitting* (98-95%) during subject dependent and independent training when the *unknown* class is not used. When the *unknown* activity is incorporated, the performance drops dramatically for *sitting* and *standing* during subject independent training. This is because subjects were mainly *standing* and *sitting* while resting during the unlabeled periods of time of the data collection (*unknown* activity).

The confusion matrices for subject dependent and independent training shown in Figure 5-40 illustrate that the activities most confused are *standing* with *sitting*, and *sitting* with *kneeling*. The confusion matrix for subject independent training also shows a relatively high degree of confusion between *lying down* and *sitting*. These confusions however, are not large enough to affect the recognition performance as shown in Table 5-46.

Table 5-47 and Table 5-48 present the true positive and false positive rate obtained when different sensor combinations are used. Figure 5-41 and Figure 5-42 show the true positive rate as a grayscale image normalized to highlight the differences in performance per class. The best performance is represented by the color white and the worse by the color black. Consequently, poor areas of performance can be identified by dark regions in the image.

These tables show an excellent performance for all the sensor combinations explored during subject dependent training. For example, all sensor combinations using two or more sensors have a true positive rate greater or equal than 98.8%. The best performing sensor combinations are Hip+DFoot, Hip+DWrist+DFoot, and DWrist+DFoot. The maximum difference in performance between these sensor combinations is just 0.2%. Again, the combination of a sensor at the hip and a sensor at the lower body is performing as well as the combination of a sensor at the hip, a sensor in the upper body and a sensor in the lower body. The single sensors with higher performance for subject dependent training in decreasing order are DThigh, Hip, and DFoot. The DThigh sensor is slightly better (+2.3%) than the Hip sensor at recognizing *kneeling*. The sensor DFoot is slightly better in recognizing *standing* (+1.4%) than the DThigh and DFoot sensors. The worse performing sensor is the DUpperArm sensor with an overall true positive rate of 96.7%. It seems that during subject dependent training, all the sensor combinations explored can be used to recognize postures with excellent results.

For subject independent training, the best sensor combinations in decreasing order are DWrist+DFoot, Hip+DWrist+DFoot, and Hip+DFoot. It is interesting to note that the two sensor combinations with higher performance include the sensors DWrist and DFoot. When either of these sensors is not included in a sensor combination, the performance drops approximately 9%. Consequently, during subject independent training, the best sensor combination to use to recognize postures is DWrist+DFoot. The single sensors with best overall performance during subject independent training are DFoot (75.9%), DUpperArm (75.4%), and Hip (71%). The decrease in performance with respect to the DWrist+DFoot combination when these single sensors are used is around 17%. When the performance per posture is inspected, it is found that the sensor DFoot also outperforms the other single sensors in almost all categories. The DUpperArm sensor only outperforms the DFoot sensor in recognizing *lying down* (+11.7%) while the DWrist sensor outperforms all the other single sensors in recognizing *sitting*. The confusion matrix for the DFoot sensor shows that the postures being confused the most are *standing* and *sitting*. This is expected since the orientation of this sensor is very similar or identical

		Subject Dependent			Subject Independent		
Activities to recognize	**Random Guess**	**Total Accuracy**	**TPR Range**	**FPR Range**	**Total Accuracy**	**TPR Range**	**FPR Range**
All (51)	1.9%	87.9 ± 2.0	80 - 96	0.1 - 0.4	50.6 ± 5.1	34 - 47	0.5 – 1.3
All with no intensities (31)	3.2%	91.4 ± 1.6	80 - 98	0.1 – 0.5	72.0 ± 5.7	44 - 84	0.4 – 1.2
Postures, ambulation and two MET intensity categories (11)	9%	96.5 ± 1.1	93 - 97	0.1 – 2.4	81.3 ± 4.7	64 - 91	0.5 – 13
Postures and Ambulation with no intensity (8)	12.5%	98.4 ± 0.8	95 - 98	0.1 – 0.4	92.9 ± 3.9	85 – 96	0.3 – 2.1
Postures (4)	25%	99.3 ± 0.7	98 - 100	0.1 – 0.5	98.0 ± 2.8	96 – 100	0 – 1.4

Table 5-49: Random guess, total accuracy, and ranges for the true positive (TPR) and false positive rates (FPR) obtained over all activity categories when recognizing different sets of activities from the MIT dataset in a subject dependent and independent manner without including the *unknown* class.

during both activities. The DFoot sensor can better recognize *sitting* over *standing* when the foot's orientation with respect to ground changes (e.g. foot is raised from the floor in an angle) or when feet are moved in distinctive patterns during *sitting* such when fidgeting feet.

In conclusion, if subject dependent training is to be used, any of the sensor combinations explored can produce an excellent performance in recognizing postures (TPR>96.7%). During subject independent training, the best sensor combination to use is the DWrist+DFoot. This sensor combination produces a true positive rate of 92.4% with a maximum false positive rate of 3.7% per posture.

5.4.9.7 Summary of Results

The results presented in this section indicate that the highest total accuracy obtained while recognizing all the 51 activities contained in the MIT dataset (without the *unknown* class) using the final implementation of the activity recognition algorithm is 87.9% for subject dependent training and 50.6% for subject independent training. The performance of 50.6% obtained during subject dependent training is low, but it represents a substantial improvement over the performance obtained by random guessing (2%). As the number of activities to recognize is decreased either by excluding or merging activities, total accuracy and performance per class increases as shown in Table 5-49. The table also illustrates that excellent recognition results can be obtained using subject dependent training. During subject independent training, a reasonable performance of 72% can be obtained if discrimination among the intensity levels of activities is not required.

When different sensor combinations are analyzed to find the best performing ones with most convenient locations, it is found that the best combination to use is Hip+DWrist+DFoot for both, subject dependent and independent training. This is because this sensor combination is able to detect upper body motion, lower body motion, and overall body motion at the hip. Table 5-50 shows the three best sensor combinations and the three best single sensors to utilize while recognizing several sets of activities during subject dependent and independent training. From the table, it can be concluded

	Subject Dependent		Subject Independent	
Activities to recognize (Number of activities)	**Sensor combinations with higher performance**	**Single sensors with higher performance**	**Sensor combinations with higher performance**	**Single sensors with higher performance**
All (51)	Hip + DWrist + DFoot Hip + DWrist Hip + DFoot	Hip DFoot DThigh	Hip + DWrist + DFoot DWrist + DThigh DWrist + DFoot	DUpperArm DWrist Hip
All with No intensities (31)	Hip + DWrist + DFoot Hip + DWrist Hip + DFoot	Hip DFoot DThigh	Hip + DWrist + DFoot DWrist + DThigh DWrist + DFoot	DUpperArm DWrist Hip
Postures, ambulation and two MET intensity categories (11)	Hip + DFoot Hip + DWrist + DFoot DHip	Hip DThigh DUpperArm	DWrist + DThigh Hip + DWrist + DFoot DUpperArm	DUpperArm Hip DWrist
Postures and Ambulation with no intensity (8)	Hip + DFoot Hip + DWrist + DFoot Hip + DWrist	Hip DThigh DUpperArm	Hip + DWrist + DFoot DUpperArm DWrist + DFoot	DUpperArm Hip DThigh
Postures (4)	Hip + DFoot Hip + DWrist + DFoot DWrist + DFoot	DThigh Hip DFoot	DWrist + DFoot Hip + DWrist + DFoot Hip + DFoot	DFoot DUpperArm Hip

Table 5-50: The three sensor combinations and the three single sensors with higher performance while recognizing different sets of activities from the MIT dataset using the final implementation of the activity recognition algorithm. The performance is higher for sensor combinations shown at the top and lower for the sensor combinations shown at the bottom.

that during subject dependent training, a sensor located at the hip and another sensor located either at the dominant wrist (Hip+DWrist) or the dominant foot (Hip+DFoot) achieves reasonable performance. This is because upper body and lower body activity induce changes in the acceleration at the hip that allows some degree of discrimination among upper body and lower body activities.

During subject independent training the best performing sensor combinations are the ones utilizing a sensor located at the dominant wrist to detect upper body motion and Another sensor located either at the dominant thigh or foot to detect lower body motion (DWrist+DThigh or DWrist+DFoot). Finally, when the number of activities to recognize is decreased, the number of sensors can also be decreased with relatively small decreases in performance. From Table 5-50, it can also be seen that the best single sensors to use while recognizing activities in a subject dependent manner are Hip, DThigh, and DFoot. For subject independent training they are DUpperArm, DWrist, and Hip. The good performance of the DUpperArm sensor might be explained by the fact that most activities contained in the MIT dataset include a high degree of upper body motion and ambulatory activities in the case of household activities.

5.5 How Does the Activity Recognition Algorithm and its Interactive Training Interface Perform in Real-Time?

This section presents exploratory results of evaluating the real-time implementation of the activity recognition system as well as a user interface designed to train the algorithm interactively. The results presented are based on a short study performed with five participants that trained and tested the performance of the activity recognition algorithm in real-time at MIT.

The final activity recognition algorithm and a user interface that allows users to interactively train the algorithm were implemented in Java and executed on a laptop computer with a 1GHz Intel core microprocessor running the Windows Vista operating system. The only difference in the implementation of the algorithm with respect the parameters found in this work was the utilization of a slightly shorter sliding window of 4.2s in length (instead of a window length of 5.6s). This is because the sampling frequency per sensor was increased in practice from 45Hz to 60Hz when the number of sensors was reduced from seven to three [199]. The new window length was the closest one to the original (5.6s) permitted by the constraint of using a number of samples in a power of two (e.g. 256) to efficiently estimate the fast Fourier transform algorithm.

Five participants, three males and two females, from the author's research group were recruited to participate in this short study and provided with the instructions presented in Appendix A9. Three of the participants were familiar with the activity recognition research being carried out at the lab, and one of them had taken several courses in machine learning and pattern classification. The two other participants had a background in architecture and were not familiar with the inner workings of the algorithms or technical aspects of the research. Participants were asked to "train a computer program to recognize 10 physical activities, exercises, postures, or activities done in a particular posture of their choice". Participants were also instructed to wear three MITes wireless accelerometers [199] at the hip, dominant wrist, and dominant foot. Figure 5-43 presents an image indicating the placement of the wireless accelerometers on the body during this short study. Once the accelerometers were attached to the body, participants were asked to type in 10 physical activities, exercises, postures, or activities done in a particular posture that they wanted the computer program to recognize and that could be executed continuously for 2 minutes. Once the activities were entered, the application guided the participant to provide examples of the activities specified by performing each of them for two minutes continuously. The application showed the activity the participant needed to perform and indicated training progress using a counter that reached zero once the participant had completed two minutes worth of examples for a particular activity, checking for signal loss and ensuring that all examples are of good signal quality. Finally, once the training phase was finished, the application trained the activity recognition algorithm on the data provided and started recognizing the activities entered in real-time. After training the activity models, the application also tested the performance over the training examples collected using 10-fold cross-validation and recorded the results in a file for later analysis. The cross-validation evaluation over the activity examples collected took from 2.5 to 4.4 seconds, depending on the complexity of the activities provided. Participants were finally instructed to evaluate the performance of the algorithm by re-executing the activities as many times as they wished. They were also encouraged to experiment and suggest ideas on how the training or recognition of activities could be improved in future versions of the system.

5.5.1 Real-Time and 10 Fold Cross-Validation Performance

Table 5-51 presents the activities specified by the participants, the total accuracy per subject, and the range of the true positive and false positive rates obtained per activity

Figure 5-43: Placement of the three wireless accelerometers during the real-time evaluation experiment. The sensors were worn at the hip, dominant wrist, and dominant foot, right on top of the shoe laces.

using 10 fold cross-validation. Appendix A9 presents the performance measures per activity and the confusion matrix for each subject. The table shows that participants provided a wide set of activities, ranging from postures (e.g. *sitting still*) to complex activities involving a high degree of variability in motion such as *Taekwondo forms*. The total accuracy per subject presented in the table was high, consistent with the results presented in Section 5.4.8.1, ranging from 78.9% to 91.7%. In general, the algorithm performed extremely well on most of the activities provided by participants, reflecting the high accuracies obtained from the cross-validation evaluation. The worst case accuracy of 78.9% was obtained for Subject 3 because he specified several activities involving very similar upper body motion such as *throwing*, *bowling*, and *tennis serve*; these were confused several times during testing.

Table 5-52 lists the activities confused most often when participants tested the performance of the activity recognition algorithm in real-time. In general, the algorithm had problems differentiating activities with similar postures and upper body motion (e.g. hand movement). This is because the motion of the upper limbs is relatively unconstrained and the algorithms seem to have difficulty differentiating random motion patterns that occur occasionally from the distinctive patterns associated with an activity. For example, Table 5-51 and Table 5-52 show that the worse performance was obtained for Subject 3 because three of the activities he wanted to recognize (*throwing*, *bowling*, and *tennis serve*) involved very similar high energy motion on the hands. These activities were also difficult to recognize because they are disjointed and not strongly periodic. For example, during *tennis serve*, the subject executed the motion walking some steps forward and had to return to his original position after completing the example, which introduced examples of *walking* in the sequences. The same situation was observed for the *throwing* and *bowling* activities. Another problem experienced during these activities (*throwing*, *bowling*, and *tennis serve*) was the higher loss of wireless signals due to the high energy motion involved and the position of the hands during these activities. Another example of activities being confused by similar posture or upper body motion can be observed in Table 5-52 for Subjects 4 and 5. For example, drawing on paper and talking on the phone (while sitting) were confused with eating because all involved the sitting position and upper body motion. During drawing, the subject brought the pencil to her mouth several times, which looks similar to eating. When talking on the phone, the subject frequently switched the phone from hand to hand while he performed gestures with the opposite arm (as when explaining something). For subject 5, the activities confused were knitting with filing nails, filing nails with applying cream, and wash dish with wash hands. Again, all these activities involve similar posture and movement of the upper arms. *Knitting* and *filing nails* were also confused because they involve motion at the fingers that is poorly detected by the accelerometer at the wrist. One interesting observation related to the confusion between *filing nails* and *applying cream* observed during real-time testing and later confirmed by inspecting the C4.5 classifier, was that during training, the C4.5 classifier attempted to find any difference between the activities that did not involve the use of the upper arms. For example, *applying cream* (sitting on a chair) was not detected if the subject did not raise her dominant leg from the floor to apply cream on it. In general, the algorithm performed best recognizing activities involving characteristic motion of a particular limb, a particular speed of execution, or repetitive execution style, as expected.

5.5.2 Training Usability

Subjects reported being more conscious of time when they provided examples of the activities to recognize for two minutes. They expressed that at first they thought that two minutes was a short time but that during the study it felt much longer. Obviously some activities indeed *did* take longer to train because data was not collected when wireless signals were. However, subjects commented on training length even during training of activities where the accelerometer signal was of excellent quality. Participants suggested that the training process would be more amenable and realistic if examples could be collected when activities are executed in free-living. Two participants suggested using a mobile phone application to allowed people to collect activity examples by simply specifying the amount of data to be collected (e.g. in minutes) at the press of a button. Data would be collected immediately after entering the time and pressing the button and would stop being collected right after the timer expired. Participants were members of the House_*n* research group and their familiarity with wearable devices, particularly mobile phone technologies was high. Therefore, it is not surprising that they suggested mobile phone based solutions to the activity recognition interactive training problem.

Participants were more tolerant of the errors committed by the system when they made sense to the subjects. For example when *wash hands* and *wash dishes* were being confused, one subject with a background in architecture with no programming experience declared “this makes sense; this computer is wrong but pretty smart”. The same subject, as well as others, also expressed a desire for being able to “fix” the recognition algorithm by providing more training examples for activities being poorly recognized or confused. Nevertheless, participants showed some level of frustration when the activity being recognized made no sense to them. For example, during the confusion between *talking on*

Subject	Activities performed		Total Accuracy (%)	True Positive Range (%)	False Positive Range (%)
1	Bouncing on a ball Waving hand Shaking my leg Taekwondo Form #1 Side stretch	Jumping jacks Punching as I walk forward Lifting dumbbells Riding a bike Playing the drums	89.6	89.3 – 94.8	0.8 - 1.0
2	Walking Sitting still Scratching head Carrying box Washing dishes	Shaking hands Tossing ball in air Typing Talking on phone	91.7	84.5 – 98.2	0.4 – 0.17
3	Throwing Bowling Bouncing Typing Stepping	Stretching arm Walking Tennis serve Stretching legs Bending	78.9	70.7 – 93.2	1.3 – 3.8
4	Walk Type in computer Washing window Drawing in paper Wiping surface	Talking on the phone Sweeping Combing my hair Hammering a nail Eating	89.3	74.1 – 94.8	0.6 – 2.1
5	Walk Bicep curls Stretching Applying cream Brushing teeth	Wash dish Knitting Wash hands Filing nails Play piano	85.2	77.6 – 94.8	0.6 – 2.7

Table 5-51: Performance obtained by recognizing participant's activities using a C4.5 classifier with the *invariant reduced* feature set computed per axis over window lengths of 5.6s in length. Performance was measured using 10-fold cross-validation. The random guess probability is 10% for all activities shown in this table.

Subject	Activities Most Often Confused		Brief Explanation
	Activity Performed	Activity Confused With	
1	Playing the drums	Shaking my leg	Participant shook leg rhythmically when playing the drum.
1	Taekwondo Form #1	Punching as I walk forward	One of the sequences in the form involved punching walking forward.
2	Typing	Sitting	Sitting recognized as typing when subject typed slowly.
3	Throwing Bowling Tennis serve	Throwing Bowling Tennis serve	Activities often confused due to their similarity in upper body limb motion.
3	Bending	Stretching legs	The lower body limb motion was very similar for these activities.
4	Drawing on paper	Eating	These activities were confused due to their similar posture (sitting) and upper body motion. The algorithm usually defaulted to eating when drawing and talking on the phone were performed.
4	Talking on the phone	Eating	
5	Knitting	Filing nails	Similar posture of overall body (sitting), posture of hands, and high motion on the fingers poorly detected by the accelerometer at the wrist.
5	Filing nails	Applying cream	Same posture (sitting) and motion upper body motion similarity.
5	Wash dish	Wash hands	Similar body posture (standing) and motion at the upper body (hands).

Table 5-52: Activities confused the most found when participants tested the performance of the activity recognition algorithm in real-time.

the phone and *eating*, one of the participants with no familiarity with computer programming, machine learning or pattern classification techniques lightheartedly expressed, “stupid computer, does it look to you like I am eating? Maybe you are hungry”. The confusion between the activities did indeed make sense to the algorithm designer because of the postures and upper limb body motion involved, but the participant did not understand at all why the confusion was happening.

In summary, the exploratory study confirms that a real-time implementation of the final activity recognition algorithm proposed in Section 5.4 can do well detecting activities with a modest amount of training data. In this case, cross-validation accuracies per subject ranged from 78.9% to 91.7%. In general, the algorithm performed best recognizing activities involving characteristic motion of a particular limb, a particular speed of execution, or repetitive execution style. Not surprisingly, the algorithm has more difficulties when trying to discriminate activities involving similar posture and similar motion, particularly at the upper body. This is most likely because the motion of upper limbs is so unconstrained in everyday life that during the short execution of some activities it is perceived as noise by the recognition algorithm. The study also suggests that better tools are necessary to allow people to (1) collect data during free-living conditions and to (2) fix the algorithms when activities are either being poorly recognized or confused with others. Both are challenging problems to solve and test. This exploratory study also suggests, however, that excellent results can be obtained using subject dependent training even when relatively small amounts of training data per activity is available. The challenge, therefore, is to create the necessary user interface applications to allow end-users who are unfamiliar with sensors or machine learning to easily and interactively provide the training data in a manner that is not perceived as intrusive, tedious, or boring. This will require the development of tools that acquire training data in fun, entertaining, and educational ways, perhaps by interleaving activity recognition applications with other applications, such as games.

5.6 Energy Expenditure Algorithm Experiments

This section presents a set of experiments to determine an effective regression algorithm, feature set, sliding window length, feature computation method, and signal filtering techniques amenable for real-time estimation of energy expenditure. The section also presents experiments to measure the impact of adding sensors worn on various body locations and the value of adding a wireless heart rate sensor when estimating energy expenditure. The experiments are organized so that each answers a relevant question about the algorithm parameters incrementally, starting from the most restrictive parameters (e.g. regression algorithm, feature set) to the least restrictive parameters (sensor modality and location). Where tradeoffs must be made, settings that might permit real-time performance are preferred.

5.6.1 Overview

All the experiments presented in this section are evaluated utilizing the MIT energy expenditure dataset (see Section 4.6.4). This data set is particularly challenging for energy estimation for the following reasons: (1) it contains energy expenditure data for a large number of activities (52) collected from 16 subjects, (2) it includes energy expenditure data for 26 activities with different intensity levels such as *walking* at different speeds and inclinations, *running* at different speeds, *cycling* at different speeds and resistance levels, and *rowing* at different resistance levels, (3) it incorporates energy expenditure data for 18 household activities containing examples of the unconstrained motion found in everyday life, and (4) it includes data for an activity labeled as *garbage* class or *unknown* activity that contains the energy expenditure data for all the time periods with no associated activity labels during the data collection. The energy expenditure of the garbage class is difficult to estimate because it contains data for periods when participants were resting after an exercise session and, consequently, the heart rate and energy expenditure data sometimes have high readings but there is no accelerometer motion associated with these readings.

Currently, equipment to collect energy expenditure data of free-living individuals is bulky and expensive. Therefore, it is unlikely that the equipment would be available to a new user of an affordable, consumer-based EE estimation system – the goal of this work. Therefore, in this section results are only presented for subject independent training. As in the previous section, the results presented in this section will also be clustered by activity categories that are helpful while analyzing the results. These activity categories are *postures*, *ambulation*, *exercise*, *resistance exercise*, and *household* activities. Appendix A2 presents a table indicating what activities are included in each of the aforementioned categories.

Finally, all the experiments presented in this section utilize same signal preprocessing and segmentation strategies, described in Sections 5.4.2 and 5.4.3.

Activity	MIT Dataset METs (Mean ± Std)	Boston University Dataset METs (Mean ± Std)	Difference between MIT and Boston university readings
Lying down	0.9 ± 0.1	0.9 ± 0.1	0.0
Standing	1.0 ± 0.2	0.9 ± 0.0	0.1
Sitting	1.0 ± 0.2	0.9 ± 0.0	0.1
Walking - Treadmill 3mph 0	3.4 ± 0.4	3.2 ± 0.1	0.2
Walking - Treadmill 3mph 6	4.9 ± 0.4	4.9 ± 0.2	0.0
Walking - Treadmill 3mph 9	5.7 ± 0.6	5.7 ± 0.5	0.0
Running - Treadmill 5mph 0	7.0 ± 0.8	6.9 ± 1.3	0.1
Cycling - 100 rpm 1.0 kg	5.8 ± 0.8	5.7 ± 1.3	0.1
Cycling - 60 rpm 1.0 kg	3.3 ± 0.5	3.1 ± 0.6	0.2
Cycling - 80rpm 1.5 kg	5.6 ± 0.7	5.9 ± 2.5	-0.3
Calisthenics - Bicep curls 5lb	1.4 ± 0.5	2.5 ± 0.3	-1.1
Calisthenics - Crunches	1.4 ± 1.2	1.8 ± 0.0	-0.4
Calisthenics - Sit ups	4.3 ± 1.2	0.6 ± 0.0	3.7
Unknown Activity	2.4 ± 1.0	2.2 ± 0.3	0.2

Table 5-53: Average energy expenditure readings in METs for 14 activities (mean and standard deviation) collected using the Cosmed K4b2 indirect calorimeter from 16 subjects at MIT and the Parvo Medics indirect calorimeter from 2 subjects at the Boston Medical Center

5.6.2 MIT Energy Expenditure Dataset Validation

The quality of the energy expenditure data collected from an indirect calorimeter depends on the brand of device, the proper calibration of the equipment before the data collection, and the proper attachment of the face mask required to collect the O_2 and CO_2 readings. Consequently, collecting good quality energy expenditure data can be a challenging task. The goal of this section is to validate the quality of the energy expenditure data collected for this work by comparing it to the quality of energy expenditure data collected for similar activities by researchers at another institution utilizing an indirect calorimeter of different brand.

The energy expenditure data collected for this work was measured using the Cosmed K4b2 portable indirect calorimeter [125]. The K4b2 indirect calorimeter has been found to be a valid instrument to measure energy expenditure as compared with the Douglas bag in a wide range of activities and intensities [208]. However, the quality of the data collected can suffer from improper calibration of the equipment or improper attachment of the face mask to the face of the participant.

To validate that the portable K4b2 indirect calorimeter used in this work was providing quality data, the energy expenditure data collected using this indirect calorimeter for 14 activities was compared against the energy expenditure data collected for these same activities by researchers at the Boston Medical Center utilizing the Parvo Medics TrueOne 2400 stationary metabolic measurement system [126]. Before performing the comparison, the data collected using the K4b2 indirect calorimeter was filtered using a 15s running average filter to reduce noisy readings. Table 5-53 presents the average number of METs obtained per activity for the data collected at MIT and the Boston Medical Center. The duration of each activity is between 3-4mins for both datasets, except for physically demanding activities such as *crunches*, *sit-ups* and *bicep curls* that sometimes have durations of less than one minute. Non-steady state energy expenditure readings were not eliminated for any of the activities in both datasets.

Visual inspection of Table 5-53 reveals that the difference in average METs readings per activity is near zero for most activities. This indicates that the data collected at both institutions is comparable in quality. The only two activities that show a large difference are *bicep curls* and *sit-ups*. *Bicep curls* present a lower value for the MIT dataset perhaps because a bicep curls chair that allowed reclining the elbows was used during the MIT data collection. During the Boston Medical Center data collection, the subjects executed bicep curls without reclining the elbows on any surface. The extremely low value associated with *sit-up*s of 0.6 METs for the Boston Medical Center dataset suggests either a problem while collecting the data for this activity (e.g. air escaping from collector tube) or that the short duration of the examples for this activity (<40s) was not enough to reach steady state. Finally, it can be observed from the table that the standard deviation over the MIT dataset is higher than the one observed for the Boston Medical Center dataset. This is because the MET values were computed over 16 subjects for the MIT dataset and only over two subjects for the Boston Medical Center dataset.

In conclusion, from Table 5-53, we can see that the energy expenditure data collected for most activities is very similar; suggesting that the quality of the data collected using the Cosmed K4b2 indirect calorimeter is reasonable for the experiments performed in this work. Prior work utilizing the Cosmed K4b2 indirect calorimeter to measure energy expenditure such as the one performed by Bassett et al. [200] has measured standard deviations ranging from 0.31 to 1.58 MET for a set of 20 activities including household and exercise activities with moderate intensities. The work by Strath et al. [174] found standard deviations between 0.4 to 1.1MET over 14 lifestyle activities, and the work by Crouter et al. [34] standard deviations between 0.13 and 1.63MET for 18 exercise and lifestyle activates. Therefore, the standard deviations obtained for the MIT energy expenditure dataset during this analysis ranging between 0.1 and 1.2MET are within the limits reported in prior work.

5.6.1 How Well Has Energy Expenditure been Estimated From Accelerometer and Heart Rate Data in the Past?

This section discusses some of the most recent results in the area of energy expenditure estimation from accelerometer and heart rate data. The objective is to give the reader some background to better interpret the results later presented in this thesis. In addition, this section defines what would be considered to be a significant result in this work with respect to prior work. There is a large body of research in estimating energy expenditure from accelerometer and heart rate data. As a result, this section discusses only some relevant results published after year 2000.

Presently, the two state-of-the-art algorithms to estimate energy expenditure from a single accelerometer placed at the hip are the work by Crouter et al. [34] and Rothney [152, 181]. Crouter et al. [34] discriminates between sedentary, ambulatory, and lifestyle activities using the coefficient of variation computed over windows of 10s in length and applies two different regression equations for ambulatory and lifestyle activities. When sedentary activities are detected, a constant MET value of 1 is predicted. The subject independent evaluation of this algorithm presented by the authors indicates that energy expenditure can be predicted with a correlation coefficient (r) of 0.96, a standard error of the estimate (SEE) of 0.73MET, and a maximum absolute error deviation (MAED) of 0.75MET (with respect to ground truth energy expenditure). The algorithm was evaluated over 17 activities collected from 20 subjects. These results are strong with respect to prior work; nevertheless, the performance measures presented are computed over mean values per activity instead of over prediction values obtained over minute-by-minute windows. In other words, error measures are computed by comparing the mean value of the predictions for each activity and the mean value of the energy expenditure measured using the indirect calorimeter for each activity. This smoothes out possible over and under predictions that could have happened during minute by minute estimates. This study also excluded the data collected for the *cycling* activity from analysis because the Actigraph activity monitor placed at the hip was not able to record any activity counts for this activity. This reveals one of the main problems of predicting energy expenditure from accelerometers at the hip: poor estimation of energy expenditure for upper body and non-ambulatory lower body motion. Analysis of performance per activity for this study showed that the largest errors occurred for activities involving upper body motion such as *basketball*, *racquetball*, *vacuuming*, and *mowing the lawn*. This is consistent with other studies that have found that accelerometers mounted at the hip significantly underestimate lower body activities such as *cycling* and *sliding* [33]. The work by Crouter et al. also explored the performance of commonly employed regression equations such as the Freedson equation [145], the Swartz equation [148], and the Heldenman equation[146] in estimating energy expenditure. The study found that these equations overestimate energy expenditure for activities with associated energy expenditures of less than 2METs and underestimate the energy expenditure for activities with energy expenditure values greater than 2MET.

The work by Rothney [152, 181] presents an algorithm that estimates energy expenditure using an artificial neural network (ANN) trained with the following features computed from a single accelerometer at the hip over one minute windows: Power spectral density, number of signal peaks, inter-quartile range, and coefficient of variation. The ANN is trained from nearly 24 hours of data collected from 81 participants. This approach achieves a correlation coefficient of r=0.93 and a root mean squared error (RMSE) of 0.47kcal/min. The difference in total daily energy expenditure achieved is 21±115 kcal/day. This compares favorably with the measurement intervals of 100-250kcal/day required for sustainable weight loss interventions. This work also explored the performance of the IDEEA device [41] and an Actigraph at the hip using the Freedson equation in estimating energy expenditure. The results obtained were r=0.92, RMSE=0.59 kcal/min for the IDEEA monitor and r=0.9, RMSE=0.74 kcal/day for the Actigraph located at the hip. Thus, the improvement in the correlation coefficient achieved by this method ranges between 0.01 and 0.03 units and between 0.12 and 0.27 kcal/min for the RMSE error.

Prior work by Basset et al. [200] found that the Caltrac, Kenz, Yamax SW-701, and CSA activity monitors (using different regression equations) underestimate energy expenditure for *lifestyle* activities such as *ironing*, *cooking*, *washing dishes* and overestimate energy expenditure for *walking*. The same work also found that energy expenditure was best predicted using the Hendelman's regression equation computed from the counts generated by a single CSA activity monitor placed at the hip over 28 activities. The mean error score (criterion - prediction) obtained was 0.05MET. However, this evaluation measure does not accurately reflect estimation error since underestimations (predicted<real) and overestimations (predicted>real) might cancel out during the averaging of error scores giving a false impression of low overall error. The mean absolute error (MAE) or the root mean squared error (RMSE) that computes the absolute value of the error score or the squared of the error score before averaging would have produced a more reliable estimate of the real error. One disadvantage of the Hendelman's equation is that it predicts 2.9 MET by default when no motion is present so it would likely overestimate energy expenditure over the course of a normal day [200]. The mean error scores obtained were 0.97 MET for the work energy theorem [32] from a CSA monitor, 0.47 MET for the Freedson's equation [145] using a CSA monitor, 0.83 MET using the Caltrac, 0.96MET using Kenz (select 2), and 1.12 MET using the Yamax device. The correlation coefficients between these sensors and energy expenditure readings obtained were r=0.62 for work energy theorem and CSA; r=0.32 for Freedson's equation and CSA; r=0.58 for Caltrac; r=0.55 for Kenz; and r=0.49 for Yamax. The authors explain that these relatively low correlations were obtained because the activities explored included a wide variety of moderate intensity activities. The authors also point out that previous studies analyzing only treadmill *walking* and *jogging* have reported correlations between 0.80 and 0.92 [145, 146, 178, 231-233].

Prior work has also explored the combination of acceleration and heart rate data to predict energy expenditure. For example, The work by Haskell et al. [48] found that the correlation coefficient increased from r=0.83 to r=0.9 (+0.07units) when an accelerometer at the arm was incorporated to heart rate data during subject dependent estimation of energy expenditure. This result was obtained over data collected from 19 participants performing a wide range of activities in a laboratory setting. The same work found that the difference in the correlation coefficient between subject independent and subject dependent estimation of energy expenditure was only 0.09units (r=0.94 for subject dependent and r=0.85 for subject independent).

The work by Strath et al. [83] explored the estimation of energy expenditure by applying two different subject dependent heart rate regression equations depending on upper body or lower body motion as detected by two accelerometer placed at the wrist and thigh (HR+M technique). The model was trained over arm and leg activities (treadmill waking and arm ergometry) collected from 30 participants at a laboratory and tested over lifestyle activities performed for 15min each by the same individuals. It was found that a linear regression equation trained over heart rate data alone (subject dependent training) achieved a correlation coefficient of r=0.81, and on average overestimated energy expenditure by 0.4 MET. When two different heart rate regression equations were applied depending on upper or lower body motion, the correlation coefficient increased to r=0.9. This combination was also found to not significantly over or under estimate energy expenditure. Follow up validation work performed also by Strath et al. [174] found that energy expenditure can be predicted in a subject dependent manner with r=0.79 and SEE=0.76 MET using the heart rate flex method (FlexHR). Other work (e.g. [234, 235]) has also found correlation coefficients between 0.54 and 0.98 using the Flex HR method (subject dependent training). In contrast, Strath et al. [174] found that the HR+M technique achieved a performance of r=0.9 and SEE=0.55MET. This work also found that the FlexHR method overestimated energy expenditure over most activities while the HR+M technique did not. Thus, the difference in performance found in this work was 0.11units for the correlation coefficient and 0.21MET for the SEE. These results were obtained from data collected from 10 participants performing physical tasks in a field setting over 6 hours.

Most recent work by Strath et al. 2005 [49] compared the performance of two methods that combine acceleration and heart rate data: The HR+M technique [83] (previously discussed) and the branched model [175]. This work evaluated the performance of these techniques in a subject dependent and independent manner, and compared their performance with the one obtained using a single accelerometer at the hip. The subject dependent results obtained were r=0.9, RMSE=0.64 MET for the HR+M technique and r=0.86, RMSE=0.67 MET for the Branched model. During subject independent evaluation, the performance found was r=0.81, RMSE=1.07 MET for the HR+M technique, r =0.86 and RMSE=0.76 MET for the Branched model, and r=0.64 and RMSE=1.22 METs when energy expenditure is predicted using the Freedson equation from a single accelerometer at the hip. Thus, the difference in performance between subject dependent and independent training for the HR+M technique is 0.09units for the correlation coefficient, and 0.43 MET for the RMSE. For the branched model, the difference is 0 for the correlation coefficient and 0.09 for the RMSE. The difference in performance between the branched model (best performing) and a single accelerometer at the hip was 0.22 for the correlation coefficient and 0.46 for the RMSE during subject independent evaluation.

The work by Swartz et al. [148] explored the performance obtained while estimating energy expenditure by combining a CSA accelerometer at the hip and another one at the dominant wrist. The data used in the evaluation was collected from 70 participants performing one to six activities from categories such as yardwork, housework, family care, occupation, recreation and conditioning. Linear regression equations were created for the sensor at the hip, the wrist, and the hip and wrist combination. The results obtained were r=0.56 and SEE= 1.1MET for the hip sensor, r=0.18 and SEE=1.38MET for the wrist sensor, and r=0.58 and SEE=1.14MET for the combination hip and wrist. The work found that the variance explained by the accelerometer at the wrist was only 5% and the variance explained by the accelerometer at the hip was 31.7%. Consequently, the authors concluded that the addition of the accelerometer at the wrist was not worth the extra cost and data analysis involved. Unfortunately, it is unclear from this work if energy expenditure is estimated in a subject dependent or independent manner. Furthermore, the result obtained in this work contradict prior findings by Melanson and Freedson [233]. These authors estimated energy expenditure using three accelerometers at the hip, wrist, and ankle during *walking* and *jogging* and found that activity counts significantly correlated with energy expenditure, no matter what accelerometer is used to estimate energy expenditure. The correlation coefficients found ranged from 0.66 to 0.81. The authors also found that the combination hip and wrist or wrist and ankle produced the highest correlation coefficient of r=0.94.

Finally, recent work [96] validating the performance of the SenseWear Pro armband in estimating energy expenditure in a subject independent manner found performances of r=0.77 and percent difference of 6.9 ± 8.5% for walking, r=0.28 and percent difference of 28.9 ± 13.5% for cycle ergometry, r = 0.63 and percent difference of 17.7 ± 11.8% for stepping exercise, and r = 0.74 and percent difference: 21.7 ± 8.7% for arm ergometry using data collected from 40 participants. Thus the lowest correlation coefficient and largest percentage error was obtained for cycling ergometry. This is because from its location at the upper arm, this armband presents difficulties detecting non-ambulatory

Work	Approach	Features	Sensors	Num	Results
2006 [34]	**Use single accelerometer at hip but create activity dependent regression models** Classify activities into walking/running, lifestyle, and sedentary and apply different regression models to each.	Activity counts, coefficient of variation	One uniaxial accelerometer at hip	17/20 3hrs per subject	**Subject independent** Maximum absolute error deviation MAED = 0.75 Within 0.75 of Measured METs. r = 0.96, SEE = 0.73 MET.
2007 [152]	**Use single accelerometer at hip but extract features over signal and use non-linear regression** Use a neural network to map features computed over the accelerometer data into energy expenditure.	Peak intensity, IQI, min CV, low Energy, and moderate to vigorous energy.	2-axis accelerometer at hip	12/81 24hrs per subject	**Subject independent** Neural network: r=0.93, RMSE=0.47 kcal/min Difference in TEE of 21±115 kcal/day IDEEA monitor: r=0.92, RMSE=0.59 kcal/min Actigraph at hip, Freedson equation r=0.9, RMSE=0.74 kcal/day
2005 [49]	**Combine accelerometer and heart rate data and use different regression equations for upper or lower body motion.** Estimate energy expenditure using two models: arm-leg HR+M and branched model	Activity counts, HR above resting HR	Three accelerometers at hip, wrist, and thigh and a chest heart rate monitor	2/10 6hours per subject	**Subject dependent** Arm-leg- heart rate + M: r = 0.9, RMSE = 0.64 MET Branched model: r=0.86, RMSE = 0.67 MET **Subject independent** Arm-leg- heart rate + M: r =0.81, RMSE = 1.07 MET Branched model: r =0.86, RMSE = 0.76 MET hip accelerometer alone using Freedson Eq: r = 0.64, RMSE = 1.22 METs
2004 [96]	**Combine multiple sensor types at single body location** Estimate energy expenditure from five wearable sensors located at the dominant arm over the triceps muscle using proprietary regression formulas.	Proprietary features extracted from the five sensors	2-axis acc, heat flux, galvanic skin response, skin temperature, and near body temperature.	4/40 1.6 hours per subject	**Subject independent** walking r=0.77, percent difference: 6.9 ± 8.5% cycle ergometry r=0.28, percent difference: 28.9 ± 13.5% stepping exercise r = 0.63, percent difference: 17.7 ± 11.8% arm ergometer r = 0.74, percent difference: 21.7 ± 8.7%
2001 [83]	**Apply to different heart rate regression equations depending on upper body or lower body motion as detected by an accelerometer at the wrist and an accelerometer at the thigh.**	Activity counts, beats per minute	Three CSA Actigraphs at the arm, thigh, and hip.	2/30	**Subject independent** hip accelerometer alone using Freedson Eq: r=0.73, average underestimation of 1.1MET **Subject dependent** Heart rate: r=0.81, average overestimation of 0.4MET Heart rate and Arm + thigh accelerometers r=0.9, No significant over or under prediction

Table 5-54: Summary of some relevant results in energy expenditure estimation from accelerometer and heart rate data after year 2001. The numbers in the column labeled as Num indicate Number of activities/number of subjects.

lower body activity. As discussed in Section 3.2.3, the armband utilizes five sensors to estimate energy expenditure from its location at the dominant upper arm: A 2-axis accelerometer, heat flux, galvanic skin response, skin temperature, and near body temperature.

Table 5-54 presents a summary of some of the most recent results (after 2001) obtained while estimating energy expenditure from accelerometers and heart rate monitors.

In summary, it can be concluded from prior work that in general, subject dependent regression models perform better than subject independent models [49, 152]. However, the difference in performance is relatively small. For example, the difference in performance between subject dependent and independent training for two state of the art methods that combine accelerometer and heart rate data ranges from 0 and 0.09 for the correlation coefficient and between 0.09 and 0.43MET for the RMSE [49]. The difference in performance between the branched model (state-of-the-art algorithm that combines accelerometer and heart rate data) and a single accelerometer at the hip was 0.22 for the correlation coefficient and 0.46 for the RMSE during subject independent evaluation [49].

When energy expenditure is estimated from a single accelerometer at the hip, the state of the art results are the ones obtained by Crouter et al.: r=0.96, SEE=0.73MET, and MAED=0.75MET obtained over 17 activities. Prior algorithms have achieved correlation coefficients between 0.80 and 0.92 for treadmill *walking* and *jogging* activities [145, 146, 178, 231-233]. When the number of activities is increased, the correlation coefficient decreases according. For example, the work in [200] found correlation coefficients between 0.32 and 0.62 using four different brands of activity monitors placed at the hip.

Finally, the performance of utilizing several accelerometers to improve energy expenditure estimation is controversial. The work by Swartz et al. [148] found that the addition of an accelerometer at the wrist to an accelerometer at the hip improved the correlation coefficient only 0.02units and SEE by 0.04MET. Conversely, the work by Melanson and Freedson [233] found that activity counts significantly correlated with energy expenditure, no matter what accelerometer was used. The authors also found that the sensor combination hip and wrist or wrist and ankle produced the highest correlation coefficient of r=0.94. The analysis was performed on data collected from 15 subjects performing treadmill *walking* and *running* activities at different grades.

Therefore, in this work, it would be considered a significant result if energy expenditure for 52 activities can be estimated with a correlation coefficient between 0.80 and 0.92. This range is the best one obtained for *jogging* and *walking* using a single accelerometer at the hip and using heart rate data in a subject independent manner. A strong result would also be to obtain a RMSE between 0.64 and 0.86, the lowest RMSE obtained by combining accelerometer and heart rate data (HR+M and branched model) and using a single accelerometer at the hip (RMSE~0.73) as evaluated over less than 18 activities. An excellent result would also be to corroborate that the utilization of several accelerometers improves energy expenditure estimation, as one might intuitively expect at least for activities involving upper body and lower body motion.

5.6.2 How Well Can Energy Expenditure be Estimated Using Leading Algorithms from Prior Work?

This section explores the performance of several energy expenditure estimation algorithms that can be considered either state-of-the-art or popular by the medical community during research studies. These algorithms include the Crouter et al. 2006 [34] Actigraph based algorithm, estimation of energy expenditure using multivariable linear regression, estimation of energy expenditure using the Compendium of Physical Activities assuming the activities performed are known (e.g. from questionnaires or diaries), and estimation of energy expenditure using activity dependent regression models such as multivariable linear regression and non-linear regression when the activities performed are also known. The section also compares the performance of the different approaches to establish a performance baseline as a way to compare results obtained in upcoming sections where a new energy expenditure estimation algorithm is proposed.

5.6.2.1 How Well Can Energy Expenditure be Estimated Using a State-of the-Art Actigraph-Based Algorithm?

There exist several algorithms that have been developed to estimate energy expenditure from the acceleration counts (per minute) generated by the Actigraph activity monitor [32] (uniaxial accelerometer). Most of these algorithms assume that the device is worn at the hip (e.g. [145, 146, 148, 200]) and predict energy expenditure over one minute intervals. The current state-the-art Actigraph-based algorithm is the recently published 2-regression method proposed by Crouter et al. [34]. The main idea behind this algorithm is to classify activities into three categories before estimating energy expenditure: (1) *sedentary* activities, (2) ambulatory activities such as *walking* and *running*, and (3) *lifestyle* activities. Once the activities are recognized, different regression models are applied for each activity type to estimate energy expenditure. The algorithm recognizes sedentary activities by simply setting a threshold over the acceleration counts. Once they are recognized, they are assigned an energy expenditure equivalent to 1MET. Ambulatory activities such as *walking* and *running* are differentiated from *lifestyle* activities by setting a threshold over the coefficient of variation (CV) as computed over 10s windows. If *walking* and/or *running* are detected, a linear regression model is applied to estimate their energy expenditure; otherwise, an exponential regression model is applied to estimate the energy expenditure associated with *lifestyle* activities. The pseudo code for this algorithm is presented in Figure 5-44.

This section explores how well energy expenditure can be estimated utilizing this algorithm by running it over the Actigraph data collected at the hip during the data collections performed for this work. The Actigraph data was originally collected using a 1s epoch (window) and thus, it had to be converted to 10s epochs as required by this algorithm. The algorithm was re-implemented in Java in order to present energy expenditure estimation results per activity. In order to validate the proper implementation of the algorithm in Java, its output (overall energy expenditure estimate) was compared against the output generated by the original implementation of this algorithm included in the Actigraph activity monitor software [32].

$$
\begin{array}{l}
\text{if (counts/min} \le 50) \text{ EE\_METS} = 1.0, \\
\text{else if (counts/min} > 50) \{ \\
\quad \text{if (CV} == 0 \text{ or CV} > 10) \\
\qquad \text{EE\_METS} = 2.330519 + (0.001646 \times \text{counts/min} - \\
\qquad \left[1.2017 \times 10^{-7} \times \text{counts/min}^2\right] + \left[3.3779 \times 10^{-12} \times \text{counts/min}^3\right] \\
\qquad \left(R^2 = 0.854; \text{SEE} = 0.940\right) \\
\quad \text{else if (CV/10s} \le 10) \\
\qquad \text{EE\_METS} = 2.379833 \times \exp(0.00013529 \times \text{counts/min}) \\
\qquad \left(R^2 = 0.701; \text{SEE } 0.275\right) \\
\}
\end{array}
$$

Figure 5-44: Pseudo code for the 2-regression Crouter et al. [34] Actigraph-based energy expenditure estimation algorithm. CV stands for coefficient of variation and is computed by dividing the standard deviation by the mean over a window of 10s.

Table 5-55 presents the performance over all the activities and Table 5-56 the performance per activity category when estimating energy expenditure using the Crouter et al. algorithm over the MIT energy expenditure dataset. From Table 5-55, it can be seen that the coefficient of correlation is 0.36 (relatively low) and that the RMSE is 2.66 METs. Table 5-56 shows that the root mean squared error (RMSE) is lower for postures and household activities and higher for resistance exercise, all exercise in general, and lower body activities. The algorithm generates small errors for postures because they are easily recognized by simple thresholding of the acceleration counts and assigned a MET value of one. Household activities have a small error because most of them involve either lifestyle activities or ambulation that the algorithm differentiates well using the coefficient of variation to then apply the corresponding regression model. A high error was expected for exercise and resistance exercise activities for two reasons: (1) accelerometers have difficulties recognizing the effort and resistance load associated with some of these activities (e.g. *rowing at 30spm* at different resistance levels), and (2) most activities in these categories include either lower body (e.g. *cycling*) or upper body motion (e.g. *bench weight lifting* and *bicep curls*) that is difficult to measure properly from an single accelerometer (Actigraph) located at the hip. In fact, the lower body category also presents a high error due to the poor detection of motion at the legs during *cycling*. When Actigraph vs. Cosmed energy expenditure is plotted (as shown in Appendix B1), it can be observed that the energy expenditure predicted for activities involving upper or lower body motion such as *cycling*, *bench weight lifting*, and *bicep curls* is 1MET (energy expenditure associated with sedentary activities). This is because these activities are confused with sedentary activities by the algorithm due to the inability of the accelerometer at the hip to capture these motions. Figure 5-45 presents the energy expenditure estimated for subject MIT-018 during the (a) cycling activity and (b) the bicep curls activity using the Crouter et al. algorithm from a single Actigraph accelerometer at the hip. The important thing to notice from these Figures is that the

Error Measures over all activities	Error Measures Values in METs
Correlation Coefficient (r)	0.36 ± 0.09
Root Mean Square Error (RMSE)	2.66 ± 0.62
Mean Absolute Error (MAE)	1.94 ± 0.45
Maximum absolute error Deviation (MAED)	6.94 ± 1.77

Table 5-55: Error statistics for estimating energy expenditure for 52 activities using the 2-regression Crouter et al. Actigraph-based algorithm with respect to the energy expenditure measured using the Cosmed K4b2 indirect calorimeter for the MIT energy expenditure dataset (n=16).

Activity category	RMSE (MAE)
Postures	0.6±0.2 (0.5±0.2)
Ambulation	2.4±0.5 (2.4±0.5)
Exercise	2.8±0.8 (2.8±0.8)
Resistance	3.4±0.7 (3.4±0.7)
Household	1.0±0.3 (1.0±0.3)
Upper Body	1.2±0.3 (1.2±0.3)
Lower Body	2.7±0.5 (2.7±0.5)

Table 5-56: Root Mean Squared Error and Mean Absolute Error (shown in parenthesis) per activity category when estimating energy expenditure using the 2-regression Crouter et al. Actigraph-based algorithm. Errors are computed with respect to the energy expenditure measured using the Cosmed K4b2 indirect calorimeter for the MIT energy expenditure dataset (n=16).

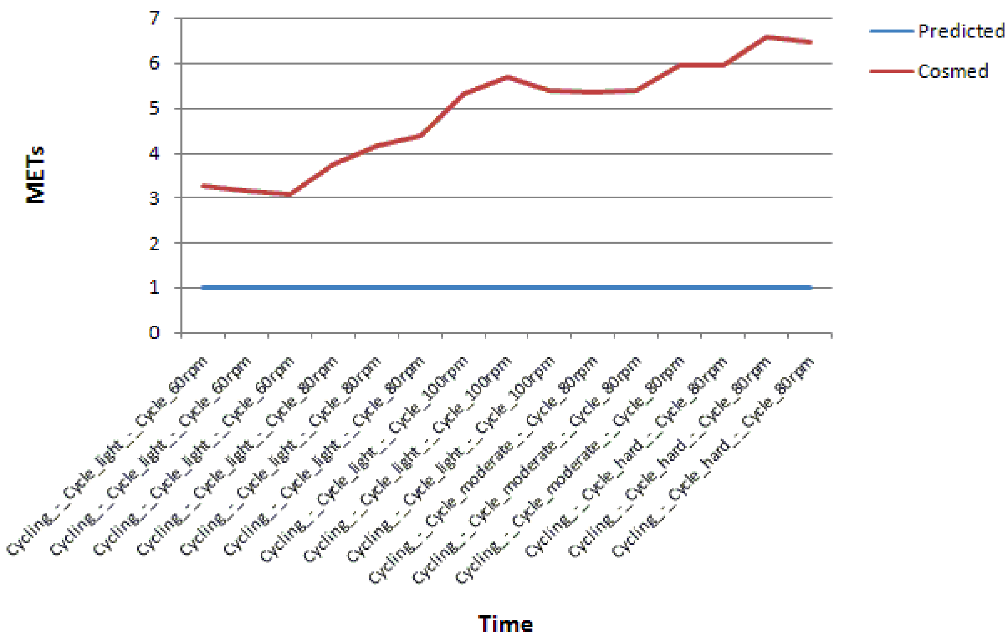
Error Measures over all activities	*Error Measures Values in METs*
Correlation Coefficient (r)	0.40 ± 0.14
Root Mean Square Error (RMSE)	3.23 ± 0.39
Mean Absolute Error (MAE)	2.45 ± 0.18
Maximum absolute error Deviation (MAED)	7.01 ± 2.27

Table 5-57: Performance over all activities when estimating energy expenditure for 11 activities using the 2-regression Crouter et al. algorithm over the Boston University dataset (n=2).

Activity	RMSE	MAE	MAED
Lying down	0.24 ± 0.02	0.17 ± 0.02	0.66 ± 0.11
Standing	0.10 ± 0.00	0.08 ± 0.01	0.18 ± 0.02
Sitting	0.11 ± 0.02	0.10 ± 0.02	0.15 ± 0.05
Walking - Treadmill 3mph 0	4.53 ± 0.41	4.52 ± 0.40	5.05 ± 0.50
Walking - Treadmill 3mph 6	3.30 ± 0.95	3.26 ± 0.96	4.11 ± 1.00
Walking - Treadmill 3mph 9	2.62 ± 1.03	2.54 ± 1.03	3.56 ± 1.20
Running - Treadmill 5mph 0	3.16 ± 0.74	2.89 ± 0.77	5.03 ± 0.96
Cycling - 60 rpm 1.0 kg	3.06 ± 0.83	3.05 ± 0.82	3.28 ± 0.95
Cycling - 80rpm 1.5 kg	5.65 ± 1.70	5.63 ± 1.72	6.00 ± 1.58
Cycling - 100 rpm 1.0 kg	5.46 ± 1.18	5.38 ± 1.11	5.99 ± 1.44
Unknown	3.31 ± 0.50	2.77 ± 0.23	6.71 ± 2.70

Table 5-58: Performance per activity when estimating energy expenditure using the 2-regression Crouter et al. algorithm over the Boston University dataset (n=2). RMSE stands for root mean squared error, MAE for mean absolute error, and MAED for maximum absolute error deviation.

(a)



(b)

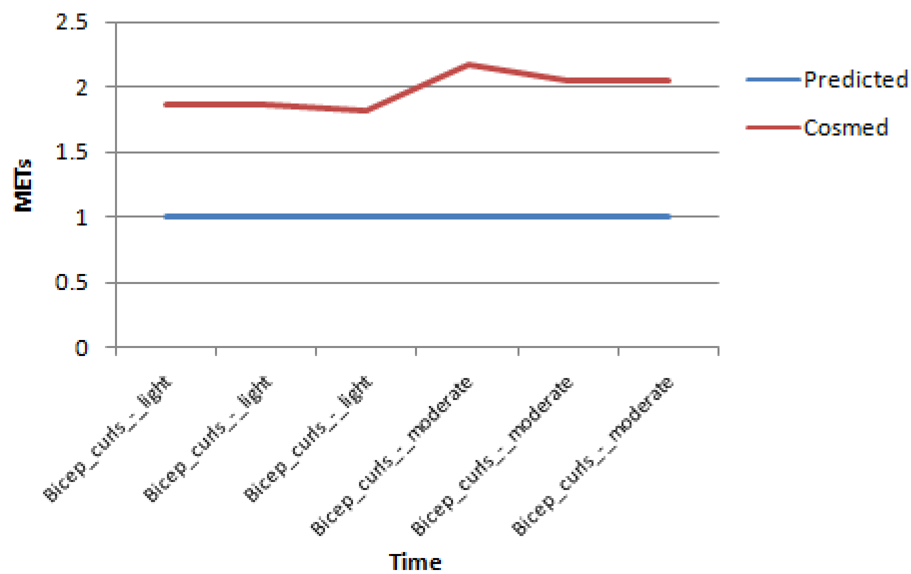


Figure 5-45 Graphical representation of the energy expenditure estimated for the (a) cycling activity and (b) bicep curls activity using the Crouter et al. method from a single Actigraph placed at the hip for subject MIT-018. The label 'Prediced' corresponds to the estimated energy expenditure and the label 'Cosmed' to the ground truth energy expenditure data collected from the Cosmed K4b2 indirect calorimeter.

inability of a single accelerometer at the hip to measure lower body and upper body activity produces underestimations of energy expenditure for the *cycling* and *bicep curls* activities. Obviously, any accelerometer placed at the hip might generate readings for intense upper body or lower body activity if it is not properly attached; nevertheless, estimates of energy expenditure from these readings would be unreliable because they could be generated by any type of activity and would most likely bias the energy expenditure predictions for other activities if a single regression model is utilized for all activities.

When the errors per activity are analyzed for the Crouter et al. algorithm over the MIT energy expenditure dataset as shown in Appendix B1, it is found that the highest maximum absolute error deviations happen for the following activities: *bench weight lifting* different weight loads (2.2-2.32 METs), *sit-ups* (4.5), *cycling* at different resistance levels (5.6-6.6), *rowing* at different resistance levels (5.5-6.5), *ascending stairs* (4.3), *walking* on a treadmill at different inclinations (4.2-5.9), and for the *unknown* activity (5.4). All of these activities include changes in resistance or work load effort or upper body motion that is poorly detected by an accelerometer at the hip. The *unknown* class has a high MAED because it consisted primarily of resting episodes after exhausting exercise where the subject was *standing* or *sitting*. Consequently, the MET readings where high during these periods of time because subjects had just finished the exercise routine but the amount of motion from the accelerometer was uncharacteristically low.

The Crouter et al. algorithm was also run over the Boston Medical Center dataset (n=2). Table 5-57 and Table 5-58 present the results. From these tables, it can be observed that the coefficient of correlation of 0.4 is very similar to the one obtained over the MIT dataset (0.36). Table 5-57 shows that the RMSE obtained over this dataset is higher (+0.57MET) than the one obtained over the MIT dataset. This increased error is the result of the poorer performance for *cycling* activities as compared with the MIT dataset and the higher impact of this error over the reduced set of activities in this dataset (11). The Actigraph readings for *cycling* were close to zero for all the activity duration (see the Actigraph vs. Parvo indirect calorimeter plots in Appendix B1) As a result, *cycling* was confused with sedentary activities and assigned a MET value of one. If one compares the plots of energy expenditure predictions from the Actigraph for both datasets, one finds that the Actigraph readings are not zero during *cycling* for some MIT data collections (e.g. subject MIT-004 in Appendix B1). The reason is that the Actigraph was located inside a pouch on a belt during the MIT data collections that oscillated more during the *cycling* activity than the Actigraph used in the Boston Medical Center data collection. This Actigraph was tightly attached using a belt clip and Velcro.

In conclusion, the prediction of energy expenditure using the Crouter et al. method from an accelerometer at the hip performs poorly for activities involving primarily upper body or lower body motion and activities involving load or resistance effort. One potential problem with the Crouter algorithm, as well as with other standard EE estimation algorithms used in the medical community, is the prediction of energy expenditure over one minute intervals. This relatively long window of time may be a problem because (1) EE for short duration activities (<1min) might be poorly predicted and (2) this window introduces a relatively long real-time prediction delay that might be restrictive for some real-time medical interventions.

5.6.2.2 How Well Can Energy Expenditure be Estimated Using Simple Linear Regression Algorithms?

This section explores how well energy expenditure can be estimated using simple regression algorithms in order to obtain a baseline on performance. Table 5-59 presents the form of the simple regression equations explored in this section to estimate energy expenditure. The equations in the table are presented in increasing order of complexity. The general procedure followed in this section is to first present the form of the energy expenditure prediction equation (from Table 5-59), explain the intuition behind the form of the equation being assumed, and then to learn the equation coefficients from the energy expenditure data contained in the MIT energy expenditure dataset. The coefficients of the formulas are found by minimizing the least-squares error with respect to the data in the MIT energy expenditure dataset. This is achieved by utilizing the LSQCURVEFIT function in MATLAB [227]. This function is able find the coefficients that best fit the linear or non-linear equation provided in the least-squares sense with respect to the training data provided (MIT energy expenditure dataset). The value of the initial guess used for all the coefficients was one.

Equation (a) is the simplest one in Table 5-59 and predicts energy expenditure by simply multiplying the overall motion experienced by the body (*ACTotalAbsArea*) by a constant. Appendix A3 provides an explanation of the *ACTotalAbsArea* feature, as well as the other features used in the equations shown in Table 5-59 (*ACAbsArea*, *ACTotalSF*, and *ACSF*). The intuition behind equation (a) is that energy expenditure should be proportional to the overall amount of motion (acceleration) experienced by the body. The proportionality constant simply scales overall motion to match the ground truth energy expenditure values. Table 5-60 presents the coefficients of equation (a) as learned from the data and Table 5-61 presents the performance of predicting energy expenditure over the data in the MIT dataset using subject independent training. Table 5-61 shows that the overall RMSE is 1.75 METs, and that the correlation coefficient is relatively high 0.68 (maximum possible is one). The improvement in performance over Crouter et al. is 0.32 units for the correlation coefficient and 0.91MET for the RMSE. This is a considerable improvement and is achieved mostly due to the utilization of more sensors (7) that are capable of measuring upper body and lower body motion. The table also shows that the lowest RMSE errors are obtained for the household activity category. This is because most activities in the household category include motion patterns that are easy to detect from accelerometers (e.g. ambulation). The household activities that show the highest errors are activities involving effort due to resistance or work load such as *carrying groceries*, *gardening*, *weeding*, *scrubbing a surface*, and *washing windows* whose RMSE error oscillates around 1 MET. The activity categories with higher RMSE errors are exercise and resistance exercise. This is also because some activities in this category involve different resistance levels or work loads such as *cycling* and *rowing* at different resistance levels.

Equation	Form of prediction equation assumed
(a)	$METs = C_1 \cdot ACTotalAbsArea$
(b)	$METs = C_1 \cdot ACTotalAbsArea + C_2$
(c)	$METs = C_1 \cdot ACAbsArea_{Hip} + C_2 \cdot ACAbsArea_{NDWrist} + C_3 \cdot ACAbsArea_{DWrist} + C_4 \cdot ACAbsArea_{DFoot} + C_5 \cdot ACAbsArea_{NDFoot} + C_6 \cdot ACAbsArea_{DThigh} + C_7 \cdot ACAbsArea_{DUpperArm} + C_8$
(d)	$METs = C_1 \cdot ACTotalSF + C_2$ where $ACTotalSF = 0.578 \cdot ACAbsArea_{Hip} + 0.05 \cdot ACAbsArea_{NDWrist} + 0.05 \cdot ACAbsArea_{DWrist} + 0.161 \cdot ACAbsArea_{DFoot} + 0.161 \cdot ACAbsArea_{NDFoot}$
(e)	$METs = C_1 \cdot ACAbsArea_{Hip} + C_2 \cdot ACAbsArea_{NDWrist} + C_3 \cdot ACAbsArea_{DWrist} + C_4 \cdot ACAbsArea_{DFoot} + C_5 \cdot ACAbsArea_{NDFoot} + C_6$

Table 5-59: Form of the simple regression equations explored to estimate energy expenditure from the MIT energy expenditure dataset. Appendix A3 explains how *ACTotalAbsArea* is computed.

Equation	Activities	Prediction equation learned from data
(a)	All	$METs = 0.021 \cdot ACTotalAbsArea$
(b)	All	$METs = 0.013 \cdot ACTotalAbsArea + 1.58$
(c)	All	$METs = -0.026 \cdot ACAbsArea_{Hip} + 0.012 \cdot ACAbsArea_{NDWrist} + 0.019 \cdot ACAbsArea_{DWrist} + 0.019 \cdot ACAbsArea_{DFoot} + 0.015 \cdot ACAbsArea_{NDFoot} + 0.024 \cdot ACAbsArea_{DThigh} + 0.017 \cdot ACAbsArea_{DUpperArm} + 1.49$
(d)	All	$METs = 0.080 \cdot ACTotalSF + 1.83$
(e)	All	$METs = -0.0086 \cdot ACAbsArea_{Hip} + 0.015 \cdot ACAbsArea_{NDWrist} + 0.025 \cdot ACAbsArea_{DWrist} + 0.021 \cdot ACAbsArea_{DFoot} + 0.021 \cdot ACAbsArea_{NDFoot} + 1.53$
(e)	Accelerometer Recognizable Activities	$METs = 0.022 \cdot ACAbsArea_{Hip} + 0.020 \cdot ACAbsArea_{NDWrist} + 0.017 \cdot ACAbsArea_{DWrist} + 0.0097 \cdot ACAbsArea_{DFoot} + 0.014 \cdot ACAbsArea_{NDFoot} + 1.34$
(e)	Postures and Ambulation	$METs = 0.029 \cdot ACAbsArea_{Hip} + 0.018 \cdot ACAbsArea_{NDWrist} + 0.012 \cdot ACAbsArea_{DWrist} + 0.009 \cdot ACAbsArea_{DFoot} + 0.019 \cdot ACAbsArea_{NDFoot} + 0.88$

Table 5-60: Regression equations and their coefficients learned from the energy expenditure data contained in the MIT energy expenditure dataset.

Equation	Correlation	All	Postures	Ambulation	Exercise	Resistance	Household
(a)	0.68 ± 0.06	1.75 ± 0.38 (1.33 ± 0.27)	0.8±0.2 (0.7±0.2)	1.4±0.5 (1.3±0.5)	2.1±0.8 (2.0±0.8)	1.6±0.6 (1.5±0.6)	0.9±0.2 (0.8±0.2)
(b)	0.68 ± 0.06	1.36 ± 0.31 (1.03 ± 0.17)	0.8±0.2 (0.7±0.2)	1.0±0.4 (0.9±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.3±0.6)	0.7±0.2 (0.6±0.2)
(c)	0.68 ± 0.06	1.36 ± 0.30 (1.02 ± 0.17)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.6±0.2)
(d)	0.65 ± 0.07	1.41 ± 0.33 (1.07 ± 0.18)	0.9±0.2 (0.9±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.7±0.2 (0.7±0.2)
(e)	0.67 ± 0.05	1.37 ± 0.30 (1.03 ± 0.17)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.7±0.2)

Table 5-61: Correlation coefficient (r), root mean squared error, and mean absolute error (shown in parenthesis) obtained when estimating energy expenditure using the regression formulas shown in Table 5-58.

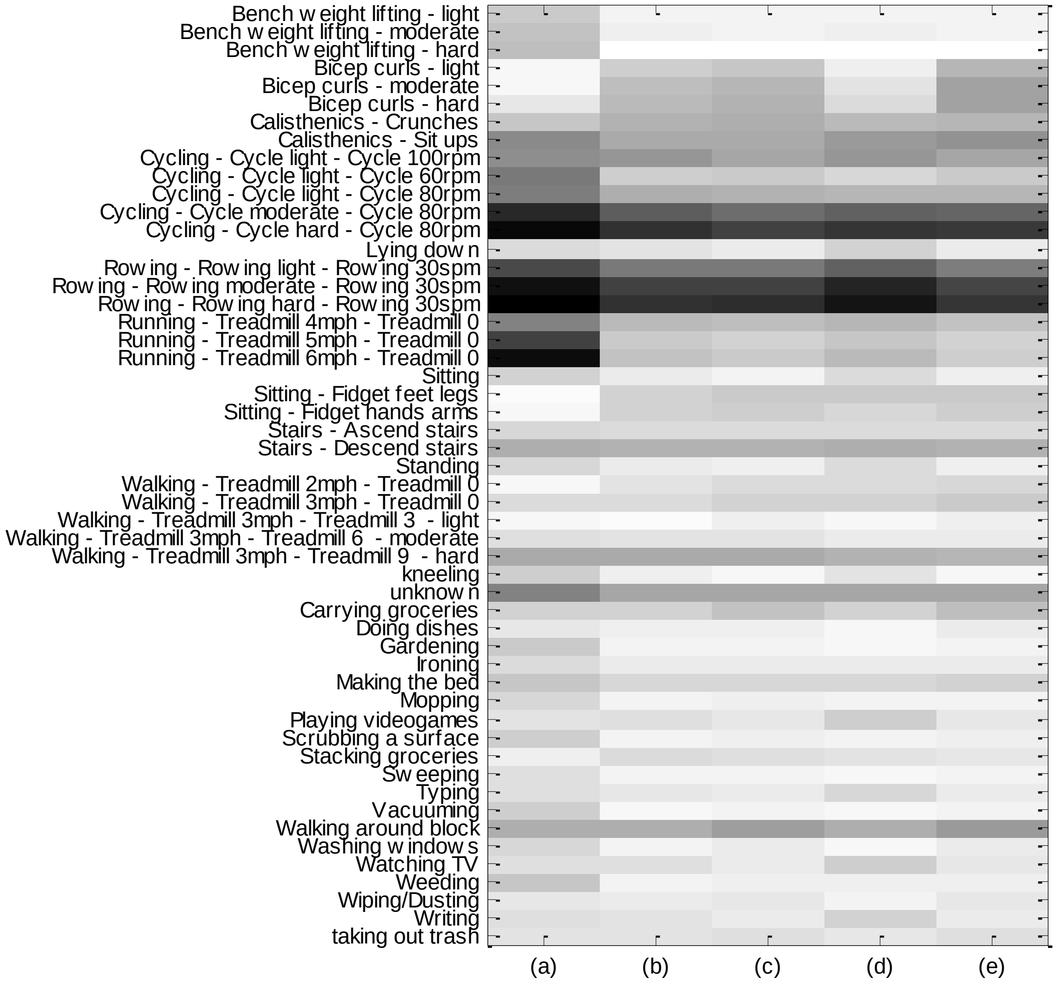


Figure 5-46: Root mean squared error (RMSE) when predicting energy expenditure using the equations in Table 5-59 shown as a grayscale image. The image is scaled to present the lowest RMSE of 0.36 in white and the highest of 3.7 in black. The X axis corresponds to the regression equation used to predict energy expenditure from Table 5-59.

The poor performance over these activities can also be seen in Figure 5-46. Figure 5-46 presents the RMSE as a grayscale image scaled to highlight differences in performance per activity. The image represents a RMSE of 0.36 MET in white and a RMSE of 3.7 MET in black. From this figure, it can also be seen that the RMSE of *running* at different speeds is high. This is because equation (a) lacks a constant or coefficient representing the DC offset of energy expenditure. When the performance per activity is inspected for the postures category, it is found that they all have RMSE errors close 1MET. This suggests that the energy predicted for postures by equation (a) is zero. This intuitively makes sense, since equation (a) does not have a coefficient representing the DC offset of the energy expenditure signal. As a result, since postures involve almost no motion, the *ACTotalAbsArea* feature is zero and the predicted energy is zero for these activities.

In response to the shortcomings of equation (a), a coefficient representing the DC offset of the energy expenditure signal was added resulting in equation (b). From Table 5-61 and Figure 5-46 it can be observed that the performance over *postures*, *running* at different speeds, *bench weight lifting*, *cycling* and *rowing* has been improved. Table 5-61 shows that the performance over the ambulation and household activities has also been improved. However, the table deceptively shows that the performance for postures has not changed. When the performance per activity is inspected (see Appendix B2 for detailed results per activity), it is found that the performance for *standing*, *sitting*, and *kneeling* has been improved, but the performance over *sitting fidgeting hands arms* and *sitting fidgeting legs* has increased. As a result, the overall RMSE over the postures category remains the same as for equation (a). The value of the DC coefficient (1.58 MET) for equation (b) shown in Table 5-60 implies that the energy expenditure associated with sedentary activities (with MET values close to 1) will be always overestimated. This is because if there is no motion, the minimum prediction would be a value of 1.58 MET. This might be because a single regression model is utilized to estimate energy expenditure and thus, it has to optimize the coefficients for all activities simultaneously. As a result, this model is forced to increase the DC coefficient to produce better estimates for physically demanding activities that produced high values of energy expenditure such as *cycling*, *bicep curls*, and *bench weight lifting*.

Equation (c) in Table 5-59 improves over equation (b) by estimating energy expenditure multiplying the motion (acceleration) experienced by each body segment (with an accelerometer attached to it) by a constant. This equation also includes a coefficient representing the DC offset of the energy expenditure signal so that energy expenditure for sedentary activities can be better predicted. These coefficients can be thought as weights that can be tuned by the regression model during learning to better represent the individual contribution of each body segment to energy expenditure. Inspection of the results per activity from Figure 5-46 and Appendix B2 indicates that the RMSE slightly redistributes over all activities. As a result, Table 5-61 indicates that the overall RMSE and RMSE per activity category remain practically unchanged. Thus there is no clear advantage of using equation (c) over equation (b). In fact, equation (b) should be preferred over equation (c) given its lower computational requirements when only overall body motion (e.g. *ACTotalAbsArea* or *ACAbsArea* feature) is utilized to estimate energy expenditure. This might be because the overall amount of motion is the same when it is summed over all body segments or analyzed per body segment.

Another simple technique that can be used to predict energy expenditure derived from the work energy theorem is to compute the force associated with each body segment and multiply it by a scaling constant to obtain energy expenditure. Segmental force can be estimated by multiplying the motion or acceleration experienced at each body segment (ACAbsArea) by the approximate mass of the body segment. Equation (d) performs exactly this operation by obtaining the body segment masses from the Depmster's body segment model [236]. Equation (d) also includes a constant representing the DC offset of the energy expenditure signal. When the performance of equation (d) is evaluated, it is found that the overall coefficient of correlation decreases by 0.03 and overall RMSE decreases 0.05 METs as shown in Table 5-58. At first glance, this result is counter intuitive since it makes perfect sense to think that the energy expenditure associated with manipulating a body segment is directly proportional to the mass of that body segment.

When the results are inspected per activity, it is found that energy expenditure prediction worsens for sedentary activities such as *writing*, *typing*, *playing video games*, *sitting*, and *standing* and for some resistance activities such as *rowing* and *cycling*. Performance decreases for sedentary activities because the DC offset learned using equation (d) is 1.83 and will always over predict the energy expenditure associated with sedentary activities. The only activities for which performance improves between 0.1 and 0.57 METs by the use of equation (d) are activities involving motion at the upper limbs such as *bicep curls, sitting fidgeting hands arms, carrying groceries, scrubbing a surface, and wiping/dusting.* This might be a result of equation (d) better capturing energy expenditure at the upper body due to the weighing of the accelerometer signal by the mass of the arms.

In order to better understand why equation (d) does not improve performance over equation (c), the coefficients representing the mass associated with each body segment were learned from the MIT dataset instead of being specified a priori using the Dempter's body segment model. This corresponds to equation (e) in Table 5-59. Ideally, when the coefficients are learned from the data, they should reflect the mass distribution of the body segments. For example, the coefficient for the accelerometer at the hip should be larger than the coefficient for the accelerometers at the wrists (arms) and feet (legs). Similarly, the coefficient for the accelerometers at the feet (legs) should also be larger than the coefficient for the accelerometers at the wrists (arms). Table 5-60 presents the coefficients learned from all the activities contained in the MIT EE dataset for equation (e). It is clear that not all coefficient values reflect the mass distribution of the body segments. For example, the coefficient of the accelerometer at the hip has a negative value and the coefficients for the wrists are not equal. The coefficient at the dominant wrist is also larger than the coefficient for both feet. One explanation for the distribution of values obtained for the coefficients is that most activities in the MIT EE dataset include different levels of resistance or work load effort associated with upper body and lower body extremities. For example, the high values of energy expenditure obtained during *bench weight lifting*, which primarily involve upper body motion, could distort (increase) the coefficient values associated with the wrists. A similar situation would happen during *cycling* at different resistance levels, leading to distorted values for the coefficients of all body segments. If this explanation is correct, that would indicate that energy expenditure is strongly depend on the activity being performed and that energy expenditure predicted for any activity involving the sightless amount of effort or resistance work using equations similar to equation (d) would be off. This might be one reason why the Crouter et al. regression model has been shown to estimate energy expenditure well since it utilizes activity dependent regression models for sedentary, ambulation and lifestyle activities.

To test if activities involving resistance or work load effort are distorting the coefficient values learned for the body segments in equation (e), they were eliminated from the training data. Appendix B3 shows what activities were preserved in the training data under the column labeled as "Accelerometer recognizable". Table 5-60 presents the coefficients learned for equation (e) using the "Accelerometer recognizable" activities set. It can be seen that now the hip has a positive coefficient larger than the coefficient for the wrists (arms) and feet (legs). Moreover, the coefficient for the DWrist is close to the value of the NDWrist and the DFoot coefficient is close to the NDFoot coefficient.

However, the coefficient for the wrists (arms) is larger than the coefficients for the legs. This is because some activities contained in the “Accelerometer recognizable” category either contain some degree of effort or high motion associated with upper body activity such as *doing dishes*, *gardening*, *weeding*, *wiping/dusting* and *ironing*. In a final attempt to improve the distribution of the coefficient values equation (e) was re-trained using only postures and ambulation activities. The activities included in this category are also shown in Appendix B3 under the column labeled as “Posture and Ambulation”. The final row of Table 5-60 present the final coefficients learned from this activity category. It can be seen that the distribution of the weights indeed improved since the coefficient for the hip increased, and the coefficient at the NDFoot also increased now being larger than the coefficients at the wrists (arms). The value of the coefficient representing the DC offset of the energy expenditure signal also improved since now is closer to 1MET, the ideal value for sedentary activities.

In summary, energy expenditure can be estimated using simple multivariable linear regression algorithms such as equation (c) obtaining a final correlation coefficient of 0.68 and a root mean squared error of 1.36MET. The incorporation of a coefficient representing the DC offset of the energy expenditure signal improves the estimate for sedentary activities such as postures, and other activities such as *cycling* and *running*. Finally, energy expenditure cannot be predicted reliably utilizing equation (d) (based on the work energy theorem) because different activities include different levels of upper body and lower body effort. Consequently, the importance weight or coefficient for each limb is dependent on the activity being performed. For example, if *bench weight lifting* is being performed, the acceleration at the upper limbs needs to be weighted more to predict energy expenditure reliably. Similarly, during *cycling* at high resistances, the weight for the lower limbs needs to be increased according. Nonetheless, during activities such as *walking* and *running*, the weight for upper body and lower body limbs could potentially be very close, thus contributing equally to overall energy expenditure. The results obtained using equation (c) are better than the ones obtained using the Crouter et al. algorithm. Obviously, this is mostly due to the utilization of seven sensors that better capture overall, upper body and lower body motion. The upcoming sections will investigate how well can energy expenditure can be estimated by creating regression models that depend on the activity being performed. In this way, the regression coefficients for the models used can have optimal values depending on the activity being performed.

5.6.2.3 How Well Can Energy Expenditure be Estimated Using the Compendium of Physical Activities?

One of the standard methods that the medical community utilizes to estimate energy expenditure during free-living is to collect information about subjects’ activities using direct observation or self-report and later rate their energy expenditure according to the Compendium of Physical Activities [122]. The Compendium of Physical Activities consists of a list of the most common everyday physical activities and their associated average energy expenditure in metabolic equivalents (METs). Given the popularity of this method, this section explores how well it can estimate energy expenditure over the

Error Measures	Comparable Activities	Closest Activities
Total Correlation Coefficient	0.86 ± 0.10	0.80 ± 0.09
Total Root Mean Square Error	1.27 ± 0.33	1.61 ± 0.41
Total Mean Absolute Error	0.85 ± 0.21	1.12 ± 0.28
Maximum Absolute Deviation	4.17 ± 0.86	5.57 ± 1.33

Table 5-62: Performance of estimating energy expenditure using the Compendium of Physical Activities over the *comparable* and *closest* activity sets. Energy expenditure was predicted over windows of one minute in length.

Activity Set	Total Number of Activities	Postures	Ambulation	Exercise	Resistance	Household
Comparable	29	0.2±0.1 (0.2±0.1)	1.4±0.5 (1.3±0.5)	2.1±0.7 (2.0±0.8)	2.1±0.4 (2.0±0.4)	0.9±0.3 (0.9±0.3)
Closest	52	0.3±0.2 (0.3±0.2)	1.5±0.4 (1.4±0.4)	2.3±0.7 (2.2±0.7)	2.0±0.5 (2.0±0.6)	0.9±0.3 (0.9±0.3)

Table 5-63: Root mean squared error and mean absolute error (shown in parenthesis) per activity category when estimating energy expenditure using the Compendium of Physical Activities over the *comparable* and *closest* activity sets.

MIT dataset assuming that the activities performed are known from the activity labels collected during the data collections.

This experiment is performed over two sets of activities: (1) the *comparable* set of activities and (2) the *closest* set of activities. The *comparable* set of activities includes only the activities in the MIT dataset that are directly comparable with those found in the Compendium of Physical Activities. In other words, this set of activities completely matches the physical activity description, speed of execution, and/or resistance level found in the Compendium of Physical Activities. The *closest* set of activities consists of all the activities contained in the MIT dataset and their corresponding closest match found in the compendium. For example, *cycling at 80rmp* at a moderate intensity level (resistance level of 7 in a Precor C846 recumbent stationary bicycle) was not found in the Compendium. However, the closest activity in the compendium is *cycling* at a 100W power level. Appendix B4 presents the activities contained in the MIT dataset, their corresponding closest activities from the Compendium, and whether or not they are included in the *comparable* activity set.

Table 5-62 presents the performance of estimating energy expenditure using the Compendium of Physical Activities over the *comparable* and *closest* activities sets assuming the activity being performed is known. In order to be able to compare the estimation performance with the results obtained using the Crouter et al. Actigraph-based algorithm, energy expenditure is predicted over windows of one minute in length. Table 5-62 shows that the correlation coefficient and RMSE error obtained over both activity sets are higher than the results obtained using the Crouter et al. Actigraphs-based algorithm (r=0.4, RMSE=3.23). As expected, performance is slightly better over the *comparable* activities set because it contains 23 fewer activities than the *closest* activity set. The maximum absolute error deviation of 4.2 METs and 5.6 METs for the *comparable* and *closet* activity sets, respectively, is also lower than the one obtained using the Crouter et al. method (7.0 METs). The largest decrease in RMSE error with respect to the Crouter et al. method was observed for the following activity categories: postures (-0.4 METs), ambulation (-1 MET), exercise (-0.7 METs), and resistance exercise (-1.3 MET).

When the RMSE per activity is analyzed from Appendix B5, it is found that the Compendium tends to overestimate the energy expenditure associated with some household activities such as *gardening*, *making the bed*, *scrubbing a surface*, *weeding* and *vacuuming*. These activities are highly variable and unconstrained since they can be performed with differently styles, intensities and objects (e.g. industrial vacuum cleaner vs. portable vacuum cleaner). Therefore, their energy expenditure value is difficult to predict from just the average value listed in the Compendium of Physical Activities. The Compendium of Physical Activities also overestimates energy expenditure for some physically demanding activities such as *ascending stairs*, *sit-ups*, and *running* at 6mph. This is because the activity examples collected for these activities have individual durations of less than a minute, thus preventing energy expenditure from reaching steady state (which is the average value listed in the Compendium of Physical Activities). This effect can also be seen in Appendix B5, which presents plots of the energy expenditure estimated using the Compendium of Physical Activities vs. the measurements using the Cosmed K4b2 indirect calorimeter. Finally, energy expenditure is better predicted for activities that reached steady state during the data collection such as postures and ambulation (*walking* and *running*).

In summary, if the activity performed is known, energy expenditure can be estimated well by simply predicting the average METs value associated with an activity. Obviously, the quality of the estimate depends on how close the average METs value utilized on the predictions and the truth energy expenditure of the activity of interest are. The main disadvantages of applying this method to estimate energy expenditure are: (1) the type and duration of the physical activities performed needs to be known in advance and (2) the physical activities performed need to be listed in the Compendium of Physical Activities.

5.6.2.4 Estimating Energy Expenditure Using One Linear Regression Model per Activity.

The results presented in previous sections and some recent work [34, 96] suggest that energy expenditure can be better estimated if the activities being performed are known. For example, Section 5.6.2.2 indicated that the optimal value for the coefficients of a regression equation used to estimate energy expenditure depend on the activity being performed. For example, during the execution of *bicep curls*, it might be necessary to assign a greater weight to the regression coefficients representing the acceleration at upper extremities. Conversely, during *cycling*, it might be necessary to assign a greater weight to the coefficients representing the acceleration at the lower limbs. One way to achieve this it to model energy expenditure utilizing independent regression models whose coefficients can be tuned depending on the activities being performed. In fact, Section 5.6.2.3 showed that a good performance in energy expenditure estimation with respect to state-of-the-art Actigraph algorithms can be achieved by simply predicting the average energy expenditure value for each activity. As a result, this section explores how well energy expenditure can be estimated if it is modeled using one independent multivariable linear regression model per activity.

Error Measures	Results
Total Correlation Coefficient	0.87 ± 0.10
Total Root Mean Square Error	1.02 ± 0.45
Total Mean Absolute Error	0.63 ± 0.19
Maximum Absolute Error Deviation	4.21 ± 2.89

Table 5-64: Performance obtained over the MIT energy expenditure dataset while estimating energy expenditure using one multivariable linear regression model per activity. The regression models per activity were trained using the *ACAbsArea* feature computed per sensor over windows of one minute in length. Performance is measured with respect to energy expenditure data collected from the Cosmed K4b2 indirect calorimeter

Activity Category	RMSE (MAE)
Postures	0.3±0.2 (0.3±0.2)
Ambulation	0.9±0.7 (0.8±0.7)
Exercise	1.1±0.9 (1.1±0.8)
Resistance	0.8±0.5 (0.8±0.5)
Household	0.5±0.3 (0.4±0.3)
Upper Body	0.4±0.3 (0.4±0.2)
Lower Body	0.9±0.5 (0.8±0.5)

Table 5-65: Root mean squared error and mean absolute error (shown in parenthesis) obtained over the MIT energy expenditure dataset when estimating energy expenditure using one multivariable linear regression model per activity. The regression models per activity were trained using the *ACAbsArea* feature computed per sensor over windows of one minute in length. Performance is measured with respect to energy expenditure data collected from the Cosmed K4b2 indirect calorimeter

Table 5-64 presents the performance of predicting energy expenditure over the MIT dataset using one multivariable linear regression model per activity. For simplicity, the activities performed are assumed to be known from the labels and timestamps recorded during the data collections. Performance is measured using the *ACAbsArea* feature, one of the most commonly employed features when estimating energy expenditure in prior work. Appendix A3 explains how the *ACAbsArea* feature is computed. Energy is estimated over windows of one minute in length to facilitate comparison with prior work. Table 5-64 shows that the coefficient of correlation (0.87) and RMSE error (1.02) obtained are the lowest achieved so far. This indicates that performance is clearly improved when activity dependent regression models are used. Appendix B7 presents plots of energy expenditure estimated versus measured using the Cosmed K4b2 indirect calorimeter for two subjects. The plots show that energy expenditure estimated closely follows energy expenditure measured except for activities involving different levels of resistance or work load. This is because the effort associated with these activities is not captured well from accelerometers since the motion signature of activities (e.g. speed of execution or motion patterns involved) does not change or is not detectable in a subject independent manner.

Table 5-65 shows the performance per activity category obtained using one linear regression model per activity. The best performance is obtained over postures and household activities and the worse over exercise, resistance exercise, and lower body activities, as found in previous sections. Lower body activities present a relatively high RMSE because this category consists mainly of the *cycling* activities that contain different levels of resistance work not detectable from accelerometers. Overall, the performance per activity category is also the highest found so far.

When the performance per activity is inspected from Appendix B7, it is found that the activities with lowest RMSE are *bench weight lifting* (0.16 MET), *doing dishes* (0.16 MET), and *watching TV* (0.18 MET). The activities with higher RMSE are calisthenics *crunches* and *sit-ups*, *descending stairs*, and *running* on a treadmill at different speeds. The maximum absolute error deviation is also the highest for these activities. As explained before, error is high for *crunches* and *sit-ups* because they were executed for short periods of time (<1min) and steady-state energy expenditure was never reached. The high error in *descending stairs* can be explained also by its short duration (<1min) and by the fact that it was executed almost immediately after *ascending stairs*. As a result, the indirect calorimeter readings were still high (from ascending stairs) when this activity was being executed. Thus, the amounts of motion present during the execution of this activity did not justify the high energy expenditure values observed. Finally, the poor performance over the *running* activities can be explained by the different physical fitness level of individuals. For example, energy expenditure observed during running was higher for obese participants than for lean and physically fit participants.

In conclusion, the results presented in this section indicate that the use of activity dependent regression models improve energy expenditure estimation considerably. One obvious concern with the applicability of method in practice is that activities have to be first recognized in order to apply the corresponding regression models. Section 5.6.11.2 will later explore how well energy expenditure can be estimated in practice using this method by recognizing activities using the algorithm implemented in Section 5.4.9.

5.6.2.5 How Well Can Energy Expenditure be Estimated Using One Non-Linear Regression Model per Activity?

Following up on the preceding section, this section explores the performance of estimating energy expenditure using one non-linear regression model per activity when the activities performed are assumed to be known. The non-linear regression model used is a M5' model tree trained using the *ACAbsArea* feature computed per sensor over windows of one minute in length. Appendix A3 explains how the *ACAbsArea* feature is computed. The parameters of the M5' model tree used are shown in Table 5-70. The main objective of this section is to measure the improvement in performance with respect to one linear regression model per activity.

Table 5-67 presents the error measures obtained when estimating energy expenditure using one non-linear regression model per activity over the MIT energy expenditure dataset. The table shows that performance is improved for all error measures. For example, the correlation coefficient improves +0.04 units and RMSE improves 0.14 MET with respect to one linear regression model per activity. The largest improvement in performance of 0.85 MET is observed for the maximum absolute error deviation.

Table 5-67 illustrates the root mean squared error and mean absolute error per activity category. It can be seen that RMSE error is uniformly distributed for the household and upper body activity categories (0.4 MET) and for the ambulation, resistance exercise and lower body activity categories (0.8 MET). RMSE error is higher (1 MET) for exercise activities because this category contains more activities than the other categories (n=19). The only RMSE error that does not improve with respect to Table 5-65 and practically

Error Measures	Results
Total Correlation Coefficient	0.91 ± 0.04
Total Root Mean Square Error	0.88 ± 0.25
Total Mean Absolute Error	0.59 ± 0.15
Maximum Absolute Deviation	3.36 ± 1.18

Table 5-66: Performance obtained over the MIT energy expenditure dataset when estimating energy expenditure using one non-linear regression model (M5' model tree) per activity. The regression models per activity were trained using the *ACAbsArea* feature computed per sensor over windows of one minute in length. Performance is measured with respect to energy expenditure data measured using the Cosmed K4b2 indirect calorimeter

Activity Category	RMSE (MAE)
Postures	0.2±0.2 (0.2±0.2)
Ambulation	0.8±0.4 (0.7±0.4)
Exercise	1.0±0.6 (1.0±0.6)
Resistance	0.8±0.5 (0.7±0.5)
Household	0.4±0.3 (0.4±0.2)
Upper Body	0.4±0.3 (0.4±0.2)
Lower Body	0.8±0.4 (0.8±0.4)

Table 5-67: Root mean squared error and mean absolute error (shown in parenthesis) obtained over the MIT energy expenditure dataset when estimating energy expenditure using one non-linear regression model (M5' model tree) per activity. The regression models per activity were trained using the *ACAbsArea* feature computed per sensor over windows of one minute in length. Performance is measured with respect to energy expenditure data measured using the Cosmed K4b2 indirect calorimeter

remains unchanged is the error for the resistance exercise category. Apparently, this error is already as low as it can be given that energy expenditure associated with different resistance level and work load effort is poorly detected using accelerometers.

When the RMSE is inspected per activity and compared to the one obtained using one linear regression model per activity, it is found that it slightly improves for most activities and that improvement is higher for *crunches* (-1.6 MET), *ascending stairs* (-0.9 MET), and *bicep curls moderate* (-0.44 MET). The maximum absolute error deviation for these activities also improves substantially (0.9-1.7 MET). Intuitively this improvement makes sense, since the energy expenditure associated with these activities increases exponentially over time, and is better captured using non-linear regression models. The same improvements in RMSE are observed when visualizing the energy expenditure plots presented in Appendix B8.

In summary, utilizing one non-linear regression model per activity improves performance considerably over one linear regression model per activity for some activities. Knowledge of which activities are improved the most might allow the application of non-linear regression models only for those activities that benefit from it, thus, successfully reducing computational complexity since linear models would still be applied for most activities.

5.6.2.6 Summary of Baseline Results

In summary, the results presented in previous sections indicate that overall performance and performance per activity are improved the most when the activities performed are known. Section 5.6.2.3 illustrated that excellent results with respect to state-of-the-art

Error Measures	Crouter et al. Actigraph	Compendium Comparable Activities	Compendium Closest Activities	Linear Regression	One Linear Regression model per activity	One non-linear regression model per activity
Total Correlation Coefficient	0.36 ± 0.09	0.86 ± 0.10	0.80 ± 0.09	0.73 ± 0.06	0.87 ± 0.10	0.91 ± 0.04
Total Root Mean Square Error	2.66 ± 0.62	1.27 ± 0.33	1.61 ± 0.41	1.28 ± 0. 29	1.02 ± 0.45	0.88 ± 0.25
Total Mean Absolute Error	1.94 ± 0.45	0.85 ± 0.21	1.12 ± 0.28	0.95 ± 0.16	0.63 ± 0.19	0.59 ± 0.15
Maximum Absolute Deviation	6.94 ± 1.77	4.17 ± 0.86	5.57 ± 1.33	4.12 ± 1.21	4.21 ± 2.89	3.36 ± 1.18

Table 5-68: Comparison of the performance obtained using the energy expenditure estimation methods explored in this section. All methods estimate energy expenditure over sliding windows of one minute in length. The methods that utilize linear or non-linear regression are trained using the *ACAbsArea* feature computed per sensor.

Activity Category	Crouter et al. Actigraph	Compendium Comparable Activities	Compendium Closest Activities	Linear Regression	One Linear Regression model per activity	One Non-linear regression model per activity
Postures	0.6±0.2 (0.5±0.2)	0.2±0.1 (0.2±0.1)	0.3±0.2 (0.3±0.2)	0.6±0.2 (0.6±0.2)	0.3±0.2 (0.3±0.2)	0.2±0.2 (0.2±0.2)
Ambulation	2.4±0.5 (2.4±0.5)	1.4±0.5 (1.3±0.5)	1.5±0.4 (1.4±0.4)	1.0±0.5 (1.0±0.5)	0.9±0.7 (0.8±0.7)	0.8±0.4 (0.7±0.4)
Exercise	2.8±0.8 (2.8±0.8)	2.1±0.7 (2.0±0.8)	2.3±0.7 (2.2±0.7)	1.5±0.8 (1.4±0.7)	1.1±0.9 (1.1±0.8)	1.0±0.6 (1.0±0.6)
Resistance	3.4±0.7 (3.4±0.7)	2.1±0.4 (2.0±0.4)	2.0±0.5 (2.0±0.6)	1.3±0.6 (1.3±0.6)	0.8±0.5 (0.8±0.5)	0.8±0.5 (0.7±0.5)
Household	1.0±0.3 (1.0±0.3)	0.9±0.3 (0.9±0.3)	0.9±0.3 (0.9±0.3)	0.7±0.3 (0.6±0.3)	0.5±0.3 (0.4±0.3)	0.4±0.3 (0.4±0.2)
Upper Body	1.2±0.3 (1.2±0.3)	0.8±0.3 (0.8±0.3)	1.3±0.3 (1.3±0.3)	0.7±0.3 (0.7±0.3)	0.4±0.3 (0.4±0.2)	0.4±0.3 (0.4±0.2)
Lower Body	2.7±0.5 (2.7±0.5)	-	1.3±0.5 (1.3±0.5)	1.6±0.8 (1.6±0.8)	0.9±0.5 (0.8±0.5)	0.8±0.4 (0.8±0.4)

Table 5-69: Root mean squared error and mean absolute error (shown in parenthesis) obtained using the different energy expenditure estimation methods explored in this section. All methods estimate energy expenditure over sliding windows of one minute in length. The methods that utilize linear or non-linear regression are trained using the *ACAbsArea* feature computed per sensor.

Actigraph-based algorithms can be obtained by just predicting the average energy expenditure associated with each activity from the Compendium of Physical Activities. The results obtained with this method are also competitive with the performance obtained using multivariable linear regression and the *ACAbsArea* feature computed over all the seven accelerometer sensors. Section 5.6.8 will later explore the impact of reducing the number of sensor while estimating energy expenditure using multivariable linear regression. Clearly, another advantage of estimating energy expenditure by recognizing activities is that the knowledge of the activities performed is important information that can be used for medical purposes or in just-in-time interventions to motivate increases in physical activity levels.

Energy expenditure estimation can be further improved by applying linear and non-linear activity dependent models. The performance of both methods improves over a single multivariable linear regression model applied to all activities at once. In particular, one non-linear regression model per activity improves performance for activities whose energy expenditure patterns are non-linear such as *ascending stairs* and *crunches*. These results hold when there is enough data to train the linear or non-linear regression models per activity as in the analysis presented previously, since only one feature *ACAbsArea* is utilized. Results might be different; for example, if more features are used to estimate energy expenditure and the amounts of data available are insufficient to train the large number of linear and/or non-linear regression models (as later found in Section 5.6.3).

Table 5-68 and Table 5-69 present a comparison of the performance obtained using the different methods explored in this section to estimate energy expenditure. Table 5-68 shows that the Crouter et al. Actigraph-based energy expenditure estimation method presents the worse performance. The most likely reason for this poor performance is that this method predicts energy expenditure from just one accelerometer located at the hip (Actigraph) while the methods that use linear or non-linear regression utilize the data from the best case scenario of seven accelerometers located at different body segments. Using one single accelerometer at the hip to estimate energy expenditure (as most medical research studies do) has the disadvantage of poorly detecting energy expenditure associated with upper body and lower body activity. In fact, most of the energy expenditure predicted from an accelerometer at the hip comes from ambulatory activities. Table 5-69 clearly shows that the Crouter et al. method has the worst performance in estimating energy expenditure for upper body and lower body activities. For example, the Crouter et al. method presents a RMSE of 6.4 MET for *cycling hard at 80rmp* while multivariable linear regression using all sensors presents an error of just 2.9 MET, mostly due to the inability of the accelerometers to capture information that can differentiate *cycling* at different resistance levels. Similarly, the Crouter et al. method presents a RMSE error of ~2.0 MET for *bicep curls moderate* and *hard* while linear regression presents an error between 0.2-0.5 MET for these activities. Energy expenditure algorithms capable of detecting upper body and lower body activity are likely to be superior in performance to algorithms based on single accelerometers located at the hip.

The following sections will perform systematic experiments in increasing order of complexity to determine the most suitable parameters for the energy expenditure estimation algorithm developed in this work with the ultimate goal of achieving real-time performance.

5.6.3 Can Fast Run-Time Regression Algorithms Produce Acceptable Performance?

This section compares the performance of regression algorithms with fast prediction times that are amenable for real-time performance with other regression algorithms with longer training and prediction times. The goal of the section is to identify the regression algorithm that provides the best trade-off between computational complexity and performance.

The algorithms compared in this section are multivariable linear regression, M5' regression and model trees [237, 238], and epsilon support vector regression (ε-SVR) [239, 240]. The performance of multivariable linear regression, M5' regression trees, and M5' model trees was evaluated using the Weka toolkit [226], and the performance of epsilon support vector regression was evaluated using the LibSVM library for support vector machines [241]. Table 5-70 presents a brief description of each regression algorithm as well as the parameters used for each of them during the experiments.

Regression Algorithm	Description	Parameters	Ref
Linear Regression (LR)	A regression algorithm that models the statistical relationship between predictor (x) and predicted (y) variables employing the following linear equation: $$y = \sum_{i=1}^{n} w_i \cdot x_i + w_0$$ The coefficients w are found by minimizing the sum of the square of the residuals (y_i - x_i) or least square error with respect to a set of training data points.	Multivariable linear regression using the M5 attribute selection method (based on the Akaike information criterion), elimination of collinear attributes, and a Ridge parameter value of 1.0E-8.	
M5' Regression Trees (RT)	A non-linear regression algorithm that builds tree-based models very similar to decision trees but that have numerical values representing the predicted variable at their leaves instead of predicted class values.	Regression tree built with the M5' algorithm using pruning, a minimum of four instances per leaf, and smoothed predictions.	[237] [238]
M5' Model Trees (MT)	A non-linear regression algorithm that builds tree-based models very similar to regression trees but that have multivariate linear models at their leaves instead of class values. As a result, predicted variables are approximated by piecewise linear functions. This algorithm can handle problems with higher dimensionality than MARS [242] and generate smaller and more accurate trees than CART [243].	Model tree built with the M5' algorithm using pruning, a minimum of four instances per leaf, and smoothed predictions.	[237] [238]
Epsilon Support Vector Regression (ε-SVR)	A regression algorithm based on support vector machines [216] that, when used in combination with a radial basis function kernel, is able to learn complex non-linear relationships between predictor and predicted variables.	Epsilon support vector regression using a radial basis function kernel, the shrinking heuristics, and parameters cost (C), gamma (γ), and epsilon (ε) found by performing a grid search over the parameter space. The optimal values found for these parameters were: *ACAbsArea* feature C=64, γ=1.0, and ε=0.5 *MaxAcceleration* feature set C=8.0, γ=0.0625, ε=0.0625	[239] [240]

Table 5-70: Brief description of the regression algorithms explored in this section and their parameters. Ref stands for reference and points to literature describing the algorithms in full detail.

	Feature Set	LR	RT	MT	ε-SVR
Total training time (Average time per instance)	*ACAbsArea*	0.71s (0.03ms)	211.5s (8.1ms)	285s (11ms)	176s (7.4ms)
Total prediction time (Average time per instance)	*ACAbsArea*	1.0s (0.5ms)	0.9s (0.5ms)	1.0s (0.5ms)	8.5s (4.0ms)
Total training time (Average time per instance)	*MaxAcceleration*	285.8s (12.064ms)	528s (22.32ms)	1387s (58.5ms)	4227s (178.4ms)
Total prediction time (Average time per instance)	*MaxAcceleration*	1.5s (0.7ms)	1.4s (0.7ms)	4.4s (2.1ms)	82.8s (38.7ms)

Table 5-71: Total training and prediction times in seconds obtained during the first round of subject independent training for the linear and non-linear regression algorithms explored in this work. The total number of instances learned is 25, 832.

In this work, support vector regression (SVR) was chosen over multilayer neural networks regression for four reasons. (1) Unlike neural networks, SVR does not suffer from local minima problems since training involves solving a linearly constrained quadratic programming problem that always has a unique and globally optimal solution [239]. (2) SVR has fewer parameters to optimize (e.g. C, γ, and ε when the radial basis function kernel is used) than neural networks (e.g. number of network layers, number of nodes per layer, learning rate, momentum, form of transfer function, number of epoch, etc). Furthermore, there exist well-tested procedures to systematically find the optimal values for SVR parameters when the radial basis function kernel is used [244]. (3) SVR has capacity control of the regression function learned, which means that the complexity of the solution found is the minimal required to solve the problem at hand. (4) Finally, SVR has been found to be resistant to overfitting and to the curse of dimensionality [239].

The performance of each algorithm is analyzed in two extreme computational complexity conditions: (1) a best case scenario where energy expenditure is predicted from just one feature per sensor (*ACAbsArea*), and (2) a worse-case scenario where energy expenditure is predicted using all the accelerometer-based features computed per sensor (*MaxAcceleration* feature set). Features are computed over sliding windows of 5.6s in length.

Table 5-71 presents the total training and prediction times for each of the algorithms explored in seconds as well as the average training and prediction times per example (instance) in milliseconds. First, it can be observed that the training and prediction times are lower for the *ACAbsArea* feature set than for the *MaxAcceleration* feature set. This is because the *ACAbsArea* feature set has a vector size of only 7 while the *MaxAcceleration* feature set has a vector size of 247. The table shows that the algorithms with longer training times are model trees and ε-SVR. This is because model trees have to learn the tree structure from the data using the M5' algorithm and also one multivariable linear regression model (over subsets of the features) per leaf node. For ε-SVR, training involves the solution of a quadratic optimization problem that is computationally expensive ($O(nNSV + NSV$ were *n* is number of training examples and *NSV* number of support vectors [245]) and that is why it presents the long training times observed in Table 5-71. From the table, it can also be observed that the prediction times for linear regression, regression trees, and model trees are considerably lower than prediction times for ε-SVR. This is because prediction in linear regression only involves summations and multiplications over the features. For regression trees, it mainly involves the evaluation of fast if-then clauses over several feature values that depend on the structure of the tree learned. Once a leaf node is reached, the prediction made is a simple constant representing the average value of the predicted variable for the training examples that fall under that branch of the tree. In model trees, prediction also involves the evaluation of several if-then clauses over several feature values but it also requires the evaluation of the multivariable linear regression model at the leaf node. On the contrary, prediction in ε-SVR involves dot products over the number of support vectors found during training (subset of training data points that represent the final solution). As a result, prediction time depends on the number of support vectors found for a given problem. For the *ACAbsArea* feature, the number of support vectors found consists of 38% of the total number of training data points (25,832). For the *MaxAcceleration* set, the number of support vectors found is 30% of the total training examples. This large number of support vectors lead to the long prediction times observed in Table 5-71. The large number of support vectors found also suggests that energy expenditure prediction over the MIT EE dataset is difficult. In summary, from Table 5-71, we can conclude that the regression algorithms with best prediction times in increasing order are regression trees, linear regression, model trees, and support vector regression. The ordering of the algorithms with respect to training times in increasing order is: linear regression, regression trees,

Algorithm	Correlation Coefficient	All	Postures	Ambulation	Exercise	Resistance	Household
LR	0.68 ± 0.06	1.36 ± 0.30 (1.02 ± 0.17)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.6±0.2)
RT	0.73 ± 0.07	1.25 ± 0.29 (0.88 ± 0.18)	0.6±0.3 (0.5±0.2)	1.1±0.5 (1.0±0.5)	1.3±0.7 (1.1±0.7)	1.1±0.6 (1.0±0.5)	0.6±0.3 (0.5±0.2)
MT	0.72 ± 0.08	1.24 ± 0.29 (0.86 ± 0.19)	0.6±0.3 (0.5±0.2)	1.1±0.4 (0.9±0.4)	1.3±0.7 (1.2±0.7)	1.1±0.6 (1.0±0.6)	0.6±0.3 (0.5±0.2)
ε-SVR	0.74 ± 0.06	1.28 ± 0.29 (0.89 ± 0.21)	0.5±0.2 (0.4±0.2)	1.1±0.5 (1.0±0.5)	1.3±0.7 (1.2±0.7)	1.1±0.6 (1.0±0.6)	0.6±0.3 (0.5±0.3)

Table 5-72: Root mean squared error and mean absolute error (shown in parenthesis) per activity category when estimating energy expenditure using different regression algorithms and the *ACAbsArea* feature computed per sensor over sliding windows of 5.6s in length.

Algorithm	Correlation Coefficient	All	Postures	Ambulation	Exercise	Resistance	Household
LR	0.74 ± 0.10	1.24 ± 0.30 (0.91 ± 0.20)	0.7±0.3 (0.6±0.3)	1.2±0.5 (1.0±0.5)	1.2±0.7 (1.1±0.7)	1.1±0.6 (1.0±0.6)	0.7±0.3 (0.6±0.3)
RT	0.75 ± 0.06	1.21 ± 0.31 (0.86 ± 0.20)	0.6±0.3 (0.5±0.3)	1.1±0.4 (0.9±0.4)	1.2±0.7 (1.1±0.7)	1.1±0.6 (1.0±0.5)	0.6±0.2 (0.5±0.2)
MT	0.64 ± 0.17	1.56 ± 0.67 (0.94 ± 0.24)	1.0±1.5 (0.7±0.7)	1.2±0.5 (1.0±0.5)	1.3±0.7 (1.2±0.7)	1.1±0.6 (1.0±0.5)	0.8±0.5 (0.6±0.4)
ε-SVR	0.80 ± 0.06	1.10 ± 0.27 (0.78 ± 0.17)	0.5±0.2 (0.4±0.2)	0.9±0.4 (0.8±0.4)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.8±0.5)	0.6±0.2 (0.5±0.2)

Table 5-73: Root mean squared error and mean absolute error (shown in parenthesis) per activity category when estimating energy expenditure using different regression algorithms and all the accelerometer-based features (*MaxAcceleration*) computed per sensor over sliding windows of 5.6s in length.

model trees, and support vector regression. Given that training time is not too important in energy expenditure prediction (since subjects cannot perform subject dependent training due to the lack of equipment), the best algorithms to use in increasing order of desirability based on runtime are: linear regression, regression trees, and model trees.

Table 5-72 presents the root mean squared error and mean absolute error per activity category found using the regression algorithms explored when the *ACAbsArea* feature is computed per sensor over windows of 5.6s in length. Surprisingly, the table shows that the performance of linear regression is very close to the performance of all the other more complex non-linear regression algorithms. One possible explanation for this is that the complexity of energy expenditure prediction in the MIT energy expenditure dataset is so high that linear regression performs as good as the other algorithms due to the unavailability of enough amounts of training data. In other words, due to the relatively small amount of training data available (6 hours of data for 16 subjects), regression trees, model trees and ε-SVR may be unable to learn models that outperform linear regression considerably. Nevertheless, Table 5-72 still shows that the performance of regression trees, model trees, and ε-SVR is higher than the performance of multivariable linear regression. For example, the improvement achieved by ε-SVR over LR is +0.4 units for the coefficient of correlation, and +0.08 MET for the root mean squared error. Obviously, the extra computation incurred by ε-SVR does not justify the epsilon improvement in performance obtained over this dataset. As observed in previous sections, Table 5-72 also shows that the activity categories whose energy expenditure is easier to estimate are postures and household activities. This is because they consist primarily of activities with sedentary and light levels of energy expenditure whose motion is easy to detect from

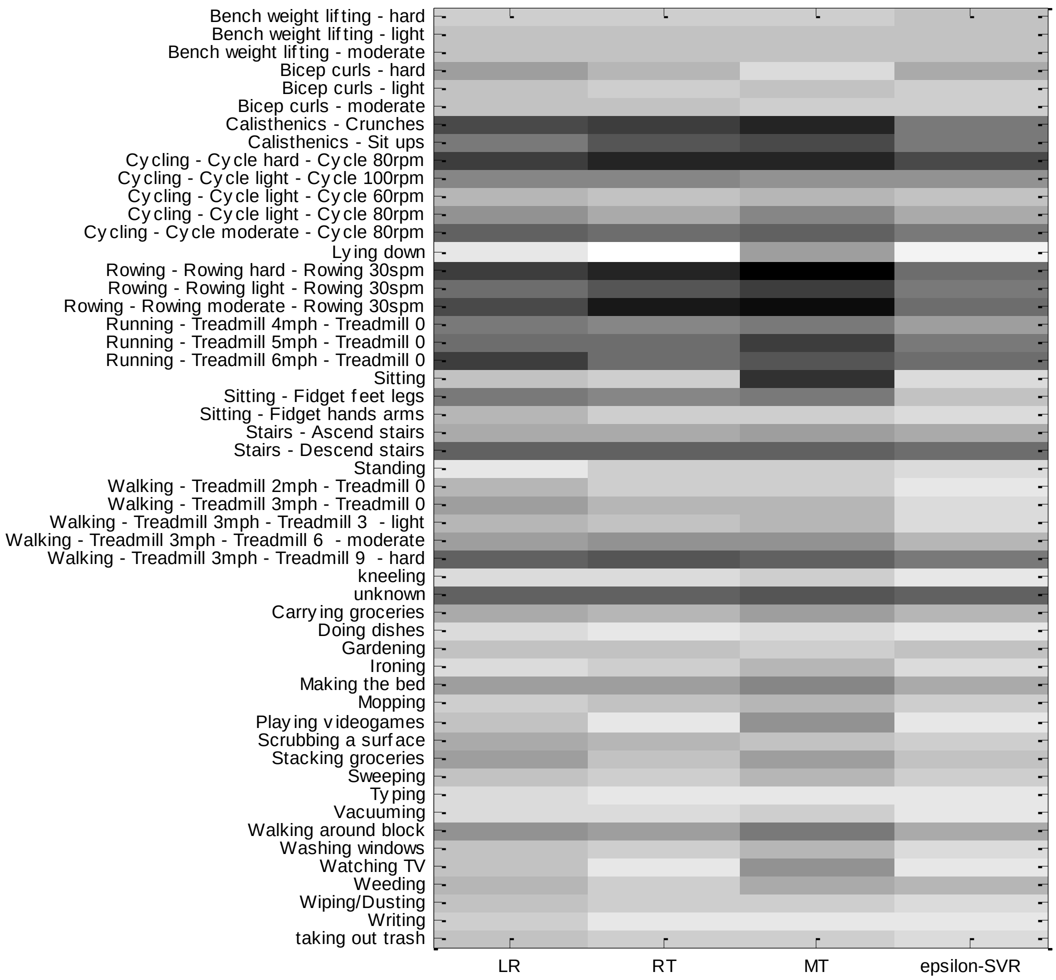


Figure 5-47: Root mean squared error per activity as a gray scale image obtained when estimating energy expenditure with different linear and non-linear regression algorithms using all the accelerometer-based features computed per sensor over sliding windows of 5.6s in length. The image has been scaled to show the lowest RMSE of 0.2MET in white and the largest of 2.3MET in black.

accelerometers. Some household activities such as *scrubbing a surface*, *carrying groceries*, and *washing windows* do involve some level of effort not detectable from accelerometers. The level of effort, however, is substantially lower than that found during gymnasium activities. The table also shows that the activity categories that present the higher RMSE are exercise and resistance exercise. This is because they involve high levels of energy expenditure in most cases due to different levels of resistance level or work load that is not detectable from accelerometers. Some of these activities include *walking* at different incline grades, *rowing* and *cycling* at different resistance levels, *bench weight lifting*, and *bicep curls*.

Table 5-73 presents the same results as Table 5-72 but when the *MaxAcceleration* feature set is used. In general, the table presents the same tendencies found in Table 5-72.

RMSE is lower for the postures and household activity categories and higher for exercise and resistance exercise activities. Nonetheless, the table shows that the performance of model trees suffers with the increase in the number of features (7 to 247). The performance of model trees is worse than the performance for linear regression because there is not enough training data available at the leaf nodes of the tree to train the associated multivariable linear regression models. Regression trees on the contrary does not suffer from this phenomenon because they predict energy expenditure by estimating average EE values over the set of examples falling under

Each leaf node of the tree and these values (averages) can be learned well even from small number of examples.

The performance of ε-SVR on the other hand, is the highest in the table reflecting well the fact that ε-SVR is usually little affected by the curse of dimensionality (decrease in performance due to the increase of predictor variables) [239]. Performance per activity for the different regression algorithms can be found in Appendix B9. Figure 5-47 presents the root mean square error per activity for all the regression algorithms as a gray scale image normalized to show the lowest RMSE of 0.2 MET in white and the largest of 2.3 MET in black. Overall, the figure shows that all algorithms have difficulties predicting energy expenditure for the same activities. These activities are activities involving different intensity levels due to changes in speed, resistance level, or work load, activities involving high levels of energy expenditure, and activities of short duration. Figure 5-47 also illustrates the best overall performance of ε-SVR and the poor performance of the model tree with respect to the performance of linear regression.

In conclusion, the results presented in this section indicate that two good choices of algorithms to use when predicting energy expenditure are multivariable linear regression and regression trees. This is because these algorithms have fast prediction times and their performance is close to the best performance obtained using epsilon support vector regression. The advantage of regression trees over multivariable linear regression is that regression trees are able to learn non-linear relationships in the data. The disadvantage is that its training time is considerably longer than the training time for multivariable linear regression, particularly when a small number of features are used. The small differences found in this work between linear and non-linear regression algorithms agree with prior work that has also found that non-linear regression algorithms do not improve performance substantially over linear regression techniques [246]. However, the main reason suspected for this little difference is unavailability of enough training data.

5.6.4 Does Band-Pass Filtering of the Acceleration Signals Improve Performance?

One procedure commonly applied in prior work during the estimation of energy expenditure from accelerometer data is to band-pass filter the raw acceleration signals between 0.1 and 20Hz (e.g. [32, 47, 153, 200]). The rationale behind this is that low pass filtering the signal at 20Hz eliminates signal components generated by non-human motion and high frequency noise and that high pass filtering at 0.1Hz eliminates posture information in the form of static acceleration (DC signal component) that does not contribute to energy expenditure considerably. However, to the best of the author’s knowledge, no work has evaluated the impact in performance of band-pass filtering the accelerometer signals. As this section investigates the difference in performance obtained

Error Measures	ACAbsArea Feature		ACFFTPeaks Feature	
	Without Band-pass Filtering	With Band-pass Filtering	Without Band-pass Filtering	With Band-pass Filtering
Correlation Coefficient	0.56 ± 0.11	0.68 ± 0.06	0.68 ± 0.16	0.72 ± 0.07
Root Mean Square Error	1.66 ± 0.50	1.36 ± 0.30	1.34 ± 0.34	1.28 ± 0.30
Mean Absolute Error	1.32 ± 0.40	1.02 ± 0.17	1.01 ± 0.24	0.93 ± 0.17
Maximum Absolute Error Deviation	5.55 ± 1.16	5.02 ± 1.08	5.48 ± 1.32	5.48 ± 1.10

Table 5-74: Performance obtained while estimating energy expenditure using multivariable linear regression when band-pass filtering is applied and when it is not. The features computed are *ACAbsArea* and *ACFFTPeaks* computed per sensor over sliding windows of 5.6s in length.

when band-pass filtering is applied and when it is not during the estimation of energy expenditure.

The experiments performed in this section utilize multivariable linear regression to measure the impact of applying and not applying the band-pass filter during the estimation of energy expenditure. The band-pass filter applied is a Chebyshev infinite impulse response filter designed using the parameters shown in Table 5-2. Performance is measured using two features: *ACAbsArea* and *ACFFTPeaks*. This is because the quality of these features is likely to be affected by the application of the band-pass filter.

Table 5-74 shows the performance of applying and not applying the filter while estimating energy expenditure using multivariable linear regression and the *ACAbsArea* and *ACFFTPeaks* features computed per sensor over windows of 5.6s in length. Performance per activity is shown in Appendix B10. The table clearly shows that the performance is higher when the filter is applied. In fact, the improvement in performance observed is more substantial than the improvements observed using more complex non-linear regression algorithms (see Section 5.6.3). For example, RMSE increased +0.3 MET for the *ACAbsArea* feature and +0.06 MET for the *ACFFTPeaks* feature. Performance improves for the *ACAbsArea* feature because band-pass filtering smoothes the signals this reducing the amount of noise. Similarly, performance improves for the *ACFFTPeaks* feature because high frequency noise is reduced leading to more consistent estimations of the frequency components of the signal. Performance improves less for the *ACFFTPeaks* feature because it is less dependent on the magnitude of the accelerometer signal (since it does not include the DC component of the signal), and the magnitude of the accelerometer signal is the most affected by the application of the filter.

In summary, the results presented in Table 5-74 indicate that band-pass filtering the signal significantly improves the performance of energy expenditure estimation. As a result, all experiments presented in this thesis utilize band-pass filtering between frequencies of 0.1 and 20Hz. One potential problem with band-pass filtering the acceleration signals is that potentially useful information about postures (static acceleration) is lost. It might be possible that this information is indeed necessary to better estimate energy expenditure since different postures have different energy expenditure costs [122] (e.g. 1 MET for *lying down* vs. 1.2 MET for *standing*) even when they involve no motion. Furthermore, energy expenditure can add up for postures executed over long periods of time. As a result, Section 5.6.7 will later explore the performance of energy expenditure estimation when features that capture posture information are used and when they are not.

5.6.5 Can Feature Computation Per Axis Improve Performance Over Feature Computation per Sensor?

Most prior work in energy expenditure estimation utilizes features computed over signals summarizing the overall motion (acceleration) experienced by a particular body segment. For example, the overall motion experienced by a triaxial accelerometer at the hip is summarized by computing the sum ($x+y+z$) or the signal vector magnitude over the accelerometer axes ($\sqrt{x^2+y^2+z^2}$). The rationale behind this is that overall motion per body segment is sufficient to estimate energy expenditure well since energy expended is directly proportional to the amount of motion per body segment. One advantage of this approach, referred as feature computation per sensor in this work, is that the amount of computation is reduced since features are computed over a single signal instead of over three different signals (x, y, and z). Nevertheless, some prior work [33, 151, 160, 247] [218] also suggests that analyzing motion over individual axis (e.g. *x*, *y*, or *z*), particularly the vertical component of acceleration, can improve energy expenditure estimates. As a result, this section investigates the difference in performance obtained when estimating energy expenditure using features computed over signals summarizing overall motion per sensor and using features computed over individual acceleration axis (referred as feature computation per axis).

In the experiments presented in this section, feature computation per sensor is performed by first summarizing the motion experienced at each sensor by summing the acceleration values at each individual axis ($x+y+z$) sample by sample. Feature computation per axis is performed by computing the features of interest over each individual axis (*x*, *y*, and *z*). Thus, feature vectors corresponding to feature computation per axis are three times longer that feature vectors for feature computation per sensor.

The performance of feature computation per sensor and per axis is measured by estimating energy expenditure in two extreme conditions: (1) when few simple features are used to estimate energy expenditure (*ACAbsArea*), and (2) when all the accelerometer-based features are used to estimate energy expenditure. The performance over both feature sets is also analyzed using a linear regression algorithm (multivariable linear regression) and a non-linear regression algorithm (M5' model trees). All features are computed over sliding windows of 5.6s in length. As will be explained later, this is the final window length selected for estimating energy expenditure in Section 5.6.6.

Table 5-75 presents the performance obtained over the MIT energy expenditure dataset when energy expenditure is estimated using multivariable linear regression and the *ACAbsArea* feature computed per sensor and per axis. Results per activity can be found in Appendix B11. The table shows that feature computation per axis improves the coefficient of correlation 0.03 units and RMSE 0.07 METs. The improvement obtained in RMSE is distributed across the postures, exercise, and resistance exercise activity categories. When the RMSE per activity is inspected (see Figure 5-48) it is found that performance is slightly better (-0.2 to -0.8 MET) for activities involving postures and upper body motion such as *writing*, *typing*, *wiping/dusting*, *playing video games*, *doing dishes*, and *sitting fidgeting hands and arms, and bicep curls*. At the same time, the performance over *bench weight lifting* (another activity involving upper body motion) slightly decreased between 0.1 and 0.3 MET.

Activity Category	Linear Regression Per Sensor	Linear Regression Per Axis	Change in RMSE Performance (Per Axis – Per Sensor)
Correlation Coefficient	0.68 ± 0.06	0.71 ± 0.13	-
All	1.36 ± 0.30 (1.02 ± 0.17)	1.29 ± 0.29 (0.92 ± 0.18)	0.07 Improvement
Postures	0.7±0.2 (0.7±0.2)	0.5±0.2 (0.4±0.2)	0.2 Improvement
Ambulation	1.1±0.4 (1.0±0.4)	1.1±0.4 (1.0±0.4)	0 Unchanged
Exercise	1.5±0.7 (1.4±0.7)	1.3±0.8 (1.2±0.8)	0.2 Improvement
Resistance Exercise	1.4±0.6 (1.3±0.6)	1.2±0.7 (1.1±0.7)	0.2 Improvement
Household	0.7±0.2 (0.6±0.2)	0.7±0.3 (0.6±0.3)	0 Unchanged

Table 5-75: Correlation coefficient, root mean squared error, and mean absolute error (shown in parenthesis) per activity category when estimating energy expenditure with multivariable linear regression using the *ACAbsArea* feature computed per sensor and per axis over windows of 5.6s in length.

Activity Category	M5' Model Tree Per Sensor	M5' Model Tree Per Axis	Change in RMSE Performance (Per Axis – Per Sensor)
Correlation Coefficient	0.72 ± 0.08	0.70 ± 0.15	-
All	1.24±0.29 (0.86±0.19)	1.34±0.43 (0.92 ± 0.23)	0.1 Decline
Postures	0.6±0.3 (0.5±0.2)	0.5±0.2 (0.4±0.2)	0.1 Improvement
Ambulation	1.1±0.4 (0.9±0.4)	1.1±0.4 (1.0±0.4)	0 Unchanged
Exercise	1.3±0.7 (1.2±0.7)	1.3±0.9 (1.2±0.8)	0 Unchanged
Resistance Exercise	1.1±0.6 (1.0±0.6)	1.3±0.8 (1.1±0.7)	0.2 Decline
Household	0.6±0.3 (0.5±0.2)	0.7±0.3 (0.6±0.3)	0.1 Decline

Table 5-76: Correlation coefficient, root mean squared error, and mean absolute error (shown in parenthesis) per activity category when estimating energy expenditure with a M5' model tree using the *ACAbsArea* feature set computed per sensor and per axis over windows of 5.6s in length.

Activity Category	Linear Regression Per Sensor	Linear Regression Per Axis	Change in RMSE Performance (Per Axis – Per Sensor)
Correlation Coefficient	0.74 ± 0.10	0.73 ± 0.12	-
All	1.24 ± 0.30 (0.91 ± 0.20)	1.27 ± 0.26 (0.93 ± 0.19)	0.03 Decline
Postures	0.7±0.3 (0.6±0.3)	0.6±0.3 (0.5±0.3)	0.1 Improvement
Ambulation	1.2±0.5 (1.0±0.5)	1.1±0.5 (0.9±0.4)	0.1 Improvement
Exercise	1.2±0.7 (1.1±0.7)	1.2±0.7 (1.1±0.7)	0 Unchanged
Resistance Exercise	1.1±0.6 (1.0±0.6)	1.1±0.6 (1.0±0.6)	0 Unchanged
Household	0.7±0.3 (0.6±0.3)	0.8±0.4 (0.7±0.4)	0.1 Decline

Table 5-77: Correlation coefficient, root mean squared error, and mean absolute error (shown in parenthesis) per activity category when estimating energy expenditure with multivariable linear regression using the *MaxAcceleration* feature set computed per sensor and per axis over windows of 5.6s in length.

Activity Category	M5' Model Tree Per Sensor	M5' Model Tree Per Axis	Change in RMSE Performance (Per Axis – Per Sensor)
Correlation Coefficient	0.64 ± 0.17	0.64 ± 0.12	-
All	1.56 ± 0.67 (0.94 ± 0.24)	1.46 ± 0.23 (1.02 ± 0.16)	0.1 Improvement
Postures	1.0±1.5 (0.7±0.7)	0.6±0.3 (0.5±0.3)	0.4 Improvement
Ambulation	1.2±0.5 (1.0±0.5)	1.3±0.7 (1.2±0.6)	0.1 Decline
Exercise	1.3±0.7 (1.2±0.7)	1.5±0.8 (1.3±0.7)	0.2 Decline
Resistance Exercise	1.1±0.6 (1.0±0.5)	1.3±0.6 (1.2±0.5)	0.2 Decline
Household	0.8±0.5 (0.6±0.4)	0.9±0.5 (0.8±0.4)	0.1 Decline

Table 5-78: Correlation coefficient, root mean squared error, and mean absolute error (shown in parenthesis) per activity category when estimating energy expenditure with the M5' model tree using the *MaxAcceleration* feature set computed per sensor and per axis over windows of 5.6s in length.

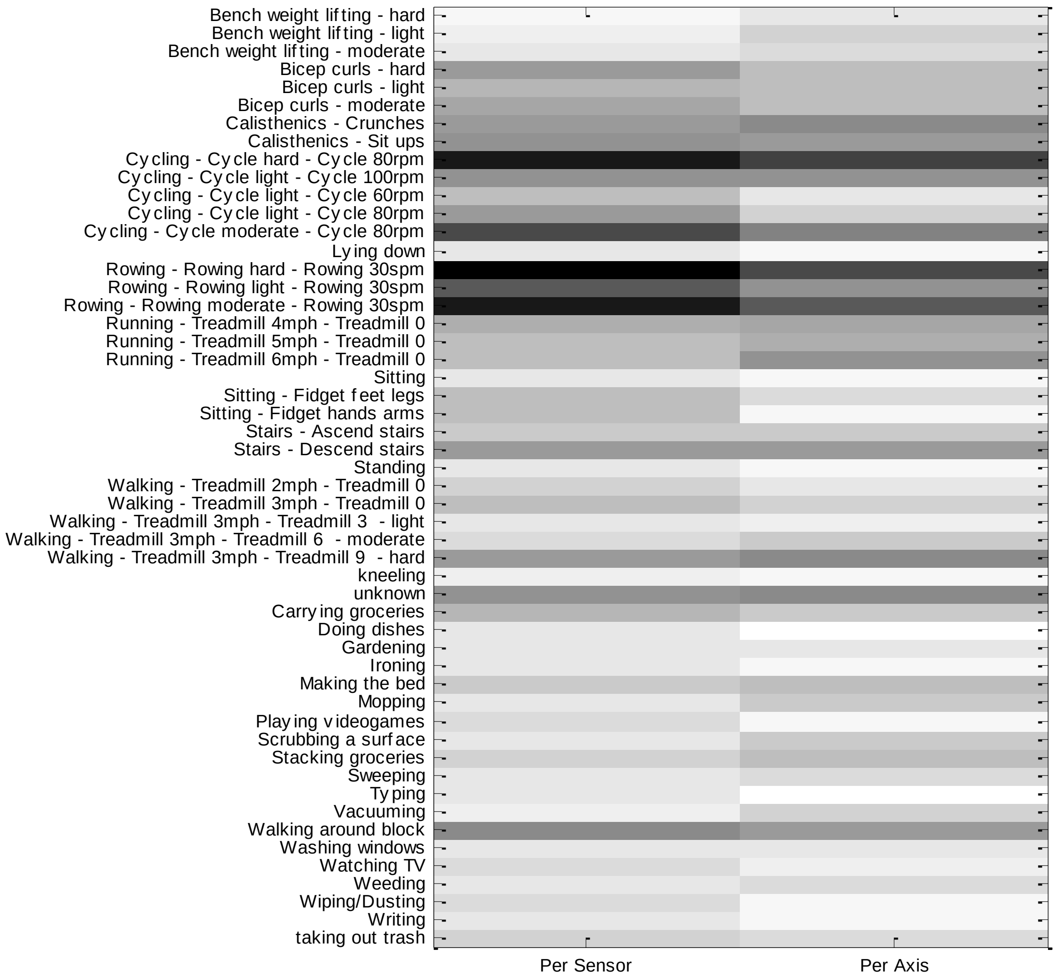


Figure 5-48: Root mean squared error represented as a gray scale image when energy expenditure is estimated using multivariable linear regression using the ACAbsArea feature computed per sensor and per axis over windows of 5.6s in length. The image is scaled to show the lowest RMSE of 0.3 MET in white and the largest RMSE of 3.1 in black.

It seems that analyzing motion per sensor improves energy expenditure for upper body activities except for *bench weight lifting*. One possible reason for this is that the motion of *bench weight lifting* is so periodic that it is well captured using feature computation per sensor and using feature computation per axis only reduces the amount of training data available to train each predictor variable.

Table 5-76 presents the performance of estimating energy expenditure using an M5' model tree and the *ACAbsArea* feature computed per sensor and per axis over windows of 5.6s in length. The first thing to notice is that the performance obtained during feature computation per sensor is better than the performance obtained during feature computation per axis when multivariable linear regression is used. This is expected since model trees are more complex regression algorithms capable of learning non-linear relationships in the data. However, when the performance per sensor and per axis are compared for the M5’ model tree, it is found that feature computation per axis has a lower performance than feature computation per sensor. One possible explanation is that feature computation per axis produces a three-fold increase in the vector size of the features and consequently, the training data available at the leaf nodes of the M5’ tree is insufficient to learn the multivariable linear regression models associated with each leaf node. Table 5-77 and Table 5-78 also illustrate the decline in performance of feature computation per axis when the number of features used is large. Given the amount of training data available in this work, it is unclear if feature computation per axis will improve performance over feature computation per sensor. The only improvement observed in this section was obtained with the *ACAbsArea* feature, which has a very low feature vector size of 7.

In conclusion, the results presented in this section suggest that when the number of features is low, feature computation per axis slightly improves performance over feature computation per sensor. The improvement in performance observed using the *ACAbsArea* feature and multivariable linear regression was +0.03 units for the correlation coefficient and 0.07 MET for the RMSE. Even so, when the number of features used is large and/or the regression algorithm used has large training data requirements, feature computation per axis damages performance by increasing the total number of features by a factor of three when not enough data is available for training. For these reasons, from this point on, feature computation per sensor will be used when presenting results in upcoming sections.

5.6.6 What is the Optimal Sliding Window Length to Use?

Most existing algorithms that estimate energy expenditure from accelerometer data generate estimates over sliding windows of one minute in length. This relatively long window length (also known as the epoch) was originally used due to hardware limitations in storage capacity and battery life of the first off-the-shelf accelerometers that appeared in the market. Nowadays, however, these limitations no longer exist. It may make sense to reduce the size of this window for two reasons: (1) shorter windows will allow shorter real-time estimation delays that would also enable faster interventions at the point of decision, and (2) motion can vary considerably over one minute windows, so reducing the window length might improve estimation of energy expenditure. As a result, this section explores the impact in performance of varying the length of the sliding window during the estimation of energy expenditure.

The length of the sliding window also affects the quality or resolution of some of the features used in this work such as the FFT transformation and the Pearson’s correlation coefficients. Usually, the longer the window length, the better these features can be estimated. On the other hand, the longer the window length, the longer the end-user of an energy expenditure estimation system has to wait for a recognition result. Consequently, this section determines the most appropriate window length by measuring the performance of multivariable linear regression and M5’model trees over the two features whose quality is most likely to vary with the window length: FFT peaks (*ACFFTPeaks*) and Pearson correlation coefficients (*ACCorr*). As a baseline, the performance is also computed utilizing the *ACAbsArea* feature. Linear regression and model trees are used in this experiment because they represent the linear and non-linear regression algorithms with best performance over all features as found in Section 5.6.3.

The features will be first computed over window lengths ranging from 1.4 to 91 seconds (64 to 2048 accelerometer samples) using linear regression and feature computation per sensor, and later on a reduced set of window lengths using the M5' model tree algorithm. This procedure is followed to minimize the time and number of experiments to run while maximizing interpretability of results. Window lengths shorter than 1.4s were not considered because they are intuitively too short to capture the repetitive motion patterns found in some periodic activities such as *walking* slowly at 2mph. Similarly, window lengths longer than 91s were not considered due to the extremely long real-time classification delay they introduce into the system.

The lengths of the sliding windows explored in this section are constrained to be a power of two by the algorithms required to compute the Fourier and Wavelet transformations efficiently. Table 5-11 shows the window lengths explored in this section in number of acceleration samples and corresponding time in seconds assuming a sampling rate of 45Hz.

Figure 5-49 presents the plot of the root mean squared error obtained while varying the window length from 1.4s to 91s. Appendix B12 presents the same information in a tabular manner. The plot indicates that the RMSE error decreases as the window length is increased when both the *ACAbsArea* and *FFTCorr* feature sets are used. For example, RMSE decreases -0.22 MET when the window length is increased from 1.4 to 91s for the *ACAbsArea* feature and -0.16 MET for the *FFTCorr* feature set.

This modest improvement might be due to the increased smoothing of the values for the *ACAbsArea* feature and for the ground truth energy expenditure signals. Another possible reason for the improvement is that the quality or resolution for the *ACFFTPeaks* and *ACCorr* features increases as longer window lengths are used. Figure 5-49 also illustrates that the RMSE for the ambulation and exercise categories remains practically unchanged up to a window length of 22.7s for the *ACAbsArea* feature and up to a window length of 44.5s for the *FFTCorr* feature set. Figure 5-49 shows that the RMSE for the postures category increases at window lengths of 11.3s and 45.5s, but later decreases at a window length of 91s. Plot Figure 5-49a on the contrary, illustrates that the RMSE for postures indeed decreases as the window length is increased, most likely due to the smoothing effect of longer windows.

When the RMSE is analyzed per activity for the *FFTCorr* feature set (see Figure 5-51 and Appendix B12), it is found that it changes little among all activities up to a window length of 11.3s. Once this window is reached, RMSE for all activities decreases between 0.1-0.2 METs at a window of 11.3s and between 0.1-0.6 METs at a final window length of 90s. One possible reason why the improvements are so minimal is that the estimated and ground truth energy expenditure values follow one another independently of the window length utilized. In other words, the error depends on the difference between the estimated and ground truth energy expenditure signals so changing how these signals are partitioned does not impact error significantly. One of the main problems of using long windows; however, is that performance decreases for physically intense activities of short duration such as *ascending stairs* and *descending stairs*. This can be seen in Figure 5-51 where the error is the maximum (black area) for these activities at a window length of 90s. The examples collected for these activities have individual durations of less than a

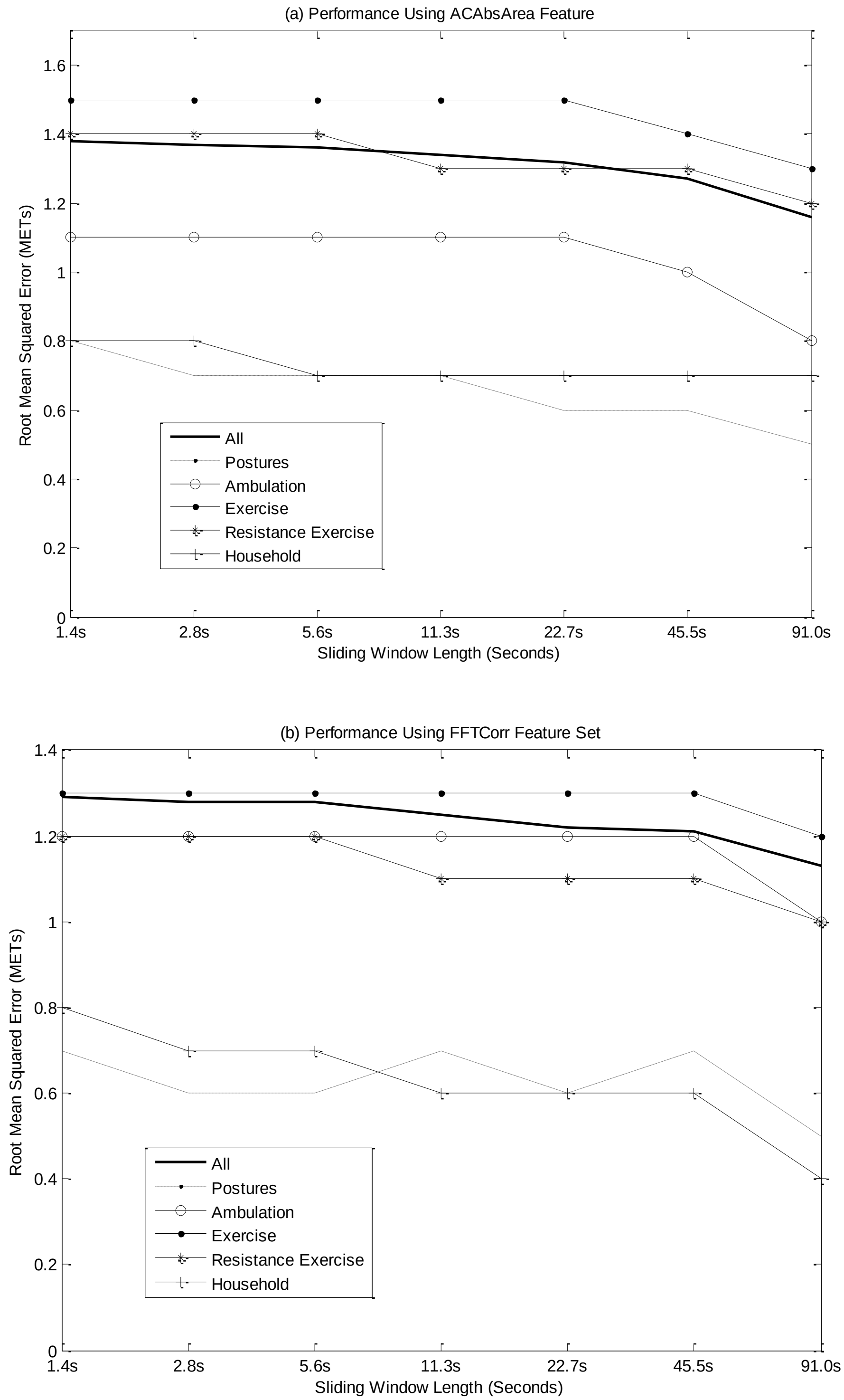
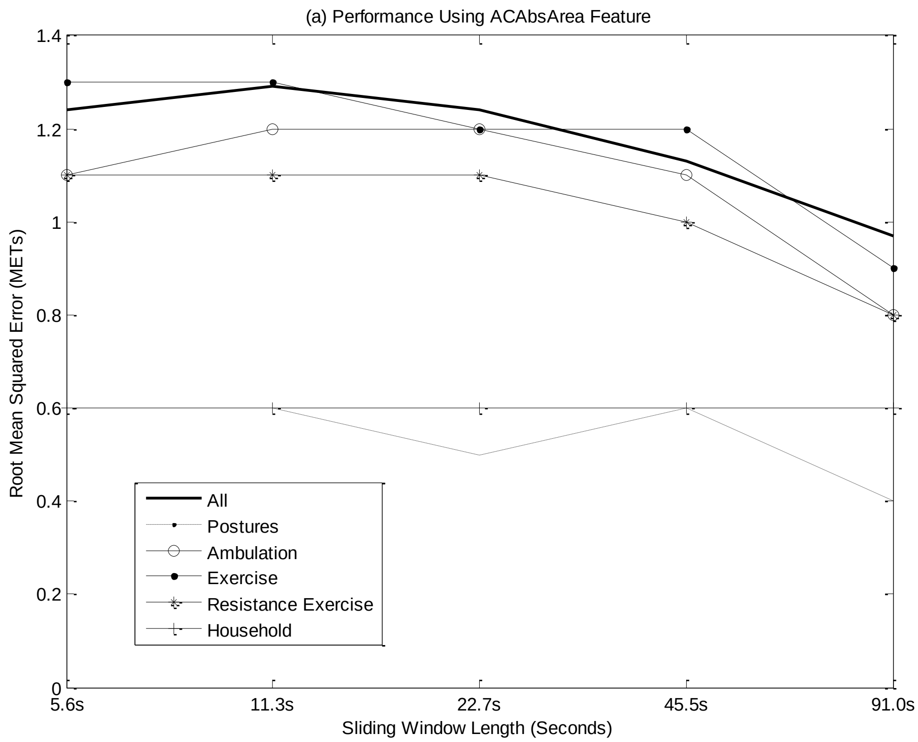


Figure 5-49: Root mean squared error obtained when estimating energy expenditure in a subject independent manner over the MIT dataset using multivariable linear regression, the *ACAbsArea* and *FFTCorr* (*ACFFTPeaks+ACCorr*) feature sets computed per sensor over windows of varying lengths.



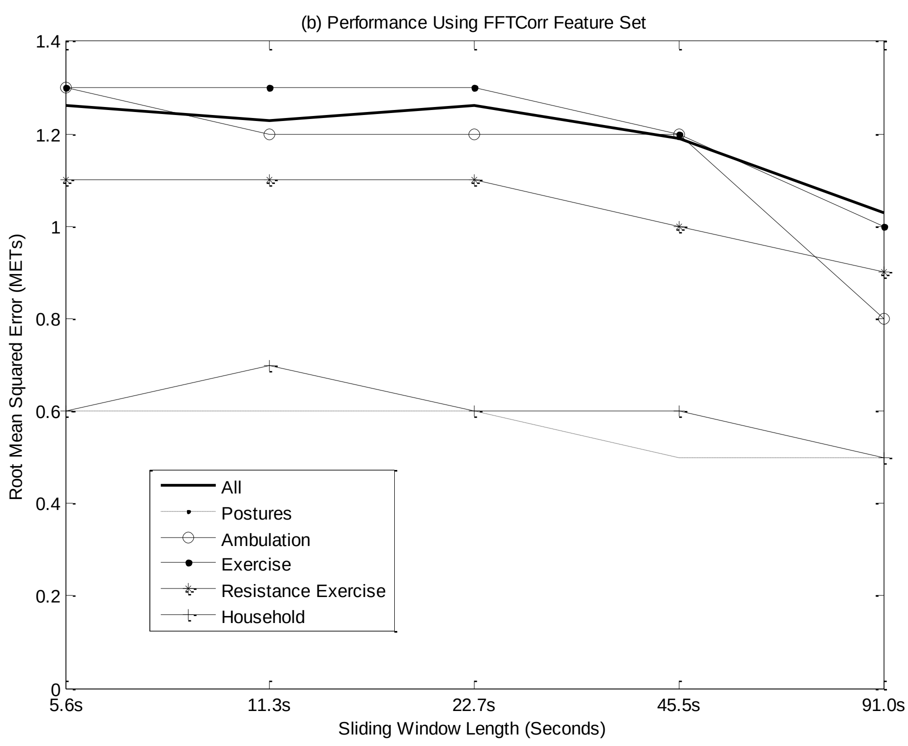


Figure 5-50: Root mean squared error obtained when estimating energy expenditure in a subject independent manner over the MIT dataset using a M5' model trees, the *ACAbsArea* and *FFTCorr* (*ACFFTPeaks+ACCorr*) feature sets computed per sensor over windows of varying lengths.

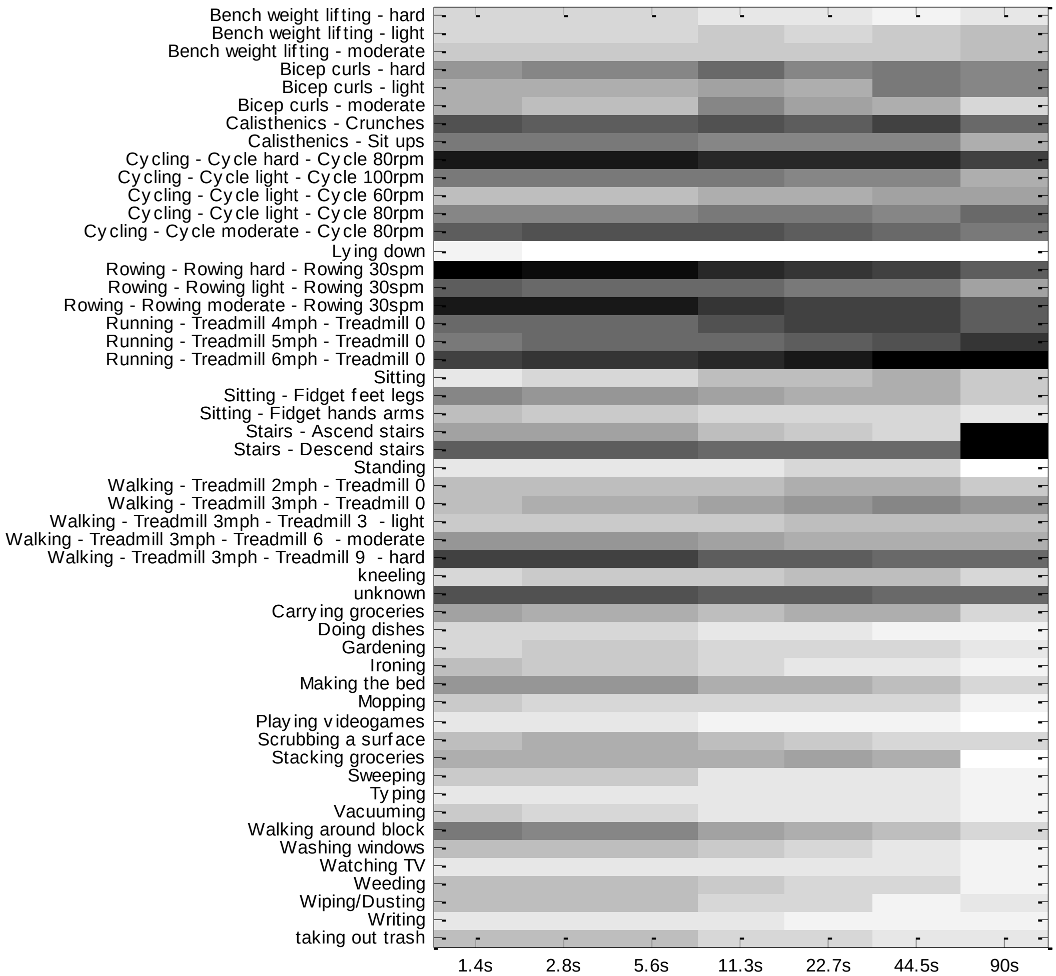


Figure 5-51: Root mean squared error (RMSE) represented as a grayscale image when estimating energy expenditure using multivariable linear regression using the *FFTCorr* feature set computed per sensor over sliding windows of varying length. The image is scaled to show the largest RMSE of 2.2MET in black and the lowest RMSE of 0.3MET in white.

minute, and are followed by resting periods. As a result, their energy expenditure is poorly detected with a window length of 90s because energy expenditure associated with *ascending stairs* is averaged with the energy expenditure associated with resting. This effect can also be seen for *running at 6mph* in Figure 5-51 since its error increases after a window length of 11.3s. This is because most examples for this physically demanding activity have durations of less than 1.5min. Another problem is that at large window lengths, the number of training examples per activity is reduced considerably thus impacting performance. Figure 5-51 also shows that RMSE decreases between -0.1 and -0.6 METs for household activities.

Figure 5-50 presents plots of the root mean square error per activity category when the M5' model tree is used to predict energy expenditure using the *ACAbsArea* and *FFTCorr* features over varying window lengths. Overall, the plots in Figure 5-50 indicate that the RMSE also decreases as the window length is increased. The RMSE is slightly lower (-0.14 MET for *ACAbsArea* and -0.03 for the *FFTCorr* feature set) than the one obtained using linear regression because model trees can capture non-linear relationships in the data. However, one might question if the improvement obtained justifies the utilization of this more complex algorithm. As the window is increased from 5.6s to 91s, overall RMSE decreases 0.27 MET for the *ACAbsArea* feature and 0.23 MET for the *FFTCorr* feature set. The improvement obtained is little and the activity categories that present the higher decrease in error are ambulation (0.3-0.5 MET) and exercise (0.3-0.4 MET). The category that experiences the least decrease in error (0.0 MET for *ACAbsArea* and 0.1 MET for *FFTCorr*) is household activities.

In summary, the results presented in this section suggest that in general, root mean squared error decreases as the window length increases but this decrease in RMSE is modest (e.g. between 0.16 and 0.27 MET when length is increased from 1.4s to 91s). RMSE error decreases as the window length increases because the feature values and the ground truth energy expenditure values are smoothed out as the window length is increased, particularly non-steady state intervals. It also increases because the quality or resolution of some features (e.g. *ACFFTPeaks* and *ACCorr*) also increases as the window length increases. As a result, small windows can be utilized to estimate energy expenditure without affecting error considerably. This is an intuitive result because the most important information to estimate energy expenditure from accelerometer data is overall amount of motion, which can be estimated well even when small windows are used. The results also indicate than long window lengths increase RMSE in short duration activities such as *ascending stairs*, *descending stairs*, and physically demanding activities (of short duration) such *as running at 6mph*. This is because their energy expenditure data is averaged with the energy expenditure data associated with activities preceding or following these short duration activities. As a result, a window length of 5.6s will be used to estimate energy expenditure for the remaining of this work. This window length allows prediction of energy expenditure over short duration activities, minimizes energy expenditure estimation lag (during real-time implementations), and it has shown good performance with respect to windows of shorter duration. Finally, this is the same window length used to recognize activities in Section 5.4.6. Using the same window length to recognize activities and estimate energy expenditure simultaneously reduces computational complexity since features do not have to be computed twice over different window lengths (assuming some features are used in both algorithms).

5.6.7 Which Features Improve Energy Expenditure Estimation and Maintain Computational Cost Low?

Most prior work in estimating energy expenditure from accelerometer data utilizes raw accelerometer values summed over windows of one minute in length as the predictor variables (features) in the regression equations. However, recent work [152, 181] suggests that more complex features computed over the accelerometer signal such as the inter-quartile interval, skew, kurtosis, and frequency domain energy combined with non-linear regression algorithms can improve energy expenditure estimation. The intuition behind this is that more complex features might capture important motion information that would be otherwise lost if simple sums of accelerometer values over one minute windows are used. As a result, this section investigates the performance of estimating energy expenditure using combinations of a large set of 41 features. The main goal of the section is to identify the subset of features that maximizes performance when considering the computational requirements of the features. To the best of the author knowledge, no prior work has analyzed the impact in performance of such a large set of features in estimating energy expenditure.

This section first evaluates the performance over individual features to identify those with higher performance. Later, the performance over combinations of individual features with high performance is evaluated to determine the best subset of features to use. All experiments performed in this section utilize feature computation per sensor, sliding windows of 5.6s in length (window length selected in the previous Section), and multivariable linear regression to estimate energy expenditure in a subject independent manner. As shown in Section 5.6.3, the performance obtained using multivariable linear regression is comparable to the one obtained using more complex non-linear regression algorithms, at least over the dataset explored in this work. The experiments are performed in a best case scenario where all the seven accelerometers are used for estimating energy expenditure. Section 5.6.8 will later analyze what is the best combination of sensors to use and where should they be worn.

A complete list of all the features explored in this section is shown in Appendix A3. These features consist on a superset of features used in prior work to recognize activities that have shown good performance as well as some new features not explored before. Table 5-12 presents a list of the features explored and a brief explanation of the information they attempt to capture. Features are computed after preprocessing the acceleration signals to better differentiate between motion information and posture information. The features intended to capture motion information are computed over the accelerometer signals after applying a band-pass filter between the frequencies of 0.1 and 20Hz. This preprocessing has two goals: (1) eliminate the DC or static component of the acceleration signal due to the orientation of the sensors with respect to ground (posture information) and (2) filter high frequency noise and motion not generated by the human body. The features intended to capture posture information are computed over the accelerometer signals after low-pass filtering them at a cut-off frequency of 1Hz. This has the purpose of eliminating most of the signal information due to body motion and preserving the information due to static acceleration or posture. Features that capture motion information start with the prefix “AC” and those that capture posture information start with the prefix “DC”.

Table 5-79 presents the performance obtained while individual features are used to estimate energy expenditure in a subject independent manner using multivariable linear regression. The features shown in Table 5-79 are ordered to present the ones with higher correlation coefficients at the top and the ones with lower correlation coefficients at the bottom. Table 5-79 shows that the best performing features is *ACFFTPeaks* with a correlation coefficient of 0.72 and a RMSE of 1.28. This is a good result because this feature does not strongly depend on the magnitude of the accelerometer signal. Invariance to the magnitude of the accelerometer signal is important because it can vary with changes in the location and orientation of the sensors (during installation on the body) and with hardware differences across accelerometers. The *ACFFTPeaks* feature

Features subsets (Number of features)	Correlation coefficient for All Activities	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
ACFFTPeaks (70)	0.72 ± 0.07	1.28 ± 0.30 (0.93 ± 0.17)	0.6±0.2 (0.6±0.2)	1.2±0.5 (1.1±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.1±0.7)	0.7±0.2 (0.6±0.2)
ACFFTCoeff (889)	0.72 ± 0.06	1.34 ± 0.25 (0.97 ± 0.17)	0.6±0.2 (0.5±0.2)	1.4±0.6 (1.2±0.6)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.0±0.7)	0.6±0.2 (0.5±0.2)
ACIQR (7)	0.70 ± 0.06	1.32 ± 0.31 (0.98 ± 0.16)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.7±0.2 (0.6±0.2)
ACQ3 (7)	0.69 ± 0.06	1.33 ± 0.30 (0.99 ± 0.16)	0.7±0.2 (0.7±0.2)	1.0±0.4 (0.9±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.7±0.2 (0.6±0.2)
ACTotalAbsArea (1)	0.68 ± 0.06	1.36 ± 0.31 (1.03 ± 0.17)	0.8±0.2 (0.7±0.2)	1.0±0.4 (0.9±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.3±0.6)	0.7±0.2 (0.6±0.2)
ACAbsArea(7)	0.68 ± 0.06	1.36 ± 0.30 (1.0 ± 0.2)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.6±0.2)
ACAbsMean (7)	0.68 ± 0.06	1.36 ± 0.30 (1.02 ± 0.17)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.6±0.2)
ACMCR (7)	0.68 ± 0.06	1.37 ± 0.32 (1.03 ± 0.20)	0.7±0.4 (0.6±0.4)	1.4±0.5 (1.3±0.5)	1.4±0.7 (1.2±0.7)	1.2±0.5 (1.1±0.5)	0.8±0.2 (0.7±0.2)
ACModVigEnergy (7)	0.68 ± 0.09	1.37 ± 0.36 (1.02 ± 0.19)	0.9±0.2 (0.8±0.2)	1.2±0.4 (1.0±0.4)	1.4±0.7 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.7±0.2 (0.7±0.2)
ACSF (5)	0.67 ± 0.05	1.37 ± 0.30 (1.03 ± 0.17)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.7±0.2)
ACTotalSF (1)	0.65 ± 0.07	1.41 ± 0.33 (1.07 ± 0.18)	0.9±0.2 (0.9±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.7±0.2 (0.7±0.2)
ACBandEnergy (7)	0.64 ± 0.06	1.46 ± 0.31 (1.10 ± 0.17)	0.8±0.3 (0.7±0.3)	1.1±0.4 (0.9±0.4)	1.6±0.7 (1.5±0.7)	1.3±0.6 (1.3±0.6)	0.9±0.3 (0.8±0.3)
ACRange(7)	0.64 ± 0.07	1.45 ± 0.31 (1.11 ± 0.18)	0.8±0.3 (0.8±0.3)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.8±0.3 (0.7±0.2)
ACEntropy (7)	0.63 ± 0.07	1.46 ± 0.34 (1.11 ± 0.21)	0.8±0.2 (0.8±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.5 (1.2±0.5)	0.8±0.2 (0.7±0.2)
ACVar (7)	0.60 ± 0.06	1.50 ± 0.32 (1.17 ± 0.18)	1.1±0.2 (1.1±0.2)	1.1±0.5 (1.0±0.5)	1.7±0.7 (1.6±0.7)	1.5±0.6 (1.4±0.6)	0.8±0.2 (0.7±0.2)
ACLowEnergy (7)	0.60 ± 0.10	1.52 ± 0.35 (1.17 ± 0.21)	1.0±0.2 (1.0±0.2)	1.3±0.5 (1.2±0.5)	1.6±0.7 (1.5±0.7)	1.4±0.6 (1.3±0.6)	0.8±0.2 (0.7±0.2)
ACDomFreqRatio (7)	0.53 ± 0.11	1.58 ± 0.31 (1.27 ± 0.19)	1.0±0.3 (0.9±0.3)	1.2±0.5 (1.1±0.5)	1.8±0.8 (1.7±0.8)	1.6±0.6 (1.5±0.6)	1.1±0.4 (1.0±0.3)
ACEnergy (7)	0.50 ± 0.08	1.66 ± 0.34 (1.33 ± 0.20)	1.4±0.4 (1.3±0.3)	1.3±0.5 (1.2±0.5)	1.8±0.8 (1.8±0.8)	1.6±0.6 (1.6±0.6)	0.9±0.3 (0.9±0.3)
DCPostureDist (21)	0.42 ± 0.16	1.75 ± 0.30 (1.35 ± 0.18)	1.3±0.5 (1.3±0.5)	1.6±0.6 (1.5±0.6)	1.8±0.9 (1.7±0.9)	1.4±0.8 (1.4±0.8)	1.1±0.6 (1.1±0.6)
ACCorr (21)	0.39 ± 0.16	1.66 ± 0.32 (1.31 ± 0.19)	1.4±0.4 (1.3±0.4)	1.5±0.7 (1.4±0.7)	1.8±0.9 (1.7±0.9)	1.6±0.7 (1.5±0.7)	1.0±0.3 (0.9±0.2)
ACPitch (7)	0.26 ± 0.10	1.78 ± 0.31 (1.41 ± 0.20)	2.2±0.5 (2.0±0.5)	1.5±0.5 (1.5±0.5)	1.9±0.7 (1.8±0.7)	1.6±0.6 (1.5±0.6)	1.0±0.3 (0.9±0.3)
DCMean (7)	0.22 ± 0.18	1.85 ± 0.36 (1.51 ± 0.22)	1.8±0.4 (1.8±0.5)	1.7±0.6 (1.7±0.6)	2.1±0.8 (2.0±0.8)	1.6±0.6 (1.6±0.6)	1.1±0.4 (1.1±0.4)
DCArea (7)	0.22 ± 0.18	1.85 ± 0.36 (1.51 ± 0.22)	1.8±0.4 (1.8±0.5)	1.7±0.6 (1.7±0.6)	2.1±0.8 (2.0±0.8)	1.6±0.6 (1.6±0.6)	1.1±0.4 (1.1±0.4)
DCTotalMean (7)	0.21 ± 0.19	1.82 ± 0.36 (1.48 ± 0.21)	1.8±0.3 (1.8±0.3)	1.6±0.5 (1.5±0.5)	2.1±0.8 (2.0±0.8)	1.7±0.6 (1.6±0.6)	1.1±0.3 (1.0±0.3)
ACSkew (7)	0.17 ± 0.08	1.83 ± 0.33 (1.49 ± 0.20)	1.6±0.3 (1.6±0.3)	1.7±0.5 (1.6±0.5)	2.1±0.8 (2.0±0.8)	1.7±0.6 (1.6±0.6)	1.1±0.3 (1.0±0.3)
ACKur (7)	0.11 ± 0.04	1.83 ± 0.33 (1.49 ± 0.21)	1.8±0.2 (1.8±0.3)	1.7±0.5 (1.6±0.5)	2.1±0.8 (2.0±0.8)	1.7±0.6 (1.6±0.6)	1.0±0.3 (1.0±0.3)
ACAbsCV (7)	0.13 ± 0.06	1.83 ± 0.33 (1.49 ± 0.22)	1.8±0.3 (1.8±0.3)	1.7±0.5 (1.6±0.5)	2.1±0.8 (2.0±0.8)	1.7±0.6 (1.6±0.6)	1.0±0.3 (1.0±0.3)

Table 5-79: Root mean squared error and mean absolute error (shown in parenthesis) when estimating energy expenditure in a subject independent manner using linear regression over individual features computed per sensor over windows of 5.6s in length.

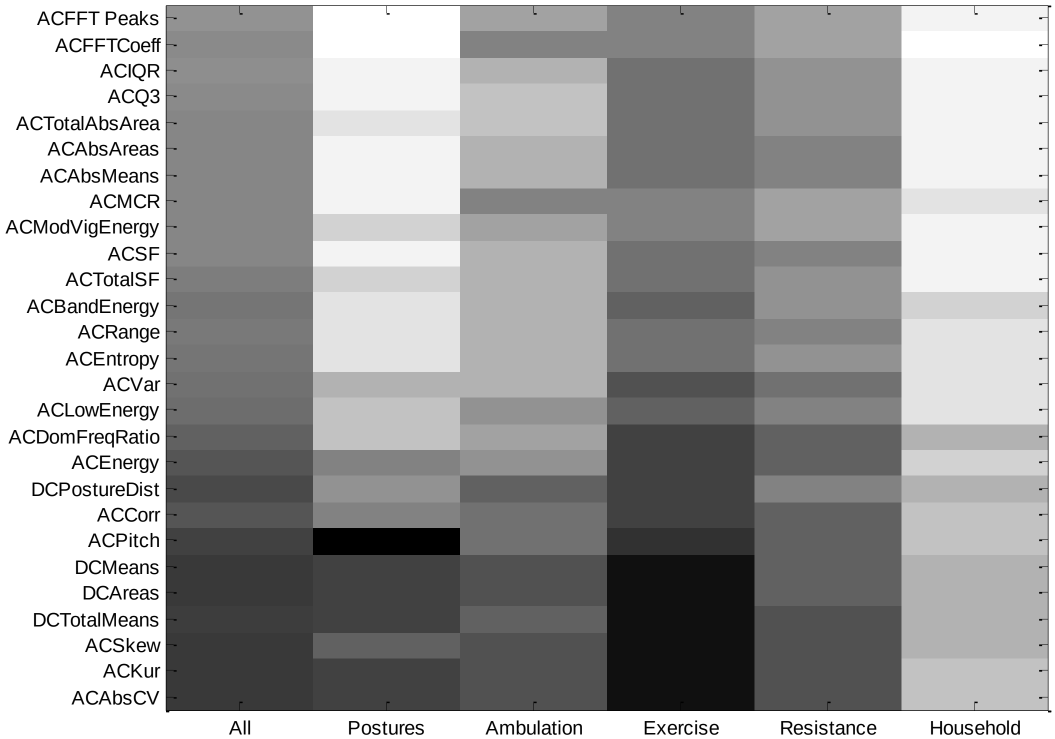


Figure 5-52: Root mean squared error per activity category obtained when estimating energy expenditure over individual features computed per sensor over windows of 5.6s in length using multivariable linear regression. The grayscale image is scaled to show the lowest RMSE of 0.6MET in white and the largest RMSE of 2.2MET in black. In other words, poor areas of performance are shown as dark regions in the image.

was not expected to perform too well on the postures activity category because the first FFT coefficient representing the DC offset of the signal (posture information) is not used in this feature. However, this feature is able to predict energy expenditure for these sedentary activities by detecting very low frequency motion associated with these activities (0.1-3Hz) as observed from the variables included in the regression models learned. One disadvantage of this feature is its relatively high computational complexity of O(*n*log*n*).

The difference in RMSE values between the best and worst performing features in Table 5-79 is 0.55 MET reflects the difficulty of predicting energy expenditure over the MIT energy expenditure dataset. This dataset contains data for 51 activities collected at a gym and at a residential home. Furthermore, some of these activities include different intensity levels due to both changes in the speed of execution of the activities and changes in resistance level or work load. The dataset also contains examples of rapid changes in energy expenditure such as when someone walks upstairs (rapid increase in energy expenditure) for one minute and later rests for another minute (decreases in energy expenditure) repeated continuously up to three times in a row.

Moreover, unlabeled periods of time (*unknown* activity) when subjects rest after exhaustive exercise sessions were not eliminated from the dataset. Finally, periods of time where energy expenditure does not reach steady state were also not eliminated from the dataset. From Table 5-79, a more reliable indicator of the performance of individual features appears to be the correlation coefficient since the difference in this value for the best and worst performing activities is 0.59. The difference between the best and worst possible correlation coefficients is one.

Interestingly, the *ACFFTCoeff* feature expected to have a poor performance due to its large size (889); nonetheless, it is the second best performing feature. This is because the linear regression algorithm used performs feature selection using the M5 method and therefore was able to successfully find a subset of the 889 features that provided good performance. As observed by inspecting the variables included in the regression model learned. Table 5-79 also shows that the inter-quartile range feature (*ACIQR*) is the third best performing feature. This feature achieves a better performance than the *ACTotalAbsArea* and the *ACAbsArea* features, the two features most used to predict energy expenditure in prior work. The problem with the *ACIQR* feature is its high computational complexity since all acceleration values inside a given window need to be ordered in ascending order before this feature can be computed ($O(n^2)$ if bubble, insertion, selection, and shell sorts are utilized and $O(n \log n)$ if quick sort is utilized). Clearly, the improvement in performance over the *ACAbsArea* feature of only 0.02MET does not justify the extra computation incurred. The performance of the *ACAbsArea* and *ACTotalAbsArea* features is similar because they both capture similar information on overall body motion. It seems that computing body motion per limb (*ACAbsArea*) does not improve over computing overall body motion (*ACTotalAbsArea*), perhaps because the regression coefficients need to be optimized for all activities at once. The *ACAbsArea* feature might provide an advantage if different regression models are used to estimate energy expenditure over different sets of activities. When the performance of features capturing motion energy is compared (*ACEnergy*, *ACBandEnergy*, *ACModVigEnergy*, *ACLowEnergy*), it is found that the best performing features are *ACModVigEnergy* and *ACBandEnergy*. This is likely because most activities in the MIT energy expenditure dataset include moderate to vigorous motion that may be better captured by the ACModVigEnergy feature since it computes energy over the frequency range for these motion intensities (0.71 – 10 Hz). Similarly, the *ACBandEnergy* feature computes energy over a frequency range that overlaps with the range of moderate and vigorous motion (0.3-3.5Hz).

Figure 5-52 presents the root mean squared as a gray scale image that highlights the difference in performance among activity categories. From this figure, it can be seen that the best performing features achieve the lowest RMSE error for the postures and household activity categories (white areas located at the top of Figure 5-52). This is because these activities have low levels of energy expenditure as compared to the other activity categories (ambulation, exercise and resistance exercise activities). It is true that some household activities involve some levels of effort (e.g. *scrubbing a surface*) or work load (e.g. *carrying groceries*) but the energy expenditure associated with these activities is low compared to the energy expenditure values found during exercise or resistance exercise activities performed at the gym. As a result, the RMSE for household activities is lower than the one found in the exercise and resistance exercise categories. The high RMSE error associated with exercise and resistance exercise activities can be observed in Figure 5-52 as darker regions for these categories, particularly for the

Information captured by the features	Features
Measures of body posture	*DCPostureDist, DCArea, DCMean, and DCTotalMean.*
Measures of motion shape	*ACTotalAbsArea, ACAbsArea, ACAbsMean, ACQ3, ACQ1, ACQ2, ACTotalSVM, ACEntropy, ACSkew, and ACKur*.
Measures of motion variation	*ACIQR, ACRange, ACVar, and ACAbsCV,*
Measures of motion spectral content	*ACFFTPeaks, ACFFTCoeff*, and *FWTCoeff.*
Measures of motion energy	*ACModVigEnergy, ACBandEnergy, ACLowEnergy, and ACEnergy.*
Measures of motion periodicity	*ACMCR, ACPitch, and ACDomFreqRatio*.
Measures of motion similarity across body segments	*ACCorr*
Measures of force employed per body segment	*ACSF and ACTotalSF.*

Table 5-80: Ordering of the features according to their individual performance and computational requirements (decreasing order of usefulness from left to right) clustered based on the information they attempt to capture from the accelerometer signals.

Features subsets	Correlation	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
All Features: MaxAcceleration	0.74 ± 0.10	1.24 ± 0.30 (0.91 ± 0.20)	0.7±0.3 (0.6±0.3)	1.2±0.5 (1.0±0.5)	1.2±0.7 (1.1±0.7)	1.1±0.6 (1.0±0.6)	0.7±0.3 (0.6±0.3)
Fast to compute: ACAbsArea, DCArea, ACVar, ACRange, ACMCR	0.72 ± 0.11	1.27 ± 0.27 (0.94 ± 0.19)	0.7±0.4 (0.7±0.4)	1.2±0.5 (1.1±0.5)	1.2±0.7 (1.1±0.7)	1.1±0.6 (1.0±0.6)	0.8±0.5 (0.7±0.5)
Invariant reduced DCPostureDist, ACVar, ACBandEnergy, ACFFTPeaks,	0.72 ± 0.11	1.28 ± 0.29 (0.95 ± 0.19)	0.7±0.3 (0.6±0.3)	1.2±0.5 (1.1±0.5)	1.3±0.8 (1.2±0.8)	1.2±0.6 (1.1±0.6)	0.8±0.4 (0.7±0.4)
S1: ACFFTPeaks. ACAbsArea	0.73 ± 0.07	1.27 ± 0.29 (0.92 ± 0.17)	0.6±0.2 (0.5±0.2)	1.2±0.5 (1.1±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.6 (1.1±0.6)	0.7±0.2 (0.6±0.2)
S2: ACFFTPeaks. ACEntropy ACMCR ACModVigEnergy	0.75 ± 0.06	1.23 ± 0.29 (0.89 ± 0.18)	0.7±0.3 (0.6±0.3)	1.1±0.5 (1.0±0.5)	1.3±0.7 (1.2±0.7)	1.1±0.6 (1.0±0.6)	0.7±0.2 (0.6±0.2)
S3: ACFFTPeaks. ACMCR ACModVigEnergy	0.74 ± 0.06	1.24 ± 0.28 (0.89 ± 0.17)	0.7±0.3 (0.6±0.3)	1.2±0.5 (1.0±0.5)	1.3±0.8 (1.2±0.7)	1.1±0.6 (1.0±0.6)	0.7±0.2 (0.6±0.2)
ACFFTPeaks	0.72 ± 0.07	1.28 ± 0.30 (0.93 ± 0.17)	0.6±0.2 (0.6±0.2)	1.2±0.5 (1.1±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.1±0.7)	0.7±0.2 (0.6±0.2)
ACAbsArea	0.68 ± 0.06	1.36 ± 0.30 (1.0 ± 0.2)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.6±0.2)

Table 5-81: Root mean squared error and mean absolute error (shown in parenthesis) for the six subsets of accelerometer-based features with highest performance found when estimating energy expenditure in a subject independent manner using linear regression over the MIT dataset. Features are computed per sensor over windows of 5.6s in length.

features located at the bottom of the figure (poor performing features). Figure 5-52 highlights that the ACPitch feature has a very high RMSE error for the postures category. This is expected since this feature captures the periodicity of motion (fundamental frequency) and motion is minimal for sedentary activities.

Once the performance over individual features was found, they were ordered in decreasing order of usefulness by taking into account their computational requirements. Table 5-80 presents the final ordering of the features according to their individual performance (from Table 5-79) and computational requirements clustered based on the information they attempt to capture. The ordering of features presented in this table was then used to measure the performance over different combinations of features. These features are more invariant to the magnitude of the accelerometer signal than other features and showed high discrimination during activity recognition tasks. The *fast to compute* feature set also includes high discriminant features for activity recognition but that are fast to compute such as the *ACAbsArea*, *DCArea*, *ACVar*, *ACRange*, and *ACMCR*. Table 5-81 also presents the performance for a set of features labeled as *MaxAcceleration* set which contains all the accelerometer-based features.

This set provides a baseline for the best performance that can be obtained when all the accelerometer-based features are used to estimate energy expenditure. Performance per activity for these feature sets is presented in Appendix B13.

Table 5-81 presents the feature sets with highest performance found when estimating energy expenditure in a subject independent manner over the MIT energy expenditure dataset. The feature sets labeled as *fast to compute* and *invariant reduced* correspond to two of the sets of features found with higher performance during the activity recognition experiments in Section 5.4.7. As a reminder to the reader, the *invariant reduced* feature set consists on the *DCPostureDist*, *ACVar*, *ACBandEnergy*, *ACFFTPeaks* features.

From Table 5-81, we can observe that the feature set with highest correlation coefficient (0.75) and lowest RMSE is the one containing the features *ACFFTPeaks*, *ACMCR*, and *ACModVigEnergy*. This set is the best performing because the features *ACFFTPeaks* and *ACMCR* capture the frequencies at which body segments are being moved. Intuitively, it makes sense that higher energy expenditure will be associated with rapid or high frequency motion. The *ACModVigEnergy* feature captures the energy associated with the body limb movement over the moderate and vigorous motion levels. As explained before, most activities contained in the MIT dataset involve either moderate or vigorous motion, so this feature outperforms the other features measuring motion energy (*ACBandEnergy*, *ACLowEnergy*, and *ACEnergy*). Overall, the performance using all six subsets of features is similar and very close. For example, the difference between the best and worse correlation coefficient is just 0.03 and the difference between the best and worse RMSE is only 0.05 MET for the feature combinations. One possible explanation is that the unavailability of enough training data due to the utilization of a large number of features (since they are computed over all seven sensors) prevents the differences from being larger.

To better understand the difference in performance among these feature sets, the RMSE per activity was analyzed. Figure 5-53 shows RMSE as a gray scale image scaled to highlight the difference in performance per activity. The image shows the lowest RMSE of 0.2 MET in white and the largest of 2.2 MET in black. From this gray scale image, it can be observed that as expected, the feature set with lowest RMSE per activity is the *MaxAcceleration* set. The second subset with lowest RMSE per activity is the set labeled as S3 including the *ACFFTPeaks*, *ACMCR*, and *ACModVigEnergy* features. This is because the fast to compute feature shows slightly higher RMSE for *walking around block*, *gardening* and *weeding* perhaps because it does not contain the *ACFFTPeaks* feature that captures frequency of motion at the limbs. The *invariant reduced* and S1 feature set shows a slightly higher RMSE for *running at 6mph* than the S3 feature set. The fact that the S3 feature set is the highest performing one is good news since it includes only features that are relatively invariant to the magnitude of the accelerometer signal. Nevertheless, this feature set improves the correlation coefficient only 0.02 units

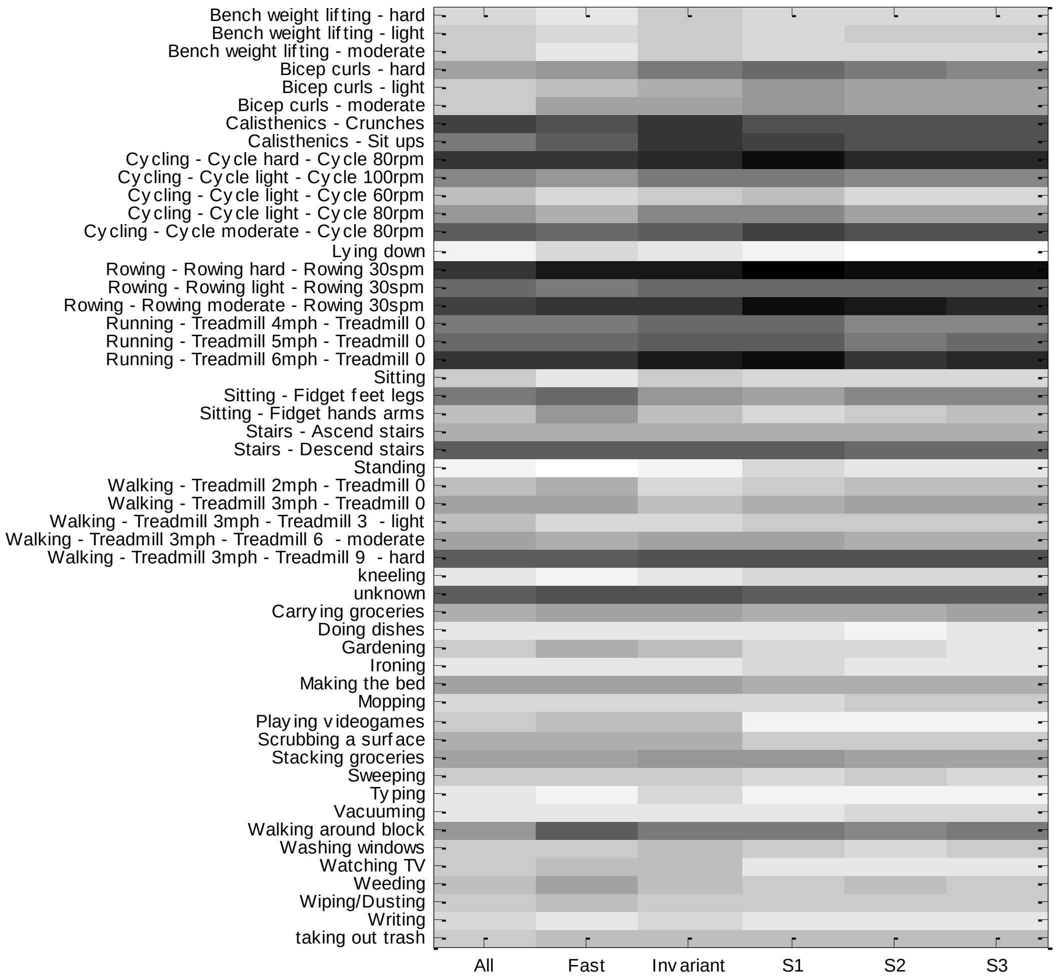


Figure 5-53: Root mean squared error per activity as a gray scale image when multivariable linear regression is used to estimate energy expenditure over several subset of accelerometer-based features computed per sensor over windows of 5.6s in length. The image is scaled to show the lowest RMSE error of 0.2MET in white and the largest of 2.2MET in black. Subset labeled as S1 corresponds to the *ACFFTPeaks* and *ACAbsArea* features, S2 corresponds to the *ACFFTPeaks*, *ACEntropy*, *ACMRC*, and *ACModVigEnergy*, and the S3 to the *ACFFTPeaks*, *ACMRC*, and *ACModVigEnergy* features.

and overall RMSE only 0.04MET over the performance obtained using the *ACFFTPeaks* feature alone.

In conclusion, the best single feature with best performance for estimating energy expenditure is the *ACFFTPeaks* feature. This is because this feature captures the frequency of motion of the body segments, and intuitively, the more rapid the motion (higher frequency), the higher energy expenditure will be. This feature improves the correlation coefficient +0.04 units and overall RMSE 0.08 MET over the *ACAbsArea* feature, which is the feature normally used to predict energy expenditure in prior work. However, the main advantage of the *ACFFTPeaks* feature over the *ACAbsArea* is that is more invariant to the magnitude of the accelerometer signal. Unfortunately, this feature is not as computationally efficient as one would hope since it computational complexity is *O(nlogn).* Nevertheless, the utilization of only the five FFT coefficients with larger magnitude (peaks) per accelerometer signal effectively reduces the number of features (or predictor variables) from 889 to only 70 when all seven sensors and windows of 256 samples in length are used. Given the small differences found for the highest performing feature combinations, it is necessary to explore the performance of these feature sets over subsets of accelerometers to better understand their importance. Consequently, the next section explores the performance of the five highest performing feature sets over subsets of accelerometers.

5.6.8 How Well can Energy Expenditure Be Estimated by Computing the Highest Performing Features Over Subsets of Accelerometers?

The previous section identified the best performing subsets of accelerometer-based features when they were computed over all seven accelerometers. However; in practice, wearing so many accelerometers would be difficult and intrusive. Consequently, it is necessary to explore the performance of these features when the number of accelerometers is reduced. This section explores this question by evaluating five of the highest performing sets of accelerometer-based features found in the previous section in a subject independent manner over eleven subsets of accelerometers. The five feature sets explored in this section are (1) *ACAbsArea*, (2) *ACFFTPeaks*, (3) *ACFFTPeaks* + *ACModVigEnergy* + *ACMCR*, (4) the *fast to compute* feature set, and (5) the *invariant reduced* feature set. For a detailed description of the features included in the *fast to compute* and *invariant reduced* feature sets refer to Section 5.4.7. Energy expenditure is estimated by utilizing a single multivariable linear regression model trained using features computed per sensor over windows of 5.6s in length over the different sensor combinations.

Table 5-82 through Table 5-86 present the results obtained using the five feature sets computed over eleven sensor combinations. From these tables, it can be seen that in general, feature sets containing multiple features other than the *ACAbsArea* feature improve performance, particularly when single sensors are used to estimate energy expenditure. For example, the performance of the *ACFFTPeaks* + *ACModVigEnergy* + *ACMCR* feature set over different subsets of accelerometers is higher than the performance obtained using single features such as the *ACAbsArea* and the *ACFFTPeaks.* For instance, the *ACFFTPeaks* + *ACModVigEnergy* + ACMCR feature set achieves a correlation coefficient of 0.70 and a RMSE of 1.34MET over the hip sensor, while the *ACFFTPeaks* feature alone only achieves a correlation coefficient of *0.49* and a RMSE of 1.62MET. Similarly, the *ACAbsArea* feature alone achieves a correlation coefficient of 0.61 and a RMSE of 1.62MET over the hip sensor. The performance of the *ACFFTPeaks* + *ACModVigEnergy* + *ACMCR* feature set is also higher over the other single accelerometers (DWrist, DFoot, DThigh, and DUpperArm) than when the *ACFFTPeaks* or *ACAbsArea* features are used alone. This indicates that computing features that capture additional information other than overall amount of motion usually captured by the *ACAbsArea* feature (often used by the medical community) indeed improves energy

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	0.68 ± 0.06	1.36 ± 0.30 (1.0 ± 0.2)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.6±0.2)
Hip + DWrist + DFoot	0.67 ± 0.05	1.38 ± 0.29 (1.04 ± 0.15)	0.8±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.8±0.3 (0.7±0.2)
Hip + DWrist	0.61 ± 0.07	1.49 ± 0.33 (1.16 ± 0.19)	1.0±0.2 (1.0±0.2)	1.1±0.5 (1.0±0.5)	1.7±0.8 (1.6±0.7)	1.4±0.6 (1.4±0.6)	0.8±0.2 (0.8±0.2)
Hip + DFoot	0.64 ± 0.08	1.43 ± 0.33 (1.08 ± 0.17)	1.0±0.2 (0.9±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.7±0.2 (0.7±0.2)
DWrist + DThigh	0.65 ± 0.08	1.42 ± 0.32 (1.09 ± 0.17)	0.9±0.3 (0.9±0.3)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.5±0.7)	1.4±0.6 (1.3±0.6)	0.8±0.2 (0.7±0.2)
DWrist + DFoot	0.67 ± 0.05	1.38 ± 0.29 (1.04 ± 0.15)	0.8±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.8±0.3 (0.7±0.2)
Hip	0.61 ± 0.08	1.51 ± 0.34 (1.16 ± 0.20)	1.1±0.2 (1.1±0.2)	1.1±0.5 (1.0±0.5)	1.6±0.8 (1.5±0.8)	1.4±0.6 (1.3±0.6)	0.8±0.2 (0.7±0.2)
DWrist	0.45 ± 0.15	1.66 ± 0.30 (1.37 ± 0.20)	1.2±0.3 (1.2±0.3)	1.4±0.5 (1.3±0.5)	2.0±0.8 (1.9±0.8)	1.8±0.7 (1.8±0.7)	1.2±0.3 (1.1±0.3)
DFoot	0.63 ± 0.08	1.45 ± 0.33 (1.10 ± 0.17)	1.0±0.2 (1.0±0.2)	1.2±0.5 (1.1±0.5)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.8±0.2 (0.7±0.2)
DUpperArm	0.54 ± 0.11	1.56 ± 0.31 (1.25 ± 0.19)	1.0±0.3 (0.9±0.3)	1.1±0.5 (1.0±0.5)	1.8±0.8 (1.7±0.8)	1.6±0.6 (1.5±0.6)	1.1±0.4 (1.0±0.3)
DThigh	0.63 ± 0.09	1.44 ± 0.34 (1.11 ± 0.19)	1.1±0.3 (1.1±0.3)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.7±0.2)

Table 5-82: Root mean squared error and mean absolute error (shown in parenthesis) obtained when estimating energy expenditure in a subject independent manner using linear regression and the *ACAbsArea* feature computed per sensor using windows of 5.6s in length over different subsets of accelerometers. Energy expenditure is estimated for the 51 activities contained in the MIT energy expenditure dataset.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	0.72 ± 0.07	1.28 ± 0.30 (0.93 ± 0.17)	0.6±0.2 (0.6±0.2)	1.2±0.5 (1.1±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.1±0.7)	0.7±0.2 (0.6±0.2)
Hip + DWrist + DFoot	0.72 ± 0.06	1.28 ± 0.31 (0.93 ± 0.18)	0.6±0.2 (0.5±0.2)	1.1±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.6 (1.1±0.6)	0.7±0.3 (0.6±0.2)
Hip + DWrist	0.51 ± 0.09	1.59 ± 0.31 (1.28 ± 0.20)	1.2±0.2 (1.1±0.3)	1.3±0.5 (1.2±0.5)	1.9±0.8 (1.8±0.8)	1.7±0.6 (1.6±0.6)	0.9±0.3 (0.9±0.3)
Hip + DFoot	0.71 ± 0.06	1.29 ± 0.30 (0.94 ± 0.18)	0.6±0.2 (0.6±0.2)	1.1±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.6 (1.1±0.6)	0.7±0.2 (0.6±0.2)
DWrist + DThigh	0.66 ± 0.06	1.39 ± 0.29 (1.02 ± 0.15)	0.7±0.2 (0.6±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.8 (1.4±0.7)	1.4±0.7 (1.3±0.7)	0.8±0.3 (0.7±0.2)
DWrist + DFoot	0.71 ± 0.07	1.29 ± 0.31 (0.93 ± 0.17)	0.6±0.2 (0.5±0.2)	1.1±0.4 (1.0±0.4)	1.4±0.8 (1.3±0.8)	1.3±0.7 (1.1±0.7)	0.7±0.3 (0.6±0.2)
Hip	0.49 ± 0.10	1.62 ± 0.32 (1.31 ± 0.22)	1.3±0.2 (1.2±0.2)	1.3±0.5 (1.2±0.5)	1.9±0.8 (1.9±0.8)	1.7±0.6 (1.6±0.6)	0.9±0.2 (0.8±0.2)
DWrist	0.44 ± 0.15	1.66 ± 0.29 (1.36 ± 0.20)	1.2±0.3 (1.2±0.3)	1.4±0.5 (1.3±0.5)	2.0±0.8 (1.9±0.8)	1.9±0.7 (1.8±0.7)	1.1±0.3 (1.0±0.3)
DFoot	0.70 ± 0.07	1.31 ± 0.30 (0.96 ± 0.17)	0.7±0.2 (0.6±0.2)	1.1±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.3±0.7 (1.2±0.7)	0.7±0.3 (0.6±0.2)
DUpperArm	0.66 ± 0.08	1.41 ± 0.34 (1.05 ± 0.20)	0.8±0.3 (0.8±0.3)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.7±0.2 (0.6±0.2)
DThigh	0.61 ± 0.09	1.49 ± 0.35 (1.11 ± 0.18)	1.0±0.2 (0.9±0.2)	1.2±0.5 (1.1±0.5)	1.6±0.8 (1.5±0.8)	1.3±0.6 (1.2±0.6)	0.8±0.2 (0.7±0.2)

Table 5-83: Root mean squared error and mean absolute error (shown in parenthesis) obtained when estimating energy expenditure in a subject independent manner using linear regression and the *ACFFTPeaks* feature computed per sensor using windows of 5.6s in length over different subsets of accelerometers. Energy expenditure is estimated for the 51 activities contained in the MIT energy expenditure dataset.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	0.74 ± 0.06	1.24 ± 0.28 (0.89 ± 0.17)	0.7±0.3 (0.6±0.3)	1.2±0.5 (1.0±0.5)	1.3±0.8 (1.2±0.7)	1.1±0.6 (1.0±0.6)	0.7±0.2 (0.6±0.2)
Hip + DWrist + DFoot	0.73 ± 0.05	1.25 ± 0.29 (0.91 ± 0.18)	0.5±0.2 (0.5±0.2)	1.1±0.4 (1.0±0.4)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.1±0.6)	0.7±0.2 (0.6±0.2)
Hip + DWrist	0.70 ± 0.06	1.33 ± 0.29 (1.01 ± 0.20)	0.6±0.2 (0.5±0.2)	1.2±0.5 (1.1±0.5)	1.4±0.7 (1.3±0.7)	1.3±0.6 (1.2±0.6)	0.8±0.3 (0.7±0.2)
Hip + DFoot	0.73 ± 0.05	1.25 ± 0.28 (0.91 ± 0.18)	0.6±0.2 (0.5±0.2)	1.2±0.4 (1.0±0.4)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.1±0.6)	0.7±0.2 (0.6±0.2)
DWrist + DThigh	0.71 ± 0.06	1.32 ± 0.29 (0.96 ± 0.17)	0.7±0.4 (0.7±0.4)	1.1±0.4 (1.0±0.4)	1.4±0.8 (1.3±0.7)	1.2±0.7 (1.1±0.6)	0.7±0.2 (0.6±0.2)
DWrist + DFoot	0.72 ± 0.07	1.28 ± 0.30 (0.92 ± 0.17)	0.6±0.2 (0.5±0.2)	1.1±0.4 (1.0±0.4)	1.4±0.8 (1.2±0.8)	1.2±0.7 (1.1±0.6)	0.7±0.2 (0.6±0.2)
Hip	0.70 ± 0.06	1.34 ± 0.29 (1.02 ± 0.20)	0.6±0.2 (0.6±0.2)	1.3±0.5 (1.2±0.5)	1.4±0.7 (1.3±0.7)	1.3±0.6 (1.1±0.6)	0.8±0.2 (0.7±0.2)
DWrist	0.53 ± 0.10	1.58 ± 0.31 (1.26 ± 0.20)	1.0±0.3 (0.9±0.3)	1.3±0.4 (1.2±0.4)	1.9±0.8 (1.8±0.8)	1.7±0.7 (1.6±0.7)	1.1±0.3 (1.0±0.3)
DFoot	0.71 ± 0.06	1.29 ± 0.29 (0.94 ± 0.17)	0.6±0.2 (0.6±0.2)	1.1±0.4 (1.0±0.4)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.1±0.7)	0.7±0.2 (0.6±0.2)
DUpperArm	0.68 ± 0.08	1.36 ± 0.34 (1.02 ± 0.19)	0.6±0.2 (0.6±0.3)	1.1±0.4 (1.0±0.4)	1.4±0.7 (1.3±0.7)	1.3±0.6 (1.2±0.6)	0.8±0.2 (0.7±0.2)
DThigh	0.66 ± 0.08	1.40 ± 0.33 (1.03 ± 0.19)	0.9±0.4 (0.9±0.4)	1.2±0.5 (1.1±0.5)	1.4±0.7 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.7±0.2 (0.6±0.2)

Table 5-84: Root mean squared error and mean absolute error (shown in parenthesis) obtained when estimating energy expenditure in a subject independent manner using linear regression and the *ACFFTPeaks + ACModVigEnergy + ACMCR* features computed per sensor using windows of 5.6s in length over different subsets of accelerometers. Energy expenditure is estimated for the 51 activities contained in the MIT energy expenditure dataset.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	0.72 ± 0.11	1.27 ± 0.27 (0.94 ± 0.19)	0.7±0.4 (0.7±0.4)	1.2±0.5 (1.1±0.5)	1.2±0.7 (1.1±0.7)	1.1±0.6 (1.0±0.6)	0.8±0.5 (0.7±0.5)
Hip + DWrist + DFoot	0.69 ± 0.12	1.33 ± 0.33 (0.99 ± 0.24)	0.6±0.3 (0.5±0.3)	1.2±0.5 (1.1±0.5)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.1±0.6)	0.9±0.6 (0.8±0.6)
Hip + DWrist	0.69 ± 0.06	1.37 ± 0.28 (1.04 ± 0.18)	0.6±0.2 (0.5±0.2)	1.2±0.5 (1.1±0.5)	1.3±0.7 (1.3±0.6)	1.2±0.6 (1.1±0.6)	0.9±0.3 (0.8±0.3)
Hip + DFoot	0.66 ± 0.13	1.38 ± 0.35 (1.03 ± 0.24)	0.7±0.3 (0.7±0.3)	1.3±0.6 (1.2±0.6)	1.3±0.7 (1.2±0.7)	1.1±0.6 (1.0±0.6)	0.9±0.6 (0.8±0.6)
DWrist + DThigh	0.72 ± 0.06	1.28 ± 0.25 (0.95 ± 0.15)	0.9±0.5 (0.8±0.5)	1.1±0.4 (1.0±0.4)	1.2±0.6 (1.1±0.6)	1.1±0.6 (1.0±0.5)	0.7±0.3 (0.6±0.3)
DWrist + DFoot	0.69 ± 0.10	1.33 ± 0.33 (0.99 ± 0.23)	0.7±0.3 (0.6±0.3)	1.1±0.5 (1.0±0.5)	1.3±0.7 (1.2±0.7)	1.2±0.7 (1.2±0.6)	0.9±0.6 (0.8±0.6)
Hip	0.67 ± 0.07	1.40 ± 0.31 (1.06 ± 0.19)	0.7±0.2 (0.7±0.2)	1.3±0.5 (1.2±0.5)	1.4±0.7 (1.3±0.6)	1.2±0.6 (1.1±0.5)	0.8±0.2 (0.7±0.2)
DWrist	0.49 ± 0.13	1.63 ± 0.31 (1.32 ± 0.20)	1.1±0.4 (1.1±0.4)	1.3±0.5 (1.2±0.5)	2.0±0.8 (1.9±0.8)	1.8±0.7 (1.7±0.7)	1.2±0.4 (1.1±0.4)
DFoot	0.63 ± 0.10	1.42 ± 0.35 (1.07 ± 0.20)	0.9±0.3 (0.9±0.3)	1.3±0.5 (1.2±0.5)	1.4±0.7 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.9±0.4 (0.8±0.4)
DUpperArm	0.60 ± 0.07	1.48 ± 0.31 (1.14 ± 0.19)	0.7±0.3 (0.7±0.3)	1.1±0.4 (1.0±0.4)	1.6±0.8 (1.5±0.8)	1.5±0.7 (1.4±0.7)	1.1±0.3 (1.0±0.3)
DThigh	0.69 ± 0.09	1.32 ± 0.28 (0.99 ± 0.15)	1.0±0.5 (1.0±0.5)	1.1±0.4 (1.0±0.4)	1.2±0.6 (1.1±0.6)	1.1±0.5 (1.0±0.5)	0.7±0.3 (0.6±0.2)

Table 5-85: Root mean squared error and mean absolute error (shown in parenthesis) obtained when estimating energy expenditure in a subject independent manner using linear regression and the *Fast to compute* feature set computed per sensor using windows of 5.6s in length over different subsets of accelerometers. Energy expenditure is estimated for the 51 activities contained in the MIT energy expenditure dataset.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	0.72 ± 0.11	1.28 ± 0.29 (0.95 ± 0.19)	0.7±0.3 (0.6±0.3)	1.2±0.5 (1.1±0.5)	1.3±0.8 (1.2±0.8)	1.2±0.6 (1.1±0.6)	0.8±0.4 (0.7±0.4)
Hip + DWrist + DFoot	0.70 ± 0.11	1.31 ± 0.34 (0.97 ± 0.23)	0.6±0.3 (0.5±0.3)	1.2±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.1±0.6)	0.8±0.5 (0.7±0.5)
Hip + DWrist	0.58 ± 0.08	1.53 ± 0.28 (1.20 ± 0.18)	1.0±0.4 (1.0±0.4)	1.3±0.4 (1.1±0.5)	1.8±0.8 (1.7±0.8)	1.5±0.6 (1.5±0.6)	1.0±0.3 (0.9±0.3)
Hip + DFoot	0.71 ± 0.11	1.29 ± 0.32 (0.96 ± 0.22)	0.6±0.2 (0.5±0.2)	1.2±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.8±0.5 (0.7±0.5)
DWrist + DThigh	0.68 ± 0.05	1.35 ± 0.29 (1.00 ± 0.17)	0.8±0.3 (0.7±0.3)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.7±0.3 (0.6±0.3)
DWrist + DFoot	0.69 ± 0.12	1.32 ± 0.36 (0.97 ± 0.23)	0.6±0.3 (0.5±0.3)	1.1±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.3±0.7 (1.2±0.7)	0.8±0.5 (0.7±0.5)
Hip	0.55 ± 0.09	1.55 ± 0.28 (1.24 ± 0.18)	1.0±0.3 (1.0±0.3)	1.3±0.5 (1.2±0.5)	1.8±0.8 (1.7±0.8)	1.6±0.6 (1.5±0.6)	1.0±0.3 (0.9±0.3)
DWrist	0.48 ± 0.15	1.62 ± 0.32 (1.30 ± 0.21)	1.2±0.3 (1.2±0.3)	1.2±0.5 (1.2±0.5)	1.9±0.8 (1.9±0.8)	1.7±0.7 (1.7±0.7)	1.0±0.3 (1.0±0.3)
DFoot	0.69 ± 0.11	1.32 ± 0.34 (0.97 ± 0.21)	0.7±0.3 (0.6±0.3)	1.1±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.3±0.7 (1.2±0.7)	0.8±0.4 (0.7±0.4)
DUpperArm	0.66 ± 0.08	1.39 ± 0.33 (1.04 ± 0.19)	0.7±0.2 (0.7±0.2)	1.1±0.5 (1.0±0.5)	1.5±0.8 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.8±0.2 (0.7±0.2)
DThigh	0.64 ± 0.09	1.42 ± 0.33 (1.07 ± 0.18)	0.9±0.3 (0.9±0.3)	1.2±0.5 (1.1±0.5)	1.5±0.7 (1.4±0.7)	1.3±0.6 (1.2±0.6)	0.8±0.3 (0.7±0.3)

Table 5-86: Root mean squared error and mean absolute error (shown in parenthesis) obtained when estimating energy expenditure in a subject independent manner using linear regression and the *Invariant reduced* feature set computed per sensor using windows of 5.6s in length over different subsets of accelerometers. Energy expenditure is estimated for the 51 activities contained in the MIT energy expenditure dataset.

expenditure estimation. This effect was perhaps not observed in the previous section because of the relatively limited amount of training data available with respect to the large number of features being computed (since features were computed over all seven accelerometers). This effect produced by computing a large number of features when training data is limited can also be observed by comparing Table 5-86 and Table 5-84. These tables show that the overall performance of the *invariant reduced* feature set is slightly lower than the performance of the *ACFFTPeaks* + *ACModVigEnergy* + *ACMCR* feature set. This is because the *invariant reduced* feature set contains more features (*ACFFTPeaks*, *ACBandEnergy*, *ACVar*, and *DCPostureDist*) and consequently, the training data available to train the regression model (containing more variables) is not enough. The result that multiple features achieve higher performance over single sensors and combinations of sensors than single features (e.g. *ACAbsArea*) confirms recent findings by Rothney [152, 181]. This work also found that extracting multiple features such as the coefficient of variation, inter-quartile range, and power spectral density improves the performance in energy expenditure estimation when a single accelerometer at the hip is used. The work presented in this section goes a step further by showing, as one might expect, that multiple features also improve overall performance and performance per activity when multiple sensors are used provided there is enough training data to train the regression models. In this paragraph, 'multiple features' refer to features other than the *ACAbsArea* feature that capture motion information other than overall amount of motion that helps in estimating energy expenditure better.

From Table 5-82 through Table 5-86 it can also be observed that overall, the sensor combinations with higher performance in decreasing order are All Sensors, Hip + DWrist

+ DFoot, and DWrist + DFoot. As explained in previous sections, the Hip + DWrist + DFoot sensor combination is able to capture upper body, lower body, and overall body motion well enough to achieve a performance similar to the one obtained using all seven accelerometers. Interestingly, the sensor combination DWrist + DFoot also achieves a performance that is very close to the one obtained using all the seven sensors. For example, the difference in the correlation coefficient between all sensors and the DWrist + DFoot sensor combination is between 0.01 and 0.02 for all tables. The difference for the RMSE is between 0.01 and 0.04MET. One possible explanation for the good performance of this sensor combination is that it effectively detects upper body and lower body motion since one sensor at the wrist and another at the foot are used. At the same time, overall body motion due to activities such as ambulation is also picked up at these two sensors locations. This is an important result because it can be argued that sensors at the wrist and at the foot are easier to wear than sensors at the hip, particularly for women (e.g. women wearing dresses). The accelerometer at the wrist can also be embedded in devices already worn at this location such as wrist watches and the sensor at the foot in shoe pods. The sensor combinations Hip + DWrist, Hip + DFoot, and DWrist + DThigh also achieve a competitive performance (with respect to the all sensors combination) although their ordering with respect to performance depends on the features being computed. The result obtained in this section are in agreement with prior work by Melanson and Freedson [233] who found that the sensor combination hip + wrist or wrist + ankle (foot in our case) produced a correlation coefficient of r=0.94 during *walking* and *jogging*. Obviously, the correlation coefficients obtained in this work are lower (r between 0.51 and 0.72) because energy expenditure is estimated for 52 activities some of them containing different levels of resistance work and work load.

Overall, the sensor combinations that present the lowest performance in the tables (Table 5-82 through Table 5-86) are the single accelerometer at the wrist (DWrist), and the single accelerometer at the hip (Hip). For example, when the wrist sensor is used, the difference in the correlation coefficient with respect to the all sensors combination is 0.23 units and the difference in RMSE is 0.3MET for the *ACAbsArea* feature (Table 5-82). When the *ACFFTPeaks* feature is used, the difference in the correlation coefficient for this sensor again, with respect to the all sensors combination, is 0.24units and 0.3MET for the RMSE. The differences are reduced slightly when the *ACFFTPeaks* + *ACModVigEnergy* + ACMCR is used. The poor performance of the DWrist sensor can be explained by the fact that the wrist presented the highest motion variability (as observed during the data collections) for most activities, particularly during household activities since the RMSE is higher over these categories for the wrist sensor. The low performance of the DUpperArm sensor can be explained by the fact that it has difficulties detecting upper body and non-ambulatory lower body motion. For example, when the performance per activity is analyzed for the Hip sensor for the five feature sets, it is found that the activities with lowest performance are activities involving lower body motion such as *cycling* at different speeds and resistance levels and *rowing* at different resistance levels. For these activities, the RMSE ranged between 1 and 3.5MET. Upper body activities such as *bench weight lifting*, *bicep curls*, and *wiping a surface* also presented the lowest performance. Appendix B15 presents the performance per activity for some of the highest performing features computed over the accelerometers at the hip, dominant wrist, and dominant foot.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
ACFFTPeaks + ACModVigEnergy + ACMCR	0.73 ± 0.05	1.25 ± 0.29 (0.91 ± 0.18)	0.5±0.2 (0.5±0.2)	1.1±0.4 (1.0±0.4)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.1±0.6)	0.7±0.2 (0.6±0.2)
ACFFTPeaks	0.72 ± 0.06	1.28 ± 0.31 (0.93 ± 0.18)	0.6±0.2 (0.5±0.2)	1.1±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.6 (1.1±0.6)	0.7±0.3 (0.6±0.2)
Invariant Reduced	0.70 ± 0.11	1.31 ± 0.34 (0.97 ± 0.23)	0.6±0.3 (0.5±0.3)	1.2±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.1±0.6)	0.8±0.5 (0.7±0.5)
Fast to compute	0.69 ± 0.12	1.33 ± 0.33 (0.99 ± 0.24)	0.6±0.3 (0.5±0.3)	1.2±0.5 (1.1±0.5)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.1±0.6)	0.9±0.6 (0.8±0.6)
ACAbsArea	0.67 ± 0.05	1.38 ± 0.29 (1.04 ± 0.15)	0.8±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.8±0.3 (0.7±0.2)

Table 5-87: Root mean squared error and mean absolute error (shown in parenthesis) obtained when estimating energy expenditure in a subject independent manner using linear regression and the five highest performing feature sets computed per sensor using windows of 5.6s in length over the accelerometers at the hip, dominant wrist, and dominant foot. Energy expenditure is estimated for the 51 activities contained in the MIT energy expenditure dataset.

Table 5-87 presents a summary of the results obtained using the five feature sets explored over the accelerometers located at the hip, dominant wrist, and dominant foot. This sensor combination (Hip+DWrist+DFoot) was the highest performing with respect to the performance obtained using all seven accelerometers. From the table, it can be seen that the performance of the *ACFFTPeaks* + *ACModVigEnergy* + *ACMCR* is the highest, followed by the performance of the *ACFFTPeaks*. The difference in performance between the two highest performing feature sets is r=+0.01 and RMSE = -0.03MET. As a result, it can be argued that even when the *ACFFTPeaks* + ACModVigEnergy + *ACMCR*, the *ACFFTPeaks* feature achieves a close performance but with lower computational requirements. As a result, the final implementation of the energy expenditure algorithm will be utilizing the *ACFFTPeaks* feature to estimate energy expenditure. Performance will also be measured using the *ACAbsArea* feature given its low computational requirements. The final implementation of the EE estimation algorithm is discussed later in Section 5.6.11.

5.6.9 Does Heart Rate Data Improve Energy Expenditure Estimation?

In previous sections, the lowest performance while estimating energy expenditure was obtained for activities involving different levels of resistance or work load effort. Examples of these activities include *cycling* and *rowing* at different resistance levels, performing *bicep curls* and *bench weight lifting* with different weights (at the same speed of motion), *walking on a treadmill* at different inclination grades and walking *carrying groceries*. This is because accelerometers have difficulties detecting the extra effort associated with these activities because they can only measure amount of motion (acceleration). Heart rate on the other hand, can detect changes in effort and resistance load because it has a linear relationship with energy expenditure during moderate and vigorous activities [47, 48, 81]. As a result, this section explores if combining accelerometer and heart rate data improves estimation of energy expenditure.

This section first evaluates the performance over individual heart rate features (*HRMean*, *HRAboveRest*, *ScaledHR*, *HRVar*, and *HRTrend*) to identify the single features

Heart Rate Features	Algorithm	Correlation Coefficient	All	Postures	Ambulation	Exercise	Resistance Exercise	*Household*
ScaledHR (1)	LR	0.83 ± 0.09	1.01 ± 0.3 (0.8± 0.2)	0.5±0.3 (0.5±0.3)	0.9±0.5 (0.9±0.4)	1.3±0.7 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.5±0.3 (0.5±0.2)
HRAboveRest (1)	LR	0.83 ± 0.10	1.1 ± 0.4 (0.9 ± 0.3)	0.5±0.3 (0.5±0.3)	1.0±0.6 (1.0±0.6)	1.5±0.8 (1.4±0.8)	1.3±0.7 (1.2±0.7)	0.5±0.3 (0.5±0.2)
HRMean (1)	LR	0.82 ± 0.09	1.3 ± 0.4 (1.0 ± 0.4)	0.8±0.4 (0.8±0.4)	1.2±0.7 (1.2±0.7)	1.6±0.9 (1.5±0.9)	1.3±0.8 (1.3±0.8)	0.6±0.3 (0.6±0.3)
HRVar (1)	LR	0.08 ± 0.05	1.8 ± 0.3 (1.5 ± 0.2)	1.7±0.2 (1.7±0.2)	1.8±0.5 (1.7±0.5)	2.1±0.8 (2.0±0.8)	1.7±0.6 (1.6±0.6)	1.0±0.3 (1.0±0.3)
HRTrend (1)	LR	0.04 ± 0.05	1.8 ± 0.3 (0.0 ± 0.0)	1.8±0.2 (1.7±0.2)	1.8±0.5 (1.7±0.5)	2.1±0.8 (2.0±0.8)	1.7±0.6 (1.6±0.6)	1.0±0.3 (1.0±0.3)
ScaledHR (1)	MT	0.84 ± 0.09	1.0 ± 0.3 (0.8 ± 0.3)	0.5±0.3 (0.5±0.3)	1.0±0.5 (0.9±0.5)	1.3±0.8 (1.2±0.8)	1.2±0.7 (1.1±0.6)	0.5±0.2 (0.5±0.2)

Table 5-88: Root mean squared error and mean absolute error (shown in parenthesis) obtained while estimating energy expenditure in a subject independent manner over the MIT EE dataset using multivariable linear regression and individual heart rate features computed over windows of 5.6s in length. LR stands for linear regression and MT for model trees (M5').

with highest performance. Appendix A3 provides an explanation of how these features are computed and what information they attempt to capture. Once the heart rate feature with highest performance is identified, it is incorporated to the best set of accelerometer-based features found in Section 5.4.7. Energy expenditure is then estimated using multivariable linear regression with feature computation per sensor over sliding windows of 5.6s in length for both, accelerometer and heart rate data. The heart rate signal is preprocessed to reduce noise by applying a 15s running average filter. When the accelerometer data is included, the heart rate window length extends from the end of the acceleration window backwards in time as shown in Figure 5-24. Finally, heart rate windows and their associated acceleration windows are discarded when no sensor values are available for heart rate over a given window. All results presented in this section are evaluated using subject independent training unless otherwise indicated.

Table 5-88 presents the root mean squared error and mean absolute error (shown in parenthesis) obtained over individual heart rate features. It can be seen that the heart rate feature with higher overall performance is *ScaledHR*. The correlation coefficient obtained is 0.83 (out of a max of 1) and the overall RMSE error is 1.0MET when linear regression is used. The activity categories with higher RMSE are exercise and resistance exercise activities with RMSE values between 1.2 and 1.3MET respectively for the *ScaledHR* feature. This is because most of the activities contained in these categories involve resistance or work load effort. Heart rate can detect changes in resistance or work load effort during moderate and vigorous activities [47, 48, 81]; however, the main challenge in estimating energy expenditure for these activities is inter-individual differences due to fitness level and body composition (e.g. weight and fat mass). This is a problem because two subjects performing the same activity but with different fitness level will produce different heart rate readings. For example, more fit individuals tend to have lower heart rates than non-fit individuals [47] when they perform the same activity. This is why the lowest performance is obtained for the exercise and resistance exercise categories. Table 5-88 also shows that the performance of the *ScaledHR* feature is slightly higher than the one obtained for the *HRAboveRest* feature. This is because the *ScaledHR* feature normalizes heart rate readings to fall between 0 and 1 for resting heart rate and heart rate while *running on a treadmill at 5mph* for each subject.

Heart Rate Features	Correlation Coefficient	All	Postures	Ambulation	Exercise	Resistance Exercise	*Household*
ScaledHR (1)	0.83 ± 0.09	0.92 ± 0.29 (0.71 ± 0.22)	0.5±0.3 (0.5±0.3)	0.9±0.4 (0.8±0.4)	1.2±0.6 (1.2±0.6)	1.1±0.5 (1.1±0.5)	0.5±0.2 (0.4±0.2)
HRAboveRest (1)	0.83 ± 0.10	0.93 ± 0.30 (0.71 ± 0.23)	0.5±0.3 (0.5±0.3)	0.9±0.4 (0.8±0.4)	1.2±0.6 (1.2±0.6)	1.1±0.5 (1.1±0.5)	0.5±0.2 (0.4±0.2)

Table 5-89: Root mean squared error and mean absolute error (shown in parenthesis) obtained while estimating energy expenditure in a subject dependent manner over the MIT dataset using multivariable linear regression and individual heart rate features computed over windows of 5.6s in length.

This normalization helps in reducing inter-individual variations in heart rate because two individuals with different heart rate readings would be performing in the same intensity zone with respect to resting and sub-maximal heart rate (running at 5mph). Even when the overall difference in performance between the *ScaledHR* and *HRAboveRest* features is tiny (0.09MET in overall RMSE); performance per activity category is improved between 0.1 and 0.2MET for the ambulation, exercise, and resistance exercise categories. These are the activity categories that one would expect to benefit the most from the heart rate data normalization. One possible explanation of why the difference in performance is not larger is that heart rate while running on a treadmill at 5mph was used as a substitute for maximum heart rate during the normalization procedure. The measurement of maximal heart rate requires individuals to perform physically intense exercise (e.g. running on a treadmill) until heart rate reaches a maximum and no longer increases. Thus, this test is inconvenient in practice because it requires individuals to perform maximal physical effort. Furthermore, some individuals suffering from physical conditions might not even be able to perform such a test. Table 5-88 also shows that the features with lowest performance are *HRTrend* and *HRVar*.

This is because *HRVar* measures the variance over the heart rate data and this value is similar for most activities: high at the beginning of an activity due to non-steady state conditions and low towards the end of activities due to steady-state conditions. Similarly, *HRTrend* tells if heart rate is increasing (slope>0), decreasing (slope<0), or in steady state over time (slope~0). Thus, most activities present the same trends in this value: positive at the beginning of activities when energy expenditure is increasing and near zero towards the end of the activity when energy expenditure reaches steady-state condition. The last row of Table 5-88 presents the performance of the *ScaledHR* feature when a M5' model tree is used to estimate energy expenditure. The performance of the M5' model tree was tested over the best performing heart rate feature because this regression algorithm is able to capture non-linear relationships in the data and thus, could improve energy expenditure estimation. From the table, it can be observed that the performance indeed increases as expected, but the increase is so small (+0.01 for both, RMSE and *r*) that it does not justify the additional complexity of running this non-linear regression algorithm. One reason for this small improvement could be the unavailability of enough training examples at the leaf nodes of the model tree to allow adequate training of the linear regression models. For example, the model trees generated during the evaluation of the algorithm contained between 43 and 76 leaf nodes. This means that between 43 and 76 multivariable linear regression models have to be trained over each leaf node in order to predict energy expenditure. This partition of the available training data into 43-76

Features	Correlation (*r*)	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
ScaledHR	0.83 0.09	1.01 ± 0.3 (0.8 ± 0.2)	0.5±0.3 (0.5±0.3)	0.9±0.5 (0.9±0.4)	1.3±0.7 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.5±0.3 (0.5±0.2)
ScaledHR + Weight	0.83 ± 0.09	1.01 ± .32 (0.7 ± 0.2)	0.5±0.3 (0.5±0.3)	0.9±0.5 (0.9±0.5)	1.3±0.7 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.5±0.3 (0.5±0.2)
ScaledHR + FatPercent	0.83 ± 0.09	1.01 ± 0.32 (0.8 ± 0.2)	0.5±0.3 (0.5±0.3)	0.9±0.5 (0.9±0.5)	1.3±0.7 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.5±0.3 (0.5±0.3)
ScaledHR + FitnessIndex	0.83 ± 0.10	1.07 ± 0.36 (0.8 ± 0.3)	0.6±0.3 (0.5±0.3)	1.0±0.6 (0.9±0.5)	1.5±0.8 (1.4±0.8)	1.3±0.7 (1.2±0.7)	0.5±0.3 (0.5±0.3)
ScaledHR + FitnessIndex + Weight + Height + Age + Gender + FatPercent	0.83 ± 0.09	1.06 ± 0.34 (0.8 ± 0.3)	0.5±0.3 (0.5±0.3)	1.0±0.5 (0.9±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.2±0.7)	0.6±0.3 (0.5±0.3)

Table 5-90: Root mean squared error and mean absolute error (shown in parenthesis) obtained while combining features that attempt to describe the fitness level of an individual with heart rate features (*ScaledHR*) during subject independent evaluation of energy expenditure using linear regression. The target activities were the 51 activities contained in the MIT energy expenditure dataset.

nodes limits the amount of data available for training at each leaf node.

When plots are generated for subject independent estimation of energy expenditure using the *ScaledHR* feature (see Appendix B14 for an example) it is found that heart rate overestimates energy expenditure of upper body activities involving resistance exercise such as *bicep curls* and *bench weight lifting* and for postures such as *standing*, *kneeling*, and *sitting* (including sitting fidgeting feet and legs and hands and arms). Heart rate also underestimates the energy expenditure for most household activities (e.g. *sweeping*, *mopping* and *vacuuming*), for walking and for exercise activities such as *running*, *cycling* and *rowing* at different speeds and resistance levels. The worse overestimation of energy expenditure was observed for the *bicep curls* and *bench weightlifting* activities. One explanation for this is that these activities were performed after the *cycling hard* activity, one of the most physically demanding activities for which data was collected, so heart rate might have been still altered (with a high value) when these activities were performed even after participants rested for at least 5min before the activities. This highlights one of the problems of utilizing heart rate data to estimate energy expenditure: Heart rate lags physical activity and remains altered once a physically demanding activity has being finished. The time heart rate remains altered is subject dependent (e.g. depending on the fitness level of individuals).

Table 5-89 presents the results for subject dependent estimation of energy expenditure using the two highest performing heart rate features: *ScaledHR* and *HRAboveRest*. The first thing to observe is that the performance does not increase substantially with respect to the performance obtained during subject independent evaluation. For example, the increase in performance in RMSE with respect to subject independent training for the *ScaledHR* feature is +0.09MET and +0.17MET for the *HRAboveRest* feature. The coefficient of correlation remains practically unchanged. One possible explanation is that intra-individual variations in heart rate are as difficult to overcome during the regression procedure as inter-individual variations due to fitness level, age and gender. These results are in agreement with the results obtained by Haskell et al. [48] where a small difference of only 0.09units in the correlation coefficient was found between subject dependent and independent estimation of energy expenditure using heart rate data.

One possibility to reduce the differences in heart rate readings due to differences in fitness levels of individuals would be to include features that directly or indirectly capture the fitness level of individuals. Therefore, an experiment was run to determine if the addition of these features improves subject independent estimation of energy expenditure when the highest performing heart rate feature is used (*ScaledHR*). The features used in this experiment to directly or indirectly capture the fitness level of individuals are *Weight*, *Height*, *Age*, *Gender*, *FatPercent*, and *FitnessIndex*. These features are described in detail in Appendix A3. Table 5-90 presents the results of this experiment. In short, the table shows that adding these features does not improve energy expenditure estimation. In fact, performance is slightly degraded when some of these features are incorporated as observed for the *FitnessIndex* feature. The incorporation of the *Weight* figure was not expected to improve energy expenditure estimation because energy expenditure is being predicted in METs, a measurement unit that already normalizes energy expenditure with respect to body weight [246]. In other words, MET units normalize energy expenditure so that it is identical for a slim subject and an obese subject performing the same activity. Obviously, one assumption is that the mechanical efficiency of both individuals is the same. One possible explanation for why the incorporation of all these features does not improve energy expenditure estimation is that the number of subjects (n=16) included in the MIT energy expenditure dataset is not large enough so that relationships between energy expenditure and subject's physical characteristics or fitness level are captured. Another explanation is that these features are practically constants for each subject and consequently, some of them are eliminated by the M5 feature selection algorithm used by the linear regression algorithm employed as confirmed in practice by observing the resulting regression models. When the M5 feature selection algorithm is turned off, the same results were observed: No significant improvements in performance for most features and slight decreases in performance when all these features are incorporated at once and when the *FitnessIndex* feature is incorporated. Again, this might be due to the relatively limited number of subjects included in the dataset used.

Prior work has successfully incorporated subject's characteristics such as body mass, height and gender in the regression equations to compensate for inter-individual variations in energy expenditure [145, 246, 248]. Although body mass and height have been shown to improve energy expenditure estimates, gender has been found to not impact energy expenditure at least when body mass and speed are held constant during walking activities [246, 249, 250]. Appendix B14 presents the results per activity for energy expenditure estimation when the *ScaledHR* feature and the *ScaledHR + ACFFTPeaks* feature are utilized.

5.6.10 How Well can Energy Expenditure be Estimated by Combining Acceleration and Heart Rate Data?

In this section, the highest performing heart rate feature found in the previous section (*ScaledHR*) is incorporated to the highest performing set of acceleration-based features found in Section 5.4.7 (*invariant reduced* feature set). Table 5-91 presents the results of combining both feature sets using linear regression during subject independent evaluation. Both feature sets are computed over windows of 5.6s in length and the accelerometer features are computed per sensor over all the seven accelerometers.

Features subsets	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	*Household*
ScaledHR	0.84 ± 0.09	1.01 ± 0.3 (0.8 ± 0.2)	0.5±0.3 (0.5±0.3)	0.9±0.5 (0.9±0.4)	1.3±0.7 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.5±0.3 (0.5±0.2)
ACFFTPeaks + ACModVigEnergy +ACMCR	0.74 ± 0.06	1.24 ± 0.28 (0.9 ± 0.17)	0.7±0.3 (0.6±0.3)	1.2±0.5 (1.0±0.5)	1.3±0.8 (1.2±0.7)	1.1±0.6 (1.0±0.6)	0.7±0.2 (0.6±0.2)
ACFFTPeaks + ACModVigEnergy +ACMCR + ScaledHR	0.88 ± 0.05	0.88 ± 0.20 (0.7 ± 0.14)	0.5±0.3 (0.5±0.3)	0.8±0.4 (0.7±0.4)	1.0±0.6 (0.9±0.6)	0.8±0.5 (0.8±0.5)	0.5±0.2 (0.4±0.2)
ACFFTPeaks	0.72 ± 0.07	1.28 ± 0.30 (0.9 ± 0.2)	0.6±0.2 (0.6±0.2)	1.2±0.5 (1.1±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.1±0.7)	0.7±0.2 (0.6±0.2)
ACFFTPeaks + ScaledHR	0.88 ± 0.05	0.89 ± 0.21 (0.7 ± 0.2)	0.5±0.2 (0.4±0.2)	0.8±0.4 (0.7±0.4)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.8±0.5)	0.5±0.2 (0.4±0.2)
ACAbsArea	0.68 ± 0.06	1.36 ± 0.30 (1.0 ± 0.2)	0.7±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.7±0.2 (0.6±0.2)
ACAbsArea + ScaledHR	0.87 ± 0.06	0.90 ± 0.24 (0.7 ± 0.2)	0.4±0.2 (0.4±0.2)	0.7±0.4 (0.6±0.3)	1.1±0.6 (1.1±0.6)	1.0±0.6 (0.9±0.6)	0.5±0.3 (0.4±0.2)
Invariant Reduced	0.72 ± 0.11	1.28 ± 0.29 (0.9 ± 0.2)	0.7±0.3 (0.6±0.3)	1.2±0.5 (1.1±0.5)	1.3±0.8 (1.2±0.8)	1.2±0.6 (1.1±0.6)	0.8±0.4 (0.7±0.4)
Invariant Reduced + ScaledHR	0.88 ± 0.05	0.90 ± 0.22 (0.7 ± 0.2)	0.5±0.3 (0.5±0.3)	0.8±0.4 (0.7±0.4)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.8±0.5)	0.5±0.2 (0.4±0.2)
Fast to compute	0.72 ± 0.11	1.27 ± 0.27 (0.9 ± 0.2)	0.7±0.4 (0.7±0.4)	1.2±0.5 (1.1±0.5)	1.2±0.7 (1.1±0.7)	1.1±0.6 (1.0±0.6)	0.8±0.5 (0.7±0.5)
Fast to compute + ScaledHR	0.88 ± 0.05	0.89 ± 0.20 (0.7 ± 0.2)	0.5±0.3 (0.5±0.3)	0.8±0.4 (0.7±0.4)	1.0±0.6 (0.9±0.6)	0.9±0.5 (0.8±0.5)	0.5±0.3 (0.5±0.3)

Table 5-91: Root mean squared error and mean absolute error (shown in parenthesis) obtained while estimating energy expenditure using linear regression when the most discriminating accelerometer (*invariant reduced* feature set) and heart rate feature (*ScaledHR*) are used and computed per sensor over all the seven accelerometers. Energy expenditure was predicted over the 51 activities contained in the MIT energy expenditure dataset. The definition of the *Invariant* and *fast to compute* feature sets can be found in Section 5.4.7. Energy expenditure is evaluated in a subject independent manner.

The first result that is highlighted by Table 5-91 is that the performance of estimating energy expenditure using the *ScaledHR* feature alone is higher than the one obtained by utilizing any of the highest performing accelerometer-based features alone. For instance, the *ScaledHR* feature alone achieves a correlation coefficient +0.14units higher than the *ACFFTPeaks* feature alone. The *ScaledHR* feature also achieves a RMSE 0.27MET lower than the *ACFFTPeaks* feature alone. Similarly, the *ScaledHR* feature improves the correlation coefficient +0.16units and the RMSE in +0.35MET over the performance of the *ACAbsArea* feature alone. One explanation for this result is that most of the activities in the MIT energy expenditure dataset have different intensity levels due to varying resistance work or load effort. Thus, their energy expenditure is better estimated using heart rate data. It is important to remember that when the accelerometer-based features are used to estimate energy expenditure, a single multivariable linear regression model is used to model the energy expenditure associated with all the activities performed. Section 5.6.11.2 will explore if activity dependent regression models improve energy expenditure estimation over the utilization of single regression model for all activities based on accelerometer features.

Even though the performance of the *ScaledHR* feature is superior to the performance of accelerometer-based features, when both feature sets are combined, overall performance and performance per activity is improved. For example, it can be seen from Table 5-91 that when the *ScaledHR* feature is incorporated, the correlation coefficient improves

+0.16 for the *ACFFTPeaks* feature, +0.19 for the *ACAbsArea* feature, +0.16 for the *invariant reduced* and *fast to compute* feature sets. The RMSE improves 0.38MET for the *ACFFTPeaks* feature, 0.46MET for the *ACAbsArea* feature, and 0.38MET for the *invariant reduced* and *fast to compute* feature sets. Thus, the single feature that benefits the most with the incorporation of the *ScaledHR* feature is the *ACAbsArea* feature. Interestingly, the improvement over the *invariant reduced* and *fast to compute* feature sets when the *ScaledHR* feature is incorporated is almost identical. This is because the performance of these feature sets is almost already identical before the incorporation of the heart rate feature as can be seen in Table 5-91. In general, although all activity categories benefit from the incorporation of the *ScaledHR* feature, the categories that benefit the most are ambulation (+0.4MET in RMSE on average), exercise activities (+0.2-0.4MET) and resistance exercise activities (+0.2-0.4MET). This is because they incorporate more activities that involve different intensity levels due to changes in resistance work or load effort. Finally, from Table 5-91, it can be concluded that the best feature combinations to utilize when estimating energy expenditure from seven accelerometers (at least in this work) are *ACFFTPeaks*+*ScaledHR* and *ACAbsArea*+*ScaledHR*. This is because their performance is very close to the performance obtained using the *invariant reduced* and *fast to compute* feature sets but their computational requirements are lower (less number of accelerometer-based features).

Table 5-92 presents the performance of combining heart rate and accelerometer-based features when two subsets of accelerometers are used: (a) three sensors worn at the hip, dominant wrist, and dominant foot and (b) a single sensor worn at the hip. It can be observed that the performance utilizing three sensors at the hip, dominant wrist, and dominant foot is very close to the performance obtained when all seven sensors are used. This is because three sensors at these locations are able to capture upper body, lower body, and overall body motion well enough to produce estimates close to the ones obtained using all the accelerometers. This is explained in detail in Section 5.4.7.

From Table 5-92, it can also be seen that the best two feature combination to utilize when estimating energy expenditure are still the *ACFFTPeaks* + *ScaledHR* and *ACAbsArea* + *ScaledHR*. This is because their performance per activity category is either almost identical or slightly higher to the one obtained using the same features but computed over all seven accelerometers. For example, the correlation coefficients remain practically unchanged, and the RMSE increases +0.01MET for the *ACFFTPeaks* feature when only three sensors are used, and the RMSE increases +0.1MET for the exercise category when the *ACAbsArea* feature is computed over three sensors only (hip, dominant wrist, and dominant foot). The slight improvement in performance is due to the reduction in the number of predictor variables (since features are computed over fewer sensors). In general, the incorporation of accelerometer-based features to the *ScaledHR* feature improves performance only slightly. For example, the correlation coefficient improves between 0.02 and 0.03units and the RMSE decreases between 0.03 and 0.1MET when the features computed over the accelerometer at the hip are incorporated to the *ScaledHR* feature. Similarly, the correlation coefficient improves between 0.03 and 0.04units and the RMSE decreases between 0.11 and 0.13MET when the features computed over the accelerometers at the hip, dominant wrist, and dominant foot are incorporated to the *ScaledHR* feature. Finally, the improvement in RMSE per activity

Features subsets	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	*Household*
ACFFTPeaks + ScaledHR Hip	0.84 ± 0.08	0.98 ± 0.28 (0.8 ± 0.2)	0.6±0.3 (0.5±0.3)	0.9±0.4 (0.9±0.4)	1.2±0.7 (1.1±0.7)	1.1±0.6 (1.1±0.6)	0.6±0.2 (0.5±0.2)
ACFFTPeaks + ScaledHR Hip + DWrist + DFoot	0.88 ± 0.05	0.88 ± 0.22 (0.7 ± 0.2)	0.5±0.2 (0.4±0.2)	0.8±0.3 (0.7±0.3)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.9±0.5)	0.5±0.2 (0.4±0.2)
ACAbsAreas + ScaledHR Hip	0.86 ± 0.07	0.95 ± 0.28 (0.7 ± 0.2)	0.4±0.2 (0.4±0.2)	0.8±0.4 (0.7±0.4)	1.2±0.7 (1.2±0.7)	1.1±0.6 (1.0±0.6)	0.5±0.2 (0.4±0.2)
ACAbsAreas + ScaledHR Hip + DWrist + DFoot	0.87 ± 0.06	0.90 ± 0.25 (0.7 ± 0.2)	0.4±0.2 (0.4±0.2)	0.7±0.3 (0.6±0.3)	1.2±0.6 (1.1±0.6)	1.0±0.6 (1.0±0.6)	0.5±0.2 (0.4±0.2)
Invariant Reduced + ScaledHR Hip	0.86 ± 0.08	0.94 ± 0.27 (0.7 ± 0.2)	0.6±0.3 (0.5±0.3)	0.9±0.4 (0.8±0.4)	1.2±0.7 (1.1±0.7)	1.0±0.6 (0.9±0.6)	0.5±0.2 (0.5±0.2)
Invariant Reduced + ScaledHR Hip + DWrist + DFoot	0.88 ± 0.05	0.88 ± 0.23 (0.7 ± 0.2)	0.5±0.3 (0.4±0.3)	0.8±0.4 (0.7±0.3)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.8±0.5)	0.5±0.3 (0.5±0.2)
Fast to compute + ScaledHR Hip	0.87 ± 0.06	0.91 ± 0.25 (0.7 ± 0.2)	0.4±0.3 (0.4±0.3)	0.8±0.4 (0.7±0.4)	1.1±0.6 (1.1±0.6)	1.0±0.6 (0.9±0.5)	0.5±0.2 (0.4±0.2)
Fast to compute + ScaledHR Hip + DWrist + DFoot	0.88 ± 0.05	0.89 ± 0.22 (0.7 ± 0.2)	0.4±0.3 (0.4±0.3)	0.8±0.4 (0.7±0.4)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.9±0.5)	0.5±0.3 (0.5±0.3)

Table 5-92: Root mean squared error and mean absolute error (shown in parenthesis) obtained while estimating energy expenditure in a subject independent manner using linear regression when the most discriminating accelerometer (*invariant reduced* feature set) and heart rate (*ScaledHR*) features are used. Features are computed per sensor over two sets of accelerometers: (a) hip, dominant wrist, and dominant foot, and (b) hip. Energy expenditure was predicted over the 51 activities contained in the MIT energy expenditure dataset.

category ranges between 0 and 0.3MET when accelerometer-based features are incorporated to the *ScaledHR* feature. The activity category that benefits the least from the incorporation of accelerometer-based features is the household category. The performance per activity for ScaledHR+ACFFTPeaks features computed over the accelerometers at the hip, dominant wrist, and dominant foot can be found in Appendix B14.

5.6.11 How Well Can Energy Expenditure be Estimated Using the Selected Window Length, Feature Set, and Signal Preprocessing Techniques?

This section evaluates the performance of the final implementation of the energy expenditure estimation algorithm using the set of parameters incrementally selected in the previous sections. These parameters consist on the *ACFFTPeaks* feature set, feature computation per sensor over sliding windows of 5.6s in length, and the multivariable linear regression algorithm. The algorithm computes features over the accelerometers

Evaluation Method	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
ACAbsArea Subject independent	0.67 ± 0.05	1.38 ± 0.29 (1.04 ± 0.15)	0.8±0.2 (0.7±0.2)	1.1±0.4 (1.0±0.4)	1.5±0.7 (1.4±0.7)	1.4±0.6 (1.3±0.6)	0.8±0.3 (0.7±0.2)
ACFFTPeaks Subject independent	0.72 ± 0.06	1.28 ± 0.31 (0.93 ± 0.18)	0.6±0.2 (0.5±0.2)	1.1±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.6 (1.1±0.6)	0.7±0.3 (0.6±0.2)
ACFFTPeaks + ACModVigEnergy + ACMCR Subject independent	0.73 ± 0.05	1.25 ± 0.29 (0.91 ± 0.18)	0.5±0.2 (0.5±0.2)	1.1±0.4 (1.0±0.4)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.1±0.6)	0.7±0.2 (0.6±0.2)
Fast to Compute Subject Independent	0.69 ± 0.12	1.33 ± 0.33 (0.99 ± 0.24)	0.6±0.3 (0.5±0.3)	1.2±0.5 (1.1±0.5)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.1±0.6)	0.9±0.6 (0.8±0.6)
Invariant Reduced Subject Independent	0.70 ± 0.11	1.31 ± 0.34 (0.97 ± 0.23)	0.6±0.3 (0.5±0.3)	1.2±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.1±0.6)	0.8±0.5 (0.7±0.5)
ACAbsArea Subject dependent	0.70 ± 0.05	1.24 ± 0.31 (0.93 ± 0.25)	0.8±0.4 (0.8±0.4)	1.0±0.4 (0.9±0.4)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.2±0.6)	0.7±0.3 (0.6±0.3)
ACFFTPeaks Subject dependent	0.79 ± 0.04	1.06 ± 0.24 (0.78 ± 0.19)	0.7±0.3 (0.6±0.3)	1.0±0.3 (0.8±0.3)	1.0±0.4 (0.9±0.4)	0.9±0.4 (0.8±0.3)	0.6±0.3 (0.5±0.2)
ACFFTPeaks + ACModVigEnergy + ACMCR Subject dependent	0.80 ± 0.04	1.02 ± 0.23 (0.75 ± 0.18)	0.6±0.3 (0.5±0.3)	0.9±0.3 (0.8±0.2)	0.9±0.4 (0.8±0.3)	0.9±0.3 (0.8±0.3)	0.6±0.2 (0.5±0.2)
Fast to Compute Subject dependent	0.79 ± 0.05	1.06 ± 0.24 (0.79 ± 0.19)	0.7±0.3 (0.6±0.3)	0.9±0.3 (0.8±0.3)	1.0±0.4 (0.8±0.4)	0.9±0.4 (0.8±0.3)	0.6±0.3 (0.5±0.2)
Invariant Reduced Subject dependent	0.81 ± 0.04	1.01 ± 0.23 (0.75 ± 0.18)	0.7±0.3 (0.6±0.3)	0.9±0.3 (0.8±0.2)	0.9±0.4 (0.8±0.3)	0.8±0.3 (0.7±0.3)	0.6±0.3 (0.5±0.2)

Table 5-93: Root mean squared error and mean absolute error (shown in parenthesis) obtained by estimating energy expenditure in a subject independent manner using linear regression and different feature sets computed per sensor over windows of 5.6s in length over three accelerometers located at the hip, dominant wrist, and dominant foot.

located at the hip, dominant wrist, and dominant foot. The section starts by presents a summary of how well can energy expenditure be estimated in a subject independent and dependent manner using the five feature sets with highest performance as found in Section 5.6.7. Later, the section analyzes how well can energy expenditure be estimated by utilizing activity dependent regression models using the final set of features in a subject dependent and independent manner. During this evaluation, the 51 activities contained in the MIT dataset are recognized using the final implementation of the activity recognition algorithm (see Section 5.4.9). The section also explores how well can energy expenditure be predicted when the number of activities to recognize is reduced to a set of 11 activities that would be useful to recognize during medical studies in practice. Finally, the section briefly explores how well can energy expenditure be predicted when the mean energy expenditure value for each activity is predicted after recognizing activities.

5.6.11.1 How Well Can Energy Expenditure be Estimated Using Linear Regression?

Table 5-93 presents a summary of how well can energy expenditure be predicted in a subject dependent and independent manner using the five feature sets with higher performance from Section 5.6.7. During this analysis, features are computed per sensor over windows of 5.6s in length using the accelerometers located at the hip, dominant wrist, and dominant foot. Energy expenditure is estimated using multivariable linear regression. The table shows that during subject independent evaluation, the feature set that achieves the highest performance is the *ACFFTPeaks* + *ACModVigEnergy* +

ACMCR feature set (r=0.73, RMSE=1.25). The improvement obtained with respect to the *ACAbsArea* feature is +0.06units in the correlation coefficient and 0.13MET for the RMSE. The table also shows that the performance of the *ACAbsArea* feature is lower than any of the other feature combinations. This confirms, as found in the previous sections, that computing features that capture information other than overall amount of motion (captured by *ACAbsArea*) improves energy expenditure estimation. From Table 5-93 it can also be seen that the performance of the *fast to compute* and *invariant reduced* feature sets is lower than for the one obtained for the *ACFFTPeaks* and the *ACFFTPeaks* + *ACModVigEnergy* + *ACMCR* feature sets. As explained previously, this is because the number of predictor variables increases and there is insufficient amount of data to train the regression models (now containing a larger set of variables).

The performance of the *ACFFTPeaks* feature set is slightly lower than the performance of the *ACFFTPeaks* + *ACModVigEnergy* + *ACMCR* feature combination but it requires fewer computations since the *ACModVigEnergy* and the *ACMCR* features do not have to be computed. The decrease in the correlation coefficient is just 0.01units and the increase in the RMSE is 0.03MET with respect to the *ACFFTPeaks* + *ACModVigEnergy* + *ACMCR* feature set when the *ACFFTPeaks* feature is utilized. The difference in performance between estimating energy expenditure using the *ScaledHR* feature and the *ACFFTPeaks* feature set during subject independent evaluation is 0.11units for the correlation coefficient and 0.27MET for the RMSE.

During subject dependent evaluation, it can be seen that the feature sets with highest performance in decreasing order are: the *invariant reduced* feature set (r=0.81, RMSE=1.01), followed by the *ACFFTPeaks* + *ACModVigEnergy* + *ACMCR* (r=0.80, RMSE=1.02), the *fast to compute* (r=0.79, RMSE=1.06) and the *ACFFTPeaks* (r=0.79, RMSE=1.06) feature set. One possible reason why the *invariant reduced* feature set achieves the highest performance despite its larger vector size (predictor variables) is that since there are no inter-individual variations in motion during subject dependent training (there is less variability per activity in the training data), the regression model is able to capture motion characteristics well for each activity despite the limited amount of training data. It can also be observed that all feature sets improve performance over the *ACAbsArea* feature during both, subject dependent and independent training. When the performance of the *ACFFTPeaks* feature is compared to the one obtained using the *invariant reduced* feature set, it is found that the difference in the correlation coefficient is 0.02units and 0.05MET for the RMSE. Moreover, the performance achieved by any of the feature sets but the *ACAbsArea* feature is close to the one obtained using the *ScaledHR* feature during subject independent evaluation (r=0.83, RMSE=1.01). This is a good result, since it can be argued that wearing accelerometers longitudinally is more comfortable than wearing heart rate monitors placed on the chest. Unfortunately, subject dependent energy expenditure data is presently difficult to collect due to the high cost of the equipment (e.g. indirect calorimeter) and expertise required to operate it.

Thus, from the results shown in Table 5-93, it can be argued that the *ACFFTPeaks* feature set presents a good compromise between subject dependent and independent performance and computational complexity with respect to the other features shown in the table.

5.6.11.2 How Well Can Energy Expenditure be Estimated Using One Linear Regression Model Per Activity?

This section explores the performance of utilizing activity dependent regression models during the estimation of energy expenditure when the activities performed are recognized using the activity recognition algorithm implemented in Section 5.4.9. Specifically; in this section, activities being performed are recognized using the C4.5 decision tree classifier trained over features computed per sensor over windows of 5.6s in length over different accelerometer combinations. This activity recognition algorithm is evaluated over the two highest performing feature sets found for activity recognition: (1) the *fast to compute* feature set and (2) the *invariant reduced* feature set. For a detailed description of the features included in these feature sets refer to Section 5.4.7. Once activities are recognized using this algorithm, activity dependent linear regression models are used to estimate energy expenditure. These multivariable linear regression models are trained in a subject independent manner over the energy expenditure data collected for each activity. No analysis is presented in this section for subject dependent estimation of energy expenditure due to the unavailability (for most people) of the necessary equipment to collect energy expenditure data during free-living.

Table 5-94 presents the performance of estimating energy expenditure by (1) recognizing the 51 activities contained in the MIT energy expenditure dataset in a subject independent manner using the algorithm implemented in Section 5.4.9 and (2) applying a multivariable linear regression model per activity trained in a subject independent manner. Activities are recognized using the *fast to compute* feature set and energy expenditure is estimated using the *ACAbsArea* feature. Both feature sets are computed per sensor over windows of 5.6s in length over the different sensor combinations. The objective of analyzing this feature pair (*fast to compute*, *ACAbsArea*) is to determine how well energy expenditure can be estimated using features that are not as computationally intensive as the other feature sets explored in this work. Table 5-94 shows that the highest overall performance (r=0.82, RMSE=1.12) is obtained using all the seven accelerometers. The second highest performing sensor combination is Hip+DWrist+DFoot, followed by the DWrist+DFoot and by the Hip+DWrist sensor combination. The performance of the DWrist+DFoot combination is almost identical to the one obtained using the Hip+DWrist+DFoot sensor combination as highlighted in Section 5.6.8. Between these two sensor combinations, there is only a 0.01MET difference in RMSE for the postures and ambulation categories. The performance obtained for the Hip+DWrist+DFoot sensor combination (r=0.80, RMSE=1.17) using activity dependent regression models is higher than the performance obtained using a single multivariable linear regression trained over the *ACAbsArea* feature (r=0.67, RMSE=1.38). This indicates that activity dependent regression models indeed improve energy expenditure estimation, even when a large set of activities is recognized in a subject independent manner. It is interesting to note that energy expenditure can be predicted well even when the overall accuracy of recognizing 51 activities (without the *unknown* class) in a subject independent manner using the *fast to compute* feature set is only ~45% (see Section 5.4.9). One possible explanation is that even when the activity recognition algorithm performs misclassifications, these misclassifications correspond to activities that are similar (in motion patterns) to the real

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	0.82 ± 0.07	1.12 ± 0.26 (0.78 ± 0.21)	0.5±0.3 (0.4±0.3)	1.3±0.4 (1.1±0.4)	1.2±0.6 (1.1±0.6)	1.1±0.5 (1.0±0.4)	0.7±0.4 (0.6±0.3)
Hip + DWrist + DFoot	0.80 ± 0.09	1.17 ± 0.35 (0.79 ± 0.21)	0.4±0.3 (0.4±0.3)	1.2±0.5 (1.0±0.5)	1.3±0.7 (1.1±0.7)	1.2±0.6 (1.0±0.6)	0.7±0.4 (0.6±0.3)
Hip + DWrist	0.78 ± 0.05	1.21 ± 0.24 (0.82 ± 0.18)	0.5±0.3 (0.4±0.2)	1.3±0.6 (1.1±0.5)	1.2±0.7 (1.1±0.7)	1.1±0.6 (1.0±0.6)	0.8±0.5 (0.6±0.4)
Hip + DFoot	0.80 ± 0.08	1.20 ± 0.38 (0.83 ± 0.25)	0.5±0.3 (0.4±0.2)	1.3±0.6 (1.1±0.5)	1.2±0.7 (1.1±0.7)	1.1±0.6 (1.0±0.6)	0.8±0.5 (0.6±0.4)
DWrist + DThigh	0.78 ± 0.07	1.21 ± 0.24 (0.83 ± 0.18)	0.7±0.5 (0.5±0.4)	1.2±0.4 (1.1±0.4)	1.3±0.6 (1.1±0.6)	1.2±0.5 (1.1±0.5)	0.7±0.3 (0.5±0.2)
DWrist + DFoot	0.80 ± 0.06	1.18 ± 0.28 (0.81 ± 0.20)	0.5±0.3 (0.4±0.3)	1.3±0.5 (1.1±0.4)	1.3±0.7 (1.1±0.6)	1.2±0.6 (1.1±0.5)	0.7±0.4 (0.6±0.3)
Hip	0.71 ± 0.07	1.40 ± 0.28 (0.96 ± 0.20)	0.4±0.3 (0.4±0.2)	1.5±0.5 (1.3±0.5)	1.5±0.7 (1.3±0.6)	1.3±0.6 (1.1±0.6)	1.0±0.4 (0.7±0.3)
DWrist	0.46 ± 0.14	1.85 ± 0.28 (1.32 ± 0.24)	1.1±0.6 (0.8±0.4)	1.8±0.6 (1.6±0.6)	2.1±0.8 (1.8±0.8)	1.9±0.6 (1.6±0.6)	1.4±0.5 (1.1±0.4)
DFoot	0.75 ± 0.07	1.31 ± 0.29 (0.94 ± 0.20)	0.7±0.4 (0.6±0.3)	1.5±0.6 (1.3±0.5)	1.4±0.7 (1.2±0.6)	1.2±0.5 (1.1±0.5)	0.9±0.4 (0.7±0.3)
DUpperArm	0.54 ± 0.09	1.76 ± 0.35 (1.23 ± 0.29)	0.8±0.6 (0.6±0.4)	1.6±0.5 (1.4±0.5)	2.0±0.8 (1.7±0.8)	1.9±0.7 (1.6±0.7)	1.3±0.5 (1.0±0.4)
DThigh	0.76 ± 0.06	1.29 ± 0.23 (0.88 ± 0.17)	0.8±0.4 (0.6±0.4)	1.2±0.4 (1.1±0.4)	1.4±0.7 (1.2±0.7)	1.3±0.6 (1.1±0.6)	0.8±0.3 (0.6±0.2)

Table 5-94: Root mean squared error and mean absolute error (shown in parenthesis) obtained by estimating energy expenditure by first recognizing 51 activities in a subject independent manner and then applying a multivariable linear regression model per activity trained in a subject independent manner. The *fast to compute* feature set is used to recognize activities and the *ACAbsArea* feature to estimate energy expenditure. Both feature sets are computed per sensor over windows of 5.6s in length.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	0.77 ± 0.07	1.30 ± 0.28 (0.85 ± 0.21)	0.6±0.4 (0.4±0.3)	1.4±0.6 (1.2±0.5)	1.4±0.6 (1.1±0.6)	1.3±0.6 (1.1±0.5)	0.8±0.5 (0.6±0.3)
Hip + DWrist + DFoot	0.77 ± 0.11	1.31 ± 0.40 (0.87 ± 0.25)	0.6±0.4 (0.5±0.3)	1.5±0.7 (1.3±0.6)	1.4±0.8 (1.2±0.7)	1.3±0.6 (1.0±0.5)	0.9±0.5 (0.6±0.3)
Hip + DWrist	0.75 ± 0.08	1.29 ± 0.33 (0.87 ± 0.21)	0.8±1.1 (0.5±0.6)	1.3±0.5 (1.1±0.5)	1.3±0.6 (1.1±0.5)	1.2±0.5 (1.0±0.4)	0.9±0.5 (0.7±0.3)
Hip + DFoot	0.78 ± 0.12	1.26 ± 0.42 (0.85 ± 0.27)	0.7±0.5 (0.5±0.4)	1.4±0.6 (1.2±0.6)	1.3±0.7 (1.1±0.7)	1.2±0.6 (1.0±0.6)	0.9±0.6 (0.6±0.4)
DWrist + DThigh	0.79 ± 0.07	1.21 ± 0.27 (0.81 ± 0.17)	0.6±0.6 (0.5±0.5)	1.2±0.4 (1.0±0.4)	1.3±0.6 (1.1±0.6)	1.2±0.6 (1.0±0.5)	0.7±0.3 (0.6±0.2)
DWrist + DFoot	0.77 ± 0.11	1.31 ± 0.43 (0.86 ± 0.25)	0.6±0.5 (0.5±0.4)	1.4±0.6 (1.2±0.6)	1.3±0.7 (1.1±0.6)	1.3±0.7 (1.1±0.5)	0.9±0.7 (0.7±0.5)
Hip	0.77 ± 0.07	1.22 ± 0.20 (0.85 ± 0.17)	0.5±0.3 (0.4±0.2)	1.4±0.5 (1.1±0.5)	1.3±0.5 (1.2±0.5)	1.2±0.4 (1.0±0.4)	0.9±0.4 (0.6±0.3)
DWrist	0.60 ± 0.12	1.59 ± 0.29 (1.08 ± 0.22)	0.9±0.5 (0.7±0.4)	1.5±0.6 (1.3±0.6)	1.7±0.8 (1.5±0.8)	1.6±0.6 (1.3±0.6)	1.2±0.5 (0.9±0.4)
DFoot	0.74 ± 0.16	1.45 ± 0.78 (0.90 ± 0.31)	0.6±0.5 (0.5±0.4)	1.3±0.5 (1.1±0.4)	1.4±0.9 (1.2±0.7)	1.4±1.0 (1.2±0.8)	1.1±1.2 (0.8±0.7)
DUpperArm	0.78 ± 0.04	1.25 ± 0.31 (0.83 ± 0.19)	0.5±0.4 (0.4±0.3)	1.3±0.5 (1.1±0.5)	1.3±0.7 (1.2±0.6)	1.3±0.6 (1.1±0.5)	0.7±0.3 (0.6±0.2)
DThigh	0.77 ± 0.05	1.25 ± 0.26 (0.87 ± 0.18)	0.7±0.4 (0.5±0.4)	1.3±0.4 (1.1±0.4)	1.4±0.6 (1.2±0.6)	1.3±0.5 (1.1±0.5)	0.8±0.3 (0.6±0.2)

Table 5-95: Root mean squared error and mean absolute error (shown in parenthesis) obtained by estimating energy expenditure by first recognizing 51 activities in a subject independent manner and then applying a multivariable linear regression model per activity trained in a subject independent manner. The *invariant reduced* feature set is used to recognize activities and the *ACFFTPeaks* feature to estimate energy expenditure. Both feature sets are computed per sensor over windows of 5.6s in length.

activity being performed and thus, the energy expenditure estimated is close to the one of the target activity.

The performance of the Hip+DWrist+DFoot sensor combination (r=0.80, RMSE=1.17) is similar to the performance obtained using a single linear regression model and the *fast to compute* feature set (r=0.80, RMSE=1.18). This is because in Table 5-94, energy expenditure is predicted using only the *ACAbsArea* feature but the improved performance obtained is mainly due to the use of activity dependent regression models. This suggests that energy expenditure could be further improved by including features other than the *ACAbsArea* feature (e.g. *fast to compute* feature set) provided there is enough training data to train the activity dependent models.

Table 5-95 presents the performance of estimating energy expenditure also utilizing activity dependent linear regression models; however, the 51 activities contained in the MIT energy expenditure dataset are now recognized using the *invariant reduced* feature set and energy expenditure is predicted using the *ACFFTPeaks* feature. Activities and energy expenditure are evaluated in a subject independent manner. Both feature sets are again computed per sensor over windows of 5.6s in length over the different sensor combinations. The objective of evaluating the performance over these feature sets is to (1) test how better recognition of activities (from the *invariant reduced* feature set) improves energy expenditure estimation and (2) how a more complex feature set (*ACFFTPeaks*) improves energy expenditure estimation. However, a quick inspection of Table 5-95 reveals that the correlation coefficients and RMSE obtained have a lower performance than the one obtained in Table 5-94. The reason for this is that there is less training data available to train each of the linear regression models due to the utilization of 51 activity dependent regression models. This is mainly due to the relatively large feature vector size (70 features per sensor) of the *ACFFTPeaks* feature with respect to the training data available per activity. This is also highlighted by the fact that performance increases as the number of sensors is decreased for some sensor combinations in Table 5-95. For example, the performance of the single sensor at the hip is r=0.77 and RMSE=1.22 while the performance over the Hip+DWrist+DFoot is r=0.77 and RMSE=1.31. For this reason, feature combinations incorporating more features than the *ACFFTPeaks* feature set are not evaluated during the analysis of energy expenditure estimation using activity dependent models. This does not mean that incorporating more features would not improve energy expenditure estimation. Estimating energy expenditure using the *fast to compute* and *ACFFTPeaks* feature sets have already been shown to improve performance when a single linear regression model is used to estimate energy expenditure (Section 5.6.11.1). This only means that the amount of data contained in the MIT energy expenditure dataset is insufficient to evaluate the performance over larger number of features when activity dependent regression models are used to estimate energy expenditure. Nevertheless, even when training data is insufficient, Table 5-95 still shows that overall performance and performance per activity for the sensor combinations all sensors, Hip+DWrist+DFoot, DWrist+DFoot, and DWrist+DThigh is similar as observed in previous sections.

Table 5-96 presents the results obtained when energy expenditure is estimated by recognizing the 51 activities in a subject dependent manner and when activity dependent linear regression models trained in a subject independent manner are used. Activities are recognized using the C4.5 decision tree classifier trained using the *fast to compute* feature

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	0.88 ± 0.05	0.98 ± 0.27 (0.65 ± 0.16)	0.3±0.2 (0.2±0.1)	1.0±0.4 (0.8±0.4)	1.2±0.6 (1.1±0.6)	0.9±0.5 (0.8±0.4)	0.5±0.2 (0.4±0.2)
Hip + DWrist + DFoot	0.89 ± 0.04	0.93 ± 0.28 (0.61 ± 0.15)	0.3±0.2 (0.2±0.1)	0.9±0.3 (0.7±0.3)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.8±0.5)	0.5±0.2 (0.4±0.2)
Hip + DWrist	0.88 ± 0.04	0.91 ± 0.21 (0.60 ± 0.13)	0.3±0.2 (0.2±0.1)	0.9±0.3 (0.7±0.3)	1.1±0.6 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.6±0.2 (0.5±0.2)
Hip + DFoot	0.88 ± 0.06	0.93 ± 0.31 (0.62 ± 0.16)	0.3±0.2 (0.2±0.1)	0.9±0.3 (0.7±0.3)	1.1±0.6 (1.0±0.6)	1.0±0.5 (0.8±0.5)	0.5±0.2 (0.4±0.2)
DWrist + DThigh	0.89 ± 0.03	0.88 ± 0.18 (0.60 ± 0.13)	0.4±0.3 (0.3±0.2)	0.9±0.3 (0.8±0.3)	1.0±0.5 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.6±0.2 (0.5±0.2)
DWrist + DFoot	0.89 ± 0.03	0.91 ± 0.22 (0.61 ± 0.13)	0.4±0.3 (0.3±0.2)	0.9±0.3 (0.8±0.3)	1.0±0.6 (0.9±0.5)	0.9±0.5 (0.8±0.4)	0.5±0.2 (0.5±0.2)
Hip	0.87 ± 0.05	0.96 ± 0.24 (0.64 ± 0.14)	0.4±0.2 (0.3±0.2)	0.9±0.3 (0.8±0.3)	1.1±0.5 (0.9±0.5)	1.0±0.5 (0.8±0.4)	0.7±0.3 (0.5±0.2)
DWrist	0.81 ± 0.07	1.12 ± 0.23 (0.74 ± 0.15)	0.7±0.4 (0.4±0.2)	1.1±0.4 (0.9±0.3)	1.2±0.6 (1.0±0.5)	1.1±0.5 (0.9±0.4)	0.9±0.4 (0.7±0.3)
DFoot	0.87 ± 0.04	0.97 ± 0.26 (0.66 ± 0.16)	0.4±0.2 (0.3±0.1)	1.1±0.4 (0.9±0.3)	1.1±0.6 (0.9±0.5)	1.0±0.5 (0.9±0.4)	0.6±0.2 (0.5±0.2)
DUpperArm	0.82 ± 0.04	1.08 ± 0.22 (0.72 ± 0.15)	0.5±0.3 (0.4±0.2)	1.1±0.4 (0.9±0.3)	1.2±0.5 (1.0±0.5)	1.2±0.5 (0.9±0.4)	0.8±0.3 (0.6±0.3)
DThigh	0.88 ± 0.03	0.91 ± 0.21 (0.62 ± 0.14)	0.4±0.3 (0.3±0.2)	1.0±0.4 (0.8±0.3)	1.0±0.5 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.6±0.2 (0.5±0.2)

Table 5-96: Root mean squared error and mean absolute error (shown in parenthesis) obtained by estimating energy expenditure by first recognizing 51 activities in a subject dependent manner and then applying a multivariable linear regression model per activity trained in a subject independent manner. The *fast to compute* feature set is used to recognize activities and the *ACAbsArea* feature to estimate energy expenditure. Both feature sets are computed per sensor over windows of 5.6s in length.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
All sensors	0.82 ± 0.08	1.21 ± 0.41 (0.70 ± 0.17)	0.4±0.2 (0.3±0.1)	1.1±0.6 (0.9±0.4)	1.4±0.8 (1.1±0.6)	1.1±0.5 (0.9±0.4)	0.7±0.3 (0.5±0.2)
Hip + DWrist + DFoot	0.88 ± 0.03	0.99 ± 0.27 (0.66 ± 0.18)	0.4±0.2 (0.3±0.2)	1.0±0.4 (0.8±0.4)	1.2±0.6 (1.0±0.5)	1.0±0.5 (0.8±0.4)	0.6±0.2 (0.5±0.2)
Hip + DWrist	0.88 ± 0.04	0.93 ± 0.20 (0.63 ± 0.16)	0.4±0.3 (0.3±0.2)	1.0±0.4 (0.8±0.3)	1.1±0.5 (0.9±0.4)	0.9±0.4 (0.8±0.4)	0.6±0.2 (0.5±0.2)
Hip + DFoot	0.88 ± 0.03	0.98 ± 0.28 (0.65 ± 0.17)	0.3±0.2 (0.3±0.2)	1.0±0.4 (0.8±0.4)	1.2±0.6 (1.0±0.5)	1.0±0.5 (0.8±0.4)	0.6±0.2 (0.5±0.2)
DWrist + DThigh	0.88 ± 0.03	0.93 ± 0.19 (0.61 ± 0.12)	0.3±0.2 (0.2±0.2)	0.9±0.3 (0.8±0.3)	1.1±0.6 (0.9±0.5)	1.0±0.5 (0.8±0.4)	0.6±0.2 (0.5±0.2)
DWrist + DFoot	0.86 ± 0.06	1.05 ± 0.44 (0.65 ± 0.15)	0.3±0.2 (0.2±0.1)	1.0±0.4 (0.8±0.3)	1.2±0.7 (1.0±0.6)	1.1±0.6 (0.9±0.5)	0.6±0.3 (0.5±0.2)
Hip	0.88 ± 0.04	0.91 ± 0.21 (0.62 ± 0.15)	0.4±0.3 (0.3±0.2)	1.0±0.4 (0.8±0.4)	1.0±0.5 (0.9±0.4)	0.9±0.4 (0.7±0.3)	0.7±0.3 (0.5±0.2)
DWrist	0.83 ± 0.05	1.07 ± 0.21 (0.70 ± 0.14)	0.6±0.4 (0.4±0.2)	1.0±0.3 (0.8±0.3)	1.2±0.5 (1.0±0.4)	1.1±0.4 (0.9±0.4)	0.9±0.4 (0.6±0.3)
DFoot	0.85 ± 0.09	1.18 ± 0.93 (0.67 ± 0.17)	0.3±0.2 (0.3±0.1)	1.0±0.4 (0.8±0.3)	1.3±1.0 (1.0±0.7)	1.2±0.9 (0.9±0.6)	0.6±0.3 (0.5±0.2)
DUpperArm	0.86 ± 0.09	1.02 ± 0.45 (0.64 ± 0.18)	0.4±0.2 (0.3±0.2)	1.0±0.3 (0.8±0.3)	1.2±0.7 (1.0±0.7)	0.9±0.4 (0.8±0.4)	0.6±0.2 (0.5±0.2)
DThigh	0.87 ± 0.04	0.96 ± 0.25 (0.65 ± 0.15)	0.3±0.2 (0.3±0.2)	1.0±0.3 (0.8±0.3)	1.1±0.5 (0.9±0.5)	1.0±0.5 (0.9±0.4)	0.7±0.3 (0.5±0.2)

Table 5-97: Root mean squared error and mean absolute error (shown in parenthesis) obtained by estimating energy expenditure by first recognizing 51 activities in a subject dependent manner and then applying a multivariable linear regression model per activity trained in a subject independent manner. The *invariant reduced* feature set is used to recognize activities and the *ACFFTPeaks* feature to estimate energy expenditure. Both feature sets are computed per sensor over windows of 5.6s in length.

set. The linear regression models are trained using the *ACAbsArea* feature. Both features are computed per sensor over non-overlapping sliding windows of 5.6s in length. The table shows that overall performance and performance per activity is higher than when activities are recognized in a subject independent manner. This is an expected result since the overall accuracy obtained when the 51 activities are recognized in a subject dependent manner using the *fast to compute* feature set is ~80% (+35% higher). From Table 5-96, it can also be observed that the feature sets with higher performance are DWrist+DThigh (r=0.89, RMSE=0.88), DWrist+DFoot (r=0.89, RMSE=0.91), and Hip+DWrist (r=0.88, RMSE=0.91). Again, the fact that performance increases as the number of sensors decreases (contrary to the behavior observed when a single linear regression model is used) indicates that the amount of data available is insufficient to evaluate performance when a large number of features are computed (over several sensors). It would be expected that given more training data, the performance of the Hip+DWrist+DFoot and all sensors combinations would be higher than the one obtained for the DWrist+DThigh sensor combination. Still, the results obtained using the DWrist+DThigh sensor combination (r=0.89, RMSE=0.88) are outstanding since they are higher than the results obtained using heart rate data (*ScaledHR* feature) using subject dependent (r=0.83, RMSE=0.92) and independent evaluation (r=0.83, RMSE=1.01). Furthermore, the performance of the DWrist+DThigh sensor combination is higher than the best results obtained using a single linear regression model trained over the *fast to compute* feature set during subject independent evaluation (r=0.80, RMSE-1.18). The performance of the DWrist+DThigh combination is also close to the performance obtained during subject dependent evaluation of a single regression model trained using the *ACFFTPeaks* feature (r=0.87, RMSE=0.86). This confirms that activity dependent regression models indeed improve energy expenditure estimation.

When the performance of the Hip+DWrist+DFoot sensor combination is analyzed per activity during the use activity dependent regression models using the *invariant reduced* feature set (r=0.88, RMSE=0.99) and a single regression model (r=0.80, RMSE=1.18), it is found that the performance over the ambulation and resistance exercise categories increases 0.3MET when activity dependent models are used. One important advantage of estimating energy expenditure by utilizing activity dependent regression models is that 51 activities are simultaneously recognized with an overall accuracy of 45% during subject independent training and ~80% during subject dependent training. This could allow for the development of health related interventions that trigger based on context and/or physical activity level. Obviously, one disadvantage of such approach if subject dependent training is utilized is that end-users need to provide examples of the activities to recognize. Nonetheless, the amount of training data required can be as low as 2mins as discussed in Section 5.6.11.

Table 5-97 presents the results obtained when activities are recognized using the *invariant reduced* feature set and when energy expenditure is predicted using the *ACFFTPeaks* feature set. The table shows that the performance of the all sensors and the Hip+DWrist+DFoot sensor combinations is lower than the one obtained in Table 5-96. This is because the number of features increased from one feature per sensor (*ACAbsArea*) to ten features per sensor (*ACFFTPeaks*). The table also shows that the performance of all single sensors is higher than the performance obtained using the all sensors combination. This contradicts the results obtained when a single regression model is used and intuition, since it has been already show that the computation of more features and the utilization of more sensors improve energy expenditure estimation. This indicates again that the available training data is insufficient to learn the large number of regression coefficients (features) during the utilization of activity dependent regression models. During this situation, the sensor at the hip achieves the highest performance overall (r=0.88, RMSE=0.91) and per activity. It is important to note that the performance of this sensor is higher than the performance for the same sensor in Table 5-96 (r=0.87, RMSE=0.96). This corroborates the fact that the inclusions of features that better capture motion signatures improve energy expenditure estimation.

In summary, this section has shown that the utilization of activity dependent linear regression models in estimation of energy expenditure indeed improves performance. In fact, energy expenditure can be estimated with higher performance than when heart rate data alone is utilized during subject independent evaluation. The performance obtained using activity dependent models is also close to the performance obtained using heart rate data alone during subject dependent evaluation. The section has also shown that the incorporation of features others than the *ACAbsArea* improve energy expenditure estimation. These results hold when there is enough training data to train the activity dependent regression models or the single regression models containing large number of predictor variables (features). Finally, another finding was that although activity dependent linear regression models achieve higher performance (with respect to the use of single models); they require more data during training.

5.6.11.3 How well Can Energy Expenditure be Estimated if the Number of Activities to Recognize is Reduced?

One of the main problems found in the previous section was that the amount of training data available per activity was not sufficient to reliably test the performance of dependent regression models when a large number of features are utilized during the recognition of 51 activities. The number of features can be large either because several features are computed or because a large number of sensors is used (e.g. seven). As a result, this section explores if reducing the number of activities being recognized (and thus, the number of regression models to train) from 51 to 11 improves energy expenditure estimation. The activities being recognized in this section are the same as the ones recognized in Section 5.4.9.4. These 11 activities are *lying down*, *standing*, *sitting*, *kneeling*, *walking at 2mph* and *3mph*, *running at 4*, *5*, and *6mph*, and the *moderate* and *vigorous* MET intensity categories. Appendix A2 shows a detailed list of the activities that were merged into the *moderate* and *vigorous* intensity categories according to their associated number of METs from the Compendium of Physical Activities [122]. This set of activities is explored because most daily energy expenditure is spent in sedentary or light activities such as postures and ambulation. Moreover, when medical interventions are designed to foster an increase in physical activity levels, it is important to know if the target population is exercising at *moderate* or *vigorous* intensity levels. If they are, there may be no need for an intervention. However, if they are not, it might be important to know what activities are being performed (e.g. postures, ambulation type and intensity) to plan the intervention according.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
Fast to compute All sensors	0.79 ± 0.08	1.26 ± 0.22 (0.91 ± 0.14)	0.5±0.3 (0.4±0.2)	1.4±0.6 (1.3±0.6)	1.4±0.7 (1.3±0.7)	1.2±0.5 (1.1±0.5)	0.9±0.3 (0.7±0.3)
Fast to compute Hip + DWrist + DFoot	0.77 ± 0.07	1.28 ± 0.25 (0.92 ± 0.16)	0.5±0.2 (0.4±0.2)	1.3±0.6 (1.2±0.6)	1.4±0.7 (1.2±0.6)	1.3±0.6 (1.1±0.5)	1.0±0.4 (0.8±0.3)
Fast to compute Hip	0.71 ± 0.07	1.43 ± 0.23 (1.06 ± 0.16)	0.8±0.4 (0.6±0.4)	1.4±0.5 (1.2±0.5)	1.5±0.6 (1.3±0.6)	1.3±0.6 (1.2±0.5)	1.1±0.4 (0.9±0.4)
Invariant reduced All sensors	0.78 ± 0.12	1.24 ± 0.31 (0.86 ± 0.21)	0.6±0.3 (0.4±0.3)	1.4±0.6 (1.2±0.6)	1.3±0.7 (1.1±0.6)	1.2±0.6 (1.0±0.6)	0.9±0.5 (0.7±0.4)
Invariant reduced Hip + DWrist + DFoot	0.79 ± 0.09	1.23 ± 0.34 (0.86 ± 0.19)	0.5±0.2 (0.4±0.2)	1.4±0.7 (1.2±0.7)	1.4±0.7 (1.2±0.7)	1.3±0.6 (1.1±0.5)	0.9±0.5 (0.7±0.3)
Invariant reduced Hip	0.72 ± 0.09	1.33 ± 0.17 (0.96 ± 0.13)	0.7±0.4 (0.5±0.3)	1.3±0.5 (1.1±0.5)	1.4±0.6 (1.2±0.6)	1.3±0.5 (1.1±0.4)	1.1±0.4 (0.9±0.3)

Table 5-98: Root mean squared error and mean absolute error (shown in parenthesis) obtained when energy expenditure is estimated by first recognizing 11 activities in a subject independent manner and activity dependent linear regression models trained in a subject independent manner are applied. When activities are recognized using the *fast to compute* feature set, energy expenditure is predicted using the *ACAbsArea* feature. When the *invariant reduced* feature set is used to recognize activities, energy expenditure is predicted using the *ACFFTPeaks* feature.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
Fast to compute All sensors	0.80 ± 0.07	1.22 ± 0.24 (0.87 ± 0.15)	0.3±0.2 (0.3±0.1)	1.3±0.5 (1.2±0.5)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.0±0.6)	0.9±0.3 (0.7±0.3)
Fast to compute Hip + DWrist + DFoot	0.81 ± 0.05	1.18 ± 0.24 (0.84 ± 0.15)	0.3±0.2 (0.2±0.2)	1.2±0.4 (1.1±0.4)	1.3±0.6 (1.2±0.6)	1.1±0.6 (1.0±0.6)	0.9±0.4 (0.7±0.3)
Fast to compute Hip	0.79 ± 0.07	1.21 ± 0.25 (0.87 ± 0.17)	0.4±0.2 (0.3±0.2)	1.2±0.4 (1.0±0.4)	1.3±0.6 (1.2±0.6)	1.2±0.6 (1.1±0.5)	1.0±0.4 (0.8±0.4)
Invariant reduced All sensors	0.81 ± 0.08	1.15 ± 0.22 (0.78 ± 0.16)	0.4±0.2 (0.3±0.1)	1.3±0.5 (1.1±0.5)	1.2±0.5 (1.0±0.5)	1.1±0.6 (0.9±0.5)	0.9±0.5 (0.7±0.4)
Invariant reduced Hip + DWrist + DFoot	0.84 ± 0.05	1.07 ± 0.20 (0.77 ± 0.15)	0.4±0.2 (0.3±0.1)	1.2±0.5 (1.0±0.4)	1.2±0.5 (1.0±0.5)	1.0±0.5 (0.9±0.4)	0.8±0.4 (0.7±0.3)
Invariant reduced Hip	0.76 ± 0.14	1.24 ± 0.21 (0.85 ± 0.13)	0.4±0.3 (0.3±0.2)	1.1±0.5 (0.9±0.4)	1.3±0.6 (1.1±0.5)	1.2±0.5 (1.0±0.4)	1.1±0.6 (0.9±0.5)

Table 5-99: Root mean squared error and mean absolute error (shown in parenthesis) obtained when energy expenditure is estimated by first recognizing 11 activities in a subject dependent manner and activity dependent linear regression models trained in a subject independent manner are applied. When activities are recognized using the *fast to compute* feature set, energy expenditure is predicted using the *ACAbsArea* feature. When the *invariant reduced* feature set is used to recognize activities, energy expenditure is predicted using the *ACFFTPeaks* feature

Table 5-98 presents the results obtained when energy expenditure is predicted by first recognizing 11 activities in a subject independent manner and then applying activity dependent linear regression models. Activities are recognized using the C4.5 decision tree classifier trained over two sets of features: the *fast to compute* feature set and the *invariant reduced* feature set. Energy expenditure is estimated using the *ACAbsArea* feature when activities are recognized using the *fast to compute* feature set and using the *ACFFTPeaks* feature set when activities are recognized using the *invariant reduced* feature set. Both feature sets are computed per sensor over windows of 5.6s in length. Although the number of activities being recognized is 11, energy expenditure estimation performance is tested over the 51 activities contained in the MIT energy expenditure dataset.

Table 5-98 shows that the performance obtained using the *fast to compute* feature set is lower than the performance obtained in Table 5-94 when the 51 activities were recognized. For example, in Table 5-98 the correlation coefficient ranges between 0.71 and 0.79 and RMSE between 1.26 and 1.43 while for Table 5-94 the correlation coefficient ranges between 0.71 and 0.82 and the RMSE between 1.12 and 1.40 for the *fast to compute* feature set. Performance is also slightly lower for the sensor at the hip in Table 5-98 for the *invariant reduced* feature set (r=0.72, RMSE=1.33) than the one obtained in Table 5-95 (r=0.77, RMSE=1.22). This indicates that energy expenditure is not improved by reducing the number of activities to recognize from 51 to 11. In fact, overall performance and performance per activity using the *fast to compute* and *invariant reduced* feature sets slightly degrades for most activities when the number of activities to recognize is reduced suggesting that energy expenditure better estimated as more activities are recognized. This is an intuitive result because as the number of activities to recognize increases, there are more linear regression models available to perform fine tuned energy expenditure predictions per activity. Nevertheless, Table 5-98 also shows that the performance obtained using the *invariant reduced* feature set slightly increases for the sensor combinations all sensors and Hip+DWrist+DFoot when the number of activities is reduced from 51 to 11. For example, the correlation coefficient in Table 5-98 ranges between 0.78 and 0.79 and RMSE between 1.23 and 1.24 for these sensor combinations while in Table 5-95 the correlation coefficient is 0.77 and the RMSE ranges between 1.31 and 1.32. Given the relatively large vector size of the *invariant reduced* feature set (13 features per sensor), the increase in performance is most likely caused due to an increase in the amount of training data available to train the reduced number of linear regression models for each activity. One would expect that given the availability of more training data (e.g. more subjects in the MIT energy expenditure dataset), overall performance and performance per activity would degrade as fewer numbers of activities are recognized as shown for the *fast to compute* feature set.

Table 5-99 presents the performance obtained when energy expenditure is predicted by first recognizing 11 activities in a subject dependent manner and then activity dependent linear regression models trained in a subject independent manner are applied. The feature sets explored in this table are the same as the ones explored in Table 5-98. Table 5-99 shows that the highest performance (r=0.84, RMSE=1.07) is obtained for the *invariant reduced* feature set computed over the accelerometers at the hip, dominant wrist, and dominant foot. The difference in performance of this feature/sensor combination with respect to subject independent recognition of activities is +0.05 for the correlation coefficient and -0.17MET for the RMSE. The fact that the *invariant reduced* feature set computed over the sensors at the hip, wrist and foot achieved the highest overall performance and performance per activity in Table 5-98 and Table 5-99, suggests that this is a good feature/sensor combination to use. This feature/sensor combination also achieved either the best performance or a performance very close to the highest one in Table 5-94 through Table 5-97. The good performance of the *fast to compute* feature set over the accelerometers at the hip, dominant wrist, and dominant foot is also considered a strong result since the computational requirements of this feature set are lower than the ones required by the *invariant reduced* feature set.

One obvious disadvantage of applying activity dependent regression models to estimate energy expenditure is that misclassifications generated by the activity recognition algorithm could affect energy expenditure estimation. Some misclassification errors might not impact energy expenditure considerably since they would consist on activities similar (in the motion pattern) to the real activity being performed. For example, *running at 4mph* could be recognized when someone is *running at 5mph*. Consequently, the regression model for *running at 4mph* would be applied for *running at 5mph.* Although incorrect, energy expenditure estimates would be close since these activities are closely related. In other scenarios where the activity being performed is completely different from the ones on which the activity recognition algorithm was trained, energy expenditure prediction could be off. For example, *dancing* could be confused with *running* if the activity recognizer is only trained on postures and ambulatory activities. In this scenario, the energy expenditure predictions would be most likely significantly off from the true values associated with the real activity being performed. Obviously, the easiest way to handle this situation is to train the activity recognizer over a large set of mutually exclusive activities (the ones most likely to be performed by individuals). Another possibility to handle this scenario is to train the activity recognition algorithm over an '*unknown*' activity. Then, when the activity being performed considerably differs from the ones available during training, the *unknown* activity could be predicted and a single generic linear regression model trained over a large variety of activities can be applied. A different technique to address this problem could be to mark periods of time where the *unknown* activity is recognized for extended periods of time so that individuals can be latter prompted for the label of the true activity performed (thus improving activity labeling and energy expenditure estimates). During the activity dependent algorithms presented in this section, the *unknown* class was not incorporated in the regression models because a relatively large set of mutually exclusive activities was being recognized (51 and 11 activities).

5.6.11.4 How Well Can Energy Expenditure be Estimated by Predicting Mean Values per Activity?

One of the main problems found when energy expenditure was estimated using linear regression models per activities in the previous sections was the limited amount of training data available to train the regression models in part due to the utilization of a large set of features. Therefore, this section explores the performance of estimating energy expenditure when no features are used. In other words, this section explores how well can energy expenditure be estimated by just predicting the average energy expenditure value associated with each activity. This has the main advantage of requiring very little training data since the average energy expenditure value per activity can be computed over a few set of examples.

Table 5-100 illustrates the results obtained when energy expenditure is estimated by first recognizing the activity being performed (out of a set of 51) in a subject independent manner and then predicting the average MET value associated with each activity recognized. The feature sets used to recognize activities are the *fast to compute* and the *invariant reduced* computed per sensor over windows of 5.6s in length. Average MET values for each activity are computed in a subject independent manner. As expected, the table shows that the best performance is obtained using the all sensors combination,

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
Fast to compute All sensors	0.83 ± 0.05	1.09 ± 0.28 (0.76 ± 0.20)	0.5±0.3 (0.4±0.3)	1.2±0.5 (1.1±0.4)	1.2±0.6 (1.0±0.6)	1.1±0.5 (0.9±0.4)	0.7±0.4 (0.6±0.3)
Fast to compute Hip + DWrist + DFoot	0.81 ± 0.07	1.12 ± 0.30 (0.78 ± 0.20)	0.5±0.3 (0.4±0.3)	1.3±0.5 (1.1±0.5)	1.2±0.7 (1.1±0.6)	1.1±0.5 (1.0±0.5)	0.7±0.4 (0.6±0.3)
Fast to compute Hip	0.71 ± 0.07	1.41 ± 0.29 (0.98 ± 0.21)	0.5±0.3 (0.4±0.2)	1.5±0.5 (1.3±0.5)	1.5±0.7 (1.3±0.6)	1.4±0.6 (1.2±0.6)	1.0±0.4 (0.8±0.3)
Invariant reduced All sensors	0.82 ± 0.04	1.12 ± 0.24 (0.77 ± 0.17)	0.5±0.3 (0.4±0.2)	1.2±0.4 (1.0±0.4)	1.2±0.6 (1.1±0.6)	1.1±0.5 (1.0±0.5)	0.7±0.3 (0.5±0.2)
Invariant reduced Hip + DWrist + DFoot	0.80 ± 0.08	1.15 ± 0.31 (0.80 ± 0.23)	0.5±0.3 (0.4±0.2)	1.3±0.6 (1.2±0.5)	1.2±0.7 (1.0±0.6)	1.1±0.5 (1.0±0.5)	0.7±0.3 (0.6±0.3)
Invariant reduced Hip	0.75 ± 0.06	1.27 ± 0.27 (0.87 ± 0.19)	0.5±0.3 (0.4±0.2)	1.3±0.5 (1.1±0.4)	1.4±0.6 (1.2±0.6)	1.2±0.5 (1.1±0.5)	0.9±0.4 (0.6±0.3)

Table 5-100: Root mean squared error and mean absolute error (shown in parenthesis) obtained when energy expenditure is estimated by first recognizing the activity being performed (out of a set of 51) in a subject independent manner and then predicting the average MET value associated with the activity recognized. The feature sets used to recognize activities are the *fast to compute* and the *invariant reduced* computed per sensor over windows of 5.6s in length. Average MET values for each activity are computed in a subject independent manner.

Sensor Combination	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
Fast to compute All sensors	0.90 ± 0.04	0.83 ± 0.23 (0.57 ± 0.14)	0.3±0.2 (0.2±0.1)	0.8±0.3 (0.7±0.3)	1.0±0.5 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.5±0.2 (0.5±0.2)
Fast to compute Hip + DWrist + DFoot	0.90 ± 0.03	0.84 ± 0.23 (0.58 ± 0.14)	0.3±0.2 (0.2±0.1)	0.9±0.3 (0.7±0.3)	1.0±0.5 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.5±0.2 (0.5±0.2)
Fast to compute Hip	0.87 ± 0.05	0.93 ± 0.21 (0.63 ± 0.14)	0.4±0.2 (0.3±0.2)	0.9±0.3 (0.8±0.3)	1.0±0.5 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.7±0.3 (0.6±0.2)
Invariant reduced All sensors	0.90 ± 0.03	0.83 ± 0.23 (0.57 ± 0.14)	0.3±0.2 (0.2±0.2)	0.8±0.3 (0.7±0.3)	1.0±0.5 (0.9±0.5)	0.8±0.4 (0.7±0.4)	0.5±0.2 (0.5±0.2)
Invariant reduced Hip + DWrist + DFoot	0.90 ± 0.04	0.84 ± 0.23 (0.58 ± 0.14)	0.3±0.2 (0.2±0.1)	0.8±0.3 (0.7±0.3)	1.0±0.5 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.6±0.2 (0.5±0.2)
Invariant reduced Hip	0.88 ± 0.04	0.90 ± 0.22 (0.61 ± 0.14)	0.4±0.2 (0.3±0.2)	0.9±0.3 (0.7±0.3)	1.0±0.5 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.7±0.3 (0.5±0.2)

Table 5-101: Root mean squared error and mean absolute error (shown in parenthesis) obtained when energy expenditure is estimated by first recognizing the activity being performed (out of a set of 51) in a subject dependent manner and then predicting the average MET value associated with the activity recognized. The feature sets used to recognize activities are the *fast to compute* and the *invariant reduced* computed per sensor over windows of 5.6s in length. Average MET values for each activity are computed in a subject independent manner.

followed by the Hip+DWrist+DFoot and Hip sensor combinations. This is because the activity recognition algorithm recognizes activities better as the number of sensors is increased. Table 5-101 also follows the same trend during subject dependent evaluation, although the difference in performance when the number of sensors is reduced is lower (as found in Section 5.4.7 for subject dependent recognition of activities). In Table 5-100, the Hip+DWrist+DFoot sensor combination achieves a performance of r=0.81, RMSE=1.12 using the *fast to compute* feature set and a performance of r=80, RMSE=1.15 using the *invariant reduced* feature set. These results are better than the ones obtained when activity dependent linear regression models are used to estimate energy expenditure using the *fast to compute* (r=0.80, RMSE=1.17) and *invariant reduced* (r=0.77, RMSE=1.31) feature sets. The performance using the *ACAbsArea* feature (vector size of 3) is +0.01 units higher in the correlation coefficient and -0.05MET lower in the RMSE when energy expenditure is estimated by predicting the average METs values associated with each activity than when activity dependent linear regression models are utilized. Although this improvement is small, the fact that performance did not decrease indicates that the utilization of activity dependent regression models is more important than the complexity of the models used to estimate energy expenditure. In other words, if activities can be reliably recognized, energy expenditure can be predicted well by only predicting the average number of METs associated with each activity.

Table 5-101 presents the results obtained when activities are recognized in a subject dependent manner. The results obtained for the *fast to compute* (r=0.9 and RMSE=0.84) and *invariant reduced* (r=0.90, RMSE=0.84) feature sets are higher than the ones obtained using subject independent recognition of activities. This is expected since activities are better recognized in a subject dependent manner. These results presented in Table 5-101 are the highest results obtained for energy expenditure estimation so far. These results improve the correlation coefficient in +0.21units and RMSE in 0.48METs with respect to the use of a single linear regression model. Performance per activity category is also improved between 0.3 and 0.4MET over the utilization of a single linear regression model. In fact, these results also improve the correlation coefficient ~+0.1units and the RMSE ~0.2MET with respect to subject dependent estimation of energy expenditure using a single linear regression model. These results are outstanding since it means that energy expenditure can be estimated better by recognizing activities than by collecting subject specific energy expenditure data using expensive and intrusive laboratory equipment (indirect calorimeter). These results obtained in this section also improve the correlation coefficient +0.07units and the RMSE in 0.08MET with respect to subject dependent estimation of energy expenditure using the *ScaledHR* feature. This is also outstanding since subject dependent estimation of energy expenditure using heart rate data is currently considered one of the most accurate methods available to estimate energy expenditure. The main disadvantages of subject dependent estimation of energy expenditure using heart rate data has been the need of subject specific calibration of regression equations using data collected from an indirect calorimeter in laboratory settings and the need to wear an uncomfortable heart rate monitor at the chest.

One disadvantage of estimating energy expenditure by recognizing activities and predicting average MET values per activity in practice is that steady-state energy expenditure values are predicted even when activities are performed for a short time. This is a problem particularly for physically demanding activities such as *ascending stairs* or *sit-ups* where energy expenditure increases constantly over time until steady state energy expenditure is reached. For example, if someone *ascends stairs* for a short time (e.g. the short stairs located at the entry door of a building), the energy expenditure predicted for this short duration activity would be close to the energy expenditure of that activity at steady state (as if the activity was performed over a long period of time). Consequently, energy expenditure would be overestimated for physically demanding activities performed for short durations of time. Chapter 6 discusses how this situation might be overcome in future work.

5.6.11.5 Summary of Results

Table 5-102 presents a brief summary of the results obtained for subject independent estimation of energy expenditure using the algorithms implemented in this chapter. In

Method	Feature set	Correlation	All	Postures	Ambulation	Exercise	Resistance Exercise	Household
Single LR	Fast to compute	0.69 ± 0.12	1.33 ± 0.33 (0.99 ± 0.24)	0.6±0.3 (0.5±0.3)	1.2±0.5 (1.1±0.5)	1.3±0.7 (1.2±0.7)	1.2±0.6 (1.1±0.6)	0.9±0.6 (0.8±0.6)
Single LR	Invariant reduced	0.70 ± 0.11	1.31 ± 0.34 (0.97 ± 0.23)	0.6±0.3 (0.5±0.3)	1.2±0.5 (1.0±0.5)	1.4±0.8 (1.3±0.8)	1.2±0.7 (1.1±0.6)	0.8±0.5 (0.7±0.5)
Single LR	ScaledHR	0.83 ± 0.09	1.02 ± 0.3 (0.8± 0.2)	0.5±0.3 (0.5±0.3)	0.9±0.5 (0.9±0.4)	1.3±0.7 (1.3±0.7)	1.2±0.6 (1.1±0.6)	0.5±0.3 (0.5±0.2)
Single LR	Fast to compute ScaledHR	0.88 ± 0.05	0.89 ± 0.22 (0.7 ± 0.2)	0.4±0.3 (0.4±0.3)	0.8±0.4 (0.7±0.4)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.9±0.5)	0.5±0.3 (0.5±0.3)
Single LR	Invariant reduced ScaledHR	0.88 ± 0.05	0.88 ± 0.23 (0.7 ± 0.2)	0.5±0.3 (0.4±0.3)	0.8±0.4 (0.7±0.3)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.8±0.5)	0.5±0.3 (0.5±0.2)
51 activities ARSI LR	Fast to compute	0.80 ± 0.09	1.17 ± 0.35 (0.79 ± 0.21)	0.4±0.3 (0.4±0.3)	1.2±0.5 (1.0±0.5)	1.3±0.7 (1.1±0.7)	1.2±0.6 (1.0±0.6)	0.7±0.4 (0.6±0.3)
51 activities ARSI LR	Invariant reduced	0.77 ± 0.11	1.31 ± 0.40 (0.87 ± 0.25)	0.6±0.4 (0.5±0.3)	1.5±0.7 (1.3±0.6)	1.4±0.8 (1.2±0.7)	1.3±0.6 (1.0±0.5)	0.9±0.5 (0.6±0.3)
51 activities ARSD LR	Fast to compute	0.89 ± 0.04	0.93 ± 0.28 (0.61 ± 0.15)	0.3±0.2 (0.2±0.1)	0.9±0.3 (0.7±0.3)	1.1±0.6 (1.0±0.6)	0.9±0.5 (0.8±0.5)	0.5±0.2 (0.4±0.2)
51 activities ARSD LR	Invariant reduced	0.88 ± 0.03	0.99 ± 0.27 (0.66 ± 0.18)	0.4±0.2 (0.3±0.2)	1.0±0.4 (0.8±0.4)	1.2±0.6 (1.0±0.5)	1.0±0.5 (0.8±0.4)	0.6±0.2 (0.5±0.2)
11 activities ARSI LR	Fast to compute	0.77 ± 0.07	1.28 ± 0.25 (0.92 ± 0.16)	0.5±0.2 (0.4±0.2)	1.3±0.6 (1.2±0.6)	1.4±0.7 (1.2±0.6)	1.3±0.6 (1.1±0.5)	1.0±0.4 (0.8±0.3)
11 activities ARSI LR	Invariant reduced	0.79 ± 0.09	1.23 ± 0.34 (0.86 ± 0.19)	0.5±0.2 (0.4±0.2)	1.4±0.7 (1.2±0.7)	1.4±0.7 (1.2±0.7)	1.3±0.6 (1.1±0.5)	0.9±0.5 (0.7±0.3)
11 activities ARSD LR	Fast to compute	0.81 ± 0.05	1.18 ± 0.24 (0.84 ± 0.15)	0.3±0.2 (0.2±0.2)	1.2±0.4 (1.1±0.4)	1.3±0.6 (1.2±0.6)	1.1±0.6 (1.0±0.6)	0.9±0.4 (0.7±0.3)
11 activities ARSD LR	Invariant reduced	0.84 ± 0.05	1.07 ± 0.20 (0.77 ± 0.15)	0.4±0.2 (0.3±0.1)	1.2±0.5 (1.0±0.4)	1.2±0.5 (1.0±0.5)	1.0±0.5 (0.9±0.4)	0.8±0.4 (0.7±0.3)
51 activities ARSI mean	Fast to compute	0.81 ± 0.07	1.12 ± 0.30 (0.78 ± 0.20)	0.5±0.3 (0.4±0.3)	1.3±0.5 (1.1±0.5)	1.2±0.7 (1.1±0.6)	1.1±0.5 (1.0±0.5)	0.7±0.4 (0.6±0.3)
51 activities ARSI Mean	Invariant reduced	0.80 ± 0.08	1.15 ± 0.31 (0.80 ± 0.23)	0.5±0.3 (0.4±0.2)	1.3±0.6 (1.2±0.5)	1.2±0.7 (1.0±0.6)	1.1±0.5 (1.0±0.5)	0.7±0.3 (0.6±0.3)
51 activities ARSD Mean	Fast to compute	0.90 ± 0.03	0.84 ± 0.23 (0.58 ± 0.14)	0.3±0.2 (0.2±0.1)	0.9±0.3 (0.7±0.3)	1.0±0.5 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.5±0.2 (0.5±0.2)
51 activities ARSD Mean	Invariant reduced	0.90 ± 0.04	0.84 ± 0.23 (0.58 ± 0.14)	0.3±0.2 (0.2±0.1)	0.8±0.3 (0.7±0.3)	1.0±0.5 (0.9±0.5)	0.9±0.4 (0.8±0.4)	0.6±0.2 (0.5±0.2)

Table 5-102: Root mean squared error and mean absolute error (shown in parenthesis) obtained when estimating energy expenditure using different methods and two sets of features (*fast to compute* and *invariant reduced*) computed over the accelerometers located at the hip, dominant wrist, and dominant ankle. ARSI stands for subject independent recognition of activities, ARSD for subject dependent recognition of activities, and LR for linear regression. Energy expenditure is always predicted in a subject independent manner.

Table 5-102 'LR' stands for multivariable linear regression, 'ARSI' for subject independent recognition of activities, 'ARSD' for subject dependent recognition of activities, and 'Mean' for estimation of energy expenditure by predicting average MET values per activity. From the table, it can be seen that energy expenditure can be best predicted by first recognizing activities in a subject dependent manner and then predicting the average energy expenditure associated with each activity in METs (51 activities ARSD Mean). This technique improves the correlation coefficient +0.01units and RMSE 0.12MET over the utilization of linear regression models per activity (51 activities ARSD LR) using either the *fast to compute* or *invariant reduced* feature sets. This is an important result since highlights the fact that activity recognition is more important than the complexity of the model used to estimate energy expenditure. This is also supported by the fact that performance does not improve when the number of activities to recognize is reduced from 51 to 11 during subject dependent and independent recognition of activities (11 activities ARSD and ARSI LR). This, suggests that energy expenditure is better predicted when more activity dependent regression models are used. The table also shows that subject dependent recognition of 51 activities (and the use of activity dependent regression models) outperforms energy expenditure estimation using heart rate data (*ScaledHR*) using a single linear regression model. This is also an important result since chest strap heart rate monitors, the most commonly available type of heart rate monitor, are uncomfortable to wear and can cause skin irritation when used longitudinally. Finally, estimation of energy expenditure by recognition of activities has the advantage of providing contextual information that might be valuable for real-time interventions designed to foster increases in physical activity levels.

This section also found that given enough training data, energy expenditure estimation improves as the number of wearable sensors used is increased. This is an intuitive result since more sensors are able to better capture the motion characteristics of individuals. Nevertheless, it was also found that a performance close to the one obtained using all the seven accelerometers (explored in this work) can be obtained using just three sensors located at the hip, dominant wrist, and dominant foot or just two sensors worn at the dominant wrist and dominant foot. These sets of sensors are able to capture upper body, lower body and overall body motion well to produce good estimates of energy expenditure for most of the activities explored in this work (51). In general, when single sensors are used to estimate energy expenditure, the highest performance is obtained from sensor located at the foot, hip, and thigh, and the worse performance is obtained from the sensor located at the dominant wrist. The sensor at the dominant wrist obtains the worse performance perhaps due to the high motion variability experienced at the wrists during most activities. This section also found that given sufficient amount of training data, the computation of features that capture additional information than overall amount of motion (*ACAbsArea* feature) such as the *ACFFTPeaks*, *ACModVigEnergy*, and the *ACMCR* improve energy expenditure estimates, particularly when single sensors are used to estimate energy expenditure. Finally, the section found that when activity dependent models are not used, energy expenditure is best estimated using heart rate data alone and that the combination of accelerometer and heart rate data improves energy expenditure estimation (although only slightly over the dataset utilized in this analysis).

5.6.12 How Well Can Time Spent in Physical Activity Level be Recognized?

This section explores how well the energy expenditure estimation algorithms explored in this section can recognize time spent in *sedentary*, *light*, *moderate*, *vigorous*, and *very vigorous* physical activity. This is achieved by thresholding the energy expenditure estimates provided by the algorithms using the thresholds shown in Table 5-103. These MET thresholds were obtained from the study performed by Cradock et al. [251]. These threshold values are commonly utilized by the medical community during research studies. To test the recognition accuracy, predicted MET intensity levels (computed by thresholding the estimated energy expenditure) were compared against the ground truth physical activity levels obtained by thresholding the energy expenditure readings collected using the Cosmed K4b2 [125] indirect calorimeter.

Physical Activity Level	MET Range
Sedentary	≤ 1.5
Light	> 1.5 and < 3.0
Moderate	≥ 3.0 and ≤ 6
Vigorous	> 6 and ≤ 9
Very Vigorous	> 9

Table 5-103: Classification of physical activity level into sedentary, light, moderate, vigorous, and very vigorous by thresholding the MET intensity value.

Method	Feature set	Sedentary (%)	Light (%)	Moderate (%)	Vigorous (%)	Very Vigorous (%)	Total (%)
Single LR	*Fast to compute*	31.9	59.7	82.8	30.4	0.0	57.9
Single LR	*Invariant reduced*	43.3	60.3	80.5	32.5	0.0	60.5
Single LR	*ScaledHR*	53.7	71.1	76.2	29.9	38.7	65.6
Single LR	Fast to compute ScaledHR	58.0	65.5	85.9	49.7	0.0	70.0
Single LR	Invariant reduced ScaledHR	60.4	71.3	80.2	50.8	29.3	70.1
51 activities ARSI LR	*Fast to compute*	78.4	65.1	64.8	41.3	0.0	65.9
51 activities ARSI LR	*Invariant reduced*	77.4	65.9	60.3	44.8	2.7	64.7
51 activities ARSD LR	*Fast to compute*	81.2	73.6	75.1	46.2	0.0	73.3
51 activities ARSD LR	*Invariant reduced*	81.6	71.9	71.2	50.0	13.7	71.9
11 activities ARSI LR	*Fast to compute*	73.0	54.5	76.6	30.4	0.0	64.2
11 activities ARSI LR	*Invariant reduced*	72.3	58.6	72.5	39.0	8.0	64.8
11 activities ARSD LR	*Fast to compute*	69.6	61.3	81.4	38.4	0.0	67.9
11 activities ARSD LR	*Invariant reduced*	68.1	64.5	80.0	44.4	6.7	68.7
51 activities ARSI mean	*Fast to compute*	75.5	62.0	68.9	39.5	0.0	65.4
51 activities ARSI Mean	*Invariant reduced*	74.5	65.0	69.0	36.0	0.0	65.9
51 activities ARSD Mean	*Fast to compute*	77.6	72.2	79.6	44.7	0.0	73.3
51 activities ARSD Mean	*Invariant reduced*	77.5	73.2	79.6	44.1	0.0	73.6

Table 5-104: Accuracy in recognizing time spent sedentary, light, moderate, vigorous, and very vigorous physical activity using the different energy expenditure estimation algorithms explored in this section when accelerometers at the hip, dominant wrist, and dominant foot are utilized.

Table 5-104 presents the accuracy of recognizing the different physical activity levels using the algorithms explored in this section. It can be seen that the highest overall performance is obtained by recognizing 51 activities in a subject dependent manner using the *invariant reduced* feature set and predicting the average MET value associated with each activity (51 Activities ARSD Mean). This algorithm achieves an overall recognition accuracy of 73.6%. It is outstanding that this algorithm achieves a higher overall performance than when the *ScaledHR* feature is utilized (65.6%) and that when the *ScaledHR* feature is combined with the *fast to compute* (70%) and *invariant reduced*

(70.1%) feature sets using a single linear regression model.

This algorithm (51 Activities ARSD Mean) also achieves a relatively good performance over most physical activity levels (ranging from 44.1% to 79.6%) except for the very vigorous intensity level (accuracy of zero). This intensity level is only recognized relatively well using a single linear regression model trained over the ScaledHR feature (38.7% accuracy). In fact, the recognition accuracy for this intensity level is only different from zero when the ScaledHR feature or the invariant reduced feature sets are utilized in combination with linear regression models to estimate energy expenditure. This is because when this intensity level is reached, it is confused with the vigorous and moderate intensity levels. The reason is that energy expenditure reached the very vigorous intensity level mostly during the cycling hard at 80rpm activity, which involves resistance work or load effort. Thus, energy expenditure for this activity is under predicted when most accelerometer-based features were utilized. The only accelerometer-based feature that is able to recognize the very vigorous intensity level is the invariant reduced feature set because it combines the ACFFTPeaks and ACBandEnergy features that detect some of the extra physical effort involved during the cycling hard at 80rmp activity. Heart rate data on the other hand (ScaledHR feature), is able to better estimate energy expenditure for the cycling hard at 80rmp activity and thus, able to better recognize the very vigorous intensity level. The very vigorous intensity level was only reached during 0.4% of the time (75 windows out of 17746) during the data collections.

The second highest performance in Table 5-104 is obtained when 51 activities are recognized in a subject dependent manner and activity dependent linear regression models (trained in a subject independent manner) are utilized to estimate energy expenditure. In This scenario, the *fast to compute* feature set achieves a higher accuracy than the *invariant reduced* feature set (+1.4%) but the *invariant reduced* feature set is able to recognize the *very vigorous* intensity level to some extent (13.7%). An important advantage of the *fast to compute* feature set over the *invariant reduced* feature set is that its computational complexity is significantly lower since the *ACFFTPeaks* feature is not computed (the fast Fourier transformation does not need to be computed). The difference in performance between these algorithms (51 Activities ARSD) and the one obtained using a single linear regression model trained over the same accelerometer-based features (*fast to compute* and *invariant reduced*) ranges between +11.4% and +15.4%. The difference in performance decreases to lie between +4.2% and +8% (with respect to a single linear regression model) when activities are recognized in a subject independent manner (51 Activities ARSI). Utilizing a linear regression model per activity improves recognition of some physical activity levels over prediction of mean values per activity. For example, the *sedentary* and *vigorous* intensity levels are estimated with an accuracy +4% higher than when mean MET values are predicted for each activity recognized. This is because a linear regression is able to better model the energy expenditure associated with these intensity levels.

Finally from Table 5-104, it can be seen that the lowest recognition accuracy is obtained using a single linear regression model trained over the *fast to compute* and *invariant reduced* feature sets (57.9 - 60.5%). Therefore, the main result that can be drawn from Table 5-104 is that activity dependent regression models also improve recognition of time spent in different physical activity levels, particularly when activities are recognized in a subject dependent manner.

6 Conclusions

This chapter presents a summary of the major findings and results presented in this work, including a summary of the primary contributions and a discussion on how well the design goals stated in Section 5.1 were met. In addition, some areas for future research are identified.

6.1 Summary of Results

Presently, the most accurate technologies to measure energy expenditure are only suitable for laboratory settings (e.g. room or portable indirect calorimeters) due to their cost, intrusiveness, and complexity. Other technologies more amenable for free-living such as paper and electronic diaries are burdensome and time consuming. Accelerometers offer a promising strategy to recognize physical activity and estimate energy expenditure in free-living people. However, existing accelerometer-based devices provide little or no contextual information (activity information) or have difficulties detecting upper or non-ambulatory lower body activity or do not make the data available in real-time. As a result, the goal of the work presented in this thesis was to develop algorithms based on wireless accelerometers to (1) recognize activity type, intensity, and duration and (2) estimate energy expenditure while achieving a reasonable real-time performance from sensors worn at convenient locations. This work explored the trade-offs that needed to be made in order to achieve these goals.

6.1.1 Activity Recognition

There exists a large body of prior work in recognizing activities from accelerometer data. However, most of this work relies on researchers as subjects or evaluates the algorithms implemented over few subjects (often less than five). Furthermore, researchers often explore a fixed set of activities (often less than 15) and select the algorithm parameters (e.g. classifier, feature set, window length, etc) as well as the type, number and placement of the sensors using common sense depending on the activities being explored. Finally, most prior work has been evaluated off-line and few real-time implementations of the algorithms presented exist (see section 3 for a full discussion of prior work and a discussion of some of the exceptions to the statements made in this paragraph).

The main contributions of this work to the area of activity recognition with respect to prior work are: (1) to explore the recognition of 52 activities collected from 20 non-researchers (120hrs of data) at a gymnasium and a residential home, (2) recognize the activity type and intensity, (3) perform a set of systematic experiments to determine the algorithm parameters, value of accelerometers vs. heart rate, location and number of sensors, and (4) to perform a proof of viability of a real-time system to recognize arbitrary activities.

The final activity recognition algorithm implemented in this work uses three accelerometers located at the hip, dominant wrist, and dominant foot and consists on the following steps: (1) segmentation of the accelerometer data into 5.6s overlapping windows. (2) Interpolation of the signals over each window using cubic splines interpolation to compensate for values lost during wireless transmission. (3) Digital filtering of each acceleration axis using a band-pass filter (0.1-20Hz) and low-pass filter (1Hz) to separate motion from posture information. (4) The computation of features over each band-pass filtered acceleration axis such as the variance to capture the signal variability, the top five peaks of the FFT coefficients to capture the frequency or periodicity of motion, the energy between 0.3-3.5Hz to capture the intensity of activity, and the distances between each low-pass filtered axis (e.g. xz, xy, yz) to capture posture information. (5) The training of a C4.5 decision tree classifier using the features computed to create a set of rules to discriminate among the activities of interest. This algorithm was found by performing a set of systematic experiments evaluated in a subject dependent and independent manner and targeted to identify the set of parameters that allowed reasonable real-time performance, ease-of-use, and comfort of usage. The final feature set selected maximized performance and reduced dependency of the algorithm on small variations in the placement of the sensors on the body.

The final activity recognition algorithm presented achieved a subject independent accuracy of 50.6% and a subject dependent accuracy of 87.9% over a set of 51 activities. The large percent change of 73% from subject independent to subject dependent evaluation indicates that activities are easier to recognize if subjects provide examples of the activities. In general, it was found that the activities with higher performance were postures and exercises and the activities with poorer performance were household and resistance activities. Postures were relatively easy to recognize because they do not involve too much variability. Some exercises were relatively easy to recognize because they involved the use of a particular limb or a particular speed of execution. Household activities were more difficult to recognize due to their high variability (e.g. *making the bed* or *wiping/dusting*) and because they often involve sequences of postures and ambulation. Resistance activities presented a poorer performance because accelerometers have difficulties detecting resistance or work load effort. The activities confused most often were household activities, activities involving different intensity levels, and activities involving similar upper body motion. Activities with different intensity levels were confused because some intensity levels involved changes in resistance or work load that was poorly detectable from accelerometers. Activities with similar upper body motion were confused due to the high variability of motion found at the wrists during everyday life.

Due to the significantly higher performance (73% percent difference) of subject dependent training vs. subject independent training over 51 activities, experiments were performed to determine the amount of data required to achieve reasonable performance during subject dependent training. After partitioning each activity example into 75% training data and 25% testing data, and training the C4.5 classifier with varying amounts of training data, it was found that 60% of the training data achieved an overall accuracy of 76% over 51 activities. At this percentage of training data, most activities were 2 minutes in length except for physically demanding activities which were less than a minute in length. This indicated that a reasonable performance could be obtained by just providing 2 minutes of data per activity even when the number of activities to recognize was large (51).

The performance of the final activity recognition algorithm was also tested over subsets of activities that might be important to recognize during medical research studies or ubiquitous computing applications (e.g. 31, 11, 8 and 4 activities). It was found that if recognition of the intensity of activities is not important (e.g. if the intensity levels are merged into a single class), total overall accuracies of 72% and 91.4% can be obtained during subject independent and dependent evaluation respectively. This is an interesting result because it indicates that a total of 31 activities can be recognized with a subject independent accuracy of 72% in practice. The analysis also indicated that postures, ambulation (including intensity levels), and two MET intensity levels (moderate and vigorous) could be recognized with accuracies of 96.5% and 81.3% during subject dependent and independent evaluation respectively. The results also indicate that postures and ambulation can be recognized with accuracies of 98.4% and 92.9% during subject dependent and independent evaluation respectively. Finally, four postures can be recognized with accuracies over 98% during both subject dependent and independent evaluation.

When the performance of 11 subsets of sensors out of a total of seven sensors was explored, it was found that the best performing subset during both, subject dependent and independent training was the combination hip + dominant wrist + dominant foot. This sensor combination was able to capture upper, lower, and overall body motion that was important to recognize the 51 activities of interest. In general, when the number of activities to recognize was decreased, the number of sensors could also be decreased with relatively small decreases in performance. During subject dependent evaluation, it was found that a sensor located at the hip and another sensor located either at the dominant wrist (Hip+DWrist) or the dominant foot (Hip+DFoot) achieved reasonable performance (with respect to the use of all seven accelerometers). This is because upper body and lower body activity induced changes in the acceleration at the hip that allowed some degree of discrimination among upper body and lower body activities during subject dependent training. The highest performing single sensors during subject dependent training were the sensor at the hip, and the sensors at the lower body (foot and thigh). During subject independent evaluation, the best performing sensor combinations were those using a sensor located at the dominant wrist to detect upper body motion and another sensor located either at the dominant thigh or the dominant foot to detect lower body motion (DWrist+DThigh or DWrist+DFoot). The best performing single sensors during subject independent evaluation were DUpperArm, DWrist, and Hip. The good performance of the DUpperArm sensor might be explained by the fact that most activities contained in the MIT dataset included a high degree of upper body motion and ambulatory activities in the case of household activities.

It was also found that the length of the sliding window to utilize strongly depends on the activities to recognize. For example, postures are better recognized using short duration windows (<5.6s) and household activities with longer windows (e.g. >22s). This is because the variability of motion in postures is low and the variability in motion in household activities is high. The main disadvantage found for the use of long windows was low performance over short duration activities (e.g. physically demanding activities) and long real-time classification delays. Even though the window length depends on the activity to recognize, it is computationally expensive to have different window length for each activity since features have to be recomputed for each window of different length.

Consequently, a single sliding window of 5.6s in length was selected in this work to maximize performance over most activities, reduce classification delay, and to improve performance over short duration activities.

Heart rate data was not used in the final implementation of the activity recognition algorithm because the performance obtained with the highest performing heart rate feature alone (*ScaledHR*) was 38.4% and 13.8% during subject dependent and independent evaluation respectively. This performance was considerably lower than the one obtained using the highest performing accelerometer-based features. When the highest performing heart rate feature (*ScaledHR*) was added to the highest performing accelerometer-based feature set (*invariant reduced*), it is found that overall accuracy increased only between 2-4% during both subject dependent and independent evaluation. As expected, the activities for which recognition improved most substantially with the incorporation of heart rate data were those involving resistance or work load effort (e.g. *cycling*, *rowing*, *bicep curls*, etc). Several reasons explain the poor performance of heart rate data. First, heart rate lags physical activity and remains altered once an activity has ended. This produces errors at the beginning and at the end of each activity. Moreover, activities for which heart rate data constantly increases as the activity is performed (e.g. physically demanding activities such as *ascending stairs*) do not present a single heart rate value characteristic of that activity. Finally, heart rate presents inter-individual variations due to fitness level (e.g. more physically fit individuals tend to have lower heart rate readings) and intra-individual variations due to emotional state, nicotine consumption, and even environmental temperature.

Finally, the activity recognition algorithm was implemented on a laptop computer and tested in real-time during a short pilot study. Five participants were asked to (1) wear three accelerometers at the hip, dominant wrist, and dominant foot, (2) to type in 10 physical activities, exercises, postures, or activities of their choice that they wanted the system to recognize, (3) to provide 2min of data for each activity, and (4) to test the performance of the recognition algorithm in real-time. The participants provided a variety of complex activities such as Taekwondo forms, scratching head, bowling, tennis serve, hammering a nail, applying cream, knitting, filing nails and drawing on a piece of paper. The cross-validation accuracy obtained during the study for each participant ranged from 79% to 92%. During the study, participants expressed the desire to provide the training data during free-living (and consequently not over a single tedious session of repeating an activity for 2min) and the desire to ‘fix’ the algorithms in real time when they did not perform as expected by providing more training examples of the problematic activities.

6.1.2 Energy Expenditure Estimation

The two most popular approaches to estimate energy expenditure employed by the medical community are the use of linear regression equations based on accelerometer data and the use of the Compendium of Physical Activities [122]. The use of linear regression equations based on accelerometer data consists on the following steps: (1) Collect accelerometer and ground truth energy expenditure data from a subject wearing an indirect calorimeter and a single accelerometer at the hip, (2) segment the accelerometer and ground truth data into one minute windows, (3) sum the accelerometer values (or counts) over the one minute intervals and compute the mean value over the energy expenditure windows, and (4) create a single linear regression model to map the acceleration sums into the mean ground truth energy expenditure values. The Compendium of Physical Activities can be used to estimate energy expenditure by collecting information about the activity type being performed and its duration (e.g. using diaries). Once this information is collected, it can be converted to energy expenditure by using the mean energy expenditure values listed for a variety of activities in the Compendium of Physical Activities.

Presently, the state-of-the-art algorithm to estimate energy expenditure from an accelerometer at the hip is the work by Crouter et al [34]. This algorithm first classifies activities into *sedentary*, *ambulatory* and *lifestyle* activities and then applies different regression models depending on the type of activity detected. For example, if *sedentary* activities are detected, a MET value of one is predicted; if *ambulatory* activities are detected a linear regression model is applied; and if *lifestyle* activities are detected, an exponential regression model is applied. This algorithm achieves a correlation coefficient of 0.96, a maximum absolute error deviation of 0.75MET, and a RMSE of 0.73MET when evaluated over a set of 17 activities collected from 20 participants (3 hours per participant). However, the authors excluded the *cycling* activity from analysis because it did not generate any sensor readings at the accelerometer at the hip.

The work presented in this thesis extends the work by Crouter et al. by exploring the use of 51 activity-dependent regression models, the use of seven accelerometers and subsets of them, the exploration of 41 features computed over the raw accelerometer data, the use of shorter window lengths (less than a minute long), and the use of non-linear regression models in the estimation of energy expenditure. Finally, the algorithms implemented are evaluated over data collected from 16 individuals between 18 and 40 years old performing 52 activities at two locations: A gymnasium and a residential home.

After running the Crouter et al. algorithm over the dataset collected for this work, it was found that its performance (r=0.4, RMSE=2.7) on 52 activities was considerably lower than the one reported by the authors (r=0.92, RMSE=0.73) for 17 activities. One of the reasons for the poor performance obtained was the inability of the single accelerometer at the hip to capture upper body (e.g. *bicep curls*) and non-ambulatory lower body activity (e.g. *cycling*), because the sensor readings at the hip for these activities were mostly zero. When information about activity type and duration from the labels collected was converted to energy expenditure using the Compendium of Physical Activities, it was found that the performance obtained (r=0.9, RMSE=1.27) represented an improvement of ~100% for the correlation coefficient and ~50% for the RMSE with respect to the Crouter et al. algorithm. These results indicated that knowledge of the activities being performed was very important since this technique only predicted the average energy expenditure values listed in the Compendium of Physical Activities for each activity. In order to obtain a baseline on performance, a single linear regression model was created to estimate energy expenditure from the accelerometer sums computed over one minute windows for each of the seven accelerometers. The results obtained (r=0.73, RMSE=1.4) were also considerably higher than those obtained by Crouter et al. For example, the improvement over the correlation coefficient was 82% and over the RMSE was 48%. The improvements obtained were mainly due to the use of seven accelerometers located at different body segments that captured upper, lower, and overall body motion more fully than a single accelerometer at the hip. When activity-dependent linear regression models were applied to estimate energy expenditure assuming the activity being performed was known, it was found that the performance obtained (r=0.87, RMSE=1) was also considerably higher than the performance obtained for the Crouter et al algorithm. For example, the improvement was 117% for the correlation coefficient and 63% for the RMSE. The improvement achieved over the use of a single linear regression model was 19% for the correlation coefficient and 28.5% for the RMSE. Activity-dependent regression models helped by allowing regression coefficients to be tuned for each activity instead of being globally optimized for all activities at once. Finally, activity dependent non-linear regression models (M5' model trees) were applied to estimate energy expenditure over the dataset assuming the activities performed were also known. The results obtained (r=0.91, RMSE=0.88) represented an improvement of 127% for the correlation coefficient and 67% for the RMSE with respect to the one obtained by Crouter et al. The improvement obtained over activity-dependent linear regression models was 5% for the correlation coefficient and 12% for the RMSE. The improvement over the use of a single linear regression model was 25% for the correlation coefficient and 37% for the RMSE.

In general, the lowest performance in energy expenditure estimation was obtained for activities involving resistance work or load effort. This is because accelerometers have difficulties detecting resistance work or load effort. The activities with highest performance were postures and household activities. This is because energy expenditure changed little for these activities with respect to the changes observed for physically intense activities such as gymnasium activities. The use of a single linear regression model trained over seven accelerometers overestimated energy expenditure for sedentary activities. This is because the regression coefficient representing the DC offset of the energy expenditure signal was increased during training to compensate for the high energy expenditure observed for physically intense activities involving resistance work (e.g. *cycling*). This single linear regression model also estimated energy expenditure well for upper body and lower body activity due to the use of additional (six) accelerometers at different body locations. The Compendium of Physical Activities was found to overestimate energy expenditure for household activities and short duration activities. This is because the energy expenditure value listed in the Compendium of Physical Activities is the one measured during steady-state conditions. Thus, energy expenditure is overestimated for household and short duration physically demanding activities because steady-state energy expenditure was not reached. The Compendium of Physical Activities was found to estimate energy expenditure better for activities that reached steady-state during the data collections such as *walking*, *running*, *cycling*, and *rowing*.

In summary, the first set of experiments on energy expenditure estimation indicated that accelerometers at the upper and lower body as well as activity-dependent regression models improved energy expenditure performance. A new set of systematic experiments was performed to explore if the number of accelerometers could be reduced, if heart rate data improved performance (over accelerometer data), and if the use of the activity recognition algorithm previously implemented could produced reasonable performance (with respect to the assumption of known activity). This new set of experiments as will be later explained in detail indicated that reasonable performance could be achieved by the use of only three accelerometers located at the hip, dominant wrist, and dominant foot. It was also found that the top five peaks of the FFT coefficients used as features and computed over sliding windows of 5.6s in length achieved a good compromise between performance and computational complexity.

When eleven subsets of the seven accelerometers were analyzed to find the most comfortable combination with highest performance, it was found that the combination of hip, dominant wrist, and dominant foot achieved the highest performance. The decrease in performance with respect to the use of all seven accelerometers was less than 3% for both the correlation coefficient and the RMSE during subject independent evaluation. The second best performing sensor subset was the combination of a sensor at the dominant wrist and another sensor at the dominant foot. Using this subset, the decrease in performance for both the correlation coefficient and the RMSE with respect to all seven accelerometers was approximately 3%. This is an important result since it can be argued that sensors at the wrist and at the foot are easier to wear since they can be embedded in convenient devices such as wristwatches and shoe pods. When the performance of single sensors was analyzed, it was found that the best single sensors to use depend on the activities with highest energy expenditure levels in the dataset. For example, in this work, the activity with highest energy expenditure was *cycling hard*. As a result, the highest performing single sensors were the sensors worn at the lower body: The sensor at the dominant foot and the sensor at the dominant thigh.

When the activity recognition algorithm was used to estimate energy expenditure using activity dependent regression models, it was found that the performance for subject independent recognition of activities was r=0.77, RMSE=1.31. Performance for subject dependent recognition of activities was r=0.88, RMSE=0.99. The performance obtained using subject dependent recognition of activities was close to the performance obtained when the activities were assumed to be known (<2%). This was an interesting result since the accuracy of recognizing activities in a subject dependent manner was only ~80%. The reason why performance was high despite this non-perfect accuracy was that the classification errors performed by the recognition algorithm involved activities similar in their motion patterns and thus, with similar energy expenditure values. As a result, even when errors were made, activity-dependent regression models similar to the ones of the 'true' activity being performed were applied thus achieving estimates close to the true values expected.

Experiments using heart rate data to estimate energy expenditure showed that the best single feature to use was the *ScaledHR* feature. This feature consisted of the number of heart beats per minute normalized to lie between zero and one for resting and running on a treadmill at 5mph. This feature achieved a performance of r=0.84, RMSE=1.01 over the dataset explored. This performance was better than any of the results obtained using accelerometer-based features. However, the performance obtained using subject dependent recognition of activities and activity-dependent linear regression models was as good (r=0.88, RMSE=0.99) as the one obtained using the *ScaledHR* feature alone. This indicates that activity dependent regression models improve energy expenditure estimation considerably and can compensate for the use of uncomfortable sensors such as chest strap heart rate monitors.

The work presented here also suggests that features that capture information other than overall amount of motion (*ACAbsArea* feature) improve performance, particularly when single sensors are used to estimate energy expenditure. For example, estimating energy expenditure using the top five FFT peaks, the band energy, and the mean crossing rate improved r by 13% and RMSE by 21% over the use of the overall amount of motion feature computed from a single accelerometer at the hip. This work also found that the addition of heart rate data to the best accelerometer-based feature (top five FFT peaks) improved the correlation coefficient 22% and the RMSE 31%.

Finally, this work explored the performance of estimating energy expenditure by first recognizing the activities being performed using the implemented algorithm and then predicting the average energy expenditure value per activity as computed from the data collected. The performance of this technique during subject dependent recognition of activities was the highest obtained in this work (r=0.90, RMSE=0.84). This technique achieved an improvement in the correlation coefficient between 2-4% and an improvement on the RMSE between 12-15% with respect to the use of activity-dependent linear regression models. The improvement is modest, but the fact that performance did not degrade when such a relatively simple technique is used to estimate energy expenditure is notable. Estimating energy expenditure by recognizing activities and then predicting mean energy expenditure values per activity has some limitations. For example, this technique is likely to overestimate energy expenditure for short duration activities, particularly physically demanding ones. Steady-state energy expenditure might not be reached in this case. Another potential problem is that misclassifications could affect the energy expenditure estimates. For example, if the activity recognition algorithm is not trained to recognize *dancing* but it is trained to recognize *running*, *dancing* might be confused with *running* and, consequently, the mean energy expenditure for *running* would be predicted for *dancing*. These energy expenditure estimates could be significantly off, thus affecting the overall performance of energy expenditure estimation. Other classification errors might not affect energy expenditure considerably. Confusing *running at 6mph* with *running at 5mph*, for example, would produce energy expenditure estimates that although incorrect would still be close to the true energy expenditure value. One possible improvement might be to train the activity recognition algorithm on a larger set of mutually exclusive activities, the ones that end-users of the system are most likely to perform over the course of a day. Another possibility is to train the activity recognition algorithm to recognize an *unknown* activity. Then, when this *unknown* activity is recognized, a generic regression model can be applied to estimate energy expenditure. Another option is to ask the user at the end of the day for the real label of the activity performed when the *unknown* activity was recognized to better estimate energy expenditure and improve activity labeling. Finally, another potential problem is that activity recognition algorithms tend to generate spurious classifications while people transition between activities. Thus, it is necessary to filter these spurious classifications, perhaps utilizing information about how people transition between activities to reduce the errors introduced in the energy expenditure estimates.

6.2 Primary Contributions

In summary, the main contributions of this work to the field of activity recognition from wearable sensors are:

1. The recognition of 52 activities and subsets of these activities on data collected from 20 non-researchers. A dataset larger and more complex than the ones used in prior work to the best of the Author's knowledge.
2. The recognition of not only the type of activity but also the intensity of some activities.
3. The exploration of subject dependent recognition of activities using 2min of data as a promising strategy to recognize activities in practice.
4. The presentation of results that indicate that three sensors at hip, dominant wrist, and dominant foot offer a good compromise to recognize the 52 activities explored in this work, as well as arbitrary activities provided by users.
5. The presentation of results that indicate that acceptable activity recognition performance can be obtained without using heart rate data.
6. The proof of viability of a real-time system than can be trained to recognize arbitrary activities.
7. The presentation of an activity recognition algorithm that is amenable for real-time performance in low-processing power devices such as mobile phones.
8. The exploration of the impact of different parameters of the activity recognition algorithm such as the type of classifier (four types of classifiers explored), feature set (41 feature types explored), feature computation technique (e.g. per sensor vs. per axis), sliding window length (varied from 1s to 91s), signal processing techniques (e.g. digital filtering applied, interpolation technique), and sensor subsets required (eleven subsets of seven sensors explored).

The main contributions to the field of energy expenditure estimation from wearable sensors are:

1. The estimation of energy expenditure for 52 activities and some subsets of these activities on data collected from 20 non-researchers. A dataset larger and more complex than the ones used in prior work to the best of the Author's knowledge.
2. The presentation of results that indicate that activity-dependent models improve energy expenditure estimation performance over the use of single linear regression models trained over accelerometer or heart rate data alone. Furthermore, activity-dependent regression models achieved a performance similar to the one obtained by combining the highest performing accelerometer and heart rate features explored in this work when single regression models are used (e.g. differences in r of 0.04 and in RMSE of 0.02 were found).
3. The presentation of experiments that demonstrate that when activity-dependent models are used, prediction of mean energy expenditure values per activity outperforms the use of linear regression models per activity in the dataset explored in this work.
4. The presentation of results that strongly suggest that heart rate data outperforms the use of accelerometer data during the estimation of energy expenditure, at least in the dataset explored in this work.
5. The presentation of results that indicate that features that capture information additional to overall amount of motion (e.g. FFT peaks, frequency domain energy,

mean crossing rate) improve energy expenditure performance, particularly when single sensors are used to estimate energy expenditure.

6. The presentation of results that indicate that sensors at the dominant wrist and dominant foot are important to measure upper body and non-ambulatory lower body activity and corresponding energy expenditure. Reasonable performance can be obtained by using only these two sensors and no sensor at the hip.
7. The exploration of the impact of different parameters of the energy expenditure algorithm such as the type of regressor (four types of regressors explored), feature set (41 feature types explored), feature computation technique (e.g. per sensor vs. per axis), sliding window length (varied from 1s to 91s), signal processing techniques (e.g. digital filtering applied, interpolation technique), and sensor subsets required (eleven sensor subsets explored).

6.3 Revisiting the Design Goals

This section briefly revisits the design goals stated at the beginning of this work and/or the evaluation measures neglected in most prior work to identify which ones were met and which ones were not met.

- **Complexity of the activities to recognize**:
    - *Number of activities to recognize*: This work explored the recognition and energy expenditure estimation of a set of 52 diverse activities, a number that to the best of the author's knowledge is larger than any number of activities explored in prior work.
    - *Complexity of the types of activities to recognize*: The 52 activities explored in this work contained 26 activities with different intensity levels due to different speeds of execution and resistance work, 18 household activities containing examples of unconstrained motion in a residential home, and activities involving upper, lower, and overall body motion. This work also evaluated the recognition performance over subsets of the 52 activities to identify how reducing the number of activities to recognize impacts performance.
    - *Complexity of the training data collected for the activities*: The training data for this work was collected from 20 participants executing a total of 52 activities at two locations: A gymnasium and a residential home. The activities at the gymnasium were relatively constrained due to the use of gymnasium equipment such as a treadmill and stationary machines (e.g. cycling and rowing machines). However, the data collection at the residential home was less constrained since participants were allowed to perform the activities as they pleased.
- **Training data requirements of an algorithm**
    - *Subject independent recognition of activities*: This work showed that a subject independent accuracy of 51% can be achieved over 52 activities. In contrast, the accuracy obtained using subject dependent training was

80%. However, if the intensity of physical activities does not need to be recognized, a subject independent accuracy of 72% can be achieved.

- *Amount of training data required for subject dependent recognition of activities*: Given that the performance of subject dependent training consistently outperformed the performance of subject independent training, experiments were performed to determine the minimum amount of training data required to achieve a reasonable performance. It was found that 2 minutes of data per activity achieved a total accuracy of 72% over 52 activities. Experiments using this amount of training data per activity were also performed in real-time where five individuals provided a list of 10 arbitrary activities that they wanted the system to recognize. The 10-fold cross-validation accuracies obtained during the short study ranged from 79% to 90%.

- **Sensor data requirements for the algorithm**
  - *Number of sensors required to recognize activities*: This work explored the performance of eleven subsets of seven accelerometers to identify the best performing subset with most convenient locations. It was found that three sensors at the hip, dominant wrist, and dominant foot provided the highest performance during both activity recognition and estimation of energy expenditure (with respect to the use of all seven accelerometers).
  - *Intrusiveness of the sensors required to recognize activities*: This work compared the performance of accelerometer data and heart rate data during the recognition of activities and estimation of energy expenditure. It was found that heart rate data performs poorly during activity recognition (e.g. accuracies of 14% during subject independent evaluation). During energy expenditure estimation, heart rate data performs well (e.g. r=0.84, RMSE=1.01) and better than accelerometer-based features. However, a performance of r=0.88, RMSE=0.99 can be obtained using activity dependent regression models based on accelerometer data alone. As a result, good performance can be obtained during both, activity recognition and estimation of energy expenditure without using heart rate data. This was an important result since heart rate monitors are presently uncomfortable to wear and intrusive.
  - *Location of the sensors required to recognize activities*: Only three accelerometers at the hip, dominant wrist, and dominant foot were found to achieve reasonable performance during activity recognition and estimation of energy expenditure. For example, decreases in performance of less than 3% were observed during energy expenditure estimation and between 2-8% during recognition of activities using these three sensors with respect to the use of all seven accelerometers. Sensors at these locations could be conveniently embedded in objects such as wristwatches, shoe pods, belt clips or simply put inside the pocket in the case of the sensor at the hip.
- **Usability factors imposed by the algorithm**
  - *Real-time recognition of activities*: The algorithm presented in this work to recognize activities achieved real-time performance on a 1GHz laptop

computer. The energy expenditure algorithm presented is also amenable for real-time performance due to its lightweight computational requirements. Presently the House_*n* research group at MIT is working on implementing both algorithms for existing mobile phones.

- *Real-time recognition delay*: The algorithms presented to recognize activities and estimate energy expenditure have an overall real-time delay of 5.6 seconds. This delay is short enough to allow just-in-time interventions and real-time behavioral feedback.

In summary, it has been shown that the algorithms presented in this work offer a reasonable compromise between overall performance as evaluated using standard evaluation measures and evaluation measures often neglected in prior work such as complexity of the activities to recognize, training data requirements of the algorithms, sensor data requirements of the algorithms, and usability factors imposed by the algorithm.

6.4 Unresolved Issues for Long-Term Deployment

This section briefly discusses some of the unresolved issues for long-term deployment of activity recognition and energy expenditure estimation algorithms based on mobile phones during free-living.

6.4.1 Hardware Limitations for Mobile Interventions

There exist some hardware limitations that need to be overcome in order to exploit mobile phone based interventions using activity recognition and energy expenditure estimation algorithms in practice. For example, sensors need to be built in small form factors so that they can be worn comfortably and unobtrusively over the course of a day. Existing semiconductor manufacturing technologies already allow the production of wireless sensor nodes that are as small as $6.6mm^3$ [252]. However, two remaining challenges are (1) how to power the sensors continuously since batteries are presently inefficient and have relatively large form factors (with respect to the size of the sensor nodes that can be presently achieved), and (2) how to transmit the wireless signals efficiently using antennas that are as tiny as the sensor nodes themselves. Thus, it seems that a practical strategy would be to create sensors nodes that are relatively small (e.g. the size of an American quarter coin) with rechargeable batteries that last for at least a day. In this way, sensors could be embedded in objects such as wrist watches and shoe pods that people could recharge every day after use.

6.4.2 Usability Issues and Impact on Algorithms

There also exist some usability challenges that need to be overcome in order to make mobile phone based interventions using activity recognition and energy expenditure estimation algorithms a reality in practice. For example, if subject dependent training is used to recognize activities, intuitive and easy-to-use user interfaces would be required to allow individuals to interactively train and test the performance of the algorithms in real-time. It would also be necessary to come up with strategies to allow individuals to provide the necessary training data when they are actually engaged in the activities of interest during free living instead of providing simulated examples of the activities of interest over a single long session. Furthermore, it is expected that the activity recognition algorithms would inevitably make mistakes during the recognition of activities in free-living. Some possible reasons for these mistakes are insufficient training data for a given activity, motion similarities with other activities being recognized, or changes in the patterns of activity execution over time. Thus, there would be a need for strategies to allow individuals to 'fix' the recognition algorithm when it does not perform as expected. One possible strategy would be to allow individuals to provide more training examples for the problematic activities. Another strategy, although more challenging, would be to allow individuals to directly modify the activity models used by the algorithms to recognize activities. The challenge here would be to create activity recognition algorithms that utilize models that are easy to interpret by end-users with no technical background.

6.5 Future Research Directions

This section discusses some research directions for future work based on some of the findings of this work and some of the limitations of the algorithms presented.

6.5.1 Activity Recognition

Some future research directions in activity recognition are:

- Create intuitive and easy-to-use user interfaces to allow individuals train and test the performance of activity recognition algorithms in real-time.
- Create strategies and user interfaces to allow individuals to 'fix' the recognition algorithms when they do not perform as expected. This could be achieved by allowing individuals to provide more training examples for the problematic activities or by allowing individuals to directly modify the activity models utilized by the recognition algorithm.
- Use hierarchical models to recognize highly complex and variable activities such as household activities. For example, since household activities include sequences of postures and ambulation in their execution, it might be beneficial to first have a classifier to recognize postures and ambulation and later use the output of this classifier to better identify household activities. In this scenario, *wiping/dusting* might be better recognized by detecting sequences of postures, ambulation, and wiping dusting patterns executed during the activity duration.
- Use activity-dependent window lengths to improve the performance over activities of interest. For example, longer window lengths could be used to better capture the variability found in complex household activities. This technique is

obviously more computationally expensive but might bring benefits for activities that are challenging to recognize such as household activities.

- Repeat some or all of the experiments performed in this work over data collected from a given set of individuals over different days. This would allow testing the performance of the recognition algorithms when the position and orientation of the sensors changes slightly from day to day.
- Include hand gesture recognition as a high level feature in activity recognition. This strategy might be helpful because the wrists presented high motion variability during the data collections. For example, the household activity *wiping/dusting* might be easier to recognize if a hand gesture recognition algorithm first recognizes *high energy circular motion* and then the recognition algorithm uses this recognized gesture as a high level feature to recognize *wiping/dusting*.

6.5.2 Energy Expenditure Estimation

Some future research directions in the area of energy expenditure estimation are:

- Incorporate information about the duration of activities when estimating energy expenditure. This technique might be useful for better estimating the energy expenditure associated with activities whose energy expenditure increases constantly over time. For example, the energy expenditure for *ascending stairs* might be better estimated if information about when the activity started is incorporated. In this way, the algorithm could predict that energy expenditure is expected to increase linearly if *ascending stairs* has been executed for less than 10 minutes but would reach steady state (a constant value) after being executed for longer than 10 minutes.
- Filter the energy expenditure estimates using information about how energy expenditure transitions from activity to activity. As discussed previously, activity recognition algorithms might generate spurious classifications while transitioning from one activity to another. These spurious transitions might be filtered by incorporating information on how people transition from activity to activity.
- Repeat some or all of the experiments presented in this work over data collected from more individuals, ideally more than one hundred and when energy expenditure is recorded continuously over 24 hours.

Appendix A1: Performance Measures for Activity Recognition

Performance Measure	Description	Computed by
Confusion Matrix	Also known as contingency table. It is a square matrix that shows the correctly and incorrectly classified instances ("confusions") The columns of the matrix correspond to the predictions or classifications done by the model and the rows correspond to the actual classification or "ground truth" labels. Most performance measures presented in this table can be computed from the confusion matrix.	Increase the count at each corresponding matrix cell by one whenever a new classification is made available using the pair of values (predicted, actual). The matrix is given in the format: confusionMatrix[predicted][actual] confusionMatrix[columns][rows] An element of a matrix is represented as $x_{column,row} = x_{i\,j}$
Total Accuracy (Success rate)	It is the fraction of correct classifications and is computed as the sum over the diagonal elements of the confusion matrix divided by total number of instances or examples in the matrix. All other instances outside the diagonal are incorrect classifications. Accuracy puts equal weight on relevant and irrelevant classes, and it is often the case that there are more irrelevant classes than relevant ones.	$\dfrac{\sum_{i=1}^{N} x_{ii}}{\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ij}}$
True Positive rate (Recall or sensitivity)	The proportion of examples which were classified as class x, among all examples which truly have class x, i.e. how much part of the class was captured. It is equivalent to Recall. In the confusion matrix, this is the diagonal element divided by the sum over the relevant row. Measure widely used in information retrieval that represents the fraction of relevant documents that are retrieved. Pr[retrieved|relevant]. You can get a perfect recall (but low precision) by retrieving all docs for all queries!	$\dfrac{x_{ii}}{\sum_{j=1}^{N} x_{ij}}$
False Positive Rate	Is the proportion of examples which were classified as class x, but belong to a different class, among all examples which are not of class x. In the matrix, this is the column sum of class x minus the diagonal element, divided by the rows sums of all other classes.	$\dfrac{\sum_{j=1}^{N} x_{ij} - x_{ii}}{\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ij} - \sum_{j=1}^{N} x_{ij}}$
F-Measure	It is a combined measure of precision and recall computed as the harmonic average over precision and recall.	$\dfrac{2 \cdot presion_i \cdot recall_i}{presion_i + recall_i}$

Table A1-1: Performance measures utilized to evaluate activity recognition algorithms in this work. All performance measures are multiplied by 100 to be expressed as percentages.

Appendix A2: Clustering of Activities for Presentation of Results

Activity **(Number of METs from the Compendium of physical activities)**	**Static Postures**	**Ambulation**	**Exercise Activity**	**Resistance Activity**	**House-hold**
Bench weight lifting – hard (6.0)			√	√	
Bench weight lifting – light (3.0)			√	√	
Bench weight lifting – moderate (>3.0)			√	√	
Bicep curls – hard (6.0)			√	√	
Bicep curls – light (3.0)			√	√	
Bicep curls – moderate (>3.0)			√	√	
Calisthenics – Crunches (8.0)			√		
Calisthenics - Sit ups (8.0)			√		
Cycling - Cycle hard - Cycle 80rpm (>8.0)			√	√	
Cycling - Cycle light - Cycle 100rpm (7.0)			√		
Cycling - Cycle light - Cycle 60rpm (3.0)			√		
Cycling - Cycle light - Cycle 80rpm (5.5)			√	√	
Cycling - Cycle moderate - Cycle 80rpm (8.0)			√	√	
Lying down (1.0)	√				
Rowing - Rowing hard - Rowing 30spm (8.5)			√	√	
Rowing - Rowing light - Rowing 30spm (3.5)			√	√	
Rowing - Rowing moderate - Rowing 30spm (7.0)			√	√	
Running - Treadmill 4mph - Treadmill 0 (5.0)		√	√		
Running - Treadmill 5mph - Treadmill 0 (8.0)		√	√		
Running - Treadmill 6mph - Treadmill 0 (10.0)		√	√		
Sitting (1.0)	√				
Sitting - Fidget feet legs (1.0)	√				
Sitting - Fidget hands arms (1.0)	√				
Stairs - Ascend stairs (8.0)		√		√	
Stairs - Descend stairs (3.0)		√			
Standing (1.2)	√				
Walking - Treadmill 2mph - Treadmill 0 (2.5)		√			
Walking - Treadmill 3mph - Treadmill 0 (3.3)		√			
Walking - Treadmill 3mph - Treadmill 3 - light (>3.3)		√		√	
Walking - Treadmill 3mph - Treadmill 6 - moderate (>3.3)		√		√	
Walking - Treadmill 3mph - Treadmill 9 - hard (>3.3)		√		√	
Kneeling (1.0)	√				
Unknown (N/A)					
Carrying groceries (3.0)		√		√	√
Doing dishes (2.3)					√
Gardening (4.0)					√
Ironing (2.3)					√
Making the bed (2.0)					√
Mopping (3.5)					√
Playing videogames (1.5)					√
Scrubbing a surface (3.8)				√	√
Stacking groceries (2.5)					√
Sweeping (3.3)					√
Typing (1.8)					√
Vacuuming (3.5)					√
Walking around block (3.5)		√			√
Washing windows (3.0)				√	√
Watching TV (1.0)					√
Weeding (4.5)					√
Wiping/Dusting (2.5)					√
Writing (1.8)					√
Taking out trash (2.5)					√

Table A2-1: The 51 activities contained in the MIT dataset and their categorization according to increasing order of classification complexity: (1) postures, (2) postures and ambulation, (3) exercise activities, and (4) household activities. Activities that are included in the garbage class are represented with G and activities eliminated from the dataset with E. Activities including in the training process are marked with a check mark.

Activity (Number of METs from the Compendium of physical activities)	**Upper Body**	**Lower Body**	**Postures and Ambulation**	**Postures and Ambulation with METs Intensity**	**All Activities with No Intensity**
Bench weight lifting – hard (6.0)	√			Moderate	√ (Bench)
Bench weight lifting – light (3.0)	√			Moderate	√(Bench)
Bench weight lifting – moderate (>3.0)	√			Moderate	√(Bench)
Bicep curls – hard (6.0)	√			Moderate	√(Biceps)
Bicep curls – light (3.0)	√			Moderate	√(Biceps)
Bicep curls – moderate (>3.0)	√			Moderate	√(Biceps)
Calisthenics – Crunches (8.0)				Vigorous	√
Calisthenics - Sit ups (8.0)				Vigorous	√
Cycling - Cycle hard - Cycle 80rpm (>8.0)		√		Vigorous	√(Cycling)
Cycling - Cycle light - Cycle 100rpm (7.0)		√		Vigorous	√(Cycling)
Cycling - Cycle light - Cycle 60rpm (3.0)		√		Moderate	√(Cycling)
Cycling - Cycle light - Cycle 80rpm (5.5)		√		Moderate	√(Cycling)
Cycling - Cycle moderate - Cycle 80rpm (8.0)		√		Vigorous	√(Cycling)
Lying down (1.0)			√	√	√
Rowing - Rowing hard - Rowing 30spm (8.5)				Vigorous	√(Rowing)
Rowing - Rowing light - Rowing 30spm (3.5)				Moderate	√(Rowing)
Rowing - Rowing moderate - Rowing 30spm (7.0)				Vigorous	√(Rowing)
Running - Treadmill 4mph - Treadmill 0 (5.0)			√ (Running)	√	√ (Running)
Running - Treadmill 5mph - Treadmill 0 (8.0)			√ (Running)	√	√ (Running)
Running - Treadmill 6mph - Treadmill 0 (10.0)			√ (Running)	√	√ (Running)
Sitting (1.0)			√ (Sitting)	√ (Sitting)	√ (Sitting)
Sitting - Fidget feet legs (1.0)		√	√ (Sitting)	√ (Sitting)	√ (Sitting)
Sitting - Fidget hands arms (1.0)	√		√ (Sitting)	√ (Sitting)	√ (Sitting)
Stairs - Ascend stairs (8.0)			√	Vigorous	√
Stairs - Descend stairs (3.0)			√	Moderate	√
Standing (1.2)			√	√	√
Walking - Treadmill 2mph - Treadmill 0 (2.5)			√ (walking)	√	√ (walking)
Walking - Treadmill 3mph - Treadmill 0 (3.3)			√ (walking)	√ (walking 3)	√ (walking)
Walking - Treadmill 3mph - Treadmill 3 - light (>3.3)			√(walking)	√(walking 3)	√(walking)
Walking - Treadmill 3mph - Treadmill 6 - moderate (>3.3)			√(walking)	√(walking 3)	√(walking)
Walking - Treadmill 3mph - Treadmill 9 - hard (>3.3)			√(walking)	√(walking 3)	√(walking)
Kneeling (1.0)			√	√	√
Unknown (N/A)					
Carrying groceries (3.0)					√(walking)
Doing dishes (2.3)	√				√
Gardening (4.0)				Moderate	√
Ironing (2.3)	√				√
Making the bed (2.0)					√
Mopping (3.5)				Moderate	√
Playing videogames (1.5)	√				√
Scrubbing a surface (3.8)	√			Moderate	√
Stacking groceries (2.5)					√
Sweeping (3.3)				Moderate	√
Typing (1.8)	√				√
Vacuuming (3.5)				Moderate	√
Walking around block (3.5)					√(walking)
Washing windows (3.0)	√				√
Watching TV (1.0)					√
Weeding (4.5)				Moderate	√
Wiping/Dusting (2.5)	√				√
Writing (1.8)	√				√
Taking out trash (2.5)					√

Table A2-2: The 51 activities contained in the MIT dataset and their categorization according to increasing order of classification complexity: (1) postures, (2) postures and ambulation, (3) exercise activities, and (4) household activities. Activities that are included in the garbage class are represented with G and activities eliminated from the dataset with E. Activities including in the training process are marked with a check mark.

Appendix A3: The 41 Features Explored in This Work

Features	Abbreviation	Description
Measures of body posture		
• Mean	DCMean	Mean or average over the signal window after low-pass filtering the acceleration signal at 1Hz. This is a measure of the DC value or the static component of acceleration that changes with body posture.
• Mean over all acceleration axis	DCTotalMean	Same as DCMean but computed over the summation of all the acceleration signals over all axis and accelerometers available (sensors). This feature captures the overall posture information contained in the DC component of the acceleration signals.
• Area under signal	DCArea	The area under the signal simply computed by summing the acceleration samples contained in a given window. $$DCArea = \sum_{i=1}^{total\_samples\_per\_window} acceleration_i$$
• Mean distances between axis	DCPostureDist	The differences between the mean values of the X-Y, X-Z, and Y-Z acceleration axis per sensor. These three values capture the orientation of the sensor with respect to ground or body posture information. The feature is computed after low-pass filtering the acceleration signals at 1Hz.
Measures of motion shape		
• Mean of absolute signal value	ACAbsMean	Mean or average over the absolute value of the band-pass filtered (0.1-20Hz) accelerometer signals. Acceleration can have positive and negative values, so computing the absolute value guarantees the mean will not be zero for perfect oscillatory motion with equal positive and negative acceleration magnitudes.
• Cumulative sum over absolute signal value	ACAbsArea	The area under the absolute value of the signal computed by simply summing the accelerometer samples inside a given window. The sum is computed after band-pass filtering (0.1-20Hz) the accelerometer signals. Acceleration can have positive and negative values, so computing the absolute value guarantees the area will not be zero for perfect oscillatory motion with equal positive and negative acceleration magnitudes. $$ACAbsArea_{PerSensor} = \sum_{i=1}^{windowLength} \left\|a_{X_i}\right\| + \left\|a_{Y_i}\right\| + \left\|a_{Z_i}\right\|$$ $$ACAbsArea_{PerAxis} = \sum_{i=1}^{windowLength} \left\|a_{Axis_i}\right\|$$
• Total Cumulative sum over absolute signals value	ACTotalAbsArea	Same as ACAbsArea but computed over the summation of all the signals over all axis and accelerometers available (sensors). This feature captures the overall motion experienced by the human body as experienced by all the accelerometers worn. $$ACTotalAbsArea = \sum_{i=1}^{numberSensors} ACAbsArea_{PerSensor_i}$$ $$ACTotalAbsArea = \sum_{i=1}^{numberAxis} ACAbsArea_{PerAxis_i}$$
• Total signal vector magnitude	ACTotalSVM	The average value of the signal vector magnitude of all the accelerometer samples for a given window. This feature is computed after band-pass filtering (0.1-20Hz) the accelerometer signals. The Signal vector magnitude for all samples at a given time is computed using the following formula: $$SVM == \sqrt{\sum_{i=1}^{total\_number\_of\_axes} a_i^2}$$
• Entropy	ACEntropy	Measures the degree of "disorder" in the band-pass filtered (0.1-20Hz) accelerometer signals. It can be computed from $$H = -\sum_{i=1}^{window\_length} v \cdot \log_2(v)$$ Where *v* corresponds to the normalized values of the FFT magnitude.

		$$v = \frac{mag(i)}{\sum_{i=1}^{window\_length} mag(i)}$$ The final value of the entropy is normalized to fall in the range [0, 1] by dividing each entropy value by the entropy of the uniform distribution.
• Skewness (signal moment)	ACSkew	It is a measure of the "peakedness" of the accelerometer signal over a given window. Larger values indicate that more of the variance is due to infrequent extreme deviations, as opposed to frequent modestly-sized deviations. It is computed over the band-pass filtered acceleration using the following formula: $$\frac{\sqrt{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^3}{\left(\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2\right)^{\frac{3}{2}}}$$
• Kurtosis (signal moment)	ACKur	It is a measure of the "peakedness" of the accelerometer signal over a given window or a measure of its relative flatness as compared to the normal distribution. It is computed over the band-pass filtered (0.1-20Hz) accelerometer signals using the following formula: $$\frac{n\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^4}{\left(\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2\right)^2} - 3$$
• Quartiles (first, second, and third)	ACQ1 ACQ2 ACQ3	Quartiles are computed by partitioning the accelerometer signal over a given window into four quarters each containing 25% of the data (Q1=25, Q2=50, and Q3=75%). This is achieved by sorting the signal values according to increasing magnitude and finding the values at 25%, 50% and 75% of the window length. The values measure the distribution of the accelerometer magnitude across the window. The quartiles are computed over the band-pass filtered (0.1-20Hz) accelerometer signals.
Measures of motion variation		
• Variance	ACVar	The variance of the accelerometer signal computed over a given window. It is computed after band-pass filtering (0.1-20Hz) the accelerometer signals.
• Coefficient of variation over the absolute value of the signal	ACAbsCV	Computed as the ratio of the standard deviation and the mean over each signal window multiplied by 100. This measures the dispersion of the acceleration signal. Acceleration is band-pass filtered (0.1-20Hz) before computing this feature.
• Inter quartile range	ACIQR	Computed as the difference between quartiles three and one (Q3-Q1). This value describes the dispersion of the acceleration signal. This feature is computed after band-pass filtering (0.1-20Hz) the accelerometer signals.
• Range or maximum signal amplitude	ACRange	Difference between the maximum and minimum values of the accelerometer signal over a given window. This is a measure of peak acceleration or maximum motion inside the window. Accelerometer signals are band-pass filtered (0.1-20Hz) before computing this feature.
Measures of motion spectral content		
• Fast Fourier transform (FFT) coefficients	ACFFTCoeff	The coefficients of the fast Fourier transform computed over the accelerometer signal for a given window. The signal is first band-pass filtered (0.1-20Hz) and the first coefficient (DC component) is not utilized. There number of coefficients is the length of the window divided by 2 minus one. It is a measure of the magnitudes of the frequencies contained within the accelerometer signal.
• Fast Fourier transform (FFT) peaks	ACFFTPeaks	The X number of frequencies with maximum magnitudes computed over the FFT coefficients. These consist on X number of frequency, magnitude pairs (freq, mag). In this work, X=5. It is a measure of the X number of largest frequencies present in the signal and their magnitudes. This feature does not include the DC component of the signal or magnitude at frequency zero. Before computing this feature, signals are band-pass filtered (0.1-

		20Hz).
• Fast wavelet transform (FWT) coefficients	ACFWTCoeff	The coefficients of the Haar wavelet transform computed over the accelerometer signal for a given window. There are as many coefficients as signal samples in the window. The coefficients are a measure of the frequencies contained in the accelerometer signals at different time scale resolutions. Accelerometer signals are band-pass filtered (0.1-20Hz) before computing this feature. The coefficient corresponding to the DC component of the signals is not included.
Measures of motion energy		
• Total energy	ACEnergy	It is computed as follows from the FFT coefficient magnitudes: $$energy = \sum_{i=1}^{window\_length/2} magnitude^2$$ Note that the index i starts from 1 and not from zero to avoid computing the energy of the DC component. The index also goes to only half of the window since the FFT components after half of the window are redundant. This is the total energy contained in all the frequencies. The FFT coefficients are computed over the band-pass filtered (0.1-20Hz) accelerometer signals.
• Activity band energy (0.3-3.5Hz)	ACBandEnergy	Computed as the sum of the energy contained between frequencies of 0.3 – 3.5Hz. This has been found to be the major energy band for human activities in previous work. This feature does not include the DC component of the signal. The energy is computed from the FFT coefficients computed over the band-pass filtered (0.1-20Hz) accelerometer signals.
• Energy of low intensity physical activity (0 – 0.7Hz)	ACLowEnergy	Computed as the sum of the energy contained between frequencies of 0 – 0.7Hz. This has been found to be Associated with sedentary activities in previous work. This energy does include the DC component of the signal.
• Energy of moderate to vigorous physical activity (0.71 – 10 Hz)	ACModVigEnergy	Computed as the sum of the energy contained between frequencies of 0.71 – 10Hz. This has been found to be associated with locomotion and high intensity activities in previous work.
• Heart rate mean	HRMean	This feature is the average value of the heart rate data in beats-per-minute over the heart rate data window length.
• Heart rate above resting heart rate	HRAboveRest	Computed by subtracting the resting heart rate (RHR) from the mean heart rate value (in bmp) over each window. It measures the intensity associated with an activity. The value will be near zero for sedentary activities and will increase with the activity intensity.
• Heart rate normalized to lie between the range resting heart rate (RHR) and the mean heart rate measured while running at 5mph on a treadmill.	ScaledHR	Computed by scaling the mean heart rate value (in bmp) over each window to lie between the range 0 – 1 using the resting heart rate and the mean heart rate value obtained while subjects run at 5mph on a treadmill. It measures the intensity associated with an activity.
• The variance of the heart rate data.	HRVar	This feature is simply the variance computed over the heart rate data window.
Measures of tendency in physical activity intensity		
• Heart rate trend line	HRTrend	Slope of the regression line computed over the heart rate signal window. This feature captures if hear rate is increasing, decreasing or in steady-state over time.
Measures of motion periodicity		
• Pitch	ACPitch	Computed as the magnitude of the second peak of the autocorrelation function after Rx (0). It measures the magnitude of the fundamental frequency contained in the acceleration signal. Accelerometer signals are band-pass filtered (0.1-20Hz) before computing this feature.
• Ratio of energy in dominant frequency	ACDomFreqRatio	Computed by dividing the magnitude of the FFT coefficient with largest magnitude by the sum of the coefficients in all other frequencies. It measures how much of the signal is dominated by a particular frequency. The FFT is computed over the band-pass filtered (0.1-20Hz) accelerometer signals.
• Mean crossing rate	ACMCR	Number of times the acceleration signal crosses its mean value over the window. It measures how fast the acceleration signal changes over time. The acceleration signal is band-pass filtered (0.1-20Hz) before computing this feature.
Measures of motion similarity across body		

segments		
• Pearson's Correlation Coefficients	ACCorr	The correlation coefficients among each pair of acceleration signals over a given window. The correlation coefficients are computed according to the following formula: $$R(i, j) = \frac{\text{cov}(i, j)}{\sqrt{\text{cov}(i,i) \cdot \text{cov}(j, j)}}$$ Cov stands for the covariance function. The correlation coefficients measure the linear dependence between two acceleration signals. The coefficient lies between [-1, +1] were the sign indicates the correlation direction or the orientation of the line. Two acceleration signals that are identical would give a correlation coefficient of one. In simple terms, the coefficients characterize how similar is the simultaneous motion of limbs.
Measure of force per body segment		
• Segmental Force	ACSF	Computed by multiplying the ACAbsArea feature for the accelerometer at the hip, wrists, and feet by the segment mass per limb obtained from the Depmster's body segment model [236]. This feature consists of five coefficients given by the following formulas: $$ACSF_{Trunk} = ACAbsArea_{Hip} \cdot BodyTrunkMass$$ $$ACSF_{DWrist} = ACAbsArea_{DWrist} \cdot ArmMass$$ $$ACSF_{NDWrist} = ACAbsArea_{NDWrist} \cdot ArmMass$$ $$ACSF_{DFoot} = ACAbsArea_{DFoot} \cdot LegMass$$ $$ACSF_{NDFoot} = ACAbsArea_{NDFoot} \cdot LegMass$$ Were the prefix "D" stands for dominant and "ND" stands for non dominant.
• Total Segmental Force	ACTotalSF	ACTotalSF is the sum of the five coefficients of the segmental force. $$ACTotalSF = ACSF_{Trunk} + ACSF_{DArm} + ACSF_{NDArm} + ACSF_{DFoot} + ACSF_{NDFoot}$$
Measures of subject characteristics		
• Gender	Gender	A number specifying the gender of the subject: 0- Male, 1-Female
• Age	Age	A number specifying the age of the subject.
• Height	Height	A number specifying the height of the subject in meters
• Weight	Weight	A number specifying the body weight of the subject in Kg
Measures of subject fitness		
• BMI	BMI	Computed by dividing body weight of a subject (in Kg) by the squared of its height (in meters)
• Fat percentage	FatPercent	A number representing the percentage of fat or non-muscle tissue in the subject.
• Fitness Index	FitnessIndex	This feature is computed by dividing the number of steps per minute by the average heart rate value (in beats-per-minute) per minute of a subject running on a treadmill at 5mph. This is an approximation of the FitnessIndex utilized in [230].

Table A3-1: List of features explored in this work to (1) recognize activities and (2) estimate energy expenditure from wearable accelerometers and a heart rate monitor. The list is a superset of most features found in previous work. Features starting with the prefix "AC" were computed over the accelerometer signals after applying a band-pass filter between the frequencies of 0.1 and 20Hz. Features starting with the prefix "DC" were computed over the accelerometer signals after applying a low-pass filter with a cutoff frequency of 1Hz.

Appendix A4: Amount of Data in the MIT Dataset

Activity	**Amount of training time (in minutes)**	**Average amount of training data per subject (in minutes)**	**Number of Training Examples when using a window of 5.6s**
Bench weight lifting – Light	30.4	1.52	326
Bench weight lifting – Moderate	21.8	1.09	234
Bench weight lifting – Hard	11.5	0.575	124
Bicep curls – Light	31.7	1.585	340
Bicep curls – Moderate	21.8	1.09	234
Bicep curls – Hard	21.3	1.065	229
Calisthenics Crunches	19.6	0.98	211
Calisthenics Sit ups	25.0	1.25	268
Cycling Cycle 100rpm (15mph, 120.4W) – Light	45.0	2.25	483
Cycling Cycle 60rpm (8.9mph, 66.9W) – Light	54.0	2.7	579
Cycling Cycle 80rpm (11.2mph, 100.4W) – Light	52.9	2.645	567
Cycling Cycle 80rpm – Moderate	46.2	2.31	496
Cycling Cycle 80rpm – Hard	34.8	1.74	373
Lying down	149.1	7.455	1,598
Rowing 30spm – Light	50.4	2.52	540
Rowing 30spm – Moderate	42.7	2.135	458
Rowing 30spm – Hard	35.0	1.75	376
Running Treadmill 4mph Treadmill 0	47.7	2.385	512
Running Treadmill 5mph Treadmill 0	44.6	2.23	478
Running Treadmill 6mph Treadmill 0	31.1	1.555	334
Sitting	28.4	1.42	305
Sitting Fidget feet legs	27.8	1.39	298
Sitting Fidget hands arms	27.8	1.39	298
Stairs Ascend stairs	46.4	2.32	498
Stairs Descend stairs	42.7	2.135	458
Standing	29.9	1.495	321
Walking Treadmill 2mph Treadmill 0	57.1	2.855	612
Walking Treadmill 3mph Treadmill 0	56.5	2.825	606
Walking Treadmill 3mph Treadmill 3 – Light	56.2	2.81	603
Walking Treadmill 3mph Treadmill 6 – Moderate	57.4	2.87	616
Walking Treadmill 3mph Treadmill 9 – Hard	56.5	2.825	606
Kneeling	29.4	1.47	315
Carrying groceries	50.4	2.52	541
Doing dishes	54.9	2.745	589
Gardening	32.2	1.61	345
Ironing	57.8	2.89	620
Making the bed	53.7	2.685	576
Mopping	43.1	2.155	462
Playing videogames	58.9	2.945	632
Scrubbing a surface	39.2	1.96	421
Stacking groceries	38.4	1.92	412
Sweeping	42.9	2.145	460
Typing	60.9	3.045	653
Vacuuming	44.4	2.22	476
Walking around block	53.1	2.655	569
Washing windows	48.90	2.445	524
Watching TV	59.9	2.995	642
Weeding	30.1	1.505	323
Wiping/Dusting	52.1	2.605	559
Writing	61.5	3.075	659
Taking out trash	42.3	2.115	454
Unknown	938.1	46.905	10,052

Table A4-1: Amount of training data available (or duration of each activity) for the 52 activities contained in the MIT dataset and explored in this work.

Appendix A5: Sliding Window Length for Activity Recognition

Activity Category	1.4s	2.8s	5.6s	11.3s	22.7s	45.5s	91.0s
All	58.20±7.32	62.55±7.58	65.51±6.33	66.83±6.24	67.09±5.81	60.06±6.58	23.31±10.11
Postures	51.37±9.98 (0.78±0.24)	54.57±11.99 (0.73±0.27)	53.10±14.09 (0.67±0.33)	52.52±16.48 (0.68±0.39)	45.42±22.41 (0.82±0.49)	18.97±11.75 (1.13±0.69)	12.39±3.58 (2.45±1.29)
Ambulation	60.80±10.92 (0.81±0.26)	68.76±11.39 (0.66±0.26)	73.36±11.30 (0.57±0.28)	76.86±14.88 (0.52±0.28)	75.85±17.95 (0.57±0.36)	68.09±24.47 (0.88±0.59)	6.45±15.05 (2.79±1.61)
Exercise	66.35±13.33 (0.55±0.21)	70.28±12.85 (0.48±0.21)	73.31±14.06 (0.44±0.23)	74.58±16.44 (0.43±0.26)	69.74±23.43 (0.51±0.38)	58.01±31.93 (0.84±0.59)	5.18±10.99 (2.94±1.53)
Resistance Exercise	52.11±14.46 (0.85±0.29)	57.92±14.91 (0.74±0.30)	62.68±15.71 (0.65±0.32)	66.18±18.16 (0.62±0.33)	64.39±23.95 (0.69±0.47)	52.38±31.56 (0.96±0.63)	4.49±10.90 (3.02±1.68)
Household	39.49±11.86 (1.15±0.44)	44.18±13.78 (1.07±0.45)	48.79±14.98 (0.99±0.46)	52.05±17.93 (0.97±0.52)	56.00±21.76 (0.98±0.61)	50.71±29.45 (1.17±0.84)	6.63±14.03 (3.24±2.10)

Table A5-1: Performance of the C4.5 decision tree classifier using the ACAbsArea feature over window lengths varying from 1.4 to 45.5 seconds during subject dependent evaluation.

Activity Category	1.4s	2.8s	5.6s	11.3s	22.7s	45.5s	91.0s
All	33.62 ± 4.04	35.00 ± 4.27	36.82 ± 5.51	38.32 ± 5.19	39.40 ± 5.34	43.46 ± 6.17	42.31 ± 7.26
Postures	18.63±11.54 (0.94±0.39)	19.62±13.19 (0.88±0.42)	21.19±15.12 (0.87±0.51)	23.97±18.12 (0.84±0.65)	26.54±20.04 (0.94±0.65)	35.70±29.14 (0.93±0.78)	51.06±42.66 (1.64±1.38)
Ambulation	23.33±18.34 (1.14±0.72)	23.85±22.03 (1.07±0.84)	26.48±22.65 (1.09±0.95)	28.33±26.35 (1.05±1.02)	34.58±31.13 (1.23±1.16)	39.51±34.98 (1.51±1.39)	39.40±35.13 (1.82±1.64)
Exercise	20.00±19.44 (0.61±0.50)	20.18±21.34 (0.61±0.57)	22.80±24.12 (0.64±0.69)	25.96±28.60 (0.73±0.74)	28.01±26.29 (0.96±0.94)	35.96±31.07 (1.25±1.13)	41.42±35.31 (2.18±1.51)
Resistance Exercise	13.04±13.39 (0.85±0.56)	13.50±15.85 (0.79±0.61)	14.96±17.99 (0.79±0.70)	16.32±22.00 (0.82±0.76)	18.86±22.58 (1.08±0.96)	27.19±26.95 (1.29±1.09)	33.29±37.79 (2.42±1.65)
Household	12.53±10.02 (1.13±0.49)	14.68±12.36 (1.12±0.58)	16.62±14.49 (1.11±0.65)	18.92±18.33 (1.08±0.74)	22.05±22.58 (1.15±0.80)	29.17±28.09 (1.25±1.00)	35.00±37.20 (1.87±1.48)

Table A5-2: Performance of the C4.5 decision tree classifier using the ACAbsArea feature over window lengths varying from 1.4 to 45.5 seconds during subject independent evaluation

Activity Category	1.4s	2.8s	5.6s	11.3s	22.7s	45.5s	91.0s
All	56.82 ± 7.51	62.58 ± 6.89	66.36 ± 6.34	66.33 ± 7.44	64.81 ± 6.29	55.20 ± 7.38	21.34 ± 9.04
Postures	44.39±9.97 (1.01±0.29)	51.52±10.68 (0.85±0.32)	55.00±14.08 (0.75±0.32)	49.54±16.28 (0.79±0.41)	45.21±21.83 (0.93±0.59)	26.58±22.71 (1.41±0.97)	13.25±3.10 (2.24±1.24)
Ambulation	65.38±9.81 (0.71±0.24)	71.24±10.13 (0.58±0.22)	75.79±10.99 (0.48±0.23)	80.02±13.98 (0.44±0.27)	76.72±20.43 (0.50±0.38)	65.97±30.36 (0.87±0.71)	4.50±11.39 (2.46±1.49)
Exercise	65.60±11.51 (0.54±0.19)	71.40±12.27 (0.45±0.19)	75.82±11.41 (0.39±0.17)	74.42±16.69 (0.43±0.26)	67.82±20.62 (0.54±0.39)	51.26±32.96 (0.89±0.66)	4.56±10.00 (2.95±1.54)
Resistance Exercise	53.64±12.74 (0.80±0.25)	60.97±13.99 (0.68±0.25)	67.62±13.12 (0.56±0.23)	67.31±17.08 (0.58±0.31)	63.19±20.99 (0.64±0.44)	48.92±30.27 (1.01±0.72)	4.55±10.74 (2.96±1.67)
Household	38.73±12.04 (1.21±0.47)	45.74±12.89 (1.07±0.43)	49.98±15.48 (0.99±0.46)	52.13±18.16 (1.00±0.55)	52.80±22.81 (1.04±0.65)	43.44±30.38 (1.41±0.99)	7.11±14.73 (3.23±1.84)

Table A5-3: Performance of the C4.5 decision tree classifier using the ACFFTPeaks + ACCorr features over window lengths varying from 1.4 to 45.5 seconds. Subject dependent evaluation

Activity Category	1.4s	2.8s	5.6s	11.3s	22.7s	45.5s	91.0s
All	34.74 ± 3.79	38.16 ± 3.76	41.23 ± 5.04	43.38 ± 4.71	45.32 ± 6.23	46.40 ± 6.46	45.38 ± 8.50
Postures	18.56±11.48 (0.98±0.34)	22.63±13.62 (0.90±0.37)	25.60±17.39 (0.84±0.46)	28.97±20.94 (0.80±0.48)	30.65±22.44 (0.90±0.61)	42.39±29.68 (0.94±0.84)	55.05±44.27 (1.56±1.34)
Ambulation	22.77±18.39 (1.04±0.67)	25.17±21.08 (0.98±0.69)	28.56±23.79 (1.02±0.84)	31.08±28.16 (1.00±0.94)	35.50±33.85 (1.07±1.10)	38.11±33.75 (1.49±1.43)	46.01±32.08 (1.85±1.63)
Exercise	21.03±19.45 (0.59±0.46)	23.48±22.09 (0.54±0.53)	27.54±25.82 (0.60±0.58)	31.91±27.31 (0.75±0.79)	38.24±33.74 (0.95±0.98)	47.40±35.60 (1.02±0.98)	48.75±39.75 (2.09±1.58)
Resistance Exercise	15.28±14.76 (0.79±0.53)	16.49±15.82 (0.75±0.56)	20.01±20.92 (0.79±0.63)	22.46±22.00 (0.92±0.88)	29.45±28.91 (1.07±0.95)	39.02±33.13 (1.23±1.05)	35.82±40.85 (2.20±1.51)
Household	15.33±11.30 (1.17±0.45)	17.78±13.56 (1.13±0.51)	20.26±16.85 (1.10±0.63)	22.52±20.31 (1.06±0.70)	25.61±23.10 (1.03±0.70)	30.93±28.60 (1.23±0.96)	43.28±38.52 (1.76±1.41)

Table A5-4: Performance of the C4.5 decision tree classifier using the ACFFTPeaks + ACCorr features over window lengths varying from 1.4 to 45.5 seconds. Subject independent evaluation

Activity Category	1.4s	5.6s	11.3s	45.5s
All	58.22 ± 3.43	67.44 ± 2.04	67.85 ± 2.96	52.42 ± 4.28
Postures	47.1±9.2 (0.9±0.2)	59.7±12.1 (0.6±0.2)	53.4±15.0 (0.7±0.3)	23.6±18.6 (1.1±0.7)
Ambulation	70.7±9.0 (0.5±0.1)	78.8±10.8 (0.3±0.2)	81.2±12.4 (0.3±0.2)	64.3±27.8 (0.7±0.5)
Exercise	69.3±11.2 (0.4±0.1)	78.4±11.4 (0.3±0.1)	78.0±14.3 (0.3±0.2)	49.9±31.6 (0.8±0.5)
Resistance Exercise	59.2±12.9 (0.6±0.2)	72.1±12.6 (0.4±0.2)	72.5±16.3 (0.4±0.2)	46.6±31.0 (0.9±0.6)
Household	45.6±10.8 (0.9±0.3)	55.5±13.1 (0.7±0.3)	57.3±16.6 (0.7±0.3)	45.6±26.1 (1.1±0.8)

Table A5-5: Performance of the C4.5 decision tree classifier using the ACFFTPeaks + ACCorr features over window lengths varying from 1.4 to 45.5 seconds. Subject dependent evaluation feature computation per axis

Activity Category	1.4s	5.6s	11.3s	45.5s
All	38.01 ± 2.94	44.36 ± 3.98	47.47 ± 4.74	51.84 ± 5.23
Postures	29.4±11.0 (1.0±0.3)	37.9±16.0 (0.8±0.4)	40.4±20.0 (0.8±0.4)	51.9±33.7 (0.9±0.8)
Ambulation	32.3±17.0 (0.9±0.5)	38.3±24.9 (0.8±0.6)	43.0±28.1 (0.8±0.7)	53.8±34.1 (1.0±1.0)
Exercise	34.6±17.7 (0.6±0.4)	38.0±24.9 (0.6±0.5)	42.8±27.9 (0.6±0.5)	55.4±32.9 (0.8±0.8)
Resistance Exercise	25.6±14.3 (0.8±0.4)	29.1±21.6 (0.8±0.5)	32.9±26.9 (0.8±0.6)	43.1±34.0 (1.0±0.8)
Household	28.0±11.1 (1.1±0.3)	35.3±16.4 (1.0±0.4)	38.6±19.2 (0.9±0.5)	47.4±29.1 (1.0±0.8)

Table A5-6: Performance of the C4.5 decision tree classifier using the ACFFTPeaks + ACCorr features over window lengths varying from 1.4 to 45.5 seconds. Subject independent evaluation feature computation per axis

	True Positive Rate						
Class	**1.4s**	**2.8s**	**5.6s**	**11.3s**	**22.7s**	**44.5s**	**90s**
Bench weight lifting - hard	23.02 ± 12.84	33.82 ± 13.76	44.76 ± 11.77	46.64 ± 15.05	17.50 ± 15.41	0.00 ± 0.00	0.00 ± 0.00
Bench weight lifting - light	45.47 ± 13.49	58.23 ± 18.42	61.40 ± 11.16	58.81 ± 25.34	48.05 ± 15.60	54.55 ± 37.34	0.00 ± 0.00
Bench weight lifting - moderate	33.33 ± 9.45	35.42 ± 16.06	45.17 ± 12.02	35.64 ± 22.76	27.80 ± 15.39	15.62 ± 24.57	0.00 ± 0.00
Bicep curls - hard	51.09 ± 9.67	66.89 ± 12.80	73.60 ± 11.74	74.58 ± 12.11	65.13 ± 15.64	45.83 ± 42.49	16.67 ± 25.82
Bicep curls - light	61.45 ± 18.03	70.45 ± 16.73	75.95 ± 12.55	76.74 ± 17.48	81.07 ± 17.01	59.17 ± 32.97	8.33 ± 20.41
Bicep curls - moderate	53.30 ± 14.01	62.28 ± 12.54	68.43 ± 9.00	65.20 ± 22.12	60.83 ± 27.88	41.67 ± 42.72	0.00 ± 0.00
Calisthenics - Crunches	81.81 ± 11.20	84.25 ± 8.37	89.95 ± 8.47	83.57 ± 9.03	76.29 ± 23.73	33.33 ± 42.16	0.00 ± 0.00
Calisthenics - Sit ups	88.42 ± 4.47	92.58 ± 2.91	91.54 ± 5.36	91.79 ± 8.37	85.60 ± 16.73	69.05 ± 41.31	0.00 ± 0.00
Cycling - Cycle hard - Cycle 80rpm	67.52 ± 19.58	71.68 ± 19.30	76.86 ± 19.49	70.25 ± 26.34	62.95 ± 25.45	36.54 ± 30.53	4.55 ± 15.08
Cycling - Cycle light - Cycle 100rpm	90.51 ± 9.95	94.13 ± 7.82	94.50 ± 6.00	92.45 ± 15.79	84.12 ± 25.90	72.22 ± 31.29	7.69 ± 18.78
Cycling - Cycle light - Cycle 60rpm	85.24 ± 9.12	85.82 ± 10.58	86.58 ± 8.39	82.52 ± 13.29	78.96 ± 17.36	63.89 ± 30.65	12.50 ± 22.36
Cycling - Cycle light - Cycle 80rpm	80.26 ± 10.21	84.41 ± 8.91	85.00 ± 10.30	80.97 ± 14.58	75.35 ± 18.37	56.02 ± 25.21	11.54 ± 21.93
Cycling - Cycle moderate - Cycle 80rpm	67.70 ± 11.08	70.99 ± 9.41	72.47 ± 17.26	68.59 ± 14.40	65.65 ± 25.89	44.67 ± 41.48	0.00 ± 0.00
Lying down	56.09 ± 11.60	69.99 ± 12.01	78.19 ± 7.99	76.51 ± 13.29	75.48 ± 15.92	83.62 ± 16.49	79.50 ± 18.62
Rowing - Rowing hard - Rowing 30spm	53.36 ± 12.69	63.38 ± 14.88	70.82 ± 15.50	73.97 ± 16.07	70.66 ± 27.95	64.39 ± 31.64	4.55 ± 15.08
Rowing - Rowing light - Rowing 30spm	60.11 ± 14.95	65.62 ± 19.65	79.74 ± 11.45	78.76 ± 13.96	81.34 ± 14.59	62.75 ± 31.61	13.64 ± 32.33
Rowing - Rowing moderate - Rowing 30spm	51.09 ± 14.29	56.35 ± 15.74	64.68 ± 15.67	66.14 ± 20.51	57.67 ± 26.06	44.64 ± 35.75	0.00 ± 0.00
Running - Treadmill 4mph - Treadmill 0	86.66 ± 5.69	89.73 ± 6.31	88.02 ± 9.16	92.78 ± 10.01	85.85 ± 15.57	68.85 ± 27.64	7.14 ± 18.16
Running - Treadmill 5mph - Treadmill 0	85.05 ± 6.55	87.34 ± 6.03	86.69 ± 9.12	88.75 ± 10.25	88.39 ± 10.71	66.67 ± 40.37	0.00 ± 0.00
Running - Treadmill 6mph - Treadmill 0	81.02 ± 11.40	83.14 ± 12.88	84.33 ± 12.39	85.74 ± 29.60	75.34 ± 36.46	74.07 ± 36.43	0.00 ± 0.00
Sitting	16.61 ± 9.43	28.95 ± 9.94	35.94 ± 12.81	24.26 ± 17.77	18.13 ± 22.43	7.69 ± 18.78	0.00 ± 0.00
Sitting - Fidget feet legs	85.14 ± 12.10	81.55 ± 13.41	83.54 ± 12.62	80.38 ± 15.29	70.24 ± 18.97	27.78 ± 24.96	0.00 ± 0.00
Sitting - Fidget hands arms	73.30 ± 13.66	76.60 ± 12.35	71.50 ± 20.82	69.48 ± 19.28	61.43 ± 25.38	31.25 ± 45.81	0.00 ± 0.00
Stairs - Ascend stairs	66.48 ± 6.68	70.60 ± 9.76	80.80 ± 7.18	84.46 ± 12.18	76.54 ± 19.74	80.00 ± 21.08	0.00 ± 0.00
Stairs - Descend stairs	57.20 ± 9.59	67.71 ± 8.39	74.46 ± 13.39	81.77 ± 10.58	58.33 ± 27.32	51.11 ± 35.34	0.00 ± 0.00
Standing	17.34 ± 7.93	24.47 ± 8.13	30.31 ± 10.62	21.69 ± 13.80	18.22 ± 15.42	4.17 ± 14.43	0.00 ± 0.00
Walking - Treadmill 2mph - Treadmill 0	80.57 ± 7.02	83.05 ± 7.43	86.03 ± 7.53	85.26 ± 12.22	90.48 ± 9.09	80.98 ± 25.08	4.55 ± 15.08
Walking - Treadmill 3mph - Treadmill 0	56.91 ± 9.80	65.24 ± 9.04	66.34 ± 9.43	75.22 ± 14.23	79.57 ± 20.81	68.82 ± 32.95	16.67 ± 30.86
Walking - Treadmill 3mph - Treadmill 3 - light	45.08 ± 11.57	55.63 ± 11.98	64.65 ± 11.78	69.63 ± 12.19	73.47 ± 23.09	61.88 ± 23.17	3.33 ± 12.91
Walking - Treadmill 3mph - Treadmill 6 - moderate	45.88 ± 10.49	51.71 ± 11.66	63.51 ± 13.31	65.82 ± 15.00	72.86 ± 16.53	50.20 ± 32.19	3.85 ± 13.87
Walking - Treadmill 3mph - Treadmill 9 - hard	61.01 ± 12.73	67.26 ± 11.23	73.09 ± 9.73	74.04 ± 15.34	77.38 ± 24.11	54.02 ± 27.82	3.85 ± 13.87
kneeling	17.86 ± 5.12	27.55 ± 8.26	30.51 ± 19.63	24.91 ± 18.24	27.78 ± 32.85	5.00 ± 15.81	0.00 ± 0.00
unknown	61.60 ± 11.79	65.53 ± 11.37	66.87 ± 11.96	66.16 ± 12.26	65.08 ± 10.59	61.56 ± 17.00	50.74 ± 25.93
Carrying groceries	62.73 ± 13.83	71.13 ± 15.05	71.47 ± 16.97	80.31 ± 13.31	70.66 ± 20.54	69.33 ± 34.04	11.54 ± 21.93
Doing dishes	35.16 ± 9.70	42.74 ± 14.08	49.39 ± 17.85	53.19 ± 13.78	54.05 ± 25.81	50.00 ± 35.92	20.83 ± 33.43
Gardening	39.03 ± 14.88	47.83 ± 15.37	49.61 ± 25.36	54.00 ± 27.24	50.22 ± 27.20	48.50 ± 35.20	7.14 ± 18.90
Ironing	38.05 ± 11.31	47.39 ± 10.98	51.36 ± 17.58	50.73 ± 14.10	55.11 ± 21.71	53.96 ± 38.80	10.00 ± 28.03
Making the bed	26.72 ± 7.47	33.14 ± 11.86	38.80 ± 11.30	43.20 ± 15.81	48.45 ± 18.14	55.78 ± 33.82	24.24 ± 36.03
Mopping	35.06 ± 12.82	38.49 ± 14.67	48.30 ± 18.09	46.86 ± 19.69	49.11 ± 28.15	35.14 ± 23.99	18.18 ± 33.71
Playing videogames	47.47 ± 18.31	57.92 ± 19.37	57.26 ± 18.84	57.35 ± 21.35	45.67 ± 26.95	32.56 ± 27.17	6.94 ± 16.60
Scrubbing a surface	38.43 ± 12.70	42.81 ± 13.73	44.95 ± 11.72	49.13 ± 16.32	57.15 ± 26.85	44.03 ± 14.80	7.14 ± 18.90
Stacking groceries	26.56 ± 12.49	35.90 ± 15.09	44.07 ± 18.35	48.73 ± 22.44	52.45 ± 19.09	42.42 ± 33.63	0.00 ± 0.00
Sweeping	30.98 ± 15.94	38.98 ± 17.74	41.68 ± 15.35	49.56 ± 19.89	49.94 ± 23.95	20.00 ± 20.37	0.00 ± 0.00
Typing	68.82 ± 14.65	75.33 ± 13.09	73.71 ± 13.78	73.99 ± 15.70	69.98 ± 26.60	47.55 ± 26.76	3.85 ± 13.87
Vacuuming	33.44 ± 11.06	37.27 ± 8.86	42.25 ± 9.14	48.95 ± 14.58	65.38 ± 20.83	29.10 ± 29.12	11.11 ± 33.33
Walking around block	55.96 ± 12.37	62.37 ± 11.79	70.14 ± 11.88	76.43 ± 12.81	71.80 ± 21.21	65.67 ± 28.20	3.03 ± 10.05
Washing windows	36.61 ± 13.75	41.55 ± 13.88	44.79 ± 19.20	41.00 ± 18.70	52.58 ± 28.50	39.36 ± 30.29	0.00 ± 0.00
Watching TV	21.55 ± 6.60	25.75 ± 7.70	35.39 ± 13.21	28.23 ± 16.43	19.81 ± 12.63	15.31 ± 21.15	0.00 ± 0.00
Weeding	28.75 ± 13.56	38.77 ± 8.37	41.19 ± 13.53	41.31 ± 23.56	41.45 ± 19.89	50.37 ± 29.22	11.11 ± 19.25
Wiping/Dusting	24.66 ± 10.61	31.91 ± 14.03	36.40 ± 17.16	38.81 ± 21.55	41.68 ± 20.73	39.17 ± 30.27	0.00 ± 0.00
Writing	66.93 ± 12.36	73.08 ± 12.32	73.36 ± 12.55	69.12 ± 19.71	65.22 ± 25.63	43.43 ± 34.61	0.00 ± 0.00
taking out trash	18.72 ± 5.06	23.78 ± 7.85	30.53 ± 8.48	36.57 ± 16.29	46.80 ± 22.96	44.23 ± 34.33	0.00 ± 0.00

Table A5-7: True positive rate when training classifiers using the *FFTCorr* feature and subject dependent evaluation

	False Positive Rate						
Class	**1.4s**	**2.8s**	**5.6s**	**11.3s**	**22.7s**	**44.5s**	**90s**
Bench weight lifting - hard	0.92 ± 0.15	0.80 ± 0.18	0.60 ± 0.09	0.62 ± 0.30	0.88 ± 0.34	0.91 ± 0.47	3.82 ± 1.62
Bench weight lifting - light	0.85 ± 0.34	0.74 ± 0.35	0.71 ± 0.27	0.73 ± 0.54	1.06 ± 0.57	1.13 ± 0.77	3.61 ± 2.41
Bench weight lifting - moderate	0.96 ± 0.26	0.81 ± 0.31	0.67 ± 0.28	0.86 ± 0.42	1.06 ± 0.63	1.56 ± 0.78	3.68 ± 2.11
Bicep curls - hard	0.76 ± 0.27	0.57 ± 0.26	0.36 ± 0.13	0.42 ± 0.29	0.31 ± 0.19	1.00 ± 0.73	3.10 ± 1.63
Bicep curls - light	0.72 ± 0.31	0.55 ± 0.31	0.47 ± 0.30	0.51 ± 0.27	0.60 ± 0.37	0.93 ± 1.15	3.38 ± 1.62
Bicep curls - moderate	0.80 ± 0.27	0.66 ± 0.29	0.66 ± 0.30	0.54 ± 0.35	0.58 ± 0.26	0.81 ± 0.37	2.24 ± 1.15
Calisthenics - Crunches	0.29 ± 0.16	0.17 ± 0.08	0.20 ± 0.08	0.25 ± 0.16	0.23 ± 0.32	0.79 ± 0.76	1.79 ± 0.72
Calisthenics - Sit ups	0.19 ± 0.11	0.16 ± 0.05	0.10 ± 0.11	0.15 ± 0.14	0.28 ± 0.37	0.38 ± 0.39	3.33 ± 1.91
Cycling - Cycle hard - Cycle 80rpm	0.37 ± 0.12	0.37 ± 0.14	0.34 ± 0.15	0.37 ± 0.27	0.60 ± 0.65	1.34 ± 0.73	3.91 ± 1.67
Cycling - Cycle light - Cycle 100rpm	0.11 ± 0.05	0.11 ± 0.07	0.12 ± 0.08	0.13 ± 0.12	0.16 ± 0.24	0.28 ± 0.38	3.33 ± 1.66
Cycling - Cycle light - Cycle 60rpm	0.26 ± 0.14	0.25 ± 0.13	0.32 ± 0.19	0.41 ± 0.30	0.57 ± 0.50	0.91 ± 0.86	3.30 ± 1.51
Cycling - Cycle light - Cycle 80rpm	0.34 ± 0.17	0.33 ± 0.14	0.34 ± 0.20	0.42 ± 0.26	0.45 ± 0.45	0.76 ± 0.85	2.56 ± 1.44
Cycling - Cycle moderate - Cycle 80rpm	0.58 ± 0.14	0.46 ± 0.16	0.38 ± 0.16	0.55 ± 0.27	0.65 ± 0.51	1.00 ± 0.61	1.77 ± 0.40
Lying down	2.16 ± 0.76	1.75 ± 0.78	1.32 ± 0.56	1.31 ± 0.64	1.57 ± 0.92	1.97 ± 1.86	2.04 ± 1.69
Rowing - Rowing hard - Rowing 30spm	0.78 ± 0.22	0.66 ± 0.24	0.46 ± 0.13	0.51 ± 0.26	0.68 ± 0.42	0.61 ± 0.60	2.90 ± 1.75
Rowing - Rowing light - Rowing 30spm	0.69 ± 0.21	0.51 ± 0.27	0.42 ± 0.19	0.44 ± 0.23	0.62 ± 0.47	0.98 ± 0.58	2.95 ± 2.10
Rowing - Rowing moderate - Rowing 30spm	0.84 ± 0.16	0.69 ± 0.20	0.57 ± 0.21	0.65 ± 0.28	0.57 ± 0.29	1.17 ± 0.62	2.96 ± 1.64
Running - Treadmill 4mph - Treadmill 0	0.29 ± 0.17	0.23 ± 0.13	0.25 ± 0.16	0.21 ± 0.14	0.30 ± 0.23	0.82 ± 0.68	3.09 ± 2.25
Running - Treadmill 5mph - Treadmill 0	0.29 ± 0.14	0.23 ± 0.13	0.22 ± 0.10	0.27 ± 0.19	0.40 ± 0.30	0.78 ± 0.71	2.97 ± 1.52
Running - Treadmill 6mph - Treadmill 0	0.21 ± 0.13	0.22 ± 0.12	0.20 ± 0.12	0.18 ± 0.14	0.27 ± 0.23	0.75 ± 0.56	1.30 ± 0.13
Sitting	1.22 ± 0.22	0.96 ± 0.30	1.03 ± 0.37	1.07 ± 0.44	1.19 ± 0.72	1.35 ± 0.54	3.76 ± 2.19
Sitting - Fidget feet legs	0.22 ± 0.19	0.24 ± 0.23	0.25 ± 0.20	0.21 ± 0.17	0.39 ± 0.39	1.38 ± 1.14	2.18 ± 1.38
Sitting - Fidget hands arms	0.37 ± 0.23	0.33 ± 0.19	0.39 ± 0.32	0.41 ± 0.28	0.46 ± 0.38	1.17 ± 0.65	1.95 ± 1.02
Stairs - Ascend stairs	0.66 ± 0.16	0.51 ± 0.18	0.29 ± 0.11	0.28 ± 0.20	0.31 ± 0.26	0.53 ± 0.54	0.00 ± 0.00
Stairs - Descend stairs	0.74 ± 0.23	0.56 ± 0.26	0.45 ± 0.28	0.34 ± 0.20	0.55 ± 0.34	0.63 ± 0.65	0.00 ± 0.00
Standing	1.13 ± 0.17	0.96 ± 0.23	0.82 ± 0.25	1.01 ± 0.48	1.02 ± 0.37	1.53 ± 1.13	1.66 ± 0.51
Walking - Treadmill 2mph - Treadmill 0	0.45 ± 0.18	0.38 ± 0.12	0.38 ± 0.19	0.35 ± 0.30	0.52 ± 0.44	0.73 ± 0.54	2.04 ± 0.87
Walking - Treadmill 3mph - Treadmill 0	1.01 ± 0.23	0.78 ± 0.25	0.68 ± 0.21	0.50 ± 0.24	0.57 ± 0.45	1.02 ± 0.78	3.74 ± 2.77
Walking - Treadmill 3mph - Treadmill 3 - light	1.23 ± 0.34	1.08 ± 0.30	0.85 ± 0.31	0.78 ± 0.29	0.60 ± 0.46	1.28 ± 0.69	3.84 ± 3.40
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.18 ± 0.33	1.02 ± 0.32	0.80 ± 0.27	0.74 ± 0.21	0.77 ± 0.54	1.65 ± 0.89	4.47 ± 2.67
Walking - Treadmill 3mph - Treadmill 9 - hard	0.82 ± 0.29	0.68 ± 0.29	0.56 ± 0.30	0.51 ± 0.31	0.46 ± 0.38	0.92 ± 0.87	2.68 ± 1.38
kneeling	0.95 ± 0.18	0.87 ± 0.22	0.69 ± 0.24	0.76 ± 0.44	0.97 ± 0.77	1.05 ± 0.52	1.86 ± 0.65
unknown	16.64 ± 4.12	14.86 ± 4.51	13.68 ± 3.73	12.67 ± 4.58	11.49 ± 4.80	8.77 ± 3.32	10.08 ± 6.54
Carrying groceries	0.71 ± 0.29	0.54 ± 0.24	0.50 ± 0.28	0.51 ± 0.45	0.50 ± 0.37	0.58 ± 0.83	2.97 ± 1.42
Doing dishes	1.46 ± 0.50	1.27 ± 0.50	1.24 ± 0.79	1.14 ± 0.51	0.94 ± 0.69	1.58 ± 1.23	3.43 ± 2.39
Gardening	1.29 ± 0.57	1.10 ± 0.39	0.99 ± 0.53	0.96 ± 0.64	0.78 ± 0.66	1.24 ± 0.75	2.80 ± 2.18
Ironing	1.48 ± 0.47	1.18 ± 0.31	1.12 ± 0.39	1.00 ± 0.46	1.01 ± 0.53	1.25 ± 0.78	4.19 ± 3.21
Making the bed	1.63 ± 0.47	1.41 ± 0.45	1.19 ± 0.31	1.26 ± 0.52	1.26 ± 0.90	1.77 ± 1.44	2.49 ± 1.42
Mopping	1.22 ± 0.36	1.19 ± 0.44	1.06 ± 0.41	1.20 ± 0.62	1.09 ± 0.75	1.28 ± 0.55	4.04 ± 2.74
Playing videogames	1.25 ± 0.51	1.01 ± 0.46	0.96 ± 0.43	1.13 ± 0.70	1.37 ± 0.91	1.57 ± 1.21	3.12 ± 1.54
Scrubbing a surface	1.10 ± 0.37	0.98 ± 0.41	1.07 ± 0.51	1.06 ± 0.55	0.78 ± 0.53	1.02 ± 0.85	2.40 ± 1.24
Stacking groceries	1.29 ± 0.45	1.20 ± 0.54	0.87 ± 0.45	1.07 ± 0.76	0.83 ± 0.54	0.86 ± 0.74	0.00 ± 0.00
Sweeping	1.30 ± 0.54	1.22 ± 0.50	1.13 ± 0.65	1.07 ± 0.68	1.13 ± 0.70	1.72 ± 0.93	2.58 ± 1.64
Typing	0.61 ± 0.32	0.56 ± 0.32	0.53 ± 0.27	0.86 ± 0.54	0.85 ± 0.51	1.45 ± 0.92	3.44 ± 1.48
Vacuuming	1.29 ± 0.56	1.22 ± 0.52	1.09 ± 0.44	1.09 ± 0.50	0.90 ± 0.54	1.92 ± 1.17	3.53 ± 1.53
Walking around block	0.88 ± 0.40	0.72 ± 0.32	0.63 ± 0.39	0.58 ± 0.53	0.74 ± 0.50	0.77 ± 0.75	2.40 ± 1.53
Washing windows	1.19 ± 0.42	1.18 ± 0.40	1.03 ± 0.46	0.99 ± 0.39	0.89 ± 0.68	1.01 ± 0.95	2.36 ± 1.58
Watching TV	1.78 ± 0.56	1.49 ± 0.41	1.40 ± 0.57	1.44 ± 0.64	1.82 ± 0.73	2.10 ± 1.18	6.17 ± 3.33
Weeding	1.03 ± 0.57	1.00 ± 0.51	1.15 ± 0.67	1.13 ± 0.78	1.37 ± 0.74	1.53 ± 0.92	3.36 ± 1.33
Wiping/Dusting	1.35 ± 0.46	1.22 ± 0.52	1.14 ± 0.44	0.99 ± 0.52	1.07 ± 0.62	1.71 ± 1.05	3.62 ± 1.84
Writing	0.71 ± 0.40	0.60 ± 0.37	0.57 ± 0.36	0.54 ± 0.33	0.81 ± 0.62	1.65 ± 1.44	3.78 ± 1.53
taking out trash	1.30 ± 0.52	1.18 ± 0.45	1.14 ± 0.45	0.96 ± 0.38	1.38 ± 0.73	1.32 ± 1.06	3.94 ± 2.46

Table A5-8: False positive rate when training the C4.5 classifier using the *FFTCorr* feature and subject dependent evaluation

	F-Measure						
Class	**1.4s**	**2.8s**	**5.6s**	**11.3s**	**22.7s**	**44.5s**	**90s**
Bench weight lifting - hard	22.04 ± 12.49	32.13 ± 13.54	43.83 ± 10.66	44.96 ± 13.51	18.52 ± 16.73	0.00 ± 0.00	0.91 ± 0.47
Bench weight lifting - light	45.13 ± 13.54	56.92 ± 16.46	58.83 ± 11.25	56.53 ± 24.45	45.99 ± 15.42	46.55 ± 28.62	1.13 ± 0.77
Bench weight lifting - moderate	32.25 ± 9.22	35.87 ± 15.46	45.86 ± 11.33	34.88 ± 21.95	28.30 ± 15.78	14.13 ± 19.98	1.56 ± 0.78
Bicep curls - hard	51.42 ± 10.61	66.17 ± 12.31	74.65 ± 10.51	74.81 ± 10.87	70.13 ± 10.34	44.46 ± 41.46	1.00 ± 0.73
Bicep curls - light	61.41 ± 16.88	70.60 ± 15.96	76.12 ± 11.80	75.11 ± 14.58	76.64 ± 16.79	57.55 ± 32.70	0.93 ± 1.15
Bicep curls - moderate	52.44 ± 13.85	61.36 ± 12.00	65.65 ± 9.75	65.11 ± 22.11	60.29 ± 25.38	38.93 ± 37.27	0.81 ± 0.37
Calisthenics - Crunches	80.00 ± 11.54	85.57 ± 6.24	87.76 ± 6.68	82.44 ± 8.87	77.77 ± 20.16	36.67 ± 44.57	0.79 ± 0.76
Calisthenics - Sit ups	88.01 ± 5.11	90.91 ± 2.71	92.45 ± 6.19	91.25 ± 6.46	84.90 ± 14.76	67.35 ± 36.39	0.38 ± 0.39
Cycling - Cycle hard - Cycle 80rpm	67.39 ± 19.51	70.32 ± 19.57	73.08 ± 22.06	69.27 ± 24.99	63.89 ± 28.33	32.65 ± 27.82	1.34 ± 0.73
Cycling - Cycle light - Cycle 100rpm	90.86 ± 9.14	93.17 ± 7.50	92.96 ± 5.87	90.70 ± 15.44	84.08 ± 24.58	74.76 ± 29.35	0.28 ± 0.38
Cycling - Cycle light - Cycle 60rpm	85.01 ± 9.09	85.65 ± 9.71	84.88 ± 8.39	80.75 ± 12.43	76.56 ± 17.08	60.40 ± 27.92	0.91 ± 0.86
Cycling - Cycle light - Cycle 80rpm	80.61 ± 10.38	83.20 ± 8.67	83.45 ± 10.05	79.10 ± 12.56	75.24 ± 16.93	57.88 ± 24.34	0.76 ± 0.85
Cycling - Cycle moderate - Cycle 80rpm	66.68 ± 10.48	71.41 ± 9.44	73.37 ± 14.09	67.94 ± 12.28	64.14 ± 23.38	41.37 ± 36.79	1.00 ± 0.61
Lying down	55.62 ± 11.02	68.08 ± 11.02	76.25 ± 7.15	75.14 ± 12.32	73.06 ± 13.22	77.54 ± 15.96	1.97 ± 1.86
Rowing - Rowing hard - Rowing 30spm	53.00 ± 12.96	61.93 ± 14.61	70.04 ± 13.46	71.10 ± 15.70	65.81 ± 27.46	62.45 ± 28.44	0.61 ± 0.60
Rowing - Rowing light - Rowing 30spm	58.74 ± 15.50	65.79 ± 20.39	78.20 ± 10.92	77.53 ± 12.33	76.31 ± 15.39	57.17 ± 27.00	0.98 ± 0.58
Rowing - Rowing moderate - Rowing 30spm	50.84 ± 13.71	56.95 ± 15.18	65.06 ± 14.12	64.11 ± 17.47	59.26 ± 22.65	39.78 ± 29.54	1.17 ± 0.62
Running - Treadmill 4mph - Treadmill 0	85.95 ± 6.40	88.93 ± 5.69	87.62 ± 7.78	90.72 ± 7.74	85.38 ± 12.69	64.12 ± 26.74	0.82 ± 0.68
Running - Treadmill 5mph - Treadmill 0	84.53 ± 6.48	87.13 ± 5.88	86.96 ± 6.36	87.37 ± 7.53	84.42 ± 9.80	60.77 ± 36.15	0.78 ± 0.71
Running - Treadmill 6mph - Treadmill 0	80.38 ± 10.81	81.38 ± 12.67	83.87 ± 11.91	83.49 ± 27.50	73.78 ± 34.78	66.09 ± 32.41	0.75 ± 0.56
Sitting	15.83 ± 9.20	28.64 ± 10.01	33.67 ± 12.73	23.43 ± 17.64	17.64 ± 21.45	5.64 ± 13.84	1.35 ± 0.54
Sitting - Fidget feet legs	84.11 ± 12.73	81.67 ± 14.28	82.25 ± 12.04	81.19 ± 14.55	71.62 ± 20.41	22.57 ± 21.32	1.38 ± 1.14
Sitting - Fidget hands arms	72.81 ± 14.48	75.70 ± 12.48	71.04 ± 19.63	68.77 ± 17.52	61.58 ± 24.05	27.50 ± 41.32	1.17 ± 0.65
Stairs - Ascend stairs	64.81 ± 6.90	70.41 ± 8.81	81.26 ± 7.35	83.12 ± 10.43	76.65 ± 13.58	76.32 ± 18.61	0.53 ± 0.54
Stairs - Descend stairs	56.57 ± 9.74	67.07 ± 9.27	73.25 ± 13.71	80.24 ± 9.40	56.84 ± 23.33	52.86 ± 35.75	0.63 ± 0.65
Standing	16.49 ± 7.05	24.37 ± 7.88	31.13 ± 10.99	20.85 ± 12.95	17.55 ± 13.47	2.38 ± 8.25	1.53 ± 1.13
Walking - Treadmill 2mph - Treadmill 0	79.88 ± 6.34	82.65 ± 5.70	84.32 ± 7.43	84.27 ± 11.88	85.25 ± 9.03	74.72 ± 21.79	0.73 ± 0.54
Walking - Treadmill 3mph - Treadmill 0	55.36 ± 9.27	64.34 ± 8.77	66.75 ± 8.27	75.09 ± 12.47	76.93 ± 19.64	63.44 ± 28.95	1.02 ± 0.78
Walking - Treadmill 3mph - Treadmill 3 - light	44.14 ± 10.83	53.56 ± 10.82	62.98 ± 12.06	66.97 ± 11.06	72.84 ± 21.00	57.13 ± 20.27	1.28 ± 0.69
Walking - Treadmill 3mph - Treadmill 6 - moderate	45.62 ± 10.73	51.81 ± 11.61	62.89 ± 11.94	65.18 ± 12.53	70.65 ± 16.67	45.30 ± 28.06	1.65 ± 0.89
Walking - Treadmill 3mph - Treadmill 9 - hard	61.17 ± 12.71	67.63 ± 10.91	73.60 ± 9.76	74.45 ± 14.31	77.07 ± 21.50	55.31 ± 28.62	0.92 ± 0.87
kneeling	18.26 ± 4.87	27.91 ± 8.79	32.07 ± 19.31	26.04 ± 16.96	25.87 ± 28.24	4.00 ± 12.65	1.05 ± 0.52
unknown	61.11 ± 11.71	65.03 ± 11.42	66.55 ± 11.85	66.60 ± 12.41	66.27 ± 10.91	64.00 ± 15.57	8.77 ± 3.32
Carrying groceries	63.18 ± 13.94	71.46 ± 14.42	72.27 ± 14.45	79.04 ± 11.71	71.77 ± 18.16	70.29 ± 31.85	0.58 ± 0.83
Doing dishes	34.77 ± 9.56	42.11 ± 13.33	48.35 ± 17.76	52.31 ± 12.13	55.08 ± 23.04	46.09 ± 31.83	1.58 ± 1.23
Gardening	38.62 ± 14.49	47.07 ± 13.92	49.55 ± 24.36	53.75 ± 25.79	52.54 ± 24.56	43.59 ± 31.17	1.24 ± 0.75
Ironing	37.37 ± 10.69	47.34 ± 10.81	50.85 ± 16.92	51.99 ± 13.23	55.33 ± 21.05	49.64 ± 35.09	1.25 ± 0.78
Making the bed	26.81 ± 7.35	33.83 ± 11.86	40.08 ± 10.42	43.23 ± 14.10	48.34 ± 15.35	50.46 ± 31.31	1.77 ± 1.44
Mopping	35.57 ± 12.44	38.88 ± 14.59	47.28 ± 14.88	45.67 ± 18.91	47.52 ± 26.08	35.39 ± 23.64	1.28 ± 0.55
Playing videogames	47.93 ± 17.53	58.15 ± 18.49	58.07 ± 17.35	56.91 ± 20.26	45.32 ± 25.72	33.08 ± 24.86	1.57 ± 1.21
Scrubbing a surface	39.39 ± 13.06	44.25 ± 14.04	45.38 ± 11.74	48.88 ± 16.21	57.33 ± 22.66	46.95 ± 18.95	1.02 ± 0.85
Stacking groceries	27.12 ± 12.93	35.96 ± 15.66	45.89 ± 18.37	48.20 ± 23.36	52.74 ± 17.19	42.77 ± 31.12	0.86 ± 0.74
Sweeping	31.77 ± 15.75	38.72 ± 16.64	42.82 ± 15.98	50.25 ± 19.56	49.52 ± 24.15	20.94 ± 19.59	1.72 ± 0.93
Typing	70.18 ± 13.93	75.28 ± 11.97	74.71 ± 10.99	70.23 ± 14.75	66.44 ± 23.84	44.69 ± 22.03	1.45 ± 0.92
Vacuuming	34.49 ± 11.31	38.51 ± 9.56	43.69 ± 9.55	48.59 ± 12.71	63.06 ± 19.20	28.05 ± 26.21	1.92 ± 1.17
Walking around block	57.24 ± 11.86	63.95 ± 11.35	70.90 ± 11.74	76.25 ± 13.14	69.79 ± 16.97	66.31 ± 26.57	0.77 ± 0.75
Washing windows	38.17 ± 13.45	42.20 ± 12.54	46.39 ± 18.15	43.46 ± 18.80	52.63 ± 26.29	42.66 ± 29.87	1.01 ± 0.95
Watching TV	22.06 ± 6.22	27.34 ± 7.64	36.71 ± 13.04	29.82 ± 15.31	20.42 ± 12.77	13.82 ± 18.18	2.10 ± 1.18
Weeding	31.11 ± 14.15	42.04 ± 7.89	42.92 ± 13.66	41.57 ± 20.50	40.34 ± 18.72	44.67 ± 26.59	1.53 ± 0.92
Wiping/Dusting	26.43 ± 11.40	33.69 ± 13.60	38.21 ± 16.96	41.40 ± 20.44	44.33 ± 21.22	36.38 ± 28.72	1.71 ± 1.05
Writing	68.15 ± 11.62	73.65 ± 11.87	74.04 ± 12.55	70.98 ± 17.07	65.05 ± 22.36	41.54 ± 32.10	1.65 ± 1.44
taking out trash	20.58 ± 5.14	26.14 ± 9.06	32.68 ± 8.28	39.27 ± 17.10	43.33 ± 19.05	40.78 ± 26.82	1.32 ± 1.06

Table A5-9: F-Measure when training the C4.5 classifier using the *FFTCorr* feature and subject dependent evaluation

	True Positive Rate						
Class	**1.4s**	**2.8s**	**5.6s**	**11.3s**	**22.7s**	**44.5s**	**90s**
Bench weight lifting - hard	4.76 ± 8.96	2.27 ± 3.39	3.06 ± 5.22	3.33 ± 7.67	9.09 ± 30.15	8.33 ± 20.41	0.00 ± 0.00
Bench weight lifting - light	13.33 ± 13.19	15.47 ± 16.26	14.82 ± 21.56	19.38 ± 26.61	13.24 ± 16.93	23.72 ± 32.25	25.00 ± 46.29
Bench weight lifting - moderate	8.46 ± 9.39	7.31 ± 9.24	7.35 ± 11.40	14.32 ± 17.90	8.35 ± 18.05	18.75 ± 32.20	30.00 ± 44.72
Bicep curls - hard	11.09 ± 14.57	15.21 ± 19.95	8.92 ± 13.49	36.17 ± 28.00	40.67 ± 39.34	53.57 ± 50.89	33.33 ± 51.64
Bicep curls - light	17.94 ± 19.31	19.76 ± 18.93	24.05 ± 19.87	32.17 ± 22.70	56.25 ± 37.10	55.56 ± 47.14	60.00 ± 54.77
Bicep curls - moderate	9.91 ± 13.51	15.47 ± 20.52	23.42 ± 24.31	17.42 ± 19.61	53.65 ± 42.83	83.33 ± 27.89	60.00 ± 54.77
Calisthenics - Crunches	10.02 ± 21.58	9.80 ± 22.69	11.97 ± 24.76	25.41 ± 39.89	24.53 ± 38.18	8.33 ± 18.00	0.00 ± 0.00
Calisthenics - Sit ups	38.08 ± 40.32	38.99 ± 44.24	56.88 ± 42.13	55.05 ± 42.00	67.90 ± 36.95	72.22 ± 37.27	60.00 ± 54.77
Cycling - Cycle hard - Cycle 80rpm	11.97 ± 17.72	9.70 ± 12.03	14.99 ± 23.31	9.88 ± 17.62	16.87 ± 22.44	19.64 ± 30.42	12.50 ± 25.00
Cycling - Cycle light - Cycle 100rpm	54.94 ± 32.78	62.65 ± 36.84	62.95 ± 36.29	76.13 ± 33.34	74.00 ± 39.06	90.62 ± 27.20	100.00 ± 0.00
Cycling - Cycle light - Cycle 60rpm	41.28 ± 23.31	54.69 ± 33.90	55.76 ± 34.56	56.34 ± 34.97	68.51 ± 34.54	76.04 ± 33.18	90.62 ± 27.20
Cycling - Cycle light - Cycle 80rpm	28.59 ± 25.29	35.86 ± 26.29	39.78 ± 37.10	33.50 ± 27.93	70.34 ± 32.29	76.28 ± 31.52	50.00 ± 47.14
Cycling - Cycle moderate - Cycle 80rpm	11.46 ± 11.02	9.65 ± 9.92	23.52 ± 24.73	25.38 ± 28.38	19.34 ± 29.14	40.52 ± 34.54	40.91 ± 49.08
Lying down	50.32 ± 12.94	66.09 ± 13.63	71.70 ± 22.54	74.29 ± 18.31	74.77 ± 21.69	78.13 ± 23.39	85.83 ± 18.95
Rowing - Rowing hard - Rowing 30spm	14.20 ± 14.71	15.48 ± 18.90	21.60 ± 28.91	7.45 ± 11.09	15.75 ± 29.33	47.92 ± 39.28	50.00 ± 57.74
Rowing - Rowing light - Rowing 30spm	19.74 ± 15.36	19.88 ± 19.30	24.69 ± 28.96	44.71 ± 28.11	35.13 ± 37.71	55.60 ± 41.32	44.44 ± 52.70
Rowing - Rowing moderate - Rowing 30spm	17.82 ± 14.75	16.54 ± 16.79	18.44 ± 21.65	20.34 ± 24.00	20.00 ± 26.66	22.50 ± 38.10	50.00 ± 53.45
Running - Treadmill 4mph - Treadmill 0	23.61 ± 22.22	25.14 ± 28.59	26.24 ± 25.02	34.38 ± 36.23	47.05 ± 41.91	39.26 ± 46.97	59.38 ± 49.05
Running - Treadmill 5mph - Treadmill 0	35.23 ± 27.58	41.13 ± 31.06	36.32 ± 32.86	37.71 ± 31.66	40.84 ± 42.17	57.58 ± 42.40	80.00 ± 42.16
Running - Treadmill 6mph - Treadmill 0	27.17 ± 24.05	31.17 ± 30.90	48.54 ± 34.51	57.28 ± 41.23	45.04 ± 46.28	50.91 ± 45.44	80.00 ± 44.72
Sitting	5.63 ± 5.02	3.71 ± 3.96	5.39 ± 6.43	6.36 ± 9.06	12.78 ± 16.89	14.91 ± 22.84	50.00 ± 52.70
Sitting - Fidget feet legs	30.01 ± 26.41	34.74 ± 31.53	32.64 ± 30.28	38.23 ± 34.32	51.18 ± 38.06	70.51 ± 37.98	66.67 ± 50.00
Sitting - Fidget hands arms	12.08 ± 15.13	14.95 ± 17.17	17.11 ± 17.52	24.32 ± 32.51	10.00 ± 18.47	52.94 ± 37.38	71.43 ± 48.80
Stairs - Ascend stairs	38.06 ± 26.24	40.30 ± 27.87	51.20 ± 33.87	50.11 ± 38.40	59.99 ± 36.03	80.95 ± 28.39	0.00 ± 0.00
Stairs - Descend stairs	27.04 ± 19.53	31.46 ± 24.64	43.87 ± 31.20	35.37 ± 34.17	47.69 ± 43.33	52.38 ± 38.60	0.00 ± 0.00
Standing	5.99 ± 4.49	7.70 ± 6.69	10.99 ± 10.76	17.13 ± 14.83	17.67 ± 19.01	20.00 ± 31.62	20.00 ± 44.72
Walking - Treadmill 2mph - Treadmill 0	35.99 ± 24.64	40.26 ± 25.69	41.44 ± 31.78	47.56 ± 33.72	47.94 ± 33.92	58.53 ± 40.96	92.31 ± 18.78
Walking - Treadmill 3mph - Treadmill 0	14.50 ± 10.57	16.00 ± 15.32	17.37 ± 15.06	17.87 ± 16.41	25.30 ± 33.88	13.44 ± 21.35	33.33 ± 32.57
Walking - Treadmill 3mph - Treadmill 3 - light	9.62 ± 8.03	10.97 ± 7.31	14.76 ± 12.87	15.03 ± 16.90	22.58 ± 21.79	16.57 ± 21.33	35.00 ± 41.16
Walking - Treadmill 3mph - Treadmill 6 - moderate	9.20 ± 8.67	8.64 ± 9.16	11.09 ± 12.23	9.07 ± 14.42	13.64 ± 23.83	20.83 ± 31.98	33.33 ± 35.36
Walking - Treadmill 3mph - Treadmill 9 - hard	14.07 ± 15.59	12.54 ± 13.52	7.89 ± 10.05	15.51 ± 17.40	21.01 ± 25.65	19.89 ± 29.76	16.67 ± 32.57
kneeling	7.31 ± 4.89	8.59 ± 8.77	15.76 ± 16.83	13.52 ± 16.60	17.50 ± 20.49	17.86 ± 24.86	36.36 ± 50.45
unknown	53.22 ± 3.07	55.76 ± 3.25	58.70 ± 3.78	61.93 ± 3.28	64.78 ± 6.01	64.43 ± 9.70	64.22 ± 16.37
Carrying groceries	22.19 ± 19.46	27.95 ± 23.54	28.58 ± 27.65	28.99 ± 31.32	31.49 ± 31.18	23.44 ± 25.11	57.14 ± 47.46
Doing dishes	15.93 ± 9.71	20.22 ± 15.50	23.43 ± 17.88	28.29 ± 23.93	35.16 ± 27.79	41.93 ± 32.05	67.86 ± 37.25
Gardening	10.22 ± 12.14	11.38 ± 13.47	14.90 ± 17.12	18.00 ± 22.72	28.80 ± 34.42	32.50 ± 42.51	22.73 ± 34.38
Ironing	16.90 ± 10.93	22.42 ± 13.51	28.44 ± 18.43	27.78 ± 24.98	28.89 ± 25.60	30.75 ± 30.19	50.00 ± 39.22
Making the bed	15.40 ± 10.44	18.30 ± 13.25	27.20 ± 21.74	33.72 ± 23.63	46.77 ± 29.91	60.94 ± 32.68	55.95 ± 39.01
Mopping	14.57 ± 13.10	17.57 ± 15.61	18.76 ± 18.05	20.28 ± 19.94	21.65 ± 22.57	35.00 ± 25.74	50.00 ± 42.26
Playing videogames	14.83 ± 10.22	15.89 ± 11.79	14.14 ± 11.79	15.12 ± 17.33	12.19 ± 12.88	23.43 ± 30.82	39.29 ± 40.09
Scrubbing a surface	8.60 ± 8.40	10.29 ± 10.28	13.69 ± 15.93	15.09 ± 17.47	18.22 ± 23.98	25.83 ± 28.04	35.00 ± 41.16
Stacking groceries	8.08 ± 7.98	11.30 ± 11.57	13.90 ± 14.41	17.90 ± 19.83	21.32 ± 20.75	35.56 ± 36.66	0.00 ± 0.00
Sweeping	7.92 ± 7.46	10.70 ± 9.83	12.48 ± 13.13	17.86 ± 16.66	19.60 ± 18.20	29.90 ± 28.71	33.33 ± 44.38
Typing	38.47 ± 20.02	41.90 ± 22.07	40.92 ± 24.32	41.22 ± 27.83	29.31 ± 28.33	29.44 ± 22.69	26.92 ± 38.81
Vacuuming	12.39 ± 10.80	13.12 ± 12.19	13.20 ± 12.67	15.53 ± 15.25	21.91 ± 20.50	22.13 ± 27.78	29.17 ± 39.65
Walking around block	16.55 ± 14.14	16.46 ± 15.31	15.47 ± 18.44	24.06 ± 26.03	23.45 ± 26.25	23.53 ± 32.73	65.00 ± 41.16
Washing windows	12.59 ± 9.86	13.86 ± 11.85	22.02 ± 19.33	21.50 ± 17.89	22.70 ± 20.00	35.00 ± 33.83	46.43 ± 41.44
Watching TV	7.89 ± 4.76	9.79 ± 6.79	13.67 ± 8.36	14.56 ± 9.20	10.61 ± 11.15	10.58 ± 12.80	32.29 ± 34.68
Weeding	3.01 ± 3.38	2.74 ± 3.54	3.49 ± 5.61	3.97 ± 6.48	4.82 ± 7.77	8.33 ± 16.14	42.86 ± 44.99
Wiping/Dusting	10.42 ± 7.56	11.54 ± 8.14	16.93 ± 14.74	20.27 ± 16.27	32.26 ± 26.37	43.75 ± 26.19	68.18 ± 46.22
Writing	44.06 ± 27.30	49.17 ± 30.43	51.57 ± 33.21	48.19 ± 34.87	57.30 ± 35.38	52.13 ± 35.87	46.88 ± 38.60
taking out trash	4.58 ± 4.11	5.69 ± 5.72	5.55 ± 6.45	8.18 ± 11.50	12.80 ± 16.79	18.44 ± 22.31	45.00 ± 43.78

Table A5-10: True positive rate when training classifiers using the *FFTCorr* feature and subject independent evaluation

	False Positive Rate						
Class	**1.4s**	**2.8s**	**5.6s**	**11.3s**	**22.7s**	**44.5s**	**90s**
Bench weight lifting - hard	0.38 ± 0.22	0.23 ± 0.14	0.25 ± 0.18	0.26 ± 0.17	0.60 ± 0.50	0.89 ± 0.35	1.97 ± 0.57
Bench weight lifting - light	0.73 ± 0.29	0.70 ± 0.41	0.57 ± 0.42	0.64 ± 0.58	0.77 ± 0.62	0.80 ± 0.40	1.66 ± 1.11
Bench weight lifting - moderate	0.54 ± 0.22	0.47 ± 0.25	0.54 ± 0.38	0.44 ± 0.29	0.67 ± 0.62	0.81 ± 0.49	2.43 ± 1.11
Bicep curls - hard	0.54 ± 0.51	0.64 ± 0.63	0.53 ± 0.53	0.99 ± 0.84	0.85 ± 0.83	1.27 ± 0.77	2.41 ± 0.96
Bicep curls - light	0.54 ± 0.55	0.52 ± 0.46	0.53 ± 0.43	1.54 ± 1.77	1.04 ± 1.18	0.77 ± 1.07	2.95 ± 1.76
Bicep curls - moderate	0.46 ± 0.49	0.46 ± 0.54	0.99 ± 0.77	0.88 ± 0.55	1.94 ± 1.62	0.68 ± 0.65	2.96 ± 3.52
Calisthenics - Crunches	0.25 ± 0.11	0.27 ± 0.32	0.23 ± 0.13	0.48 ± 0.90	0.37 ± 0.49	0.98 ± 0.73	1.86 ± 1.11
Calisthenics - Sit ups	0.16 ± 0.08	0.13 ± 0.16	0.16 ± 0.21	0.16 ± 0.18	0.33 ± 0.74	0.34 ± 0.56	1.05 ± 1.01
Cycling - Cycle hard - Cycle 80rpm	0.63 ± 0.52	0.72 ± 0.79	0.84 ± 0.73	0.67 ± 0.51	1.13 ± 0.94	1.27 ± 1.02	1.68 ± 0.26
Cycling - Cycle light - Cycle 100rpm	0.48 ± 0.51	0.31 ± 0.40	0.52 ± 1.06	0.58 ± 1.37	0.40 ± 0.85	0.22 ± 0.46	0.46 ± 1.26
Cycling - Cycle light - Cycle 60rpm	0.61 ± 0.56	0.52 ± 0.69	0.32 ± 0.20	0.30 ± 0.24	0.99 ± 2.16	0.80 ± 1.40	2.02 ± 3.03
Cycling - Cycle light - Cycle 80rpm	0.89 ± 0.91	0.93 ± 1.00	0.56 ± 0.53	1.00 ± 1.21	1.46 ± 1.41	1.16 ± 1.03	2.68 ± 2.41
Cycling - Cycle moderate - Cycle 80rpm	0.68 ± 0.33	0.63 ± 0.35	0.91 ± 0.72	1.39 ± 1.33	0.78 ± 0.60	0.84 ± 0.72	2.50 ± 2.14
Lying down	2.33 ± 0.86	1.86 ± 0.79	1.62 ± 0.93	1.46 ± 0.85	1.86 ± 1.07	1.15 ± 1.25	0.98 ± 1.12
Rowing - Rowing hard - Rowing 30spm	0.72 ± 0.53	0.67 ± 0.70	0.76 ± 0.96	0.71 ± 0.88	1.15 ± 0.97	1.66 ± 1.26	2.61 ± 2.03
Rowing - Rowing light - Rowing 30spm	0.82 ± 0.58	0.72 ± 0.81	0.82 ± 0.85	0.92 ± 0.85	1.51 ± 1.16	1.21 ± 1.75	2.19 ± 1.23
Rowing - Rowing moderate - Rowing 30spm	0.87 ± 0.65	0.69 ± 0.65	0.71 ± 0.67	0.84 ± 0.65	1.02 ± 0.98	1.72 ± 1.22	2.42 ± 0.98
Running - Treadmill 4mph - Treadmill 0	0.64 ± 0.62	0.41 ± 0.45	0.75 ± 0.74	0.87 ± 0.99	1.06 ± 1.20	1.63 ± 2.53	3.34 ± 3.55
Running - Treadmill 5mph - Treadmill 0	0.76 ± 0.63	0.78 ± 0.73	0.58 ± 0.43	0.85 ± 0.90	0.70 ± 0.74	1.11 ± 0.87	1.37 ± 1.37
Running - Treadmill 6mph - Treadmill 0	0.47 ± 0.51	0.52 ± 0.59	0.82 ± 1.03	0.71 ± 0.75	1.20 ± 1.00	1.31 ± 1.28	1.18 ± 0.70
Sitting	0.94 ± 0.32	0.87 ± 0.25	0.81 ± 0.37	0.87 ± 0.55	0.89 ± 0.61	0.90 ± 0.62	1.72 ± 1.67
Sitting - Fidget feet legs	0.30 ± 0.20	0.33 ± 0.19	0.45 ± 0.39	0.34 ± 0.31	0.36 ± 0.40	0.45 ± 0.62	0.75 ± 1.40
Sitting - Fidget hands arms	0.52 ± 0.18	0.54 ± 0.35	0.55 ± 0.45	0.60 ± 0.42	0.57 ± 0.50	0.79 ± 1.18	1.16 ± 1.22
Stairs - Ascend stairs	1.05 ± 0.56	0.85 ± 0.34	0.55 ± 0.34	0.53 ± 0.59	0.37 ± 0.46	0.51 ± 0.78	0.00 ± 0.00
Stairs - Descend stairs	1.40 ± 0.86	1.04 ± 0.77	0.76 ± 0.58	0.59 ± 0.54	0.83 ± 1.24	0.67 ± 0.83	0.00 ± 0.00
Standing	0.91 ± 0.26	0.90 ± 0.29	0.82 ± 0.28	0.82 ± 0.40	0.89 ± 0.54	1.11 ± 0.67	2.58 ± 1.32
Walking - Treadmill 2mph - Treadmill 0	0.87 ± 0.73	0.74 ± 0.89	0.92 ± 1.55	0.61 ± 0.42	0.72 ± 0.97	1.66 ± 1.80	1.62 ± 1.93
Walking - Treadmill 3mph - Treadmill 0	1.21 ± 0.61	1.43 ± 0.79	1.28 ± 0.84	1.31 ± 1.06	1.55 ± 1.56	1.91 ± 1.17	3.04 ± 1.99
Walking - Treadmill 3mph - Treadmill 3 - light	1.00 ± 0.58	1.20 ± 0.50	1.23 ± 0.70	1.34 ± 1.17	1.68 ± 1.26	1.71 ± 1.65	2.86 ± 2.48
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.02 ± 0.49	1.05 ± 0.62	1.08 ± 0.62	1.03 ± 0.65	1.32 ± 1.45	1.82 ± 1.77	3.05 ± 2.29
Walking - Treadmill 3mph - Treadmill 9 - hard	1.12 ± 1.03	0.73 ± 0.39	1.06 ± 0.76	0.94 ± 0.96	0.90 ± 0.78	1.91 ± 1.32	1.95 ± 1.78
kneeling	0.87 ± 0.24	0.88 ± 0.36	0.81 ± 0.34	0.70 ± 0.35	0.84 ± 0.53	1.23 ± 0.72	2.17 ± 1.32
unknown	27.80 ± 4.75	27.03 ± 4.00	24.11 ± 5.33	22.04 ± 6.30	18.79 ± 5.48	14.61 ± 6.51	10.17 ± 4.50
Carrying groceries	1.26 ± 0.62	1.19 ± 0.97	1.43 ± 1.20	1.50 ± 2.15	0.87 ± 1.14	1.98 ± 1.88	2.29 ± 1.63
Doing dishes	1.53 ± 0.40	1.48 ± 0.45	1.17 ± 0.52	1.17 ± 0.68	1.06 ± 0.72	0.98 ± 0.91	1.29 ± 1.40
Gardening	0.86 ± 0.38	0.78 ± 0.40	0.72 ± 0.44	0.63 ± 0.43	0.92 ± 0.60	1.12 ± 1.38	2.55 ± 1.56
Ironing	1.40 ± 0.48	1.34 ± 0.50	1.33 ± 0.62	1.15 ± 0.70	1.24 ± 0.64	1.42 ± 1.32	1.88 ± 0.96
Making the bed	1.60 ± 0.66	1.49 ± 0.60	1.27 ± 0.77	1.04 ± 0.79	0.87 ± 0.73	0.41 ± 0.36	1.41 ± 1.44
Mopping	1.13 ± 0.46	1.19 ± 0.70	1.57 ± 1.47	0.86 ± 0.48	0.96 ± 0.44	0.70 ± 0.68	1.31 ± 0.94
Playing videogames	1.37 ± 0.56	1.32 ± 0.58	1.38 ± 0.67	1.51 ± 0.67	1.64 ± 0.83	2.05 ± 1.07	2.51 ± 2.33
Scrubbing a surface	0.94 ± 0.47	0.94 ± 0.44	0.95 ± 0.58	0.85 ± 0.52	1.21 ± 1.03	1.43 ± 0.79	2.39 ± 2.41
Stacking groceries	1.12 ± 0.42	0.96 ± 0.37	0.90 ± 0.34	0.94 ± 0.63	0.59 ± 0.45	1.18 ± 0.85	2.37 ± 0.51
Sweeping	1.05 ± 0.37	1.04 ± 0.40	0.94 ± 0.38	0.88 ± 0.50	0.96 ± 0.61	0.89 ± 0.66	1.67 ± 1.68
Typing	0.95 ± 0.43	0.86 ± 0.40	0.87 ± 0.61	0.90 ± 0.67	1.34 ± 0.92	1.12 ± 0.98	2.65 ± 2.49
Vacuuming	0.95 ± 0.31	0.89 ± 0.29	0.86 ± 0.31	0.77 ± 0.38	0.79 ± 0.48	1.54 ± 1.07	1.22 ± 1.10
Walking around block	1.72 ± 0.77	1.87 ± 1.29	1.74 ± 1.32	1.71 ± 1.11	1.63 ± 1.42	1.60 ± 1.23	1.48 ± 1.81
Washing windows	0.96 ± 0.40	1.02 ± 0.45	0.92 ± 0.47	1.01 ± 0.75	1.12 ± 0.66	1.13 ± 0.77	1.06 ± 0.91
Watching TV	1.55 ± 0.37	1.46 ± 0.35	1.41 ± 0.53	1.59 ± 0.54	1.68 ± 0.74	1.56 ± 1.09	2.82 ± 1.61
Weeding	0.67 ± 0.22	0.63 ± 0.22	0.63 ± 0.29	0.69 ± 0.37	0.78 ± 0.56	0.95 ± 0.50	1.72 ± 1.26
Wiping/Dusting	1.16 ± 0.50	1.14 ± 0.49	1.04 ± 0.53	1.10 ± 0.73	0.72 ± 0.66	1.24 ± 0.95	1.77 ± 1.43
Writing	0.78 ± 0.38	0.70 ± 0.46	0.62 ± 0.41	0.79 ± 0.55	0.74 ± 0.52	1.00 ± 0.75	1.05 ± 1.23
taking out trash	0.96 ± 0.42	0.96 ± 0.32	0.96 ± 0.41	0.88 ± 0.49	0.66 ± 0.41	1.23 ± 0.75	0.72 ± 1.16

Table A5-11: False positive rate when training the C4.5 classifier using the *FFTCorr* feature and subject independent evaluation

	F-Measure						
Class	1.4s	2.8s	5.6s	11.3s	22.7s	44.5s	90s
Bench weight lifting - hard	5.26 ± 9.21	3.24 ± 4.89	3.78 ± 5.85	4.48 ± 10.49	4.78 ± 15.87	8.33 ± 20.41	0.00 ± 0.00
Bench weight lifting - light	14.84 ± 13.74	16.47 ± 16.85	15.19 ± 18.11	17.50 ± 20.92	13.86 ± 17.78	21.58 ± 25.79	25.00 ± 46.29
Bench weight lifting - moderate	9.48 ± 10.07	8.40 ± 10.20	7.82 ± 10.41	14.94 ± 16.67	8.95 ± 20.21	15.83 ± 24.58	20.00 ± 27.39
Bicep curls - hard	11.65 ± 15.04	14.83 ± 18.13	10.30 ± 15.29	34.56 ± 24.33	37.19 ± 33.83	43.10 ± 42.17	17.78 ± 28.80
Bicep curls - light	19.14 ± 20.86	21.96 ± 20.14	27.31 ± 20.99	32.49 ± 21.18	50.85 ± 33.34	56.30 ± 46.80	36.00 ± 40.99
Bicep curls - moderate	10.45 ± 13.54	15.70 ± 19.13	20.81 ± 20.30	17.09 ± 17.02	38.57 ± 28.61	71.39 ± 19.68	32.38 ± 33.40
Calisthenics - Crunches	11.67 ± 23.95	10.55 ± 23.91	14.11 ± 27.55	26.61 ± 40.31	26.27 ± 36.76	11.67 ± 24.91	0.00 ± 0.00
Calisthenics - Sit ups	40.68 ± 42.28	39.74 ± 44.63	58.82 ± 41.34	57.68 ± 40.96	67.80 ± 35.72	72.78 ± 35.20	53.33 ± 50.55
Cycling - Cycle hard - Cycle 80rpm	12.45 ± 14.01	9.00 ± 9.42	13.70 ± 18.82	9.70 ± 16.82	15.87 ± 19.24	19.68 ± 26.58	12.50 ± 25.00
Cycling - Cycle light - Cycle 100rpm	56.02 ± 30.53	62.70 ± 34.30	63.65 ± 35.07	74.60 ± 33.44	73.26 ± 39.19	87.80 ± 26.14	93.33 ± 17.73
Cycling - Cycle light - Cycle 60rpm	44.21 ± 22.25	55.05 ± 32.71	58.53 ± 31.95	59.50 ± 32.72	62.72 ± 30.57	71.81 ± 31.23	70.21 ± 29.45
Cycling - Cycle light - Cycle 80rpm	27.93 ± 18.54	35.06 ± 23.50	38.91 ± 30.65	32.36 ± 20.64	55.16 ± 24.31	63.06 ± 24.04	39.67 ± 41.35
Cycling - Cycle moderate - Cycle 80rpm	13.51 ± 12.41	11.74 ± 11.40	22.07 ± 19.81	20.34 ± 19.04	17.75 ± 21.76	38.60 ± 31.09	30.30 ± 37.13
Lying down	49.28 ± 12.27	63.57 ± 10.21	67.33 ± 18.95	71.65 ± 13.25	68.98 ± 16.62	77.14 ± 16.59	85.08 ± 11.97
Rowing - Rowing hard - Rowing 30spm	14.89 ± 13.28	15.52 ± 16.24	21.38 ± 24.54	8.31 ± 10.49	13.54 ± 21.82	38.33 ± 26.31	37.50 ± 47.87
Rowing - Rowing light - Rowing 30spm	21.08 ± 13.74	21.46 ± 18.60	22.95 ± 20.93	42.58 ± 21.45	26.95 ± 25.37	48.51 ± 33.67	29.26 ± 35.50
Rowing - Rowing moderate - Rowing 30spm	18.22 ± 13.47	17.07 ± 16.44	18.19 ± 16.19	20.76 ± 22.43	17.57 ± 25.25	14.72 ± 26.77	29.17 ± 31.81
Running - Treadmill 4mph - Treadmill 0	26.30 ± 23.28	28.56 ± 29.77	28.85 ± 26.52	32.09 ± 31.30	41.69 ± 38.01	30.07 ± 37.14	43.50 ± 43.81
Running - Treadmill 5mph - Treadmill 0	35.27 ± 26.26	38.79 ± 26.44	35.43 ± 28.82	36.64 ± 26.62	38.37 ± 36.24	47.97 ± 34.18	64.00 ± 39.40
Running - Treadmill 6mph - Treadmill 0	25.51 ± 21.02	27.23 ± 25.98	39.38 ± 27.49	44.56 ± 34.19	30.25 ± 29.91	42.53 ± 37.20	60.00 ± 36.51
Sitting	6.35 ± 5.86	4.15 ± 4.50	6.38 ± 7.54	6.98 ± 10.02	14.25 ± 19.43	16.24 ± 26.18	41.67 ± 46.65
Sitting - Fidget feet legs	34.75 ± 29.29	37.59 ± 31.36	35.60 ± 30.93	40.85 ± 35.50	53.32 ± 36.59	67.69 ± 35.55	66.67 ± 50.00
Sitting - Fidget hands arms	14.09 ± 15.73	16.83 ± 17.77	19.86 ± 18.69	23.08 ± 26.86	10.86 ± 18.78	48.57 ± 35.61	57.14 ± 44.99
Stairs - Ascend stairs	36.55 ± 23.17	38.96 ± 25.34	50.05 ± 31.73	50.03 ± 35.55	60.24 ± 34.55	75.77 ± 21.33	0.00 ± 0.00
Stairs - Descend stairs	24.96 ± 18.25	31.08 ± 24.03	42.66 ± 29.01	35.63 ± 32.42	44.21 ± 40.89	53.03 ± 33.60	0.00 ± 0.00
Standing	6.75 ± 5.06	8.52 ± 7.62	12.01 ± 11.24	18.55 ± 15.56	17.09 ± 17.51	17.00 ± 29.26	13.33 ± 29.81
Walking - Treadmill 2mph - Treadmill 0	37.46 ± 23.50	42.21 ± 23.93	42.06 ± 31.50	48.48 ± 32.21	49.18 ± 31.87	48.87 ± 34.18	76.96 ± 17.77
Walking - Treadmill 3mph - Treadmill 0	15.67 ± 10.78	15.16 ± 11.38	17.84 ± 13.07	18.08 ± 15.62	20.02 ± 21.80	11.23 ± 17.50	26.55 ± 25.25
Walking - Treadmill 3mph - Treadmill 3 - light	10.65 ± 8.07	12.12 ± 7.04	14.97 ± 11.45	14.05 ± 14.23	19.73 ± 15.95	16.62 ± 19.89	26.19 ± 34.36
Walking - Treadmill 3mph - Treadmill 6 - moderate	10.44 ± 8.72	9.52 ± 8.96	11.41 ± 11.27	8.43 ± 11.71	10.95 ± 16.82	15.54 ± 24.26	25.93 ± 26.50
Walking - Treadmill 3mph - Treadmill 9 - hard	14.27 ± 12.78	14.94 ± 14.39	9.30 ± 10.95	16.10 ± 14.75	20.82 ± 23.42	18.96 ± 28.98	17.78 ± 32.33
kneeling	8.06 ± 5.36	8.93 ± 8.70	15.59 ± 15.96	13.96 ± 16.48	15.57 ± 18.00	12.78 ± 18.67	25.76 ± 37.54
unknown	48.31 ± 7.29	50.37 ± 7.72	53.66 ± 7.62	56.70 ± 8.43	59.62 ± 8.81	60.08 ± 11.10	59.22 ± 16.11
Carrying groceries	22.07 ± 18.11	26.78 ± 21.89	24.92 ± 20.69	29.16 ± 27.64	35.48 ± 32.00	23.31 ± 25.34	42.41 ± 35.47
Doing dishes	16.18 ± 9.78	19.66 ± 14.09	23.80 ± 16.75	29.36 ± 21.96	36.33 ± 27.18	43.46 ± 31.97	60.48 ± 35.56
Gardening	11.76 ± 13.94	13.06 ± 15.33	17.60 ± 20.37	20.45 ± 25.44	27.82 ± 32.44	27.89 ± 38.22	20.91 ± 33.00
Ironing	17.95 ± 11.12	23.46 ± 13.49	28.46 ± 16.78	28.87 ± 22.93	29.31 ± 22.34	31.28 ± 28.48	44.76 ± 33.04
Making the bed	15.05 ± 9.71	17.35 ± 11.50	25.28 ± 18.05	33.12 ± 22.52	45.81 ± 25.87	64.39 ± 28.38	53.81 ± 33.61
Mopping	15.23 ± 13.38	16.87 ± 13.90	17.00 ± 15.82	21.98 ± 21.09	23.32 ± 22.56	38.14 ± 25.03	44.44 ± 36.00
Playing videogames	16.55 ± 11.11	17.86 ± 12.70	15.73 ± 12.30	15.79 ± 16.52	13.00 ± 13.31	18.47 ± 22.26	32.38 ± 31.34
Scrubbing a surface	10.02 ± 9.48	11.55 ± 10.93	14.39 ± 15.05	16.72 ± 17.86	18.75 ± 22.80	24.04 ± 26.30	35.67 ± 41.93
Stacking groceries	9.10 ± 9.00	12.22 ± 11.82	15.26 ± 15.84	17.73 ± 19.19	24.90 ± 24.60	32.86 ± 33.23	0.00 ± 0.00
Sweeping	9.01 ± 8.61	11.50 ± 10.69	14.47 ± 14.95	19.69 ± 17.77	20.80 ± 19.02	30.25 ± 25.98	34.72 ± 45.20
Typing	39.82 ± 19.47	43.68 ± 22.16	42.25 ± 22.76	41.80 ± 25.67	28.31 ± 23.48	33.84 ± 23.70	29.49 ± 40.91
Vacuuming	14.27 ± 12.27	15.19 ± 13.27	16.03 ± 15.12	18.52 ± 17.82	25.93 ± 23.01	20.95 ± 24.44	30.56 ± 41.34
Walking around block	15.89 ± 12.33	15.22 ± 12.67	15.80 ± 17.86	22.49 ± 20.77	23.37 ± 23.98	22.76 ± 28.40	63.33 ± 38.26
Washing windows	14.70 ± 11.49	15.41 ± 12.91	23.60 ± 19.90	23.95 ± 19.08	25.35 ± 20.46	33.95 ± 30.83	46.43 ± 39.86
Watching TV	9.09 ± 5.71	10.97 ± 7.39	15.43 ± 9.96	15.99 ± 10.41	11.68 ± 12.63	12.87 ± 15.37	29.17 ± 28.97
Weeding	3.75 ± 4.41	3.72 ± 4.72	4.72 ± 7.62	5.01 ± 8.06	6.67 ± 10.76	8.35 ± 15.70	37.62 ± 36.25
Wiping/Dusting	11.64 ± 8.40	12.64 ± 8.72	18.17 ± 15.22	22.24 ± 16.89	35.98 ± 28.59	44.31 ± 26.72	51.86 ± 37.37
Writing	45.29 ± 25.82	49.81 ± 29.15	52.07 ± 30.12	46.78 ± 32.37	56.42 ± 32.71	48.89 ± 30.76	47.71 ± 37.86
taking out trash	5.52 ± 4.85	6.96 ± 6.53	6.27 ± 7.11	9.35 ± 11.55	14.58 ± 19.15	20.94 ± 26.24	50.00 ± 45.13

Table A5-12: F-Measure when training the C4.5 classifier using the *FFTCorr* feature and subject independent evaluation

Appendix A6: Feature Selection for Activity Recognition

Features subsets (Number of features)	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
ACFFT Peaks (70)	41.59 ± 4.31	27.19±19.59 (0.82±0.47)	28.19±22.73 (0.97±0.69)	28.16±24.28 (0.60±0.56)	20.11±18.42 (0.82±0.64)	19.77±16.57 (1.05±0.59)
ACAbsMean	38.14 ± 4.95	23.3±15.0 (0.8±0.4)	26.4±24.5 (1.1±1.0)	21.4±23.7 (0.7±0.7)	14.2±17.8 (0.8±0.7)	16.8±15.0 (1.0±0.6)
ACIQR (7)	37.92 ± 4.46	21.86±13.79 (0.88±0.49)	25.52±20.29 (1.13±0.86)	26.16±25.03 (0.69±0.66)	16.19±17.98 (0.89±0.75)	15.36±13.75 (1.05±0.61)
ACQ3 (7)	37.01 ± 4.47	20.13±12.54 (0.85±0.46)	24.08±19.07 (1.10±0.78)	22.59±22.73 (0.63±0.56)	13.84±16.16 (0.86±0.64)	14.24±12.58 (1.09±0.59)
ACAbsArea(7)	36.82 ± 5.51	21.19±15.12 (0.87±0.51)	26.48±22.65 (1.09±0.95)	22.80±24.12 (0.64±0.69)	14.96±17.99 (0.79±0.70)	16.62±14.49 (1.11±0.65)
ACFFTCoeff (889)	36.76 ± 3.78	23.15±14.79 (0.93±0.41)	24.25±18.60 (1.09±0.67)	25.45±21.07 (0.67±0.49)	17.88±16.13 (0.89±0.60)	14.24±11.90 (1.18±0.52)
ACVar (7)	34.81 ± 4.49	18.64±3.40 (2.20±0.78)	25.84±23.77 (1.07±1.02)	20.80±24.37 (0.62±0.60)	15.61±19.44 (0.78±0.76)	9.97±10.01 (0.72±0.52)
ACPitch (7)	34.79 ± 6.91	7.00±9.76 (0.30±0.20)	18.42±16.88 (1.19±0.84)	21.65±16.70 (0.71±0.62)	13.45±11.48 (0.84±0.56)	2.64±3.16 (0.37±0.22)
ACBandEnergy (7)	34.19 ± 4.55	18.47±5.62 (1.00±0.46)	20.60±17.14 (1.22±0.72)	16.93±16.53 (0.71±0.54)	9.00±10.20 (0.87±0.52)	7.84±7.66 (0.88±0.45)
ACSF (5)	34.14 ± 4.61	20.50±14.35 (0.86±0.53)	24.90±22.44 (1.10±0.93)	18.98±20.63 (0.78±0.77)	12.90±15.44 (0.89±0.73)	13.22±12.16 (1.10±0.61)
ACRange(7)	32.94 ± 3.43	20.55±12.28 (0.92±0.51)	18.67±17.41 (1.19±0.90)	18.28±18.85 (0.70±0.54)	12.57±13.88 (0.92±0.63)	13.51±11.77 (1.06±0.53)
ACTotalAbsArea (1)	32.48 ± 6.73	14.24±5.03 (0.73±0.39)	22.33±13.86 (1.25±0.63)	11.07±6.51 (0.52±0.31)	2.87±2.97 (0.69±0.28)	2.79±2.95 (0.41±0.24)
ACTotalSF (1)	32.46 ± 7.82	13.50±4.63 (1.05±0.54)	20.63±16.16 (1.24±0.73)	10.19±7.43 (0.41±0.24)	3.46±3.36 (0.60±0.30)	1.00±1.16 (0.25±0.17)
ACMCR (7)	31.75 ± 3.32	22.75±11.23 (1.24±0.45)	11.61±11.32 (1.32±0.78)	14.89±14.55 (0.79±0.54)	9.64±10.66 (0.96±0.49)	10.90±10.48 (0.96±0.47)
ACLowEnergy (7)	31.0 ± 5.6	12.80±8.43 (1.63±0.70)	15.7±12.5 (1.3±0.7)	14.4±11.4 (0.7±0.5)	9.1±8.7 (0.7±0.4)	1.6±2.2 (0.4±0.2)
ACModVigEnergy (7)	30.80 ± 4.88	9.69±8.16 (1.25±0.52)	20.88±17.01 (1.22±0.73)	20.81±15.18 (0.74±0.50)	12.12±10.63 (0.90±0.52)	3.13±3.50 (0.79±0.32)
DCTotalMean	29.25 ± 7.54	4.7±5.4 (0.8±1.0)	2.4±4.2 (0.5±0.5)	1.6±2.5 (0.5±0.3)	0.9±1.7 (0.4±0.2)	0.0±0.0 (0.2±0.2)
ACDomFreqRatio (7)	28.87 ± 4.65	13.67±4.97 (1.06±0.46)	11.49±11.29 (1.33±0.69)	10.16±9.02 (0.84±0.45)	6.20±6.08 (0.91±0.38)	5.13±5.43 (0.87±0.38)
DCPostureDist	28.38 ± 5.48	33.0±22.0 (0.4±0.5)	18.7±25.0 (1.0±1.1)	18.8±27.2 (0.8±1.1)	14.8±23.6 (0.9±1.2)	15.0±19.3 (1.2±1.3)
ACEnergy (7)	27.99 ± 4.93	7.75±8.02 (1.25±0.51)	19.95±18.78 (1.21±0.96)	14.54±13.89 (0.84±0.53)	9.11±10.62 (0.97±0.57)	3.59±4.19 (0.82±0.44)
ACEntropy (7)	27.89 ± 6.98	11.44±4.42 (1.41±0.68)	14.52±13.71 (1.28±0.77)	6.61±6.72 (0.63±0.36)	3.80±4.66 (0.75±0.39)	1.78±2.25 (0.51±0.29)
ACAbsCV (7)	27.56 ± 2.96	13.83±7.57 (1.07±0.44)	14.03±13.76 (1.24±0.74)	14.28±16.91 (0.86±0.59)	10.22±11.93 (1.01±0.64)	9.64±8.27 (1.16±0.47)
ACFWTCoeff ()	26.61 ± 3.47	17.10±10.08 (1.08±0.44)	14.86±11.00 (1.31±0.50)	16.68±14.38 (0.87±0.42)	11.59±10.36 (1.07±0.46)	6.94±5.87 (1.35±0.42)
DCMean (7)	24.69 ± 6.81	14.41±15.85 (0.66±1.14)	8.60±15.94 (0.94±1.22)	12.80±21.77 (0.79±1.01)	7.40±14.17 (0.94±1.28)	7.04±11.37 (1.26±1.52)
DCArea (7)	24.53 ± 6.63	12.23±16.16 (0.57±0.78)	8.87±17.00 (0.99±1.42)	12.52±21.85 (0.86±1.11)	7.75±14.77 (0.90±1.10)	7.72±13.16 (1.22±1.38)
ACCorr (21)	24.11 ± 4.29	9.19±4.11 (1.35±0.56)	14.02±17.11 (0.94±0.83)	11.90±16.34 (0.75±0.74)	10.47±13.85 (0.82±0.75)	6.98±7.09 (1.36±0.60)
ACKur (7)	21.81 ± 3.36	9.74±4.54 (1.31±0.46)	7.92±8.37 (1.29±0.57)	7.25±10.05 (1.03±0.51)	5.82±7.91 (1.09±0.52)	5.57±5.08 (1.12±0.39)
ACSkew (7)	17.15 ± 2.47	6.50±3.91 (1.42±0.40)	9.18±10.83 (1.26±0.67)	4.86±6.65 (1.09±0.40)	3.97±5.28 (1.15±0.42)	2.79±3.28 (1.14±0.37)

Table A6-1: True positive rate per activity category while evaluating different subsets of features using the C4.5 decision tree classifier using a sliding window of 5.6s and evaluating the results in a subject independent manner. False positive rate is shown in parenthesis.

Features subsets (Number of features)	All Activities	Postures	Ambulation	Exercise	Resistance Exercise	Household
ACEnergy, ACEntropy	26.01 ± 3.95	10.43±8.60 (1.33±0.67)	19.26±20.19 (1.23±0.98)	14.13±14.28 (0.85±0.54)	9.78±11.78 (0.98±0.59)	5.03±5.29 (1.10±0.52)
ACIQR, ACQ1, ACQ2,ACQ3	36.51 ± 4.41	22.13±13.16 (0.93±0.48)	25.23±21.83 (1.09±0.83)	23.64±23.07 (0.66±0.56)	15.56±16.49 (0.88±0.67)	15.62±13.66 (1.18±0.65)
ACAbsArea, ACArea, ACVar	39.87 ± 6.44	40.46±31.35 (0.48±0.62)	20.81±22.99 (1.13±1.21)	22.16±26.84 (0.70±0.82)	15.95±21.81 (0.95±1.08)	19.20±21.03 (0.97±0.91)
ACAbsArea, ACArea	40.14 ± 5.95	39.78±31.23 (0.49±0.60)	22.48±24.87 (1.02±1.14)	24.56±29.00 (0.70±0.83)	16.39±23.79 (0.91±1.04)	18.70±20.97 (0.92±0.84)
ACAbsArea, ACVar, ACLowEnergy, AC Range, ACMCR	40.40 ± 4.57	23.40±17.36 (0.82±0.43)	28.80±24.20 (0.98±0.88)	25.70±25.13 (0.67±0.66)	18.36±19.97 (0.85±0.74)	19.90±17.28 (1.04±0.57)
ACAbsArea, ACArea, ACVar, ACRange, ACMCR, ACIQR	41.00 ± 6.01	40.26±33.45 (0.53±0.74)	24.53±25.78 (0.91±0.85)	24.72±27.86 (0.66±0.77)	17.93±23.98 (0.81±0.84)	20.73±22.07 (0.92±0.73)
ACFFTPeaks, ACCorr	41.23 ± 5.04	25.60±17.39 (0.84±0.46)	28.56±23.79 (1.02±0.84)	27.54±25.82 (0.60±0.58)	20.01±20.92 (0.79±0.63)	20.26±16.85 (1.10±0.63)
ACAbsArea, ACArea, ACVar, ACRange, ACMCR	41.69 ± 6.58	41.55±33.26 (0.45±0.60)	24.44±24.35 (0.97±0.99)	23.66±28.15 (0.70±0.76)	16.89±22.20 (0.89±0.90)	21.78±23.35 (0.94±0.80)
ACVar, ACEnergy, ACEntropy, ACFFTPeaks, ACCorr	41.70 ± 4.74	26.65±19.30 (0.82±0.43)	30.71±23.68 (0.98±0.95)	26.29±25.13 (0.59±0.61)	18.96±20.44 (0.73±0.63)	20.63±16.92 (1.05±0.57)
ACVar, ACEnergy, ACEntropy, ACFFTPeaks	41.73 ± 4.19	27.52±19.16 (0.79±0.42)	30.48±22.91 (0.97±0.68)	28.50±23.22 (0.62±0.55)	20.44±19.05 (0.82±0.61)	20.38±16.31 (1.06±0.56)
ACVar, ACFFTPeaks	41.82 ± 4.22	27.19±19.46 (0.79±0.43)	29.04±23.39 (1.00±0.75)	27.94±24.71 (0.60±0.56)	19.44±19.00 (0.81±0.66)	19.96±16.20 (1.06±0.59)
ACVar,AC FFTPeaks, ACBandEnergy	41.83 ± 4.35	27.52±20.01 (0.78±0.41)	29.86±23.93 (1.01±0.74)	27.85±24.39 (0.63±0.59)	19.72±18.40 (0.84±0.67)	20.08±16.16 (1.04±0.57)
ACVar, ACBandEnergy, ACEntropy, ACFFTPeaks, ACCorr	41.82 ± 5.28	27.06±17.97 (0.83±0.42)	30.40±24.72 (0.96±0.83)	28.61±26.69 (0.63±0.64)	20.13±21.35 (0.77±0.69)	20.96±17.09 (1.07±0.61)
ACVar, ACEntropy, ACBandEnergy, ACFFTPeaks	42.14 ± 4.16	28.19±19.51 (0.77±0.42)	30.70±23.61 (0.98±0.68)	28.05±23.92 (0.61±0.55)	20.29±19.75 (0.82±0.63)	20.96±17.10 (1.05±0.58)
ACFFTPeaks, ACVar, ACIQR	42.21 ± 4.74	27.66±19.14 (0.76±0.42)	27.65±23.94 (1.02±0.78)	27.53±25.45 (0.65±0.61)	20.53±19.99 (0.86±0.65)	21.08±17.80 (1.01±0.51)
ACVar, ACFFTPeaks, ACBandEnergy, ACIQR	42.30 ± 4.18	27.38±18.33 (0.80±0.41)	28.96±23.36 (1.02±0.79)	26.85±24.63 (0.63±0.61)	19.79±19.26 (0.84±0.65)	21.00±17.39 (1.01±0.52)
ACAbsArea, ACArea, ACVar, ACRange, ACPitch,	42.85 ± 6.56	39.20±31.82 (0.46±0.58)	24.25±24.83 (0.99±1.04)	26.57±29.94 (0.69±0.76)	19.38±24.79 (0.86±0.90)	20.58±22.33 (0.93±0.79)
ACAbsArea ,ACArea, ACVar, ACEnergy, ACEntropy, ACFFT Peaks,ACCorr, ACRange, ACMCR, ACPitch	42.94 ± 5.61	38.92±31.03 (0.48±0.64)	25.23±24.47 (0.92±0.88)	26.91±28.63 (0.63±0.71)	19.26±22.89 (0.84±0.83)	21.43±22.06 (0.94±0.75)
All features but heart rate based and subject characteristics	43.12 ± 6.70	44.56±34.74 (0.45±0.50)	27.98±25.55 (0.96±1.04)	26.71±28.78 (0.62±0.73)	18.72±23.77 (0.85±0.93)	21.36±21.81 (1.00±0.92)
ACAbsArea, ACArea, ACBandEnergy, ACFFTPeaks, ACVar	44.24 ± 6.88	44.54±34.18 (0.48±0.60)	26.44±26.37 (1.02±1.08)	28.79±30.93 (0.69±0.76)	21.39±25.62 (0.90±0.99)	23.38±22.85 (0.93±0.82)
ACAbsArea, ACArea, ACVar, ACRange, ACEnergy, ACEntropy, ACFFTPeaks, ACCorr	44.39 ± 6.58	44.66±35.12 (0.52±0.59)	28.58±26.63 (0.93±0.94)	27.85±28.62 (0.61±0.67)	19.84±22.67 (0.78±0.77)	22.79±22.78 (0.94±0.80)
ACAbsArea, ACArea, ACFFTPeaks	44.49 ± 6.56	44.08±34.00 (0.51±0.65)	27.36±27.06 (0.98±0.91)	27.79±29.10 (0.64±0.71)	21.18±24.90 (0.85±0.89)	22.95±22.67 (0.92±0.79)
ACAbsArea, ACArea, ACVar, ACEntropy, ACFFTPeaks, ACBandEnergy,	44.65 ± 6.84	45.82±34.22 (0.47±0.58)	28.17±25.93 (0.96±1.02)	28.23±29.25 (0.66±0.73)	21.22±24.32 (0.86±0.89)	23.07±22.18 (0.90±0.75)
ACAbsArea, ACArea, ACVar, ACFFTPeaks, ACCorr, ACRange, ACMCR, ACPitch,	44.72 ± 6.82	44.85±32.86 (0.47±0.60)	29.89±26.52 (0.96±0.80)	30.60±28.91 (0.63±0.70)	20.38±23.76 (0.86±0.86)	22.33±22.47 (0.99±0.84)
All Features but heart rate based	44.82 ± 6.16	42.96±35.25 (0.44±0.59)	29.07±25.78 (0.95±1.03)	27.40±30.12 (0.59±0.70)	20.08±25.04 (0.82±0.88)	23.83±22.75 (0.92±0.73)

Table A6-2: True positive rate per activity category while evaluating different subsets of features using the C4.5 decision tree classifier, a sliding window of 5.6s and subject independent training. False positive rate is shown in parenthesis.

	True Positive Rate				
Activity	**AllButHR**	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	87.4 ± 8.5	89.5 ± 7.6	91.1 ± 5.6	85.4 ± 11.4	88.7 ± 10.1
Bench weight lifting - light	91.1 ± 8.8	90.7 ± 11.8	92.0 ± 10.1	91.5 ± 11.3	93.2 ± 10.4
Bench weight lifting - moderate	87.9 ± 17.4	91.1 ± 9.9	88.4 ± 12.5	89.5 ± 12.9	88.2 ± 17.1
Bicep curls - hard	92.4 ± 7.1	91.4 ± 8.5	91.5 ± 7.4	90.4 ± 6.8	92.2 ± 6.8
Bicep curls - light	94.5 ± 6.5	94.6 ± 3.6	94.0 ± 2.9	94.4 ± 5.3	95.1 ± 4.4
Bicep curls - moderate	85.0 ± 11.1	91.5 ± 4.9	92.1 ± 5.5	86.9 ± 9.9	90.5 ± 6.0
Calisthenics - Crunches	95.0 ± 2.4	92.0 ± 5.8	90.9 ± 8.1	94.0 ± 6.4	96.5 ± 3.2
Calisthenics - Sit ups	91.4 ± 2.9	93.1 ± 4.3	92.8 ± 4.2	90.0 ± 4.9	91.2 ± 5.3
Cycling - Cycle hard - Cycle 80rpm	80.8 ± 22.5	76.9 ± 21.7	79.6 ± 22.4	83.1 ± 15.7	79.6 ± 22.0
Cycling - Cycle light - Cycle 100rpm	94.1 ± 8.1	93.7 ± 7.6	92.7 ± 11.8	91.9 ± 16.1	93.3 ± 12.0
Cycling - Cycle light - Cycle 60rpm	89.9 ± 6.8	90.4 ± 6.8	91.9 ± 6.8	89.6 ± 6.8	91.6 ± 7.8
Cycling - Cycle light - Cycle 80rpm	90.4 ± 7.3	91.0 ± 9.3	91.5 ± 5.4	91.2 ± 9.4	88.3 ± 12.4
Cycling - Cycle moderate - Cycle 80rpm	81.6 ± 10.0	79.6 ± 10.0	81.0 ± 10.2	81.4 ± 8.5	80.6 ± 11.9
Lying down	98.8 ± 1.4	98.8 ± 1.5	98.7 ± 1.6	98.7 ± 1.1	99.0 ± 0.9
Rowing - Rowing hard - Rowing 30spm	77.2 ± 18.4	79.6 ± 16.1	79.5 ± 16.0	76.5 ± 18.7	79.6 ± 13.1
Rowing - Rowing light - Rowing 30spm	83.3 ± 11.2	80.6 ± 11.6	82.5 ± 11.1	83.1 ± 9.5	83.1 ± 9.1
Rowing - Rowing moderate - Rowing 30spm	74.6 ± 16.6	74.1 ± 14.2	76.6 ± 14.6	77.4 ± 13.5	77.1 ± 16.1
Running - Treadmill 4mph - Treadmill 0	91.4 ± 6.0	88.4 ± 8.7	89.4 ± 8.2	91.2 ± 6.3	89.6 ± 7.8
Running - Treadmill 5mph - Treadmill 0	86.8 ± 9.6	87.5 ± 7.6	88.9 ± 6.4	87.6 ± 8.3	86.5 ± 7.9
Running - Treadmill 6mph - Treadmill 0	83.1 ± 11.2	87.4 ± 9.3	86.6 ± 10.2	83.2 ± 9.0	85.6 ± 7.2
Sitting	87.0 ± 7.9	90.9 ± 7.3	91.6 ± 6.1	88.7 ± 7.5	92.5 ± 5.8
Sitting - Fidget feet legs	87.8 ± 7.6	90.0 ± 9.5	90.0 ± 8.6	90.6 ± 10.2	88.2 ± 12.4
Sitting - Fidget hands arms	84.7 ± 11.2	89.2 ± 7.4	89.8 ± 4.2	83.7 ± 13.2	85.8 ± 10.4
Stairs - Ascend stairs	84.2 ± 6.5	80.3 ± 10.1	82.9 ± 7.4	86.9 ± 7.6	84.5 ± 8.4
Stairs - Descend stairs	80.6 ± 8.2	78.2 ± 11.0	77.4 ± 8.2	78.8 ± 9.2	76.4 ± 13.8
Standing	85.1 ± 8.0	87.2 ± 10.9	87.3 ± 10.1	82.5 ± 10.2	82.0 ± 11.2
Walking - Treadmill 2mph - Treadmill 0	88.1 ± 5.2	88.6 ± 4.8	89.7 ± 4.6	90.5 ± 4.4	89.7 ± 4.1
Walking - Treadmill 3mph - Treadmill 0	78.0 ± 7.8	77.0 ± 8.8	73.3 ± 11.0	75.4 ± 10.4	74.4 ± 10.0
Walking - Treadmill 3mph - Treadmill 3 - light	70.8 ± 12.4	67.4 ± 13.2	65.5 ± 11.6	68.6 ± 13.8	65.4 ± 13.5
Walking - Treadmill 3mph - Treadmill 6 - moderate	69.8 ± 14.1	70.8 ± 15.8	71.2 ± 11.0	69.3 ± 15.3	70.1 ± 11.4
Walking - Treadmill 3mph - Treadmill 9 - hard	80.2 ± 11.0	81.2 ± 10.4	78.9 ± 10.8	77.6 ± 11.4	80.4 ± 9.9
kneeling	93.0 ± 7.6	94.7 ± 4.7	94.4 ± 4.8	92.1 ± 6.9	95.2 ± 5.8
unknown	76.8 ± 8.2	77.9 ± 8.2	79.1 ± 8.5	77.0 ± 8.5	76.1 ± 9.2
Carrying groceries	83.8 ± 9.7	84.0 ± 9.4	84.9 ± 9.3	83.4 ± 9.8	82.8 ± 11.9
Doing dishes	77.5 ± 12.2	81.8 ± 10.0	82.3 ± 9.3	76.2 ± 15.2	77.2 ± 15.9
Gardening	74.8 ± 14.5	75.6 ± 19.5	78.6 ± 17.2	73.4 ± 20.6	73.1 ± 21.5
Ironing	77.4 ± 10.2	79.6 ± 9.8	82.2 ± 11.3	77.4 ± 11.8	80.8 ± 8.5
Making the bed	53.3 ± 11.6	57.6 ± 11.7	59.6 ± 11.5	49.8 ± 13.3	54.3 ± 12.3
Mopping	62.3 ± 12.5	65.9 ± 14.1	66.7 ± 14.6	63.0 ± 13.1	59.8 ± 14.5
Playing videogames	93.2 ± 5.7	94.3 ± 4.0	93.1 ± 5.0	93.4 ± 6.2	93.2 ± 5.1
Scrubbing a surface	77.0 ± 17.5	77.8 ± 13.5	79.5 ± 15.4	75.2 ± 14.1	78.2 ± 14.5
Stacking groceries	57.8 ± 13.6	61.3 ± 16.7	63.0 ± 12.8	59.0 ± 10.3	64.8 ± 12.9
Sweeping	54.7 ± 13.2	56.2 ± 11.6	60.5 ± 11.3	53.8 ± 16.7	60.4 ± 13.6
Typing	94.8 ± 3.5	94.1 ± 5.7	95.0 ± 4.3	95.2 ± 3.9	95.0 ± 4.0
Vacuuming	65.2 ± 13.8	67.6 ± 7.4	62.2 ± 10.7	63.1 ± 11.2	63.9 ± 13.9
Walking around block	82.2 ± 7.2	82.0 ± 8.2	82.9 ± 8.2	85.6 ± 7.3	83.5 ± 7.4
Washing windows	60.4 ± 10.4	63.3 ± 13.1	64.9 ± 9.7	59.6 ± 11.5	59.6 ± 8.6
Watching TV	93.0 ± 6.8	92.8 ± 6.5	94.6 ± 4.6	93.1 ± 6.3	93.2 ± 5.6
Weeding	76.6 ± 13.2	75.8 ± 9.6	75.3 ± 7.5	71.5 ± 14.8	71.8 ± 11.5
Wiping/Dusting	54.5 ± 14.9	57.1 ± 15.0	56.5 ± 15.8	56.2 ± 14.4	59.4 ± 15.5
Writing	93.9 ± 4.1	96.5 ± 2.4	96.4 ± 3.3	94.0 ± 5.8	95.7 ± 3.4
taking out trash	44.8 ± 11.3	48.2 ± 13.8	52.3 ± 10.9	44.1 ± 12.0	47.9 ± 11.4

Table A6-3: True positive rate when evaluating the four highest performing feature subsets computed per sensor using the C4.5 classifier in a subject dependent manner.

	False Positive Rate				
Activity	**AllButHR**	**AbsCumSum, CumSum, Var, Range, MCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.2
Bench weight lifting - light	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.0	0.1 ± 0.1	0.1 ± 0.1
Bench weight lifting - moderate	0.2 ± 0.2	0.1 ± 0.1	0.2 ± 0.1	0.2 ± 0.2	0.2 ± 0.2
Bicep curls - hard	0.3 ± 0.2	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Bicep curls - light	0.2 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.1	0.1 ± 0.1
Bicep curls - moderate	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.2
Calisthenics - Crunches	0.1 ± 0.1	0.1 ± 0.1	0.0 ± 0.1	0.1 ± 0.0	0.1 ± 0.1
Calisthenics - Sit ups	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.1	0.1 ± 0.0
Cycling - Cycle hard - Cycle 80rpm	0.2 ± 0.1	0.3 ± 0.2	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Cycling - Cycle light - Cycle 100rpm	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Cycling - Cycle light - Cycle 60rpm	0.2 ± 0.2	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.2
Cycling - Cycle light - Cycle 80rpm	0.2 ± 0.1	0.3 ± 0.2	0.2 ± 0.2	0.3 ± 0.2	0.3 ± 0.2
Cycling - Cycle moderate - Cycle 80rpm	0.2 ± 0.1	0.3 ± 0.2	0.3 ± 0.1	0.3 ± 0.2	0.3 ± 0.2
Lying down	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Rowing - Rowing hard - Rowing 30spm	0.3 ± 0.2	0.4 ± 0.2	0.3 ± 0.2	0.4 ± 0.2	0.4 ± 0.2
Rowing - Rowing light - Rowing 30spm	0.4 ± 0.2	0.3 ± 0.2	0.3 ± 0.2	0.3 ± 0.1	0.3 ± 0.1
Rowing - Rowing moderate - Rowing 30spm	0.4 ± 0.3	0.5 ± 0.3	0.5 ± 0.3	0.4 ± 0.2	0.4 ± 0.2
Running - Treadmill 4mph - Treadmill 0	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.2	0.2 ± 0.1
Running - Treadmill 5mph - Treadmill 0	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Running - Treadmill 6mph - Treadmill 0	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Sitting	0.2 ± 0.2	0.2 ± 0.2	0.1 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Sitting - Fidget feet legs	0.2 ± 0.2	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.2
Sitting - Fidget hands arms	0.3 ± 0.3	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Stairs - Ascend stairs	0.3 ± 0.2	0.4 ± 0.2	0.3 ± 0.2	0.3 ± 0.1	0.3 ± 0.2
Stairs - Descend stairs	0.3 ± 0.2	0.3 ± 0.2	0.3 ± 0.2	0.3 ± 0.2	0.5 ± 0.2
Standing	0.2 ± 0.1	0.2 ± 0.2	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Walking - Treadmill 2mph - Treadmill 0	0.3 ± 0.2	0.3 ± 0.2	0.2 ± 0.2	0.3 ± 0.2	0.2 ± 0.1
Walking - Treadmill 3mph - Treadmill 0	0.5 ± 0.2	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.6 ± 0.3
Walking - Treadmill 3mph - Treadmill 3 - light	0.7 ± 0.2	0.8 ± 0.3	0.9 ± 0.4	0.7 ± 0.3	0.8 ± 0.3
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.6 ± 0.2	0.7 ± 0.3	0.6 ± 0.4	0.7 ± 0.3	0.7 ± 0.3
Walking - Treadmill 3mph - Treadmill 9 - hard	0.4 ± 0.3	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.2
kneeling	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.2	0.2 ± 0.1
unknown	9.0 ± 2.0	8.0 ± 1.8	8.0 ± 1.9	8.6 ± 2.2	8.4 ± 2.1
Carrying groceries	0.3 ± 0.2	0.3 ± 0.2	0.3 ± 0.2	0.3 ± 0.2	0.3 ± 0.2
Doing dishes	0.5 ± 0.3	0.5 ± 0.3	0.4 ± 0.3	0.5 ± 0.4	0.5 ± 0.3
Gardening	0.5 ± 0.4	0.4 ± 0.4	0.4 ± 0.3	0.6 ± 0.3	0.4 ± 0.3
Ironing	0.5 ± 0.2	0.5 ± 0.2	0.4 ± 0.3	0.5 ± 0.3	0.5 ± 0.3
Making the bed	1.1 ± 0.5	1.0 ± 0.4	0.9 ± 0.4	1.0 ± 0.4	1.0 ± 0.4
Mopping	0.8 ± 0.4	0.7 ± 0.4	0.7 ± 0.4	0.9 ± 0.3	0.8 ± 0.5
Playing videogames	0.2 ± 0.2	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.2	0.2 ± 0.2
Scrubbing a surface	0.4 ± 0.2	0.4 ± 0.3	0.4 ± 0.3	0.4 ± 0.3	0.5 ± 0.3
Stacking groceries	0.7 ± 0.5	0.8 ± 0.7	0.5 ± 0.3	0.6 ± 0.4	0.7 ± 0.6
Sweeping	0.8 ± 0.4	0.8 ± 0.4	0.8 ± 0.4	0.8 ± 0.4	0.7 ± 0.3
Typing	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.2
Vacuuming	0.6 ± 0.3	0.6 ± 0.4	0.7 ± 0.4	0.6 ± 0.3	0.7 ± 0.4
Walking around block	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.3	0.4 ± 0.2
Washing windows	0.9 ± 0.4	0.7 ± 0.4	0.7 ± 0.3	0.9 ± 0.4	0.7 ± 0.4
Watching TV	0.3 ± 0.2	0.2 ± 0.1	0.2 ± 0.2	0.2 ± 0.1	0.2 ± 0.1
Weeding	0.6 ± 0.5	0.5 ± 0.3	0.4 ± 0.2	0.5 ± 0.3	0.6 ± 0.4
Wiping/Dusting	0.8 ± 0.4	0.8 ± 0.2	0.8 ± 0.4	0.8 ± 0.4	0.8 ± 0.4
Writing	0.1 ± 0.1	0.2 ± 0.2	0.2 ± 0.2	0.2 ± 0.2	0.2 ± 0.1
taking out trash	0.9 ± 0.2	0.8 ± 0.2	0.8 ± 0.3	1.0 ± 0.4	0.9 ± 0.3

Table A6-4: False positive rate when evaluating the four of the highest performing feature subsets computed per sensor using the C4.5 classifier in a subject dependent manner.

	F-Measure				
Activity	**AllButHR**	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	90.5 ± 7.1	91.0 ± 7.9	90.8 ± 5.6	87.2 ± 10.8	F-Measure
Bench weight lifting - light	90.8 ± 9.1	90.6 ± 10.3	91.7 ± 7.4	90.8 ± 11.2	88.3 ± 9.4
Bench weight lifting - moderate	88.0 ± 13.1	90.1 ± 9.2	86.9 ± 13.0	89.3 ± 11.8	91.9 ± 9.8
Bicep curls - hard	89.2 ± 8.9	90.8 ± 7.5	90.9 ± 5.8	90.1 ± 6.0	85.8 ± 15.4
Bicep curls - light	93.3 ± 5.8	94.4 ± 2.9	93.8 ± 3.1	93.6 ± 4.5	90.8 ± 6.3
Bicep curls - moderate	88.2 ± 8.5	91.3 ± 4.1	91.2 ± 3.7	87.6 ± 7.3	95.1 ± 4.1
Calisthenics - Crunches	93.1 ± 3.4	92.7 ± 4.9	93.3 ± 6.3	94.0 ± 3.8	88.7 ± 6.0
Calisthenics - Sit ups	91.9 ± 3.6	94.0 ± 2.9	94.1 ± 2.5	90.0 ± 5.6	94.2 ± 4.4
Cycling - Cycle hard - Cycle 80rpm	79.9 ± 20.8	76.1 ± 22.7	78.7 ± 21.1	82.1 ± 15.7	91.9 ± 3.9
Cycling - Cycle light - Cycle 100rpm	93.6 ± 6.0	93.6 ± 6.1	92.0 ± 11.2	91.8 ± 11.7	79.0 ± 20.9
Cycling - Cycle light - Cycle 60rpm	89.7 ± 5.9	89.6 ± 5.2	90.5 ± 5.2	88.7 ± 5.9	92.7 ± 9.1
Cycling - Cycle light - Cycle 80rpm	89.1 ± 6.2	88.5 ± 10.0	89.4 ± 6.3	88.4 ± 8.5	89.7 ± 6.9
Cycling - Cycle moderate - Cycle 80rpm	82.6 ± 8.4	79.4 ± 9.9	81.3 ± 9.6	80.8 ± 8.8	86.3 ± 10.0
Lying down	98.3 ± 1.1	98.1 ± 1.6	98.2 ± 1.2	98.1 ± 1.2	80.0 ± 10.2
Rowing - Rowing hard - Rowing 30spm	77.0 ± 18.9	78.2 ± 15.7	79.7 ± 14.0	76.2 ± 19.3	98.3 ± 1.1
Rowing - Rowing light - Rowing 30spm	82.0 ± 10.5	80.9 ± 10.5	82.7 ± 9.6	83.0 ± 8.3	78.3 ± 13.8
Rowing - Rowing moderate - Rowing 30spm	74.0 ± 16.0	73.1 ± 14.0	75.4 ± 13.6	76.2 ± 12.8	83.6 ± 8.0
Running - Treadmill 4mph - Treadmill 0	90.0 ± 4.9	88.4 ± 7.0	88.8 ± 6.6	89.4 ± 5.6	76.0 ± 14.8
Running - Treadmill 5mph - Treadmill 0	86.8 ± 7.3	88.0 ± 5.8	88.6 ± 4.7	87.0 ± 6.8	88.7 ± 6.8
Running - Treadmill 6mph - Treadmill 0	83.6 ± 10.4	85.9 ± 9.0	84.3 ± 11.8	84.3 ± 9.8	86.3 ± 6.3
Sitting	86.8 ± 7.4	90.2 ± 7.8	91.3 ± 5.2	86.8 ± 7.8	86.1 ± 7.4
Sitting - Fidget feet legs	86.8 ± 8.1	90.3 ± 8.3	89.6 ± 7.5	90.9 ± 8.9	88.9 ± 5.4
Sitting - Fidget hands arms	83.0 ± 12.4	88.0 ± 6.4	89.4 ± 6.1	84.0 ± 10.4	88.1 ± 10.4
Stairs - Ascend stairs	82.5 ± 6.8	79.1 ± 9.2	81.5 ± 7.5	84.4 ± 7.3	86.3 ± 9.5
Stairs - Descend stairs	80.1 ± 8.0	78.2 ± 8.3	78.8 ± 7.3	78.8 ± 8.5	82.8 ± 7.8
Standing	85.5 ± 6.1	86.4 ± 9.8	86.6 ± 9.7	83.1 ± 9.5	74.4 ± 10.8
Walking - Treadmill 2mph - Treadmill 0	86.7 ± 4.9	88.1 ± 4.4	89.2 ± 4.5	87.7 ± 5.0	83.4 ± 9.4
Walking - Treadmill 3mph - Treadmill 0	77.4 ± 8.1	74.9 ± 7.7	73.5 ± 10.8	75.4 ± 9.3	89.1 ± 3.1
Walking - Treadmill 3mph - Treadmill 3 - light	69.2 ± 11.1	66.2 ± 11.0	63.5 ± 10.9	67.0 ± 12.0	72.7 ± 9.4
Walking - Treadmill 3mph - Treadmill 6 - moderate	69.4 ± 10.7	69.4 ± 13.3	71.0 ± 10.5	68.6 ± 14.9	64.1 ± 11.2
Walking - Treadmill 3mph - Treadmill 9 - hard	79.8 ± 10.3	80.7 ± 8.1	79.3 ± 9.4	77.8 ± 10.8	68.5 ± 11.9
kneeling	91.8 ± 6.1	93.0 ± 5.1	93.1 ± 4.9	89.8 ± 7.5	79.7 ± 8.6
unknown	77.0 ± 8.3	78.6 ± 8.0	79.4 ± 8.2	77.4 ± 8.8	91.7 ± 5.6
Carrying groceries	83.4 ± 9.4	83.8 ± 9.0	84.9 ± 9.1	83.2 ± 9.5	77.1 ± 9.3
Doing dishes	77.9 ± 11.2	81.1 ± 9.2	82.0 ± 7.1	76.2 ± 14.4	83.3 ± 11.4
Gardening	74.5 ± 14.4	76.2 ± 18.6	78.1 ± 14.8	71.9 ± 20.3	76.8 ± 14.1
Ironing	77.6 ± 9.4	79.2 ± 9.1	82.9 ± 10.4	77.4 ± 10.0	73.9 ± 21.0
Making the bed	53.4 ± 11.6	56.9 ± 10.8	59.4 ± 10.3	51.1 ± 12.5	80.1 ± 8.0
Mopping	61.5 ± 11.9	65.1 ± 14.3	65.9 ± 14.5	61.0 ± 12.8	55.0 ± 11.4
Playing videogames	92.1 ± 5.0	93.1 ± 3.5	93.2 ± 4.1	92.1 ± 6.3	60.3 ± 15.5
Scrubbing a surface	76.9 ± 15.6	78.4 ± 12.8	79.5 ± 13.8	76.0 ± 13.9	92.3 ± 4.3
Stacking groceries	59.5 ± 13.3	60.7 ± 16.2	65.1 ± 10.9	61.6 ± 10.8	77.4 ± 13.2
Sweeping	55.3 ± 13.4	57.9 ± 11.1	61.3 ± 10.4	56.2 ± 15.4	64.8 ± 14.0
Typing	94.9 ± 2.3	94.0 ± 4.4	95.0 ± 3.2	95.0 ± 2.9	61.7 ± 12.6
Vacuuming	67.6 ± 12.6	68.6 ± 8.2	63.8 ± 11.2	65.4 ± 10.4	94.4 ± 3.0
Walking around block	83.2 ± 5.6	81.9 ± 6.6	82.2 ± 6.6	84.8 ± 6.4	65.2 ± 12.8
Washing windows	60.5 ± 10.3	64.5 ± 12.8	65.1 ± 10.8	60.2 ± 11.2	82.8 ± 6.0
Watching TV	91.6 ± 5.9	92.4 ± 5.1	93.2 ± 4.6	92.2 ± 5.2	62.0 ± 9.3
Weeding	75.7 ± 11.8	76.6 ± 8.3	77.6 ± 5.4	73.4 ± 13.0	93.0 ± 4.0
Wiping/Dusting	56.8 ± 14.9	59.0 ± 13.4	57.9 ± 14.7	57.5 ± 13.5	72.8 ± 9.5
Writing	94.2 ± 3.1	95.3 ± 2.8	95.2 ± 3.6	93.2 ± 5.3	60.4 ± 14.3
taking out trash	47.3 ± 10.9	50.3 ± 12.4	53.9 ± 9.9	45.3 ± 12.5	94.5 ± 3.0

Table A6-5: F-Measure rate when evaluating the four of the highest performing feature subsets computed per sensor using the C4.5 classifier in a subject dependent manner.

	True Positive Rate				
Activity	**AllButHR**	**ACAbsArea, DCArea, ACVar, AC Range, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	16.7 ± 29.2	9.5 ± 22.0	10.9 ± 24.0	7.2 ± 13.5	13.4 ± 29.5
Bench weight lifting - light	15.6 ± 28.2	35.6 ± 39.4	29.7 ± 40.6	18.0 ± 29.6	25.2 ± 33.7
Bench weight lifting - moderate	11.6 ± 18.5	3.7 ± 6.3	1.4 ± 4.6	3.9 ± 13.1	1.3 ± 2.9
Bicep curls - hard	19.9 ± 37.1	24.8 ± 33.0	24.4 ± 32.2	21.5 ± 34.1	12.8 ± 28.7
Bicep curls - light	18.8 ± 27.3	17.3 ± 28.2	14.8 ± 24.8	23.3 ± 31.8	26.6 ± 35.7
Bicep curls - moderate	12.2 ± 26.7	12.9 ± 27.4	23.6 ± 36.0	21.4 ± 32.4	17.8 ± 26.8
Calisthenics - Crunches	16.0 ± 31.9	15.0 ± 31.7	16.4 ± 30.6	15.8 ± 29.6	24.7 ± 37.0
Calisthenics - Sit ups	44.8 ± 42.9	34.2 ± 39.7	26.5 ± 39.5	47.4 ± 45.3	42.8 ± 44.7
Cycling - Cycle hard - Cycle 80rpm	18.0 ± 29.9	10.7 ± 22.1	6.4 ± 11.3	10.2 ± 22.2	6.1 ± 10.1
Cycling - Cycle light - Cycle 100rpm	70.6 ± 37.7	63.6 ± 37.9	74.2 ± 31.4	70.3 ± 36.6	69.7 ± 40.8
Cycling - Cycle light - Cycle 60rpm	39.6 ± 36.2	33.1 ± 32.3	34.1 ± 36.5	46.3 ± 37.9	50.6 ± 38.9
Cycling - Cycle light - Cycle 80rpm	43.0 ± 39.9	20.1 ± 29.4	13.9 ± 22.2	44.8 ± 38.2	42.5 ± 39.8
Cycling - Cycle moderate - Cycle 80rpm	16.1 ± 19.4	10.2 ± 12.2	17.6 ± 29.4	12.7 ± 19.1	24.2 ± 35.2
Lying down	76.9 ± 34.3	75.6 ± 36.1	79.1 ± 29.1	73.2 ± 36.1	70.0 ± 37.8
Rowing - Rowing hard - Rowing 30spm	19.5 ± 25.5	17.6 ± 20.0	24.0 ± 33.1	16.0 ± 22.0	24.2 ± 29.9
Rowing - Rowing light - Rowing 30spm	24.3 ± 23.7	15.7 ± 17.5	16.9 ± 19.3	30.0 ± 29.5	23.2 ± 29.1
Rowing - Rowing moderate - Rowing 30spm	18.7 ± 21.5	17.1 ± 30.6	16.4 ± 29.8	22.7 ± 28.6	15.9 ± 18.0
Running - Treadmill 4mph - Treadmill 0	28.2 ± 30.7	26.6 ± 35.6	28.7 ± 36.6	29.0 ± 31.0	28.5 ± 39.9
Running - Treadmill 5mph - Treadmill 0	49.0 ± 34.9	47.3 ± 31.5	35.8 ± 34.7	43.4 ± 36.8	44.6 ± 29.3
Running - Treadmill 6mph - Treadmill 0	38.3 ± 31.0	34.5 ± 38.2	51.2 ± 34.6	42.8 ± 36.4	48.7 ± 34.8
Sitting	15.3 ± 26.4	27.8 ± 38.9	22.7 ± 34.0	24.6 ± 35.9	15.1 ± 33.7
Sitting - Fidget feet legs	28.8 ± 36.8	24.1 ± 27.3	19.8 ± 26.2	22.1 ± 24.0	29.1 ± 31.9
Sitting - Fidget hands arms	28.5 ± 32.2	16.3 ± 25.3	14.1 ± 25.1	23.7 ± 28.7	24.1 ± 28.2
Stairs - Ascend stairs	49.4 ± 33.6	37.7 ± 29.6	23.4 ± 31.4	51.0 ± 34.7	51.3 ± 36.4
Stairs - Descend stairs	39.7 ± 30.7	24.4 ± 24.0	16.1 ± 19.3	42.4 ± 29.8	28.2 ± 25.2
Standing	41.3 ± 38.6	37.0 ± 33.1	36.5 ± 34.4	41.3 ± 34.8	40.3 ± 36.4
Walking - Treadmill 2mph - Treadmill 0	45.6 ± 34.2	42.0 ± 34.5	41.5 ± 37.4	42.9 ± 34.4	48.3 ± 31.5
Walking - Treadmill 3mph - Treadmill 0	24.3 ± 25.4	9.0 ± 13.8	8.6 ± 17.8	14.2 ± 19.2	13.1 ± 18.0
Walking - Treadmill 3mph - Treadmill 3 - light	10.1 ± 12.6	12.8 ± 14.5	5.6 ± 9.2	20.2 ± 23.7	14.2 ± 16.4
Walking - Treadmill 3mph - Treadmill 6 - moderate	10.5 ± 14.9	12.2 ± 18.0	18.2 ± 25.9	11.7 ± 13.0	11.3 ± 18.6
Walking - Treadmill 3mph - Treadmill 9 - hard	15.1 ± 23.2	9.1 ± 11.1	9.8 ± 13.7	8.0 ± 15.6	12.3 ± 18.9
kneeling	66.9 ± 43.1	68.6 ± 38.8	66.5 ± 38.6	57.6 ± 42.0	53.8 ± 45.8
unknown	64.0 ± 5.2	65.1 ± 6.0	65.1 ± 6.4	63.6 ± 4.9	62.4 ± 4.8
Carrying groceries	19.8 ± 20.3	16.6 ± 17.8	18.3 ± 22.8	18.4 ± 17.6	21.6 ± 25.8
Doing dishes	29.3 ± 28.4	31.6 ± 31.2	27.7 ± 25.3	32.0 ± 31.4	35.7 ± 29.6
Gardening	14.4 ± 20.8	14.7 ± 20.9	7.6 ± 13.0	17.3 ± 21.7	12.1 ± 19.3
Ironing	37.1 ± 31.5	34.0 ± 31.6	27.7 ± 28.9	39.6 ± 29.8	33.1 ± 33.6
Making the bed	26.0 ± 17.8	25.8 ± 18.8	24.6 ± 20.0	27.0 ± 19.2	28.5 ± 20.2
Mopping	24.2 ± 21.5	21.4 ± 21.0	22.7 ± 21.8	22.6 ± 22.7	24.2 ± 24.9
Playing videogames	29.2 ± 34.7	16.9 ± 26.8	17.3 ± 30.5	24.1 ± 30.8	18.8 ± 28.9
Scrubbing a surface	13.9 ± 17.8	11.8 ± 14.9	11.6 ± 14.5	13.6 ± 21.8	10.3 ± 13.4
Stacking groceries	11.5 ± 12.0	13.9 ± 14.9	9.0 ± 12.0	14.5 ± 14.0	14.4 ± 14.9
Sweeping	16.5 ± 17.9	12.8 ± 17.9	12.6 ± 17.3	14.5 ± 14.7	13.1 ± 15.8
Typing	49.2 ± 37.5	37.4 ± 33.9	36.1 ± 35.2	45.0 ± 36.2	50.0 ± 37.3
Vacuuming	23.0 ± 21.7	25.1 ± 23.4	15.0 ± 16.6	26.5 ± 26.8	22.0 ± 20.8
Walking around block	18.9 ± 18.0	21.0 ± 23.6	12.6 ± 15.2	17.6 ± 16.5	17.1 ± 17.2
Washing windows	22.4 ± 19.2	20.3 ± 20.6	20.0 ± 18.3	22.9 ± 20.9	26.4 ± 24.3
Watching TV	20.1 ± 30.1	17.4 ± 25.2	15.8 ± 29.1	14.9 ± 26.3	18.7 ± 29.8
Weeding	4.5 ± 7.8	9.8 ± 23.5	3.8 ± 7.3	5.4 ± 5.8	6.8 ± 13.6
Wiping/Dusting	21.6 ± 20.1	21.7 ± 21.8	17.9 ± 18.3	22.5 ± 20.2	22.7 ± 21.6
Writing	51.1 ± 40.0	42.3 ± 37.2	39.4 ± 37.4	43.2 ± 37.0	49.8 ± 38.6
taking out trash	10.1 ± 10.4	9.1 ± 10.2	8.6 ± 8.3	10.5 ± 12.6	8.6 ± 8.8

Table A6-6: True positive rate when evaluating the four of the highest performing feature subsets computed per sensor using the C4.5 classifier in a subject independent manner.

	False Positive Rate				
Activity	**AllButHR**	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	0.6 ± 0.6	0.4 ± 0.4	0.2 ± 0.2	0.4 ± 0.4	0.5 ± 0.6
Bench weight lifting - light	0.6 ± 0.7	0.8 ± 0.9	0.7 ± 0.9	0.6 ± 0.7	0.6 ± 0.8
Bench weight lifting - moderate	0.6 ± 0.6	0.3 ± 0.4	0.2 ± 0.3	0.4 ± 0.4	0.4 ± 0.4
Bicep curls - hard	0.8 ± 1.1	0.7 ± 0.7	1.0 ± 0.8	0.7 ± 0.7	0.4 ± 0.4
Bicep curls - light	0.9 ± 1.2	1.2 ± 1.1	0.8 ± 0.9	0.8 ± 1.1	1.0 ± 1.1
Bicep curls - moderate	0.5 ± 0.6	1.1 ± 0.9	1.2 ± 1.1	1.5 ± 0.9	1.0 ± 0.9
Calisthenics - Crunches	0.2 ± 0.4	0.3 ± 0.6	0.2 ± 0.4	0.4 ± 0.6	0.5 ± 0.8
Calisthenics - Sit ups	0.1 ± 0.1	0.2 ± 0.4	0.4 ± 0.4	0.2 ± 0.2	0.3 ± 0.5
Cycling - Cycle hard - Cycle 80rpm	1.0 ± 1.1	0.7 ± 0.7	1.0 ± 1.1	0.8 ± 0.8	0.7 ± 0.6
Cycling - Cycle light - Cycle 100rpm	0.1 ± 0.2	0.6 ± 1.2	0.7 ± 1.4	0.1 ± 0.2	0.1 ± 0.1
Cycling - Cycle light - Cycle 60rpm	0.2 ± 0.2	0.5 ± 0.4	0.4 ± 0.4	0.3 ± 0.3	0.3 ± 0.2
Cycling - Cycle light - Cycle 80rpm	1.1 ± 1.3	1.2 ± 1.2	1.2 ± 1.3	1.3 ± 1.2	1.7 ± 1.6
Cycling - Cycle moderate - Cycle 80rpm	0.8 ± 0.9	1.1 ± 0.8	0.9 ± 1.3	0.8 ± 0.8	1.1 ± 1.2
Lying down	0.7 ± 1.1	0.8 ± 1.5	1.0 ± 1.7	0.8 ± 1.2	0.8 ± 1.3
Rowing - Rowing hard - Rowing 30spm	0.7 ± 0.8	0.9 ± 1.0	0.9 ± 1.2	0.7 ± 0.8	1.3 ± 1.3
Rowing - Rowing light - Rowing 30spm	0.7 ± 0.7	0.8 ± 1.1	0.7 ± 0.9	1.0 ± 0.9	0.5 ± 0.7
Rowing - Rowing moderate - Rowing 30spm	0.8 ± 0.8	0.9 ± 1.1	0.8 ± 1.2	0.8 ± 0.7	0.9 ± 0.8
Running - Treadmill 4mph - Treadmill 0	0.7 ± 0.9	0.4 ± 0.6	0.4 ± 0.5	0.4 ± 0.3	0.5 ± 0.4
Running - Treadmill 5mph - Treadmill 0	0.7 ± 0.6	0.8 ± 0.7	0.8 ± 0.6	1.0 ± 0.8	0.8 ± 0.6
Running - Treadmill 6mph - Treadmill 0	0.3 ± 0.5	0.4 ± 0.5	0.8 ± 0.8	0.7 ± 1.0	1.0 ± 1.4
Sitting	0.7 ± 0.9	0.6 ± 0.7	0.8 ± 0.7	0.6 ± 0.7	1.1 ± 2.4
Sitting - Fidget feet legs	0.3 ± 0.3	0.4 ± 0.4	0.2 ± 0.3	0.4 ± 0.5	0.3 ± 0.4
Sitting - Fidget hands arms	0.5 ± 0.8	0.4 ± 0.4	0.4 ± 0.3	0.3 ± 0.3	0.4 ± 0.3
Stairs - Ascend stairs	0.6 ± 0.5	0.7 ± 0.5	1.1 ± 1.3	0.5 ± 0.2	0.7 ± 0.8
Stairs - Descend stairs	0.9 ± 0.9	1.1 ± 1.1	1.2 ± 1.2	0.9 ± 0.8	1.0 ± 0.5
Standing	0.4 ± 0.3	0.4 ± 0.5	0.4 ± 0.4	0.4 ± 0.3	0.4 ± 0.3
Walking - Treadmill 2mph - Treadmill 0	0.8 ± 1.4	1.0 ± 1.4	0.7 ± 0.8	0.6 ± 0.8	0.8 ± 0.7
Walking - Treadmill 3mph - Treadmill 0	1.4 ± 1.4	1.0 ± 1.1	1.1 ± 1.5	1.5 ± 1.2	1.1 ± 0.8
Walking - Treadmill 3mph - Treadmill 3 - light	1.0 ± 0.9	1.2 ± 1.1	0.8 ± 0.8	1.9 ± 1.3	1.2 ± 1.1
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.8 ± 0.8	1.1 ± 1.0	1.7 ± 2.1	1.0 ± 0.9	1.2 ± 1.5
Walking - Treadmill 3mph - Treadmill 9 - hard	0.9 ± 1.2	0.6 ± 0.5	0.8 ± 1.0	0.7 ± 1.0	0.8 ± 0.8
kneeling	0.1 ± 0.1	0.1 ± 0.2	0.2 ± 0.2	0.2 ± 0.2	0.2 ± 0.2
unknown	30.0 ± 8.0	32.8 ± 7.5	34.9 ± 8.7	27.2 ± 5.9	27.8 ± 6.6
Carrying groceries	1.3 ± 1.4	1.3 ± 1.4	0.9 ± 0.7	1.0 ± 0.8	1.2 ± 1.4
Doing dishes	0.7 ± 0.5	0.7 ± 0.6	0.7 ± 0.5	1.0 ± 0.7	1.0 ± 0.8
Gardening	0.6 ± 0.5	0.6 ± 0.5	0.8 ± 0.6	0.7 ± 0.5	0.7 ± 0.7
Ironing	0.8 ± 0.5	0.7 ± 0.6	0.7 ± 0.5	0.8 ± 0.6	0.8 ± 0.8
Making the bed	1.2 ± 0.7	1.1 ± 0.5	1.1 ± 0.5	1.2 ± 0.7	1.2 ± 0.7
Mopping	0.9 ± 0.5	0.8 ± 0.6	0.7 ± 0.5	1.0 ± 1.0	1.0 ± 1.1
Playing videogames	1.2 ± 1.3	1.0 ± 0.8	0.9 ± 1.0	1.2 ± 1.4	1.2 ± 1.5
Scrubbing a surface	0.8 ± 0.8	1.0 ± 1.1	0.8 ± 1.0	0.8 ± 0.8	0.9 ± 0.9
Stacking groceries	0.9 ± 0.5	0.8 ± 0.6	1.1 ± 0.9	0.8 ± 0.4	0.7 ± 0.5
Sweeping	0.8 ± 0.6	0.8 ± 0.5	0.7 ± 0.5	0.9 ± 0.4	0.8 ± 0.4
Typing	0.6 ± 0.6	1.0 ± 1.3	1.0 ± 1.2	0.7 ± 0.7	0.6 ± 0.6
Vacuuming	0.7 ± 0.5	0.7 ± 0.4	0.8 ± 0.5	0.7 ± 0.3	0.7 ± 0.3
Walking around block	1.8 ± 1.6	2.2 ± 2.0	1.9 ± 2.4	1.8 ± 2.2	1.9 ± 1.4
Washing windows	0.9 ± 0.5	1.2 ± 1.5	1.4 ± 1.5	1.1 ± 1.2	1.0 ± 0.8
Watching TV	1.0 ± 1.0	1.2 ± 1.3	1.2 ± 1.3	1.5 ± 1.2	1.3 ± 1.4
Weeding	0.7 ± 0.5	0.4 ± 0.3	0.5 ± 0.4	0.6 ± 0.5	0.7 ± 0.6
Wiping/Dusting	0.9 ± 0.5	1.0 ± 0.8	1.0 ± 1.0	0.8 ± 0.6	1.0 ± 0.5
Writing	0.6 ± 0.8	0.4 ± 0.4	0.4 ± 0.5	1.1 ± 1.3	0.9 ± 1.0
taking out trash	1.0 ± 0.5	0.9 ± 0.4	0.8 ± 0.6	1.0 ± 0.5	0.9 ± 0.3

Table A6-7: False positive rate when evaluating the four of the highest performing feature subsets computed per sensor using the C4.5 classifier in a subject independent manner.

	F-Measure				
Activity	**AllButHR**	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	13.0 ± 18.8	10.1 ± 21.8	11.2 ± 22.3	7.9 ± 13.5	9.8 ± 20.7
Bench weight lifting - light	14.6 ± 21.4	30.3 ± 30.2	23.6 ± 28.3	16.6 ± 23.7	25.0 ± 29.5
Bench weight lifting - moderate	11.3 ± 16.2	6.0 ± 10.2	2.2 ± 7.3	3.4 ± 11.0	2.1 ± 5.1
Bicep curls - hard	12.8 ± 20.1	19.6 ± 23.3	18.5 ± 21.1	16.1 ± 24.7	10.5 ± 21.8
Bicep curls - light	17.8 ± 19.2	13.0 ± 18.2	15.6 ± 26.8	21.4 ± 24.0	22.4 ± 23.5
Bicep curls - moderate	10.1 ± 19.2	9.7 ± 16.6	16.0 ± 21.8	16.0 ± 19.3	14.2 ± 20.1
Calisthenics - Crunches	18.2 ± 35.5	16.6 ± 32.0	19.9 ± 33.8	17.2 ± 31.7	24.5 ± 37.6
Calisthenics - Sit ups	48.8 ± 44.2	36.9 ± 41.7	27.2 ± 37.3	49.0 ± 45.0	44.0 ± 44.4
Cycling - Cycle hard - Cycle 80rpm	10.2 ± 12.6	8.1 ± 15.3	7.6 ± 13.4	7.8 ± 14.4	5.6 ± 7.1
Cycling - Cycle light - Cycle 100rpm	73.4 ± 36.4	61.2 ± 33.4	70.4 ± 27.5	73.5 ± 33.5	71.1 ± 39.1
Cycling - Cycle light - Cycle 60rpm	44.3 ± 37.1	36.4 ± 32.6	36.2 ± 34.9	49.4 ± 37.2	53.0 ± 37.5
Cycling - Cycle light - Cycle 80rpm	35.6 ± 31.1	16.3 ± 22.2	13.4 ± 20.2	35.7 ± 24.9	30.2 ± 25.8
Cycling - Cycle moderate - Cycle 80rpm	16.0 ± 15.7	10.7 ± 11.6	14.3 ± 18.2	12.2 ± 14.4	17.9 ± 22.0
Lying down	75.3 ± 31.2	73.6 ± 31.4	76.7 ± 23.9	71.2 ± 31.9	68.3 ± 33.4
Rowing - Rowing hard - Rowing 30spm	19.5 ± 22.7	16.4 ± 14.7	19.3 ± 20.7	15.1 ± 17.4	19.4 ± 20.0
Rowing - Rowing light - Rowing 30spm	24.8 ± 21.4	16.2 ± 15.8	17.0 ± 17.8	27.6 ± 25.8	23.5 ± 23.7
Rowing - Rowing moderate - Rowing 30spm	18.6 ± 19.1	12.9 ± 18.3	11.7 ± 16.4	21.5 ± 23.3	15.0 ± 14.9
Running - Treadmill 4mph - Treadmill 0	30.7 ± 29.8	27.0 ± 33.9	30.2 ± 35.0	32.4 ± 32.0	26.8 ± 34.5
Running - Treadmill 5mph - Treadmill 0	46.2 ± 26.5	44.8 ± 26.8	33.0 ± 28.0	36.8 ± 26.8	44.1 ± 25.9
Running - Treadmill 6mph - Treadmill 0	38.9 ± 28.8	31.4 ± 28.3	44.6 ± 28.0	36.0 ± 26.8	37.3 ± 20.2
Sitting	12.3 ± 19.4	24.7 ± 34.4	18.2 ± 26.8	21.6 ± 29.4	12.1 ± 26.4
Sitting - Fidget feet legs	30.7 ± 38.1	27.4 ± 28.1	25.0 ± 31.2	27.2 ± 27.7	33.1 ± 33.2
Sitting - Fidget hands arms	30.3 ± 31.3	18.8 ± 27.2	14.6 ± 25.0	26.8 ± 28.4	27.7 ± 29.4
Stairs - Ascend stairs	49.6 ± 32.1	38.6 ± 27.3	20.2 ± 25.8	50.5 ± 31.2	49.3 ± 33.0
Stairs - Descend stairs	38.5 ± 29.0	22.5 ± 18.7	14.3 ± 15.9	40.4 ± 27.7	27.3 ± 22.1
Standing	39.9 ± 34.3	39.3 ± 32.6	38.6 ± 34.1	42.6 ± 34.7	39.8 ± 34.5
Walking - Treadmill 2mph - Treadmill 0	45.4 ± 32.6	39.8 ± 32.6	40.6 ± 34.9	44.6 ± 32.2	49.0 ± 27.7
Walking - Treadmill 3mph - Treadmill 0	21.0 ± 20.0	8.7 ± 11.6	6.9 ± 12.8	13.0 ± 15.1	12.2 ± 14.0
Walking - Treadmill 3mph - Treadmill 3 - light	10.0 ± 10.1	12.5 ± 11.6	5.6 ± 8.3	14.9 ± 13.8	13.5 ± 13.2
Walking - Treadmill 3mph - Treadmill 6 - moderate	11.1 ± 12.6	11.1 ± 12.1	13.7 ± 15.6	12.2 ± 11.0	10.8 ± 12.0
Walking - Treadmill 3mph - Treadmill 9 - hard	12.6 ± 16.2	11.1 ± 11.8	10.5 ± 15.3	8.0 ± 10.5	12.7 ± 15.2
kneeling	65.7 ± 42.2	69.0 ± 37.0	66.5 ± 36.6	58.6 ± 41.3	53.9 ± 45.2
unknown	54.0 ± 8.9	53.2 ± 8.4	52.0 ± 8.2	55.2 ± 9.0	54.0 ± 8.9
Carrying groceries	21.3 ± 20.7	18.1 ± 19.1	20.4 ± 24.8	21.1 ± 19.5	21.5 ± 24.4
Doing dishes	28.8 ± 25.6	31.9 ± 26.7	29.3 ± 24.2	30.4 ± 25.9	33.3 ± 24.5
Gardening	16.3 ± 22.9	16.3 ± 22.3	9.0 ± 15.1	18.5 ± 22.7	13.0 ± 21.2
Ironing	37.9 ± 29.7	35.4 ± 30.8	29.4 ± 27.5	40.6 ± 28.4	33.1 ± 30.4
Making the bed	25.6 ± 17.6	25.6 ± 17.2	24.7 ± 17.5	26.7 ± 17.9	28.0 ± 18.2
Mopping	24.7 ± 21.3	23.0 ± 21.1	25.0 ± 23.4	21.3 ± 20.6	23.2 ± 23.1
Playing videogames	27.7 ± 31.0	17.5 ± 25.8	16.1 ± 27.1	22.5 ± 27.4	17.6 ± 25.6
Scrubbing a surface	14.9 ± 18.6	13.3 ± 15.6	13.4 ± 15.1	14.9 ± 21.1	12.1 ± 15.6
Stacking groceries	13.5 ± 14.0	16.0 ± 16.9	10.1 ± 12.6	16.6 ± 16.0	16.8 ± 16.8
Sweeping	17.9 ± 19.0	14.0 ± 16.8	14.3 ± 18.3	16.3 ± 16.6	15.3 ± 17.6
Typing	50.1 ± 35.5	38.0 ± 33.4	35.4 ± 32.2	45.4 ± 35.6	50.6 ± 35.4
Vacuuming	25.9 ± 23.9	27.8 ± 25.2	17.2 ± 17.6	28.2 ± 26.7	25.5 ± 22.5
Walking around block	18.9 ± 16.3	20.1 ± 23.2	13.0 ± 14.0	19.1 ± 17.8	17.8 ± 18.4
Washing windows	24.7 ± 21.1	19.9 ± 17.3	19.1 ± 16.8	23.5 ± 21.1	28.3 ± 24.3
Watching TV	19.1 ± 24.9	18.2 ± 23.6	15.4 ± 26.4	15.1 ± 26.0	19.3 ± 29.6
Weeding	6.0 ± 10.1	7.0 ± 11.8	5.6 ± 10.7	7.2 ± 7.7	6.6 ± 11.0
Wiping/Dusting	23.7 ± 21.1	21.9 ± 19.9	19.3 ± 17.6	24.7 ± 22.0	23.9 ± 22.6
Writing	51.6 ± 38.4	44.6 ± 35.2	41.7 ± 35.9	38.9 ± 31.3	47.6 ± 35.6
taking out trash	11.5 ± 11.7	10.4 ± 11.3	10.6 ± 9.9	11.7 ± 13.6	10.2 ± 9.9

Table A6-8: F-Measure when evaluating the four of the highest performing feature subsets computed per sensor using the C4.5 classifier in a subject independent manner.

	True Positive Rate				
Activity	**AllButHR**	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	89.6 ± 10.3	87.3 ± 8.5	89.2 ± 7.2	90.3 ± 7.5	90.8 ± 10.5
Bench weight lifting - light	93.6 ± 6.4	90.3 ± 15.3	92.9 ± 8.1	91.2 ± 9.4	93.8 ± 7.6
Bench weight lifting - moderate	84.9 ± 16.4	85.8 ± 12.7	87.0 ± 11.0	86.4 ± 13.7	89.1 ± 11.5
Bicep curls - hard	90.9 ± 12.0	91.3 ± 11.9	91.4 ± 10.2	91.6 ± 8.1	88.4 ± 14.5
Bicep curls - light	89.7 ± 8.8	88.6 ± 10.6	89.3 ± 8.7	89.1 ± 9.7	88.8 ± 9.6
Bicep curls - moderate	91.5 ± 8.5	90.8 ± 8.3	91.0 ± 8.6	89.5 ± 9.9	89.8 ± 8.7
Calisthenics - Crunches	91.9 ± 5.2	95.4 ± 3.8	95.5 ± 3.7	93.0 ± 5.4	95.2 ± 5.5
Calisthenics - Sit ups	92.3 ± 4.8	95.0 ± 4.3	94.3 ± 5.3	93.2 ± 5.0	95.2 ± 4.7
Cycling - Cycle hard - Cycle 80rpm	83.5 ± 18.9	84.0 ± 13.2	85.8 ± 13.6	85.4 ± 12.8	86.8 ± 13.4
Cycling - Cycle light - Cycle 100rpm	95.8 ± 5.4	94.2 ± 5.4	93.4 ± 7.2	94.9 ± 5.8	94.6 ± 5.1
Cycling - Cycle light - Cycle 60rpm	88.6 ± 7.3	91.2 ± 5.6	92.3 ± 5.4	91.1 ± 4.8	92.4 ± 4.9
Cycling - Cycle light - Cycle 80rpm	92.6 ± 5.5	91.8 ± 5.6	93.1 ± 5.6	92.9 ± 5.7	91.7 ± 8.7
Cycling - Cycle moderate - Cycle 80rpm	86.2 ± 8.2	83.8 ± 8.9	85.6 ± 8.9	85.0 ± 8.4	85.7 ± 7.1
Lying down	99.5 ± 0.8	99.2 ± 1.4	99.2 ± 1.2	99.6 ± 0.6	99.2 ± 1.0
Rowing - Rowing hard - Rowing 30spm	81.6 ± 15.2	80.8 ± 16.0	83.2 ± 13.4	82.8 ± 13.0	85.3 ± 12.2
Rowing - Rowing light - Rowing 30spm	86.5 ± 9.3	84.5 ± 12.5	86.9 ± 9.0	82.8 ± 10.3	83.6 ± 11.8
Rowing - Rowing moderate - Rowing 30spm	81.6 ± 15.8	78.2 ± 14.6	79.6 ± 13.4	80.1 ± 14.9	81.4 ± 11.5
Running - Treadmill 4mph - Treadmill 0	88.8 ± 8.7	92.0 ± 7.6	88.9 ± 8.6	89.8 ± 10.2	90.0 ± 8.5
Running - Treadmill 5mph - Treadmill 0	87.7 ± 6.1	87.3 ± 8.6	88.5 ± 6.9	86.9 ± 5.7	86.6 ± 8.6
Running - Treadmill 6mph - Treadmill 0	87.2 ± 15.9	86.8 ± 13.2	90.4 ± 8.0	79.8 ± 19.3	78.9 ± 19.2
Sitting	92.4 ± 6.6	91.4 ± 5.8	92.0 ± 6.7	89.6 ± 7.9	93.9 ± 4.9
Sitting - Fidget feet legs	91.2 ± 7.3	91.9 ± 7.0	94.6 ± 6.1	90.1 ± 9.9	91.0 ± 9.1
Sitting - Fidget hands arms	88.9 ± 8.9	91.7 ± 6.4	92.4 ± 6.5	83.2 ± 12.4	91.6 ± 7.5
Stairs - Ascend stairs	85.4 ± 5.8	86.1 ± 9.5	87.2 ± 7.0	86.1 ± 9.1	82.7 ± 8.2
Stairs - Descend stairs	85.1 ± 7.3	85.5 ± 8.0	85.8 ± 5.6	84.6 ± 8.1	83.8 ± 7.7
Standing	88.4 ± 5.8	89.9 ± 6.8	90.7 ± 6.1	85.2 ± 13.9	87.4 ± 9.9
Walking - Treadmill 2mph - Treadmill 0	89.1 ± 4.5	91.2 ± 5.0	92.0 ± 6.3	90.9 ± 4.9	92.1 ± 5.0
Walking - Treadmill 3mph - Treadmill 0	82.6 ± 6.9	84.2 ± 7.6	83.0 ± 8.5	79.1 ± 7.2	80.2 ± 8.9
Walking - Treadmill 3mph - Treadmill 3 - light	76.4 ± 11.4	75.5 ± 11.9	79.1 ± 10.2	74.4 ± 10.0	70.0 ± 15.0
Walking - Treadmill 3mph - Treadmill 6 - moderate	76.8 ± 13.6	74.8 ± 11.9	78.5 ± 11.1	75.2 ± 12.0	72.4 ± 11.7
Walking - Treadmill 3mph - Treadmill 9 - hard	83.0 ± 12.4	86.3 ± 10.3	85.3 ± 9.2	82.9 ± 11.0	81.4 ± 12.4
kneeling	93.0 ± 5.9	96.2 ± 4.0	95.3 ± 4.0	94.4 ± 5.0	95.2 ± 3.9
unknown	74.8 ± 5.5	75.6 ± 5.2	76.4 ± 5.9	73.5 ± 7.0	73.6 ± 6.4
Carrying groceries	86.6 ± 7.4	87.2 ± 8.7	88.8 ± 6.8	84.9 ± 10.6	87.0 ± 10.8
Doing dishes	81.5 ± 10.9	83.1 ± 9.7	83.8 ± 7.5	75.3 ± 10.8	80.4 ± 11.0
Gardening	80.8 ± 10.4	80.9 ± 14.8	81.0 ± 10.7	74.5 ± 13.4	74.1 ± 12.4
Ironing	79.4 ± 10.2	81.9 ± 9.6	84.1 ± 8.6	77.0 ± 12.8	77.6 ± 13.1
Making the bed	54.5 ± 13.4	58.5 ± 13.8	59.4 ± 11.3	54.8 ± 9.0	53.0 ± 10.2
Mopping	62.0 ± 12.1	65.6 ± 13.0	67.7 ± 10.9	60.2 ± 12.8	60.2 ± 13.9
Playing videogames	96.1 ± 3.8	95.4 ± 3.6	95.5 ± 4.0	94.6 ± 6.2	95.1 ± 5.0
Scrubbing a surface	79.3 ± 12.9	79.5 ± 15.8	80.0 ± 14.5	77.1 ± 14.6	79.0 ± 14.4
Stacking groceries	58.2 ± 13.2	61.3 ± 15.5	64.6 ± 14.6	59.6 ± 13.0	58.4 ± 14.6
Sweeping	66.0 ± 13.7	66.8 ± 13.1	65.0 ± 14.4	62.4 ± 14.0	64.7 ± 14.8
Typing	96.8 ± 4.4	96.6 ± 3.4	96.3 ± 3.8	96.1 ± 3.9	96.7 ± 4.1
Vacuuming	71.6 ± 9.2	71.4 ± 10.4	70.0 ± 10.6	64.6 ± 10.4	67.9 ± 11.5
Walking around block	84.2 ± 9.9	85.3 ± 9.9	85.2 ± 8.2	80.6 ± 9.1	83.8 ± 9.0
Washing windows	66.9 ± 8.4	68.6 ± 10.4	67.0 ± 10.1	62.9 ± 11.4	63.8 ± 8.8
Watching TV	91.0 ± 6.9	94.0 ± 4.7	92.2 ± 6.6	92.9 ± 4.3	94.5 ± 5.8
Weeding	72.1 ± 16.5	78.9 ± 10.3	76.5 ± 12.4	68.0 ± 14.6	69.7 ± 14.2
Wiping/Dusting	63.7 ± 13.2	65.5 ± 13.0	66.8 ± 13.5	57.3 ± 13.2	60.0 ± 13.6
Writing	95.6 ± 3.9	96.5 ± 3.6	96.1 ± 3.8	96.7 ± 3.7	96.9 ± 2.6
taking out trash	45.8 ± 11.7	56.1 ± 13.2	59.2 ± 9.8	48.4 ± 11.4	53.9 ± 12.8

Table A6-9: True positive rate when evaluating the four of the highest performing feature subsets computed per axis using the C4.5 classifier in a subject dependent manner.

	False Positive Rate				
Activity	**AllButHR**	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Bench weight lifting - light	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Bench weight lifting - moderate	0.1 ± 0.1	0.1 ± 0.0	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Bicep curls - hard	0.2 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Bicep curls - light	0.1 ± 0.1	0.2 ± 0.1	0.2 ± 0.2	0.2 ± 0.1	0.2 ± 0.2
Bicep curls - moderate	0.2 ± 0.2	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.2	0.2 ± 0.2
Calisthenics - Crunches	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.0
Calisthenics - Sit ups	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Cycling - Cycle hard - Cycle 80rpm	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Cycling - Cycle light - Cycle 100rpm	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.0
Cycling - Cycle light - Cycle 60rpm	0.1 ± 0.1	0.2 ± 0.1	0.1 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Cycling - Cycle light - Cycle 80rpm	0.2 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.1	0.1 ± 0.1
Cycling - Cycle moderate - Cycle 80rpm	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Lying down	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Rowing - Rowing hard - Rowing 30spm	0.2 ± 0.1	0.3 ± 0.2	0.2 ± 0.2	0.2 ± 0.2	0.2 ± 0.2
Rowing - Rowing light - Rowing 30spm	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Rowing - Rowing moderate - Rowing 30spm	0.3 ± 0.2	0.3 ± 0.2	0.3 ± 0.2	0.4 ± 0.2	0.3 ± 0.2
Running - Treadmill 4mph - Treadmill 0	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Running - Treadmill 5mph - Treadmill 0	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Running - Treadmill 6mph - Treadmill 0	0.1 ± 0.1	0.1 ± 0.0	0.1 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Sitting	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Sitting - Fidget feet legs	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.1	0.1 ± 0.1
Sitting - Fidget hands arms	0.2 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.2 ± 0.2	0.1 ± 0.1
Stairs - Ascend stairs	0.2 ± 0.1	0.2 ± 0.2	0.2 ± 0.1	0.2 ± 0.1	0.3 ± 0.2
Stairs - Descend stairs	0.2 ± 0.2	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Standing	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.0	0.2 ± 0.1	0.1 ± 0.1
Walking - Treadmill 2mph - Treadmill 0	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1
Walking - Treadmill 3mph - Treadmill 0	0.3 ± 0.2	0.4 ± 0.1	0.3 ± 0.2	0.3 ± 0.1	0.4 ± 0.2
Walking - Treadmill 3mph - Treadmill 3 - light	0.4 ± 0.2	0.5 ± 0.2	0.4 ± 0.2	0.5 ± 0.1	0.6 ± 0.2
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.2	0.5 ± 0.2
Walking - Treadmill 3mph - Treadmill 9 - hard	0.3 ± 0.1	0.3 ± 0.1	0.2 ± 0.1	0.3 ± 0.2	0.3 ± 0.2
kneeling	0.1 ± 0.1	0.1 ± 0.0	0.1 ± 0.0	0.0 ± 0.1	0.1 ± 0.0
unknown	7.6 ± 1.4	7.3 ± 1.4	7.2 ± 1.3	8.2 ± 1.4	7.6 ± 1.5
Carrying groceries	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.2
Doing dishes	0.3 ± 0.2	0.4 ± 0.2	0.2 ± 0.2	0.4 ± 0.2	0.4 ± 0.2
Gardening	0.3 ± 0.2	0.3 ± 0.2	0.3 ± 0.1	0.4 ± 0.2	0.4 ± 0.2
Ironing	0.4 ± 0.2	0.3 ± 0.2	0.3 ± 0.2	0.5 ± 0.2	0.4 ± 0.2
Making the bed	0.8 ± 0.3	0.7 ± 0.3	0.7 ± 0.3	0.8 ± 0.3	0.8 ± 0.2
Mopping	0.7 ± 0.3	0.6 ± 0.2	0.6 ± 0.2	0.7 ± 0.2	0.7 ± 0.3
Playing videogames	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Scrubbing a surface	0.3 ± 0.2	0.2 ± 0.1	0.3 ± 0.2	0.3 ± 0.2	0.3 ± 0.2
Stacking groceries	0.6 ± 0.3	0.5 ± 0.3	0.6 ± 0.3	0.6 ± 0.2	0.6 ± 0.3
Sweeping	0.6 ± 0.4	0.6 ± 0.3	0.6 ± 0.3	0.7 ± 0.3	0.6 ± 0.3
Typing	0.1 ± 0.0	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Vacuuming	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.6 ± 0.2	0.5 ± 0.3
Walking around block	0.3 ± 0.2	0.2 ± 0.2	0.2 ± 0.1	0.3 ± 0.1	0.3 ± 0.1
Washing windows	0.5 ± 0.1	0.5 ± 0.2	0.5 ± 0.2	0.6 ± 0.2	0.6 ± 0.2
Watching TV	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.2 ± 0.1	0.1 ± 0.0
Weeding	0.4 ± 0.2	0.4 ± 0.2	0.3 ± 0.2	0.4 ± 0.2	0.4 ± 0.2
Wiping/Dusting	0.6 ± 0.3	0.5 ± 0.2	0.6 ± 0.2	0.7 ± 0.4	0.8 ± 0.4
Writing	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
taking out trash	0.7 ± 0.2	0.7 ± 0.3	0.6 ± 0.2	0.7 ± 0.3	0.7 ± 0.2

Table A6-10: False positive rate when evaluating the four of the highest performing feature subsets computed per axis using the C4.5 classifier in a subject dependent manner.

Activity	F-Measure				
	AllButHR	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	89.8 ± 10.6	88.7 ± 7.6	89.7 ± 6.3	89.1 ± 8.0	91.1 ± 9.9
Bench weight lifting - light	90.7 ± 7.8	88.2 ± 13.6	91.0 ± 8.4	89.6 ± 9.3	91.1 ± 9.2
Bench weight lifting - moderate	84.7 ± 13.3	86.4 ± 11.2	87.7 ± 9.5	84.9 ± 12.4	88.6 ± 10.3
Bicep curls - hard	88.9 ± 12.2	90.5 ± 10.8	91.2 ± 8.2	90.3 ± 8.5	87.6 ± 15.2
Bicep curls - light	90.2 ± 7.3	88.8 ± 10.1	89.0 ± 8.4	88.8 ± 8.9	87.7 ± 9.1
Bicep curls - moderate	90.6 ± 8.8	89.6 ± 7.6	90.1 ± 8.1	88.6 ± 9.4	88.1 ± 8.6
Calisthenics - Crunches	92.5 ± 4.4	95.4 ± 2.9	94.7 ± 2.9	92.5 ± 4.3	94.9 ± 3.1
Calisthenics - Sit ups	92.0 ± 4.2	92.8 ± 5.1	92.6 ± 5.5	92.3 ± 4.2	93.2 ± 5.0
Cycling - Cycle hard - Cycle 80rpm	81.9 ± 18.6	82.6 ± 12.5	83.0 ± 12.9	84.0 ± 13.7	84.9 ± 13.4
Cycling - Cycle light - Cycle 100rpm	94.3 ± 5.3	93.3 ± 5.6	93.5 ± 6.5	94.2 ± 6.0	93.6 ± 6.4
Cycling - Cycle light - Cycle 60rpm	89.7 ± 5.0	90.9 ± 4.8	91.9 ± 4.4	90.2 ± 3.3	90.8 ± 4.6
Cycling - Cycle light - Cycle 80rpm	91.6 ± 5.3	91.4 ± 5.1	92.2 ± 4.6	91.6 ± 4.3	91.6 ± 6.5
Cycling - Cycle moderate - Cycle 80rpm	86.3 ± 7.2	84.3 ± 6.8	85.6 ± 7.1	85.2 ± 7.0	84.8 ± 6.8
Lying down	99.0 ± 0.8	98.6 ± 1.4	98.7 ± 1.0	98.9 ± 0.8	98.8 ± 1.0
Rowing - Rowing hard - Rowing 30spm	81.4 ± 14.3	79.6 ± 16.0	83.0 ± 13.0	82.2 ± 12.4	84.2 ± 11.3
Rowing - Rowing light - Rowing 30spm	85.8 ± 8.0	84.7 ± 11.5	86.5 ± 7.9	84.2 ± 8.7	83.7 ± 10.0
Rowing - Rowing moderate - Rowing 30spm	80.1 ± 15.2	78.0 ± 14.2	79.3 ± 13.2	78.3 ± 14.4	79.8 ± 11.5
Running - Treadmill 4mph - Treadmill 0	88.5 ± 6.4	89.9 ± 6.7	88.5 ± 6.2	89.2 ± 7.7	88.7 ± 7.0
Running - Treadmill 5mph - Treadmill 0	87.2 ± 5.1	87.6 ± 6.6	88.8 ± 5.2	86.1 ± 5.7	87.3 ± 6.1
Running - Treadmill 6mph - Treadmill 0	86.1 ± 13.3	84.6 ± 12.4	89.0 ± 7.4	80.4 ± 17.3	79.8 ± 17.3
Sitting	89.6 ± 6.4	89.3 ± 6.4	90.9 ± 5.5	88.5 ± 7.6	90.5 ± 4.6
Sitting - Fidget feet legs	90.4 ± 6.0	92.3 ± 5.6	94.0 ± 4.9	88.4 ± 9.7	89.2 ± 6.8
Sitting - Fidget hands arms	85.8 ± 8.4	91.3 ± 5.6	90.9 ± 4.3	82.4 ± 11.6	89.2 ± 7.3
Stairs - Ascend stairs	85.4 ± 5.8	84.3 ± 8.2	86.2 ± 7.0	84.9 ± 8.1	81.6 ± 7.2
Stairs - Descend stairs	83.1 ± 7.4	85.2 ± 6.5	85.7 ± 5.7	84.2 ± 7.5	82.9 ± 7.2
Standing	87.4 ± 6.2	90.0 ± 5.2	91.0 ± 4.2	83.6 ± 13.3	87.1 ± 8.8
Walking - Treadmill 2mph - Treadmill 0	88.4 ± 3.9	89.8 ± 4.2	90.6 ± 5.6	89.9 ± 3.9	90.5 ± 4.1
Walking - Treadmill 3mph - Treadmill 0	82.5 ± 6.1	81.8 ± 7.1	82.3 ± 8.1	79.9 ± 6.3	79.6 ± 8.5
Walking - Treadmill 3mph - Treadmill 3 - light	75.5 ± 9.6	74.4 ± 11.2	77.1 ± 9.1	73.0 ± 7.8	68.7 ± 13.5
Walking - Treadmill 3mph - Treadmill 6 - moderate	76.9 ± 12.4	74.5 ± 11.1	77.7 ± 10.0	74.6 ± 11.1	71.6 ± 11.0
Walking - Treadmill 3mph - Treadmill 9 - hard	83.3 ± 10.7	85.5 ± 9.2	85.2 ± 8.4	83.5 ± 10.3	81.4 ± 11.5
kneeling	92.5 ± 4.6	95.1 ± 3.1	93.9 ± 3.7	94.6 ± 5.0	93.7 ± 3.7
unknown	75.3 ± 5.4	76.2 ± 5.2	76.8 ± 5.2	73.7 ± 6.9	74.5 ± 6.0
Carrying groceries	86.4 ± 7.4	86.9 ± 7.2	88.7 ± 5.8	85.2 ± 9.4	87.4 ± 9.9
Doing dishes	81.4 ± 10.0	82.2 ± 9.0	84.9 ± 6.2	76.4 ± 9.3	78.8 ± 9.6
Gardening	80.3 ± 10.2	80.3 ± 15.3	79.9 ± 10.0	73.7 ± 12.9	75.5 ± 12.8
Ironing	79.4 ± 9.3	82.1 ± 8.7	83.1 ± 8.3	75.9 ± 11.4	78.0 ± 11.6
Making the bed	54.8 ± 13.2	59.0 ± 13.4	59.7 ± 10.8	55.0 ± 8.8	54.3 ± 8.8
Mopping	62.2 ± 12.4	66.0 ± 11.6	67.8 ± 10.6	61.2 ± 11.9	60.0 ± 14.0
Playing videogames	95.2 ± 3.3	95.2 ± 2.7	94.8 ± 3.2	94.1 ± 4.5	94.3 ± 4.1
Scrubbing a surface	80.4 ± 11.1	82.2 ± 12.6	81.3 ± 13.1	78.4 ± 14.5	80.9 ± 13.7
Stacking groceries	59.5 ± 12.9	62.9 ± 16.0	64.2 ± 13.5	60.2 ± 12.9	59.5 ± 14.9
Sweeping	65.7 ± 12.5	66.7 ± 13.0	67.0 ± 14.0	62.7 ± 13.2	65.4 ± 13.2
Typing	96.5 ± 3.0	95.9 ± 2.9	95.9 ± 3.2	94.7 ± 2.8	95.4 ± 3.2
Vacuuming	70.8 ± 9.6	72.7 ± 10.1	71.3 ± 10.5	65.9 ± 9.2	69.4 ± 11.2
Walking around block	83.9 ± 9.7	85.9 ± 8.7	86.5 ± 6.9	81.3 ± 8.2	84.4 ± 6.7
Washing windows	69.1 ± 7.3	70.6 ± 9.4	69.7 ± 9.0	64.9 ± 9.7	65.7 ± 7.4
Watching TV	91.0 ± 6.4	92.1 ± 4.9	91.8 ± 5.5	92.3 ± 4.2	93.5 ± 4.2
Weeding	73.8 ± 14.8	77.6 ± 10.6	78.1 ± 10.5	70.7 ± 13.7	71.5 ± 13.4
Wiping/Dusting	63.8 ± 12.8	67.0 ± 12.1	67.0 ± 11.6	58.7 ± 14.3	60.0 ± 14.2
Writing	94.8 ± 3.8	95.2 ± 2.6	95.5 ± 2.6	95.5 ± 3.8	95.6 ± 2.3
taking out trash	48.9 ± 11.3	56.9 ± 12.1	60.6 ± 8.9	50.1 ± 11.3	54.5 ± 10.9

Table A6-11: F-Measure rate when evaluating the four of the highest performing feature subsets computed per axis using the C4.5 classifier in a subject dependent manner.

Activity	True Positive Rate				
	AllButHR	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	12.8 ± 31.2	21.2 ± 35.5	27.5 ± 36.0	4.8 ± 9.5	14.1 ± 27.0
Bench weight lifting - light	39.5 ± 39.0	38.2 ± 38.6	59.6 ± 39.3	28.3 ± 29.6	28.5 ± 32.4
Bench weight lifting - moderate	26.3 ± 34.3	29.2 ± 35.9	27.3 ± 33.1	25.6 ± 31.3	31.9 ± 40.8
Bicep curls - hard	44.8 ± 34.7	32.4 ± 39.4	28.1 ± 38.5	30.8 ± 32.0	31.3 ± 37.4
Bicep curls - light	31.8 ± 39.1	25.6 ± 35.2	30.2 ± 38.0	25.1 ± 28.8	19.0 ± 29.2
Bicep curls - moderate	22.0 ± 31.7	20.2 ± 30.9	36.6 ± 34.7	28.3 ± 34.6	28.4 ± 33.8
Calisthenics - Crunches	55.1 ± 40.0	58.4 ± 40.7	60.0 ± 38.1	57.2 ± 37.9	48.2 ± 38.1
Calisthenics - Sit ups	74.6 ± 34.9	70.6 ± 36.7	53.9 ± 42.5	87.5 ± 22.8	66.9 ± 36.2
Cycling - Cycle hard - Cycle 80rpm	25.7 ± 27.0	18.7 ± 32.2	7.4 ± 9.6	19.1 ± 26.5	30.8 ± 32.4
Cycling - Cycle light - Cycle 100rpm	67.1 ± 35.1	89.7 ± 19.7	85.4 ± 22.4	65.6 ± 34.2	85.3 ± 25.2
Cycling - Cycle light - Cycle 60rpm	63.4 ± 34.6	64.0 ± 38.8	58.8 ± 36.7	72.2 ± 27.3	70.3 ± 33.7
Cycling - Cycle light - Cycle 80rpm	28.8 ± 27.6	34.4 ± 39.7	44.6 ± 43.6	22.6 ± 30.6	34.9 ± 36.3
Cycling - Cycle moderate - Cycle 80rpm	26.7 ± 26.2	22.4 ± 27.3	21.9 ± 23.3	28.8 ± 25.7	21.4 ± 15.2
Lying down	88.4 ± 25.6	90.9 ± 18.6	85.2 ± 26.8	83.0 ± 28.1	82.9 ± 23.7
Rowing - Rowing hard - Rowing 30spm	29.0 ± 29.3	39.2 ± 36.7	32.0 ± 41.4	30.2 ± 33.9	21.6 ± 30.2
Rowing - Rowing light - Rowing 30spm	41.9 ± 40.0	53.6 ± 33.6	42.3 ± 38.4	26.0 ± 29.8	32.2 ± 29.4
Rowing - Rowing moderate - Rowing 30spm	22.9 ± 35.7	8.1 ± 15.3	19.6 ± 37.2	28.7 ± 30.7	22.1 ± 23.4
Running - Treadmill 4mph - Treadmill 0	44.8 ± 28.8	53.5 ± 41.6	41.6 ± 41.3	44.8 ± 40.4	50.4 ± 38.7
Running - Treadmill 5mph - Treadmill 0	48.7 ± 34.7	46.6 ± 39.6	55.2 ± 35.0	36.1 ± 32.6	42.7 ± 32.4
Running - Treadmill 6mph - Treadmill 0	51.0 ± 35.5	51.4 ± 35.1	63.8 ± 38.1	42.0 ± 37.2	49.5 ± 34.1
Sitting	64.2 ± 39.9	61.8 ± 41.2	47.3 ± 41.2	37.8 ± 44.2	30.7 ± 40.7
Sitting - Fidget feet legs	45.2 ± 32.8	46.3 ± 39.3	40.0 ± 38.8	44.4 ± 35.2	51.6 ± 36.9
Sitting - Fidget hands arms	48.5 ± 36.2	45.3 ± 32.6	40.3 ± 35.0	51.1 ± 30.5	42.8 ± 28.6
Stairs - Ascend stairs	66.3 ± 21.0	44.1 ± 21.8	37.4 ± 22.6	59.9 ± 27.6	66.5 ± 22.5
Stairs - Descend stairs	69.9 ± 27.3	50.5 ± 26.2	47.8 ± 29.8	63.5 ± 25.6	50.7 ± 28.0
Standing	65.4 ± 32.1	49.8 ± 37.2	59.0 ± 36.5	64.6 ± 27.5	44.6 ± 36.8
Walking - Treadmill 2mph - Treadmill 0	50.9 ± 31.2	43.6 ± 30.5	48.9 ± 32.4	54.2 ± 29.8	54.4 ± 27.5
Walking - Treadmill 3mph - Treadmill 0	23.4 ± 24.6	8.3 ± 11.4	16.7 ± 19.0	21.5 ± 22.4	17.1 ± 16.3
Walking - Treadmill 3mph - Treadmill 3 - light	18.8 ± 20.4	11.1 ± 17.8	9.8 ± 12.2	16.0 ± 17.8	18.1 ± 28.0
Walking - Treadmill 3mph - Treadmill 6 - moderate	16.1 ± 23.8	15.6 ± 22.4	15.0 ± 23.2	19.3 ± 21.8	14.3 ± 16.4
Walking - Treadmill 3mph - Treadmill 9 - hard	22.0 ± 24.6	22.5 ± 24.3	28.2 ± 25.7	28.9 ± 25.7	21.1 ± 24.1
kneeling	89.5 ± 21.5	93.8 ± 7.3	88.0 ± 16.6	74.1 ± 40.7	74.5 ± 37.4
unknown	65.4 ± 6.6	64.0 ± 6.4	62.6 ± 7.5	63.8 ± 5.3	61.7 ± 4.6
Carrying groceries	55.5 ± 26.5	33.8 ± 23.9	34.5 ± 29.5	49.1 ± 26.1	52.2 ± 29.0
Doing dishes	45.2 ± 30.0	53.6 ± 26.1	54.1 ± 22.9	48.0 ± 24.2	44.1 ± 23.1
Gardening	14.0 ± 21.4	19.1 ± 22.4	14.1 ± 17.9	15.2 ± 19.0	11.8 ± 14.8
Ironing	51.3 ± 28.5	51.9 ± 27.5	56.7 ± 26.4	43.8 ± 30.6	45.5 ± 27.6
Making the bed	37.8 ± 15.7	44.4 ± 17.9	40.5 ± 20.6	32.1 ± 12.5	36.8 ± 15.7
Mopping	31.5 ± 20.0	31.3 ± 16.5	26.5 ± 17.7	30.9 ± 11.9	31.1 ± 9.4
Playing videogames	49.7 ± 39.6	46.5 ± 43.9	45.3 ± 44.1	36.2 ± 39.8	47.1 ± 43.2
Scrubbing a surface	36.7 ± 26.3	38.5 ± 19.7	40.1 ± 25.7	34.3 ± 28.2	31.1 ± 27.4
Stacking groceries	34.4 ± 15.4	32.3 ± 15.3	28.7 ± 17.2	25.8 ± 14.9	29.2 ± 16.4
Sweeping	33.8 ± 21.0	31.6 ± 18.1	30.2 ± 18.4	29.8 ± 15.5	27.9 ± 13.8
Typing	60.0 ± 37.6	70.8 ± 27.6	59.6 ± 37.4	58.8 ± 36.2	64.0 ± 33.9
Vacuuming	41.8 ± 21.2	44.5 ± 19.1	38.4 ± 19.9	40.5 ± 21.0	43.2 ± 24.6
Walking around block	29.4 ± 13.7	25.4 ± 18.7	23.8 ± 19.1	26.0 ± 17.0	23.6 ± 16.3
Washing windows	36.7 ± 21.6	35.4 ± 17.8	36.7 ± 18.2	38.2 ± 20.9	40.7 ± 20.8
Watching TV	35.6 ± 39.5	35.5 ± 38.7	20.7 ± 32.9	39.8 ± 41.0	41.7 ± 40.4
Weeding	10.6 ± 14.0	20.6 ± 25.8	15.7 ± 18.0	14.3 ± 23.1	14.5 ± 25.7
Wiping/Dusting	39.9 ± 19.5	38.9 ± 17.4	39.2 ± 17.7	33.8 ± 18.6	36.4 ± 19.6
Writing	56.8 ± 42.9	71.5 ± 34.3	67.0 ± 40.8	65.8 ± 35.9	63.1 ± 37.3
taking out trash	18.5 ± 11.3	20.1 ± 10.9	18.4 ± 12.2	18.2 ± 12.1	16.0 ± 10.0

Table A6-12: True positive rate when evaluating the four of the highest performing feature subsets computed per axis using the C4.5 classifier in a subject independent manner.

	False Positive Rate				
Activity	**AllButHR**	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	0.3 ± 0.4	0.4 ± 0.5	0.2 ± 0.3	0.4 ± 0.5	0.3 ± 0.5
Bench weight lifting - light	0.5 ± 0.7	0.7 ± 0.8	0.6 ± 0.6	0.5 ± 0.5	0.6 ± 0.7
Bench weight lifting - moderate	0.4 ± 0.5	0.6 ± 0.5	0.4 ± 0.4	0.6 ± 0.5	0.8 ± 0.8
Bicep curls - hard	1.4 ± 0.8	1.0 ± 1.2	0.8 ± 0.9	0.9 ± 0.9	1.1 ± 1.0
Bicep curls - light	0.9 ± 1.0	0.8 ± 0.9	0.5 ± 0.6	0.5 ± 0.6	0.6 ± 0.6
Bicep curls - moderate	0.5 ± 0.5	1.0 ± 1.0	1.1 ± 1.0	0.8 ± 0.8	0.9 ± 0.8
Calisthenics - Crunches	0.1 ± 0.2	0.1 ± 0.1	0.1 ± 0.2	0.4 ± 0.8	0.3 ± 0.5
Calisthenics - Sit ups	0.2 ± 0.3	0.2 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Cycling - Cycle hard - Cycle 80rpm	0.9 ± 0.7	0.8 ± 0.9	0.4 ± 0.3	0.9 ± 0.9	1.1 ± 1.1
Cycling - Cycle light - Cycle 100rpm	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.3 ± 0.5
Cycling - Cycle light - Cycle 60rpm	0.1 ± 0.1	0.3 ± 0.2	0.3 ± 0.4	0.2 ± 0.3	0.2 ± 0.2
Cycling - Cycle light - Cycle 80rpm	0.9 ± 1.0	1.2 ± 1.2	1.2 ± 1.1	0.6 ± 0.8	0.9 ± 1.0
Cycling - Cycle moderate - Cycle 80rpm	0.9 ± 0.7	0.6 ± 0.7	0.7 ± 1.0	1.0 ± 0.8	0.7 ± 0.6
Lying down	0.1 ± 0.1	0.2 ± 0.3	0.2 ± 0.3	0.4 ± 0.6	0.3 ± 0.4
Rowing - Rowing hard - Rowing 30spm	0.6 ± 0.6	0.8 ± 0.9	0.8 ± 0.8	1.0 ± 1.1	0.6 ± 0.8
Rowing - Rowing light - Rowing 30spm	1.2 ± 1.1	1.6 ± 1.0	1.4 ± 1.4	0.8 ± 0.8	0.9 ± 0.8
Rowing - Rowing moderate - Rowing 30spm	0.9 ± 1.0	0.4 ± 0.5	0.6 ± 1.0	1.1 ± 0.9	1.0 ± 1.0
Running - Treadmill 4mph - Treadmill 0	0.6 ± 0.6	0.9 ± 1.5	0.3 ± 0.4	0.4 ± 0.3	0.7 ± 0.6
Running - Treadmill 5mph - Treadmill 0	0.5 ± 0.6	0.6 ± 0.5	0.6 ± 0.6	0.7 ± 0.6	0.6 ± 0.4
Running - Treadmill 6mph - Treadmill 0	0.3 ± 0.4	0.5 ± 0.6	0.6 ± 0.8	0.4 ± 0.4	0.5 ± 0.6
Sitting	0.5 ± 0.8	0.6 ± 0.9	0.9 ± 1.0	0.6 ± 0.8	0.6 ± 1.0
Sitting - Fidget feet legs	0.4 ± 0.6	0.3 ± 0.4	0.4 ± 0.5	0.3 ± 0.3	0.3 ± 0.2
Sitting - Fidget hands arms	0.2 ± 0.2	0.4 ± 0.5	0.3 ± 0.3	0.4 ± 0.2	0.5 ± 0.5
Stairs - Ascend stairs	0.3 ± 0.1	1.0 ± 0.9	0.7 ± 0.5	0.4 ± 0.3	0.5 ± 0.4
Stairs - Descend stairs	0.3 ± 0.2	0.5 ± 0.4	0.6 ± 0.4	0.9 ± 1.4	0.5 ± 0.3
Standing	0.4 ± 0.4	0.2 ± 0.2	0.3 ± 0.2	0.3 ± 0.3	0.3 ± 0.3
Walking - Treadmill 2mph - Treadmill 0	0.4 ± 0.5	0.3 ± 0.2	0.3 ± 0.2	0.5 ± 0.5	0.5 ± 0.2
Walking - Treadmill 3mph - Treadmill 0	1.0 ± 1.0	0.6 ± 0.4	1.0 ± 0.8	0.8 ± 0.5	1.0 ± 0.6
Walking - Treadmill 3mph - Treadmill 3 - light	0.9 ± 0.6	0.7 ± 0.7	0.7 ± 0.6	0.6 ± 0.4	1.3 ± 1.2
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.2 ± 1.2	1.4 ± 1.3	1.2 ± 1.0	1.2 ± 1.0	0.9 ± 0.8
Walking - Treadmill 3mph - Treadmill 9 - hard	0.8 ± 0.6	1.1 ± 0.8	1.0 ± 1.2	1.1 ± 1.0	1.2 ± 1.2
kneeling	0.1 ± 0.1	0.2 ± 0.3	0.1 ± 0.1	0.2 ± 0.6	0.2 ± 0.5
unknown	24.0 ± 7.2	23.5 ± 6.7	25.1 ± 5.8	24.8 ± 6.6	24.2 ± 5.4
Carrying groceries	1.3 ± 1.7	1.2 ± 1.3	1.1 ± 0.8	0.9 ± 1.1	0.8 ± 0.8
Doing dishes	0.7 ± 0.3	0.6 ± 0.3	0.5 ± 0.3	0.9 ± 0.5	0.8 ± 0.3
Gardening	0.6 ± 0.5	0.7 ± 0.7	0.6 ± 0.5	0.8 ± 0.4	0.8 ± 0.4
Ironing	0.8 ± 0.6	0.8 ± 0.4	0.7 ± 0.4	0.7 ± 0.4	0.8 ± 0.4
Making the bed	1.2 ± 0.5	1.2 ± 0.8	1.3 ± 0.8	1.3 ± 0.8	1.3 ± 0.7
Mopping	1.1 ± 0.4	1.1 ± 0.4	1.1 ± 0.5	1.2 ± 0.4	1.1 ± 0.5
Playing videogames	0.5 ± 0.7	0.8 ± 0.8	1.0 ± 1.0	0.7 ± 0.9	0.7 ± 0.9
Scrubbing a surface	0.9 ± 0.7	1.3 ± 1.0	1.2 ± 1.1	1.0 ± 0.6	1.0 ± 0.7
Stacking groceries	0.9 ± 0.4	0.9 ± 0.3	0.9 ± 0.5	0.8 ± 0.4	0.8 ± 0.3
Sweeping	1.0 ± 0.4	1.0 ± 0.6	1.2 ± 0.8	0.9 ± 0.3	1.1 ± 0.4
Typing	0.3 ± 0.5	0.3 ± 0.4	0.4 ± 0.5	0.5 ± 0.6	0.5 ± 0.7
Vacuuming	0.6 ± 0.2	0.6 ± 0.3	0.9 ± 0.4	0.7 ± 0.3	0.8 ± 0.3
Walking around block	2.2 ± 2.4	2.0 ± 1.5	2.4 ± 2.2	1.9 ± 1.7	2.0 ± 2.3
Washing windows	1.0 ± 0.4	0.9 ± 0.5	0.9 ± 0.3	0.9 ± 0.3	0.8 ± 0.5
Watching TV	1.2 ± 2.3	1.1 ± 1.2	1.0 ± 1.2	0.9 ± 1.0	0.6 ± 0.5
Weeding	0.6 ± 0.5	0.5 ± 0.3	0.6 ± 0.4	0.8 ± 0.5	0.7 ± 0.5
Wiping/Dusting	0.8 ± 0.4	0.9 ± 0.5	0.9 ± 0.4	0.9 ± 0.5	0.9 ± 0.4
Writing	0.4 ± 0.6	0.4 ± 0.4	0.6 ± 1.1	0.3 ± 0.3	0.3 ± 0.4
taking out trash	1.1 ± 0.5	1.0 ± 0.4	1.1 ± 0.5	1.0 ± 0.3	1.0 ± 0.4

Table A6-13: False positive rate when evaluating the four of the highest performing feature subsets computed per axis using the C4.5 classifier in a subject independent manner.

	F-Measure				
Activity	**AllButHR**	**ACAbsArea, DCArea, ACVar, ACRange, ACMCR**	**ACAbsArea DCArea**	**Total Invariant**	**Invariant Reduced**
Bench weight lifting - hard	8.0 ± 16.9	18.2 ± 31.2	29.5 ± 35.8	5.4 ± 11.4	12.2 ± 17.2
Bench weight lifting - light	34.8 ± 31.0	30.0 ± 27.0	49.3 ± 29.5	26.8 ± 22.4	26.8 ± 27.4
Bench weight lifting - moderate	19.8 ± 22.8	21.3 ± 21.5	24.8 ± 25.8	19.2 ± 18.7	20.0 ± 20.3
Bicep curls - hard	32.3 ± 20.1	19.2 ± 21.6	19.5 ± 23.4	24.4 ± 21.0	23.5 ± 27.7
Bicep curls - light	22.3 ± 21.9	20.6 ± 22.7	28.3 ± 32.2	24.1 ± 20.9	17.3 ± 23.2
Bicep curls - moderate	21.2 ± 23.8	13.4 ± 16.6	27.1 ± 20.3	21.2 ± 20.0	21.2 ± 20.1
Calisthenics - Crunches	57.7 ± 37.7	61.1 ± 39.0	64.2 ± 37.8	54.2 ± 35.7	49.3 ± 35.2
Calisthenics - Sit ups	74.4 ± 31.3	70.1 ± 32.2	56.5 ± 41.2	87.8 ± 22.5	70.0 ± 34.9
Cycling - Cycle hard - Cycle 80rpm	20.0 ± 18.9	14.7 ± 21.2	9.2 ± 11.1	14.6 ± 16.6	21.1 ± 18.5
Cycling - Cycle light - Cycle 100rpm	72.1 ± 31.9	90.0 ± 14.2	87.1 ± 17.4	71.7 ± 29.3	82.6 ± 20.6
Cycling - Cycle light - Cycle 60rpm	68.0 ± 32.6	64.5 ± 34.5	61.3 ± 33.2	74.3 ± 23.6	72.0 ± 32.5
Cycling - Cycle light - Cycle 80rpm	27.6 ± 22.2	24.4 ± 22.6	29.5 ± 27.4	22.2 ± 21.0	29.4 ± 27.3
Cycling - Cycle moderate - Cycle 80rpm	23.5 ± 17.9	21.8 ± 22.4	20.2 ± 16.7	24.2 ± 17.8	22.9 ± 13.9
Lying down	90.3 ± 22.2	92.7 ± 12.0	87.5 ± 23.8	84.1 ± 24.4	86.1 ± 16.9
Rowing - Rowing hard - Rowing 30spm	27.3 ± 23.0	32.1 ± 28.4	26.1 ± 33.1	23.4 ± 18.6	18.6 ± 18.4
Rowing - Rowing light - Rowing 30spm	27.8 ± 23.5	37.6 ± 17.2	28.3 ± 15.8	22.3 ± 19.7	28.3 ± 17.9
Rowing - Rowing moderate - Rowing 30spm	15.8 ± 21.8	8.1 ± 13.6	12.4 ± 21.9	22.4 ± 20.6	19.1 ± 16.0
Running - Treadmill 4mph - Treadmill 0	46.1 ± 28.2	46.9 ± 37.1	41.4 ± 36.4	45.0 ± 37.9	47.9 ± 35.8
Running - Treadmill 5mph - Treadmill 0	46.8 ± 30.5	42.6 ± 30.6	53.0 ± 31.4	34.6 ± 25.1	40.8 ± 25.4
Running - Treadmill 6mph - Treadmill 0	52.2 ± 35.9	45.3 ± 32.6	52.7 ± 30.2	37.0 ± 28.3	44.5 ± 25.4
Sitting	55.8 ± 35.0	53.2 ± 36.9	38.4 ± 36.0	34.5 ± 40.6	27.3 ± 36.7
Sitting - Fidget feet legs	49.0 ± 32.9	47.8 ± 36.2	39.6 ± 34.5	47.1 ± 33.4	50.9 ± 32.0
Sitting - Fidget hands arms	50.2 ± 31.6	46.5 ± 31.1	41.6 ± 32.6	50.5 ± 24.4	41.8 ± 24.6
Stairs - Ascend stairs	68.7 ± 17.4	41.2 ± 17.8	39.3 ± 20.4	59.8 ± 24.8	65.7 ± 18.1
Stairs - Descend stairs	69.0 ± 23.6	51.3 ± 24.1	45.8 ± 24.8	58.7 ± 25.4	51.4 ± 24.5
Standing	60.5 ± 29.5	50.1 ± 35.2	57.4 ± 33.5	62.4 ± 26.2	43.7 ± 34.4
Walking - Treadmill 2mph - Treadmill 0	54.5 ± 26.4	48.6 ± 29.1	53.8 ± 28.2	55.7 ± 27.8	56.9 ± 24.0
Walking - Treadmill 3mph - Treadmill 0	20.7 ± 17.3	10.3 ± 13.3	16.7 ± 18.4	21.6 ± 20.4	17.3 ± 15.4
Walking - Treadmill 3mph - Treadmill 3 - light	17.8 ± 15.6	11.0 ± 11.6	10.9 ± 12.2	17.2 ± 16.8	13.7 ± 16.3
Walking - Treadmill 3mph - Treadmill 6 - moderate	12.2 ± 14.2	11.8 ± 14.6	11.9 ± 16.0	15.8 ± 14.3	14.5 ± 15.8
Walking - Treadmill 3mph - Treadmill 9 - hard	21.9 ± 20.0	22.7 ± 20.4	27.0 ± 24.5	27.4 ± 21.3	19.2 ± 18.6
kneeling	88.1 ± 18.2	89.6 ± 9.9	88.9 ± 11.4	71.1 ± 39.6	71.2 ± 35.6
unknown	54.7 ± 7.1	54.2 ± 7.2	52.0 ± 7.4	53.2 ± 6.9	52.2 ± 6.2
Carrying groceries	50.0 ± 22.2	32.6 ± 22.8	32.7 ± 23.8	48.3 ± 21.8	52.0 ± 25.9
Doing dishes	44.7 ± 26.1	53.9 ± 20.7	57.1 ± 18.5	46.4 ± 20.4	43.6 ± 19.3
Gardening	14.8 ± 21.7	21.3 ± 22.8	16.7 ± 20.5	16.5 ± 19.5	14.1 ± 17.1
Ironing	50.3 ± 24.9	51.3 ± 23.0	55.9 ± 21.8	43.7 ± 27.1	45.1 ± 23.9
Making the bed	35.8 ± 13.1	41.8 ± 13.6	37.2 ± 14.8	31.3 ± 10.5	34.8 ± 11.7
Mopping	30.7 ± 15.6	31.3 ± 14.6	26.3 ± 15.5	31.0 ± 10.4	31.8 ± 8.3
Playing videogames	48.4 ± 34.5	43.2 ± 38.1	39.3 ± 37.2	34.6 ± 35.4	43.9 ± 37.4
Scrubbing a surface	36.3 ± 23.4	36.2 ± 17.6	36.4 ± 21.4	33.2 ± 24.6	30.1 ± 23.6
Stacking groceries	35.4 ± 14.4	32.7 ± 15.6	28.6 ± 15.8	27.1 ± 14.5	31.1 ± 16.0
Sweeping	34.3 ± 17.7	33.0 ± 15.5	31.3 ± 17.4	32.0 ± 14.2	29.8 ± 13.1
Typing	62.4 ± 36.4	73.9 ± 23.5	60.8 ± 34.8	58.9 ± 31.8	63.4 ± 29.1
Vacuuming	44.7 ± 18.0	47.3 ± 16.4	39.9 ± 19.3	42.2 ± 19.5	43.7 ± 21.9
Walking around block	27.2 ± 11.6	20.9 ± 13.7	21.3 ± 14.6	23.2 ± 15.5	23.7 ± 16.3
Washing windows	37.6 ± 22.1	37.6 ± 18.9	38.5 ± 19.0	39.6 ± 21.0	42.9 ± 21.4
Watching TV	31.7 ± 33.6	32.8 ± 33.6	19.9 ± 29.0	36.8 ± 36.4	41.2 ± 37.8
Weeding	12.5 ± 15.1	20.0 ± 20.3	18.7 ± 20.2	14.8 ± 19.9	14.7 ± 22.9
Wiping/Dusting	40.7 ± 18.8	39.8 ± 16.1	39.6 ± 16.0	34.6 ± 17.2	37.1 ± 16.4
Writing	56.0 ± 41.0	70.5 ± 28.6	62.8 ± 38.4	66.5 ± 34.1	64.0 ± 34.3
taking out trash	19.1 ± 10.6	21.6 ± 11.5	19.7 ± 12.9	20.0 ± 13.0	17.3 ± 10.3

Table A6-14: F-Measure when evaluating the four of the highest performing feature subsets computed per axis using the C4.5 classifier in a subject independent manner.

E X A M P L E   C L A S S I F I E D   A S

O R I G I N A L   L A B E L

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
A	18	48	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	44	0	0	0	0	0	0	0	0	0	0	3	0	0	0	1	0	0	0	0
B	36	144	47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	78	0	0	0	0	0	0	0	0	0	0	16	0	0	0	1	0	0	2	1
C	21	83	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	82	0	0	0	0	0	0	0	0	0	0	18	0	0	0	2	0	0	7	0
D	0	0	0	81	82	47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	68	48	141	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	65	78	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	1	0	0	0	46	18	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	137	0	0	0	0	0	0	0	6	0	0	0	0	0	1	0	0	0	0	0
H	0	0	0	0	0	0	0	150	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	61	0	0	0	0	0	1	0	1	37	0	0	0	0	1	0	0	0	0	0
I	0	0	0	0	0	0	0	0	38	47	0	114	64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	110	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	19	329	0	15	34	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	83	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	0	0	3	6	0	184	17	15	0	0	0	1	0	0	0	0	31	1	3	0	0	0	0	0	0	0	0	308	0	0	0	1	0	0	1	0	0	5	0	2	0	0	0	0	1	0	0
L	0	0	0	0	0	0	0	0	93	22	14	123	114	0	0	0	0	0	0	0	0	0	0	0	0	0	16	1	4	0	0	0	170	1	0	0	0	1	0	0	0	0	0	0	0	6	0	0	0	0	0	2
M	0	0	0	0	0	0	0	0	35	70	6	204	47	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	132	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0	0	1096	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	256	0	0	0	0	0	0	78	0	0	0	108	0	0	0	60	0	0	0	0
O	0	0	0	0	0	0	0	0	0	0	0	0	0	0	71	84	117	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	76	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0
P	0	0	0	0	0	0	8	4	0	0	2	1	2	0	64	75	96	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	234	0	0	0	0	1	8	0	0	0	8	0	0	0	37	0	0	0	0	0
Q	0	0	0	0	0	0	0	1	2	0	0	0	6	0	85	67	90	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	175	0	0	0	0	0	0	0	0	0	0	0	0	0	32	0	0	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	168	59	0	0	0	0	0	6	0	0	6	51	11	4	0	147	56	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	236	56	0	0	0	0	0	0	0	0	0	0	0	0	165	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	30	114	93	0	0	0	0	0	0	0	0	0	0	0	0	96	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	96	2	1	0	0	0	0	0	0	0	0	0	127	0	0	0	0	0	0	18	0	0	0	2	0	0	6	38	0	0	3	0
V	0	0	0	0	0	0	0	1	2	0	14	0	6	0	0	0	0	0	0	0	9	100	0	0	1	0	2	0	0	0	0	0	147	0	0	1	0	0	0	3	0	0	0	6	2	0	4	0	0	0	0	0
W	0	0	0	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	66	0	0	0	0	0	0	0	0	0	156	0	20	21	0	2	0	14	1	0	2	0	0	0	1	0	4	0	0	2
X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	226	42	0	12	0	0	1	0	0	176	7	0	0	0	10	0	0	0	0	3	0	0	5	2	0	0	2	0	12
Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	38	137	0	11	6	3	6	5	0	175	15	0	0	0	15	1	0	0	0	1	0	0	33	0	0	0	1	0	10
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	155	0	0	0	0	0	0	159	0	0	0	1	0	1	0	3	0	0	0	0	0	1	0	1	0	0	0
[	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	22	0	299	5	2	5	5	0	190	6	0	0	0	6	1	0	0	0	3	0	2	28	0	0	0	0	0	3
\	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	1	37	0	29	59	93	40	27	0	164	29	0	0	0	0	0	0	0	0	0	0	0	122	0	0	0	0	0	1
]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	7	0	26	74	85	70	25	0	156	39	0	0	0	0	0	0	0	0	0	0	0	111	0	0	0	0	0	3
^	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	6	0	0	0	0	0	2	7	0	41	60	70	89	37	0	137	68	0	0	0	0	0	0	0	0	0	0	0	95	0	0	0	0	0	3
_	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	2	39	0	46	42	49	102	59	0	116	55	0	0	0	1	0	0	0	0	0	0	0	85	0	0	0	0	0	0
`	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	244	65	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	4	0
a	6	22	21	14	24	8	19	20	26	36	89	66	48	35	32	44	33	47	55	19	79	75	64	86	123	101	94	58	61	67	31	31	6600	96	110	35	88	143	84	124	99	86	100	80	117	113	150	121	54	118	69	131
b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	13	15	0	9	39	20	33	28	0	179	123	1	0	0	3	0	0	0	0	0	0	4	71	0	0	0	0	0	1
c	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	3	0	0	0	0	0	0	224	0	211	15	74	2	4	0	6	1	2	0	0	0	11	0	0	16	0	12
d	0	0	0	0	0	0	3	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	89	0	0	104	0	10	0	1	62	0	5	0	9	0	0	0	44	5	0	6
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	218	0	67	1	274	0	5	0	32	3	2	0	3	0	2	1	0	8	0	0
f	0	0	0	0	0	3	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	12	0	1	0	0	0	0	0	192	4	1	4	1	199	22	0	14	11	14	0	10	9	7	0	5	21	0	34
g	0	0	1	0	0	0	9	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	146	0	3	0	3	36	152	0	2	30	36	0	12	0	10	0	0	15	0	2
h	0	5	0	0	0	0	0	0	0	0	0	0	0	121	0	0	0	0	0	0	34	0	10	0	0	0	0	0	0	0	0	0	256	0	1	0	0	0	0	122	0	0	0	4	0	0	1	74	2	0	2	0
i	0	0	0	0	0	0	2	4	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	162	0	4	46	6	11	3	0	75	8	8	0	2	0	28	0	20	22	0	12
j	0	0	0	0	0	0	1	2	0	0	0	0	0	0	3	1	2	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	165	0	3	0	8	25	28	0	9	79	18	0	6	0	29	1	0	19	0	10
k	0	0	0	0	0	7	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	3	0	1	0	0	0	0	0	186	1	0	6	3	33	49	0	2	17	96	0	18	0	1	0	2	17	0	14
l	1	8	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	268	0	0	0	0	0	0	4	4	0	0	291	0	0	21	1	0	0	46	0
m	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	5	7	0	0	0	0	0	0	0	181	5	3	3	2	16	13	0	4	1	11	0	186	1	3	0	1	14	0	14
n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	15	14	0	19	35	15	41	17	0	169	57	0	0	0	3	0	0	0	0	0	0	0	157	0	0	0	0	0	5
o	3	0	2	0	0	0	5	0	0	0	0	0	0	0	0	2	5	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	196	0	4	3	13	10	8	0	21	34	2	1	2	0	151	1	3	51	0	5
p	0	0	1	0	0	0	0	0	0	0	0	0	0	79	0	0	0	0	0	0	68	4	0	0	0	7	0	0	0	0	0	0	299	0	1	0	0	0	1	48	0	0	0	0	0	0	0	123	0	0	11	0
q	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	2	0	0	0	0	1	2	12	0	0	0	1	0	0	0	0	2	129	1	0	51	1	18	1	0	23	2	3	0	9	0	5	0	35	1	0	13
r	0	0	0	0	0	0	18	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	3	0	0	1	0	0	0	0	190	0	13	6	17	14	15	0	7	20	11	0	18	1	39	0	0	165	0	15
s	0	15	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	2	3	2	0	0	18	0	0	0	0	0	0	168	0	0	0	0	0	0	3	0	0	0	69	0	0	0	56	0	0	320	0
t	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	11	12	0	1	0	1	1	2	0	228	3	13	6	2	34	5	0	6	4	26	0	7	5	3	0	9	9	0	62

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0

S -> Running_-_Treadmill_5mph_-_Treadmill_0_T ->
Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3_-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6_-
_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9_-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes

d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-1: Confusion Matrix for C4.5 Classifier using the *ACAbsArea, DCArea, ACVar, ACRange, and ACMCR* feature set computed per sensor and evaluated in a subject independent manner.

EXAMPLE CLASSIFIED AS / ORIGINAL LABEL

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
A	12	34	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	47	0	4	0	5	0	1	0	1	1	0	0	0	0	0	0	0	0	0	2
B	36	78	72	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	116	0	7	0	6	0	0	0	0	2	0	3	0	0	0	0	0	0	1	0
C	19	74	28	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	92	0	4	0	5	0	0	1	1	1	0	2	0	0	0	1	1	0	0	0
D	0	0	0	48	102	63	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	47	194	74	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
F	0	3	0	51	100	63	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	1	4	4	0	0	0	44	2	0	0	0	0	0	0	0	3	4	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	121	0	2	0	0	7	2	1	4	2	5	0	0	0	2	0	0	0	0	0
H	0	0	0	0	0	0	4	199	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	47	0	0	0	0	0	1	0	0	11	0	0	0	0	0	0	0	0	0	4
I	0	0	0	0	0	0	0	0	54	6	9	119	67	0	0	0	0	0	0	0	0	0	0	3	9	0	0	0	1	0	0	0	97	0	0	0	0	4	0	0	0	0	1	0	0	0	0	0	1	1	0	1
J	0	0	0	0	0	0	0	0	4	333	0	8	5	0	0	0	0	0	0	0	0	0	0	0	0	0	4	13	3	8	3	0	99	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
K	0	0	0	0	0	0	0	2	8	0	402	0	10	0	0	0	0	0	0	0	0	11	0	1	0	0	1	0	0	0	0	0	142	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
L	0	0	0	0	0	0	0	0	64	3	6	208	135	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	149	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	71	5	6	157	99	0	0	0	0	0	0	0	0	2	0	1	4	0	2	0	0	0	0	0	146	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	2	0	0	0
N	0	0	0	0	0	0	1	0	0	0	0	0	0	1210	0	0	0	0	0	0	47	0	1	0	0	35	0	0	0	0	0	31	63	0	0	0	0	0	0	77	0	0	0	0	0	0	0	131	0	0	2	0
O	0	0	0	0	0	0	4	0	0	0	0	0	0	0	70	107	89	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	65	0	0	0	0	2	30	0	1	5	2	0	0	0	0	0	0	0	0	1
P	0	0	0	0	0	0	9	0	0	0	0	0	0	0	60	140	89	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	115	0	0	2	4	26	56	0	5	20	5	0	0	0	4	0	2	1	0	1
Q	1	0	0	0	1	0	7	0	0	0	0	0	0	0	58	118	98	0	0	0	0	0	1	6	0	0	0	0	0	0	0	0	80	0	6	3	3	16	42	0	0	4	5	0	2	0	0	0	3	0	0	4
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	175	42	15	0	0	0	2	0	0	0	19	8	14	20	0	198	4	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	47	184	142	0	0	0	0	0	0	0	0	3	0	0	0	95	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	102	176	0	0	0	0	0	0	0	0	11	0	0	0	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	1	0	0	0	0	0	0	0	0	0	0	0	58	0	0	0	0	0	0	30	0	0	0	0	45	0	0	0	0	0	26	94	0	2	0	0	0	0	6	0	0	0	1	0	0	0	40	0	0	2	0
V	0	0	0	0	0	0	0	0	3	0	5	0	7	1	0	0	0	0	0	0	0	165	5	0	0	6	0	0	0	0	0	1	79	0	0	0	1	0	1	1	0	0	0	11	0	0	0	10	0	1	1	0
W	0	11	1	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	129	0	0	0	0	0	0	0	0	2	58	0	33	2	8	2	0	3	2	0	1	21	0	0	4	2	6	0	3	2
X	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	312	27	0	14	1	1	1	0	0	104	8	0	0	0	3	2	0	0	1	2	0	2	5	0	0	6	2	0	4
Y	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	2	0	0	0	1	0	30	173	0	10	3	5	7	5	0	145	18	0	0	0	9	2	0	0	0	5	0	4	27	0	0	2	0	0	7
Z	0	0	0	0	0	0	1	0	0	0	0	0	0	42	0	0	0	0	0	0	43	0	0	0	0	40	0	0	0	0	0	31	116	0	0	0	0	0	0	9	2	0	0	1	0	0	0	32	0	0	4	0
[	0	0	0	0	0	0	0	0	2	2	1	3	5	0	0	0	0	0	0	0	0	0	0	10	28	0	328	4	3	1	7	0	188	10	0	0	0	0	0	0	0	0	1	0	1	14	0	0	0	1	0	3
\	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	32	0	0	0	0	0	3	7	0	13	139	96	84	73	0	81	17	0	0	0	0	0	0	0	0	0	0	0	55	0	0	1	0	0	0
]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	6	11	0	15	110	87	73	67	0	98	27	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	0	0
^	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	18	0	0	0	0	0	5	15	0	34	94	89	75	79	0	85	42	0	0	0	0	0	0	0	0	0	0	0	78	0	0	0	0	0	1
_	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	27	0	0	0	0	0	2	17	0	26	69	52	104	105	0	98	36	0	0	0	0	0	0	0	0	0	0	0	65	0	0	0	0	0	3
`	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	36	0	2	0	0	28	0	0	0	0	0	35	113	0	1	0	0	0	0	10	0	0	0	4	0	0	0	40	0	0	3	0
a	28	57	52	14	17	13	54	11	35	35	80	39	60	89	12	37	71	74	42	39	91	63	58	103	113	107	97	73	52	57	41	93	6004	87	189	57	176	168	100	103	84	125	126	87	175	119	66	148	79	100	83	169
b	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	15	0	0	0	0	0	18	18	0	17	33	27	34	14	0	130	151	0	0	0	2	0	0	0	0	0	0	4	71	0	0	1	0	0	3
c	6	5	8	0	0	0	6	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	29	0	0	1	0	0	0	0	0	0	221	0	166	13	66	2	1	2	8	8	3	0	0	0	12	0	7	13	2	8
d	1	2	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	5	0	0	0	0	0	0	0	0	0	80	0	15	110	11	8	0	0	24	4	0	1	6	0	6	2	30	27	0	10
e	10	3	9	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	9	0	0	2	0	0	0	0	0	0	242	1	82	13	191	2	4	2	5	0	5	2	5	0	7	0	9	9	1	5
f	0	0	0	0	0	0	0	1	0	0	2	0	1	0	2	3	2	0	0	0	0	0	1	9	13	0	2	1	0	0	0	0	207	3	3	11	5	168	15	0	8	14	24	0	7	3	14	0	7	12	0	38
g	1	2	1	0	0	0	0	0	0	0	0	0	0	0	2	9	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	152	0	5	3	6	29	162	0	2	25	25	0	18	0	4	0	4	1	0	9
h	0	6	3	0	0	0	0	0	0	0	0	0	0	93	0	0	0	0	0	0	21	10	4	0	1	15	0	0	0	0	0	16	171	0	0	0	4	0	1	128	0	1	0	64	0	0	0	51	0	1	42	0
i	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	4	2	0	0	0	0	0	3	0	0	0	0	0	0	0	0	2	89	0	16	18	10	13	2	0	91	7	10	0	0	0	79	0	13	57	0	2
j	2	7	2	0	0	0	0	5	0	0	1	0	0	0	0	2	1	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	168	1	3	1	5	28	35	1	7	94	7	0	8	0	18	0	0	11	0	2
k	0	1	1	0	0	0	0	2	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	2	0	2	1	0	0	0	0	166	0	2	3	2	46	39	0	4	19	113	0	17	0	11	0	7	9	0	10
l	0	5	3	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	3	14	11	0	0	3	0	0	0	0	0	4	134	0	0	0	4	0	0	84	0	0	0	323	0	0	0	9	0	0	54	0
m	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	3	1	1	1	0	0	0	0	1	235	1	0	3	4	9	23	0	3	10	28	0	119	0	2	0	12	8	0	8
n	0	0	0	0	0	0	0	0	1	5	0	0	0	0	0	0	0	5	1	0	0	0	0	6	24	0	25	54	26	41	17	0	143	73	0	0	0	2	0	0	0	0	0	0	0	146	0	0	0	0	0	0
o	0	1	0	1	0	1	0	0	0	0	0	0	1	0	4	3	1	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	155	1	6	14	10	13	5	0	70	24	9	0	0	1	127	0	14	58	0	2
p	0	3	1	0	0	0	0	0	0	0	0	0	0	203	0	0	0	0	0	0	55	1	1	0	0	37	0	0	0	0	0	25	132	0	3	1	2	0	0	42	0	0	0	8	0	0	0	112	0	1	15	0
q	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	5	0	0	0	0	0	0	0	0	127	2	2	24	14	16	5	2	21	2	13	0	10	0	15	0	30	19	0	12
r	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	173	0	23	37	12	16	4	0	57	10	15	0	2	0	58	0	15	123	0	7
s	0	8	2	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	10	2	0	0	0	15	0	0	0	0	0	8	91	0	1	0	0	0	0	31	0	0	0	69	0	0	0	20	0	0	398	0
t	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	2	1	0	0	0	0	0	1	4	8	0	3	0	1	1	1	0	234	2	12	12	14	44	10	0	2	9	13	0	7	5	4	0	15	8	0	38

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3_-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6_-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9_-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes
d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-2: Confusion Matrix for C4.5 Classifier using the *ACFFTPeaks* feature computed per sensor and evaluated in a subject independent manner.

E X A M P L E   C L A S S I F I E D   A S

O R I G I N A L   L A B E L

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	
30	47	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	0	1	0	0	7	0	2	0	0	0	1	0	0	0	0	A
20	127	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	81	0	0	0	0	0	0	0	0	17	0	32	0	0	5	0	0	0	3	0	B
24	72	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88	0	0	0	1	0	0	0	0	14	0	21	0	0	0	3	0	0	5	0	C
0	0	0	59	63	89	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	D
0	0	0	85	50	129	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	72	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	E
0	0	0	63	63	80	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	F
0	0	3	0	0	1	66	17	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	115	0	0	1	0	0	0	0	5	0	0	0	0	0	2	0	0	0	0	0	G
0	0	0	0	0	0	0	123	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	93	0	0	0	0	6	0	0	0	39	1	0	0	0	3	0	0	0	0	0	H
0	0	0	0	0	0	0	0	13	34	7	142	75	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	102	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	I
0	0	0	0	0	0	0	0	21	325	0	12	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	103	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	J
0	0	0	0	0	0	0	9	30	0	190	11	3	0	0	0	0	0	0	0	12	0	2	0	0	0	0	0	0	0	0	0	303	0	1	0	1	0	0	0	0	0	0	0	1	15	1	0	0	0	0	0	K
0	0	0	0	0	0	0	0	95	39	8	71	64	0	0	1	0	0	0	0	0	0	0	3	3	0	23	0	0	0	0	0	257	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	L
0	0	0	0	0	0	0	0	42	67	2	116	85	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	184	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	M
0	0	0	0	0	0	0	0	0	0	0	0	0	1138	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	253	0	0	0	0	0	0	88	0	0	0	60	0	0	0	59	0	0	0	0	N
0	0	0	0	0	0	0	0	0	0	0	0	0	0	104	79	92	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	73	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	O
0	0	0	0	0	0	4	1	0	0	0	0	9	0	88	81	82	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	198	0	0	9	0	2	2	0	0	30	0	0	0	0	33	0	1	0	0	0	P
0	0	0	0	0	0	0	0	0	0	0	0	6	0	100	73	82	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	159	0	0	7	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	Q
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	176	76	12	0	0	0	0	2	0	1	7	11	6	1	0	201	9	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	R
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	186	123	0	0	0	0	0	0	0	0	0	0	0	0	157	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	S
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	110	167	0	0	0	0	0	0	0	0	0	0	0	0	56	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	T
0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	65	1	0	0	0	0	0	0	0	0	0	0	125	0	0	2	0	0	0	36	0	0	0	4	0	0	6	48	5	0	1	0	U
0	0	0	0	0	0	0	0	0	0	5	6	0	0	0	0	0	0	0	0	15	78	0	0	1	0	0	0	0	0	0	0	138	1	0	1	0	0	0	3	0	0	0	13	0	9	3	7	6	0	12	0	V
0	1	0	0	2	1	9	20	0	0	0	0	0	0	0	0	0	0	0	0	7	0	55	0	0	0	0	0	0	0	0	0	159	0	2	15	0	0	0	11	4	0	0	1	0	0	0	1	9	0	0	1	W
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	145	50	0	18	1	0	0	0	0	242	9	0	0	0	4	0	0	0	0	1	0	3	12	0	0	1	1	0	11	X
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	65	89	0	2	4	2	13	15	0	209	13	0	0	0	8	1	0	0	0	0	0	2	16	0	0	3	0	0	14	Y
0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	153	0	0	0	0	0	0	138	0	2	0	1	0	1	0	0	0	0	0	0	0	0	22	1	0	0	0	Z
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	83	9	0	270	2	3	14	21	0	143	4	0	0	0	1	0	0	0	0	0	0	0	62	0	0	0	0	0	0	[
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	7	34	0	8	58	21	120	58	0	199	25	0	0	0	0	0	0	0	0	0	0	0	73	0	0	0	0	0	0	\
0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	4	0	0	0	0	0	0	28	0	9	65	31	110	58	0	186	20	0	0	0	0	0	0	0	0	0	0	0	86	0	0	0	0	0	1	]
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4	0	0	0	0	0	3	36	0	28	80	38	109	45	0	186	25	0	0	0	0	0	0	0	0	0	0	0	60	0	0	0	0	0	1	^
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	26	43	0	12	91	47	77	64	0	170	17	0	0	0	0	0	0	0	0	0	0	0	54	0	0	0	0	0	0	_
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	236	70	0	0	2	0	0	0	0	1	0	1	0	0	0	0	0	2	0	0	0	`
9	16	24	12	21	12	14	20	35	30	100	47	41	38	16	35	49	56	51	34	71	59	83	103	109	98	76	48	43	64	38	33	6580	107	118	66	133	146	76	93	56	92	71	80	158	130	138	125	76	130	56	136	a
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	10	0	0	0	0	0	15	30	0	5	9	32	29	14	0	158	141	0	0	0	5	0	0	0	0	0	0	1	86	0	0	2	0	0	3	b
0	0	0	0	1	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	259	0	179	1	56	3	9	0	5	7	3	0	0	0	10	1	0	31	1	16	c
0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	7	145	0	0	52	0	7	0	0	58	1	1	0	6	0	23	0	34	0	1	3	d
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	294	0	40	0	223	0	7	0	30	5	3	0	0	0	2	0	0	10	0	0	e
0	0	0	0	0	0	5	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	15	0	0	0	0	0	1	0	192	1	2	7	2	187	23	0	8	25	24	0	22	3	7	0	8	11	0	27	f
1	0	0	0	0	0	5	6	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	158	0	2	1	6	17	164	0	2	18	28	0	19	0	7	0	1	9	0	14	g
0	5	1	0	0	0	0	0	0	0	0	0	0	145	0	0	0	0	0	0	34	0	5	0	0	0	0	0	0	0	0	0	217	0	0	1	0	0	0	141	1	0	0	9	0	0	0	66	0	0	7	0	h
0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	5	177	0	1	50	1	19	5	0	73	4	15	0	0	0	33	0	14	19	0	1	i
0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	167	1	7	3	4	27	23	0	14	49	12	0	12	0	50	0	0	23	0	7	j
0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	182	1	2	1	4	37	45	0	2	16	87	0	27	0	4	0	3	18	0	19	k
2	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	296	0	0	0	0	0	0	0	1	0	0	260	0	0	24	14	0	0	40	0	l
0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	5	0	0	1	0	0	0	0	0	276	4	2	1	0	22	10	0	2	0	12	0	117	0	1	0	2	8	0	7	m
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	14	23	0	20	40	25	39	22	0	217	56	0	0	0	5	0	0	0	1	0	0	0	94	0	0	0	1	0	2	n
0	9	9	0	1	0	1	2	0	0	0	0	0	0	0	4	8	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	184	0	9	10	15	11	10	0	23	31	1	0	0	0	149	0	4	34	1	5	o
0	0	1	0	0	0	0	0	0	0	0	0	0	82	0	0	0	0	0	0	56	0	0	0	0	8	0	0	0	0	0	0	285	0	0	0	0	0	0	67	0	0	0	4	0	0	0	132	0	0	7	0	p
0	0	0	0	0	0	0	10	2	0	0	0	0	0	1	0	0	0	0	0	1	2	5	2	0	2	0	0	0	0	0	11	166	0	0	39	0	5	1	0	20	1	8	0	1	3	7	1	30	1	0	4	q
0	0	0	0	0	0	9	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	238	1	21	4	7	10	15	0	6	35	7	0	9	2	46	0	0	133	0	6	r
0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	1	0	2	0	0	19	0	0	0	0	0	0	201	0	0	0	0	0	0	2	0	0	0	83	0	0	0	40	4	0	300	0	s
0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	13	0	1	0	0	1	5	0	217	5	9	4	3	39	12	0	4	3	31	0	10	3	5	0	4	12	0	60	t

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0
S -> Running_-_Treadmill_5mph_-_Treadmill_0_T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes
d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-3: Confusion Matrix for C4.5 Classifier using the *ACAbsArea and DCArea* features computed per sensor and evaluated in a subject independent manner.

EXAMPLE CLASSIFIED AS (columns) / ORIGINAL LABEL (rows)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
A	39	35	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
B	67	71	87	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91	0	0	0	0	0	0	3	0	0	1	3	0	0	1	1	0	0	1	0
C	51	56	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	84	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	2	1	0	0
D	0	0	0	59	118	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
E	0	0	0	96	87	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	118	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	59	84	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	61	0	0	0	0	0	0	3	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	111	0	0	0	0	0	0	0	1	25	1	0	0	0	3	0	0	0	0	0
H	0	0	0	0	0	0	2	179	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	56	0	0	1	1	0	0	0	3	19	1	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0	47	1	4	118	79	0	0	0	1	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	117	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	0	396	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	82	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	64	0	247	13	10	0	0	2	2	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	211	0	0	0	0	15	0	0	0	0	2	0	0	0	0	0	0	3	0	1
L	0	0	0	0	0	0	0	0	65	0	0	241	113	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	142	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	79	1	3	138	96	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	166	9	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0
N	0	0	0	0	0	0	0	0	0	0	0	0	0	1167	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	267	0	0	0	0	0	0	67	0	0	0	1	0	0	0	60	0	0	36	0
O	0	0	0	0	0	0	1	0	6	0	0	0	0	0	96	73	82	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	110	0	0	0	0	0	0	0	5	0	3	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	12	8	3	0	1	0	1	0	62	137	81	0	0	0	0	0	0	15	1	0	0	0	0	0	0	0	195	0	0	0	0	1	1	0	4	3	13	0	0	0	1	0	0	1	0	0
Q	0	0	0	0	0	0	4	1	8	0	2	0	0	0	85	78	98	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	154	0	0	0	0	1	0	0	2	0	24	0	0	0	1	0	0	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	142	98	0	0	0	0	1	0	0	0	29	28	17	14	0	175	6	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	261	47	0	0	0	0	0	0	0	0	0	0	0	0	116	7	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	4	54	141	0	0	0	0	0	0	0	0	0	0	0	0	134	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	51	2	0	0	0	11	0	0	0	0	0	0	161	0	0	0	0	0	0	4	0	0	0	0	0	0	0	72	0	0	2	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	112	4	7	1	4	0	0	0	0	0	1	135	1	0	6	0	0	0	0	0	0	0	6	1	0	1	0	14	0	4	0
W	0	0	2	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	115	0	0	0	0	0	0	0	0	0	117	0	19	6	0	0	0	1	0	15	3	5	0	0	2	1	5	1	0	0
X	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	304	16	0	4	2	1	5	0	0	110	27	0	0	0	8	0	0	1	0	3	0	3	6	1	0	0	1	0	2
Y	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	3	0	0	0	0	1	19	219	0	4	8	3	0	9	0	131	5	0	0	0	7	0	0	0	0	1	0	2	36	0	0	0	0	0	8
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	165	0	0	0	0	0	0	154	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
[	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	22	0	331	17	7	5	10	0	155	16	0	0	0	0	0	0	0	0	1	0	1	31	0	0	0	0	0	2
\	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	1	14	0	17	176	46	56	64	0	121	27	0	0	0	0	0	0	0	0	0	0	0	77	0	0	0	0	0	0
]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	18	0	23	113	65	51	69	0	113	64	0	0	0	0	0	0	0	0	0	0	0	81	0	0	0	0	0	2
^	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	2	24	0	53	79	72	74	88	0	88	51	0	0	0	0	0	0	0	0	0	0	0	75	0	0	0	0	0	5
_	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	3	33	0	45	73	73	48	103	0	106	24	0	0	0	0	0	0	0	0	0	0	0	70	0	0	0	0	0	4
`	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	1	0	0	0	0	0	250	58	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
a	9	37	15	14	13	5	30	10	39	33	47	59	46	74	29	44	45	48	47	37	108	58	69	88	102	85	82	69	44	46	50	34	6453	117	100	49	108	170	106	189	77	92	94	64	138	110	122	132	101	119	60	135
b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	11	28	0	11	29	31	37	16	0	153	139	0	0	0	2	0	0	0	0	0	0	2	64	0	0	0	0	0	3
c	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1	2	0	0	0	0	0	0	231	0	206	9	67	1	1	0	7	3	1	0	2	0	8	0	0	28	0	19
d	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	34	0	0	0	0	0	0	0	0	0	82	0	0	101	0	6	1	0	58	1	2	0	1	0	6	0	40	0	0	10
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	198	0	58	0	297	1	1	0	0	28	6	0	1	0	7	1	0	19	0	2
f	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	4	0	0	3	0	0	0	0	188	1	4	3	0	199	26	0	7	21	27	0	12	3	10	0	12	11	0	34
g	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	116	0	3	2	5	32	171	0	3	31	41	0	20	1	12	0	2	9	0	9
h	0	0	2	0	0	0	0	0	0	0	0	0	0	78	0	0	0	0	0	0	7	0	9	0	0	0	0	0	0	0	0	0	297	0	0	0	0	0	0	207	0	0	0	17	0	0	0	14	1	0	0	0
i	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	19	0	1	1	0	0	0	0	0	3	144	3	1	44	2	14	1	0	91	8	3	3	3	0	33	0	18	12	0	13
j	0	0	1	0	2	0	1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	167	0	10	1	21	29	35	0	6	71	14	0	4	0	21	0	2	11	0	12
k	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	1	0	1	0	0	0	0	0	155	0	3	2	4	35	57	0	2	10	120	0	19	0	7	0	3	19	0	19
l	0	5	0	0	0	0	2	0	0	0	0	0	0	2	1	0	0	0	0	0	0	3	5	0	0	0	0	0	0	0	0	1	135	0	0	0	12	0	0	24	1	0	0	389	0	0	0	2	1	0	70	0
m	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	4	0	0	0	1	0	0	0	200	6	0	0	2	17	23	0	1	4	18	0	171	1	2	0	9	7	0	9
n	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	11	0	0	0	0	0	6	35	0	20	61	25	25	8	0	159	57	0	0	0	6	1	0	0	0	0	0	1	145	0	0	1	0	0	7
o	2	0	2	0	0	0	1	4	0	0	0	0	0	0	0	5	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	164	2	12	6	13	11	11	0	43	24	2	1	2	0	169	0	5	33	0	9
p	0	0	0	0	0	0	0	0	0	0	0	0	0	51	0	0	0	0	0	0	82	1	0	0	0	0	0	0	0	0	0	0	302	0	2	1	0	0	0	34	0	0	0	3	0	0	0	163	0	0	3	0
q	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	1	24	0	0	3	1	1	0	2	0	1	141	2	1	37	0	8	0	3	28	0	2	1	3	1	11	0	31	5	1	12
r	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	178	0	19	6	20	27	20	0	9	11	11	0	10	1	64	0	6	162	0	12
s	0	0	0	0	0	0	4	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	1	0	0	6	0	0	0	0	0	0	196	0	0	0	0	0	0	2	0	0	0	68	0	0	0	17	0	0	353	0
t	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	12	7	0	3	0	1	0	2	0	212	0	11	9	3	41	11	0	12	10	13	2	15	1	2	0	5	10	0	71

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0
S -> Running_-_Treadmill_5mph_-_Treadmill_0_T ->
Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-
_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes
d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-4: Confusion Matrix for C4.5 Classifier using the *MaxAcceleration* feature set computed per sensor and evaluated in a subject independent manner.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	
25	27	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	A
46	103	33	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	110	0	0	0	0	0	0	4	0	2	0	5	0	0	2	0	0	3	5	0	B
39	33	18	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	113	0	0	0	0	0	0	7	1	1	0	6	0	0	6	0	0	0	5	0	C
0	0	0	50	100	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	26	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	D
0	0	0	61	183	73	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	E
0	0	0	59	107	53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	F
0	0	0	0	4	0	38	17	0	0	0	0	0	17	2	11	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	99	0	0	0	0	0	0	2	5	0	0	0	0	0	0	0	0	0	0	0	G
0	0	0	0	0	0	1	206	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51	0	0	0	2	0	1	1	0	6	0	0	0	0	0	0	0	0	0	0	H
0	0	0	0	0	0	0	2	35	1	4	160	76	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	3	0	0	0	I
0	0	0	0	0	0	0	0	19	323	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	110	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	J
1	0	1	0	0	0	1	5	13	0	353	0	12	0	0	0	0	0	0	0	0	17	0	0	0	0	15	0	0	0	0	0	156	0	0	0	0	0	0	0	1	0	0	3	0	0	0	1	0	0	0	0	K
0	0	0	0	0	0	0	2	104	4	0	195	101	0	0	0	0	5	0	0	0	2	0	0	0	0	0	0	0	0	0	0	154	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	L
0	0	0	0	0	0	0	0	65	2	6	206	93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	123	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	M
1	0	0	0	0	0	0	0	0	0	0	0	0	1140	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	242	0	0	0	0	0	0	110	0	0	0	0	0	0	0	105	0	0	0	0	N
0	0	0	0	0	0	4	0	0	0	0	0	0	0	131	85	71	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	6	28	0	0	0	0	0	0	0	4	0	1	0	0	0	O
0	0	0	0	0	0	1	1	0	0	0	0	0	0	147	136	58	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	125	0	0	0	0	20	31	0	1	1	1	0	0	0	18	0	0	0	0	0	P
0	0	0	0	0	0	16	0	0	0	0	0	0	0	141	71	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	113	0	0	0	0	22	32	0	3	2	0	0	0	0	8	0	0	0	0	0	Q
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	157	79	26	0	0	0	0	0	0	0	11	29	14	12	0	106	57	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	R
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	255	74	0	0	0	0	0	0	0	0	0	0	0	0	115	3	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	S
0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	25	117	88	0	0	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	T
0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	101	1	1	0	0	22	0	0	0	0	0	1	87	0	0	0	1	0	0	20	0	0	0	1	0	0	0	62	1	0	2	0	U
0	0	1	0	0	0	0	0	0	0	2	5	0	0	0	0	0	0	0	0	4	143	4	0	1	0	10	0	0	0	0	0	111	0	0	0	0	0	0	2	0	0	0	0	0	0	1	7	0	0	4	3	V
0	0	0	2	0	3	0	2	0	0	1	0	0	0	0	0	0	0	0	0	5	7	87	0	0	0	0	0	0	0	0	0	140	0	2	10	1	0	0	3	3	0	0	3	0	0	5	0	11	12	1	0	W
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	299	24	0	9	0	1	0	0	0	108	7	0	1	0	16	1	0	1	0	5	0	2	10	2	0	1	8	0	3	X
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	34	153	1	15	3	4	4	5	0	148	27	0	1	0	14	0	0	0	0	9	0	9	14	3	0	0	5	0	7	Y
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	176	0	0	0	0	0	0	144	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	Z
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	27	0	343	8	2	3	9	0	143	11	0	0	0	1	0	0	0	0	4	0	0	41	0	0	0	0	0	13	[
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	9	0	0	0	0	0	0	3	0	18	102	119	103	34	0	138	29	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	\
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	4	7	0	23	78	123	99	50	0	111	50	0	0	0	4	0	0	0	0	0	0	0	43	0	0	0	0	0	1	]
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	1	3	0	47	83	52	111	60	0	89	78	0	0	0	8	0	0	0	0	0	0	0	73	0	0	0	0	0	3	^
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	18	5	0	45	89	51	96	74	0	87	52	0	0	0	6	0	0	0	0	0	0	0	68	0	0	0	0	0	1	_
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	229	73	0	0	0	0	0	0	0	3	0	0	0	0	0	1	0	5	2	1	0	`
20	20	25	19	16	10	27	8	41	18	82	46	40	84	35	31	22	62	48	29	78	91	50	83	108	109	115	68	52	40	38	50	6419	92	129	47	107	152	93	95	102	101	125	64	153	110	109	134	85	126	71	173	a
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	12	21	0	20	19	35	17	28	0	160	132	0	1	0	2	0	0	0	0	0	0	5	69	0	0	0	1	0	2	b
0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	182	0	269	0	62	4	1	0	10	5	6	0	1	0	12	2	0	23	0	7	c
0	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	1	25	0	0	0	0	0	0	0	0	1	81	0	0	115	0	6	0	0	48	0	0	0	6	0	2	0	42	8	0	7	d
1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	1	216	0	86	0	269	2	5	0	1	4	4	0	0	0	6	0	0	19	0	2	e
0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	6	7	1	3	0	0	1	0	0	172	2	3	12	0	200	22	0	9	10	21	0	19	6	11	0	15	10	0	41	f
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	115	0	4	1	4	24	179	0	3	30	41	0	18	0	14	3	1	9	0	12	g
0	0	0	0	0	0	0	0	0	0	1	0	0	97	0	0	0	0	0	0	4	4	4	0	0	3	0	0	0	0	0	0	296	0	1	1	0	0	0	153	0	0	0	12	0	0	0	46	0	0	10	0	h
0	2	0	0	0	0	5	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	3	124	0	14	54	3	16	0	0	67	4	6	0	1	0	47	0	44	22	0	4	i
0	2	0	0	0	0	1	2	0	0	1	0	0	0	1	2	2	0	0	0	0	1	0	1	1	1	0	0	0	0	0	0	182	0	13	1	7	12	27	0	5	84	10	0	6	0	33	0	2	12	0	3	j
0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	2	4	0	1	0	0	0	0	0	157	0	7	1	2	34	52	0	5	10	127	0	18	0	3	0	4	12	0	18	k
4	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	4	1	0	0	0	0	0	0	0	0	0	212	0	0	0	0	0	0	4	0	0	0	341	0	0	0	5	0	0	75	0	l
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	2	1	1	0	0	0	0	0	249	1	2	0	1	28	11	0	6	8	13	0	120	0	1	0	15	4	0	9	m
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	7	0	0	0	0	0	9	21	0	24	57	34	42	26	0	171	34	0	0	0	2	0	0	0	0	3	0	1	135	0	0	0	0	0	2	n
0	1	1	0	0	0	5	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	2	0	0	1	2	0	0	0	0	0	136	0	10	4	5	12	6	0	41	18	4	1	1	1	189	1	8	66	0	5	o
0	0	0	0	0	0	0	0	0	0	0	0	0	67	0	0	0	0	0	0	71	1	0	0	0	13	0	0	0	0	0	0	248	0	1	0	2	0	0	43	0	0	0	21	0	0	0	167	0	0	8	0	p
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	4	3	10	0	0	0	0	0	0	0	0	2	156	1	0	38	1	13	1	1	25	0	1	0	4	1	4	0	53	1	0	3	q
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	6	1	0	0	0	0	0	0	180	1	27	5	9	24	12	0	19	11	10	0	12	0	34	0	0	200	0	5	r
0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	2	7	0	0	12	0	0	0	0	0	1	206	0	0	0	0	0	0	0	0	0	0	81	0	0	0	9	0	0	294	0	s
0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	8	5	0	5	0	1	0	0	1	217	1	11	7	3	43	11	0	8	9	29	0	11	6	2	0	9	9	0	56	t

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0
S -> Running_-_Treadmill_5mph_-_Treadmill_0_T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes
d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-5: Confusion Matrix for C4.5 Classifier using the *ACAbsArea, DCArea,* and *ACFFTPeaks* computed per sensor and evaluated in a subject independent manner.

EXAMPLE CLASSIFIED AS (columns) / ORIGINAL LABEL (rows)

ORIGINAL LABEL	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
A	25	47	13	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0
B	42	102	70	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	98	0	0	0	0	0	0	8	0	0	0	2	0	0	0	0	0	0	2	0
C	30	76	13	0	0	0	2	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	3	86	0	0	14	0	0	0	4	0	2	0	1	0	0	0	0	0	0	0	0
D	0	0	0	93	87	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	83	112	57	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	88	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	96	82	31	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	10	2	0	9	0	62	4	0	0	0	0	0	0	4	5	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	68	0	0	0	0	6	0	10	0	19	3	0	0	0	6	0	0	0	0	0
H	0	0	0	0	0	0	3	217	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0
I	0	0	0	0	0	0	0	2	45	1	7	122	126	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	46	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	3	407	0	1	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	69	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	1	0	0	0	0	1	0	28	0	334	0	11	0	0	0	0	1	0	0	0	3	0	0	0	0	1	0	3	11	2	0	170	0	0	0	0	5	0	0	1	1	1	0	1	3	1	0	0	0	0	0
L	0	0	0	0	0	0	0	2	59	0	0	217	160	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	129	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	109	1	3	130	160	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	80	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2
N	0	1	0	0	0	0	0	0	0	0	0	0	0	962	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	247	0	0	0	0	0	0	166	0	0	0	0	0	0	0	169	0	0	53	0
O	0	0	0	0	0	0	8	0	0	0	1	0	0	0	94	114	42	0	0	0	0	0	1	0	0	0	0	0	0	0	0	3	49	0	0	0	0	3	56	0	0	0	0	0	0	0	5	0	0	0	0	0
P	0	0	0	0	0	0	37	1	2	0	11	0	0	0	61	175	66	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	114	0	0	0	0	2	30	0	2	25	0	0	0	0	12	0	0	0	0	0
Q	0	0	0	0	0	0	11	0	1	0	5	0	0	0	84	144	40	0	0	0	0	0	3	0	5	0	0	0	0	0	0	3	114	0	0	0	0	0	42	0	0	0	0	0	0	0	6	0	0	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	203	53	36	0	0	0	0	6	0	0	7	13	12	28	0	126	22	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	252	114	0	0	0	0	0	0	0	2	0	0	0	0	82	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	4	89	160	0	0	0	0	0	0	0	0	0	0	0	0	79	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	118	0	0	0	0	20	0	0	0	0	0	0	85	0	0	0	0	0	0	8	0	0	0	1	0	0	0	67	0	0	5	0
V	0	0	0	0	0	0	0	0	0	0	1	0	0	5	0	0	0	0	0	0	2	126	6	0	0	0	7	0	0	9	0	0	122	3	0	0	0	0	0	2	0	0	0	2	0	0	0	4	1	0	2	6
W	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	4	94	0	0	1	0	0	0	0	0	10	121	0	2	6	3	0	0	12	11	0	0	11	0	0	1	1	6	9	1	0
X	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	293	31	0	4	1	0	0	1	0	137	11	0	0	0	5	0	0	1	0	1	0	4	3	0	0	0	3	0	2
Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	12	0	0	0	0	0	25	230	0	8	3	5	4	9	0	105	17	0	1	0	4	1	0	0	0	7	0	2	14	0	0	1	0	0	9
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	180	0	0	0	0	0	0	136	0	1	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	1
[	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	1	0	21	12	0	275	39	11	7	5	0	161	27	0	0	0	2	0	0	0	1	0	0	2	36	0	0	0	0	0	0
\	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	3	0	0	0	0	0	3	21	0	19	108	58	62	36	0	122	52	0	0	0	5	0	0	0	0	0	0	0	116	0	0	0	0	0	0
]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	9	0	29	77	61	102	52	0	135	52	0	0	0	0	0	0	0	0	0	0	0	76	0	0	0	0	0	0
^	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	12	0	38	70	54	117	82	0	125	48	0	0	0	0	0	0	0	0	0	0	0	57	0	0	0	0	0	0
_	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	8	8	0	31	57	54	84	77	0	180	36	0	0	0	1	0	0	0	0	0	0	0	53	0	0	0	0	0	1
`	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	3	0	1	0	0	0	0	0	0	0	0	240	61	0	0	3	0	0	0	0	2	0	0	1	0	0	1	0	1	0	0	0
a	15	34	20	12	22	5	22	10	37	35	65	49	63	89	47	38	34	52	46	38	61	51	39	93	98	88	78	57	40	53	35	45	6533	116	136	36	118	170	112	117	80	95	95	76	121	124	119	139	98	99	60	137
b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	19	0	0	0	0	0	2	35	0	3	11	27	28	22	0	150	131	0	0	0	1	0	0	0	0	1	0	8	102	0	0	0	0	0	0
c	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	5	0	0	0	0	0	1	206	0	185	0	86	2	5	0	1	6	11	0	1	0	32	0	1	33	0	12
d	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	4	0	0	0	0	0	0	32	0	0	3	0	0	0	0	0	1	91	1	1	88	1	2	0	0	45	4	7	0	2	0	6	0	42	12	0	2
e	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	181	0	95	10	283	5	5	0	1	1	1	0	2	0	8	0	0	22	0	3
f	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	2	5	0	0	0	1	0	0	0	176	1	2	4	2	218	21	0	7	16	33	0	8	3	6	0	17	19	0	32
g	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	2	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	140	1	3	0	10	27	167	0	4	26	45	0	6	0	7	0	0	7	0	8
h	0	1	0	0	0	0	0	0	0	0	0	0	0	99	0	0	0	0	0	0	5	1	7	0	0	3	0	0	0	0	0	0	290	0	0	1	3	0	0	123	0	0	0	12	0	0	0	47	2	0	38	0
i	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	5	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	7	130	0	8	49	1	19	0	0	87	2	2	0	1	0	46	0	36	19	0	4
j	0	0	2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	165	0	10	0	13	18	31	0	8	80	15	0	4	0	31	0	1	17	0	15
k	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	1	0	0	0	0	0	0	188	0	5	2	7	19	63	0	1	11	121	0	9	0	7	0	1	6	0	14
l	1	7	2	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	4	3	2	0	0	1	0	0	0	0	0	0	189	0	0	0	3	0	0	9	0	0	0	344	0	0	0	4	0	0	83	0
m	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	2	0	1	0	0	0	0	0	198	8	1	2	1	20	14	0	6	5	11	0	181	0	3	0	7	5	0	8
n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	4	29	0	15	40	23	36	19	0	177	56	0	0	0	0	0	0	0	0	1	0	0	158	0	0	0	0	0	3
o	1	2	0	0	0	0	0	0	0	0	1	0	0	0	0	2	1	0	0	0	0	0	1	0	0	4	0	0	0	0	0	0	160	0	6	6	11	7	8	0	47	21	8	0	1	2	177	1	3	49	0	5
p	0	1	1	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	73	0	1	0	0	11	0	0	0	0	0	0	228	0	0	0	0	0	0	38	0	0	0	22	0	0	0	173	1	0	43	0
q	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	0	1	1	17	1	2	0	2	0	0	0	0	7	153	1	1	32	0	7	0	0	23	1	3	0	7	0	5	3	42	1	1	9
r	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	1	0	0	0	0	200	0	19	2	20	24	14	0	15	23	7	0	7	0	63	0	2	144	0	15
s	0	0	1	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	2	5	0	0	17	0	0	0	0	0	0	192	0	0	0	0	0	0	5	0	0	0	87	0	0	0	16	0	0	287	0
t	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	1	0	0	1	1	1	220	3	12	9	4	40	16	0	3	5	29	0	14	3	9	0	5	11	0	61

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0

S -> Running_-_Treadmill_5mph_-_Treadmill_0_T ->
Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-
_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes

d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-6: Confusion Matrix for C4.5 Classifier using the *ACAbsArea, DCArea, ACRange, ACVar, ACFFTPeaks, ACCorr, ACMCR,* and *ACPitch* computed per sensor evaluated in a subject independent manner.

EXAMPLE CLASSIFIED AS

ORIGINAL LABEL

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[
A	113	3	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
B	0	304	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	4	7	216	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
D	0	0	0	208	3	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	5	321	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	7	6	214	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	194	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
H	0	0	2	1	0	0	0	250	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0
I	0	0	0	0	0	0	0	0	313	0	1	5	21	0	0	0	0	0	0	0	0	0	0	1	0	0	0
J	0	0	0	0	0	0	0	0	1	459	0	2	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
K	0	0	0	0	0	0	0	0	0	0	524	0	1	0	0	0	0	0	0	0	0	1	2	0	0	0	0
L	0	0	0	0	1	0	0	0	4	0	0	516	22	0	0	0	0	0	0	0	0	0	0	0	1	0	0
M	0	0	0	0	0	0	0	0	26	1	0	29	399	0	0	1	0	0	0	0	0	0	1	2	1	0	1
N	0	1	0	0	0	0	1	0	0	0	0	0	0	1583	0	0	0	0	0	0	0	0	0	0	0	0	0
O	0	0	0	0	1	0	0	0	0	0	0	0	0	0	308	14	44	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	2	0	0	0	0	0	0	0	10	436	56	0	0	0	0	1	0	0	0	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	53	45	340	0	0	0	0	0	0	0	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	453	9	0	0	0	0	1	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	417	12	0	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	8	297	0	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	277	1	2	0	0	3	0
V	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	268	3	0	0	1	0
W	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	2	0	0	0	5	1	266	0	0	0	0
X	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	405	25	0	3
Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	20	357	0	7
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	280	0
[	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	5	5	0	543
\	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
^	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
_	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
`	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
a	4	13	9	10	9	10	9	11	37	19	61	48	52	29	13	32	27	46	36	38	25	18	25	67	60	37	67
b	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
c	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
d	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2	0
f	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0
g	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0
h	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	1	0	0	0	0
i	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
j	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
k	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
l	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
m	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
n	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0
o	0	3	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0
p	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	3	1	1	0	0	0
r	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
s	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
t	0	1	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	0	0	0	0	0	2	1	1	0	0

	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
A	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B	0	0	0	0	0	9	0	0	0	1	0	0	0	0	0	0	3	0	0	1	0	0	0	0	0
C	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
D	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
E	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	0	0	0	8	0	1	0	0	1	0	0	0	0	0	0	0	1	1	0	0	1	0	0
I	0	0	0	0	1	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	3	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
L	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
N	0	0	0	0	0	10	0	0	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
O	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	33	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Q	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0
R	1	0	0	4	0	42	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
T	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	1	18	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1
V	0	0	0	0	1	20	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0
W	0	0	0	0	0	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0
X	0	0	2	1	0	52	0	0	0	0	1	1	0	0	1	0	0	1	1	0	0	0	1	0	1
Y	1	0	3	1	0	59	0	0	0	0	2	1	0	0	0	0	0	3	1	0	0	0	0	0	0
Z	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
[	0	1	1	0	0	55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
\	468	73	8	3	0	52	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
]	90	406	66	6	0	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
^	8	68	437	55	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
_	3	13	62	491	0	36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
`	0	0	0	0	298	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
a	64	58	54	48	24	7957	42	61	20	68	97	60	42	36	63	62	27	76	64	71	43	22	67	28	86
b	1	1	0	1	0	42	457	0	0	0	3	0	0	0	0	0	0	1	25	1	0	0	2	0	5
c	0	0	0	0	0	50	0	485	1	27	1	1	0	0	1	1	0	0	0	3	0	0	16	0	1
d	0	0	0	0	0	29	0	1	264	1	2	0	0	7	0	1	0	2	1	5	0	28	2	0	1
e	0	0	0	0	0	76	0	22	0	495	1	2	0	1	2	1	0	1	0	2	0	0	11	0	2
f	0	0	0	0	0	106	6	1	1	3	330	14	0	4	14	17	0	10	2	13	0	1	15	0	35
g	0	0	0	0	0	48	0	2	1	2	14	304	0	1	27	30	0	9	0	7	0	0	5	0	8
h	0	0	0	0	0	25	0	0	0	0	0	0	596	0	0	0	0	0	0	0	5	0	0	1	0
i	0	0	0	0	1	37	0	0	3	1	6	5	0	327	1	5	0	2	0	14	0	5	6	0	6
j	0	0	0	0	0	60	0	2	2	1	17	21	0	1	252	14	0	3	1	13	0	2	15	0	7
k	0	0	0	0	0	72	1	2	3	1	21	31	0	9	16	261	0	11	0	7	0	0	11	0	12
l	0	0	0	0	0	23	0	0	0	0	0	0	2	2	0	0	616	0	0	2	0	0	0	8	0
m	0	0	0	0	0	77	1	0	1	3	15	13	0	2	5	16	0	320	1	3	0	3	7	0	6
n	2	0	1	1	0	61	17	0	0	0	7	0	0	0	0	0	0	0	468	0	0	0	0	0	7
o	0	0	0	0	0	72	0	11	3	5	12	10	0	15	14	6	0	3	1	330	0	4	29	0	3
p	0	0	0	0	0	37	0	0	0	0	0	0	5	0	0	0	0	0	0	0	596	0	0	2	0
q	0	0	0	0	0	25	0	0	35	0	1	0	0	4	1	0	0	6	0	2	0	241	1	0	1
r	0	0	0	0	0	113	2	19	2	13	17	4	0	1	15	11	0	10	0	25	0	1	320	0	5
s	0	0	0	0	1	12	0	0	0	0	0	0	0	0	0	0	8	0	0	0	1	0	1	636	0
t	0	0	0	0	0	114	12	2	1	2	40	5	0	5	13	14	0	7	3	2	0	0	3	0	222

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0

S -> Running_-_Treadmill_5mph_-_Treadmill_0_T ->
Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes

d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-7: Confusion Matrix for C4.5 Classifier using the *ACAbsArea, DCArea, ACVar, ACRange, and ACMCR* feature set computed per sensor and evaluated in a subject independent manner.

EXAMPLE CLASSIFIED AS

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	ORIGINAL LABEL
52	18	35	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	A
19	195	56	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	43	0	2	0	3	0	1	2	0	0	0	0	1	0	0	1	0	0	0	0	B
34	60	105	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	3	0	2	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	C
0	0	0	164	22	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	D
0	0	0	23	254	46	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	E
0	0	0	42	47	140	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	F
0	4	2	0	0	2	171	0	0	0	0	0	0	0	0	3	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	16	0	3	0	1	0	0	0	0	1	0	0	0	0	1	0	0	2	0	1	G
0	0	0	1	0	0	2	242	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	17	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	H
0	0	0	0	0	0	0	0	282	0	3	14	46	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	21	0	0	0	0	0	0	0	0	0	0	0	4	1	0	0	1	0	0	0	I
0	0	0	0	0	0	0	0	1	453	0	1	2	0	0	0	0	0	0	0	0	1	0	1	1	0	1	1	1	1	1	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	J
0	1	0	0	0	0	0	0	2	0	501	1	1	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	64	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	1	1	0	0	K
0	0	0	0	0	0	0	0	18	0	3	467	39	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	L
0	0	1	0	0	0	0	0	48	0	3	44	346	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	48	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	1	0	0	M
0	0	0	0	0	0	0	0	0	0	0	0	0	1256	0	0	0	0	0	0	44	1	0	0	0	44	0	0	0	0	0	25	37	0	0	0	0	0	0	40	0	0	0	3	0	0	0	143	0	0	5	0	N
0	0	0	0	0	0	0	0	0	0	0	0	0	0	269	20	68	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	O
0	0	0	0	0	0	1	0	0	0	0	0	0	0	14	425	59	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	30	0	0	0	0	2	2	0	0	0	1	0	1	0	0	0	0	1	0	1	P
0	0	0	2	0	0	0	0	0	0	0	0	0	0	75	69	285	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	Q
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	459	4	0	0	0	0	0	3	0	0	0	0	1	0	0	37	2	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	R
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	420	15	0	0	0	0	0	0	0	0	0	0	0	0	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	S
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	11	291	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	T
0	0	0	0	0	0	0	0	0	0	0	0	0	59	0	0	0	0	0	0	96	0	1	0	0	30	0	0	0	0	0	23	65	0	1	0	0	0	0	3	0	0	0	1	0	0	1	21	0	0	4	0	U
0	0	0	0	0	0	0	0	1	1	2	0	0	1	0	0	0	0	0	0	0	241	4	0	3	2	0	0	0	0	0	0	30	0	1	0	0	0	0	0	0	1	2	4	1	0	0	1	1	0	1	1	V
1	2	0	1	0	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	1	224	0	0	2	0	0	0	0	0	0	43	0	8	0	5	0	0	2	0	0	1	3	0	0	0	0	1	0	0	0	W
0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0	396	10	0	4	0	0	2	3	0	57	1	0	0	0	4	1	0	1	2	0	0	2	3	1	0	2	2	0	3	X
0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	2	0	12	321	0	2	0	1	3	4	0	86	5	0	0	0	7	0	0	0	0	0	0	3	6	1	0	0	0	0	2	Y
0	0	0	0	0	0	0	0	0	0	1	0	0	53	0	0	0	0	0	0	41	1	1	0	0	85	0	0	0	0	0	22	86	0	1	0	1	0	0	11	1	0	1	2	0	0	0	12	0	0	2	0	Z
0	0	0	0	0	0	0	0	0	1	1	0	2	0	0	0	0	0	0	0	0	1	0	0	6	0	537	1	2	2	0	0	49	2	0	0	1	0	0	0	0	0	1	0	0	3	1	0	0	2	0	0	[
0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	2	395	113	18	11	0	50	4	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	\
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	98	342	96	15	0	36	5	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	]
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	4	0	2	23	106	343	79	0	51	3	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	^
0	0	0	0	0	0	0	0	0	3	0	0	1	0	0	0	1	1	0	0	0	0	0	1	5	0	3	9	17	83	441	0	36	1	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	_
0	0	0	0	0	0	0	0	0	0	2	0	0	56	0	0	0	0	0	0	26	1	0	0	0	12	0	0	0	0	0	102	83	0	0	0	0	0	0	7	0	0	0	3	1	0	0	16	0	0	6	0	`
24	41	31	18	19	11	24	19	32	20	76	57	62	58	20	31	37	48	46	30	63	31	49	65	78	61	60	69	61	61	53	67	6929	64	154	52	159	144	84	81	48	83	91	62	111	83	65	88	58	93	51	130	a
0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	2	10	0	2	3	7	3	2	0	57	381	0	1	0	1	0	1	0	1	0	0	1	58	0	0	0	1	0	6	b
3	2	2	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	7	0	0	3	0	0	0	0	0	1	188	0	269	8	50	3	0	1	10	4	0	2	1	0	7	1	6	12	0	7	c
0	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	52	1	19	180	7	6	6	3	12	0	4	0	5	0	5	1	24	10	0	7	d
0	6	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	164	0	53	5	344	5	2	0	5	4	3	0	0	0	8	0	5	10	0	1	e
0	0	1	0	0	0	0	0	0	0	0	2	2	0	3	5	2	0	0	0	0	0	0	11	8	1	1	0	0	0	0	0	138	2	3	14	8	212	31	0	6	20	26	0	7	3	15	0	2	11	0	42	f
0	1	0	0	0	0	0	0	0	0	2	0	1	0	1	2	1	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	90	1	0	3	0	21	224	0	7	19	43	1	19	0	6	0	4	9	0	3	g
0	1	0	0	0	0	0	0	0	0	1	0	0	44	0	0	0	0	0	0	4	0	2	0	0	9	0	0	0	0	0	7	95	0	3	1	2	0	0	368	0	0	0	18	0	0	0	50	1	1	25	0	h
0	2	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	59	0	8	13	9	12	6	0	197	9	9	0	4	0	39	1	5	42	0	3	i
0	0	0	0	0	0	1	2	0	0	0	0	0	0	2	1	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	109	0	5	2	6	11	27	0	7	183	12	0	6	0	13	1	1	12	0	8	j
0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	0	0	0	1	0	99	1	2	5	6	24	49	0	7	14	191	0	17	0	4	0	5	10	0	18	k
1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	3	3	5	0	0	4	0	0	0	0	0	2	79	0	1	0	1	0	0	24	0	0	0	487	0	0	0	8	1	1	32	0	l
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	1	2	3	0	0	0	0	1	0	0	159	0	1	6	0	7	20	0	2	7	28	0	207	0	5	0	7	9	0	5	m
0	0	0	0	0	0	0	0	0	3	0	1	0	0	0	0	1	1	0	0	0	1	0	4	10	0	3	9	9	7	7	0	79	59	0	0	0	2	0	0	0	0	3	0	0	367	0	0	0	0	0	3	n
0	1	1	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	2	1	1	0	0	0	0	0	0	1	92	0	13	9	11	14	2	2	36	17	7	1	8	1	232	0	3	62	0	4	o
0	0	0	0	0	0	0	0	0	0	1	0	0	163	0	0	0	0	0	0	28	2	1	0	0	19	0	0	0	0	0	19	115	1	2	0	4	0	0	47	0	0	0	10	0	0	0	212	0	0	18	0	p
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0	0	0	0	0	89	1	5	28	6	3	0	0	4	1	6	1	11	0	10	0	138	11	0	4	q
0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	2	1	0	0	1	0	1	0	0	0	0	0	130	0	21	12	9	15	8	0	50	15	11	0	16	1	51	0	6	199	0	7	r
0	0	0	0	0	0	0	0	0	0	1	0	0	5	0	0	0	0	0	0	9	1	1	0	0	5	0	0	0	0	0	7	63	0	0	0	0	0	0	26	1	0	0	38	0	0	0	15	0	0	487	0	s
1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	1	1	0	0	0	0	0	3	2	0	2	0	0	0	0	0	174	6	6	6	5	45	11	0	2	4	8	0	13	5	8	0	1	11	0	136	t

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_

S -> Running_-_Treadmill_5mph_-_Treadmill_0_T ->
Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3_-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6_-
_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9_-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes

d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-8: Confusion Matrix for C4.5 Classifier using the *ACFFTPeaks* feature computed per sensor and evaluated in a subject independent manner.

EXAMPLE CLASSIFIED AS (columns) / ORIGINAL LABEL (rows)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
A	114	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
B	0	307	8	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	3	7	213	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
D	0	0	0	208	4	6	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	5	320	5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	8	6	215	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	2	2	0	0	1	1	192	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
H	0	0	0	0	0	0	0	249	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
I	0	0	0	0	0	0	0	0	319	0	0	5	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	1	0	0	0	0	0	0	0	3	459	0	2	0	0	0	0	0	0	0	0	0	0	1	2	0	0	1	1	0	0	1	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	1	0	0	0	0	0	0	0	532	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
L	0	0	0	0	0	0	0	0	1	1	2	519	13	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	21	1	0	23	405	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
N	1	0	0	0	0	0	0	0	0	0	0	0	0	1581	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
O	0	0	0	0	1	0	0	0	0	0	0	0	0	0	307	8	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	0	0	0	0	0	0	5	0	7	446	46	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	44	46	350	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	459	7	0	0	0	0	1	0	0	0	0	0	1	3	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	424	9	0	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	9	300	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	279	3	5	0	0	1	0	0	0	0	0	1	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	268	3	0	0	2	0	0	0	0	0	0	18	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0
W	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	268	0	0	1	0	0	0	0	0	0	21	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0
X	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	411	24	0	2	0	0	0	2	0	52	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0	0	0	1
Y	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	0	25	354	0	3	0	1	1	0	0	69	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	280	0	0	0	0	0	0	40	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
[	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	6	0	550	0	3	0	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
\	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	2	447	91	10	4	0	48	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
]	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	2	0	0	95	396	56	12	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
^	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	6	77	439	52	0	37	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
_	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	4	0	0	0	0	0	2	3	0	1	3	11	60	477	0	42	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
`	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	297	16	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
a	5	10	15	9	7	11	7	9	35	23	61	45	50	25	13	32	21	41	38	35	19	21	19	53	47	36	59	51	60	53	44	26	8075	41	52	20	60	93	46	34	30	53	69	24	91	61	78	44	24	70	28	79
b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	44	463	0	0	0	1	0	0	0	0	1	0	1	23	0	0	0	0	0	5
c	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	48	0	488	1	14	0	0	0	0	3	0	0	0	0	9	0	0	20	0	2
d	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29	0	1	276	0	0	0	1	8	1	0	0	0	1	3	0	21	1	1	1
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	56	1	25	0	510	1	2	0	0	1	1	0	0	0	4	0	0	16	0	0
f	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	2	0	0	0	0	0	0	0	92	3	0	2	1	341	15	0	6	7	16	0	15	6	14	0	2	14	0	36
g	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	56	0	0	0	0	15	307	0	0	15	33	1	7	0	8	0	0	8	0	9
h	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	29	0	0	1	0	0	0	589	0	0	0	0	0	0	0	7	0	0	1	0
i	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	37	0	0	6	1	8	4	1	335	0	2	0	2	0	10	0	4	6	0	2
j	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	64	0	3	0	2	15	24	1	2	258	6	0	4	0	6	0	2	15	1	9
k	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	64	1	0	0	0	20	39	0	4	6	277	0	12	2	6	0	2	8	0	16
l	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	21	0	0	0	0	0	0	1	0	0	0	621	0	0	1	1	0	0	7	0
m	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	113	3	0	1	0	16	12	0	1	2	12	0	296	0	5	0	2	11	0	1
n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	1	0	0	2	0	59	15	0	0	0	6	0	0	0	0	2	0	1	472	1	0	0	0	0	7
o	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	69	0	6	3	4	9	8	1	19	14	6	0	5	2	338	0	3	29	0	4
p	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	0	2	0	0	0	0	0	0	0	608	0	0	0	0
q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	29	1	0	31	0	1	0	0	5	1	0	0	4	0	4	0	240	1	0	3
r	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	108	1	15	3	16	16	10	0	2	15	8	0	10	0	28	0	0	316	0	9
s	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	1	635	0
t	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	110	6	4	2	0	33	4	0	4	4	19	0	8	5	5	0	1	7	0	239

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0

S -> Running_-_Treadmill_5mph_-_Treadmill_0_T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes

d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-9: Confusion Matrix for C4.5 Classifier using the *ACAbsArea and DCArea* features computed per sensor and evaluated in a subject independent manner.

EXAMPLE CLASSIFIED AS

ORIGINAL LABEL	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
A	110	3	5	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B	0	302	7	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0
C	4	5	215	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
D	0	0	0	210	4	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	5	320	4	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	16	7	197	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	1	0	0	0	0	201	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	0	1	0	0	1	245	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	10	0	0	0	1	2	1	0	1	0	1	0	0	0	2	0	0	0	0	0
I	0	0	0	0	0	0	0	0	325	0	1	4	13	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	0	462	0	1	2	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	3	0	522	0	1	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	48	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
L	0	0	0	0	0	0	0	0	2	0	0	512	12	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	15	1	0	18	408	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
N	1	1	0	0	0	0	1	0	0	0	0	0	0	1581	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
O	0	0	0	0	0	0	1	0	0	0	0	0	0	0	298	12	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P	0	0	0	0	0	0	0	1	0	0	0	0	0	0	10	451	44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	54	42	341	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	469	5	0	0	0	0	0	1	0	0	0	0	2	1	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	8	414	14	0	0	0	0	0	0	0	0	0	0	0	0	41	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	291	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	265	0	4	0	0	1	0	0	0	0	0	0	34	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
V	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	3	261	4	1	1	2	0	0	0	0	0	1	16	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	3	0
W	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	2	2	253	0	0	0	0	0	0	0	0	0	35	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0
X	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	422	11	0	5	0	0	0	2	0	52	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0
Y	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	10	369	0	2	3	4	1	1	0	60	0	0	0	0	1	1	0	0	0	1	0	1	0	0	0	0	0	0	1
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	1	273	0	0	0	0	0	0	42	0	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0
[	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	6	2	0	542	0	0	0	0	0	58	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0
\	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	473	65	9	3	0	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
]	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	63	428	54	3	0	52	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
^	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	9	66	432	71	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
_	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	5	0	2	3	7	67	487	0	32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
`	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	293	15	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1
a	3	15	11	16	14	5	10	17	31	26	57	44	43	24	12	45	23	46	40	31	35	28	43	63	60	35	74	62	55	52	43	26	7854	52	65	29	72	104	56	52	33	65	65	19	75	62	68	47	37	84	23	101
b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	55	458	0	0	0	2	1	0	0	0	1	0	1	18	0	0	0	0	0	3
c	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	72	0	462	0	22	1	1	0	0	0	3	0	0	0	10	1	0	13	0	1
d	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	30	0	1	259	0	4	1	0	7	2	1	0	1	0	6	0	30	0	0	0
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	80	0	23	0	480	1	1	0	0	1	0	2	0	0	9	0	0	19	0	1
f	0	0	0	0	0	0	2	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	2	1	0	1	0	0	0	0	0	128	5	2	2	2	307	21	0	7	9	10	0	10	3	9	1	3	12	0	34
g	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	56	2	2	1	3	15	287	0	3	29	37	0	13	0	5	0	0	3	0	6
h	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	1	591	0	0	0	0	0	0	0	7	0	0	0	0
i	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	32	1	0	12	3	8	2	0	321	1	8	0	0	0	19	0	3	8	0	1
j	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	74	0	1	0	1	16	28	0	1	238	9	1	6	0	18	0	4	5	0	9
k	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	1	0	0	0	0	0	0	0	1	80	1	2	3	1	21	44	0	4	10	247	0	10	0	8	0	3	10	0	10
l	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	0	0	0	0	0	0	1	0	1	0	619	0	0	2	2	0	0	9	0
m	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	3	0	0	0	0	0	0	0	98	0	0	0	1	20	7	0	1	6	10	0	309	0	4	0	0	5	0	8
n	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	5	0	0	1	1	0	1	0	60	17	0	0	0	5	0	0	0	1	1	0	0	469	0	0	0	0	0	5
o	0	1	0	0	0	2	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	83	1	7	4	5	9	9	0	16	9	13	1	0	2	315	1	3	36	0	3
p	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	1	0	0	0	2	0	1	0	1	0	0	0	598	0	0	0	0
q	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	0	0	25	0	0	30	0	6	0	0	3	1	4	0	2	2	3	0	240	0	2	1
r	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	102	0	19	1	20	19	8	0	12	7	9	0	3	0	38	0	0	305	0	11
s	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	25	0	0	0	0	0	0	0	0	0	0	6	0	0	0	2	0	0	619	0
t	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0	1	0	1	1	3	0	0	0	0	0	0	0	140	4	6	3	2	32	4	0	4	9	17	0	4	0	3	0	3	8	0	206

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3_-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6_-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9_-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes
d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-10: Confusion Matrix for C4.5 Classifier using the *MaxAcceleration* feature set computed per sensor and evaluated in a subject independent manner.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	
111	4	2	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	A
0	304	8	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	B
6	6	210	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	C
0	0	0	210	3	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	D
0	0	0	5	318	5	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	E
0	0	0	11	7	211	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	F
3	0	0	0	1	0	193	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	G
0	0	1	0	0	0	1	251	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	H
0	0	0	0	0	0	0	0	318	0	4	2	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	I
0	0	0	0	0	0	0	0	4	460	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	J
0	0	1	0	0	0	0	0	3	0	529	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	K
0	0	0	0	0	0	0	0	1	0	3	503	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	L
0	0	0	0	0	0	0	0	20	1	0	18	409	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	M
0	1	0	0	0	0	1	0	0	0	0	0	0	1583	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	9	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	0	N
0	0	0	1	0	1	0	0	0	0	0	0	0	0	304	14	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	O
0	0	0	0	0	1	1	0	0	1	2	0	0	0	15	460	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	P
0	0	0	0	0	1	0	0	0	0	0	0	0	0	49	45	344	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Q
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	468	5	0	0	0	0	0	0	0	0	0	0	1	1	0	32	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	R
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	422	11	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	S
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	293	0	0	0	0	0	0	0	0	0	0	0	0	32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	T
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	278	0	1	0	0	2	0	0	0	0	0	1	20	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	U
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	269	1	0	0	1	0	0	0	0	0	1	20	0	0	0	0	0	0	0	1	0	1	0	0	1	0	1	0	1	0	0	V
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	5	4	256	0	0	1	0	0	0	0	0	0	26	0	1	0	0	0	0	0	1	0	0	2	0	0	0	0	1	0	0	0	W
0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	422	17	0	2	0	2	1	0	0	46	0	0	0	0	0	0	0	0	1	0	0	2	2	0	0	0	0	0	0	X
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	355	0	1	1	2	3	0	0	71	0	0	0	0	2	0	0	0	0	0	0	1	1	1	0	0	0	0	1	Y
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	280	0	0	0	0	0	0	38	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	Z
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	8	4	0	548	2	1	2	0	0	44	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	[
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	3	0	1	457	77	8	6	0	53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	\
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	81	401	65	10	0	44	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	]
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	14	78	445	48	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	^
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	4	0	0	4	7	67	479	0	42	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	_
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	296	13	0	0	2	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	`
6	11	4	11	10	13	10	21	37	29	61	53	50	24	17	32	24	47	39	32	30	16	28	54	78	39	69	72	55	57	46	38	7827	38	63	19	80	94	51	53	34	69	64	24	103	54	64	49	20	101	28	104	a
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	3	1	0	0	41	465	0	0	1	0	0	0	0	0	0	0	0	26	0	0	0	0	0	1	b
0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	0	0	0	0	0	0	60	0	468	0	18	1	0	0	1	1	1	0	1	0	10	0	0	20	0	1	c
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	25	0	4	260	0	1	1	0	6	1	1	1	0	0	9	1	32	1	0	0	d
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	0	0	0	0	0	1	80	1	26	0	484	1	1	0	0	1	0	0	1	0	4	0	0	14	0	2	e
0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	4	0	2	1	0	0	1	1	114	3	3	0	2	293	16	0	11	12	15	0	10	9	10	0	2	23	0	39	f
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	64	0	1	1	1	11	283	0	3	26	39	0	15	0	4	0	0	7	0	5	g
0	0	0	0	0	0	0	0	1	0	0	1	0	3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	0	588	0	0	0	0	0	0	0	7	0	0	2	0	h
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	33	1	0	7	2	9	4	0	323	6	8	0	4	0	14	0	1	4	0	2	i
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	78	0	0	0	4	10	25	0	1	246	9	0	7	0	13	0	1	10	0	5	j
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	97	0	2	3	2	21	37	0	3	7	242	0	12	0	5	0	2	9	0	15	k
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	18	0	0	0	2	0	0	1	3	0	0	616	0	0	1	1	0	0	9	0	l
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	109	0	0	1	3	11	11	0	1	2	15	0	303	0	2	0	1	5	0	8	m
0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	1	0	0	2	0	1	0	0	0	1	0	54	17	0	0	0	5	1	0	0	1	1	0	0	478	0	0	0	0	0	4	n
1	0	1	0	0	1	0	3	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	80	1	13	6	8	4	7	0	22	14	3	0	2	2	314	0	3	32	0	4	o
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0	9	0	0	0	0	0	0	0	592	0	0	1	0	p
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	37	0	0	32	0	4	0	0	2	2	4	0	1	1	1	0	235	1	0	1	q
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	103	0	14	0	18	15	7	0	5	9	14	0	7	0	31	0	0	323	0	10	r
0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	1	629	0	s
0	0	1	0	0	0	0	4	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	129	9	3	0	4	42	7	0	6	6	8	0	9	1	2	0	0	6	0	213	t

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0
S -> Running_-_Treadmill_5mph_-_Treadmill_0_T ->
Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3_-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6_-
_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9_-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes
d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-11: Confusion Matrix for C4.5 Classifier using the *ACAbsArea, DCArea,* and *ACFFTPeaks* computed per sensor and evaluated in a subject independent manner.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t
A	109	4	3	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
B	0	300	7	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0
C	5	6	213	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
D	0	0	0	205	4	11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
E	0	0	0	3	322	5	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	12	6	207	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	1	202	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
H	0	0	0	0	1	0	1	242	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	1	0	2	0	0	0	0	1	13	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0	0	0	0	1
I	0	0	0	0	0	0	0	0	329	0	1	2	16	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	2	461	0	1	1	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	1	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	3	0	0	0	0	0	3	0	518	2	0	0	0	0	0	0	0	0	0	2	0	1	1	0	0	0	0	0	0	0	48	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
L	0	0	0	0	0	0	0	0	2	1	0	507	24	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	16	2	1	23	405	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
N	1	1	0	0	0	0	1	0	0	0	0	0	0	1581	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	9	0	0	0	0	0	0	2	0	0	0	2	0	0	0	0	0	0	0	0
O	0	0	0	0	0	0	1	0	0	0	0	0	0	0	287	15	66	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
P	0	0	0	1	0	0	1	1	0	0	0	0	0	0	14	441	39	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	2	1	0	0	0	0	1	0	0	0	0	0	0	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51	42	345	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	461	6	0	0	0	0	1	2	0	0	3	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	424	10	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	14	285	0	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	269	0	2	0	0	3	0	0	0	0	0	0	27	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
V	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	1	269	4	0	0	1	0	0	0	0	0	1	16	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0
W	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	6	4	244	0	0	0	0	0	0	0	0	0	34	0	1	1	1	0	0	0	0	0	0	2	0	0	0	0	2	0	0	1
X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	427	10	0	2	0	0	1	0	0	51	2	0	0	0	0	1	0	0	1	0	0	2	1	0	0	0	0	0	0
Y	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	379	1	1	1	1	2	2	0	52	0	0	0	0	1	1	0	0	0	0	0	4	0	0	0	0	0	0	0
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	270	0	0	0	0	0	0	46	0	0	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
[	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	3	0	553	0	1	1	0	0	48	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0
\	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	449	79	12	4	0	58	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
]	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	3	74	423	56	6	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
^	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	75	431	66	0	33	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
_	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	2	3	0	1	4	9	61	482	0	40	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
`	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	2	0	0	0	0	0	286	20	0	0	1	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0
a	5	14	8	10	13	8	6	12	26	26	64	47	44	27	14	39	23	48	44	32	32	20	36	71	59	40	68	60	63	49	55	36	7818	51	69	31	91	101	49	44	39	70	65	22	91	57	62	45	29	98	22	99
b	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	2	1	0	0	0	43	465	0	0	1	1	0	0	0	0	0	0	1	18	0	0	0	0	0	8
c	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	0	0	0	0	0	70	0	464	0	19	0	0	0	0	2	1	0	2	0	7	0	0	19	0	0
d	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	27	1	3	259	0	1	0	0	6	0	0	1	0	0	9	1	33	0	0	1
e	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	3	0	0	0	0	0	0	80	1	36	0	470	1	2	0	0	1	0	0	2	0	6	0	0	12	0	4
f	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	1	0	0	0	0	0	0	1	1	2	0	2	0	0	0	0	0	121	4	2	2	1	309	13	0	8	11	8	0	17	9	8	0	3	18	0	32
g	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62	1	1	2	2	15	284	0	3	25	36	0	12	0	5	0	0	8	0	5
h	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	585	1	0	0	1	0	0	0	4	0	0	1	0
i	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	34	2	1	7	3	7	2	0	319	2	6	0	0	0	15	0	5	9	0	6
j	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	65	0	3	0	4	14	28	0	2	243	14	0	8	0	15	0	2	7	0	6
k	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	2	79	0	4	3	3	19	45	0	7	12	246	0	16	0	4	0	2	8	0	8
l	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	0	0	0	0	0	0	1	3	0	0	623	0	0	1	1	0	0	9	0
m	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	97	2	0	0	8	16	12	0	3	5	14	0	305	0	3	0	0	5	0	4
n	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	1	0	2	0	54	14	0	0	0	5	1	0	1	1	0	0	0	477	0	0	0	0	0	9
o	1	0	1	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	72	1	9	6	4	3	6	0	26	13	5	0	3	2	318	1	2	40	0	6
p	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	8	0	0	0	0	0	0	0	595	0	0	3	0
q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	45	0	1	30	0	7	0	0	5	2	2	0	2	0	0	0	227	0	0	0
r	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	100	0	19	3	15	20	5	0	12	9	11	0	9	0	35	0	0	309	0	11
s	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	25	0	0	0	0	0	0	0	0	0	0	5	0	0	0	2	0	0	623	0
t	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	3	2	0	0	0	0	0	0	0	122	6	6	3	2	49	4	0	5	6	9	0	10	4	1	0	2	6	0	209

EXAMPLE CLASSIFIED AS (columns); ORIGINAL LABEL (rows)

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0
S -> Running_-_Treadmill_5mph_-_Treadmill_0_T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3_-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6_-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9_-_hard
` -> kneeling
a -> unknown
b -> Carrying_groceries
c -> Doing_dishes
d -> Gardening
e -> Ironing
f -> Making_the_bed
g -> Mopping
h -> Playing_videogames
i -> Scrubbing_a_surface
j -> Stacking_groceries
k -> Sweeping
l -> Typing
m -> Vacuuming
n -> Walking_around_block
o -> Washing_windows
p -> Watching_TV
q -> Weeding
r -> Wiping/Dusting
s -> Writing
t -> taking_out_trash

Figure A6-12: Confusion Matrix for C4.5 Classifier using the *ACAbsAreas*, AC*Range*, *ACVar*, *ACFFTPeaks*, *ACCorr*, *ACMCR*, and *ACPitch* computed per sensor and evaluated in a subject independent manner.

Appendix A7: Activity Recognition Using Heart Rate Data

EXAMPLE CLASSIFIED AS

ORIGINAL LABEL

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s
A	13	21	3	2	10	3	2	5	2	4	5	1	6	0	0	1	1	2	8	8	0	0	0	4	2	0	0	1	5	5	3	0	1	0	0	0	1	0	0	0	0	0	0	0	4	0	0	1	0	0	0
B	8	108	15	18	16	15	8	2	1	1	16	7	2	0	3	2	6	7	0	1	0	0	0	8	0	0	5	11	20	16	7	3	2	0	2	0	5	0	0	1	2	0	0	2	5	0	0	1	0	0	0
C	6	32	29	9	16	9	7	0	4	4	10	1	10	0	3	1	3	0	6	2	0	0	0	0	2	1	4	14	15	9	4	0	2	4	0	4	3	3	0	1	1	1	0	4	6	0	0	0	4	0	0
D	3	10	8	85	34	9	1	0	0	0	13	1	2	2	2	2	2	4	0	0	0	0	0	3	0	0	0	7	6	15	6	0	4	0	0	0	3	1	0	3	0	0	0	0	3	0	0	0	0	0	0
E	9	13	7	23	98	25	1	1	2	1	13	5	11	0	0	2	0	12	0	0	0	0	0	5	3	0	0	11	27	37	9	0	8	0	0	0	1	1	0	9	0	0	0	1	5	0	0	0	0	0	0
F	4	21	10	21	40	39	11	0	0	1	4	2	0	0	0	0	0	3	0	0	0	0	0	2	5	1	0	11	10	18	3	0	7	0	0	0	2	3	0	9	0	0	0	1	4	2	0	0	0	0	0
G	4	3	1	4	7	10	64	0	0	1	14	7	4	0	9	0	11	5	1	1	0	0	0	3	4	1	5	4	7	9	1	0	2	0	0	0	9	3	0	2	1	2	0	3	3	4	0	0	1	0	1
H	3	5	6	1	5	4	0	81	6	19	5	13	24	0	5	10	4	10	18	3	0	0	0	4	1	0	0	0	8	19	13	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I	2	0	2	0	1	0	0	7	234	33	2	5	26	7	6	3	2	0	13	0	2	0	0	1	0	1	0	0	0	1	11	1	0	0	0	4	1	5	0	0	0	1	0	1	0	0	0	0	0	1	0
J	2	2	4	0	6	1	0	14	25	201	0	12	68	0	4	5	20	9	64	7	0	0	0	3	0	0	1	2	0	10	17	0	2	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2
K	0	5	5	2	4	4	4	0	0	0	388	1	2	0	3	9	2	9	0	0	0	0	0	10	6	2	1	24	44	16	2	2	6	6	0	0	4	5	0	3	1	2	0	0	2	2	0	0	0	0	3
L	1	13	2	2	7	4	3	26	0	2	6	249	6	0	8	28	46	25	3	2	0	0	0	13	5	2	2	2	30	40	34	0	2	0	0	0	0	1	0	2	0	0	0	0	0	0	0	0	0	0	1
M	3	0	8	5	9	0	2	18	5	23	4	13	240	9	1	14	5	8	29	1	0	0	0	5	0	0	1	1	10	17	39	0	10	0	1	0	1	0	0	4	1	1	0	0	2	0	0	0	1	4	1
N	0	0	0	0	0	0	0	0	0	0	0	0	0	1409	0	0	0	0	0	0	19	3	2	0	0	1	0	0	0	0	0	4	0	3	0	0	0	0	59	0	0	0	26	0	0	1	45	0	1	25	0
O	1	1	0	0	2	1	2	3	5	1	8	4	5	0	168	30	62	8	9	11	0	0	0	1	0	0	7	10	3	4	29	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P	0	4	0	2	5	1	1	17	8	11	10	31	24	0	7	198	35	9	28	11	0	0	0	8	2	0	7	5	18	31	57	0	0	0	2	0	0	4	0	2	0	0	0	0	0	1	0	0	0	0	1
Q	1	1	1	1	0	0	1	7	8	14	7	28	9	0	28	53	216	12	13	9	0	0	0	4	5	0	8	0	6	4	17	0	0	0	2	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0
R	1	4	0	6	14	4	4	9	3	8	45	45	9	0	15	20	20	146	13	7	0	0	0	9	2	0	1	3	9	53	58	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	1
S	4	1	4	0	3	0	0	8	9	31	0	10	22	0	2	15	19	17	269	27	0	0	0	1	0	0	0	0	0	8	27	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T	4	1	0	0	0	0	0	10	0	16	1	3	4	0	7	5	6	6	23	229	0	0	0	2	0	0	1	0	0	6	6	0	0	0	0	0	3	0	0	0	0	0	0	0	1	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	1	0	0	29	0	0	0	0	0	0	67	23	19	0	3	12	5	3	2	0	0	21	1	4	0	22	3	0	15	2	7	0	25	2	2	1	1	1	4	30	0
V	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	10	94	63	2	0	8	2	0	0	0	0	8	0	16	0	19	6	1	16	5	1	0	13	4	0	5	4	0	3	15	0
W	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	7	34	99	0	0	12	7	1	0	0	0	13	2	9	2	36	2	3	7	0	4	4	12	5	3	4	5	0	11	12	2
X	7	14	3	9	13	8	5	7	3	5	37	40	19	0	0	27	11	13	0	1	0	1	0	14	16	2	6	48	54	49	33	1	10	2	5	2	8	6	0	4	0	6	0	2	2	2	0	1	0	0	2
Y	2	2	3	0	6	6	5	3	2	3	30	20	6	0	2	6	9	2	1	0	2	1	1	9	52	6	20	64	51	16	18	2	23	5	4	2	18	10	0	1	1	16	2	5	9	4	0	3	1	0	4
Z	0	0	1	0	0	0	1	0	1	0	1	0	0	2	0	0	0	0	0	0	6	13	20	1	3	79	34	10	4	0	0	10	2	23	5	20	9	4	6	3	6	4	1	6	11	1	2	14	6	4	8
[	0	6	5	0	0	0	4	0	0	2	4	1	1	0	4	3	15	1	0	2	4	4	9	4	4	21	261	17	0	1	0	3	15	23	5	16	25	16	0	11	7	26	0	13	26	19	0	4	22	0	8
\	0	19	4	5	6	5	2	0	3	0	26	2	1	0	0	1	1	1	0	0	2	1	2	13	26	9	13	342	21	0	0	5	12	0	4	0	13	12	0	2	4	18	0	10	12	4	0	3	1	0	1
]	3	13	5	10	12	8	8	0	1	2	36	12	4	0	1	11	2	2	1	1	0	0	0	13	10	2	4	35	332	20	0	1	23	3	1	0	8	6	0	4	0	4	0	1	4	0	0	0	0	0	0
^	1	7	3	8	33	5	6	4	0	12	39	37	18	2	0	21	2	21	2	2	0	0	0	17	5	0	5	5	30	316	11	0	1	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0
_	7	9	4	5	9	7	2	7	14	16	5	58	29	0	27	21	24	38	6	2	0	0	0	4	2	0	0	3	3	21	282	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
`	0	2	2	0	0	0	1	0	0	0	0	0	0	7	0	0	0	0	0	0	15	16	36	2	2	14	11	6	0	0	0	82	6	14	3	9	1	0	11	3	5	2	8	7	12	2	6	5	16	4	5
a	3	2	1	3	6	12	2	0	0	3	13	1	19	0	0	2	0	0	1	0	0	2	2	4	16	1	12	25	27	1	3	7	159	11	21	11	29	23	3	24	5	25	0	9	18	15	0	5	4	1	10
b	0	0	0	0	0	0	0	0	2	0	6	0	0	11	0	0	0	0	0	0	2	15	20	0	7	11	23	0	1	0	0	10	9	159	8	65	13	10	4	12	22	20	3	26	16	24	4	3	51	13	19
c	0	2	0	0	0	0	0	0	0	0	1	0	0	5	0	1	1	0	0	0	2	1	5	7	4	7	13	8	9	0	0	6	14	6	66	11	13	9	7	23	6	8	11	8	14	15	6	18	6	24	8
d	0	1	2	0	0	0	0	0	0	0	3	0	0	9	0	0	0	0	0	0	6	12	18	1	4	13	16	0	0	0	0	4	8	74	3	227	5	5	6	8	19	6	11	13	14	25	2	10	64	18	13
e	1	14	3	7	5	4	11	2	2	0	10	1	1	0	0	0	0	0	0	2	3	4	2	5	21	4	31	37	10	3	0	4	33	19	12	13	74	36	2	25	16	22	0	21	43	19	2	10	16	1	25
f	0	0	3	2	3	9	2	0	2	1	20	2	3	2	0	5	2	2	0	0	0	1	0	11	7	5	23	21	12	4	2	1	29	10	10	7	31	97	0	22	9	28	2	19	14	14	0	5	6	1	13
g	0	0	0	0	0	0	0	0	0	0	0	0	0	168	0	0	0	0	0	0	8	13	5	0	0	3	0	0	0	0	0	3	0	2	9	5	1	0	217	0	0	0	44	0	0	0	75	1	2	74	2
h	0	3	0	5	10	9	2	0	0	0	12	4	2	0	0	1	3	0	0	0	3	2	1	7	15	6	18	11	10	1	2	4	20	18	16	11	28	20	0	49	17	27	3	20	7	14	0	13	12	4	11
i	0	4	3	2	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	4	3	8	0	2	5	9	6	3	0	0	11	12	36	7	41	7	10	2	15	64	17	8	25	15	14	0	6	43	12	15
j	0	3	1	0	1	0	4	0	1	0	7	0	1	0	0	2	0	0	0	0	1	2	2	7	15	6	43	21	2	2	1	2	24	24	5	11	27	23	0	21	12	90	0	34	13	14	0	7	13	3	15
k	0	0	0	0	0	0	0	0	0	0	0	0	0	146	0	0	0	0	0	0	16	10	7	0	0	0	1	0	0	0	0	3	0	4	10	21	0	1	58	2	5	1	210	1	0	1	32	8	3	105	8
l	0	2	4	0	0	0	3	0	2	0	5	0	0	0	0	0	0	0	0	0	0	6	6	0	11	6	31	9	3	1	0	5	15	30	5	21	20	27	0	25	19	39	0	100	23	17	0	5	23	4	9
m	4	5	7	7	4	2	3	0	0	0	2	2	1	0	0	0	0	0	0	0	3	0	4	3	7	9	31	29	2	5	2	10	27	24	7	20	44	15	0	14	16	19	0	25	161	9	0	9	25	0	12
n	0	5	1	0	0	5	4	0	1	0	1	3	1	5	0	4	3	0	0	0	3	5	9	0	9	7	25	22	5	2	0	3	23	38	18	31	17	27	1	21	18	15	10	25	11	79	1	9	24	7	26
o	0	0	0	0	0	0	0	0	1	0	0	0	0	263	0	0	0	0	0	0	10	3	5	0	0	3	1	0	0	0	0	5	0	4	1	8	1	0	106	0	1	0	29	0	1	3	145	1	2	48	1
p	1	7	1	0	0	0	0	0	0	0	4	0	2	7	0	0	0	0	0	0	1	4	1	3	5	11	12	13	3	0	0	6	7	18	21	16	9	14	2	19	6	10	12	9	20	6	0	46	16	5	6
q	0	6	2	0	0	0	0	0	2	0	2	0	1	14	0	0	0	0	0	0	5	2	11	0	2	9	23	2	0	0	0	8	7	74	6	72	12	13	1	13	31	16	4	33	19	18	1	4	125	6	15
r	0	0	0	0	0	0	0	0	1	0	0	0	1	68	0	0	0	0	0	0	19	7	8	0	0	1	0	0	0	0	0	10	0	9	7	24	3	0	44	0	4	0	77	0	0	4	39	2	4	323	4
s	0	0	0	0	0	0	4	0	0	3	9	3	5	3	0	5	0	0	0	2	2	2	5	2	5	6	16	2	1	2	3	6	12	22	19	24	28	19	6	15	32	11	12	18	16	24	2	5	20	7	76

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3_-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6_-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9_-_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m -> Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash

Figure A7-1: Confusion Matrix for C4.5 Classifier using the *ScaledHR* feature and evaluated in a subject dependent manner without the garbage class (unknown) when the feature is computed over windows of 5.6s.

EXAMPLE CLASSIFIED AS (columns) / **ORIGINAL LABEL** (rows)

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	
147	2	5	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	A
0	445	10	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	2	0	0	2	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	B
5	12	307	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	C
1	0	1	448	1	16	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	D
0	0	0	8	517	28	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	2	2	0	0	0	0	0	0	1	0	0	0	0	0	E
0	0	0	22	22	507	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	F
1	3	1	1	1	1	429	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	G
1	0	0	0	1	0	0	457	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	3	1	0	0	0	0	0	0	0	1	0	1	1	0	1	0	1	0	1	0	0	1	1	0	0	0	0	0	H
0	0	0	0	0	0	0	0	442	0	3	0	17	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	I
0	0	0	0	0	0	0	0	0	561	0	4	2	0	0	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	J
0	0	0	0	0	0	0	0	1	0	637	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	K
0	0	0	0	0	0	0	0	3	4	5	614	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	L
0	0	0	0	0	0	0	0	19	3	1	8	557	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	M
0	0	0	0	0	0	0	0	0	0	1	0	0	2130	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	N
0	0	1	0	0	0	1	0	0	0	0	0	0	0	486	8	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	O
0	0	0	0	0	0	0	1	0	0	0	0	0	1	9	570	51	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	P
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0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	13	536	20	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	S
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	23	379	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	T
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	420	0	6	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	U
0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	403	3	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1	0	0	2	2	0	0	0	0	V
0	0	1	1	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	6	4	393	0	0	2	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	2	0	0	1	0	0	0	2	1	W
0	0	0	1	0	0	0	3	0	0	0	0	1	2	0	0	0	0	0	0	1	0	1	534	21	0	7	0	0	0	0	0	0	1	1	2	3	2	0	0	2	2	0	2	1	0	0	1	0	0	4	X
0	1	0	0	0	0	1	1	0	1	0	1	0	1	0	1	0	0	0	0	0	1	0	21	493	1	6	2	1	3	0	0	1	0	0	0	2	1	0	2	0	0	1	1	0	0	0	0	0	0	1	Y
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	421	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	Z
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	5	6	0	700	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	0	1	[
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	2	2	0	2	657	43	4	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	\
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	47	627	30	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	]
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0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	3	0	3	47	657	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	_
0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	408	0	0	1	1	0	0	0	2	0	0	0	0	0	0	0	0	0	1	0	`
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0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	3	1	651	1	35	2	4	0	2	6	3	1	2	0	9	0	1	24	6	1	b
0	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	3	1	0	0	1	0	0	0	0	2	1	4	372	4	7	5	0	7	2	4	1	1	1	7	0	28	3	3	1	c
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	2	684	2	6	0	0	3	3	2	2	0	8	1	0	31	3	5	d
0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	4	0	3	1	0	0	0	1	7	5	5	0	499	29	1	11	17	24	1	9	6	16	0	4	31	0	53	e
0	0	0	0	1	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	2	1	3	2	24	554	0	8	32	60	0	29	0	19	0	4	2	0	11	f
0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	799	0	0	0	0	0	0	0	2	0	0	2	0	g
0	0	0	1	0	2	3	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	1	1	1	0	0	1	0	0	0	5	0	3	10	0	6	7	0	600	6	8	0	4	1	13	0	15	5	0	2	h
0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	9	1	8	8	40	0	2	450	28	0	13	0	16	0	4	17	0	7	i
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	0	0	0	1	1	1	1	0	1	0	0	0	0	1	3	3	5	4	33	47	0	8	21	521	0	38	1	11	0	11	15	1	25	j
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	765	0	0	0	2	0	0	9	0	k
0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	2	7	8	2	12	42	2	6	15	32	1	578	1	8	0	6	15	1	17	l
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	2	0	0	0	0	2	1	0	2	2	1	1	0	0	29	0	0	0	8	4	0	1	1	2	0	0	667	1	0	0	1	0	9	m
1	3	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	5	2	1	2	0	0	0	2	0	1	1	14	5	11	11	19	2	9	19	7	0	16	0	515	1	15	27	3	7	n
0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	3	0	0	0	796	0	0	1	1	o
1	0	0	0	0	0	1	2	0	0	0	0	0	0	2	0	0	0	0	0	1	0	3	1	1	0	1	1	0	0	0	0	1	4	25	2	3	7	0	9	3	11	0	5	3	10	0	331	3	2	8	p
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2	2	0	0	0	0	1	2	28	2	23	31	10	0	5	14	18	1	13	0	18	0	1	540	0	14	q
0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	1	0	1	0	1	0	2	1	0	0	0	9	0	0	0	0	0	0	765	0	r
0	0	0	0	0	1	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	3	1	3	0	4	0	0	0	0	0	18	3	7	15	52	18	0	4	15	26	1	15	9	7	0	6	11	0	421	s

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m -> Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash

Figure A7-2: Confusion Matrix for C4.5 Classifier using the *ScaledHR* feature and evaluated in a subject independent manner without the garbage class (unknown) when the feature is computed over windows of 5.6s.

EXAMPLE CLASSIFIED AS

ORIGINAL LABEL

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s
A	37	74	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	1	0	0	1	0	1	0	0	0	1	0	0	0	0
B	99	176	140	2	0	0	4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	2	0	3	0	0	4	3	0	1	20	0	0	4	5	0	0	0	0
C	64	147	77	2	0	0	7	0	0	0	0	0	0	4	0	0	0	0	0	0	3	0	1	0	0	0	0	0	0	0	0	0	0	1	0	3	0	0	2	0	2	1	10	1	0	1	3	0	0	2	0
D	2	0	21	194	96	89	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	12	13	2	0	4	0	0	2	0	0	0	0	2	0	0	2	0	0
E	0	3	20	188	159	163	12	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	3	0	4	1	3	0	0	1	1	0	0	0	1	0	0	0	0	0
F	0	3	26	222	136	93	39	0	0	0	0	0	0	0	3	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	11	4	4	0	5	0	0	0	0	0	0	0	0	0	0	4	0	0
G	0	2	8	2	6	0	343	1	0	0	2	0	0	4	0	4	2	0	0	0	0	2	9	23	0	0	0	0	0	0	0	0	0	1	0	0	2	18	0	4	0	0	0	4	0	6	0	0	0	0	1
H	0	0	28	3	0	0	31	366	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	12	0	0	1	0	0	0	0	0	0	0	0	0	9	9	0	1	11	0	0	1	0	0	0	0	0	0	0
I	0	0	0	0	0	0	0	0	187	3	10	133	129	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	0	2	557	0	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	1	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	29	0	561	0	1	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	9	0	0	28	1	0	0	0	5	0	0	0
L	0	0	0	0	0	0	0	0	96	24	1	284	222	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
M	0	0	0	0	0	0	0	0	176	4	6	221	177	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0
N	0	0	0	0	0	1	7	0	0	0	0	0	0	2045	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	54	0	0	0	2	0	0	0	23	0	0	0	0
O	0	0	0	3	2	0	6	3	0	0	0	0	0	0	104	245	149	0	0	0	0	2	0	0	2	0	0	0	0	0	0	0	7	0	7	0	0	0	0	0	0	0	0	0	0	2	0	9	0	0	0
P	0	0	0	0	2	1	17	9	0	0	0	0	0	0	76	255	203	0	0	0	0	0	6	13	6	0	0	0	0	0	0	0	4	0	5	0	6	0	0	0	15	7	0	0	0	0	0	7	0	0	1
Q	0	0	0	2	3	4	10	13	0	0	0	1	0	0	65	251	183	0	0	0	0	2	9	4	2	0	0	0	0	0	0	0	4	0	21	0	9	1	0	4	20	2	0	1	0	2	0	1	0	0	0
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	343	164	13	0	0	0	0	0	0	28	9	7	8	19	0	13	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	109	369	68	0	0	0	0	4	0	0	0	0	0	0	0	3	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	0
T	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	35	113	256	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
U	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	230	4	23	0	0	2	0	0	0	0	0	0	0	1	0	1	0	0	27	1	0	1	29	0	0	1	91	1	1	15	0
V	1	0	0	0	0	0	0	2	0	0	6	2	1	0	0	0	0	0	0	0	14	286	11	1	1	4	3	0	0	0	1	0	0	2	4	12	2	0	31	4	0	5	15	1	2	2	4	1	1	0	4
W	0	10	0	1	0	1	1	1	8	0	0	0	0	0	0	0	0	0	0	0	10	1	205	0	0	6	0	0	0	0	0	0	0	19	23	11	2	3	42	17	0	2	8	0	0	5	20	13	0	2	8
X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	1	0	0	0	0	0	439	23	1	12	0	0	2	7	0	4	0	0	1	33	3	0	20	1	7	0	7	5	1	0	6	8	0	4
Y	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0	0	1	0	43	320	2	23	6	1	3	15	0	12	0	0	3	33	5	0	1	1	15	0	5	27	0	0	8	2	0	14
Z	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	25	0	1	1	0	354	0	0	0	0	0	0	0	31	0	4	0	1	1	0	0	0	0	0	0	7	1	2	1	0	0
[	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	6	0	11	18	1	516	2	0	17	17	0	35	0	0	0	6	9	0	0	0	2	0	9	58	1	0	0	0	0	12
\	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	6	0	0	0	0	0	0	24	0	11	185	145	54	22	0	41	0	0	0	0	0	0	0	0	0	0	0	227	0	0	0	0	0	0
]	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	9	0	0	0	0	0	0	20	0	7	147	154	116	105	0	71	0	0	0	0	0	0	0	0	0	0	0	79	0	0	0	0	0	0
^	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	33	2	0	24	50	49	257	269	0	19	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0
_	0	0	0	0	0	0	0	0	0	3	0	1	0	0	0	0	0	22	0	0	0	0	0	34	17	0	34	0	21	180	401	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
`	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	407	0	1	0	2	2	0	0	4	0	0	0	0	0	0	0	2	0	1	0
a	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	8	0	0	0	9	0	9	46	0	32	24	12	7	7	0	474	0	0	1	5	2	8	0	1	1	0	5	84	0	0	5	1	0	9
b	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	6	0	0	0	0	0	1	0	435	21	106	6	14	2	10	6	11	4	3	0	22	11	2	38	0	25
c	0	1	15	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	7	1	4	3	1	0	0	0	0	0	0	2	0	17	154	4	21	8	3	99	2	9	0	14	0	10	0	48	25	0	12
d	2	2	2	1	2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	43	0	0	22	0	0	0	0	0	0	0	80	9	430	9	17	2	15	12	11	6	7	0	27	7	4	59	1	14
e	0	0	0	0	2	0	1	3	0	0	0	1	0	0	0	0	0	0	0	0	1	0	6	4	15	0	7	0	0	2	4	1	2	9	11	1	301	45	0	28	22	58	0	28	6	34	0	24	28	0	91
f	0	0	0	1	3	1	2	2	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	2	3	1	1	0	0	0	0	0	3	14	7	20	56	246	0	16	89	127	0	59	0	28	0	9	32	0	32
g	0	4	2	1	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	83	3	34	0	0	1	1	0	0	0	0	0	0	0	1	3	0	0	509	0	0	0	10	0	0	0	124	0	0	24	2
h	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	2	9	0	0	3	0	0	0	0	0	3	0	17	82	8	36	9	1	298	10	11	6	13	0	68	2	42	66	0	9
i	1	0	1	2	1	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	3	0	0	0	0	0	0	0	0	21	6	13	43	91	0	17	222	48	1	29	0	26	0	17	27	0	25
j	0	2	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	3	4	3	7	2	3	0	0	0	0	0	1	10	24	6	90	121	0	26	35	251	8	34	0	24	0	25	37	0	38
k	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	29	5	36	0	0	1	0	0	0	0	0	0	0	1	0	34	0	1	12	0	0	0	535	0	0	0	97	0	0	26	0
l	0	0	0	0	0	0	0	5	1	0	0	0	0	0	0	0	0	0	0	0	2	3	2	8	12	1	2	0	0	0	0	0	10	7	20	15	43	51	0	10	30	24	2	415	0	5	0	43	31	1	17
m	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29	0	1	0	0	0	8	34	0	32	126	44	27	2	0	63	0	1	0	35	0	0	0	0	3	0	0	312	0	0	1	1	0	19
n	1	3	1	6	0	1	4	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	7	0	0	4	0	0	0	0	0	1	2	16	12	24	22	26	0	54	46	14	9	11	1	349	1	23	51	0	12
o	1	3	3	0	0	0	1	1	0	0	0	0	0	65	0	0	0	0	0	0	128	4	7	0	0	16	0	0	0	0	0	1	0	2	0	1	0	0	145	1	0	0	35	2	0	1	376	3	0	14	0
p	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	1	0	0	0	0	5	3	6	7	5	4	1	0	0	1	0	5	3	2	37	4	33	15	2	73	13	23	6	25	0	22	0	103	24	1	14
q	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	4	1	1	1	0	0	0	0	0	2	50	15	50	29	37	0	41	40	35	4	32	1	52	1	4	300	0	23
r	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	67	5	4	0	0	65	0	0	0	0	0	4	0	4	0	27	0	2	29	0	0	0	37	0	0	1	51	5	1	481	0
s	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	5	11	17	3	9	0	0	1	0	0	12	25	15	20	102	46	0	10	25	58	0	39	11	7	0	12	31	0	183

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3_-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6_-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9_-_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m -> Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash

Figure A7-3: Confusion Matrix for C4.5 Classifier using the Invariant reduced and ScaledHR features evaluated in a subject dependent manner without the garbage class (unknown) when the all the features are computed over windows of 5.6s.

EXAMPLE CLASSIFIED AS / ORIGINAL LABEL

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	
0	2	3	2	4	4	1	2	0	4	3	8	6	0	6	3	4	8	6	9	0	0	0	3	3	0	1	7	5	5	13	0	4	0	0	0	1	1	0	3	0	0	0	0	2	1	0	0	0	0	0	A
2	11	7	10	14	6	8	5	0	9	19	25	12	0	3	3	8	7	1	0	2	1	0	10	11	3	10	25	32	20	11	0	5	1	0	0	6	8	0	6	1	0	0	9	4	4	0	0	4	0	3	B
1	9	4	3	4	2	1	5	2	8	12	14	5	0	4	6	7	7	0	0	0	2	2	10	6	2	7	12	10	17	14	0	9	6	3	1	6	5	0	6	2	1	0	7	3	4	0	1	4	0	0	C
2	8	6	15	12	8	4	4	0	1	13	13	22	2	8	8	6	8	0	0	0	0	0	6	3	0	0	12	28	13	6	1	11	0	0	0	5	1	0	1	0	0	0	0	2	0	0	0	0	0	0	D
2	13	6	11	8	5	3	3	5	9	30	26	12	0	9	12	5	11	0	0	0	0	0	13	18	2	6	22	32	30	17	1	10	0	0	0	8	0	0	3	0	0	0	1	4	3	0	0	0	0	0	E
7	8	3	10	5	6	1	2	3	2	16	13	1	0	9	14	5	6	1	0	0	0	0	7	5	0	8	22	23	14	13	1	10	0	1	0	7	1	0	3	0	1	0	1	3	2	0	0	0	0	0	F
1	5	1	5	1	7	5	3	3	11	8	8	1	0	2	8	12	11	1	1	2	0	2	6	4	1	9	21	13	14	11	1	9	1	0	0	3	5	0	1	3	3	0	1	1	5	0	0	0	0	1	G
4	7	4	3	3	2	4	10	3	21	5	29	9	0	8	12	6	9	38	33	0	0	0	6	1	0	0	1	4	9	34	0	2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	H
0	3	2	0	13	6	0	1	6	53	9	16	39	7	9	7	6	9	33	43	0	0	1	3	2	0	1	3	8	8	28	0	1	3	0	34	5	0	0	5	0	0	0	0	5	0	0	0	0	2	2	I
8	7	15	6	5	3	6	20	10	49	4	19	21	0	29	21	24	19	107	46	0	0	0	6	2	0	0	1	0	9	45	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	J
2	16	4	14	36	7	15	3	6	6	57	38	8	0	3	21	11	24	0	0	0	0	0	27	11	5	8	31	75	44	20	4	21	1	3	1	11	8	0	8	0	3	0	1	16	4	0	0	2	0	4	K
4	30	13	12	25	11	9	18	12	25	41	41	17	0	24	31	21	34	30	0	0	0	0	15	3	0	2	8	26	55	45	0	6	0	0	0	3	1	0	1	0	1	0	0	2	1	0	0	0	0	0	L
4	19	6	4	8	3	3	46	10	33	22	30	24	9	8	13	12	37	84	13	0	0	0	10	3	0	6	9	9	14	38	0	2	1	1	2	1	1	2	0	2	2	0	0	3	0	0	0	0	2	0	M
0	0	0	0	0	0	0	0	0	0	0	0	0	1425	0	0	0	0	0	0	10	3	2	0	1	1	0	0	0	0	0	0	0	4	0	2	0	0	49	0	0	0	26	0	0	1	50	1	1	21	1	N
1	3	3	7	11	6	2	7	18	21	4	33	7	0	5	35	56	19	16	51	0	0	0	6	1	0	1	0	1	26	33	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	O
5	9	9	14	15	9	8	11	6	28	44	39	14	0	23	40	44	25	68	33	0	0	0	11	2	0	2	2	21	31	16	0	3	0	0	0	2	1	0	3	0	1	0	0	1	0	0	0	0	0	0	P
1	13	8	10	5	8	9	10	4	33	12	20	15	0	28	49	57	14	42	39	0	0	0	9	4	0	4	6	5	22	23	0	3	0	0	0	1	2	0	1	0	0	0	0	1	0	0	0	0	0	0	Q
9	13	11	7	11	2	7	12	10	27	40	48	31	0	19	25	28	40	22	14	0	0	0	10	4	0	3	2	29	42	41	0	3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	R
4	0	2	0	0	0	1	15	11	37	0	4	18	0	7	19	5	16	273	40	0	0	0	2	0	0	1	0	4	3	15	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	S
6	1	0	0	0	1	0	5	11	21	1	1	2	0	23	9	12	2	28	202	0	0	0	0	0	0	0	0	1	2	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	T
0	2	1	1	0	0	0	0	0	0	0	0	0	59	0	0	0	0	0	0	9	6	7	2	2	10	1	0	2	0	0	6	4	18	3	34	3	2	26	3	4	6	21	1	3	3	23	0	12	31	0	U
0	0	3	0	0	0	1	0	0	0	0	0	0	5	0	0	0	0	0	0	7	14	15	0	0	9	15	0	0	0	0	11	2	15	3	24	1	2	32	4	9	2	29	3	8	7	13	1	17	41	5	V
0	0	4	0	0	0	1	0	1	0	0	0	0	6	0	0	0	0	0	0	8	14	6	0	0	7	7	4	1	0	0	9	2	29	9	29	4	4	19	6	10	4	19	6	3	5	7	4	14	53	3	W
6	25	10	12	18	11	8	8	9	18	48	33	5	0	13	12	12	16	2	1	2	1	0	16	11	3	5	25	36	23	22	3	15	6	8	0	12	8	0	8	1	2	0	3	8	8	0	2	1	0	2	X
3	15	7	6	18	11	7	8	4	10	20	16	7	0	2	4	7	9	2	4	1	0	3	16	12	5	18	37	29	24	10	2	18	7	8	6	27	18	0	10	2	10	1	9	3	6	0	3	4	2	7	Y
1	3	2	0	4	2	0	0	1	0	5	2	0	10	0	0	0	0	0	0	6	10	7	1	8	3	17	11	6	2	0	6	12	21	6	27	7	16	12	4	9	11	14	6	15	10	9	5	15	9	6	Z
0	8	9	2	4	5	2	3	1	2	11	9	2	0	1	2	5	2	2	2	3	11	7	7	20	19	74	34	5	13	4	7	15	48	7	22	30	19	0	10	20	20	4	37	19	22	0	12	34	0	17	[
6	27	16	10	18	16	11	1	2	0	37	15	4	0	1	5	5	1	0	0	2	0	4	21	36	9	29	55	46	15	2	4	29	5	11	3	34	34	0	17	3	18	1	11	12	14	0	7	4	0	5	\
9	38	11	15	35	18	11	6	4	3	71	26	7	0	2	16	8	17	9	0	2	0	0	31	24	1	3	36	51	33	16	2	27	0	7	0	23	8	0	7	0	7	0	1	11	4	0	3	0	0	0	]
5	23	11	14	34	12	14	10	5	18	58	62	10	2	18	30	20	29	10	8	0	0	1	21	14	1	6	10	37	81	32	2	7	0	0	0	4	0	0	1	0	0	0	0	6	0	0	0	0	0	0	^
9	16	16	6	20	10	11	24	19	57	20	42	44	0	24	24	24	37	40	25	0	0	0	10	11	0	1	2	20	31	62	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	_
0	1	1	0	1	0	1	0	0	0	4	0	0	3	0	0	0	0	0	0	10	11	7	8	4	8	20	5	1	6	0	6	6	14	6	22	7	8	20	8	5	3	16	7	6	9	6	4	12	52	7	`
4	9	7	10	22	9	4	1	3	4	39	13	4	0	1	2	6	5	2	0	5	1	2	14	18	14	19	51	40	13	6	7	18	12	7	13	25	17	1	11	9	11	2	17	20	10	3	6	16	4	4	a
0	5	5	1	0	1	1	0	1	0	4	0	1	24	0	0	0	0	0	0	23	16	16	5	13	16	54	10	0	0	0	11	8	32	12	57	13	10	15	16	21	18	24	21	18	22	4	13	34	26	18	b
3	1	4	1	4	1	2	0	1	0	8	0	0	10	0	0	1	0	0	0	4	10	15	7	5	7	17	29	14	1	0	8	8	20	12	27	16	11	1	7	11	13	7	10	10	10	3	1	8	14	3	c
0	2	2	0	1	0	0	0	1	0	2	0	1	11	0	0	0	0	0	0	23	24	31	2	6	14	26	7	0	0	0	20	14	59	19	88	14	10	15	6	18	16	27	11	12	22	13	9	46	40	8	d
3	17	9	8	16	6	8	1	5	0	21	6	1	1	1	2	2	4	0	0	4	3	7	11	29	15	40	41	39	8	2	7	27	19	12	16	20	26	3	13	14	30	1	19	12	17	0	7	17	2	4	e
5	11	5	1	5	2	4	0	0	3	12	6	2	2	1	2	4	3	0	0	3	5	8	11	22	13	27	50	15	4	1	5	17	20	14	15	18	16	0	11	8	27	0	15	16	21	1	5	17	1	8	f
0	0	0	0	0	0	0	0	0	0	0	0	0	215	0	0	0	0	0	0	16	21	15	0	0	12	0	0	0	0	0	12	1	9	1	16	1	0	95	0	2	0	86	0	1	0	60	1	2	64	2	g
6	6	3	5	12	3	3	1	1	0	7	1	2	0	0	2	1	0	0	0	4	8	3	10	15	15	30	36	12	2	1	7	14	29	8	19	20	16	1	15	11	18	3	15	12	16	0	8	10	5	5	h
0	1	2	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	10	12	16	1	4	8	39	8	1	0	0	11	9	38	12	43	15	12	5	9	11	11	17	20	9	9	1	10	35	25	5	i
2	7	8	1	1	1	10	0	2	0	5	1	3	0	2	0	0	0	0	0	4	8	5	6	23	5	48	30	11	1	2	5	15	27	8	18	28	20	0	16	11	24	3	25	17	16	0	6	19	2	14	j
0	1	0	0	0	0	0	0	0	0	0	0	1	169	0	0	0	0	0	0	17	37	21	0	0	6	6	1	0	0	0	12	0	23	10	36	3	1	93	1	13	1	54	4	0	5	40	0	12	80	6	k
0	7	6	0	2	2	2	0	2	0	3	0	3	3	0	1	1	0	0	0	1	3	5	4	12	12	56	19	1	0	0	7	20	38	14	23	21	20	0	12	17	27	2	17	39	21	0	7	28	0	18	l
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	m
1	8	6	2	5	1	7	1	1	0	10	0	1	5	2	1	1	0	0	0	8	13	14	6	13	15	50	26	9	2	1	7	29	30	9	31	18	20	3	15	13	17	9	27	19	13	0	10	28	10	7	n
0	0	0	0	0	0	0	0	0	0	0	0	0	323	0	0	0	0	0	0	15	18	12	0	7	1	0	0	0	0	8	0	13	0	9	1	0	80	0	1	1	43	1	0	0	43	0	7	58	1	0	o
1	5	3	0	3	2	2	0	0	0	4	0	0	10	2	0	0	1	0	0	3	4	9	5	8	9	31	19	4	0	0	4	13	28	7	19	12	6	0	12	15	10	5	16	13	10	2	3	14	2	7	p
1	3	7	0	1	0	1	0	0	0	2	0	0	14	0	0	0	0	0	0	15	21	16	3	4	21	56	12	2	0	0	11	4	47	16	74	14	7	2	15	33	20	10	29	17	14	4	7	32	22	2	q
0	0	2	0	0	0	0	0	0	0	0	0	0	92	0	0	0	0	0	0	21	32	38	0	1	13	1	0	0	0	0	28	2	25	12	48	3	0	72	1	16	0	74	1	0	5	61	0	9	97	5	r
1	4	3	2	0	2	4	2	1	2	13	4	2	6	1	0	3	4	1	0	3	10	13	5	13	14	35	27	4	2	5	11	12	42	6	29	13	23	7	7	6	14	10	16	16	10	4	8	17	15	2	s

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m -> Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash

Figure A7-4: Confusion Matrix for C4.5 Classifier using the *Invariant reduced* and *ScaledHR* features evaluated in a subject independent manner without the garbage class (*unknown*) when the all the features are computed over windows of 5.6s.

	Subject Dependent			Subject Independent		
Activity	**TP Rate**	**FP Rate**	**F-Measure**	**TP Rate**	**FP Rate**	**F-Measure**
Bench weight lifting - hard	8.74 ± 9.83	1.00 ± 0.50	8.85 ± 9.93	0.00 ± 0.00	0.57 ± 0.28	0.00 ± 0.00
Bench weight lifting - light	29.60 ± 23.90	1.86 ± 1.06	25.84 ± 18.34	2.15 ± 3.45	1.77 ± 0.59	2.27 ± 3.55
Bench weight lifting - moderate	12.32 ± 12.36	1.10 ± 0.66	13.80 ± 12.81	0.82 ± 2.21	1.13 ± 0.59	1.01 ± 2.55
Bicep curls - hard	38.33 ± 28.41	1.59 ± 0.86	35.79 ± 27.13	2.59 ± 4.31	0.94 ± 0.43	3.35 ± 5.29
Bicep curls - light	28.19 ± 17.48	2.42 ± 1.59	24.88 ± 14.40	1.13 ± 2.17	1.70 ± 0.65	1.44 ± 2.79
Bicep curls - moderate	16.58 ± 10.40	1.55 ± 0.53	17.36 ± 10.34	1.00 ± 2.40	0.89 ± 0.35	1.43 ± 3.33
Calisthenics - Crunches	27.19 ± 30.80	1.11 ± 0.57	24.94 ± 26.87	1.02 ± 2.12	0.82 ± 0.41	1.37 ± 2.99
Calisthenics - Sit ups	28.04 ± 27.09	1.27 ± 0.85	26.36 ± 19.83	1.88 ± 3.23	1.12 ± 0.97	2.74 ± 4.55
Cycling - Cycle hard - Cycle 80rpm	65.06 ± 33.80	0.70 ± 0.87	65.11 ± 30.76	1.07 ± 3.09	0.78 ± 0.30	1.51 ± 4.14
Cycling - Cycle light - Cycle 100rpm	38.50 ± 26.39	1.06 ± 0.65	39.47 ± 24.51	9.90 ± 7.38	2.15 ± 1.22	9.92 ± 7.72
Cycling - Cycle light - Cycle 60rpm	66.59 ± 25.15	2.00 ± 0.87	54.94 ± 20.76	8.67 ± 7.81	3.05 ± 1.00	7.74 ± 7.12
Cycling - Cycle light - Cycle 80rpm	44.42 ± 20.08	1.72 ± 0.88	41.67 ± 16.17	6.96 ± 5.41	2.79 ± 1.56	6.18 ± 4.83
Cycling - Cycle moderate - Cycle 80rpm	46.06 ± 27.38	1.70 ± 1.17	40.53 ± 23.80	4.34 ± 5.40	1.47 ± 0.84	5.04 ± 6.61
Lying down	87.53 ± 9.39	3.12 ± 3.84	78.36 ± 15.96	88.44 ± 19.64	4.16 ± 4.18	73.02 ± 19.34
Rowing - Rowing hard - Rowing 30spm	44.50 ± 34.83	0.92 ± 0.74	44.43 ± 33.97	0.98 ± 2.29	1.34 ± 1.05	1.33 ± 3.14
Rowing - Rowing light - Rowing 30spm	36.24 ± 25.92	1.46 ± 0.74	34.81 ± 20.36	6.84 ± 12.09	1.81 ± 1.38	6.68 ± 10.34
Rowing - Rowing moderate - Rowing 30spm	47.04 ± 17.90	1.69 ± 1.06	43.86 ± 15.72	10.25 ± 19.92	1.78 ± 1.48	8.24 ± 11.61
Running - Treadmill 4mph - Treadmill 0	29.05 ± 19.31	1.25 ± 0.74	32.02 ± 17.16	6.25 ± 5.93	1.64 ± 0.79	7.00 ± 6.49
Running - Treadmill 5mph - Treadmill 0	56.20 ± 26.75	1.23 ± 0.75	52.95 ± 22.92	53.61 ± 20.51	2.80 ± 2.61	44.32 ± 20.07
Running - Treadmill 6mph - Treadmill 0	64.14 ± 37.51	0.64 ± 0.67	62.05 ± 35.34	52.88 ± 32.31	1.98 ± 2.91	44.39 ± 27.77
Sitting	22.22 ± 22.02	0.89 ± 0.50	23.05 ± 21.58	2.08 ± 4.39	1.06 ± 0.65	2.79 ± 5.94
Sitting - Fidget feet legs	31.44 ± 20.30	1.10 ± 0.42	30.83 ± 18.09	3.28 ± 4.08	1.38 ± 0.86	4.17 ± 5.48
Sitting - Fidget hands arms	33.48 ± 30.64	1.66 ± 0.78	27.06 ± 22.24	1.40 ± 3.57	1.30 ± 0.67	1.89 ± 4.91
Stairs - Ascend stairs	2.89 ± 3.92	0.96 ± 0.40	3.78 ± 4.95	2.65 ± 3.61	1.58 ± 0.57	3.12 ± 4.30
Stairs - Descend stairs	11.35 ± 8.14	1.12 ± 0.67	13.84 ± 9.98	2.12 ± 2.91	1.79 ± 0.68	2.14 ± 2.97
Standing	24.87 ± 25.85	1.13 ± 0.43	23.62 ± 22.84	0.73 ± 1.77	1.30 ± 0.49	0.90 ± 2.21
Walking - Treadmill 2mph - Treadmill 0	41.60 ± 33.11	2.24 ± 0.88	36.44 ± 28.34	10.75 ± 11.59	3.24 ± 1.77	9.02 ± 8.62
Walking - Treadmill 3mph - Treadmill 0	55.93 ± 20.29	2.37 ± 0.65	46.54 ± 17.53	7.78 ± 6.45	3.17 ± 1.42	7.14 ± 5.39
Walking - Treadmill 3mph - Treadmill 3 - light	54.20 ± 29.34	2.38 ± 1.02	44.60 ± 22.21	7.23 ± 5.85	2.83 ± 1.08	7.66 ± 7.01
Walking - Treadmill 3mph - Treadmill 6 - moderate	51.67 ± 21.17	2.25 ± 1.07	45.30 ± 17.21	11.68 ± 9.66	2.50 ± 1.35	12.00 ± 9.51
Walking - Treadmill 3mph - Treadmill 9 - hard	47.08 ± 25.48	2.18 ± 1.42	42.06 ± 19.64	9.71 ± 6.19	2.51 ± 1.26	10.15 ± 6.34
kneeling	26.51 ± 25.41	0.99 ± 0.40	26.63 ± 21.69	1.43 ± 2.25	1.05 ± 0.48	1.93 ± 3.06
Carrying groceries	27.43 ± 19.63	2.08 ± 0.96	27.99 ± 20.18	2.55 ± 3.57	1.96 ± 0.70	2.88 ± 4.13
Doing dishes	24.80 ± 15.94	2.86 ± 1.48	22.35 ± 12.92	4.28 ± 4.48	2.94 ± 1.43	3.94 ± 4.18
Gardening	19.26 ± 14.88	2.11 ± 1.54	19.37 ± 13.44	1.75 ± 3.08	1.04 ± 0.55	2.59 ± 4.52
Ironing	36.28 ± 24.77	2.79 ± 0.69	31.43 ± 20.39	11.46 ± 12.58	3.00 ± 1.88	9.83 ± 10.56
Making the bed	12.76 ± 8.64	2.28 ± 0.90	13.59 ± 8.69	2.56 ± 3.02	1.94 ± 0.76	3.11 ± 3.78
Mopping	21.19 ± 11.49	2.11 ± 0.81	20.70 ± 9.09	2.36 ± 4.83	1.55 ± 0.75	2.89 ± 5.59
Playing videogames	34.88 ± 24.73	2.12 ± 1.66	33.02 ± 21.44	11.26 ± 10.44	2.07 ± 1.24	12.64 ± 11.92
Scrubbing a surface	11.54 ± 8.40	2.14 ± 0.88	11.36 ± 6.76	2.21 ± 2.88	1.19 ± 0.62	2.83 ± 3.68
Stacking groceries	14.96 ± 10.26	1.71 ± 0.70	15.48 ± 9.19	1.71 ± 2.40	1.27 ± 0.63	2.01 ± 2.74
Sweeping	18.52 ± 15.97	2.08 ± 0.83	17.95 ± 14.13	3.59 ± 3.81	1.46 ± 0.79	4.04 ± 4.30
Typing	30.93 ± 24.48	1.60 ± 0.93	31.80 ± 21.01	6.97 ± 6.18	2.02 ± 1.21	8.12 ± 7.04
Vacuuming	20.80 ± 16.28	2.17 ± 1.25	20.42 ± 15.47	2.30 ± 3.12	1.66 ± 1.24	2.75 ± 3.62
Walking around block	27.40 ± 21.53	2.04 ± 0.85	27.26 ± 20.99	2.76 ± 3.33	1.52 ± 0.68	3.18 ± 3.69
Washing windows	14.70 ± 8.78	1.78 ± 0.82	16.72 ± 9.25	1.80 ± 2.58	1.38 ± 0.52	2.36 ± 3.39
Watching TV	27.34 ± 30.35	1.70 ± 1.60	26.21 ± 28.00	5.25 ± 5.99	1.31 ± 0.83	7.10 ± 8.35
Weeding	14.25 ± 16.77	1.48 ± 1.02	14.34 ± 13.67	0.39 ± 0.92	0.65 ± 0.30	0.61 ± 1.46
Wiping/Dusting	22.09 ± 16.10	2.36 ± 1.69	20.85 ± 11.81	4.29 ± 4.08	1.99 ± 1.15	4.51 ± 3.91
Writing	48.00 ± 31.74	2.18 ± 1.18	40.73 ± 23.94	12.52 ± 12.30	2.55 ± 1.17	12.80 ± 12.75
taking out trash	16.75 ± 11.93	1.79 ± 1.20	17.89 ± 10.75	0.28 ± 0.85	0.82 ± 0.45	0.41 ± 1.28

Table A7-1: Subject dependent and subject independent performance results using the C4.5 and the *ScaledHR* feature without considering the garbage class (*unknown* activity) when the feature is computed over windows of 5.6s.

	Subject Dependent			Subject Independent		
Activity	**TP Rate**	**FP Rate**	**F-Measure**	**TP Rate**	**FP Rate**	**F-Measure**
Bench weight lifting - hard	8.1 ± 9.2	1.0 ± 0.5	8.4 ± 9.4	0.5 ± 1.6	0.7 ± 0.4	0.6 ± 2.0
Bench weight lifting - light	28.9 ± 22.2	1.8 ± 1.0	25.6 ± 17.1	3.5 ± 5.0	1.9 ± 0.9	3.2 ± 4.5
Bench weight lifting - moderate	12.0 ± 12.2	1.0 ± 0.6	12.8 ± 12.0	0.7 ± 1.6	1.0 ± 0.4	0.8 ± 2.1
Bicep curls - hard	34.3 ± 29.2	1.7 ± 0.9	32.4 ± 28.6	5.7 ± 20.0	1.0 ± 0.5	5.1 ± 16.0
Bicep curls - light	30.4 ± 18.4	2.6 ± 1.5	25.8 ± 15.3	5.2 ± 7.4	1.9 ± 0.8	5.7 ± 8.4
Bicep curls - moderate	16.7 ± 10.8	1.5 ± 0.5	17.8 ± 10.6	2.8 ± 5.6	1.1 ± 0.5	3.3 ± 6.2
Calisthenics - Crunches	23.8 ± 22.7	1.3 ± 1.1	22.6 ± 21.7	0.6 ± 1.6	0.9 ± 0.6	0.7 ± 1.8
Calisthenics - Sit ups	28.4 ± 27.9	1.3 ± 0.8	26.6 ± 20.2	2.9 ± 3.3	1.2 ± 0.5	3.3 ± 3.6
Cycling - Cycle hard - Cycle 80rpm	65.1 ± 33.8	0.7 ± 0.9	64.7 ± 30.8	1.3 ± 3.5	1.1 ± 0.5	1.6 ± 4.3
Cycling - Cycle light - Cycle 100rpm	38.9 ± 26.2	1.1 ± 0.7	39.6 ± 24.3	8.4 ± 7.0	2.4 ± 1.6	8.0 ± 7.2
Cycling - Cycle light - Cycle 60rpm	64.0 ± 26.1	2.1 ± 0.9	52.5 ± 20.7	6.0 ± 6.4	3.2 ± 1.2	5.2 ± 6.3
Cycling - Cycle light - Cycle 80rpm	45.3 ± 19.0	1.8 ± 0.9	42.1 ± 15.6	5.3 ± 5.7	2.8 ± 1.3	5.0 ± 5.4
Cycling - Cycle moderate - Cycle 80rpm	46.0 ± 27.1	1.7 ± 1.2	40.9 ± 23.7	3.7 ± 4.4	1.7 ± 0.8	4.2 ± 5.1
Lying down	87.0 ± 9.6	3.1 ± 3.6	78.2 ± 16.7	90.6 ± 21.3	4.3 ± 4.4	73.4 ± 21.7
Rowing - Rowing hard - Rowing 30spm	44.5 ± 34.8	0.9 ± 0.7	44.6 ± 33.9	5.7 ± 8.3	1.7 ± 1.1	6.2 ± 8.4
Rowing - Rowing light - Rowing 30spm	35.8 ± 26.0	1.4 ± 0.8	34.7 ± 20.6	6.9 ± 6.0	2.8 ± 1.0	6.3 ± 5.0
Rowing - Rowing moderate - Rowing 30spm	46.6 ± 18.2	1.7 ± 1.1	43.5 ± 15.9	6.4 ± 4.8	2.1 ± 1.0	6.6 ± 5.4
Running - Treadmill 4mph - Treadmill 0	28.0 ± 20.2	1.3 ± 0.7	30.6 ± 18.3	3.6 ± 4.1	1.7 ± 0.8	4.3 ± 5.1
Running - Treadmill 5mph - Treadmill 0	56.2 ± 26.5	1.2 ± 0.8	53.0 ± 22.8	7.7 ± 10.0	1.8 ± 1.2	7.2 ± 9.1
Running - Treadmill 6mph - Treadmill 0	63.9 ± 37.5	0.6 ± 0.6	62.0 ± 35.2	14.2 ± 29.8	1.2 ± 0.9	6.9 ± 10.2
Sitting	20.9 ± 22.4	0.9 ± 0.5	22.6 ± 22.5	2.2 ± 3.0	0.9 ± 0.5	2.9 ± 4.0
Sitting - Fidget feet legs	33.1 ± 21.8	1.2 ± 0.4	30.6 ± 19.6	3.6 ± 4.7	1.3 ± 0.7	4.3 ± 5.5
Sitting - Fidget hands arms	36.0 ± 27.7	1.6 ± 0.8	30.2 ± 19.5	4.7 ± 6.6	1.5 ± 1.0	5.8 ± 8.8
Stairs - Ascend stairs	1.5 ± 2.8	1.0 ± 0.5	2.1 ± 4.0	2.6 ± 3.2	1.6 ± 0.6	3.1 ± 3.8
Stairs - Descend stairs	11.6 ± 8.5	1.3 ± 0.8	13.7 ± 10.2	3.5 ± 3.4	2.0 ± 0.6	3.8 ± 3.8
Standing	22.1 ± 24.9	1.1 ± 0.4	21.4 ± 22.0	1.9 ± 3.2	1.2 ± 0.5	2.0 ± 3.5
Walking - Treadmill 2mph - Treadmill 0	45.1 ± 30.2	2.3 ± 0.8	38.7 ± 26.3	6.8 ± 6.0	3.3 ± 1.8	7.0 ± 6.9
Walking - Treadmill 3mph - Treadmill 0	48.5 ± 26.0	2.4 ± 0.7	41.0 ± 22.6	7.6 ± 9.1	3.1 ± 1.1	7.1 ± 7.5
Walking - Treadmill 3mph - Treadmill 3 - light	57.4 ± 28.1	2.3 ± 1.0	47.8 ± 21.6	4.9 ± 5.5	2.9 ± 1.2	5.1 ± 6.9
Walking - Treadmill 3mph - Treadmill 6 - moderate	51.6 ± 21.4	2.2 ± 1.0	45.3 ± 17.5	3.2 ± 3.2	2.5 ± 1.1	3.3 ± 3.5
Walking - Treadmill 3mph - Treadmill 9 - hard	46.9 ± 25.4	2.2 ± 1.4	42.0 ± 19.6	7.0 ± 6.6	2.5 ± 1.3	6.8 ± 6.3
kneeling	26.4 ± 23.6	0.9 ± 0.3	27.3 ± 20.0	2.4 ± 3.0	0.9 ± 0.5	3.2 ± 4.0
Carrying groceries	33.0 ± 17.4	2.1 ± 0.8	31.9 ± 16.5	1.8 ± 2.6	2.0 ± 0.5	2.2 ± 3.2
Doing dishes	25.0 ± 18.3	2.8 ± 1.4	22.1 ± 14.6	3.4 ± 3.7	2.2 ± 1.0	3.4 ± 3.4
Gardening	18.0 ± 14.8	2.1 ± 1.5	18.4 ± 13.6	0.6 ± 1.2	0.8 ± 0.4	0.9 ± 1.9
Ironing	37.0 ± 24.9	2.7 ± 0.9	32.5 ± 19.9	10.0 ± 11.0	3.0 ± 1.6	9.2 ± 11.0
Making the bed	10.3 ± 6.2	2.4 ± 1.0	11.0 ± 6.4	0.5 ± 1.0	1.8 ± 0.9	0.5 ± 1.0
Mopping	19.1 ± 12.3	2.1 ± 0.9	19.0 ± 10.8	2.2 ± 3.5	1.4 ± 0.6	2.7 ± 4.2
Playing videogames	33.6 ± 21.8	2.3 ± 1.6	31.8 ± 19.9	9.7 ± 11.1	1.8 ± 0.9	11.5 ± 13.0
Scrubbing a surface	11.8 ± 9.6	2.2 ± 1.0	11.3 ± 7.4	0.3 ± 1.1	1.0 ± 0.5	0.5 ± 1.6
Stacking groceries	14.3 ± 9.8	1.7 ± 0.8	15.0 ± 9.5	1.8 ± 3.0	1.0 ± 0.4	2.6 ± 4.4
Sweeping	18.1 ± 13.1	2.0 ± 0.8	18.2 ± 13.2	3.9 ± 5.1	1.5 ± 0.8	4.6 ± 5.7
Typing	33.0 ± 25.9	1.7 ± 1.1	33.0 ± 22.6	10.6 ± 11.3	2.5 ± 1.1	10.7 ± 11.3
Vacuuming	19.1 ± 16.4	2.0 ± 1.2	19.1 ± 15.4	2.2 ± 2.8	1.3 ± 0.7	2.9 ± 3.7
Walking around block	30.6 ± 21.1	2.2 ± 0.8	29.3 ± 20.0	4.8 ± 5.2	2.0 ± 0.8	5.7 ± 6.5
Washing windows	11.3 ± 8.3	1.6 ± 0.8	13.5 ± 9.2	1.5 ± 2.6	1.2 ± 0.7	1.8 ± 2.9
Watching TV	26.9 ± 29.2	1.7 ± 1.6	27.1 ± 27.7	8.1 ± 10.4	1.2 ± 0.6	10.4 ± 13.2
Weeding	13.7 ± 16.4	1.7 ± 1.0	13.0 ± 12.4	0.4 ± 1.3	0.6 ± 0.4	0.6 ± 1.9
Wiping/Dusting	20.6 ± 14.7	2.4 ± 1.6	19.9 ± 11.6	4.6 ± 4.3	1.9 ± 1.2	5.5 ± 5.2
Writing	46.6 ± 31.8	2.0 ± 1.2	40.6 ± 24.3	10.7 ± 8.1	3.1 ± 1.6	10.3 ± 8.7
taking out trash	14.3 ± 9.5	2.0 ± 1.1	15.4 ± 9.9	0.7 ± 1.3	1.1 ± 0.7	1.1 ± 2.0

Table A7-2: Subject dependent and subject independent performance results using the C4.5 and the *HRAboveRest* feature without considering the garbage class (*unknown* activity) when the feature is computed over windows of 5.6s.

Activity	ScaledHR	ScaledHR + Weight	ScaledHR + FitnessIndex	ScaledHR + FatPercent
Bench weight lifting - hard	0.00 ± 0.00	0.0 ± 0.0	1.8 ± 4.1	1.8 ± 2.7
Bench weight lifting - light	2.15 ± 3.45	2.2 ± 7.9	2.9 ± 8.1	2.9 ± 5.4
Bench weight lifting - moderate	0.82 ± 2.21	0.5 ± 1.5	3.4 ± 8.0	2.1 ± 4.2
Bicep curls - hard	2.59 ± 4.31	6.0 ± 10.6	5.7 ± 16.1	1.3 ± 3.0
Bicep curls - light	1.13 ± 2.17	2.3 ± 3.7	1.0 ± 2.2	0.3 ± 1.0
Bicep curls - moderate	1.00 ± 2.40	1.2 ± 2.4	1.2 ± 2.4	0.0 ± 0.0
Calisthenics - Crunches	1.02 ± 2.12	6.4 ± 13.4	5.1 ± 13.2	1.0 ± 3.1
Calisthenics - Sit ups	1.88 ± 3.23	4.7 ± 9.6	10.4 ± 16.6	3.6 ± 8.6
Cycling - Cycle hard - Cycle 80rpm	1.07 ± 3.09	0.4 ± 1.1	15.4 ± 37.6	0.5 ± 1.8
Cycling - Cycle light - Cycle 100rpm	9.90 ± 7.38	12.3 ± 21.5	14.6 ± 22.0	7.8 ± 12.8
Cycling - Cycle light - Cycle 60rpm	8.67 ± 7.81	5.9 ± 15.1	1.7 ± 4.7	8.1 ± 17.0
Cycling - Cycle light - Cycle 80rpm	6.96 ± 5.41	10.7 ± 17.3	6.8 ± 16.4	9.7 ± 18.2
Cycling - Cycle moderate - Cycle 80rpm	4.34 ± 5.40	2.7 ± 7.1	3.6 ± 6.2	4.4 ± 11.4
Lying down	88.44 ± 19.64	85.1 ± 21.0	84.2 ± 21.8	85.8 ± 22.7
Rowing - Rowing hard - Rowing 30spm	0.98 ± 2.29	19.4 ± 35.0	11.0 ± 26.0	1.4 ± 3.1
Rowing - Rowing light - Rowing 30spm	6.84 ± 12.09	2.4 ± 3.9	5.4 ± 16.8	9.3 ± 21.1
Rowing - Rowing moderate - Rowing 30spm	10.25 ± 19.92	15.2 ± 20.2	13.7 ± 23.2	7.8 ± 19.2
Running - Treadmill 4mph - Treadmill 0	6.25 ± 5.93	3.0 ± 5.2	5.6 ± 12.4	3.1 ± 6.9
Running - Treadmill 5mph - Treadmill 0	53.61 ± 20.51	41.3 ± 27.8	40.6 ± 28.0	45.0 ± 29.0
Running - Treadmill 6mph - Treadmill 0	52.88 ± 32.31	42.8 ± 40.3	47.9 ± 47.8	32.7 ± 27.6
Sitting	2.08 ± 4.39	9.0 ± 15.1	9.7 ± 18.1	9.6 ± 18.1
Sitting - Fidget feet legs	3.28 ± 4.08	7.0 ± 16.1	12.4 ± 21.1	10.7 ± 26.5
Sitting - Fidget hands arms	1.40 ± 3.57	9.9 ± 21.9	8.9 ± 20.8	6.5 ± 14.4
Stairs - Ascend stairs	2.65 ± 3.61	1.3 ± 2.3	3.0 ± 4.0	2.9 ± 5.0
Stairs - Descend stairs	2.12 ± 2.91	6.4 ± 9.4	4.2 ± 4.8	1.8 ± 2.5
Standing	0.73 ± 1.77	1.8 ± 3.0	2.4 ± 3.4	0.3 ± 1.2
Walking - Treadmill 2mph - Treadmill 0	10.75 ± 11.59	13.2 ± 20.1	11.2 ± 18.4	14.0 ± 24.0
Walking - Treadmill 3mph - Treadmill 0	7.78 ± 6.45	17.6 ± 26.3	9.2 ± 16.9	5.1 ± 8.2
Walking - Treadmill 3mph - Treadmill 3 - light	7.23 ± 5.85	14.0 ± 26.2	20.6 ± 26.9	10.1 ± 14.2
Walking - Treadmill 3mph - Treadmill 6 - moderate	11.68 ± 9.66	11.1 ± 16.6	10.3 ± 21.2	6.3 ± 14.1
Walking - Treadmill 3mph - Treadmill 9 - hard	9.71 ± 6.19	6.4 ± 8.6	7.9 ± 18.2	4.8 ± 13.0
kneeling	1.43 ± 2.25	1.5 ± 3.8	5.5 ± 8.1	2.9 ± 9.1
Carrying groceries	2.55 ± 3.57	6.2 ± 12.3	4.9 ± 9.7	7.0 ± 12.9
Doing dishes	4.28 ± 4.48	3.6 ± 9.0	4.5 ± 8.6	4.7 ± 10.5
Gardening	1.75 ± 3.08	2.2 ± 5.1	4.0 ± 10.0	0.8 ± 1.7
Ironing	11.46 ± 12.58	8.3 ± 15.8	8.8 ± 12.8	4.2 ± 8.6
Making the bed	2.56 ± 3.02	3.5 ± 4.2	5.6 ± 8.6	3.3 ± 5.1
Mopping	2.36 ± 4.83	2.0 ± 3.4	4.6 ± 9.8	2.7 ± 5.4
Playing videogames	11.26 ± 10.44	14.7 ± 20.2	22.1 ± 24.6	12.4 ± 18.5
Scrubbing a surface	2.21 ± 2.88	2.2 ± 2.5	2.1 ± 2.8	6.0 ± 12.8
Stacking groceries	1.71 ± 2.40	2.7 ± 4.4	1.1 ± 1.9	1.4 ± 2.1
Sweeping	3.59 ± 3.81	2.6 ± 5.6	5.2 ± 6.4	2.2 ± 3.6
Typing	6.97 ± 6.18	6.8 ± 10.5	11.2 ± 16.4	10.6 ± 17.3
Vacuuming	2.30 ± 3.12	4.8 ± 7.2	6.7 ± 8.6	2.6 ± 3.8
Walking around block	2.76 ± 3.33	9.8 ± 22.6	4.5 ± 6.7	1.5 ± 2.8
Washing windows	1.80 ± 2.58	1.3 ± 2.4	2.2 ± 3.6	2.1 ± 3.0
Watching TV	5.25 ± 5.99	5.0 ± 7.6	13.7 ± 22.9	4.0 ± 5.8
Weeding	0.39 ± 0.92	2.1 ± 6.5	2.2 ± 4.9	0.4 ± 1.3
Wiping/Dusting	4.29 ± 4.08	5.2 ± 7.4	10.9 ± 17.5	2.3 ± 6.4
Writing	12.52 ± 12.30	13.0 ± 21.3	4.3 ± 6.7	10.6 ± 18.0
taking out trash	0.28 ± 0.85	0.7 ± 1.8	0.2 ± 0.8	1.4 ± 5.0

Table A7-3: Performance obtained when adding the Weight, FatPercent, and FitnessIndex to the ScaledHR feature during subject independent evaluation using the C4.5 classifier. Features are computed over windows of 5.6s in length and the activities to recognize are the 51 activities included in the MIT dataset, without including the *unknown* class.

Class	TP Rate	FP Rate	F-Measure
Bicep curls - hard	46.8 ± 35.0	36.7 ± 27.5	38.6 ± 25.5
Bicep curls - light	46.7 ± 39.5	34.1 ± 32.9	39.0 ± 27.8
Bicep curls - moderate	26.9 ± 37.1	35.5 ± 32.0	20.8 ± 25.8

Table A7-4: Performance while recognizing only among the intensity levels of bicep curls in a subject independent manner using the C4.5 Decision tree classifier and the ScaledHR feature computed over windows of 5.6s.

Class	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	28.3 ± 21.1	14.1 ± 17.5	36.2 ± 26.3
Bench weight lifting - light	78.9 ± 35.4	63.8 ± 39.4	59.9 ± 26.7
Bench weight lifting - moderate	48.7 ± 17.5	60.1 ± 26.8	34.6 ± 8.2

Table A7-5: Performance while recognizing only among the intensity levels of bench weight lifting in a subject independent manner using the C4.5 Decision tree classifier and the ScaledHR feature computed over windows of 5.6s.

Class	TP Rate	FP Rate	F-Measure
Rowing - Rowing hard - Rowing 30spm	17.4 ± 26.7	31.8 ± 22.3	15.2 ± 17.9
Rowing - Rowing light - Rowing 30spm	44.7 ± 29.4	40.8 ± 30.0	38.6 ± 19.9
Rowing - Rowing moderate - Rowing 30spm	21.3 ± 21.9	34.2 ± 23.7	20.9 ± 15.0

Table A7-6: Performance while recognizing only among the intensity levels of rowing in a subject independent manner using the C4.5 Decision tree classifier and the ScaledHR feature computed over windows of 5.6s.

Class	TP Rate	FP Rate	F-Measure
Walking - Treadmill 3mph - Treadmill 0	56.0 ± 42.3	10.7 ± 9.2	50.4 ± 33.9
Walking - Treadmill 3mph - Treadmill 3 - light	44.1 ± 29.3	27.9 ± 11.7	36.9 ± 21.4
Walking - Treadmill 3mph - Treadmill 6 - moderate	28.6 ± 22.5	20.0 ± 12.7	28.6 ± 20.9
Walking - Treadmill 3mph - Treadmill 9 - hard	56.5 ± 43.1	21.9 ± 18.2	41.0 ± 27.2

Table A7-7: Performance while recognizing only among the intensity levels of walking at 3mph in a subject independent manner using the C4.5 Decision tree classifier and the ScaledHR feature computed over windows of 5.6s.

Activity Category	5.6	11.3	22.7	44.5
All	38.4 ± 7.8	35.5 ± 8.0	32.0 ± 6.7	25.0 ± 5.6
Postures	37.7±22.3 (1.5±1.0)	32.1±20.5 (1.6±1.1)	28.2±22.8 (1.7±1.2)	19.8±15.5 (2.1±1.4)
Ambulation	39.0±22.2 (1.7±0.8)	37.8±22.9 (1.9±0.9)	33.7±22.7 (1.9±1.1)	27.0±28.0 (2.4±1.2)
Exercise	38.3±23.9 (1.4±0.8)	35.6±24.6 (1.5±0.9)	31.0±26.1 (1.7±1.0)	22.6±26.1 (2.0±1.2)
Resistance Exercise	34.2±20.6 (1.6±0.9)	31.0±22.1 (1.7±0.9)	27.3±22.8 (1.8±1.1)	21.2±24.5 (2.4±1.3)
Household	24.0±18.0 (2.0±1.1)	21.3±19.3 (2.2±1.2)	19.2±20.2 (2.4±1.6)	13.7±19.5 (2.8±1.8)

Table A7-8: True positive rate and false positive rate (shown in parenthesis) obtained utilizing the C4.5 classifier when the *ScaledHR* feature is computed over varying window lengths as evaluated with subject dependent training. The target activities are the 51 activities contained in the MIT dataset without including the *unknown* class.

Activity Category	5.6	11.3	22.7	44.5
All	7.7±1.9	7.6 ± 1.9	7.6 ± 3.2	7.2 ± 2.9
Postures	9.7±9.4 (3.8±1.2)	5.2±6.5 (3.1±1.3)	5.1±5.2 (3.0±1.5)	5.8±4.4 (3.0±1.6)
Ambulation	5.0±7.1 (1.7±0.9)	5.5±7.9 (2.4±1.3)	4.9±9.6 (2.7±1.6)	6.9±10.6 (3.1±1.9)
Exercise	8.6±11.1 (1.9±0.9)	9.7±12.7 (2.7±1.2)	7.3±13.9 (2.7±1.4)	7.1±14.7 (2.9±1.8)
Resistance Exercise	8.6±10.4 (1.9±0.9)	9.6±11.6 (2.6±1.3)	8.1±14.0 (2.7±1.5)	9.1±15.0 (3.2±1.9)
Household	4.0±6.0 (1.5±0.8)	4.5±7.4 (2.3±1.5)	4.8±9.4 (2.5±1.8)	2.9±8.2 (3.1±2.0)

Table A7-9: True positive rate and false positive rate (shown in parenthesis) obtained utilizing the C4.5 classifier when the *HRVar* feature is computed over varying window lengths as evaluated with subject dependent training. The target activities are the 51 activities contained in the MIT dataset without including the *unknown* class.

Activity Category	5.6	11.3	22.7	44.5
All	8.2 ± 1.8	7.62 ± 1.65	6.28 ± 2.81	5.87 ± 2.96
Postures	10.3±8.4 (3.8±1.0)	6.1±8.5 (3.0±1.4)	4.7±5.2 (3.3±1.7)	5.5±7.3 (3.7±2.0)
Ambulation	4.9±7.0 (1.7±0.8)	7.0±7.9 (2.6±1.3)	6.1±11.1 (2.5±1.4)	6.8±9.9 (2.9±2.2)
Exercise	8.8±11.0 (1.9±0.9)	9.7±13.2 (2.6±1.2)	5.9±10.6 (2.9±1.4)	5.2±10.3 (2.9±1.9)
Resistance Exercise	9.2±11.3 (1.9±0.9)	11.3±13.3 (2.6±1.3)	7.6±11.7 (2.7±1.4)	8.0±11.9 (3.1±2.0)
Household	4.0±6.0 (1.5±0.8)	4.4±6.6 (2.3±1.5)	3.3±7.3 (2.4±1.7)	2.9±6.0 (3.1±2.1)

Table A7-10: True positive rate and false positive rate (shown in parenthesis) obtained utilizing the C4.5 classifier when the *HRTrend* feature is computed over varying window lengths as evaluated with subject dependent training. The target activities are the 51 activities contained in the MIT dataset without including the *unknown* class.

Activity Category	5.6	11.3	22.7	44.5
All	13.8 ± 3.2	13.5 ± 3.4	15.7 ± 3.7	15.95 ± 3.39
Postures	16.2±5.9 (1.7±1.2)	16.7±7.7 (1.7±1.4)	17.7±9.4 (1.7±1.5)	17.9±9.1 (1.9±1.6)
Ambulation	14.2±9.3 (2.3±1.3)	13.7±10.7 (2.3±1.4)	16.0±13.1 (2.3±1.5)	17.9±18.8 (2.4±1.7)
Exercise	9.0±7.5 (1.6±1.0)	8.6±8.0 (1.6±1.1)	10.8±10.3 (1.6±1.1)	10.6±12.2 (2.0±1.4)
Resistance Exercise	4.1±5.2 (1.7±0.8)	4.1±6.1 (1.7±0.9)	5.2±7.9 (1.7±1.0)	6.5±10.1 (2.0±1.2)
Household	*4.3±4.9* *(1.7±0.9)*	4.3±5.4 (1.7±1.0)	5.6±8.9 (1.8±1.1)	5.9±10.6 (2.1±1.3)

Table A7-11: True positive rate and false positive rate (shown in parenthesis) obtained utilizing the C4.5 classifier when the *ScaledHR* feature is computed over varying window lengths as evaluated with subject independent training. The target activities are the 51 activities contained in the MIT dataset without including the *unknown* class.

Activity Category	5.6	11.3	22.7	44.5
All	6.4 ± 1.3	5.2 ± 1.6	4.5 ± 1.9	4.8 ± 2.4
Postures	11.9±4.2 (7.7±1.8)	9.8±5.1 (6.5±1.9)	7.8±5.9 (4.3±1.5)	6.0±6.9 (3.4±1.6)
Ambulation	2.2±2.4 (1.2±0.6)	1.8±3.0 (1.6±0.8)	2.0±4.7 (2.0±1.0)	4.5±8.5 (2.3±1.3)
Exercise	2.7±4.1 (1.2±0.6)	1.1±2.5 (1.4±0.6)	1.2±3.1 (1.7±0.8)	1.2±3.9 (2.0±1.1)
Resistance Exercise	3.1±4.3 (1.4±0.6)	1.6±3.0 (1.4±0.6)	1.9±4.7 (1.8±0.9)	3.1±6.0 (2.2±1.2)
Household	1.2±1.8 (1.0±0.4)	1.1±2.3 (1.1±0.6)	0.9±2.3 (1.5±0.8)	1.8±5.0 (2.0±1.1)

Table A7-12: True positive rate and false positive rate (shown in parenthesis) obtained utilizing the C4.5 classifier when the *HRVar* feature is computed over varying window lengths as evaluated with subject independent training. The target activities are the 51 activities contained in the MIT dataset without including the *unknown* class.

Activity Category	5.6	11.3	22.7	44.5
All	7.6 ± 1.2	5.20 ± 1.12	4.65 ± 1.15	5.78 ± 2.36
Postures	13.0±4.5 (7.0±2.2)	7.7±3.5 (5.1±1.0)	6.6±4.0 (4.5±0.9)	6.8±2.8 (4.9±1.5)
Ambulation	5.2±4.2 (1.4±0.6)	3.7±4.0 (1.8±0.7)	3.8±5.4 (1.9±1.0)	5.8±9.1 (2.1±1.3)
Exercise	2.7±3.2 (1.2±0.6)	1.1±2.0 (1.5±0.6)	1.2±2.8 (1.8±0.9)	1.2±4.1 (1.9±1.1)
Resistance Exercise	4.4±3.9 (1.5±0.7)	2.5±3.0 (1.7±0.7)	3.0±4.5 (1.9±1.0)	4.1±6.5 (2.0±1.2)
Household	1.8±2.2 (1.1±0.4)	1.8±2.8 (1.3±0.5)	1.3±2.7 (1.5±0.8)	1.7±4.6 (1.8±1.1)

Table A7-13: True positive rate and false positive rate (shown in parenthesis) obtained utilizing the C4.5 classifier when the *HRTrend* feature is computed over varying window lengths as evaluated with subject independent training. The target activities are the 51 activities contained in the MIT dataset without including the *unknown* class.

Activity	True Positive Rate			
	Subject Dependent		Subject Independent	
	Invariant Reduced	Invariant Reduced + ScaledHR	Invariant Reduced	Invariant Reduced + ScaledHR
Bench weight lifting - hard	93.3 ± 8.3	93.3 ± 8.3	14.5 ± 22.4	13.1 ± 25.2
Bench weight lifting - light	93.6 ± 9.6	93.6 ± 9.6	38.8 ± 37.0	34.0 ± 35.4
Bench weight lifting - moderate	91.3 ± 10.9	91.3 ± 10.9	28.4 ± 36.4	24.8 ± 33.7
Bicep curls - hard	94.1 ± 10.0	94.1 ± 10.0	43.0 ± 40.5	39.9 ± 39.4
Bicep curls - light	91.9 ± 8.1	91.9 ± 8.1	20.5 ± 31.7	27.0 ± 36.4
Bicep curls - moderate	91.6 ± 9.9	91.8 ± 9.8	21.8 ± 30.8	17.7 ± 26.6
Calisthenics - Crunches	96.2 ± 4.4	96.2 ± 4.4	66.6 ± 38.4	66.6 ± 38.4
Calisthenics - Sit ups	96.6 ± 3.1	96.6 ± 3.1	80.5 ± 35.0	81.4 ± 34.1
Cycling - Cycle hard - Cycle 80rpm	88.4 ± 8.7	92.9 ± 7.7	33.4 ± 31.9	35.8 ± 31.2
Cycling - Cycle light - Cycle 100rpm	98.1 ± 2.3	98.1 ± 2.3	97.0 ± 5.8	97.6 ± 6.1
Cycling - Cycle light - Cycle 60rpm	99.5 ± 1.2	99.5 ± 1.2	87.6 ± 25.2	87.7 ± 25.3
Cycling - Cycle light - Cycle 80rpm	97.5 ± 3.2	97.5 ± 3.2	41.6 ± 39.1	44.2 ± 41.5
Cycling - Cycle moderate - Cycle 80rpm	92.6 ± 5.2	94.2 ± 5.3	32.6 ± 32.0	31.5 ± 29.6
Lying down	99.9 ± 0.3	99.9 ± 0.3	95.9 ± 12.3	96.0 ± 12.3
Rowing - Rowing hard - Rowing 30spm	85.2 ± 14.2	88.1 ± 14.6	34.2 ± 33.5	27.2 ± 30.8
Rowing - Rowing light - Rowing 30spm	88.9 ± 10.3	90.0 ± 9.6	41.9 ± 32.3	41.3 ± 35.0
Rowing - Rowing moderate - Rowing 30spm	81.4 ± 13.7	83.8 ± 11.9	24.0 ± 23.6	31.7 ± 29.4
Running - Treadmill 4mph - Treadmill 0	97.7 ± 2.9	97.7 ± 2.9	57.4 ± 39.6	55.4 ± 39.2
Running - Treadmill 5mph - Treadmill 0	93.7 ± 4.8	93.7 ± 5.2	56.8 ± 29.1	68.0 ± 25.4
Running - Treadmill 6mph - Treadmill 0	88.4 ± 15.1	88.6 ± 15.2	64.0 ± 36.0	56.1 ± 36.2
Sitting	97.4 ± 4.1	97.4 ± 4.1	58.1 ± 43.0	57.9 ± 43.3
Sitting - Fidget feet legs	95.3 ± 5.3	95.3 ± 5.3	66.7 ± 30.2	67.7 ± 31.1
Sitting - Fidget hands arms	93.4 ± 8.0	93.7 ± 8.1	57.8 ± 32.6	51.9 ± 34.9
Stairs - Ascend stairs	91.1 ± 6.7	90.3 ± 7.2	71.8 ± 28.6	72.7 ± 29.5
Stairs - Descend stairs	90.7 ± 6.6	90.7 ± 6.6	59.6 ± 26.4	57.9 ± 29.3
Standing	97.9 ± 3.2	97.9 ± 3.2	86.3 ± 21.1	86.3 ± 21.1
Walking - Treadmill 2mph - Treadmill 0	96.8 ± 4.7	96.8 ± 4.7	70.9 ± 25.5	70.5 ± 23.8
Walking - Treadmill 3mph - Treadmill 0	84.5 ± 10.2	91.5 ± 7.2	20.1 ± 23.7	27.5 ± 20.4
Walking - Treadmill 3mph - Treadmill 3 - light	76.2 ± 14.6	88.3 ± 10.9	24.4 ± 25.8	23.8 ± 26.7
Walking - Treadmill 3mph - Treadmill 6 - moderate	77.0 ± 10.3	89.5 ± 8.2	14.8 ± 18.8	35.5 ± 27.4
Walking - Treadmill 3mph - Treadmill 9 - hard	88.4 ± 9.5	92.1 ± 5.0	27.7 ± 24.8	56.4 ± 35.9
kneeling	97.3 ± 3.7	97.3 ± 3.7	97.3 ± 5.0	97.3 ± 5.0
Carrying groceries	91.1 ± 7.6	91.6 ± 7.5	56.7 ± 27.9	58.3 ± 29.7
Doing dishes	85.1 ± 7.3	85.7 ± 6.7	55.9 ± 25.4	57.2 ± 24.0
Gardening	79.6 ± 11.8	79.9 ± 11.4	20.7 ± 25.9	20.3 ± 25.0
Ironing	85.4 ± 6.3	86.4 ± 5.1	53.3 ± 28.4	53.2 ± 28.7
Making the bed	62.2 ± 10.8	68.1 ± 10.1	40.5 ± 18.3	39.4 ± 17.8
Mopping	72.4 ± 11.8	73.0 ± 12.1	33.3 ± 18.4	32.3 ± 14.6
Playing videogames	99.0 ± 2.3	99.0 ± 2.3	64.4 ± 42.2	63.8 ± 42.0
Scrubbing a surface	85.0 ± 12.9	85.5 ± 11.7	40.0 ± 35.4	40.3 ± 35.2
Stacking groceries	71.0 ± 16.0	74.0 ± 13.4	33.8 ± 20.9	33.8 ± 21.3
Sweeping	68.3 ± 15.2	70.6 ± 14.5	34.4 ± 20.6	32.4 ± 20.6
Typing	98.3 ± 2.4	98.3 ± 2.4	75.0 ± 29.4	71.5 ± 33.5
Vacuuming	74.5 ± 10.1	76.0 ± 8.6	53.4 ± 23.9	54.2 ± 22.8
Walking around block	90.4 ± 7.7	90.0 ± 7.4	34.9 ± 18.6	40.0 ± 21.7
Washing windows	71.2 ± 9.4	72.9 ± 8.9	44.2 ± 21.5	43.9 ± 21.0
Watching TV	98.2 ± 2.5	98.2 ± 2.5	48.2 ± 43.6	45.8 ± 44.0
Weeding	75.2 ± 11.0	75.2 ± 10.4	15.5 ± 19.1	14.8 ± 20.4
Wiping/Dusting	69.4 ± 13.9	74.0 ± 12.1	39.4 ± 21.6	38.6 ± 21.0
Writing	97.3 ± 3.0	97.3 ± 3.0	61.7 ± 40.6	61.7 ± 40.6
taking out trash	62.2 ± 13.6	65.4 ± 14.9	23.0 ± 14.1	25.3 ± 15.2

Table A7-14: True positive rate obtained when adding the *ScaledHR* feature to *the invariant reduced* feature set using the C4.5 classifier. The sliding window length for accelerometer data and heart rate is 5.6s. The activities to recognize are the 51 contained in the MIT dataset without including the *unknown* class.

Activity	False Positive Rate			
	Subject Dependent		Subject Independent	
	Invariant Reduced	Invariant Reduced + ScaledHR	Invariant Reduced	Invariant Reduced + ScaledHR
Bench weight lifting - hard	0.1 ± 0.1	0.1 ± 0.1	0.7 ± 0.8	0.7 ± 0.8
Bench weight lifting - light	0.1 ± 0.1	0.1 ± 0.1	0.8 ± 0.8	0.8 ± 0.8
Bench weight lifting - moderate	0.1 ± 0.2	0.1 ± 0.2	1.1 ± 1.3	1.1 ± 1.3
Bicep curls - hard	0.1 ± 0.2	0.1 ± 0.2	1.6 ± 1.2	1.6 ± 1.3
Bicep curls - light	0.1 ± 0.1	0.1 ± 0.1	0.6 ± 0.9	0.8 ± 1.1
Bicep curls - moderate	0.2 ± 0.2	0.2 ± 0.2	1.1 ± 1.1	0.9 ± 1.0
Calisthenics - Crunches	0.0 ± 0.0	0.0 ± 0.0	0.6 ± 1.2	0.6 ± 1.2
Calisthenics - Sit ups	0.1 ± 0.2	0.1 ± 0.1	0.2 ± 0.2	0.2 ± 0.2
Cycling - Cycle hard - Cycle 80rpm	0.1 ± 0.1	0.1 ± 0.1	1.1 ± 1.4	1.1 ± 1.2
Cycling - Cycle light - Cycle 100rpm	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.4	0.1 ± 0.4
Cycling - Cycle light - Cycle 60rpm	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.2	0.1 ± 0.2
Cycling - Cycle light - Cycle 80rpm	0.1 ± 0.1	0.1 ± 0.1	1.3 ± 1.4	1.2 ± 1.2
Cycling - Cycle moderate - Cycle 80rpm	0.2 ± 0.1	0.1 ± 0.1	1.2 ± 1.0	1.2 ± 0.9
Lying down	0.0 ± 0.1	0.0 ± 0.1	0.3 ± 0.6	0.3 ± 0.7
Rowing - Rowing hard - Rowing 30spm	0.2 ± 0.2	0.2 ± 0.2	1.1 ± 0.8	0.7 ± 0.6
Rowing - Rowing light - Rowing 30spm	0.2 ± 0.2	0.2 ± 0.2	1.8 ± 1.2	1.7 ± 1.3
Rowing - Rowing moderate - Rowing 30spm	0.4 ± 0.3	0.3 ± 0.3	1.0 ± 0.9	1.2 ± 1.1
Running - Treadmill 4mph - Treadmill 0	0.1 ± 0.1	0.1 ± 0.1	0.8 ± 1.0	0.7 ± 1.0
Running - Treadmill 5mph - Treadmill 0	0.1 ± 0.1	0.1 ± 0.1	0.9 ± 0.7	1.0 ± 1.0
Running - Treadmill 6mph - Treadmill 0	0.1 ± 0.1	0.1 ± 0.1	0.7 ± 0.8	0.3 ± 0.4
Sitting	0.1 ± 0.1	0.0 ± 0.1	1.3 ± 1.2	1.3 ± 1.2
Sitting - Fidget feet legs	0.0 ± 0.1	0.0 ± 0.1	0.2 ± 0.2	0.2 ± 0.2
Sitting - Fidget hands arms	0.1 ± 0.1	0.1 ± 0.1	0.9 ± 0.9	0.9 ± 0.9
Stairs - Ascend stairs	0.2 ± 0.2	0.2 ± 0.2	0.5 ± 0.5	0.7 ± 1.0
Stairs - Descend stairs	0.2 ± 0.2	0.1 ± 0.1	0.7 ± 0.8	0.8 ± 0.8
Standing	0.1 ± 0.1	0.1 ± 0.1	0.5 ± 0.9	0.5 ± 0.9
Walking - Treadmill 2mph - Treadmill 0	0.1 ± 0.1	0.1 ± 0.1	0.6 ± 0.9	0.7 ± 1.4
Walking - Treadmill 3mph - Treadmill 0	0.4 ± 0.2	0.2 ± 0.2	1.2 ± 1.0	1.2 ± 1.0
Walking - Treadmill 3mph - Treadmill 3 - light	0.6 ± 0.3	0.3 ± 0.2	1.6 ± 0.9	1.0 ± 0.8
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.5 ± 0.3	0.3 ± 0.2	1.5 ± 1.0	1.4 ± 1.1
Walking - Treadmill 3mph - Treadmill 9 - hard	0.3 ± 0.2	0.1 ± 0.1	1.5 ± 1.5	1.5 ± 1.6
kneeling	0.0 ± 0.1	0.1 ± 0.1	0.0 ± 0.1	0.1 ± 0.1
Carrying groceries	0.2 ± 0.2	0.2 ± 0.2	0.9 ± 0.6	1.0 ± 0.9
Doing dishes	0.4 ± 0.1	0.4 ± 0.2	1.2 ± 0.9	1.2 ± 1.0
Gardening	0.4 ± 0.3	0.4 ± 0.2	1.0 ± 0.8	1.1 ± 0.8
Ironing	0.4 ± 0.3	0.4 ± 0.2	1.3 ± 0.8	1.3 ± 0.8
Making the bed	0.8 ± 0.4	0.7 ± 0.3	2.0 ± 0.9	2.0 ± 0.9
Mopping	0.9 ± 0.3	0.8 ± 0.3	1.8 ± 0.9	1.8 ± 0.9
Playing videogames	0.0 ± 0.0	0.0 ± 0.0	1.2 ± 1.2	1.2 ± 1.1
Scrubbing a surface	0.3 ± 0.3	0.3 ± 0.2	1.5 ± 0.8	1.5 ± 0.9
Stacking groceries	0.6 ± 0.3	0.5 ± 0.3	1.2 ± 0.8	1.2 ± 0.9
Sweeping	0.7 ± 0.3	0.7 ± 0.3	1.5 ± 0.4	1.5 ± 0.5
Typing	0.1 ± 0.1	0.1 ± 0.1	0.8 ± 1.0	0.8 ± 1.0
Vacuuming	0.5 ± 0.3	0.5 ± 0.2	1.1 ± 0.6	1.1 ± 0.6
Walking around block	0.2 ± 0.1	0.2 ± 0.1	3.1 ± 2.5	1.7 ± 1.1
Washing windows	0.6 ± 0.2	0.5 ± 0.2	1.2 ± 0.7	1.2 ± 0.7
Watching TV	0.0 ± 0.0	0.0 ± 0.0	1.5 ± 1.6	1.5 ± 1.6
Weeding	0.6 ± 0.3	0.5 ± 0.2	1.1 ± 0.7	1.0 ± 0.6
Wiping/Dusting	0.8 ± 0.3	0.6 ± 0.3	1.5 ± 0.6	1.5 ± 0.6
Writing	0.1 ± 0.1	0.1 ± 0.1	0.3 ± 0.4	0.3 ± 0.4
taking out trash	0.7 ± 0.3	0.6 ± 0.3	1.2 ± 0.4	1.2 ± 0.4

Table A7-15: False positive rate obtained when adding the *ScaledHR* feature to *the invariant reduced* feature set using the C4.5 classifier. The sliding window length for accelerometer data and heart rate is 5.6s. The activities to recognize are the 51 contained in the MIT dataset without including the *unknown* class.

Activity	F-Measure			
	Subject Dependent		Subject Independent	
	Invariant Reduced	Invariant Reduced + ScaledHR	Invariant Reduced	Invariant Reduced + ScaledHR
Bench weight lifting - hard	93.5 ± 8.2	93.5 ± 8.2	12.8 ± 18.5	9.3 ± 15.4
Bench weight lifting - light	94.1 ± 8.4	94.1 ± 8.4	33.5 ± 26.2	29.7 ± 23.1
Bench weight lifting - moderate	91.1 ± 11.4	91.1 ± 11.4	18.7 ± 22.1	16.5 ± 17.4
Bicep curls - hard	92.4 ± 12.7	92.4 ± 12.7	28.3 ± 26.9	26.8 ± 26.3
Bicep curls - light	92.8 ± 6.6	92.9 ± 6.5	18.5 ± 20.0	22.3 ± 22.3
Bicep curls - moderate	91.2 ± 9.3	91.3 ± 9.3	17.5 ± 20.2	15.1 ± 18.8
Calisthenics - Crunches	96.8 ± 3.2	97.0 ± 3.0	63.8 ± 38.2	64.2 ± 38.0
Calisthenics - Sit ups	94.8 ± 5.3	95.4 ± 3.8	77.6 ± 32.8	79.6 ± 32.3
Cycling - Cycle hard - Cycle 80rpm	89.5 ± 7.8	93.1 ± 7.4	27.6 ± 22.8	31.5 ± 26.0
Cycling - Cycle light - Cycle 100rpm	98.2 ± 1.9	98.2 ± 1.9	95.6 ± 9.5	95.2 ± 8.7
Cycling - Cycle light - Cycle 60rpm	98.8 ± 1.4	98.8 ± 1.4	89.2 ± 21.8	89.3 ± 21.9
Cycling - Cycle light - Cycle 80rpm	97.4 ± 2.5	97.4 ± 2.5	33.8 ± 26.7	36.4 ± 31.0
Cycling - Cycle moderate - Cycle 80rpm	92.2 ± 5.2	94.6 ± 4.0	27.7 ± 24.3	26.7 ± 20.0
Lying down	99.7 ± 0.7	99.7 ± 0.7	95.8 ± 8.6	95.8 ± 8.7
Rowing - Rowing hard - Rowing 30spm	85.0 ± 13.6	87.4 ± 14.1	30.7 ± 24.5	26.5 ± 22.9
Rowing - Rowing light - Rowing 30spm	89.1 ± 10.4	89.9 ± 9.8	31.0 ± 17.2	31.0 ± 20.5
Rowing - Rowing moderate - Rowing 30spm	80.8 ± 13.9	84.0 ± 12.2	23.2 ± 17.7	27.0 ± 22.0
Running - Treadmill 4mph - Treadmill 0	96.5 ± 2.6	96.5 ± 2.6	53.1 ± 36.5	54.1 ± 38.2
Running - Treadmill 5mph - Treadmill 0	93.7 ± 3.9	93.8 ± 4.1	54.5 ± 21.0	62.3 ± 24.2
Running - Treadmill 6mph - Treadmill 0	90.0 ± 12.0	90.2 ± 12.2	54.8 ± 26.0	57.5 ± 34.1
Sitting	96.6 ± 3.3	96.8 ± 3.0	45.9 ± 34.6	45.3 ± 34.8
Sitting - Fidget feet legs	95.8 ± 4.4	95.8 ± 4.4	70.3 ± 25.0	70.7 ± 25.0
Sitting - Fidget hands arms	91.9 ± 6.2	92.0 ± 6.2	50.1 ± 28.1	45.8 ± 29.4
Stairs - Ascend stairs	91.4 ± 5.7	90.8 ± 5.9	68.9 ± 25.1	67.2 ± 25.6
Stairs - Descend stairs	90.8 ± 7.0	91.1 ± 6.4	58.5 ± 22.0	55.4 ± 24.5
Standing	97.0 ± 3.2	96.9 ± 3.4	81.6 ± 20.9	81.3 ± 20.9
Walking - Treadmill 2mph - Treadmill 0	95.9 ± 4.0	95.9 ± 4.0	70.1 ± 21.1	70.6 ± 20.2
Walking - Treadmill 3mph - Treadmill 0	83.8 ± 8.4	91.2 ± 7.0	19.0 ± 19.1	28.1 ± 18.6
Walking - Treadmill 3mph - Treadmill 3 - light	75.4 ± 13.8	87.6 ± 10.4	20.6 ± 17.2	24.7 ± 24.4
Walking - Treadmill 3mph - Treadmill 6 - moderate	78.0 ± 9.8	88.5 ± 7.0	13.5 ± 13.7	33.6 ± 23.1
Walking - Treadmill 3mph - Treadmill 9 - hard	88.4 ± 7.8	93.7 ± 3.7	24.8 ± 15.4	47.8 ± 29.7
kneeling	96.6 ± 3.2	96.5 ± 3.7	96.7 ± 3.5	96.5 ± 3.8
Carrying groceries	90.5 ± 8.3	90.8 ± 8.1	56.1 ± 23.8	57.3 ± 27.3
Doing dishes	85.2 ± 5.6	85.1 ± 5.5	52.4 ± 20.6	53.9 ± 19.4
Gardening	79.9 ± 11.7	80.5 ± 10.9	23.1 ± 25.1	22.8 ± 24.2
Ironing	84.4 ± 6.6	85.6 ± 5.6	50.5 ± 23.9	50.5 ± 24.1
Making the bed	64.2 ± 9.9	69.2 ± 10.4	36.0 ± 14.9	35.6 ± 15.2
Mopping	69.6 ± 10.1	71.1 ± 10.0	31.0 ± 14.1	30.6 ± 12.0
Playing videogames	98.9 ± 1.5	98.9 ± 1.5	58.9 ± 37.8	57.0 ± 36.7
Scrubbing a surface	85.9 ± 12.1	86.4 ± 11.2	35.9 ± 27.7	35.9 ± 27.7
Stacking groceries	71.1 ± 14.6	73.9 ± 12.5	34.0 ± 19.0	33.5 ± 18.4
Sweeping	68.8 ± 12.4	70.1 ± 11.6	32.8 ± 17.5	31.2 ± 17.9
Typing	97.2 ± 2.6	97.4 ± 2.0	70.8 ± 27.3	67.9 ± 30.5
Vacuuming	75.9 ± 9.7	77.8 ± 7.9	51.8 ± 18.8	53.0 ± 17.6
Walking around block	91.6 ± 5.6	91.6 ± 5.1	29.4 ± 16.0	37.8 ± 16.8
Washing windows	72.9 ± 9.0	74.6 ± 7.9	44.8 ± 20.7	45.3 ± 20.8
Watching TV	98.6 ± 1.6	98.6 ± 1.6	42.4 ± 37.6	39.1 ± 36.6
Weeding	74.8 ± 8.6	75.9 ± 8.8	17.1 ± 17.6	16.4 ± 18.3
Wiping/Dusting	68.7 ± 12.6	73.8 ± 11.4	37.6 ± 18.5	37.0 ± 18.0
Writing	96.3 ± 3.1	96.3 ± 3.1	63.8 ± 38.9	63.9 ± 38.9
taking out trash	93.5 ± 8.2	67.3 ± 13.5	25.7 ± 15.3	26.9 ± 15.8

Table A7-16: F-Measure obtained when adding the *ScaledHR* feature to *the invariant reduced* feature set using the C4.5 classifier. The sliding window length for accelerometer data and heart rate is 5.6s. The activities to recognize are the 51 contained in the MIT dataset without including the *unknown* class.

Appendix A8: Activity Recognition – Final Performance

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	93.3 ± 8.3	0.1 ± 0.1	93.5 ± 8.2	14.5 ± 22.4	0.7 ± 0.8	12.8 ± 18.5
Bench weight lifting - light	93.6 ± 9.6	0.1 ± 0.1	94.1 ± 8.4	38.8 ± 37.0	0.8 ± 0.8	33.5 ± 26.2
Bench weight lifting - moderate	91.3 ± 10.9	0.1 ± 0.2	91.1 ± 11.4	28.4 ± 36.4	1.1 ± 1.3	18.7 ± 22.1
Bicep curls - hard	94.1 ± 10.0	0.1 ± 0.2	92.4 ± 12.7	43.0 ± 40.5	1.6 ± 1.2	28.3 ± 26.9
Bicep curls - light	91.9 ± 8.1	0.1 ± 0.1	92.8 ± 6.6	20.5 ± 31.7	0.6 ± 0.9	18.5 ± 20.0
Bicep curls - moderate	91.6 ± 9.9	0.2 ± 0.2	91.2 ± 9.3	21.8 ± 30.8	1.1 ± 1.1	17.5 ± 20.2
Calisthenics - Crunches	96.2 ± 4.4	0.0 ± 0.0	96.8 ± 3.2	66.6 ± 38.4	0.6 ± 1.2	63.8 ± 38.2
Calisthenics - Sit ups	96.6 ± 3.1	0.1 ± 0.2	94.8 ± 5.3	80.5 ± 35.0	0.2 ± 0.2	77.6 ± 32.8
Cycling - Cycle hard - Cycle 80rpm	88.4 ± 8.7	0.1 ± 0.1	89.5 ± 7.8	33.4 ± 31.9	1.1 ± 1.4	27.6 ± 22.8
Cycling - Cycle light - Cycle 100rpm	98.1 ± 2.3	0.0 ± 0.0	98.2 ± 1.9	97.0 ± 5.8	0.1 ± 0.4	95.6 ± 9.5
Cycling - Cycle light - Cycle 60rpm	99.5 ± 1.2	0.0 ± 0.0	98.8 ± 1.4	87.6 ± 25.2	0.1 ± 0.2	89.2 ± 21.8
Cycling - Cycle light - Cycle 80rpm	97.5 ± 3.2	0.1 ± 0.1	97.4 ± 2.5	41.6 ± 39.1	1.3 ± 1.4	33.8 ± 26.7
Cycling - Cycle moderate - Cycle 80rpm	92.6 ± 5.2	0.2 ± 0.1	92.2 ± 5.2	32.6 ± 32.0	1.2 ± 1.0	27.7 ± 24.3
Lying down	99.9 ± 0.3	0.0 ± 0.1	99.7 ± 0.7	95.9 ± 12.3	0.3 ± 0.6	95.8 ± 8.6
Rowing - Rowing hard - Rowing 30spm	85.2 ± 14.2	0.2 ± 0.2	85.0 ± 13.6	34.2 ± 33.5	1.1 ± 0.8	30.7 ± 24.5
Rowing - Rowing light - Rowing 30spm	88.9 ± 10.3	0.2 ± 0.2	89.1 ± 10.4	41.9 ± 32.3	1.8 ± 1.2	31.0 ± 17.2
Rowing - Rowing moderate - Rowing 30spm	81.4 ± 13.7	0.4 ± 0.3	80.8 ± 13.9	24.0 ± 23.6	1.0 ± 0.9	23.2 ± 17.7
Running - Treadmill 4mph - Treadmill 0	97.7 ± 2.9	0.1 ± 0.1	96.5 ± 2.6	57.4 ± 39.6	0.8 ± 1.0	53.1 ± 36.5
Running - Treadmill 5mph - Treadmill 0	93.7 ± 4.8	0.1 ± 0.1	93.7 ± 3.9	56.8 ± 29.1	0.9 ± 0.7	54.5 ± 21.0
Running - Treadmill 6mph - Treadmill 0	88.4 ± 15.1	0.1 ± 0.1	90.0 ± 12.0	64.0 ± 36.0	0.7 ± 0.8	54.8 ± 26.0
Sitting	97.4 ± 4.1	0.1 ± 0.1	96.6 ± 3.3	58.1 ± 43.0	1.3 ± 1.2	45.9 ± 34.6
Sitting - Fidget feet legs	95.3 ± 5.3	0.0 ± 0.1	95.8 ± 4.4	66.7 ± 30.2	0.2 ± 0.2	70.3 ± 25.0
Sitting - Fidget hands arms	93.4 ± 8.0	0.1 ± 0.1	91.9 ± 6.2	57.8 ± 32.6	0.9 ± 0.9	50.1 ± 28.1
Stairs - Ascend stairs	91.1 ± 6.7	0.2 ± 0.2	91.4 ± 5.7	71.8 ± 28.6	0.5 ± 0.5	68.9 ± 25.1
Stairs - Descend stairs	90.7 ± 6.6	0.2 ± 0.2	90.8 ± 7.0	59.6 ± 26.4	0.7 ± 0.8	58.5 ± 22.0
Standing	97.9 ± 3.2	0.1 ± 0.1	97.0 ± 3.2	86.3 ± 21.1	0.5 ± 0.9	81.6 ± 20.9
Walking - Treadmill 2mph - Treadmill 0	96.8 ± 4.7	0.1 ± 0.1	95.9 ± 4.0	70.9 ± 25.5	0.6 ± 0.9	70.1 ± 21.1
Walking - Treadmill 3mph - Treadmill 0	84.5 ± 10.2	0.4 ± 0.2	83.8 ± 8.4	20.1 ± 23.7	1.2 ± 1.0	19.0 ± 19.1
Walking - Treadmill 3mph - Treadmill 3 - light	76.2 ± 14.6	0.6 ± 0.3	75.4 ± 13.8	24.4 ± 25.8	1.6 ± 0.9	20.6 ± 17.2
Walking - Treadmill 3mph - Treadmill 6 - moderate	77.0 ± 10.3	0.5 ± 0.3	78.0 ± 9.8	14.8 ± 18.8	1.5 ± 1.0	13.5 ± 13.7
Walking - Treadmill 3mph - Treadmill 9 - hard	88.4 ± 9.5	0.3 ± 0.2	88.4 ± 7.8	27.7 ± 24.8	1.5 ± 1.5	24.8 ± 15.4
kneeling	97.3 ± 3.7	0.0 ± 0.1	96.6 ± 3.2	97.3 ± 5.0	0.0 ± 0.1	96.7 ± 3.5
Carrying groceries	91.1 ± 7.6	0.2 ± 0.2	90.5 ± 8.3	56.7 ± 27.9	0.9 ± 0.6	56.1 ± 23.8
Doing dishes	85.1 ± 7.3	0.4 ± 0.1	85.2 ± 5.6	55.9 ± 25.4	1.2 ± 0.9	52.4 ± 20.6
Gardening	79.6 ± 11.8	0.4 ± 0.3	79.9 ± 11.7	20.7 ± 25.9	1.0 ± 0.8	23.1 ± 25.1
Ironing	85.4 ± 6.3	0.4 ± 0.3	84.4 ± 6.6	53.3 ± 28.4	1.3 ± 0.8	50.5 ± 23.9
Making the bed	62.2 ± 10.8	0.8 ± 0.4	64.2 ± 9.9	40.5 ± 18.3	2.0 ± 0.9	36.0 ± 14.9
Mopping	72.4 ± 11.8	0.9 ± 0.3	69.6 ± 10.1	33.3 ± 18.4	1.8 ± 0.9	31.0 ± 14.1
Playing videogames	99.0 ± 2.3	0.0 ± 0.0	98.9 ± 1.5	64.4 ± 42.2	1.2 ± 1.2	58.9 ± 37.8
Scrubbing a surface	85.0 ± 12.9	0.3 ± 0.3	85.9 ± 12.1	40.0 ± 35.4	1.5 ± 0.8	35.9 ± 27.7
Stacking groceries	71.0 ± 16.0	0.6 ± 0.3	71.1 ± 14.6	33.8 ± 20.9	1.2 ± 0.8	34.0 ± 19.0
Sweeping	68.3 ± 15.2	0.7 ± 0.3	68.8 ± 12.4	34.4 ± 20.6	1.5 ± 0.4	32.8 ± 17.5
Typing	98.3 ± 2.4	0.1 ± 0.1	97.2 ± 2.6	75.0 ± 29.4	0.8 ± 1.0	70.8 ± 27.3
Vacuuming	74.5 ± 10.1	0.5 ± 0.3	75.9 ± 9.7	53.4 ± 23.9	1.1 ± 0.6	51.8 ± 18.8
Walking around block	90.4 ± 7.7	0.2 ± 0.1	91.6 ± 5.6	34.9 ± 18.6	3.1 ± 2.5	29.4 ± 16.0
Washing windows	71.2 ± 9.4	0.6 ± 0.2	72.9 ± 9.0	44.2 ± 21.5	1.2 ± 0.7	44.8 ± 20.7
Watching TV	98.2 ± 2.5	0.0 ± 0.0	98.6 ± 1.6	48.2 ± 43.6	1.5 ± 1.6	42.4 ± 37.6
Weeding	75.2 ± 11.0	0.6 ± 0.3	74.8 ± 8.6	15.5 ± 19.1	1.1 ± 0.7	17.1 ± 17.6
Wiping/Dusting	69.4 ± 13.9	0.8 ± 0.3	68.7 ± 12.6	39.4 ± 21.6	1.5 ± 0.6	37.6 ± 18.5
Writing	97.3 ± 3.0	0.1 ± 0.1	96.3 ± 3.1	61.7 ± 40.6	0.3 ± 0.4	63.8 ± 38.9
taking out trash	62.2 ± 13.6	0.7 ± 0.3	64.4 ± 12.4	23.0 ± 14.1	1.2 ± 0.4	25.7 ± 15.3

Table A8-1: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using all the accelerometers (7) and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	90.8 ± 9.3	0.1 ± 0.1	90.5 ± 7.2	16.9 ± 33.0	0.8 ± 0.9	10.6 ± 15.3
Bench weight lifting - light	93.5 ± 7.7	0.1 ± 0.2	92.2 ± 7.9	41.3 ± 41.9	1.1 ± 1.3	31.2 ± 28.3
Bench weight lifting - moderate	83.4 ± 18.3	0.1 ± 0.1	85.4 ± 12.8	22.0 ± 33.1	0.7 ± 0.7	15.4 ± 20.8
Bicep curls - hard	90.0 ± 8.9	0.2 ± 0.2	88.6 ± 10.1	39.2 ± 32.4	1.7 ± 1.3	27.0 ± 18.0
Bicep curls - light	91.1 ± 8.8	0.2 ± 0.2	91.5 ± 8.8	32.4 ± 37.4	1.4 ± 1.4	25.3 ± 20.5
Bicep curls - moderate	88.7 ± 9.3	0.2 ± 0.2	88.7 ± 8.9	16.2 ± 19.1	0.7 ± 0.6	17.4 ± 17.6
Calisthenics - Crunches	96.1 ± 5.1	0.0 ± 0.0	96.9 ± 3.4	51.1 ± 38.0	0.6 ± 0.8	53.4 ± 36.9
Calisthenics - Sit ups	92.7 ± 5.7	0.1 ± 0.1	93.3 ± 5.9	34.1 ± 33.7	0.6 ± 0.8	36.2 ± 33.2
Cycling - Cycle hard - Cycle 80rpm	88.1 ± 8.3	0.2 ± 0.2	87.3 ± 9.4	19.6 ± 28.4	1.3 ± 1.3	16.8 ± 21.2
Cycling - Cycle light - Cycle 100rpm	98.1 ± 2.3	0.0 ± 0.1	97.3 ± 3.6	90.1 ± 19.5	0.2 ± 0.2	88.1 ± 18.5
Cycling - Cycle light - Cycle 60rpm	98.1 ± 3.4	0.0 ± 0.1	97.8 ± 2.6	81.5 ± 23.6	0.4 ± 0.4	80.0 ± 16.0
Cycling - Cycle light - Cycle 80rpm	95.9 ± 4.9	0.1 ± 0.1	96.0 ± 4.7	43.9 ± 33.3	1.2 ± 1.2	39.3 ± 25.1
Cycling - Cycle moderate - Cycle 80rpm	91.2 ± 6.2	0.2 ± 0.1	91.0 ± 5.9	35.7 ± 27.7	1.2 ± 1.0	30.6 ± 18.5
Lying down	99.9 ± 0.4	0.0 ± 0.0	99.8 ± 0.4	89.0 ± 20.9	0.3 ± 0.8	90.8 ± 15.3
Rowing - Rowing hard - Rowing 30spm	81.9 ± 12.4	0.4 ± 0.2	80.5 ± 11.8	13.6 ± 23.8	1.1 ± 0.8	11.5 ± 17.4
Rowing - Rowing light - Rowing 30spm	82.7 ± 10.7	0.3 ± 0.2	84.4 ± 10.0	35.8 ± 32.9	1.4 ± 1.2	28.1 ± 25.3
Rowing - Rowing moderate - Rowing 30spm	75.5 ± 12.9	0.6 ± 0.3	74.3 ± 12.2	28.2 ± 22.8	1.1 ± 1.0	27.1 ± 18.3
Running - Treadmill 4mph - Treadmill 0	96.4 ± 4.4	0.1 ± 0.0	96.7 ± 2.8	41.8 ± 42.8	1.3 ± 1.3	36.8 ± 35.8
Running - Treadmill 5mph - Treadmill 0	95.2 ± 4.2	0.1 ± 0.1	94.5 ± 3.2	55.0 ± 32.1	1.4 ± 0.9	46.3 ± 21.3
Running - Treadmill 6mph - Treadmill 0	89.9 ± 17.2	0.1 ± 0.1	90.3 ± 13.8	47.3 ± 35.2	0.6 ± 0.6	42.5 ± 27.6
Sitting	97.0 ± 4.8	0.1 ± 0.1	95.6 ± 5.4	60.9 ± 39.8	1.2 ± 1.5	51.5 ± 35.9
Sitting - Fidget feet legs	93.8 ± 7.2	0.1 ± 0.1	93.6 ± 6.2	58.4 ± 27.9	0.5 ± 0.6	57.2 ± 22.4
Sitting - Fidget hands arms	95.6 ± 5.1	0.1 ± 0.1	94.7 ± 4.4	38.2 ± 32.7	0.6 ± 0.7	36.8 ± 28.5
Stairs - Ascend stairs	90.2 ± 7.0	0.1 ± 0.1	91.1 ± 5.9	55.3 ± 26.5	1.0 ± 0.7	51.7 ± 21.2
Stairs - Descend stairs	88.4 ± 6.2	0.2 ± 0.1	89.4 ± 5.6	50.7 ± 24.5	0.9 ± 0.7	50.2 ± 22.5
Standing	95.8 ± 4.8	0.0 ± 0.1	96.2 ± 3.6	73.1 ± 36.9	0.7 ± 1.3	67.6 ± 34.6
Walking - Treadmill 2mph - Treadmill 0	97.4 ± 4.2	0.1 ± 0.1	96.4 ± 2.6	69.8 ± 31.1	0.8 ± 1.3	67.7 ± 27.5
Walking - Treadmill 3mph - Treadmill 0	81.8 ± 10.6	0.4 ± 0.3	82.3 ± 9.0	19.4 ± 22.7	1.3 ± 0.8	18.3 ± 18.9
Walking - Treadmill 3mph - Treadmill 3 - light	73.4 ± 12.2	0.7 ± 0.3	72.3 ± 11.2	22.1 ± 24.2	1.6 ± 1.5	18.0 ± 15.3
Walking - Treadmill 3mph - Treadmill 6 - moderate	74.6 ± 13.7	0.6 ± 0.3	73.5 ± 12.0	15.4 ± 19.4	1.3 ± 1.1	14.6 ± 16.7
Walking - Treadmill 3mph - Treadmill 9 - hard	83.4 ± 9.0	0.3 ± 0.2	84.7 ± 8.1	16.1 ± 23.2	1.0 ± 0.9	15.6 ± 20.3
kneeling	97.4 ± 2.9	0.0 ± 0.0	96.9 ± 2.2	81.6 ± 35.4	0.6 ± 1.2	77.3 ± 33.9
Carrying groceries	93.4 ± 7.0	0.3 ± 0.2	90.9 ± 8.1	57.8 ± 31.3	1.3 ± 1.5	53.6 ± 26.5
Doing dishes	81.0 ± 9.0	0.5 ± 0.2	80.2 ± 7.5	47.1 ± 23.0	1.3 ± 0.6	44.1 ± 18.2
Gardening	80.1 ± 12.2	0.5 ± 0.3	78.4 ± 11.4	19.4 ± 22.0	1.0 ± 0.9	20.5 ± 20.3
Ironing	82.9 ± 8.5	0.5 ± 0.3	82.5 ± 8.2	42.0 ± 25.0	1.4 ± 0.9	39.9 ± 18.9
Making the bed	61.0 ± 10.0	1.0 ± 0.4	61.3 ± 9.4	38.1 ± 19.4	2.4 ± 2.3	34.0 ± 17.7
Mopping	68.8 ± 13.7	0.9 ± 0.4	66.5 ± 12.8	29.5 ± 12.0	2.0 ± 1.3	28.1 ± 9.8
Playing videogames	98.8 ± 1.9	0.1 ± 0.1	98.2 ± 2.9	64.6 ± 38.9	1.3 ± 1.6	58.0 ± 32.7
Scrubbing a surface	84.0 ± 14.3	0.3 ± 0.3	85.0 ± 14.0	41.6 ± 28.9	1.7 ± 1.3	37.9 ± 25.2
Stacking groceries	64.0 ± 17.0	0.7 ± 0.4	64.1 ± 16.6	35.6 ± 15.5	1.4 ± 0.5	34.2 ± 13.7
Sweeping	66.2 ± 16.7	0.8 ± 0.4	66.9 ± 15.5	32.5 ± 16.9	1.3 ± 0.5	33.2 ± 15.2
Typing	98.5 ± 2.5	0.0 ± 0.1	98.1 ± 2.2	75.2 ± 31.6	0.5 ± 0.8	75.2 ± 29.9
Vacuuming	73.5 ± 11.4	0.6 ± 0.3	74.7 ± 10.8	52.3 ± 22.3	1.1 ± 0.6	51.6 ± 19.2
Walking around block	90.0 ± 7.0	0.2 ± 0.2	90.4 ± 6.0	24.6 ± 15.2	2.8 ± 2.3	21.4 ± 12.6
Washing windows	69.1 ± 11.6	0.6 ± 0.2	71.7 ± 10.1	45.0 ± 24.1	1.3 ± 0.7	44.2 ± 24.0
Watching TV	97.5 ± 3.1	0.0 ± 0.0	98.3 ± 1.7	52.7 ± 43.1	0.6 ± 0.5	49.5 ± 38.2
Weeding	73.5 ± 15.5	0.6 ± 0.2	74.0 ± 13.7	14.8 ± 23.6	1.2 ± 1.0	11.2 ± 13.7
Wiping/Dusting	66.6 ± 9.6	0.7 ± 0.4	68.6 ± 11.6	38.2 ± 22.5	1.3 ± 0.8	37.3 ± 20.0
Writing	97.7 ± 2.8	0.1 ± 0.1	96.7 ± 2.4	77.0 ± 29.1	0.8 ± 1.4	73.5 ± 27.9
taking out trash	59.9 ± 14.7	0.8 ± 0.4	61.3 ± 14.0	25.9 ± 16.8	1.2 ± 0.5	27.7 ± 17.2

Table A8-2: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers hip, dominant wrist, and dominant foot and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	80.8 ± 26.8	0.1 ± 0.1	82.5 ± 25.5	5.8 ± 8.6	0.4 ± 0.4	6.9 ± 11.0
Bench weight lifting - light	90.5 ± 11.6	0.2 ± 0.2	89.1 ± 12.4	47.3 ± 30.3	0.9 ± 0.8	42.0 ± 23.6
Bench weight lifting - moderate	80.6 ± 24.5	0.2 ± 0.2	81.0 ± 23.5	23.3 ± 29.2	0.7 ± 0.6	18.7 ± 19.3
Bicep curls - hard	82.1 ± 18.6	0.3 ± 0.2	82.1 ± 17.1	39.6 ± 21.9	1.3 ± 1.1	36.1 ± 19.7
Bicep curls - light	86.4 ± 12.0	0.3 ± 0.3	86.2 ± 11.9	32.5 ± 30.9	0.9 ± 0.9	29.2 ± 24.6
Bicep curls - moderate	80.1 ± 16.1	0.4 ± 0.4	79.9 ± 16.4	25.8 ± 29.0	1.1 ± 0.9	23.0 ± 18.0
Calisthenics - Crunches	96.6 ± 4.2	0.1 ± 0.1	96.0 ± 3.3	51.0 ± 40.8	0.8 ± 0.9	48.9 ± 37.1
Calisthenics - Sit ups	91.7 ± 5.7	0.1 ± 0.1	91.6 ± 5.2	33.5 ± 31.9	0.7 ± 1.2	35.6 ± 31.6
Cycling - Cycle hard - Cycle 80rpm	83.3 ± 16.5	0.3 ± 0.2	81.9 ± 17.9	7.7 ± 9.6	0.9 ± 1.2	9.7 ± 11.0
Cycling - Cycle light - Cycle 100rpm	91.9 ± 18.3	0.1 ± 0.1	92.2 ± 17.7	57.9 ± 29.6	1.2 ± 2.0	53.6 ± 28.8
Cycling - Cycle light - Cycle 60rpm	96.2 ± 4.2	0.1 ± 0.2	95.0 ± 4.1	64.2 ± 32.3	0.8 ± 0.7	59.3 ± 25.3
Cycling - Cycle light - Cycle 80rpm	93.0 ± 8.2	0.1 ± 0.2	93.3 ± 8.3	32.7 ± 29.7	1.9 ± 1.3	24.7 ± 19.1
Cycling - Cycle moderate - Cycle 80rpm	83.2 ± 11.6	0.2 ± 0.2	84.8 ± 9.5	23.1 ± 20.6	1.2 ± 0.8	21.6 ± 18.8
Lying down	99.9 ± 0.4	0.0 ± 0.0	99.7 ± 0.5	86.4 ± 21.8	0.6 ± 1.0	87.7 ± 14.0
Rowing - Rowing hard - Rowing 30spm	79.3 ± 10.6	0.4 ± 0.3	78.9 ± 11.3	16.8 ± 19.1	0.9 ± 0.7	17.6 ± 19.4
Rowing - Rowing light - Rowing 30spm	81.2 ± 9.7	0.4 ± 0.3	81.2 ± 9.5	38.2 ± 26.1	1.7 ± 1.0	31.1 ± 17.1
Rowing - Rowing moderate - Rowing 30spm	72.3 ± 12.4	0.6 ± 0.2	71.9 ± 10.8	28.8 ± 22.0	1.4 ± 0.9	25.4 ± 15.4
Running - Treadmill 4mph - Treadmill 0	95.6 ± 3.7	0.1 ± 0.1	95.3 ± 3.2	31.8 ± 32.5	1.2 ± 1.5	29.5 ± 30.6
Running - Treadmill 5mph - Treadmill 0	91.8 ± 5.6	0.2 ± 0.2	91.2 ± 5.5	55.5 ± 35.9	1.1 ± 0.8	47.7 ± 27.2
Running - Treadmill 6mph - Treadmill 0	83.3 ± 25.0	0.1 ± 0.1	83.1 ± 24.2	57.6 ± 34.6	1.1 ± 1.2	46.3 ± 27.2
Sitting	97.3 ± 3.6	0.1 ± 0.1	96.3 ± 3.4	42.5 ± 42.8	1.1 ± 1.5	34.2 ± 33.9
Sitting - Fidget feet legs	94.3 ± 4.5	0.1 ± 0.1	93.1 ± 3.9	40.1 ± 35.6	1.3 ± 1.5	35.4 ± 32.8
Sitting - Fidget hands arms	91.9 ± 8.1	0.1 ± 0.1	91.6 ± 7.2	35.0 ± 29.9	0.8 ± 0.7	35.1 ± 28.1
Stairs - Ascend stairs	88.2 ± 7.4	0.2 ± 0.1	87.5 ± 6.0	50.8 ± 33.6	1.4 ± 1.8	47.6 ± 31.0
Stairs - Descend stairs	87.2 ± 7.0	0.2 ± 0.2	87.5 ± 6.8	51.3 ± 27.6	1.4 ± 1.6	44.8 ± 22.6
Standing	95.6 ± 4.4	0.1 ± 0.1	95.5 ± 4.1	40.6 ± 42.6	0.8 ± 0.7	34.9 ± 37.0
Walking - Treadmill 2mph - Treadmill 0	96.2 ± 3.0	0.1 ± 0.1	95.6 ± 2.7	56.4 ± 30.7	1.1 ± 1.0	51.5 ± 26.8
Walking - Treadmill 3mph - Treadmill 0	82.6 ± 9.2	0.4 ± 0.3	82.5 ± 9.3	13.0 ± 16.4	1.3 ± 1.2	13.1 ± 15.4
Walking - Treadmill 3mph - Treadmill 3 - light	72.1 ± 12.8	0.6 ± 0.3	71.8 ± 11.6	12.1 ± 14.5	1.1 ± 0.7	12.7 ± 13.6
Walking - Treadmill 3mph - Treadmill 6 - moderate	75.2 ± 12.2	0.6 ± 0.3	74.2 ± 11.1	19.1 ± 22.6	1.2 ± 1.3	17.3 ± 17.0
Walking - Treadmill 3mph - Treadmill 9 - hard	85.2 ± 9.1	0.3 ± 0.2	86.2 ± 8.0	23.7 ± 25.9	1.6 ± 1.3	20.4 ± 19.0
kneeling	95.4 ± 5.0	0.1 ± 0.1	94.6 ± 4.4	31.8 ± 33.4	1.2 ± 1.1	26.3 ± 26.7
Carrying groceries	90.2 ± 9.1	0.3 ± 0.2	88.7 ± 8.6	52.6 ± 32.0	1.3 ± 1.1	49.5 ± 25.7
Doing dishes	77.8 ± 11.3	0.6 ± 0.3	77.3 ± 11.7	42.8 ± 24.3	1.6 ± 1.0	38.4 ± 18.2
Gardening	74.4 ± 17.6	0.6 ± 0.3	73.5 ± 16.3	22.7 ± 25.2	1.0 ± 0.6	23.4 ± 23.2
Ironing	78.1 ± 11.0	0.6 ± 0.5	77.1 ± 11.5	44.3 ± 22.0	1.4 ± 0.7	42.8 ± 18.6
Making the bed	55.3 ± 10.0	1.0 ± 0.3	56.3 ± 8.7	35.6 ± 15.8	2.0 ± 1.1	32.1 ± 12.5
Mopping	60.5 ± 12.6	1.0 ± 0.4	59.6 ± 11.6	31.8 ± 14.4	2.1 ± 1.0	29.4 ± 12.5
Playing videogames	98.6 ± 2.9	0.0 ± 0.1	98.4 ± 2.5	57.7 ± 38.1	0.9 ± 1.4	56.2 ± 36.2
Scrubbing a surface	73.8 ± 11.3	0.6 ± 0.3	74.4 ± 11.8	37.4 ± 19.6	1.3 ± 0.7	36.6 ± 16.2
Stacking groceries	56.7 ± 18.0	0.8 ± 0.4	57.9 ± 18.1	30.2 ± 17.0	1.6 ± 0.9	27.2 ± 12.9
Sweeping	63.9 ± 16.9	0.9 ± 0.5	62.7 ± 14.8	33.8 ± 15.9	1.4 ± 0.6	35.0 ± 15.1
Typing	98.0 ± 2.3	0.1 ± 0.1	97.6 ± 2.4	84.8 ± 25.6	0.4 ± 0.7	84.5 ± 23.0
Vacuuming	72.9 ± 13.0	0.6 ± 0.3	73.0 ± 12.1	51.2 ± 18.5	1.0 ± 0.5	51.6 ± 14.0
Walking around block	90.1 ± 6.0	0.2 ± 0.2	90.2 ± 5.6	30.8 ± 21.2	2.7 ± 2.4	27.1 ± 17.5
Washing windows	65.2 ± 8.6	0.7 ± 0.3	67.8 ± 8.7	43.0 ± 20.4	1.2 ± 0.6	43.2 ± 19.8
Watching TV	96.2 ± 4.3	0.0 ± 0.1	97.0 ± 3.1	61.6 ± 42.2	1.3 ± 1.6	52.8 ± 36.4
Weeding	69.3 ± 13.3	0.7 ± 0.3	69.2 ± 12.6	15.4 ± 23.3	1.0 ± 0.4	12.6 ± 13.6
Wiping/Dusting	60.6 ± 16.0	0.7 ± 0.3	63.0 ± 14.0	35.2 ± 17.0	1.4 ± 0.6	35.3 ± 15.9
Writing	97.9 ± 3.2	0.1 ± 0.1	97.0 ± 2.9	74.2 ± 37.5	0.5 ± 0.7	70.9 ± 35.0
taking out trash	52.1 ± 11.6	1.0 ± 0.3	53.3 ± 11.0	24.4 ± 13.0	1.4 ± 0.5	25.5 ± 13.2

Table A8-3: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers at the hip and wrist, and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	91.3 ± 8.8	0.1 ± 0.1	91.6 ± 7.9	17.7 ± 30.5	0.8 ± 0.6	11.5 ± 19.7
Bench weight lifting - light	92.5 ± 10.8	0.1 ± 0.2	91.2 ± 11.3	21.1 ± 31.1	1.1 ± 1.1	18.8 ± 23.7
Bench weight lifting - moderate	87.1 ± 15.3	0.2 ± 0.1	87.3 ± 12.7	11.5 ± 28.7	0.5 ± 0.4	8.0 ± 17.4
Bicep curls - hard	91.5 ± 7.3	0.2 ± 0.2	90.0 ± 8.8	22.1 ± 33.8	1.2 ± 1.4	14.8 ± 19.7
Bicep curls - light	90.0 ± 10.0	0.2 ± 0.2	90.9 ± 9.0	33.5 ± 32.1	1.1 ± 1.5	32.1 ± 24.1
Bicep curls - moderate	89.0 ± 8.6	0.2 ± 0.2	88.7 ± 8.8	42.1 ± 41.0	1.3 ± 1.3	30.4 ± 25.6
Calisthenics - Crunches	97.4 ± 3.6	0.0 ± 0.0	97.5 ± 2.8	53.2 ± 40.0	0.4 ± 0.7	56.4 ± 39.0
Calisthenics - Sit ups	92.1 ± 6.6	0.1 ± 0.1	92.4 ± 5.7	42.6 ± 32.4	0.6 ± 0.4	44.7 ± 31.6
Cycling - Cycle hard - Cycle 80rpm	86.9 ± 9.3	0.2 ± 0.2	86.6 ± 7.8	15.9 ± 25.1	1.1 ± 1.0	14.0 ± 18.7
Cycling - Cycle light - Cycle 100rpm	97.8 ± 3.2	0.0 ± 0.0	97.0 ± 3.7	90.4 ± 20.0	0.2 ± 0.3	89.4 ± 15.5
Cycling - Cycle light - Cycle 60rpm	98.3 ± 3.3	0.0 ± 0.1	97.9 ± 2.9	80.9 ± 22.8	0.3 ± 0.4	81.1 ± 16.4
Cycling - Cycle light - Cycle 80rpm	95.6 ± 4.6	0.1 ± 0.1	95.8 ± 4.4	48.5 ± 38.1	1.3 ± 1.2	41.0 ± 27.4
Cycling - Cycle moderate - Cycle 80rpm	89.2 ± 6.9	0.2 ± 0.1	89.7 ± 6.1	36.9 ± 32.0	1.4 ± 1.1	31.1 ± 24.6
Lying down	100.0 ± 0.2	0.0 ± 0.0	99.9 ± 0.3	89.5 ± 20.4	0.6 ± 1.0	89.7 ± 13.2
Rowing - Rowing hard - Rowing 30spm	79.0 ± 17.5	0.4 ± 0.3	77.0 ± 16.6	21.7 ± 23.5	1.0 ± 0.9	18.1 ± 17.1
Rowing - Rowing light - Rowing 30spm	81.9 ± 9.4	0.3 ± 0.2	83.6 ± 9.6	33.4 ± 31.9	1.2 ± 1.1	29.6 ± 23.7
Rowing - Rowing moderate - Rowing 30spm	72.3 ± 17.5	0.5 ± 0.3	72.1 ± 15.2	30.1 ± 32.2	1.4 ± 1.2	23.7 ± 17.7
Running - Treadmill 4mph - Treadmill 0	97.1 ± 4.0	0.0 ± 0.1	97.2 ± 3.0	40.2 ± 42.2	1.8 ± 2.1	33.9 ± 34.1
Running - Treadmill 5mph - Treadmill 0	95.5 ± 3.8	0.1 ± 0.1	95.2 ± 3.0	52.6 ± 30.6	1.2 ± 0.9	46.5 ± 21.4
Running - Treadmill 6mph - Treadmill 0	93.2 ± 7.1	0.1 ± 0.1	93.4 ± 4.9	48.8 ± 33.8	0.6 ± 0.5	46.8 ± 27.3
Sitting	97.5 ± 3.9	0.1 ± 0.1	95.9 ± 5.7	25.8 ± 37.0	1.2 ± 1.5	22.8 ± 33.8
Sitting - Fidget feet legs	94.3 ± 5.5	0.1 ± 0.1	94.2 ± 5.7	60.9 ± 30.7	0.4 ± 0.5	61.1 ± 24.3
Sitting - Fidget hands arms	96.1 ± 4.7	0.1 ± 0.1	94.6 ± 4.2	50.0 ± 32.0	0.9 ± 0.8	45.0 ± 27.8
Stairs - Ascend stairs	90.5 ± 7.4	0.2 ± 0.1	90.4 ± 6.2	43.5 ± 25.9	1.3 ± 1.1	39.4 ± 22.6
Stairs - Descend stairs	88.5 ± 7.4	0.2 ± 0.2	88.9 ± 7.0	44.2 ± 22.3	1.0 ± 0.9	43.2 ± 20.2
Standing	95.3 ± 5.6	0.1 ± 0.1	95.5 ± 4.1	46.9 ± 41.6	0.9 ± 0.8	38.8 ± 29.4
Walking - Treadmill 2mph - Treadmill 0	97.1 ± 3.7	0.1 ± 0.1	95.6 ± 3.3	53.8 ± 35.6	0.7 ± 1.1	56.1 ± 32.0
Walking - Treadmill 3mph - Treadmill 0	79.9 ± 10.3	0.4 ± 0.3	80.6 ± 10.1	24.5 ± 25.1	1.7 ± 1.6	20.1 ± 17.2
Walking - Treadmill 3mph - Treadmill 3 - light	70.7 ± 14.9	0.7 ± 0.3	70.6 ± 14.2	20.1 ± 28.6	1.4 ± 1.3	15.4 ± 18.6
Walking - Treadmill 3mph - Treadmill 6 - moderate	75.1 ± 13.2	0.7 ± 0.3	72.9 ± 12.7	13.3 ± 21.4	1.1 ± 1.2	12.7 ± 14.8
Walking - Treadmill 3mph - Treadmill 9 - hard	81.9 ± 11.0	0.3 ± 0.2	83.4 ± 10.0	21.9 ± 26.1	1.5 ± 1.3	19.7 ± 19.5
kneeling	96.7 ± 3.1	0.0 ± 0.0	96.4 ± 3.0	72.0 ± 39.8	1.0 ± 1.6	65.3 ± 38.7
Carrying groceries	89.1 ± 10.4	0.3 ± 0.2	88.6 ± 9.5	44.4 ± 27.2	1.8 ± 1.4	40.2 ± 24.4
Doing dishes	80.9 ± 12.0	0.6 ± 0.3	79.4 ± 11.1	38.5 ± 24.5	1.2 ± 0.7	37.5 ± 22.6
Gardening	77.0 ± 10.3	0.6 ± 0.3	76.1 ± 11.3	14.7 ± 20.4	1.4 ± 1.2	15.8 ± 20.7
Ironing	82.1 ± 8.8	0.5 ± 0.4	81.3 ± 9.4	42.0 ± 28.4	1.6 ± 0.9	37.1 ± 23.1
Making the bed	58.8 ± 9.6	1.1 ± 0.4	58.5 ± 8.8	36.7 ± 15.8	2.2 ± 1.7	33.6 ± 15.0
Mopping	63.8 ± 13.8	1.0 ± 0.4	62.9 ± 13.9	20.4 ± 11.2	1.7 ± 0.6	20.1 ± 10.4
Playing videogames	97.2 ± 4.7	0.1 ± 0.1	97.5 ± 3.6	35.9 ± 36.1	1.9 ± 2.1	30.6 ± 30.5
Scrubbing a surface	82.0 ± 16.2	0.4 ± 0.3	83.1 ± 15.3	38.5 ± 28.6	1.4 ± 1.8	37.0 ± 27.2
Stacking groceries	61.9 ± 18.0	0.8 ± 0.4	61.8 ± 16.6	22.3 ± 15.3	1.5 ± 0.6	21.4 ± 12.7
Sweeping	57.3 ± 18.0	0.9 ± 0.4	58.8 ± 16.6	28.9 ± 14.6	2.1 ± 1.4	27.8 ± 13.2
Typing	96.5 ± 4.6	0.1 ± 0.1	95.8 ± 4.4	54.3 ± 32.8	1.2 ± 0.8	49.8 ± 27.9
Vacuuming	67.7 ± 14.9	0.8 ± 0.5	67.2 ± 14.8	40.5 ± 20.1	1.6 ± 0.8	38.8 ± 17.1
Walking around block	87.0 ± 7.9	0.3 ± 0.2	87.5 ± 7.8	20.1 ± 20.4	2.0 ± 1.2	17.9 ± 15.6
Washing windows	65.2 ± 13.2	0.7 ± 0.3	67.5 ± 12.6	34.4 ± 16.9	1.4 ± 0.7	34.7 ± 16.3
Watching TV	96.8 ± 4.5	0.1 ± 0.1	97.1 ± 4.2	37.3 ± 34.2	1.2 ± 1.4	33.9 ± 27.5
Weeding	72.2 ± 16.5	0.6 ± 0.4	72.3 ± 15.2	16.7 ± 23.8	1.4 ± 1.2	13.6 ± 15.0
Wiping/Dusting	60.3 ± 12.9	0.8 ± 0.4	62.7 ± 13.7	26.0 ± 13.3	1.5 ± 0.7	27.3 ± 13.7
Writing	96.9 ± 4.2	0.1 ± 0.1	96.4 ± 3.6	54.8 ± 40.8	0.8 ± 1.0	51.9 ± 37.5
taking out trash	57.9 ± 14.9	0.9 ± 0.4	58.9 ± 14.0			

Table A8-4: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers at the hip and foot, and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	75.8 ± 27.2	0.2 ± 0.2	77.3 ± 27.3	6.5 ± 14.9	0.9 ± 1.1	5.4 ± 10.7
Bench weight lifting - light	87.8 ± 13.3	0.1 ± 0.2	88.0 ± 13.6	29.0 ± 38.1	0.8 ± 0.7	25.1 ± 28.9
Bench weight lifting - moderate	83.7 ± 18.8	0.2 ± 0.3	82.2 ± 20.4	18.8 ± 26.1	0.5 ± 0.4	19.2 ± 22.8
Bicep curls - hard	82.1 ± 19.0	0.3 ± 0.2	81.0 ± 16.6	34.3 ± 34.2	1.3 ± 1.3	25.7 ± 23.2
Bicep curls - light	85.4 ± 12.9	0.3 ± 0.3	85.6 ± 11.4	35.4 ± 35.0	1.3 ± 1.1	27.8 ± 21.5
Bicep curls - moderate	80.9 ± 13.9	0.4 ± 0.4	80.7 ± 14.2	9.9 ± 14.8	0.6 ± 0.4	11.7 ± 13.3
Calisthenics - Crunches	96.8 ± 6.0	0.1 ± 0.1	96.4 ± 4.9	53.8 ± 40.1	0.6 ± 1.0	53.8 ± 36.8
Calisthenics - Sit ups	88.0 ± 10.6	0.2 ± 0.2	87.2 ± 10.9	18.3 ± 24.2	0.7 ± 0.3	20.3 ± 25.2
Cycling - Cycle hard - Cycle 80rpm	78.4 ± 20.5	0.3 ± 0.2	78.1 ± 19.6	9.5 ± 16.1	1.0 ± 1.1	9.5 ± 16.0
Cycling - Cycle light - Cycle 100rpm	92.3 ± 18.4	0.1 ± 0.1	92.7 ± 17.3	60.1 ± 36.0	1.2 ± 2.3	56.1 ± 35.6
Cycling - Cycle light - Cycle 60rpm	96.5 ± 4.0	0.1 ± 0.1	95.4 ± 4.6	64.4 ± 28.6	0.9 ± 0.7	59.6 ± 21.5
Cycling - Cycle light - Cycle 80rpm	93.3 ± 7.2	0.1 ± 0.1	93.8 ± 6.7	40.5 ± 33.4	1.8 ± 1.7	31.8 ± 25.7
Cycling - Cycle moderate - Cycle 80rpm	84.3 ± 8.5	0.3 ± 0.2	84.6 ± 7.3	24.4 ± 28.1	1.2 ± 1.1	21.3 ± 22.1
Lying down	99.7 ± 0.6	0.0 ± 0.0	99.6 ± 0.6	88.9 ± 20.5	0.6 ± 1.5	89.6 ± 16.5
Rowing - Rowing hard - Rowing 30spm	74.6 ± 15.9	0.5 ± 0.3	73.8 ± 15.4	31.9 ± 27.9	1.1 ± 0.8	26.9 ± 20.2
Rowing - Rowing light - Rowing 30spm	78.9 ± 12.5	0.4 ± 0.2	79.5 ± 11.5	42.2 ± 30.5	1.5 ± 1.8	36.0 ± 19.5
Rowing - Rowing moderate - Rowing 30spm	68.8 ± 16.0	0.6 ± 0.3	68.5 ± 14.4	25.5 ± 22.1	1.0 ± 0.8	24.4 ± 17.0
Running - Treadmill 4mph - Treadmill 0	96.7 ± 3.3	0.1 ± 0.1	96.5 ± 2.2	39.6 ± 37.7	1.1 ± 0.9	36.0 ± 29.2
Running - Treadmill 5mph - Treadmill 0	93.6 ± 4.2	0.1 ± 0.1	93.3 ± 4.2	65.7 ± 31.1	1.0 ± 1.1	58.6 ± 20.8
Running - Treadmill 6mph - Treadmill 0	89.4 ± 12.8	0.1 ± 0.1	88.9 ± 12.2	60.8 ± 33.2	0.6 ± 0.7	51.6 ± 28.1
Sitting	95.9 ± 3.8	0.1 ± 0.1	94.5 ± 3.6	29.9 ± 35.9	1.0 ± 0.8	26.2 ± 29.3
Sitting - Fidget feet legs	94.5 ± 3.9	0.1 ± 0.1	93.2 ± 4.6	31.4 ± 29.1	1.2 ± 0.9	26.0 ± 22.7
Sitting - Fidget hands arms	92.9 ± 7.5	0.1 ± 0.1	91.5 ± 6.2	48.8 ± 32.7	0.6 ± 0.4	47.9 ± 29.1
Stairs - Ascend stairs	89.2 ± 8.1	0.2 ± 0.1	88.2 ± 8.1	53.0 ± 27.5	0.9 ± 0.4	49.6 ± 23.4
Stairs - Descend stairs	86.3 ± 8.2	0.2 ± 0.2	86.5 ± 7.4	44.3 ± 22.2	1.8 ± 1.5	37.9 ± 20.1
Standing	92.2 ± 10.2	0.1 ± 0.2	91.9 ± 9.3	19.4 ± 23.8	1.5 ± 0.9	14.7 ± 14.0
Walking - Treadmill 2mph - Treadmill 0	95.7 ± 4.0	0.1 ± 0.2	94.9 ± 4.6	50.6 ± 33.2	0.8 ± 0.7	50.3 ± 30.0
Walking - Treadmill 3mph - Treadmill 0	83.4 ± 8.7	0.4 ± 0.2	82.8 ± 8.9	14.2 ± 19.1	1.7 ± 1.5	11.7 ± 14.1
Walking - Treadmill 3mph - Treadmill 3 - light	71.2 ± 13.5	0.6 ± 0.3	72.0 ± 12.7	15.2 ± 15.1	1.5 ± 1.2	14.8 ± 13.5
Walking - Treadmill 3mph - Treadmill 6 - moderate	75.6 ± 12.1	0.7 ± 0.4	73.7 ± 12.2	20.6 ± 24.5	1.4 ± 1.2	17.5 ± 16.8
Walking - Treadmill 3mph - Treadmill 9 - hard	83.8 ± 11.2	0.3 ± 0.2	84.6 ± 10.2	20.5 ± 25.0	1.5 ± 1.2	18.2 ± 19.5
kneeling	93.7 ± 6.6	0.1 ± 0.1	93.5 ± 6.1	22.4 ± 24.3	1.3 ± 1.2	19.4 ± 19.9
Carrying groceries	85.2 ± 12.0	0.4 ± 0.3	84.9 ± 12.2	38.0 ± 22.5	1.6 ± 1.2	35.5 ± 18.0
Doing dishes	72.7 ± 12.1	0.7 ± 0.3	71.8 ± 10.9	32.2 ± 20.0	1.6 ± 0.8	30.3 ± 17.9
Gardening	65.0 ± 16.8	0.8 ± 0.2	64.4 ± 14.7	15.8 ± 18.7	1.3 ± 0.7	15.9 ± 17.0
Ironing	70.9 ± 11.5	0.8 ± 0.4	70.6 ± 11.2	32.1 ± 16.3	1.7 ± 1.1	30.9 ± 13.8
Making the bed	55.2 ± 9.4	1.1 ± 0.3	55.0 ± 8.5	34.1 ± 12.2	2.2 ± 1.4	30.7 ± 11.5
Mopping	53.5 ± 14.8	1.2 ± 0.4	53.1 ± 13.8	22.6 ± 11.3	2.0 ± 0.7	21.6 ± 9.1
Playing videogames	96.6 ± 5.2	0.1 ± 0.1	96.4 ± 4.4	27.4 ± 35.6	1.7 ± 1.3	23.7 ± 31.2
Scrubbing a surface	65.8 ± 19.6	0.8 ± 0.4	65.9 ± 18.9	29.2 ± 16.6	1.8 ± 1.0	27.0 ± 14.4
Stacking groceries	49.5 ± 15.1	1.0 ± 0.3	49.2 ± 14.2	19.5 ± 12.2	2.0 ± 0.8	17.0 ± 10.0
Sweeping	52.8 ± 17.4	1.0 ± 0.4	53.2 ± 15.8	27.3 ± 14.8	1.9 ± 0.5	26.3 ± 14.5
Typing	94.7 ± 6.3	0.2 ± 0.2	93.6 ± 5.7	44.0 ± 35.4	0.8 ± 0.4	44.9 ± 31.8
Vacuuming	59.3 ± 17.9	1.0 ± 0.5	58.9 ± 17.5	31.8 ± 19.7	1.8 ± 0.7	29.4 ± 15.8
Walking around block	87.4 ± 7.7	0.3 ± 0.2	86.9 ± 7.1	26.9 ± 24.9	2.5 ± 1.9	21.4 ± 18.0
Washing windows	46.1 ± 13.9	1.1 ± 0.4	48.2 ± 13.5	21.2 ± 13.2	1.7 ± 0.7	22.0 ± 13.5
Watching TV	94.8 ± 5.2	0.1 ± 0.1	96.0 ± 3.8	46.8 ± 40.8	1.3 ± 1.2	40.5 ± 34.4
Weeding	60.1 ± 11.9	0.8 ± 0.2	62.1 ± 9.9	8.5 ± 9.8	1.0 ± 0.7	10.3 ± 11.6
Wiping/Dusting	53.9 ± 17.7	1.0 ± 0.5	54.7 ± 17.5	21.6 ± 13.4	1.5 ± 0.5	22.1 ± 12.0
Writing	94.3 ± 6.9	0.1 ± 0.2	94.4 ± 5.8	37.7 ± 30.8	1.8 ± 1.8	32.8 ± 24.6
taking out trash	44.0 ± 10.9	1.0 ± 0.4	46.0 ± 10.2	19.5 ± 11.6	1.5 ± 0.4	20.7 ± 11.6

Table A8-5: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers at the hip, and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	83.9 ± 14.5	0.2 ± 0.3	82.0 ± 16.6	19.3 ± 26.9	0.5 ± 0.6	16.4 ± 19.2
Bench weight lifting - light	89.6 ± 13.0	0.2 ± 0.2	85.9 ± 13.6	36.5 ± 25.1	0.7 ± 0.6	37.0 ± 22.7
Bench weight lifting - moderate	81.1 ± 16.4	0.2 ± 0.1	81.3 ± 15.1	14.1 ± 16.6	1.0 ± 0.8	11.1 ± 12.8
Bicep curls - hard	85.8 ± 13.8	0.2 ± 0.2	86.2 ± 12.4	27.4 ± 27.1	1.0 ± 1.0	24.3 ± 20.3
Bicep curls - light	86.1 ± 10.8	0.3 ± 0.2	86.5 ± 10.3	30.1 ± 31.1	1.2 ± 1.4	26.2 ± 18.4
Bicep curls - moderate	84.8 ± 11.7	0.3 ± 0.2	84.0 ± 10.6	27.2 ± 26.9	1.1 ± 0.9	24.0 ± 19.5
Calisthenics - Crunches	95.6 ± 5.1	0.1 ± 0.1	94.8 ± 4.9	20.9 ± 21.3	0.7 ± 0.7	23.0 ± 21.9
Calisthenics - Sit ups	95.2 ± 4.0	0.1 ± 0.1	93.2 ± 4.6	36.8 ± 33.7	0.7 ± 0.6	37.6 ± 33.0
Cycling - Cycle hard - Cycle 80rpm	82.0 ± 14.9	0.3 ± 0.2	82.2 ± 12.9	30.0 ± 32.2	1.3 ± 1.0	23.2 ± 19.4
Cycling - Cycle light - Cycle 100rpm	98.5 ± 2.7	0.0 ± 0.1	97.6 ± 2.6	84.8 ± 27.8	0.5 ± 1.0	79.2 ± 30.4
Cycling - Cycle light - Cycle 60rpm	96.5 ± 4.4	0.1 ± 0.1	96.7 ± 3.2	80.4 ± 25.5	0.4 ± 0.4	79.8 ± 20.0
Cycling - Cycle light - Cycle 80rpm	91.3 ± 8.2	0.2 ± 0.2	91.2 ± 8.2	38.9 ± 26.4	1.0 ± 1.0	38.9 ± 17.3
Cycling - Cycle moderate - Cycle 80rpm	84.0 ± 12.8	0.3 ± 0.2	84.0 ± 12.0	33.0 ± 24.7	1.0 ± 0.8	31.5 ± 17.5
Lying down	99.9 ± 0.3	0.0 ± 0.0	99.7 ± 0.4	91.6 ± 18.4	0.5 ± 1.0	91.2 ± 13.9
Rowing - Rowing hard - Rowing 30spm	74.3 ± 18.9	0.5 ± 0.4	72.6 ± 19.0	26.0 ± 28.5	1.2 ± 1.1	22.2 ± 18.2
Rowing - Rowing light - Rowing 30spm	77.8 ± 15.6	0.4 ± 0.3	77.9 ± 15.2	40.3 ± 30.9	1.4 ± 1.1	33.4 ± 20.4
Rowing - Rowing moderate - Rowing 30spm	66.5 ± 16.1	0.6 ± 0.3	67.0 ± 15.8	22.4 ± 29.4	1.1 ± 1.1	19.2 ± 18.6
Running - Treadmill 4mph - Treadmill 0	93.0 ± 5.8	0.1 ± 0.1	93.2 ± 4.4	27.9 ± 31.2	1.3 ± 1.4	29.8 ± 31.3
Running - Treadmill 5mph - Treadmill 0	92.1 ± 6.7	0.1 ± 0.1	92.6 ± 4.4	45.4 ± 32.7	1.3 ± 0.9	39.7 ± 24.0
Running - Treadmill 6mph - Treadmill 0	93.8 ± 5.0	0.1 ± 0.1	93.3 ± 5.8	52.6 ± 36.1	0.9 ± 0.9	40.3 ± 26.4
Sitting	96.5 ± 3.5	0.1 ± 0.1	96.0 ± 4.1	27.1 ± 38.8	1.2 ± 1.2	24.9 ± 35.2
Sitting - Fidget feet legs	91.6 ± 7.2	0.1 ± 0.1	92.0 ± 5.2	48.8 ± 32.0	0.6 ± 0.6	48.6 ± 25.0
Sitting - Fidget hands arms	93.4 ± 6.1	0.1 ± 0.1	92.0 ± 5.4	44.2 ± 32.6	0.6 ± 0.3	43.2 ± 27.7
Stairs - Ascend stairs	77.8 ± 11.8	0.4 ± 0.2	77.7 ± 11.2	56.1 ± 22.3	1.0 ± 0.4	52.4 ± 18.9
Stairs - Descend stairs	76.4 ± 11.8	0.5 ± 0.2	75.3 ± 10.6	43.9 ± 21.0	1.2 ± 0.8	40.6 ± 17.8
Standing	95.8 ± 5.1	0.1 ± 0.1	95.1 ± 3.9	77.9 ± 32.1	0.5 ± 0.9	71.8 ± 29.9
Walking - Treadmill 2mph - Treadmill 0	96.2 ± 3.4	0.1 ± 0.1	95.2 ± 3.1	66.0 ± 35.2	0.9 ± 1.8	64.3 ± 31.4
Walking - Treadmill 3mph - Treadmill 0	67.3 ± 12.6	0.7 ± 0.3	67.7 ± 11.2	20.6 ± 24.0	1.4 ± 1.2	17.9 ± 16.9
Walking - Treadmill 3mph - Treadmill 3 - light	59.6 ± 15.4	1.0 ± 0.5	58.0 ± 15.4	15.7 ± 15.7	1.3 ± 0.9	16.0 ± 14.0
Walking - Treadmill 3mph - Treadmill 6 - moderate	56.4 ± 12.0	1.0 ± 0.3	56.9 ± 11.2	15.5 ± 17.3	1.3 ± 1.1	14.6 ± 14.0
Walking - Treadmill 3mph - Treadmill 9 - hard	70.8 ± 11.8	0.6 ± 0.3	71.8 ± 11.4	14.1 ± 14.3	1.4 ± 1.1	13.7 ± 12.8
kneeling	97.9 ± 2.4	0.0 ± 0.0	98.2 ± 1.9	87.4 ± 23.2	0.5 ± 1.0	83.7 ± 24.8
Carrying groceries	90.8 ± 6.7	0.3 ± 0.2	89.7 ± 7.3	60.3 ± 29.7	1.2 ± 0.8	57.2 ± 26.1
Doing dishes	73.3 ± 11.6	0.6 ± 0.3	73.0 ± 10.5	42.5 ± 22.4	1.5 ± 0.7	38.2 ± 17.1
Gardening	73.6 ± 11.9	0.7 ± 0.3	72.5 ± 11.0	22.9 ± 21.9	1.2 ± 1.1	24.4 ± 22.8
Ironing	80.8 ± 9.3	0.6 ± 0.3	79.2 ± 9.5	47.4 ± 27.9	1.6 ± 0.9	42.9 ± 21.2
Making the bed	47.2 ± 8.7	1.3 ± 0.4	47.9 ± 9.3	33.0 ± 19.0	2.0 ± 1.2	28.8 ± 16.3
Mopping	57.9 ± 18.3	1.1 ± 0.4	57.2 ± 17.4	26.3 ± 12.1	2.0 ± 1.2	24.9 ± 11.6
Playing videogames	97.0 ± 4.2	0.1 ± 0.1	97.2 ± 3.5	55.4 ± 41.3	1.3 ± 1.4	48.3 ± 35.2
Scrubbing a surface	78.6 ± 19.5	0.5 ± 0.4	78.7 ± 18.5	41.8 ± 29.4	1.7 ± 1.8	36.8 ± 22.9
Stacking groceries	65.0 ± 17.7	0.6 ± 0.3	66.2 ± 16.9	31.1 ± 16.7	1.9 ± 1.2	28.7 ± 15.6
Sweeping	62.3 ± 12.7	1.0 ± 0.4	62.5 ± 13.0	33.7 ± 16.3	1.5 ± 0.7	32.7 ± 13.5
Typing	97.7 ± 2.7	0.1 ± 0.1	97.6 ± 2.4	77.4 ± 27.3	0.6 ± 1.0	76.2 ± 25.0
Vacuuming	69.4 ± 10.5	0.7 ± 0.3	70.2 ± 10.0	45.4 ± 27.4	1.1 ± 0.6	44.0 ± 23.4
Walking around block	83.8 ± 11.8	0.4 ± 0.3	84.0 ± 10.4	37.2 ± 20.6	2.8 ± 1.6	29.6 ± 14.8
Washing windows	64.7 ± 12.1	0.7 ± 0.3	66.5 ± 10.7	40.6 ± 24.0	1.2 ± 0.7	42.1 ± 24.6
Watching TV	96.8 ± 2.6	0.1 ± 0.1	96.6 ± 3.0	30.9 ± 30.5	1.5 ± 1.1	31.4 ± 28.5
Weeding	59.3 ± 22.6	0.8 ± 0.4	61.0 ± 20.5	10.1 ± 16.2	1.5 ± 1.7	10.0 ± 13.3
Wiping/Dusting	56.9 ± 13.7	0.9 ± 0.4	58.8 ± 13.3	38.2 ± 17.4	1.3 ± 0.6	38.6 ± 16.8
Writing	96.8 ± 3.4	0.1 ± 0.1	95.6 ± 2.9	67.9 ± 35.4	0.9 ± 1.6	66.3 ± 35.0
taking out trash	52.4 ± 11.5	1.0 ± 0.4	53.9 ± 12.3	21.6 ± 14.2	1.3 ± 0.6	23.5 ± 14.4

Table A8-6: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers at the dominant wrist and dominant foot, and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	87.5 ± 12.9	0.2 ± 0.2	84.7 ± 12.5	8.0 ± 23.4	0.4 ± 0.6	5.6 ± 11.5
Bench weight lifting - light	93.5 ± 8.2	0.1 ± 0.2	93.3 ± 8.3	41.5 ± 38.4	0.8 ± 0.7	37.2 ± 31.6
Bench weight lifting - moderate	84.8 ± 13.6	0.1 ± 0.1	85.5 ± 12.5	29.0 ± 26.5	0.9 ± 1.0	23.6 ± 16.6
Bicep curls - hard	85.7 ± 11.6	0.2 ± 0.2	86.4 ± 10.7	30.7 ± 34.6	1.1 ± 1.1	25.6 ± 26.2
Bicep curls - light	86.2 ± 9.4	0.3 ± 0.3	86.4 ± 9.8	36.4 ± 35.9	1.1 ± 1.1	30.5 ± 24.5
Bicep curls - moderate	81.0 ± 14.7	0.4 ± 0.3	80.7 ± 13.7	22.6 ± 29.7	1.2 ± 1.0	18.1 ± 18.7
Calisthenics - Crunches	98.2 ± 3.7	0.0 ± 0.0	98.0 ± 2.0	65.2 ± 37.1	0.5 ± 0.9	62.4 ± 35.4
Calisthenics - Sit ups	94.6 ± 4.0	0.1 ± 0.1	93.4 ± 3.2	61.9 ± 32.0	0.3 ± 0.3	63.4 ± 29.3
Cycling - Cycle hard - Cycle 80rpm	81.9 ± 10.8	0.3 ± 0.2	81.4 ± 11.2	27.0 ± 29.0	0.7 ± 0.7	25.5 ± 26.3
Cycling - Cycle light - Cycle 100rpm	98.3 ± 3.9	0.0 ± 0.0	97.7 ± 3.7	90.4 ± 17.8	0.1 ± 0.4	92.0 ± 12.3
Cycling - Cycle light - Cycle 60rpm	99.2 ± 1.5	0.0 ± 0.0	98.6 ± 1.4	91.8 ± 11.8	0.2 ± 0.3	91.4 ± 9.1
Cycling - Cycle light - Cycle 80rpm	94.1 ± 6.4	0.1 ± 0.1	93.9 ± 6.0	50.4 ± 34.8	1.3 ± 1.0	41.9 ± 25.1
Cycling - Cycle moderate - Cycle 80rpm	83.4 ± 10.0	0.3 ± 0.2	84.4 ± 8.6	34.0 ± 27.5	1.3 ± 0.7	29.0 ± 16.3
Lying down	99.9 ± 0.4	0.0 ± 0.0	99.6 ± 0.4	83.0 ± 27.6	1.1 ± 1.5	80.6 ± 23.8
Rowing - Rowing hard - Rowing 30spm	76.8 ± 14.9	0.4 ± 0.3	76.6 ± 14.3	35.1 ± 25.5	1.2 ± 0.9	32.2 ± 19.5
Rowing - Rowing light - Rowing 30spm	83.0 ± 12.5	0.4 ± 0.3	82.9 ± 12.4	42.6 ± 31.8	1.6 ± 1.3	33.8 ± 19.3
Rowing - Rowing moderate - Rowing 30spm	71.4 ± 15.2	0.6 ± 0.3	71.6 ± 15.2	27.5 ± 28.2	1.1 ± 1.1	24.5 ± 19.0
Running - Treadmill 4mph - Treadmill 0	91.8 ± 6.7	0.2 ± 0.1	91.4 ± 5.3	53.2 ± 38.9	0.7 ± 1.0	53.4 ± 37.2
Running - Treadmill 5mph - Treadmill 0	89.2 ± 7.9	0.2 ± 0.1	89.4 ± 6.7	68.0 ± 26.3	1.0 ± 0.9	61.3 ± 21.7
Running - Treadmill 6mph - Treadmill 0	81.6 ± 19.7	0.1 ± 0.1	83.4 ± 17.5	52.0 ± 31.3	0.6 ± 0.6	49.2 ± 28.3
Sitting	96.5 ± 4.7	0.1 ± 0.1	95.9 ± 4.1	43.8 ± 44.5	1.2 ± 1.2	33.6 ± 34.6
Sitting - Fidget feet legs	93.1 ± 9.9	0.1 ± 0.1	93.4 ± 7.5	50.4 ± 34.2	0.4 ± 0.5	52.7 ± 29.9
Sitting - Fidget hands arms	93.4 ± 8.0	0.1 ± 0.2	92.0 ± 7.4	37.2 ± 28.2	0.7 ± 0.7	36.8 ± 23.8
Stairs - Ascend stairs	85.1 ± 7.5	0.4 ± 0.2	83.3 ± 7.8	62.7 ± 23.1	1.0 ± 0.7	56.6 ± 18.7
Stairs - Descend stairs	79.8 ± 7.8	0.3 ± 0.2	80.3 ± 8.2	48.3 ± 24.4	0.7 ± 0.4	48.6 ± 20.1
Standing	95.0 ± 7.4	0.1 ± 0.1	94.3 ± 7.6	68.8 ± 34.8	0.6 ± 0.8	62.7 ± 31.0
Walking - Treadmill 2mph - Treadmill 0	94.6 ± 4.3	0.2 ± 0.1	94.2 ± 3.6	75.5 ± 22.8	0.5 ± 0.7	75.3 ± 18.0
Walking - Treadmill 3mph - Treadmill 0	77.3 ± 13.7	0.6 ± 0.2	76.2 ± 12.0	29.3 ± 24.2	2.0 ± 1.4	24.3 ± 16.0
Walking - Treadmill 3mph - Treadmill 3 - light	60.6 ± 14.4	0.8 ± 0.3	61.3 ± 14.2	11.2 ± 12.2	1.0 ± 0.6	12.4 ± 11.8
Walking - Treadmill 3mph - Treadmill 6 - moderate	67.9 ± 13.6	0.8 ± 0.4	66.5 ± 13.2	17.1 ± 13.4	1.7 ± 1.0	16.4 ± 10.8
Walking - Treadmill 3mph - Treadmill 9 - hard	78.8 ± 11.3	0.5 ± 0.3	79.1 ± 10.6	23.2 ± 25.7	1.2 ± 0.9	21.7 ± 21.4
kneeling	95.4 ± 4.1	0.1 ± 0.1	94.5 ± 3.6	49.4 ± 36.0	0.5 ± 0.5	49.4 ± 30.8
Carrying groceries	87.6 ± 9.8	0.3 ± 0.2	87.8 ± 8.0	53.4 ± 30.1	1.0 ± 0.5	52.9 ± 26.6
Doing dishes	74.1 ± 16.1	0.6 ± 0.4	73.8 ± 14.0	51.1 ± 23.2	1.5 ± 1.1	46.3 ± 19.0
Gardening	75.9 ± 14.7	0.6 ± 0.4	75.4 ± 15.5	19.9 ± 19.5	0.8 ± 0.4	22.8 ± 21.0
Ironing	74.3 ± 15.4	0.7 ± 0.4	72.9 ± 14.3	53.3 ± 24.3	1.4 ± 0.7	49.3 ± 16.5
Making the bed	51.1 ± 12.2	1.2 ± 0.4	51.0 ± 11.8	34.0 ± 13.1	2.1 ± 0.9	30.6 ± 11.2
Mopping	53.0 ± 13.3	1.2 ± 0.3	51.8 ± 11.8	31.4 ± 13.9	1.9 ± 0.6	29.2 ± 11.2
Playing videogames	99.1 ± 1.6	0.0 ± 0.0	99.2 ± 1.2	42.0 ± 36.8	1.1 ± 1.2	41.1 ± 33.7
Scrubbing a surface	68.1 ± 16.5	0.8 ± 0.3	67.6 ± 14.7	29.0 ± 16.5	1.8 ± 0.9	27.4 ± 14.6
Stacking groceries	56.1 ± 15.0	0.8 ± 0.3	57.0 ± 15.2	36.9 ± 18.6	1.4 ± 0.8	34.6 ± 15.0
Sweeping	56.9 ± 11.0	0.9 ± 0.5	58.9 ± 11.8	31.4 ± 12.9	1.5 ± 0.6	32.1 ± 11.9
Typing	99.2 ± 1.2	0.0 ± 0.0	98.9 ± 0.8	77.8 ± 30.4	0.4 ± 0.7	77.5 ± 27.6
Vacuuming	71.2 ± 12.6	0.6 ± 0.2	72.6 ± 10.6	48.4 ± 17.6	1.1 ± 0.5	49.1 ± 13.2
Walking around block	83.8 ± 10.1	0.4 ± 0.2	84.4 ± 8.7	35.7 ± 17.1	2.6 ± 2.2	32.3 ± 16.3
Washing windows	60.8 ± 10.9	0.8 ± 0.4	63.1 ± 11.2	41.3 ± 20.9	1.5 ± 1.3	40.8 ± 22.4
Watching TV	98.5 ± 1.9	0.0 ± 0.0	98.8 ± 1.3	27.5 ± 30.1	2.4 ± 2.5	23.8 ± 25.4
Weeding	62.4 ± 15.2	0.8 ± 0.5	63.9 ± 15.1	8.6 ± 9.2	1.2 ± 0.8	10.3 ± 10.3
Wiping/Dusting	55.6 ± 14.1	1.1 ± 0.4	55.0 ± 14.3	35.5 ± 18.6	1.3 ± 0.6	35.4 ± 16.8
Writing	98.1 ± 2.8	0.1 ± 0.1	97.5 ± 2.2	58.8 ± 38.6	0.6 ± 0.6	58.3 ± 34.4
taking out trash	49.1 ± 13.2	1.0 ± 0.3	50.5 ± 12.8	28.1 ± 16.6	1.4 ± 0.4	28.0 ± 14.3

Table A8-7: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers at the dominant wrist and dominant thigh, and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	50.0 ± 17.9	0.4 ± 0.2	52.2 ± 17.8	15.5 ± 15.4	0.7 ± 0.7	14.0 ± 14.0
Bench weight lifting - light	71.6 ± 15.0	0.5 ± 0.3	71.0 ± 15.1	40.1 ± 24.2	0.8 ± 0.6	41.0 ± 20.7
Bench weight lifting - moderate	59.3 ± 21.0	0.6 ± 0.3	57.4 ± 19.2	22.4 ± 20.1	0.7 ± 0.4	20.1 ± 16.4
Bicep curls - hard	71.2 ± 14.5	0.6 ± 0.3	69.9 ± 14.8	37.4 ± 28.0	1.4 ± 0.8	30.1 ± 19.6
Bicep curls - light	68.5 ± 14.1	0.6 ± 0.3	69.3 ± 13.8	33.7 ± 21.1	1.2 ± 0.6	32.4 ± 16.7
Bicep curls - moderate	62.4 ± 14.4	0.7 ± 0.3	62.7 ± 13.0	22.4 ± 15.0	0.9 ± 0.7	24.6 ± 12.6
Calisthenics - Crunches	87.0 ± 9.9	0.2 ± 0.2	87.0 ± 9.4	35.6 ± 33.8	0.8 ± 0.9	35.8 ± 32.0
Calisthenics - Sit ups	90.7 ± 5.9	0.2 ± 0.2	88.2 ± 6.9	40.0 ± 31.2	0.8 ± 1.2	38.5 ± 30.2
Cycling - Cycle hard - Cycle 80rpm	67.2 ± 24.5	0.6 ± 0.4	65.5 ± 24.6	15.8 ± 21.7	1.3 ± 0.8	13.7 ± 16.3
Cycling - Cycle light - Cycle 100rpm	80.2 ± 10.8	0.4 ± 0.2	79.4 ± 10.8	47.9 ± 27.2	1.1 ± 1.1	45.1 ± 24.0
Cycling - Cycle light - Cycle 60rpm	84.4 ± 12.6	0.4 ± 0.3	82.5 ± 12.4	57.2 ± 25.6	1.2 ± 0.8	51.0 ± 21.3
Cycling - Cycle light - Cycle 80rpm	77.1 ± 19.9	0.5 ± 0.5	76.6 ± 20.2	25.4 ± 20.6	1.7 ± 1.2	24.1 ± 19.2
Cycling - Cycle moderate - Cycle 80rpm	65.7 ± 16.3	0.7 ± 0.4	65.1 ± 16.5	16.4 ± 15.0	1.7 ± 0.7	15.0 ± 12.8
Lying down	99.4 ± 0.9	0.0 ± 0.1	99.3 ± 0.8	57.8 ± 37.8	1.2 ± 1.4	59.6 ± 37.1
Rowing - Rowing hard - Rowing 30spm	66.5 ± 16.5	0.6 ± 0.3	65.7 ± 15.8	31.6 ± 26.0	1.1 ± 0.7	27.1 ± 16.3
Rowing - Rowing light - Rowing 30spm	71.1 ± 13.2	0.7 ± 0.4	69.4 ± 13.5	35.1 ± 17.7	1.2 ± 0.8	34.6 ± 11.8
Rowing - Rowing moderate - Rowing 30spm	56.3 ± 13.3	0.8 ± 0.2	56.9 ± 12.7	25.5 ± 17.3	1.1 ± 1.0	25.6 ± 11.2
Running - Treadmill 4mph - Treadmill 0	87.7 ± 7.5	0.4 ± 0.3	85.3 ± 9.5	29.1 ± 27.3	1.5 ± 1.5	28.4 ± 26.4
Running - Treadmill 5mph - Treadmill 0	88.6 ± 6.7	0.3 ± 0.2	87.1 ± 7.5	40.5 ± 33.1	0.9 ± 0.6	37.3 ± 25.2
Running - Treadmill 6mph - Treadmill 0	84.3 ± 13.4	0.2 ± 0.1	84.1 ± 11.2	30.8 ± 28.1	0.6 ± 0.8	32.2 ± 26.7
Sitting	92.5 ± 6.9	0.1 ± 0.1	91.9 ± 6.7	29.2 ± 36.8	1.6 ± 1.6	23.5 ± 27.8
Sitting - Fidget feet legs	88.7 ± 10.9	0.2 ± 0.2	88.3 ± 11.8	27.6 ± 31.8	0.8 ± 0.8	27.2 ± 28.9
Sitting - Fidget hands arms	81.5 ± 17.1	0.2 ± 0.1	80.7 ± 13.8	28.0 ± 23.4	0.8 ± 0.7	28.9 ± 20.3
Stairs - Ascend stairs	70.5 ± 14.8	0.7 ± 0.3	67.7 ± 13.6	42.6 ± 29.6	1.1 ± 0.5	38.8 ± 24.4
Stairs - Descend stairs	62.5 ± 12.4	0.6 ± 0.2	62.6 ± 11.2	41.4 ± 24.9	1.5 ± 1.0	34.7 ± 18.1
Standing	92.3 ± 7.9	0.1 ± 0.1	91.6 ± 7.7	26.8 ± 31.7	0.8 ± 0.7	24.1 ± 26.5
Walking - Treadmill 2mph - Treadmill 0	90.4 ± 6.4	0.3 ± 0.2	89.0 ± 6.9	51.3 ± 29.7	1.1 ± 1.3	49.3 ± 23.8
Walking - Treadmill 3mph - Treadmill 0	64.8 ± 12.9	0.8 ± 0.3	64.2 ± 11.6	21.1 ± 21.5	1.6 ± 1.0	19.1 ± 16.4
Walking - Treadmill 3mph - Treadmill 3 - light	51.8 ± 15.8	1.2 ± 0.4	50.7 ± 14.5	9.9 ± 19.3	1.1 ± 1.5	8.4 ± 10.4
Walking - Treadmill 3mph - Treadmill 6 - moderate	52.6 ± 13.8	1.1 ± 0.3	52.4 ± 12.6	12.0 ± 18.1	1.3 ± 0.9	11.3 ± 12.1
Walking - Treadmill 3mph - Treadmill 9 - hard	66.0 ± 12.7	0.7 ± 0.3	66.6 ± 12.8	26.5 ± 27.1	1.5 ± 1.2	22.4 ± 18.2
kneeling	91.2 ± 8.1	0.1 ± 0.1	91.9 ± 7.6	42.4 ± 37.0	1.0 ± 1.0	32.6 ± 25.2
Carrying groceries	85.2 ± 11.4	0.4 ± 0.3	84.0 ± 9.4	56.8 ± 35.7	1.0 ± 0.8	54.4 ± 32.6
Doing dishes	48.6 ± 14.6	1.3 ± 0.4	47.7 ± 14.7	37.8 ± 16.1	1.8 ± 0.8	34.4 ± 12.8
Gardening	52.6 ± 19.4	0.9 ± 0.4	53.4 ± 18.4	27.6 ± 25.5	1.0 ± 0.4	28.9 ± 25.5
Ironing	57.8 ± 15.8	1.2 ± 0.5	56.9 ± 15.7	27.3 ± 13.2	2.2 ± 2.0	26.0 ± 11.0
Making the bed	35.3 ± 9.4	1.7 ± 0.5	34.9 ± 8.8	23.6 ± 13.5	1.9 ± 0.8	22.1 ± 12.2
Mopping	41.5 ± 16.8	1.4 ± 0.5	41.1 ± 15.5	22.9 ± 10.6	2.2 ± 1.3	21.1 ± 8.5
Playing videogames	95.9 ± 4.7	0.1 ± 0.2	95.6 ± 4.8	59.7 ± 37.8	1.1 ± 1.3	54.8 ± 31.9
Scrubbing a surface	47.2 ± 13.0	1.1 ± 0.4	48.7 ± 13.5	26.0 ± 18.4	1.7 ± 1.0	25.2 ± 16.5
Stacking groceries	45.2 ± 18.1	1.0 ± 0.5	46.0 ± 19.1	33.4 ± 18.0	1.7 ± 1.0	31.3 ± 15.8
Sweeping	52.4 ± 14.1	1.1 ± 0.5	52.9 ± 12.8	29.6 ± 13.5	1.6 ± 0.6	29.8 ± 13.4
Typing	96.1 ± 3.3	0.1 ± 0.1	96.2 ± 2.8	72.4 ± 31.9	0.4 ± 0.6	74.6 ± 31.0
Vacuuming	55.6 ± 14.2	0.8 ± 0.3	57.9 ± 12.3	49.0 ± 16.4	1.2 ± 0.4	48.5 ± 12.1
Walking around block	78.1 ± 13.5	0.5 ± 0.3	79.1 ± 12.3	28.9 ± 20.6	2.5 ± 1.9	25.1 ± 16.1
Washing windows	56.8 ± 13.8	0.8 ± 0.3	59.6 ± 12.8	39.8 ± 21.0	1.3 ± 1.0	41.1 ± 21.5
Watching TV	92.4 ± 7.5	0.1 ± 0.2	93.7 ± 6.4	26.5 ± 21.9	2.8 ± 2.2	21.9 ± 17.9
Weeding	41.3 ± 16.1	1.3 ± 0.4	41.6 ± 14.9	5.0 ± 6.8	1.0 ± 0.5	6.4 ± 8.6
Wiping/Dusting	43.6 ± 16.9	1.2 ± 0.4	45.4 ± 16.2	25.3 ± 13.8	1.5 ± 0.5	26.1 ± 13.1
Writing	93.4 ± 4.6	0.2 ± 0.1	92.6 ± 4.4	70.3 ± 34.5	1.1 ± 2.2	66.6 ± 32.9
taking out trash	34.6 ± 14.4	1.2 ± 0.3	35.8 ± 13.6	15.0 ± 11.3	1.4 ± 0.4	15.8 ± 11.0

Table A8-8: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers at the dominant wrist, and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	**FP Rate**	**F-Measure**	**TP Rate**	**FP Rate**	**F-Measure**
Bench weight lifting - hard	82.4 ± 19.5	0.2 ± 0.2	82.5 ± 17.9	9.3 ± 14.5	0.5 ± 0.4	8.6 ± 12.9
Bench weight lifting - light	84.2 ± 15.3	0.2 ± 0.2	83.5 ± 14.8	20.1 ± 19.3	1.0 ± 0.5	19.3 ± 17.2
Bench weight lifting - moderate	80.2 ± 17.8	0.2 ± 0.2	80.9 ± 16.8	15.7 ± 15.6	0.9 ± 0.6	14.6 ± 14.2
Bicep curls - hard	86.4 ± 12.2	0.3 ± 0.2	85.8 ± 11.5	23.3 ± 29.3	1.4 ± 1.0	16.6 ± 18.2
Bicep curls - light	81.0 ± 15.6	0.3 ± 0.3	82.1 ± 15.6	24.2 ± 25.6	1.3 ± 1.1	20.9 ± 16.9
Bicep curls - moderate	82.4 ± 15.1	0.4 ± 0.3	81.2 ± 13.8	17.9 ± 21.0	1.0 ± 1.0	16.6 ± 16.1
Calisthenics - Crunches	91.8 ± 9.1	0.2 ± 0.2	90.8 ± 8.4	6.1 ± 9.7	1.4 ± 0.9	5.4 ± 7.2
Calisthenics - Sit ups	93.9 ± 7.0	0.2 ± 0.2	91.3 ± 8.0	26.2 ± 25.4	1.2 ± 1.8	24.2 ± 20.9
Cycling - Cycle hard - Cycle 80rpm	79.9 ± 14.7	0.3 ± 0.3	80.0 ± 12.5	18.7 ± 23.3	0.9 ± 0.8	17.6 ± 18.7
Cycling - Cycle light - Cycle 100rpm	98.7 ± 2.5	0.0 ± 0.0	97.8 ± 2.1	93.3 ± 17.3	0.2 ± 0.2	90.5 ± 13.4
Cycling - Cycle light - Cycle 60rpm	97.4 ± 3.5	0.0 ± 0.1	97.7 ± 2.4	87.4 ± 20.5	0.2 ± 0.3	87.4 ± 15.1
Cycling - Cycle light - Cycle 80rpm	86.4 ± 10.5	0.3 ± 0.2	86.2 ± 9.6	39.2 ± 29.4	1.2 ± 1.0	37.3 ± 23.4
Cycling - Cycle moderate - Cycle 80rpm	76.1 ± 13.8	0.4 ± 0.3	76.4 ± 13.1	45.2 ± 23.9	1.7 ± 1.0	37.0 ± 11.7
Lying down	99.2 ± 1.7	0.1 ± 0.1	99.0 ± 1.7	85.4 ± 22.5	0.9 ± 1.3	84.9 ± 15.9
Rowing - Rowing hard - Rowing 30spm	64.2 ± 25.3	0.6 ± 0.4	64.4 ± 24.6	21.6 ± 28.7	1.0 ± 1.3	18.8 ± 19.5
Rowing - Rowing light - Rowing 30spm	74.3 ± 15.6	0.6 ± 0.4	73.2 ± 15.7	34.8 ± 32.0	1.5 ± 1.0	29.8 ± 23.1
Rowing - Rowing moderate - Rowing 30spm	63.7 ± 19.0	0.8 ± 0.5	63.3 ± 18.6	24.0 ± 23.8	1.0 ± 0.8	23.8 ± 21.9
Running - Treadmill 4mph - Treadmill 0	94.7 ± 4.1	0.1 ± 0.1	94.1 ± 3.1	29.2 ± 23.6	1.6 ± 1.7	28.2 ± 22.5
Running - Treadmill 5mph - Treadmill 0	90.0 ± 6.1	0.2 ± 0.1	89.8 ± 4.6	42.2 ± 23.0	1.0 ± 0.8	42.6 ± 22.9
Running - Treadmill 6mph - Treadmill 0	90.6 ± 6.8	0.1 ± 0.1	91.4 ± 5.3	62.0 ± 29.8	0.8 ± 0.8	51.7 ± 26.7
Sitting	94.3 ± 7.7	0.1 ± 0.1	93.8 ± 7.8	22.4 ± 36.0	1.4 ± 1.7	18.0 ± 25.1
Sitting - Fidget feet legs	89.1 ± 9.4	0.2 ± 0.2	88.3 ± 9.5	50.3 ± 31.5	0.5 ± 0.6	51.7 ± 27.6
Sitting - Fidget hands arms	90.7 ± 8.9	0.2 ± 0.1	89.8 ± 8.6	36.6 ± 25.0	1.1 ± 0.7	31.3 ± 20.2
Stairs - Ascend stairs	71.6 ± 12.1	0.5 ± 0.2	72.9 ± 10.8	41.9 ± 24.6	1.3 ± 0.8	36.8 ± 18.5
Stairs - Descend stairs	73.7 ± 9.0	0.6 ± 0.2	71.5 ± 9.0	37.1 ± 15.7	1.4 ± 0.8	33.9 ± 15.2
Standing	92.7 ± 9.6	0.1 ± 0.1	92.3 ± 8.4	26.6 ± 40.4	1.3 ± 1.1	21.1 ± 30.1
Walking - Treadmill 2mph - Treadmill 0	96.0 ± 3.2	0.2 ± 0.1	94.9 ± 3.2	47.2 ± 29.9	1.2 ± 2.4	50.4 ± 25.3
Walking - Treadmill 3mph - Treadmill 0	58.7 ± 15.1	1.0 ± 0.4	58.1 ± 14.5	20.4 ± 16.5	1.7 ± 1.2	18.9 ± 13.3
Walking - Treadmill 3mph - Treadmill 3 - light	49.2 ± 15.3	1.3 ± 0.4	47.9 ± 15.2	17.7 ± 16.2	1.4 ± 0.9	17.3 ± 12.0
Walking - Treadmill 3mph - Treadmill 6 - moderate	50.5 ± 14.6	1.1 ± 0.4	51.0 ± 14.6	11.9 ± 10.1	1.3 ± 0.8	12.2 ± 9.4
Walking - Treadmill 3mph - Treadmill 9 - hard	57.9 ± 20.3	0.9 ± 0.4	58.6 ± 19.2	13.6 ± 13.4	1.3 ± 0.6	13.8 ± 12.8
kneeling	93.9 ± 9.0	0.0 ± 0.1	95.0 ± 8.1	60.4 ± 36.9	1.7 ± 2.8	52.4 ± 36.5
Carrying groceries	79.1 ± 10.8	0.5 ± 0.3	79.1 ± 11.0	41.4 ± 27.3	1.5 ± 0.8	39.6 ± 23.4
Doing dishes	73.0 ± 13.6	0.7 ± 0.4	72.0 ± 13.0	31.1 ± 17.4	1.7 ± 1.0	28.8 ± 14.8
Gardening	68.3 ± 15.0	0.7 ± 0.4	68.2 ± 14.7	11.8 ± 12.2	1.7 ± 1.6	12.0 ± 13.3
Ironing	77.2 ± 12.9	0.7 ± 0.4	75.9 ± 13.0	28.3 ± 20.4	1.8 ± 0.8	26.8 ± 16.6
Making the bed	45.5 ± 14.1	1.5 ± 0.5	44.5 ± 13.4	23.9 ± 14.5	1.9 ± 0.8	22.5 ± 12.0
Mopping	45.3 ± 20.7	1.4 ± 0.6	45.2 ± 21.1	18.7 ± 11.7	2.0 ± 0.8	17.6 ± 10.8
Playing videogames	87.8 ± 12.1	0.3 ± 0.3	87.7 ± 11.8	12.2 ± 17.1	1.3 ± 0.9	13.2 ± 17.5
Scrubbing a surface	74.6 ± 24.6	0.6 ± 0.6	74.3 ± 24.7	33.8 ± 29.5	2.1 ± 1.8	28.2 ± 23.6
Stacking groceries	46.3 ± 19.1	1.1 ± 0.5	46.0 ± 18.8	11.2 ± 7.9	1.7 ± 0.8	10.8 ± 7.4
Sweeping	39.4 ± 16.3	1.5 ± 0.5	39.3 ± 15.0	15.6 ± 8.0	2.0 ± 0.5	15.8 ± 8.1
Typing	90.3 ± 9.0	0.3 ± 0.3	89.9 ± 8.6	41.0 ± 29.7	1.4 ± 1.0	38.0 ± 21.8
Vacuuming	43.5 ± 20.2	1.3 ± 0.5	44.2 ± 19.6	18.4 ± 13.6	1.7 ± 0.7	18.2 ± 10.7
Walking around block	71.7 ± 15.0	0.6 ± 0.4	72.8 ± 14.5	26.8 ± 12.2	2.4 ± 1.3	23.9 ± 9.8
Washing windows	53.1 ± 14.8	1.1 ± 0.4	53.8 ± 13.8	23.5 ± 16.0	2.0 ± 1.7	23.8 ± 16.2
Watching TV	87.1 ± 15.0	0.4 ± 0.3	86.5 ± 13.5	24.5 ± 28.4	1.9 ± 1.2	21.4 ± 23.5
Weeding	51.5 ± 22.7	0.9 ± 0.6	54.6 ± 23.1	9.4 ± 22.6	1.2 ± 0.9	5.4 ± 7.4
Wiping/Dusting	44.0 ± 12.2	1.1 ± 0.4	46.4 ± 12.6	16.0 ± 9.4	1.7 ± 0.8	16.2 ± 8.7
Writing	92.2 ± 7.7	0.2 ± 0.2	91.8 ± 7.6	43.2 ± 27.1	1.5 ± 1.6	41.9 ± 24.5
taking out trash	45.2 ± 15.9	1.1 ± 0.4	45.9 ± 14.7	9.4 ± 7.2	1.2 ± 0.5	11.0 ± 7.8

Table A8-9: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers at the dominant foot, and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	74.9 ± 21.7	0.3 ± 0.3	74.4 ± 22.0	0.3 ± 1.2	0.7 ± 1.0	0.2 ± 0.8
Bench weight lifting - light	91.0 ± 11.4	0.1 ± 0.1	91.3 ± 9.7	11.8 ± 19.2	1.5 ± 1.3	10.1 ± 18.0
Bench weight lifting - moderate	80.5 ± 17.3	0.2 ± 0.2	82.9 ± 16.0	4.8 ± 11.7	1.8 ± 3.0	2.3 ± 4.3
Bicep curls - hard	80.0 ± 19.7	0.3 ± 0.2	80.7 ± 19.0	10.0 ± 23.1	0.9 ± 1.4	7.9 ± 15.2
Bicep curls - light	86.2 ± 12.8	0.3 ± 0.3	85.7 ± 12.5	16.2 ± 26.3	1.4 ± 1.2	14.6 ± 21.2
Bicep curls - moderate	81.1 ± 14.2	0.4 ± 0.4	80.4 ± 14.8	20.0 ± 31.2	1.5 ± 1.4	14.4 ± 19.8
Calisthenics - Crunches	98.0 ± 2.6	0.0 ± 0.0	97.6 ± 2.2	63.0 ± 41.2	0.9 ± 2.2	65.0 ± 41.4
Calisthenics - Sit ups	94.0 ± 7.5	0.1 ± 0.1	93.1 ± 6.4	80.0 ± 27.8	0.2 ± 0.3	80.0 ± 26.7
Cycling - Cycle hard - Cycle 80rpm	73.2 ± 14.3	0.4 ± 0.3	73.2 ± 14.8	21.4 ± 33.6	1.0 ± 1.0	15.8 ± 20.6
Cycling - Cycle light - Cycle 100rpm	98.4 ± 3.9	0.0 ± 0.0	97.4 ± 3.7	90.4 ± 17.4	0.3 ± 0.8	88.6 ± 17.0
Cycling - Cycle light - Cycle 60rpm	99.2 ± 1.5	0.1 ± 0.0	98.2 ± 1.5	91.9 ± 22.0	0.1 ± 0.2	91.9 ± 20.8
Cycling - Cycle light - Cycle 80rpm	92.8 ± 6.8	0.2 ± 0.2	92.3 ± 7.8	50.2 ± 42.3	1.4 ± 1.4	37.5 ± 29.2
Cycling - Cycle moderate - Cycle 80rpm	76.5 ± 14.5	0.4 ± 0.3	76.9 ± 14.0	42.9 ± 35.6	1.4 ± 1.0	32.3 ± 21.1
Lying down	99.3 ± 1.2	0.1 ± 0.1	99.1 ± 1.4	33.4 ± 27.4	2.2 ± 2.2	36.7 ± 28.5
Rowing - Rowing hard - Rowing 30spm	72.0 ± 18.7	0.5 ± 0.3	71.6 ± 17.8	31.9 ± 31.3	1.0 ± 0.9	27.4 ± 22.4
Rowing - Rowing light - Rowing 30spm	80.7 ± 13.2	0.5 ± 0.3	79.4 ± 13.8	36.3 ± 30.2	1.1 ± 1.0	33.0 ± 23.1
Rowing - Rowing moderate - Rowing 30spm	64.5 ± 19.2	0.7 ± 0.4	65.1 ± 19.1	24.6 ± 30.7	1.1 ± 1.3	21.4 ± 22.8
Running - Treadmill 4mph - Treadmill 0	93.4 ± 5.6	0.2 ± 0.1	92.8 ± 4.4	50.4 ± 35.4	0.7 ± 0.7	50.5 ± 33.2
Running - Treadmill 5mph - Treadmill 0	88.3 ± 9.5	0.2 ± 0.2	89.2 ± 8.6	61.2 ± 26.7	0.8 ± 0.4	58.2 ± 19.5
Running - Treadmill 6mph - Treadmill 0	85.7 ± 11.9	0.2 ± 0.2	85.3 ± 11.6	59.6 ± 37.1	0.6 ± 0.7	52.2 ± 33.0
Sitting	94.3 ± 7.4	0.1 ± 0.2	93.1 ± 7.9	3.5 ± 5.4	1.8 ± 1.4	3.2 ± 5.6
Sitting - Fidget feet legs	92.2 ± 5.8	0.1 ± 0.1	93.5 ± 4.8	41.8 ± 32.9	0.7 ± 0.6	41.4 ± 32.3
Sitting - Fidget hands arms	90.8 ± 11.6	0.1 ± 0.2	90.2 ± 11.0	4.8 ± 11.0	1.9 ± 1.9	2.7 ± 5.4
Stairs - Ascend stairs	81.9 ± 8.7	0.4 ± 0.2	81.1 ± 8.1	54.4 ± 28.2	0.9 ± 0.6	52.8 ± 22.8
Stairs - Descend stairs	77.4 ± 8.2	0.4 ± 0.2	77.9 ± 8.5	40.0 ± 18.7	1.2 ± 0.6	38.1 ± 16.7
Standing	89.5 ± 8.4	0.2 ± 0.2	88.1 ± 8.6	19.7 ± 22.8	1.0 ± 0.6	18.3 ± 18.0
Walking - Treadmill 2mph - Treadmill 0	94.9 ± 4.8	0.2 ± 0.1	93.0 ± 4.3	65.8 ± 28.2	0.6 ± 0.4	65.8 ± 22.9
Walking - Treadmill 3mph - Treadmill 0	71.0 ± 15.5	0.8 ± 0.4	69.2 ± 15.7	20.2 ± 19.3	1.4 ± 1.0	18.8 ± 13.4
Walking - Treadmill 3mph - Treadmill 3 - light	56.2 ± 17.2	1.0 ± 0.4	55.9 ± 17.5	18.9 ± 13.5	1.2 ± 0.9	19.8 ± 11.8
Walking - Treadmill 3mph - Treadmill 6 - moderate	58.3 ± 15.6	0.9 ± 0.4	58.5 ± 14.9	17.0 ± 16.0	1.4 ± 1.0	16.2 ± 12.0
Walking - Treadmill 3mph - Treadmill 9 - hard	74.2 ± 16.2	0.6 ± 0.4	74.0 ± 15.6	18.3 ± 16.0	1.4 ± 1.0	18.3 ± 13.6
kneeling	92.2 ± 8.2	0.2 ± 0.2	90.1 ± 9.1	12.9 ± 23.0	1.0 ± 0.8	13.2 ± 23.3
Carrying groceries	64.8 ± 17.3	0.7 ± 0.4	66.4 ± 17.7	29.8 ± 27.0	2.3 ± 1.2	24.0 ± 18.1
Doing dishes	67.6 ± 16.1	0.9 ± 0.6	65.8 ± 16.3	22.5 ± 13.4	3.0 ± 1.8	17.6 ± 9.2
Gardening	60.0 ± 18.5	1.0 ± 0.5	58.6 ± 19.0	6.7 ± 7.3	2.0 ± 1.3	7.0 ± 8.2
Ironing	63.0 ± 14.9	1.0 ± 0.4	62.7 ± 14.9	29.3 ± 18.9	2.6 ± 1.6	24.4 ± 13.8
Making the bed	43.6 ± 13.1	1.6 ± 0.5	42.4 ± 12.7	23.8 ± 11.1	2.0 ± 0.6	22.7 ± 8.9
Mopping	44.4 ± 11.5	1.6 ± 0.4	42.4 ± 11.5	23.4 ± 15.3	1.8 ± 0.7	22.3 ± 11.1
Playing videogames	97.8 ± 4.6	0.1 ± 0.1	96.8 ± 4.7	19.1 ± 31.5	2.2 ± 2.1	15.4 ± 20.9
Scrubbing a surface	60.7 ± 20.8	0.8 ± 0.4	61.6 ± 19.3	18.6 ± 11.8	2.7 ± 1.9	15.3 ± 9.1
Stacking groceries	39.1 ± 18.3	1.2 ± 0.5	39.9 ± 18.9	14.8 ± 8.8	1.7 ± 0.6	14.5 ± 9.0
Sweeping	29.8 ± 14.0	1.5 ± 0.5	31.1 ± 13.8	13.8 ± 9.8	2.3 ± 0.9	12.8 ± 7.5
Typing	93.2 ± 11.7	0.2 ± 0.4	92.5 ± 11.7	20.0 ± 35.6	1.4 ± 1.6	17.5 ± 28.0
Vacuuming	38.5 ± 10.6	1.4 ± 0.4	39.4 ± 11.0	21.9 ± 10.2	1.6 ± 0.5	22.3 ± 9.5
Walking around block	67.6 ± 16.7	0.7 ± 0.4	68.1 ± 14.8	24.9 ± 19.4	3.0 ± 2.4	20.3 ± 12.8
Washing windows	40.6 ± 12.3	1.3 ± 0.4	41.9 ± 12.3	18.4 ± 11.8	1.8 ± 0.7	18.9 ± 12.8
Watching TV	96.7 ± 5.5	0.1 ± 0.1	96.3 ± 5.0	5.4 ± 13.9	1.4 ± 1.4	5.4 ± 10.1
Weeding	49.2 ± 15.0	0.9 ± 0.4	52.9 ± 13.5	6.7 ± 7.8	1.6 ± 1.4	8.3 ± 10.4
Wiping/Dusting	35.8 ± 15.3	1.3 ± 0.3	37.2 ± 14.7	12.2 ± 8.2	1.6 ± 0.8	13.3 ± 8.6
Writing	94.2 ± 9.9	0.2 ± 0.3	93.8 ± 9.6	1.1 ± 2.6	2.6 ± 2.8	1.4 ± 3.2
taking out trash	43.8 ± 14.0	1.1 ± 0.3	44.7 ± 13.3	17.9 ± 12.1	1.7 ± 0.8	18.2 ± 11.8

Table A8-10: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers at the dominant thigh, and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting - hard	46.2 ± 20.2	0.5 ± 0.2	45.2 ± 18.9	7.4 ± 11.5	0.4 ± 0.3	8.5 ± 13.6
Bench weight lifting - light	70.4 ± 18.6	0.5 ± 0.3	68.1 ± 16.9	44.4 ± 22.1	1.4 ± 1.4	38.7 ± 21.1
Bench weight lifting - moderate	50.0 ± 18.6	0.6 ± 0.3	50.7 ± 19.0	13.0 ± 12.8	1.1 ± 1.1	13.2 ± 13.4
Bicep curls - hard	71.8 ± 18.9	0.5 ± 0.4	71.0 ± 18.0	14.4 ± 19.0	1.0 ± 0.9	13.3 ± 17.0
Bicep curls - light	69.5 ± 14.6	0.6 ± 0.3	69.5 ± 14.2	16.6 ± 19.6	1.8 ± 1.9	14.7 ± 15.9
Bicep curls - moderate	64.9 ± 17.2	0.7 ± 0.4	64.9 ± 17.5	14.0 ± 18.3	1.3 ± 1.0	12.1 ± 13.0
Calisthenics - Crunches	92.0 ± 8.1	0.1 ± 0.1	92.8 ± 7.0	54.9 ± 42.6	0.5 ± 0.6	52.0 ± 38.6
Calisthenics - Sit ups	94.5 ± 5.0	0.1 ± 0.1	93.7 ± 4.5	87.0 ± 24.1	0.2 ± 0.4	85.2 ± 22.8
Cycling - Cycle hard - Cycle 80rpm	78.2 ± 17.4	0.2 ± 0.1	79.2 ± 14.7	37.9 ± 36.3	1.2 ± 1.1	27.3 ± 24.6
Cycling - Cycle light - Cycle 100rpm	97.8 ± 4.1	0.0 ± 0.0	97.8 ± 2.8	98.1 ± 4.4	0.1 ± 0.3	96.5 ± 6.2
Cycling - Cycle light - Cycle 60rpm	98.4 ± 2.4	0.0 ± 0.1	98.0 ± 1.9	95.2 ± 7.3	0.1 ± 0.2	95.0 ± 5.6
Cycling - Cycle light - Cycle 80rpm	93.4 ± 6.9	0.2 ± 0.2	93.1 ± 7.2	33.6 ± 35.2	1.1 ± 1.2	30.0 ± 26.3
Cycling - Cycle moderate - Cycle 80rpm	85.9 ± 11.5	0.3 ± 0.3	84.5 ± 11.9	40.1 ± 34.5	1.2 ± 1.0	33.3 ± 21.8
Lying down	99.9 ± 0.4	0.1 ± 0.1	99.5 ± 0.8	72.4 ± 24.8	0.7 ± 1.3	77.6 ± 15.1
Rowing - Rowing hard - Rowing 30spm	67.8 ± 17.1	0.6 ± 0.3	67.0 ± 16.3	29.3 ± 19.6	1.1 ± 0.8	28.1 ± 14.5
Rowing - Rowing light - Rowing 30spm	72.0 ± 16.2	0.6 ± 0.3	70.7 ± 14.6	50.2 ± 20.3	1.6 ± 0.7	42.8 ± 13.7
Rowing - Rowing moderate - Rowing 30spm	65.1 ± 14.9	0.7 ± 0.3	64.5 ± 13.5	15.0 ± 11.2	0.8 ± 0.6	17.9 ± 10.7
Running - Treadmill 4mph - Treadmill 0	96.2 ± 4.6	0.1 ± 0.1	95.5 ± 4.5	52.5 ± 33.0	1.2 ± 1.3	46.9 ± 27.6
Running - Treadmill 5mph - Treadmill 0	95.0 ± 5.6	0.1 ± 0.1	94.7 ± 4.5	55.2 ± 32.6	0.9 ± 0.7	51.7 ± 25.2
Running - Treadmill 6mph - Treadmill 0	94.0 ± 6.4	0.1 ± 0.1	94.3 ± 4.9	65.7 ± 31.5	0.6 ± 0.9	56.9 ± 29.6
Sitting	88.4 ± 14.2	0.2 ± 0.2	87.3 ± 13.2	16.1 ± 18.1	1.1 ± 0.6	14.7 ± 15.4
Sitting - Fidget feet legs	90.4 ± 7.7	0.2 ± 0.1	87.7 ± 7.4	68.1 ± 34.6	0.4 ± 0.3	64.4 ± 28.7
Sitting - Fidget hands arms	79.4 ± 12.9	0.3 ± 0.2	79.7 ± 13.0	24.7 ± 22.4	1.5 ± 1.5	22.0 ± 20.0
Stairs - Ascend stairs	86.6 ± 10.5	0.3 ± 0.2	84.8 ± 9.8	76.9 ± 23.7	0.6 ± 0.4	73.4 ± 21.3
Stairs - Descend stairs	80.2 ± 12.6	0.3 ± 0.2	80.2 ± 12.1	62.0 ± 27.4	1.0 ± 1.0	56.9 ± 23.8
Standing	84.7 ± 13.4	0.2 ± 0.2	83.6 ± 12.8	28.8 ± 26.0	0.9 ± 0.8	26.9 ± 19.8
Walking - Treadmill 2mph - Treadmill 0	92.0 ± 5.4	0.2 ± 0.2	91.9 ± 5.0	67.0 ± 25.1	0.8 ± 1.2	66.5 ± 22.8
Walking - Treadmill 3mph - Treadmill 0	75.7 ± 14.0	0.6 ± 0.4	74.9 ± 14.1	17.6 ± 17.9	1.3 ± 1.0	17.5 ± 17.4
Walking - Treadmill 3mph - Treadmill 3 - light	67.0 ± 15.6	0.8 ± 0.4	65.5 ± 14.5	13.2 ± 16.1	1.3 ± 0.9	12.4 ± 12.2
Walking - Treadmill 3mph - Treadmill 6 - moderate	64.3 ± 19.1	0.8 ± 0.3	64.2 ± 17.6	20.6 ± 16.4	1.6 ± 1.0	19.9 ± 13.6
Walking - Treadmill 3mph - Treadmill 9 - hard	78.9 ± 11.2	0.4 ± 0.3	80.1 ± 11.5	30.0 ± 22.3	1.1 ± 0.8	31.1 ± 18.9
kneeling	85.3 ± 10.0	0.3 ± 0.2	83.4 ± 11.6	25.4 ± 20.0	1.3 ± 0.9	23.7 ± 19.0
Carrying groceries	76.4 ± 9.1	0.6 ± 0.3	75.9 ± 9.7	25.7 ± 19.7	2.0 ± 1.1	24.2 ± 17.3
Doing dishes	58.7 ± 15.0	1.0 ± 0.3	57.8 ± 13.0	28.2 ± 12.2	2.2 ± 1.1	25.6 ± 11.0
Gardening	54.0 ± 17.1	1.2 ± 0.5	52.7 ± 18.4	15.8 ± 15.0	1.3 ± 0.7	16.9 ± 15.8
Ironing	64.4 ± 12.3	1.0 ± 0.4	62.9 ± 11.7	37.2 ± 14.6	1.5 ± 0.6	37.5 ± 11.5
Making the bed	38.3 ± 10.2	1.5 ± 0.4	38.8 ± 10.0	29.3 ± 11.8	2.0 ± 0.8	27.2 ± 9.0
Mopping	47.6 ± 13.7	1.4 ± 0.4	46.1 ± 13.8	26.0 ± 11.5	1.9 ± 0.5	25.0 ± 10.3
Playing videogames	94.1 ± 6.8	0.2 ± 0.2	93.4 ± 6.6	23.4 ± 33.1	1.9 ± 1.4	19.9 ± 23.9
Scrubbing a surface	53.2 ± 16.8	1.0 ± 0.4	53.7 ± 16.2	21.2 ± 13.9	2.1 ± 1.2	20.1 ± 12.2
Stacking groceries	45.4 ± 14.6	1.0 ± 0.4	46.2 ± 13.9	19.6 ± 9.7	1.5 ± 0.7	19.8 ± 9.5
Sweeping	41.6 ± 16.5	1.4 ± 0.4	41.6 ± 15.9	17.6 ± 5.3	1.9 ± 0.4	17.7 ± 5.3
Typing	89.6 ± 13.3	0.3 ± 0.4	89.6 ± 12.1	14.9 ± 26.9	2.0 ± 1.3	11.7 ± 17.9
Vacuuming	53.0 ± 13.3	0.9 ± 0.4	55.6 ± 13.4	35.8 ± 12.2	1.6 ± 0.9	35.6 ± 11.4
Walking around block	74.0 ± 11.1	0.6 ± 0.2	74.6 ± 9.9	21.0 ± 10.7	3.0 ± 1.8	17.2 ± 8.4
Washing windows	48.1 ± 10.6	1.1 ± 0.4	50.2 ± 11.5	24.8 ± 18.4	1.8 ± 1.0	23.2 ± 14.6
Watching TV	93.8 ± 5.5	0.2 ± 0.2	93.2 ± 6.1	8.0 ± 12.7	1.7 ± 1.2	9.2 ± 15.0
Weeding	46.7 ± 15.1	0.9 ± 0.2	49.8 ± 15.5	16.6 ± 23.2	0.9 ± 0.3	14.6 ± 14.6
Wiping/Dusting	43.9 ± 13.6	1.2 ± 0.4	45.1 ± 13.0	22.1 ± 9.3	1.5 ± 0.7	23.3 ± 9.4
Writing	90.3 ± 13.4	0.2 ± 0.2	90.8 ± 11.8	47.7 ± 37.2	1.7 ± 1.6	40.0 ± 29.3
taking out trash	42.5 ± 16.0	1.1 ± 0.4	43.9 ± 15.4	21.7 ± 13.6	1.4 ± 0.5	22.6 ± 12.7

Table A8-11: Performance of the C4.5 classifier in recognizing the 51 activities in the MIT dataset (without the *unknown* class) using the accelerometers at the dominant upper arm, and the *invariant reduced* feature set over windows of 5.6s in length during subject dependent and independent evaluation.

EXAMPLE CLASSIFIED AS

ORIGINAL LABEL

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0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	408	0	0	1	0	0	0	0	2	0	0	0	1	0	0	0	0	0	1	0	`
0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	1	0	2	0	0	0	1	0	2	0	0	1	1	1	1	0	0	689	0	1	2	4	2	0	1	1	1	0	2	23	1	0	2	2	0	9	a
0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	2	1	646	1	36	4	5	0	3	5	1	4	1	0	11	0	1	25	6	1	b
0	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	3	2	1	0	1	0	0	0	0	2	1	3	371	3	6	4	0	6	1	2	1	2	1	6	0	33	4	3	2	c
0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29	1	675	4	7	0	0	5	2	2	4	0	9	1	0	41	3	7	d
0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	0	3	0	1	0	0	1	6	5	5	6	454	33	1	11	23	30	1	12	8	16	0	4	41	0	64	e
0	0	0	0	1	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	3	0	3	4	22	549	0	9	34	49	0	30	0	21	0	3	10	0	14	f
0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	799	0	0	0	0	0	0	0	2	0	0	2	0	g
0	0	0	1	0	2	3	0	1	0	0	1	0	1	0	0	0	0	0	0	0	1	1	1	1	0	0	1	0	0	0	5	0	1	12	0	5	7	0	597	5	9	0	4	0	11	0	22	5	0	2	h
0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	10	0	7	11	45	0	4	430	35	0	14	0	17	0	7	14	0	9	i
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	1	1	1	0	1	0	0	0	0	1	3	3	7	8	32	58	0	8	25	504	0	33	1	15	0	9	17	1	24	j
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	765	0	0	0	2	0	0	9	0	k
0	0	0	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	7	7	4	14	45	2	4	17	32	1	566	1	10	0	4	20	1	18	l
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3	2	0	0	0	0	1	1	0	2	0	1	1	2	0	29	0	0	0	9	4	0	0	1	1	0	1	670	2	0	1	1	0	5	m
1	3	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	5	1	1	2	0	0	0	2	0	1	0	18	5	11	11	16	2	12	24	9	0	16	0	503	1	14	31	3	7	n
0	1	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	3	0	0	0	796	0	0	1	1	o
1	0	0	0	0	0	1	2	0	0	0	0	0	2	0	0	0	0	0	0	1	0	4	1	2	0	1	0	0	0	1	0	1	5	31	2	2	3	0	9	2	8	0	6	3	9	0	331	4	2	7	p
0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	2	1	0	0	0	0	0	2	25	3	33	36	17	0	7	10	21	1	19	0	23	0	2	507	0	15	q
0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	1	0	1	0	0	0	2	1	0	0	0	9	1	0	0	0	0	0	765	0	r
0	0	0	0	0	1	0	4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2	6	4	0	3	0	0	0	0	0	19	4	6	11	67	20	0	5	14	21	1	21	8	7	0	6	11	0	401	s

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m -> Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash

Figure A8-1: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject dependent manner when features are computed per axis over windows of 5.6s. The activities to recognize are the 51 activities contained in the MIT dataset without including the unknown class.

EXAMPLE CLASSIFIED AS

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	`	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	ORIGINAL LABEL
38	71	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	1	0	0	1	0	1	0	0	0	1	0	0	0	0	A
76	198	142	1	0	0	4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	0	2	0	3	0	0	4	3	0	1	20	0	0	4	4	0	0	0	0	B
68	127	96	2	0	0	7	0	0	0	0	0	0	4	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	1	0	3	0	0	2	0	2	1	10	1	0	1	2	0	0	1	0	C
1	0	21	211	80	90	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	12	13	2	0	4	0	0	2	0	0	0	0	2	1	0	0	0	0	D
0	3	20	184	121	203	12	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	3	0	4	1	3	2	0	1	1	0	0	0	1	0	0	0	0	0	E
0	3	26	243	95	116	39	0	0	0	0	0	0	0	3	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	11	4	4	0	5	0	0	0	0	0	0	0	0	0	0	1	0	0	F
0	3	8	2	6	0	343	0	0	0	2	0	0	4	0	4	2	0	0	0	0	2	8	23	0	0	0	0	0	0	0	0	0	1	1	0	2	18	0	4	0	0	0	4	0	6	0	0	0	0	1	G
0	0	28	3	0	0	31	362	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	12	0	0	1	0	0	0	0	0	0	0	3	0	9	10	0	1	11	0	0	1	0	0	0	0	0	0	0	H
0	0	0	0	0	0	0	0	180	3	10	155	115	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	I
0	0	0	0	0	0	0	0	2	559	0	5	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	J
0	0	0	0	0	0	0	0	31	0	560	0	1	0	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	9	0	0	28	1	0	0	0	5	0	0	0	K
0	0	0	0	0	0	0	0	120	25	2	255	224	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	L
0	0	0	0	0	0	0	0	189	3	6	215	169	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	M
0	0	0	0	0	1	9	0	0	0	0	0	0	2043	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55	0	0	0	2	0	0	0	22	0	0	0	0	N
0	0	0	3	2	0	6	3	0	0	0	0	0	0	143	245	110	0	0	0	0	2	0	0	2	0	0	0	0	0	0	0	7	0	7	0	0	0	0	0	0	0	0	0	0	2	0	9	0	0	0	O
0	0	0	0	2	1	17	9	0	0	0	0	0	0	130	243	161	0	0	0	0	0	6	13	6	0	0	0	0	0	0	0	4	0	5	0	6	0	0	0	15	7	0	0	0	0	0	7	0	0	1	P
0	0	0	2	3	4	10	13	0	0	0	1	0	0	104	262	132	0	0	0	0	2	9	5	2	0	0	0	0	0	0	0	4	0	21	0	9	1	0	4	20	2	0	1	0	2	0	1	0	0	0	Q
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	344	99	32	0	0	0	0	0	0	0	15	1	9	7	0	31	0	0	0	0	0	0	0	0	0	0	0	75	0	0	0	0	0	0	R
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	99	292	150	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	19	0	0	0	0	0	0	6	0	0	0	0	0	0	S
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	42	122	240	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	T
0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	231	4	23	0	0	2	0	0	0	0	0	0	0	1	0	1	0	0	27	1	0	1	29	0	0	1	90	1	1	15	0	U
1	0	0	0	0	0	0	2	0	0	6	5	1	0	0	0	0	0	0	0	14	282	11	1	1	4	3	0	0	0	1	0	0	2	4	12	2	0	31	2	1	6	15	1	2	3	4	1	1	0	4	V
0	12	0	1	0	1	1	1	8	0	0	0	0	0	0	0	0	0	0	0	9	1	228	0	0	4	0	0	0	0	0	0	0	19	8	11	2	3	32	17	2	2	8	0	0	5	20	14	3	2	5	W
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	434	21	1	13	0	1	3	0	0	4	0	0	1	33	5	0	20	1	8	0	7	12	0	0	6	8	0	7	X
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	1	0	37	330	2	24	3	0	12	4	0	15	0	0	3	31	5	0	1	1	15	0	5	28	0	0	8	2	0	14	Y
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	25	0	1	0	0	354	0	0	0	0	0	0	0	31	0	4	0	1	1	0	0	0	0	0	0	7	1	2	1	0	1	Z
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0	0	8	19	1	518	5	1	22	24	0	27	0	0	0	7	7	0	0	0	2	0	9	64	1	0	0	0	0	4	[
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	5	0	0	0	0	0	0	0	0	9	127	180	129	81	0	12	0	0	0	0	0	0	0	0	0	0	0	172	0	0	0	0	0	0	\
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	3	0	8	80	166	112	122	0	31	0	0	0	0	0	0	0	0	1	0	0	181	2	0	0	0	0	0	]
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	15	0	15	94	156	109	144	0	15	0	0	0	0	0	0	0	0	0	0	0	171	0	0	0	0	0	2	^
0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	14	0	0	0	0	0	0	38	0	38	69	114	96	185	0	11	0	0	0	0	0	0	0	0	0	0	0	147	0	0	0	0	0	0	_
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	407	0	1	0	2	2	0	0	4	0	0	0	0	0	0	0	2	0	1	0	`
0	0	0	0	0	0	0	0	2	2	0	2	1	0	0	1	0	15	1	0	0	9	0	11	28	0	31	21	13	20	8	0	457	0	0	1	5	2	8	0	0	1	0	5	91	2	0	5	1	0	10	a
0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	36	0	0	6	0	0	0	0	0	1	0	424	17	109	5	18	2	12	7	4	4	4	0	33	12	2	42	0	17	b
1	0	15	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	7	1	6	3	1	0	0	0	0	0	0	1	0	13	156	5	24	6	3	95	3	12	0	17	0	11	3	46	20	0	11	c
2	0	2	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	44	0	0	22	0	0	0	0	0	0	0	77	9	430	11	18	2	15	12	11	7	7	0	29	8	4	59	1	12	d
0	0	0	0	3	0	1	3	0	0	0	1	0	0	0	0	0	0	0	0	1	0	5	6	17	0	6	0	0	0	2	1	2	10	11	1	308	48	0	28	21	53	0	29	8	35	0	24	28	0	83	e
0	0	0	1	3	1	2	3	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	2	3	1	1	0	0	0	1	0	4	12	8	21	57	252	0	15	75	132	0	56	1	26	0	9	33	0	35	f
0	4	2	1	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	87	4	35	0	0	1	1	0	0	0	0	0	0	0	0	3	0	0	514	1	0	0	10	0	0	1	114	0	0	24	2	g
0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	9	0	0	3	0	0	0	0	1	3	0	21	83	8	33	9	1	296	9	10	6	14	0	65	2	45	68	1	8	h
1	0	1	2	1	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	3	0	0	0	0	0	0	0	0	21	6	13	40	90	0	16	224	38	1	29	0	28	0	22	26	0	26	i
0	2	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	3	3	4	8	2	3	0	0	0	0	0	1	14	21	6	85	109	0	23	29	268	8	37	1	26	0	25	36	0	39	j
0	0	1	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	29	9	36	0	0	1	0	0	0	0	0	0	0	1	0	34	0	1	3	0	0	0	557	0	0	0	70	0	0	27	0	k
0	0	0	0	0	0	0	6	1	0	0	0	0	0	0	0	0	0	0	0	2	3	2	8	12	1	2	0	0	0	0	0	10	8	20	15	46	49	0	9	26	32	2	408	0	5	0	45	30	1	17	l
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	50	1	0	0	0	0	15	32	0	38	42	62	60	43	0	72	0	0	0	35	0	0	0	0	4	0	0	272	0	0	1	1	0	9	m
1	3	1	6	0	1	4	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	7	0	0	4	0	1	0	0	0	1	2	16	14	22	23	26	0	52	45	11	9	10	1	352	1	24	51	0	13	n
1	3	3	0	0	0	1	1	0	0	0	0	0	64	0	0	0	0	0	0	127	5	8	0	0	16	0	0	0	0	0	1	0	2	0	1	0	0	143	2	0	0	38	2	0	1	375	3	0	13	0	o
0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	1	0	0	0	0	5	3	6	4	4	4	1	0	0	1	0	4	2	2	32	4	33	17	2	76	12	22	6	25	1	21	0	110	24	1	14	p
0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	4	1	1	1	0	0	0	0	0	1	49	14	48	26	38	0	40	39	36	4	29	1	55	2	5	306	0	24	q
0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	67	5	4	0	0	65	0	0	0	0	0	4	0	4	0	27	0	2	20	0	0	0	47	0	0	1	50	5	1	481	0	r
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	5	12	17	3	11	0	0	2	2	0	10	25	11	22	101	52	0	10	21	63	0	40	14	10	0	17	26	0	167	s

A -> Bench_weight_lifting_-_hard
B -> Bench_weight_lifting_-_light
C -> Bench_weight_lifting_-_moderate
D -> Bicep_curls_-_hard
E -> Bicep_curls_-_light
F -> Bicep_curls_-_moderate
G -> Calisthenics_-_Crunches
H -> Calisthenics_-_Sit_ups
I -> Cycling_-_Cycle_hard_-_Cycle_80rpm
J -> Cycling_-_Cycle_light_-_Cycle_100rpm
K -> Cycling_-_Cycle_light_-_Cycle_60rpm
L -> Cycling_-_Cycle_light_-_Cycle_80rpm
M -> Cycling_-_Cycle_moderate_-_Cycle_80rpm
N -> Lying_down
O -> Rowing_-_Rowing_hard_-_Rowing_30spm
P -> Rowing_-_Rowing_light_-_Rowing_30spm
Q -> Rowing_-_Rowing_moderate_-_Rowing_30spm
R -> Running_-_Treadmill_4mph_-_Treadmill_0_
S -> Running_-_Treadmill_5mph_-_Treadmill_0_
T -> Running_-_Treadmill_6mph_-_Treadmill_0_
U -> Sitting
V -> Sitting_-_Fidget_feet_legs
W -> Sitting_-_Fidget_hands_arms
X -> Stairs_-_Ascend_stairs
Y -> Stairs_-_Descend_stairs
Z -> Standing
[-> Walking_-_Treadmill_2mph_-_Treadmill_0_
\ -> Walking_-_Treadmill_3mph_-_Treadmill_0_
] -> Walking_-_Treadmill_3mph_-_Treadmill_3__-_light
^ -> Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate
_ -> Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard
` -> kneeling
a -> Carrying_groceries
b -> Doing_dishes
c -> Gardening
d -> Ironing
e -> Making_the_bed
f -> Mopping
g -> Playing_videogames
h -> Scrubbing_a_surface
i -> Stacking_groceries
j -> Sweeping
k -> Typing
l -> Vacuuming
m -> Walking_around_block
n -> Washing_windows
o -> Watching_TV
p -> Weeding
q -> Wiping/Dusting
r -> Writing
s -> taking_out_trash

Figure A8-2: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject independent manner when features are computed per axis over windows of 5.6s. The activities to recognize are the 51 activities contained in the MIT dataset without including the *unknown* class.

All Activities without Discriminating Intensity Levels

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Bench weight lifting	96.2 ± 7.4	0.1 ± 0.1	96.7 ± 4.7	79.4 ± 27.4	0.6 ± 0.9	78.4 ± 24.3
Bicep curls	99.3 ± 0.9	0.1 ± 0.0	99.1 ± 0.6	81.1 ± 32.3	0.4 ± 0.6	81.8 ± 30.2
Calisthenics - Crunches	95.5 ± 5.5	0.0 ± 0.1	96.1 ± 3.8	65.6 ± 34.8	0.8 ± 1.2	62.5 ± 31.4
Calisthenics - Sit ups	95.3 ± 4.5	0.1 ± 0.1	94.4 ± 4.2	76.2 ± 32.2	0.3 ± 0.4	74.4 ± 29.9
Cycling	99.8 ± 0.4	0.0 ± 0.0	99.7 ± 0.3	98.3 ± 2.8	0.4 ± 1.1	97.4 ± 4.2
Lying down	100.0 ± 0.2	0.0 ± 0.0	99.8 ± 0.4	95.9 ± 12.6	0.3 ± 0.6	95.8 ± 8.8
Rowing	99.7 ± 0.5	0.0 ± 0.0	99.6 ± 0.6	89.8 ± 21.0	0.0 ± 0.1	92.5 ± 17.2
Running	99.2 ± 1.3	0.1 ± 0.1	99.0 ± 1.0	83.2 ± 24.6	0.5 ± 0.8	84.3 ± 23.1
Sitting	97.7 ± 2.2	0.1 ± 0.1	97.6 ± 1.8	51.0 ± 26.3	1.8 ± 1.8	50.1 ± 19.0
Stairs - Ascend stairs	91.6 ± 6.0	0.2 ± 0.2	90.4 ± 5.7	79.2 ± 23.6	0.4 ± 0.4	76.3 ± 20.6
Stairs - Descend stairs	89.3 ± 9.7	0.2 ± 0.2	88.7 ± 8.2	60.8 ± 25.5	0.6 ± 0.6	60.4 ± 22.7
Standing	94.2 ± 5.5	0.0 ± 0.1	95.2 ± 3.9	93.4 ± 8.8	0.2 ± 0.3	89.6 ± 9.1
Walking	97.4 ± 2.1	0.5 ± 0.4	97.4 ± 2.0	90.2 ± 7.6	1.6 ± 1.2	90.7 ± 5.6
kneeling	97.1 ± 3.6	0.0 ± 0.1	96.8 ± 3.3	95.4 ± 6.1	0.1 ± 0.3	93.7 ± 8.5
Doing dishes	87.3 ± 5.5	0.4 ± 0.2	86.5 ± 4.3	59.0 ± 28.5	1.2 ± 0.7	52.2 ± 20.9
Gardening	81.8 ± 7.4	0.4 ± 0.2	82.2 ± 8.8	14.1 ± 20.8	1.1 ± 1.0	14.8 ± 18.4
Ironing	85.1 ± 7.8	0.4 ± 0.2	85.6 ± 7.2	48.6 ± 28.6	1.0 ± 0.4	48.0 ± 24.3
Making the bed	61.0 ± 11.3	0.9 ± 0.3	62.2 ± 9.0	38.4 ± 16.3	1.6 ± 0.8	37.1 ± 14.6
Mopping	67.4 ± 13.9	0.8 ± 0.4	66.6 ± 13.6	36.8 ± 14.0	1.9 ± 1.0	33.8 ± 9.2
Playing videogames	99.3 ± 2.3	0.0 ± 0.0	98.9 ± 1.3	60.3 ± 45.0	1.3 ± 1.5	54.2 ± 40.6
Scrubbing a surface	84.2 ± 11.7	0.4 ± 0.3	83.6 ± 12.1	39.7 ± 33.1	1.5 ± 1.7	35.4 ± 26.7
Stacking groceries	67.1 ± 17.3	0.6 ± 0.2	67.0 ± 15.3	33.5 ± 21.6	0.9 ± 0.4	34.6 ± 19.5
Sweeping	66.0 ± 16.7	0.7 ± 0.3	66.7 ± 13.5	34.9 ± 19.4	1.5 ± 0.6	34.4 ± 17.6
Typing	97.8 ± 2.2	0.0 ± 0.1	98.2 ± 2.2	66.3 ± 37.4	0.6 ± 0.6	64.9 ± 34.8
Vacuuming	77.3 ± 10.9	0.6 ± 0.2	77.0 ± 8.8	58.1 ± 23.2	1.0 ± 0.5	56.2 ± 19.7
Washing windows	70.9 ± 9.6	0.6 ± 0.3	72.0 ± 9.2	47.4 ± 22.2	1.3 ± 0.9	46.2 ± 21.3
Watching TV	99.0 ± 2.2	0.1 ± 0.1	98.5 ± 1.9	43.6 ± 43.2	1.1 ± 1.0	40.0 ± 39.4
Weeding	74.4 ± 11.2	0.6 ± 0.3	74.8 ± 9.9	17.6 ± 24.5	1.1 ± 0.6	14.3 ± 15.4
Wiping/Dusting	70.0 ± 11.3	0.7 ± 0.3	70.0 ± 9.9	39.6 ± 21.2	1.5 ± 0.9	37.4 ± 17.8
Writing	98.0 ± 2.7	0.1 ± 0.1	97.1 ± 2.5	76.4 ± 25.4	1.2 ± 1.9	71.3 ± 28.5
taking out trash	64.9 ± 10.7	0.8 ± 0.4	65.4 ± 10.4	26.1 ± 15.0	1.2 ± 0.5	28.3 ± 15.2

Table A8-12: Subject dependent and independent performance of the C4.5 classifier in recognizing the activities contained in the MIT dataset without discriminating among the intensity level of activities (31 activities in total) and without including the *unknown* class. The feature set utilized is the *invariant reduced* feature set computed per axis over windows of 5.6s in length using all the accelerometers (7) available.

E X A M P L E C L A S S I F I E D A S

ORIGINAL LABEL	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_
A	936	2	4	0	0	1	2	0	3	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	2	1	0	0	0	0
B	1	1575	0	0	0	0	0	0	3	0	0	1	0	0	2	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2	0
C	1	2	425	2	0	0	4	0	2	0	0	1	0	1	0	0	0	0	0	0	1	3	0	0	0	0	2	0	0	0	0
D	0	1	0	453	0	0	1	0	1	2	2	0	3	0	0	0	0	0	2	0	2	0	1	0	2	0	0	2	0	0	1
E	0	0	0	0	2890	2	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0
F	1	0	0	0	0	2131	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	2	1	1	0	1	0	1782	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	1	0	2	0	0	1578	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
I	0	4	1	0	2	0	0	0	1244	3	2	2	0	2	0	0	1	0	0	2	3	0	0	1	0	2	2	1	0	1	0
J	0	0	0	5	0	0	0	0	0	541	19	3	3	0	0	0	1	7	0	0	2	0	1	0	2	0	1	3	1	0	3
K	1	1	0	4	0	1	1	3	3	11	486	2	18	0	0	0	0	4	2	0	3	0	0	0	1	0	2	0	0	0	1
L	1	0	3	0	0	0	0	0	4	1	0	405	0	2	4	3	1	0	0	0	2	0	0	1	1	2	0	0	0	0	0
M	0	0	0	2	1	0	1	13	3	15	17	1	4946	0	0	0	0	15	5	0	1	4	4	0	5	0	1	2	4	0	35
N	0	0	0	0	0	0	0	0	0	0	0	1	0	407	0	1	2	0	0	0	5	0	0	0	1	1	0	0	0	1	0
O	0	0	0	0	0	0	0	0	2	0	0	0	0	2	664	0	32	8	0	0	0	2	1	0	6	11	1	1	23	3	2
P	2	0	0	2	1	0	0	0	1	4	2	0	0	1	3	381	0	4	1	0	6	2	7	0	5	2	1	34	1	0	2
Q	0	0	0	0	0	0	0	0	0	0	0	3	0	0	38	3	675	7	6	0	1	3	4	1	5	10	0	0	27	5	3
R	0	0	0	3	0	0	0	1	2	8	5	0	27	0	2	1	6	449	28	0	9	19	31	0	18	16	1	5	39	0	65
S	0	0	0	1	1	0	0	0	0	0	1	0	7	0	6	4	3	24	509	0	10	39	61	0	36	18	0	2	21	0	14
T	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	801	2	0	0	0	0	0	1	0	0	1	0
U	5	4	0	0	1	1	0	0	0	1	1	1	0	3	0	9	1	6	11	0	590	2	11	0	4	23	0	18	3	1	3
V	1	1	1	0	0	1	0	0	1	0	1	0	0	0	9	2	5	20	51	0	5	413	26	0	21	17	0	5	15	0	13
W	0	0	0	3	0	0	0	0	0	4	1	0	9	0	2	7	3	34	73	0	11	36	485	0	20	20	0	5	11	0	32
X	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	762	0	1	3	0	0	9	0
Y	0	0	0	1	0	0	0	0	0	2	1	0	2	2	2	3	7	20	30	2	8	15	26	0	586	11	0	5	15	1	21
Z	3	3	1	2	0	0	0	0	4	0	2	1	3	0	15	4	5	14	22	2	26	22	9	0	12	500	0	14	33	1	5
[	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	803	1	0	0	1
\	1	0	1	1	0	1	0	0	1	8	3	0	2	1	1	31	1	6	2	0	13	8	7	0	8	7	1	326	4	2	5
]	0	0	0	0	0	0	0	0	0	0	1	0	4	1	26	1	33	32	18	0	6	17	20	0	13	31	0	2	512	0	11
^	1	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	7	2	0	0	0	0	770	2
_	0	0	0	0	0	0	0	0	1	4	3	0	40	0	6	6	7	48	15	0	1	17	24	1	13	10	0	7	20	1	419

A -> Bench_weight_lifting
B -> Bicep_curls
C -> Calisthenics_-_Crunches
D -> Calisthenics_-_Sit_ups
E -> Cycling
F -> Lying_down
G -> Rowing
H -> Running
I -> Sitting
J -> Stairs_-_Ascend_stairs
K -> Stairs_-_Descend_stairs
L -> Standing
M -> Walking
N -> kneeling
O -> Doing_dishes
P -> Gardening
Q -> Ironing
R -> Making_the_bed
S -> Mopping
T -> Playing_videogames
U -> Scrubbing_a_surface
V -> Stacking_groceries
W -> Sweeping
X -> Typing
Y -> Vacuuming
Z -> Washing_windows
[-> Watching_TV
\ -> Weeding
] -> Wiping/Dusting
^ -> Writing
_ -> taking_out_trash

Figure A8-3: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject dependent manner when features are computed per axis over windows of 5.6s. The activities to recognize are the activities contained in the MIT dataset without discriminating among intensity levels of an activity (31 activities in total) and without including the unknown class.

EXAMPLE CLASSIFIED AS

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	[	\	]	^	_	ORIGINAL LABEL
837	18	30	0	1	0	0	0	13	0	0	0	0	0	2	5	8	0	5	12	3	2	1	1	0	2	9	1	1	2	1	A
82	1349	133	0	1	0	3	0	1	0	0	0	0	0	4	1	4	1	4	1	0	0	0	1	0	0	0	0	0	0	1	B
69	16	294	17	0	1	2	0	1	0	0	0	0	0	0	1	1	3	4	0	2	0	0	1	20	12	0	0	0	0	0	C
0	33	1	353	5	1	1	0	28	1	1	0	0	0	0	3	0	6	4	0	0	10	19	1	3	1	1	0	0	0	1	D
0	0	0	0	2850	0	0	8	23	1	0	0	13	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	E
2	0	7	0	0	2043	0	0	0	0	0	0	0	0	0	0	0	0	0	56	1	0	0	0	0	0	23	0	0	0	0	F
0	13	15	10	0	0	1625	0	11	5	1	0	12	0	0	1	0	16	39	0	9	8	10	0	0	0	0	12	1	0	0	G
0	0	0	0	19	0	0	1374	0	0	1	0	196	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	H
5	2	0	5	6	1	0	0	645	1	0	23	3	2	67	13	23	1	3	131	15	1	19	88	11	12	113	9	1	63	10	I
0	0	0	1	0	0	2	0	1	481	21	0	41	0	0	0	0	12	3	0	0	0	8	0	2	0	0	6	4	1	9	J
0	0	0	1	3	0	0	1	0	36	341	1	89	0	0	2	0	26	4	0	0	0	8	0	4	0	0	3	7	0	18	K
0	0	0	0	0	0	0	0	3	0	0	402	0	0	2	0	8	0	1	1	0	2	0	3	0	6	1	0	0	0	1	L
0	0	0	0	93	0	1	139	3	49	106	0	4567	1	0	0	0	24	10	0	1	0	6	0	21	5	0	7	2	0	40	M
0	0	1	0	0	1	0	0	1	0	0	0	0	399	2	4	0	1	0	0	6	0	0	0	0	0	0	3	0	0	1	N
0	0	0	0	0	0	0	0	14	0	0	2	0	0	446	11	78	7	18	1	29	9	6	0	4	33	12	7	56	2	23	O
16	0	1	0	0	0	1	0	27	1	2	1	0	6	7	103	7	8	5	1	102	1	27	0	11	19	3	79	28	0	6	P
1	1	1	0	0	0	0	0	20	0	0	8	0	0	119	23	393	32	20	2	12	9	7	5	25	20	16	13	47	6	11	Q
0	2	6	4	1	0	1	2	2	8	11	0	25	1	10	7	4	299	58	0	32	25	55	0	20	29	0	30	22	0	81	R
0	6	0	4	0	0	1	0	2	3	4	2	1	1	10	5	17	71	278	0	20	91	91	0	49	18	0	11	40	0	32	S
5	1	0	0	0	8	0	0	152	0	0	0	0	0	8	0	1	0	0	484	0	0	1	7	0	0	30	1	0	108	0	T
0	0	1	0	0	0	0	0	12	0	1	2	1	8	17	90	11	19	7	5	295	5	5	0	10	74	0	46	63	9	18	U
0	1	1	21	0	1	0	0	2	0	1	2	0	0	16	17	20	32	114	0	22	220	32	0	20	43	0	9	20	0	14	V
0	0	1	3	0	0	0	0	3	7	5	1	9	0	15	18	8	77	110	10	23	48	268	0	31	16	0	23	36	0	44	W
0	0	0	0	0	0	0	0	27	0	0	5	1	9	2	22	7	0	0	1	0	0	0	524	0	1	61	0	0	119	0	X
0	0	0	3	0	0	0	0	2	8	11	1	2	6	6	24	12	25	54	1	21	19	39	0	443	6	0	38	25	0	14	Y
1	3	6	1	0	0	0	0	10	0	2	2	6	1	24	13	26	18	17	2	48	23	9	3	11	374	1	29	58	0	15	Z
1	1	0	1	0	64	0	0	148	0	0	17	1	1	0	1	1	0	0	139	2	1	0	11	0	1	345	1	0	74	0	[
0	0	3	5	0	0	1	0	20	9	3	2	8	1	3	41	7	27	27	2	60	8	32	3	21	25	9	89	21	5	9	\
0	1	0	0	0	0	0	0	4	1	5	0	6	0	41	19	48	18	38	0	57	15	33	0	26	77	2	9	306	1	21	]
6	0	0	0	0	0	0	0	23	0	0	0	0	2	3	1	12	0	4	12	5	0	0	77	0	0	41	3	0	597	0	^
0	0	0	1	0	0	0	1	8	9	15	2	29	1	23	19	15	98	46	0	16	19	52	0	30	19	0	21	32	0	187	_

A -> Bench_weight_lifting
B -> Bicep_curls
C -> Calisthenics_-_Crunches
D -> Calisthenics_-_Sit_ups
E -> Cycling
F -> Lying_down
G -> Rowing
H -> Running
I -> Sitting
J -> Stairs_-_Ascend_stairs

K -> Stairs_-_Descend_stairs
L -> Standing
M -> Walking
N -> kneeling
O -> Doing_dishes
P -> Gardening
Q -> Ironing
R -> Making_the_bed
S -> Mopping
T -> Playing_videogames

U -> Scrubbing_a_surface
V -> Stacking_groceries
W -> Sweeping
X -> Typing
Y -> Vacuuming
Z -> Washing_windows
[-> Watching_TV
\ -> Weeding
] -> Wiping/Dusting
^ -> Writing
_ -> taking_out_trash

Figure A8-4: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject independent manner when features are computed per axis over windows of 5.6s. The activities to recognize are the activities contained in the MIT dataset without discriminating among intensity levels of an activity (31 activities in total) and without including the unknown class.

Postures and Ambulatory Motions with MET Intensity Levels

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Lying down	99.9 ± 0.3	0.0 ± 0.0	99.7 ± 0.3	99.3 ± 1.3	0.1 ± 0.4	99.1 ± 1.9
Moderate	96.4 ± 1.7	2.4 ± 1.2	96.4 ± 1.4	86.8 ± 5.4	13.0 ± 5.4	83.8 ± 3.6
Running - Treadmill 4mph - Treadmill 0	97.7 ± 2.3	0.1 ± 0.1	97.0 ± 2.6	53.0 ± 36.1	1.9 ± 2.3	47.9 ± 30.6
Running - Treadmill 5mph - Treadmill 0	94.7 ± 3.3	0.1 ± 0.1	94.9 ± 2.8	52.8 ± 34.1	1.4 ± 1.1	47.5 ± 26.2
Running - Treadmill 6mph - Treadmill 0	91.0 ± 13.2	0.1 ± 0.1	91.9 ± 10.2	51.3 ± 40.0	0.8 ± 0.9	45.0 ± 33.4
Sitting	96.1 ± 3.9	0.2 ± 0.2	96.2 ± 3.2	73.7 ± 19.3	1.6 ± 1.8	73.3 ± 16.8
Standing	93.3 ± 7.0	0.1 ± 0.1	94.5 ± 6.0	94.2 ± 12.1	0.2 ± 0.7	92.8 ± 13.6
Vigorous	93.3 ± 3.5	1.3 ± 0.6	93.8 ± 2.9	66.0 ± 15.4	5.3 ± 2.9	69.2 ± 10.7
Walking - Treadmill 2mph - Treadmill 0	97.8 ± 2.4	0.2 ± 0.1	96.4 ± 2.8	75.8 ± 34.2	0.3 ± 0.4	77.7 ± 29.5
Walking - Treadmill 3mph	99.0 ± 1.2	0.2 ± 0.1	98.9 ± 0.8	89.0 ± 23.3	0.7 ± 1.0	89.6 ± 20.5
kneeling	96.6 ± 3.9	0.0 ± 0.1	97.3 ± 3.2	97.9 ± 4.4	0.1 ± 0.2	97.4 ± 5.1

Table A8-13: Subject dependent and independent performance of the C4.5 classifier in recognizing postures and ambulation including METs intensity levels (11 activities in total) and without including the *unknown* class. The feature set utilized is the *invariant reduced* feature set computed per axis over windows of 5.6s in length using all the accelerometers (7) available.

EXAMPLE CLASSIFIED AS / **ORIGINAL LABEL**

A	B	C	D	E	F	G	H	I	J	K	
2130	0	0	0	0	0	2	0	0	0	0	A
3	8552	3	3	0	23	7	228	17	18	8	B
0	0	599	7	0	0	0	2	0	5	0	C
0	0	10	542	19	0	0	0	0	1	0	D
0	0	0	18	387	0	0	0	0	0	0	E
0	41	0	0	0	1223	6	2	1	0	0	F
0	16	0	0	0	12	401	1	0	0	0	G
6	247	3	0	0	4	0	4020	4	6	0	H
0	7	1	0	0	2	1	0	706	5	0	I
0	6	6	0	0	0	0	3	14	2833	0	J
0	7	0	0	0	4	2	1	0	0	405	K

A -> Lying_down
B -> Moderate
C -> Running_-_Treadmill_4mph_-_Treadmill_0_
D -> Running_-_Treadmill_5mph_-_Treadmill_0_
E -> Running_-_Treadmill_6mph_-_Treadmill_0_
F -> Sitting
G -> Standing
H -> Vigurous
I -> Walking_-_Treadmill_2mph_-_Treadmill_0_
J -> Walking_-_Treadmill_3mph
K -> kneeling

Figure A8-5: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject dependent manner when features are computed per axis over windows of 5.6s. The activities to recognize are postures and ambulation including METs intensity levels (11 activities in total) and without including the unknown class.

EXAMPLE CLASSIFIED AS / **ORIGINAL LABEL**

A	B	C	D	E	F	G	H	I	J	K	
2118	4	0	0	0	8	0	2	0	0	0	A
6	7697	0	0	0	319	7	777	17	31	8	B
0	21	308	167	32	0	0	14	0	71	0	C
0	1	132	297	127	0	0	4	0	11	0	D
0	6	59	118	217	0	0	4	0	1	0	E
17	235	0	0	0	940	41	33	0	0	7	F
0	12	0	0	0	9	405	4	0	0	0	G
0	1330	38	1	0	21	0	2876	16	8	0	H
0	104	0	0	0	0	0	55	543	20	0	I
0	63	155	1	0	0	0	75	32	2536	0	J
1	6	0	0	0	1	1	0	0	0	410	K

A -> Lying_down
B -> Moderate
C -> Running_-_Treadmill_4mph_-_Treadmill_0_
D -> Running_-_Treadmill_5mph_-_Treadmill_0_
E -> Running_-_Treadmill_6mph_-_Treadmill_0_
F -> Sitting
G -> Standing
H -> Vigurous
I -> Walking_-_Treadmill_2mph_-_Treadmill_0_
J -> Walking_-_Treadmill_3mph
K -> kneeling

Figure A8-6: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject dependent manner when features are computed per axis over windows of 5.6s. The activities to recognize are postures and ambulation including METs intensity levels (11 activities in total) and without including the unknown class.

Postures and Ambulatory Motions

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Lying down	99.9 ± 0.3	0.1 ± 0.1	99.8 ± 0.3	100.0 ± 0.0	0.2 ± 0.9	99.6 ± 1.9
Running	99.2 ± 1.4	0.2 ± 0.2	98.8 ± 1.2	85.6 ± 23.7	1.6 ± 2.8	85.6 ± 22.5
Sitting	99.0 ± 1.3	0.1 ± 0.1	99.2 ± 0.8	90.9 ± 21.7	0.3 ± 0.5	92.3 ± 19.3
Stairs - Ascend stairs	93.1 ± 5.1	0.3 ± 0.2	93.4 ± 3.9	94.4 ± 6.4	0.7 ± 0.9	91.5 ± 6.6
Stairs - Descend stairs	90.6 ± 8.4	0.4 ± 0.3	91.4 ± 6.8	68.0 ± 25.6	1.3 ± 1.5	68.5 ± 24.4
Standing	97.5 ± 3.9	0.2 ± 0.2	96.5 ± 3.7	96.3 ± 9.6	0.7 ± 2.3	92.7 ± 15.5
Walking	98.9 ± 0.9	0.7 ± 0.7	99.0 ± 0.8	93.2 ± 6.5	4.9 ± 3.5	93.3 ± 4.4
kneeling	99.0 ± 2.0	0.0 ± 0.1	99.1 ± 1.6	98.4 ± 4.3	0.0 ± 0.1	98.6 ± 2.5

Table A8-14: Performance of the C4.5 classifier when recognizing postures and ambulation using the *invariant reduced* feature set computed per axis over windows of 5.6s in length during subject dependent and independent training. All sensors (7) were utilized and the *unknown* class was not included in this experiment.

EXAMPLE CLASSIFIED AS								ORIGINAL LABEL
A	B	C	D	E	F	G	H	
2129	0	1	0	0	2	0	0	A
0	1578	0	0	1	0	11	0	B
1	0	1261	0	5	5	0	1	C
1	0	1	552	19	7	12	0	D
0	4	1	15	493	3	26	2	E
0	0	5	2	2	419	2	0	F
2	19	1	17	13	3	5019	1	G
2	0	0	2	0	0	0	415	H

A -> Lying_down	E -> Stairs_-_Descend_stairs
B -> Running	F -> Standing
C -> Sitting	G -> Walking
D -> Stairs_-_Ascend_stairs	H -> kneeling

Figure A8-7: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject dependent manner when features are computed per axis over windows of 5.6s. The activities to recognize are postures and ambulation (9 activities in total) and without including the unknown class.

EXAMPLE CLASSIFIED AS								ORIGINAL LABEL
A	B	C	D	E	F	G	H	
2132	0	0	0	0	0	0	0	A
0	1425	0	1	1	0	163	0	B
19	0	1160	1	0	83	7	3	C
0	2	0	545	17	0	28	0	D
0	0	0	24	378	0	142	0	E
0	0	15	0	0	414	1	0	F
0	168	4	47	129	0	4725	2	G
0	0	6	0	0	0	1	412	H

A -> Lying_down	E -> Stairs_-_Descend_stairs
B -> Running	F -> Standing
C -> Sitting	G -> Walking
D -> Stairs_-_Ascend_stairs	H -> kneeling

Figure A8-8: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject independent manner when features are computed per axis over windows of 5.6s. The activities to recognize are postures and ambulation (9 activities in total) and without including the unknown class.

Postures

Activity	Subject Dependent			Subject Independent		
	TP Rate	FP Rate	F-Measure	TP Rate	FP Rate	F-Measure
Lying down	99.96 ± 0.20	0.48 ± 0.76	99.83 ± 0.23	100.00 ± 0.00	1.35 ± 6.03	99.59 ± 1.82
Sitting	98.56 ± 2.74	0.30 ± 0.45	98.23 ± 2.50	95.93 ± 17.73	0.94 ± 3.00	95.01 ± 16.96
Standing	97.65 ± 3.22	0.17 ± 0.30	98.22 ± 2.16	98.10 ± 8.52	0.80 ± 2.94	96.83 ± 8.58
kneeling	98.55 ± 2.75	0.10 ± 0.24	98.91 ± 2.00	100.00 ± 0.00	0.00 ± 0.00	100.00 ± 0.00

Table A8-15: Performance per class while recognizing postures using the C4.5 classifier using the invariant reduced feature set computed per axis over windows of 5.6s in length. The unknown class is not considered.

EXAMPLE CLASSIFIED AS				
A	B	C	D	ORIGINAL LABEL
2131	0	1	0	A
1	425	4	1	B
3	5	420	2	C
2	4	0	413	D

A -> Lying_down
B -> Sitting
C -> Standing
D -> kneeling

Figure A8-9: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject dependent manner when features are computed per axis over windows of 5.6s. The activities to recognize are postures (4 activities in total) and without including the *unknown* class.

EXAMPLE CLASSIFIED AS				
A	B	C	D	ORIGINAL LABEL
2132	0	0	0	A
17	395	19	0	B
0	8	422	0	C
0	19	5	395	D

A -> Lying_down
B -> Sitting
C -> Standing
D -> kneeling

Figure A8-10: Confusion Matrix for C4.5 Classifier using the *invariant reduced* feature evaluated in a subject independent manner when features are computed per axis over windows of 5.6s. The activities to recognize are postures (4 activities in total) and without including the *unknown* class.

Appendix A9: Real-Time Interactive Training Study

Recognizing 10 activities of your choice in real-time using three wireless accelerometers

During this short study, you are provided with a software application that will allow you to train a computer program to recognize 10 physical activities, exercises, postures, or activities done in a particular poster of your choice. The computer program will recognize the activities you provide by sensing the motion at your hip, dominant wrist, and dominant foot by means of three small wireless sensors that you will be provided with during this study.

The procedure you need to follow to train the computer program to recognize your activities is simple:

1. Wear the tiny sensor at the following locations: Hip, dominant wrist, and dominant foot.
2. Type in 10 physical activities, exercises, postures, or activities done in a particular poster you want the computer program to recognize that can be executed continuously for 2 minutes.
3. Provide examples of the activities you specified by performing them for two minutes each as indicated by the application. The application will show on the screen the activities you need to perform one at a time, and a counter that indicates your progress. The counter will reach zero once you have finished the training process for a particular activity.

Once you finish the training process, you will hear a message informing you of the successful termination of this phase. The computer program will then start recognizing the activities you provided on the fly. Please feel free to evaluate the performance of the algorithm by executing the activities as many times as you wish. Feel free to experiment and suggest ideas on how the training or recognition of activities can be improved in future versions.

Please be aware that the computer program cannot collect activity examples if the motion signals coming from the sensors are lost due to body blocking or environmental noise. As a result, you might feel at times that the counter on the screen does not decrease as fast as expected. This because signals are not being received, so please be patient.

Subject One

```
Correctly Classified Instances         518               89.6194 %
Incorrectly Classified Instances        60               10.3806 %
Kappa statistic                          0.8847
Mean absolute error                      0.0263
Root mean squared error                  0.1394
Relative absolute error                 14.5864 %
Root relative squared error             46.4629 %
Maximum absolute error deviation             0
Total Number of Instances              578


TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
  0.893     0.017      0.847     0.893     0.87       0.946    bouncing_on_a_ball
  0.948     0.008      0.932     0.948     0.94       0.976    waving_my_hand_to_say_hello
  0.914     0.006      0.946     0.914     0.93       0.969    shaking_my_leg
  0.776     0.025      0.776     0.776     0.776      0.893    Taekwondo_Form_#1
  0.845     0.019      0.831     0.845     0.838      0.935    side_stretch
  0.948     0.01       0.917     0.948     0.932      0.976    jumping_jacks
  0.897     0.008      0.929     0.897     0.912      0.955    punching_as_I_walk_forward
  0.897     0.006      0.945     0.897     0.92       0.961    lifting_dumbells
  0.931     0.01       0.915     0.931     0.923      0.964    riding_a_bike
  0.914     0.008      0.93      0.914     0.922      0.966    playing_the_drums


=== Confusion Matrix ===

  a  b  c  d  e  f  g  h  i  j   <-- classified as
 50  1  0  3  2  0  0  0  0  0 |  a = bouncing_on_a_ball
  3 55  0  0  0  0  0  0  0  0 |  b = waving_my_hand_to_say_hello
  2  2 53  1  0  0  0  0  0  0 |  c = shaking_my_leg
  0  1  2 45  4  3  2  1  0  0 |  d = Taekwondo_Form_#1
  4  0  1  4 49  0  0  0  0  0 |  e = side_stretch
  0  0  0  0  2 55  1  0  0  0 |  f = jumping_jacks
  0  0  0  4  0  2 52  0  0  0 |  g = punching_as_I_walk_forward
  0  0  0  1  2  0  1 52  0  2 |  h = lifting_dumbells
  0  0  0  0  0  0  0  2 54  2 |  i = riding_a_bike
  0  0  0  0  0  0  0  0  5 53 |  j = playing_the_drums
```

Subject Two

```
Correctly Classified Instances         477               91.7308 %
Incorrectly Classified Instances        43                8.2692 %
Kappa statistic                          0.907
Mean absolute error                      0.0222
Root mean squared error                  0.1285
Relative absolute error                 11.2626 %
Root relative squared error             40.8777 %
Maximum absolute error deviation             0
Total Number of Instances              520



=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
  0.982     0.006      0.948     0.982     0.965      0.998    walking
  0.948     0.009      0.932     0.948     0.94       0.987    sitting_still
  0.931     0.017      0.871     0.931     0.9        0.975    scratching_hfead
  0.897     0.009      0.929     0.897     0.912      0.961    carrying_box
  0.897     0.004      0.963     0.897     0.929      0.954    washing_dishes
  0.914     0.019      0.855     0.914     0.883      0.951    shaking_hands
  0.931     0.011      0.915     0.931     0.923      0.966    tossing_ball_in_air
  0.845     0.013      0.891     0.845     0.867      0.928    typing
  0.914     0.004      0.964     0.914     0.938      0.985    talkin_gon_phone



=== Confusion Matrix ===

  a  b  c  d  e  f  g  h  i   <-- classified as
 55  1  0  0  0  0  0  0  0 |  a = walking
  3 55  0  0  0  0  0  0  0 |  b = sitting_still
  0  3 54  0  0  1  0  0  0 |  c = scratching_hfead
  0  0  3 52  0  1  1  1  0 |  d = carrying_box
  0  0  2  1 52  2  1  0  0 |  e = washing_dishes
  0  0  1  1  0 53  1  2  0 |  f = shaking_hands
  0  0  1  1  0  2 54  0  0 |  g = tossing_ball_in_air
  0  0  0  1  2  2  2 49  2 |  h = typing
  0  0  1  0  0  1  0  3 53 |  i = talkin_gon_phone
```

Subject 3

```
Correctly Classified Instances         456               78.8927 %
Incorrectly Classified Instances       122               21.1073 %
Kappa statistic                          0.7655
Mean absolute error                      0.046
Root mean squared error                  0.1953
Relative absolute error                 25.5448 %
Root relative squared error             65.111  %
Maximum absolute error deviation              0
Total Number of Instances              578



=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
  0.768     0.013      0.86      0.768     0.811      0.89     throwing
  0.776     0.038      0.692     0.776     0.732      0.887    bowling
  0.931     0.013      0.885     0.931     0.908      0.962    bouncing
  0.828     0.025      0.787     0.828     0.807      0.915    typing
  0.81      0.021      0.81      0.81      0.81       0.934    stepping
  0.81      0.025      0.783     0.81      0.797      0.906    streching_arm
  0.845     0.013      0.875     0.845     0.86       0.927    walking
  0.707     0.037      0.683     0.707     0.695      0.873    Tennis_serve
  0.638     0.033      0.685     0.638     0.661      0.818    streching_legs
  0.776     0.015      0.849     0.776     0.811      0.901    bending



=== Confusion Matrix ===

  a  b  c  d  e  f  g  h  i  j   <-- classified as
 43  4  0  1  1  0  0  5  2  0 |  a = throwing
  2 45  0  2  1  0  0  5  3  0 |  b = bowling
  1  0 54  0  0  1  1  0  1  0 |  c = bouncing
  0  2  0 48  5  1  1  1  0  0 |  d = typing
  0  2  2  3 47  2  0  1  1  0 |  e = stepping
  0  1  3  2  1 47  1  0  2  1 |  f = streching_arm
  0  1  0  1  3  1 49  3  0  0 |  g = walking
  1  6  0  2  0  3  4 41  1  0 |  h = Tennis_serve
  1  2  2  2  0  3  0  4 37  7 |  i = streching_legs
  2  2  0  0  0  2  0  0  7 45 |  j = bending
```

Subject 4

```
Correctly Classified Instances         516               89.2734 %
Incorrectly Classified Instances        62               10.7266 %
Kappa statistic                          0.8808
Mean absolute error                      0.0242
Root mean squared error                  0.1358
Relative absolute error                 13.4529 %
Root relative squared error             45.2635 %
Maximum absolute error deviation              0
Total Number of Instances              578



=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
  0.929     0.008      0.929     0.929     0.929      0.981    walk
  0.931     0.01       0.915     0.931     0.923      0.987    type_in_computer
  0.741     0.021      0.796     0.741     0.768      0.883    washing_window
  0.948     0.013      0.887     0.948     0.917      0.973    drawing_in_paper
  0.931     0.01       0.915     0.931     0.923      0.977    wiping_surface
  0.914     0.012      0.898     0.914     0.906      0.969    talking_on_the_phone
  0.897     0.013      0.881     0.897     0.889      0.962     sweeping
  0.897     0.01       0.912     0.897     0.904      0.961    combing_my_hair
  0.862     0.017      0.847     0.862     0.855      0.953    hammering_a_nail
  0.879     0.006      0.944     0.879     0.911      0.961    eating


=== Confusion Matrix ===

  a  b  c  d  e  f  g  h  i  j   <-- classified as
 52  2  0  0  0  0  0  1  0  1 |  a = walk
  2 54  2  0  0  0  0  0  0  0 |  b = type_in_computer
  2  2 43  0  0  3  3  1  2  2 |  c = washing_window
  0  0  0 55  1  0  1  0  1  0 |  d = drawing_in_paper
  0  0  0  3 54  0  0  0  1  0 |  e = wiping_surface
  0  0  0  0  3 53  0  0  2  0 |  f = talking_on_the_phone
  0  0  3  1  0  2 52  0  0  0 |  g =  sweeping
  0  0  2  1  0  0  1 52  2  0 |  h = combing_my_hair
  0  0  2  2  0  1  1  2 50  0 |  i = hammering_a_nail
  0  1  2  0  1  0  1  1  1 51 |  j = eating
```

Subject 5

```
Correctly Classified Instances         493               85.2941 %
Incorrectly Classified Instances        85               14.7059 %
Kappa statistic                          0.8366
Mean absolute error                      0.0348
Root mean squared error                  0.1625
Relative absolute error                 19.3456 %
Root relative squared error             54.1615 %
Maximum absolute error deviation              0
Total Number of Instances              578



=== Detailed Accuracy By Class ===

TP Rate   FP Rate   Precision   Recall  F-Measure   ROC Area  Class
  0.946     0.011      0.898     0.946     0.922      0.98     walk
  0.879     0.027      0.785     0.879     0.829      0.952    bicep_curls
  0.776     0.027      0.763     0.776     0.769      0.875    stretching
  0.862     0.023      0.806     0.862     0.833      0.936    applying_cream
  0.793     0.023      0.793     0.793     0.793      0.913    brushing_theet
  0.776     0.015      0.849     0.776     0.811      0.898    wash_dish
  0.879     0.01       0.911     0.879     0.895      0.938    knitting
  0.862     0.01       0.909     0.862     0.885      0.93     wash_hands
  0.81      0.012      0.887     0.81      0.847      0.919    filing_nails
  0.948     0.006      0.948     0.948     0.948      0.98     play_piano



=== Confusion Matrix ===

  a  b  c  d  e  f  g  h  i  j   <-- classified as
 53  0  2  0  0  0  0  0  1  0 |  a = walk
  3 51  2  1  1  0  0  0  0  0 |  b = bicep_curls
  0  7 45  3  0  2  0  0  1  0 |  c = stretching
  0  1  2 50  1  1  3  0  0  0 |  d = applying_cream
  1  2  3  3 46  1  0  1  1  0 |  e = brushing_theet
  1  1  1  1  7 45  0  2  0  0 |  f = wash_dish
  1  0  1  1  1  3 51  0  0  0 |  g = knitting
  0  1  1  2  0  1  2 50  1  0 |  h = wash_hands
  0  2  2  0  2  0  0  2 47  3 |  i = filing_nails
  0  0  0  1  0  0  0  0  2 55 |  j = play_piano
```

Table A9-1. Performance obtained by recognizing participant's activities using a C4.5 classifier with the *invariant reduced* feature set computed per axis over window lengths of 5.6s in length. Performance was measured using 10 Fold Cross-validation.

Appendix A10: Boston Medical Center Data Collection Protocol

In this protocol, two participants performed the script of activities shown in the table below. Each activity was performed one at a time for three to four minutes while participants wore the same set of sensors utilized in the MIT protocol. The indirect calorimeter utilized in this study was the Parvo Medics TrueOne 2400 metabolic measurement system [126].

Activity Performed
Lying quietly on back, arms at side
Sitting in chair
Standing hands at sides, feet shoulder-width apart
Walking on TM, 3 mph, 0% grade
Walking on TM, 3 mph, 4% grade
Walking on TM, 3 mph, 8% grade
Jog on treadmill, 5 mph, 0% (optional activity depending on subject's capacity)
Cycle ergometer (legs), 60 RPM, "light" resistance
Cycle ergometer (legs), 100 RPM, "light" resistance
Cycle ergometer (legs), 60 RPM, "hard" resistance
Carry box with both hands in front of subject (elbows bent at 90 degrees) and walk at 2 mph on treadmill
Jumping Jacks
Perform sit-ups with knees bent and hands behind head—15 in one minute or as many as comfortable
Perform push-ups from the knees—15 in one minute or as many as comfortable
Perform biceps curl with both arms (3 or 5 pound weight)—15 curls in one minute or as many as comfortable

Table A10-1: Boston Medical Center data collection protocol. The activities listed in the table were performed in the order indicated starting from the one at the top of the table and ending with the one at the bottom of the table.

Appendix A11: Stanford and Boston University Data Collection Protocols

Script for Laboratory/Gymnasium Activities

Session #1

- Each activity was performed for a period of two minutes unless otherwise specifically noted.
- The subject's exertion perception on the RPE scale was annotated for each activity involving different activity levels.

Bout A

Activity	**Annotation Guide**
Lying quietly on back, arms at side	Lying Down n/a n/a
Sitting in chair very quietly—hands on knees, feet flat on floor	Sitting n/a n/a
Standing very quietly, hands at sides, feet shoulder-width apart	Standing n/a n/a
Getting ready and annotation	
Walking on Treadmill (TM), 2 miles per hour (mph), 0% grade	Walking Treadmill 2 mph Treadmill 0%
Walking on TM, 3 mph, 0% grade	Walking Treadmill 3 mph Treadmill 0%
Walking on TM, 4 mph, 0% grade	Walking Treadmill 4 mph Treadmill 0%
Getting ready and annotation	
Walking on TM, 3 mph, 4% grade	Walking Treadmill 3 mph Treadmill 3%
Walking on TM, 3 mph, 8% grade	Walking Treadmill 3 mph Treadmill 6%
Walking on TM, 3 mph, 12% grade	Walking Treadmill 3 mph Treadmill 9%
Getting ready and annotation	
Jog on treadmill, 5 mph, 0% (optional activity depending on subject's capacity)	Running Treadmill 5 mph Treadmill 0%

Break—end of *Bout A*

- Subjects rested for approximately five minutes and prepared for the cycling bout (*Bout B*)
- Before the beginning of *Bout B*, the light, moderate and hard resistance levels were determined for each subject using 80 rpm on the cycle ergometer (legs).
- Note: a rowing machine may be used interchangeably with the arm cycle ergometer and will be indicated by the annotation

Bout B

Activity	Annotation Guide
Cycle ergometer (legs), 60 RPM, “light” resistance	Cycling Cycle light Cycle 60 rpm
Cycle ergometer (legs), 80 RPM, “light” resistance	Cycling Cycle moderate Cycle 80 rpm
Cycle ergometer (legs), 100 RPM, “light” resistance	Cycling Cycle light Cycle 100 rpm
Sit in chair and fidget with feet and legs	Sitting Fidget feet legs n/a
Cycle ergometer (legs), 80 RPM, “light” resistance	Cycling Cycle light Cycle 80 rpm
Cycle ergometer (legs), 80 RPM, “moderate” resistance	Cycling Cycle moderate Cycle 80 rpm
Cycle ergometer (legs), 80 RPM, “hard” resistance	Cycling Cycle hard Cycle 80 rpm
Sit in chair and fidget with hands and arms	Sitting Fidget hands arms n/a
Cycle ergometer (arms), 60 RPM, 25 watts OR Rowing machine, 30 strokes per minute (SPM), “light” resistance	Rowing Rowing light Cycle 60 rpm (*Rowing 30 spm)
Cycle ergometer (arms), 75 RPM, 25 watts OR Rowing machine, 30 SPM, “moderate” resistance	Rowing Rowing moderate Cycle 75 rpm (*Rowing 30 spm)
Cycle ergometer (arms), 90 RPM, 25 watts OR Rowing machine, 30 SPM, “heavy” resistance	Rowing Rowing hard Cycle 90 rpm (*Rowing 30 spm)

*Use annotations in parentheses () for the rowing machine where appropriate

End of Session #1

Session #2

- Research assistant carried the laptop for data recording within 10 feet of the subject.
- For activities involving the use of a box, a box or similar object (i.e.—plate weight) weighing approximately five pounds was utilized for activities in *Bout A*.

Bout A

Activity	*Annotation Guide*
Move box from floor to table—subject picks up box from floor, turns 90 degrees, takes 2-3 steps to place box on table, wait 1 second, then return box to the original position (Note: the table should be about waist high on the subject)	Move weight Move wt low n/a
Move box from floor to high shelf—subject picks up box from floor, turns 90 degrees, takes 2-3 steps to place box on shelf, wait 1 second, then return box to the original position (Note: the shelf should be at least should high on the subject)	Move weight Move wt high n/a
Stand at table and move box from one side of person to the other side of the person while standing in one place (Note: sit box down for 2 seconds between moves)	Move weight Move wt side n/a
Carry box with both hands in front of subject (elbows bent at 90 degrees) and walk at 2 mph on treadmill	Move weight Carry wt 2mph n/a

Bout B

Activity	***Annotation Guide***
Stair climbing—go up and down three flights of stairs for a period of two minutes, annotate “ascending” and “descending” appropriately (Please note the number of stairs in the “flight” used)	Stairs Ascend stairs OR descend stairs n/a
Rest	
Stair climbing—go up and down three flights of stairs for a period of two minutes, annotate “ascending” and “descending” appropriately (Please note the number of stairs in the “flight” used)	Stairs Ascend stairs OR descend stairs n/a
Rest and move to area for calisthenics	
Perform sit-ups with knees bent and hands behind head—15 in one minute or as many as comfortable	Calisthenics Sit ups n/a
Rest	
Perform push-ups from the knees—15 in one minute or as many as comfortable	Calisthenics Push ups n/a
Rest	
Jumping jacks—20 in one minute or as many as comfortable	Calisthenics n/a Jumping jacks n/a
Rest	
Perform biceps curl with both arms (3 or 5 pound weight)—15 curls in one minute or as many as comfortable	Calisthenics Bicep curl n/a

End of Session #2

Once data collection was complete, subjects removed the heart rate strap/monitor and accelerometers and performed and end of study interview.

Script for Home Cleaning Activities

During this data collection, participants performed the activities listed in the order shown in the table below, one at a time. Participants were also allowed to complete activities at their own pace and for however long they wished. The research assistant; however, keep track of the length of the activities and suggest moving on to another activity for those taking longer than 15 minutes. This was only a general rule and was left up to the discretion of the research assistant.

List of Activities

- stacking groceries—to be simulated by un-stacking several shelves into a bag, then re-stacking them
- doing dishes/putting away dishes
- folding and stacking laundry
- making beds
- emptying trashcans
- scrubbing toilet and/or bathtub or shower
- dusting
- vacuuming
- washing windows
- sweeping
- scrubbing the floor
- mopping

Activity	Description of Activity
U activity	Unknown activity: performing an activity not otherwise specified below.
Dishes	Cleaning dishes by hand
Bed	Actions involved in making a bed, including removing sheets/blankets from a bed, putting sheets/blankets onto a bed, stuffing pillowcases, and carrying sheets/blankets to/from a bed.
Scrub	Making quick and rapid movements with the arm. This involves more intensity than wiping/dusting.
Stack	Includes stacking supplies or linens on a shelf.
Sweep	Using a broom to sweep a floor.
Trashcans	Emptying trashcans or carrying a trashcan or trash bag.
Vacuum	Includes vacuuming and also moving a vacuum cleaner to a different location.
Wipe/dust	Similar to scrub, but with shorter and slower arm movements. Less intense than cleaning a toilet.
Mop	Using a mop to clean a floor. Does not include carrying a mop.
Laundry	Folding laundry
Shifting objects	ONLY includes extended periods of moving objects around (greater than 5 seconds)

Appendix A12: MIT Data Collection Protocol

The following data collection protocol was used during each of the two data collection sessions that took take place at (1) the MIT Zesiger Sports and Fitness Center and (2) at the PlaceLab instrumented residential home.

Data collection protocol

1. The participant's demographic, medical, and physical activity information was recorded.
2. Seven wireless accelerometers (Onbody MITes) were placed on the participant at the feet (on shoe laces), wrists, hip (non-dominant side), dominant upper arm (near bicep muscle), and dominant thigh.
3. The participant was asked to wear the polar chest strap heart rate monitor and to place the heart rate MITes transceiver in his/her pocket.
4. The participant was asked to wear the bodybugg armband on his/her dominant upper arm.
5. Two Actigraph activity monitors were then firmly attached to the participant at the belt around the dominant side of the hip (on the outer edge of the hip bone) and another at the dominant wrist.
6. The K4b2 portable indirect calorimeter was installed on the participant. The participant was instructed not to talk and to breathe mainly through the nose during the experiment to increase the accuracy of the VO_2 and VCO_2 measurements.
7. The participant's resting metabolic rate (RMR) and resting heart rate were measured by having the participant lie down for a period of 5 minutes.
8. The participant was asked to perform a script of activities depending o the location of the data collection. The two scripts utilized during the MIT Zesiger Sports and Fitness Center and PlaceLab instrumented residential home are presented below.

Activity Script for the MIT Zesiger Sports and Fitness Center Data Collection

Activity	Description of Activity
Lying down (5min)	Lying quietly on back, arms at side
Sitting*	Sitting in chair very quietly—hands on knees, feet flat on floor
Sitting fidgeting* hands and arms	Sit in chair and fidget with hands and arms
Standing still*	Standing very quietly, hands at sides, feet shoulder-width apart
Kneeling*	Supporting the body on your knees, both knees on the floor.
Walking	Walking on a treadmill at the specified speed and inclination
Walking upstairs	Walk upstairs three flights of stairs for a period of two minutes, annotate "ascending" and "descending" appropriately
Walking downstairs	Walk downstairs three flights of stairs for a period of two minutes, annotate "ascending" and "descending" appropriately. (Please note the number of stairs in the "flight" used)
Running	Running on a treadmill at the specified speed and inclination
Cycle ergometer	Cycling on a leg ergometer at the specified speed.
Rowing	
Sit-ups	Perform sit-ups with knees bent and hands behind head. 15 in one minute or as many as comfortable.
Crunches	Perform crunches. 15 in one minute or as many as comfortable
Biceps curls	Perform biceps curl with both arms using the specified weight. 15 curls in one minute or as many as comfortable.
Weight lifting	Perform bench weight lifting with both arms using the specified weight. 15 repetitions in one minute or as many as comfortable.

Table A12-1: Description of the activities performed at MIT Zesiger Sports and Fitness center. (*Data collected for 2mins only)

This session was divided into several activity periods of 20-30 minutes, separated by 5 minute rest periods. Even though this data collection lasted for about three hours, each activity was only performed for three to four minutes and there were pauses between activities to allow the participant's to have some rest. The participants were asked to perform the activities in the order listed, one at a time for three to four minutes or for as long as was comfortable, if the activity was physically demanding. The participants were also asked to remove the sensors and put them on at least two times during the data collections. In this way, slight variations in orientation due to sensor installation were captured in each dataset. If the participant found any of the activities too physically demanding the activity was no longer performed. The participant's heart rate was also monitored during the data collection to assure it did not exceed the participant's maximum estimated peak exercise heart rate. A member of the study team quietly annotated the activities and let the participant know when it was time to pause or start the next activity.

Bout A

Activity	Annotation guide		
	Category	**Intensity**	**Difficulty**
Lying down (5 minutes)	Lying down	n/a	n/a
Sitting (2min)	Sitting	n/a	n/a
Sit in chair and fidget with feet and legs (2min)	Sitting	Fidget feet legs	n/a
Sitting fidgeting hands and arms (2min)	Sitting	Fidget hands arms	n/a
Standing still (2min)	Standing still	n/a	n/a
Kneeling (2min)	Kneeling	n/a	n/a

Break—end of *Bout A*

- Allow subject to rest for approximately five minutes and get ready for *Bout B*

Bout B

Walking on TM, 2 mph, 0% grade	Walking	Treadmill 2 mph	Treadmill 0%
Walking on TM, 3 mph, 0% grade	Walking	Treadmill 3 mph	Treadmill 0%
Walking on TM, 3 mph, 3% grade **"light"**	Walking	Treadmill 3 mph	Treadmill **3**%
Walking on TM, 3 mph, 6% grade **"moderate"**	Walking	Treadmill 3 mph	Treadmill **6**%
Walking on TM, 3 mph, 9% grade **"hard"**	Walking	Treadmill 3 mph	Treadmill **9**%
Walking upstairs	Stairs	Ascend stairs	n/a
Walking downstairs	Stairs	Descend stairs	n/a
Running on TM, 4 mph, 0% grade	Running	Treadmill 4 mph	Treadmill 0%
Running on TM, 5 mph, 0% grade (optional depending on subject)	Running	Treadmill 5 mph	Treadmill 0%
Running on TM, 6 mph, 0% grade (optional depending on subject)	Running	Treadmill 6 mph	Treadmill 0%

Break—end of *Bout B*

- Allow subject to rest for approximately five minutes and get ready for *Bout C*
- Before beginning *Bout C*, determine light, moderate, and hard resistance for subject using 80 rpm on the cycle ergometer (legs). Document resistances used in "Notes" section of electronic data when data is merged/cleaned.
- Note: a rowing machine may be used interchangeably with the arm cycle ergometer and will be indicated by the annotation

Bout C

Activity	**Annotation guide**		
	Category	**Intensity**	**Difficulty**
Cycle ergometer (legs), 60 RPM, **"light"** resistance	Cycling	Cycle light **(2 R)**	Cycle 60 rpm
Cycle ergometer (legs), 80 RPM, **"light"** resistance	Cycling	Cycle light **(2 R)**	Cycle 80 rpm
Cycle ergometer (legs), 100 RPM, **"light"** resistance	Cycling	Cycle light **(2 R)**	Cycle 100 rpm
Cycle ergometer (legs), 80 RPM, **"moderate"** resistance	Cycling	Cycle moderate **(7 R)**	Cycle 80 rpm
Cycle ergometer (legs), 80 RPM, **"hard"** resistance	Cycling	Cycle hard **(13 R)**	Cycle 80 rpm

*Use annotations in parentheses () for the rowing machine where appropriate

Break—end of *Bout C*

- Allow subject to rest for approximately five minutes and get ready for *Bout D*
- Before beginning *Bout D*, determine light, moderate, and hard resistance for subject using 80 rpm on the cycle ergometer (arms). Document resistances used in "Notes" section of electronic data when data is merged/cleaned.
- Note: a rowing machine may be used interchangeably with the arm cycle ergometer and will be indicated by the annotation

Bout D

Cycle ergometer (arms), 60 RPM, 25 watts OR Rowing machine, 30 strokes per minute (SPM), **“light”** resistance	Rowing	Rowing light **(2 R)**	Cycle 60 rpm (*Rowing 30 spm)
Cycle ergometer (arms), 75 RPM, 25 watts OR Rowing machine, 30 SPM, **“moderate”** resistance	Rowing	Rowing moderate **(5 R)**	Cycle 75 rpm (*Rowing 30 spm)
Cycle ergometer (arms), 90 RPM, 25 watts OR Rowing machine, 30 SPM, **“hard”** resistance	Rowing	Rowing hard **(8 R)**	Cycle 90 rpm (*Rowing 30 spm)

Break—end of *Bout D*

- Allow subject to rest for approximately five minutes and get ready for *Bout D*
- Before beginning *Bout E*, determine light, moderate, and hard weights for subject for “Bicep curls” and “Bench weight lifting”. Document weights used in “Notes” section of electronic data when data is merged/cleaned.

Bout E

Activity	**Annotation guide**		
	Category	**Intensity**	**Difficulty**
Sit-ups	Calisthenics	Sit ups	n/a
Crunches	Calisthenics	Push ups	n/a
Bicep curls **“light”**	Resistance	Bicep curl light **(2 Lb)**	n/a
Bicep curls **“moderate”**	Resistance	Bicep curl moderate **(5 Lb)**	n/a
Bicep curls **“hard”**	Resistance	Bicep curl hard **(8 Lb)**	n/a
Bench weight lifting **“light”**	Resistance	Bench light **(2 Lb)**	n/a
Bench weight lifting **“moderate”**	Resistance	Bench moderate **(7 Lb)**	n/a
Bench weight lifting **“hard”**	Resistance	Bench hard **(17 Lb)**	n/a

The *walking* and *running* activities were collected on a Precor C956 treadmill, the *cycling* activities on a Precor C846 recumbent stationary bicycle, and the *rowing* activities on a Concept2 PM2 Rowing machine.

Stationary Machine Utilized	Image
Precor C846 recumbent stationary bicycle	
Precor C956 treadmill	
Concept2 PM2 Rowing machine	

Table A12-2: Stationary exercise equipment utilized during the MIT gymnasium data collections.

Activity Script for the PlaceLab Residential Home Data Collection

Activity	Description of Activity
Lying down	Lying down on a bed with hands on sides
Watching TV	Watching TV while sitting on a couch
Playing videogames	Playing video games while sitting on a couch
Typing	Typing on a computer while sitting.
Writing	Handwriting on a piece of paper while sitting.
Making the bed	Actions involved in making a bed, including removing sheets/blankets from a bed, putting sheets/blankets onto a bed, stuffing pillowcases, and carrying sheets/blankets to/from a bed.
Taking out trash	Emptying trashcans or carrying a trashcan or trash bag.
Walking around block	Walking at normal speed around the PlaceLab block
Carrying groceries	Carrying grocery bags either with one or two hands. The weight of the bags should be greater than 2kg.
Stacking groceries	Includes stacking supplies or linens on a shelf.
Ironing	Ironing clothes by hand using a hand ironing machine while standing up or sitting.
Doing dishes	Washing dishes by hand.
Wiping/dusting	Similar to scrub, but with shorter and slower arm movements. Less intense than cleaning a toilet.
Sweeping	Using a broom to sweep a floor. Does not include carrying a broom.
Mopping	Using a mop to clean a floor. Does not include carrying a mop.
Vacuuming	Includes vacuuming floor and also moving a vacuum cleaner to a different location.
Washing windows	Washing a window by scrubbing while standing up.
Scrubbing a surface	Making quick and rapid movements with the arm. This involves more intensity than wiping/dusting such as cleaning the bath tub.
Weeding	Weeding grass at PlaceLab patio
Gardening	Gardening at PlaceLab patio

Table A12-3: Description of the activities performed at the PlaceLab.

During this data collection, the participant was asked to perform the activities in the order listed, one at a time for three to four minutes. A member of the study team quietly annotated the activities using a laptop computer. The participant was also asked to remove the sensors and put them on at least two times during the data collection. In this way, slight variations in orientation due to sensor installation will be captured in each dataset.

Appendix A13: Activity Recognition Using Different Classifiers

Activity	True Positive Rate			
	NN	NB	LogitBoost	C4.5
Bench weight lifting - hard	7.49 ± 13.72	6.35 ± 15.14	5.15 ± 10.60	16.66 ± 29.15
Bench weight lifting - light	20.07 ± 20.51	27.56 ± 29.41	37.68 ± 37.08	15.56 ± 28.17
Bench weight lifting - moderate	8.71 ± 11.20	14.25 ± 22.02	12.61 ± 21.93	11.64 ± 18.54
Bicep curls - hard	24.50 ± 24.14	31.10 ± 40.89	14.89 ± 25.14	19.88 ± 37.06
Bicep curls - light	24.49 ± 16.65	10.22 ± 14.82	49.48 ± 33.58	18.75 ± 27.29
Bicep curls - moderate	19.43 ± 21.12	8.69 ± 12.85	28.11 ± 31.30	12.19 ± 26.74
Calisthenics - Crunches	42.41 ± 44.87	19.20 ± 34.53	48.65 ± 42.82	15.96 ± 31.90
Calisthenics - Sit ups	69.76 ± 37.44	63.16 ± 46.40	68.77 ± 39.12	44.79 ± 42.87
Cycling - Cycle hard - Cycle 80rpm	11.62 ± 12.17	38.14 ± 37.45	16.74 ± 27.66	17.97 ± 29.91
Cycling - Cycle light - Cycle 100rpm	65.05 ± 39.10	78.87 ± 34.77	79.70 ± 35.49	70.55 ± 37.69
Cycling - Cycle light - Cycle 60rpm	62.35 ± 29.28	74.81 ± 35.76	74.04 ± 29.94	39.57 ± 36.19
Cycling - Cycle light - Cycle 80rpm	33.84 ± 25.04	35.22 ± 35.21	49.42 ± 37.08	42.97 ± 39.93
Cycling - Cycle moderate - Cycle 80rpm	27.46 ± 17.83	6.72 ± 9.04	28.94 ± 25.49	16.14 ± 19.43
Lying down	65.50 ± 14.32	95.63 ± 8.71	87.46 ± 24.64	76.90 ± 34.28
Rowing - Rowing hard - Rowing 30spm	27.40 ± 24.62	52.11 ± 40.42	32.49 ± 40.79	19.49 ± 25.54
Rowing - Rowing light - Rowing 30spm	29.76 ± 23.59	36.82 ± 35.18	36.90 ± 34.98	24.27 ± 23.73
Rowing - Rowing moderate - Rowing 30spm	20.00 ± 14.68	16.32 ± 29.88	21.96 ± 33.29	18.72 ± 21.51
Running - Treadmill 4mph - Treadmill 0	33.10 ± 29.07	39.80 ± 46.32	53.67 ± 40.94	28.20 ± 30.71
Running - Treadmill 5mph - Treadmill 0	60.31 ± 33.35	63.54 ± 41.47	61.53 ± 37.93	48.97 ± 34.91
Running - Treadmill 6mph - Treadmill 0	46.11 ± 42.27	62.90 ± 47.34	57.85 ± 37.82	38.31 ± 30.97
Sitting	4.68 ± 6.65	20.97 ± 17.24	26.27 ± 35.41	15.29 ± 26.44
Sitting - Fidget feet legs	33.05 ± 33.93	55.90 ± 41.30	42.83 ± 39.44	28.83 ± 36.85
Sitting - Fidget hands arms	26.00 ± 25.91	48.64 ± 43.71	42.17 ± 35.81	28.51 ± 32.18
Stairs - Ascend stairs	48.07 ± 38.29	63.44 ± 38.83	53.41 ± 37.71	49.43 ± 33.57
Stairs - Descend stairs	53.34 ± 35.25	55.70 ± 34.50	48.98 ± 35.71	39.71 ± 30.67
Standing	22.05 ± 14.14	4.84 ± 9.25	48.37 ± 35.76	41.26 ± 38.65
Walking - Treadmill 2mph - Treadmill 0	49.94 ± 35.46	71.81 ± 37.44	64.46 ± 33.33	45.61 ± 34.16
Walking - Treadmill 3mph - Treadmill 0	13.71 ± 13.78	43.30 ± 38.47	29.00 ± 23.39	24.28 ± 25.45
Walking - Treadmill 3mph - Treadmill 3 - light	8.14 ± 8.56	18.61 ± 25.83	13.24 ± 22.25	10.06 ± 12.60
Walking - Treadmill 3mph - Treadmill 6 - moderate	16.89 ± 19.18	31.50 ± 34.97	12.05 ± 12.89	10.52 ± 14.89
Walking - Treadmill 3mph - Treadmill 9 - hard	27.46 ± 26.66	21.07 ± 30.95	26.17 ± 31.53	15.11 ± 23.20
kneeling	14.01 ± 12.05	13.68 ± 9.79	70.32 ± 36.57	66.94 ± 43.12
unknown	52.78 ± 5.16	5.89 ± 2.42	76.89 ± 4.84	63.97 ± 5.18
Carrying groceries	27.08 ± 24.99	37.92 ± 29.05	27.48 ± 30.35	19.75 ± 20.28
Doing dishes	31.75 ± 19.94	39.19 ± 29.22	45.58 ± 25.90	29.34 ± 28.43
Gardening	16.33 ± 18.81	28.14 ± 32.12	25.89 ± 30.41	14.44 ± 20.82
Ironing	44.71 ± 25.93	57.39 ± 35.17	37.69 ± 32.58	37.07 ± 31.48
Making the bed	40.23 ± 29.15	28.24 ± 21.62	31.61 ± 22.27	25.95 ± 17.78
Mopping	28.25 ± 25.94	22.88 ± 24.33	25.02 ± 24.17	24.21 ± 21.46
Playing videogames	12.01 ± 10.77	11.14 ± 19.14	28.20 ± 30.41	29.18 ± 34.66
Scrubbing a surface	14.72 ± 16.70	18.16 ± 21.13	20.10 ± 27.82	13.91 ± 17.77
Stacking groceries	18.28 ± 21.20	23.04 ± 25.00	13.93 ± 13.66	11.49 ± 12.03
Sweeping	20.03 ± 20.50	30.99 ± 30.60	18.83 ± 16.22	16.52 ± 17.90
Typing	39.10 ± 20.13	34.84 ± 31.44	53.33 ± 35.33	49.25 ± 37.47
Vacuuming	28.43 ± 25.22	40.81 ± 37.09	30.54 ± 25.49	23.05 ± 21.70
Walking around block	22.61 ± 20.55	26.91 ± 26.45	19.04 ± 22.89	18.94 ± 17.99
Washing windows	25.45 ± 21.92	17.07 ± 17.67	27.49 ± 26.54	22.42 ± 19.23
Watching TV	7.25 ± 5.85	5.32 ± 4.81	21.67 ± 27.42	20.12 ± 30.06
Weeding	5.72 ± 9.12	12.18 ± 18.22	9.55 ± 24.66	4.51 ± 7.78
Wiping/Dusting	31.64 ± 23.52	20.89 ± 17.93	30.43 ± 26.30	21.58 ± 20.09
Writing	25.75 ± 14.98	56.85 ± 36.69	45.84 ± 34.44	51.11 ± 39.97
taking out trash	15.81 ± 16.03	13.51 ± 15.59	2.69 ± 3.67	10.09 ± 10.42

Table A13-1: True positive rate when training classifiers using the *MaxAccelerationSet1* feature set computed per sensor evaluated in a subject independent manner.

Activity	False Positive Rate			
	NN	NB	LogitBoost	C4.5
Bench weight lifting - hard	0.38 ± 0.26	0.23 ± 0.20	0.26 ± 0.19	0.64 ± 0.64
Bench weight lifting - light	0.85 ± 0.76	0.92 ± 1.01	0.66 ± 0.67	0.56 ± 0.68
Bench weight lifting - moderate	0.51 ± 0.39	1.25 ± 0.76	0.49 ± 0.91	0.57 ± 0.58
Bicep curls - hard	0.77 ± 0.55	1.37 ± 1.49	0.84 ± 1.00	0.83 ± 1.07
Bicep curls - light	0.57 ± 0.51	0.38 ± 0.50	2.00 ± 1.26	0.90 ± 1.20
Bicep curls - moderate	0.75 ± 0.57	0.56 ± 0.55	0.83 ± 0.76	0.51 ± 0.63
Calisthenics - Crunches	0.03 ± 0.03	1.16 ± 0.72	0.12 ± 0.22	0.22 ± 0.38
Calisthenics - Sit ups	0.02 ± 0.06	0.20 ± 0.39	0.05 ± 0.08	0.12 ± 0.13
Cycling - Cycle hard - Cycle 80rpm	0.50 ± 0.40	1.91 ± 1.28	0.92 ± 1.08	0.98 ± 1.14
Cycling - Cycle light - Cycle 100rpm	0.76 ± 1.41	0.56 ± 1.22	0.14 ± 0.21	0.12 ± 0.18
Cycling - Cycle light - Cycle 60rpm	0.88 ± 0.64	0.51 ± 0.51	0.24 ± 0.19	0.17 ± 0.18
Cycling - Cycle light - Cycle 80rpm	1.24 ± 1.09	0.61 ± 0.62	1.10 ± 1.18	1.08 ± 1.31
Cycling - Cycle moderate - Cycle 80rpm	1.26 ± 0.75	0.37 ± 0.40	0.80 ± 0.83	0.76 ± 0.87
Lying down	1.44 ± 1.00	4.84 ± 1.91	0.91 ± 1.54	0.68 ± 1.10
Rowing - Rowing hard - Rowing 30spm	1.09 ± 0.77	1.96 ± 1.45	1.08 ± 1.16	0.67 ± 0.81
Rowing - Rowing light - Rowing 30spm	0.79 ± 0.69	0.91 ± 1.09	1.07 ± 1.10	0.70 ± 0.67
Rowing - Rowing moderate - Rowing 30spm	0.74 ± 0.65	0.54 ± 0.99	0.88 ± 0.95	0.77 ± 0.82
Running - Treadmill 4mph - Treadmill 0	0.46 ± 0.49	0.75 ± 1.18	0.57 ± 0.67	0.71 ± 0.90
Running - Treadmill 5mph - Treadmill 0	1.02 ± 0.79	1.14 ± 0.97	0.83 ± 0.89	0.66 ± 0.65
Running - Treadmill 6mph - Treadmill 0	0.33 ± 0.36	0.84 ± 1.02	0.37 ± 0.56	0.33 ± 0.47
Sitting	0.30 ± 0.17	2.47 ± 1.03	0.54 ± 0.79	0.69 ± 0.88
Sitting - Fidget feet legs	0.24 ± 0.22	1.34 ± 0.93	0.10 ± 0.09	0.26 ± 0.28
Sitting - Fidget hands arms	0.32 ± 0.14	1.58 ± 0.93	0.26 ± 0.33	0.51 ± 0.84
Stairs - Ascend stairs	0.32 ± 0.24	1.27 ± 0.76	0.33 ± 0.39	0.63 ± 0.54
Stairs - Descend stairs	0.30 ± 0.24	1.32 ± 0.87	0.38 ± 0.33	0.91 ± 0.90
Standing	0.61 ± 0.44	0.30 ± 0.27	0.29 ± 0.33	0.37 ± 0.34
Walking - Treadmill 2mph - Treadmill 0	0.79 ± 1.34	1.05 ± 1.46	0.96 ± 1.93	0.85 ± 1.45
Walking - Treadmill 3mph - Treadmill 0	0.86 ± 0.62	2.41 ± 1.68	1.30 ± 1.21	1.40 ± 1.40
Walking - Treadmill 3mph - Treadmill 3 - light	1.08 ± 0.81	1.24 ± 1.20	1.12 ± 1.29	1.05 ± 0.94
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.39 ± 1.02	2.02 ± 1.82	0.90 ± 0.73	0.85 ± 0.78
Walking - Treadmill 3mph - Treadmill 9 - hard	1.07 ± 0.92	0.73 ± 1.02	1.45 ± 1.72	0.94 ± 1.22
kneeling	0.53 ± 0.24	0.76 ± 0.40	0.13 ± 0.21	0.14 ± 0.12
unknown	18.18 ± 5.33	2.02 ± 2.01	23.84 ± 9.87	30.04 ± 7.98
Carrying groceries	1.42 ± 1.21	0.72 ± 0.73	1.60 ± 2.55	1.31 ± 1.45
Doing dishes	1.66 ± 0.57	2.08 ± 1.30	0.50 ± 0.39	0.74 ± 0.50
Gardening	0.55 ± 0.35	2.06 ± 1.22	0.42 ± 0.48	0.59 ± 0.46
Ironing	2.65 ± 1.35	2.08 ± 1.47	0.58 ± 0.50	0.78 ± 0.52
Making the bed	1.37 ± 0.85	0.81 ± 0.55	0.83 ± 0.67	1.23 ± 0.70
Mopping	0.74 ± 0.46	0.78 ± 0.61	0.61 ± 0.78	0.86 ± 0.49
Playing videogames	1.54 ± 0.63	0.97 ± 0.80	0.61 ± 0.87	1.20 ± 1.33
Scrubbing a surface	0.84 ± 0.72	2.19 ± 1.80	0.55 ± 0.50	0.84 ± 0.83
Stacking groceries	0.67 ± 0.54	1.33 ± 0.69	0.46 ± 0.36	0.92 ± 0.46
Sweeping	1.17 ± 0.59	1.81 ± 1.11	0.25 ± 0.20	0.85 ± 0.64
Typing	2.67 ± 1.03	0.74 ± 0.54	0.58 ± 0.67	0.61 ± 0.62
Vacuuming	1.00 ± 0.48	3.44 ± 1.56	0.37 ± 0.64	0.70 ± 0.52
Walking around block	1.94 ± 2.34	1.02 ± 0.70	1.08 ± 1.01	1.75 ± 1.65
Washing windows	0.87 ± 0.48	1.46 ± 0.74	0.59 ± 0.44	0.92 ± 0.48
Watching TV	1.19 ± 0.37	1.00 ± 0.73	0.99 ± 1.26	1.00 ± 1.01
Weeding	0.50 ± 0.31	2.32 ± 1.44	0.66 ± 1.21	0.70 ± 0.49
Wiping/Dusting	1.79 ± 0.81	0.89 ± 0.58	0.59 ± 0.59	0.88 ± 0.50
Writing	1.82 ± 0.73	1.58 ± 1.25	0.58 ± 0.58	0.64 ± 0.84
taking out trash	1.02 ± 0.49	2.04 ± 0.64	0.15 ± 0.08	0.96 ± 0.53

Table A13-2: False positive rate obtained when training different classifiers using the *MaxAcceleration* feature set computed per sensor in a subject independent manner.

Activity	F-Measure			
	NN	NB	LogitBoost	C4.5
Bench weight lifting - hard	8.59 ± 13.12	7.05 ± 15.01	5.75 ± 10.77	13.02 ± 18.84
Bench weight lifting - light	19.42 ± 19.83	24.61 ± 22.60	35.03 ± 31.22	14.60 ± 21.42
Bench weight lifting - moderate	9.77 ± 11.74	9.71 ± 12.91	11.38 ± 17.39	11.28 ± 16.20
Bicep curls - hard	23.76 ± 21.60	18.29 ± 22.43	13.08 ± 17.56	12.82 ± 20.10
Bicep curls - light	27.98 ± 19.13	11.90 ± 14.64	32.97 ± 17.10	17.80 ± 19.20
Bicep curls - moderate	18.91 ± 19.46	9.46 ± 11.93	23.00 ± 23.07	10.07 ± 19.18
Calisthenics - Crunches	46.28 ± 46.19	13.66 ± 23.76	52.63 ± 41.74	18.15 ± 35.46
Calisthenics - Sit ups	74.77 ± 37.20	62.23 ± 45.99	72.66 ± 37.37	48.81 ± 44.17
Cycling - Cycle hard - Cycle 80rpm	13.40 ± 12.77	23.49 ± 21.93	13.58 ± 17.73	10.15 ± 12.56
Cycling - Cycle light - Cycle 100rpm	62.84 ± 37.66	74.23 ± 35.78	80.20 ± 35.06	73.43 ± 36.38
Cycling - Cycle light - Cycle 60rpm	56.21 ± 24.38	68.71 ± 31.13	75.40 ± 27.41	44.29 ± 37.10
Cycling - Cycle light - Cycle 80rpm	31.00 ± 21.79	32.89 ± 28.43	41.59 ± 28.05	35.55 ± 31.09
Cycling - Cycle moderate - Cycle 80rpm	24.97 ± 11.69	9.39 ± 12.15	27.55 ± 19.33	15.97 ± 15.68
Lying down	66.48 ± 9.69	65.01 ± 7.79	82.61 ± 22.18	75.30 ± 31.19
Rowing - Rowing hard - Rowing 30spm	24.36 ± 17.48	31.21 ± 22.46	21.67 ± 25.47	19.46 ± 22.66
Rowing - Rowing light - Rowing 30spm	30.31 ± 22.11	32.82 ± 24.43	31.42 ± 25.99	24.81 ± 21.45
Rowing - Rowing moderate - Rowing 30spm	23.46 ± 15.34	14.89 ± 22.10	16.53 ± 21.53	18.61 ± 19.06
Running - Treadmill 4mph - Treadmill 0	36.99 ± 29.94	33.88 ± 37.66	50.64 ± 35.89	30.71 ± 29.80
Running - Treadmill 5mph - Treadmill 0	51.38 ± 26.01	51.23 ± 31.51	55.74 ± 32.00	46.21 ± 26.53
Running - Treadmill 6mph - Treadmill 0	41.36 ± 32.92	45.10 ± 35.42	50.75 ± 30.04	38.91 ± 28.79
Sitting	6.74 ± 9.40	13.46 ± 11.07	23.58 ± 29.90	12.27 ± 19.43
Sitting - Fidget feet legs	36.40 ± 33.74	41.35 ± 30.90	47.34 ± 39.98	30.68 ± 38.11
Sitting - Fidget hands arms	30.16 ± 26.00	33.46 ± 30.84	46.15 ± 35.80	30.29 ± 31.26
Stairs - Ascend stairs	48.35 ± 34.79	49.65 ± 28.54	54.29 ± 36.42	49.64 ± 32.06
Stairs - Descend stairs	55.29 ± 34.47	43.68 ± 27.22	50.19 ± 33.78	38.48 ± 29.02
Standing	24.23 ± 15.46	6.68 ± 12.78	49.64 ± 33.30	39.90 ± 34.33
Walking - Treadmill 2mph - Treadmill 0	48.18 ± 31.74	61.77 ± 31.54	60.80 ± 28.68	45.42 ± 32.64
Walking - Treadmill 3mph - Treadmill 0	15.59 ± 13.25	30.15 ± 26.38	26.14 ± 17.12	20.95 ± 20.02
Walking - Treadmill 3mph - Treadmill 3 - light	8.75 ± 8.02	14.60 ± 16.07	10.79 ± 14.36	10.01 ± 10.12
Walking - Treadmill 3mph - Treadmill 6 - moderate	14.68 ± 12.66	19.89 ± 19.69	13.01 ± 12.33	11.08 ± 12.60
Walking - Treadmill 3mph - Treadmill 9 - hard	25.52 ± 22.72	18.79 ± 22.57	19.63 ± 17.78	12.58 ± 16.20
kneeling	15.96 ± 13.32	15.30 ± 11.44	73.36 ± 35.83	65.70 ± 42.25
unknown	53.10 ± 6.33	10.48 ± 3.85	65.60 ± 10.02	53.97 ± 8.88
Carrying groceries	27.40 ± 26.54	39.80 ± 28.13	28.01 ± 28.14	21.34 ± 20.68
Doing dishes	28.38 ± 17.79	29.18 ± 21.95	50.50 ± 23.69	28.82 ± 25.60
Gardening	19.05 ± 22.00	19.53 ± 22.36	27.67 ± 30.44	16.27 ± 22.88
Ironing	32.52 ± 19.51	42.52 ± 24.06	40.06 ± 31.37	37.94 ± 29.72
Making the bed	34.31 ± 24.03	30.08 ± 19.99	32.94 ± 21.00	25.64 ± 17.56
Mopping	28.57 ± 24.48	22.86 ± 23.06	27.02 ± 24.96	24.69 ± 21.27
Playing videogames	12.57 ± 10.52	10.85 ± 15.89	31.55 ± 28.34	27.73 ± 30.98
Scrubbing a surface	16.90 ± 18.41	14.06 ± 15.91	20.88 ± 26.06	14.89 ± 18.59
Stacking groceries	20.35 ± 22.41	19.88 ± 20.07	17.52 ± 16.40	13.52 ± 14.04
Sweeping	19.15 ± 19.40	22.90 ± 22.75	25.39 ± 19.23	17.86 ± 19.00
Typing	30.27 ± 16.07	36.56 ± 30.16	53.72 ± 34.37	50.10 ± 35.50
Vacuuming	29.33 ± 25.21	24.77 ± 23.41	38.12 ± 27.47	25.90 ± 23.87
Walking around block	22.41 ± 19.53	27.07 ± 22.82	18.76 ± 18.25	18.92 ± 16.26
Washing windows	26.70 ± 20.89	15.69 ± 14.76	30.23 ± 26.31	24.71 ± 21.09
Watching TV	9.03 ± 7.11	7.30 ± 6.82	23.12 ± 26.29	19.12 ± 24.91
Weeding	7.69 ± 11.34	9.18 ± 14.05	5.92 ± 8.06	5.95 ± 10.07
Wiping/Dusting	26.12 ± 19.21	23.20 ± 19.28	33.86 ± 27.83	23.66 ± 21.09
Writing	24.01 ± 13.37	44.62 ± 27.94	47.73 ± 33.54	51.55 ± 38.41
taking out trash	16.71 ± 15.99	11.06 ± 12.11	4.66 ± 6.29	11.52 ± 11.70

Table A13-3: F-Measure obtained when training different classifiers using the *MaxAcceleration* feature set computed per sensor in a subject independent manner.

Appendix A14: Description of the 52 Activities Contained in the MIT Dataset

Activity	Intensity Level	Collection Place	Description
Bench weight lifting – Light	√	Gym	Sitting leaning back lifting 0.9Kg (2Lb) weight with both hands
Bench weight lifting – Moderate	√	Gym	Sitting leaning back lifting 3.1Kg (7Lb) weight with both hands
Bench weight lifting – Hard	√	Gym	Sitting leaning back lifting 7.7Kg (17Lb) weight with both hands
Bicep curls – Light	√	Gym	Sitting leaning forward with 0.9Kg (2Lb) weight on each hand
Bicep curls – Moderate	√	Gym	Sitting leaning forward with 2.2Kg (5Lb) weight on each hand
Bicep curls – Hard	√	Gym	Sitting leaning forward with 3.6Kg (8Lb) weight on each hand
Calisthenics Crunches	-	Gym	
Calisthenics Sit ups	-	Gym	Sit-ups using body as weight
Cycling Cycle 100rpm (15mph, 120.4W) – Light	√	Gym	Speed 100rmp, resistance of 2
Cycling Cycle 60rpm (8.9mph, 66.9W) – Light	√	Gym	Speed 60rmp, resistance of 2
Cycling Cycle 80rpm (11.2mph, 100.4W) – Light	√	Gym	Speed 80rpm, resistance of 2
Cycling Cycle 80rpm – Moderate	√	Gym	Speed 80rmp, resistance of 7
Cycling Cycle 80rpm – Hard	√	Gym	Speed 80rmp, resistance of 13
Lying down	-	Gym	Lying down still
Rowing 30spm – Light	√	Gym	Speed 30spm, resistance of 2
Rowing 30spm – Moderate	√	Gym	Speed 30spm, resistance of 5
Rowing 30spm – Hard	√	Gym	Speed 30spm, resistance of 8
Running Treadmill 4mph Treadmill 0	√	Gym	Speed 4mph, 0% incline
Running Treadmill 5mph Treadmill 0	√	Gym	Speed 5mph, 0% incline
Running Treadmill 6mph Treadmill 0	√	Gym	Speed 5mph, 0% incline
Sitting	√	Gym	Sitting still, hands on thighs
Sitting Fidget feet legs	√	Gym	
Sitting Fidget hands arms	√	Gym	Upstairs 4 floors continuously
Stairs Ascend stairs	-	Gym	downstairs 4 floors continuously
Stairs Descend stairs	-	Gym	
Standing	-	Gym	Standing still
Walking Treadmill 2mph Treadmill 0	√	Gym	Speed 2mph, 0% incline
Walking Treadmill 3mph Treadmill 0	√	Gym	Speed 3mph, 0% incline
Walking Treadmill 3mph Treadmill 3 – Light	√	Gym	Speed 3mph, 3% incline
Walking Treadmill 3mph Treadmill 6 – Moderate	√	Gym	Speed 3mph, 6% incline
Walking Treadmill 3mph Treadmill 9 – Hard	√	Gym	Speed 3mph, 9% incline
Kneeling	-	PlaceLab	Kneeling still
Carrying groceries	√	PlaceLab	Walking normal speed with one 3Kg bag on each hand
Doing dishes	-	PlaceLab	Doing dishes while standing
Gardening	-	PlaceLab	Planting seeds with small shovel on the floor
Ironing	-	PlaceLab	Ironing while standing using a handheld iron
Making the bed	-	PlaceLab	
Mopping	-	PlaceLab	Mopping using a wet mop
Playing videogames	-	PlaceLab	Handheld Nintendo DS
Scrubbing a surface	-	PlaceLab	Scrubbing bathtub
Stacking groceries	-	PlaceLab	From bag on floor to shelf
Sweeping	-	PlaceLab	
Typing	-	PlaceLab	Typing on a computer while sitting
Vacuuming	-	PlaceLab	
Walking around block	-	PlaceLab	Normal walking speed
Washing windows	-	PlaceLab	Standing washing glass door
Watching TV	-	PlaceLab	Watching and changing channel
Weeding	-	PlaceLab	Using bare hands
Wiping/Dusting	-	PlaceLab	Using Clorox wipes
Writing	-	PlaceLab	
Taking out trash	-	PlaceLab	1Kg trash bag
Unknown	-	Both	Any unlabeled time period during the data collections

Table A14-1: Description of the 52 activities contained in the MIT dataset.

Appendix A15: Feature Computation per Sensor vs. Feature Computation per Axis

True positive rate Using Subject Dependent Evaluation				
Activity	**NB Per Sensor**	**NB Per Axis**	**C4.5 Per Sensor**	**C4.5 Per Axis**
Bench weight lifting - hard	71.7 ± 19.8	79.2 ± 20.8	93.1 ± 9.1	93.6 ± 8.2
Bench weight lifting - light	87.7 ± 11.8	91.9 ± 6.1	93.3 ± 10.1	97.0 ± 4.3
Bench weight lifting - moderate	76.9 ± 24.2	77.9 ± 23.7	92.1 ± 10.3	93.9 ± 10.2
Bicep curls - hard	93.4 ± 6.5	91.7 ± 9.3	92.8 ± 5.3	93.2 ± 11.7
Bicep curls - light	86.6 ± 16.4	90.4 ± 7.3	96.4 ± 4.9	92.9 ± 8.8
Bicep curls - moderate	83.9 ± 6.0	87.9 ± 8.3	91.5 ± 6.4	92.8 ± 10.9
Calisthenics - Crunches	97.9 ± 3.0	96.4 ± 3.8	94.2 ± 2.7	95.8 ± 3.3
Calisthenics - Sit ups	97.0 ± 2.3	97.2 ± 2.5	92.4 ± 6.1	95.4 ± 5.2
Cycling - Cycle hard - Cycle 80rpm	81.7 ± 17.6	86.2 ± 17.7	91.6 ± 8.8	89.6 ± 8.6
Cycling - Cycle light - Cycle 100rpm	99.8 ± 0.8	99.9 ± 0.6	97.7 ± 4.2	98.6 ± 2.0
Cycling - Cycle light - Cycle 60rpm	97.5 ± 2.6	98.7 ± 1.9	97.8 ± 2.5	99.0 ± 1.5
Cycling - Cycle light - Cycle 80rpm	97.2 ± 5.0	97.6 ± 3.6	94.2 ± 6.3	95.8 ± 5.4
Cycling - Cycle moderate - Cycle 80rpm	90.7 ± 6.9	95.8 ± 4.7	88.8 ± 9.7	92.8 ± 6.4
Lying down	98.9 ± 1.8	98.0 ± 1.9	100.0 ± 0.0	99.9 ± 0.3
Rowing - Rowing hard - Rowing 30spm	84.2 ± 12.2	84.8 ± 16.8	84.0 ± 13.7	83.4 ± 13.4
Rowing - Rowing light - Rowing 30spm	90.4 ± 8.9	93.4 ± 6.3	86.7 ± 10.9	91.8 ± 7.2
Rowing - Rowing moderate - Rowing 30spm	85.5 ± 11.7	86.4 ± 10.7	77.0 ± 14.5	82.1 ± 14.3
Running - Treadmill 4mph - Treadmill 0	99.6 ± 1.1	99.2 ± 1.4	98.4 ± 2.4	97.0 ± 3.6
Running - Treadmill 5mph - Treadmill 0	98.4 ± 2.9	99.0 ± 2.7	95.1 ± 3.6	94.2 ± 4.0
Running - Treadmill 6mph - Treadmill 0	89.2 ± 15.3	92.6 ± 20.6	88.7 ± 13.3	91.3 ± 14.4
Sitting	92.6 ± 4.3	84.3 ± 8.8	96.8 ± 2.9	95.6 ± 4.4
Sitting - Fidget feet legs	96.2 ± 4.4	97.0 ± 3.2	95.6 ± 7.6	94.4 ± 6.8
Sitting - Fidget hands arms	96.6 ± 4.3	95.2 ± 4.8	94.8 ± 4.2	93.5 ± 5.1
Stairs - Ascend stairs	95.9 ± 3.4	97.6 ± 2.0	89.2 ± 7.0	93.3 ± 4.4
Stairs - Descend stairs	94.6 ± 5.3	96.7 ± 3.2	88.7 ± 9.1	92.0 ± 6.1
Standing	91.2 ± 7.1	86.3 ± 10.2	95.0 ± 6.0	96.1 ± 5.9
Walking - Treadmill 2mph - Treadmill 0	97.9 ± 2.3	97.5 ± 3.2	94.9 ± 4.4	97.6 ± 2.8
Walking - Treadmill 3mph - Treadmill 0	89.2 ± 6.0	91.2 ± 5.4	81.7 ± 9.5	87.4 ± 8.0
Walking - Treadmill 3mph - Treadmill 3 - light	83.9 ± 7.7	90.0 ± 6.8	72.8 ± 16.0	84.5 ± 11.1
Walking - Treadmill 3mph - Treadmill 6 - moderate	81.8 ± 9.9	86.6 ± 10.8	74.0 ± 9.4	82.5 ± 11.0
Walking - Treadmill 3mph - Treadmill 9 - hard	85.9 ± 9.5	93.1 ± 6.8	84.1 ± 9.4	90.3 ± 6.7
kneeling	92.6 ± 4.3	84.6 ± 7.7	96.9 ± 2.8	96.1 ± 3.7
Carrying groceries	91.7 ± 6.0	97.1 ± 4.4	90.1 ± 8.1	91.8 ± 5.8
Doing dishes	85.6 ± 6.4	91.4 ± 5.0	85.4 ± 7.4	87.8 ± 8.6
Gardening	84.0 ± 15.2	88.0 ± 9.8	84.9 ± 10.8	84.9 ± 9.8
Ironing	81.9 ± 9.4	87.2 ± 6.6	85.1 ± 7.7	88.1 ± 7.4
Making the bed	69.9 ± 18.4	78.7 ± 12.4	64.9 ± 11.1	67.7 ± 12.2
Mopping	73.4 ± 12.5	81.2 ± 10.2	64.8 ± 14.6	72.8 ± 13.0
Playing videogames	94.3 ± 5.3	93.2 ± 3.9	98.9 ± 2.1	98.2 ± 2.2
Scrubbing a surface	81.2 ± 13.0	88.6 ± 7.4	80.5 ± 12.9	88.6 ± 8.6
Stacking groceries	74.7 ± 10.4	82.1 ± 9.6	69.4 ± 16.1	74.0 ± 11.6
Sweeping	70.4 ± 15.1	74.6 ± 12.1	64.9 ± 19.9	73.4 ± 14.0
Typing	95.2 ± 3.7	95.5 ± 2.8	97.0 ± 3.9	98.4 ± 2.3
Vacuuming	76.9 ± 8.8	80.7 ± 7.6	78.9 ± 10.8	77.9 ± 8.2
Walking around block	93.4 ± 6.2	96.1 ± 2.7	90.8 ± 6.6	89.1 ± 7.4
Washing windows	77.2 ± 13.6	87.3 ± 8.0	64.4 ± 7.8	75.8 ± 9.3
Watching TV	91.5 ± 4.4	89.6 ± 6.7	97.2 ± 4.4	97.7 ± 2.6
Weeding	80.4 ± 13.1	82.0 ± 8.7	81.7 ± 13.6	80.5 ± 8.4
Wiping/Dusting	62.4 ± 13.1	75.2 ± 11.6	62.2 ± 14.9	68.4 ± 14.8
Writing	95.2 ± 4.4	94.7 ± 3.6	98.5 ± 1.8	97.2 ± 2.3
taking out trash	70.6 ± 10.9	76.7 ± 8.9	60.3 ± 15.7	68.8 ± 11.7

Table A15-1: True positive rate obtained using the naïve Bayes (NB) and C4.5 classifiers using the *MaxAccelerationSet1* feature set computed per sensor and per axis during subject dependent evaluation without the *unknown* class.

False positive rate Using Subject dependent Evaluation				
Activity	**NB Per Sensor**	**NB Per Axis**	**C4.5 Per Sensor**	**C4.5 Per Axis**
Bench weight lifting - hard	0.2 ± 0.2	0.2 ± 0.2	0.1 ± 0.1	0.0 ± 0.1
Bench weight lifting - light	0.2 ± 0.2	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Bench weight lifting - moderate	0.5 ± 0.5	0.1 ± 0.1	0.2 ± 0.2	0.1 ± 0.1
Bicep curls - hard	0.2 ± 0.1	0.1 ± 0.1	0.2 ± 0.2	0.2 ± 0.2
Bicep curls - light	0.2 ± 0.2	0.2 ± 0.2	0.1 ± 0.1	0.1 ± 0.1
Bicep curls - moderate	0.4 ± 0.6	0.2 ± 0.2	0.2 ± 0.1	0.1 ± 0.2
Calisthenics - Crunches	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.1	0.0 ± 0.1
Calisthenics - Sit ups	0.0 ± 0.1	0.0 ± 0.0	0.1 ± 0.1	0.1 ± 0.0
Cycling - Cycle hard - Cycle 80rpm	0.2 ± 0.2	0.1 ± 0.1	0.2 ± 0.2	0.1 ± 0.1
Cycling - Cycle light - Cycle 100rpm	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.1	0.0 ± 0.0
Cycling - Cycle light - Cycle 60rpm	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.1	0.0 ± 0.1
Cycling - Cycle light - Cycle 80rpm	0.1 ± 0.2	0.0 ± 0.0	0.2 ± 0.2	0.1 ± 0.1
Cycling - Cycle moderate - Cycle 80rpm	0.3 ± 0.2	0.1 ± 0.1	0.2 ± 0.2	0.2 ± 0.2
Lying down	0.0 ± 0.1	0.2 ± 0.2	0.0 ± 0.0	0.0 ± 0.0
Rowing - Rowing hard - Rowing 30spm	0.3 ± 0.2	0.2 ± 0.2	0.4 ± 0.3	0.3 ± 0.2
Rowing - Rowing light - Rowing 30spm	0.1 ± 0.1	0.1 ± 0.1	0.3 ± 0.2	0.2 ± 0.2
Rowing - Rowing moderate - Rowing 30spm	0.4 ± 0.2	0.3 ± 0.3	0.5 ± 0.3	0.3 ± 0.2
Running - Treadmill 4mph - Treadmill 0	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.1	0.1 ± 0.1
Running - Treadmill 5mph - Treadmill 0	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Running - Treadmill 6mph - Treadmill 0	0.0 ± 0.0	0.0 ± 0.0	0.1 ± 0.1	0.1 ± 0.1
Sitting	0.0 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Sitting - Fidget feet legs	0.0 ± 0.1	0.0 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Sitting - Fidget hands arms	0.1 ± 0.2	0.0 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Stairs - Ascend stairs	0.0 ± 0.1	0.0 ± 0.0	0.2 ± 0.2	0.1 ± 0.1
Stairs - Descend stairs	0.2 ± 0.2	0.0 ± 0.1	0.3 ± 0.2	0.1 ± 0.1
Standing	0.0 ± 0.0	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Walking - Treadmill 2mph - Treadmill 0	0.0 ± 0.0	0.0 ± 0.0	0.2 ± 0.2	0.1 ± 0.1
Walking - Treadmill 3mph - Treadmill 0	0.3 ± 0.1	0.1 ± 0.1	0.5 ± 0.4	0.2 ± 0.2
Walking - Treadmill 3mph - Treadmill 3 - light	0.5 ± 0.3	0.3 ± 0.2	0.8 ± 0.4	0.4 ± 0.2
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.7 ± 0.5	0.2 ± 0.2	0.8 ± 0.4	0.4 ± 0.2
Walking - Treadmill 3mph - Treadmill 9 - hard	0.3 ± 0.2	0.2 ± 0.1	0.5 ± 0.4	0.2 ± 0.2
kneeling	0.0 ± 0.1	0.1 ± 0.1	0.1 ± 0.1	0.0 ± 0.1
Carrying groceries	0.2 ± 0.2	0.1 ± 0.1	0.3 ± 0.2	0.2 ± 0.2
Doing dishes	0.5 ± 0.4	0.2 ± 0.2	0.6 ± 0.5	0.3 ± 0.2
Gardening	0.9 ± 0.9	0.5 ± 0.6	0.5 ± 0.6	0.3 ± 0.2
Ironing	0.3 ± 0.2	0.2 ± 0.2	0.5 ± 0.2	0.4 ± 0.2
Making the bed	1.1 ± 0.4	0.8 ± 0.3	1.2 ± 0.7	0.8 ± 0.4
Mopping	0.6 ± 0.5	0.5 ± 0.4	1.2 ± 0.7	0.7 ± 0.3
Playing videogames	0.1 ± 0.2	0.1 ± 0.1	0.1 ± 0.1	0.0 ± 0.0
Scrubbing a surface	0.9 ± 0.7	0.5 ± 0.5	0.5 ± 0.4	0.3 ± 0.3
Stacking groceries	0.6 ± 0.7	0.2 ± 0.2	0.8 ± 0.7	0.5 ± 0.3
Sweeping	0.9 ± 0.8	0.6 ± 0.4	0.9 ± 0.6	0.7 ± 0.3
Typing	0.1 ± 0.2	0.1 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
Vacuuming	0.3 ± 0.2	0.1 ± 0.1	0.6 ± 0.4	0.5 ± 0.2
Walking around block	0.3 ± 0.2	0.1 ± 0.1	0.3 ± 0.3	0.2 ± 0.1
Washing windows	1.9 ± 1.0	1.1 ± 0.6	1.0 ± 0.3	0.6 ± 0.3
Watching TV	0.2 ± 0.3	0.2 ± 0.1	0.0 ± 0.1	0.1 ± 0.0
Weeding	0.9 ± 0.6	0.6 ± 0.4	0.5 ± 0.4	0.4 ± 0.3
Wiping/Dusting	0.8 ± 0.4	0.4 ± 0.4	1.0 ± 0.4	0.7 ± 0.4
Writing	0.1 ± 0.2	0.0 ± 0.1	0.1 ± 0.1	0.1 ± 0.1
taking out trash	1.4 ± 0.7	0.8 ± 0.4	1.2 ± 0.4	0.7 ± 0.4

Table A15-2: False positive rate obtained using the naïve Bayes (NB) and C4.5 classifiers using the *MaxAccelerationSet1* feature set computed per sensor and per axis during subject dependent evaluation without the *unknown* class.

True positive rate Using Subject Independent Evaluation				
Activity	**NB Per Sensor**	**NB Per Axis**	**C4.5 Per Sensor**	**C4.5 Per Axis**
Bench weight lifting - hard	9.2 ± 17.7	11.3 ± 18.4	4.2 ± 9.4	13.1 ± 25.8
Bench weight lifting - light	35.4 ± 28.4	24.4 ± 19.2	33.6 ± 32.4	41.5 ± 35.1
Bench weight lifting - moderate	15.8 ± 22.7	59.1 ± 32.2	11.6 ± 20.5	30.2 ± 35.7
Bicep curls - hard	56.0 ± 40.1	15.4 ± 18.6	32.1 ± 40.2	35.1 ± 36.9
Bicep curls - light	13.6 ± 15.3	15.8 ± 17.6	36.3 ± 39.0	50.7 ± 43.4
Bicep curls - moderate	11.6 ± 13.8	73.7 ± 25.4	8.5 ± 21.9	30.5 ± 36.2
Calisthenics - Crunches	22.9 ± 37.1	72.0 ± 37.9	20.1 ± 35.2	72.7 ± 40.9
Calisthenics - Sit ups	68.0 ± 44.8	86.8 ± 30.2	44.7 ± 41.0	74.3 ± 32.7
Cycling - Cycle hard - Cycle 80rpm	41.5 ± 36.6	34.8 ± 29.3	8.5 ± 7.9	35.0 ± 36.7
Cycling - Cycle light - Cycle 100rpm	88.7 ± 22.9	97.0 ± 10.5	95.7 ± 8.0	98.8 ± 4.5
Cycling - Cycle light - Cycle 60rpm	79.3 ± 31.6	93.8 ± 20.1	85.7 ± 27.0	93.4 ± 15.5
Cycling - Cycle light - Cycle 80rpm	38.2 ± 34.1	64.4 ± 39.2	58.5 ± 37.6	38.9 ± 37.0
Cycling - Cycle moderate - Cycle 80rpm	9.2 ± 9.4	29.0 ± 24.0	30.3 ± 30.6	32.4 ± 26.4
Lying down	95.9 ± 8.0	94.8 ± 10.7	84.5 ± 27.0	92.0 ± 18.5
Rowing - Rowing hard - Rowing 30spm	66.6 ± 33.2	55.6 ± 40.3	27.0 ± 27.9	27.8 ± 32.2
Rowing - Rowing light - Rowing 30spm	41.7 ± 34.6	49.2 ± 33.8	41.1 ± 36.3	43.8 ± 35.4
Rowing - Rowing moderate - Rowing 30spm	19.1 ± 32.7	16.0 ± 20.4	24.3 ± 22.6	29.0 ± 34.0
Running - Treadmill 4mph - Treadmill 0	44.2 ± 46.8	72.6 ± 39.5	42.7 ± 40.6	61.0 ± 35.5
Running - Treadmill 5mph - Treadmill 0	67.5 ± 39.4	66.2 ± 39.7	77.7 ± 25.9	62.4 ± 38.0
Running - Treadmill 6mph - Treadmill 0	72.6 ± 43.0	87.2 ± 17.1	61.2 ± 37.3	72.4 ± 34.1
Sitting	21.2 ± 17.3	30.9 ± 9.4	43.0 ± 40.6	73.6 ± 38.1
Sitting - Fidget feet legs	60.2 ± 42.6	88.2 ± 19.9	39.1 ± 45.4	65.9 ± 29.0
Sitting - Fidget hands arms	51.1 ± 43.1	79.4 ± 27.5	37.9 ± 39.1	60.3 ± 40.5
Stairs - Ascend stairs	63.9 ± 38.6	83.3 ± 23.8	57.2 ± 35.4	67.0 ± 27.6
Stairs - Descend stairs	57.0 ± 34.0	78.9 ± 25.4	44.4 ± 26.7	69.1 ± 24.7
Standing	11.3 ± 12.2	84.9 ± 12.1	82.4 ± 34.0	90.1 ± 22.9
Walking - Treadmill 2mph - Treadmill 0	79.9 ± 30.2	91.9 ± 12.3	60.2 ± 39.6	61.7 ± 33.7
Walking - Treadmill 3mph - Treadmill 0	43.7 ± 38.3	45.9 ± 37.9	16.8 ± 20.3	18.4 ± 21.9
Walking - Treadmill 3mph - Treadmill 3 - light	19.7 ± 26.1	20.6 ± 26.4	10.7 ± 12.1	23.2 ± 23.6
Walking - Treadmill 3mph - Treadmill 6 - moderate	31.6 ± 35.2	38.4 ± 25.4	13.9 ± 15.5	31.2 ± 29.7
Walking - Treadmill 3mph - Treadmill 9 - hard	23.3 ± 31.8	64.6 ± 31.8	19.7 ± 25.0	22.2 ± 28.5
kneeling	16.4 ± 9.0	56.1 ± 22.7	65.2 ± 44.3	95.3 ± 7.4
Carrying groceries	41.9 ± 27.3	73.3 ± 27.6	23.2 ± 19.6	56.5 ± 28.8
Doing dishes	46.4 ± 25.9	66.6 ± 24.0	42.7 ± 34.4	56.1 ± 30.5
Gardening	33.8 ± 33.3	41.6 ± 34.4	16.9 ± 22.0	20.0 ± 24.2
Ironing	67.6 ± 27.4	72.4 ± 16.9	54.9 ± 31.8	60.2 ± 25.2
Making the bed	31.6 ± 20.7	39.2 ± 19.9	37.8 ± 22.5	46.6 ± 21.4
Mopping	35.6 ± 21.4	48.4 ± 22.4	28.3 ± 25.7	36.7 ± 18.8
Playing videogames	12.3 ± 19.4	30.0 ± 25.2	33.4 ± 36.1	77.8 ± 30.9
Scrubbing a surface	19.5 ± 21.6	54.5 ± 30.2	20.1 ± 22.7	41.5 ± 30.7
Stacking groceries	27.3 ± 25.0	56.1 ± 27.1	25.4 ± 25.1	39.5 ± 18.8
Sweeping	41.5 ± 28.6	57.7 ± 14.9	21.1 ± 22.6	41.2 ± 17.4
Typing	36.7 ± 31.2	47.0 ± 30.0	58.2 ± 36.4	84.8 ± 29.4
Vacuuming	48.5 ± 36.0	67.6 ± 21.4	37.4 ± 31.1	56.8 ± 20.5
Walking around block	28.3 ± 26.7	53.3 ± 26.3	26.2 ± 21.9	43.1 ± 23.2
Washing windows	17.5 ± 18.1	50.1 ± 26.8	25.8 ± 21.8	39.6 ± 21.5
Watching TV	5.2 ± 4.8	14.3 ± 6.8	23.6 ± 29.5	66.1 ± 37.9
Weeding	12.9 ± 20.2	23.3 ± 27.5	17.8 ± 27.0	23.0 ± 27.8
Wiping/Dusting	27.3 ± 15.0	38.9 ± 20.4	34.9 ± 18.7	45.4 ± 19.6
Writing	56.9 ± 36.8	81.7 ± 25.4	53.6 ± 39.5	85.5 ± 29.2
taking out trash	13.9 ± 15.9	32.5 ± 20.0	19.9 ± 16.4	27.9 ± 15.4

Table A15-3: True positive rate obtained using the naïve Bayes (NB) and C4.5 classifiers using the *MaxAccelerationSet1* feature set computed per sensor and per axis during subject independent evaluation without the *unknown* class.

False positive rate Using Subject independent Evaluation				
Activity	**NB Per Sensor**	**NB Per Axis**	**C4.5 Per Sensor**	**C4.5 Per Axis**
Bench weight lifting - hard	0.3 ± 0.3	0.3 ± 0.3	0.8 ± 0.7	0.6 ± 0.7
Bench weight lifting - light	1.1 ± 1.2	0.4 ± 0.4	1.4 ± 1.5	1.2 ± 1.3
Bench weight lifting - moderate	0.8 ± 0.8	1.2 ± 0.7	0.8 ± 0.7	1.1 ± 1.2
Bicep curls - hard	3.0 ± 1.8	0.3 ± 0.4	1.8 ± 1.6	1.4 ± 1.3
Bicep curls - light	0.6 ± 0.8	0.4 ± 0.4	1.5 ± 1.8	1.6 ± 1.4
Bicep curls - moderate	0.8 ± 0.7	2.5 ± 0.9	0.8 ± 0.9	1.2 ± 1.0
Calisthenics - Crunches	0.5 ± 0.5	0.2 ± 0.2	0.3 ± 0.3	0.4 ± 1.0
Calisthenics - Sit ups	0.3 ± 0.8	0.1 ± 0.3	0.2 ± 0.4	0.2 ± 0.4
Cycling - Cycle hard - Cycle 80rpm	2.7 ± 1.7	1.0 ± 1.2	1.0 ± 0.8	1.4 ± 1.3
Cycling - Cycle light - Cycle 100rpm	0.6 ± 1.4	0.2 ± 0.6	0.0 ± 0.1	0.0 ± 0.1
Cycling - Cycle light - Cycle 60rpm	0.2 ± 0.4	0.0 ± 0.2	0.3 ± 0.3	0.1 ± 0.2
Cycling - Cycle light - Cycle 80rpm	0.7 ± 0.8	1.1 ± 1.0	2.1 ± 2.0	1.4 ± 1.4
Cycling - Cycle moderate - Cycle 80rpm	0.7 ± 0.9	1.1 ± 1.1	1.8 ± 1.7	1.1 ± 0.8
Lying down	5.9 ± 2.6	4.1 ± 1.6	1.9 ± 2.5	0.0 ± 0.0
Rowing - Rowing hard - Rowing 30spm	3.2 ± 1.5	1.8 ± 1.2	3.1 ± 7.0	1.1 ± 1.3
Rowing - Rowing light - Rowing 30spm	1.2 ± 1.5	1.4 ± 1.3	1.9 ± 1.4	1.8 ± 1.2
Rowing - Rowing moderate - Rowing 30spm	0.8 ± 1.3	0.5 ± 0.7	1.2 ± 1.1	1.2 ± 1.1
Running - Treadmill 4mph - Treadmill 0	0.8 ± 1.5	0.8 ± 1.1	1.6 ± 3.8	0.6 ± 0.8
Running - Treadmill 5mph - Treadmill 0	1.3 ± 1.3	0.7 ± 0.8	1.3 ± 1.0	0.8 ± 0.9
Running - Treadmill 6mph - Treadmill 0	1.1 ± 1.4	0.6 ± 1.0	0.5 ± 0.8	0.5 ± 0.6
Sitting	1.2 ± 0.9	0.6 ± 0.3	1.1 ± 1.8	0.9 ± 1.2
Sitting - Fidget feet legs	0.3 ± 0.3	0.3 ± 0.3	0.3 ± 0.2	0.2 ± 0.3
Sitting - Fidget hands arms	0.8 ± 0.8	0.7 ± 0.7	0.6 ± 0.6	0.4 ± 0.5
Stairs - Ascend stairs	0.6 ± 0.6	0.3 ± 0.4	0.8 ± 0.5	0.4 ± 0.5
Stairs - Descend stairs	1.0 ± 0.9	0.6 ± 0.5	1.2 ± 0.8	0.6 ± 0.4
Standing	0.0 ± 0.0	0.0 ± 0.1	0.2 ± 0.6	0.3 ± 0.5
Walking - Treadmill 2mph - Treadmill 0	0.8 ± 2.0	0.4 ± 1.3	1.0 ± 1.5	0.9 ± 1.7
Walking - Treadmill 3mph - Treadmill 0	3.0 ± 2.3	1.5 ± 1.4	1.4 ± 1.4	1.5 ± 1.4
Walking - Treadmill 3mph - Treadmill 3 - light	1.6 ± 1.6	1.0 ± 0.9	1.3 ± 1.5	1.5 ± 1.0
Walking - Treadmill 3mph - Treadmill 6 - moderate	2.6 ± 2.4	1.6 ± 1.3	1.7 ± 1.3	2.4 ± 1.8
Walking - Treadmill 3mph - Treadmill 9 - hard	0.9 ± 1.3	1.3 ± 2.1	1.1 ± 1.0	1.2 ± 1.4
kneeling	0.2 ± 0.2	0.1 ± 0.2	0.3 ± 0.4	0.1 ± 0.2
Carrying groceries	1.0 ± 1.0	0.4 ± 0.4	2.8 ± 3.7	1.2 ± 1.0
Doing dishes	2.0 ± 1.5	0.8 ± 0.6	1.2 ± 1.2	0.7 ± 0.6
Gardening	2.2 ± 1.6	1.4 ± 0.6	1.0 ± 0.8	1.2 ± 1.0
Ironing	1.8 ± 1.6	0.8 ± 0.6	1.4 ± 1.4	1.1 ± 1.0
Making the bed	0.9 ± 0.8	0.8 ± 0.9	1.7 ± 0.9	1.3 ± 0.6
Mopping	0.9 ± 0.7	1.0 ± 0.7	1.5 ± 1.0	1.6 ± 0.8
Playing videogames	0.9 ± 1.2	0.8 ± 0.9	2.1 ± 3.0	1.1 ± 1.2
Scrubbing a surface	1.8 ± 2.2	1.7 ± 2.7	2.1 ± 2.2	1.4 ± 0.8
Stacking groceries	0.9 ± 0.8	0.8 ± 0.4	1.5 ± 1.0	1.2 ± 0.5
Sweeping	2.1 ± 1.2	1.4 ± 0.5	1.0 ± 0.7	1.5 ± 0.4
Typing	0.6 ± 0.6	0.1 ± 0.1	1.0 ± 1.3	0.6 ± 1.0
Vacuuming	1.4 ± 1.3	0.9 ± 0.6	0.8 ± 0.8	0.8 ± 0.4
Walking around block	0.8 ± 0.8	1.1 ± 1.2	2.6 ± 1.9	2.2 ± 2.1
Washing windows	0.9 ± 0.8	0.9 ± 0.6	2.2 ± 2.5	1.3 ± 0.9
Watching TV	0.8 ± 0.8	0.6 ± 0.4	1.9 ± 2.3	1.2 ± 1.9
Weeding	1.0 ± 1.0	1.0 ± 0.7	1.0 ± 0.6	0.9 ± 0.6
Wiping/Dusting	0.9 ± 0.6	0.7 ± 0.4	1.4 ± 0.7	1.4 ± 0.7
Writing	1.8 ± 1.7	1.0 ± 0.7	1.4 ± 1.4	0.5 ± 0.8
taking out trash	1.2 ± 0.9	1.3 ± 0.7	1.6 ± 1.2	1.7 ± 0.6

Table A15-4: True positive rate obtained using the naïve Bayes (NB) and C4.5 classifiers using the *MaxAccelerationSet1* feature set computed per sensor and per axis during subject independent evaluation without the *unknown* class.

Appendix A16: Summary of Recent Work in Activity Recognition from Accelerometer Data

Ref	Approach	Activities Explored	Sensors Utilized	Results	Data collection
[38]	C4.5 decision tree classifier with the following features: Mean, energy, entropy, and correlation.	Total: 20 Postures, ambulation, exercise and household activities such as vacuuming eating, scrubbing and brushing teeth	Five biaxial accelerometers at dominant wrist, ankle, hip and non-dominant upper arm, and thigh.	Subject dependent: 10-fold cross-validation 71.5% accuracy Subject independent: 84.3% accuracy Accelerometers at thigh and wrist achieve ~80% accuracy	Twenty subjects under laboratory and semi-naturalistic conditions.
[37]	Combine discriminative and generative algorithms (Adaboost + HMMs) to improve discrimination and smoothness Features: linear and Mel-scale FFT coefficients, cepstral coefficients, entropy, band-pass filter coefficients, integrals, means and variances.	Total: 10 Sitting Standing Walking Jogging Walking upstairs Walking downstairs Riding bike Riding car elevator up elevator down	Eight sensors: One triaxial accelerometer, Microphone, IR light and visible light sensors, temperature, barometric pressure, humidity and Compass. All sensors were mounted at the shoulder strap of a backpack.	Trained in 80% of data, tested on 20%. Accuracy: 95% Precision: 98% Recall: 84%	Two subjects under naturalistic conditions
[116]	Naïve Bayes classifier combined with the means and variance as features.	Total: 8 Sitting Standing Walking Ascending stairs Descending stairs Writing, typing Shaking hands	Twelve sensors in total: Ankles, knees, hip (both sides), wrists, elbows, and shoulders.	Subject dependent using all sensors: 70-95% accuracy Lower body activity using sensors at hip and ankle ~80—92% accuracy Upper body activity using sensors at shoulder and wrist: ~40-95% accuracy	Number of subjects unknown, probably one. Data collection conditions also not reported. 18.7 minutes of data.
[98]	Handcrafted dynamic Bayesian networks combined with Rao-Blackwellized particle filters	Total: 8 walking, running, upstairs, downstairs, or driving a vehicle	Eight sensors: One triaxial accelerometer, Microphone, IR light and visible light sensors, temperature, barometric pressure, humidity and Compass. All sensors were mounted at the shoulder strap of a backpack.	Performance of DBN and particle filter very similar to results obtained using simple HMMs. 64% accuracy for DBN + particle filter with GPS data. 72% accuracy for HMMs without GPS	Number of subjects not specified. Data collected in naturalistic conditions. 2 hours of data
[99]	Handcrafted dynamic Bayesian networks in a hierarchy combined with Rao-Blackwellized particle filters	Total: 8 stationary, walking, running, driving vehicle, up-stairs, down stairs, situation assessment from cover, incapacitated	Eight sensors: One triaxial accelerometer, Microphone, IR light and visible light sensors, temperature, barometric pressure, humidity and Compass. All sensors were mounted at the shoulder strap of a backpack.	Evaluation approach not described in detail. Total Accuracy 77% Adaboost 86% DBN + particle filter	Eight subjects collecting data under naturalistic conditions. Approximately 30min of data per subject.

[253]	Adaboost with decision stumps in combination with the following features: mean, variance, and energy in different frequency bands.	Total: 14 Running Crawling Lying down Weapon up Kneeling Driving Walking Sitting Ascending stairs Descending stairs Situation assessment Shaking hands Opening door Standing still	Six triaxial accelerometers at the wrists, thigh, hip, chest, and at the soldier's machine gun.	Subject independent evaluation 78.8% accuracy with null misclassifications 90.3% accuracy over periods of activity	3.3 hours of data from soldiers under naturalistic
[101]	Handcrafted HMMs using Gaussian distributions as observation nodes	Total: 9 Saw, drill, screw, hammer, sand, file, drawer, vice, and clap.	Three triaxial accelerometers and two Microphones Accelerometers were mounted at wrists and forearm, microphones at dominant wrist and neck, near the chest.	Subject dependent leave-one-out cross-validation 93.3% total accuracy	One subject under laboratory conditions
[103]	Handcrafted HMMs with mixture of Gaussians as observation nodes using the following features: Mean, variance, number of peaks, and mean amplitude of the peaks.	Total: 9 hammer, saw, file, drill, sand, grind, screwed, vise, drawer, null	3 triaxial axis accelerometer 2 microphones Wrists+upper arm(acc) Wrist+chest (microphone)	Subject independent 44.5% total accuracy, 46.2% of false positives	One subject under laboratory conditions
[254]	Self-organizing maps (SOM)	Total: 10 Lying Kneeling Sitting Standing Walking Running Climbing stairs Descending stairs Bicycling jumping	20 biaxial accelerometers 90 Ball switch Both legs	93% (SOM) self organizing maps	Number of subjects not specified. Data collected at a laboratory.
[40]	Decision tables, decision trees, support vector machines (SVMs), nearest-neighbor, and naïve Bayes classifiers individually and in different meta-classifier configurations such as boosting, bagging, stacking, and plurality voting. Combined with the following features: mean, standard deviation, energy, and correlation	Total: 8 standing walking running upstairs downstairs sit-ups vacuuming brushing teeth	One triaxial accelerometer at the hip (pelvic region).	Subject independent evaluation using leave-one-subject-out Boosted SVMs: 73% accuracy Naïve Bayes: 64% accuracy Subject dependent evaluation using crossvalidation Plurality voting: 99.6% accuracy Naive Bayes: 98.9% accuracy	2 subjects under data collection conditions not specified.

[119]	Analysis of the performance of different features and window lengths using K-means clustering	Total: 6 walking standing jogging skipping hopping riding a bus	One triaxial accelerometer mounted on a the shoulder strap of a backpack	Priority was not recognition accuracy. Main result: there is no single feature or window length optimal for all activities. The choice of features and window length depends on the activities to recognize	Two subjects under naturalistic conditions (200 minutes of data)
[39]	HMMs with Gaussian observation vectors using the following features: means and variances.	Total: 8 Sit-down, Run, Squat, Walk, Stand, Crawl, Lay down, Hand movements	Three triaxial accelerometers placed at the hip, dominant wrist, and chest.	Subject dependent 9-fold crossvalidation 62% accuracy using single accelerometer at chest. 92% accuracy using sensor combination wrist+chest+hip	Three subjects under data collection conditions not specified. 90s of data per activity.

Table A16-1: Summary of recent work in the area of recognizing physical activities from accelerometer data. L stands for data collected in laboratory settings and N for data collected under naturalistic conditions. Ref stands for bibliographical reference to the work.

Appendix B1: Estimating Energy Expenditure Using the 2-Regression Crouter Algorithm

Activity	RMSE	MAE	MAED
Bench weight lifting - hard	2.06 ± 0.22	2.05 ± 0.21	2.21 ± 0.28
Bench weight lifting - light	1.87 ± 0.54	1.86 ± 0.53	2.05 ± 0.69
Bench weight lifting - moderate	2.09 ± 0.63	2.08 ± 0.63	2.32 ± 0.68
Bicep curls - hard	1.47 ± 0.51	1.47 ± 0.51	1.55 ± 0.57
Bicep curls - light	1.81 ± 0.32	1.80 ± 0.31	1.99 ± 0.48
Bicep curls - moderate	1.53 ± 0.38	1.51 ± 0.36	1.68 ± 0.50
Calisthenics - Crunches	1.72 ± 1.29	1.62 ± 1.31	2.15 ± 1.45
Calisthenics - Sit ups	3.91 ± 0.82	3.84 ± 0.88	4.57 ± 0.55
Cycling - Cycle hard - Cycle 80rpm	6.40 ± 0.69	6.40 ± 0.69	6.61 ± 0.72
Cycling - Cycle light - Cycle 100rpm	1.28 ± 0.56	1.23 ± 0.58	1.58 ± 0.61
Cycling - Cycle light - Cycle 60rpm	0.51 ± 0.34	0.49 ± 0.35	0.60 ± 0.35
Cycling - Cycle light - Cycle 80rpm	1.10 ± 0.54	1.08 ± 0.55	1.28 ± 0.57
Cycling - Cycle moderate - Cycle 80rpm	5.48 ± 0.79	5.48 ± 0.79	5.64 ± 0.85
Lying down	0.17 ± 0.08	0.15 ± 0.08	0.29 ± 0.12
Rowing - Rowing hard - Rowing 30spm	6.15 ± 1.97	6.12 ± 1.94	6.57 ± 2.19
Rowing - Rowing light - Rowing 30spm	5.14 ± 1.54	5.11 ± 1.51	5.56 ± 1.78
Rowing - Rowing moderate - Rowing 30spm	5.96 ± 1.85	5.93 ± 1.84	6.38 ± 2.01
Running - Treadmill 4mph - Treadmill 0	0.88 ± 0.45	0.81 ± 0.44	1.16 ± 0.58
Running - Treadmill 5mph - Treadmill 0	1.19 ± 0.69	1.14 ± 0.72	1.47 ± 0.76
Running - Treadmill 6mph - Treadmill 0	2.40 ± 0.99	2.38 ± 0.99	2.66 ± 1.02
Sitting	0.21 ± 0.14	0.19 ± 0.14	0.26 ± 0.18
Sitting - Fidget feet legs	1.28 ± 0.27	1.27 ± 0.27	1.36 ± 0.27
Sitting - Fidget hands arms	1.16 ± 0.22	1.16 ± 0.22	1.21 ± 0.24
Stairs - Ascend stairs	4.14 ± 0.30	4.13 ± 0.30	4.37 ± 0.24
Stairs - Descend stairs	0.92 ± 0.30	0.88 ± 0.34	1.07 ± 0.32
Standing	0.24 ± 0.17	0.23 ± 0.17	0.28 ± 0.18
Walking - Treadmill 2mph - Treadmill 0	0.29 ± 0.30	0.27 ± 0.31	0.37 ± 0.33
Walking - Treadmill 3mph - Treadmill 0	0.30 ± 0.26	0.28 ± 0.26	0.39 ± 0.29
Walking - Treadmill 3mph - Treadmill 3 - light	4.08 ± 0.38	4.08 ± 0.38	4.23 ± 0.36
Walking - Treadmill 3mph - Treadmill 6 - moderate	4.84 ± 0.43	4.84 ± 0.43	5.03 ± 0.43
Walking - Treadmill 3mph - Treadmill 9 - hard	5.69 ± 0.57	5.69 ± 0.57	5.86 ± 0.60
Kneeling	0.29 ± 0.13	0.26 ± 0.11	0.38 ± 0.18
Unknown	2.72 ± 0.55	2.44 ± 0.53	5.41 ± 1.17
Carrying groceries	3.34 ± 0.75	3.32 ± 0.75	3.60 ± 0.85
Doing dishes	0.66 ± 0.25	0.66 ± 0.25	0.75 ± 0.25
Gardening	1.79 ± 0.41	1.78 ± 0.40	1.99 ± 0.41
Ironing	0.80 ± 0.25	0.77 ± 0.27	0.97 ± 0.22
Making the bed	1.35 ± 0.58	1.23 ± 0.55	1.75 ± 0.69
Mopping	0.84 ± 0.38	0.80 ± 0.40	1.05 ± 0.41
Playing videogames	0.99 ± 0.14	0.99 ± 0.13	1.08 ± 0.21
Scrubbing a surface	1.23 ± 0.47	1.21 ± 0.47	1.47 ± 0.55
Stacking groceries	0.42 ± 0.38	0.41 ± 0.38	0.47 ± 0.37
Sweeping	0.82 ± 0.27	0.77 ± 0.28	1.06 ± 0.32
Typing	0.75 ± 0.14	0.74 ± 0.15	0.84 ± 0.15
Vacuuming	1.07 ± 0.43	1.05 ± 0.46	1.27 ± 0.41
Walking around block	0.84 ± 0.36	0.80 ± 0.35	1.08 ± 0.46
Washing windows	0.79 ± 0.35	0.77 ± 0.37	0.96 ± 0.40
Watching TV	0.14 ± 0.07	0.12 ± 0.07	0.20 ± 0.10
Weeding	2.17 ± 0.43	2.13 ± 0.47	2.50 ± 0.43
Wiping/Dusting	0.50 ± 0.21	0.46 ± 0.22	0.66 ± 0.23
Writing	0.79 ± 0.18	0.79 ± 0.18	0.86 ± 0.17
Taking out trash	0.42 ± 0.23	0.37 ± 0.18	0.59 ± 0.34

Table B1-1: Error statistics per activity while estimating energy expenditure using the 2-regression Crouter Actigraph-based algorithm with respect to the measurements obtained using the Cosmed K4b2 indirect calorimeter for the MIT energy expenditure dataset. Energy expenditure was computed over one minute sliding windows. RMSE stands for root mean squared error, MAE for mean absolute error, and MAED for maximum absolute error deviation.

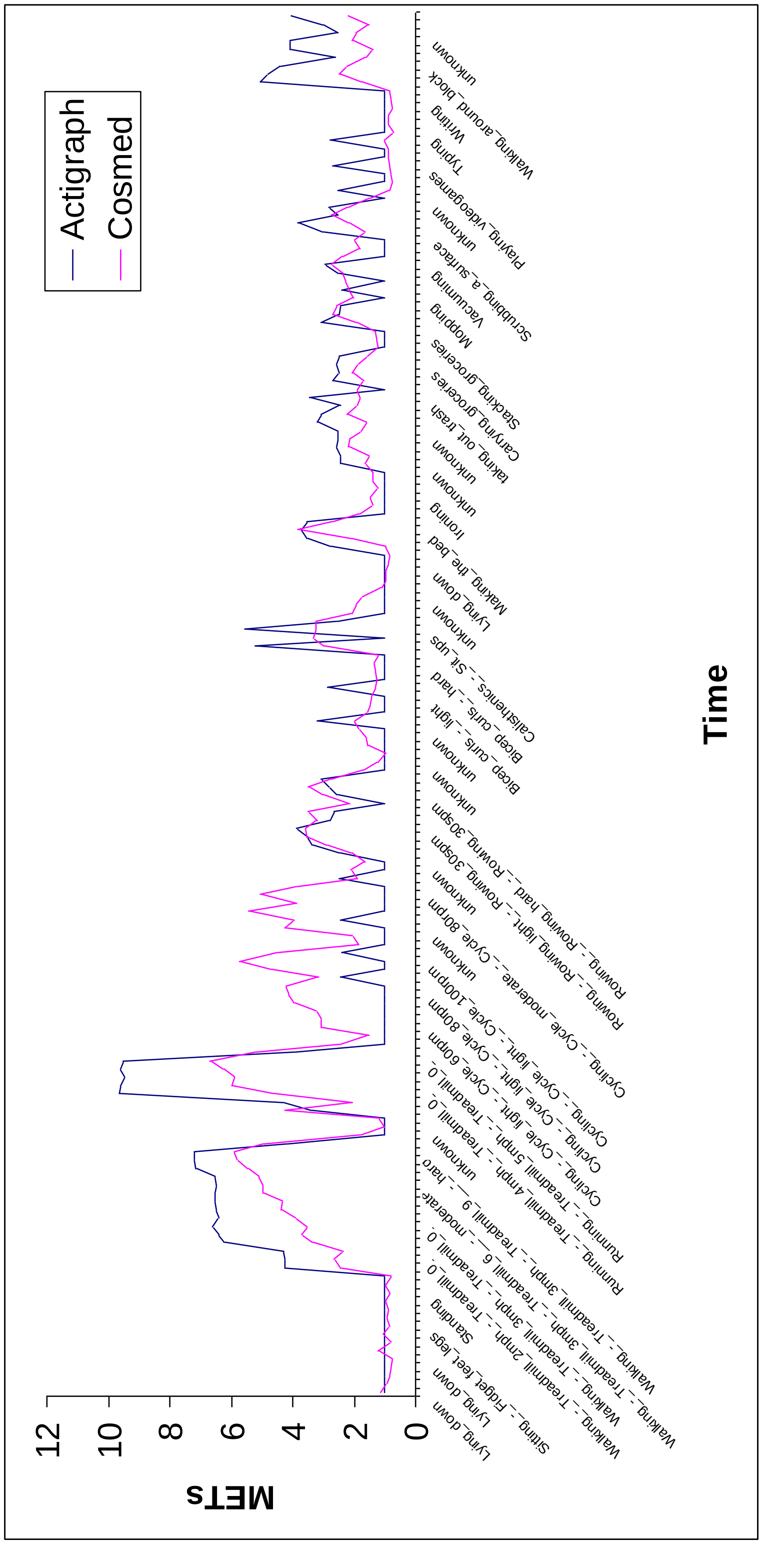

Figure B1-1. Plot of energy expenditure (in METS) computed from the Actigraph using the 2-regression Crouter Method and the Cosmed K4b2 Indirect Calorimeter for Subject MIT-001 over one minute windows.

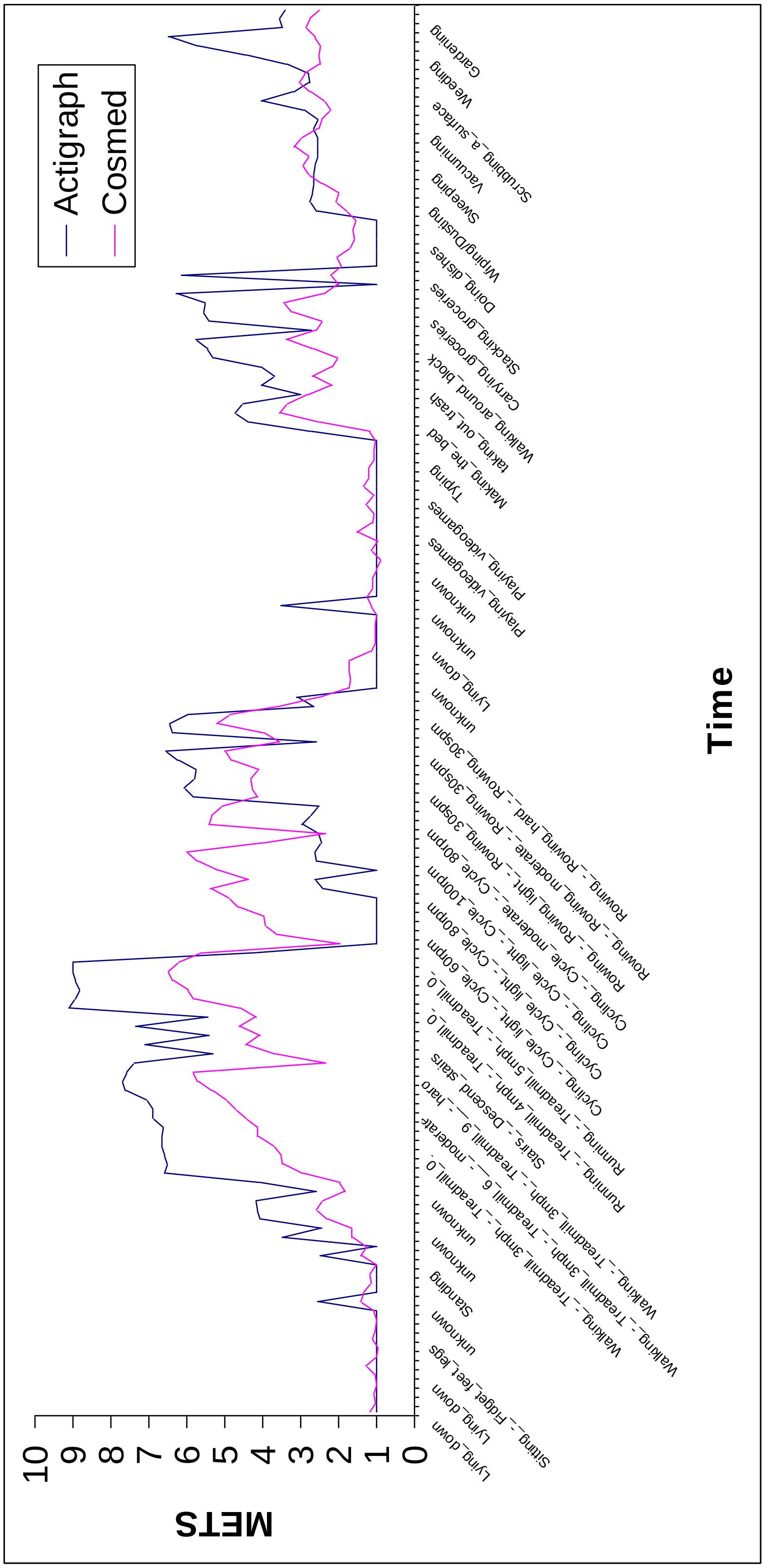

Figure B1-2. Plot of energy expenditure (in METS) computed from the Actigraph using the 2-regression Crouter Method and the Cosmed K4b2 Indirect Calorimeter for Subject MIT-003 over one minute windows.

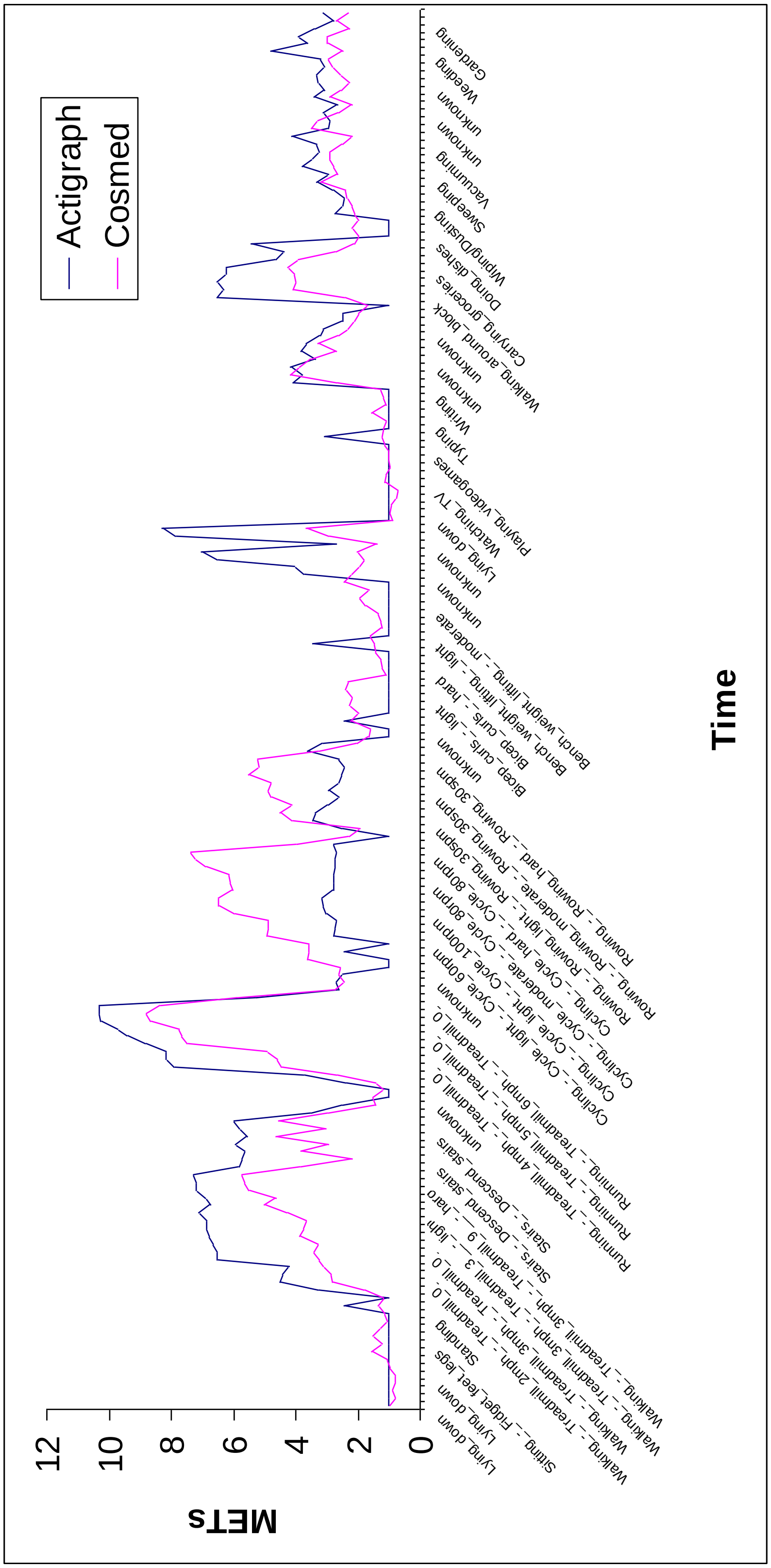

Figure B1-3: Plot of energy expenditure (in METS) computed from the Actigraph using the 2-regression Crouter Method and the Cosmed K4b2 Indirect Calorimeter for Subject MIT-004 over one minute windows.

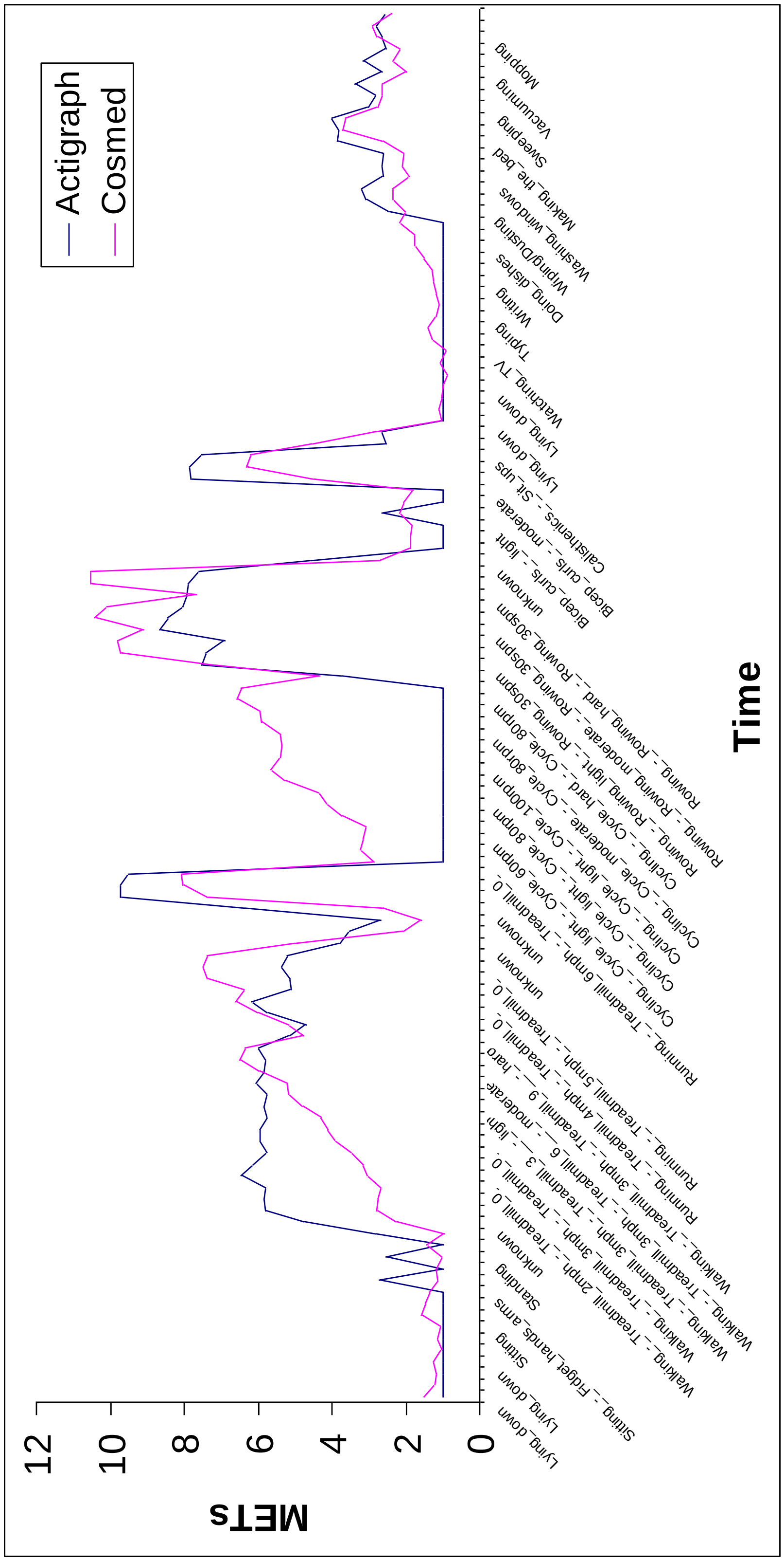

Figure B1-4: Plot of energy expenditure (in METS) computed from the Actigraph using the 2-regression Crouter Method and the Cosmed K4b2 Indirect Calorimeter for Subject MIT-018 over one minute windows.

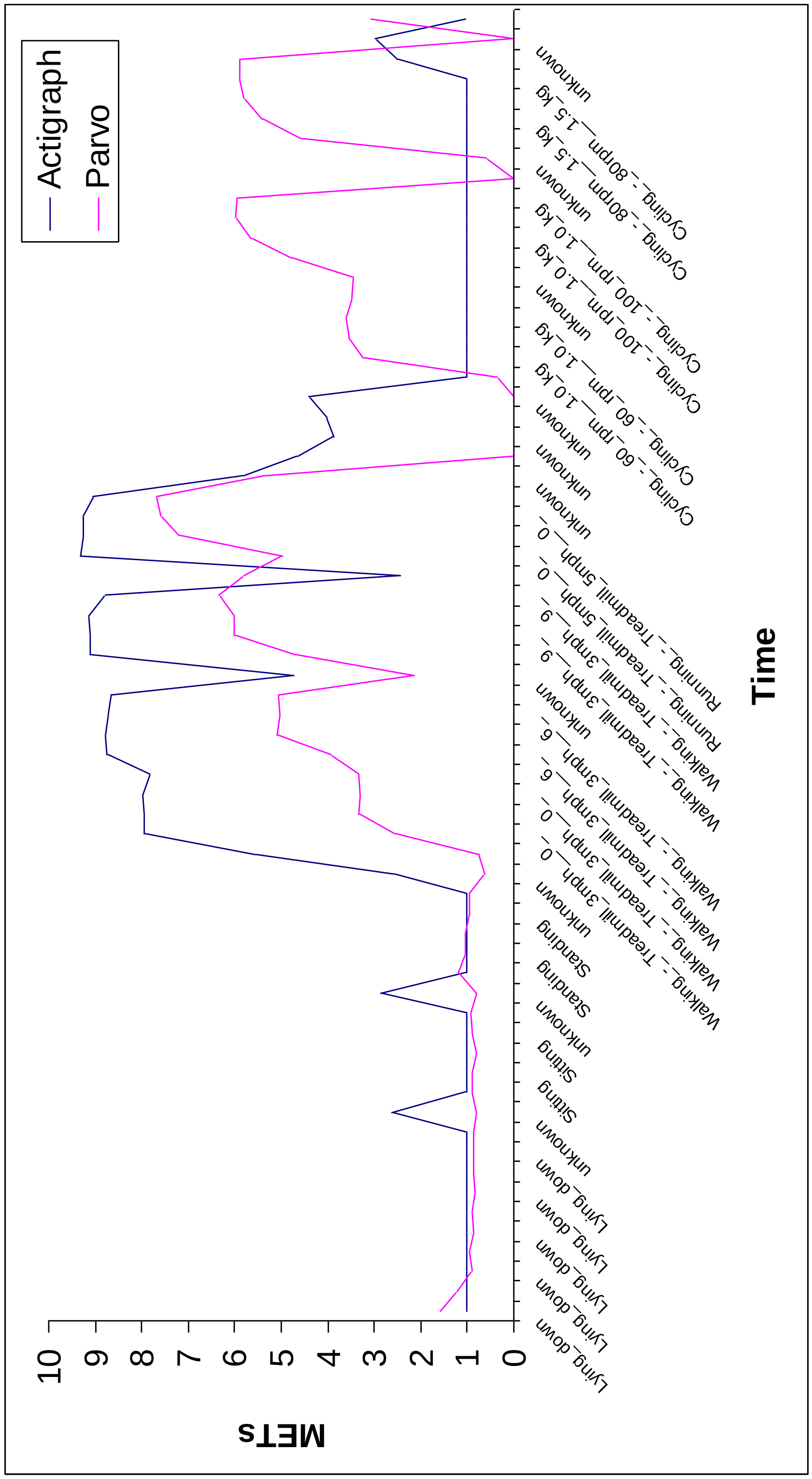

Figure B1-5: Comparison of Parvo indirect calorimeter data and energy expenditure estimated using the 2-regression Crouter algorithm from an Actigraph worn at the hip for subject BU-001.Energ expenditure was computed over one minute sliding windows.

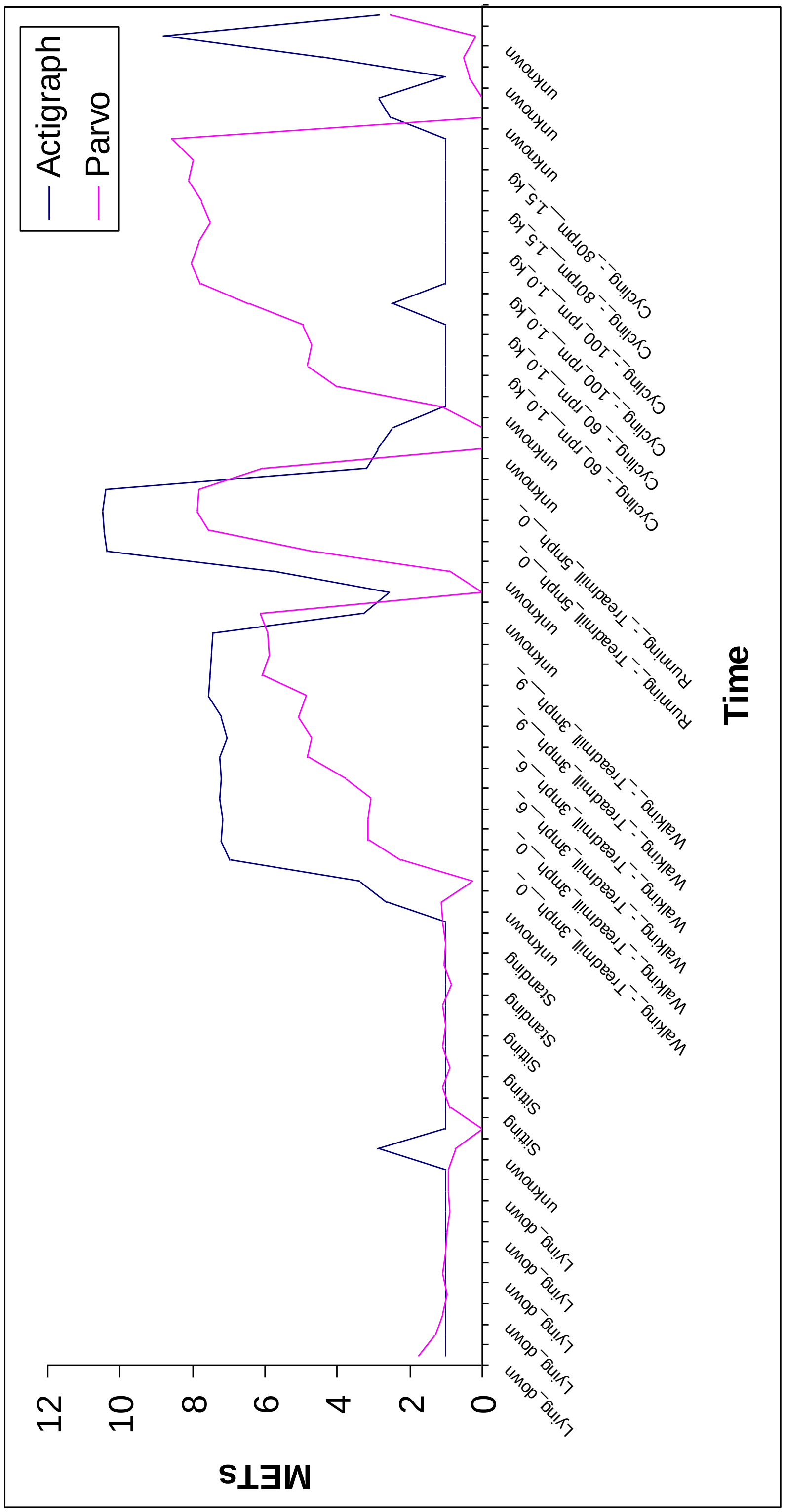

Figure B1-6: Comparison of Parvo indirect calorimeter data and energy expenditure estimated using the 2-regression Crouter algorithm from an Actigraph worn at the hip for subject BU-003.

Appendix B2: Estimating Energy Expenditure Using Simple Regression Algorithms

Activity	Root Mean Squared Error				
	(a)	(b)	(c)	(d)	(e)
Bench weight lifting - light	1.06 ± 0.46	0.54 ± 0.22	0.54 ± 0.21	0.54 ± 0.24	0.52 ± 0.25
Bench weight lifting - moderate	1.15 ± 0.52	0.57 ± 0.22	0.56 ± 0.25	0.57 ± 0.22	0.54 ± 0.25
Bench weight lifting - hard	1.21 ± 0.30	0.38 ± 0.23	0.39 ± 0.25	0.36 ± 0.21	0.36 ± 0.24
Bicep curls - light	0.51 ± 0.26	1.02 ± 0.29	1.09 ± 0.37	0.58 ± 0.24	1.31 ± 0.44
Bicep curls - moderate	0.50 ± 0.16	1.23 ± 0.29	1.32 ± 0.32	0.75 ± 0.27	1.56 ± 0.35
Bicep curls - hard	0.70 ± 0.15	1.29 ± 0.52	1.38 ± 0.57	0.86 ± 0.36	1.60 ± 0.64
Calisthenics - Crunches	1.13 ± 0.45	1.38 ± 0.63	1.40 ± 0.68	1.26 ± 0.64	1.34 ± 0.57
Calisthenics - Sit ups	1.88 ± 0.91	1.46 ± 0.65	1.48 ± 0.67	1.68 ± 0.76	1.79 ± 0.91
Cycling - Cycle light - Cycle 100rpm	1.85 ± 0.93	1.73 ± 0.85	1.54 ± 0.83	1.73 ± 0.84	1.54 ± 0.84
Cycling - Cycle light - Cycle 60rpm	2.12 ± 0.58	1.03 ± 0.48	1.04 ± 0.46	0.92 ± 0.43	1.05 ± 0.49
Cycling - Cycle light - Cycle 80rpm	2.06 ± 0.92	1.41 ± 0.72	1.39 ± 0.63	1.34 ± 0.66	1.31 ± 0.70
Cycling - Cycle moderate - Cycle 80rpm	3.12 ± 0.93	2.46 ± 0.79	2.26 ± 0.93	2.43 ± 0.76	2.37 ± 0.85
Cycling - Cycle hard - Cycle 80rpm	3.56 ± 1.25	3.01 ± 0.91	2.83 ± 1.06	2.99 ± 0.81	2.95 ± 0.94
Lying down	0.84 ± 0.16	0.73 ± 0.16	0.62 ± 0.15	0.96 ± 0.16	0.64 ± 0.15
Rowing - Rowing light - Rowing 30spm	2.72 ± 1.16	2.09 ± 1.28	2.12 ± 1.31	2.39 ± 1.40	2.05 ± 1.31
Rowing - Rowing moderate - Rowing 30spm	3.45 ± 1.43	2.83 ± 1.58	2.85 ± 1.60	3.18 ± 1.73	2.77 ± 1.62
Rowing - Rowing hard - Rowing 30spm	3.68 ± 1.60	3.05 ± 1.72	3.07 ± 1.75	3.39 ± 1.83	2.99 ± 1.75
Running - Treadmill 4mph - Treadmill 0	2.01 ± 0.99	1.26 ± 0.51	1.22 ± 0.50	1.34 ± 0.68	1.17 ± 0.39
Running - Treadmill 5mph - Treadmill 0	2.85 ± 0.92	1.05 ± 0.53	0.98 ± 0.53	1.13 ± 0.56	0.96 ± 0.42
Running - Treadmill 6mph - Treadmill 0	3.50 ± 1.01	1.14 ± 0.72	1.05 ± 0.66	1.25 ± 0.83	1.01 ± 0.54
Sitting	0.94 ± 0.27	0.65 ± 0.17	0.56 ± 0.15	0.84 ± 0.21	0.58 ± 0.15
Sitting - Fidget feet legs	0.43 ± 0.25	0.97 ± 0.24	1.05 ± 0.33	1.07 ± 0.22	1.04 ± 0.29
Sitting - Fidget hands arms	0.47 ± 0.23	0.98 ± 0.26	1.00 ± 0.35	0.91 ± 0.20	0.99 ± 0.30
Stairs - Ascend stairs	0.92 ± 0.18	0.84 ± 0.21	0.87 ± 0.23	0.84 ± 0.20	0.87 ± 0.21
Stairs - Descend stairs	1.43 ± 0.39	1.38 ± 0.28	1.35 ± 0.30	1.42 ± 0.27	1.37 ± 0.29
Standing	0.93 ± 0.26	0.67 ± 0.16	0.58 ± 0.13	0.86 ± 0.20	0.58 ± 0.14
Walking - Treadmill 2mph - Treadmill 0	0.50 ± 0.29	0.76 ± 0.26	0.84 ± 0.35	0.87 ± 0.29	0.89 ± 0.38
Walking - Treadmill 3mph - Treadmill 0	0.87 ± 0.45	0.84 ± 0.35	0.97 ± 0.42	0.97 ± 0.39	1.06 ± 0.41
Walking - Treadmill 3mph - Treadmill 3 - light	0.48 ± 0.24	0.43 ± 0.17	0.57 ± 0.28	0.47 ± 0.21	0.60 ± 0.30
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.78 ± 0.38	0.75 ± 0.37	0.73 ± 0.42	0.66 ± 0.31	0.63 ± 0.40
Walking - Treadmill 3mph - Treadmill 9 - hard	1.49 ± 0.70	1.50 ± 0.63	1.45 ± 0.72	1.36 ± 0.62	1.31 ± 0.71
kneeling	1.00 ± 0.21	0.57 ± 0.20	0.48 ± 0.19	0.77 ± 0.21	0.49 ± 0.19
unknown	1.99 ± 0.50	1.52 ± 0.37	1.53 ± 0.35	1.53 ± 0.38	1.54 ± 0.35
Carrying groceries	0.98 ± 0.32	0.97 ± 0.24	1.14 ± 0.29	0.97 ± 0.27	1.20 ± 0.33
Doing dishes	0.69 ± 0.14	0.61 ± 0.16	0.60 ± 0.16	0.50 ± 0.22	0.63 ± 0.15
Gardening	1.05 ± 0.36	0.52 ± 0.28	0.56 ± 0.34	0.48 ± 0.18	0.54 ± 0.28
Ironing	0.83 ± 0.29	0.66 ± 0.18	0.62 ± 0.17	0.67 ± 0.22	0.62 ± 0.18
Making the bed	1.09 ± 0.30	0.88 ± 0.29	0.93 ± 0.30	0.90 ± 0.31	0.94 ± 0.32
Mopping	0.90 ± 0.33	0.54 ± 0.21	0.58 ± 0.22	0.52 ± 0.29	0.55 ± 0.24
Playing videogames	0.76 ± 0.18	0.79 ± 0.17	0.68 ± 0.17	1.00 ± 0.17	0.71 ± 0.16
Scrubbing a surface	1.01 ± 0.25	0.54 ± 0.16	0.61 ± 0.18	0.52 ± 0.19	0.61 ± 0.19
Stacking groceries	0.58 ± 0.22	0.85 ± 0.26	0.78 ± 0.28	0.73 ± 0.27	0.72 ± 0.25
Sweeping	0.81 ± 0.20	0.52 ± 0.23	0.56 ± 0.30	0.47 ± 0.15	0.55 ± 0.28
Typing	0.82 ± 0.13	0.72 ± 0.13	0.63 ± 0.12	0.89 ± 0.14	0.66 ± 0.12
Vacuuming	1.00 ± 0.37	0.49 ± 0.22	0.54 ± 0.26	0.48 ± 0.21	0.52 ± 0.24
Walking around block	1.43 ± 0.25	1.43 ± 0.25	1.63 ± 0.29	1.41 ± 0.28	1.67 ± 0.30
Washing windows	0.90 ± 0.27	0.55 ± 0.13	0.62 ± 0.20	0.51 ± 0.21	0.62 ± 0.23
Watching TV	0.79 ± 0.13	0.78 ± 0.14	0.67 ± 0.14	0.99 ± 0.15	0.69 ± 0.13
Weeding	1.13 ± 0.34	0.56 ± 0.23	0.57 ± 0.31	0.57 ± 0.19	0.57 ± 0.29
Wiping/Dusting	0.71 ± 0.19	0.65 ± 0.22	0.70 ± 0.29	0.54 ± 0.17	0.68 ± 0.21
Writing	0.78 ± 0.18	0.75 ± 0.19	0.65 ± 0.19	0.95 ± 0.19	0.67 ± 0.18
taking out trash	0.76 ± 0.13	0.73 ± 0.19	0.78 ± 0.20	0.72 ± 0.17	0.81 ± 0.21

Table B2-1: Root mean squared error per activity when estimating energy expenditure using the simple linear regression equations (a), (b), (c), (d), and (e).

Error Measures	***Results***
Total Correlation Coefficient	0.73 ± 0.06
Total root Mean Square Error	1.28 ± 0.29
Total mean Absolute Error	0.95 ± 0.16
Total relative Absolute Error	63.63 ± 5.04
Total root Relative Squared Error	69.73 ± 5.27
Maximum absolute Deviation	4.12 ± 1.21

Table B2-2: Performance of estimating energy expenditure using multivariable linear regression and the *ACAbsArea* feature set computed per sensor over one minute windows with respect to energy expenditure measured using the Cosmed K4b2 indirect calorimeter for the MIT dataset.

$$\begin{aligned} \textit{Energy expenditure (METs)} = \; & -0.0043 * \textit{absarea 1T} + \\ & 0.0013 * \textit{absarea 4T} + \\ & 0.0024 * \textit{absarea 7T} + \\ & 0.0025 * \textit{absarea 8T} + \\ & 0.0024 * \textit{absarea 11T} + \\ & 0.0026 * \textit{absarea 14T} + \\ & 0.0019 * \textit{absarea 17T} + \\ & 1.3746 \end{aligned}$$

Table B2-3: Prediction equation learned using multivariable linear regression and the *ACAbsArea* feature set computed per sensor over one minute windows from the MIT energy expenditure dataset.

Activity	RMSE	MAE	MAED
Bench weight lifting - hard	0.27 ± 0.18	0.24 ± 0.16	0.34 ± 0.25
Bench weight lifting - light	0.58 ± 0.19	0.54 ± 0.20	0.70 ± 0.23
Bench weight lifting - moderate	0.53 ± 0.28	0.49 ± 0.27	0.63 ± 0.35
Bicep curls - hard	1.41 ± 0.63	1.40 ± 0.64	1.53 ± 0.64
Bicep curls - light	1.10 ± 0.41	1.09 ± 0.44	1.25 ± 0.32
Bicep curls - moderate	1.40 ± 0.37	1.38 ± 0.40	1.55 ± 0.26
Calisthenics - Crunches	1.31 ± 0.85	1.17 ± 0.80	1.62 ± 1.00
Calisthenics - Sit ups	1.40 ± 0.79	1.17 ± 0.65	1.88 ± 1.06
Cycling - Cycle hard - Cycle 80rpm	2.92 ± 1.19	2.90 ± 1.20	3.19 ± 1.22
Cycling - Cycle light - Cycle 100rpm	1.50 ± 0.78	1.43 ± 0.82	1.82 ± 0.79
Cycling - Cycle light - Cycle 60rpm	1.05 ± 0.51	1.03 ± 0.53	1.19 ± 0.50
Cycling - Cycle light - Cycle 80rpm	1.36 ± 0.62	1.32 ± 0.64	1.59 ± 0.65
Cycling - Cycle moderate - Cycle 80rpm	2.04 ± 1.06	2.01 ± 1.04	2.24 ± 1.19
Lying down	0.49 ± 0.15	0.48 ± 0.16	0.61 ± 0.14
Rowing - Rowing hard - Rowing 30spm	2.94 ± 1.70	2.84 ± 1.64	3.38 ± 1.99
Rowing - Rowing light - Rowing 30spm	1.95 ± 1.29	1.82 ± 1.19	2.37 ± 1.56
Rowing - Rowing moderate - Rowing 30spm	2.73 ± 1.55	2.62 ± 1.54	3.21 ± 1.77
Running - Treadmill 4mph - Treadmill 0	1.19 ± 0.56	1.06 ± 0.60	1.63 ± 0.68
Running - Treadmill 5mph - Treadmill 0	1.00 ± 0.63	0.93 ± 0.63	1.28 ± 0.79
Running - Treadmill 6mph - Treadmill 0	0.92 ± 0.76	0.91 ± 0.76	1.07 ± 0.83
Sitting	0.43 ± 0.17	0.42 ± 0.17	0.50 ± 0.16
Sitting - Fidget feet legs	1.01 ± 0.36	1.00 ± 0.35	1.09 ± 0.41
Sitting - Fidget hands arms	0.96 ± 0.38	0.95 ± 0.39	1.05 ± 0.39
Stairs - Ascend stairs	0.60 ± 0.34	0.54 ± 0.34	0.83 ± 0.39
Stairs - Descend stairs	1.11 ± 0.36	1.08 ± 0.33	1.25 ± 0.43
Standing	0.45 ± 0.14	0.43 ± 0.13	0.55 ± 0.18
Walking - Treadmill 2mph - Treadmill 0	0.88 ± 0.41	0.85 ± 0.42	1.11 ± 0.39
Walking - Treadmill 3mph - Treadmill 0	1.08 ± 0.49	1.05 ± 0.50	1.32 ± 0.56
Walking - Treadmill 3mph - Treadmill 3 - light	0.66 ± 0.37	0.63 ± 0.38	0.88 ± 0.45
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.67 ± 0.42	0.63 ± 0.43	0.85 ± 0.44
Walking - Treadmill 3mph - Treadmill 9 - hard	1.28 ± 0.79	1.25 ± 0.78	1.49 ± 0.90
Kneeling	0.33 ± 0.18	0.31 ± 0.19	0.39 ± 0.19
Unknown	1.31 ± 0.33	1.02 ± 0.24	3.26 ± 0.87
Carrying groceries	1.26 ± 0.37	1.17 ± 0.40	1.70 ± 0.45
Doing dishes	0.56 ± 0.18	0.55 ± 0.18	0.65 ± 0.20
Gardening	0.51 ± 0.41	0.47 ± 0.41	0.65 ± 0.44
Ironing	0.55 ± 0.18	0.51 ± 0.18	0.72 ± 0.27
Making the bed	0.84 ± 0.36	0.70 ± 0.30	1.28 ± 0.59
Mopping	0.50 ± 0.24	0.46 ± 0.23	0.70 ± 0.35
Playing videogames	0.55 ± 0.17	0.54 ± 0.18	0.63 ± 0.17
Scrubbing a surface	0.48 ± 0.23	0.42 ± 0.22	0.73 ± 0.31
Stacking groceries	0.66 ± 0.30	0.63 ± 0.32	0.79 ± 0.30
Sweeping	0.47 ± 0.28	0.41 ± 0.24	0.72 ± 0.44
Typing	0.52 ± 0.12	0.50 ± 0.12	0.62 ± 0.14
Vacuuming	0.47 ± 0.32	0.44 ± 0.30	0.63 ± 0.42
Walking around block	1.78 ± 0.27	1.71 ± 0.30	2.24 ± 0.33
Washing windows	0.58 ± 0.28	0.51 ± 0.27	0.80 ± 0.42
Watching TV	0.53 ± 0.14	0.52 ± 0.14	0.63 ± 0.17
Weeding	0.46 ± 0.30	0.39 ± 0.26	0.64 ± 0.44
Wiping/Dusting	0.69 ± 0.37	0.64 ± 0.33	0.91 ± 0.53
Writing	0.54 ± 0.19	0.53 ± 0.19	0.61 ± 0.18
Taking out trash	0.65 ± 0.23	0.60 ± 0.23	0.90 ± 0.29

Table B2-4: Performance per class while predicting energy expenditure using multivariable linear regression and the *ACAbsArea* feature set computed per sensor over one minute windows for the MIT energy expenditure dataset.

Appendix B3: Activities Utilized to Predict Energy Expenditure using Equation (e)

Activity	Accelerometer Recognizable	Posture and Ambulation
Bench weight lifting – Light		
Bench weight lifting – Moderate		
Bench weight lifting – Hard		
Bicep curls – Light		
Bicep curls – Moderate		
Bicep curls – Hard		
Calisthenics Crunches	√	
Calisthenics Sit ups	√	
Cycling Cycle 100rpm (15mph, 120.4W) – Light		
Cycling Cycle 60rpm (8.9mph, 66.9W) – Light		
Cycling Cycle 80rpm (11.2mph, 100.4W) – Light		
Cycling Cycle 80rpm – Moderate		
Cycling Cycle 80rpm – Hard		
Lying down	√	√
Rowing 30spm – Light		
Rowing 30spm – Moderate		
Rowing 30spm – Hard		
Running Treadmill 4mph Treadmill 0	√	√
Running Treadmill 5mph Treadmill 0	√	√
Running Treadmill 6mph Treadmill 0	√	√
Sitting	√	√
Sitting Fidget feet legs	√	√
Sitting Fidget hands arms	√	√
Stairs Ascend stairs		
Stairs Descend stairs		
Standing	√	√
Walking Treadmill 2mph Treadmill 0	√	√
Walking Treadmill 3mph Treadmill 0	√	√
Walking Treadmill 3mph Treadmill 3 – Light		
Walking Treadmill 3mph Treadmill 6 – Moderate		
Walking Treadmill 3mph Treadmill 9 – Hard		
Kneeling	√	√
Carrying groceries		
Doing dishes	√	
Gardening	√	
Ironing	√	
Making the bed	√	
Mopping		
Playing videogames	√	√
Scrubbing a surface		
Stacking groceries		
Sweeping		
Typing	√	√
Vacuuming		
Walking around block	√	√
Washing windows		
Watching TV	√	
Weeding	√	
Wiping/Dusting	√	
Writing	√	√
Taking out trash		
Unknown	√	

Table B3-1: Activities utilized to learn the coefficients of equation (e). The column 'Accelerometer Recognizable' includes only activities that can be recognized from accelerometer data and consequently, those activities that do not contain resistance work or load effort. The column 'Posture and Ambulation' includes only activities involving posture or ambulation.

Appendix B4: Comparison of Activities Contained in the MIT Energy Expenditure Dataset and the Ones Found in the Compendium of Physical Activities

Gymnasium Dataset Activity	Closest Compendium Activity	METs	Comparable Activity
Lying down	Lying in bed awake, listening to music (not talking or reading	1.0	√
Sitting	Sitting quietly and watching television	1.0	√
Sitting - Fidget feet legs	Sitting quietly and watching television	1.0	
Sitting - Fidget hands arms	Sitting - knitting, sewing, lt. wrapping (presents)	1.5	
Standing	Standing quietly (standing in a line)	1.2	√
Kneeling	Kneeling in church/at home (praying)	1.0	√
Walking - Treadmill 2mph - Treadmill 0%	Walking, 2.0 mph, level, slow pace, firm surface	2.5	√
Walking - Treadmill 3mph - Treadmill 0%	Walking, 3.0 mph, level, moderate pace, firm surface	3.3	√
Walking - Treadmill 3mph - Treadmill 3% - light	Walking, 3.5 mph, uphill	6.0	
Walking - Treadmill 3mph - Treadmill 6% - moderate	Walking, 3.5 mph, uphill	6.0	
Walking - Treadmill 3mph - Treadmill 9% - hard	Walking, 3.5 mph, uphill	6.0	
Stairs - Ascend stairs	Upstairs, using or climbing up ladder	8.0	√
Stairs - Descend stairs	Downstairs	3.0	√
Running - Treadmill 4mph - Treadmill 0%	Walking, 4.0 mph, level, firm surface, very brisk pace	5.0	√
Running - Treadmill 5mph - Treadmill 0%	Running, 5 mph (12 min/mile)	8.0	√
Running - Treadmill 6mph - Treadmill 0%	Running, 6 mph (10 min/mile)	10.0	√
Cycling - Cycle light - Cycle 60rpm (8.9mph or 66.9W)	Bicycling, stationary, 50watt, very light effort	3.0	√
Cycling - Cycle hard - Cycle 80rpm (11.2mph or 100W)	Bicycling, stationary, 100watts, light effort	5.5	√
Cycling - Cycle light - Cycle 100rpm (15mph or 140W)	Bicycling, stationary, 150watts, moderate effort	7.0	√
Cycling - Cycle moderate - Cycle 80rpm	Bicycling, stationary, 100watts, light effort	5.5	
Cycling - Cycle hard - Cycle 80rpm	Bicycling, stationary, 100watts, light effort	5.5	
Rowing - Rowing light - Rowing 30spm	Rowing, stationary, 50 watts, light effort	3.5	
Rowing - Rowing moderate - Rowing 30spm	Rowing, stationary, 100 watts, moderate effort	7.0	
Rowing - Rowing hard - Rowing 30spm	Rowing, stationary, 150 watts, vigorous effort	8.5	
Bench weight lifting - hard	Weight lifting (free weight, nautilus or universal-type), power lifting or body building, vigorous effort	6.0	
Bench weight lifting - moderate	Weight lifting (free, nautilus or universal-type), light or moderate effort, light workout, general	3.0	
Bench weight lifting - light	Weight lifting (free, nautilus or universal-type), light or moderate effort, light workout, general	3.0	
Bicep curls - hard	Weight lifting (free, nautilus or universal-type), light or moderate effort, light workout, general	3.0	
Bicep curls - moderate	Weight lifting (free, nautilus or universal-type), light or moderate effort, light workout, general	3.0	
Bicep curls - light	Weight lifting (free, nautilus or universal-type), light or moderate effort, light workout, general	3.0	
Calisthenics - Crunches	Calisthenics (e.g. pushups, sit-ups, pull-ups, jumping jacks), heavy, vigorous effort	8.0	
Calisthenics - Sit ups	Calisthenics (e.g. pushups, sit-ups, pull-ups, jumping jacks), heavy, vigorous effort	8.0	√

Table B4-1: Mapping between gymnasium dataset activities for which data was collected and the activities listed in the Compendium of Physical Activities. The METs column indicates energy expenditure in METs from the Compendium and the column “Comparable Activity” indicates if the Compendium activity was used for comparison in the energy expenditure experiments.

Home Dataset Activity	Closest Compendium Activity Description	METs	Comparable Activity
Lying down	Lying in bed awake, listening to music (not talking or reading	1.0	√
Writing	Sitting - writing, desk work, typing	1.8	√
Typing	Sitting - writing, desk work, typing	1.8	√
Watching TV	Lying quietly, watching television	1.0	√
Playing videogames	Sitting - card playing, playing board games	1.5	
Making the bed	Making bed	2.0	
Taking out trash	Cleaning, light (dusting, straightening up, changing linen, carrying out trash	2.5	√
Ironing	Ironing	2.3	√
Doing dishes	Wash dishes - standing or in general (not broken into stand/walk components	2.3	√
Wiping/Dusting	Cleaning, light (dusting, straightening up, changing linen, carrying out trash)	2.5	√
Walking around block	Walking for pleasure	3.5	√
Carrying groceries (one 3kg bag on each hand)	Walking 2.5mph slowly and carrying light objects less than 25Lb	3.0	
Stacking groceries	Putting away groceries (e.g. carrying groceries, shopping without a grocery cart), carrying packages.	2.5	√
Sweeping	Carpet sweeping, sweeping floors	3.3	√
Mopping	Mopping	3.5	√
Vacuuming	Vacuuming	3.5	√
Washing windows	Cleaning, heavy or major (e.g. wash car, wash windows, clean garage), vigorous effort	3.0	√
Weeding	Weeding, cultivating garden	4.5	√
Gardening	Gardening, general	4.0	√
Scrubbing a surface	Scrubbing floors, on hands and knees, scrubbing bathroom, bathtub	3.8	√

Table B4-2: Mapping between household dataset activities for which data was collected and the activities listed in the Compendium of Physical Activities. The METs column indicates energy expenditure in METs from the Compendium and the column "Comparable Activity" indicates if the Compendium activity was used for comparison in the energy expenditure experiments.

Appendix B5: Estimating Energy Expenditure Using the Compendium of Physical Activities

Activity	RMSE	MAE	MAED
Calisthenics - Sit ups	3.91 ± 0.82	3.84 ± 0.88	4.57 ± 0.55
Lying down	0.17 ± 0.08	0.15 ± 0.08	0.29 ± 0.12
Running - Treadmill 4mph - Treadmill 0	0.88 ± 0.45	0.81 ± 0.44	1.16 ± 0.58
Running - Treadmill 5mph - Treadmill 0	1.19 ± 0.69	1.14 ± 0.72	1.47 ± 0.76
Running - Treadmill 6mph - Treadmill 0	2.40 ± 0.99	2.38 ± 0.99	2.66 ± 1.02
Sitting	0.21 ± 0.14	0.19 ± 0.14	0.26 ± 0.18
Stairs - Ascend stairs	4.14 ± 0.30	4.13 ± 0.30	4.37 ± 0.24
Stairs - Descend stairs	0.92 ± 0.30	0.88 ± 0.34	1.07 ± 0.32
Standing	0.24 ± 0.17	0.23 ± 0.17	0.28 ± 0.18
Walking - Treadmill 2mph - Treadmill 0	0.29 ± 0.30	0.27 ± 0.31	0.37 ± 0.33
Walking - Treadmill 3mph - Treadmill 0	0.30 ± 0.26	0.28 ± 0.26	0.39 ± 0.29
kneeling	0.29 ± 0.13	0.26 ± 0.11	0.38 ± 0.18
Doing dishes	0.66 ± 0.25	0.66 ± 0.25	0.75 ± 0.25
Gardening	1.79 ± 0.41	1.78 ± 0.40	1.99 ± 0.41
Ironing	0.80 ± 0.25	0.77 ± 0.27	0.97 ± 0.22
Making the bed	1.35 ± 0.58	1.23 ± 0.55	1.75 ± 0.69
Mopping	0.84 ± 0.38	0.80 ± 0.40	1.05 ± 0.41
Scrubbing a surface	1.23 ± 0.47	1.21 ± 0.47	1.47 ± 0.55
Stacking groceries	0.42 ± 0.38	0.41 ± 0.38	0.47 ± 0.37
Sweeping	0.82 ± 0.27	0.77 ± 0.28	1.06 ± 0.32
Typing	0.75 ± 0.14	0.74 ± 0.15	0.84 ± 0.15
Vacuuming	1.07 ± 0.43	1.05 ± 0.46	1.27 ± 0.41
Walking around block	0.84 ± 0.36	0.80 ± 0.35	1.08 ± 0.46
Washing windows	0.79 ± 0.35	0.77 ± 0.37	0.96 ± 0.40
Watching TV	0.14 ± 0.07	0.12 ± 0.07	0.20 ± 0.10
Weeding	2.17 ± 0.43	2.13 ± 0.47	2.50 ± 0.43
Wiping/Dusting	0.50 ± 0.21	0.46 ± 0.22	0.66 ± 0.23
Writing	0.79 ± 0.18	0.79 ± 0.18	0.86 ± 0.17
taking out trash	0.42 ± 0.23	0.37 ± 0.18	0.59 ± 0.34

Table B5-1: Results of estimating energy expenditure using only the *comparable* Compendium activities over the MIT energy expenditure dataset assuming activity is known. MAE stands for mean absolute error, RMSE for root mean squared error, MAED for maximum absolute error deviation over a one minute window.

Activity	RMSE	MAE	MAED
Bench weight lifting - hard	4.08 ± 0.14	4.08 ± 0.14	4.16 ± 0.22
Bench weight lifting - light	1.30 ± 0.50	1.27 ± 0.52	1.43 ± 0.44
Bench weight lifting - moderate	1.17 ± 0.40	1.12 ± 0.46	1.31 ± 0.37
Bicep curls - hard	4.55 ± 0.49	4.55 ± 0.49	4.65 ± 0.44
Bicep curls - light	1.20 ± 0.26	1.19 ± 0.27	1.36 ± 0.26
Bicep curls - moderate	1.42 ± 0.36	1.40 ± 0.38	1.56 ± 0.21
Calisthenics - Crunches	6.22 ± 1.37	6.18 ± 1.41	6.68 ± 1.22
Calisthenics - Sit ups	4.39 ± 0.75	4.26 ± 0.85	5.44 ± 0.56
Cycling - Cycle hard - Cycle 80rpm	1.74 ± 0.68	1.71 ± 0.69	2.10 ± 0.70
Cycling - Cycle light - Cycle 100rpm	1.45 ± 0.59	1.39 ± 0.60	1.89 ± 0.67
Cycling - Cycle light - Cycle 60rpm	0.50 ± 0.31	0.48 ± 0.32	0.61 ± 0.31
Cycling - Cycle light - Cycle 80rpm	1.22 ± 0.53	1.19 ± 0.55	1.53 ± 0.57
Cycling - Cycle moderate - Cycle 80rpm	2.74 ± 0.82	2.70 ± 0.86	3.05 ± 0.76
Lying down	0.17 ± 0.08	0.15 ± 0.08	0.29 ± 0.15
Rowing - Rowing hard - Rowing 30spm	2.92 ± 1.35	2.81 ± 1.47	3.45 ± 1.31
Rowing - Rowing light - Rowing 30spm	1.62 ± 1.39	1.46 ± 1.29	2.06 ± 1.68
Rowing - Rowing moderate - Rowing 30spm	2.09 ± 0.88	1.95 ± 0.96	2.62 ± 0.91
Running - Treadmill 4mph - Treadmill 0	1.03 ± 0.31	0.91 ± 0.28	1.42 ± 0.48
Running - Treadmill 5mph - Treadmill 0	1.38 ± 0.68	1.29 ± 0.71	1.85 ± 0.81
Running - Treadmill 6mph - Treadmill 0	2.51 ± 0.93	2.46 ± 0.93	2.89 ± 1.17
Sitting	0.26 ± 0.20	0.23 ± 0.19	0.34 ± 0.25
Sitting - Fidget feet legs	0.30 ± 0.20	0.29 ± 0.21	0.34 ± 0.20
Sitting - Fidget hands arms	0.36 ± 0.17	0.35 ± 0.17	0.42 ± 0.19
Stairs - Ascend stairs	5.09 ± 0.26	5.08 ± 0.26	5.44 ± 0.25
Stairs - Descend stairs	1.22 ± 0.42	1.17 ± 0.39	1.41 ± 0.52
Standing	0.25 ± 0.19	0.22 ± 0.17	0.32 ± 0.25
Walking - Treadmill 2mph - Treadmill 0	0.32 ± 0.28	0.29 ± 0.29	0.45 ± 0.30
Walking - Treadmill 3mph - Treadmill 0	0.35 ± 0.23	0.31 ± 0.23	0.49 ± 0.26
Walking - Treadmill 3mph - Treadmill 3 - light	2.00 ± 0.38	1.99 ± 0.38	2.28 ± 0.41
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.27 ± 0.42	1.25 ± 0.43	1.59 ± 0.45
Walking - Treadmill 3mph - Treadmill 9 - hard	0.64 ± 0.28	0.60 ± 0.30	0.87 ± 0.33
kneeling	0.32 ± 0.16	0.30 ± 0.16	0.41 ± 0.19
Carrying groceries	0.74 ± 0.38	0.70 ± 0.38	0.96 ± 0.47
Doing dishes	0.64 ± 0.26	0.64 ± 0.26	0.70 ± 0.28
Gardening	1.79 ± 0.44	1.79 ± 0.44	1.96 ± 0.46
Ironing	0.82 ± 0.26	0.78 ± 0.28	0.98 ± 0.30
Making the bed	1.23 ± 0.55	1.09 ± 0.49	1.63 ± 0.67
Mopping	0.88 ± 0.40	0.84 ± 0.41	1.10 ± 0.44
Playing videogames	0.51 ± 0.14	0.50 ± 0.15	0.57 ± 0.12
Scrubbing a surface	1.34 ± 0.41	1.31 ± 0.41	1.63 ± 0.42
Stacking groceries	0.50 ± 0.35	0.47 ± 0.37	0.58 ± 0.33
Sweeping	0.85 ± 0.27	0.79 ± 0.29	1.12 ± 0.33
Typing	0.69 ± 0.14	0.67 ± 0.14	0.82 ± 0.16
Vacuuming	1.06 ± 0.39	1.03 ± 0.41	1.26 ± 0.39
Walking around block	0.98 ± 0.34	0.90 ± 0.36	1.33 ± 0.44
Washing windows	0.79 ± 0.35	0.77 ± 0.35	0.94 ± 0.37
Watching TV	0.16 ± 0.05	0.13 ± 0.05	0.24 ± 0.07
Weeding	2.19 ± 0.38	2.15 ± 0.41	2.53 ± 0.51
Wiping/Dusting	0.51 ± 0.23	0.49 ± 0.24	0.64 ± 0.26
Writing	0.78 ± 0.18	0.77 ± 0.19	0.85 ± 0.18
taking out trash	0.43 ± 0.22	0.38 ± 0.20	0.64 ± 0.29

Table B5-2: Results of estimating energy expenditure using the *closest* Compendium activities over the MIT energy expenditure dataset assuming activity is known. MAE stands for mean absolute error, RMSE for root mean squared error, and MAED for maximum absolute error deviation.

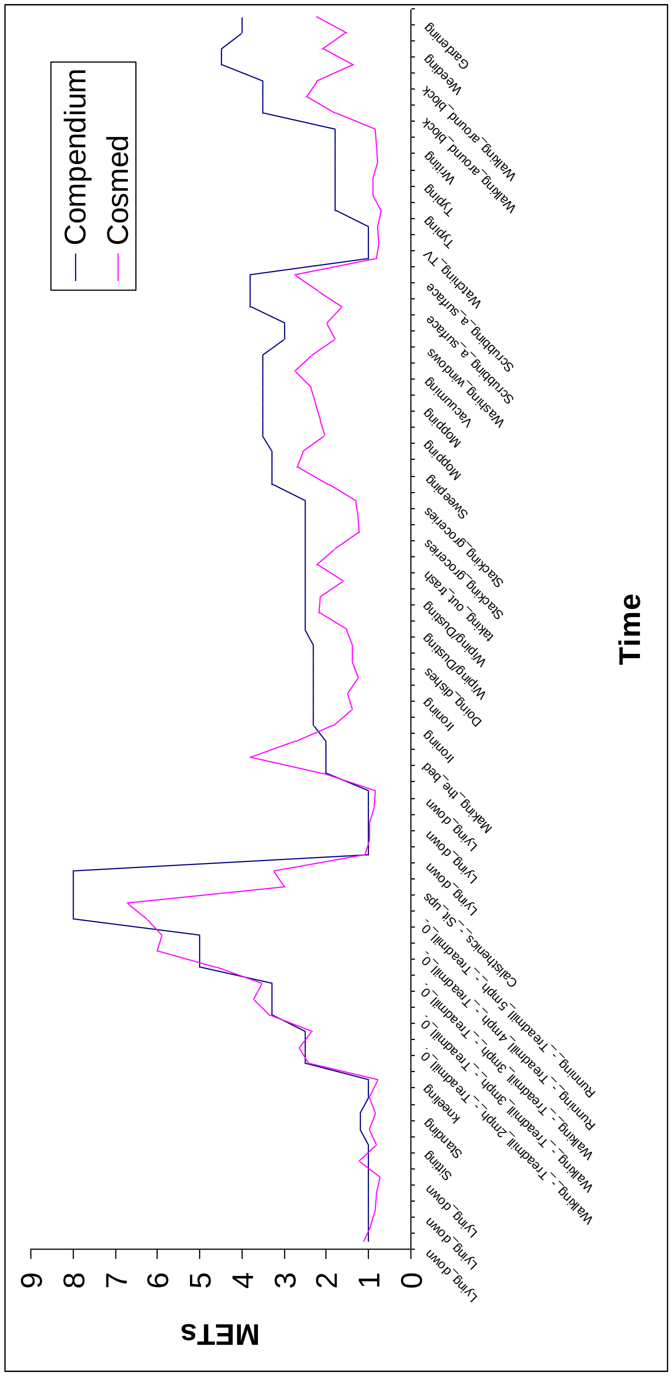

Figure B5-1: Plot of energy expenditure estimated using the Compendium of Physical Activities vs. the one measured using the Cosmed K4b2 Indirect Calorimeter for subject MIT-001. The activities shown are only the directly comparable to the compendium Activities (*comparable* set).

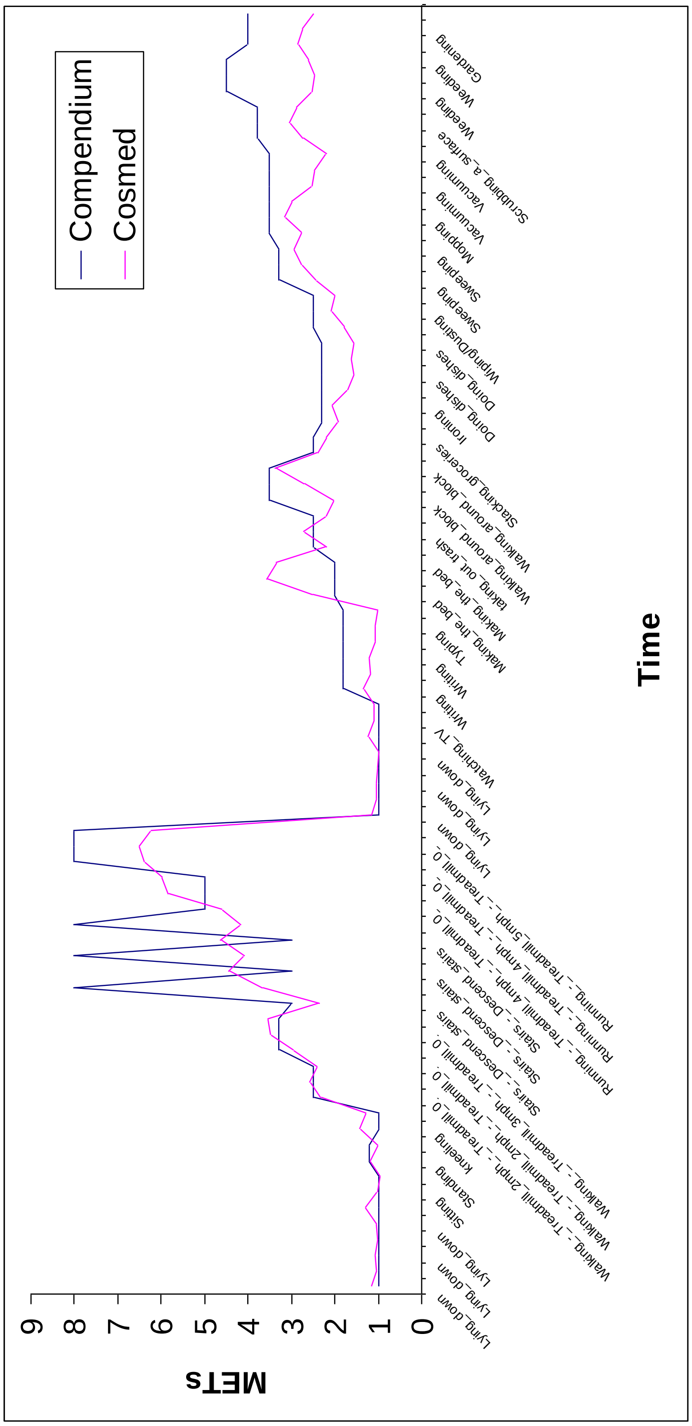

Figure B5-2: Plot of energy expenditure estimated using the Compendium of Physical Activities vs. the one measured using the Cosmed K4b2 Indirect Calorimeter for subject MIT-003. The activities shown are only the directly comparable to the compendium Activities (*comparable* set).

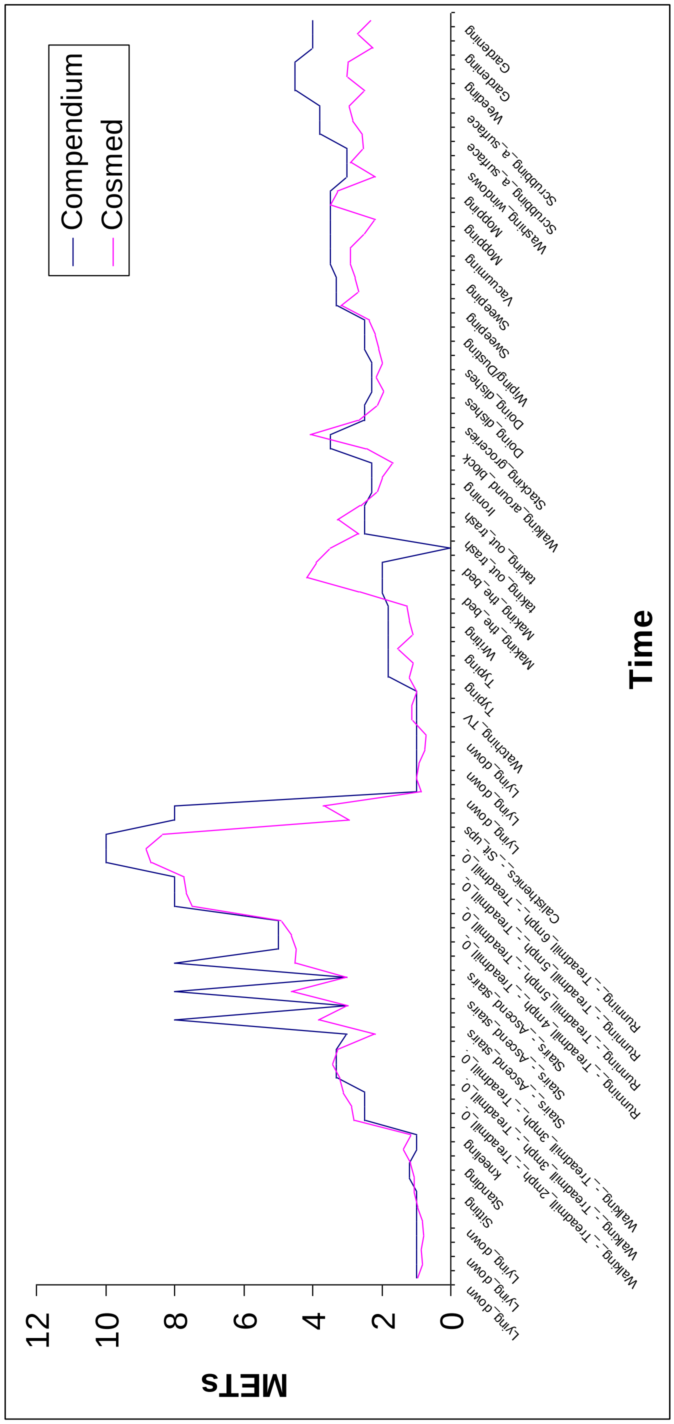

Figure B5-3: Plot of energy expenditure estimated using the Compendium of Physical Activities vs. the one measured using the Cosmed K4b2 Indirect Calorimeter for subject MIT-004. The activities shown are only the directly comparable to the compendium Activities (*comparable* set).

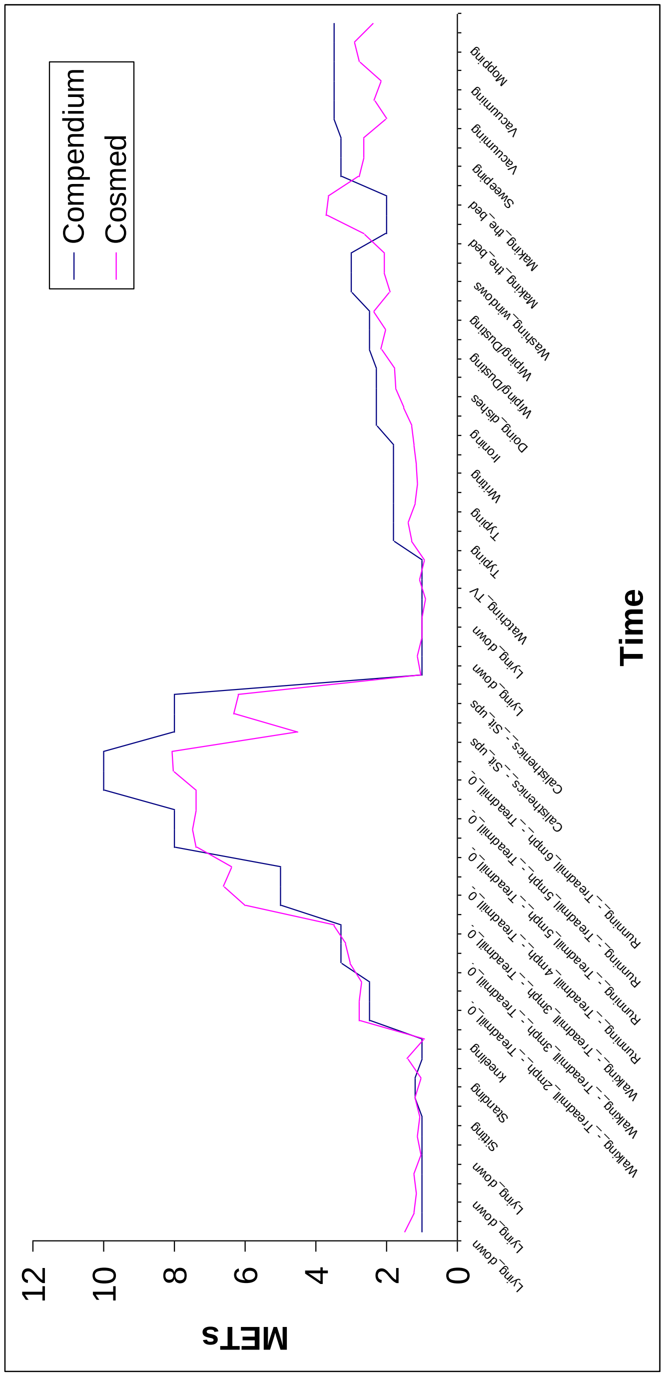

Figure B5-4: Plot of energy expenditure estimated using the Compendium of Physical Activities vs. the one measured using the Cosmed K4b2 Indirect Calorimeter for subject MIT-018. The activities shown are only the directly comparable to the compendium Activities (*comparable* set).

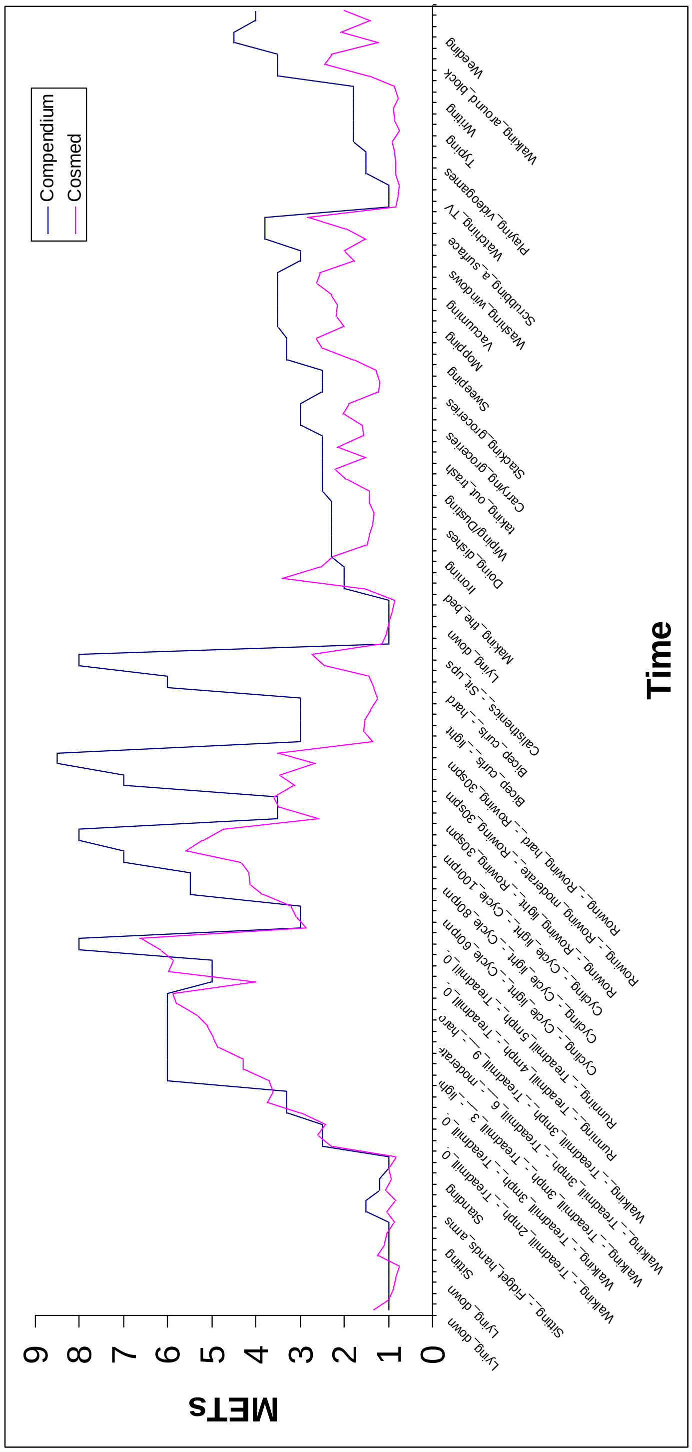

Figure B5-4: Plot of energy expenditure estimated using the Compendium of Physical Activities vs. the one measured using the Cosmed K4b2 indirect calorimeter for subject MIT-001. The activities shown are the closest with respect to the compendium activities (*closest* set).

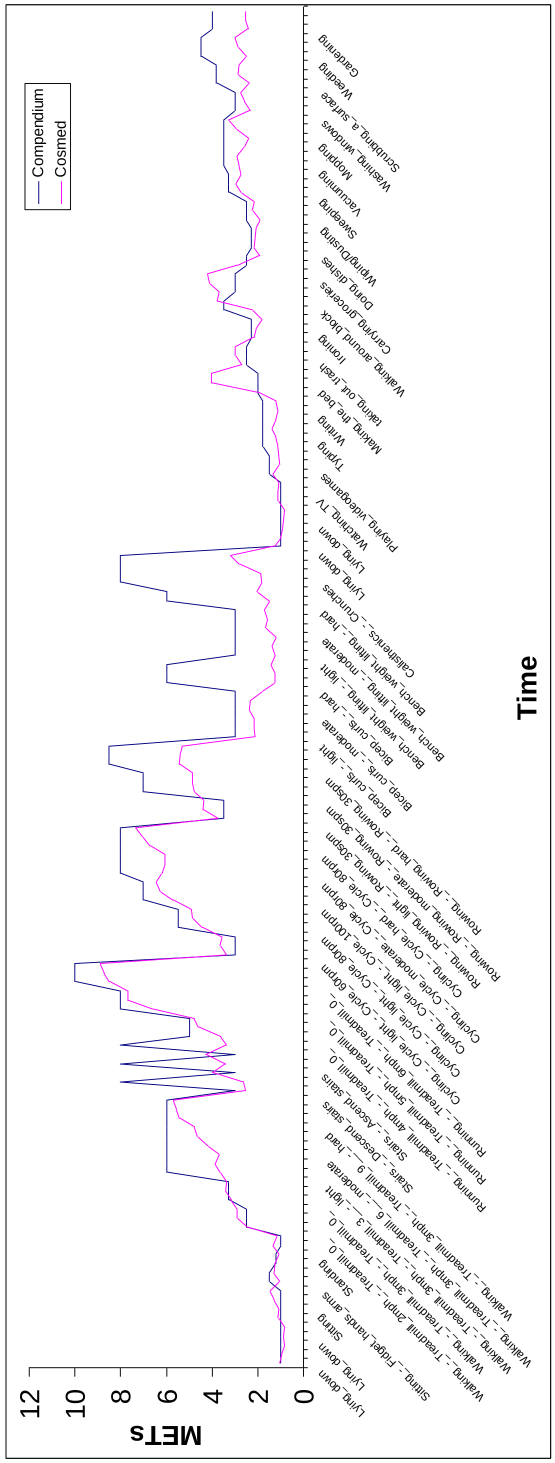

Figure B5-5. Plot of energy expenditure estimated using the Compendium of Physical Activities vs. the one measured using the Cosmed K4b2 indirect calorimeter for subject MIT-004. The activities shown are the closest with respect to the compendium activities (*closest* set).

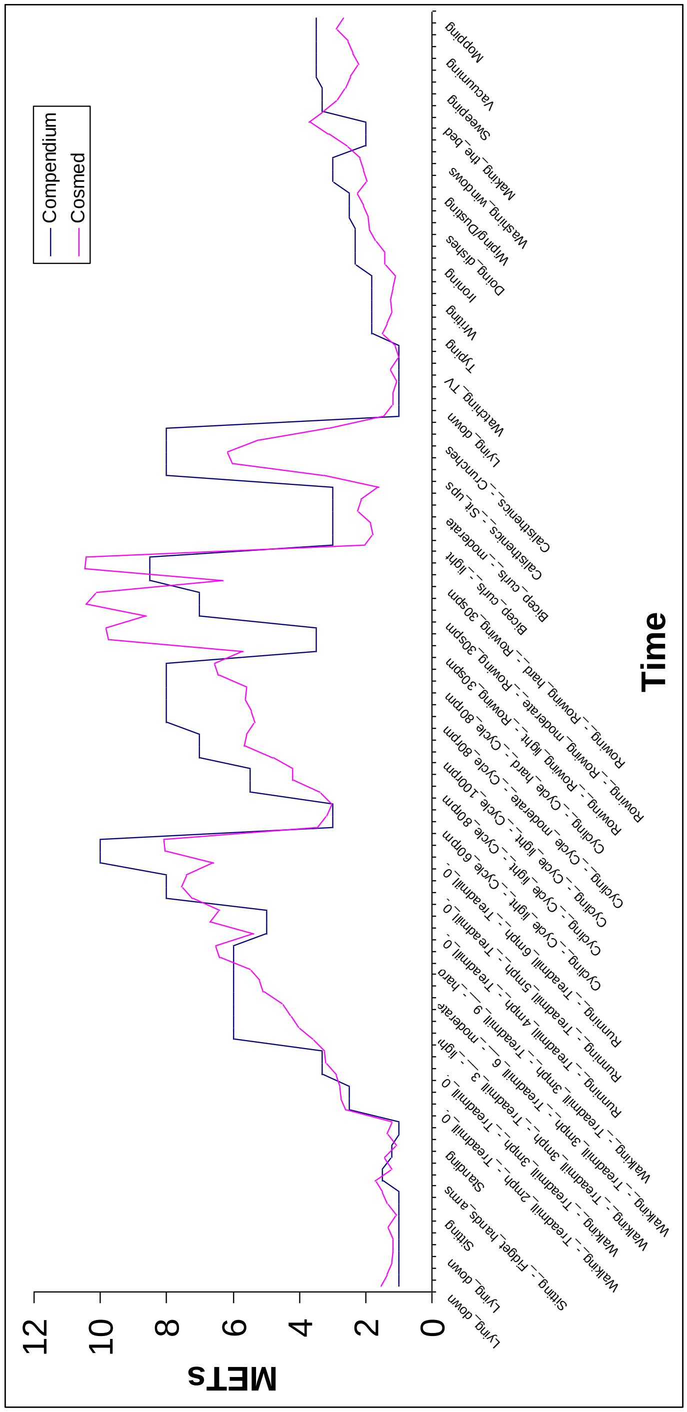

Figure B5-6: Plot of energy expenditure estimated using the Compendium of Physical Activities vs. the one measured using the Cosmed K4b2 indirect calorimeter for subject MIT-018. The activities shown are the closest with respect to the compendium activities (*closest* set).

Appendix B6: Estimating Energy Expenditure Using Linear Regression and the ACAbsArea Feature Computed over One Minute Windows.

Activity	RMSE	MAE	MAED
Bench_weight_lifting_-_hard	0.27 ± 0.18	0.24 ± 0.16	0.34 ± 0.25
Bench_weight_lifting_-_light	0.58 ± 0.19	0.54 ± 0.20	0.70 ± 0.23
Bench_weight_lifting_-_moderate	0.53 ± 0.28	0.49 ± 0.27	0.63 ± 0.35
Bicep_curls_-_hard	1.41 ± 0.63	1.40 ± 0.64	1.53 ± 0.64
Bicep_curls_-_light	1.10 ± 0.41	1.09 ± 0.44	1.25 ± 0.32
Bicep_curls_-_moderate	1.40 ± 0.37	1.38 ± 0.40	1.55 ± 0.26
Calisthenics_-_Crunches	1.31 ± 0.85	1.17 ± 0.80	1.62 ± 1.00
Calisthenics_-_Sit_ups	1.40 ± 0.79	1.17 ± 0.65	1.88 ± 1.06
Cycling_-_Cycle_hard_-_Cycle_80rpm	2.92 ± 1.19	2.90 ± 1.20	3.19 ± 1.22
Cycling_-_Cycle_light_-_Cycle_100rpm	1.50 ± 0.78	1.43 ± 0.82	1.82 ± 0.79
Cycling_-_Cycle_light_-_Cycle_60rpm	1.05 ± 0.51	1.03 ± 0.53	1.19 ± 0.50
Cycling_-_Cycle_light_-_Cycle_80rpm	1.36 ± 0.62	1.32 ± 0.64	1.59 ± 0.65
Cycling_-_Cycle_moderate_-_Cycle_80rpm	2.04 ± 1.06	2.01 ± 1.04	2.24 ± 1.19
Lying_down	0.49 ± 0.15	0.48 ± 0.16	0.61 ± 0.14
Rowing_-_Rowing_hard_-_Rowing_30spm	2.94 ± 1.70	2.84 ± 1.64	3.38 ± 1.99
Rowing_-_Rowing_light_-_Rowing_30spm	1.95 ± 1.29	1.82 ± 1.19	2.37 ± 1.56
Rowing_-_Rowing_moderate_-_Rowing_30spm	2.73 ± 1.55	2.62 ± 1.54	3.21 ± 1.77
Running_-_Treadmill_4mph_-_Treadmill_0_	1.19 ± 0.56	1.06 ± 0.60	1.63 ± 0.68
Running_-_Treadmill_5mph_-_Treadmill_0_	1.00 ± 0.63	0.93 ± 0.63	1.28 ± 0.79
Running_-_Treadmill_6mph_-_Treadmill_0_	0.92 ± 0.76	0.91 ± 0.76	1.07 ± 0.83
Sitting	0.43 ± 0.17	0.42 ± 0.17	0.50 ± 0.16
Sitting_-_Fidget_feet_legs	1.01 ± 0.36	1.00 ± 0.35	1.09 ± 0.41
Sitting_-_Fidget_hands_arms	0.96 ± 0.38	0.95 ± 0.39	1.05 ± 0.39
Stairs_-_Ascend_stairs	0.60 ± 0.34	0.54 ± 0.34	0.83 ± 0.39
Stairs_-_Descend_stairs	1.11 ± 0.36	1.08 ± 0.33	1.25 ± 0.43
Standing	0.45 ± 0.14	0.43 ± 0.13	0.55 ± 0.18
Walking_-_Treadmill_2mph_-_Treadmill_0_	0.88 ± 0.41	0.85 ± 0.42	1.11 ± 0.39
Walking_-_Treadmill_3mph_-_Treadmill_0_	1.08 ± 0.49	1.05 ± 0.50	1.32 ± 0.56
Walking_-_Treadmill_3mph_-_Treadmill_3__-_light	0.66 ± 0.37	0.63 ± 0.38	0.88 ± 0.45
Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate	0.67 ± 0.42	0.63 ± 0.43	0.85 ± 0.44
Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard	1.28 ± 0.79	1.25 ± 0.78	1.49 ± 0.90
kneeling	0.33 ± 0.18	0.31 ± 0.19	0.39 ± 0.19
Unknown	1.31 ± 0.33	1.02 ± 0.24	3.26 ± 0.87
Carrying_groceries	1.26 ± 0.37	1.17 ± 0.40	1.70 ± 0.45
Doing_dishes	0.56 ± 0.18	0.55 ± 0.18	0.65 ± 0.20
Gardening	0.51 ± 0.41	0.47 ± 0.41	0.65 ± 0.44
Ironing	0.55 ± 0.18	0.51 ± 0.18	0.72 ± 0.27
Making_the_bed	0.84 ± 0.36	0.70 ± 0.30	1.28 ± 0.59
Mopping	0.50 ± 0.24	0.46 ± 0.23	0.70 ± 0.35
Playing_videogames	0.55 ± 0.17	0.54 ± 0.18	0.63 ± 0.17
Scrubbing_a_surface	0.48 ± 0.23	0.42 ± 0.22	0.73 ± 0.31
Stacking_groceries	0.66 ± 0.30	0.63 ± 0.32	0.79 ± 0.30
Sweeping	0.47 ± 0.28	0.41 ± 0.24	0.72 ± 0.44
Typing	0.52 ± 0.12	0.50 ± 0.12	0.62 ± 0.14
Vacuuming	0.47 ± 0.32	0.44 ± 0.30	0.63 ± 0.42
Walking_around_block	1.78 ± 0.27	1.71 ± 0.30	2.24 ± 0.33
Washing_windows	0.58 ± 0.28	0.51 ± 0.27	0.80 ± 0.42
Watching_TV	0.53 ± 0.14	0.52 ± 0.14	0.63 ± 0.17
Weeding	0.46 ± 0.30	0.39 ± 0.26	0.64 ± 0.44
Wiping/Dusting	0.69 ± 0.37	0.64 ± 0.33	0.91 ± 0.53
Writing	0.54 ± 0.19	0.53 ± 0.19	0.61 ± 0.18
taking_out_trash	0.65 ± 0.23	0.60 ± 0.23	0.90 ± 0.29

Table B6-1: Performance per activity obtained when estimating energy expenditure using a multivariable linear model per activity over the MIT dataset. The models are trained using the *ACAbsArea* feature computed per sensor over one minute sliding windows.

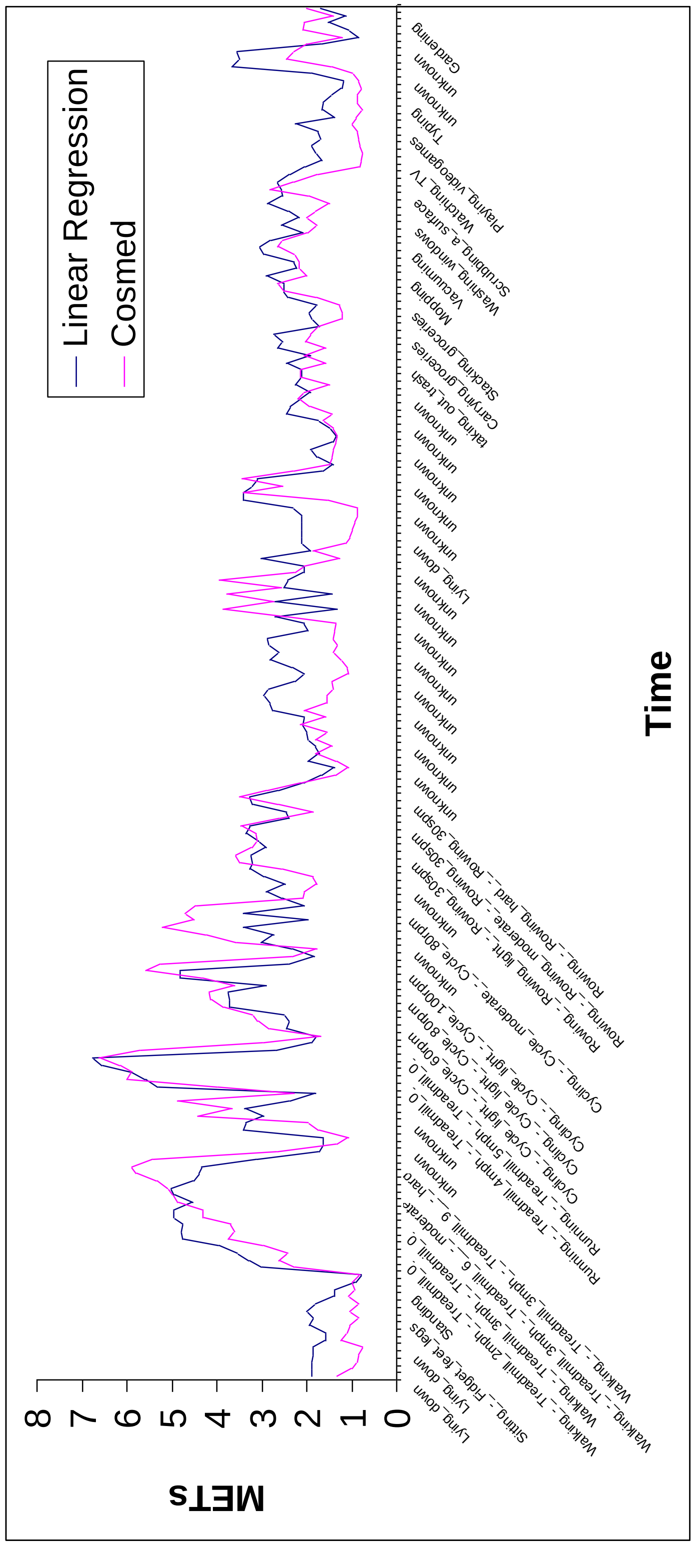

Figure B6-1. Plot of energy expenditure (in METS) computed using linear regression over the sum of the areas over all axis per sensor (7) and the Cosmed K4b2 Indirect Calorimeter for Subject MIT-001 over one minute windows.

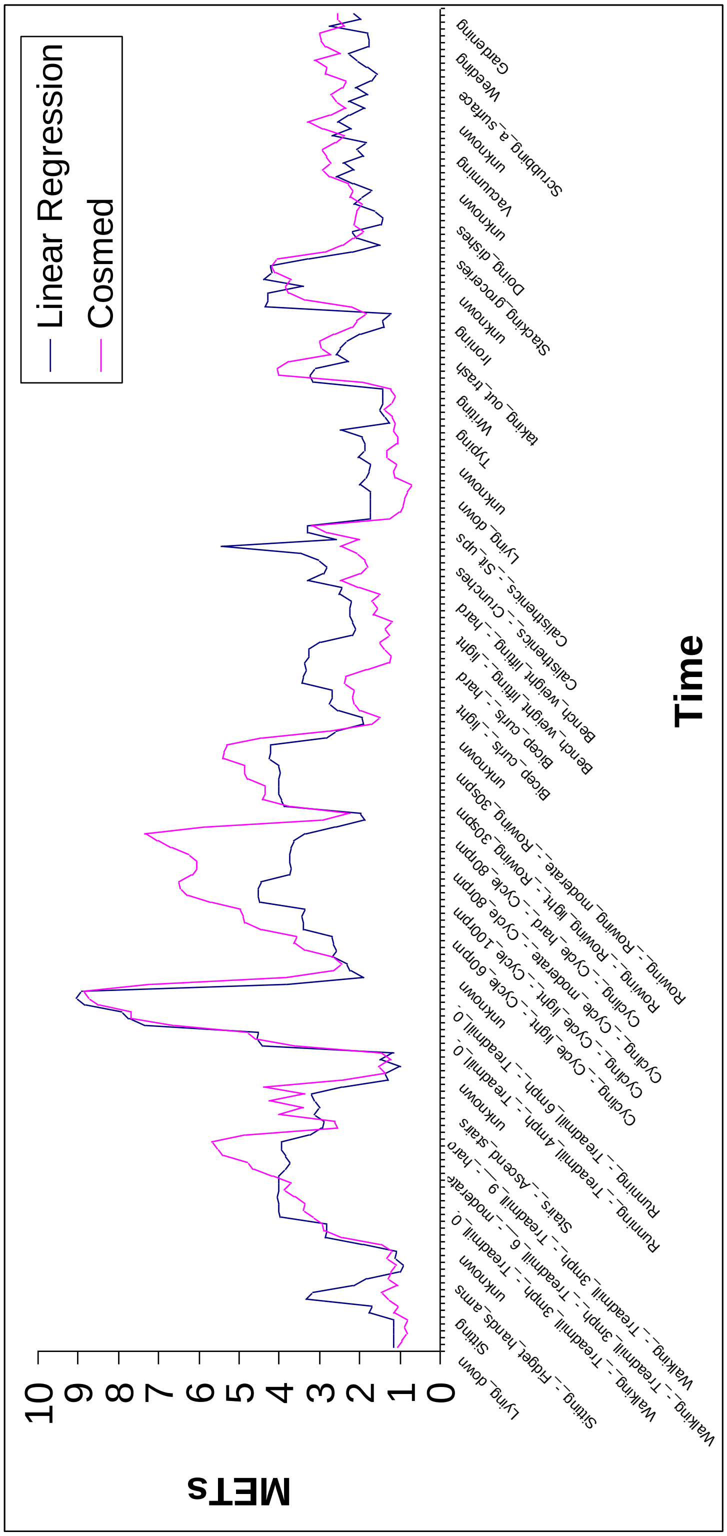

Figure B6-2. Plot of energy expenditure (in METS) computed using linear regression over the sum of the areas over all axis per sensor (7) and the Cosmed K4b2 Indirect Calorimeter for Subject MIT-004 over one minute windows.

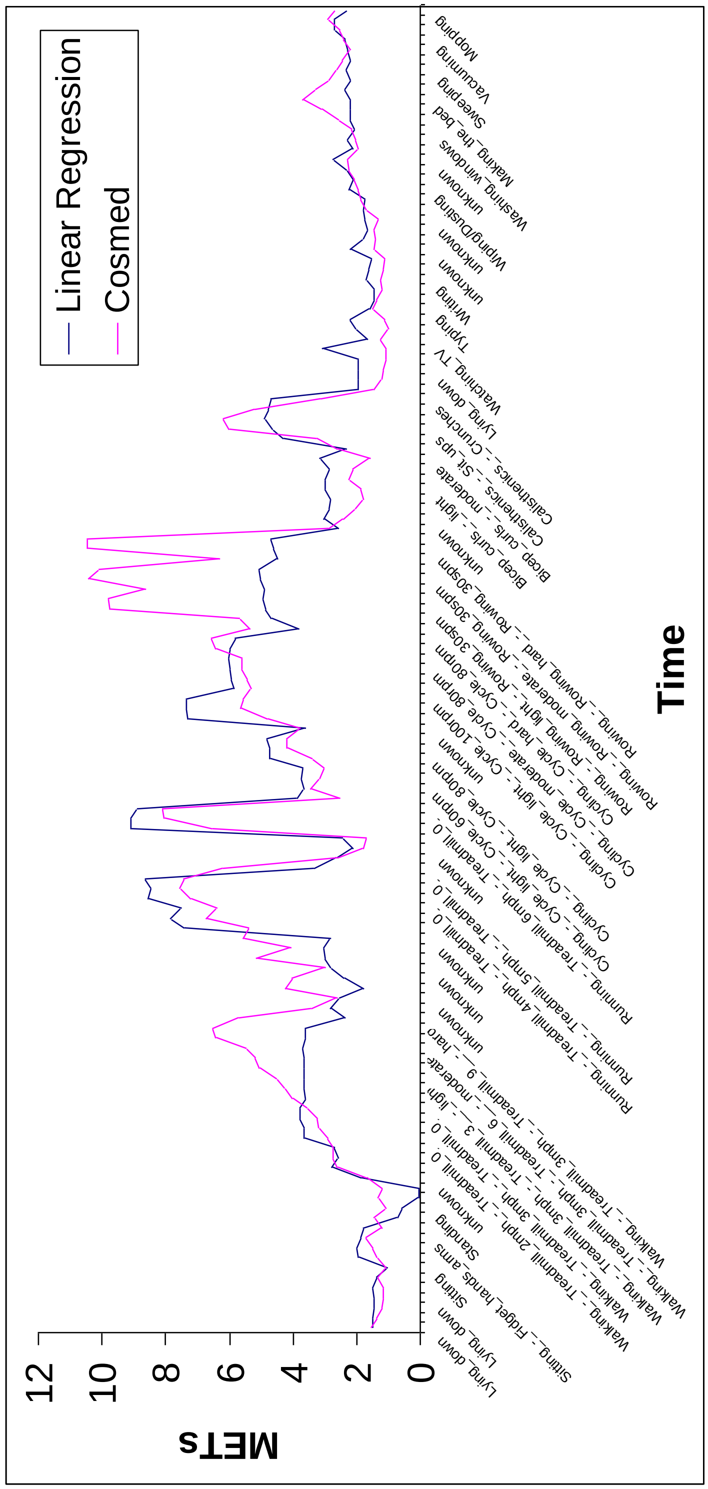

Figure B6-3. Plot of energy expenditure (in METS) computed using linear regression over the sum of the areas over all axis per sensor (7) and the Cosmed K4b2 Indirect Calorimeter for Subject MIT-018 over one minute windows.

Appendix B7: Estimating Energy Expenditure Using One Linear Regression Model Per Known Activity

Activity	RMSE	MAE	MAED
Bench_weight_lifting_-_hard	0.16 ± 0.16	0.14 ± 0.14	0.21 ± 0.20
Bench_weight_lifting_-_light	1.01 ± 0.74	0.94 ± 0.66	1.25 ± 0.98
Bench_weight_lifting_-_moderate	1.07 ± 0.49	0.96 ± 0.39	1.37 ± 0.73
Bicep_curls_-_hard	0.31 ± 0.15	0.28 ± 0.16	0.40 ± 0.17
Bicep_curls_-_light	0.62 ± 0.40	0.50 ± 0.26	1.05 ± 0.97
Bicep_curls_-_moderate	0.80 ± 0.47	0.79 ± 0.46	0.93 ± 0.56
Calisthenics_-_Crunches	3.27 ± 5.09	3.13 ± 5.11	3.76 ± 5.39
Calisthenics_-_Sit_ups	1.54 ± 0.56	1.39 ± 0.52	2.03 ± 0.79
Cycling_-_Cycle_hard_-_Cycle_80rpm	1.24 ± 0.46	1.17 ± 0.47	1.53 ± 0.50
Cycling_-_Cycle_light_-_Cycle_100rpm	1.07 ± 0.57	1.02 ± 0.55	1.37 ± 0.73
Cycling_-_Cycle_light_-_Cycle_60rpm	0.64 ± 0.59	0.62 ± 0.59	0.77 ± 0.66
Cycling_-_Cycle_light_-_Cycle_80rpm	0.87 ± 0.59	0.82 ± 0.60	1.10 ± 0.67
Cycling_-_Cycle_moderate_-_Cycle_80rpm	1.14 ± 0.60	1.07 ± 0.59	1.36 ± 0.66
Lying_down	0.21 ± 0.09	0.18 ± 0.09	0.34 ± 0.16
Rowing_-_Rowing_hard_-_Rowing_30spm	1.49 ± 0.72	1.38 ± 0.73	1.89 ± 0.83
Rowing_-_Rowing_light_-_Rowing_30spm	1.51 ± 1.13	1.40 ± 1.11	1.89 ± 1.21
Rowing_-_Rowing_moderate_-_Rowing_30spm	1.49 ± 1.18	1.42 ± 1.19	1.87 ± 1.30
Running_-_Treadmill_4mph_-_Treadmill_0_	1.10 ± 0.64	0.97 ± 0.60	1.52 ± 0.88
Running_-_Treadmill_5mph_-_Treadmill_0_	1.16 ± 0.61	1.05 ± 0.62	1.54 ± 0.74
Running_-_Treadmill_6mph_-_Treadmill_0_	1.29 ± 1.06	1.23 ± 1.05	1.51 ± 1.24
Sitting	0.26 ± 0.22	0.25 ± 0.21	0.31 ± 0.28
Sitting_-_Fidget_feet_legs	0.34 ± 0.12	0.32 ± 0.12	0.40 ± 0.15
Sitting_-_Fidget_hands_arms	0.22 ± 0.15	0.21 ± 0.15	0.27 ± 0.18
Stairs_-_Ascend_stairs	0.31 ± 0.15	0.27 ± 0.13	0.46 ± 0.25
Stairs_-_Descend_stairs	2.46 ± 2.66	2.39 ± 2.67	2.81 ± 2.75
Standing	0.30 ± 0.28	0.27 ± 0.26	0.40 ± 0.35
Walking_-_Treadmill_2mph_-_Treadmill_0_	0.49 ± 0.36	0.45 ± 0.37	0.65 ± 0.38
Walking_-_Treadmill_3mph_-_Treadmill_0_	0.57 ± 0.49	0.53 ± 0.50	0.75 ± 0.56
Walking_-_Treadmill_3mph_-_Treadmill_3__-_light	0.62 ± 0.49	0.57 ± 0.51	0.81 ± 0.54
Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate	0.70 ± 0.54	0.65 ± 0.54	0.94 ± 0.63
Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard	0.85 ± 0.65	0.82 ± 0.66	1.07 ± 0.72
kneeling	0.33 ± 0.26	0.30 ± 0.26	0.40 ± 0.30
Unknown	1.33 ± 0.34	1.02 ± 0.25	3.11 ± 0.90
Carrying_groceries	0.57 ± 0.25	0.52 ± 0.26	0.76 ± 0.33
Doing_dishes	0.16 ± 0.12	0.14 ± 0.12	0.24 ± 0.17
Gardening	0.80 ± 0.63	0.77 ± 0.60	1.03 ± 0.88
Ironing	0.34 ± 0.22	0.29 ± 0.17	0.50 ± 0.36
Making_the_bed	1.02 ± 0.62	0.91 ± 0.60	1.42 ± 0.73
Mopping	0.55 ± 0.36	0.50 ± 0.33	0.74 ± 0.52
Playing_videogames	0.21 ± 0.10	0.19 ± 0.09	0.31 ± 0.16
Scrubbing_a_surface	0.48 ± 0.22	0.39 ± 0.17	0.72 ± 0.35
Stacking_groceries	0.59 ± 0.23	0.55 ± 0.26	0.71 ± 0.19
Sweeping	0.35 ± 0.12	0.30 ± 0.11	0.52 ± 0.19
Typing	0.22 ± 0.10	0.19 ± 0.08	0.32 ± 0.18
Vacuuming	0.60 ± 0.50	0.54 ± 0.49	0.79 ± 0.60
Walking_around_block	0.60 ± 0.23	0.52 ± 0.20	0.83 ± 0.34
Washing_windows	0.42 ± 0.25	0.39 ± 0.23	0.57 ± 0.34
Watching_TV	0.18 ± 0.07	0.16 ± 0.07	0.24 ± 0.10
Weeding	0.65 ± 0.64	0.60 ± 0.62	0.87 ± 0.77
Wiping/Dusting	0.46 ± 0.27	0.43 ± 0.25	0.63 ± 0.37
Writing	0.27 ± 0.17	0.25 ± 0.16	0.35 ± 0.25
taking_out_trash	0.37 ± 0.11	0.33 ± 0.11	0.53 ± 0.14

Table B7-1: Performance per activity when estimating energy expenditure using a multivariable linear model per activity over the MIT dataset. The models are trained using the *ACAbsArea* feature computed per sensor over one minute sliding windows.

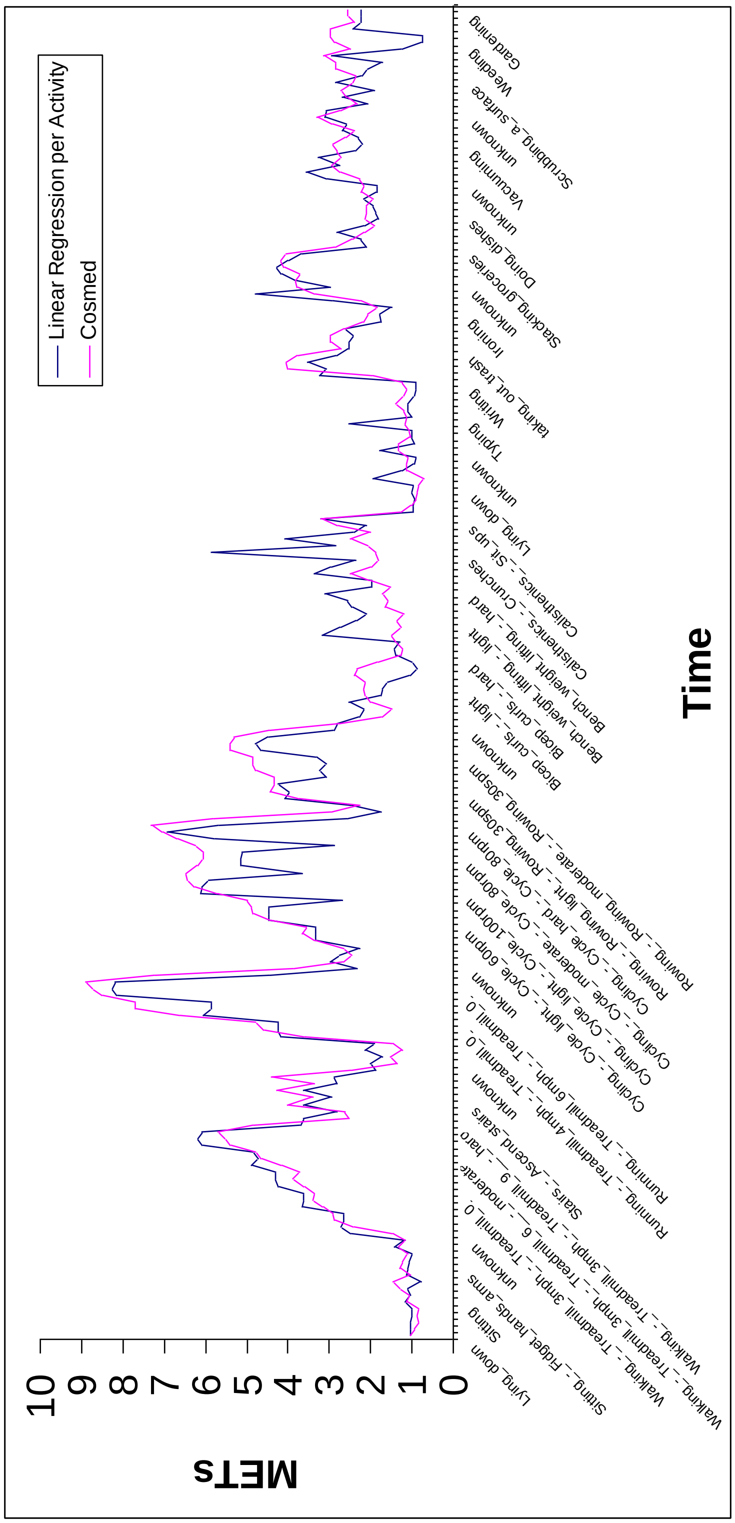

Figure B7-1. Plot of energy expenditure (in METS) estimated using one linear regression model per activity vs. energy expenditure measured using the Cosmed K4b2 Indirect Calorimeter for Subject MIT-004. Energy is predicted using the *ACAbsArea* feature (7) computed per sensor over one minute windows when activities are assumed to be known.

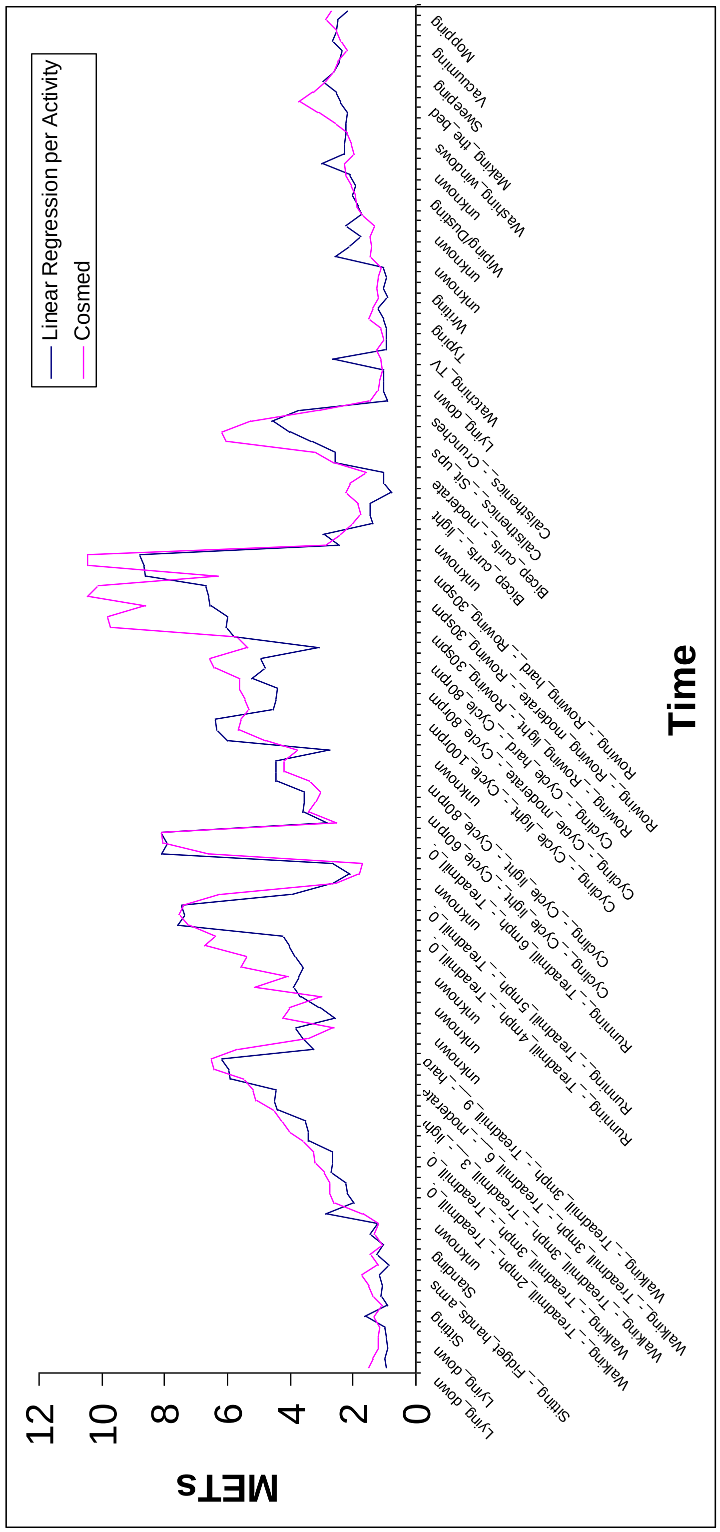

Figure B7-2. Plot of energy expenditure (in METS) estimated using one linear regression model per activity vs. energy expenditure measured using the Cosmed K4b2 Indirect Calorimeter for Subject MIT-018. Energy is predicted using the *ACAbsArea* feature (7) computed per sensor over one minute windows when activities are assumed to be known.

Appendix B8: Estimating Energy Expenditure Using One Non-Linear Regression Model Per Known Activity

Activity	**RMSE**	**MAE**	**MAED**
Bench_weight_lifting_-_hard	0.19 ± 0.21	0.17 ± 0.19	0.24 ± 0.27
Bench_weight_lifting_-_light	0.94 ± 0.66	0.91 ± 0.65	1.09 ± 0.81
Bench_weight_lifting_-_moderate	0.93 ± 0.58	0.91 ± 0.56	1.12 ± 0.73
Bicep_curls_-_hard	0.48 ± 0.29	0.46 ± 0.29	0.58 ± 0.34
Bicep_curls_-_light	0.65 ± 0.43	0.49 ± 0.23	1.14 ± 1.04
Bicep_curls_-_moderate	0.36 ± 0.29	0.32 ± 0.24	0.44 ± 0.37
Calisthenics_-_Crunches	1.64 ± 1.15	1.45 ± 1.03	2.11 ± 1.51
Calisthenics_-_Sit_ups	1.88 ± 1.30	1.77 ± 1.30	2.24 ± 1.39
Cycling_-_Cycle_hard_-_Cycle_80rpm	1.12 ± 0.23	1.04 ± 0.25	1.51 ± 0.35
Cycling_-_Cycle_light_-_Cycle_100rpm	1.10 ± 0.52	1.05 ± 0.50	1.41 ± 0.65
Cycling_-_Cycle_light_-_Cycle_60rpm	0.62 ± 0.47	0.60 ± 0.49	0.74 ± 0.48
Cycling_-_Cycle_light_-_Cycle_80rpm	0.78 ± 0.48	0.73 ± 0.49	1.00 ± 0.54
Cycling_-_Cycle_moderate_-_Cycle_80rpm	1.07 ± 0.58	1.01 ± 0.58	1.28 ± 0.63
Lying_down	0.21 ± 0.08	0.18 ± 0.08	0.35 ± 0.14
Rowing_-_Rowing_hard_-_Rowing_30spm	1.47 ± 1.10	1.34 ± 1.04	1.89 ± 1.21
Rowing_-_Rowing_light_-_Rowing_30spm	1.63 ± 1.32	1.47 ± 1.34	2.10 ± 1.48
Rowing_-_Rowing_moderate_-_Rowing_30spm	1.50 ± 0.71	1.43 ± 0.74	1.87 ± 0.78
Running_-_Treadmill_4mph_-_Treadmill_0_	1.02 ± 0.60	0.89 ± 0.54	1.43 ± 0.85
Running_-_Treadmill_5mph_-_Treadmill_0_	1.11 ± 0.53	1.01 ± 0.54	1.47 ± 0.68
Running_-_Treadmill_6mph_-_Treadmill_0_	1.23 ± 0.62	1.17 ± 0.60	1.45 ± 0.75
Sitting	0.25 ± 0.23	0.24 ± 0.22	0.30 ± 0.28
Sitting_-_Fidget_feet_legs	0.31 ± 0.12	0.29 ± 0.12	0.37 ± 0.13
Sitting_-_Fidget_hands_arms	0.22 ± 0.16	0.20 ± 0.15	0.27 ± 0.19
Stairs_-_Ascend_stairs	0.36 ± 0.21	0.31 ± 0.19	0.53 ± 0.30
Stairs_-_Descend_stairs	1.59 ± 0.42	1.47 ± 0.35	1.91 ± 0.65
Standing	0.23 ± 0.24	0.21 ± 0.23	0.28 ± 0.31
Walking_-_Treadmill_2mph_-_Treadmill_0_	0.41 ± 0.36	0.37 ± 0.37	0.58 ± 0.39
Walking_-_Treadmill_3mph_-_Treadmill_0_	0.51 ± 0.43	0.47 ± 0.44	0.68 ± 0.48
Walking_-_Treadmill_3mph_-_Treadmill_3__-_light	0.48 ± 0.43	0.43 ± 0.44	0.66 ± 0.50
Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate	0.67 ± 0.53	0.62 ± 0.54	0.88 ± 0.58
Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard	0.88 ± 0.57	0.84 ± 0.58	1.12 ± 0.61
kneeling	0.28 ± 0.21	0.26 ± 0.20	0.35 ± 0.27
Unknown	1.36 ± 0.34	1.08 ± 0.26	3.37 ± 1.07
Carrying_groceries	0.51 ± 0.26	0.46 ± 0.27	0.70 ± 0.32
Doing_dishes	0.15 ± 0.09	0.14 ± 0.09	0.23 ± 0.12
Gardening	0.79 ± 0.60	0.76 ± 0.56	1.02 ± 0.85
Ironing	0.34 ± 0.23	0.29 ± 0.18	0.50 ± 0.39
Making_the_bed	1.09 ± 0.68	1.02 ± 0.67	1.43 ± 0.76
Mopping	0.63 ± 0.36	0.57 ± 0.32	0.85 ± 0.51
Playing_videogames	0.21 ± 0.10	0.18 ± 0.09	0.31 ± 0.17
Scrubbing_a_surface	0.44 ± 0.15	0.38 ± 0.14	0.60 ± 0.18
Stacking_groceries	0.53 ± 0.31	0.48 ± 0.31	0.65 ± 0.35
Sweeping	0.33 ± 0.11	0.28 ± 0.10	0.49 ± 0.17
Typing	0.23 ± 0.09	0.21 ± 0.09	0.32 ± 0.12
Vacuuming	0.53 ± 0.34	0.48 ± 0.32	0.71 ± 0.47
Walking_around_block	0.63 ± 0.28	0.54 ± 0.23	0.88 ± 0.42
Washing_windows	0.46 ± 0.30	0.42 ± 0.29	0.64 ± 0.38
Watching_TV	0.16 ± 0.07	0.15 ± 0.06	0.22 ± 0.09
Weeding	0.48 ± 0.33	0.43 ± 0.29	0.66 ± 0.46
Wiping/Dusting	0.43 ± 0.26	0.40 ± 0.24	0.58 ± 0.36
Writing	0.26 ± 0.16	0.24 ± 0.15	0.35 ± 0.24
taking_out_trash	0.35 ± 0.13	0.31 ± 0.14	0.50 ± 0.18

Table B8-1: Performance per activity when estimating energy expenditure using a non-linear model (M5' model tree) per activity over the MIT dataset. The models are trained using the *ACAbsArea* feature computed per sensor over one minute sliding windows.

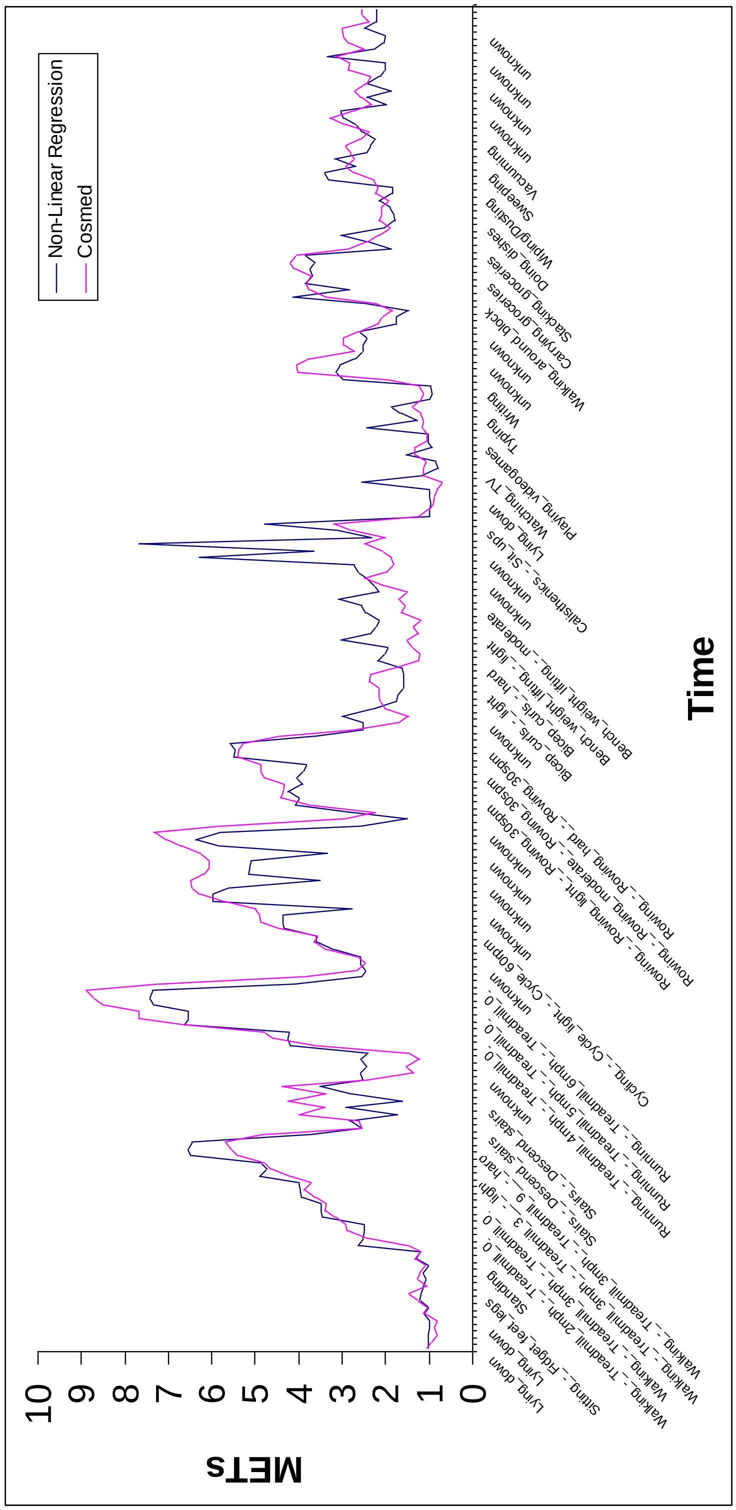

Figure B8-1: Plot of energy expenditure (in METS) estimated using one non-linear regression model per activity (M5' model tree) vs. energy expenditure measured using the Cosmed K4b2 Indirect Calorimeter for Subject MIT-004. Energy is predicted using the *ACAbsArea* feature (7) computed per sensor over one minute windows when activities are assumed to be known.

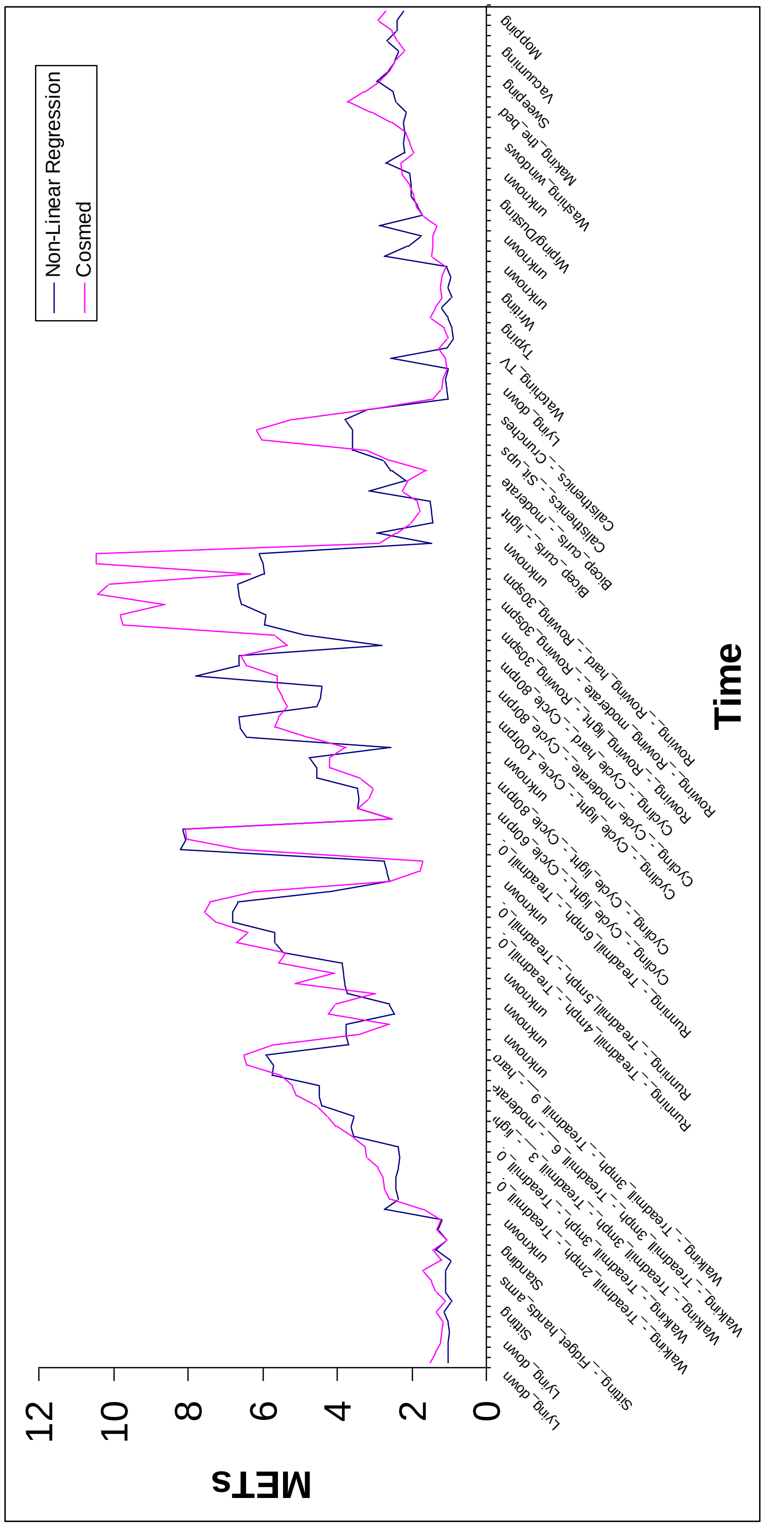

Figure B8-2: Plot of energy expenditure (in METS) estimated using one non-linear regression model per activity (M5' model tree) vs. energy expenditure measured using the Cosmed K4b2 Indirect Calorimeter for Subject MIT-018. Energy is predicted using the *ACAbsArea* feature (7) computed per sensor over one minute windows when activities are assumed to be known.

Appendix B9: Estimating Energy Expenditure Using Linear and Non-linear Regression Algorithms

Activity	LR	RT	MT	ε-SVR
Bench weight lifting - hard	0.6 ± 0.4	0.6 ± 0.3	0.6 ± 0.3	0.7 ± 0.4
Bench weight lifting - light	0.7 ± 0.3	0.7 ± 0.3	0.7 ± 0.3	0.7 ± 0.4
Bench weight lifting - moderate	0.7 ± 0.4	0.7 ± 0.4	0.7 ± 0.4	0.7 ± 0.5
Bicep curls - hard	1.0 ± 0.4	0.8 ± 0.4	0.5 ± 0.3	0.9 ± 0.5
Bicep curls - light	0.7 ± 0.2	0.6 ± 0.2	0.7 ± 0.5	0.6 ± 0.4
Bicep curls - moderate	0.7 ± 0.3	0.7 ± 0.3	0.6 ± 0.5	0.6 ± 0.2
Calisthenics - Crunches	1.7 ± 0.9	1.8 ± 0.8	2.0 ± 1.0	1.3 ± 0.9
Calisthenics - Sit ups	1.3 ± 0.4	1.6 ± 0.6	1.7 ± 0.6	1.3 ± 0.4
Cycling - Cycle hard - Cycle 80rpm	1.8 ± 1.0	2.0 ± 1.0	2.0 ± 1.1	1.7 ± 0.9
Cycling - Cycle light - Cycle 100rpm	1.2 ± 0.8	1.2 ± 0.7	1.1 ± 0.4	1.1 ± 0.5
Cycling - Cycle light - Cycle 60rpm	0.8 ± 0.5	0.7 ± 0.4	0.8 ± 0.5	0.7 ± 0.4
Cycling - Cycle light - Cycle 80rpm	1.1 ± 0.8	0.9 ± 0.3	1.2 ± 0.7	0.9 ± 0.6
Cycling - Cycle moderate - Cycle 80rpm	1.5 ± 0.7	1.4 ± 0.9	1.5 ± 0.6	1.3 ± 0.5
Lying down	0.4 ± 0.2	0.2 ± 0.1	1.0 ± 2.8	0.3 ± 0.1
Rowing - Rowing hard - Rowing 30spm	1.8 ± 1.6	2.0 ± 1.5	2.3 ± 1.4	1.4 ± 1.2
Rowing - Rowing light - Rowing 30spm	1.4 ± 1.1	1.6 ± 1.1	1.8 ± 0.9	1.3 ± 0.8
Rowing - Rowing moderate - Rowing 30spm	1.7 ± 1.5	2.1 ± 1.6	2.2 ± 1.3	1.4 ± 1.2
Running - Treadmill 4mph - Treadmill 0	1.3 ± 0.7	1.2 ± 0.6	1.3 ± 0.7	1.0 ± 0.5
Running - Treadmill 5mph - Treadmill 0	1.4 ± 0.8	1.4 ± 0.9	1.8 ± 1.0	1.3 ± 0.5
Running - Treadmill 6mph - Treadmill 0	1.8 ± 1.1	1.4 ± 1.1	1.6 ± 1.1	1.4 ± 0.8
Sitting	0.7 ± 0.2	0.6 ± 0.2	1.9 ± 4.7	0.5 ± 0.2
Sitting - Fidget feet legs	1.3 ± 0.5	1.2 ± 0.9	1.3 ± 0.6	0.7 ± 0.3
Sitting - Fidget hands arms	0.8 ± 0.4	0.6 ± 0.2	0.6 ± 0.3	0.5 ± 0.2
Stairs - Ascend stairs	0.9 ± 0.2	0.9 ± 0.2	1.0 ± 0.2	0.9 ± 0.3
Stairs - Descend stairs	1.5 ± 0.3	1.5 ± 0.2	1.5 ± 0.2	1.4 ± 0.5
Standing	0.4 ± 0.1	0.6 ± 0.3	0.6 ± 0.3	0.5 ± 0.2
Walking - Treadmill 2mph - Treadmill 0	0.8 ± 0.5	0.6 ± 0.3	0.6 ± 0.3	0.4 ± 0.2
Walking - Treadmill 3mph - Treadmill 0	1.0 ± 0.6	0.8 ± 0.3	0.8 ± 0.2	0.5 ± 0.2
Walking - Treadmill 3mph - Treadmill 3 - light	0.8 ± 0.5	0.7 ± 0.2	0.8 ± 0.4	0.5 ± 0.2
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.0 ± 0.5	1.1 ± 0.4	1.1 ± 0.6	0.8 ± 0.3
Walking - Treadmill 3mph - Treadmill 9 - hard	1.5 ± 0.7	1.6 ± 0.6	1.5 ± 0.7	1.3 ± 0.6
kneeling	0.5 ± 0.2	0.5 ± 0.2	0.6 ± 0.2	0.4 ± 0.2
unknown	1.5 ± 0.3	1.5 ± 0.4	1.6 ± 0.4	1.5 ± 0.4
Carrying groceries	0.9 ± 0.2	0.8 ± 0.2	1.0 ± 0.2	0.8 ± 0.3
Doing dishes	0.5 ± 0.3	0.4 ± 0.2	0.5 ± 0.2	0.4 ± 0.2
Gardening	0.7 ± 0.4	0.7 ± 0.2	0.6 ± 0.2	0.7 ± 0.3
Ironing	0.5 ± 0.2	0.6 ± 0.2	0.8 ± 1.0	0.5 ± 0.2
Making the bed	1.0 ± 0.4	1.0 ± 0.4	1.2 ± 0.5	0.9 ± 0.3
Mopping	0.6 ± 0.2	0.7 ± 0.3	0.8 ± 0.3	0.6 ± 0.2
Playing videogames	0.7 ± 0.4	0.4 ± 0.2	1.1 ± 1.9	0.4 ± 0.2
Scrubbing a surface	0.9 ± 0.5	0.8 ± 0.3	0.7 ± 0.2	0.6 ± 0.2
Stacking groceries	1.0 ± 0.5	0.7 ± 0.2	1.0 ± 0.5	0.7 ± 0.2
Sweeping	0.7 ± 0.4	0.6 ± 0.3	0.8 ± 0.4	0.6 ± 0.3
Typing	0.5 ± 0.2	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.1
Vacuuming	0.5 ± 0.1	0.5 ± 0.2	0.6 ± 0.2	0.4 ± 0.1
Walking around block	1.1 ± 0.5	1.0 ± 0.2	1.3 ± 0.9	0.9 ± 0.5
Washing windows	0.7 ± 0.4	0.6 ± 0.3	0.8 ± 0.5	0.5 ± 0.2
Watching TV	0.7 ± 0.5	0.4 ± 0.2	1.1 ± 2.0	0.4 ± 0.2
Weeding	0.8 ± 0.2	0.6 ± 0.2	0.9 ± 0.2	0.8 ± 0.3
Wiping/Dusting	0.7 ± 0.6	0.6 ± 0.2	0.6 ± 0.3	0.5 ± 0.2
Writing	0.6 ± 0.2	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.1
taking out trash	0.7 ± 0.2	0.6 ± 0.2	0.6 ± 0.2	0.5 ± 0.1

Table B9-1: Root mean square error obtained while estimating energy expenditure using different linear and non-linear regression algorithms utilizing all the accelerometer-based features computed per sensor over sliding windows of 5.6s in length. LR stands for linear regression, RT for regression trees, MT for model trees and ε-SVR for epsilon support vector regression.

Activity	LR	RT	MT	ε-SVR
Bench weight lifting - hard	0.5 ± 0.4	0.5 ± 0.2	0.5 ± 0.2	0.6 ± 0.3
Bench weight lifting - light	0.6 ± 0.3	0.6 ± 0.3	0.6 ± 0.3	0.6 ± 0.4
Bench weight lifting - moderate	0.6 ± 0.4	0.6 ± 0.4	0.6 ± 0.4	0.6 ± 0.5
Bicep curls - hard	0.9 ± 0.5	0.7 ± 0.3	0.5 ± 0.3	0.8 ± 0.5
Bicep curls - light	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.4	0.6 ± 0.3
Bicep curls - moderate	0.6 ± 0.3	0.5 ± 0.2	0.4 ± 0.4	0.5 ± 0.2
Calisthenics - Crunches	1.5 ± 0.8	1.6 ± 0.8	1.8 ± 0.9	1.2 ± 0.8
Calisthenics - Sit ups	1.2 ± 0.3	1.4 ± 0.6	1.5 ± 0.5	1.1 ± 0.4
Cycling - Cycle hard - Cycle 80rpm	1.7 ± 1.0	1.9 ± 1.0	1.9 ± 1.0	1.6 ± 0.9
Cycling - Cycle light - Cycle 100rpm	1.1 ± 0.8	1.1 ± 0.8	1.0 ± 0.4	1.0 ± 0.6
Cycling - Cycle light - Cycle 60rpm	0.7 ± 0.5	0.6 ± 0.4	0.8 ± 0.5	0.6 ± 0.4
Cycling - Cycle light - Cycle 80rpm	1.0 ± 0.8	0.8 ± 0.3	1.0 ± 0.6	0.8 ± 0.6
Cycling - Cycle moderate - Cycle 80rpm	1.4 ± 0.7	1.3 ± 0.9	1.3 ± 0.5	1.2 ± 0.5
Lying down	0.4 ± 0.3	0.2 ± 0.1	0.7 ± 1.9	0.3 ± 0.1
Rowing - Rowing hard - Rowing 30spm	1.7 ± 1.5	1.8 ± 1.5	2.1 ± 1.4	1.3 ± 1.2
Rowing - Rowing light - Rowing 30spm	1.2 ± 1.0	1.4 ± 1.1	1.6 ± 0.9	1.1 ± 0.8
Rowing - Rowing moderate - Rowing 30spm	1.6 ± 1.5	1.9 ± 1.6	1.9 ± 1.2	1.3 ± 1.2
Running - Treadmill 4mph - Treadmill 0	1.1 ± 0.7	1.1 ± 0.6	1.1 ± 0.6	0.9 ± 0.4
Running - Treadmill 5mph - Treadmill 0	1.2 ± 0.8	1.2 ± 1.0	1.4 ± 0.9	1.2 ± 0.5
Running - Treadmill 6mph - Treadmill 0	1.6 ± 1.1	1.3 ± 1.1	1.4 ± 1.2	1.3 ± 0.9
Sitting	0.6 ± 0.2	0.4 ± 0.2	0.7 ± 1.0	0.4 ± 0.2
Sitting - Fidget feet legs	1.2 ± 0.5	1.0 ± 0.8	1.1 ± 0.5	0.6 ± 0.3
Sitting - Fidget hands arms	0.7 ± 0.4	0.5 ± 0.2	0.5 ± 0.3	0.4 ± 0.2
Stairs - Ascend stairs	0.8 ± 0.2	0.7 ± 0.1	0.8 ± 0.2	0.8 ± 0.2
Stairs - Descend stairs	1.3 ± 0.3	1.3 ± 0.2	1.2 ± 0.2	1.2 ± 0.5
Standing	0.4 ± 0.1	0.5 ± 0.3	0.5 ± 0.2	0.4 ± 0.2
Walking - Treadmill 2mph - Treadmill 0	0.7 ± 0.5	0.5 ± 0.2	0.5 ± 0.2	0.4 ± 0.2
Walking - Treadmill 3mph - Treadmill 0	0.9 ± 0.6	0.6 ± 0.3	0.6 ± 0.3	0.4 ± 0.2
Walking - Treadmill 3mph - Treadmill 3 - light	0.7 ± 0.5	0.6 ± 0.2	0.7 ± 0.3	0.4 ± 0.1
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.9 ± 0.5	1.0 ± 0.4	0.9 ± 0.5	0.7 ± 0.3
Walking - Treadmill 3mph - Treadmill 9 - hard	1.4 ± 0.7	1.5 ± 0.7	1.4 ± 0.7	1.2 ± 0.6
kneeling	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.1	0.4 ± 0.2
unknown	1.2 ± 0.2	1.1 ± 0.3	1.2 ± 0.3	1.1 ± 0.3
Carrying groceries	0.7 ± 0.2	0.7 ± 0.2	0.8 ± 0.1	0.7 ± 0.3
Doing dishes	0.4 ± 0.3	0.3 ± 0.2	0.4 ± 0.2	0.4 ± 0.2
Gardening	0.6 ± 0.4	0.6 ± 0.2	0.6 ± 0.2	0.6 ± 0.3
Ironing	0.4 ± 0.2	0.5 ± 0.2	0.5 ± 0.3	0.4 ± 0.2
Making the bed	0.8 ± 0.3	0.8 ± 0.3	1.0 ± 0.4	0.7 ± 0.3
Mopping	0.5 ± 0.2	0.6 ± 0.3	0.6 ± 0.3	0.5 ± 0.2
Playing videogames	0.6 ± 0.4	0.3 ± 0.2	0.8 ± 1.4	0.3 ± 0.2
Scrubbing a surface	0.8 ± 0.4	0.6 ± 0.2	0.6 ± 0.2	0.5 ± 0.2
Stacking groceries	0.9 ± 0.5	0.6 ± 0.2	0.7 ± 0.2	0.6 ± 0.2
Sweeping	0.6 ± 0.4	0.5 ± 0.2	0.6 ± 0.4	0.5 ± 0.3
Typing	0.4 ± 0.2	0.3 ± 0.1	0.3 ± 0.2	0.3 ± 0.1
Vacuuming	0.4 ± 0.1	0.4 ± 0.2	0.5 ± 0.2	0.4 ± 0.1
Walking around block	1.0 ± 0.5	0.8 ± 0.2	0.9 ± 0.2	0.8 ± 0.5
Washing windows	0.6 ± 0.3	0.5 ± 0.2	0.6 ± 0.3	0.4 ± 0.2
Watching TV	0.6 ± 0.5	0.3 ± 0.2	0.8 ± 1.5	0.4 ± 0.2
Weeding	0.7 ± 0.2	0.5 ± 0.2	0.7 ± 0.2	0.7 ± 0.3
Wiping/Dusting	0.6 ± 0.5	0.5 ± 0.2	0.5 ± 0.2	0.4 ± 0.2
Writing	0.5 ± 0.2	0.3 ± 0.2	0.4 ± 0.2	0.3 ± 0.1
taking out trash	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.1	0.4 ± 0.1

Table B9-2: Mean absolute error obtained while estimating energy expenditure using different linear and non-linear regression algorithms utilizing all the accelerometer-based features computed per sensor over sliding windows of 5.6s in length.

Activity	LR	RT	MT	ε-SVR
Bench weight lifting - hard	0.9 ± 0.5	1.1 ± 0.5	1.2 ± 0.6	1.2 ± 0.5
Bench weight lifting - light	1.4 ± 0.5	1.2 ± 0.4	1.4 ± 0.5	1.2 ± 0.5
Bench weight lifting - moderate	1.2 ± 0.5	1.3 ± 0.5	1.3 ± 0.9	1.2 ± 0.6
Bicep curls - hard	1.9 ± 0.4	1.8 ± 1.0	1.2 ± 0.8	1.4 ± 0.7
Bicep curls - light	1.7 ± 0.4	1.9 ± 1.0	2.6 ± 1.6	1.3 ± 1.0
Bicep curls - moderate	1.4 ± 0.5	1.9 ± 0.9	1.5 ± 1.6	1.3 ± 0.2
Calisthenics - Crunches	2.8 ± 1.1	3.5 ± 0.8	3.9 ± 2.4	2.5 ± 1.5
Calisthenics - Sit ups	2.4 ± 0.7	2.6 ± 0.7	3.3 ± 1.3	2.1 ± 0.5
Cycling - Cycle hard - Cycle 80rpm	2.6 ± 1.0	3.0 ± 1.4	3.7 ± 2.4	2.5 ± 1.0
Cycling - Cycle light - Cycle 100rpm	2.1 ± 1.1	2.0 ± 0.9	2.3 ± 0.9	2.0 ± 0.7
Cycling - Cycle light - Cycle 60rpm	1.3 ± 0.6	1.3 ± 0.7	1.6 ± 0.7	1.2 ± 0.5
Cycling - Cycle light - Cycle 80rpm	1.9 ± 1.0	1.8 ± 0.6	2.6 ± 2.1	1.5 ± 0.7
Cycling - Cycle moderate - Cycle 80rpm	2.3 ± 0.9	2.4 ± 1.1	2.8 ± 0.9	2.2 ± 0.6
Lying down	1.0 ± 0.4	0.5 ± 0.2	1.8 ± 4.3	0.7 ± 0.2
Rowing - Rowing hard - Rowing 30spm	2.8 ± 2.0	3.0 ± 1.6	3.9 ± 1.7	2.3 ± 1.4
Rowing - Rowing light - Rowing 30spm	2.4 ± 1.3	2.7 ± 1.2	3.3 ± 1.4	2.4 ± 1.1
Rowing - Rowing moderate - Rowing 30spm	2.5 ± 1.8	3.2 ± 1.8	4.1 ± 2.0	2.2 ± 1.4
Running - Treadmill 4mph - Treadmill 0	2.6 ± 1.2	2.4 ± 0.9	3.1 ± 1.7	2.1 ± 1.0
Running - Treadmill 5mph - Treadmill 0	2.7 ± 1.0	2.7 ± 1.1	4.2 ± 2.8	2.3 ± 0.8
Running - Treadmill 6mph - Treadmill 0	3.3 ± 1.3	2.2 ± 1.3	3.0 ± 1.8	2.2 ± 1.0
Sitting	1.6 ± 0.5	1.4 ± 0.7	7.6 ± 21.9	1.0 ± 0.3
Sitting - Fidget feet legs	1.9 ± 0.6	2.0 ± 1.3	2.6 ± 1.0	1.3 ± 0.6
Sitting - Fidget hands arms	1.6 ± 0.6	1.1 ± 0.4	1.2 ± 0.5	1.1 ± 0.4
Stairs - Ascend stairs	1.8 ± 0.4	2.0 ± 0.4	2.2 ± 0.4	2.0 ± 0.5
Stairs - Descend stairs	2.6 ± 0.4	2.9 ± 0.5	3.1 ± 0.7	2.6 ± 0.8
Standing	1.0 ± 0.2	1.4 ± 0.7	1.4 ± 0.8	1.0 ± 0.4
Walking - Treadmill 2mph - Treadmill 0	1.5 ± 0.6	1.4 ± 0.6	1.5 ± 0.8	0.9 ± 0.3
Walking - Treadmill 3mph - Treadmill 0	1.8 ± 0.6	1.6 ± 0.5	1.8 ± 0.4	1.0 ± 0.3
Walking - Treadmill 3mph - Treadmill 3 - light	1.5 ± 0.6	1.4 ± 0.4	1.8 ± 0.7	1.0 ± 0.4
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.8 ± 0.7	1.8 ± 0.5	2.1 ± 0.8	1.4 ± 0.4
Walking - Treadmill 3mph - Treadmill 9 - hard	2.3 ± 0.8	2.6 ± 0.8	2.8 ± 1.1	2.0 ± 0.8
kneeling	1.2 ± 0.5	1.2 ± 0.5	1.3 ± 0.5	0.8 ± 0.2
unknown	5.3 ± 0.8	5.0 ± 1.1	6.8 ± 3.2	5.2 ± 1.2
Carrying groceries	2.0 ± 0.8	1.8 ± 0.4	2.3 ± 0.7	1.7 ± 0.8
Doing dishes	1.0 ± 0.5	0.9 ± 0.4	1.1 ± 0.4	0.8 ± 0.2
Gardening	1.6 ± 0.7	1.2 ± 0.2	1.4 ± 0.2	1.3 ± 0.5
Ironing	1.2 ± 0.4	1.3 ± 0.5	3.1 ± 6.8	1.1 ± 0.6
Making the bed	2.1 ± 1.0	2.7 ± 1.3	3.2 ± 1.9	2.0 ± 0.7
Mopping	1.6 ± 0.6	1.5 ± 0.7	1.9 ± 0.5	1.2 ± 0.3
Playing videogames	1.5 ± 0.6	1.0 ± 0.5	1.9 ± 2.8	0.9 ± 0.5
Scrubbing a surface	2.2 ± 1.3	2.2 ± 0.9	1.8 ± 0.7	1.4 ± 0.5
Stacking groceries	2.1 ± 0.9	1.9 ± 0.6	3.0 ± 2.4	1.4 ± 0.4
Sweeping	1.5 ± 0.5	1.5 ± 0.7	2.0 ± 1.2	1.3 ± 0.5
Typing	1.1 ± 0.4	0.9 ± 0.4	0.9 ± 0.5	0.9 ± 0.4
Vacuuming	1.2 ± 0.2	1.2 ± 0.5	1.7 ± 0.6	0.9 ± 0.4
Walking around block	2.3 ± 0.6	2.3 ± 0.6	4.5 ± 7.0	1.8 ± 0.7
Washing windows	1.7 ± 0.7	1.7 ± 1.1	2.6 ± 2.2	1.2 ± 0.3
Watching TV	1.4 ± 0.7	1.2 ± 0.5	2.0 ± 2.7	0.9 ± 0.5
Weeding	1.7 ± 0.7	1.2 ± 0.6	1.9 ± 0.8	1.5 ± 0.5
Wiping/Dusting	1.6 ± 0.9	1.3 ± 0.4	1.5 ± 0.7	1.1 ± 0.4
Writing	1.2 ± 0.4	1.0 ± 0.6	1.0 ± 0.5	0.8 ± 0.3
taking out trash	1.6 ± 0.4	1.6 ± 0.4	1.7 ± 0.4	1.2 ± 0.3

Table B9-3: Maximum absolute error deviation obtained while estimating energy expenditure using different linear and non-linear regression algorithms utilizing all the accelerometer-based features computed per sensor over sliding windows of 5.6s in length.

Appendix B10: Estimating Energy Expenditure When Band-Pass Filtering the Accelerometer Signal and When Not

Gymnasium Activity	RMSE ACAbsArea Without Band-pass Filtering	RMSE ACAbsArea with Band-pass Filtering	RMSE ACFFTPeaks without Band-pass Filtering	RMSE ACFFTPeaks with Band-pass Filtering
Bench weight lifting - hard	0.89 ± 0.69	0.39 ± 0.25	0.53 ± 0.27	0.54 ± 0.28
Bench weight lifting - light	0.70 ± 0.47	0.54 ± 0.21	0.65 ± 0.27	0.63 ± 0.32
Bench weight lifting - moderate	0.81 ± 0.59	0.56 ± 0.25	0.64 ± 0.38	0.64 ± 0.41
Bicep curls - hard	1.02 ± 0.37	1.38 ± 0.57	1.47 ± 0.65	1.44 ± 0.74
Bicep curls - light	0.81 ± 0.43	1.09 ± 0.37	1.17 ± 0.38	1.13 ± 0.61
Bicep curls - moderate	0.70 ± 0.43	1.32 ± 0.32	1.37 ± 0.41	1.24 ± 0.56
Calisthenics - Crunches	1.19 ± 0.54	1.40 ± 0.68	1.44 ± 0.63	1.56 ± 0.66
Calisthenics - Sit ups	2.21 ± 0.81	1.48 ± 0.67	1.71 ± 0.72	1.62 ± 0.60
Cycling - Cycle hard - Cycle 80rpm	2.59 ± 1.08	2.83 ± 1.06	2.10 ± 1.18	2.10 ± 1.13
Cycling - Cycle light - Cycle 100rpm	1.82 ± 0.88	1.54 ± 0.83	1.33 ± 0.62	1.22 ± 0.52
Cycling - Cycle light - Cycle 60rpm	0.82 ± 0.45	1.04 ± 0.46	0.76 ± 0.35	0.80 ± 0.37
Cycling - Cycle light - Cycle 80rpm	1.32 ± 0.67	1.39 ± 0.63	1.20 ± 0.61	1.24 ± 0.68
Cycling - Cycle moderate - Cycle 80rpm	2.10 ± 1.09	2.26 ± 0.93	1.65 ± 1.01	1.62 ± 0.95
Lying down	2.11 ± 1.41	0.62 ± 0.15	0.58 ± 0.72	0.35 ± 0.06
Rowing - Rowing hard - Rowing 30spm	3.01 ± 1.78	3.07 ± 1.75	2.23 ± 1.63	2.30 ± 1.73
Rowing - Rowing light - Rowing 30spm	1.98 ± 1.36	2.12 ± 1.31	1.47 ± 1.15	1.46 ± 1.34
Rowing - Rowing moderate - Rowing 30spm	2.67 ± 1.59	2.85 ± 1.60	2.08 ± 1.44	2.13 ± 1.62
Running - Treadmill 4mph - Treadmill 0	1.14 ± 0.45	1.22 ± 0.50	1.38 ± 0.56	1.42 ± 0.70
Running - Treadmill 5mph - Treadmill 0	1.38 ± 0.70	0.98 ± 0.53	1.34 ± 0.87	1.45 ± 0.93
Running - Treadmill 6mph - Treadmill 0	1.37 ± 0.75	1.05 ± 0.67	2.02 ± 1.51	2.03 ± 1.54
Sitting	1.08 ± 0.52	0.56 ± 0.15	0.47 ± 0.19	0.59 ± 0.25
Sitting - Fidget feet legs	1.22 ± 0.43	1.05 ± 0.33	1.12 ± 0.42	1.11 ± 0.48
Sitting - Fidget hands arms	1.02 ± 0.48	1.00 ± 0.35	0.67 ± 0.28	0.62 ± 0.29
Stairs - Ascend stairs	0.93 ± 0.24	0.87 ± 0.23	0.87 ± 0.21	0.91 ± 0.27
Stairs - Descend stairs	1.30 ± 0.37	1.35 ± 0.30	1.44 ± 0.32	1.44 ± 0.35
Standing	1.26 ± 0.31	0.58 ± 0.13	0.60 ± 0.17	0.56 ± 0.12
Walking - Treadmill 2mph - Treadmill 0	0.66 ± 0.31	0.84 ± 0.35	0.77 ± 0.29	0.78 ± 0.30
Walking - Treadmill 3mph - Treadmill 0	0.68 ± 0.31	0.97 ± 0.42	0.87 ± 0.44	0.89 ± 0.40
Walking - Treadmill 3mph - Treadmill 3 - light	0.55 ± 0.32	0.57 ± 0.28	0.66 ± 0.29	0.66 ± 0.28
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.13 ± 0.45	0.73 ± 0.43	0.97 ± 0.44	0.96 ± 0.39
Walking - Treadmill 3mph - Treadmill 9 - hard	1.93 ± 0.63	1.45 ± 0.72	1.59 ± 0.64	1.64 ± 0.62
Kneeling	2.02 ± 0.53	0.48 ± 0.19	0.44 ± 0.15	0.56 ± 0.18
Unknown	1.73 ± 0.45	1.53 ± 0.35	1.61 ± 0.36	1.55 ± 0.36
Carrying groceries	1.05 ± 0.66	1.14 ± 0.29	0.99 ± 0.33	0.91 ± 0.26
Doing dishes	1.20 ± 1.12	0.60 ± 0.16	0.77 ± 0.51	0.53 ± 0.09
Gardening	1.62 ± 1.10	0.56 ± 0.34	0.85 ± 0.40	0.55 ± 0.20
Ironing	1.11 ± 0.88	0.62 ± 0.17	0.92 ± 0.36	0.60 ± 0.15
Making the bed	1.19 ± 0.72	0.93 ± 0.30	1.01 ± 0.41	0.91 ± 0.31
Mopping	1.13 ± 1.16	0.58 ± 0.22	0.74 ± 0.61	0.63 ± 0.17
Playing videogames	1.93 ± 1.77	0.68 ± 0.17	0.92 ± 0.98	0.46 ± 0.13
Scrubbing a surface	1.10 ± 0.64	0.61 ± 0.18	1.00 ± 0.45	0.71 ± 0.27
Stacking groceries	1.25 ± 1.34	0.78 ± 0.28	1.10 ± 0.85	1.08 ± 0.52
Sweeping	1.07 ± 1.37	0.56 ± 0.30	0.87 ± 0.99	0.59 ± 0.25
Typing	1.41 ± 0.98	0.63 ± 0.12	0.71 ± 0.34	0.47 ± 0.10
Vacuuming	0.92 ± 0.82	0.54 ± 0.26	0.60 ± 0.34	0.50 ± 0.20
Walking around block	1.39 ± 1.01	1.63 ± 0.29	1.39 ± 0.64	1.22 ± 0.33
Washing windows	0.97 ± 0.74	0.62 ± 0.20	0.98 ± 0.48	0.67 ± 0.22
Watching TV	2.00 ± 1.83	0.67 ± 0.14	0.84 ± 0.92	0.48 ± 0.16
Weeding	1.87 ± 1.17	0.57 ± 0.31	0.83 ± 0.50	0.64 ± 0.22
Wiping/Dusting	0.89 ± 0.98	0.70 ± 0.29	0.90 ± 0.48	0.66 ± 0.22
Writing	1.27 ± 1.03	0.65 ± 0.19	0.76 ± 0.35	0.52 ± 0.16
Taking out trash	1.04 ± 0.77	0.78 ± 0.20	0.97 ± 0.33	0.79 ± 0.23

Table B-10: Performance of multivariable linear regression per activity in predicting energy expenditure when band-pass filtering is applied and not. The features utilized are the *ACAbsArea* feature and the *ACFFTPeaks* feature computed per sensor over windows of 5.6s in length.

Appendix B11: Feature Computation per Sensor vs. Feature Computation per Axis for Energy Expenditure Estimation

Activity	Feature Computation Per Sensor			Feature Computation Per Axis		
	RMSE	MAE	MAED	RMSE	MAE	MAED
Bench weight lifting - hard	0.4 ± 0.2	0.3 ± 0.2	0.8 ± 0.5	0.6 ± 0.5	0.6 ± 0.5	1.1 ± 0.6
Bench weight lifting - light	0.5 ± 0.2	0.5 ± 0.2	0.9 ± 0.3	0.8 ± 0.5	0.7 ± 0.5	1.1 ± 0.5
Bench weight lifting - moderate	0.6 ± 0.2	0.5 ± 0.2	0.8 ± 0.3	0.7 ± 0.5	0.7 ± 0.5	1.1 ± 0.5
Bicep curls - hard	1.4 ± 0.6	1.4 ± 0.6	1.8 ± 0.6	1.0 ± 0.9	1.0 ± 0.9	1.4 ± 1.0
Bicep curls - light	1.1 ± 0.4	1.0 ± 0.4	1.6 ± 0.4	1.0 ± 0.7	1.0 ± 0.7	1.5 ± 0.9
Bicep curls - moderate	1.3 ± 0.3	1.3 ± 0.3	1.8 ± 0.2	1.0 ± 0.8	0.9 ± 0.8	1.3 ± 0.8
Calisthenics - Crunches	1.4 ± 0.7	1.2 ± 0.7	2.1 ± 0.8	1.6 ± 0.8	1.5 ± 0.8	2.4 ± 1.2
Calisthenics - Sit ups	1.5 ± 0.7	1.3 ± 0.6	2.4 ± 0.7	1.4 ± 0.5	1.2 ± 0.5	2.4 ± 0.8
Cycling - Cycle hard - Cycle 80rpm	2.8 ± 1.1	2.8 ± 1.1	3.4 ± 1.0	2.4 ± 0.9	2.4 ± 0.9	3.0 ± 1.0
Cycling - Cycle light - Cycle 100rpm	1.5 ± 0.8	1.5 ± 0.9	2.1 ± 0.8	1.5 ± 1.6	1.3 ± 1.6	2.3 ± 1.9
Cycling - Cycle light - Cycle 60rpm	1.0 ± 0.5	1.0 ± 0.5	1.3 ± 0.4	0.6 ± 0.3	0.6 ± 0.3	1.0 ± 0.3
Cycling - Cycle light - Cycle 80rpm	1.4 ± 0.6	1.3 ± 0.6	1.8 ± 0.6	0.8 ± 0.6	0.7 ± 0.6	1.3 ± 0.8
Cycling - Cycle moderate - Cycle 80rpm	2.3 ± 0.9	2.2 ± 0.9	2.8 ± 1.0	1.7 ± 0.9	1.6 ± 0.9	2.3 ± 1.0
Lying down	0.6 ± 0.2	0.6 ± 0.2	0.8 ± 0.1	0.4 ± 0.2	0.4 ± 0.2	0.6 ± 0.2
Rowing - Rowing hard - Rowing 30spm	3.1 ± 1.8	3.0 ± 1.6	3.8 ± 2.0	2.3 ± 1.5	2.2 ± 1.4	3.1 ± 1.7
Rowing - Rowing light - Rowing 30spm	2.1 ± 1.3	2.0 ± 1.2	2.8 ± 1.6	1.5 ± 1.1	1.3 ± 1.0	2.4 ± 1.2
Rowing - Rowing moderate - Rowing 30spm	2.8 ± 1.6	2.7 ± 1.6	3.5 ± 1.8	2.1 ± 1.4	1.9 ± 1.4	2.8 ± 1.7
Running - Treadmill 4mph - Treadmill 0	1.2 ± 0.5	1.0 ± 0.5	2.6 ± 1.1	1.3 ± 0.5	1.0 ± 0.5	2.8 ± 1.2
Running - Treadmill 5mph - Treadmill 0	1.0 ± 0.5	0.9 ± 0.5	1.9 ± 1.1	1.2 ± 0.7	1.0 ± 0.6	2.1 ± 0.8
Running - Treadmill 6mph - Treadmill 0	1.0 ± 0.7	1.0 ± 0.7	1.8 ± 1.1	1.5 ± 0.8	1.4 ± 0.8	2.4 ± 1.4
Sitting	0.6 ± 0.2	0.5 ± 0.2	0.8 ± 0.1	0.4 ± 0.2	0.4 ± 0.2	0.6 ± 0.2
Sitting - Fidget feet legs	1.0 ± 0.3	1.0 ± 0.3	1.4 ± 0.4	0.7 ± 0.4	0.7 ± 0.4	1.0 ± 0.4
Sitting - Fidget hands arms	1.0 ± 0.4	1.0 ± 0.4	1.4 ± 0.5	0.4 ± 0.2	0.4 ± 0.2	0.7 ± 0.3
Stairs - Ascend stairs	0.9 ± 0.2	0.8 ± 0.2	1.6 ± 0.4	0.9 ± 0.2	0.7 ± 0.2	1.8 ± 0.4
Stairs - Descend stairs	1.4 ± 0.3	1.2 ± 0.3	2.3 ± 0.3	1.4 ± 0.4	1.2 ± 0.4	2.5 ± 0.4
Standing	0.6 ± 0.1	0.6 ± 0.1	0.9 ± 0.2	0.4 ± 0.2	0.4 ± 0.2	0.7 ± 0.2
Walking - Treadmill 2mph - Treadmill 0	0.8 ± 0.4	0.8 ± 0.4	1.4 ± 0.4	0.6 ± 0.2	0.6 ± 0.2	1.1 ± 0.4
Walking - Treadmill 3mph - Treadmill 0	1.0 ± 0.4	0.9 ± 0.4	1.6 ± 0.6	0.8 ± 0.4	0.8 ± 0.4	1.4 ± 0.5
Walking - Treadmill 3mph - Treadmill 3 - light	0.6 ± 0.3	0.5 ± 0.3	1.0 ± 0.4	0.5 ± 0.2	0.4 ± 0.2	0.9 ± 0.3
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.7 ± 0.4	0.7 ± 0.4	1.1 ± 0.4	0.9 ± 0.4	0.8 ± 0.4	1.3 ± 0.5
Walking - Treadmill 3mph - Treadmill 9 - hard	1.4 ± 0.7	1.4 ± 0.7	1.9 ± 0.8	1.6 ± 0.5	1.6 ± 0.5	2.2 ± 0.6
kneeling	0.5 ± 0.2	0.4 ± 0.2	0.9 ± 0.3	0.4 ± 0.2	0.3 ± 0.2	0.7 ± 0.3
unknown	1.5 ± 0.4	1.2 ± 0.2	4.9 ± 1.1	1.6 ± 0.4	1.2 ± 0.3	5.4 ± 1.3
Carrying groceries	1.1 ± 0.3	1.0 ± 0.3	2.2 ± 0.6	0.9 ± 0.4	0.8 ± 0.4	2.1 ± 0.7
Doing dishes	0.6 ± 0.2	0.6 ± 0.2	1.0 ± 0.4	0.3 ± 0.1	0.3 ± 0.1	0.7 ± 0.2
Gardening	0.6 ± 0.3	0.5 ± 0.3	1.1 ± 0.5	0.6 ± 0.2	0.5 ± 0.2	1.2 ± 0.3
Ironing	0.6 ± 0.2	0.6 ± 0.2	1.1 ± 0.4	0.4 ± 0.2	0.3 ± 0.1	1.0 ± 0.6
Making the bed	0.9 ± 0.3	0.8 ± 0.2	2.0 ± 0.7	1.0 ± 0.3	0.9 ± 0.3	1.9 ± 0.4
Mopping	0.6 ± 0.2	0.5 ± 0.2	1.3 ± 0.5	0.9 ± 0.6	0.8 ± 0.6	1.5 ± 0.8
Playing videogames	0.7 ± 0.2	0.7 ± 0.2	1.0 ± 0.3	0.4 ± 0.2	0.4 ± 0.2	0.7 ± 0.2
Scrubbing a surface	0.6 ± 0.2	0.5 ± 0.2	1.4 ± 0.3	0.9 ± 0.4	0.8 ± 0.4	1.6 ± 0.6
Stacking groceries	0.8 ± 0.3	0.7 ± 0.3	1.4 ± 0.3	1.0 ± 0.5	0.8 ± 0.4	2.0 ± 1.1
Sweeping	0.6 ± 0.3	0.4 ± 0.2	1.1 ± 0.4	0.7 ± 0.4	0.6 ± 0.4	1.4 ± 0.5
Typing	0.6 ± 0.1	0.6 ± 0.1	0.9 ± 0.2	0.3 ± 0.1	0.3 ± 0.1	0.5 ± 0.2
Vacuuming	0.5 ± 0.3	0.5 ± 0.3	1.2 ± 0.4	0.8 ± 0.6	0.7 ± 0.6	1.5 ± 0.8
Walking around block	1.6 ± 0.3	1.5 ± 0.3	2.7 ± 0.3	1.4 ± 0.4	1.2 ± 0.5	2.5 ± 0.6
Washing windows	0.6 ± 0.2	0.5 ± 0.2	1.3 ± 0.4	0.6 ± 0.4	0.6 ± 0.3	1.3 ± 0.6
Watching TV	0.7 ± 0.1	0.6 ± 0.1	1.0 ± 0.3	0.5 ± 0.2	0.4 ± 0.2	0.8 ± 0.2
Weeding	0.6 ± 0.3	0.5 ± 0.3	1.3 ± 0.8	0.7 ± 0.4	0.6 ± 0.4	1.3 ± 0.6
Wiping/Dusting	0.7 ± 0.3	0.6 ± 0.3	1.6 ± 0.5	0.4 ± 0.2	0.4 ± 0.2	1.0 ± 0.6
Writing	0.6 ± 0.2	0.6 ± 0.2	0.8 ± 0.2	0.4 ± 0.2	0.4 ± 0.2	0.5 ± 0.2
taking out trash	0.8 ± 0.2	0.6 ± 0.2	1.7 ± 0.4	0.7 ± 0.4	0.6 ± 0.4	1.4 ± 0.5

Table B11-1: Performance obtained using multivariable linear regression for estimating energy expenditure using all the accelerometer-based features computed per sensor and per axis over sliding windows of 5.6s in length.

Appendix B12: Window Length Selection for Energy Expenditure Estimation

Activity Category	1.4s	2.8s	5.6s	11.3s	22.7s	45.5s	91.0s
All	1.38 ± 0.30 (1.04 ± 0.17)	1.37 ± 0.30 (1.03 ± 0.17)	1.36 ± 0.30 (1.02 ± 0.17)	1.34 ± 0.30 (1.01 ± 0.17)	1.32 ± 0.30 (0.98 ± 0.17)	1.27 ± 0.27 (0.9 ± 0.16)	1.16 ± 0.24 (0.87 ± 0.15)
Postures	0.8±0.2 (0.7±0.2)	0.7±0.2 (0.7±0.2)	0.7±0.2 (0.7±0.2)	0.7±0.2 (0.7±0.2)	0.6±0.2 (0.6±0.2)	0.6±0.2 (0.6±0.2)	0.5±0.2 (0.5±0.2)
Ambulation	1.1±0.4 (1.0±0.4)	1.1±0.4 (1.0±0.4)	1.1±0.4 (1.0±0.4)	1.1±0.4 (1.0±0.4)	1.1±0.5 (1.0±0.5)	1.0±0.5 (1.0±0.5)	0.8±0.4 (0.8±0.5)
Exercise	1.5±0.7 (1.4±0.7)	1.5±0.7 (1.4±0.7)	1.5±0.7 (1.4±0.7)	1.5±0.7 (1.4±0.7)	1.5±0.7 (1.4±0.7)	1.4±0.7 (1.4±0.7)	1.3±0.7 (1.3±0.7)
Resistance Exercise	1.4±0.6 (1.3±0.6)	1.4±0.6 (1.3±0.6)	1.4±0.6 (1.3±0.6)	1.3±0.6 (1.3±0.6)	1.3±0.6 (1.3±0.6)	1.3±0.6 (1.2±0.6)	1.2±0.6 (1.2±0.6)
Household	0.8±0.2 (0.7±0.2)	0.8±0.2 (0.7±0.2)	0.7±0.2 (0.6±0.2)	0.7±0.2 (0.6±0.2)	0.7±0.2 (0.6±0.2)	0.7±0.3 (0.6±0.3)	0.7±0.3 (0.6±0.3)

Table B12-1: Root mean squared error and mean absolute error (shown in parenthesis) obtained by estimating energy expenditure in a subject independent manner using multivariable linear regression and the *ACAbsArea* feature computed per sensor over window of varying lengths.

Activity Category	1.4s	2.8s	5.6s	11.3s	22.7s	45.5s	91.0s
All	1.29 ± 0.28 (0.94 ± 0.16)	1.28 ± 0.29 (0.93 ± 0.17)	1.28 ± 0.29 (0.93 ± 0.17)	1.25 ± 0.30 (0.91 ± 0.18)	1.22 ± 0.29 (0.88 ± 0.18)	1.21 ± 0.29 (0.87 ± 0.18)	1.13 ± 0.29 (0.79 ± 0.16)
Postures	0.7±0.2 (0.6±0.2)	0.6±0.2 (0.6±0.2)	0.6±0.2 (0.6±0.2)	0.7±0.3 (0.6±0.3)	0.6±0.3 (0.6±0.3)	0.7±0.3 (0.6±0.3)	0.5±0.3 (0.5±0.3)
Ambulation	1.2±0.5 (1.1±0.5)	1.2±0.5 (1.1±0.5)	1.2±0.5 (1.1±0.5)	1.2±0.6 (1.0±0.6)	1.2±0.7 (1.1±0.7)	1.2±0.7 (1.1±0.7)	1.0±0.6 (0.9±0.6)
Exercise	1.3±0.7 (1.2±0.7)	1.3±0.7 (1.2±0.7)	1.3±0.7 (1.2±0.7)	1.3±0.8 (1.2±0.8)	1.3±0.8 (1.2±0.8)	1.3±0.9 (1.2±0.9)	1.2±0.9 (1.2±0.9)
Resistance Exercise	1.2±0.6 (1.1±0.6)	1.2±0.6 (1.0±0.6)	1.2±0.6 (1.0±0.6)	1.1±0.7 (1.0±0.7)	1.1±0.7 (1.0±0.7)	1.1±0.7 (1.0±0.7)	1.0±0.7 (0.9±0.7)
Household	0.8±0.2 (0.6±0.2)	0.7±0.2 (0.6±0.2)	0.7±0.2 (0.6±0.2)	0.6±0.2 (0.5±0.2)	0.6±0.2 (0.5±0.2)	0.6±0.3 (0.5±0.2)	0.4±0.3 (0.4±0.2)

Table B12-2: Root mean squared error and mean absolute error (shown in parenthesis) obtained by estimating energy expenditure in a subject independent manner using multivariable linear regression and the *FFTCorr (ACFFTPeaks + ACCorr)* feature set computed per sensor over windows of varying lengths.

Activity Category	5.6s	11.3s	22.7s	45.5s	91.0s
All	1.24 ± 0.29 (0.86 ± 0.19)	1.29 ± 0.31 (0.90 ± 0.20)	1.24 ± 0.27 (0.87 ± 0.18)	1.13 ± 0.23 (0.8 ± 0.2)	0.97 ± 0.22 (0.7 ± 0.2)
Postures	0.6±0.3 (0.5±0.2)	0.6±0.3 (0.5±0.3)	0.5±0.3 (0.5±0.3)	0.6±0.4 (0.5±0.3)	0.4±0.3 (0.4±0.3)
Ambulation	1.1±0.4 (0.9±0.4)	1.2±0.5 (1.1±0.5)	1.2±0.6 (1.1±0.6)	1.1±0.5 (1.0±0.5)	0.8±0.5 (0.8±0.5)
Exercise	1.3±0.7 (1.2±0.7)	1.3±0.7 (1.2±0.7)	1.2±0.7 (1.1±0.7)	1.2±0.6 (1.1±0.6)	0.9±0.6 (0.9±0.6)
Resistance Exercise	1.1±0.6 (1.0±0.6)	1.1±0.6 (1.0±0.6)	1.1±0.6 (1.0±0.6)	1.0±0.5 (0.9±0.5)	0.8±0.5 (0.7±0.5)
Household	0.6±0.3 (0.5±0.2)	0.6±0.3 (0.5±0.3)	0.6±0.3 (0.5±0.3)	0.6±0.3 (0.5±0.3)	0.6±0.3 (0.6±0.3)

Table B12-3: Root mean squared error and mean absolute error (shown in parenthesis) obtained by estimating energy expenditure in a subject independent manner using M5' model trees and the *ACAbsArea* feature computed per sensor over windows of varying lengths

Activity Category	5.6s	11.3s	22.7s	45.5s	91.0s
All	1.26 ± 0.33 (0.88 ± 0.21)	1.23 ± 0.34 (0.88 ± 0.22)	1.26 ± 0.35 (0.87 ± 0.21)	1.19 ± 0.35 (0.83 ± 0.20)	1.03 ± 0.24 (0.74 ± 0.17)
Postures	0.6±0.3 (0.5±0.2)	0.6±0.3 (0.4±0.2)	0.6±0.3 (0.5±0.3)	0.5±0.4 (0.4±0.3)	0.5±0.4 (0.5±0.4)
Ambulation	1.3±0.5 (1.1±0.5)	1.2±0.4 (1.0±0.4)	1.2±0.7 (1.1±0.7)	1.2±0.6 (1.1±0.6)	0.8±0.5 (0.8±0.5)
Exercise	1.3±0.7 (1.1±0.7)	1.3±0.7 (1.1±0.6)	1.3±0.9 (1.2±0.9)	1.2±0.8 (1.1±0.8)	1.0±0.8 (1.0±0.8)
Resistance Exercise	1.1±0.5 (1.0±0.5)	1.1±0.6 (0.9±0.6)	1.1±0.7 (1.0±0.7)	1.0±0.7 (0.9±0.6)	0.9±0.7 (0.8±0.7)
Household	0.6±0.2 (0.5±0.2)	0.7±0.3 (0.5±0.2)	0.6±0.3 (0.5±0.2)	0.6±0.3 (0.5±0.3)	0.5±0.3 (0.5±0.3)

Table B12-4: Root mean squared error and mean absolute error (shown in parenthesis) obtained by estimating energy expenditure in a subject independent manner using M5' model trees and the *FFTCorr (ACFFTPeaks + ACCorr)* feature computed per sensor over windows of varying lengths.

Activity	Root Mean Squared Error						
	1.4s	**2.8s**	**5.6s**	**11.3s**	**22.7s**	**44.5s**	**90s**
Bench weight lifting - hard	0.6 ± 0.2	0.6 ± 0.2	0.6 ± 0.2	0.5 ± 0.4	0.5 ± 0.4	0.4 ± 0.5	0.5 ± 0.4
Bench weight lifting - light	0.6 ± 0.2	0.6 ± 0.3	0.6 ± 0.3	0.7 ± 0.4	0.6 ± 0.4	0.7 ± 0.5	0.8 ± 0.5
Bench weight lifting - moderate	0.7 ± 0.2	0.7 ± 0.3	0.7 ± 0.3	0.7 ± 0.4	0.7 ± 0.4	0.7 ± 0.3	0.8 ± 0.4
Bicep curls - hard	1.1 ± 0.4	1.2 ± 0.6	1.2 ± 0.6	1.4 ± 0.8	1.2 ± 0.7	1.3 ± 0.8	1.2 ± 0.7
Bicep curls - light	0.9 ± 0.3	0.9 ± 0.3	0.9 ± 0.3	1.0 ± 0.6	0.9 ± 0.5	1.3 ± 0.8	1.2 ± 0.9
Bicep curls - moderate	0.9 ± 0.1	0.8 ± 0.3	0.8 ± 0.3	1.2 ± 0.5	1.0 ± 0.3	0.9 ± 0.6	0.6 ± 0.5
Calisthenics - Crunches	1.6 ± 1.0	1.5 ± 0.9	1.5 ± 0.9	1.6 ± 0.8	1.5 ± 0.6	1.7 ± 0.7	1.4 ± 0.9
Calisthenics - Sit ups	1.3 ± 0.4	1.3 ± 0.5	1.3 ± 0.5	1.2 ± 0.3	1.2 ± 0.3	1.2 ± 0.5	0.9 ± 0.3
Cycling - Cycle hard - Cycle 80rpm	2.0 ± 1.1	2.0 ± 1.1	2.0 ± 1.1	1.9 ± 1.1	1.9 ± 1.0	1.9 ± 1.1	1.7 ± 1.3
Cycling - Cycle light - Cycle 100rpm	1.3 ± 0.7	1.3 ± 0.6	1.3 ± 0.6	1.3 ± 0.7	1.2 ± 0.8	1.2 ± 0.7	0.9 ± 0.8
Cycling - Cycle light - Cycle 60rpm	0.8 ± 0.3	0.8 ± 0.4	0.8 ± 0.4	0.9 ± 0.4	0.9 ± 0.4	1.0 ± 0.4	1.0 ± 0.6
Cycling - Cycle light - Cycle 80rpm	1.2 ± 0.5	1.2 ± 0.6	1.2 ± 0.6	1.3 ± 0.7	1.3 ± 0.7	1.2 ± 0.7	1.4 ± 0.9
Cycling - Cycle moderate - Cycle 80rpm	1.5 ± 0.9	1.6 ± 0.9	1.6 ± 0.9	1.6 ± 0.9	1.5 ± 0.9	1.4 ± 0.9	1.3 ± 1.1
Lying down	0.4 ± 0.1	0.3 ± 0.1	0.3 ± 0.1	0.3 ± 0.1	0.3 ± 0.1	0.3 ± 0.1	0.3 ± 0.1
Rowing - Rowing hard - Rowing 30spm	2.2 ± 1.8	2.1 ± 1.8	2.1 ± 1.8	1.9 ± 1.9	1.8 ± 1.7	1.7 ± 1.8	1.5 ± 1.1
Rowing - Rowing light - Rowing 30spm	1.5 ± 1.3	1.4 ± 1.3	1.4 ± 1.3	1.4 ± 1.3	1.3 ± 1.2	1.3 ± 1.2	1.0 ± 1.0
Rowing - Rowing moderate - Rowing 30spm	2.0 ± 1.6	2.0 ± 1.7	2.0 ± 1.7	1.8 ± 1.7	1.7 ± 1.6	1.7 ± 1.8	1.5 ± 1.5
Running - Treadmill 4mph - Treadmill 0	1.4 ± 0.6	1.4 ± 0.7	1.4 ± 0.7	1.6 ± 0.8	1.7 ± 0.9	1.7 ± 1.1	1.5 ± 1.1
Running - Treadmill 5mph - Treadmill 0	1.3 ± 0.6	1.4 ± 0.8	1.4 ± 0.8	1.4 ± 1.0	1.5 ± 1.1	1.6 ± 1.4	1.8 ± 1.6
Running - Treadmill 6mph - Treadmill 0	1.7 ± 1.3	1.8 ± 1.2	1.8 ± 1.2	1.9 ± 1.3	2.0 ± 1.6	2.2 ± 2.1	2.2 ± 1.1
Sitting	0.5 ± 0.1	0.6 ± 0.2	0.6 ± 0.2	0.8 ± 0.3	0.8 ± 0.4	0.9 ± 0.4	0.7 ± 0.4
Sitting - Fidget feet legs	1.2 ± 0.4	1.1 ± 0.4	1.1 ± 0.4	1.0 ± 0.5	0.9 ± 0.5	0.9 ± 0.6	0.7 ± 0.5
Sitting - Fidget hands arms	0.8 ± 0.4	0.7 ± 0.4	0.7 ± 0.4	0.6 ± 0.3	0.6 ± 0.3	0.6 ± 0.3	0.5 ± 0.4
Stairs - Ascend stairs	1.0 ± 0.2	1.0 ± 0.2	1.0 ± 0.2	0.8 ± 0.2	0.7 ± 0.3	0.6 ± 0.3	0.0 ± -0.0
Stairs - Descend stairs	1.5 ± 0.3	1.5 ± 0.3	1.5 ± 0.3	1.4 ± 0.4	1.4 ± 0.5	1.4 ± 0.4	0.0 ± -0.0
Standing	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.2	0.6 ± 0.2	0.6 ± 0.2	0.3 ± 0.2
Walking - Treadmill 2mph - Treadmill 0	0.8 ± 0.4	0.8 ± 0.4	0.8 ± 0.4	0.8 ± 0.4	0.9 ± 0.4	0.9 ± 0.4	0.7 ± 0.4
Walking - Treadmill 3mph - Treadmill 0	0.8 ± 0.4	0.9 ± 0.4	0.9 ± 0.4	1.0 ± 0.6	1.1 ± 0.6	1.2 ± 0.6	1.1 ± 0.7
Walking - Treadmill 3mph - Treadmill 3 - light	0.7 ± 0.4	0.7 ± 0.3	0.7 ± 0.3	0.7 ± 0.5	0.8 ± 0.6	0.8 ± 0.5	0.8 ± 0.4
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.1 ± 0.4	1.1 ± 0.4	1.1 ± 0.4	1.0 ± 0.4	0.9 ± 0.4	0.9 ± 0.5	0.9 ± 0.6
Walking - Treadmill 3mph - Treadmill 9 - hard	1.7 ± 0.7	1.7 ± 0.8	1.7 ± 0.8	1.5 ± 0.7	1.5 ± 0.7	1.4 ± 0.7	1.4 ± 0.8
kneeling	0.6 ± 0.2	0.7 ± 0.2	0.7 ± 0.2	0.7 ± 0.3	0.8 ± 0.3	0.8 ± 0.4	0.6 ± 0.4
unknown	1.6 ± 0.4	1.6 ± 0.4	1.6 ± 0.4	1.5 ± 0.4	1.5 ± 0.4	1.4 ± 0.4	1.4 ± 0.6
Carrying groceries	1.0 ± 0.2	0.9 ± 0.2	0.9 ± 0.2	0.8 ± 0.2	0.9 ± 0.3	0.9 ± 0.3	0.6 ± 0.4
Doing dishes	0.6 ± 0.1	0.6 ± 0.1	0.6 ± 0.1	0.5 ± 0.1	0.5 ± 0.1	0.4 ± 0.2	0.4 ± 0.2
Gardening	0.6 ± 0.2	0.7 ± 0.1	0.7 ± 0.1	0.6 ± 0.1	0.6 ± 0.1	0.6 ± 0.2	0.5 ± 0.2
Ironing	0.8 ± 0.1	0.7 ± 0.2	0.7 ± 0.2	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.4 ± 0.3
Making the bed	1.1 ± 0.3	1.1 ± 0.4	1.1 ± 0.4	0.9 ± 0.3	0.9 ± 0.3	0.8 ± 0.4	0.6 ± 0.3
Mopping	0.7 ± 0.2	0.6 ± 0.2	0.6 ± 0.2	0.6 ± 0.2	0.6 ± 0.3	0.6 ± 0.4	0.4 ± 0.3
Playing videogames	0.5 ± 0.2	0.5 ± 0.3	0.5 ± 0.3	0.4 ± 0.1	0.4 ± 0.1	0.4 ± 0.1	0.3 ± 0.1
Scrubbing a surface	0.8 ± 0.3	0.9 ± 0.4	0.9 ± 0.4	0.8 ± 0.3	0.7 ± 0.3	0.6 ± 0.3	0.6 ± 0.5
Stacking groceries	0.9 ± 0.2	0.9 ± 0.2	0.9 ± 0.2	0.9 ± 0.4	1.0 ± 0.4	0.9 ± 0.4	0.3 ± 0.0
Sweeping	0.7 ± 0.2	0.7 ± 0.2	0.7 ± 0.2	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.1	0.4 ± 0.2
Typing	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.2	0.5 ± 0.2	0.4 ± 0.2
Vacuuming	0.7 ± 0.2	0.6 ± 0.2	0.6 ± 0.2	0.5 ± 0.3	0.5 ± 0.3	0.5 ± 0.3	0.4 ± 0.4
Walking around block	1.3 ± 0.3	1.2 ± 0.2	1.2 ± 0.2	1.0 ± 0.3	0.9 ± 0.3	0.8 ± 0.4	0.6 ± 0.3
Washing windows	0.8 ± 0.2	0.8 ± 0.3	0.8 ± 0.3	0.7 ± 0.3	0.6 ± 0.3	0.5 ± 0.3	0.4 ± 0.4
Watching TV	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.4 ± 0.2
Weeding	0.8 ± 0.2	0.8 ± 0.2	0.8 ± 0.2	0.7 ± 0.2	0.6 ± 0.2	0.6 ± 0.2	0.4 ± 0.3
Wiping/Dusting	0.8 ± 0.2	0.8 ± 0.2	0.8 ± 0.2	0.6 ± 0.2	0.6 ± 0.2	0.4 ± 0.2	0.5 ± 0.2
Writing	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.1	0.4 ± 0.1	0.4 ± 0.2	0.4 ± 0.2
taking out trash	0.8 ± 0.2	0.8 ± 0.1	0.8 ± 0.1	0.6 ± 0.2	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.2

Table B12-5: Root mean squared error when predicting energy expenditure in a subject independent manner using multivariable linear regression with the *FFTCorr* feature computed per sensor over sliding windows of varying length.

Appendix B13: Feature Selection for Energy Expenditure Estimation

Activity	All	Fast to compute	Invariant Reduced	ACFFTPeaks ACAbsArea	ACFFTPeaks. ACEntropy ACMCR, ACModVigEnergy	ACFFTPeaks., ACMCR ACModVigEnergy
Bench weight lifting - hard	0.6 ± 0.4	0.5 ± 0.4	0.7 ± 0.3	0.6 ± 0.3	0.6 ± 0.2	0.6 ± 0.2
Bench weight lifting - light	0.7 ± 0.3	0.6 ± 0.3	0.7 ± 0.2	0.6 ± 0.3	0.7 ± 0.3	0.7 ± 0.3
Bench weight lifting - moderate	0.7 ± 0.4	0.5 ± 0.2	0.7 ± 0.3	0.6 ± 0.4	0.6 ± 0.4	0.6 ± 0.4
Bicep curls - hard	1.0 ± 0.4	1.1 ± 0.5	1.3 ± 0.6	1.4 ± 0.6	1.3 ± 0.6	1.2 ± 0.6
Bicep curls - light	0.7 ± 0.2	0.8 ± 0.3	0.9 ± 0.4	1.1 ± 0.5	1.0 ± 0.4	1.0 ± 0.4
Bicep curls - moderate	0.7 ± 0.3	1.0 ± 0.2	1.0 ± 0.4	1.1 ± 0.4	1.0 ± 0.5	1.0 ± 0.4
Calisthenics - Crunches	1.7 ± 0.9	1.6 ± 0.8	1.8 ± 0.9	1.6 ± 0.7	1.6 ± 0.6	1.6 ± 0.6
Calisthenics - Sit ups	1.3 ± 0.4	1.5 ± 0.5	1.8 ± 0.8	1.7 ± 0.6	1.6 ± 0.5	1.6 ± 0.5
Cycling - Cycle hard - Cycle 80rpm	1.8 ± 1.0	1.8 ± 1.0	1.9 ± 1.2	2.1 ± 1.2	1.9 ± 0.9	1.9 ± 1.0
Cycling - Cycle light - Cycle 100rpm	1.2 ± 0.8	1.1 ± 0.5	1.3 ± 0.6	1.3 ± 0.6	1.2 ± 0.6	1.2 ± 0.6
Cycling - Cycle light - Cycle 60rpm	0.8 ± 0.5	0.6 ± 0.4	0.7 ± 0.4	0.8 ± 0.4	0.6 ± 0.4	0.6 ± 0.4
Cycling - Cycle light - Cycle 80rpm	1.1 ± 0.8	0.9 ± 0.6	1.2 ± 0.6	1.2 ± 0.6	1.0 ± 0.7	1.0 ± 0.7
Cycling - Cycle moderate - Cycle 80rpm	1.5 ± 0.7	1.4 ± 0.7	1.5 ± 0.8	1.7 ± 1.0	1.6 ± 0.7	1.6 ± 0.7
Lying down	0.4 ± 0.2	0.6 ± 0.4	0.5 ± 0.3	0.4 ± 0.1	0.3 ± 0.1	0.3 ± 0.1
Rowing - Rowing hard - Rowing 30spm	1.8 ± 1.6	2.0 ± 1.6	2.0 ± 1.6	2.2 ± 1.7	2.1 ± 1.7	2.1 ± 1.7
Rowing - Rowing light - Rowing 30spm	1.4 ± 1.1	1.3 ± 1.1	1.4 ± 1.2	1.4 ± 1.3	1.4 ± 1.3	1.4 ± 1.3
Rowing - Rowing moderate - Rowing 30spm	1.7 ± 1.5	1.8 ± 1.4	1.8 ± 1.6	2.1 ± 1.6	2.0 ± 1.6	1.9 ± 1.6
Running - Treadmill 4mph - Treadmill 0	1.3 ± 0.7	1.3 ± 0.7	1.4 ± 0.6	1.4 ± 0.8	1.2 ± 0.6	1.2 ± 0.6
Running - Treadmill 5mph - Treadmill 0	1.4 ± 0.8	1.4 ± 0.8	1.5 ± 0.9	1.5 ± 0.9	1.3 ± 0.7	1.4 ± 0.8
Running - Treadmill 6mph - Treadmill 0	1.8 ± 1.1	1.8 ± 0.8	2.0 ± 1.3	2.1 ± 1.5	1.8 ± 1.3	1.9 ± 1.4
Sitting	0.7 ± 0.2	0.5 ± 0.2	0.7 ± 0.2	0.6 ± 0.3	0.6 ± 0.3	0.6 ± 0.3
Sitting - Fidget feet legs	1.3 ± 0.5	1.4 ± 0.7	1.1 ± 0.4	1.0 ± 0.4	1.2 ± 0.5	1.2 ± 0.5
Sitting - Fidget hands arms	0.8 ± 0.4	1.1 ± 0.9	0.8 ± 0.4	0.6 ± 0.2	0.7 ± 0.6	0.8 ± 0.6
Stairs - Ascend stairs	0.9 ± 0.2	0.9 ± 0.2	0.9 ± 0.2	0.9 ± 0.3	0.9 ± 0.2	0.9 ± 0.2
Stairs - Descend stairs	1.5 ± 0.3	1.5 ± 0.3	1.5 ± 0.4	1.5 ± 0.3	1.4 ± 0.3	1.4 ± 0.3
Standing	0.4 ± 0.1	0.3 ± 0.2	0.4 ± 0.1	0.6 ± 0.1	0.5 ± 0.1	0.5 ± 0.1
Walking - Treadmill 2mph - Treadmill 0	0.8 ± 0.5	0.9 ± 0.4	0.6 ± 0.3	0.7 ± 0.3	0.8 ± 0.4	0.8 ± 0.4
Walking - Treadmill 3mph - Treadmill 0	1.0 ± 0.6	1.0 ± 0.5	0.8 ± 0.4	0.9 ± 0.4	1.0 ± 0.4	1.0 ± 0.5
Walking - Treadmill 3mph - Treadmill 3 - light	0.8 ± 0.5	0.6 ± 0.4	0.6 ± 0.3	0.7 ± 0.3	0.7 ± 0.3	0.7 ± 0.3
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.0 ± 0.5	0.9 ± 0.4	1.0 ± 0.4	1.0 ± 0.4	0.9 ± 0.4	0.9 ± 0.4
Walking - Treadmill 3mph - Treadmill 9 - hard	1.5 ± 0.7	1.5 ± 0.7	1.6 ± 0.6	1.6 ± 0.6	1.6 ± 0.7	1.6 ± 0.7
kneeling	0.5 ± 0.2	0.4 ± 0.3	0.5 ± 0.2	0.6 ± 0.2	0.6 ± 0.2	0.6 ± 0.2
unknown	1.5 ± 0.3	1.6 ± 0.4	1.6 ± 0.3	1.5 ± 0.4	1.5 ± 0.4	1.5 ± 0.4
Carrying groceries	0.9 ± 0.2	1.0 ± 0.4	1.0 ± 0.3	0.9 ± 0.2	0.9 ± 0.2	1.0 ± 0.2
Doing dishes	0.5 ± 0.3	0.5 ± 0.6	0.5 ± 0.4	0.5 ± 0.1	0.4 ± 0.1	0.5 ± 0.1
Gardening	0.7 ± 0.4	0.9 ± 0.9	0.8 ± 0.7	0.6 ± 0.2	0.6 ± 0.2	0.5 ± 0.2
Ironing	0.5 ± 0.2	0.5 ± 0.3	0.5 ± 0.2	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.2
Making the bed	1.0 ± 0.4	1.0 ± 0.5	1.0 ± 0.4	0.9 ± 0.3	0.9 ± 0.3	0.9 ± 0.3
Mopping	0.6 ± 0.2	0.6 ± 0.3	0.6 ± 0.2	0.6 ± 0.2	0.7 ± 0.2	0.7 ± 0.2
Playing videogames	0.7 ± 0.4	0.8 ± 0.6	0.8 ± 0.5	0.4 ± 0.1	0.4 ± 0.1	0.4 ± 0.1
Scrubbing a surface	0.9 ± 0.5	0.9 ± 0.6	0.9 ± 0.5	0.7 ± 0.4	0.7 ± 0.2	0.7 ± 0.2
Stacking groceries	1.0 ± 0.5	1.0 ± 0.6	1.1 ± 0.6	1.1 ± 0.5	1.0 ± 0.3	1.0 ± 0.4
Sweeping	0.7 ± 0.4	0.7 ± 0.7	0.7 ± 0.6	0.6 ± 0.2	0.7 ± 0.2	0.6 ± 0.2
Typing	0.5 ± 0.2	0.4 ± 0.3	0.6 ± 0.3	0.4 ± 0.1	0.4 ± 0.1	0.4 ± 0.1
Vacuuming	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.1	0.5 ± 0.2	0.6 ± 0.2	0.6 ± 0.2
Walking around block	1.1 ± 0.5	1.5 ± 0.6	1.3 ± 0.6	1.3 ± 0.3	1.2 ± 0.2	1.3 ± 0.2
Washing windows	0.7 ± 0.4	0.7 ± 0.4	0.8 ± 0.3	0.7 ± 0.2	0.6 ± 0.2	0.7 ± 0.2
Watching TV	0.7 ± 0.5	0.8 ± 0.5	0.8 ± 0.5	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2
Weeding	0.8 ± 0.2	1.0 ± 0.5	0.8 ± 0.4	0.7 ± 0.2	0.8 ± 0.2	0.7 ± 0.2
Wiping/Dusting	0.7 ± 0.6	0.8 ± 0.8	0.7 ± 0.4	0.7 ± 0.3	0.7 ± 0.3	0.7 ± 0.2
Writing	0.6 ± 0.2	0.5 ± 0.4	0.6 ± 0.3	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2
taking out trash	0.7 ± 0.2	0.8 ± 0.2	0.8 ± 0.3	0.8 ± 0.2	0.8 ± 0.2	0.8 ± 0.2

Table B13-1: Root mean square error per activity obtained when estimating energy expenditure using multivariable linear regression and different subsets of features computed per sensor over windows of 5.6s in length.

Activity	All	Fast to compute	Invariant reduced	ACFFTPeaks ACAbsArea	ACFFTPeaks. ACEntropy ACMCR, ACModVigEnergy	ACFFTPeaks. ACMCR ACModVigEnergy
Bench weight lifting - hard	0.5 ± 0.4	0.5 ± 0.3	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2
Bench weight lifting - light	0.6 ± 0.3	0.5 ± 0.2	0.6 ± 0.2	0.6 ± 0.3	0.6 ± 0.3	0.6 ± 0.3
Bench weight lifting - moderate	0.6 ± 0.4	0.5 ± 0.2	0.6 ± 0.3	0.6 ± 0.4	0.6 ± 0.4	0.6 ± 0.4
Bicep curls - hard	0.9 ± 0.5	1.0 ± 0.5	1.2 ± 0.6	1.2 ± 0.7	1.2 ± 0.6	1.1 ± 0.6
Bicep curls - light	0.6 ± 0.2	0.7 ± 0.3	0.8 ± 0.4	1.0 ± 0.5	0.9 ± 0.4	0.8 ± 0.4
Bicep curls - moderate	0.6 ± 0.3	1.0 ± 0.2	1.0 ± 0.5	1.0 ± 0.5	0.9 ± 0.5	0.9 ± 0.5
Calisthenics - Crunches	1.5 ± 0.8	1.5 ± 0.8	1.7 ± 0.9	1.4 ± 0.6	1.4 ± 0.5	1.4 ± 0.6
Calisthenics - Sit ups	1.2 ± 0.3	1.3 ± 0.5	1.6 ± 0.7	1.4 ± 0.5	1.4 ± 0.5	1.4 ± 0.5
Cycling - Cycle hard - Cycle 80rpm	1.7 ± 1.0	1.7 ± 1.0	1.9 ± 1.2	2.0 ± 1.2	1.8 ± 1.0	1.8 ± 1.0
Cycling - Cycle light - Cycle 100rpm	1.1 ± 0.8	1.0 ± 0.5	1.2 ± 0.6	1.2 ± 0.6	1.1 ± 0.6	1.0 ± 0.6
Cycling - Cycle light - Cycle 60rpm	0.7 ± 0.5	0.6 ± 0.4	0.7 ± 0.4	0.7 ± 0.4	0.6 ± 0.4	0.6 ± 0.4
Cycling - Cycle light - Cycle 80rpm	1.0 ± 0.8	0.9 ± 0.6	1.1 ± 0.6	1.1 ± 0.6	0.9 ± 0.6	0.9 ± 0.7
Cycling - Cycle moderate - Cycle 80rpm	1.4 ± 0.7	1.3 ± 0.7	1.4 ± 0.8	1.6 ± 1.0	1.4 ± 0.7	1.4 ± 0.7
Lying down	0.4 ± 0.3	0.6 ± 0.4	0.4 ± 0.3	0.3 ± 0.0	0.3 ± 0.0	0.3 ± 0.0
Rowing - Rowing hard - Rowing 30spm	1.7 ± 1.5	1.8 ± 1.5	1.8 ± 1.6	2.1 ± 1.6	2.0 ± 1.6	1.9 ± 1.6
Rowing - Rowing light - Rowing 30spm	1.2 ± 1.0	1.2 ± 1.0	1.2 ± 1.1	1.3 ± 1.2	1.2 ± 1.2	1.2 ± 1.2
Rowing - Rowing moderate - Rowing 30spm	1.6 ± 1.5	1.7 ± 1.4	1.7 ± 1.6	2.0 ± 1.6	1.8 ± 1.6	1.8 ± 1.6
Running - Treadmill 4mph - Treadmill 0	1.1 ± 0.7	1.1 ± 0.7	1.2 ± 0.6	1.2 ± 0.7	1.0 ± 0.5	1.0 ± 0.5
Running - Treadmill 5mph - Treadmill 0	1.2 ± 0.8	1.2 ± 0.8	1.3 ± 0.9	1.2 ± 0.9	1.1 ± 0.7	1.2 ± 0.8
Running - Treadmill 6mph - Treadmill 0	1.6 ± 1.1	1.6 ± 0.8	1.8 ± 1.3	1.9 ± 1.6	1.6 ± 1.3	1.7 ± 1.4
Sitting	0.6 ± 0.2	0.4 ± 0.2	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2
Sitting - Fidget feet legs	1.2 ± 0.5	1.4 ± 0.7	1.0 ± 0.5	1.0 ± 0.4	1.2 ± 0.5	1.2 ± 0.5
Sitting - Fidget hands arms	0.7 ± 0.4	1.0 ± 0.8	0.7 ± 0.4	0.5 ± 0.2	0.6 ± 0.6	0.7 ± 0.6
Stairs - Ascend stairs	0.8 ± 0.2	0.7 ± 0.2	0.8 ± 0.2	0.8 ± 0.2	0.8 ± 0.2	0.7 ± 0.2
Stairs - Descend stairs	1.3 ± 0.3	1.3 ± 0.3	1.3 ± 0.4	1.3 ± 0.3	1.3 ± 0.3	1.3 ± 0.3
Standing	0.4 ± 0.1	0.3 ± 0.2	0.4 ± 0.1	0.5 ± 0.1	0.4 ± 0.1	0.4 ± 0.1
Walking - Treadmill 2mph - Treadmill 0	0.7 ± 0.5	0.8 ± 0.4	0.6 ± 0.3	0.6 ± 0.3	0.8 ± 0.4	0.8 ± 0.4
Walking - Treadmill 3mph - Treadmill 0	0.9 ± 0.6	0.9 ± 0.5	0.8 ± 0.5	0.8 ± 0.4	0.9 ± 0.5	0.9 ± 0.5
Walking - Treadmill 3mph - Treadmill 3 - light	0.7 ± 0.5	0.6 ± 0.4	0.6 ± 0.3	0.6 ± 0.3	0.6 ± 0.3	0.6 ± 0.3
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.9 ± 0.5	0.8 ± 0.4	0.9 ± 0.4	0.9 ± 0.4	0.8 ± 0.4	0.8 ± 0.4
Walking - Treadmill 3mph - Treadmill 9 - hard	1.4 ± 0.7	1.4 ± 0.7	1.6 ± 0.6	1.5 ± 0.6	1.5 ± 0.7	1.5 ± 0.7
kneeling	0.4 ± 0.2	0.4 ± 0.3	0.4 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2
unknown	1.2 ± 0.2	1.2 ± 0.2	1.2 ± 0.2	1.2 ± 0.3	1.1 ± 0.3	1.1 ± 0.3
Carrying groceries	0.7 ± 0.2	0.8 ± 0.3	0.8 ± 0.2	0.7 ± 0.2	0.8 ± 0.2	0.8 ± 0.2
Doing dishes	0.4 ± 0.3	0.4 ± 0.5	0.4 ± 0.4	0.4 ± 0.1	0.4 ± 0.1	0.4 ± 0.1
Gardening	0.6 ± 0.4	0.8 ± 0.9	0.8 ± 0.7	0.4 ± 0.1	0.4 ± 0.1	0.4 ± 0.1
Ironing	0.4 ± 0.2	0.4 ± 0.3	0.4 ± 0.2	0.5 ± 0.1	0.4 ± 0.1	0.4 ± 0.1
Making the bed	0.8 ± 0.3	0.8 ± 0.4	0.8 ± 0.3	0.8 ± 0.2	0.8 ± 0.3	0.8 ± 0.3
Mopping	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2	0.6 ± 0.2	0.6 ± 0.2
Playing videogames	0.6 ± 0.4	0.8 ± 0.6	0.7 ± 0.5	0.4 ± 0.1	0.3 ± 0.1	0.3 ± 0.1
Scrubbing a surface	0.8 ± 0.4	0.8 ± 0.5	0.8 ± 0.5	0.6 ± 0.3	0.5 ± 0.2	0.6 ± 0.2
Stacking groceries	0.9 ± 0.5	0.9 ± 0.6	0.9 ± 0.6	1.0 ± 0.4	0.9 ± 0.3	0.9 ± 0.4
Sweeping	0.6 ± 0.4	0.6 ± 0.7	0.6 ± 0.6	0.5 ± 0.2	0.5 ± 0.2	0.5 ± 0.2
Typing	0.4 ± 0.2	0.4 ± 0.3	0.5 ± 0.3	0.4 ± 0.1	0.3 ± 0.1	0.3 ± 0.1
Vacuuming	0.4 ± 0.1	0.4 ± 0.1	0.4 ± 0.1	0.4 ± 0.2	0.5 ± 0.2	0.5 ± 0.2
Walking around block	1.0 ± 0.5	1.3 ± 0.6	1.2 ± 0.6	1.1 ± 0.3	1.1 ± 0.2	1.1 ± 0.3
Washing windows	0.6 ± 0.3	0.6 ± 0.4	0.6 ± 0.3	0.6 ± 0.2	0.5 ± 0.2	0.5 ± 0.2
Watching TV	0.6 ± 0.5	0.8 ± 0.6	0.7 ± 0.5	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.2
Weeding	0.7 ± 0.2	0.8 ± 0.4	0.7 ± 0.4	0.6 ± 0.2	0.6 ± 0.2	0.6 ± 0.2
Wiping/Dusting	0.6 ± 0.5	0.7 ± 0.7	0.6 ± 0.4	0.6 ± 0.2	0.6 ± 0.3	0.6 ± 0.3
Writing	0.5 ± 0.2	0.5 ± 0.4	0.6 ± 0.3	0.4 ± 0.2	0.4 ± 0.2	0.4 ± 0.1
taking out trash	0.6 ± 0.2	0.6 ± 0.2	0.7 ± 0.3	0.7 ± 0.2	0.6 ± 0.2	0.7 ± 0.2

Table B13-2: Mean absolute error per activity obtained when estimating energy expenditure using multivariable linear regression and different subsets of features computed per sensor over windows of 5.6s in length.

Activity	All	Fast to compute	Invariant Reduced	ACFFTPeaks ACAbsArea	ACFFTPeaks. ACEntropy ACMCR, ACModVigEnergy	ACFFTPeaks. ACMCR ACModVigEnergy
Bench weight lifting - hard	0.9 ± 0.5	1.0 ± 0.6	1.2 ± 0.4	1.1 ± 0.4	1.0 ± 0.4	1.1 ± 0.4
Bench weight lifting - light	1.4 ± 0.5	1.1 ± 0.4	1.3 ± 0.4	1.2 ± 0.4	1.3 ± 0.5	1.3 ± 0.4
Bench weight lifting - moderate	1.2 ± 0.5	0.9 ± 0.3	1.2 ± 0.4	1.1 ± 0.5	1.1 ± 0.6	1.1 ± 0.6
Bicep curls - hard	1.9 ± 0.4	1.6 ± 0.5	2.2 ± 0.5	2.4 ± 0.6	2.3 ± 0.8	2.2 ± 0.7
Bicep curls - light	1.7 ± 0.4	1.4 ± 0.5	1.8 ± 0.5	2.1 ± 0.5	2.0 ± 0.6	1.9 ± 0.6
Bicep curls - moderate	1.4 ± 0.5	1.5 ± 0.2	1.9 ± 0.6	2.1 ± 0.6	1.9 ± 0.6	1.9 ± 0.6
Calisthenics - Crunches	2.8 ± 1.1	2.4 ± 0.9	2.9 ± 1.2	2.8 ± 1.2	2.8 ± 1.2	2.8 ± 1.1
Calisthenics - Sit ups	2.4 ± 0.7	2.4 ± 0.7	2.9 ± 0.8	2.8 ± 0.6	2.8 ± 0.6	2.7 ± 0.6
Cycling - Cycle hard - Cycle 80rpm	2.6 ± 1.0	2.4 ± 1.2	2.6 ± 1.3	2.8 ± 1.3	2.8 ± 1.1	2.7 ± 1.1
Cycling - Cycle light - Cycle 100rpm	2.1 ± 1.1	1.8 ± 0.7	2.1 ± 0.9	2.1 ± 0.9	2.2 ± 0.8	2.1 ± 0.8
Cycling - Cycle light - Cycle 60rpm	1.3 ± 0.6	1.1 ± 0.5	1.1 ± 0.5	1.2 ± 0.4	1.1 ± 0.5	1.1 ± 0.5
Cycling - Cycle light - Cycle 80rpm	1.9 ± 1.0	1.6 ± 0.9	1.9 ± 0.8	2.0 ± 0.9	1.9 ± 1.1	1.9 ± 1.1
Cycling - Cycle moderate - Cycle 80rpm	2.3 ± 0.9	2.1 ± 0.9	2.2 ± 1.0	2.5 ± 1.1	2.5 ± 0.9	2.4 ± 0.9
Lying down	1.0 ± 0.4	0.8 ± 0.4	1.2 ± 0.5	0.9 ± 0.5	0.9 ± 0.5	0.9 ± 0.5
Rowing - Rowing hard - Rowing 30spm	2.8 ± 2.0	2.9 ± 1.8	2.8 ± 1.9	3.2 ± 2.0	3.1 ± 2.0	3.1 ± 2.0
Rowing - Rowing light - Rowing 30spm	2.4 ± 1.3	2.2 ± 1.3	2.2 ± 1.4	2.3 ± 1.5	2.4 ± 1.5	2.3 ± 1.5
Rowing - Rowing moderate - Rowing 30spm	2.5 ± 1.8	2.5 ± 1.7	2.5 ± 1.8	2.9 ± 1.8	2.8 ± 1.8	2.7 ± 1.8
Running - Treadmill 4mph - Treadmill 0	2.6 ± 1.2	2.7 ± 1.3	2.8 ± 1.3	2.9 ± 1.6	2.6 ± 1.4	2.6 ± 1.4
Running - Treadmill 5mph - Treadmill 0	2.7 ± 1.0	2.4 ± 1.1	2.8 ± 1.1	3.0 ± 1.2	2.8 ± 1.0	2.9 ± 1.1
Running - Treadmill 6mph - Treadmill 0	3.3 ± 1.3	2.8 ± 1.0	3.5 ± 1.5	3.7 ± 1.6	3.4 ± 1.6	3.4 ± 1.6
Sitting	1.6 ± 0.5	0.9 ± 0.2	1.3 ± 0.4	1.2 ± 0.6	1.2 ± 0.6	1.2 ± 0.6
Sitting - Fidget feet legs	1.9 ± 0.6	2.0 ± 0.7	1.6 ± 0.4	1.6 ± 0.5	1.8 ± 0.6	1.8 ± 0.6
Sitting - Fidget hands arms	1.6 ± 0.6	1.7 ± 1.1	1.4 ± 0.5	1.2 ± 0.4	1.4 ± 0.8	1.4 ± 0.9
Stairs - Ascend stairs	1.8 ± 0.4	1.8 ± 0.3	1.8 ± 0.4	1.7 ± 0.4	1.8 ± 0.4	1.8 ± 0.4
Stairs - Descend stairs	2.6 ± 0.4	2.6 ± 0.5	2.6 ± 0.5	2.5 ± 0.4	2.3 ± 0.3	2.3 ± 0.4
Standing	1.0 ± 0.2	0.5 ± 0.2	0.9 ± 0.3	1.1 ± 0.3	1.1 ± 0.3	1.1 ± 0.3
Walking - Treadmill 2mph - Treadmill 0	1.5 ± 0.6	1.6 ± 0.5	1.3 ± 0.4	1.3 ± 0.5	1.5 ± 0.5	1.5 ± 0.5
Walking - Treadmill 3mph - Treadmill 0	1.8 ± 0.6	1.7 ± 0.6	1.5 ± 0.6	1.7 ± 0.4	1.7 ± 0.5	1.7 ± 0.5
Walking - Treadmill 3mph - Treadmill 3 - light	1.5 ± 0.6	1.3 ± 0.5	1.2 ± 0.4	1.4 ± 0.6	1.4 ± 0.4	1.4 ± 0.5
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.8 ± 0.7	1.7 ± 0.6	1.8 ± 0.4	1.8 ± 0.5	1.7 ± 0.6	1.7 ± 0.6
Walking - Treadmill 3mph - Treadmill 9 - hard	2.3 ± 0.8	2.2 ± 0.9	2.4 ± 0.8	2.4 ± 0.8	2.4 ± 0.7	2.4 ± 0.8
kneeling	1.2 ± 0.5	0.8 ± 0.3	1.0 ± 0.3	1.2 ± 0.3	1.2 ± 0.4	1.2 ± 0.4
unknown	5.3 ± 0.8	5.1 ± 1.0	5.0 ± 1.0	5.0 ± 1.1	5.0 ± 1.1	5.0 ± 1.1
Carrying groceries	2.0 ± 0.8	2.0 ± 0.9	2.0 ± 0.8	2.0 ± 0.6	2.0 ± 0.6	2.1 ± 0.6
Doing dishes	1.0 ± 0.5	1.0 ± 0.8	0.9 ± 0.5	1.0 ± 0.3	1.0 ± 0.2	1.0 ± 0.2
Gardening	1.6 ± 0.7	1.7 ± 1.1	1.6 ± 1.0	1.3 ± 0.3	1.3 ± 0.5	1.2 ± 0.4
Ironing	1.2 ± 0.4	1.0 ± 0.4	1.0 ± 0.4	1.2 ± 0.5	1.3 ± 0.5	1.3 ± 0.5
Making the bed	2.1 ± 1.0	2.4 ± 1.2	2.0 ± 0.9	2.0 ± 0.7	2.0 ± 0.7	2.0 ± 0.7
Mopping	1.6 ± 0.6	1.4 ± 0.5	1.5 ± 0.7	1.6 ± 0.4	1.5 ± 0.3	1.4 ± 0.3
Playing videogames	1.5 ± 0.6	1.1 ± 0.6	1.5 ± 0.6	1.1 ± 0.6	1.1 ± 0.7	1.0 ± 0.7
Scrubbing a surface	2.2 ± 1.3	2.0 ± 0.9	2.0 ± 1.2	1.7 ± 1.1	1.5 ± 0.4	1.6 ± 0.5
Stacking groceries	2.1 ± 0.9	1.7 ± 0.9	2.0 ± 0.9	2.1 ± 0.9	1.9 ± 0.4	1.9 ± 0.6
Sweeping	1.5 ± 0.5	1.5 ± 0.8	1.4 ± 0.8	1.3 ± 0.3	1.5 ± 0.3	1.4 ± 0.3
Typing	1.1 ± 0.4	0.8 ± 0.6	1.1 ± 0.6	1.0 ± 0.4	1.0 ± 0.4	1.0 ± 0.4
Vacuuming	1.2 ± 0.2	1.2 ± 0.2	1.1 ± 0.4	1.1 ± 0.4	1.4 ± 0.2	1.3 ± 0.3
Walking around block	2.3 ± 0.6	2.7 ± 0.7	2.4 ± 0.7	2.4 ± 0.6	2.3 ± 0.4	2.4 ± 0.4
Washing windows	1.7 ± 0.7	1.8 ± 0.9	1.6 ± 0.6	1.6 ± 0.5	1.5 ± 0.3	1.5 ± 0.3
Watching TV	1.4 ± 0.7	1.1 ± 0.7	1.3 ± 0.6	0.9 ± 0.2	1.0 ± 0.3	1.0 ± 0.2
Weeding	1.7 ± 0.7	1.7 ± 0.8	1.6 ± 0.8	1.5 ± 0.5	1.5 ± 0.5	1.5 ± 0.5
Wiping/Dusting	1.6 ± 0.9	1.7 ± 1.0	1.5 ± 0.7	1.4 ± 0.4	1.5 ± 0.4	1.5 ± 0.4
Writing	1.2 ± 0.4	0.8 ± 0.5	1.2 ± 0.4	1.0 ± 0.2	1.0 ± 0.2	1.0 ± 0.2
taking out trash	1.6 ± 0.4	1.8 ± 0.4	1.8 ± 0.5	1.9 ± 0.5	1.7 ± 0.4	1.8 ± 0.4

Table B13-3: Maximum absolute error deviation per activity obtained when estimating energy expenditure using multivariable linear regression and different subsets of features computed per sensor over windows of 5.6s in length.

Appendix B14: Energy Expenditure Estimation Using Heart Rate Data

Activity	RMSE	MAE	MAED
Bench_weight_lifting_-_hard	1.93 ± 1.22	1.86 ± 1.19	2.49 ± 1.65
Bench_weight_lifting_-_light	1.70 ± 0.59	1.68 ± 0.58	2.11 ± 0.74
Bench_weight_lifting_-_moderate	1.63 ± 0.69	1.60 ± 0.66	2.19 ± 1.10
Bicep_curls_-_hard	1.97 ± 0.72	1.96 ± 0.72	2.39 ± 0.81
Bicep_curls_-_light	1.65 ± 0.63	1.62 ± 0.64	1.95 ± 0.61
Bicep_curls_-_moderate	1.83 ± 0.62	1.80 ± 0.65	2.35 ± 0.68
Calisthenics_-_Crunches	1.86 ± 0.82	1.77 ± 0.75	2.39 ± 0.92
Calisthenics_-_Sit_ups	1.43 ± 0.76	1.30 ± 0.82	2.29 ± 0.78
Cycling_-_Cycle_hard_-_Cycle_80rpm	1.86 ± 1.67	1.79 ± 1.67	2.45 ± 1.93
Cycling_-_Cycle_light_-_Cycle_100rpm	0.85 ± 0.66	0.81 ± 0.66	1.14 ± 0.71
Cycling_-_Cycle_light_-_Cycle_60rpm	0.48 ± 0.26	0.46 ± 0.26	0.75 ± 0.33
Cycling_-_Cycle_light_-_Cycle_80rpm	0.63 ± 0.34	0.60 ± 0.34	0.92 ± 0.38
Cycling_-_Cycle_moderate_-_Cycle_80rpm	1.34 ± 1.07	1.22 ± 1.06	2.20 ± 1.54
Lying_down	0.25 ± 0.11	0.23 ± 0.10	0.47 ± 0.19
Rowing_-_Rowing_hard_-_Rowing_30spm	0.92 ± 0.45	0.84 ± 0.45	1.57 ± 0.78
Rowing_-_Rowing_light_-_Rowing_30spm	0.73 ± 0.42	0.66 ± 0.41	1.19 ± 0.52
Rowing_-_Rowing_moderate_-_Rowing_30spm	0.73 ± 0.37	0.68 ± 0.36	1.09 ± 0.48
Running_-_Treadmill_4mph_-_Treadmill_0_	0.97 ± 0.53	0.86 ± 0.50	1.61 ± 0.96
Running_-_Treadmill_5mph_-_Treadmill_0_	1.34 ± 0.77	1.28 ± 0.77	1.89 ± 0.92
Running_-_Treadmill_6mph_-_Treadmill_0_	1.63 ± 0.98	1.55 ± 0.95	2.29 ± 1.41
Sitting	0.54 ± 0.18	0.41 ± 0.14	1.27 ± 0.48
Sitting_-_Fidget_feet_legs	0.34 ± 0.21	0.30 ± 0.20	0.61 ± 0.35
Sitting_-_Fidget_hands_arms	0.49 ± 0.26	0.45 ± 0.26	0.71 ± 0.30
Stairs_-_Ascend_stairs	0.83 ± 0.41	0.73 ± 0.38	1.57 ± 0.68
Stairs_-_Descend_stairs	0.94 ± 0.39	0.80 ± 0.33	1.72 ± 0.69
Standing	0.89 ± 0.49	0.86 ± 0.50	1.20 ± 0.54
Walking_-_Treadmill_2mph_-_Treadmill_0_	0.56 ± 0.37	0.49 ± 0.29	1.05 ± 0.99
Walking_-_Treadmill_3mph_-_Treadmill_0_	0.58 ± 0.26	0.55 ± 0.26	0.87 ± 0.33
Walking_-_Treadmill_3mph_-_Treadmill_3__-_light	0.74 ± 0.29	0.71 ± 0.30	1.04 ± 0.31
Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate	0.95 ± 0.43	0.91 ± 0.44	1.47 ± 0.73
Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard	1.10 ± 0.54	1.07 ± 0.55	1.47 ± 0.64
kneeling	0.65 ± 0.43	0.58 ± 0.45	1.03 ± 0.49
unknown	1.11 ± 0.38	0.89 ± 0.30	3.44 ± 1.67
Carrying_groceries	0.88 ± 0.42	0.81 ± 0.40	1.25 ± 0.57
Doing_dishes	0.45 ± 0.10	0.40 ± 0.10	0.77 ± 0.18
Gardening	0.40 ± 0.16	0.32 ± 0.15	0.93 ± 0.36
Ironing	0.46 ± 0.17	0.39 ± 0.15	0.88 ± 0.42
Making_the_bed	0.80 ± 0.35	0.71 ± 0.32	1.34 ± 0.45
Mopping	0.74 ± 0.40	0.67 ± 0.39	1.25 ± 0.70
Playing_videogames	0.25 ± 0.12	0.22 ± 0.11	0.50 ± 0.21
Scrubbing_a_surface	0.68 ± 0.33	0.60 ± 0.30	1.31 ± 0.75
Stacking_groceries	0.54 ± 0.16	0.49 ± 0.13	0.96 ± 0.36
Sweeping	0.57 ± 0.17	0.50 ± 0.16	1.07 ± 0.42
Typing	0.31 ± 0.13	0.27 ± 0.12	0.60 ± 0.24
Vacuuming	0.65 ± 0.47	0.59 ± 0.47	1.13 ± 0.66
Walking_around_block	0.67 ± 0.19	0.58 ± 0.18	1.18 ± 0.29
Washing_windows	0.63 ± 0.30	0.52 ± 0.27	1.26 ± 0.53
Watching_TV	0.25 ± 0.12	0.21 ± 0.13	0.51 ± 0.17
Weeding	0.58 ± 0.27	0.54 ± 0.27	0.93 ± 0.38
Wiping/Dusting	0.42 ± 0.24	0.36 ± 0.20	0.81 ± 0.44
Writing	0.30 ± 0.15	0.28 ± 0.15	0.49 ± 0.18
taking_out_trash	0.71 ± 0.50	0.63 ± 0.48	1.28 ± 0.89

Table B14-1: Estimation of energy expenditure estimation using linear regression and the *ScaledHR* feature evaluated in a subject independent manner. The heart rate feature was computed over sliding windows of 5.6s in length.

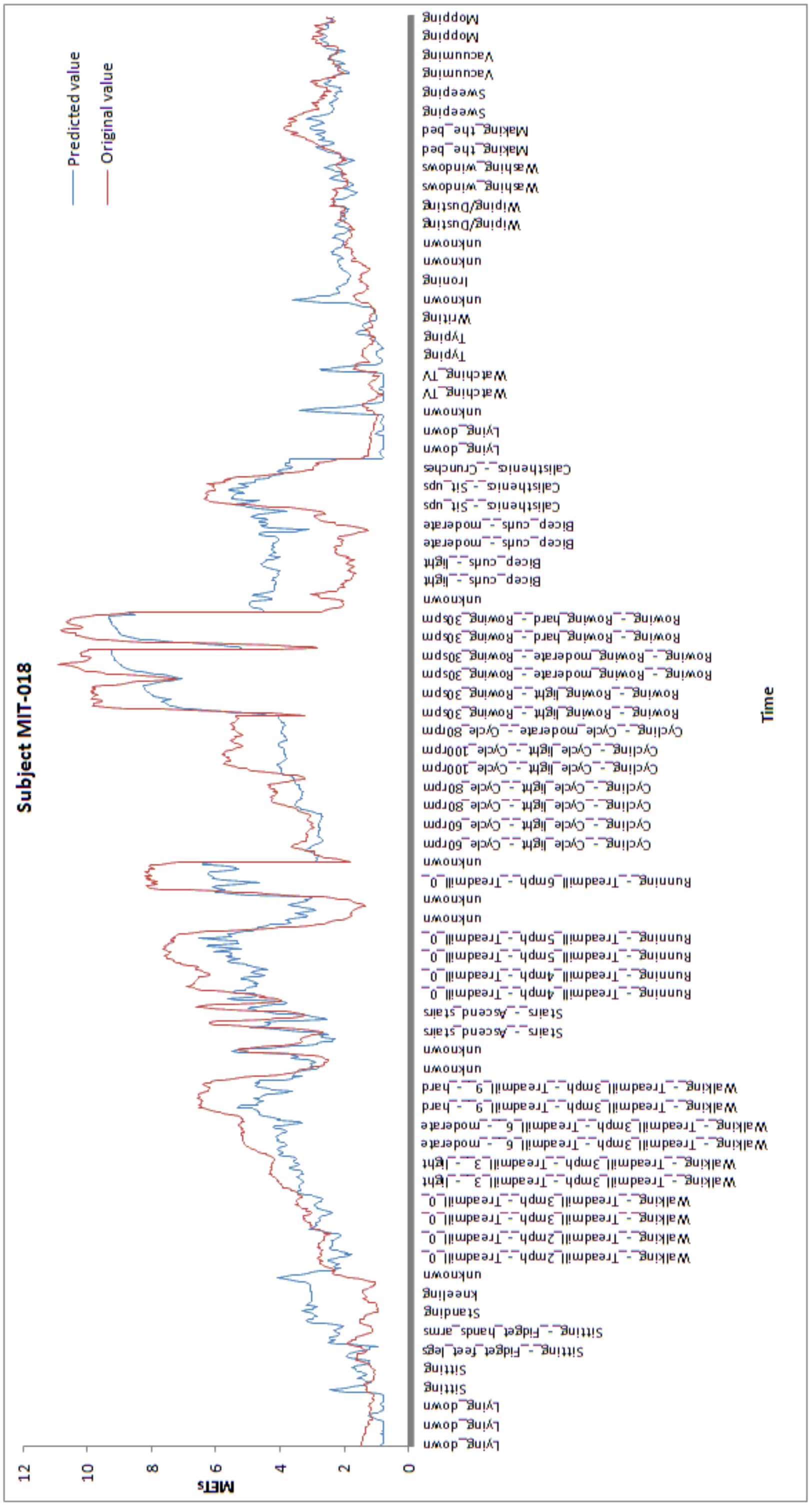

Figure B14-1. Subject independent estimation of energy expenditure using linear regression and the *ScaledHR* feature computed over windows of 5.6s in length.

Activity	RMSE	MAE	MAED
Bench_weight_lifting_-_hard	1.87 ± 0.91	1.79 ± 0.89	2.43 ± 1.24
Bench_weight_lifting_-_light	1.70 ± 0.64	1.69 ± 0.63	2.10 ± 0.82
Bench_weight_lifting_-_moderate	1.52 ± 0.71	1.49 ± 0.69	2.04 ± 1.09
Bicep_curls_-_hard	1.82 ± 0.36	1.81 ± 0.36	2.23 ± 0.44
Bicep_curls_-_light	1.63 ± 0.49	1.61 ± 0.49	1.95 ± 0.52
Bicep_curls_-_moderate	1.72 ± 0.48	1.70 ± 0.49	2.26 ± 0.65
Calisthenics_-_Crunches	1.67 ± 0.61	1.59 ± 0.58	2.19 ± 0.63
Calisthenics_-_Sit_ups	1.30 ± 0.45	1.14 ± 0.52	2.27 ± 0.47
Cycling_-_Cycle_hard_-_Cycle_80rpm	1.67 ± 1.46	1.58 ± 1.45	2.29 ± 1.71
Cycling_-_Cycle_light_-_Cycle_100rpm	0.69 ± 0.45	0.65 ± 0.45	1.00 ± 0.49
Cycling_-_Cycle_light_-_Cycle_60rpm	0.40 ± 0.24	0.37 ± 0.25	0.69 ± 0.33
Cycling_-_Cycle_light_-_Cycle_80rpm	0.47 ± 0.28	0.44 ± 0.28	0.74 ± 0.35
Cycling_-_Cycle_moderate_-_Cycle_80rpm	1.17 ± 0.98	1.07 ± 0.95	1.92 ± 1.49
Lying_down	0.39 ± 0.26	0.37 ± 0.26	0.60 ± 0.29
Rowing_-_Rowing_hard_-_Rowing_30spm	0.83 ± 0.39	0.71 ± 0.40	1.60 ± 0.86
Rowing_-_Rowing_light_-_Rowing_30spm	0.66 ± 0.33	0.57 ± 0.33	1.16 ± 0.44
Rowing_-_Rowing_moderate_-_Rowing_30spm	0.69 ± 0.42	0.62 ± 0.43	1.15 ± 0.50
Running_-_Treadmill_4mph_-_Treadmill_0_	0.90 ± 0.38	0.81 ± 0.35	1.55 ± 0.77
Running_-_Treadmill_5mph_-_Treadmill_0_	1.25 ± 0.65	1.20 ± 0.64	1.79 ± 0.82
Running_-_Treadmill_6mph_-_Treadmill_0_	1.32 ± 1.01	1.25 ± 0.96	1.96 ± 1.51
Sitting	0.56 ± 0.25	0.46 ± 0.26	1.25 ± 0.46
Sitting_-_Fidget_feet_legs	0.36 ± 0.23	0.33 ± 0.23	0.60 ± 0.39
Sitting_-_Fidget_hands_arms	0.45 ± 0.28	0.41 ± 0.28	0.66 ± 0.33
Stairs_-_Ascend_stairs	0.79 ± 0.35	0.68 ± 0.32	1.50 ± 0.58
Stairs_-_Descend_stairs	0.91 ± 0.36	0.76 ± 0.31	1.65 ± 0.58
Standing	0.81 ± 0.49	0.78 ± 0.50	1.13 ± 0.58
Walking_-_Treadmill_2mph_-_Treadmill_0_	0.62 ± 0.31	0.56 ± 0.24	1.10 ± 0.85
Walking_-_Treadmill_3mph_-_Treadmill_0_	0.65 ± 0.20	0.62 ± 0.20	0.97 ± 0.29
Walking_-_Treadmill_3mph_-_Treadmill_3__-_light	0.75 ± 0.23	0.72 ± 0.24	1.05 ± 0.24
Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate	0.96 ± 0.33	0.91 ± 0.34	1.51 ± 0.82
Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard	1.04 ± 0.42	1.01 ± 0.43	1.44 ± 0.49
kneeling	0.68 ± 0.48	0.64 ± 0.49	1.01 ± 0.51
unknown	1.03 ± 0.33	0.83 ± 0.26	3.33 ± 1.64
Carrying_groceries	0.81 ± 0.31	0.76 ± 0.29	1.18 ± 0.45
Doing_dishes	0.40 ± 0.15	0.36 ± 0.14	0.70 ± 0.25
Gardening	0.35 ± 0.14	0.28 ± 0.14	0.84 ± 0.32
Ironing	0.39 ± 0.19	0.32 ± 0.17	0.79 ± 0.45
Making_the_bed	0.79 ± 0.30	0.71 ± 0.29	1.32 ± 0.43
Mopping	0.67 ± 0.33	0.60 ± 0.32	1.16 ± 0.58
Playing_videogames	0.22 ± 0.17	0.19 ± 0.16	0.41 ± 0.20
Scrubbing_a_surface	0.57 ± 0.29	0.49 ± 0.26	1.19 ± 0.72
Stacking_groceries	0.46 ± 0.18	0.41 ± 0.17	0.88 ± 0.30
Sweeping	0.49 ± 0.08	0.41 ± 0.04	0.97 ± 0.37
Typing	0.30 ± 0.12	0.26 ± 0.12	0.61 ± 0.24
Vacuuming	0.60 ± 0.47	0.55 ± 0.47	1.07 ± 0.73
Walking_around_block	0.67 ± 0.15	0.59 ± 0.16	1.13 ± 0.22
Washing_windows	0.62 ± 0.31	0.51 ± 0.28	1.25 ± 0.50
Watching_TV	0.23 ± 0.15	0.19 ± 0.13	0.49 ± 0.26
Weeding	0.51 ± 0.31	0.46 ± 0.32	0.83 ± 0.30
Wiping/Dusting	0.41 ± 0.28	0.35 ± 0.25	0.82 ± 0.50
Writing	0.27 ± 0.19	0.25 ± 0.19	0.45 ± 0.23
taking_out_trash	0.66 ± 0.42	0.59 ± 0.40	1.21 ± 0.80

Table B14-2: Estimation of energy expenditure using linear regression and the *ScaledHR* feature evaluated in a subject dependent manner. The heart rate feature was computed over sliding windows of 5.6s in length.

Activity	MAE	RMSE	MAED
Bench_weight_lifting_-_hard	1.21 ± 0.98	1.28 ± 1.00	1.79 ± 1.27
Bench_weight_lifting_-_light	1.02 ± 0.53	1.06 ± 0.53	1.52 ± 0.65
Bench_weight_lifting_-_moderate	0.94 ± 0.59	1.00 ± 0.59	1.53 ± 0.87
Bicep_curls_-_hard	0.96 ± 0.79	1.02 ± 0.76	1.62 ± 0.83
Bicep_curls_-_light	0.72 ± 0.44	0.80 ± 0.42	1.40 ± 0.50
Bicep_curls_-_moderate	0.84 ± 0.51	0.93 ± 0.47	1.63 ± 0.45
Calisthenics_-_Crunches	1.26 ± 0.64	1.39 ± 0.67	2.21 ± 0.77
Calisthenics_-_Sit_ups	1.22 ± 0.31	1.33 ± 0.33	2.13 ± 0.58
Cycling_-_Cycle_hard_-_Cycle_80rpm	1.70 ± 1.26	1.78 ± 1.27	2.46 ± 1.38
Cycling_-_Cycle_light_-_Cycle_100rpm	0.92 ± 0.53	0.99 ± 0.51	1.52 ± 0.59
Cycling_-_Cycle_light_-_Cycle_60rpm	0.46 ± 0.33	0.50 ± 0.32	0.84 ± 0.40
Cycling_-_Cycle_light_-_Cycle_80rpm	0.61 ± 0.47	0.65 ± 0.46	1.03 ± 0.55
Cycling_-_Cycle_moderate_-_Cycle_80rpm	1.14 ± 0.90	1.26 ± 0.90	2.18 ± 1.28
Lying_down	0.23 ± 0.10	0.27 ± 0.10	0.67 ± 0.37
Rowing_-_Rowing_hard_-_Rowing_30spm	1.08 ± 0.70	1.18 ± 0.70	1.88 ± 0.87
Rowing_-_Rowing_light_-_Rowing_30spm	0.82 ± 0.55	0.91 ± 0.59	1.44 ± 0.82
Rowing_-_Rowing_moderate_-_Rowing_30spm	0.96 ± 0.54	1.02 ± 0.57	1.50 ± 0.77
Running_-_Treadmill_4mph_-_Treadmill_0_	0.76 ± 0.34	0.92 ± 0.43	2.08 ± 1.06
Running_-_Treadmill_5mph_-_Treadmill_0_	0.94 ± 0.43	1.07 ± 0.45	2.11 ± 0.74
Running_-_Treadmill_6mph_-_Treadmill_0_	1.15 ± 0.64	1.27 ± 0.67	2.19 ± 1.14
Sitting	0.34 ± 0.14	0.43 ± 0.19	0.94 ± 0.46
Sitting_-_Fidget_feet_legs	0.42 ± 0.17	0.46 ± 0.18	0.81 ± 0.33
Sitting_-_Fidget_hands_arms	0.38 ± 0.15	0.42 ± 0.16	0.73 ± 0.20
Stairs_-_Ascend_stairs	0.72 ± 0.30	0.83 ± 0.31	1.61 ± 0.52
Stairs_-_Descend_stairs	0.86 ± 0.30	0.98 ± 0.35	1.72 ± 0.56
Standing	0.57 ± 0.33	0.62 ± 0.34	1.00 ± 0.38
Walking_-_Treadmill_2mph_-_Treadmill_0_	0.37 ± 0.26	0.44 ± 0.33	0.96 ± 0.83
Walking_-_Treadmill_3mph_-_Treadmill_0_	0.38 ± 0.20	0.45 ± 0.20	0.93 ± 0.33
Walking_-_Treadmill_3mph_-_Treadmill_3__-_light	0.40 ± 0.17	0.45 ± 0.18	0.87 ± 0.29
Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate	0.57 ± 0.27	0.64 ± 0.27	1.24 ± 0.42
Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard	0.84 ± 0.48	0.89 ± 0.47	1.43 ± 0.58
kneeling	0.47 ± 0.34	0.52 ± 0.33	0.90 ± 0.37
unknown	0.82 ± 0.21	1.04 ± 0.27	3.51 ± 1.30
Carrying_groceries	0.55 ± 0.28	0.62 ± 0.31	1.14 ± 0.52
Doing_dishes	0.34 ± 0.12	0.40 ± 0.13	0.85 ± 0.27
Gardening	0.34 ± 0.16	0.40 ± 0.18	0.89 ± 0.38
Ironing	0.33 ± 0.15	0.40 ± 0.20	0.85 ± 0.49
Making_the_bed	0.60 ± 0.30	0.69 ± 0.31	1.36 ± 0.50
Mopping	0.58 ± 0.31	0.67 ± 0.32	1.25 ± 0.51
Playing_videogames	0.23 ± 0.14	0.28 ± 0.14	0.63 ± 0.26
Scrubbing_a_surface	0.60 ± 0.28	0.71 ± 0.29	1.45 ± 0.54
Stacking_groceries	0.51 ± 0.22	0.62 ± 0.29	1.29 ± 0.66
Sweeping	0.47 ± 0.17	0.55 ± 0.16	1.11 ± 0.23
Typing	0.29 ± 0.10	0.34 ± 0.11	0.71 ± 0.24
Vacuuming	0.54 ± 0.39	0.61 ± 0.38	1.22 ± 0.46
Walking_around_block	0.46 ± 0.15	0.56 ± 0.17	1.18 ± 0.35
Washing_windows	0.50 ± 0.21	0.61 ± 0.23	1.31 ± 0.39
Watching_TV	0.24 ± 0.14	0.28 ± 0.15	0.62 ± 0.24
Weeding	0.51 ± 0.31	0.58 ± 0.29	0.97 ± 0.42
Wiping/Dusting	0.34 ± 0.17	0.42 ± 0.20	0.90 ± 0.35
Writing	0.25 ± 0.12	0.29 ± 0.12	0.54 ± 0.20
taking_out_trash	0.50 ± 0.34	0.58 ± 0.35	1.15 ± 0.61

Table B14-3: Estimation of energy expenditure using linear regression and the *ScaledHR+ACFFTPeaks* feature evaluated in a subject independent manner. The features were computed over sliding windows of 5.6s in length.

Appendix B15: Feature Selection over Subsets of Accelerometers for Energy Expenditure Estimation

Activity	RMSE	MAE	MAED
Bench_weight_lifting_-_hard	0.37 ± 0.25	0.32 ± 0.21	0.77 ± 0.50
Bench_weight_lifting_-_light	0.53 ± 0.25	0.48 ± 0.25	0.88 ± 0.35
Bench_weight_lifting_-_moderate	0.56 ± 0.26	0.53 ± 0.24	0.86 ± 0.33
Bicep_curls_-_hard	1.22 ± 0.54	1.20 ± 0.55	1.57 ± 0.58
Bicep_curls_-_light	0.92 ± 0.42	0.86 ± 0.44	1.46 ± 0.60
Bicep_curls_-_moderate	1.13 ± 0.35	1.08 ± 0.35	1.63 ± 0.28
Calisthenics_-_Crunches	1.31 ± 0.42	1.17 ± 0.42	2.07 ± 0.70
Calisthenics_-_Sit_ups	1.75 ± 0.86	1.54 ± 0.77	2.58 ± 1.04
Cycling_-_Cycle_hard_-_Cycle_80rpm	2.94 ± 0.95	2.89 ± 0.98	3.50 ± 0.91
Cycling_-_Cycle_light_-_Cycle_100rpm	1.60 ± 0.89	1.51 ± 0.93	2.24 ± 0.85
Cycling_-_Cycle_light_-_Cycle_60rpm	1.00 ± 0.48	0.97 ± 0.50	1.31 ± 0.45
Cycling_-_Cycle_light_-_Cycle_80rpm	1.33 ± 0.72	1.28 ± 0.74	1.72 ± 0.75
Cycling_-_Cycle_moderate_-_Cycle_80rpm	2.36 ± 0.87	2.29 ± 0.87	2.94 ± 0.84
Lying_down	0.70 ± 0.16	0.69 ± 0.16	0.90 ± 0.13
Rowing_-_Rowing_hard_-_Rowing_30spm	3.06 ± 1.80	2.95 ± 1.70	3.70 ± 2.14
Rowing_-_Rowing_light_-_Rowing_30spm	2.10 ± 1.35	1.94 ± 1.23	2.77 ± 1.59
Rowing_-_Rowing_moderate_-_Rowing_30spm	2.82 ± 1.67	2.70 ± 1.64	3.49 ± 1.92
Running_-_Treadmill_4mph_-_Treadmill_0_	1.19 ± 0.48	0.97 ± 0.43	2.68 ± 1.25
Running_-_Treadmill_5mph_-_Treadmill_0_	1.03 ± 0.38	0.88 ± 0.36	2.07 ± 0.98
Running_-_Treadmill_6mph_-_Treadmill_0_	0.99 ± 0.49	0.90 ± 0.47	1.79 ± 1.04
Sitting	0.63 ± 0.16	0.60 ± 0.18	0.86 ± 0.12
Sitting_-_Fidget_feet_legs	1.03 ± 0.35	1.01 ± 0.35	1.39 ± 0.45
Sitting_-_Fidget_hands_arms	1.00 ± 0.31	0.98 ± 0.32	1.34 ± 0.35
Stairs_-_Ascend_stairs	0.85 ± 0.22	0.73 ± 0.21	1.66 ± 0.40
Stairs_-_Descend_stairs	1.39 ± 0.29	1.27 ± 0.30	2.34 ± 0.27
Standing	0.64 ± 0.15	0.61 ± 0.16	0.90 ± 0.19
Walking_-_Treadmill_2mph_-_Treadmill_0_	0.87 ± 0.43	0.83 ± 0.45	1.49 ± 0.53
Walking_-_Treadmill_3mph_-_Treadmill_0_	1.00 ± 0.48	0.94 ± 0.50	1.64 ± 0.68
Walking_-_Treadmill_3mph_-_Treadmill_3__-_light	0.60 ± 0.37	0.53 ± 0.37	1.10 ± 0.52
Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate	0.73 ± 0.41	0.67 ± 0.42	1.16 ± 0.45
Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard	1.42 ± 0.73	1.38 ± 0.73	1.89 ± 0.79
kneeling	0.54 ± 0.19	0.51 ± 0.20	0.87 ± 0.24
unknown	1.54 ± 0.35	1.16 ± 0.24	5.15 ± 1.17
Carrying_groceries	1.12 ± 0.40	0.97 ± 0.40	2.23 ± 0.81
Doing_dishes	0.69 ± 0.16	0.64 ± 0.17	1.21 ± 0.33
Gardening	0.62 ± 0.41	0.54 ± 0.39	1.17 ± 0.65
Ironing	0.65 ± 0.18	0.59 ± 0.18	1.15 ± 0.44
Making_the_bed	0.93 ± 0.30	0.79 ± 0.27	1.93 ± 0.57
Mopping	0.59 ± 0.22	0.51 ± 0.22	1.31 ± 0.47
Playing_videogames	0.76 ± 0.16	0.75 ± 0.17	1.05 ± 0.32
Scrubbing_a_surface	0.86 ± 0.27	0.71 ± 0.24	1.91 ± 0.55
Stacking_groceries	0.84 ± 0.29	0.77 ± 0.31	1.43 ± 0.39
Sweeping	0.55 ± 0.28	0.45 ± 0.23	1.18 ± 0.44
Typing	0.71 ± 0.14	0.68 ± 0.14	1.00 ± 0.21
Vacuuming	0.55 ± 0.25	0.47 ± 0.24	1.17 ± 0.47
Walking_around_block	1.60 ± 0.36	1.48 ± 0.39	2.73 ± 0.44
Washing_windows	0.83 ± 0.37	0.71 ± 0.34	1.67 ± 0.77
Watching_TV	0.75 ± 0.15	0.74 ± 0.15	1.04 ± 0.34
Weeding	0.63 ± 0.27	0.54 ± 0.23	1.27 ± 0.64
Wiping/Dusting	0.85 ± 0.26	0.74 ± 0.24	1.78 ± 0.53
Writing	0.74 ± 0.19	0.73 ± 0.20	0.95 ± 0.21
taking_out_trash	0.78 ± 0.21	0.65 ± 0.18	1.65 ± 0.37

Table B15-1: Energy expenditure estimation using linear regression and the *ACAbsArea* feature computed per sensor over the accelerometers at the hip, dominant wrist and dominant foot evaluated in a subject independent manner. The feature is computed over windows of 5.6s in length.

Activity	RMSE	MAE	MAED
Bench_weight_lifting_-_hard	0.46 ± 0.21	0.39 ± 0.18	0.94 ± 0.34
Bench_weight_lifting_-_light	0.59 ± 0.22	0.52 ± 0.22	1.12 ± 0.35
Bench_weight_lifting_-_moderate	0.62 ± 0.30	0.56 ± 0.28	1.06 ± 0.44
Bicep_curls_-_hard	1.54 ± 0.74	1.45 ± 0.77	2.38 ± 0.75
Bicep_curls_-_light	1.22 ± 0.55	1.11 ± 0.57	2.12 ± 0.53
Bicep_curls_-_moderate	1.44 ± 0.44	1.33 ± 0.46	2.47 ± 0.53
Calisthenics_-_Crunches	1.50 ± 0.60	1.31 ± 0.53	2.75 ± 1.27
Calisthenics_-_Sit_ups	1.77 ± 0.88	1.56 ± 0.79	2.75 ± 1.07
Cycling_-_Cycle_hard_-_Cycle_80rpm	2.22 ± 1.08	2.14 ± 1.10	3.02 ± 1.15
Cycling_-_Cycle_light_-_Cycle_100rpm	1.26 ± 0.71	1.16 ± 0.72	2.09 ± 0.91
Cycling_-_Cycle_light_-_Cycle_60rpm	0.72 ± 0.43	0.68 ± 0.45	1.10 ± 0.48
Cycling_-_Cycle_light_-_Cycle_80rpm	1.09 ± 0.67	1.00 ± 0.68	1.83 ± 0.87
Cycling_-_Cycle_moderate_-_Cycle_80rpm	1.76 ± 0.93	1.66 ± 0.92	2.56 ± 1.08
Lying_down	0.37 ± 0.08	0.31 ± 0.08	0.86 ± 0.37
Rowing_-_Rowing_hard_-_Rowing_30spm	2.30 ± 1.79	2.15 ± 1.69	3.24 ± 2.13
Rowing_-_Rowing_light_-_Rowing_30spm	1.49 ± 1.32	1.35 ± 1.22	2.27 ± 1.64
Rowing_-_Rowing_moderate_-_Rowing_30spm	2.13 ± 1.66	2.01 ± 1.65	2.88 ± 1.85
Running_-_Treadmill_4mph_-_Treadmill_0_	1.31 ± 0.73	1.08 ± 0.60	2.94 ± 1.76
Running_-_Treadmill_5mph_-_Treadmill_0_	1.51 ± 0.65	1.27 ± 0.64	3.23 ± 0.95
Running_-_Treadmill_6mph_-_Treadmill_0_	1.65 ± 1.05	1.40 ± 1.04	3.37 ± 1.67
Sitting	0.51 ± 0.20	0.45 ± 0.19	0.91 ± 0.32
Sitting_-_Fidget_feet_legs	1.05 ± 0.40	1.00 ± 0.41	1.55 ± 0.45
Sitting_-_Fidget_hands_arms	0.71 ± 0.32	0.65 ± 0.33	1.19 ± 0.43
Stairs_-_Ascend_stairs	0.85 ± 0.20	0.72 ± 0.18	1.72 ± 0.40
Stairs_-_Descend_stairs	1.48 ± 0.38	1.31 ± 0.35	2.66 ± 0.52
Standing	0.49 ± 0.14	0.43 ± 0.15	0.92 ± 0.19
Walking_-_Treadmill_2mph_-_Treadmill_0_	0.72 ± 0.32	0.64 ± 0.32	1.41 ± 0.48
Walking_-_Treadmill_3mph_-_Treadmill_0_	0.82 ± 0.36	0.72 ± 0.35	1.67 ± 0.67
Walking_-_Treadmill_3mph_-_Treadmill_3__-_light	0.65 ± 0.29	0.55 ± 0.29	1.36 ± 0.43
Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate	0.97 ± 0.45	0.87 ± 0.47	1.85 ± 0.59
Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard	1.69 ± 0.62	1.62 ± 0.64	2.58 ± 0.78
kneeling	0.51 ± 0.15	0.44 ± 0.15	1.00 ± 0.24
unknown	1.53 ± 0.37	1.16 ± 0.26	5.22 ± 1.10
Carrying_groceries	0.88 ± 0.33	0.75 ± 0.29	1.92 ± 0.78
Doing_dishes	0.64 ± 0.12	0.58 ± 0.11	1.23 ± 0.20
Gardening	0.57 ± 0.24	0.50 ± 0.22	1.15 ± 0.35
Ironing	0.62 ± 0.17	0.54 ± 0.15	1.21 ± 0.41
Making_the_bed	0.93 ± 0.30	0.78 ± 0.26	2.01 ± 0.71
Mopping	0.63 ± 0.19	0.52 ± 0.17	1.57 ± 0.50
Playing_videogames	0.55 ± 0.18	0.49 ± 0.19	1.06 ± 0.32
Scrubbing_a_surface	0.76 ± 0.26	0.62 ± 0.21	1.84 ± 0.62
Stacking_groceries	1.13 ± 0.68	0.99 ± 0.58	2.05 ± 1.30
Sweeping	0.61 ± 0.28	0.49 ± 0.22	1.32 ± 0.46
Typing	0.54 ± 0.13	0.48 ± 0.13	1.05 ± 0.31
Vacuuming	0.52 ± 0.16	0.43 ± 0.15	1.18 ± 0.34
Walking_around_block	1.11 ± 0.33	0.95 ± 0.32	2.33 ± 0.54
Washing_windows	0.75 ± 0.28	0.63 ± 0.27	1.64 ± 0.55
Watching_TV	0.55 ± 0.21	0.50 ± 0.21	1.02 ± 0.34
Weeding	0.60 ± 0.31	0.50 ± 0.26	1.31 ± 0.71
Wiping/Dusting	0.72 ± 0.24	0.61 ± 0.23	1.56 ± 0.42
Writing	0.57 ± 0.20	0.52 ± 0.20	1.02 ± 0.27
taking_out_trash	0.76 ± 0.23	0.63 ± 0.21	1.59 ± 0.41

Table B15-2: Energy expenditure estimation using linear regression and the *ACFFTPeaks* feature computed per sensor over the accelerometers at the hip, dominant wrist and dominant foot evaluated in a subject independent manner. The feature is computed over windows of 5.6s in length.

Activity	MAE	RMSE	MAED
Bench_weight_lifting_-_hard	0.42 ± 0.24	0.49 ± 0.27	0.92 ± 0.45
Bench_weight_lifting_-_light	0.52 ± 0.26	0.59 ± 0.26	1.11 ± 0.34
Bench_weight_lifting_-_moderate	0.57 ± 0.40	0.64 ± 0.44	1.11 ± 0.58
Bicep_curls_-_hard	1.36 ± 0.63	1.47 ± 0.60	2.37 ± 0.67
Bicep_curls_-_light	1.05 ± 0.55	1.17 ± 0.54	2.08 ± 0.50
Bicep_curls_-_moderate	1.21 ± 0.51	1.33 ± 0.47	2.27 ± 0.60
Calisthenics_-_Crunches	1.34 ± 0.56	1.55 ± 0.64	2.89 ± 1.44
Calisthenics_-_Sit_ups	1.55 ± 0.77	1.75 ± 0.87	2.81 ± 1.06
Cycling_-_Cycle_hard_-_Cycle_80rpm	2.01 ± 0.90	2.09 ± 0.89	2.91 ± 1.00
Cycling_-_Cycle_light_-_Cycle_100rpm	1.02 ± 0.50	1.14 ± 0.49	2.04 ± 0.63
Cycling_-_Cycle_light_-_Cycle_60rpm	0.65 ± 0.41	0.70 ± 0.39	1.12 ± 0.42
Cycling_-_Cycle_light_-_Cycle_80rpm	0.90 ± 0.62	1.00 ± 0.61	1.81 ± 0.86
Cycling_-_Cycle_moderate_-_Cycle_80rpm	1.52 ± 0.76	1.63 ± 0.78	2.47 ± 0.92
Lying_down	0.28 ± 0.06	0.34 ± 0.07	0.87 ± 0.47
Rowing_-_Rowing_hard_-_Rowing_30spm	2.05 ± 1.63	2.20 ± 1.72	3.11 ± 1.99
Rowing_-_Rowing_light_-_Rowing_30spm	1.29 ± 1.16	1.43 ± 1.25	2.25 ± 1.44
Rowing_-_Rowing_moderate_-_Rowing_30spm	1.90 ± 1.57	2.00 ± 1.58	2.71 ± 1.79
Running_-_Treadmill_4mph_-_Treadmill_0_	0.98 ± 0.51	1.18 ± 0.61	2.58 ± 1.42
Running_-_Treadmill_5mph_-_Treadmill_0_	1.18 ± 0.74	1.37 ± 0.73	2.76 ± 0.89
Running_-_Treadmill_6mph_-_Treadmill_0_	1.51 ± 0.90	1.73 ± 0.90	3.36 ± 1.50
Sitting	0.41 ± 0.17	0.48 ± 0.20	0.89 ± 0.36
Sitting_-_Fidget_feet_legs	0.95 ± 0.39	1.00 ± 0.38	1.50 ± 0.47
Sitting_-_Fidget_hands_arms	0.49 ± 0.23	0.56 ± 0.22	1.10 ± 0.37
Stairs_-_Ascend_stairs	0.72 ± 0.18	0.85 ± 0.18	1.67 ± 0.34
Stairs_-_Descend_stairs	1.31 ± 0.30	1.44 ± 0.27	2.37 ± 0.30
Standing	0.34 ± 0.11	0.40 ± 0.11	0.81 ± 0.23
Walking_-_Treadmill_2mph_-_Treadmill_0_	0.95 ± 0.38	1.00 ± 0.37	1.63 ± 0.49
Walking_-_Treadmill_3mph_-_Treadmill_0_	0.83 ± 0.46	0.91 ± 0.44	1.65 ± 0.54
Walking_-_Treadmill_3mph_-_Treadmill_3__-_light	0.48 ± 0.19	0.56 ± 0.19	1.17 ± 0.35
Walking_-_Treadmill_3mph_-_Treadmill_6__-_moderate	0.76 ± 0.42	0.85 ± 0.40	1.58 ± 0.57
Walking_-_Treadmill_3mph_-_Treadmill_9__-_hard	1.55 ± 0.65	1.61 ± 0.64	2.34 ± 0.79
kneeling	0.41 ± 0.16	0.49 ± 0.17	1.07 ± 0.37
unknown	1.15 ± 0.27	1.53 ± 0.37	4.96 ± 1.12
Carrying_groceries	0.82 ± 0.17	0.97 ± 0.18	2.05 ± 0.55
Doing_dishes	0.39 ± 0.08	0.46 ± 0.08	0.98 ± 0.15
Gardening	0.49 ± 0.14	0.58 ± 0.17	1.22 ± 0.30
Ironing	0.41 ± 0.13	0.50 ± 0.18	1.11 ± 0.46
Making_the_bed	0.79 ± 0.29	0.93 ± 0.31	1.99 ± 0.75
Mopping	0.55 ± 0.17	0.66 ± 0.17	1.52 ± 0.27
Playing_videogames	0.38 ± 0.15	0.44 ± 0.16	0.94 ± 0.28
Scrubbing_a_surface	0.54 ± 0.20	0.66 ± 0.24	1.57 ± 0.50
Stacking_groceries	0.93 ± 0.53	1.07 ± 0.61	2.07 ± 1.21
Sweeping	0.51 ± 0.21	0.63 ± 0.26	1.36 ± 0.39
Typing	0.40 ± 0.12	0.47 ± 0.13	1.03 ± 0.34
Vacuuming	0.44 ± 0.20	0.52 ± 0.22	1.19 ± 0.44
Walking_around_block	1.17 ± 0.26	1.31 ± 0.24	2.39 ± 0.26
Washing_windows	0.54 ± 0.22	0.67 ± 0.23	1.55 ± 0.49
Watching_TV	0.43 ± 0.20	0.49 ± 0.20	0.96 ± 0.33
Weeding	0.48 ± 0.23	0.59 ± 0.30	1.26 ± 0.70
Wiping/Dusting	0.55 ± 0.23	0.66 ± 0.23	1.51 ± 0.52
Writing	0.45 ± 0.15	0.52 ± 0.15	1.02 ± 0.27
taking_out_trash	0.68 ± 0.20	0.81 ± 0.22	1.66 ± 0.42

Table B15-3: Energy expenditure estimation using linear regression and the *ACFFTPeaks + ACModVigEnergy + ACMCR* feature computed per sensor over the accelerometers at the hip, dominant wrist and dominant foot evaluated in a subject independent manner. The feature is computed over windows of 5.6s in length.

Appendix B16: MIT Energy Expenditure Dataset Statistics

Activity	Energy Expenditure In METs (Mean ± Std)
Bench weight lifting - hard	2.041 ± 0.234
Bench weight lifting - light	1.859 ± 0.5
Bench weight lifting - moderate	1.887 ± 0.474
Bicep curls - hard	1.456 ± 0.485
Bicep curls - light	1.852 ± 0.35
Bicep curls - moderate	1.582 ± 0.372
Calisthenics - Crunches	1.751 ± 1.161
Calisthenics - Sit ups	3.788 ± 0.808
Cycling - Cycle hard - Cycle 80rpm	5.719 ± 1.569
Cycling - Cycle light - Cycle 100rpm	5.607 ± 0.781
Cycling - Cycle light - Cycle 60rpm	3.372 ± 0.438
Cycling - Cycle light - Cycle 80rpm	4.362 ± 0.602
Cycling - Cycle moderate - Cycle 80rpm	5.4 ± 0.72
Lying down	0.99 ± 0.16
Rowing - Rowing hard - Rowing 30spm	5.984 ± 1.831
Rowing - Rowing light - Rowing 30spm	4.92 ± 1.376
Rowing - Rowing moderate - Rowing 30spm	5.776 ± 1.798
Running - Treadmill 4mph - Treadmill 0	4.844 ± 0.799
Running - Treadmill 5mph - Treadmill 0	6.736 ± 0.765
Running - Treadmill 6mph - Treadmill 0	7.352 ± 1.017
Sitting	1.139 ± 0.264
Sitting - Fidget feet legs	1.254 ± 0.245
Sitting - Fidget hands arms	1.176 ± 0.203
Stairs - Ascend stairs	3.104 ± 0.23
Stairs - Descend stairs	3.417 ± 0.748
Standing	1.131 ± 0.255
Walking - Treadmill 2mph - Treadmill 0	2.627 ± 0.361
Walking - Treadmill 3mph - Treadmill 0	3.352 ± 0.351
Walking - Treadmill 3mph - Treadmill 3 - light	4.033 ± 0.372
Walking - Treadmill 3mph - Treadmill 6 - moderate	4.77 ± 0.431
Walking - Treadmill 3mph - Treadmill 9 - hard	5.633 ± 0.548
kneeling	1.221 ± 0.222
unknown	2.666 ± 0.561
Carrying groceries	3.211 ± 0.697
Doing dishes	1.665 ± 0.263
Gardening	2.219 ± 0.425
Ironing	1.606 ± 0.427
Making the bed	3.094 ± 0.541
Mopping	2.746 ± 0.521
Playing videogames	1 ± 0.151
Scrubbing a surface	2.53 ± 0.452
Stacking groceries	2.031 ± 0.409
Sweeping	2.522 ± 0.283
Typing	1.123 ± 0.143
Vacuuming	2.53 ± 0.534
Walking around block	2.777 ± 0.51
Washing windows	2.418 ± 0.619
Watching TV	0.985 ± 0.129
Weeding	2.312 ± 0.48
Wiping/Dusting	2.098 ± 0.34
Writing	1.03 ± 0.186
taking out trash	2.452 ± 0.417

Table B16-1: Average energy expenditure per activity in METs (Mean ± STD) computed for all the subjects included in the MIT energy expenditure dataset. The average was computed over all the activity duration, without eliminating periods corresponding to non steady-state energy expenditure.

Activity	Energy Expenditure in Kcal/Min (Mean ± Std)
Bench weight lifting - hard	2.88 ± 0.515
Bench weight lifting - light	2.503 ± 0.776
Bench weight lifting - moderate	2.581 ± 0.638
Bicep curls - hard	1.908 ± 0.696
Bicep curls - light	2.389 ± 0.427
Bicep curls - moderate	2.054 ± 0.489
Calisthenics - Crunches	2.314 ± 1.551
Calisthenics - Sit ups	4.908 ± 1.141
Cycling - Cycle hard - Cycle 80rpm	7.268 ± 2.113
Cycling - Cycle light - Cycle 100rpm	6.967 ± 1.008
Cycling - Cycle light - Cycle 60rpm	4.272 ± 0.497
Cycling - Cycle light - Cycle 80rpm	5.519 ± 0.621
Cycling - Cycle moderate - Cycle 80rpm	6.708 ± 0.928
Lying down	1.292 ± 0.285
Rowing - Rowing hard - Rowing 30spm	7.896 ± 2.915
Rowing - Rowing light - Rowing 30spm	6.423 ± 2.092
Rowing - Rowing moderate - Rowing 30spm	7.575 ± 2.719
Running - Treadmill 4mph - Treadmill 0	6.054 ± 1.074
Running - Treadmill 5mph - Treadmill 0	8.457 ± 1.366
Running - Treadmill 6mph - Treadmill 0	9.33 ± 2.023
Sitting	1.478 ± 0.442
Sitting - Fidget feet legs	1.626 ± 0.431
Sitting - Fidget hands arms	1.524 ± 0.371
Stairs - Ascend stairs	3.899 ± 0.574
Stairs - Descend stairs	4.319 ± 1.16
Standing	1.45 ± 0.401
Walking - Treadmill 2mph - Treadmill 0	3.298 ± 0.603
Walking - Treadmill 3mph - Treadmill 0	4.198 ± 0.6
Walking - Treadmill 3mph - Treadmill 3 - light	5.048 ± 0.658
Walking - Treadmill 3mph - Treadmill 6 - moderate	5.97 ± 0.746
Walking - Treadmill 3mph - Treadmill 9 - hard	7.084 ± 1.181
kneeling	1.566 ± 0.389
unknown	3.468 ± 0.806
Carrying groceries	4.274 ± 1.229
Doing dishes	2.199 ± 0.483
Gardening	3.106 ± 0.94
Ironing	2.077 ± 0.437
Making the bed	3.981 ± 0.927
Mopping	3.385 ± 0.615
Playing videogames	1.329 ± 0.24
Scrubbing a surface	3.09 ± 0.528
Stacking groceries	2.598 ± 0.637
Sweeping	3.13 ± 0.516
Typing	1.493 ± 0.35
Vacuuming	3.098 ± 0.519
Walking around block	3.738 ± 1.185
Washing windows	3.116 ± 0.718
Watching TV	1.318 ± 0.277
Weeding	3.221 ± 0.995
Wiping/Dusting	2.685 ± 0.532
Writing	1.342 ± 0.22
taking out trash	3.144 ± 0.712

Table B16-2: Average energy expenditure per activity in Kcal/min (Mean ± STD) computed for all the subjects included in the MIT energy expenditure dataset. The average was computed over all the activity duration, without eliminating periods corresponding to non steady-state energy expenditure.

Activity	Heart Rate in BPM (Mean ± Std)
Bench weight lifting - hard	105.803 ± 17.434
Bench weight lifting - light	105.219 ± 14.674
Bench weight lifting - moderate	104.009 ± 15.293
Bicep curls - hard	103.279 ± 18.848
Bicep curls - light	103.816 ± 15.641
Bicep curls - moderate	104.364 ± 14.466
Calisthenics - Crunches	105.112 ± 15.706
Calisthenics - Sit ups	125.837 ± 18.782
Cycling - Cycle hard - Cycle 80rpm	124.149 ± 28.561
Cycling - Cycle light - Cycle 100rpm	144.068 ± 27.564
Cycling - Cycle light - Cycle 60rpm	110.288 ± 19.285
Cycling - Cycle light - Cycle 80rpm	125.54 ± 25.041
Cycling - Cycle moderate - Cycle 80rpm	129.489 ± 26.728
Lying down	64.764 ± 10.693
Rowing - Rowing hard - Rowing 30spm	144.113 ± 16.766
Rowing - Rowing light - Rowing 30spm	132.423 ± 20.585
Rowing - Rowing moderate - Rowing 30spm	141.078 ± 17.359
Running - Treadmill 4mph - Treadmill 0	129.144 ± 27.538
Running - Treadmill 5mph - Treadmill 0	150.453 ± 24.984
Running - Treadmill 6mph - Treadmill 0	157.564 ± 22.615
Sitting	74.005 ± 13.449
Sitting - Fidget feet legs	76.991 ± 14.33
Sitting - Fidget hands arms	78.385 ± 14.099
Stairs - Ascend stairs	115.256 ± 21.955
Stairs - Descend stairs	107.139 ± 22.107
Standing	85.288 ± 14.404
Walking - Treadmill 2mph - Treadmill 0	94.879 ± 24.702
Walking - Treadmill 3mph - Treadmill 0	103.268 ± 23.886
Walking - Treadmill 3mph - Treadmill 3 - light	112.353 ± 24.231
Walking - Treadmill 3mph - Treadmill 6 - moderate	121.403 ± 25.435
Walking - Treadmill 3mph - Treadmill 9 - hard	134.084 ± 27
kneeling	81.124 ± 12.448
unknown	102.588 ± 16.651
Carrying groceries	100.205 ± 10.553
Doing dishes	82.965 ± 14.384
Gardening	90.935 ± 8.824
Ironing	80.428 ± 13.641
Making the bed	97.61 ± 14.814
Mopping	94.711 ± 12.615
Playing videogames	70.771 ± 10.447
Scrubbing a surface	95.536 ± 10.933
Stacking groceries	84.708 ± 10.772
Sweeping	90.987 ± 12.919
Typing	69.467 ± 10.497
Vacuuming	88.993 ± 10.27
Walking around block	94.379 ± 9.452
Washing windows	89.432 ± 14.269
Watching TV	67.808 ± 11.203
Weeding	88.933 ± 12.831
Wiping/Dusting	83.843 ± 12.822
Writing	71.034 ± 10.211
taking out trash	92.181 ± 11.946

Table B16-3: Average heart rate per activity in beats-per-minute (BPM) (Mean ± STD) computed for all the subjects included in the MIT energy expenditure dataset. The average was computed over all the activity duration, without eliminating periods corresponding to non steady-state heart rate.

Activity	METs (Mean ± Std)
Bench weight lifting - hard	2.122 ± 0.51
Bench weight lifting - light	1.946 ± 0.532
Bench weight lifting - moderate	1.967 ± 0.623
Bicep curls - hard	1.485 ± 0.508
Bicep curls - light	1.781 ± 0.312
Bicep curls - moderate	1.538 ± 0.317
Calisthenics - Crunches	1.493 ± 1.205
Calisthenics - Sit ups	4.306 ± 1.201
Cycling - Cycle hard - Cycle 80rpm	5.927 ± 1.528
Cycling - Cycle light - Cycle 100rpm	5.862 ± 0.824
Cycling - Cycle light - Cycle 60rpm	3.395 ± 0.484
Cycling - Cycle light - Cycle 80rpm	4.544 ± 0.62
Cycling - Cycle moderate - Cycle 80rpm	5.655 ± 0.737
Lying down	0.931 ± 0.143
Rowing - Rowing hard - Rowing 30spm	6.412 ± 2.157
Rowing - Rowing light - Rowing 30spm	5.458 ± 1.701
Rowing - Rowing moderate - Rowing 30spm	6.183 ± 1.958
Running - Treadmill 4mph - Treadmill 0	5.273 ± 0.959
Running - Treadmill 5mph - Treadmill 0	7.035 ± 0.776
Running - Treadmill 6mph - Treadmill 0	7.469 ± 0.978
Sitting	1.076 ± 0.241
Sitting - Fidget feet legs	1.274 ± 0.26
Sitting - Fidget hands arms	1.145 ± 0.213
Stairs - Ascend stairs	3.352 ± 0.311
Stairs - Descend stairs	4.409 ± 1.433
Standing	1.055 ± 0.254
Walking - Treadmill 2mph - Treadmill 0	2.722 ± 0.365
Walking - Treadmill 3mph - Treadmill 0	3.478 ± 0.379
Walking - Treadmill 3mph - Treadmill 3 - light	4.157 ± 0.373
Walking - Treadmill 3mph - Treadmill 6 - moderate	4.919 ± 0.432
Walking - Treadmill 3mph - Treadmill 9 - hard	5.766 ± 0.599
kneeling	1.177 ± 0.24
unknown	2.484 ± 1.016
Carrying groceries	3.427 ± 0.755
Doing dishes	1.672 ± 0.266
Gardening	2.271 ± 0.405
Ironing	1.564 ± 0.31
Making the bed	3.447 ± 0.733
Mopping	2.894 ± 0.618
Playing videogames	0.984 ± 0.128
Scrubbing a surface	2.656 ± 0.523
Stacking groceries	2.051 ± 0.558
Sweeping	2.601 ± 0.34
Typing	1.051 ± 0.169
Vacuuming	2.517 ± 0.533
Walking around block	3.086 ± 0.607
Washing windows	2.511 ± 0.661
Watching TV	0.949 ± 0.127
Weeding	2.486 ± 0.584
Wiping/Dusting	2.202 ± 0.432
Writing	1.022 ± 0.182
taking out trash	2.575 ± 0.485

Table B16-4: Average energy expenditure per activity in METs (Mean ± STD) computed for all the subjects included in the MIT energy expenditure dataset. The average was computed over the activity duration after eliminating 33.3% (1/3) of the data at the beginning of the activity. In other words, non-steady state energy expenditure periods at the beginning of each activity were first eliminated.

Activity	Kcal/min (Mean ± Std)
Bench weight lifting - hard	2.974 ± 0.716
Bench weight lifting - light	2.606 ± 0.763
Bench weight lifting - moderate	2.686 ± 0.825
Bicep curls - hard	1.949 ± 0.735
Bicep curls - light	2.299 ± 0.414
Bicep curls - moderate	1.995 ± 0.411
Calisthenics - Crunches	1.973 ± 1.583
Calisthenics - Sit ups	5.602 ± 1.705
Cycling - Cycle hard - Cycle 80rpm	7.526 ± 2.09
Cycling - Cycle light - Cycle 100rpm	7.289 ± 1.09
Cycling - Cycle light - Cycle 60rpm	4.293 ± 0.498
Cycling - Cycle light - Cycle 80rpm	5.75 ± 0.632
Cycling - Cycle moderate - Cycle 80rpm	7.009 ± 0.824
Lying down	1.212 ± 0.246
Mask off	2.075 ± 1.319
Rowing - Rowing hard - Rowing 30spm	8.446 ± 3.289
Rowing - Rowing light - Rowing 30spm	7.137 ± 2.55
Rowing - Rowing moderate - Rowing 30spm	8.118 ± 2.985
Running - Treadmill 4mph - Treadmill 0	6.57 ± 1.149
Running - Treadmill 5mph - Treadmill 0	8.842 ± 1.456
Running - Treadmill 6mph - Treadmill 0	9.481 ± 2.043
Sitting	1.402 ± 0.436
Sitting - Fidget feet legs	1.652 ± 0.442
Sitting - Fidget hands arms	1.482 ± 0.363
Stairs - Ascend stairs	4.191 ± 0.472
Stairs - Descend stairs	5.615 ± 2.17
Standing	1.353 ± 0.398
Walking - Treadmill 2mph - Treadmill 0	3.413 ± 0.586
Walking - Treadmill 3mph - Treadmill 0	4.349 ± 0.588
Walking - Treadmill 3mph - Treadmill 3 - light	5.205 ± 0.68
Walking - Treadmill 3mph - Treadmill 6 - moderate	6.159 ± 0.786
Walking - Treadmill 3mph - Treadmill 9 - hard	7.251 ± 1.211
kneeling	1.511 ± 0.399
unknown	3.177 ± 1.269
Carrying groceries	4.544 ± 1.242
Doing dishes	2.21 ± 0.502
Gardening	3.185 ± 0.959
Ironing	2.034 ± 0.353
Making the bed	4.426 ± 1.084
Mopping	3.571 ± 0.746
Playing videogames	1.31 ± 0.243
Scrubbing a surface	3.238 ± 0.592
Stacking groceries	2.618 ± 0.799
Sweeping	3.225 ± 0.525
Typing	1.388 ± 0.301
Vacuuming	3.072 ± 0.471
Walking around block	4.149 ± 1.31
Washing windows	3.24 ± 0.784
Watching TV	1.269 ± 0.273
Weeding	3.486 ± 1.275
Wiping/Dusting	2.811 ± 0.584
Writing	1.331 ± 0.214
taking out trash	3.297 ± 0.764

Table B16-5: Average energy expenditure per activity in Kcal/min (Mean ± STD) computed for all the subjects included in the MIT energy expenditure dataset. The average was computed over the activity duration after eliminating 33.3% (1/3) of the data at the beginning of the activity. In other words, non-steady state energy expenditure periods at the beginning of each activity were first eliminated.

Activity	Heart rate In BPM (Mean ± Std)
Bench weight lifting - hard	108.849 ± 18.292
Bench weight lifting - light	107.459 ± 16.378
Bench weight lifting - moderate	105.803 ± 14.457
Bicep curls - hard	103.969 ± 21.227
Bicep curls - light	104.206 ± 15.464
Bicep curls - moderate	104.839 ± 16.127
Calisthenics - Crunches	103.747 ± 14.175
Calisthenics - Sit ups	129.052 ± 16.831
Cycling - Cycle hard - Cycle 80rpm	124.215 ± 28.577
Cycling - Cycle light - Cycle 100rpm	147.408 ± 28.928
Cycling - Cycle light - Cycle 60rpm	110.627 ± 20.166
Cycling - Cycle light - Cycle 80rpm	127.33 ± 25.803
Cycling - Cycle moderate - Cycle 80rpm	132.088 ± 28.317
Lying down	63.215 ± 10.275
Rowing - Rowing hard - Rowing 30spm	147.396 ± 18.017
Rowing - Rowing light - Rowing 30spm	136.31 ± 21.743
Rowing - Rowing moderate - Rowing 30spm	144.858 ± 18.085
Running - Treadmill 4mph - Treadmill 0	131.842 ± 29.207
Running - Treadmill 5mph - Treadmill 0	152.657 ± 25.488
Running - Treadmill 6mph - Treadmill 0	159.805 ± 22.842
Sitting	71.226 ± 14.892
Sitting - Fidget feet legs	77.391 ± 14.46
Sitting - Fidget hands arms	78.595 ± 14.396
Stairs - Ascend stairs	119.833 ± 23.442
Stairs - Descend stairs	115.07 ± 27.293
Standing	84.344 ± 14.72
Walking - Treadmill 2mph - Treadmill 0	94.794 ± 25.079
Walking - Treadmill 3mph - Treadmill 0	103.981 ± 23.966
Walking - Treadmill 3mph - Treadmill 3 - light	113.649 ± 24.526
Walking - Treadmill 3mph - Treadmill 6 - moderate	122.897 ± 25.634
Walking - Treadmill 3mph - Treadmill 9 - hard	135.759 ± 27.694
kneeling	79.729 ± 13.307
unknown	97.78 ± 22.956
Carrying groceries	103.357 ± 10.957
Doing dishes	84.161 ± 13.878
Gardening	93.015 ± 8.096
Ironing	80.183 ± 12.836
Making the bed	99.07 ± 15.228
Mopping	96.53 ± 13.969
Playing videogames	70.829 ± 10.693
Scrubbing a surface	97.137 ± 12.125
Stacking groceries	85.968 ± 7.527
Sweeping	92.062 ± 14.429
Typing	69.155 ± 10.716
Vacuuming	89.592 ± 10.741
Walking around block	96.73 ± 9.189
Washing windows	91.046 ± 15.489
Watching TV	67.345 ± 11.389
Weeding	91.688 ± 13.852
Wiping/Dusting	84.183 ± 13.725
Writing	70.87 ± 10.487
taking out trash	93.797 ± 12.284

Table B16-6: Average heart rate per activity in beats-per-minute (Mean ± STD) computed for all the subjects included in the MIT energy expenditure dataset. The average was computed over the activity duration after eliminating 33.3% (1/3) of the data at the beginning of the activity. In other words, non-steady state heart rate periods at the beginning of each activity were first eliminated.

Appendix B17: Data Collection Sessions Included in the MIT Energy Expenditure Dataset

Subject	Gym Dataset	Cleaning Dataset
MIT-001	Yes	Yes
MIT-002	Yes	Yes
MIT-003	Yes	Yes
MIT-004	Yes	Yes
MIT-005	No	No
MIT-006	Yes	Yes
MIT-007	Yes	No
MIT-008	No	No
MIT-009	Yes	No
MIT-010	No	No
MIT-011	Yes	Yes
MIT-012	No	No
MIT-013	Yes	Yes
MIT-014	Yes	Yes
MIT-015	No	Yes
MIT-016	Yes	No
MIT-017	Yes	Yes
MIT-018	Yes	Yes
MIT-019	Yes	Yes
MIT-020	Yes	No

Table A17-1: Datasets utilized in energy expenditure experiments. The datasets marked as No were left out from the analysis due to consistent low readings from the Cosmed K4b2 indirect calorimeter perhaps caused by an improper attachment of the face mask as identified by visual inspection of the datasets.

	Gym Dataset	Cleaning Dataset
Total datasets	15	12
Different subjects	16	

Table A17-1: Total number of datasets utilized in the energy expenditure experiments and total number of different subjects utilized in the experiments after eliminating datasets with suspicious Cosmed K4b2 indirect calorimeter readings identified by visual inspection.

Appendix B18: Performance Measures for Energy Expenditure Estimation

Error Measure	Brief Description	Formula
Root Mean Squared Error (RMSE)	It is the most often used measure of error. It is also known as the Standard Error for the Estimate (SEE) in linear regression. The smaller the RMSE, the better the fit to the data. It shows the error in the same units and scale as the predicted values	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(p_i - a_i\right)^2}$
Mean Absolute Error (MAE)	Also known as the average absolute deviation. It is a weighted average of the absolute errors, similar to RMSE but less sensitive to large prediction errors and preferred over small datasets. It shows the error in the same units and scale as the predicted values	$\frac{1}{N}\sum_{i=1}^{N}\left\|p_i - a_i\right\|$
Maximum Absolute Error Deviation (MAED)	It is the maximum absolute error between predicted and actual values over all the data points. It gives an idea of the maximum magnitude in the prediction error one can expect.	$\max(\left\|p_1 - a_1\right\|,\ldots,\left\|p_N - a_N\right\|)$
Pearl's Correlation Coefficient (r)	Measures the linear relationship between the predicted and actual values. The value varies between [-1, +1], -1 indicating a decreasing linear relationship and +1 indicating an increasing linear relationship. The larger the absolute value of the number, the better the fit to the data.	$r = \frac{S_{PA}}{S_P S_A}$ *where* $S_{PA} = \frac{\sum_i (p_i - \bar{p})(a_i - \bar{a})}{N-1}$ $S_P = \frac{\sum_i (p_i - \bar{p})^2}{N-1}$ $S_A = \frac{\sum_i (a_i - \bar{a})^2}{N-1}$
Squared Pearson's Correlation Coefficient (r^2)	Also known as coefficient of determination. Its value varies from zero to one and it may be interpreted as the proportion of variance in the dependent variable that can be accounted for by the regression equation. For example, $r^2 = 0.62$ indicates that 62% of the variance in the dependent variable can be explained by the given regression equation. The remaining 38% is unexplained.	$r^2 = \left(\frac{S_{PA}}{S_P S_A}\right)^2$

Table B18-1: Some popular performance measures utilized during energy expenditure estimation. The performance measures utilized in this work are shown in bold letters.

Appendix B19: Activity-dependent Regression Models

Activity	RMSE	MAED
Bench weight lifting - hard	0.60 ± 0.26	1.32 ± 0.65
Bench weight lifting - light	0.88 ± 0.73	2.30 ± 2.52
Bench weight lifting - moderate	1.29 ± 0.92	3.17 ± 2.80
Bicep curls - hard	0.55 ± 0.18	1.28 ± 0.38
Bicep curls - light	0.63 ± 0.37	1.66 ± 1.00
Bicep curls - moderate	0.54 ± 0.40	1.39 ± 1.50
Calisthenics - Crunches	1.53 ± 0.79	4.05 ± 2.92
Calisthenics - Sit ups	2.18 ± 0.93	3.74 ± 1.37
Cycling - Cycle hard - Cycle 80rpm	1.96 ± 0.75	3.30 ± 0.79
Cycling - Cycle light - Cycle 100rpm	1.41 ± 0.79	2.85 ± 1.04
Cycling - Cycle light - Cycle 60rpm	0.96 ± 0.55	2.18 ± 0.99
Cycling - Cycle light - Cycle 80rpm	1.24 ± 0.50	2.50 ± 0.73
Cycling - Cycle moderate - Cycle 80rpm	1.35 ± 0.53	2.90 ± 1.13
Lying down	0.20 ± 0.08	0.41 ± 0.15
Rowing - Rowing hard - Rowing 30spm	1.84 ± 0.99	3.78 ± 2.49
Rowing - Rowing light - Rowing 30spm	1.88 ± 1.29	4.58 ± 5.44
Rowing - Rowing moderate - Rowing 30spm	1.90 ± 1.07	3.79 ± 2.20
Running - Treadmill 4mph - Treadmill 0	1.43 ± 0.58	2.88 ± 0.95
Running - Treadmill 5mph - Treadmill 0	1.99 ± 1.61	4.03 ± 2.98
Running - Treadmill 6mph - Treadmill 0	1.96 ± 1.68	3.17 ± 2.79
Sitting	0.30 ± 0.14	0.71 ± 0.36
Sitting - Fidget feet legs	1.70 ± 1.46	4.23 ± 2.81
Sitting - Fidget hands arms	0.73 ± 0.53	1.66 ± 1.27
Stairs - Ascend stairs	1.03 ± 0.19	2.64 ± 0.75
Stairs - Descend stairs	1.52 ± 0.32	2.93 ± 0.64
Standing	0.31 ± 0.13	0.72 ± 0.47
Walking - Treadmill 2mph - Treadmill 0	1.10 ± 0.48	2.65 ± 0.98
Walking - Treadmill 3mph - Treadmill 0	1.26 ± 0.44	2.34 ± 0.92
Walking - Treadmill 3mph - Treadmill 3 - light	1.30 ± 0.33	2.36 ± 0.65
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.60 ± 0.51	2.76 ± 0.66
Walking - Treadmill 3mph - Treadmill 9 - hard	2.10 ± 0.83	3.22 ± 0.88
kneeling	0.34 ± 0.15	0.73 ± 0.45
Carrying groceries	1.13 ± 0.43	2.97 ± 0.95
Doing dishes	0.62 ± 0.36	1.98 ± 2.05
Gardening	0.85 ± 0.53	2.47 ± 1.69
Ironing	0.75 ± 0.47	2.29 ± 2.55
Making the bed	1.15 ± 0.59	2.95 ± 1.83
Mopping	0.91 ± 0.48	2.33 ± 1.33
Playing videogames	0.43 ± 0.44	1.81 ± 2.60
Scrubbing a surface	0.79 ± 0.40	1.90 ± 0.84
Stacking groceries	1.10 ± 0.48	3.18 ± 1.97
Sweeping	1.08 ± 0.79	3.00 ± 1.87
Typing	0.31 ± 0.13	1.13 ± 0.96
Vacuuming	0.89 ± 0.81	3.42 ± 4.60
Walking around block	1.46 ± 0.42	3.69 ± 1.07
Washing windows	1.16 ± 1.01	4.57 ± 4.51
Watching TV	0.29 ± 0.19	0.98 ± 1.21
Weeding	1.42 ± 1.38	4.93 ± 7.79
Wiping/Dusting	0.89 ± 0.55	2.84 ± 2.43
Writing	0.26 ± 0.10	0.69 ± 0.47
taking out trash	0.90 ± 0.32	3.09 ± 1.16

Table B19-1: Estimation of energy expenditure using activity-dependent linear regression models in a subject independent manner using the *invariant reduced* feature set during activity recognition and the *ACFFTPeaks* and a linear regression model per activity during energy expenditure estimation (ARSISI LR). Features were computed over sliding windows of 5.6s in length. Features are also computed over sensors at the hip, dominant wrist, and dominant foot.

Activity	RMSE	MAED
Bench weight lifting - hard	0.56 ± 0.23	1.19 ± 0.45
Bench weight lifting - light	0.71 ± 0.45	1.41 ± 0.87
Bench weight lifting - moderate	0.85 ± 0.49	1.66 ± 0.84
Bicep curls - hard	0.57 ± 0.30	1.04 ± 0.78
Bicep curls - light	0.53 ± 0.34	1.37 ± 0.95
Bicep curls - moderate	0.49 ± 0.28	1.12 ± 1.10
Calisthenics - Crunches	1.45 ± 0.65	2.63 ± 1.42
Calisthenics - Sit ups	2.12 ± 1.11	3.47 ± 1.18
Cycling - Cycle hard - Cycle 80rpm	1.81 ± 0.89	3.13 ± 1.01
Cycling - Cycle light - Cycle 100rpm	1.18 ± 0.76	2.59 ± 1.09
Cycling - Cycle light - Cycle 60rpm	0.90 ± 0.53	1.90 ± 0.82
Cycling - Cycle light - Cycle 80rpm	1.15 ± 0.51	2.23 ± 0.66
Cycling - Cycle moderate - Cycle 80rpm	1.22 ± 0.64	2.64 ± 1.27
Lying down	0.19 ± 0.08	0.38 ± 0.15
Rowing - Rowing hard - Rowing 30spm	1.70 ± 1.08	3.06 ± 1.69
Rowing - Rowing light - Rowing 30spm	1.69 ± 0.69	3.39 ± 1.46
Rowing - Rowing moderate - Rowing 30spm	1.81 ± 0.85	3.34 ± 1.03
Running - Treadmill 4mph - Treadmill 0	1.33 ± 0.55	2.72 ± 1.19
Running - Treadmill 5mph - Treadmill 0	1.57 ± 1.05	2.86 ± 1.02
Running - Treadmill 6mph - Treadmill 0	1.45 ± 1.26	2.32 ± 1.37
Sitting	0.29 ± 0.13	0.75 ± 0.54
Sitting - Fidget feet legs	1.30 ± 0.80	3.15 ± 1.54
Sitting - Fidget hands arms	0.64 ± 0.35	1.40 ± 1.02
Stairs - Ascend stairs	0.98 ± 0.16	2.34 ± 0.77
Stairs - Descend stairs	1.47 ± 0.33	2.81 ± 0.77
Standing	0.30 ± 0.12	0.74 ± 0.50
Walking - Treadmill 2mph - Treadmill 0	1.07 ± 0.49	2.58 ± 1.01
Walking - Treadmill 3mph - Treadmill 0	1.15 ± 0.51	2.07 ± 0.85
Walking - Treadmill 3mph - Treadmill 3 - light	1.14 ± 0.34	1.98 ± 0.42
Walking - Treadmill 3mph - Treadmill 6 - moderate	1.48 ± 0.50	2.30 ± 0.50
Walking - Treadmill 3mph - Treadmill 9 - hard	2.09 ± 0.77	3.02 ± 0.82
kneeling	0.35 ± 0.16	0.79 ± 0.60
Carrying groceries	1.06 ± 0.39	2.67 ± 0.81
Doing dishes	0.66 ± 0.44	1.62 ± 0.99
Gardening	0.66 ± 0.42	2.00 ± 1.52
Ironing	0.71 ± 0.37	1.88 ± 1.22
Making the bed	1.06 ± 0.41	2.47 ± 1.22
Mopping	0.91 ± 0.44	2.27 ± 1.15
Playing videogames	0.34 ± 0.23	1.38 ± 1.44
Scrubbing a surface	0.65 ± 0.23	1.50 ± 0.56
Stacking groceries	0.91 ± 0.40	2.31 ± 1.12
Sweeping	1.02 ± 0.92	2.14 ± 1.30
Typing	0.33 ± 0.18	1.29 ± 1.28
Vacuuming	0.64 ± 0.25	1.81 ± 0.94
Walking around block	1.34 ± 0.35	3.33 ± 0.65
Washing windows	0.79 ± 0.37	1.69 ± 0.66
Watching TV	0.23 ± 0.10	0.57 ± 0.30
Weeding	0.87 ± 0.29	2.01 ± 0.94
Wiping/Dusting	0.81 ± 0.37	2.28 ± 1.41
Writing	0.25 ± 0.12	0.65 ± 0.59
taking out trash	0.85 ± 0.25	2.76 ± 1.03

Table B19-2: Estimation of energy expenditure using activity-dependent models in a subject independent manner using the *invariant reduced* feature set during activity recognition and mean value predictions per activity during energy expenditure estimation (ARSISI Mean). Features were computed over sliding windows of 5.6s in length. Features are also computed over sensors at the hip, dominant wrist, and dominant foot.

Activity	RMSE	MAED
Bench weight lifting - hard	0.59 ± 0.19	1.22 ± 0.57
Bench weight lifting - light	0.78 ± 0.21	1.62 ± 0.55
Bench weight lifting - moderate	0.91 ± 0.36	1.95 ± 0.89
Bicep curls - hard	0.72 ± 0.37	1.18 ± 0.37
Bicep curls - light	0.47 ± 0.25	1.18 ± 0.74
Bicep curls - moderate	0.50 ± 0.29	1.07 ± 0.58
Calisthenics - Crunches	2.01 ± 1.25	5.46 ± 4.60
Calisthenics - Sit ups	1.96 ± 0.98	4.07 ± 1.54
Cycling - Cycle hard - Cycle 80rpm	1.61 ± 0.98	2.74 ± 1.22
Cycling - Cycle light - Cycle 100rpm	1.13 ± 0.40	2.36 ± 0.67
Cycling - Cycle light - Cycle 60rpm	0.57 ± 0.25	1.15 ± 0.53
Cycling - Cycle light - Cycle 80rpm	0.92 ± 0.37	2.17 ± 1.02
Cycling - Cycle moderate - Cycle 80rpm	1.11 ± 0.40	2.42 ± 1.16
Lying down	0.20 ± 0.08	0.47 ± 0.25
Rowing - Rowing hard - Rowing 30spm	2.47 ± 1.45	5.57 ± 5.11
Rowing - Rowing light - Rowing 30spm	1.51 ± 0.88	3.35 ± 2.09
Rowing - Rowing moderate - Rowing 30spm	1.54 ± 0.48	3.46 ± 1.28
Running - Treadmill 4mph - Treadmill 0	1.26 ± 0.60	2.52 ± 1.07
Running - Treadmill 5mph - Treadmill 0	1.44 ± 0.82	3.54 ± 3.33
Running - Treadmill 6mph - Treadmill 0	1.32 ± 0.61	2.34 ± 1.00
Sitting	0.33 ± 0.21	0.75 ± 0.45
Sitting - Fidget feet legs	0.53 ± 0.43	1.57 ± 1.62
Sitting - Fidget hands arms	0.38 ± 0.22	0.98 ± 0.62
Stairs - Ascend stairs	0.95 ± 0.28	2.14 ± 0.89
Stairs - Descend stairs	1.51 ± 0.31	3.04 ± 0.68
Standing	0.32 ± 0.20	0.74 ± 0.52
Walking - Treadmill 2mph - Treadmill 0	0.53 ± 0.34	1.49 ± 1.21
Walking - Treadmill 3mph - Treadmill 0	0.74 ± 0.26	1.91 ± 0.67
Walking - Treadmill 3mph - Treadmill 3 - light	0.78 ± 0.23	1.72 ± 0.53
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.90 ± 0.44	2.17 ± 0.81
Walking - Treadmill 3mph - Treadmill 9 - hard	1.00 ± 0.57	2.18 ± 0.93
kneeling	0.36 ± 0.18	0.90 ± 0.81
Carrying groceries	0.74 ± 0.19	1.80 ± 0.49
Doing dishes	0.33 ± 0.13	0.98 ± 0.40
Gardening	0.66 ± 0.24	1.56 ± 0.54
Ironing	0.48 ± 0.28	1.22 ± 0.73
Making the bed	1.02 ± 0.31	2.42 ± 0.53
Mopping	0.73 ± 0.32	1.88 ± 0.85
Playing videogames	0.28 ± 0.20	0.90 ± 1.22
Scrubbing a surface	0.82 ± 0.31	2.46 ± 1.91
Stacking groceries	0.73 ± 0.19	1.83 ± 0.76
Sweeping	0.62 ± 0.24	1.48 ± 0.72
Typing	0.27 ± 0.11	0.80 ± 0.42
Vacuuming	0.60 ± 0.20	1.48 ± 0.62
Walking around block	0.68 ± 0.12	1.51 ± 0.38
Washing windows	0.70 ± 0.33	2.11 ± 1.42
Watching TV	0.28 ± 0.24	1.07 ± 1.49
Weeding	0.73 ± 0.39	1.45 ± 0.80
Wiping/Dusting	0.51 ± 0.14	1.23 ± 0.35
Writing	0.26 ± 0.09	0.71 ± 0.45
taking out trash	0.57 ± 0.18	1.43 ± 0.37

Table B19-3: Estimation of energy expenditure using activity-dependent linear regression models in a subject dependent manner using the *invariant reduced* feature set during activity recognition and the *ACFFTPeaks* and a linear regression model per activity during energy expenditure estimation (ARSDSI LR). Features were computed over sliding windows of 5.6s in length. Features are also computed over sensors at the hip, dominant wrist, and dominant foot.

Activity	RMSE	MAED
Bench weight lifting - hard	0.40 ± 0.21	0.78 ± 0.45
Bench weight lifting - light	0.54 ± 0.24	0.90 ± 0.34
Bench weight lifting - moderate	0.55 ± 0.33	0.82 ± 0.45
Bicep curls - hard	0.41 ± 0.40	0.69 ± 0.50
Bicep curls - light	0.45 ± 0.31	1.14 ± 1.11
Bicep curls - moderate	0.46 ± 0.17	0.79 ± 0.19
Calisthenics - Crunches	1.29 ± 0.91	2.68 ± 2.00
Calisthenics - Sit ups	1.41 ± 0.39	2.62 ± 0.52
Cycling - Cycle hard - Cycle 80rpm	1.27 ± 1.00	2.22 ± 1.31
Cycling - Cycle light - Cycle 100rpm	0.93 ± 0.37	2.05 ± 0.90
Cycling - Cycle light - Cycle 60rpm	0.48 ± 0.24	0.95 ± 0.62
Cycling - Cycle light - Cycle 80rpm	0.77 ± 0.32	1.78 ± 0.74
Cycling - Cycle moderate - Cycle 80rpm	0.98 ± 0.53	2.33 ± 1.28
Lying down	0.20 ± 0.08	0.49 ± 0.38
Rowing - Rowing hard - Rowing 30spm	1.92 ± 1.03	2.81 ± 1.30
Rowing - Rowing light - Rowing 30spm	1.62 ± 0.88	2.85 ± 0.98
Rowing - Rowing moderate - Rowing 30spm	1.86 ± 0.98	2.84 ± 1.07
Running - Treadmill 4mph - Treadmill 0	1.14 ± 0.46	2.33 ± 0.99
Running - Treadmill 5mph - Treadmill 0	1.06 ± 0.34	2.41 ± 1.20
Running - Treadmill 6mph - Treadmill 0	1.02 ± 0.57	1.88 ± 1.26
Sitting	0.27 ± 0.21	0.51 ± 0.43
Sitting - Fidget feet legs	0.46 ± 0.24	1.25 ± 1.12
Sitting - Fidget hands arms	0.31 ± 0.22	0.75 ± 0.58
Stairs - Ascend stairs	0.91 ± 0.22	2.01 ± 0.76
Stairs - Descend stairs	1.40 ± 0.33	2.50 ± 0.75
Standing	0.31 ± 0.23	0.71 ± 0.67
Walking - Treadmill 2mph - Treadmill 0	0.44 ± 0.28	1.19 ± 0.85
Walking - Treadmill 3mph - Treadmill 0	0.56 ± 0.17	1.51 ± 0.46
Walking - Treadmill 3mph - Treadmill 3 - light	0.59 ± 0.15	1.49 ± 0.36
Walking - Treadmill 3mph - Treadmill 6 - moderate	0.72 ± 0.20	1.72 ± 0.37
Walking - Treadmill 3mph - Treadmill 9 - hard	0.76 ± 0.30	1.86 ± 0.64
kneeling	0.37 ± 0.28	0.93 ± 1.37
Carrying groceries	0.86 ± 0.35	1.82 ± 0.70
Doing dishes	0.36 ± 0.16	0.88 ± 0.34
Gardening	0.63 ± 0.30	1.64 ± 1.10
Ironing	0.51 ± 0.31	1.30 ± 0.82
Making the bed	1.01 ± 0.34	2.24 ± 0.59
Mopping	0.66 ± 0.32	1.36 ± 0.45
Playing videogames	0.26 ± 0.22	0.93 ± 1.36
Scrubbing a surface	0.62 ± 0.24	1.39 ± 0.62
Stacking groceries	0.58 ± 0.20	1.20 ± 0.25
Sweeping	0.53 ± 0.13	1.12 ± 0.29
Typing	0.27 ± 0.13	0.73 ± 0.44
Vacuuming	0.59 ± 0.32	1.26 ± 0.49
Walking around block	0.74 ± 0.22	1.43 ± 0.45
Washing windows	0.70 ± 0.28	1.53 ± 0.60
Watching TV	0.28 ± 0.20	1.06 ± 1.36
Weeding	0.65 ± 0.33	1.44 ± 0.69
Wiping/Dusting	0.52 ± 0.25	1.46 ± 0.94
Writing	0.22 ± 0.07	0.54 ± 0.42
taking out trash	0.60 ± 0.19	1.39 ± 0.27

Table B19-4: Estimation of energy expenditure using activity-dependent models in a subject dependent manner using the *invariant reduced* feature set during activity recognition and mean value predictions per activity during energy expenditure estimation (ARSDSI Means). Features were computed over sliding windows of 5.6s in length. Features are also computed over sensors at the hip, dominant wrist, and dominant foot.

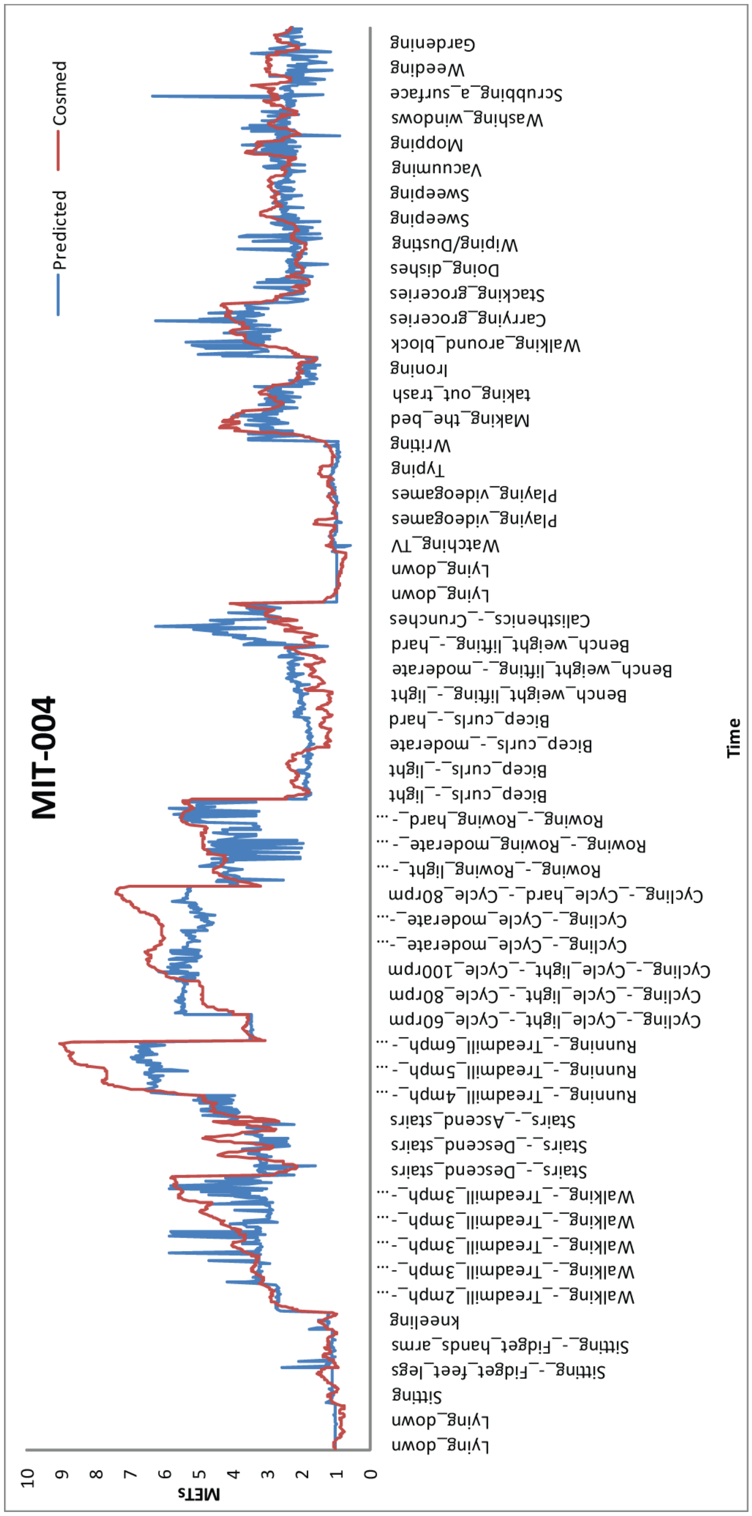

Figure B19-1: Estimation of energy expenditure using activity-dependent linear regression models in a subject independent manner using the *invariant reduced* feature set during activity recognition and the *ACFFTPeaks* and a linear regression model per activity during energy expenditure estimation (ARSISI LR). Features were computed over sliding windows of 5.6s in length. Features are also computed over sensors at the hip, dominant wrist, and dominant foot.

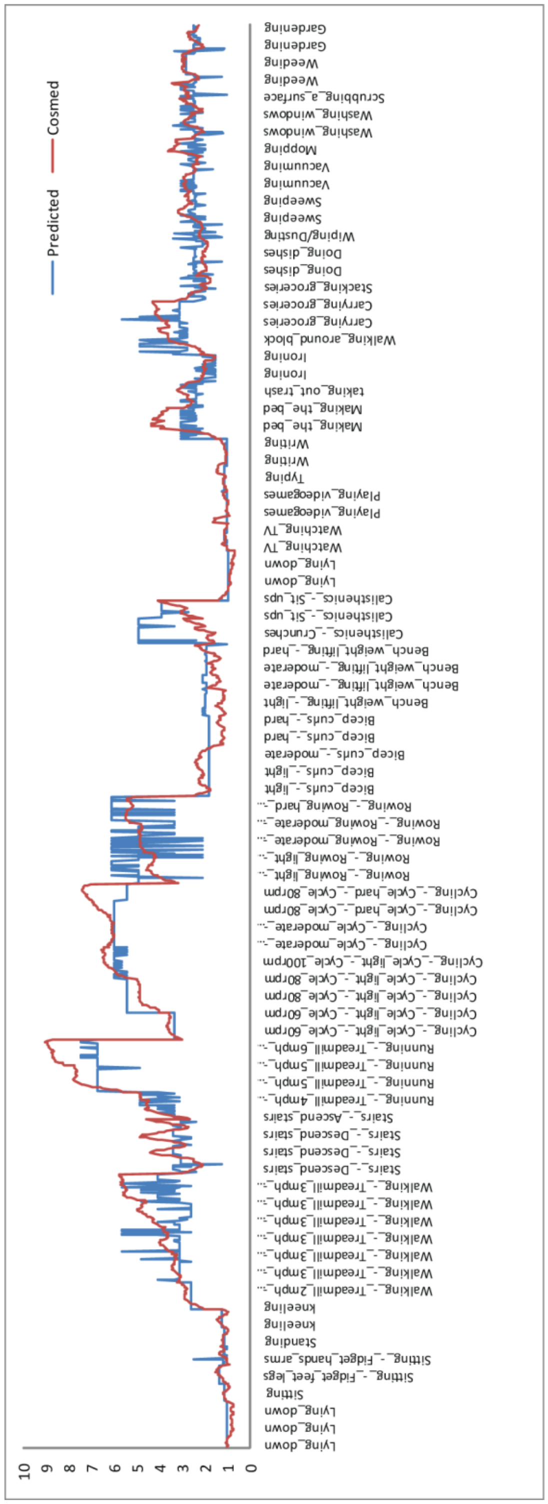

Figure B19-2: Estimation of energy expenditure using activity-dependent models in a subject independent manner using the *invariant reduced* feature set during activity recognition and mean value predictions per activity during energy expenditure estimation (ARSISI Mean). Features were computed over sliding windows of 5.6s in length. Features are also computed over sensors at the hip, dominant wrist, and dominant foot.

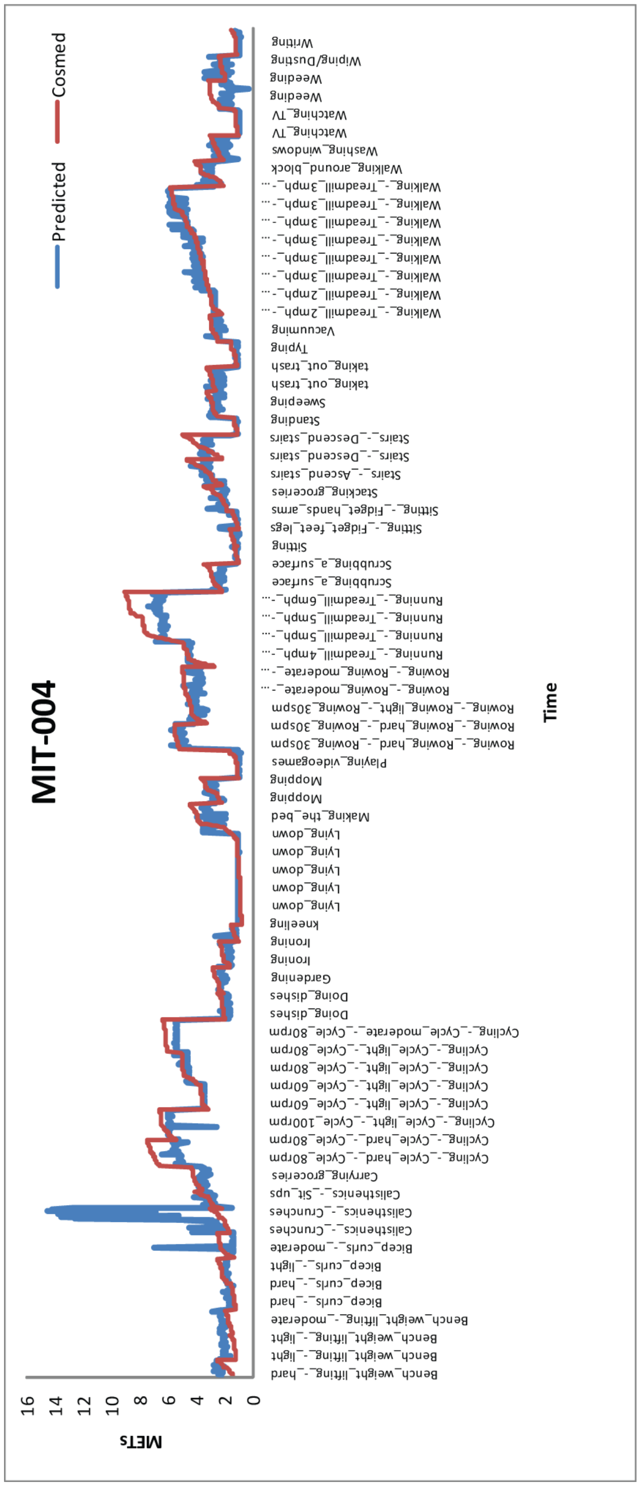

Figure B19-3: Estimation of energy expenditure using activity-dependent linear regression models in a subject dependent manner using the *invariant reduced* feature set during activity recognition and the *ACFFTPeaks* and a linear regression model per activity during energy expenditure estimation (ARSDSI LR). Features were computed over sliding windows of 5.6s in length. Features are also computed over sensors at the hip, dominant wrist, and dominant foot.

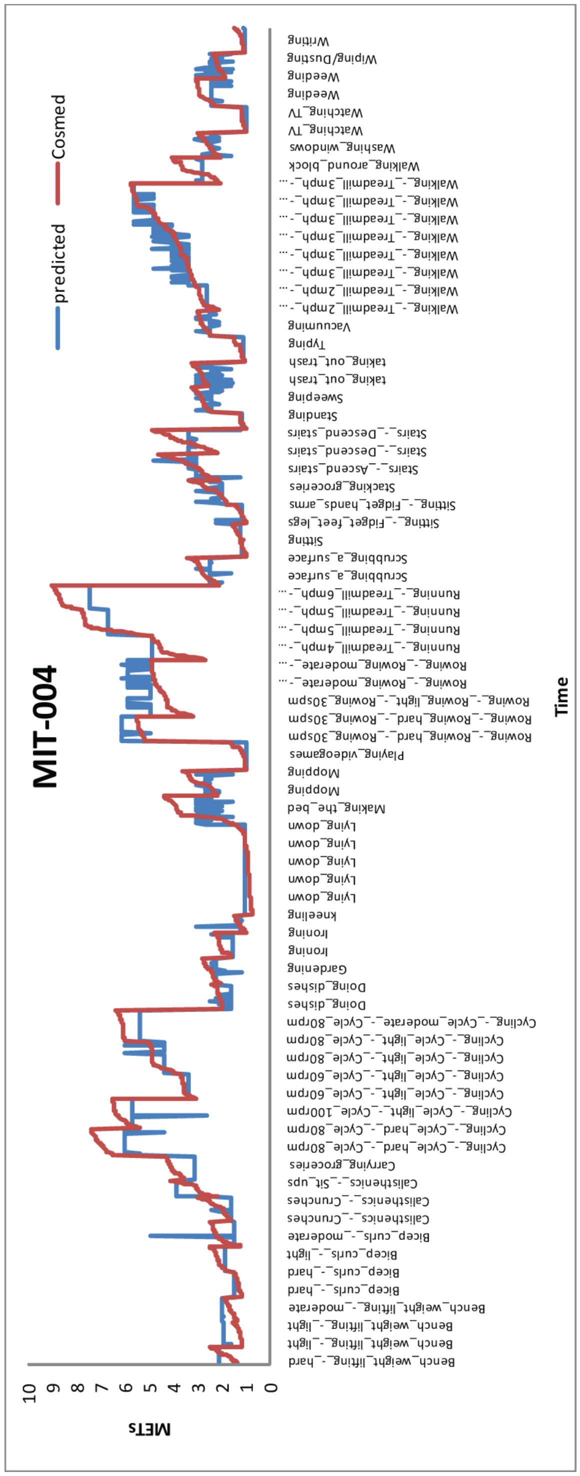

Figure B19-4: Estimation of energy expenditure using activity-dependent models in a subject dependent manner using the *invariant reduced* feature set during activity recognition and mean value predictions per activity during energy expenditure estimation (ARSDSI Means). Features were computed over sliding windows of 5.6s in length. Features are also computed over sensors at the hip, dominant wrist, and dominant foot.

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