Footwear-Based Wearable Sensors for Physical Activity Monitoring

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Abstract. Monitoring of posture allocations and activities is important for such applications as physical activity management, energy expenditure estimation, stroke rehabilitation and others. At present, accurate devices rely on multiple sensors distributed on the body and thus may be too obtrusive for everyday use. This chapter presents an overview of a novel wearable footwear sensor (SmartShoe), which is capable of very accurate recognition of most common postures and activities while being minimally intrusive to the subject. SmartShoe relies on capturing information from patterns of heel acceleration and plantar pressure to differentiate weight-bearing and non-weight-bearing activities (such as for example, sitting and standing, walking/jogging and cycling). Validation results obtained in several studies demonstrate applicability to widely varying populations such as healthy individuals and individuals post-stroke, while achieving high (95%-98%) average accuracy of posture and activity classification, high (root-mean-square error of 0.69 METs) accuracy of energy expenditure prediction, and reliable (error of 2.6–18.6%) identification of temporal gait parameters. High accuracy and minimal intrusiveness of SmartShoe should enable its use in a wide range of research and clinical applications.

Keywords: smartshoe, energy expenditure prediction, temporal gait parameters.

1 Introduction

Monitoring of Physical Activity (PA), Energy Expenditure (EE) and human gait is used in a variety of clinical and research applications. For example, measuring of daily PA and EE has been widely used in obesity research. Many adults worldwide are overweight or obese [1]. Obesity is due to a sustained positive energy balance (energy intake > energy expenditure) and is typically coupled with low levels of physical activity (i.e. sedentary lifestyles) [2]. Weight management programs designed to prevent and treat obesity recommend increased energy expenditure via lifestyle alterations that increase physical activity levels. There is also evidence that sedentary posture allocations may be related to obesity. For example, [3] reported that obese individuals spent more time seated and less time ambulating than lean individuals. Overall, obesity researchers are constantly looking for better ways to quantify PA and EE of individuals in their natural environment.

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Physical Activity Classification (PAC) and gait monitoring also have direct applications in post-stroke rehabilitation. People who experience a stroke are less active than healthy individuals and many of them require assistance to walk [4]. Even individuals with relatively good recovery of walking ability are often inactive and may not be able to effectively access their community. This inactivity leads to further deconditioning, which in turn plays a role in the development of secondary complications and may increase the risk of another stroke and an increased dependence in activities of daily living. Common goals of stroke survivors' are to improve their physical activity level and social participation [5]. Monitoring of physical activity of during post-stroke rehabilitation may provide important insight into the effectiveness of rehabilitation interventions. Monitoring of gait and comparing the performance of the affected limb versus the unaffected one during walking provide important information on the symmetry of the person's walking pattern. These measures provide an assessment of motor recovery after stroke [6].

Accelerometry has emerged as one of the most popular approaches to PA monitoring and EE prediction [7–10]. Although useful, single accelerometers have one major drawback in that they are not very accurate in recognition of static postures and thus tend to significantly underestimate the energy cost of such postures (e.g., household tasks) and non-weight-bearing activities (e.g. cycling). As a result, they fail to explain a considerable portion of energy expenditure variability in daily living tasks. Accelerometers also do not behave well in estimation of gait in individuals with neurological disorders due to the disease-related changes in the gait patterns.

One strategy to improve PA, EE and gait estimation has been to use multiple sensors. For example, wrist, upper arm, hip, ankle and thigh accelerometers were used in [11]; chest and wrist accelerometers were used in [12]; 9 different sensor locations on the body were used in [13]. Such multi-sensor systems typically have very limited practical applicability due to high intrusiveness and high subject burden. Several attempts have been made to recognize postures and activities using multiple sensor modalities concentrated in a single location on the body. In [14] authors achieved 90-95% accuracy of recognizing 8-10 various activities from a single unit including 8 different sensors: accelerometer, audio, light, high-frequency light, barometric pressure, humidity, temperature and compass. However, not all activities are recognized equally well by the current devices. For example, [12] did not differentiate between sitting and standing, grouping these postures together. Other studies [13] reported challenges in recognizing such activities as cycling and ascending and descending stairs. Overall, reliable recognition of static postures and typical daily activities, energy expenditure and gait from a single location of the body remains a challenge.

Shoe-based sensors have been used in several studies with the focus of these efforts to detect gait characteristics rather than classify activity or estimate energy expenditure [9], [15], [16]. An array of 32 plantar pressure sensors was used in [17] to classify locomotion (walking, running and up/down stairs) with reported accuracies of ~98%. A study reported in [18] used a foot-contact pedometer to estimate daily energy expenditure but did not attempt to classify postures or specific activities with the device. These results suggest that shoe-based sensors have the potential to accurately classify posture/activity and estimate energy expenditure, while also being minimally obtrusive.

This chapter presents the SmartShoe – a sensor system integrated into conventional footwear and its applications for monitoring of PA, EE and gait, which has been developed in the Laboratory of Ambient and Wearable Systems at the University of Alabama. The chapter is organized as follows. First, the hardware of SmartShoe sensor system is presented. Second, two human studies, one on healthy and one on individuals recovering after stroke are presented as fundamental datasets for development of the classification and estimation models. Third, a method for PA classification both in healthy and post-stroke individuals is presented. Fourth, a method for measuring gait parameters in post-stroke and healthy individuals is described. Fifth, a branched approach for accurate prediction of EE from SmartShoe data is presented. Finally, the concluding remarks summarize the findings.

2 Sensor System

SmartShoe sensor system combines a 3D accelerometer and several pressure sensors placed in the insole of conventional footwear. The choice of sensing modalities and placement in the insole serves several purposes.

First, in most cultures people wear shoes or equivalent footwear throughout the day, every day. SmartShoe presents zero additional burden to wear in comparison to conventional activity monitors that require additional effort to attach to wrist, waist, hips, chest, etc. From research perspective, reducing the wear burden improves compliance and reduces the observation effect where subjects change behaviour in response to monitoring. From consumer perspective, reducing wear burden enhances usability of the product and improves chances for long-term use.

Second, the body support in many postures and activities comes fully or partially through feet. Thus, monitoring plantar pressure can tell volumes about postures and activities of a person. Specifically, use of pressure sensors can differentiate between weight-bearing and non-weight-bearing postures and activities such as sitting and standing, walking and cycling that many accelerometer-based PA monitors fail to distinguish.

Third, motion of the feet is characteristic to different activities. For example, the trajectory of a foot during cycling is substantially different from trajectory during walking. Using an accelerometer provides additional information about the activity being performed as well as delivers a metric of intensity of motion in a given activity.

Fourth, positioning of the sensor system in footwear enables monitoring of several important human characteristics such as gait parameters (for example, very important characteristic of rehabilitation progress for stroke patients) or body weight. Overall, the sensor system of SmartShoe provides a highly informative data stream that is capable of extensive characterization of human PA.

Over the years, several variations of the SmartShoe design have been assembled and tested in human studies. The following description refers to one of the most recent designs used in [19], [20]. Each shoe incorporates five pressure-sensitive resistors (0.5” FSR, Interlink Electronics, Camarillo, CA, USA) embedded in a flexible insole and positioned under the critical points of contact: heel, 1st, 3rd and 5th metatarsal heads and the great toe (hallux) – total of 10 sensors from the two shoes. In addition to pressure sensors, a 3-dimensional ±3g MEMS accelerometer (ADXL335, Analog Devices, Norwood, MA, USA) was attached to the heel of each shoe.

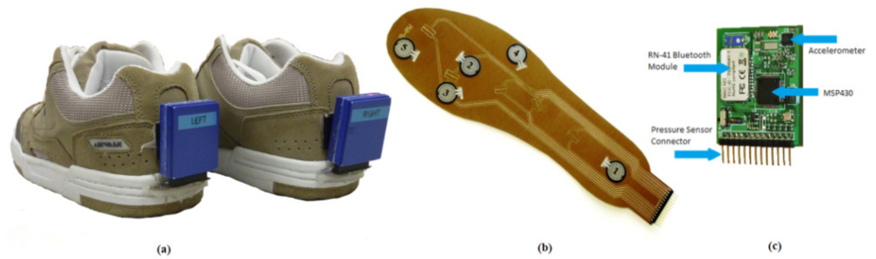

Fig. 1. SmartShoe device: (a) Overall view of the shoe device with attached accelerometer, battery and power switch on the back; (b) Pressure-sensitive insole with 5 pressure sensors: heel (1), 3rd metatarsal head (2), 1st metatarsal head (3), 5th metatarsal head (4), hallux (5); (c) The wireless electronics board

All sensors were sampled at 400Hz by a microcontroller from MSP430 series (MSP430, Texas Instruments, Dallas, TX, USA), averaged to effective rate of 25Hz and sent to a Windows Mobile smart phone via a Bluetooth link implemented by using a Serial Port Profile communication module (RN-41, Roving Networks, Los Gatos, CA, USA). The phone contained custom-designed software that performed time synchronization of the data coming from the shoes and logging of the data as text files [21].

3 Human Studies

Since SmartShoe’s primary purpose is monitoring of humans in their everyday life, human studies are necessary to develop and validate computer algorithms that process sensor information. The methods presented in this chapter have been developed in two human subject experiments, which were conducted at the Clarkson University, Postdam, NY, USA. All studies were approved by the Institutional Review Board and informed consent was obtained from all subjects participating in the studies.

In the first human study (Human Study 1, HS1) data collection was performed on a group of 16 human subjects, 8 males and 8 females (Table 1) with stable weight (<2 kg weight fluctuation) over the previous 6 months [19], [22].

Individuals were healthy, non-smokers who were sedentary to moderately active (< 2-3 bouts of exercise/wk or participation in any sporting activities < 3 hr/wk). Participants reported to the laboratory in a fasted state (>4 hours) for a single three hour visit. Each participant was asked to perform a variety of postures/activities while wearing a portable metabolic mask system and the appropriately sized SmartShoe. The postures included sitting and standing and the activities included walking, jogging, stair ascent/descent and cycling (Table 2). Each posture/activity trial was six minutes in duration and subjects were allowed five minutes rest between trials. Trial order was not randomized. Metabolic data was not collected during stair ascent/descent, as this activity was performed in two-story stairwell which did not allow establishment of metabolic steady-state. Participants were not restricted in the way they assumed postures and or performed activities. Standing did not require any specialized equipment; a chair with a rigid back was used for sitting; walking/jogging was performed on a motorized treadmill (Gait Trainer 1, Biodex, Shirley, NY); cycling utilized a bicycle ergometer (Erogomedic 828E, Monark, Sweden). During the fidgeting trials, subjects were allowed to make small, normal leg movements (e.g. crossing legs or shifting weight). To determine metabolic rate and associated EE during each trial, we measured the rates of oxygen consumption (VO_2) and carbon dioxide production (VCO_2) using a portable open circuit respirometry system (Oxycon Mobile, Viasys, Yorba Linda, CA). Before the experimental trials, the system was calibrated with known gas concentrations and volumes. For each trial, the subjects were allowed four minutes to reach steady state (no significant increase in VO_2 during the final two minutes and a respiratory exchange ratio (RER) <1.0) and calculated the average VO_2 and VCO_2 (ml/sec) during minutes 4-6 of each trial. We calculated gross metabolic rate (W/kg) from VO_2 and VCO_2 using a standard equation [23]. Energy expenditure was then calculated from VO_2 and RER.

The subjects also performed two experiments where they were asked to walk over a GAITRite® commercial test system (CIR Systems, Inc.). This commercial system provides reliable automated means of measuring spatial and temporal parameters of gait consisting on an electronic walkway with a useful area of 61x366 cm (24x144 inches) connected to a Windows based PC.

Table 1. Subject characteristics of HS1

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

Table 2. Protocol of HS1

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

* Metabolic data not collected during stair ascent/descent

In the second human study (Human Study 2, HS2) data was collected from subjects with stroke who had completed their rehabilitation [20]. Inclusion criteria were: at least three months post stroke, able to walk in their home and/or community without physical assistance, able to stand without physical assistance for >60 seconds, able to transition from sitting to standing from a standard height chair without physical assistance, and Mini Mental State Exam score >=24. Subjects were excluded if they had some other health condition, which affected their ability to stand or walk independently. Subject characteristics are listed in Table 3. All subjects wore appropriately sized SmartShoe during the experiment. Sensor data were collected in three main postures: sitting, standing, and walking. Within the sitting posture there were four positions that the subjects assumed: self-selected comfortable position, sitting with both feet on the floor, sitting with legs crossed so that one foot was on the floor and one foot off the floor, and reaching forward while sitting. In standing there were also four positions the subjects assumed: static standing in a comfortable position, standing while reaching towards the unaffected side, standing while reaching towards the affected side, and standing while reaching forward. Data was collected in four different positions within sitting and standing in order to better mimic real life conditions. Subjects walked under two conditions: self-selected, comfortable pace and fastest, safe pace. Subjects walked continuously over a level surface for 1 minute. Each position and walking condition was performed 4 times. During the data collection process all subjects were supervised by a physical therapist for safety. The order in which each position trial was performed was randomized. The degree of motor and mobility function of the subjects was tested by the following clinical tests: Berg Balance Scale, lower extremity motor section of the Fugl Meyer, and Stroke Impact Scale 16.

Table 3. Subject characteristics of HS2

Age (years)	60.1 (9.9)
Time since stroke (months)	51.7 (45.1)
Berg Balance Scale	44.3 (11.7)
Fugl Meyer LE motor score	25.8 (5.9)
Self-selected gait speed (m/s)	0.69 (0.35)
Stroke Impact Scale 16	65.4 (22.0)
Mini Mental State Exam	28.7 (2.1)
Ankle Foot Orthotic Use (yes:no)	2:6

Post-stroke subjects were also asked to walk over GAITRite® in two different manners: walking comfortably and walking as fast as they could. Both of these experiments were repeated four times.

It should be noted that the sensor hardware on SmartShoe devices in HS1 and HS2 was slightly different. Specifically, the shoes in HS1 were equipped with currently discontinued accelerometer LIS3L02AS4 and the wireless connection was performed over WISAN link [24] rather than Bluetooth. The difference in type of used accelerometer does not interfere with general principle of operation of SmartShoe, but due to differences in calibration does allow use of models developed in HS1 for subjects in HS2.

4 Models for Posture and Activity Recognition

Posture and activity recognition models were developed for subjects participating in HS1 and HS2. In both cases the developed models were group models that could be applied to any subject without individual calibration. The goal was develop PAC models for healthy individuals and for individuals post-stroke and show that SmartShoe can reliably perform classification in healthy individuals and individuals with neurological impairment affecting lower extremity.

Before training of classification models, minimal pre-processing consisting of feature vector forming and normalization was applied to the sensor data. Feature vectors were formed to represent a time period (epoch) of two seconds in duration. Time histories of pressure and acceleration from both shoes were used as follows. A single sample of data from a shoe is represented by vector

$$S = \{A_{AP}, A_{ML}, A_{SI}, P_H, P_{5M}, P_{3M}, P_{1M}, P_{HX}\},$$

where A_{AP} is anterior-posterior acceleration, A_{ML} is medial-lateral acceleration, A_{SI} is superior-inferior acceleration, P_H is heel pressure, P_{M5}, P_{M3}, P_{M1} are pressures from 5th, 3rd and 1st metatarsal head sensors, respectively, and P_{HX} is pressure from the hallux sensor. The time series of data from both shoes were combined as

$$f_i = \{S_L, S_R\}_i, i = \{1, \dots, M\},$$

where S_L, S_R are the data samples from the left and right shoe, respectively, and M is the length of time series. Depending on sensor configuration, the data samples either included all or just some of the sensor signals from f_i.The size of the feature vectors with all sensors included consisted of 800 values (2 shoes x 8 sensors x 25 samples per second x 2 seconds = 800 samples). The features vectors from all epochs in the experiment were combined in a feature matrix $\bar{F}_{e,d}$ and all columns of the matrix were normalized to the scale of [0,1]. Normalization used max values of acceleration and pressure acquired over all subjects and experiments.

The pairs of feature vectors and class labels $\{F_{e,d}, L_e\}$ were presented to a supervised classification algorithm for training and validation. The labels L_e represented a distinct class {1-sitting, 2-standing, 3-walk/jog, 4-ascending stairs, 5-descending stairs, 6-cycling}. The selected classifier was a variation of Support Vector Machine (SVM) implemented as a Matlab package (libSVM, [25]). The SVM classifier utilized Gaussian kernel ($\exp\big(-\gamma * (\boldsymbol{u} - \boldsymbol{v})^{2))}\big)$.) The best values of parameter C=10 (cost of misclassification) and $\gamma = 0.0156$ (width of Gaussian kernel) were found in grid search procedure varying C as $C = 10^x$, $x = \{-1, \dots, 3\}$ and γ as $\gamma = 2^y$, $y = \{-8, \dots, -2\}$.

A four-fold holdout cross-validation procedure was used to develop six-class ('sit', 'stand', 'walk/jog', 'cycle', 'ascend stairs', 'descend stairs') prediction models for HS1. In this procedure three quarters of the data was used to train the SVM classifier. The remaining one-quarter of the data was tested against the SVM classifier to determine accuracy. The folds were organized by including the full dataset from each individual subject that belonged to a fold. Data from the same subject were never split between training and validation sets.

Due to a smaller dataset, a leave-one-out cross validation procedure was used to develop three-class ('sit', 'stand', 'walk') PAC models for HS2. All the data in one posture for all the subjects except one were used to train the group SVM classifier. The data from the one subject that was not used to create the SVM classifier was validated for accuracy using the group SVM classifier created by the data from the other subjects. This process was repeated such that the acceleration and pressure data from each subject was validated for accuracy against the group SVM classifiers created from all the other subjects combined.

Accuracy of PAC models in both cases were estimated by building cumulative confusion matrices that combine validation results from all subjects in the population. Postures predicted by the SVM classifier were compared against actual postures. The rows of the table correspond to actual postures/activities assumed by subjects and columns correspond to predicted postures/activities made by the classifier from the sensor data. Results from four folds or leave-one-out validation were averaged for reporting. The average classification precision was defined as the ratio of the sum of diagonal elements of the confusion matrix (True Positives) to the sum of all elements of the confusion matrix (True Positives + False Positives).

Figure 2 shows 6-class average validation accuracy obtained by the group model obtained for healthy individuals in HS1. The population average accuracy for a model that included data from all acceleration and pressure sensors was 95.2±3.5%. The highest recognition accuracy of 98.1%±2.3% was achieved in a configuration using sensors $\{A_{AP}, A_{ML}, A_{SI}, P_H, P_{1M,} P_{HX}\}$. The population-cumulative confusion matrix for recognition using the best sensor configuration is presented in Figure 3.

Figure 4 shows 3-class cumulative confusion matrix for recognition of postures and activities in post-stroke individuals from HS2. The recognition accuracy is comparable to that achieved on healthy individuals, thus indicating ability of

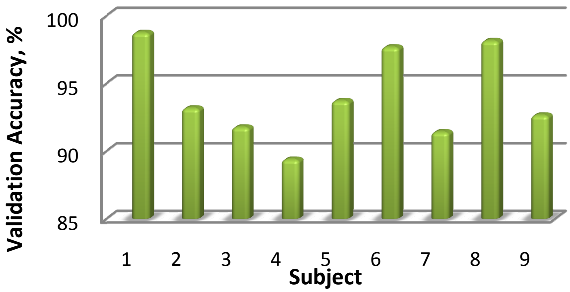

Fig. 2. Average validation accuracy in 6-class recognition for each healthy individual from HS1

Predicted class

Actual class	Sit	Stand	Walk Jog	Ascend	Descend	Cycle	**Class-specific recall**
Sit	*3202*	*2*	*0*	*0*	*0*	*14*	**0.99**
Stand	*7*	*3191*	*2*	*7*	*0*	*0*	**0.99**
Walk/Jog	*0*	*0*	*10647*	*74*	*0*	*0*	**0.99**
Ascend	*0*	*0*	*34*	*500*	*15*	*1*	**0.90**
Descend	*0*	*0*	*41*	*60*	*405*	*0*	**0.80**
Cycle	*146*	*3*	*0*	*0*	*0*	*2539*	**0.94**
Class-specific precision	**0.95**	**1.00**	**0.99**	**0.78**	**0.96**	**0.99**	**0.98**

Fig. 3. Population-cumulative confusion matrix showing classification accuracy for the best sensor configuration { A_{AP}, A_{ML}, A_{SI}, P_H, P_{M1}, P_{HX}.} for healthy individuals in HS1. Numbers in italic show the quantity of 2-second time intervals for each class. Class-specific recall is the proportion of a class instances that were correctly identified. It is defined as a ratio of the respective diagonal value to the sum of a row. Class-specific precision is the proportion of the predicted class cases that were correct. It is defined as a ratio of the corresponding diagonal value to the sum of a column.

Actual class	Sit	Stand	Walk	**Class-specific recall**
Sit	*3515*	*21*	*86*	**0.97**
Stand	*7*	*3409*	*290*	**0.91**
Walk	*0*	*22*	*1548*	**0.99**
Class-specific precision	**0.99**	**0.98**	**0.82**	**0.95**

Fig. 4. Population-cumulative confusion matrix for 3-class PA recognition for individuals post-stroke (HS2)

SmartShoe accurately classify PA both of healthy and individuals with neurological disorders.

Overall, SmartShoe in these experiments achieved greater recognition rates than previous experiments that used similar postures and activities in healthy individuals. For example, [26] demonstrated 88% percent accuracy with 6 postures and activities and [7] reported accuracies of 87% (cycling) to 100% (running) using a single hip-mounted accelerometer. SmartShoe also matched or outperformed other single-location methodologies such as [14] which reported a 95% accuracy across 8 postures and activities. SmartShoe also demonstrated excellent recognition rates for identifying basic postures (sitting, standing, and walking) in people with stroke. SmartShoe is unique compared to other accelerometer-based sensors that have been studied in people with stroke to detect movement as they required multiple sensor placements that may not be comfortable or convenient for patients to wear [10], [27], [28]. While further tests and development of SmartShoe system are needed for large-scale validation, these results show high accuracy of PA monitoring across different population indicating robustness of the proposed approach.

5 Detection of Temporal Gait Parameters

Algorithms for extracting gait parameters were developed to show that SmartShoe is capable of accurate estimation of temporal gait parameters both in healthy and in individuals post-stroke and thus can be used in place of a stationary gait lab that is typically used to assess gait of individuals.

Data obtained from the pressure sensors was used to estimate the following temporal gait parameters: cadence, step time, cycle time, percentage of gait cycle in swing for each lower extremity, percentage of gait cycle in stance for each lower extremity, percentage of gait cycle in single limb support for each lower extremity, and percentage of gait cycle in double limb support for each lower extremity. The algorithm for estimation of gait parameters was based purely on pressure signals as methods based on inertial sensors may present significant differences between unaffected and affected limb in subjects with gait abnormalities due to stroke and significant individual traits [27].

The first step in estimation of gait parameters is detection of Heel-Strike (H) and Toe-Off (T) events as these events define contact of the foot with the ground. To detect H and T events, for each foot the sum of all 5 pressure sensors was calculated as:

$$sumFSR(t) = \sum_{s=1}^{5} FSR_s(t)$$

Next, an adaptive threshold τ was calculated by defining the average maxima and minima of the *sumFSR* signal. For the *sumFSR* signal, all the local maxima and local minima were obtained. The average of this data points defined maxima and minima thresholds as:

$$Th_{MAX} = \frac{1}{k}\sum_{a=1}^{k} Max_a; Th_{MIN} = \frac{1}{l}\sum_{b=1}^{l} Min_b,$$

where Max_a, for a=1,2,…,k, are the local maxima data points found and Min_b, b=1,2,…,l are the local minima data points found. The difference between Th_{MAX} and Th_{MIN} defined the threshold used to obtain the H and T:

$$\tau = Th_{MIN} + \alpha(Th_{MAX} - Th_{MIN}),$$

where α=0.1725 was a free parameter that resulted in the highest accuracy of recognition of temporal gait parameters. The intersection points of the threshold τ with the *sumFSR* signal correspond to H and T events (Figure 5).

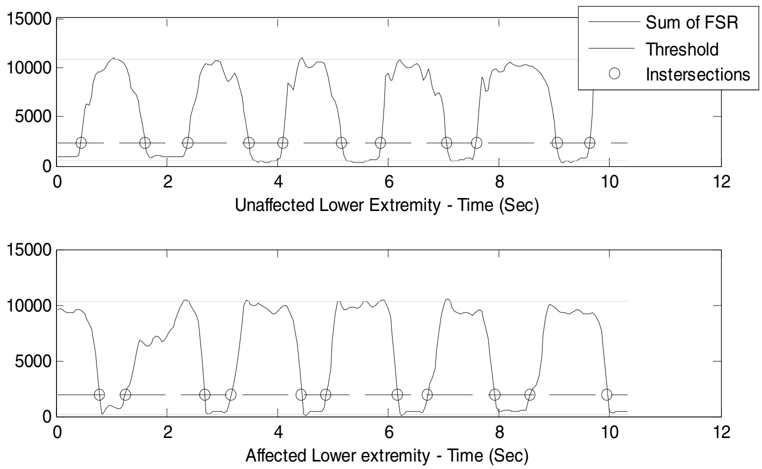

Fig. 5. Heel-strike and Toe-off detection for unaffected (top) and affected (bottom) lower extremity of a post-stroke subject from HS2

To discriminate detection of H from T, a simple criterion was met: immediate points located before a local minima were considered T and those located immediately after a local minima were considered H. After all H and T points were identified for both feet, they were used to obtain the corresponding temporal gait parameters (Table 4).

Table 4. Temporal gait parameters calculation from detected H and T events. The second letter indicates the foot (L for left and R for right).

Parameter	Left	Right
Gait cycle time	$GTL_i = HL_{i+1} - HL_i$	$GTR_j = HR_{j+1} - HR_j$
Step time %	$SL_i = HL_i - HR_j \quad (HL_i > HR_j)$	$SR_j = HR_j - HL_i \quad (HL_i < HR_j)$
Stance %	$STL_i = \dfrac{TL_i - HL_i}{GTL_i} x100$	$STR_j = \dfrac{TR_j - HR_j}{GTR_j} x100$
Swing %	$SWL_i = \dfrac{HL_{i+1} - TL_i}{GTL_i} x100$	$SWR_j = \dfrac{HR_{j+1} - TR_j}{GTR_j} x100$
Single support %	$SSL_i = \dfrac{HR_{j+1} - TR_j}{GTL_i} x100$	$SSR_j = \dfrac{HL_{i+1} - TL_i}{GTR_j} x100$
Double support %	$DSL_i = \left(\dfrac{(TL_i - HR_j) + (TR_j - HL_i)}{GTL_i} \right) x100$	$DSR_j = \left(\dfrac{(TR_j - HL_i) + (TL_i - HR_j)}{GTR_j} \right) x1$

Sensor data from SmartShoe collected in HS1 and HS2 (healthy and post-stroke subjects, respectively), were collected and processed by the algorithm described above. The temporal gait parameters computed from SmartShoe sensors were compared to the data collected with the GAITRite® system. These results are shown in the Tables 5 and 6.

For healthy subjects, the statistical *t-test* using a confidence value of 95% was performed to compare data recorded with the GAITRite® system and the shoe-based wearable sensor; no significant difference in the mean across all subjects for cadence ($p>0.35$) and for parameters calculated for each lower extremity ($p>0.18$) was observed.

Results from the *t-test* statistical test with a 95% confidence for post-stroke subjects also did not show significant difference between GAITRite® and the shoe-based wearable sensor for cadence ($p>0.29$) and for parameters calculated for each lower extremity ($p>0.51$).

The relative difference between SmartShoe estimates related to the GAITRite® results was calculated for both types of subjects as:

$$Difference\ \% = |Shoe - Gaitrite| \ / \ Gaitrite\ x\ 100,$$

where *'Gaitrite'* represents the GAITRite® reported gait parameters used as the gold standard and *'Shoe'* represents the gait parameters obtained from the shoe-based wearable sensor. Table 7 shows the relative error obtained for the healthy subjects. Table 8 shows relative error obtained for subjects post-stroke, separated by type of experiment, e.g. walking comfortable and walking fast.

Table 5. Comparison of temporal gait parameters measured by SmartShoe and GAITRite® system for the healthy individuals in HS1

	Healthy Subjects					
	GAITRite®			SmartShoe		
	Mean	**95% CI**		**Mean**	**95% CI**	
Cadente (Step/sec)	1.31	1.20	1.42	1.24	1.13	1.35
	Left foot					
	GAITRite®			**SmartShoe**		
	Mean	**95% CI**		**Mean**	**95% CI**	
Step time (Sec)	0.59	0.56	0.63	0.63	0.58	0.69
Cycle time (Sec)	1.17	1.06	1.28	1.17	1.07	1.28
Swing %	35.65	32.81	38.49	37.58	34.52	40.64
Stance %	60.77	56.07	65.47	59.17	54.54	63.80
Single support %	35.77	32.90	38.64	36.27	33.37	39.17
Double support %	24.75	22.32	27.18	22.58	20.11	25.05
	Right foot					
	GAITRite®			**SmartShoe**		
	Mean	**95% CI**		**Mean**	**95% CI**	
Step time (Sec)	0.61	0.58	0.64	0.61	0.58	0.65
Cycle time (Sec)	1.16	1.06	1.27	1.21	1.14	1.28
Swing %	36.01	33.10	38.92	37.18	36.18	38.18
Stance %	60.43	55.73	65.12	62.82	61.83	63.82
Single support %	35.89	33.00	38.77	37.07	36.13	38.02
Double support %	25.10	22.68	27.52	26.06	24.53	27.59

These results indicate that SmartShoe sensors were able to accurately identify temporal aspects of the gait cycle in both healthy people and individuals post-stroke. The relative difference from GAITRite® for these temporal aspects of the gait cycle, except for step time, were comparable to the error in other acceleration and pressure based methods of determining gait parameters [27]. Computation of temporal gait parameters using only pressure signals was used since pressure measurements from the insole of a shoe involve a more direct representation of the walking behavior. When using accelerometers the signal tends to be noisy since acceleration is the derivative of velocity and involves higher frequency components [9].

Table 6. Comparison of temporal gait parameters measured by SmartShoe and GAITRite® system for the individuals post-stroke (HS2)

	Subjects post-stroke					
	GAITRite®			SmartShoe		
	Mean	**95% CI**		**Mean**	**95% CI**	
Cadente (Step/sec)	1.07	0.95	1.18	1.00	0.92	1.07
	Affected Lower Extremity					
	GAITRite®			**SmartShoe**		
	Mean	**95% CI**		**Mean**	**95% CI**	
Step time (Sec)	0.67	0.59	0.74	0.65	0.59	0.71
Cycle time (Sec)	1.34	1.25	1.44	1.37	1.26	1.48
Swing %	32.80	30.58	35.02	33.73	31.67	35.80
Stance %	67.20	64.98	69.42	66.88	64.79	68.98
Single support %	34.17	32.36	35.97	34.66	32.74	36.59
Double support %	32.82	29.94	35.71	31.60	29.17	34.03
	Unaffected Lower Extremity					
	GAITRite®			**SmartShoe**		
	Mean	**95% CI**		**Mean**	**95% CI**	
Step time (Sec)	0.68	0.61	0.74	0.69	0.62	0.76
Cycle time (Sec)	1.34	1.24	1.44	1.37	1.25	1.48
Swing %	34.22	32.38	36.06	34.26	32.18	36.35
Stance %	65.79	63.95	67.62	65.75	63.66	67.84
Single support %	32.88	30.61	35.14	32.08	29.85	34.31
Double support %	33.26	30.42	36.11	33.99	30.78	37.21

Table 7. Relative difference between SmartShoe and GAITRite® estimates (healthy subjects, HS1)

	Healthy subjects		
Parameter	**Relative Difference %**	**95% CI**	
Cadence	10.4	8.4	12.5
Step time (Sec)	18.4	14.8	22.1
Cycle time (Sec)	3.1	2.4	3.9
Swing %	6.4	5.3	7.4
Stance %	3.6	2.9	4.4
Single support %	5.5	4.3	6.7
Double support %	10.9	8.3	13.6

Table 8. Relative difference between SmartShoe and GAITRite® estimates (post-stroke subjects, HS2)

	Comfortable Walking			Fast Walking		
Parameter	**Relative Difference %**	**95% CI**		**Relative Difference %**	**95% CI**	
Cadence	9.5	5.2	13.8	8.8	4.8	12.8
Step time	18.67	10.2	27.2	15.4	11.1	19.7
cycle time	2.70	1.6	3.8	2.6	1.7	3.4
swing %	8.56	5.9	11.2	10.7	7.8	13.7
stance %	3.37	2.7	4.0	5.2	3.7	6.8
S support %	7.78	5.3	10.3	9.9	7.1	12.6
D support %	10.3	8.3	12.2	12.4	9.5	15.3

As discussed in the literature, with the use of gyroscopes it is possible to estimate spatial gait parameters in addition to temporal parameters as long as its axis is parallel to the mediolateral axis [29]. However, it is important to notice that the use of gyroscopes require more sophisticated techniques for Heel-strike and Toe-off detection, i.e., wavelet transform, finite-impulse response, etc., since gait events are transitory signals that cannot be properly enhanced by simple traditional signal processing. Also, gyroscopes are more sensitive to temperature and mechanical shock that may be significant in non-laboratory conditions. Thus, use of pressure information in SmartShoe provides a simple and reliable way to estimate gait parameters.

6 Estimation of Caloric Energy Expernditure

Being capable of differentiating between weight-bearing and non-weight bearing activities, SmartShoe is capable of accurate energy expenditure estimation by reducing prediction error in sedentary postures (for example, sitting vs standing) and some activities (walking/jogging vs cycling). Presented below is a methodology for estimating EE of healthy individuals from HS1.

The EE estimation model was constructed as a group model: the data used for training were pooled from several subjects and such model was then tested on the validation set which included data from subject(s) that were not in the training set. The EE model was by branched activity (“Sit”, “Stand”, “Walk”, “Cycle”) where activity prediction was performed using the SVM classifier from Section 4 and each activity (branch) had its own regression for predicting EE (Figure 6). To match time resolution of the system used measure EE during the experiments, EE estimation was based on the sensor data collected during 1 minute intervals in which subjects were in metabolic steady state (minutes 4-6 of each trial of HS1). Each one minute recording resulted in approximately 1500 (25Hz·60s) points of pressure and acceleration data per channel. For the 16 subjects who participated in the study there were a total of 208 such recordings.

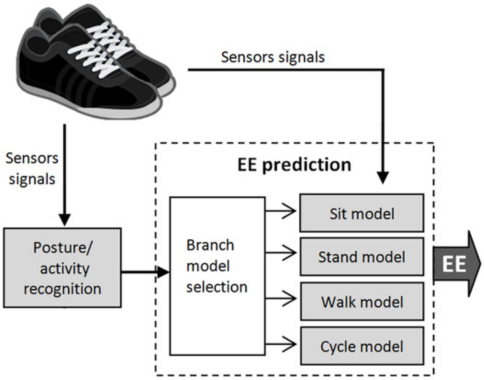

Fig. 6. Branched approach to EE estimation from SmartShoe sensors

The following data were available for each recording:

- response variable: energy expenditure, EE, kcal·min^{-1};
- anthropometric measurements (weight, height, BMI, age, gender, shoe size);
- triaxial accelerometer signals: superior-inferior acceleration ($\boldsymbol{A_{SI}}$), medial-lateral acceleration ($\boldsymbol{A_{ML}}$), anterior-posterior acceleration($\boldsymbol{A_{AP}}$);
- pressure sensors signals: heel (P_H), 3rd meta (P_{M3}), 1st meta (P_{M1}), 5th meta (P_{M5}), and hallux (P_{HL});

Accelerometer and pressure sensors signals expressed in ADC units (as digitized by a 12-bit analog-to-digital converter) were preprocessed to extract meaningful metrics to be used as predictors for the model. For each sensor all of the following metrics were extracted and tested for the inclusion into each model as predictors:

- coefficient of variation (*cv*);
- standard deviation (*std*);
- number of "zero crossings" (*zc*), i.e. number of times the signal crosses its median normalized by the signal's length;
- entropy H of the distribution X of signal values (*ent*) computed as: $H(X) = -\Sigma\, pk \log pk$, where pk is the relative frequency of values fallen into the k-th interval (out of 20 equally sized intervals) in the sample distribution of signal values.

These metrics were selected for the following reasons. Coefficient of variation and standard deviation of a signal should indicate the amount of motion produced during recording. Number of median crossings is an indicator of the frequency of changes in the signal, which is important to identify the intensity of motion (like speed of walking). Entropy reflects the distribution of the signal across the range of its values and is a valuable predictor for walking due to the fact that as speed of walking increases the time of feet ground contact decreases relative to the swing time and, thus, signal values become more uniformly distributed across the range, leading to an increased entropy. These metrics were used as possible predictors for the ordinary least squares linear regression. The transformed predictors (log, inverse and square root) and interactions (as products of 2 or more candidate predictors) were also considered as separate linear terms within regression. **A** separate model was constructed for each type posture/activity: “Sit”, “Stand”, “Walk” and “Cycle”. The selection of the most significant set of predictors was performed using the forward selection procedure. “Leave-one-out” approach was used for cross-validation when training and predicting the EE for each type of activity for every subject. For every left out subject all of the data related to this subject were removed from the training set for each model. Model (coefficients) computed using the rest of the subjects was then used to predict the EE for all trials of the left out subject. The best set of predictors had to provide the best fit (by producing the maximum adjusted coefficient of determination, R^2_{adj} and the minimum Akaike Information Criterion, AIC) in the training step and the best predictive performance (the minimum Mean Squared Error, MSE and the minimum Mean Absolute Error, MAE) in the validation step.

Two models were built using the described approach. First model, BACC-PS included metrics derived from signals from all shoe sensors. The second model, BACC did not include metrics derived from pressure sensors in the forward selection process. Comparison of BACC-PS and BACC models is performed to evaluate impact of pressure sensors on accuracy of EE estimation in SmartShoe.

Measured and predicted energy expenditure values in kcal·min^{-1} for each experiment were then converted to METs by representing the energy expenditure for any given epoch as a multiple of resting energy expenditure. Energy expenditure during quiet sitting was used as a valid estimate of resting metabolic rate for each subject. This conversion was performed to enable direct comparison of results obtained by SmartShoe with those that have been recently published [8], [30], [31]. Tables 9 and 10 show the regression coefficients obtained for EE estimation model for BACC-PS and BACC models, respectively. Per-minute error (Root-Mean-Square Error, RMSE) for BACC-PS and BACC models is shown in Table 11. Aggregated error of 0.69 METS for BACC-PS model that includes pressure sensor data is lower than 0.78 METS error for BACC model that uses only accelerometer signals. Figure 7 shows Bland-Altman plots constructed for both EE, kcal•min-1 and EE, METs prediction) for both models. The common characteristic for both models is that the accuracy of prediction is slightly better for small than for large EE values (i.e. better accuracy for sitting and standing).

Table 9. Regression coefficients in the BACC-PS model

Branch model	Predictors, units	Average values of coefficients	CV of coefficients
Sit	<Intercept>	5.2862	0.0687
	Weight, kg	0.0352	0.0504
	log(BMI), log(kg·m^{-2})	-1.7594	-0.0854
	log($A_{SI.CV}$)	0.1331	0.0550
Stand	<Intercept>	4.5758	0.1148
	Weight, kg	0.0364	0.0580
	log(BMI), log(kg·m^{-2})	-1.8339	-0.1147
	$P_{H.STD} \cdot P_{M3.STD} \cdot P_{M1.STD} \cdot P_{M5.STD}$, (ADC units)	$2.04 \cdot 10^{-12}$	0.0452
Walk	<Intercept>	0.8406	0.9662
	Weight, kg	0.0745	0.0387
	log(BMI), log(kg·m^{-2})	-2.0513	-0.1431
	$P_{M1.ZC} \cdot P_{M5.ZC}$	277.0277	0.1246
	$A_{AP.STD}$, ADC units	0.0001	2.3021
	$A_{SI.ENT} \cdot A_{ML.ENT} \cdot A_{AP.ENT}$	0.3542	0.0805
Cycle	<Intercept>	-2.7295	-0.6184
	Weight, kg	0.0770	0.1067
	log(BMI), log(kg·m^{-2})	-1.4837	-0.4172
	$A_{SI.STD}$, ADC units	0.0014	0.3445
	$P_{M1.STD} \cdot P_{M5.STD}$, (ADC units)	$8.7 \cdot 10^{-6}$	0.1069
	$A_{AP.ENT}$	1.9431	0.1685

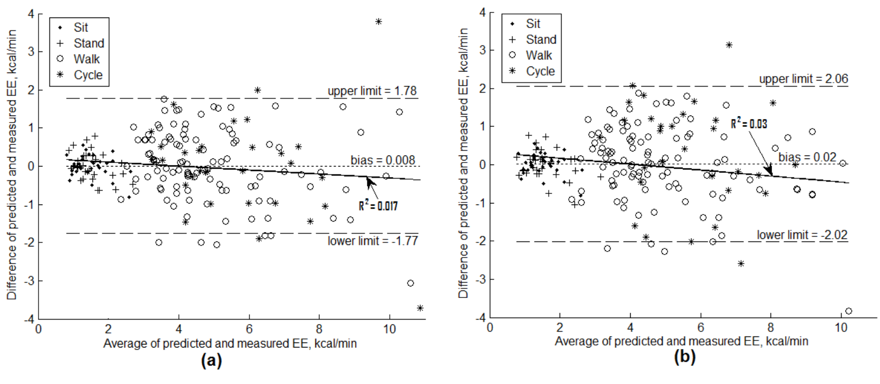

Fig. 7. Bland-Altman plots for BACC-PS (a) and BACC (b) models

Table 10. Regression coefficients in the BACC model

Branch model	Predictors, units	Average values of coefficients	CV of coefficients
Sit	<Intercept>	5.2862	0.0687
	Weight, kg	0.0352	0.0504
	log(BMI), log(kg·m^{-2})	-1.7594	-0.0854
	log($A_{SI.CV}$)	0.1331	0.0550
Stand	<Intercept>	6.5636	0.0713
	Weight, kg	0.0418	0.0525
	log(BMI), log(kg·m^{-2})	-2.2433	-0.0875
	log($A_{ML.CV}$), ADC units	0.1530	0.0513
Walk	<Intercept>	1.4050	0.5644
	Weight, kg	0.0798	0.0364
	log(BMI), log(kg·m^{-2})	-2.7433	-0.1086
	$A_{AP.STD}$, ADC units	0.0012	0.1661
	$A_{AP.ENT}\cdot A_{ML.ENT}\cdot A_{SI.ENT}$	0.5812	0.0248
Cycle	<Intercept>	11.4745	0.2013
	Weight, kg	0.1220	0.0703
	log(BMI), log(kg·m^{-2})	-5.4759	-0.1583
	$A_{SI.STD}$, ADC units	0.0058	0.0746

Table 11. Per-minute error (Root-Mean-Square Error, RMSE) for BACC-PS and BACC models

Model	Branch model	Number of 1-min recordings	$RMSE_{MET}$	Bias, METs
BACC-PS	Sit	31	0.26	0.0276
	Stand	32	0.32	0.0323
	Walk	103	0.76	0.0466
	Cycle	31	0.97	0.0617
	Aggregated	**197**	**0.69**	**0.0437**
BACC	Sit	31	0.26	0.0276
	Stand	32	0.33	0.0408
	Walk	103	0.75	0.0385
	Cycle	31	1.30	0.1517
	Aggregated	**197**	**0.77**	**0.0550**

These results suggest that SmartShoe can be used to accurately predict energy expenditure during typical postures/physical activities. The EE prediction accuracy of SmartShoe with activity-branched EE prediction models is similar to recent studies that have used single accelerometers, multiple accelerometers and heart rate/accelerometer combinations. Choi et al. [32] used Actigraph accelerometers placed at the hip, wrist and/or ankle and distributed lag and spline modeling to predict EE and reported RMSE of ~0.6 kcal/min (0.5 METs) across a range of activities with the accelerometer mounted at the ankle. Staudenmayer et al. [30] used a single hip-mounted accelerometer (Actigraph) and an artificial neural network to estimate EE of a variety of activites and reported an RMSE of 0.75 and

1.22 METs using activity and minute-by-minute estimates of EE, respectively. Brage et al. [8] used a device that measured heart rate and accelerometry (Actiheart) to estimate EE and found that the RMSE was within [0.87, 1.11] METs during walking/running activities. Thus, the results obtained from SmartShoe are at least as accurate or better compared to other recently proposed methodologies. These results also support use of plantar pressure as a way to improve EE prediction compared to a single accelerometer. As shown in Table 11, inclusion of pressure sensor metrics (BACC-PS model) reduced RMSE approximately 10% (from 0.77 to 0.69 METs). Inclusion of pressure metrics also improves EE estimation within an activity branch. In particular, there was a significant decrease in error rate in estimating cycling EE. This likely due to the changes in plantar pressure that are associated with changes in the intensity of cycling, something difficult to detect using an accelerometer. Overall, results of this experiment suggest that signals arising from acceleration and insole pressure of shoes can be used to accurately estimate the EE associated with common daily postures and activities.

7 Conclusions

The results from SmartShoe testing in various applications demonstrate its high accuracy and minimal intrusiveness. From the point of view of PA classification, SmartShoe was able to differentiate postures and activities that remain a challenge to other monitors (walking vs. cycling, sitting vs. standing, ascending stairs vs. descending stairs). SmartShoe demonstrated comparable accuracy of PAC both healthy and post-stroke individuals thus demonstrating applicability to various populations without a need for individual calibration. Temporal gait parameter estimation was reliable both in healthy and neurologically impaired individuals, justifying use of plantar pressure sensors for gait event detection. Branched approach to energy expenditure estimation resulted in accurate measurement comparable to the best methodologies available today. Again, use of pressure information improved the accuracy of EE estimation. Overall, SmartShoe is versatile multi-sensor system that is minimally intrusive through incorporation into everyday wear (shoes) and that can provide accurate monitoring of postures, activities, energy expenditure and gait of individuals in daily life.

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