Triaxial Accelerometry for Assessment of Physical Activity in Young Children

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Abstract

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Objective: The purpose of the present study was to derive linear and non-linear regression equations that estimate energy expenditure (EE) from triaxial accelerometer counts that can be used to quantitate activity in young children. We are unaware of any data regarding the validity of triaxial accelerometry for assessment of physical activity intensity in this age group.

Research Methods and Procedures: EE for 27 girls and boys (6.0 ± 0.3 years) was assessed for nine activities (lying down, watching a video while sitting and standing, line drawing for coloring-in, playing blocks, walking, stair climbing, ball toss, and running) using indirect calorimetry and was then estimated using a triaxial accelerometer (ActivTracer, GMS).

Results: Significant correlations were observed between synthetic (synthesized tri-axes as the vector), vertical, and horizontal accelerometer counts and EE for all activities (0.878 to 0.932 for EE). However, linear and non-linear regression equations underestimated EE by >30% for stair climbing (up and down) and performing a ball toss. Therefore, linear and non-linear regression equations were calculated for all activities except these two activities, and then evaluated for all activities. Linear and non-linear regression equations using combined vertical and horizontal acceleration counts, synthetic counts, and horizontal counts demonstrated a better relationship between accelerometer counts and EE than did regression equations using vertical acceleration counts. Adjustment of the predicted value by the regression equations using the vertical/horizontal counts ratio improved the overestimation of EE for performing a ball toss.

Discussion: The results suggest that triaxial accelerometry is a good tool for assessing daily EE in young children.

Key words: energy expenditure, physical activity, children, accelerometry, indirect calorimetry

Introduction

Childhood obesity is a health and social problem in many countries, including Japan (1). Obesity in young children leads to obesity and metabolic disorders in adults (2). Therefore, a countermeasure of obesity in young children is important. Decreased physical activity (PA)[1] is likely a major contributor to obesity in young children (3,4). Recent studies have revealed that not only programmed exercise but also non-exercise activity thermogenesis (NEAT), a component with large interindividual variability (5,6), can prevent weight gain in adults (7,8). Because young children are not usually engaged in prolonged exercise, it is important to evaluate PA, and NEAT in particular, in young children.

The doubly labeled water (DLW) method has been well known as the gold standard for measurement of energy expenditure (EE) under free-living conditions. However, this method is expensive and requires the collection of several urine samples. Moreover, it does not provide specific information on the nature of PA. In contrast, the questionnaire (e.g., activity diary) and accelerometer methods are relatively non-invasive. However, self-reported measures for PA may be difficult in young children. The

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[1] Nonstandard abbreviations: PA, physical activity; NEAT, non-exercise activity thermogenesis; DLW, doubly labeled water; EE, energy expenditure; PAR, physical activity ratio; BMR, basal metabolic rate; SEE, standard error of estimate.

questionnaire is subjective, and the measures for PA depend on the observer. An objective measurement approach using an accelerometer may avoid these limitations of a questionnaire, as an accelerometer can count movements in sedentary to vigorous activities (9).

Accelerometers can be used to predict EE and to classify levels of PA (9–12). Validation studies of accelerometers have been performed in both children and adults; however, such studies for classification of PA in young children have only recently been reported (13,14). The principal purpose of the study by Reilly et al. (13) was only to determine cut-off values for accelerometry output. They validated the same type of accelerometer (Actigraph, CSA/MTI) against the DLW method later (15) and indicated that the accelerometer was not appropriate to estimate total EE in preschool-age children. Pfeiffer et al. (14) calibrated an accelerometer (Actical) for use with preschool children during rest, slow and brisk walking, and jogging. However, light to moderate intensity lifestyle activities, except for rest, were not included in the study. These lifestyle activities are known to be underestimated using uniaxial or a single summary measure of the triaxial acceleration counts in adults (12). In these studies (13–15), uniaxial and omniaxial accelerometers were used, respectively. Because the nature of PA in young children is different from that in older children and adults (11), triaxial accelerometry may provide more useful information in young children than uniaxial accelerometry. We are unaware of any data regarding the validity of triaxial accelerometry for assessment of PA intensity in young children, although Hoos et al. (16) validated the triaxial accelerometer (Tracmor2) in 6.9 ± 2.2-year-old children for the estimation of total EE against the DLW method. Some studies have evaluated the validity of the accelerometer in older children (11,17); however, the modeling equations used in these studies assumed a linear relationship between accelerometer counts and EE, while a non-linear model using vertical and horizontal acceleration counts independently may be more appropriate (10,18).

The purpose of the present study was to derive the best models using linear or non-linear equations that estimate EE and physical activity ratio (PAR) from triaxial accelerometer counts in young children.

Research Methods and Procedures

Subjects

Subjects were 5- to 6-year-old Japanese girls ($n = 11$) and boys ($n = 16$) (mean age, 6.0 ± 0.3 years), living in the Tokyo metropolitan area, and going to kindergarten. All of the subjects reported being in good health, without any anamnesis affecting EE, such as abnormal thyroid gland function. The sample size was determined based on the results of similar studies published previously. Informed consent was obtained from a parent, and the Ethical Committee of the J.F. Oberlin University approved the study protocol.

Measurement Items and Methods

Body height and weight were measured to the nearest 0.1 cm and 0.1 kg, respectively. EE was assessed for nine activities using indirect calorimetry by the Douglas bag method. The 27 subjects performed the nine activities while wearing a 57-gram triaxial accelerometer (ActivTracer, GMS, Tokyo, Japan) (19) on the left side of the waist and a mask for collecting expired air using the Douglas bag method. An ActivTracer recorded triaxial acceleration every 5 seconds. The triaxial accelerometer obtained three-dimensional accelerations every 40 ms with a sensitivity of 2 mG and with a band-pass filter of 0.3 to 100 Hz. The acceleration count was calculated as the average of the absolute values for acceleration in each direction for a given interval (5 seconds). Anteroposterior (x-axis), mediolateral (y-axis), vertical (z-axis), and synthetic (synthesized tri-axes as vector) accelerations were obtained from the triaxial accelerometer during the nine activities. The acceleration data were uploaded to a personal computer. In addition, because the triaxial accelerometer could shift horizontally during measurements, the x- and y-axes were synthesized as "horizontal acceleration" for the analysis.

For a subgroup of subjects, another accelerometer (actigraph, model RC; Ambulatory Monitoring, Inc., Ardsley, NY), which weighs about 9 g, was worn on the wrist of the dominant arm ($n = 14$). The actigraph is designed to detect a wide range of limb movements related to sleep/wake behavior and PA. The actigraph was set to operate in "Proportional Integral Mode" (low) to record the number of movements within a 1-minute interval. Calculations were performed with Action-W software, version 2.0 (Ambulatory Monitoring, Inc.). The activity counts during each PA were calculated as an average while the EE for the PA was determined.

The measurements began approximately 2 hours after breakfast to limit additional variability in EE due to the thermic effect of food. Subjects were permitted only drinking water during the experiment. The selected activities were resting while lying down, watching a video while sitting and standing, line drawing for coloring-in, playing blocks, walking at personal normal speed, stair climbing (up and down) at personal normal speed, performing a ball toss, and running at personal normal speed. These nine activities were chosen as representative activities of daily life, based on our observations in a preliminary study using the activity records of observers of 4- to 6-year-old children in a nursery school. Moreover, the selected activities in the present study were able to be conducted with a facemask and Douglas bag attached to 5- to 6-year-old children.

Initially, subjects were attached to a facemask connected to the Douglas bag and lay resting to determine resting metabolic rate. Oxygen consumption measurements were made for 10 minutes, from 30 to 40 minutes after resting. Subsequently, watching a video while sitting and standing, line drawing for coloring-in, and playing blocks were performed, and respiratory measurements were made during the last 5 minutes of each activity after the steady states were obtained. The walking and playing ball toss activities were performed for 4 minutes, and respiratory measurements were made during the last 2 minutes. Stair climbing (up and down) was performed three times using stairs with 32 steps in one direction; the first up-down was performed to obtain a steady state, and then respiratory measurements were made during the second and third up-downs (for ~2 minutes). Running was performed twice over a distance of 220 m, at an interval time of ~5 seconds between each run. Measurements of EE were made during the second set (for ~2 minutes). These procedures were determined so that the steady states for respiratory measurements could be obtained, based on the results in young children.

Expired air volume was measured with a certified dry gas meter (SHINAGAWA DC-5, Tokyo, Japan). Expired air was sampled and the O_2 and CO_2 concentrations were measured using a gas analyzer (Minato Medical Co., AE-300S, Tokyo, Japan). EE was calculated from O_2 consumption and CO_2 production using Weir's equation (20). Before each measurement, the gas analyzer was calibrated using room air and a certified gas. In addition, PAR was calculated as EE during each activity divided by the predicted basal metabolic rate (BMR) (21–23). The predicted BMR was estimated using the resting EE with an assumption that the thermic effect of food is 10% of BMR. The equation for predicted BMR was: predicted BMR = (resting EE/1.1).

Statistics

Statistical analyses were performed with SPSS version 14.0J for Windows (SPSS, Inc., Chicago, IL). All results are shown as the mean ± standard deviation. The relationship between two variables was evaluated by Pearson's correlation. Linear and non-linear regression models were used to develop equations predicting EE or PAR from accelerometer counts. The non-linear regression equation using accelerations individually was as follows:

$$EE = a + b1 \times (\sqrt{Ax^2 + Ay^2})^{p^1} + b2 \times Az^{p^2}$$

Ax and Ay: these counts were combined to represent acceleration in the horizontal plane; Az: the vertical acceleration counts; a, b1, b2, p^1, p^2: the coefficients. Non-linear regression equations were developed using one of the vertical, horizontal, or synthetic accelerations.

$$EE = a + b \times A^p$$

A: vertical, horizontal, or synthetic acceleration.

The percentage difference was calculated as [(predicted value − observed value)/observed value] × 100. A multiple linear stepwise regression model was used to consider the contribution of two accelerometers to EE, and the standard error of estimate (SEE) was calculated. A stepwise discriminant analysis was conducted to discriminate different types of medium-intensity activities using 1) vertical and horizontal acceleration counts or 2) synthetic acceleration counts and the vertical/horizontal counts ratio. The F critical value for entry into the equation was set at 0.05, and the F critical value for removal from the equation was set at 0.10. Using the best model obtained in the above process, thresholds for classifying accelerometer counts into light and moderate-to-vigorous PA were determined. PAR of moderate to vigorous PA was defined as 3 or more. Sensitivity (true positives/true positives + false negatives) and specificity (true negatives/true negatives + false negatives) were calculated. All statistical tests were regarded as significant when the probabilities were <0.05.

Table 1. Physical characteristics of subjects (n = 24)

Variable	Mean ± standard deviation
Age (yrs)	6.1 ± 0.3
Height (cm)	113.4 ± 4.8
Weight (kg)	20.3 ± 3.5
BMI (kg/m^2)	15.8 ± 2.0
Predicted basal metabolic rate (MJ/d)*	3.75 ± 0.59

* Predicted from observed resting energy expenditure in the supine position.

Results

The physical characteristics of the subjects are shown in Table 1. Most of the subjects in the present study were of normal weight. The numbers of overweight girls and boys based on BMI (24) were one and two, respectively.

Observed EE, PAR, and accelerometer counts for each activity are shown in Table 2. Correlation coefficients between the predicted and observed EE or PAR were 0.878 to 0.932 for EE and 0.859 to 0.920 for PAR in all activities. Pearson correlation coefficients were not significant for resting and watching a video while standing. In general, horizontal accelerometer counts provided a slightly better EE or PAR assessment than vertical accelerometer counts. There were no gender differences, so the following analyses were performed using the combined data.

Table 2. Observed energy expenditure, physical activity ratio, and accelerometer counts for each activity

Activity	Energy expenditure *n*	Energy expenditure (kJ/kg per min)	Physical activity ratio *n*	Physical activity ratio	Accelerometer counts (per 5 secs) *n*	Synthetic	Vertical	Horizontal
Resting while lying down	24	0.140 ± 0.022			24	5 ± 2	1 ± 1	3 ± 2
Watching television while sitting	25	0.144 ± 0.023	22	1.14 ± 0.09	27	8 ± 6	1 ± 2	6 ± 5
Watching television while standing	24	0.147 ± 0.025	21	1.16 ± 0.12	26	13 ± 8	3 ± 3	10 ± 6
Line drawing for coloring-in	24	0.175 ± 0.029	21	1.39 ± 0.14	24	30 ± 13	5 ± 3	25 ± 11
Playing blocks	26	0.190 ± 0.028	23	1.51 ± 0.17	26	67 ± 20	10 ± 5	60 ± 18
Walking	27	0.327 ± 0.055	24	2.60 ± 0.47	27	315 ± 79	213 ± 73	163 ± 44
Stair climbing (up and down)	27	0.513 ± 0.074	24	4.10 ± 0.63	25	356 ± 66	256 ± 55	179 ± 29
Performing a ball toss	27	0.463 ± 0.084	24	3.64 ± 0.82	27	266 ± 59	144 ± 53	173 ± 27
Running	26	0.706 ± 0.104	23	5.58 ± 1.27	26	945 ± 150	780 ± 131	380 ± 75

Figure 1 shows the relationship between PAR and synthetic acceleration counts. When linear and non-linear regression models were applied to the data of all activities, these equations underestimated EE by ~30% or more for stair climbing (up and down) and performing a ball toss. Therefore, linear and non-linear regression equations were calculated for all activities except these two activities, and then evaluated for all activities. Table 3 shows the results of the regression equations for EE and PAR for all activities except these two activities. The linear and non-linear regression equations demonstrated a comparable relationship between the accelerometer counts and EE. In non-linear equations

$$EE = a + b1 \times (\sqrt{Ax^2 + Ay^2})^{p^1} + b2 \times Az^{p^2} \text{ or}$$

$$EE = a + b \times A^p$$

p Values were near 1. SEE values were slightly better for models with synthetic or "vertical and horizontal" counts than for those with only vertical or horizontal counts.

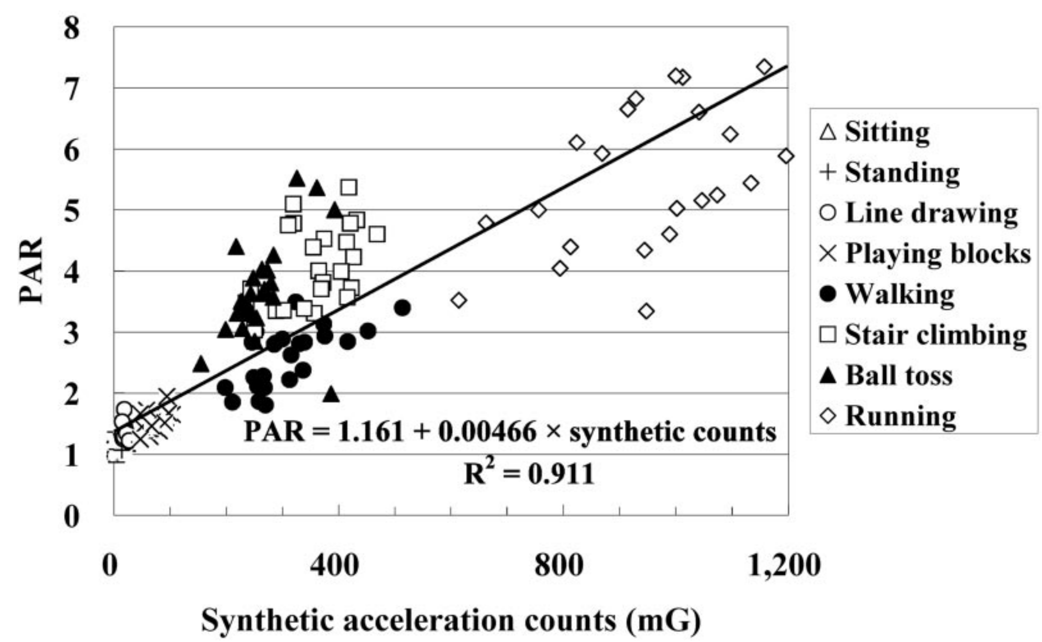

Figure 1: Relationship between predicted PAR and synthetic acceleration counts. The regression line is obtained from all activities except stair climbing and performing a ball toss.

Table 3. Regression equations of energy expenditure and PAR for all activities except stair climbing and performing a ball toss

	Regression equations	SEE (kJ/kg per min)	R^2	*p*
Energy expenditure (kJ/kg per min)				
Linear				
Synthetic	kJ/kg per min = 0.1453 + 0.000586 × synthetic accelerometer counts	0.0454	0.948	<0.05
Vertical and horizontal	kJ/kg per min = 0.1432 + 0.000369 × vertical accelerometer counts +0.000698 × horizontal accelerometer counts	0.0459	0.947	<0.05
Vertical	kJ/kg per min = 0.1610 + 0.000694 × vertical accelerometer counts	0.0520	0.931	<0.05
Horizontal	kJ/kg per min = 0.1281 + 0.001435 × horizontal accelerometer counts	0.0531	0.928	<0.05
Non-linear				
Synthetic	kJ/kg per min = 0.1383 + 0.00109 × synthetic accelerometer counts$^{0.910}$	0.0450	0.949	<0.05
Vertical and horizontal	kJ/kg per min = 0.1373 + 0.00027 × vertical accelerometer counts$^{1.054}$ + 0.00164 × horizontal accelerometer counts$^{0.850}$	0.0460	0.948	<0.05
Vertical	kJ/kg per min = 0.1506 + 0.00271 × vertical accelerometer counts$^{0.797}$	0.0498	0.938	<0.05
Horizontal	kJ/kg per min = 0.1361 + 0.00080 × horizontal accelerometer counts$^{1.098}$	0.0528	0.930	<0.05
Physical activity ratio				
Linear				
Synthetic	PAR = 1.161 + 0.00466 × synthetic accelerometer counts	0.503	0.911	<0.05
Vertical and horizontal	PAR = 1.117 + 0.00253 × vertical accelerometer counts +0.00638 × horizontal accelerometer counts	0.503	0.911	<0.05
Vertical	PAR = 1.313 + 0.00547 × vertical accelerometer counts	0.555	0.892	<0.05
Horizontal	PAR = 0.992 + 0.01148 × horizontal accelerometer counts	0.539	0.898	<0.05
Non-linear				
Synthetic	PAR = 1.127 + 0.00653 × synthetic accelerometer counts$^{0.951}$	0.504	0.912	<0.05
Vertical and horizontal	PAR = 1.179 + 0.00453 × vertical accelerometer counts$^{0.907}$ + 0.00194 × horizontal accelerometer counts$^{1.200}$	0.505	0.913	<0.05
Vertical	PAR = 1.238 + 0.01650 × vertical accelerometer counts$^{0.836}$	0.547	0.896	<0.05
Horizontal	PAR = 1.116 + 0.00405 × horizontal accelerometer counts$^{1.172}$	0.530	0.902	<0.05

PAR, physical activity ratio; SEE, standard error of the estimate.

Table 4. Percent differences between the predicted and the observed physical activity ratio

Physical activity ratio	Linear				Non-linear			
	Synthetic	Vertical and horizontal	Vertical	Horizontal	Synthetic	Vertical and horizontal	Vertical	Horizontal
Total activities	−6.6 ± 19.9	−5.8 ± 19.1	−6.8 ± 23.8	−4.2 ± 19.2	−6.5 ± 19.4	−6.0 ± 19.5	−6.2 ± 21.6	−4.6 ± 19.0
Light	1.4 ± 9.7	0.5 ± 9.4	5.3 ± 14.2	−0.9 ± 13.0	0.4 ± 9.4	1.5 ± 9.8	1.8 ± 12.5	1.7 ± 10.5
Moderate	−19.8 ± 21.5	−16.5 ± 22.5	−25.5 ± 21.9	−9.4 ± 23.7	−18.3 ± 21.9	−18.1 ± 22.1	−19.2 ± 23.8	−14.2 ± 22.5
Vigorous	3.4 ± 22.4	2.5 ± 21.3	3.7 ± 23.4	−0.5 ± 21.0	2.9 ± 22.2	2.3 ± 21.2	3.3 ± 23.1	0.4 ± 21.6
Watching television while sitting	5.5 ± 7.0	2.1 ± 6.8	16.0 ± 8.1	−6.3 ± 6.9	3.3 ± 6.8	5.8 ± 7.0	10.4 ± 7.3	1.5 ± 6.8
Watching television while standing	5.9 ± 9.4	3.1 ± 9.1	15.3 ± 10.7	−3.9 ± 9.0	4.2 ± 9.2	6.1 ± 9.4	10.6 ± 9.9	2.3 ± 9.1
Line drawing for coloring-in	−5.8 ± 8.6	−6.6 ± 8.9	−2.7 ± 8.7	−7.5 ± 10.7	−6.5 ± 8.7	−6.3 ± 8.5	−5.5 ± 8.3	−6.3 ± 9.4
Playing blocks	−0.9 ± 9.2	2.7 ± 9.8	−8.4 ± 9.0	13.7 ± 12.5	−0.2 ± 9.3	−0.3 ± 9.3	−9.5 ± 8.5	8.7 ± 11.3
Walking	2.3 ± 14.7	4.8 ± 18.9	−3.5 ± 16.7	11.3 ± 20.8	4.2 ± 15.0	2.8 ± 18.5	4.6 ± 18.7	5.2 ± 19.6
Stair climbing (up and down)	−29.6 ± 9.8	−27.4 ± 10.3	−32.4 ± 9.3	−23.8 ± 11.4	−28.4 ± 10.0	−28.8 ± 10.2	−26.9 ± 10.0	−27.8 ± 11.0
Performing a ball toss	−32.1 ± 18.9	−26.8 ± 19.7	−40.6 ± 17.8	−15.7 ± 21.6	−30.8 ± 19.2	−28.4 ± 19.4	−35.5 ± 19.2	−20.2 ± 20.7
Running	3.4 ± 22.4	2.5 ± 21.3	3.7 ± 23.4	−0.5 ± 21.0	2.9 ± 22.2	2.3 ± 21.2	3.3 ± 23.1	0.4 ± 21.6

Table 4 shows the percentage differences between the predicted and observed PAR. Similar results were obtained for EE. Linear and non-linear regression equations using vertical acceleration counts overestimated PAR for very low intensity activities and underestimated PAR for stair climbing and ball tossing more than the other models. In general, the other models demonstrated a good prediction of PAR for light to vigorous activities. However, all models underestimated EE and PAR, while stair climbing and ball tossing were underestimated to the same degree, as shown in Table 4. Therefore, an additional analysis was applied to discriminate these activities from walking. In a stepwise discriminant analysis using synthetic acceleration counts and vertical/horizontal acceleration counts ratios as independent variables, only the vertical/horizontal acceleration ratio was entered. As a result, the obtained classification criteria were as follows:

- Walking: vertical/horizontal ratio: 1.19 or more
- The other two activities: vertical/horizontal ratio: $<$1.19.

Performing a ball toss was correctly classified in 26 of 27 cases, whereas climbing stairs was misclassified as walking in many cases. In the case of a linear model with synthetic acceleration counts, after adjustment of EE using the average percentage difference, the obtained average percentage difference was improved from $-32.1 \pm 18.9\%$ to $-4.7 \pm 15.5\%$ for performing a ball toss, while that for climbing stairs did not change ($-29.6 \pm 9.8\%$ to $-29.7 \pm 12.9\%$). In the other cases using the stepwise discriminant analysis with both the vertical and horizontal acceleration counts or for PAR, similar results were obtained (data not shown). The obtained thresholds between light and moderate and moderate and vigorous activities for activities, except activities identified as ball toss or climbing stairs, were 395 mG and 1038 mG, respectively. The sensitivity and specificity to discriminate light and moderate intensity were 77% and 94%, respectively, when using the synthetic acceleration counts and the criterion of vertical/horizontal acceleration counts.

In a subgroup of subjects ($n = 15$), the correlation coefficient between EE and Actigraph counts for all activities was 0.788 ($n = 141$, $p < 0.05$), while those between EE and horizontal and vertical acceleration counts by ActivTracer were 0.919 and 0.863, respectively. A stepwise regression analysis of the original data indicated that horizontal accelerometer counts obtained by ActivTracer alone explained 84.3% of EE variance, while Actigraph added only 1.4% of EE variance.

Discussion

This study developed regression equations to predict EE and PAR from three-dimensional accelerometer counts in young children. Because EE correlates closely with body size, PA must be evaluated after adjustment for body size. For this reason, we examined EE/kg and PAR (EE divided by the BMR) as measurements of PA. Significant correlations were found between synthetic, vertical, and horizontal accelerometer counts and observed EE or PAR for all activities using a linear regression model. Although many studies have utilized accelerometry to assess PA in adults and children (11,12,25), few studies to validate the estimation of PA intensity have been conducted in young children (13,14). Based on correlation coefficients or the other statistics, the relationship between accelerometer counts and observed EE in young children appears better than in previous reports in adolescents and adults (25).

Many previous studies have addressed the question of whether multiaxis accelerometers provide more valid assessments of EE than do single axis accelerometers. Eston et al. (17) showed that three-dimensional accelerometers may provide a better evaluation of children's free-play activities than uniaxial accelerometers. The triaxial or omnidirectional accelerometer-based monitor may capture total body movement better than uniaxial devices (10,12,25).

The degree of underestimation and overestimation by accelerometers depends on the type of activity (12,26,27). In the present study, EE and PAR for most activities were relatively correctly predicted. Moreover, prediction errors obtained using linear and non-linear regression equations were comparable. In non-linear equations, p values were near 1, which indicated that the relationship between EE and acceleration counts was almost linear in all activities except two medium intensity activities, and non-linear equations are not needed, at least for young children. Although this result is inconsistent with that of Chen and Sun (18) and Campbell et al. (28), for adults, it is similar to that of Bouten et al. (29), who showed that the quadratic relationship between EE and the accelerometer output was inferior to the linear relationship in adults. The difference in activities may explain the diverse results. Thus, this result indicates that a non-linear model is not needed for prediction of EE and PAR, at least in young children.

In general, horizontal, synthetic, and combined vertical and horizontal accelerometer counts provided a comparable assessment of predicted EE. However, the prediction error obtained by vertical accelerometer counts using linear regression equations was larger than that obtained by horizontal accelerometer counts for resting while lying down, watching TV while sitting and standing, climbing stairs, and performing a ball toss. Variation of vertical acceleration counts was larger than that of horizontal counts, particularly in higher intensity activities. This may be related to the overestimation of EE for low intensity activities. EE of low intensity activities is not high, but these activities are likely observed very frequently. Therefore, the prediction errors obtained by vertical acceleration counts may cause a significant problem. Thus, the present study indicates that the prediction of EE and PAR using vertical acceleration counts is inferior to prediction using horizontal counts in young children. On the other hand, the prediction errors for playing with blocks and walking that were obtained by horizontal acceleration counts were slightly larger than those obtained by synthetic acceleration counts, in addition to slightly higher SEE values of linear and non-linear regression models that did not include ball toss and stairs climbing. Thus, the synthetic acceleration counts may be slightly better to use, and the linear equation using synthetic counts is recommended, in combination with a criterion of the vertical/horizontal counts ratio for better discrimination of medium intensity activities.

The most significant problem we found was the underestimation of EE for climbing stairs and ball tossing, due to the different balance of vertical and horizontal acceleration counts for these activities and the different relationship of the acceleration counts with EE. While performing these activities, horizontal acceleration counts increase compared with vertical acceleration counts. Increases in horizontal acceleration are associated much more with increases in EE than are increases in vertical acceleration. Therefore, based on the results from discriminant analysis, the large prediction error for performing a ball toss could be reduced. Moreover, similar types of activities, including lifestyle activities and playing, might be adjusted using the classification functions. On the other hand, the large underestimation of EE for climbing stairs would persist. The time for this activity is likely short, probably several minutes a day, although this is a representative activity in daily life. For example, if climbing stairs costs 16 kJ (4 kcal)/min and the time spent in this activity is 5 minutes, then the predicted underestimation of EE is ~80 kJ (20 kcal). Thus, the obtained prediction error would result in a small prediction error for total EE. Therefore, a combination of vertical and horizontal acceleration counts may be needed for discrimination of medium intensity activities and a slight improvement in EE or PAR prediction, although synthetic or even horizontal acceleration counts alone can predict EE for most activities.

In some previous studies, subjects were asked to perform activities at a set pace. Puyau et al. (30) pointed out that treadmill walking/running has the advantage of being precisely controlled and reproducible: it does not reflect all torsional accelerations associated with free-living activities. R^2 values are actually higher while walking and running on a treadmill (30,31) than in lifestyle conditions (9,17,27,32). Fewer researchers have allowed subjects to perform activities at a self-selected pace. It is likely that a self-selected pace more precisely reflects actual EE or the accelerometer counts of young children doing the activities in the real world, as children do not perform activities at predetermined speeds. Therefore, each activity in the present study was performed at a self-selected pace, except for the ball toss, which was conducted with a researcher.

For some applications, categorizing levels of PA in children and adults is of interest (9,12,30). The threshold counts for each activity can be calculated using an equation presented in the present study and then used to classify each PA into light, moderate, or vigorous activity for young children. Although it is difficult to compare the sensitivity and specificity values between studies because types of PA are different, the obtained values, particularly specificity, are good.

Previous studies have shown that waist-worn accelerometers underestimate the EE of free-living individuals (10). One of the reasons for underestimation may be a failure to detect the additional EE resulting from other kinds of movements. Thus, in the present study, the wrist-worn accelerometer was used to detect simultaneous upper body movement measurements, and the combined model further improved the accuracy of EE prediction. The combined quantification of trunk movement with an accelerometer on the waist and upper limb movement with an accelerometer on the wrist is a unique approach, as previous papers typically measured trunk movement only with a uniaxial accelerometer on the waist (25). Melanson and Freedson (33) validated Computer Science and Applications, Inc. monitors on the ankle, hip, and wrist in adults on a treadmill. The contributions of the uniaxial accelerometers on the hip and wrist were comparable for overall and each intensity PA. However, our results showed that waist-worn accelerometer counts were superior to wrist-worn accelerometer counts. A stepwise regression analysis in the present study indicated that the wrist-worn accelerometer counts explained just 1.4% of the variance in EE. Our data revealed that waist-worn accelerometer counts were highly correlated with EE and that wrist-worn accelerometer counts added minor contributions. The different results between Melanson and Freedson's study (33) and our study may be due to the types of performed PA (on treadmill vs. various kinds of PA), in addition to the different age groups studied (adults vs. young children). The degree to which the wrist acceleration counts explain the variance in EE depends on the chosen activities. Moreover, it should be carefully noted that different accelerometers were used to detect movements of the waist and wrist. In general, however, it is likely that the detection of wrist movements does not contribute significantly to more accurate predictions of PAR and EE.

The sample size of this study was not large. However, the high correlation coefficients found between acceleration counts and EE or PAR, and mean and standard deviation values of % differences of prediction in various activities, suggest that the findings of the present study are robust. The more important limitation of the present study may be that there are relatively small numbers of data points, in particular between 500 and 800 counts of synthetic acceleration. In addition, only running was examined as a vigorous activity. This selection of a single activity could have led to less robust results for predictions of moderate to vigorous activities.

The triaxial accelerometer used in this study provided valid measures of young children's EE and PAR and can be used to discriminate light, moderate, and vigorous levels of PA. Our results also suggest that even a linear model contributes to the assessment of daily EE when horizontal or synthetic acceleration counts combined with the vertical/horizontal counts ratio are used for better discrimination of medium intensity activities. Future studies are required to further validate accurate predictions of EE and PAR under free-living conditions. Our results will make it possible to objectively and accurately assess PA in young children and thereby contribute to the prevention of childhood obesity.

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