This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2016.2636906, IEEE Transactions on Biomedical Engineering

Validation of Energy Expenditure Prediction Models Using Real-Time Shoe-Based Motion Detectors

Shih-Yun Lin, Ying-Chih Lai*, Chi-Chun Hsia, Pei-Fang Su, and Chih-Han Chang

***Abstract*— *Objective:* This study aimed to verify and compare the accuracy of energy expenditure (EE) prediction models using shoe-based motion detectors with embedded accelerometers. *Methods:* Three physical activity (PA) data sets (unclassified, recognition, and intensity segmentation) were used to develop three prediction models. A multiple classification flow and these models were used to estimate EE. The "unclassified" data set was defined as the data without PA recognition, the "recognition" as the data classified with PA recognition, and the "intensity segmentation" as the data with intensity segmentation. The three data sets contained accelerometer signals (quantified as signal magnitude area, SMA) and net heart rate (HR_{net}). The accuracy of these models was assessed according to the deviation between physically-measured EE and model-estimated EE. *Results:* The variance between physically-measured EE and model-estimated EE expressed by simple linear regressions was increased by 63% and 13% using SMA and HR_{net}, respectively. The accuracy of the EE predicted from accelerometer signals is influenced by the different activities that exhibit different count-EE relationships within the same prediction model. *Conclusion:* The recognition model provides a better estimation and lower variability of EE compared with the unclassified and intensity segmentation models. *Significance:* The proposed shoe-based motion detectors can improve the accuracy of EE estimation and has great potential to be used to manage everyday exercise in real time.**

***Index Terms*—Prediction Model, Energy Expenditure, Shoes, Accelerometer, Physical Activity.**

I. Introduction

Energy expenditure (EE) refers to the amount of energy a person burns for daily activities. These include both internal and external functions: the former involves two main processes, the digestion of food and basal metabolism; the latter indicates physical activity (PA). EE is regarded as the single largest contributor to the activity parameter, even in clinical contexts [1]. Because the measurement of EE from PA is complex, an accurate and efficient approach to monitor and quantify EE is desirable, especially in epidemiology.

The main determinants of EE are body size and PA [2]. Although body size can be simply determined, the assessment of PA is still a challenge due to diverse individual behaviors and the complexity of human activities [3]. With the advance in electronics and semiconductors, low-cost, light-weight, and power-efficient inertial sensors such as accelerometers and gyroscopes provide individualized solutions for monitoring PA [4, 5]. These sensors measure the motion of an object and can quantify the PA of a body in terms of counts of some specific movements, such as walking, running or biking. Correlations between movement counts quantified via accelerometers and EE measured via indirect calorimetry have been calculated, and prediction models have been developed to predict the metabolic cost of PA in many studies. Najafi *et al*. [6] utilized wavelet analysis from a waist-mounted inertial device composed of a biaxial accelerometer and a uniaxial gyroscope to detect body postures. To assess the validity of this method, EE obtained from a waist-mounted accelerometer module, RT3 (Stayhealthy Inc.) [7], was compared to physiological EE obtained via a wireless portable ergospirometric system. Gafurov *et al*. [8] used an ankle-mounted triaxial accelerometer and a cycle-matching method to recognize gait types. Since footwear is an irreplaceable part of our daily life, shoe-based systems have attracted a lot of attention and are available on the market or in research laboratories [5]. Inertial sensors are widely used in shoe-based systems to perform posture and PA recognition and EE estimation [9-11].

Although accelerometers are widely used, the measurement of the intensity of a PA and the corresponding amount of EE remains difficult. There are relatively few shoe-based systems used for EE estimation [5]. Welk *et al*. [12] found that acceleration was moderately correlated with EE but tended to overestimate EE during walking. To improve EE estimation, many methods to detect the type, duration, trajectory and intensity of the PA performed have been introduced; however, these methods require multi-step classifications and are often complicated [3, 13-15]. Another method utilizes a variety of complex sensors to improve PA recognition [5, 9, 16-20]. Swartz *et al*. [16] presented a wrist-mounted accelerometer incorporated with a hip-mounted accelerometer. The IDEEA

Manuscript submitted September 23, 2015. This study received partial financial support from the Department of Industrial Technology (DoIT), Ministry of Economic Affairs (MOEA), Taiwan, R.O.C., under grant No. 100-EC-17-A-99-I1-0014. The authors gratefully acknowledge the assistance of Da Sheng Enterprise Corp. for their technological and material support for the shoes.

S.-Y. Lin is with the Department of Biomedical Engineering, National Cheng Kung University, No.1, University Road, Tainan 70101, Taiwan, and the Information and Communications Research Laboratories, Industrial Technology Research Institute, No.31, Gongye 2nd Rd., Annan Dist., Tainan 70955, Taiwan.

*Y.-C. Lai is with the Department of Aerospace and Systems Engineering, Feng Chia University, No. 100, Wenhwa Rd., Seatwen, Taichung 40724, Taiwan (e-mail: yingclai@fcu.edu.tw).

C.-C. Hsia is with the Information and Communications Research Laboratories, Industrial Technology Research Institute, No.31, Gongye 2nd Rd., Annan Dist., Tainan 70955, Taiwan.

P.-F. Su is with the Department of Statistics, National Cheng Kung University, No.1, University Road, Tainan 70101, Taiwan.

C.-H. Chang is with the Department of Biomedical Engineering, National Cheng Kung University, No.1, University Road, Tainan 70101, Taiwan.

(Intelligent Device for Energy Expenditure and Activity, MiniSun) [20], consisting of one recorder and five small sensors that are placed on the chest, thighs, and feet, was introduced to measure the acceleration and angle of each body segment. Moreover, a shoe-based system, named SmartShoe, developed by Sazonov *et al.* [9] has been validated extensively in EE (in controlled laboratory environments) [17, 21, 22]. The most recent incarnation of the SmartShoe system, named SmartStep by Hegde *et al.*, has shown the capability to be accurate in posture and activity classification [10, 23, 24]. Both SmartShoe and SmartStep systems are based on a combination of two sensor modalities: acceleration and pressure-sensing insoles.

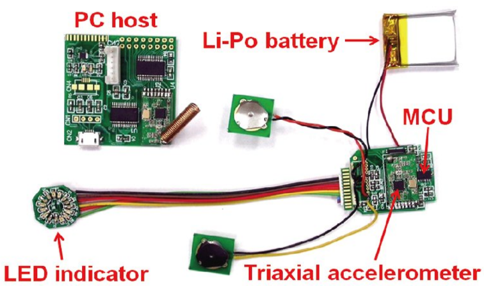
These recent studies have provided evidence that footwear is an ideal way to recognize lower-extremity PA. However, most of these shoe-based activity monitoring systems work through PC post-processing due to high memory requirements and execution times. Therefore, a system based on real-time feedback often uses only pressure-sensing elements to process the data and generate the biofeedback [5].

Furthermore, integrating physiological sensors, such as heart rate (HR) monitors and respiratory sensors, with inertial sensors has often been recommended because of the strong within-subject correlation between physiological responses and EE [5, 18, 19]. However, emotional, environmental, or dietary factors can cause variation in HR, introducing errors in EE estimation. Moreover, personalized, proper calibrations for each individual are also crucial to reduce inter-individual differences. Spierer *et al*. [19] found that there was no significant difference in EE estimation between the Actical (a wrist-mounted monitor with only accelerometer, Respironics Inc., OR, USA) and the Actiheart (a torso-mounted monitor combining accelerometer and HR, CamNtech Ltd, Cambridge, UK).

Following Freedson *et al*. [25], the "cut point" method, based on the count ranges of the accelerometer signals, was used to represent the boundaries of activity intensity during walking and running. Hendelman *et al*. [26] and Swartz *et al*. [16] also determined "cut points" based on 3-, 6-, and 9- Metabolic Equivalent of Task (MET) regression equations from hip and wrist accelerometer counts. Based on these investigations, estimation of EE can be simplified by defining the activity intensities in terms of the counts of an accelerometer. However, for the same EE level, the same type of activity often exhibits a wide range of counts and yields different regression equations [16, 26]. These variances could be due to the accelerometers being affixed to different locations, different count values for different types of accelerometers, or misclassifications of the type of activity performed and personal activity habits. Therefore, large discrepancies in the "cut point" method have been observed, and few studies have quantitatively analyzed the accuracy of this prediction method. To solve these problems, this study investigates different prediction models to more accurately and reliably estimate EE for lower extremity locomotion applications.

To estimate EE accurately and reduce obtrusiveness of technologies in daily life, the inertial sensing of feet has been validated as a promising tool for the analysis of gait cycles and walking speed [27]. Sazonova *et al*. [17] presented a SmartShoe system combined acceleration, pressure and posture classification information in a branched algorithm; this study achieved a lower error rate compared with branched and non-branched accelerometer models. In this study, the developed shoe-based system used embedded non-obtrusive accelerometers in the midsole that did not impact measured PA. A multiple segmentation and recognition classification flow was proposed to simplify the process and achieve real-time processing of PA recognition by using only one data source, a triaxial accelerometer. The accelerometer data were collected from 10 volunteers who wore the shoe-based motion detectors to perform five pre-defined PA types. The activity segments that corresponded to a movement were detected based on the standard deviation of the accelerometer signals. The duration of the activity segment was used as a pre-classification factor. The action accuracy, which was penalized for substitution, deletion and insertion errors, was introduced to evaluate the performance of the proposed method. Finally, the prediction models were established that correlate EE and the signal magnitude area (SMA, calculated from accelerometer signals), as well as EE and HR.

SMA was selected to be the major feature of the EE prediction models since it has been found to be a suitable measure for distinguishing between periods of user activity and rest using triaxial accelerometer signals [28]. This characteristic is also applied to PA recognition. Since HR is a widely used feature in EE prediction, it was selected to be another feature for the purpose of comparison with other studies. Additionally, real-time feedback of estimated EE levels was shown on an LED indicator using different colors and flashing frequencies on the surface of the shoes. The



(a)


(b)

Fig. 1. (a) Sensor module and PC host module. (b) A shoe with an embedded accelerometer.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2016.2636906, IEEE Transactions on Biomedical Engineering

different EE levels were also recorded in the storage module in real-time when the sensor module was off-line. Moreover, the entire shoe-based sensor module is fully modular and can be replaced and recharged easily from the outside of the shoe. Those novel and user-friendly designs could improve the acceptance of the technology in real life situations.

Accelerometers are widely used to perform posture and PA recognition. However, there are relatively few shoe-based systems used for the validation of different EE prediction models. The primary goal of this study was to develop a reliable PA-recognition approach using a stand-alone shoe-based system with embedded accelerometers in real time. The secondary goal was to validate the accuracy of different prediction models of EE estimation from the shoe data.

II. Materials and Methods

A. Shoe-Based Motion Detectors

To acquire adequate and reliable acceleration information regarding PA, and its relationship with EE, a pair of shoes with embedded microprocessors and accelerometers was developed. This system consists of one sensor module in each shoe and one PC host module that communicates with the sensor module through a radio frequency module (Fig. 1(a)). The rechargeable and replaceable sensor module includes a triaxial accelerometer, a microprocessor, a storage module, a LED indicator, and a Li-Po battery. The applied accelerometer is an ADXL345 digital accelerometer manufactured by Analog Devices, Inc. (USA). The full scale is set to ±8 g with a 13-bit resolution, and the sampling rate is set to 60 Hz. The accelerometers are mounted under the foot arch within the midsole foam of the shoes (Fig. 1(b)), because this location is easily accessible and encounters lower pressure during PA.

PA recognition and EE estimation algorithms were developed based on the foot acceleration information acquired by the sensor modules and implemented into the microprocessor of the sensor module for real-time recognition and estimation. Additionally, a LED indicator using different colors and flashing frequencies was used to display different levels of EE estimation results, which were also recorded in the storage module in real-time when the sensor module was off-line. All the recorded data are wirelessly uploaded to the PC, which runs a custom exercise management program for analyzing daily activities.

As mentioned above, the “cut point” method yields different regression equations for the same type of activity due to a wide range of counts. To overcome this problem, scalar calibration [29] was introduced to calibrate the accelerometers in random orientations by gravitational force. Because the non-orthogonal angles of the triaxial accelerometer have been confirmed to be small enough to be ignored [30], only three scale factors and three biases were estimated. The errors of the measured acceleration of gravity of the applied sensor triad were less than 0.02 g. After the calibration method was applied, the acceleration measured from the interested objects was close to 9.8 m/s^2.

B. Physical Characteristics and Physiological Signal Measurement

Ten male volunteers between the ages of 30 and 40 years old were recruited. The recruitment criteria were (1) absence of cardiovascular limitations or musculoskeletal disorders, (2) free of medications known to alter metabolic rate and PA, and (3) body mass index (BMI) less than 27 kg/m^2. Participants wore correctly-sized shoes that were mounted with the sensor module. Before testing, all volunteers were notified of potential risks and signed an informed consent document approved by the Institutional Review Board of Industrial Technology Research Institute (Case No. A003003). The mean values (± SD) for age, height, body mass, BMI, and resting oxygen consumption ($\dot{V}O_{2rest}$) of these participants were 33.1 years (± 3.1), 171.6 cm (± 6.7), 70.4 kg (± 4.0), 20.5 kg/m^2 (± 1.2), and 3.3 ml/kg/min (± 0.2), respectively.

Because approximately 5 kcal of energy can be released from

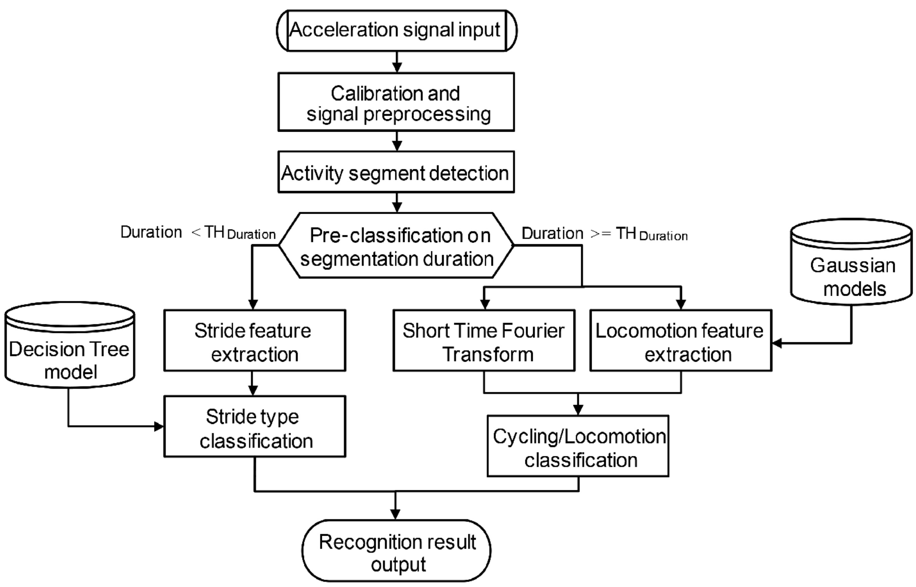


Fig. 2. The multiple classification flow of the proposed PA recognition algorithm.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2016.2636906, IEEE Transactions on Biomedical Engineering

1 liter of oxygen consumed by the human body, the EE associated with a specific PA was calculated individually from the oxygen consumption ($\dot{V}O_2$) [31]. In this study, when subjects carried out the PA tests, the gross $\dot{V}O_2$ ($\dot{V}O_{2gross}$) measured via oxygen uptake assessment using a Cosmed K4b^2 (Rome, Italy) indirect calorimeter was taken as the reference of EE estimation. This calorimeter is a portable metabolic system and used for the analysis of pulmonary gas exchange validated in many studies [16, 32, 33]. Before each test, the calorimeter was calibrated according to the manufacturer's instructions, and the gender, age, height, and weight of participants were entered to define individual differences. The gross HR (HR_{gross}) was measured using the Polar belt (T31 transmitter, Polar, Finland), which consists of a sensor and transmitter on an adjustable strap around the participant's chest.

The absolute values of pulmonary gas exchange at rest and during exercise were measured using K4b^2. After each participant was familiarized with the equipment, the resting HR (HR_{rest}) and $\dot{V}O_{2rest}$ were recorded while the participant sat quietly at rest for at least 10 minutes. Each prescribed activity was performed for at least 6 minutes and was stopped when the HR_{gross} and $\dot{V}O_{2gross}$ of the participant maintained a metabolic steady state for 2 minutes. A steady state was defined by no significant increases in $\dot{V}O_{2gross}$ during the final 2 minutes and a respiratory exchange ratio (RER) <1.0 [17, 34]. The values of HR_{gross} and $\dot{V}O_{2gross}$ were averaged during the last minute of a metabolic steady state. Tests were performed at random and with a rest period to allow the metabolic rate to return to baseline between intervals. All tests were divided into three days within one week to allow recovery between tests.

We calculated net oxygen consumption ($\dot{V}O_{2net}$) by subtracting the $\dot{V}O_{2rest}$ from the $\dot{V}O_{2gross}$ to determine the oxygen cost of the activity. The values of net HR (HR_{net}) were also calculated by deducting HR_{rest} from measured HR_{gross}. For the purpose of this study, EE is defined as $\dot{V}O_{2net}$.

C. Activity Segmentation and Classification Flow

Regarding to the methods commonly used in the activity recognition process, several studies have categorized the main steps: preprocessing, segmentation, feature extraction, dimensionality reduction and classification [15, 21, 35-37]. In the classification and recognition step, the most widely used classification and recognition methods are threshold-based, pattern recognition, support vector machines, decision trees, and artificial neural networks. In this study, the design of algorithm developed for PA recognition is based on the common activity recognition process, and the integration of threshold-based and pattern recognition technologies is used as the adopted recognition method since there are five target PA types and three levels of intensity. It is difficult to use only one systematic approach to classify different PA types and intensity levels at the same time. Therefore, we designed a multiple classification flow based on the data gained from empirical experiments. To avoid over-fitting, we designed the activity segment detection and pre-classification based on the characteristics of different PA types and the threshold-based method.

Due to the complicated features of different PA types, we proposed a multiple classification flow based on various signal processing methods and classification algorithms, which include the short-time Fourier transform (STFT), decision tree models, and Gaussian models. The target PA types are five general daily activities, including locomotion (Loco), stepping (Step), cycling (Cycle), walking upstairs (WUS), and walking downstairs (WDS). The "Loco" includes walking, jogging, and running. The daily activities were divided into short- and long-duration activities. The short-duration activities are walking, Step, WUS and WDS, and the long-duration activities are jogging and running and Cycle. When the activity was recognized as short-duration, the stride types of walking, Step, WUS and WDS were recognized using the decision tree. When the activity was recognized as long-duration, Gaussian models and STFT were adopted to distinguish jogging and running and Cycle. Jogging and running were recognized by the Gaussian models, and Cycle was recognized by STFT. The activity segments were detected based on the standard deviation of the acceleration signals, and a classification flow based on the activity duration was designed to simplify the PA recognition process (Fig. 2). The activity duration was quantified using the accumulating signal vector magnitude (SVM) every second:

$$SVM(t) = \sum_{i=0}^{59} \sqrt{x^2(t+i) + y^2(t+i) + z^2(t+i)} \qquad (1)$$

where $x(t)$, $y(t)$, and $z(t)$ denote the acceleration signals in the forward-backward, right-left and up-down directions, respectively. Because the sampling frequency was 60 Hz, the summation was from i=0 to i=59. For each second, if the SVM was greater than a predefined threshold TH_{AD}, the signal was considered "active". If the activity duration was greater than a predefined threshold $TH_{Duration}$, it was recognized as a long-duration activity. Otherwise, the activity was recognized as a short-duration activity. $TH_{Duration}$ was set to 4 seconds in this study. When the activity was recognized as long-duration, a sliding window was applied, and the standard deviation of $SVM(t)$ in the sliding window was calculated. The interval of the sliding window was set to 4 seconds and shifted every 0.5 seconds.

The difference between the short- and long-duration activities is determined by using the characteristic of zero velocity of the stance phase when walking [38]. During the stance phase of walking, the gravitational acceleration measured from the shoes is approximately 9.8 m/s^2 when walking slowly. When people walk or move fast, the stance phase will gradually reduce, and the measured signal will become continuous. Therefore, we define PA types with continuous signal as long-duration activities. Considering the duration of the activity segment, for regular daily human activities, the frequencies of different movements are between 0.4 and 5 Hz [38]. In other word, the slowest and fastest movements take 2.5 to 0.2 seconds, respectively. In order to analyze all kinds of human movements, the interval of the sliding window is set to 4 seconds.

D. EE Estimation Prediction Models

To validate the accuracy of the $\dot{V}O_{2net}$ prediction based on the SMA or HR_{net}, three prediction models acquired from the test data were applied in this study. These models are as follows:

1) *U-M (unclassified model)*. The model comprised all data without PA recognition.
2) *R-M (recognition model)*. The model comprised five separate activities as follows:
   - PA type 1, Loco: locomotion on a treadmill (SportsArt T620) with no inclination. Includes grade 1: walking at 5 km/h (1.39 m/s), grade 2: jogging at 7 km/h (1.94 m/s), and grade 3: running at 9 km/h (2.50 m/s).
   - PA type 2, Step: stepping at grade 1: 120 beats per minute (bpm), grade 2: 140 bpm, and grade 3: 160 bpm.
   - PA type 3, Cycle: riding on a stationary bike (SportsArt C532U) with no resistance at grade 1: 40 revolutions per minute (rpm), grade 2: 60 rpm, and grade 3: 80 rpm.
   - PA type 4, WUS: walking upstairs in a twenty-floor building (25 stairs per floor and 160 mm per stair) at grade 1: 60 bpm, grade 2: 80 bpm, and grade 3: 100 bpm.
   - PA type 5, WDS: walking downstairs in a twenty-floor building (25 stairs per floor and 160 mm per stair) at grade 1: 60 bpm, grade 2: 80 bpm, and grade 3: 100 bpm.
3) *IS-M (intensity segmentation model)*. The model comprised three separated intensity segmentations. The intensity segmentation grade was used as a factor according to the “cut point” method, as described below:
   - 3-6 METs, a moderate-intensity grade. PAs with EE values of 3-6 METs were assigned into this grade, including Cycle at 40, 60, and 80 rpm, Step at 120 bpm, walking at 5 km/h, and WDS at 60, 80, and 100 bpm.
   - 6-9 METs, a high-intensity grade. PAs with EE values of 6-9 METs were assigned into this grade, including Step at 140 and 160 bpm, jogging at 7 km/h, and WUS at 60 and 80 bpm.
   - Ex9 METs (Exceeding 9 METs), a very-high-intensity grade. PAs with EE values greater than 9 METs were assigned into this grade, including running at 9 km/h and WUS at 100 bpm.

To construct the PA recognition algorithm, three subjects who were not in the 10 volunteer set were requested to perform the assigned five PA types. The accelerometer signals were collected as training data, and the features were extracted from those tests using the classification methods mentioned above. All 10 participants performed all five types of PAs, with each PA including three activity grades, for a total of 150 test recordings. The test data were used to calculate the SMA, the most widely used feature for measuring PA, calculated as the normalized integral of the original triaxial accelerometer signals. SMA is defined as:

$$SMA\,(t) = \frac{1}{t}\left(\int_0^t |x(t)|dt + \int_0^t |y(t)|dt + \int_0^t |z(t)|dt \right) \tag{2}$$

E. Statistical analysis

Outcomes from individuals were assumed to be statistically independent, whereas those within an individual were correlated. To take into account the correlation among repeated measurements from the same participant, the generalized estimating equation (GEE) was used. Statistical parameters, including the estimate, standard error (SE), 95% confidence interval (95% CI), p-value, and mean absolute prediction error (MAE), were provided. Each test was compared at the 0.05 significance level.

The GEE method was applied to establish prediction models correlating accelerometer signals (SMA) and $\dot{V}O_{2net}$, as well as HR_{net} and $\dot{V}O_{2net}$. Each model-estimated $\dot{V}O_{2net}$ was separately calculated from the GEE prediction models. To validate the model-estimated $\dot{V}O_{2net}$, Passing-Bablok regression (P-B regression) diagrams were plotted to compare the deviations between the physically-measured $\dot{V}O_{2net}$ and the model-estimated $\dot{V}O_{2net}$. As the P-B regression line approaches the 45° identity line, the deviation is smaller, which indicates that the model-estimated $\dot{V}O_{2net}$ values are similar to the physically-measured $\dot{V}O_{2net}$ values.

The SE was used to quantify the variability of the estimators. The correlation coefficient, r, was calculated, and a simple linear regression was performed to determine the relationship between the physically-measured $\dot{V}O_{2net}$ and model-estimated $\dot{V}O_{2net}$ values. The coefficient of determination, R^2, indicates the proportion of the variance that can be explained by a simple linear regression.

III. Results

A. Recognition of PA type

To verify the capabilities of the proposed shoe-based motion detectors and PA classification flow, 7,104 inertial signal recordings, containing six types of PA, were used to test the recognition accuracies (%) (Table I). The estimated accuracies of the applied PAs were greater than 91.7%. Comparing with the results of SmartShoe [21], this system used pressure and acceleration data, four classes, which were Sit, Stand, Walk/Jog, and Cycle, and post-processing to achieve the accuracy of >95% for Walk/Jog and Cycle. In our study, we used only acceleration data, five PA types, and real-time processing to achieve the accuracy of >94.7% for Walking, Running, and Cycle. The results show that the proposed activity-monitoring shoes and the PA recognition algorithm can fulfill the exercise management function of analyzing daily activities.

TABLE I
ACCURACY OF PHYSICAL ACTIVITY RECOGNITION

	Walking	Running	Step	Cycle	WUS	WDS	Accuracy (%)
Walking	1,268	0	0	0	5	25	97.69
Running	50	1,115	0	3	4	5	94.73
Step	0	0	770	0	24	26	93.90
Cycle	93	4	0	2,227	0	0	95.80
WUS	9	0	0	0	663	40	93.12
WDS	27	0	0	0	37	709	91.72

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TBME.2016.2636906, IEEE Transactions on Biomedical Engineering

B. EE Estimation

The primary goal of this study was to validate the accuracy of prediction models of EE estimation. Experimental results from data analyses and prediction models are as follows

Mean and SD values of experimental results. The SMA, $\dot{V}O_{2net}$, and HR_{net} data are presented in Table II. For the five PA recognition types, the SMA values of Loco and Step were approximately 2-3 times greater than those of Cycle and WUS. In Loco, the larger SMA value for the larger limb movement amplitude reflected higher physiological reactions (including $\dot{V}O_{2net}$ and HR_{net}). In Cycle, the smaller SMA value for the smaller limb movement amplitude reflected lower physiological reactions. However, in WUS and WDS, the relationships between the SMA and physiological reactions were reversed. For the three grades of IS-M, the SMA and physiological reactions were directly correlated.

TABLE II
MEAN AND SD VALUES (MEAN ± SD) PER MINUTE OF THE R-M AND IS-M

	PA type	SMA (g)	$\dot{V}O_{2net}$ (ml/kg/min)	HR_{net} (beats/min)
R-M	Loco (n=30)	1.58 ± 0.34	24.63 ± 8.71	78.43 ± 28.02
	Step (n=30)	1.06 ± 0.16	17.82 ± 3.80	55.40 ± 16.35
	Cycle (n=30)	0.56 ± 0.35	12.11 ± 3.49	43.46 ± 10.82
	WUS (n=30)	0.59 ± 0.19	27.81 ± 4.44	83.67 ± 16.96
	WDS (n=30)	0.64 ± 0.19	8.50 ± 1.50	43.87 ± 11.22
IS-M	3-6 METs (n=80)	0.71 ± 0.33	11.29 ± 3.41	44.29 ± 11.31
	6-9 METs (n=50)	0.96 ± 0.46	23.36 ± 4.60	71.36 ± 17.26
	Ex9 METs (n=20)	1.39 ± 0.59	32.76 ± 3.33	101.70 ± 14.30

Regression results obtained using the GEE. Table III shows the relationships between SMA and $\dot{V}O_{2net}$ (SMA-$\dot{V}O_{2net}$) and between HR_{net} and $\dot{V}O_{2net}$ (HR_{net}-$\dot{V}O_{2net}$) determined using GEE prediction models. These results indicate a significant influence (p<0.001) for all groups, i.e., U-M, R-M and IS-M. In the R-M, the regression coefficient indicates that the change in the rate of model-estimated $\dot{V}O_{2net}$, under the SMA or HR_{net} models, is the largest for Loco and the smallest for WDS. In the IS-M, the change in the rate of model-estimated $\dot{V}O_{2net}$, regardless of the SMA or HR_{net} models, is directly correlated with the activity intensity. Table III also presents the mean absolute prediction error (MAE) for each PA type. In summary, the MAE values of most PA types, except for "Loco", are smaller than 3, which indicates good accuracy.

Linear relationship between the physically-measured $\dot{V}O_{2net}$ and model-estimated $\dot{V}O_{2net}$. Fig. 3(a) - (f) illustrate the linear regression model between the $\dot{V}O_{2net}$ measured from indirect calorimetry and the $\dot{V}O_{2net}$ estimated from each GEE model: (a) U-M predicted from the SMA, r=0.51, p<0.001; (b) R-M predicted from the SMA, r=0.94, p<0.001; (c) U-M predicted from HR_{net}, r=0.86, p<0.001; (d) R-M predicted from HR_{net}, r=0.93, p<0.001; (e) IS-M predicted from the SMA; and (f) IS-M predicted from HR_{net}.

The recognition model (Fig. 3(b)) provides a better estimation of $\dot{V}O_{2net}$ than the unclassified model (Fig. 3(a)), as indicated by the P-B regression line approaching the 45° identity line in the former. A larger dispersion in the scatter plots is noticeable in Fig. 3(a) than in Fig. 3(b) even though both relationships between the physically-measured $\dot{V}O_{2net}$ and model-estimated $\dot{V}O_{2net}$ yield significant correlation (p<0.001). In Fig. 3(a), the model-estimated $\dot{V}O_{2net}$ values for the high or very high activity intensity are underestimates; for the lower activity intensity they are overestimates. Furthermore, the variance in the model-estimated $\dot{V}O_{2net}$ that can be explained by the simple linear regression is 63% greater for the R-M (Fig. 3(b), R^2=0.89) than for the U-M (Fig. 3(a), R^2=0.26) when predicting based on SMA.

Fig. 3(d) shows a slightly better estimation of the $\dot{V}O_{2net}$ and a smaller dispersion in the scatter plots than Fig. 3(c). In Fig. 3(c), the model-estimated $\dot{V}O_{2net}$ values are slight underestimates for high-intensity activities. Furthermore, the variance in the model-estimated $\dot{V}O_{2net}$ predicted from the HR_{net} is 13% greater in the R-M (Fig. 3(d), R^2=0.86) than in the U-M (Fig. 3(c), R^2=0.73). In Fig. 3(e), the scatter plots based on the SMA are separated into three distinct groups. Each group of the three segmentations exhibits underestimates for the high-intensity PAs and overestimates for the low-intensity PAs. However, clustering is decreased in Fig. 3(f), which shows the results for predictions based on HR_{net}.

In the U-M, the model-estimated $\dot{V}O_{2net}$ values predicted from the HR_{net} (Fig. 3(c), R^2=0.73) exhibit a 47% increase in explained proportion of variance compared with the values predicted from the SMA (Fig. 3(a), R^2=0.26). Conversely, in the R-M, the model-estimated $\dot{V}O_{2net}$ values predicted from the HR_{net} (Fig. 3(d), R^2=0.86) exhibit a 3% decrease in explained

TABLE III
REGRESSION AND LEAVE-ONE-OUT CROSS-VALIDATION RESULTS

Model		SMA-$\dot{V}O_{2net}$					HR_{net}-$\dot{V}O_{2net}$				
		Estimate	SE	95% CI	p	MAE	Estimate	SE	95% CI	p	MAE
U-M (n=150)		9.51	0.56	[8.41, 10.62]	<0.001	-	0.34	0.02	[0.30, 0.39]	<0.001	-
R-M	Loco (n=30)	23.2	1.29	[20.68, 25.72]	<0.001	4.089	0.3	0.02	[0.25, 0.35]	<0.001	3.875
	Step (n=30)	21.23	2.2	[16.91, 25.54]	<0.001	2.183	0.24	0.03	[0.18, 0.30]	<0.001	2.714
	Cycle (n=30)	7.71	0.63	[6.48, 8.95]	<0.001	2.146	0.25	0.03	[0.20, 0.30]	<0.001	2.251
	WUS (n=30)	17.73	1.14	[15.49, 19.98]	<0.001	2.74	0.28	0.03	[0.22, 0.34]	<0.001	3.462
	WDS (n=30)	4.98	0.39	[4.22, 5.75]	<0.001	1.103	0.13	0.02	[0.09, 0.16]	<0.001	1.367
IS-M	3-6 METs (n=80)	-	-	-	-	2.144	-	-	-	-	4.388
	6-9 METs (n=50)	11.53	0.43	[10.68, 12.38]	<0.001	2.425	7.02	0.57	[5.90, 8.13]	<0.001	2.895
	Ex9 METs (n=20)	20.02	0.8	[18.46, 21.58]	<0.001	0.766	10.75	0.8	[9.19, 12.31]	<0.001	1.289

The 3-6 METs group was set as a baseline in the IS-M.

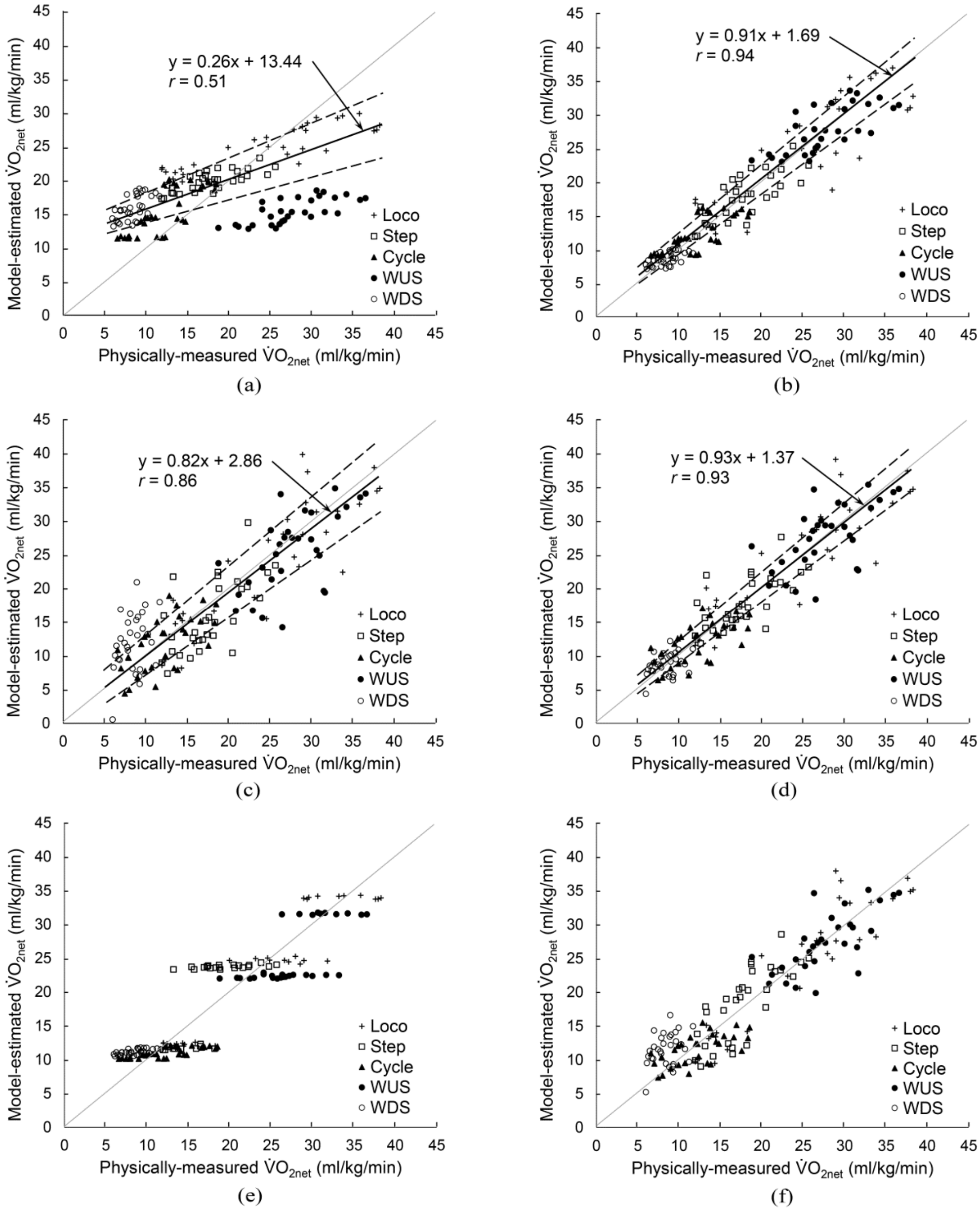


Fig. 3. Passing-Bablok regression plots for the linear relationship between the physically-measured $\dot{V}O_{2net}$ and model-estimated $\dot{V}O_{2net}$: (a) Unclassified model (U-M) predicted from SMA. The U-M comprised all data without PA recognition; (b) Recognition model (R-M) predicted from SMA. The R-M comprised the five separate activities; (c) U-M predicted from HR_{net}; (d) R-M predicted from HR_{net}; (e) Intensity segmentation model (IS-M) predicted from SMA. The IS-M comprised three separated intensity segmentations: 3-6, 6-9, and Ex9METs (the lowest, middle, and highest clustering group, respectively). The intensity segmentation grades were used as a factor according to the "cut point" method; (f) IS-M predicted from HR_{net}. These plots show the regression line (solid line), the confidence interval line (dashed lines) and 45° identity line (gray line), which corresponds to *x*=*y*. The "Loco" includes walking, jogging, and running.

TABLE IV
DIFFERENCE BETWEEN THE PHYSICALLY-MEASURED $\dot{V}O_{2NET}$ AND MODEL-ESTIMATED $\dot{V}O_{2NET}$

Type	Difference (%)																	
	SMA-$\dot{V}O_{2net}$									HR_{net}-$\dot{V}O_{2net}$								
	U-M			R-M			IS-M			U-M			R-M			IS-M		
	Grade 1	Grade 2	Grade 3	Grade 1	Grade 2	Grade 3	3-6 MET	6-9 MET	Ex9 MET	Grade 1	Grade 2	Grade 3	Grade 1	Grade 2	Grade 3	3-6 MET	6-9 MET	Ex9 MET
Loco	51.9	(3.7)	(14.3)	12.1	(3.2)	1.1	(11.1)	(4.7)	2.6	(9.1)	(5.4)	1.1	8.9	(1.3)	1.2	(13.8)	(1.2)	3.8
Step	29.8	15.5	0.1	2.1	3.8	(2.0)	(17.2)	24.9	-	(10.9)	(18.3)	(4.2)	9.7	(3.9)	(1.1)	(15.5)	12.4	-
Cycle	34.5	24.7	27.3	7.8	0.2	2.5	(2.9)	-	-	4.8	(5.8)	(1.4)	13.9	(3.4)	(6.9)	(0.5)	-	-
WUS	(43.2)	(44.7)	(44.2)	2.3	0.2	1.5	-	(11.8)	0.3	(9.8)	(8.3)	(5.8)	2.9	(0.2)	(1.2)	-	(2.0)	2.4
WDS	90.3	94.7	89.3	2.7	4.8	1.5	35.9	-	-	31.6	49.5	46.9	7.4	8.9	(0.5)	39.9	-	-

Difference (%): difference between the physically-measured $\dot{V}O_{2net}$ and model-estimated $\dot{V}O_{2net}$. Numbers in parentheses have negative values.
The calculation formula of differences (%): *[(model-estimated $\dot{V}O_{2net}$ value − physically-measured $\dot{V}O_{2net}$ value) / physically-measured $\dot{V}O_{2net}$ value]* $\times$ *100 %*

proportion of variance compared with the SMA (Fig. 3(b), R^2=0.89).

Difference between the physically-measured $\dot{V}O_{2net}$ and model-estimated $\dot{V}O_{2net}$. The differences (%) between the physically-measured $\dot{V}O_{2net}$ and model-estimated $\dot{V}O_{2net}$ of five PA types are presented in Table IV. In the U-M, the model-estimated $\dot{V}O_{2net}$ values predicted from the SMA and HR_{net} are 43.2-44.7% and 5.8-9.8% underestimates for WUS and 89.3-94.7% and 31.6-49.5% overestimates for WDS, respectively. Regardless of the type of PA, the predictions for the model-estimated $\dot{V}O_{2net}$ are much more precise when predicting from the HR_{net} in the U-M. In the R-M, the prediction results are superior to the U-M. Moreover, except for WDS, all PAs in the IS-M are underestimated for moderate activity intensities (3-6 MET) and slightly overestimated for very high activity intensities (Ex9 MET).

IV. Discussion

The functioning of PA recognition and EE prediction greatly depends on the attached position and orientation of the motion detection sensors. Most shoe-based sensor systems use more than one type of sensor, including accelerometer, pressure, angular velocity, inclination, or elevation detect sensors [17, 39-42]. However, some studies pointed out that the superiority is offset by the extra time, cost, and effort required to obtain and analyze the data [16, 17]. Furthermore, previous studies established models to estimate EE using three separate PA recognition methods, namely, unclassified, recognition, and intensity segmentation. However, according to the results found in a survey of the literature, few studies have quantitatively analyzed those prediction models. In this study, we developed a real-time shoe-based system with embedded microprocessors and accelerometers and implemented a multiple segmentation and recognition classification flow to simplify the process of PA recognition using only acceleration data. This is one of the first studies to systematically investigate the comparative validity of different prediction models and to measure the EE for moderate to very-high activity intensities. Moreover, the EE estimation results were provided as real-time feedback on an LED indicator on the surface of the shoes.

Relationship between SMA and physiological responses

Because the main function of the accelerometer is to measure the movement amplitude of an activity, the accelerometer signal is directly proportional to limb movement amplitude. The results of the R-M in Table II indicate that the SMA values could reflect physiological responses in Loco and Cycle. The similar relationships also show in the three grades of the IS-M which was segmented according to the "cut point" method. However, the opposite relationships of WUS and WDS indicate that the movement amplitude does not directly represent physiological reactions when only using signals from a single accelerometer as an explanatory variable. The lower physiological reaction of WDS shows that most of the generated impact forces may be absorbed by the knee joint.

Comparisons of three prediction models

In the present study, the validity of the model-estimated $\dot{V}O_{2net}$ was determined by quantifying the deviations and the differences between the physically-measured $\dot{V}O_{2net}$ and model-estimated $\dot{V}O_{2net}$ values. In agreement with previous research [17, 22], without activity recognition in the U-M in Table IV, the model-estimated $\dot{V}O_{2net}$ was underestimated (43.2-44.7% for SMA and 5.8-9.8% for HR_{net}) for high-intensity activities with low limb movement amplitudes, such as WUS. Conversely, the model-estimated $\dot{V}O_{2net}$ was overestimated (89.3-94.7% for SMA and 31.6-49.5% for HR_{net}) by nearly two-folds when estimating low-intensity activities with high limb movement amplitudes, such as WDS. In addition, Freedson *et al*. [25] reported that activity counts measured from accelerometers were proportional to physiological responses based on the "cut point" method. However, as shown in Fig. 3(e), the model-estimated $\dot{V}O_{2net}$ was inaccurate when considering activity intensities without performing any recognition steps. The experimental results showed that IS-M is only able to roughly measure the intensity of a PA and is prone to cluster the PA data. Each clustering group exhibits underestimates for the high-intensity PAs and overestimates for the low-intensity PAs. When making predictions based on SMA, for moderate activity intensities (3-6 MET), the Loco, Step, and Cycle were underestimated by 11.1, 17.2, and 2.9%, respectively, and the WDS was overestimated by 35.9%; for high activity intensities (6-9 MET), the Loco and WUS were underestimated 4.7 and 11.8%, respectively, and the Step was 24.9% overestimated. The possible reasons for these observed discrepancies could be due to different movement amplitudes and patterns, which could have caused activities within the same intensity segmentation grade to have different count-EE relationships. As stated by Swartz *et al*. [16] and Hendelman *et al*. [26], the development of consistent cut points and regression equations to predict the metabolic costs of multiple types of activities was difficult because different types of movement patterns were not sufficiently distinct. These results may easily lead to misinterpretations of the validity of "cut point" predictions.

As mentioned earlier, measuring physiological signals directly from HR monitors [18] and adding an activity classification method while using inertial sensors [13-15] have often been suggested to improve the accuracy of EE estimation. Early research demonstrated that activity intensity and HR are highly correlated [43], and activity intensity plays a significant role in predicting EE using HR. Hence, the pattern recognition of a PA became a minor part in EE estimation based on HR. However, unlike HR, the signals of an accelerometer contain movement data. Thus, PA pattern recognition is necessary to enhance the accuracy of predictions. In this study, we recommended a multiple-activity segmentation and recognition process and fit simple linear regressions to determine the relationship between the physically-measured $\dot{V}O_{2net}$ and model-estimated $\dot{V}O_{2net}$. The R-M increased the explained proportion of variance by 63% and 13% when estimating the EE using accelerometer data and HR_{net}, respectively, compared with the U-M. Moreover, in terms of the activity classification status, the proportion of variance obtained using accelerometer data was 3% higher than when HR_{net} was used. Furthermore, without PA recognition, the consistency of the PA affects the correlation. Hendelman *et al*. [26] noted the correlations became weaker when the activities were more homogeneous, such as longer sedentary or low-level activity periods, and when longer periods were considered. Therefore, for EE estimation, the segmentation and recognition of the PA can reduce the variability tremendously when using only accelerometer signals.

Comparisons with other shoe-based sensor systems

Following the PA recognition in this study, the experimental results show that the signals form the wearable system can achieve a good recognition rate (91.72-97.69%) with a single triaxial accelerometer embedded in the shoes for lower extremity locomotion actions. The R-M provides a better estimation and lower variability of EE estimation (63% greater) compared with the U-M when making predictions based on accelerometer signals. These results are in agreement with Sazonova *et al.* [17, 21, 39] who pointed out that the prediction markedly improves for the activity-specific branched model (root mean squared error decrease ~25%), and that the logical discrimination and branched models can reduce execution time and memory requirements. With the combination of acceleration, pressure, and posture-classification information, the classification accuracy was extremely good (100%) [17]. Furthermore, Ceaser [44] compared three commercialized products and reported that none of the devices were able to estimate EE across a range of activities. Therefore, for EE estimation, our study confirmed that the segmentation and recognition of PA can reduce variability tremendously when using accelerometer signals.

In addition, most shoe-based motion detector systems adopt more than one type of sensor to increase PA recognition and EE prediction. A previous study [41] developed instrumented shoes with five types of embedded sensors to devise an activity classification algorithm. Lee *et al.* [42] introduced shoes with an embedded accelerometer and gyroscope to observe lower limb locomotion and concluded that acceleration combined with angular velocity can be employed to identify locomotion and intensity levels. Kim *et al.* [45] estimated EE with accelerometers attached to four parts of body and found that EE can be conveniently predicted using an accelerometer on the watch or shoes. However, some studies pointed out that the superiority is offset by the extra time, cost, and effort required to obtain and analyze the data [16, 17]. Therefore, we developed shoes with only one accelerometer inside the shoes and implemented a recognition classification flow to simplify the process of PA recognition for lower extremity locomotion applications.

Concerning the establishment of a GEE model, we used $\dot{V}O_{2net}$ as a parameter to establish prediction models correlating to accelerometer signals (SMA) and physiological reactions. The $\dot{V}O_{2net}$ is the true amount of change of oxygen consumption from the activity; it is different from $\dot{V}O_{2gross}$, which considers total body oxygen consumption from the activity [46]. Therefore, verification will obtain more accurate results using $\dot{V}O_{2net}$.

Comparisons with other commercialized products

Several commercialized products can be added into consideration, to compare the performance of EE prediction. One is the IDEEA [20]. Its average accuracy for male subjects was about 95.8% and 94.2% as compared with indirect calorimeter and chamber test, respectively. Another two commercially available monitors are the Actical and the Actiheart [19]. Examined across seven activities, the Actical and Actiheart produced estimates that were less than the K4b^2 by approximately 28 and 24%, respectively. In the R-M of our study, the model-estimated $\dot{V}O_{2net}$ values predicted from the SMA have 87.9-97.9, 95.2-99.8, and 97.5-98.9% accuracy for moderate, high, and very high activity intensity grades, respectively, as compared with K4b^2 indirect calorimeter.

Another product is the RT3 [7]. The correlation coefficient, *r*, of EE was obtained to determine the relationship between the RT3 and the indirect calorimetry from r=0.56 for walking at 3 km/h to r=0.84 for running at 9 km/h. In our study, the value of the correlation coefficient increased from r=0.51 in the U-M to r=0.94 in the R-M. The R-M increased the explained proportion of variance by 63% and 13% when estimating the EE using accelerometer data and HR_{net}, respectively, compared with the U-M. The comparison of results shows that our performance of the developed EE monitor is similar to the IDEEA, which uses five sensors, and is better than the Actical, Actiheart, and RT3, which use, respectively, one waist-mounted accelerometer, one torso-mounted monitor combining accelerometer and HR, and one waist-mounted accelerometer.

Moreover, Dannecker *et al.* [22] developed models to estimate EE using the shoe-based PA monitor (SmartShoe) and compared the validity against five research and consumer PA monitors including Actical, ActiGraph, IDEEA, DirectLife, and Fitbit. The results showed that the SmartShoe provides a valid estimate of EE: the percentage of the root-mean-square error (RMSE%) was 6.2%. However, other PA monitors had a wide range of validity when estimating EE. The RMSE% were 20.2, 13.6, 17.5, 26.8, and 28.7% for Actical, DirectLife, IDEEA, ActiGraph, and Fitbit, respectively. In the R-M of our study, we comprised three separated intensity grades of each activity. The RMSE% were 7.3-14.1, 7.7-8.8, 9.0-13.5, 6.0-7.6, and 7.2-9.7% for Loco, Step, Cycle, WUS, and WDS, respectively. The Loco had the largest RMSE% since it included relatively large variation of action from walking at 5 km/h to running at 9 km/h. Moreover, variance in personal activity habits may influence accelerometer counts and EE estimation especially using a shoe-based system. Generally, the accuracy and precision of predicting EE in this study were reasonably acceptable. They were as great as, or slightly less than, the SmartShoe, which is equipped with a pressure-sensing insole and an accelerometer.

Advantages and limitations

Regardless of the method used to measure the HR (e.g., using an electrocardiography device, a Polar belt or a hand rim with an HR monitor function), user acceptance is low. In addition to restricting the user's daily routine, skin inflammation and allergic reactions have been reported to result from various wearable motion-detecting apparatuses [47]. Another criticism is that heart rates are susceptible to emotional and external factors. To address this criticism, accelerometer-based activity monitors with complex recognition algorithms have been recommended to replace HR monitors [14]. This study presented a comparison of three prediction models used to estimate EE. With shoe-based motion detectors we developed, different levels of EE were displayed in real time on an LED indicator on the surface of the shoes, and the recorded data were uploaded to a remote PC host. Furthermore, there are many other factors that can be used as variables in EE prediction models, such as standard deviation and variation. In light of our goal of real-time implementation, they were not used in this study.

However, since most PAs in daily life, such as lying down, sitting, standing, and housework [17, 33], are limited in activity intensity, being above resting and below lowest exercise thresholds ($\leqq$2.99 MET), these activities require less energy than general exercise, and may be the cause for miscalculations. Moreover, even when utilizing multiple, complicated algorithms, the EE within those activities did not differ much from each other and did not offer sufficient advantages to adults who require athletic training or wellness management. Hendelman *et al*. [26] reported the inaccuracies in extrapolating data from low activity intensity grades to high ones; even for the same intensity grade, count discrepancies were observed for various equations. To overcome these problems, we investigated five PA types that varied from moderate to very-high intensities. The selected activities are effective exercises and yield positive health outcomes for adults who suffer from metabolic or cardiopulmonary disorders. Moreover, we agree that a more straightforward PA recognition method would yield more value, and is the target of our future studies.

Different intensities of activities that have different EE values may correspond to similar movement profiles. There were a few limitations in estimating EE using accelerometer signals from shoes. For example, the inertial sensors have limited applicability and were unable to detect certain activities, such as walking while carrying a load, cycling or jogging on fitness equipment with resistance or slope, and upper body workouts [5]. Since the accelerometer used is embedded inside the shoes, activities especially focusing on the upper body may be inappropriate for our models. These limitations can be compensated for by using more sensors attached to different body segments, such as the sensors used in Swartz *et al*. [16] and IDEEA [20] modules. However, the shortcoming from the extra load required to obtain and analyze the data also need to be taken into account [16, 17].

Also, we focused on five PA types and recruited healthy, young males to participate in this study. Other activities or age groups and other types of PA not within our experiment parameters may not be applicable or appropriate for our models and may lead to misinterpreted results. For other groups that are not included in this study, we suggest that experiments be conducted separately, or that relativity estimation based on our outcome be performed in order to expand the applicable research area.

V. Conclusion

Our results reveal that the accuracy of the EE predicted from accelerometer signals is influenced by differences among PAs, which exhibit different limb movement amplitudes and patterns. The recognition model using accelerometer signals was a better estimation for EE with smaller dispersions and lower variability than that of recognition model using HR and an unclassified model using accelerometer signals. The deviations in the estimates could not be solved using the “cut point” method because the discrepancies could be influenced by the different count-EE relationships within the same intensity segmentation grade. The reliable calculation and easy operation of the methods we present can help users conveniently and precisely self-treat and manage their PAs. The proposed shoe-based motion detectors can provide real-time feedback about EE on the surface of the shoes and have great potential to be used to manage everyday exercise.

References

[1] C.-C. Yang and Y.-L. Hsu, "A review of accelerometry-based wearable motion detectors for physical activity monitoring," vol. 10, pp. 7772-7788, 2010.

[2] K. R. Westerterp, "Physical activity as determinant of daily energy expenditure," *Physiol. Behav.*, vol. 93, pp. 1039-1043, Mar. 2008.

[3] Y. C. Lin *et al.*, "Human recognition based on kinematics and kinetics of gait," *J. Med. Biol. Eng.*, vol. 31, pp. 255-263, Nov. 2011.

[4] H. Zhou and H. Hu, "Human motion tracking for rehabilitation—a survey," *Biomed. Signal Process. Control*, vol. 3, pp. 1-18, Jan. 2008.

[5] N. Hegde *et al.*, "A comparative review of footwear-based wearable systems," *Electronics*, vol. 5, p. 48, Aug. 2016.

[6] B. Najafi *et al.*, "Ambulatory system for human motion analysis using a kinematic sensor monitoring of daily physical activity in the elderly," *IEEE Trans. Biomed. Eng.*, vol. 50, pp. 711-723, Jun. 2003.

[7] J. Hussey *et al.*, "Validation of the RT3 in the measurement of physical activity in children," *J. Sci. Med. Sport.*, vol. 12, pp. 130-133, Jan. 2007.

[8] D. Gafurov and E. Snekkenes, "Gait recognition using wearable motion recording sensors," *EURASIP J. Adv. Signal Process.*, vol. 2009, p. 415817, Jun. 2009.

[9] E. S. Sazonov *et al.*, "Monitoring of posture allocations and activities by a shoe-based wearable sensor," *IEEE Trans. Biomed. Eng.*, vol. 58, pp. 983-990, Apr. 2011.

[10] E. S. Sazonov *et al.*, "Development of SmartStep: an insole-based physical activity monitor," in *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Osaka, Japan, 2013, pp. 7209-7212.

[11] F. Kawsar *et al.*, "A novel activity detection system using plantar pressure sensors and smartphone.," in *IEEE 39th Annual Computer Software and Applications Conference (COMPSAC)*, Taichung, Taiwan, 2015, pp. 44-49.

[12] G. J. Welk *et al.*, "A comparative evaluation of three accelerometery-based physical activity monitors," *Med. Sci. Sports Exerc.*, vol. 32, pp. S489-497, Sep. 2000.

[13] F. R. Allen *et al.*, "Classification of a known sequence of motions and postures from accelerometry data using adapted Gaussian mixture models," *Physiol. Meas.*, vol. 27, pp. 935-951, Oct. 2006.

[14] A. G. Bonomi *et al.*, "Detection of type, duration, and intensity of physical activity using an accelerometer," *Med. Sci. Sports Exerc.*, vol. 41, pp. 1770-1777, Sep. 2009.

[15] K. Kiani *et al.*, "Computerized analysis of daily life motor activity for ambulatory monitoring," *Technol. Health Care.*, vol. 5, pp. 307-318, Oct. 1997.

[16] A. M. Swartz *et al.*, "Estimation of energy expenditure using CSA accelerometers at hip and wrist sites," *Med. Sci. Sports Exerc.*, vol. 32, pp. S450-456, Sep. 2000.

[17] N. A. Sazonova *et al.*, "Accurate prediction of energy expenditure using a shoe-based activity monitor," *Med. Sci. Sports Exerc.*, vol. 43, pp. 1312-21, Jul. 2011.

[18] S. Liu *et al.*, "Computational methods for estimating energy expenditure in human physical activities," *Med. Sci. Sports Exerc.*, vol. 44, pp. 2138-2146, Nov. 2012.

[19] D. K. Spierer *et al.*, "A comparison of energy expenditure estimates from

the Actiheart and Actical physical activity monitors during low intensity activities, walking, and jogging," *Eur. J. Appl. Physiol.*, vol. 111, pp. 659-67, Apr. 2011.
[20] K. Zhang *et al.*, "Improving energy expenditure estimation for physical activity," *Med Sci Sports Exerc.*, vol. 36, pp. 883-889, May. 2004.
[21] N. Sazonova *et al.*, "Posture and activity recognition and energy expenditure prediction in a wearable platform," in *IEEE Engineering in Medicine and Biology Society*, Chicago, IL, 2014, pp. 4163-4167.
[22] K. L. Dannecker *et al.*, "A comparison of energy expenditure estimation of several physical activity monitors," *Med. Sci. Sports Exerc.*, vol. 45, pp. 2105-2012, Nov. 2013.
[23] N. Hegde and E. Sazonov, "SmartStep: a fully integrated, low-power insole monitor," *Electronics*, vol. 3, pp. 381-397, Jun. 2014.
[24] N. Hegde and E. Sazonov, "SmartStep 2.0-a completely wireless, versatile insole monitoring system," in *IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Washington, DC, USA, 2015, pp. 746-749.
[25] P. S. Freedson *et al.*, "Calibration of the computer science and applications, inc. accelerometer," *Med. Sci. Sports Exerc.*, vol. 30, pp. 777-781, May. 1998.
[26] D. Hendelman *et al.*, "Validity of accelerometry for the assessment of moderate intensity physical activity in the field," *Med. Sci. Sports Exerc.*, vol. 32, pp. S442-449, Sep. 2000.
[27] A. M. Sabatini *et al.*, "Assessment of walking features from foot inertial sensing," *IEEE Trans. Biomed. Eng.*, vol. 52, pp. 486-494, Mar. 2005.
[28] D. M. Karantonis *et al.*, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory nonitoring," *IEEE Trans. Inf. Technol. Biomed.*, vol. 10, pp. 156-167, Jan. 2006.
[29] J. Včelák *et al.*, "AMR navigation systems and methods of their calibration," *Sens. Actuators A Phys.*, vol. 123-124, pp. 122-128, Sep. 2005.
[30] Y. C. Lai *et al.*, "Development of a low-cost attitude and heading reference system using a three-axis rotating platform," *Sensors*, vol. 10, pp. 2472-2491, Mar. 2010.
[31] D. P. Swain, "Energy cost calculations for exercise prescription," *Sports Med.*, vol. 30, pp. 17-22, Jul. 2000.
[32] J. E. McLaughlin *et al.*, "Validation of the COSMED K4b2 portable metabolic system," *Int. J. Sports Med.*, vol. 22, pp. 280-284, May. 2001.
[33] S. E. Crouter *et al.*, "A novel method for using accelerometer data to predict energy expenditure," *J. Appl. Physiol.*, vol. 100, pp. 1324-1331, Dec. 2006.
[34] T. J. Overend *et al.*, "Physiological responses of young and elderly men to prolonged exercise at critical power," *Eur. J. Appl. Physiol.*, vol. 64, pp. 187-193, Mar. 1992.
[35] S. Sprager and M. B. Juric, "Inertial sensor-based gait recognition: a review," *Sensors (Basel)*, vol. 15, pp. 22089-22127, Sep. 2015.
[36] A. Avci *et al.*, "Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: a survey," in *Architecture of Computing Systems*, Hannover, Germany, 2010.
[37] H. Ghasemzadeh *et al.*, "Wireless medical-embedded systems: a review of signal-processing techniques for classification," *IEEE Sens. J.*, vol. 13, pp. 423 - 437, Feb. 2013.
[38] J. S. Wang *et al.*, "Walking pattern classification and walking distance estimation algorithms using gait phase information," *IEEE Trans. Biomed. Eng.*, vol. 59, pp. 2884-2892, Oct. 2012.
[39] N. A. Sazonova *et al.*, "Prediction of bodyweight and energy expenditure using point pressure and foot acceleration measurements," *Open Biomed. Eng. J.*, vol. 5, pp. 110-115, Dec. 2011.
[40] D. Schuldhaus *et al.*, "An adaptable inertial sensor fusion-based approach for energy expenditure estimation," in *The 15th International Conference on Biomedical Engineering*, Switzerland, 2014.
[41] C. M. e. Achkar *et al.*, "Instrumented shoes for activity classification in the elderly," *Gait Posture*, vol. 44, pp. 12-17, Feb. 2016.
[42] Y.-S. Lee *et al.*, "Assessment of walking, running, and jumping movement features by using the inertial measurement unit," *Gait Posture*, pp. 877-881, May. 2015.
[43] B. D. Levine, "V̇O2,max: what do we know, and what do we still need to know?," *J. Physiol.*, vol. 586, pp. 25-34, Jan. 2008.
[44] T. G. Ceaser, "The estimation of caloric expenditure using three triaxial accelerometers," PhD Dissertations, The University of Tennessee, 2012.
[45] T. Kim *et al.*, "A preliminary study on estimation of energy expenditure at different locations of acceleration sensor during submaximal exercise," in *IEEE Engineering in Medicine and Biology Society*, Minneapolis, Minnesota, USA, 2009.
[46] K. Allen *et al.*, *ACSM's guidelines for exercise testing and prescription*, 9th ed. Philadelphia, PA: Lippincott Williams & Wilkins, 2013.
[47] E. Nemati *et al.*, "A wireless wearable ECG sensor for long-term applications," *IEEE Communications Magazine*, vol. 50, pp. 36-43, Jan. 2012.