

A Novel Wireless System to Monitor Gait Using Smartshoe-Worn Sensors

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Abstract—The aim of this paper is to present a multisensory system that studies abnormal walking patterns to prevent a fall. Due to the growing elderly population, scientific research on smartphone-based gait detection systems has recently become an imperative component in decreasing elderly injuries due to falls. To address the issue of smart gait detection, we propose a gait classification system using smartshoe sensor data in this paper. We used shoe-worn pressure sensors on the foot and validated algorithms to extract the gait parameters during walking trials in a lab environment. This smartshoe contains four pressure sensors with a Wi-Fi communication module to unobtrusively collect data. To the best of our knowledge, this is the first system which can automatically detect abnormalities in walking patterns. A unique signal classification approach is presented by recognizing the abnormality in a subject's gait, and modeling the dynamics of a system as they are captured in a reconstructed phase space. Based on our experiments, we have found an 89% walking-based classification accuracy to help prevent falls.

Keywords—Smart gait, Falls, Smartshoe, Smartphone, reconstructed phase spaces (RPS), Gaussian mixture models (GMM).

I. INTRODUCTION

Gait analysis is an important human locomotion study to recognize normal or pathological patterns of walking. Gathering the results from gait analysis has proved useful in medical programs, fall prediction in the elderly [15], physical therapy [23], and sports training [24]. For instance, with detailed gait feature analysis, therapists can quantify the rehabilitation progress of the patients after surgery, and the corresponding treatment and training can be customized according to an individual's status [25]. One can predict a fall by looking at the abnormality in individual's status.

Accidental falls have a plethora of social and economic impacts and dramatic health consequences among the elderly. In 2010 alone, 2.3 million nonfatal fall injuries were treated in emergency departments, and approximately 21,700 of those culminated in death, with direct medical costs totaling \$30 billion [26]. For people 70-75 years old, the estimated incidence of falls is over 30% per year [1]. Most falls happen during the activities of daily living that involve a small loss of balance, such as standing or walking. Gait analysis can be used for a comprehensive study of falling in old age [6]. Falls are considered to be a major source of morbidity and mortality in older adults and impose huge costs to the healthcare systems [7]. Therefore, the classical foot trajectory descriptors such as

stride length, stride velocity, and temporal parameters have been extensively investigated to determine the fall-related fact.

However, to address the lack of empirical gait evidence regarding the aforementioned factors, and due to the recent developments in mobile technology, we explore low cost smartshoe empirical data collection. Since mobile phones are highly portable, smartphone-based gait detection systems have the potential to function almost everywhere [15, 16]. With the recent development in mobile technology, the smartphone-based gait detection systems have become more popular as their computational abilities have increased. Ideally, integrated sensors along with the pressure sensor shoes (*smartshoe*) can automatically analyze gait. Therefore, we focus on smart gait detection for preventing fall injuries and assessing gait in general. To address these issues, we propose a smartphone-based gait detection system that can alert the user to their abnormal walking patterns.

In order to do so, we use the signal classification technique to identify abnormal gaits using the sensor data. Almost all work in signal classification or identification is based on linear systems analysis, using features based on a frequency domain representation. Signal detection and signal classification in the field of activity recognition and communications has been studied based on a statistical decision theory [12]. Alternatives to these established approaches include nonlinear classifiers such as neural networks or support vector machines, as well as clustering and likeness quantity techniques from the relatively new field of time series data mining [13].

Moreover, many existing time-domain approaches to the task of signal classification are based on a fairly simple underlying pattern, or template, which is either known or can be learned from the data. In the case of real signals with complex underlying systems, such as walking, running, or climbing stairs, patterns rarely exist. Frequency-based techniques are reliant on the existence of spectral patterns, which from a random processes perspective capture only the first and second order characteristics of the system. Yet, little work has been done in directly modeling signals in the reconstructed phase space, which is the approach introduced here for classifying time series. A statistical learner is applied to the space, and the resulting maximum likelihood classifier approach.

Finally, previous research has not studied gait monitoring using only smartshoe sensors data. Our system is useful for fall

prevention not only among the elderly, but also in gait disorders identification among children, physical rehabilitation patients, environmental monitoring, human behavior analysis, and social networking research.

A. Major Contributions

We propose to use smartphones as the platform for developing a smart gait detection system, as they naturally combine detection and communication components. We conducted experiments on 15 different users (with different ages, heights, and genders) wearing a smartshoe and carrying a smartphone, and found that our system can identify abnormality in users' gait patterns. Our major contributions in this paper are as follows:

- Developed a smartphone-based gait detection system for analysis of human locomotion patterns.
- Used pressure distribution data from the smartshoe in the first system to identify abnormal gait pattern in users.
- Developed a Wi-Fi network for the communication between the smartphone and smartshoe.
- Proposed a new signal classification technique to identify any abnormality in users' gait patterns.

The rest of the paper is organized as follows: in the next section, we discuss relevant related work and differentiate the difference between our system and the existing ones. Then we discuss the details of the system. This section is followed by the evaluation of our iPhone-based prototype system. Finally, we conclude the paper with some research that predicts the direction of gait analysis.

II. RELATED WORK

In past research, many scientists have discussed mobility and privacy issues [5], but they did not discuss wearing a sensor. Most of them focus on gait detection techniques, but not prevention of the fall. Moreover, other researchers do not account for the cost effectiveness of the system as well. Early machine-based gait recognition research typically utilized a combination of visual techniques or radar systems [18, 19]. An inherent advantage of vision-based technology is that it captures the gait of the person from a distance when other types of biometrics (e.g. fingerprints) are not accessible. Currently, the performance of the vision based biometrics is lower than stronger biometrics (e.g. fingerprints) [19]. In a multi-biometric system, vision-based gait recognition is combined with other biometrics, (e.g., face recognition) [20] or shoe pressure sensors [21] to improve performance. Finally, another approach relies on the use of radar [22]. A continuous wave radar measures the Doppler shift of the signal bouncing off of people while walking. Since radar is less sensitive to the color and texture of the individual's clothing and the ambient light condition, it is more readily detected by a mobile device. Both vision and radar based solutions require deploying external sensors in the infrastructure, rendering them unsuitable for user authentication of gait.

Majumder et al. [15] developed i-Prevention, a smartphone based fall prevention system that can alert the users about their

abnormal walking patterns. The authors validated their approach using a decision tree with cross validation and found 99.8 % accuracy in gait abnormality detection for only smartphone sensors data. They also developed the smartPrediction system [16] which equips a smartshoe with smartphone sensors to analyze the data using the same technique to show the fall prediction accuracy. Verghese et al., introduced three domains in their study to characterize gait performance in elderly persons [2]; The "Rhythm" domain is best represented by cadence, swing time and stance time. The "Pace" domain is best represented by gait speed and stride length. Finally, the "Variability" domain is best represented by stride length variability. Additionally, researchers have studied how to promote the walking speed as a general indicator that reflects functional and physiological changes in the health state and helps to predict falls [3, 4].

Furthermore, Pappas et al. [7] used a pattern recognition algorithm to define the changes during the gait cycle using their device comprising of three force-sensitive resistors (FSR) located on an insole (one under the heel, and two at the first and fourth metatarsal heads) and a gyroscope. The system was tested on two subjects with incomplete spinal injuries and was used to trigger functional electrical stimulation (FES), with demonstrated benefit for both subjects. In [8], the author proposes a method that uses a network of fixed motes to provide location information about the victim after a fall has been detected.

TABLE I. COMPARISON OF EXISTING WORK BASED ON DIFFERENT FEATURES

Approach	Cyber Physical System	Interoperable	Support High Sampling Rate	Minimize Integration effort	Cost Effective
Bamberg [37]	Yes	Yes	No	No	No
Zhang [36]	Yes	Yes	Yes	Yes	No
Lee [35]	Yes	Yes	No	No	No
Erez [34]	Yes	Yes	No	Yes	No
B-Shoe [33]	No	No	No	Yes	No
Lane [32]	Yes	Yes	No	Yes	No
Mellone [31]	No	No	No	Yes	No
Sposaro [30]	No	No	No	Yes	No
Jiangpeng [29]	No	No	No	Yes	No
Pedro [28]	No	No	No	Yes	No
Jiang [27]	No	No	No	Yes	Yes
Popescu [38]	No	No	Yes	Yes	No
Bourke [39]	Yes	No	No	Yes	No
Alwan [5]	No	No	Yes	Yes	No
Our Approach	Yes	Yes	Yes	Yes	Yes

Similarly, iFall [7] is an Android application that has been developed as a falls detection system. Data from the

accelerometer is assessed using several threshold-based algorithms and position data to detect a fall. The fall detection algorithm requires significant threshold adjustment without any guarantee of its performance. It therefore, requires extra processing. The PerFallD [9] is also a pervasive fall detection system tailored for mobile phones with two different detection algorithms based on the mobile phone platforms. It implements a prototype system on the Android G1 only.

To address the drawbacks of the above-mentioned systems, in this paper, we propose a smartphone-based gait detection system using shoe-worn sensors. Our system has been designed to directly address some of the drawbacks of the existing systems and yields good prediction results. It is highly secure, and is inexpensive because it requires only a smartphone with low cost smartshoes. Our system also supports high sampling rates during data collections, interoperable with minimum integration complexity. The most important aspect of our system is the warning that allows the user to prevent fall before it actually happens. Again we believe that our system is the first smartphone-based gait detection system, which can prevent a fall by automatically detecting abnormal gait patterns. We illustrate the difference between our system and the other related works in table I.

III. ARCHITECTURE OF THE SYSTEM

The strength of our proposed architecture is relying on existing wireless communication to provide a low price with maximum freedom of movement to users in their physical activity. In addition, we have used small, light-weight devices that are user friendly, like the smartphone and the smartshoe. This overall architecture was developed by assessing iterative designs of the prototypes with 15 subjects in the laboratory environment. To integrate the regulated sensors we used output of both the smartshoe and the smartphone and performed an extensive set of experiments to evaluate and distinguish between normal and abnormal walking patterns. Subjects wore the smartshoe like any other regular walking shoes and carried their smartphone in their pocket or held it in their hand. In the system, the smartshoe collected foot pressure value while the subject was asked to perform three different types of simulated walking patterns: normal, stiff leg or peg leg, and leg length discrepancy. After receiving the data through Wi-Fi communication, the smartphone processed it to classify whether the user's gait pattern is normal or abnormal. We have implemented the quantitative gait analysis in the iOS platforms. However, our system is also compatible with the Android platform.

A. Design Overview

This section provides an overview of the system's work flow. We briefly describe each architectural component and in turn, present a high-level overview of how they work in unison. In reality, the gait detection system waits until it gets a substantial amount of walking data, extracts features, and compares it to the particular user. The architecture of the

system is shown in figure 1. Our proposed analysis technique for gait detection comprises the following key components:

Preprocessing. In this stage, smartshoe data is segmented into frames. A frame is the unit for feature extraction and classification. Not all frames are considered for processing.

Feature Extraction. A set of features are extracted from the projected frame for walking detection. For efficiency, this set of features is lightweight yet still provides enough information for normal and abnormal walking classification. More relevant features are extracted for gait analysis. These features are more computationally intensive and will be used for gait classifications.

Walking Detector. Gait analysis is only meaningful during walking. This stage distinguishes the walking data from other activities. A decision tree classifier is applied using feature sets computed by feature extraction. We are analyzing only the walking signals for gait abnormality detection.

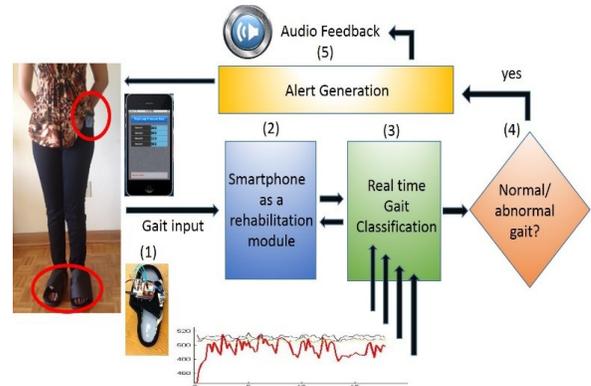


Figure 1. The Gait Detection system with its components: (1) Smartshoe-worn sensors, (2) Rehabilitation module, (3) Abnormality in gait detection, (4) Decision, and (5) Feedback.

Gait Analysis. We use a reconstructed phase space (RPS) and a Gaussian Mixture Model (GMM) framework [24] for gait detection. The design objective is to differentiate between signals generated by three different walking patterns, and to adapt the gait model so that it could account for different walking patterns and the variance in the user's gait over time.

B. Physical Implementation

Using all of the electronics (including the sensors located at the bottom of the shoe), a Wi-Fi module for the wireless transmission, and a power supply, we were able to engineer a smartshoe.

TABLE II. INSOLE SENSING POSITION

Position Number	Name
1	Posterior Metatarsal
2	Heel (Hind foot)
3	Great Ball (Forefoot)
4	Little Ball (Forefoot)

The smartshoe system is comprised of an amplifier circuit, Wi-Fi module, and a power supply unit with four insole pressure sensors. Each shoe module consisted of an

instrumented insole placed beneath the foot and an attachment that mounted to the back of the shoe. A sample insole of the smartshoe and the enclosed sensors and hardware are detailed in figure 2. Our goal is to optimize the number of measurement points. Most of the body pressure is measured from the rear foot and the fore foot. Considering these issues we have placed two of our sensors in the fore foot region and two of them in the rear foot region as shown in figure 3(b). The four sensors insole locations are listed in table II.

In order to process smartshoe sensors data, the communication module has two different software tasks. One is for the arduino and another is for the iPhone. The arduino is programmed to read analog signals from the shoe sensors and to create a data packet that converts the signal into digital form. Subsequently, arduino sends those packets to the phone with a response to the data sending request. It also manages the Wi-Fi communication coordinating with the WiFly shield. In the iPhone we developed an application that communicates with a WiFly shield and collects the sensor data by a polling request. Then, the data is saved and analyzed through a parsing packet and calculates real pressure values from the sensors. From here we identify the threshold value of the individual subject.

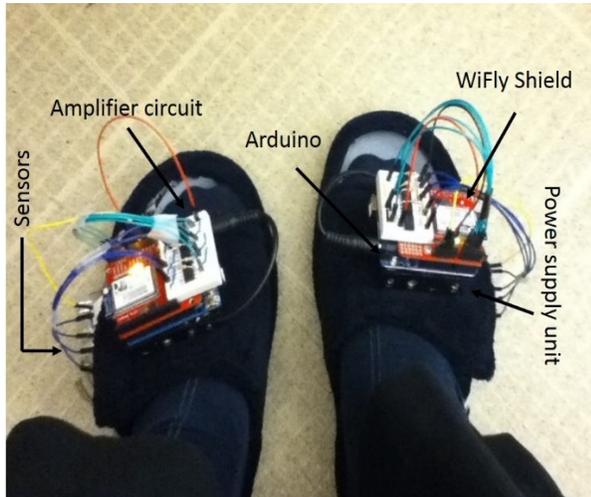


Figure 2. Early prototype of smartshoe hardware mounted on shoe

IV. OVERVIEW OF OUR APPROACH

We use the following approaches of signal classification to analyze the smartshoe sensors data to identify any abnormality in gait patterns.

A. Phase Space Reconstruction

The basis of this approach is that, given access to the state structure of a system, a classification of such systems can be developed. We start by presenting a theoretical construct of the problem. Given a finite-dimensional system state space M and $\varphi: M \rightarrow M$, the dynamics of the system, a system is described by the pair $\langle \varphi, M \rangle$. We then define a set ϕ of all possible dynamics on M with a topology ζ . Without loss of generality,

we assume M to be d -dimensional, because given any $M' \subset M$, M can be replaced by $M' \cup M$. The system classification then becomes one of partitioning ϕ according to the requirements of the classification problem with a particular dynamics φ identified with a particular partition P_i such that $\phi = \cup P_i$, where $P_i \cap P_j = \emptyset, i \neq j$. The problem for real world systems is how to gain access to and represent φ for a particular system. The approach used here is phase space reconstruction, also known as phase space embedding, and was first proposed in [14].

The works of Takens [9] and Sauer et al. [10] are used as a theoretical basis for our signal classification process. This work states that a time series of observations sampled from a single state variable of a system can be used to reconstruct a space topologically equivalent to the original system.

Given a time series $x = x_n, n = 1 \dots N$, a sequence of state variable observations, a trajectory matrix X of dimension d and time lag ζ is defined as,

$$X = \begin{bmatrix} X_{1+(d-1)\zeta} \\ X_{2+(d-1)\zeta} \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} X_{1+(d-1)\zeta} & \dots & X_{1+\zeta} & \dots & x_1 \\ X_{2+(d-1)\zeta} & \dots & X_{2+\zeta} & \dots & x_2 \\ \vdots & & \vdots & & \vdots \\ X_N & \dots & X_{N-(d-2)\zeta} & \dots & x_{N-(d-1)\zeta} \end{bmatrix} \quad (1)$$

Where, each row vector in the matrix represents a single point in the space;

$$X_n = x_{n-(d-1)\zeta} \quad \dots \quad x_{n-\zeta} \quad x_n \quad (2)$$

Where, $n = (1 + (d - 1)\zeta) \dots N$. a row vector x_n is a point in the RPS.

The dimension d is greater than twice the box counting dimension of the original system which is a sufficient condition for topological equivalence [14]. Most real systems do not have a known d , but it may be estimated using the false nearest-neighbor technique [11], which calculates the percentage of neighboring points which are near because of projection rather than dynamics. In Takens' original work, $\zeta=1$. However, in practice, it has been found that the appropriate selection of the time lag can reduce the required RPS dimension. A common empirical for determining time lag is to use the first minimum of the automutual information function [11].

The proposed classification algorithm is theoretically capable of differentiating between signals generated by topologically different systems because of the representational capability of RPSs. It can differentiate between deterministic nonlinear signals with identical linear characteristics but different nonlinearities. This theoretical capability is demonstrated empirically across different complex real-world application domains.

B. Gaussian Mixture Models

The second step of the approach is to learn a GMM probability distribution for each walking pattern. This is done by creating an RPS using the time lag and dimension and

inserting all the signals for a particular class into this space as described by (1) above.

A GMM is defined as:

$$p(x) = \sum_{m=1}^M \omega_m p_m(x) = \sum_{m=1}^M \omega_m \mathcal{N}(x; \mu_m, \Sigma_m) \quad (3)$$

where M is the number of mixtures, $\mathcal{N}(x; \mu_m, \Sigma_m)$ is a normal distribution with mean μ_m and covariance matrix Σ_m , and w_m is the mixture weight with the constraint that $\sum w_m = 1$. The required number of mixtures is related to the underlying distribution of the RPS density. The classification accuracy tends toward an asymptote as the number of mixtures increases provided there is sufficient training data. This iterative method yields a Maximum Likelihood (ML) estimate, via the estimation formulas:

$$\begin{aligned} \mu'_m &= \frac{\sum_{t=1}^T p_m(x_t) x_t}{\sum_{t=1}^T p_m(x_t)}, \\ \Sigma'_m &= \frac{\sum_{t=1}^T p_m(x_t) (x_t - \mu_m)^T (x_t - \mu_m)}{\sum_{t=1}^T p_m(x_t)}, \quad (4) \\ w'_m &= \frac{\sum_{t=1}^T p_m(x_t)}{\sum_{t=1}^T \sum_{m=1}^M p_m(x_t)}, \end{aligned}$$

Which are then substituted into (3). These signal classification approaches are useful for our system as they have the ability to distinguish the transition in walking patterns over a short period of time and allow us to evaluate gait abnormality.

V. EVALUATION

To evaluate our proposed system, we have developed a prototype application and investigated its performance with extensive experiments. In this section, we first introduce how the data was collected. Then we present how the data was analyzed and the performance measured.

A. Data Collection Procedure

We have developed a prototype application of the system for iPhone. The screenshots of the prototype application are shown in figure 4. In figure 4(a), the interface is shown which is used to collect the smartshoe data for a period of time. We have also developed the interface for user alert which is shown in figure 4(b). However, we are still working on the background process of alert generation mechanism. We have used our prototype application for data collection and for evaluating our system.

We collected data for a normal walking pattern and two different abnormal walking patterns in different environments for a total of 15 samples per person. Each sample was 18 seconds long. We simulated the abnormal walking patterns that are caused by two physical abnormalities common in most elderly people- stiff leg and leg length discrepancy. These abnormalities lead to a huge number of falls every year. We simulated the “leg length discrepancy” situation by taking one shoe off (at the right leg) and wearing an extra heel on top of

the regular heel on the left shoe. We simulated the “stiff leg” situation by walking with a straightened left knee.

Smartshoe gathers pressure values from the foot through sensors in order to identify impaired balance. Foot pressure is also an indicator of body balance. It is necessary to identify abnormal walking patterns due to gait impairment in order to predict the risk of injury.

For the smartshoe data collection process we used arduino, Wifly shield, and an amplifier circuit as the Wi-Fi communication module on the shoe shown in figure 3(a). This module would amplify the signal and convert it into a digital signal. The pressure data from the shoe are transferred to the smartphone through a my_adhoc Wi-Fi communication network. Pressure data was collected for the people over a period of time and each subject was tested with standing and three different walking patterns.

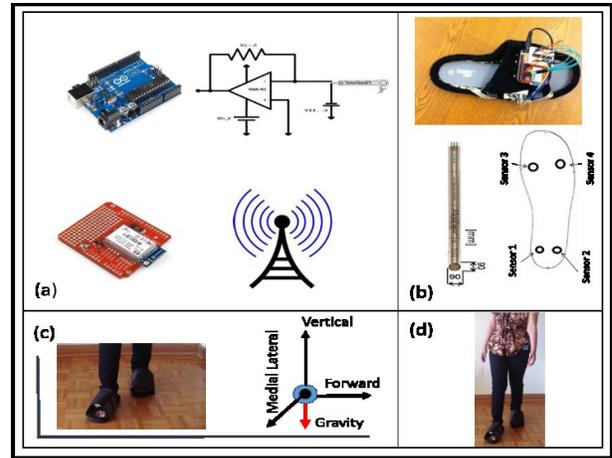


Figure 3. (a) Components of a wireless shoe ; (b) Sensors attachment to the shoe with anatomical locations; (c) Illustration of the orientation of the smartshoe relative to the global frame of the measurement; (d) An example of the walking trial in the lobby.

We first used this dataset for the training of our system. Later, we will use the trained system with real people to verify the gait abnormality detection accuracy. Since we cannot test potential fall injuries with real elderly people, we recruited 15 students to participate, ages from 20 to 35 years old. Twelve of them were 170-180 cm, two were 158-169 cm tall, and one was less than 150 cm tall. Two persons weighed less than 60 kg, eleven weighed 61–90 kg, and two were more than 100kg.

The data collected from the shoe showed which sensor we were getting maximum pressure from during the experiments with respect to subject’s sex/age, height and weight. For example, when subject one was performing his assigned task we observed that sensor 2 in both shoes was getting more pressure than the other. Figure 5 shows the variation of maximum pressure for different subjects while walking. We used this maximum pressure value while determining the threshold for each subject in his or her walking pattern. Figure 6 is the histogram of maximum pressure sensor count for 15

test subjects. We observed that sensor 2 Heel (Hind foot) having maximum pressure for 7 different subjects while walking.



(a) Smartshoe sensors data collection interface (b) Audio alert message generation based on abnormal gait
Figure 4. Screenshots of wireless smart gait collector prototype

To evaluate the effectiveness of the proposed method in recognition, we choose four kinds of basic movements: which are standing still, walking with no abnormality, walking with leg length discrepancy, and walking with stiff leg discrepancy.

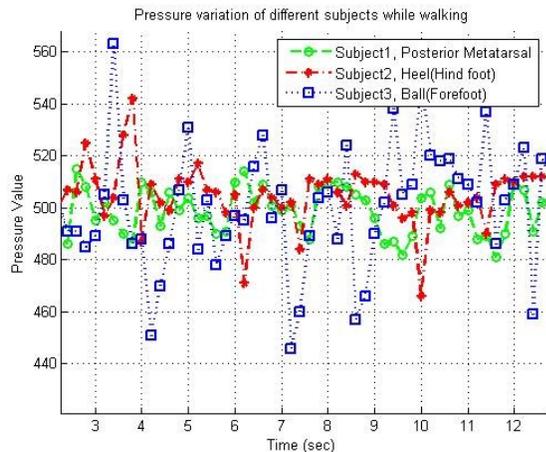


Figure 5. Maximum Pressure variation of different subjects' walking

Raw data on foot pressure distributions for each moving pattern were acquired with the developed foot pressure sensing shoes. The sample variation of foot pressure for each kind of movement is displayed in figure 7. Pressure value represents the output value of analog information into which voltage is converted. Though there is a spike in standing data, it is still easily distinguishable from the walking signal. The measurement allows the data to be integrated to a standard clinical assessment of a person's postural stability and/or risk of injury. The measurements may include any other test that measures pressure using the pressure sensor value.

It is important to differentiate if the user is walking on a flat surface or on a surface with considerable vertical variation. Using our system, we will also assess the effects of balance abnormality on human walking patterns and the variability of the extracted features.

B. Result Analysis

In this section, we will first discuss the performance of the system. We built the reconstructed phase space model for normal and two different abnormal walking patterns. Finally, we analyzed the patterns to show the differences in normal walking versus abnormal patterns to predict injury.

We collected data for a normal walking pattern and two different abnormal walking patterns in a lab-environment. We also collected standing data using the smartshoe and compared them with the walking pressure data. It was observed that the pressure distribution was different from one subject to another as the walking pattern was different in each subject.

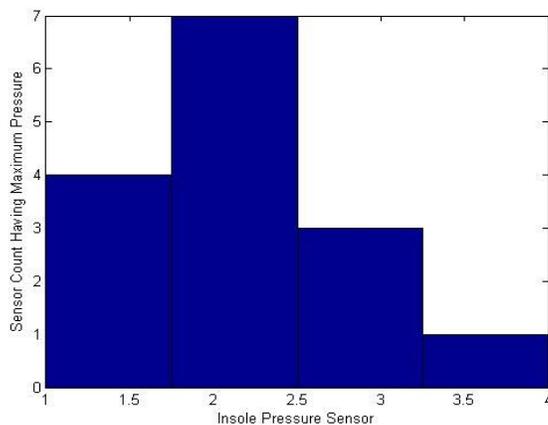


Figure 6: Histogram of Maximum Pressure Variation for 15 Subjects.

We can easily distinguish between normal and abnormal waking patterns by analyzing the collected pressure data. Using the Weka machine learning toolkit, a powerful data mining toolkit [17]. We performed a 10-fold cross-validation in which we folded the data by session in order to avoid over-fitting (i.e., training and testing sets would never contain examples from the same subject). We ran our 3-class classifier per user and averaged the results to obtain an overall accuracy of 89%. The confusion matrix for this classification is shown in table III. Also, our system can avoid new training by training a universal model with data from all the subjects and to test new users gait without new training.

TABLE III. CONFUSION MATRIX OF WALKING BASED CLASSIFICATION

	Normal	Stiff leg	Leg length	Actual Class
Normal	92.1	4.2	3.7	
Stiff leg	6.2	88.3	5.6	
Leg length	3.8	9.6	86.7	
Predicted Class				

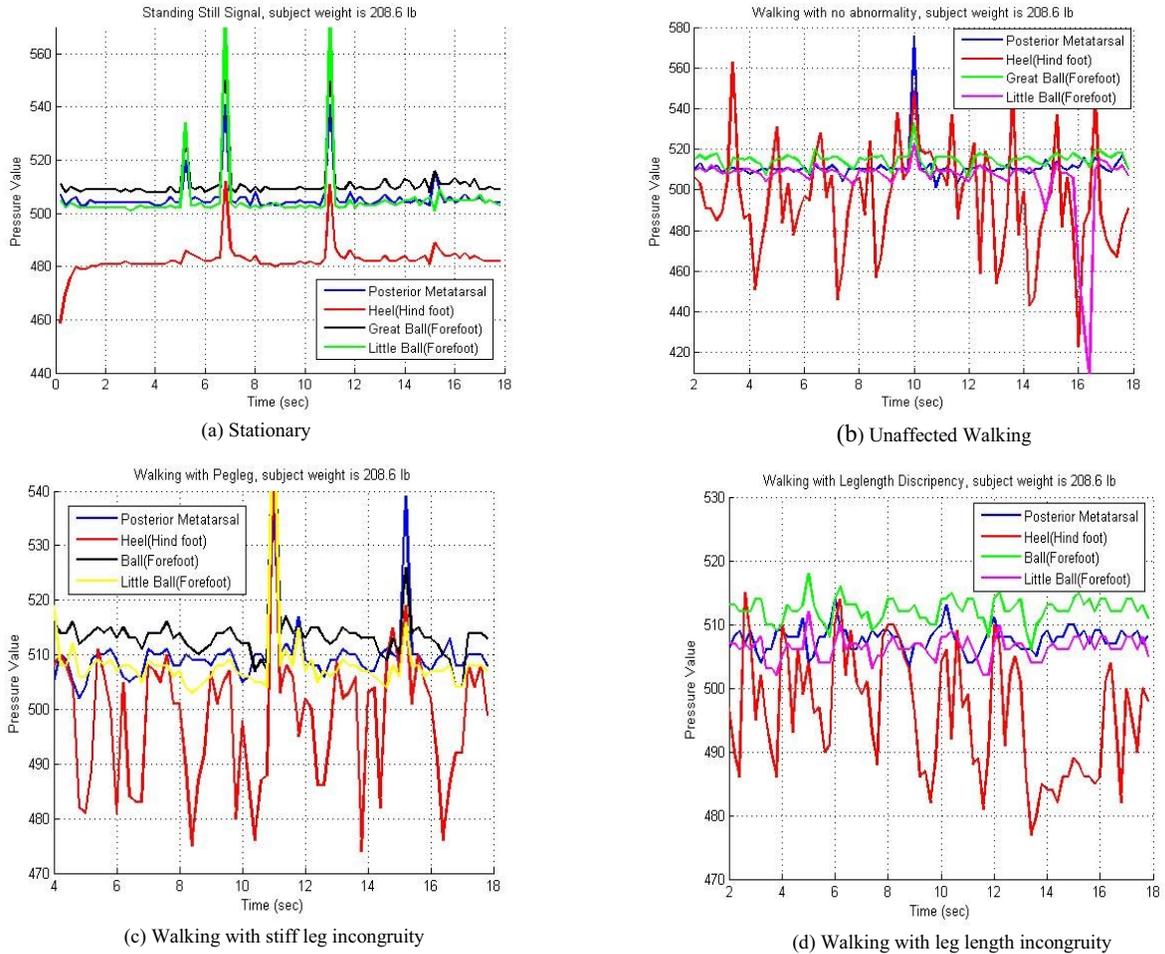


Figure 7. Foot pressure distribution of: (a) stationary (b) unaffected walking (c) walking with leg length discrepancy (d) walking with stiff leg discrepancy

As discussed above, our approach to signal classification is to build GMMs of signal trajectory densities in an RPS and differentiate between signals. This is done in three steps. The first step, data analysis, includes embedding the signals and estimating the time lag and dimension of the RPS. The second step is learning the GMMs for each signal class. The final step is signal classification, which is done with a maximum likelihood estimator (MLE) technique.

Using the data set from the maximum pressure sensors, we plotted the RPS 3-D phase plot for three different walking patterns. We found different patterns for each different walking as shown in figure 8.

We applied our technique to three data sets, the first data set is generated from normal walking, and second and third data sets are from two simulated abnormal walking patterns. It was observed that we were getting maximum pressure with one or two sensors during assessment with respect to the subject's sex, age, height and weight.

We used this maximum pressure value while determining the threshold for each subject in his or her walking pattern. We can also see the variations of different walking patterns for different subjects.

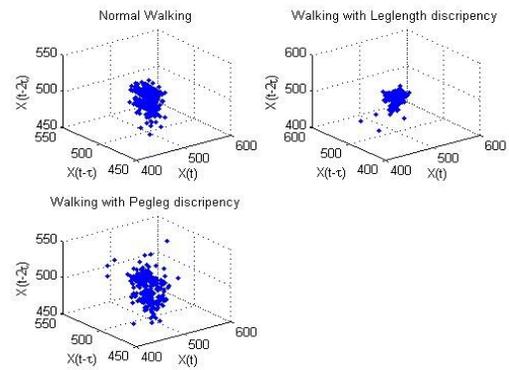


Figure 8. Reconstructed 3-D phase space of Normal, and simulated walking with Stiff leg and Leg length discrepancy for maximum foot pressure value when $\zeta = 11$

Then, we modeled the dynamics using Gaussian mixture models (GMM). First, learning the GMM for each type of embedded time series and then testing the mix function of GMM on embedded time series to get the GMM. The particular models used here are statistical distributions that

can be learned over RPS and then used to classify unseen signals. Nonparametric distributions based on three different walking and the distributions based on Gaussian mixture model distributions are also illustrated. A visualization of a GMM is shown in figure 9, where the principle axes of the ellipses indicate the one standard deviation of each mixture in the model.

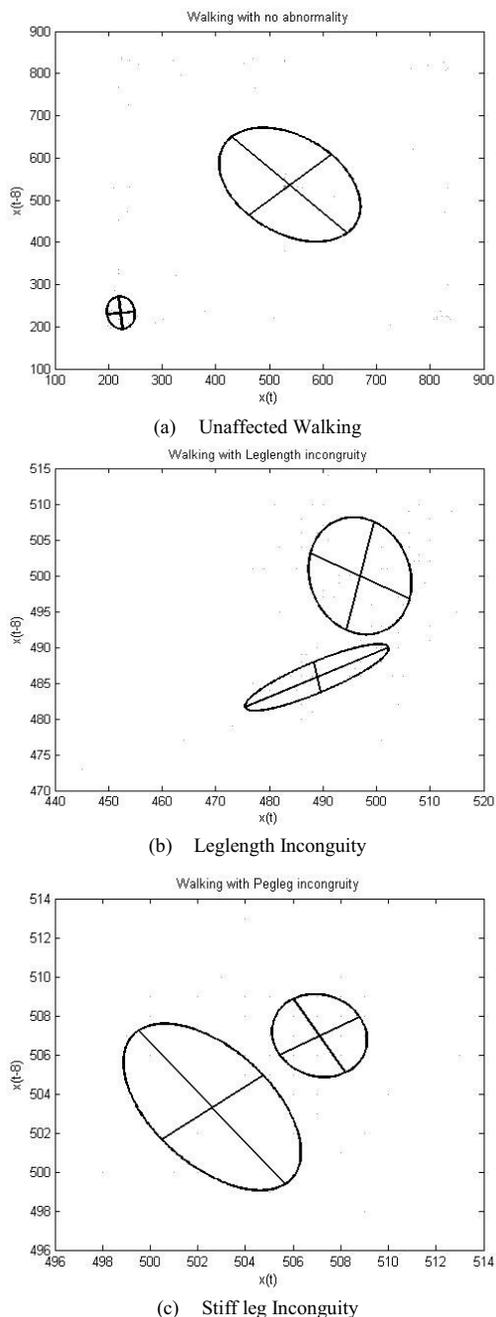


Figure 9. GMM-based gait classification modeling for three different walking patterns (2 Mixtures): (a) Walking without abnormality, (b) Walking with simulated leg length discrepancy, and (c) Walking with simulated stiff leg

Our experimental results do not show the desired accuracy with the GMM for walking, as our analysis is for simulated data. However, for GMM, there is still room for classification accuracy improvement to greater satisfaction. We expect our accuracy to improve when data is collected from a real subject with a chronic gait problem.

VI. CONCLUSION

In this paper, we presented a wireless system to analyze gait using smartshoe-worn sensors through a real-time detection of abnormality in users' gait patterns. The results from three different data sets are also presented to show that this approach provides a high rate of classification correctness in distinguishing between normal and abnormal walking patterns. The system may also find broad applications in abnormal gait behavior detection for people with various disabilities who are at a high risk of injury.

To test the temporal stability and long-term feasibility of our approach in the future, we hope to test our system with data from elderly people who suffer from chronic gait problems. We plan to have the smartphone contact a caregiver and a loved one in the event of a high risk injury situation so that they can take appropriate action. We also plan to measure the walking speed of the user. Additionally, the shoe could potentially also help us in identifying the specific causes for gait abnormalities.

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