Use of a Two-Regression Model for Estimating Energy Expenditure in Children

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ABSTRACT

CROUTER, S. E., M. HORTON, and D. R. BASSETT Jr. Use of a Two-Regression Model for Estimating Energy Expenditure in Children. *Med. Sci. Sports Exerc.*, Vol. 44, No. 6, pp. 1177–1185, 2012. **Purpose**: The purpose of this study was to develop two new two-regression models (2RM), for use in children, that estimate energy expenditure (EE) using the ActiGraph GT3X: 1) mean vector magnitude (VM) counts or 2) vertical axis (VA) counts. The new 2RMs were also compared with existing ActiGraph equations for children. **Methods**: Fifty-seven boys and 52 girls (mean ± SD: age = 11 ± 1.7 yr, body mass index = 21.4 ± 5.5 $kg{\cdot}m^{-2}$) performed 30-min supine rest and 8 min of six different activities ranging from sedentary behaviors to vigorous physical activity. Eighteen activities were split into three routines with each routine performed by 38–39 participants. Seventy-seven participants were used for the development group, and 39 participants were used for the cross-validation group. During all testing, activity data were collected using an ActiGraph GT3X, worn on the right hip, and oxygen consumption was measured using a Cosmed K4b^2. All energy expenditure values are expressed as MET_{RMR} (activity $\dot{V}O_2$/resting $\dot{V}O_2$). **Results**: For each activity, a coefficient of variation was calculated using 10-s epochs for the VA and VM to determine whether the activity was continuous walking/running or an intermittent lifestyle activity. Separate regression equations were developed for walking/running and intermittent lifestyle activity. In the cross-validation group, the VM and VA 2RMs were within 0.8 MET_{RMR} of measured MET_{RMR} for all activities except Sportwall and running (all $P > 0.05$). The other existing ActiGraph equations had mean errors ranging from 0.0 to 2.6 MET_{RMR} for the activities. **Conclusions**: The new 2RMs for use in children with the ActiGraph GT3X provide a closer estimate of mean measured MET_{RMR} than other currently available prediction equations. In addition, they improve the individual prediction errors across a wide range of activity intensities. **Key Words:** MOTION SENSOR, PHYSICAL ACTIVITY, OXYGEN CONSUMPTION, ACTIVITY COUNTS VARIABILITY

The accurate measurement of physical activity (PA) in children is important because PA plays an important role in the prevention and treatment of obesity, cardiovascular disease, and other chronic diseases. One approach for measuring PA involves the use of small waist-mounted accelerometers with internal clocks and data storage capabilities, which allows for an objective measurement of movement duration, intensity, and frequency. During the past decade, these devices (e.g., ActiGraph [Actigraph, Pensacola, FL] and Actical [Philips Respironics, Mini Mitter, Bend, OR] accelerometers) have become more widely used by PA researchers, which is evident in the inclusion of the ActiGraph accelerometer in the ongoing National Health and Nutrition Examination Survey (26) and the Actical accelerometer being included in the Canadian Health Measures Survey (24).

Generally, researchers develop regression equations that relate the movement counts to energy expenditure (EE), and on the basis of these regression equations, estimates of EE and time spent in sedentary behaviors (<1.5 METs), light PA (1.5–2.99 METs), moderate PA (3–5.99 METs), and vigorous PA (VPA, ≥6 METs) can be obtained. There have been several single-regression equations developed for use in children (12,15,18,19,25,29); however, in general, the single-regression equations developed for use in children suffer from the same limitations as what has been shown in adults in that no single-regression equation is able to accurately predict EE or time spent in different intensity categories across a wide range of activities (9,28). Alternatively, researchers have examined other approaches for analyzing accelerometer data, including receiver operating characteristics, for use in children, (11,13,28), whereas in adults, approaches such as a two-regression model (2RM) (5,6,8) and pattern recognition (e.g., hidden Markov models [17] and artificial neural networks [23]) have been used. Recently, we developed a 2RM for use in adults for both the ActiGraph (6,8) and Actical (5,7) accelerometers. The 2RM is able to discriminate between continuous walking/running

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Submitted for publication September 2011.
Accepted for publication November 2011.

Supplemental digital content is available for this article. Direct URL citations appear in the printed text and are provided in the HTML and PDF versions of this article on the journal's Web site (www.acsm-msse.org).

0195-9131/12/4406-1177/0
MEDICINE & SCIENCE IN SPORTS & EXERCISE®

DOI: 10.1249/MSS.0b013e3182447825

and intermittent lifestyle activities on the basis of the variability in the accelerometer counts, and it has been shown to be a significant improvement over the more widely used single-regression equations for assessment of EE and time spent in light PA, moderate PA, and VPA (6,7).

Because of differences in resting metabolic rate (RMR) (14,22), movement economy (16), and activity patterns (1), accelerometer methods developed using adult populations cannot be applied to younger age groups. Therefore, the purpose of this study was to develop two new 2RMs for children using the ActiGraph GT3X accelerometer: 1) mean vector magnitude counts, which use the newest ActiGraph triaxial accelerometers, and 2) vertical axis counts, for researchers who still want to collect ActiGraph data using older single-axis devices. A secondary purpose was to compare the new 2RMs to four commonly used single-regression equations used in children for predicting EE during structured bouts of PA.

METHODS

Participants. Fifty-five girls and 61 boys between the ages of 8 and 15 yr volunteered to participate in the study. The procedures were reviewed and approved by the University of Massachusetts Boston and Boston Public School Institutional Review Board before the start of the study. The parent of each participant signed a written informed consent and filled out a health history questionnaire, and each participant signed a written assent before participation in the study. Participants were excluded from the study if they had any contraindications to exercise or were physically unable to complete the activities. In addition, none of the participants were taking any medications that would affect their metabolism (e.g., Concerta [Johnson & Johnson, New Brunswick, NJ] or Ritalin [Novartis, Basel, Switzerland]).

Procedures. Testing was performed during a 2-d period. On day 1, participants had their anthropometric measures taken and completed 30 min of rest, lying on a table in a quiet room. On day 2, participants performed various lifestyle and sporting activities that were broken into three routines (Table 1). Participants were first categorized as either normal weight or overweight/obese, on the basis of their body mass index (BMI) percentile. They were then randomly assigned to an activity routine on the basis of their BMI group so that randomization to each routine was done separately for normal-weight and overweight/obese participants. This was done so that there were approximately equal numbers of normal-weight and overweight/obese participants performing each routine. All participants performed the resting measurement and one of the three routines (six activities). Routine 1 was completed by 38 participants, and routines 2 and 3 were completed by 39 participants. Participants performed each activity in a routine for 8 min, with a 1- to 2-min break between each activity. Oxygen consumption ($\dot{V}O_2$) was measured continuously throughout the resting measure and each activity by indirect calorimetry (Cosmed K4b^2; Rome, Italy), and simultaneously, activity data were collected using

TABLE 1. Description of activities performed by routine.

Routine	Activity	Description
0	Lying rest	Lying on a massage table in supine position with arms at the side, in a quiet room.
1	Reading	Sitting on a chair at a desk, reading a self-selected book/magazine.
	Sweeping	Sweeping dirt on wood gymnasium floor continuously with a broom.
	Nintendo Wii (Nintendo of America, Redmond, WA)	Playing Wii Boxing for half the time and Wii Tennis for half the time with a partner.
	Lightspace Floor (Lightspace Corp., Boston, MA)	Choosing from a variety of games that require users to follow and activate different points on a pressure sensor pad on the floor that reacts to movement.
	Slow walking	Walking at a self-selected comfortable speed around an outdoor track (weather permitting) or a marked hallway perimeter inside.
	Brisk walking	Walking at a self-selected comfortable speed around an outdoor track (weather permitting) or a marked hallway perimeter inside.
2	Watching TV	Sitting in a chair at a desk and watching a self-selected TV show on a computer.
	Lightspace Wall (Lightspace Corp., Boston, MA)	Choosing from a variety of games that require users to follow and activate different points on a pressure sensor pad on the wall that reacts to movement.
	Dance Dance Revolution (Konami Corp., Tokyo, Japan)	Following movement patterns on a screen that are set to music by stepping on appropriate arrows on a pad. Songs are selected at random and were set to easy level.
	Playing catch	Standing at a comfortable distance from partner, throw and catch a football.
	Walking with a backpack	Wearing a 4.5-kg weighted vest, walk at a self-selected comfortable speed around an outdoor track (weather permitting) or a marked hallway perimeter inside.
	Soccer around cones	Dribbling a soccer ball back and forth around three to four cones set up in a zigzag pattern. Playing outside on grass (weather permitting) or inside in a designated space.
3	Searching the Internet	While sitting on a chair at a desk, using a mouse and keyboard to search self-selected items on the Internet.
	Vacuuming	While standing and continuously moving around, vacuuming carpet.
	Sportwall (Exercise Technology, Ventura, CA)	Standing 20–25 ft away from a wall, run to the wall and hit the illuminated dot on wall, then run back to the starting point and repeat. Try to get as many points as you can within a time frame.
	Trazer (Traq Ltd., Bay Village, OH)	Wearing a motion sensor belt clipped around waist, which, when moved, controls the screen avatar's movement. Playing Goalie Wars for half the time and Jump Explosion for half the time.
	Workout video	Following along to an age-specific aerobics video.
	Track running	Running at a self-selected comfortable speed around an outdoor track (weather permitting) or a marked hallway perimeter inside.

Lying rest was performed for 30 min, and all other activities were performed for 8 min.

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an ActiGraph GT3X accelerometer positioned on the right hip. This study was part of a larger study, and in addition to the ActiGraph worn on the hip, the participants also had several other accelerometers positioned at different body locations; however, only the ActiGraph hip data are presented here. To account for the additional weight of the Cosmed $K4b^2$, ActiGraph, and additional devices, 2 kg was added to the participant's body weight.

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. BMI was calculated according to the formula body mass (kg) divided by height squared (m^2), and gender- and age-specific BMI percentiles were calculated using Centers for Disease Control and Prevention algorithms (4).

Indirect calorimetry. The participants wore a Cosmed $K4b^2$ for the duration of each routine and the resting measure. 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-L syringe (Hans-Rudolph, Shawnee, KS). Finally, a delay calibration was performed to adjust for the lag time that occurs between the expiratory flow measurement and the gas analyzers.

ActiGraph accelerometer. The ActiGraph GT3X accelerometer is a small ($3.8 \times 3.7 \times 1.8$ cm) lightweight (27 g) water-resistant triaxial accelerometer. The GT3X measures accelerations in the range of 0.05*g* to 2*g*, which is digitized by a 12-bit analog-to-digital converter at a rate of 30 Hz. Once digitized, the data are filtered using a band-limited frequency of 0.25 to 2.5 Hz. These values correspond to the range in which most human activities are performed. During all testing, the ActiGraph GT3X was worn at waist level at the right anterior axillary line attached to a nylon belt. The GT3X was initialized using 1-s epochs and the low-frequency extension turned on. The GT3X 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 GT3X data were downloaded for subsequent analysis.

Data analysis. Breath-by-breath data were collected by the Cosmed $K4b^2$, which was averaged over a 1-min period. For each activity, the $\dot{V}O_2$ ($mL{\cdot}min^{-1}$) was converted to $\dot{V}O_2$ ($mL{\cdot}kg^{-1}{\cdot}min^{-1}$). In adults, 3.5 $mL{\cdot}kg^{-1}{\cdot}min^{-1}$ is used to define 1 MET; however, children and adolescents have higher RMR than adults, and if the standard definition of 3.5 $mL{\cdot}kg^{-1}{\cdot}min^{-1}$ is used in children, it will result in an overestimation of the measured energy cost (i.e., MET value) of an activity (14,22). Thus, METs were calculated by dividing the $\dot{V}O_2$ ($mL{\cdot}kg^{-1}{\cdot}min^{-1}$) for each activity by the participant's supine resting $\dot{V}O_2$ ($mL{\cdot}kg^{-1}{\cdot}min^{-1}$). Hereafter, the use of MET_{RMR} will refer to measured activity $\dot{V}O_2$ divided by measured supine resting $\dot{V}O_2$, and $MET_{3.5}$ will refer to the standard definition used for adults of 1 MET = 3.5 $mL{\cdot}kg^{-1}{\cdot}min^{-1}$. For each activity, the MET_{RMR} values for minutes 4 to 7 were averaged and used for the subsequent analysis.

The ActiGraph accelerometer data for each axis were collected in 1-s epochs. Mean vector magnitude was also calculated as the square root of the sum of the squared activity counts in each vector. The 1-s epochs for each axis and vector magnitude were converted to counts per 10 s and counts per minute. For each activity, mean counts per 10 s, counts per minute, and coefficient of variation (CV) were calculated. Following the methods we previously used in developing the refined 2RM for adults (8), a CV was calculated for each 10-s epoch by examining each 10-s epoch and the surrounding five 10-s epochs in the following manner: the 10-s epoch of interest and 1) the five 10-s epochs before, 2) the four 10-s epochs before and one 10-s epoch after, 3) the three 10-s epochs before and two 10-s epochs after, 4) the two 10-s epochs before and three 10-s epochs after, 5) the 10-s epoch before and four 10-s epochs after, and 6) the five 10-s epochs that followed. After the CV was calculated for each condition, the lowest CV from the six possible conditions was used as the CV for that 10-s epoch. Examining each 10-s epoch and all combinations of the five surrounding 10-s epochs, in this manner, allows for the determination of whether a specific 10-s epoch falls within a continuous walking/running bout or is part of an intermittent lifestyle activity. The mean counts and CV were calculated for minutes 4–7 of each activity to match what was done with the Cosmed data (for further detail and sample calculations, see Crouter et al. [8]).

Lastly, EE was also predicted using the child-specific regression equations of Freedson et al. (12), Trost et al. (29), Treuth et al. (25), and Puyau et al. (18) (see Table, Supplemental Digital Content 1, which describes each equation; http://links.lww.com/MSS/A142). Because we chose to express our measured EE value as MET_{RMR}, we felt it was necessary to convert all prediction equations to comparable MET_{RMR} values to ensure a fair evaluation of the prediction equations. For the equations of Freedson et al. and Treuth et al., which both predict $MET_{3.5}$, we multiplied the predicted $MET_{3.5}$ value for each activity by 3.5 $mL{\cdot}kg^{-1}{\cdot}min^{-1}$ to obtain a predicted $\dot{V}O_2$ value, which was then divided by the supine resting $\dot{V}O_2$ to get a predicted MET_{RMR}. The equations of Trost et al. and Puyau et al. predict kilocalories per minute and kilocalories per kilogram per minute, respectively; thus, they were also converted to MET_{RMR} values using the measured resting values.

Statistical treatment. Statistical analyses were carried out using SPSS version 17.0 for Windows (SPSS, Inc., Chicago, IL). For all analyses, an α level of 0.05 was used to indicate statistical significance. All values are reported as mean ± SD. Seventy-seven participants were randomly selected for the development of the new 2RM, leaving 39 participants for cross-validation of the new equation.

TABLE 2. Descriptive characteristics of the participants in the development and cross-validation groups.

	Development Group (n = 73)	Cross-Validation Group (n = 33)
Age (yr) (mean ± SD (range))	11.3 ± 1.6 (8–15)	12.1 ± 1.4 (8–14)
8–9 (n)	21	4
10–11 (n)	24	15
≥12 (n)	28	14
Male (%)	50.7	55.6
Activity routine (n)		
1	27 (10 male, 17 female)	11 (7 male, 4 female)
2	23 (12 male, 11 female)	13 (8 male, 5 female)
3	23 (15 male, 8 female)	12 (5 male, 7 female)
BMI classification (%)		
Normal weight (5th–85th percentile)	58.4	66.7
Overweight (85th–95th percentile)	15.6	12.8
Obese (≥95th percentile)	26.0	20.5
Race/ethnicity (%)		
Hispanic	29.9	35.9
Black/African American	39.0	59.0
Native American/Alaskan	2.6	0.0
Asian	11.7	10.3
White	46.8	30.7

Initially, using the developmental group, the mean counts and percentile distribution were used to determine an inactivity threshold (i.e., lying, reading, video watching, and searching Internet activities), and the mean CV and percentile distribution were used to determine a CV threshold to determine whether a 10-s epoch is part of a continuous walking/running bout or intermittent lifestyle activity. Regression analysis was then used to predict MET_{RMR} from the counts per 10 s on the basis of a low CV (continuous walk/run activity) or a high CV (intermittent lifestyle activity). This process was completed using both the mean vector magnitude counts and vertical axis counts.

A one-way repeated-measures ANOVA was used to compare measured (Cosmed) and predicted MET_{RMR} for each activity using the cross-validation group. 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 MET_{RMR} minus estimated MET_{RMR}) (2). This allowed for the mean error score and the 95% prediction interval (PI) to be shown. Data points below zero signify an overestimation, whereas points above zero signify an underestimation. The Bland–Altman plots were modified by plotting the criterion measure on the x axis; this is different from the original method in which the x axis is the average of two methods that attempted to measure the same construct (2).

RESULTS

Data for four participants from the developmental group and three participants from the cross-validation group were excluded because of missing a resting measurement (three participants) or accelerometer malfunction resulting in data loss (four participants).

Participant descriptive characteristics for the development group and cross-validation group are shown in Table 2. Mean ± SD measured MET_{RMR} values and ActiGraph counts per minute and CV of the counts per 10 s (x axis and vector magnitude) for each activity are shown in Table 3 (developmental group only).

ActiGraph vertical axis model. On the basis of the examination of the mean CV values, for the vertical axis, and percentile distributions, a CV of 35 was chosen to distinguish between continuous walking/running and intermittent lifestyle activity. Specifically, during walking and running activities, the CV was less than 35% (CV ≤ 35) 96.1% of the time, whereas for intermittent lifestyle activities, the CV threshold was greater than 35% (CV > 35) 94.4% of the time. One exception was for sedentary activities where count values could be zero for a full minute; thus the CV was not able to be calculated. For these activities,

TABLE 3. Mean ± SD measured (Cosmed) MET_{RMR} (measured $\dot{V}O_2$ for the activity divided by measured resting $\dot{V}O_2$) and counts per minute (vertical axis and vector magnitude) and CV for the 10-s counts (vertical axis and vector magnitude) from the ActiGraph accelerometer for each activity using the developmental group.

			ActiGraph Vertical Axis		ActiGraph Vector Magnitude	
Activity	Measured $\dot{V}O_2$ ($mL \cdot kg^{-1} \cdot min^{-1}$)	Measured MET_{RMR}	Counts per Minute	CV	Counts per Minute	CV
Supine rest (n = 73)	4.8 ± 1.5	1.0 ± 0.0	34 ± 55.9	70 ± 68.5	84 ± 141.2	89 ± 72.2
Watching television (n = 23)	5.0 ± 1.4	1.1 ± 0.3	6 ± 11.9	44 ± 68.3	59 ± 94.0	105 ± 83.0
Searching the Internet (n = 23)	4.9 ± 1.4	1.1 ± 0.3	9 ± 28.9	33 ± 52.7	41 ± 55.9	107 ± 75.2
Reading (n = 27)	4.9 ± 1.7	1.1 ± 0.4	11 ± 31.4	56 ± 66.4	61 ± 99.7	109 ± 63.6
Workout video (n = 23)	9.7 ± 3.3	2.1 ± 0.7	669 ± 483.6	117 ± 34.5	1637 ± 773.2	64 ± 23.8
Nintendo Wii (n = 27)	11.4 ± 6.4	2.4 ± 1.1	372 ± 404.8	120 ± 37.9	1548 ± 1034.9	73 ± 24.2
Vacuuming (n = 23)	11.2 ± 3.3	2.5 ± 0.7	343 ± 205.0	79 ± 35.8	2272 ± 677.2	28 ± 10.4
Sweeping (n = 27)	12.1 ± 3.8	2.7 ± 1.1	454 ± 398.1	78 ± 36.8	2152 ± 1072.8	33 ± 18.4
Slow track walking (n = 27, average (avg) = 75 $m \cdot min^{-1}$)	14.9 ± 3.7	3.3 ± 1.2	3063 ± 805.0	13 ± 7.2	4172 ± 763.3	10 ± 5.5
Dance Dance Revolution (n = 23)	15.7 ± 4.4	3.4 ± 1.0	1036 ± 568.1	106 ± 26.2	2107 ± 818.5	71 ± 18.2
Playing catch (n = 23)	17.4 ± 5.2	3.7 ± 1.1	1507 ± 720.5	79 ± 36.0	3630 ± 1151.6	46 ± 20.9
Walk with a 4.5-kg backpack (n = 23, avg = 81 $m \cdot min^{-1}$)	17.5 ± 4.4	3.8 ± 1.3	3300 ± 1037.4	16 ± 15.7	4206 ± 937.1	11 ± 6.4
Brisk track walking (n = 27, avg = 93 $m \cdot min^{-1}$)	19.3 ± 4.3	4.3 ± 1.5	4061 ± 897.8	14 ± 7.7	5401 ± 845.7	12 ± 6.3
Trazer (n = 23)	18.8 ± 7.1	4.3 ± 1.9	4193 ± 2358.1	64 ± 24.6	6627 ± 2071.5	44 ± 18.0
Lightspace Floor (n = 27)	21.5 ± 7.5	4.6 ± 1.7	2242 ± 1230.8	69 ± 20.2	4869 ± 1597.3	51 ± 15.6
Lightspace Wall (n = 23)	21.5 ± 6.2	4.8 ± 1.8	1935 ± 753.1	83 ± 23.9	4544 ± 1256.0	55 ± 12.0
Sportwall (n = 23)	21.7 ± 6.9	4.9 ± 1.9	3126 ± 1650.0	68 ± 31.7	5260 ± 1895.8	46 ± 23.5
Track running (n = 23, avg = 122 $m \cdot min^{-1}$)	21.9 ± 10.4	5.0 ± 2.6	5163 ± 1574.8	17 ± 11.8	6304 ± 1481.4	14 ± 8.2
Soccer around cones (n = 23)	22.7 ± 8.9	5.1 ± 2.5	2118 ± 1046.8	41 ± 22.5	4467 ± 1257.9	23 ± 8.1

the CV was defined as zero and was included in the CV > 35 group for the purpose of developing the model.

For activities where the vertical axis CV was ≤35, an exponential equation using the vertical axis counts per 10 s provided the best fit, whereas for activities where the vertical axis CV was >35, a linear regression equation using the vertical axis counts provided the best fit. In addition, we propose an inactivity threshold of 25 vertical axis counts per 10 s to distinguish inactivity from light activity. Thus, when the vertical axis counts per 10 s are ≤25, the individual is credited with 1.0 MET_{RMR}. The 2RM to predict gross EE (MET_{RMR}) from the ActiGraph vertical axis counts consists of three parts (inactivity threshold and two separate regression models) and hereafter will be called the child vertical axis 2RM (VA2RM):

1. If the vertical axis counts per 10 s are ≤25, then EE = 1.0 MET_{RMR}.
2. If the vertical axis counts per 10 s are >25

   a. and the CV of the vertical axis counts per 10 s is ≤35, then EE (MET_{RMR}) = 1.982 (exp(0.00101 × ActiGraph vertical axis counts per 10 s)) (R^2 = 0.304, SEE = 0.347),
   b. or the CV of the vertical axis counts per 10 s is >35, then EE (MET_{RMR}) = 2.842 + (0.00288 × ActiGraph vertical axis counts per 10 s) (R^2 = 0.222, SEE = 1.450).
3. Once a MET_{RMR} value has been calculated for each 10-s epoch within a minute on the ActiGraph clock, the average MET_{RMR} value of six consecutive 10-s epochs within each minute is calculated to obtain the average MET_{RMR} value for that minute.

ActiGraph vector magnitude model. On the basis of the examination of the mean CV values, for the mean vector magnitude, and percentile distributions, a CV of 25 was chosen to distinguish between continuous walking/running and intermittent lifestyle activity. Specifically, during walking and running activities, the CV was less than 25% (CV ≤ 25) 97% of the time, whereas for intermittent lifestyle activities, the CV threshold was greater than 25% (CV > 25) 89.5% of the time. As described previously for the model using only the vertical axis, when the CV was defined as zero, it was included in the CV > 25 group for the purpose of developing the model.

For activities where the mean vector magnitude CV was ≤25, an exponential equation using the natural log (ln) of the mean vector magnitude counts per 10 s provided the best fit, whereas for activities where the mean vector magnitude CV was >25, a cubic equation using the ln of the mean vector magnitude counts per 10 s provided the best fit. In addition, we propose an inactivity threshold of 75 mean vector magnitude counts per 10 s to distinguish inactivity from light activity. The 2RM to predict gross EE (MET_{RMR}) from the ActiGraph vector magnitude counts hereafter will be called the child vector magnitude 2RM (VM2RM):

1. If the vector magnitude counts per 10 s are ≤75, then EE = 1.0 MET_{RMR}.
2. If the vector magnitude counts per 10 s are >75

   a. and the CV of the vector magnitude counts per 10 s is ≤25, then EE (MET_{RMR}) = 0.0137 (exp(0.848 × (ln(ActiGraph vector magnitude counts per 10 s)))) (R^2 = 0.388, SEE = 0.358),
   b. or the CV of the vector magnitude counts per 10 s is >25, then EE (MET_{RMR}) = 1.219 − (0.145 × (ln(ActiGraph vector magnitude counts per 10 s))) − (0.0586 (ln(ActiGraph vector magnitude counts per 10 s))^2) + (0.0229 (ln(ActiGraph vector magnitude counts per 10 s))^3) (R^2 = 0.589, SEE = 1.248).
3. Once a MET_{RMR} value has been calculated for each 10-s epoch within a minute on the ActiGraph clock, the average MET_{RMR} value of six consecutive 10-s epochs within each minute is calculated to obtain the average MET_{RMR} value for that minute.

Figure 1A shows the measured and predicted MET_{RMR} values for each of the activities using the current ActiGraph single-regression equations in the cross-validation group. Figure 1B shows the measured and predicted MET_{RMR} values for the cross-validation group using the child VA2RM and VM2RM. The child VM2RM was within 0.6 MET_{RMR} compared with measured MET_{RMR} for each of the 19 activities, except for Sportwall (1.8-MET_{RMR} difference) and track running (1.1-MET_{RMR} difference) and was not significantly different from actual MET_{RMR} for any activity (all $P > 0.05$). The VA2RM was within 0.8 MET_{RMR} compared with measured MET_{RMR} for each of the 19 activities, except for Sportwall (2.0-MET_{RMR} difference) and track running (1.1-MET_{RMR} difference), and was not significantly different from actual MET_{RMR} for any activity ($P > 0.05$). The single-regression equations generally overestimated activities below 2 MET_{RMR}, slow and brisk walking, and walking with a 4.5-kg backpack and underestimated most other activities. The equations of Freedson et al. (12), Treuth et al. (25), and Puyau et al. (18) all significantly overestimated the mean MET_{RMR} value, for all activities combined, compared with measured MET_{RMR} ($P <$ 0.001), whereas the child VA2RM and VM2RM were both within 0.2 MET_{RMR} of actual MET_{RMR}, and the equation of Trost et al. (29) was within 0.3 MET_{RMR} of actual MET_{RMR} for all activities combined ($P > 0.05$) (see Table, Supplemental Digital Content 2, which shows the measured MET_{RMR} and estimated MET_{RMR} for the cross-validation for each activity; http://links.lww.com/MSS/A143).

The Bland–Altman plots (Figs. 2A–C) show that, compared with the other models, the child VM2RM was the most accurate model with a mean bias of 0.06 MET_{RMR} (95% PI = −2.18 to 2.30); however, it had a trend to have greater underestimation of measured values greater than 7 MET_{RMR}. The child VA2RM had a mean bias of 0.15 MET_{RMR} (95% PI = −2.19 to 2.49); however, it had a

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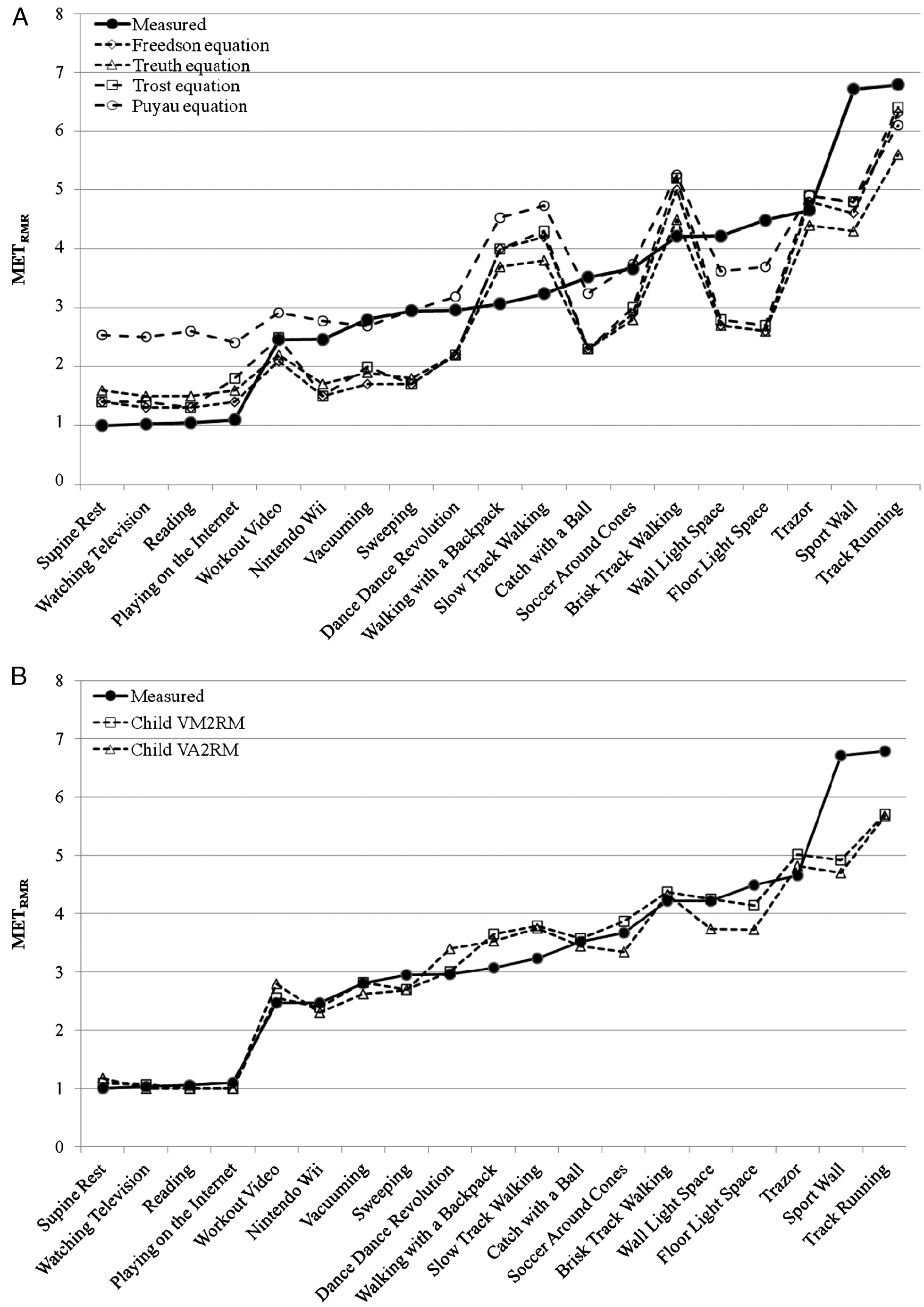

FIGURE 1—Measured (Cosmed K4b^2) and predicted MET_{RMR} across 19 different activities for the cross-validation group, using the regression equations of Treuth et al. (25), Freedson et al. (12), Trost et al. (29), and Puyau et al. (18) for children (A) and the child VM2RM and child VA2RM (B).

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significant trend to overestimate measured values below 4 MET_{RMR} and underestimate measured values greater than 6 MET_{RMR}. All the single-regression equations performed similarly, with the equation of Treuth et al. (mean bias = 0.42 MET_{RMR}, 95% PI = −2.10 to 2.94) performing the best among the single-regression equations. In addition, all single-regression equations showed similar trends as the child VA2RM, to overestimate light to moderate activities and underestimate moderate to vigorous activities (see Figure, Supplemental Digital Content 3, which shows the Bland–Altman plots for the equations of Freedson et al., Trost et al., and Puyau et al.; http://links.lww.com/MSS/A144).

DISCUSSION

This study describes a new approach to estimating EE in children, using the ActiGraph accelerometer. In addition,

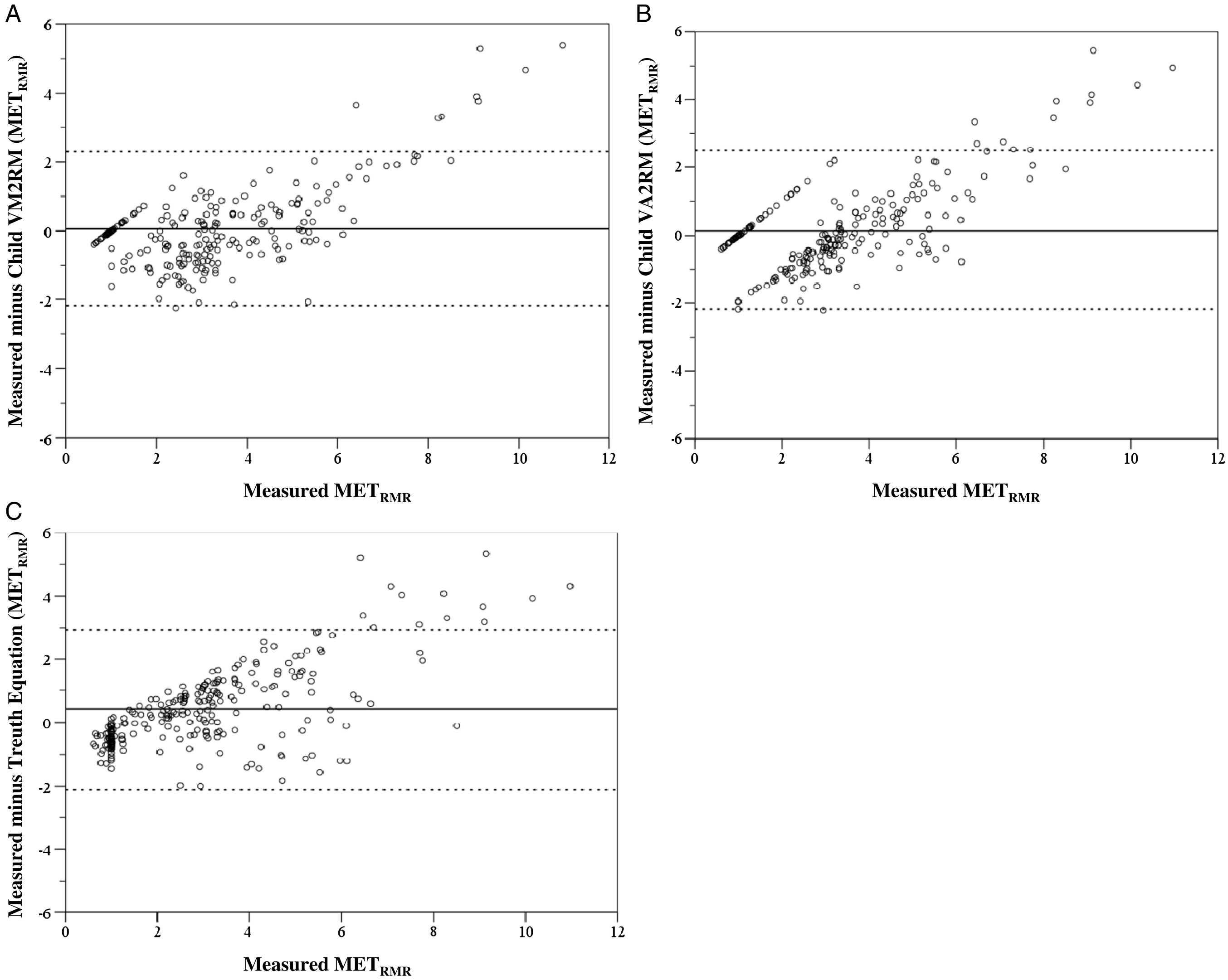

FIGURE 2—Bland–Altman plots depicting error scores (measured minus estimation) for the child VM2RM (A), the child VA2RM (B), and the single-regression equation of Treuth et al. (25) (C). The *solid line* represents the mean, and *dashed lines* represent the 95% confidence interval of the observations.

this is the first study to present a 2RM for use in children that uses either the vertical axis or the vector magnitude from the ActiGraph GT3X accelerometer. The main advantage of this method is that it uses the CV to distinguish between continuous walking/running and intermittent lifestyle activities and then it applies one of two regression equations to obtain improved estimates of EE during specific activities.

Previously, research has shown in adults that the use of a 2RM is a significant improvement over using single-regression equations (5–8) and compares more favorably to doubly labeled water (20). We acknowledge that there are more sophisticated accelerometer analytical techniques that use pattern recognition (e.g., artificial neural networks); however, these models are not readily available for use in children. The new child VM2RM and VA2RM provide a simpler alternative to the more sophisticated pattern recognition methods that provides a more accurate prediction of EE and can be implemented into any study that currently has either the vertical axis or vector magnitude ActiGraph data available in 10-s epochs.

In previous research on children, it has been controversial as to whether age should be included in accelerometer prediction equation; whereas some studies have found that age should be included in the regression equations (12,15), others have not (18,25,29). In a recent validation study, Trost et al. (28) examined the validity of several currently available regression equations across a wide range of activities in participants between 5 and 15 yr. They observed that regression equations that include age have similar accuracy for estimating time spent in various activity intensity categories, compared with equations that only include counts in the regression equations. This suggests that age is not the primary factor affecting accuracy of the prediction equations in children (28). Although the current study did not investigate time in each intensity category, the results from the cross-validation group provide further evidence that all

TABLE 4. MET_{RMR} (mean ± SD) values of the cross-validation group for the Cosmed K4b^2 (measured METs) and predicted MET_{RMR} and $MET_{3.5}$ for the prediction equations of Freedson et al. (12) and Treuth et al. (25) during various structured activities.

Activity	Measured MET_{RMR}	Equation of Freedson et al. $MET_{3.5}$	Equation of Freedson et al. MET_{RMR}	Equation of Treuth et al. $MET_{3.5}$	Equation of Treuth et al. MET_{RMR}
Supine rest (*n* = 33)	1.0 ± 0.0	1.8 ± 0.2*	1.4 ± 0.3*	2.1 ± 0.1*	1.6 ± 0.4*
Watching television (*n* = 13)	1.0 ± 0.4	1.8 ± 0.1*	1.3 ± 0.3	2.0 ± 0.0*	1.5 ± 0.4*
Searching the Internet (*n* = 12)	1.1 ± 0.2	1.7 ± 0.1*	1.4 ± 0.2	2.0 ± 0.0*	1.6 ± 0.3*
Reading (*n* = 11)	1.0 ± 0.2	1.8 ± 0.2*	1.3 ± 0.4	2.0 ± 0.0*	1.5 ± 0.4
Workout video (*n* = 12)	2.5 ± 0.6	2.6 ± 0.9	2.1 ± 0.8	2.8 ± 0.6	2.2 ± 0.6
Nintendo Wii (*n* = 11)	2.5 ± 1.3	2.1 ± 0.3	1.5 ± 0.6	2.3 ± 0.3	1.7 ± 0.7
Vacuuming (*n* = 12)	2.8 ± 0.5	2.2 ± 0.4	1.7 ± 0.4*	2.4 ± 0.3	1.9 ± 0.4*
Sweeping (*n* = 11)	3.0 ± 1.4	2.4 ± 0.4	1.7 ± 0.5	2.5 ± 0.3	1.8 ± 0.6
Slow track walking (*n* = 11, avg = 75 m·min^{-1})	3.2 ± 1.0	5.6 ± 1.3*	4.2 ± 1.9	5.1 ± 0.9*	3.8 ± 1.6
Dance Dance Revolution (*n* = 13)	3.0 ± 0.9	2.9 ± 0.7	2.2 ± 0.7	3.0 ± 0.6	2.2 ± 0.7
Playing catch (*n* = 13)	3.5 ± 1.2	3.1 ± 0.7	2.3 ± 0.6*	3.1 ± 0.5	2.3 ± 0.6*
Walk with a 4.5-kg backpack (*n* = 13, avg = 76 m·min^{-1})	3.1 ± 0.4	5.4 ± 0.8*	4.0 ± 0.8	4.9 ± 0.6*	3.7 ± 0.8
Brisk track walking (*n* = 11, avg = 92 m·min^{-1})	4.2 ± 1.1	6.6 ± 1.4*	5.0 ± 2.0	5.9 ± 1.0*	4.5 ± 1.8
Trazer (*n* = 12)	4.7 ± 1.6	6.0 ± 2.2	4.8 ± 2.0	5.5 ± 1.8	4.4 ± 1.7
Lightspace Floor (*n* = 11)	4.5 ± 1.9	3.7 ± 0.8	2.6 ± 0.8	3.6 ± 0.6	2.6 ± 0.8*
Lightspace Wall (*n* = 13)	4.2 ± 1.2	3.7 ± 0.8	2.7 ± 0.5*	3.6 ± 0.5	2.7 ± 0.4*
Sportwall (*n* = 12)	6.7 ± 2.3	5.8 ± 1.8	4.6 ± 1.6*	5.4 ± 1.5	4.3 ± 1.5*
Track running (*n* = 12, avg = 120 m·min^{-1})	6.8 ± 2.0	8.1 ± 0.9	6.3 ± 1.5	7.2 ± 0.8	5.6 ± 1.5
Soccer around cones (*n* = 13)	3.7 ± 0.9	3.9 ± 1.1	2.9 ± 0.8	3.8 ± 0.9	2.8 ± 0.7
Total for all activities	3.1 ± 2.0	3.6 ± 2.1*	2.7 ± 1.8*	3.5 ± 1.7*	2.7 ± 1.5*

MET_{RMR}, measured $\dot{V}O_2$ divided by measured lying RMR $\dot{V}O_2$; $MET_{3.5}$, measured $\dot{V}O_2$ divided by 3.5 mL·kg^{-1} ·min^{-1}.
* Significantly different from Cosmed K4b^2 , $P < 0.05$.

the single-regression equations work in a similar fashion for estimating the energy cost of specific activities, regardless of whether age is included in the prediction model.

The current study investigated multiple regression models that included factors such as age and gender, and the best models overall included only counts. Rather than chronological age, it seems that growth-dependent factors (e.g., change in RMR) seem to play a greater role in the relationship between accelerometer output and EE (27). Several earlier studies involving child participants have used adult values for the estimated RMR (i.e., 1 $MET_{3.5}$ = 3.5 mL·kg^{-1}·min^{-1}) (12,25). When adult RMR values are used in children, this will overestimate the intensity of the activity because of their higher RMR. For the cross-validation in the current study, we chose to convert the predicted $MET_{3.5}$ values for the equations of Freedson et al. and Treuth et al. to predicted MET_{RMR} values. To illustrate the difference in the predicted values, Table 4 shows the predicted $MET_{3.5}$ and MET_{RMR} values for the equations of Freedson et al. and Treuth et al. compared with the measured MET_{RMR} values. PA researchers need to be aware of how prediction equations are developed because it has implications for implementation into studies and the predictive accuracy of the equations.

Previous research in children and adults has suggested that the use of triaxial accelerometers has the potential to provide better estimates of PA than using a single-axis accelerometer (3,10,21,30). This could be potentially true for children given their inherent movement patterns during free-play activities (e.g., short sporadic burst and varied movements in multiple planes) (1); however, there is no conclusive evidence to suggest that using a single axis versus multiple axes is superior to the other. In the current study, a child 2RM was developed using a single axis (vertical axis) and all three axes (vector magnitude). On the basis of the results from the cross-validation group in the current study, both models worked in a similar fashion and had similar mean errors for the prediction of specific activities. In addition, the Bland–Altman plots show similar accuracy between the child VM2RM (mean bias = 0.06 MET_{RMR}, 95% PI = −2.18 to 2.3 MET_{RMR}) and the child VA2RM (mean bias = 0.15 MET_{RMR}, 95% PI = −2.19 to 2.49 MET_{RMR}). However, the child VA2RM tended to overestimate activities less than 4 MET_{RMR} and underestimate activities over 4 MET_{RMR}. Further work is needed to examine how the different models work in a true free-living environment.

The current study does have strengths and weaknesses. Strengths of the study are that the new child 2RMs were developed on a wide range of activities ranging from sedentary behaviors to vigorous exercise. In addition, we used a large sample size with a range of ages and BMI levels. This is in contrast to most previous studies that developed single-regression equations on a limited number of activities (i.e., walking/running or moderate-intensity lifestyle activities), a single sex, or limited age range. In addition, although the activities were performed in a structured manner (i.e., 8-min bouts of specific activities), the participants were encouraged to perform the activity as they generally would under normal circumstances. In addition, when possible, activities were performed outside of the laboratory in more of a free-living environment. For example, the walking and running were performed overground at self-selected speeds. Limitations of the study include a small cross-validation group (11–13 participants per activity). In addition, the new child 2RMs were validated using the same activities that they were developed on, which could influence the results to show that they work better than they might in an independent sample on different activities. 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. An additional limitation to the study is that we relied on the participants to tell us when their last meal was and when they last performed previous VPA; thus, it is possible that the measured resting values are higher than expected for some because of not following the protocol as asked. This has the potential to affect the activity MET_{RMR} values because an elevated resting MET_{RMR} value would result in a lower activity MET_{RMR} value.

In conclusion, the new child VM2RM and VA2RM improve upon currently available methods for the prediction of EE (MET_{RMR}) in children during structured bouts of PA. The new child VM2RM was the most accurate on both a group and an individual basis. It has a bias of 0.06 MET_{RMR} (95% PI of −2.18 to 2.30 MET_{RMR}). Further work is needed to examine the accuracy of these new models in an independent sample of children, in a free-living setting.

This research was supported by National Institutes of Health grant NIH 5R21HL093407. No financial support was received from any of the activity monitor manufacturers, importers, or retailers. There are no declared conflicts of interest for any of the authors.

The authors thank the research participants and Prince Owusu, Larry Kennard, Katie Dooley, Shawn Pedicini, Rachel Mclellan, and Sarah Sullivan for help with data collection.

The results of the present study do not constitute endorsement by the American College of Sports Medicine.

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