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ORIGINAL RESEARCH

Assessment of Physical Activity and Energy Expenditure by GPS Combined With Accelerometry in Real-Life Conditions

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Background**:** Physical activity (PA) and related energy expenditure (EE) is often assessed by means of a single technique. Because of inherent limitations, single techniques may not allow for an accurate assessment both PA and related EE. The aim of this study was to develop a model to accurately assess common PA types and durations and thus EE in free-living conditions, combining data from global positioning system (GPS) and 2 accelerometers. ***Methods*****:** Forty-one volunteers participated in the study. First, a model was developed and adjusted to measured EE with a first group of subjects (Protocol I, n = 12) who performed 6 structured and supervised PA. Then, the model was validated over 2 experimental phases with 2 groups (n = 12 and n = 17) performing scheduled (Protocol I) and spontaneous common activities in real-life condition (Protocol II). Predicted EE was compared with actual EE as measured by portable indirect calorimetry. ***Results*****:** In protocol I, performed PA types could be recognized with little error. The duration of each PA type could be predicted with an accuracy below 1 minute. Measured and predicted EE were strongly associated ($r = .97$, $P < .001$). ***Conclusion*****:** Combining GPS and 2 accelerometers allows for an accurate assessment of PA and EE in free-living situations.

Keywords**:** free-living conditions, global positioning system, sedentary, model classification, physical activity recognition, obesity

Over the last decades, the rise in sedentary and inactive lifestyles caused serious health-related concerns.[2] Worldwide, prevention programs and recommendations to the general and to specific populations with regard to physical activity (PA) have been published.[3] Recommendations for daily physical activity encompass precise quantitative characteristics of the PA such as intensity, duration and frequency, as well as the type of activity.[3] To assess the effectiveness of these programs and guidelines, accurate and reliable assessment methods are required. Moreover, the ability to assess accurately the type, the intensity and the duration of the activity allows for an accurate estimation of the energy expenditure (EE) associated to PA.[4]

Common techniques used to quantify PA and PA-related EE include subjective methods such self-activity diary and questionnaires, and objective measure such as doubly labeled water (DLW), heart-rate monitoring (HR) or indirect calorimetry. These techniques provide information about either usual daily PA or the EE associated to PA. Accelerometers have been largely used to quantify PA in humans.[5–9] Used in combination with classification models, classification trees and neural networks,[10] types of PA can be assessed by means of accelerometers and provide a relatively robust estimation of PA and EE.[11,12] The use of a single accelerometer however have some limitations as it does not detect certain types of activities, or detects them erroneously.[5,6] Sensitive and accurate detection of PA may however be achieved by means of multiple sensors.[4,10,13,14] Combining different types of sensors, such as accelerometers, heart rate monitors and Global Positioning Systems (GPS),[4] allows researchers to circumventing drawbacks associated to the use of a single method/accelerometer. Actually, by combining heart rate and accelerometers, Strath et al showed an improved accuracy in the estimation of EE as compared with a single accelerometer.[12] Since slope and speed at which an individual travels markedly influence walking EE,[15,16] previous studies attempted to estimate the slope[17,18] and speed[18] of displacement using a neural network method. However, the accuracy of slope and speed assessment were low,[17–19] and speed of displacement could not be assessed while uphill or downhill walking.[18] Combining accelerometers and GPS to determine elevation changes, Perrin et al demonstrated that walking speed prediction could be improved by correcting for altitude changes.[19] Altogether, these data suggest that the accuracy of the PA recognition is improved when different sensors are combined and a valid assessment of EE and PA can be achieved.[10,13,14]

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Taken together, this suggests that a combination of accelerometers together with a GPS is of great interest, since it would allow an accurate assessment of essentially all activities performed indoors and outdoors, and thus all components of PA-related EE. A mathematical model able to combine data from these devices and to detect the type and intensity of each activity over short (seconds) to long (hours) periods of time is however required. Ermes et al[20] combined 2 accelerometers (attached at the waist and wrist) and 1 GPS device for speed measurement for a more accurate PA type detection. However, they reported that activities such as cycling and footsteps could not be well discriminated. In addition, the system was cumbersome since a backpack had to be carried by the volunteers for data storage. Furthermore, they did not attempt to calculate EE.

In this context, the aim of this study was to develop a model able to determine simultaneously the type and duration of common PA, and to predict the related EE based on the combination of 2 accelerometers, attached at the waist and ankle, as well as a GPS sensor.

Methods

Participants

Forty-one young and healthy subjects volunteered to participate in this study (Table 1). They were divided in 3 groups. First, the model was developed and adjusted using data from a first group (D group, n = 12, Table 1) and validated with data from a second group of volunteers (VM group, n = 12; protocol I). A third group (SVM group, n = 17) was used to validate the model (protocol II). All volunteers were healthy nonsmokers with no metabolic disorders and able to engage in normal walking activities. After being fully informed of the procedures of the study protocol, all participants gave written informed consent. This study was conducted according to the guidelines laid down in the Declaration of Helsinki and all procedures involving human subjects/patients were approved by the local Ethics Committee.

Experimental Overview

Two study protocols have been carried out for the development, characterization, and validation of the model. The first protocol consisted in imposing a known and timed PA program in order 1) to develop, by observation, a hierarchical model for PA recognition and EE estimation, the predicted PA and EE being compared with the actual PA and EE; 2) to adjust the model and determine correction factors when required; and 3) to validate the model. The second protocol aimed at validating the accuracy of the model in "real-life" conditions (ie, while performing spontaneously and continuously activities such as shopping, walking, watching TV, running, desk working, or lying on a bed). Estimated EE by the model was compared with the measured EE while performing various 2h spontaneous PA.

Protocol I

On 1 occasion, subjects (D and VM groups) reported to the laboratory in the morning, at least 3 hours after their last meal. The experiments were not carried out during adverse meteorological conditions.

First, height and weight were measured, and body fat estimated using 4 standard skinfold measurements.[21] Then, the subjects were equipped with 2 accelerometers (Lifecorder Kenz EX and Step Watch 3 Activity Monitor) and a GPS (FRWD Technologies, Finland), which were worn on waist, ankle and shoulder, respectively. Since the model for PA recognition (described in details below) requires spontaneous walking characteristics (ie, speed and step frequency at slow, preferred, and fast walking speed), the subjects performed a calibration trial in a circuit outdoors, under supervision. This calibration trial consisted in performing the following sequence: first participants walked 200 m on the level at their own spontaneous speed; then, 200 m at their fastest walking speed, and followed by 300 m on a 7% to 9% grade at a spontaneous pace, and finally 300 m downhill walking on a –7% to –9% slope at the fastest speed they could achieve walking.

Table 1 Anthropometrical Characteristics of the 41 Subjects Involved in the Validation Study

	Protocol I (structured PA)	Protocol II (spontaneous PA)
Physical characteristics	Mean (SD)	Mean (SD)
Gender (M/F)	12/12	9/8
Age (y)	25 (4)	24.5 (5)
Weight (kg)	63 (8)	67 (9)
Height (cm)	172 (9)	174 (8)
BMI ($kg{\cdot}m^{-2}$)	21 (2)	22 (3)
Body fat (%)	26 (5)	21 (9)

Abbreviations: M, male; F, female; BMI, body mass index.

Note. No significant difference was observed among the subjects of the 2 protocols.

After the calibration trial, subjects were driven to another outdoor place, in which they could walk, run and cycle safely and freely. Upon arrival, the subjects were equipped with a portable indirect calorimeter (Metamax 3B, Cortex, Germany), previously calibrated according to the manufacturer instructions. Then, their baseline resting metabolic rate was measured for 15 min, with the subject lying comfortably. The last 3 min were averaged to calculate baseline metabolic rate from oxygen consumption.[22] Immediately after, the subjects were asked to perform 8 different supervised and timed PA consisting of walking, running and cycling bouts, as follows: 1) burst walking that consisted of 3 times walking for 30 sec followed by 30 sec sitting, 2) preferred speed walking at 10% slope (6 min), 3) preferred speed walking at –10% slope (5 min), 4) walking slowly on the level (5 min), 5) walking on the level at their preferred speed (5 min), 6) above their preferred speed (5 min), 7) running at a moderate pace (5 min), and 8) cycling 2 laps of a horizontal circuit at a moderate speed (8–12 min). After each single activity bout, subjects were asked to sit until oxygen consumption reached the values closed to their baseline metabolic rate. Upon completion, data of all sensors were stored for subsequent analysis. Area under curve (AUC) method was used to calculate total oxygen consumption and carbon dioxide production for each single activity, considering that this approach does not require a steady state for calculation of the EE.

Experimental Protocol II

Similarly to protocol I, subjects (SVM group) reported to the laboratory in the morning, at least 3 hours after eating their last meal. After giving informed consent, anthropometric measurements were performed, as described above. Then, the subjects were equipped with the 2 accelerometers and the GPS. To determine their walking spontaneous characteristics, subjects performed the same calibration trial as described above. The subjects were then equipped with the portable indirect calorimeter, and baseline metabolic rate was measured for 15 minutes, with the subject lying on a bed. Immediately after, the subjects were asked to perform randomly and spontaneously 5 different activities indoors or outdoors over 2 hours: 1) walking (outdoor), 2) shopping, 3) running (outdoor), 4) watching TV/Desk working (indoor), and 5) lying (outdoor or indoor). The sequence and duration of PAs were not imposed, and subjects were asked to perform them spontaneously. Upon completion, data from the different sensors were stored for subsequent analysis.

Equipment

Three sensors were used along with the hierarchical model for PA type recognition and EE estimation: an accelerometer worn on the waist, another accelerometer worn on the ankle and a portable GPS.

The Uniaxial Accelerometer Lifecorder Kenz EX (LC; Suzuken Co. Ltd., Nagoya, Japan) weighs 60 g, is the size of a pager, and is worn on the waist. The device detects vertical accelerations of the body. Activities are classified into 11 levels of intensity (0, 0.5, and 1–9). Walking corresponds to an intensity level between 3–7.

The Dual-Axis Accelerometer Step Watch 3 Activity Monitor (SAM, Cyma Corporation, Mountlake Terrace, WA, USA). The device dimensions are 10.6 × 6.8 × 3.1 cm, and it weighs 150g. It is worn on the ankle. The SAM combines acceleration, position and time to count the number of strides. The strides are recorded at intervals of 6 sec synchronized with an internal clock. According to Busse et al,[23] the accuracy of SAM is 99,6% for a large population, as well as for subjects presenting slow or varying strides.

The Global positioning system (GPS; FRWD Technologies, Finland). The device dimensions are 95 × 55 × 15 mm and it weighs 85 g. It is worn on the shoulder. It records data of longitude, latitude, speed, slope, altitude, air temperature and distance. The receiver is capable of treating simultaneously 12 satellites' signals. According to the manufacturer, the precision in distance is greater than 99%; speed, altitude and temperature are measured with a precision error of less than 0.2 m/s, 1 m, and 0.2°C, respectively. GPS tracking has been extensively used in the past few years to determine speed profile during outdoor exercise.[24]

A portable indirect calorimeter (Metamax 3B, Cortex, Germany) was used as a reference method with which the predicted EE was compared. The accuracy and the reproducibility of this indirect calorimeter have been previously validated.[25] Before each experiment, indirect calorimeter was calibrated according to the manufacturer's instructions. EE was calculated using Weir's equation.[22]

Model Development Based on a Hierarchical Classification

A model combining the raw data obtained from the 3 different sensors was developed in Matlab language (MathWorks; Natick, MA). Overall, the model allows the classification of different PA on a minute-by-minute basis. It requires the speed of displacement (km/h), the level of vertical acceleration (classified from 0.5–9 given by the waist accelerometer (Lifecorder, Kenz, Japan), and the step frequency (SF, steps/min) for PA classification. The development of the model comprised the selection of useful features for the classification of PA and the definition of logical conditions to steer the classification. There are many different ways to achieve a given activity in real life condition for a given individual. Therefore, to develop a model which encompassed the different ways to perform PA, and determine the constant threshold values, the lowest and highest SF, speed, and levels of intensity for each PA category assessed during supervised tests (protocol I) were used. The lower (LI) and highest (HI) threshold of walking activity intensity was set at 3 and 7.[26] Figure 1 summarizes the developed model as well as the selected thresholds values used in the identification of PAs. Then, based on the data collected during

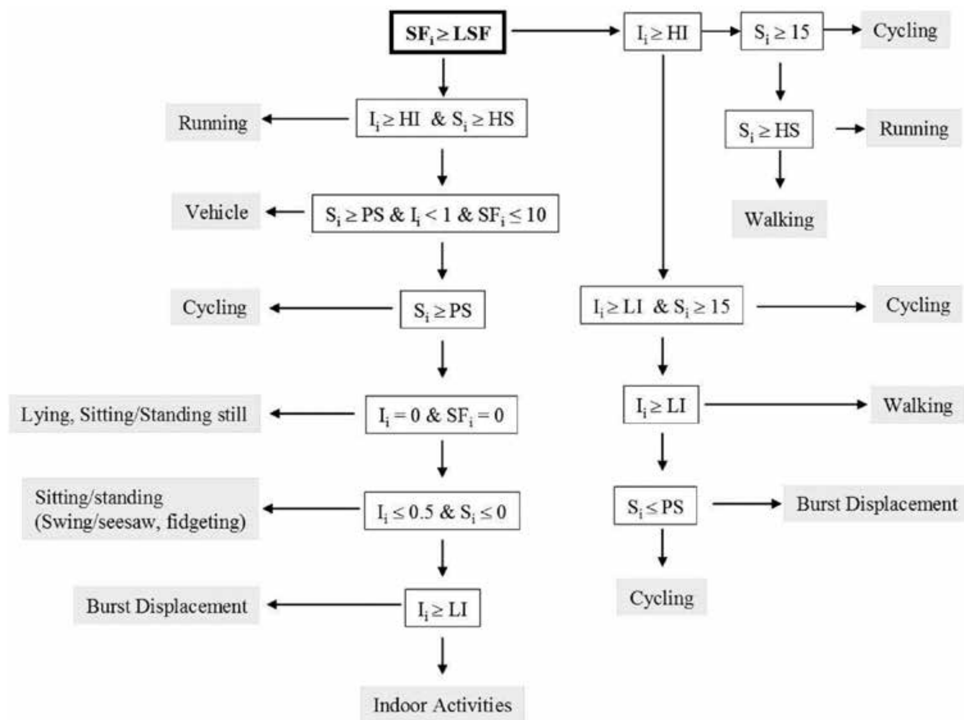

Figure 1 — Classification tree for defining the nature of PA. The model uses a classification partitioned into 8 categories and is applied for the data on each i-th minute. SF_i, I_i, and S_i are the stride frequency (strides/min), the intensity and the speed (km/h) at the minuteI, respectively. The thresholds to steer the classification are the SF during preferred speed uphill walking (LSF), the intensity during preferred speed uphill walking (LI), the intensity during fast downhill walking (HI), the preferred speed on level walking (PS) and the speed while downhill walking (HS). The different coefficients used in the algorithm as thresholds are explained in the Methods section. →: YES. ↓:NO.

the individual calibration phase, from which individual walking pattern can be derived, the required individual thresholds to steer the classification were determined for each individual: the lowest SF value (LSF), the speed during fast downhill walking (HS) and the preferred speed while walking on the level (PS), respectively.

PA-related EE was estimated using standard predictive anthropometrical characteristics [sex, age (y), height (cm) and body weight (kg)], activity type, and intensity, as derived from temperature (°K), speed of displacement (km/h), and incline of terrain (%). Estimates of EE are based upon validated equations.[1,15,16,27–29]

The data obtained from the 3 sensors were processed according to the following procedures:

1. Synchronization of data: First, the model averages the data of the 3 different sensors at 1 minute interval, a reasonable duration when EE over 24 hours is calculated. Then, synchronized matrices of SF, walking speed, intensity, incline, and temperature were generated. Thus, data in each matrix begins and ends at the same time.
2. Second, the PA types were categorized each minute by means of the model. Each mean minute–by-minute based data of SF, intensity, and speed was processed by the model to classify spontaneous PA into 8 categories, which were 1) walking, 2) burst displacement, 3) use of a motorized vehicle, 4) running, 5) sitting/standing (swing/seesaw, fidgeting), 6) indoor sedentary activities, 7) sitting/lying still, and 8) cycling. The slope and speed of different PA performed was determined by the GPS device.
3. Third, the EE related to the classified PA was computed. For the prediction of a) resting metabolic rate (RMR),[16] b) EE of running,[30] c) EE of walking,[27] and d) EE of cycling,[1] validated equations were used (Equ. 1 to 5). VO_2 consumption during running obtained from Equ. 3 was transformed into EE, assuming that a consumption of 1 liter of oxygen equals 4.9 kcal. EE during cycling was calculated according to Martin et al,[1] the power being transformed into kcal per unit of time and converted to the energy cost of cycling assuming an efficiency of 25%. Predicted EE during the following PA categories were obtained using published compendiums of PA that expressed the PA intensity in METs:[15] burst displacement, lying, sitting, using a vehicle, and indoor sedentary activities. During these activities, GPS data are not useful. Then, knowing the duration of each activity (1min) and the RMR, the EE of PA could be predicted by the following model:

$$RMR_{female}(kcal / day) = (9.99 \times M + 6.25 \times H - 4.92 \times age - 161) \quad \text{Equ. 1}$$

$$RMR_{male}(kcal / day) = (9.99 \times M + 6.25 \times H - 4.92 \times age + 5) \quad \text{Equ. 2}$$

where M is the body mass (kg), and H the height (cm).

$$VO_{2,running}\left(\frac{ml}{kg \cdot \min}\right) = 0.2 \times \frac{s \times 1000}{60} + 0.9 \times \frac{s \times 1000}{60} \times i + 3.5 \quad \text{Equ. 3}$$

where s is the speed (km/h), and i the incline.

$$EE_{walking}\left(\frac{J}{kg \times m}\right) = 1.866 \times a \times \left(\frac{s}{3.6}\right)^2 - 3.773 \times b \times \frac{s}{3.6} + c + 4.456 \quad \text{Equ. 4}$$

with $a = e^{4.911¥i}$, $b = e^{3.416¥i}$ and $c = 45.72¥i^2 + 18.9¥i$

where i is the incline and s the speed of displacement (km/h).

$$P_{cycling}(W) = \left(V_a^2 V_G \frac{1}{2} \rho \left(C_D A + F_W \right) + V_G C_{RR} m_T g + V_G \left(91 + 8.7 V_G \right) 10^{-3} + V_G m_T G_R + \frac{1}{2}\left(m_T + \frac{I}{r^2} \right) \frac{\left(V_{Gf}^2 - V_{Gi}^2 \right)}{t_i - t_f} \right) \Big/ E_c \quad \text{Equ.5}$$

where $A\left(m^2\right) = \left(\frac{H \times M}{3600}\right)^{1/2}$ is the body surface area,[31] H the height of the rider, M the body mass (kg), V_a the air velocity, V_G the velocity of the bike and rider (km/h), F_w a factor associated with wheel rotation representing the incremental drag area of the spokes, C_{RR} the coefficient of rolling resistance, m_T the total mass of the bike and the rider (kg), I the moment of inertia of the flywheel, r the outside radius of the tire, V_{Gi} the initial ground velocity, V_{Gf} the final ground velocity, t_i the initial time, t_f the final time, G_R the road gradient, C_D the coefficient of drag, ρ the air density, and E_C the chain efficiency factor (1).

Statistical Analysis

Univariate linear regression was used to analyze the relationship between measured and predicted intensity and EE using the Pearson product-moment correlation. Estimation of error (criterion minus estimate) was graphically represented with Bland-Altman plots with 95% limits of agreement.[32] Differences between measured and predicted durations of PA were evaluated using a 2-sample paired t test. Matlab (MathWorks; Natick, MA) and the language and environment for statistical computing and graphics (R Development Core Team, USA, 2008) were used for statistical analysis. Data are shown as mean ± SD. P-values < 0.05 were considered statistically significant.

Results

Protocol I

Activity Types and Duration. All types of PA, performed by the VM group during protocol I, could be classified without error into the PA categories.

The accuracy of the predicted activity was less than 1 minute (Table 2). The duration for burst walking was 100% correctly predicted, whereas predicted durations for uphill, downhill, on level walking, and running were significantly lower than the actual duration (Table 2), except for cycling. Although the confidence intervals indicate that the model systematically underestimated

Table 2 Protocol I, Validation Group: Accuracy of the Model for Estimation of the Duration of PA

Physical activities	Reference duration (min)	Mean duration of PA estimated by the model (min)	95% confidence interval	*P*-value
Burst displacement	3	3	–	–
Uphill walking	6	5.3 ± 0.5	[–0.9, –0.2]	0.01
Downhill walking	5	4.6 ± 0.5	[–0.9, –0.2]	0.01
On level walking	15	14.6 ± 0.6	[–0.7, 0.05]	0.08
Running	5	4.7 ± 0.5	[–0.8, –0.04]	0.03
Cycling	8–12	11 ± 0.5	[–0.7, 0.05]	0.2

Note. Overall, the accuracy was below 1 minute, although the difference was statistically significant for uphill &downhill walking, as well as for running.

the activity duration for most activities (Table 2), the error in the prediction did not exceed 1 min (Table 2). Mean differences between predicted and measured PA were 0.6 ± 0.5, 0.6 ± 0.5, 0.3 ± 0.5, 0.4 ± 0.5, and 0.3 ± 0.5 min, for walking uphill, downhill, on level, running and cycling, respectively. No significant correlation between PA duration and error magnitude was found ($r = .06$, $P = .5$).

Baseline Metabolic Rate. The actual baseline metabolic rates of D and VM groups were 1.53 ± 0.27 kcal/min and 1.34 ± 0.21 kcal/min, respectively.

Energy Expenditure of Different PA Categories. A strong significant correlation between measured and predicted EE values ($r = .96$ and $P < .001$) was found in the D group. The equation of the linear regression model was $predictedEE = 0.8 \times measuredEE - 18$. The Bland-Altman technique showed that 95% limits of agreement were –150 kJ to 29 kJ (mean difference –61 kJ). The model estimation errors were negatively correlated with EE ($r = –0.4$, $P < .001$).

Depending on the nature of PA, the mean error ranged from 15%–25%. This justified the calculation of correction factors. The correction factor of a PA category was calculated by averaging the errors measured on the D group in that PA category. Since most values were underestimated, the correction factors were greater than 1: 1.2, 1.16, 1.15, 1.17, and 1.25 for downhill walking, uphill walking, walking on the level, running, cycling, and RMR, respectively. Those correction factors were then applied on the calculated EE value for each PA category.

Using these different correction factors, a significant strong positive correlation between measured and predicted EE values was found in the VM group ($r = .97$, $P < .001$; Figure 2a). A Bland-Altman plot (Figure 2b) shows the agreement between estimated EE and measured EE as well as a mean bias of –3 kJ.

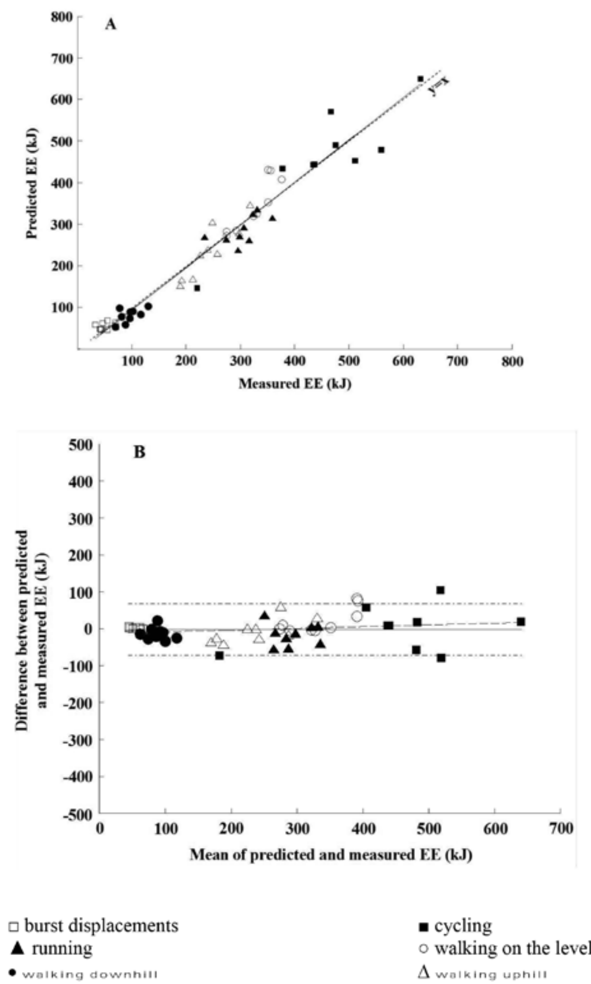

Figure 2 — Protocol I. **A:** relationship between measured and predicted energy expenditure (EE, kJ) values of structured PA ($r = .97$, $P < .001$). The equation of the linear regression model was $predictedEE = 1 \times measureEE - 8$. **B:** Agreement between measured and predicted EE (kJ) using the Bland-Altman technique. The mean (solid line) ± 2 SD ranges (dashed lines) are shown. Each PA category is denoted by the following same symbols as above.

Protocol II

Energy Expenditure Over 2 Hours. A significant correlation between measured and predicted EE values ($r = .97$ and $P < .001$) was found in the SVM group (Figure 3a). A Bland-Altman plot (Figure 3b) shows the agreement between estimated EE and measured EE. The 95% limits of agreement were –184 kJ to 209 kJ. The mean difference was 12 kJ. The model estimation errors were significantly correlated with EE ($r = .6$, $P < .01$). However, the differences did not exceed 10%.

Baseline Metabolic Rate. The actual baseline metabolic rate of the SVM groups was 1.36 ± 0.29 kcal/min.

Discussion

In the current study, we report an accurate model to assess PA and a reliable estimate of EE in real-life condition, using 2 accelerometers placed at the waist and ankle, and 1 GPS. To provide estimates of activity types, duration and intensity as well as an estimate of the associated EE, combination of sensors appears to provide more reliable data than when a single technique is used.[10,13,14]

This model was based on defining several thresholds assessed during the imposed PA program and during the individual calibration period. The results in protocol I showed that the model is capable of recognizing each of the 8 activities with very little error. This can be attributed to the fact that the classification model uses wide ranges for each parameter and for each PA, wide enough to encompass interindividual variability in gait characteristics in real-life conditions.

The current study needs to be considered as exploratory, given the small number of subjects evaluated and the little time frame used for the validation of the new

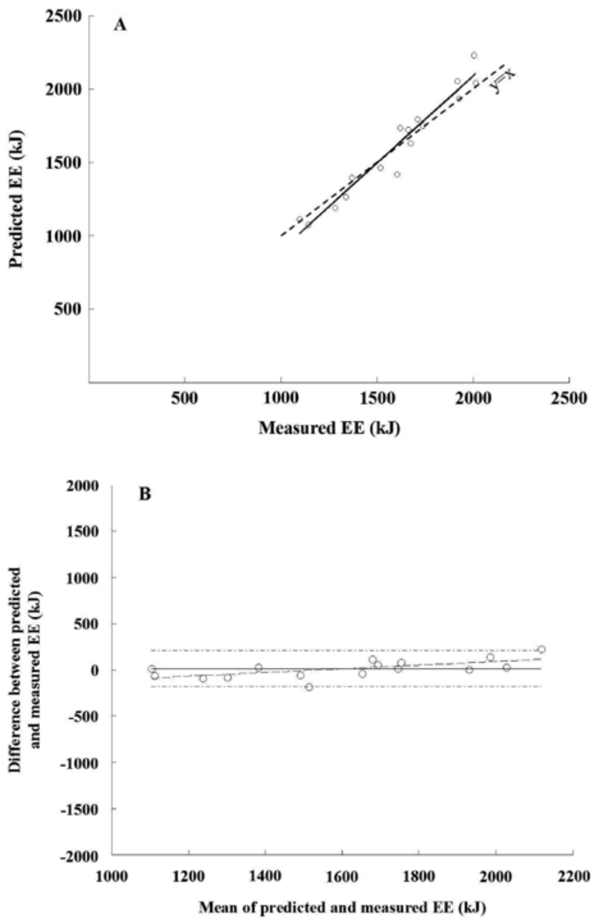

Figure 3 — Protocol II. A: Relationship between measured and predicted EE values (kJ) of 2h ad libitum PA in free-living conditions ($r = .97$, $P < .001$). The equation of the linear regression model was $predictedEE = 1.18 \times measureEE - 280$. B: Agreement between measured and predicted EE (kJ), using the Bland-Altman technique. The mean (solid line) ± 2 SD ranges (dashed lines) are shown.

model. Nevertheless, our results indicate that an accurate identification of the different types of PA could be achieved within 1 min accuracy and that it did not depend on PA duration. Furthermore, durations of walking and running activities (protocol I) were significantly lower than the actual duration by ca. 1 min. Although the confidence intervals calculations indicate that the model systematically underestimated the activity duration for most activities (Table 2), the error in the prediction did not exceed 1 min (Table 2). Given that the model classifies PA by analyzing the average of data from the 3 sensors within an epoch of 1 min, a 1-minute window can be composed of different sequential activities. Therefore, the average values calculated within that 1-minute window represents a composite, particularly during nonimposed PA in free-living conditions (protocol II). It should be noted that this uncertainty does not represent a substantial error as compared with the total duration of measurement. Moreover, the identification of PA types appears not to be crucial for EE determination for such short periods: it can be estimated that an EE error of 100% over 1 min period, if not compensated by a similar but opposite error, will produce a total error of less than 0.1% over an average day-time of 900 min, and even less over 24 hours.

The activity-related EE was evaluated from the determination of the PA types. Compared with using a single accelerometer,[33] it has been demonstrated that the latter, combined to the assessment of slope and speed, improved the EE estimation. A few accelerometers, used as tools for EE estimation, have been validated.[4] The accelerometers that were used generally presented a wide range of correlations with EE.[33] In the current study (protocol I and II), a highly statistically significant relationship was obtained between predicted and actual EE, strongly suggesting that the proposed combination of sensors and classification model would provide a reliable estimate of EE over prolonged study periods in real-life conditions.

The GPS technique constitutes a promising method for PA assessment.[34,35] However, GPS has several limitations, such as the inability to track displacement indoors, or the so-called "canopy effect" when satellite signals are lost and the position and speed of displacement cannot be tracked anymore by GPS. However, most of PA performed indoors is performed on the level, and since we used 2 accelerometers in conjunction with GPS, continuous PA monitoring can be successfully assured.

This model has some limitations that should be acknowledged. First, the classification of PA and EE assessment in the present model covers a limited number of activities, and particularly usual activities which are mostly performed during daily living. However, since these activities have been detected with limited errors, a more comprehensive list of activities may be subsequently added to this model. The latter may be detected adequately by means of the proposed combination of sensors. Second, this model required a calibration period to determine spontaneous walking characteristics of the subjects. Initially, it was hypothesized that the individual calibration was essential for accurately identifying the different PA types. We reanalyzed the data using the average thresholds for all subjects, assessed during the different calibration periods for the model development as well as the validation groups, to explore whether the accuracy of the model was substantially degraded. Interestingly, the imposed PA types were also correctly identified without individual calibration. Almost no difference was observed between the model used with vs. without calibration, at least for the types of activities we used. We believe that the ranges of thresholds values associated to each parameter are wide enough to encompass interindividual variability in gait characteristics. However, the nature of PA would be misclassified in case of individual data close to the preset averaged thresholds values of the classification tree. To prevent this type of misclassification, it is preferred to use a calibration rather than standard values (ie, threshold average for the whole group). To what extent standard values may be suitable while achieving accurate determination of PA remains to be further studied.

Conclusion

This exploratory study demonstrates that both PA and EE can be accurately tracked by a model combining GPS and accelerometry data, which allows for the assessment of unstructured indoor and outdoor PA, inactivity, as well as EE within 1 min accuracy. This algorithm could be easily implemented into commercially available "smart phones" with imbedded GPS, accelerometers and wireless communication technologies. Pairing such equipped devices with ankle/shoe wearable sensors such as accelerometers and connecting them to internet databases could provide researchers and physicians accurate and affordable tools to track PA behaviors in individuals in free-living conditions during extended periods.[36] Future technological improvements of the sensors, threshold values to detect other PA together with adjustment of the EE equations, in particular for children or elderly as well as health and disease, can be added into the present model and could represent an effective tool to track PA in real life.

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