Posture and Activity Recognition and Energy Expenditure Prediction in a Wearable Platform

Nadezhda Sazonova, Raymond Browning, Edward Melanson and Edward Sazonov, *EMBS Senior Member*

Abstract— **The use of wearable sensors coupled with the processing power of mobile phones may be an attractive way to provide real-time feedback about physical activity and energy expenditure (EE). Here we describe use of a shoe-based wearable sensor system (SmartShoe) with a mobile phone for real-time prediction and display of time spent in various postures/physical activities and the resulting EE. To deal with processing power and memory limitations of the phone, we introduce new algorithms that require substantially less computational power. The algorithms were validated using data from 15 subjects who performed up to 15 different activities of daily living during a four-hour stay in a room calorimeter. Use of Multinomial Logistic Discrimination (MLD) for posture and activity classification resulted in an accuracy comparable to that of Support Vector Machines (SVM) (90% vs. 95%-98%) while reducing the running time by a factor of 190 and reducing the memory requirement by a factor of 104. Per minute EE estimation using activity-specific models resulted in an accurate EE prediction (RMSE of 0.53 METs vs. RMSE of 0.69 METs using previously reported SVM-branched models). These results demonstrate successful implementation of real-time physical activity monitoring and EE prediction system on a wearable platform.**

I. Introduction

Objectively monitoring physical activity (PA), including the type, intensity and duration of activities, is an important component of programs designed to prevent/treat metabolic syndrome/obesity. PA monitoring and the associated estimates of instantaneous and cumulative energy expenditure (EE) can provide important feedback that would allow a person to regulate his/her PA and energy balance in order to maintain or achieve a healthy weight/lifestyle. Several physical activity monitors have been developed that provide continuous feedback of EE through heart rate, accelerometry and/or other sensor measurements [1]–[3]. While some of these products can provide reasonably accurate assessments of EE, they have the disadvantage of being obtrusive and/or uncomfortable to wear continuously.

An attractive practical opportunity for convenient, unobtrusive PA monitoring is to use mobile devices (e.g. smart phones) equipped with software that provides an instantaneous estimation and display of physical activity and EE. Recent research has demonstrated the implementation of software for posture/activity recognition and energy expenditure prediction in cell phones using built-in 3-axis accelerometer [4], [5]. However, the accuracy of posture and activity recognition and EE estimation is likely to be limited due the wide variety of ways a cell phone can be worn or carried by a person.

We have recently developed a wireless shoe-based sensor system (SmartShoe) that records insole pressure and foot acceleration data. These data could be used for the subsequent development of models for posture/activity classification [6], [7] and EE prediction [8]. The use of SmartShoe is advantageous for accurate EE prediction because it provides monitoring of key body weight support points; is capable of differentiating static postures (such as sitting and standing), weight-bearing and non-weight bearing activities (such as walking and cycling); and is unobtrusive, lightweight and easy to use. In this respect, use of SmartShoe is distinctly different form commonly reported gait parameter measurements [9]–[11].

Methods for Posture and Activity Classification and EE prediction (PAC/EE) reported in [6], [8] are not well suited for use on a cell phone due to computational intensity and high memory requirements. A combination of SmartShoe sensors, efficient PAC/EE algorithms with the audio/visual capabilities of a modern smart phone can potentially lead to development of biofeedback-based interventions for increasing physical activity and weight management. Therefore, it is highly desirable to execute PAC/EE algorithms on a mobile computing platform in real time.

In this study we suggest novel PAC/EE models that can operate on a cell phone platform with low computational capability. The proposed models are validated in a room calorimeter study with 15 subjects performing various activities.

II. Methods

A. Subjects and protocol

Nineteen subjects (10 male, 9 female) were recruited to participate in this study. The protocol was approved by the

This work was supported in part by National Institutes of Health grants 1R43DK083229 and UL 1 TR001082.

N.A. Sazonova is formerly with the Department of Electrical and Computer Engineering, the University of Alabama, Tuscaloosa, AL 35487 USA.

R. Browning is with Department of Health and Exercise Science, Colorado State University, Fort Collins, CO 80523 USA.

E. Melanson is with Division of Endocrinology, Diabetes, and Metabolism and the Division of Geriatric Medicine at the University of Colorado Anschutz Medical Campus, Denver, CO 80045 USA.

E.S. Sazonov is with Department of Electrical and Computer Engineering, The University of Alabama, Tuscaloosa, AL 35487 (phone: (205) 348-1981, email: esazonov@eng.ua.edu).

Colorado State University Institutional Review Board. Based on self-report, subjects were sedentary to moderately active (less than six hours of physical exercise per week), not taking any medications known to alter metabolism, and weight stable over the past six months.

Each subject performed one 4-hour stay in a room calorimeter following a 4-hour fast. Metabolic data was collected while each individual performed a series of randomly assigned postures and activities that were recorded by a video camera (Table I). The subjects wore SmartShoe of appropriate size ranging from female size 7 to male size 12 (US).

Sensor data from each experiment were manually annotated with every minute of each activity labeled from the set activity classes shown in Table I. The annotated data were later used for training and validation of automatic computer algorithms for posture and activity classification.

Oxygen consumption and carbon dioxide production were recorded using the whole-room indirect calorimeter located in the Clinical Translational Research Center of the University of the Colorado Hospital [12]. EE and substrate oxidation were calculated using the non-protein RQ [13]. Measured oxygen consumption and associated EE was recorded on per minute basis. The first 30 minutes of data were excluded to permit adequate equilibration of respiratory gas within the room. The average EE of the last 5 minutes of the supine period for each subject was used as an estimate of resting metabolic rate/EE in kcal/min.

Four subjects had incomplete data as a result of an error in the recording system, shoe sensors or power grid failures during the experiment and were excluded from the analysis. The anthropometric characteristics for the remaining 15 subjects are given in Table II.

B. Sensors

The sensor data for this study were collected by a SmartShoe with embedded wearable sensor system (Figure 1). Five force-sensitive resistors were embedded in a flexible insole and positioned under the critical points of contact: heel, metatarsal bones and the great toe (hallux), allowing for differentiation of static postures and weight bearing and non-weight bearing activities. The acceleration data were collected from a 3-dimensional MEMS accelerometer (ADXL335) positioned on the back of the shoe. Pressure and acceleration data were sampled at 400Hz, downsampled to 25Hz by averaging of 16 consecutive samples and sent over a Bluetooth link to a smartphone storing the signals for further processing.

C. Data processing

The data processing in the proposed PAC/EE model is outlined in Figure 2. Algorithmically the processing of the signals consists of two major steps. First, sensor data from shoes are used to classify every 2-second epochs into one of four states: Sit, Stand, Walk/Jog or Cycle. Second, the same sensor data along with the result from the posture/activity classification are used to predict energy expenditure on 1-minute time intervals by selecting an appropriate branch model (Sit, Stand, Walk/Jog or Cycle) and applying it to the metrics extracted from the sensor data.

TABLE I. ACTIVITIES IN THE PROTOCOL

Activity	Description	Time	Class label
Equilibration	Quiet resting, data excluded	30 min	N/A
Supine	laying on bed, data excluded	20 min	N/A
Sitting	watching TV	20 min	Sit
	performing computer work	20 min	Sit
Standing	Quiet	10 min	Stand
	Active	10 min	Stand
Random assignment; 6 of 8 possible activities	Walking, 2.5mph	10 min each; 60 min total	Walk/Jog
	Walking, 3.5mph		Walk/Jog
	Walking uphill, 2.5% grade, 2.5mph		Walk/Jog
	Stepping		Walk/Jog
	Sweeping		Stand
	Cycling, 75W		Cycle
	Standing		Stand
	Sitting		Sit
Free-living	Any of the above activities, self-selected pace and posture	60 min, or until 4 hours total	Selected class

TABLE II. SUBJECT CHARACTERISTICS

Characteristic	Males (n = 9)		Females (n = 6)	
	Mean(SD)	Range	Mean(SD)	Range
Age, years	28.1(6.9)	(20-38)	23.7(3.1)	(20-29)
Height, cm	178.1(10.2)	(162.6-193)	167.5(8.5)	(157.5-180)
Weight, kg	79.3(16.7)	(57.6-98.5)	72.0(18.0)	(49.2-99)
BMI	24.8(3.6)	(19.6-31.1)	25.6(6.3)	(18.7-37.3)

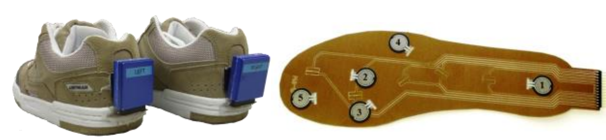

Figure 1. SmartShoe device: (left) Overall view of the shoe device with attached accelerometer, battery and power switch on the back; (right) Pressure-sensitive insole with 5 pressure sensors: heel (1), 3rd metatarsal head (2), 1st metatarsal head (3), 5th metatarsal head (4), hallux (5).

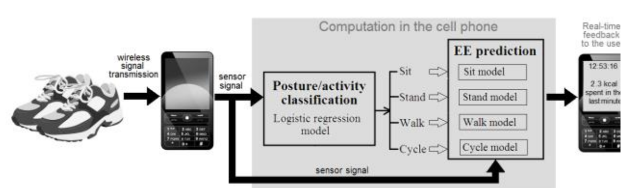

Figure 2. Outline of the smart-phone integrated shoe-based system for EE prediction.

D. Posture and Activity classification

The posture/activity classification algorithm automatically recognizes activities and assigns class labels from the set of {Sit, Stand, Walk/Jog, Cycle} to 2-second periods of sensor data. In order to meet the time and space requirements of mobile devices we propose a substantially less computationally intensive model based on multinomial logistic discrimination (MLD) [14]. The MLD algorithm requires computation of metrics from the raw 2-second signal (length 50 samples) for each sensor which are then used as possible predictors: mean value (***mean***), entropy (***ent***) and standard deviation (***std***). The extraction of the above metrics provided a total of 24 possible predictors (8 sensors per shoe x 3 features per sensor). The recognition model was a multinomial logistic discrimination with 4 classes (Sit, Stand, Walk/Jog and Cycle) with three logit functions being the linear combinations of possible predictors (cycle was selected as the baseline class):

$$Logit(p_i) = \log\left(\frac{p_i}{p_{CYCLE}}\right) = X\beta_i, i=\{Sit,\ Stand,\ Walk/Jog\}.$$

Selection of the best combination of predictors for the logistic model was done using forward selection procedure with accuracy of the validation data set as the criterion. In turn, validation was done using leave-one-out procedure in which data from all subjects but one are used for training of the model and the remaining subject is used for validation.

E. Energy Expenditure prediction

In this study we developed a new model for EE prediction using linear regression branched by the activity type (Sit, Stand, Walk/Jog or Cycle) based on 1 minute intervals (EEM1m). The sensor signals with 1 minute duration were used with the posture/activity classification to produce thirty posture/activity labels (one for each of the 2 second intervals in that minute). Out of these thirty predictions the activity with the highest frequency was selected to represent the activity for the entire 1 minute interval and choose the branch for EE model prediction.

To train the EE prediction model we first classified 1 minute into 4 activity groups (Sit, Stand, Walk/Jog and Cycle) using the MLD model. We then extracted a set of predictor metrics and then trained each of the four branch (based on the predicted activity classification) models using ordinary least squares regression. The following metrics were computed: (***max)*** maximal value of the signal, used only for the pressure sensors, (***zc)*** number of crossings of the median of the signal, (***std)*** standard deviation of the signal, and (**ent)** entropy of the signal. To provide the robustness against the pressure sensors failures we combined similar metrics for the 5 pressure sensors by computing the medians of appropriate values: thus, the 5 ***max*** metrics for the pressure sensors were combined into a single predictor $\boldsymbol{Sens_{med(max)}}$, 5 ***zc*** metrics were combined into $\boldsymbol{Sens_{med(zc)}}$, 5 ***std*** and 5 ***ent*** metrics resulted in $\boldsymbol{Sens_{med(std)}}$ and $\boldsymbol{Sens_{med(ent)}}$ respectively.

The selection of the best set of predictors was done using forward selection procedure with the following criteria: the best model had to have a low value for the Akaike Information Criterion (AIC), a high adjusted coefficient determination (R^2_{ADJ}) and a low root-mean squared error.

Validation of EE prediction was done using the leave-one-out approach: for each subject all epochs corresponding to that subject were excluded from the training set and the resulting trained model was used to predict EE for every epoch of the left out subject.

F. Model comparison

Proposed PAC/EE models were compared with those in [6], [8] in terms of computational burden, memory requirements and prediction accuracy. All models were coded in Visual C++, compiled using Windows Mobile Professional SDK, and tested on Samsung Omnia II phone with an 800Mhz processor to obtain running time estimates.

Computational time and space requirements of different models were compared using one or more of the following metrics: 1) time complexity (number of elementary operations needed to be performed during execution) for the model's testing stage, 2) space complexity (number of elementary objects needed to be stored during execution) for the model's testing stage, 3) space requirements for model storage (number of elementary floating point objects to be stored between execution steps), 4) actual time (ms) to run the model on the Omnia smart phone.

Prediction accuracy was assessed in the following comparisons: 1) automatic classification by MLD was compared to classification by a human observer who manually annotated the experiment and expressed as a per-minute cumulative confusion matrix pooled from the subject population with overall classification accuracy being the ratio of sum of diagonal elements in confusion matrix to the sum of all elements in the matrix. 2) Accuracy of EE prediction of the MLD-branched EEM_{1m} model were compared with the EE measurements of the room calorimeter by the following performance characteristics: a) total error of prediction, computed as the average total error of prediction across all subjects: $totERR = \frac{1}{N}\sum_{i=1}^{N}\frac{|totEE_i - totEE_i^{pred}|}{totEE_i}$, where N is the number of subjects, $totEE_i = \sum_{t=1}^{T} EE_{ti}$ is total EE measured by the room calorimeter and $totEE_i^{pred} = \sum_{t=1}^{T} EE_{ti}^{pred}$ is total EE predicted by a model, and where T is the number of 1 minute EE values in an experiment, b) per-minute root-mean squared error (RMSE): $RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(EE_t - EE_t^{pred})^2}$, where EE_t is EE measured by room calorimeter for a given 1-minute interval; EE_t^{pred} is EE estimated by a model for the same 1-minute interval. RMSE can be computed using EE expressed in kcal/min or METs. Conversion of kcal predictions to METs was done as using resting energy expenditure calculated as 2-second or 1-minute average from the last 5 minutes of the supine period for each subject. Thus, EE in METs was computed as the multiples of resting EE.

III. Results

The training of the MLD model for posture and activity classification resulted in selection of 12 predictors (included as linear models for the three logit functions) from 3 accelerometer and the 3 pressure sensors: $\{PSens1_{mean}, PSens2_{mean}, PSens5_{mean}, Acc1_{ent}, Acc2_{ent}, Acc3_{ent}, Acc1_{std}, Acc2_{std}, Acc3_{std}, PSens1_{std}, PSens2_{std}, PSens5_{std}\}$ where *PSensX* is pressure sensor *X* and *AccY* is *Y*-s dimension of the accelerometer. The logit function equations were:

$$Logit\ (p_{Sit}) = \log\left(\frac{p_{Sit}}{p_{Cycle}}\right) = 18 - 5.49 \cdot Acc1_{ent} - 0.59 \cdot Acc2_{ent} + 0.67 \cdot Acc3_{ent} -$$
$$- 0.002 \cdot Sens1_{mean} + 0.002 \cdot Sens2_{mean} - 0.0015 \cdot Sens5_{mean} - 0.023 \cdot Acc1_{std} +$$
$$+ 0.07 \cdot Acc2_{std} - 0.006 \cdot Acc3_{std} - 0.002 \cdot Sens1_{std} - 0.003 \cdot Sens2_{std} - 0.004 \cdot Sens5_{std}$$

$$Logit\ (p_{STand}) = \log\left(\frac{p_{STand}}{p_{Cycle}}\right) = -2.72 - 8.76 \cdot Acc1_{ent} + 2.91 \cdot Acc2_{ent} + 2.82 \cdot Acc3_{ent} +$$
$$+ 0.004 \cdot Sens1_{mean} + 0.006 \cdot Sens2_{mean} + 0.0029 \cdot Sens5_{mean} - 0.057 \cdot Acc1_{std} +$$
$$+ 0.063 \cdot Acc2_{std} + 0.014 \cdot Acc3_{std} + 0.004 \cdot Sens1_{std} - 0.002 \cdot Sens2_{std} - 0.002 \cdot Sens5_{std}$$

$$Logit\ (p_{Walk}) = \log\left(\frac{p_{Walk}}{p_{Cycle}}\right) = 9.97 - 5.96 \cdot Acc1_{ent} + 0.74 \cdot Acc2_{ent} - 2.03 \cdot Acc3_{ent} -$$
$$- 0.0007 \cdot Sens1_{mean} + 0.0037 \cdot Sens2_{mean} - 0.0004 \cdot Sens5_{mean} - 0.014 \cdot Acc1_{std} +$$
$$+0.054 \cdot Acc2_{std} - 0.0004 \cdot Acc3_{std} + 0.005 \cdot Sens1_{std} - 0.003 \cdot Sens2_{std} + 0.004 \cdot Sens5_{std}$$

Comparison of the time and space requirement of the MLD model and the SVM model [6] is shown in Table III. The space required to store MLD model is equivalent to storing 12x3 element matrix of floating point numbers, while for the SVM model it is necessary to store 700 support vectors used in [6] (as a 700x600 element matrix) and a 4x700 element matrix of discrimination function coefficients. Thus, the relative difference in the model's storage space requirements is at least 10^4-fold for the SVM model compared to the MLD model. When tested on Samsung Omnia II cell phone the SVM model failed to fit within the available memory. In order to evaluate its running time, we implemented a simulated version of the SVM model testing where the same type and number of iterations is performed on the same type of variables as in the actual model testing.

The accuracy of posture and activity classification for 1-minute intervals and four class labels (Sit, Stand, Walk/Jog and Cycle) is presented in Table IV. The overall accuracy for MLD classifier was 90%, close to those of an SVM classifier (95%-98%) reported in [6].

Table V shows the best set of predictors and corresponding EE prediction equations for EEM_{1m} model branched by the activity. Running time of the EEM_{1m} model on the smart phone was 16 ms. The accuracy of EE prediction by MLD-branched EEM_{1m} is shown in Table VI. The error is comparable to the RMSE of 0.69 METs reported in [8].

Figure 3 shows a Bland-Altman plot in kcal/min for all 1-min instances from all 15 subjects. The plot demonstrates that the errors of prediction do not follow any specific pattern, and is not biased to either side (under- or overprediction) with average bias being negligibly small (-0.004 kcal/min).

IV. DISCUSSION

In this study we proposed computationally efficient PAC/EE algorithms allowing real-time execution on a mobile phone. Given that mobile devices have limited computational power, memory and storage, some methodological issues needed to be addressed in order to allow for the successful implementation of PAC and EE algorithms. In particular, a new MLD-based algorithm for posture and activity classification was developed to replace SVM classification. Logistic discrimination decreased the running time 190 times (from 655ms to 3.5ms), and produced a very efficient and accurate classification. Very high processor load (O(ns)) with SVM implementation would be detrimental to latency of the output, computing resources available to other programs and battery life. MLD substantially reduces impact of real-time PAC on computational resources available on a mobile device.

TABLE III. TIME AND SPACE COMPLEXITY FOR THE POSTURE/ACTIVITY CLASSIFICATION MODELS

Posture / activity classification method	**Space complexity**	**Space requirement, floating point numbers**	**Time Complexity**	**Actual running time, ms**
SVM	O(ns)	422800	O(ns)	655
MLD	O(n)	36	O(n)	3.5

n is the size of input data, s is number of support vectors

TABLE IV. POPULATION-CUMULATIVE CONFUSION MATRIX OF MLD CLASSIFIER.

Actual class \ Predicted class	Sit	Stand	Walk/ Jog	Cycle	**Class-specific recall**
Sit	*1228*	*4*	*2*	*1*	**0.99**
Stand	*189*	*315*	*13*	*1*	**0.6**
Walk/Jog	*16*	*2*	*440*	*0*	**0.96**
Cycle	*6*	*0*	*0*	*108*	**0.95**
Class-specific precision	**0.85**	**0.98**	**0.98**	**0.98**	**0.9**

TABLE V. EE PREDICTION MODEL BRANCHED BY ACTIVITY

Branch	EEM_{1m} model
Sit	$EE = 1.44 + 0.014 \cdot \boldsymbol{Weight} - 0.45 \cdot \boldsymbol{log(BMI)} + 25.9 \cdot \boldsymbol{Sens_{med(std)}} + 1.9 \cdot 10^{-3} \cdot \boldsymbol{Acc1_{std}} + 0.64 \cdot \boldsymbol{Acc1_{zc}} + 0.51 \cdot \boldsymbol{Acc2_{zc}} + 1.2 \cdot 10^{-3} \cdot \boldsymbol{Acc3_{std}}$
Stand	$EE = 4.93 + 3.22 \cdot 10^{-2} \cdot \boldsymbol{Weight} - 2.01 \cdot \boldsymbol{log(BMI)} + 1.2 \cdot 10^{-3} \cdot \boldsymbol{Sens_{med(zc)}} + 3.7 \cdot 10^{-3} \cdot \boldsymbol{Acc1_{std}} + 12.4 \cdot \boldsymbol{Sens_{med(std)}} + 1.44 \cdot \boldsymbol{Acc1_{zc}}$
Walk	$EE = -3.39 + 6.4 \cdot 10^{-2} \cdot \boldsymbol{Weight} - 0.16 \cdot \boldsymbol{log(BMI)} + 42.3 \cdot \boldsymbol{Sens_{med(std)}} + 9.33 \cdot \boldsymbol{Acc3_{zc}} + 1.8 \cdot 10^{-3} \cdot \boldsymbol{Acc2_{std}}$
Cycle	$EE = 6.4 + 1.14 \cdot 10^{-2} \cdot \boldsymbol{Weight} - 0.84 \cdot \boldsymbol{log(BMI)} + 3.3 \cdot 10^{-3} \cdot \boldsymbol{Acc1_{std}}$

TABLE VI. EE PREDICTION PERFORMANCE OF EEM_{1M} MODEL

Total Error, %	**RMSE, METs**		**Limits of agreement, METs**
	Sit model:	0.40	(-0.80,0.81)
	Stand model:	0.42	(-0.84,0.84)
	Walk/Jog model:	0.81	(-1.61,1.63)
	Cycle model:	1.11	(-2.34,2.04)
5.7	**Average:**	**0.53**	**(-1.06,1.06)**

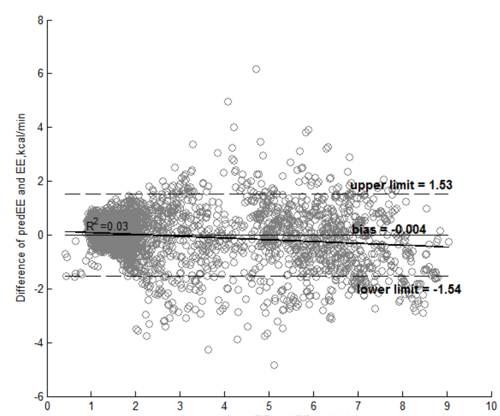

Figure 3. Bland-Altman plot for the error of prediction.

Use of MLD also substantially reduced the memory requirement as the amount of memory to store scalar discriminants' coefficients is far less than the amount of memory required to store hundreds multi-dimensional support vectors needed by SVM: the space storage due to the introduction of the MLD in place of the SVM was thus reduced 10^4 times. The reduction in memory requirements is probably one of the most significant advantages of MLD classification as the amount of memory needed to store a classification model for SVM may substantially exceed the capabilities of modern mobile devices.

The accuracy of posture and activity classification (90%) obtained by MLD classifier in this study was comparable but somewhat lower than previously reported 95%-98% [6], [15]. To some extent this reduction in accuracy happens due to transitions between activities where a class label is assigned to a whole minute although several different activities may happen within this minute. With at least 12 transitions in any given visit, this may generate a substantial difference between manual annotation and automatic class labels. Another source of error was confusion between standing and sitting. A potential reason is that both SVM and MLD algorithms are population-based and do not require individual calibration. This feature is convenient, however, it may potentially create some confusion for light-weight subjects that exhibit less pressure on the shoe sensors. Simple individual calibration of sit vs. stand should largely eliminate this source of error.

It should be noted that cycling (average recognition accuracy 96.5%) was differentiated from walking (average recognition accuracy 97%) with high degree of precision. Such differentiation is typically considered difficult for accelerometer-based activity monitor and highlights the benefits of utilizing of pressure sensors and in-shoe sensor locations for differentiation of weight-bearing and non-weight-bearing activities.

The overall high accuracy of EE estimation (5.7% TE, 0.53METs RMSE) also highlights the benefits of the proposed sensor system. Our previous research [8] has clearly demonstrated an increase in estimation accuracy by models utilizing pressure sensor data which most likely is result of accurate branching between EE models between weight-bearing and non-weight-bearing activities.

Overall, the proposed wearable sensor system and PAC and EE estimation methodologies are sufficiently accurate and computationally lightweight to be utilized on most modern mobile devices and provide real-time feedback on activity levels and energy expenditure. With increased penetration of mobile devices into all aspects of life, real-time feedback capabilities present new opportunities for behavioral interventions aimed at maintaining energy balance or achieving a healthy lifestyle.

V. Conclusion

In the paper we introduced a wearable system consisting of the SmartShoe sensor system and a mobile phone for signal processing, pattern recognition and real-time user feedback of expended calories and other physical activity information. Use of logistic discrimination instead of previously reported support vector machines reduced the execution time more than two orders of magnitude and reduced memory requirements for model storage by a factor of 10^4 while maintaining comparable classification accuracy. The PAC/EE algorithms were validated on approximately 60 hours of data from 15 subjects performing a wide range of activities in a room calorimeter and indicated accurate EE reduction (total EE error of 5.74%, RMSE of 0.53 METs on 1 minute predictions). These results pave the way for an implementation of physical activity monitoring and EE prediction system with real-time biofeedback on a wearable smart phone based system which could potentially be used in physical activity interventions.

References

[1] Polar Electro, *http://www.polar.fi/en/*, 01-Feb-2011. [Online]. Available: http://www.polar.fi/en/. [Accessed: 01-Feb-2011].

[2] Dynastream, *http://dynastream.com/*, 01-Feb-2011. [Online]. Available: http://dynastream.com/. [Accessed: 01-Feb-2011].

[3] D. Andre, R. Pelletier, J. Farringdon, S. Safier, W. Talbott, R. Stone, N. Vyas, J. Trimble, D. Wolf, S. Vishnubhatla, S. Boehmke, J. Stivoric, and A. Teller, "The Development of the SenseWear® armband, a Revolutionary Energy Assessment Device to Assess Physical Activity and Lifestyle." Bodymedia white paper, 2006.

[4] Y. Kawahara, N. Ryu, and T. Asami, "Monitoring Daily Energy Expenditure using a 3-Axis Accelerometer with a Low-Power Microprocessor," *E-Minds Int. J. Hum.-Comput. Interact.*, vol. 1, no. 5, 2009.

[5] Y. Kawahara, H. Kurasawa, and H. Morikawa, "Recognizing User Context Using Mobile Handsets with Acceleration Sensors," in *Portable Information Devices, 2007. PORTABLE07. IEEE International Conference on*, 2007, pp. 1–5.

[6] E. S. Sazonov, G. Fulk, J. Hill, Y. Schutz, and R. Browning, "Monitoring of Posture Allocations and Activities by a Shoe-Based Wearable Sensor," *Biomed. Eng. IEEE Trans. On*, vol. 58, no. 4, pp. 983–990, 2011.

[7] W. Tang and E. S. Sazonov, "Highly Accurate Recognition of Human Postures and Activities Through Classification With Rejection," *IEEE J. Biomed. Health Inform.*, vol. 18, no. 1, pp. 309–315, Jan. 2014.

[8] N. Sazonova, R. C. Browning, and E. Sazonov, "Accurate Prediction of Energy Expenditure Using a Shoe-Based Activity Monitor," *Med. Sci. Sports Exerc.*, vol. 43, no. 7, pp. 1312–1321, Jul. 2011.

[9] S. J. M. Bamberg, A. Y. Benbasat, D. M. Scarborough, D. E. Krebs, and J. A. Paradiso, "Gait analysis using a shoe-integrated wireless sensor system," *IEEE Trans. Inf. Technol. Biomed. Publ. IEEE Eng. Med. Biol. Soc.*, vol. 12, no. 4, pp. 413–423, Jul. 2008.

[10] P. J. M. Havinga, M. Marin-Perianu, and J. P. Thalen, "SensorShoe: Mobile Gait Analysis for Parkinson's Disease Patients," 2007.

[11] H. Jagos and J. Oberzaucher, "Development of a Wearable Measurement System to Identify Characteristics in Human Gait - eSHOE -," in *Computers Helping People with Special Needs*, 2008, pp. 1301–1304.

[12] E. L. Melanson, J. P. Ingebrigtsen, A. Bergouignan, K. Ohkawara, W. M. Kohrt, and J. R. B. Lighton, "A new approach for flow-through respirometry measurements in humans," *Am. J. Physiol. Regul. Integr. Comp. Physiol.*, vol. 298, no. 6, pp. R1571–1579, Jun. 2010.

[13] E. Jéquier and Y. Schutz, "Long-term measurements of energy expenditure in humans using a respiration chamber," *Am. J. Clin. Nutr.*, vol. 38, no. 6, pp. 989–998, Dec. 1983.

[14] J. Hilbe, *Logistic Regression Models*, vol. 79. Boca Raton,FL: Chapman & Hall/CRC Press, 2009.

[15] G. Fulk and E. Sazonov, "Using Sensors to Measure Activity in People with Stroke," *Top. Stroke Rehabil.*, vol. 18, no. 6, pp. 746–757, Jan. 2011.