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Measuring slope to improve energy expenditure estimates during field-based activities

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Abstract

This technical note describes methods to improve activity energy expenditure estimates using a multi-sensor board (MSB) by measuring slope. Ten adults walked over a 2.5-mile course wearing an MSB and mobile calorimeter. Energy expenditure was estimated using accelerometry alone (base) and four methods to measure slope. The barometer and GPS methods improved accuracy 11% from the base ($P < 0.05$) to 86% overall. Measuring slope using the MSB improves energy expenditure estimates during field-based activities.

Keywords

Accelerometry; Accuracy; Barometry; Energy Expenditure; GPS; Methodology; Slope

Introduction

We developed a multi-sensor board (MSB) to infer physical activity type using statistical machine learning (Brunette et al. 2005; Lester et al. 2005; Lester et al. 2006). The device also estimates horizontal velocity and energy expenditure, as well as movement through space using a global positioning system (GPS) (Lester et al. 2009). We recently evaluated the device under laboratory and field settings and found that it provided accurate measures of physical activity type and energy expenditure; however, the device underestimated energy expenditure in the field (Duncan et al. 2011).

In this technical note, we extend our previous findings by describing an approach to improve energy expenditure estimates during field-based activity by measuring vertical acceleration.

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Methods

Participants and procedures

Volunteers were recruited from a large urban university using print media. Interested individuals contacted study staff and were screened for conditions limiting mobility. Eligible participants were then scheduled for the field test. Each participant signed an informed consent form reviewed and approved by the local Institutional Review Board.

Age, sex, and ethnicity/race were obtained by self-report. Subjects were weighed on a self-zeroing digital scale and height was obtained using a wall-mounted stadiometer. During the test, subjects wore a single MSB on the right hip, clipped to a fanny pack secured around the waist, and a heart rate monitor (model T34, Polar Electro Oy, Kempele, Finland). They were also connected to a portable metabolic system (K4b², Cosmed Srl, Pavona di Albano – Rome, Italy), used as the criterion for energy expenditure. The system was calibrated indoors according to the manufacturer's instructions, and all tests were performed during a period when the outdoor and indoor temperatures were close to each other.

Subjects were guided over a 2.5-mile course with substantial elevation changes (Fig. 1). They walked at their self-selected pace; however, pace and route were often altered (at random) because of normal activities that occurred in and around campus (e.g., stopping at a cross-walk, navigating about mass groups of people when classes let out, detours around construction projects, etc.). The test lasted 45–60 min., preceded and followed by three minutes of sitting. Direct visual observation was used as the standard for activity classification. Two experimenters conducted each data collection; one would verbally instruct the subject using a script while the other recorded ground truth activities, times, and any explanatory notes on a tablet PC.

Sensor board and data processing

The MSB consists of a small sensing unit (2 3/8" × 3 1/8" × 7/8"), Bluetooth sensor node, and USB rechargeable battery (~25 grams for total unit). The unit includes a suite of multiple sensing (3-axis accelerometry, barometric pressure, humidity, temperature, light, audio, and GPS), data storage, communication, and local computation abilities. The main system components include: 1) an activity inference engine which classifies activities into different types (sitting, standing, walking, running, cycling, and stepping); 2) a step counter which uses signal analysis to detect steps and infer horizontal velocity (given subject sex and height); and, 3) prediction formulas (ACSM 2006) for converting the activity types listed above, body weight, and the horizontal, vertical (the calculation of which is described in the subsequent paragraphs), and resting components into an estimate of oxygen consumption. Energy expenditure is computed using estimated oxygen consumption and the caloric equivalent per liter of oxygen consumed (i.e., 1 L of O₂ liberates ~5 kilocalories of energy) (ACSM 2006). This approach is similar to others (Zhang et al. 2004) in which metabolic equivalents (METs) (Ainsworth et al. 2000) are used to estimate energy expenditure for detected movements.

Technical details of the MSB and approach for classifying activity type (Brunette et al. 2005; Lester et al. 2005; Lester et al. 2006) and estimating energy expenditure (Duncan et al. 2011; Lester et al. 2009) have been published. Although the accelerometer is the primary data stream for detecting activity types and movement speed, we also collect barometric pressure and GPS data. These two sensors alone or in combination, plus additional external sources (e.g., topographic data), can be used to provide a slope estimate. Together, our system has four methods available for estimating slope, which requires two parameters, the "rise" (change in elevation) and "run" (distance covered). These methods provide the

vertical component of the metabolic prediction equations that are used to estimate energy expenditure.

Barometric Pressure—Although barometric pressure varies and the elevation estimate may be off $\pm$ an offset value, the shape it traces will be a fairly accurate measure of change in elevation. The “rise” is combined with a form of “dead reckoning” to estimate the “run”, using current position based on estimated speed from the activity-inference and step speed estimates of the MSB, direction of travel, and elapsed time since the last determined position (or fix). This method has the advantage of being the lowest power consumer (i.e., the least data intensive solution).

GPS—Devices that are GPS-enabled are capable of estimating position in a 3-dimensional space when they have a good “lock” on four or more satellites. Depending on signal quality and the device used, the GPS position and altitude estimate can estimate grade. GPS only solutions are appealing to mobile phone platforms in which no barometer is available. However, they suffer from limitations in GPS signal reception, especially when indoors or in urban “canyons”.

Barometric Pressure + GPS—When GPS information is available, we can use the distance traveled with the barometric pressure elevation to estimate terrain profile. With a Kalman filter, the GPS readings combined with their error bars are used to generate an estimate of distance traveled.

GPS + GIS Sources—Several Geographic Information Systems (GIS) surface elevation profiles are available. The USGS-DEM (US Geological Survey – Digital Elevation Model) covers most of the U.S. with 15-meter accuracy; this was used as the elevation source here.

Statistical analysis

The criterion measure of energy expenditure was computed using the average oxygen consumption and respiratory exchange ratio (RER) values from the calorimeter over the entire test period. Average RER was converted to a thermal (caloric) equivalent using accepted standards (McArdle et al. 1996). We calculated accuracy for activity inference using equation 1 (top) and energy expenditure (C) using equation 2 (bottom). Means and units of variability were computed for each measure.

$$Inference = \frac{N_{\text{correctly identified activities}}}{N_{\text{all activities}}} * 100\%$$

$$Absolute\ accuracy = 100\% - \left| \frac{C_{\text{device}} - C_{\text{calorimetry}}}{C_{\text{calorimetry}}} \right| * 100\%$$

Improvement in accuracy was expressed as the percent difference in absolute accuracy for each of the grade estimation methods from the base estimate derived using the accelerometer alone. Statistical differences in each of the methods from the base estimate were analyzed using a mixed-linear model and generalized estimating equation to account for the correlated measures. Differences in energy expenditure for the two most accurate methods against the criterion were also analyzed using a mixed-linear model and generalized estimating equation. Analyses were performed using SAS version 9.2 (Carey, NC), with significance $P < 0.05$ *a priori*.

Results

Twelve adults were enrolled. Data was unavailable from two subjects because of corrupted MSB files for portions of those subject's data, leaving a final analytic sample of 10 with the following descriptive information: age 28.5 ± 4.7 years; 40% female; 86% White, not Hispanic; and body mass index 23.4 ± 3.3 kg/m².

Overall, accuracy of inferred activities compared with the ground truth was $98.4 \pm 0.8\%$. A plot of the estimated grades the person in Fig. 1 walked on is shown in Fig. 2.

Mean accuracy and variability of the energy expenditure estimates using the various grade methods are provided in Table 1. No single method consistently proved most accurate across all subjects; overall estimates improved 8–11% compared to the base estimate. The barometer and GPS methods provided the most accurate estimates, and both were different ($P < 0.05$) than the base method. In contrast, the Barometer + GPS and GPS + USGS DEM methods were not different ($P > 0.05$) than the base method. Table 2 shows differences in energy expenditure using the two best methods of grade estimation compared to indirect calorimetry. The differences in energy expenditure for these two methods compared to the calorimeter were relatively small, and neither method was different than the calorimeter or from each other ($P > 0.05$).

Discussion

The results of this technical note build on our previous work (Duncan et al. 2011) by showing methods to measure vertical acceleration to improve energy expenditure estimates during over-ground walking. Energy expenditure estimates improved 11% over accelerometry alone using a barometer and GPS signal, independently of each other, and these two methods provided estimates that were not different than the “gold-standard” calorimeter.

In our recent study (Duncan et al. 2011), we reported that accuracy in the field suffered because subjects exerted an increased amount of energy sweeping and walking while carrying a heavy load that the MSB was not able to detect. Instead, the MSB merely detected walking and estimated energy expenditure based on the speed of walking alone. Overall, estimates were 76% accurate in the field. Similarly, in the present study we found that overall accuracy was 74% using accelerometry alone. Although accuracy of this base estimate did not suffer in the present study because of an inability to detect specific activity types as was the case in our previous study, it was decreased because our subjects walked over a larger spatial course that included many elevation changes that accelerometry alone was not able to detect. This demonstrates one of the major limitations in using standard accelerometers for estimating energy expenditure. Another recent study (Yamazaki et al. 2009) demonstrated that oxygen consumption estimates by accelerometry alone during incline treadmill walking could be improved by the addition of altitude changes measured by barometry. Our study extends the literature by showing how barometry and other methods for estimating vertical acceleration can be applied in “real-world” settings that involve different topographies.

The low failure rate of the MSB, the rigorous field course used for evaluating accuracy, and comparison to a “gold-standard” are strengths of the present study. In addition, our absolute accuracy estimates are not artificially inflated as compared to calculating the “simple” average, which merely averages positive and negative deviations from the standard and results in an average difference that approaches the standard even though each individual measurement may have a large magnitude of absolute error.

There are also several limitations. First, accuracy for activity recognition may be artificially high because a limited range of activity types were performed. Second, energy expenditure estimates were influenced by a number of factors, including the following: resting energy expenditure was estimated using a MET value ($3.5 \text{ ml O}_2 \cdot \text{kg}^{-1} \cdot \text{min}^{-1}$) and the caloric equivalent per liter of oxygen consumed (5 kcal) was used to convert estimated oxygen consumption to energy expenditure, both of which may have reduced accuracy. Using prediction equations for subsequent energy expenditure estimates also likely led to error because they are not applicable for all speeds and types of activity. Despite these issues, our energy expenditure estimates were still quite accurate. Further, we estimated energy expenditure using the entire period of activity including transitions when subjects were not in steady-state. Although this may be a major source of error, transition is a natural part of physical activity, particularly in regularly active persons who frequently change from one activity to another. Finally, this technical note included only 10 subjects and thus has limited statistical power. This is evident by examining the slightly overlapping 95% CIs between both the barometer and GPS methods and the base estimate. However, it should be appreciated that our primary purpose was to explore whether we could improve upon field-based energy expenditure estimates previously reported for the MSB by measuring vertical acceleration. In future studies, we will extend proof-of-concept findings presented here by using the doubly-labeled water technique as the gold standard over an extended period in a larger, more diverse sample based on the effect sizes derived in this pilot study. Taking the higher mean accuracy and lower root mean squared error of the barometer method into account, compared to the base and other grade estimation methods, suggests that this method may provide more accurate and precise energy expenditure estimates than accelerometry alone.

Despite the limitations, coupling data from accelerometry with additional data sources including GPS, and barometry, is a practical approach to improve energy expenditure estimates during free-living physical activity that holds promise in the activity measurement field.

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Figure 1.

A global positioning systems (GPS) trace (orange line) for one subject navigating the field course (white line) plotted on top of a satellite view (image ©2009 Google and ©2009 Europa Technologies). Note the annotations indicating inferred activities (walking and standing are shown for this subject).

Figure 2.

A plot of the estimated grades the person in Figure 1 walked on using four methods to determine slope, including global positioning systems (GPS), barometric, and geographic information systems (GIS; noted as USGS DEM) data sources.

Table 1

Mean accuracy and variability of caloric expenditure estimates using different methods of grade estimation.

	Absolute Accuracy				Improvement *	
	Mean	SD	95% CI	Range	RMSE	
Base estimate	74.4	7.2	69.3 – 79.6	64.0 – 85.2	27.5	
Barometer only	83.0 [†]	7.6	77.5 – 88.5	71.7 – 94.6	23.0	10.8%
Barometer + GPS	81.3	6.8	76.4 – 86.1	72.6 – 89.3	22.7	8.7%
GPS + USGS DEM	80.9	8.0	75.1 – 86.6	69.8 – 89.8	26.5	8.2%
GPS only	83.1 [†]	8.3	77.2 – 89.0	70.9 – 93.4	34.3	10.9%

Data for accuracy presented as the mean percent with units of variability (standard deviation, SD; 95% confidence interval, CI; range; and root mean square error, RMSE). Absolute accuracy calculated as $(100 - \text{absolute percentage error})$; where $\text{absolute percentage error} = [\text{total kilocalories computed from device} - \text{total kilocalories from the calorimeter}] \div \text{total kilocalories from the calorimeter} \times 100$. The RMSE was calculated from separate regression models for each of the four grade estimation methods with the calorimetry standard as the dependent variable.

Abbreviations: GPS, global positioning systems; and USGS DEM, United States Geological Survey - Digital Elevation Model.

* Improvement expressed as the percent difference in absolute accuracy for each of four grade estimation methods from the base estimate derived using accelerometer data only.

[†] Indicates significant improvement vs. base estimate at $P < 0.05$.

Table 2

Differences in caloric expenditure estimates using best methods of grade estimation compared to indirect calorimetry.

	Caloric Expenditure	Difference [*]	
		Compared to Calorimeter	Compared to Barometer
Calorimeter	245.0 (205.1 – 285.0)		
Barometer only	200.5 (160.5 – 240.4)	44.6 (–11.9 – 101.0)	
GPS Only	206.8 (166.9 – 246.7)	38.2 (–18.2 – 94.7)	–6.4 (–62.8 – 50.1)

Data for caloric expenditure presented as least squares means with 95% confidence limits.

Abbreviation: GPS, global positioning systems.

^{*} Difference expressed as: difference between least squares means for the standard (calorimetry) and each of the two grade estimation methods, and between each of the two grade methods.