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The Effects of ActiGraph Bandpass Filtering on Activity Counts During Continuous and Intermittent Lifestyle Activity

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I am submitting herewith a thesis written by Samuel Robert LaMunion entitled "The Effects of ActiGraph Bandpass Filtering on Activity Counts During Continuous and Intermittent Lifestyle Activity." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Kinesiology.

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The Effects of ActiGraph Bandpass Filtering on Activity Counts During Continuous and Intermittent Lifestyle Activity

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DEDICATION

I would like to dedicate this thesis to my family, friends, and faculty. I would not have been able to achieve this accomplishment without your consistent love and support throughout. Thank you to my family for never doubting me, thank you to my friends for being there to celebrate when the time was right and to pick me up after failures, and thank you to my faculty for providing me with all of the resources and instruction to help me succeed both in and out of the classroom. Special thanks to Ashton for being there for me through it all, I could not have done it without you.

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ABSTRACT

PURPOSE: The purpose of this study was to explore how increasing the upper limit of the bandpass filter frequency range affected accelerometer counts collected during treadmill walking and running, car driving and intermittent lifestyle activities **METHODS:** Part A included treadmill walking, running, and car driving (N=20) (mean ± [plus or minus] SD; age, 24.4±3.4 years; body mass index (BMI, 26.4±3.3 kg/m^2 [kilograms per meter squared]). Part B included ten lifestyle activities ranging from sedentary behaviors to vigorous intensities (N=30) (mean±SD; age, 23.0±2.3 years; BMI, 25.1±3.8 kg/m^2). Participants wore an ActiGraph accelerometer (GT3X+ in Part A and GT9X in Part B. on the hip. Participants completing Part B wore a Cosmed K4b^2 [K4b squared] as a criterion measure of energy expenditure. Acceleration data were processed using a beta version of Actilife containing additional bandpass filter frequencies with upper limits of 5.0 Hz [Hertz] and 9.0 Hz, as well as, the 2.5 Hz default filter. Data were converted to 5-s epochs and the low frequency extension feature was employed. Cosmed data (VO_2 [volume of oxygen] ml/min) were averaged over 30-s and then converted to relative VO_2 (ml/kg/min) and metabolic equivalents (METs) for each activity. **RESULTS:** Part A: compared to the default bandpass filter, using a bandpass filter range of 0.25-9.0 Hz reduces the plateau effect seen during treadmill walking and running and significantly increases count values during car driving for all axes and vector magnitude. Part B: Increasing the bandpass filter frequency, significantly increased the count values on all axes during the lifestyle activities. Across all activities, the default filter had the strongest association between counts and METs, while the 5.0 Hz filter had the strongest association for lifestyle activities and the 9.0 Hz filter had the strongest association for locomotive activities. **CONCLUSION:** The plateau effect seen with the ActiGraph accelerometer can be reduced by increasing the bandpass filter frequency range. However, increasing the bandpass filter frequency range significantly increased the counts during car driving and lifestyle activities. Future work is needed to understand the impact that the increased count values will have on estimating energy expenditure.

Key Words: Accelerometer; Indirect Calorimetry; Energy Expenditure, Physical Activity Counts, Plateau Effect

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CHAPTER I: INTRODUCTION

Research has shown that being physically inactive across one's lifespan can be detrimental to overall health. Physical inactivity has been linked to an increased risk for development of non-communicable diseases, negative health consequences, and even premature death from all causes (29, 30, 31, 37). Physical activity research is conducted to develop general guidelines that can help adults achieve and maintain health. These recommendations include performing a minimum of 150 minutes of moderate, or 75 minutes of vigorous intensity aerobic activity per week to achieve most health benefits (1, 37). Despite the guidelines only recommending 150 minutes of physical activity per week, most U.S. adults do not reach that threshold. For instance, Troiano et al. (54), reported when examining an objective measurement of physical activity in a sample of U.S. adults that less than 5% of the population were not meeting the recommendations for physical activity when data were broken down into 8-10 minute bouts. This value is considered an underestimate by many but illustrates the need for more research to be conducted to help improve the measurements of free-living activity.

Researchers, using a variety of methods to measure physical activity, are able to establish guidelines for health, as well as gain insight into the metabolic requirements of various activities for locomotion and free-living activities. Historically, researchers have used short recall questionnaires and physical activity surveys and logs to get an estimate of how much physical activity was performed (58). These methods, while inexpensive and easy to administer rely heavily on participants' ability to accurately estimate energy expenditure or intensity (58). The standard method of measuring physical activity in recent years has shifted to using more objective measurement techniques using wearable monitors that are better at measuring intensity and duration and estimating energy expenditure (58).

There are several criterion measures for developing energy expenditure prediction equations using objective monitors to measure physical activity. These methods include the doubly labeled water method, indirect calorimetry and direct observation. Of those measures, the gold standard of measuring free-living energy expenditure is the doubly labeled water method. This method, while being very effective for measuring total daily energy expenditure, does not allow for specific details related to type, duration, intensity, or frequency of physical activity in free-living settings. This method is also relatively expensive and is therefore not an option for many physical activity measurement validation studies (23). A second method for measuring energy expenditure is indirect calorimetry which involves gas exchange analysis through capturing ventilatory data during physical activity while wearing a mask over the nose and mouth. This method allows for physical activity energy expenditure to be calculated for an exact time frame and is often used to validate energy expenditure estimations made using other methods. An additional validation method that is used to further classify intensity of an activity or estimate energy expenditure is direct observation. This method is inexpensive and is used to validate the amount of time spent performing various activities, but it is not ideal for classifying intensity.

Motion sensors provide an additional method for measuring physical activity intensity, frequency, and duration and they can be used to estimate energy expenditure using the real-time data collected (4, 18, 57). However, researchers have found that no one sensor can capture all data necessary to accurately capture all dimensions of physical activity but they do allow researchers to forgo less precise methods previously used to gather physical activity information (18). One wearable monitor that uses motion sensor technology is an accelerometer. These devices are small, non-invasive, and can be worn for extended periods of time (4, 6, 18, 55, 56).

Accelerometers are traditionally worn on the hip attached to an elastic or nylon belt but can also be worn on the wrist, ankle, thigh, and other locations. This type of technology has evolved greatly in the last decade moving from uniaxial accelerometers, basic heart rate monitors, and pedometers to multiple sensor units that have the ability to collect all of that same data with sensors housed in just one unit. For example, most of the newer accelerometers contain a triaxial accelerometer that measures acceleration in three planes, anteroposterior (z-axis), mediolateral (x-axis) and vertical (y-axis). This is an improvement from older generations that featured a uniaxial accelerometer that only measured acceleration in a single vertical plane.

Chen and Bassett (10) compiled a comprehensive overview of the process through which acceleration signal is measured, filtered, and recorded. Accelerometers work by measuring the magnitude of acceleration and deceleration of the body. These data are typically collected at a given frequency (e.g. 30 Hz). This frequency is preset when the device is initialized meaning all acceleration data captured will be recorded at this frequency and then initially filtered through what is known as a low-pass filter in order to reduce the noise in the acceleration signal. This filter passes acceleration signal below a pre-set frequency and attenuates acceleration signal above this frequency. After acceleration signal passes through the low-pass filter, data is considered to be in raw form. The raw data is used in some cases but more commonly, the raw data is converted into more usable device output through a series of amplification, filtering and digitization (10). Raw acceleration signal is full-wave rectified meaning the bi-directional acceleration signal becomes uni-directional and only contains positive values (10). It is at this point the digital signal can be integrated and processed through a bandpass filter, a range of frequencies through which any acceleration signal outside of the upper and lower limits of the range is attenuated. The integration process yields the usable device output often referred to as activity counts or simply counts (10). These counts can be accumulated over 1-minute or even smaller intervals, down to 1-second. These time periods are known as epochs (10). These more refined time stamped activity counts can be used to develop regression models and energy expenditure prediction equations when paired with measured energy expenditure data from a criterion measure, most often indirect calorimetry.

One primary difference between devices is the bandpass filter frequency range employed during the acceleration signal filtering process. This filter frequency range varies based on the device that is used with some devices having a narrow filter frequency range while others have a wider filter frequency range. This accounts for some of the variability in the energy expenditure estimations across devices. This difference can account for additional acceleration being recorded at the low end of the spectrum through activities such as driving or computer work. The wider the bandpass frequency filter range, the more sensitive the device is to recording a broader range of acceleration signal which will directly affect counts. An example of this is provided by work conducted by John et al., (24, 26) with the ActiGraph GT3X+ and the Actical as well as the ActiGraph and the GENEA. These devices have different filter frequency ranges with the ActiGraph using a filtering range of 0.25-2.5 Hz and the Actical using a higher filtering range of 0.5-3.0 Hz while the GENEA is open source and programs can be created through software such as Matlab (Matlab, Mathworks, Natick, MA) to establish bandpass filter ranges. Schaefer et al., in 2014 (49) reported that the greater range for the Actical causes less acceleration to be filtered out while the ActiGraph filters out more acceleration (24, 26). While there are other device differences, the bandpass filter frequency range was listed as a primary difference that would impact device output and account for most differences.

There has been substantial research conducted to establish the use of accelerometers as a valid and reliable method for estimating energy expenditure and measuring physical activity (5, 25). One of the more commonly used accelerometers in research is made by ActiGraph (Pensacola, FL). Researchers have shown that energy expenditure equations are most valid and reliable for the activities that were used to develop the equation meaning that an equation developed using walking and running data will underestimate energy expenditure for lifestyle activities (12, 13). Several researchers have identified that while ActiGraph counts increase linearly up to about 6 miles per hour (10 km/hr) at which point the counts begin to level off and eventually begins to decrease as speed continues to increase beyond this threshold. This is known as the plateau effect (7, 21, 25, 44).

Since counts are used to predict energy expenditure, any alteration of the count values will directly impact the way energy expenditure is predicted. Therefore if count values are leveling off or decreasing as exercise intensity is increasing, then the estimation of energy expenditure will result in an underestimate as is seen in the study of John et al. (25). While energy expenditure was not estimated in the study, a clear plateau and decline in counts was seen beyond running at 10 km/hr. Researchers believe that the plateau effect is partly due to the bandpass filter frequency range of 0.25-2.5 Hz ActiGraph uses (7, 21, 25, 44). It has been hypothesized that increasing the upper limit of the bandpass filter frequency range ActiGraph uses could alter count values generated potentially leading to a reduction in the plateau effect (7, 25). This could lead to the count values having a more linear relationship with intensity.

Statement of the Problem

The plateau effect occurs specifically when examining activity counts from a device placed on the hip with a uniaxial accelerometer (25). Researchers initially hypothesized that when using a triaxial accelerometer such as the ActiGraph GT3X+ that the acceleration would not decrease at the anteroposterior (z-axis) and mediolateral (x-axis) axes like they do at the vertical axis (y-axis) (7). With the anterioposterior and mediolateral axes not being affected by the inverted-U phenomenon, it was further hypothesized that using vector magnitude counts (VM) would not exhibit the plateau effect (7, 25).

The intensity and acceleration that occurs when running at approximately 6 mph occurs frequently when performing other moderate intensity lifestyle activities such as playing basketball or tennis so it has been hypothesized that this same effect is occurring at the hip for these activities as well and that is one of the primary focuses of this study. The lifestyle activities could potentially be affected by the change in bandpass filter frequency range similarly to walking and running because at certain time points during the lifestyle activities, the instantaneous acceleration generated can be equal to or greater than the acceleration generated when running at 6 mph. The aims of this two-part study are as follows:

Part 1. <u>Treadmill Walking and Running</u>

Aim: to reduce the plateau effect that occurs during treadmill walking and running by increasing the upper limit of the bandpass filter frequency range.

Part 2. <u>Lifestyle Activity</u>

Aim: to investigate whether lifestyle activities are also affected by the plateau effect and how increasing the upper limit of the bandpass filter frequency range affects counts for lifestyle activities.

Statement of Purpose

The primary purpose of this study is to determine if increasing the upper limit of the bandpass filter frequency range for the acceleration data collected at the hip using an ActiGraph GT3X+

accelerometer will affect the relationship between activity counts and intensity and reduce the plateau effect. A secondary purpose of this study is to investigate if the plateau effect occurs at the hip using an ActiGraph GT9X accelerometer during lifestyle activities and how increasing the upper limit of the bandpass filter frequency range affects counts measured for those activities.

Research Questions

Question 1: Does increasing the upper limit of the bandpass filter frequency range for acceleration data collected at the hip reduce the plateau in counts during treadmill walking and running?

Hypothesis 1: It is hypothesized that increasing the upper limit of the bandpass filter frequency range will reduce the plateau in counts during treadmill walking and running.

Question 2: Do counts generated from performing lifestyle activities exhibit the plateau effect? If so, will increasing the bandpass filter frequency range reduce the plateau effect seen during these activities?

Hypothesis 2: It is hypothesized that counts generated while performing lifestyle activities will exhibit the plateau effect. It is also hypothesized that increasing the bandpass filter frequency range will reduce the plateau effect and increase counts generated during these activities.

Question 3: Does increasing the frequency range of the bandpass filter change the relationship between estimated and measured energy expenditure?

Hypothesis 3: It is hypothesized that increasing the bandpass filter frequency range will change the relationship between estimated and measured energy expenditure.

Delimitations

1. Participants shall be between 18-65 years
2. Participants must be able to answer “No” to all questions on a PAR-Q.
3. Participants will be excluded if they are obese, pregnant, or have orthopedic or musculoskeletal issues that would limit activity.

Limitations

1. Participants will be exposed to some risk inherent to vigorous intensity PA, and are expected to answer the PAR-Q truthfully.
2. Weather and campus events may interfere with outdoor activities.
3. Reasonable time commitment for participants will limit the total duration of data collection; data should be collected within one hour and thirty minutes.

CHAPTER II: REVIEW OF LITERATURE

Introduction

Physical activity is defined as any bodily movement that requires the contraction of skeletal muscle which in turn increases energy expenditure above the resting value (9). Physical activity measurement has been of interest to researchers, physiologists, and epidemiologists alike for decades because of the implications of physical inactivity and related negative health outcomes such as chronic disease associated morbidity and mortality. Examples of these outcomes are summarized in a pair of reviews by Kokkinos et al. (29, 30). These reviews document the close inverse association between physical activity and fitness with chronic disease and overall mortality (29, 30). Chronic diseases highlighted by these reviews include Type 2 diabetes mellitus, obesity, and hypertension to name a few of the most common and also most prevalent conditions in U.S. adults. These reviews contrast one another by highlighting the detriments of physical inactivity on health across the lifespan compared with the health benefits gained from performing adequate levels of physical activity and the reduced mortality risk associated with it.

Troiano et al. (54) reported that most U.S. adults do not participate in sufficient physical activity to maintain health and gain protection from development of chronic diseases. These results are found through nationally representative population surveys such as the National Health and Nutrition Examination Survey (NHANES). An example of this is seen in the 2003-2004 NHANES data analyzed by Troiano et al. (54) that was collected using accelerometers and was the first objective measurement of physical activity in a national survey. These data provided insight into how much physical activity U.S. adults were getting from a method other than self-report. These findings were in contrast to self-report data from other representative population surveys that found anywhere from 25-33% of U.S. adults were meeting the recommendations based on self-report. These findings call into question the reliability of the self-report measurements as well as how accurate the accelerometers are assessing physical activity. Additional evidence of this is seen in a 2011 paper by Tucker et al., (57) that showed similar lack of adherence to the 2008 Physical Activity Guidelines for U.S. Adults with less than 10% of American adults meeting the recommendation of 150 minutes of moderate, 75 minutes of vigorous activity per week, or a combination of the two when measured by accelerometer. This is in stark contrast to the self-report data for the same population which showed over 60% meeting the recommendation (57).

There is a disparity between the amount of physical activity being self-reported and the amount of physical activity being measured by accelerometers and with this being the case, researchers have set out to develop more accurate methods for using accelerometers to measure physical activity and estimate energy expenditure. The purpose of this review of literature is to further explore how physical activity and energy expenditure are measured, and the validity and reliability of these methods. In addition, it will examine how accelerometers are used to estimate energy expenditure.

Criterion Measures of Energy Expenditure

Doubly Labeled Water

The doubly labeled water (DLW) method is the criterion measure for free-living energy expenditure. Originally developed for use in animals, this method was refined and approved for use in human subjects and has been found to be useful but somewhat cost inefficient in most situations. The DLW method involves taking a dose of $^{2}H^{18}O$ isotope water that is proportional to the amount of total body water a participant has which is often approximately 60% of total body weight. The loaded dose of DLW equilibrates with the body water within a few hours and over the course of one to several weeks is used to determine total energy expenditure. This is determined through the examination of bodily fluid, most commonly urine. The isotopes are excreted as carbon dioxide and water at different rates as energy is expended. Water is excreted through the body in several forms including urine and sweat whereas carbon dioxide exits only through expired breath. This being the case, the ^{18}O isotope exits the body more quickly than the ^{2}H isotope. The difference in rate at which the isotopes are lost from the body is used to determine the rate and amount of carbon dioxide produced and this in turn is used to estimate energy expenditure (38).

It has been noted that the DLW method is between 92-98% accurate for measuring total daily energy expenditure based upon the dosage level taken and amount of time given to expire (50). While this method is reliable and valid, many researchers are interested in more refined measures of energy expenditure that can be narrowed down to a more precise time period or interval rather than the broad total energy expenditure values obtained using the DLW method.

Room Calorimetry

Room calorimetry measures energy expenditure using an open circuit system that measures total daily energy expenditure. This measure includes the thermic effect of food, basal metabolic rate, resting energy expenditure and individual activity energy expenditure (32). This type of system is useful but for most research unfeasible. A room calorimetry system is very costly, often times a million dollars in addition to requiring a trained technician to run the system plus maintenance. For this reason, in addition to the fact that behavior is altered from normal daily life, these systems are not used as often. As useful as these systems are, Seale and Rumpler

(51) concluded that room calorimetry underestimates total daily energy expenditure by 2-8% and they recommend using the DLW method instead when applicable.

Indirect Calorimetry

Indirect calorimetry involves measuring gas exchange, specifically the amount of oxygen consumed and carbon dioxide produced. These measurements allow a ratio to be calculated, the respiratory exchange ratio, which indicates which metabolic substrate is being used. Stationary metabolic carts such as the ParvoMedics metabolic cart are often used when performing exercise tests to obtain a measure of energy expenditure but due to their lack of portability they are limited to controlled, lab based activities such as treadmill walking and running and cycle ergometry. Portable versions of the metabolic cart have been developed and they too use indirect calorimetry for measurement. Two popular devices are the Cosmed K4b^2 and the Oxycon Mobile. Both devices have been validated as a reliable method of measuring energy expenditure and are both useful especially in free-living situations (2, 34, 39, 43). These devices use a facemask and tubes to capture expired gas for analysis. These tubes run into a battery powered unit that reads and records the values obtained during collection.

Cosmed K4b^2

The Cosmed K4b^2 (Cosmed, Rome, Italy) is a portable indirect calorimeter (170 x 55 x 100 mm) that provides measures of oxygen consumption (VO_2) and carbon dioxide production (VCO_2). The Cosmed system has two units, a gas analyzer unit that is affixed to the chest and a battery unit that is affixed to the back, both via a manufacturer designed harness. The device is lightweight (approximately 800 grams) and is accompanied by a facemask that covers the mouth and nose for inspired and expired air collection. The Cosmed K4b^2 is valid for measuring oxygen consumption during physical activity (34, 39). In order to initialize the device there are four calibration steps to run through before each use. The calibration process involves a room air calibration using the temperature and relative humidity of the room as well as a known reference gas calibration with a specialized gas mixture 15.98% O_2 and 4.008% CO_2 (11). In addition to this, a turbine calibration is performed using a 3 L Hans Rudolf syringe. Lastly, a delay calibration is conducted to account for any delay that may occur between exhalation and measurement by the gas analyzer sensors (11).

Measurement of Physical Activity: Self-Report and Objective Methods

Self-Report Methods

Self-report measurements of physical activity have long been used in research for their practicality, feasibility, low cost, and general familiarity and acceptance in most populations (23, 46). Self-report methods include survey instruments, recall questionnaires, diaries and logs, all of which involve the subjective response that varies with each participant (23, 46). This subjectivity leaves room for large amounts of fluctuation in responses which leads to discrepancies in the types of activities being performed and at what intensity (23, 46). Comparisons between self-report methods and more direct measurements have been made in work by Prince et al. (42) who compiled an exhaustive review of these comparisons. Prince et al. (42) found that on average, accelerometers were used most often to directly measure physical activity and that the mean percent difference between self-report physical activity and the accelerometer measured physical activity was 44%. Correlations between self-report methods and directly measured methods varied greatly (-0.71 to 0.96) with the majority being low-to-moderately correlated (42).

Accelerometer Methods

Accelerometer-based devices are used in physical activity research as a means of objectively measuring physical activity. Researchers have identified multiple advantages to using an accelerometer for physical activity measurement. These advantages include more specific information related to volume, frequency, intensity, and time spent in physical activity and activities of daily living in contrast to the DLW method which can provide accurate energy expenditure measurement over longer periods of time. A combination of these methods is recommended for best outcomes (41). It is noted that it is rarely feasible and that energy expenditure prediction equations derived from the DLW measurements are sufficient in most cases as they are found to be valid (41).

Acceleration data has been used to calibrate objective monitors and to develop energy expenditure prediction equations for locomotive activities such treadmill walking and running to activities of daily living such as sweeping and cleaning as well as recreational sports like tennis and basketball. Accelerometers measure and store the magnitude of acceleration and deceleration and this raw acceleration signal can be processed and filtered through a series of steps outlined in detail by Chen and Bassett (10). Raw digital acceleration signal passes through a low-pass filter first where a pre-set frequency passes all acceleration signal below that threshold while attenuating acceleration signal above that threshold. The acceleration signal is bi-directional by nature and in order to further process it, full-wave rectification is used to convert negative signal to positive values (10). It is at this point that a bandpass filter can be applied before the signal is fully integrated and generated into output per unit of time better known as counts per epoch (e.g. counts per 30 seconds) (10).The bandpass filtering process involves the digital acceleration signal passing through a range of frequencies with an upper and lower limit (e.g. 0.25-2.5 Hz) where any acceleration signal that falls outside of those limits is attenuated. This process provides researchers with output that can be interpreted to determine time spent in different activities as well as the intensity at which an activity is performed. There are a variety of prediction equations that exist in the literature, all of which are developed using a specific set of activities. Some equations are walking and running specific and valid only for those activities while others are more encompassing as they were developed using a more diverse routine of activities. The processing of the raw acceleration signals for each device vary as the filtering of the signal is done differently across devices with much of the process being proprietary. This allows for little direct comparison across devices when using counts.

Accelerometer technology has evolved over time with early uniaxial (vertical axis) devices measuring acceleration in a single plane. Current models have triaxial accelerometers in addition to other sensors such as magnetometers to measure direction, gyroscopes to measure rotation, and even thermometers to measure temperature. In addition to being able to measure acceleration in more planes, the accelerometer technology has also improved making accelerometers a more cost-effective method than they have been historically (59). This improvement in technology has shifted from an analog signal measured using a mechanical cantilever beam that required calibration before use to a digital signal measured with a micro-electromechanical system (MEMS) that requires no calibration and uses less battery allowing for longer periods of data collection (10, 59). Accelerometers operate based on a mechanical sensing element that is generally comprised of a seismic mass that is mechanically suspended (59). The mass is then acted on by inertial forces from both gravity and acceleration and the displacement of the mass is measured electrically and that is the raw acceleration signal recorded and stored on the device (59). The most commonly used types of accelerometers are piezoresistive, piezoelectric, and differential capacitive models.

There have been many energy expenditure prediction equations developed using accelerometers with some being more frequently used than others. Some examples are the

Freedson 1998 (20) and Swartz 2000 (53) equations both of which use a linear regression between measured energy expenditure via calorimetry to the predicted energy expenditure calculated using counts collected using the accelerometers. These equations were developed using a CSA accelerometer, now known as ActiGraph, which is one of the more commonly studied research devices. ActiGraph has produced several generations of accelerometers that have been researched heavily and have been shown to perform reliably and provide valid results when compared to criterion measures. de Vries et al (17) reported that the ActiGraph models were the most studied physical activity monitor and the literature supported the continued use of ActiGraph devices with them being used in nationally representative studies such as NHANES.

With the ActiGraph being the most widely used and many of the energy expenditure prediction models having been developed on ActiGraph devices, the remainder of this literature review will focus on ActiGraph devices specifically as well as an issue that is specifically related to the ActiGraph.

Validation of energy expenditure prediction equations is vital to ensure the proper performance and function of a device to collect reliable data for the activities on which the equations were developed. One of the main issues with equation validation is the wide variety of protocols used by researchers. The most common criterion measure that equations are validated against is indirect calorimetry since it can be used in free-living situations and provide measures of energy expenditure over short time intervals as well as provide information on intensity of physical activity. This method is often used for validation procedures lasting for a few hours with anything longer than that requiring use of the DLW method. While indirect calorimetry is more cost-effective, the gold standard for energy expenditure equation validation is the DLW method.

Review Articles

Plasqui and colleagues (40, 41) conducted reviews of the work done validating energy expenditure prediction equations against the DLW method. These reviews intended to identify the best DLW derived energy expenditure equations and corresponding accelerometer models to assess physical activity during free-living activities. In 2007, Plasqui et al. (41) identified a total of 28 studies highlighting 8 different accelerometer models. Of these models, the CSA/MTI/ActiGraph was one of the two most extensively validated devices along with the Tracmor. The authors note that many of the other devices including the Lifecorder, Caltrac, Actiwatch AW16, Tritrac-R3D, and ActiReg, performed poorly and had little to no correlation for count values and obtained from the devices and energy expenditure (41). In 2013, Plasqui and colleagues (40), reviewed additional models of accelerometers validated against the DLW method including 25 studies published between 2007 and 2011 that highlighted 18 different models of accelerometers from 15 different manufacturers. There was high variability among devices with correlations ranging from 0.06 for the Lifecorder between physical activity level and activity counts up to 0.91 for the Actiheart when predicting Total Energy Expenditure (TEE) after correcting for participant characteristics (40). These reviews highlighted that the ActiGraph was the most validated accelerometer and that when used to predict Activity Energy Expenditure (AEE) accounting for body mass the correlation with activity counts was 0.37 (40, 41). The sample populations for the studies reviewed were broad and included participants of all age groups, both healthy and unhealthy, men and women, children and adults, and pregnant and non-pregnant so the results cover a diverse range of populations which makes it more challenging to compare results across devices. Plasqui at al., (40) noted that while more sensors are being added to current accelerometers, there is little evidence to show that these additional sensors significantly improve energy expenditure estimation.

Device Comparison

John et al., (28) published a study comparing four different ActiGraph models in 2010 to determine if there was any variability between models for measuring activity counts for walking and running. Participants walked and ran at ten different speeds ranging from 3 km/hr to 20 km/hr on a treadmill for three minutes at each stage. The study compared three versions of the GT1M model as well as the 7164 model. The monitors were worn on the left and right hips using an elastic belt and testing was done on separate days to account for differences between device placements to account for test-retest bias (28). No significant differences between count values at any speed for walking and running were seen (28). This indicates that all devices are valid for use in research investigating walking and running and that using any of the four models will be sufficient as there are no significant differences in performance. A major finding of this study was that energy expenditure prediction equations developed using the ActiGraph 7164 can also be used for all generations of the ActiGraph GT1M as well (28).

In 2011, Sasaki et al. (48) conducted a study to compare the ActiGraph GT1M model and the newer GT3X model during treadmill walking and running (4.8, 6.4, 9.7, and 12 km/hr). Fifty participants were recruited and all wore the ActiGraph devices on the hip in addition to an Oxycon Mobile portable metabolic system which was the criterion measure. Data for participants who could complete all four stages for at least 1 minute were included in analyses with the mean counts per minute for each stage being used as the metric. This allowed the authors to compare the count values across devices for the vertical (VT) axis as well as the anterioposterior (AP) axis and vector magnitude (VM2) of both axes (48). Results indicated significant differences between the mean AP counts between ActiGraph models. The GT1M AP counts were significantly higher than GT3X AP counts at 4.8 km/hr, 9.7 km/hr, and 12 km/hr with absolute mean percent differences of 21%, 38%, and 45% respectively. There were no significant differences between VT counts between devices but there were differences between VM2 counts between devices that the authors attributed to the significant differences between AP counts between devices. The VM2 counts for the GT1M were significantly higher than the VM2 counts for the GT3X by 5%, 15%, and 25% at the speeds of 4.8, 9.7, and 12 km/hr, respectively. Authors noted a leveling off in count values for the VM2 in the GT1M while a downward trend in counts was seen at 12 km/hr for the GT3X (48).

Dannecker et al. in 2013 (16) conducted a device validation for a new physical activity monitor, a prototype device that is worn on the shoe. In this validation, comparisons were made with other popular research accelerometers, among those were the Actical and the ActiGraph GT3X. Nineteen total subjects were used for the study all of which fasted for four hours prior to a four hour testing window in a room calorimeter (16). EE estimates made using the respective devices were compared to total energy expenditure (TEE) from the three and a half hours of testing as the first half hour was omitted. Authors used the Actical as the primary device for comparing the new prototype shoe device to but some general conclusions were drawn about the performance of the ActiGraph. Results determined that like other previous studies, the ActiGraph does significantly underestimate EE over a range of low intensity to vigorous intensity lifestyle activities. In fact, the Freedson equation (20) underestimated EE by an average of 132.6 kcals (26.8%) which does model performance seen in other studies using DLW and portable indirect calorimetry methods (16). The primary reason listed for this error in estimation was the wide range of activities used and the flaw in accelerometry based EE estimation not mirroring the metabolic demand of such a range of activities (16).

Anastasopoulou et al. (3) conducted a comparison and validation study on two means of studying energy expenditure during activities of daily living, namely, locomotion. The study compared using a single regression model for the entire bout of activities to an activity specific model that is entirely activity dependent. For the single regression model EE estimate, an ActiGraph GT3X was used (3). Participants included nineteen participants, a mix of males and females and all wore the ActiGraph GT3X as well as the Move II accelerometers during the entire bout of locomotive activities. A portable indirect calorimeter, the MetaMax 3B was used as the criterion measure for this study (3). Activities performed were mostly locomotive in nature including sitting, standing, slow and fast walking, jogging, walking up and down a hill and walking up and down stairs. Results showed that the Freedson VM3 equation (48) overestimated EE using the single regression model for both walking speeds, as well as walking up and down the hill and walking up and down stairs and then underestimated EE for sitting, standing, and jogging (3). The largest differences were seen for walking up and down stairs (-2.45 and 1.92 kcals/min). These results are understandable as this shortcoming is well known about accelerometers, especially those worn on the hip and using a single regression model to predict EE for free-living activities.

Evaluation of Energy Expenditure Prediction Equations

Lyden et al. in 2011 (33) performed an evaluation of the most commonly used energy expenditure and MET prediction equations. The study included 277 participants that completed on average six treadmill tests ranging from 1.34-2.23 m/s and between 0-3% grade in addition to five self-paced activities of daily living chosen at random from a list of fourteen different activities ranging from sweeping and doing laundry to basketball and tennis (33). Participants wore accelerometers (ActiGraph GT1M, Actical, RT3) in addition to the Oxycon mobile portable metabolic system which was used as the criterion measure. In total, eleven different energy expenditure prediction models were used for analyses, four ActiGraph, five Actical, and 2 RT3 (33). Results showed that for all activities each model used significantly underestimated energy expenditure (-0.1 to -1.4 METS, -0.5 to -1.3 kcals). In addition to this, energy expenditure for the activities of daily living was also significantly underestimated by all models (-0.2 to -2.0 METS and -0.2 to -2.8 kcals) (33). On the contrary, there were mixed results of over- and under-estimation for the treadmill activity with seven equations underestimating and four equations overestimating energy expenditure. Lastly, it should be noted that vigorous activity was most often misclassified as moderate activity. Authors concluded that there are limitations with current methodologies to estimate energy expenditure using accelerometer count values (33).

McMinn et al. in 2013 (35) compared energy expenditure predictions using an ActiGraph GT3X+ and an Actiheart accelerometer to measured energy expenditure for 19 participants during three categories of treadmill walking speeds (slow, medium, and fast) for ten minutes at each speed. Participants wore an ActiGraph GT3X+ on the right wrist and right hip, an Actiheart on the chest, and an Ultima CPX indirect calorimeter. All devices were calibrated and initialized prior to each trial which was conducted in the same environmental conditions of 18°C and 50% humidity inside a controlled chamber. Results showed that mean speeds for the three phases were 2.59, 3.74, and 5.12 km/hr for slow, medium, and fast, respectively. There were no significant differences between device derived EE using the Freedson VM3 equation (48) and measured EE using the Ultima CPX for the medium walking trial but there were significant differences for the slow and fast trials ($p < 0.01$; $p = 0.02$) for both the waist and the wrist (35).

For the slow trial, the ActiGraph underestimated EE at the waist and wrist significantly ($p = 0.04$; $p = 0.02$) and for the fast trial the ActiGraph overestimated EE at the waist and wrist significantly ($p < 0.01$). Authors note that there were no significant differences between measured EE using the Ultima CPX and EE estimates for the Actiheart, made using the branched heart rate equation, for any of the three trials (35). Conclusions drawn from the study include the high correlation between EE estimates using the ActiGraph GT3X+ on the waist and wrist and measured EE. It should be noted that authors warn against using the Freedson VM3 (48) equation for the wrist since it was developed on waist worn device data. It should also be noted that the low frequency extension feature was turned on for this study to register the slow walking data yet despite this precaution, energy expenditure was significantly underestimated during slow walking.

Santos-Lozano et al. (47) conducted a study in 2013 to compare EE estimates made using the Work-Energy Theorem, the combined equation, and the Freedson VM3 equation (48) to measured EE using indirect calorimetry. The study involved 97 participants across three age group categories of youth (N = 31), adults (N = 31), and older adults (N = 35). Participants completed six activities for ten minutes each. The activities included rest, treadmill walking and running at 4 speeds (3, 5, 7, and 9 km/hr), and repeated sit to stand exercises. The analyses included three factors, (METs, Activity, and Age) to determine between EE predictions and EE obtained through indirect calorimetry. It was determined that the GT3X counts increased as speed increased for the treadmill activities (47). These findings including the VM results obtained using the GT3X for treadmill walking and running were in accordance with the results of previous work such as that of Sasaki et al. in 2011 (48).

Use of Accelerometers to Determine Minute-by-Minute Energy Expenditure

Crouter, Churilla, and Bassett (12) examined in 2006 energy expenditure prediction equations developed for the ActiGraph, Actical, and AMP-331 accelerometers. There were 14 ActiGraph equations, two Actical equations, and one AMP equation. Forty-eight participants were asked to complete a minimum of one out of three structured activity routines comprised of six activities, each lasting for ten minutes allotting one to two minutes rest between each activity. In total there were 18 activities between the three routines. Each of the three routines was completed by at least 20 participants with most participants completing only one routine. Throughout each routine, participants wore all three devices in addition to a Cosmed $K4b^2$. A primary finding from the study was that no one equation was found to predict energy expenditure accurately for all 18 activities. Overall, the results indicate that the equations do not work well across light, moderate, and vigorous intensity activities as there was misclassification between categories as well as time spent in each category. Most notably, the equations developed on lifestyle activities overestimated all sedentary activities in addition to slow and fast walking and underestimated all activities over 6 METs meaning that only light to moderate intensity lifestyle activities between 3 and 6 METs were measured closely which is a pretty narrow window. In addition to this, the equations developed on walking and running activities closely measured those activities while overestimating light intensity activity but underestimating moderate and vigorous intensity activities (12). Although the results were in agreement with the study of Bassett et al. 2000 (4) showing that the Hendelman lifestyle equation for the ActiGraph estimated on average for 28 different activities energy expenditure within 0.5 METs of the criterion measurement using the Cosmed $K4b^2$, there was an overestimation for walking and an underestimation for nearly all of the other lifestyle activities (12). These results called for the development of a new approach to estimate energy expenditure.

Crouter, Clowers, and Bassett (13) developed a novel approach for estimating energy expenditure by developing a two regression model to improve the under- and over-estimation of energy expenditure encountered with previously developed equations. Forty-eight participants were asked to complete at least one of three structured activity routines comprised of six activities, each lasting for ten minutes allowing for a one to two minute rest between each activity. In total there were 18 activities between the three routines. Each of the three routines was completed by a minimum of 20 participants with most participants completing only one of the three routines. Throughout each routine, participants wore a Cosmed K4b^2 in addition to the Actigraph on the hip. Of the tests completed, 45 tests were selected at random for analyses and development of the two-regression model (C2RM). Fifteen of the 45 tests were selected for cross-validation against previously developed single regression models. To determine which regression equation should be used, the coefficient of variation (CV) was used. If the CV $\leq$ 10, a walking/running equation was used and if CV > 10 then a lifestyle equation was used (13). The results of the study determined that the new predictions made with the C2RM were more accurate than using any single regression equation previously developed for the ActiGraph for either walking and running or lifestyle or leisure time physical activities for (13).

Use of Accelerometers to Determine Time Spent in Activity

Strath et al. (52) conducted a study examining the accuracy of accelerometer equations to predict time in different intensity categories (light, moderate, hard) over a six hour period. The equations examined include the Freedson equation (20), the Swartz equation (53), the Nichols equation (36), and two versions of the Hendelman equation (24), one for lifestyle activity and one for walking and running only: Hendelman1 and Hendelman2, respectively. For all equations, the prediction of time spent in hard activity did not differ from the Cosmed values. The Freedson (20) equation significantly overestimated time spent in light intensity activity by 13% and significantly underestimated time spent in moderate intensity activity by 60%. Hendelman1 (24) significantly underestimated light intensity activity by 29% and significantly overestimated moderate activity by 120% (52). In contrast, Hendelman2 (24) significantly overestimated light intensity activity by 14% and significantly underestimated moderate intensity by 60% (52). Additionally, the Nichols (36) equation significantly overestimated light intensity activity by 12% and significantly underestimated moderate intensity by 55% (52). Finally, there were no significant mean differences for all three categories using the Swartz equation (52, 53). These findings illustrate that there is great variability between prediction equations for time spent in intensity using accelerometers worn on the hip. This serves as a warning that it is difficult to accurately determine time spent in activity intensity using current methods.

Crouter et al. (14) examined the validity of the 2006 Crouter (13) and 2010 Crouter (15) algorithms for assessing free-living activity over the course of a six hour period. These algorithms use a two regression approach instead of the standard single regression approach that had been previously used. When compared to mean measured energy expenditure (1.90 ± 0.68 METs) for the bout, the Crouter 2010 (15) algorithm (2.08 ± 0.77 METs) was not significantly different but the 2006 Crouter (13) algorithm (2.32 ± 0.84 METs) was significantly different ($p < 0.05$). The Crouter 2010 (15) algorithm significantly underestimated sedentary time by 20.8% ($p < 0.05$) but significantly underestimated time spent in light, moderate and vigorous activity by 9.5%, 44.5% and 62.4% ($p < 0.05$) respectively. In contrast, the Crouter 2006 (13) algorithm showed no significant differences between measured time and time spent in sedentary behavior and vigorous activity. Light intensity activity was significantly underestimated by 34.4% ($p < 0.05$) and moderate intensity activity was significantly overestimated by 76.5% ($p < 0.05$). Additionally, there were significant differences between algorithms for time spent in sedentary, light and moderate activity but not vigorous activity ($p < 0.05$). The findings in this study call in to question the ability of two regression models to be more accurate than single regression models. While the Crouter 2010 (15) algorithm was an improvement from the Crouter 2006 (13) algorithm, there are still issues that need to be resolved to reduce the over-and under-estimation that occurs across all activity types.

The Plateau Effect

One major flaw that has been with the ActiGraph is best known as the plateau effect. This issue stems from the error that occurs when count values do not increase as energy expenditure and running speed or exercise intensity increases. Several notable articles have been published outlining this flaw with the ActiGraph devices (7, 12, 13, 22, 25, 26, 28, 44). The most studied example of this occurs during high intensity vigorous running at and above approximately 6 miles per hour (22, 25, 26, 28). This phenomena was first noted when Brage et al (7) were examining the ActiGraph, formerly CSA, accelerometer model 7164 for walking and running activities. The results indicated that the device output increased linearly for walking but not during running beginning at speeds of 9 km/hr. The margins of error ranged from 11% at 10 km/hr all the way up to 48% at 16 km/hr (7). The error was attributed to the fact that there is relatively constant vertical acceleration at faster running speeds and the model 7164 device utilizes a uniaxial accelerometer exclusively (7).

The inverted-u phenomenon has been seen not only in the uniaxial models of the ActiGraph such as the 7164 but also in the triaxial GT3X devices for the vertical axis as well

(25, 27). It should also be noted that the activity counts were similar across all generations of ActiGraph models for the vertical axis (25). The underlying issue is the inability of the ActiGraph to detect acceleration above a specific threshold of approximately 2.5 Hz, the known upper limit of the ActiGraph's default bandpass filter frequency range (7, 44, 45). This means that as running speed or exercise intensity increases count values level off and decrease due to the higher acceleration signal frequency associated with higher intensity activity being filtered out by the bandpass filter limits. This results in similar activity count values and thus similar EE prediction values for two very different intensities (22). In addition to the upper limit of the bandpass filter being important, recent research has explored the low frequency extension (LFE) feature available for the ActiGraph GT3X+ devices in the Actilife software. Cain et al. (8) studied whether the LFE being turned on or off impacted results, specifically for low intensity activities. Results indicated that the LFE should be used for low intensity activities because it increases sensitivity at the low end of the bandpass frequency filter range. In doing so, results gathered using newer ActiGraph devices such as the GT3X+ can be more readily compared to older devices such as the 7164 (8).

The factors that cause the plateau effect are unknown. An early theory suggested that it was because the ActiGraph models were uniaxial and only measured acceleration along the vertical axis (7, 25). This theory is incorrect because even the triaxial GT3X+ model still experiences the plateau effect for other axes including the vector magnitude of the axes for data collected at the hip. Another theory is that the plateau effect is due to the acceleration signal filtering properties of the device (7, 44, 45). The study of John et al., (26) noted that the peak acceleration measured occurred when running at speeds between 10 and 12 km/hr rather than 18 to 20 km/hr illustrating marked attenuation of the acceleration signal at the fastest running speeds. This suggests that increasing the upper limit of the bandpass filter frequency range would reduce the attenuation of the acceleration signal at faster running speeds and thus given a better representation of the energy expenditure for those intensities via more accurate count values.

CHAPTER III: MANUSCRIPT

Introduction

Obtaining an accurate measure of physical activity is vital for establishing guidelines for health and to better understand the metabolic requirements of physical activity. This is especially true for free-living physical activity, which can be more challenging for researchers to measure. Objective monitoring through the use of wearable, accelerometer-based devices has been shown to be an effective method for measuring physical activity over short durations ranging from one day down to 1-minute in free-living environments (12, 13, 14, 33). One of these devices, the ActiGraph, has been shown to provide valid and reliable measures of physical activity for a wide range of lifestyle and locomotive activity (33). The ActiGraph can be used to estimate energy expenditure through the use of prediction equations developed using criterion methods such as indirect calorimetry or doubly labeled water (12, 13, 33). This process, known as calibration, uses the device output from the ActiGraph, typically counts, to predict energy expended during specific time points and activities (10).

Counts are derived from the instantaneous acceleration signal detected by the device, which corresponds to the intensity of an activity (10). The instantaneous acceleration signal is passed through a low-pass filter that allows acceleration below a certain threshold to pass while attenuating any acceleration above that threshold. Acceleration data is then full-wave rectified where the absolute value of all the acceleration signals is essentially taken, converting any negative values to positive values (10). ActiGraph employs a bandpass filter that includes a range of frequencies with an upper and lower limit (e.g. 0.25-2.5 Hz). The bandpass filter is applied to the positive acceleration values where any acceleration signal falling outside of the upper and lower limits of the bandpass filter frequency range is attenuated. At this time, an algorithm is used to integrate the digital acceleration signal and generate output in the form of counts per epoch e.g. counts per 30 seconds) (10). The filtering properties employed by ActiGraph have a direct impact on the counts generated from collected data. This is evident with running speeds above 6 miles per hour where count values begin to level off and eventually begin decreasing (7, 22, 26, 45). This issue been termed the plateau effect and is characteristic of all ActiGraph models (26). This plateau effect is believed to be related to the filtering properties of the ActiGraph, specifically bandpass filter employed by ActiGraph (0.25-2.5 Hz) (7, 22, 26). While the plateau effect has been well documented in the literature, it has become of point of interest to resolve the issue. With the help of ActiGraph, a beta version of their ActiLife software has been developed that allows for structured manipulation of the upper limit of the bandpass filter frequency range.

To date, no study has investigated manipulating the bandpass filter frequency range of the ActiGraph mostly due to the inability to do so in the device software, Actilife. In order to explore the effects of the bandpass filter issue further, ActiGraph provided a beta version of Actilife with additional bandpass frequency filtering options. The purposes of this study were: 1) to explore how increasing the bandpass filter frequency range affected counts collected during treadmill walking and running, car driving, as well as light, moderate, and vigorous intensity lifestyle activities, 2) to investigate to see if increasing the bandpass filter frequency range would reduce the plateau in counts with increasing intensity during treadmill running, 3) to explore how increasing the bandpass filter frequency range affected sedentary activities such as car driving with the low frequency extension (LFE) feature turned on, and 4) to investigate to see if there was also a plateau in counts for moderate to vigorous lifestyle activities with a similar MET value to running at 6 mph and if so how the plateau would be affected by increasing the bandpass filter frequency range. It was hypothesized that: 1) increasing the bandpass filter frequency range would reduce the plateau in counts with increasing running speeds and result in a more linear relationship between speed and counts 2) counts for sedentary activity such as car driving will increase as the bandpass frequency filter range is increased 3) moderate to vigorous intensity lifestyle activities would experience a plateau in counts but increasing the bandpass filter frequency range would reduce the plateau resulting in a more linear relationship between counts and intensity.

Methods

Participants

Participants were recruited via word of mouth, flyers, and email from The University of Tennessee, Knoxville and the Knoxville Community. Exclusion criteria included pregnancy, Class II obesity (BMI $\geq$ 35 kg/m^2), or orthopedic or musculoskeletal issues that would limit activity. Participants were given a verbal explanation of the study, screened for exclusion criteria using the Physical Activity Readiness Questionnaire (PAR-Q), and prior to participation, signed an informed consent form. This study was conducted with approval from The University of Tennessee Institutional Review Board.

Procedures

This study was divided into two parts. Part A included treadmill walking and running, as well as car driving and included twenty participants (mean ± SD; age, 24.4 ± 3.4 years; Body Mass Index (BMI, 26.4 ± 3.3 kg/m^2). Part B included lifestyle activities and included thirty participants (mean ± SD; age, 23.0 ± 2.3 years; BMI, 25.1 ± 3.8 kg/m^2).

In part A, participants (N = 20) were asked to walk (3, 5, 7 km/hr) and run (8, 10, 12, 14, 16, 18, 20 km/hr) on a treadmill for 30 seconds at each speed with a 30 second rest between stages.

Following the treadmill walking and running, participants drove a car for approximately 12 minutes around a pre-measured loop totaling about three miles with a maximum speed of 45 miles per hour. In part B, participants (N = 30) were asked to complete a structured routine of physical activities consisting of ten total activities that took approximately 90 minutes to complete. Start and completion times for each activity were recorded. Participants were asked to perform each activity for seven minutes, with a minimum of two minutes of transition time between activities. Activities were completed as follows:

1) Supine rest
2) Seated computer work
3) Table top cleaning
4) Sweeping the floor
5) Overground walking at a self-selected pace on a tennis court, track, or gym floor
6) Ascending and descending stairs at a self-selected pace
7) One-on-one basketball
8) Singles tennis
9) Over-ground slow running at a self-selected pace on a tennis court, track, or gym floor
10) Over-ground fast running at a self-selected pace on a tennis court, track, or gym floor

Participant's height and weight were measured in light clothing and without shoes, using a stadiometer and calibrated physician's scale, respectively. All Participants were fitted with a heart rate monitor. Participants in part A wore an ActiGraph GT3X+ while participants in part B wore an ActiGraph GT9X (right hip, each wrist, each ankle). In addition to the ActiGraph

GT9X, part B participants were fitted with a Cosmed $K4b^2$ portable calorimeter as a criterion measure of energy expenditure.

<u>Devices</u>

ActiGraph GT3X+: The ActiGraph GT3X+ is a small (4.6 x 3.3 x 1.5 cm) tri-axial accelerometer that can be mounted to the wrist, ankle, waist, and thigh. It is lightweight (19 grams) and has a sampling rate of 30-100 Hz that measures acceleration in the dynamic range of ±6 G’s. Devices were initialized to sample data at 30 Hz.

ActiGraph GT9X Link: The ActiGraph GT9X is a small (3.5 x 3.5 x 1.0 cm) tri-axial accelerometer that is lightweight (14 grams) and has a sampling rate of 30-100 Hz that measures acceleration in the dynamic range of ±8 G’s. Devices were initialized to sample data at 80 Hz.

Cosmed $K4b^2$: Participants wore a Cosmed $K4b^2$ (Cosmed, Rome, Italy) portable metabolic system (170 x 55 x 100 mm) for the entirety of the activity routine. The Cosmed system consists of a gas analyzer unit and a battery unit. The device is lightweight (approximately 800 grams) and is worn using a harness designed by the manufacturer in addition to a facemask. The Cosmed $K4b^2$ is valid for use in measuring oxygen consumption during physical activity (30, 34). Following manufacturer guidelines, a 4-step calibration was performed before each test (11). A room air calibration was performed using the temperature and relative humidity of the room. Next, a reference gas calibration was performed with a specialized gas mixture 15.98% O_2 and 4.008% CO_2. A flow meter calibration was performed using a 3-L Hans Rudolf syringe. Lastly, a delay calibration is conducted to account for any delay that may occur between exhalation and the gas analyzer sensors.

Data Processing

All acceleration data collected were analyzed using a beta version of ActiGraph's Actilife software that was exclusively provided for the purpose of this study. This software includes several band pass filter frequency ranges that allowed acceleration data to be filtered at several different frequencies including ActiGraph's default filter (0.25-2.5 Hz) as well filters with upper limits of 5.0 Hz and a 9.0 Hz, respectively. All acceleration data were downloaded and converted to 5-second epochs to provide a mean count value per five seconds. The low frequency extension (LFE) feature was enabled for all analyses.

VO_2 (ml/min) data collected by the Cosmed were averaged over 30-second time periods and then converted to relative VO_2 (ml/kg/min) for each activity performed. Each participant's body weight in kilograms was used for supine rest and computer work. An additional 2 kilograms was added to bodyweight for the other eight activities to account for the weight of all devices. These values were then converted to METs by dividing by 3.5. MET values from the average of minutes 1.5-5.5 for each activity were used for comparative analysis between measured energy expenditure and count values for each bandpass filter frequency.

Statistical Analysis

Statistical analyses were conducted through IBM SPSS statistical software version 23 (IBM, Armonk, NY). For all analyses, alpha of 0.05 was used to denote statistical significance. All data are presented as mean ± standard deviation.

For the treadmill walking and running a one-way 3x10 repeated measures ANOVA (counts x speed) was used to determine main effects and interaction effects between speeds for each bandpass filter frequency condition for each axis. Pairwise comparisons with Bonferroni adjustments were performed to determine significant differences in counts between speeds within a single bandpass filter condition for each axis.

For car driving, a one-way repeated measures ANOVA (counts x bandpass filter) was used to determine main effects and interaction effects between counts and each bandpass filter frequency condition for each axis. Pairwise comparisons with Bonferroni adjustments were performed to determine significant differences in counts between bandpass filter conditions for a single axis.

For the lifestyle activities a one-way repeated measures ANOVA (counts x bandpass filter) was used to determine main and interaction effects between counts and each bandpass filter frequency condition for each activity. Pairwise comparisons with Bonferroni adjustments were performed to determine significant differences in counts between bandpass filter conditions within a single activity for each axis. Regression analyses were performed to determine the relationship between count values and measured energy expenditure. These analyses were performed for all activities. Strong associations were defined as $R = 0.8 – 1.0$, moderate associations were $R = 0.4 - 0.79$, and weak associations were $R = 0.1 - 0.39$.

Results

Participant characteristics are presented in Table 1 for treadmill walking, running and car driving and in Table 2 for lifestyle activities.

Treadmill Walking and Running

For treadmill walking and running, there were significant main effects for speed ($F=231.34$, $df=2$, $p<0.001$) and bandpass filter condition ($F=452.57$, $df=2$, $p<0.001$) as well as a significant interaction effect for speed x bandpass filter ($F=100.59$, $df=18$, $p<0.001$) for axis 1. Significant differences between speeds within each bandpass filter frequency condition were examined with Bonferroni adjustments and can be seen in Table 3 showing count values for axis 1. Using the default bandpass filter (0.25-2.5 Hz) counts increase significantly ($p < 0.05$) between speeds up to 10 km/hr at which point counts begin to level off and eventually decrease significantly ($p < 0.05$) from 16 to 20 km/hr . For axis 1 using the 0.25-5.0 Hz filter, counts increase significantly ($p < 0.05$) up to 12 km/hr at which point they continue to increase but not significantly up to 16 km/hr where counts level off and decrease but not significantly. For axis 1 using the 0.25-9.0 Hz filter, counts increase significantly ($p < 0.05$) up to 16 km/hr at which point they continue to increase but not significantly.

Table 4 presents results for axis 2 where there were significant main effects for speed ($F=132.13$, $df=2$, $p<0.001$) and bandpass filter condition (F= $F=278.78$, $df=2$, $p<0.001$) as well as a significant interaction effect for speed x bandpass filter ($F=52.06$, $df=18$, $p<0.001$). Bonferroni adjustments showed intermittent significant ($p < 0.05$) increases across speeds for all three bandpass filter frequency ranges with the most consistent significant increases in counts between speeds occurring when using the 0.25-9.0 Hz filter. For all three bandpass filter frequency ranges, counts increased across speed with no leveling off or decreases in counts occurring. Table 5 presents results for axis 3 where there were again significant main effects for speed ($F=13.46$, $df=2$, $p<0.001$) and bandpass filter condition ($F=143.77$, $df=2$, $p<0.001$) as well as a significant interaction effect for speed x bandpass filter ($F=103.58$, $df=18$, $p<0.001$). Also similarly to axis 2, axis 3 Bonferroni adjustments show continuous increases between speeds for all three bandpass filter frequency ranges. There were no significant differences between speeds for the default filter and only intermittent significant ($p < 0.05$) increases in speeds for the 0.25-5.0 and 0.25-9.0 Hz filters.

Table 6 shows results for the vector magnitude of axes 1, 2, and 3 where there were significant main effects for speed (F=405.49, df=2, $p<0.001$) and bandpass filter condition (F= F=560.60, df=2, $p<0.001$) as well as a significant interaction effect for speed x bandpass filter (F=193.12, df=18, $p<0.001$). Similarly to axis 1, Bonferroni adjustments showed significant ($p < 0.05$) increases in counts for the default filter up to 10 km/hr at which point counts begin to level off and decrease and eventually significantly decrease from 18-20 km/hr. Using the 0.25-5.0 Hz filter showed significant ($p < 0.05$) increases in counts up to 12 km/hr at which point counts continued to increase and eventually leveled off between 18-20 km/hr. The 0.25-9.0 Hz filter showed significant ($p < 0.05$) increases in counts between all speeds.

Figure 1 illustrates the relationship between mean counts per five seconds and speed for all three axes and vector magnitude. For all axes and vector magnitude, an improvement in R^2 was seen indicating an improvement in the linearity of the relationship between counts and intensity. This is most evident in the change in R^2 for the default filter to 9.0 Hz filter for axis 1 and vector magnitude. R^2 changed from 0.43 to 0.83 for axis 1 and 0.53 to 0.90 for vector magnitude showing significant improvement.

Car Driving

For car driving, there was a significant main effect for bandpass frequency filter condition on counts for all axes and vector magnitude with axis 1 (F=161.39, df=2, $p<0.001$), axis 2 (F=53.93, df=2, $p<0.001$), axis 3 (F=72.05, df=2, $p<0.001$), and vector magnitude (F=135.82, df=2, $p<0.001$), respectively. Bonferroni adjustments were performed to determine significant differences in counts between bandpass filter conditions for each axis. These results can be seen in Figure 2. There were significant differences ($p < 0.05$) between each bandpass filter frequency condition for all axes and vector magnitude.

Lifestyle Activity

Mean measured METs for each of the 10 lifestyle activities are presented in Table 7. There were significant main effects for bandpass filter frequency condition ($F=1203.06$, $df=2$, $p<0.001$) and activity ($F=349.49$, $df=2$, $p<0.001$) as well as an interaction effect for bandpass filter x activity ($F=113.42$, $df=18$, $p<0.001$) for axis 1. For axis 2, there were significant main effects for bandpass filter frequency condition ($F=558.10$, $df=2$, $p<0.001$) and activity ($F=204.99$, $df=2$, $p<0.001$) as well as an interaction effect for bandpass filter x activity ($F=51.98$, $df=18$, $p<0.001$). For axis 3, there were significant main effects for bandpass filter frequency condition ($F=261.86$, $df=2$, $p<0.001$) and activity ($F=181.91$, $df=2$, $p<0.001$) as well as an interaction effect for bandpass filter x activity ($F=68.87$, $df=18$, $p<0.001$). Lastly for vector magnitude, there were significant main effects for bandpass filter frequency condition ($F=1593.44$, $df=2$, $p<0.001$) and activity ($F=348.52$, $df=2$, $p<0.001$) as well as an interaction effect for bandpass filter x activity ($F=180.73$, $df=18$, $p<0.001$). Bonferroni adjustments were performed to determine significant differences in count values between bandpass filter frequency conditions for each activity. Significant differences were seen for the following activities: table cleaning, sweeping, walking, stair walking, basketball, tennis, slow running, and fast running for all axes including vector magnitude (Tables 8 through 11, $p < 0.05$). No significant differences in counts were seen between the default and 0.25-5.0 Hz filter conditions for supine rest. For computer work there were no significant differences between the default and 0.25-5.0 Hz bandpass filter frequency conditions for axis 3 only.

Regression lines were generated for each axis for 1) the full activity routine (Figures 3, 4, 5, 6), 2) locomotive activity only (Figures 7, 8, 9, 10), and 3) lifestyle activity only (Figures 11, 12, 13, 14).

For the full activity routine axis 1 (Figure 3), all three bandpass filter conditions showed strong associations ($R \geq 0.80$) with the default filter producing the best result ($R = 0.87$). For axis 2 (Figure 4), all three bandpass filters again showed strong associations between counts and energy expenditure with the 0.25-5.0 Hz filter producing the strongest result ($R = 0.87$). For axis 3 (Figure 5), the 0.25-5.0 Hz and 0.25-9.0 Hz filter produced strong associations ($R \geq 0.80$) while the default filter showed a moderate association ($R = 0.74$). The best result for axis 3 was the 0.25-5.0 Hz filter with an $R = 0.85$. Lastly, the results from the vector magnitude (Figure 6) showed that similar to axis 1 the default filter performed the best with an $R = 0.91$ but all three bandpass filters produced a strong association between counts and energy expenditure.

For the locomotive activity, axis 1 (Figure 7) and vector magnitude (Figure 10) showed the 0.25-5.0 and 0.25-9.0 Hz filters produced similar results both having strong associations ($R \geq 0.80$) between counts and energy expenditure with $R = 0.92$. Axis 2 (Figure 8) and axis 3 (Figure 9) showed lower R values with the highest being the moderate associations of the 0.25-9.0 Hz filter with an $R = 0.77$ and $R = 0.71$, respectively.

For the lifestyle activities (Figures 11 through 14), all three bandpass filter conditions produced strong associations ($R \geq 0.80$) for all axes including vector magnitude. The highest performing bandpass filter was the 0.25-5.0 Hz filter with R values = 0.94, 0.93, 0.87, and 0.95 for axis 1 (Figure 11), 2 (Figure 12), 3 (Figure 13), and vector magnitude (Figure 14), respectively

Discussion

The primary findings from this study are that: 1) increasing the bandpass filter frequency range significantly alters count values for all activities including laboratory-based as well as intermittent, lifestyle activities, 2) increasing the bandpass filter frequency range reduces the plateau in counts at increasing speeds for treadmill walking and running, and 3) There is no discernable plateau in counts based on the results for the activities chosen for this study.

As hypothesized, increasing the upper limit of the bandpass filter frequency range improved the relationship between counts and intensity for treadmill walking and running. The relationship between counts and speed becomes more linear, and counts no longer level out and then decrease at higher running speeds. Improvement was seen from the default setting by increasing the upper limit of the bandpass filter frequency range to 5.0 Hz but the best results are seen when using an upper limit of 9.0 Hz as there is a significant increase in counts between all speeds for vector magnitude. This illustrates an improved relationship between counts and speed as thus should allow for improved energy expenditure estimation and a more linear relationship between counts and energy expenditure for these activities since the plateau effect can be minimized. Conversely, increasing the upper limit of the bandpass filter frequency range also significantly altered the count values for car driving. This issue is one of the reasons the low frequency of 2.5 Hz was employed as the upper limit of the default filter frequency range to begin with. As the filter frequency range was increased, count values for each axis also significantly increased producing nearly 40 counts per 5 seconds for vector magnitude with the 0.25-9.0 Hz filter. This could significantly impact energy expenditure estimation for sedentary activities such as car driving since count values could be going from < 100 counts per minute to nearly 250 counts per minute. This would become an issue since the standard cut-point for sedentary activity is 100 counts per minute, and thus car driving would then be considered light intensity physical activity unless a new threshold and cut-point for sedentary behavior were to be developed.

It was hypothesized that there would be a plateau in counts for moderate to vigorous lifestyle activities that generate similar acceleration values and have similar MET values to running at 6 mph, where the plateau effect starts to be exhibited. This however was not the case, as no discernable plateau was seen in the counts for the lifestyle activities with increasing intensity for the activities selected for this study. It was hypothesized that increasing the bandpass filter frequency would increase the counts for light, moderate, and vigorous intensity lifestyle activities. This hypothesis was correct as significant differences were seen in count values across bandpass filters and the strength of association and linearity of the relationship between count and METs also varied across bandpass filter conditions depending on the type of activity being performed.

After studying the results from the Crouter 2-regression (13) model (C2RM) it was believed that increasing the bandpass frequency filter would cause counts to increase causing convergence of the two regression lines in the C2RM (13) model. The C2RM (13) model was developed to improve the accuracy of energy expenditure estimation. It uses two regression lines instead of the traditional single regression to better fit the locomotive activity and lifestyle activity. Together those two regression lines do a better job of predicting energy expenditure in most cases. Results from this study show the opposite occurring with the two lines diverging instead of converging and becoming singularly more linear. This is evident with the default filter producing the most linear results for axis 1 and vector magnitude when looking at the full routine. As the bandpass filter is increased, the counts for locomotive and lifestyle activities diverge and produce a less linear relationship for the full activity routine. When split out individually, results for locomotive and lifestyle activities differed. Increasing the upper limit of the bandpass filter frequency range to 9.0 Hz for locomotive activity produced the best results similarly to what is seen with the results from treadmill walking and running, while the upper limit of 5.0 Hz produced the strongest results for lifestyle activities.

There are several strengths and limitations to this study with one of the main limitations stemming from the 9.0 Hz bandpass filter. ActiGraph confirmed after consultation that there is an error in the software for the 9.0 Hz filter that led to errors with counts most notably the low intensity lifestyle activities such as supine rest and computer work. This issue will be resolved and results corrected to reflect the changes but it should be noted that the significant differences seen for supine rest and computer work across bandpass filters may be due to this software error. A major strength of this study is the combination of lifestyle activities coupled with treadmill walking and running as well as car driving. These activities give a broad overview of how the bandpass filter affects different activities for all axes as well as vector magnitude at the hip. Additionally, this study is the first to attempt to manipulate the bandpass filter frequency range for the ActiGraph.

The results of this study are promising for the continued use of ActiGraph devices. More work needs to be done to refine this process but there is promise in the ability to manipulate the bandpass filter frequency for future research. This could lead to more accurate energy expenditure prediction models developed using counts obtained through a wider bandpass filter frequency range.

In conclusion, it should be noted that increasing the upper limit of the bandpass filter frequency range to 9.0 Hz for the ActiGraph will improve the relationship between counts and energy expenditure for treadmill walking and running therefore reducing the plateau effect. Additionally, increasing the bandpass filter frequency range for lifestyle activities can produce more linear results between measured METs and counts but this should be done with caution as this improvement is activity-specific. Using the upper limit of 9.0 Hz for locomotive activities and 5.0 Hz for lifestyle activities excluding locomotive activity such as walking and running worked best. If the dataset contains a mix of both types of activities the default bandpass filter setting remains the most effective option.

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<u>APPENDIX</u>

Table 1. Physical characteristics of participants – treadmill walking, running, and car driving. Values are mean ± SD.

	Male (N = 17)	Female (N = 3)	All Participants (N=20)
Age (years)	24.4 ± 3.4	23.0 ± 3.0	24.2 ± 3.3
Height (cm)	181.2 ± 5.2	168.0 ± 5.7	179.2 ± 11.3
Weight (kg)	86.6 ± 8.3	64.8 ± 6.8	83.4 ± 11.3
BMI (kg/m^2)	26.4 ± 2.2	22.9 ± 2.1	25.9 ± 2.5

BMI: body mass index.

Table 2. Physical characteristics of participants – lifestyle activities. Values are mean ± SD.

	Male (N = 20)	Female (N = 10)	All Participants (N = 30)
Age (years)	23.1 ± 2.5	22.9 ± 1.9	23.0 ± 2.3
Height (cm)	179.0 ± 7.6	161.8 ± 6.4	173.2 ± 10.9
Weight (kg)	85.1 ± 15.0	59.4 ± 12.6	76.5 ± 18.7
BMI (kg/m^2)	26.4 ± 3.3	22.5 ± 3.5	25.1 ± 3.8

BMI: body mass index.

Table 3. Mean counts ± SD treadmill walking and running ActiGraph GT3X+ hip axis 1.

Speed	Default	0.25-5.0 Hz	0.25-9.0 Hz
3 km/hr	94.1 ± 27.3	189.9 ± 42.2	246.0 ± 58.0
5 km/hr	268.1 ± 45.1*	475.3 ± 69.9*	550.2 ± 76.0*
7 km/hr	417.1 ± 84.9*	866.2 ± 262.5*	990.4 ± 330.3*
8 km/hr	662.3 ± 134.1*	1742.0 ± 340.1*	2037.5 ± 405.9*
10 km/hr	728.0 ± 129.7*	2022.6 ± 312.6*	2368.7 ± 356.6*
12 km/hr	735.5 ± 123.1	2160.0 ± 316.1*	2558.5 ± 359.3*
14 km/hr	706.9 ± 125.5	2208.3 ± 308.1	2663.4 ± 342.5*
16 km/hr	664.5 ± 118.5*	2237.5 ± 301.0	2754.5 ± 337.4*
18 km/hr	603.6 ± 121.3*	2211.4 ± 336.8	2785.9 ± 368.6
20 km/hr	543.7 ± 109.7*	2157.4 ± 339.3	2802.0 ± 386.1
ANOVA	F=75.46, df=9, p<0.001	F=267.86, df=9, p<0.001	F=156.08, df=9, p<0.001

Average Counts per 5 seconds; * significantly different from previous speed, Alpha < p = 0.05; Default equal to 0.25-2.5 Hz

Table 4. Mean counts ± SD treadmill walking and running ActiGraph GT3X+ hip axis 2.

Speed	Default	0.25-5.0 Hz	0.25-9.0 Hz
3 km/hr	109.6 ± 43.4	189.1 ± 56.0	236.6 ± 60.7
5 km/hr	147.6 ± 43.0*	306.8 ± 80.6*	390.0 ± 98.0*
7 km/hr	202.7 ± 56.9*	467.0 ± 117.2*	605.1 ± 145.3*
8 km/hr	143.2 ± 65.8*	410.2 ± 133.1	570.9 ± 147.9
10 km/hr	163.3 ± 86.8	484.6 ± 175.5*	690.8 ± 191.3*
12 km/hr	183.4 ± 94.0*	560.0 ± 193.8*	834.0 ± 227.2*
14 km/hr	189.8 ± 87.7	623.0 ± 186.6	956.3 ± 238.7*
16 km/hr	210.9 ± 88.4*	689.3 ± 185.4*	1096.4 ± 263.1*
18 km/hr	240.1 ± 98.5*	779.8 ± 191.6*	1291.7 ± 286.2*
20 km/hr	272.4 ± 102.8	897.7 ± 169.9*	1554.5 ± 276.4*
ANOVA	F=14.92, df=9, p<0.001	F=95.70, df=9, p<0.001	F=143.04, df=9, p<0.001

Average Counts per 5 seconds; * significantly different from previous speed, Alpha < p = 0.05; Default equal to 0.25-2.5 Hz

Table 5. Mean counts ± SD treadmill walking and running ActiGraph GT3X+ hip axis 3.

Speed	Default	0.25-5.0 Hz	0.25-9.0 Hz
3 km/hr	94.1 ± 54.0	126.2 ± 56.0	142.7 ± 51.9
5 km/hr	94.4 ± 45.6	169.3 ± 64.1*	206.4 ± 65.6*
7 km/hr	110.7 ± 64.8	239.4 ± 103.0*	308.4 ± 110.5*
8 km/hr	142.0 ± 71.5	378.9 ± 172.9*	427.5 ± 191.4*
10 km/hr	152.5 ± 79.3	410.1 ± 189.1	522.7 ± 205.7*
12 km/hr	161.1 ± 76.6	428.7 ± 203.2	569.3 ± 226.5
14 km/hr	178.5 ± 73.9	480.2 ± 202.2	647.7 ± 237.7
16 km/hr	190.8 ± 74.3	494.5 ± 196.5	692.3 ± 229.5*
18 km/hr	203.1 ± 64.0	525.1 ± 199.8	776.8 ± 238.0*
20 km/hr	219.7 ± 68.2	551.1 ± 193.4	867.5 ± 246.1*
ANOVA	F=8.082, df=9, p=0.001	F=10.01, df=9, p<0.001	F=15.37, df=9, p<0.001

Average Counts per 5 seconds; * significantly different from previous speed, Alpha < p = 0.05; Default equal to 0.25-2.5 Hz

Table 6. Mean counts ± SD treadmill walking and running ActiGraph GT3X+ hip vector magnitude.

Speed	Default	0.25-5.0 Hz	0.25-9.0 Hz
3 km/hr	184.7 ± 37.4	306.0 ± 51.1	377.5 ± 68.8
5 km/hr	328.0 ± 42.1*	599.7 ± 75.6*	713.6 ± 94.7*
7 km/hr	483.8 ± 93.8*	1024.1 ± 267.4*	1213.2 ± 337.8*
8 km/hr	698.4 ± 142.3*	1841.0 ± 349.2*	2179.9 ± 417.5*
10 km/hr	769.4 ± 140.6*	2135.1 ± 318.0*	2536.3 ± 368.9*
12 km/hr	783.1 ± 135.7	2288.1 ± 327.8*	2766.0 ± 384.9*
14 km/hr	761.3 ± 136.3	2360.0 ± 315.7	2920.2 ± 368.2*
16 km/hr	731.2 ± 127.2	2408.4 ± 301.0	3063.2 ± 352.0*
18 km/hr	690.1 ± 130.1*	2420.1 ± 329.8	3188.1 ± 380.6*
20 km/hr	657.9 ± 117.0*	2417.1 ± 321.7	3341.8 ± 371.7*
ANOVA	F=46.56, df=9, p<0.001	F=452.64, df=9, p<0.001	F=250.75, df=9, p<0.001

Average Counts per 5 seconds; * significantly different from previous speed, Alpha < p = 0.05; Default equal to 0.25-2.5 Hz

Table 7: Measured metabolic equivalents (METs) by activity.

Activity	METS ± SD
Supine Rest	1.45 ± 0.25
Computer Work	1.52 ± 0.27
Table Cleaning	2.78 ± 0.68
Sweeping	3.39 ± 0.93
Walking (m/min)	3.62 ± 0.85
Stair Walking	6.48 ± 1.22
Basketball	7.83 ± 1.72
Tennis	7.40 ± 1.85
Slow Running (m/min)	8.14 ± 1.48
Fast Running (m/min)	9.68 ± 1.62

Table 8. Mean counts ± SD lifestyle activities ActiGraph GT9X hip axis 1.

Activity	Default	0.25-5.0 Hz	0.25-9.0 Hz	ANOVA
Supine Rest	0.0 ± 0.04	0.0 ± 0.06	62.7 ± 68.9*#	F=12.14, df=2, p<0.001
Computer Work	0.1 ± 0.16	1.0 ± 0.98*	331.2 ± 64.6*#	F=380.20, df=2, p<0.001
Table Cleaning	32.7 ± 32.0	74.5 ± 40.2*	342.1 ± 52.0*#	F=412.47, df=2, p<0.001
Sweeping	44.7 ± 36.9	93.0 ± 42.7*	370.1 ± 57.7*#	F=531.06, df=2, p<0.001
Walking	285.1 ± 85.8	508.8 ± 158.8*	680.1 ± 145.8*#	F=659.28, df=2, p<0.001
Stair Walking	327.6 ± 56.5	551.7 ± 111.2*	709.9 ± 112.3*#	F=708.26, df=2, p<0.001
Basketball	424.3 ± 111.3	765.5 ± 200.6*	976.4 ± 207.1*#	F=797.91, df=2, p<0.001
Tennis	314.9 ± 74.6	618.9 ± 162.0*	876.9 ± 214.2*#	F=203.51, df=2, p<0.001
Slow Running	701.0 ± 121.1	1890.7 ± 307.4*	2280.9 ± 330.8*#	F=565.28, df=2, p<0.001
Fast Running	767.5 ± 107.2	2151.3 ± 257.8*	2568.8 ± 304.7*#	F=742.29, df=2, p<0.001

Average Counts per 5 seconds; * significantly different from Default, # significantly different from 5.0 Hz, Alpha < p = 0.05; Default equal to 0.25-2.5 Hz

Table 9. Mean counts ± SD lifestyle activities ActiGraph GT9X hip axis 2 counts.

Activity	Default	0.25-5.0 Hz	0.25-9.0 Hz	ANOVA
Supine Rest	0.0 ± 0.0	0.0 ± 0.1	256.6 ± 65.8*#	F=220.70, df=2, p<0.001
Computer Work	0.7 ± 1.0	0.9 ± 1.2*	20.9 ± 34.7*#	F=12.40, df=2, p<0.001
Table Cleaning	81.8 ± 27.0	119.3 ± 36.3*	172.4 ± 50.9*#	F=83.94, df=2, p<0.001
Sweeping	104.5 ± 47.4	138.3 ± 53.0*	192.2 ± 79.4*#	F=127.29, df=2, p<0.001
Walking	165.2 ± 38.4	337.1 ± 88.7*	441.7 ± 119.3*#	F=115.82, df=2, p<0.001
Stair Walking	157.4 ± 25.0	300.9 ± 61.0*	398.9 ± 83.6*#	F=162.17, df=2, p<0.001
Basketball	266.8 ± 40.3	465.8 ± 79.5*	604.4 ± 104.1*#	F=339.00, df=2, p<0.001
Tennis	279.0 ± 33.6	469.1 ± 74.2*	607.4 ± 105.6*#	F=257.39, df=2, p<0.001
Slow Running	221.0 ± 59.1	558.0 ± 151.5*	812.6 ± 204.1*#	F=195.92, df=2, p<0.001
Fast Running	272.5 ± 69.2	732.1 ± 167.3*	1107.3 ± 237.5*#	F=244.66, df=2, p<0.001

Average Counts per 5 seconds; * significantly different from Default, # significantly different from 5.0 Hz, Alpha < p = 0.05; Default equal to 0.25-2.5 Hz

Table 10. Mean counts ± SD lifestyle activities ActiGraph GT9X hip axis 3.

Activity	Default	0.25-5.0 Hz	0.25-9.0 Hz	ANOVA
Supine Rest	0.0 ± 0.1	0.0 ± 0.1	150.9 ± 85.4*#	F=45.35, df=2, p<0.001
Computer Work	1.8 ± 3.0	2.1 ± 3.7	50.3 ± 61.7*#	F=13.59, df=2, p<0.001
Table Cleaning	110.0 ± 53.6	120.9 ± 55.6*	134.1 ± 57.7*#	F=87.57, df=2, p<0.001
Sweeping	141.6 ± 62.8	153.4 ± 65.6*	170.8 ± 66.0*#	F=65.44, df=2, p<0.001
Walking	113.8 ± 55.5	184.5 ± 74.3*	233.7 ± 81.0*#	F=95.80, df=2, p<0.001
Stair Walking	188.1 ± 39.0	234.2 ± 41.6*	269.2 ± 50.0*#	F=63.90, df=2, p<0.001
Basketball	267.3 ± 51.5	372.1 ± 85.4*	429.3 ± 100.2*#	F=155.81, df=2, p<0.001
Tennis	289.9 ± 48.0	392.8 ± 65.4*	449.4 ± 71.8*#	F=269.86, df=2, p<0.001
Slow Running	170.8 ± 67.3	422.4 ± 160.9*	553.4 ± 180.0*#	F=165.08, df=2, p<0.001
Fast Running	213.1 ± 71.8	495.5 ± 167.6*	648.5 ± 200.4*#	F=175.98, df=2, p<0.001

Average Counts per 5 seconds; * significantly different from Default, # significantly different from 5.0 Hz, Alpha < p = 0.05; Default equal to 0.25-2.5 Hz

Table 11. Mean counts ± SD lifestyle activities ActiGraph GT9X hip vector magnitude.

Activity	Default	0.25-5.0 Hz	0.25-9.0 Hz	ANOVA
Supine Rest	0.0 ± 0.1	0.0 ± 0.1	323.5 ± 62.3*#	F=391.28, df=2, p<0.001
Computer Work	2.3 ± 3.1	3.2 ± 3.9*	343.3 ± 66.1*#	F=391.34, df=2, p<0.001
Table Cleaning	152.0 ± 61.9	195.5 ± 70.1*	419.1 ± 54.6*#	F=540.48, df=2, p<0.001
Sweeping	193.7 ± 80.7	236.9 ± 88.0*	463.3 ± 87.1*#	F=220.23, df=2, p<0.001
Walking	356.3 ± 83.7	645.2 ± 173.0*	849.4 ± 849.4*#	F=547.99, df=2, p<0.001
Stair Walking	418.4 ± 53.6	680.6 ± 111.7*	864.6 ± 127.9*#	F=409.43, df=2, p<0.001
Basketball	581.8 ± 112.1	985.8 ± 211.5*	1238.5 ± 231.3*#	F=1008.76, df=2, p<0.001
Tennis	527.1 ± 81.5	888.0 ± 172.2*	1169.9 ± 230.1*#	F=228.45, df=2, p<0.001
Slow Running	761.3 ± 117.8	2029.4 ± 303.0*	2499.1 ± 333.2*#	F=658.36, df=2, p<0.001
Fast Running	849.3 ± 104.0	2338.9 ± 256.6*	2888.3 ± 316.5*#	F=855.74, df=2, p<0.001

Average Counts per 5 seconds; * significantly different from Default, # significantly different from 5.0 Hz, Alpha < p = 0.05; Default equal to 0.25-2.5 Hz

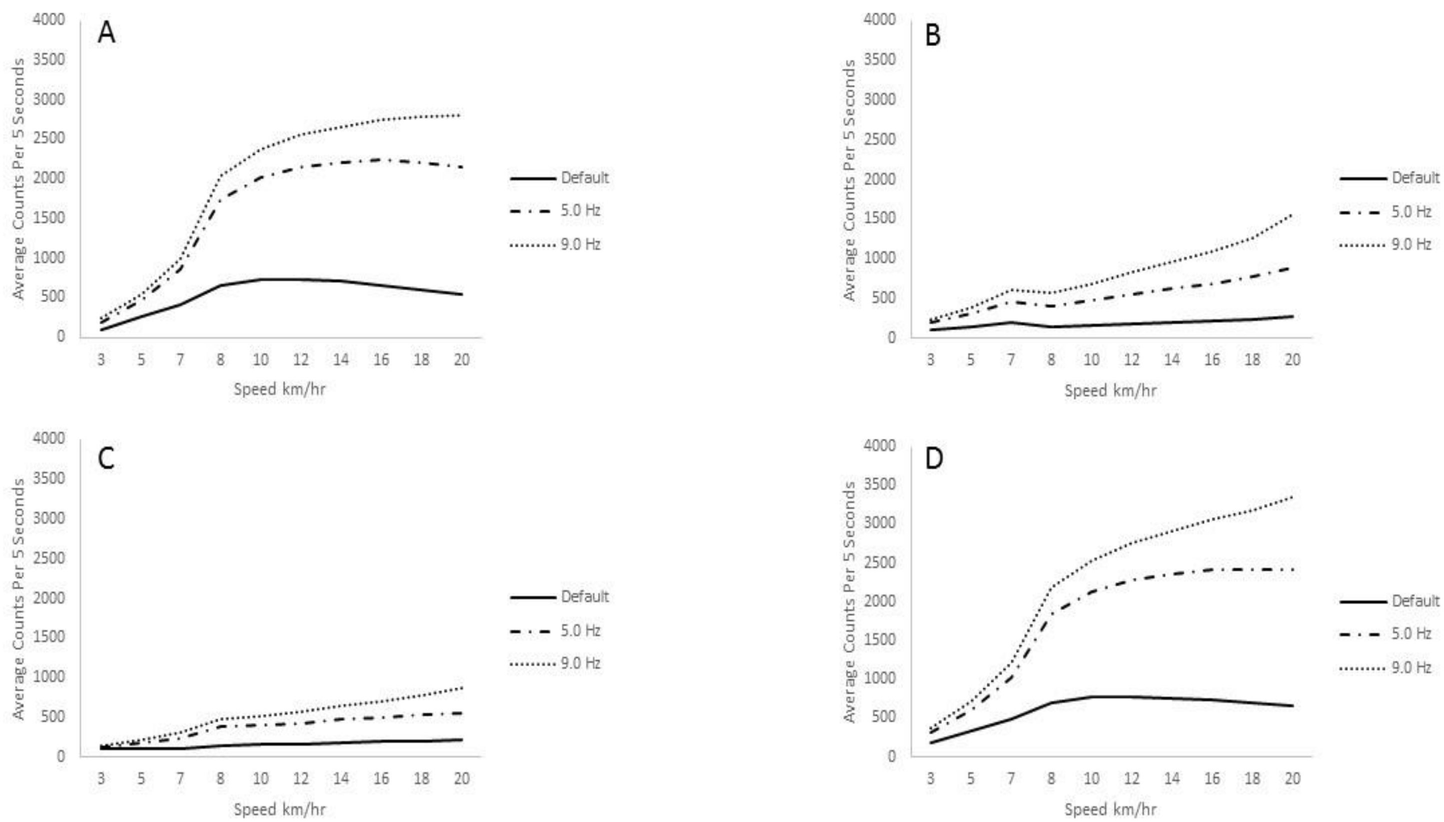
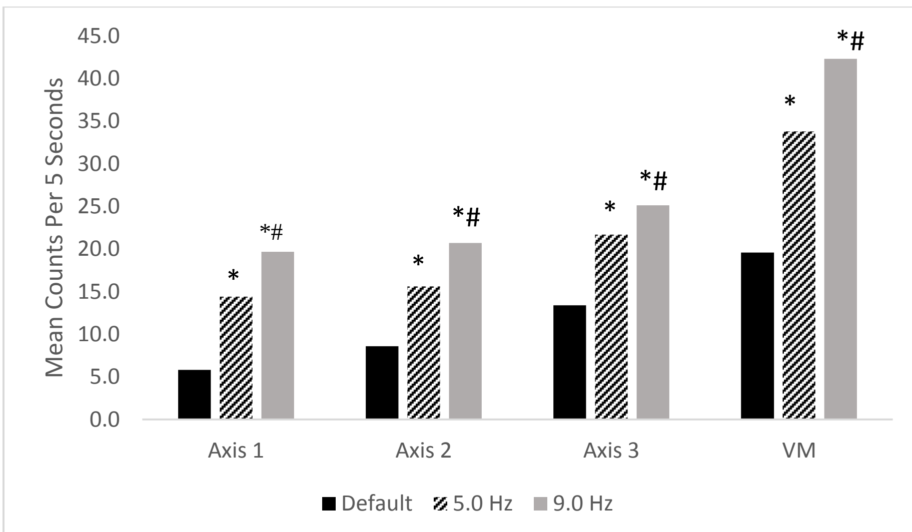


Figure 1: Mean ActiGraph GT3X+ hip counts per 5 seconds by bandpass filter: A) axis 1, B) axis 2, C) axis 3, D) vector magnitude



* Significantly different from Default, # significantly different from 5.0 Hz, Alpha < p = 0.05

Figure 2: Mean ActiGraph GT3X+ hip counts per 5 seconds, bandpass filter by axis – car driving

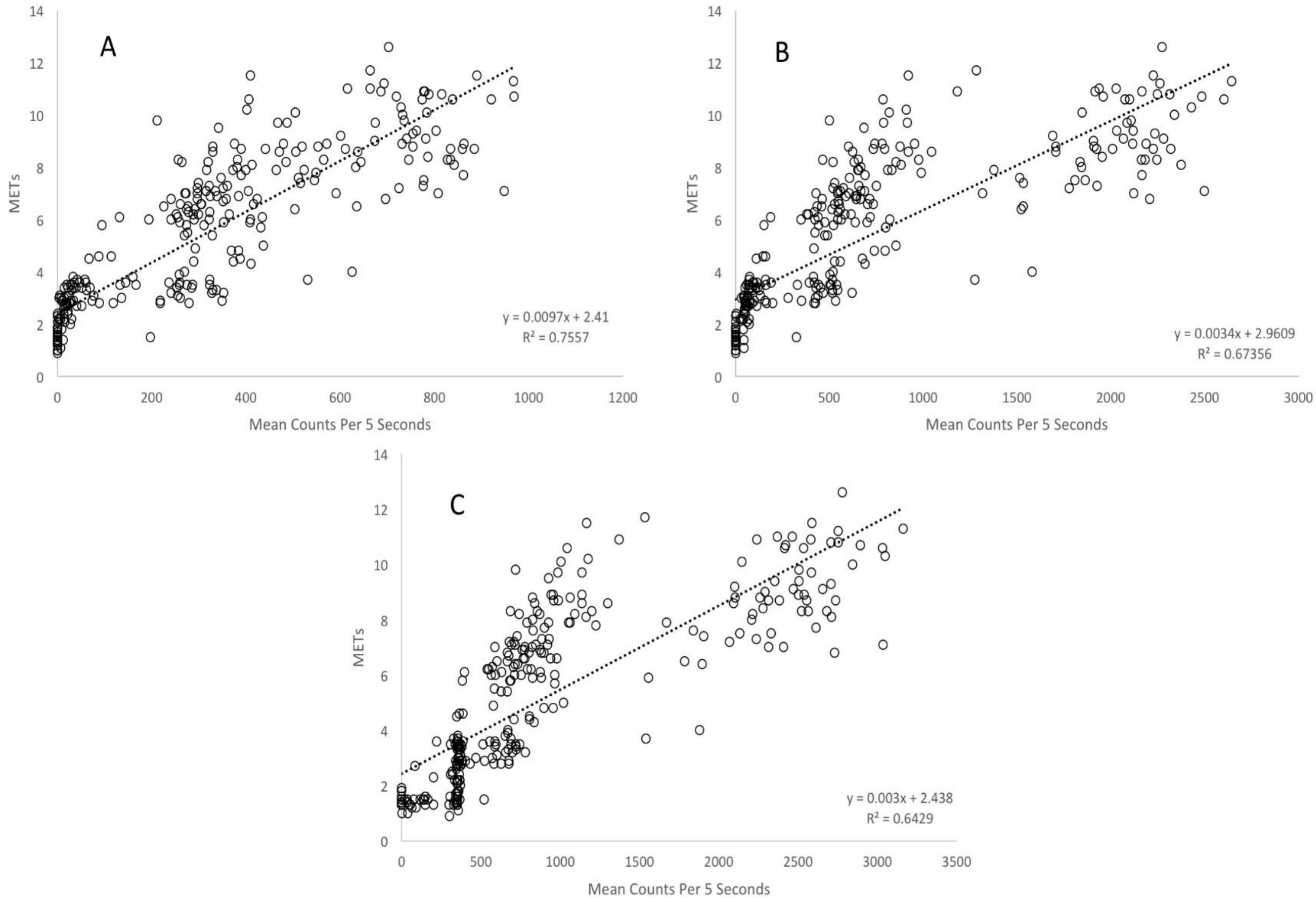


Figure 3: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip axis 1 by bandpass filter frequency – full activity routine: A) Default, B) 5.0 Hz, C) 9.0 Hz

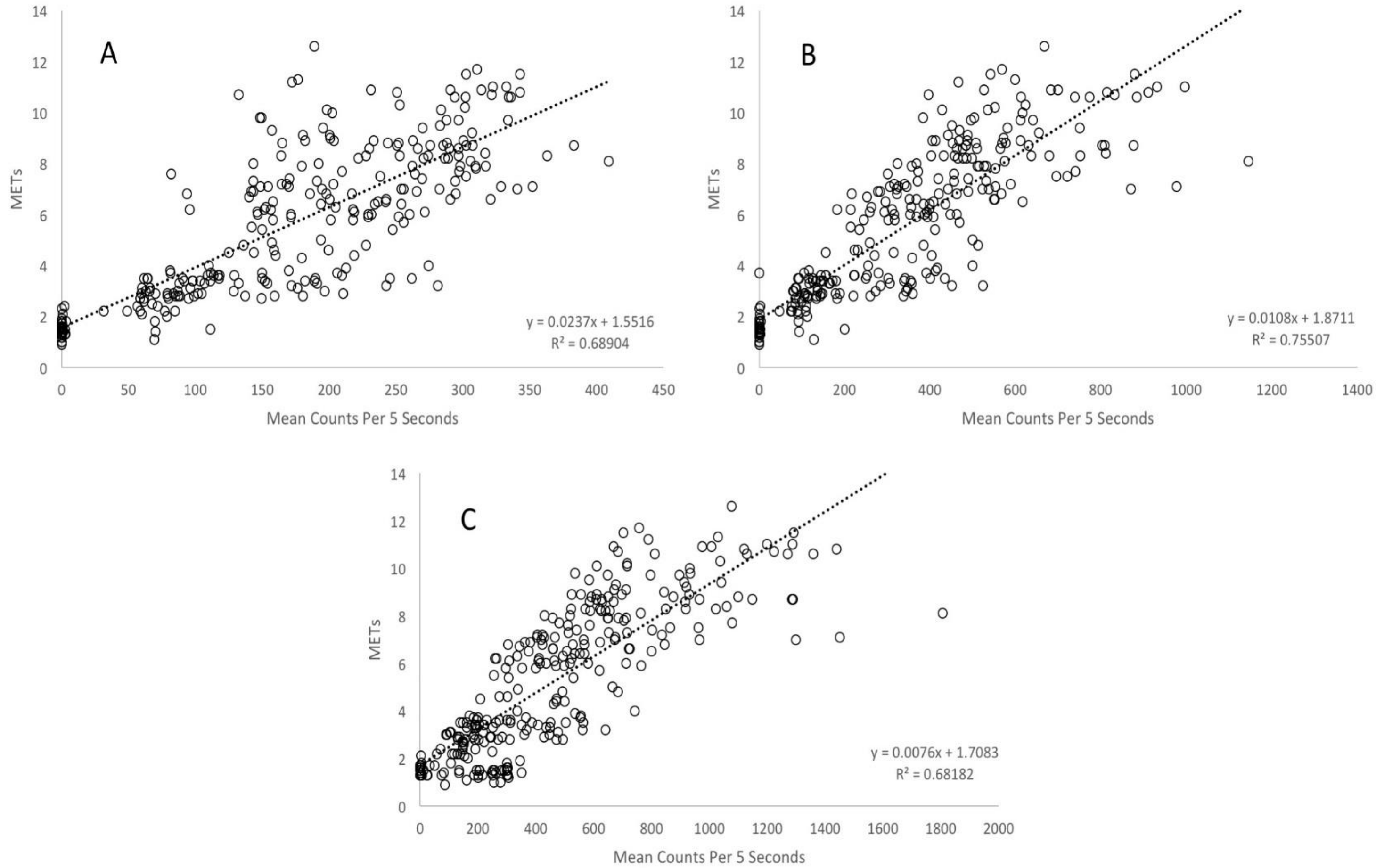


Figure 4: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip axis 2 by bandpass filter frequency – full activity routine: A) Default, B) 5.0 Hz, C) 9.0 Hz

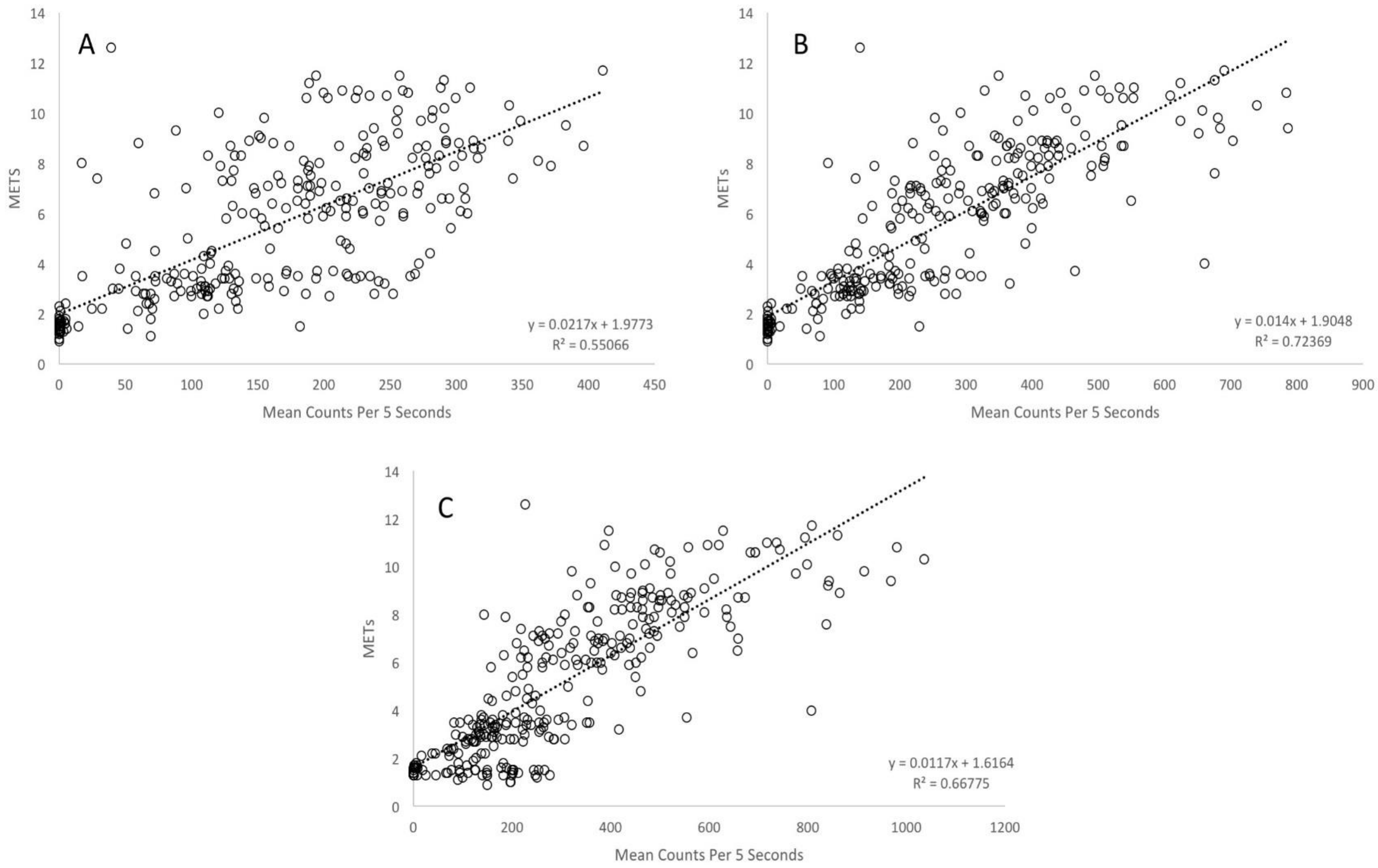


Figure 5: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip axis 3 by bandpass filter frequency – full activity routine: A) Default, B) 5.0 Hz, C) 9.0 Hz

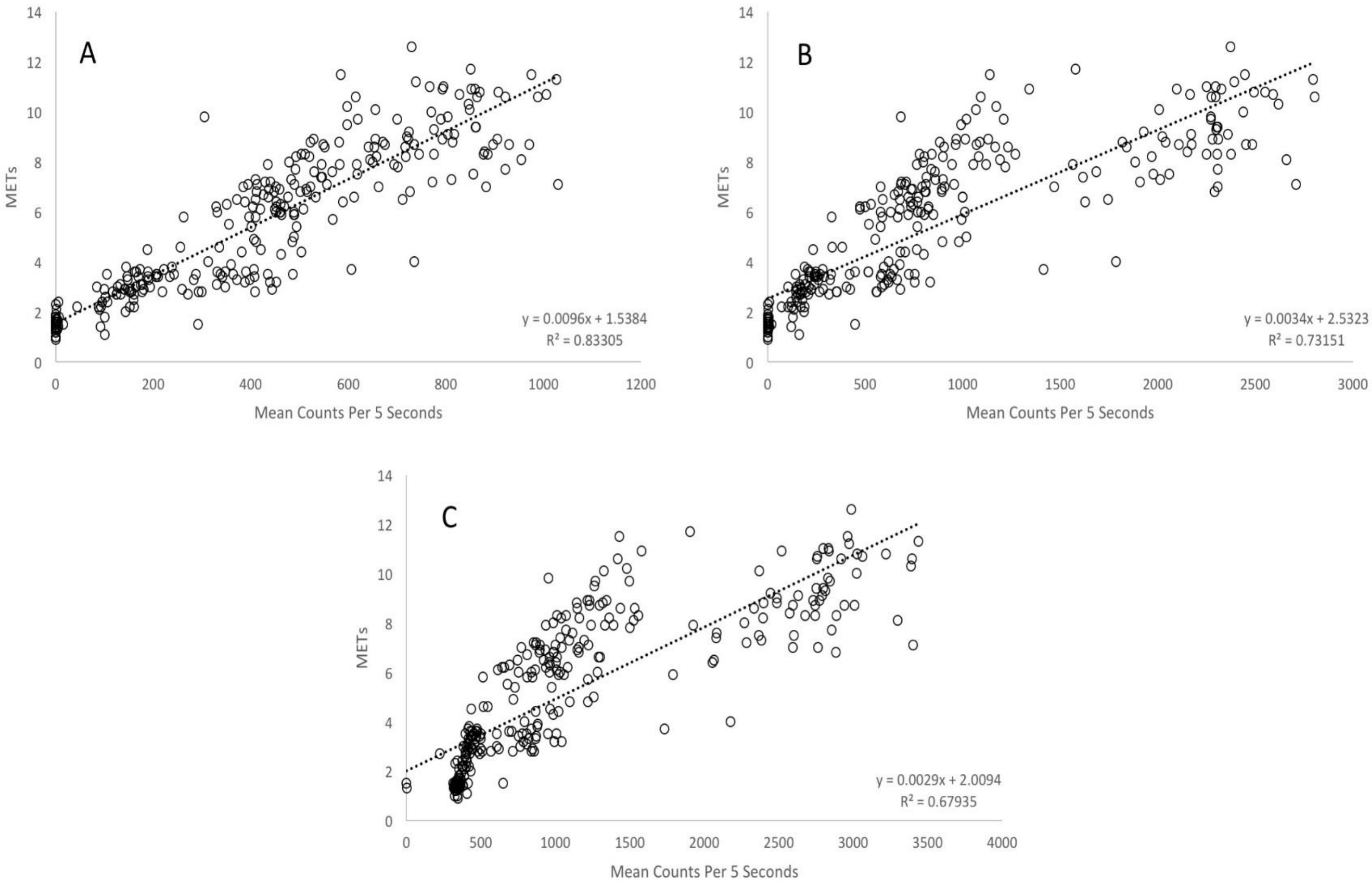


Figure 6: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip vector magnitude by bandpass filter frequency – full activity routine: A) Default, B) 5.0 Hz, C) 9.0 Hz

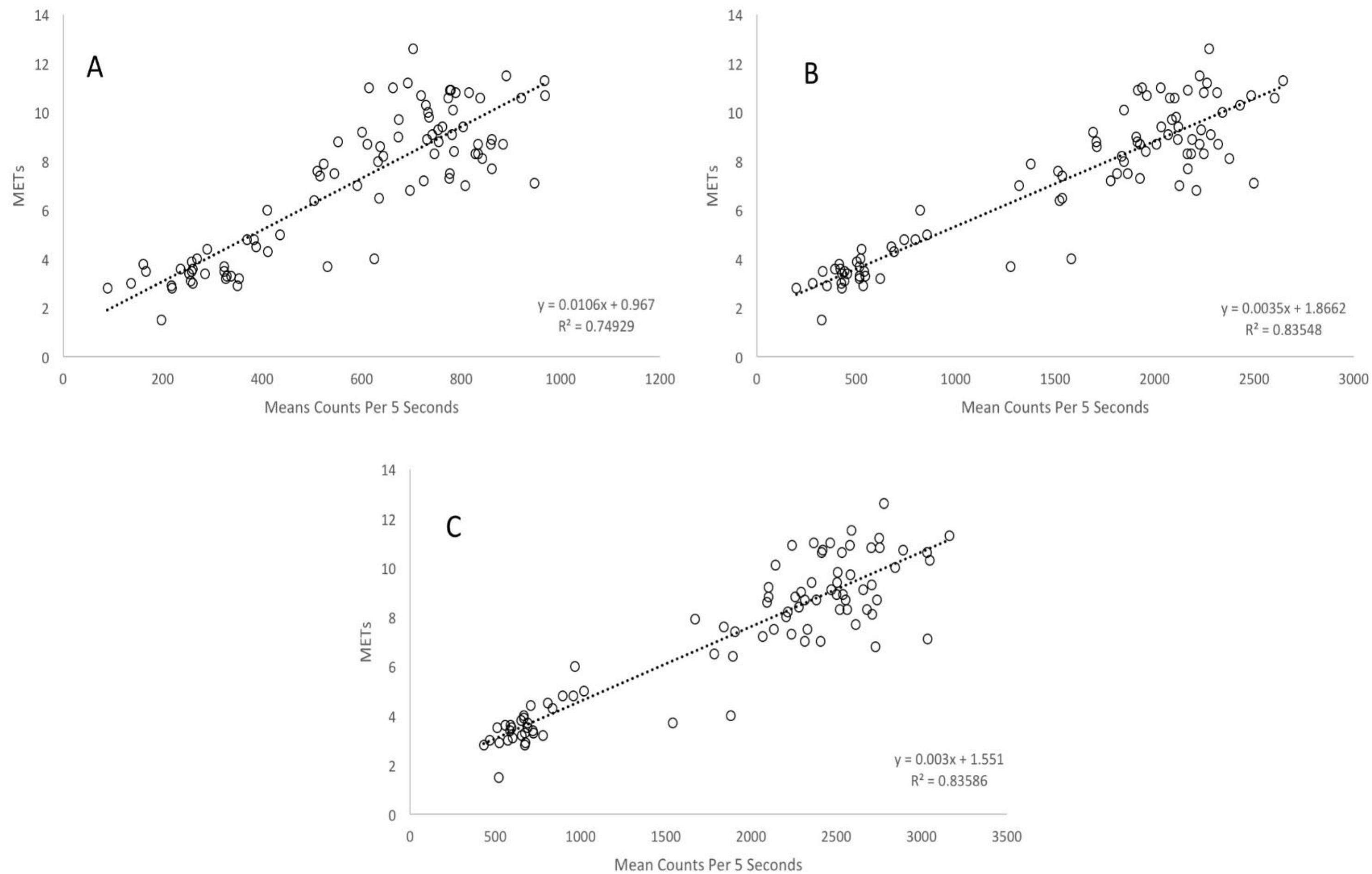


Figure 7: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip axis 1 by bandpass filter frequency – locomotive activities only: A) Default, B) 5.0 Hz, C) 9.0 Hz

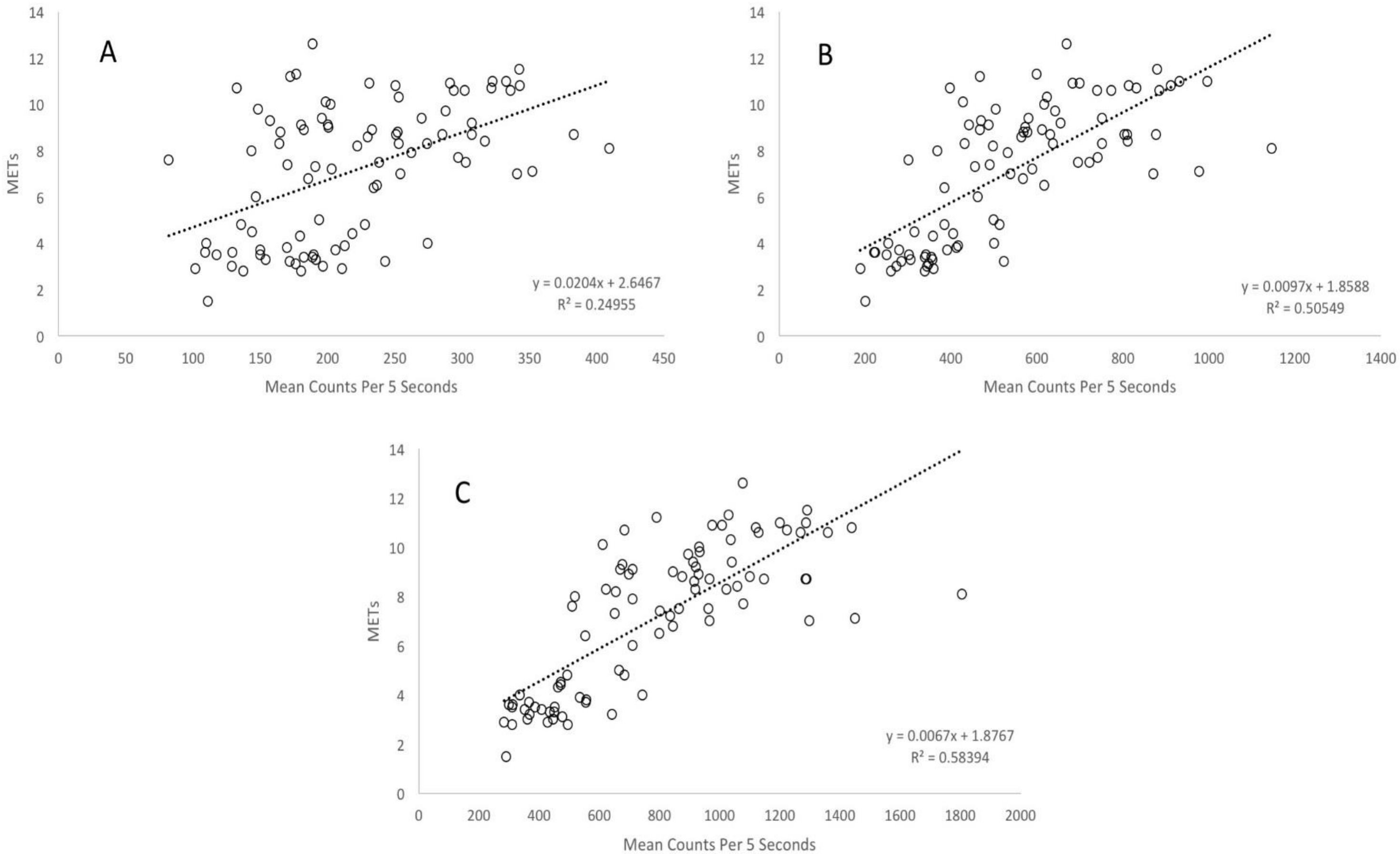


Figure 8: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip axis 2 by bandpass filter frequency – locomotive activities only: A) Default, B) 5.0 Hz, C) 9.0 Hz

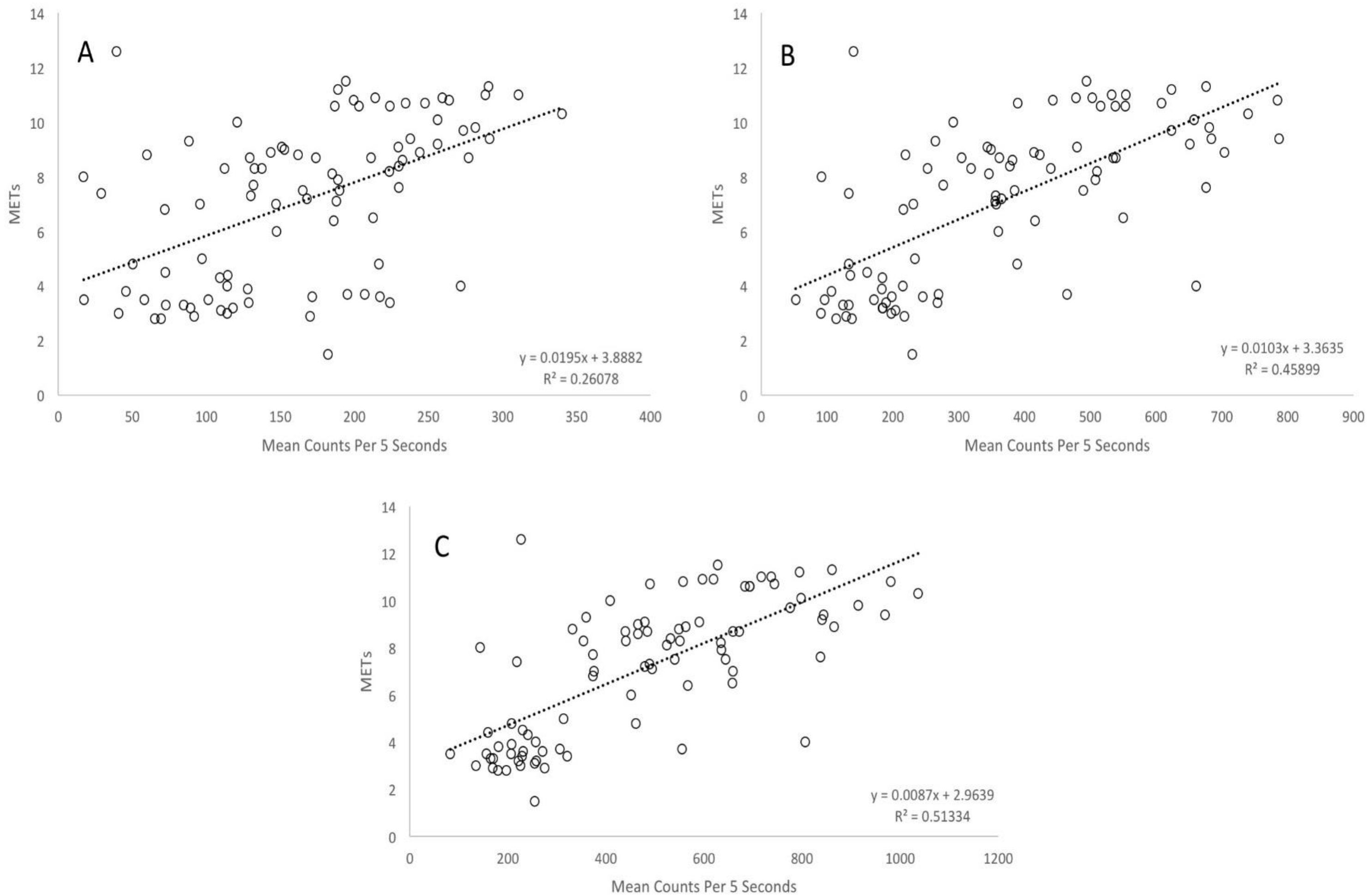


Figure 9: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip axis 3 by bandpass filter frequency – locomotive activities only: A) Default, B) 5.0 Hz, C) 9.0 Hz

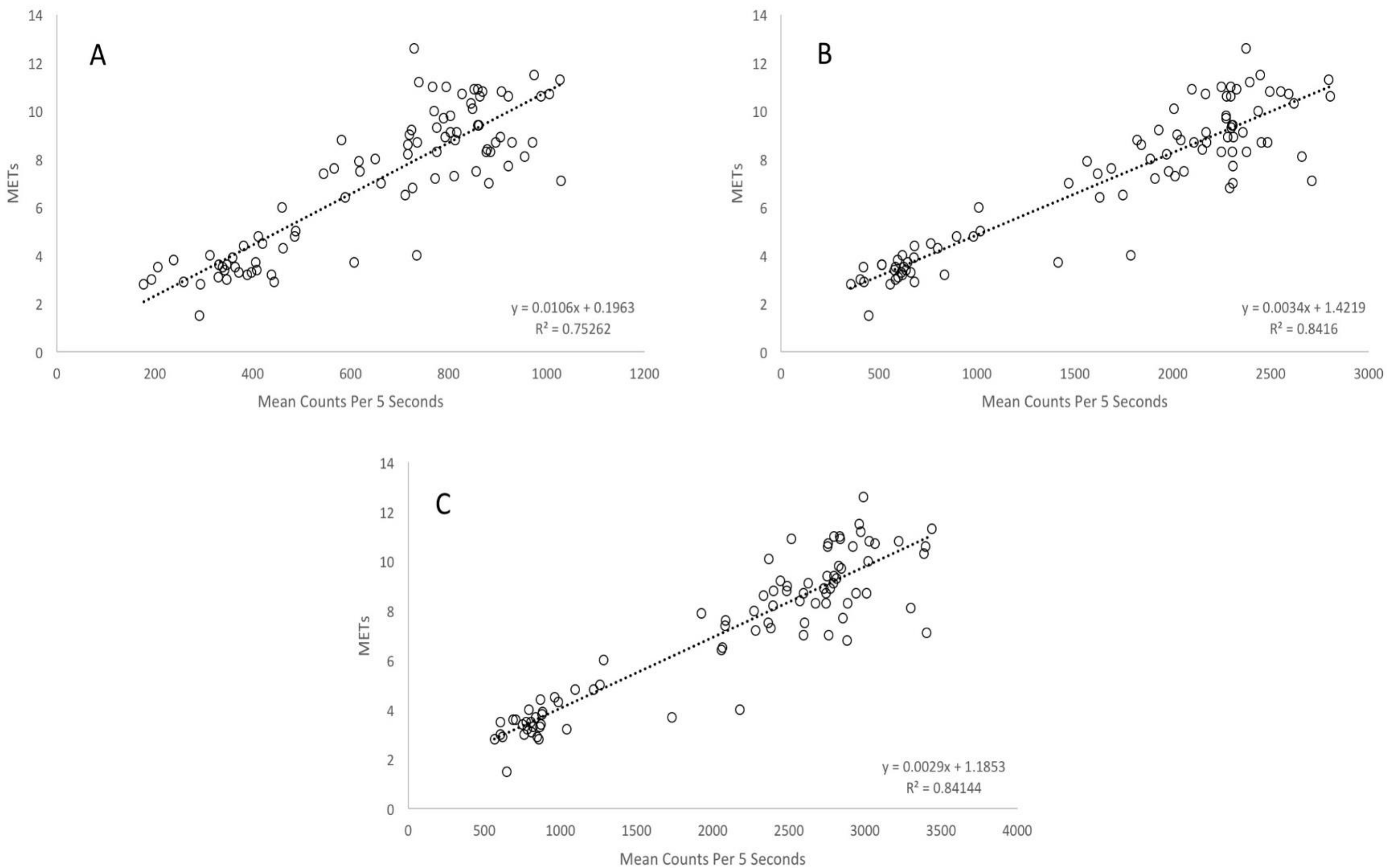


Figure 10: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip vector magnitude by bandpass filter frequency – locomotive activities only: A) Default, B) 5.0 Hz, C) 9.0

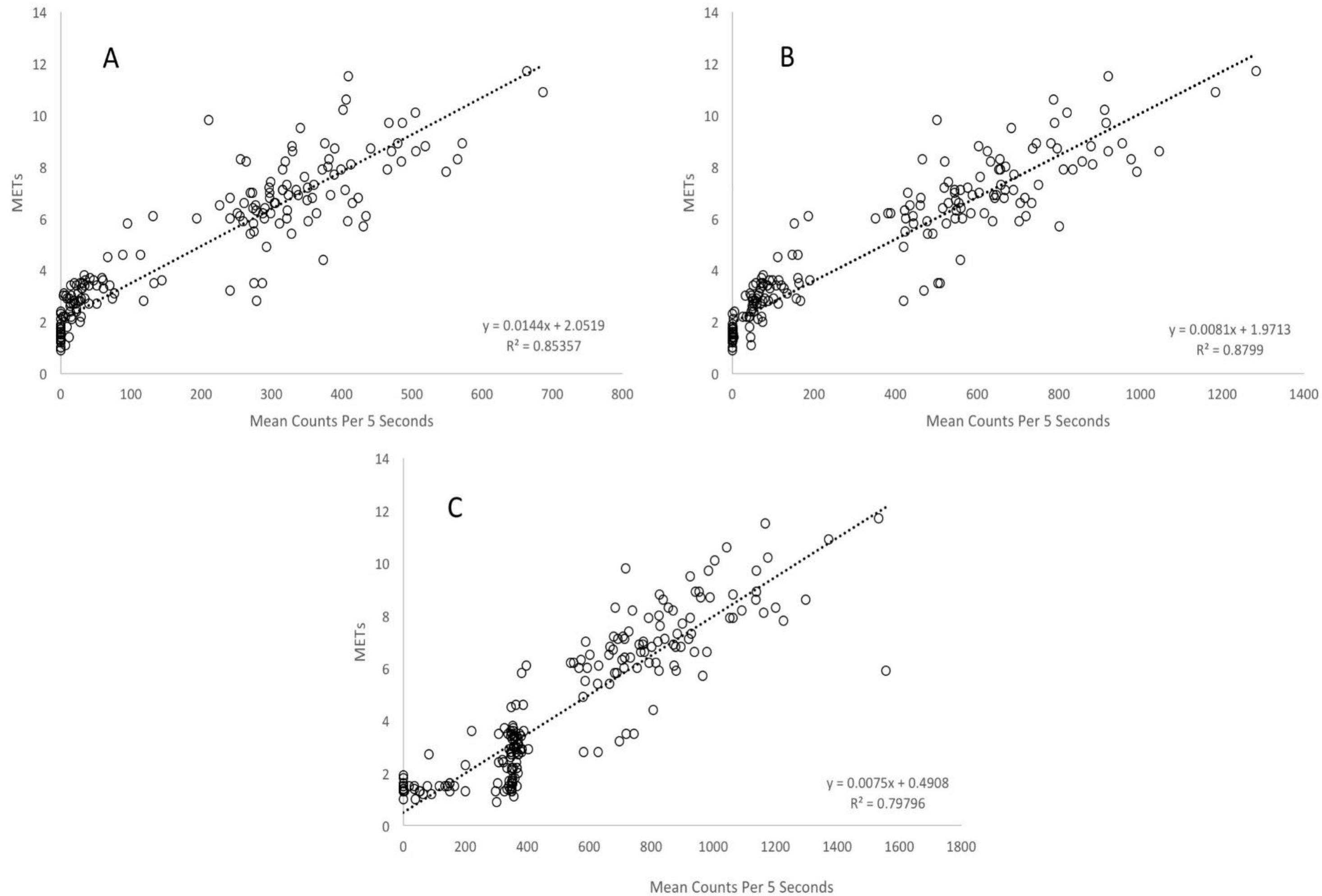


Figure 11: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip axis 1 by bandpass filter frequency – lifestyle activities only: A) Default, B) 5.0 Hz, C) 9.0 Hz

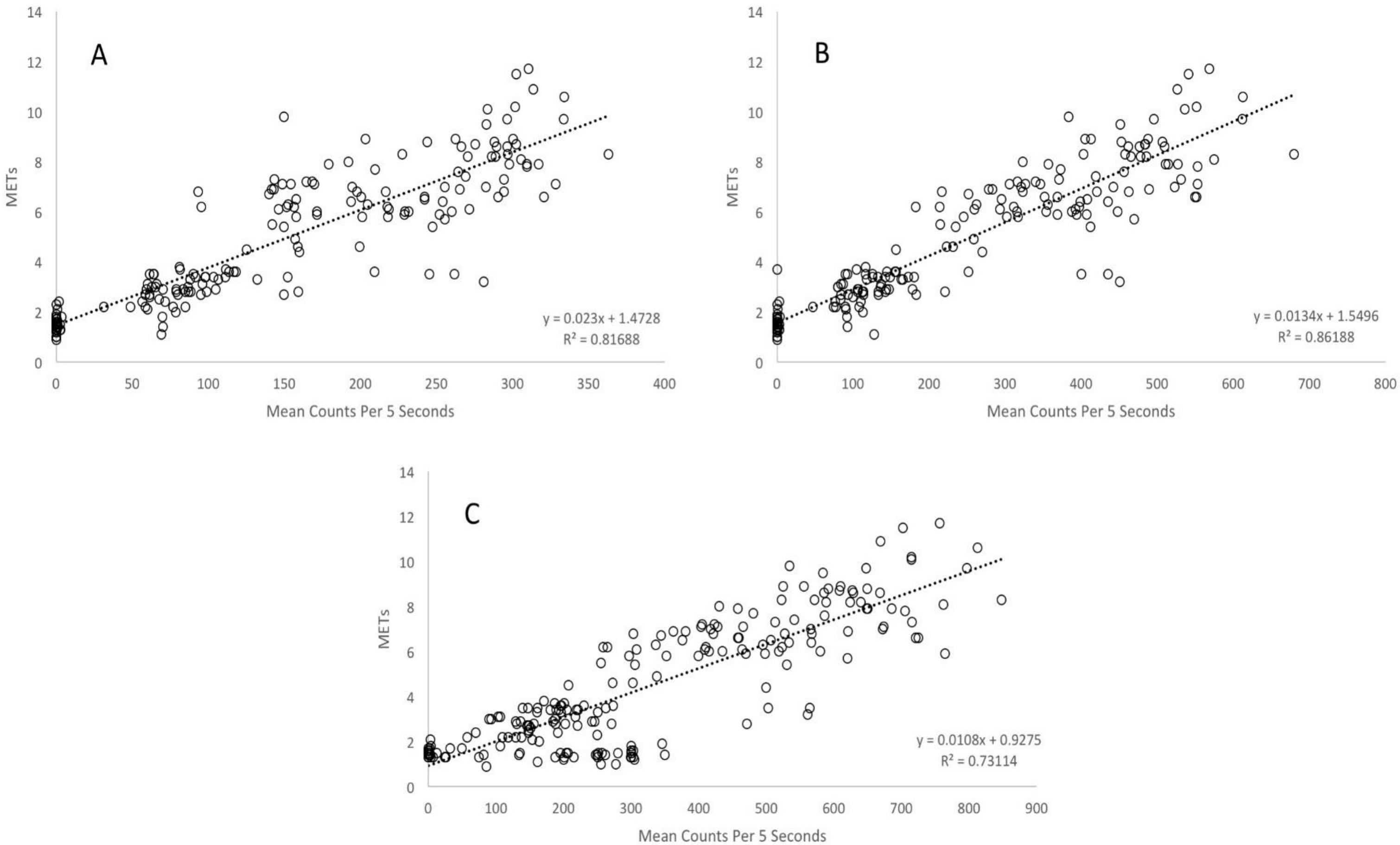


Figure 12: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip axis 2 by bandpass filter frequency – lifestyle activities only: A) Default, B) 5.0 Hz, C) 9.0 Hz

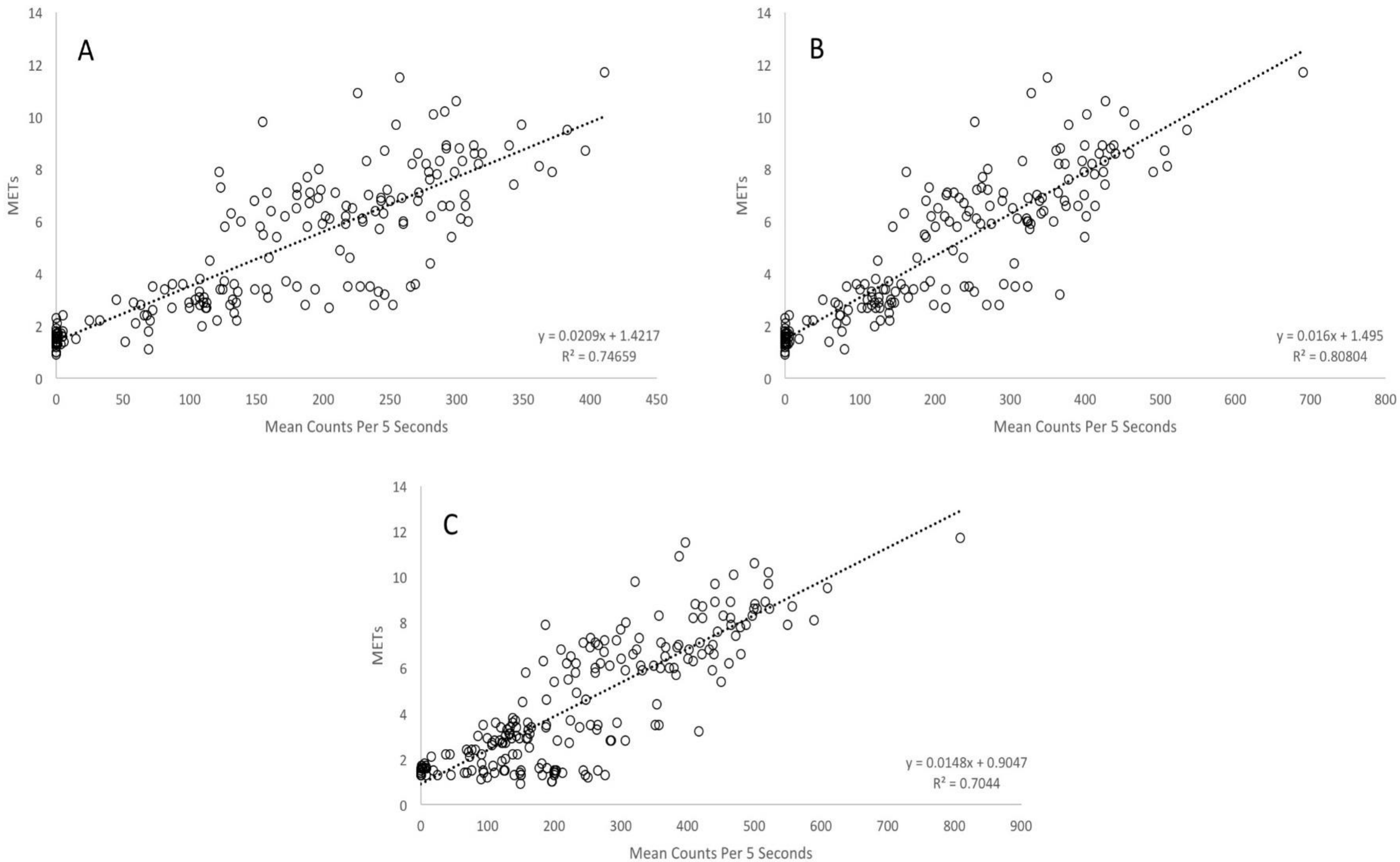


Figure 13: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip axis 3 by bandpass filter frequency –lifestyle activities only: A) Default, B) 5.0 Hz, C) 9.0 Hz

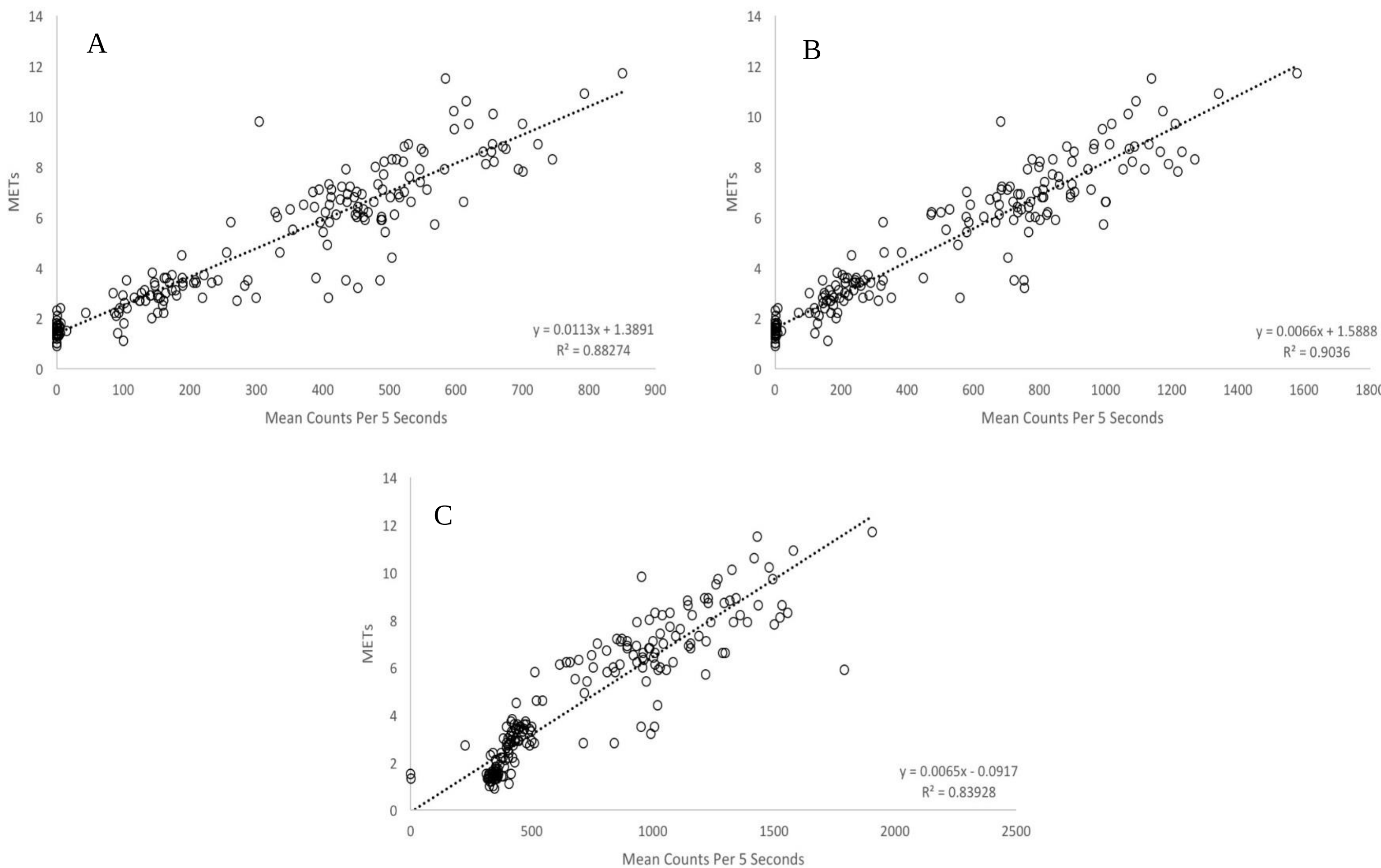


Figure 14: Relationship between ActiGraph GT9X means counts per 5 seconds versus measured energy expenditure [metabolic equivalents (METs)] for hip vector magnitude by bandpass filter frequency – lifestyle activities only: A) Default, B) 5.0 Hz, C) 9.0 Hz

Informed Consent Statement

Title of Research: Use of wearable physical activity monitors to predict energy expenditure

Principal Investigators: Dr. Scott Crouter and Dr. David Bassett

Location: Applied Physiology Laboratory, 1914 Andy Holt Ave., University of Tennessee, Knoxville, TN 37996

PURPOSE

You are invited to participate in a research study. The purpose of this study is to examine the use of motion sensors, positioned at various body locations (e.g., hip, ankle, and wrist), to estimate energy expenditure. If you give your consent, you will be asked to perform the testing listed below. Before exercising, you will be given a brief questionnaire to determine your health status and you will be measured for height, weight, and percent body fat in the laboratory.

PARTICIPANT'S INVOLVEMENT IN THIS STUDY

1. You will receive this informed consent form and be allowed to ask any questions you may have about anything that is unclear. If you choose to participate, you will be asked to fill out a Physical Activity Readiness Questionnaire to determine whether it is safe for you to participate.
2. You will have your height and weight and body composition measured.
3. You will have your maximal aerobic capacity estimated
4. You will be asked to complete 6 to 8 activities (highlighted below) from the following list:

    1) Supine rest
    2) Standing
    3) Sitting working at a computer
    4) Standing doing office work
    5) Walking up and down stairs
    6) Stationary cycling at approximately 75 watts
    7) Stationary cycling at approximately 125 watts
    8) Over-ground cycling at self-selected speed
    9) Over-ground walking at approximately 3 mph
    10) Over-ground walking at approximately 4 mph
    11) Walking on a treadmill at 1.0 mph
    12) Walking on a treadmill at 1.5 mph
    13) Walking on a treadmill at 2.0 mph
    14) Walking on a treadmill at 2.5 mph
    15) Walking on a treadmill at 3.0 mph
    16) Walking on a treadmill at 3.5 mph
    17) Walking on a treadmill at 4.0 mph
    18) Walking on a treadmill at 2.5 mph and 5% grade
    19) Walking on a treadmill at 3.0 mph and 5% grade
    20) Walking on a treadmill at 3.5 mph and 5% grade
    21) Walking on a treadmill at 4.0 mph and 5% grade
    22) Over-ground running at approximately 5 mph
    23) Over-ground running at approximately 7 mph
    24) Running on a treadmill at 5 mph
    25) Running on a treadmill at 6 mph
    26) Running on a treadmill at 7 mph
    27) Running on a treadmill at 8 mph
    28) Running on a treadmill at 5 mph and 5% grade
    29) Running on a treadmill at 6 mph and 5% grade
    30) Playing basketball
    31) Playing singles racquetball
    32) Playing singles tennis
    33) Vacuuming
    34) Sweeping/mopping floors
    35) Washing windows
    36) Washing dishes
    37) Raking leaves/grass
    38) Lawn mowing
    39) Packing and moving boxes

5. All activities will be performed on the campus at the University of Tennessee, except household chores (activities 33-38), which will be performed at the university, at your place of residence, or the researcher's place of residence. If testing takes place at your place of residence or the researcher's place of residence, the two researchers will be present. Each activity listed will be performed for 7 minutes and a 1-3 minute recovery will be given between each activity.
6. To measure energy expenditure during the routine you will be asked to wear a face mask that will be attached to a portable unit that will be worn on your upper body using a harness. The entire unit weighs approximately 4 pounds.

________ **Participant's Initials**

IRB NUMBER: UTK IRB-14-01988-XP
IRB APPROVAL DATE: 03/17/2015
IRB EXPIRATION DATE: 03/16/2016

7. While completing the activities you will wear activity monitors at the following body locations:

   Ankle__________. Wrist______. Hip________. Thigh____________. Arm_______.

8. It is important for you to realize that you may stop when you wish because of feelings of fatigue or any other discomfort. We may stop the test at any time because of signs of fatigue, symptoms you may experience, or equipment malfunction.

Your total time commitment for the study will be 2 hours.

RISKS
The risks associated with exercising are slight in a healthy population. They include an abnormal blood pressure response and heart rhythm disturbances. In a healthy population, the risk of sudden death is 1 in 10,000 and the risk of a non-fatal cardiac event is 4 in 10,000. In addition, this study involves only submaximal exercise at intensities ranging from approximately two to five times the resting metabolic rate. To further minimize the risk of exercise, subjects will be screened using a Physical Activity Readiness Questionnaire. In addition the investigators are certified in Cardiopulmonary Resuscitation (CPR). There is also a slight risk that you could suffer an accidental injury in the course of performing the physical activities, although we will attempt to minimize the risk to the greatest extent possible. In the unlikely event that physical injury occurs as a result of participating in this study, financial compensation is not automatically available and medical treatment will not be provided free of charge.

BENEFITS
You will receive a report containing information about your body composition. Upon completion of the study, we hope to gain new information on the validity of research and consumer devices for estimating energy expenditure. In addition, we will provide ways to improve those estimates, which will benefit the scientific community as well as the general consumer.

CONFIDENTIALITY
Information and records included in this study will be kept confidential in the Health, Physical Education and Recreation Building Room 317. Data will be stored in a secure location and will only be made available to the people conducting the study, unless you specifically give permission in writing to do otherwise. The results of the study will be published, but no reference will be made in oral or written reports that could link you to the study.

COMPENSATION
There will be no compensation for participating in this research study.

EMERGENCY MEDICAL TREATMENT
The University of Tennessee does not "automatically" reimburse subjects for medical claims or other compensation. If physical injury is suffered in the course of research, or for more information, please notify the investigator in charge, Dr. Scott Crouter, at (865) 974-1272.

CONTACT INFORMATION
If you have questions at any time about the study or the procedures (or you experience adverse effects as a result of participating in this study), you should immediately contact the principal investigators, Dr. Scott Crouter, 334 HPER Building, The University of Tennessee, Knoxville, TN 37996, (865) 974-1272 or Dr. David Bassett, 325 HPER Building, The University of Tennessee, Knoxville, TN 37996, (865) 974-8766. If you have questions concerning your rights as a participant, contact Ms. Sonya Sullivan with the Compliance Section of the Office of Research at (865) 974-7697.

________ **Participant's Initials**

IRB NUMBER: UTK IRB-14-01988-XP
IRB APPROVAL DATE: 03/17/2015
IRB EXPIRATION DATE: 03/16/2016

PARTICIPATION
Your participation in this study is voluntary; you may decline to participate without penalty. If you decide to participate, you may withdraw from the study at any time without penalty and without loss of benefits to which you are otherwise entitled. If you withdraw from the study before data collection is completed your data will be returned to you or destroyed.

STATEMENT OF CONSENT
I have read the above information, and I have received a copy of this form. I agree to participate in this study.

Participant's signature ________________________________ Date _______

Investigator's signature ________________________________ Date _______

I GIVE FURTHER PERMISSION TO BE CONTACTED IN THE FUTURE FOR ADDITIONAL STUDIES.

______________________________ ______________________________
Printed Name of Participant Signature of Participant

____
Typed/Printed Name of Investigator/Staff

IRB NUMBER: UTK IRB-14-01988-XP
IRB APPROVAL DATE: 03/17/2015
IRB EXPIRATION DATE: 03/16/2016

Physical Activity Readiness Questionnaire (PARQ)

Regular physical activity is fun and healthy, and increasingly more people are starting to become more active every day. Being more active is very safe for most people. However, people should check with their doctor before they start becoming much more physically active.

If you are planning to become much more physically active than you are now, start by answering the seven questions in the box below. If you are between the ages of 15 and 69, the PAR-Q will tell you if you should check with your doctor before you start. If you are over 69 years of age, and you are not used to being very active, check with your doctor.

Common sense is your best guide when you answer these questions. Please read the questions carefully and answer each one honestly: check YES or NO.

YES NO 1. Has your doctor ever said that you have a heart condition and that you should only do physical activity recommended by a doctor?

YES NO 2. Do you feel pain in your chest when you do physical activity?

YES NO 3. In the past month, have you had chest pain when you were not doing physical activity?

YES NO 4. Do you lose your balance because of dizziness or do you ever lose consciousness?

YES NO 5. Do you have a bone or joint problem that could be made worse by a change in your physical activity?

YES NO 6. Do you know of any other reason why you should not be doing physical activity?

I have read, understood and completed this questionnaire. Any questions I had were answered to my full satisfaction.

Name (Print): ________________________________

Signature: __________________________________ Date: __________________

VITA

Samuel Robert LaMunion, born January 29, 1992 to Hurshel V. LaMunion and Sara Catherine “Cathy” Corley LaMunion. Samuel completed his Bachelor’s of Science with magna cum laude honors in Exercise and Sports Science with a Basic Sciences concentration at the University of South Carolina Aiken in August of 2014. In Fall of 2014 he enrolled in the Kinesiology Master’s of Science program with a concentration in Exercise Physiology at The University of Tennessee Knoxville. Samuel Graduated from the Master’s program in the August of 2016 at which time he re-enrolled at The University of Tennessee Knoxville for Fall 2016 to begin work as a doctoral candidate in Kinesiology and Sports Studies with a concentration in Kinesiology and a specialization in Exercise Physiology. Samuel intends to pursue a post-doctoral research fellowship upon completion of his doctoral studies and then begin a career teaching at the University level as well as doing research.