Estimating activity-related energy expenditure under sedentary conditions using a tri-axial seismic accelerometer.

Estimating Activity-related Energy Expenditure Under Sedentary Conditions Using a Tri-axial Seismic Accelerometer

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Activity-related energy expenditure (AEE) is difficult to quantify, especially under sedentary conditions. Here, a model was developed using the detected type of physical activity (PA) and movement intensity (MI), based on a tri-axial seismic accelerometer (DynaPort MiniMod; McRoberts B.V., The Hague, the Netherlands), with energy expenditure for PA as a reference. The relation between AEE (J/min/kg), MI, and the type of PA was determined for standardized PAs as performed in a laboratory including: lying, sitting, standing, and walking. AEE (J/min/kg) was calculated from total energy expenditure (TEE) and sleeping metabolic rate (SMR) as assessed with indirect calorimetry ((TEE × 0.9) – SMR). Subsequently, the model was validated over 23-h intervals in a respiration chamber. Subjects were 15 healthy women (age: 22 ± 2 years; BMI: 24.0 ± 4.0 kg/m^2). Predicted AEE in the chamber was significantly related to measured AEE both within (r^2 = 0.81 ± 0.06, P < 0.00001) and between (r^2 = 0.70, P < 0.001) subjects. The explained variation in AEE by the model was higher than the explained variation by MI alone. This shows that a tri-axial seismic accelerometer is a valid tool for estimating AEE under sedentary conditions.

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INTRODUCTION

The role of physical activities (PAs) in obesity, diabetes type 2, and cardiovascular disease is still not fully understood (1). A major reason for our lack of knowledge is the practical hurdle of quantifying activity-related energy expenditure (AEE) (1). PA monitors are considered a promising tool for predicting AEE in daily life (2–6). In order to test the capability of a PA monitor to predict energy expenditure, validation against indirect calorimetry is necessary (4).

Man spends most of the day in sedentary PAs (7–9). The confined conditions of a respiration chamber can be used as a model for a sedentary lifestyle (10). The ratios of 41 and 47% as observed for AEE in a respiration chamber and AEE in daily life indicate that a substantial part of AEE is expended in sedentary PAs (10–12).

Several studies have assessed the validity of a PA monitor in a respiration chamber (13–22). In each of these studies, bouts of exercise were added to the experimental protocol to improve the resemblance to daily life conditions. However, the addition of exercise bouts to the protocol has one disadvantage; the validity of the PA monitor to estimate AEE under sedentary conditions becomes mixed with its validity to estimate AEE under exercise conditions. Therefore, from this perspective the exercise bouts added to the protocol act as a confounding variable in the assessment of monitor validity.

Piezoelectric acceleration sensors are applied in most PA monitors, as reviewed by Chen and Bassett (23). Piezoelectric sensors are not sensitive to gravitation acceleration in static situations but are sensitive to gravitation acceleration in dynamic situations. A static situation refers to a situation in which the acceleration is constant and a dynamic one in which the acceleration is not constant, relative to the orientation of the sensor. Seismic acceleration sensors are less commonly applied. They are sensitive to gravitational acceleration in both static and dynamic situations. In static situations, this sensitivity provides information about inclination of the subject, used as posture detection (24).

The DynaPort is a tri-axial seismic accelerometer (DynaPort MiniMod; McRoberts B.V., The Hague, the Netherlands). Recently, an algorithm was developed to detect the type (mode) of PA based on DynaPort output. Most PA monitors use the intensity of PA (expressed in counts) to predict energy expenditure (23). The type of PA contains information not derivable from the intensity alone; therefore, it is possible that addition of the detected type of PA to the prediction model may improve model validity. The first aim of this study was to combine the type and the intensity of PA into one model for energy expenditure prediction. The second aim was to assess model validity under exclusively sedentary conditions. No consensus has been achieved on how to adjust AEE for

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body weight (25,26). Besides expressing AEE per kilogram body weight, this study will evaluate the alternative correction factors for body weight.

METHODS AND PROCEDURES

Subjects

Fifteen healthy female subjects participated. Subjects were informed about the objective and the protocol of the study, in both written and oral forms. All subjects gave written informed consent. The Ethics Committee of Maastricht University approved the study.

Experimental design

Standardized PAs were performed in a laboratory to determine the relation between AEE (J/min/kg), the intensity of movement, and the type of PA. Here, AEE was estimated with indirect calorimetry, using a facemask (described below). The intensity of movement and the type of PA were estimated by using an accelerometer (DynaPort MiniMod; McRoberts B.V.). Standardized PAs took place in the early afternoon. Subjects were requested to refrain from strenuous exercise in the morning preceding the measurement. The resulting model for energy expenditure prediction was validated in a respiration chamber. Subjects stayed in the respiration chamber overnight from 7:00 PM until 6:00 PM the next day, which equals 23 h. Subjects were woken at 7:00 AM and, with the exception of doing exercise and sleeping, were free to spend the time how they pleased. At night, subjects were supposed to sleep from 11:00 PM until 7:00 AM, when lights were switched off. To standardize the influence of diet-induced thermogenesis on total energy expenditure (TEE), the amount of energy intake was set at 1.4 times measured sleeping metabolic rate (SMR) (10), except for dinner on the first evening, which was based on estimated SMR (27). Further dinner, breakfast, and lunch were administered at set times, respectively, 7:15 PM, 8:30 AM, and 1:00 PM. Body weight was assessed to the nearest 0.1 kg in fasting state and body height was assessed to the nearest 0.5 cm.

Standardized activities

Subjects performed the following standardized activities (in chronological order): lying on a bed (25 min); lying on a bed and moving sideways every 30 s (5 min); and then repeated every 15 s (5 min); sitting on a chair (10 min); sitting on a chair and moving an empty plastic bottle held with both hands sideways every 2 s over 50 cm (5 min); standing (5 min); standing and moving an empty plastic bottle held with both hands sideways every 2 s over 50 cm (5 min); and then repeated over 100 cm (5 min); and walking on a treadmill (J440 OM; Tunturi OY, Turku, Finland) at three different speeds (1.5, 3.0, and 4.5 km/h) for 5 min each. These activities were chosen to represent three levels of intensity for lying, standing, and walking, and two levels of intensity for sitting. Repetitive movements during lying, sitting, and standing were cued with a beep sound produced by self programmed software in Matlab 7.4.0 (R2007a; Mathworks, Natick, MA). The standardized activities were chosen because the movements involved are common in daily living for many people.

PA assessment

The accelerometer was attached to the lower back with an elastic belt (neoprene). The three sensors in the accelerometer (resolution: 0.001*g*) are mounted orthogonally for sensing in three directions: anterior–posterior, medial–lateral, and longitudinal, reliability of which are described elsewhere (28). The accelerometer measures $51 \times 84 \times 8.5\,mm^3$ and weighed 45 g (lithium polymer battery included). The measurement duration is limited to 72 h by internal energy supply but can be extended to 7 days by connecting an external battery to the main device by a wire. The dimensions of the external battery are $64 \times 40 \times 5\,mm^3$ (weight: 30 g). Analog signals were low-pass filtered (3 dB filter, cutoff frequency: 30 Hz) and stored on a commercially available SD-card. The sample frequency was set at 100 Hz, as required for appropriate functioning of the activity detection algorithm.

Since seismic sensors measure gravitational acceleration (g) in static situations, the acceleration signal is expressed relative to g ($1g = 9.81\,m/s^2$). To calculate movement intensity (MI), the three raw signals are band-pass filtered using a fourth order Butterworth filter (ω_0: 0.2–10 Hz) and combined by taking the root of the summed squared values. The fourth order Butterworth filter used in the current study is a standard supplied with Matlab (http://www.mathworks.com/access/helpdesk/help/toolbox/signal/index.html?/access/helpdesk/help/toolbox/signal/butter.html). The Butterworth algorithm has been described elsewhere (29) and is not owned by the Matlab Company. The cutoff frequency of the analog low-pass filter is far above the upper cutoff frequency of the Butterworth filter. This indicates that the exact configuration of the analog filter does not affect the resulting digital signal. Filtering is performed to remove gravitational acceleration in static situations and to remove noise. Combining the three signals makes the MI value insensitive to the orientation of the accelerometer with regard to the body. The orientation of the accelerometer with regard to the body may be affected by excess body fat (30) or by an accidentally tilted accelerometer attachment. Average MI (g) value per second is then used for further calculations. The activity detection algorithm detects four types of activity: lying, sitting, standing, and walking. Additionally, a fifth category is used for nonclassifiable activities. The first three types of activity are related to a posture but can also represent a combination of a posture and a body movement (e.g., dish washing or desk work). **Figure 1** shows the output from the activity detection algorithm for one subject performing several standardized tasks.

Energy expenditure

An automated open-circuit gas analyzer (Omnical, Maastricht University, Maastricht, the Netherlands) was used to measure O_2 consumption and CO_2 production in the standardized activities. A facemask was used as a breathing assembly. The analysis system consisted of dual paramagnetic O_2 and dual infrared CO_2 analyzers (type 1156, 1507, 1520; Servomex, Crowborough, UK). Respiratory gas measurements were corrected for standard temperature, pressure, and dry conditions as described previously (31). Whole-room calorimeter measures were taken in a dual-respiration chamber system with automated calibration. The chamber ($14\,m^3$) was equipped with a bed, washing bowl, freeze toilet, chair, computer, television, and radio, as described previously (32). No exercise equipment was provided. The analysis system consisted of dual pairs of infrared CO_2 (ABB/Hartman&Braun Uras, Frankfurt a.M., Germany) and paramagnetic O_2 analyzers (Servomex 4100; Servomex, Crowborough, UK and ABB/Hartman&Braun Magnos, Frankfurt

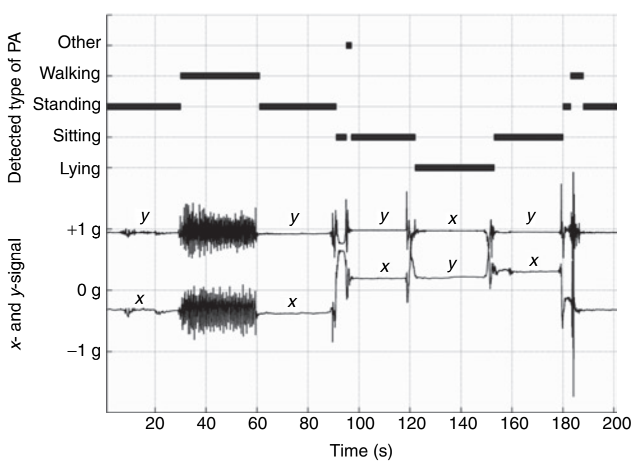

Figure 1 Example of the monitor output for one subject performing several standardized tasks (horizontal bars: detected posture by activity detection algorithm, x = anterior–posterior signal, y = longitudinal signal). PA, physical activity.

a.M., Germany). Flow was measured using electronically modified dry gas meters (G6, gasmeterfabriek; Schlumberger, Dordrecht, the Netherlands) (33). The calculation of $\dot{V}O_2$ and $\dot{V}CO_2$ was performed over 0.5-h intervals as previously described (32,34).

Data analysis

For both the standardized activities and the respiration chamber, TEE was calculated according to Weir (35). AEE (J/min/kg) was calculated from TEE and SMR as ((TEE × 0.9) − SMR), assuming diet-induced thermogenesis to be 10% of TEE (10). SMR was defined as the lowest observed TEE for three consecutive hours during the night (36). In standardized activities, only the average over the last 2 min per intensity level was used for further calculations as these minutes were characterized by steady-state oxygen consumption, observed as a VO_2 time gradient being shallower than 0.01 ml/min. For each detectable type of PA, a best-fit linear equation was derived from standardized activities to predict AEE (J/min/kg) from MI. In the final model, the detected type of PA per second was used to determine which one of the four prediction equations should be applied to the MI value. In the respiration chamber experiment, AEE (J/min/kg) was predicted using MI and the specified equation. If the type of PA was not classifiable, the walking equation was applied. Correction for body weight was evaluated by repeating the whole data analysis for 28 times with weight factor in AEE (J/min/kg^n) varying from 0 to 1.35 with steps of 0.05—where $n = 1$ represents dividing by weight and $n = 0$ represents dividing by one.

Statistics

Pearson's correlation coefficient was calculated to assess strength of relations. Within-subject validity was assessed by comparing 30-min averages. Between-subject validity was assessed by comparing 23-h averages and averages over waking hours (15 h). The standard error of the estimate (SEE) was calculated to assess measurement agreement. Relative SEE (%) was calculated as ((SEE/average measured value) × 100). Theoretically SEE (%) covers the errors resulting from the prediction model and from overcorrection or under correction for body weight. The n resulting in the lowest SEE (%) relates to minimal confounding by variation in body weight. At each n value SEE (%) was calculated for AEE_{23h} and AEE_{15h}. The minimal average SEE (%) for both was also calculated. Paired sample t-test was used to test for significant difference between predicted and measured values (SPSS 14.0 for Windows; SPSS, Chicago, IL). All other analyses were performed using Matlab 7.4.0 (R2007a; Mathworks). A significance of $P < 0.05$ indicated a considerable difference.

Table 1 Subject characteristics

	Mean (s.d.)	Range
Age (years)	22 (2)	20–26
Height (m)	1.70 (0.05)	1.63–1.80
Weight (kg)	69.2 (12.2)	55.4–100.1
BMI (kg/m^2)	24.0 (4.0)	19.3–31.1
TEE_{23h} (J/min)	5,714 (440)	5,155–6,620
TEE_{15h} (J/min)	6,388 (475)	5,713–7,185
SMR (J/min)	4,169 (425)	3,631–5,275

TEE, total energy expenditure; SMR, sleeping metabolic rate.

RESULTS

Participant characteristics are shown in **Table 1**. Best-fit prediction equations were generated for the four categories of activities (Eqs. 1–4).

$$AEE_{lying}\ (\text{J/min/kg}) = 1{,}085 \cdot MI(g), \quad (r^2 = 0.85, P < 0.001), \quad (1)$$

$$AEE_{sitting}\ (\text{J/min/kg}) = 263 \cdot MI(g) + 14, \quad (r^2 = 0.18, P < 0.01), \quad (2)$$

$$AEE_{standing}\ (\text{J/min/kg}) = 405 \cdot MI(g) + 13, \quad (r^2 = 0.58, P < 0.001), \quad (3)$$

$$AEE_{walking}\ (\text{J/min/kg}) = 987 \cdot MI(g) + 34, \quad (r^2 = 0.79, P < 0.001), \quad (4)$$

The slope of AEE with respect to MI for lying (1,085 J/min/kg (95% confidence interval: 943–1,227 J/min/kg)) was not significantly different from the slope for walking (987 J/min/kg (95% confidence interval: 831–1,143 J/min/kg)). The slopes for sitting and standing, respectively, 263 J/min/kg (95% confidence interval: 42–483 J/min/kg) and 405 J/min/kg (95% confidence interval: 299–512 J/min/kg) were significantly smaller than that for lying and walking ($P < 0.01$). The prediction equations were applied to the data of the respiration chamber experiment. For each subject, the 30-min averages of predicted AEE were significantly correlated to the measured $AEE_{30\,min}$ (J/min/kg): $r^2 = 0.81 \pm 0.06$ ($P < 0.00001$). Measured $AEE_{30\,min}$ (J/min/kg) also correlated significantly to MI for all subjects: $r^2 = 0.74 \pm 0.06$ ($P < 0.00001$). The variation in measured $AEE_{23\,h}$ (J/min/kg) between subjects was best explained by model predictions ($r^2 = 0.70$, $P < 0.001$), compared to MI ($r^2 = 0.58$, $P < 0.01$). The correlation (r^2) between weight and $MI_{23\,h}$ and $MI_{15\,h}$ was 0.37 ($P < 0.05$) and 0.38 ($P < 0.05$), respectively. SEE, relative SEE (%), and r^2 values for the model are summarized in **Table 2**. The model significantly overestimated $AEE_{23\,h}$ by 2.5 J/min/kg ($P < 0.01$); no significant differences were found for $AEE_{15\,h}$ (**Table 2**). No significant correlation was found between the mean of both methods and the difference between both methods for $AEE_{23\,h}$ and $AEE_{15\,h}$ (**Figures 2** and **3**). Measured $TEE_{23\,h}$ was 5,714.1 ± 440.2 J/min and measured SMR was 4,094.9 ± 317.2 J/min. The weight correction factor resulted in a minimal SEE (%) for $AEE_{23\,h}$ and $AEE_{15\,h}$ at $n = 0.6$ and $n = 0.4$, respectively. The minimal average SEE (%) for $AEE_{23\,h}$ and $AEE_{15\,h}$ was found at $n = 0.5$ (**Figure 4**). These results indicate that when AEE is corrected for the square root of body

Table 2 Between-subject validity for AEE as predicted by the model

Input	Output	Measured AEE	Predicted AEE	SEE	SEE (%)	R^2
MI (g) and type of PA	AEE_{15h} (J/min/kg)	24.5 ± 5.7	23.9 ± 3.1	3.57	14.6	0.69*
MI (g) and type of PA	AEE_{23h} (J/min/kg)	15.5 ± 3.6	18.0 ± 2.2**	2.12	13.7	0.70*
MI (g) and type of PA	AEE_{15h} (J/min/kg$^{0.5}$)	200.9 ± 37.2	200.0 ± 25.8	23.2	11.4	0.62*
MI (g) and type of PA	AEE_{23h} (J/min/kg$^{0.5}$)	127.0 ± 24.1	150.8 ± 18.7**	15.7	12.4	0.58*

Values are means ± s.d.
AEE, activity-related energy expenditure; EE, energy expenditure; g, gravity; MI, movement intensity; SEE, standard error of the estimate.
*$P < 0.001$. **Significantly different from measured, $P < 0.01$.

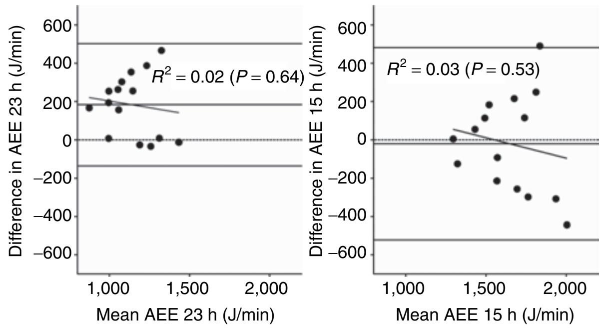

Figure 2 Difference between activity-related energy expenditure (AEE) measured by the respiration chamber and AEE predicted by the model against the average of both methods for 15-h and 23-h averages.

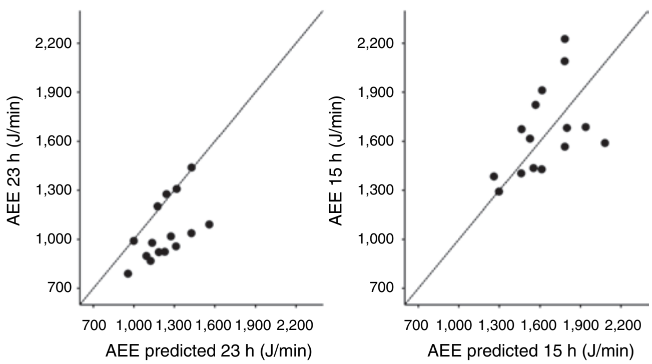

Figure 3 Measured vs. predicted activity-related energy expenditure (AEE) (J/min).

weight the model is least confounded by differences in body weight. New best-fit equations were generated for the four categories of activities (Eqs. 5–8):

$$AEE_{lying}\ (J/min/kg^{0.5}) = 9{,}000 \cdot MI(g) - 1, \quad (r^2 = 0.84, P < 0.001), \quad (5)$$
$$AEE_{sitting}\ (J/min/kg^{0.5}) = 2{,}242 \cdot MI(g) + 115, \quad (r^2 = 0.17, P < 0.01), \quad (6)$$
$$AEE_{standing}\ (J/min/kg^{0.5}) = 3{,}424 \cdot MI(g) + 103, \quad (r^2 = 0.57, P < 0.001), \quad (7)$$
$$AEE_{walking}\ (J/min/kg^{0.5}) = 8{,}229 \cdot MI(g) + 281, \quad (r^2 = 0.72, P < 0.001), \quad (8)$$

The new equations did not affect the ability of the model to explain within-subject variation because weight is a constant in a subject. The variation in measured AEE_{23h} (J/min/kg$^{0.5}$) between subjects was again best explained by model predictions (r^2 = 0.58, P < 0.001) compared to MI (r^2 = 0.44, P <.001). For AEE_{15h} (J/min/kg$^{0.5}$) an equal pattern was observed, r^2 = 0.62 (P < 0.001) and r^2 = 0.48 (P < 0.001), respectively (**Table 2**). Lying, sitting, and standing were the most dominant types of PA according to the detection algorithm (**Figure 5**). On average, 0.2% of experimental time (23 h) was classified as walking and 0.5% was not classifiable; further, 2.7% of AEE was on average expended in walking and 6.9% in nonclassifiable activities.

DISCUSSION

This is the first study showing a significant relationship between PA monitor output and energy expenditure during sedentary conditions. The standard deviation of measured TEE was 440 J/min. Other studies assessing the validity of a PA monitor

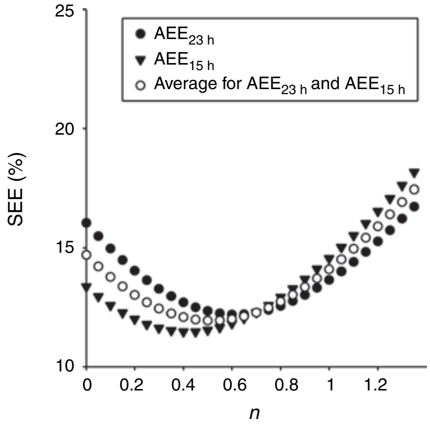

Figure 4 Standard error of the estimate (SEE) (%) as function of weight factor "*n*." AEE, activity-related energy expenditure.

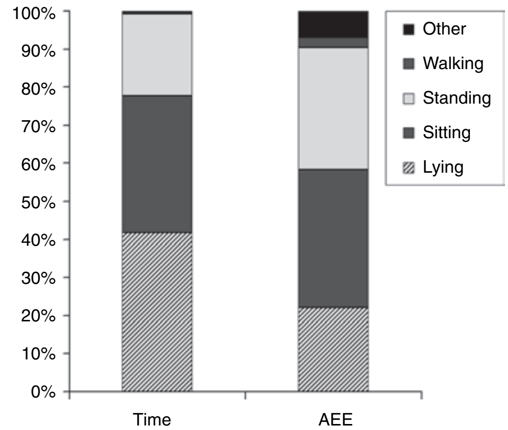

Figure 5 Time spent in each type of physical activity (PA) (left) and activity-related energy expenditure (AEE) spent in each type of PA (right), both based on accelerometer measurements during the 23-h stay in the respiration chamber.

in a respiration chamber have reported much higher standard deviations: 1,410 J/min (16), 974 J/min (15), or was not calculated (13,14,17). Within subjects, the average variation in AEE (J/min/kg) explained by the model was 81%. Between subjects, the prediction model explained 70% of the variation in AEE_{23h} (J/min/kg) and 58% of the variation in AEE_{23h} (J/min/kg$^{0.5}$).

The type of PA improved the prediction of energy expenditure. The contribution of its type could be explained by three things. First, the ability to account for differences in mechanical efficiency between types of activity. Mechanical efficiency is known to differ between stepping and walking activity (37). No literature was found for investigating mechanical efficiency in sedentary PA. The slope of the prediction equation for sitting and standing was lower compared to the slope for lying and walking. Theoretically, the amount of vertical trunk movement in sitting and standing activities is likely to be lower than in the walking and lying activities. A lower amount of vertical trunk movement could have increased mechanical efficiency and thus decreased the slope of the prediction equation. Second, the ability to account for posture-related energy expenditure as predicted by the y-intercept of the energy equation; and third, the ability to account for differences in the relation between MI and mechanical work among types of PA. In biomechanics, MI can be seen as an estimation of mechanical work. Mechanical work refers to energy converted into external power (muscle force and velocity). Mechanical work represents a part of AEE. Probably, the relation between MI and mechanical work is not constant among types of PA.

Measured and predicted energy expenditure did not significantly differ for AEE_{15h} but however, did so for AEE_{23h}, suggesting that the sleeping hours are the main source of systematic overestimation during a 23-h period. This is supported by **Figure 5**, showing 20% of AEE to be expended in lying during the 23-h period. AEE_{lying} was modeled in nonsleeping subjects; this is possibly not sufficient for the prediction of AEE_{lying} in sleeping subjects, partly due to the small energy cost of arousal.

The prediction equation for sitting and standing was based on sideward rotations of trunk and arms. This was an easy task to assess and was assumed to represent common daily movements. An additional study is needed to test whether the sideward rotation is indeed a good approximation of daily movements compared to other kinds of experimental tasks or not.

The validity of the detection algorithm is a critical point. Mistakes by the detection algorithm affect the predicted energy expenditure directly and hence also the model validity. An expansion of the types of PA assessed could perhaps improve the model. Once the detection algorithm is able to detect other types of PA this can be realized. Posture transition is not classified into an individual type of PA, but split up into one of the two adjacent postures. Modeling energy expenditure related to posture transition could possibly improve total model validity.

PA monitors based on piezoelectric sensors use counts as output value. Counts are tallied in proprietary, manufacturer-specific units, and only allow the comparison of data among similar systems (2). The MI calculated in this study has gravitational acceleration as its unit of measurement, which is manufacturer independent. The advantages of using a manufacturer-independent unit is that it allows for the comparison of data between several PA monitors and gives a physical meaning to the measured value.

Results indicate that the most appropriate way to correct AEE under sedentary conditions for differences in body weight is to divide AEE (J/min) by the square root of body weight. This correction minimizes the role of body weight as a confounding variable. Interindividual correlation coefficients were slightly lower after application of weight factor $n = 0.5$ compared to $n = 1$. The small sample size might have resulted in overfitting of the correction factor for body weight; the optimal correction factor might be sample dependent. However, the conclusions related to the additional value of the detection of the type PA remained unchanged regardless of the correction factor used.

In the present study, only young healthy women were included; other populations should be studied in future to expand our observations. A tri-axial seismic accelerometer is a valid tool for estimating energy expenditure related to sedentary PAs.

DISCLOSURE

V.T.v.H. and R.C.v.L. were employed by McRoberts B.V. at the time of investigation. This company is manufacturer of the DynaPort and sponsored this investigation.

REFERENCES

1. Hamilton MT, Hamilton DG, Zderic TW. Role of low energy expenditure and sitting in obesity, metabolic syndrome, type 2 diabetes, and cardiovascular disease. *Diabetes* 2007;56:2655–2667.
2. Esliger DW, Tremblay MS. Physical activity and inactivity profiling: the next generation. *Can J Public Health* 2007;98(Suppl 2):S195–S207.
3. Schutz Y, Weinsier RL, Hunter GR. Assessment of free-living physical activity in humans: an overview of currently available and proposed new measures. *Obes Res* 2001;9:368–379.
4. Plasqui G, Westerterp KR. Physical activity assessment with accelerometers: an evaluation against doubly labeled water. *Obesity (Silver Spring)* 2007;15:2371–2379.
5. Bouten CV, Westerterp KR, Verduin M, Janssen JD. Assessment of energy expenditure for physical activity using a triaxial accelerometer. *Med Sci Sports Exerc* 1994;26:1516–1523.
6. Westerterp KR. Physical activity assessment with accelerometers. *Int J Obes Relat Metab Disord* 1999;23(Suppl 3):S45–S49.
7. Hoos MB, Kuipers H, Gerver WJ, Westerterp KR. Physical activity pattern of children assessed by triaxial accelerometry. *Eur J Clin Nutr* 2004;58:1425–1428.
8. Meijer EP, Goris AH, Wouters L, Westerterp KR. Physical inactivity as a determinant of the physical activity level in the elderly. *Int J Obes Relat Metab Disord* 2001;25:935–939.
9. Brown WJ, Miller YD, Miller R. Sitting time and work patterns as indicators of overweight and obesity in Australian adults. *Int J Obes Relat Metab Disord* 2003;27:1340–1346.
10. Westerterp KR, Kester AD. Physical activity in confined conditions as an indicator of free-living physical activity. *Obes Res* 2003;11:865–868.
11. Snitker S, Tataranni PA, Ravussin E. Spontaneous physical activity in a respiratory chamber is correlated to habitual physical activity. *Int J Obes Relat Metab Disord* 2001;25:1481–1486.
12. Joosen AM, Gielen M, Vlietinck R, Westerterp KR. Genetic analysis of physical activity in twins. *Am J Clin Nutr* 2005;82:1253–1259.
13. Rothney MP, Neumann M, Beziat A, Chen KY. An artificial neural network model of energy expenditure using nonintegrated acceleration signals. *J Appl Physiol* 2007;103:1419–1427.
14. Zhang K, Pi-Sunyer FX, Boozer CN. Improving energy expenditure estimation for physical activity. *Med Sci Sports Exerc* 2004;36:883–889.
15. Chen KY, Acra SA, Majchrzak K *et al*. Predicting energy expenditure of physical activity using hip- and wrist-worn accelerometers. *Diabetes Technol Ther* 2003;5:1023–1033.
16. Chen KY, Sun M. Improving energy expenditure estimation by using a triaxial accelerometer. *J Appl Physiol* 1997;83:2112–2122.
17. Bray MS, Wong WW, Morrow JR Jr, Butte NF, Pivarnik JM. Caltrac versus calorimeter determination of 24-h energy expenditure in female children and adolescents. *Med Sci Sports Exerc* 1994;26:1524–1530.
18. Dorminy CA, Choi L, Akohoue SA, Chen KY, Buchowski MS. Validity of a multisensor armband in estimating 24-h energy expenditure in children. *Med Sci Sports Exerc* 2008;40:699–706.
19. Rothney MP, Schaefer EV, Neumann MM, Choi L, Chen KY. Validity of physical activity intensity predictions by ActiGraph, Actical, and RT3 accelerometers. *Obesity (Silver Spring)* 2008;16:1946–1952.
20. Puyau MR, Adolph AL, Vohra FA, Butte NF. Validation and calibration of physical activity monitors in children. *Obes Res* 2002;10:150–157.
21. Zakeri I, Adolph AL, Puyau MR, Vohra FA, Butte NF. Application of cross-sectional time series modeling for the prediction of energy expenditure from heart rate and accelerometry. *J Appl Physiol* 2008;104:1665–1673.
22. Puyau MR, Adolph AL, Vohra FA, Zakeri I, Butte NF. Prediction of activity energy expenditure using accelerometers in children. *Med Sci Sports Exerc* 2004;36:1625–1631.

23. Chen KY, Bassett DR Jr. The technology of accelerometry-based activity monitors: current and future. *Med Sci Sports Exerc* 2005;37:S490–S500.
24. Veltink PH, Bussmann HB, de Vries W, Martens WL, Van Lummel RC. Detection of static and dynamic activities using uniaxial accelerometers. *IEEE Trans Rehabil Eng* 1996;4:375–385.
25. Schoeller DA, Jefford G. Determinants of the energy costs of light activities: inferences for interpreting doubly labeled water data. *Int J Obes Relat Metab Disord* 2002;26:97–101.
26. Ekelund U, Yngve A, Brage S, Westerterp K, Sjostrom M. Body movement and physical activity energy expenditure in children and adolescents: how to adjust for differences in body size and age. *Am J Clin Nutr* 2004;79:851–856.
27. Harris JA, Benedict FG. A biometric study of human basal metabolism. *Proc Natl Acad Sci USA* 1918;4:370–373.
28. van Hees VT, Slootmaker SM, Groot G, van Mechelen W, van Lummel RC. Reproducibility of a tri-axial seismic accelerometer (DynaPort). *Med Sci Sports Exerc*, in press.
29. Selesnick I, Burrus C. Generalized Digital Butterworth Filter Design. *IEEE Trans Signal Process* 1998;46:1138–1141.
30. Corder K, Brage S, Ekelund U. Accelerometers and pedometers: methodology and clinical application. *Curr Opin Clin Nutr Metab Care* 2007;10:597–603.
31. Adriaens MP, Schoffelen PF, Westerterp KR. Intra-individual variation of basal metabolic rate and the influence of daily habitual physical activity before testing. *Br J Nutr* 2003; 90:419–423.
32. Schoffelen PF, Westerterp KR, Saris WH, Ten Hoor F. A dual-respiration chamber system with automated calibration. *J Appl Physiol* 1997;83: 2064–2072.
33. Schoffelen PF, Westerterp KR. Intra-individual variability and adaptation of overnight- and sleeping metabolic rate. *Physiol Behav* 2008;94: 158–163.
34. Murgatroyd PR, Davies HL, Prentice AM. Intra-individual variability and measurement noise in estimates of energy expenditure by whole body indirect calorimetry. *Br J Nutr* 1987;58:347–356.
35. Weir JB. New methods for calculating metabolic rate with special reference to protein metabolism. *J Physiol* 1949;109:1–9.
36. Plasqui G, Joosen AM, Kester AD, Goris AH, Westerterp KR. Measuring free-living energy expenditure and physical activity with triaxial accelerometry. *Obes Res* 2005;13:1363–1369.
37. Chen KY, Acra SA, Donahue CL, Sun M, Buchowski MS. Efficiency of walking and stepping: relationship to body fatness. *Obes Res* 2004;12:982–989.