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Improving the assessment of daily energy expenditure by identifying types of physical activity using a single accelerometer

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Abstract

BACKGROUND: Accelerometers are often used to quantify the acceleration of the body in arbitrary units (counts) to measure physical activity (PA) and to estimate energy expenditure. OBJECTIVE: The present study investigated whether the identification of types of PA using one accelerometer could improve the estimation of energy expenditure as compared to activity counts. METHOD: Total energy expenditure (TEE) of 15 subjects was measured using doubly-labeled water. The physical activity level (PAL) was derived dividing TEE by sleeping metabolic rate. Simultaneously, PA was measured using one accelerometer. Accelerometer output was processed to calculate activity counts per day (AC_D) and to determine the daily duration of 6 types of common activities identified using a classification tree model. A daily metabolic value (MET_D) was calculated as mean of the MET compendium value of each activity type weighed by the daily duration. RESULTS: TEE was predicted by AC_D and body weight and by AC_D and fat free mass with a standard error of estimate (SEE) of 1.47 $MJ \cdot d^{-1}$, and 1.2 $MJ \cdot d^{-1}$, respectively. The replacement in these models of AC_D with MET_D increased the explained variation in TEE by 9%, decreasing SEE by 0.14 $MJ \cdot d^{-1}$, and 0.18 $MJ \cdot d^{-1}$, respectively. The correlation between PAL and MET_D (R^2=51%) was higher than PAL and AC_D (R^2=46%). CONCLUSION: Identification of activity types combined with MET intensity values improves the assessment of energy expenditure as compared to activity counts. Future studies could develop models to objectively assess activity type and intensity to further increase accuracy of the energy expenditure estimation.

Keywords

doubly-labeled water, motion sensor, classification tree, activity recognition

Introduction

In many metabolic disorders there is a need to measure daily energy expenditure. The main determinants of energy expenditure are body size and physical activity (PA) (30). Although body size can be easily determined, the assessment of PA represents a challenge, because of the diversified individuals' behaviors and because of the complex nature of human activities. Several methods have been proposed to objectively measure PA (18). Ideally, PA should be measured in free-living conditions, over a period of time representative for the habitual activity level, and with minimal discomfort to the subject. Accelerometers reasonably satisfy these requirements and, therefore, have been widely used for the assessment of PA (16, 18). Traditionally, accelerometer output has been expressed as activity counts to quantify PA. This measure of the acceleration of the body is commonly defined as the area under the rectified acceleration signal measured over a fixed time interval like one minute (4). Activity counts have been used to describe the pattern of PA, i.e. the frequency, the duration and intensity of PA. Furthermore, activity counts proved to be linearly related to the total energy expenditure (TEE), to the activity-related energy expenditure (AEE), and to the physical activity level (PAL) as measured using doubly-labeled water (8, 14, 21). TEE is defined as the daily metabolic rate, while AEE corresponds to the portion of TEE consumed for PA. PAL is also commonly used to describe the amount of energy consumed for PA as a fraction of the energy required to maintain basal metabolic functions. Linear models have been developed to predict TEE and AEE using activity counts and subject characteristics such as body weight as independent variables (8, 20). On the contrary, when indirect calorimetry was used to assess the metabolic rate during specific activities, the relationship between the intra-individual variability in AEE and activity counts varied according to the type of activity (19). Similar to TEE and AEE, PAL has been repeatedly predicted by linear models based on activity counts. However, as shown for AEE, the relationship between PAL and activity counts depends on the type of activity (19). Thus, prediction models that account for the type of activity performed could result in more accurate estimates of TEE, AEE and PAL.

In recent years, accelerometers have been used in combination with classification models to identify types of PA by evaluating information (features) derived from the acceleration of the body (3, 9, 22, 28, 32). Classification trees (9), neural networks (32), and hidden Markov models (22), are some of the existing classification models used to identify activity type. Zhang et al. (32) developed a neural network to identify up to 32 human movements recording the acceleration of the body using 5 accelerometers. In more recent studies, the identification of activity types was based on the acceleration features measured using a single accelerometer (9, 12). However, the simplification of the measurement system, using one accelerometer, implied a decrease in the number of activities that could be accurately identified by the classification model.

In this study PA was measured during daily life in a population of healthy adults using a single accelerometer. Simultaneously, TEE was assessed using the gold standard technique of doubly-labeled water. The aim was to investigate whether the identification of activity type combined with a simple methodology to define activity type intensity could improve the estimation of TEE, AEE, and PAL as compared to daily activity counts.

Methods

Subjects

Fifteen healthy non-smoking adults (9 men and 6 women) were recruited by advertisement in local newspapers to participate in the study. The study was approved by the Ethics Committee of the Maastricht University Medical Center, and written informed consent was obtained from the participants.

Study design

Subjects reported to the laboratory on day 0 at 0900PM for an overnight stay in a respiration chamber. The study included a two weeks observation period for the measurements of energy expenditure, from the morning of day 1 until the morning of day 15. The PA was monitored from the morning of day 1 until the morning of day 6.

Anthropometrics

Anthropometric measurements were taken in the morning after an overnight fast. Body mass (BM) was measured on an electronic scale (Mettler Toledo ID1 Plus, Giessen, Germany) to the nearest 0.01 kg. Height was measured to the nearest 0.1 cm (SECA Mod.220, Hamburg, Germany). Body volume was determined by underwater weighting. During the underwater weighting the residual lung volume was measured using the helium dilution technique (Volugraph 2000, Mijnhardt, Bunnik, The Netherlands). TBW was determined using deuterium dilution, according to the Maastricht protocol (31). Body composition was calculated from body mass, body volume and total body water (TBW) using the Siri's three-compartment model (25).

Sleeping metabolic rate

Sleeping metabolic rate (SMR) was measured during an overnight stay in the respiration chamber. The room measured 14 m^3 and was equipped with bed, table, chair, freeze toilet, washing bowl, radio, television, and a computer (24). Energy expenditure was calculated from O_2-consumption and CO_2-production according to Weir's formula (29). SMR was defined as the lowest observed energy expenditure for three consecutive hours during the night. Room temperature was held constant at 20 ± 1 °C.

Energy expenditure

The TEE was measured using doubly-labeled water according to the Maastricht protocol (31). On the evening of day 0, after the collection of a background urine sample, subjects drank a weighted amount of $^2H_2{}^{18}O$ such that baseline levels were increased with 100 ppm for ^2H and 200 ppm for ^{18}O. Additionally, urine samples were collected in the morning (from second voiding) of day 1, day 8, and day 15, and in the evening of day 1, day 7, and day 14. The activity energy expenditure (AEE) was measured as (0.9 x TEE) – SMR, assuming the diet-induced thermogenesis to be 10 % of TEE. The mean PAL was calculated as TEE/SMR (20).

Physical activity monitoring

The motion sensor used was a modified version of the previously validated Tracmor (Philips Research, Eindhoven, The Netherlands) (4, 20). The device was equipped with a tri-axial piezo-capacitive (micro-electro-mechanical system [MEMS]) acceleration sensor and recorded acceleration samples 20 times per second. The accelerometer measured $8 \times 3.5 \times 1$ cm and weighed 34.8 g, including the battery, and was placed at the lower back using an elastic belt.

The x-, y-, and z-axes of the accelerometer were oriented along the vertical, medio-lateral and antero-posterior directions of the body, respectively. PA was monitored for 5 consecutive days (2 weekend days and 3 weekdays). Subjects were instructed to wear the accelerometer during waking hours, except during showering and water activities. A diary was used to report periods in which the subject was not wearing the accelerometer during the day.

The raw acceleration signal was downloaded to a personal computer and processed for two purposes. Firstly, to determine the number of activity counts scored daily. The total activity counts accumulated during the monitoring period was divided by the number of days to determine the average activity counts per day (AC_D). Secondly, the raw acceleration signal was processed to identify types of PA performed during the day. The acceleration signal was segmented in non-overlapping intervals of 6.4 seconds. This segment length was selected because the accuracy of classification models used to identify activity types could decrease when the acceleration signal is analyzed in portion of shorter time length (3). In each segment of the acceleration and for each sensing axis, the following acceleration features were determined: average, standard deviation, peak-to-peak distance, and dominant frequency in the power spectral density. Because of the high accuracy in identifying activity types (3, 9), a classification tree algorithm was employed to evaluate the features and to classify the acceleration in one of 6 activity classes: “lie”, sitting or standing (“Sit-Stand”), active standing (“AS”), “walk”, “run” and “cycle”. The AS class was defined to represent dynamic activities not related to ambulation performed in the standing position. The outcome of the classification tree allowed the definition of the duration of the 6 activity types during the monitoring period. The average daily duration (AD_D) of each activity type was calculated as the total duration of each activity divided by the number of monitoring days. The AD_D of lying was determined by integrating the sleeping time, as reported with the diary, to the time spent lying during waking hours.

The AD_D of the identified activity types was used for the assessment of PA by defining a daily metabolic equivalent value (MET_D). The MET_D was calculated as the mean of the standard metabolic equivalent value (MET) of each activity type weighed by the AD_D, as shown in the equation below:

$$MET_D = \frac{1}{k}\sum_{i=1}^{6} MET^i \times AD_D{}^i$$

where *i* is an index that corresponds to each of the 6 activity types considered; MET^i is the standard MET value for the *i*-activity; $AD_D{}^i$ is the average daily duration for the *i*-activity (minutes$\cdot$d^{-1}); and *k* represents the number of monitoring minutes during the day. According to the diaries, the non-wearing time during waking hours was removed from the dataset. This operation was analogue to consider the MET_D of the non-wearing time equal to the average MET_D of the wearing time. The standard MET for each activity type was obtained from a published compendium of PA (1). Since the MET of walking, running, and cycling depends on movement speed, the speed of these activities was estimated by employing recently developed prediction models based on acceleration features (3). The speed of each walking, running, and cycling bout was measured and averaged over the monitoring period and over each subject to have an indication of which MET value would be more suitable to describe the average intensity of the walking, running, and cycling activities.

Classification tree

A classification tree is a model in which the classification process is defined by a sequence of logical conditions based on the features of the object to classify. The development of a classification tree comprises the selection of the features that are most useful for the classification, and the definition of logical conditions to steer the classification. The classification tree employed in the current investigation was developed using data collected during a supervised test, conducted in a separate study with a population characterized by a broad range of weight, height and age: 20 men and 20 women, (mean ± s.d. [min.–max.]) weight = 82 ± 23 [48 - 182] kg, height = 1.71 ± 0.09 [1.49 – 1.97] m, age = 41 ± 16 [23 - 70] y, and BMI = 28.1 ± 7.1 [18.6 – 53.9] $kg \cdot m^{-2}$. The supervised test included activities such as lying, sitting, standing still, walking, running, cycling, washing dishes and sweeping the floor. The acceleration collected during the dishwashing and floor-sweeping activities were used to define the AS category. The acceleration collected during sitting and standing still was used to define the Sit-Stand category. These two activities have been grouped together to form a single category because the use of one accelerometer to measure PA did not allow the accurate distinction of the sitting and standing still postures (3). Figure 1 shows the structure of the developed classification tree and the features selected for the identification of activity type. Table 1 shows the performances of the classification tree as tested on 5 subjects not included in the population used to develop the model (26). The development of the classification tree was conducted using Weka machine learning toolkit (University of Waikato, Hamilton, New Zealand) (10). The processing scripts used for the features calculation and for the validation of the decision tree were developed using Matlab (The MathWorks, Natick, MA).

Statistical analysis

Simple linear regression was used to develop prediction models for PAL using as independent variable AC_D or MET_D. The Bland-Altman plot was used to determine the agreement between measured and predicted PAL (2). Stepwise multiple-linear regression analysis was used to select the best independent variables to predict TEE and AEE. Three different sets of independent variables were considered to account for the differences in body size: SMR, basic body characteristics (BM, height, age, and gender) and advanced body characteristics (fat mass, fat free mass [FFM], age, gender). The independent variable used to describe differences in PA was AC_D or MET_D. The independent variables considered in the regression analysis of AEE were the same as in the regression analysis of TEE with the exception of SMR. The correlation between two variables was evaluated by measuring the Pearson's correlation coefficient (R). The measured parameters are presented as mean ± standard deviation. The statistical software SigmaStat (Systat software, San Jose, CA) was used for statistical analysis. The significance level was set to $p<0.05$.

Results

Descriptive results

Physical characteristics of the subjects are presented in Table 2. Subjects wore the accelerometer on average 15.7 ± 0.4 $h \cdot d^{-1}$, which was 93 ± 5 % of their waking hours. Sedentary activities like lying, sitting and standing occupied on average more than 75 % of the day (Table 3). The average walking, running and cycling speed of the population was 4.2 ± 0.4 $km \cdot h^{-1}$, 10.6 ± 7.1 $km \cdot h^{-1}$, and 20.3 ± 6.0 $km \cdot h^{-1}$, respectively. The MET values selected for each activity type are presented in Table 3. According to a published compendium of physical activities (1), the intensity of lying was considered equal to the MET value of lying quietly. The intensity of sitting or standing was considered equal to the average MET value of sitting quietly, standing quietly, and sitting doing deskwork. The intensity of AS was considered equal to the MET value of multiple household tasks. The intensity of walking and running was considered equal to the MET value of walking at 2.5 miles·h^{-1} (4.0 km·h^{-1}), and of running at 6.7 miles·h^{-1} (10.8 km·h^{-1}), respectively. The intensity of cycling was considered equal to the weighted on speed average of MET for cycling between 10 and 11.9 miles·h^{-1} (16.1 and 19.1 km·h^{-1}) and for cycling between 12 and 13.9 miles·h^{-1} (19.3 and 22.4 km·h^{-1}). MET_D and AC_D were linearly related (R = 0.90, $p<0.001$).

PAL regression models

The model based on AC_D explained 46 % of the variation in PAL (R = 0.68, $p<0.05$) with a standard error of estimate (SEE) of 0.13 or 7.4 % of the mean measured PAL (Figure 2A). The limits of agreement between predicted and measured PAL were from -0.243 to +0.245 (Figure 2B). The model based on MET_D explained 51 % of the variation in PAL (R = 0.71, $p<0.05$) with a SEE of 0.12 or 6.8 % (Figure 2C). The limits of agreement between predicted and measured PAL were from -0.233 to 0.235 (Figure 2D). None of the physical characteristics of the population was correlated to the residual of these prediction models.

TEE regression models

The model based on SMR and AC_D explained 85 % (R = 0.92) of the variation in TEE, with a SEE of 0.8 MJ·d^{-1} or 6.4 %. The model based on SMR and MET_D explained 87 % (R =

0.93) of the variation in TEE, with a SEE of 0.75 MJ·d^{-1} or 6 %. When basic body characteristics and AC_D were used in the stepwise regression analysis, only BM and AC_D were included in the prediction model, and the explained variation in TEE was 51 % (R = 0.71), with a SEE of 1.47 MJ·d^{-1} or 11.7 %. The model based on BM and MET_D, explained 60 % (R = 0.77) of the variation in TEE, with a SEE of 1.33 MJ·d^{-1} or 10.6 %. Considering advanced body characteristics and AC_D, the stepwise regression analysis selected FFM and AC_D in the prediction model of TEE. The explained variation in TEE of this model was 67 % (R = 0.82), with a SEE of 1.2 MJ·d^{-1} or 9.6 %. When advanced body characteristics and MET_D were used in the stepwise regression analysis, FFM and MET_D were included in the prediction model. The explained variation in TEE of this model was 76 % (R = 0.87), with a SEE of 1.02 MJ·d^{-1} or 8.2 %. None of the physical characteristics of the population was correlated to the residual of the prediction models. Coefficients, significance level, and partial correlations of all models are summarized in Table 4.

AEE regression models

When subject characteristics and AC_D were entered as independent variables in a stepwise regression analysis, BM and AC_D, significantly contributed to the explained variation in AEE. The model explained 47 % (R = 0.68) of the variation in AEE, with a SEE of 0.98 MJ·d^{-1} or 21.7 %. Moreover, BM and MET_D were selected as significant predictors of AEE. The explained variation in AEE of this model was 60 % (R = 0.77), with a SEE of 0.85 MJ·d^{-1} or 20.7 %. When advanced body characteristics and AC_D were used in the stepwise regression analysis, FFM and AC_D were included in the prediction model. The explained variation in AEE was 60 % (R = 0.77), with a SEE of 0.85 MJ·d^{-1} or 20.7 %. Furthermore, FFM and MET_D were selected as significant predictors of AEE. This model explained 73 % (R = 0.85) of the variation in AEE, with a SEE of 0.70 $MJ \cdot d^{-1}$ or 17 %. None of the physical characteristics of the population was correlated to the residual of the prediction models. Coefficients, significance level, and partial correlations of all models are summarized in Table 5.

Discussion

This study showed that the identification of types of PA, such as lying, sitting or standing, active standing, walking, running, and cycling, performed during the day combined with a simple methodology to define activity type intensity improved the estimation of TEE, AEE, and PAL as compared to activity counts. The MET_D value was calculated to assess the metabolic cost of PA using the duration and the standard MET compendium value, as presented in literature, of 6 common types of activity, identified using a newly developed classification tree model. MET_D improved the explained variation in PAL by 5 % as compared to AC_D. Furthermore, depending on which independent variables were considered to represent differences in body size, the models based on MET_D improved the explained variation in TEE from 2 to 9 % and improved the explained variation in AEE by 13 %, as compared to the models based on AC_D.

Only a small number of accelerometers have been validated against the gold standard technique of doubly-labeled water. Those that were validated, often showed poor correlations with energy expenditure or the main contribution to the explained variation in TEE, or AEE was determined by subjects' physical characteristics (21). Very few studies reported a higher accuracy in predicting TEE, AEE and PAL than the accuracy of the models obtained in the current study (5, 20, 21). Plasqui et al (20) developed a prediction model of TEE using as independent variables SMR, and AC_D. The explained variation of the model was 90 %. In our model based on the same independent variables, the explained variation in TEE was 85 %. Carter et al. (5) developed a model to predict TEE using as independent variables body height and AC_D in a population of male young adults. The explained variation of the model was 73 % and AC_D accounted for 27 % of the explained variation in TEE. Plasqui et al. (20) developed a model to predict TEE using as independent variables age, BM, height, and AC_D in a population of young adults. The explained variation of the model was 83 % and AC_D accounted for 19 % to the explained variation in TEE. In our study, TEE was predicted by BM and AC_D. This model explained 51 % of the variation in TEE while AC_D accounted for 9 % to the explained variation in TEE. Although comparing these prediction models is difficult because of the different independent variables included in the regression, it appeared that the ones developed in the current study showed a lower explained variance in TEE. Additionally, the contribution of AC_D to explain the variation in TEE was lower. This was also observed in the models to predict AEE and PAL as compared to the study of Plasqui et al. (20). A limitation of this study was the fact that the habitual PA was determined during a monitoring period of 5 days, while the TEE was assessed in a period of two weeks, according to the doubly-labeled water protocol. This could have determined a decrease in the contribution of AC_D to the explained variation in TEE, AEE and PAL, because of a reduced ability of AC_D to describe PA. However, some studies have shown that as little as 3 to 4 days of monitoring were sufficient to achieve a reliability of more than 80 % in measurements of PA using accelerometers (15, 17). In the study of Plasqui et al. (20) the activity monitor was equipped with a piezo-electric acceleration sensor, while in the current study the Tracmor was equipped with a piezo-capacitive sensor that allowed the identification of postures by detecting static accelerations. Additional research is required to understand whether the use of piezo-capacitive acceleration sensors determined a decrease in the ability of AC_D to account for the explained variance in TEE, AEE, and PAL as compared to the AC_D measured using activity monitors equipped with piezo-electric sensors. Furthermore, it should be also carefully considered a different data processing of the acceleration signal as a confounding factor when comparing the ability of piezo-electric and piezo-capacitive sensors in measuring PA.

The MET_D value provided a more accurate assessment of PA as compared to AC_D, since the developed model to predict TEE, AEE and PAL showed a higher accuracy. The calculation of MET_D was based on the use of a newly developed classification algorithm for the identification of types of physical activity performed during the day. The assessment of PA by identifying activity types was hypothesized to improve the estimation of energy expenditure. This assumption was based on the evidence that the relation between energy expenditure and accelerometer output depends on the type of activity performed. A few studies (19, 27) showed that different linear equations could be developed to estimate the MET of activities such as sitting, standing, walking, and housework, using activity counts. Furthermore, a unique linear relationship between activity counts and activity intensity is not suitable for both running and cycling activities. In fact, these two activities generate a diverse amount of activity counts even at a similar level of METs. In this study, the MET_D value accounted for the different contribution of 6 activity types to TEE, AEE, and PAL. This was possible because the assessment of activity intensity was independent from activity counts. The intensity of lying, sitting or standing and AS was assumed to be equal to a specific MET value as obtained from a published compendium of PA (1). The intensity of each walking, running and cycling activity was assumed to be equal to the MET value of walking at 2.5 miles·h^{-1}, running at 6.7 miles·h^{-1}, and cycling between 10 and 13.9 miles·h^{-1}, as these MET values were representative of the activity intensity at the average speed measured during the monitoring period. The only independent variable determining MET_D was the daily duration of the 6 activity types, since activity intensity was considered constant. This might allow the applicability of the prediction models based on MET_D to any method able to accurately detect the daily duration of the types of activity considered in this study. However, a methodology that allows the detection of activity intensity for each activity type and for each activity bout, could be considered to further improve the estimation accuracy of TEE, AEE, and PAL. The challenge would be represented mainly by the determination of intensity for sedentary and unspecified dynamic activities, such as Sit-stand or AS, which occupy a large part of the daytime and could importantly contribute to the definition of the metabolic cost of PA (27).

In the literature, some attempts have been made to improve accelerometer-based estimation of energy expenditure by defining specific regression equation to relate the metabolic cost of PA to activity counts for specific groups of activities such as locomotive and lifestyle activities (7), or sedentary, locomotive or housework activities (19, 27). Additionally, non-linear models such as artificial neural networks have been applied to the raw acceleration of the body to improve the prediction accuracy of energy expenditure (6, 23). However, none of these computationally sophisticated techniques have been validated yet in free-living conditions by using, as a reference measure of energy expenditure, doubly-labeled water. In this study, PA was assessed by a MET_D parameter that accounted for the different contribution to the metabolic cost of PA of each identified type of activity. This approach was similar to that implemented in the ActiReg activity monitor to estimate TEE (11). The ActiReg includes 2 accelerometers. They are positioned on the chest and on the thigh to determine body posture and to categorize PA in 3 classes of intensity. Depending on the posture and on the activity intensity a MET value is used to describe the energy cost of PA. Thus, the definition of energy expenditure was derived from information on posture (lying, sitting, and standing), and the intensity of PA. The ActiReg has been validated against doubly-labeled water, and a standard error of 1.24 MJ/day was obtained in the estimation of TEE (11). Therefore, the prediction accuracy was poorer than the one achieved by the models developed using MET_D.

In this study, PAL and AEE were calculated from measurements of TEE and SMR. In literature, TEE is often corrected by resting metabolic rate (RMR) to determine PAL and AEE. The choice of using SMR instead of RMR derived from the fact that measurements of SMR showed a high reproducibility. Indeed, the intra-individual coefficient of variation of SMR measured in a respiration chamber has been estimated to be below 2% (24). Considering that SMR is about 5 % lower than RMR (13), the mean values of PAL and AEE measured in this study were systematically higher than those derived from TEE and RMR. However, the variability in PAL and AEE was not significantly affected by the use of SMR instead of RMR. Thus, the estimation accuracy of the models to predict PAL and AEE was not influenced by the selection of SMR as correction factor for TEE.

In conclusion, identification of activity types combined with standard MET compendium values improved the assessment of energy expenditure as compared to activity counts. Future studies could focus on the development of models to objectively measure the intensity of common types of PA to further increase the accuracy of the energy expenditure estimation.

Disclosure

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Figures legend

Figure 1. Classification tree developed to identify types of physical activity. In the circles are noted the features used to identify activity types (lie, sit or stand [Sit-stand], active standing [AS], walk, run, cycle). The features selected for the classification were: the standard deviation of the acceleration in the vertical, and medio-lateral directions of the body (σ_X, σ_Y); the average acceleration in the vertical direction of the body (α_X); the peak-to-peak distance of the acceleration measured in the medio-lateral, and antero-posterior direction of the body (a_Y^{pp}, a_Z^{pp}); and the frequency peak of the power spectral density of the acceleration measured in the vertical direction of the body (f_X).

Figure 2. Accuracy of the prediction models of the physical activity level (PAL). (A) Regression plots of the PAL prediction models based on activity counts a day (AC_D) and (C) based on metabolic equivalent a day (MET_D). R, represents the Pearson correlation coefficient of the models. (B) Bland-Altman plot of the models used to predict PAL based on AC_D, and (D) based on MET_D. p, represents the significance level of the association between the residual PAL and the mean PAL.

Table 1. Performance of the model used to identify types of physical activity

		Classification categories					
		Lie	Sit-stand	AS	Walk	Run	Cycle
True categories	Lie	100	0	0	0	0	0
	Sit-stand	2	95	3	0	0	0
	AS	0	22	69	3	0	6
	Walk	0	0	0	99	0	1
	Run	0	0	0	0	100	0
	Cycle	0	1	5	7	0	87
Sensitivity, %		100	95	69	99	100	87
Specificity, %		99	98	98	98	100	99
F-score, %		100	96	81	99	100	93

Numbers in the matrix represent the percentage of objects belonging to the true category that are classified as each classification category; Sensitivity was calculated to describe the ability to avoid false negative classifications for each activity type; Specificity was calculated to define the ability to generate true positive classifications for each activity type; F-score was calculated as the harmonic mean between sensitivity and positive predictive values to evaluate the overall performance of the model in classifying each activity type (26); AS, active standing; Sit-Stand, sitting or standing.

Table 2. Subjects characteristics (n = 15).

Parameter	Mean ± SD	Range
n (men/women)	15 (9/6)	
Age, y	41 ± 11	26 – 59
BM, kg	76.6 ± 11.4	62.1 – 103.4
Height, m	1.77 ± 0.08	1.66 – 1.89
BMI, kg·m^{-2}	24.4 ± 3.0	19.6 – 29.5
FM, kg	20.2 ± 6.1	8.4 – 33.2
FFM, kg	56.4 ± 7.6	44.1 – 70.2
SMR, MJ·d^{-1}	7.1 ± 0.8	5.7 – 8.3
TEE, MJ·d^{-1}	12.5 ± 1.9	9.7 – 15.5
AEE, MJ·d^{-1}	4.1 ± 1.2	2.1 – 6.4
PAL	1.75 ± 0.17	1.43 – 2.06
AC_D, kcounts·d^{-1}	228 ± 60	116 – 341
MET_D	1.72 ± 0.14	1.48 – 1.98

BM, body mass; BMI, body mass index; FM, fat mass; FFM, fat free mass; SMR, sleeping metabolic rate; TEE, total daily energy expenditure; AEE, activity energy expenditure; PAL, physical activity level; AC_D, daily activity counts; MET_D, daily metabolic equivalent.

Table 3. Types of activity performed during the day.

Activity type	MET	Minutes·d^{-1}	
		Mean ± SD	Range
Lie	1	513 ± 67	382 – 683
Sit-Stand	1.3	560 ± 111	370 – 683
AS	3.5	128 ± 45	55 – 231
Walk	3	187 ± 55	85 – 291
Run	11	3 ± 4	0 – 14
Cycle	6.7	28 ± 14	8 – 54

MET, metabolic equivalent (1); AS, active standing.

Table 4. Prediction models of TEE.

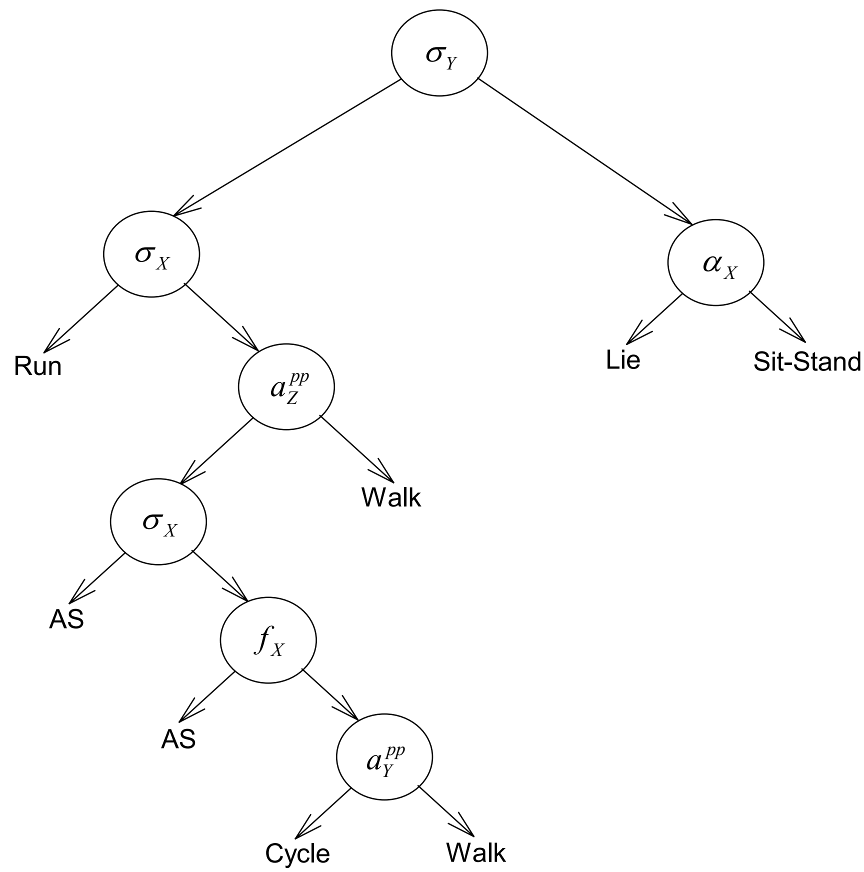
Dependent	Independent	Coefficient	P	pR^2	Dependent	Independent	Coefficient	p	pR^2
TEE	INT	- 9.3			TEE	INT	- 19.1		
	SMR	2.5	<0.001	0.59		SMR	2.5	<0.001	0.59
	AC_D	$1.8 \cdot 10^{-5}$	<0.001	0.26		MET_D	8.4	<0.001	0.28
Model				0.85	Model				0.87
TEE	INT	0.8			TEE	INT	- 8.9		
	BM	0.1	<0.05	0.42		BM	0.1	<0.05	0.42
	AC_D	$1 \cdot 10^{-5}$	<0.05	0.09		MET_D	6.5	<0.05	0.18
Model				0.51	Model				0.60
TEE	INT	- 2.4			TEE	INT	- 13.1		
	FFM	0.2	<0.001	0.54		FFM	0.2	<0.001	0.54
	AC_D	$1.2 \cdot 10^{-5}$	<0.05	0.13		MET_D	7.3	<0.05	0.22
Model				0.67	Model				0.76

p, significance level; pR^2, partial correlation; Model, R^2 of the prediction model; TEE, total daily energy expenditure; INT, intercept; SMR, sleeping metabolic rate; AC_D, activity counts per day; MET_D, daily metabolic equivalent; BM, body mass; FFM, fat free mass.

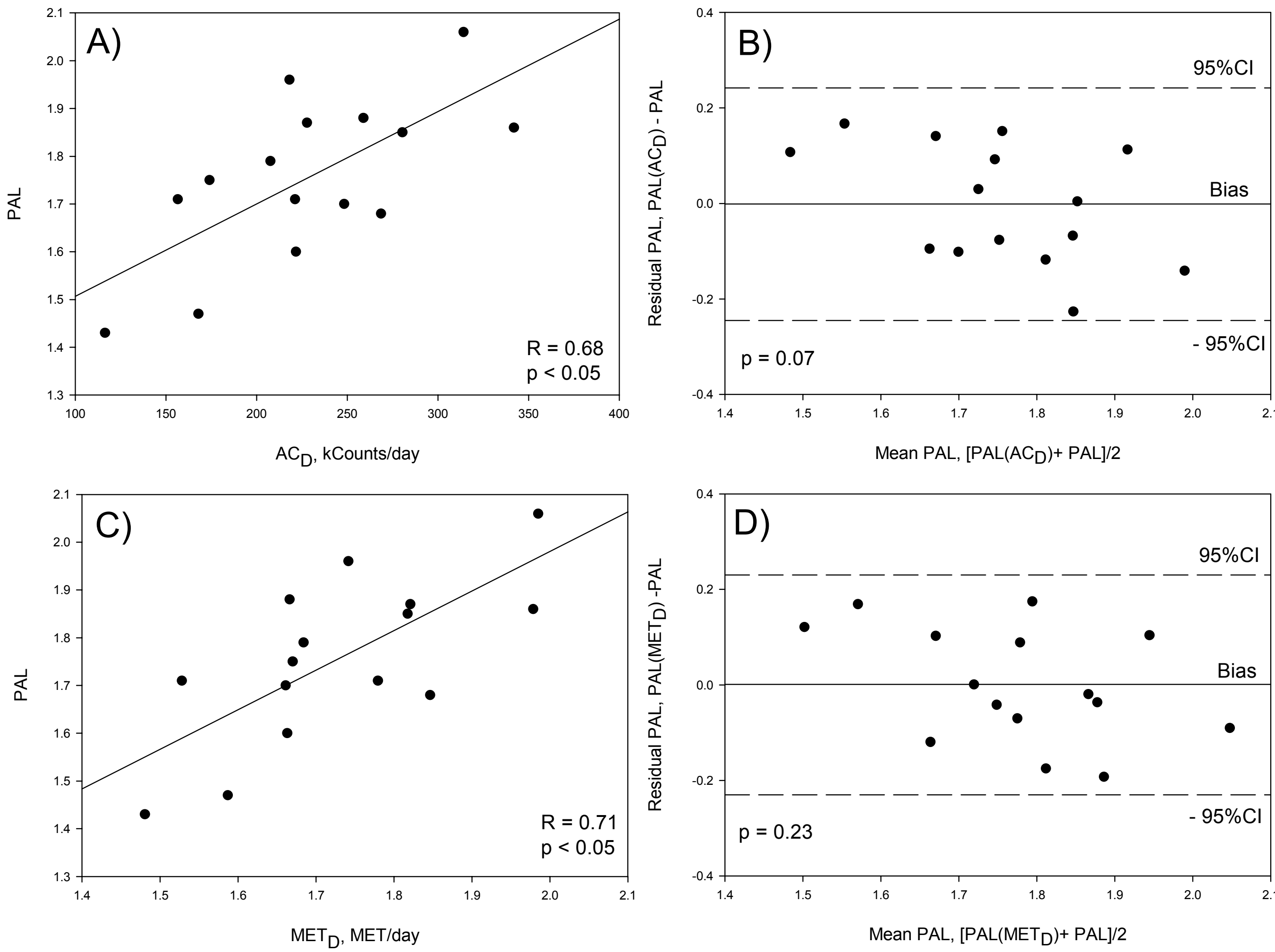
Table 5. Prediction models of AEE.

Dependent	Independent	Coefficient	P	pR^2	Dependent	Independent	Coefficient	p	pR^2
AEE	INT	- 3.0			AEE	INT	- 12.4		
	BM	0.05	<0.05	0.26		BM	0.07	<0.05	0.35
	AC_D	$1.2 \cdot 10^{-5}$	<0.05	0.21		MET_D	6.7	<0.001	0.25
Model				0.47	Model				0.60
AEE	INT	- 4.9			AEE	INT	- 14.7		
	FFM	0.1	<0.05	0.21		FFM	0.12	<0.001	0.48
	AC_D	$1.3 \cdot 10^{-5}$	<0.05	0.38		MET_D	7.1	<0.001	0.25
Model				0.60	Model				0.73

p, significance level; pR^2, partial correlation; Model, R^2 of the prediction model; AEE, activity energy expenditure; INT, intercept; AC_D, activity counts per day; MET_D, daily metabolic equivalent; BM, body mass; FFM, fat free mass.



σ_Y
σ_X
α_X
Run
a_Z^{pp}
Lie
Sit-Stand
σ_X
Walk
AS
f_X
AS
a_Y^{pp}
Cycle
Walk



A)
PAL
R = 0.68
p < 0.05
AC_D, kCounts/day
B)
Residual PAL, PAL(AC_D) - PAL
95%CI
Bias
- 95%CI
p = 0.07
Mean PAL, [PAL(AC_D)+ PAL]/2
C)
PAL
R = 0.71
p < 0.05
MET_D, MET/day
D)
Residual PAL, PAL(MET_D) -PAL
95%CI
Bias
- 95%CI
p = 0.23
Mean PAL, [PAL(MET_D)+ PAL]/2