Using Plantar Pressure for Free-living Posture Recognition and Sedentary Behaviour Monitoring

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Abstract

Health authorities in numerous countries and even the World Health Organization (WHO) are concerned with low levels of physical activity and increasing sedentary behaviour amongst the general population. In fact, emerging evidences identify sedentary behaviour as a ubiquitous characteristic of contemporary lifestyles. This has major implications for the general health of people worldwide particularly for the prevalence of non-communicable conditions (NCDs) such as cardiovascular disease, diabetes and cancer and their risk factors such as raised blood pressure, raised blood sugar and overweight. Moreover, sedentary time appears to be uniquely associated with health risks independent of physical activity intensity levels. However, habitual sedentary behaviour may prove complex to be accurately measured as it occurs across different domains, including work, transport, domestic duties and even leisure. Since sedentary behaviour is mostly reflect as too much sitting, one of the main concerns is being able to distinguish among different activities, such as sitting and standing. Widely used devices such as accelerometer-based activity monitors have a limited ability to detect sedentary activities accurately. Thus, there is a need of a viable large-scale method to efficiently monitor sedentary behaviour.

This thesis proposes and demonstrates how a plantar pressure based wearable device and machine learning classification techniques have significant capability to monitor daily life sedentary behaviour. Firstly, an in-depth review of research and market ready plantar pressure and force technologies is performed to assess their measurement capabilities and limitations to measure sedentary behaviour. Afterwards, a novel methodology for measuring daily life sedentary behaviour using plantar pressure data and a machine learning predictive model is developed. The proposed model and its algorithm are constructed using a dataset of 20 participants collected at both

laboratory-based and free-living conditions. Sitting and standing variations are included in the analysis as well as the addition of a potential novel activities, such as leaning. Video footage is continuously collected using of a wearable camera as an equivalent of direct observation to allow the labelling of the training data for the machine learning model. The optimal parameters of the model such as feature set, epoch length, type of classifier is determined by experimenting with multiple iterations. Different number and location of plantar pressure sensors are explored to determine the optimal trade-off between low computational cost and accurate performance. The model's performance is calculated using both subject dependent and subject independent validation by performing 10-fold stratified cross-validation and leave-one-user-out validation respectively. Furthermore, the proposed model activity performance for daily life monitoring is validated against the current criterion (i.e. direct observation) and against the de facto standard, the activPAL.

The results show that the proposed machine learning classification model exhibits excellent recall rates of 98.83% with subject dependent training and 95.93% with independent training. This work sets the groundwork for developing a future plantar pressure wearable device for daily life sedentary behaviour monitoring in free-living conditions that uses the proposed machine leaning classification model. Moreover, this research also considers important design characteristics of wearable devices such as low computational cost and improved performance, addressing the current gap in the physical activity and sedentary behaviour wearable market.

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Nomenclature and Abbreviations

- ACC: Accelerometer
- AEE: Active Energy Expenditure
- BMI: Body Mass Index
- BMR: Basal Metabolic Rate
- CSV: Comma Separated Value
- DLW: Double labelled water
- EE: Energy Expenditure
- GPS: Global Positioning System
- IG: Information Gain
- LBM: Lean body mass
- LR_SUM: Left, Right and Both per Sole Values
- LTPA: Leisure time physical activity
- MET: Metabolic Equivalent of Task
- MVPA: Moderate to vigorous physical activity
- NB: Naïve Bayes
- NCDs: non-communicable diseases
- NEAT: Non-exercise activity thermogenesis
- NN: Nearest Neighbour
- PA: physical activity
- REE: Resting Energy Expenditure
- RTLS: real-time locating system
- Std. Dev: Standard Deviation
- SVM: Support Vector Machine
- TEE: Total Energy Expenditure
- WEKA: Waikato Environment for Knowledge Analysis

Chapter 1: Introduction

1.1 Background

Physical inactivity has been identified as the fourth leading risk factor for global mortality (6% of deaths globally). It ranks just behind high blood pressure (13%), tobacco use (9%) and high blood glucose (6%). It is also believe to be the principal cause for approximately 21–25% of breast and colon cancers, 27% of diabetes and 30% of ischemic heart disease as well being a risk factor for overweight and obesity which are responsible for 5% of global mortality [1]. Advances in transportation and the time spent working with technology at the workplace or place of study have also contributed to the reduction of everyday physical activity and encouraging sedentary behaviours. Common examples of sedentary behaviour are usually expressed in terms of posture and lack of movement such as job-related sitting [2]. Furthermore, many leisure activities such as sports and outdoor activities have been increasingly replaced by sedentary behaviours such as television viewing and internet browsing [3, 4]. As such, measurements of physical activity and sedentary behaviour have been shown to be a predictor to large public non-communicable diseases like diabetes, hypertension, stroke, cancer, and metabolic syndrome [5, 6]. While physical activity and sedentary behaviour are related, they have been recently classified as two distinct behaviours [7]. An increasing body of evidence has shown that time spent in sedentary behaviour is an important determinant of health status independent of physical activity levels [8]. Thus, measuring sedentary behaviour specifically along with physical activity is becoming useful, not only to assess the effectiveness of interventions programs, but to understand the association between health and sedentary behaviour. Given the widespread difficulties and challenges, various subjective and objective methods have been developed in order to better measure physical activity and identify daily activities in everyday life [9]. Accelerometer-based activity monitors are currently one of the most widely used devices for objectively monitoring physical activity in clinical and free-living settings [10]. Unfortunately, accelerometer-based activity monitors have shown a limited ability to detect sedentary behaviour accurately [11, 12]. Driving in a car, standing and sitting activities such as computer use, are sometimes classified as sedentary behaviour when using a simple accelerometer [13]. Moreover, it is important to note the distinction caused by sitting and standing, despite the narrow range and potentially overlapping Metabolic Energy Equivalents (MET) values of these behaviours. For example, too much sitting time in adults (which can span from 6-10 hours a day), has been reported to be related to risk for type 2 diabetes, cardiovascular disease, breast and colon cancer and poor mental health outcomes [14-16]. On the other hand, accumulating epidemiological and clinical trial evidences suggest that non-seated behaviours such as standing could contribute to better health. For instance, a recent study revealed that muscle activation was almost 2.5 times higher when standing as compared to sitting [17]. For example, the de facto standard for measuring sedentary behaviour in the research sector is the ActivPAL. This device measures sedentary time though an accelerometer and detecting with gravitational components depending based on the inclination of the device. Unfortunately, it is still primarily used in scientific studies and has the limitations described above. In the commercial sector, examples of accelerometer-based wearable technologies include devices such as the Lumo Back, but unfortunate none of these devices were specifically designed to measure sitting. On the other hand, devices such as the Darma cushion uses optical sensors to assess sitting posture but it has clear limitations due to its size and its impracticality of having to be placed in the chair being sit on. [18] Thus, there is a general agreement in the literature that there is a need of a viable large-scale method to efficiently monitor sedentary behaviour. Such method will help researchers further understand how small changes in the user's sedentary behaviour could positively impact their health. Unfortunately, current commercial devices are unable to provide reliable and continuous measure of sedentary behaviour and body posture [19]. A method that shows significant potential for improved sedentary behaviour monitoring is the tracking of plantar pressure. Data from such pressure or ground reaction forces measurements has been commonly used in posture and gait studies for diagnosing lower limb problems, footwear design, sport biomechanics, injury prevention and several other applications [20]. In this particular application, the ability to correlate plantar pressure and weight bearing creates a potential opportunity to monitor some body postures and sedentary behaviour. Moreover, the estimation of body weight bearing across daily activities would be an important contribution to sedentary behaviour daily monitoring since it allows the prediction of postures such as sitting or standing. Partial body weight bearing changes are directly related to posture such as standing or sitting, which correspondingly correlates to changes in leg muscle activation [17]. This monitoring technology would focus in achieving accurate daily life sedentary behaviour measurements during free-living conditions. In summary, there is a need for an alternative low burden wearable technology that is viable in free-living conditions, inexpensive, easy to use and unobtrusive so that people are willing to use it continuously and has the ability to close the gap in daily life sedentary behaviour monitoring.

1.2 Motivation

As the popularity of wearable technology such as wristbands, watches, and smart garments increases and their cost decreases, opportunities for novel healthcare applications arise. Since wearable devices can be often carried with people nearly everywhere they go as long as the user keeps wearing them and charged [21], data can be collected over long periods of time during "real-life" conditions. Given the current health problems relating to cardiovascular diseases in overweight populations, an increased interest has arisen in physical activity monitoring, and in the last few years, also extended to sedentary behaviour due to its independent influence on our health. Hence, the focus of this thesis is to study the use of wearable technology to reliably measure long-term sedentary behaviour, since available commercial devices are currently unable to provide reliable and continuous measure of sedentary behaviour. Specific monitoring of sedentary behaviour would enable the collection of large data sets, which would help to improve the understanding of the relationship between sitting behaviour and health as well as proposing solutions to mitigate this health effects. Moreover, private or public health organizations could use this data to better measure sitting behaviour and create better suited strategies to solve or mitigate the problem and improve the overall population's health. Another significant contribution of such wearable technology is accurately identifying postures such as sitting and standing during daily life activities in free-living conditions. Furthermore, being able to discern variations in sitting or standing, as well as unexplored activities such as leaning where body weight is partially supported, would lead to a better and clearer definition of sedentary behaviour. Recent results suggest that the cumulative effect of small movements and posture variations throughout the day may be a significant contributor to our total energy expenditure [22]. Moreover, research-based devices high price, bulkiness, or lack of consumer appeal limit their ability to be effectively used for the general population. At the same time, current commercial devices do not meet the technical requirements for free living sedentary behaviour monitoring due to their trade-off between accurate measurements and robust technical specification in exchange for increased wearability, marketability and consumer appeal. Thus, the proposed plantar pressure-based device specifically designed for sedentary behaviour monitoring which reliably measures sitting time and meets the crucial technical specifications such as unobtrusiveness, low cost, and low computational requirement may prove to be a key addition to the current wearable technology field. In addition, it is important to highlight the advantage that the development of such a technology would represent given the numerous number of new start-ups, fitness companies (e.g. Fitbit) and multinational companies (e.g., Apple, Samsung) have shown in the field [23, 24].

1.3 Research Objectives and Scope

The main purpose of the work presented in this thesis is to demonstrate the viability of technology that can reliably monitor sedentary behaviour in real time via detecting posture and other related activities using a wearable plantar pressure-based device. Current methods for sedentary behaviour monitoring have proved inaccurate when measuring sedentary behaviour: questionnaires are time consuming and suffer from bias due to their reliance on the user's ability to recall his or her activities, indirect calorimetry is ineffective for activities of daily life in free-living conditions due to its cost and size and the equipment involved, while accelerometer-based devices such as the activPAL are only used in research-based studies, have difficulty discerning static activities such as sitting and standing and may prove uncomfortable to use in the long-term since it has to be attached to the person's thigh. Therefore, the main research objectives of this work are:

1) To collect daily life data in both laboratory and free-living conditions along with continuous video footage of the individual with two main purposes:
    a. To allow the collection and labelling of the daily life training data for the machine learning model.
    b. To enable the validation of the predictive model against the current criterion (i.e. direct observation) of sedentary behaviour monitoring

2) To develop a novel methodology able to accurately measure total daily sedentary time by using plantar pressure and supervised machine learning techniques
3) To find the optimal parameters of the machine learning model that allow the best trade-off between computational cost and performance to ensure the viability of a potential future marketable device

In order to achieve this, this work is divided into the following stages:

- Identification of an optimal wearable device thorough a scoping review of current plantar pressure technologies both in the market and in the literature. Identified technologies are listed and reviewed in regard of their number of features such as battery power and storage and their ability to continuously collect daily pressure data during free-living conditions.
- Design a both laboratory-based and a free-living study protocol and recruit participants to collect their plantar pressure and accelerometer data during different tasks and corresponding postures variations. Continuous video footage of the individual via a wearable camera was captured during the free-living component. Data is processed, synchronized and visually labelled following to the proposed method to create the supervised training data set for the proposed model.
- Proposition, design and implementation of a sensor-based methodology for sedentary behaviour monitoring that utilizes a set of plantar pressure sensors and continuous recording of real-world daily life activities as training input.
- Perform several experiments to determine what combination of parameters such as sliding, window length, type of classifier and feature set, accomplish the best trade-off in terms of sedentary behaviour monitoring performance and computational requirements.

An analysis of the number and location of pressure sensors is also performed to further lower the computational cost.

- Validation of the proposed method in sedentary behaviour monitoring against the accelerometer-based de facto standard, the activPAL, and the current criterion, direct observation.

1.4 Thesis organization

The report is developed in a logical order by laying out the background, motivation, objectives and scope of this work in Chapter 1. Chapter 2 covers the literature review, which details the problems related to the increasing amount of sedentary behaviour and the current measurement techniques and technologies involved in measuring it. Once the literature review has provided the foundations of the topic, Chapter 3 discussed the use of plantar pressure in a wearable technology as a promising parameter to predict sedentary behaviour. Furthermore, a scoping review of plantar pressure technologies in the literature and in the market is performed to identify a clear gap and discuss their limitations. In Chapter 4, a novel methodology that uses plantar pressure and supervised machine learning techniques. Daily life activities' data is collected during both laboratory-based and free-living settings using plantar pressure insoles as well as the de facto standard device in sedentary behaviour studies the activPAL. A wearable camera, a GoPro HERO Session 4 is also used to ensure independence in the participant. Data is then processed, synchronized and visually labelled using the video footage and following to the proposed method to create the supervised training data set. In Chapter 5, the method is optimised by evaluating different model´s parameters such as type of classifier, feature set, window length, type and number of sensors, to accomplish the highest performance while keeping low computational load. The results of the aforementioned experiments and the final model performances along with a discussion are also covered. Further improvement of the method is done in Chapter 6, by incorporating data from foot accelerometers to the calculations. Afterwards, validation is performed by comparing and discussing the results of the proposed model, the ActivPAL and the direct observation in terms of recall and total time recognised for each task. Finally, the overall conclusions, contributions and future work directions are presented in Chapter 7.

Chapter 2: Literature review

2.1 Scope of the review

Since physical activity has become a major concern in government and healthcare frameworks, the first focus of this literature review is to clearly define physical activity and sedentary behaviour. More importantly, the difference between lack of physical activity and sedentary behaviour, as well as their independent health effects is also analysed. Once the scope of the problem is established, the second focus is on the use of different methods to measure physical activity and more specifically, sedentary behaviour. These are divided into subjective tools such as questionnaires and direct observations, energy expenditure-based methods such as indirect calorimetry, and different sensors such as accelerometers and Global Positioning Systems (GPS).

2.2 Physical activity and Sedentary Behaviour

Physical activity can be defined as any bodily movement produced by skeletal muscles that results in energy expenditure [25]. In turn, physical activity *behaviour*, expressed as human movement, imparts physiological consequences (i.e., energy expenditure and physical fitness) that have effects on specific health outcomes. It is noted that physical activity behaviour can occur in different domains of life, including leisure and recreation, occupation, household work, care giving, and active transport. The volume (i.e., intensity, duration, frequency) and mode or type of activity can vary within each domain [26]. Furthermore, many aspects of physical activity behaviour can be characterized as either discretionary or nondiscretionary. In general, occupational physical activity is not discretionary, whereas exercise is. For example, physical activity performed during domestic chores may be quite varied among individuals and may harder to define its duration or what specific tasks were done. Exercise is a specific type of physical activity behaviour that is defined as planned physical activity engaged in for the purpose of enjoyment and/or improvement in some aspect of physical fitness or motor skill [27]. Because exercise and the more general domain of leisure-time physical activity are considered to be almost always discretionary, they have been a primary focus of physical activity interventions [2]. A comprehensive representation of the multiple dimensions that physical activity comprehends developed by Troiano et al. [2] is shown in Figure 2-1.

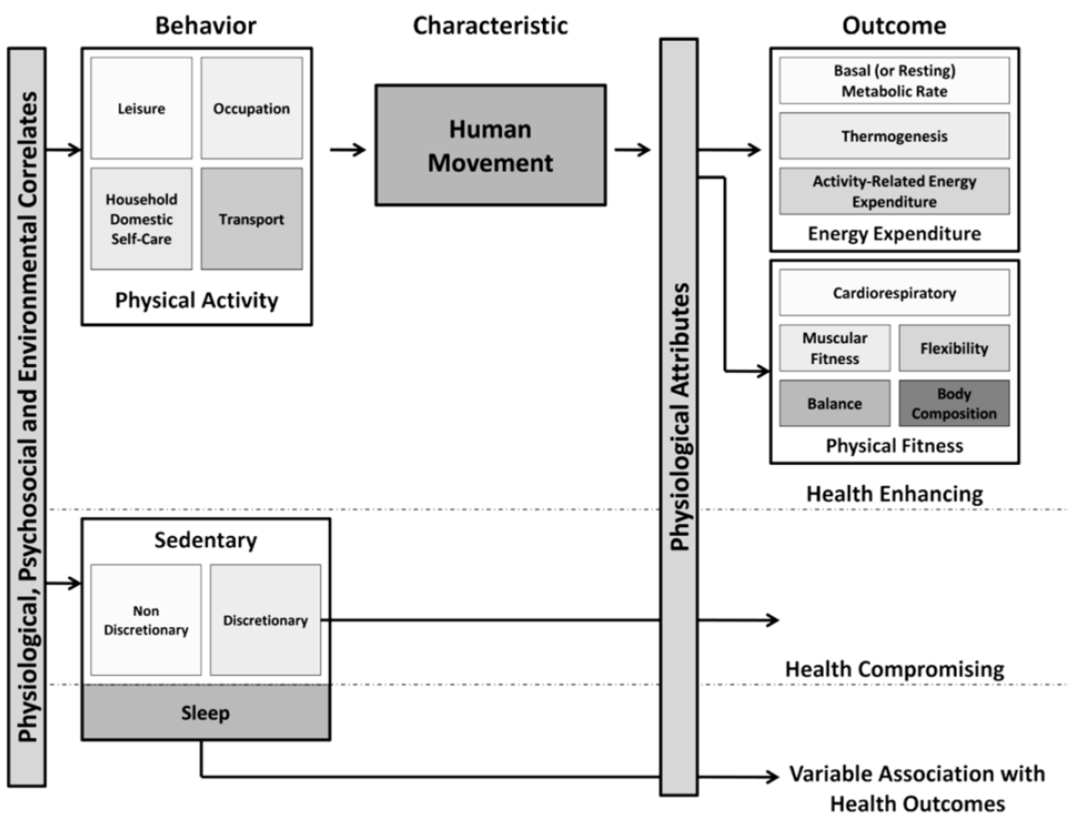


Figure 2-1**.** A conceptual framework for physical activity as a complex and multidimensional behaviour [2].

As shown in Figure 2-1, the different classifications of physical activity as well as its health enhancing effects are clearly identified. These effects are relatively easy to measure due to their short-term effect on the human body. On the other hand, classification of sedentary behaviour is less understood which in consequence affects the ability to draw a correlation to its compromising health effects further complicated by their long-term nature. Consequentially, the focus will be on sedentary behaviour. In fact, in the context of the major ‘diseases of inactivity’ [28], sedentary behaviour has emerged as a significant additional element of the chronic disease prevention agenda [29]. According to the Sedentary Behaviour Research Network, sedentary behaviour is defined as “any waking behaviour characterized with levels of energy expenditure less or equal than 1.5 Metabolic Equivalents of Tasks (METs) while in a sitting or reclining posture” [30]. One of the most common methods to measure physical activity is by using a Metabolic Equivalent of Tasks. One metabolic equivalent (MET) is defined as the amount of oxygen consumed while sitting at rest and is equal to 3.5 ml of oxygen per kilogram of body weight per minute. The energy cost of an activity can be determined by dividing the relative oxygen cost of the activity (ml O2/kg/min) and multiply it by 3.5. Since physical activities are frequently classified by their intensity, MET is also used to define sedentary behaviour [31]. However, this definition seems to focus on the absence of other activities instead of the number of activities that may fall within the equal or lower than 1.5 METs. For instance, non-purposeful exercise, measured as ‘energy expenditure of spontaneous physical activity’ or non-exercise activity thermogenesis (NEAT) would fall within the definition of sedentary behaviour in contrast with volitional exercise, commonly measured as leisure-time physical activity (LTPA), which would be categorised as physical activity. NEAT accounts for the remainder of the total daily energy expenditure for most individuals with sedentary lifestyles, encompassing the combined energy costs of the light physical activities of daily living, fidgeting, spontaneous muscle contraction and maintaining posture when not recumbent. In the case of individuals who do not partake in any purposeful sporting exercise, most of their activities related activity energy expenditure are reflected in various levels of NEAT. These activities may go unnoticed by standard monitoring technologies since they are classified as NEAT and, in some cases, sedentary behaviour. Although the energy expended in every individual movement may be small, the cumulative effect of the many activities falling into this category generally make it a significant contributor to total energy expenditure, with significant variations across individuals [22]. Unfortunately, these variations are most commonly ignored by current monitoring technologies.

Sedentary behaviour is often represented in the lower end of the physical activity continuum and as a lack of physical activity. Increasing evidence suggests that sedentary behaviour should be targeted separately as it has independent effects on human metabolism and health outcomes [7]. Sedentary behaviour is distinct from lack of physical activity; put simply, it is *too much sitting, as distinct from too little exercise* [15]. Other studies [32] have further concluded that sedentary behaviour may be independent of physical activity both behaviourally and biologically. For example, an individual can be sufficiently active according to the physical activity guidelines but still can spend prolonged time sitting in front of TV. The generic term *sedentary behaviour* identifies a class of behaviours associated with low levels of metabolic energy expenditure characterized primarily by sitting [33]. Table 2-1 illustrates the terms used found in literature and their definitions. Lastly, similar to the aforementioned description of physical activity, sedentary behaviour, expressed in terms of posture and lack of movement, may be discretionary, such as television viewing, or nondiscretionary, such as job-related sitting, and may also have distinct effects on health outcomes [2].

Table 2-1. Important terms used in the field of physical activity and sedentary behaviour [7]

Term	Definition
Sedentary	A distinct class of behaviours (e.g., sitting, watching TV, driving) characterized by little physical movement and low energy expenditure (<1.5 METs)
Sedentarism	Extended engagement in behaviours characterized by minimal movement, low energy expenditure, and rest
Physically active	Meeting established guidelines for physical activity (usually reflected in achieving a threshold number of minutes of moderate to vigorous physical activity per day)
Physically inactivity	The absence of physical activity; usually reflected as the amount or proportion of time not engaged in physical activity of some predetermined intensity

It is important to further highlight that sedentary behaviour differs from a lack of physical activity due to the distinct physiological effects of sedentary behaviour and the methodology used to measure it [34-36]. In fact, studies have illustrated how reductions in sedentary behaviour may be achieved through almost limitless micro intervention opportunities designed to promote energy expenditure, whereas physical activity or exercise interventions have more constraints (e.g., time, location, equipment, logistics) [37]. Sedentary behaviour can also be reduced with less financial or time requirements. Furthermore, the physiological effects and changes to sedentary behaviours are not necessarily the opposite of exercise and may differ amongst individuals. Monitoring of sedentary behaviour may also require distinct measurement parameters than those usually used to measure physical activity and exercise [22]. However, initial reviews of levels of physical activity did not consider them as independent factors. Many studies have recently discussed the severity and prevalence of the problem [14, 36, 38-40]. In fact, recent international policy frameworks acknowledged the importance of physical activity and time spent in sedentary behaviour independently [41]. Since the adoption of the Global Strategy on Diet, Physical Activity and Health by the World Health Assembly in 2004 [42], a lack of physical activity has become the fourth-leading risk factor in Western Europe and other high-income regions and among the top 10 globally, being associated with about 3 million deaths per year [43] and 6–10% of the major noncommunicable diseases (NCDs) such as coronary heart disease, type 2 diabetes, and breast and colon cancers [28]. Sedentary time accumulates each day while commuting, at school, in the workplace, at home and in leisure contexts. Figure 2-2 illustrates how long children and adults spend their time in sedentary behaviour and physical activity as reported in the United States National Health and Nutrition Examination Survey data of 2013 [44].

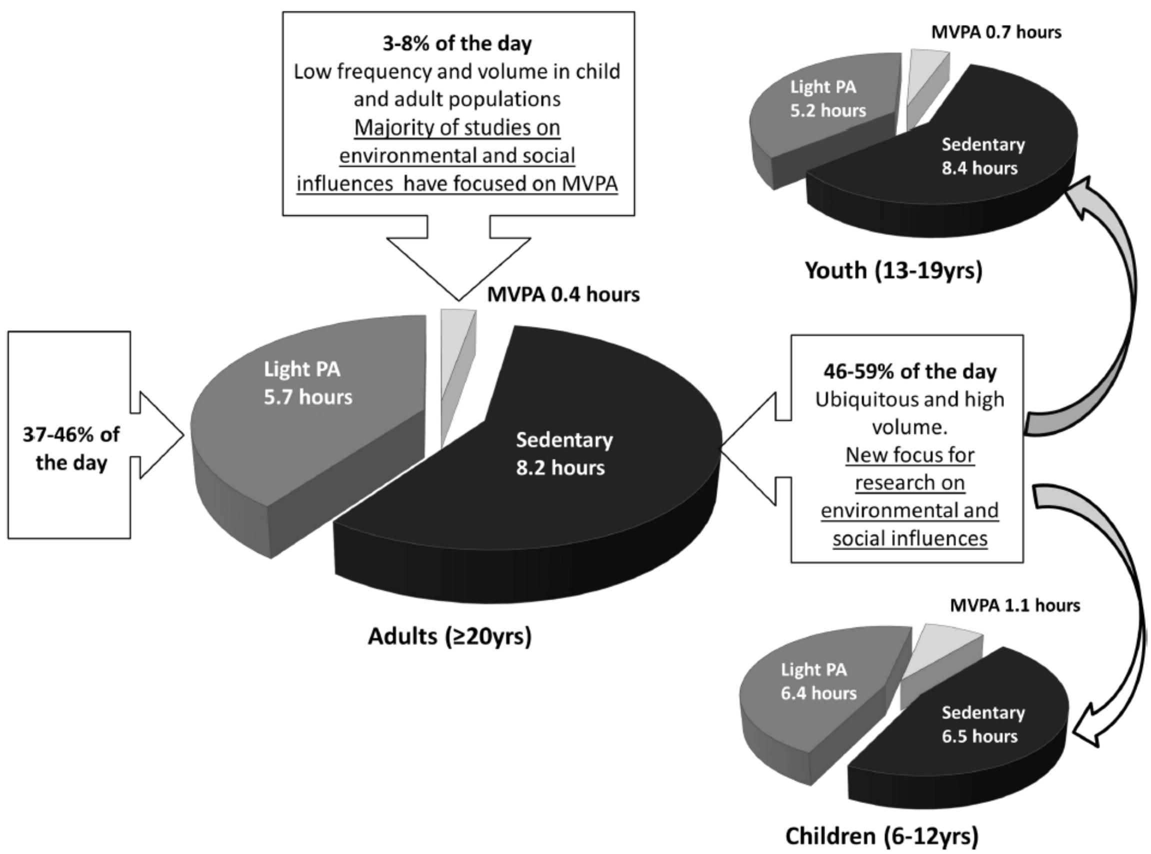


Figure 2-2. How adults and children typically allocate their time spent sedentary, in light-intensity physical activity and MVPA. [44]

Out of the several possible sedentary behaviours, prolonged sitting time, being a common feature of contemporary society, is ubiquitously present and therefore received more attention [36]. A recent rapidly developing body of evidence has identified prolonged sitting time in specific as a population-wide, ubiquitous health risk [45]. There are deleterious metabolic consequences of the 6–10 hours of sitting to which a population can be exposed to each day [14, 16, 29]. In adults, too much sitting is related to risk for type 2 diabetes, cardiovascular disease, breast and colon cancer and poor mental health outcomes [15]. Sitting has become the most common sedentary behaviour of adults; people can sit for many hours at a time every day of the year. This sitting time, together with reduced requirements for physical activity [46, 47], has increased significantly over the past several decades, due to a range of economic, social, environmental and technological changes [29]. Children are also not exempt from the problem that excess of sedentary behaviour represents. On average, children spend 5 or 6 hours per day engaging in some form of sedentary activity such as playing video games, watching television, and using the internet [48]. Approximately 25% of children in the United States spending 4 or more hours a day watching television [49]. Additionally, children who watch more than 3 hours of television a day are 50% more likely to be obese as compared to children who watch fewer than 2 hours per day [50-52]. For children, sedentary time is related to overweight and obesity, some cardiovascular risk factors (e.g., elevated systolic blood pressure) and poor cognitive development (e.g., language delay) [53]. The increasing rates of children who are overweight and obese suggest that they are experiencing a chronic positive energy balance, with energy intake exceeding energy expenditure. A study carried out on a global scale compiled overweight and obesity rates from 1980 to 2005 for school-age children in 25 countries and preschool-age children in 42 countries [54]. Similar studies show that physical activity participation drops precipitously between 15-21 years of age [55]. Although Asia is the largest and most populous continent in the world, most of the information about physical activity prevalence in youth comes from Western countries [56]. A review of physical activity prevalence by Sallis et al. [57] in 2000 was largely based on Western in scope, with more than 80% of the articles published in the United States. A more recent review by Horst et al. [58] in 2007 also revealed only a few are studies from Asia. The lack of studies focused on PA rates of Asian school-age children and adolescents and the absence of any assessment of those studies is problematic because data are underused and their value unrealized [55]. In fact, many countries in the Asia-Pacific region show the highest levels and the fastest increase of obesity in the world [59]. For example, in Vietnam 9.6% of the adolescent population is obese and 10.9% are overweight [60]. Furthermore, 18.3% of school-age children and adolescents are overweight or obese in Malaysia [61], 20% of children are overweight or obese in China [62], and 11.7% of male adolescents and 14.7% of female adolescents in Saudi Arabia are also overweight or obese [55, 63]. The situation is similar in many East Asian countries, where young adults are in average less physically active than their Western counterparts [64, 65]. Moreover, these studies usually treat lack of physical activity as sedentary behaviour, and as discussed before, this limits the ability to fully understand the health consequences due to their independent physiological effects. Reducing and regularly breaking up sedentary time may also be an important adjunct health message, alongside the well-established recommendation for regular participation in exercise. Moreover, the current health problem is tightly related not only to the low levels of energy expenditure due to sedentary behaviours but also to energy intake as well. Energy intake should be balanced with energy output in order to maintain a stable body weight [66]. Furthermore, the total energy requirement decreases as age increases due to the related loss of muscle mass and replacement of muscle with adipose tissue, which has a lower rate of metabolism [67]. In the case of industrialized countries where food supplies are plentiful, such as the United States, about 45 per cent of daily energy intake is derived from carbohydrates, 40 per cent from fats, and 15 per cent from proteins [68]. If caloric intake tends to periodically exceed energy, the body weight increases, and most of the excess energy would be stored as fat, eventually causing excessive adiposity (obesity) [69]. Once a person obtains a stable weight after becoming obese, energy intake once again equals energy output. For a person to lose weight, energy intake must be *less* than energy expenditure. This highlights the relevance of maintaining an adequate level of physical activity and low levels of sedentary behaviour to prevent excess fat stores. This energy imbalance brings about the issue of low–energy consumption lifestyles caused by insufficient physical activity and sedentary behaviour. In fact, the continuous rise of health issues related to sedentary behaviour caused that sedentary behaviour physiology began to be specifically studied as a related but independent field from inactivity [7]. Moreover, recent evidence suggests that sedentary behaviour has a direct influence on metabolism, bone mineral content, and vascular health [7]. For instance, it has been suggested that prolonged times of sedentary behaviour can cause metabolic dysfunction, which is characterized by increased plasma triglyceride levels, decreased levels of high-density lipoprotein (HDL) cholesterol, and decreased insulin sensitivity [70]. In addition, some studies report that sedentary behaviour affects carbohydrate metabolism through changes in muscle glucose transporter (GLUT) protein content, which are critical to basal, insulin, and exercise stimulated glucose uptake [71]. Another well-documented negative health effect of sedentary behaviour is a reduction in bone mineral density and increased risk of osteoporosis due to changes in the equilibrium between osseous tissue resorption and deposition [72-74]. Furthermore, evidences shown that exercise alone may not be sufficient to prevent these changes in osseous metabolism, but a reduction in sedentary behaviour may also be necessary [75-78].

Given all the evidences, it can be seen that global health is being influenced the ageing of the population and by unhealthy behaviours due to the rapid unplanned urbanization and globalization. Moreover, the constant and rapid evolving of innovations in communications, transportation, and workplace technologies prolonged sedentary time is further contributing to the problem [38]. It is in fact quite possible that the world has not yet reached its full prolonged sitting problematic nor realized the potential for dire future consequences, despite the ubiquity of the problems [33-35].

2.3 Current Measurement Techniques

2.3.1 Subjective methods

Indirect methods of measurements are used most frequently to assess physical activity and sedentary behaviour levels in clinical and research settings to identify a subject's physical activity and to evaluate the types of activity performed. They can generally be divided into 3 main different categories: Records or log books, Questionnaires and Direct observations.

Physical activity records provide detailed accounts of activity types and patterns that are written into a record or diary format. These can identify the type (e.g., chores, exercise), purpose (e.g., work-related activities, commuting), duration, intensity and body posture such as sitting or standing for activities completed within a defined observation period [79]. However, the main disadvantage is that evaluating each record can be a long and laborious task for the subjects and the researchers.

Self-report questionnaires are one of the most frequently used methods to classify physical activity levels. They may be sent by electronic mail, self-administered, or collected online. Although most questionnaires are self-administered, interviews are sometimes used instead in the case of some population groups, such as the elderly, those with low literacy, or children with limited ability to recall details about past physical activity [40]. According to the Sedentary Behaviour Research Network, there are 13 different widely used questionnaires for measuring sedentary behaviour depending on the needs of the study [80]. Some questionnaires briefly survey about one's general physical activity level, they are easy to complete and score, take less than a minute, and are best suited to obtain simple classifications such as rating of inactive or active [81]. However, most questionnaires seek more detailed information and ask the participants to list the amount of time they spend sitting in different scenarios. These questionnaires are usually longer and identify details about the frequency, duration and types of activity performed over the previous day, week, or month. Scores may include ordinal scales or continuous data expressed as kilocalories per day or MET-minutes per day [82]. The questions vary in terms of the type of sedentary behaviour they aim to measure (total sedentary time, occupational sedentary behaviours, home-based sedentary behaviours, TV viewing, driving time, etc) and their target population (kids, adults, older adults, and hospitalized populations, etc). They also rely on the participant ability to recall their activities and use activity scoring scale. For example, the Bouchard Physical Activity Questionnaire [83] is a 3-day activity diary, with each day divided into 96 periods of minute each. Participants then must code the activity performed using a scale from 1 to 9. In the case of the IPAQ questionnaire [84], participants are asked to list the amount of time that they spend sitting at work, at home, while doing course work, during leisure time (including watching television), as well as time spent in a motor vehicle [85]. Other Questionnaires such as the Occupational Sitting and Physical Activity Questionnaire OSPAQ [86] focus on workplace sitting and physical activity. These recall questionnaires are often used to determine whether a patient has met public health activity guidelines. Although used frequently, they have several limitations associated with measurement error:

subjects may be subject to recall bias with time spent in vigorous-intensity activities being over-estimated [87]; habitual activities such as walking, are difficult to recall and may be difficult to report accurately [88] and answers may be biased based on the age, gender or other characteristics of the respondents [89].

Finally, there is direct observation. Despite being the current criterion and satisfactory inter-observer agreement (84–99%) among simultaneous observations, direct observation is labour-intensive, time consuming and therefore costly. Events studied must be observable and classifiable, while observers or video cameras need to be in the same environment as the subject. The extent to which even well trained observers affect subject behaviour (subject reactivity) is problematic [90]. Furthermore, it may be impossible to follow the subject for a full day [91], making reliance solely on direct observation impractical. However, recent improvements in wearable cameras may be able solve some the associated issues (e.g. cost, amount of personnel required) of personal direct observation.

2.3.2 Objective methods based on energy expenditure

Direct calorimetry, Indirect calorimetry and Double labelled water are three main objective methods to detect sedentary behaviour and physical activity by measuring oxygen consumption and estimating energy expenditure. Application of direct calorimetry is in the domain of highly specialized laboratories where direct heat loss measurements are of specific value. Unfortunately, the instruments used are both expensive to build and operate, requiring at least one full-time trained technician. They require enormous expertise to establish and maintain and offer little to most investigators beyond less expensive and complex indirect calorimeters [92]. Indirect calorimetry, or the measurement of metabolic free energy conversion, is the method by which metabolic rate is estimated from measurements of gas exchange measurements of oxygen (O_2) consumption and carbon dioxide (CO_2) production [93, 94]. Finally, double labelled water (DLW), estimates energy expenditure by extrapolation from variables that relate to energy expenditure. The DLW technique is considered a 'gold standard' and can be easily used for daily life) participants. It has low reactivity and is accurate to within 3 to 4% of calorimeter values in adults [95]. Unfortunately, all these 3 methods have several major limitations. The equipment involved is bulky, difficult to obtain and relatively expensive, limiting its usefulness for wide scale population-based research. The physical characteristics and obtrusiveness of the equipment also hampers the subject's ability to carry out his daily activities [96]. Moreover only overall energy expenditure can be obtained, offering little or no information regarding hourly patterns, duration, frequency, or type of sedentary behaviour [91].

2.3.3 Accelerometers

Accelerometers are one of the most important technologies that have been used by researchers to more accurately measure daily life sedentary to very vigorous activity over several days. Moreover, accelerometers have allowed researchers to overcome the limitations of subjective methods such as recall questionnaires and to conduct studies on public health to examine the causes and health consequences of increased to sedentary time. Large-scale studies such as the United States National Health and Nutrition Examination Survey (NHANES) have reported there is a high prevalence of sedentary time in modern society [97], remarkably low levels of moderate to vigorous physical activity (MVPA) time [98], and a more typical focus on physical activity and exercise physiology. Furthermore, some studies involving accelerometers have allowed the portrayal of variations between individuals sedentary time and the amount of time they spend on physical activity. For example, as shown in Figure 2-3 from Dunstan et al. 2010a [99], the typical behaviour pattern of the two subjects is compared. The first subject labelled as Active couch potato spends most of his day with 3-hour break doing physical activity. In comparison, the other subject labelled as Active non-couch potato spends most of his day performing light-intensity activity (>1.5 to <3.0 METs). According to public health guidelines both subjects would be classified as physically active as they spend a similar amount of time performing moderate to vigorous activates (more than 3 METs), even though their energy expenditure may be significantly different.

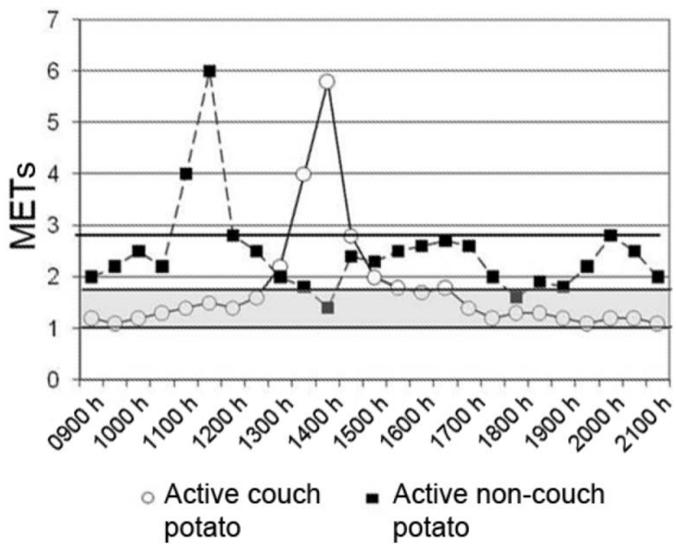


Figure 2-3. Illustration of accelerometer data portraying two subjects with similar MVPA but different levels of sedentary behaviour. [99]

Furthermore, accelerometers are not only able to measure total sedentary behaviour, but they also can detect patterns in sedentary behaviour [36]. For instance, individuals with similar amount of total sedentary time may still have quite different behavioural patterns. Some evidence suggests that the number and duration of sedentary behaviour interruptions such as standing up or taking a brief walk regardless of total sedentary time, are significantly associated with health issues and physiological parameters such as blood glucose levels [100, 101]. Unfortunately, most studies using accelerometer-based data have mostly studied variables such as time spent in moderate- to vigorous-intensity physical activity (MVPA), with sedentary behaviour occasionally been erroneously equalled to a lack of physical activity [102], limiting the researcher ability to detect the independent health risk of sedentary behaviour regardless of physical activity levels [103, 104]. Furthermore, accelerometers have several limitations. A couple of serious ones are their inability to provide context regarding the type of sedentary behaviour and their inability to distinguish among potential variations within sedentary behaviour [11, 12]. A recent validity study among 40 participants found that daily life sitting behaviours such as television viewing, computer use and administrative activities, along with riding in a car or standing, would be sometimes classified as sedentary behaviour when using a simple accelerometer [13]. Most postures are usually encompassed as sedentary behaviour despite having distinct cardio metabolic and public health implications. In fact, an accurate identification of sitting behaviour specifically (the most prevalent type of sedentary behaviour) may lead to a better prediction of certain cardio-metabolic and inflammatory outcomes than physical activity alone [105]. Furthermore, proprietary reasons on commercial accelerometer-based devices limit the disclosure of information about the inner configuration and algorithms implemented. Although understandable, this significantly limits the ability of researchers to make reasonable comparisons among all different devices and research protocols compare across devices. This lack of standardization across study protocols would increase the difficulty of making comprehensive comparisons across the literature. Despite accelerometer-based measurements of physical activity and sedentary behaviour playing an increasingly important role, there are still several challenges to overcome such as the lack of understanding about on to classify variations in sedentary behaviour, how to select the most appropriate instrument and which protocols of monitor wear to use. Overcoming these limitations would be useful for the development of intervention targets and public health messaging on how to classify sedentary activities and to reduce overall sedentary time.

2.3.4 GPS and RFID

Sedentary time spent on activities such as eating, working at the computer or watching television tend to occur indoors at work, school or home [106]. In fact, adults spend approximately 90% of time indoors [107] and approximately 60% of their time in sedentary behaviour [108]. This large proportion of sedentary time spent indoors suggests that contextual information such as where behaviour occurs indoors would be useful for physical activity and sedentary behaviour monitoring [109]. Moreover, the location of a behaviour may influence the correlating factors that cause it as well as the intervention strategies needed to change it.

Although several technologies are currently used to monitor the location of physical activity or sedentary behaviour, the most popular two are global positioning system (GPS) and radio-frequency identification (RFID) [110]. Recent technological improvements have resulted in portable GPS units with adequate memory to store positional data over time, thus offering opportunities for obtaining location information at low cost. Researchers have begun to integrate GPS technology into physical activity related studies, however the implementation of this technology on this field is still relatively new, only a handful of such research studies is currently reported. The first real applications of GPS technology appeared in the sports industry when it was found that human locomotion could be assessed [111]. Following these initial studies, GPS has been used to assed a variety of sports such as hockey [112], rugby [113], orienteering[114], and others [115]. So far these studies have found GPS to be a promising technology to measure parameters in sport, such as walking speed or cycling speed under controlled conditions [116]. Nevertheless, no studies have shown that GPS by itself is a sufficiently reliable and valid measurement technique, due to issues such as signal dropout and limited battery power [117]. Furthermore, since GPS devices need to have a line of sight to at least three orbiting satellites, GPS are usually unable to determine precise indoor location [118]. This is of great importance considering that, as has been previously mentioned that up to 90% of our time is spent indoors [107]. A second issue arises due to the fact that GPS units usually require a period of initialization when they are first powered on, which is when it acquires the signal from the satellites to obtain positional data. This initialization period varies depending on the model, ranging from 15 seconds to 5 minutes. These different periods are important because GPS data may not be logged even when the device is moving, which has implications when interpreting and cleaning the data [119]. The third limitation is not related directly to the technology per se, but to the research field. To date, there are no established approaches or guidelines to the analysis and interpretation of GPS data [117].

Another technology that is currently used in health care [120] and warehouse environments is wireless localization technology (commercially referred as RFID, real-time locating systems) due to its ability to assess the location of people or goods within an indoor environment via the known location of fixed components. Some manufacturers utilize existing Wi-Fi points within buildings as fixed reference while others require the installation of proprietary fixed reference points. Sometimes infrared (IR) location beacons may also be provided for increased location accuracy in areas of poor signal strength [121, 122]. A floor plan of the environment being monitored is required to visualize the location of the mobile component on a cartesian plane. According to the most manufacturers, the Real Time Location Systems (RTLS) are generally accurate to within 2 to 3 meters [123]. It is important to note that many RTLS systems are designed for a specific application and may have to be significantly modified to work in other applications. Unfortunately, these physical requirements and these technical characteristics greatly limit their wide-spread use. Moreover, the feasibility of incorporating RTLS data with other data such as accelerometery is still in the early stages, as they have been just recently started to be used in physical activity or sedentary behaviour research [124-126].

Despite this, RTLS show potential to be used in physical activity and sedentary behaviour research to provide information related to specific indoor locations. Instead of asking participants to record how much time they spend at a determined area (e.g. kitchen, their desks) though a questionnaire, RTLS systems can be used to objectively quantify how much time participants spend at a certain location and estimate sedentary behaviour with greater certainty [110].

2.4 Machine learning in Activity Detection

Identifying types of human activity using machine learning in combination with sensors has been performed previously [127]. Furthermore, it has been demonstrated that the use of machine learning techniques for activity classifications in physical activity applications is more effective than biomechanical methods or conventional statistics [128, 129]. However, most studies attempt to recognize human daily activities from an accelerometer signal by using an ensemble of classifiers for accelerometer-based activity recognition [130, 131]. This work builds on existing research and presents a novel methodology for measuring sedentary behaviour by classifying sitting amongst other types of activities. Since developing a machine learning methodology for activity detection involves feature selection and choosing an optimal classifier, both stages are described in Sections 2.4.1 and 2.4.2. Moreover, confusion matrices are discussed in Section 2.4.3 as they are commonly used in machine learning to better visualize different measurements of performance such as Recall and Precision [132].

2.4.1 Feature Computation

Features are an individual measurable property that serve as input for the machine learning model's training data to discriminate different activities [133]. Features are usually numeric variables obtained through statistical techniques that characterize windows of the raw sensor data. Thus, feature selection is a crucial step for effective algorithms in pattern recognition, and classification. Time domain features and Frequency domain are the two most commonly used types of features in physical activity studies [127, 134]. Time-domain features are normally computed using statistical measurements such as mean, standard deviation, correlation, etc. of each window of pressure or acceleration data and are commonly used in accelerometer-based activity recognition models [135, 136]. On the other hand, Frequency domain features are computed from the coefficients of time-frequency transforms after applying Fast Fourier Transform to the set of data [137]. Features over the frequency domain such as the spectrum spread, spectral entropy, signal energy, distribution of signal energy, and bandpass filter coefficients are popular choices [135, 138-140]. Nevertheless, Frequency-domain features have a higher computational cost since they imply the computation of a Fourier transform [141]. As stated in Section 1.3, one of the design objectives is a low computational cost to ensure the viability of a future wearable device. Consequently, time domain features are preferred in this work due to their lower computational cost.

2.4.2 Machine Learning and Classification

Machine learning generally uses two main types of techniques: supervised learning and unsupervised learning [142, 143]. While unsupervised learning finds hidden patterns or intrinsic structures in data by drawing inferences from a dataset without labelled responses, supervised learning builds a model that makes predictions by taking a known set of labelled data and generate reasonable predictions for a new set of unidentified data. Once the model is trained, the classifier will be able to classify an unknown set of data (segmented by windows) and assign a value which corresponds to a specific type of activity. In this work, supervised learning is chosen for activity selection due to its ease of use and higher accuracy in defining specific type of activities (aided by the precise labelling done with direct video observation) [144].

Furthermore, classifiers can be grouped into generative and discriminative, each with different computational requirements and performance. Generative classifiers first model how the data was generated by learning the joint probability of the inputs (pressured data) and the label (type of activity) and then make their prediction by applying Bayes rule to calculate the conditional probability. On the other hand, Discriminate classifiers directly compute the conditional probability from the data. Examples of both popular generative and discriminate classifiers in activity detection monitoring are: simple Kernel-Estimation classifiers such as Nearest Neighbour [145], Bayesian classifiers such as Naïve Bayes [146], Decision Tables, Decision Tree based classifiers such as J48 (commonly known as C4.5) [147], and more complex algorithms such as Support Vector Machines (SVM) [148] or Artificial Neural Networks (ANN) [149]. A comparison by Kotsiantis et al. (2007) is shown in Table 2-2.

Table 2-2. Comparison of different classifiers (**** stars represent the best and * star the worst performance) [150]

	Decision Trees	Neural Networks	Naïve Bayes	kNN	SVM	Rule-learners
Accuracy in general	**	***	*	**	****	**
Speed of learning with respect to number of attributes and the number of instances	***	*	****	****	*	**
Speed of classification	****	****	****	*	****	****
Tolerance to missing values	***	*	****	*	**	**
Tolerance to irrelevant attributes	***	*	**	**	****	**
Tolerance to redundant attributes	**	**	*	**	***	**
Tolerance to highly interdependent attributes (e.g. parity problems)	**	***	*	*	***	**
Dealing with discrete/binary/continuous attributes	****	***(not discrete)	***(not continuous)	***(not directly discrete)	**(not discrete)	***(not directly continuous)
Tolerance to noise	**	**	***	*	**	*
Dealing with danger of overfitting	**	*	***	***	**	**
Attempts for incremental learning	**	***	****	****	**	*
Explanation ability/transparency of knowledge/classifications	****	*	****	**	*	****
Model parameter handling	***	*	****	***	*	***

As can be seen in Table 2-2, complex classifiers such as Support Vector Machines or Artificial Neural Networks have the best performance among the reviewed classifiers. However, they are also known to be too computationally expensive for wearable applications [151]. The remaining classifiers appear to have a reasonable range of performance and computational cost according to the design goals of this work. Consequently, the classifiers to be used in this work are Nearest Neighbour, Decision Trees, Naïve Bayes. Furthermore, ensemble methods such as Random Forest [152], Bagging[153] or Logit Boost [154], will be included as well due to their popularity, relatively low computational cost and reported increase in activity recognition performance [154].

2.4.3 Confusion Matrix

In the field of machine learning, a confusion matrix is a specific table layout that allows visualization of the performance of an algorithm [132]. Each row of the matrix represents the instances in a predicted class while each column represents the instances in an actual class (or vice versa). The overall performance of a classifier, including recall (true positive rate), false positive rate (probability of false alarm), precision and F-Score is calculated based on the confusion matrix. An example of a confusion matrix and the necessary calculations to obtain the aforementioned performance measurements are shown in Table 2-3.

Table 2-3. Two-class classifier Confusion Matrix and different performance measurements

		True condition		
		True positive	True negative	
	Total Population	Condition Positive	Condition Negative	Accuracy = (Σ True positive + Σ True negative)/ Σ Total population
Predicted condition	Predicted positive	True positive	False positive	Precision = Σ True positive/ Σ Predicted positive
	Predicted negative	False negative	True negative	
		Recall = Σ True positive/ Σ Condition positive	False positive rate (FPR) = Σ False positive/ Σ Condition negative	F1 score = 2/1/Recall + 1/Precision

However, it is important to note that even when improving the accuracy of overall activity classification is important, improvements represented by specific performance measures can be misleading. For instance, while overall performance may increase, the performance on some individual activities may in fact decrease. Thus, the classification results that are obtained by the proposed model algorithms developed in this work will be mainly shown using Recall, as it measures the proportion of actual positives that are correctly identified as such. Furthermore, results for every activity will be discussed to highlight specific improvements and their relevance over the final performance. Although every activity is important, a special attention will be given to sitting since one of the design objectives of this work is measuring time spent in sedentary behaviour.

2.5 Summary

In summary, one of the major limitations constantly mentioned in physical activity and sedentary behaviour research to date has been the lack of objective, practical and inexpensive tools to measure them on a large scale and consistently. Subjective methods described previously such as questionnaires are time consuming and suffer from bias due to their reliance on the user's ability to recall his or her activities. Objective methods such as indirect calorimetry need expensive equipment that is difficult to operate without training, limiting its use for wide-scale monitoring. Moreover, the size and bulkiness of the equipment often impedes the user to move freely and conduct his daily activities. Secondary measures such accelerometers which provide an indication of user motion, provide objective assessment of physical activity, but have been shown inaccurate when measuring sedentary behaviour such as sitting time. Moreover, they have difficulty noting the important distinction caused by posture such as sitting and standing, despite the narrow but significantly different MET values of these behaviours. Previous studies have found that two of the most well-known acceleration-based activity monitors, the activPAL and the ActiGraph, tend to underestimated sitting time [11]. Other available tools such as GPS and RFID have shown limitations due to data loss, limited battery power, poor protocol adherence and signal dropout. Consequently, a clear gap exists in effective sedentary behaviour monitoring. Furthermore, although using machine learning techniques in accelerometer data for activity classification has been reported to be relatively successful, the aforementioned limitations of accelerometers still apply. Thus, a clear need exists for devices with technical characteristics specifically developed for sedentary behaviour monitoring. In the case of research-based devices, factors such as prohibitive high cost to the average consumer, device bulkiness, or lack of consumer appeal of research-based devices limit their ability to be used for widespread large-scale general population monitoring. Although a few available commercial devices seem to trade off accuracy and robust technical specifications in exchange for some of the requirements for daily life monitoring such as wearability and consumer appeal, they do not meet all the technical requirements or processing methods required to efficiently provide reliable measurements of sedentary behaviour. Thus, current limitations of wearable technology indicate a need for the development of a new sedentary behaviour monitoring technology. This gap fuels the search for less sophisticated sedentary behaviour devices, which provides a unique opportunity for researchers to explore an alternative wearable technology that meets the appropriate criteria such as unobtrusiveness, low cost, low computational requirement to extend battery life, minimum storage, long-term monitoring capability and acceptable performance for daily life sedentary behaviour.

Chapter 3: In-Depth scoping analysis of market ready and research-based Plantar Pressure and Force monitoring technologies

3.1 Preliminary Work: Rationale for choosing Plantar Pressure

As mentioned in the Section 2.3, accelerometers are one of the most common approaches to physical activity and sedentary behaviour monitoring. Initial approaches involve the use of multiple sensors at multiple locations, limiting their practicality into everyday use. Popular technologies such as the activPAL address this limitation in wearability by using a single sensor. However, single accelerometers devices occasionally struggle in daily life conditions when attempting to differentiate between sitting and standing and recognizing activities such as cycling and descending or ascending stairs [138, 155]. Furthermore, new challenges in terms of long-term use or accuracy arise depending on the location of the accelerometer. For example, in the case of the ActivPAL, the device must be attached to the skin of the participant's thigh making it impractical and unappealing for commercial use, creating a need to find a viable alternative in cases where typical accelerometer-based devices may prove inadequate. Plantar pressure and ground reaction forces have been commonly used in posture and gait studies for diagnosing lower limb problems, footwear design, sport biomechanics, injury prevention, diabetic ulcers, elderly fall and several other applications [20]. Given the increased interest in physical activity monitoring, researchers have an increased interest in using plantar pressure for activity detection and recent studies have shown promising results [156] [157]. In fact, plantar pressure systems have significant potential to monitor sedentary behaviour since different user activities generate different plantar pressures measurements. In this particular application, the ability to correlate plantar pressure and daily weight bearing across daily activities would be an important contribution, since they are directly related to postures such as standing or sitting, which in turn correlates to changes in leg muscle activation [17]. By measuring the amount of pressure that acts over the foot and the supporting surface during everyday activities, stationary activities such as sitting, limited mobile activities such as standing or high mobile activities like running or cycling can be detected and differentiated [158]. Another important advantage of using plantar pressure relies in the computational cost of the processing techniques involved. Existing accelerometer-based methods not only compute a large number of time and frequency domain features but also require a relatively high sampling frequency in order to achieve acceptable activity recognition[135]. The processing of a high number of frequency-domain features and the increased sampling frequency demand higher processing capabilities and power consumption, potentially increasing the cost of the processing unit and the sensors. Finally, another advantage of using plantar pressure to monitor sedentary behaviour is that it allows future studies to explore additional beneficial applications of the same plantar pressure data in specific populations. For example, in the case of individuals with lower limb amputations or knee replacement, tracking sedentary time as well as body weight bearing distribution over each foot throughout the day would provide physicians valuable information to assess the patient's rehabilitation progress. Furthermore, basic gait parameters such as balance or cadence can be easily computed from the same plantar pressure data without adding significant computational cost, offering interesting applications on individuals with pathological gait. For example, monitoring a patient's sedentary behaviour together with these basic gait parameters could provide physicians a more comprehensive profile regarding how daily sedentary time may influence rehabilitation progress.

Hence, a preliminary data collection is performed to review the plantar pressure data collected using the available technology and to assess if the data patterns and characteristics can be used to recognise typical activities such as sitting, standing, walking, leaning, cycling and climbing or descending stairs. An office chair with a rigid back is used for sitting while standing is done without any specialized equipment. Walking is performed on a treadmill and cycling is performed in a stationary bike. Finally, the stairs activity is performed by climbing and descending stairs between the ground the fourth floor with a railing available if necessary. Data is collected using a pair of pressure insoles (Novel Pedar model W, Germany) [159] inserted in the shoes for the measurement of plantar pressure at 100 Hz. There are 99 sensors in each insole, covering the whole plantar pressure. Afterwards, the OpenGo (Moti-con) wireless insole pressure measurement system [160] is used to measure plantar pressure at 10Hz and with 13 sensors in each insole. The Pedar system (Novel USA, Inc.) is chosen as a reference due to its reliability and validated accurate measurements while the OpenGo is selected due to its wearability and unobtrusiveness. Further information of the equipment is shown in Section 4.3.1. Each activity is performed for 10 minutes except in the case of climbing and descending stairs in which it is performed it for 5 minutes. One-minute excerpts of plantar pressure data collected are shown in Figure 3-1 while statistical computations are shown in Table 3-1. Since sitting is the primordial sedentary activity of interest as it is the most prevalent sedentary activity, it is important to accurately discriminate it from all other type of activities. In fact, sitting can be visually identified by detecting the lower pressure observed in the data pattern in comparison to the rest, since the body weight would be mainly supported by the surface on which the user may be sitting on (usually a chair).

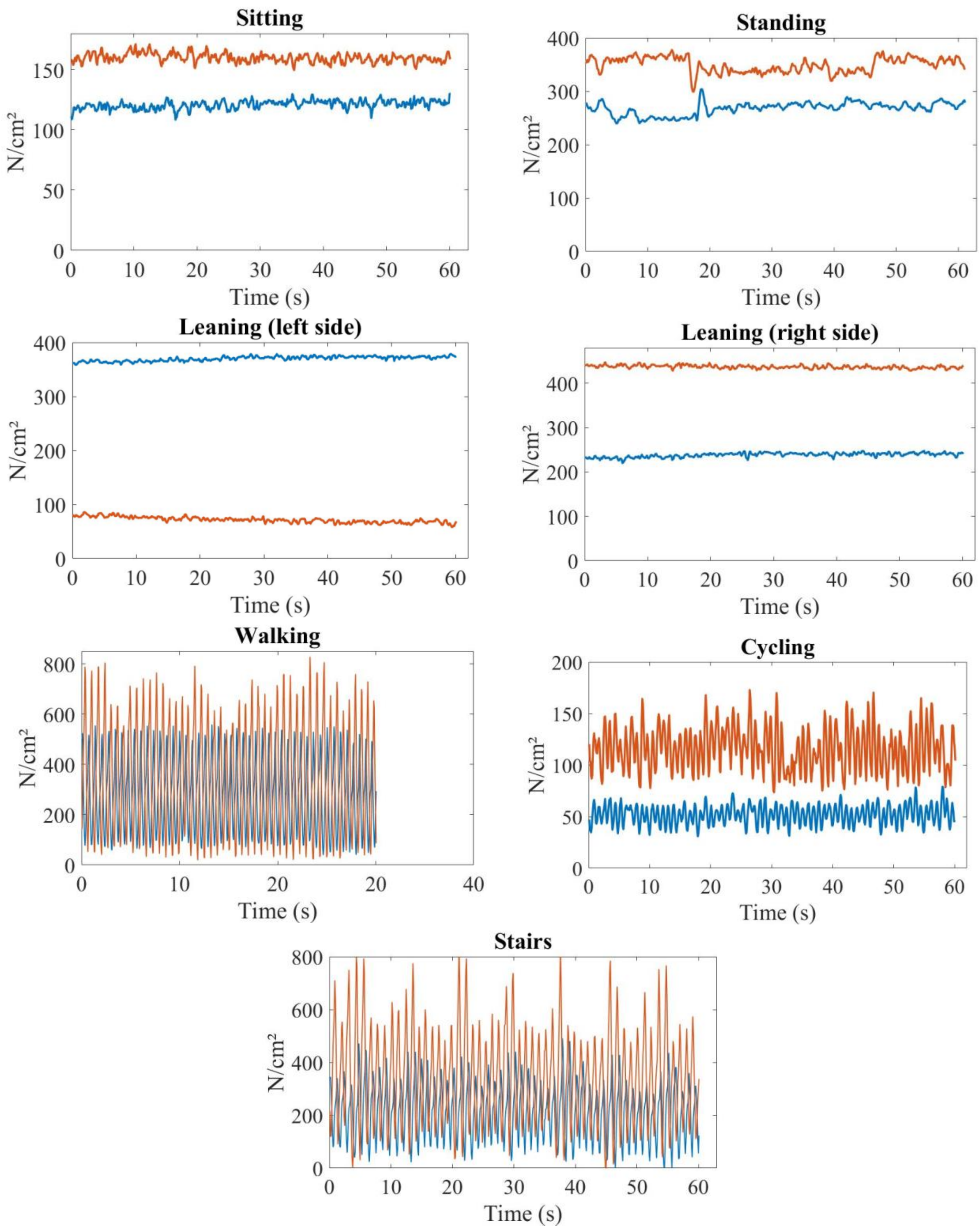


Figure 3-1. Experimental overall plantar pressure patterns during each activity. Force on the left foot is shown in red while the force on the right foot is shown in blue.

Table 3-1. Statistical parameters (in Newtons) of foot force during different activities

	Sitting		**Standing**		**Leaning**	
	Left	*Right*	*Left*	*Right*	*Left*	*Right*
Force	121 ± 3.4	159.8 ± 3.7	267.7 ± 11.7	349.5 ± 13.9	370.1 ± 4.3	71.66 ± 5.2
Min - Max	108.4 - 130.2	149.6-171.3	239.1-304.4	298.6-377.6	357.9-378.8	58.05-86.3
Range	21.79	21.67	65.31	79.07	20.92	28.31
Correlation	-.1845		-.3153		-.6725	
	Walking		**Cycling**		**Stairs**	
	Left	*Right*	*Left*	*Right*	*Left*	*Right*
Force	276.7 ± 140.9	348.6 ± 216.6	52.02 ± 9.3	115.7 ± 21.1	216.6 ± 104.9	339 ± 176.2
Min - Max	39.1-558.4	18.93-827.8	30.7-79.1	73.4-173	0-491	0-831.8
Range	519.3	808.8	48.4	99.5	491	831.8
Correlation	-.6653		.4899		-.2615	

On the other hand, while standing, the user's total body weight is transferred onto both feet at all time with a relative distinctive pattern between each foot due to the natural leaning left to right to ensure balance. This loading difference can be also identified by comparing the mean and maximum force values of both activities and the typical balancing movement that occurs between the two feet. Leaning was defined as one the activities to detect since it not uncommon for users to partially support their body weight against a wall or a prop while prolonged standing. Like standing, sitting and leaning differ in the fact that the entire body weight being supported by the feet. Unlike standing though, the whole-body weight is mainly supported by one foot at the time. When the person leans on his left side, most of the body weight is supported by the left leg, and if the user leans on his right side, the opposite occurs. This change in body weight support can be detected by inferring the user total body weight while standing. Although a higher pressure may be observed on one side, overall pressure remains lower when compared to standing. Moreover, pressure data shows less variation as observed in the lower standard deviation of both activities since the person does not need to keep in balance by alternating his body weight on both legs.

Given the fact that both sitting, standing and leaning are stationary or very limited mobile activities, it is hard to detect any period waveforms in data patterns. However, in the case of walking or running, both activities generate easy to identify periodic waveforms with a much higher standard deviation value, since they have far more peaks and troughs. This can be further detected by comparing the correlation values of both feet of the aforementioned static activities and walking. Furthermore, the apparent body weight changes due to the acceleration of the legs can be observed by the significant increase in maximum force and range.

Some similarities can be found between walking and cycling. However, cycling generates a considerably smoother waveform with much smaller amplitudes since only pressure on the pedals is detected as body weight is not fully supported (most of the weight is supported by the bike's seat). Thus, the higher correlation compared to the static activities and the low force values hint some form of periodic movement while sitting, which matched the cycling activities. Finally, climbing or descending stairs also generates a similar waveform to walking, due to the similarity of both activities. Nevertheless, a different pattern can be easily appreciated in the waveform caused a small dip or incisure in the wave due to the pressure loading sequence. This can be also identified by the significantly higher standard deviation.

In summary, the use of plantar pressure shows great potential to improve the range of activity recognition. In fact, plantar pressure is not only able to distinguish activities such as sitting, standing or walking as traditional long-term monitors but it may be able to recognise different locomotion activities often misclassified such as stairs climbing and cycling due to their distinctive pressure patterns. Perhaps more importantly, it would allow the recognition of currently undetected activities by accelerometers such as leaning, which would in turn may possibly broaden our definition of sedentary behaviour and increase the understanding of its health effects. Furthermore, plantar pressure allows unobtrusive long-term recognition of these activities offering a novel advantage when monitoring large populations. Thus, prior to further explore the capabilities of plantar pressure, an in-depth scoping review of the measurement capabilities and limitations of all currently available plantar pressure devices and their potential to measure sedentary time was performed.

3.2 Methodology

After a critical analysis of the advantages and disadvantages of each technology, the most promising method will be selected as the focus of this review. Hence, an exhaustive scoping review of current plantar pressure technologies is done to fully identify the issues existing devices possess. Moreover, an analysis of technical specifications of current technology as well as the optimal requirements of a sedentary behaviour monitoring technology are discussed. Scientific databases, internet search engines and grey literature are used to ensure both research-based and commercially oriented technologies are included. Prototypes found in the literature are also included. The full list of identified devices with references can be found in Appendix A.

3.2.1 Devices scoring and classification

Several studies have amply discussed many of the characteristics and technical specifications that physical activity or sedentary behaviour monitoring devices must have to successfully work in free-living conditions [161, 162]. After reviewing these characteristics or attributes, a list of the most common attributes is shown in Table 3-2.

Table 3-2. List and brief description of selected attributes.

Attribute	Description
IMU	An accelerometer, gyroscope and/or magnetometer are incorporated into the device
Add-on Sensor	The system integrates another type of sensor besides pressure sensors or IMU. (E.g. GPS or bend sensors)
User interface	Any kind of interface has been developed either on a PC or a smartphone. (e.g. LabVIEW)
Bluetooth:	Bluetooth 2.0 or 4.0 (BLE) capabilities.
Smartphone app	An app (Android or iOS) has been developed as interface
Battery	A battery incorporated into the system. (e.g. Lithium battery)
Full-day power	The system's battery is able to support the system for at least 12 hours continuously.
Storage	Incorporates memory to enable "offline" functionality. (e.g. an SD card)
Full-day storage	Able to store data for at least 12 hours to enable offline measurements.
Integrated data analysis	Provides a calculable measurement after some data internal data analysis (i.e. calories, activity detection, etc.)
Publications	Any publication regarding the system's validity or reliability.
Cost	Costs less than 500 USD.
Access to raw data	Raw data from the sensors can be directly extracted.
Feedback	Provides visual, auditory or haptic feedback to the user in relation to the parameters calculated.

Characteristics related to the practical implementation of the final device such as weight, wearability, size, cost are often second to achieving certain recognition rate or overall performance in research-based devices. In the case of commercial devices, the opposite tends to occur when performance may be sacrificed to a certain degree to favour the viability of the final product and ultimately create profit. Most requirements are related to the necessity for a long-term monitoring protocol to monitor daily activities occurring across different settings such as work, school, home and when driving or commuting.

Although the importance of each attribute in reality may vary according to the application, the scoring systems presented here is designed in an attempt to reflect the device's overall potential and suitability for daily life sedentary behaviour monitoring, instead of solely focusing in specific attributes. For example, in the case of research-based devices, performance is often the main concern of the researchers, while devices in the market may sacrifice performance to prioritise other attributes such as aesthetics, smart-phone integration, internet-based applications or cost [161, 163]. Since a viable daily life wearable device should have most of the listed attribute and this review aims to identify a device that may reduce the gap between market and research-based device, all attributes are given the same weight. Furthermore, it simplifies the comparison and selection of an optimal device that ensure viability for sedentary behaviour daily life monitoring by maximising all the necessary attributes. Thus, each device is designated a score based on the total number of attributes it has. If one of the attributes (e.g. battery) is not explicitly mentioned by the article or website and could not be confirmed, it will not be reflected in the attributes count. Attributes such as low-cost are considered only if the systems specifically declared a total cost of less than 500 USD. Similarly, due to the relevance of the system ability for full day monitoring, independent scores are also given if the device's battery is able to continuously power the system for at least 12 hours or the storage is able to store at least 12 hours of data.

3.3 Results

3.3.1 Review Statistics

As seen in Figure 3-2, database searches found a total of 26,158 articles. Afterwards, articles are removed if they are found duplicate and based on title and abstract eligibility. A total of 287 articles were found to be potentially relevant and retrieved for full text review. Papers were further excluded for the following reasons:

1) Non-wearable devices: Studies such as platform based, or movement analysis labs are excluded to their inability to meet the inclusion criteria of non-laboratory based continuous monitoring capability.

2) Proof of concept: studies where only proof of concept information is available, and no system or technology has been developed.

3) Independent Sensors: studies in which a single sensor characteristics or material is discussed.

4) Health Outcome: articles are excluded if the device is not the main focus of the paper and they only examine the relationship between pressure and a disease (e.g. diabetes) or a particular health outcome (e.g. foot ulcers).

5) Data analysis: articles are excluded if the sole objective of the study is only to analyse a new data processing procedure or algorithm.

Afterwards, 176 papers were further excluded if they do not meet inclusion criteria, resulting in a total of 111 papers from which 87 devices were identified for a more detailed analysis [156, 164-273]. Of these, 13 articles reported fully developed systems and 74 of them reported systems at the prototype stage.

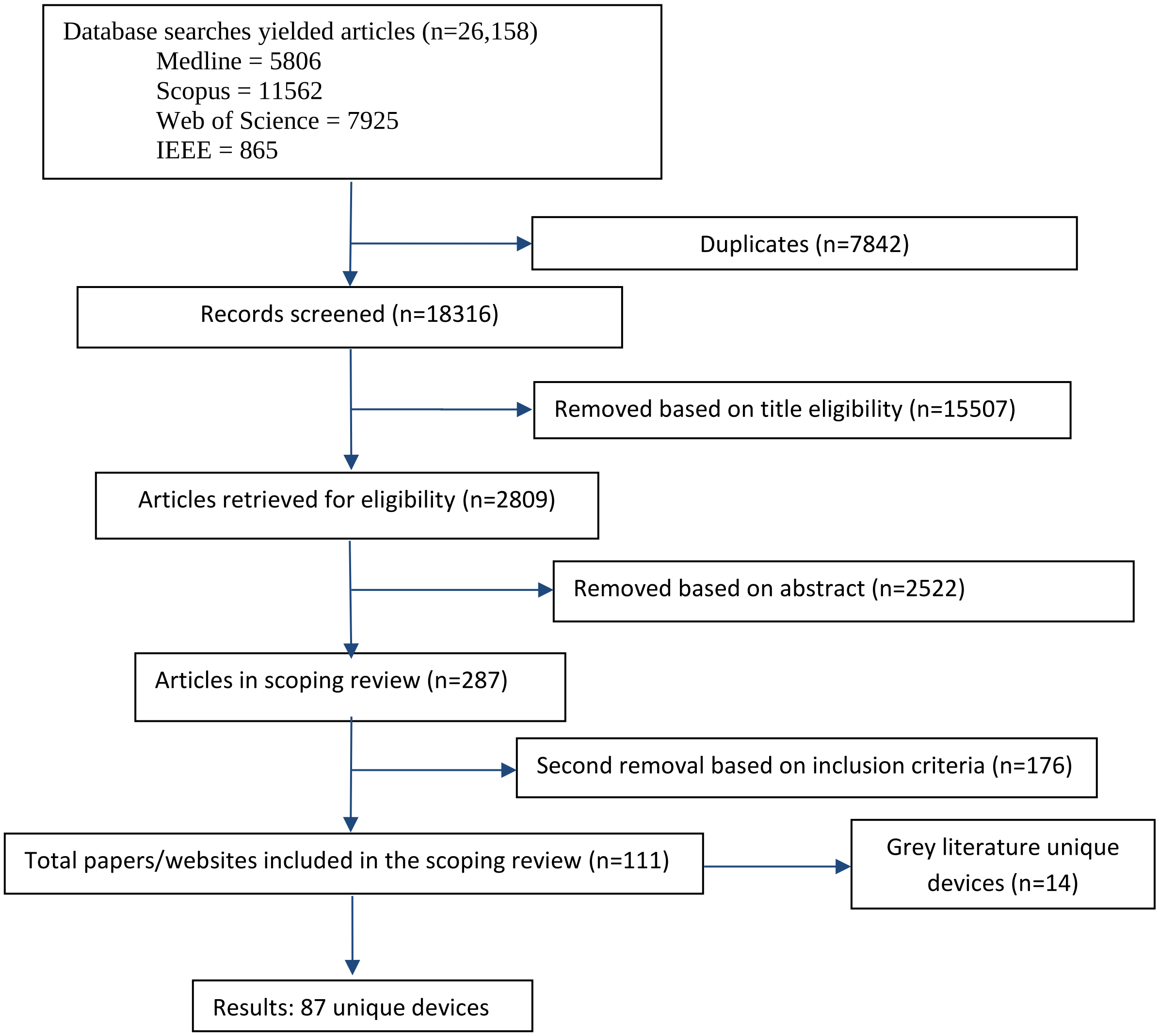


Figure 3-2. Flow diagram showing the articles filtering and final devices selection

3.3.2 Plantar Pressure Monitoring Systems

To offer a better comparison among technologies, Figure 3-3 and Figure 3-4 present plantar pressure devices in the prototype stage while Figures 3-5 and 3-6 present commercially available devices. It is worth noting that commercial devices and prototypes tend to change continuously meaning that attributes may be constantly added or removed. Since most of the prototypes do not have a name yet, the names of the authors are used instead to identify each technology. An excerpt of the full table with the identified devices and their attributes is shown in Appendix A.

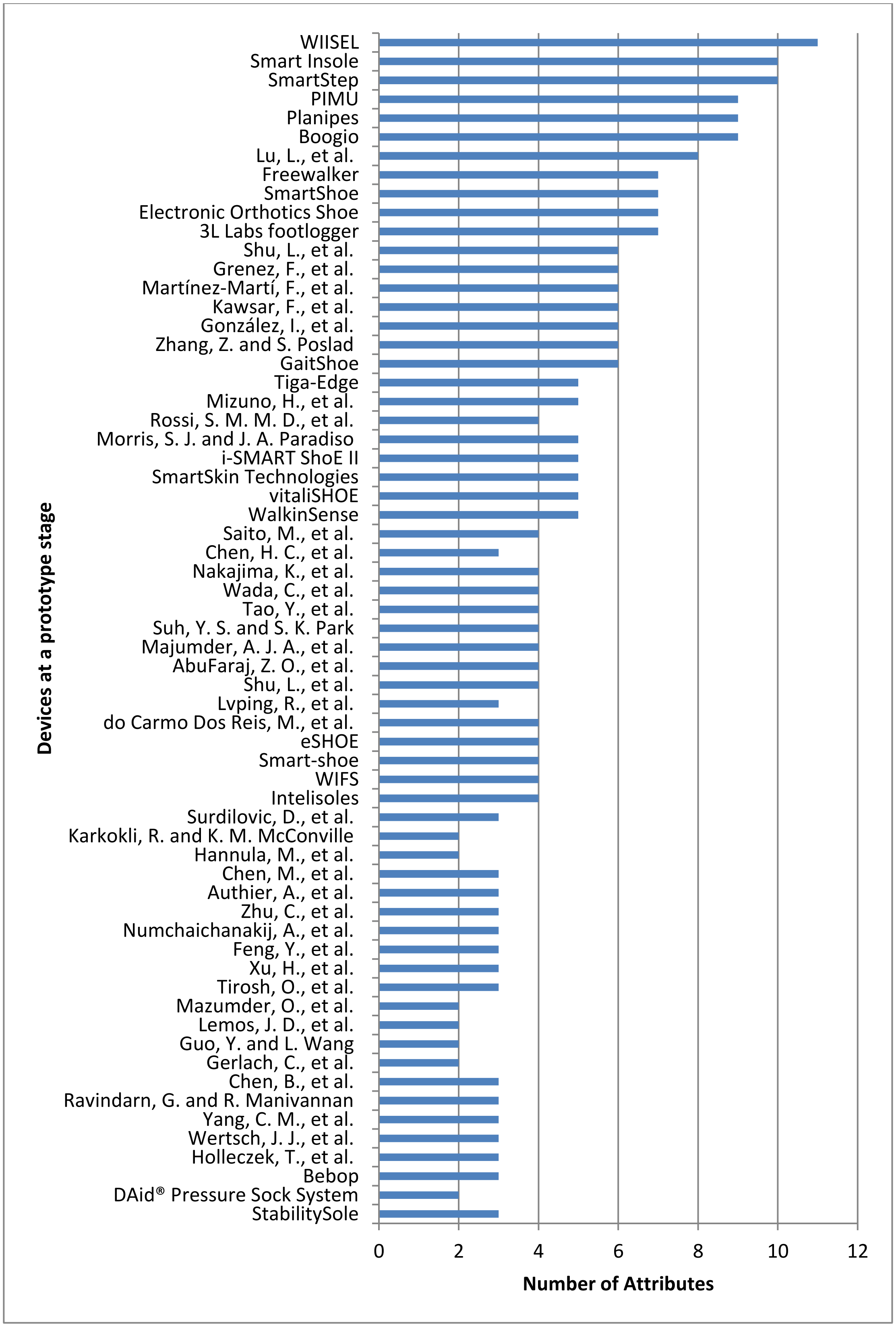


Figure 3-3. Technologies found at a prototype stage ordered by number of selected attributes (technologies with 1 attribute are not plotted).

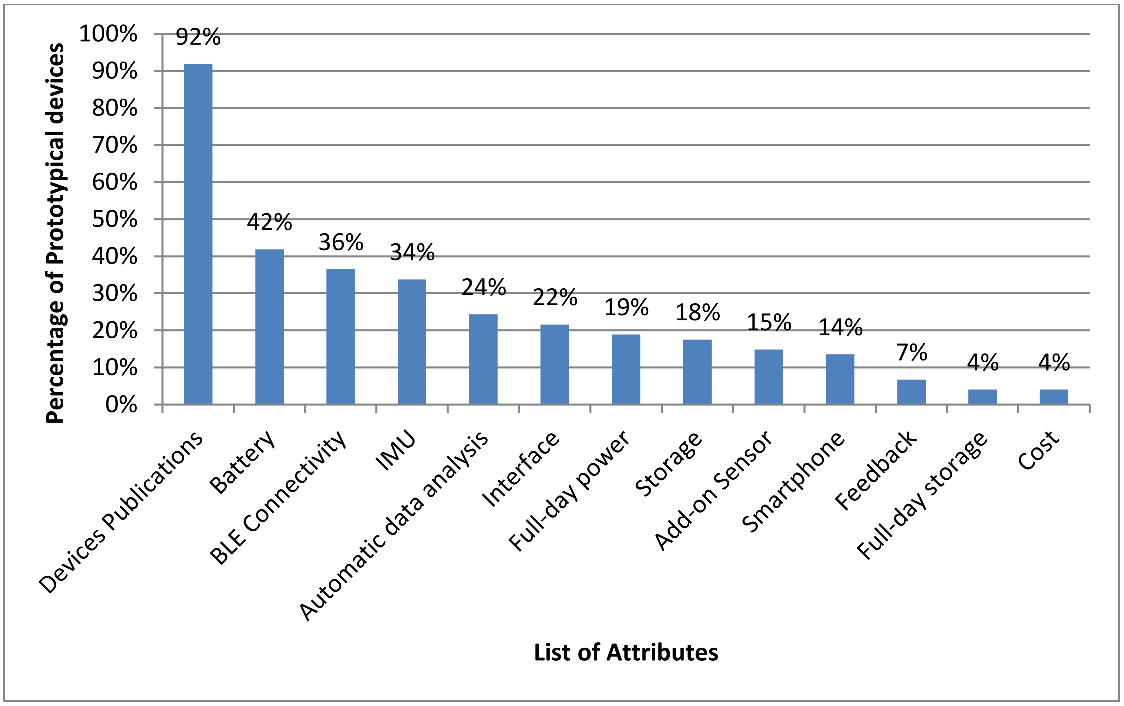


Figure 3-4. Percentage of prototypical devices found that possess each selected attribute.

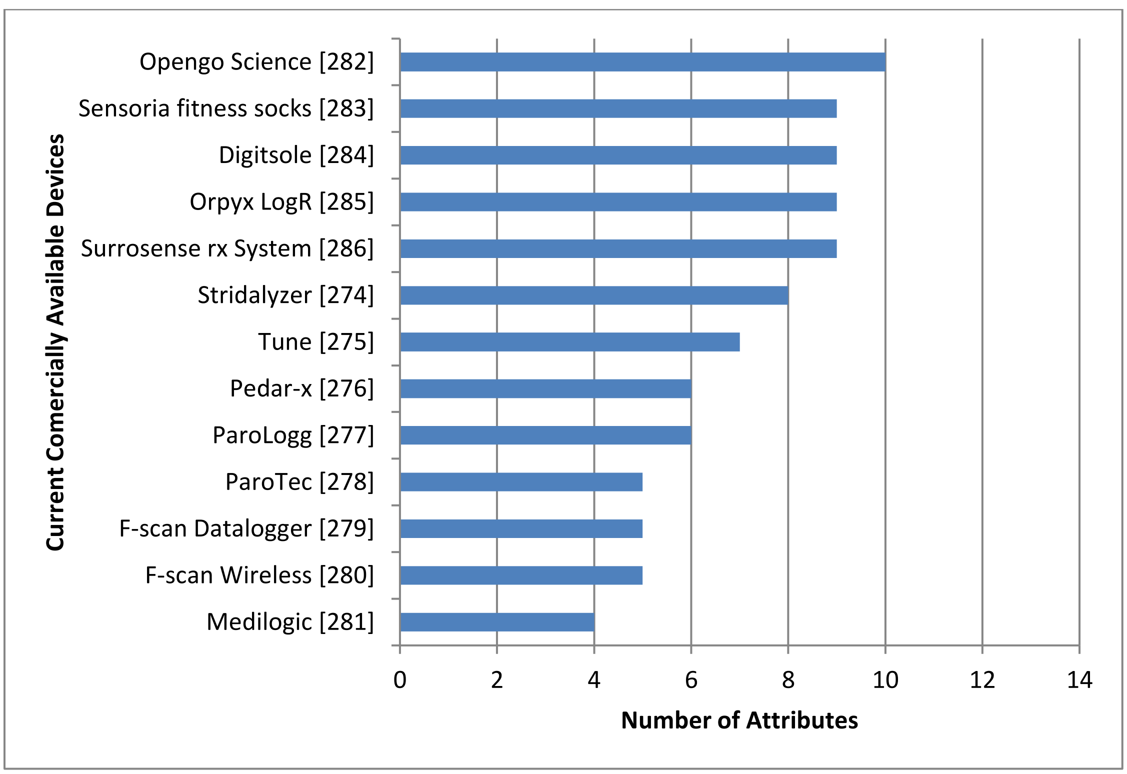


Figure 3-5. Current available technologies found ordered by number of selected attributes [160, 274-285]

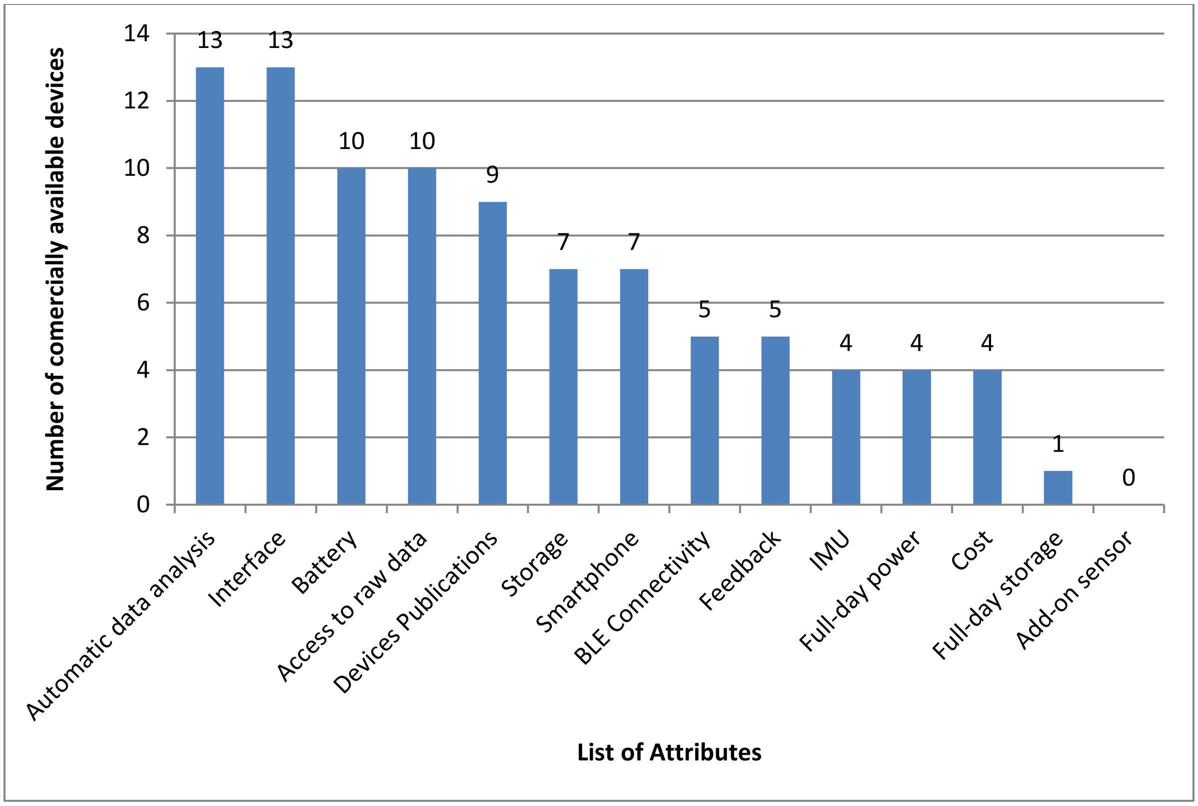


Figure 3-6. Percentage of commercial devices found that possess each selected attribute.

The commercially available device with the highest number of attributes was the OpenGo Science with 10 of 14 relevant attributes. The most common attributes found in commercial devices were the design of a user interface and internal data analysis to provide useful output to researchers and user alike. The least common attribute was the incorporation of a sensor which seems to indicate that other parameters besides pressure and motion are still mostly present at the prototype stage. Likewise, most devices do not have a storage capacity of more than 12 hours except for the OpenGo. In the case of devices at the prototypical stage, the device with the highest number of attributes was the WIISEL (Wireless Insole for Independent and Safe Elderly Living) [286] with 11 of 14 relevant attributes followed by the Smart Insole [287] with 10 of 14 attributes. The most common attributes found in all prototype devices are available publications. This is to be expected as most devices come were research-based. The second most common attribute was having a battery with 31 of 74 devices incorporating one. Considering power source is one of the key challenges when designing a daily life wearable device, the low incidence reveals that most prototypes are at the early stages of development. Moreover only 14 of these 24 devices have a battery able to support the device for longer than 12 hours. Another interesting attribute is Bluetooth connectivity with 31 of 74 devices supporting it. This reinforces the idea that recent developments are increasingly concerned in being able to connect to other devices and take advantage of the user's smartphone.

3.4 Discussion

There has been an increased interest over the years in developing less obtrusive plantar pressure devices. In fact, 74% of the selected articles were published since 2010. Out of 87 identified devices found, 13 were commercially available while the others are at various stages of being prototyped, meaning that most of the technologies found are on their early stages and they are likely to be continuously being modified or in some cases abandoned. Available devices can be further divided into research-oriented and consumer-oriented categories. Research oriented devices include well-known systems such as the F-scan system (Tekscan, Inc., South Boston, USA) [288], the Pedar system (Novel USA, Inc.) [159] or the ParoLogg (Paromed GmbH & Co. KG, Germany) [289]. Despite the excellent reliability and accuracy of these systems measurements, their cost, relative bulkiness and limited ability for lengthy and continuous non-laboratory measurements greatly limit their ability to be used for large-scale monitoring. It is also not easy for a consumer to obtain them. Recent studies have placed an increased emphasis on portability and long-term wear, to allow constant monitoring of gait parameters, activities of daily living, diabetic ulcers or elderly falls depending on the application. For example, the OpenGo (Moticon) [290], a recently developed device, has most of the desired attributes such as being fully wireless, unobtrusive and having long-term storage and battery. However, the high cost in the order of thousands of Euros, its scope is still limited to scientific studies instead of being useful the general population. This gap fuels the search for less sophisticated, user oriented and fully wearable devices. The Orpyx LogR (Orpyx Medical Technologies) may be another example of a device that attempts to cater to the needs of researchers and the general consumers by providing a simple interface with useful feedback to the user in the form of a Smartwatch [291]. Unfortunately, its cost of thousands of US dollars greatly limits the accessibility of the device to the public. Finally, there are devices priced available for less than 500 USD such as the Sensoria (Sensoria Inc) [282]. Commercial companies aim to sell their technology to specific populations such as runners who are interested in real-time feedback and information regarding useful parameters such as impact force or force applied on each limb. However, some of these devices such as the Stridalyzer (ReTiSense Inc) [274]or Tune (Kinematix, SA.) [275] tend to limit the access to the raw data to protect their intellectual property. Moreover, despite their improvements in wearability and consumer-oriented design, they still lack supporting publications or independent reviews for their validity and reliability [292].

Although many of these technologies measure physical activity, very few of them are specifically designed to measure sedentary behaviour despite the current need for such technologies. While some characteristics such as unobtrusiveness, wireless, and long-term monitoring capability are both key attributes for both physical activity and sedentary behaviour, further research is needed to determine the trade-offs to be made to improve overall wearability, battery and storage. In terms of technical characteristics, the main differences among the devices are found in the type of sensor technologies used, the number of sensors, the data analysis methodology, their dependence on external computing unit and how they communicate with the user. Most of the technologies share the basic configurations, with the main variations being on the technology of the pressure sensors themselves or in the method of analysing the raw data. Most of the design choices and technical specifications are mostly adjusted for biomechanics studies or gait analysis, the field of diabetes and its health consequences and fall detection of elderly population. Consequently, current devices do not meet all the technical requirements or data processing methods that sedentary behaviour monitoring would require. However, over the last few years there has been a clear increase in interest in plantar pressure devices with the capability of monitoring all day activities. For example, most recent developments incorporate wireless capabilities via Radio Frequency or Bluetooth communication, since the functionality of being able to connect to a smartphone is highly valued due to the ubiquity of these devices. The addition of longer battery life, larger storage capacity and seamless smartphone communication seem to be the target to enable these devices to be worn unobtrusively and monitor the user throughout the entire day. This is highly valuable in the case of sedentary behaviour monitoring, as continuous technology developments seem to have reached the stage where wide-spread day-to-day monitoring is becoming possible, thus opening the opportunity to measure sedentary behaviour.

In summary, using a plantar pressure measuring device for daily life monitoring sedentary behaviour is a promising technology that has shown the reliability needed in free-living conditions and high acceptability for participants due to its wearability. A critical and in-depth review of plantar pressure technologies has been carried to evaluate an extensive range of technologies found in the literature, other media and in the commercial market. Most pressure-based devices are focused in pressure ulcers detection due to diabetes and gait analysis and the ones targeting physical activity are mostly at various prototyping stages. Although a few available commercial devices meet some of the requirements for daily life monitoring such as portability and long-term battery life, current devices are able to provide reliable measurements of sedentary behaviour. In the case of devices specifically designed for scientific study, factors such as prohibitive high cost for wide-distribution to the average consumer, device bulkiness, or lack of consumer appeal limit their ability to be used for widespread large-scale general population monitoring. In contrast, commercial devices seem to trade off accuracy and robust technical specifications in exchange for wearability. Thus, current limitations of wearable technology indicate a need for the development of a new wearable sedentary behaviour monitoring technology that meets key attributes such as accurate measurements, affordability, unobtrusiveness, wearability, and long-term monitoring capability. Moreover, further research is needed to determine the trade-offs necessary to reduce the device technical requirements or computational cost and still meet the accuracy and reliability levels necessary to successfully monitor sedentary behaviour.

Chapter 4: A novel machine learning model for sedentary behaviour monitoring and data collection

4.1 Design considerations

Before discussing the development of the proposed sedentary behaviour monitoring model in this thesis, the design considerations of developing a wearable daily life monitoring system must be discussed. Based on literature in Chapter 2 and the in-depth scoping review in Chapter 3, the design objectives proposed in decreasing order of importance are:

1) **Accurate daily life activity recognition.** Currently, long term monitoring devices focus on recognising mobile activities such as walking, running or cycling to reasonable levels of accuracy. In the case of the lower activity spectrum (i.e. sedentary behaviour), monitoring devices encompass all postures such as sitting and standing without offering any other meaningful differentiation into other possible classifications. Accelerometers are also not able to correctly differentiate sitting behaviour with different weight bearing levels and avoid misclassification due to the confounding factors such as sitting on a bike or partially sitting on a tall stool. Training and test data collected in laboratory settings tends to be more accurate and easier to classify compared to data collected in free-living conditions, since real-world sitting behaviour varies considerably and is dependent upon several factors such as age, location, gender and occupation. Individuals tends to behave differently and during formal and constrained laboratory settings. Thus, this work utilised both constrained laboratory-based data by giving the participant's a specific set of instructions and free-living data by letting the participant's take the sensors while continuing with their routine. Direct observation done during the entire data collection by using GoPro HERO Session 4 (GoPro, Inc.) cameras to create the labels of the activities performed and validate the final prediction.

2) **Improved accuracy over the de facto standard currently used for sedentary behaviour monitoring.** The trade-off between the use of plantar pressure and the activPAL (PAL Technologies Ltd) will be evaluated. The activPAL is an accelerometer-based device located on the thigh frequently used on long-term daily life sedentary behaviour monitoring studies [103]. The advantages of the location and improved number of types and number of recognized activities will also be validated. Nevertheless, comparing the performance of different devices or models may prove difficult due to the different validation techniques, the type of activities targeted by each device, the trade-offs considered by each model or device, the type of populations involved and the condition in which the data was collected (laboratory versus free-living). Consequentially, it is hard to establish the degree of overall improvement over other prediction models when targeting only a specific attribute such as wearability, accuracy or long-term life.

3) **Minimization of number of sensors and improved wearability.** Using pressure sensors may be easier and more comfortable to use in comparison to accelerometer since these usually require probes to be stuck on the body such as the activPAL located at the subject's thigh. Due to the popularity of wearable technology, users are gradually more used to wearing extra sensors in the form of a watch or in this case, pressure sensors inside the shoe. Wearing the sensors inside the shoes is more unobtrusive and less visually unappealing allowing the user to wear it for longer periods of time. Besides unobtrusiveness, small sensors offer other advantages in free-living applications such as higher participant compliance and location versatility. Fewer sensors would have lower energy and computational requirements since the amount of data processing can be reduced. The final device may also be easier to wear if fewer sensors are needed. Furthermore, the affordability of the technology can also be improved by reducing overall cost.

4) **Minimization of computational requirements.** To be able to have a long battery life, portability and other wearability requirements, light data computation is optimal. Furthermore, since this is meant to be worn by the final user independently, additional applications in terms of communication such as Bluetooth and haptic or visual feedback must be considered when distributing computing resources [293]. As mentioned in Chapter 2, current wearable technologies struggle to balance the wearability features of monitoring devices and the desired accuracy. Thus, the proposed methodology considered the optimal trade-off amongst the minimization of computational requirements in term of data processing, number of features, amount and complexity of numerical calculations and sedentary behaviour recognition.

5) **Subject independent performance with minimal or no individual-specific training**. Current work on activity detection models suggests that subject independent recognition of activities is hard to accomplish due to the high variability of each individual sedentary behaviour. Increasing the number of activities to be identified, the type of sensors used and factors such as gender, age and body types further complicate the challenge of an accurate activity recognition. In an ideal scenario, a prediction model trained with a sample population would be able to recognize activities on the general population without the need for further training data from each user. Most current models train their algorithms with training data specific to each participant. Some of this data is easy to collect individually such as weight, height, age or gender (assuming the final device has a user interface). However, in some cases training data involves some standard activities to calibrate the device. For example, the device may require the user to sit, stand or walk for one minute to incorporate this information to the model, perform the necessary computations and finally improve the recognition. Ideally this training should be avoided to reduce the computational requirements of the final device, but if the improvement is significant, its duration and complexity

should be kept to the minimum. Thus, this thesis will also evaluate the performance of the model using both independent and dependent subject training and will attempt to entirely avoid individual-specific training or at least keep it to the minimum.

6) **Wider range of sedentary or low-energy expenditure activities classification.** To better discern sedentary behaviour during daily life, richer activity recognition is needed by expanding the detection ability to distinguish different types of low energy expenditure activities. Furthermore, people may show different behaviour depending on the activity, setting or even the type of furniture. For instance, various level of activity can be seen depending on the activity performed such as small arm movements in the case of light manual labour while sitting, arm and leg movements while driving or fidgeting while typing or using a Personal Computer (PC). Different sitting activities such as slouching or leaning may also be more common during leisure activities such as watching television (TV), reading or watching a movie in the cinema while sitting straight maybe more common at work or in school. Furthermore, sitting behaviour can also dramatically change depending among demographics. For example, children can be more active and keep fidgeting or change postures while sitting. Females may also exhibit different sitting postures due to anatomical differences, deportment or even due to the clothes or shoes they may be wearing (heels for example). To expand the sedentary behaviour monitoring capability, the algorithm performance is evaluated when attempting to identify both common sedentary activities such as sitting, low energy activities such as standing or leaning and moderate physical activities such as cycling or walking.

4.2 Overview and Research Approach

This section provides an overview of the research approach and design of the machine learning model presented in this thesis. The proposed model is developed using plantar pressure sensors in combination with constant direct observation via a GoPro camera to improve sedentary behaviour recognition in free-living settings. Not only traditional postures such as sitting and standing will be inferred but also commonly disregarded or not previously identified activities such as leaning will be attempted to be recognised to obtain a more comprehensive information of sedentary behaviour. As evaluated previously, plantar pressure sensors may be more capable to identify the aforementioned motion-less activities than accelerometers. Although the focus is in sedentary behaviour and sitting, other activities such as cycling, and stairs will be included. Thus, the following model architecture is designed to evaluate how well does plantar pressure sensors perform for a more detailed and accurate sedentary behaviour in comparison with the facto standard (i.e. ActivPAL) and the current criterion (direct observation).

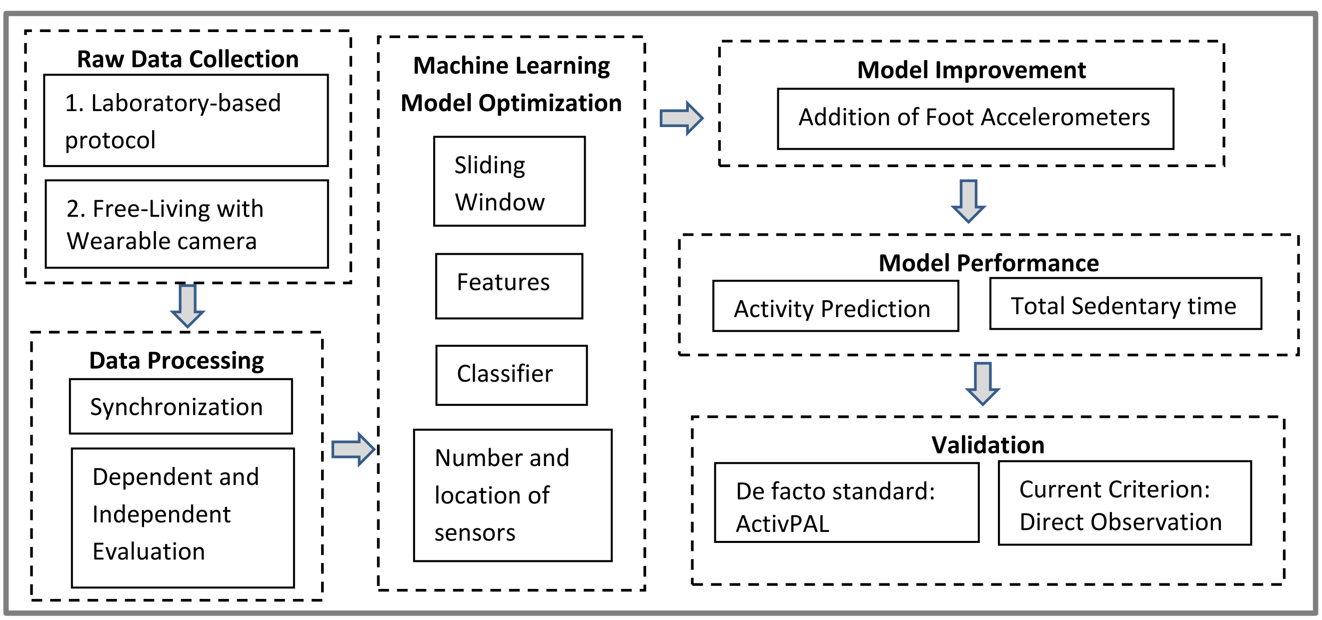


Figure 3-7. Overview of Sedentary Behaviour Classification

Six main phases can be identified in the model presented in Figure 3-7: Raw data collection, the Processing of the data, the Training of the machine learning model with the corresponding optimisations of window, features and classifier, the Improvement of the model with the addition of the foot accelerometers, the Results in terms of recall performance and sedentary time and the Final validation of the proposed model against the activPAL and the direct observation. First, data was collected from 20 participants in the laboratory followed by another data collection in a free-living setting. In the laboratory, data was collected under relatively controlled conditions since each participant was asked to perform specific tasks with a specific posture, as well as modifying said posture or activity according to the laboratory instructor requests. During the free-living settings, the participants were entirely free to continue with their normal daily activities. Once the data was obtained, it had to be filtered, synchronized, and labelled using the GoPro footage to train the supervised machine learning algorithm. At the same time, recognition of activities from direct observation of the video were obtained to validate the model at the Validation phase. Afterwards, different iterations of experiments were conducted to determine the optimal specifications that would ensure an optimal trade-off between the desired performance and the model's prediction accuracy. Some of these specifications include, the sliding window length, features, classifier and the optimal location and number of sensors. Grouping data in an appropriate window length is particularly important since features later used in the machine learning model are not computed over single data points but over these windows. For example, if a relatively long window of 30 seconds is chosen, an activity such as briefly standing up, taking a few steps, grabbing an object and sitting down again, will affect any feature computed due to the averaging of these three different activities. Having a short epoch instead will ensure these activities overlaps are minimized proving particularly relevant if the user changes type of activity continuously, which is a common case in younger populations. A potential drawback is that a short window may create statistically weak features by only covering a small data segment. Nevertheless, this is partially remedied by the fact that the model specifically concentrates on sedentary behaviour and only a small set of activities should be identified. It is also important to note technical requirements such as reduced battery duration and limited memory capacity were considered in choosing the size of the window [294]. After segmenting the data in an optimal window size, features are extracted to detect any relevant patterns. Thus, the type of features selected and how are they computed can greatly influence the model's overall performance. Time domain and frequency domain are the two main types of features commonly used when classifying activities. Time domain parameters such as mean, standard deviation, median, maximum values, and correlation are used in this work as they are to provide valuable information on different activity patterns. Since one of the major objectives is to be able to classify activities such as sitting or standing during free-living and for longer periods of time, time domain features were preferred as they satisfy the model accuracy criteria and demand lower computational requirements [141]. Once all the features have been selected and computed, it is necessary to choose an appropriate machine learning model according to the objectives of this thesis.

As mentioned in Section 2.4.2, the following classifiers were considered when creating the machine learning model: nearest neighbour [145], the naïve Bayes classifier [146], Decision Tables [295], J48 classifier [147] (commonly known as C4.5), Bagging methods [153], Logit Boost classifier [154], and the Random Forest classifier [152]. These classifiers were chosen due to their various degrees of simplicity in comparison to other complex widely-used classifiers such Hidden Markov Models. Furthermore, these classifiers have been widely used and validated in studies involving activity recognition and sedentary behaviour. For example, the Naïve Bayes was applied to detect activities from wearable accelerometers [296-298]. Similarly, the original implementation of the J48 classifier, the C4.5, is one of most commonly used classifiers in activity recognition [138] [299] . For example, Bao and Intille [136] used the C4.5 decision tree classifier to explore the activity recognition algorithms proposed on data from 20 participants in non-laboratory settings during semi-naturalistic conditions with performance rates ranging from 85-95% for ambulatory activities and postures. Similarly, Lester et al. [135] explored the overall performance of the Adaboost classifier in comparison to other more complex classifiers such the Hidden Markov Model. Furthermore, studies such as the one performed by Ravi et al. [300] and H. Martin et al. [141] evaluated the performance of different classifiers in recognizing activities such as Decision Tables, Decision Trees, Support Vector Machines, Nearest-Neighbour, and naïve Bayes classifiers individually. Despite the relatively common usage of these classifiers, several limitations exist when evaluating their performance. Thus, several performance measures such as true positive rate and false positive rate are incorporated into this work as discussed in Section 5. Besides validation found in the literature, performance measures and technical characteristics such as good performance in relation to computational cost were considered when choosing which classifiers to incorporate into this work. For example, The Nearest Neighbour classifier is selected because it is not only one of the most commonly used algorithms in machine learning, it is also one of the simplest ones to implement. The Naïve Bayes classifier is chosen because it is easy to implement, its overall simplicity, and great performance. The Decision tables classifier is selected because their similar characteristics and advantages as Decision Trees. The J48 decision tree classifier is also chosen because it is also well-known for its fast classification, great performance, and low computational costs. The Bagging method is implemented with a REPtree classifier which is fast decision tree learner that builds a decision tree using Information Gain and prunes it. Bagging methods also create separate samples of the training dataset and creates a classifier for each sample, giving each classifier that is trained, a subtly different focus and perspective on the problem. Boosting classifiers are also considered because they have been shown to occasionally provide improvements in performance by its approach of taking a weighted majority vote of the sequence of classifiers by sequentially applying the algorithm to reweighted versions of the training data. The LogitBoost is chosen since it has been shown to outperform Adaptative Boosting (AdaBoostM1), a similar machine learning algorithm in activity classification problems, as it uses logistic regression techniques. Random forest is also considered because its usual performance improvement over simple decision tree due to their multiple randomization of the algorithm, which helps to limit overfitting as well as error due to bias. The number and location of pressure sensors is also analysed to further lower the computational cost. Once the optimal parameters (i.e. window, classifier and feature set) and sensor configuration is identified, the proposed model will be trained and discussed. Afterwards, a possible addition of raw accelerometer data from the foot and the thigh will be evaluated to determine if any significant improved in performance is obtained. Finally, the proposed model recall performance will be validated against the de facto standard, the activPAL, and the current criterion, direct observation using confusion charts and recall tables. Total recognised sedentary time will also be evaluated since it is the ultimate output in most devices that measure sedentary behaviour.

4.3 Protocol Design

All study procedures were approved by the Ethics Approvals Sub-Committee at Loughborough University and the Institutional Review Board at Nanyang Technological University. A total of 20 male participants between an age range from 21 to 32 were recruited via word of mouth, posters and a global email. Written informed consent was obtained from all participants and they were also made aware that if they choose to withdraw, no reason needs to be provided, and the anonymised data collected to date can be erased and not used in the final analysis. Participants were also screened using a Health Screen Questionnaire. Data collection was performed over a 9-month period. The study consisted first in a laboratory-based phase followed by a free-living one. The laboratory-based data was collected in a controlled environment where the participants were asked to undertake a series of structured activities (i.e. sitting, standing, walking etc.). In the case of the free-living component the participants were free to do any activities in their daily routine.

Inclusion Criteria for both Studies

- Participant uses a shoe size of EU 40 -43 or UK 7 - 8 ½
- Participant is willing and able to comply with the study testing protocol
- Participant is physically able to sit and stand freely or without assistance.
- Participant is able to provide informed consent and assent (read and understand English)

Exclusion Criteria for both Studies

- Participant does not use a shoe size of EU 40 -43 or UK 7 - 8 ½
- Participant has an injury or other health condition that precludes their ability to sit and stand freely or they need assistance to do so.
- Participant has insufficient proficiency in English to comply with the study protocol

Although the data of 20 participants was collected, the data of 5 of the participants was not included due to a combination of human error, equipment mishandle, non-compliance by the participant and technical issues. One of the participants failed to appropriately record his daily activities using the Go-Pro after erroneously taking intermittent photos instead of video. Thus, data could not be labelled nor validated against direct observation. A second participant had issues with the place-ment of the sensors during the free-living component of the data collection. A total of 3 pressure insoles were used in this work: an initial 2 insole sets of 40-41 EU size and 42-43 EU size, and a replacement of the original 42-43 EU insole pair. Finally, in the middle of the study, some of the pressure sensors of the 42-43 EU size insole became faulty. Possible causes might be suboptimal initial conditions due to previous studies or mechanical damage due to inappropriate usage during the insertion into the shoes or during the free-living data collection. It is worth noting that although participants were encouraged not to remove the insoles from their shoes to avoid damaging them during reinsertion, some did not comply. Once the faulty insoles were detected, there were replaced by a second pair of insoles of the same size which performed without issues for the remaining trials. Thus, the data of only 15 participants was included in the rest of this work. The characteristics of the 15 subjects finally included in the sedentary behaviour data collection protocol are presented in Table 4-1. It is worth noting that since female rarely use the aforementioned shoe sizes all of the participants were male. Sections 4.3 and 4.4 will discuss the laboratory-based and free-living data collection respectively, while computations, experiment iterations and results are presented in Chapter 5. Lastly, accelerometer integration and the proposed model's validation is further discussed in Chapter 6.

Table 4-1. Characteristics of all the participants included in the study.

Characteristics	Participants (n=20), 5 excluded
Age	25.16 ± 2.97
Height	1.74 ± 0.06
Weight	64.32 ± 15.53
Fat percentage	18.31 ± 4.53
Body Mass Index (BMI)	22.36 ± 2.02
Visceral Fat	4.79 ± 2.07

Furthermore, the number of participants and length of each participant's laboratory and free-living data is similar or greater than similar studies in the field of plantar pressure analysis and activity detection analysis (e.g. 9 participants by Sazonov at al. or 16 participants by Morris et al.) [156, 287, 301, 302] . Unlike these studies where annotated data is limited, all pressure and accelerometer data collected in this work is annotated using the video captured simultaneously. As a result, a complete annotated large dataset is obtained, ensuring that enough training points are available for an optimal performance using supervised machine leaning approach while also ensuring a sufficiently large independent sample remains for validation purposes. Sample size is also preliminarily checked by creating a classifier's learning curve using data collected to inverse power law models, as previous studies have shown that learning classifier curves generally follow inverse power law [303]. Additionally, both the participant's individual data duration and all the participants aggregated data is reviewed since both subject dependent and independent evaluation validation methods are used in this work (as discussed in Section 4.7.2). Thus, it would be reasonable to expect good recognition performance with even a sample size if a reasonable performance is obtained during dependent validation in which a much smaller set of training instances (one participant) is available compared to the much large set available (14 participants) during independent training.

4.3.1 Equipment

The OpenGo system (Moticon, Inc) consists in a pair of fully integrated sensor shoe insoles and a data analysis software. It measures the plantar pressure distribution, total loads and dynamics of the human foot. The sensor insole is completely wireless. The ActivPAL (PAL Technologies Ltd, Glasgow, UK) is a small lightweight motion sensor. The ActivPAL uses information from static acceleration (due to gravity) and angle of the thigh to classify static activities (lying/sitting vs upright) and dynamic acceleration (due to body movement) to determine mobile activities. Both devices sampling rate is 10Hz and can be summarised in epochs (see Section 5.1.2) or by events.

All the predicted activities were compared against the ActivPAL since it is considered the current criterion used by most researchers for daily life activity monitoring. The GoPro HERO Session (GoPro, Inc) is a well-known High Definition quality, waterproof, video recording cubic shaped device. Due to its reduced size, features and wearability it can be used in any type of environment or conditions. This device will provide the ground truth for the labelling and validation phases. A portable battery pack RAV power of 12000mAh was provided with the purpose of charging the GoPro. Pictures of all the devices are shown below in Figure 4-1. A treadmill and stationary bike were used during the walking and cycling activities for the laboratory-based component of the data collection.

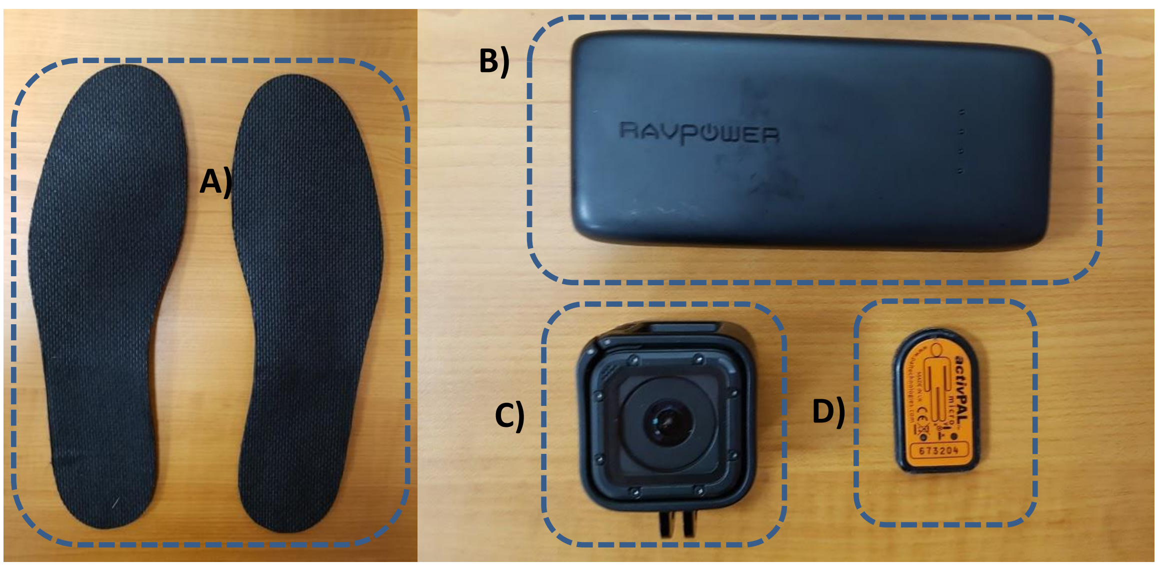


Figure 4-1. Photos of the sensors used for data collection. A) OpenGo insoles, B) Raw Power, 12000 mAh Power Bank, C) GoPro HERO Session 4 and D) activPAL.

Since wearable sensors are used in this work, it is important to note that all the sensors are initially configured using the PC and their respective software. Moreover, as most of the data collection occurs outside the laboratory, both calibration and the selection of sampling frequency must be carried out before the study. The purpose of unit calibration is to reduce inter-instrument variability and to ensure that each device is measuring correctly the acceleration to which they are being submitted. The OpenGo insoles have to be calibrated in a static condition during standing by resetting them to zero while the subject wore them inside the shoes supporting the subject's whole-body weight. Similar to most contemporary accelerometers, the activPAL initial calibration was performed at the factory and it should remain calibrated for the lifespan of the device [304]. Nevertheless, during the initial data collection, the output was checked for any irregularities since some of these standard calibrating techniques may not always reflect daily life conditions.

Regarding the selection of an appropriate sampling frequency for all the sensors, three main factors must be considered: the resulting accuracy for modelling, the battery demand and the amount of memory storage (particularly in the case of the OpenGo and the GoPro). According to the Nyquist criterion [305], the sampling frequency must be at least twice the frequency of any movement highest frequency. The general frequency in standard nonimpact physical activity of the human centre of mass is below 8 Hz (when running in the vertical direction) [306]. Although the upper limit could be as high as 25 Hz in some the cases of arm movements, as the accelerometers are located inside the shoes, this is not a concern. Regarding the technical limitations, the OpenGo sampling frequency choices are 10, 25 or 50Hz while in the case of the activPAL the options are 10Hz and 20 Hz. Although the activPAL has enough internal storage for several days, the internal storage of the insoles will only allow the desired 12 hours of data if 10 Hz is the sampling frequency. The GoPro camera does not need any calibration [307], it is only checked that it works properly during setup and during the laboratory-based data collection. The GoPro camera video settings are 720p as video resolution and 30s frame rate per second. Both cameras are equipped with a 128GB SD card as each 12 minutes of footage is saved as 2.1 GB file. Finally, all devices are initialised and synchronized to the PC clock.

4.3.2 Fitting and Initialization

Data collection started with the laboratory-based phase, where the participant was asked reported to the Institute of Sports and Research at the School of Mechanical and Aerospace Engineering in Nanyang Technological University at a pre-arranged appointment time. Participants were previously informed to wear comfortable closed shoes (no heels) and socks to allow insertion for the insoles. Afterwards the participant was fitted with a wearable sensor placed on the thigh, and two insoles inside their shoes. Shorts were provided for the fitting of the activPAL (located at the thigh), being able to change back to their own clothes afterwards. For determination of sample characteristics, anthropometric and demographic information were collected. After participants were asked to remove shoes and socks, height was measured using a stadiometer, and weight and percentage body fat measured using a bioelectrical impedance scale (Omron, Model BF508). Body mass index (BMI) was be calculated by dividing weight (kg) by squared height (m^2). Combining BMI with impedance determined fat mass will provide a robust measure of body composition. Regarding the demographic data, participants were asked to self-report information including date of birth, gender, ethnicity, and any additional diagnoses of injury or chronic medical condition that may diminish his ability to sit and stand freely or without assistance. A sedentary behaviour profile was obtained from each participant as well since it is important to understand the long-term sedentary behaviours of the participants. This data was collected via asking the participant to complete 3 different questionnaires (paper-based methods). The International Physical Activity Questionnaires (IPAQ) short version form was used to provide common instruments that can be used to obtain internationally comparable data on health–related physical activity [84]. The second one, the Sedentary Behaviour Questionnaire assesses the amount of time spent doing 9 behaviours (such as watching television or driving) [308]. The 9 items were completed separately for weekdays and weekend days. Finally, the SIT-Q-7d questionnaire quantifies time spent sedentary in the last 7 days during meals, transportation, occupation, leisure time and others, enabling calculation of domain-specific and total sedentary time [309]. To minimise the duration of the whole data collection, the filling of the questionnaires was one of the included structured activities.

The activPAL was affixed using a piece of medical dressing (Hypafix® Transparent, BSN Medical) to the anterior aspect of the right thigh approximately a third of the way down from the hip as indicated by the activPAL manufacturer. The OpenGo insoles were inserted into the participant shoes following the recommendations from the supplier. Afterwards, the insoles were zeroed following the software instructions: asking the participant to unload each insole by lifting first each corresponding foot from the ground. The GoPro is worn only during free-living data collection, either on the right or left side of the body depending on the participant's preference. All devices remained attached during the laboratory collection and for the next 24 hours during the free-living component of the study (except during sleeping). The locations for attachment onto the body for all devices are shown in Figure 4-2.

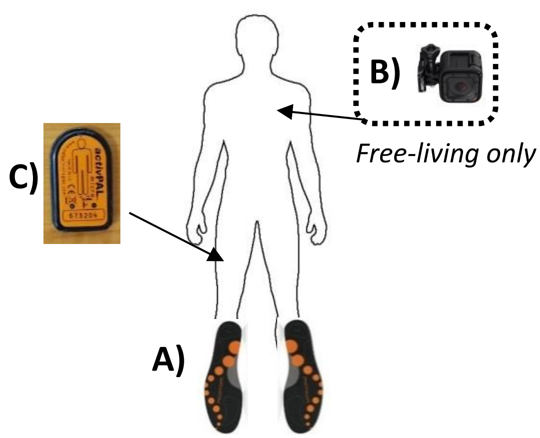


Figure 4-2. Anterior view of device's location. Insoles are inserted inside the subject's shoes. A) OpenGo insoles B) GoPro HERO Session 4 and C) activPAL.

Prior to fitting the devices, the ActivPAL is programmed using the activPAL3 software provided by the manufacturer to collect data during a specific set of time (for example 9am to 9pm). On the other hand, the OpenGo insoles must be manually started using the software and will collect data as soon as the data are collected as they are disconnected from the PC. Thus, the insoles must be inserted into the shoes immediately afterwards. To ensure data from all 4 devices is collected throughout this period, the insoles are set to collect data a few minutes before the start time since they must be connected to the PC. The GoPro has a start button that has to be manually pushed. In a similar way, the OpenGo camera is turned on using the start button minutes before the starting time of the ActivPAL. This is because the ActivPAL can be configured to program the time when it will start and stop collecting data, while the OpenGo insoles and the GoPro session have to be manually triggered (by either using the PC in the case of the insoles and pressing the ON button in the case of the camera). All devices have enough battery life except for the GoPro. To address this issue, two identical cameras are provided to the subject as well as a portable battery. Both cameras are fully charged at the beginning of the trial. The participant is instructed that when the first camera runs out of power, it should be substituted with the second camera while connecting the first one to the portable battery for charging. The process is repeated continuously until the end of the data collection (this process usually occurs around 6 times since battery lasts for about 2 hours).

Privacy concerns were expressed by the participants since continuous video recording is taken throughout all their activities. To address these issues, several measures are taken. First, the camera is located at the chest of the participant facing downwards, meaning that only his legs are recorded, and the video will not show the participants surroundings, their face, or anyone´s else around them. Secondly, the participants are informed that they are completely free to turn off the camera whenever they want privacy or during any activity they may not want recorded. Moreover, they are informed that they can ask to delete certain sections of the video at the end of the day data collection. Thirdly, all audio from the files is deleted to ensure all conversations were erased from the recordings. Participants are also assured that if any of the recorded data are used, they will be fully anonymized.

4.4 Data Collection Part 1: Laboratory-based component

After the participants have been fitted with the sensors, they are informed of the activities they are to perform. Participants are instructed when to start and stop each activity by the researcher, and the exact start time and stop time of all activities is recorded by the camera and later obtained manually by the researcher. Whilst these activities are undertaken the researcher is present to observe the participants and answer any questions regarding the activities' execution. In addition, all validation activities are recorded using a video camera to provide a reserve copy of the observation period and allow a more accurate labelling of the data (see Section 5.1.1). The full list of activities was completed in the specified order are shown in Table 4-2.

Table 4-2. Validation activities simulating some of the multiple variations on different tasks that occur during daily life at work and home environment

	Constraint	Type of Activity	Location	Activity
1	Free	sitting	Chair	Questionnaire
2	Free	sitting	Chair	Typing
3	Free	sitting	Chair	light activity (UNO cards)
4	Free	sitting	Couch	Questionnaire
5	Free	sitting	Couch	watch video
6	Free	sitting	Couch	light activity (UNO bricks)
7	Free	sitting	Floor	watch video - no back support
8	Free	sitting	Floor	watch video - against the wall
9	Free	sitting	Floor	using smartphone
10	Free	sitting	Floor	using smartphone - against the wall
11	Free	Standing	Standing Desk	Questionnaire
12	Free	Standing	Standing Desk	watch video
13	Free	Standing	Standing Desk	write on white board
14	Free	Standing	Floor	talking
15	Free	leaning	Back to the wall	using smartphone
16	Free	leaning	Back to the wall	talking
17	Free	leaning	Side to the wall	listening to music
18	Free	leaning	Side to the wall	reading
19	Instructed	sitting	Chair	Sitting at 90 hip and knee angles
20	Instructed	sitting	Chair	90 hip and knee angles plus laptop
21	Instructed	sitting	Chair	90 hip and knee angles plus backpack
22	Instructed	sitting	Chair	legs crossed at the knee (Right over left)
23	Instructed	sitting	Chair	legs crossed at the knee (Left over right)
24	Instructed	sitting	Chair	legs crossed ankle over opposite knee (Right over left)
25	Instructed	sitting	Chair	legs crossed ankle over opposite knee (Left over right)
26	Instructed	sitting	Chair	legs crossed at the ankle (Right over left)
27	Instructed	sitting	Chair	legs crossed at the ankle (Left over right)
28	Instructed	sitting	Chair	legs stretched forwards
29	Instructed	sitting	Chair	legs stretched forwards ankles crossed (Right over left)
30	Instructed	sitting	Chair	legs stretched forwards ankles crossed (Left over right)
31	Instructed	sitting	Chair	legs bent backwards
32	Instructed	sitting	Chair	legs bent backwards ankles crossed (Right over left)
33	Instructed	sitting	Chair	legs bent backwards ankles crossed (Left over right)
34	Instructed	Standing	Floor	natural standing
35	Instructed	Standing	Floor	Standing with feet 40 cm apart
36	Instructed	Standing	Floor	leaning on right leg
37	Instructed	Standing	Floor	leaning on left leg
38	Instructed	Standing	Floor	“on one foot” crossing the legs (Right over left)
39	Instructed	Standing	Floor	“on one foot” crossing the legs (Left over right)
40	Instructed	Standing	Floor	carrying grocery bag (5 kg) on left hand
41	Instructed	Standing	Floor	carrying grocery bag (5 kg) on right hand
42	Instructed	Standing	Floor	with backpack (10 kg)
43	Instructed	Standing	Floor	grocery bag (5 kg) on right and (5 kg) backpack on left
44	Instructed	Walking	Treadmill	1-6 m/s
45	Instructed	Cycling	Bike	Resistance 2 and 4
46	Instructed	Stairs	Stairs	10 floors up and 10 floors down

Six main activities are selected: Sitting, Standing, Leaning, Walking, Cycling and Stairs. The activities are chosen to simulate the multiple variations that occur in daily life at work and home environment. To further maximise possible variations, two different levels of constrained are implemented: free and instructed. In the first case, the participant was given an activity during sitting or standing but is not instructed how they should sit or stand. Thus, different sitting or standing positions is taken according to the participants' comfort. On the other hand, the instructed tasks are the ones where the participant is specifically instructed to sit or stand in a particular way. Furthermore, several locations such as a standard chair, a couch and the floor are included since the type of chair or surface where the person sits may considerably influence its sitting behaviour. Activities with different degrees of movement is also included: activities with light movements such as filling a questionnaire or typing, activities with a greater degree of possible movement such as board games, and finally relatively static activities such as watching a video.

Participants are also asked to either stand up if they are sitting (or sitting if they were standing) between each activity to provide an easy method to identify a marker on the pressure data that will help discern each activity when visualizing the raw data. Illustrations of some of the activities are shown in Figure 4-3.

Figure 4-3. Examples of a participant performing some of the activities during laboratory-based data collection. To preserve anonymity, the participant's face was covered.

4.5 Data Collection Part 2: Free-Living Component

Following the completion of all the activities in the laboratory, all sensors remain fitted to the participant in order to monitor the ensuing free-living component of the study. A GoPro (*HERO Session)* camera attached is provided to the participant in order to accurately monitor their daily activities throughout the duration of the free-living component of the study. Several options are given to the participant to wear the GoPro: a strap, a shoulder mount, a magnetic clip and clip which could be attached to the bag provided (or their own bag). Despite being the most noticeable, most participants opt for the shoulder mount since they do not have to worry about the camera position. The GoPro, the ActivPAL, the ActiGraph and the OpenGo insoles within their shoes are worn for the next 24 hours to capture all the participants' daily activities. No constraints are given to the participants regarding their activities of the day (for instance, they could go to work or stay at home as they preferred). The only constraint was keeping the sensors on which meant avoiding activities where they would need to be removed such as water-based activities, sports participation or sleep. One particular problem arises in the case of the OpenGo insoles, since in Singapore it was the prevailing culture that shoes are not customarily worn inside many homes. However, for the sake of this data collection, participants are asked to cover their shoes with cloth casings provided to avoid removing the shoe once inside home and avoid missing valuable information regarding home-based activities. This solution ensures the shoes and consequently the insoles, are not removed until going to sleep. Finally, to address the limited battery issue of the GoPro camera and ensure continuous recording, participants are also given a second GoPro camera and a portable battery in a pouch. This additional camera is provided to replace the first camera while it separately charges. All devices are returned the following day.

As mentioned previously, the objective of the live recording is to create the labels to both train the algorithm and serve as ground truth when examining the model's accuracy when predicting activities. An example of how each classified activity can be identified on the video are shown in Figure 4-4.

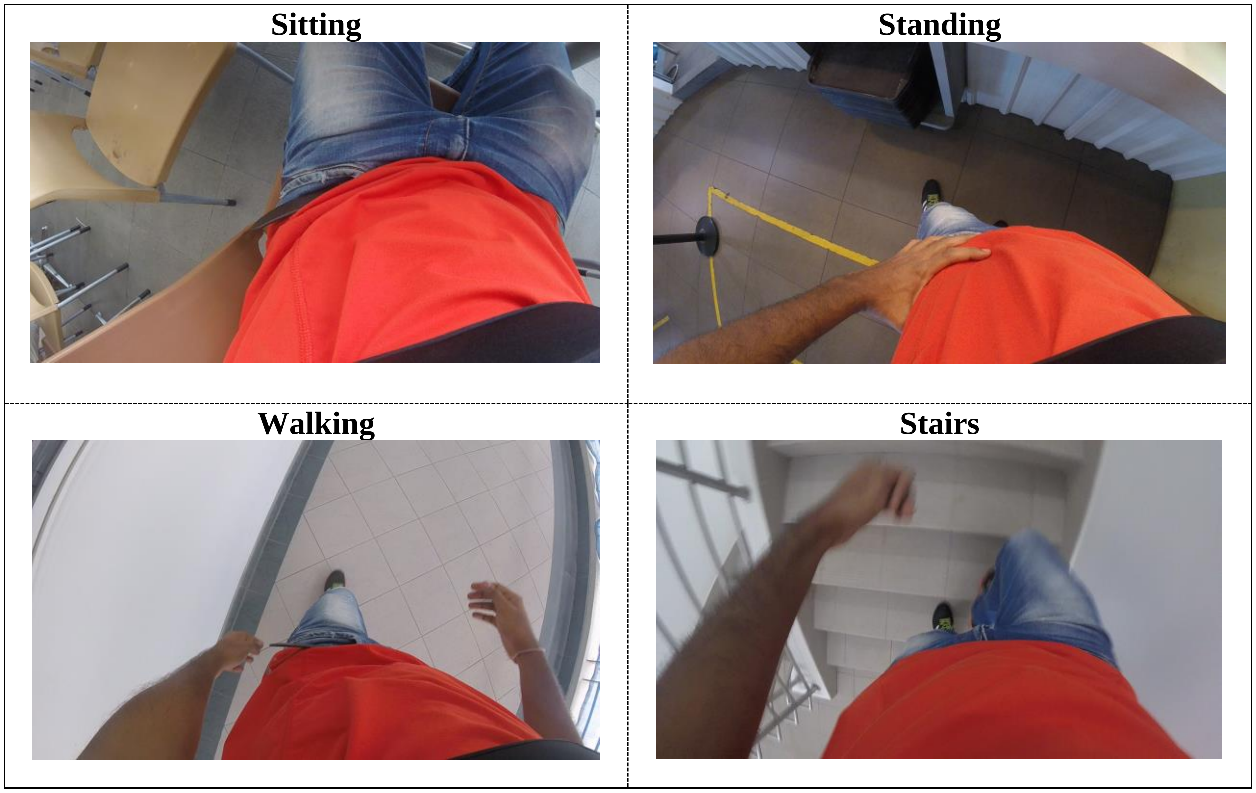


Figure 4-4. Examples of still images from the GoPro video: Sitting, Standing, Walking and Climbing Stairs.

A total of 211 hours of video, accelerometer and pressure data were collected and reviewed. After video processing and manual labelling, a total amount of 136 hours was analysed and incorporated into the supervised machine learning model.

4.6 Data Processing and Training considerations

Before introducing the data processing, the experiment performed and the model performance, certain training considerations and general assumptions are made. The following section discusses and explores the underlying reasoning upon which these assumptions and their impact when evaluating the training of the model and assessing its performance.

4.6.1 Truncation and Synchronization

The Open Go insoles data is exported in .txt format and then later is transformed into "Comma-Separate Values" (CSV) file format using MATLAB (2017a, MathWorks). MATLAB is used to process the data due to the previous familiarity of the author with the software, its ease of use, its ability to manipulate tables, plot data, create user interfaces and the applications of its Machine Learning Toolbox. This raw data set includes accelerometer data and raw pressure values each sensor and centre of pressure and force from each foot. In the case of the ActivPAL, the company's software organizes and exports the data in CSV format in two different modalities: raw acceleration data or by the duration of each activity until a transition is detected. Since the main interest in this thesis is to compare the pressure-base only proposition against the direct observation (video footage) and the ActivPAL (de facto standard), raw acceleration data from both the insoles and the ActivPAL is incorporated to pressure data and evaluated in section 6.1.1 and section 6.1.2 respectively. The ActivPAL proprietary algorithm identifies three different activities: sedentary (=0), standing (=1) and stepping (=2). Since the ActivPAL sampling rate is set at 20 Hz as the factory default and the Go Pro insoles sampling rate is set at 10 Hz (the same as the pressure sensors), data had to be resampled, to fix the discrepancy of between the two sources of acceleration data. Finally, the GoPro data is extracted from the Secure Digital (SD) cards in the form of 12 min video of 2.1GB each. To avoid any unnecessary video processing, the video files are not merged.

To be able to identify and compare each activity on each device, data across all devices have to be truncated and synchronized. As mentioned previously, the Open Go insoles and the ActivPAL internal clocks are synchronized to the internal clock of the PC. Nevertheless, due to different starting methods of each device the starting and ending of each device's raw data differed by between a few seconds to a few minutes. Since the all sensors have a fixed starting and ending time, for the sake of simplicity data duration was adjusted to whichever collected the shortest data. For example, if the GoPro has started later than the rest of the sensors, the data from the rest of the sensors is truncated and ignored for eventual computations. Similarly, data is truncated at the time the first sensor stopped collecting data. In the case of the GoPro, video files have a start time that matches the time of the smartphone in which they were synchronized using the downloadable app from the Google Play Store. Since the ActivPAL are the only sensors which could be programmed and not manually started, it usually set the timeline for the rest of the sensors. Despite being able to synchronize all devices to the PC or the Smartphone, mismatches occasionally occurred during data collection and manual synchronization by direct observation had to be carried out. To determine the size of the delay for each sensor, the exact starting and stopping points of several specific events are visually identified by analysing the plotted raw data of each sensor. These events were mostly transitions of sitting to standing (or vice versa) since they were easy to identify in all the sensors' data, being the pressure data, the GoPro video or the ActivPAL event marker. Since all participants started their respective data collection with the standardised test at the laboratory, a noticeable pattern of events across all participants was detected when examining the raw data, an example is shown in Figure 4-5.

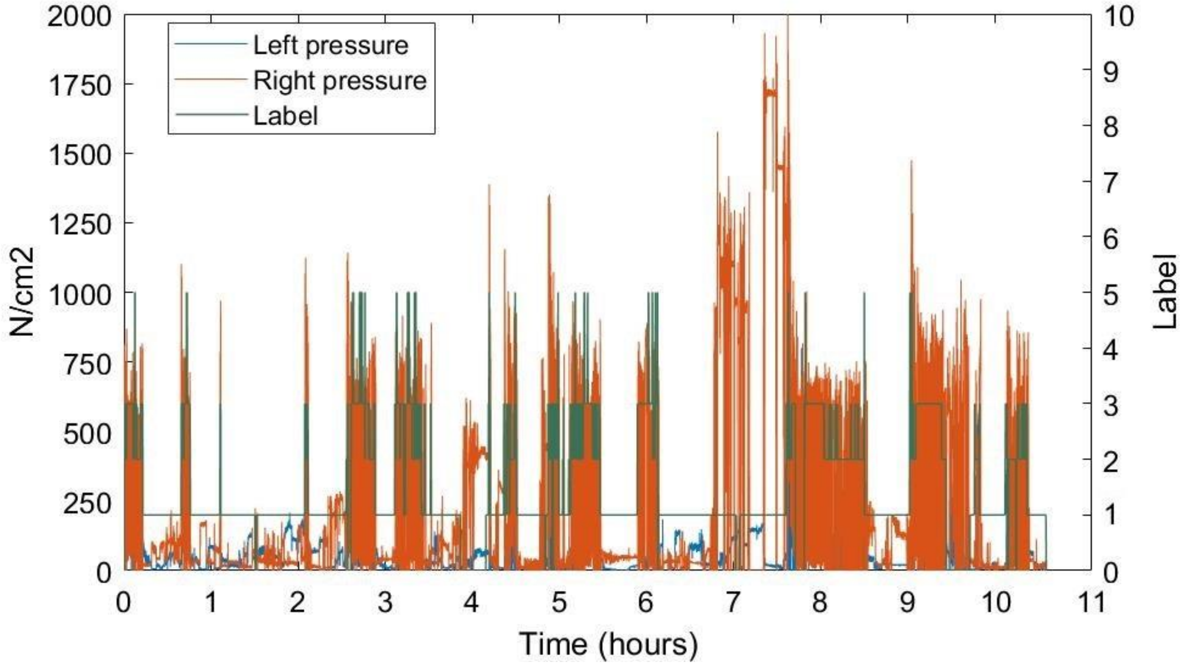


Figure 4-5. Example of raw pressure data visualization during one participant's laboratory-based data collection. Each activity is labelled as follows: 1-sitting, 2-standing, 3-walking, 4-cycling, 5 -stairs, 6-leaning.

Data is shifted accordingly to match these events while also checking that future events in the free-living part of the data also were synchronized. It is important to highlight that these discrepancies in start and end time and the consequent loss of data were observed to be minimal (e.g. few seconds or minutes) as all sensors were manually started and stopped at the same time.

4.7 Training considerations

4.7.1 Transitions Between Activities

One of the main sources of possible variability in the labelling and feature computation process is the transition between each activity. The most common ones occur when transitioning from sitting to standing and vice versa, followed by standing and walking. These transitions can become problematic as they may introduce significant variability in the pressure data depending on the type of transition. Furthermore, depending on the context, each transition can show different trends. For example, standing up from a chair and standing up from the floor represent two different behaviours. If these transitions are to be detected, a small window size such as 1 or 2 seconds would have to be implemented since these transitions tend to be quick (1 to 3 seconds). However, as later discussed in section 5.1.2, a window size that small will be suboptimal to the general recognition performance of the model and will also increase its computational cost. Consequently, transitions are not specifically targeted or attempted to be predicted. Nevertheless, they are not eliminated or filtered in any from the data set during the training of the machine learning model in order to ensure the conditions are as realistic as possible. Another reason why transitions are not specifically labelled as such is the difficulty to identify them during the labelling process shown later in section 5.1.1. For example, activity variations such as briefly leaning against a wall briefly while standing or pausing during a walk are hard to detect due to their brevity. In fact, further complication arises when transitions from different activities happen in quick succession such as walking immediately after sitting with a brief pause of standing in between. Labelling these brief changes independently would introduce unnecessarily variability to the data and would most likely be not useful or even detrimental to the overall result.

4.7.2 Subject Evaluation

Two types of subject validation are implemented in this work: 10-fold cross validation to test subject dependant performance and leave-one-out validation to test subject independent performance. Cross validation is a common method used to evaluate the result of the model's analysis on relatively small datasets [310]. This technique can also tell us how the results can be generalised as an independent data set from the sample data. Cross-validation involves splitting the data into two subsets, performing the computations on one subset known as the training set, and validating the model obtained on the remaining subset known as the testing set [311]. The subject dependent evaluation is performed in order to assess the model's ability to classify a participant's activity using each participant's own sample data. First, the original sample of each participant is randomly partitioned into 10 subsample sets. Nine of these subsets are used as the training data and the remaining subset is used as the testing data. This process is repeated 10 times, using each one the 10 subsets as testing data, and averaging the results of all participants and each fold (hence the name of 10-fold cross validation). Theoretical evidence, extensive tests on numerous datasets and related work with different learning techniques have shown that 10 is an appropriate number of folds to get the best estimate of error [310]. Furthermore, related work supports that 10 folds may the optimum number of folds when evaluation models related to machine learning classifiers [311]. One of the main advantages of this method over repeated other validation methods such as random sub-sampling is that the whole sample data set is analysed only once, and it is also used for both validation and testing, so the resulting metric is approximation of the expected value of the true evaluation measure. This methodology will also allow to determine if there are any significant variation of sitting or standing behaviour among each participant that justifies or favours a small training period before the algorithm is tested on a new participant. For example, asking the user to do each task for a couple minutes may greatly improve the model's accuracy. However, it would be ideal that the model could classify activities across all participants by using a determined set of collected data in advance without requiring no such training from each one of them. Thus, to assess if subject independent training is viable, leave-one-out validation is also performed. The model is trained with all the participant's data except one and tested on this excluded participant while repeating the process for each one of the other participants (excluding and testing one at a time). If the model’s performance is not significantly affected compared to the subject dependent evaluation, it may suggest that no user’s individual training is necessary.

Chapter 5: Daily life recognition model, experiments and validation

5.1 Model training and Optimisation

As mentioned in Chapter 3, a more reliable and accurate predictive model is desired in terms of choosing the window size used, the number and type of features, the classifier, and the number and location of sensors. Different experiments were performed to select the optimal parameters for the proposed model taking into consideration their accuracy trade-off and the design objectives. Furthermore, one of the main limitations found in the literature was collecting reliable data outside of the laboratory and including in the model calculations. Collecting data under controlled conditions does not fully consider the diversity across the participants' own behaviour and among different participants and contexts. Thus, to create a reliable method to monitor sedentary behaviour for long term monitoring across a wide population, daily life data including the one collected in free-living conditions, was used to train and evaluate the model's performance.

5.1.1 Data Labelling to set Criterion Standard

The GoPro video from each participant is visually screened in its entirety to create the data which served as the ground truth used as the response to the model's predictors. To ensure accurate labelling, the video is reproduced at a standard reproduction speed. In some cases, speed is increased depending on the length of the task undertaken by the participant (i.e. sitting for an hour) and the ability to discern the participant's activity by the viewer. In the case of the laboratory-based component, correct labelling is easier to assess since tasks were previously defined by the study. However, in the case of the free-living data, assigning a label to each data sample is considerably laborious due to the complexity, diversity and duration of annotating every task. The GoPro creates a video file for each 12 min of 2.1 GB and each participant accumulated 10-14 hours of usable data translating into a total of 750-1050 video files or 1234 GB of data. Since combining the files would be a very resource intensive process, the timestamp of the start and beginning of each task is annotated along with the video file where it occurred. Afterwards, a continuous time line is constructed using these timestamps and multiplying the video file number by its duration (usually 12 min). Occasionally, files ended before their reached their 12 min mark if the participant turned off the camera or if the battery is depleted. Whenever it occurred, the start time of these files as well the start time of the file has to be identified to create an offset by deducting the extra time cause by the standard addition of 12 min per video file. An example of the table developed for the labelling process is shown in Appendix B-1. An example of a raw data sample along with labels from both the GoPro and ActivPAL is shown in Figure 5-1.

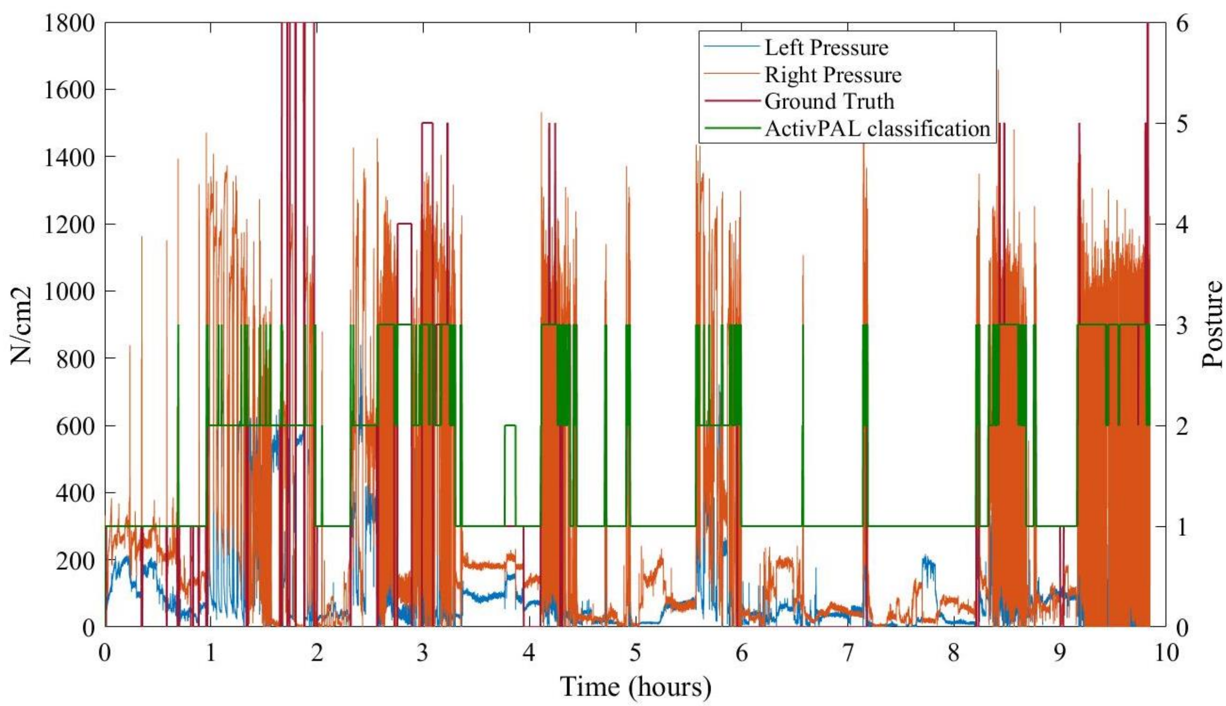


Figure 5-1. Example of raw pressure data visualization during one participant's laboratory-based data collection. The ground truth labels are as follows: 1-sitting, 2-standing, 3-walking, 4- cycling, 5-stairs and 6-leaning. In the case of the ActivPAL the values shown are 1-sitting. 2-standing and 3-stepping.

In the case of mostly relatively sedentary participants a typical weekday routine can be relatively well defined into specific periods of sitting, standing and walking times by identify posture changes (e.g. sitting to standing) of the subject and mark the time they occurred. However, some of the participants are considerably more active and performed numerous activities which translated into frequent transitions among activities. After labelling each participant's GoPro data, a label column is created in MATLAB using a nominal value to classify each of the activities of interest: Sitting, Standing, Walking, Cycling, Leaning and Stairs.

As mentioned previously, participants had the liberty to turn off the camera if they desire to do so. The periods where video footage is not collected ranged between a few minutes to a couple hours. During this periods, pressure and accelerometer data cannot be labelled and is consequently discarded. Additionally, periods in which any technical malfunction of the activPAL, pressure sensors or Go Pro Camera occur were also discarded to ensure all data from all sources is collected and properly labelled. The total amount of useful training data available is shown in Table 5-1.

Table 5-1: Total amount of time and training data available for each different task explored in this work. Standard deviation is shown in parenthesis.

Activity	Total training time (hr:min:ss)	Average amount of training time per subject (hr:min:ss)	Total number of training points per 6 seconds window
Sitting	77:59:30	5:11:58 (1:41:31)	46795
Standing	23:40:30	1:34:42 (0:42:09)	14205
Leaning	5:01:54	0:20:08 (0:08:14)	3019
Walking	15:02:12	1:00:09 (0:24:25)	9022
Cycling	2:42:18	0:10:49 (0:03:24)	1623
Stairs	2:10:00	0:08:40 (0:02:48)	1300
TOTAL	126:36:24	8:26:26 (3:02:31)	75964

5.1.2 Optimal Window calculations

The selection of an appropriate sliding window size is a crucial requirement as it divides the data into smaller useful segments from which future features will be computed. As previously discussed in section 2.4.1, time-domain features such as mean value or standard deviation are used in this work since they require less computational resources. The size and type of this window varies depending on the type of input signal as well as the parameter to be identified. Prior to determining the window length for the analysis, two of the common windowing methods for activity monitoring were considered: the sliding windows and overlapping windows [312, 313]. For the first method, data is grouped into windows of a specific size with no overlap or gap between each window, while in the second method a degree of overlap is permitted between consecutive segments. Consequentially, the overlapping windows method entails a larger amount of computations as compared to the non-overlapping methods. Since lower computational requirements is one of the main design objectives, non-overlapping sliding windowing method is preferred in this work.

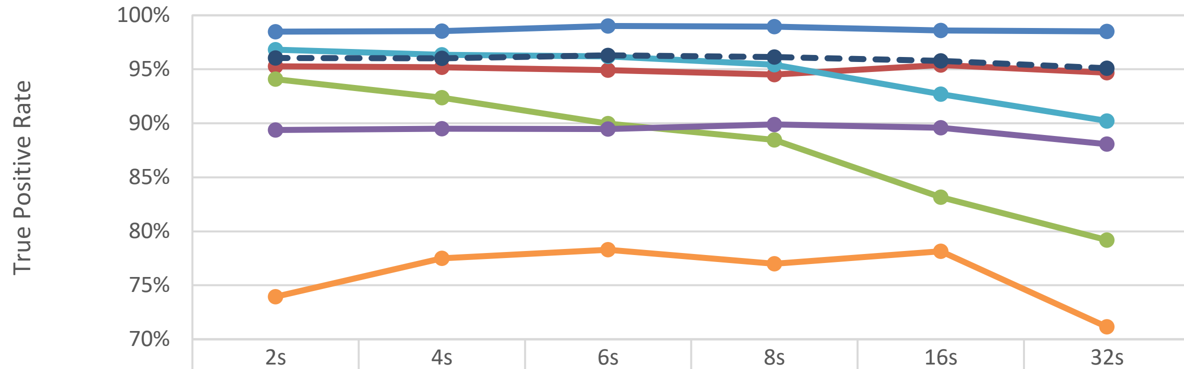
As previously discussed, choosing an optimal window size is very important since the time period over which features are computed can heavily affect its interpretation, as there is an important trade-off between choosing shorter versus longer epochs. Choosing an optimal window size contributes to selecting better discriminating features [133]. For example, if a window of 30 seconds is chosen, and the user is sitting down and decides to grab a bottle of water nearby, he will stand up, take a few steps and sit down again, covering several activities within the same 30 seconds. Any feature computed will be affected due to the averaging of these three different activities (sitting, standing and walking). Thus, a short epoch will ensure such activities overlaps are minimal, which proves to be particularly relevant if the user changes activities continuously as exemplify above. Unfortunately, a potential drawback is that a short window may create further variability by only covering a small data segment and amplifying small variations. This may be partially compensated by the fact that only a small set of activities are to be identified, the large overall data sample (12~ hours) and that subjects tend to remain in one posture for long periods of time. It is also important to note technical requirements such as reduced battery duration and limited memory capacity may play an important role is choosing the size of the window [294]. Furthermore, the effectiveness of some of the features computed are heavily influenced by the length of the window. For instance, a short window may not be able to detect the correlation between left and right foot pressure while balancing overall weight during standing or each foot's periodic landing during walking. In the case of a long window, a significant delay will be created when attempting to classify in real-time, which depending on the objectives and purpose of the model, may prove to be a serious or mild problem.

In order to find the optimal trade-off of window length, a series of experiments are designed using the Random Forest algorithm, later determined as the optimal model's classifier in Section 5.1.3. MATLAB and the Weka Toolkit 3.8 (Waikato Environment for Knowledge Analysis) [314] are used to evaluate the performance over two different feature sets: one with all the available pressure related features and a second one with a smaller set of features obtained using the Information Gain method from Section 5.1.4. All features are computed over windows length ranging from 2 to 32 seconds at a sampling rate of 10Hz meaning 260 data pointes per second for all 26 sensors, at an increasing rate of the power of 2 seconds (see Table 5-2). After reviewing the results at the end of this section, another window length of 6 seconds is considered to observe if any significant difference exists between the window of 4 and 8 seconds.

Table 5-2. Window lengths considered while searching for the optimal length for the proposed model

Pressure Samples (Per sensor)	**Pressure Samples (Per insole)**	**Time (s)**
20	520	2
40	1040	4
60	1560	6
80	2080	8
160	2600	16
320	3120	32

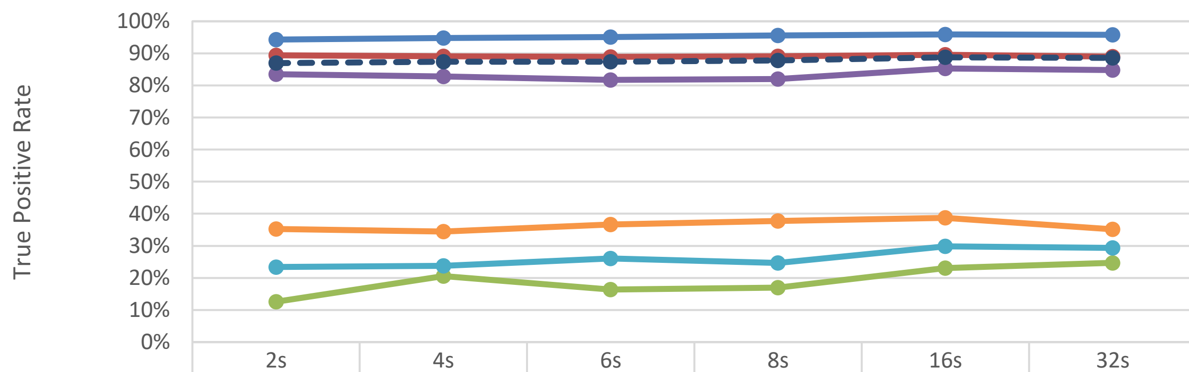
As mentioned in Section 4.3.1, the chosen sampling rate is deliberately kept low to allow long term data storage in the insoles and to prolong battery life. A window length shorter than 2 seconds is deemed too small to include due to the low sampling rate of the pressure sensors, the low predictive power and the objective of monitoring overall sedentary behaviour meaning that brief changes are not very significant. A window length longer than 32 seconds is deemed too long due to the overall reduced number of instances per feature and participant in the model. Furthermore, long windows would risk “averaging” one or more transitions among activities hampering one of the final objectives to determine the overall effect of such transitions over both short and longs periods of sedentary behaviour. The recalls during both subject independent and dependent training for each activity over the aforementioned different window lengths while evaluating the performance of the Random Forest classifier using all features are shown in Figures 5-2 and 5-3. The full extent of the computations can be found in Appendix C.



	2s	4s	6s	8s	16s	32s
sitting	98.49%	98.53%	99.01%	98.95%	98.59%	98.50%
standing	95.29%	95.18%	94.91%	94.52%	95.40%	94.68%
leaning	94.09%	92.36%	89.96%	88.46%	83.16%	79.19%
walking	89.38%	89.49%	89.47%	89.90%	89.58%	88.07%
cycling	96.82%	96.36%	96.21%	95.41%	92.70%	90.22%
stairs	73.95%	77.49%	78.29%	76.99%	78.15%	71.14%
All	96.05%	96.03%	96.29%	96.13%	95.80%	95.10%

Window Size (seconds)

Figure 5-2. Recall per activity when computing all features using sliding windows of different lengths, the Random Forest classifier and dependent training evaluation.



	2s	4s	6s	8s	16s	32s
sitting	94.30%	94.81%	95.12%	95.56%	95.90%	95.82%
standing	89.39%	89.14%	88.92%	89.09%	89.55%	89.01%
leaning	12.57%	20.55%	16.38%	16.96%	23.08%	24.71%
walking	83.53%	82.79%	81.73%	82.03%	85.29%	84.81%
cycling	23.41%	23.74%	26.05%	24.62%	29.83%	29.41%
stairs	35.21%	34.45%	36.62%	37.74%	38.71%	35.17%
All	86.96%	87.43%	87.40%	87.76%	88.77%	88.62%

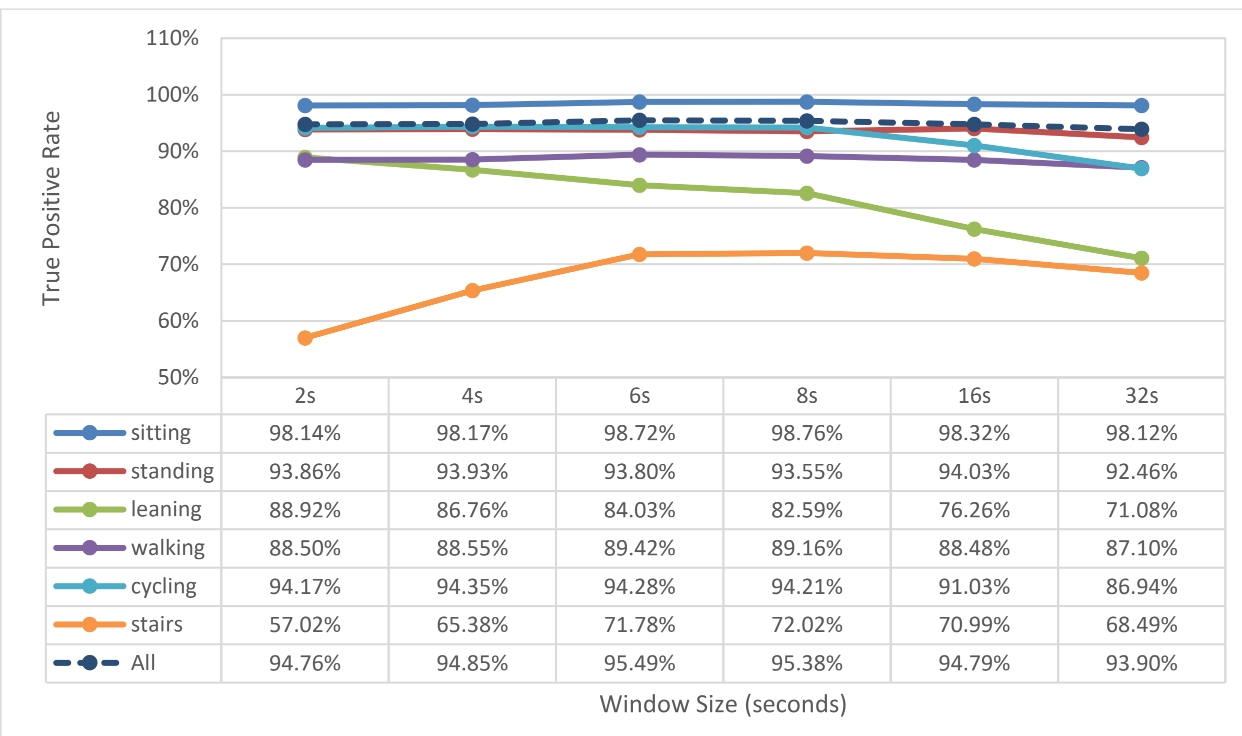
Window Size (seconds)

Figure 5-3. Recall per activity when computing all features using sliding windows of different lengths, the Random Forest classifier and independent training evaluation.

Figure 5-2 shows that maximum performance for all activities during subject dependent training is at a window length of 6 seconds. However, in the case of activities such as standing and walking, recall reaches its maximum at 16 and 8 seconds respectively. The characteristics of these activities seem to be better captured by features computed over longer windows, while sitting is better captured by a slightly shorter window. At higher window lengths beyond 6 seconds, overall performance understandably falls, since a higher window length drastically reduces the number of training instances available for the model, particularly in the case of activities that scarcely occur, such as climbing stairs and cycling. For example, 1 minute of pressure data at 10 Hz using a 2 second window yields 30 training data points per feature while a 32 second windows yields almost 2 training data points, showing a drastic reduction in usable data. In fact, one of the main problems with uncommon activities such as leaning or brief activities such as climbing or descending stairs is the small amount of training data point available for the model to make accurate predictions. A graphical representation of this problem is shown in Figure 5-2 where activities such as stairs, leaning and cycling get gradually worse as the window length increases and activities with longer duration are significantly less affected.

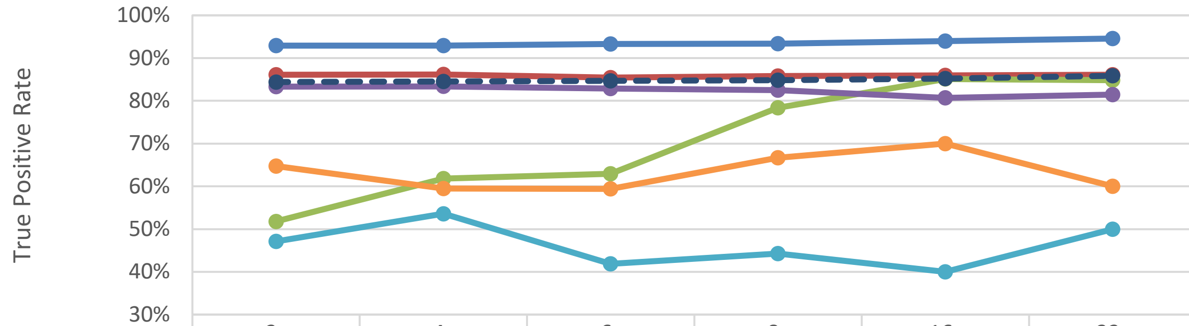
During subject independent training, the maximum recall for all activities occurs at a window length of 16 seconds. An increase in performance can be observed as the window length increases. Such increment can be explained by the fact that longer window lengths may smoothen the variability among the participants' variations on each activity and improve the model's ability to predict them. Similar to dependent training evaluation but to a lesser extent, the reduction of available training data as the window increases gradually affects the overall performance of scarce and short duration activities such as cycling and leaning. In fact, the time spent of most participants in cycling is minimal in comparison with time spent sitting or standing during the day. Participants rarely engage in cycling, meaning that a very small set of data is available during training to accurately construct the model to accurately predict it. Thus, the model is prone to misclassify cycling due to the potentially low pressures involved depending on the resistance of the bike. Stairs and leaning suffer from the same problem as they probably are being classified as standing. It seems that dependent training supports shorter window lengths while independent training supports longer window lengths mainly due to the discrepancies of how each individual participant performs his or her activities. Furthermore, in the case of subject dependent training, the amount of data available is smaller compared to the one used in independent training since only one participants' data is used at a time.

The results of the computations using features obtained using Information Gain are presented in Figures 5-4 and 5-5.



	2s	4s	6s	8s	16s	32s
sitting	98.14%	98.17%	98.72%	98.76%	98.32%	98.12%
standing	93.86%	93.93%	93.80%	93.55%	94.03%	92.46%
leaning	88.92%	86.76%	84.03%	82.59%	76.26%	71.08%
walking	88.50%	88.55%	89.42%	89.16%	88.48%	87.10%
cycling	94.17%	94.35%	94.28%	94.21%	91.03%	86.94%
stairs	57.02%	65.38%	71.78%	72.02%	70.99%	68.49%
All	94.76%	94.85%	95.49%	95.38%	94.79%	93.90%

Figure 5-4. Recall per activity when computing Information Gain features using sliding windows of different lengths, the Random Forest classifier and dependent training evaluation.



	2s	4s	6s	8s	16s	32s
sitting	92.92%	92.95%	93.32%	93.34%	94.00%	94.57%
standing	86.09%	86.16%	85.44%	85.83%	85.97%	86.13%
leaning	51.8%	61.8%	62.9%	78.4%	85.1%	84.8%
walking	83.32%	83.37%	82.85%	82.53%	80.70%	81.49%
cycling	47.1%	53.6%	41.9%	44.3%	40.0%	50.0%
stairs	64.7%	59.5%	59.4%	66.7%	70.0%	60.0%
All	84.40%	84.49%	84.69%	84.81%	85.18%	85.86%

Window Size (seconds)

Figure 5-5. Recall per activity when computing Information Gain features using sliding windows of different lengths, the Random Forest classifier and independent training evaluation.

The results indicate that despite the performance drop due to the smaller number of features used, recall behaves similarly as with using the sensor pressures individually. More common activities such as sitting, standing and walking have the smaller decrease in performance, while more uncommon activities such as leaning and stairs, are much more negatively affected.

As shown in Figure 5-4, a window length of 6 seconds obtains the best overall performance in regards of individual and overall activity recognition during dependent training. Thus, after analysing the model's prediction accuracy with different sliding window lengths, the results indicate that the best window length depends on the activity and its characteristics, such as its duration or being static or dynamic. Unfortunately, having a different sliding window for each different activity would negatively affect one of the key design goals of keeping a low computational cost.

In summary, two different sets of features are tested at increasing window lengths during both subject dependent and independent training. Afterwards, the optimal trade-off between the possible loss of accuracy of some activities and meeting the design goal is determined. In the end, a window of 6 seconds is shown to be sufficiently short to avoid any significant delay in activity recognition and detect quick transition of activities as well as minimising any issues of introducing variability to static activities such as sitting. Specifically, in the case of subject dependent training, optimal recognition of infrequent activities such as stairs or leaning was found, allowing an accurate identification despite the overall smaller sample size of a single participant. Furthermore, this window length produces a relatively short real-time recognition delay, allowing the user to ultimately receive possibly useful feedback. The main disadvantage of not using a larger window was a reduction of overall performance during independent training. Nevertheless, since the main goal is to monitor sedentary behaviour (i.e. sitting time) the trade-off is considered advantageous in the end.

5.1.3 Optimal Classifier selection

In order to select an optimal classifier in terms of low computation cost, fast training and accurate classification times, the Weka Toolkit 3.8 (Waikato Environment for Knowledge Analysis) [314] is used to make a comparison among popular classifiers in activity detection monitoring. As discussed in section 2.4.2, the following classifiers selected in this work are the naïve Bayes classifier, Decision Tables, the J48 classifier (commonly known as C4.5), the Nearest Neighbour classifier, the Logit Boost classifier, the Bagging classifier and finally the Random Forest classifier. Regarding the classifier's parameters, different approaches have been taken to improve some of the classifier's performance. Before applying the Naïve Bayes classifier, data is discretised to transform numerical variables into categorical counterparts and improve performance. In the case of Nearest Neighbour classifier, Euclidian distance and the value of "10 K" (10 nearest neighbours) were the optimal parameters. The number of nearest neighbours is determined by dividing the data into training and evaluation sets and evaluating which value of K does the best job of classifying the evaluation data set based on the training set. For the J48 classifier, multiple iterations with different confidence factors is performed to find the optimal parameter. Pruning is done as well to reduce the number of leaves on the tree and consequentially lessen the training times and computational cost. The LogitBoost classifier uses 10 iterations (i.e. number of trees) and one level decision tree called Decision Stump, which is often used as components in machine learning ensemble techniques such as boosting. Similarly, for the Bagging method, 10 iterations are also used with the REPtree Classifier as the base classifier. For the Random Forest classifier, the standard 100 iterations (i.e. number of trees) and an unlimited tree depth is selected to ensure the maximum possible performance is reached.

The classifiers are evaluated by comparing their performance during both training and classification when using all features and subset of features obtained by applying the Information Gain criterion (see Section 5.1.4). The complete table with all relevant performance measurements is shown in Appendix D. Features are computed using 6 seconds sliding windows as previously discussed and determined in section 5.1.2. Two main parameters are compared to assess each classifier overall performance. The first is training and classification time since lower times mean lower computational cost while the second is overall accuracy during both subject dependent and independent methods. After running the model in the Weka Toolkit with each classifier and each combination of features using a 2.5 GHz Intel core microprocessor, training and classification times are extracted and presented in Tables 5-3 and 5-4. Training and classification times are individually obtained for each participant in the case of the subject dependent method and across all participants in the case of the subject independent method.

Table 5-3. Average times in seconds required by each classifier for training and classification when using subject dependent training

Classifier	All features (s)		Information Gain Features (s)	
	Training	Classification	Training	Classification
Nearest Neighbour	0.0003	0.5335	0.218	0.425
Naïve Bayes	0.2045	0.0432	0.215	0.027
Decision Tables	5.6884	0.0019	3.890	0.002
J48	0.3679	0.0002	0.282	0.002
Bagging	3.44	0.0013	.80	0.006
LogitBoost	3.5574	0.0013	0.723	0.003
Random Forest	0.5338	0.0031	0.346	0.005

Table 5-4. Average times in seconds required by each classifier for training and classification when using subject independent training

Classifier	All features (s)		Information Gain Features (s)	
	Training	Classification	Training	Classification
Nearest Neighbour	0.004	69.151	6.305	16.322
Naïve Bayes	8.167	0.495	5.019	0.096
Decision Tables	115.181	0.027	19.294	0.014
J48	24.666	0.004	4.976	0.014
Bagging	41.52	0.010	12.05	0.020
LogitBoost	89.555	0.009	8.219	0.015
Random Forest	17.783	0.058	6.737	0.045

From to the results obtained using all features, the Nearest Neighbour (NN) classifier have the fastest training times and the highest classification time in both. This is to be expected due to its simplicity during training in which only the distances among all training examples are computed. On the other hand, classification times are considerably longer (around 140 times longer) than the rest of the classifiers since every instance must be compared among each other before being classified. In fact, a classification time of 69 seconds would be too long for any real-time implementation. Despite its flexibility, the Nearest Neighbour classifier may be too computationally expensive for this application since it also needs all training data points to be locally stored.

High memory requirements should be avoided since one of the key design goals to have a low-cost implementation, meaning the Nearest Neighbour classifier in its current form is suboptimal. Following the Nearest Neighbour classifier, the Naïve Bayes (NB) behaves similarly having the second fastest training time and the second longest classification time. Although Naïve Bayes is 12 times faster than Nearest Neighbour, it is also at least 14 times slower compared to the rest of the classifiers. Moreover, Naïve Bayes, like the Nearest Neighbour classifier, are only based on memory/training data, meaning that they require the parameters of a Gaussian distribution to be stored in the internal memory. Depending on the specifications of the final device, this may be too taxing for low power computational processors. Regarding training time, J48 and Random Forest are the third and fourth fastest classifiers respectively during dependent evaluation training. During independent training, their orders are reversed, and Random Forest becomes the faster of the two, showing that when training with a larger data set, the Random Forest classifier can outperform the J48 classifier. However, in terms of classification time, J48 is the fastest of all classifiers, while Random Forest is the fourth slowest. Both performances can be explained by the fact that J48 classification consists only simple splitting of the “best” decision tree rule using the “best” feature, while random forest involves potentially unlimited decision trees with random selection of features to split on. Bagging and LogitBoost have the fifth and the sixth longest training times during both dependent and independent evaluation. LogitBoost is 4 to 7 times slower than Random Forest and J48 while Bagging is 2 to 3 times slower. This performance makes sense since both Bagging and Boosting are iterative method (10 iterations in this case) with different approaches. In Bagging each model uses a different sample, giving them a subtly different focus and perspective on the problem, while in LogitBoost new models are influenced by putting extra weight on weaker features and misclassified instances of previously built models. Long training times are a significant issue during subject dependent training, since the user would have to endure the long waiting time first for the training to be completed with his own data, delaying his actual activity classification. Finally, the Decision Table classifier has the worst performance during training in all cases.

Some significant changes in classifier performance occur when training using Information Gain features due to the filtering done when selecting features. First, Nearest Neighbour classifier no longer has the fastest training times of all classifiers. In fact, with the exclusion of Decision Tables, training times for all classifiers are relatively similar in both Dependent evaluation (0.35 ± 0.21 seconds) and Independent Evaluation (6.25 ±1.34 seconds). In terms of classification times, Nearest Neighbour is still the slowest classifier followed by the Naïve Bayes classifier. Among the remaining classifiers, Random Forest exhibits the seconds slowest classification time although it still is 2 to 6 times faster than Naïve Bayes in subject dependent and independent evaluation respectively. Finally, classification times for J48, Bagging, Decision Tables and LogitBoost are not very significant.

To summarise, the best classifiers in terms of computational performance for all presented scenarios are the J48 classifier and the Random Forest classifier. Both classifiers have relatively low computational cost and medium range training and classification times. However, LogitBoost, Bagging and Naïve Bayes may also be good choices. Naïve Bayes is the second fastest during training while Bagging and LogitBoost have an acceptable performance during classification and during training when using Information Gain features instead of all features. Once computational cost is considered by examining training and classification times, activity recognition must be evaluated to finally choose the optimal classifier. Each classifier is tested using every feature combination presented previously and using a 6 second sliding window as in the case of training and processing times. Training and classification are done with 10 different random seed times to minimise the impact of a single randomisation and obtain more realistic results. The performance of each classifier while using all available features is shown Table 5-5 when using the subject dependent approach and in Table 5-6 when using the subject independent approach.

Table 5-5. Recall per activity using all available features and subject dependent training.

Activity	Recall of each classifier using all features and dependent evaluation						
	Nearest Neighbour	Naïve Bayes	Decision Tables	J48	Bagging	Logit-Boost	Random Forest
Sitting	98.96%	95.46%	98.70%	98.47%	98.85%	98.61%	99.01%
Standing	92.72%	71.62%	86.95%	88.88%	93.34%	91.75%	94.91%
Leaning	85.87%	88.86%	81.90%	89.25%	89.18%	87.98%	89.96%
Walking	90.04%	85.04%	79.10%	85.89%	88.56%	88.38%	89.47%
Cycling	96.35%	95.71%	86.20%	93.25%	92.76%	93.86%	96.21%
Stairs	76.95%	84.40%	68.40%	74.16%	75.71%	77.37%	78.29%
ALL	95.73%	89.31%	83.54%	94.24%	95.64%	95.18%	96.29%

Table 5-6. Recall per activity using all available features and subject independent training.

Activity	Recall of each classifier using all features and independent evaluation						
	Nearest Neighbour	Naïve Bayes	Decision Tables	J48	Bagging	Logit-Boost	Random Forest
Sitting	98.56%	85.51%	92.33%	94.05%	96.76%	97.25%	98.38%
Standing	76.53%	42.08%	68.00%	74.24%	83.13%	79.23%	92.89%
Leaning	55.60%	78.45%	18.60%	32.16%	38.11%	29.99%	68.23%
Walking	83.11%	73.71%	32.25%	70.90%	81.64%	87.58%	88.03%
Cycling	54.09%	76.09%	30.18%	45.83%	60.36%	50.59%	75.97%
Stairs	43.89%	65.55%	42.58%	35.99%	45.63%	39.18%	64.70%
ALL	89.13%	73.43%	47.32%	83.68%	88.25%	87.74%	94.00%

As shown in Tables 5-5 and 5-6, overall recall for all classifiers during subject dependent evaluation are significantly better compared to subject independent. This can be partly explained due to the evaluation methods since dependent training is evaluated using 10 -fold cross validation and independent training is evaluated using an independent test set (the excluded participant), which tends to give a more pessimistic result. The Random Forest classifier has the best overall performance with Nearest Neighbour having the second best one. The Naïve Bayes classification rates are not surprising since the classifier considers all features independently and given the unequal number of data for each activity, trouble discerning among them would be expected. On the other hand, the Random Forest performance makes sense since each iteration of the classifier further concentrates on the weaker features discovered in previous iterations. In summary, the performance of all classifiers during subject dependent evaluation is within a small margin (94.24% - 96.29%) excluding both the Naïve Bayes and the Decision Table classifiers.

In the case of independent subject evaluation, the drop of performance for some activities is more pronounced. The hardest activities to classify correctly are stairs or leaning depending on the classifier. This is understandable since the pressure both activities have a small number of training points and vary considerably among participants. Features obtained from accelerometery which is further discussed in section 6.1.1, would most likely improve its accuracy in classification. Similarly, leaning may be misclassified as standing since the leaning activity is relatively different among participants and consequentially, the angle at which they lean against the wall will vary the overall weight supported. Thus, the highest rate for leaning is 78.45% using Naïve Bayes, while on the case of stairs, the best rate is 65.55% also using Naïve Bayes. Unfortunately, Naïve Bayes' sitting and standing recognition is the worst of all classifiers, which significantly drops its average recall due to the high prevalence of these activities. Furthermore, there seems to be a trade-off between accurately detecting common activities such as standing, sitting and walking compared to less frequent activities such as leaning, stairs and cycling. However, Random Forest seems to be the exception as it has the highest performance for both sitting and standing and also relatively good performances in leaning and stairs. Nevertheless, all classifiers except Naïve Bayes show a good performance recognizing sitting (92.33% to 98.56%), which is the activity of greatest interest since it is the most prevalent form of sedentary behaviour. Furthermore, it should be noted that during subject dependent evaluation, classifiers still show good performance when classifying all activities. A possible explanation may be that the model detects and learns using the participant's own variation of uncommon activities such as leaning, improving the recognition rate for that participant in specific.

The same set of experiments is performed to assess how does the classifiers performance is affected when using the features selected using the Information Gain criterion. Each classifier is tested using a 6 second sliding window, while training and classification was also done with 10 different random seed times to minimise the impact of a single randomisation and obtain a more realistic result. Performances of each classifier is shown Table 5-7 when using the subject dependent approach and in Table 5-8 when using the subject independent approach.

Table 5-7. Recall clustered per activity using Information Gain features and subject dependent training.

Activity	Recall of each classifier using Information Gain features and dependent evaluation						
	Nearest Neighbour	**Naïve Bayes**	**Decision Tables**	**J48**	**Bagging**	**LogitBoost**	**Random Forest**
Sitting	98.82%	97.36%	98.70%	97.85%	98.22%	98.32%	98.71%
Standing	82.62%	90.86%	86.95%	87.74%	90.47%	89.81%	93.79%
Leaning	86.71%	85.04%	81.90%	79.30%	80.37%	83.09%	84.03%
Walking	90.55%	87.52%	79.10%	84.37%	85.16%	87.09%	89.42%
Cycling	96.59%	97.72%	86.20%	84.97%	87.69%	92.71%	94.25%
Stairs	75.27%	82.06%	68.40%	62.92%	60.99%	72.73%	71.87%
ALL	94.36%	95.05%	83.54%	92.67%	93.56%	94.18%	95.51%

Table 5-8. Recall clustered per activity using Information Gain features and subject in independent training.

Activity	Recall of each classifier using Information Gain features and independent evaluation						
	Nearest Neighbour	**Naïve Bayes**	**Decision Tables**	**J48**	**Bagging**	**LogitBoost**	**Random Forest**
Sitting	98.42%	83.18%	95.74%	94.26%	93.52%	96.88%	94.70%
Standing	66.00%	55.14%	64.30%	69.54%	78.86%	69.52%	88.18%
Leaning	32.70%	75.14%	6.10%	14.38%	15.40%	15.10%	12.50%
Walking	92.68%	77.72%	47.88%	69.08%	77.10%	68.78%	83.08%
Cycling	24.28%	75.59%	1.08%	15.26%	11.26%	12.36%	2.68%
Stairs	20.32%	63.86%	12.84%	18.54%	13.10%	9.72%	5.46%
ALL	86.26%	75.53%	79.72%	80.88%	83.46%	83.88%	85.60%

The results indicate that overall performances while using subject dependent training are again significantly better compared to subject independent training. The different number of features does not significantly change overall performance subject dependent evaluation. Random Forest is still the classifier with the best performance followed by Nearest Neighbour, which is followed closely by Bagging and Logit Boost. Nevertheless, the performance of all classifiers is within a small margin of 92.05% to 95.51% (excluding the case of the Decision table classifier).

In the case of independent subject evaluation, the Nearest Neighbour and Random Forest classifiers have the highest performance with overall performance drops of 8.1% and 11.59% respectively. The Naïve Bayes overall recall dropped the most at 19.52%, but it also the highest recall when detecting leaning and stairs, following the trend observed while using all features. In fact, all classifiers perform considerably worse when predicting leaning with the highest recall rate after Naïve Bayes being Nearest Neighbour with 32.70% and the lowest being J48 with 14.38%. After feature selection, features computed from individual pressure sensors are mostly disregarded in favour of features computed with overall foot pressure data since most frequent activities such as sitting and standing perform well with overall pressure, unlike leaning. Interestingly, overall sitting prediction rate did not vary significantly when using all features or Information Gain features. This result suggests that sitting is easier to discern among all other activities due to its unique characteristics captured in just a few features. However, another possible explanation for this variation in activity prediction performance relies on the amount of training examples available for each activity as participants spend more time sitting, standing and walking than leaning, cycling or climbing stairs. It is noted that the Naïve Bayes classifier has the best performances for the least frequent activities (i.e. leaning, cycling and stairs) while using Information Gain features as the Naïve Bayes classifier may be able to better learn distinctive motion patterns per participant in comparison to the other classifiers. Interestingly, all ensemble decision tree-based classifiers (Bagging, LogitBoost and Random Forest) perform well when discerning the remaining and more frequent activities (i.e. sitting, standing and walking).

After reviewing all the classifiers performance, it is found that some of the ensemble classifiers with more complex decision trees implementations such as the Bagging, LogitBoost and Random Tree classifiers show promising performance but have non-optimal training times. Hence, further manipulation of the model parameters is done to find the optimal trade-off between computational cost and optimal performance by evaluating the loss of accuracy when gradually decreasing the number of trees and the reduced classifier training time. The results of these experiments are shown in Figures 5-6 and 5-7 when using all features and in Figures 5-8 and 5-9 when using only features obtained after applying the Info Gain criterion.

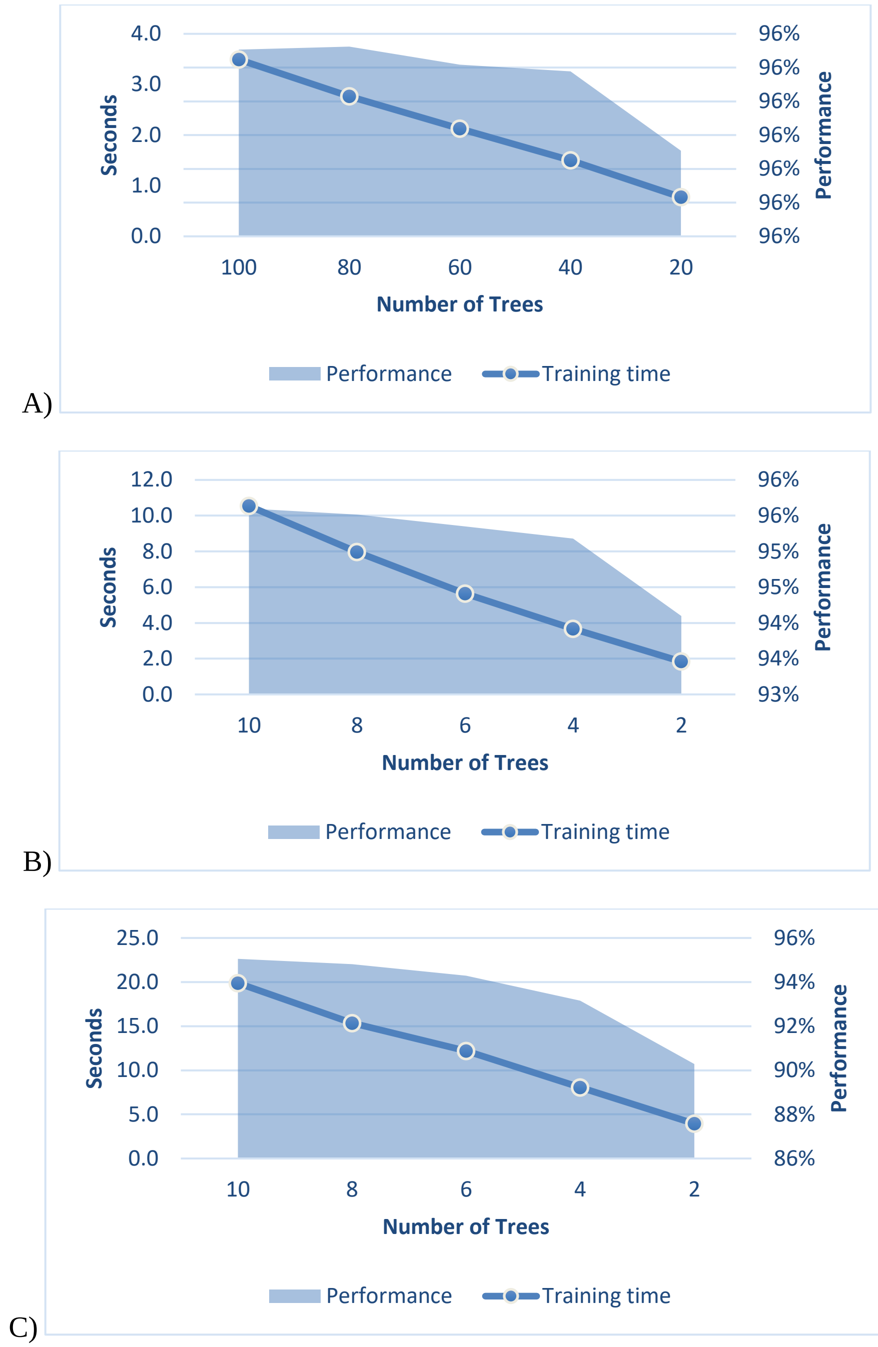
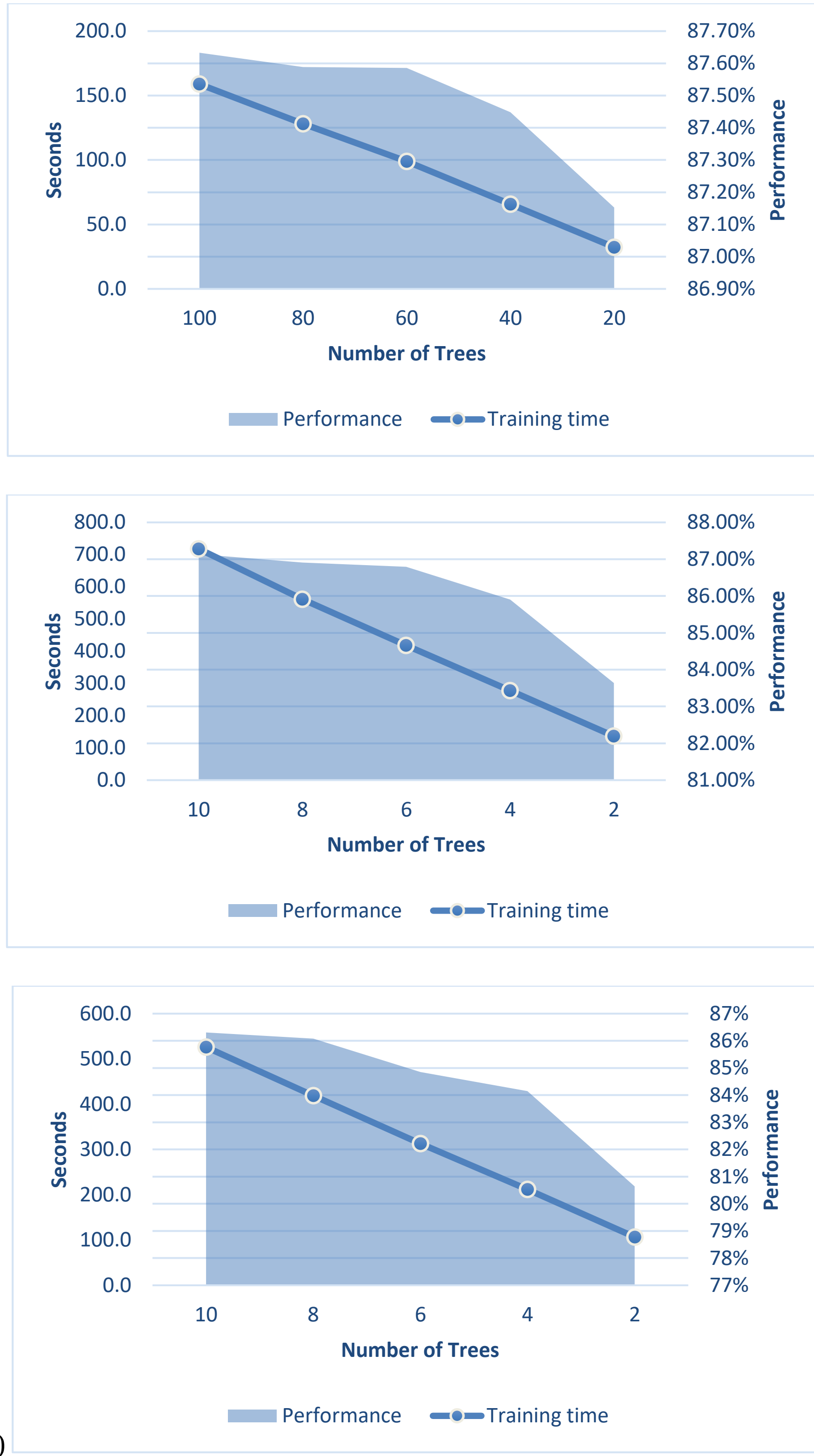


Figure 5-6. Average training times when computing all features over decreasing number of trees using the A) Random Forest, B) Bagging and C) LogitBoost classifiers during dependent training

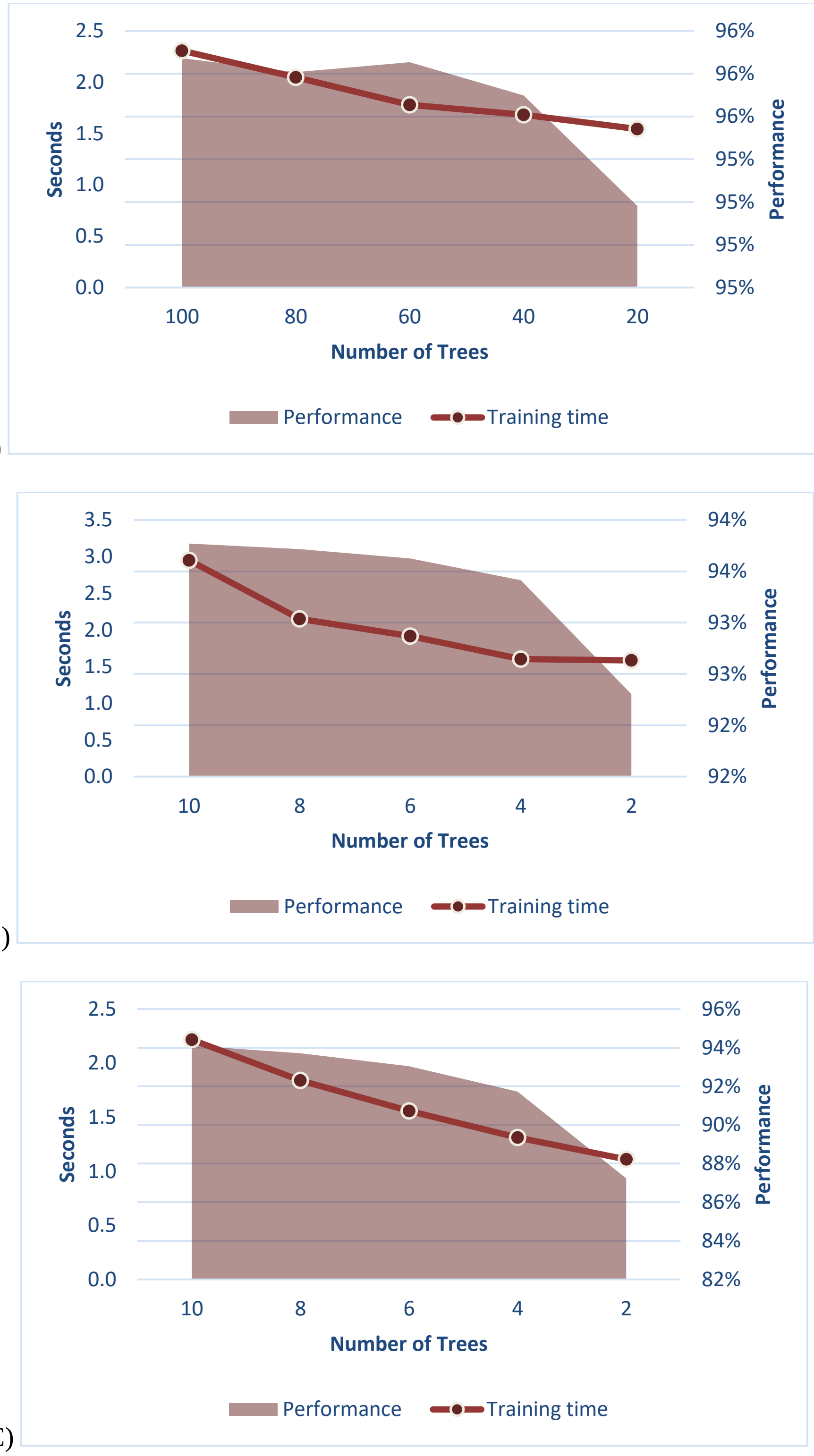


A)

B)

C)

Figure 5-7. Average training times when computing all features over decreasing number of trees using the A) Random Forest, B) Bagging and C) LogitBoost classifiers during independent training



A)

B)

C)

Figure 5-8. Average training times when computing Information Gain features over decreasing number of trees using the A) Random Forest, B) Bagging and C) LogitBoost classifiers during dependent training

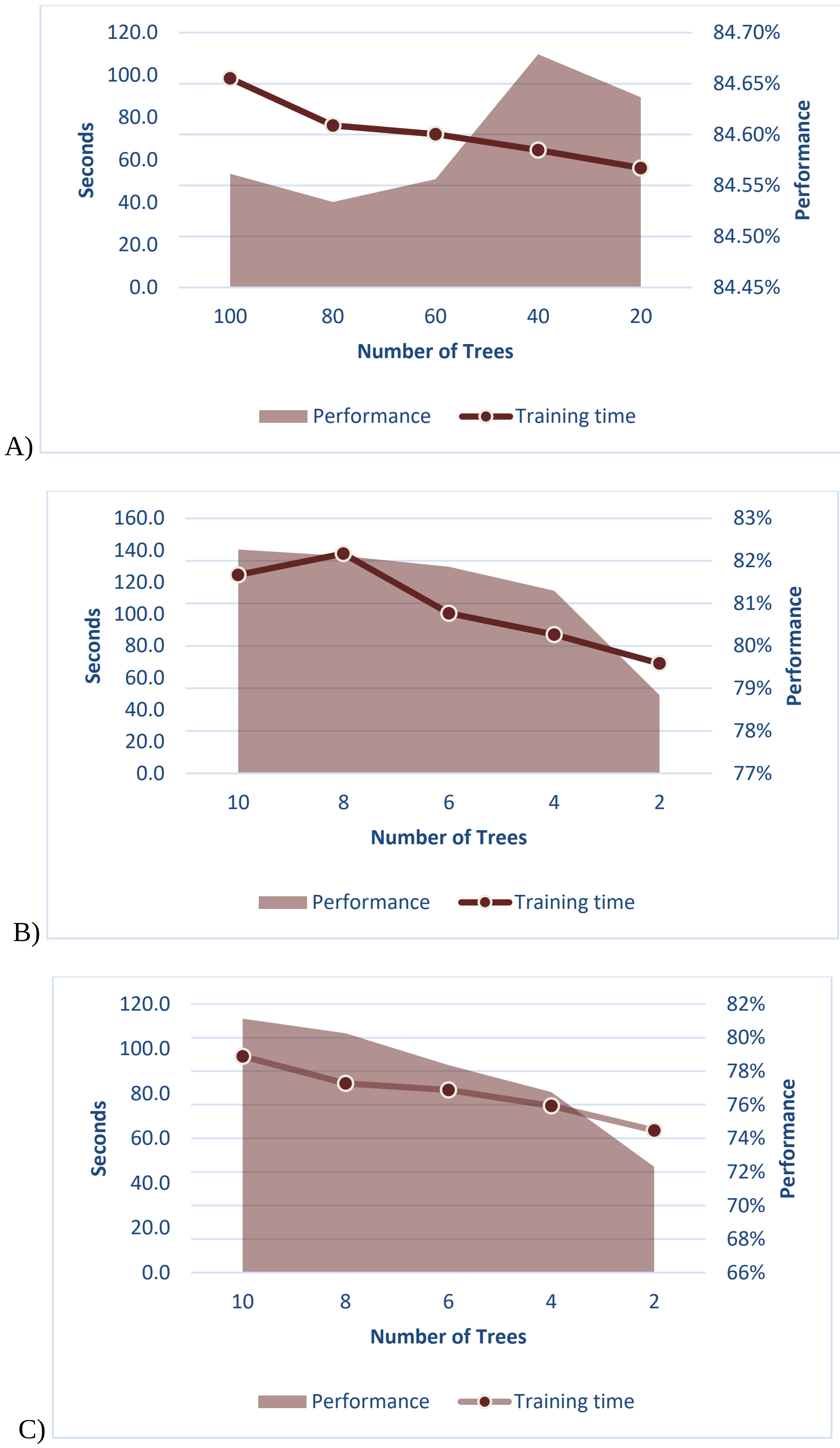


Figure 5-9. Average training times when using Information Gain features and A) Random Forest, B) Bagging and C) LogitBoost classifiers over decreasing number of trees during independent training

As can be seen in the Figures 5-6 to 5-9, all three classifiers training times gradually decrease in most of the cases when reducing the number of trees. In order to determine the best trade-off, an overall comparison of the lowest training time and performance (shaded area) among all scenarios (all features vs Information Gain features, dependent vs independent evaluation) is considered. In the case of the Random Forest, when using only the subset of Information Gain features, performance is relatively stable until a sharp decline when less than 40 iterations are used during subject dependent evaluation. Interestingly, in the case of subject independent evaluation, the highest performance occurs at 40 iterations. When using all the features available, performance decreases with slight fluctuations during dependent evaluations and more dramatic changes in performance during independent evaluation. From these comparisons, it is concluded that the lowest training time of the Random Forest Classifier prior to the biggest reduction in overall performance is obtained when using 40 iterations. In the case of the Bagging classifier, both performance and training times gradually decrease, with the highest drop in performance occurring between 4 and 2 trees. Thus, it seems that 4 trees offer the best trade off the Bagging Classifier. Finally, a similar behaviour is observed in the case of the Logit Boost, as the biggest reduction in performance occurs while using 2 trees.

After reviewing the performance of all classifiers, the best two classifiers with the best prediction rate are found to be the Nearest Neighbour and Random Forest classifiers. Unfortunately, Nearest Neighbour high classification times make it impractical in this application. Thus, the next best classifier with the third highest performance would be the LogitBoost. To better portray the difference in performance per class of the Random Forest and LogitBoost classifiers, confusion matrices are generated and shown in Tables 5-9 to 5-12 to allow a better assessment of what activities recognition would be sacrificed by choosing one classifier over the other.

Table 5-9. Confusion Matrix when computing all features using the LogitBoost classifier and dependent training evaluation.

True Class		Predicted Class					
		Sitting	Standing	Leaning	Walking	Stairs	Cycling
	Sitting	98.87%	0.62%	0.02%	0.44%	0.03%	0.01%
	Standing	2.42%	90.92%	0.89%	5.43%	0.06%	0.29%
	Leaning	1.62%	12.09%	85.56%	0.63%	0.00%	0.10%
	Walking	1.85%	9.74%	0.14%	86.74%	0.15%	1.38%
	Stairs	4.63%	0.38%	0.00%	1.27%	92.90%	0.82%
	Cycling	1.33%	2.78%	0.00%	15.25%	0.51%	80.13%

Table 5-10. Confusion Matrix when computing all features using the LogitBoost classifier and independent training evaluation.

True Class		Predicted Class					
		Sitting	Standing	Leaning	Walking	Stairs	Cycling
	Sitting	95.46%	3.88%	0.00%	0.43%	0.18%	0.04%
	Standing	13.69%	76.11%	2.06%	7.86%	0.04%	0.23%
	Leaning	12.06%	77.08%	10.17%	0.70%	0.00%	0.00%
	Walking	2.04%	15.66%	0.08%	83.26%	0.11%	1.51%
	Stairs	93.60%	2.03%	0.00%	1.78%	5.39%	0.13%
	Cycling	1.39%	9.05%	0.00%	49.37%	0.38%	22.09%

Table 5-11. Confusion Matrix when computing all features using the Random Forest classifier and dependent training evaluation.

True Class		Predicted Class					
		Sitting	Standing	Leaning	Walking	Stairs	Cycling
	Sitting	99.15%	0.60%	0.00%	0.24%	0.00%	0.00%
	Standing	1.18%	94.73%	0.06%	3.91%	0.00%	0.12%
	Leaning	0.99%	10.24%	88.41%	0.33%	0.00%	0.03%
	Walking	1.04%	9.85%	0.02%	88.31%	0.02%	0.75%
	Stairs	2.41%	0.38%	0.00%	0.95%	95.37%	0.89%
	Cycling	0.70%	2.78%	0.00%	15.25%	0.38%	80.89%

Table 5-12. Confusion Matrix when computing all features using the Random Forest classifier and independent training evaluation.

True Class							
True Class	**Sitting**	95.57%	3.95%	0.00%	0.44%	0.00%	0.03%
	Standing	5.01%	88.08%	1.56%	5.20%	0.00%	0.15%
	Leaning	3.08%	77.24%	19.21%	0.43%	0.00%	0.03%
	Walking	1.79%	13.98%	0.11%	85.05%	0.00%	1.73%
	Stairs	69.37%	2.98%	0.00%	0.19%	30.37%	0.00%
	Cycling	1.20%	6.20%	0.06%	40.38%	0.00%	34.43%
		Sitting	**Standing**	**Leaning**	**Walking**	**Stairs**	**Cycling**
		Predicted Class					

As observed in Figures 5-9 to 5-12, the Random Tree classifier performs significantly better than the LogitBoost classifier in all activities. Furthermore, during independent evaluation, there is a larger difference in performance when predicting standing and cycling. Random Forest is misclassifying 10.21% of the standing activity as sitting and walking (5.01% and 5.20% respectively) while LogitBoost is mostly confusing standing as sitting (13.69%). Both classifiers perform similarly for walking with a difference less than 1.79%, both mostly misclassifying it as standing. Finally, both classifiers perform well when classifying sitting during both subject dependent and independent training. Total training times during independent evaluation of both LogitBoost and the Random Forest after modifications are also compared and shown in Table 5-13.

Table 5-13. Average training and classification times in seconds required by each classifier during subject dependent and independent training

Classifier	**All features**		**Info Gain Features**	
	Training	**Classification**	**Training**	**Classification**
Subject Dependent				
LogitBoost	8.067	0.008	1.311	0.027
Random Forest	1.504	0.707	1.684	0.017
Subject Independent				
LogitBoost	211.725	.624	74.566	1.141
Random Forest	65.816	0.225	64.674	0.371

As shown in Table 5-13, the LogitBoost classifier still shows a longer training and classification times than the Random Forest classifier. Thus, after considering all advantages and disadvantages of each classifier, this thesis will use the Random Forest classifier with 40 iterations as the final classification algorithm due to its optimal trade-off of computational cost and overall performance. Furthermore, as later discussed in Section 6.1, the lower performance of motion-based activities such as cycling, stairs and leaning, will be addressed using accelerometers.

5.1.4 Optimal Feature Selection

Features must be extracted from the data set to accurately detect activity by detecting relevant patterns or characteristics in the pressure signal. Furthermore, it is crucial to carefully choose the number and type of features by examining their contribution for activity detection and the computational cost they have. According to the stated design purposes, the minimal number of features must be selected to keep computational cost as low as possible and keep a final potential device portable, relatively inexpensive and with a prolong battery life. In a similar approach to finding the optimal window length, this section covers the set of experiments performed to determine the optimal set of features in terms of best performance and lowest computational cost. Features are calculated using aggregated data from both feet as well as using data from each foot independently. Similarly, features are calculated on all pressure sensors. Some of these features are extracted after reviewing previous based on machine learning theory [141, 315]. Based on the main design considerations (see Section 4.1), only time-domain features are used since they require less computational resources than frequency-domain features. The complete list of time-domain features computed from each window of data is as follows: Mean, Standard Deviation, Variance, Maximum Value, Range, Root mean square, Mean Crossings, Total Area under Signal, Kurtosis, Skewness, Quartiles (First, Second and Third), Interquartile Range (Q1 and Q3), Mean difference, Signal magnitude area, Signal magnitude vector and Cross Correlation of Left and Right Foot. Simple features such as Mean and Maximum Value should clearly indicate the difference between full weight-bearing activities such as standing, partially weight-bearing ones such as leaning and non-bearing such as sitting. Standard variation and the coefficient of variation (CV) should indicate the amount of motion produced during data collection, with the difference that CV are affected by the signals' mean value (e.g., the gravitational component of acceleration), although standard deviation is not. The number of median crossings is an indicator of the frequency of changes in the signal. This would help to detect the amount or intensity of motion by identifying sedentary activity such as sitting, as well as distinguishing walking and running.

Features are ranked based on the importance of the information they provide to the model by determining which ones discern better among the activities and have a lower computational cost. To perform this selection, a technique called Information Gain criterion will be used. The Information Gain criterion feature selection technique is chosen because it is one of the fastest methods of supervised featured selection. This method provides a ranking of the most relevant features ranked by entropy (probabilistic measure of uncertainty). To obtain this optimal subset of features, computations are done per each sensor (26 pressure sensors) over sliding windows of 6 seconds in length as suggested in Section 5.1.2. Table 5-14 presents specific features classified them according to their importance based on the Information Gain criterion.

Table 5-14. List of features ordered by their Information Gain score and their significance.

Rank	Feature	Entropy
1	Total Mean of Both Insoles	0.892
2	Total RMS of Both Insoles	0.876
3	Total Max of Both Insoles	0.838
4	Total Range of Both Insoles	0.835
5	Total third Quartile Range of Both Insoles	0.834
6	Total Standard Deviation of Both Insoles	0.83
7	Total Variance of Both Insoles	0.83
8	Total Area under the Curve of Both Insoles	0.815
9	Total Interquartile Range of Both Insoles	0.744
10	RMS of Left Sensor #10	0.699
11	Max of Left Sensor #10	0.68
12	Mean of Left Sensor #10	0.664
13	Area under the Curve of Left Sensor #10	0.663
14	Maximum value of Right Sensor #5	0.641
15	Total Range of Left Insole	0.634
16	RMS of Left Sensor #7	0.633
17	Total Max of Left Insole	0.632
18	Mean of Left Sensor #7	0.632
19	Total RMS of Left Insole	0.619
20	Third Quartile Range of Left Sensor #10	0.611
21	Standard Deviation of Right Sensor #5	0.613
22	Area under the curve of Left Sensor #7	0.61
23	Variance of Right Sensor #5	0.613
24	Total Variance of Left Insole	0.606
25	Total Standard Deviation of Left Insole	0.606
26	Total Standard Deviation of Right Insole	0.604
27	Maximum value of Left Sensor #7	0.605
28	RMS of Left Sensor #11	0.604
29	Total Variance of Right Insole	0.604
30	RMS of Left Sensor #12	0.601

It is worth noting that not all sensors may necessarily be used in the final implementation since accurate prediction may be obtained using only specific sensors as discussed in section 5.1.5. Once all the relevant features are identified, their performance with discerning among all the activities of interest will be evaluated using both subject independent and dependent evaluation and Random Forest Classifier.

As can be observed in Table 5-14, the most important features are the ones computed from combining the data set of both insoles instead of computing them per sensor or per foot. Following these, the results show that features computed per foot are more important than per sensor features. This is good news according to the design goals, since reducing the number of sensors or reducing computational data per sensor would reduce computational cost. Therefore, the performance of this subset of features will be analysed to determine the model's behaviour if these features are preselected. Furthermore, it will help to determine if features obtained from just overall pressure data or obtained form only one foot are necessary to accomplish acceptable performance and perhaps reduce the required number sensors. In the current implementation, each feature is computed 26 times due to the 13 sensors on each left and right insole. However, if only overall pressure data is required, it would be possible to reduce the number of necessary sensors, reducing features computational load as well as minimising the model's training and classification times. Moreover, if features computed from only either the left or right foot are required, computational cost could be further reduced by half. Features are grouped into three different classifications presented in Table 5-15.

Table 5-15. Features grouped depending if their calculations are per individual sensors, per insole or for the sum of both insoles.

Subsets	Abbrev.	Number
Features selected with Info Gain	*Info Gain*	~150
Features per Sensor from Left Insole	*L_sensor*	170
Features per Sensor from Right Insole	*R_sensor*	170
Features from total sum of all sensors data from Left Insole	*L_Sum*	14
Features from total sum of all sensors data from Right Insole	*R_Sum*	14
Features from total sum of all sensors data from Both Insoles	*LR_Sum*	44

Features for each foot are computed after combining the overall data of the 13 sensors per insole over the 6 second window, or in the case of the features for both insoles, after combining all 26 sensors. This process keeps computationally cost low since it only involves simple linear operations. In the specific case of features that involve only one of the feet, the correlation feature is not computed. The model's performance trade-off will be evaluated when using the features filtered with the Information Gain criterion, preselected features computed from the prior sum of both feet pressure data and features obtained from each of the respective foot. Although it is reasonable to expect that performance to be similar when using Left foot or Right Foot features, both feet are evaluated independently for varication purposes. A sliding window of 6 seconds is used in the modelling using both subject dependent and independent training. Table 5-16 and 5-17 present the comparison of the activity recognition performance of each subset of features while using Random Forest, which is determined as the optimal classifier in the previous section (see Section 5.1.3). Full results are shown in Appendix E.

Table 5-16. Average recall of each feature subset using the Random Forest trained over a 6-second sliding windows using subject dependent training.

Activity	Average recall using Random Forest						
	ALL	**Info Gain**	**L_Sensor**	**R_Sensor**	**L_Sum**	**R_Sum**	**LR_Sum**
Sitting	99.01%	98.71%	98.78%	98.59%	97.46%	96.97%	98.79%
Standing	94.91%	93.79%	91.14%	90.08%	83.15%	80.04%	93.33%
Leaning	89.96%	84.03%	84.74%	81.58%	68.11%	63.62%	84.37%
Walking	89.47%	89.42%	88.52%	89.08%	83.62%	85.00%	87.62%
Stairs	96.21%	94.25%	95.38%	95.53%	81.78%	77.76%	89.20%
Cycling	78.29%	71.87%	76.95%	76.61%	54.66%	59.11%	64.73%
All	96.29%	95.51%	95.08%	94.70%	90.80%	89.91%	94.99%

Table 5-17. Average recall of each feature subset using the Random Forest classifier trained over a 6-second sliding windows using subject independent training.

Activity	Average recall using Random Forest						
	ALL	**Info Gain**	**L_Sensor**	**R_Sensor**	**L_Sum**	**R_Sum**	**LR_Sum**
Sitting	95.12%	93.99%	94.67%	94.70%	90.76%	88.87%	90.74%
Standing	88.92%	86.30%	76.45%	73.42%	66.69%	65.59%	83.32%
Leaning	16.38%	11.37%	8.39%	10.02%	14.04%	5.67%	17.38%
Walking	81.73%	81.20%	82.93%	79.94%	77.12%	71.66%	78.01%
Stairs	26.05%	1.05%	10.35%	31.40%	26.75%	11.35%	17.17%
Cycling	36.63%	13.34%	37.89%	32.40%	9.98%	6.69%	7.11%
All	87.40%	83.92%	84.49%	84.01%	79.68%	76.99%	82.57%

A minimal decrease in overall performance during subject dependent training is observed when using all features computed per sensor of both insoles and when using only the left insole (1.21%) or the right insole (1.59%). Expectedly, a relatively insignificant difference exists between right or left foot (0.38%). Stairs, leaning and stairs have a very significant drop in performance occur during independent training. Similar behaviour can be observed when features are computed per insole, with overall performance dropping more, particularly in the case. A possible explanation is that leaning relies more on features computed per sensor since one of the main differences between standing and leaning is the area of the foot where pressure is applied. Finally, when combining features from both feet and adding features computed from the sum of both insoles pressure data, a similar performance is achieved. Thus, it can be assumed that static activities are successfully discerned without analysing sensors individually.

In the case of subject independent training, overall performance was at its worst when using *L_sensor* or *R_Sensor* feature subsets. The left and right insoles have a relatively similar performance with differences of 0.48% when using computations per sensor and larger difference of 3.69% when using the sum of all sensors per insole. Differences in performance may also be influenced by the fact that sensors from the one side may have become weaker faster over the duration of the study. Although another possible explanation could be that the pressure on the right foot provides better information in terms of activity recognition, subject dependent training did not show this behaviour. Thus, before making any definite assumptions, a bigger set of data collection with different pair of insoles should be done to discard the possibility of a being a specific problem of the insoles used in this study. Regarding the performance when using both subsets *L_Sum* and *R_Sum*, overall performance became unsurprisingly worse due to the small number of features. Furthermore, a considerable decline in walking, stairs and cycling is noticed as using only overall features of one foot do not provide information to the algorithm regarding the cadence of these activities. For instance, while using feature subset *L_sensor* or *R_sensor*, using information from each individual sensor allows the algorithm to identify walking or stairs by detecting the traditional heel strike, foot flat, heel off, toe off cycle that occurs during gait.

Interestingly, the reduction in performance (1.3% and 4.87% during subject dependent and independent training respectively) for some activities is not very significant when using overall features per insole from both feet (subset *LR_Sum*) compared to using all features. It seems that using features computed from overall pressure data over both insoles achieves acceptable performance and reduces the unnecessary complexity, computational cost and added power requirements introduced by having to compute features from every single sensor. Finally, the computational cost is evaluated for each feature subset as shown in Table 5-18.

Table 5-18. Average training and classification times in seconds required by each classifier when using subject independent training.

	Training Time	**Classification Time**
All	46.651	0.225
Info Gain	27.97	0.21
L_Sensor	22.996	0.136
R_Sensor	26.806	0.138
L_Sum	11.721	0.194
R_Sum	12.497	0.199
LR_Sum	17.592	0.16

To summarise, using all available features performance has the best performance but also the highest computational cost while the feature subset obtained after applying the Information Gain criterion with a .5 entropy threshold produced the second-best performance. However, using the LR_Sum feature set achieved a similar performance with significantly reduced training times. Based on the results, it can be concluded that using overall features of both feet or features per sensor of one foot produces the optimal true positive prediction rate. Furthermore, computational cost in terms of training time is also the third lowest (17.592 seconds). Thus, in the final implementation of this work, the subset of 44 features computed with overall pressure data was used. Although it is not the least computational expensive option, it offers optimal performance for a minimal increase in computational cost. Although a possible concern arises in terms of drop of performance in stairs and cycling due to limited amount of training examples, the total impact over weighted average performance is equally small since these tasks seldom occur during daily life.

5.1.5 Optimal Sensor Location

Previous studies have shown that just a few sensors are frequently necessary to obtain acceptable performance, depending the design goals [156]. Since the objective is to recognize sitting among other types of activities, having a detailed pressure map of the foot sole is likely to be unnecessary. In fact, the previous section (see Section 5.1.4) supported this hypothesis by showing that computing and using features from overall pressure instead of individual sensors produces only a small drop in performance (1.3% during subject dependent training and 4.87% during independent training) and a significant improvement in training times and computational cost. Thus, the goal of this section is to evaluate the contribution of each individual sensor to activity recognition accuracy and determine the optimal sensor configuration in terms of performance and computational cost. The analysis in this work is performed using a backward selection method. First, the baseline accuracy for all sensors is determined using all sensors (previously done in section 5.1.5). Next, sensors are excluded one at a time from the baseline configuration and performance is evaluated. Afterwards, the configuration with the best performance becomes the new base configuration. This procedure is repeated until only one sensor is left. It is worth noting that Force related features such as Overall Force Correlation are removed from the whole procedure since Force values are obtained with resultant force from all sensors. Instead, the correlation between the sum of pressures of remaining sensors is computed and included. Sensors numbering, and location can be seen in Figure 5-10. Overall performance using each configuration is shown in Table 5-19. All computations are done using the Random Forest classifier, a sliding window of 6 seconds and both subject dependent and independent evaluation.

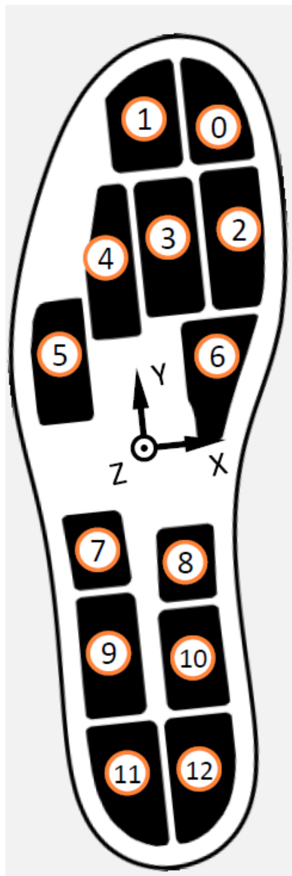


Figure 5-10. Distribution of the 13 pressure sensors across the insole. Sensor location was equal in both right and left insoles. Only one insole is shown for the sake of simplicity.

Table 5-19. Backward selection of the best sensor configuration. Bold font highlights the best average performance for each number of active sensors.

Sensor Removed	Number of Active Sensors											
	13	**12**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**
0	87.84	88.88	88.76	**89.80**	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul
1	87.39	87.69	88.67	88.91	**89.98**	Nul	Nul	Nul	Nul	Nul	Nul	Nul
2	87.63	87.84	88.86	87.83	89.17	89.73	**89.85**	Nul	Nul	Nul	Nul	Nul
3	87.75	88.41	**89.24**	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul
4	**88.26**	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul
5	86.06	86.36	86.21	86.84	87.61	87.26	87.74	86.35	86.45	85.78	82.33	**79.23**
6	87.30	87.70	88.16	88.72	89.56	89.51	89.03	88.03	87.28	86.49	**84.46**	Nul
7	86.52	87.47	87.59	87.60	88.37	88.54	88.51	88.74	87.94	**87.20**	Nul	Nul
8	86.66	87.54	87.46	88.32	89.12	89.33	88.62	**90.14**	Nul	Nul	Nul	Nul
9	86.98	**89.66**	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul	Nul
10	86.07	87.67	86.18	86.63	87.11	87.11	87.63	87.57	87.46	77.41	68.81	68.22
11	86.32	87.36	88.45	88.43	89.39	88.71	88.03	88.03	**88.19**	Nul	Nul	Nul
12	88.13	88.79	88.92	89.21	89.82	**90.02**	Nul	Nul	Nul	Nul	Nul	Nul

As shown in Table 5-19, pressure data of all available sensors is clearly redundant. The best overall performance is obtained when using only 6 sensors, namely 5, 6, 7, 8, 10 and 11. A possible explanation of the lower overall performance may be that sensors 0, 1, 3, 4, and 9 insert counterproductive variability in pressure patterns. Sensors 0 and 1 are located in the toe area suggesting that measuring pressure in the frontal area of the foot may be unnecessary. In fact, the first sensors to be removed are the ones in the upper half of the foot (0 to 4) with performance improving slightly. After crossing the optimal performance at 6 sensors, performance starts to drop at rate of 3-5% when removing some of the sensors at the heel and central foot area. Furthermore, the last sensor to be removed and the one with the most important information for activity recognition is sensor 10, located in the heel area. This may indicate that the heel area of the foot is more relevant for activity recognition, a result that agrees with other studies found in the literature [156]. Finally, the computational cost is evaluated for each sensor configuration as shown in Table 5-20. Training times gradually decrease as sensors are removed with some surprising exception in which they slightly increase.

Table 5-20. Average training and classification times in seconds required by each sensor configuration.

Time	Number of Sensors											
	13	**12**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**
Training	7.85	8.85	8.23	8.32	7.74	6.60	6.65	6.57	6.96	6.18	5.88	6.53
Classifi-cation	0.033	0.034	0.037	0.041	0.027	0.029	0.034	0.033	0.032	0.036	0.034	0.040

5.2 Results: Model Integration

Once the best parameters are identified, the proposed model's performance is evaluated. Three different sets of features are considered for the calculations: a worst-case scenario using all features, a set with features calculated with the Information Gain criterion, and an optimal scenario where the LR_Sum feature set is used which is the least computationally expensive of the three. These last two features sets are considered since they showed similar performance as shown in section 5.5.4. Furthermore, computations are also done using two configurations: one with all sensors and the other one using only 6 sensors (5,6,7,8,10 and 11), which is deemed to be the one with the optimal trade-off in terms of accuracy and computational cost in Section 5.1.5. A sliding window of 6 seconds is used in the modelling and both subject dependent and independent evaluation is considered. Tables 5-21 and 5-22 present the comparison of the activity recognition performance of each case while using Random Forest, determined as the optimal classifier in section 5.1.3. Full performance measurements are shown in Appendix F.

Table 5-21. Average recall using both Laboratory and Free-living data and the Random Forest classifier over a 6 second sliding windows during subject dependent training.

Activity	All features		LR_SUM Features		Information Gain Features	
	All sensors	Optimal Sensors	All sensors	Optimal Sensors	All sensors	Optimal Sensors
Sitting	99.01% ± 1.39%	98.9% ± 1.62%	98.79% ± 1.86%	98.67% ± 1.74%	98.73% ± 2.08%	98.72% ± 2.01%
Standing	94.91% ± 2.5%	94.2% ± 2.87%	93.33% ± 3.15%	92.92% ± 3.03%	93.87% ± 2.88%	92.86% ± 3.56%
Leaning	89.96% ± 7.72%	87% ± 8.15%	84.37% ± 9.83%	84.7% ± 9.73%	84.01% ± 9.65%	82.27% ± 9.4%
Walking	89.47% ± 11.86%	88.82% ± 12.27%	87.62% ± 12.37%	86.78% ± 13.48%	89.38% ± 12.11%	88.57% ± 12.55%
Cycling	96.21% ± 6.31%	94.93% ± 6.47%	89.2% ± 10.67%	87.52% ± 10.98%	94.43% ± 7.99%	92.59% ± 10.2%
Stairs	78.29% ± 14.65%	76.39% ± 14.48%	64.73% ± 19.99%	68.39% ± 16.55%	72.15% ± 17.08%	67.71% ± 18.2%
ALL	96.29% ± 4.32%	95.83% ± 4.79%	94.99% ± 6.32%	94.8% ± 6.08%	95.51% ± 5.28%	95.03% ± 6.02%

Table 5-22. Average recall using both Laboratory and Free-living data and the Random Forest classifier over a 6 second sliding windows during subject independent training.

Activity	All features		LR_SUM Features		Information Gain Features	
	All sensors	Optimal Sensors	All sensors	Optimal Sensors	All sensors	Optimal Sensors
Sitting	95.12% ± 5.91%	94.75% ± 5.86%	90.74% ± 6.27%	92.91% ± 5.95%	93.32% ± 5.49%	93.31% ± 5.18%
Standing	88.92% ± 7.38%	87.52% ± 8.23%	83.32% ± 10.19%	85.1% ± 10.02%	85.44% ± 9.87%	87.35% ± 8.73%
Leaning	16.38% ± 18.72%	22.22% ± 23.98%	17.38% ± 16.09%	16.66% ± 17.68%	9.84% ± 11.34%	10.41% ± 11.89%
Walking	81.73% ± 16.55%	82.77% ± 14.91%	78.01% ± 16.47%	81.93% ± 15.45%	82.85% ± 19.54%	84.2% ± 13.37%
Cycling	26.05% ± 30.66%	35.78% ± 34.67%	17.17% ± 19.82%	22.73% ± 27.49%	1.26% ± 2.86%	5.93% ± 9.3%
Stairs	36.62% ± 22.81%	36.96% ± 17.12%	7.11% ± 5.78%	14.16% ± 13.73%	14.03% ± 13.15%	8.11% ± 9.45%
ALL	87.4% ± 18.3%	87.44% ± 16.72%	82.57% ± 19.26%	84.92% ± 19.04%	84.69% ± 21.51%	85.18% ± 21.43%

5.3 Discussion

As shown in Tables 5-21 and 5-22, overall recalls for all configurations during subject dependent evaluation are significantly better compared to subject independent evaluation. It is worth noting that this difference in performance may be due to the different validations methods since independent evaluation uses an independent test set. Unsurprisingly, the best overall performance occurs when using all available features and six sensors. However, this just occurs when using all features, since computations with the rest of the feature sets follow closely behind. Nevertheless, there is only a small drop in overall performance (≤0.53%), particularly in the case of sitting, and standing. A more significant change occurs in the case of cycling and stairs, and, to a lesser extent, in leaning. This makes senses, since the same behaviour is observed when analysing the changes in performance when using different features sets in Section 5.1.4 and different sensor configurations in Section 5.1.5.

In the case of independent evaluation, the best overall performance occurs when all features and only 6 sensors are used. More interestingly, overall performance is slightly higher (0.04% to 2.35%) in the rest of the 6-sensor configurations, an encouraging result that suggests a general good performance of the selected parameters. Unfortunately, a sharp drop in performance occurred when predicting both leaning and climbing stairs in comparison to subject dependent training. A possible explanation for this considerably low recognition rate is that these two activities may vary considerably among participants. This misclassification intensifies due to the complexity of both activities during free-living settings. In fact, leaning is an activity not strictly defined and relatively difficult to assess. Moreover, leaning can be further divided into different degrees depending on the inclination of the participant and how much weight is being supported by the object, structure or wall. For example, during daily life, participants lean against elevator walls, benches, walls, cubicles, poles, windows, etc. depending on their relevant locations such as work, home or while commuting. Furthermore, it is observed that all leaning activities are relatively different among participants compared to standing or sitting. In fact, some participants rarely lean at all, reducing the quality of the model to recognize the activity by offering few training examples or biasing the model with a certain leaning activity by a specific participant. A similar situation occurred with stairs since the number of stairs and stair climbing duration of each participant varied significantly. Moreover, many different types of stairs are observed such as number of steps, width, length and step distribution, further introducing confounding factors to the model. Another problem found with cycling was the limited amount of training examples since almost none of the participants cycled during the free-living component. That being said, recalls of both activities performed relatively well during subject dependent evaluation suggesting it is mostly an issue when trying to predict these activities without first training the model with own user data. In the case of cycling, it can be observed that using less features or sensors drastically reduces its recognition performance. This is supported by similar behaviour being observed in section 5.1.4 when exploring different features sets. Fortunately, activities of greater interest such as sitting standing and walking show good acceptable performance rates.

The second main consideration to assess each configuration overall viability are classifications and training times since they reflect computational cost. As in previous occasions, each configuration is tested with the Weka Toolkit using a 2.5 GHz Intel core microprocessor; training and classification times are extracted and presented in Table 5-23. Training and classification times were individually obtained for each participant and averaged in the case of the subject dependent method and across all participants in the case of the subject independent method.

Table 5-23. Average training and classification times in seconds required by each classifier.

	All features		LR_Sum Features		Information Gain Features	
	All sensors	**Optimal Sensors**	**All sensors**	**Optimal Sensors**	**All sensors**	**Optimal Sensors**
Subject Dependent						
Training	1.697	1.594	0.856	0.997	1.559	1.257
Classification	0.009	0.011	0.008	0.015	0.012	.013
Subject Independent						
Training	81.350	65.353	35.169	46.623	107.962	47.947
Classification	0.106	0.112	0.095	0.139	0.235	0.125

The configuration in which all sensors and features have the highest training time occurs while using all sensors and Information Gain features during independent training. It seems that the additional calculations to obtain the highest ranked features using the Information Gain method prolonged training time more than all the features. The lowest training times are found while using the LR_Sum feature set and only 6 sensors. This is to be expected, since the LR_Sum feature set has the smallest number of attributes (44). Similarly, the amount of data from the sensors handled by the model is reduced by more than half (7/13) by omitting redundant sensors, further reducing the computational cost. The same trend can be observed in both dependent and independent evaluation. To summarise, the best configuration in terms of overall performance and computational performance is the one using 6 sensors and the LR_Sum feature set with a recall of 94.8% and training times of 0.856 seconds using subject dependent training and a recall of 84.92% and training times of 35.169 seconds using independent training.

Chapter 6: Model Improvement, Validation and Discussion

6.1 Performance combining plantar pressure and acceleration data

The proposed model presented in section 5.2 has a reasonable performance of 94.8% during dependent training and 84.92% during independent training while using a 6-seconds sliding window, Random Forest classifier, all features, and 6 plantar pressure sensors. This section will further explore if incorporating accelerometer data to the model improves its overall performance, particularly in the case of dynamic activates such as climbing stairs, cycling and walking.

6.1.1 Incorporation of Foot Accelerometer

As discussed in Section 2.3.3, accelerometers have been one of the most important technologies used for activity recognition and physical activity monitoring. They have been incorporated into large-scale public health research and have shown to be instrumental due to their low energy requirements, small size and overall reliability. Unfortunately, they are not well suited for activities which are mostly static and underperform when used to measure sedentary behaviour monitoring. Nevertheless, as discussed in Section 2.3.3, accelerometers have shown excellent performance when identifying non-static activities with period motions such as walking. Thus, this section will explore if the addition of foot-based accelerometers sufficiently improves the proposed model performance to justify the added computational cost.

Data is extracted at a sampling rate of 10 Hz (same as the pressure sensors) from an accelerometer located at the centre of each insole. Performance is obtained by training the model using features only from the insoles' accelerometer data, while also identifying the most discriminant features using the info gain criterion. In general, adding both the accelerometer sensor and the accelerometer data to the current model structure may not present a significant problem due to their small size and weight to current pressure sensors. Nevertheless, the added computational expense as well as any increase in cost should be considered to determine if the trade-off is justifiable in the potential final implementation. The same activities to recognize are the same as in previous experiment's and data processing techniques are used as with the pressure data. Accelerometer features are also computed over 6 seconds windows and using the same Random Forest classifier. Overall results are shown in Tables 6-1 and 6-2 while other measurements of performance are shown in Appendix G.

Table 6-1. Average recall using different features sets while adding different acceleration data (ACC) from each foot. Computations are performed over a 6 second sliding window using the Random Forest classifier and subject dependent training (10- fold cross validation).

Activity	**All Features**		**LR_SUM Features**		**Information Gain Features**	
	Pressure	**Pressure + Foot ACC**	**Pressure**	**Pressure + Foot ACC**	**Pressure**	**Pressure + Foot ACC**
Sitting	98.9% ± 1.62%	98.98% ± 1.7%	98.67% ± 1.74%	98.83% ± 1.94%	98.72% ± 2.01%	98.74% ± 2.24%
Standing	94.2% ± 2.87%	94.73% ± 2.9%	92.92% ± 3.03%	94.47% ± 2.77%	92.86% ± 3.56%	94.21% ± 2.9%
Leaning	87% ± 8.15%	87.29% ± 8.34%	84.7% ± 9.73%	84.71% ± 10.6%	82.27% ± 9.4%	81.64% ± 9.14%
Walking	88.82% ± 12.27%	89.48% ± 12.91%	86.78% ± 13.48%	89.49% ± 13.75%	88.57% ± 12.55%	89.15% ± 13.53%
Cycling	94.93% ± 6.47%	96.71% ± 5.16%	87.52% ± 10.98%	95.93% ± 6.15%	92.59% ± 10.2%	94.81% ± 9.95%
Stairs	76.39% ± 14.48%	77.45% ± 15.29%	68.39% ± 16.55%	76.59% ± 16.01%	67.71% ± 18.2%	67.02% ± 19.63%
ALL	95.83% ± 4.79%	96.03% ± 2.95%	94.8% ± 6.08%	95.79% ± 3.04%	95.03% ± 6.02%	95.4% ± 3.34%

Table 6-2. Average recall using different features sets while adding different acceleration data (ACC) from each foot. Computations are performed over a 6 second sliding window using the Random Forest classifier and subject independent training.

Activity	All Features		LR_SUM Features		IG Features	
	Pressure	Pressure + Foot ACC	Pressure	Pressure + Foot ACC	Pressure	Pressure + Foot ACC
Sitting	94.75% ± 5.86%	96.25% ± 4.21%	92.91% ± 5.95%	95.93% ± 4.38%	93.31% ± 5.18%	96.47% ± 3.93%
Standing	87.52% ± 8.23%	90.24% ± 6.62%	85.1% ± 10.02%	90.55% ± 6.95%	87.35% ± 8.73%	90.03% ± 7.47%
Leaning	22.22% ± 23.98%	21.59% ± 19.32%	16.66% ± 17.68%	4.4% ± 6.21%	10.41% ± 11.89%	13.96% ± 10.87%
Walking	82.77% ± 14.91%	88.3% ± 11.99%	81.93% ± 15.45%	88.27% ± 11.67%	84.2% ± 13.37%	88.17% ± 11.82%
Cycling	35.78% ± 34.67%	91.55% ± 15.48%	22.73% ± 27.49%	82.43% ± 25.02%	5.93% ± 9.3%	95.65% ± 8.58%
Stairs	36.96% ± 17.12%	54.45% ± 19.53%	14.16% ± 13.73%	15.25% ± 11.52%	8.11% ± 9.45%	60.79% ± 17.58%
ALL	87.44% ± 16.72%	89.98% ± 6.27%	84.92% ± 19.04%	88.31% ± 7.62%	85.18% ± 21.43%	89.83% ± 6.64%

As expected, Table 6-1 shows a slight increase of 0.2% to 0.99% in overall performance in all pressure feature sets when adding the foot acceleration features during the dependent evaluation. An even larger improvement of 2.54% to 4.65% in overall performance is observed during independent evaluation. In the case of individual classes or activities, it is found that the addition of feet acceleration improved mobile activities such as leaning, cycling and stairs. However, this improvement comes at the cost of slightly diminishing walking recognition rate, possibly due to misclassifying walking as climbing stairs since both activities have similar acceleration patterns. A significant improvement is observed during independent evaluation for “cycling” (55.77%-89.72%) and to a lesser extend “stairs” (1.10% - 52.68%), which is expected due to both activities easily identifiable periodicity. However, in some cases, “leaning” experiences a drop (-.64% to -12.26%) in recognition rate. A possible explanation is that incorporating the features from the accelerometers would increase misclassification of leaning as standing because the accelerometers are located at the base of the foot and their readings are practically the same during both activities.

Finally, an additional cross validation analysis is performed to evaluate the performance of the proposed method while using 50% of the training data (2-folds) instead of the 90% in the 10-fold method. Although related work and extensive tests on numerous datasets with different learning techniques have shown that 10 is an appropriate number of folds to get the best estimate of error, a good performance in this additional analysis would suggest that a smaller data set might be sufficient in future implementations, creating the potential of further reducing computational cost and overall data collection times [311]. Similar to the 10-fold validation method, the results from the iterations are averaged to produce a single estimated performance. Recall results are shown in Table 6-3.

Table 6-3. Average recall using different feature sets while adding different acceleration data (ACC) from each foot. Computations are performed over a 6 second sliding window using the Random Forest classifier and subject dependent training (2-fold cross validation).

Activity	All Features		LR_SUM Features		Information Gain Features	
	Pressure	Pressure + Foot ACC	Pressure	Pressure + Foot ACC	Pressure	Pressure + Foot ACC
Sitting	98.79% ± 1.83%	98.89% ± 1.87%	98.54% ± 1.94%	98.85% ± 2.04%	98.34% ± 3.13%	98.47% ± 3.11%
Standing	93.77% ± 2.95%	94.39% ± 2.94%	92.11% ± 3.41%	94.02% ± 3.19%	91.31% ± 4.75%	93.49% ± 3.87%
Leaning	84.1% ± 9.16%	84.42% ± 9.51%	81.71% ± 10.68%	82.22% ± 11.43%	76.07% ± 21%	76.23% ± 21.01%
Walking	88.06% ± 13.05%	89.15% ± 13.79%	85.94% ± 14.12%	89.06% ± 14.23%	86.28% ± 18.38%	87.56% ± 18.78%
Cycling	92.67% ± 8.54%	96.12% ± 6.2%	84.68% ± 12.98%	95.92% ± 7.06%	86.06% ± 16.88%	90.15% ± 17.63%
Stairs	73.46% ± 15.59%	74.59% ± 15.59%	64.6% ± 18.63%	71.47% ± 17%	63.04% ± 20.81%	63.21% ± 21.1%
ALL	95.37% ± 5.39%	95.79% ± 5.09%	94.22% ± 6.83%	95.53% ± 5.58%	93.76% ± 7.33%	94.49% ± 7.04%

Interestingly, recall rates are relatively similar between both validation methods. The biggest drop predictably occurred during the two activities with the lowest performance: a 2.49 % reduction during leaning and a 5.12% reduction during stairs. Nevertheless, acceptable performance was obtained for overall recognition as well as specific activities. Thus, it seems that using half of the total data for training purposed achieves similar results than using 90% in 10-fold cross validation. Such results not only support the generalisation of the method but are also encouraging in terms of real-life feasibility since minimising the amount of training data translates into a reduction of the time the end-user needs to spend training the potential device.

In summary, the improvement achieved by incorporating accelerometer data during subject dependent evaluation is small (less than 1%). In the case of subject independent evaluation, a higher improvement of 2.54% to 4.65% is noticed with a significant improvement for the cycling activity. Finally training and classification times are presented in Table 6-4 to illustrate the respective changes in computational cost when adding accelerometer data and while using different feature sets.

Table 6-4. Average training and classification times in seconds required by each configuration. Computations are performed over a 6 second sliding window using the Random Forest classifier and both subject dependent and independent training.

	All features		**LR_SUM Features**		**Information Gain Features**	
	Pressure	**Pressure + ACC**	**Pressure**	**Pressure + ACC**	**Pressure**	**Pressure + ACC**
Subject Dependent						
Training	1.594	1.632	1.266	1.901	1.257	1.979
Classification	0.011	0.009	0.015	0.012	0.014	0.016
Subject Independent						
Training	65.353	107.445	46.623	51.168	47.947	106.901
Classification	0.112	0.173	0.139	0.092	0.125	0.186

The highest training times are found during independent training when using all features algorithm and adding the foot's accelerometer features. Interestingly, similar classification times increase is found when using all features and the Information Gain feature set. A possible explanation to this increase in classification time may be that a finer discretisation is needed when incorporating accelerometer features in comparison to just using pressure-based features. This means that using Information Gain features and accelerometer features may not be the optimal choice considering the goal of keeping a low computational cost. However, the model has the lowest training times during dependent training while including acceleration data when using both the LB_Sum feature set and the Information Gain feature set. This time reduction can be easily explained due to the reduced number of features. Interestingly, in the case of the LB_Sum feature set, adding the accelerometer data cause only a small increase in training times compared to using only pressure sensors in both dependent and independent training. Thus, the use of an accelerometer to increase the recognition of dynamic activities may be justified in this case in terms of computational cost. Nevertheless, further considerations should be made when translating the method to a wearable device, since adding the accelerometers might increase the cost, battery demands and size. In fact, maintaining the width of the device to a minimum may be of particular interest since the proposed location of the device will be inside the shoe and beneath the participant's feet.

6.1.2 Incorporation of Thigh Raw Acceleration

This section explores if incorporating accelerometer data from the ActivPAL (located at the thigh) improves the overall performance of the model, particularly in the case of dynamic activates such as climbing stairs, cycling and walking. Accelerometer data from the ActivPAL will be incorporated to the previous model of pressure plus foot acceleration. This second evaluation will be done to determine if there is any value of incorporating a secondary accelerometer sensor on the thigh, considering both recognition performance and everyday convenience. Despite the small size of the ActivPAL, it is only used for research purpose as it has to be attached to the subject's thigh, proving to be more invasive than general wearable technology in the market. Accelerometer features are computed over 6 second windows and using the same Random Forest classifier. Overall results are shown in Table 6-5 and Table 6-6 while more detailed results of the ActivPAL can be found in Appendix H. Performance using the previous configuration of pressure sensors and foot accelerometer is added to facilitate its comparison.

Table 6-5. Recall using different features sets while adding acceleration data (ACC) from the ActivPAL. Computations are performed over a 6 second sliding window using the Random Forest classifier and subject dependent training.

Activity	**All Features**		**LR_SUM Features**		**Information Gain Features**	
	Feet ACC	**Feet + Thigh ACC**	**Feet ACC**	**Feet + Thigh ACC**	**Feet ACC**	**Feet + Thigh ACC**
Sitting	98.98% ± 1.7%	99.43% ± 0.45%	98.83% ± 1.94%	99.42% ± 0.49%	98.74% ± 2.24%	99.27% ± 0.59%
Standing	94.73% ± 2.9%	95.54% ± 2.4%	94.47% ± 2.77%	95.07% ± 2.46%	94.21% ± 2.9%	94.71% ± 2.78%
Leaning	87.29% ± 8.34%	89.41% ± 6.44%	84.71% ± 10.6%	88.85% ± 7.75%	81.64% ± 9.14%	83.22% ± 8.99%
Walking	89.48% ± 12.91%	92.09% ± 5.6%	89.49% ± 13.75%	91.7% ± 5.92%	89.15% ± 13.53%	91.43% ± 6.22%
Cycling	96.71% ± 5.16%	96.79% ± 6.26%	95.93% ± 6.15%	96.38% ± 6.87%	94.81% ± 9.95%	93.75% ± 12.16%
Stairs	77.45% ± 15.29%	79.11% ± 14.77%	76.59% ± 16.01%	78.7% ± 15.57%	67.02% ± 19.63%	72.82% ± 21.01%
ALL	96.03% ± 2.95%	96.97% ± 3.97%	95.79% ± 3.04%	96.8% ± 4.14%	95.4% ± 3.34%	96.21% ± 5.2%

Table 6-6. Recall using different features sets while adding acceleration data (ACC) from the ActivPAL. Computations are performed over a 6 second sliding window using the Random Forest classifier and subject independent training.

Activity	All Features		LR_SUM Features		Information Gain Features	
	Feet ACC	Feet + Thigh ACC	Feet ACC	Feet + Thigh ACC	Feet ACC	Feet + Thigh ACC
Sitting	96.25% ± 4.21%	97.89% ± 2.87%	95.93% ± 4.38%	97.73% ± 2.87%	96.47% ± 3.93%	97.8% ± 2.92%
Standing	90.24% ± 6.62%	89.06% ± 8.4%	90.55% ± 6.95%	88.75% ± 7.82%	90.03% ± 7.47%	82.73% ± 25.03%
Leaning	21.59% ± 19.32%	22.37% ± 20.39%	4.4% ± 6.21%	16.96% ± 17.94%	13.96% ± 10.87%	3.95% ± 4.54%
Walking	88.3% ± 11.99%	86.94% ± 12.13%	88.27% ± 11.67%	86.94% ± 11.7%	88.17% ± 11.82%	79.22% ± 25.12%
Cycling	91.55% ± 15.48%	88.42% ± 22.27%	82.43% ± 25.02%	93.19% ± 10.76%	95.65% ± 8.58%	77.65% ± 30.06%
Stairs	54.45% ± 19.53%	54.57% ± 22.64%	15.25% ± 11.52%	55.12% ± 25.3%	60.79% ± 17.58%	19.3% ± 16.79%
ALL	89.98% ± 6.27%	91.53% ± 14.79%	88.31% ± 7.62%	91.29% ± 15.62%	89.83% ± 6.64%	88.03% ± 20.02%

As can be seen in Tables 6-4 and 6-5, a further overall improvement of 0.81 % - 1.01% is observed when using features from both accelerometer locations during subject dependent evaluation. In fact, most activities show a small improvement while dynamic activities such as walking and stairs, show the highest improvement. Furthermore, the thigh location of the accelerometer slightly improved leaning recognition accuracy by 1.58% - 4.14 %, since the thigh location offers some information regarding the body inclination unlike the accelerometers located at the foot. This improvement is more pronounced during independent subject evaluation with performance increasing to similar or slightly higher levels only using foot acceleration. On the other hand, cycling shows a very similar performance as with the accelerometers located at the feet, since the information obtained from thigh movements is less obviously related to the cycling motion. A considerable improvement in stairs has been obtained during subject independent evaluation when using the LR_Sum feature set. Training and classification times are presented in Table 6-7 to illustrate the respective changes when adding the ActivPAL accelerometer components and while using different feature sets.

Table 6-7. Average training and classification times in seconds required by each configuration. Computations are performed over a 6 second sliding window using the Random Forest classifier and both subject dependent and independent training.

	All features			LR_SUM Features			Information Gain Features		
	Pres-sure	**Feet ACC**	**Feet + Thigh ACC**	**Pres-sure**	**Feet ACC**	**Feet + Thigh ACC**	**Pres-sure**	**Feet ACC**	**Feet + Thigh ACC**
Subject Dependent									
Training	1.594	1.632	1.956	1.266	1.901	1.748	1.257	1.979	4.727
Classifi-cation	0.011	0.009	0.010	0.015	0.012	0.011	0.014	0.016	0.061
Subject Independent									
Training	65.353	107.445	97.492	46.623	51.168	83.701	47.947	106.901	141.568
Classifi-cation	0.112	0.173	0.143	0.139	0.092	0.117	0.125	0.186	0.328

As shown in Table 6-6, training time during dependent training remain low for all configuration with occasional exceptions when using the Information Gain feature set and foot plus thigh acceleration. In the case of independent training, there is also a sharp increase in training time when using the Information Gain feature set and foot plus thigh acceleration. In the case of LR_Sum features, a sharper increase occurs in training time compared to using only pressure or a combination of pressure and foot acceleration. In summary, it seems the small improvements in performance obtained by adding acceleration in the thigh may not sufficiently justify the burden of having to wear an extra device or the increase in computational expense dedicated to processing and possible wireless communication between a possible CPU and the thigh sensor.

6.2 Proposed Model's Validation

6.1.2 Validation against the de facto-standard

The performance of the final configuration of the proposed machine learning model using the optimal parameters selected in Chapter 5 is presented and discussed in this section. The model's performance is compared to the results obtained with the ActivPAL since it is currently regarded as the *de facto* technology for measuring sedentary behaviour [316]. As with the proposed model, the ActivPAL performance is assessed by comparing it with the current criterion. No extra computations are made by the author since the proprietary software provides the activities predictions directly. Since the ActivPAL does not detects leaning, stairs or cycling, both recall and precision are 0% and undetermined respectively for these activities. The proposed model set of parameters consists in using a sliding window of 6 seconds, Random Forest classifier with 40 iterations, the LR_SUM time-based feature set, a 6 sensors configuration, using both Laboratory and Free-Living data for training, incorporating the accelerometers in the foot and using both subject dependent and independent training. Table 6-8 presents the recall obtained during both types of training and for comparison purposes. Furthermore, the ActivPAL' s predictions are compared to the criterion standard with a confusion matrix as shown in Table 6-9.

Table 6-8. Recall of the proposed model with optimal parameters and the ActivPAL. Computations are performed over a 6 second sliding window using the Random Forest classifier and both subject dependent and independent training. The results of the ActivPAL are extracted directly from the proprietary software.

Activity	Proposed Model - Dependent		Proposed Model - Independent		ActivPAL	
	Recall	Precision	Recall	Precision	Recall	Precision
Sitting	98.83% ± 1.94%	99.07% ± 2.06%	95.93% ± 4.38%	97.14% ± 3.42%	96.38%	98.68%
Standing	94.47% ± 2.77%	91.08% ± 5.32%	90.55% ± 6.95%	71.75% ± 13.27%	88.73%	71.91%
Leaning	84.71% ± 10.6%	99.38% ± 0.89%	4.4% ± 6.21%	57.97% ± 36.11%	0.00%	-
Walking	89.49% ± 13.75%	89.5% ± 8.57%	88.27% ± 11.67%	85.19% ± 10.95%	87.92%	65.26%
Cycling	95.93% ± 6.15%	99.18% ± 1.27%	82.43% ± 25.02%	99.34% ± 1.86%	0.00%	-
Stairs	76.59% ± 16.01%	93.42% ± 4.28%	15.25% ± 11.52%	83.12% ± 11.48%	0.00%	-
ALL	95.79% ± 3.04%	96.37% ± 4.14%	88.31% ± 7.62%	89.91% ± 5.98%	85.86%	85.86%

Table 6-9. Confusion Matrix of ActivPAL with direct observation as true condition.

Activity	Sitting	Standing	Leaning	Walking	Cycling	Stairs
Sitting	96.38%	2.85%	0.00%	0.77%	0.00%	0.00%
Standing	1.82%	88.73%	0.00%	9.45%	0.00%	0.00%
Leaning	0.00%	97.82%	0.00%	2.18%	0.00%	0.00%
Walking	2.20%	9.88%	0.00%	87.92%	0.00%	0.00%
Cycling	1.60%	4.81%	0.00%	93.59%	0.00%	0.00%
Stairs	2.31%	4.63%	0.00%	93.06%	0.00%	0.00%

To facilitate the analysis of overall sedentary behaviour throughout the day, results in terms of accumulated time spent during each task are presented below. Figure 6-1 to 6-3 compare the results of the proposed model and the ActivPAL.

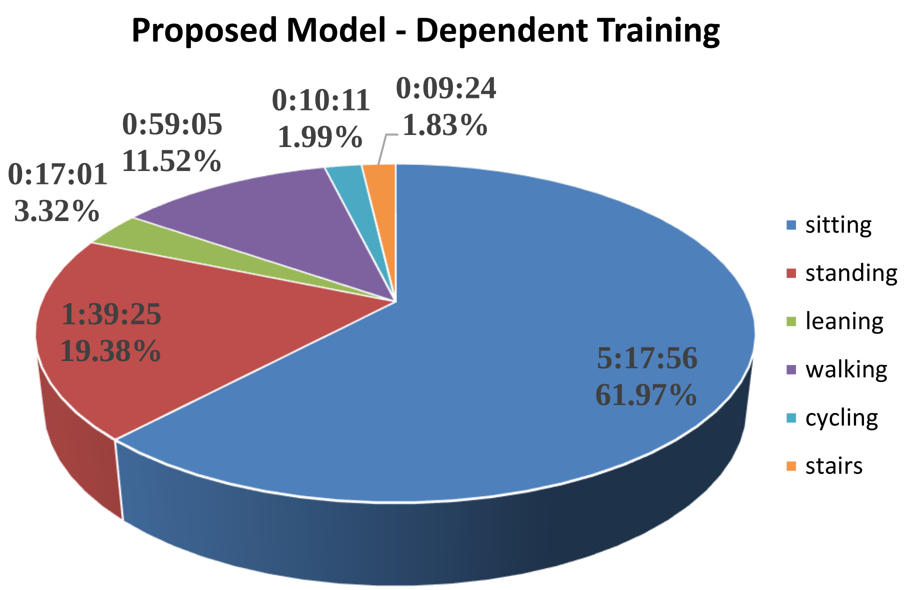


Figure 6-1. Average time spent in each task according to proposed model with optimal parameters when using dependent training.

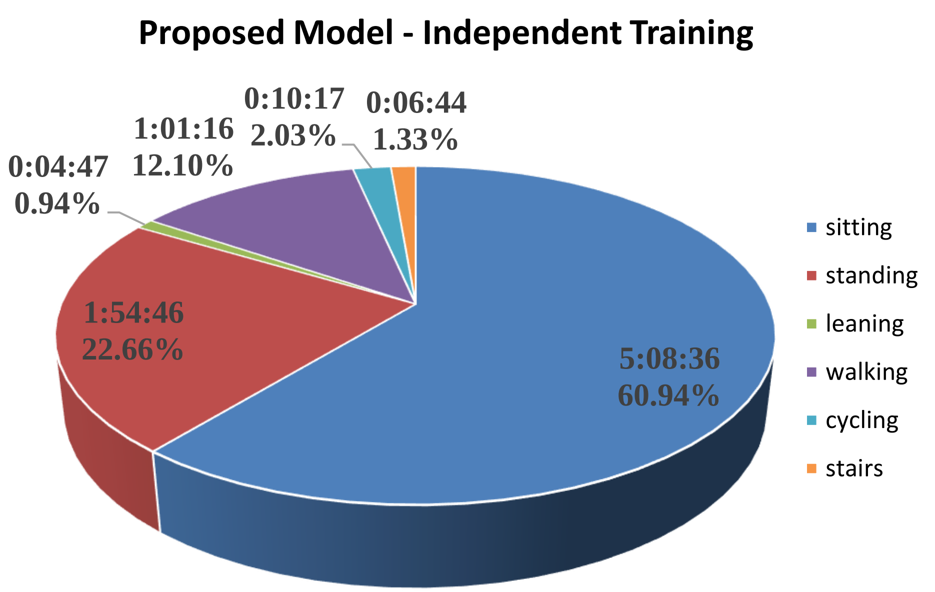


Figure 6-2. Average time spent in each task according to proposed model with optimal parameters when using independent training.

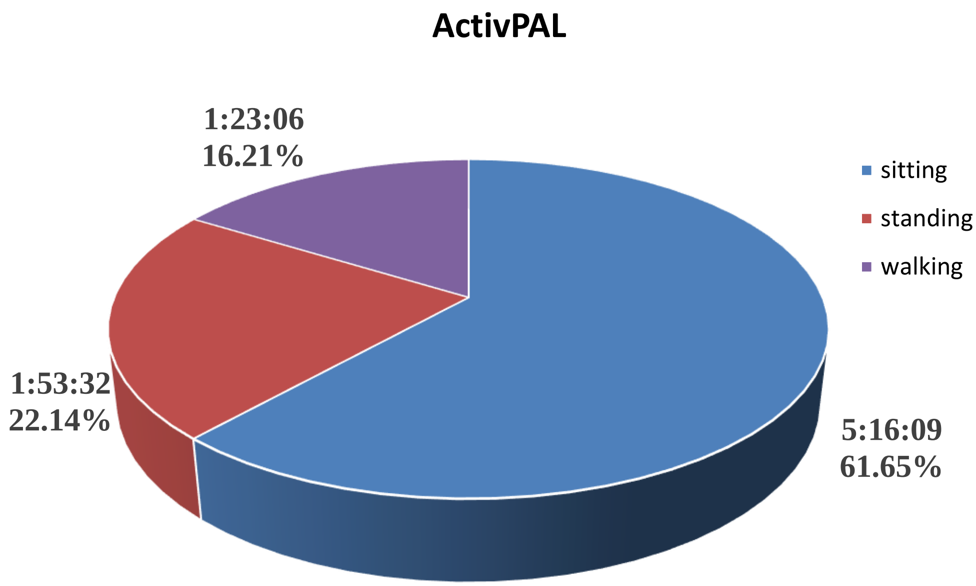


Figure 6-3. Average time spent in each task according to the de facto standard (activPAL).

As observed in Figures 6-1 to 6-3 the recognition rate of stairs, leaning and cycling is zero since the ActivPAL only recognises sitting, standing and stepping activities. Nevertheless, it can still be observed in the misclassification percentages that most of the leaning activity is classified as standing, similar to the problematic found with the proposed model. Cycling and stairs activities is also misclassified as walking (or steps) since walking stairs and cycling are motion-based activities albeit with potentially very different energy expenditures. Regarding the case of standing and walking, similar behaviour is observed as with the proposed model with standing being misclassified as walking and vice versa. This behaviour suggests that the activPAL may have the same problem of correctly discerning among a few steps (or brief walking) and standing or other similar transitions. Lastly, the activPAL performs relatively well when predicting sitting with a recall of 96.38%.

One of the key differences to be noted from the ActivPAL and the proposed model is the number of tasks identified and the impact it will have on performance. As observed in Figures 6-1, to 6-3, the proposed model predicts a similar amount of sitting time on average as the ActivPAL with a difference of 1 minutes and 48 seconds during dependent training and 7 minutes 33 seconds during independent training. Interestingly, standing time measured by the proposed model during independent training and the ActivPAL is very similar, with a significant difference observed in the case of dependent training. As later shown in Section 6.2.2, total standing time determined by direct observation is in fact much closer to the dependent training estimation with a difference of less than 4 minutes and 43 seconds. It seems that the lower performance of the proposed model to detect leaning during independent training, produces a similar standing overestimation as the activPAL, since leaning is not recognised at all and is probably classified as standing. The proposed model with subject dependent training offers the ability to recognise it to certain degree and open the possibility of studying in future work the difference between standing and leaning in terms of energy expenditure or overall sedentary behaviour. Lastly, the activPAL seems to be considerably overestimate the amount of walking performed in comparison with both the proposed model with a difference of 24 minutes and 1 second during dependent training and 21 minutes and 51 seconds during independent training. A possible explanation for this lower performance may be the inclusion of cycling and possibly leaning in the free-living component of the data. Since the activPAL does not differentiate any of these two activities, it is reasonable that "climbing or descending stairs" and cycling (to a lesser extent since it may be misclassified as standing) are classified as walking as they all are motion-based activities.

The results indicate the proposed model had a similar or better performance as the activPAL when predicting most tasks during both dependent and independent training. Furthermore, in the case of sitting and standing, the proposed model significantly outperforms the activPAL during dependent training and offers a slight improvement during independent training. Furthermore, sitting recognition is significantly improved during both dependent and independent training. Regarding the three remaining activities, leaning, cycling and stairs, it is not possible to perform a direct comparison since the activPAL does not measure these activities.

6.1.2 Validation against direct observation

Results are then compared to the criterion standard which is direct observation through the GoPro, to establish their recognition accuracy and compare the method's overall performance against the proposed method using both independent and dependent evaluation. To better illustrate this comparison, a confusion matrix is provided in Tables 6-10 and 6-11 with all predictions being compared against the ground truth.

Table 6-10. Confusion Matrix of the proposed model predictions with optimal parameters using dependent evaluation and direct observation as true condition

Activity	Sitting	Standing	Leaning	Walking	Cycling	Stairs
Sitting	99.03%	0.64%	0.00%	0.31%	0.00%	0.02%
Standing	1.43%	93.96%	0.30%	4.18%	0.00%	0.12%
Leaning	1.22%	18.12%	80.28%	0.32%	0.00%	0.06%
Walking	1.56%	9.38%	0.03%	88.00%	0.08%	0.95%
Cycling	1.02%	0.32%	0.00%	1.15%	96.75%	0.76%
Stairs	0.80%	2.21%	0.00%	18.14%	0.06%	78.80%

Table 6-11. Confusion Matrix of the proposed model predictions with optimal parameters using independent evaluation and direct observation as true condition

Activity	Sitting	Standing	Leaning	Walking	Cycling	Stairs
Sitting	96.55%	2.90%	0.01%	0.46%	0.02%	0.06%
Standing	5.23%	87.66%	1.57%	5.34%	0.00%	0.20%
Leaning	2.91%	81.25%	15.40%	0.40%	0.00%	0.03%
Walking	1.95%	9.85%	0.29%	86.47%	0.00%	1.44%
Cycling	4.93%	0.31%	0.00%	0.25%	94.33%	0.18%
Stairs	1.54%	4.69%	0.00%	30.69%	0.00%	63.08%

Considering one of the design goals is to potentially implement this work into an alternative future wearable device, presenting the results in terms of time spent during each task at the end of the day may be more useful to the end-users. Furthermore, researchers of sedentary behaviour and physical commonly profile participants according to time spent in different activities to finally assess sedentary time [317]. Figure 6-4 shows the amount of time spent on each activity based on direct observation.

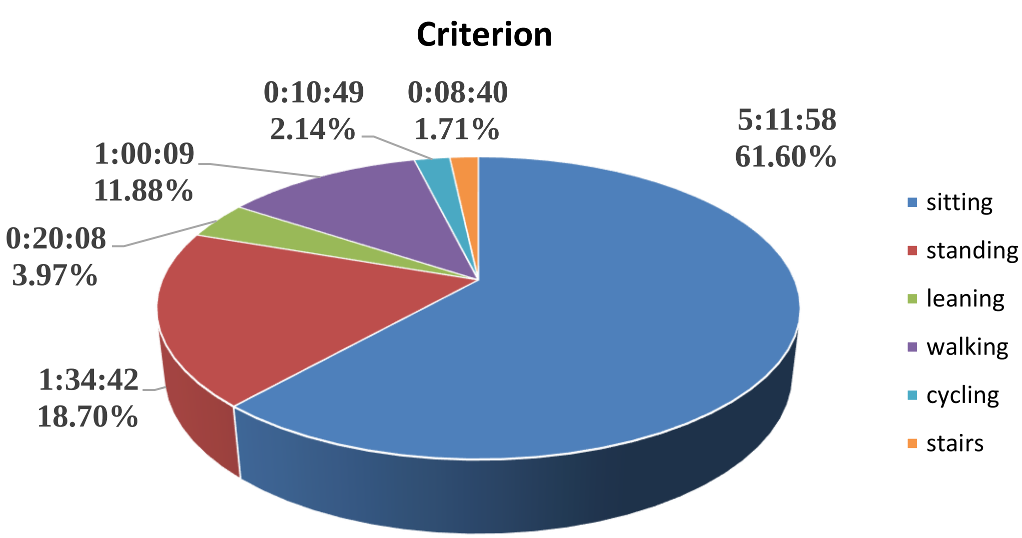


Figure 6-4. Average time spent in each task according to the current criterion (direct observation).

Finally, a direct comparison levels of energy expenditure over time can be done between both methods, by linking previously classified levels of energy expenditure related to specific activities. Although double labelled water is considered to be the gold standard for daily energy expenditure measurements, these classified levels of energy expenditure were obtained by using indirect calorimetry as it allows activity specific measurements during short durations (unlike double labelled water) as mentioned in Section 2.3.2 [318]. Default MET values for all activities were obtained from the Compendium of Physical Activities. Nevertheless, it is important to remember that the Compendium was developed to classify physical activity and standardize MET estimations in population health research, not to determine the precise energy cost of physical activity, since these estimates may be inaccurate across individuals of different body mass and body fat category [319-321]. In the case of the activPAL estimation, the activPAL software utilises these same values used for sitting, standing and walking (or stepping, in the case of the ActivPAL) activities for energy expenditure estimation [322]. Pre-classified values along with the different energy expenditure estimations obtained using the activPAL, direct observation and the proposed method are shown in Table 6-12.

Table 6-12. Estimated energy expenditures of identified activities based on pre-classified values of the Compendium of Physical Activities.

Activity	**Pre-classified values (METs)***	**Sum of Energy Expenditure Estimation (METs)**			
		Proposed Model		**Validation**	
		Dependent Training	**Independent Training**	**ActivPAL**	**Direct Observation**
Sitting	***1***	5.30	5.14	5.27	5.20
Standing	***1.3***	2.32	2.68	2.65	2.21
Leaning	***1.3***	0.37	0.10	-	0.44
Walking	***3.5***	3.45	3.57	4.85	3.51
Cycling	***6.8***	1.15	1.17	-	1.23
Stairs	***6***	0.94	0.67	-	0.87
Total:		13.53	13.34	12.77	13.45

6.1.3 Discussion

As seen in Table 6-8, the best per activity recognition and overall performance is obtained during subject dependent training. A drop of 7.48% in overall performance observed when using independent training. Moreover, leaning and stairs are the most affected activities with drops in performance of 80.31% and 61.34% respectively. This illustrates the fact that recognizing complex activities across participants is considerably more complex without using their own data since each participant's activity can be different from one other. Furthermore, when using free-living data each participant's routine included different types and amount of time spent on each activity. Sitting has the best recognition rate for both subject dependent and subject independent training (98.83% and 95.93% respectively). This seems reasonable, since its pressure signal shape is considerably different from the rest of the activities identified. Furthermore, sitting has the highest amount of available training data. Thus, performance only drops by a small percentage (2.90%) even when considering variations across multiple individuals during independent training. This shows that despite the numerous variations of sitting activities either by the way the person behaves or interacts with the environment, predominant features used by the algorithm are still identifiable across all sitting activities. Similarly, standing also shows good performance during both subject dependent and independent training (94.47% and 90.55% respectively). It may be possible to increase the recall by discarding leaning since it seems to be a source of misclassification as it is a similar activity. Likewise, walking and stairs can also be easily confused due to their similarity as ambulatory activities and their main difference only relies in the change of pace and force applied. Furthermore, the model has a large inequivalence between the amount of training examples available. For instance, "climbing or descending stairs" usually occurs for short periods of time and in between longer walking bouts, increasing the probabilities of being confused with the large sample of “walking”. Moreover, these activities may not be well classified because a different window length than 6 seconds may be required due to their higher motion variability, which includes sequences of events (gait and activity transitions). “Climbing or descending stairs” is the activity with the worst performance during dependent training and the second worst during independent training. Brief bouts of climbing or descending stairs with less than five steps may have introduced the observed variability since the length of the activity (less than 3 seconds) would be too short to be detected by the longer 6 seconds window selected, causing stairs to be confused as walking. This situation may represent a problem when interpreting the results: If longer and more significant “climbing or descending stairs” occurred, these short bouts would represent most of the stairs activity defined by the current criterion which would in turn, significantly lower the model’s recognition rate. Even though the model misclassifies brief sessions (less than 2 seconds) of “climbing or descending stairs” (e.g. stairs with 1 or 2 steps) as walking, this misclassification might not be too serious in terms of energy expenditure, as the overall difference in energy expenditure between them would likely be relatively small. Leaning has the second lowest recall (84.71%) during dependent training and the lowest (4.40%) during independent training by a considerable margin. This is not completely unexpected since its recognition accuracy has been consistently the lowest during all the experiments. It seems that particularly during independent training, the variability of how each participant leans and the different type of props they lean against, significantly hamper the model to discern leaning from standing. Based on the video recordings of each participant leaning activities are very varied ranging across leaning against many different surfaces: a regular wall at various angles, a pole in the Mass Rapid Transport (public transport in Singapore), a rail while waiting for a bus, an elevator wall, stair banisters, tables, desks, etc. Furthermore, leaning and foot positions also change considerably as some participants lean intermittently, on their side or using only one foot. All these variations seem to drastically lower the amount or quality of identifiable features the model could use to predict leaning. An excellent performance of 95.93 % during dependent training and is obtained in the case of cycling since the combination of the pressure data and the accelerometers located at the foot provided enough information to discern among other activities. A confusion with sitting is primarily avoided due to the addition of accelerometers as mentioned in Chapter 6.1.1.

As shown in Tables 6-10 and 6-11, walking has a relatively low ratio of misclassifications as standing among both dependent and independent trainings (12 % and 13.53% respectively). This confusion may be due to a similar problem encountered for stairs recognition: the brevity of the activity being shorter than the selected window size. Consequentially, a few steps are labelled as walking in accordance to the ground truth, may be predicted erroneously as standing as the window averages the small amount of motion that occurred within its limits. Although a shorter window may improve brief walking or a few stairs steps recognition to a certain extent, it would most likely introduce variability and further misclassifications in the remaining activities as discussed in Section 5.1.2. Thus, this reduced recognition rate for these two activities is an optimal trade-off to avoid lowering the performance of the proposed model when predicting sitting and standing. Understandably, a similar problem also occurs with standing as it has misclassification rates as walking of 4.18% during subject dependent and 5.34% during subject independent training. It should be noted that also has misclassifications rates as sitting of 1.43% during subject dependent and 5.23 % during subject independent training. Both misclassification rates are probably related to the various transitions that occur before and after standing. Subjects are sitting down before standing up, sitting after standing up, walking before stopping to stand still or standing before walking. All these transitions further introduce more variability as in the all the cases previously discussed. In some cases, subjects are involved in tasks which involved numerous consecutive transitions, such as doing chores at home or doing activities that involved making intermittent pauses while walking. Nevertheless, the relatively small amount of accumulated time spent during these transitions is considerably lower compared to the total amount of time spent standing longer than the selected window size of 6 seconds.

Aa shown in Figures 6-1 and 6-2 compared against Figure 6-4, the proposed model has excellent results when recognizing the total amount of sitting action in comparison to direct observation. Comparing the average amount of time spent sitting of all participants, the model overestimates bit only 5 minutes and 58 seconds during dependent training and underestimates it by 3 minutes and 22 during independent training. Regarding standing, the model overestimates total time spend on average by 4 minutes and 43 seconds during dependent training and 20 minutes and 4 seconds during independent training. A possible explanation for this overestimation is the variability that the leaning activity creates during independent training. As mentioned previously, definite criteria to differentiate between standing and leaning is hard to obtain due to the ample variability of leaning angles and surfaces used among participants. Consequently, standing overestimation leads to leaning underestimation by 3 min and 6 seconds during dependent training and 15 minutes and 21 seconds during independent training. On the other hand, walking time recognition is excellent as the proposed model underestimated it by only 1 minute and 24 seconds during dependent training and only 38 seconds during independent training. Similarly, the model underestimates cycling time by only 38 and 32 seconds during dependent and independent respectively. As described in Section 6.1.1, the addition of the foot accelerometers greatly improves cycling recognition avoiding its misclassification as sitting or walking. Finally, in the case of stairs, although previous recall rates are low (76.59 % and 15.25% during dependent and independent respectively), this does not translate into a large misclassified of overall time spent on each task throughout the day. In fact, the time spent over the day cycling, leaning, or climbing stairs seems to be minimal on all participants. As a result, lower or higher recognition rates do not significantly impact the overall performance of the model since the main focus relies in accurately measuring amount of sedentary time by discerning sitting and standing among the activities.

As observed in Table 6-12, when comparing total MET values per session instead of time, it can be observed that the proposed model has a better performance than the activPAL when estimating the overall energy expenditure based on the pre-classified values found in the Compendium of Physical Activity. It seems that the identification of the cycling and descending/ascending stairs activities contributes to a better energy expenditure. Although a direct comparison with direct calorimetry or double labelled water would provide a much stronger validation, the results based on these pre-classified values is encouraging.

Finally, it should be noted that some of the factors mentioned to explain the model's reduction in performance such as limited amount of data of specific activities, are related to the usual difficulties found when collecting real-time data during free-living conditions in many wearable devices. For example, due to the limitations of the current technology in terms of both battery and storage size, data collection is not extended beyond 24 hours for each participant. Thus, insufficient training data of occasional activities such as leaning, cycling or unaccounted activities such as squatting or kneeling, are not included in the study. Similarly, changes in daily routine and consequently activities during the weekend are not considered. Due to limited power or storage there is also the inability to experiment with higher sampling rates. Furthermore, some challenges specifically relate to using plantar pressure data are encountered such as restrictions of certain activities such as vigorous sports where unusually high pressure may be applied to the pressure sensors, water-based activities or any activity that involves shoe removal (dance or martial arts class for example). Thus, further improvement is needed in the following areas: how to provide enough power to either the sensors and possibly processing unit without sacrificing wearability or affordability, how to either transmit or store the data, and how to address shoe wear limitations when using pressure sensors under to monitor sedentary behaviour.

In summary, it seems the proposed model outperforms the activPAL by classifying an overall amount of classifying closer to the values obtained during direct observation. Most importantly, sitting has the best performance across all activities during both subject dependent and independent training with recognition rates of 98.83% and 95.93% respectively. Considering sitting has misclassifications rates as standing of 0.64% during subject dependent and 2.90% during subject independent training and is scarcely confused with any of the remaining activities, it seems that using pressure data from the insoles is an effective method of accurately detecting sitting among any other activities.

Chapter 7: Conclusions

7.1 Conclusion

This thesis investigated different activities and sedentary behaviour recognition using plantar pressure and applying machine learning techniques to construct a predictive model. The following problems are studied: to identify a wearable non-obtrusive technology that could monitor daily life sedentary behaviour, to design a study protocol to monitor different daily life activities in free-living conditions and obtain a ground truth, to develop a predictive model able to accurate discern sitting among different activities, and to find the optimal trade-off between computational cost and performance based on wearable design factors.

First, an extensive literature review of current physical activity and sedentary behaviour measuring methods and their limitations has been carried out to identify a niche technology. After identifying plantar pressure due to its potential benefits, a thorough and in-depth scoping review of available plantar pressure devices in both the commercial market and the literature is performed. Afterwards, a novel methodology for developing a predictive model using machine learning is proposed taking into consideration the design characteristics of wearable devices available in both the market and research field. These characteristics include small size, low computational cost and accurate performance. The trade-off between the design considerations and activity recognition is the basis for data collection, processing, training and evaluation discussed in the subsequent chapters. Moreover, to validate the proposed implementation, a comparison is performed to the current standard criterion for sedentary behaviour, the activPAL. After collecting pressure, acceleration and video data from 20 participants, data processing and labelling is performed to provide the machine learning model with training data. In order to determine the parameters that allow an optimal trade-off between performance and computational expense, multiple experiments have been performed to evaluate the recognition accuracy of the model using numerous iterations of different sliding window length, types of classifiers, number and type of features, and number and location of pressure sensors. Furthermore, activity recognition is also compared using laboratory-based data and free-living data and incorporating thigh acceleration data. All predictions are also evaluated using both subject dependent and subject independent methods ensuring both intra and inter-participant reliability. The final classification model is built using a 6 second sliding window, a Random Forest classifier, features computed using the sum of overall pressure in each foot. Most importantly, optimal performance occurs when training with free-living data, using only six pressure sensors instead of the 13 sensors from the initial approach and using only statistical parameters such as mean or max pressure on each foot instead of localised sensor readings. Furthermore, incorporating a foot accelerometer increases the proposed model's performance specifically improving the recognition of more complex activities such as stairs or stairs. Final validation is performed by comparing the model's prediction against the ground truth obtained using the recordings of all participants. An average performance of overall recall of 95.79% is obtained for subject dependent training and 88.21% for subject independent training in comparison to the 86.14% of the activPAL. In the specific case of sitting, a recall of 98.83% and 95.93% is achieved during dependent and independent evaluation respectively. Results expressed in terms of sedentary time spend throughout the day are very encouraging as well. An average sitting time of 5 hours 11 minutes and 38 seconds have been measured by direct observation, while an average amount of sitting of 5 hours 17 minutes and 56 seconds and 5 hours 8 minutes and 36 seconds during dependent and independent training respectively have been obtained. Thus, the results obtained in this work support the claim that a pressure-based device and an optimised machine learning algorithm is a viable option over current methods to monitor daily life sedentary behaviour.

7.2 Contributions

Several key contributions are made to the field of sedentary behaviour monitoring and wearable sensors.

- The collection of daily life data together with uninterrupted video footage of 20 participants is collected. The use of a wearable camera to obtain ground truth with the purposes of training, classification and validation is novel and has not been reported in previous work.
- The exploration of certain sitting and standing variations and how they impact accuracy recognition as well as the addition of a potential new activity classification, such as leaning.
- The use of a combination of live recording, machine learning, plantar pressure and foot accelerometers to measure sedentary behaviour.
- The validation of the proposed model using current de facto standard, the ActivPAL, and the current criterion, direct observation, in the form of actual footage of the participants via a wearable camera. This is novel and has never been reported before as most related studies recreate daily life activities in semi-controlled environments.
- The use of using both subject dependent and subject independent as different training and validation strategies to be used in the development of future wearable devices.
- The exploration of different parameters of the classification machine learning model such as optimal sliding window length, type and characteristics of different classifiers, feature sets and sensor configurations. Specifically, the finding that statistical parameters such as mean

pressure over the whole foot instead of localised features per sensor, significantly reducing the computational cost without sacrificing performance.

- The exploration of different plantar pressure configurations including the number and location of sensors as a viable method of main posture recognition without the use of traditional hip or leg accelerometers. Specifically, the finding that only 6 sensors is sufficient to obtain accurate performance instead of a grid of sensors over the whole area of the foot.
- The comparison of using laboratory-based data and/or free-living data when measuring sedentary behaviour using a plant pressure and machine learning predictive models.
- The development of a novel method which uses and compare its performance against the current criterion (i.e. direct observation) in sedentary behaviour studies to obtain criterion validity. Furthermore, the prosed method ensures absolute independence in the participant and while also accurately monitoring sedentary behaviour.

In summary, this research contributes to the sedentary behaviour monitoring field by not only proposing a novel methodology that accurately measures sedentary behaviour using plantar pressure but also by identifying the parameters that allow an optimal trade-off between performance in free-living settings and final commercial product viability. By performing multiple experiment iterations, the proposed model is developed with low computational costs so design considerations such as small size, unobtrusiveness, reliability during free-living conditions and low-power consumption are met. Resources such as processing power required for computations and number of sensors are minimised without significantly sacrificing the overall accuracy recognition of the model. Consequently, this work can be applied to the future development of an accurate, low-cost and unobtrusive consumer-based wearable device that is viable for daily life monitoring and fits the demands of the wearable market. Furthermore, the possibility of continuous feedback of daily sedentary activities could increase the user's personal knowledge of its own sedentary behaviour and allow further studies to monitor "real-life" sedentary behaviours and its health effects. In addition, such a device could easily integrate and contribute to the recent increase in physical activity research devices, ubiquitous devices such as smartphones and popular wearable devices in the market such as the Apple Watch or Fitbit.

7.3 Future work

Based on the findings of this work, future research directions are outlined as follow:

- **Wearable Device Product Development or Integration.** Developing a prototype based on the proposed methodology. Furthermore, the developed device can be integrated to current popular wearable technology or smartphones in order to add reliable sedentary behaviour monitoring. Given the high ownership of smartphones, working with available sensors and technologies of the user own smartphones will likely prove more beneficial than adding extra sensors or expanding the current device. For example, future studies could obtain Global Positioning Systems data from an individual's smartphone to provide further context of certain activities that vary significantly according to the environment to further improve the model's accuracy.
- **Type and size of sample.** Increasing the number of participants and more importantly, diversifying the profile and background of the participants involved. Comparing sedentary behaviour patterns using the proposed methodology on participants across different genders, ages, work and home environment would be ideal since daily activities, posture and footwear may vary greatly. Collecting data from participant over several days including both

weekdays and weekends would also provide the model with more training examples and allow testing its performance during a greater variety of work and leisure activities.

- **Substitute or complement current sedentary behaviour devices.** Perform studies to validate using the proposed methodology as a viable alternative in cases where typical accelerometer-based devices may prove inadequate. For example, accelerometer detachment can be a concern when performing physical activity and sedentary behaviour studies on children at school. Using a plantar pressure-based device might ensure children are oblivious to the wearable device allowing constant monitoring. Furthermore, issues such as skin irritation due to sensor adhesion can also be avoided.
- **Weight-bearing rehabilitation applications.** Besides the proposed application of sedentary behaviour monitoring, future studies can be performed to explore the proposed model ability of using the same plantar pressure data to also estimate body weight bearing distribution. For example, in the case of individuals with lower limb amputations or knee replacement, tracking sedentary time as well as how much weight is applied over each foot throughout the day would provide physicians valuable information to assess the patient's rehabilitation progress. Furthermore, the possibility of giving real-time feedback to the individual may prove a valuable tool to improve the rehabilitation process. Similar research on diabetic populations may be relevant as well, since tracking the relationship between daily sedentary behaviour and plantar pressure throughout the day may contribute to the development of offloading techniques to avoid pressure ulcers.
- **Sedentary behaviour of people with pathological gait.** Future work on population with pathological gait is another possible future implementation of this research. For example, people with multiple sclerosis tend to press their feet harder and have difficulty controlling

their foot movements, while victims from stroke tend to lean on their non-paretic side. Since the proposed methodology uses plantar pressure to monitor sedentary behaviour, basic gait parameters such as balance or cadence can be easily computed from the same plantar pressure data without adding significant computational cost. Monitoring a patient's sedentary behaviour together with these basic gait parameters could provide physicians a more comprehensive profile regarding how daily sedentary time may influence rehabilitation progress.

- **Analyse specific work-related activities.** Work related sedentary behaviour is a public health concern due to long working hours and the increase of deskbound activities such as computer usage. Thus, one important application of the model proposed in this thesis is measuring sitting time of individuals on mostly sedentary jobs (e.g. lorry and taxi drivers, desk-bound workers, etc). Furthermore, additional leg-based physical activity cause by operating machinery (e. g. pushing pedals) may be able to be detected and classified differently from regular sitting.
- **Study more complex activities and postures.** Creating a follow-up study to assess the confounding factors discussed in this work that lowered the model's performance, specifically for leaning and stairs. Since complex or uncommon activities suffer from a relative low amount of training examples, a larger amount of training data in free-living conditions may ultimately improve their recognition and overall performance. Further experimentation may be needed to determine if different set of calculations would improve these activities. Future work should be done to determine if there are any significant variations in plantar pressure that may influence the model's prediction ability. Moreover, detecting certain types of footwear such as heels and flat shoes would allow studying how shoe wear may influence daily activities and sedentary behaviour.

- **Develop Smart Devices with real-time adaptability.** Create a smart model that changes its machine learning approach and parameters depending on the user and activity. For example, changing the sliding window length according on the activity would reduce misclassification between static and dynamic activities. Although this approach would be more computationally expensive, further work could be done to better determine what would be the optimal trade-off between personalisation and generalisation and under what circumstances. Furthermore, specific population type (age, gender, occupation, etc.) studies could be done to determine what kind of algorithm suits each one of them better to ensure it eventually fits the needs of the market.

References

1. WHO, *GLOBAL HEALTH RISKS Mortality and burden of disease attributable to selected major risks*. 2009.
2. Troiano, R.P., et al., *Reported Physical Activity and Sedentary Behavior: Why Do You Ask?* Journal of Physical Activity & Health, 2012. **9**: p. S68-S75.
3. Hu, F.B., et al., *Physical activity and television watching in relation to risk for type 2 diabetes mellitus in men.* Arch Intern Med, 2001. **161**(12): p. 1542-8.
4. Must, A. and D.J. Tybor, *Physical activity and sedentary behavior: a review of longitudinal studies of weight and adiposity in youth.* Int J Obes (Lond), 2005. **29 Suppl 2**: p. S84-96.
5. WHO, *Global Recommendations on Physical Activity for Health*. 2010, Switzerland.
6. Spear, B.A., et al., *Recommendations for treatment of child and adolescent overweight and obesity.* Pediatrics, 2007. **120 Suppl 4**: p. S254-88.
7. Tremblay, M.S., et al., *Physiological and health implications of a sedentary lifestyle.* Applied Physiology, Nutrition & Metabolism, 2010. **35**(6): p. 725-740.
8. Wilmot, E.G., et al., *Sedentary time in adults and the association with diabetes, cardiovascular disease and death: systematic review and meta-analysis.* Diabetologia, 2012. **55**(11): p. 2895-905.
9. Skotte, J., et al., *Detection of Physical Activity Types Using Triaxial Accelerometers.* Journal of Physical Activity & Health, 2014. **11**(1): p. 76-84.
10. Boerema, S.T., et al., *Optimal sensor placement for measuring physical activity with a 3D accelerometer.* Sensors (Basel), 2014. **14**(2): p. 3188-206.
11. Kozey-Keadle, S., et al., *Validation of wearable monitors for assessing sedentary behavior.* Med Sci Sports Exerc, 2011. **43**(8): p. 1561-7.
12. Oliver, M., et al., *Utility of accelerometer thresholds for classifying sitting in office workers.* Prev Med, 2010. **51**(5): p. 357-60.
13. Kerr, J., et al., *Using the SenseCam to improve classifications of sedentary behavior in free-living settings.* Am J Prev Med, 2013. **44**(3): p. 290-6.
14. Owen, N., et al., *Sedentary Behavior: Emerging Evidence for a New Health Risk.* Mayo Clinic Proceedings, 2010. **85**(12): p. 1138-1141.
15. Owen, N., et al., *Too Much Sitting: The Population-Health Science of Sedentary Behavior.* Exercise and Sport Sciences Reviews, 2010. **38**(3): p. 105-113.
16. Healy, G.N., et al., *Measurement of adults' sedentary time in population-based studies.* Am J Prev Med, 2011. **41**(2): p. 216-27.
17. Tikkanen, O., et al., *Muscle activity and inactivity periods during normal daily life.* PLoS One, 2013. **8**(1): p. e52228.
18. Sanders, J.P., et al., *Devices for Self-Monitoring Sedentary Time or Physical Activity: A Scoping Review.* Journal of Medical Internet Research, 2016. **18**(5): p. e90.
19. Sanders, J.P., et al., *Devices for Self-Monitoring Sedentary Time or Physical Activity: A Scoping Review.* J Med Internet Res, 2016. **18**(5): p. e90.
20. Abdul Razak, A.H., et al., *Foot Plantar Pressure Measurement System: A Review.* Sensors, 2012. **12**(7).
21. Patel, S.N., et al., *Farther Than You May Think: An Empirical Investigation of the Proximity of Users to Their Mobile Phones*, in *UbiComp 2006: Ubiquitous Computing: 8th International Conference, UbiComp 2006 Orange County, CA, USA, September 17-21, 2006 Proceedings*, P. Dourish and A. Friday, Editors. 2006, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 123-140.

22. Tremblay, M.S., et al., *Incidental movement, lifestyle-embedded activity and sleep: new frontiers in physical activity assessmentThis article is part of a supplement entitledAdvancing physical activity measurement and guidelines in Canada: a scientific review and evidence-based foundation for the future of Canadian physical activity guidelinesco-published byApplied Physiology, Nutrition, and Metabolismand theCanadian Journal of Public Health. It may be cited as Appl. Physiol. Nutr. Metab. 32(Suppl. 2E) or as Can. J. Public Health 98(Suppl. 2).* Applied Physiology, Nutrition, and Metabolism, 2007. **32**(S2E): p. S208-S217.
23. Graziano, D., *The best fitness trackers you can buy right now*, CNET, Editor. 2015: US edition.
24. Bryson, D., *17 - Smart clothes and wearable technology for the health and well-being market*, in *Smart Clothes and Wearable Technology*. 2009, Woodhead Publishing. p. 335-345.
25. Caspersen, C.J., K.E. Powell, and G.M. Christenson, *Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research.* Public Health Reports, 1985. **100**(2): p. 126-131.
26. Armstrong, N. and J.R. Welsman, *The Physical Activity Patterns of European Youth with Reference to Methods of Assessment.* Sports Medicine, 2006. **36**(12): p. 1067-1086.
27. Caspersen, C.J., K.E. Powell, and G.M. Christenson, *Physical Activity, Exercise, and Physical Fitness: Definitions and Distinctions for Health-Related Research.* Public Health Reports (1974-), 1985(2): p. 126.
28. Lee, I.M., et al., *Effect of physical inactivity on major non-communicable diseases worldwide: an analysis of burden of disease and life expectancy.* Lancet, 2012. **380**(9838): p. 219-29.
29. Owen, N., et al., *Sedentary behaviour and health: mapping environmental and social contexts to underpin chronic disease prevention.* British Journal of Sports Medicine, 2014. **48**(3): p. 174-177.
30. Sedentary Behaviour Research, N., *Letter to the editor: standardized use of the terms "sedentary" and "sedentary behaviours".* Appl Physiol Nutr Metab, 2012. **37**(3): p. 540-2.
31. Jette, M., K. Sidney, and G. Blumchen, *Metabolic equivalents (METS) in exercise testing, exercise prescription, and evaluation of functional capacity.* Clin Cardiol, 1990. **13**(8): p. 555-65.
32. Katzmarzyk, P.T., *Physical Activity, Sedentary Behavior, and Health: Paradigm Paralysis or Paradigm Shift?* Diabetes, 2010. **59**(11): p. 2717-2725.
33. Owen, N., et al., *Environmental determinants of physical activity and sedentary behavior.* Exerc Sport Sci Rev, 2000. **28**(4): p. 153-8.
34. Hamilton, M.T., D.G. Hamilton, and T.W. Zderic, *Role of low energy expenditure and sitting in obesity, metabolic syndrome, type 2 diabetes, and cardiovascular disease.* Diabetes, 2007. **56**(11): p. 2655-2667.
35. Hamilton, M.T., et al., *Too Little Exercise and Too Much Sitting: Inactivity Physiology and the Need for New Recommendations on Sedentary Behavior.* Current cardiovascular risk reports, 2008. **2**(4): p. 292-298.
36. Healy, G.N., et al., *Objectively measured sedentary time, physical activity, and metabolic risk: the Australian Diabetes, Obesity and Lifestyle Study (AusDiab).* Diabetes Care, 2008. **31**(2): p. 369-71.
37. Claude Bouchard, P.K., *Physical Activity and Obesity-2nd Edition* Human Kinetics. Vol. 2. 2010: Cloth. 432.
38. Healy, G.N., et al., *Sedentary time and cardio-metabolic biomarkers in US adults: NHANES 2003–06*. Vol. 32. 2011. 590-597.
39. Zi, Y. and B.J. Cardinal, *Increasing Asian International College Students' Physical Activity Behavior: A Review of the Youth Physical Activity Promotion Model.* Health Educator, 2013. **45**(1): p. 35-45.
40. Prince, S.A., et al., *Measurement of sedentary behaviour in population health surveys: a review and recommendations.* PeerJ, 2017. **5**: p. e4130.

41. Kahlmeier, S., et al., *National physical activity recommendations: systematic overview and analysis of the situation in European countries.* BMC Public Health, 2015. **15**(1): p. 1-14.
42. Lee, E., *World Health Organization's Global Strategy on Diet, Physical Activity, and Health: Turning Strategy into Action, The.* Food & Drug LJ, 2005. **60**: p. 569.
43. Lim, S.S., et al., *A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the Global Burden of Disease Study 2010.* Lancet, 2012. **380**(9859): p. 2224-2260.
44. Centers for Disease Control and Prevention; CDC, N.C.f.H. and S. NCHS, *National health and nutrition examination survey data 2003–*

2004, 2005-2006, 2009. http://www.cdc.gov/nchs/nhanes/nhanes2003-2004/nhanes03_04.htm, 2013.
45. Veerman, J.L., et al., *Television viewing time and reduced life expectancy: a life table analysis.* Br J Sports Med, 2012. **46**(13): p. 927-30.
46. Ng, S.W. and B.M. Popkin, *Time use and physical activity: a shift away from movement across the globe.* Obes Rev, 2012. **13**(8): p. 659-80.
47. Lakerveld, J., et al., *Abdominal obesity, TV-viewing time and prospective declines in physical activity.* Prev Med, 2011. **53**(4-5): p. 299-302.
48. D. Stookey, A., L.M. Mealey, and M. Shaughnessy, *Physical Activity Assessment in Children.* Journal of Exercise Physiology, 2011. **14**(5).
49. Eston, R.G., A.V. Rowlands, and D.K. Ingledew, *Validity of heart rate, pedometry, and accelerometry for predicting the energy cost of children's activities.* J Appl Physiol (1985), 1998. **84**(1): p. 362-71.
50. Tremblay, M.S. and J.D. Willms, *Is the Canadian childhood obesity epidemic related to physical inactivity?* Int J Obes Relat Metab Disord, 2003. **27**(9): p. 1100-5.
51. *Surgeon General's report on physical activity and health. From the Centers for Disease Control and Prevention.* Jama, 1996. **276**(7): p. 522.
52. Sirard, J.R. and R.R. Pate, *Physical activity assessment in children and adolescents.* Sports Med, 2001. **31**(6): p. 439-54.
53. Salmon, J., et al., *Health risks, correlates, and interventions to reduce sedentary behavior in young people.* Am J Prev Med, 2011. **41**(2): p. 197-206.
54. Wang, Y. and T. Lobstein, *Worldwide trends in childhood overweight and obesity.* Int J Pediatr Obes, 2006. **1**(1): p. 11-25.
55. Müller, A.M., S. Khoo, and R. Lambert, *Review of physical activity prevalence of Asian school-age children and adolescents.* Asia-Pacific Journal of Public Health, 2013. **25**(3): p. 227-238.
56. Chen, L.J., A.M. Haase, and K.R. Fox, *Physical activity among adolescents in Taiwan.* Asia Pac J Clin Nutr, 2007. **16**(2): p. 354-61.
57. Sallis, J.F., J.J. Prochaska, and W.C. Taylor, *A review of correlates of physical activity of children and adolescents.* Med Sci Sports Exerc, 2000. **32**(5): p. 963-75.
58. Van Der Horst, K., et al., *A brief review on correlates of physical activity and sedentariness in youth.* Med Sci Sports Exerc, 2007. **39**(8): p. 1241-50.
59. Collaboration, A.P.C.S., *The burden of overweight and obesity in the Asia-Pacific region.* Obes Rev, 2007. **8**(3): p. 191-6.
60. Nguyen, T.H., et al., *Association between physical activity and metabolic syndrome: a cross sectional survey in adolescents in Ho Chi Minh City, Vietnam.* BMC Public Health, 2010. **10**: p. 141.
61. Zalilah, M.S., et al., *Dietary intake, physical activity and energy expenditure of Malaysian adolescents.* Singapore Med J, 2006. **47**(6): p. 491-8.

62. Tudor-Locke, C., et al., *Physical activity and inactivity in Chinese school-aged youth: the China Health and Nutrition Survey.* Int J Obes Relat Metab Disord, 2003. **27**(9): p. 1093-9.
63. Mahfouz, A.A., et al., *Nutrition, Physical Activity, and Gender Risks for Adolescent Obesity in Southwestern Saudi Arabia.* Saudi Journal of Gastroenterology : Official Journal of the Saudi Gastroenterology Association, 2011. **17**(5): p. 318-322.
64. Lindner, K.J., *Sport Participation and Perceived Academic Performance of School Children and Youth.* Pediatric Exercise Science, 1999. **11**(2): p. 129.
65. Seo, D.C., et al., *A comparison of factors associated with physical inactivity among East Asian college students.* Int J Behav Med, 2012. **19**(3): p. 316-23.
66. Grundy, S.M., *Obesity, metabolic syndrome, and cardiovascular disease.* J Clin Endocrinol Metab, 2004. **89**(6): p. 2595-600.
67. Guyton, A.C. and J.E. Hall, *Textbook Of Medical Physiology*. 11th edition ed. 2006.
68. *Clinical Guidelines on the Identification, Evaluation, and Treatment of Overweight and Obesity in Adults--The Evidence Report. National Institutes of Health.* Obes Res, 1998. **6 Suppl 2**: p. 51S-209S.
69. Jequier, E. and L. Tappy, *Regulation of body weight in humans.* Physiol Rev, 1999. **79**(2): p. 451-80.
70. Hamburg, N.M., et al., *Physical inactivity rapidly induces insulin resistance and microvascular dysfunction in healthy volunteers.* Arterioscler Thromb Vasc Biol, 2007. **27**(12): p. 2650-6.
71. Henriksen, E.J., et al., *Glucose transporter protein content and glucose transport capacity in rat skeletal muscles.* Am J Physiol, 1990. **259**(4 Pt 1): p. E593-8.
72. Kim, H., et al., *Changes in bone turnover markers during 14-day 6 degrees head-down bed rest.* J Bone Miner Metab, 2003. **21**(5): p. 311-5.
73. Zerwekh, J.E., et al., *The effects of twelve weeks of bed rest on bone histology, biochemical markers of bone turnover, and calcium homeostasis in eleven normal subjects.* J Bone Miner Res, 1998. **13**(10): p. 1594-601.
74. Smith, S.M., et al., *Evaluation of treadmill exercise in a lower body negative pressure chamber as a countermeasure for weightlessness-induced bone loss: a bed rest study with identical twins.* J Bone Miner Res, 2003. **18**(12): p. 2223-30.
75. Bleeker, M.W., et al., *Vascular adaptation to deconditioning and the effect of an exercise countermeasure: results of the Berlin Bed Rest study.* J Appl Physiol (1985), 2005. **99**(4): p. 1293-300.
76. Schrage, W.G., *Not a search in vein: novel stimulus for vascular dysfunction after simulated microgravity.* J Appl Physiol (1985), 2008. **104**(5): p. 1257-8.
77. Demiot, C., et al., *WISE 2005: chronic bed rest impairs microcirculatory endothelium in women.* Am J Physiol Heart Circ Physiol, 2007. **293**(5): p. H3159-64.
78. Zwart, S.R., et al., *Lower body negative pressure treadmill exercise as a countermeasure for bed rest-induced bone loss in female identical twins.* Bone, 2007. **40**(2): p. 529-537.
79. Ainsworth, B.E., *How do I measure physical activity in my patients? Questionnaires and objective methods.* Br J Sports Med, 2009. **43**(1): p. 6-9.
80. Network, S.B.R. *Sedentary Behaviour Questionnaire*. [cited 2018 28 May 2018]; Available from: http://www.sedentarybehaviour.org/sedentary-behaviour-questionnaires/.
81. Kruger, J., et al., *Is participation in occupational physical activity associated with lifestyle physical activity levels?* J Occup Environ Med, 2006. **48**(11): p. 1143-8.
82. Craig, C.L., et al., *International physical activity questionnaire: 12-country reliability and validity.* Med Sci Sports Exerc, 2003. **35**(8): p. 1381-95.
83. Barbosa, N., et al., *A Physical Activity Questionnaire: Reproducibility and Validity*. Vol. 6. 2007. 505-18.

84. Hagstromer, M., P. Oja, and M. Sjostrom, *The International Physical Activity Questionnaire (IPAQ): a study of concurrent and construct validity.* Public Health Nutr, 2006. **9**(6): p. 755-62.
85. Ainsworth, B.E., et al., *Comparison of three methods for measuring the time spent in physical activity.* Med Sci Sports Exerc, 2000. **32**(9 Suppl): p. S457-64.
86. Chau, J.Y., et al., *Validity of the occupational sitting and physical activity questionnaire.* Med Sci Sports Exerc, 2012. **44**(1): p. 118-25.
87. Rutten, A., et al., *Using different physical activity measurements in eight European countries. Results of the European Physical Activity Surveillance System (EUPASS) time series survey.* Public Health Nutr, 2003. **6**(4): p. 371-6.
88. Bassett, D.R., Jr., A.L. Cureton, and B.E. Ainsworth, *Measurement of daily walking distance-questionnaire versus pedometer.* Med Sci Sports Exerc, 2000. **32**(5): p. 1018-23.
89. Ferrari, P., C. Friedenreich, and C.E. Matthews, *The role of measurement error in estimating levels of physical activity.* Am J Epidemiol, 2007. **166**(7): p. 832-40.
90. DuRant, R.H., et al., *Evaluation of the Children's Activity Rating Scale (CARS) in young children.* Med Sci Sports Exerc, 1993. **25**(12): p. 1415-21.
91. Sirard, J.R. and R.R. Pate, *Physical Activity Assessment in Children and Adolescents.* Sports Medicine, 2001. **31**(6): p. 439-454.
92. Levine, J.A., *Measurement of energy expenditure.* Public Health Nutr, 2005. **8**(7a): p. 1123-32.
93. Ferrannini, E., *The theoretical bases of indirect calorimetry: a review.* Metabolism: Clinical And Experimental, 1988. **37**(3): p. 287-301.
94. Jequier, E. and J.P. Felber, *Indirect calorimetry.* Baillieres Clin Endocrinol Metab, 1987. **1**(4): p. 911-35.
95. Schoeller, D.A. and P. Webb, *Five-day comparison of the doubly labeled water method with respiratory gas exchange.* Am J Clin Nutr, 1984. **40**(1): p. 153-8.
96. Klein, P.D., et al., *Calorimetric validation of the doubly-labelled water method for determination of energy expenditure in man.* Hum Nutr Clin Nutr, 1984. **38**(2): p. 95-106.
97. Matthews, C.E., et al., *Amount of time spent in sedentary behaviors in the United States, 2003-2004.* Am J Epidemiol, 2008. **167**(7): p. 875-81.
98. Troiano, R.P., et al., *Physical activity in the United States measured by accelerometer.* Med Sci Sports Exerc, 2008. **40**(1): p. 181-8.
99. Dunstan, D., et al., *'Too Much Sitting' and Metabolic Risk – Has Modern Technology Caught Up with Us?* Vol. 06. 2010.
100. Healy, G.N., et al., *Breaks in sedentary time: beneficial associations with metabolic risk.* Diabetes Care, 2008. **31**(4): p. 661-6.
101. Fritschi, C., et al., *Association Between Daily Time Spent in Sedentary Behavior and Duration of Hyperglycemia in Type 2 Diabetes.* Biological Research for Nursing, 2016. **18**(2): p. 160-166.
102. Rosenberger, M.E., et al., *Estimating activity and sedentary behavior from an accelerometer on the hip or wrist.* Med Sci Sports Exerc, 2013. **45**(5): p. 964-75.
103. Hart, T.L., B.E. Ainsworth, and C. Tudor-Locke, *Objective and subjective measures of sedentary behavior and physical activity.* Med Sci Sports Exerc, 2011. **43**(3): p. 449-56.
104. Hart, T.L., et al., *How many days of monitoring predict physical activity and sedentary behaviour in older adults?* Int J Behav Nutr Phys Act, 2011. **8**: p. 62.
105. Bonomi, A.G., et al., *Improving assessment of daily energy expenditure by identifying types of physical activity with a single accelerometer.* J Appl Physiol (1985), 2009. **107**(3): p. 655-61.
106. Sallis, J.F. and N. Owen, *Physical Activity and Behavioral Medicine*. 1998: SAGE Publications.
107. European Commission, E., *How Europeans Spend Their Time: Everyday Life of Women and Men.* Office for Official Publications of the European Communities, 2004. **Luxembourg City, Luxembourg**.

108. Sugiyama, T., et al., *Too Much Sitting and Metabolic Risk¿Has Modern Technology Caught Up with Us.* 2009.
109. Welk, G., *Physical Activity Assessments for Health-related Research*. 2002: Human Kinetics.
110. Loveday, A., et al., *Technologies That Assess the Location of Physical Activity and Sedentary Behavior: A Systematic Review.* J Med Internet Res, 2015. **17**(8): p. e192.
111. Witte, T.H. and A.M. Wilson, *Accuracy of WAAS-enabled GPS for the determination of position and speed over ground.* J Biomech, 2005. **38**(8): p. 1717-22.
112. Macutkiewicz, D. and C. Sunderland, *The use of GPS to evaluate activity profiles of elite women hockey players during match-play.* J Sports Sci, 2011. **29**(9): p. 967-73.
113. Waldron, M., et al., *Concurrent validity and test-retest reliability of a global positioning system (GPS) and timing gates to assess sprint performance variables.* J Sports Sci, 2011. **29**(15): p. 1613-9.
114. Larsson, P. and K. Henriksson-Larsen, *The use of dGPS and simultaneous metabolic measurements during orienteering.* Med Sci Sports Exerc, 2001. **33**(11): p. 1919-24.
115. Aughey, R.J., *Applications of GPS technologies to field sports.* Int J Sports Physiol Perform, 2011. **6**(3): p. 295-310.
116. Molinos Domene, A., *Evaluation of movement and physiological demands of full-back and center-back soccer players using global positioning systems.* Journal of Human Sport and Exercise; Vol 8, No 4 (2013): Number 4, 2013.
117. Maddison, R. and C. Ni Mhurchu, *Global positioning system: a new opportunity in physical activity measurement.* Int J Behav Nutr Phys Act, 2009. **6**: p. 73.
118. Krenn, P.J., et al., *Use of global positioning systems to study physical activity and the environment: a systematic review.* Am J Prev Med, 2011. **41**(5): p. 508-15.
119. Stopher, P., C. FitzGerald, and J. Zhang, *Search for a global positioning system device to measure person travel.* Transportation Research: Part C, 2008. **16**(3): p. 350-369.
120. Kamel Boulos, M.N. and G. Berry, *Real-time locating systems (RTLS) in healthcare: a condensed primer.* Int J Health Geogr, 2012. **11**: p. 25.
121. Hui, L., et al., *Survey of Wireless Indoor Positioning Techniques and Systems.* Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 2007. **37**(6): p. 1067-1080.
122. Curran, K., et al., *An evaluation of indoor location determination technologies.* J. Locat. Based Serv., 2011. **5**(2): p. 61-78.
123. Al Nuaimi, K. and H. Kamel. *A survey of indoor positioning systems and algorithms*. in *Innovations in Information Technology (IIT), 2011 International Conference on*. 2011.
124. Loveday, A., et al., *Technologies That Assess the Location of Physical Activity and Sedentary Behavior: A Systematic Review.* Journal of Medical Internet Research, 2015. **17**(8): p. e192.
125. Loveday, A., et al., *Novel technology to help understand the context of physical activity and sedentary behaviour.* Physiol Meas, 2016. **37**(10): p. 1834-1851.
126. Magistro, D., et al., *A Novel Algorithm for Determining the Contextual Characteristics of Movement Behaviors by Combining Accelerometer Features and Wireless Beacons: Development and Implementation.* JMIR Mhealth Uhealth, 2018. **6**(4): p. e100.
127. Mannini, A. and A.M. Sabatini, *Machine learning methods for classifying human physical activity from on-body accelerometers.* Sensors (Basel), 2010. **10**(2): p. 1154-75.
128. Barshan, B. and M.C. Yüksek, *Recognizing Daily and Sports Activities in Two Open Source Machine Learning Environments Using Body-Worn Sensor Units.* The Computer Journal, 2014. **57**(11): p. 1649-1667.
129. Dalton, A. and G. ÓLaighin, *Comparing Supervised Learning Techniques on the Task of Physical Activity Recognition.* IEEE Journal of Biomedical and Health Informatics, 2013. **17**(1): p. 46-52.

130. Wang, J., et al., *Recognizing Human Daily Activities From Accelerometer Signal.* Procedia Engineering, 2011. **15**: p. 1780-1786.
131. Catal, C., et al., *On the use of ensemble of classifiers for accelerometer-based activity recognition.* Applied Soft Computing, 2015. **37**: p. 1018-1022.
132. Fawcett, T., *An introduction to ROC analysis.* Pattern Recognition Letters, 2006. **27**(8): p. 861-874.
133. Bishop, C.M., *Pattern Recognition and Machine Learning (Information Science and Statistics)*. 2006: Springer-Verlag.
134. Mannini, A. and A. Sabatini, *Classification of Human Physical Activities from On-body Accelerometers - A Markov Modeling Approach*. 2011. 201-208.
135. Lester, J., et al., *A hybrid discriminative/generative approach for modeling human activities*, in *Proceedings of the 19th international joint conference on Artificial intelligence*. 2005, Morgan Kaufmann Publishers Inc.: Edinburgh, Scotland. p. 766-772.
136. Bao, L. and S.S. Intille. *Activity Recognition from User-Annotated Acceleration Data*. in *Pervasive Computing*. 2004. Berlin, Heidelberg: Springer Berlin Heidelberg.
137. Dongarra, J. and F. Sullivan, *Guest Editors Introduction to the top 10 algorithms.* Computing in Science & Engineering, 2000. **2**(1): p. 22-23.
138. Parkka, J., et al., *Activity classification using realistic data from wearable sensors.* IEEE Transactions on Information Technology in Biomedicine, 2006. **10**(1): p. 119-128.
139. Lester, J., T. Choudhury, and G. Borriello. *A Practical Approach to Recognizing Physical Activities*. in *Pervasive Computing*. 2006. Berlin, Heidelberg: Springer Berlin Heidelberg.
140. #226, m. Huynh, and B. Schiele, *Analyzing features for activity recognition*, in *Proceedings of the 2005 joint conference on Smart objects and ambient intelligence: innovative context-aware services: usages and technologies*. 2005, ACM: Grenoble, France. p. 159-163.
141. Martín, H., et al., *Activity logging using lightweight classification techniques in mobile devices.* Personal and Ubiquitous Computing, 2013. **17**(4): p. 675-695.
142. Kuonen, D., *Data Mining and Statistics: What is the Connection?* 2004.
143. Jain, A.K., R.P.W. Duin, and M. Jianchang, *Statistical pattern recognition: a review.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 2000. **22**(1): p. 4-37.
144. Babubhai Rana, J., R. Shetty, and T. Jha, *Application of Machine Learning Techniques in Human Activity Recognition*. 2015.
145. Fix, E. and J.L. Hodges, *Discriminatory Analysis. Nonparametric Discrimination: Consistency Properties.* International Statistical Review / Revue Internationale de Statistique, 1989. **57**(3): p. 238-247.
146. Langley, P., a. Wayne Iba, and K. Thompson, *An analysis of Bayesian classifiers*, in *Proceedings of the tenth national conference on Artificial intelligence*. 1992, AAAI Press: San Jose, California. p. 223-228.
147. Witten, I.H., E. Frank, and M.A. Hall, *Chapter 4 - Algorithms: The Basic Methods*, in *Data Mining: Practical Machine Learning Tools and Techniques (Third Edition)*. 2011, Morgan Kaufmann: Boston. p. 85-145.
148. Cortes, C. and V. Vapnik, *Support-vector networks.* Machine Learning, 1995. **20**(3): p. 273-297.
149. Simon, H., *Neural Network: A Comprehensive Foundation*. 1994.
150. Kotsiantis, S., *Supervised Machine Learning: A Review of Classification Techniques*. Vol. 31. 2007. 249-268.
151. Chapelle, O., *Training a support vector machine in the primal.* Neural Comput, 2007. **19**(5): p. 1155-78.
152. Breiman, L., *Random Forests.* Machine Learning, 2001. **45**(1): p. 5-32.
153. Breiman, L., *Bagging Predictors.* Machine Learning, 1996. **24**(2): p. 123-140.

154. Friedman, J., T. Hastie, and R. Tibshirani, *Additive logistic regression: a statistical view of boosting (With discussion and a rejoinder by the authors).* Ann. Statist., 2000. **28**(2): p. 337-407.

155. Ermes, M., et al., *Detection of Daily Activities and Sports With Wearable Sensors in Controlled and Uncontrolled Conditions.* IEEE Transactions on Information Technology in Biomedicine, 2008. **12**(1): p. 20-26.

156. Sazonov, E.S., et al., *Monitoring of Posture Allocations and Activities by a Shoe-Based Wearable Sensor.* IEEE Transactions on Biomedical Engineering, 2011. **58**(4): p. 983-990.

157. Zhang, K., et al., *Assessment of human locomotion by using an insole measurement system and artificial neural networks.* J Biomech, 2005. **38**(11): p. 2276-87.

158. Sazonova, N., R.C. Browning, and E. Sazonov, *Accurate prediction of energy expenditure using a shoe-based activity monitor.* Med Sci Sports Exerc, 2011. **43**(7): p. 1312-21.

159. Putti, A.B., et al., *The Pedar in-shoe system: repeatability and normal pressure values.* Gait Posture, 2007. **25**(3): p. 401-5.

160. Moticon, G. *Opengo Science*. 2013 2016-03-02]; Available from: http://www.moticon.de/products/science-research.

161. Ferguson, T., et al., *The validity of consumer-level, activity monitors in healthy adults worn in free-living conditions: a cross-sectional study.* The International Journal of Behavioral Nutrition and Physical Activity, 2015. **12**: p. 42.

162. Bort-Roig, J., et al., *Measuring and influencing physical activity with smartphone technology: a systematic review.* Sports Med, 2014. **44**(5): p. 671-86.

163. Byun, W., Y. Kim, and T.A. Brusseau, *The Use of a Fitbit Device for Assessing Physical Activity and Sedentary Behavior in Preschoolers.* J Pediatr, 2018.

164. Cavanagh, P.R., F.G.H. Jr, and J.E. Perry, *In-shoe plantar pressure measurement: a review.* The Foot, 1992. **2**(4): p. 185-194.

165. Zhu, H., et al., *Microprocessor-based data-acquisition system for monitoring foot pressures.* IEEE/Engineering in Medicine and Biology Society Annual Conference, 1988. **10 pt 4**: p. 1599-1600.

166. Rosenbaum, D. and H.P. Becker, *Plantar pressure distribution measurements. Technical background and clinical applications.* Foot and Ankle Surgery, 1997. **3**(1): p. 1-14.

167. McPoil, T.G., M.W. Cornwall, and W. Yamada, *A comparison of two in-shoe plantar pressupe measurement systems.* Lower Extremity, 1995. **2**(2): p. 95-103.

168. Gerald, F.H., et al., *Holter type system for study of plantar foot pressures.* Biomedical Engineering - Applications, Basis and Communications, 1995. **7**(4): p. 409-415.

169. Yuan, G., et al., *Measuring system for plantar pressure distribution and its clinical application.* Chinese Journal of Clinical Rehabilitation, 2004. **8**(29): p. 6502-6505.

170. Surdilovic, D., Z. Jinyü, and R. Bernhardt, *Gait phase and centre of pressure measuring system.* 2nd IEEE International Conference on Industrial Informatics, INDIN'04, 2004: p. 331-334.

171. Miyawaki, K., et al., *Gait estimation using foot-pressure sensors.* 20th Anniversary MHS 2009 and Micro-Nano Global COE - 2009 International Symposium on Micro-NanoMechatronics and Human Science, 2009: p. 62-67.

172. Benocci, M., et al., *A wireless system for gait and posture analysis based on pressure insoles and inertial measurement units.* 2009 3rd International Conference on Pervasive Computing Technologies for Healthcare - Pervasive Health 2009, PCTHealth 2009, 2009.

173. Mizuno, H., et al., *Wearable sensor system for human behavior recognition (First report: Basic architecture and behavior prediction method).* TRANSDUCERS and EUROSENSORS '07 - 4th International Conference on Solid-State Sensors, Actuators and Microsystems, 2007: p. 435-438.

174. Karkokli, R. and K.M. McConville, *Design and development of a cost effective plantar pressure distribution analysis system for the dynamically moving feet.* Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference, 2006: p. 6008-6011.
175. Hannula, M., A. Säkkinen, and A. Kylmänen, *Development of EMFI-sensor based pressure sensitive insole for gait analysis.* MeMeA 2007 2nd - IEEE International Workshop on Medical Measurement and Applications, 2007: p. 18-20.
176. Chen, M., et al., *An intelligent shoe-integrated system for plantar pressure measurement.* 2006 IEEE International Conference on Robotics and Biomimetics, ROBIO 2006, 2006: p. 416-421.
177. Chen, H.C., et al., *Instrumented shoes for measuring ground-reaction force of persons with stroke in level walking, stair ascending and descending.* IFMBE Proceedings, 2007. **15**: p. 197-200.
178. Authier, A., et al., *A proof of concept for a wireless ambulatory weight bearing measurement system in rehabilitation and telerehabilitation applications.* 3rd IEEE International Conference on Wireless and Mobile Computing, Networking and Communications, WiMob 2007, 2007.
179. Zhu, C., A. Song, and Y. Ma, *A wireless gait measuring instrument based on plantar pressure measuring.* Proceedings - IEEE 2011 10th International Conference on Electronic Measurement and Instruments, ICEMI 2011, 2011. **1**: p. 146-150.
180. Vlaskamp, F., et al., *BioSensing: Using motion sensors in real life care situations.* Assistive Technology Research Series, 2011. **29**: p. 48-56.
181. Schroeder, J.W., et al., *Electrocutaneous feedback system to improve the estimation of pressure applied to the foot.* BIODEVICES 2011 - Proceedings of the International Conference on Biomedical Electronics and Devices, 2011: p. 386-390.
182. Saeedi, A., F. Almasganj, and M. Pourebrahim, *Plantar pressure monitoring by developing a real-time wireless system.* 2014 21st Iranian Conference on Biomedical Engineering, ICBME 2014, 2014: p. 211-214.
183. Paulick, P., H. Djalilian, and M. Bachman, *StabilitySole: Embedded sensor insole for balance and gait monitoring.* Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2011. **6777 LNCS**: p. 171-177.
184. Numchaichanakij, A., K. Chitsakul, and S. Tretriluxana, *An insole point pressure monitoring system.* BMEiCON-2011 - 4th Biomedical Engineering International Conference, 2011: p. 198-201.
185. Nakajima, K., et al., *Evaluation of ambulatory function by using the shoe device.* IFMBE Proceedings, 2011. **37**: p. 868-871.
186. Feng, Y., Y. Ge, and Q. Song, *A human identification method based on dynamic plantar pressure distribution.* 2011 IEEE International Conference on Information and Automation, ICIA 2011, 2011: p. 329-332.
187. Rossi, S.M.M.D., et al., *Development of an in-shoe pressure-sensitive device for gait analysis.* Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2011: p. 5637-5640.
188. Blanco, S.M.R., D.A. Zamudio, and S.J. Delgado, *Telemetry system to monitor plantar pressure.* IFMBE Proceedings, 2008. **18**: p. 686-689.
189. Zhao, J., Y. Guo, and L. Wang, *An insole plantar pressure measurement system based on 3D forces piezoelectric sensor.* Sensors and Transducers, 2013. **160**(12): p. 49-54.
190. Xu, H., et al., *Walking phases detection on structured terrains by using a shoe-integrated system.* Proceedings of the 2013 IEEE 8th Conference on Industrial Electronics and Applications, ICIEA 2013, 2013: p. 1501-1505.

191. Wang, X., et al., *A wearable plantar pressure measurement system: Design specifications and first experiments with an amputee.* Advances in Intelligent Systems and Computing, 2013. **194 AISC**: p. 273-281.
192. Wada, C. and M. Tokunaga, *Estimating standing-up motion by using foot pressure to assist standing up for the elderly.* Proceedings of the SICE Annual Conference, 2012: p. 1956-1958.
193. Wada, C., et al., *Improvement research of shoe-type measurement device for a walking rehabilitation support system.* Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2013. **8024 LNCS**: p. 157-164.
194. Tirosh, O., et al., *Wearable textile sensor sock for gait analysis.* Proceedings of the International Conference on Sensing Technology, ICST, 2013: p. 618-622.
195. Tao, Y., et al., *An intelligent shoe system: Evaluation of weight load approaches by gait analysis.* ICCH 2012 Proceedings - International Conference on Computerized Healthcare, 2012: p. 145-151.
196. Takeda, T., et al., *Biometrics personal identification by wearable pressure sensor.* International Conference on Emerging Trends in Engineering and Technology, ICETET, 2012: p. 120-123.
197. Suh, Y.S. and S.K. Park, *Monitoring of basic daily activities with inertial sensors and wireless modules.* 2010 IEEE Sensors Applications Symposium, SAS 2010 - Proceedings, 2010: p. 200-205.
198. Stassi, S., et al., *Wearable and flexible pedobarographic insole for continuous pressure monitoring.* IEEE SENSORS 2013 - Proceedings, 2013.
199. Shu, L., et al., *Monitoring diabetic patients by novel intelligent footwear system.* ICCH 2012 Proceedings - International Conference on Computerized Healthcare, 2012: p. 91-94.
200. Sazonov, E.S., N. Hegde, and W. Tang, *Development of SmartStep: an insole-based physical activity monitor.* Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference, 2013. **2013**: p. 7209-7212.
201. Razak, A.H.A. and Y. Wahab, *Enhanced performances of a wireless system-on-chip for MEMS biomedical plantar pressure sensor.* Sensors and Transducers, 2012. **17**(SPL 12): p. 22-29.
202. Ramanathan, A.K., et al., *Repeatability of the Pedar-X® in-shoe pressure measuring system.* Foot and Ankle Surgery, 2010. **16**(2): p. 70-73.
203. Mori, T., et al., *Insole-type simultaneous measurement system of plantar pressure and shear force during gait for diabetic patients.* Journal of Robotics and Mechatronics, 2012. **24**(5): p. 766-772.
204. Mazumder, O., A.S. Kundu, and S. Bhaumik, *Development of wireless insole foot pressure data acquisition device.* Proceedings of the 2012 International Conference on Communications, Devices and Intelligent Systems, CODIS 2012, 2012: p. 302-305.
205. Lin, S.W., et al., *Recognition of gait patterns with partial weight bearing using insole plantar pressure sensor.* Proceedings of the 3rd IASTED Asian Conference on Modelling, Identification, and Control, AsiaMIC 2013, 2013: p. 14-20.
206. Lemos, J.D., et al., *Development of a plantar pressure measuring system.* Pan American Health Care Exchanges, PAHCE, 2013.
207. Jagos, H., et al., *A multimodal approach for insole motion measurement and analysis.* Procedia Engineering, 2010. **2**: p. 3103-3108.
208. Healy, A., et al., *Repeatability of WalkinSense ® in shoe pressure measurement system: A preliminary study.* Foot, 2012. **22**(1): p. 35-39.
209. Guo, Y., L. Wang, and R. Xue, *Design and development on piezoelectric ceramic type insole 3D force measurement system based on LabVIEW.* Advanced Materials Research, 2012. **383-390**: p. 774-779.

210. Guo, Y., L. Wang, and Y. Ge, *Study on piezoelectric CeramicType insole plantar pressure measurement system based on testpoint.* Advanced Materials Research, 2012. **383-390**: p. 5148-5153.
211. Guo, Y. and L. Wang, *Development on insole 3D plantar pressure measurement system based on Zigbee technology.* Advances in Intelligent and Soft Computing, 2012. **145 AISC**: p. 303-308.
212. Guo, Y. and L. Wang, *Recent advance in plantar pressure measurement systems.* Sensors and Transducers, 2012. **145**(10): p. 96-105.
213. Guo, Y., *An insole device based on piezoelectric sensor to assess plantar pressure during daily human activity.* Sensors and Transducers, 2012. **147**(12): p. 53-60.
214. Grenez, F., et al., *Wireless prototype based on pressure and bending sensors for measuring gate quality.* Sensors (Basel, Switzerland), 2013. **13**(8): p. 9679-9703.
215. Ferber, R., et al., *Validation of plantar pressure measurements for a novel in-shoe plantar sensory replacement unit.* Journal of diabetes science and technology, 2013. **7**(5): p. 1167-1175.
216. Kati, R.E., S. Forrester, and P. Fleming, *Evaluation of pressure insoles during running.* Procedia Engineering, 2010. **2**: p. 3053-3058.
217. David, V., et al., *Instrumented insole for mobile and long distance motion pattern measurement.* Procedia Engineering, 2012. **34**: p. 760-765.
218. Adelsberger, R. and G. Troster, *PIMU: A wireless pressure-sensing IMU.* Proceedings of the 2013 IEEE 8th International Conference on Intelligent Sensors, Sensor Networks and Information Processing: Sensing the Future, ISSNIP 2013, 2013. **1**: p. 271-276.
219. Wahab, Y., et al., *Low power shoe integrated intelligent wireless gait measurement system.* Journal of Physics: Conference Series, 2014. **495**(1).
220. Talavera, G., et al., *Fully-wireless sensor insole as non-invasive tool for collecting gait data and analyzing fall risk.* Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2015. **9456**: p. 15-25.
221. Martínez-Martí, F., et al., *Embedded sensor insole for wireless measurement of gait parameters.* Australasian Physical and Engineering Sciences in Medicine, 2014. **37**(1): p. 25-35.
222. Hegde, N. and E. Sazonov, *Smartstep: A fully integrated, low-power insole monitor.* Electronics, 2014. **3**(2): p. 381-397.
223. Cao, C., Z. Peng, and W. Pan, *Wearable motion recognition system based on foot pressure sensing.* WIT Transactions on Information and Communication Technologies, 2014. **51**: p. 45-53.
224. Oks, A., et al., *Development of smart sock system for gate analysis and foot pressure control.* IFMBE Proceedings, 2016. **57**: p. 466-469.
225. Martínez-Martí, F., et al., *Validation of Instrumented Insoles for Measuring Height in Vertical Jump.* International Journal of Sports Medicine, 2016. **37**(5): p. 374-381.
226. Majumder, J.A., et al., *A wireless smart-shoe system for gait assistance.* 2015 IEEE Great Lakes Biomedical Conference, GLBC 2015 - Proceedings, 2015.
227. Majumder, A.J.A., et al., *A Novel Wireless System to Monitor Gait Using Smartshoe-Worn Sensors.* Proceedings - International Computer Software and Applications Conference, 2015. **2**: p. 733-741.
228. Lu, L., R. Ji, and M. Liu, *Design of real-time body weight monitor systems based on smart phones.* Proceedings - 2014 International Conference on Mechatronics and Control, ICMC 2014, 2014: p. 1392-1396.
229. Lin, F., et al., *A comparative study of smart insole on real-world step count.* 2015 IEEE Signal Processing in Medicine and Biology Symposium - Proceedings, 2015.
230. Light, J., S. Cha, and M. Chowdhury, *Optimizing pressure sensor array data for a smart-shoe fall monitoring system.* 2015 IEEE SENSORS - Proceedings, 2015.

231. Kawsar, F., et al., *A novel activity detection system using plantar pressure sensors and Smartphone.* Proceedings - International Computer Software and Applications Conference, 2015. **1**: p. 44-49.
232. Kawsar, F., S. Ahamed, and R. Love, *Remote monitoring using smartphone based plantar pressure sensors: Unimodal and multimodal activity detection.* Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2015. **8456**: p. 138-146.
233. González, I., et al., *An ambulatory system for gait monitoring based on wireless sensorized insoles.* Sensors (Switzerland), 2015. **15**(7): p. 16589-16613.
234. Gerlach, C., et al., *Printed MWCNT-PDMS-Composite Pressure Sensor System for Plantar Pressure Monitoring in Ulcer Prevention.* IEEE Sensors Journal, 2015. **15**(7): p. 3647-3656.
235. Corbellini, S., et al., *Low-cost wearable measurement system for continuous real-time pedobarography.* 2015 IEEE International Symposium on Medical Measurements and Applications, MeMeA 2015 - Proceedings, 2015: p. 639-644.
236. AbuFaraj, Z.O., et al., *A Holter-type, microprocessor-based, rehabilitation instrument for acquisition and storage of plantar pressure data.* Journal of Rehabilitation Research and Development, 1997. **34**(2): p. 187-194.
237. Stacy, J.M.B., et al., *Gait analysis using a shoe-integrated wireless sensor system.* Ieee Transactions on Information Technology in Biomedicine, 2008. **12**(4): p. 413-423.
238. Shu, L., et al., *In-Shoe Plantar Pressure Measurement and Analysis System Based on Fabric Pressure Sensing Array.* Ieee Transactions on Information Technology in Biomedicine, 2010. **14**(3): p. 767-775.
239. Saito, M., et al., *An in-shoe device to measure plantar pressure during daily human activity.* Medical Engineering & Physics, 2011. **33**(5): p. 638-645.
240. George, D.F., et al., *Identifying Activity Levels and Steps of People With Stroke Using a Novel Shoe-Based Sensor.* Journal of Neurologic Physical Therapy, 2012. **36**(2): p. 100-107.
241. Zhang, X., et al., *Design and Test of a Soft Plantar Force Measurement System for Gait Detection.* Sensors, 2012. **12**(12): p. 16628-16640.
242. Zhang, Z. and S. Poslad, *Design and Test of a Hybrid Foot Force Sensing and GPS System for Richer User Mobility Activity Recognition.* Sensors, 2013. **13**(11): p. 14918-14953.
243. Rosevall, J., et al., *A wireless sensor insole for collecting gait data.* Studies in health technology and informatics, 2014. **200**: p. 176-8.
244. Mann, R., et al., *Reliability and validity of pressure and temporal parameters recorded using a pressure-sensitive insole during running.* Gait & Posture, 2014. **39**(1): p. 455-459.
245. Bae, J. and M. Tomizuka, *A tele-monitoring system for gait rehabilitation with an inertial measurement unit and a shoe-type ground reaction force sensor.* Mechatronics, 2013. **23**(6): p. 646-651.
246. Price, C., D. Parker, and C. Nester, *Validity and repeatability of three in-shoe pressure measurement systems.* Gait & Posture, 2016. **46**: p. 69-74.
247. Chen, B., et al., *A foot-wearable interface for locomotion mode recognition based on discrete contact force distribution.* Mechatronics, 2015. **32**: p. 12-21.
248. Morris, S.J. and J.A. Paradiso, *Shoe-integrated sensor system for wireless gait analysis and real-time feedback.* Engineering in Medicine and Biology, 2002. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference, 2002. Proceedings of the Second Joint, 2002. **3**: p. 2468-2469 vol.3.
249. Ravindarn, G. and R. Manivannan, *Measurement and analysis of pressure at various points on the sole of the foot during gait.* Engineering in Medicine and Biology Society, 1992 14th Annual International Conference of the IEEE, 1992. **1**: p. 56-57.

250. Lawrence, T.L. and R.N. Schmidt, *Wireless in-shoe force system [for motor prosthesis].* Engineering in Medicine and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE, 1997. **5**: p. 2238-2241 vol.5.
251. Lvping, R., et al., *Design of in-shoe plantar pressure monitoring system for daily activity exercise stress assessment.* 2011 4th International Conference on Biomedical Engineering and Informatics (BMEI), 2011. **3**: p. 1367-1370.
252. Abu-Faraj, Z.U., et al., *Holter system development for recording plantar pressures: design and instrumentation.* Engineering in Medicine and Biology Society, 1994. Engineering Advances: New Opportunities for Biomedical Engineers. Proceedings of the 16th Annual International Conference of the IEEE, 1994: p. 934-935 vol.2.
253. Lin, F., et al., *Smart Insole: A Wearable Sensor Device for Unobtrusive Gait Monitoring in Daily Life.* IEEE Transactions on Industrial Informatics, 2016. **PP**(99): p. 1-1.
254. Castro, M.P.d., et al., *Accuracy and repeatability of the gait analysis by the WalkinSense system.* 2014.
255. Hurkmans, H.L., et al., *Accuracy and repeatability of the Pedar Mobile system in long-term vertical force measurements.* 2005.
256. Sazonova, N., R.C. Browning, and E. Sazonov, *Accurate prediction of energy expenditure using a shoe-based activity monitor.* 2010.
257. Rossi, S.M.M.D., et al. *Development of an in-shoe pressure-sensitive device for gait analysis*. in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2011.
258. Wang, B., et al. *FreeWalker: a smart insole for longitudinal gait analysis*. in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. 2015.
259. do Carmo Dos Reis, M., et al., *Insole with pressure control and tissue neoformation induction systems for diabetic foot.* Conf Proc IEEE Eng Med Biol Soc, 2010. **2010**: p. 5748-51.
260. Zhu, H.S., et al., *A microprocessor-based data-acquisition system for measuring plantar pressures from ambulatory subjects.* IEEE Trans Biomed Eng, 1991. **38**(7): p. 710-4.
261. Yang, C.M., et al., *A novel dynamic sensing of wearable digital textile sensor with body motion analysis.* Conf Proc IEEE Eng Med Biol Soc, 2010. **2010**: p. 4898-901.
262. Schaff, P.S., *An overview of foot pressure measurement systems.* Clin Podiatr Med Surg, 1993. **10**(3): p. 403-15.
263. Wertsch, J.J., J.G. Webster, and W.J. Tompkins, *A portable insole plantar pressure measurement system.* J Rehabil Res Dev, 1992. **29**(1): p. 13-8.
264. Sazonova, N.A., R. Browning, and E.S. Sazonov, *Prediction of Bodyweight and Energy Expenditure Using Point Pressure and Foot Acceleration Measurements.* The Open Biomedical Engineering Journal, 2011. **5**: p. 110-115.
265. Herbaut, A., et al., *A reliable measure of footwear upper comfort enabled by an innovative sock equipped with textile pressure sensors.* Ergonomics, 2016. **59**(10): p. 1327-1334.
266. Stoggl, T. and A. Martiner, *Validation of Moticon's OpenGo sensor insoles during gait, jumps, balance and cross-country skiing specific imitation movements.* J Sports Sci, 2017. **35**(2): p. 196-206.
267. Sawacha, Z., *Validation of plantar pressure measurements for a novel in-shoe plantar sensory replacement unit.* J Diabetes Sci Technol, 2013. **7**(5): p. 1176-8.
268. Crea, S., et al., *A Wireless Flexible Sensorized Insole for Gait Analysis.* Sensors (Basel, Switzerland), 2014. **14**(1): p. 1073-1093.
269. Jagos, H. and J. Oberzaucher, *Development of a Wearable Measurement System to Identify Characteristics in Human Gait - eSHOE*, in *Computers Helping People with Special Needs: 11th*

International Conference, ICCHP 2008, Linz, Austria, July 9-11, 2008. Proceedings, K. Miesenberger, et al., Editors. 2008, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 1301-1304.
270. Martínez-Nova, A., et al., *BioFoot® in-shoe system: Normal values and assessment of the reliability and repeatability.* The Foot, 2007. **17**(4): p. 190-196.
271. Holleczek, T., et al. *Textile pressure sensors for sports applications*. in *2010 IEEE Sensors*. 2010.
272. Pfaffen, S., et al., *Planipes: mobile foot pressure analysis*, in *Proceedings of the First ACM Workshop on Mobile Systems, Applications, and Services for Healthcare*. 2011, ACM: Seattle, Washington. p. 1-6.
273. Dabiri, F., et al. *Electronic orthotics shoe: Preventing ulceration in diabetic patients*. in *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2008.
274. Retisense. *Strydalizer*. 2014 2016-03-02]; Available from: http://www.retisense.com/stridalyzer-smart-insole/.
275. Kinematix. *TUNE*. 2016 2016-03-02]; Available from: http://kinematix.pt/.
276. Novel. *Pedar-x*. 2012 2016-03-02]; Available from: http://www.novel.de/novelcontent/pedar.
277. Paromed. *ParoLogg*. 2016-03-02]; Available from: http://www.paromed.biz/paroTec-3-2.html.
278. Paromed. *ParoTec*. 2016-03-02]; Available from: http://www.paromed.biz/paroTec-3-2.html.
279. Tekscan. *F-Scan Datalogger*. 2008 2016-03-02]; Available from: https://www.tekscan.com/products-solutions/systems/f-scan-system.
280. Tekscan. *F-scan Wireless*. 2008 2016-03-02]; Available from: https://www.tekscan.com/products-solutions/systems/f-scan-system.
281. Medilogic. *Medilogic Insole*. 2016-03-02]; Available from: http://www.medilogic.com/en/products-human/footpressure-measurement/medilogic-insole/.
282. Sensoria, I. *Sensoria Socks*. 2013 2016-03-02]; Available from: http://www.sensoriafitness.com/.
283. DigitSole. *DigitSole*. 2016 2016-03-02]; Available from: http://www.sensoriafitness.com/.
284. Orpyx. *Orpyx LogR*. 2013 2016-03-02]; Available from: http://orpyx.com/pages/logr.
285. Orpyx. *SurroSense rx System*. 2013 2016-03-02]; Available from: http://orpyx.com/pages/surrosense-rx.
286. Talavera, G., et al., *Fully-Wireless Sensor Insole as Non-invasive Tool for Collecting Gait Data and Analyzing Fall Risk*. 2015. 15-25.
287. Lin, F., et al., *Smart Insole: A Wearable Sensor Device for Unobtrusive Gait Monitoring in Daily Life.* IEEE Transactions on Industrial Informatics, 2016. **12**(6): p. 2281-2291.
288. Ahroni, J.H., E.J. Boyko, and R. Forsberg, *Reliability of F-scan in-shoe measurements of plantar pressure.* Foot Ankle Int, 1998. **19**(10): p. 668-73.
289. Razak, A.H.A., et al., *Foot Plantar Pressure Measurement System: A Review.* Sensors (Basel, Switzerland), 2012. **12**(7): p. 9884-9912.
290. Oerbekke, M.S., et al., *Concurrent validity and reliability of wireless instrumented insoles measuring postural balance and temporal gait parameters.* Gait Posture, 2017. **51**: p. 116-124.
291. Ferber, R., et al., *Validation of Plantar Pressure Measurements for a Novel In-Shoe Plantar Sensory Replacement Unit.* Journal of Diabetes Science and Technology, 2013. **7**(5): p. 1167-1175.
292. R. Aguilar, K.F.L., M. Zecca, D. Esliger, *ALTERNATIVE MEASURING DEVICES FOR SEDENTARY BEHAVIOUR: A SCOPING REVIEW*, in *International Conference in Sports Science & Technology* 2016: Singapore.
293. Baek, J. and B.J. Yun, *Posture Monitoring System for Context Awareness in Mobile Computing.* IEEE Transactions on Instrumentation and Measurement, 2010. **59**(6): p. 1589-1599.
294. Ward, D.S., et al., *Accelerometer Use in Physical Activity: Best Practices and Research Recommendations.* Medicine & Science in Sports & Exercise, 2005. **37**(Supplement): p. S582-S588.

295. Becker, B.G. *Visualizing decision table classifiers*. in *Proceedings IEEE Symposium on Information Visualization (Cat. No.98TB100258)*. 1998.
296. Khosrow-Pour, M., *Systems and Software Development, Modeling, and Analysis: New Perspectives and Methodologies: New Perspectives and Methodologies*. 2014: IGI Global.
297. Maurer, U., et al. *Activity recognition and monitoring using multiple sensors on different body positions*. in *International Workshop on Wearable and Implantable Body Sensor Networks (BSN'06)*. 2006.
298. John, G.H. and P. Langley, *Estimating continuous distributions in Bayesian classifiers*, in *Proceedings of the Eleventh conference on Uncertainty in artificial intelligence*. 1995, Morgan Kaufmann Publishers Inc.: Montréal, Qué, Canada. p. 338-345.
299. Benbasat, A.Y. and J.A. Paradiso, *A framework for the automated generation of power-efficient classifiers for embedded sensor nodes*, in *Proceedings of the 5th international conference on Embedded networked sensor systems*. 2007, ACM: Sydney, Australia. p. 219-232.
300. Ravi, N., et al., *Activity recognition from accelerometer data*, in *Proceedings of the 17th conference on Innovative applications of artificial intelligence - Volume 3*. 2005, AAAI Press: Pittsburgh, Pennsylvania. p. 1541-1546.
301. Bamberg, S.J.M., et al., *Gait Analysis Using a Shoe-Integrated Wireless Sensor System.* IEEE Transactions on Information Technology in Biomedicine, 2008. **12**(4): p. 413-423.
302. Jagos, H. and J. Oberzaucher. *Development of a Wearable Measurement System to Identify Characteristics in Human Gait - eSHOE*. in *Computers Helping People with Special Needs*. 2008. Berlin, Heidelberg: Springer Berlin Heidelberg.
303. Cortes, C., et al., *Learning curves: Asymptotic values and rate of convergence*, in *NIPS 1994*, J.D. Cowan, G. Tesauro, and J. Alspector, Editors. 1994, Morgan Kaufmann Publishers, Inc. p. 327-334.
304. Bassett, D.R., Jr., A. Rowlands, and S.G. Trost, *Calibration and validation of wearable monitors.* Med Sci Sports Exerc, 2012. **44**(1 Suppl 1): p. S32-8.
305. OPPENHEIM, A.V., A. L. WILLSKY, and W. T. YOUNG, *Signals and Systems*. 1983, Englewood Cliffs, NJ: Prentice-Hall.
306. Winter, D.A., A.O. Quanbury, and G.D. Reimer, *Analysis of instantaneous energy of normal gait.* J Biomech, 1976. **9**(4): p. 253-7.
307. Welk, G.J., J. Almeida, and G. Morss, *Laboratory calibration and validation of the Biotrainer and Actitrac activity monitors.* Med Sci Sports Exerc, 2003. **35**(6): p. 1057-64.
308. Rosenberg, D.E., et al., *Reliability and validity of the Sedentary Behavior Questionnaire (SBQ) for adults.* J Phys Act Health, 2010. **7**(6): p. 697-705.
309. Wijndaele, K., et al., *Reliability and validity of a domain-specific last 7-d sedentary time questionnaire.* Med Sci Sports Exerc, 2014. **46**(6): p. 1248-60.
310. Witten, I.H., E. Frank, and M.A. Hall, *Chapter 5 - Credibility: Evaluating What's Been Learned*, in *Data Mining: Practical Machine Learning Tools and Techniques (Third Edition)*. 2011, Morgan Kaufmann: Boston. p. 147-187.
311. Kohavi, R., *A study of cross-validation and bootstrap for accuracy estimation and model selection*, in *Proceedings of the 14th international joint conference on Artificial intelligence - Volume 2*. 1995, Morgan Kaufmann Publishers Inc.: Montreal, Quebec, Canada. p. 1137-1143.
312. Bao, L. and S.S. Intille, *Activity Recognition from User-Annotated Acceleration Data*, in *Pervasive Computing: Second International Conference, PERVASIVE 2004, Linz/Vienna, Austria, April 21-23, 2004. Proceedings*, A. Ferscha and F. Mattern, Editors. 2004, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 1-17.

313. Song-Mi, L., Y. Sang Min, and C. Heeryon. *Human activity recognition from accelerometer data using Convolutional Neural Network*. in *2017 IEEE International Conference on Big Data and Smart Computing (BigComp)*. 2017.
314. Witten, I.H., E. Frank, and M.A. Hall, *Chapter 10 - Introduction to Weka*, in *Data Mining: Practical Machine Learning Tools and Techniques (Third Edition)*. 2011, Morgan Kaufmann: Boston. p. 403-406.
315. Preece, S.J., et al., *Activity identification using body-mounted sensors--a review of classification techniques.* Physiol Meas, 2009. **30**(4): p. R1-33.
316. A Baumgartner, T., et al., *Measurement for Evaluation in Kinesiology*. 2015.
317. Donaldson, S.C., et al., *Variability of Objectively Measured Sedentary Behavior.* Med Sci Sports Exerc, 2016. **48**(4): p. 755-61.
318. Whybrow, S., et al., *An evaluation of the IDEEA™ activity monitor for estimating energy expenditure.* British Journal of Nutrition, 2013. **109**(1): p. 173-183.
319. Ainsworth, B.E., et al., *Compendium of physical activities: classification of energy costs of human physical activities.* Med Sci Sports Exerc, 1993. **25**(1): p. 71-80.
320. Ainsworth, B.E., et al., *Compendium of physical activities: an update of activity codes and MET intensities.* Med Sci Sports Exerc, 2000. **32**(9 Suppl): p. S498-504.
321. Ainsworth, B.E., et al., *2011 Compendium of Physical Activities: a second update of codes and MET values.* Med Sci Sports Exerc, 2011. **43**(8): p. 1575-81.
322. Ltd, P.T., *Activpal Operating Guide.* PAL Technologies Ltd, Glasgow, Scotland: 2010.
323. Labs, R. *Boogio*. 2014 2016-03-02]; Available from: https://boogiobeta.squarespace.com/.
324. Labs, L. *3L Labs Footlogger*. 2016 2016-03-02]; Available from: http://www.footlogger.com/.
325. Plantiga. *Tiga-Edge*. TBD 2016-03-02]; Available from: http://www.plantiga.com/.
326. Intelisoles. *Intelisoles*. TBD 2016-03-02]; Available from: http://www.intelisoles.com/.
327. Bebop. *Bebop*. 2016 2016-03-02]; Available from: https://www.bebopsensors.com/.
328. JumpStartCSR. *Holmz*. 2015 2016-03-02]; Available from: http://www.jumpstartcsr.com/index.html.

Appendices

A. Scoping review full list of references and devices

Name	Proto-type	Manufacturer	Debut year	Battery	Battery duration (hrs)	Sensor Type	Number of Sensors	Connectivity
Opengo Science	No	Moticon	2013	Rechargeable Coin cell	48	13 capacitive pressure sensing pads	13	ANT+, USB
Orpyx LogR	No	Orpyx	2013+	180 mHh Rechargeable	8	8 pressure sensors	8	BLE
Surrosense rx System	No	Orpyx	2013	Coin cell battery (6 months)	48	Pressure grid	8	ANT+, USB , WiFi
Pedar-x	No	Novel	2012	NIMh battery	4.5	Pressure sensors (capacitive)	85-99	USB/SD card or Classic Bluetooth
F-scan Wireless	No	Tekscan	2008	Li-on Battery	-	Pressure sensors (resistive)	960 sensing elements	USB, Wi-Fi
F-scan Datalogger	No	Tekscan	2008	Li-on Battery	2	Pressure sensors (resistive)	960 sensing elements	USB
ParoTec	No	Paromed	-			Pressure sensors (hydrocell	24 or 36	W-LAN
ParoLogg	No	Paromed	-			Accelerometer, Pressure (hydrocell	32	W-LAN
Boogio	Yes	REFLX Labs	2014	Yes	72	Accelerometer, Pressure	-	BLE
Stridalyzer	No	ReTiSense	2014	Rechargeable	20	Accelerometer, Pressure	-	BLE
Sensoria fitness socks	No	Sensoria	2013	Rechargeable Battery	6	3 Pressure sensors (fifth and first	3	BLE
Tune	No	Kinematix	2016	Yes	10	FSR	4	BLE
3L Labs footlogger	Yes	3L Labs	2015	Rechargeable Battery	24		8	Bluetooth 2.1 , WiFi Gateway
Tiga-Edge	Yes	Plantiga	To be released				-	BLE
Intelisoles	Yes	Imtelisoles	To be released			Accelerometer, Pressure	-	BLE
Digitsole	No	Digitsole	2016	Yes	48	-	-	
Medilogic insole	No	**Medilogic**				Resistive	240	Wireless
WIFS	Yes	-		9V	50	force sensor	4	RF
Freewalker	Yes	-		Yes	24	FSR	8	RF, nRF24L01 by Nordic
Smart Sock	Yes	**®Texisense**				knitted piezoresistive	4	
Chen, H. C., et al.	Yes	-		7.2V rechargeable Li-ion	2	Load cells	14	
Authier, A., et al.	Yes	-		600 mAh Li-ions	7..5	load cells	4	
Zhu, C., et al.	Yes	-				FSR	15	Bluetooth 2.0
Numchaichanakij, A., et al.	Yes	-		one 9-volt		Piezoresistive force sensor	1	Serial
Nakajima, K., et al.	Yes	-		lithium, 3V, 850 mAh	20	conductive rubber sensors	7	wireless ZigBee protocol
Rossi, S. M. M. D., et al.	Yes	-		Li-poly 700mAh	7	silicone-covered opto-electronic pressure	64	Bluetooth

Appendix A-1: Excerpt of the form developed for this work to list the technologies found, their attributes and their technical specifications.

Device	**Source**	**Device**	**Source**
OpenGo Science	[282]	Chen, M., et al.	[172]
Orpyx LogR	[285]	Chen, H. C., et al.	[173]
Surrosense rx System	[286]	Authier, A., et al.	[174]
Pedar-x	[276]	Zhu, C., et al.	[175]
F-scan Wireless	[280]	Saeedi, A., et al.	[178]
F-scan Datalogger	[279]	Numchaichanakij, A., et al.	[180]
ParoTec	[278]	Nakajima, K., et al.	[181]
ParoLogg	[277]	Feng, Y., et al.	[182]
Boogio	[323]	Rossi, S. M. M. D., et al.	[183]
Stridalyzer	[274]	Xu, H., et al.	[186]
Sensoria fitness socks	[283]	Wang, X., et al.	[187]
Tune	[275]	Wada, C. and M. Tokunaga	[188]
3L Labs Footlogger	[324]	Wada, C., et al.	[189]
Tiga-Edge	[325]	Tirosh, O., et al.	[190]
Intelisoles	[326]	Tao, Y., et al.	[191]
Digitsole	[284]	Takeda, T., et al.	[192]
Bebop	[327]	Suh, Y. S. and S. K. Park	[193]
Holmz	[328]	Stassi, S., et al.	[194]
StabilitySole	[179]	Shu, L., et al.	[195]
SmartShoe	[196]	Mazumder, O., et al.	[200]
SmartStep	[218]	Lemos, J. D., et al.	[202]
vitaliSHOE	[203]	Guo, Y. and L. Wang	[205]
WalkinSense	[204]	Grenez, F., et al.	[210]
PIMU	[214]	Martínez-Martí, F., et al.	[221]
i-SMART ShoE II	[215]	Majumder, A. J. A., et al.	[222]
WIISEL	[216]	Lu, L., et al.	[224]
DAid® Pressure Sock System	[220]	Kawsar, F., et al.	[227]
Smart-shoe	[222]	González, I., et al.	[229]
Smart Insole	[225]	Gerlach, C., et al.	[230]
SmartSkin Technologies	[249]	Corbellini, S., et al.	[231]
GaitShoe	[233]	AbuFaraj, Z. O., et al.	[232]
Runalyser	[240]	Shu, L., et al.	[234]
Medilogic insole	[281]	Saito, M., et al.	[335]
WIFS	[246]	Zhang, X., et al.	[237]
Freewalker	[254]	Zhang, Z. and S. Poslad	[238]
Smart Sock	[262]	Chen, B., et al.	[243]
eSHOE	[266]	Morris, S. J. and J. A. Paradiso	[244]
BioFoot	[267]	Ravindarn, G. and R. Manivannan	[245]
Planipes	[268]	Lvping, R., et al.	[247]
Electronic Orthotics Shoe	[269]	do Carmo Dos Reis, M., et al.	[253]
Surdilovic, D., et al.	[166]	Yang, C. M., et al.	[258]
Mizuno, H., et al.	[169]	Wertsch, J. J., et al.	[260]
Karkokli, R. and K. M. McConville	[170]	Holleczek, T., et al.	[268]
Hannula, M., et al.	[171]		

Appendix A-2: List of technologies found and their source.

B. Criterion - GoPro tasks annotation

								Sampling rate						
	Go Pro video		Duration	Insole time (s)		Duration (s)	Activity Type	10						
File number	Start	End		Start	End									
								Activity_type(	1	:	89850	) =	0	;
1	00:00	06:15	06:15	0	191	191	1	Activity_type(	1	:	1920	) =	1	;
1	06:16	11:35	05:19	192	511	319	1	Activity_type(	1921	:	5120	) =	1	;
2	11:50	17:20	05:30	1246	1576	330	1	Activity_type(	12461	:	15770	) =	1	;
2	05:40	12:20	06:40	876	1276	400	1	Activity_type(	8761	:	12770	) =	1	;
3	00:21	05:30	05:09	1277	1586	309	1	Activity_type(	12771	:	15870	) =	1	;
3	05:50	11:20	05:30	1606	1936	330	1	Activity_type(	16061	:	19370	) =	1	;
3	11:50	16:50	05:00	1966	2266	300	2	Activity_type(	19661	:	22670	) =	2	;
4	04:51	11:00	06:09	2267	2636	369	2	Activity_type(	22671	:	26370	) =	2	;
4	11:20	17:15	05:55	2656	3011	355	2	Activity_type(	26561	:	30120	) =	2	;
5	05:16	11:15	05:59	3012	3371	359	2	Activity_type(	30121	:	33720	) =	2	;
6	00:00	03:04	03:04	3416	3600	184	1	Activity_type(	34161	:	36010	) =	1	;
6	03:05	05:30	02:25	3601	3746	145	1	Activity_type(	36011	:	37470	) =	1	;
6	06:00	09:20	03:20	3776	3976	200	1	Activity_type(	37761	:	39770	) =	1	;
6	09:21	12:15	02:54	3977	4151	174	1	Activity_type(	39771	:	41520	) =	1	;
7	00:45	06:26	05:41	4181	4522	341	6	Activity_type(	41811	:	45230	) =	6	;
7	06:27	12:05	05:38	4523	4861	338	6	Activity_type(	45231	:	48620	) =	6	;
8	00:05	04:50	04:45	4861	5146	285	6	Activity_type(	48611	:	51470	) =	6	;
8	05:20	09:50	04:30	5176	5446	270	6	Activity_type(	51761	:	54470	) =	6	;
8	11:00	12:09	01:09	5516	5585	69	1	Activity_type(	55161	:	55860	) =	1	;
9	00:10	01:09	00:59	5586	5645	59	1	Activity_type(	55861	:	56460	) =	1	;
9	01:10	02:24	01:14	5646	5720	74	1	Activity_type(	56461	:	57210	) =	1	;
9	02:25	12:31	10:06	5721	6327	606	1	Activity_type(	57211	:	63280	) =	1	;
9	03:38	04:44	01:06	5794	5860	66	1	Activity_type(	57941	:	58610	) =	1	;
9	04:49	06:04	01:15	5865	5940	75	1	Activity_type(	58651	:	59410	) =	1	;
9	06:05	07:19	01:14	5941	6015	74	1	Activity_type(	59411	:	60160	) =	1	;
9	07:20	08:28	01:08	6016	6084	68	1	Activity_type(	60161	:	60850	) =	1	;
9	08:29	09:16	00:47	6085	6132	47	1	Activity_type(	60851	:	61330	) =	1	;
9	09:17	09:43	00:26	6133	6159	26	1	Activity_type(	61331	:	61600	) =	1	;
9	09:44	11:51	02:07	6160	6287	127	1	Activity_type(	61601	:	62880	) =	1	;
9	11:52	12:05	00:13	6288	6301	13	1	Activity_type(	62881	:	63020	) =	1	;
10	01:06	02:05	00:59	6362	6421	59	1	Activity_type(	63621	:	64220	) =	1	;
10	02:15	03:29	01:14	6431	6505	74	2	Activity_type(	64311	:	65060	) =	2	;
10	03:30	04:48	01:18	6506	6584	78	2	Activity_type(	65061	:	65850	) =	2	;
10	04:49	06:04	01:15	6585	6660	75	2	Activity_type(	65851	:	66610	) =	2	;
10	06:05	07:21	01:16	6661	6737	76	2	Activity_type(	66611	:	67380	) =	2	;
10	07:22	08:32	01:10	6738	6808	70	2	Activity_type(	67381	:	68090	) =	2	;
10	08:33	09:43	01:10	6809	6879	70	2	Activity_type(	68091	:	68800	) =	2	;
10	09:44	10:49	01:05	6880	6945	65	2	Activity_type(	68801	:	69460	) =	2	;
10	10:50	12:00	01:10	6946	7016	70	2	Activity_type(	69461	:	70170	) =	2	;
11	00:05	01:20	01:15	7021	7096	75	2	Activity_type(	70211	:	70970	) =	2	;
11	01:50	02:50	01:00	7126	7186	60	2	Activity_type(	71261	:	71870	) =	2	;
11	03:20	12:30	09:10	7216	7766	550	3	Activity_type(	72161	:	77670	) =	3	;
12	01:25	10:10	08:45	7821	8346	525	4	Activity_type(	78211	:	83470	) =	4	;
13	01:10	07:13	06:03	8621	8984	363	5	Activity_type(	86211	:	89850	) =	5	;

Appendix B-1: Excerpt of the standardized form developed for this work to create the time-based labels or annotations. Time spent in each activity was coded to create a single vector with corresponding offsets whenever necessary.

C. Sliding Window Length Experiments for Optimal Performance

Window Size (s)	Activities	Accuracy	False Positive Rate	Precision	F-Measure
2	**Sitting**	98.87% ± 1.21%	1.18% ± 1.05%	98.52% ± 2.32%	98.5% ± 2.11%
	Standing	97.47% ± 2.55%	2.25% ± 2.94%	92.31% ± 4.83%	93.73% ± 3.59%
	Leaning	99.7% ± 0.31%	0.03% ± 0.05%	99.73% ± 0.4%	96.74% ± 2.82%
	Walking	97.54% ± 2.25%	1.32% ± 1%	90.43% ± 6.52%	89.77% ± 8.13%
	Stairs	99.92% ± 0.16%	0.02% ± 0.04%	99% ± 2.6%	97.83% ± 4.45%
	Cycling	99.43% ± 0.31%	0.14% ± 0.14%	92.73% ± 3.96%	80.88% ± 12.75%
	ALL	98.54% ± 0.73%	1.29% ± 0.59%	96.38% ± 3.31%	96.13% ± 3.72%
4	**Sitting**	98.82% ± 1.33%	1.26% ± 1.25%	98.39% ± 2.51%	98.45% ± 2.16%
	Standing	97.36% ± 2.9%	2.35% ± 3.26%	92.29% ± 5.39%	93.66% ± 3.99%
	Leaning	99.61% ± 0.45%	0.02% ± 0.04%	99.69% ± 0.55%	95.7% ± 4.18%
	Walking	97.55% ± 2.48%	1.31% ± 1.06%	90.68% ± 7.1%	89.89% ± 9.18%
	Stairs	99.91% ± 0.18%	0.01% ± 0.03%	99.25% ± 1.94%	97.63% ± 4.69%
	Cycling	99.5% ± 0.3%	0.13% ± 0.16%	93.53% ± 4.31%	83.34% ± 12.53%
	ALL	98.48% ± 0.74%	1.35% ± 0.61%	96.35% ± 3.2%	96.08% ± 3.49%
8	**Sitting**	98.99% ± 1.4%	1.18% ± 1.41%	99.06% ± 1.8%	99% ± 1.67%
	Standing	96.89% ± 3.02%	2.84% ± 3.51%	91.2% ± 5.02%	92.73% ± 3.55%
	Leaning	99.43% ± 0.56%	0.04% ± 0.05%	99% ± 1.22%	93.03% ± 5.19%
	Walking	97.49% ± 2.42%	1.37% ± 0.9%	90.17% ± 6.23%	89.73% ± 9.53%
	Stairs	99.88% ± 0.18%	0.02% ± 0.05%	98.98% ± 2.84%	96.91% ± 4.6%
	Cycling	99.52% ± 0.29%	0.1% ± 0.13%	95.22% ± 3.35%	84.36% ± 10.35%
	ALL	98.47% ± 0.92%	1.42% ± 0.75%	96.48% ± 3.79%	96.17% ± 3.9%
16	**Sitting**	98.66% ± 1.9%	1.45% ± 1.95%	98.78% ± 2.46%	98.67% ± 2.25%
	Standing	96.71% ± 3.38%	3.18% ± 3.83%	90.05% ± 5.27%	92.53% ± 3.9%
	Leaning	99.2% ± 0.71%	0.05% ± 0.08%	98.65% ± 1.82%	89.28% ± 6.75%
	Walking	97.53% ± 2.66%	1.33% ± 1.02%	90.36% ± 8.15%	89.59% ± 11.11%
	Stairs	99.83% ± 0.24%	0.01% ± 0.04%	99.2% ± 2.6%	95.14% ± 6.63%
	Cycling	99.52% ± 0.26%	0.1% ± 0.11%	95.33% ± 4.83%	84.93% ± 10.06%
	ALL	98.23% ± 0.85%	1.65% ± 0.82%	96.11% ± 3.94%	95.75% ± 3.96%
32	**Sitting**	98.55% ± 2.03%	1.77% ± 2.26%	98.67% ± 2.52%	98.57% ± 2.38%
	Standing	96.32% ± 3.62%	3.58% ± 4.14%	89.05% ± 5.61%	91.58% ± 4.19%
	Leaning	99.03% ± 0.79%	0.07% ± 0.12%	98.11% ± 3.19%	85.87% ± 8.09%
	Walking	97.26% ± 2.99%	1.5% ± 1.14%	89.47% ± 9.61%	88.03% ± 12.19%
	Stairs	99.76% ± 0.34%	0.01% ± 0.03%	99.17% ± 3.23%	94.03% ± 6.64%
	Cycling	99.49% ± 0.29%	0.08% ± 0.22%	97.55% ± 4.01%	90.84% ± 9.27%
	ALL	98.04% ± 0.96%	1.94% ± 0.91%	95.77% ± 4.33%	95.29% ± 4.39%

Appendix C-1. Measurements of performance obtained using pressure data. Computations are performed using a different sizes of sliding window, the Random Forest classifier and all features in a subject dependent manner.

Window Size (s)	Activities	Accuracy	False Positive Rate	Precision	F-Measure
2	**Sitting**	98.52% ± 1.57%	1.7% ± 1.3%	98.02% ± 2.88%	98.07% ± 2.6%
	Standing	96.82% ± 3.22%	2.8% ± 3.66%	90.62% ± 5.66%	92.14% ± 4.3%
	Leaning	99.47% ± 0.46%	0.04% ± 0.11%	99.66% ± 0.32%	93.79% ± 4.21%
	Walking	96.99% ± 2.75%	1.85% ± 1.37%	86.94% ± 8.85%	87.56% ± 9.67%
	Stairs	99.86% ± 0.23%	0.02% ± 0.04%	98.96% ± 2.7%	96.29% ± 6.52%
	Cycling	99.15% ± 0.39%	0.12% ± 0.17%	92.33% ± 4.49%	68.12% ± 18.04%
	ALL	98.12% ± 0.87%	1.76% ± 0.71%	95.36% ± 4.24%	94.85% ± 5.33%
4	**Sitting**	98.5% ± 1.66%	1.69% ± 1.43%	97.99% ± 2.99%	98.07% ± 2.6%
	Standing	96.78% ± 3.32%	2.86% ± 3.79%	90.54% ± 5.93%	92.12% ± 4.39%
	Leaning	99.37% ± 0.59%	0.04% ± 0.07%	99.49% ± 0.74%	92.36% ± 5.68%
	Walking	97.14% ± 2.73%	1.7% ± 1.28%	87.96% ± 8.42%	88.02% ± 9.82%
	Stairs	99.87% ± 0.2%	0.01% ± 0.02%	99.49% ± 1.37%	96.62% ± 5.21%
	Cycling	99.31% ± 0.33%	0.13% ± 0.15%	92.09% ± 4.98%	75.24% ± 15.28%
	ALL	98.11% ± 0.85%	1.75% ± 0.73%	95.43% ± 4.03%	94.96% ± 4.6%
8	**Sitting**	98.84% ± 1.64%	1.35% ± 1.47%	98.96% ± 1.91%	98.86% ± 1.97%
	Standing	96.31% ± 3.45%	3.35% ± 4.06%	89.51% ± 5.62%	91.35% ± 3.92%
	Leaning	99.21% ± 0.64%	0.03% ± 0.04%	99.06% ± 1.17%	89.46% ± 6.25%
	Walking	97.15% ± 2.79%	1.66% ± 1.12%	88.23% ± 8.03%	88.4% ± 10.91%
	Stairs	99.86% ± 0.2%	0.01% ± 0.02%	99.49% ± 1.56%	96.49% ± 4.87%
	Cycling	99.41% ± 0.34%	0.13% ± 0.18%	93.72% ± 4.57%	79.81% ± 13.27%
	ALL	98.22% ± 1.08%	1.66% ± 0.9%	95.86% ± 4.58%	95.42% ± 4.75%
16	**Sitting**	98.43% ± 2.02%	1.76% ± 2.05%	98.61% ± 2.61%	98.45% ± 2.41%
	Standing	95.98% ± 3.77%	3.82% ± 4.19%	88.06% ± 5.38%	90.81% ± 4.01%
	Leaning	98.93% ± 0.73%	0.07% ± 0.09%	98.15% ± 2.29%	84.53% ± 7.71%
	Walking	97.18% ± 2.86%	1.61% ± 1.14%	88.19% ± 9.07%	87.92% ± 11.78%
	Stairs	99.79% ± 0.28%	0.01% ± 0.04%	99.37% ± 1.97%	93.97% ± 7.35%
	Cycling	99.37% ± 0.3%	0.15% ± 0.2%	94.17% ± 4.98%	81.92% ± 9.64%
	ALL	97.9% ± 1.04%	1.99% ± 0.99%	95.34% ± 4.8%	94.82% ± 4.93%
32	**Sitting**	98.19% ± 2.06%	2.2% ± 1.96%	98.38% ± 2.36%	98.23% ± 2.46%
	Standing	95.42% ± 3.86%	4.26% ± 4.44%	86.37% ± 5.28%	89.04% ± 4.1%
	Leaning	98.69% ± 0.72%	0.14% ± 0.1%	96.2% ± 2.82%	79.73% ± 7.96%
	Walking	96.89% ± 3.34%	1.79% ± 1.42%	87.83% ± 10.2%	86.49% ± 13.33%
	Stairs	99.67% ± 0.33%	0.03% ± 0.07%	98.15% ± 4.32%	91.48% ± 6.9%
	Cycling	99.36% ± 0.37%	0.16% ± 0.29%	94.71% ± 6.94%	88.07% ± 10.31%
	ALL	97.6% ± 1.16%	2.37% ± 1.06%	94.75% ± 5.2%	94.08% ± 5.58%

Appendix C-2. Measurements of performance obtained using pressure data. Computations are performed using a different sizes of sliding window, the Random Forest classifier and the Information Gain feature set in a subject dependent manner.

Window Size (s)	Activities	Accuracy	False Positive Rate	Precision	F-Measure
2	Sitting	94.01% ± 3.85%	6.91% ± 3.76%	95.67% ± 4.01%	94.88% ± 4%
	Standing	89.93% ± 5.3%	9.89% ± 6.07%	65.71% ± 16.29%	74.5% ± 12.35%
	Leaning	96.78% ± 1.49%	0.17% ± 0.24%	58.49% ± 37.32%	19.75% ± 22.11%
	Walking	95.8% ± 3.46%	2.52% ± 1.89%	81.6% ± 10.53%	82.34% ± 11.05%
	Stairs	98.48% ± 1.07%	0.01% ± 0.02%	74.46% ± 42.65%	36.16% ± 32.84%
	Cycling	98.66% ± 0.49%	0.29% ± 0.28%	71.48% ± 21.59%	44.06% ± 15.61%
	ALL	93.76% ± 2.06%	6.44% ± 2.61%	86.64% ± 12.89%	85.22% ± 17.48%
4	Sitting	94.34% ± 3.92%	6.96% ± 3.77%	95.71% ± 3.89%	95.15% ± 4.04%
	Standing	90.47% ± 5.49%	9.12% ± 6.36%	67.84% ± 17.47%	75.58% ± 12.81%
	Leaning	96.93% ± 1.51%	0.3% ± 0.38%	68.14% ± 32.59%	26.08% ± 28.37%
	Walking	95.8% ± 3.53%	2.52% ± 2%	81.55% ± 10.62%	81.84% ± 11.99%
	Stairs	98.47% ± 1.09%	0.01% ± 0.02%	88.74% ± 29.63%	40.41% ± 32.84%
	Cycling	98.68% ± 0.5%	0.26% ± 0.24%	72.27% ± 20.35%	43.22% ± 18.47%
	ALL	94.07% ± 1.92%	6.34% ± 2.44%	87.67% ± 11.48%	85.81% ± 16.46%
8	Sitting	94.7% ± 3.33%	7.3% ± 4.22%	95.53% ± 4.03%	95.46% ± 3.63%
	Standing	90.88% ± 4.8%	8.63% ± 5.57%	68.46% ± 14.91%	76.26% ± 10.53%
	Leaning	96.72% ± 1.43%	0.38% ± 0.43%	59.67% ± 33.19%	24.81% ± 22.78%
	Walking	95.87% ± 3.53%	2.39% ± 2.08%	82.54% ± 10.86%	81.84% ± 12.4%
	Stairs	98.5% ± 1.07%	0% ± 0.01%	99.61% ± 1.17%	46.89% ± 31.05%
	Cycling	98.8% ± 0.51%	0.22% ± 0.3%	80.44% ± 20.03%	49.59% ± 19.47%
	ALL	94.38% ± 1.82%	6.46% ± 2.44%	87.84% ± 11.75%	86.33% ± 16.06%
16	Sitting	95.02% ± 3.28%	6.96% ± 4.15%	95.69% ± 4.03%	95.73% ± 3.59%
	Standing	91.68% ± 4.59%	7.69% ± 5.37%	71.14% ± 14.52%	78.15% ± 9.43%
	Leaning	96.81% ± 1.46%	0.48% ± 0.49%	63.2% ± 29.62%	34.52% ± 23.51%
	Walking	96.19% ± 3.44%	2.37% ± 2.16%	83.01% ± 11.2%	83.89% ± 10.99%
	Stairs	98.63% ± 1.09%	0% ± 0%	100% ± 0%	53.71% ± 34.25%
	Cycling	98.87% ± 0.53%	0.17% ± 0.22%	81.68% ± 21.16%	48.63% ± 23.06%
	ALL	94.76% ± 1.63%	6.08% ± 2.22%	88.61% ± 10.74%	87.52% ± 14.33%
32	Sitting	94.86% ± 3.42%	7.07% ± 4.04%	95.61% ± 3.89%	95.63% ± 3.53%
	Standing	91.63% ± 4.15%	7.66% ± 5.06%	70.7% ± 14.82%	77.55% ± 9.65%
	Leaning	96.89% ± 1.36%	0.48% ± 0.58%	66.73% ± 34.93%	36.28% ± 23.98%
	Walking	96.19% ± 3.23%	2.4% ± 1.95%	82.42% ± 10.6%	83.18% ± 11.31%
	Stairs	98.62% ± 1.03%	0% ± 0%	100% ± 0%	56.33% ± 23.7%
	Cycling	98.97% ± 0.49%	0.06% ± 0.09%	87.51% ± 20.4%	52.9% ± 21.46%
	ALL	94.66% ± 1.64%	6.15% ± 2.24%	88.67% ± 10.54%	87.51% ± 13.8%

Appendix C-3. Measurements of performance obtained using pressure data. Computations are performed using a different sizes of sliding window, the Random Forest classifier and all features in a subject independent manner.

Window Size (s)	Activities	Accuracy	False Positive Rate	Precision	F-Measure
2	**Sitting**	94.01% ± 3.85%	6.91% ± 3.76%	95.67% ± 4.01%	94.88% ± 4%
	Standing	89.93% ± 5.3%	9.89% ± 6.07%	65.71% ± 16.29%	74.5% ± 12.35%
	Leaning	96.78% ± 1.49%	0.17% ± 0.24%	58.49% ± 37.32%	19.75% ± 22.11%
	Walking	95.8% ± 3.46%	2.52% ± 1.89%	81.6% ± 10.53%	82.34% ± 11.05%
	Stairs	98.48% ± 1.07%	0.01% ± 0.02%	74.46% ± 42.65%	36.16% ± 32.84%
	Cycling	98.66% ± 0.49%	0.29% ± 0.28%	71.48% ± 21.59%	44.06% ± 15.61%
	ALL	93.76% ± 2.06%	6.44% ± 2.61%	86.64% ± 12.89%	85.22% ± 17.48%
4	**Sitting**	92.36% ± 3.74%	8.69% ± 4.47%	94.4% ± 4.57%	93.54% ± 3.89%
	Standing	88.24% ± 5.24%	11.15% ± 5.8%	62.07% ± 16.64%	70.62% ± 13.3%
	Leaning	96.53% ± 1.18%	0.25% ± 0.51%	56.78% ± 33.76%	13.22% ± 11.83%
	Walking	95.27% ± 3.57%	3.31% ± 2.16%	77.19% ± 10.32%	79.49% ± 13.76%
	Stairs	98.06% ± 1.05%	0% ± 0%	80% ± 44.72%	8.09% ± 7.88%
	Cycling	98.49% ± 0.54%	0.06% ± 0.08%	77.18% ± 20.08%	22.32% ± 13.43%
	ALL	92.33% ± 2.41%	7.89% ± 3%	84.83% ± 13.6%	82.21% ± 20.96%
8	**Sitting**	92.64% ± 3.51%	8.71% ± 4.51%	94.47% ± 4.33%	93.79% ± 3.67%
	Standing	88.43% ± 5.03%	10.83% ± 5.59%	62.5% ± 16.44%	70.81% ± 12.73%
	Leaning	96.62% ± 1.32%	0.25% ± 0.38%	61.92% ± 36.91%	18.47% ± 13.46%
	Walking	95.29% ± 3.61%	3.2% ± 2.25%	77.84% ± 10.46%	79.27% ± 14.38%
	Stairs	98.05% ± 1.06%	0% ± 0.01%	95% ± 10%	8.19% ± 5.83%
	Cycling	98.57% ± 0.56%	0.12% ± 0.2%	78.92% ± 23.47%	31.76% ± 19.36%
	ALL	92.55% ± 2.37%	7.83% ± 2.96%	85.53% ± 13.15%	82.73% ± 20%
16	**Sitting**	93.26% ± 3.11%	8.33% ± 4.3%	94.79% ± 4.1%	94.3% ± 3.47%
	Standing	89.11% ± 4.54%	10.08% ± 5.39%	64.05% ± 16.07%	71.94% ± 11.74%
	Leaning	96.52% ± 1.32%	0.48% ± 0.69%	59.51% ± 37.59%	22.88% ± 16.17%
	Walking	95.1% ± 3.48%	3.3% ± 2.4%	76.87% ± 11.13%	77.73% ± 15.53%
	Stairs	98.07% ± 1.06%	0% ± 0%	100% ± 0%	11.41% ± 8.25%
	Cycling	98.6% ± 0.52%	0.08% ± 0.14%	80.3% ± 25.82%	35.81% ± 18.51%
	ALL	93.04% ± 2.16%	7.49% ± 2.72%	85.93% ± 13.15%	83.35% ± 19.23%
32	**Sitting**	93.7% ± 2.93%	8.23% ± 4.04%	94.96% ± 3.77%	94.69% ± 3.32%
	Standing	89.74% ± 4.08%	9.46% ± 5.2%	65.24% ± 13.8%	73.05% ± 9.19%
	Leaning	96.59% ± 1.3%	0.51% ± 0.54%	56.51% ± 30.31%	24.68% ± 14.75%
	Walking	95.27% ± 3.35%	3.19% ± 2.31%	77.85% ± 10.77%	78.76% ± 13.32%
	Stairs	98.09% ± 1.02%	0.01% ± 0.05%	75% ± 50%	24.27% ± 14.39%
	Cycling	98.63% ± 0.62%	0.1% ± 0.22%	79.4% ± 20.57%	35.3% ± 18.48%
	ALL	93.45% ± 2%	7.3% ± 2.61%	85.79% ± 12.95%	84.3% ± 18.06%

Appendix C-4. Measurements of performance obtained using pressure data. Computations are performed using a different sizes of sliding window, the Random Forest classifier and the Information Gain feature set in a subject independent manner.

D. Classifier Experiments for Optimal Performance

Classifiers	Activities	Accuracy	False Positive Rate	Precision	F-Measure
Nearest Neighbour	**Sitting**	98.92% ± 1.6%	1.27% ± 1.66%	98.91% ± 2.22%	98.93% ± 1.89%
	Standing	96.67% ± 3%	2.71% ± 3.24%	91.26% ± 5%	91.89% ± 3.55%
	Leaning	99.28% ± 0.54%	0.11% ± 0.12%	97.36% ± 2.32%	90.75% ± 5.31%
	Walking	97.3% ± 2.54%	1.61% ± 0.93%	88.35% ± 6.86%	88.9% ± 10.19%
	Stairs	99.89% ± 0.16%	0.04% ± 0.06%	97.93% ± 3%	96.79% ± 5.45%
	Cycling	99.46% ± 0.29%	0.17% ± 0.19%	92.53% ± 5.48%	83.2% ± 9.4%
	ALL	98.36% ± 0.98%	1.49% ± 0.68%	96.05% ± 4.07%	95.76% ± 4.33%
		Accuracy	**False Positive Rate**	**Precision**	**F-Measure**
Naïve Bayes	**Sitting**	96.6% ± 2.67%	1.45% ± 1.93%	98.59% ± 2.68%	96.97% ± 2.72%
	Standing	91.48% ± 5.33%	3.42% ± 1.78%	81.76% ± 9.61%	75.24% ± 10.15%
	Leaning	95.5% ± 3.63%	4.21% ± 3.53%	53.06% ± 15.71%	65.17% ± 12.8%
	Walking	95.89% ± 4.46%	2.48% ± 2.42%	82.81% ± 15.5%	83.71% ± 15.92%
	Stairs	99.34% ± 1.83%	0.58% ± 1.78%	90.93% ± 19.69%	92.01% ± 14.79%
	Cycling	98.45% ± 2%	1.3% ± 1.96%	68.68% ± 24.51%	72.93% ± 20.75%
	ALL	95.61% ± 2.06%	2.02% ± 0.91%	91.02% ± 11.26%	89.51% ± 10.28%
		Accuracy	**False Positive Rate**	**Precision**	**F-Measure**
Decision Tables	**Sitting**	98.48% ± 2.41%	1.96% ± 2.37%	98.36% ± 3.09%	98.48% ± 2.84%
	Standing	96.28% ± 3.69%	2.79% ± 3.44%	90.78% ± 5.51%	91.19% ± 4.83%
	Leaning	99.25% ± 0.89%	0.19% ± 0.23%	95.79% ± 4.41%	91.35% ± 8.16%
	Walking	96.92% ± 3.1%	1.84% ± 1.59%	87.32% ± 10.04%	87.73% ± 11.09%
	Stairs	99.8% ± 0.32%	0.06% ± 0.11%	97.32% ± 5.14%	95.31% ± 6.91%
	Cycling	99.38% ± 0.35%	0.24% ± 0.18%	87.52% ± 8.15%	80.9% ± 11.59%
	ALL	97.96% ± 1%	1.96% ± 0.63%	95.32% ± 4.28%	95.16% ± 4.57%
		Accuracy	**False Positive Rate**	**Precision**	**F-Measure**
J48	**Sitting**	98.29% ± 2.05%	2.27% ± 1.97%	98.26% ± 2.53%	98.36% ± 2.45%
	Standing	95.62% ± 3.74%	2.88% ± 2.95%	89.61% ± 4.92%	89.17% ± 4.84%
	Leaning	99.12% ± 0.76%	0.43% ± 0.39%	91.09% ± 5.54%	89.93% ± 5.77%
	Walking	96.4% ± 3.31%	2.13% ± 1.9%	85.34% ± 10.53%	85.49% ± 10.86%
	Stairs	99.71% ± 0.34%	0.14% ± 0.15%	93.94% ± 5.36%	93.24% ± 6.19%
	Cycling	99.1% ± 0.45%	0.45% ± 0.23%	76.03% ± 14.02%	74.14% ± 14.7%
	ALL	97.65% ± 1.19%	2.21% ± 0.6%	94.31% ± 5.51%	94.21% ± 5.77%

Appendix D-1. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, different classifiers, and all features in a subject dependent manner. (Part 1)

Classifiers	Activities	Accuracy	False Positive Rate	Precision	F-Measure
Random Forest	**Sitting**	99.06% ± 1.2%	1.09% ± 1.22%	99.18% ± 1.49%	99.09% ± 1.43%
	Standing	97.01% ± 2.86%	2.77% ± 3.36%	91.29% ± 5.02%	92.99% ± 3.63%
	Leaning	99.53% ± 0.51%	0.02% ± 0.03%	99.64% ± 0.61%	94.24% ± 4.75%
	Walking	97.49% ± 2.39%	1.33% ± 0.92%	90.38% ± 6.35%	89.69% ± 9.39%
	Stairs	99.9% ± 0.18%	0.01% ± 0.03%	99.37% ± 1.58%	97.59% ± 4.22%
	Cycling	99.51% ± 0.28%	0.13% ± 0.12%	93.93% ± 4.33%	84.19% ± 9.87%
	ALL	98.54% ± 0.91%	1.35% ± 0.74%	96.6% ± 3.81%	96.33% ± 3.89%
		Accuracy	**False Positive Rate**	**Precision**	**F-Measure**
Bagging	**Sitting**	98.73% ± 1.53%	1.66% ± 1.69%	98.71% ± 2.2%	98.77% ± 1.82%
	Standing	96.7% ± 2.88%	2.75% ± 3.07%	90.84% ± 4.64%	91.99% ± 3.49%
	Leaning	99.38% ± 0.55%	0.13% ± 0.06%	96.81% ± 1%	92.48% ± 4.92%
	Walking	97.26% ± 2.47%	1.49% ± 0.97%	89% ± 6.5%	88.57% ± 9.33%
	Stairs	99.76% ± 0.2%	0.08% ± 0.07%	96.23% ± 3.39%	94.12% ± 4.4%
	Cycling	99.37% ± 0.33%	0.21% ± 0.15%	89.36% ± 6.32%	81.1% ± 10.48%
	ALL	98.24% ± 0.91%	1.72% ± 0.64%	95.79% ± 4.01%	95.61% ± 4.38%
		Accuracy	**False Positive Rate**	**Precision**	**F-Measure**
Logit Boost	**Sitting**	98.48% ± 2.41%	1.96% ± 2.37%	98.36% ± 3.09%	98.48% ± 2.84%
	Standing	96.28% ± 3.69%	2.79% ± 3.44%	90.78% ± 5.51%	91.19% ± 4.83%
	Leaning	99.25% ± 0.89%	0.19% ± 0.23%	95.79% ± 4.41%	91.35% ± 8.16%
	Walking	96.92% ± 3.1%	1.84% ± 1.59%	87.32% ± 10.04%	87.73% ± 11.09%
	Stairs	99.8% ± 0.32%	0.06% ± 0.11%	97.32% ± 5.14%	95.31% ± 6.91%
	Cycling	99.38% ± 0.35%	0.24% ± 0.18%	87.52% ± 8.15%	80.9% ± 11.59%
	ALL	97.96% ± 1%	1.96% ± 0.63%	95.32% ± 4.28%	95.16% ± 4.57%

Appendix D-2. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, different classifiers, and all features in a subject dependent manner. (Part 2)

		Accuracy	False Positive Rate	Precision	F-Measure
Nearest Neighbor	Sitting	96.26% ± 2.21%	6.19% ± 3.21%	95.6% ± 3.91%	97.01% ± 2.11%
	Standing	92.28% ± 2.7%	4% ± 1.71%	78.88% ± 10.98%	76.93% ± 8.4%
	Leaning	96.33% ± 1.17%	1.7% ± 1.34%	62.6% ± 17.37%	56.04% ± 7.76%
	Walking	95.58% ± 1.5%	2.53% ± 1.22%	80.54% ± 6.17%	81.36% ± 4.12%
	Stairs	98.61% ± 0.95%	0.24% ± 0.4%	87.06% ± 18.3%	65.53% ± 16.2%
	Cycling	97.66% ± 1.15%	1.13% ± 1.13%	54.04% ± 28.64%	44.2% ± 12.45%
	ALL	95.56% ± 1.58%	4.86% ± 1.7%	89.79% ± 9.96%	88.91% ± 12.45%
		Accuracy	False Positive Rate	Precision	F-Measure
Naïve Bayes	Sitting	83.85% ± 9.96%	3.53% ± 4.44%	96.62% ± 5.04%	90.06% ± 7.07%
	Standing	82.3% ± 7.5%	6.11% ± 6.11%	66.66% ± 22.91%	45.57% ± 5.64%
	Leaning	87.34% ± 5.79%	10.29% ± 4.28%	25.99% ± 11.49%	37.75% ± 12.72%
	Walking	92.88% ± 4.17%	3.87% ± 2.61%	72.64% ± 12.95%	72.45% ± 12.38%
	Stairs	92.74% ± 3.99%	3.73% ± 3.25%	39.83% ± 26.51%	49.55% ± 28.26%
	Cycling	94.76% ± 3.92%	2.99% ± 1.91%	34.13% ± 22.79%	40.69% ± 16.06%
	ALL	85.1% ± 3.51%	3.96% ± 1.53%	84.47% ± 19.14%	75.49% ± 19.4%
		Accuracy	False Positive Rate	Precision	F-Measure
Decision Tables	Sitting	89.42% ± 2.1%	20.58% ± 7.38%	89.78% ± 5.42%	92.52% ± 2.37%
	Standing	86.91% ± 5.45%	8.18% ± 4.24%	59.5% ± 24.26%	60.74% ± 16.46%
	Leaning	94.65% ± 3.43%	1.68% ± 2.37%	30.82% ± 29.15%	18.58% ± 17.19%
	Walking	94.5% ± 2.07%	2.64% ± 1.27%	73.32% ± 12.26%	70.1% ± 25.75%
	Stairs	96.98% ± 0.72%	0.18% ± 0.13%	10.42% ± 19.29%	1.94% ± 3.38%
	Cycling	97.61% ± 0.84%	0.3% ± 0.56%	73.92% ± 31.63%	14.54% ± 9.38%
	ALL	90.04% ± 2.63%	15.62% ± 7.77%	80.9% ± 18%	80.3% ± 22.35%
		Accuracy	False Positive Rate	Precision	F-Measure
J48	Sitting	91.98% ± 7.35%	9.25% ± 3.34%	94.25% ± 3.15%	93.94% ± 5.59%
	Standing	87.82% ± 4.75%	8.49% ± 5.25%	65% ± 21.4%	67.4% ± 15.28%
	Leaning	94.89% ± 1.18%	1.93% ± 0.77%	36.41% ± 18.5%	32.7% ± 19.74%
	Walking	94.04% ± 0.96%	2.78% ± 0.8%	73.98% ± 10.23%	71.93% ± 14.52%
	Stairs	97.89% ± 1.39%	0.68% ± 0.75%	65.75% ± 31.45%	52.95% ± 27.11%
	Cycling	97.44% ± 0.83%	1.08% ± 0.8%	45.31% ± 18.98%	36.21% ± 9.62%
	ALL	91.8% ± 2.23%	7.83% ± 2.7%	84.95% ± 15.95%	83.74% ± 16.61%

Appendix D-3. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, different classifiers, and all features in a subject independent manner. (Part 1)

Classifier		Accuracy	False Positive Rate	Precision	F-Measure
Random Forest	**Sitting**	91.11% ± 12.02%	3.43% ± 5.04%	97.65% ± 3.94%	97.95% ± 3.36%
	Standing	90.37% ± 7.61%	4.38% ± 4.8%	85.49% ± 10.8%	88.59% ± 8.94%
	Leaning	93.75% ± 6.9%	0.11% ± 0.22%	88.53% ± 23.83%	76.35% ± 29.56%
	Walking	95.65% ± 3.89%	1.97% ± 2.04%	86.51% ± 11.96%	87.28% ± 12.35%
	Stairs	97.22% ± 2.98%	0.01% ± 0.03%	99.45% ± 1.36%	83.29% ± 32.68%
	Cycling	97.03% ± 3.26%	0.15% ± 0.17%	90.2% ± 9.01%	72.84% ± 19.13%
	ALL	91.82% ± 1.88%	3.48% ± 1.11%	94.53% ± 5.49%	94.27% ± 6.41%
Bagging		**Accuracy**	**False Positive Rate**	**Precision**	**F-Measure**
	Sitting	94.52% ± 5.33%	6.58% ± 6.25%	95.04% ± 7.27%	95.63% ± 4.59%
	Standing	90.29% ± 5.42%	6.98% ± 4.7%	71.43% ± 20.58%	74.51% ± 14.34%
	Leaning	96.21% ± 1.3%	1.08% ± 0.83%	57.24% ± 28.16%	44.56% ± 19.74%
	Walking	96.41% ± 1.05%	1.86% ± 0.56%	83.25% ± 5.41%	81.23% ± 16.3%
	Stairs	99.01% ± 0.61%	0.06% ± 0.11%	82.89% ± 33.78%	68.13% ± 32.51%
	Cycling	98.47% ± 0.47%	0.39% ± 0.4%	75.76% ± 19.27%	53.01% ± 16.48%
	ALL	94.21% ± 2.06%	5.18% ± 2.14%	89.38% ± 11.02%	87.91% ± 12.96%
Logit Boost		**Accuracy**	**False Positive Rate**	**Precision**	**F-Measure**
	Sitting	96.78% ± 1.82%	8.71% ± 4.98%	94.15% ± 5.98%	95.51% ± 3.36%
	Standing	91.76% ± 2.6%	6.1% ± 2.65%	71.51% ± 17.99%	73.45% ± 11.67%
	Leaning	95.64% ± 0.93%	1.24% ± 1.27%	63.04% ± 29.55%	36.65% ± 18.39%
	Walking	95.61% ± 1.02%	2.5% ± 0.95%	81.44% ± 3.45%	84.11% ± 5.58%
	Stairs	98.78% ± 0.88%	0.14% ± 0.18%	86.64% ± 15.4%	59.81% ± 28.05%
	Cycling	98.5% ± 0.4%	0.31% ± 0.33%	77.59% ± 17.52%	46.8% ± 19.92%
	ALL	95.79% ± 1.94%	6.74% ± 2.69%	88.61% ± 10.09%	87.1% ± 14.46%

Appendix D-4. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, different classifiers, and all features in a subject independent manner. (Part 2)

Classifier		Accuracy	False Positive Rate	Precision	F-Measure
Nearest Neigh-bor	Sitting	98.84% ± 1.52%	1.34% ± 1.29%	98.89% ± 1.8%	98.85% ± 1.84%
	Standing	96.38% ± 3.17%	2.65% ± 3.45%	91.55% ± 5.42%	91.06% ± 3.83%
	Leaning	99.28% ± 0.61%	0.14% ± 0.14%	96.69% ± 2.69%	91.07% ± 5.65%
	Walking	97.01% ± 2.68%	2% ± 1.17%	86.1% ± 7.75%	88.05% ± 10.17%
	Stairs	99.91% ± 0.15%	0.03% ± 0.03%	98.8% ± 1.67%	97.44% ± 4.83%
	Cycling	99.39% ± 0.31%	0.21% ± 0.23%	90.45% ± 6.2%	81% ± 10.78%
	ALL	98.22% ± 1.08%	1.57% ± 0.66%	95.77% ± 4.58%	95.44% ± 4.72%
Naïve Bayes		Accuracy	False Positive Rate	Precision	F-Measure
	Sitting	97.31% ± 2.47%	1.25% ± 1.96%	98.72% ± 2.7%	97.51% ± 2.81%
	Standing	93.65% ± 5.12%	3.38% ± 2.21%	85.19% ± 6.36%	83.56% ± 7.72%
	Leaning	97.69% ± 2.57%	1.75% ± 2.32%	73.83% ± 17.25%	78.08% ± 13.15%
	Walking	96.16% ± 4.2%	2.58% ± 3.11%	83.4% ± 13.22%	85.18% ± 11.93%
	Stairs	99.51% ± 1.18%	0.45% ± 1.14%	89.77% ± 15.85%	92.8% ± 11.49%
	Cycling	98.8% ± 0.67%	0.91% ± 0.6%	66.39% ± 20.49%	71.66% ± 17.09%
	ALL	96.59% ± 1.51%	1.8% ± 0.88%	92.57% ± 8.46%	92.07% ± 7.33%
Deci-sion Tables		Accuracy	False Positive Rate	Precision	F-Measure
	Sitting	95.72% ± 2.77%	8.63% ± 4.06%	94.55% ± 4.04%	96.18% ± 3.29%
	Standing	93.38% ± 4.41%	4.37% ± 4.41%	84.19% ± 5.48%	82.43% ± 5.21%
	Leaning	98.08% ± 1.07%	0.61% ± 0.36%	83.04% ± 7.09%	73.78% ± 9.53%
	Walking	95.53% ± 3.2%	2.56% ± 1.33%	79.79% ± 9.68%	79.56% ± 12.72%
	Stairs	99.15% ± 0.58%	0.23% ± 0.19%	85.32% ± 11.4%	76.65% ± 13.88%
	Cycling	98.62% ± 0.53%	0.3% ± 0.19%	70.44% ± 18.19%	47.3% ± 22.63%
	ALL	95.48% ± 1.27%	6.46% ± 2.9%	89.75% ± 6.43%	89.37% ± 9.93%
J48		Accuracy	False Positive Rate	Precision	F-Measure
	Sitting	97.67% ± 2.23%	3.07% ± 2.09%	97.72% ± 2.86%	97.78% ± 2.72%
	Standing	94.67% ± 4.01%	4.11% ± 4.11%	85.75% ± 5.6%	86.59% ± 4.36%
	Leaning	98.62% ± 0.92%	0.51% ± 0.29%	87.29% ± 5.39%	82.55% ± 7.89%
	Walking	96.35% ± 3.13%	2.01% ± 1.31%	84.61% ± 9.33%	84.25% ± 11.89%
	Stairs	99.47% ± 0.38%	0.22% ± 0.13%	89.93% ± 5.88%	86.63% ± 9.16%
	Cycling	98.91% ± 0.42%	0.45% ± 0.23%	75.06% ± 10.56%	67.01% ± 13.14%
	ALL	97.06% ± 1.28%	2.92% ± 0.94%	92.92% ± 6.31%	92.64% ± 7.05%

Appendix D-5. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, different classifiers, and Information Gain features in a subject dependent manner. (Part 1)

		Accuracy	False Positive Rate	Precision	F-Measure
Random Forest	Sitting	98.86% ± 1.48%	1.31% ± 1.28%	99.05% ± 1.52%	98.89% ± 1.79%
	Standing	96.44% ± 3.26%	3.28% ± 3.86%	89.66% ± 5.6%	91.62% ± 3.88%
	Leaning	99.28% ± 0.65%	0.02% ± 0.02%	99.49% ± 0.63%	90.64% ± 6.19%
	Walking	97.21% ± 2.62%	1.62% ± 1.12%	88.4% ± 7.73%	88.7% ± 9.99%
	Stairs	99.86% ± 0.23%	0.01% ± 0.03%	99.33% ± 1.92%	96.49% ± 5.35%
	Cycling	99.4% ± 0.32%	0.13% ± 0.16%	93.77% ± 3.58%	80.41% ± 11.62%
	ALL	98.27% ± 1.04%	1.61% ± 0.88%	95.98% ± 4.55%	95.59% ± 4.57%
		Accuracy	False Positive Rate	Precision	F-Measure
Bagging	Sitting	98.13% ± 2.03%	2.45% ± 1.8%	98.19% ± 2.41%	98.2% ± 2.47%
	Standing	95.33% ± 3.81%	3.95% ± 4.21%	86.79% ± 5.8%	88.48% ± 4.41%
	Leaning	98.93% ± 0.72%	0.24% ± 0.13%	93.5% ± 2.53%	85.91% ± 6.15%
	Walking	96.46% ± 3.05%	2.02% ± 1.3%	84.8% ± 9.02%	84.74% ± 11.44%
	Stairs	99.62% ± 0.29%	0.11% ± 0.12%	94.88% ± 5.82%	90.61% ± 6.18%
	Cycling	99.08% ± 0.37%	0.27% ± 0.18%	83.07% ± 9.1%	68.45% ± 15.45%
	ALL	97.49% ± 1.21%	2.5% ± 0.92%	93.94% ± 5.73%	93.56% ± 6.54%
		Accuracy	False Positive Rate	Precision	F-Measure
Logit Boost	Sitting	98.19% ± 2.34%	2.38% ± 2.14%	98.13% ± 2.8%	98.22% ± 2.8%
	Standing	95.4% ± 4.37%	3.53% ± 4.35%	88.38% ± 6.28%	89.01% ± 5.3%
	Leaning	98.94% ± 1.07%	0.3% ± 0.29%	92.86% ± 6.29%	87.29% ± 9.85%
	Walking	96.64% ± 3.31%	2.01% ± 1.65%	86.04% ± 10.72%	86.38% ± 12.06%
	Stairs	99.77% ± 0.4%	0.07% ± 0.13%	97.01% ± 5.61%	94.5% ± 8.27%
	Cycling	99.27% ± 0.38%	0.25% ± 0.17%	86.8% ± 8.61%	77.64% ± 11.77%
	ALL	97.57% ± 1.2%	2.38% ± 0.8%	94.44% ± 4.99%	94.19% ± 5.45%

Appendix D-6. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, different classifiers, and Information Gain features in a subject dependent manner. (Part 2)

		Accuracy	False Positive Rate	Precision	F-Measure
Nearest Neighbor	Sitting	89.81% ± 7.18%	19.14% ± 9.57%	88.98% ± 11.47%	93.1% ± 6.6%
	Standing	90.37% ± 7.31%	2.24% ± 0.75%	80.88% ± 12.78%	71.68% ± 7.75%
	Leaning	95.5% ± 2.43%	1.02% ± 0.89%	54.54% ± 29.77%	40.1% ± 24.05%
	Walking	96.05% ± 1.55%	3.02% ± 0.93%	77.58% ± 4.52%	84.36% ± 4.25%
	Stairs	97.48% ± 0.65%	0.34% ± 0.24%	58.14% ± 30.89%	33.26% ± 19.79%
	Cycling	97.55% ± 1.07%	0.48% ± 0.69%	65.34% ± 25.58%	25.8% ± 14.43%
	ALL	91.11% ± 2.49%	12.56% ± 8.18%	86.22% ± 8.74%	84.76% ± 15.91%
		Accuracy	False Positive Rate	Precision	F-Measure
Naïve Bayes	Sitting	84.1% ± 8.93%	2.4% ± 2.75%	97.65% ± 3.17%	89.08% ± 8.45%
	Standing	82.46% ± 4.27%	6.8% ± 6.02%	68.49% ± 24.49%	57.8% ± 12.55%
	Leaning	91.18% ± 5.19%	7.88% ± 4.15%	30.79% ± 9.92%	42.47% ± 10.99%
	Walking	94.34% ± 3.35%	3.51% ± 2.22%	74.16% ± 12.35%	74.83% ± 13.78%
	Stairs	92.38% ± 4.02%	4.41% ± 4.26%	41.51% ± 29.83%	48.97% ± 28.05%
	Cycling	95.43% ± 3.68%	2.86% ± 2.53%	40.34% ± 25.15%	42.83% ± 15.22%
	ALL	85.6% ± 3.96%	3.39% ± 1.84%	85.99% ± 18.34%	78.26% ± 15.22%
		Accuracy	False Positive Rate	Precision	F-Measure
Decision Tables	Sitting	87.66% ± 2.65%	28.18% ± 11.13%	85.98% ± 8.92%	90.28% ± 4.2%
	Standing	86.56% ± 2.24%	8.58% ± 3.04%	55.36% ± 23.14%	57.52% ± 14.44%
	Leaning	95.2% ± 1.48%	0.86% ± 0.63%	19.62% ± 21.92%	9.02% ± 9.94%
	Walking	93.35% ± 1.76%	2.08% ± 1.05%	67.68% ± 14.57%	53.02% ± 29.09%
	Stairs	97.07% ± 0.67%	0.16% ± 0.05%	10.42% ± 19.29%	1.94% ± 3.38%
	Cycling	97.72% ± 0.47%	0.38% ± 0.69%	51% ± 37.34%	16.8% ± 14.48%
	ALL	88.75% ± 2.86%	20% ± 11.39%	77.32% ± 18.96%	77.12% ± 24.05%
		Accuracy	False Positive Rate	Precision	F-Measure
J48	Sitting	91.44% ± 3.26%	17.88% ± 11.87%	88.92% ± 12.01%	90.78% ± 6.29%
	Standing	86.96% ± 4.75%	8.26% ± 7.26%	61.34% ± 27.17%	60.16% ± 13.18%
	Leaning	95% ± 1.82%	1.28% ± 0.76%	31.94% ± 17.36%	19.28% ± 10.8%
	Walking	93.06% ± 3.53%	2.46% ± 1.21%	73.38% ± 14.9%	69.7% ± 25.69%
	Stairs	96.61% ± 0.69%	0.44% ± 0.31%	45.86% ± 29.08%	22.6% ± 12.91%
	Cycling	97.28% ± 1.28%	0.68% ± 0.65%	50.2% ± 28.45%	23.22% ± 9.88%
	ALL	91.16% ± 2.3%	11.88% ± 6.64%	82.8% ± 15.81%	80.04% ± 20.06%

Appendix D-7. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, different classifiers, and Information Gain features in a subject independent manner. (Part 1)

Classifier		Accuracy	False Positive Rate	Precision	F-Measure
Random Forest	**Sitting**	91.92% ± 5.64%	9.53% ± 5.1%	92.97% ± 5.54%	93.23% ± 4.3%
	Standing	89.12% ± 6.47%	11.23% ± 6.66%	64.77% ± 18.95%	72.23% ± 14.58%
	Leaning	96.47% ± 0.92%	0.21% ± 0.3%	69.9% ± 34.45%	20.75% ± 14.58%
	Walking	96.12% ± 0.78%	3.28% ± 2.13%	77.09% ± 10.31%	78.05% ± 14.54%
	Stairs	97.37% ± 0.51%	0.01% ± 0.03%	80% ± 44.72%	5.9% ± 6.55%
	Cycling	97.83% ± 0.38%	0.11% ± 0.19%	80.4% ± 22.46%	27.44% ± 15.06%
	ALL	92.28% ± 2.28%	8.27% ± 3.19%	84.17% ± 11.36%	81.6% ± 19.84%
		Accuracy	**False Positive Rate**	**Precision**	**F-Measure**
Bagging	**Sitting**	90.8% ± 5.73%	11.14% ± 5.66%	93.52% ± 5.24%	93.08% ± 4.59%
	Standing	87.27% ± 6.49%	10.46% ± 7.37%	59.2% ± 23.44%	65.14% ± 17.37%
	Leaning	95.96% ± 1.17%	0.58% ± 0.38%	51.14% ± 19.48%	23.12% ± 9.65%
	Walking	94.93% ± 1.16%	2.86% ± 1.48%	75.22% ± 9.29%	75.38% ± 14.38%
	Stairs	97.26% ± 0.25%	0.28% ± 0.13%	49.86% ± 34.66%	17.98% ± 12.93%
	Cycling	97.64% ± 0.7%	0.38% ± 0.59%	49.74% ± 37.74%	17.98% ± 13.09%
	ALL	91.08% ± 2.57%	9.18% ± 3.58%	84.98% ± 16.09%	82.64% ± 20.1%
		Accuracy	**False Positive Rate**	**Precision**	**F-Measure**
Logit Boost	**Sitting**	87.1% ± 8.26%	18.88% ± 4.5%	90.62% ± 3.76%	93.54% ± 1.35%
	Standing	85.84% ± 7.83%	8.48% ± 5.74%	62.28% ± 19.27%	62.86% ± 14.14%
	Leaning	95.63% ± 2.28%	0.48% ± 0.48%	56.16% ± 24.93%	23.2% ± 14.92%
	Walking	94.72% ± 2.7%	2.26% ± 0.97%	76.42% ± 7.77%	70.02% ± 21.65%
	Stairs	97.21% ± 0.8%	0.18% ± 0.19%	51.12% ± 33.29%	18.68% ± 16.78%
	Cycling	97.58% ± 0.52%	0.3% ± 0.3%	54.08% ± 27.86%	14.4% ± 10.37%
	ALL	88.44% ± 3.41%	14.5% ± 7.09%	83.3% ± 13.32%	81.96% ± 20.99%

Appendix D-8. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, different classifiers, and Information Gain features in a subject independent manner. (Part 2)

E. Feature Set Selection Experiments for Optimal Performance

		Accuracy	False Positive Rate	Precision	F-Measure
Left	Sitting	98.19% ± 1.44%	3.21% ± 1.71%	97.89% ± 1.83%	98.33% ± 1.77%
	Standing	96.2% ± 3.15%	2.98% ± 3.54%	90.11% ± 5.21%	90.51% ± 4.23%
	Leaning	99.31% ± 0.58%	0.04% ± 0.06%	99.04% ± 1.47%	90.96% ± 5.46%
	Walking	97.26% ± 2.5%	1.46% ± 1.06%	89.57% ± 6.8%	88.84% ± 9.32%
	Stairs	99.88% ± 0.21%	0.02% ± 0.04%	99.23% ± 2.13%	96.98% ± 5.25%
	Cycling	99.44% ± 0.31%	0.17% ± 0.15%	91.82% ± 3.58%	82.01% ± 11.26%
	ALL	97.82% ± 0.92%	2.71% ± 0.96%	95.42% ± 3.75%	95.11% ± 4.38%
Right		Accuracy	False Positive Rate	Precision	F-Measure
	Sitting	97.73% ± 1.75%	4.09% ± 2.82%	97.26% ± 2.36%	97.91% ± 1.99%
	Standing	95.99% ± 3.1%	3.04% ± 3.45%	89.86% ± 5.14%	89.84% ± 4.42%
	Leaning	99.17% ± 0.71%	0.05% ± 0.06%	98.79% ± 1.54%	88.66% ± 7.82%
	Walking	97.37% ± 2.38%	1.42% ± 0.92%	89.61% ± 6.52%	89.1% ± 9.35%
	Stairs	99.89% ± 0.19%	0.01% ± 0.03%	99.42% ± 1.36%	97.21% ± 4.66%
	Cycling	99.48% ± 0.28%	0.13% ± 0.14%	93.15% ± 4.63%	83.22% ± 9.37%
	ALL	97.5% ± 0.88%	3.26% ± 1.29%	95.01% ± 3.54%	94.7% ± 4.33%

Appendix E-1. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, Random Forest classifier, features per sensor from each insole in a subject dependent manner.

		Accuracy	False Positive Rate	Precision	F-Measure
Left	Sitting	95.57% ± 2.97%	8.28% ± 3.53%	94.56% ± 4.14%	95.98% ± 3.61%
	Standing	93.85% ± 4.77%	4.06% ± 4.44%	85.76% ± 6.34%	84.29% ± 5.7%
	Leaning	98.35% ± 1.16%	0.34% ± 0.32%	90.26% ± 7.35%	76.63% ± 12.06%
	Walking	96.24% ± 3.3%	2.2% ± 1.57%	83.29% ± 10.33%	83.13% ± 12.76%
	Stairs	99.39% ± 0.49%	0.21% ± 0.14%	89.16% ± 7.51%	84.19% ± 10.27%
	Cycling	98.94% ± 0.47%	0.27% ± 0.19%	79.92% ± 10.15%	63.13% ± 17.39%
	ALL	95.58% ± 1.21%	6.14% ± 2.86%	91.02% ± 4.74%	90.61% ± 7.48%
Right		Accuracy	False Positive Rate	Precision	F-Measure
	Sitting	94.54% ± 3.43%	10.56% ± 6.17%	93.42% ± 4.44%	95.15% ± 3.77%
	Standing	93.34% ± 4.58%	4.19% ± 4.26%	84.86% ± 6.71%	82.17% ± 6.49%
	Leaning	98.19% ± 1.16%	0.3% ± 0.19%	90.04% ± 5.35%	73.06% ± 14.27%
	Walking	96.49% ± 3.09%	2.05% ± 1.49%	84.74% ± 9.58%	84.64% ± 11.11%
	Stairs	99.27% ± 0.61%	0.25% ± 0.14%	87.61% ± 6.87%	81.3% ± 12.08%
	Cycling	99% ± 0.44%	0.31% ± 0.21%	81.01% ± 8.6%	66.46% ± 16.73%
	ALL	94.88% ± 1.42%	7.55% ± 3.93%	90.3% ± 4.13%	89.74% ± 7.45%

Appendix E-2. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, Random Forest classifier, features per sum of values per insole in a subject dependent manner.

		Accuracy	False Positive Rate	Precision	F-Measure
Sum of Left and Right	Sitting	98.64% ± 1.57%	1.96% ± 1.8%	98.64% ± 1.91%	98.71% ± 1.87%
	Standing	96.39% ± 3.29%	3.22% ± 3.68%	89.65% ± 5.37%	91.35% ± 3.93%
	Leaning	99.15% ± 0.74%	0.15% ± 0.14%	96.35% ± 2.85%	89.49% ± 6.63%
	Walking	97.04% ± 2.74%	1.68% ± 1.19%	87.6% ± 8.14%	87.38% ± 10.22%
	Stairs	99.71% ± 0.38%	0.05% ± 0.05%	97.5% ± 2.66%	92.65% ± 7.28%
	Cycling	99.25% ± 0.36%	0.15% ± 0.17%	91.25% ± 4.58%	73.76% ± 14.59%
	ALL	98.09% ± 0.99%	2.02% ± 0.76%	95.41% ± 4.49%	95.01% ± 5.33%
		Accuracy	False Positive Rate	Precision	F-Measure
All Features	Sitting	98.64% ± 1.57%	1.96% ± 1.8%	98.64% ± 1.91%	98.71% ± 1.87%
	Standing	96.39% ± 3.29%	3.22% ± 3.68%	89.65% ± 5.37%	91.35% ± 3.93%
	Leaning	99.15% ± 0.74%	0.15% ± 0.14%	96.35% ± 2.85%	89.49% ± 6.63%
	Walking	97.04% ± 2.74%	1.68% ± 1.19%	87.6% ± 8.14%	87.38% ± 10.22%
	Stairs	99.71% ± 0.38%	0.05% ± 0.05%	97.5% ± 2.66%	92.65% ± 7.28%
	Cycling	99.25% ± 0.36%	0.15% ± 0.17%	91.25% ± 4.58%	73.76% ± 14.59%
	ALL	98.09% ± 0.99%	2.02% ± 0.76%	95.41% ± 4.49%	95.01% ± 5.33%

Appendix E-3. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, Random Forest classifier and two feature sets: features per sum of values from both insoles and all features in a subject dependent manner.

		Accuracy	False Positive Rate	Precision	F-Measure
Left	Sitting	90.57% ± 5.96%	16.45% ± 7.01%	90.37% ± 7.97%	92.17% ± 6.31%
	Standing	88.87% ± 6.03%	8.35% ± 6.75%	67.13% ± 15.44%	69.79% ± 10.85%
	Leaning	96.58% ± 1.59%	0.22% ± 0.28%	49.25% ± 35.76%	14.11% ± 14.07%
	Walking	95.65% ± 3.7%	2.59% ± 2.29%	81.5% ± 11.67%	81.85% ± 11.25%
	Stairs	98.23% ± 0.96%	0.02% ± 0.02%	77.86% ± 32.09%	23.31% ± 21.14%
	Cycling	98.76% ± 0.58%	0.24% ± 0.24%	73.96% ± 19.57%	47.54% ± 19.82%
	ALL	91.36% ± 2.53%	12.25% ± 5.93%	83.3% ± 10.99%	82.22% ± 18.45%
		Accuracy	False Positive Rate	Precision	F-Measure
Right	Sitting	90.55% ± 4.17%	17.11% ± 8.65%	90.21% ± 6.86%	92.23% ± 4.84%
	Standing	88.43% ± 5.2%	8.19% ± 5.11%	65.89% ± 15.72%	67.87% ± 9.75%
	Leaning	96.53% ± 1.48%	0.34% ± 0.68%	46.89% ± 36.78%	16.01% ± 14.78%
	Walking	95.41% ± 3.49%	2.78% ± 2.26%	79.77% ± 11.33%	78.9% ± 15.69%
	Stairs	98.59% ± 1.1%	0.05% ± 0.11%	84.02% ± 32.36%	61.3% ± 25.95%
	Cycling	98.58% ± 0.44%	0.32% ± 0.31%	68% ± 24.78%	42.71% ± 14.5%
	ALL	91.24% ± 2.58%	12.67% ± 6.2%	82.72% ± 11.61%	82.31% ± 16.98%

Appendix E-4. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, Random Forest classifier, features per sensor from each insole in a subject independent manner.

		Accuracy	False Positive Rate	Precision	F-Measure
Left	Sitting	86.72% ± 5.04%	18.83% ± 7.27%	88.48% ± 8.53%	89.2% ± 5.54%
	Standing	85.3% ± 5.14%	10.36% ± 5.67%	58.56% ± 17.93%	59.77% ± 12.16%
	Leaning	96.35% ± 1.42%	0.72% ± 0.5%	35.72% ± 26.2%	19.3% ± 17.07%
	Walking	94.38% ± 3.72%	3.11% ± 1.62%	75.18% ± 11.61%	75.37% ± 15.02%
	Stairs	98.19% ± 1.05%	0.39% ± 0.22%	44.43% ± 31.35%	34.55% ± 27.28%
	Cycling	97.33% ± 2.26%	1.23% ± 2.22%	22.6% ± 13.51%	11.41% ± 6.5%
	ALL	88.1% ± 3.6%	14.23% ± 6.59%	77.88% ± 16.5%	77.62% ± 19.21%
		Accuracy	False Positive Rate	Precision	F-Measure
Right	Sitting	84.74% ± 6.04%	22.75% ± 11.2%	86.81% ± 8.26%	87.58% ± 6.19%
	Standing	83.81% ± 5.78%	12.02% ± 5.43%	53.7% ± 15.14%	56.92% ± 12.27%
	Leaning	96.21% ± 1.66%	0.53% ± 0.54%	29.32% ± 25.39%	9.19% ± 8.35%
	Walking	93.94% ± 3.55%	3.5% ± 2.78%	72.41% ± 15.28%	71.03% ± 18.85%
	Stairs	97.68% ± 1.44%	0.6% ± 0.75%	29.79% ± 24.91%	16.22% ± 15.46%
	Cycling	97.8% ± 0.82%	0.69% ± 0.47%	16.29% ± 15.83%	9.05% ± 6.28%
	ALL	86.51% ± 4.19%	17.04% ± 8.11%	75.02% ± 18.41%	74.83% ± 21.23%

Appendix E-5. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, Random Forest classifier, features per sum of values per insole in a subject independent manner.

		Accuracy	False Positive Rate	Precision	F-Measure
Sum of Left and Right	Sitting	90.43% ± 4.35%	9.56% ± 4.34%	93.59% ± 4.63%	92% ± 4.19%
	Standing	87.01% ± 5.67%	11.94% ± 5.97%	59.8% ± 17.26%	67.83% ± 14.21%
	Leaning	96.59% ± 1.44%	0.57% ± 0.45%	41.01% ± 33.28%	23.96% ± 21.2%
	Walking	94.63% ± 3.79%	3.17% ± 2.45%	77.05% ± 10.99%	76.91% ± 12.34%
	Stairs	98.08% ± 1.4%	0.32% ± 0.75%	58.6% ± 35.12%	24.62% ± 23.78%
	Cycling	97.84% ± 1.29%	0.66% ± 1.05%	24.38% ± 24.06%	9.82% ± 7.96%
	ALL	90.81% ± 2.71%	8.59% ± 3.26%	82.07% ± 17.29%	80.94% ± 19.2%
		Accuracy	False Positive Rate	Precision	F-Measure
All Features	Sitting	94.5% ± 3.93%	7.05% ± 3.89%	95.66% ± 3.89%	95.29% ± 3.99%
	Standing	90.56% ± 5.11%	9.03% ± 5.95%	67.62% ± 16.63%	75.49% ± 12.33%
	Leaning	96.78% ± 1.43%	0.31% ± 0.34%	56.07% ± 36.36%	23.79% ± 22.95%
	Walking	95.8% ± 3.5%	2.47% ± 2.09%	81.66% ± 10.96%	81.23% ± 13.3%
	Stairs	98.51% ± 1.09%	0.01% ± 0.01%	82.63% ± 38.62%	39.33% ± 35.1%
	Cycling	98.75% ± 0.55%	0.24% ± 0.27%	75.28% ± 19.84%	47.91% ± 21.3%
	ALL	94.18% ± 1.9%	6.38% ± 2.45%	87.13% ± 12.37%	85.79% ± 16.7%

Appendix E-6. Measurements of performance obtained using pressure data. Computations are performed using a 6-seconds sliding window, Random Forest classifier and two feature sets: features per sum of values from both insoles and all features in a subject dependent manner.

F. Performance measurements while using only pressure data and optimal parameters

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	98.87% ± 1.49%	1.42% ± 1.51%	98.91% ± 1.93%	98.9% ± 1.77%
Standing	96.73% ± 3.1%	2.97% ± 3.53%	90.49% ± 5.13%	92.23% ± 3.81%
Leaning	99.37% ± 0.57%	0.04% ± 0.05%	98.93% ± 1.12%	92.23% ± 5.24%
Walking	97.34% ± 2.52%	1.42% ± 0.94%	89.43% ± 7.08%	88.89% ± 9.89%
Stairs	99.88% ± 0.18%	0.01% ± 0.03%	99.34% ± 1.67%	96.86% ± 4.32%
Cycling	99.47% ± 0.31%	0.13% ± 0.12%	93.37% ± 5.11%	83% ± 10.2%
ALL	98.35% ± 0.94%	1.6% ± 0.75%	96.14% ± 4.07%	95.86% ± 4.22%

Appendix F-1. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, all features, and 6 pressure sensors in a subject dependent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	98.4% ± 1.74%	2.34% ± 2.13%	98.28% ± 2.41%	98.47% ± 2.06%
Standing	96.19% ± 3.53%	3.27% ± 3.78%	89.45% ± 5.59%	91.06% ± 4.18%
Leaning	99.21% ± 0.7%	0.11% ± 0.09%	97.19% ± 1.98%	90.05% ± 6.65%
Walking	96.97% ± 2.84%	1.66% ± 1.1%	87.24% ± 8.2%	86.72% ± 11.03%
Stairs	99.64% ± 0.41%	0.07% ± 0.08%	96.51% ± 3.61%	91.04% ± 7.96%
Cycling	99.26% ± 0.35%	0.21% ± 0.21%	89.14% ± 6.97%	75.96% ± 11.62%
ALL	97.9% ± 0.98%	2.25% ± 0.78%	95.08% ± 4.51%	94.77% ± 5.2%

Appendix F-2. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the LR_Sum feature set, and 6 pressure sensors in a subject dependent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	98.71% ± 1.56%	1.69% ± 1.52%	98.78% ± 1.78%	98.75% ± 1.88%
Standing	96.22% ± 3.23%	3.39% ± 3.78%	89.18% ± 5.56%	90.85% ± 3.82%
Leaning	99.19% ± 0.62%	0.04% ± 0.06%	98.89% ± 1.38%	89.3% ± 5.9%
Walking	97.01% ± 2.67%	1.77% ± 1.1%	87.28% ± 7.84%	87.69% ± 10.28%
Stairs	99.82% ± 0.27%	0.01% ± 0.02%	99.34% ± 1.43%	95.42% ± 6.73%
Cycling	99.31% ± 0.34%	0.15% ± 0.17%	92.72% ± 5.22%	76.71% ± 12.72%
ALL	98.1% ± 1.08%	1.89% ± 0.85%	95.55% ± 4.78%	95.09% ± 5.13%

Appendix F-3. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the Information Gain feature set, and 6 pressure sensors in a subject dependent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	94.4% ± 4.02%	6.6% ± 3.75%	95.85% ± 3.81%	95.2% ± 4.03%
Standing	90.6% ± 5.25%	8.65% ± 5.73%	68.55% ± 17.49%	75.4% ± 12.57%
Leaning	96.7% ± 1.32%	0.62% ± 0.59%	54.11% ± 33.75%	31.73% ± 24.88%
Walking	95.78% ± 3.64%	2.59% ± 2.39%	81.49% ± 10.99%	81.72% ± 12.12%
Stairs	98.68% ± 1.15%	0.02% ± 0.05%	89.1% ± 29.69%	50.49% ± 38.44%
Cycling	98.66% ± 0.52%	0.31% ± 0.28%	65.88% ± 23.39%	45.27% ± 17.27%
ALL	94.12% ± 1.88%	6.05% ± 2.25%	87.29% ± 12.58%	86.23% ± 15.19%

Appendix F-4. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, all features, and 6 pressure sensors in a subject independent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	92.82% ± 3.87%	7.21% ± 3.59%	95.21% ± 4.06%	93.93% ± 3.9%
Standing	89.39% ± 5.04%	9.61% ± 4.92%	64.71% ± 17.29%	72.19% ± 13.6%
Leaning	96.31% ± 1.41%	0.87% ± 0.85%	44.63% ± 33.81%	25.8% ± 21.41%
Walking	95.1% ± 3.62%	3.21% ± 2.43%	77.5% ± 10.81%	79.15% ± 12.03%
Stairs	98.11% ± 1.46%	0.37% ± 0.64%	35.77% ± 37.97%	29.33% ± 31.45%
Cycling	98.1% ± 0.81%	0.52% ± 0.58%	37.31% ± 29.19%	17.97% ± 15.55%
ALL	92.79% ± 2.03%	6.7% ± 2.38%	83.9% ± 16.91%	83.49% ± 18.4%

Appendix F-5. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the LR_Sum feature set, and 6 pressure sensors in a subject independent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	92.64% ± 3.38%	8.77% ± 4.13%	94.46% ± 4.22%	93.78% ± 3.62%
Standing	88.95% ± 5.06%	10.51% ± 5.42%	63.64% ± 15.88%	72.16% ± 12.22%
Leaning	96.56% ± 1.18%	0.33% ± 0.71%	52.64% ± 39.56%	20.98% ± 17.65%
Walking	95.32% ± 3.82%	3.22% ± 2.56%	77.81% ± 11.14%	80.67% ± 11.52%
Stairs	98.14% ± 1.05%	0% ± 0.01%	96.81% ± 5.28%	21.51% ± 15.87%
Cycling	98.46% ± 0.51%	0.05% ± 0.08%	67.54% ± 34.19%	15.31% ± 14.23%
ALL	92.64% ± 2.22%	7.82% ± 2.91%	85.25% ± 13.69%	83.2% ± 19.47%

Appendix F-6. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the Information Gain feature set, and 6 pressure sensors in a subject independent manner.

G. Performance measurements while using pressure data and foot acceleration

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	99% ± 1.56%	1.14% ± 1.49%	99.07% ± 2%	99.02% ± 1.85%
Standing	96.89% ± 3.18%	2.83% ± 3.59%	91.08% ± 5.16%	92.8% ± 3.94%
Leaning	99.4% ± 0.57%	0.02% ± 0.03%	99.38% ± 0.81%	92.55% ± 5.39%
Walking	97.36% ± 2.68%	1.45% ± 1.06%	89.5% ± 7.62%	89.27% ± 10.57%
Stairs	99.92% ± 0.13%	0.01% ± 0.03%	99.18% ± 2.15%	97.83% ± 3.83%
Cycling	99.49% ± 0.31%	0.13% ± 0.12%	93.42% ± 5.34%	83.56% ± 10.84%
ALL	98.46% ± 0.94%	1.4% ± 0.76%	96.37% ± 3.99%	96.13% ± 4.07%

Appendix G-1. Measurements of performance obtained using pressure and foot acceleration data. Computations are performed using a 6-seconds sliding window, Random Forest classifier, all features, and 6 pressure sensors in a subject dependent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	98.96% ± 1.68%	1.14% ± 1.53%	99.02% ± 2.06%	98.97% ± 1.99%
Standing	96.71% ± 3.41%	3.03% ± 3.93%	90.58% ± 5.52%	92.47% ± 4.14%
Leaning	99.26% ± 0.75%	0.05% ± 0.08%	98.74% ± 1.81%	90.54% ± 7.3%
Walking	97.28% ± 2.77%	1.49% ± 1.06%	89.05% ± 7.94%	88.88% ± 11.1%
Stairs	99.92% ± 0.13%	0.01% ± 0.03%	99.39% ± 2.12%	97.92% ± 4.03%
Cycling	99.45% ± 0.31%	0.15% ± 0.12%	92.06% ± 5.97%	82.35% ± 11.33%
ALL	98.39% ± 0.99%	1.44% ± 0.83%	96.14% ± 4.19%	95.89% ± 4.33%

Appendix G-2. Measurements of performance obtained using pressure and foot acceleration data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the LR_Sum feature set, and 6 pressure sensors in a subject dependent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	98.84% ± 1.76%	1.28% ± 1.55%	98.95% ± 2.1%	98.86% ± 2.1%
Standing	96.41% ± 3.49%	3.32% ± 3.97%	89.53% ± 5.46%	91.68% ± 4.14%
Leaning	99.17% ± 0.66%	0.03% ± 0.04%	99.03% ± 0.97%	88.89% ± 6.25%
Walking	97.09% ± 2.89%	1.71% ± 1.2%	87.69% ± 8.73%	88.18% ± 11.34%
Stairs	99.88% ± 0.19%	0.01% ± 0.03%	99.31% ± 1.83%	96.63% ± 6.44%
Cycling	99.32% ± 0.32%	0.15% ± 0.15%	92.66% ± 5.59%	76.85% ± 12.43%
ALL	98.23% ± 1.06%	1.61% ± 0.9%	95.77% ± 4.68%	95.38% ± 4.98%

Appendix G-3. Measurements of performance obtained using pressure and foot acceleration data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the Information Gain feature set, and 6 pressure sensors in a subject dependent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	99% ± 1.56%	2.77% ± 2.67%	97.48% ± 3.23%	96.81% ± 2.97%
Standing	96.89% ± 3.18%	7.84% ± 4.7%	72.84% ± 14.42%	79.58% ± 10.15%
Leaning	99.4% ± 0.57%	0.41% ± 0.47%	59.23% ± 36.71%	28.59% ± 23.65%
Walking	97.36% ± 2.68%	2.27% ± 1.97%	83.78% ± 10.87%	85.86% ± 10.94%
Stairs	99.92% ± 0.13%	0.01% ± 0.03%	99.83% ± 0.67%	94.75% ± 9.83%
Cycling	99.49% ± 0.31%	0.21% ± 0.22%	84.11% ± 12.93%	63.35% ± 17.09%
ALL	98.46% ± 0.94%	3.5% ± 2.14%	90.41% ± 11.29%	89.3% ± 13.94%

Appendix G-4. Measurements of performance obtained using pressure and foot acceleration data. Computations are performed using a 6-seconds sliding window, Random Forest classifier, all features, and 6 pressure sensors in a subject independent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	98.96% ± 1.68%	3.44% ± 3.06%	97% ± 3.52%	96.39% ± 3.16%
Standing	96.71% ± 3.41%	9.12% ± 4.78%	69.67% ± 13.49%	77.82% ± 9.89%
Leaning	99.26% ± 0.75%	0.06% ± 0.08%	72.58% ± 29.25%	12.77% ± 10.64%
Walking	97.28% ± 2.77%	3.28% ± 2.22%	78.38% ± 10.38%	82.93% ± 10.48%
Stairs	99.92% ± 0.13%	0% ± 0%	99.79% ± 0.8%	87.91% ± 18.71%
Cycling	99.45% ± 0.31%	0.07% ± 0.12%	87.31% ± 16.61%	25.4% ± 15.29%
ALL	98.39% ± 0.99%	4.29% ± 0%	88.44% ± 0%	86.41% ± 0%

Appendix G-5. Measurements of performance obtained using pressure and foot acceleration data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the LR_Sum feature set, and 6 pressure sensors in a subject independent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	98.84% ± 1.76%	3.26% ± 2.83%	97.14% ± 3.42%	96.75% ± 2.94%
Standing	96.41% ± 3.49%	8.03% ± 4.14%	71.75% ± 13.27%	78.93% ± 9.64%
Leaning	99.17% ± 0.66%	0.34% ± 0.47%	57.97% ± 36.11%	21.09% ± 15.15%
Walking	97.09% ± 2.89%	2.07% ± 2.01%	85.19% ± 10.95%	86.61% ± 11.12%
Stairs	99.88% ± 0.19%	0.03% ± 0.08%	99.34% ± 1.86%	97.23% ± 4.93%
Cycling	99.32% ± 0.32%	0.23% ± 0.21%	83.12% ± 11.48%	68.54% ± 15.4%
ALL	98.23% ± 1.06%	3.79% ± 0%	89.91% ± 0%	89.01% ± 0%

Appendix G-6. Measurements of performance obtained using pressure and foot acceleration data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the Information Gain feature set, and 6 pressure sensors in a subject independent manner.

H. Performance measurements while using pressure data and both foot and thigh accelerometer data

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	99.43% ± 0.41%	0.64% ± 0.46%	99.53% ± 0.55%	99.48% ± 0.47%
Standing	97.56% ± 1.75%	2.08% ± 1.69%	92.73% ± 3%	94.07% ± 2.58%
Leaning	99.5% ± 0.43%	0.03% ± 0.02%	99.37% ± 0.61%	93.89% ± 3.96%
Walking	97.88% ± 1.55%	1.29% ± 0.89%	91% ± 5.12%	91.45% ± 5.21%
Stairs	99.93% ± 0.13%	0.01% ± 0.03%	99.38% ± 1.54%	97.91% ± 4.28%
Cycling	99.54% ± 0.27%	0.11% ± 0.11%	94.53% ± 4.58%	85.17% ± 9.84%
ALL	98.92% ± 0.82%	0.94% ± 0.61%	97.16% ± 3.46%	96.99% ± 3.5%

Appendix H-1. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, all features, and 6 pressure sensors in a subject dependent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	99.38% ± 0.47%	0.79% ± 0.57%	99.44% ± 0.63%	99.43% ± 0.54%
Standing	97.46% ± 1.9%	2.13% ± 1.89%	92.7% ± 3.3%	93.82% ± 2.7%
Leaning	99.43% ± 0.57%	0.06% ± 0.08%	98.53% ± 1.65%	93.16% ± 5.13%
Walking	97.81% ± 1.57%	1.32% ± 0.88%	90.76% ± 5.29%	91.15% ± 5.49%
Stairs	99.92% ± 0.15%	0.01% ± 0.03%	99.43% ± 1.78%	97.68% ± 4.73%
Cycling	99.51% ± 0.26%	0.14% ± 0.12%	92.71% ± 3.55%	84.05% ± 10.11%
ALL	98.85% ± 0.84%	1.04% ± 0.59%	97% ± 3.5%	96.82% ± 3.68%

Appendix H-2. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the LR_Sum feature set, and 6 pressure sensors in a subject dependent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	99.24% ± 0.53%	0.92% ± 0.62%	99.35% ± 0.65%	99.31% ± 0.6%
Standing	97.03% ± 2.08%	2.61% ± 2.18%	90.93% ± 3.42%	92.73% ± 2.84%
Leaning	99.23% ± 0.62%	0.04% ± 0.06%	98.94% ± 1.5%	89.97% ± 5.86%
Walking	97.64% ± 1.66%	1.47% ± 0.94%	89.82% ± 5.6%	90.52% ± 5.72%
Stairs	99.87% ± 0.22%	0.01% ± 0.02%	99.36% ± 1.15%	95.88% ± 8.34%
Cycling	99.41% ± 0.31%	0.15% ± 0.15%	92.64% ± 4.67%	79.55% ± 14.28%
ALL	98.66% ± 0.94%	1.23% ± 0.73%	96.52% ± 4.08%	96.21% ± 4.38%

Appendix H-3. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the Information Gain feature set, and 6 pressure sensors in a subject dependent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	97.57% ± 2.56%	3.54% ± 3.94%	97.76% ± 3.2%	97.82% ± 2.96%
Standing	93.16% ± 4.43%	6.13% ± 4.22%	75.76% ± 8.87%	81.56% ± 7.12%
Leaning	96.89% ± 1.59%	0.43% ± 0.65%	66.35% ± 38.17%	29.71% ± 24.61%
Walking	96.45% ± 3.65%	2.17% ± 2.24%	84.48% ± 11.15%	85.56% ± 11.1%
Stairs	99.69% ± 0.7%	0% ± 0%	100% ± 0%	92.07% ± 16.46%
Cycling	99.08% ± 0.49%	0.21% ± 0.2%	82.45% ± 16.67%	62.87% ± 20.68%
ALL	96.7% ± 1.72%	3.6% ± 1.47%	91.04% ± 9.94%	90.47% ± 13.88%

Appendix H-4. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, all features, and 6 pressure sensors in a subject independent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	97.54% ± 2.59%	3.21% ± 3.61%	97.88% ± 3.06%	97.8% ± 2.91%
Standing	92.9% ± 4.09%	6.42% ± 4.08%	74.64% ± 9.29%	80.75% ± 7.18%
Leaning	96.7% ± 1.42%	0.43% ± 0.57%	54.61% ± 31.03%	22.53% ± 21.09%
Walking	96.43% ± 3.63%	2.19% ± 2.22%	84.24% ± 11.53%	85.45% ± 11.16%
Stairs	99.82% ± 0.33%	0.01% ± 0.04%	99.56% ± 1.34%	95.93% ± 6.08%
Cycling	99.13% ± 0.45%	0.17% ± 0.16%	83.08% ± 16.13%	62.98% ± 23.07%
ALL	96.64% ± 1.81%	3.44% ± 1.58%	90.48% ± 11.44%	90.13% ± 15.09%

Appendix H-5. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the LR_Sum feature set, and 6 pressure sensors in a subject independent manner.

	Accuracy	False Positive Rate	Precision	F-Measure
Sitting	94.2% ± 11.36%	11.15% ± 25.43%	94.56% ± 11.36%	95.75% ± 7.44%
Standing	90.75% ± 7.13%	6.9% ± 4.75%	70.26% ± 12.24%	78.1% ± 11.02%
Leaning	96.51% ± 1.59%	0.16% ± 0.34%	60% ± 40.82%	7.4% ± 7.59%
Walking	95.34% ± 3.8%	2.64% ± 2.34%	80.1% ± 11.32%	82.26% ± 11.42%
Stairs	99.46% ± 0.76%	0.05% ± 0.13%	96.95% ± 6.72%	89.01% ± 13.8%
Cycling	98.63% ± 0.51%	0.06% ± 0.07%	74.91% ± 27.97%	30.48% ± 21.02%
ALL	93.98% ± 1.8%	8.63% ± 3.73%	87.12% ± 11%	86.79% ± 18.41%

Appendix H-6. Measurements of performance obtained using pressure data from 6 sensors. Computations are performed using a 6-seconds sliding window, Random Forest classifier, the Information Gain feature set, and 6 pressure sensors in a subject independent manner.

I. MATLAB code used for data extraction, processing and computation

```
% Options for all: Yes or No options
ACC = 1;
AP_raw = 1;

Data_output_type = 0; %0.Only Pressure, 1.Pressure+Acc, 2.Pressure+Acc+AP,3.Pressure+Acc+AP
Pn = 15; %number of participants
Wn = 1; %total number of windows
Wf = 6; %Base factor of exponential windows

%For export only
LRB = 0; %To obtain only LRB or others features
Force_include = 0;
Only_Lab = 0; %0 - Lab+FL , 1 - Lab only

Remove_Sensor = 0;   %0 = no, 1 = yes .For removal of sensors
if Remove_Sensor == 1
sn_number = [5 6 7 8 10 11]+1; %Number of analysed sensors
Number_of_Sensors_removed = 13-length(sn_number);
N_S = 13-Number_of_Sensors_removed;   %Number of remaining sensors
else
sn_number = 13;
N_S = 13;
end

Remove_Sensor_Ind = 0;
view_plot = 0; %(p = 1 means plot force)
%%
C_LRB = cell(Pn,Wn);
C_all = cell(Pn,Wn);
C_L_Sensor = cell(Pn,Wn);
C_R_Sensor = cell(Pn,Wn);
C_L_Sum = cell(Pn,Wn);
C_R_Sum = cell(Pn,Wn);
C_lab = cell(Pn,Wn);
C_lab_LRB = cell(Pn,Wn);
C_EachSensor = cell(Pn,13);
AP_prediction = cell(Pn,Wn);
Ground_truth = cell(Pn,Wn);
size_data = zeros(Pn,Wn);
size_data_EachSensor = zeros(Pn,Wn);
start_lab = ones(1,Pn);
end_lab = ones(1,Pn);
findings = cell(Pn,1);

for j = 1:Pn %Participants
N = j;
    for sn = sn_number  %Removing individual sensors
        Remove_Sensor_N = sn;
```

```
        for g = 1:Wn
        window = Wf.^g;  % Window Size
        e = window;
            if e == 64
            window = 6;
            end
run import_Pnumber.m

        if N==6 || N== 11
        raw_lab_0   =   import_insole_data(filename,c,b);
        else
        raw_lab_0   =   import_insole_data(filename,a,d);
        end

run Replace_NaN.m %output raw_lab_1


if N == 12
%To correct insoles data anomaly
    raw_lab_P_L = array2table(vertcat(raw_lab_1{1:105000,21:33},raw_lab_1{105001:end,21:33}*.4));
    raw_lab_P_L.Properties.VariableNames = {'VarName21','VarName22','VarName23','Var-
Name24','VarName25',...
        'VarName26','VarName27','VarName28','VarName29','VarName30','VarName31','VarName32','Var-
Name33'};
    raw_lab_F_L = array2table(vertcat(raw_lab_1{1:105000,37},raw_lab_1{105001:end,37}*.4));
    raw_lab_F_L.Properties.VariableNames = {'VarName37'};
    raw_lab = [raw_lab_1(:,1:20) raw_lab_P_L raw_lab_1(:,34:36) raw_lab_F_L raw_lab_1(:,38:39)] ;
elseif N== 15
    raw_lab_P_L = array2ta-
ble(vertcat(raw_lab_1{1:110000,21:33},raw_lab_1{110001:224800,21:33}*.3,raw_lab_1{224801:end,21
:33}*.5));
    raw_lab_P_L.Properties.VariableNames = {'VarName21','VarName22','VarName23','Var-
Name24','VarName25',...
        'VarName26','VarName27','VarName28','VarName29','VarName30','VarName31','VarName32','Var-
Name33'};
    raw_lab_F_L = array2ta-
ble(vertcat(raw_lab_1{1:110000,37},raw_lab_1{110001:224800,37}*.3,raw_lab_1{224801:end,37}*.5))
;
    raw_lab_F_L.Properties.VariableNames = {'VarName37'};
    raw_lab = [raw_lab_1(:,1:20) raw_lab_P_L raw_lab_1(:,34:36) raw_lab_F_L raw_lab_1(:,38:39)] ;
else
raw_lab = raw_lab_1;
end
clearvars filename a b c d raw_lab_0 raw_lab_P_L raw_lab_F_L

%% Create the activity labels
run labelling.m
%Named as GoPro_label

%% Run ActivPal code
```

```
run ActivPAL_calculations.m
%output: activpal_event_offset and T_AP_raw_offset

%% Transpose data
%This code will create the index "q" adding n values (n=Hz) each cell which wil be used
%for the "for" cycle used to transpose the data into n second windows with no overlap

run transpose_data.m

input = activpal_event_offset;
input_2 = T_AP_raw_offset;
run transpose_activpal.m
%obtain T_activpal_raw and AP_label

clearvars data_transpose input input_2 T_AP_raw_offset %activpal_event_offset
%% Obtain Activity_transposed and T_data (data rearranged into the
% window size and per variable name without label)

%Divide T_data into Pressure Data and Acceleration Data
T_data_Pr_forCC = T_data_full(:,1:26);
T_data_Pr_test = T_data_full(:,1:26);
T_data_F = T_data_full(:,27:28);
T_data_Acc = T_data_full(:,29:34);

T_data_AP = T_activpal_raw;

T_data_Pr = T_data_Pr_test;

if Remove_Sensor == 1   %Change T_Data_Pr depending on number of sensors
T_data_Pr_L = T_data_Pr_test(:,1:13);
T_data_Pr_R = T_data_Pr_test(:,14:26);
% T_data_Pr_L(:,Remove_Sensor_N) = [];
% T_data_Pr_R(:,Remove_Sensor_N) = [];
T_data_Pr_L.Left_Pressure9 = [];
T_data_Pr_R.Right_Pressure9 = [];
T_data_Pr_L.Left_Pressure4 = [];
T_data_Pr_R.Right_Pressure4 = [];
T_data_Pr_L.Left_Pressure3 = [];
T_data_Pr_R.Right_Pressure3 = [];
T_data_Pr_L.Left_Pressure0 = [];
T_data_Pr_R.Right_Pressure0 = [];
T_data_Pr_L.Left_Pressure1 = [];
T_data_Pr_R.Right_Pressure1 = [];
T_data_Pr_L.Left_Pressure12 = [];
T_data_Pr_R.Right_Pressure12 = [];
T_data_Pr_L.Left_Pressure2 = [];
T_data_Pr_R.Right_Pressure2 = [];
% T_data_Pr_L.Left_Pressure8 = [];
% T_data_Pr_R.Right_Pressure8 = [];
% T_data_Pr_L.Left_Pressure11 = [];
% T_data_Pr_R.Right_Pressure11 = [];
```

```
% T_data_Pr_L.Left_Pressure7 = [];
% T_data_Pr_R.Right_Pressure7 = [];
% T_data_Pr_L.Left_Pressure6 = [];
% T_data_Pr_R.Right_Pressure6 = [];
T_data_Pr = [T_data_Pr_L T_data_Pr_R];
end

%% Pre-process data: *Feature Extraction* - Pressure Data
%The sensor data contains window of 10 seconds (10 points/window). As discussed, the table created
above is used to calculate the different feature outputs displayed below which use a variety of anonymous
functions.
run CorrCoefficient.m
if Remove_Sensor == 1
% T_CC(:,Remove_Sensor_N) = [];
T_CC.CC9 = [];
T_CC.CC4 = [];
T_CC.CC3 = [];
T_CC.CC0 = [];
T_CC.CC1 = [];
T_CC.CC12 = [];
T_CC.CC2 = [];
%T_CC.CC8 = [];
%T_CC.CC11 = [];
%T_CC.CC7 = [];
%T_CC.CC6 = [];
end
clearvars T_data_Pr_forCC

%Body Posture
T_Mean=varfun(@Wmean,T_data_Pr); %generates the mean of windowed data per sensor
   T_TotalMean_L = mean(T_Mean{:,1:N_S},2); %generates the mean of windowed data of all left sen-
sors
   T_TotalMean_R = mean(T_Mean{:,N_S+1:N_S*2},2);
   T_TotalMean_B = (T_TotalMean_L + T_TotalMean_R)/2;

T_Stdv=varfun(@Wstd,T_data_Pr); %generates the standard deviation of windowed data
   T_TotalStdv_L = std(table2array(T_data_Pr(:,1:N_S)),0,2);
   T_TotalStdv_R = std(table2array(T_data_Pr(:,N_S+1:N_S*2)),0,2);
   T_TotalStdv_B = std(table2array(T_data_Pr),0,2);

T_Var=varfun(@Wvar,T_data_Pr); %Motion variation
   T_TotalVar_L = var(table2array(T_data_Pr(:,1:N_S)),0,2);
   T_TotalVar_R = var(table2array(T_data_Pr(:,N_S+1:N_S*2)),0,2);
   T_TotalVar_B = var(table2array(T_data_Pr),0,2);

T_Max = varfun(@Wmax,T_data_Pr); %finds the max point in the window
   T_TotalMax_L = max(T_Max{:,1:N_S},[],2);
   T_TotalMax_R = max(T_Max{:,N_S+1:N_S*2},[],2);
   T_TotalMax_B = max(T_Max{:,1:N_S*2},[],2);

T_Range = varfun(@Wrange,T_data_Pr); %finds the max point in the window
```

```
  T_TotalRange_L = range(table2array(T_data_Pr(:,1:N_S)),2);
  T_TotalRange_R = range(table2array(T_data_Pr(:,N_S+1:N_S*2)),2);
  T_TotalRange_B = range(table2array(T_data_Pr),2);

T_Rms=varfun(@Wrms,T_data_Pr); %generates the root mean square of the windowed data
  T_TotalRms_L = rms(table2array(T_data_Pr(:,1:N_S)),2);
  T_TotalRms_R = rms(table2array(T_data_Pr(:,N_S+1:N_S*2)),2);
  T_TotalRms_B = rms(table2array(T_data_Pr),2);

%Motion periodicity
T_MCross = varfun(@WMcross,T_data_Pr); %finds the mean crossings
    T_TotalMCross_L = table2array(varfun(@WMcross,table(table2array(T_data_Pr(:,1:N_S)))));
    T_TotalMCross_R = table2array(varfun(@WMcross,table(table2ar-
ray(T_data_Pr(:,N_S+1:N_S*2)))));
    T_TotalMCross_B = table2array(varfun(@WMcross,table(table2array(T_data_Pr))));

T_Area = varfun(@Warea, T_data_Pr);
  T_TotalArea_L = sum(T_Area{:,1:N_S},2);
  T_TotalArea_R = sum(T_Area{:,N_S+1:N_S*2},2);
  T_TotalArea_B = T_TotalArea_L + T_TotalArea_R;

T_Kurt = varfun(@Wkurt,T_data_Pr);
  T_TotalKurt_L = kurtosis(table2array(T_data_Pr(:,1:N_S)),1,2);
  T_TotalKurt_R = kurtosis(table2array(T_data_Pr(:,N_S+1:N_S*2)),1,2);
  T_TotalKurt_B = kurtosis(table2array(T_data_Pr),1,2);

T_Skew = varfun(@Wskew,T_data_Pr);
  T_TotalSkew_L = skewness(table2array(T_data_Pr(:,1:N_S)),1,2);
  T_TotalSkew_R = skewness(table2array(T_data_Pr(:,N_S+1:N_S*2)),1,2);
  T_TotalSkew_B = skewness(table2array(T_data_Pr),1,2);

T_Quart = varfun(@WQuartile,T_data_Pr);
  T_TotalQuart_L = prctile(table2array(T_data_Pr(:,1:N_S)),[25 50 75],2);
  T_TotalQuart_R = prctile(table2array(T_data_Pr(:,N_S+1:N_S*2)),[25 50 75],2);
  T_TotalQuart_B = prctile(table2array(T_data_Pr),[25 50 75],2);

T_IQR = varfun(@Wrange,T_Quart);
  T_TotalIQR_L = range(T_TotalQuart_L,2);
  T_TotalIQR_R = range(T_TotalQuart_R,2);
  T_TotalIQR_B = range(T_TotalQuart_B,2);

%% Pre-process data: *Feature Extraction* - Acc Data

%Body Posture
T_Mean_Acc =varfun(@Wmean,T_data_Acc); %generates the mean of windowed data per sensor
  T_TotalMean_L_Acc = mean(T_Mean_Acc{:,1:3},2); %generates the mean of windowed data of all
left sensors
  T_TotalMean_R_Acc = mean(T_Mean_Acc{:,4:6},2); %generates the mean of windowed data of all
right sensors
  T_TotalMean_B_Acc = (T_TotalMean_L_Acc + T_TotalMean_R_Acc)/2;
```

```
T_Mean_Dif_Acc_XY_L = T_Mean_Acc{:,1} - T_Mean_Acc{:,2};
T_Mean_Dif_Acc_XZ_L = T_Mean_Acc{:,1} - T_Mean_Acc{:,3};
T_Mean_Dif_Acc_YZ_L = T_Mean_Acc{:,2} - T_Mean_Acc{:,3};
T_Mean_Dif_Acc_XY_R = T_Mean_Acc{:,4} - T_Mean_Acc{:,5};
T_Mean_Dif_Acc_XZ_R = T_Mean_Acc{:,4} - T_Mean_Acc{:,6};
T_Mean_Dif_Acc_YZ_R = T_Mean_Acc{:,5} - T_Mean_Acc{:,6};

T_Mean_Dif_Acc = ta-
ble(T_Mean_Dif_Acc_XY_L,T_Mean_Dif_Acc_XZ_L,T_Mean_Dif_Acc_YZ_L,...
   T_Mean_Dif_Acc_XY_R,T_Mean_Dif_Acc_XZ_R,T_Mean_Dif_Acc_YZ_R);

T_Stdv_Acc =varfun(@Wstd,T_data_Acc); %generates the standard deviation of windowed data
   T_TotalStdv_L_Acc = std(table2array(T_data_Acc(:,1:3)),0,2);
   T_TotalStdv_R_Acc = std(table2array(T_data_Acc(:,4:6)),0,2);
   T_TotalStdv_B_Acc = std(table2array(T_data_Acc),0,2);

T_Var_Acc =varfun(@Wvar,T_data_Acc); %Motion variation
   T_TotalVar_L_Acc = var(table2array(T_data_Acc(:,1:3)),0,2);
   T_TotalVar_R_Acc = var(table2array(T_data_Acc(:,4:6)),0,2);
   T_TotalVar_B_Acc = var(table2array(T_data_Acc),0,2);

T_Max_Acc =varfun(@Wmax,T_data_Acc); %finds the max point in the window
   T_TotalMax_L_Acc = max(T_Max_Acc{:,1:3},[],2);
   T_TotalMax_R_Acc = max(T_Max_Acc{:,4:6},[],2);
   T_TotalMax_B_Acc = max(T_Max_Acc{:,1:6},[],2);

T_Range_Acc = varfun(@Wrange,T_data_Acc);
   T_TotalRange_L_Acc = range(table2array(T_data_Acc(:,1:3)),2);
   T_TotalRange_R_Acc = range(table2array(T_data_Acc(:,4:6)),2);
   T_TotalRange_B_Acc = range(table2array(T_data_Acc),2);

T_Rms_Acc =varfun(@Wrms,T_data_Acc); %generates the root mean square of the windowed data
   T_TotalRms_L_Acc = rms(table2array(T_data_Acc(:,1:3)),2);
   T_TotalRms_R_Acc = rms(table2array(T_data_Acc(:,4:6)),2);
   T_TotalRms_B_Acc = rms(table2array(T_data_Acc),2);

%Motion periodicity
T_MCross_Acc =varfun(@WMcross,T_data_Acc); %finds the mean crossings
    T_TotalMCross_L_Acc = table2array(varfun(@WMcross,table(table2array(T_data_Acc(:,1:3)))));
    T_TotalMCross_R_Acc = table2array(varfun(@WMcross,table(table2array(T_data_Acc(:,4:6)))));
    T_TotalMCross_B_Acc = table2array(varfun(@WMcross,table(table2array(T_data_Acc))));

%Motion shape
T_Area_Acc = varfun(@Warea, T_data_Acc);
   T_TotalArea_L_Acc = sum(T_Area_Acc{:,1:3},2);
   T_TotalArea_R_Acc = sum(T_Area_Acc{:,4:6},2);
   T_TotalArea_B_Acc = T_TotalArea_L_Acc + T_TotalArea_R_Acc;

   T_TotalSMA_L_Acc = sum(abs(table2array(T_data_Acc(:,1:3))),2); %Signal Magnitude Area
   T_TotalSMA_R_Acc = sum(abs(table2array(T_data_Acc(:,4:6))),2);
   T_TotalSMA_B_Acc = (T_TotalSMA_L_Acc + T_TotalSMA_R_Acc)/2;
```

```
LR = table2array(varfun(@Wsmv, T_data_Acc)); %Signal Magnitude Vector
   T_TotalSMV_L_Acc = sqrt(sum(LR(:,1:3),2));
   T_TotalSMV_R_Acc = sqrt(sum(LR(:,4:6),2));
   T_TotalSMV_B_Acc = sqrt(sum(LR,2));
   clearvars LR

T_Kurt_Acc = varfun(@Wkurt,T_data_Acc);
   T_TotalKurt_L_Acc = kurtosis(table2array(T_data_Acc(:,1:3)),1,2);
   T_TotalKurt_R_Acc = kurtosis(table2array(T_data_Acc(:,4:6)),1,2);
   T_TotalKurt_B_Acc = kurtosis(table2array(T_data_Acc),1,2);

T_Skew_Acc = varfun(@Wskew,T_data_Acc);
   T_TotalSkew_L_Acc = skewness(table2array(T_data_Acc(:,1:3)),1,2);
   T_TotalSkew_R_Acc = skewness(table2array(T_data_Acc(:,4:6)),1,2);
   T_TotalSkew_B_Acc = skewness(table2array(T_data_Acc),1,2);

T_Quart_Acc = varfun(@WQuartile,T_data_Acc);
   T_TotalQuart_L_Acc = prctile(table2array(T_data_Acc(:,1:3)),[25 50 75],2);
   T_TotalQuart_R_Acc = prctile(table2array(T_data_Acc(:,4:6)),[25 50 75],2);
   T_TotalQuart_B_Acc = prctile(table2array(T_data_Acc),[25 50 75],2);

T_IQR_Acc = varfun(@WIQR,T_Quart_Acc);
   T_TotalIQR_L_Acc = range(T_TotalQuart_L_Acc,2);
   T_TotalIQR_R_Acc = range(T_TotalQuart_R_Acc,2);
   T_TotalIQR_B_Acc = range(T_TotalQuart_B_Acc,2);


run AP_features.m

clearvars Hz window_size T_Mean_Dif_Acc_XY_L T_Mean_Dif_Acc_XY_L
T_Mean_Dif_Acc_XY_L...
   T_Mean_Dif_Acc_XY_L T_Mean_Dif_Acc_XY_L T_Mean_Dif_Acc_XY_L

%% Pre-process data: *Feature Extraction* - Force Data

if Remove_Sensor == 1
run kurt_skew_Nan_Sensors.m
else
run kurt_skew_Nan.m
end


%% Group all the features %collects all data
run Features_array2table.m

%% Combine all features
features_lab =[T_Mean T_Stdv T_Max T_Range T_Rms T_MCross T_Area T_Kurt T_Skew T_Var
T_Quart T_IQR T_CC...
   T_TotalMean_L T_TotalMean_R T_TotalMean_B T_TotalStdv_L T_TotalStdv_R T_TotalStdv_B...
   T_TotalVar_L T_TotalVar_R T_TotalVar_B T_TotalArea_L T_TotalArea_R T_TotalArea_B...
```

```
    T_TotalKurt_L T_TotalKurt_R T_TotalKurt_B T_TotalSkew_L T_TotalSkew_R T_TotalSkew_B...
    T_TotalMax_L T_TotalMax_R T_TotalMax_B T_TotalRange_L T_TotalRange_R T_TotalRange_B...
    T_TotalRms_L T_TotalRms_R T_TotalRms_B T_TotalMCross_L T_TotalMCross_R T_TotalM-
Cross_B...
    T_TotalIQR_L T_TotalIQR_R T_TotalIQR_B T_TotalQuart_L T_TotalQuart_R T_TotalQuart_B...
    T_Force_CC...
    T_Mean_Acc T_Mean_Dif_Acc T_Stdv_Acc T_Max_Acc T_Range_Acc T_Rms_Acc
T_MCross_Acc T_Area_Acc T_Kurt_Acc T_Skew_Acc T_Var_Acc...
    T_Quart_Acc T_IQR_Acc...
    T_TotalMean_L_Acc T_TotalMean_R_Acc T_TotalMean_B_Acc T_TotalStdv_L_Acc T_To-
talStdv_R_Acc T_TotalStdv_B_Acc...
    T_TotalVar_L_Acc T_TotalVar_R_Acc T_TotalVar_B_Acc T_TotalArea_L_Acc T_To-
talArea_R_Acc T_TotalArea_B_Acc...
    T_TotalKurt_L_Acc T_TotalKurt_R_Acc T_TotalKurt_B_Acc T_TotalSkew_L_Acc T_To-
talSkew_R_Acc T_TotalSkew_B_Acc...
    T_TotalMax_L_Acc T_TotalMax_R_Acc T_TotalMax_B_Acc T_TotalRange_L_Acc T_To-
talRange_R_Acc T_TotalRange_B_Acc...
    T_TotalRms_L_Acc T_TotalRms_R_Acc T_TotalRms_B_Acc T_TotalMCross_L_Acc T_TotalM-
Cross_R_Acc T_TotalMCross_B_Acc...
    T_TotalIQR_L_Acc T_TotalIQR_R_Acc T_TotalIQR_B_Acc T_TotalQuart_L_Acc T_To-
talQuart_R_Acc T_TotalQuart_B_Acc...
    T_TotalSMA_L_Acc T_TotalSMA_R_Acc T_TotalSMA_B_Acc T_TotalSMV_L_Acc T_To-
talSMV_R_Acc T_TotalSMV_B_Acc...
    T_AP_features...
    F_Table_L F_Table_R F_Table_B...
    ];

%% Obtain Activity label and copy free-living features table with labels added

Activity_mode = mode (Activity_transposed,2);
features_lab_label = features_lab;
features_lab_label.activity=Activity_mode;

clearvars Activity_transposed features_lab

%% Eliminates voids of the data from GoPro features table
%Obtain features table with and without activity labels
a = Activity_mode == 0;
features_lab_label_noVoids = features_lab_label;
features_lab_label_noVoids(a,:) = [];

AP_label_noVoids = mode(table2array(AP_label),2);
AP_label_noVoids(a,:) = [];

AP_label_export = AP_label_noVoids;
GoPro_label_export = features_lab_label_noVoids.activity;

% You end up with raw_data, T_data (reorganized data), data_features and the model

Weka_data = features_lab_label_noVoids;
```

```
run Feature_selection.m

run Labels2segments.m
if Remove_Sensor == 1
Weka_data_Pr_all.T_Force_CC = [];
end

clearvars trial weka_trial

%% To export location of lab session and fix N=6 and N=11
if N == 1
    e2 = 25;
else
    e2= 10;
end

if e == 64
    e1 = 6;
else
    e1 = e;
end

if N==6
mm = sum(features_lab_label.activity(:) == 0);
inicio_lab = round(230498/(e1*e2)-mm+75,0);
fin_lab = height(Weka_data_Pr_all); %Works for any feature set
elseif N==11
mm = sum(features_lab_label.activity(:) == 0);
inicio_lab = round(258051/(e1*e2)-mm+66,0);
fin_lab = height(Weka_data_Pr_all); %Works for any feature set
end

if N == 6 || N == 11
Weka_data_Pr_all = vertcat(Weka_data_Pr_all(inicio_lab:fin_lab,:),Weka_data_Pr_all(1:inicio_lab-1,:));
Weka_data_Pr_LRB = vertcat(Weka_data_Pr_LRB(inicio_lab:fin_lab,:),Weka_data_Pr_LRB(1:ini-
cio_lab-1,:));
Weka_data_L_Sensor = vertcat(Weka_data_L_Sensor(inicio_lab:fin_lab,:),Weka_data_L_Sen-
sor(1:inicio_lab-1,:));
Weka_data_R_Sensor = vertcat(Weka_data_R_Sensor(inicio_lab:fin_lab,:),Weka_data_R_Sen-
sor(1:inicio_lab-1,:));
Weka_data_L_Sum = vertcat(Weka_data_L_Sum(inicio_lab:fin_lab,:),Weka_data_L_Sum(1:inicio_lab-
1,:));
Weka_data_R_Sum = vertcat(Weka_data_R_Sum(inicio_lab:fin_lab,:),Weka_data_R_Sum(1:inicio_lab-
1,:));

AP_label_export = vertcat(AP_label_export(inicio_lab:fin_lab,:),AP_label_export(1:inicio_lab-1,:));
GoPro_label_export = vertcat(GoPro_label_export(inicio_lab:fin_lab,:),GoPro_label_export(1:inicio_lab-
1,:));
end

[jj,~]=find(Weka_data_Pr_all.activity=='stairs');
```

```
findings{N,1} = jj;
if N == 15 && window == 32
kk = length(jj);
else
kk = find(diff(jj)> 10);
end
end_lab(1,N) = jj(kk(1));

          C_LRB{j,g} = Weka_data_Pr_LRB;
       C_all{j,g} = Weka_data_Pr_all;
       C_L_Sensor{j,g} = Weka_data_L_Sensor;
       C_R_Sensor{j,g} = Weka_data_R_Sensor;
       C_L_Sum{j,g} = Weka_data_L_Sum;
       C_R_Sum{j,g} = Weka_data_R_Sum;

       AP_prediction{j,g} = AP_label_export;
       Ground_truth{j,g} = GoPro_label_export;

       size_data(j,g) = height(Weka_data);
       size_data_EachSensor(j,sn) = height(Weka_data);
       end
  end
       if view_plot == 1
       run Manual_synchro.m
       end
end

clearvars j g e e1 e2 f sn start_lab end_lab jj kk mm
```

Appendix I-1. Excerpt of MATLAB code used for data extraction, filtering, processing, feature computation, ground truth labelling and final data export.