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A novel method for using accelerometer data to predict energy expenditure

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Crouter, Scott E., Kurt G. Clowers, and David R. Bassett, Jr. A novel method for using accelerometer data to predict energy expenditure. *J Appl Physiol* 100: 1324–1331, 2006. First published December 1, 2005; doi:10.1152/japplphysiol.00818.2005.—The purpose of this study was to develop a new two-regression model relating Actigraph activity counts to energy expenditure over a wide range of physical activities. Forty-eight participants [age 35 yr (11.4)] performed various activities chosen to represent sedentary, light, moderate, and vigorous intensities. Eighteen activities were split into three routines with each routine being performed by 20 individuals, for a total of 60 tests. Forty-five tests were randomly selected for the development of the new equation, and 15 tests were used to cross-validate the new equation and compare it against already existing equations. During each routine, the participant wore an Actigraph accelerometer on the hip, and oxygen consumption was simultaneously measured by a portable metabolic system. For each activity, the coefficient of variation (CV) for the counts per 10 s was calculated to determine whether the activity was walking/running or some other activity. If the CV was $\leq$10, then a walk/run regression equation was used, whereas if the CV was $>$10, a lifestyle/leisure time physical activity regression was used. In the cross-validation group, the mean estimates using the new algorithm (2-regression model with an inactivity threshold) were within 0.75 metabolic equivalents (METs) of measured METs for each of the activities performed ($P \geq 0.05$), which was a substantial improvement over the single-regression models. The new algorithm is more accurate for the prediction of energy expenditure than currently published regression equations using the Actigraph accelerometer.

motion sensor; physical activity; oxygen consumption; activity counts variability

THE ASSOCIATION BETWEEN PHYSICAL activity and positive health benefits has been well established (3, 4, 10, 14). This has lead to the Centers for Disease Control and Prevention and the American College of Sports Medicine recommendation that every US adult should accumulate 30 min of moderate-intensity physical activity on most, preferably all, days of the week (15). Although the benefits of regular, moderate-intensity physical activity have been shown, quantifying physical activity has proven to be a difficult task.

Accelerometers are objective measurement tools that allow researchers to estimate how much energy individuals are expending, as well as to quantify the amount time spent in light [$<$3 metabolic equivalents (METs)], moderate (3–5.99 METs), and vigorous ($\geq$6 METs) physical activity. The Actigraph (formerly the Manufacturing Technology Incorporated Actigraph, and the Computer Science Applications accelerometer) is a commonly used device for assessing physical activity. Several regression equations have been developed relating the Actigraph activity counts to energy expenditure (EE) (6–8, 11, 13, 17, 18). Theoretically, this allows researchers to estimate total EE over a given period of time. In addition, these regression equations allow researchers to establish cut points (based on counts/min) for classification of light, moderate, and vigorous physical activity.

Over the past 5 yr, there has been a great increase in the number of prediction equations relating the Actigraph activity counts to EE. The current regression equations for estimating EE based on the counts per minute from the Actigraph accelerometer were developed either during walking and running (6–8, 11, 13, 18) or during moderate-intensity lifestyle activities (8, 17). However, these different equations pose a problem for researchers because no single regression line is able to accurately predict EE or time spent in different intensity categories, across a wide range of activities. In addition, all of these equations assume a linear relationship between counts per minute and EE. Previously, it has been shown that regression equations developed on walking and jogging slightly overestimate the energy cost of walking and light activities, whereas they greatly underestimate the energy cost of moderate-intensity lifestyle activities (2). The lifestyle regression equations provide a closer estimate of EE for moderate-intensity activities, but they greatly overestimate the energy cost of sedentary and light activities and underestimate the energy cost of vigorous activities (2).

Using data previously collected in our laboratory, we observed that walking and running can be distinguished from other activities on the basis of variability in the activity counts from the Actigraph. Generally, locomotor activities (i.e., walking and running) yielded more consistent minute-to-minute counts than other activities (e.g., vacuuming, raking leaves, racquetball, sweeping, etc.), which have more erratic movement patterns. Specifically, the variability in minute-to-minute counts was less for walking than for other activities. In addition, we noted that the slope of the regression line relating counts per minute (x-axis) to METs (y-axis) was steeper for walking and running activities than it was for moderate-intensity lifestyle activities, meaning that two separate regression lines should be used for the prediction of these activities.

Thus we hypothesized that by calculating the coefficient of variation (CV) for six 10-s epochs within a 1-min period, we could distinguish walking and running from all other activities. We further hypothesized that by using the appropriate regression line, we could obtain a closer estimate of EE across a wide range of activities. Therefore, the purpose of this study was to develop a new prediction equation for use with the Actigraph accelerometer that would be composed of two regression lines; one for walking and running and one for all other activities.

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The determination of which line to use was based on the CV of the counts per 10 s over a 1-min period. A secondary purpose was to examine the ability of these equations to predict time spent in light (<3 METs), moderate (3–6 METs), and vigorous (>6 METs) physical activity.

METHODS

Subjects. Forty-eight participants [age 35 yr (11.4), body mass index 24.2 kg/m^2 (4.8)] from the University of Tennessee, Knoxville and surrounding community volunteered to participate in the study. The procedures were reviewed and approved by the University of Tennessee Institutional Review Board before the start of the study. Each participant signed a written, informed consent and completed a Physical Activity Readiness Questionnaire before participating in the study. Participants were excluded from the study if they had any contraindications to exercise or if they were physically unable to complete the activities. The physical characteristics of the participants are shown in Table 1.

Anthropometric measurements. Before testing, participants had their height and weight measured (in light clothing, without shoes) using a stadiometer, and a physician's scale, respectively. Body mass index was calculated according to the following formula: body mass (kg) divided by height squared (m^2).

Procedures. Participants performed various lifestyle and sporting activities that were broken into three routines.

1) *Routine 1*: lying, standing, sitting doing computer work, filing articles, walking up and down stairs at a self-selected speed, cycling at a self-selected work rate.

2) Routine 2: walking at ~3 miles/h (mph) around a track, walking at ~4 mph around a track, playing one-on-one basketball, playing singles racquetball, running at ~5 mph around a track, running at ~7 mph around a track.

3) Routine 3: vacuuming, sweeping and/or mopping, washing windows, washing dishes, lawn mowing with a push mower, raking grass and/or leaves.

Twenty participants performed each routine, with most performing only 1 routine. Specifically, two participants performed all three routines, and eight participants performed two routines. Participants performed each activity in a routine for 10 min, with a 1- to 2-min break between each activity. Oxygen consumption ($\dot{V}O_2$) was measured continuously throughout the routine by indirect calorimetry (Cosmed K4b^2, Cosmed, Rome, Italy). Participants wore an Actigraph accelerometer on the right hip for the duration of the routine. For the Cosmed K4b^2 and Actigraph, 2 kg was added to account for the added weight of the devices. *Routine 1* was performed in the Applied Physiology Laboratory, *routine 2* was performed at University facilities, and *routine 3* was performed at either the participant's home or the investigator's home. The participants who did not perform *routine 1* were asked to sit quietly for 5 min before the start of the routine so that a resting $\dot{V}O_2$ could be measured.

Indirect calorimetry. The participants wore a Cosmed K4b^2 for the duration of each routine. The Cosmed K4b^2 weighs 1.5 kg, including the battery and a specially designed harness. The Cosmed K4b^2 has been shown to be a valid device compared with the Douglas bag method during cycle ergometry (12). In addition, the present study found that there was close agreement between the measured $\dot{V}O_2$ from the Cosmed K4b^2 during the stationary cycling (range: 44–172 W) and the predicted values from the formula of the American College of Sports Medicine's *Guidelines for Graded Exercise and Prescription* (1) [R^2 = 0.917, standard error of estimate (SEE) = 134.1 ml/min, $P < 0.05$]. Before each test, the oxygen and carbon dioxide analyzers were calibrated according to the manufacturer's instructions. This consisted of performing a room air calibration and a reference gas calibration using 15.93% oxygen and 4.92% carbon dioxide. The flow turbine was then calibrated using a 3.00-liter syringe (Hans-Rudolph). Finally, a delay calibration was performed to adjust for the lag time that occurs between the expiratory flow measurement and the gas analyzers. During each test, a gel seal was used to help prevent air leaks from the face mask.

Actigraph accelerometer. The Actigraph accelerometer (model 7164) is a small (2.0 × 1.6 × 0.6 in.) and lightweight (42.5 g) uniaxial accelerometer and can measure accelerations in the range of 0.05–2 G and a band-limited frequency of 0.25–2.5 Hz. These values correspond to the range in which most human activities are performed. An 8-bit analog-to-digital converter samples at a rate of 10 Hz, and these values are then summed for the specified time period (epoch). If a 1-min epoch is used, the Actigraph can store 22 days worth of data, which is downloaded to a personal computer via a reader interface unit. The Actigraph was worn at waist level at the right anterior axillary line in a nylon pouch that was attached to a belt. The Actigraph was initialized using 1-s epochs, and the time was synchronized with a digital clock so the start time could be synchronized with the Cosmed K4b^2. At the conclusion of the test, the Actigraph data were downloaded to a laptop computer for subsequent analysis. The Actigraph accelerometer was calibrated at the start and end of the study. On both occasions, the calibration fell within ±3.5% of the reference value, which is within the manufacturer's standards.

Data analysis. Breath-by-breath data were collected by the Cosmed K4b^2, which was averaged over a 30-s period. For each activity, the $\dot{V}O_2$ (ml/min) was converted to $\dot{V}O_2$ (ml·kg^{-1}·min^{-1}) and then to METs by dividing by 3.5. For each activity, the MET value for *minutes 4–9* were averaged and used for the subsequent analysis.

Because of a technical problem with the Cosmed K4b^2, 11 of the walking and running trials had to be repeated. For the 11 trials that were repeated, eight of the participants were the same ones who performed the original trials and three were new participants. The walking and running trials were part of a routine that included indoor and outdoor trials, and calibration was conducted indoors. The oxygen analyzer in the K4b^2 is affected by the large changes in ambient temperature, and going from a warm environment to a colder outdoor environment will cause it to overestimate expired fraction of oxygen, and thus underestimate $\dot{V}O_2$ (Paolo Brugnoli, Cosmed, Srl, Pavonadi Albano-Rome, Italy), personal communication, September 1, 2005). The carbon dioxide analyzer remains stable when undergoing changes in ambient temperature. The 11 tests that had to be repeated were originally performed in early spring when the outdoor temperature was well below the indoor temperature by 20–30°. The other tests were performed during a period when the outdoor and indoor temperatures were close to each other. The most recent version of the

Table 1. *Physical characteristics of the participants*

Variable	Men (n = 24)	Women (n = 24)	All Participants (n = 48)
Age, yr	36±12.8 (21–69)	35±10.3 (22–55)	35±11.4 (21–69)
Height, in.	70.9±2.8 (62.8–74.2)*	65.1±2.3 (60.2–68.5)	68.0±3.8 (60.2–74.2)
Body mass, kg	83.9±20.2 (59.4–141.0)*	62.3±12.3 (45.4–109.0)	73.1±19.6 (45.4–141.0)
BMI, kg/m^2	25.8±5.2 (19.1–40.6)*	22.7±4.0 (17.9–36.4)	24.2±4.8 (17.9–40.6)
Resting $\dot{V}O_2$, ml·kg^{-1}·min^{-1}	3.6±0.8 (2.1–5.0)	3.4±0.8 (2.0–4.9)	3.5±0.9 (2.0–5.0)

Values are means (SD) with range in parentheses; *n,* no. of subjects. BMI, body mass index; $\dot{V}O_2$, oxygen consumption. *Significantly different from women, $P < 0.05$.

Cosmed K4b^2 uses an internal pneumatic modification that adds a miniaturized valve for performing automatic room air calibrations at programmable time intervals correcting for changes in temperature.

The Actigraph accelerometer data were collected in 1-s epochs and were converted to counts per 10 s and counts per minute using a Visual Basic program, written specifically for this study. We chose to use 1-s epochs to allow greater flexibility during our data analysis, but to apply the newly developed method data can be collected in 10-s epochs. The CV was calculated for each minute by using six 10-s epochs. The average CV and the average counts per minute were calculated for *minutes 4–9* of each activity.

Statistical treatment. Statistical analyses were carried out using SPSS version 13.0 for windows (SPSS, Chicago, IL). For all analyses, an alpha level of 0.05 was used to indicate statistical significance. All values are reported as means (SD). Independent *t*-tests were used to examine the difference between genders for anthropometric variables.

Forty-five tests were randomly selected for the development of the new two-regression model, thus leaving 15 tests for cross-validation of the new equation. Because of waist-mounted accelerometers not being able to detect cycling activity, it was excluded from all analyses. Stationary cycling was included to confirm that the Cosmed K4b^2 was providing reasonable $\dot{V}O_2$ values. For the group used to develop the new regression equation, each activity performed by an individual was classified on the basis of the CV value of the 10-s counts: CV from 0.1 to 10 (CV $\leq$ 10), and CV of 0 and >10 (CV > 10). During the walking and running, the CV was almost always <10, whereas for the other activities the CV was almost always >10 (Fig. 1). One exception was during activities such as lying, sitting, and standing where the counts per minute could be zero for a full minute, thus giving a CV of 0. In these cases, they were placed in the CV > 10 group for the purpose of developing the regression equation. This was done because these activities more closely resemble lifestyle activities, and it also provided an anchor point for the lifestyle regression line. We also chose to include lawn mowing and stair climbing in the lifestyle regression not only because their CV was >10 but also because they have factors that increase the energy cost of the activity beyond what would be expected for walking and running. Regression analyses were then used to predict METs from the counts per minute for the CV $\leq$ 10 group and the CV > 10 group.

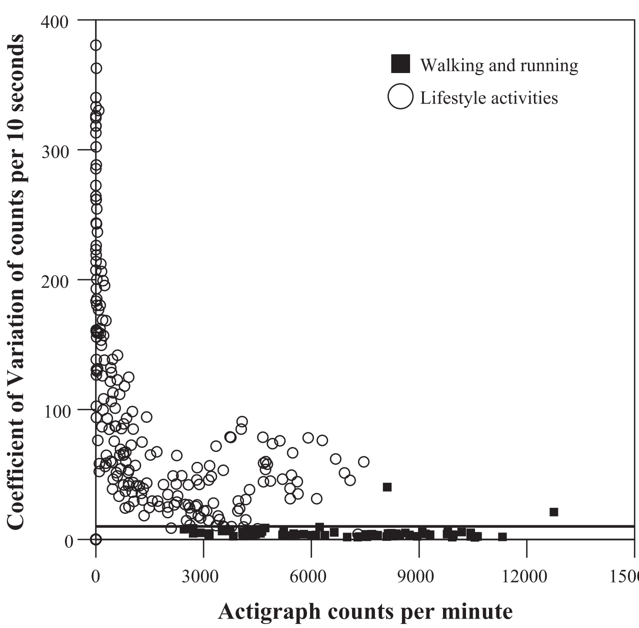

Fig. 1. Relationship between counts per minute from an Actigraph accelerometer and the coefficient of variation (CV) of the 10-s counts for various activities. Eleven CVs between 400 and 600 were excluded from the graph, all of which were lifestyle activities.

To compare the newly developed equation with current regression models, we also estimated METs from the regression equations of Freedson et al. (7), Hendelman et al. (8), and Swartz et al. (17). A one-way repeated-measures ANOVA was used to compare actual and predicted METs for each activity using the cross-validation group. In addition, a one-way repeated-measures ANOVA was used to compare actual and predicted METs for all 18 activities combined. Pairwise comparisons with Bonferroni adjustments were performed to locate significant differences when necessary.

Modified Bland-Altman plots were used to graphically show the variability in individual error scores (actual METs minus estimated METs) (5). This allowed for the mean error score and the 95% prediction interval to be shown. Devices that display a tight prediction interval around zero are deemed accurate. Data points below zero signify an overestimation, while points above zero signify an underestimation.

To examine time spent in light (<3 METs), moderate (3–6 METs), and vigorous (>6 METs) physical activity, the minute-by-minute values for the Cosmed K4b^2 (criterion) and each accelerometer regression formula (estimate) were compared using the entire routine (including structured activities and transition between activities) for each participant in the cross-validation group. A one-way repeated-measures ANOVA was used to detect differences between the Cosmed K4b^2 and each accelerometer regression formula. Pairwise comparisons with Bonferroni adjustments were used to locate significant differences when necessary.

RESULTS

The data for one participant in the developmental group (*routine 3*) are missing because of error that occurred during the downloading process. Mean (SD) counts per minute and CV of the counts per 10 s for each activity from the Actigraph accelerometer are shown in Table 2 (developmental group only).

Initially, linear regression lines were used to predict METs from the counts per minute for activities where the CV was $\leq$10 and activities where the CV was >10. Further examination of the data revealed that a linear regression did not yield the best fit. For example, the linear regression for activities where the CV is $\leq$10 significantly underestimated walking at 2 mph as well as running speeds >7 mph. Therefore, we chose an exponential curve for activities where the CV was $\leq$ 10 (Fig. 2). To verify the use of an exponential curve, we plotted the mean counts per minute vs. METs during treadmill walking and running from the study of King et al. (9) in Fig. 2.

For activities where the CV was >10, a cubic curve was found to be the best fit (Fig. 3). Certain activities such as lying and sitting have counts per minute that are <50 but that are commonly overpredicted by 0.5–2.5 METs depending on the regression equation used. Therefore, we propose using a threshold of 50 counts/min to distinguish inactivity (e.g., sitting and lying) from light activity. Thus, when the value is <50 counts/min, an individual would be credited with 1.0 MET, because this more accurately predicts these sedentary activities.

The newly developed equation to predict gross EE (METs) from the Actigraph counts would consist of a three-part algorithm (2-regression model with an inactivity threshold), which will be referred to as the new 2-regression model:

Table 2. *Counts per minute and CV for the 10-s counts from the Actigraph accelerometer for all activities (17) using the developmental group*

Activity	*n*	Actigraph, counts/min	CV for 10-s Counts
Lying	15	0.2 (0.5)	109.5 (226.8)
Standing	15	13.4 (22.0)	235.3 (145.6)
Computer work	15	3.3 (7.7)	228.1 (234.8)
Filing	15	59.8 (120.1)	186.4 (114.1)
Ascending/descending stairs	15	3,211.7 (621.3)	17.4 (9.3)
Slow walk (avg 81 m/min)	15	3,600.8 (669.7)	5.4 (1.9)
Brisk walk (avg 104 m/min)	15	5,271.7 (828.6)	4.5 (2.0)
Basketball	15	5,570.8 (999.8)	52.3 (13.0)
Racquetball	15	3,574.6 (1116.3)	57.7 (17.8)
Slow run (avg 159 m/min)	15	8,932.5 (1692.8)	7.0 (10.3)
Fast run (avg 192 m/min)	15	9,908.0 (2773.8)	5.3 (5.5)
Vacuum	14	788.7 (304.2)	74.3 (33.5)
Sweep/mop	14	719.0 (340.8)	75.0 (33.7)
Washing windows	14	420.0 (274.1)	145.3 (45.3)
Washing dishes	14	107.2 (154.1)	193.2 (117.6)
Lawn mowing	14	2,560.7 (804.5)	25.6 (9.7)
Raking grass/leaves	14	1,114.0 (481.6)	49.9 (21.5)

Values are means (SD). CV, coefficient of variation; avg, average.

$$\text{if the counts/min are} \leq 50,\ \text{EE} = 1.0\ \text{MET}, \quad (1)$$

$$\text{if the counts/min are} > 50 \quad (2)$$

and the CV of the counts per 10 s are

$$\leq 10,\ \text{then EE (METs)} = 2.379833 \cdot [\exp(0.00013529 \cdot \text{Actigraph counts/min})]\ (R^2 = 0.701;\ \text{SEE} = 0.275), \quad (2a)$$

or the CV of the counts per 10 s are 0 or >10, then

$$\text{EE (METs)} = 2.330519 + (0.001646 \cdot \text{Actigraph counts/min}) - [1.2017 \times 10^{-7} \cdot (\text{Actigraph counts/min})^2] + [3.3779 \times 10^{-12} \cdot (\text{Actigraph counts/min})^3]\ (R^2 = 0.854;\ \text{SEE} = 0.940) \quad (2b)$$

Table 3 shows the measured METs and estimated METs for the cross-validation group using the new two-regression model and three other commonly used Actigraph equations, for each activity. Figure 4 shows the measured and predicted MET values for each of the activities using the current Actigraph regression equations in the cross-validation group. Figure 5 shows the measured and predicted MET values for the cross-validation group using the new two-regression model. The new two-regression model was within 0.75 METs compared with measured METs for each of the 17 activities and was not significantly different from actual METs for any activity, or for all activities combined. In addition, the correlation between the predicted METs from the new two-regression model and measured METs was $r = 0.96$, SEE = 0.73 ($P < 0.001$). The other equations generally overestimated most activities below 2 METs and walking, and they underestimated most other activities. The Freedson equation was the only one that was significantly different from actual EE for all 17 activities combined ($P < 0.001$). The new two-regression model, the Swartz equation, and the Hendelman equation all gave close overall estimates of EE.

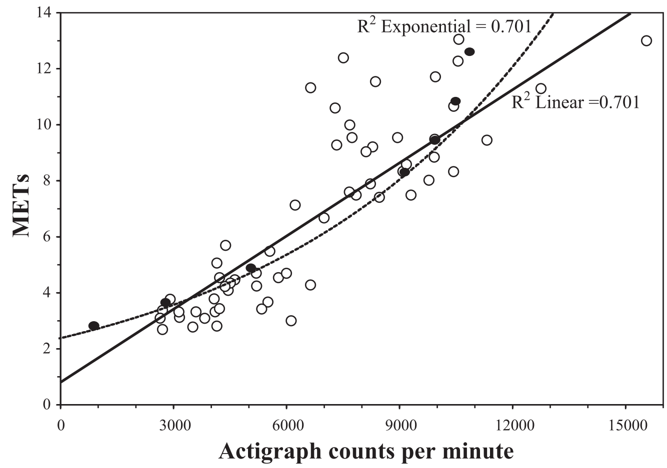

Fig. 2. Regression lines for the Actigraph counts per minute vs. measured energy expenditure [metabolic equivalents (METs)] for activities where CV ≤ 10 (developmental group). ○, Data points from the present study; ● data points from the study of King et al. (9), which were collected during treadmill walking and running, in male subjects, at speeds of 54, 80, 107, 134, 161, 188, and 214 m/min.

The Bland-Altman plots show that there was improved accuracy of individual activities with the new equation (Fig. 6). The Freedson equation ($r = 0.124$, $P < 0.05$), Swartz equation ($r = 0.189$, $P < 0.001$), and the Hendelman equation ($r = 0.696$, $P < 0.001$) all had problems estimating EE. Specifically, they tended to overestimate sedentary behaviors, light-intensity activities, and walking, whereas they underestimated many moderate-intensity lifestyle activities, vigorous sports, and stair climbing.

Figure 7 shows the error scores (prediction equation minus Cosmed K4b^2) for each regression equation during light, moderate, and hard physical activity. On average, [mean (SD)], the actual minutes spent in light, moderate, and vigorous physical activity were 31.0 (14.1), 22.5 (14.4), and 17.5 min (15.4), respectively. The new two-regression model did not significantly under- or overestimate time spent in light, moderate, or

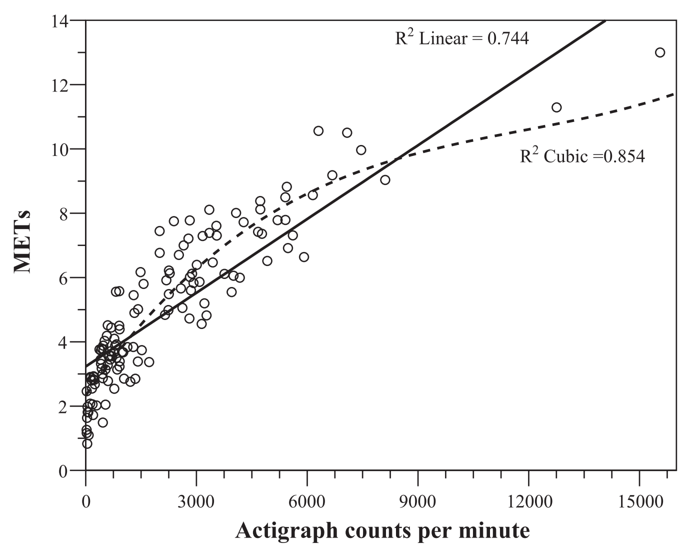

Fig. 3. Regression lines for the Actigraph counts per minute vs. measured energy expenditure (METs) for activities where CV > 10 (developmental group).

Table 3. *MET values of the cross-validation group for the Cosmed K4b² (measured METs), the new Actigraph 2-regression model, and 3 other Actigraph prediction equations during various activities*

	Measured METs	Actigraph New 2-Regression Model	Actigraph Freedson MET Equation	Actigraph Swartz Equation	Actigraph Hendelman Lifestyle Equation
Lying	0.91 (0.20)	1.00 (0.00)	1.44 (0.00)*	2.61 (0.00)*	2.92 (0.00)*
Standing	1.19 (0.18)	1.00 (0.00)	1.44 (0.03)	2.61 (0.03)*	2.93 (0.02)*
Computer work	1.03 (0.13)	1.00 (0.00)	1.44 (0.00)*	2.61 (0.00)*	2.92 (0.00)*
Filing papers	1.56 (0.16)	1.30 (0.67)	1.46 (0.03)	2.62 (0.03)*	2.93 (0.02)*
Ascending/descending stairs	6.83 (0.65)	6.08 (1.29)	4.21 (0.65)*	5.00 (0.56)	4.35 (0.34)*
Slow walk (avg 83 m/min)	3.33 (0.32)	3.73 (0.42)	4.04 (0.65)	4.85 (0.56)*	4.26 (0.34)*
Fast walk (avg 98 m/min)	4.41 (0.82)	4.71 (0.58)	5.41 (0.69)	6.04 (0.60)*	4.97 (0.36)*
Basketball	7.33 (0.52)	7.89 (0.99)	6.11 (0.95)	6.64 (0.82)	5.33 (0.49)*
Racquetball	6.63 (0.46)	7.29 (0.64)	4.73 (0.62)*	5.45 (0.53)	4.62 (0.32)*
Slow run (avg 160 m/min)	8.06 (0.63)	7.76 (0.96)	8.35 (0.68)	8.57 (0.59)	6.48 (0.35)*
Fast run (avg 183 m/min)	9.41 (1.63)	8.91 (0.35)	8.61 (0.96)	8.80 (0.83)	6.61 (0.50)
Vacuum	3.37 (0.51)	3.58 (0.76)	2.09 (0.43)	3.17 (0.37)	3.26 (0.22)
Sweep/mop	3.32 (0.56)	3.26 (0.76)	1.92 (0.32)*	3.02 (0.28)	3.17 (0.16)
Washing windows	2.86 (0.93)	2.86 (0.40)	1.71 (0.21)	2.84 (0.18)	3.06 (0.11)
Washing dishes	1.98 (0.33)	1.61 (0.83)	1.49 (0.05)	2.65 (0.04)	2.95 (0.03)*
Lawn mowing	6.06 (0.59)	5.50 (0.73)	3.27 (0.53)*	4.19 (0.46)*	3.87 (0.27)*
Raking grass/leaves	3.69 (0.89)	3.73 (0.70)	2.17 (0.35)*	3.24 (0.30)	3.30 (0.18)
Total for all activities	4.23 (2.68)	4.15 (2.62)	3.53 (2.42)*	4.41 (2.09)	4.00 (1.24)

Values are means (SD). MET, metabolic equivalents. *Significantly different from Cosmed K4b², $P < 0.05$.

vigorous physical activity. Both the Freedson and Swartz equations significantly underpredicted time spent in vigorous physical activity ($P < 0.05$), but they were not different from the criterion for light and moderate physical activity. The Hendelman lifestyle equation significantly underestimated time spent in light and vigorous physical activity and overestimated time spent in moderate physical activity ($P < 0.05$).

DISCUSSION

This study describes a new approach to estimating EE using an Actigraph accelerometer. By using the coefficient of variation to distinguish between walking/running and lifestyle activities and then applying one of two regression equations, the estimate of EE during specific activities is improved, both on a group and individual basis, which has important implications for the estimation of EE. In addition, the new equation allows a researcher to separate the amount of energy expended in walking, running, and other activities.

The new two-regression model had a mean bias for the prediction of EE of 0.1 METs (95% prediction interval; −1.4, 1.5 METs), whereas the next best prediction of EE was with the Swartz equation, which had a bias of −0.4 METs (95% prediction interval; −3.1, 2.4 METs). Thus the new two-regression model results in a significant improvement over current single regression models.

It is important to examine the differences between the new two-regression model and other single linear regression models that are currently being used. To assist in explaining how the new two-equation model is an advancement for the field, we pooled all of our data together and drew in our two-regression model, Freedson's regression line, and Swartz's regression line (Fig. 8). It is clear that no single regression line can accurately

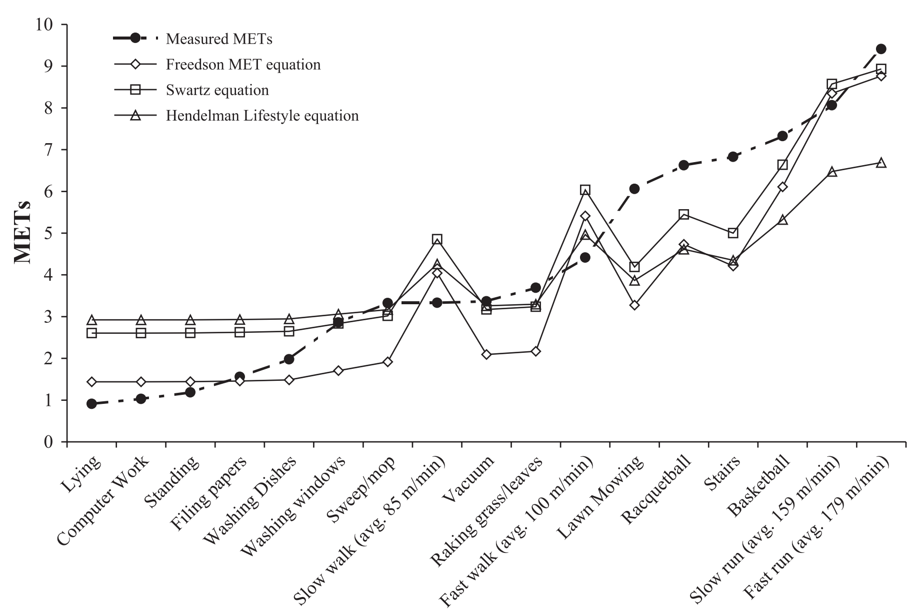

Fig. 4. Measured and estimated METs for the cross-validation group using 3 different regression equations for various activities. avg, Average.

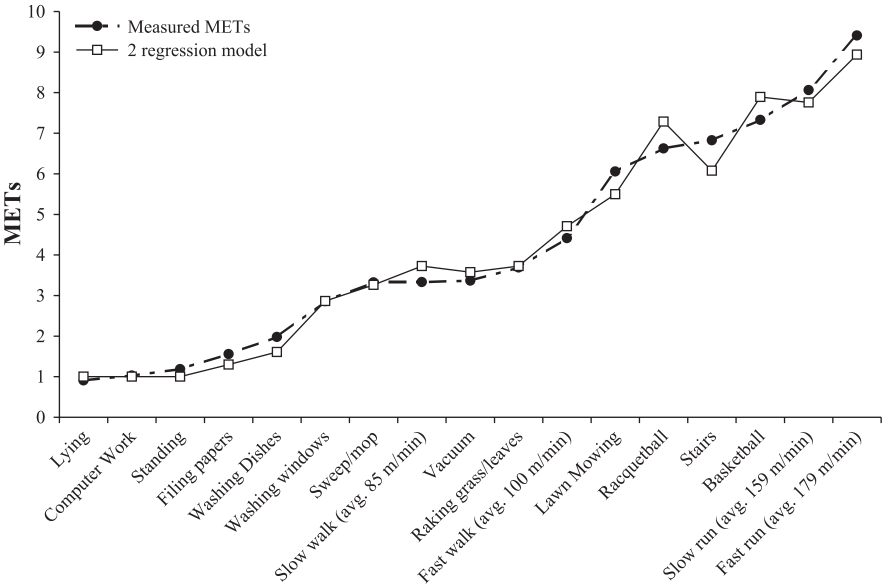

Fig. 5. Measured and estimated METs for the cross-validation group using the new 2-regression model for various activities.

predict the energy cost of specific activities. There is a trade-off, with some predicting the energy cost of walking better than others, and others predicting the energy cost of moderate-intensity lifestyle activities more accurately. It can clearly be seen that the new 2-regression model provides a better prediction across all activities.

Walking and running are rhythmic, locomotor physical activities with highly consistent acceleration counts across time. Other lifestyle physical activities (e.g., vacuuming, sweeping, raking, mowing) and leisure time physical activities (e.g., basketball and racquetball) have a more erratic movement pattern, resulting in greater variability in counts over time. This is an important consideration when estimating EE using accelerometer counts, because lifestyle activities have a higher oxygen cost at the same counts per minute, compared with walking and running. Lifestyle activities may include components in them that increase EE, but they are not measured by the Actigraph. This includes arm activities, lifting and carrying objects, hill climbing, stairs, and changing directions in the horizontal plane (8). The advantage of the new method is that we can account for this increased EE that occurs during lifestyle activities by using two-regression lines to estimate EE.

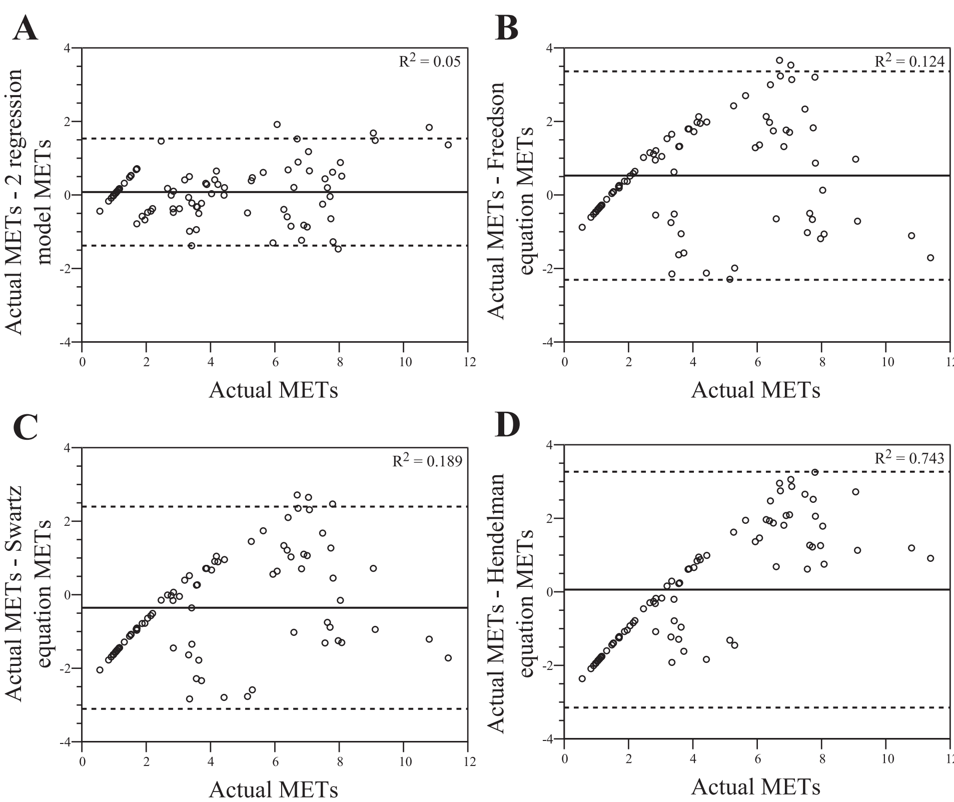

Fig. 6. Bland-Altman plots depicting error scores (actual minus estimation) for the new 2-regression model (*A*), Freedson MET equation (*B*), Swartz equation (*C*), and Hendelman equation (*D*). Solid line, mean; and dashed lines, 95% confidence interval of the observations.

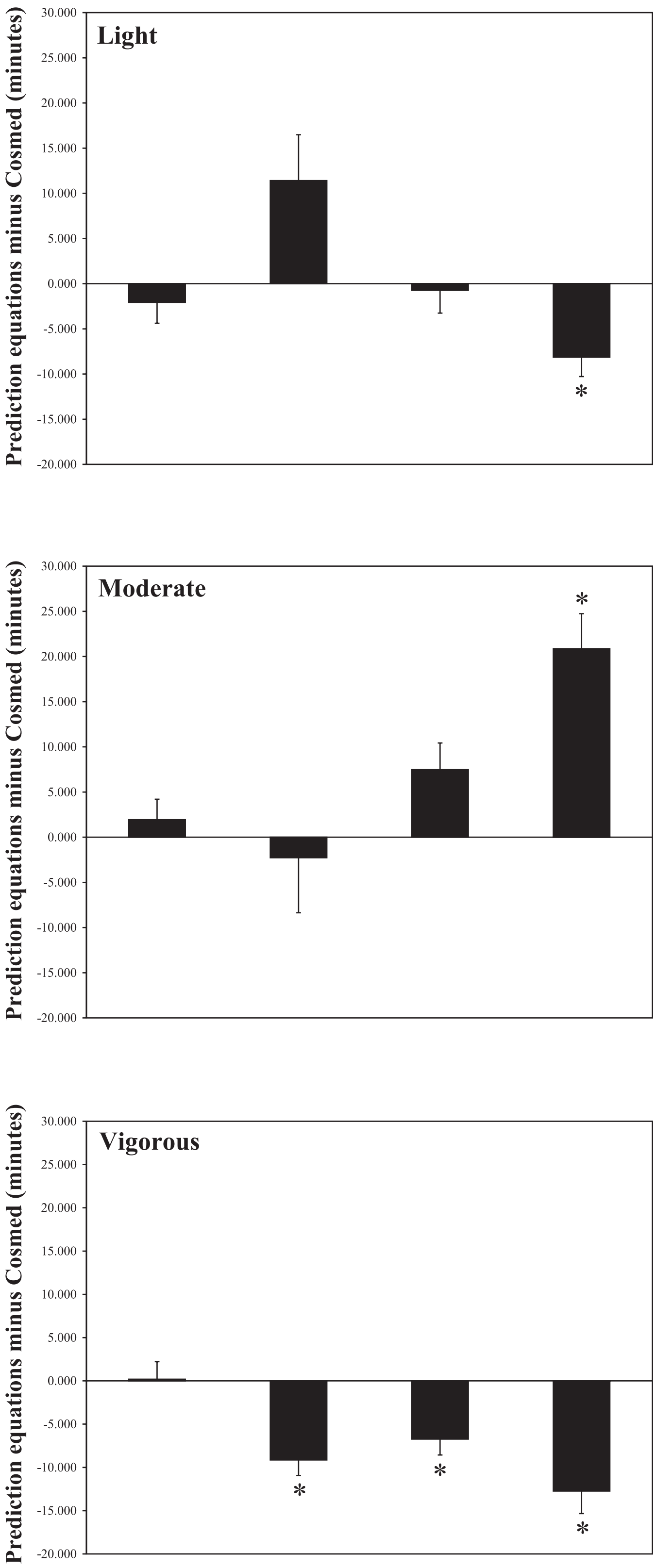

Fig. 7. Mean error scores (estimate minus criterion) for minutes spent in light (<3 METs), moderate (3–6 METs), and vigorous (>6 METs) physical activity, in the cross-validation group. Values are means ± SE. *Significantly different from criterion, $P < 0.05$.

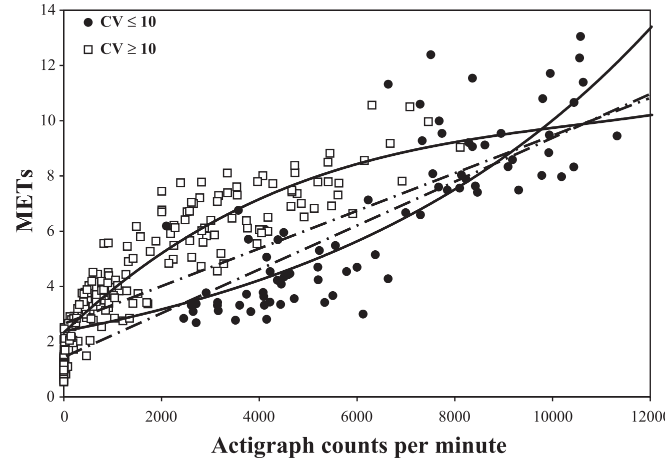

Fig. 8. Relationship between Actigraph counts per minute and measured energy expenditure (METS) for various activities. ●, Activities with a CV 0.1–10; □ activities with a CV 0 or >10. Solid lines, new 2-regression model; dashed line with 2 dots, Swartz equation; the dashed line with 1 dot, Freedson MET equation.

Given that ambulatory physical activity is an important component of overall EE, the new approach has the added benefit of being able to distinguish between walking, running, and other activities, which could be useful to researchers. For the discrimination between walking and running, we propose that a threshold of 6,500 counts/min be used. This is similar to the threshold of 6,683 counts/min chosen by Brage et al. (6) in a study which used treadmill walking and running. Epidemiologists can now examine how much walking individuals perform and distinguish it from running and other moderate-intensity lifestyle activities for the purpose of validating "walking" items on questionnaires. In addition, those interested in weight loss interventions can track individuals in walking programs with better accuracy and determine how much walking individuals are doing during unsupervised sessions.

This study provides some insight into how the new two-regression model would work for detecting time spent in light, moderate, and vigorous physical activity. The mean predicted values for time spent in light, moderate, and vigorous physical activity were within 2.1 min of the actual values. This is in contrast to the single-regression equations that may work well for classifying moderate activity but fail elsewhere. These results are in agreement with Strath et al. (16), who found similar over- and underestimations for the single-regression equations during free-living activity. However, our results should be interpreted with caution because the activities were performed in structured bouts lasting 10 min. Future studies are needed to examine the accuracy of the two-regression model during free-living physical activity.

The present study does have strengths and weaknesses. Strengths of the study are that the new two-regression model was developed on a wide range of activities ranging from sedentary behaviors to vigorous exercise. This is in contrast to previous studies that developed single regression equations on a limited number of activities (i.e., walking/running or moderate-intensity lifestyle activities). In addition, this study examined activities outside of the laboratory, which should enhance the generalizability to free-living situations. Limitations of the study include a small cross-validation group, but there was still enough statistical power (>0.9 for 16 of the 17 activities) to find significant differences between the measured and predicted EE values. Future research should be designed to validate this method in a wide range of individuals for 24-h EE (i.e., with doubly labeled water) and with indirect calorimetry using other types of physical activities.

Because 10-s epochs must be used for the newly developed model, researchers should be aware of the storage capacity of their Actigraph accelerometer. An Actigraph model 7164 with 64 kilobits of memory can store ~3.5 days of activity data only or 1.8 days of activity and step data, in 10-s epochs. A model 7164 with 256 kilobits of memory can store ~15 days of activity data only or 7.5 days of activity and step data in 10-s epochs. However, the new Actigraph GT1M with 1 megabyte of memory can store 60 days of activity data only or 30 days of activity and step data in 10-s epochs.

In conclusion, the new two-regression model, which is based on the counts per minute and variability in counts between 10-s epochs, improves on currently available methods for the prediction of EE (METs). The new method is more accurate on both a group and individual basis and has a bias of 0.1 METs (95% prediction interval of −1.4, 1.5 METs). In addition, this new method has the advantages of being able to distinguish between walking, running, and other activities, and it predicts the energy cost of specific activities with improved accuracy, which should ultimately result in a closer estimate of 24-h EE. Lastly, the new two-regression model shows promise for providing a better estimate of time spent in light, moderate, and vigorous physical activity compared with the single-regression models.

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GRANTS

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