THESIS

ENERGY EXPENDITURE PREDICTION VIA A FOOTWEAR-BASED PHYSICAL ACTIVITY MONITOR: ACCURACY AND COMPARISON TO OTHER DEVICES

Submitted by

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ABSTRACT

ENERGY EXPENDITURE PREDICTION VIA A FOOTWEAR-BASED PHYSICAL ACTIVITY MONITOR: ACCURACY AND COMPARISON TO OTHER DEVICES

Accurately estimating free-living energy expenditure (EE) is important for monitoring or altering energy balance and quantifying levels of physical activity. The use of accelerometers to monitor physical activity and estimate physical activity EE is common in both research and consumer settings. Recent advances in physical activity monitors include the ability to identify specific activities (e.g. stand vs. walk) which has resulted in improved EE estimation accuracy. Recently, a multi-sensor footwear-based physical activity monitor that is capable of achieving 98% activity identification accuracy has been developed. However, no study has compared the EE estimation accuracy for this monitor and compared this accuracy to other similar devices. **PURPOSE:** To determine the accuracy of physical activity EE estimation of a footwear-based physical activity monitor that uses an embedded accelerometer and insole pressure sensors and to compare this accuracy against a variety of research and consumer physical activity monitors. **METHODS:** Nineteen adults (10 male, 9 female), mass: 75.14 (17.1) kg, BMI: 25.07(4.6) kg/m^2 (mean (SD)), completed a four hour stay in a room calorimeter. Participants wore a footwear-based physical activity monitor, as well as three physical activity monitoring devices used in research: hip-mounted Actical and Actigraph accelerometers and a multi-accelerometer IDEEA device with sensors secured to the limb and chest. In addition, participants wore two consumer devices: Philips DirectLife and Fitbit. Each individual performed a series of randomly assigned and ordered postures/activities including lying, sitting (quietly and using a computer), standing, walking, stepping, cycling, sweeping, as well as a period of self-selected activities. We developed branched (i.e. activity specific) linear regression models to estimate EE from the footwear-based device, and we used the manufacturer's software to estimate EE for all other devices. **RESULTS:** The shoe-based device was not significantly different than the mean measured EE (476(20) vs. 478(18) kcal) (Mean(SE)), respectively, and had the lowest root mean square error (RMSE) by two-fold (29.6 kcal (6.19%)). The IDEEA (445(23) kcal) and DirecLlife (449(13) kcal) estimates of EE were also not different than the measured EE. The Actigraph, Fitbit and Actical devices significantly underestimated EE (339 (19) kcal, 363(18) kcal and 383(17) kcal, respectively ($p<.05$)). Root mean square errors were 62.1 kcal (14%), 88.2 kcal(18%), 122.2 kcal (27%), 130.1 kcal (26%), and 143.2 kcal (28%) for DirectLife, IDEEA, Actigraph, Actical and Fitbit respectively. **CONCLUSIONS:** The shoe based physical activity monitor was able to accurately estimate EE. The research and consumer physical activity monitors tested have a wide range of accuracy when estimating EE. Given the similar hardware of these devices, these results suggest that the algorithms used to estimate EE are primarily responsible for their accuracy, particularly the ability of the shoe-based device to estimate EE based on activity classifications.

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CHAPTER I

INTRODUCTION

Adult and child obesity rates continue to rise despite a nationwide initiative to lower overweight and obesity levels (U.S. Department of Health and Human Services, 2001). Over 60% of the United States population is currently overweight, and concerns of the health risks associated with overweight and obesity are pervasive (Flegal, Carroll, Ogden, & Curtin, 2010). Low levels of physical activity and sedentary lifestyles are generally associated with weight gain because a lack of physical activity can result in a positive energy balance, where daily energy intake exceeds energy expenditure. Energy intake consists of the calories we consume in the food we eat, whereas energy expenditure (EE) includes the various ways that our bodies use energy (i.e. digestion, organ function, physical activity). The magnitude of positive energy balance that results in gradual weight gain may be as small as 25-100 kcal/day (Hill, Wyatt, Reed, & Peters, 2003). Changes to total daily energy expenditure (TEE) can be made primarily through changes in physical activity energy expenditure (PAEE), either via exercise or non-exercise activity thermogenesis (NEAT). NEAT consists of the energy expenditure associated with all active, non-exercise activities (i.e. standing, walking, and other activities of daily living) (Levine, 2002).

The benefits of regular physical activity for weight maintenance and weight loss are well known (Hill & Wyatt, 2005), and recent data shows that prolonged sitting and sedentary lifestyles may increase the risk of common chronic diseases (Owen, Sparling, Healy, Dunstan, & Matthews, 2010; Tremblay, Colley, Saunders, Healy, & Owen, 2010). As a result, individuals attempting to lose or maintain weight are recommended to modify their diets to reduce energy intake, sit less and increase physical activity to increase EE. However, most methods to estimate free-living EE have limitations that may prevent weight management success. Subjective measures of energy intake and expenditure (i.e. self-report surveys) can increase energy balance awareness but individuals typically under-report energy intake and over-report physical activity (Corder, Ekelund, Steele, Wareham, & Brage, 2008; Walsh, Hunter, Sirikul, & Gower, 2004). Objective EE assessment techniques include the gold-standard methods of indirect calorimetry and doubly labeled water, but these methods are restricted to research settings because they are expensive and/or require specialized technical equipment. Therefore the best option for estimating EE is to use objective but minimally obtrusive devices that accurately quantify NEAT and exercise PAEE. Objectively measuring physical activity may help individuals make changes to their posture allocation (e.g. reduce time spent sitting) and time spent engaged in physical activity/exercise which may increase daily EE.

Accelerometers are a common sensor to measure the duration and intensity of PA as they can measure acceleration of the body in up to three planes of motion. New technology has resulted in small, relatively unobtrusive accelerometers, making them appealing to both researchers and consumers. Accelerometers typically use validated algorithms to estimate EE, achieving moderate to high accuracy at estimating PAEE in a research setting (SE between 7.4% and 48.1% (Bonomi, Plasqui, Goris, & Westerterp, 2010; Crouter, Churilla, & Bassett, 2006)). However, accelerometers are less successful when used in free-living environments (Plasqui & Westerterp, 2007a) as they tend to underestimate PAEE and TEE (Crouter, Churilla, et al., 2006; Leenders, Sherman, Nagaraja, & Kien, 2001). Additionally, non weight-bearing activities such as cycling are poorly estimated using accelerometers (Hendelman, Miller, Baggett, Debold, & Freedson, 2000). While there are several brands of accelerometers that are currently used in research or are available to consumers, no study has examined the EE estimation accuracy of these devices in a single study against a gold-standard measure such as indirect room calorimetry.

Multi-sensor devices which consist of a combination of accelerometers, heart rate monitors, gyroscopes, global positioning systems and/or other movement sensors are successful at gathering information about the body's position (i.e. posture) and level of physical activity. These devices generally attain greater EE estimation accuracy than single sensor devices. For example, accelerometers combined with heart rate provide better estimates of energy expenditure especially at higher physical activity intensity levels (Brage et al., 2004; S. E. Crouter, Albright, & Bassett, 2004). Zhang, Pi-Sunyer, and Boozer used a device that included five motion sensors located on the chest, thighs and feet (Zhang, Pi-Sunyer, & Boozer, 2004) and Hustvedt et al used a combination of motion sensors, tilt switches and heart rate monitoring to estimate energy expenditure with an accuracy of at least 90% (B.-E. Hustvedt et al., 2004). However, with the addition of more sensors, these devices also tend to be obtrusive and may be impractical for free-living use.

To further improve estimates of PAEE using an objective measuring tool, new devices and algorithms that have the ability to detect posture and type of activity have recently been developed. These devices/algorithms are able to more accurately estimate PAEE as they can distinguish between activities that have different metabolic rates (e.g. stand vs. walk) and use activity specific energy expenditure relationships (Bonomi, Plasqui, Goris, & Westerterp, 2009; Staudenmayer, Pober, Crouter, Bassett, & Freedson, 2009; V. van Hees & Ekelund, 2009). For instance, a neural network developed by Staudenmayer et al. improved the activity specific root mean squared error of the Actigraph accelerometer by up to 1.19 MET compared to the Freedson regression equation (Staudenmayer, et al., 2009).

We have recently developed a footwear-based physical activity monitor that was intended to do three things: classify activity, measure weight, and estimate energy expenditure. In previous work, we demonstrated that this device is able to classify 6 major postures and activities (sitting, standing, walking, ascending stairs, descending stairs and cycling) with 98% accuracy (Sazonov, Fulk, Hill, Schutz, & Browning, 2011). In a follow-up study, activity classification was used to develop accurate activity-specific EE estimation (Sazonova, Browning, & Sazonov, 2011) but other physical activity monitoring devices were not tested simultaneously. Additionally, in order to improve the practicality of this device for weight management, a new prototype has been developed that has new accelerometry hardware and a new method of wireless communication with a mobile phone. Therefore, this study aimed to validate the use of this footwear-based physical activity monitor to estimate EE, while simultaneously estimating EE using research and consumer devices. We hypothesized that the footwear-based device would be able to estimate EE with 95% accuracy compared to room calorimetry by classifying activities using pattern recognition techniques and applying activity-specific EE models. Additionally, we hypothesized that research and consumer physical activity monitoring devices would not be capable of achieving such accuracy at estimating EE.

Statement of Problem

The primary purpose of this study was to determine if a shoe-based device with integrated pressure sensors and accelerometer is capable of accurately estimating energy expenditure and posture allocation. A secondary purpose was to compare the relative accuracies of consumer and research physical activity monitoring devices with this prototype device.

Hypotheses

1. A shoe-based physical activity monitoring device can estimate energy expenditure with 95% accuracy as defined by a total error of less than 5%.
2. Consumer and research devices will have a range of accuracies lower than that of the shoe-based device

Delimitations, Limitations and Assumptions

Subject selection was limited to lean to moderately obese individuals (BMI 18-35 kg/m^2) between the ages of 18 and 45 years old. Participants were sedentary or moderately active and participated in less than six hours of physical activity per week. Exclusion criteria included pregnant or lactating women, individuals who smoke, report alcohol or substance abuse, or report the use of pharmacologic steroids or obesity pharmacotherapeutic agents. Subjects did not need to wear orthotics or have orthopedic, psychologic or neurologic impairments that prevent physical activity. It was assumed that if used properly, all calorimetry instrumentation gives valid and reliable measures of metabolic rate.

CHAPTER II

LITERATURE REVIEW

Childhood and adult obesity rates have continued to rise throughout the United States and show no indication of improvement from year to year (Ker, 1999). In addition to the increasing prevalence of obesity, recent studies suggest that Americans are becoming more sedentary and the combination of obesity and sedentary lifestyles are likely leading to increased incidence of diseases such as diabetes, heart disease, hypertension and cancer (Bray, 2004). This is an extremely costly problem for the United States, leading to about $90 billion spent annually in medical expenses (Friedman & Fanning, 2004). A ten year initiative, *Healthy People 2020,* developed by the Department of Health and Human Services began in the year 2010 called and provides nationwide goals for the primary health concerns in the United States. *Healthy People 2010* aimed to reduce obesity rates to less than 15% in adults and less than five percent for children by the year 2010. This goal was far from being achieved (Smith & Martin, 2007) as 68% of adults and 17% of children are currently overweight (Nguyen & El-Serag, 2010).

Weight gain can be attributed to a positive energy balance, in which more energy is being consumed than is being expended. Individuals attempting to lose weight and lower their body mass index (BMI) are instructed to adjust their diets and incorporate physical activity into their daily lives to increase energy expenditure (EE). Measurements of posture allocation (i.e. time spent sitting and standing) are thought to be good indicators of obesity, as obese individuals tend to be more sedentary (Levine et al., 2005). Many people are unsuccessful at losing or maintaining weight, possibly due to a lack of simple, objective and direct ways to track their posture allocation and activity levels throughout the day. Simple, single sensor devices such as a pedometer, heart rate monitor, global positioning system, and accelerometer can be used to measure physical activity but are unable to reliably and accurately measure EE over a wide spectrum of physical activities. Weight management monitors that incorporate a combination of these single sensors may be better suited to accurately determine physical activity by identifying the type of activity and making estimations of EE.

The obesity epidemic

Consequences of overweight and obesity

Overweight (BMI 25-30 kg/m^2) and obesity (BMI > 30kg/m^2) are some of the most significant risk factors for many of our societies' most prevalent diseases. Obesity is caused by an accumulation of fat stores in the body which contributes to an increased fat cell size and total body mass. An increase in fat mass can affect a person both emotionally and physically, as it contributes to an unfavorable social stigma, osteoarthritis, metabolic diseases, and disorders such as sleep apnea. (Bray, 2004)

The metabolic consequences of excess fat cells can lead to liver disease, gall bladder disease, cardiovascular disease (CVD), diabetes and cancer. The Office of the

Surgeon General reported 80% of individuals with type 2 diabetes are considered overweight or obese, and that modest weight gains of 11 to 18 pounds can result in a two fold increase a person's risk of developing type 2 diabetes over those who have not gained weight (Freedson et al., 2008). The American Heart Association recognizes that the obesity epidemic is a major contributor to increased incidence of coronary heart disease (Eckel & Krauss, 1998). Meanwhile diabetes is one of the largest health risks and fastest growing disorders in an overweight population (Boyle, Thompson, Gregg, Barker, & Williamson, 2010).

Obesity is among the leading factors of preventable deaths in the United States. The Office of the Surgeon General warns that obese individuals have a 50 to 100% increased risk of death from all cause mortality compared to a healthy weight individual (Freedson, et al., 2008). The risk of obesity-related death is positively correlated with BMI, as Allison et al estimated that 80% of the obesity-attributable mortality occurred in individuals with a BMI greater than 30kg/m^2 (Allison, Fontaine, Manson, Stevens, & VanItallie, 1999). Flegal and colleagues investigated the leading causes of mortality associated with obesity in 2004 and determined that obesity-related mortality is most commonly due to CVD, kidney disease or diabetes and cancer (MacIntyre, Hill, Fellows, Ellis, & Wilson, 2006). Furthermore, obesity is linked to diseases that decrease life-span as well as quality years of life. In a 33-year follow-up study, older obese individuals had an equivalent risk of death due to coronary heart disease (CHD) as non-obese hypertensive men. Additionally, younger obese individuals with low systolic blood pressure had an increased risk of CHD mortality, and all obese individuals were among those with the greatest risk for cancer death (Carmelli, Zhang, & Swan, 1997).

Physical activity and inactivity

As obesity levels have risen in recent years, physical activity levels have declined. Similarly to obesity, physical inactivity is a modifiable condition that if left untreated may lead to death from the advanced stages of diseases such as diabetes, CVD, hypertension, stroke and cancer (Danaei et al., 2009). Danaei and colleagues estimated that the death of one in ten individuals could be attributed to obesity, lack of physical activity or high blood glucose, and many thousand more deaths to diseases associated with other indicators of poor nutrition that often accompany weight gain (Danaei, et al., 2009). However, there is strong evidence supporting the inverse relationship between physical activity and cardiovascular risk factors such as blood pressure, diabetes and obesity (Kokkinos, Sheriff, & Kheirbek, 2011). In addition to the role of physical activity in preventing early death, disease and obesity, the benefits of physical activity include strengthening bones and muscles, improving mental health and mood, and improving the quality of life as we age (*Physical Activity and Health*, 2011).

There is an emerging body of literature linking sedentary lifestyles to cardiovascular risk factors (Owen, et al., 2010; Tremblay, et al., 2010). Regardless of time spent in moderate-to-vigorous physical activity, individuals who participate in more sitting time are at higher risk of all-cause mortality (Patel et al., 2010) and greater waist circumferences (Healy, Wijndaele, et al., 2008). Recently, Stamatakis and colleagues reported a direct relationship between television viewing hours and increased mortality and CVD risk regardless of exercise participation. This relationship was partially explained by inflammatory and metabolic risk factors which were thought to be a consequence of prolonged sitting (Stamatakis, Hamer, & Dunstan, 2011). Furthermore, frequent interruptions to sedentary time may have a positive effect, as Healey et al measured periods of interrupted sedentary time using objective tools and concluded that breaks in sedentary time correlate to fewer metabolic risk factors (Healy, Dunstan, et al., 2008).

Preventing Obesity

The energy gap

Determining the cause of disease and mortality is complicated by the fact that weight gain and physical inactivity have interacting effects explained by the energy balance. Weight loss results from a “negative” energy imbalance when energy intake (EI) is equal to or less than energy expenditure (EE). Energy intake is the calories we consume in the food we eat. Total energy expenditure, TEE, is comprised of several measures: basal metabolic rate, more commonly measured as resting metabolic rate, is the rate of energy expenditure associated with vital functions; thermic effect of food which is the energy required to eat, digest, absorb, transport, metabolize and sort unusable forms of energy consumed from food; and physical activity, which is the energy associated with contracting skeletal muscles to move the body. Physical activity is the only modifiable contribution to TEE and can vary significantly within and between individuals. (Keim, Blanton, & Kretsch, 2004)

The EE associated with physical activity can further be attributed to planned exercise and lifestyle physical activity, also called non-exercise activity thermogenesis (NEAT). NEAT is the energy expenditure not associated with sleeping, eating or planned exercise (Donnelly et al., 2009), or in other words the energy expended to, walk, sit, stand, perform household and other lifestyle activities. Measuring NEAT when considering daily EE is important because it is estimated to account for a considerable amount of total EE (Levine, Melanson, Westerterp, & Hill, 2001).

Sedentary lifestyles often result in a positive energy balance, where EI exceeds EE because fewer calories are being burned daily compared to the calories consumed. Hill defined the energy gap as “the required change in energy expenditure relative to energy intake necessary to restore energy balance.” In other words, it is the excess of calories consumed, or deficiency in physical activity that need to be adjusted for in order to maintain weight. Assuming a modest yearly weight gain, Hill estimated that a median of just 15 Calories per day is consumed in excess, and 90% of the population could overcome weight gain by increasing energy expenditure or reducing energy intake by just 100 calories per day (Hill, et al., 2003). Others have estimated this number to be more on the order of 300-400kcal per day (Swinburn et al., 2009), and there is currently disagreement over the accuracy of both these estimates (Hall & Chow, 2010; Heymsfield, 2009; Millward, 2010); however, the public health message is similar:

increasing energy expenditure and/or decreasing energy intake by relatively small amounts each day may prevent the weight gain that leads to overweight and obesity.

Behaviors contributing to obesity

Various behaviors unique to today's society create an environment where EE must occur by more intentional means, and opportunities for EI are abundant. We are therefore at risk of living a more sedentary and unhealthy lifestyle. Many communities lack sidewalks and bike paths, or are designed having poor access to many locations by foot. This discourages people from walking or biking, and averts children from playing outside. As a result, the majority of Americans own a car and drive it to travel even a short distance. People also rely on equipment or technology to do many of the jobs that were once done using physical labor (Peters, 2006), thereby eliminating the need to be active at work. Individuals who are required to be active at work are more likely to reach publicly promoted physical activity recommendations, such as 10,000 steps per day (McCormack, Giles-Corti, & Milligan, 2006). McCormack, Giles-Corti and Milligan discovered that those most likely to meet the 10,000 steps per day recommendation were individuals who walked in the workplace, did vigorous activity at work, or were employed in a blue-collar occupation, while both older and obese men and women were least successful at meeting the daily step goal. Despite a decrease in the norm regarding physical activity, the abundance of inexpensive energy-dense foods has only increased (Drewnowski, 2007; Hill, et al., 2003; Peters, 2006). Also, food portions have gotten larger (Steenhuis & Vermeer, 2009) and convenience food and supermarkets have utilized the popular marketing of “more for less” (Hill, et al., 2003).

Methods of achieving physical activity for weight loss and weight maintenance

Increasing physical activity is one of the most frequently prescribed regiments for losing and maintaining weight because it is safe and accessible to most people ("Clinical Guidelines on the Identification, Evaluation, and Treatment of Overweight and Obesity in Adults--The Evidence Report. National Institutes of Health," 1998). Physical activity increases muscular demand to utilize the energy from calories consumed, thereby reducing the positive energy imbalance that leads to weight gain. Since physical activity is also one of the best predictors of successful prevention of weight gain and maintenance of weight loss (Goldberg & King, 2007), it is common, if not routine to incorporate changes in physical activity alongside diet changes when weight loss is the goal. For instance, walking is a popular and common form of exercise, and literature shows support for walking as a method to achieve physical activity recommendations and to promote weight loss and overall health (Morris & Hardman, 1997). Schneider et al assessed the effect of 10,000 steps per day on sedentary, overweight and obese adults. Those who adhered to the regiment showed improvements in body weight, BMI, body fat percentage, waist and hip circumference (Schneider, Bassett, Thompson, Pronk, & Bielak, 2006).

The current public health recommendation is 30 minutes of moderate-to-vigorous intensity exercise per day for adults and 60 minutes per day for children

(Freedson, et al., 2008). Various state-based programs for increasing physical activity are largely based around the recommendations put forth by the Centers for Disease Control (CDC). The CDC would like to promote more physical activity by requiring 150 to 225 minutes per week of physical education in schools, increasing opportunities for extracurricular activities, improving access to outdoor recreation facilities, and improving infrastructure to support bicycling and walking (Smith & Martin, 2007). The Office of the Surgeon General recommends adding bouts of physical activity into every day, and using short bouts of walking to bridge the energy gap. Closing the energy gap by 100 calories per day could be achieved by just walking an extra mile per day (Hill, et al., 2003). Unfortunately, the vast majority of individuals do not achieve the recommended amount of moderate-to-vigorous physical activity each week (Metzger et al., 2008). It is estimated that only 3.2% of U.S. Americans are meeting the public recommendation, and this figure is even lower for individuals who are obese (Tudor-Locke, Brashear, Johnson, & Katzmarzyk, 2010).

While traditionally, physical activity was recommended in long bouts at moderate-to-vigorous intensity, recent research indicates the success of participating in either short or long duration physical activity. For instance, in a study of middle-aged women, individuals participating in multiple short bouts of exercise on a treadmill experienced more long term weight loss than groups either doing a single long or short bout per day over an 18 month intervention (Jakicic, Winters, Lang, & Wing, 1999). Similarly, Strath and colleagues interpreted objectively measured physical activity levels form the National Health and Nutrition Examination Survey (NHANES), and determined that those who received that recommended daily level of moderate-to-vigorous physical activity in bouts lasting less than 10 minutes, were more likely to have a lower waist circumference and BMI (Strath, Holleman, Ronis, Swartz, & Richardson, 2008). On the other end of the duration spectrum, a study by Jakicic showed that a combination of exercise and dietary intervention improves weight loss but is dependent on the intensity and duration of exercise. Vigorous intensity and high duration activity showed the greatest improvement in weight loss and BMI improvements (Jakicic, Marcus, Gallagher, Napolitano, & Lang, 2003).

Recent evidence linking sedentary time to cardiovascular risk factors leads to the conclusion that health, even overweight can be improved by decreasing sedentary time. Literature supports this idea of non-exercise physical activity contributing substantially to weight loss and non-sedentary time throughout the day. Levine and colleagues examined the effect of NEAT on obesity by measuring posture allocation (time spent laying, sitting and standing) throughout the day. They determined that moderately obese individuals spent 164 more minutes seated per day and 158 more waking minutes lying down. It was estimated that if these moderately obese individuals had acquired the posture allocation as healthy weight individuals, they would have expended an additional 352 average calories. Promoting NEAT as a weight management initiative may trigger weight loss even if energy intake is unchanged (Levine, et al., 2005).

Measuring and estimating energy expenditure

Energy Expenditure can be compared to EI to determine if a person is in a healthy energy balance, however individuals need accurate and reliable ways to measure EE (Melanson & Freedson, 1996). Quantifying the EE associated with physical activity is important because even small modifications to EE over the course of the day may significantly contribute to weight loss and prevent weight regain (Bobbert, Alvarez, van Weeren, Roepstorff, & Weishaupt, 2007; Hill & Wyatt, 2005). Additionally, researchers need accurate methods in order to appropriately track trends and make associations between physical activity and disease. There are a variety of ways to either measure or estimate EE. These methods range from research and clinical methods, which are validated and highly precise, to consumer and epidemiologically suitable methods which are only approximations and are commonly reported to be relatively inaccurate at measuring EE. A common observation is that highly accurate methods for measuring EE may not be portable or are limited in that they are expensive or require laboratory test equipment, while devices which are more convenient may have less accuracy (Melanson & Freedson, 1996).

EE measurement and estimation techniques can be either subjective or objective in nature. Five general classes of techniques exist, including calorimeters, doubly labeled water, observations, physiological measurements, and motion or movement related (kinematic) recordings, (Jequier, Acheson, & Schutz, 1987). An important attribute to make EE measurements of value for health monitoring is the ability to estimate EE in what can be described as a “free-living” environment, meaning outside of a research or clinical setting so as to capture EE as we go about our normal daily routines. In the laboratory or clinical setting, highly precise calorimeters, either can use a direct or indirect methods to measure TEE. The “gold standard” method to accurately quantify TEE over longer periods of time is the doubly labeled water technique, and physical activity monitors used in the research setting or for personal use are routinely validated using calorimetry or doubly labeled water (Westerterp, 2009).

Direct and indirect calorimetry

Direct calorimetry works based on the fact that all EE eventually ends up released from the body as heat, and so the rate at which heat leaves the body can be directly measured. Large, whole room direct calorimetry set-ups can be costly and difficult to use, which is why this method is not often employed for validation studies of calorie counting devices. Additionally, the response time of this method is relatively slow, however the result is highly accurate (Brychta, Wohlers, Moon, & Chen, 2010).

Room calorimeters and metabolic carts are two widely used methods of indirect calorimetry used to measure EE. This method is based on the fact that food energy in the presence of oxygen will convert to carbon dioxide. EE is calculated from an equation based on a volumetric measurement of oxygen taken in and carbon dioxide produced. This method is accurate to within 2% and has a fast response time. The difference between the room calorimeter and the metabolic cart approach is the container used to collect the gas exchange between oxygen and carbon dioxide. A room calorimeter is a moderately sized chamber, which tests the composition of the air as it enters and leaves the room. It is ideal for measuring total EE because an individual can remain in the room for up to several days. Since this apparatus may limit human movement and confines researchers to a simplified environment, portable metabolic carts are customarily used for short-duration free-living studies. The metabolic cart is worn as a facemask and analyzes gas as it passes through a mouthpiece. For research purposes it can be configured into being somewhat “portable” because the power supply and gas analyzer are worn on the back. Still, this method restricts individuals from speaking clearly and eating so it is not practical for day-to-day consumer use. (Brychta, et al., 2010)

Doubly labeled water

The doubly labeled water technique is a novel approach that was developed to solve the limitations of calorimeters. It is considered the “gold standard” for measuring free-living EE. This method requires an individual to drink water tagged with the stable isotopes of ^2H and ^{18}O. The ingested $^2H_2{}^{18}O$ will be converted to ^2H_2O, $H_2{}^{18}O$ or $C^{18}O_2$ within the body and all water is assumed to be tagged as it is eliminated in the urine or saliva. The difference in the rates that ^2H and ^{18}O are eliminated indicates the rate of CO_2 expired. Total EE over the course of several days to weeks can be determined from the calculated rate of expired CO_2. For this reason, doubly labeled water is the method of choice by metabolic researchers for determining free-living EE over long periods of time. However, this method has many limitations that make it impractical for consumer use. For one, it cannot determine EE on a minute-by-minute basis and EE attributed to specific activities cannot be resolved from TEE. In addition, the isotopes are expensive and costly to analyze (Brychta, et al., 2010; Jequier, et al., 1987).

Subjective measures of physical activity

Subjectively reporting physical activity levels is common for personal weight management, as well as in research, but these strategies are likely to contain errors of the true measurement of EE (Keim, et al., 2004). Subjective methods include keeping a weight loss diary, self-reported daily physical activity and using questionnaires to assess large groups of people. These methods tend to have poor outcomes as free-living EE and the contribution of NEAT to TEE is difficult, if not impossible, to quantify using subjective measures.

Tracking diet and physical activity patters subjectively has been an integral part of professional programs for years. In a cross-sectional study of 629 female and 155 male subjects who had successfully lost weight (average of 29% weight loss), 55% reported using the help of a formal program or professional assistance such as Weight Watchers, Overeaters Anonymous or a dietitian to track weight goals. Most of these individuals lost weight by using a combination of diet restriction and increased physical activity combined. After their successful weight loss most subjects continued to use self-report strategies (Keim, et al., 2004). Fujimoto and colleagues reported that obese individuals who maintain documentation of their weight loss progress several times daily were more successful at losing weight and maintaining weight loss for years (Fujimoto et al., 1992). On the other hand, monitoring body weight with an electronic scale cannot determine the physical activity contributors to weight loss, and scales are not always available when a person leaves his or her house. Overall, self-reporting seems to allow individuals to be more aware of overeating and to make appropriate lifestyle changes.

When accuracy of tracking EE or posture allocation patterns is the goal, subjective measures of physical activity are not ideal. As Jakicic et al demonstrated, inaccuracy and inconsistency are two of the major limitations to using subjective measures to quantify physical activity. In this study, some overweight women who self-reported exercise had discrepancies between reported duration of exercise and accelerometry data recording real duration of exercise. These women were less likely to lose weight at the end of a 20 week intervention. (Jakicic, Polley, & Wing, 1998)

Objective measures of physical activity

Pedometer Based Devices

A pedometer is a low cost physical activity monitor which is easy to use and inexpensive to produce. A conventional pedometer estimates EE by counting the steps that a person takes, but an alternative approach is a pedometer that estimates EE by measuring the length of time that the foot is in contact with the ground (Tharion, Yokota, Buller, DeLany, & Hoyt, 2004). To most people, steps counts, or steps per day, is a logical measurement which makes pedometers good tools for generalizing the amount of walking that has been done in a day. Correlating the number of step counts with EE is less well understood. Pedometers are useful tools to encourage movement (Chan, Ryan, & Tudor-Locke, 2004; Clarke et al., 2007); however, traditionally pedometers cannot track the intensity or duration of physical activity, which are key parameters to forming reliable estimations of EE. Companies such as Nike (Nike+ Sportband) and New Balance (VIA pedometer) have also created their version of a calorie counting pedometer, although these devices have not been validated for accuracy.

Literature suggests that the ability of a Pedometer to estimate EE is limited, yet the device is more successful when used to quantify step counts. A thorough review of pedometers by Kumahara and colleagues confirmed the poor accuracy of estimating EE in the light-to-moderately vigorous physical activity range suggesting that they would be poor tools to use as weight management devices (Kumahara, Tanaka, & Schutz, 2009). The accuracy of different pedometers methods to estimate EE was examined in a comparison study of three pedometers: Omron HF-100 piezoelectric pedometer; Accusplit spring-levered pedometer; Stepwatch™ dual-axis accelerometer pedometer (Foster et al., 2005). This study determined that prediction equations that used body weight and step count had a 10-24% error compared to indirect calorimetry during a walking-only task. Similar studies confirm the findings that pedometers are relatively accurate tools for quantifying step counts, but much less accurate at estimating EE (S. E. Crouter, Schneider, Karabulut, & Bassett, 2003). The concept of pedometers was used uniquely by Tharion et al (2004) who created regression equations to estimate EE from pedometers which were capable of measuring foot-contact time. They determined that the device was accurate in measuring TEE in the range of 9-15MJ per day, but underestimated greater TEE (Tharion, et al., 2004). Generally it can be concluded that traditional pedometers, while suited for behavior modification, should not be relied upon for measurement of daily EE. Additionally, the concept of using foot contact time as a parameter for making EE estimations is promising.

Inclinometers

Inclinometers are tilt sensors which can be mounted to the body and have been used to monitor posture allocation and the contribution from NEAT to EE. Levine and colleagues used two sensors which were sensitive to horizontal and vertical orientations to determine if a subject was laying, sitting or standing (Levine, Melanson, Westerterp, & Hill, 2001). They could also use these devices to determine how many transitions were made. Measured EE from metabolic cart data was used to create regression equations that could determine EE associated with altering posture. An inclinometer alone is not practical to calculate total energy expenditure because it cannot distinguish between activities done while standing (such as walking or jogging).

Heart Rate Monitors

Heart rate information is valuable for estimating EE because it is directly related to oxygen consumption, however it is dependent on several biological factors unique to each individual (Brage, et al., 2004). Therefore, individual calibration may be beneficial for using heart rate to estimate EE. At high intensity heart rate is relatively accurate, but not at low-to-moderate intensity activity where elevations in heart rate may be due to other physiological factors. Considering most of the population spends their day only in low-to-moderate intensity activities, heart rate is often used alongside accelerometry to make more robust estimates of EE throughout the day.

Polar® heart rate monitors are one of the most popular brands of commercially available heart rate monitors. In an experiment to validate the accuracy of the Polar S410 heart rate monitor for estimating EE, this heart rate monitor was shown to be only moderately accurate at counting calories. For medium to high intensity activities in males, the Polar® heart rate monitor had a mean error of 2-4%, which equated to .1-.4 kcal/min. In females, the mean error was 12-33%, or .7-2.4 kcal/min (S. E. Crouter, et al., 2004). The intensities of the activities in these studies ranged from about 11 to 18 kcal/min. Therefore these overestimates, especially in females in this study, highlight the potential error to using heart rate for long durations to estimate EE. The literature provides insight into heart rate monitors during planned exercise, but considering that non-exercise EE is a major contribution to daily EE, heart rate monitoring is not a practical tool to use long-term. Additionally, reliable heart rate monitoring requires an individual to wear a chest strap which maybe uncomfortable for day-to-day wear. (Brage, et al., 2004; S. E. Crouter, Churilla, & Bassett, 2008; Strath, Bassett, Swartz, & Thompson, 2001)

Global Positioning System

A global positioning system (GPS) determines an individual's location relative to satellites above the earth, and can be used to determine the speed and distance of an individuals' activity (Maddison & Mhurchu, 2009; Townshend, Worringham, & Stewart, 2008). It is also practical for free-living situations, especially outdoor activities. The main challenge of GPS is that it is not reliable on its own to estimate total EE throughout the day because it cannot correlate the speed and distance of an activity with the type or intensity of the body's movements. It also has other serious limitation such as an inability to function inside buildings or structures which block the satellite connection (Schutz & Herren, 2000). No study has concluded that a GPS is a feasible device to measure physical activity or EE on its own (Maddison & Ni Mhurchu, 2009). However, investigators have assessed the potential for GPS to be used in combination with accelerometry (Troped et al., 2008) or heart rate (Duncan, Badland, & Schofield, 2009) to provide more information about physical activity levels. When used in combination with a uniaxial accelerometer (ActiGraph), a GPS device (GeoStats Wearable GeoLogger™) was capable of about 90% accuracy in activity classification which was a slight advantage over using an accelerometer alone (Troped, et al., 2008). This finding was valuable because activity classification is emerging as a technique to improve estimations of EE using objective tools. However, activity classification from GPS is still not a highly accurate method to determine individual EE.

Accelerometer Based Devices

Accelerometers mounted on the back, hip, wrist or ankle, have become well recognized means of studying human movement and progress is being made towards using these tools to classifying activities as well (Bonomi, et al., 2009; Wong, Webster, Montoye, & Washburn, 1981). They can be used independently or in conjunction with previously mentioned devices as multi-sensor physical activity monitors. Accelerometers measure acceleration of the body in up to three planes depending on whether the device is uni-, bi-, tri-axial or omnidirectional. If the accelerometer is uniaxial the technology within the device can detect accelerations in just one plane such as side-to-side movements, and it may miss activities with high vertical accelerations. Biaxial and triaxial accelerometers can pick up accelerations in two and three planes respectively (vertical, horizontal or lateral), and an omnidirectional accelerometer is sensitive to accelerations in all directions (Sabatini, Solari, & Secchi, 2005). The advantage of using an accelerometer based device rather than other types of physical activity monitors is that it produces a measure of the time series data in terms of an “activity count.” Therefore it can determine the frequency, duration and intensity of many common activities. During activity, acceleration is detected by the sensor as a voltage signal. This signal is averaged over an epoch, or predetermined length of time. The greater the average acceleration is, the higher the activity count. Acceleration is typically proportional to intensity for a given activity, thus it is generally accepted that activity counts from an accelerometer are a better predictor of EE and more meaningful than step counts from a pedometer (Kumahara, et al., 2009). Either activity counts or raw acceleration data can be converted by algorithms which have been experimentally derived to relate acceleration output into EE estimations.

In research, accelerometers have been used to assess children of preschool age to the elderly and in healthy, diseased and pathological populations. Many studies have assesed the validity of using commercially available accelerometers and their prediction equations to measure EE in both laboratory and free-living conditions. In a review of eight brands of accelerometers, only the Tracmor® triaxial and Actigraph uniaxial accelerometer had data to support a correlation with EE measured using the gold-standard doubly labeled water technique (Plasqui & Westerterp, 2007b). However, in validation, these devices both have at least an average 8% error (Sarbassov, Guertin, Ali, & Sabatini, 2005; Staudenmayer, et al., 2009). Others have reported single accelerometers significantly under-estimated EE by more than 50% (Welk, Blair, Wood, Jones, & Thompson, 2000).

The Actical and Actigraph accelerometers are two well studied physical activity monitors that utilize accelerometry. Several regression equations have been developed for these devices in recent years as they have become common research tools; however, few are valid for a range of free-living activities which limits the effectiveness of these tools in the field. Crouter and colleagues investigated several published regression equations for the Actical and Actigraph accelerometers and reported the accuracy of each equation during a mixed protocol of sedentary to vigorous activities. In general, each regression equation tends to work best for the activities with which it was calibrated (Crouter, Churilla, et al., 2006; Crouter, Clowers, & Bassett, 2006). The Actical single regression equation (Heil, 2006) tended to accurately estimate sedentary activities and slow running, while overestimating walking and underestimating all other activities. The most accurate equation for the Actigraph was the Freedson equation (Freedson, Melanson, & Sirard, 1998), but this algorithm underestimated most activities except for walking. The Actigraph (CSA/MTI) has been reported by other investigators to significantly underestimate TEE compared to doubly labeled water. Leenders and colleagues reported an underestimate of 59% in estimating PAEE over seven days, which accounted for 20 to 47% of TEE (Leenders, et al., 2001).

Some devices that were developed and well documented in the literature have also become consumer devices. One such accelerometer is the DiretLife activity monitor which is based off the Tracmor triaxial accelerometer (Westerterp & Bouten, 1997), and now sold with software that simplifies the interpretation of physical activity EE from count values so that it is easy for a consumer to use. Tracmor (Philips Research, Eindhoven, The Netherlands) was able to achieve high correlation between device output and EE, with SE values between 0.7MJ per day and 1.0MJ per day (Plasqui, Joosen, Kester, Goris, & Westerterp, 2005). This is equivalent to 167 to 239kcal per day, which is on par or better than other accelerometry-based devices. Bonomi et al reported the 14-day accuracy of DirectLife compared to double labeled water (Bonomi, et al., 2010) and reported a standard error of the estimated TEE of .9MJ per day, or 7.4% of the measured TEE. When only physical activity EE was considered, the standard error was .87MJ per day, representing 22% of the measured PAEE. Therefore, the device performed more poorly at estimating the EE associated with movement, highlighting the limitation of accelerometers to capture some movements which may contribute greatly to PAEE over the course of several days, but which may not produce large accelerations to a hip-mounted device.

Since accelerometers are sensitive to the direction and magnitude of acceleration during movement, the location and directionality of the sensor matters. For instance, unidirectional accelerometers will be most accurate when measuring activities with little or no vertical acceleration (Bassett et al., 2000), and hip mounted accelerometers may miss movements of the limbs that do not require the torso to move such as fidgeting, or cycling (Levine, et al., 2001) Additionally, accelerometers have a limited ability to estimate RMR from activity counts (Dellava & Hoffman, 2009). The benefits and limitations of using an accelerometer often compliment the weaknesses and strengths of other sensors. Therefore they are often a key component to multi-sensor devices.

Multi-sensor devices

There is evidence that when used in conjunction with each other, the previously mention stand-alone devices can more accurately estimate EE and type or intensity of physical activity. For example, heart rate data alone are highly variable and cannot make reliable estimations of EE, but when heart rate is combined with accelerometers it makes estimations of EE with less than 5% error during a limited set of activities (Brage, et al., 2004). The ActiReg® device combines heart rate with two motion sensors which record the presence of movement, and two tilt switches which record body position (Hustvedt et al., 2004). This multi-sensor device is incorporated with computer software to interpret the signals from the sensors. ActiReg® classifies activity levels in low, moderate and high intensity and makes relatively accurate estimates of EE. However, this device is not practical for the consumer because it is expensive, difficult to use, and inconvenient to wear out of a research setting.

Accelerometry and GPS is another combination used to make more meaningful interpretations of physical activity data. In a study by Troped et al, physical activity classification was made using an Actigraph accelerometer alone and together with a GPS device. The authors desired to determine if there was a difference in ability to classify physical activity, and revealed that more accurate classification was made using a combination of GPS and accelerometry recordings. Together the devices had an accuracy of 91% or greater in all validation tests (Felson et al., 2007).

Others have incorporated several sensors of the same type into a multi-sensor device. For instance, Zhang et al acquired foot-based pressure sensor data from 32 sensors placed in the in-sole of a shoe and an artificial neural network was created which was capable of mathematically determining the characteristics of the physical activity performed based upon pressure sensor data (Zhang et al., 2005). The device was capable of measuring duration, frequency, type and intensity of locomotion with high accuracy, but activities of daily living were not addressed and the device did not calculate TEE. This study does however show that artificial neural networks can make accurate predictions of physical activity measures which can be expanded upon in future studies.

Recently, the Intelligent Device for Energy Expenditure and Activity (IDEEA, MiniSun, CA) has gained popularity because of its high accuracy. It is capable of measuring the type, onset, duration, intensity and frequency of physical activity by means of five sensors placed around the body and sophisticated algorithms. Zhang and colleagues estimated TEE with an average accuracy of 95% during a 23-hour room calorimeter stay (Zhang, et al., 2004). The success of this device appears to be the accuracy with which it assigns specific EE algorithms to different activity classes. An early study determined that the IDEEA device could identify postures and limb movement type with 98.9% accuracy, and gait type with 98.5% accuracy (Zhang, Werner, Sun, Pi-Sunyer, & Boozer, 2003). The authors highlighted limitations to accuracy such as an inability to measure arm movements, over or underestimation of the EE during transitions, and the underestimation of EE due to fidgeting (Zhang, et al., 2004). In addition to these limitations, the device is composed of several sensors and wires mounted to the chest, thigh and foot, and it is therefore unlikely to be a marketable device for individuals attempting to monitor their activity with little obtrusiveness.

The trend to classify

As such is the case with the IDEEA device, a recent trend in activity monitoring whether it be single accelerometers or multi-sensor devices, is to classify activities with different metabolic requirements in order to more accurately estimate EE over a wide range of activities. Methods for classification range from simple such as multiple linear regressions, to complex such as artificial neural networks (ANN). Investigators have used the Actigraph and Actical accelerometers in a similar fashion to create two-regression equations. All published Actigraph and Actical two-regression equations, although differing slightly in accuracy, have been developed for the same basic function: to make better estimations of PAEE by distinguishing between activities with distinct metabolic demands, namely sedentary behavior, walking/running, and lifestyle activities. Crouter et al developed a two-regression equation for the Actigraph accelerometer which can more accurately estimate EE from the Actigraph, and then improved upon this equation in future work (Crouter, Churilla, et al., 2006; Crouter, Kuffel, Haas, Frongillo, & Bassett, 2009). Likewise, the two-regression method has been used to more accurately estimate EE from the Actical (Crouter & Bassett, 2008; Crouter et al., 2010). Both use similar technology to measure the duration and intensity of physical activity, however the devices have differences, such as filter type and epoch length that prevent the algorithms developed on one device from being used on the other (Crouter & Bassett, 2008). Therefore, unique regression equations have been developed for each to relate counts per minute to METs.

The most recent two-regression method specific to the Actigraph uses a threshold value of the coefficient of variation of the signal to determine which regression equation to apply to each 10-second interval of data. This method was a significant improvement over the previous single regression equation because it considered the different energetic demands of a lifestyle activity compared to more vigorous activities such as walking or running. Recently, Crouter's two-regression was validated against 24-hour room calorimetry as well as doubly labeled water. It overestimated the rate of EE by 10.15 (±11.42)%, but this was reduced to 2.72 (±10.9)% after applying a low-pass filter to the data. Validation against the doubly labeled water technique similarly revealed an overestimation using the two-regression equation alone, but an improvement with the low-pass filter model. (Rothney, Brychta, Meade, Chen, & Buchowski)

The most recent Actical specific two-regression equations developed by Crouter and Bassett (2008, 2010) examine 15-second epochs and apply a regression equation based on achieving a minimum count threshold and/or a coefficient of variation threshold. The two-regression equations developed by Crouter and Bassett (2008, 2010) and Klippel and Heil (2003) were validated against six-hour indirect calorimetry over a wide range of sedentary to vigorous activities. The equations estimated EE within .2 METs which was slightly greater than previously reported estimations under different testing conditions which were within .1 METs. The two-regression method improved upon the previous single regression method (Crouter & Bassett, 2008; Crouter, et al., 2010).

An additional consideration is the significant contribution of NEAT to TEE as it includes the EE associated with laying, sitting, standing, leisure activities such as walking, and occupational or household activities. However, activity counts alone will tend to under-estimate the EE associated with many of these postures (Levine, 2007). Methods have been employed using single accelerometers to identify and distinguish between low-to-moderate activities that contribute to NEAT (Midorikawa et al., 2007; V. van Hees & Ekelund, 2009; Westerterp, 2009), and also to classify a wide range of activities from sedentary to vigorous (Bonomi, et al., 2009; Staudenmayer, et al., 2009). Midorikawa et al. classified activities, such as sitting, standing, housework work and walking, by using threshold values of the ratio between vertical and horizontal acceleration. Regression equations were then developed to estimate total EE within 4.4 (+-6.2)% difference (Midorikawa, et al., 2007). Similarly, van Hees and colleagues expressed activities such as laying, sitting, standing and walking in terms of movement intensity of the acceleration signal (van Hees & Ekelund, 2009). This method significantly overestimated EE over 23 hours. Neither study reported the accuracy of the classification scheme.

Others have used multiple features of the acceleration signal to classify activities ranging from those that contribute to NEAT to those which are common for exercise. For instance, Bonomi and colleagues used classification tree model applied to the raw acceleration signal from a Tracmor accelerometer to distinguish between up to six different activity types. The classifications were used to estimate EE based on compendium MET values for each classification. This model was better able to estimate EE than using accelerometer counts alone (Bonomi, et al., 2009). Staudenmayer and colleagues used artificial neural networks applied to Actigraph accelerometer data to estimate EE as well as classify activities into four categories: low level, household, locomotion and sports (Staudenmayer, et al., 2009). The developed algorithm for EE had a lesser bias, standard error, and root mean square error than the algorithms developed by Crouter et al. (Crouter, Clowers, & Bassett, 2006), Swartz et al. (Swartz et al., 2000), and Freedson et al. (Freedson, et al., 1998). In the studies by Bonomi et al. and Staudenmayer et al., algorithms achieved relatively high overall classification accuracy which ranged from 69 to 100% and 90 to 97% respectively. The limitation to these methods was that low level activities, such as standing and cycling were most likely to be misclassified.

Correct classification is central to achieving high EE estimation accuracy. While single accelerometers mounted to the waist tend to be less obtrusive, one main limitation of using a single accelerometer is the classification accuracy of the detection algorithms during activities with little to no trunk movement (i.e. standing and cycling) (van Hees & Ekelund, 2009). The IDEEA device achieves impressive classification accuracy (Zhang, et al., 2004); however it is bulky and not practical for daily wear. In the future, devices which are minimally obtrusive, while being able to classify activity and estimate EE accurately will be critical contributions to the field of physical activity monitoring. Better physical activity monitors will aid individuals in justifying the positive energy balance that leads to eventual weight gain.

CHAPTER III

METHODS

Subjects

Nineteen subjects (10 male, 9 female) were recruited from Colorado State University, as well as the Fort Collins and Denver communities to participate in this study. The protocol was approved by the Colorado State University Institutional Review Board and participants gave written informed consent prior to beginning the study. Subjects completed a physical activity and health-history questionnaire (Franklin, Whaley, & Howley, 2000), and were determined to be in good health by a physician. Based on self-report, subjects were sedentary to moderately active (less than six hours of physical exercise per week), not taking any medications known to alter metabolism, and weight stable over the past six months.

Study design

Each subject completed one 4-hour stay in a room calorimeter following a 4-hour fast. Prior to data collection we measured each subject's height and weight. Subjects wore six physical activity monitoring devices: one prototype shoe device (pair of shoes), three devices used in research, and two consumer devices. Metabolic data was collected while each individual performed a series of randomly assigned postures and activities. Prior to entering the room calorimeter, subjects were instructed in how to use the equipment available to them in the room. Data collection began with a 30-minute equilibration to assure that gas exchange within the room was representative of the current subject. This period of data collection was not used in our analysis. The remaining three and half hours of data collection consisted of 20 minutes of lying quietly in the supine position, 20 minutes of sitting and watching TV, 20 minutes of sitting with computer use, 10 minutes of quite standing and 10 minutes of active standing. Subjects were then asked to perform six of eight randomly assigned activities for 10 minutes each, which included walking on a treadmill at 2.5miles per hour, walking at 3.5 miles per hour and walking at 2.5 miles per hour at an incline of 2.5%, stepping, sweeping, pedaling a cycle ergometer (75W), standing, and sitting. The last hour of data collection consisted of free-living activities of the individual's choice. The remaining ten minutes of data collection was reserved for transition between the various activities.

Table 1: Description of Protocol

Activity	**Description**	**Time**
Equilibration	Quiet resting, data excluded	30 min
Supine	laying on bed	20 min
Sitting	watching TV	20 min
	performing computer work	20 min
Standing	Quiet	10 min
	Active	10 min
Random assignment; 6 of 8 possible activities	Walking, 2.5mph	10 min each; 60 min total
	Walking, 3.5mph	
	Uphill, 2.5%, 2.5mph	
	Stepping	
	Sweeping	
	Cycling, 75W	
	Standing	
	Sitting	
Free-living	Any of the above activities, self-selected pace and posture	60 min, or until completion of 4 hours of data collection

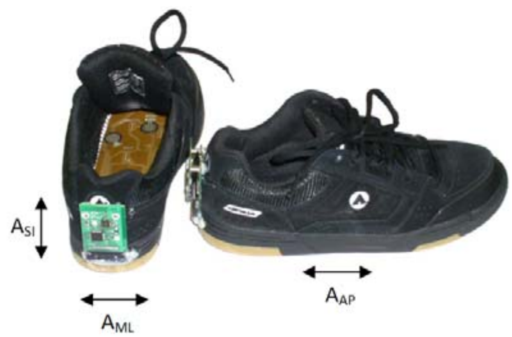
Subjects were not restricted in how they performed activities. Walking activities were performed on a treadmill (Gold's Gym Merchandising Inc., Trainer 480 Treadmill, Irving, TX), cycling was performed on a stationary bicycle (Lode, Corival, Groningen, NED), and stepping was performed by stepping up and down on a single eight-inch step (Reebok International, Reebok Step, Canton, MA).

Metabolic measurements

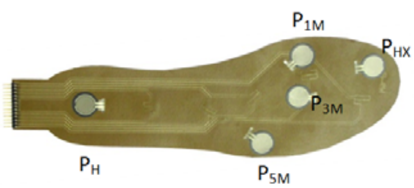
Oxygen consumption and carbon dioxide production were recorded using the whole-room indirect calorimeter located in the Clinical Translational Research Center of the University of the Colorado Hospital (Melanson et al., 2010). The accuracy and precision of the system is tested monthly using propane combustion tests. The expected volume of $O2$ and $CO2$ is determined based on expected production of 2.55 and 1.53 liter of $O2$ and $CO2$, respectively, per gram of propane burned (Withers, 2001). The average $O2$ and $CO2$ recoveries over the most recent 12 month period have been 99.4±1.5 and 99.5±1.5% (mean±SD), respectively. EE and substrate oxidation are calculated using the non-protein RQ based on the equations of Jequier et al. (Jequier & Schutz, 1983).

Prototype device

Participants were fitted with the appropriately sized recreational walking shoes, equipped with a pressure sensing insole and accelerometer (Figure 1). The prototype device is explained in detail in previous work (Sazonov, et al., 2011; Sazonova, et al., 2011). Pressure and accelerometer data was sampled at 25 Hz by a 12-bit analog-to-digital converter and transmitted using a Bluetooth transmitter to the computer. The sensor system was lightweight (<40g) and created no visible interference with the motion patterns in subjects.



a)



b)

Figure 1: a) A pair of shoes equipped with sensors, wireless transmitter and batteries. Arrows show Anterior-Posterior (A_{AP}), Medial-Lateral (A_{ML}) and Superior-Inferior (A_{SI}) axes of accelerometer. b) A pressure sensitive insole with FSRs. P_H is heel pressure sensor, P_{MO},P_{MM},P_{MI} are 5th, 3rd and 1st metatarsal head sensors, respectively, and P_{HX} is the hallux sensor.

Activity monitoring devices

Participants were equipped with three physical activity monitoring devices that are used in research: Actigraph GT3X (Actigraph, LLC., Pensacoloa, FL), Actical (Phillips Respironics, Inc., Bend, OR), and IDEEA (MiniSun, Fresno, CA). The Actigraph and Actical are capable of measuring the intensity and duration of activity in order to estimate

PAEE. Actigraph is a small (3.8cm x 3.7cm x 1.8cm) tri-axial accelerometer. It was set to an epoch length of one second, which was summed each hour of the day to give an hour-by-hour estimate of PAEE. It uses an equation developed by Freedson et al and the factory default cutpoints to relate counts per minute to EE (Freedson, et al., 1998). The Actical is a small (2.8cm x 2.7cm x 10cm) multidirectional, piezoelectric accelerometer. The Actical was set to record one minute epochs. This device used a single regression model with cut points set at .04 kcal/min/kg for the light/moderate cutpoint and .10 kcal/min/kg for the moderate/vigorous cutpoint in order to estimate PAEE (Heil, 2006). Both devices were worn on an elastic belt directly over either the right or left hip. The IDEEA has five sensors, which were placed under the sole of each foot, on each thigh and over the sternum. The device is capable of classifying physical activity types as well as estimating total energy expenditure. Each sensor is 18mm x 15mm x 3 mm and is capable of measuring body segment angles and accelerations in two directions. EE is estimated each second using the EE equation corresponding to the classification of the activity at that time, and these values were summed to provide minute-by-minute EE data at the end of the recording.

In addition to three research devices, participants wore two devices currently marketed to consumers: The Fitbit Tracker (Fitbit, Inc., San Francisco, CA) and Directlife activity monitor (Philips Electronics, Andover, MA). The Fitbit Tracker uses an accelerometer to track intensity and duration of physical activity. The device is docked to a computer which downloads the data directly to a web-based software program. Total energy expenditure is calculated using a proprietary algorithm and reported in five-minute intervals based in the subject's height, weight and activity intensity. The Directlife activity monitor is a small (3.1cm x 3.3cm x 1.1cm) triaxial accelerometer. Directlife also uses a web-based software program to track physical activity intensity and calories burned. Activity energy expenditures are recorded each hour of the day as long as a minimum threshold of activity is met. Both devices were worn on the same elastic belt that held the research activity monitors. The EE from the consumer devices was estimated and extracted from the web-based software provided by the manufacturers.

Development and Validation of EE Model

Our previous work determined that an activity-specific branched algorithm using acceleration and pressure sensors to classify activity provided the most accurate estimates of EE (Sazonova, et al., 2011). In this study, we used shoes with new accelerometer and data transfer hardware. Therefore, the energy expenditure models were re-established using the current device. Validation of the shoe-based device was performed using a leave-one-out validation technique in which the data used for training were pooled from all but one subject and the model was then tested on the validation set using the left out subject.

During each posture and activity, sensor data was collected from eight channels/shoe at 25Hz per channel. The eight channels included three accelerometer signals: superior-inferior acceleration (Acc1), medial-lateral acceleration (Acc2), anterior-posterior acceleration (Acc3); and five pressure sensors: heel (Sens1), 3rd metatarsal (Sens2), 1st metatarsal (Sens3), 5th metatarsal (Sens4), and hallux (Sens5).

Resting EE was calculated from the average EE over the last five minutes of the supine period. A lag time of two minutes between the activity that the subject performed and the room calorimeter was determined experimentally by producing the least error in the EE estimation. The model used a branching approach in which recordings were classified into one of four posture/activity groups: “sit”, “Stand”, “Walk”, and “Cycle”, using a previously developed algorithm for posture/activity recognition (Sazonov, et al., 2011). This algorithm is capable of achieving up to 98% accuracy using an optimized sensor set. After classification, energy expenditure was estimated using a separate model for each of the four activities/postures.

Anthropometric measurements, accelerometer and pressure sensor signals were used as predictors for an ordinary least squares linear regression. The Accelerometer and pressure sensor signals were preprocessed to extract meaningful metrics to be used in the models. For each of the eight sensors, the following four metrics were computed: coefficient of variation (cv); standard deviation (std); number of zero crossings (zc), i.e. the number of times the signal crosses its median normalized by the signal’s length; and entropy H of the distribution X of signal values (ent) computed as: $H(X) = -\Sigma p_k \log p_k$, where p_k is the relative frequency of values fallen into the k^{th} interval (out of 20 equally sized intervals) in the sample distribution of signal values. The median value of each of the four kinds of metrics combined from all five pressure sensors was used to form a single pressure sensor metric (med(metric)). The complete set of potential predictors consisted of 16 metrics: twelve (3x4) metrics from accelerometer sensors and four metrics from pressure sensors. For each posture/activity a model was developed using the derived metrics as possible predictors of EE using ordinary least squares linear regression.

We used the "leave-one-out" approach for cross-validation when training and estimating the EE for each type of activity for every subject. For every left out subject all of the data related to this subject were removed from the training set. Model (coefficients) computed using the rest of the subjects sample was then used to estimate the EE for all trials of the left out subject. The best set of predictors had to provide the best fit (by producing the maximum adjusted coefficient of determination, R^2_{adj} and the minimum Akaike Information Criterion, AIC) in the training step and the best predictive performance (the minimum mean squared error, MSE and the minimum mean absolute error, MAE) in the validation step.

Subjects that experienced multiple sensor failures or incomplete data were excluded from the analysis, leaving 17 subjects with complete metabolic and sensor data from at least one shoe. Previous work described that only one shoe is required to get accurate EE estimation from the device (Sazonov, et al., 2011). In the "cycle" activity group, only twelve subjects performed this activity.

Device Comparison

Total energy expenditure was calculated from the room calorimeter for the time period that that corresponded with data collected from each device. For the Actigraph and Directlife, three full hours of activity could be calculated from the hour-by-hour data. Three and a half hours of estimated EE could be calculated from Fitbit, Actical, and IDEEA. Because some devices only calculated activity energy expenditure while others estimated total energy expenditure, we adjusted for the difference by estimating resting energy expenditure. Twenty-four hour room calorimeter data was not available to make a precise estimation of basal metabolic rate (BMR), and for practical purposes, consumers would not have this information when using any of these devices. Therefore, to make an adequate comparison of total EE across all devices, BMR was calculated using the Harris-Benedict equation (Harris, 1919) and then added to the EE estimated from Actical, Actigraph and Directlife because these devices only record EE associated with activity.

The EE estimated by the shoe-based device during validation were compared alongside estimations made from the five other devices. The shoe-based device used the previously described algorithms to calculate EE on a minute-to-minute basis over the entire three and a half hours of activity.

A further comparison was made with the Fitbit device to see if manually classifying activities via the web-based software would improve the accuracy of the device. The activity labeling works by classifying each activity performed while wearing the device, which then allows the software to apply to that time period a MET equivalent based on a compendium of physical activities.

In an attempt to make a comparison of one of the research devices to the prototype device which was validated using a group-specific model, two group-specific regression equations were created using the Actical as well. We plotted the average measured EE value over the last three minutes of each activity against the average count value associated with that time. The first regression equation included all activities, while the second excluded cycling, as this activity was not well detected by the accelerometer.

Statistical Analysis

Mean standard error (SE), root mean squared error (RMSE) and the percentage of the RMSE with respect to the measured value (%RMSE) were calculated for each device. Paired t-tests were used to test for significance between the measured and estimated values. A p-value less than .05 was considered significant.

CHAPTER IV

RESULTS

Subject Characteristics

Subject characteristics for each device are reported in Table 2. Overall, subjects had an average mass of 75.1 (17.1) kg, and a BMI of 25.1(4.6) kg/m^2 (mean (SD)). During data collection and analysis, some subjects were excluded from Fitbit, Actigraph, IDEEA and the Shoe device results due to incomplete or missing data (see Table 2). Each device was analyzed separately with only valid subjects.

EE Measurement

The mean measured EE for all subjects for three hours of activity was 455.4 (17.8) kcal (mean (S.E.)) and for 3.5 hours of activity was 503.3 (19.2) kcals. Table 2 shows how EE measured by the room compared each device.

Table 2: Subject characteristics and measured energy expenditure (EE)

Device	Subjects (M,F)	Age (yrs)	Height (m)	Weight (kg)	BMI (kg/m^2)	EE Hours	EE (kcals (SE))
Shoes	17 (9,8)	27.4 (6.8)	1.73m (.10)	75.7kg (17.7)	25.1 (4.8)	3.5	478 (20.0)
DirectLife	19 (10,9)	26.9 (6.6)	1.73m (.10)	75.1kg (17.1)	25.1 (4.6)	3.0	499 (17.8)
Actical	19 (10,9)	26.9 (6.6)	1.73m (.10)	75.1kg (17.1)	25.1 (4.6)	3.5	447 (19.2)
Fitbit	16 (7,9)	27.6 (7.0)	1.71m (.10)	73.6kg (18.0)	25.0 (4.0)	3.5	503 (23.8)
Actigraph	16 (9,7)	26.8 (7.1)	1.73m (.09)	73.1kg (16.1)	24.3 (3.8)	3.0	504 (20.0)
IDEEA	18 (10,8)	27.2 (6.7)	1.72m (.11)	75.6kg (17.5)	25.2 (4.6)	3.5	455 (20.3)

Values are mean (SD) except EE. EE hours is the number of hours of room calorimeter data used in the analysis.

Energy expenditure models for Shoe device

The performance of the models used to estimate EE from the shoe-based device compared to measured values are presented in Table 3.

Table 3: Branched model results

Branch model	1-min prediction model, kcal/min	RMSE kcal (%)	Total Error
Sit	$EE = 1.92 + 0.015 \cdot \textbf{\textit{Weight}} - 0.61 \cdot \textbf{\textit{log(BMI)}} + 1.52 \cdot 10^{-3} \cdot \textbf{\textit{Sens}}_{med(zc)} + 0.59 \cdot \textbf{\textit{Acc2}}_{zc} + 2.05 \cdot 10^{-3} \cdot \textbf{\textit{Acc1}}_{std} + 0.50 \cdot \textbf{\textit{Acc1}}_{zc} - 5.33 \cdot 10^{-4} \cdot \textbf{\textit{Acc2}}_{std}$	45.76 (1.35)	4.55%
Stand	$EE = 3.23 + 2.64 \cdot 10^{-2} \cdot \textbf{\textit{Weight}} - 1.38 \cdot \textbf{\textit{log(BMI)}} + 1.69 \cdot 10^{-3} \cdot \textbf{\textit{Sens}}_{med(zc)} + 4.29 \cdot 10^{-3} \cdot \textbf{\textit{Acc1}}_{std} + 1.83 \cdot \textbf{\textit{Acc1}}_{zc}$	68.74 (8.11)	
Walk	$EE = -2.46 + 7.21 \cdot 10^{-2} \cdot \textbf{\textit{Weight}} - 0.72 \cdot \textbf{\textit{log(BMI)}} + 41.9 \cdot \textbf{\textit{Sens}}_{med(std)} + 10.5 \cdot \textbf{\textit{Acc3}}_{zc} + 2.08 \cdot 10^{-3} \cdot \textbf{\textit{Acc2}}_{std}$	76.88 (2.49)	
Cycle	$EE = 5.47 + 2.13 \cdot 10^{-2} \cdot \textbf{\textit{Weight}} - 1.54 \cdot \textbf{\textit{log(BMI)}} + 36.7 \cdot \textbf{\textit{Sens}}_{med(std)} + 3.92 \cdot \textbf{\textit{Acc2}}_{zc}$	71.78 (8.84)	
Average		**29.61 (6.19)**	

Metrics: ***zc*** – number of zero crossings; ***std*** – standard deviation of a signal: ***med(metric)*** is the median metric from all pressure sensors (1 value).

Device Comparison

The shoe device considerably out-performed all other devices. Out of the five research and consumer devices, only IDEEA and Directlife were not significantly different than the mean measured EE ($p=.065$ and $.758$ respectively). Table 4 presents each device with the respective root mean squared error (RMSE) and percent RMSE. Fitbit was the least accurate device ($p<.001$), however after labeling activities (Fitbit-CL), the mean (SE) improved from 362(19) kcal to 516(13) kcal vs. 499(24) kcal, and the RMSE was reduced to 64.25kcals (12.9%). The unlabeled estimates always underestimated EE, while the classified values were underestimated about half of the time, and were more accurate in all but two subjects (Figure 3).

Table 4: Mean measured and estimated energy expenditure

	Measured (SE) kcal	Estimated(SE) kcal	RMSE (kcal)	%RMSE
Shoes	478.08(19.95)	476.54(18.36)	29.61	6.19
Fitbit	499.02(23.79)	362.81(18.88)$^{+}$	143.24	28.70
Actigraph*^	447.22(19.95)	339.06(20.58)$^{+}$	122.23	27.33
Actical*	503.33(19.24)	383.19(16.92)$^{+}$	130.16	25.86
IDEEA	504.22(20.32)	445.26(23.16)	88.21	17.49
Directlife*^	455.37(17.82)	448.52(13.10)	62.11	13.64
Fitbit-CL	499.02(23.79)	515.80(13.00)	64.25	12.87

Mean room-measured and device-estimated energy expenditure, standard error (SE), root mean squared error (RMSE) and %RMSE. * denotes Harris-Benedict equation adjustment. ^ denotes a 3-hour comparison. $^{+}$Denotes significant difference from measured.

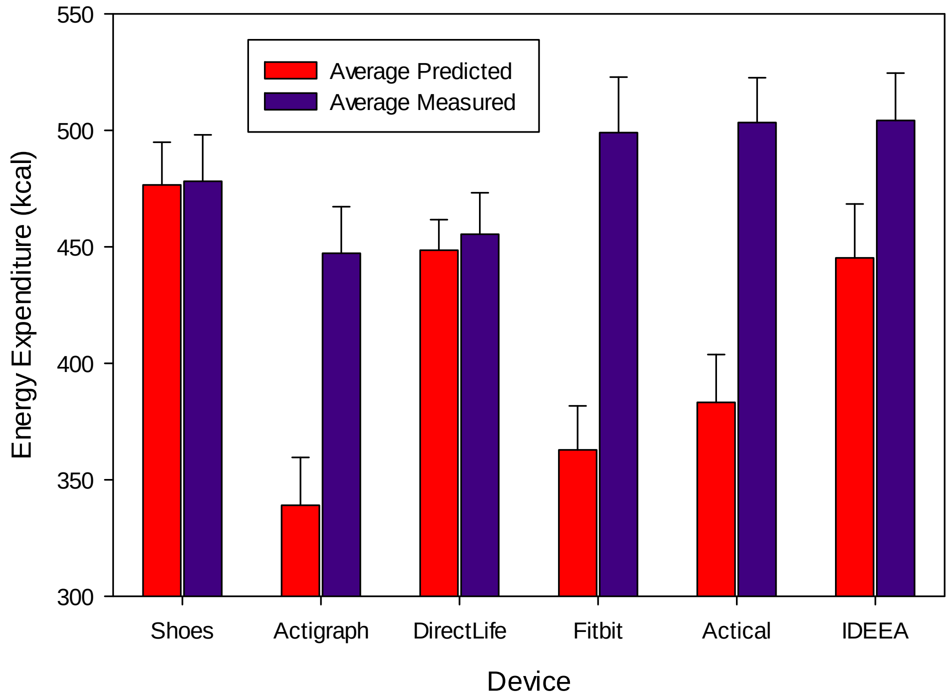


Figure 2: Mean measured and estimated energy expenditure using each device. Error bars represent standard error of the mean.

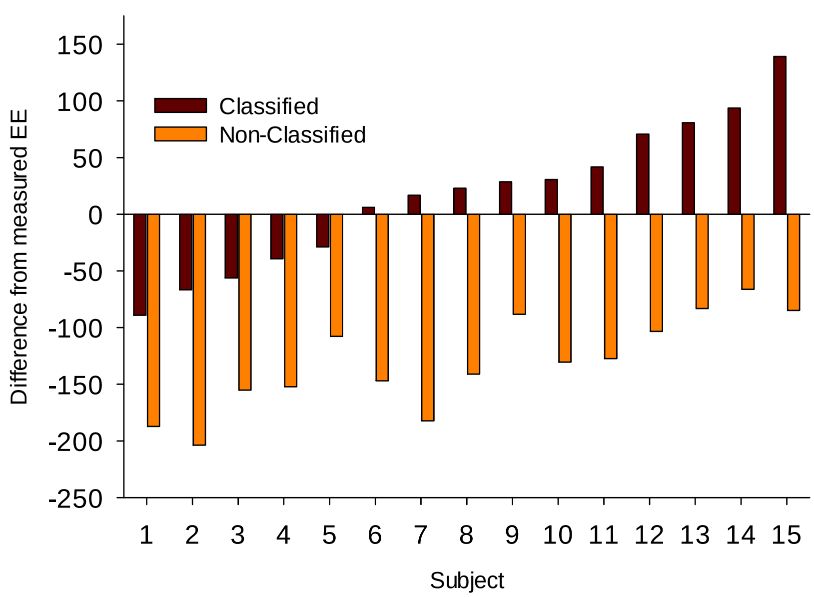


Figure 3: Difference between estimated and measured energy expenditure for each subject using the Fitbit device with (red) and without (orange) manual classification of activities

Group-specific Actical regression

Figure 4 depicts the regression equations that were developed using the subjects from this study using the Actical device. The regressions were applied to the count values each minute, and summed over the entire three and a half hours. Both equations improved the estimation of EE, while the regression without cycling was most accurate. Mean predicted EE from the models was 562.4 kcal and 498.1 for the “all activities” and “no cycling” regressions respectively, compared to the measured value of 503.3kcal. RMSE values improved from 130.2 kcal (25.9%) using the manufacturer’s software, to 107.2 kcal (21.3%) using the “all activities” regression and 90.4 kcal (17.6%) using the “no cycling” regression.

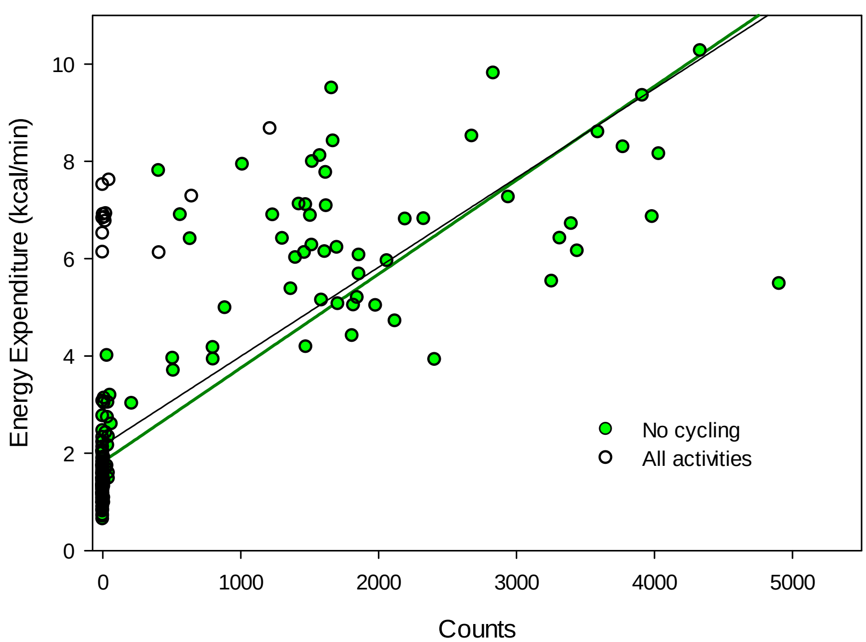


Figure 4: Results of the Actical regressions using all activities vs. all activities except for cycling. All activity regression equation: y = 0.0018x + 2.1581 (R^2 = 0.5666) (black line, white and green circles); No cycling regression equation: y = 0.0019x + 1.8228 (R^2 = 0.7244) (green line, green circles)

CHAPTER V

DISCUSSION

In this study, we aimed to validate the use of a shoe-based physical activity monitor which incorporates insole pressure sensors and triaxial accelerometry to classify major postures/activities and estimate EE. We hypothesized that this device would be able to accurately estimate EE with less than 5% error compared to room calorimetry. Additionally, we hypothesized that consumer and research devices would not be able to estimate EE with comparable accuracy. Our results confirmed that the shoe-based device could estimate EE within 5% (478.1 vs. 476.5 kcal), with a %RMSE of 6.19%. Furthermore, of the five consumer and research devices, only DirectLife and IDEEA were not significantly different than the measured value. DirectLife and IDEEA had a %RMSE of 13.64 and 17.49% respectively, which were both at least twice that of the shoe-based device.

Subjects performed a range of activities from sedentary to moderately vigorous intensity during a three and a half hour protocol in a room calorimeter, and measured EE values were similar to previous reports of physical activity monitoring device validation studies. Values of EE ranged from 96.5kcal per hour in a female subject, up to 202.8 kcal per hour in a male subject. The average EE per hour was 151.8(5.94) kcal per hour (mean(SE)). Others have reported an average of between 80 and 115 kcal per hour for longer protocols which commonly consisted of sleeping as well as a greater proportion of light intensity activities (Chen et al., 2003; Chen & Sun, 1997; Midorikawa, et al., 2007; V. van Hees & Ekelund, 2009).

Prototype device

The values and accuracy obtained in this study using the shoe-based device are consistent with a previous validation of the older version of the device. This leads us to conclude that the new hardware has not changed the ability of the device or the models to classify activity and estimate EE. Previously, the device was found to have an RMSE of .66 MET, and when we convert the results from the current study to METs, we determined the RMSE to be .54 MET. The current study was able to achieve slightly higher accuracy while using a device with similar hardware, possibly owing to the length of the current study using a room calorimeter lasting about twice as long as the previous study using a portable metabolic cart.

This study demonstrates that an unobtrusive shoe-based physical activity monitoring device that combines plantar pressure and accelerometry can more accurately estimate EE than five other currently available consumer and research physical activity monitors. The accuracy of this device is likely to be due to the EE models being based on activity classification and the ability to accurately make these classifications by picking up subtle changes in posture which literature shows are contributors to NEAT. The activities with the greatest EE estimation accuracy were sitting (1.35 %RMSE) and walking (2.49 %RMSE), while standing and cycling were only slightly less accurate (8.11 and 8.84 %RMSE respectively). The lower accuracy of standing may be attributed to the wide range of activities that were included in this classification, such as transitioning, active standing, quiet standing, and lifestyle activities that requires only arm movement.

Each of the models developed to estimate EE utilized a different combination of the 14 possible metrics in the linear regressions, including each channel of sensor data as well as weight and BMI. The subject's weight and the log(BMI) were understandably predictive characteristics of EE in all four models, owing to the fact that an individual's weight is predictive of their resting metabolic rate, which contributes a substantial amount to total EE. Pressure and acceleration sensors at the foot allow the device to extract important information from the movement of the limbs which relate to an individual's specific activity. For instance, during walking activity, the number of zero crossings (zc) of the acceleration in the anterior-posterior direction (Acc3) contributed to the prediction of energy expenditure. As the step frequency increase with an increase in the speed of ambulation, the number of zero crossing of the anterior-posterior acceleration will increase and thus contribute to the prediction of EE during walking.

Overall, these results suggest that multiple sensor types located at the foot is an effective method for estimating EE given that it allows for accurate classification. Although this begs the question of how many classes need to be used to distinguish between postures/activities with distinctly different metabolic demands. Currently, the prototype shoe-based device only makes estimations of EE based on four activity classes (lay, sit, stand and walk). Others have used similar or more classes with moderate to high success. For instance, Khan et al. achieved 98% accuracy at classifying 15 activities (Khan, Lee, Lee, & Kim, 2010), while Lee et al. achieved 85% accuracy classifying seven activities (Lee, Khan, Kim, Cho, & Kim, 2010), Bonomi et al. classified six activities with 93% accuracy (Bonomi, et al., 2009), and Staudenmayer et al. also classified four activities with 89% accuracy (Staudenmayer, et al., 2009). Each of these groups used single accelerometers and pattern recognition techniques for classification. This study classified by means of a branched algorithm, as did Madorikawa (Midorikawa, et al., 2007), while others have used two-regression equations, decision tree models (Bonomi, et al., 2009), Bayesian classifiers (Atallah, Leong, Lo, & Yang, 2010), support vector machines (Lau, Tong, & Zhu, 2008), and ANNs (de Vries, Garre, Engbers, Hildebrandt, & van Buuren, 2010; Khan, et al., 2010; Lee, et al., 2010; Staudenmayer, et al., 2009) with varying degrees of success.

There is likely to be a balance between the number of necessary activity classifications, and maintaining high classification accuracy. Recent attempts at classification have been employed in order to identify and distinguish between the low-to-moderate activities that contribute to NEAT (Midorikawa, et al., 2007; van Hees, van Lummel, & Westerterp, 2009), and also to classify a wide range of activities from sedentary, to those which are common for exercise (Bonomi, et al., 2009; Staudenmayer, et al., 2009). Therefore, future work to the footwear-based physical activity monitor should examine which activities are necessary for highly accurate models and also practical for the function of the device as a weight management tool (i.e. how many classifications are enough?).

Several investigators have used the Actigraph and Actical accelerometers with pseudo-classification by using two-regression equations. All published Actigraph and Actical two-regression equations, although differing slightly in accuracy, have been developed for the same basic function: to make better estimations of PAEE by distinguishing between activities with distinct metabolic demands, namely sedentary behavior, walking/running, and lifestyle activities. These equations work by using the variability of the acceleration signal as a classifier to determine if the timeframe in question represents a locomotor or lifestyle task. Since lifestyle tasks tend to have accelerations that have more variability around the mean, a separate regression equation can be used to predict EE based on the intensity of these activities (Crouter & Bassett, 2008; Crouter, Churilla, et al., 2006; Crouter, Clowers, et al., 2006; Crouter, et al., 2009).

Generally, algorithms developed to estimate EE through classification have a lesser bias, standard error and RMSE than estimations made by regression equations alone (Staudenmayer, et al., 2009). However, the limitation to methods which use accelerometers was that movements with little or no trunk movement, such as standing and cycling were most likely to be misclassified (van Hees & Ekelund, 2009). This provides rational for using a shoe-based device which uses multiple sensor types, and is therefore capable of classifying standing and cycling activities with high accuracy.

Evidence towards the importance of classification of activities was further confirmed by our finding of an improvement in the accuracy of the Fitbit device after classifying activities. The RMSE of the estimation dropped from 143 to 64 kcal, and the estimation was more accurate in all but two subjects. IDEEA algorithms also have the ability to classify activities, and we found that this device was moderately accurate and had a lower RMSE of 88 kcal, compared to other devices which cannot classify activities (i.e. unclassified Fitbit, Actical and Actigraph).

In addition to classifying activities, the high accuracy of the device may be due to the nature of our leave-one-out validation technique which used the same subjects to calibrate and validate the device. It is well known that group-specific models are most accurate when they are applied to the same group from which they were created (Edwards, Hill, Byrnes, & Browning, 2010). For this reason, we elected to develop two group-based regression equations using the Actical to make a comparison of the shoe-based device with another device that used a group specific model. The Actical regression which used all the activities was significantly different from the mean measured value (p=.012), but the regression which did not include cycling was not significantly different than the mean (p=.640), and both were more accurate than using the manufacturer's software to estimate EE. Software that uses group-based models a current limitation in the field of physical activity monitoring because manufacturers supply the user with a regression based on a population of healthy, lean individuals, yet the device may be used by individuals who do not fit this group. Future work should be done to validate whether the current algorithms are valid on a variety of populations (i.e. physically active, obese, children and elderly), and possibly provide options within physical activity monitor software as to which algorithms should be used to estimate EE.

An accurate shoe-based physical activity monitor such as this would be a practical tool for weight management purposes. This device is minimally obtrusive as it would fit into an existing shoe, and the software can be accessed using a Smartphone. Individuals would be able to track their EE as well as be able to see how they are spending their time. For instance, this device is able to pick up the changes in posture which are contributors to NEAT such as the time spent lying, sitting or standing, and could alert an individual to make more transitions to standing; which research shows may have health benefits (Healy, Dunstan, et al., 2008; Kokkinos, et al., 2011). Activity counts alone will tend to under-estimate the EE associated with many of these postures (Levine, 2007). This device could therefore be implemented into existing weight management programs (i.e. Weightwatchers) or be a device prescribed by physicians under the justification that "exercise is medicine". Future work should incorporate the use of the shoe-based device during a longer protocol (i.e. 24-hour) in order to represent true levels of physical activity and NEAT as they occur in an individual's typical day.

Research and consumer devices

The use of commercially available physical activity monitors is becoming increasingly popular in research to objectively quantify physical activity at the individual and group level and for personal use to monitor physical activity levels related to weight management and/or fitness goals. The accuracy of these devices is critical to quantifying current and changing levels in physical activity. Of the three research-based devices, only IDEEA was not significantly different than the mean EE, yet had a greater error than previously reported (Zhang, et al., 2004), and a moderately high RMSE. The mean EE estimated by the device had an 11.7% error against the room calorimeter, and the RMSE was 88.21 kcal in three and a half hours of data collection.

Like previous investigations, we found the Actical and Actigraph significantly underestimated EE during a protocol of sedentary to moderately vigorous activities (Crouter, Churilla, et al., 2006; Crouter, Clowers, et al., 2006; Leenders, et al., 2001). Actical and Actigraph devices also had high %RMSE values of 25.87 and 26.33% respectively. Considering that the energy imbalance may be as low as 25kcal per day, this degree of error would certainly be unreasonable for weight management purposes.

In this study, we used a range of activities, including cycling, uphill walking and stepping, which may have been under-estimated by research and consumer devices due to the limitations in the hardware of these devices to correctly interpret these movement as requiring greater metabolic demand. For instance, accelerometers located at the hip are unable to sense the limb movement during cycling, are not sensitive to the vertical work performed during stepping and uphill walking, as these movement do not create greater magnitude or frequency accelerations in proportion to the increase in metabolic demand (Hendelman, et al., 2000; Swan, Byrnes, & Haymes, 1997; Terrier, Aminian, & Schutz, 2001). Furthermore, The IDEEA device was unique among the commercially available devices validated in this study because it uses multiple sensors and sensor types, and more sophisticated algorithms to calculate EE, and the higher accuracy of this device may be due to the ability to capture more data with multiple sensors placed at different sites on the body. While being impractical for use outside of a research lab, the success of this device illustrates the effectiveness of multiple sensors and types to provide the means for classifying activities. Additionally, this device was calibrated using activities of similar intensity to those that were performed in the current study, which may have led to a better accuracy during validation.

This study was the first to compare the accuracy of several consumer and research activity monitoring devices together against room calorimetry, and there was no consistent pattern to research devices outperforming consumer devices or vice versa. Furthermore, to our knowledge it was the first validation of the Fitbit tracker, a device marketed for consumer use. Two of the most accurate devices overall were the consumer devices, Fitbit and Diretlife with an RMSE of 64kcal (12.9%), and 62.1kcal (14%) respectively; However, Fitbit only outperformed all other devices after manual activity classification, and this process was timely and requires continual documentation which is inconvenient if not implausible for the average consumer. With respect to the other consumer device, the DirectLife activity monitor, we found no significant difference between measured and estimated values, which is consistent with the literature on the accuracy of this device. Bonomi et al reported the device to be accurate over a 14-day period using double labeled water with a standard error of the estimated TEE to be .9MJ per day, (8.96 kcal per hour) or 7.4% of the measured TEE (Bonomi, et al., 2010). Our results determined that the SE was .44MJ per day, or 2.9%.

This device is minimally obtrusive because it can be configured to be worn in multiple places (e.g. hip, chest, and pocket). On the other hand, it has important limitations. The main disadvantage of Directlife device is the simplicity of the web-based software which only provides information about the user's EE when activity is observed by the device. This software only allows a user to determine EE on an hourly basis. While the hourly resolution may be sufficient for monitoring EE patterns over the course of several days, it would be inconvenient for individuals attempting to track changes in EE during specific period of the day (e.g. after work only). The time resolution also likely contributed to the error in a shorter study such as this. Additionally individuals see only PAEE, such that RMR needed to be estimated from a prediction equation to make similar comparisons of TEE among all devices. In comparison, Fitbit did this process automatically for the user within the web-based software. This evidence along with existing literature validating the DirectLife device, suggests that it would be a useful tool to consumers and researchers alike, provided that the appropriate software was provided (Bonomi, et al., 2010; Plasqui, et al., 2005).

Conclusion

In the current study, we present a device which is minimally obtrusive but is capable of high classification and total EE accuracy. This shoe based physical activity monitor estimated EE with a total error of 4.55% and a RMSE of 29.6kcal (6.19%). This device outperformed each of the research and consumer physical activity monitors which had a range of RMSE values between 62.1 kcal (14%) to 143.2 kcal (28%). Only IDEEA and DirectLife EE estimations were not significantly different than the mean. Considering the similar hardware of these research and consumer-based devices, EE estimation accuracy can primarily be contributed to the algorithms used to estimate EE, which with the exception of the IDEEA device, do not rely on activity classification. Activity classification is central to achieving the high EE estimation accuracy of the shoe based device, and the future of physical activity monitor hinges around this function.

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