THE USE OF GPS TO PREDICT ENERGY EXPENDITURE

FOR OUTDOOR WALKING

By

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ABSTRACT

The purpose of this study was to determine the ability of GPS-reported position and elevation to estimate actual energy expenditure (EE_{ACT}) for outdoor walking. An accurate method for assessing EE in the field could greatly influence the scope of future studies of free-living activities.

Thirteen subjects (8 male, 5 female) completed a 2303 m course of varying grades at slow and fast self-selected paces. Data from a portable metabolic unit was used to compare the GPS-predicted EE (EE_{GPS}). Calculations of EE_{GPS} were made by compiling an equation accounting for ground speed, grade, (Minetti, et al., 2002) and wind resistance (Pugh, 1970).

Differences between EE_{ACT} and EE_{GPS} were statistically and practically significant for the slow walking trials. Fast trials showed no significant differences. The combined data differed significantly from EE_{ACT}, but was similar to the error for accelerometer-based activity monitors. The wrist and hip-worn GPS monitors provided similar results for EE_{GPS} throughout the data set. Separating the data by grade type showed that EE_{GPS} was most problematic for uphill walking. Additional analyses performed on the data showed no meaningful changes in the results. These analyses included increasing the sampling interval for the GPS monitors and implementing rudimentary smoothing techniques in an effort to reduce the error in the GPS-reported elevation data.

The GPS monitor data were able to estimate EE_{ACT} for fast walking and the combined data within the error range consistently reported for activity monitors (±5 – 25%). The EE_{GPS} for the slow walking trials could not reasonably predict actual EE. Despite the troubles with predicting EE_{ACT}, the two GPS monitors tested provided very similar estimates of EE when compared to each other, ruling out reliability as a potential source of error. The addition of wind resistance to the EE_{GPS} equation accounted for less than 2% of the differences between actual and GPS-predicted EE. Sources of error include the accuracy of GPS technology, and the suitability of the equation for calculating EE based on speed and grade. Future studies should focus on the use of other GPS monitors, or creating a custom algorithm for estimating EE for walking.

CHAPTER ONE

INTRODUCTION

Background

The ability to accurately estimate energy expenditure (EE) is important in occupational, clinical, recreational, and research settings. For example, wildland firefighters and military personnel may find the ability to accurately estimate EE the difference between adequately fueling for the job, and risking death when the fuel fails to meet energy demands (Demczuk, 1998; Heil, 2002). Assessment of EE can also be used in clinical settings to determine if patients are performing the necessary physical activity to address their chronic disease risk (Schultz, Weinsier, & Hunter, 2001). Orienteers and adventure racers can benefit from EE research because of the interest in carrying a limited amount of gear while ensuring that there is enough food to sustain the caloric demands of the given task. Finally, researchers are interested in studies estimating EE in order to improve data collection while field-testing.

Energy expenditure is a measure of the body's combustion of fuels over a prescribed time period. Lavoisser first measured EE in the late 1700's using animals in a sealed chamber. The heat produced by the animals was estimated from the volume of ice melted from a surrounding chamber (Ainslie, Reilly, & Westerterp, 2003; Goran & Treuth, 2001). While methods similar to those used by Lavoisser are still employed today, there has been a push to develop methods that will accurately estimate EE and minimize impediments to the subject's normal activity. Lavoisser required subjects to live in a sealed chamber in order to collect data, which is not representative of everyday life. To rectify the problem of studies that are not characteristic of real world activities, researchers have studied methods of estimating EE for free-living activities that allow for more realistic and generalizable studies.

Electronic monitoring devices include heart rate (HR) monitors, pedometers, accelerometers, and global positioning system (GPS) technology. Each device is beneficial in the research setting due to the ease of use and minimal subject burden. These electronic devices are lightweight, easy to carry, and do not require supplemental equipment to measure, record, or download data. In addition, these devices are not encumbering, can be worn without the knowledge of passers-by, and are not difficult to accommodate for long periods of time, making them unobtrusive and socially acceptable (Beghin et al., 2000). Reducing the burden on the subject is paramount in making any research tool simple for use in free-living research.

Studies using electronic devices have shown them to be reliable and valid for research purposes. Studies have also shown that there are limitations to be considered before using these electronic devices for research. Heart rate monitors, for example, measure the physiologic response to activity, but do not provide information on the task being performed (Beghin et al., 2000). Pedometers measure the number of steps taken, but will not measure the intensity of the steps (e.g., differentiating between a walking step and a running step). Accelerometers can measure both body movements and the intensities of these movements. Pedometers and accelerometers both fail to accurately account for gravity while assessing movement (Westerterp, 1999). It is important to account for gravity because a subject will be forced to work against gravity when walking uphill and will be able to utilize gravity when walking downhill to move the center of mass. Thus, without accounting for gravity, uphill walking will appear to require the same EE as level walking. With knowledge of the specific gradient of the course, accelerometers may be used to accurately determine EE while walking over a course of varying altitude (Perrin et al., 2000). This, however, defeats the principle of a free-living analysis because the course is pre-determined.

While research on GPS monitoring is recent, it shows promise to address some drawbacks of other electronic tools while still maintaining the benefits that other devices provide. Speed of locomotion can be calculated from GPS monitor data by analyzing the changes in position and time measurements. Knowledge of the speed of travel allows for a determination of EE for the activity. The position data from the GPS monitor also provides altitude, which can be paired with distance traveled to calculate the gradient of the path. Use of GPS monitors may improve on the abilities of HR and accelerometry studies by allowing the researcher to collect speed and grade data more precisely for free-living studies, while minimizing the burden on the subject.

Statement of Purpose

The purpose of this study was to validate the use of GPS monitor data for predicting the EE of outdoor walking, as well as walking at fast and slow speeds, when compared to an actual measurement of EE. The final purpose of this study was to determine any difference in GPS predicted EE between hip-worn and wrist-worn GPS monitors.

Hypotheses

For the purpose of this study, the primary null hypothesis was that the actual EE for outdoor walking would not equal the predicted EE for outdoor walking from GPS data.

Primary Hypothesis:

H_0: $\mu_{EE} \neq \mu_{GPS}$

H_A: $\mu_{EE} = \mu_{GPS}$

The secondary null hypothesis was that the actual EE for slow and fast paced outdoor walking would not equal predicted EE for slow and fast paced outdoor walking, respectively.

Secondary Hypothesis:

H_0: $\mu_{EE\ Fast} \neq \mu_{GPS\ Fast}$ and $\mu_{EE\ Slow} \neq \mu_{GPS\ Slow}$

H_A: $\mu_{EE\ Fast} = \mu_{GPS\ Fast}$ and $\mu_{EE\ Slow} = \mu_{GPS\ Slow}$

The tertiary null hypothesis was that the GPS predicted EE for the hip-worn GPS monitor would not equal the GPS predicted EE for the wrist-worn GPS monitor.

Tertiary Hypothesis:

H_0: $\mu_{HIP} \neq \mu_{WRIST}$

H_A: $\mu_{HIP} = \mu_{WRIST}$

Where: μ_{EE} is the mean population value for energy expenditure

μ_{GPS} is the mean population value for GPS predicted energy expenditure

$\mu_{EE\ Fast}$ is the mean population value for energy expenditure at a fast walking pace

$\mu_{EE\ Slow}$ is the mean population value for energy expenditure at a slow walking pace

$\mu_{GPS\ Fast}$ is the mean population value for GPS predicted energy expenditure at a fast walking pace

$\mu_{GPS\ Slow}$ is the mean population value for GPS predicted energy expenditure at a slow walking pace

μ_{HIP} is the mean population value for GPS predicted energy expenditure using a hip-worn GPS monitor.

μ_{WRIST} is the mean population value for GPS predicted energy expenditure using a wrist-worn GPS monitor.

Limitations

This study was limited by variations in environmental factors such as temperature, precipitation, and ground surface conditions, which could affect the conditions in which the subjects were tested.

A precise estimate of standard error was difficult to determine because of the lack of previous research on this particular topic. This may affect the determination of sample size to ensure sufficient statistical power.

Using GPS, there is the possibility of insufficient satellite coverage to obtain and maintain an adequate signal to receive reliable data on speed and grade.

Delimitations

This study included subjects between 20 and 30 years of age from the Bozeman, Montana area. The subjects were required to be physically active and capable of vigorous intensity hiking. Furthermore, subjects were required to be defined as ‘low risk’ as determined by the American College of Sports Medicine (2000).

Operational Definitions

EE	Energy Expenditure, measured in units of Kcals • min^{-1}.
GPS	Global Positioning System. Satellite system developed by the U.S.A. for navigation and guidance systems.
dGPS	Differential GPS. A method of decreasing GPS signal error using ground stations to correct the signal.
WAAS	Wide Area Augmentation System. System similar to dGPS further improving GPS resolution.
Free-Living Activity	A task which is unconstrained and performed in the environment of routine, daily activities.
HR	Measurement of the number of ventricular contractions of the heart, measured in units of beats per minute (bpm).

HR_{MAX}	Maximal number of ventricular contractions of the heart, measured in units of bpm.
Age Predicted HR_{MAX}	220 – age, measured in units of bpm.
EE_{ACT}	Actual EE, measured in units of Kcals.
EE_{GPS}	GPS predicted EE, measured in units of Kcals.
EE_{HIP}	Hip-worn GPS predicted EE, measured in units of Kcals.
EE_{WRIST}	Wrist-worn GPS predicted EE, measured in units of Kcals.

CHAPTER TWO

REVIEW OF THE LITERATURE

Introduction

The measurement of energy expenditure (EE) has been evolving for 200 years (Ainslie et al., 2003; Goran & Treuth, 2001) and advances in technology have driven this progress. Estimating EE has become much less intensive, invasive, and costly due to advances such as metabolic carts, heart rate (HR) monitors, and activity monitors. Lavoisser's primitive methods of direct calorimetry have advanced to indirect measures utilizing radioactive isotopes, exhaled gases, and electronic devices to estimate EE. Electronic devices such as activity monitors allow researchers to estimate EE without collecting any physiologic data such as HR or exhaled gases. Measurement of body movements to estimate EE has been done with pedometers and accelerometers, which measure steps and body accelerations, respectively (Basset Jr, 2000). Expanding on the use of body movements Schutz and Herren (2000) have shown that global positioning system (GPS) monitors are a valid research tool.

Measurement of Energy Expenditure

Direct calorimetry was the first method to measure energy expenditure, in both animals and humans. This method required subjects to stay in a thermally isolated chamber for the duration of the trial. The difference in the temperature of the room was then attributed to the subject's metabolic rate (Ainslie et al., 2003; Goran & Treuth, 2001). Knowing the size of the room, and having accurate measures of initial and final temperature allows the researcher to determine the energy expenditure using thermodynamics. Although this method of measurement is very accurate, it is also very limited. Due to the constraints on the subject, direct calorimetry is not a good measure of EE for free-living activities (Ainslie et al., 2003).

The doubly labeled water method (DLW) is considered to be the ‘gold standard’ for measuring EE through indirect calorimetry (Ainslie et al., 2003). The DLW method relies on a sample of water made up of non-radioactive isotopes of oxygen (^{18}O) and hydrogen (^{2}H). These samples will be utilized by the body, the same as the common isotopes of oxygen and hydrogen, and measurements of expired gases are used to determine the ratio of the isotopes found in water lost (through breathing, sweat, urine, and other evaporations) as compared to the oxygen isotope present in expired CO_2. Given that the oxygen isotope is expired more rapidly than the hydrogen (because oxygen is in both carbon dioxide and water), the relative quantities of each element, along with their original quantities, can be used to estimate EE (Schoeller & van Santen, 1982). Despite the accuracy of this method, it is not often used because of the expense of the isotopes, the high level of technical expertise required to collect and process the data, and it cannot be used for brief bouts of activity.

Indirect calorimetry allows for greater freedom in measuring EE for free-living activities. Indirect calorimetry is a measure of the total energy production by the body, as measured by comparing inhaled and exhaled gases (Ainslie et al., 2003; Goran & Treuth, 2001). Systems for indirect calorimetry measurement are available both as lab-based metabolic carts and portable metabolic systems, but are generally limited to measurement periods of 1-5 hours (Ainslie et al., 2003). A metabolic cart will measure EE for brief bouts of activity, an advantage over the DLW method for relatively short collection periods.

Portable Metabolic Systems

Portable metabolic systems measure exhaled gases and are lightweight and battery powered to allow for mobile testing. These systems are generally more expensive than their lab-based counterparts, but allow researchers to leave the confines of the laboratory. Early designs failed to include a sensor for CO_2 (Bigard & Guezennec, 1995; Crandall, Taylor, & Raven, 1994; Peel & Utsey, 1993) or included a CO_2 sensor that was unable to accurately measure the CO_2 produced (Wideman et al., 1996). The Aerosport KB1-C portable metabolic system does include a CO_2 sensor, and performs at an acceptable level when compared to the Douglas Bag method (King et al., 1999) as well a Parvo Medics 2400 metabolic measurement system (Subudhi & Walker, 1999). Subdhdi and Walker (1999) concluded that the KB1-C measured VO_2 consistent with the Parvo Medics 2400 at all exertion levels (<1.5 L · min^{-1}, 1.5-2.0 L · min^{-1}, 2.0-2.5 L · min^{-1}, 2.5-3.0 L · min^{-1}, 3.0-3.5 L · min^{-1}, and >3.5 L · min^{-1}). The results of this study also show that the KB1-C was not significantly different in the measurement of VCO_2 when compared to the Parvo Medics 2400 at intensities less than 1.5 L · min^{-1}. The study by King et al. (1999) concluded that the KB1-C was acceptable for use in studies including exertions in the range of 1.5 to 3.5 L · min^{-1}. Statistically significant differences between the KB1-C and the Douglas Bag method were within the 6% criterion for the Douglas Bag method, and the errors in VO_2 and VCO_2 "may be physiologically unimportant" (King et al., 1999, p 308). Although both of these studies employed cycle ergometer testing, the range of acceptable use for the KB1-C includes the VO_2 for walking, generally between 0.5 and 2.0 $L \cdot min^{-1}$.

Electronic Tools for Estimating EE

New techniques for estimating EE attempt to minimize the problems of cost, invasiveness, and the ability to recall specific activity involved in current research. Advances in technology allow for EE estimation using electronic devices that are affordable, effective measurement tools for research studies. Methods of estimating EE with electronic tools include accelerometry and HR monitoring (Ainslie et al., 2003).

Accelerometers measure the accelerations caused by movements of the body. Assuming that each of these accelerations require an expenditure of energy, an estimation of EE can be made based on the number and magnitude of the accelerations recorded over the length of the trial. Accelerometers have been validated for use in research estimating EE in numerous studies (Brage et al., 2003; Heil, 2002; Herren, Sparti, Aminian, & Schutz, 1999; Melanson & Freedson, 1995; Perrin, Terrier, Ladetto, Merminod, & Schutz, 2000; Rowlands, Thomas, Eston, & Topping, 2004; Schutz et al., 2001; Terrier, Ladetto, Merminod, & Schutz, 2001; Welk, Almeida & Morss, 2003). Although accelerometers provide accurate estimates of EE for walking on level surfaces, several research studies (Brage et al., 2003; Melanson & Freedson, 1995; Perrin et al., 2003; Schutz et al., 2001; Terrier et al., 2001) note that they are unsuitable for estimating EE when walking on inclines or declines, which could prove to be a "serious limitation in field settings" (Melanson & Freedson, 1995). The study by Herren et al. (1995) supports that walking EE on a grade can be estimated because there is a greater vertical acceleration measured by the accelerometer during uphill walking in order to overcome gravity, and Terrier et al. (2001) found that accelerometers could be used to estimate walking EE on a grade if the grade was known and constant.

Like accelerometry, HR monitoring is relatively non-invasive and simple for the subject, requiring only the use of a HR monitor chest strap and wristwatch receiver unit. Several studies validated the effectiveness of HR monitoring for estimating EE in free-living activities (Brage et al., 2003; Hiilloskorpi, Pasanen, Fogelholm, Laukkanen, & Manttari, 2003; Livingstone, Robson & Totton, 2000; McCrory, Mole, Nommsen-Rivers, & Dewey, 1997; Schutz et al., 2001; Treuth, Adolph & Butte, 1998). As with accelerometers, HR monitors have the advantage of collecting data for long periods of time (several days, based on memory capacity). Heart rate monitoring is not without limitations though. Brage et al. (2003) noted that there could be substantial variation in HR between subjects that must be controlled with a calibration of the HR-VO_2 curve for each subject for a given activity. Other variables may also influence HR, such as stress, ambient temperature, relative humidity, dehydration, and illness (Schutz & Deurenberg, 1996; Spurr et al, 1988). Heart rate can estimates EE very well from moderate to high intensity exercise (HR of 110 BPM to 85% HR_{MAX}) due to the linear relationship between HR and VO_2 in this range. Heart rate does not estimate EE well at low intensity physical activity because of the small changes in HR relative to VO_2 from rest to low intensity activity (Ainslie et al., 2003; Hiilloskorpi et al., 2003; Livingstone et al., 2000; Schutz et al., 2001).

Global Positioning System

Background

The global positioning system was developed and implemented by the U.S. Department of Defense (DoD) for navigation and guidance purposes. The GPS consists of approximately 30 satellites, each fitted with an atomic clock and capable of communicating with receivers on earth. The satellites transmit time to the receiver, and signal transmission time is used to determine location. In order to determine latitude and longitude, three satellites must be transmitting to the receiver. A fourth satellite will provide the resolution to determine altitude. Additional satellites may provide higher resolution. Speed can be determined either using a simple distance and time equation, or by measuring Doppler shift. GPS was originally developed with a selective availability (SA) function allowing the DoD to scramble the satellite signal. Selective availability reduced accuracy to about ±100 m and mitigated the risk of 'hijacking' by hostile forces. The SA function was turned off in 1999 (Larsson, 2003). Accuracy of GPS without SA is about ±15 m. To further improve the accuracy of the system, ground stations are used to provide corrections to the satellite signals. These ground stations are at a known location (latitude, longitude, and altitude), and provide a calibration for the satellites. This technology is employed by both differential GPS (dGPS) and the wide area augmentation systems (WAAS). Accuracy using dGPS is about ±3-5 m, and generally less than ±3 m using WAAS. Currently, WAAS is only available in North America, although similar systems are available in Europe (Euro Geostationary Navigation Overlay System, EGNOS), and Japan (Multi-functional Satellite Augmentation System, MSAS).

Validity and Reliability

Use of GPS as a research tool requires that it be a valid and reliable instrument. Although the use of GPS outside of military and commercial navigation is relatively recent, there have been several studies testing GPS as a potential tool for research. Speed measurements taken by the GPS receivers are sufficient for "any practical utilization in sport physiology and medicine" (Schutz & Herren, 2000). Position reported by GPS monitors is within ± 3 m of actual (for a static position), although errors in elevation data may be up to 40 m (Demczuk, 1998). Demczuk (1998) reported occasional loss of the satellite system, implying a potential confound to the validation. Mean differences in GPS reported distance were found to be 0.8 m over a 115 m course by Larsson and Henriksson-Larsen (2001), as well as a correlation coefficient of 0.9995 for GPS reported speed when compared to manual chronometry. GPS reported speed of ambulation from 2.9 km•hr^{-1} (slow walking) to 25.2 km•hr^{-1} (fast running) has a standard error of prediction to be 0.1 km•hr^{-1} when compared to actual speed, equivalent to the error of calculating speed by manual chronometry (Schutz & Herren, 2000). The validity of GPS speed measurements have been corroborated by other studies as well (Terrier, Ladetto, Merminod, & Schutz, 2000). Underestimations of speed on grades from 5 to 30 degrees have been reported as 0.4% to 15.5% when based on calculations using distance and time

(Larsson & Henriksson-Larsen, 2001; Larsson, 2003). Researchers suggested replacing the distance/time speed assessment with GPS as the gold standard for field research (Larsson & Henriksson-Larsen, 2001; Schutz & Herren, 2000; Terrier, et al., 2000). This suggestion was prompted by excellent results from the studies, as well as the difficulty in using time and distance equations for free-living activities when compared to GPS. All of the studies mentioned tested dGPS, which was found to be substantially more accurate (8 to 10 times) than uncorrected GPS from previous studies (Schutz & Chambaz, 1997; Schutz & Herren, 2000).

Research Utilizing GPS

With GPS gaining credibility as a research tool, some researchers have started using GPS in studies beyond validation of the technology. GPS data has been used to calculate distance or speed, or to correlate EE and HR to the profile of the course being traversed. The Demczuk (1998) study was designed to predict EE in walking soldiers, although the GPS was used simply to measure distance, while the Close Action Environment battle simulation was used to estimate EE. Conversely, GPS is also used to analyze the biomechanics of walking. Terrier et al. (2001) utilized dGPS for a kinetic analysis of the mechanical power of walking. In this case dGPS was accurate enough to measure changes in trunk position in the gait cycle to calculate the change in potential energy, although it wass noted that full validation had not been performed. Research has also been conducted using dGPS for a kinematic analysis of the gait cycle (stride rate, stride frequency, and walk ratio) for unconstrained walking at three speeds (Terrier & Schutz, 2003). In two studies researchers collected metabolic data along with GPS data

(Larsson, Burlin, Jakobsson, & Henriksson-Larsen, 2002; Larsson & Henriksson-Larsen, 2001). Larrson and Henriksson-Larsen (2001) had subjects wear a portable metabolic unit while completing a 4.3 km orienteering course, but only HR and RER were used as part of the analysis. In a subsequent study researchers again used a portable metabolic system to record data while orienteering a 4.3 km orienteering course (Larsson, Burlin, Jakobsson, & Henriksson-Larsen, 2002),. For this study, mean VO_2 was reported along with HR and RER, however these values were only used as a correlation to the speed reported by the GPS monitors without further examination. Other studies considered the use of metabolic measurement in conjunction with GPS measurements (Perrin et al., 2000; Terrier et al., 2000), although one was focused on the prospect of studying the biomechanical efficiency of walking (Terrier et al., 2000).

Summary

Field research presents the paradox in the desire for laboratory precision and accuracy, and the need for a realistic, free-living setting. With this delicate balance it appears that researchers must sacrifice the validity of their measures, or the realism of their study. Direct calorimetry requires a subject to be confined in a room for an extended period. Portable metabolic units can be used in place of lab-based systems, but are burdensome on the subject, restricting communication and nutrition, and are limited to short periods of use. While DLW is a great method for EE of free-living activities, it is costly, it cannot be used for short bouts of activity, and does not provide any record of body movements.

Technological advancements have made many electronic devices more reliable, user-friendly, accessible, and economical. Pedometers, accelerometers, and HR monitors are popular tools for research due to their ease of operation, low subject burden, and relative low cost, however each has drawbacks for true free-living research. The use of GPS monitors in research provides an interesting and promising approach to studying free-living activities. Because the two principle measures for estimating walking EE are speed and grade (Larsson, 2003; Perrin et al., 2000), GPS seems to be an ideal instrument to predict EE for outdoor walking or hiking. This provides a small, lightweight, low cost research tool with the potential to estimate EE without collecting any physiologic parameters for a wide range of activities. In addition to being able to monitor subjects during free-living activities, researchers also noted that GPS allows for greater data collection periods, limited only by the battery life and memory capacity of the GPS receiver (Terrier et al., 2000; Terrier et al., 2001; Terrier & Schutz, 2003).

CHAPTER THREE

METHODOLOGY

Subjects

Subjects were recruited directly by the researchers through classes at Montana State University, and from the Bozeman, MT, community. Exclusion criteria included anyone with an injury, disease, or ailment that altered the individual's gait, and any individual falling outside the designation of 'low risk' as defined by the American College of Sports Medicine (American College of Sports Medicine, 2000). In accordance with the MSU Human Subjects Committee guidelines, all subjects signed an approved informed consent document before data collection began.

Protocol

General Procedures

Each subject performed one walking session consisting of two trials: slow and fast walking. Subjects were brought to the Movement Science Lab at Montana State University to measure height and weight. Testing then commenced at the area between Bozeman Deaconess Hospital and Sunset Hills Cemetery in Bozeman. Elevation at the starting point was 1510 m. The course featured two out-and-back sections. The first headed north then returned to the starting area, followed by the second out-and-back section headed south of the starting area. The starting point of the course also served as the finishing point. The first out and back section included a downhill section of approximately 100 m followed by a level section to the first turnaround at a distance of 508 m from the start. The second out-and-back section began with an uphill section of approximately 200 m followed by a section of level ground for 170 m. Following the level section was an uphill section of 205 m, which leveled out briefly at the second turnaround, 1660 m from the start of the course. At this point the subject then back-tracked to the starting area. The course measured a total distance of 2303 m (7600 ft). The course was measured using a calibrated wheel (Rolatape 400, Rolatape, Watseka, IL, USA), and a handheld altimeter (Barigo Model 39 6000m analogue altimeter and barometer, BARIGO Barometerfabrik GmbH, Villingen-Schwenningen, Germany). . The course elevation profile is shown in Figure 3.1.

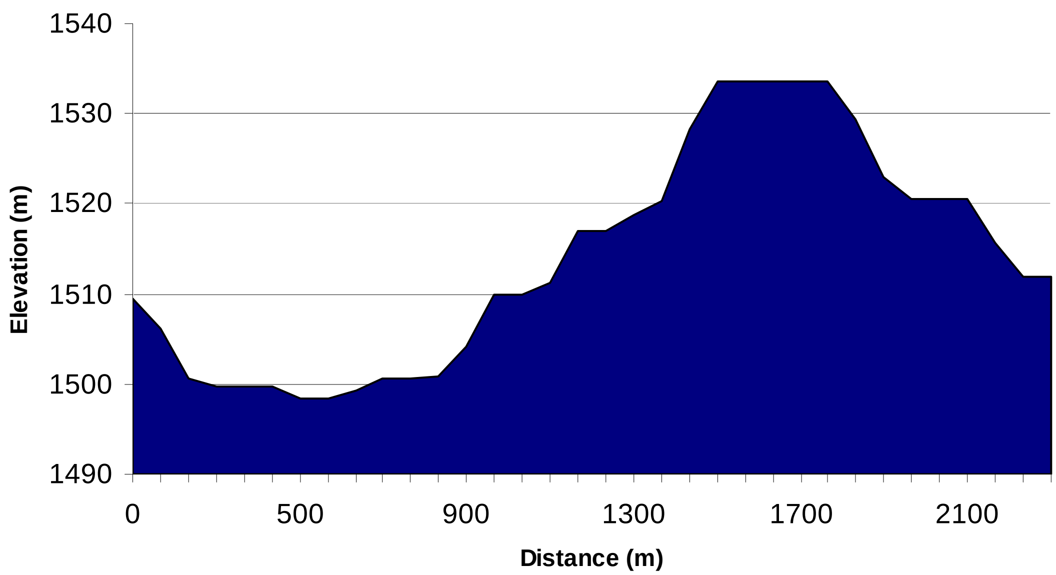

Figure 3.1. Elevation profile of the walking course.

The field-testing measured energy expenditure (EE), heart rate (HR), global positioning system (GPS) data, and time to complete the course. Subjects were instructed to refrain from exercise 24 hours prior to testing and eating the 2 hours prior to testing.

Testing Protocol

Each subject hiked the course twice, once at a self-selected slow pace, and again at a self-selected fast pace. The fast and slow paces were determined during the warm-up period with the assistance of the investigator. The subjects were instructed to walk the slow-paced trial at an intensity that allowed the fast-paced trial to be at least 15 bpm higher than the slow-paced trial. The fast-paced trial was also described as the fastest sustainable walking intensity. The subjects were also briefed on reading the HR monitor. The investigator accompanied the subject walking the first trial to monitor HR, emphasizing the need to maintain a consistent intensity. Care was taken to ensure that the subject had a clear understanding of the procedure for self-monitoring the second trial. After the first trial the investigator reminded the subject of the pacing instructions, and provided a HR limit to assure a difference between the intensity of the two trials.

The order of the trials for each subject was determined through a counter-balanced design to control for possible testing order effects. Each subject walked the specified course wearing a portable metabolic system, a HR monitor, as well as two different models of GPS monitors. The portable metabolic system was mounted on a backpack for ease of carriage as well as simulation of a hiking scenario. Data was collected from the GPS monitors worn by the subject to provide distance, speed, and altitude. Time was also measured using a chronograph, and HR was recorded using a heart rate monitor. Heart rate was monitored to provide a reference for the intensity of the subject's walking, and provide a baseline measure of intensity for the first trial.

Speed as reported by the GPS monitor was verified using the time to complete the course and the measured distance. The length of the course was determined so that there was enough time to collect data over various grades, but short enough so that subject fatigue was not a factor in the energy expenditure measurements. Most subjects completed each trial in 20 – 30 minutes (1.34 – 2.01 $m \cdot s^{-1}$ walking speed). The decision to test in the Hospital/Cemetery area was made due to the elevation changes in the area, and the apparently unhindered satellite coverage (which can be blocked by dense tree cover or tall buildings).

Testing Conditions

To minimize the effects of weather, testing was conducted under similar conditions for each subject. Temperature ranged from 15˚ to 25˚ Celsius (59˚ to 77˚ Fahrenheit). To account for wind, testing was only conducted on calm days with still air, or a slight, occasional breeze. Any consistent or strong wind was justification to cancel a test. In order to maximize the GPS signal all tests were conducted under clear to partly cloudy skies.

Instrumentation

Oxygen consumption was measured via open-circuit spirometry using an Aerosport KB1-C portable metabolic system (Medical Graphics Corporation, Saint Paul, MN, USA). The metabolic system was calibrated using pressurized gases of known concentration before each test. The metabolic system was also calibrated for flow rate prior to each test using a one-liter calibration syringe. Heart rate was recorded using a Polar Accurex heart rate monitor (Polar Electro Inc, Lake Success, NY, USA). Data from the GPS was recorded using a Garmin Geko 201 GPS monitor as well as a Garmin Foretrex 201 GPS monitor (Garmin International Inc, Olathe, KS, USA). The Garmin Foretrex GPS monitor was worn on the wrist as was the Polar Accurex HR monitor. The Garmin Geko GPS monitor was carried on the backpack, with the metabolic system, by a belt clip and lanyard. The total mass of the equipment carried by each subject was 2.35 Kg.

The GPS monitors were turned on at least 15 minutes prior to data collection in order to acquire signals from the satellites. All GPS monitors were set to the 'WAAS-Enabled' setting prior to testing. Data from the GPS monitors were downloaded to a computer following each data collection session. Time was measured using the chronometer function on the Polar Accurex HR monitor. The sampling interval for the metabolic system and HR monitor was set to 60 seconds. The sampling interval for the GPS monitor was set to 15 seconds. The sampling rate for the GPS was set higher for greater resolution of the data. By collecting four GPS data points for every metabolic data point, the investigator had a better chance of identifying aberrant data. The higher sampling interval of GPS data collection also allowed the investigator to adjust the data for analysis at lower sampling intervals (e.g., making the adjustments to analyze the data in 60 second intervals).

Technical Specifications of the GPS Monitors

The difference in the two GPS monitors used was limited to the monitor housing. The GPS mechanism in each monitor is the same, however the Garmin Geko 201 was designed to be worn on a belt at the waist and the Garmin Foretrex 201 was designed to be worn on the wrist. The dimensions of the Garmin Geko 201 are 48.3 x 99.1 x 24.4 mm with a mass of 0.088 Kg, with the batteries installed. The dimensions of the Garmin Foretrex 201 are 83.8 x 43.2 x 17.5 mm with a mass of 0.078 Kg, including the internal, rechargeable battery.

Accuracy for both GPS monitors using WAAS is reported to be < 3 m, with velocity accuracy of ± 0.05 m/s. The monitors are reported to have satellite acquisition times of less than one minute (15 s for warm conditions and 45 s for cold conditions). The operating temperature range for these monitors is –20˚ to 60˚ Celsius. The data storage capacity of the monitors is reported to be indefinite, not requiring a memory battery.

Data Processing

Calculating Actual EE

In order to reasonably compare the actual EE to the GPS predicted EE, each set of values must be presented in the same units. Estimates of EE from the GPS data were calculated in terms of Kcals. Values recorded by the metabolic system included measures of oxygen consumption (VO_2) and carbon dioxide production (VCO_2), both in units of $L \bullet min^{-1}$ as well as derivations of these measures. Measurements from the portable metabolic system had to be transformed into values of Kcals for comparison. In order to accomplish this, the equation developed by Weir (1949) was implemented:

(1) $EE = 3.9 \cdot VO_2 + 1.1 \cdot VCO_2$

where EE was measured in Kcals, VO_2 was the total amount of oxygen consumed (in liters) for the trial, and VCO_2 was the total amount of carbon dioxide produced (in liters) during the trial.

Processing the GPS Data

The GPS monitors provided information for distance (ft), speed (mph), and altitude (ft). This project required the data to be formatted as horizontal distance (ft), speed ($m \bullet min^{-1}$ and $m \bullet s^{-1}$), and grade. A commercially available, web-based program with a proprietary algorithm (www.endlesspursuit.com) was used to download the GPS monitors. The output from this program has been validated by an independent study conducted in this lab (unpublished data). Grade was calculated from the change in altitude divided by the change in horizontal distance.

Predicting EE from GPS Data

The GPS data for this project was converted from units of speed and grade into units of EE, specifically values of Kcals. Wind resistance and resting metabolic rate (RMR) also had to be accounted for, in addition to the EE required to traverse the terrain at the measured speed and grade, to accurately predict the EE for walking. In order to determine the GPS predicted EE, the equation developed by Minetti, et al. (2002) was used as a starting point:

$$(2)\ EE_{WALK} = [2.5 + 19.6 \cdot G + 51.9 \cdot G^2 - 76.8 \cdot G^3 - 58.7 \cdot G^4 + 280.8 \cdot G^5]$$

Where EE is the relative energy cost of walking in units of $[J \cdot kg^{-1} \cdot m^{-1}]$ and G is the surface grade expressed as a decimal. In order to transform the values calculated into values of [Kcal · kg^{-1} · min^{-1}] a conversion factor was added to equation 1:

$$(3)\ EE_{WALK} = [2.5 + 19.6 \cdot G + 51.9 \cdot G^2 - 76.8 \cdot G^3 - 58.7 \cdot G^4 + 280.8 \cdot G^5] \cdot (V \cdot 4186^{-1})$$

Where V is the walking velocity in units of [m · min^{-1}]. Equation 3 does not account for resting metabolic rate (RMR), so a correction factor was added to include the contribution of RMR into EE:

$$(4)\ EE_{WALK} = [2.5 + 19.6 \cdot G + 51.9 \cdot G^2 - 76.8 \cdot G^3 - 58.7 \cdot G^4 + 280.8 \cdot G^5] \cdot (V \cdot 4186^{-1}) + 0.0175$$

This expresses EE in terms of Kcal · Kg^{-1} · min^{-1}. In order to find the EE for each of the 15 second sampling windows, the equation is multiplied by the total mass (M_T – the body mass of the subject plus the mass of the equipment carried; $M_T = M_B + 2.35$ Kg). Equation 4 was multiplied by 0.25 to calculate total EE for the 15-second interval (as opposed to the one minute interval Equation 4 is set up to calculate). The equation then appears as such:

$$(5)\ EE_{WALK} = [(2.5 + 19.6 \cdot G + 51.9 \cdot G^2 - 76.8 \cdot G^3 - 58.7 \cdot G^4 + 280.8 \cdot G^5) \cdot (V \cdot 4186^{-1}) + 0.0175] \cdot (M_T \cdot 0.25)$$

Further improvements were made to this model by factoring in the effects of wind resistance on EE. The equation developed by Pugh (1970) allows for the calculation of

EE to overcome wind resistance in terms of VO_2 [$L \cdot min^{-1}$]:

(6) $\Delta VO_{2WIND} = 0.00418 \cdot A \cdot V^3$

Where ΔVO_{2WIND} is the difference in oxygen consumption between stationary running (as on a treadmill) and outdoor running, A is the projected frontal area (m^2) of the subject, and V is the velocity in [$m \cdot s^{-1}$]. Projected frontal area can be determined from the equation provided by Pugh (1970) with respect to body surface area (BSA):

(7) $A = 0.266 \cdot BSA$

And BSA can be determined from body mass (M_B, Kg) and body height (H, m) as shown by Tikuisis (2001):

(8_A) $BSA_{MEN} = 128.1 \cdot M_B^{0.44} \cdot H^{0.6}$

(8_B) $BSA_{WOMEN} = 147.4 \cdot M_B^{0.47} \cdot H^{0.55}$

Equations 7 and 8 can be used with Equation 5 to determine the increase in oxygen consumption due to wind resistance as follows:

(9_A) $\Delta VO2_{WIND\ MEN} = 0.00418 \cdot [0.266 \cdot (128.1 \cdot M_B^{0.44} \cdot H^{0.6})] \cdot V^3$

(9_B) $\Delta VO2_{WIND\ WOMEN} = 0.00418 \cdot [0.266 \cdot (147.4 \cdot M_B^{0.47} \cdot H^{0.55})] \cdot V^3$

In order to add this equation to Equation 5, they must both calculate EE in terms of [Kcal · min^{-1}]. To accomplish this Equation 9 was multiplied by the conversion factor of 5.05 to convert liters of oxygen consumed to Kcal as provided by the ACSM (2000):

$(10_A)\ \Delta EE_{WIND\ MEN} = [0.00418 \cdot [0.266 \cdot (128.1 \cdot M_B^{0.44} \cdot H^{0.6})] \cdot V^3] \cdot 5.05$

$(10_B)\ \Delta EE_{WIND\ WOMEN} = [0.00418 \cdot [0.266 \cdot (147.4 \cdot M_B^{0.47} \cdot H^{0.55})] \cdot V^3] \cdot 5.05$

In order to use this equation to find the EE for each sampling period, Equation 10 was multiplied by 0.25 in order to account for the 15 second sampling interval (as was done to Equation 4 to find the EE for walking for this study). The equation then becomes:

$(11_A)\ \Delta EE_{WIND\ MEN} = [(0.00418 \cdot [0.266 \cdot (128.1 \cdot M_B^{0.44} \cdot H^{0.6})] \cdot V^3) \cdot 5.05] \cdot 0.25$

$(11_B)\ \Delta EE_{WIND\ WOMEN} = [(0.00418 \cdot [0.266 \cdot (147.4 \cdot M_B^{0.47} \cdot H^{0.55})] \cdot V^3) \cdot 5.05] \cdot 0.25$

The total EE for walking can be expressed as the EE of walking and the EE of wind resistance, as shown in equation 12:

$(12)\ EE_{GPS} = EE_{WALK} + \Delta EE_{WIND}$

Where EE_{WALK} is equation 5 and ΔEE_{WIND} is Equation 11.

Statistical Analyses

Energy expenditure was compiled as total Kcals for each subject by trial. Comparisons were based on the total EE for each measurement period. The data was analyzed using a 3-factor repeated measures ANOVA comparing actual EE and GPS predicted EE, the wrist-worn and waist-worn GPS monitors (Foretrex 201 and Geko 201, respectively), and the pace of the trials. All analyses used an alpha level of 0.05. Further analyses determined the significance of GPS as a predictor of EE for each of the uphill, level, and downhill walking portions of the trials.

CHAPTER FOUR

RESULTS

Subjects

Thirteen subjects (eight males, five females) who participated in the study were included in the statistical analyses. All of the subjects were active runners or hikers (self-reported) and had no apparent problems completing the walking trials. Two additional subjects were omitted from the data analysis due to unusually high or low metabolic data. Subject 108 had inordinately high metabolic data from the KB1-C Portable Metabolic Unit for the slow walking trial, while subject 109 had inordinately low metabolic data (also from the slow trial). Neither subject was able to repeat the faulty trials. Summary statistics for subject demographics are shown in Table 4.1.

Table 4.1. Summary statistics for subject demographics (n=13).

Subject #	Sex	Age (yrs)	Height (cm)	Mass (Kg)
101	M	28	169.9	59.4
102	M	24	178.1	68.5
103	M	24	182.9	79.5
104	M	28	170.0	76.2
105	F	30	151.0	40.9
106	M	25	180.0	78.2
107	M	27	181.6	74.5
110	F	25	168.9	72.7
111	F	22	160.0	50.0
112	M	20	170.2	69.3
113	F	22	166.4	59.5
114	M	24	182.8	81.8
115	F	24	170.1	62.7
Mean		24.8	171.7	67.2
SD		2.8	9.4	12.2
Range		20 - 30	151.0 - 182.8	40.9 - 81.8

Post hoc Data Processing

To assess the effects of GPS error in the prediction of EE, several post hoc adjustments were applied to the original data set. The uncorrected, raw data set is referred to as the 'original data set'. The original data collected from the GPS monitors were based on a 15 second sample interval. Data sets were created for 30 and 60 second sample intervals from the original data set by adjusting the GPS based EE prediction equations to account for the longer time intervals. The original data set was also used to create two additional data sets with adjustments to the GPS reported grade. The first adjustment was created by removing reported grades greater than 15% or less than –15%. These values were chosen based on the mean grade for the uphill and downhill sections of the course (as reported by GPS) ± two standard deviations of the mean grade. The limits of 15% and -15% were also known to be outside the range of the true gradient of the test course. The removed data points were replaced by averaging the preceding and following data points ($x' = [x_{t-1} + x_{t+1}]/2$). The first adjustment is referred to as the 'grade modified data set'. The second adjustment was also created from the original data set (not from the grade modified data set) using a three-point moving average. This data set uses the average of the original data point, along with the preceding and following data points for every data point in the set ($x' = [x_{t-1} + x_t + x_{t+1}]/3$) which acts as a rudimentary smoothing equation. The second adjustment to the original data is referred to as the 'moving average data set'. As a result of these adjustments, the data is presented as three data sets (original, grade modified, and moving average), each consisting of three sample intervals (15, 30, and 60 second). Data points in each set were further classified by speed to allow for comparisons of fast and slow trials for each data set. Descriptive statistics for the slow and fast walking trials can be found in Table 4.2.

Table 4.2. Summary statistics for the slow and fast walking paces.

	Time (min)		Speed (m/min)		VO2 (L/min)		HR (bpm)	
	Slow	Fast	Slow	Fast	Slow	Fast	Slow	Fast
Mean	26.44	20.02	87.78	115.25	0.76	1.13	90.85	108.62
SD	3.57	1.07	12.11	6.33	0.18	0.29	6.24	7.50

Comparison of Actual and GPS Reported Course Measurements

The original data set (15 s interval) was used to compare the GPS reported measurements of displacement and elevation change to the actual values. Displacement was reported as 2270.44 ± 36.96 m (Mean ± SD). The GPS reported displacement was within 1.5% of the actual course distance of 2303 m. Elevation change was reported as 52.17 ± 8.81 m elevation gain (+42.3%), and 52.41 ± 9.38 m elevation loss (+42.9%).

Comparison of Hip-worn and Wrist-worn GPS Monitors

Data from the original data set were used to compare the EE estimates of the wrist-worn and hip-worn GPS monitors. The GPS mechanism for both monitors was the same, so any differences in the estimates of EE for walking could be attributed to the anatomical placement of the monitors.

Comparisons between the predicted EE for the hip-worn and wrist-worn GPS monitors did not differ significantly for the 15 second sample interval (15 s interval). Predicted EE for the combined data was 127.6 ± 24.5 Kcals for the hip-worn GPS monitor, as compared to 133.3 ± 26.5 Kcals for EE_{WRIST}. The GPS monitors did not differ significantly for the slow paced (EE_{HIP} = 132.9 ± 26.7 Kcals; EE_{WRIST} = 137.7 ± 30.7 Kcals) or the fast paced walking data (EE_{HIP} = 124.7 ± 22.1 Kcals; EE_{WRIST} = 129.2 ± 22.4 Kcals). The 30 second sample interval (30 s interval) did not differ significantly upon comparison of the two GPS monitors for the combined data (EE_{HIP} = 133.5 ± 29.0 Kcals; EE_{WRIST} = 130.2 ± 24.0 Kcals), slow paced (EE_{HIP} = 141.8 ± 31.9 Kcals; EE_{WRIST} = 135.2 ± 26.7 Kcals), or fast paced walking data (EE_{HIP} = 125.3 ± 24.2 Kcals; EE_{WRIST} = 125.2 ± 20.9 Kcals). Comparisons of EE_{HIP} and EE_{WRIST} at the 60 second interval (60 s interval) did not differ significantly for the slow data (EE_{HIP} = 132.8 ± 25.6 Kcals; EE_{WRIST} = 133.8 ± 25.4 Kcals), however significant differences were noted for the combined (EE_{HIP} = 127.7 ± 23.7 Kcals; EE_{WRIST} = 128.9 ± 23.2 Kcals) and fast data (EE_{HIP} = 122.5 ± 21.4 Kcals; EE_{WRIST} = 124.0 ± 20.7 Kcals). Graphs for the comparison of hip and wrist-worn GPS predicted EE are presented in Figure 4.1. Means, standard deviations, and difference values for these comparisons are summarized in Table 4.3.

For the simplicity of further analyses, only the hip-worn GPS monitor was used for comparisons due to the similarities in EE_{GPS} by the wrist and hip-worn monitors.

Comparison of Actual and GPS Predicted EE

Actual EE was 107.4 ± 26.0 Kcals for the combined data, 101.1 ± 25.3 Kcals for slow-paced trial data, and 113.7 ± 26.2 Kcals for the fast-paced trial data. Comparisons between EE_{ACT} and EE_{HIP} were significantly different for the combined data, and for the slow-paced trial data in every data set and at every sample interval. Comparisons for the fast-paced trial data did not differ significantly in every data set and at every sample interval. Values for EE_{HIP} over-predicted actual EE in every comparison. Means, standard deviations, and difference values for each of these comparisons are presented in Table 4.3.

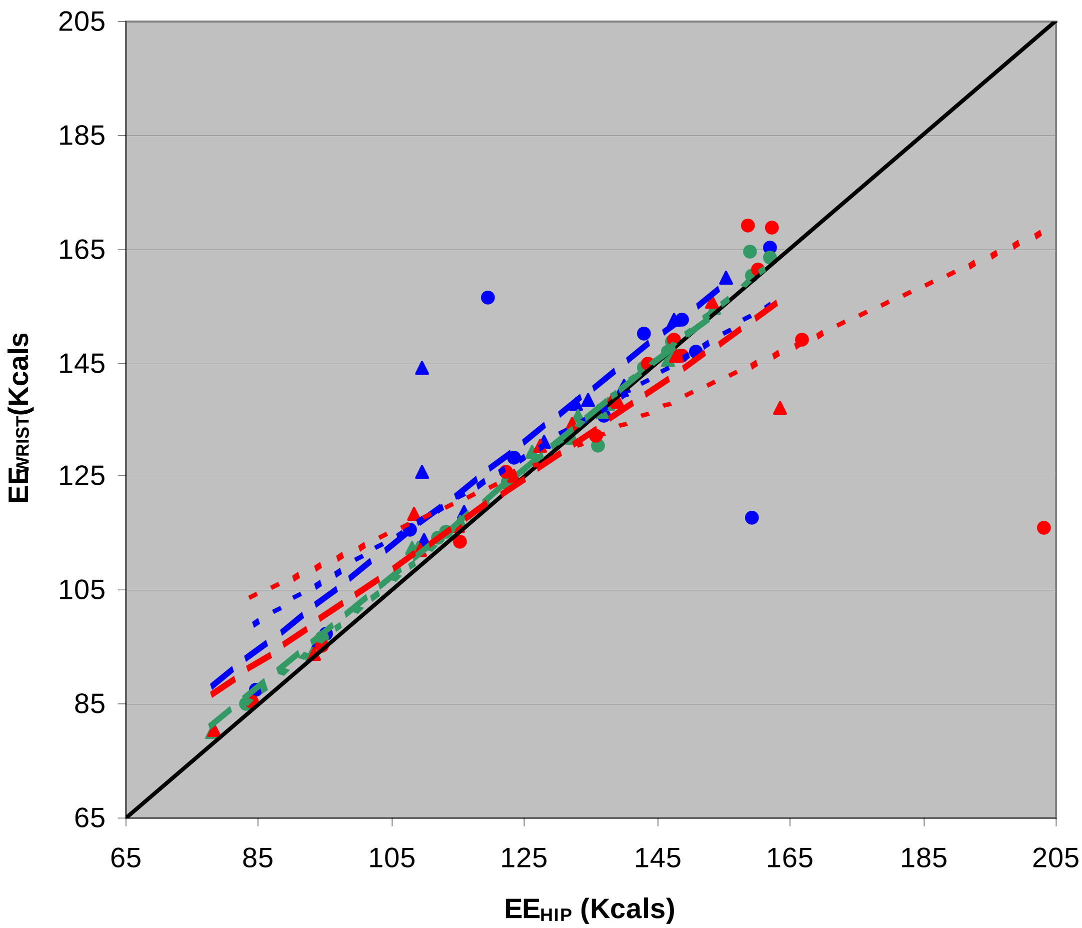

Figure 4.1. Comparison of wrist-worn (EE_{WRIST}) and hip-worn (EE_{HIP}) GPS predicted energy expenditure at fast and slow paces for the *original data set*. Blue represents the 15 second sampling interval data. Red represents the 30 second sampling interval data. Green represents the 60 second sampling interval data. Circle data markers represent the slow paced data. Triangle data markers represent the fast paced data. Dashed trendlines represent the data for fast paced trials. Dotted trendlines represent the data for slow paced trials. The black line represents the line of identity for the graph.

Table 4.3. Summary of Actual energy expenditure (EE_{ACT}), Hip-worn GPS predicted EE (EE_{HIP}), and Wrist-worn GPS predicted EE (EE_{WRIST}) in units of Kcals (Mean ± SD). Difference values are in units of Kcals.

	Combined Data			**Slow Paced Walking**			**Fast Paced Walking**		
Sample Interval	**15 s**	**30 s**	**60 s**	**15 s**	**30 s**	**60 s**	**15 s**	**30 s**	**60 s**
					Original Data Set				
EE_{ACT}	107.4 ±26.0	107.4 ±26.0	107.4 ±26.0	101.1 ±25.3	101.1 ±25.3	101.1 ±25.3	113.7 ±26.2	113.7 ±26.2	113.7 ±26.2
EE_{HIP}	127.6 ±24.5 †	133.5 ±29 †	127.7 ±23.7 †	132.9 ±26.7 †	141.8 ±31.9 †	132.8 ±25.6 †	124.7 ±22.1	125.3 ±24.2	122.5 ±21.4
EE_{WRIST}	133.3 ±26.5	130.2 ±24	128.9 ±23.2 ‡	137.7 ±30.7	135.2 ±26.7	133.8 ±25.4	129.2 ±22.4	125.2 ±20.9	124.0 ±20.7 *
EE_{H-A}	20.2	26.1	20.3	31.8	40.7	31.7	11	11.6	8.8
EE_{W-H}	5.7	-3.3	1.2	4.8	-6.6	1	4.5	-0.1	1.5
$\%_{H-A}$	18.8	24.3	18.9	31.5	40.3	31.4	9.7	10.2	7.7
					Grade Modified Data Set				
EE_{ACT}	107.4 ±26.0	107.4 ±26.0	107.4 ±26.0	101.1 ±25.3	101.1 ±25.3	101.1 ±25.3	113.7 ±26.2	113.7 ±26.2	113.7 ±26.2
EE_{HIP}	128.5 ±23.7 †	128.1 ±23.7 †	127.6 ±23.9 †	133.9 ±25.5 †	133.4 ±25.4 †	133.8 ±25.6 †	123.0 ±21.4	122.8 ±21.5	122.6 ±21.3
EE_{WRIST}	129.8 ±23.8	128.1 ±22.6	128.7 ±23.1	134.4 ±25.9	132.1 ±24.3	133.1 ±25.3	125.3 ±21.6 *	124.1 ±20.9 *	124.3 ±20.8 *
EE_{H-A}	21.1	20.7	20.2	32.8	32.3	32.7	9.3	9.1	8.9
EE_{W-H}	1.3	0	1.1	0.5	-1.3	-0.7	2.3	1.3	1.7
					Moving Average Data Set				
EE_{ACT}	107.4 ±26.0	107.4 ±26.0	107.4 ±26.0	101.1 ±25.3	101.1 ±25.3	101.1 ±25.3	113.7 ±26.2	113.7 ±26.2	113.7 ±26.2
EE_{HIP}	127.2 ±23.6 †	127.0 ±23.5 †	126.3 ±23.7 †	132.5 ±25.5 †	132.2 ±25.2 †	131.2 ±26 †	121.9 ±21.1	121.8 ±21.4	121.3 ±21
EE_{WRIST}	126.3 ±22.8	126.2 ±22.3	127.2 ±22.8	130.7 ±25	130.1 ±24 ‡	131.1 ±25.1	122.0 ±20.5	122.3 ±20.7	123.2 ±20.5 *
EE_{H-A}	19.8	19.6	18.9	31.4	31.1	30.1	8.2	8.1	7.6
EE_{W-H}	-0.9	-0.8	0.9	-1.8	-2.1	-0.1	0.1	0.5	1.9

The Original data set has not been modified. The Grade Modified data set has been modified so that and grade values [>15% or <-15%] have been replaced with the average of the immediately preceding and following data points. The Moving Average data set has been modified so that grade is a three-point moving average throughout the data set. EE_{H-A} is the difference score for Hip and Actual EE values. EE_{W-H} is the difference score for Wrist and Hip EE values. $\%_{H-A}$ is the percentage difference between EE_{ACT} and EE_{HIP}. † Denotes a significant difference ($p<0.05$) between EE_{ACT} and EE_{HIP} values. * Denotes a significant difference between EE_{HIP} and EE_{WRIST} values. ‡ Denotes a significant difference between EE_{WRIST} and EE_{ACT} values AND between EE_{WRIST} and EE_{HIP} values. EE_{W-H} values with no designation correspond to EE_{WRIST} values not significantly different from the corresponding EE_{HIP} values.

Original Data Set

Hip-worn GPS predicted EE for the 15 second sample interval was calculated as 127.6 ± 24.5 Kcals for the combined data, 132.9 ± 26.7 Kcals for slow-paced trial data, and 124.7 ± 22.1 Kcals for fast-paced trial data. Similar results were calculated for the 30 s interval (Combined data = 133.5 ± 29.0 Kcals; slow trial = 141.8 ± 31.9 Kcals; fast trial = 125.3 ± 24.2 Kcals) and the 60 s interval (Combined data = 127.7 ± 23.7 Kcals; slow trial = 132.8 ± 25.6 Kcals; fast trial = 122.5 ± 21.4 Kcals). A graph of the actual versus GPS predicted EE for the original data set is presented in Figure 4.2.

The over-prediction of actual EE based on the GPS data instigated a further analysis to determine whether the difference is accounted for by the contribution of the air resistance calculations to EE. This analysis was limited to the original data set at the 15 s interval. In all cases the calculation of air resistance accounted for a very small portion of the total GPS predicted EE. For the slow paced trials both the hip-worn and wrist worn GPS monitors predicted a 0.6 ± 0.2 Kcal contribution for air resistance, compared to a difference of 31.8 Kcals for hip-worn and actual EE, and a 36.6 Kcal difference between wrist-worn and actual EE. Fast paced trial data predicted a contribution of 1.0 ± 0.2 Kcal for air resistance (for both GPS monitors) compared to a difference of 11.0 Kcals for hip-worn and actual EE and 15.5 Kcals for wrist-worn and actual EE. The data for this comparison is presented in Table 4.4.

Grade Modified Data Set

Hip-worn GPS predicted EE for the 15 s interval was calculated as 128.5 ± 23.7 Kcals for the combined data, 133.9 ± 25.5 Kcals for the slow-paced trial, and 123.0 ±

21.4 Kcals for the fast-paced trial. The GPS predicted EE was similar for the 30 s interval (Combined data = 128.1 ± 23.7 Kcals; slow trial = 133.4 ± 25.4 Kcals; fast trial = 122.8 ± 21.5 Kcals) and the 60 s interval (Combined data = 127.6 ± 23.9 Kcals; slow trial

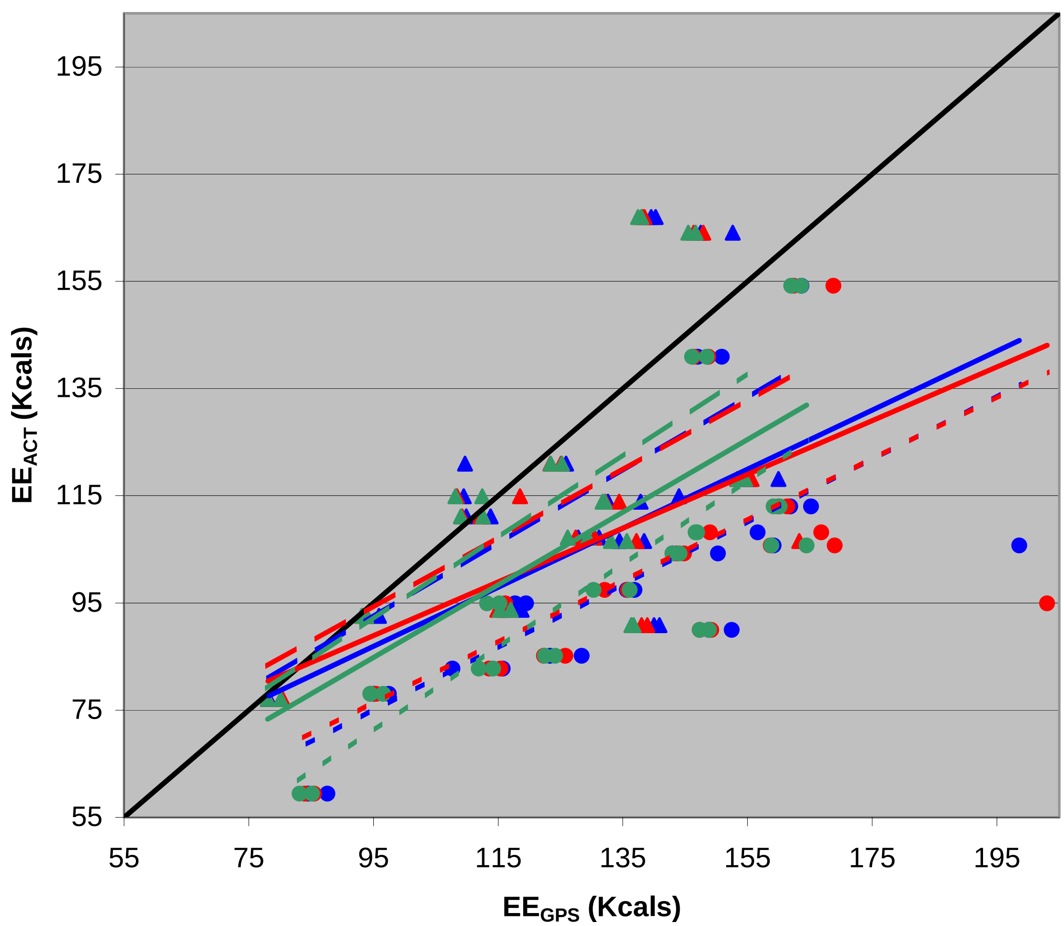

Figure 4.2. Comparison of Actual (EE_{ACT}) and GPS predicted (EE_{GPS}) energy expenditure for the *original data set*. Blue represents the 15 second sampling interval data. Red represents the 30 second sampling interval data. Green represents the 60 second sampling interval data. Circle data markers represent the slow paced data. Triangle data markers represent the fast paced data. Solid trendlines represent the data for all speeds. Dashed trendlines represent the data for fast paced trials. Dotted trendlines represent the data for slow paced trials. The black line represents the line of identity for the graph.

Table 4.4. Comparison of the contribution of air resistance calculations to GPS predicted EE (Kcals, Mean ± SD) to the difference scores of GPS – Actual EE values (Kcals) for slow and fast paced walking trials. This table was creating using the data for the 15 second sampling interval of the *original data set*. EE_{H-A} is the difference score for the hip-worn GPS and actual EE. EE_{W-A} is the difference score for the wrist-worn GPS and actual EE. EE_{DRAG} is the contribution of air resistance to GPS predicted EE.

	Hip-Worn GPS		Wrist-Worn GPS	
	EE_{H-A}	EE_{DRAG}	EE_{W-A}	EE_{DRAG}
Slow Paced Trials	31.8	0.6 ± 0.2	36.6	0.6 ± 0.2
Fast Paced Trials	11.0	1.0 ± 0.2	15.5	1.0 ± 0.2

= 133.8 ± 25.6 Kcals; fast trial = 122.6 ± 21.3 Kcals). A graph of the actual versus GPS predicted EE for the grade modified data set is presented in Figure 4.3.

Moving Average Data Set

At the 15 s interval EE_{HIP} was calculated as 127.2 ± 23.6 Kcals for the combined data, 132.5 ± 25.5 Kcals for the slow-paced trial data, and 121.9 ± 21.1 for the fast-paced trial data. Similar results were calculated for the 30 s interval (Combined data = 127.0 ± 23.5 Kcals; slow trial = 132.2 ± 25.2 Kcals; fast trial = 121.8 ± 21.4 Kcals) and the 60 s interval (Combined data = 126.3 ± 23.7 Kcals; slow trial = 131.2 ± 26.0 Kcals; fast trial = 121.3 ± 21.0 Kcals). A graph of the actual versus GPS predicted EE for the moving average data set is presented in Figure 4.4.

Comparison of Actual and GPS predicted EE by Grade Type

The 60 second sample interval for each data set was classified by grade: Downhill < –0.1%; Level ≥ –0.1% AND ≤ 0.1%; Uphill > 0.1%. There were variations

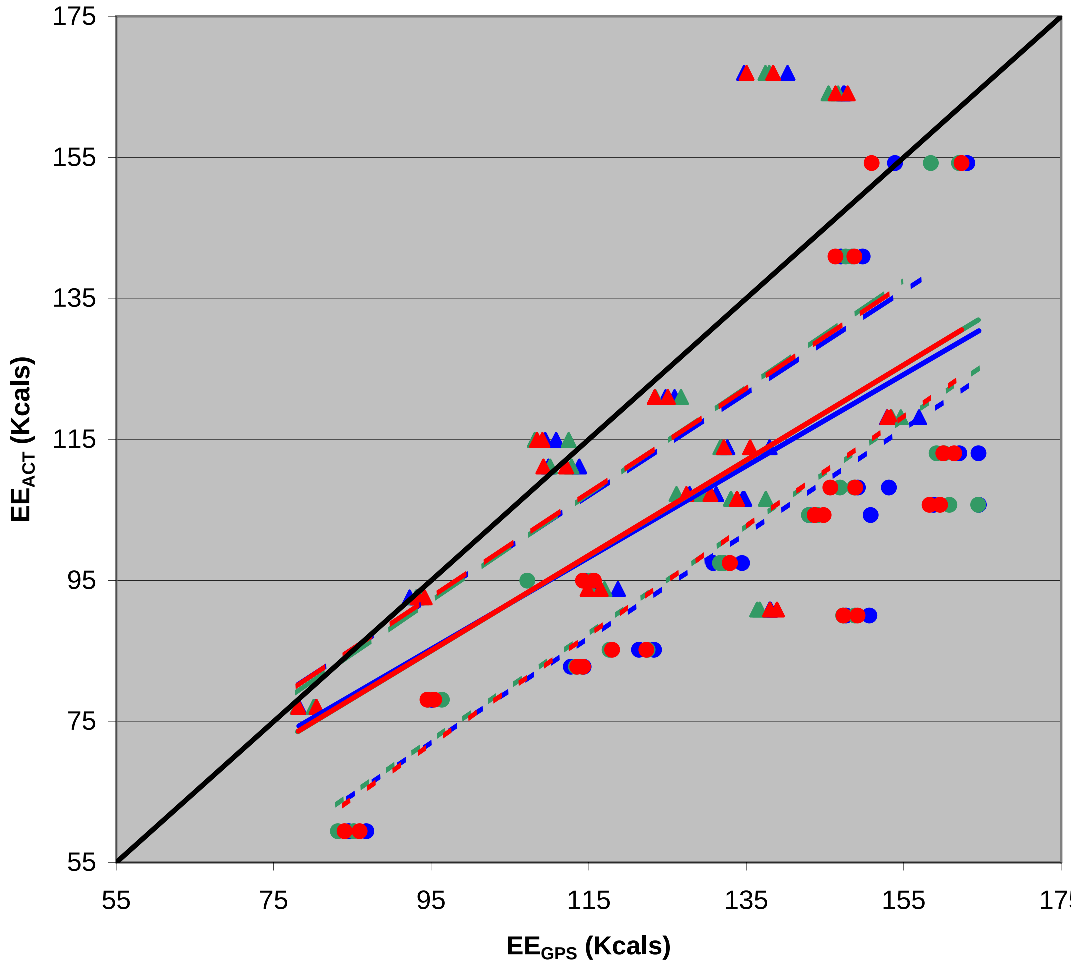

Figure 4.3. Comparison of Actual (EE_{ACT}) and GPS predicted (EE_{GPS}) energy expenditure for the *grade modified data set*. Blue represents the 15 second sampling interval data. Red represents the 30 second sampling interval data. Green represents the 60 second sampling interval data. Circle data markers represent the slow paced data. Triangle data markers represent the fast paced data. Solid trendlines represent the data for all speeds. Dashed trendlines represent the data for fast paced trials. Dotted trendlines represent the data for slow paced trials. The black line represents the line of identity for the graph.

in actual EE by grade type between data sets due to the adjustments of the grade data in the grade modified and moving average data sets. Despite the differences in actual EE by grade type, total EE_{ACT} was equal across the combined data sets. The nature of the grade adjustments caused some borderline values to 'switch' grade types between data

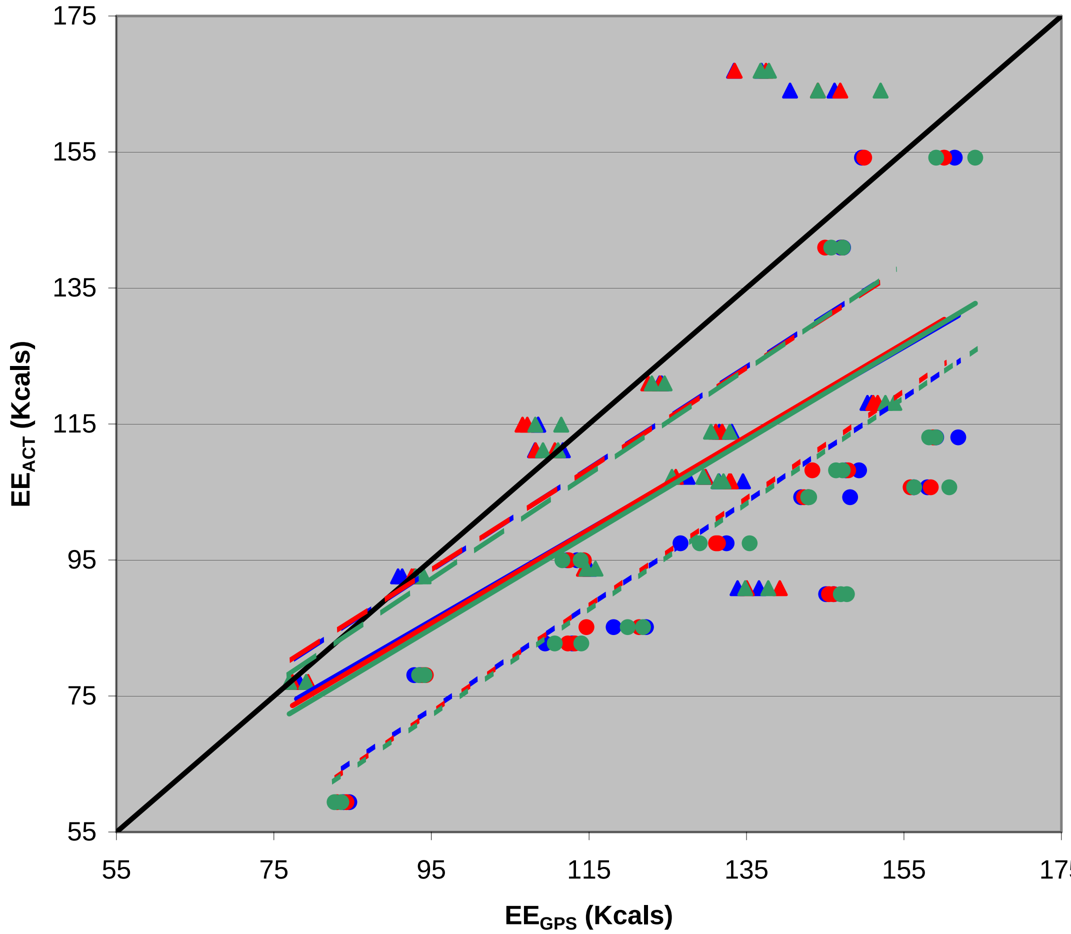

Figure 4.4. Comparison of Actual (EE_{ACT}) and GPS predicted (EE_{GPS}) energy expenditure for the *moving average data set*. Blue represents the 15 second sampling interval data. Red represents the 30 second sampling interval data. Green represents the 60 second sampling interval data. Circle data markers represent the slow paced data. Triangle data markers represent the fast paced data. Solid trendlines represent the data for all speeds. Dashed trendlines represent the data for fast paced trials. Dotted trendlines represent the data for slow paced trials. The black line represents the line of identity for the graph.

sets as a result of the rudimentary smoothing of the grade values for the grade modified and moving average data sets. Summary values for means, standard deviations, and difference values for all comparisons are presented in Table 4.5.

Table 4.5. Summary of Actual Energy Expenditure (EE_{ACT}) and Hip-worn GPS predicted EE (EE_{HIP}) for downhill, level, and uphill grades in units of Kcals (Mean ± SD). The sample interval for the data in this table is 60 seconds.

	Combined			**Slow**			**Fast**		
	Downhill	**Level**	**Uphill**	**Downhill**	**Level**	**Uphill**	**Downhill**	**Level**	**Uphill**
					Original				
EE_A	35.4 ±12.0	21.8 ±9.4	50.1 ±13.2	32.1 ±9.5	21.3 ±8.7	47.4 ±13.3	38.7 ±13.7	22.2 ±10.4	52.8 ±13.1
EE_H	37.5 ±10.9	26.2 ±10.4	63.9 ±13.6	38.8 ±11.0	28.1 ±11.3	65.9 ±13.2	36.3 ±11.1	24.4 ±9.6	61.9 ±14.2
EE_{H-A}	2.1	4.4 †	13.8 †	6.7 †	6.8 †	18.5 †	-2.4	2.2	9.1 †
$\%_{H-A}$	5.9	20.2	27.5	20.9	31.9	39.0	-6.2	9.9	17.2
					Grade Modified				
EE_A	35.6 ±12.0	21.8 ±9.4	50.0 ±13.4	32.6 ±9.8	21.3 ±8.7	47.1 ±13.6	38.7 ±13.7	22.2 ±10.4	52.8 ±13.1
EE_H	38.1 ±11.0	26.2 ±10.4	63.3 ±14.2	39.8 ±10.9	28.1 ±11.3	64.7 ±14.6	36.4 ±11.1	24.4 ±9.6	61.9 ±14.2
EE_{H-A}	2.5	4.4 †	13.3 †	7.2 †	6.8 †	17.6 †	-2.3	2.2	9.1 †
$\%_{H-A}$	7.0	20.2	26.6	22.1	31.9	37.4	-5.9	9.9	17.2
					Moving Average				
EE_A	37.9 ±10.7	17.5 ±9.3	52.1 ±14.7	33.9 ±8.1	17.7 ±11.1	49.5 ±13.5	41.8 ±11.7	17.2 ±7.6	54.6 ±16.0
EE_H	42.8 ±8.4	20.3 ±11.9	62.9 ±13.3	43.7 ±9.5	22.1 ±13.1	64.9 ±14.2	41.9 ±7.4	18.5 ±10.8	60.9 ±12.6
EE_{H-A}	4.9 †	2.8 †	10.8 †	9.8 †	4.4 †	15.4 †	0.1	1.3	6.3
$\%_{H-A}$	12.9	16.0	20.7	28.9	24.9	31.1	0.2	7.6	11.5

The Original data set has not been modified. The Grade Modified data set has been modified so that and Grade values [>15% and <- 15%] have been replaced with the average of the immediately preceding and following data points. The Moving Average data set has been modified so that Grade is a three-point moving average throughout the data set. EE_{H-A} is the difference score for Hip and Actual EE values. $\%_{H-A}$ is the percentage difference between EE_{HIP} and EE_{ACT}. † Denotes a significant difference ($p<0.05$) between EE_{ACT} and EE_{HIP} values. Downhill grades are defined as [Grade < -0.1%], level grades are defined as [-0.1% < Grade < 0.1%], and uphill grades are defined as [Grade > 0.1%]

Original Data Set

Comparisons between EE_{ACT} and EE_{HIP} did not differ significantly for downhill (EE_{ACT} = 35.4 ± 12.0 Kcals; EE_{HIP} = 37.5 ± 10.9 Kcals) or fast walking (EE_{ACT} = 38.7 ± 13.7 Kcals; EE_{HIP} = 36.3 ± 11.1 Kcals). A significant difference was found for downhill, slow paced walking (EE_{ACT} = 32.1 ± 9.5 Kcals; EE_{HIP} = 38.8 ± 11.0 Kcals). Significant differences were found for comparisons between EE_{ACT} and EE_{HIP} during level walking for all (EE_{ACT} = 21.8 ± 9.4 Kcals; EE_{HIP} = 26.2 ± 10.4 Kcals) and slow data (EE_{ACT} = 21.3 ± 8.7 Kcals; EE_{HIP} = 28.1 ± 11.3 Kcals). Fast paced data for level walking did not differ significantly (EE_{ACT} = 22.2 ± 10.4 Kcals; EE_{HIP} = 24.4 ± 9.6 Kcals). Comparisons made for uphill walking were significantly different for the combined data (EE_{ACT} = 50.1 ± 13.2 Kcals; EE_{HIP} = 63.9 ± 13.6 Kcals), slow data (EE_{ACT} = 47.4 ± 13.3 Kcals; EE_{HIP} = 65.9 ± 13.2 Kcals), and fast data (EE_{ACT} = 52.8 ± 13.1 Kcals; EE_{HIP} = 61.9 ± 14.2 Kcals). A graph of the actual versus GPS predicted EE by grade type for the original data set is presented in Figure 4.5.

Grade Modified Data Set

Values for actual and hip-worn GPS predicted EE were very similar to those reported for the original data set. Comparisons between EE_{ACT} and EE_{HIP} for the grade modified data set followed the trends in the original data set for every comparison. A graph of the actual versus GPS predicted EE by grade type for the grade modified data set is presented in Figure 4.6.

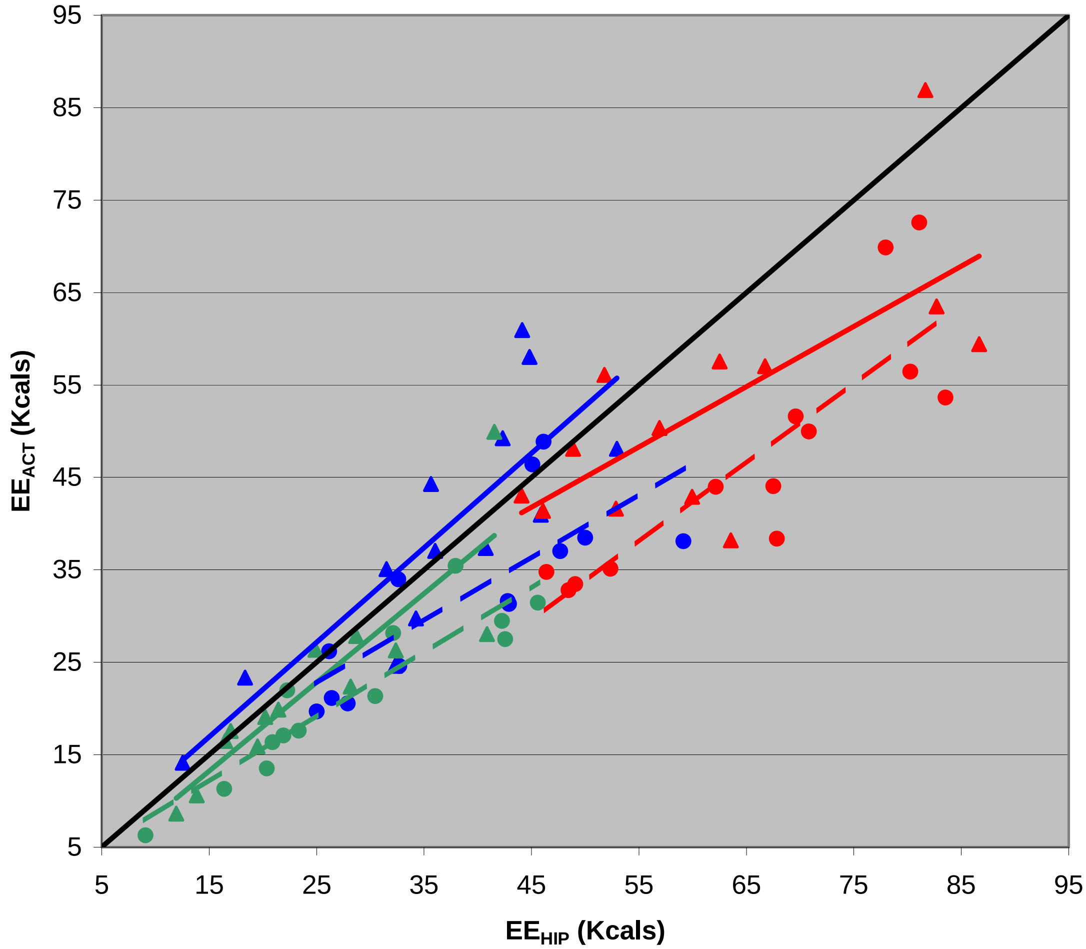

Figure 4.5. Comparison of Actual (EE_{ACT}) and Hip-worn GPS predicted energy expenditure (EE_{HIP}) at downhill, level, and uphill grades for fast and slow paces for the *original data set*. Downhill grades are defined as [Grade < -0.1%], level grades are defined as [-0.1% ≤ Grade ≤ 0.1%], and uphill grades are defined as [Grade > 0.1%]. Blue denotes downhill grade data, green denotes level grade data, and red denotes uphill grade data. The fast paced data is denoted by triangle data markers and solid trendlines. The slow paced data is denoted by circle data markers and hashed trendlines. The black trendline represents the line of identity for the graph.

Moving Average Data Set

Comparisons between EE_{ACT} and EE_{HIP} for downhill walking differed significantly for the combined data (EE_{ACT} = 37.9 ± 10.7 Kcals; EE_{HIP} = 42.8 ± 8.4 Kcals) and slow data (EE_{ACT} = 33.9 ± 8.1 Kcals; EE_{HIP} = 43.7 ± 9.5 Kcals), but did not differ significantly for fast data (EE_{ACT} = 41.8 ± 11.7 Kcals; EE_{HIP} = 41.9 ± 7.4 Kcals). Significant differences were also found for the comparisons of level walking for the combined data (EE_{ACT} = 17.5 ± 9.3 Kcals; EE_{HIP} = 20.3 ± 11.9 Kcals) and slow data (EE_{ACT} = 17.7 ± 11.1 Kcals; EE_{HIP} = 22.1 ± 13.1 Kcals). Actual (17.2 ± 7.6 Kcals) and GPS predicted EE (18.5 ± 10.8) did not differ significantly for level walking upon comparison of the fast data. A

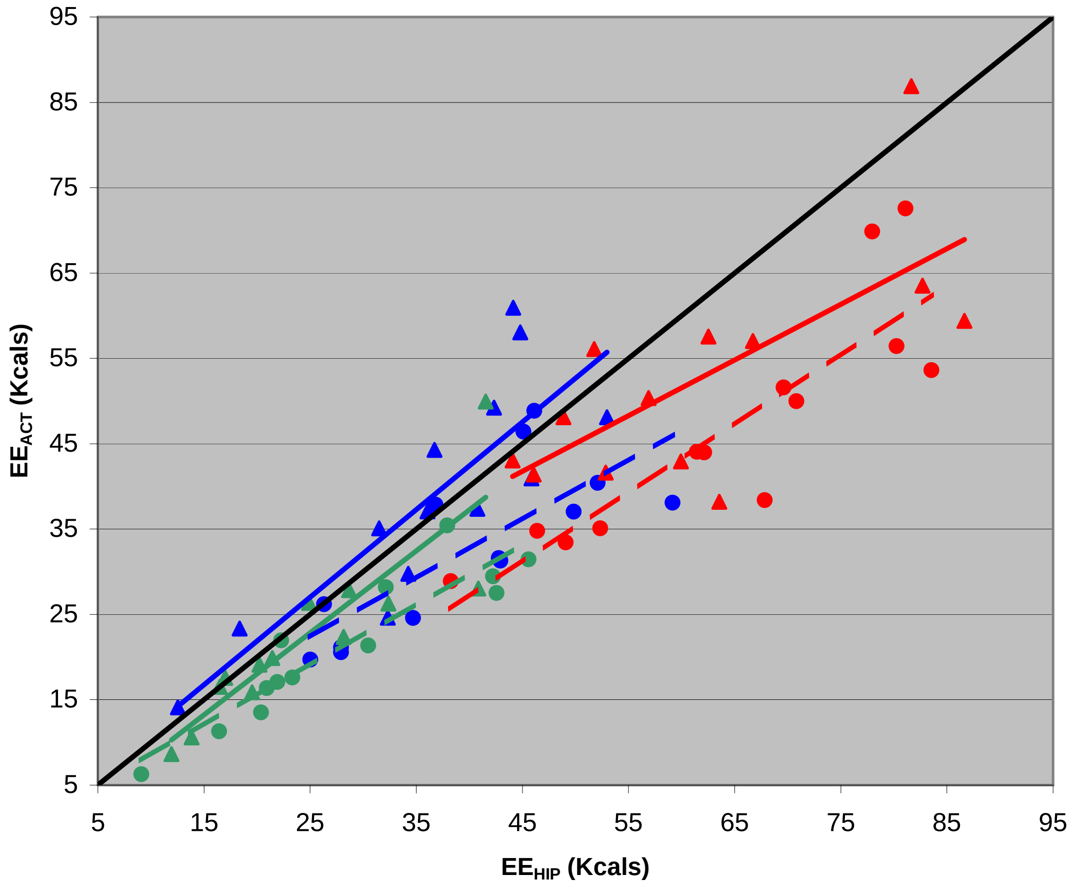

Figure 4.6. Comparison of Actual (EE_{ACT}) and Hip-worn GPS predicted energy expenditure (EE_{HIP}) at downhill, level, and uphill grades for fast and slow paces for the *grade modified data set*. Downhill grades are defined as [Grade < -0.1%], level grades are defined as [-0.1% ≤ Grade ≤ 0.1%], and uphill grades are defined as [Grade > 0.1%]. Blue denotes downhill grade data, green denotes level grade data, and red denotes uphill grade data. The fast paced data is denoted by triangle data markers and solid trendlines. The slow paced data is denoted by circle data markers and hashed trendlines. The black trendline represents the line of identity for the graph.

graph of the actual versus GPS predicted EE by grade type for the moving average data set is presented in Figure 4.7.

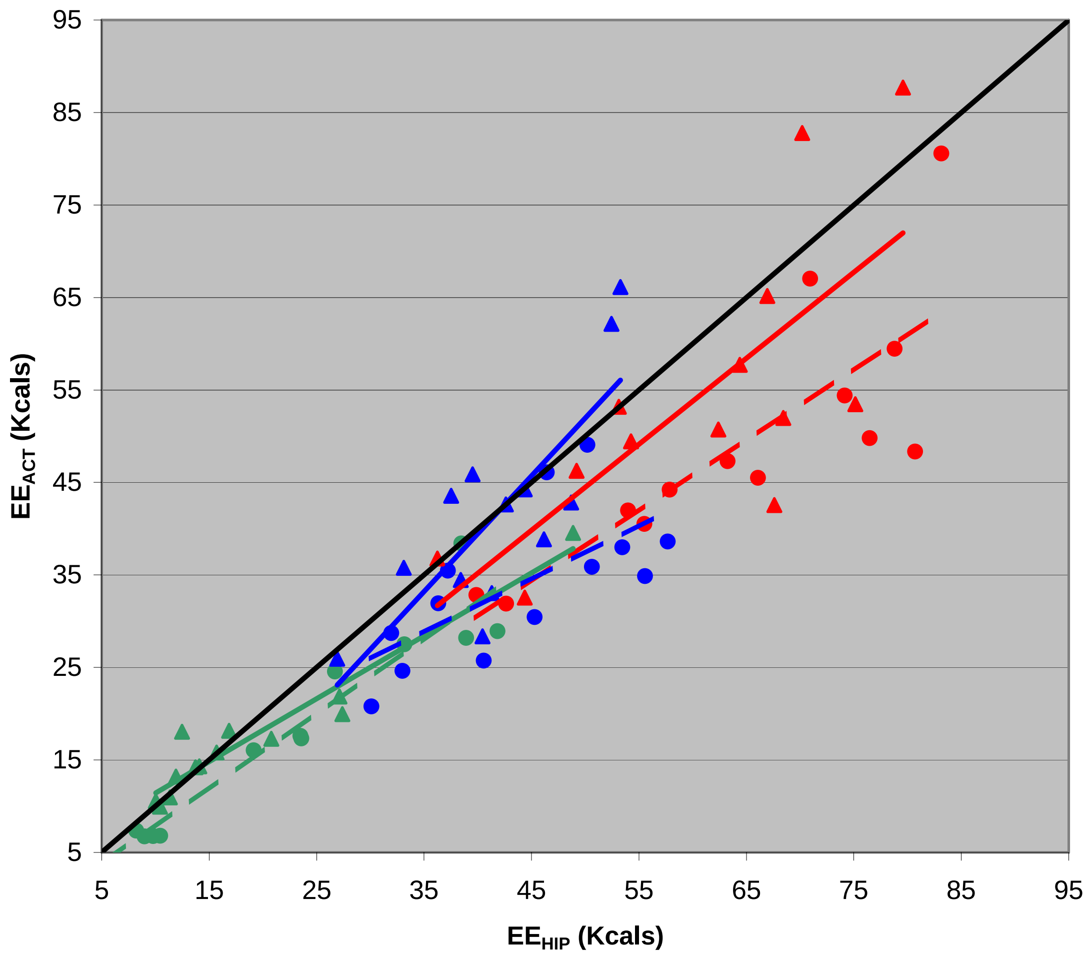

Figure 4.7. Comparison of Actual (EE_{ACT}) and GPS predicted energy expenditure (EE_{HIP}) at downhill, level, and uphill grades for fast and slow paces for the *moving average data set* in units of Kcals. Downhill grades are defined as [Grade < -0.1%], level grades are defined as [-0.1% ≤ Grade ≤ 0.1%], and uphill grades are defined as [Grade > 0.1%]. Blue denotes downhill grade data, green denotes level grade data, and red denotes uphill grade data. The fast paced data is denoted by triangle data markers and solid trendlines. The slow paced data is denoted by circle data markers and hashed trendlines. The black trendline represents the line of identity for the graph.

CHAPTER FIVE

DISCUSSION

Estimates of energy expenditure (EE) based on GPS monitor data over-predicted the actual EE (EE_{ACT}) for every comparison in this study. The fast paced walking trials were the only cases where the GPS predictions of EE_{ACT} were not significantly higher. In most cases there were no significant differences between the wrist and hip-worn GPS predicted EE, and in every case there was no practical difference in these values. Comparisons of actual versus GPS predicted EE for each grade classification showed significant differences for all classifications for the slow paced trials. The fast paced trials had significant differences only for the uphill classification. In all cases the uphill grade classification provided the greatest difficulty in predicting actual EE. Differences attributed to changes in the sampling interval and grade adjustments had little effect on the statistical or practical significance of the results.

GPS-based Predictions of EE

The over-prediction of EE by GPS-based predictions is consistent with the findings of previous motion sensors studies (Bassett et al., 2000; Crouter et al., 2003). The results of the the combined data analyses show differences of +18.9 to +26.1 Kcals (17 – 24%) when compared to actual EE for the trials. For the slow-paced trials these differences were +30.1 to +40.7 Kcals (29 – 40%). The fast-paced trials over-predicted actual EE by +7.6 to +11.6 Kcals (6 – 10%) in comparison. The relative improvement of

GPS predicted EE for the fast walking trials may be attributed to the absolute nature of the error in GPS data. The GPS error, measured as an absolute distance, will not change as ground speed increases but as the distance covered increases the relative error will be reduced.

The sources of error in the GPS predictions of EE are limited to the calculated speed and grade data (based on GPS reported displacement, time, and elevation) due to the use of these variables in the prediction equations. Reported speed was calculated from displacement and elapsed time. Time reported by GPS is referenced by an atomic clock and can therefore be eliminated as a source of error. Previous research has validated the use of GPS speed and position data (Demczuk, 1998; Larsson, 2003; Larsson & Henricksson-Larsen, 2001; Schutz & Chambaz, 1997; Schutz & Herren, 2000), and has gone so far as to suggest that GPS reported speed "could replace manual chronometry" (Larsson, 2003). Grade is based on the changes in GPS reported elevation compared to the distance traveled, and is more problematic in terms of precision. The error in reported grade may be compounded due to satellite triangulation of two variables (position and elevation), as opposed to just one (only position when reporting speed). Demczuk (1998) found GPS reported elevation to be unusable, and had to rely on a back-up system for this variable. Secondary data sets were created to account for the possibility of unreliable elevation data in the present study by making adjustments to the grade data in the original data set. The results of this study are consistent with the literature concerning GPS reported distance and grade. The GPS reported displacement was within ±1.5% of the actual course distance, but the GPS over-predicted the reported change in elevation by 42% (for both elevation gain and loss).

The nature of the error for predicting EE does not correspond with the nature of the GPS data. The error inherent in GPS data should be normally distributed in all directions around the actual position of the receiver. In contrast, the predictions of EE in the present study consistently over-predicted actual.

Contribution of Air Resistance Calculations to GPS Predicted EE

The influence of wind resistance may account for up to 16% of total EE when running at “sprint speed” (Pugh, 1970; Pugh, 1971), and 8% of total EE for running at “middle distance” speed (Pugh, 1970; Pugh, 1971), although at walking and slower running speeds (85 – 169 m/min) the contribution is negligible (Hall, et al., 2004; McMiken & Daniels, 1976).

Analysis of the data from this study showed that the addition of air resistance to GPS predicted EE was much smaller than the differences between actual and GPS predicted EE (0.5 – 1.0 Kcals per trial, as presented in Table 4.4). In the cases where the differences were statistically significant, the addition of air resistance accounts for less than 2% of the difference. Although the nature of the air resistance calculations matches the nature of the error in the GPS predictions, the values calculated for air resistance were not large enough to account for the differences in actual and GPS predicted EE.

Suitability of Using a Constant for Resting Metabolic Rate

The prediction equation for this study used a constant to account for resting metabolic rate (RMR), which may be responsible for the over-prediction of actual EE. If the value used over-estimates actual RMR, there will be an over-prediction of total EE for each minute of walking. This possibility could explain the significant differences in predicted EE during slow walking. Due to a greater time spent walking for the slow trials, an over-estimation of RMR will accumulate throughout the trial, and show a greater over-prediction of total EE as compared to the fast trials. It is also possible that an over-prediction of RMR would only be manifested in significant differences during the slow trials because RMR represents a greater proportion of total EE for slow paced walking. Studies have shown that the use of an RMR prediction equation using anthropometric data provide valid values for true RMR (Schofield, 1985; Johnstone, et al., 2006). The use of an equation to estimate RMR for this study may resolve the disparity in estimating EE for fast and slow paced walking.

Comparison of Hip-worn and Wrist-worn GPS Monitors

The comparison of the hip and wrist-worn GPS monitors was important to determine any significant differences due to the anatomical placement of each monitor. The hip-worn GPS monitor approximated the center of mass for each subject, but the wrist-worn GPS monitor moved with the arm during walking. There was a concern that arm swing during walking might increase the variance of the data reported by the wrist-worn GPS monitor, creating a difference in EE estimates when the two monitors were compared. The two GPS monitors used in this study provided similar estimates of energy expenditure (EE) for the original data set. There were only two trials where the wrist-worn and hip-worn GPS monitors differed significantly in their estimates of EE (for the combined and fast data, at the 60 s interval). Further analysis showed that despite these differences, wrist-worn GPS predicted EE (EE_{WRIST}) followed the same trend as hip-worn GPS predicted EE (EE_{HIP}) when compared to actual EE (EE_{ACT}). The lack of significant differences between the EE estimations for the monitors allowed for the omission of the wrist-worn GPS predicted EE from further analyses. Both monitors were produced by the same manufacturer, with the same technology, and marketed at a consumer level with little difference in retail cost. The similarities in the devices should minimize any technological differences between the monitors, and focus the basis of comparison on the anatomical location of each monitor.

Estimations of EE Using Other Electronic Devices

The statistical significance of these results must be weighed against the practical significance. While the majority of EE predictions in this study were statistically greater than actual EE, it is possible that the predictions are still reasonable. Due to the lack of previous studies using GPS monitors to predict EE, comparisons must be drawn based on the literature for similar electronic devices.

Pedometers are used frequently, especially in clinical settings, but are generally reserved for simply counting steps. Pedometers have great variance in their precision and accuracy depending on the brand, model, and even the internal mechanism (Berlin, Storti & Brach, 2006; Manning et al., 2006; McKenzie et al., 2005). Pedometers will overestimate actual EE by 20 – 42% (Bassett, et al., 2000; Crouter, et al., 2003; Strath, et al., 2001). Crouter (2003) found an average error of ± 30% for estimating EE across a study of ten different pedometer models (ten pedometers were tested for a variety of measures, however only the 7 models that estimated EE were included in this comparison). The results of this study are consistent with the level of accuracy found in estimating EE for walking with pedometers, although it should be noted that the primary purpose of pedometers is to count steps. Due to the high variance in the validity of pedometers, comparisons to GPS based EE estimates are difficult.

Activity monitors tend to have a greater ability to predict EE than pedometers, although the trend for over-predicting EE is still apparent. The Biotrainer activity monitor is a slight improvement over pedometers for predicting EE of walking, but still has a range of +21 to +24% (Swan, Byrnes, & Haymes, 1997). The Caltrac activity monitor over-predicts the EE for race-walking by 19%, running by 14% (Swan, Byrnes, & Haymes, 1997), and 20 and 32% for slow and brisk walking, respectively (Bassett et al., 2000). The CSA activity monitor has better accuracy, with errors of 11% and 26% for slow and brisk walking, respectively (Bassett et al., 2000), and in some cases less than ±10% (range of -8 to +4%) (Bassett et al., 2000; Melansson & Freedson, 1995; Strath et al., 2001). Activity monitors provide a better comparison for this study due to their intended purpose. Activity monitors are capable of predicting actual EE even more accurately when custom algorithms are used, but these studies represent the built-in, or manufacturer-recommended methods for predicting EE. The use of accelerometers to assess body accelerations provides better estimates of walking EE than simply counting steps. Based on the results of the activity monitor studies included above, the ability of GPS to predict EE of walking is insufficient at slow paces (+31.4 to +40.3%), but acceptable for fast paces (+7.7 to +10.2%). The prediction of EE from the combined data appears to be satisfactory (+18.8 to +24.3), but it should be noted that it is borderline when accelerometers are used as the criterion measure.

Heart rate monitors (HRM) are have also been used for predicting EE. The relationship between HR and VO_2 can be used to determine the EE of a subject in a free-living environment. Heart rate monitors are often used in conjunction with accelerometers in an attempt to further improve estimates of actual EE. Ainslie (2003) reported the Flex HR method of estimating EE over-predicted actual by 10% when compared to doubly labeled water. Strath et al (2003) found HR predicted EE to be within ±2 – 3% of actual EE for slow and brisk walking, with no improvement when a CSA activity monitor was used in conjunction with the HRM.

To compete with HRMs for accuracy in predicting EE, the error for GPS predicted EE would need to be within ±10% of actual. For the present study, that would limit the reasonable data to the fast-paced walking trials. Even limiting the comparison to the fast-paced trials, the error in predicting actual EE by GPS is still only borderline when compared with HRMs. The accuracy of HRMs must be weighed against the additional burden of their use. To accurately estimate EE using a HRM, the researcher must determine a HR-VO_2 calibration curve for each subject, which requires a specific laboratory test session.

Considering the capabilities, usage, and burdens associated with each of the devices mentioned here, it seems that GPS monitors compare best with activity monitors when used for estimating walking EE. Activity monitors are capable of predicting EE within ±1 – 2%, however it is more common to see reported error of ±5 – 25%.

Using activity monitors as a basis for comparison, the prediction of actual EE for the combined data is a reasonable estimate, despite a statistically significant difference. The differences for the combined data, ranging from +18.8 to +24.3%, are similar to the differences seen with accelerometry based EE predictions. Predictions for fast-paced walking more compared more closely with actual values, with differences ranging from +7.7 to +10.2%. Slow-paced EE estimates are not reasonable, with differences ranging from +31.4 to +40.3%, because there is significant as well as practical differences in the GPS predicted and actual EE. Percent difference of actual and hip-worn GPS predicted EE for the original data set are displayed in Table 4.3.

Comparison of Actual and GPS Predicted EE by Grade Type

An analysis of GPS predicted EE versus actual EE for each grade type was conducted to better understand what portions of the walking course caused the GPS monitor to over-predict actual EE. Studies have shown that there are differences in the energy cost of walking on different grades (Bobbert, 1960; Margaria et al, 1963), as well as differences in mechanical efficiency on varying grades (Minetti, Ardigo, & Saibene, 1993). There are small differences in the actual EE measurements between the original, grade modified, and moving average data sets for each grade type, as seen in Table 4.5. This was due to the changes in grade classification based on the GPS reported grade for each data set. The total actual EE remains the same across each data set, the alterations only effected the distribution of EE between the grade classifications for each data set.

Using the reported accuracy of activity monitors as a guideline, there is no practical difference between actual and GPS predicted EE for the combined data at each grade classification, although the results for uphill walking are borderline (+20 to +27% when compared to actual). Errors of +5 to +12% for downhill walking and +16 to +20% for level walking are reasonable despite the significant difference from actual EE for downhill walking in the moving average data set and level walking in each data set. The slow-paced data exhibited significant and practical differences in GPS predicted and actual EE. Downhill walking was the most accurate with a +20 to +28% error (a borderline range), but the ranges of level (+24 to +31%) and uphill (+31 to +39%) walking exceeded the limits outlined by the activity monitor comparison. The fast-paced walking trials only had significant differences for uphill walking in the original and grade modified data sets, and no practical differences throughout the data. As with the previous data, the fast-paced trials had the most accurate results for downhill walking (+1 to +6%), followed by level walking (+7 to +9%), and uphill walking providing the most problematic results (+11 to +17%). Percent differences between actual and GPS predicted EE at each grade classification are shown in Table 4.5.

Improvements to the Original Data Set with Data Adjustments

While difference scores were the only statistical analyses performed to determine the improvements of the changes to the original data set, it seems that there was little or no benefit to creating the grade modified and moving average data sets. Tables 4.2 and 4.4 include few differences in the trends of original data set when compared with the grade modified and moving average data sets.

The creation of the grade modified data set was only possible because the walking course was known and constant, and adjustments to the grade data could be made on an ad-hoc basis. In the case of a true free-living environment, these adjustments would not be possible due to the unspecified nature of the walking path. If the true profile of a walking course is unknown, it is impossible to determine whether a reported grade is valid or erroneous.

The moving average data set is a more viable option for data adjustments because it does not discriminate between valid and erroneous data points. The moving average data set not only averages out any erroneous data points, but it also serves to smooth the changes in velocity and grade to better align with the physiological responses of the body. The drawback to this method is that it assumes that only isolated erroneous data points will be included in the data set. In the case of multiple erroneous data points in sequence, the 'smoothing' will not moderate the erroneous with the valid data, but smooth the erroneous data points together.

Possible Sources of Error

One possible problem with GPS is the nature of data recording. The GPS monitors used in this study collected data as a 'snapshot' of the position and elevation for the first second of the sample interval. Erroneous data points are not moderated by an average of the data over the sample interval. Metabolic systems, such as the KB1-C, average the data across the entire sample interval to report an average value. In the case of an erroneous metabolic data point, the averaging mechanism mitigates the affect of the error on the reported values. In contrast, an erroneous data point may be reported by GPS without any averaging to moderate the results.

A final consideration must be given to the equations used to predict walking EE. The equation presented by Minetti et al. (2002) was developed for treadmill walking. This equation was chosen because it accounts for downhill, level, and uphill walking with a single equation. The use of one equation is possible due to the use of grade as a six factor polynomial, but this also heavily weights grade and can magnify errors in that variable. The ACSM equation (American College of Sports Medicine, 2000) for predicting EE for walking does not account for downhill walking. The ACSM equation will provide a negative value for walking EE on a –10% grade in the given range of acceptable walking speeds. Wind resistance was accounted for with an equation (Pugh, 1970), but may not be necessary for walking speeds (Hall, et al., 2004; McMiken & Daniels, 1976). Furthermore, these equations were not developed with the intention of being used together, so there must be some consideration given to the suitability of these equations when used in conjunction with each other.

CHAPTER SIX

CONCLUSIONS

The GPS monitors used to predict energy expenditure (EE) for outdoor walking consistently over-predicted for actual EE (EE_{ACT}). Only at the fast walking intensity was the GPS data able to predict EE_{ACT} without any significant difference. Despite the statistical differences in actual and GPS predicted EE, results of the combined data did not show any practical difference when compared to similar studies using activity monitors. Statistical and practical differences were found for the GPS predicted EE at slow walking paces when compared to actual. The difference in the predictive ability of GPS monitors at fast and slow walking paces may suggest that the error in the GPS monitors' reporting of position and elevation favors movement at higher speeds, because it is reported as an absolute value. The relative error is reduced due to an increase in walking speed, and concurrently the over-prediction of EE is reduced with an increase in walking speed.

The error in the GPS reported elevation data is concerning, but does not seem to greatly effect the EE predictions. Throughout the data sets walking speed seems to have the greatest effect on the EE predictions. The fast-paced walking predictions of EE were consistently more accurate than slow-paced estimates throughout the data.

Efforts to correct errors in reported grade provided no substantial improvements in the GPS predictions. There were minor improvements in the adjusted data sets (grade modified and moving average data sets), however there was no change in the trends of statistical significance across these data sets.

Anatomical location of similar GPS monitors does not affect the reported data from the monitors. No significant difference was found between the hip-worn and wrist-worn GPS monitors, despite the greater movement of the wrist-worn monitor due to the natural arm swing during walking. Placement of the monitors should not be a concern with future studies in the event that subjects must wear the monitors away from the center of mass.

When the three grade types were separated out, the GPS monitors were more capable of accurately predicting EE for downhill and level walking. It should also be noted that these results further support the finding that GPS is better at predicting EE for fast paced walking.

The practical applications of this study will be delayed by the further refinement of GPS technology and/or the ability to relate GPS data to EE. There are GPS monitors available with greater accuracy and precision, however many of these are commercial or industrial grade handheld devices too cumbersome for use in free-living research, and too high-priced for most users. Further exploration of this topic may produce more suitable prediction equations for the problem of outdoor walking, including the addition of an equation to predict resting metabolic rate based on subject anthropometry. The equations that this project was based upon were not intended for the purpose of predicting outdoor walking EE. A different equation may better account for the specific circumstances of a field test for walking and the error in GPS reported position.

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APPENDIX A

INFORMED CONSENT

SUBJECT CONSENT FORM FOR PARTICIPATION IN HUMAN RESEARCH
MONTANA STATE UNIVERSITY – BOZEMAN

Project Title: Estimating Energy Expenditure For Hiking Using GPS

Funding: This study is not a funded project.

Project Director: James McKenzie, Graduate Student, Exercise Physiology
Department of Health and Human Development
722 S. 7th Ave, Bozeman, MT 59715
406 570 7256, jmmckenzie@montana.edu

Purpose: The purpose of this study is to determine the accuracy of estimating energy expenditure (EE) using global positioning system (GPS) data when compared to EE from indirect calorimetry while hiking.

Each participant is presented with this Informed Consent Document which explains the purpose of the testing, as well as expected risks and benefits associated with participation. Each participant will also be screened by the project director using responses provided in a Health History Questionnaire. If deemed necessary, participants will be required to acquire medical clearance from his/her physician prior to testing. This procedure is in compliance with policies formulated by the American College of Sports Medicine[1].

Project Outline: You (the participant) will be required to visit the Pete's Hill area of Lindley Park for testing. The testing will last approximately one and one-half hours. It is important that you prepare for your test as you would for a hard workout. Therefore, it is advised that you abstain from strenuous activity on the days before the study. Before arriving at Pete's Hill, you should refrain from ingesting any medications, including caffeine or aspirin, for at least 2 hours. If any medications were taken (such as cold or allergy medicine) please inform the Project Director prior to any testing – we will gladly reschedule your visit. *If you use an inhaler to treat asthma, make certain to bring the inhaler with you to the test.* You should arrive at Pete's Hill ready to engage in moderate exercise. Therefore, participants should dress (running shoes, shorts, and top), eat, and drink fluids appropriately for the occasion.

Your visit to Pete's Hill will consist of two hiking tests. The main purpose of the test is to measure your EE while hiking. You will hike a pre-determined 1.5 mile course at two walking speeds corresponding to slow and a fast paced walk. You will determine the actual speed of the slow and fast walks. Both hiking tests will be performed during the same test session, and will be separated by 15 minutes of rest and active recovery.

Before testing you will need to warm up for 5-10 minutes. In addition, you will wear all of the testing equipment during the warm up to familiarize yourself with wearing the equipment. During the exercise test you will be wearing a small backpack containing a portable metabolic system and will be breathing through a mask so that the amount of oxygen you are using can be measured. At the same time, you will be wearing a heart rate monitor strap around your chest to measure heart rate via telemetry and a global positioning system unit on your wrist to collect elevation and position data. The test will end when you finish hiking the 1.5 mile course.

Potential Risks: You should be aware that the test may cause fatigue after the test and during the next day. Hiking has inherent risks, and there is a chance or injury. The chance of injury is minimal since you regularly train outdoors, are familiar with hiking, and are in good physical condition. These risks are certainly no greater than those experienced by trained athletes during a moderate intensity workout. The equipment worn (backpack, gas mask, and heart rate monitor) may feel somewhat restricting and/or uncomfortable during testing, but all possible adjustments will be used to achieve the greatest comfort to you. All possible precautions will be taken to ensure your safety and make you feel comfortable before any testing takes place.

Benefits: Each participant will receive a copy of their results from both tests as well as the results for the group as a whole.

Confidentiality: The data and personal information obtained from this project will be regarded as privileged and confidential. Nobody besides the Project Director will know your personal results. Your test results will not be released to anyone else except upon your written request/consent. Your right to privacy will be maintained in an ensuing analysis and/or presentation of the data by using coded identifications of each person's data.

Freedom of Consent: You may withdraw consent from participation in writing, by telephone, or in person without prejudice or loss of benefits (as described above). *Participation in this project is completely voluntary.*

In the *unlikely* event that your participation in this research results in physical injury to you, the Project Director will advise and assist the participant in receiving medical treatment. Montana State University cannot be held responsible for injury, accidents or expenses that may occur as a result of your participation in this project. In addition, Montana State University cannot be held responsible for injury, accidents, or expenses

that may occur as a result of traveling to and from your appointments at Pete's Hill. Further information regarding medical treatment may be obtained by calling the Project Director, James McKenzie, at 406.570.7256 (cell) or 406 994-6325 (lab). You are encouraged to express any questions, doubts, or concerns regarding this project. The Project Director will attempt to answer all questions to the best of his ability prior to any

testing. The Project Director fully intends to conduct the study with your safety and comfort in mind. Additional questions about the rights of human subjects can be answered by the Chairman of the Montana State University Human Subjects Committee, Mark Quinn, at 406 994-5721.

KEEP THIS PAGE FOR YOUR OWN RECORDS

Project Title: Estimating Energy Expenditure For Hiking Using GPS

STATEMENT OF AUTHORIZATION

I, *the participant*, have read the Informed Consent Document and understand the discomforts, inconvenience, risks, and benefits of this project. I, _____________________ (print your name), agree to participate in the project described in the preceding pages. I understand that I may later refuse to participate, and that I may withdraw from the study at any time. I have received a copy of this consent form for my own records.

Signed: ______________________________ Age ____ Date ________________