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Accurate Prediction of Energy Expenditure Using a Shoe-Based Activity Monitor

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ABSTRACT

Purpose: The aim of this study was to develop and validate a method for predicting energy expenditure (EE) using a footwear-based system with integrated accelerometer and pressure sensors. **Methods**: We developed a footwear-based device with an embedded accelerometer and insole pressure sensors for the prediction of energy expenditure. The data from the device can be used to perform accurate recognition of major postures and activities and to estimate EE using the acceleration, pressure and posture/activity classification information in a branched algorithm without the need for individual calibration. We measured EE via indirect calorimetry as sixteen adults (BMI: 19-39 $kg \cdot m^{-2}$) performed various low-to-moderate intensity activities and compared measured vs. predicted EE using several models based on the acceleration and pressure signals. **Results**: Inclusion of pressure data resulted in better accuracy of EE prediction during static postures such as sitting and standing. The activity-based branched model that included predictors from accelerometer and pressure sensors (BACC-PS) achieved the lowest error (e.g. root mean squared error (RMSE) of 0.69 METs) compared to the accelerometer-only based branched model BACC (RMSE of 0.77 METs) and non-branched model (RMSE of 0.94-0.99 METs). Comparison of EE prediction models using data from both legs vs. models using data from a single leg indicate that only one shoe need to be equipped with sensors. **Conclusion**: These results suggest that foot acceleration combined with insole pressure measurement, when used in an activity-specific branched model, can accurately estimate the energy expenditure associated with common daily postures and activities. The accuracy and unobtrusiveness of a footwear-based device may make it an effective physical activity monitoring tool.

Keywords: indirect calorimetry; pressure sensors; accelerometry; wearable sensors; shoe

INTRODUCTION

Paragraph Number 1 Physical activity (PA) levels and the energy expenditure (EE) associated with physical activity influence human health (33). As a result, individuals are advised to participate in programs that promote increased energy expenditure (EE) via exercise, physical activity and changes in posture allocation (e.g. less sitting) (16). Accurately quantifying levels of physical activity (PA) and associated EE in adults and children will provide insights into the dose-response relationship between PA/EE and health outcomes, allow evaluation of the effectiveness of interventions that aim to increase PA/EE and aid in treating metabolic disorders associated with obesity. Monitoring physical activity patterns objectively (e.g. via accelerometry) can improve PA/EE estimates, but devices that can accurately estimate total daily and activity-specific EE are essential. For example, the magnitude of positive energy balance that results in gradual weight gain is on the order of 25-100 kcal/day. In addition, instruments that are unobtrusive and easy to use may improve compliance and reduce limitations to physical activity due to the device interfering with movement.

Paragraph Number 2 Accelerometry (ACC) has emerged as one of the most popular approaches to EE prediction (6,10,12,15,25,28). Although useful, single accelerometers have one major drawback in that they tend to significantly underestimate the energy cost of static postures such as standing activities (e.g. household tasks) and non weight-bearing activities (e.g. cycling) (18). As a result, they fail to explain a considerable portion of energy expenditure variability in daily living tasks. One strategy to improve EE estimation has been to use multiple sensors, either additional accelerometers or other types of sensors (e.g. heart rate) (7,16,29,30). For example, combining heart rate and ACC has been shown to substantially improve the accuracy of energy expenditure prediction (7,29,30), as has the use of multiple accelerometers (35). Recently, several studies have demonstrated improved EE estimation with a single accelerometer by using more sophisticated modeling approaches including Artificial Neural Networks (28), distributed lag and spline modeling (11) and branched algorithms (12,13). Another way to achieve an improvement in EE accuracy has been to use the ACC data to classify activity, which is used in predictive models based on the type or intensity of the activity (6,12,28).

Paragraph Number 3 Heart rate monitoring and multiple ACCs are the most common ways explored to supplement single ACC's in energy expenditure prediction. Exploration of other approaches may lead to an improved prediction accuracy and greater convenience to a weight management participant. Recently, we developed a wearable shoe-based device (26) which has an embedded accelerometer and pressure sensors positioned in the insole. The main appeal of using the device for energy expenditure prediction is its potential accuracy, non-intrusiveness, light weight and ease of use. We have developed a posture and activity recognition model for this device which is able to achieve 98% accuracy in subject-independent classification of 6 major postures and activities (sitting, standing, walking, ascending stairs, descending stairs and cycling) (27). This enables an activity-specific branched approach to energy expenditure prediction that may result in relatively good EE estimates for a variety of daily living tasks. The inclusion of insole pressure sensors in the device also allows the exploration of whether the intensity of physical activity may be correlated with range and frequency of foot pressure changes and whether pressure data can supplement the accelerometer data for further improvement in accuracy of predicting EE. Thus, we developed and validated a method for using accelerometer and pressure sensors signals to predict EE conditioned on a specific activity group and without need of individual calibration. Several studies reported using shoe-based sensors (3,17,20), however, their research concentrated on detecting gait characteristics, rather than posture/activity classification and energy expenditure estimation. There are also several commercially distributes shoe-based systems (such as Pedar (31) and F-Scan (14)) which incorporate pressure sensors in the insoles for the dynamic pressure measurements. Although these systems have wide applicability such as kinetic analysis of gait, shoe research and design, orthotic design, podiatry and sports biomechanics, they are not designed specifically for posture/activity recognition and energy expenditure prediction. A study reported in (34) used an array of 32 plantar pressure sensors to classify locomotion (walking, running and up/down stairs). Another study (32) estimated daily energy expenditure using a foot-contact pedometer but did not attempt to classify postures or specific activities with the device. We introduce a shoe-based device that will be the first in the area of footwear-based systems to be used for accurate posture/activity recognition and energy expenditure estimation.

Paragraph Number 4 The main purpose of this study was to test the overall feasibility of energy expenditure prediction using a novel shoe-based device, in particular, we aimed to perform the following tasks : 1) to compare the accuracy of EE prediction using this device vs. existing methods using single ACC or ACC/HR sensors; 2) to compare the accuracy of prediction performance of a model using accelerometer and pressure sensors signals vs. a model that uses only accelerometer signal; 3) to validate the branched modeling approach for prediction of energy expenditure for each specific posture and activity; 4) to evaluate the need of sensors to be embedded in both shoes. We hypothesized that the combination of ACC and pressure data would provide more accurate EE estimates compared to single ACC /EE methods and that sensors would only be required in a single shoe.

METHODS

Subjects

Paragraph Number 5 Sixteen adult subjects participated in the study. The University Institutional Review Board approved the study and each subject provided informed consent. In order to test the device on a diverse population, we recruited participants who were lean to obese. Based on self-report, participants weight was stable (<2 kg weight fluctuation) over the previous 6 months. Individuals who were healthy, non-smokers, and sedentary to moderately active (< 2-3 bouts of exercise/wk or participation in any sporting activities < 3 hr/wk) were invited to participate in the study. Pregnant women and those who had impairments that prevented physical activity were excluded. The physical characteristics of participants are shown in Table 1.

Study design

Paragraph Number 6 Participants reported to the laboratory in a fasted state (>4 hours) for a single three hour visit. Each participant was asked to perform a variety of postures/activities while wearing a portable metabolic cart system and the appropriately sized shoe device with embedded sensors. The postures included sitting and standing and the activities included walking, jogging, stair ascent/descent and cycling (Table 2). Each posture/activity trial was six minutes in duration and subjects were allowed five minutes rest between trials. Trial order was not randomized. Metabolic data was not collected during stair ascent/descent, as this activity was performed in two-story stairwell which did not allow establishment of metabolic steady-state. As a result, we estimated EE as each participant performed 13 different activities from four posture/activity groups (Sit, Stand, Walk/Jog and Cycle).

Paragraph Number 7 Participants were not restricted in the way they assumed postures and or performed activities. Standing did not require any specialized equipment; a chair with a rigid back was used for sitting; walking/jogging was performed on a motorized treadmill (Gait Trainer 1, Biodex, Shirley, NY); cycling utilized a bicycle ergometer (Erogomedic 828E, Monark, Sweden). During the fidgeting trials, subjects were allowed to make small, normal leg movements (e.g. crossing legs or shifting weight).

EE measurement

Paragraph Number 8 To determine metabolic rate and associated EE during each trial, we measured the rates of oxygen consumption (VO_2) and carbon dioxide production (VCO_2) using a portable open circuit respirometry system (Oxycon Mobile, Viasys, Yorba Linda, CA). Before the experimental trials, we calibrated the system with known gas concentrations and volumes. For each trial, we allowed four minutes for subjects to reach steady state (no significant increase in VO_2 during the final two minutes and a respiratory exchange ratio (RER) <1.0) and calculated the average VO_2 and VCO_2 (ml/sec) during minutes 4-6 of each trial. We calculated gross metabolic rate (W/kg) from VO_2 and VCO_2 using a standard equation (6). Energy expenditure was then calculated from VO_2 and RER.

Movement and foot pressure measurement.

Paragraph Number 9 The sensor data for this study were collected by a wearable sensor system embedded into shoes (Fig. 1). Each shoe incorporated five force-sensitive resistors embedded in a flexible insole and positioned under the critical points of contact: heel, metatarsal bones and the great toe (hallux). The acceleration data were collected from a 3-dimensional MEMS accelerometer positioned on the back of the shoe. The goal of the accelerometer was to detect orientation of the shoe with respect to gravity, to characterize the motion trajectory and to help characterize the amount of movement in a specific posture or activity. Pressure and acceleration data were sampled at 25Hz and sent over a wireless link to the base computer.

Paragraph Number 10 The wireless system used for data acquisition was based on Wireless Intelligent Sensor and Actuator Network (WISAN) (21). The battery, power switch and the WISAN board were installed at the back of the shoe as shown on Fig. 1(b). The sensor system was lightweight (<40g) and created no visible interference with the motion patterns in subjects.

Model

Paragraph Number 11 For the model construction we used a group rather than individual approach: the data used for training were pooled from several subjects and such model was then tested on the validation set which included data from subject(s) that were not in the training set. For each posture and activity the sensor data were collected during a 1 minute interval in which subjects were in metabolic steady state (minutes 4-6 of each trial). Each one minute recording resulted in approximately 1500 (25Hz·60s) points of pressure and acceleration data per channel. For the 16 subjects who participated in the study there were a total of 208 such recordings.

The following data were available for each recording:

- response variable: energy expenditure, EE, $kcal \cdot min^{-1}$;
- anthropometric measurements (weight, height, BMI, age, gender, shoe size);
- triaxial accelerometer signals: superior-inferior acceleration (***Acc1***), medial-lateral acceleration (***Acc2***), anterior-posterior acceleration(***Acc3***);
- pressure sensors signals: heel (***Sens1***), 3rd meta (***Sens2***), 1st meta (***Sens3***), 5th meta (***Sens 4***), and hallux (***Sens5***);

Paragraph Number 12 To validate the branching approach, energy expenditure prediction was performed as a two-step process, with the step one being classification of postures/activities into one of the four groups: “Sit”, “Stand”, “Walk” and “Cycle”; and step two being prediction of energy expenditure using one of the four regression models built for a given posture/activity group. Each 1-minute interval of sensor data was first classified as belonging to one of the four activity groups using our earlier developed algorithm for posture/activity recognition (27). The same sensor data from each 1-minute interval were consequently used for training and validation of one of the four regression models for predicting energy expenditure. Thus, the branching approach involved constructing four branch models: “Sit”, “Stand”, “Walk”, “Cycle” contingent upon prior classification of every 1-min recording into one of these groups for training or validation. Another major goal was to justify the use of the pressure sensors (in addition to accelerometer) in EE prediction. This led to the development of the following four models to predict EE in kcal·min^{-1} using predictors described above:

1. BACC-PS. This model was branched by activity and consisted of four separate branch models (“Sit”, “Stand”, “Walk”, “Cycle”). The predictors included anthropometric measurements, accelerometer and pressure sensors as predictors;
2. BACC. This branched model also consisted of four separate branch models (“Sit”, “Stand”, “Walk”, “Cycle”) and included anthropometric measurements and accelerometer data as predictors but the pressure data were not used;
3. ACC-PS. This was a non-branched model (no activity classification) that used the same predictors as BACC-PS.
4. ACC. This was a non-branched model using the same predictors as BACC.

The purpose of constructing different models was to investigate if the performance is improved by branching the model (i.e. classifying the activity) and also by including predictors derived from pressure signals.

Paragraph Number 13 Accelerometer and pressure sensors signals expressed in ADC units (the signals were digitized by a 12-bit analog-to-digital converter) were preprocessed to extract meaningful metrics to be used as predictors for the model. For both pressure and acceleration sensors all of the following metrics were extracted and tested for the inclusion into each model as predictors: coefficient of variation (***cv***); standard deviation (***std***); number of “zero crossings” (***zc***), i.e. number of times the signal crosses its median normalized by the signal's length; entropy H of the distribution X of signal values (***ent***) computed as: $H(X) = -\Sigma p_k \log p_k$, where p_k is the relative frequency of values fallen into the k^{th} interval (out of 20 equally sized intervals) in the sample distribution of signal values. These metrics were selected for the following reasons. Coefficient of variation and standard deviation of a signal should indicate the amount of motion produced during recording, with the difference that coefficients of variations are affected by signals mean value (for example, the gravitational component of acceleration) while standard deviation is not. Number of median crossings is an indicator of the frequency of changes in the signal, which is important to identify the intensity of motion (like speed of walking). Entropy reflects the distribution of the signal across the range of its values and is a valuable predictor for walking due to the fact that as speed of walking increases the time of feet ground contact decreases relative to the swing time and, thus, signal values become more uniformly distributed across the range, leading to an increased entropy.

Paragraph Number 14 For each model we used the derived metrics as possible predictors for the ordinary least squares linear regression. The transformed predictors (log, inverse and square root) and interactions (as products of 2 or more candidate predictors) were also considered as separate linear terms within regression.

Paragraph Number 15 In branched models a separate model was constructed for each type posture/activity: “Sit”, “Stand”, “Walk” and “Cycle”. For all branched (as collections of the four separate branch models) and non-branched models selection of the most significant set of predictors was performed using the forward selection procedure. We used the “leave-one-out” approach for cross-validation when training and predicting the EE for each type of activity for every subject. For every left out subject all of the data related to this subject were removed from the training set. Model (coefficients) computed using the rest of the subjects sample was then used to predict the EE for all trials of the left out subject. The best set of predictors had to provide the best fit (by producing the maximum adjusted coefficient of determination, R^2_{adj} and the minimum Akaike Information Criterion, AIC) in the training step and the best predictive performance (the minimum mean squared error, MSE and the minimum mean absolute error, MAE) in the validation step.

Paragraph Number 16 The input for the models was the data from sixteen subjects who had complete metabolic and sensor data for all thirteen trials. In the “walk” activity group some subjects did not have energy expenditure record (unable to achieve metabolic steady state while jogging) or had no sensors signals recorded for some trials within this group, these 10 trials were dropped from each model's input. An additional 1-minute recording for cycling activity for a particular subject contained more than 50% of corrupted data due to sensor failure. This recording was also dropped from the analysis. Thus, the sample size of the input data for each model was 16·13 – 11 = 197 trials.

Paragraph Number 17 Measured and predicted energy expenditure values in kcal·min^{-1} for each experiment were then converted to METs for both branched ACC-PS and ACC models and their non-branched versions. The conversion from kcal·min^{-1} to METs was done by representing the energy expenditure for any given epoch as a multiple of resting energy expenditure. We used energy expenditure during quiet sitting as a valid estimate of resting metabolic rate for each subject due to established convention (1,2). This conversion was performed to enable direct comparison of our results with those that have been recently published (9,12,28).

Paragraph Number 18 One of the goals of the analysis was to establish the need of using sensors on both shoes. Several versions of the branched ACC-PS model (as a representative model) were constructed using accelerometer and pressure sensors data separately from each shoe and both shoes together.

Statistics

Paragraph Number 19 The following performance assessment measures were computed for each EE prediction model:

- **$RMSE_{MET}$**, the root mean squared error for energy expenditure prediction expressed in METs. This error is computed as the difference between model predicted EE and the measured EE for each trial.
- **95% confidence intervals for $RMSE_{MET}$**, computed as bootstrapping estimates by generating 5000 samples of absolute errors (predicted minus actual energy expenditure) drawn from the original sample, calculating $RMSE_{MET}$ for each such sample and computing bounds for the middle 95% of the created population of $RMSE_{MET}$'s.
- **ARD**, the Average Relative Difference (signed):

$ARD = mean((predEE - EE)/EE)$

- **Bias,** the mean difference between predicted and measured energy expenditure in METs: $bias = mean(predEE - EE)$

- **Interval of agreement** for prediction of energy expenditure in METs, calculated as given in (1): $(bias \pm 2 \cdot SD(bias))$

Paragraph Number 20 Bland-Altman plot analysis (4) was conducted to reveal any systematic pattern of the error (calculated as the difference between predicted and measured EE) across the range of measurements and to assess the bias and interval of agreement for prediction of EE.

Paragraph Number 21 Passing-Bablok regressions (a robust alternative to least squares regression) for all four models and for two units of prediction (kcal·min^{-1} and METs) were constructed as described by Passing and Bablok (24). Passing-Bablok regression is best suited for method comparison because it allows measurement error in both variables, does not require normality of errors and is robust against outliers. In addition, Passing-Bablok regression procedure estimates systematic errors in form of fixed (by testing if 95% CI includes 0) and proportional bias (by testing if 95% CI includes 1).

RESULTS

Paragraph Number 22 Each raw signal of the accelerometer (3 sensors) and 5 pressure sensors was represented by a vector of approximately 1500 measurements (25 measurements per second). Sample raw signal for all 8 sensors is given in Fig., SDC1 for walking 2.5 mph activity. Using the raw signal data, predictors for each model were computed by the following approach. Metrics for the accelerometer and pressure sensors signals ***(cv, std, zc*** and ***ent)*** were computed separately for the left and right shoe. Then the corresponding predictor values were formed as the average of the left and right shoe metrics for the accelerometer signals, and as the maximum value of the left or right shoe metrics for the same pressure sensor signals. The reason for the maximum (rather than the average) in combining the left and right shoe metrics is that some of the pressure sensors experienced occasional failure in three subjects. The signal from a failed sensor would register as a constant zero value (no pressure), thus, using the maximum pressure ensured that no data from failed sensor were used in training or validation. In particular, use of the maximum value resulted in the reduction of the corrupted data from 5% to around 1.7%.

Paragraph Number 23 To facilitate the branching approach, our automatic classification model (26) for posture/activity recognition was applied to each of the 197 1-minute recordings to assign it into four activity groups ("Sit", "Stand", "Walk", "Cycle") for further construction and validation of the corresponding branch models. For these data there was 100% rate of correct classification among all 1-minute recordings with respect to the four activity groups.

Paragraph Number 24 Final linear regression coefficients for the branched ACC-PS and branched ACC models after selection of the best set of predictors are reported in Table, SDC2 and Table, SDC3 respectively. The final non-branched ACC-PS and non-branched ACC model regression coefficients are given in Table, SDC4. Among the anthropometric characteristics of subjects used as possible predictors only Weight and BMI showed significance for energy expenditure prediction for all models. In particular, gender-stratified models did not show any improvement in the prediction performance. Similar effect was reported by previous studies where gender has not been shown to improve EE estimates from accelerometry data (5,6,19). The coefficients for all models were obtained by averaging the coefficients of the 11 runs (one for each left out subject) of the OLS (Ordinary Least Squares) regression on the training sets.

Most of the coefficient of variations for coefficients of all of these models were within [0.07, 0.3], which suggests that the regression coefficients were highly stable.

Paragraph Number 25 Almost all coefficients for all models were highly stable over all runs as given by low absolute values of coefficients of variation (CV). As can be expected, weight and BMI always explain part of the variability of each model, while other physical characteristics were highly correlated to weight variable and didn't add to the fit or the prediction performance of either model. Results shown in Table 3 include performance comparison of the proposed BACC-PS model, BACC model, non-branched ACC-PS, non-branched ACC.

Paragraph Number 26 Bland-Altman plots (constructed for both EE, $kcal \cdot min^{-1}$ and EE, METs prediction) for all four models are given in Fig. 2. Sub-figures (a)-(b) are Bland-Altman plots for branched models, sub-figures (c)-(d) are Bland-Altman plots for non-branched models. The common characteristic for all these plots (models) is that the accuracy of prediction is slightly better for small than for large EE values (i.e. better accuracy for sitting and standing).

Paragraph Number 27 Passing-Bablok regression analysis was conducted using Matlab implementation (23) of the method described in (24). Examination of the presence of fixed (intercept ≠ 0 if 95% CI does not contain 0) and proportional (slope ≠ 1 if 95% CI does not contain 1) bias of the models showed that except for one case (non-branched ACC model which showed fixed bias) none of the four models exhibited either kind of bias (see Table, SDC5, examination of the presence of fixed and proportional bias and linearity). All ACC-PS models (branched and non-branched) provided better prediction over the ACC models as indicated by slope values closer to the unity than those of the ACC model (see Passing-Bablok regression analysis in the supplemental materials). In addition, the branched model regression coefficients appear to be more precise since they provided the narrower confidence intervals for both slope and intercept than those for the non-branched models.

Paragraph Number 28 Linearity test indicated absence of linearity for all non-branched models while for branched models linearity was always very strong (see Table, SDC5, examination of the presence of fixed and proportional bias and linearity). Additional proof of the strength of linear relationship between predicted and measured EE values is given by correlation and concordance coefficients. There is clear tendency of both coefficients to increase from non-branched to branched models and from ACC to ACC-PS models. Lack of linearity of the non-branched models is also noticeable in their Passing-Bablok regression plots (Fig. 3), which show clear curvature in the scatter plots unlike in those of the branched models.

Paragraph Number 29 As a last step, we investigated the effect of inclusion of predictors from both shoes vs. a single shoe into the model using the BACC-PS model. We compared performance of the BACC-PS models that used the difference metrics derived from the difference between signal form left and right shoe and/or the best selected set of predictors (as metrics ***cv, std, zc*** and ***ent)*** computed separately for each shoe. Overall, models based on metrics derived for both shoes perform slightly better (RMSE was within 0.68-0.70 METs) than single shoe models (RMSE was 0.78 METs for left shoe-based model and 0.72 METs for right shoe-based model), see Table, SDC6, comparison of BACC-PS model performance using predictors from single shoe and both shoes. However, the RMSE values were still below those found for BACC and the rest of the models. Also, the improvement of both-shoe over single-shoe models can be attributed mostly to the lost of data due to sensors failure: both-shoe models were able to mitigate the effect of the corrupted data by using the fact that simultaneous sensors failure on both shoes was rare, and by applying either averaging or maximization to left and right shoe sensor metrics. Thus, for all practical purposes single shoe models can be successfully used.

DISCUSSION

Paragraph Number 30 Our results suggest that a shoe-based device with embedded accelerometer and pressure sensors can be used to accurately predict energy expenditure during typical postures/physical activities. Such a device may be a useful tool for individuals interested in weight management. The combination of posture allocation/physical activity data (e.g. minutes sitting and walking) with accurate estimates of EE can be used to help individuals modify or maintain energy balance. A shoe-based device may also be "invisible" and unobstrusive and lead to increased use, further facilitating weight management success.

Paragraph Number 31 The EE prediction accuracy of our device and branched model is similar to recent studies that have used single accelerometers, multiple accelerometers and heart rate/accelerometer combinations. Choi et al. (11) used Actigraph accelerometers placed at the hip, wrist and/or ankle and distributed lag and spline modeling to predict EE and reported RMSE of ~0.6 kcal/min (0.5 METs) across a range of activities with the accelerometer mounted at the ankle. Staudenmayer et al. used a single hip-mounted accelerometer (Actigraph) and an artificial neural network to estimate EE of a variety of activities and reported an RMSE of 0.75 and 1.22 METs using activity and minute-by-minute estimates of EE, respectively (28). A study by Crouter et al. that compared EE estimation using hip-mounted accelerometery vs. indirect calorimetery reported systematic bias of 0.1 METs with 95% limits of agreement of (-1.4, 1.5) METs (12). Although our results are not directly comparable to those from Staudenmayer et al. and Crouter et al. as our subjects did not wear a hip mounted accelerometer and we did not compare actual and predicted EE during the entire period of each trial, the similar RMSE values suggest good agreement. Brage et al. used a device that measured heart rate and accelerometry (Actiheart) to estimate EE and found that the RMSE was within [0.87, 1.11] METs during walking/running activities (8). Thus, our results suggest the use of pressure and acceleration to identify activity and predict EE are at least as accurate or better compared to other, recently proposed methodologies.

Paragraph Number 32 Our results support the measurement of plantar pressure as a way to improve EE prediction compared to a single accelerometer. As shown in Table 3, the inclusion of pressure sensor metrics improved all prediction performance measures. In particular, RMSE was reduced ~7% for branched models (0.77 to 0.69 METs) and non-branched models (0.99 to 0.94 METs). There was also clear reduction in bias and the width of the interval of agreement when comparing ACC to corresponding ACC-PS models. Because there are clear differences in the magnitude and distribution of insole pressure across postures and activities, insole pressure measurement allows for accurate classification of activity, which can then be used to develop activity-specific models that improve estimates of EE. The inclusion of insole pressure also improves EE estimation within an activity classification. In particular, there was a significant decrease in error rate in estimating cycling EE. This likely due to the changes in plantar pressure that are associated with changes in the intensity of cycling, something difficult to detect using an accelerometer. It is interesting to note that we were able to achieve accurate activity classification using only the 1st metatarsal pressure sensor and three-dimensional acceleration (27) and the EE models also used the sensors under the metatarsals. This suggests that although multiple sensors may be required to achieve a high level of classification and EE estimation accuracy, it may be possible to use fewer pressure sensors without a decrease in performance. In general, these improvements in accuracy add support to the literature demonstrating that devices that use multiple sensors improve EE estimation (7,22,35).

Paragraph Number 33 The use of activity-specific branched models significantly improved estimates of EE. In particular, RMSE decreased ~25% (0.94-0.99 to 0.69-0.77 METs) and the width of the interval of prediction is reduced by almost 1 MET when branching was used. This improvement is likely sensitive to classification accuracy as estimating EE on the wrong activity could lead to substantial errors. Our classification algorithm accuracy was 100%, in part because of the combination of sensors. We elected to classify 13 activities performed by the subjects in this study into four general activity groups based on common postures and activities, rather than include more specific categories. This classification attempted to address the most common issues encountered in EE estimation using accelerometers (underestimation of energy cost of standing and non-weight bearing activities such as cycling) by recognizing similar activities as one class and using a branched model for each activity class. For example, inclusion of level, incline/decline and loaded walking as well as running data in the "walk" class resulted in a wide range of acceleration, pressure and metabolic values that were used to develop the walk model. This likely improved the models ability to estimate EE during a locomotor task. Recently, Bonomi et al. used a single hip-mounted accelerometer combined with a branched model to classify activities and the intensity of locomotor tasks (i.e. walk and run) and reported improved estimates of activity EE vs. a non-classified approach (6). Other studies have used branching algorithms based on accelerometry variability (12) or heart rate and accelerometer thresholds (9,13) but without activity classification and have also reported improved EE accuracy. Collectively, these results support the use of branching models (with and without activity classification) to improve EE estimation.

Paragraph Number 34 Developing EE prediction models based on activity classification, while intuitively appealing, also raises important questions. Chief among them is how many different classification groups are necessary. As noted above, we used a very general activity classification. While this may have improved the prediction accuracy with our modeling approach, a narrower classification category (e.g. level walking) may allowed for the development of less complex models to predict activity-specific EE. For example, Bonomi et al. classified activity and estimated EE using a standard value from a compendium (6). Recent investigations have classified common activities based on a single accelerometer and have elected to use more classes of activities. Bonomi et al. identified six activities (lie, sit/stand, active standing, walk, run and cycle) while Staudenmayer et al. identified 18 activities ranging from washing dishes to running (6,28). If the focus of a device is to identify the time spent in various activities, a large number of potential activities would seem important. However, a large number of activity designations may make the combination of activity classification/EE estimation more complex, without a marked improvement in EE prediction accuracy given the similarity in EE form many activities. Clearly, additional research is needed to determine the relationship between activity classes and EE prediction accuracy.

Paragraph Number 35 Despite very good performance of the proposed model for energy expenditure prediction, a limitation of the stated results is a relatively small sample size (16 subjects). However, we introduced a wearable shoe-based system and aimed to test the overall feasibility of EE prediction using this new device on a relatively small pilot sample. Despite its small size the sample covers a wide range of weight/height/BMI characteristics of subjects. As seen from the confidence intervals for RMSE for the proposed BACC-PS model even the upper limit of the interval (0.86 METs) fits within the currently reported results from existing studies on EE prediction (8,28), which allows us to conclude that the current results are reliable with the current sample size. Future work will include collection of a significantly larger data set (with respect to number of subjects and the variety and length of activities) to support results provided in this paper.

Paragraph Number 36 While our results are encouraging and suggest that a footwear based system can provide accurate estimates of EE, such a system is not without limitations. For example, pressure and acceleration data outside of the laboratory may be different for a given activity (e.g. cycling) and thus present a challenge for accurate EE estimation. In addition, footwear based systems are only viable when the individual is wearing shoes. While this is a strength for worksite or school or other daytime monitoring, it may present a challenge if the objective is estimation of EE during all waking hours. Future studies that explore optimal classification categories and test devices in a free-living (including outdoor) setting are clearly needed. Footwear based systems will also have to be extremely rugged to withstand the environmental and physical challenges associated with this location.

Paragraph Number 37 In summary, our results suggest that measuring the acceleration and insole pressure in the shoe of a single foot can be used to classify activity and when combined with a branched model can accurately estimate the EE associated with common daily postures and activities. The accuracy and unobtrusiveness of a footwear-based device may become an effective weight management tool.

ACKNOWLEDGMENTS

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The results of the present study do not constitute endorsement by ACSM.

CONFLICT OF INTEREST

Dr. Sazonov and Dr. Browning have equity interest in Physical Activity Innovations LLC (recipient of NIH grant 1R43DK083229 used to support this work)

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FIGURE CAPTIONS

Fig. 1. Shoe device: (a) Overall view of the shoe device; (b) The rear view of a shoe including the accelerometer, battery and power switch; (c) Pressure-sensitive insole with 5 pressure sensors: heel (***1***), 3rd metatarsal head (***2***), 1st metatarsal head (***3***), 5th metatarsal head (***4***), hallux (***5***).

Fig. 2. Bland-Altman plots for shoe-based models: (a) BACC-PS model, kcal·min^{-1}, (b) BACC model, kcal·min^{-1}, (c) non-branched ACC-PS model, kcal·min^{-1}, (d) non-branched ACC model, kcal·min^{-1}.

Fig. 3. Passing-Bablok regression plots for shoe-based models: (a) BACC-PS model, kcal·min^{-1}, (b) BACC model, kcal·min^{-1}; (c) non-branched ACC-PS model, kcal·min^{-1}, (d) non-branched ACC model, kcal·min^{-1}.

TABLES

Table 1. Subject characteristics

Table 2. Study protocol

Table 3. Energy expenditure prediction by minute

SUPPLEMENTAL DIGITAL CONTENT FILES

SDC1.tif: Figure. Sample raw sensors signal for “walking 2.5 mph” activity: (a) 3-dim accelerometer; (b) 5 pressure sensors.

SDC2.pdf: Table . Regression coefficients for the best BACC-PS model (EE in kcal/min)

SDC3.pdf: Table. Regression coefficients for the best BACC model (EE in kcal/min)

SDC4.pdf: Table. Regression coefficients for the best non-branched ACC-PS and ACC models

SDC5.pdf: Table. Examination of the presence of fixed and proportional bias and linearity

SDC6.pdf: Table. Comparison of BACC-PS model performance using predictors from single shoe and both shoes

Figure 1

Figure 2

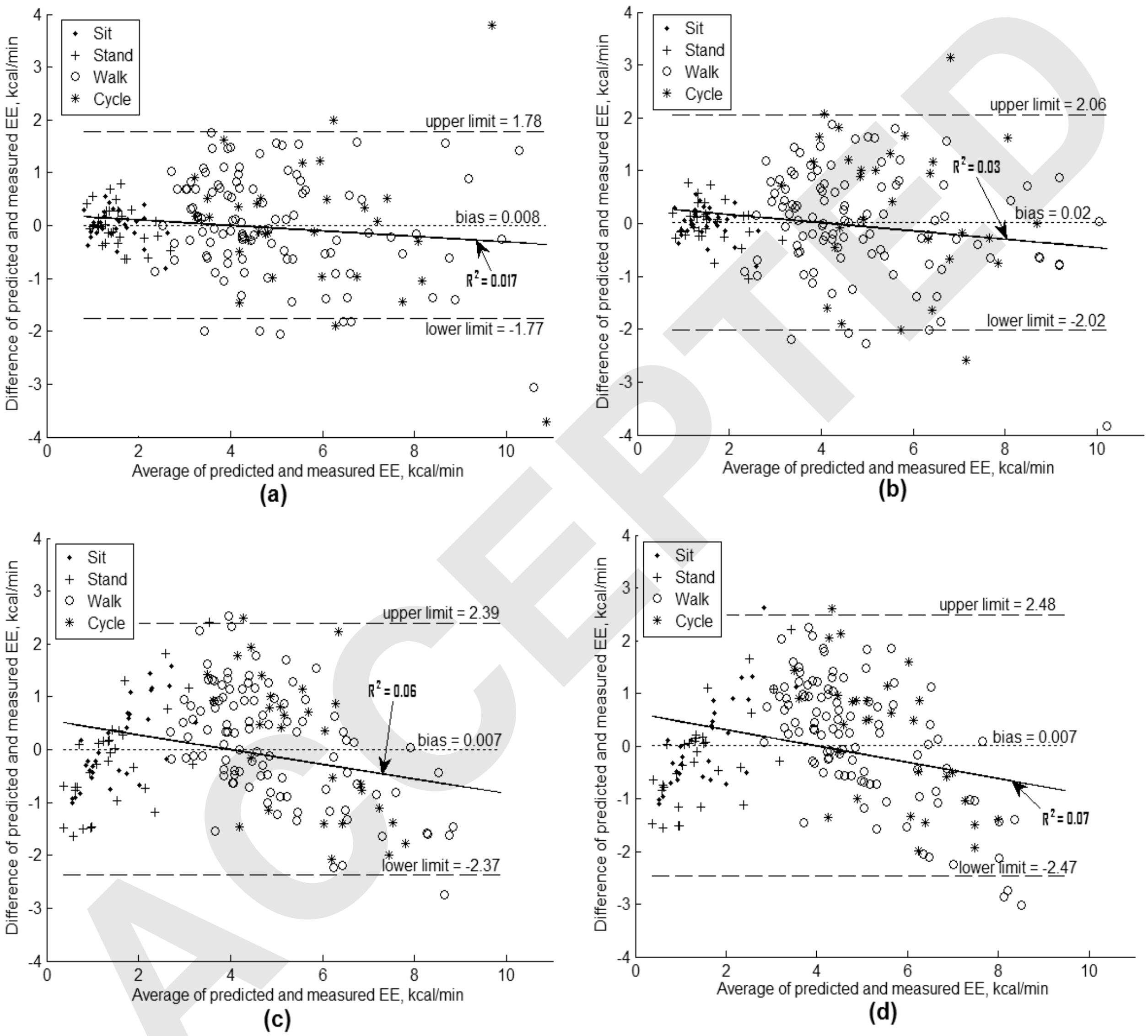
Sit
Stand
Walk
Cycle
upper limit = 1.78
bias = 0.008
R^2 = 0.017
lower limit = -1.77
Difference of predicted and measured EE, kcal/min
Average of predicted and measured EE, kcal/min
(a)
upper limit = 2.06
R^2 = 0.03
bias = 0.02
lower limit = -2.02
(b)
upper limit = 2.39
R^2 = 0.06
bias = 0.007
lower limit = -2.37
(c)
upper limit = 2.48
bias = 0.007
R^2 = 0.07
lower limit = -2.47
(d)

Figure 3

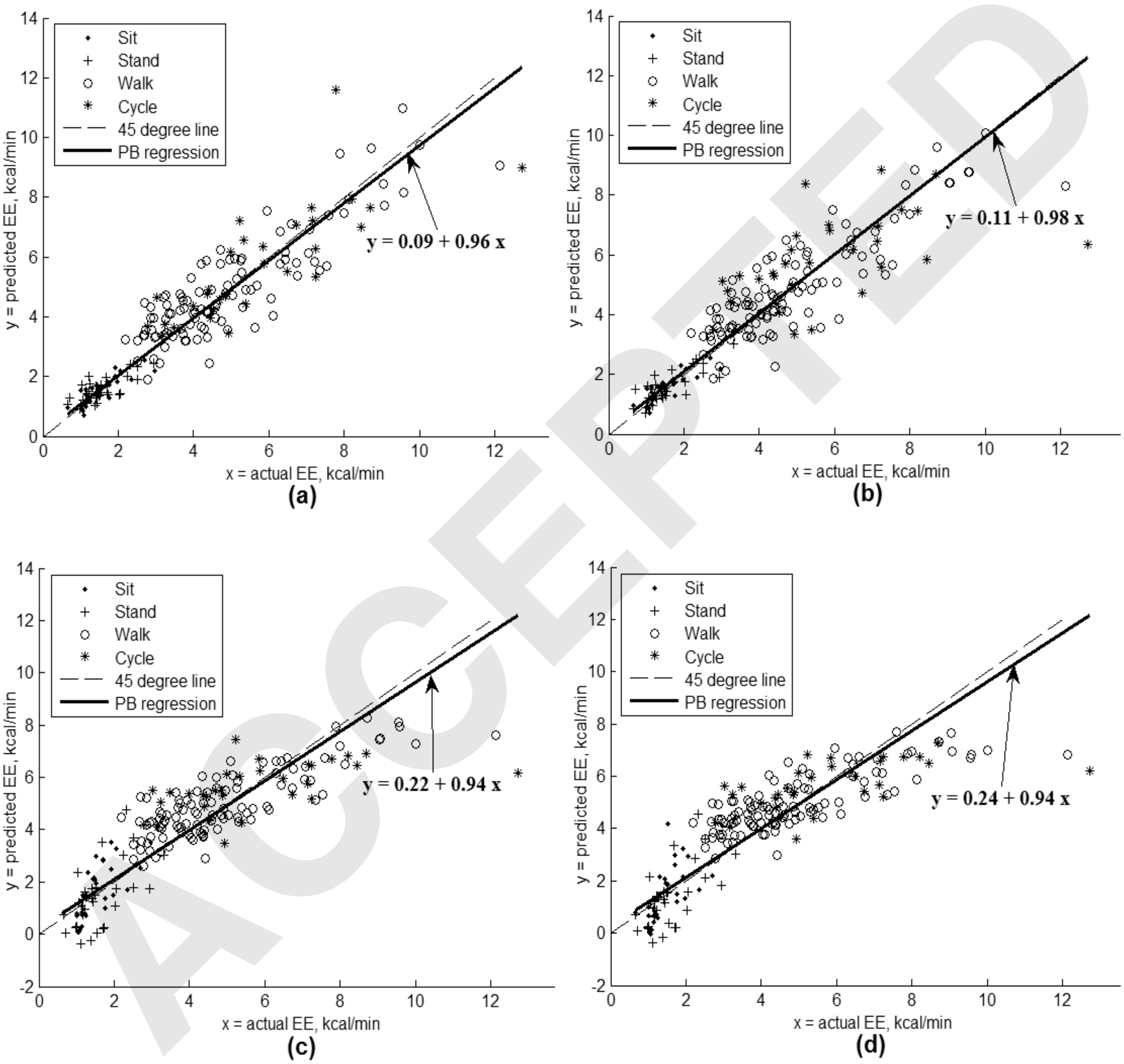
Sit
Stand
Walk
Cycle
45 degree line
PB regression
y = 0.09 + 0.96 x
y = 0.11 + 0.98 x
y = 0.22 + 0.94 x
y = 0.24 + 0.94 x
y = predicted EE, kcal/min
x = actual EE, kcal/min
(a)
(b)
(c)
(d)

Table 1. *Subject characteristics*

	Men (N=8)		Women (N=8)	
	Mean ± SD	Range	**Mean ± SD**	Range
Weight, kg	86.8 ± 20.0	59.0-119.8	66.9 ± 16.8	48.6-100.9
Height, in.	69.3 ± 1.8	67.0-72.0	64.3 ± 2.8	61.0-70.0
BMI, kg·m^{-2}	28.0 ± 5.9	18.9-35.8	25.4 ± 7.3	18.1-39.4
Age, yr	25.6 ± 8.6	18-44	24.4 ± 3.9	18-29
Shoe size, US	10.3 ± 0.6	9.5-11.0	7.9 ± 0.7	7.0-9.0

Table 2. *Study protocol*

Trial	Description	Posture/Activity Group
1	Sit quietly	Sit
2	Stand quietly	Stand
	Level Treadmill Walking/Jogging	
3	0.67 m/s (1.5 mph)	Walk/Jog
4	1.11 m/s (2.5 mph)	Walk/Jog
5	1.56 m/s (3.5 mph)	Walk/Jog
6	2.00 m/s (4.5 mph) - jogging	Walk/Jog
7	Ascend/Descend stairs*	
8	Sit with fidgeting	Sit
9	Stand with fidgeting	Stand
	Treadmill Walking	
10	1.11 m/s +1.5% grade	Walk/Jog
11	1.11 m/s -1.5% grade	Walk/Jog
12	1.11 m/s with 10% of body weight held in bags (5% held by each hand)	Walk/Jog
	Cycling:	
13	50W, 50 rpm	Cycle
14	100W, 75rpm	Cycle

* Metabolic data not collected during stair ascent/descent

Table 3. *Energy expenditure prediction by minute*

Model	Branch model	Number of 1-min recordings	$RMSE_{MET}$	95% CI for $RMSE_{MET}$	ARD, %	Bias, METs	95% interval of agreement, METs
BACC-PS	Sit	31	0.2593	(0.14, 0.37)	3.0	0.0276	(-0.50, 0.55)
	Stand	32	0.3186	(0.20, 0.42)	5.8	0.0323	(-0.61, 0.67)
	Walk	103	0.7550	(0.55, 0.96)	3.6	0.0466	(-1.47, 1.56)
	Cycle	31	0.96633	(0.60, 1.34)	3.4	0.0617	(-1.90,2.02)
	Aggregated	**197**	**0.6870**	**(0.53, 0.86)**	**3.85**	**0.0437**	**(-1.33, 1.42)**
BACC	Sit	31	0.2593	(0.14, 0.37)	3.0	0.0276	(-0.50, 0.55)
	Stand	32	0.3285	(0.18, 0.49)	5.6	0.0408	(-0.62, 0.70)
	Walk	103	0.7544	(0.53, 1.00)	3.6	0.0385	(-1.48, 1.55)
	Cycle	31	1.295	(0.92, 1.70)	8.9	0.1517	(-2.46, 2.77)
	Aggregated	**197**	**0.7679**	**(0.58, 0.98)**	**4.7**	**0.0550**	**(-1.48, 1.59)**
ACC-PS non-branched		**197**	**0.9389**	**(0.78, 1.15)**	**3.1**	**0.0395**	**(-1.84, 1.92)**
ACC non-branched		**197**	**0.9886**	**(0.76, 1.22)**	**2.7**	**0.0459**	**(-1.93, 2.03)**

BACC-PS model uses branching into 4 sub-models corresponding to sitting, standing, walking and cycling activities; it also uses signals from both accelerometer and pressure sensors for prediction of EE.

BACC is a branched model that only uses accelerometer measures for prediction of EE.

ACC-PS is a non-branched model that uses signals from both accelerometer and pressure sensors for prediction of EE.

ACC is a non-branched model that only uses accelerometer measures for prediction of EE.

Supplemental Digital Content Fig.1

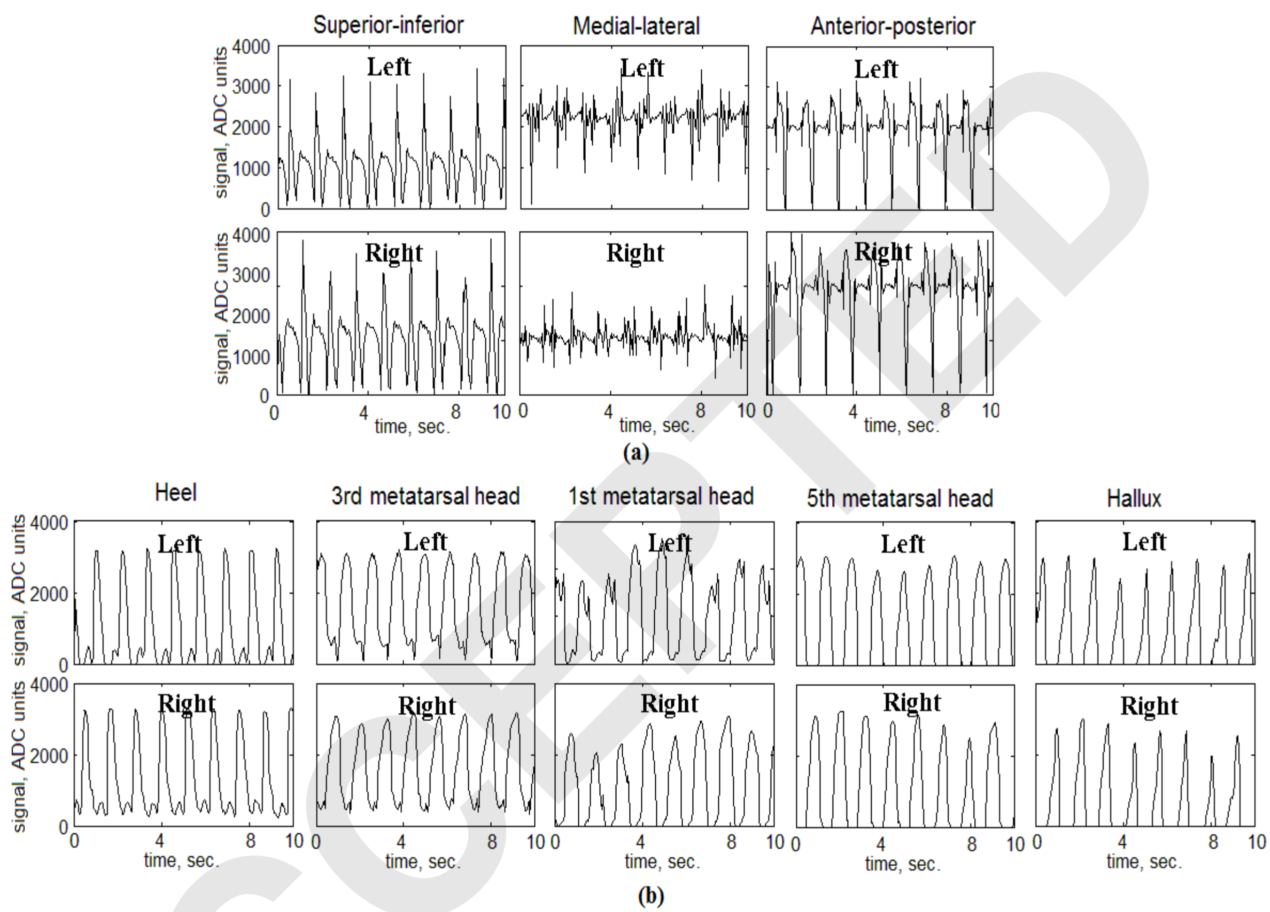

Fig. Sample raw sensors signals for "walking 2.5 mph" activity : (a) 3-dim acceleremeter; (b) 5 pressure sensors

Supplemental Digital Content Fig.2

Table . *Regression coefficients for t e best BACC-PS model (to predict EE in kcal/min)*

Branch odel	**Predictors, units**	**Average values of coefficients**	**CV of coefficients**
Sit	<Intercept>	5.2862	0.0687
	Wei ht, k	0.0352	0.0504
	lo (BMI), lo (k ·m^{-2})	-1.7594	-0.0854
	lo (Acc1.cv)	0.1331	0.0550
Stand	<Intercept>	4.5758	0.1148
	Wei ht, k	0.0364	0.0580
	lo (BMI), lo (k ·m^{-2})	-1.8339	-0.1147
	Sens1.std ·Sens2.std ·Sens3.std·Sens4.std, (ADC units)^{4}	$2.04\cdot10^{-12}$	0.0452
Walk	<Intercept>	0.8406	0.9662
	Wei ht, k	0.0745	0.0387
	lo (BMI), lo (k ·m^{-2})	-2.0513	-0.1431
	Sens3.zc·Sens4.zc	277.0277	0.1246
	Acc3.std, ADC units	0.0001	2.3021
	Acc1.ent·Acc2.ent·Acc3.ent	0.3542	0.0805
Cycle	<Intercept>	-2.7295	-0.6184
	Wei ht, k	0.0770	0.1067
	lo (BMI), lo (k ·m^{-2})	-1.4837	-0.4172
	Acc1.std, ADC units	0.0014	0.3445
	Sens3.std·Sens4.std, (ADC units)^{2}	$8.7\cdot10^{-6}$	0.1069
	Acc3.ent	1.9431	0.1685

Supplemental Digital Content Fig.3

Table 4. *Regression coefficients for t e best BACC model (to predict EE in kcal/min)*

Branc model	Predictors, units	Average values of coefficients	CV of coefficients
Sit	<Intercept>	5.2862	0.0687
	Wei ht, k	0.0352	0.0504
	lo (BMI), lo (k ·m^{-2})	-1.7594	-0.0854
	lo (Acc1.cv)	0.1331	0.0550
Stand	<Intercept>	6.5636	0.0713
	Wei ht, k	0.0418	0.0525
	lo (BMI), lo (k ·m^{-2})	-2.2433	-0.0875
	lo (Acc2.cv), ADC units	0.1530	0.0513
Walk	<Intercept>	1.4050	0.5644
	Wei ht, k	0.0798	0.0364
	lo (BMI), lo (k ·m^{-2})	-2.7433	-0.1086
	Acc3.std, ADC units	0.0012	0.1661
	Acc3.ent·Acc2.ent·Acc1.ent	0.5812	0.0248
Cycle	<Intercept>	11.4745	0.2013
	Wei ht, k	0.1220	0.0703
	lo (BMI), lo (k ·m^{-2})	-5.4759	-0.1583
	Acc1.std, ADC units	0.0058	0.0746

Supplemental Digital Content Fig.4

Table. *Regression coefficients for t e best non-branc ed ACC-PS and ACC models*

Model	Pred ctors, un ts	Average values of coeff c ents	CV of coeff c ents
Non-branched ACC-PS	<Intercept>	2.1090	0.2104
	Wei ht, k	0.0609	0.0331
	lo (BMI), lo (k $\cdot$m^{-2})	-1.9338	-0.0939
	(Acc1.ent)^2	0.3301	0.0826
	(Acc3.ent)^2	0.3468	0.1143
	Acc2.std·Sens1.zc, ADC	0.0328	0.0456
Non-branched ACC	<Intercept>	1.7563	0.2970
	Wei ht, k	0.0554	0.0411
	lo (BMI), lo (k $\cdot$m^{-2})	-1.7604	-0.1208
	(Acc1.ent)^2	0.3185	0.0927
	(Acc3.ent)^2	0.3891	0.1111
	Acc2.std, ADC units	0.0045	0.0534

Supplemental Digital Content Fig.5

Table. *Examination of the resence of fixed and ro ortional bias and linearity*

Model, u its of predictio	I tercept	95% CI for i tercept*	Fixed bias?	Slope	95% CI for slope*	Propor-tio al bias?	Test for li earity* p-value	Corr. & co cord. coefficie ts
BACC-PS, kcal·mi $^{-1}$	0.0911	(-0.04,0.27)	**No**	0.96	(0.91,1.01)	**No**	**Stro g li earity, p-value>0.1**	0.9271 0.9259
BACC-PS, METs	0.0155	(-0.10,0.14)	**No**	0.9907	(0.94,1.05)	**No**	**Stro g li earity, p-value>0.1**	0.9294 0.9291
BACC, kcal·min^{-1}	0.11445	(-0.07,0.2)	No	0.9811	(0.9 ,1.04)	No	Strong linearity, p-value>0.1	0.9022 0.8997
BACC, METs	0.0257	(-0.16,0.14)	No	1.007	(0.95,1.08)	No	Strong linearity, p-value>0.1	0.9102 0.9094
ACC-PS non-bran., kcal·min^{-1}	0.2280	(-0.0 ,0.46)	No	0.9400	(0.87,1.0)	No	No linearity p-value<0.01	0.8640 0.8568
ACC-PS non-bran., METs	-0.061	(-0. 5,0.18)	No	1.0411	(0.95,1.14)	No	No linearity p-value<0.01	0.8642 0.86 5
ACC non-bran., kcal·min^{-1}	0.2 67	(0.02,0.55)	Yes	0.9 74	(0.85,1.0)	No	No linearity p-value<0.01	0.8516 0.84 0
ACC non-bran., METs	-0.0208	(-0. ,0.16)	No	1.0549	(0.96,1.16)	No	No linearity p-value<0.01	0.8481 0.8469

* Computed as a result of Passing-Bablok regression estimation.

Supplemental Digital Content Fig.6

Table. *Comparison of B CC-PS model performance using predictors from single shoe and both shoes*

Model	RMS M T	ARD, %	Bias, M Ts	Interval of agreement, M Ts
BACC-PS$_{mean}$	0 7013	3 85	0 0354	(-1 37, 1 44)
BACC-PS$_{max}$	0 6870	3 85	0 0437	(-1 33, 1 42)
BACC-PS$_{left}$	0 7841	4 64	0 0497	(-1 52, 1 62)
BACC-PS$_{right}$	0 7203	3 52	0 0222	(-1 42, 1 47)

BACC-PS$_{mean}$ is the proposed model that used average (between left and right shoe) of the computed sensor metrics for each sensor

BACC-PS$_{max}$ is the proposed model that used maximum (between left and right shoe) of the computed sensor metrics for each sensor

BACC-PS$_{left}$ and BACC-PS$_{right}$ are versions of the proposed model that used either left or right shoe side of the computed sensor metrics for each sensor