Development of a Wireless Mobile Computing Platform for Fall Risk Prediction

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DEVELOPMENT OF A WIRELESS MOBILE COMPUTING PLATFORM FOR FALL RISK PREDICTION

by

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ABSTRACT

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Falls are a major health risk with which the elderly and disabled must contend. Scientific research on smartphone-based gait detection systems using the Internet of Things (IoT) has recently become an important component in monitoring injuries due to these falls. Analysis of human gait for detecting falls is the subject of many research projects. Progress in these systems, the capabilities of smartphones, and the IoT are enabling the advancement of sophisticated mobile computing applications that detect falls after they have occurred. This detection has been the focus of most fall-related research; however, ensuring preventive measures that predict a fall is the goal of this health monitoring system. By performing a thorough investigation of existing systems and using predictive analytics, we built a novel mobile application/system that uses smartphone and smart-shoe sensors to predict and alert the user of a fall before it happens. The major focus of this dissertation has been to develop and implement this unique system to help predict the risk of falls. We used built-in sensors --accelerometer and gyroscope-- in smartphones and a sensor embedded smart-shoe. The smart-shoe contains four pressure sensors with a Wi-Fi communication module to unobtrusively collect data. The interactions between these sensors and the user resulted in distinct challenges for this research while also creating new performance goals based on the unique characteristics of this system. In addition to providing an exciting new tool for fall prediction, this work makes several contributions to current and future generation mobile computing research.

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LIST OF ACRONYMS

ADL	Activities of Daily Living
mHealth	Mobile Health
uHealth	Ubiquitous Health
TBA	Threshold-based Algorithm
SMS	Short Message Service
MMS	Multimedia Messaging Service
GPS	Global Positioning System
GRF	Ground Reaction Force
FSR	Force-Sensitive Resistors
STFT	Short-time Fourier Transform
CPS	Cyber-physical System
IoT	Internet of Things
LoT	Lab of Things
SFP	Smart Fall Predictor
EEG	Electroencephalogram
RPS	Reconstructed Phase Space (RPS)
GMM	Gaussian Mixture Model
MLE	Maximum Likelihood Estimator
CV	Coefficient of Variation
NTP	Network Time Protocol
LE	Low Energy

CHAPTER 1 INTRODUCTION

Injuries due to gait abnormality are a major health problem all over the world [1]. These injuries are associated with significant mortality, disability, and a decrease in quality of life. Analysis of the human gait for predicting falls is the subject of many current research projects. By 2050, it is estimated that more than one in five people worldwide will be age 65 or over. Falls in the elderly are very common occurrences as approximately one-third to one-half of the population repeatedly experience falls on a yearly basis [2]. For people 70-75 years old, the estimated incidence of falls is over 30% per year [1]. Accurate reliable knowledge of one's gait characteristics at a given time, and even more importantly, monitoring and evaluating them over time, will enable early identification of abnormality in gait. This analysis will also help to predict and prevent a fall. The automatic detection of falls would help reduce the time of arrival of a medical caregiver and accordingly decrease the mortality rate [3] of the elderly.

The problem of accidental falls among elderly people has substantial social and economic impacts as well as health consequences. In 2009 the elderly population in the world reached 737 million, accounting for 10.8% of the total population. In the year 2025, it is projected to account for 15% of the total population. Among elderly people who live at home, almost half of all 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 during an activity such as standing or walking.

Falls not only cause physical injuries, but also have dramatic psychological consequences that reduce the independence of elderly people because falls can lead to an avoidance of activity that results in a pattern of increased isolation and health deterioration. These incidents can also result in significant economic expenses, including the cost of hospitalization and rehabilitation therapy. Acknowledging the need to lower the risk of falls, medical teams are often realized for interventions without much empirical evidence. Clinicians may see a patient after a long period of time and rely on the patient's memory and subjective descriptions of progress to formulate clinical decisions.

As indicated above, in our aging 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 patients who would otherwise be left unsupervised for an extended period. 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 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]. Integrated sensors along with the pressure sensor shoe (*smart-shoe*) can automatically detect falls. Researchers have already developed some fall detection systems using smartphones [7].

However, in previous studies, the system can detect a fall only after it has already occurred and the system sends an alarm to the caregivers. Even though these fall detection systems are helpful, the best way to reduce the number of falls and their consequences is to prevent them from happening. We believe that the best way to reduce the number of falls is to alert the users to their abnormal gait/walking and the possibility of falling. If abnormal walking patterns can be identified using automated processes with good accuracy, an elderly person can avoid a potential fall.

Though there has been substantial research on automated fall detection, the area of fall prediction has been understudied. Fall prediction is very challenging since to prevent a fall, first we need to identify the patterns that can lead to a fall. Therefore, we focus on fall prediction rather than fall detection. To address the issue of fall prevention, in this dissertation, we propose a smartphone-based fall prediction system that can alert the user to their abnormal walking pattern. Using the IoT systems to securely collect, analyze and automate appropriate responses and actions to real-time data collection from sensors and other devices within common environments, we developed a fall prediction system. Smartphones are integrated with two powerful sensors, accelerometer and gyroscopes. These are used in our system with pressure sensor embedded shoes to identify abnormalities in walking patterns. 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. Using smartphones with a sensor integrated shoe for fall prediction based on abnormal walking patterns has not been previously explored. Our system is not only unique, but also useful for fall prediction 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.

We built solutions using multiple disciplines. For example, we integrated theories from advanced embedded systems, applied mathematics, algorithms, electrical and electronic engineering, and principles from secure software development. This multidisciplinary approach allowed us to develop innovative solutions that otherwise would not have been possible.

1.1 Dissertation Statement

A trained wireless smartphone- and smart-shoe-based mobile computing system can collect and analyze gait patterns in real-time to predict the risk of fall in elderly with a high degree of accuracy.

1.2 Dissertation Focus

In this dissertation, we focus on the development of a smartphone-based fall prediction system that can alert the user to his or her abnormal walking pattern. Smartphones are integrated with two powerful sensors, accelerometer and gyroscopes. These are used in our system with pressure sensor embedded shoes to identify abnormalities in walking patterns. Our ongoing research work has made several contributions to address the problem of devising smartphone-based health monitoring systems, providing solutions to the following research issues:

1. Mobility and performance issues in motion sensor-based systems for mobile and ubiquitous health (mHealth and uHealth).

2. Smart-shoe for efficient monitoring and detection of gait abnormality in smartphone-based systems.
3. Multi-sensor approach and low energy issues in smart-shoe and smartphone-based healthcare and assisted care systems.
4. Addressing low response time issues to generate an alert message in predicting fall related injuries.

1.3 Major Contributions

In this section we briefly summarize the contributions of this dissertation.

1.3.3 Completed Work

1.3.3.1 *Mobility and performance issues in motion sensor-based systems for mobile and ubiquitous health (mHealth and uHealth)*

With recent improvements in mobile technology, the cost of smartphones has decreased and their computational capabilities have increased. To address the mobility and performance of our system, in this approach the accelerometer and gyroscope of the smartphone are used to collect the raw acceleration and orientation parameters while the user is walking. These data are then processed inside the mobile phone to classify whether the user's gait pattern is normal or abnormal. Though the system continuously monitors gait patterns, it only triggers a warning if the gait pattern of the user reaches a certain threshold where the user might face a potential fall.

1.3.3.2 *Smart-shoe for efficient monitoring and detection of gait abnormality in large scale smartphone-based systems*

To improve any shortcomings that may occur by only using the smartphone sensors, we added a smart-shoe. This smart-shoe 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 fall. As hardware devices, we used a pair of shoes consisting of four sensors each. The devices include Arduino, Wifly shield, amplifier circuit, a power supply unit, and a smartphone with the results of the system assessment.

1.3.3.3 *Multi sensor approach in smart-shoe and smartphone-based healthcare and assisted care systems*

After assimilating the smart-shoe and smartphone sensor data, we performed an extensive set of experiments in the lab environment to evaluate normal and abnormal walking patterns. In this contribution, we present analysis using both the smart-shoe and smartphone sensor data. We used the same analysis technique as we used in motion sensor based gait detection.

1.3.3.4 *Addressing low response time issues to generate alert message in predicting fall related injuries*

For our collected data the classification accuracy was very good when considering two subjects in the training data but was poor when attempting to classify one subject’s gait based on another subject’s gait patterns. To overcome this and to address the low response time issue, we analyzed our collected data from the smart-shoe using a signal classification approach that was based on modeling the dynamics. We used a unique signal classification approach to recognize the abnormality in a subject's gait, and modeled the dynamics of a system as they are captured in a reconstructed phase space.

1.3.4 Future Research Opportunities

The remaining work for this dissertation is presented at the end of this dissertation with a summary of future research opportunities.

1.4 Dissertation Organization

The rest of this dissertation is organized as follows:

- In Chapter 2, we present a brief description of current technology. We first discuss the background of normal walking. Next, we discuss the taxonomy of different mechanisms of falls and their constraints. Finally, we discuss the current state of the art in fall and related works.
- In Chapter 3, we present the research challenges for predicting falls due to abnormality in gait. This chapter briefly presents the details of each research challenge and our approach to address them.
- In Chapter 4, we discuss the design procedure and development process of a wireless smart-shoe. Also, in this chapter we discuss the hardware details of the smart-shoe.

• In Chapter 5, we discuss the design characteristics of the proposed fall prediction system. Then we discuss the fall prediction system architecture. The rest of the chapter briefly presents the details of the alert generation mechanism of the system.

• In Chapter 6, we introduce the design procedure of the gait logger system for data collection. The rest of the chapter briefly presents the details of features and attributes attraction from collected data.

• In Chapter 7, we introduce the evaluation and predictive analysis of the system. We introduce the results of motion sensor based analysis, results from the analysis of smart-shoe worn sensors and the multi sensor approach for gait detection. The chapter ends with a brief discussion of the present model construction for gait biomechanics.

• In Chapter 8, we conclude the dissertation with some future research directions and opportunities. A brief discussion of the impact of our work will be presented in this chapter.

1.4 Publications

- **[J1] A.K.M. Jahangir Alam Majumder**, Ishmat Zerin, Dr. Sheikh Iqbal Ahamed, and Dr. Roger O Smith, "**A Multi-Sensor Approach for Fall Risk Prediction and Prevention in Elderly**", In International Journal of the ACM SIGAPP Applied Computing Review, Vol. 14, Issue 1. pp. 41-52, March 2014.
- **[C7] AKM Jahangir Alam Majumder,** Piyush Saxena, Sheikh Iqbal Ahamed "**Your Walk is My Command: Gait Detection on Unconstrained Smartphone Using IoT System**", to appear in Proc. of the IEEE Computer Software and Applications Conference (COMPSAC 2016), Atlanta, Georgia, USA, June 2016**.**

- **[C6] AKM Jahangir Alam Majumder,** Sheikh Iqbal Ahamed, Richard J. Povinelli, Chandana P. Tamma, and Roger O. Smith, "**A Novel Wireless System to Monitor Gait Using Smartshoe-Worn Sensors**", to appear in Proc. of the IEEE Computer Software and Applications Conference (COMPSAC 2015), Taichung, Taiwan, July 2015.
- **[C5] AKM Jahangir Alam Majumder,** Ishmat Zerin, Chandana P. Tamma, Sheikh Iqbal Ahamed, and Roger O. Smith, "**A Wireless Smart-shoe System for Gait Assistance**", to appear in Proc. of the IEEE 36th Great Lakes Biomedical Conference, Milwaukee, WI, USA, May 2015.
- **[C4]** Ishmat Zerin, **AKM Jahangir Alam Majumder,** Sheikh Iqbal Ahamed, Roger O Smith "**Towards A Low Power Wireless Smartshoe System for Gait Analysis In People With Disabilities**", to appear in Proc. of the Rehabilitation Engineering and Assistive Technology Society of North America (RESNA) Conference (RESNA 2015), Denver, CO, USA, 2015.
- **[C3] AKM Jahangir Alam Majumder "A Real-time Smartphone- and Smartshoe-based Fall Prevention System**" in Proc. of ACM Symposium on Applied Computing (ACM SAC 2014) SRC. Korea, March, 2014.
- **[C2] A.K.M. Jahangir Alam Majumder**, Ishmat Zerin, Miftah Uddin and Dr. Sheikh Iqbal Ahamed, Dr. Roger O Smith, "**smartPrediction: A Real-time Smartphone-based Fall Risk Prediction and Prevention System**", in Proc. of the ACM International Conference on Reliable and Convergent Systems (RACS 2013). Montreal, QC, Canada, October, 2013.

- **[C1] AKM Jahangir Alam Majumder**, Farzana Rahman, Ishmat Zerin, Ebel Jr. William, Sheikh Iqbal Ahamed, **"iPrevention: Towards a Novel Real-time Smartphone-based Fall Prevention System**" in Proc. of ACM Symposium on Applied Computing (ACM SAC 2013). Portugal, March, 2013.

CHAPTER 2 BACKGROUND AND OVERVIEW OF CURRENT TECHNOLOGIES

2.1 Background

2.1.1 Theory of Walking

To determine abnormal gait patterns, we must first establish criteria for normal walking. Normal walking is the coordination of balanced muscle contraction, joint movement, and sensory perception. Limbs, trunk, and systemic diseases will affect a person's gait. Healthy people walk on two legs, generally able to automatically adjust their 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 change in the process of motion for coordination. So the normal gait is periodic, with the characteristics of coordination and balance [8]. Walking speed decreases as people age. This speed decline affects faster walking speeds more than 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, that predicts the subject's risk of fall when walking.

2.2. Basic Architecture

Fall detection and fall prevention systems have the same basic architecture as shown in figure 1. These systems follow three phases of operation: sense, analysis, and communication. The main difference between these systems lies in their analysis phase, which varies in their feature extraction and classification algorithms. Fall detection systems try to predict the occurrence of falls accurately by extracting the features from the output data of the sensors and then identifying falls from other activities of daily living (ADL). Fall prevention systems can predict fall events early by analyzing the outputs of the sensors. The necessary steps needed for both fall detection and prevention systems are data/signal acquisition, feature extraction and classification, and communication for notification. The number and type of sensors and notification techniques on the other hand, vary from system to system (some examples are shown in figure 1). In conventional systems, discrete hardware components are used for the implementation of each unit, whereas in smartphone-based systems, all required units may already be in-built within a smartphone.

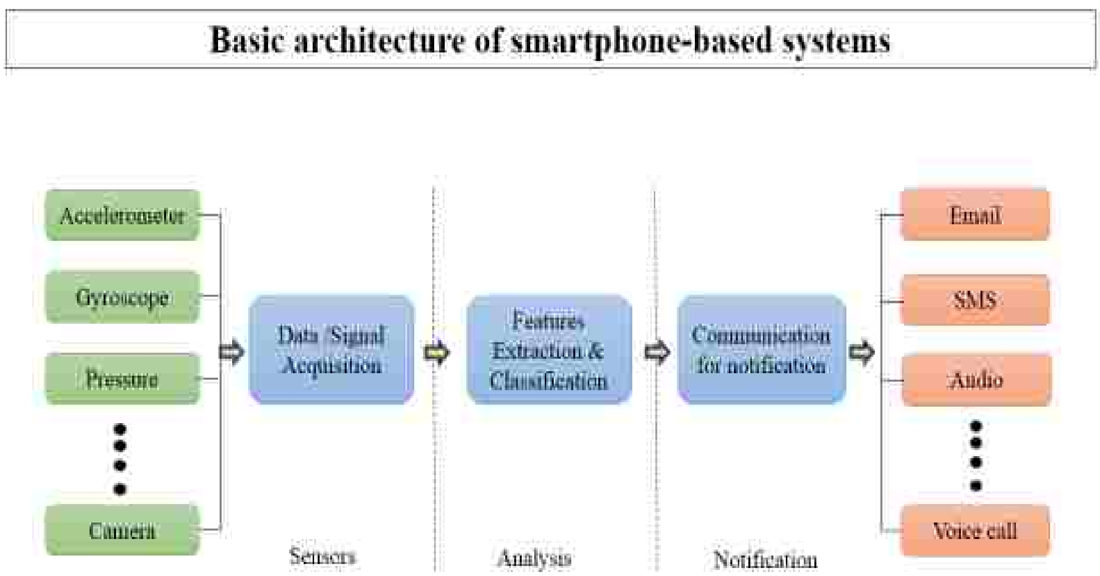


Figure 1. Basic architecture of smartphone-based systems

2.2.1. Sensing

The first phase of any fall detection and prevention system is sensor data collection. In this phase gait quantities, like stride length and stride frequency are measured using sensors. Smartphones come with built-in sensors and these are one of the reasons for choosing smartphones as an alternative for conventional fall detection and prevention platform [2]. Moreover, the users of smartphone-based systems are more likely to carry smartphones (with built-in sensors) throughout the day since mobile phones are seen as important in daily life. This use is in contrast to the users of conventional systems who may not always to wear the special micro sensors [9]. There are many types of sensors now available for smartphones. These sensors include accelerometers, gyroscopes, temperature sensors and magnetic field sensors [10-12]. These are used in various ways in smartphone-based solutions. Some solutions use only one of the aforementioned smartphone sensors for fall detection or prediction [13-14]. The tri-axial accelerometer is the most used sensor for smartphone-based fall detection and prevention. Another benefit to smartphone-based solutions is they can use combinations of two or more smartphone sensors during this sensing phase [15]. Some solutions use both smartphone sensors and external sensors for detection and prediction of falls [16]. It is also possible to use smartphones for analysis and communication in addition to sensing [17-18]. An uncommon type of solution proposed [19], they used a smartphone for sensing only, and external systems to perform the analysis and communication tasks of a fall prediction system.

2.2.2. Analysis

After measuring the physical quantities by using sensors, obtained data are analyzed. In this phase, the features are extracted from the sensor outputs and initial decisions about the abnormal gait are made by classifying and analyzing these extracted features. Most of the fall related solutions are based on Threshold-Based Algorithm (TBA). The reason it is useful to choose TBAs is that these algorithms are less complex and thus require the lowest computational power [2], which helps to reduce battery consumption [20]. To make preliminary decisions about a potential fall, these algorithms generally compare the sensor's data with predefined threshold values. TBAs may use more than one threshold [14] and threshold values that could be either fixed or adaptive. The users of any fall prediction system provide some physiological data and the system obtains the corresponding threshold that is not re-calculated during system operation. For example, the algorithm proposed in [7] uses an adaptive threshold which changes with user-provided parameters such as height, weight and level of activity.

Most solutions employ the tri-axial accelerometer for sensing which measures acceleration simultaneously in three orthogonal directions. TBAs use these acceleration values for calculating a Signal Magnitude Vector by using the following relation:

$$A_{Signal\ magnitude\ vector} = \sqrt{|A_x|^2 + |A_y|^2 + |A_z|^2} \qquad (1)$$

Where *Ax*, *Ay*, and *Az* represent accelerometer signals of the *x*, *y*, and *z*-axis respectively. If the value of signal magnitude vector for a particular incident exceeds a predetermined threshold value, then the algorithm preliminarily identifies that incident as a fall event. To make the final decision about a risk of fall, algorithms usually depend on the next communication phase.

The processing power of smartphone has increased dramatically over the past few years. The computational power of the smartphone has become comparable to that of former workstations [21] and, thus, even complex machine learning and statistical classification algorithms for fall detection and prevention can easily be implemented in smartphones [22]. Authors implemented three machine learning algorithms [23], namely C4.5, Decision Tree [24], Naïve Bayes Classifier [25] and Support Vector Machine [26], on smartphones and compared their recognition accuracy. In [27], the authors employed a combined algorithm of Fisher's Discriminant Ratio (FDR) criterion and J3 criterion [28].

2.2.3. Communication

When a smartphone-based solution detects a fall event, it communicates with the user of the system and caregivers. Most fall detection solutions carry out the third phase communication, in two steps. First the system attempts to obtain feedback from the user by verifying the preliminary decision about the user's gait patterns and thus improve the sensitivity of the system. The second step depends on the user's response. If the user rejects the predicted fall, then the system restarts. Otherwise, a notification is sent to the users and caregivers to ask for immediate assistance. Some systems may not wait for user's feedback and will instantly convey an alert message to their caregiver [29-30]. Moreover, instead of alerting the users, fall prevention systems can also activate other assistive systems (e.g., wearable airbag [31-33], intelligent walker [34-35], intelligent cane [36-37], and intelligent shoe [38]) for protecting the user from the adverse effects of fall.

The user's feedback can be collected automatically by analyzing the sensors' data. For example, the algorithm proposed by [2] generates the final decision by automatically analyzing the difference in position-data before and after the suspected falls. Other systems required manual feedback from the user. Combinations of alarm systems and graphical user interface of smartphones are also used for collecting user feedback [39]. After requesting a response from the user, the system waits for a pre-defined period (typically ≤ 1 min). If the user does not respond within that time, the system will consider the event a fall. However, fall detection systems may fail to detect a real fall event. In such cases, some systems provide *help* (or *panic*) buttons and thus allow users to seek outside help manually [40].

Smartphone-based systems generate several types of notifications to seek help from caregivers or for forewarning the users about an imminent fall such as audible alarms [41], vibrations, Short Message Service (SMS) [42], Multimedia Messaging Service (MMS) [14, 27], and even automatic voice calls [19, 42]. E-mails and Twitter messaging have also been described as a means of notifying users and caregivers about a fall [2]. Notification messages may contain information on time [14], Global Positioning System (GPS) location (coordinates) [14, 16], and location map [43]. Smartphone-based solutions can also support streaming of phone data from microphones and cameras for further analysis of the situation [19].

2.3 Taxonomy based on Sense, Analysis and Communication

This section presents a detailed taxonomy of smartphone-based fall detection and prediction systems with respect to the three different phases of operation: sense, analysis, and communication. Here we focus on the categorization of various attributes of smartphone-based solutions for fall detection and prevention. The aim of this taxonomy is to provide a complete reflection of the properties of existing as well as possible smartphone-based solutions.

2.3.1. Based on Sensing Mechanism and Sensor Placement

Figure 2 illustrates the taxonomy of smartphone-based fall detection and prevention technologies based on their sensing mechanisms and sensors placement. Existing solutions are represented with rectangles, while bold rectangles represent possible solutions that have not previously been reported to identify areas for future research. Smartphone-based solutions can be categorized into two types: context-aware and body-worn. With context-aware systems, the user should not wear any sensor or system. Sensors are placed in the user's surrounding environment and the user can move freely within the range of the sensors. Though, the main advantage of context-aware systems is that the person does not need to wear any special device, their operation is limited to those places where the sensors have been previously placed [44]. No such smartphone-based context-aware solution has been found. All the smartphone-based solutions, proposed so far, are body-worn systems and users are required to keep their smartphones close to their body. This type of solution can be further classified according to the existence of external sensors and the placement of the smartphone.

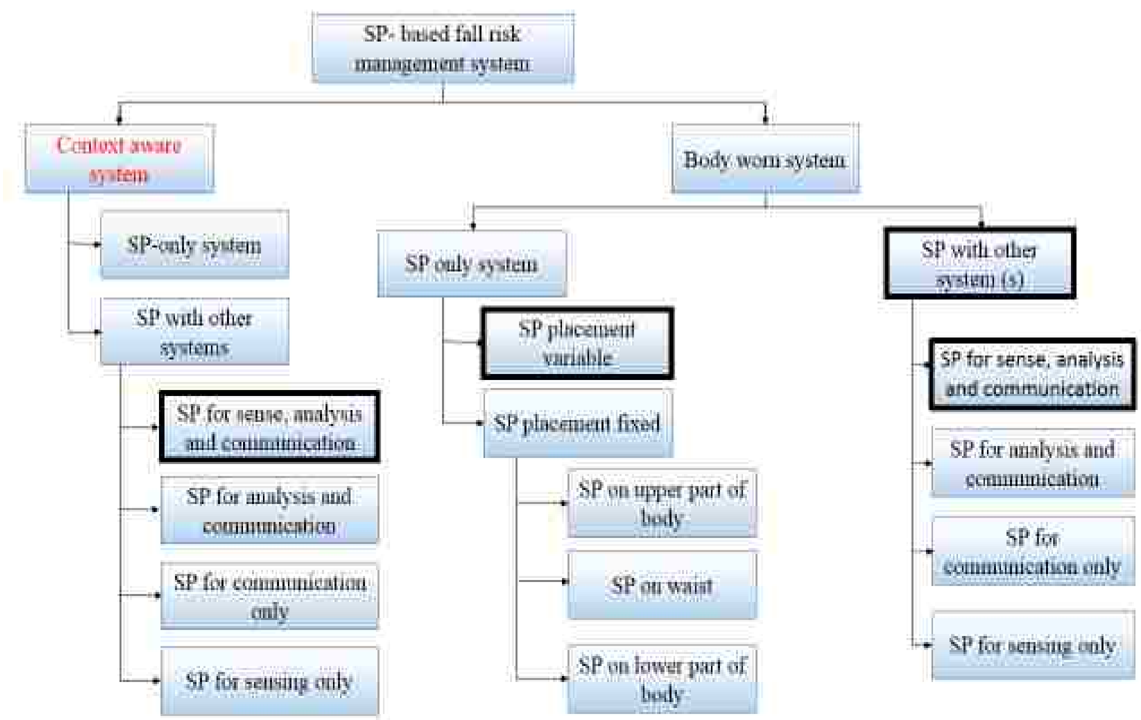


Figure 2. Taxonomy of smartphone-based systems based on sensing mechanism and sensor placement

2.3.2. Based on Algorithm Used in the Analysis

Smartphone-based solutions can also be categorized on the basis of algorithms used in the analysis phase. Figure 3 presents the taxonomy of these algorithms. Due to the lower processing capacity and low-energy storage capacity of batteries in smartphone compared to desktop or laptop computers, smartphone-based solutions mostly use TBAs for the detection of falls.

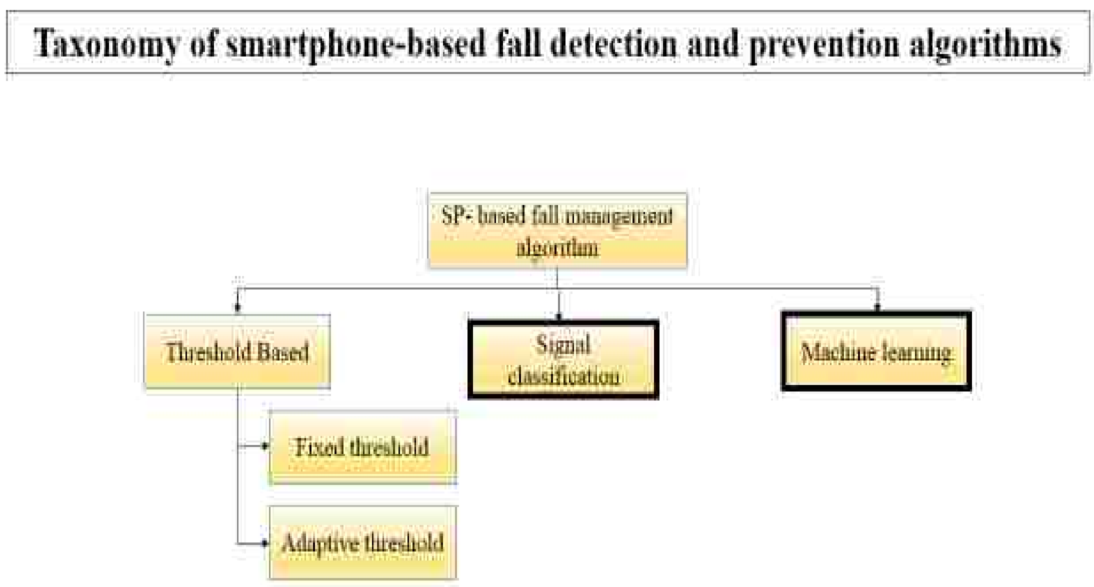


Figure 3. Taxonomy of smartphone based fall detection and prevention algorithms

2.3.3. Based on System Communication for Notification

Existing and potential smartphone-based fall detection and prevention systems communicate with the users, caregivers or assistive systems by sending an alert message. The taxonomy of communication patterns in smartphone-based fall detection and prevention is shown in figure 4. Detection systems communicate with the users to obtain feedback, whereas prediction systems communicate to alert them about their forthcoming falls. Prediction systems are only concerned with pre-fall data, but detection systems deal with pre-fall, post-fall and intermediate data. Also, detection systems notify caregivers of fall events and ask for help, whereas prediction systems attempt to prevent impending falls with the help of other assistive systems. Some smartphone-based solutions require external sensing units that may or may not have built-in processors. These external units may transmit either raw data or results after primary analysis. No article has been found, that uses assistive system or external processing units for implementing a smartphone-based fall prevention solution.

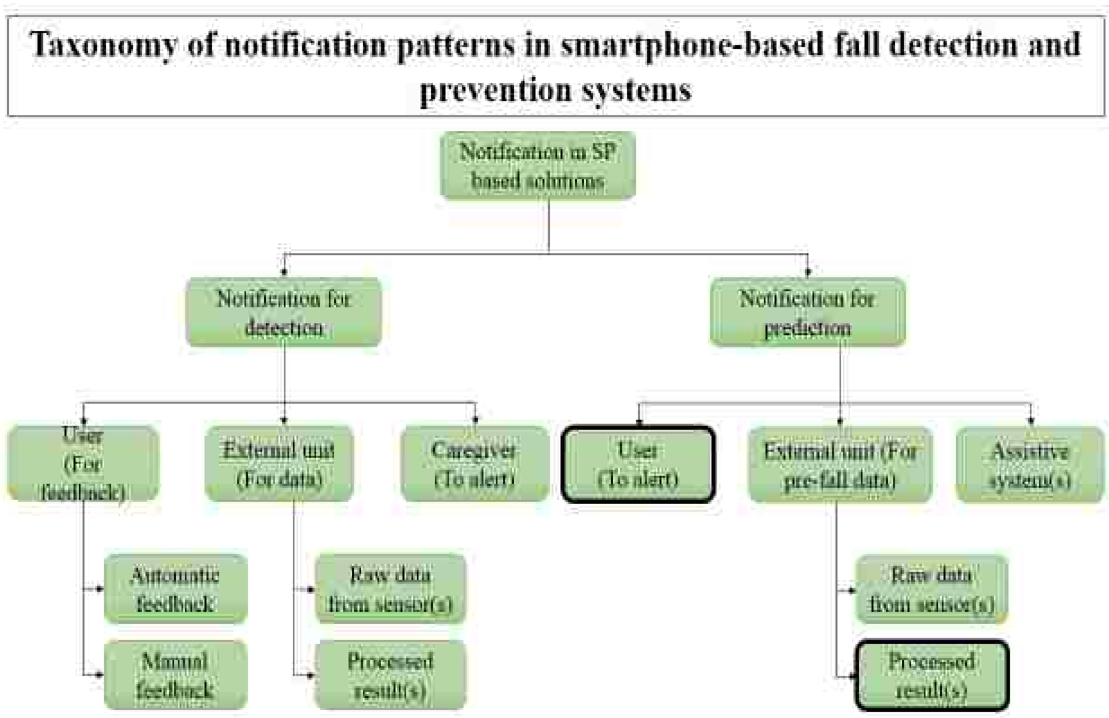


Figure 4. Taxonomy of communication patterns in smartphone-based fall detection and prevention systems

2.4 Mechanisms of fall

Elderly people rarely have a single cause for falls. A fall is usually caused by a complex interaction among the following:

- Intrinsic factors (age-related decline in function, disorders, and adverse drug effects)
- Extrinsic factors (environmental hazards)
- Situational factors (related to the activity being done, e.g., rushing to the bathroom)

Figure 5 represents a taxonomy of most common falls in elderly.

2.4.1. Intrinsic Factors

Age-related changes can impair systems involved in maintaining balance and stability (e.g., while standing, walking, or sitting). Changes in muscle activation patterns and ability to generate sufficient muscle power and velocity may impair the ability to maintain or recover balance in response to perturbations (e.g., stepping onto an uneven surface, being bumped). In fact, muscle weakness of any type is a major predictor of falls.

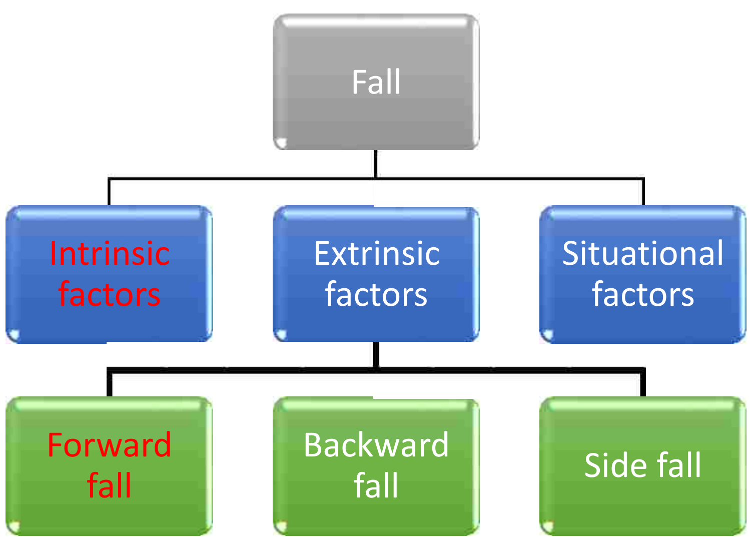


Figure 5. Taxonomy of most common falls in elderly

Chronic and acute disorders and use of drugs are major risk factors for falls. The risk of falls increases with the number of drugs taken. Psychoactive drugs are the most commonly reported as increasing the risk of falls and fall-related injuries.

2.4.2 Extrinsic Factors

Environmental factors can increase the risk of falls independently or, more importantly, by interacting with intrinsic factors. Risk is highest when the environment requires greater postural control and mobility (e.g., when walking on a slippery surface) and when the environment is unfamiliar (e.g., when relocated to a new home).

2.4.3 Situational Factors

Certain activities or decisions may increase the risk of falls and fall-related injuries. Examples are walking while talking or being distracted by multitasking and then failing to notice an environmental hazard, rushing to the bathroom, and rushing to answer the telephone.

2.5 Related Work

In past research, many scientists have focused on gait detection techniques, but not prevention of the fall. Most of them discussed mobility and privacy issues [45], but they did not discuss wearing a sensor. 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 [46-47]. In [48], the author designed a type of wearable force sensor based on a photo elastic triaxial force transducer to measure ground reaction force (GRF) in gait analysis.

Table 1. Comparison of existing work based on different features

Approach	Cyber Physical System	Interoperable	Support High Sampling Rate	Minimize Integration effort	Cost Effective
Bamberg [65]	Yes	Yes	No	No	No
Zhang [64]	Yes	Yes	Yes	Yes	No
Lee [63]	Yes	Yes	No	No	No
Erez [62]	Yes	Yes	No	Yes	No
B-Shoe [61]	No	No	No	Yes	No
Lane [60]	Yes	Yes	No	Yes	No
Mellone [59]	No	No	No	Yes	No
Sposaro [7]	No	No	No	Yes	No
Jiangpeng [58]	No	No	No	Yes	No
Pedro [57]	No	No	No	Yes	No
Jiang [56]	No	No	No	Yes	Yes
Popescu [66]	No	No	Yes	Yes	No
Bourke [67]	Yes	No	No	Yes	No
Alwan [45]	No	No	Yes	Yes	No
Our Approach	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Sensors are placed at toe or heel to recognize movements by thresholds in [49]. In [50], authors explained adopting the methodology of information cognition from multisensory systems was regarded not only efficient but also reliable. In [51-52] reviewed the use of accelerometer-based systems in human movement, such as monitoring a range of different movements, measuring physical activity levels and identifying and classify movements. Also, they discussed a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring.

Researchers introduced three domains in their study to characterize gait performance in elderly persons [53]; 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 support the walking speed as a general indicator that reflects functional and physiological changes in the health state and helps to predict falls [54-55].

Furthermore, the author 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 [68]. 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 [69], 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.

Similarly, iFall [7] is an Android application that has been developed as a fall detection system. Data from the accelerometer and position is assessed using several threshold-based algorithms 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 [41] 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 dissertation, 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 inexpensive because it requires only a smartphone with low cost smart-shoe. Our system also supports high sampling rates during data collection and is interoperable with minimum integration complexity. 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 our system is the first smartphone-based gait detection system, that can prevent a fall by automatically detecting abnormal gait patterns. We illustrate the difference between our system and the other related works in table 1. Our system is a cyber-physical system with interoperable capabilities and supports high sampling rate.

CHAPTER 3 RESEARCH CHALLENGE IDENTIFICATION

3.1 Use of Smartphone for Sensing, Analysis and Communication

The benefits of using a smartphone as a pervasive fall detection and prevention system have already been discussed in the literature [15]. Smartphone-based systems experience some critical challenges with certain issues remaining open to further research. These challenges and open issues in smartphone-based fall management systems have been identified; this section presents the most relevant ones.

3.1.1. Quality of Smartphone Sensors

It is still an open research question whether the qualities of built-in smartphone sensors in existing smartphones are adequate to develop fall detection and prevention systems with acceptable performance. When choosing a smartphones for a particular application (fall detection or fall prevention) adequate attention should be paid to the quality of the sensors. Specifications of the sensors should satisfy the minimum requirements of the applications.

3.1.2. Energy Consumption and Battery Life

A major weakness of smartphone-based solutions is the limited battery life of smartphones. Usually the battery life of a smartphone in normal use is about one day [20], but no smartphone battery will last more than a few hours with heavy usage [70]. The battery life is also directly proportional to the recording time and activities of user [71].

3.1.3. Smartphone Placement and Usability Issues

Smartphone-based fall detection and prevention systems are mostly designed for older people and individuals with neurodegenerative disorders. However, the acceptability of these solutions among older individuals has been suggested as a limiting factor [17]. Older people may also prefer to have a single phone with self-contained fall detection functionality rather than wear a separate fall detection device. Therefore, while designing new smartphone-based solution, smartphone placement and usability issues should be handled carefully.

3.2 Gait Abnormality Detection Using Smartphone Sensor Data

After measuring the physical quantities by using sensors, obtained data should be analyzed. In this phase, the significant features are extracted from sensor output and preliminary decisions are made by classifying and analyzing the extracted features. Most smartphone-based solutions, especially solutions for fall detection, use a Threshold-Based Algorithm (TBA). The most vital reason for choosing TBAs is that these algorithms are less complex and hence require the lowest computational power [2], which helps to reduce battery power consumption [20]. In order to make preliminary decisions about a potential fall, these algorithms usually compare the sensor's outputs with predefined threshold values. TBAs may use more than one threshold [14] and these threshold values are either fixed or adaptive. It should be noted that the adaptive threshold values are not calculated dynamically while using the system. Instead, users provide physiological data and the system obtains the corresponding threshold that is not re-calculated during system operation. The algorithm proposed in [7] uses an adaptive threshold which changes with user-provided parameters such as height, weight and level of activity.

As mentioned before, the computational power of the latest smartphones has become comparable to that of former workstations and, thus, even complex machine learning and statistical classification algorithms for fall detection and prevention can easily be implemented in smartphones [22]. Some fall detection and prevention solutions [72] include external sensors and processing units, using the smartphone for sensing and communicating with the users or their caregivers.

3.3 Development of a Wi-Fi Communication Network for Smart-Shoe and Integration of Different Smart-Shoe Hardware Module

For data collection from the smart-shoe, the most important challenge is to establish a dedicated communication framework. When choosing the device, we considered the popular data transmission technologies. The three most popular wireless technologies are Bluetooth, ZigBee, and Wi-Fi protocols. They correspond to the IEEE 802.15.1, 802.15.4 and 802.11a/b/g standards, respectively. Bluetooth communication has covered a relatively short range. Considering all the limitations, we developed a custom Wi-Fi communication module for the smart-shoe. The Wi-Fi communication module is able to wirelessly send smart-shoe sensors data to the smartphone.

We also had to develop a means of communication between the smartphone and smart-shoe which required different hardware modules. Putting these modules together and having them function properly was another challenges we encountered in our research.

3.4 Classification of Gait Using Hjorth Parameters

The short-time Fourier transform (STFT) has been popular for time-frequency analysis of non-stationary signals [73]. However, its high computational complexity and redundant frequency information prohibit its use in real-time applications. The Hjorth parameter is one of the ways of indicating statistical propertries of a signal in time domain. The Hjorth parameter proposed in [74] may be a good alternative for the STFT because it can extract useful information both in time and frequency domains through simple computation [75]. In this dissertation, we introduce the Hjorth parameter and compute its Fisher ratio to find the dominant frequency band and the timing in training electroencephalogram (EEG) signals. Extracting a high-informative feature in gait data analysis is carried out by computing the Hjorth parameter of a test signal at the pre-determined frequency band and timing instant. Then, the feature is used to classify gait patterns.

It has three parameters: Activity, Mobility, and Complexity. Activity parameter, the variance of the time function, can indicate the surface of power spectrum in frequency domain. The Activity returns a large/small value if the high frequency components of the signal exist many/few. Mobility 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 one as the shape of signal gets more similar to a pure sine wave.

3.5 Alert Generation Using Processed Data

Existing and potential smartphone-based fall detection and prevention systems communicate with the users and caregivers by sending alert messages to obtain the user's feedback. Prediction systems are only concerned with pre-fall data, but detection systems deal with pre-fall, post-fall and intermediate data. Finally, detection systems notify caregivers of fall events and ask for help, whereas prediction systems attempt to prevent impending falls with the help of other assistive systems. Some smartphone-based solutions require external sensing units that may or may not have built-in processors. These external units may transmit either raw data or results after primary analysis.

CHAPTER 4 LIMITATIONS OF SMARTPHONE SENSOR-BASED SYSTEMS AND DESIGN AND DEVELOPMENT OF A WIRELESS SMART-SHOE

4.1 Limitations of Smartphone Sensor-Based Analysis

The accelerometer of smartphones was used in all the previous solutions, and the GPS receiver is the second most commonly used sensor, followed by the gyroscope. Over the past few years, the number of studies on smartphone-only solutions for gait detection is higher than that of other smartphone-based solutions. However the use of external devices in smartphone-based fall detection and prevention systems is increasing gradually.

The smartphone sensor that is used by all smartphone-only solutions is the accelerometer and the usual dynamic ranges of these built-in accelerometers are insufficient for accurate fall incident detection [17]. Acceptable dynamic ranges for accelerometers from ±4 g to ±16 g have already been researched (where, 1 g = 9.8 m/s^2) [76]. Smartphones typically contain accelerometers with dynamic ranges of ±2 g or less [20], but higher dynamic ranges can be found in high-end smartphones [77].

The issue of energy consumption should be considered when designing a smartphone-based system. The battery life of the smartphone is dependent on the number of sensors used, data sampling rate [39], data recording time [78], features of algorithm [79] and mode of operation [13]. The battery life of a particular smartphone (Samsung Galaxy S II) was reduced to 30 hours when only one sensor was used, to 16 hours if three sensors were used simultaneously [39].

When developing the right algorithm, care should be taken to incorporate a minimal number of features, as fewer features decreases the usage of the processor and saves energy [79]. Experimental results of [13] show that the use of the battery per hour for foreground execution mode and background execution mode are 2.5% and 2.25% respectively. However, energy saving measures could negatively impact accuracy and usability.

People with cognitive disabilities face great difficulty using the complicated interfaces of modern smartphone-based applications [80-81]. A recent study has revealed the myth that older people avoid new technologies as a fallacy [82]. Older people have been found to be willing to accept new technologies to support their independence and safety [83]. As mentioned earlier, all smartphone-only solutions use the accelerometer as a sensor which requires fixed placement of the smartphone. Various fixed positions on the body including the shirt pocket, waist and trouser pocket [84]. This placement limits the usability of smartphone-based solutions because not everyone carries their smartphone in a fixed position and it may be difficult to convince them to do so [85]. In order to overcome this obstacle, researchers have proposed the use of external body-worn sensors in combination with smartphones. This solution is also not accepted universally because these external devices expose the frailty of the user and many users forget to put on such external devices [86].

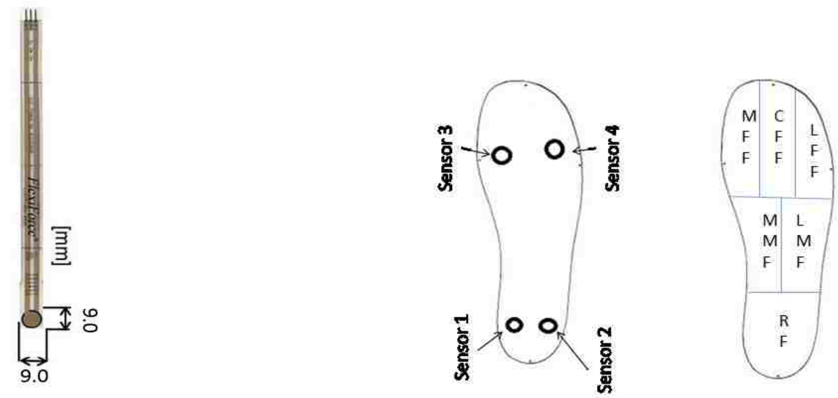
4.2 Smart-Shoe Hardware

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

As hardware devices, we used a shoe consisting of four sensors. The shoe include arduino, Wifly shield, amplifier circuit, power supply unit, and a smartphone with built-in accelerometer, gyroscopes and a display with the results of the system assessment.

4.2.1. Sensor Selection and Measurement Position

The sensors used in the smartshoe were selected with the goal of creating a system capable of sensing many parameters that characterize a user gait.



(a) (b)

Figure 6. (a) Piezoresistive Sensor [15] (b) In-sole sensors distribution (Measurement Position)

For the analysis of the kinematic motion of the foot, four piezoresistive pressure sensors were placed at the bottom of the shoe to assess the timing parameter and pressure distribution of foot. The human foot is usually divided into three different regions, Fore Foot (FF), Mid Foot (MF) and Rear foot (RF). Each insole of the shoe is equipped with four pressure sensing elements.

Table 2. Insole Sensing Position

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

The pressure sensors we employed in this system are SEN 08685, which are flexiforce force-sensitive resistor sensors. SEN 08685 sensor is a flexible printed circuit with thickness of 0.203 mm. Clearly the more sensors are placed, the higher precision of plantar pressure distribution can be measured.

Our goal is to adjust the number of pressure measurement points. Most of 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 are in the rear foot region as shown in figure 6. The four sensors are listed in table 2.

We have used piezoresistive force sensors for measuring the pressure while walking. The resistance of this sensor changes with the change in pressure. The harder the users press, the lower the sensor's resistance. Resistance changes only when pressure is applied to the round area at the end of the sensor, but the resistance does not change while being flexed.

4.2.2. Amplifier Circuit

The amplifier circuit, shown in figure 7, amplifies the output of the pressure sensor. Each sensor has its own amplifier circuit.

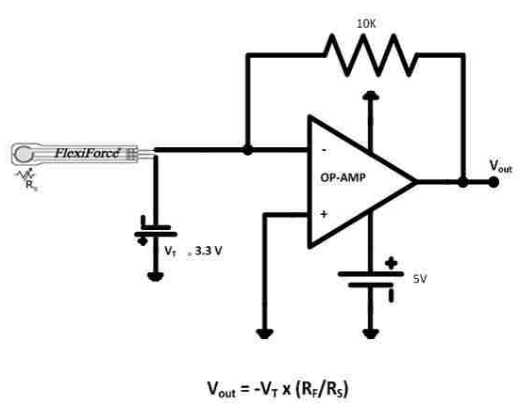


Figure 7. Amplifier circuit with pressure sensor

The circuit is an inverting operational amplifier that produces an analog output based on the sensor resistance and a feedback resistance ($R_F = 10k$). The sensor resistance (R_S) at no load condition is greater than 5M ohm. The application of a force to the active sensing area of the sensor results in a change in the resistance of the sensing element inversely proportional to the force applied. The amplified output voltage is given by, $V_0 = -V_T \times (\frac{R_F}{R_S})$.

4.2.3. Wi-Fi Communication Module

An Arduino [figure 8(a)] is used as an analog to digital converter (ADC). Arduino is an open-source physical computing platform based on a simple I/O board and a development environment that implements the processing/wiring language.

(a) (b)

Figure 8. (a) Arduino and (b) WiFly Shield [16]

The WiFly Shield [figure 8(b)] equips Arduino with the ability to connect to 802.11b/g wireless networks. The shield is a breakout board for roving networks RN- 131c WiFi chip.

4.3 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 the power supply, we were able to engineer a smart-shoe as shown in figure 9a. 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 a smart-shoe and enclosed sensors and hardware are detailed in figure 9b.

4.4 Software

To receive and analyze data from the hardware and smartphone, we have developed a gait collector software for receiving accelerometer and gyroscope value of the smartphone sensors. Also we developed Wi-Fi communication software that is capable of transmitting pressure data from the smart-shoe to the smartphone. After collecting three gyroscope and accelerometer signals (in directions of x-, y-, and z-axis) from the smartphone sensors and the shoe data we processed it to create a decision tree for identifying gait abnormality.

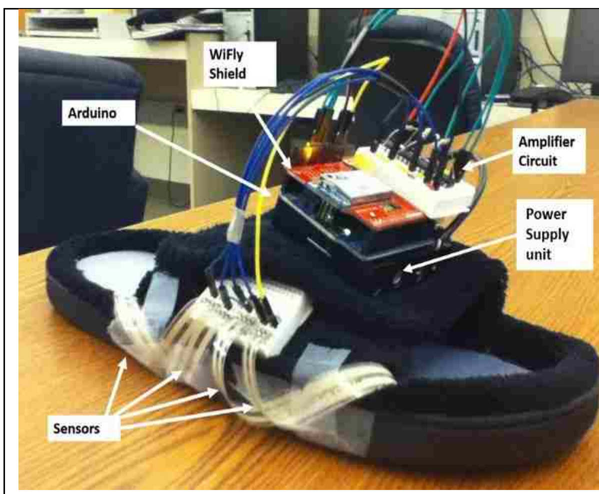
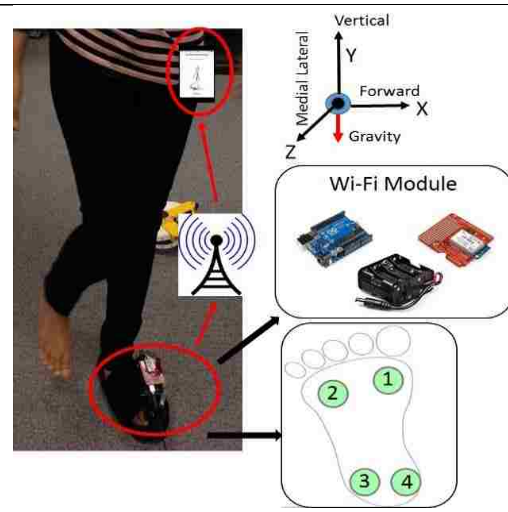
	

Figure 9a. Smartshoe hardware mounted on shoe	Figure 9b. IoT components of a wireless shoe with an example of the walking event trial in the hallway

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 smartphone. We programmed the Arduino to read an analog signal from the shoe sensors to convert the signal into digital form and to create a data packet. Subsequently, Arduino sent those packets to the phone as a response to the data sending request from the phone. The Arduino also managed the Wi-Fi communication coordination with the WiFly shield. In the smartphone, we developed an application that can communicate with the WiFly shield. It collects the sensor data with a polling request. Then the data are saved and analyzed after parsing the packet and calculates real pressure value from the sensors. From here we identify the threshold value of the individual users.

CHAPTER 5 DESIGN AND DEVELOPMENT OF A SMART FALL PREDICTION SYSTEM

Based on the findings of the system assessment, we decided to approach the overall solution from two different perspectives – motivation and automation.

5.1. Design Characteristics

As a result of the outcomes we received several important issues and a guideline about the possible desired characteristics of an automated system.

5.1.1. User friendliness

The user interface should be designed considering the target population, especially elderly. Their familiarity with certain technology, and physical capabilities should be considered during the design of the system.

5.1.2. Cyber physical system

Our objective is to enable the efficient development of distributed cyber physical systems (CPSs) whose nodes operate in a proven and correct manner in terms of functionality and timing, leading to predictable behavior of the entire system.

5.1.3. Mobility

One key characteristic of the system is to maintain the mobility of the users and caregivers. Caregivers are expected to monitor a user’s real time data using their mobile phones and receive alert message in case of emergency.

5.1.4. Continuous data collection

Continuous gait longitudinal data collection is one of the problems in monitoring the elderly. Data should be continuous and regular to have accurate information of the user's current status. Once the system is deployed, it should be able to collect data for a period of time and update the caregiver by sending an alert message in case of emergency.

5.1.5. Quality over quantity

Data collected using a smartphone-based system can be biased by different factors. For example, when a user went to bed or sat down for a long time, the caregiver or loved one might not get accurate data for that period of time. The user's response is influenced by their current status of mobility. So the quality of the gait data varies with the time and with daily activities. The way to increase the quality of the data is to record the data when it matters most. For example, recording gait parameters when the user is walking or doing simple or complex activities increases the quality of data.

5.2 System Architecture

The strength of our proposed architecture relies on existing wireless communication technology to provide a low price with maximum freedom of movement to users. In addition we have used small, light-weight devices that are easy to use by the elderly like smartphone and a smart-shoe. The architecture of the system is shown in figure 10.

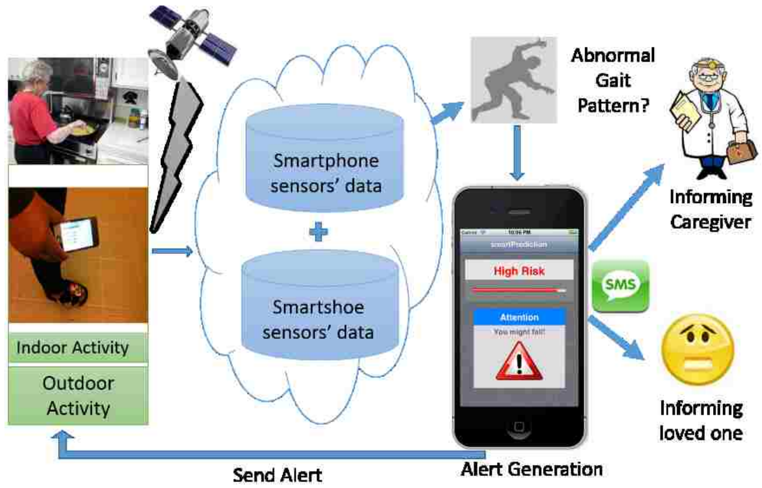


Figure 10. System architecture of proposed system

This overall architecture was developed assessing iterative designs of the prototypes with three age ranges (25-35, 35-45, and 50+ years). To integrate the sensors, we used output of both the smart-shoe and smartphone and performed a set of experiments to analyze and discriminate between normal and abnormal walking patterns. Subjects wore the smartshoe like any other regular walking shoe and carried their smartphone in their pocket or held it in their hand. (A detailed description of the system assessment follows later in this dissertation). In the system, the accelerometer and gyroscope of the smartphone provides the raw acceleration and orientation information. In the first phase of data collection, the smart-shoe collected the foot pressure values while the subject was asked to perform three different types of simulated walking patterns: normal, stiff leg and leg length discrepancy. After receiving the pressure data through Wi-Fi communication, the gait related pressure data was processed by the smartphone to classify whether the user's gait pattern was normal or abnormal. We implemented the quantative gait analysis in the iOS platforms and Android platforms.

5.2.1. Design Overview

In the system, the piezoresistive sensor from the smart-shoe is used to collect the raw insole pressure data while the user is walking. This data are then compared with the gait parameters of the biomechanical model. Then the resultant outputs are processed by the smartphone to identify the user's gait patterns. Though the system continuously monitors gait, it only triggers a warning if the gait pattern of the user reaches a certain threshold where the user might face a potential fall. At that time, the system warns the user with a message and vibration to alert him or her about an imminent fall.

5.2.1.1 Fall Prediction System Alert

As mentioned earlier, though the system will continuously monitor gait patterns, the design will only trigger a warning if the gait pattern of the user reaches a certain threshold where the user might face a potential fall. At that moment, the system detects a high-risk gait pattern and enables a warning to the subjects through an audio message and vibration, to alert him or her about an imminent fall.

Planning ahead for the design of the interface for user alert generation, we created a progress bar based on the threshold value of the gait cycle. In the progress bar, we will use three different colors to indicate three different walking patterns. The colors present three different predictive interpretations.

(I) **Normal:** The individual walks normally. For a normal walking pattern the progress bar would show green.

(II) **Vulnerable:** The system detects an abnormality in the individual's walking pattern and the system generates a visual alert message to the individual as a warning. The progress bar displays a yellow for possible upcoming fall. Yellow would indicate potential danger and that the individual must be careful. A moderate auditory and vibration alert would also be activated.

(III) **Dangerous:** Red would be shown in the progress bar if the collected pattern value crossed a predefined set of threshold values. This would prompt the individual to pay particular attention and be extra careful because they have a high fall risk. In this circumstance, our system would not only enable an auditory and vibration alert message to warn the subject, it would also send a message to the caregiver or loved ones to warn them about a possible accident, so that he or she could be proactive for any kind of unexpected situation.

The most important aspect of our system is the warning that allows the individual to prevent a fall. We posit that this real time assessment and alert methodology could reduce the risk of falls for the elderly.

CHAPTER 6 DEVELOPMENT OF A GAIT LOGGER FOR DATA COLLLECTION AND FEATURE EXTRACTION

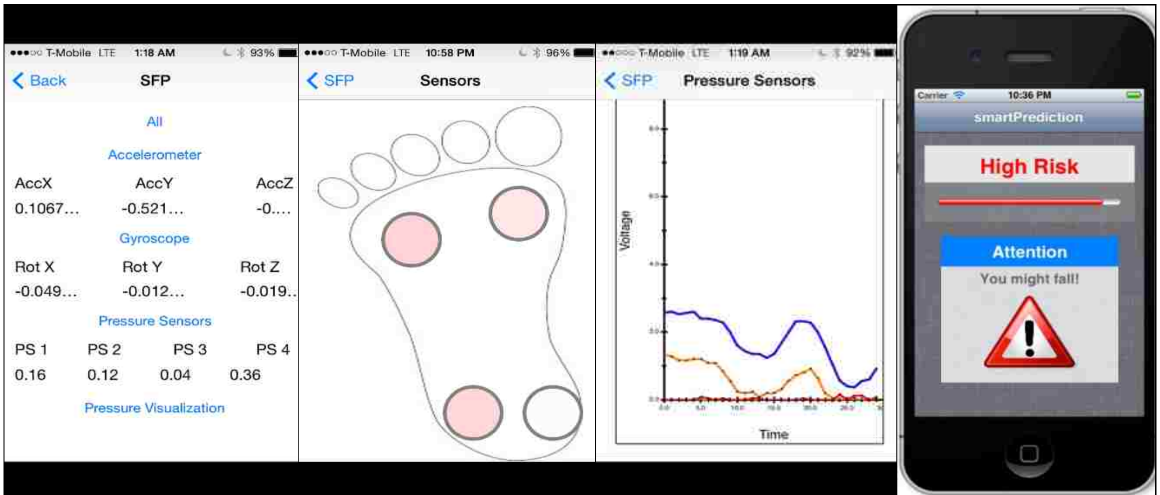
6.1 Design and Development of a Gait Logger for Data Collection

To evaluate our proposed system, we have developed a prototype application and investigated its performance with extensive iterative experiments. In this section, we introduce a gait logger system for data collection.

6.1.1. Experimental Setup

We have developed a prototype application of the Smart Fall Predictor (SFP) system for the iPhone. The screenshots of the SFP prototype application are shown in figure 11. In figure 11(a), the gait collector interface is shown, the anatomical location of insole sensors is shown in figure 11(b), and the real-time graphical representation of insole sensors pressure variation is shown in figure 11(c). We have also developed the interface for the user alert which is shown in figure 11(d). We have been using our prototype application for data collection and for system evaluation with the goal to improve the overall accuracy of the smart fall prediction system.

For the data collection, we initially recruited five test subjects who are graduate students of different heights, weights, and ages. For these five test subjects we collected different walking data using smartphone sensors-accelerometer and gyroscopes- only. In a different experiment, we tested our system by collecting data from smartphone and smart-shoe sensors for another fifteen test subjects, who are also graduate students of different heights, weights, and ages. We collected data for a normal and two different abnormal walking patterns (stiff/peg leg and leg length discrepancy). We also collected standing data using the smart-shoe and compared them with the walking pressure data. Data for each subject was collected for twelve, eighteen-second trials from a smartphone placed in the subject's pocket and from the smartshoe worn on the right foot.



(a) Gait Collector interface	(b) Anatomical Location of Insole sensors	(c) Insole pressure variation while walking	(d)Alert Generation

Figure 11. Screenshots of a Smart Fall Predictor (SFP) prototype

Then we collected data from twenty test subjects of different age groups, heights, and weights. We analyzed the data from this group for gait event detection. We also ran experiments and analyzed these data to predict simulated forward falls.

6.1.2. Data Collection Procedure

We collected data for a normal walking pattern and two different abnormal walking patterns in different environments. We simulated the abnormal walking patterns that are caused by two physical abnormalities common in most elderly people, stiff/peg 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 (on the right leg) and wearing an extra heel on top of the regular heel on the left shoe. We simulated the "stiff leg or peg leg" situation by walking with a straightened left knee.

In an another experiment, each subject first walked at his or her own self-selected natural pace for two to four trials, termed "free gait." Then walk with trendelenburg gait (reduces the step on the unaffected side in a sort of drag motion and displays a lateral deviation of the entire trunk and the affected side during the stance phase of the affected lower limb) and Spastic gait (a stiff, foot-dragging walk caused by a long muscle contraction on one side). Additionally, the subject asked to perform three different types of movement, stand still, going upstairs, and going downstairs.

6.1.3. Smart-shoe Data Collection

The smart-shoe data collection process is shown in figure 12. The pressure data from the shoe are transferred to the smartphone through an adhoc Wi-Fi communication network. Pressure data were collected for the test subjects over a period of time and each time subject was tested with standing and three different walking patterns.

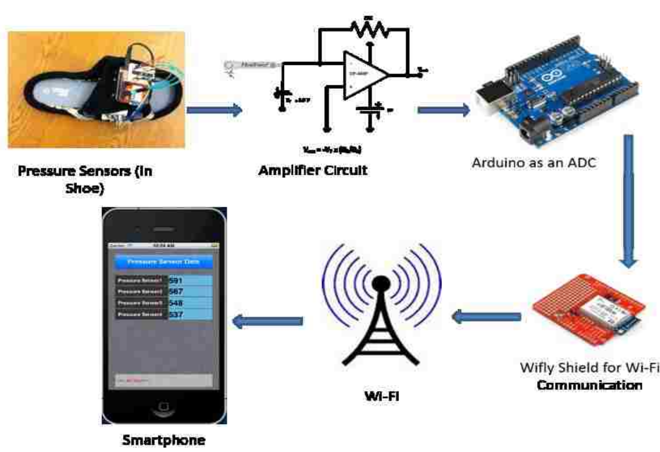
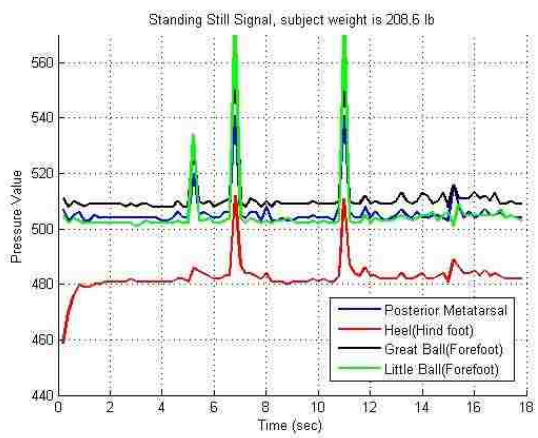
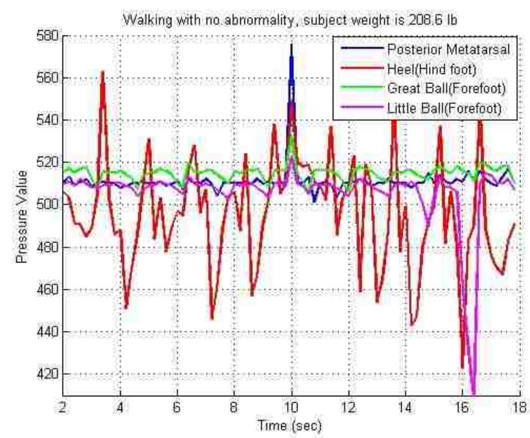


Figure 12. Data collection process from a smartshoe

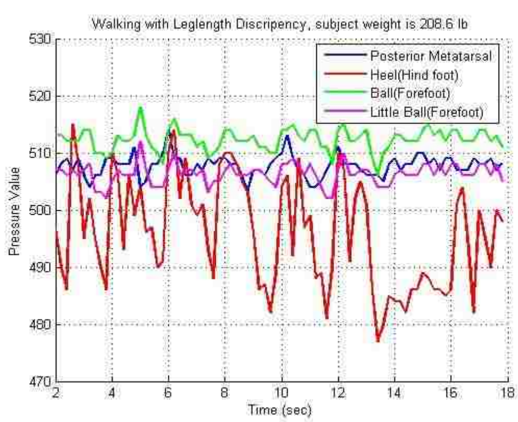
We first used this dataset for the training of our system. The data collected from the shoe showed from which sensor we get maximum pressure during the experiments with respect to a subject's sex/age, height and weight. For example, when subject one was performing his assigned task we observed that sensor two was getting more pressure than the other. We used this maximum pressure value in determining the threshold for each subject in their walking patterns.



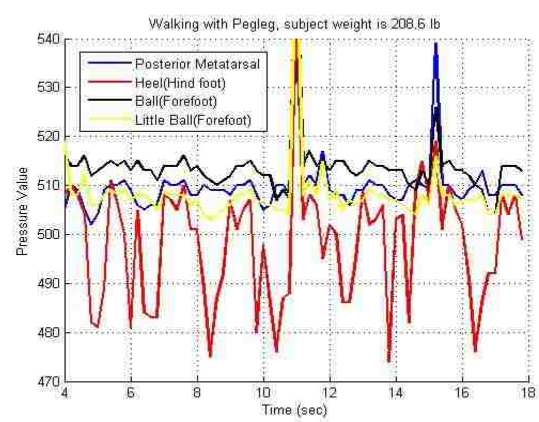
(a) Stationary



(b) Walking with no abnormality



(c) Walking with leg length discrepancy



(d) Walking with stiff /peg leg discrepancy

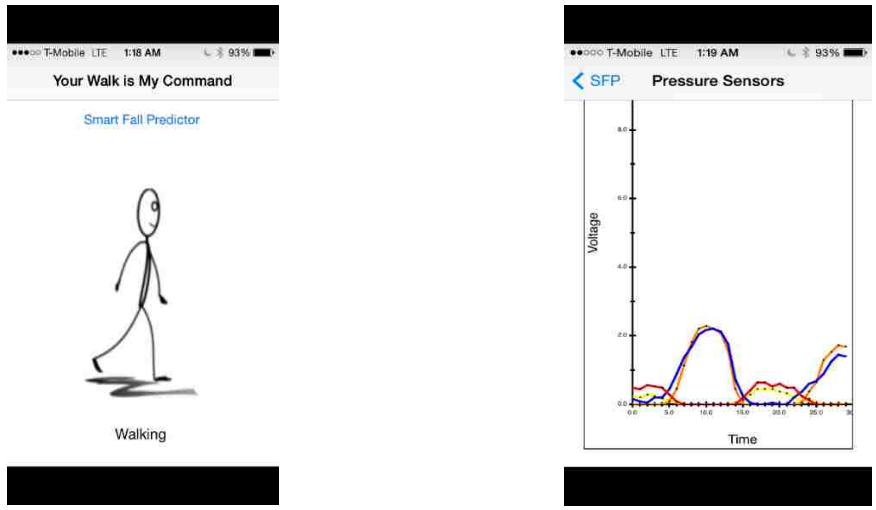
Figure 13. Foot pressure distribution of (a) standing still (b) walking with no abnormality (c) walking with leg length discrepancy (d) walking with stiff/peg leg discrepancy

Raw data on foot pressure distributions for each moving pattern were acquired with the developed foot pressure sensing shoe. The sample variation of foot pressure for each kind of movement is displayed in figure 13. Pressure value represents the discretized 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 falling. The measurements may include any other test that measures pressure using the pressure sensor value. It is necessary to differentiate if the user is walking on a flat surface or on a surface with considerable vertical variation. Using our system we can also assess the effects of balance abnormality on human walking patterns and the variability of the extracted features.

6.1.4 Data Collection and Sampling

The screenshots of the system prototype application are shown in figure 14. In figure 14(a), the gait collector interface is shown while walking. We can also monitor insole pressure variation with graphical representation on a smartphone which is shown is figure 14(b). We used our prototype application for data collection and for evaluating our system.

We collected data for different gait cycle events in different environments for twenty samples in each gait event. Each sample was 20-30 second long. The collected sample data is shown in figure 15. We choose the three aforementioned walking events of a gait cycle that might cause physical abnormalities common in most elderly people. These abnormalities also lead to a huge number of falls every year.



(a) Gait collector interface (b) Real-time Pressure Monitoring on a Smartphone

Figure 14. Screenshots of prototype system

We first used these datasets for the training of our system. Later we used the trained system with other test subjects to verify the gait detection accuracy of the system. Also, we compared the features from the gait events' data with the model parameters to predict imbalance of walking.

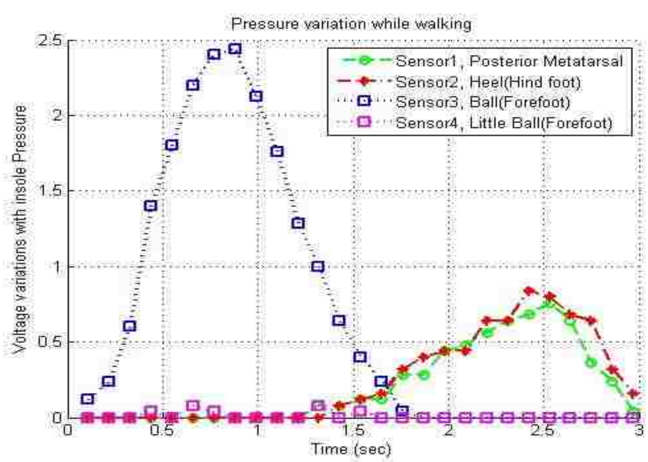


Figure 15. Pressure variations of a single support event in stance phase

To test the validity and long term feasibility of our system, we are currently testing our system at the Mobility Lab at University of Wisconsin-Milwaukee innovation campus.

Vicon Plug-in Gait Full Body model was used to dynamically capture the three-dimensional (3D) movements of the upper extremity and lower extremity joints. For this purpose, one representative participant was instrumented with 39 retro-reflective markers on bony anatomical landmarks and key locations of their full body. Motion data were collected at 120 Hz using a 15-camera 3D Vicon T-series motion capture system (Vicon Motion Systems, Oxford, UK). Table 3 shows a spatiotemporal Parameters for a sample test subject.

Table 3. Spatiotemporal Parameters for a sample test subject

Parameters / **Systems**	**Cadence (steps/min)**	**Stride length (cm)**	**Stride time (sec)**	**Speed (m/sec)**
Using our system	107.5630	112.8853	1.1156	96550
Using T-series Vicon motion capture system	103.35	108	1.161	0.93

In a different data collection phase, we recruited a set of participants from both genders, a variety of age groups, and a range of heights (see Table 4 for statistics) for data collections from both smartphone and smart-shoe. We established a baseline walk period for each of the walking traces. This was achieved by manually finding the walk-start (t_{start}) and walk-end (t_{end}) events.

Table 4. Statistics about subjects participating in our different data collection procedure

Phase	Gender	Ages [yrs]	Height [cm]	Weight [Kg]	Testing Scenarios
First	Female: 1 Male: 4	20-30: 5	150-169: 3 170-180: 2 180-189: 1	≤ 60 : 1 61-70: 2 71-80: 2	-Three Different Walking ▪ Normal ▪ Peg Leg ▪ Leg Length
Second	Female: 2 Male: 13	20-30: 10 31-35: 4 35-40: 1	145-160: 3 161-170: 7 171-180: 4 181-190: 1		-Testing Scenarios ▪ Standing Still ▪ Normal/Stiff Leg/Leg Length ▪ Climbing Up and Down Stairs
Third	Female: 4 Male: 16	20-35: 12 36-50: 4 51-70: 4	150-159: 6 160-169: 10 170-179: 2 180-189: 2		-Testing Scenarios ▪ Free gait ▪ Trendelenburg gait ▪ Spastic gait ▪ Stiff and Leg length ▪ Sydenham
On Going	At Mobility Lab, University of Wisconsin-Milwaukee				▪ Comparison test with other existing system ▪ Berg and Balance test

We optimized the model parameters using the manually-determined ground truth walk periods.

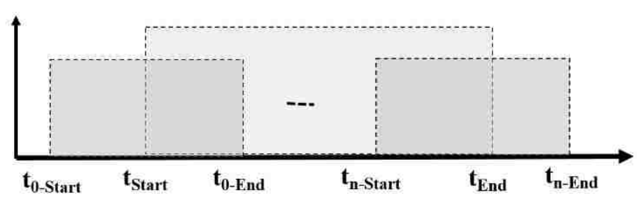


Figure 16. Illustration of Walking Intervals

For $t_{0-Start} \leq t_{Start} \leq t_{0-End}$ and $t_{n-Start} \leq t_{End} \leq t_{n-End}$ as shown in figure 16. We define the false positive error, false negative error and total error as follows,

$$\epsilon_P = (t_{Start} - t_{0-Start}) + (t_{n-End} - t_{End})$$

$$\in_N = \sum_{i=1}^{n} \left(t_{i:start} - t_{(i-1):End}\right)$$

$$\in_{total} = \in_p + \in_N \qquad (2)$$

To minimize the error in the sample data we got rid of 200 initial and end data samples in each interval of data collection. All data collections for this dissertation work was approved under the Marquette University IRB approval number HR-2851.

6.2 Feature Calculations

There are several important features for identifying normal and pathological walking patterns [87]. Some features are general and important for any kind of application, such as cadence, stride length, stride height and speed. Some features are applicable for specific domains. For example, the pressure balance of locomotion between feet is important for predicting fall [88]. Pressure mobility is critical for diabetes, foot protection and ulcer prevention [89].

6.2.1 Extracting Tilt Invariant Signals

In table 5, we summarize the notations that we are going to use to describe the methodology of our system. In our system, first, we collect three gyroscope and three accelerometer signals from the motion sensors of a smartphone (see figure 17). We then calculate and remove the gravity vector from the acceleration signals bias and perform a set of matrix rotation operations to correct the tilt of these signals. We combine the horizontal accelerometer signals as well as the pitch and roll to create four tilt-invariant signals.

Table 5. 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.
$r_{0p}\ (t),\ r_{0r}\ (t),\ r_{0y}\ (t)$	Rotation vector of pitch, roll and yaw respectively.
$B\ (t)$	Bias of the acceleration Vector
$A_h\ (t)$	Horizontal Acceleration
$\theta_1,\ \theta_2$	Tilt Angles

From these signals, we extract three quantitative features to create a feature vector. The feature extraction method applied to acceleration signals is applied here to both acceleration and gyroscope signals.

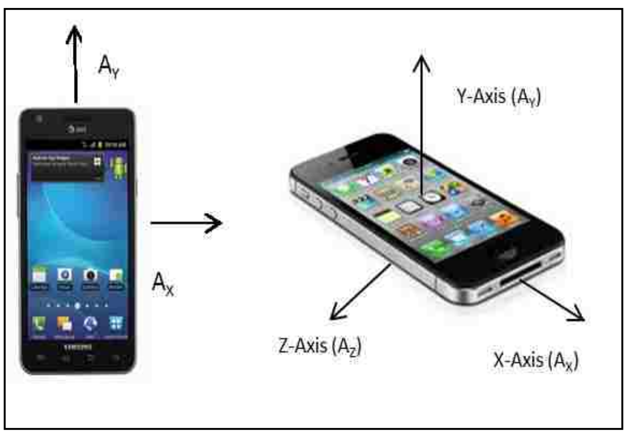


Figure 17. Acceleration and Gyroscope readings in directions of x-, y-, and z-axis that are associated with and fixed in regards to the body of the smartphone and smartphone orientation can be determined by yaw (A_x), pitch (A_y) and roll (A_z) [90].

At time t, let the following column vectors represent the current raw accelerometer and gyroscope readings:

$$\overrightarrow{a_0}(t) = [a_{0x}(t), a_{0y}(t), a_{0z}(t)]' \quad (3)$$

$$\overrightarrow{r_0}(t) = [r_{0p}(t), r_{0r}(t), r_{0y}(t)]' \quad (4)$$

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:

$$\vec{b}(t) = \frac{1}{N}\sum_{t=1}^{N} \overrightarrow{a_0}(t) \quad (5)$$

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

$$\theta_1 = \arctan\left(\frac{b_y}{b_z}\right) \quad (6)$$

$$\theta_2 = \arctan\left(\frac{b_x}{b_y \sin(\theta_1) + b_z \cos(\theta_1)}\right) \quad (7)$$

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

$$\overrightarrow{a_1}(t) = \begin{bmatrix} \cos\theta_2 & -\sin\theta_1 \sin\theta_2 & -\cos\theta_1 \sin\theta_2 \\ 0 & \cos\theta_1 & -\sin\theta_1 \\ \sin\theta_2 & \sin\theta_1 \cos\theta_2 & \cos\theta_1 \cos\theta_2 \end{bmatrix} \times \overrightarrow{a_0}(t) \quad (8)$$

$$\overrightarrow{r_1}(t) = \begin{bmatrix} \cos\theta_2 & -\sin\theta_1 \sin\theta_2 & -\cos\theta_1 \sin\theta_2 \\ 0 & \cos\theta_1 & -\sin\theta_1 \\ \sin\theta_2 & \sin\theta_1 \cos\theta_2 & \cos\theta_1 \cos\theta_2 \end{bmatrix} \times \overrightarrow{r_0}(t) \quad (9)$$

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:

$$\vec{a}_2(t) = \left[a_{1x}(t),\ a_{1y}(t), \left(a_{1z}(t) - \frac{1}{N}\sum_{i=1}^{N} a_{1z}(i)\right)\right]' \quad (10)$$

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 is $a_h(t) = \sqrt{a_{2x}(t)^2 + a_{2y}(t)^2}$, vertical acceleration is $a_v\ (t) = \left|a_{2z}\ (t)\right|$and combine the pitch and roll in the same way to create a scalar vector that describes the general tilt: $r_t(t) = \sqrt{r_{1p}(t)^2 + r_{1r}(t)^2}$, and vertical rotation is $r_v\ (t) = \left|r_{1y}\ (t)\right|$. (11)

6.2.2 Accelerometer and Gyroscope Energy

Since we are dealing with human activities, measuring the amount of physical activity is important. Time integrals of the absolute values of accelerometer readings were summed up to assess physical activity in [91]. For activities like jumping most of the energy will be vertical while for many others most of it will be horizontal. So we extracted vertical (e_v) and horizontal (e_h) energy separately. When the window size is T, these are:

$$e_{Va} = \int_{t=t_0}^{T+t_0} [\, a_v] dt\ , \quad \text{and} \qquad e_{ha} = \int_{t=t_0}^{t=T+t_0} [\, a_h]\, dt. \qquad (12)$$

Similarly the gyroscope is based on another property, which implies that all bodies that revolve around an axis develop rotational inertia (they resist changing their rotation speed and turn direction). A body's rotational inertia is determined by its moment of inertia, which is a rotating body's resistance to change in its rotation speed. The gyroscope must always face the same direction, being used as a reference to detect changes in direction. With the window size T, the rotational vertical energy is,

$$e_{Vr} = \int_{t=t_0}^{T+t_0} [r_v] dt, \text{ and } e_{hr} = \int_{t=t_0}^{t=T+t_0} [r_h]\, dt. \qquad (13)$$

Since the sampling rate is known these integrals can be estimated by taking weighted sums. It should be noted that accelerometer energy is dependent on physiological factors like body weight. So, for most activities, it will vary from person to person.

6.2.3 Hjorth Mobility and Complexity

Hjorth asserted the need for quantitative methods in the description of EEG traces because the physical system generating the signals cannot be associated with the sine function concept used for frequency domain analysis. Also, the Hjorth parameters are one of the ways of indicating statistical property of a signal in time domain and it has three kinds of parameters as in Table 6: Activity, Mobility, and Complexity.

Activity parameter, the variance of the time function, can indicate the surface of the power spectrum in the frequency domain. That is, the value of activity returns a large or small value if the high frequency components of the signal exist in large and small.

Hjorth Mobility parameters are defined as the square root of the ratio of the variance of the first derivative of the signal and that of the signal amplitude. This parameter has a proportion of standard deviation of the power spectrum. It describes the curve shape by measuring the relative average slope of the signal.

Table 6. Hjorth Parameter

Parameter	**Mathematical Notation**
Activity	var (time function, energy)
Mobility	$\sqrt{\dfrac{var(\text{the first derivative of the signal})}{var(the\ amplitude\ of\ the\ signal)}}$
Complexity	$\dfrac{mobility\ (first\ derivative\ of\ the\ signal)}{mobility(of\ the\ signal.)}$

Hjorth Complexity is the ratio between the mobility of the first derivative of the signal and the mobility of the signal itself. It measures the frequency domain irregularity. The 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 a signal approaches a sine wave.Mobility and complexity can be computed in linear time [91] using the first order difference sequence of the time series. They give us some frequency domain information without incurring a significant computational load.

The sample accelerometer-based normal, stiff/peg leg, and leglength walking features are shown in table 7.

Table 7. Accelerometer-based features attributes for a random subject

Accelerometer Attributes			
Walking / **Features**	**Normal**	**Stiff/Peg leg**	**Leg length**
Vertical Energy	8.762	4.623	0.835
Horizontal Energy	4.661	3.842	2.143
Vertical Mobility	0.741	0.593	0.698
Horizontal Mobility	0.752	0.503	0.841
Vertical Complexity	1.054	0.843	0.992
Horizontal Complexity	1.070	0.715	1.193

6.2.4 Smart-shoe-based Gait Features

Several gait features are proposed in the literature to estimate walking speed in the different models: acceleration, step cycle (frequency), and a hybrid method [92]. We examined two features for each of the insole sensors of our system: (1) standard deviation (SD), and (2) number of peaks in each sampling window. The sample smart-shoe-based walking features are shown in table 8.

Table 8. Shoe-based features attributes for a random subject

Right Shoe Attributes			
Features \ Walking	**Normal**	**Peg leg**	**Leg length**
SD-Sensor1	0.184	0.195	0.093
SD-Sensor2	0.157	0.172	0.092
SD-Sensor3	0.158	0.173	0.092
SD-Sensor4	0.157	0.175	0.089
# Peaks-Sensor1	28	28	31
# Peaks-Sensor2	19	28	30
# Peaks-Sensor3	20	27	28
# Peaks-Sensor4	19	27	31

CHAPTER 7 EVALUATION AND ANALYSIS OF THE SYSTEM

In this section, we present how the data are analyzed and performance is measured. First, we introduce performance measurements using only smartphone sensor data. Then we use only smart-shoe sensor data for detecting gait abnormality. Finally, we analyze the smart-shoe sensor data with smartphone sensor data to develop a unique gait abnormality detection system that helps to predict a fall.

7.1 Smartphone Sensor based Gait Detection

To test the effectiveness of our feature extraction and classification method, we collected data using smartphone sensors-accelerometer and gyroscope, which were analyzed and classified as previously mentioned. For this analysis, we recruited five participants who are graduate students between 20 and 30 years old for data collection. Three of them are between 170-180 cm tall and two are between 158-169 cm tall. One person is approximately 60 kg, two weigh 61–70 kg, and two weigh 71–80 kg. The feature vectors were then classified using a J48 decision tree classification algorithm found in WEKA, a powerful data mining toolkit [90]. In the first test, the algorithm attempted to distinguish between the simulated abnormal gaits while in the second test, these two classes were combined into a single abnormal walking class.

The tests attempted to classify both single subject data and cross subject data. In figure 18, we can see that the WEKA toolkit was able to identify the three different walking patterns (i.e. normal gait, stiff/peg leg, and leg length discrepancy). The gait classification was clearly represented as clusters marked by three different colors in the WEKA tool.

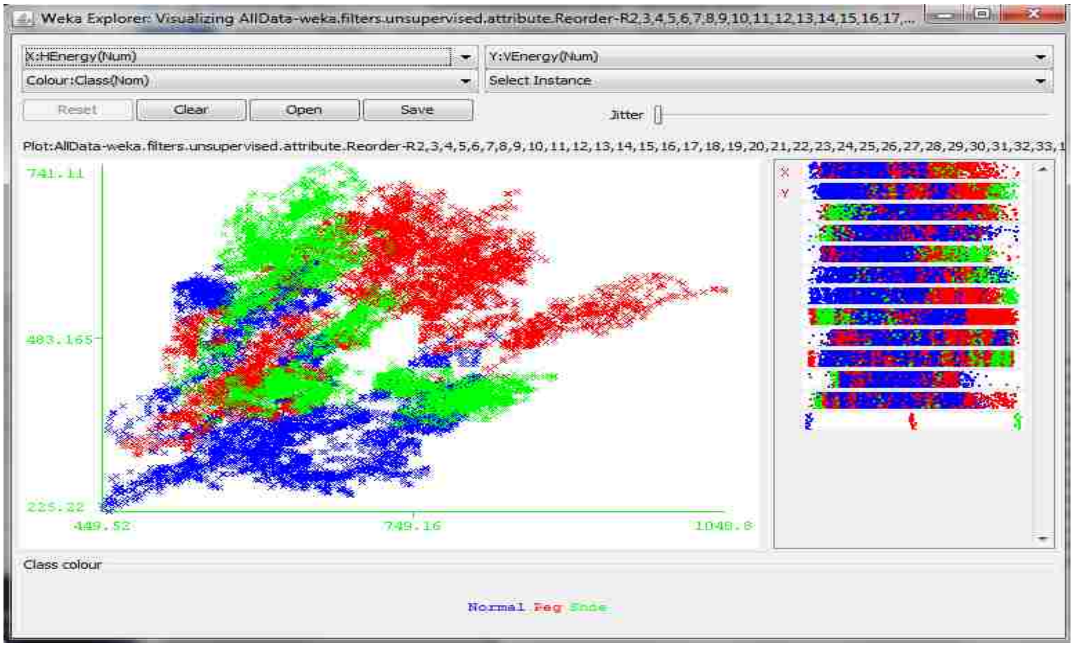
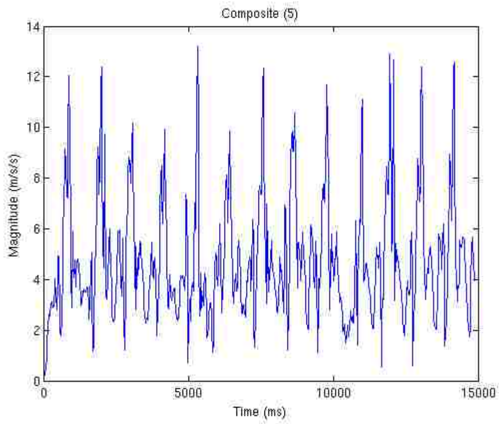
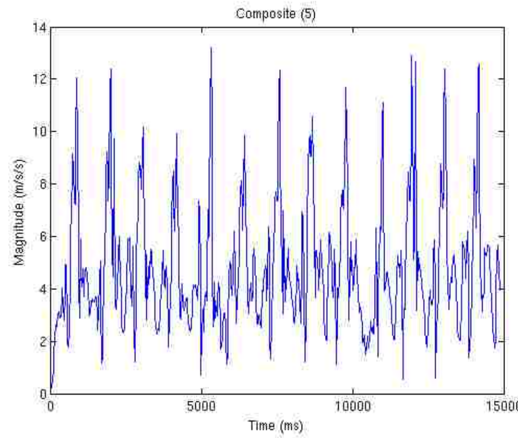


Figure 18. WEKA feature visualization tool and data analysis tool [93]

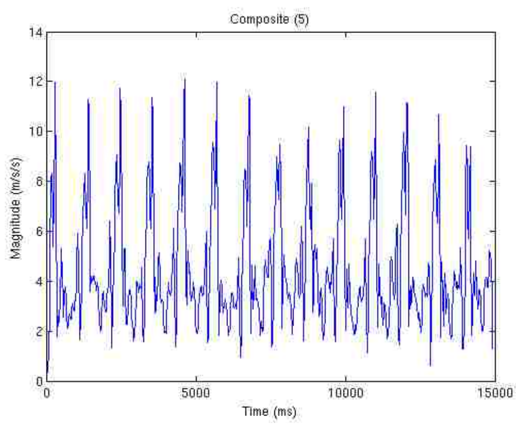
It is interesting to note that the observed acceleration for normal walking is somewhat similar to that of abnormal walking. They are basically a short period of acceleration followed by a small impact. The ability to distinguish between these events is critical to the success of our system. The average measured peak acceleration for normal walking is greater than the average peak for acceleration with stiff/peg leg and simulated leg discrepancy. As shown in figure 19, the acceleration profile for normal walking is very similar to that of an abnormal walking pattern, with a notable difference in acceleration magnitude. We have analyzed multiple cycles to compute a more accurate average peak of the acceleration value.



(a) Acceleration observed while normal walking



(b) Acceleration observed with stiff/peg leg situation



(c) Acceleration observed with simulated leg length discrepancy

Figure 19. Acceleration observed in different situation

7.1.1 Result Analysis

In this section, we first discuss the performance of motion sensors-based application.

7.1.1.1 Single Subject Data

We observed near perfect classification accuracy (see table 9) when the data to be classified was collected from the same subject as the training data. The classifier could even easily distinguish between the two different kinds of abnormality. The problem with single subject data is that it requires the subject to train the system by simulating abnormalities. Not only is this inconvenient for the subject, but the simulations will be inaccurate by virtue of the fact that they are simply simulations.

Table 9. Classification Accuracy for Single Subjects

Accuracy of Classification		
Subject	**Three Classes**	**Two classes**
Subject 1 Only	99.180%	99.438%
Subject 2 Only	99.462%	99.592%
Subject 3 Only	98.324%	99.234%
Subject 4 Only	99.125%	99.562%
Subject 5 Only	98.980%	98.658%

7.1.1.2 Multiple Subject Data

Classification accuracy was very good when considering both subjects in the training data, but was poor when attempting to classify one subject's gait based on another subject (see table 10).

Table 10. Classification Accuracy for a Multiple Subject

Accuracy of Classification		
Training Set	**Three Classes**	**Two classes**
Subject 1	28.571%	70.482%
Subject 2	29.740%	41.598%
Multiple Subjects	98.616%	99.021%

The classification accuracy was raised considerably when merging the two simulated abnormalities into a single class.

7.1.2 Related Publications

- **AKM Jahangir Alam Majumder,** Farzana Rahman, Ishmat Zerin, Ebel Jr. William, Sheikh Iqbal Ahamed, ***"iPrevention: Towards a Novel Real-time Smartphone-based Fall Prevention System"*** in Proc. of ACM Symposium on Applied Computing (ACM SAC 2013) Portugal, March, 2013.

7.2 Gait Analysis Using Smart-shoe-Worn Sensors

In the previous section, we only used smartphone sensor data. However, due to smartphone limitations, we developed and used a smart-shoe to get more accurate results. In this section, we will present our analysis based on only the smart-shoe sensor data.

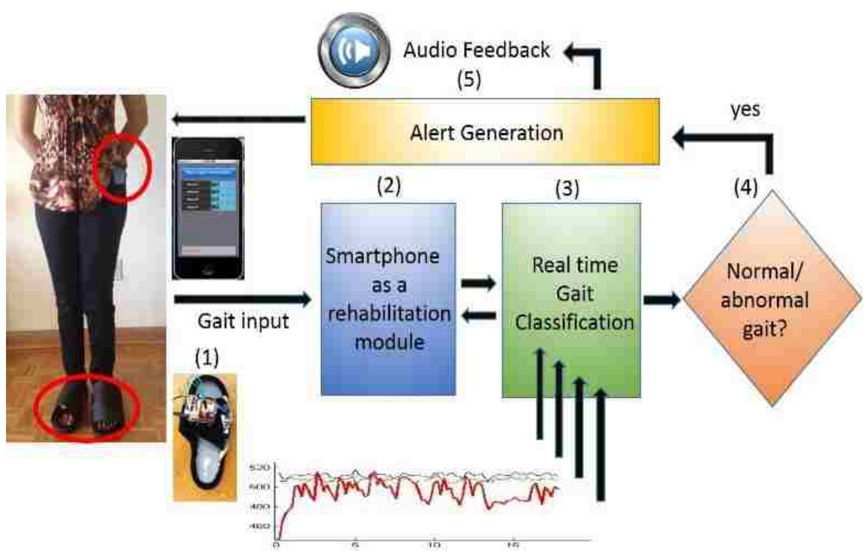


Figure 20. The Gait Detection system with its IoT components: (1) Smartshoe-worn sensors, (2) Rehabilitation module, (3) Abnormality in gait detection, (4) Decision, and (5) Feedback

For our collected data, the classification accuracy was very good when considering two subjects in the training data, but was poor when attempting to classify one subject's gait based on the other subject. To overcome this, we analyzed our collected data from the smart-shoe using a signal classification approach that is based upon modeling the dynamics of the system [94]. We used a unique signal classification approach that models the dynamics of a system as they are captured in a Reconstructed Phase Space (RPS). The architecture of the system used for this analysis is shown in figure 20.

7.2.1 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 the dynamics of the system represented by a mapping $\varphi: M \rightarrow M$, a system is described by the pair $< \varphi, M>$. We then define a set ϕ of all possible dynamics on M with a topology τ. 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 $Pi \cap P_j = \theta$, $i \neq j$ .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 [97].

The work of Takens [95] and Sauer [96] are used as a theoretical basis for our signal classification process. These works state 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 state variable observations, $x_n, \quad n = 1, \ldots, N,$ a trajectory matrix X of dimension d and time lag τ is defined as,

$$X = \begin{bmatrix} x_{1+(d-1)\tau} \\ x_{2+(d-1)\tau} \\ \vdots \\ x_N \end{bmatrix} = \begin{bmatrix} x_{1+(d-1)\tau}, & \cdots, & x_{1+\tau} & x_1 \\ x_{2+(d-1)\tau}, & \cdots, & x_{2+\tau} & x_2 \\ . & & . & \\ . & & . & \\ . & & . & \\ x_N, & \cdots, & x_{N-(d-2)\tau} & x_{N-(d-1)\tau} \end{bmatrix} \tag{14}$$

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

$$X_n = x_n \quad x_{n-\tau}, \ \cdots \ , x_{n-(d-1)\tau} \tag{15}$$

where, $n = (1 + (d - 1)\tau), \ \ldots, \ N.$ 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 [97]. Most real systems do not have a known d, but it may be estimated using the false nearest-neighbor technique [98], which calculates the percentage of neighboring points which are near because of projection rather than dynamics. In Takens' original work, τ =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 rule for determining time lag is to use the first minimum of the automutual information function [98].

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.

7.2.2 Gaussian Mixture Models (GMM)

The next step is to learn a GMM probability distribution for each gait pattern. This learning process is completed 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 (14) above.

A GMM is defined as:

$$p(x) = \sum_{m=1}^{M} \omega_{m\, P_m(x)} = \sum_{m=1}^{M} \omega_m \mathcal{N}(x;\ \mu_m, \Sigma_m) \qquad (16)$$

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 necessary 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 method yields a Maximum Likelihood (ML) estimate, via the estimation formulas for m= 1, 2,… M

$$\left\{\begin{aligned} \mu_m' &= \frac{\sum_{t=1}^{T} p_m(x_t)\, x_t}{\sum_{t=1}^{T} p_m(t)}, \\ \Sigma_m' &= \frac{\sum_{t=1}^{T} p_m(x_t)(x_t - \mu_m)'(x_t - \mu_m)}{\sum_{t=1}^{T} p_m(x_t)}, \\ w_m' &= \frac{\sum_{t=1}^{T} p_m(x_t)}{\sum_{t=1}^{T}\sum_{m=1}^{M} p_m(x_t)}, \end{aligned}\right. \qquad (17)$$

Which are then substituted into (16). These signal classification approaches are useful for our system as they have the ability to distinguish the transition in gait patterns over a short period of time and help us to evaluate gait abnormality.

7.2.3 Result Analysis

In this section, we first discuss the performance of the smart-shoe sensors. We built the reconstructed phase space model for normal and for two different abnormal walking patterns. Then, we analyzed the patterns to show the differences in normal walking versus abnormal patterns to predict a simulated falls. It was observed that the pressure distribution was different from one subject to another as the gait pattern varied in each subject.

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.

We applied our technique to three data sets just like in the smartphone sensor only system in section 7.1. The first data set is generated from normal walking, and the 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 also saw the variations of different walking patterns for different subjects. Figure 21 is the histogram of maximum pressure variation count of ten times walking for a test subject. We observed that sensor two Heel (Hind foot) has maximum pressure for five times while walking.

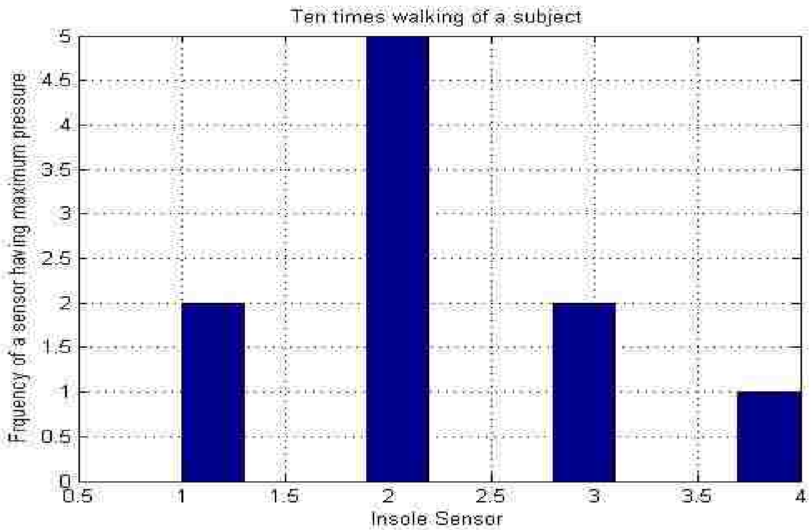


Figure 21. Histogram of maximum pressure variation for different subjects

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 class as shown in figure 22.

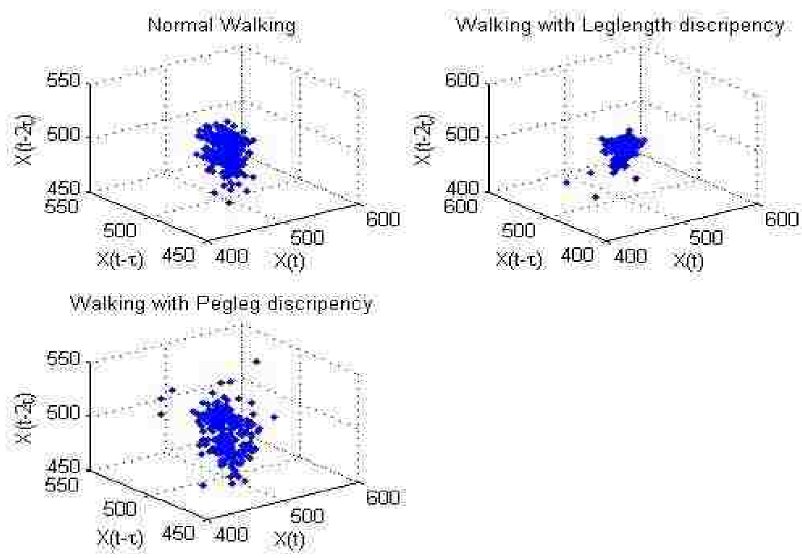
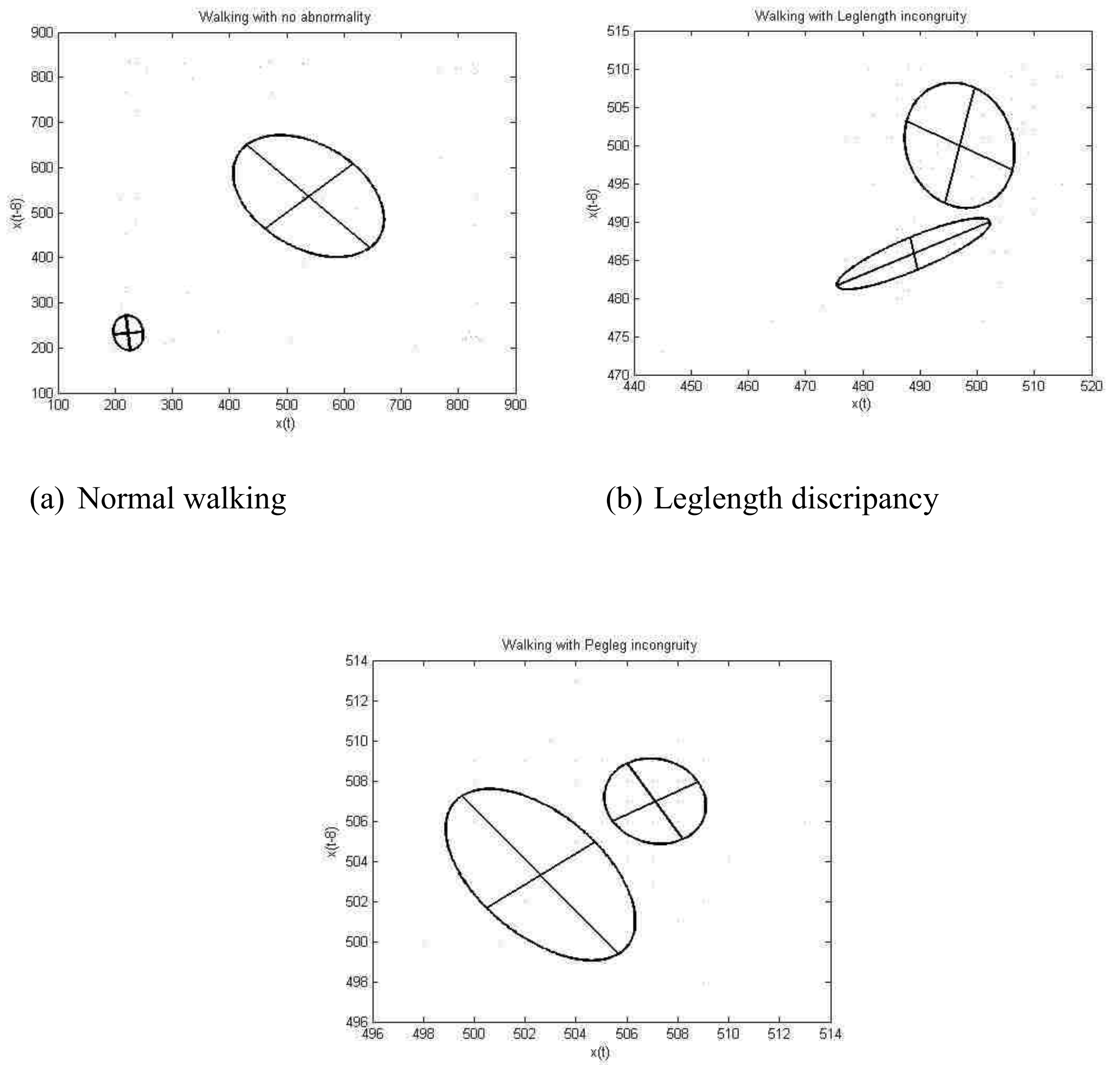


Figure 22. Reconstructed 3-D phase space of Normal, and simulated walking with Stiff/peg leg and Leg length discrepancy for maximum foot pressure variation when τ =8

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.



(a) Normal walking (b) Leglength discripancy

(c) Stiff /Peg leg discripancy

Figure 23. 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/peg leg

The particular models used here are statistical distributions that can be learned over RPSs 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 23, where the principle axes of the ellipses indicate one standard deviation of each mixture in the model.

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. Also, using the WEKA machine learning toolkit, 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 subject and averaged the results to obtain an overall accuracy of 89%. The confusion matrix for this classification is shown in table 11.

Table 11. Confusion matrix of walking based classification

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

7.2.4 Related Publications

- **AKM Jahangir A. Majumder,** Sheikh Iqbal Ahamed, Richard J. Povinelli, Chandana P. Tamma, and Roger O. Smith, ***"A Novel Wireless System to Monitor Gait Using Smartshoe-Worn Sensors",*** to appear in Proc. of the IEEE Computer Software and Applications Conference (COMPSAC 2015)**,** Taichung, Taiwan, July 2015.

7.3 A Multi-Sensor Approach for Fall Risk Prediction in Elderly

In this section, we used both smart-shoe and smartphone sensor data in order to improve the accuracy of our predictions. First, we used the same analysis technique as we used in motion sensor based gait detection. For better gait classification accuracy towards predicting fall, we collected more experimental data and analyzed those data sets to improve our accuracy.

7.3.1 Classification

After calculating the Energy, Mobility, and Complexity for each of the four signals, and features from the shoe sensors, the resulting feature vector is classified as normal or abnormal based on training data. We used a decision tree algorithm because it is a fast classification algorithm that can be implemented in real time. The abnormal class is trained by simulating multiple gaits that are indicative of falling. The pseudo code of the proposed classification algorithm on the smartphone is in the listing Algorithm 1.

7.3.2 Algorithm 1: *Fall Prevention Algorithm on smartphone;* ***Input:*** *Smartphone and smart-shoe Sensors Data;* ***Output:*** *Alert Generation.*

T ← Training set
X_1 ← getAccGyroStage()
X_2 ← getPressureStage()
C_1 ← Acc and Gyro influence coefficient from training set
C_2 ← pressure sensor influence coefficient from training set
begin loop start
    Read Acc and Gyro data
    Perform tilt-invariant calculations
    Read pressures values from smart-shoe
    Calculate: ← $P_{avg} = \frac{1}{n}\sum_{i=1}^{n}\left[P_{R,i}\right]; n = 4$
    Integrate accelerometer, gyroscope and pressures values
  Integrated stage value = $C_1X_1 + C_2X_2$
  Features(t) = Extract features from integrated signal
   if training = No
     Classify features (t)
      if Integrated Stage is abnormal
        alertUser()
      end if
      else
      Update T with features(t)
   end if
go to loop start

The fall prediction alert message will be generated using smartphone and smart-shoe sensors' data by identifying the threshold value in walking patterns. This is the key step for determining normal and abnormal walking in our system. Here getAccGyroStage() and getPressureStage() methods are used to calculate the values for individual sensors depending on the defined threshold values. The accuracy obtained for both of the methods is used to calculate the reliability weighted coefficient (C1 and C2) for multimodal decision fusion.

7.3.3 Result Analysis

In this section, we discuss the performance of our multi sensors approach.

7.3.3.1 Single Subject Data

To determine the classification accuracy of walking, we evaluate the performance of our system using 10-fold cross validation for fifteen different subjects. We observed near perfect classification accuracy (see table 12) when the experimental data were collected from the same subject. The classifier can easily distinguish between the two different kinds of abnormality. The problem with single subject data is that it requires the subject to train the system by simulating abnormalities.

Table 12. Classification accuracy for a single subject

Accuracy of Classification		
Subject	**Three Classes**	**Two classes**
Subject 1 Only	98.18%	97.44%
Subject 2 Only	91.46%	93.59%
Subject 3 Only	96.32%	92.23%
Subject 4 Only	92.13%	91.56%
Subject 5 Only	98.98%	98.66%
Subject 6 Only	88.98%	86.98%
Subject 7 Only	96.74%	94.28%
Subject 8 Only	87.58%	96.98%
Subject 9 Only	95.88%	97.25%
Subject 10 Only	98.49%	99.18%
Subject 11 Only	95.98%	94.84%
Subject 12 Only	93.22%	91.98%
Subject 13 Only	98.93%	94.98%
Subject 14 Only	98.98%	93.84%
Subject 15 Only	97.79%	95.98%

7.3.3.2 Multiple Subject Data

Classification accuracy was very good when considering two subjects in the training data, but was poor when attempting to classify one subject's gait based on another subject (see table 13). The classification accuracy was raised considerably when merging the two simulated abnormalities into a single class. However, like the smartphone sensor only data, for multiple subjects, there is still room for accuracy improvement.

Table 13. Classification accuracy for multiple subject

Accuracy of Classification		
Training Set	**Three Classes**	**Two classes**
Subject 1	41.45%	60.482%
Subject 2	44.24%	41.571%
Multiple Subjects	96.46%	94.12%

7.3.4 Related Publications

- **A.K.M. Jahangir Alam Majumder**, Ishmat Zerin, Miftah Uddin and Dr. Sheikh Iqbal Ahamed, Dr. Roger O Smith, *"**smartPrediction: A Real-time Smartphone-based Fall Risk Prediction and Prevention System**",* in Proc. of the ACM International Conference on Reliable and Convergent Systems (RACS 2013). Montreal, QC, Canada, October, 2013.
- **AKM Jahangir Alam Majumder** ***"A Real-time Smartphone- and Smartshoe-based Fall Prevention System"*** in Proc. of ACM Symposium on Applied Computing (ACM SAC 2014) SRC. Korea, March, 2014.
- **A.K.M. Jahangir Alam Majumder**, Ishmat Zerin, Dr. Sheikh Iqbal Ahamed, and Dr. Roger O Smith, *"**A Multi-Sensor Approach for Fall Risk Prediction and Prevention in Elderly**",* In International Journal of the ACM SIGAPP Applied Computing Review, Vol. 14, Issue 1. pp. 41-52, March 2014.

7.4 Development of Biomechanical Model

In this section, we discuss the details of our proposed model for gait event detection which might lead to a fall.

7.4.1 Analysis Methodology

The dynamic process of human walking can be modeled using the fundamental equation of vibration. The vibration model requires several parameters, including stiffness and damping coefficients. It is not possible to compute the stiffness and damping for the human body due to its structural complexity. Solving the vibration model requires the finite element method, which is computationally intensive and currently not suitable for a real-time mobile platform. Even if we were able to bridge the technological gap, there is another problem that makes it hard to use the vibration model. The right hand side of the equation represents a constant, or a time varying external force, which is difficult to model. However, it can be model in the case of the human body. The force in this case is primarily generated by the contracting and expanding muscle groups that try to maintain force and moment equilibrium in the system. Thus, it is not possible to quantify that force, leading to crude approximations of the vibration model.

As a solution to this problem, we propose modelling the gait cycle as a quasi-static process. We establish force and moment equilibrium for each event in the gait cycle. It is important to recognize the limitations of this approximation.

We cannot obtain the outputs the vibrational model provides. However, this is not significant since we use other parameters such as force distribution to quantify balance and predict a fall. In order for the model to be accurate, the process must be quasi-static, i.e., occur at a certain rate. Thus, the accuracy of the model decreases as we go from normal walking to running.

7.4.2 Model Construction

Consider an object of mass m and given dimensions sitting on the ground. The force distribution, as seen in the free body diagram is as follows.

The reaction to the weight of the object is a distributed force of magnitude $\frac{N_R}{L}$ the result of which acts at a distance of $\frac{L}{2}$ from point A. The sum of the force in Y, $\sum F_y = 0$.

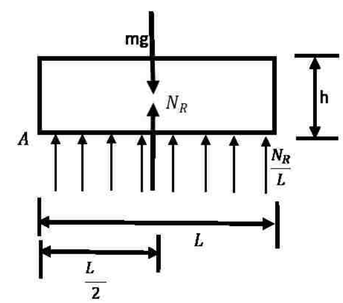


Figure 24. Free Body Diagram

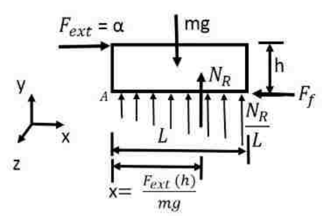
$mg - N_R = 0$, where g is the acceleration due to gravity, Force in X direction, $\sum F_x = 0$. There are no forces acting along the X direction.

To explain the principles of solid mechanics used in the biomechanical model, consider the following problem. We use the same object as figure 24 but now we add an additional force in the X direction. Force balance in Y, $\sum F_y = 0$.

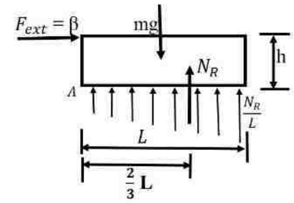
$mg - N_R = 0$, where g is the acceleration due to gravity, Force balance in X, $\sum F_x = 0$ and $F_{ext} - F_f = 0$.

The equilibrium conditions have not been satisfied. Since we have an external force in X direction, we need to ensure moment balance in the Z direction. This provides us critical input about the distribution of the normal force.

$\sum Mz\ (A) = 0$, the sum of moments in the z direction should be zero to maintain equilibrium. $F_{ext}\ (h) - N_R\ (x) = 0$, where x is the distance of the resultant normal force from point A. When $F_x = 0$ the distribution of the force is linear. For $F_x = \alpha$, the distribution is no longer linear, but trapezoidal as in figure 25 (a). The reason for this is that the trapezoidal distribution leads to a higher moment arm (x) and thus a higher stabilizing moment $N_R\ (x)$. α is a constant load ($\alpha < \beta$), where β is the load that leads to a triangular force distribution, $\beta = \frac{(mg).\left(\frac{2}{3}L\right)}{h}$.



(a) for F_{ext} = α



(b) for F_{ext} = β

Figure 25. Distribution while external load is applied

As the value of F_x increases, the force distribution becomes more and more triangular untill a value of F_x = β where the distribution is completely triangular. As expected, the triangular distribution provides the highest moment arm of $\frac{2}{3}\ (L)$ as shown in figure 25 (b). We can extend the idea to the limiting case, for example, when the overturning occurs. Right before overturning occurs, the distribution can be thought of as a concentrated load acting at the point farthest from point A, to provide the maximum moment arm. Thus, we can quantify the maximum external force that the object of a given weight and dimension can withstand before overturning.

There are different factors, such as, early heel off, inadequate push off, excessive drop of hip in different gait events that can cause falls while walking [99-100]. Research showed that the most unbalance happened during the single support event, initial contact of a loading response or pre-swing event of gait phases. To determine and measure the gait events abnormal behavior, in this analysis we have developed a biomechanical model for three of the most vulnerable gait cycle events, initial contact or pre-swing, single support and terminal stance or terminal swing. To predict balance and imbalance we analyze the force distribution on the feet during any gait cycle.

7.4.3 Initial Contact or Pre-Swing Event

We have developed a quasi-static biomechanical model that is used to determine the imbalance in initial contact of loading response in stance phase and pre-swing event of swing phase of a gait cycle.

It is important to identify the force distribution when the individual is balanced to predict an imbalanced state. The weight distribution on the foot is linear and uniform for a perfectly balanced individual. In order to maintain equilibrium, the net sum of forces and moments in all directions must be zero.

The orientation of the body provides instability in form of an overturning moment. To compensate, the body shifts as much of the weight as possible to the toe. In terms of mechanics, the force distribution of foot goes from being linear to triangular. The goal of this is to keep the body in equilibrium and specifically to maintain moment equilibrium at the heel. The triangular distribution of foot pressure provides a higher moment arm for the resultant force, leading to a bigger stabilizing moment. However, this is limited by the size of the individual's foot.

R_1 and R_2 are the pressure distribtion of the foot

(a + b) is the total stride length.

Balance Criterion: for the figure 26,

$\sum M_{A_{inplane}} = 0$, we are considering moments in the x-y plane, where, m= mass of individual.

R is the reaction due to body weight distribution.

From the following two equations, 1 and 2, we can easily solve for $R_1$and R_2.

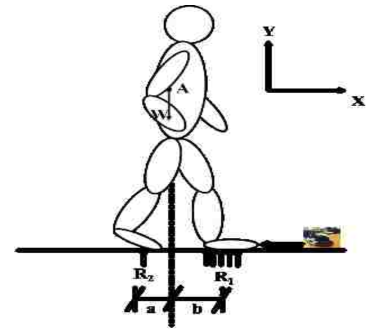


Figure 26. Modeling for Initial Contact or Pre-Swing Events

$R_1 + R_2 = W$, force equilibrium (18)

$R_2.a - R_1.b = 0$, moment equilibrium (19)

During a forward fall, the distribution would change from uniform to trapezoidal or triangular in pressure (the reading on the toe sensor will have a spike). Height only becomes a factor when the individual's torso is not straight. In that case, the perpendicular component of weight creates de-stabilizing moments. The motion of the arms provides additional stabilizing moments (elderly people have difficulty doing that).

We can convert the pressure R_1 (lb) to pressure by using the following function, $P_{gross}= (R_1/A_F)$

$$\text{So, } F_{sensor} = P_{Gross} . A_{sensor} \qquad (20)$$

Assuming, $F_1 = F_2 = F_3 = F_4$ and sensors reading from the other foot is very close to zero.

From this model, we can determine the insole pressure (R_1 and R_2), and stride length (a and b).

7.4.4 Single Support Event

Single support is another common gait event of high risk of imbalance. In this section we have developed a biomechanical model for predicting imbalance associated with this event by observing the foot pressure distribution of the user. The weight of the entire body acts along the foot in contact with the ground. For the figure 27, $\sum M_Z = 0$ and $\sum F_y = 0$

$$R_1 = mg,\ P_{Gross} = \left(\frac{R_1}{A_F}\right) \tag{21}$$

$$F_{Sensor} = P_{Gross} \cdot A_{Sensor} \tag{22}$$

When the body is imbalanced, the distribution is not uniform. It will be triangular or trapezoidal. This indicates the user is susceptible to a fall. Another foot provides the stabilizing moment.

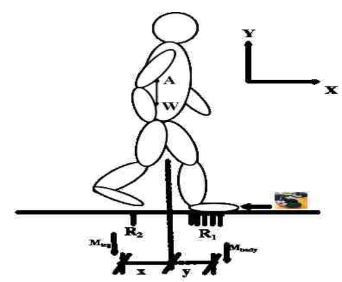


Figure 27. Modeling for Single Support Events

In an unbalanced scenario the distribution transitions from trapezoidal to triangular, thus providing a higher moment arm and thus a higher stabilizing moment. The stride length also plays an important role in providing stabilizing moment. Thus, in this scenario, both the force distribution and the weight of the leg act with variable moment arms to compensate for the destabilizing moment and maintain equilibrium

7.4.5 Terminal Stance/Swing Event

We also have developed a biomechanical model for terminal stance or swing events to predict abnormality in walking.

For the figure 28,

$$R_1 + R_2 = m.g$$

$$Ideally, \quad x = y$$

$$R_1 = R_2, \quad \text{so,} \quad P_1 = \frac{R_1}{A_{heel}}$$

$$so, F_1 = P_1 . A_{sensor}$$

For the Imperfect Balance-

$$x \neq y \text{ and}$$

$$\sum M = 0 \ (at\ any\ point)$$

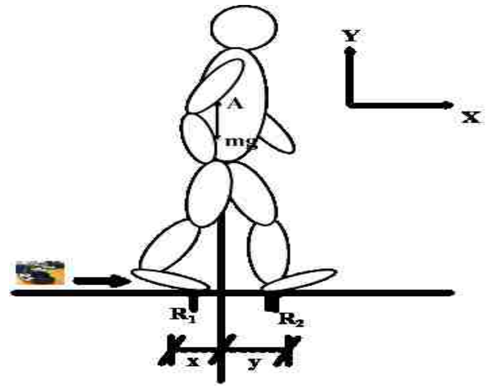


Figure 28. Modeling for Terminal Stance/Swing Events

$$so, R_1(x + y) = m.g$$

$$R_1 = \frac{mg\ (y)}{(x+y)} \text{ or } R_2 = mg - R_1 \qquad (23)$$

7.4.6 Model Parameters Analysis

The piezoresistive sensors output an equivalent voltage when a force is applied over the sensor area. Another important factor is sensor placement. To predict user's balance and imbalance, we analyze the force distribution on the feet during any gait cycle. 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.

In order to identify the quasi-static force-to-output voltage curve for each insole sensor, we applied a deformation in the range 0–0.9 mm, with a loading speed set to 0.0833 mm/s (*i.e.*, ~5 mm/min) as shown in figure 29.

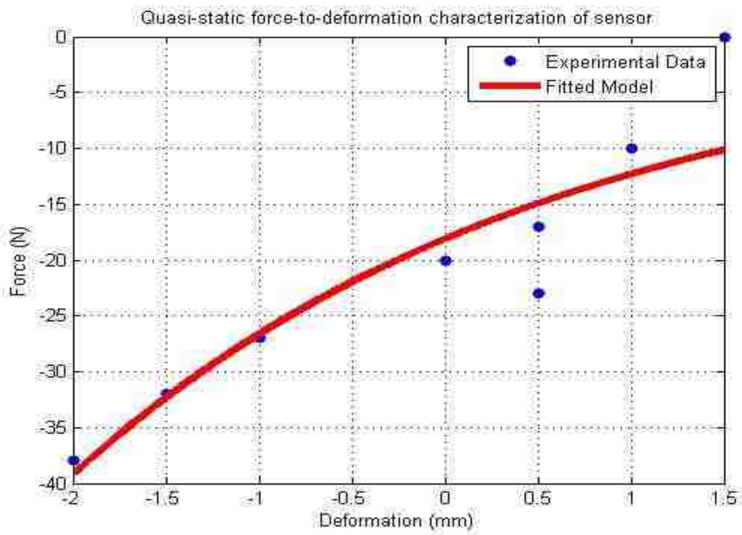


Figure 29. Quasi-static force-to-deformation characterization of sensor

Resulting data from each sensor was fitted by the sum of two exponential functions (*i.e.* $F = A_1 e^{c_1 v} + A_2 e^{c_2 v}$, where, F is the applied force and v is the output voltage), figure 30 reports the experimental curves for one representative sensor.

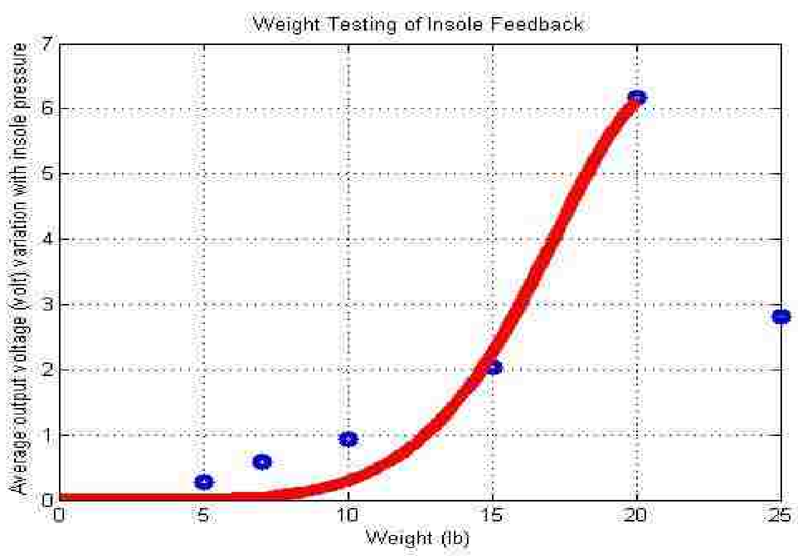


Figure 30. Quasi-static voltage-to-weight curve, experimental data of one selected sensor (blue dots) and fitting model (solid red line)

7.4.6.1 Pressure Maps

An example of pressure maps that can be extracted from the developed pressure-sensitive insoles is described in figure 31: the stated maps represent typical in-sole pressure patterns for a test subject during the pre-swing and single support phase. Figure 31 (a) represents the pressure distribution for pre-swing or initial contact phase. The push-off or single support phase pressure distribution is mostly under the forefoot area (figure 31b).

An interesting finding of this study is the relation of gait insole variation and model parameters. The variation of insole pressure with time varies person to person. Some users have the distribution of pressure from forefoot to rear foot and some users have the variation from rear foot to forefoot.

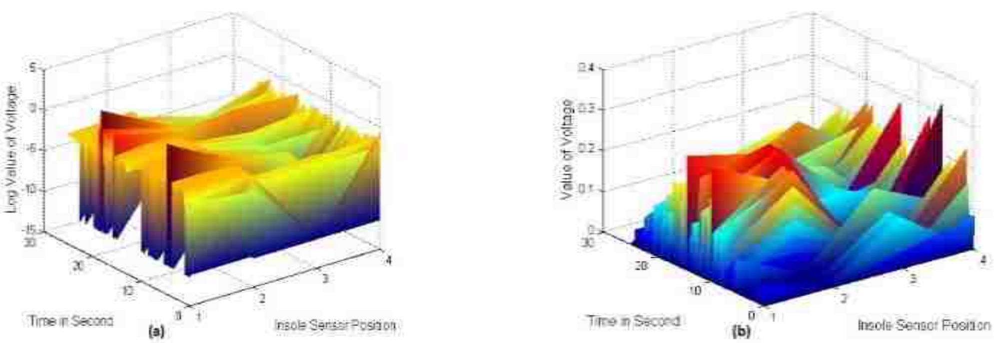


Figure 31. Pressure maps under the foot at different gait phases. (a) Pre-swing phase of the left foot. The weight is distributed on the heel region. The right foot is swinging; (b) Push-off phase of the left foot. The weight is distributed on the left forefoot. The right foot is starting to contact the ground

7.4.6.2 Gait Parameters Analysis

We calculated the average, standard deviation (SD) and coefficient of variation (CV) of the participant's test walking for each parameter used in the model. The correlation of the model parameter and the same parameters measured from the insole pressure variation from a smart-shoe was calculated to investigate common information between parameters. Weighted co-efficient matrix (on the CV value of gait model and insole parameters) was used to investigate which parameters contribute most to gait data variability in users. Parameters with a higher coefficient were interpreted as being significant contributors to normal or abnormal walking detection.

We investigate the relative error of our proposed approach with respect to parameters from the model and the insole. We detect more peaks (i.e. steps) than there actually are, so the error increases. The error might again increase if the significance difference between parameters value variation.

Also, we can easily differentiate between gait event patterns by analyzing the collected pressure data. Using the WEKA machine learning toolkit, we performed a 3-fold cross-validation in which we folded the data by session in order to avoid over-fitting. We ran our 3-class classifier for which user and averaged the results to obtain an overall accuracy of 83%. The confusion matrix for this classification is shown in table 14. Also, our system can avoid new training by training a universal model with data from all the subjects and without new training to test new users' gait event patterns.

Table 14. Confusion matrix of gait event based classification

	Initial Contact	**Single Support**	**Terminal Stance**	Actual Class
Initial Contact	83.6	3.8	4.1	
Single Support	5.2	78.3	4.7	
Terminal Stance	3.3	9.6	88.2	
Predicted Class				

7.4.6.3 Signal Classification for Gait Pattern Recognition

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.

We applied our technique to three data sets generated from three of the most vulnerable gait events. It was observed that we were getting maximum pressure with one or two sensors during assessment. We used the average pressure variation of these maximum pressure values while determining the threshold for imbalance walking for each subject in his or her gait event pattern. We can also see the variations of different walking patterns for different subjects. Using the data set from the maximum pressure sensors, we plotted the RPS 3-D phase plot for three different gait event patterns. We obtained different patterns for each different event as shown in figure 32.

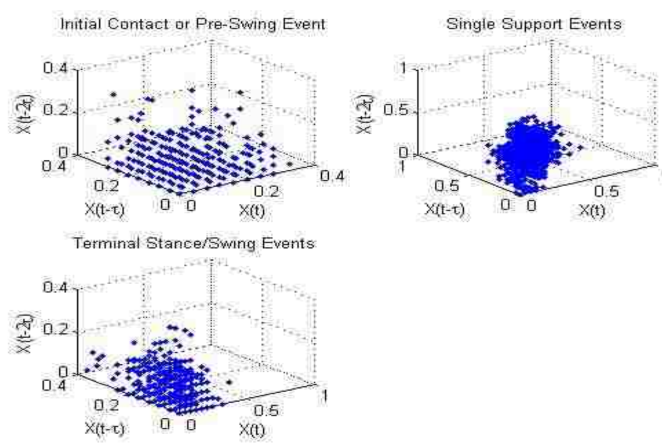


Figure 32. Reconstructed 3-D phase space of Initial Contact, Single Support and Terminal Stance/ Swing Events for maximum foot pressure value when τ = 11

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 the GMM on embedded time series to obtain the GMM. The particular models used here are statistical distributions that can be learned over RPSs and then used to classify signals. Our experimental results do not show the desired accuracy with the GMM for walking, as our analysis is for simulated data. However, for the GMM, there is still room for classification accuracy improvement.

7.4.7 Related Publications

- **AKM Jahangir Alam Majumder,** Piyush Saxena, Sheikh Iqbal Ahamed "***Your Walk is My Command: Gait Detection on Unconstrained Smartphone Using IoT System***", to appear in Proc. of the IEEE Computer Software and Applications Conference (COMPSAC 2016), Atlanta, Georgia, USA, June 2016**.**

7.5 Analysis of Simulated Forward Fall Prediction

We have collected data that simulated the forward fall in a lab environment using our smartphone and smart-shoe system. We asked test subjects to walk with our system, then suddenly pushed them forward onto a couch. The forward fall is the most common type for elderly people. We are currently in the process of analyzing the data gathered from this fall simulation.

7.5.1 Subject-Specific Dynamics Fall Model

To validate and increase the accuracy of our proposed model of gait events, we incorporate a fall model by observing the body gesture while walking. Any moving body is subjected by two opposing vertical forces as shown in figure 33, the body's weight (mg) which is downward, and the ground reaction force (N) which is upward. At a stabilizing situation, the body weight (mg) and N are always equal.

A dynamics model was developed and validated in this study to accurately predict the future fall in different walking events. The features of the dynamics model include consideration of the subject-specific effect of insole pressure, and prediction of the gait abnormality. In this study we have developed a fall model to predict the risk in walking.

$$\text{When, Overturning } > \text{Stabilizing}$$

$$\mathrm{mg}\,.\,(\cos\theta).\frac{\mathrm{L}}{2} > \mathrm{mg}\sin\theta\ .\sin\theta\ .\mathrm{S}$$

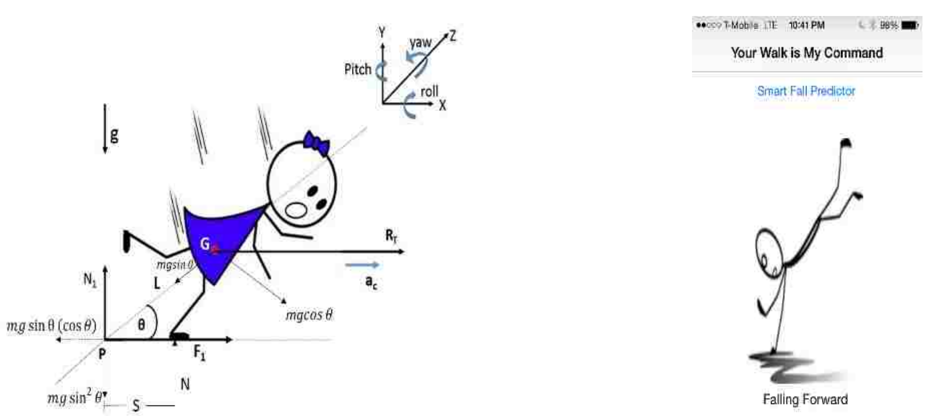
$$\mathrm{mg}\,.\,(\cos\theta).\frac{\mathrm{L}}{2} > \mathrm{mg}\sin^2\theta\ .\mathrm{S},\quad \text{or,}\quad \frac{\mathrm{Cos}\theta}{(\sin\theta)^2} > \frac{2\,\mathrm{S}}{\mathrm{L}}$$

$$\text{or } \mathrm{K} > \frac{2\,\mathrm{S}}{\mathrm{L}} \qquad (24)$$

With the increase of K, the body does not compensate automatically.

As θ decreases the risk of overturning increases. So at the fall stage we will have,

$$\mathrm{mg}\,.\cos\theta\,.\frac{\mathrm{L}}{2} > \mathrm{N.S},\text{or,}\frac{1}{\mathrm{S}}\,.\mathrm{mg}.\cos\theta\,.\frac{\mathrm{L}}{2} > \mathrm{N} \qquad (25)$$



(a) Fall Model (b)Screenshot of Alert

Figure 33. Falling scenario for model development

N will compare with the smart-shoe sensor data and θ could be determined from the rotation orientation of the phone measurement. (Please note all notations mentioned in figure 33 carry their standard mathematical meaning). Figure 33(b) is a screenshot of the fall alert in the smartphone in case of high risk of gait abnormality.

CHAPTER 8 CONCLUSION

8.1 Summary of Dissertation

In this dissertation we present a smartphone and smart-shoe-based mobile gait monitoring system that helps to predict a fall through real-time abnormality detection in users' gait patterns. The system is the first smartphone-based application that uses the combination of built-in accelerometers and gyroscopes and pressure distribution from shoe instrumented with sensors to help predict a potential fall.

8.1.1 Contributions of Dissertation

This research work has made several contributions to address the problem of smartphone-based low energy health monitoring system for current and next generation mobile computing. Since ensuring preventive measures is the common goal in almost any smartphone and smart-shoe-based risk management system, our major focus has been to develop and implement a cyber-physical system to solve the identified research issues using built-in sensors in smartphone and the sensor embedded smart-shoe. Our contributions include:

8.1.1.1 Analyzing Gait using Built-in Smartphone Sensors

We have designed and developed a smartphone-based gait monitoring system using built-in smartphone sensors (e.g. gyroscope, accelerometer, and GPS). In this research, we detected abnormal walking patterns using only smartphone sensor data processed by the smartphone. The accelerometer and gyroscope of a smartphone were used to determine the abnormal gait pattern of the user. The GPS of the smartphone was used for location information of the user.

8.1.1.2 Designing and Developing a Wireless Smart-shoe

Large scale smartphone-based health monitoring applications (such as – Elderly Care at Nursing Home and People with Gait Abnormality) are used to detect and predict risk of fall related injuries. In our initial research, we observed that smartphone built-in sensors are not able to accurately predict and detect a gait abnormality. Low dynamic range and a low resolution of smartphone sensors increase possibility of large error in signal variation. To address this problem, we have added a smart-shoe with smartphone sensors to detect and predict a fall by observing foot pressure variation while walking. We designed and developed this smart-shoe with four pressure sensors for detecting gait abnormality and established a Wi-Fi communication network for the communication between the smart-shoe and smartphone.

8.1.1.3 Predicting a Simulated Fall Risk Using an Integrated Embedded System

After assimilating the smart-shoe and smartphone sensor data, we performed a set of experiments in the lab environment to evaluate normal and abnormal gait patterns. Currently, we are working on various aspects of this research to improve the accuracy of the fall prediction algorithm for alert generation.

8.1.1.4 Addressing Low Response Time for Alert Generation

To ensure the high sampling rate for low response time of our system, in this research we used a unique signal classification approach which can recognize the abnormality in a subject's gait and model the dynamics of a system as they are captured in a Reconstructed Phase Space (RPS).

8.1.1.5 Developing a Biomechanical Model for Gait Event Detection

Scientific gait analysis with smart-shoe embedded sensors is able to improve the accuracy of fall prediction in the elderly. A biomechanical model for predicting gait abnormality in the elderly generally consider the gait related parameters. Model accuracy is limited because injuries due to falls are significantly affected by different gait events in the gait cycle. There are different factors, such as early heel off, inadequate push off, and excessive drop of hip in different gait events that can cause falls while walking. To determine and measure the gait event abnormal behavior, in this work we have developed a biomechanical model for three of the most vulnerable gait cycle events: initial contact or pre-swing, single support and terminal stance or terminal swing.

8.2 Intellectual Merit

The proposed smartphone- and smart-shoe-based gait monitoring approach for fall prediction is innovative because it provides a number of beneficial features together that current gait analysis approaches do not. It also has the benefits of mobility and direct Internet connectivity while being relatively inexpensive and non-invasive. Advances in sensor technologies provide a method to accurately monitor the daily activity of people with disabilities. This information could be used to determine the usefulness of rehabilitation interventions as well as provide behavior enhancing feedback. A combined approach that incorporates the smartphone sensor and smart-shoe sensor data may provide a more accurate clinical assessment than the current method.

8.3 Broader Impact

The proposed design is robust and reliable but, unlike current approaches, it does not require the wearing of body sensors and does not require an infrastructure. Because this approach is implemented on a smartphone with low cost sensors integrated shoe, it also has the benefits of mobility and direct internet connectivity while being relatively inexpensive and non-invasive. The system may also have broad applications in abnormal gait behavior detection for people with various disabilities who are at increased risk of falls.

8.4 Future Research Directions

As we walked through the timeline of the project we got exciting ideas that we decided to add in the future. There are many existing ideas for future work, which are outlined in this section.

8.4.1 Use mobile computing platform for smart home automation systems

Smart-homes are continuously instrumented with sensors like kinects, energy meters, cameras, digital televisions, and smart-switches. In this research we anticipate using smart-home sensor technology and the smart-shoe to monitor the mobility of older adults, which gives the elderly insights into their health status and enables them to share it with caretakers. We will use the Lab of Things (LoT) as the platform to interconnect smartphone and wearable sensors systems

8.4.2 Synchronization Challenges for Real-time Analysis

LoT for IoT systems include devices that communicate not only with the cloud but also with each other, often requiring real-time coordination and synchronization. Consider a tele-health activity where a 70-year old patient lives at home and a caregiver remotely monitors the patient's health during daily activity. Instead of using body health sensors (such as pulse, blood pressure) and room sensors (like camera, microphone), the patient can use a smartphone to capture data that together gives the caregiver an understanding of the patient. All the sensory data will be strongly correlated, taking essential data in a synchronous manner about the patient that must be aligned exactly in real-time to provide the correct insights. This relatively simple scenario illustrates many challenges to existing infrastructures (OS, network, etc.) that makes it difficult with current technology. For example, Networking Time Protocol (NTP) is being used for wide area network time resynchronization but only at the timing precision level of several milliseconds, which is not sufficient for IoT devices used in health care. New implementations, protocols, and standards are necessary to enable this rich class of applications.

8.4.3 Build a generic low-power communication platform for longitudinal data collection

Most of the IoT devices including smartphones are small and do not have access to a continuous power source. Battery size, lifetime, and cost impose significant constraints on how these devices compute and communicate. Novel wireless networking solutions can address these challenges. Also, many IoT devices serve a single, limited purpose, suggesting that these devices could have customized network interfaces, operating systems, and programming models that make the most effective use of limited computation, network, and energy resources. Research in these areas involves interdisciplinary collaboration in signal processing and wireless communication, as well as computer architecture and operating systems.

8.4.4 Develop the next generation smart-shoe

Miniaturizing the smart-shoe hardware components is another important research challenge. The current smart-shoe hardware is large in size. In this research we would like to investigate the use of Arduino and Wi-Fly mini to use for our Wi-Fi communication module. Table 15 shows the comparison of different existing and future hardware module that we wanted to use to build a next generation smart-shoe.

Table 15. Development of a Next Generation Smart-shoe

Different Smart-Shoe Module	**Advantages**	**Disadvantages**	**Anticipated Next Generation Smart-shoe Components**	**Images of Anticipated Next Generation Smart-shoe Hardware**
Smart IoT Devices	iPhone and Android platform	Not generic	Generic platform	
Arduino	Open-source platform	Large in size	Arduino Mini	
WiFly	The ability to connect to 802.11b/g wireless networks	Large in size	Wi-Fly Mini	
Sensor System	-Flexible and easy to use -In-shoe system	Number of sensor position	Use fabric based capacitive gesture sensor	
Power Supply Battery	Easy to use with Arduino and Wi Fly	Large in size	Miniature solid state battery	Will use custom battery

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APPENDIX:

a. Weight Testing of Insole Feedback

In order to test the accuracy of the fall prediction, we conducted weight testing to show the applicability of this system to a range of subjects and the stable calibration of the pressure sensors. Using smartshoe sensors as the testing weights, it was found that the output voltage from the in-sole sensor approximate linearly increased with the testing weight as shown in figure 34. However, there was residue output voltage even though there was no weight on the sensors.

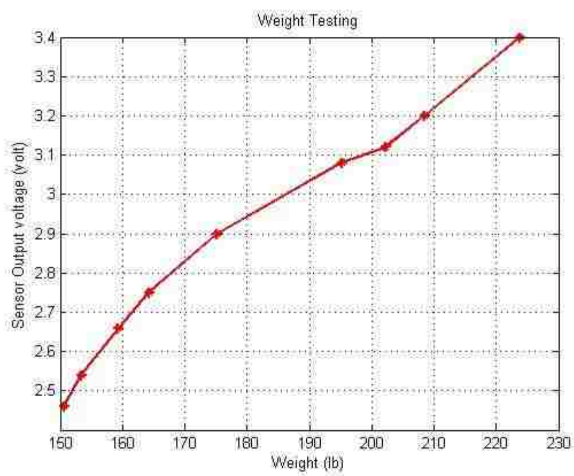


Figure 34. The relationship between testing weights and output voltages of the in-sole sensor

b. Development of a Walking Model

To validate our study, we incorporate a walking model by observing smartphone sensors data as we as the pressure sensors data from smartshoe.

Human walking is a cyclical movement, so here we use the similarity of the data between two adjacent cycles to assess the walking stability.

$$\text{Stability} = \text{Similarity } (C_i, C_{i+1}) \qquad (26)$$

Where C_i is the data of the preceding cycle, and C_{i+1} is the data of the next cycle. The dynamic symmetry of gait is defined as the discrepancy of bilateral data in gait cycle on all symmetric attributes.

$$\text{Symmetry} = \text{Discrepancy } (R_i, L_i) \qquad (27)$$

Where R_i is the data of the right-side and L_i is the data of the left-side on one attribute. Considering stability and symmetry of walking data, we propose a walking model for our system. The impulse, I, of a step of running and walking is given by, $= \int F\ dt$, where F is the force.

Using Newton's second Law, $F = ma$ and $a = \frac{F}{m}$. Where, a = Acceleration and m= mass.

From the foot pressure distribution and accelerations and orientation observed from smartphone motion sensors while walking. The first simplest approximation of the signal is an impulse function. We will assume that the acceleration curve for walking is approximated by a sinc function, $a = \frac{F}{m} = \frac{Sint}{t}$ where, $0 \leq t \leq T$

To find the impulse of the acceleration, we need to integrate the signal over time,

$$I = \int F\, dt\, I = \int ma\ dt \qquad (28)$$

$$I = m \int \frac{Sin(t)}{t}\ dt$$

$$I = m \int \frac{1}{t}[t - \frac{t^3}{3!} + \frac{t^5}{5!} - \frac{t^7}{7!} + \cdots \ldots\ldots]dt$$

$$I = m\int [1 - \frac{t^2}{3!} + \frac{t^4}{5!} - \frac{t^6}{7!} + \cdots \ldots\ldots]dt$$

$$I = m[t - at^3 + bt^5 + ct^7 + D] \qquad (29)$$

Where, a, b, c and D are constant and only D is unknown. We can calculate the D by using two boundary condition I (0) =0 and I (T) = 0. Also assume that m is constant.

By using the boundary condition we can express the impulse function as,

$$I = m[t - at^3 + bt^5 + ct^7] \qquad (30)$$

c. Resource Consumption Comparison

To test the power consumption of our system, we fully charged the iPhone and then monitor the power states continuously for 2 hours for the following two scenarios: (1) the iPhone runs without application (2) the iPhone runs with application where the application continuously collects accelerometer and gyroscope data for abnormal gait pattern identification. Figure 35 presents the two curves of battery level states versus time during the time period of 120 minutes. From this resource consumption analysis we can see that if our application keeps running normally until the battery power is exhausted, then it will last about almost 3 hours. Currently, we are working to reduce the power consumption of our system. However, even though the power consumption of our application is little bit high, the benefits it may bring to elderly lives are considerable.

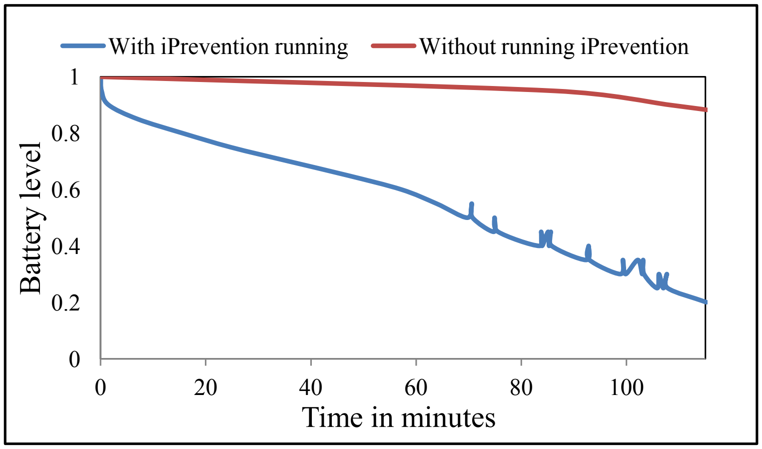


Figure 35. Blue curve presents the battery levels when the iPhone is running with application and red curve presents the battery levels when the iPhone is running without application

In this analysis, first, we have developed an Android based application with Bluetooth communication module to collect smart-shoe sensors data. In order to develop the application we have used the algorithm shown in figure 36 to establish the Bluetooth connection between smartshoe and the smartphone. At first the algorithm searches the device that supports our proposed communication features. The application will move forward to execute the next operations after accurately detect the correct devices. Enabling the Bluetooth device we initiated an action button to discover the available Bluetooth devices around our device. Among the available devices, the algorithm looked for our target device (smartshoe Bluetooth device) by its name. Subsequently getting the target device name and address, we are checking for whether the device is bonded or not. If the device is not bonded or paired the application will do that with pair code. Then we began a thread to receive and transmit the sensor data through a class 2 Bluetooth module embedded in smartshoe. Here the connections are peer-to-peer communication. We used the Bluetooth Socket to plug in the connectivity. We also have created a thread to listen always from the connected device. Thenceforth the socket was fully ready for receiving and transmitting the input and output stream.

On the other part we have programmed the Arduino with four sensors. We read the analog input data and sent it serially to the Bluetooth device of smartshoe. Smartphone Bluetooth has received these data as string. Then we displayed the data on the Android device with corresponding sensors.

As we have described earlier the application started with saving individual patient personal information. We have recorded the sensor data with respect to individual patient. We saved the data in order to train out system for individual patient. Later on by analyzing these information of individual patient we could identify their walking pattern or classify between normal and abnormal gait pattern.

Raw data on foot pressure distributions were collected with the developed foot pressure sensing shoe (smart-shoe). The pressure level represents the output value of analog information into which voltage is converted. The experiment was conducted to develop an automatic measuring system for revealing the relations between human motions and collective foot pressure characteristics. With the power supply unit, foot pressure signal was gathered by piezoresistive flexi force sensors in a time span and transmitted to the smartphone through a Bluetooth communication network.

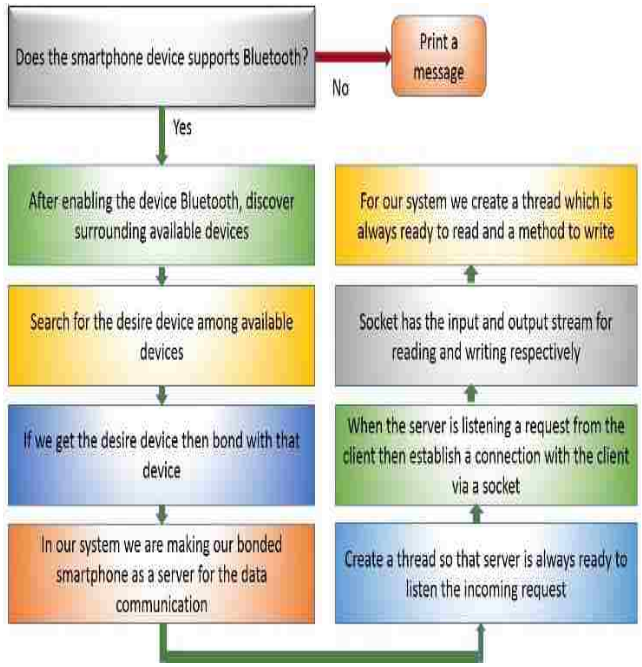
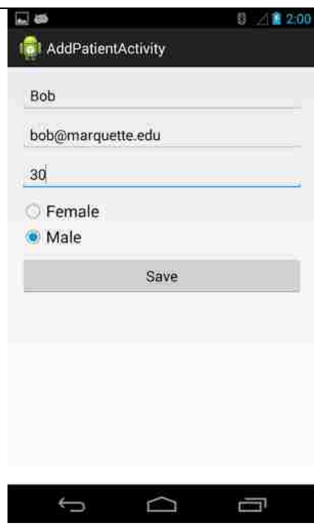


Figure 36. Algorithm on smartphone (android) for low energy communication

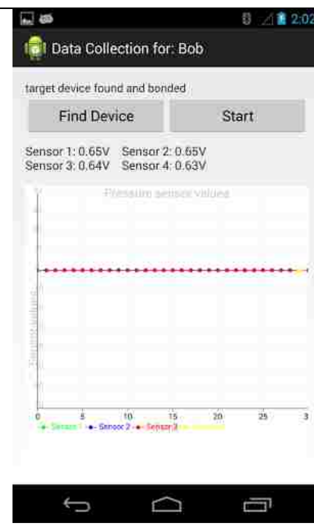
In our application we were saving each patient's personal information in the Android database SQLite. The patient name would automatically show up in the patient list. Then we can select individual patient to collect the smartshoe sensor data.

As an example, in figure 37, first we were saving Bob's information in our SQLite database and then collecting pressure sensor data from smartshoe with regard to him. Starting of this user interface a toast would show up to notify "Bluetooth is on". Afterward we pressed the "Find Device" button to get the target device. If it could find the desire device a text message would show up at the above that "target device found and bonded". If the desire device is not bonded we have bond that manually by pairing the code. Now the application is ready to receive sensor data from smartshoe. To get those data we need to press "Start" button and sensors data would start showing up continuously. The corresponding graph would show up below the sensor data. We are still working on displaying the corresponding graph for each walking pattern on smartphone. We saved those data against each patient for further experiments.

Our target is to save those data for individual patient to train our system to identify each patient's normal and abnormal gait pattern. We also observed the smartphone battery usages during our data collection process. It is noticed that the smartphone battery life using our Bluetooth communication algorithm with class 2 Bluetooth device is improved than that of general Wi-Fi or other communication system. The system has a power consumption of about less than 26μA at sleep mode, 3mA at connected situation and 30mA during data collection.



(a) Patient Activity



(b) Sensors Data

Figure 37. Screenshots of android based data collection

d. Hardware Components Information

d .1 Wi-Fi Module and Battery Holder

d. 1.1 Flexiforce Pressure Sensor

Sparkfun Part # SEN-08712 ROHS

https://www.sparkfun.com/products/8712

The overall length is about 8.5". Sensor comes with 0.1" spaced, reinforced, breadboard friendly connector. This sensor ranges from 0 to 25lbs of pressure.

d.1.2 WiFly Shield and WiFly Mini

Sparkfun Part # WRL-09954 ROHS

https://www.sparkfun.com/products/9954

- Qualified 2.4GHz IEEE 802.11b/g transceiver
- High throughput, 1Mbps sustained data rate with TCP/IP and WPA2
- Ultra-low power - 4uA sleep, 40mA Rx, 210mA Tx (max)
- Small, compact surface mount module
- On board ceramic chip antenna and U.FL connector for external antenna
- 8 Mbit flash memory and 128 KB RAM
- UART hardware interface

WiFly Shield

- 10 general purpose digital I/O
- 8 analog sensor interfaces

Sparkfun Part # WRL-10050 ROHS

https://www.sparkfun.com/products/10050

This is a revised board by adding some LED indicators and also improving the overall performance of the board. This is a breakout board for the RN-131C WiFly GSX module, an ultra-low power 802.11b/g transceiver. This board breaks out all pins of the RN-131C to two 17-pin 0.1" pitch headers. Board comes fully assembled and tested as pictured.

Dimensions: 1.2x1.8" (headers are separated by 1.1")

WiFly Mini

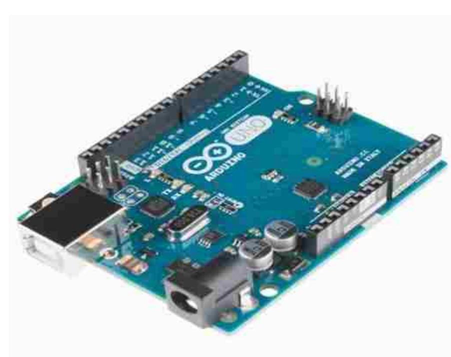
d.1.3 Arduino Uno and Arduino Mini

Sparkfun Part # DEV-11224 ROHS

https://www.sparkfun.com/products/11224

Arduino/Genuino Uno is a microcontroller board based on the ATmega328P. It has 14 digital I/O pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz quartz crystal, a USB

Arduino Uno



connection, a power jack, an ICSP header and a reset button.

Sparkfun Part # DEV-11303 ROHS

https://www.sparkfun.com/products/11303

This is the new and smaller, Arduino Mini 05 with ATmega328. The latest version of this board is built around a smaller ATmega328 package. It allows all of the parts to be populated on the top side of the board. Of course, it still requires an external serial connection for programming.

The Arduino Mini 05 is a great development module for building compact devices that need to interact with the world around them.

Arduino Mini

d.1.4 Battery Holder

Sparkfun Part #: PRT-00552 ROHS

https://www.sparkfun.com/products/552

Battery Type, Function: Cylindrical, Holder with Switch

Style: Holder (Covered)

Battery Cell Size: AA

Number of Cells: 4

Mounting Type: Custom

Termination Style: Wire Leads - 6" (152.4mm)