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Classification Accuracy of the Wrist-Worn GENEA Accelerometer During Structured Activity Bouts: A Cross-Validation Study

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To the Graduate Council:

I am submitting herewith a thesis written by Whitney Allegra Welch entitled "Classification Accuracy of the Wrist-Worn GENEA Accelerometer During Structured Activity Bouts: A Cross-Validation Study." 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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Classification Accuracy of the Wrist-Worn GENEA Accelerometer During Structured Activity Bouts: A Cross-Validation Study

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ABSTRACT

Purpose: The purpose of this study is to determine whether the left wrist cutpoints of Esliger et al., for the triaxial GENEA accelerometer, are accurate for predicting intensity categories during 14 different activities including; treadmill-based, home and office, and sport activities. **Methods**: 130 adults wore a GENEA accelerometer on their left wrist while performing various lifestyle activities. The Oxycon Mobile Portable Metabolic Unit was used to measure oxygen uptake during each activity. Statistical analysis used Spearman's rank correlations to determine the relationship between measured and estimated intensity classifications. Cross tabulation tables were constructed to describe under or over estimation of misclassified activities, and one-way chi-squares were used to test whether the accuracy rate of each activity differed from 80%. **Results**: For all activities the GENEA accelerometer-based physical activity monitor explained 41.1% of the energy expenditure. The GENEA correctly classified 52.8% of observations when all activities were combined. Five of the 14 activities showed no statistical difference in physical activity intensity classification estimation when compared to 80% accuracy, with 1 activity (treadmill jogging at 9.6 km•hr^{-1} with 0% grade) showing statistically greater accuracy than 80%. For the remainder of the activities, the GENEA showed less than 80% accuracy for predicting intensity. **Conclusion**: Cross-validation of the proposed GENEA left wrist cutpoints classified the majority of activities performed significantly below the accuracy rate of 80%. Researchers should be cautious when applying the Esliger et al. cutpoints to a different population and activities not tested by those investigators.

TABLE OF CONTENTS

Table of Contents

LIST OF TABLES v

CHAPTER 1 1

CHAPTER 2 4
- **INTRODUCTION** 4
- **PHYSICAL ACTIVITY ASSESSMENT** 4
- **ACCELEROMETERS** 7
- **ELEMENT SENSORS AND TRANSDUCERS** 11
- **INTEGRATED ACCELEROMETER TECHNIQUES** 12
- **ACCELEROMETER WEAR SITES** 16
- **ACCELEROMETER DATA ANALYSIS TECHNIQUES** 18
- **REGRESSION EQUATION ANALYSIS** 19
- **OTHER ESTIMATION TECHNIQUES** 23
- **CONCLUSION** 25

CHAPTER 3 26

LIST OF REFERENCES 46

APPENDICES 54
- **APPENDIX A** 55
  - UNIVERSITY OF TENNESSEE, KNOXVILLE INFORMED CONSENT 55
- **APPENDIX B** 58
  - Physical Activity Readiness Questionnaire (PAR-Q) 58
- **APPENDIX C** 60
  - HEALTH HISTORY QUESTIONNAIRE 60
- **APPENDIX D** 62
  - PHYSICAL ACTIVITY STATUS 62

VITA 64

LIST OF TABLES

Table 1. Activity List 40
Table 2. Average Intensity Values (METs and GENEA SVMgs) 41
Table 3. Accuracy of the GENEA left wrist intensity classifications by activity 42
Table 4. Cross tabulation of All Activities 42
Table 5. Cross tabulation of All Activities with Cycling Removed 43
Table 6. Cross tabulation of Home/Office Activities 43
Table 7. Cross tabulation of Walking/Running Activities 44
Table 8. Cross tabulation of Sport Activities 44

CHAPTER 1
INTRODUCTION

Since the mid-1980's there has been a steady increase in the evidence-based literature associating high physical activity levels with a low risk of developing chronic diseases such as type 2 diabetes, obesity, and cardiovascular disease (59). The integrity of physical activity monitoring studies, intervention studies, and epidemiology studies rely on valid and reliable assessment of physical activity (2). Doubly-labeled water, direct observation, and direct and indirect calorimetry are the most valid "criterion" measurements of physical activity (62). However, these methods are expensive, require trained professionals to administer, and are not practical for some applications (37). Movement sensors (pedometers and accelerometers) are small, inexpensive, and portable devices that allow researchers to objectively measure activity within the free-living environment (37). While pedometers were specifically designed to measure walking behaviors, such as total steps taken per day (34), accelerometer-based physical activity monitors allow researchers to track frequency, intensity, and duration of activity (45). Prior to the development of triaxial accelerometers, uni-axial accelerometers restricted researchers to movement information strictly within the vertical plane (62). Tri-axial accelerometers capture movement in the orthogonal planes, resulting in the ability to capture many more activities than the uni-axial accelerometer, and having an overall higher correlation with energy expenditure (8, 14, 29). This advancement in monitor technology has allowed tracking of both dynamic and static activity related to daily living (15).

It has been common practice to place motion sensors on the waist of human subjects, but this position does have limitations. Placed near the center of mass, waist-mounted accelerometers may fail to detect upper body movement, which could lead to significant errors in measurement and physical activity level misclassification (14). Therefore, determining alternative sites for placement that would elicit improved results compared to the waist-worn sensors could enhance future research (14). Researchers have attempted to attenuate this error by placing accelerometers on the ankle, upper arm, wrist, or multiple sites of the body (5, 65). A newly introduced wrist-worn accelerometer-based physical activity monitor, Gravity Estimator of Normal Everyday Activity (GENEA), has shown high accuracy in classifying numerous activities, including sedentary time, walking, running, and household activities (20); and will potentially encourage higher rates of wear compliance, when compared to waist-worn accelerometers (60). The physical activity classification cutpoints for the GENEA accelerometer, which were developed by Esliger et al. (20), showed high levels of criterion validity across all tested activities (r=0.85). The authors also speculate that the tight clustering of their data within each activity will allow for an increased accuracy of activity classification (20). To date these cutpoints have not been cross-validated. The purpose of this study is to determine whether the method of Esliger and colleagues for the tri-axial wrist accelerometer is accurate for predicting intensity category during 14 different activities including; ambulatory activities (lab-controlled speeds and self-paced speed), sedentary activities (computer work and filing papers), household activities (vacuuming and walking with a load), and sport activities (tennis, basketball, and cycling).

We hypothesize the intensity category of the walking/running activities that do not involve additional energy expenditure, such as walking up a hill, carrying a load, or concurrent upper body movement, will be accurately predicted by the tri-axial wrist accelerometer. Physical activity monitors have shown, over the last 12 years, that they have been successful in providing valid measurements of ambulatory activities such as walking (38). On the other end of the spectrum, motion sensors have shown to be the most appropriate activity monitor to measure sedentary activity (58). We hypothesize the home/office activities, filing papers and computer work, will also be correctly classified. However, when additional obstacles are added, such as walking up a hill, carrying a load, or upper body movements, predicted intensity categories are significantly underestimated in a single-monitor device (37, 38), which is also an inevitable limitation of using cutpoints to determine intensities (49). Chen and Bassett (14) summarized in 2005 that accelerometers underestimate the energy expenditure of activities involving upper body activity, movement in the vertical direction, carrying an object, non-weight bearing exercises, or any activity that involves quick changes in acceleration. Therefore, we hypothesize walking on a treadmill with an increased grade, walking while carrying a load, vacuuming, and all sport activities will be classified at a lower intensity by the tri-axial wrist accelerometer-based physical activity monitor.

CHAPTER 2
REVIEW OF LITERATURE

INTRODUCTION

In order to accurately determine the presence or absence of a relationship between physical activity and health-related outcomes in research studies, robust objective measurements of physical activity are needed (25). More importantly, the accurate quantification of individuals' daily activities is needed in order to fully understand total energy expenditure, beyond planned exercise (29). Motion sensors provide an objective alternative to self-report options (34). Accelerometers, a type of motion sensor, have been shown to accurately estimate intensity levels, time spent in varying intensities, breaks in sedentary periods, and body positioning, such as standing, sitting, or lying down (38). Accelerometers have shown to be valid in many populations including children, adults, and obese individuals, making the accelerometer a promising option for physical activity measurement (6). This review of literature will discuss the changes in accelerometer technology and advances in analysis of data obtained from accelerometers which over time have led to more accurate objective monitoring of physical activity.

PHYSICAL ACTIVITY ASSESSMENT

In 1962, Paffenbarger (47) began collecting data for the Harvard Alumni Health Study. Today, the Harvard Alumni Health Study has shed light on a number of correlates between physical activity and health outcomes, such as coronary heart disease (47), stroke risk (35), and mortality (36). Although a landmark study, their assessment of physical activity is reliant upon self-reported physical activity questionnaires. Prior to the development of physical activity monitors (pedometers, accelerometers), most physical activity research used surveys (34). While questionnaires are a cost-effective option for assessment, most self-report measurements fail to encompass the full continuum of physical activity (58). Researchers need measures of physical activity that are equally as easy to use but result in more objective results and capture all aspects of nonbasal energy expenditure (58). Developing an accurate assessment of physical activity is extremely important when attempting to determine a relationship between physical activity and an outcome of interest (25). If physical activity is not accurately measured the relationship could be attenuated or even found to be non-significant (25). According to Plasqui et al. (46) the ideal assessment of physical activity would be over a long period of time and within the daily life of individuals, in order to capture their actual, habitual activity levels. The criterion measures of physical activity include the doubly-labeled water technique, direct observation, and direct and indirect calorimetry (34). However, these assessments are usually time consuming, expensive, require a trained individual to administer, and are lab-based therefore probably not a realistic measure of habitual physical activity, particularly in epidemiology studies or in many interventions (37).

In 1960, using force platforms, Brouha (9) found a correlation between human movement and the acceleration of the body in the vertical plane. Two motion sensors that were developed as a direct result of Brouha's finding and that meet the criteria stated above, are pedometers and accelerometers (26). The invention of the first pedometer is often credited to Leonardo da Vinci almost 500 years ago (40), and pedometers are still used today for the main purpose of quantifying walking behavior (58). Pedometers place low burden on research participants, they can be cost-effective for the researcher, and they provide a reliable way to measure walking behavior; however, the steps given by a pedometer cannot distinguish between intensity levels (6).

New physical activity guidelines and emerging research suggested that breaking up activity into shorter, accumulated bouts could increase overall physical activity time and could provide the same health benefits as longer activity bouts (33, 43). In order to determine if the wearers are truly meeting the physical activity recommendations, a device is needed that is equally as cost-effective and low maintenance as the pedometer but provides the investigators with more information about time spent in differing intensities of activity. A motion sensor that fits this need is the accelerometer which provides physical activity assessment that can be segmented into discrete time periods to allow the researcher to assess different physical activity patterns, varying bouts, or overall total amount of physical activity (62). Accelerometers are motion sensors that measure accelerations and decelerations of the body part to which the device is attached (41). Advantages of using an accelerometer include not only that they are small, non-invasive, and non-obtrusive (14), but they are also able to measure time spent in differing activity intensities (6).

ACCELEROMETERS

The accelerometer was originally developed for the aerospace and military community and then to measure automobile crash tests, which funded the accelerometer research budget for over 60 years (61). The next major sale opportunity for accelerometry was for consumer applications, which included physical activity measurement (61). The initial statements by Laporte et al. (34) and Montoye et al. (41) that lead up to using accelerometers to estimate physical activity and energy expenditure were simple but profound in setting the stage for accelerometer development: "More active people typically move more than less active people" (34) and "All human movement requires acceleration of a body part…these accelerations are responsible for the energy expenditure that movement requires" (41).

In 1982, Henry Montoye surmised that using accelerometers to estimate energy expenditure was a promising avenue for exploration (41). Montoye and his colleagues developed a waist worn accelerometer that weighed 400 grams, was 14x8x4 centimeters, and measured accelerations in the vertical direction. A Beckman Metabolic Cart measured the participants' oxygen consumption (VO_2) while they engaged in five different activities (walking on a treadmill, running on a treadmill, stepping up and down, half knee-bends, and floor touches) at varying speeds. Their analysis showed that there was a strong relationship between the accelerometer readings and the VO_2 values (r=0.74). Using a scatterplot constructed with the data, they were able to derive an equation to estimate VO_2 based on the output of the accelerometer.

Subsequently, studies began to assess the validity and reliability of using uniaxial accelerometers in relation to physical activity measurements. Heyman et al. (30) tested a uniaxial accelerometer using participants in free-living conditions. They used doubly-labeled water as their criterion measure of total energy expenditure. Following analysis, researchers found a correlation of 0.87 between the accelerometer output and the criterion method's assessment of energy expenditure across a 10-day measurement period. Thus far, the uniaxial accelerometer had proven itself to be promising in both laboratory and free-living conditions. However, a limitation of the waist-mounted uniaxial accelerometer that Montoye and his colleagues (41) noted in their initial experiment, was the inability of the uniaxial accelerometer to detect changes in terrain or any upper body movement. A uniaxial accelerometer measures accelerations in a single direction and has shown to be reliable, valid, and provide stable measurements of some types of physical activity (37), but in Montoye's discussion, his team's solution to the uniaxial device's measurement limitations was to develop a triaxial accelerometer that would measure accelerations in three separate directions (41).

In 1994, four engineering researchers from the Netherlands experimented with the triaxial accelerometer idea by placing three uniaxial accelerometers perpendicular to one another (8). The accelerometers were cased in a small cube-like structure that weighed 0.3 grams and was 4x4x3 millimeters. The cube was then mounted onto a belt for easy wear along the lower back of participants. For testing, participants were asked to perform various seated activities (such as writing and reading), sitting down and standing up, and walking at multiple speeds. Following summation of the three orthogonal plane accelerations, the researchers found that while their triaxial accelerometer significantly underestimated energy expenditure during sedentary activities by almost 60%, the devices were able to come within 4% of the participants' actual energy expenditure during walking activities.

In 1997, the same group, using the same accelerometer, conducted a reliability study (7). To do so they affixed three separate triaxial accelerometers to a lever arm that rotated around a fixed radius. All three accelerometers rotated around the same axis, at the same time, in the same position. In other words, for the accelerometer to be deemed reliable all three accelerometers should yield the same output following rotation. The researchers found there were no significant differences between the three accelerometers. They also tested accuracy of energy expenditure estimation by having 13 young males perform various activity protocols (sedentary activities, household activities, walking, and stepping) inside of a respiration chamber that measured their actual energy expenditure. Investigators found a correlation of $r = 0.89$ between the energy expenditure and the accelerometer output when combining all activities to compute the correlation. In 1997, Chen et al. (16) wanted to test the Tritrac activity monitor and its ability to improve energy expenditure estimation and physical activity monitoring. The Tritrac activity monitor is a triaxial accelerometer that weighs 170 grams and measures 11.1x6.7x3.2 centimeters. Activities were performed over two days in a room calorimeter in order to measure actual energy expenditure. One day was considered a 'normal' activity day while the 'exercise' day was structured with specific activities provided to the participants by the investigators. Chen and colleagues (16) found that the Tritrac estimated energy expenditure values were highly correlated with the measured values for both the normal day ($r=0.855$; $p<0.01$) and the exercise day ($r=0.925$; $p<0.001$). In a summary of comparison studies by Trost et al. (57) in 2005, they found that the validity coefficients found in studies using multiaxis devices tend to be slightly higher ($r = 0.59 – 0.93$) than those for uniaxial studies ($r = 0.48 – 0.90$).

It is important to understand that physical activity is any movement by the body that results in energy expenditure above resting levels, while exercise is a subset of physical activity, and refers to energy-expending activities that are planned and structured (11). Self-report questionnaires can underestimate total daily activity energy expenditure by either inaccurate recall or only assessing time spent exercising (34). In 1995, the Center for Disease Control and Prevention and the American College of Sports Medicine (43), acknowledged that moderate-intensity daily activities, such as gardening, washing dishes, and house cleaning that are equivalent to the intensity levels reached during a bout of brisk walking can be important ways for individuals to build activity into their daily lives. Given the fact that many activitiesmake-up one's daily energy expenditure and in recognition that the public routinely engages in many types of activities, it is important that researchers find ways to objectively accurately assess them. Overall, not only have triaxial accelerometers shown higher correlations with measured energy expenditure (10), but they perform better across a wide array of daily activities, provide more information for the investigator, and show a better relationship with sole activity energy expenditure, when compared with the uniaxial accelerometer (46).

ELEMENT SENSORS AND TRANSDUCERS

Since the estimated intensity of physical activity from an accelerometer is based on the measured accelerations of the movement of the body, another important factor to consider is the types of accelerometers that record these accelerations (14). An accelerometer converts the physical movement into a quantitative measure that can be used by the researcher (15). Much like the change from uniaxial measurements to triaxial measurements, physical activity monitors have also evolved to be more reliable and research friendly. Early physical activity monitors housed sensors called piezoelectric accelerometers (14). These sensors consisted of a piezoelectric element that was easily deformed as a result of accelerations. When acceleration occurred and the mass was deformed, this deformation would be relative to the acceleration and would cause a build up of mechanical charge to the sensor. The amount of change in the charge would result in the recorded raw acceleration output (26). There are some limitations to these sensors. Since they are sensitive to dynamic accelerations they are not as valid at measuring static acceleration (body postures) (14). Also, these sensors were installed and calibrated by the manufacturer (15) and any re-calibration required experienced technicians, possibly imposing time constraints and study costs. The newest sensor type is the microelectromechanical accelerometer (15). These accelerometers are extremely small, are highly sensitive, and do not require as much power to record activities resulting in the ability to increase measurement wear time periods (15). Within this system lies a capacitance system that measures change in capacitance distance (15); where dependent on the presence of acceleration, the two plates will either be moving closer together or further apart (15). With the decreasing size of the accelerometers, increasing memory capabilities, and increasing power capabilities, researchers are able to develop more rigorous study methodologies by increasing the amount of measurement time and decreasing invasiveness of the device (15).

INTEGRATED ACCELEROMETER TECHNIQUES

In 2000, Bassett (2) theorized that future directions for increased accuracy of objective measurement should focus around combining measures together. Since the best way to estimate physical activity variables is by sensing both physiological and mechanical reactions to different movements (4), researchers began attempting to increase validity of accelerometer measurement by pairing accelerometer output with physiological measures. Heart rate and VO_2 show a linear relationship across a large range of activities, and heart rate has been considered an appropriate approach to indicate physical activity intensity (2). When using heart rate as a measure of exercise intensity, it is important to keep in mind that there are other factors that can affect heart rate such as temperature, emotions, and stress (26). Another limitation to using heart rate as an objective measure is that heart rate responses vary depending on whether the work done is primarily in the upper body or in the lower body (26). In 2001, Strath et al. (51) developed the arm-leg heart rate-motion sensor technique in order to differentiate between which half of the body is predominantly at work. The investigators attempted to determine the difference in the estimated energy expenditure using only a motion sensor, only heart rate, or integrating both heart rate and the motion sensor (53). A Computer Science and Application, Inc. (CSA) accelerometer was placed on the dominant wrist, the right hip, and the right thigh. Participants participated in various activities under three categories: yardwork, housework, and conditioning. Following analysis the investigators found the accelerometer underestimated the actual energy expenditure by 29.5% ($p<0.001$). The heart rate approach overestimated the energy expenditure by 11.1% ($p<0.001$). However, when the proposed heart rate-motion sensor technique was implemented, the estimation of energy expenditure was not significantly different from the criterion ($p=0.341$). Welk and colleagues (65) studied the validity of the Sensewear Pro II (SP2) armband monitor, which is a monitor that is worn over the right upper arm. This is a non-invasive monitor that continually measures different physical changes, such as, heat, galvanic skin response, skin temperature, and body temperature, along with body motion from the accelerometer. Participants were instructed to wear the monitor for a day and to participate in all their normal activities. Energy expenditure was measured using the IDEEA monitor, which is a device that uses a set of electrodes combined with a neural network to determine an individuals posture and motion. The results of the correlation between physical activity estimation and measured physical activity was as high as $r=0.94$ during different types of lying postures, such as lying on the back or side, and the lowest correlation value was $r=0.42$ during sitting (65).

When ambulatory movement is excluded, accelerometers, mounted on the waist, often underestimate activity concentrated in the upper body (57). Researchers have recently attempted to quantify the significant amount of time spent in daily activities involving upper body movements (38). A few studies have attempted to address this issue by placing multiple monitors on the body in order to better capture total body motion. Swartz et al. (55) placed a CSA accelerometer on the right side of the waist and one on the dominant wrist. The investigators' aim was to develop a prediction model for each site individually and also to see whether using both sites together would improve the estimation equations. Participants performed an array of lifestyle activities within the categories of yardwork, occupation, housework, family care, conditioning, and recreation. The results showed that the developed equations accounted for 3.3% ($p=0.003$) of the variance of the estimated energy expenditure at the wrist site, 31.7% ($p<0.001$) of the variance of the estimated energy expenditure at the hip site, and 34.3% ($p<0.001$) of the variance of the estimated energy expenditure using both the wrist and hip sites. Swartz et al. (55) concluded the addition of the wrist only added a slight (2.6%) improvement in energy expenditure prediction.

In 2003, Chen et al. (13) designed a study with a similar objective. They used the Tritrac-R3D triaxial accelerometer to measure waist acceleration and the Actiwatch uniaxial wrist-worn accelerometer in an attempt to increase measured energy expenditure accuracy. Walking and stepping activities were performed at varying speeds for 10 minutes within a room calorimeter in order to measure actual energy expenditure. By combining the two accelerometers accuracy of the total estimated energy expenditure was 97.7 ± 3.2% of the actual value ($p = 0.781$). When the monitors are used individually to estimate energy expenditure the Tritrac-R3D waist worn accelerometer estimated 90.0 ± 4.6% of the actual value ($p < 0.001$) and the ActiWatch estimated 86.0 ± 4.7% of the actual value ($p < 0.001$). Their analysis showed that by combining the two accelerometers significantly improved the estimation of actual energy expenditure (97.7 ± 3.2%). It is important to know that the type of activities tested by Chen et al. (13) were walking and stepping; thus helping explain the high observed correlation.

Melanson and Freedson (39) also developed estimate equations using hip, wrist, and ankle sites. These investigators used the CSA accelerometer to measure physical activity while walking and running at different speeds on the treadmill. In this study, the use of multiple accelerometer placements resulted in a slightly stronger relationship between energy expenditure and acceleration values (R^2=0.95) than a single placement (R^2=0.86). Again, these are high correlations for walking and running activities. When the activities become more complex it becomes more difficult to try and assess. Although there may be a slight increase in ability to estimate energy expenditure when measuring at multiple sites, attaching multiple devices may inhibit daily activities, may decrease compliance, and may not always be feasible for long-term studies (27). These are issues that need to be weighed when deciding on monitoring devices, especially when activity may be concentrated in a specific region of the body (i.e. lower body versus upper body activity).

ACCELEROMETER WEAR SITES

The location of accelerometers on various body sites is another avenue that has been explored in increasing accelerometer measurement accuracy (57). Although the hip/waist has been considered the ideal measurement location because it approximates the center of mass of an individual, new technologies have allowed other positioning, such as arm, ankle, and wrist to be used (38). An interesting study by Stec and Rawson (50) aimed to compare the accuracy of energy expenditure measurement by a waist-placed and wrist-placed triaxial accelerometer (ActiGraph GT3X) while resistance training. Accelerometer estimates were compared to the energy expenditure measured by the Cosmed K4b^2 portable metabolic unit. Thirty college-aged participants performed eight routine resistance exercises (Smith machine bench press, Smith machine shoulder press, Smith machine squat, leg extension, leg curl, lat pull-down, triceps pushdown, barbell biceps curl). Analysis showed that the sum of the counts at the wrist-placed accelerometer did not significantly correlate with energy expenditure ($r = -0.25$; $p = 0.18$) but the waist-placed accelerometer did significantly correlate with energy expenditure ($r = 0.50$; $p= 0.005$).

The Stepwatch dual-axis accelerometer is an ankle worn motion sensor that counts steps taken and can estimate energy expenditure (22). Foster et al. (22) found that when compared to direct observation, the Stepwatch is able to provide an accurate measure of the number of steps taken over a specific amount of time. Proof of the accuracy of the Stepwatch in free-living conditions is seen in a study by Feito et al. (21) where the Stepwatch was the criterion measure of steps taken, which were compared to Actigraph accelerometers in order to determine accuracy in both controlled and free-living conditions. These studies show sites other than the waist have the potential to be accurate alternatives to waist worn accelerometers.

The GENEA accelerometer is a wrist-worn accelerometer that has been proven valid and reliable at all manufacturer specified wear sites (right/left wrists and waist)(20). In a validation study of the device by Esliger et al. (20) participants performed 12 activities (walking, running, and household activities) while wearing a GENEA accelerometer on their left and right wrist and one on their right hip. VO_2 was measured by the Cosmed K4b^2 portable metabolic gas analysis system. Results indicated the hip positioning provided the greatest classification accuracy at 0.95, with the left wrist accuracy at 0.93 and the right wrist correctly classifying 0.90 of the activities.

The GENEA accelerometer has been proven effective in predicting energy expenditure in pregnant and non-pregnant women, in a study by van Hees et al. (60). The pregnant and non-pregnant women wore a GENEA accelerometer on their wrist and around their waist for 10 days while actual energy expenditure was being measured by doubly labeled water. Upon analysis investigators found no significant correlations between measured energy expenditure and accelerometer estimated energy expenditure ($R^2 = 0.24$). When this population was cross validated using the leave-one-out cross-validation technique, variance explained by the accelerometer dropped to 19% of the actual energy expenditure. Since this accelerometer is water-resistant and can be worn on the wrist, researchers have also found that participant compliance and satisfaction while wearing the device was greater for the GENEA accelerometer attached to the wrist than when compared with the waist attachment (60). Continuing to create more and more sophisticated accelerometers will not be beneficial unless participants are compliant with wearing the device (57). Being able to show increased compliance at a specific wear site with a accelerometer that has proved valid in a free-living environment, such as the GENEA accelerometer (20, 60), increases the validity of the physical activity assessment (57). However, the question remains whether this device (GENEA) can be used as a device to accurately measure physical activity.

ACCELEROMETER DATA ANALYSIS TECHNIQUES

The accelerometer has evolved to be a more comprehensive, reliable, and valid measure of physical activity by including all three axes, as explained above. In addition, a change has also been seen in value calibration techniques, the processes of converting the raw accelerations into outputs that are useful in research or for the consumer (4). The goal of these studies is to determine a relationship between the accelerometer signal and the physical activity actually performed (54). Accelerometers record accelerations and decelerations so the raw signal is bidirectional (14). The bidirectional signals are then converted to an absolute value, essentially making all the signals positive (14). These raw signal numbers, which are averaged over a user specified time period (epoch) are the output received from the accelerometer when the data are initially uploaded from the accelerometer's memory (14). In order to interpret these numbers, activity counts, which correspond with specified activity intensity levels, are developed for use with each accelerometer (38). Activity counts are a dimensionless unit that are unique to a specific accelerometer, activity performed, and epoch setting (6). These activity counts are derived from an acceleration-versus-time curve (4). The area under the curve of the absolute values of the observed waves for a specific time length are used to determine the activity counts (4). The epoch length set by the instrument user can dramatically effect these activity count results (14). Short epochs can result in a more precise measurement, but measuring one-second of activity is of no physiological importance unless summed into larger time periods (14). In contrast, longer epochs, such as one minute, may not be able to differentiate all types of activity performed during that minute (14), this is especially important when measuring physical activity in children whose natural play is sporadic (24).

REGRESSION EQUATION ANALYSIS

Predictive validity research is based on the established relationship between activity counts and measured energy expenditure. Knowledge of this relationship has led to the development of regression equations that can estimate activities into intensity classifications (25, 29, 40). In 1998, Freedson et al. (25) developed a regression equation to determine specific MET values, for the CSA accelerometer, so each activity performed could be placed into an intensity category. The investigators had each participant slow walk (4.8 km/h), fast walk (6.4 km/h), and jog (9.7 km/h) on a treadmill for six minutes. Along with the CSA accelerometer, positioned on the participants' right hip, VO_2 was measured by open circuit spirometry. A linear regression was used to determine the relationship between the MET values and the activity counts output by the CSA. The regression equation was arranged to solve for

METs (METs = 1.439008 + (0.000795 * cnt/min)). An equation was also developed for the case when energy expenditure is a more important outcome measure (kcal/min = (0.00094*counts/min) + (0.1346*mass in kg) – 7.37418). This equation provided a means for other researchers also using the CSA accelerometer to determine counts per minute or energy expenditure values for their sample. It is important to note in this equation and in all equations that have been developed, they are specific to the activities being performed, the population being tested, as well as the accelerometer used to measure the activities (4, 63).

A supplemental issue of *Medicine & Science in Sport & Exercise* published in 2000 focused on the objective monitoring of physical activity, and within the supplement some of the articles targeted the theme of energy expenditure regression equations (3, 29, 55). The main purpose of Hendelman and colleagues (29) was similar to Freedson et al. (25), which was to understand the relationship between accelerometer counts per minute and actual energy expenditure. However, Hendelman et al. (29) were interested in non-lab based activities. Activities in this study included walking at a self-selected pace on an indoor track, playing golf, and household tasks, such as washing windows, vacuuming, and lawn mowing. Investigators used a portable metabolic measurement system to measure VO_2 and participants wore a hip-mounted CSA accelerometer and Tritrac monitor. Following regression analysis using all activities combined, a regression equation for each accelerometer was developed to calculate corresponding MET values following determination of counts per minute (CSA METs = 2.922 + 0.000409*CSA) (Tritrac METs = 2.817 + 0.00110*TRI).

Using their own sample of CSA measured activities, Bassett et al. (3) compared the Freedson et al. equation (25), the Hendelman et al. equation (29), and the CSA manual equation (17) to determine the accuracy of each. Participants in this sample performed activities that fell within six general categories: yardwork, occupation, housework, family care, conditioning, and recreation. Each activity was performed for 15 minutes. VO_2 was measured using the Cosmed $K4b^2$ portable indirect calorimetry system and participants wore the CSA accelerometer (model 7164) placed at the waist. Following data collection the accelerometer output was run through each of the algorithms being studied. Correlations were then determined between the motion sensor algorithm output and the indirect calorimetry output. They found that the strongest relationships between actual energy expenditure and estimated energy expenditure were found when using the CSA manual (17) equation (r=0.620) and the Hendelman et al. (29) equation (r=0.620). Both accelerometers underestimated the intensity of each activity, ranging from 30.5 – 56.8% underestimation. The household activities had the largest difference between actual MET level and accelerometer estimated MET level, with four out of the five activities being underpredicted by over 50%, with the one exception being lawn mowing.

Although the results of the previous single regression equations showed reasonable correlations with the actual energy expenditure, Bassett et al. (3) found the motion sensor algorithms were overpredicting walking energy cost by up to 1.5 METs and underpredicting lifestyle activities (3). In 2005, Crouter et al. (18) theorized it was not possible for a single regression line to capture all activities throughout a range of intensities. Therefore, he proposed the development of two separate regression equations, one to be used when either walking or running, and one to be used for all other activities. In order to develop these equations, Crouter et al. (18) monitored 48 participants performing three separate routines involving office work, conditioning activities, and housework. Activity was measured using the Actigraph accelerometer on the right hip, and VO_2 was measured by the K4b^2 portable indirect calorimetry system. The authors found that using an exponential curve (instead of a straight line) to develop the regression equation was most appropriate for the walking and running activities, and using a cubic curve was most appropriate when developing the equation for all other activities. When this two-regression model was compared with the actual VO_2 values, the new model was within 0.75 METs for all activities performed and there were no significant differences for any of the 17 activities. The authors concluded that by using this new approach, the estimate of lifestyle activities improved beyond walking and running. In 2010 Crouter et al. (19) sought to refine the 2-regression model following evidence showing the equation can misclassify activities when activities are not started at the start of a minute of the ActiGraph clock. The same instruments were used to measure MET values (actual and estimated) as in the previous study. This refined equation estimated MET values every 10-seconds instead of every minute. Upon cross-validation of the updated method, no significant differences were seen between the estimated MET values and the measured MET values other than for stationary cycling.

OTHER ESTIMATION TECHNIQUES

Developing regression equations for use in predicting energy expenditure from activity counts has thus far been the most commonly used method of analysis (10). An alternative approach to establish cutpoints is to use a receiver operating characteristic (ROC) curve. ROC curves are most frequently used in the diagnosis of disease by providing thresholds to determine either “positive” or “negative” results (44). In physical activity research, ROC curves have most commonly been used to check the sensitivity and specificity, but not always to generate the cutpoints (63). An added advantage to using ROC curves to generate cutpoints, instead of regression techniques, is researchers are able to develop cutpoints that maximize sensitivity and specificity, therefore reducing the risk of false positives and false negatives (4). A ROC curve is constructed by plotting the test sensitivity on the y-axis and one minus the test specificity on the x-axis (32). Optimal cutpoints are set at the point where the two distributions cross (63). Ultimately, having the maximal amount of area under your curve (i.e. a value of 1.0 is considered a perfect ROC curve) (32). Other than Esliger et al. (20), no other study has used the ROC curve technique to generate cutpoints in adult calibration studies.

Cutpoints can also be determined by regression equations. Strath et al. (52) compared the results between five different sets of proposed cutpoints (Freedson et al. (25), Hendelman and colleagues (29) equation for walking and for all activities, Swartz et al. (55), and Nichols et al. (42)) for the Manufacturing Technology, Inc. (MTI) accelerometer. Ten participants performed a variety of activities ranging from television watching, to resistance training, to yard work, for a five-to-six hour period. During this period participants wore a Cosmed K4b^2 unit to measure oxygen uptake and an MTI accelerometer placed on the waist. Investigators found that the equations differed statistically ($p<0.001$) between one another for all light and moderate activities. Results showed that the only intensity cutpoints that did not differ at the group level when compared to the criterion measure were the cutpoints developed by Swartz et al. (55). Investigators concluded this equation may have been more applicable because it was developed based on 28 different activities.

One huge disadvantage of using either of the two prior approaches, regression equations or ROC curves, to estimate intensity categories or energy expenditure is that the cutpoints developed are specific to the device used, the population tested, and the activities performed (4, 63). In a recent (2012) supplement of *Medicine & Science in Sport & Exercise*, Freedson et al. (23) urged researchers to discontinue the development of cutpoints to categorize physical activity when using accelerometers. They cited the proliferation of different cutpoints as hindering comparisons between studies or devices (23).

Staudenmayer et al. (49) demonstrated that METs are not a function of counts per minute. This means that every x value does not correspond to a specific y value. Therefore, across a variety of activities (such as daily activities) using counts per minute poses inherent limitations (49). A new technology that is emerging is the use of pattern recognition techniques. Also known as artificial neural networks, this technique is used to directly identify activities (28). An example of a motion sensor utilizing this new technology is the IDEEA monitor mentioned previously. The IDEEA monitor is a “smart” device that is able to take the information received by the motion sensors and provides direct results of the type, duration, and intensity of activity. Zhang et al. (66) tested the accuracy of the IDEEA monitor to correctly identify activities from basic posture activities to walking and running. Researchers observed movements and recorded observations were matched with the IDEEA output. For posture activities such as standing, sitting, and reclining the IDEEA was on average 99% accurate. For walking and running activities the IDEEA was 99.7% and 99.4% accurate, respectively. While the research on this type of monitoring is still in its infancy, this method shows promise as a way to reach beyond the counts per minute analysis (48).

CONCLUSION

In the last 30 years, researchers have adapted accelerometers to be an objective measurement of physical activity (41), have developed a number of different avenues to interpret the raw accelerometer outputs (18, 25), and have envisioned increasingly intelligent uses for the accelerometer-based physical activity monitor (48, 65). Accelerometer-based physical activity monitors have become highly relevant being applied in the field setting, still one of the most practical means of physical activity measurement in small-scale intervention studies through large-scale population studies (38, 56). With the new era of pattern recognition and improved sensor technologies, these new developments will be extremely beneficial to ongoing research (31).

CHAPTER 3
MANUSCRIPT

Classification Accuracy of the Wrist-Worn GENEA Accelerometer During Structured Activity Bouts: A Cross-Validation Study

INTRODUCTION

Since the mid-1980's there has been a steady increase in the evidence-based literature associating high physical activity levels with a low risk of developing chronic diseases such as type 2 diabetes, obesity, and cardiovascular disease (59). The integrity of physical activity monitoring studies, intervention studies, and epidemiology studies rely on valid and reliable assessment of physical activity (2). Doubly-labeled water, direct observation, and direct and indirect calorimetry are the most valid "criterion" measurements of physical activity (62). However, these methods are expensive, require trained professionals to administer, and are not practical for some applications (37). Movement sensors (pedometers and accelerometers) are small, inexpensive, and portable devices that allow researchers to objectively measure activity within the free-living environment (37). While pedometers were specifically designed to measure walking behaviors such as total steps taken per day (34), accelerometer-based physical activity monitors allow researchers to track frequency, intensity, and duration of activity (45). Prior to the development of triaxial accelerometers, uniaxial accelerometers restricted the researchers to movement information strictly within the vertical plane (62). Triaxial accelerometers capture movement in the orthogonal planes. As a result, these devices provide the opportunity to capture many more activities than uniaxial accelerometers; thus, in comparison with uniaxial instruments, the output from triaxial devices has an overall higher correlation with energy expenditure (8, 14, 29). This advancement in monitor technology has allowed tracking of both dynamic and static accelerations related to daily living (15).

It has been common practice to place motion sensors on the waist of human subjects, but this site has limitations. Placed near the center of mass, the waist-mounted accelerometers can fail to detect arm movements, which leads to significant errors in measurement and physical activity level misclassification (14). Therefore, determining alternative sites for placement that would elicit improved results compared to the waist-worn sensors could enhance future research (14). Researchers have attempted to attenuate this error by placing accelerometers on the ankle, upper arm, wrist, or multiple sites of the body (5, 65). A newly introduced wrist-worn accelerometer-based physical activity monitor, Gravity Estimator of Normal Everyday Activity (GENEA), has shown high accuracy in classifying numerous activities, including sedentary time, walking, running, and household activities (20); and, due to its wristwatch-like characteristics and size, will potentially encourage higher rates of wear compliance, when compared to waist-worn accelerometers (60).

The physical activity intensity cutpoints for the GENEA accelerometer developed by Esliger et al. (20) showed high levels of criterion validity across a range of activities (r=0.85) (20). The authors speculate that the tight clustering of their data within each activity will allow for an increased accuracy of activity classification. To date, however, these cutpoints have not been cross-validated in a separate study. Thus, the purpose of this study is to examine the accuracy of the left wrist GENEA cutpoints developed by Esliger and colleagues are accurate for predicting intensity categories. Fourteen different activities falling under the general categories of ambulatory activities, home/office activities, and sport activities were examined.

METHODS

Participants

139 participants were recruited from on-campus and the surrounding community of the University of Tennessee, Knoxville and the University of Massachusetts, Amherst. Nine people from the total sample who were left hand dominant were excluded in order to have a standardized sample of right hand dominant individuals; thus the number of subjects in this analysis was 130. Participants were 20 – 60 years of age, were apparently healthy, and free from chronic disease or any joint or musculoskeletal injuries that might affect gait. Prior to testing all participants signed an informed consent (Appendix A) approved by the Institutional Review Boards at the University of Tennessee, Knoxville and the University of Massachusetts, Amherst.

Data Collection

Participants reported to the laboratory having fasted for four hours, having abstained from nicotine, caffeine, or other stimulants for four hours, and having refrained from exercise for 24 hours. Each participant filled out a Physical Activity Readiness Questionnaire (Appendix B), Health History Questionnaire (Appendix C), and Physical Activity Status questionnaire (Appendix D) in order to determine his/her ability to participate in the study. Height was measured using a stadiometer and weight was measured by the Tanita BC-418 scale (Tanita Corporation of America, Inc., Arlingtion Heights, Illinois). Body mass index was calculated from these measurements.

Participants completed a series of seven activities from one of two routines (Table 1). Each activity was performed for seven minutes with a 4-minute break between activities. Participants wore the Oxycon Mobile portable metabolic unit 2008 model (CareFusion, San Diego, CA), which measured oxygen uptake (VO_2) during testing. The GENEA was worn on the non-dominant wrist (left wrist), positioned between the radial and ulnar styloid process, and was secured by a Velcro strap. This study was part of a larger study that used another device worn on the dominant wrist, therefore the GENEA was placed on the non-dominant wrist. The GENEA (Activinsights Limited, Colworth, United Kingdom) is a triaxial accelerometer weighing 16 g, measuring 36x30x12 mm, and can be worn on the wrist, waist, or ankle. Accelerometers were initialized to sample data at 80 Hz (67). After each test, data were downloaded and stored on a laboratory computer.

Analysis

Breath-by-breath VO_2 data collected by the Oxycon were averaged over three minutes (minutes 4-6) of each activity. Because of variations between the Oxycon systems at the two testing sites, averaged VO_2 values were increased by 7.8% at The University of Tennessee, Knoxville, and decreased by 7.8% at The University of Massachusetts Amherst. This was done because relative to the ACSM-predicted VO_2's for fixed work rates on the cycle ergometer, the University of Tennessee, Knoxville data were higher than expected and the University of Massachusetts, Amherst data were lower than expected, making it necessary to align the data from the two sites. Corrected VO_2 values were converted to METs using 1 MET = 3.5 $ml \bullet kg^{-1} \bullet min^{-1}$. The MET values obtained for each activity were classified into an intensity category (sedentary (<1.5), light (1.5 -3.99), moderate (4.0 - 6.99), or vigorous (7+)) following the same thresholds used by Esliger et al. (20).

Using precisely the same methods as Esliger et al. (20), the GENEA post processing software (version 1.2.1) was used to analyze the accelerometer data to provide a Signal Magnitude Vector (gravity-subtracted) (SVM_{gs}) for each minute. This value represents a one-second average for that minute of the activity. These SVM_{gs} averages were multiplied by 60 to determine the one-minute SVM_{gs} sums. Three minutes (minutes 4-6) of each activity were used to get the average SVM_{gs} for each activity. Using the left wrist cutpoints of Esliger et al. (20), each activity was classified into an intensity category: sedentary (<217 counts/min), light (217-644 counts/min), moderate (645-1810 counts/min), or vigorous (>1810 counts/min).

Statistical analysis was performed using SPSS version 19 for Windows (Armonk, New York). Spearman's rank correlation coefficients were used to determine whether there was a linear relationship between the obtained MET levels and the GENEA SVM_{gs}. This test was chosen due to a non-normal distribution of the

GENEA data. Crosstabs were used to identify the accuracy of the device to predict intensity classifications within each activity performed. One-way chi-squares were used to test whether the accuracy rate differed from 80%. Eighty percent was chosen as an acceptable accuracy rate based on accuracy rates seen in the validation studies of accelerometers based on pattern recognition (48, 68).

RESULTS

Of the 130 adult participants, 48.5% were male and 51.5% were female. The majority of this sample was Caucasian (71.5%), followed by African American (13.1%), Asian (10.8%), and Hispanic/Latino (4.6%). On average, participants were 41.2 ± 10.9 years of age, 170.4 ± 9.0 cm tall, weighed 74.9 ± 15.2 kg, and had a BMI of 25.7 ± 4.7 kg•m^{-2}.

Table 2 gives the mean and standard deviation for the METs obtained for each activity by the Oxycon, the MET values estimated from the compendium of physical activity (1), as well as the mean and standard deviation for the GENEA estimated SVM_{gs} (g•min) for each activity. The correlation between GENEA SVM_{gs} and METs was $\rho=0.641$ ($p < 0.001$), when all activities are combined.

Table 3 shows the results of the cross tabulations and one-way chi-square. When combining all activities, the GENEA correctly classified the intensity category in 52.8% of the observations. Individually, most of the activities were significantly worse than our predetermined acceptable accuracy rate of 80%. Vacuuming, basketball, computer work, and walking on a treadmill at 4.8 km•hr^{-1} on a 5% grade were estimated with an accuracy rate that did not differ from 80% while jogging on the treadmill at 9.7 km•hr^{-1} with 0% grade shows statistically greater accuracy than 80%. All other activities were estimated with less than 80% accuracy.

A cross tabulation table for all activities combined is shown in table 4, with correct intensity classification category denoted by the shaded blocks. Since the two cycling activities recorded high misclassification, removing cycling from the rest of the activities slightly increased our accuracy rate (61.5% accurate) (table 5). Tables 6, 7, and 8 report the individual cross tabulations for the activities falling within each category; home/office activities, walking/running, and sport activities, respectively. Figure 1 depicts the relationship between the MET value and GENEA SVM_{gs} for each observation. Vertical lines are placed at each Esliger et al. (20) left wrist cutpoint and horizontal lines are placed at each MET level cutpoint creating a block of space showing agreement between the MET value and GENEA SVM_{gs} values. The observation circles that fall outside these regions for each intensity level show misclassifications of the different activities.

DISCUSSION

Based on our analysis, the left wrist GENEA cutpoints of Esliger et al. (20) for intensity category have a classification accuracy of less than 80% accurate for a number of activities. Overall, the GENEA correctly classified 52.8% of the observations, which is better than chance alone (25%). Since the inclusion of cycling in the present study may have increased our misclassification error, we also removed the cycling activities, and this increased the classification accuracy to 61.6%.

Using the proposed cutpoints, the wrist-borne GENEA, classified 5 out of our 14 activities (basketball, jogging on a treadmill at 9.6 km•hr^{-1} with 0% grade, computer work, vacuuming, and walking on a treadmill at 4.8 km•hr^{-1} with 0% grade) with an accuracy rate that did not differ from 80%. Most of the other activities were misclassified. Misclassification of intensity categories can lead to a misrepresentation of population-level estimates of meeting national physical activity recommendations. For example, activities that are actually performed at a moderate intensity but are being classified by the monitoring device as a light intensity activity, would contribute to an underestimate of time spent in moderate or vigorous physical activity (MVPA), a common outcome measure for physical activity research and physical activity guidelines (38, 56).

In our analysis of the GENEA device, the Rho-square combining all 14 activities explained 41.1% of the variance in energy expenditure. Although our data violated the normality assumption, we also calculated the Pearson's product moment correlation coefficient for the sake of comparison with other studies. Using Pearson's R^2, the GENEA worn on the left wrist explained 54.1% of the variance in energy expenditure. Esliger et al. (20) reported that the GENEA worn on the left wrist explained 73.9% of the variance in energy expenditure. Swartz et al. (55) placed a uniaxial CSA accelerometer (now the Actigraph GT1M) on the wrist while participants performed 28 different lifestyle activities. In their study, the wrist-worn CSA accelerometer explained only 3.3% of the variance in energy expenditure. Therefore, a triaxial accelerometer results in a stronger relationship with energy expenditure at the wrist site than a uniaxial accelerometer.

It is important for researchers to understand whether the wrist site is an acceptable alternative compared to the waist for physical activity measurements. In 2011, the National Health and Nutrition Examination Survey began using wrist-worn accelerometers to measure physical activity in their large population-based study (12). Esliger et al. (20) reported that a GENEA accelerometer worn at the waist yielded a nearly identical correlation with energy expenditure ($R^2 = 0.757$) as one worn at the left wrist ($R^2 = 0.739$), suggesting that either site can be used to predict energy expenditure. However, Swartz et al. (55) placed CSA accelerometers on the dominant wrist and right hip of participants while they performed 28 lifestyle activities. Upon analysis, the waist-worn accelerometer explained 31.7% of the variance in energy expenditure, while the wrist-worn accelerometer accounted for 3.3% of the variance. It appears that the ability of accelerometers to predict energy expenditure may be influence by such factors as: (a) where the accelerometer is worn on the body, (b) the types of activity performed, (c) whether a single-axis or tri-axial accelerometer is used.

Esliger et al. (20) found the left wrist placement of the GENEA to be 93% accurate in classifying physical activity intensity. Our analysis showed an average accuracy of 52.8% for all activities performed. However, it is important to note that Esliger et al. (20) did not cross-validate their cutpoints. They determined the accuracy of their developed cutpoints using the same data sets; thus the accuracy may be artificially inflated.

In the present study, the wrist-borne GENEA correctly identified the intensity category between 23.6% and 93.6% of the time for treadmill walking and running.

When speed is increased, both accelerometer activity counts and energy expenditure increases, however, when grade is increased and speed is kept constant energy expenditure increases without a subsequent increase in accelerometer activity counts (25, 41). Interestingly, at 4.8 km•hr^{-1} classification accuracy was significantly lower with no incline than at a 5% incline. Referring to the MET cutpoints used, the average MET values for walking at 4.8 km•hr^{-1} with no grade was 3.5 METs which is close to the moderate intensity cutpoint. However, adding the 5% grade increased the average MET value to 5.17 METs, which falls clearly within the moderate intensity category, without a notable change in the GENEA SVM_{gs} value. At 6.4 km•hr^{-1}, adding the 5% grade to the walking activity actually decreased classification accuracy by 15.3%. Similar to the slower speed, 6.4 km•hr^{-1} with no incline had an average MET value of 5.41 METs, which falls in the middle of the moderate intensity cutpoints. At 6.4 km•hr^{-1} (5% grade), the average MET value was 7.07 METs, straddling the moderate to vigorous intensity cutpoint. These factors likely contributed to our wide range of classification accuracy during treadmill walking and running activities.

While half of our sports activities (basketball and tennis) had classification accuracy rates of more than 80%, the two cycling bouts were both below 25% classification accuracy. During cycling at 49 watts and 98 watts, over 60% of individuals were classified by the GENEA as sedentary even though their actual energy expenditure were clearly elevated. Similarly, the wrist-borne GENEA had difficulty in correctly classifying the intensity of inclined treadmill walking due to an inability to detect the increased metabolic cost associated with vertical work. Other activities where the GENEA cutpoints resulted in a high rate of misclassification were moving a box (54.4% classification accuracy) and tennis (56.3% classification accuracy).

One reason for the high classification accuracy reported by Esliger et al. (20) may be that most of their activities were tightly clustered, and fell between the 1.5, 4, 7 MET cutpoints. In contrast, many of the actual MET values of activities in the current investigation averaged within one MET of the cutpoints, contributing to a higher rate of misclassification. For example, treadmill walking at 6.4 km•hr^{-1} (5%) grade had an average MET value of 7.07 ± 0.87 METs. 29% of subjects had values of 7 METs or higher, while 71% had values under 7 METs. Similarly, tennis had an average MET value of 7.35 ± 1.63 METs. Both of these activities had mean MET values that fell into the vigorous-intensity range, but for many of the subjects these activities were, in fact, moderate-intensity. Self-paced walking is an example of an activity that fell near the cutpoint distinguishing light versus moderate physical activity. Self-paced walking had an average MET value of 3.68 ± 0.66 METs. With MET values so close to the cutpoints, there is a greater likelihood that these activities will be misclassified.

As Bassett et al. (4) stated, when activity monitors are validated, they generally have good validity for the specific activities that were included in the accelerometer calibration study. It is interesting that two of our most accurate activities, computer work (81.8% accuracy rate) and jogging on a treadmill at 9.7 km•hr^{-1} (93.6% accuracy rate), were activities used by Esliger et al. (20) in developing the intensity cutpoints. Emerging evidence suggests that new techniques, such as pattern recognition technology, will help improve physical activity monitoring estimation (31). One other GENEA wrist-worn classification study by Zhang et al. examined pattern recognition algorithms to predict activity type. Our study focused on intensity classification not activity type, so we did not examine Zhang and colleagues' algorithms because it was outside the scope of the current investigation. However, the more advanced approaches they used may be an improvement for correctly classifying a wide range of activities. In our study, the low classification accuracy of intensity categories across all 14 activities suggests that the cutpoints developed for the GENEA left wrist placement are not generalizable to other populations and activities different from those used in the original study of Esliger et al. (20).

This study has several strengths. We had a large sample size (N = 130) with approximately equal numbers of men and women, a heterogeneous age range, and considerable racial/ethnic diversity. Our activities represented a wide range of MET levels and included ambulatory, household, office, and sport activities, as is appropriate for an activity monitor calibration study (23, 64). We used a criterion measure of VO_2 and approximated steady-state values by analyzing three minutes of breath-by-breath analysis for each activity. The values we obtained were in close agreement with values predicted by the compendium of physical activity (1) (see table 2). Another important strength of this study is that we examined classification accuracy for intensity categories, which are highly used outcome measures in physical activity research. Few studies have examined classification accuracy based on cutpoint; most other studies look at measurement error using a continuous scale of energy expenditure.

The present study also has some limitations. We only examined the validity of the wrist-worn GENEA cutpoints, and we did not determine whether a waist-worn accelerometer would yield greater classification accuracy. Wrist placement of the accelerometer could lead to an underestimation of physical activity when lower body movement occurs without concurrent arm movements (e.g. in bicycling). We were unable to examine the right-wrist cutpoints, which may have higher validity, given that 90% of the population is right-hand dominant and some activities have greater involvement of the dominant arm.

CONCLUSION

The GENEA accelerometer has previously been reported to be a valid measurement of physical activity intensity categories across a range of activities (20). Upon cross-validation of the left wrist cutpoints proposed by Esliger et al. (20), the majority of activities performed were found to be significantly below the proposed accuracy rate of 80%. When all activities were combined the average accuracy rate was 52.8%, which suggests the device is able to predict intensity category better than by chance alone, but does not yield acceptable levels of classification accuracy for intensity categories. Thus, researchers should be cautious when using the cutpoints of Esliger et al. (20) when testing different populations and activities other than those on which the cutpoints were determined. More research should be done to determine the most effective placement of the GENEA accelerometer (wrist, waist, ankle), and to explore pattern recognition techniques, in order to yield the most valid results.

Table 1. Activity list

Routine 1 (n = 70):
Filing Papers
Vacuuming
Self-Paced Walking
Treadmill Walking at 6.4 km•hr^{-1} 0% grade
Cycle 49 watts
Basketball Practice
Treadmill Running at 9.6 km•hr^{-1} 0% grade
Routine 2 (n = 68):
Computer Work
Treadmill Walking at 4.8 km•hr^{-1} 0% grade
Cycle 98 watts
Moving a Box
Treadmill Walking at 4.8 km•hr^{-1} 5% grade
Treadmill Walking at 6.4 km•hr^{-1} 5% grade
Tennis

Table 2. Average intensity values (METs and GENEA SVMgs)

	n	Compendium METs*	METs Mean(SD)	GENEA SVMgs Mean(SD)
Home/Office				
Filing Papers	69	3.0	1.49 (0.29)	310.19 (125.45)
Vacuuming	70	3.3	3.23 (0.58)	470.75 (175.66)
Computer Work	56	1.3	1.17 (0.27)	134.94 (60.0)
Moving a Box	58	4.5	4.52 (0.90)	756.39 (282.96)
Self-Paced Walking	69	NA	3.68 (0.66)	1017.13 (440.51)
Walking/Running on TM				
TM 4.8 km•hr^{-1} 0% grade	56	3.5	3.70 (0.52)	980.63 (435.64)
TM 4.8 km•hr^{-1} 5% grade	55	5.3	5.17 (0.60)	961.93 (370.92)
TM 6.4 km•hr^{-1} 0% grade	69	5	5.41 (0.65)	1735.88 (882.84)
TM 6.4 km•hr^{-1} 5% grade	46	NA	7.07 (0.87)	1553.07 (1006.52)
TM 9.6 km•hr^{-1} 0% grade	48	9.8	9.66 (1.21)	4644.55 (1682.40)
Sports				
Cycle 48 watts	54	3.5	3.76 (0.63)	203.72 (103.67)
Cycle 98 watts	68	6.8	5.94 (1.15)	252.85 (189.38)
Basketball Practice	57	9.3	8.25 (2.51)	2988.63 (1346.21)
Tennis	47	7.3	7.35 (1.63)	1742.82 (667.86)

TM = Treadmill
NA = not available in compendium
* (1)

Table 3. Accuracy of the GENEA left wrist intensity classifications by activity

Variable		% Correct by observation	80% Accuracy p-value
Home/Office			
	Filing Paper	62.9%	<0.001*
	Vacuuming	81.7%	0.722
	Computer Work	81.8%	0.736
	Moving a box	54.4%	<0.001*
	Self-Paced Walking	22.9%	<0.001*
Walking/Running on TM			
	TM 4.8 km•hr^{-1} 0% grade	23.6%	<0.001*
	TM 4.8 km•hr^{-1} 5% grade	68.9%	0.062
	TM 6.4 km•hr^{-1} 0% grade	48.6%	<0.001*
	TM 6.4 km•hr^{-1} 5% grade	33.3%	<0.001*
	TM 9.6 km•hr^{-1} 0% grade	93.6%	0.020
Sports			
	Cycle 48 watts	10.1%	<0.001*
	Cycle 98 watts	24.0%	<0.001*
	Basketball	77.6%	0.646
	Tennis	56.3%	<0.001*
	Average for Combined Activities	52.8%	

* classification accuracy is significantly less than 80% accuracy rate

Table 4. Cross tabulation of all activities combined

		GENEA cutpoint method			
		Sedentary	Light	Moderate	Vigorous
Actual	Sedentary	60	26	0	0
	Light	40	118	101	4
	Moderate	56	64	146	50
	Vigorous	9	8	29	111

Table 5. Cross tabulation of all activities with cycling removed

		GENEA cutpoint method			
		Sedentary	Light	Moderate	Vigorous
Actual	Sedentary	60	0	0	0
	Light	15	105	101	4
	Moderate	8	46	139	50
	Vigorous	0	6	29	111

Table 6. Cross tabulation of home/office activities

		GENEA cutpoint method			
		Sedentary	Light	Moderate	Vigorous
Actual	Sedentary	60	26	0	0
	Light	14	97	61	3
	Moderate	4	19	37	1
	Vigorous	0	0	0	0

Table 7. Cross tabulation of walking/running activities

		GENEA cutpoint method			
		Sedentary	Light	Moderate	Vigorous
Actual	Sedentary	0	0	0	0
	Light	1	8	37	1
	Moderate	4	26	87	36
	Vigorous	0	4	13	54

Table 8. Cross tabulation of sport activities

		GENEA cutpoint method			
		Sedentary	Light	Moderate	Vigorous
Actual	Sedentary	0	0	0	0
	Light	25	13	3	0
	Moderate	48	19	22	13
	Vigorous	9	4	15	57

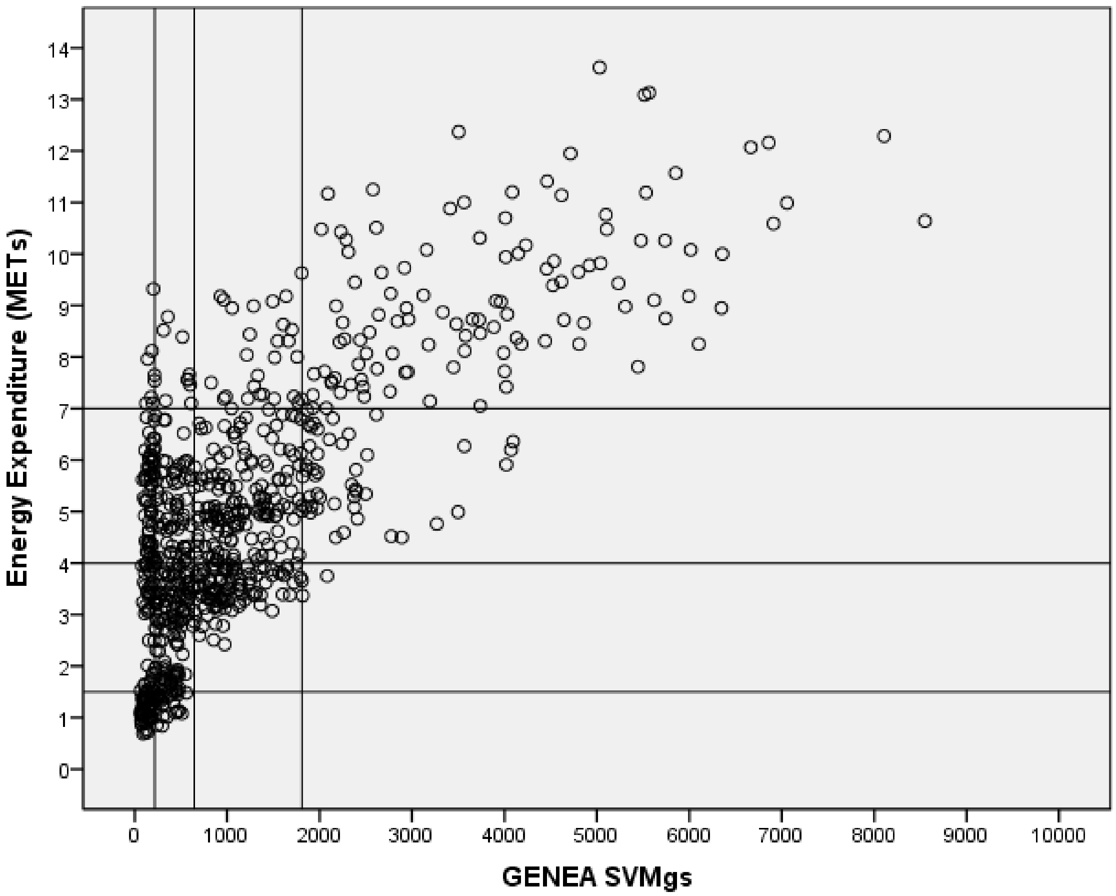

Figure 1. Relationship between METs and GENEA SVMgs

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APPENDICES

APPENDIX A

UNIVERSITY OF TENNESSEE, KNOXVILLE INFORMED CONSENT

University of Tennessee
Department of Exercise, Sport, and Leisure Studies

ADULT CONSENT FORM

Study Title: Development of an Integrated Measurement System to Assess Physical Activity

Principal Investigator: David R. Bassett, Jr.

Institution: The University of Tennessee, Knoxville

This information is provided to tell you about the research project. Please read this form carefully and ask any questions you may have about this study. Your questions will be answered before we ask you to sign it. Also, you will be given a copy of this consent form to take home.

INTRODUCTION
The purpose of this study is to test a new device that measures breathing, motion, and environmental light intensity to improve the assessment of the physical activity in a daily living situation. The improved accuracy will be useful to researchers who study physical activity.

ELIGIBILITY
To be in this study, you must be between 18 and 60 years of age, in good physical health (no diagnosed cardiovascular, pulmonary, metabolic, joint, or chronic diseases).

GENERAL TESTING SCHEDULE
Visit 1, Informed Consent Document (30 minutes)
During today's visit to the Applied Physiology Laboratory, you will be asked to review this informed consent document. In addition to the written details provided in this document, you will be given a verbal explanation of the study. You will be given ample time to review this informed consent form and to inquire about the study and the procedures. You will be provided with a copy of the informed consent form, and your blood pressure will be measured during this visit. You will also be given a health and physical activity questionnaire to complete.

If you have never walked on a treadmill or have limited experience walking on a treadmill, you will be asked to complete a short treadmill test before enrolling in the study. We will provide instructions and then you will be given time to walk on the treadmill. You will begin at a slow speed and progress to a moderate pace (2.5-3.5 mph). If you are either uncomfortable with walking on the treadmill or if it is determined that you cannot complete the protocol(s) satisfactorily, you will not be asked to continue with the study.

Visit 2, Activities (2.0-3.0 hours)

You should not eat or drink (anything but water) for 3 hours before coming to the lab. Before any exercise testing takes place, your height and weight will be measured and your resting metabolic rate and resting blood pressure will be assessed. We will measure your resting metabolic rate using the MedGem analyzer. The MedGem is a portable device that will provide an estimate of your
resting energy expenditure based on the difference in the volume of oxygen between the air that you inhale and exhale. You will be asked to lie motionless on your back on a dormitory bed. After 10-15 minutes a nose clip will be placed on your nose and you will breathe into the mouthpiece of the MedGem analyzer for approximately 10 minutes.

Next, you will be asked to complete approximately 6-8 activities and each activity will be performed continuously for approximately 7 minutes. These activities will be chosen from a broad range of behaviors in the sport, leisure, recreation, occupation, and household areas. Activities may include tasks such as walking or jogging on a flat or inclined treadmill, walking carrying a box, climbing and descending stairs, playing tennis or basketball, doing household tasks such as laundry, sweeping, vacuuming, dusting, lawn mowing, raking, and gardening, or other common activities of daily living. You will be given a 3-5 minute rest period between activities.

Prior to performing the activities, you will be fitted with the **Integrated Measurement System** (IMS) which comprises a chest strap aimed to measure your breathing frequency, a hip strap with a device that measures your physical motion, and a wrist strap with a light intensity sensor designed to detect if the activity is taking place indoor or outdoor. Thin wires will connect these 3 straps to each other and they should not bother you while you are performing the activities. You will also wear several different activity monitors and a heart rate monitor and transmitter belt when you perform the activities. The activity monitors will be worn on the hip and the wrist and fastened with elastic belts. The heart rate transmitter will be fastened around the chest with an elastic belt, and the monitor will be worn on the wrist.

In addition, you will be fitted with a respiratory gas analysis system, which will be used to measure calorie expenditure. You will be also fitted with a facemask to allow collection of expired air. Instructions on how to complete the activities will be provided as you become accustomed to breathing while wearing the facemask. At the end of the testing session, all the devices will be removed. Attempts will be made to try to fit in all of the 6-8 activities during the same visit. If they cannot be completed during the same visit, a second visit will be scheduled to complete the protocol.

RISKS

During any type of exercise, especially strenuous exercise, there are health risks, including abnormal blood pressures, fainting, muscle or skeletal injuries, and heart attack, but the risk of these things happening is remote. However, the possibility of serious events is low in people who have no prior history of heart, respiratory, or muscular diseases or injuries. In order to minimize the risks, we will attempt to screen out individuals with pre-existing health problems. In addition, in the unlikely event of an injury, laboratory personnel trained in CPR will be available to assist you.

BENEFITS

Participation in this study will give scientists insights into improved methods of measuring physical activity and this may lead to new knowledge about physical activity that would benefit many individuals.

CONFIDENTIALITY

The information obtained from this study will be treated as confidential. Confidentiality will be maintained in the analysis and presentation of the data. You will be assigned an ID number, and this is this is the only way you will be identified in published reports. Your name and ID number will be recorded at the beginning of the study and this information will be placed in a file cabinet that will be locked and only accessible to study investigators.

COMPENSATION

Compensation for completing the study will be $75. Full payment will be received only if participants complete the designated protocol. However, if an individual completes part of the study, he or she will receive partial payment that reflects the number of activities performed. Full payment will be received only if you finish the protocol that you are asked to complete for the study. However, if you finish part of the study, you will still receive partial payment that reflects the number of activities you performed. Payment will be received by check within 6-8 weeks of completing all testing.

EMERGENCY MEDICAL TREATMENT

The University of Tennessee does not have a program for automatically compensating subjects for injury or complications related to human subject research, but in the unlikely event of injury resulting directly from participation in this study, investigators will assist you in every way to ensure that you get proper medical treatment. Medical treatment will be available to you through the University of Tennessee Medical Center for a fee.

CONTACT INFORMATION

If you have questions at any time about the study or the procedures, (or you experience an adverse event while participating in this study,) you may contact the researcher, Dr. David R. Bassett, Jr., at 1914 Andy Holt Ave., 325 HPER Bldg., Knoxville, TN, and (865) 974-8766. If you have questions about your rights as a participant, contact the Office of Research Compliance Officer at (865) 974-3466.

PARTICIPATION

Your participation in this study is voluntary; you may decline to participate. If you decide to participate, you may withdraw from the study at anytime without penalty and without loss of benefits to which you are otherwise entitled.

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 __________

APPENDIX B

Physical Activity Readiness Questionnaire (PAR-Q)

Name ____________________________ Date of Birth ____________________

Home Phone _______________________ Work Phone _____________________

For most people physical activity should not pose any problem or hazard. The PAR-Q has been designed to identify the small number of adults for whom physical activity might be inappropriate or those who should have medical advice concerning the type of activity most suitable for them.

Common sense is your best guide in answering these questions. Please read them carefully and check YES or NO opposite the question if it applies to you. If a question is answered YES, please use the available space to explain your answer and give additional details.

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

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) Is your doctor currently prescribing drugs (for example, water pills) ☐ YES
☐ NO
for your blood pressure or heart condition?

7) Do you know of any other reason why you should not do physical activity? ☐ YES ☐ NO

8) Do you currently participate in any regular activity program designed to improve or maintain your physical fitness? ☐ YES ☐ NO

If yes, what activity program do you participate in?___________________________

____

Signature ______________________________ Date ________________________

APPENDIX C

HEALTH HISTORY QUESTIONNAIRE

Personal Health History

Name: ______________________ Age: ____________ Date: ______________

(if under 18)
Mother's Name: _________________________ Father's Name: ________________________

Race: ______________________ Ethnicity: Hisp/Latino Non-Hisp/Latino
(White, Black, Asian, Hawaiian/Pacific Islander, Alaskan/Native American, Other)

Street Address: ____

City: _________________________ State: ______________ ZIP: ______________

Phones: Home _____________ Work _______________ Cell ____________________

E-mail Address: ____

Emergency Contact Name: ____________________________ Phone: _____________________

1) Has a physician ever told you that you have any of the following: **(Check YES or NO)**

YES **NO** **If yes, explain:**

___ ___ High Blood Pressure ____

___ ___ Diabetes ____

___ ___ Epilepsy ____

___ ___ Asthma ____

___ ___ Heart Disease ____

___ ___ Other ____

Any recent surgery? **(circle one)** **YES** **NO**

If yes, please explain: ____

2) Are you currently taking any medications? **(circle one) YES NO**

(include vitamins, herbal remedies, over-the-counter medicine, prescriptions medicine, etc.)

Medication	Purpose	How Much	How Often

APPENDIX D

PHYSICAL ACTIVITY STATUS

Physical Activity Status

Using the descriptions below, record the highest number (0 to 7) which best describes your general activity level during the **previous month**. You did more than section 1 then move on to section 2, and so on. You want to pick the highest number in this list to represent your activity level.

Section 1: Did not participate regularly in programmed recreational sport or heavy physical activity.

- **0** Avoided walking or exertion, e.g. always used the elevator, drove whenever possible instead of walking.
- **1** Walked for pleasure, routinely used the stairs, occasionally exercised sufficiently to cause heavy breathing or perspiration.

Section 2: Participated regularly in recreation or work requiring modest physical activity, such as golf, horseback riding, calisthenics, gymnastics, table tennis, bowling, weight lifting, yard work.

- **2** 10 to 60 minutes per week.
- **3** Over 1 hour per week.

Section 3: Participated regularly in heavy physical exercise such as running or jogging, swimming, cycling, rowing, skipping rope, running in place or engaged in vigorous aerobic activity type of exercise such as tennis, basketball, or handball.

- **4** Ran less than 1 mile per week or spent less than 30 minutes per week in comparable physical activity.
- **5** Ran 1 to 5 miles per week or spent 30 to 60 minutes per week in comparable physical activity.
- **6** Ran 5 to 10 miles per week or spent 1 to 3 hours per week in comparable physical activity.
- **7** Ran more than 10 miles per week or spent over 3 hours per week in comparable physical activity.

Physical Activity Status during the previous month (highest score): ____________

Have you ever played any of the following:

Competitively		Once or Twice	For Recreation	
Yes / No	• Tennis	_______	________	________
Yes / No	• Basketball	_______	________	________

Office Use Only: **Estimated VO_2max: ______________________ ml/kg/min**

VITA

Whitney Allegra Welch was born and raised in Knoxville, TN. Following a three-year stint west of the Mississippi, Whitney graduated from Knoxville Catholic High School. Following high school, Whitney found her home with the orange and white at the University of Tennessee, Knoxville. While there she completed a Bachelors of Science in Education in Exercise Science and a Master of Science in Kinesiology.

In her free time, Whitney enjoys outdoor activities, live music, and rocking chair, front porch reading.