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Classification accuracy of the wrist-worn GENEA accelerometer

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Abstract

Purpose—The purpose of this study was to determine whether the published left-wrist cut-points for the triaxial GENEA accelerometer, are accurate for predicting intensity categories during structured activity bouts.

Methods—A convenience sample of 130 adults wore a GENEA accelerometer on their left wrist while performing 14 different lifestyle activities. During each activity, oxygen consumption was continuously measured using the Oxycon mobile. Statistical analysis used Spearman's rank correlations to determine the relationship between measured and estimated intensity classifications. Cross tabulation tables were constructed to show under- or over-estimation of misclassified intensities. One-way chi-square tests were used to determine whether the intensity classification accuracy for each activity differed from 80%.

Results—For all activities the GENEA accelerometer-based physical activity monitor explained 41.1% of the variance in energy expenditure. The intensity classification accuracy was 69.8% for sedentary activities, 44.9% for light activities, 46.2% for moderate activities, and 77.7% for vigorous activities. The GENEA correctly classified intensity for 52.9% of observations when all activities were examined; this increased to 61.5% with stationary cycling removed.

Conclusion—A wrist-worn triaxial accelerometer has modest intensity classification accuracy across a broad range of activities, when using the cut-points of Esliger et al. Although the sensitivity and specificity are less than those reported by Esliger et al., they are generally in the same range as those reported for waist-worn, uniaxial accelerometer cut-points.

Keywords

activity monitor; accelerometry; physical activity; energy expenditure

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Introduction

Since the mid-1980s there has been a steady increase in the evidence-based literature associating low levels of physical activity with an increased risk of chronic diseases such as type 2 diabetes, obesity, and cardiovascular disease (25). The integrity of physical activity monitoring studies, intervention studies, and epidemiology studies rely on the valid and reliable assessment of physical activity (2). Doubly-labeled water, direct observation, and direct and indirect calorimetry are the most valid "criterion" measures of physical activity (27). However, these methods are expensive, require trained professionals to administer, and are not practical for some applications (15).

Movement sensors, such as pedometers and accelerometers, are inexpensive portable devices that allow researchers to objectively measure activity within the free-living environment (15). While pedometers are specifically designed to measure walking behaviors such as total steps taken per day (14), accelerometer-based physical activity monitors allow researchers to track frequency, intensity, and duration of activity (18). Prior to the development of triaxial accelerometers, uniaxial accelerometers were used to measure accelerations that occurred within the vertical plane (27). 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 tends to have higher correlations with energy expenditure (5, 7, 12). In addition, advances in modern technology now allows tracking of both dynamic and static accelerations (8).

It is now common practice to place motion sensors on the waist of human subjects, but this site has limitations. Placed near the center of mass, waist-mounted accelerometers fail to detect arm movements, which leads to significant measurement errors and physical activity intensity misclassification (7). Therefore, alternative sites for placement that may elicit improved results compared to the waist-worn sensors could enhance future research (7). Researchers have attempted to place accelerometers on the ankle, upper arm, wrist, or multiple sites of the body (4, 29). A newly introduced wrist-worn accelerometer-based physical activity monitor, the Gravity Estimator of Normal Everyday Activity (GENEA), has been reported to have high accuracy for classifying physical activity intensity (e.g., sedentary, light, moderate, vigorous) (9). Furthermore, due to its wristwatch-like characteristics and size, the GENEA will potentially encourage higher rates of wear compliance, when compared to waist-worn accelerometers (26).

The physical activity intensity cutpoints for the GENEA accelerometer developed by Esliger et al. (9) showed high levels of criterion validity (r=0.85) across a range of activities, including home/office and ambulatory activities, which was approximately equal to that seen with the waist-mounted ActiGraph GT1M and the RT3(9). 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 cut-points have not been cross-validated in a separate study. Thus, the purpose of this study is to examine whether the left wrist GENEA cut-points developed by Esliger and colleagues are accurate for predicting intensity categories. Ambulatory activities, home/office activities, and sport activities were examined.

Methods

Participants

One hundred thirty-nine participants were recruited from on-campus and the surrounding community of the University of Tennessee, Knoxville or 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 (UTenn n=90; UMass n=40). 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 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, Health History Questionnaire, and Physical Activity Status questionnaire in order to determine his/her ability to participate in the study. Height was measured using a stadiometer and weight was measured by either the Tanita BC-418 scale (Tanita Corporation of America, Inc.; Arlingtion Heights, Illinois [UTenn])or a physicians' scale (Detecto; Webb City, MO [UMass]). Body mass index was calculated from these measurements.

Each participant completed a series of seven activities from one of two routines. Routine 1 (n=70) activities included: Filing papers, vacuuming, self-paced walking, treadmill walking at 6.4 km·hr^{-1}, cycling at 49 watts, basketball practice, and treadmill running at 9.6km·hr^{-1}. Routine 2 (n=68) activities included: computer work, treadmill walking at 4.8 km·hr^{-1}, cycling 98 watts, moving a box (4.5 kg), treadmill walking at a 5% incline (4.8km·hr^{-1}, 6.4 km·hr^{-1}), and tennis. Each activity was performed for seven minutes with a 4-minute break between activities. Participants wore the Oxycon Mobile portable metabolic unit (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. The GENEA was placed on the non-dominant wrist because this study was part of a larger study that used another device on the dominant wrist. The GENEA (Activinsights Limited; Colworth, United Kingdom) is a triaxial, ±6g, accelerometer weighing 16 g, measuring 36 mm ×30mm ×12 mm, and can be worn on the wrist, waist, or ankle. Accelerometers were initialized to sample data at 80 Hz (30). 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 in order to obtain steady state VO_2 data. 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 submaximal work rates (49 and 98 watts) 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 (Figure 1 and Figure 2). Corrected VO_2 values were converted to METs using 1 MET = 3.5 ml·kg^{-1}·min^{-1}. The MET values obtained for each activity were classified into an intensity category (sedentary (<1.5 MET), light (1.5 -3.99 METs), moderate (4.0 - 6.99 METs), or vigorous (7+ METs)) following the same thresholds used by Esliger et al. (9).

Using precisely the same methods as Esliger et al. (9), 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 mean r-g value, rather than a cumsum r-g, therefore these values were multiplied by 60, which has the same effect as summing the 60 1-sec epochs. Three minutes (minutes 4-6) of each activity were used to obtain the average SVM_{gs} for each activity. Using the left wrist cut-points of Esliger et al. (9), 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 (SPSS, Chicago, IL). Spearman's rank correlation coefficients were used to determine whether there was a linear relationship between METs 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-square analyses were used to test whether the accuracy rate differed from 80%. Eighty percent was chosen as an acceptable accuracy rate based on accuracy rates observed in validation studies of accelerometers analyzed by pattern recognition (20, 31).

Results

Of the 130 adult participants, 48.5% were male and 51.5% were female. Most were 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 $kg \cdot m^{-2}$.

Table 1 shows the mean and standard deviation for the METs obtained for each activity by the Oxycon, and MET estimates from the Compendium of Physical Activities (1), as well as the mean and standard deviation for the GENEA estimated SVM_{gs} (g·min) for each activity. The Spearman's correlation coefficient expressing the relationship between GENEA SVM_{gs} and METs was $\rho=0.641$ ($p < 0.001$), when all activities are combined.

A cross tabulation table for all activities combined is shown in Table 2a, with correct intensity classification category denoted by the shaded blocks. By summing the numbers in the shaded boxes (i.e. correctly classified activity bouts) and dividing this number by the sum of the numbers in the shaded and white boxes (i.e. total number of activity bouts) the total percentage of correctly classified activity bouts can be computed. The intensity classification accuracy for all of the activities was 52.9%. Since the two cycling activities had high rates of misclassification, we removed cycling from the rest of the activities and this increased the overall accuracy rate to 61.5% (Table 2b) and Spearman's correlation coefficient to $\rho=0.802$ ($p<0.001$). Figure 3 depicts the relationship between METs and GENEA SVM_{gs} for each observation. Vertical lines are placed at each Esliger et al. (9) left wrist cut-point, and horizontal lines are placed at each MET level cut-point, creating blocks of space showing agreement between the measured and predicted intensity categories. Observations that fell outside those regions for each intensity level show misclassifications of the different activities.

Table 1 shows the results of the one-way chi-square analysis. When combining all activities, the GENEA correctly classified the intensity category in 52.9% of the observations. Individually, most of the activities (9 out of 14) were significantly less than our predetermined acceptable accuracy rate of 80%. Vacuuming, basketball, computer work, and walking on a treadmill at 4.8 $km \cdot hr^{-1}$ on a 5% grade were estimated with an accuracy rate that did not differ from 80%. Jogging on the treadmill at 9.7 $km \cdot hr^{-1}$ with 0% grade showed statistically greater accuracy than 80%.

Further analyses were performed to determine the sensitivity and specificity of each proposed left wrist intensity category (Table 3). Since moderate-to-vigorous physical activity (MVPA) is a common outcome measure among physical activity research, sensitivity and specificity of an MVPA cut-point was also calculated with all activities (sensitivity = 0.710 and specificity = 0.699) and with cycling removed from the total observations (sensitivity = 0.846 and specificity = 0.632).

Discussion

Using the proposed cut-points, the wrist-worn GENEA, classified intensity for 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%. For most of the other activities, intensity was frequently misclassified. When all the activities were separated out by intensity, the percentage of activities correctly classified was 69.76% for sedentary activities, 44.86% for light activities, 46.2% for moderate activities, and 77.71% for vigorous activities. In addition, when all activity bouts were considered together, the wrist-worn GENEA correctly classified 52.9% of the total observations, or 61.5% when stationary cycling was excluded.

In our analysis of the GENEA device, the Spearman's Rho-squared explained 41.1% of the variance in energy expenditure. Even though our data violated the assumptions of normality, 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. Using Pearson's R^2, Esliger et al. (9) reported that the GENEA worn on the left wrist explained 73.9% of the variance in energy expenditure. Swartz et al. (22) 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 using Pearson's R^2. Thus, it appears that a triaxial accelerometer (worn on the wrist) results in a stronger relationship with energy expenditure, than a uniaxial accelerometer.

It is important to understand whether the wrist site is an acceptable alternative compared to the waist for measuring physical activity. In 2011, the U.S. National Health and Nutrition Examination Survey began using wrist-worn accelerometers to estimate physical activity from measured activity counts (6). Esliger et al. (9) reported that a GENEA triaxial 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. (22) placed CSA uniaxial 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 only 3.3% of the variance. Thus, it appears that if a triaxial accelerometer is used, the wrist and waist sites have similar relationships with measured energy expenditure. However, if a uniaxial accelerometer is used, then the waist-worn accelerometer has a much stronger relationship with energy expenditure.

Esliger et al. (9) found the left wrist placement of the GENEA to be 93% accurate in classifying physical activity intensity. Our analysis showed an intensity classification accuracy of 69.76% for sedentary activity, 44.86% for light activity, 46.20% for moderate activity, and 70.71% for vigorous activity. It is important to note that Esliger et al. (9) did not cross-validate their cut-points. They determined the accuracy of their cut-points using the same data set on which their cut-points were developed; thus the accuracy may be inflated, relative to what it would be when examining other people and other activities.

In the present study, the wrist-worn GENEA correctly identified the intensity category between 23.6% and 93.6% of the time for treadmill walking and running. Generally, as speed increases, both energy expenditure and accelerometer activity counts increase. However, when grade is increased and speed is kept constant, energy expenditure increases without any increase in accelerometer activity counts (11, 17). Interestingly, at 4.8 km·hr^{-1}, 0% grade classification accuracy was significantly less than at 4.8 km·hr^{-1}, 5% grade. The average MET values for walking at 4.8 km·hr^{-1},0% grade was 3.5 METs, which is close to the lower cut-point for moderate intensity. However, adding a 5% grade increased the average MET value to 5.17 METs, which fell clearly within the moderate intensity category; this greatly improved classification accuracy. Similarly, at 6.4 km·hr^{-1}, 5% grade the energy cost was 5.41 METs, which fell in the middle of the moderate intensity range; thus the classification accuracy was high. However, at 6.4 km·hr^{-1}, 0% grade the average energy cost was 7.07 METs, straddling the cut-point between moderate and vigorous intensity. Thus, classification accuracy at this speed and grade decreased by 15.3%. These factors likely contributed to our wide range of classification accuracy during treadmill walking and running activities.

One sport activity (basketball) had an intensity classification accuracy rate that did not significantly differ from 80%, but both cycling activities were below 25% intensity classification accuracy, which was not a surprise considering the type of activity and the location of the GENEA on the subject. 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-worn GENEA had reduced classification accuracy for inclined treadmill walking at 6.4 km·hr^{-1}, as compared to the accuracy recorded for level walking at the same speed. This was due to the wrist-worn GENEA's inability to detect the increased metabolic cost associated with inclined walking. Other activities where the GENEA cut-points 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 intensity classification accuracy reported by Esliger et al. (9) is that most of their activities were tightly clustered, and they fell between the 1.5, 4, 7 MET cut-points. In contrast, many of the actual MET values of activities in the current investigation fell closer to the cut-points, contributing to a higher rate of intensity 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 were in the vigorous-intensity range, but for many of the participants these activities were, in fact, moderate-intensity. Self-paced walking is an example of an activity that was near the cut-point distinguishing light versus moderate physical activity. Self-paced walking had an average MET value of 3.68 ± 0.66 METs. When actual MET values are close to the cut-points, there is a greater likelihood that the intensity of these activities will be misclassified.

As Bassett et al. (3) 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. (9) in developing the intensity cut-points.

Another way to report the intensity classification accuracy is to determine the sensitivity and specificity of individual intensity cut-points by total observations, rather than accuracy by activity type. Unlike comparison of intensity category accuracy from previous studies using the ActiGraph (19, 21), reporting sensitivity and specificity of these cut-points allows comparison of GENEA cut-points across the literature. Similar to the current study, Trost et al. (24) compared multiple proposed cut-points by cross-validation of a different population, using Actigraph accelerometers in children. Using 12 activities that ranged from sedentary (lying down, computer games) to vigorous (basketball and running), Trost et al. used sensitivity and specificity to determine which cut-point maximized the amount of true positives/true negatives reported and minimized the amount of false positives/false negatives. The authors found that the Evenson cutpoints reported the highest sensitivity and specificity with sensitivity ranging from 49.3%-100% and specificity ranging from 88.3%-93.8%. Esliger et al. (9) conducted a sensitivity and specificity analysis for the left wrist cut-points, and the values ranged from 78-97% and 72-98%, respectively. In contrast, our sensitivity analysis ranged from 45-71% and our specificity analysis ranged from 74-92%. These differences could be due to the difference in the population studied, the types of activities performed, or use of the same data set for calibration and validation in the study of Esligeret al(9).

Emerging evidence suggests that new techniques, such as pattern recognition tools, will help improve physical activity assessment (13). One other GENEA wrist-worn classification study by Zhang et al. (31) examined pattern recognition algorithms to predict activity type. Our study focused on classification of intensity category rather than activity type, so we did not examine these algorithms. However, the more advanced approaches they used may be an improvement for correctly classifying various types of activities. In our study, the low classification accuracy of intensity categories across all 14 activities suggests that the cut-points 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. (9).

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 (10, 28). 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 Activities (1) (see Table 1). Another important strength of this study is that we examined classification accuracy for intensity categories, which are widely used outcome measures in physical activity research. Few studies have examined classification accuracy based on cut-points; most of them examine 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 cut-points, and we did not determine whether a waist-worn accelerometer would yield greater classification accuracy. A wrist accelerometer can lead to an underestimation of physical activity when lower body movement occurs without concurrent arm movements, such as stationary cycling (likewise, waist-worn accelerometers also underestimate stationary cycling). We were unable to examine the right wrist cut-points, 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. Also, our population differed from the population the cut-points were developed on (participants in the current study were 20-60 years of age compared with 40-65 years of age in the study of Esliger et al. (9)), which could have affected the accuracy of the proposed cut-points and MET values used.

Conclusion

The GENEA accelerometer has previously been reported to provide a valid measure of physical activity intensity categories, across a range of activities (9). Upon cross-validation of the left wrist cut-points proposed by Esliger et al. (9), the majority of activities performed were found to be significantly below the proposed accuracy rate of 80%. When all activities were examined the intensity classification accuracy rate was 52.9%. This increased to 61.5% when stationary cycling was excluded. While this cross-validation study reported similar intensity classification accuracy to previous studies, researchers should be cautious using the cut-points of Esliger et al. (9) when testing different populations and activities other than those on which the cutpoints were determined. More research is needed 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.

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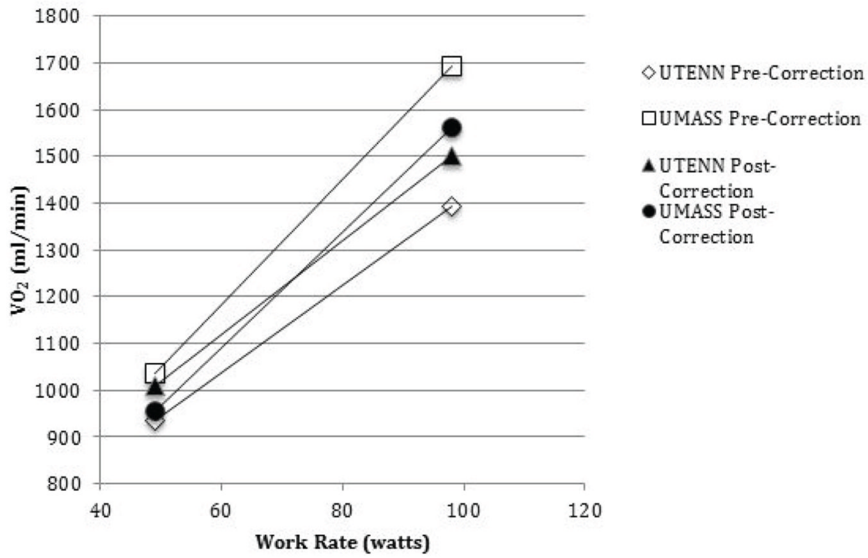

Figure 1.

Measured oxygen cost (VO_2) of stationary cycling at two different intensities, pre- and post-correction. The VO_2 values from the study sites were corrected to align them and create closer matching with the ACSM-predicted VO_2 values for 49 and 98 W (1019 ml/min and 1548 ml/min, respectively).

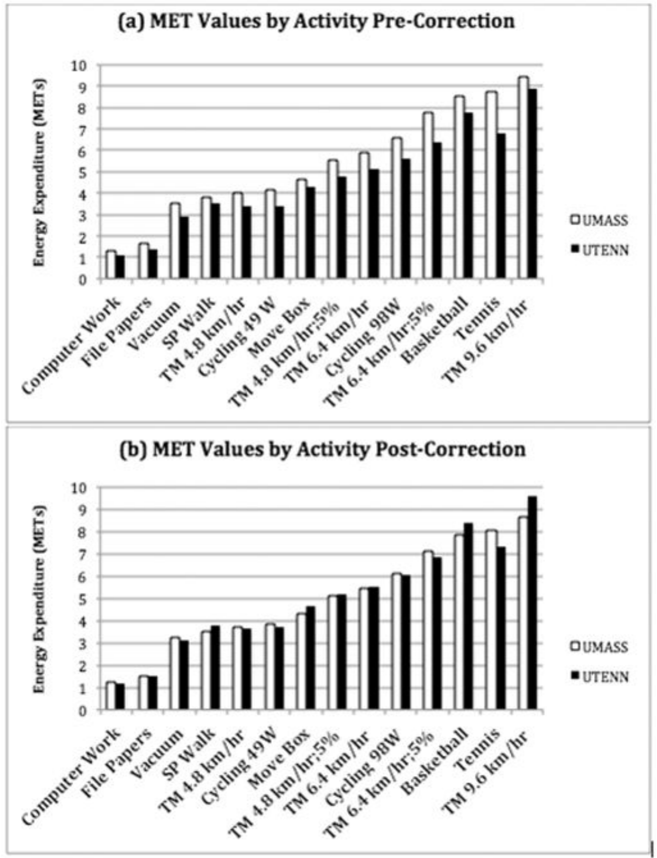

Figure 2.
Measured energy expenditure (METs) of each activity pre- and post-correction. (a) Uncorrected measured MET values at both study sites (white=UMASS; black=UTENN) across all activities. (b) Corrected measured MET values at both study sites (white=UMASS; black=UTENN) across activities.

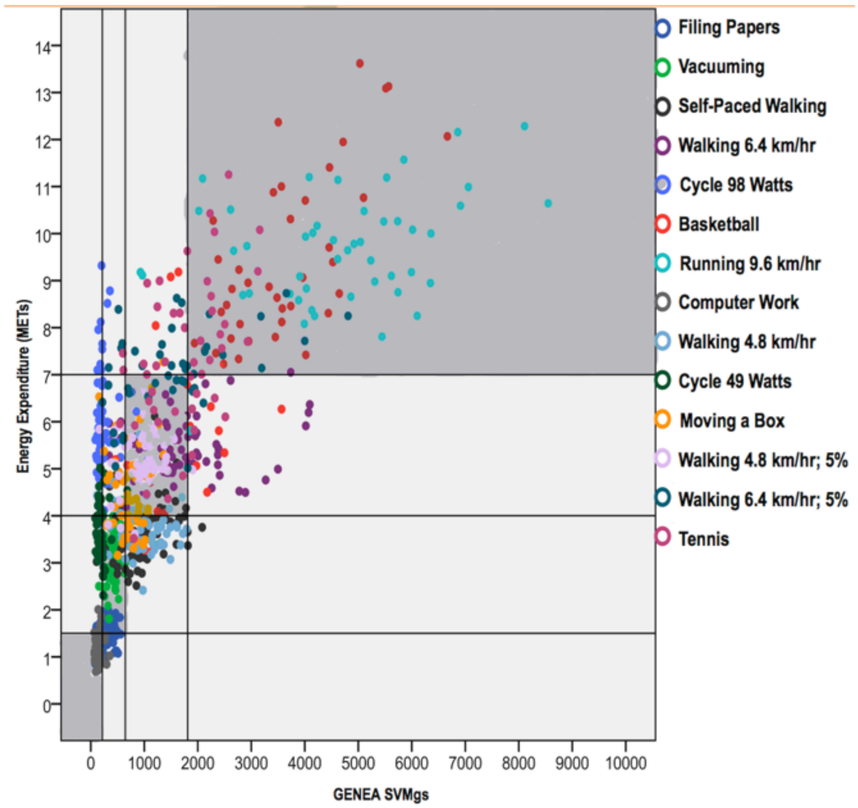

Figure 3.
Relationship between METs and GENEA SVM_{gs}. Marked lines depict cut-points for each variable.

Table 1

Average Intensity Values & Classification Accuracy by Activity

	n	Compendium METs^	METs Mean(SD)	GENEA SVMgs (g·min) Mean(SD)	Classification Accuracy	p-value (80% accuracy)
Home/Office						
Filing Papers	69	3.0	1.49 (0.29)	310.19 (125.45)	62.90%	<0.001 *
Vacuuming	70	3.3	3.23 (0.58)	470.75 (175.66)	81.70%	0.722
Computer Work	56	1.3	1.17 (0.27)	134.94 (60.0)	81.80%	0.736
Moving a Box	58	4.5	4.52 (0.90)	756.39 (282.96)	54.40%	<0.001 *
Self-Paced Walking	69	NA	3.68 (0.66)	1017.13 (440.51)	22.90%	<0.001 *
Walking/Running on TM						
TM 4.8 km·hr^{-1} 0% grade	56	3.5	3.70 (0.52)	980.63 (435.64)	23.60%	<0.001 *
TM 4.8 km·hr^{-1} 5% grade	55	5.3	5.17 (0.60)	961.93 (370.92)	68.90%	0.062
TM 6.4 km·hr^{-1} 0% grade	69	5.0	5.41 (0.65)	1735.88 (882.84)	48.60%	<0.001 *
TM 6.4 km·hr^{-1} 5% grade	46	NA	7.07 (0.87)	1553.07 (1006.52)	33.30%	<0.001 *
TM 9.6 km·hr^{-1} 0% grade	48	9.8	9.66 (1.21)	4644.55 (1682.40)	93.60%	0.020
Sports						
Cycle 48 watts	54	3.5	3.76 (0.63)	203.72 (103.67)	10.10%	<0.001 *
Cycle 98 watts	68	6.8	5.94 (1.15)	252.85 (189.38)	24.00%	<0.001 *
Basketball	57	9.3	8.25 (2.51)	2988.63 (1346.21)	77.60%	0.646
Tennis	47	7.3	7.35 (1.63)	1742.82 (667.86)	56.30%	<0.001 *
All Activities Combined					52.90%	

TM = Treadmill

NA = not available in compendium

^ (1)

* classification accuracy is significantly less than 80% accuracy rate

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Table 2

Cross tabulation tables

a. All activities					
		GENEA cutpoints			
		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
b. Activities with cycling removed					
		GENEA cutpoints			
		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 3
Sensitivity and Specificity Analysis of Left Wrist GENEA Cut-points

	Sensitivity	Specificity
Sedentary	0.697	0.857
Light	0.449	0.825
Moderate	0.462	0.743
Vigorous	0.707	0.919
MVPA (all activities)	0.710	0.699
MVPA (cycling removed)	0.846	0.632