Fall Risk Prediction

Sohan Mugdho, Sadman Sakib, Ruhul Amin Pranto, Tasrif Adnan
Bangladesh University of Engineering And Technology
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ABSTRACT

In this paper a smart phone and accelerometer and gyroscope data are used to develop a fall risk prediction. Basically, we are identifying between normal and abnormal walking patterns. We are calling the stiff walk pattern "abnormal" and considering that the subject is in fall risk. This paper gives the gait stability and gait symmetry definition only under the data condition of acceleration and rotation. Our proposed gait assessment model is used to predict the fall risk of walking subject. When the subject is in fall risk an alert is sent to the receiver end using Gmail.

Key words- stiff walk, fall risk, gait, Gmail.

1. INTRODUCTION

Accidental falls among elderly people has a great impact and dramatic consequences. According to the United Nations Population Division statistics, by the end of 2018 the elderly population reached 937 million, accounting for 11.8% of the total population. In the year 2025 it is projected to account for 15% of the total population. For people 70-75 years old, the estimated incidence of falls is over 30% per year.

[1]. Among elderly people living at home, almost half of the falls take place near or inside the house. Nearly half of nursing home patients fall each year, with 40% falling more than once [2]. Most falls happen during the activities of daily living (ADL) that involve a small loss of balance such as standing or walking. Falls not only cause physical injuries, but also have physical consequences. Acknowledging the need to lower the risk of falls medical teams are often implemented interventions without much empirical evidence.

In our society, falls and their consequences cause tremendous problems as related to fractures, quality of life and cost of healthcare. Although fall detection systems cannot directly predict falls, detection can help reduce the risk of fall, otherwise be left unsupervised for an extended period. The area of fall prediction is understudied. Fall prediction is very challenging since to prevent a fall, first we need to identify the patterns that can lead to a fall. Current research on automatic fall detection methods can be classified into three main categories in terms of the sensors they use: video-based methods [3], acoustic-based methods [4] and wearable sensor-based methods [5]. Many systems also rely on significant installation and training times. This increases the obtrusiveness of the intervention and contributes to poor acceptance of the system. With the recent developments in mobile technology, the cost of the smartphones has decreased as their computational abilities have increased. Smartphone-based fall detection systems can function almost everywhere, since mobile phones are highly portable. Currently, most smartphones now have sensors to observe acceleration, location, orientation, ambient lighting, sound, imagery, etc. [6]. Ideally integrated sensors can automatically detect falls. Researchers have already developed some fall detection systems using smartphones [7].

In all the previous studies, the system can detect fall after it has occurred. But we believe that the best way to reduce the risk is to preventing it form happening. Thus we will be to reduce the number of falls and its consequences. That's exactly what we have done in our work. we send alert to the user when the walking pattern is abnormal and there is a possibility of falling.

If abnormal walking patterns can be identified using automated processes with good accuracy, the elderly can avoid a potential fall.

Therefore, we focus on fall prediction rather than fall detection. To address the issue of fall prevention, in this paper, we propose a smartphone-based fall prediction system that can alert the user to their abnormal walking pattern. The smartphones are integrated with two powerful sensors: accelerometer and gyroscopes. Since abnormal walking patterns can lead to a fall, the identification of an abnormal gait in our system is used to alert the user regarding a potential fall. Our system is useful for fall prevention not only among elderly, but also has scope in identifying gait disorders among children, physical rehabilitation patients, and for environmental monitoring, human behavior analysis, and social networking research.

2. MOTIVATION

It is hard to understand the negative effects of falling, outside of a personal experience of a fall related injury. It can take only one fall to severely injure an individual that results in death. This risk is high with age more than 50. This situation can be understood with the help of the following scenarios:

Scenario 1: Mrs. Samia, a 65-year-old living in her house alone. One night she was walking to the bathroom at around 10pm and she fell due to unbalanced walking. This caused a severe hip fracture. Her housekeeper arrived at her home the next day at around 10am and saw her lying in the bathroom. She called 911 and took her to the hospital. Samia was in intensive care for 48 hours. If Samia had a simple, automatic, and non-invasive technology that could warn her care person during her unbalanced walking, she could have been notified to avoid the consequences of fall. If Samia had our system, smart Prediction, it would have provided a non-invasive and smart technique to identify her unbalanced gait to provide warning regarding a potential fall.

Scenario 2: Alex is a 70 year-old who has been suffering from a stroke and associated hemiparesis with abnormal gait. His walking has a limp caused by limited forefoot push off. He has suffered 3 major falls over the last year due to his unbalanced walking. He also suffers from a back injury with significant ongoing pain caused by one of the falls. Alex is psychologically so traumatized by the consequences of these falls that he prefers to sit at home and declines participating in healthy activity. Our system, smart Prediction, could have identified the severity of Alex's unbalanced gait, avoided the falls or severity of the falls and referred to therapies as early interventions to allow Alex to live a more self-dependent and normal life.

To address the challenges posed by the above-mentioned two scenarios, in our paper, we propose a smartphone-based fall risk prediction system, named smart Prediction. This system can warn the care person by generating an alert message in their smartphone to prevent this type of unforeseen risky fall consequences.

3. RELATED WORK

Most of the fall-related research is based on detection rather than prevention. Earlier, many researchers have talked about mobility and privacy issues [8], but they did not discuss wearing a sensor. Most of them focus on fall detection techniques, not prevention of the fall. Moreover, they do not take into account the cost effectiveness of the system.

iFall [7] is an Android application that has been developed to detect fall events to be implemented as a falls detection system. Data from the accelerometer is evaluated using several threshold-based algorithms and position data to detect a fall. The fall detection algorithm requires significant threshold calibration 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. They implement a prototype system on the Android G1 only. Moreover, it does not have any warning mechanism to alert the user or caregiver and it is lacking localization support.

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 injury and was used to trigger functional electrical stimulation (FES), with demonstrated benefit for both subjects. In [11], 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.

To address the drawbacks of the above-mentioned systems, in this paper, we propose a smartphone-based fall prediction and prevention system named smart Prediction. Our system is designed to directly address some of the drawbacks of the existing systems and yield good prediction results. It is highly secure, and is inexpensive. The most important aspect of our system is the warning that allows the user to prevent a fall before it actually happens. Again we believe that smart Prediction is the first smartphone-based fall prediction system, which can prevent the fall by automatically detecting abnormal gait patterns. We illustrate the difference between our system and the other related works in table 1.

Table 1. Comparison of existing work based on different features

Approach	Mobility	Prevention	No Extra Hardware	Preserve Privacy	Cost Effective
Cucchiara [18]	No	No	Yes	No	No
Miaou [19]	No	No	Yes	No	No
Anderson [20]	No	No	Yes	No	No
Huang08 [21]	No	No	Yes	No	No
Sixsmith [22]	No	No	Yes	No	No
Alwan [8]	No	No	Yes	Yes	No
Popescu [23]	No	No	Yes	Yes	No
Bourke [24]	Yes	No	No	Yes	No
Tong [25]	Yes	No	No	Yes	No
Li [26]	Yes	No	No	Yes	No
Nguyen [27]	Yes	No	No	Yes	No
Zheng [28]	Yes	No	No	Yes	No
Dinh [29]	Yes	No	No	Yes	No
Huang09 [30]	Yes	No	No	Yes	No
Sharifi [31]	No	No	Yes	No	No
Knight [32]	No	No	Yes	Yes	No
Michael [33]	No	No	Yes	Yes	No
Tacconi [2]	Yes	No	Yes	No	No
Our Approach	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

4. THEORY OF OPERATION

To determine abnormal gait patterns we must first establish criteria for normal walking. Normal walking is coordination of balanced muscle contraction, joint movement, and sensory perception. Limbs, trunk, nerve-conditioning system and systemic diseases will affect a person's gait. Healthy people walk on two legs, generally able to automatically adjust the position to achieve balance and stability. The pelvis is affected by the arm swing, resulting in periodic rotation and incline. Also ankle, knee and hip angle changes in the process of motion for coordination. So the normal gait is periodic, with the characteristics of coordination and balance

[12]. Walking speed decreases as people age. This speed decline affects faster walking speeds more than with comfortable walking speeds. Quantitative analysis of gait stability and gait symmetry has obtained a series of parameter results. On this basis and colligated other factors, we have proposed to construct an early warning system, smart Prediction, that measures the subject's signs of instability when walking, or a fall hazard. A detailed description of smart Prediction system architecture is presented below.

4.1 Architecture of *smart Prediction 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 device that is easy to use by the elderly like smartphone. The architecture of smart prediction system is given below.

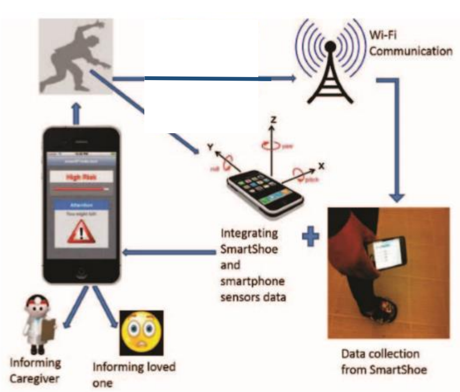

Figure 8. Flow chart

To integrate the regulated sensors we used output of the smartphone and performed an extensive set of experiments to evaluate and discriminate between normal and abnormal walking patterns. Subjects carried their smartphone in his/her pocket. (A detailed description of the system assessment follows later in this paper.) In the smart Prediction, the accelerometer and gyroscope of the smartphone collects the raw acceleration and orientation parameters.

The subject was asked to perform two different types of simulated walking patterns; normal, stiff leg discrepency. After receiving the data through Wi-Fi communication processed it inside the mobile phone to classify whether the user's gait pattern is normal or abnormal. We have implemented the quantative gait analysis in the android platforms.

Planned Falls Prediction System Alert: Though the system will continuously monitor for gait patterns, the planned design will only trigger a warning if the gait pattern of the user is identified as abnormal walking pattern where the user might face a potential fall. At that moment, the system enables a warning to the care person through a mail to alert them about an imminent fall.

5. IMPLEMENTATION DETAILS

In this section, we describe the various components of our prototype system (figure 1) and present in detail the hardware design and software algorithms used for event detection, feature extraction and classification.

5.1 Hardware

As hardware we have used android smart-phone to take accelerometer and gyroscope data. The feature extraction also takes place in the smart-phone and the extracted features are sent via internet to a desktop with the necessary software installed.

5.3 Software

We have developed a gait collector software using MATLAB's 'Simulink Support Package for Android Device' for receiving accelerometer and gyroscope value of the smartphone sensors, feature extraction and data transmission. After getting the extracted features from three gyroscope and accelerometer signals (in directions of x-, y-, and z-axis) from the motion sensors of the smartphone we classify it from the model that we trained using MATLAB's 'Classification Learner Toolbox' for identifying gait abnormality.

5.4 Extracting Tilt Invariant Signals

In table 3, we summarize the notations that we are going to use to describe the methodology of smart Prediction. We collected three gyroscope and accelerometer signals from the motion sensors of the smartphone (see figure 6) and pressure signals from both shoes. We then calculated and removed the gravity vector from the acceleration signal bias and performed a set of matrix rotation operations to correct the tilt of the signals. We combined the horizontal accelerometer signals as well as the pitch and roll to create 4 tilt -invariant signals. From these signals, we extracted 3 quantitative features to create a feature vector. Finally, we used a decision tree classifier to sort the data into classes based on the features of training data.

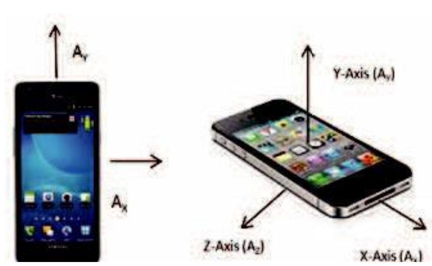

Figure 2. Acceleration and Gyroscope readings in directions of x-, y-, and z-axis that are associated with the body of the smartphone and smartphone orientation can be determined by yaw (Ax), pitch (Ay) and roll (Az) [14]

Table 2. Summary of Notations

Symbol	Meaning
$A_{0x}(t)$, $A_{0y}(t)$, $A_{0z}(t)$	Raw Accelerometer data in x, y and z-axis.
$A_{1x}(t)$, $A_{1y}(t)$, $A_{1z}(t)$	Tilt Accelerometer data in x, y, z direction.
$A_{2x}(t)$, $A_{2y}(t)$, $A_{2z}(t)$	Accelerometer data in x, y, z direction with further tilts.
$G_{0p}(t)$, $G_{0r}(t)$, $G_{0y}(t)$	Gyroscope vector of pitch, roll and yaw respectively.
$G_t(t)$	General tilt gyroscope vector
$B(t)$	Bias of the acceleration Vector
$A_h(t)$	Horizontal Acceleration
θ_1, θ_2	Tilt Angles

The feature extraction method applied to acceleration signals are applied here to both acceleration and gyroscope signals then combined with foot pressure signals. At time t, let the following column vectors represent the current raw accelerometer and gyroscope readings:

$$\overrightarrow{A_0}(t) = [A_{0x}(t), A_{0y}(t), A_{0z}(t)]' \qquad (1)$$

$$\overrightarrow{G_0}(t) = [G_{0p}(t), G_{0r}(t), G_{0y}(t)]' \qquad (2)$$

Where the elements of the gyroscope vector are pitch, roll, and yaw respectively. Now the gravity vector is found by calculating the bias of the acceleration vector. The bias is found by taking the average of N acceleration vectors where N is the total number of data instances:

$$\vec{B}(t) = \frac{1}{N}\sum_{t=1}^{N}\overrightarrow{A_0}(t) \qquad (3)$$

Here N is equal to 150 whereas the sampling interval was 10 ms.

Two tilt angles can be calculated to describe the tilt of the bias vector as follows:

$$\theta_1 = \arctan\left(\frac{B_y}{B_z}\right) \qquad (4)$$

$$\theta_2 = \arctan\left(\frac{B_x}{B_y \sin(\theta_1) + B_z \cos(\theta_1)}\right) \qquad (5)$$

A tilt compensated acceleration and gyroscope vector can then be calculated by multiplying the raw vector with a rotation matrix as follows:

$$\overrightarrow{A_1}(t) = \begin{bmatrix} \cos\theta_2 & -\sin\theta_1\sin\theta_2 & -\cos\theta_1\sin\theta_2 \\ 0 & \cos\theta_1 & -\sin\theta_1 \\ \sin\theta_2 & \sin\theta_1\cos\theta_2 & \cos\theta_1\cos\theta_2 \end{bmatrix} \times \overrightarrow{A_0}(t) \quad (6)$$

$$\overrightarrow{G_1}(t) = \begin{bmatrix} \cos\theta_2 & -\sin\theta_1\sin\theta_2 & -\cos\theta_1\sin\theta_2 \\ 0 & \cos\theta_1 & -\sin\theta_1 \\ \sin\theta_2 & \sin\theta_1\cos\theta_2 & \cos\theta_1\cos\theta_2 \end{bmatrix} \times \overrightarrow{G_0}(t) \quad (7)$$

Now the gravity vector can be removed from the accelerometer data by calculating the bias of the vertical component of the acceleration and removing it:

$$\overrightarrow{A_2}(t) = \left[A_{1x}(t), A_{1y}(t), \left(A_{1z}(t) - \frac{1}{N}\sum_{t=1}^{N}\overrightarrow{A_{1z}}(t)\right)\right]' \quad (8)$$

Because there is no other vector bias that can be used to correct another axis, we cannot distinguish between lateral and forward acceleration or between pitch and roll. We calculate the magnitude of the horizontal acceleration:

$$A_h(t) = \sqrt{A_{2x}(t)^2 + A_{2y}(t)^2}$$

combine the pitch and roll in the same way to create a vector that describes the general tilt:

$$G_t(t) = \sqrt{G_{1p}(t)^2 + G_{1r}(t)^2}.$$

5.5 Calculating Features From Signal

From the tilt compensated signals, we calculated 28 features in total. We calculated 6 features from the mean values, then 6 max values, then 6 max values of autocorrelation of the three axis of accelerometer and gyroscope data. We also calculated 4 RMS values from the vertical and horizontal components of the tilt and gravity vector compensated accelerometer and gyroscope data. The last 6 features were Hjorth parameters explained in the next section.

5.6 Calculating Hjorth Parameters

The Hjorth parameter is one of the ways of indicating statistical property of a signal in time domain and it has three kinds of parameters as in Table I: Activity, Mobility, and Complexity. Activity parameter, the variance of the time function, can indicate the surface of power spectrum in frequency domain. That is, the value of Activity returns a large/small value if the high frequency components of the signal exist many/few. Mobility parameter is defined as the square root of the ratio of the variance of the first derivative of the signal and that of the signal. This parameter has a proportion of standard deviation of power spectrum. Complexity parameter indicates how the shape of a signal is similar to a pure sine wave. The value of Complexity converges to 1 as the shape of signal gets more similar to a pure sine wave.

Table 3. The Hjorth Parameter

Parameter	Notation
Activity	$\mathrm{var}(y(t))$
Mobility	$\sqrt{\frac{\mathrm{var}(y'(t))}{\mathrm{var}(y(t))}}$
Complexity	$\frac{\mathrm{mobility}(y'(t))}{\mathrm{mobility}(y(t))}$

5.7 Classification

After calculating the 28 features, the resulting feature vector is classified as normal or abnormal based on training data. We used the 'Cubic SVM' classifier as it gave the highest accuracy out of the various classifiers we used in MATLAB's 'Classification Learner Toolbox'. The abnormal class is trained by simulating multiple gaits that are indicative of falling. The classified data is used to warn the user of an imminent fall.

The fall prediction alert message will be generated using smartphone sensors data by identifying the abnormal pattern in walking. This is the key point for determining normal and abnormal walking in our system.

6.EVALUATION OF SMART PREDICTION

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

6.1 Experimental Setup

To test the effectiveness of our feature extraction and classification method, we collected data using a smartphone sensor to be analyzed and classified. We used multiple subjects and collected data for 2 different gaits: normal walking, simulated stiff leg discrepancy. Data for each subject was collected for a total of 5 minutes trials from a smartphone placed in the subject's pocket. Features were extracted in MATLAB based on a 1.5 second sliding window with 50% overlap. The feature vectors were then classified using 'Cubic SVM' as mentioned before.

6.2 Data Collection Procedure

We have developed a prototype application of the smart Prediction system for android phones using MATLAB's 'Simulink Support Package for Android Device'. The schematic diagram of the application is shown in figure 8. In figure 8(a), the application will collect the accelerometer and gyroscope data and for every 1.5 seconds it will extract the required features and send the feature vector via internet. So far, we have used UDP protocol to send the feature vector to be predicted. That's why the system is restricted within the range of the local area network. However, there is the possibility to make the system IoT based and send the data to a specified channel from anywhere. 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. We simulated the abnormal walking pattern 'Stiff leg discrepancy' that is one of 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 "peg leg" situation by walking with a straightened left knee.

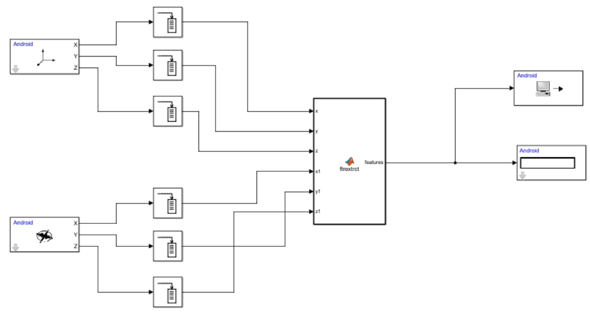

Figure 3. Schematic Diagram of the prototype application

An example plot for 30 seconds data of tilt and gravity vector compensated accelerometer and gyroscope data for normal and stiff leg walking pattern is given bellow:

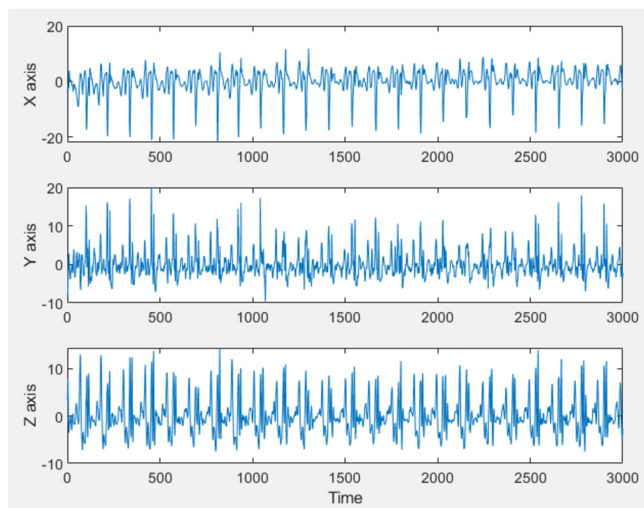

Figure 4. Accelerometer data for normal walking

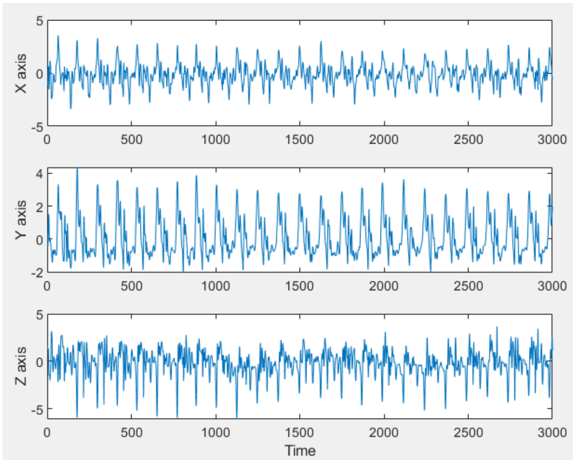

Figure 5. Gyroscope data for normal walking

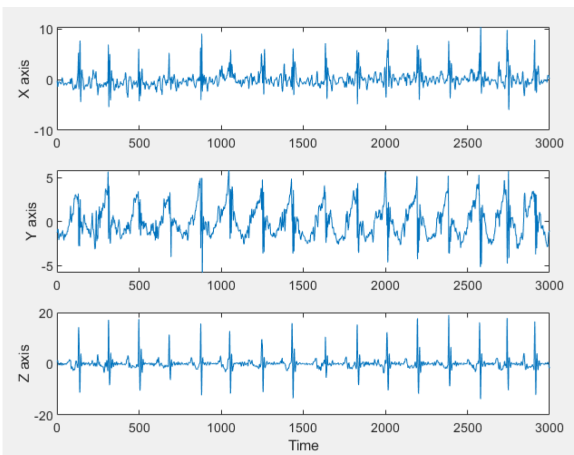

Figure 6. Accelerometer data for stiff leg walking

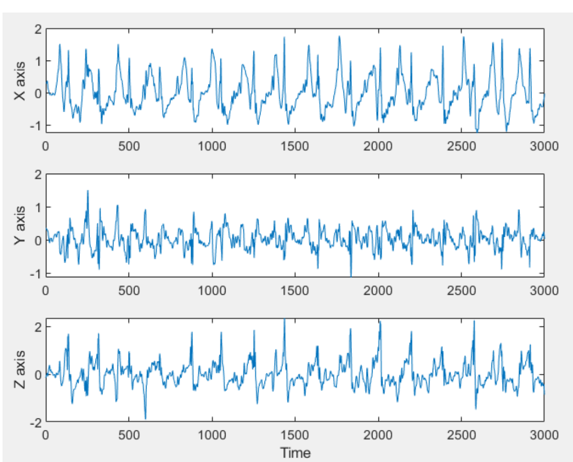

Figure 7. Gyroscope data for stiff leg walking

6.3 Result Analysis

We collected data for a normal walking pattern and two different abnormal walking patterns in - lab environment. It is interesting to note that the observed acceleration for normal walking is somewhat similar to that of abnormal walking. Explicitly, it is basically a short period of acceleration value followed by a small impact. The average measured peak acceleration for normal walking is greater than the average peak for acceleration with peg leg and simulated leg discrepancy. We have analyzed multiple cycles for getting more accurate average peak of the acceleration value. We can easily distinguish between normal and abnormal waking pattern by analyzing the collected data.

6.3.1 Single Subject Data

To determine the classification accuracy of walking, we evaluate the performance of our system using 10-fold cross validation for three different subjects. We observed near perfect classification accuracy (see table 5) when the experimental data, to be classified, was collected from the same subject, as was the training data. The classifier can easily distinguish between the two normal and abnormal patterns. The problem with single subject data is that it requires the subject to train the system by simulating abnormalities.

Table 4. Classification accuracy for a single subject

Accuracy of Classification	
Subject	***Three Classes***
Subject 1 Only	*99.7%*
Subject 2 Only	100.0%
Subject 3 Only	100.0%

7. CONCLUSIONS

In this paper we present a smartphone based fall prediction and prevention system, named smart Prediction through a real-time detection of abnormality in users' gait pattern. The system is the first iPhone-based application that uses the combination of built-in accelerometers and gyroscopes and pressure distribution from shoes to warn users regarding a potential falls. It is inexpensive, mobile, and non-invasive. From our analysis we have found that smart Prediction provides a high rate of accuracy to distinguish between normal and abnormal walking patterns. Incorporated walking model of our system will help to improve the accuracy in predicting a risk of fall. The system may also have broad application in abnormal gait behavior detection for people with various disabilities who are at increased risk of falls.

To test the temporal stability and long-term feasibility of our approach, in the future, we will test our system with real elderly people who have chronic gait problems.

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