

# Calibration of Accelerometer Output for Children

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## ABSTRACT

FREEDSON, P., D. POBER, and K. F. JANZ. Calibration of Accelerometer Output for Children. *Med. Sci. Sports Exerc.*, Vol. 37, No. 11(Suppl), pp. S523–S530, 2005. Understanding the determinants of physical activity behavior in children and youths is essential to the design and implementation of intervention studies to increase physical activity. Objective methods to assess physical activity behavior using various types of motion detectors have been recommended as an alternative to self-report for this population because they are not subject to many of the sources of error associated with children's recall required for self-report measures. This paper reviews the calibration of four different accelerometers used most frequently to assess physical activity and sedentary behavior in children. These accelerometers are the ActiGraph, Actical, Actiwatch, and the RT3 Triaxial Research Tracker. Studies are reviewed that describe the regression modeling approaches used to calibrate these devices using directly measured energy expenditure as the criterion. Point estimates of energy expenditure or count ranges corresponding to different activity intensities from several studies are presented. For a given accelerometer, the count cut points defining the boundaries for 3 and 6 METs vary substantially among the studies reviewed even though most studies include walking, running and free-living activities in the testing protocol. Alternative data processing using the raw acceleration signal is recommended as a possible alternative approach where the actual acceleration pattern is used to characterize activity behavior. Important considerations for defining best practices for accelerometer calibration in children and youths are presented. **Key Words:** PHYSICAL ACTIVITY MEASUREMENT, MOTION SENSORS, YOUTHS

The accurate measurement of free-living physical activity (counts) is essential for research studies in which physical activity (PA) is an outcome or exposure of interest. PA surveillance and observational studies of the association between PA and health outcomes require a robust activity measure to establish accurate estimates of the dose of activity needed for specific outcomes. PA intervention projects also require an accurate activity measure to determine the effectiveness of the intervention. Finally, accurate assessments of PA are necessary if the physiologic mechanisms linking PA and health are to be completely elucidated. Although self-report methods are often the measurement of choice, particularly in large-scale epidemiological investigations, they are frequently prone to error. As a result, researchers have explored a variety of objective methods to assess PA in order to validate self-reports and reduce the errors associated with these types of measurement schemes, particularly when children are the subjects of study.

The most popular objective measurement device has been the accelerometer, which evaluates both PA quantity and quality. Accelerometer devices are designed with large memory storage so that several days or weeks of activity can

be assessed in small sampling intervals (e.g., seconds and minutes). These monitors are relatively small and lightweight making them unobtrusive and practical for extended measurement periods. The small size makes them particularly appealing for use in children. Typically they are worn on the wrist, the lower leg, or the hip where they are attached to a belt or band.

In recent years, accelerometers have been widely used to characterize PA behavior in children. However, minimal attention has been directed toward standardizing methods of data collection, processing, and interpretation. One of the fundamental questions critical to understanding the meaning of PA assessed by accelerometry is how to translate and interpret the accelerometer signal into meaningful data linked to physiological outcomes or, in some cases, behavioral patterns.

Acceleration is defined as the change in velocity over time, and, as such, it quantifies the volume and intensity of movement. Volume and intensity are dimensions of PA needed by researchers to understand dose response. However, the raw acceleration signal is typically not used to directly quantify PA. In most cases the raw acceleration signal is translated, or calibrated, into a metric that is anchored to some biological variable (e.g., energy expenditure, HR) or to specific PA patterns (e.g., stationary or ambulatory). This approach gives the raw signal biological or behavioral meaning. Generally, the biological meaning for the raw acceleration signal is energy expenditure or oxygen consumption. Typically, calibration studies derive point estimates of energy expenditure from activity counts using regression modeling. Alternatively, regression analysis is used to establish ranges of accelerometer counts (cut

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points) corresponding to predefined intensity levels. These methods of data interpretation provide the type of information needed for meaningful application in PA research.

Accelerometer technology is based on biomechanical principles while energy expenditure and oxygen consumption are biological measures; therefore, it is not surprising that calibrating acceleration signals to these latter variables is challenging. This task is particularly difficult in children and adolescents because growth and maturation confound associations. For example, the metabolic cost of movement, expressed relative to body mass ( $\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ ), decreases as children mature (4). Activity energy expenditure ( $\text{kcal}\cdot\text{d}^{-1}$ ) is influenced by body mass and the metabolic economy of movement resulting in heavier children expending more energy at the same speed of movement than peers (29). In addition, the sensitivity of the acceleration signal is influenced by the interplay of stride length and step frequency so that at the same speed of movement the signal is lower when the step frequency is higher (2). Even the distance of the accelerometer from the center of gravity when the same positioning strategy is employed (e.g., at the hip) influences the acceleration signal. That is, the acceleration signal is greater when the accelerometer is further from the center of gravity, as is the case with heavier children when compared with peers (32). One solution to address these multiple issues of confounding is population-specific equations. However, a more parsimonious solution is modeling that incorporates easily measured variables that proxy for more difficult to measure attributes. In many situations, age can serve as a viable proxy for maturity while height and weight can proxy for stride length and distance from center of mass.

Using energy expenditure as the criterion for calibrating raw accelerometry signals is appropriate when the research examines obesity, heart disease risk factors, type 2 diabetes, and other metabolic risks. However, when bone outcomes are of interest, researchers should consider calibrating the raw signal to ground reaction forces (newtons) measured using force plates. Because acceleration is equal to force divided by mass, accelerometer devices might be particularly well suited for capturing bone strain and aid in our understanding of how mechanical overload contributes to healthy bone development in children.

This paper reviews and critiques the literature on accelerometer calibration in children and discusses the implications of these findings for future research on objective assessment of PA in children.

## CALIBRATION STUDIES

Calibration studies have been conducted using several accelerometers but the majority of the literature has focused on three accelerometer devices: ActiGraph (formerly known as Computer Science and Applications (CSA) and Manufacturing Technology, Inc. (MTI) (ActiGraph, LLC, Fort Walton Beach, FL)), Actical and Actiwatch (Mini Mitter Co., Inc., Bend, OR), and the RT3 Triaxial Research Tracker (formerly known as the Tritrac-R3D (StayHealthy,

Inc., Monrovia, CA)). The ActiGraph is a uniaxial accelerometer, the Actical and Actiwatch devices are omnidirectional accelerometers and the RT3 is a triaxial accelerometer. This paper focuses on these three devices because they have been the primary monitors used in calibration studies in children and adolescents.

**ActiGraph model 5032.** Janz (12) published one of the first quasi-calibration studies of an accelerometer in 7- to 15-yr-old children. This investigation used the first generation of the ActiGraph accelerometer (Model 5032). The approach Janz employed to establish the accelerometer counts representing vigorous PA was to examine the distribution of counts per minute data for the sample. The 80th percentile (256 counts per minute) was defined as the lower bound for vigorous PA. The average number of minutes in this predefined vigorous activity category ranged from 117 to 144 min, and the number of minutes where HR was above 150 bpm ranged from 20 to 29 min during 3 d of monitoring. Thus, it appears that using the 80th percentile for counts per minute to represent vigorous activity may not have been appropriate. Nevertheless, correlations between minutes where HR was above 150 bpm and minutes of counts per minute above 256 ranged from  $r = 0.50$  to  $0.70$ . This study was the first to employ the cut point method to establish a count threshold for intensity of activity and set the stage for future calibration studies in children.

**Caltrac personal activity computer (Muscle Dynamics, Torrence, CA).** As suggested earlier, in most instances, accelerometers should be calibrated using oxygen consumption or energy expenditure as the criterion variable. In fact, the original accelerometer used in PA research was the Caltrac, which used measured energy expenditure as the criterion (17). Algorithms were developed for adults in the laboratory to translate acceleration into estimates of activity energy expenditure. Sallis et al. (25) used oxygen consumption measured during treadmill walking and running to calibrate the Caltrac for children ( $N = 15$ ). They reported that one Caltrac count was equivalent to a net energy expenditure of  $0.101 \text{ kcal}\cdot\text{kg}^{-1}$  and the correlation between activity counts and net energy expenditure was  $r = 0.89$ .

**ActiGraph model 7164.** The first children's calibration study on this monitor was conducted by Trost et al. (31). They developed an equation to predict energy expenditure from activity counts using laboratory treadmill exercise. Thirty children between the ages of 10 and 14 wore the ActiGraph accelerometer and completed treadmill exercise at 3, 4, and 6 mph with oxygen consumption serving as the criterion measure. The equation was developed on 20 subjects and was cross-validated on the remaining 10 subjects ( $r = 0.93$ ,  $\text{SEE} = 0.93 \text{ kcal}\cdot\text{min}^{-1}$ ).

Freedson et al. (9) developed a regression equation to estimate METs from counts and age where 6- to 18-yr-old children and adolescents completed two treadmill walking speeds and one running speed. Respiratory gas exchange was measured using indirect calorimetry and the ActiGraph was worn on the hip and programmed to collect minute-by-minute counts. Resting energy expenditure was estimated

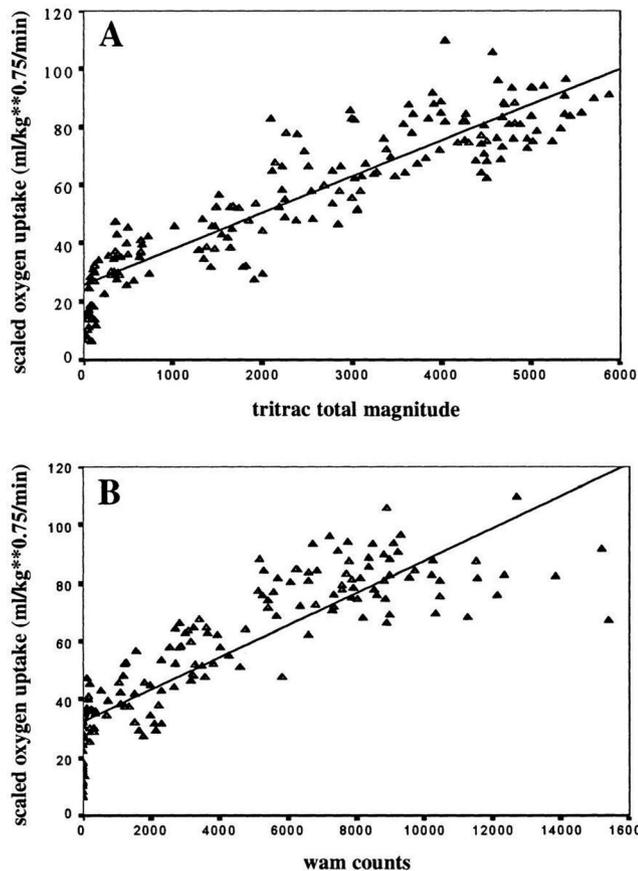


FIGURE 1—Relationship between activity counts and oxygen consumption. Reprinted with permission from Eston et al. (7).

from age specific prediction equations to derive the metabolic equivalent of MET intensity levels. The equation was

$$\text{METs} = 2.757 + (0.0015 * \text{counts per minute}) - (0.08957 * \text{age (yr)}) - (0.000038 * \text{counts per minute} * \text{age (yr)})$$

$$R^2 = 0.74 \quad \text{SEE} = 1.1 \text{ METs} \quad [1]$$

Accelerometer calibration studies should be performed in a setting where a variety of activities are included to closely represent the broad repertoire of activities that children typically perform. For example, Eston et al. (7) had children (ages 8.2–10.8) walk and run on a treadmill, play catch, play hopscotch, and color with crayons. Oxygen consumption was measured, and PA was assessed with the ActiGraph accelerometer. Although this study was designed as a validity evaluation, data were presented in a style where calibration issues could be examined. In Figure 1, the relationship between accelerometer counts and oxygen consumption is illustrated. The oxygen consumption data are scaled to body weight<sup>0.75</sup>, making it difficult to determine MET values corresponding to selected count values. However, using the average body weight of 29.8 kg, the upper boundaries for 3, 6, and 9 METs correspond to approximately 500, 4000, and 7600 counts per minute for the ActiGraph.

In another field-based study, a broad range of intensities of 11 physical activities (sedentary to vigorous) were used to calibrate the ActiGraph in 74 girls ages 13–14 (30). Energy

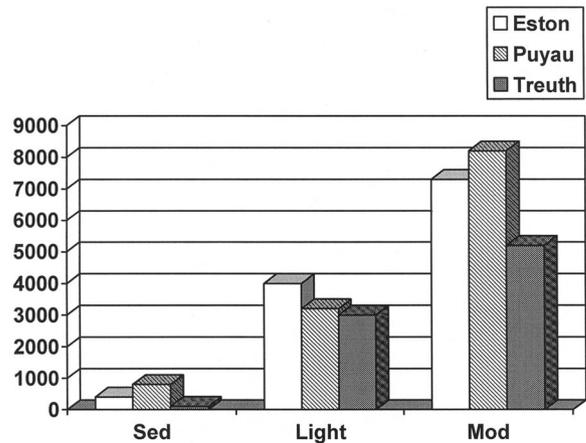


FIGURE 2—Activity count cut points (counts per minute) for sedentary, moderate, and vigorous activity for the CSA (MTI) ActiGraph. Cut points are the upper boundaries for the intensity categories.

expenditure was assessed at rest and during the activity protocol with a portable indirect calorimetry data acquisition unit while an ActiGraph was worn on each hip. A combination of regression and examination of error rates (e.g., low counts for moderate-intensity activity or high counts for low-intensity activity) were used to establish final cut points designating activity intensity categories. These cut points are illustrated in Figure 2. Also shown in Figure 2 are the cut points for intensity categories from a study by Puyau et al. (20) for 26 children between the ages of 6 and 16. The boundaries for defining intensity categories are higher than those reported by Treuth et al. (30), particularly for the upper limit for sedentary and moderate activity. The calorimetry methods, the age range of the subjects, the number of subjects per age range, and the menu of activities between these two studies are quite different and may explain the dissimilarity in cut point values. In addition to exploring movement count to energy expenditure relationships in free-living situations, both studies are notable in that they directly measured resting energy expenditure to establish MET levels. This is important because children and adolescents have a higher resting metabolic rate (RMR) than adults; therefore, using the adult standard of 3.5 mL·kg<sup>-1</sup>·min<sup>-1</sup> to represent RMR would be expected to introduce systematic error.

In addition to providing accelerometer count ranges to define intensity levels, Treuth et al. (30) and Puyau et al. (20) derived prediction equations to estimate METs or activity energy expenditure from counts. The equations and pertinent statistics are:

$$\text{METs} = 2.01 + 0.000856 (\text{counts per minute})$$

$$R^2 = 0.84 \quad \text{SEE} = 1.36 \text{ METs} \quad [2]$$

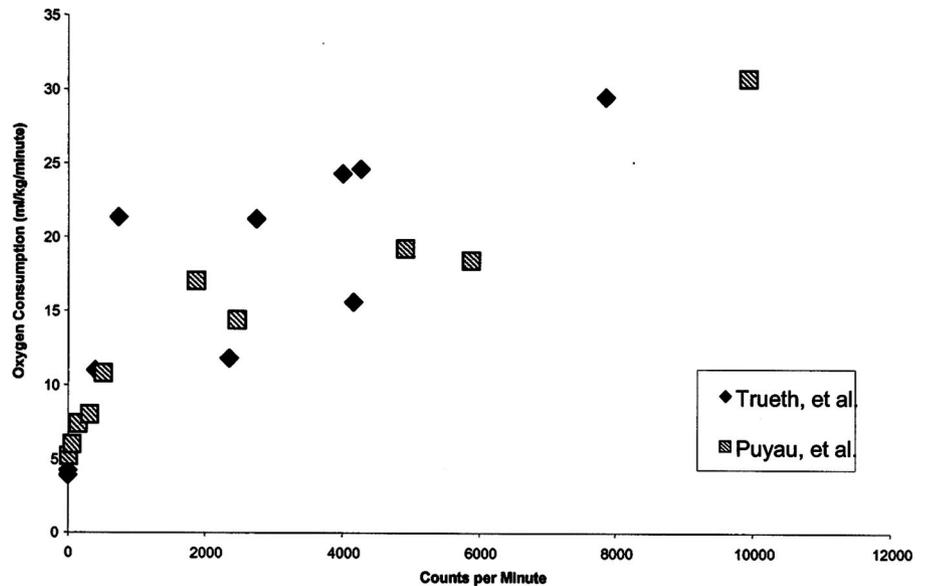
$$\text{Activity energy expenditure or AEE (kcal} \cdot \text{kg}^{-1} \cdot \text{min}^{-1})$$

$$= 0.0183 + 0.000010 (\text{counts per minute})$$

$$R^2 = 0.75 \quad \text{SEE} = 0.0172 \text{ kcal} \cdot \text{kg}^{-1} \cdot \text{min}^{-1} \quad [3]$$

Figure 3 presents the relationship between oxygen consumption and ActiGraph counts, including all of the activities from the Treuth et al. (30) and Puyau et al. (20) studies.

FIGURE 3—Relationship between Acti-Graph counts per minute and oxygen consumption for Treuth et al. (30) and Puyau et al. (20)



Because the data of Puyau et al. (20) were presented in energy expenditure units, oxygen consumption was estimated using a  $5 \text{ kcal}\cdot\text{L}^{-1} \dot{V}\text{O}_2$  constant and their mean body mass of 40 kg. Using the combined data, we developed a composite regression equation between counts and  $\dot{V}\text{O}_2$ . We did not include the data point for cycling from Treuth et al. (30) because the count value was extremely low for a relatively high  $\dot{V}\text{O}_2$ . This was expected given the poor association between cycling and accelerometer output when devices are worn on the hip. We predicted counts at MET levels of 3, 6, and 9 using  $1 \text{ MET} = 3.8 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ . The resting  $\dot{V}\text{O}_2$  of  $3.8 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$  directly measured in Treuth et al. (30) was used as the baseline  $\dot{V}\text{O}_2$ . The equation to predict  $\dot{V}\text{O}_2$  ( $\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ ) is as follows:

$$\dot{V}\text{O}_2(\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}) = 7.7104 + 0.002631974 (\text{counts per minute}) \quad [4]$$

Using these data, the counts per minute values (rounded off) corresponding to 3, 6, and 9 METs are 1400, 5700, and 10,000.

Schmitz et al. (27) reported that the slope of the line describing the relationship between ActiGraph counts and energy expenditure decreases as activity intensity increases. Thus, when accelerometer count data are used to derive point estimates of energy expenditure using simple linear models, a systematic under estimation of energy expenditure during low-intensity activities and an overestimation of energy expenditure during high-intensity exercise will occur. To overcome this limitation, Schmitz et al. (27) developed a model that includes both linear and quadratic terms to account for the change in the trajectory of the slope.

$$\text{Energy expenditure (kJ}\cdot\text{min}^{-1}) = 7.6628 + 0.1462 [(\text{counts per minute} - 3000)/100] + 0.2371 (\text{body weight (kg)})$$

$$- 0.00216 [(\text{counts per minute} - 3000)/100]^2$$

$$+ 0.004077 [((\text{counts per minute} - 3000)/100)\cdot(\text{body weight (kg)})]$$

$$\text{Model concordance correlation coefficient} = 0.85$$

$$\text{SEE} = 5.61 \text{ kJ}\cdot\text{min}^{-1} \quad [5]$$

The above equations may work reasonably well for predicting group minutes in different activity intensity categories. However, predicting an individual's energy expenditure from activity counts works only moderately well at best. One factor that contributes to the imprecise point estimates of individual energy expenditure is that the relationship between activity counts and energy expenditure exhibits large individual differences. This point is illustrated in the data of Ekelund et al. (5), who showed large variability in ActiGraph activity counts for children walking at standardized speeds. For example, ActiGraph counts ranged from approximately 400 to 2600 counts per minute at  $4 \text{ km}\cdot\text{h}^{-1}$ , and from 1000 to 5000 counts per minute at  $6 \text{ km}\cdot\text{h}^{-1}$ . In this study, the coefficients of variation for counts per minute were 21–40% at given velocities of walking. This variability contributes to large errors in predicting individual-level energy expenditure. This observation was confirmed by McMurray et al. (16). In addition, accelerometers are obviously not capturing all movement all the time and thus estimates of total daily energy expenditure from movement counts underestimate actual energy expenditure. Caution should be exercised in using these energy expenditure prediction equations to estimate individual-level energy expenditure.

To account for individual differences in the relationship between ActiGraph counts and energy expenditure, Ekelund et al. (5) proposed using the activity-related time equivalent based on accelerometry (ArteACC) method to calibrate PA behavior. This method uses ActiGraph counts to establish time at a given energy expenditure based on the energy expenditure of selected reference activities. ArteACC ( $\text{min}\cdot\text{d}^{-1}$ ) is equal to total daily activity counts divided by reference activity counts (counts per minute). The ArteACC index was shown to be valid surrogate measure of total PA and if combined with a direct measure of RMR and gender it can predict total energy expenditure (5).

Another approach for calibration used by Ekelund et al. (6) established ActiGraph cut points in 500-counts-per-

minute increments and defined sedentary activity as less than 500, light activity from 500 to 999, moderate activity from 1000 to 1999, and vigorous activity as over 3000 counts per minute. Although the purpose of this study was not to calibrate an activity monitor, these cut point standards were used to examine the association between body fatness and time spent in moderate-to-vigorous PA (MVPA) in more than 1200 children between the ages of 9 and 10. Children spending more than 2 h·d<sup>-1</sup> in MVPA had a significantly lower sum of skinfolds than children who spent less than 60 min in MVPA. This approach has some predictive validity, but lacks the more precise calibration features used by others.

**Actiwatch.** Puyau et al. (21) calibrated the Actiwatch on 26 children between the ages of 6 and 16 using direct calorimetry as the criterion measure. Three sedentary, two light, three moderate, and six vigorous activities were performed in controlled or free-living settings. The Actiwatch was worn on the hip and the leg. Counts per minute (hip) ranged from 6 (resting) to 2647 (jogging) with derived  $\dot{V}O_2$  values ranging from 3.2 mL·kg<sup>-1</sup>·min<sup>-1</sup> (rest) to 19.2 mL·kg<sup>-1</sup>·min<sup>-1</sup> (jogging). The counts per minute cutoffs for sedentary, light, and moderate activity were, respectively, 99, 899, and 2199 for the hip measurement and 199, 1799, and 4299 for the leg measurement. Point estimates of activity energy expenditure (kcal·kg<sup>-1</sup>·min<sup>-1</sup>) are determined from the following equations:

$$\text{AEE (kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}) = 0.0144 + 0.000038 (\text{counts per minute (hip)})$$

$$R^2 = 0.81 \quad \text{SEE} = 0.0147 \text{ kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1} \quad [6]$$

$$\text{AEE (kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}) = 0.0143 + 0.000020 (\text{counts per minute (leg)})$$

$$R^2 = 0.71 \quad \text{SEE} = 0.0195 \text{ kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1} \quad [7]$$

Equations were also generated for total energy expenditure where total energy expenditure where basal metabolic rate (BMR) was included (20). In these equations, age is a significant predictor of total energy expenditure because of the age-related changes in RMR. However, a study by Lopez-Alarcon et al. (15) on 4- to 6-yr-old children revealed no relationships between activity measured with the Actiwatch and total daily energy expenditure measured with doubly labeled water.

**Actical.** Puyau et al. (21) reported an equation to predict activity energy expenditure using the Actical. To develop this equation, 32 children between the ages of 7 and 18 performed a variety of activities where directly measured energy expenditure ranged from 0.025 to 0.171 kcal·kg<sup>-1</sup>·min<sup>-1</sup>. The equation is

$$\text{AEE (kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}) = 0.00423 + 0.00031 \cdot \text{activity counts}^{0.653}$$

$$R^2 = 0.81 \quad \text{SEE} = 0.0111 \text{ kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1} \quad [8]$$

Heil (10) conducted a calibration study on 14 boys (ages 8–16) in which energy expenditure was assessed using a portable indirect calorimetry system and Actical units were secured to the ankle, wrist, and hip. Ten different activities were performed including sedentary activities, housecleaning tasks, and locomotion activities (walking and jogging). Activity energy expenditure categories defining sedentary

and light, moderate, and vigorous were <0.05, ≥0.06–0.09, and ≥0.10 kcal·kg<sup>-1</sup>·min<sup>-1</sup>. A unique feature of the regression modeling approach was the use of two linear models, one for the sitting and cleaning activities and one for the locomotion activities, because the pattern of the relationship between energy expenditure and activity counts was quite different between these two sets of activity.

**Tritrac and RT3.** The original commercially available triaxial accelerometer was the Tritrac. McMurray et al. (16) developed regression models to predict energy expenditure from the Tritrac vector magnitude counts on 308 children between the ages of 8 and 18. Nine activities across a broad range of intensities comprised the activity regime and energy expenditure was assessed using a portable metabolic measurement system. The equation to estimate energy expenditure from the Tritrac vector magnitude was:

$$\dot{V}O_2 \text{ mL}\cdot\text{min}^{-1} = 0.32 (\text{vector magnitude counts per minute})$$

$$+ 6.97 (\text{height (cm)}) + 6.19 (\text{body weight (kg)}) - 857.86$$

$$r = 0.81 \quad \text{SD} = 306 \text{ mL}\cdot\text{min}^{-1} \quad [9]$$

StayHealthy, Inc. (Monrovia, CA) purchased the rights to the Tritrac design and repackaged it into a smaller device called the RT3. Rowlands et al. (24) conducted a calibration study using the triaxial accelerometer in which they compared the Tritrac to the RT3 and developed count cut points corresponding to different intensities of activity. Nineteen boys (mean age 9.5) participated in treadmill walking (two speeds) and running (two speeds), hopscotch, ball kicking, and sedentary activities. Oxygen consumption was measured using Douglas bags with the Tritrac and RT3 secured to the right and left hip. In general, the RT3 counts were higher than the Tritrac counts. The counts per minute values corresponding to 3 and 6 METs when all activities were included in the analysis were 970 and 2333 counts per minute. When only the treadmill activities were used the corresponding cut points were 1806 and 3022 counts per minute. Thus, it appears the pattern of the activity monitor response to all activities was different from the pattern with treadmill exercise alone and resulted in different cut points to represent the same exercise intensities. This observation confirms the results of Heil (10) where a two-component regression was reportedly required to improve the accuracy of prediction. Table 1 presents a summary of the calibration studies that have used these devices to establish accelerometer count cut points for this population.

**Other approaches to accelerometer calibration.** Exercise physiologists and activity epidemiologists have endorsed and emphasized the need to calibrate accelerometers to some physiological criterion such as oxygen consumption or energy expenditure. However, in some cases, it may be best to use the raw activity counts or even the raw acceleration signal as the outcome measure because use of the raw signal eliminates the errors associated with the regression model methods described earlier. This may be particularly important if accelerometer-based activity measures are used to track PA over time in longitudinal designs such as surveillance studies or intervention studies. Jackson

TABLE 1. Accelerometer count cut points defining exercise intensities.

Authors	Sample Size	Age or Age Range (yr)	Monitor	Activities	Criterion	Moderate Intensity Cut Point (counts per minute)	Vigorous Intensity Cut Point (counts per minute)
McMurray et al. (16)	308	8–18	Tritrac	W, R, FL	$\dot{V}O_2$	>400	<2200
Eston et al. (7)	30	8.2–10.8	Tritrac	W, R, FL	$\dot{V}O_2$	>300	<2200
Rowlands et al. (24)	19	9.5	Tritrac	W, R, FL	$\dot{V}O_2$	>770	<1870
Rowlands et al. (24)	19	9.5	RT3	W, R, FL	$\dot{V}O_2$	>970	<2333
Treuth et al. (30)	74	13–14	Actigraph	W, R, FL	$\dot{V}O_2$	>3000	<5200
Puyau et al. (20)	26	6–16	Actigraph	W, R, FL	Energy expenditure	>3200	<8200
Eston et al. (7)	30	8.2–10.8	Actigraph	W, R, FL	$\dot{V}O_2$	>500	<4000
Puyau et al. (21)	32	7–18	Actical	W, R, FL	Energy expenditure	>1500	<6500

Cut point values represent the lower boundaries for the intensity category. W, walking; R, running; FL, free-living.

et al. (11) used this approach to describe PA levels in a 1-yr longitudinal study of preschool children. However, a weakness of this approach is that intensity cannot be evaluated.

A limitation of using the raw counts as the outcome measure, however, was that Actiwatch activity counts (worn on the ankle, summed over 7 d) was not associated with total daily energy expenditure assessed using doubly labeled water (14). Twenty-nine children between the ages of 4 and 6 comprised the sample in this investigation. The correlation between total activity counts and total daily energy expenditure was  $r = 0.27$  ( $P > 0.05$ ) during free-living activities. It was suggested that the reason for the low correlation was the prolonged time interval of measurement and the diverse types of activities included. Further study on this particular measurement problem is warranted as the goal is to establish standards of practice in using the accelerometer to characterize habitual PA behavior.

**Calibration of accelerometers to assess sedentary behavior.** Some studies exploring the determinants of inactivity are using accelerometers to assess sedentary behavior. Additionally, studies examining factors influencing obesity may benefit by quantifying inactivity as well as activity. Reilly et al. (23) suggests that accelerometers can be used to assess sedentary behavior and developed and validated a count cut point of <1100 counts per minute for the ActiGraph to define the upper bound for inactivity in 3- to 4-yr-old children. What is unique about this work is the use of observation to calibrate activity counts. When researchers are interested in patterns and determinants of PA, calibrating activity counts to observational systems is a more direct alternative. Using this approach, accelerometers are used to classify sets of activities (e.g., stationary or slow trunk movement). The observation criterion avoids interpretation errors associated with METs and errors associated with extrapolation from treadmill exercise to free-living behaviors (23). The value of having an accelerometer cut point to define inactive behavior has yet to be realized but the potential application to studies related to adiposity rebound and physical inactivity is significant. Behaviorally based approaches for calibrating accelerometry output may be particularly useful when studying young children where measurement and interpretation of energy expenditure data are difficult tasks.

**Uniaxial versus triaxial accelerometers.** Intuitively it seems that a triaxial or omnidirectional accelerom-

eter should be better at capturing children’s activity in particular because children tend to move in all directions all the time. However, no direct evidence exists to suggest that a triaxial accelerometer is better for detecting PA than a uniaxial monitor. Analysis of the activity monitor calibration studies presented in this review does not indicate superiority of one monitor over the other and all seem to work reasonably well. Other papers in this supplement address this issue in more detail.

## NEW DIRECTIONS

An issue that requires careful consideration is whether linear regression is the correct approach to calibrate activity monitor calibration, given that it does not appear to always do what we want it to do. For example, examination of the data in Treuth et al. (30) reveals a clear violation of the typical regression assumptions (i.e., systematic errors, particularly at low count values, and an increase in variance of METs as activity intensity increases). Although the heteroscedasticity of the errors may have been handled in mixed, there remains the systematic error issue remains. Also, it appears that the relationship between counts and energy expenditure may be nonlinear in certain ranges (e.g., 0–500 counts per minute). It is possible, that a generalized (rather than general) linear model, such as the polytomous regression model, may handle some of these problems, and thus should be investigated.

Bassett et al. (1) indicate that “no single regression equation appears to accurately predict energy expenditure based on acceleration score for all activities.” Other investigators have identified this problem, and it has been suggested that separate regression relationships between accelerometer output and PA energy expenditure should be determined for all activities of interest. Because the typical data-processing methods do not identify specific activities from accelerometer data, it is currently not feasible to apply separate regression equations on an activity-by-activity basis. This issue can be addressed by improving the methods used to process accelerometer data.

A potential means of reducing error in accelerometer-based estimates is to adopt a new methodology for data processing. In particular, there is an opportunity to use the pattern of accelerometer counts rather than total acceleration. Several classes of stochastic models are available to

identify patterns in data and use those patterns to provide information about the underlying process that generated the data. As early as 1970, it was suggested that these types of models be applied in processing data from studies of human movement (28). Due to the computational complexity, however, these types of methods have been implemented infrequently.

Kiani et al. (13,14) have reported the use of a neural network approach to processing motion data in a clinical setting. They used accelerometer and goniometer signals to determine whether a patient was supine, seated, standing, or locomoting. Zhang et al. (34,35) used pattern recognition algorithms to extract information about the type, duration, and intensity of activity from a new monitor based on an array of accelerometers. These results suggest that sophisticated modeling techniques may be useful in measuring PA. The challenge is to develop a method applicable to data that can be obtained without unduly burdening the subjects or investigators. These investigations relied on data from instruments that have limited utility for application in field settings due to expense, memory capabilities, and/or complexity.

A particular class of stochastic model for which the theory and application are well developed in a pattern-recognition setting is the hidden Markov model (HMM). These models have been used with considerable success in the speech recognition literature, where they are used in natural language recognition algorithms that identify words in human speech (22). HMM also appear in analyses of neuron firing patterns, DNA sequences, analysis of patterns in viral mutations, and many other natural phenomena (e.g., see 3,8,26,33).

Our group recently reported success in applying HMM to the analysis of accelerometer data (19). Specifically, we developed an HMM that could accurately categorize two activities (uphill walking and vacuuming) as vigorous and moderate-intensity activities, respectively, using data from the ActiGraph. These activities are misclassified as moderate and sedentary, respectively, by the regression cut point method of categorizing accelerometer data. Thus, it appears that pattern recognition-based approaches in general, and HMM in particular, have good potential to improve the accuracy of objective assessment of PA. Research into alternative activity monitor calibration approaches such as the HMM are greatly needed to improve our ability to assess PA behavior.

## RECOMMENDATIONS

Several different models of accelerometers have been used to evaluate PA in children and youths. The calibration of these devices typically involves using walking and running alone or in combination with free-living activities to estimate the ranges of accelerometer counts corresponding to predefined intensity levels or to estimate energy expenditure. Recent advances have refined prediction models to

improve estimates by incorporating nonlinear components into the equations. The following recommendations are intended to help move accelerometer calibration studies forward and to provide researchers with guidelines to establish standards of practice for calibration studies in children.

- Calibration should employ an appropriate biological or behavioral standard. For example, accelerometers used to examine the impact of activity on obesity should relate output to energy expenditure while bone health research should relate output to mechanical forces.
- Study designs should include a wide variety of activities representing a broad spectrum of energy expenditure (low to vigorous intensity) and short duration of movements. The latter suggests sampling epochs of no longer than 1 min. More research is needed to identify specific epoch length to ensure that children's short bouts of activity are captured. For example, considering the sporadic and short bursts of vigorous activity performed by children (18) epochs as short as 5 s may be necessary.
- Studies should include at least 10 subjects per age group (e.g., 8–10, 10–12 yr). Because body mass is known to be a significant factor in the relationship between the accelerometer signal and energy expenditure, calibration prediction equations should be population specific.
- Reports should present activity energy expenditure and MET prediction equations. Appropriate calculation of METs will require measuring resting energy expenditure or the use of age-specific estimates of resting energy expenditure.
- Behavioral approaches (e.g., direct observation) for calibrating accelerometry output may be particularly useful when studying young children where measurement and interpretation of energy expenditure data are difficult tasks.
- Depending on the purpose of the study, the most appropriate accelerometer measure may be the raw counts or raw acceleration (e.g., tracking of PA).
- New studies should be conducted to establish calibration protocols to assess sedentary behavior and explore classification systems to identify specific movements based on the raw acceleration signal.

Use of these guidelines in conducting calibration studies will improve our ability to compare study results and interpret PA measurement schemes. The use of objective measures to assess PA will likely continue to expand and if certain standards of practice guidelines are used, our understanding of the mechanisms by which PA affects health in children will be improved.

The results of the present study do not constitute endorsement by the authors or ACSM of the products described in this paper.

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