LPcomS: Towards a Low Power Wireless Smart-Shoe System for Gait Analysis in People with Disabilities

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LPcomS: TOWARDS A LOW POWER WIRELESS SMART-SHOE SYSTEM FOR GAIT ANALYSIS IN PEOPLE WITH DISABILITIES

by

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ABSTRACT

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Gait analysis using smart sensor technology is an important medical diagnostic process and has many applications in rehabilitation, therapy and exercise training. In this thesis, we present a low power wireless smart-shoe system (LPcomS) to analyze different functional postures and characteristics of gait while walking. We have designed and implemented a smart-shoe with a Bluetooth communication module to unobtrusively collect data using smartphone in any environment. With the design of a shoe insole equipped with four pressure sensors, the foot pressure is been collected, and those data are used to obtain accurate gait pattern of a patient. With our proposed portable sensing system and effective low power communication algorithm, the smart-shoe system enables detailed gait analysis. Experimentation and verification is conducted on multiple subjects with different gait including free gait. The sensor outputs, with gait analysis acquired from the experiment, are presented in this thesis.

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LIST OF ACRONYMS

SP	Smartphone
CAGR	Compound annual growth rate
LE	Low Energy
PAN	Personal Area network
BAN	Body area network
BLE	Bluetooth Low energy
ADV_IND	Connectable undirected advertising event
CONN_REQ	Connect request by Initiator
MS	Multiple sclerosis
AES	Advanced Encryption Standard
USART	Universal Synchronous Asynchronous Receiver Transmitter
APP	Application
LPcomS	Low Power Wireless Communication System

CHAPTER 1 INTRODUCTION

Gait analysis is the process by which quantitative information is collected to understand the cause of gait abnormalities and to aid in treatment decision-making. This process is facilitated through the use of technology such as specialized, computer-interfaced video cameras to measure patient motion, electrodes placed on the surface of the skin to improve muscle activity, and force platforms fixed in a walkway to monitor the forces and torques produced between the ambulatory patient and the ground. Methodical gait analysis is the exploration of sensor patterns while walking, and its results have many applications in medical programs [1], physical therapy [2], and sports training [3]. For example, with detailed gait feature analysis, therapists can quantify the rehabilitation improvement of the users after surgery, and the corresponding treatment and training can be tailored according to an individual's status [4]. Gait analysis is primarily carried out in one of two ways: in a motion laboratory, with full analysis of the motion of body segments using highly accurate computer based force and optical tracking sensors, or in an office with the clinician making visual observations. The first method is expensive while the second method is inexpensive but requires substantial time and clinical expertise.

Shoe-based gait analysis systems are replacing the standard technique of monitoring gait abnormality and collecting the quantitative information. Now shoe-mounted wearable sensors can be used in applications, such as activity monitoring, gait analysis, and post-stroke rehabilitation. Smart-shoe with smartphone based gait monitoring systems are gaining widespread popularity in research, as well as in the commercial market place. A number of publications describe the use of shoe-based sensor systems for biofeedback in rehabilitation applications. These techniques are being used in applications ranging from studies of obesity to post-stroke rehabilitation.

The significant concerns in smart-shoe and smartphone-based systems are the organization of low-power operation and wireless transmission of the sensor data. Generally, to use smart-shoe for one day of wear (12 h), a battery with a capacity of more than 480 mAh is needed to power up the sensors in the shoe [5]. Shoe systems designed for the long-term monitoring of gait or other factors should present insignificant burden in terms of charging the shoe sensor batteries. The physical architecture of the sensor data transmission system is also challenging in terms of subject mobility, as the shoe data is typically delivered to a base station and the individuals cannot always be expected to be in the vicinity of the base station. Finally, the monitoring system has to be robust enough for extended wear.

In past studies, researchers took several approaches to minimize the power loss in wireless communication systems. Low-power consumption enables a long operating lifetime for a wireless sensor network. Though this is facilitated in part by low duty cycle operation and local signal processing, multi hop networking among sensor nodes can also be introduced to reduce the communication link range for each node in the sensor network. Since communication path loss, in scales with respect to time is a power law exponent of 4 or greater, in many applications, this reduction in link range results in massive reductions in power requirements [6-7].

There have been studies on low energy wearable devices for human gait analysis in the past. In [8], the authors presented a Force Sensing Resistive (FSR) sensor array-based system for gait analysis. Recently, in [9], the authors developed a compressed-sensing-based algorithm with a single accelerometer for precise human activity recognition. Both of these works are helpful to understand the human locomotion and status of walking. However, they cannot comprehensively and correctly address all human gait features used in actual medical applications. There is indeed a demand for a more portable approach, such as smartphone based systems with low power consumption for efficient gait analysis.

The cost of smartphones has decreased and their computational competences have rapidly increased with advances in mobile technology. A smartphone-based gait monitoring system can function almost everywhere, since mobile phones are highly portable. Currently, most smartphones have sensors to observe acceleration, location, orientation, ambient lighting, sound, imagery, etc. [10]. These integrated sensors along with the pressure sensor shoe strengthen the capabilities of the smart-shoe. The smart-shoe system can monitor all types of activities without troubling the normal life of the subject, but there is still a need of a low energy communication system for longitudinal study of gait analysis using smartphone.

In recent years, there has been increased interest in Smartphone-based monitoring of elderly people with gait abnormalities and people in rehabilitation. The activity recognition systems have increased in both number and quality. For this, it is enormously important to ensure that the intrusion level caused by the system is the lowest possible. Some of the works attempt to solve this problem by using a variety of sensors, such as accelerometers, gyroscopes, GPS and even radio-frequency identification sensors [11-13]. The communication between different sensors of the proposed system should have a low energy consumption rate. Obviously, using a smartphone is a benefit for users, since the cost of such devices and the risk of loss or of leaving the hardware behind is decreased since objects, like users' smartphones, have already been integrated into the users' daily lives. However, smartphones are used for other purposes, such as making phone calls, surfing the Internet, and listening to music. For this reason, the physical activity recognition system on a smartphone must be executed in the background mode so as to cause the least possible impact on the user. However, complexity and energy consumption must be addressed.

Another concern found in previous related studies was the number of sensors required. In [14], it can be seen that the accelerometer sensor is placed in a glove, which the user must wear, and it can recognize a large number of activities depending on the movement of the hand. In contrast, certain studies use various sensors all over the body to recognize these activities [15-16]. Obviously, with the increase of number of sensors used, the power consumption is increased. But, according to the research based on multiple sensors, this type of sensor produces results of higher accuracy. Once the most comfortable alternative for users is determined, then the various sensors can be analyzed in terms of the way data is obtained to perform the activity recognition. As noted above, much work has made use of sensors such as GPS, accelerometers and microphones, and the most efficient sensor with which to obtain the highest accuracy and comparatively low power consumption for data collection.

In order to determine the method that is most energy efficient, in a previous study, most of the researchers made a comparison between the energy consumption of the most frequently used sensors. Those comparison studies are critical in choosing the best sensor method since, together with performance; these constitute the two main issues upon which the final decision is based. The eight most used sensors (Microphone, GPS, Wi-Fi, accelerometer, NFC, Bluetooth, electrocardiograph connected by Bluetooth and gyroscope) from the literature in the field of activitiy recognition were analyzed. The result of most of this comparison showed that, the lowest power consumption is given by the microphone, after that accelerometer sensor comes in that list [17]. However the studies did not consider the energy consumption of the smartphone battery while connecting to the external devices. Also, they generate an energy cost trend line to avoid battery capacity and the energy expenditure of the smartphone without performing any action and with no user interaction. In the case of Bluetooth, advances in these sensors have reduced the energy consumption, but this technology still suffers from serious problems when being used in the field of activities recognition. The infrastructure must be installed in each location where it will be used. Furthermore, dynamic activities, such as walking, running or cycling, can hardly be recognized by only Bluetooth, unless additional devices associated with these activities are installed. It must be noted that nowadays, the smartphone is the only device (together with certain wearables, such as smart-shoe) carried continuously for most users. Therefore, the use of low energy Bluetooth devices for gait recognition systems must force the use of these devices, which would not be suitable for user acceptance of gait analysis systems. Also, Bluetooth access point networks are more expensive than embedding all of the necessary technology in the smartphone itself.

Considering the importance of smart-shoe and smartphone-based low energy communication system for gait monitoring, in this study, we designed and developed a low energy communication system, named LPcomS. This communication system is used to collect the insole pressure data from the smart-shoe using smartphone. A low cost pressure sensing embedded smart-shoe system with Bluetooth communication module is also developed for this study.

1.1 Contributions of Thesis

The contribution of this thesis is to concentrate on the development of a low energy wireless smart-shoe for user gait abnormality identification. Foot pressure signals can identify the behavior of human gait and posture as reflected in foot pressure distribution. Many studies describe foot pressure as a detection system, but few have used smartphone and a smart-shoe for the analysis. We report on a new smartphone and smart-shoe used for gait analysis. Our major contributions are as follows:

- *Developed of a low energy wireless smart-shoe*
- *Proposed a smartphone and smart-shoe-based system (LPcomS) to analyze gait in common environment*
- *Designed and developed of a Low Energy Bluetooth communication generic framework between smartphone and smart-shoe*
- *Developed an Android-based application for single subject, which can record quantitative data about a patient's walking pattern and shows graphical representation.*
- *Provide users, health care professionals and caregivers with highly personalized health feedback.*

Our system, LPcomS, targets gait detection among people with impairments that affect balance, predisposing individuals to falling. These include common rehabilitation diagnostic groups and elderly populations, but also may eventually help identify gait disorders among children, behavior analysis, and be helpful in environment monitoring.

1.2 Organization of Thesis

The rest of this thesis will be organized as follows: Chapter 2 will discuss the motivation of this work. Chapter 3 will investigate existing work in the fields of low energy consumption system in gait recognition. Chapter 4 will provide an in depth look at background and how the generic Low Energy (LE) gait monitoring system was developed. Chapter 5 will discuss the details of our proposed system (LPcomS). In chapter 6 will describe the algorithm and validation of our proposed system. Chapter 7 will conclude this thesis with a summary and suggestions for future work.

CHAPTER 2 MOTIVATION

It is hard to realize the importance of a LE system for predicting the gait abnormality if someone does not have the experience of a gait related injury. It is essential to monitor a person with gait abnormality for a longer period of time. The goal of clinical gait analysis is to assist in treatment decision-making for the person with complex and not easily understood walking problems.

People aged 65 and older are a growing segment of our population. Between 2012 and 2050, the United States will experience considerable growth in its elderly population. In 2050, the population aged 65 and over is projected to be 83.7 million, almost double its estimated population of 43.1 million in 2012 as shown in figure 1. The projected growth of the elderly population in the United States will present challenges to policy makers and programs, like Social Security and Medicare. It will also affect families, businesses and health care providers.

Among the multiple chronic diseases many people experience, a decline in mobility often occurs with aging. Falls are the major cause of mobility problems in the elderly. Almost all incidences of fall due to gait abnormality. Falls are the fifth most common cause of death in the elderly. In [19], Lilley and collaborators showed that falls are the leading cause of accidental death for people aged over 75 in their review of injuries involving older adults. Retrospective studies showed that about one third of the elderly above 65 years are fall-prone elderly and will experience at least one fall per year [20-22] while for the elderly over 80 years, the proportion increases to one half [23] for gait related problems. The impact of falls range from a reduced mobility and independence to various injuries and sometimes to death [19, 20, 24]. Because it can take only one bad fall to severely incapacitate or even kill an individual. The risk increases even more if he/she is age 50 and over. This situation can be understood with the help of following scenario1 and scenario 2.

Scenario 1: Jennifer, a 65-year-old living in her house alone, has been suffering from leg length discrepancy problems since her birth. One night she was walking to the bathroom at around 10 P.M. and she fell due to unbalanced walking. This caused a severe hip fracture. Her housekeeper arrived at her home the next day at around 10 A.M. and saw her lying in the bathroom. She called 911 and took her to the hospital. Jennifer was in intensive care for 48 hours. If Jennifer had a simple, automatic, and non-invasive technology that could warn her during her unbalanced walking, she could have taken proper steps to avoid the fall and the consequences.

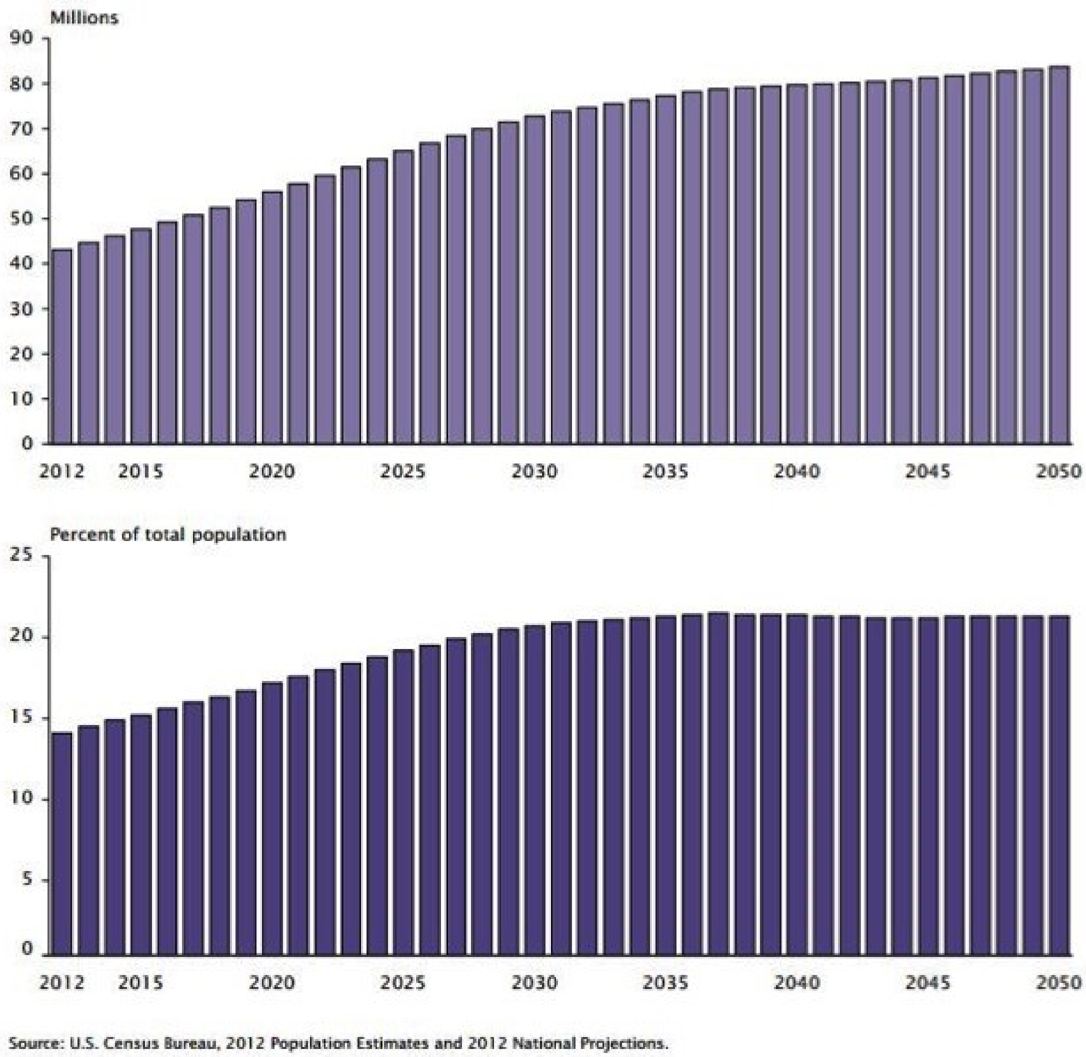


Figure 1. Population aged 65 and over for the United States: 2012 to 2050 [18]

Gait information is rarely used as an input in current medical diagnosis. This is because even though a human can intuitively watch a person walk and perform a diagnosis on users' gait pattern, actually quantifying user's gait is difficult. There are limitations with any form of optical system. The major one is that it takes a considerable amount of time to obtain quantifiable gait information from the optical images and this results in a high cost for a gait laboratory tests. Other limitations are that the field of view is restricted to approximately one to two strides and the person being investigated may behave differently when they know they are being monitored, which is known as “white coat syndrome.”

One of the most important aspect of LPcomS is to develop our application for human gait analysis after recognizing the need for “out of the gait lab” systems, which enable a person to be monitored anywhere. To do so we choose to depend on the transformative power of smartphones that comes from their size and connectivity. They have become the fastest-selling devices in history, outstripping the growth of the simple mobile phones that preceded them. Today about half the adult population owns a smartphone as shown in figure 2. By 2020, it is projected that 80% of elderly population will have their own smartphone. [25] Smartphones have also penetrated every aspect of daily life. Portability and the size of the smartphone make them the first truly personal computers.

Recently, the smartphone with smart-shoe technology is increasingly used for gait analysis research. So the future research should intend to develop new energy efficient systems with extended battery life. Smartphones are widely used for navigating numerous important life activities, from researching a health condition to accessing educational resources. Nearly two-thirds of Americans now own a smartphone, and many of these devices are a key way to access the online world. About 62% of smartphone owners have used their phone in the past year to look up information about a health condition. More than half of smartphone users have used their phone to get the health information as shown in figure 3.

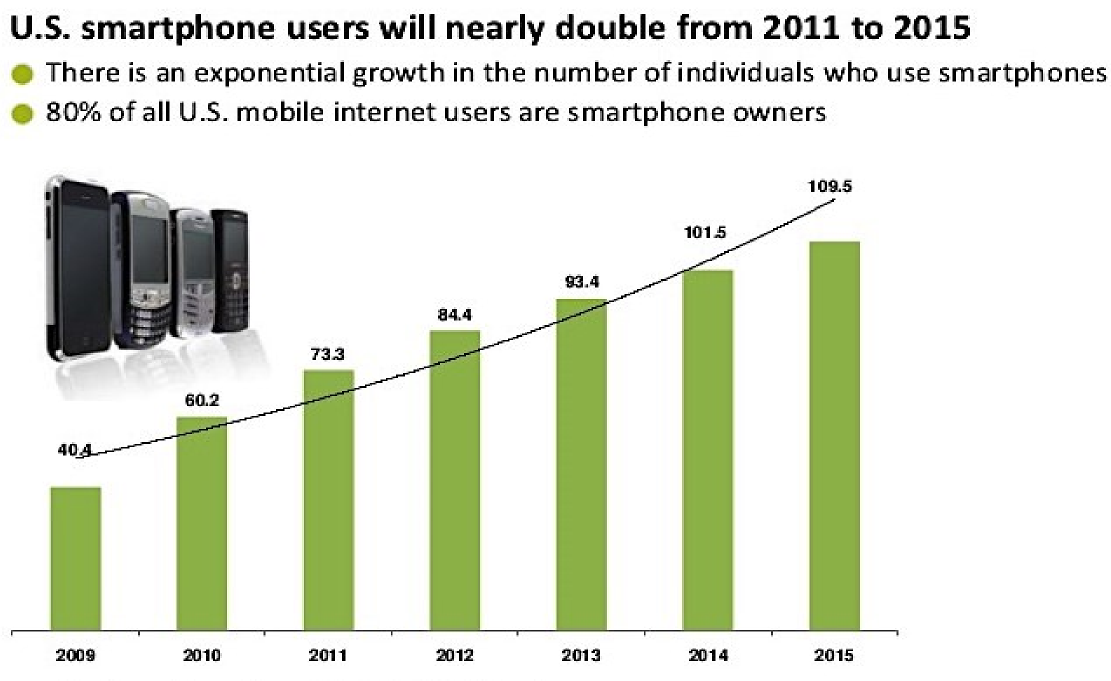


Figure 2. Increasing number of Smartphone users in USA [25]

The enormous increase of the use of mobile technologies as well as advancements in their innovative application to address health priorities has evolved into a new field of eHealth. This is known as mHealth (mobile health). The mobile healthcare market is comprised of connected medical devices, healthcare application, and with related mobile technology. The global mobile healthcare market is estimated at $6.3 billion in 2013 and is poised to reach $20.7 billion by 2018 at a compound annual growth rate (CAGR) of 26.7% [26].

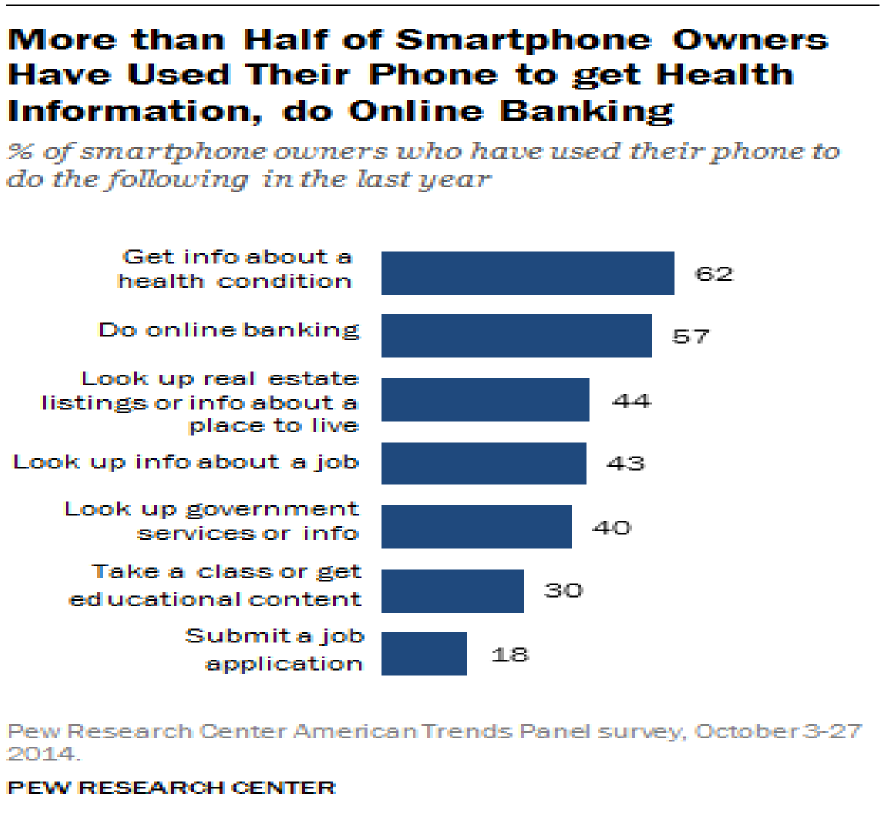


Figure 3. Smartphone users are getting health information [26]

Scenario 2: Alex is a 70-year-old who has been suffering from one of the most typical gait pattern abnormalities, which is called the "spastic gait abnormality." A stiff, foot-dragging walk caused by a long muscle contraction on one side causes this. He has suffered three major accidents over the last year due to his extreme unbalanced walking. His physician asked him to visit a gait lab for the assessment in every other week. In the lab he needs to place lots of marker in different places in his body and then walk in a long force plate for several times. Alex is psychologically so traumatized by the consequences of these accidents and the process of his treatment that he prefers to sit at home. Our system, LPcomS, can identify the unbalanced gait of Alex for a long period of time due to his abnormality and it can allow Alex to live a more independent and normal life.

To address the challenges posed by the above-mentioned scenarios, we propose a smartphone-based low energy gait analysis system using smart-shoe, which can prevent this type of unforeseen risky gait related injuries. To analyze gait, we need a dedicated long lasting connection among the mobile device, healthcare application and other technologies, such as smart-shoe system. First, we used the popular wireless networking technology that uses radio waves to provide wireless high-speed Internet and network connections, Wi-Fi module. But during the data collection process we faced a research challenge. The battery consumption was high and we failed to collect data for the expected period of time. To solve this problem, after evaluating all possible solutions we selected the LE Bluetooth device. Just like Wi-Fi Direct, LE Bluetooth is promising speedy device-to-device transfers over long distances but consuming less power than Wi-Fi devices.

We want to make our application to be workable for both android and iPhone devices. With the iOS SDK, Apple introduced the Core Bluetooth framework. Core Bluetooth allows developers to write applications that talk directly to hardware gadgets or other iOS devices but using the Bluetooth Low Energy (LE), also called Bluetooth-Smart standard. Things work differently for Bluetooth devices that do not use Bluetooth LE. But in our research for the proposed system we have used the Android device.

As a result, our model not only replaces the cost of heavy experimental equipment of laboratory set up and dedicated staff expense but also it would be an application that would assure that elderly people get their flexibility and freedom to do daily activities, even during the time we can monitor their gaits and walking patterns. It releases people from the discomfort of having markers on their body. We are assuring a low power communication module, which will be a generic model. That means it can be used to establish connection between two or more devices/ modules with minimum power consumption. Longer battery life of smartphone devices helps us to increase the sampling rate from the longitudinal gait monitoring opportunities. Moreover this application will work with both Android and iPhone devices.

CHAPTER 3 RELATED WORKS

Most of the smartphone-based gait-related research is based on adaptive system. The best way to prevent an injury of a patient with gait abnormality is continuous monitoring of a user's walking pattern. Earlier, a great number of researchers have talked about accurate gait detection systems using smartphone. But they did not talk about energy efficient gait monitoring systems. Moreover, they do not take into account the cost effectiveness of the system. Important limitations for wider acceptance of the existing systems for continuous monitoring are: a) cumbersome wires between sensors and a processing unit, b) lack of system integration of multiple sensors, c) interference on a wireless communication channel shared by multiple devices, and d) nonexistent support for massive data collection and knowledge discovery.

In [27], the authors designed a type of wearable force sensor based on a photo elastic triaxial force transducer to measure Ground Reaction Force (GRF) in gait analysis. Force sensors based on the optical fiber matrix were developed to detect the shear and compressive force during human walking [28-29]. In [30], R.C. Luo, *et al.* explained that the methodology of information reasoning from multiple sensors was regarded not only efficient but also reliable. Mathie *et al., in* [31-32] 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 classifing movements performed by subjects, and discussed a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. In [33], Morley *et al.* and in [34], Maluf *et al.* developed an insole-based system to quantify the conditions inside the shoe. Pappas *et al.*

[35] used a pattern recognition algorithm to define the changes during the gait cycle using their device comprising of three force-sensitive resistors (FSR) located on an insole (one under the heel, and two at the first and fourth metatarsal heads) and a gyroscope. The system was tested on two subjects with incomplete spinal injury and was used to trigger functional electrical stimulation (FES), which demonstrated benefit for both subjects. All of the above mentioned works have talked about the different sensors used in their research. But, they did not talk about the power consumption of their systems.

Several works those are close to social computing use microphones [36-40] and electrocardiogram (ECG) sensors [41-43] for daily activity detection. The former type, which consists of microphone and Bluetooth devices, helps to obtain contextual information about the user's environments and would be appropriate to perform a deeper analysis of the activity. However, high-level activity recognition, like, walking, playing, running or standing up, is done using other sensors. ECG can help in determining high-level activities by means of heart rate processing. In this case, some activities (walking or running) could be distinguished based on the effort needed to perform them. The problem here is that ECG sensors are expensive and uncomfortable for the user.

In all previous studies, personal medical monitoring systems have been used only to collect data for off-line processing [44]. Systems with multiple sensors for physical rehabilitation feature unwieldy wires between electrodes and the monitoring system. These wires may limit the patient's activity and level of comfort and thus negatively influence the measured results. A wearable health-monitoring device using a Personal Area Network (PAN) or Body Area Network (BAN) can be integrated into a user's clothing [45]. This system organization is unsuitable for lengthy, continuous monitoring, particularly during normal activity [46], intensive training or computer-assisted rehabilitation [47]. Recent technology advances in wireless networking [48], and integration of physical sensors, embedded single chip, promises a new generation of wireless sensors suitable for many applications [49]. However, the existing telemetric devices either use wireless communication channels exclusively to transfer raw data from sensors to the monitoring station, like smartphone. The use of standard high-level wireless protocols such as Bluetooth that are too complex, power demanding, and prone to interference by other devices operating in the same frequency range. These characteristics limit their use for extended wearable monitoring. Simple, accurate means of monitoring daily activities outside of the laboratory are not available [50]. Finally, individual monitoring sessions record are rarely integrated into research databases that would provide support for data mining and knowledge discovery relevant to specific conditions and patient categories.

In the world of wireless communication, energy consumption to sustain network connectivity and accomplish data transfer is a big concern. Mobile industries have the great challenge on managing energy consumption while running and introducing various applications. The energy cost to transfer a certain amount of data depends on the wireless technology, network condition and the type of application it is executing on.

In other works [51], it is described that the data for activity recognition are acquired through any kind of mobile device (not only mobile phones). Although, these data are sent to a server where the information is successively processed. Thus, the computational cost is not a handicap, as learning and/or recognition are performed in the server and more complex processing can be applied. Also, this might decrease the energy efficiency of the mobile device. In distinction, efficiency becomes a vital issue when processing is carried out in the mobile device itself [52]. In this manner, in order to apply a solution based on distributed computing, the device must always be connected to a data network. This does not currently represent a major drawback, since most devices have this kind of connectivity. Even though, there are still users whose devices have not been related with a continuous data connection outside the range of Wi-Fi networks. Finally, reduction of the energy cost conflicts with the need to send the data collected in a continuous way between the external device and the server or mobile devices. This means that current approaches of sensor cannot be applied and devices must be repeatedly wake up from sleep mode. Furthermore, the rigorous use of the data network has a deep impact on the energy use.

In [53] the authors showed the increase in energy consumption when 3G and Wi-Fi are used. In [54], it can also be observed that about 44% of battery usage in smartphones occurs by the use of GSM (3G or 2G). There are systems that use precise hardware [55-57] and others use general purpose hardware [58-59]. Now a days, the use of generic hardware as smartphones is a benefit to users as the cost of such devices and their versatility are assets in their favor. The risk of loss, forgetting and neglect is decreased because users' smartphones have already been integrated into the users' daily life. However, general-purpose devices are used for other purposes too, making phone calls, surfing the Internet and listening to music. Because of this, the gait analysis system must be implemented in background mode and should cause the least influence as possible on the system in terms of complexity and energy consumption.

To reduce the power consumption, the device discovery performance of classical Bluetooth protocols has been intensively inspected through real time experiments, simulations, and proper modeling methods [60]. The authors of this paper talked about the probabilistic model checking technique to compute the performance constraints of device discovery in terms of the mean time and the mean power consumption. Different types of experiments were performed to show that even though it required a long period of time for each node to become aware of all its neighbors. The Bluetooth topologies can be obtained in about six second after the connection setup through those discovered devices [60]. This is very high for applications where a fast topology construction is important. They discovered that improper parameter settings could significantly deteriorate the device discovery potential and increase meaningless energy consumption. They consequently proposed a solution to adaptively reduce the discovery latency when encountering an exceptionally long delay to be discovered by any scanner. Based on that, some researchers developed different strategies, which significantly enhanced the latency performance regarding the parameter settings.

A comprehensive experiment on real devices, discovering the parameter space to determine the relationship between parameter settings and mean discovery latency or power consumption values have been proposed in [61]. An algorithm is proposed to adaptively determine parameter settings, depending on a mobility context to reduce the mean power consumption for Bluetooth devices. The compromise between different parameters is not clearly explained. Thus the work proposed in this study cannot be applied to the next generation networks.

In [62], the authors implemented an end-to-end Bluetooth-based mobile service framework. To detect surrounding mobile services, the framework depends on machine-readable visual tags for out-of-band device and service selection rather than using the standard Bluetooth device discovery model. This work verified that a tag-based connection establishment procedure could offer substantial improvements over the standard Bluetooth device discovery model. Although, there have been rigorous studies presented for classical Bluetooth device discovery. But, these studies cannot be applied to Bluetooth low energy (BLE), since the Bluetooth standard made a fundamental change in the device discovery mechanism of BLE. Very few research work related to the performance evaluation of the BLE discovery process has been published.

In [63], the authors introduced an analytical model. They studied the performance of BLE device discovery, particularly with multiple devices. In this work, the average latency of device discovery is given by:

$$D_{CS} = \left(\frac{1}{P_{CS}} - 1\right) R + T_S + T_{IFS} + T_{CR} \qquad (1)$$

Where, T_S, T_{CR}, and T_{IFS} denote the sending time of ADV_IND and CONN_REQ packets, and inter frame space, respectively. These have been derived from the length over bit rate of R bps (44 octets over 1 Mbps), and P_{CS} means the successful probability of the connection setup. This modeling result as well as the methodology of this research may provide a potential guide to better enhance the performance of the BLE advertising process.

In addition, the author proposed an algorithm using the connection report for BLE scanner to observe the network conflict degree and adaptively adjust its scanning parameters. As a result the shorter latency could be achieved. The complexity of this proposed system is very high and it requires high energy for the scanning process. Energy consumption is an important limitation in the case of BLE implementation for short-range communications and hence it should be considered carefully.

Table 1. Comparison of existing work based on different features

Approach	**Mobility**	**Generic System**	**Low Energy System**	**Higher Sampling Rate**	**Cost Effective**
Smart-Step [80]	Yes	No	Yes	No	No
K Ylli [81]	No	No	No	No	No
Keuchul Cho [82]	No	No	Yes	No	No
W. Donkrajang [83]	No	No	Yes	No	No
Musolesi [17]	Yes	No	No	No	No
Liu [60]	No	No	Yes	Yes	No
Drula [61]	No	No	Yes	Yes	No
Duflot [65]	Yes	No	No	Yes	No
Luis [84]	Yes	No	No	Yes	No
Wahab [85]	Yes	No	Yes	Yes	No
Renato [86]	Yes	No	No	Yes	No
Our Approach	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

The previous studies on Bluetooth Low Energy discovery (BLE) are still far from thorough. It is important to know to what extent parameter settings would influence the discovery process as recurrent device discovery is commonplace in BLE networks [60, 64-65]. In fact, wide-range settings of the parameters provide new features for BLE devices to customize their performance in explicit applications [66-68]. In other words, an advertiser should be capable of choosing appropriate parameters that meet the requirements for practical BLE networks. Thus, it is necessary to develop a new and accurate discovery model for existing BLE architectures. This motivates our study of modeling the application to establish the communication between two modules, smartphone and smart-shoe.

As we said, there were several approaches for gait monitoring system. The taxonomy for wireless system for gait analysis is presented below. The green marked boxes are the methods we used to build our system [Figure 4].

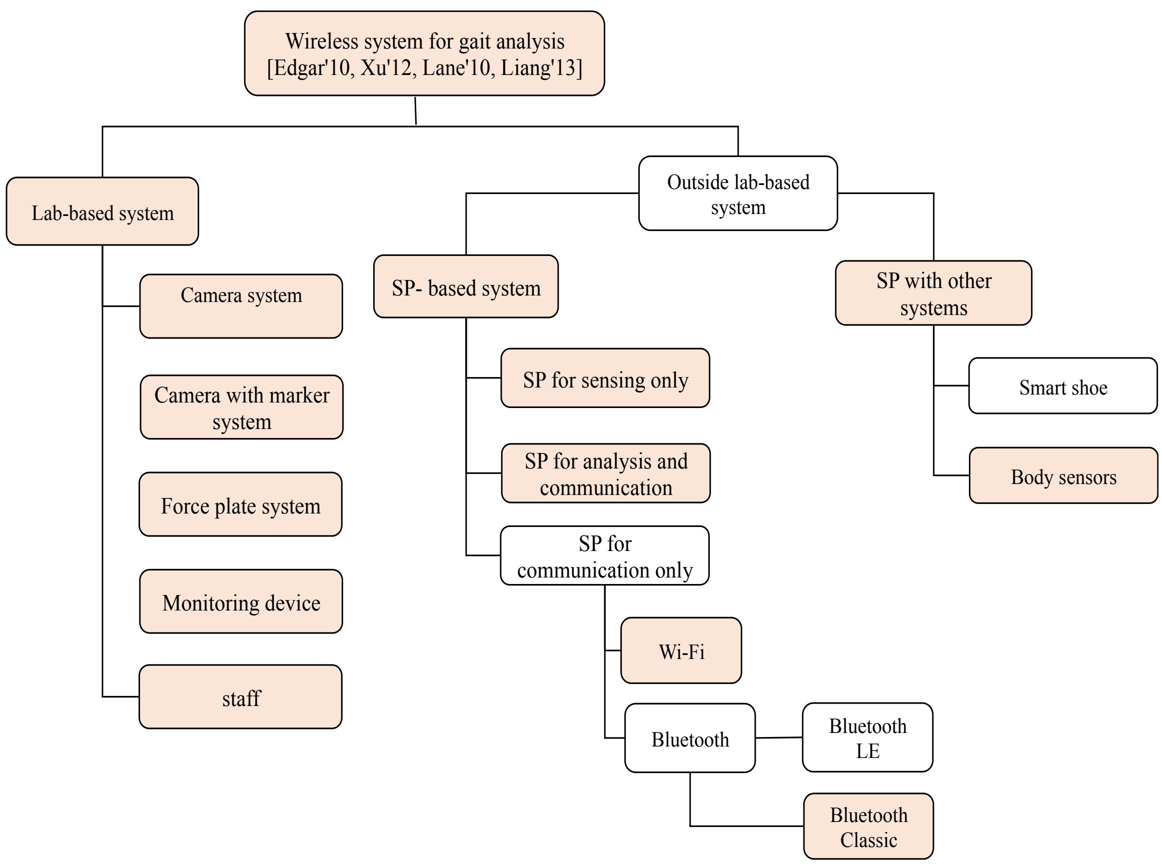


Figure 4. Taxonomy for wireless gait analysis systems

Encouraged from these examples and to address the drawbacks of the above-mentioned systems, we developed a smartphone- and smart-shoe-based LE Bluetooth communication system for human gait analysis to predict fall related injuries. Moreover our design is highly secure and inexpensive because it requires only a smartphone with low cost smart-shoes. We illustrate the difference between our system and the other related works in table 1.

CHAPTER 4 BACKGROUND

4.1 Normal Gait

To determine the abnormal gait patterns, we must first establish the criteria for normal walking. Normal walking is harmonization of balanced muscle contraction, joint movement, and sensory perception. Limbs, trunk, nerve-conditioning system and systemic diseases will affect a person's gait. Disproportion of these body parts often causes impairment which leads to risk of fall. Gait assessment is important to help identify areas of impairment for planning treatment. Generally clinical medicine is only concerned about the patient's gait analysis while normal gait is often ignored exploration. Healthy people walk on two legs, generally able to automatically adjust the position to achieve balance and stability. The pelvis is affected by the arm swing, resulting in periodic rotation and incline. Also ankle, knee and hip angle changes in the process of motion for coordination. So the normal gait is periodic, with coordination and balance about the characteristics [69]. The walking speed decreased with the increasing age, and the increasing age decreased the greatest walking speed more significantly than the decline of comfortable walking speed.

Gait assessment is used to evaluate the patient's ability to maintain proper posture during walking. This is a hope to have a way to judge more precisely whether a person's gait is normal or not. Quantitative analysis of gait stability and gait symmetry has obtained a series of parameters results. Disorders of balance and gait are particularly important in the elderly because they compromise independence and contribute to the risk of falls and injury.

Research on the human gait comprises the qualitative and quantitative evaluation of the various factors that characterize it. Depending on the field of research, the factors of interest vary. For instance, for security purposes, interest may center on distinguishing and identifying persons based on a general characterization of their silhouette and the movements between the subject's different body segments when walking [70]. From the clinical point of view, the importance of human gait analysis lies in the fact that gait disorders affect a high percentage of the world's population and are key problems in neurodegenerative diseases such as multiple sclerosis (MS), amyotrophic lateral sclerosis or Parkinson's disease. Study of human gait characteristics may be useful for clinical applications; it has been the subject of numerous studies such as Mummolo et al.'s recent work [71] and may benefit the various groups suffering from gait-related disorders. There are studies on the elderly which link changes in various gait characteristics to gait deficiency [72]. The first symptoms of some neurological diseases are poor balance, a significantly slower pace, with a stage showing support on both feet [73]. Multiple sclerosis users also show several gait alterations such as a shorter steps, lower free speed when walking and higher cadence than subjects without MS. In these cases, the knee and ankle joint rotation are distinctive for lower than normal excursion with less vertical ascent from the center of gravity and more than normal bending of the trunk [74]. Another condition related to gait and balance deficiencies is osteoporosis [75], a systemic disease characterized by lower bone mass and deteriorated bone microarchitecture, which means more fragile bones and greater risk of fractures. In the elderly, physical exercise has a major impact on osteoporosis because it significantly helps to prevent falls, which are the biggest risk factor for this age group [76]. This condition is asymptomatic and may not be noticed for many years until it is detected following a fracture. Therefore, evaluation of gait quality using smart-shoe may be valuable for early diagnosis. Smartphone and smart-shoe-based gait detection system need a LE communication system to collect longitudinal data for monitoring the patient for longer period of time.

4.2 Communication Topology Selection

In LPcomS, we have developed a smartphone and smart-shoe-based gait monitoring application. Which can perform a single-subject design tailoring data collection to the specific needs of each patient. Initially, we tried to collect walking data by only using the smartphone sensors. To overcome the constrains of using smartphone sensors only, we have developed pressure sensor embedded low cost smart-shoe. This consist of four pressure sensors which we will describe details later in this section. For data collection from the smart-shoe, the biggest challenge is to establish a low power dedicated communication framework. Selecting the right device for the communication was another crucial decision. While choosing the device we study about the popular data transmission technologies.

Table 2 shows the comparison study of three most popular wireless technologies, Bluetooth, ZigBee, and Wi-Fi protocol. They correspond to the IEEE 802.15.1, 802.15.4 and 802.11a/b/g standards, respectively. For each protocol, separate associations of companies worked to develop specifications covering the network, security and application profile layers so that the commercial potential of the standards could be realized.

Table 2. A comparison study of Bluetooth, ZigBee, and Wi-Fi protocol

Standard	**Bluetooth**	**Zigbee**	**Wi-Fi**
IEEE specification	802.15.1	802.15.4	802.11a/b/g
Frequency band	2.4GHz	868/915 MHz; 2.4 GHz	2.4 GHz; 5 GHz
Max signal rate	1 Mb/s	250kb/s	54Mb/s
Nominal range	10 m	10-100 m	100 m
Channel bandwidth	1MHZ	0.3/0.6 MHz; 2 MHz	22MHz
Topology	Star	Mesh, star, tree	Star
Power consumption	Low	Very low	High
Battery life	Days -weeks	Months-years	Hours
Application focus	Cable replacement	Monitoring and control	Web, email, video
Key verticals	Health and fitness	Building, Automation, Commercial and Industrial	Residential and commercial

From the study, we can see that the Bluetooth communication has covered a relatively short range. It was never intended to be a Wi-Fi replacement. Other frustrations stemmed from its tendency for interference from other devices in the 2.4GHz range, and the rage-inducing incompatibility issues faced when it comes to pairing some Bluetooth-enabled devices.

Bluetooth has solved its “teething” problems and found its way into low-power applications where power-hungry and CPU-hungry Wi-Fi can’t compete. Bluetooth LE includes a power-saving feature called "low-energy technology." Bluetooth LE not only uses the new low-energy technology, but also relies on high-speed data transfers. Table 3 shows the improvement of Bluetooth LE over classic Bluetooth.

Table 3. The improvement of Bluetooth LE over classic Bluetooth.

	Classic Bluetooth	**Bluetooth LE**
Network standard	IEEE 802.15.1	IEEE 802.15.1
Range	100 m	>100 m
Frequency	2.4 – 2.5 GHz	2.4 – 2.5 GHz
Over the air data rate	2.1 Mbps	1 Mbps
Application throughput	0.7 – 2.1 Mbps	0.27 Mbps
Latency	100 ms	6 ms
Peak current consumption	<30mA (Varies)	<15mA (read and transmit)

Apart from an improvement in connectivity, LE Bluetooth features a number of additional benefits. Now the only competitor of Bluetooth LE is Wi-Fi Direct. Both specifications are promising to make it easier for user to quickly transfer pictures, files and other data between two wireless devices such as smartphone and smart-shoe without the need for a Wi-Fi network or USB cable. So before selecting the device we made another comparison study (Table 4) between Bluetooth and Wi-Fi Direct.

Table 4. Comparison between LE Bluetooth and Wi-Fi Direct

	Bluetooth LE	**Wi-Fi Direct**	**Winner**
Speed	25Mbps	250Mbps	*Wi-Fi Direct*
Range	>200 feet	600 feet	*Tie (home)*
Security	AES 128-bit encryption	AES 256-bit encryption.	*Adequate in terms of security.*
Backwards Compatibility	Yes	Yes	Tie
Battery life	Weeks	Months to year	Bluetooth LE
Relative Power Consumption	Very low	High	Bluetooth LE

Key technology and simple topology reduces implementation complexity significantly. Bluetooth is made of very small silicon footprint and thereby very low cost. It is very robust through frequency hopping compared to other wireless technologies. Also it is very secure through optional 128-bit AES encryption. It consumes very low power – designed to be asleep. The low energy and 24Mbit/s transfer rate make Bluetooth an ideal solution for seemingly stalled technologies. Bluetooth LE is very easy to use; there is no need of any experience of Bluetooth protocol stack application. It is full-duplex bi-directional communication, and supports the minimum baud rate of 4800 bps, bridge mode (USART transparent transmission), and direct-drive mode. It is able to communicate with the remote reset of module by APP in mobile devices, and the setting of transmission power.

CHAPTER 5 SYSTEM DESCRIPTION

In this chapter, we describe the various components of our prototype LPcomS (figure 4) and present in detail the hardware design for low power communication.

5.1 Smart-shoe Hardware

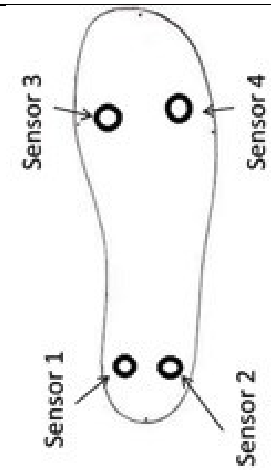
The hardware devices we used to build a shoe are four sensors included arduino, class 2 bluetooth, and a power supply unit.

5.1.1 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 gait. 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. Most of the body pressure is measured from the rear foot and the fore foot. Considering these issues we have placed two of our sensors in the fore foot region and two of them are in the rear foot region as described in table 5.

We have used piezoresistive force sensors for measuring the pressure while walking [77]. The resistance of this sensor changes with the change in pressure. The harder you 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.

Table 5. Insole Sensing Position

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

5.1.2 Arduino

An Arduino 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.

5.1.3 Class 2 Bluetooth module: RN42

The Class 2 module is a small form factor, low power, highly economic Bluetooth radio that adds wireless capability to products [78]. The class 2 module supports multiple interface protocols, is simple to design in and fully certified, making it a complete embedded Bluetooth solution. The module is functionally compatible with other Bluetooth modules. With its high performance on chip antenna and support for Bluetooth® Enhanced

Data Rate (EDR), the class 2 module delivers up to 3 Mbps data rate for distances up to 70 feet. It also comes in a package with no antenna. The device is shorter in length and has RF pads to route the antenna signal, which can be useful when the application requires an external antenna. It is fully compatible with the Bluetooth 4.0 transmission method.

5.2 Smart-shoe: prototype

Primary features of the foot pressure sensing shoes are their unobtrusiveness and portability. The wearable nature of shoes allows them to collect user's motion signal freely. The schematic of the pressure sensing system is presented in Figure 5.

With of four pressure sensors the smart-shoe is comprised one Arduino and one class 2 Bluetooth module with a battery power supply. We use an Arduino, a low power class 2 Bluetooth device as a wireless Bluetooth communication module on the shoe. This module receives the signal and transfers to the Smartphone through a Bluetooth communication network.

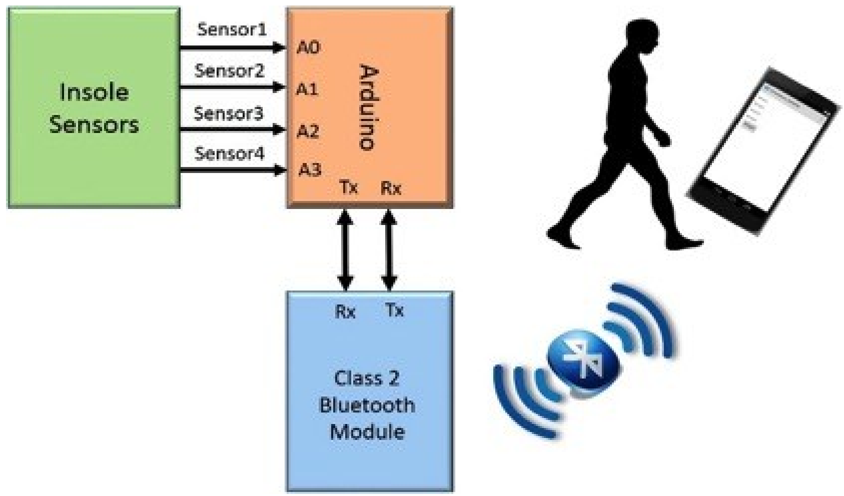


Figure 5. Overview of LPcomS

In order to process the pressure data, the communication module has two different software tasks. One is for the Arduino and another is for the Android [79]. In the Arduino, we programmed to read an analog signal from the shoe sensors and buffered the signal that is sent to the smartphone through a serial port as a string. Pressure data was collected for the users over a period of time and every time a subject was tested with different types of walking. An early prototype of Hardware Mountain of the shoe is shown in figure 6.

As we mentioned before, we have used four piezoresistance sensors in the sole embedded with an Arduino, a class 2 Bluetooth module, a power supply unit, and a smartphone with the results of a system assessment. The sensors used in the smart-shoe were selected with the goal of creating a module which is capable of sensing many motions and pressure values. Those would help us to characterize the gait.

Figure 6. Early prototype of the LPcomS

By using all of the electronics (including the sensors located at the bottom of the shoe), a class 2 module for the wireless transmission, and the power supply, we were able to engineer a smart-shoe. Figure 7 demonstrates the block diagram of the smart-shoe, along with the wireless components, and sensor encapsulated insole, in correspondence with the smartphone application.

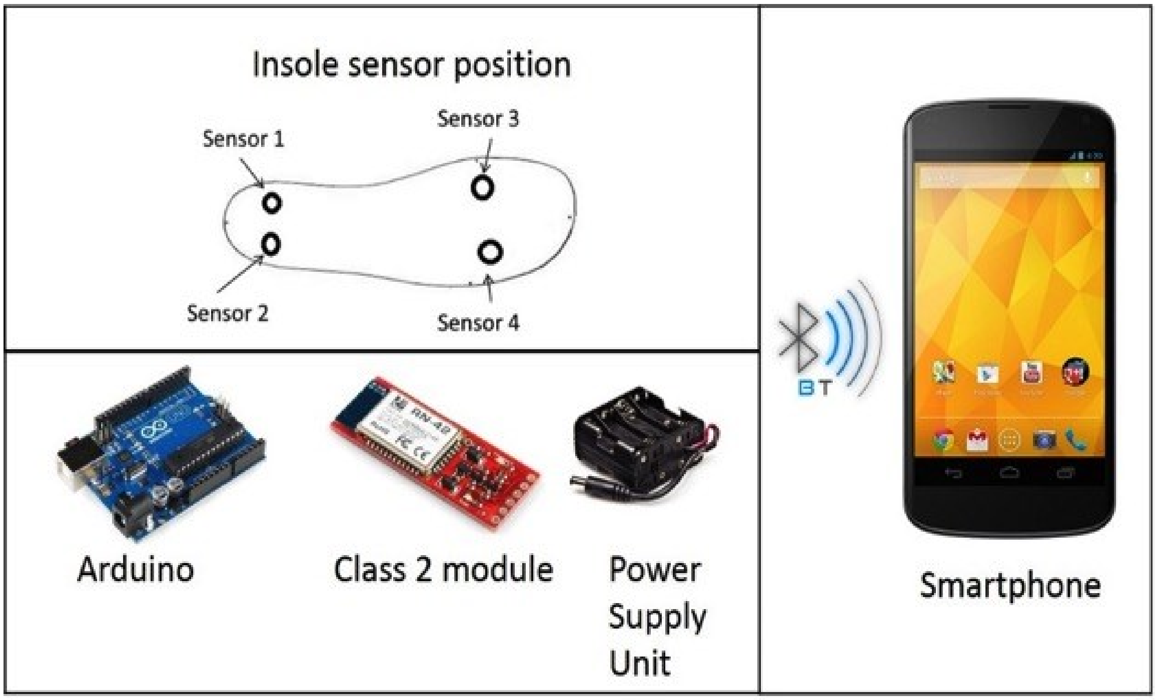


Figure 7. Components of a wireless shoe, and attachment sensors to the shoe with anatomical locations

CHAPTER 6 ALGORITHM DESIGN AND EVALUATION

6.1 Methods of Data Communication

A low-power, integrated shoe monitor system (LPcomS) was designed and developed in this study. This insole monitoring system was designed with pressure sensors, Bluetooth connectivity along with a power supply, which was integrated in the shoe. By using this technique to reduce the power consumption of the smart-shoe system we engineered various hardware devices in order to determine which low power scheme was viable.

6.1.1 Low-Power Schemes

This section describes the system design aspects utilized in LPcomS, which help in achieving low-power functionality in the system:

- When a Bluetooth device requires a service, it begins a discovery process by sending out a query for other Bluetooth devices and the information needed to establish a connection with them.
- Bluetooth class 2 device can optionally implement adaptive power control. This mechanism allows a Bluetooth radio to reduce power to the minimum level required to maintain its link, thus saving power and reducing the potential for interfering with other nearby networks.
- One of the obvious reasons to achieve the low power consumption is the ability to advertise and broadcast data without the need of establishing a complete

connection. Establishing a complete connection would require a higher radio duty cycle consume more power.

- Low duty cycle modes, which potentially lower the power consumption with two modes; sniff and hold (stand by). Each of these modes has duty cycle affecting parameters, which in turn influence power consumption.
- Comparing with slave, a master takes the same time but the sniff mode consumes about 40% more power. With the same settings for a slave sending 250 bytes the opposite occurs when comparing power consumption. However for a slave in idle state with the same settings compared above there is a vast difference in power consumption; whereas the slave in sniff mode only consumes around 25% of what a slave with the default setting consumes. Lower power consumption is achieved if the latency in sniff mode for the connection is higher. A faster and more power efficient connection is achieved when allowing a shorter interval between scan and longer time window.
- Enabling/disabling of sensor data collection was carried out in two steps. In the first step, the application finds the desire address, before enabling data communication between shoe and the phone. As a second step, the data collection process was turned on.
- For pairing mode, the module attempts to connect with the remote device matching the store remote address. Once it finds this device, it stores the address into the remote address field and auto-connects to the remote device.
- The event timers were running and the sensors were in the measurement mode as long as the system was in the walking mode. Before turning off the data collection

of the sensors, a message will show up, after which the whole system was put in a lower power mode.

- Bluetooth class 2 module allows up to 1.5Mbps sustained, 3.0Mbps of user data to be transmitted in each connection. Hence, System's connection interval is defined as 4-times that of the message set events, that System has one connection event, saving the radio power consumption.

The idea behind Bluetooth LE is to conserve battery life while maintaining an always-on environment by remaining sleeping unless data is being shared. Once a device is paired, the connection remains active only while in use. A feature that was not available in previous generations of Bluetooth technology due to difficulty in pairing and connecting some Bluetooth-ready devices. In the table 6 we explained the advantages and disadvantages of Bluetooth states when they execute the particular method. The state when Bluetooth remains in idle or standby, not connected state for discovery and connection method it may experience additional latency when pairing and connecting. We tried to focus on that point. Through our algorithm where the Bluetooth device has to discover only a target device without considering any other available signals, would reduce this possible additional latency. Hence that would show up a positive impact on power consumption.

Table 6. Advantages and disadvantages of Bluetooth states using methods

Method	Bluetooth State	Advantages	Disadvantages
Optimize Inquiry (Discovery) and Page (Connection) Window	Idle (Not Connected) or Active Connection	The current can be reduced from more than 20 mA to less than 5 mA (combining this method with Sniff mode uses less than 3 mA).	Causes additional latency when pairing or connecting.
Sniff/ Discovery Mode	Transmit Active Connection	This mode can be combined with the Optimize Inquiry (Discovery) and Page (Connection) Window or Enable Deep Sleep methods for lower power consumption.	
Enable Deep Sleep	Idle (Not Connected)	With this method, current is reduced to about 300 µA.	This method can cause latency issues and may drop the first byte if the device wakes on RX data. It also causes a loss of performance/power when the device wakes frequently.
Disable Output Drivers	Idle (Not Connected) or Active Connection	This method is simple to use. However, it depends on the load: if the device is not connected there are no power savings. This method is required for Roving Networks evaluation boards to measure power accurately.	
Lower Transmit Power	Idle or Connected	This method lowers power consumption during transmit	The device has a shorter effective range.

6.2 Android Implementation

The current implementation of the Android application (App) is based on Google's Nexus Android. We integrate this application with smart-shoe through the Bluetooth communication. This app can add patient with their personal information. From the existing patient list it can collect data tailored to individual patient. During the data collection, the sensor data notified by the application through Bluetooth communication can be displayed on the screen in real time. There is a graphical representation of those sensor values. So observer can identify the patient's walking pattern. The sensor values also can be written to a comma separated value (csv) file on the smart phone's storage for future analysis. Because of the low power communication, longitudinal data collection is possible. The sample rate of walking data is high that leads us to more correct pattern recognition. During the data logging session, if there is an accidental connection loss, the application immediately gets connected back in the same mode as it was operating.

When there is inconsistent network strength, reconnecting to the server is prone to constant disconnections, which may cause additional data loss in application. To avoid this from occurring, the application checks the signal strength during scanning and an automatic reconnection takes place only when the signal strength reach in a desire level, which is an empirically established threshold we got during experiment.

6.3 Data Collection System

Here we used a plantar pressure system for pressure data collection from shoe. Four pressure sensors are placed on the shoe. Two sensors are place on the heel and two sensors are place on the toe of the foot to collect the insole pressure data. The collected data is transmitted over Bluetooth in a smartphone. Volunteers were recruited for the validation of the smart-shoe system. The testing involved placing the smart-shoe instrumentation on the subjects' own walking shoe. Each subject was asked to perform a series of walking tasks, while systems simultaneously collect data and measure the power consumption of the smartphone battery.

Table 7. Summary of Subject Characteristics.

<table>
<tr><th></th><th>Healthy Subject</th><th>Testing Scenarios</th></tr>
<tr><td>Gender</td><td>3 males, 3 female</td><td rowspan="4">Free Gait
Propulsive Gait
Spastic Gait</td></tr>
<tr><td>Age [years]</td><td>27.3 (25-35)</td></tr>
<tr><td>Height [m]</td><td>1.65(1.5-1.8)</td></tr>
<tr><td>Weight [kg]</td><td>73.4(58.2-94)</td></tr>
</table>

A total of 10 subjects were recruited. Characteristics for each group are summarized with means (and standard deviations) in table 7. Each subject first walked at his or her own self-selected natural pace for 2 to 4 trials, termed "free gait." A sample pressure variation of insole sensors are shown in figure 8.

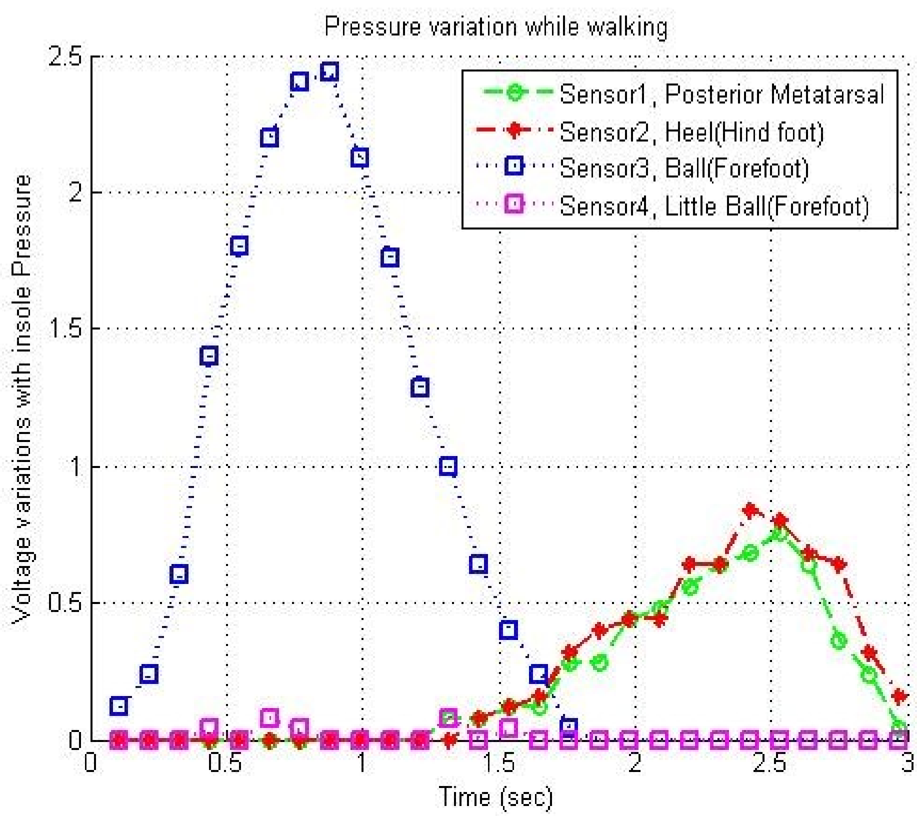


Figure 8. Insole Pressure Variation of an user while walking

6.4 Principles of the LPcomS

In our proposed system, the smart-shoe is used to collect the foot pressure values while the subject would be asked to perform different types of walking. The application on smartphone is another module to integrate with the smart-shoe. Low power communication assures longer and accurate data collection of patients. Saved data will be used to train the application for an individual. The higher sampling rate can assure, more accurate pattern recognition. The long-term plan is after receiving the data through Bluetooth communication, we will have processed it inside the mobile phone to identify the abnormality in walking pattern. At that moment, the system will detect a high-risk of gait pattern and enable a warning to the subject through an audio message and vibration to alert them about the imminent fall related injuries. The best way to help patients with gait abnormality is to prevent them from an injury. Our system will compare the real data with training set to identify individual normal and abnormal gait pattern. It will generate an alert to the user if it finds any abnormality in gait pattern. Moreover if it detects a fall then it will inform the caregiver though a text message. Another big idea is to establish a home monitoring system for the subject. Smart-shoe will be connected with smartphone, laptop, smartwatch, smartTV and smartlight to identify the patient's activity and measure walking pattern [figure 9].

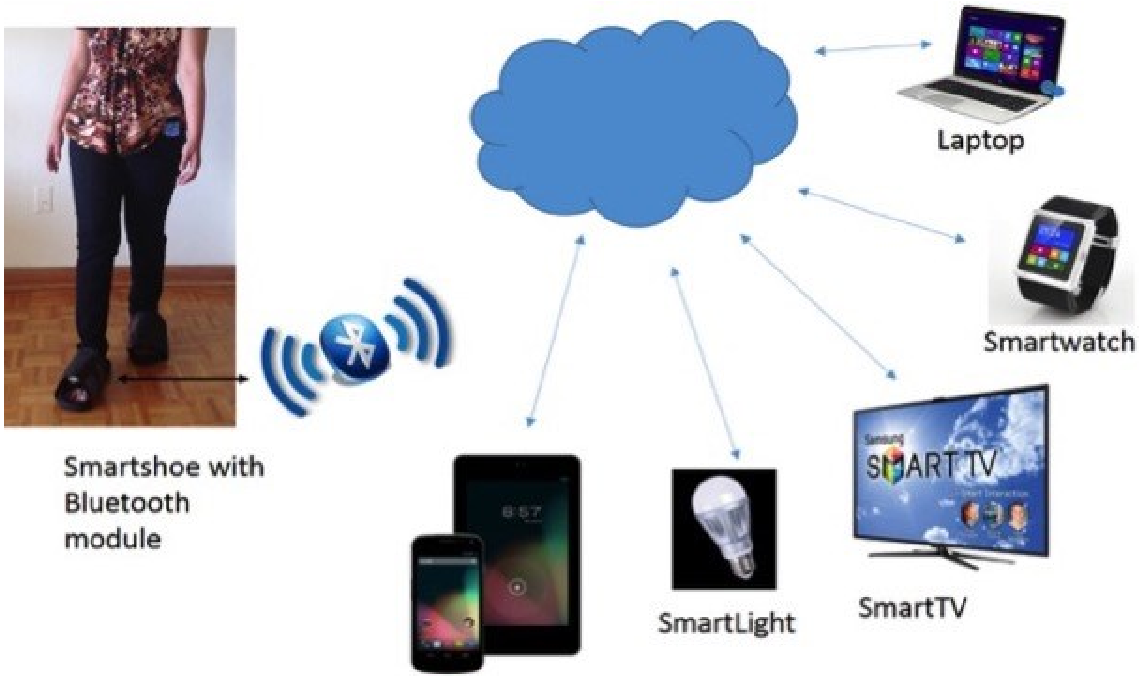


Figure 9. Proposed home monitoring system

Our target customers are elderly people as we discussed before. To accomplish the vision of home monitoring system we need to have a dedicated trusted communication among those devices that consumes low power, thereby will have a longer battery life. Our target is to make the communication model generic and will work with both iPhone and Android. Android 4.3 and higher supports BLE and Apple iOS has supported BLE since the iPhone 4S.

In our system the Bluetooth LE class-2 device operate in four different modes as shown in figure 10, depending on required functionality: advertising, scanning, initiating and connection. A device in advertising mode, named advertiser, periodically transmits advertising information. On the other hand, a BLE device in scanning mode, named scanner, periodically scans the advertising channels and listens to advertising information.

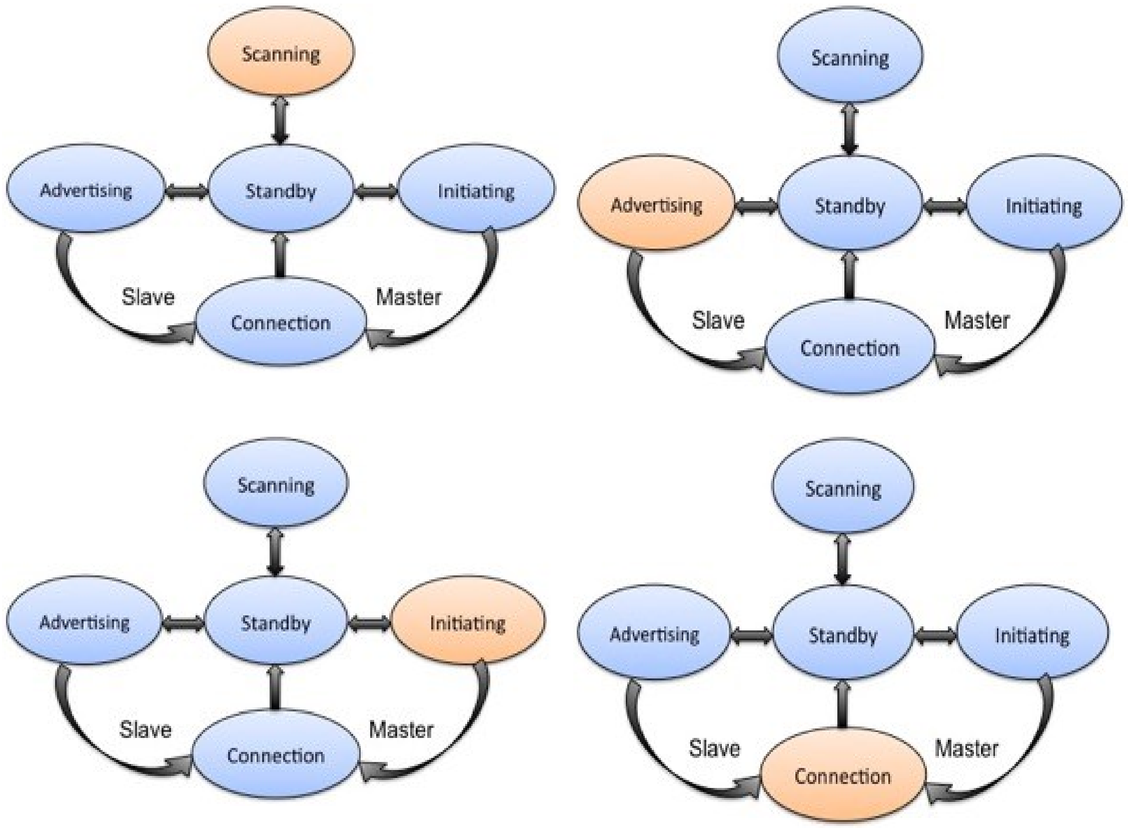


Figure 10. Different States of Bluetooth connection

In Bluetooth low energy, servers announce their presence using a procedure known as "advertising". Client devices listen for these announcements to create a list of interested partners. Once a client has located a server of interest, it initiate the process of creating a connection. After establishing a successful connection they start communicating with each other in master and slave role. The state specifications of the Bluetooth connection explained in table 8.

Table 8. State specification of Bluetooth connection

State	State Description
Standby	Does not transmit or receive packets
Advertising	Broadcasts advertisements in advertising channels
Scanning	Looks for advertisers
Initiating	Initiates connection to advertiser
Connection Master Role	Communicates with device in the Slave role, defines timings of transmissions

6.5 Algorithm design and evaluation of the LPcomS

In order to develop the application we have used the algorithm shown in figure 11 to establish the Bluetooth connection between smart-shoe and the smartphone. At first the algorithm searches for the device that supports our proposed communication features. The application will move forward to execute the next operations after accurately detecting the correct device. Enabling the Bluetooth device we initiated an action button to discover the available Bluetooth devices around the smartphone. Among the available devices, the algorithm looked for our target device (smart-shoe Bluetooth device) by its name. Subsequently getting the target device name and address, we are checking for whether the device is bonded or not. When two Bluetooth devices are ready to share data with each other, they can be bonded together. Bonded devices automatically establish a connection. Bonds are created through one-time a process called pairing. When devices pair up, they share their addresses, names, and profiles, and usually store them in memory. Also they share a common secret key, which allows them to bond whenever they're together in the future. If the device is not bonded or paired the application will do that with a pairing code. Then we began a thread to receive and transmit the sensor data through a class 2 Bluetooth module embedded in smart-shoe. Here the connections are master-slave communication. We used the Bluetooth Socket to plug in the connectivity. We also have created a thread for the server to listen always from the connected device. Thenceforth the socket is 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 send it serially to the Bluetooth device of smart-shoe. Smartphone Bluetooth receives these data as string. Then we displayed the data on the Android device with corresponding sensors.

As we have described earlier the application starts with saving individual patient information. We record the sensor data with respect to the individual patient. We save the data in order to train our system for the individual patient. Later on by analyzing this information of the 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 which is converted into voltage. 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 were gathered by piezoresistive flexi force sensors in a time span and transmitted to the smartphone through a Bluetooth communication network.

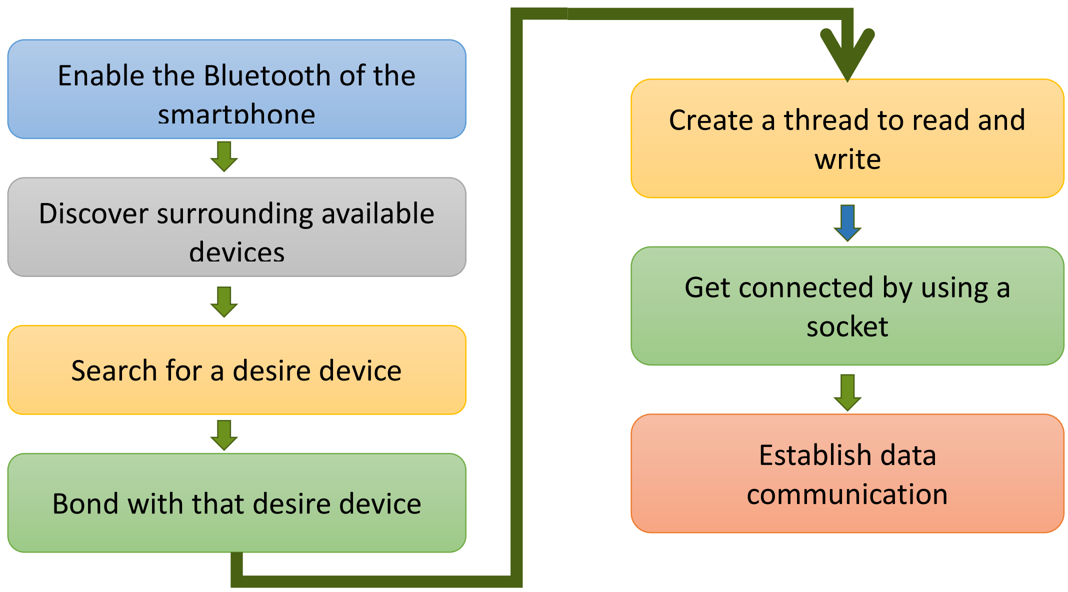
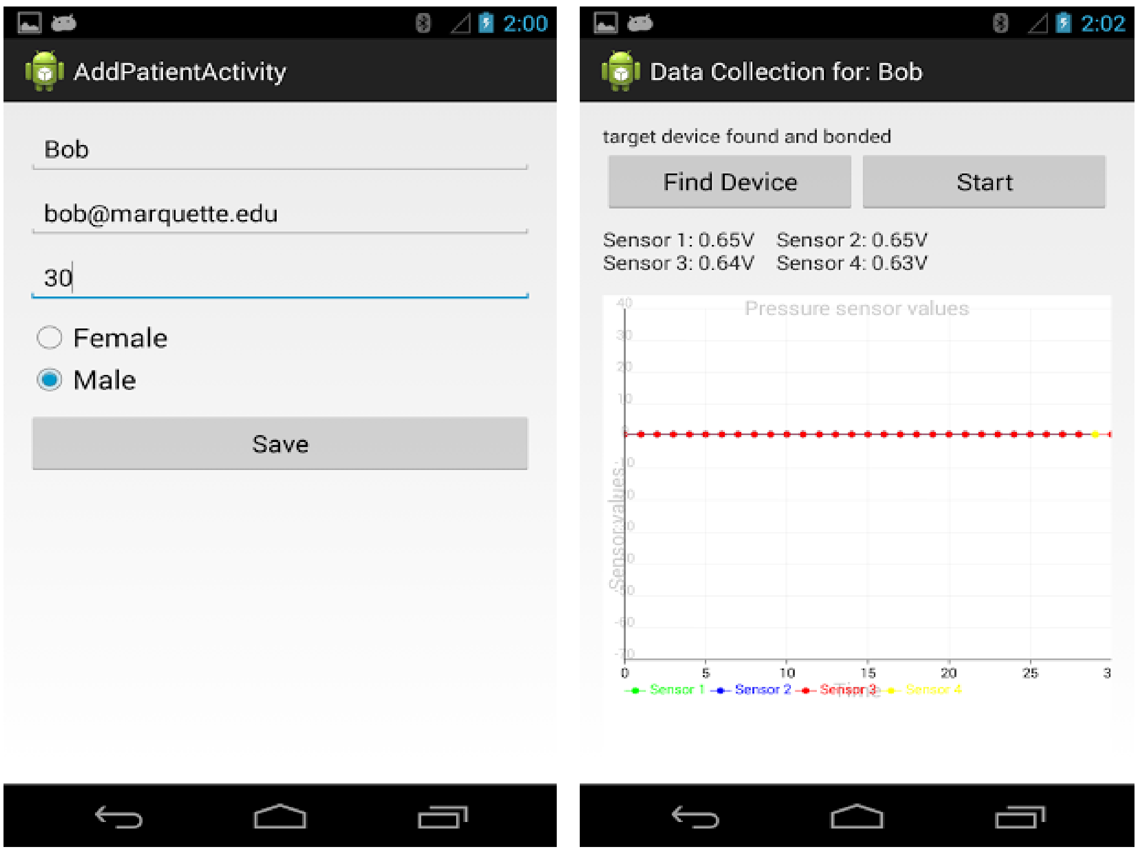


Figure 11. Algorithm on Smartphone for Bluetooth communication

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 smart-shoe sensor data.

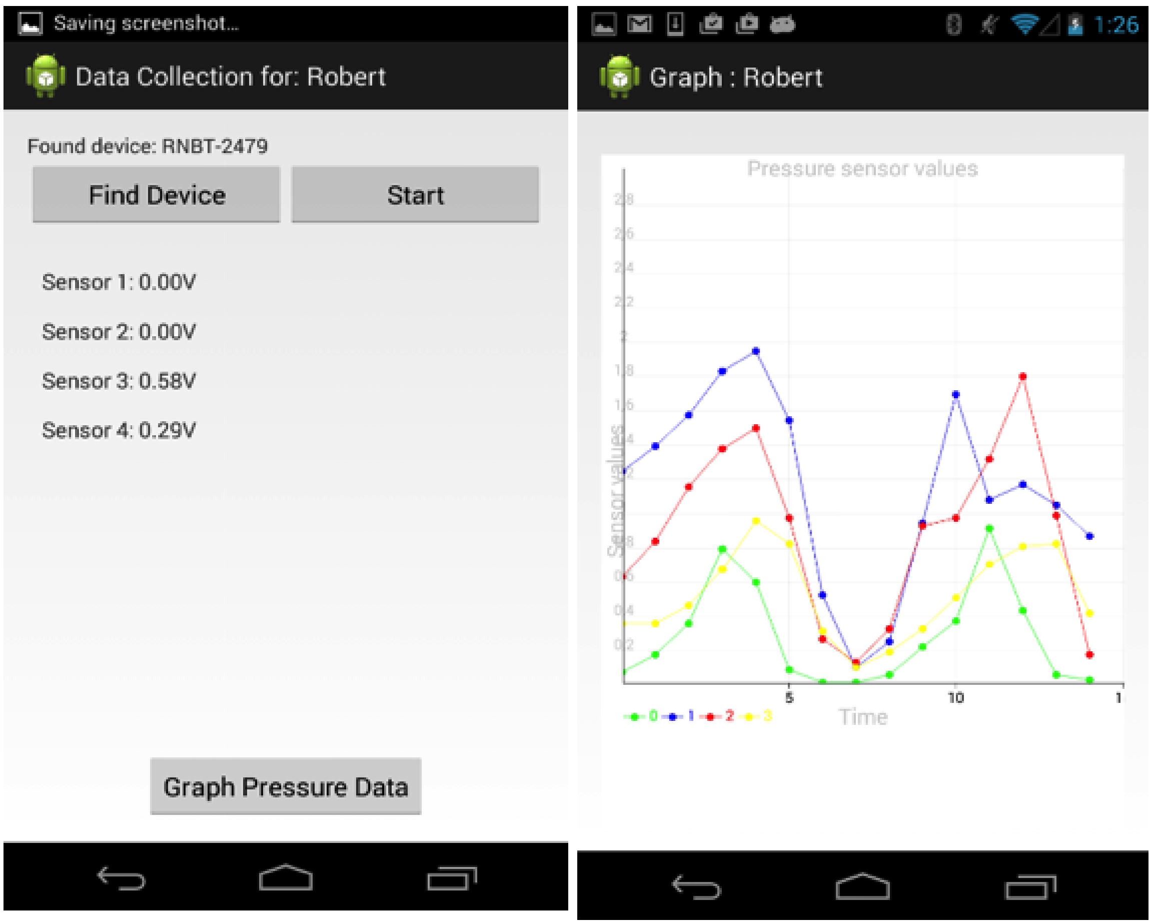
As an example, in figure 12, first save Bob's information in our SQLite database and then collect pressure sensor data from smart-shoe. When the user interface is started, a toast would show up to notify "Bluetooth is on." Afterward we press the "Find Device" button to get the target device. If the application cannot find the desired device a text message shows up that says, "Target device found and bonded." If the desired device is not bonded, we have to bond that manually by pairing the code. Now the application is ready to receive sensor data from smart-shoe. To get those data we press the "Start" button and sensor data starts showing up continuously. The corresponding graph shows up below the sensor data. We saved those data for each patient for further experiments.



(a) Patient Activity **(b) Sensors Data**

Figure 12. Screenshots of android based data collection

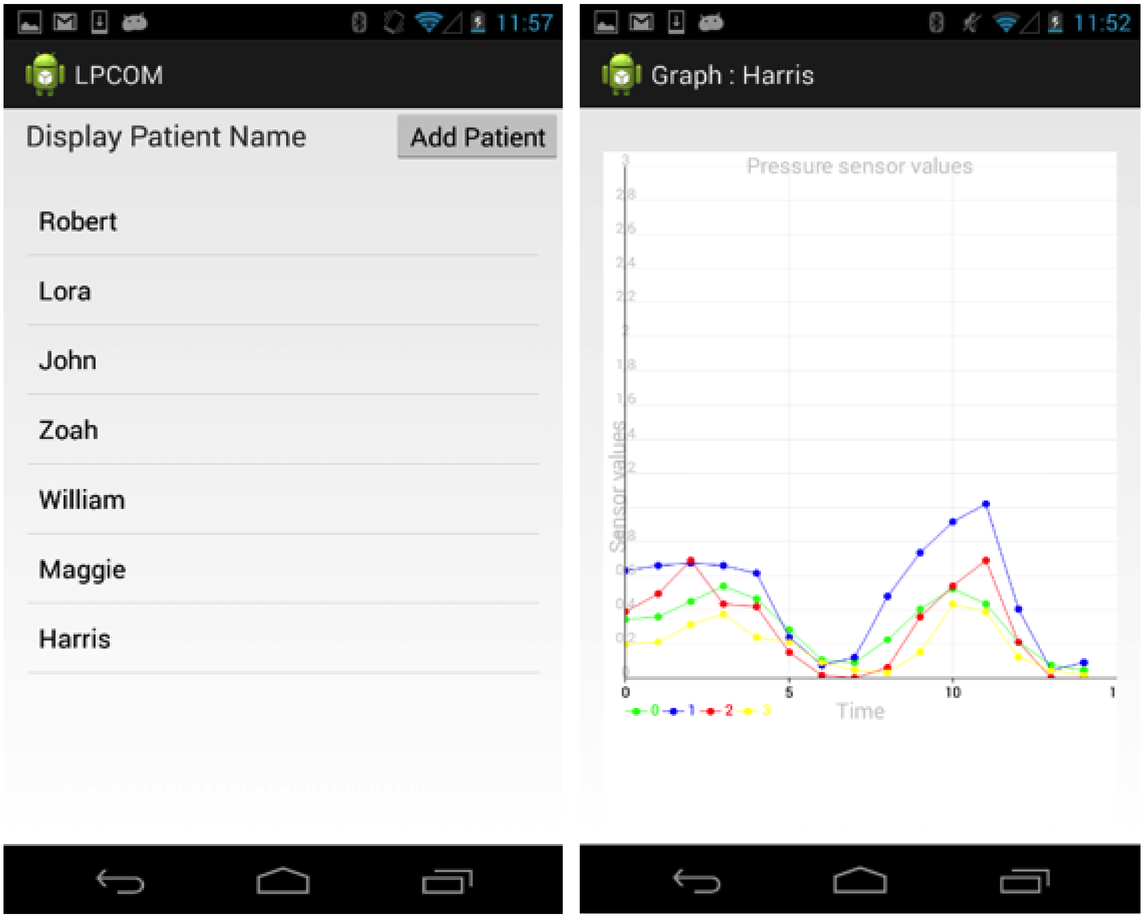
Same as in figure 13, first we save Robert's personal information in our SQLite database and then collect pressure sensor data from smart-shoe. To get the insole sensor data we need to press the "Start" button and the sensor data shows up continuously. The corresponding graphical representation of the four sensors would show up. The session ended up with saving those values in a CSV file. Afterward we will use those data to train our system to identify Robert's normal walking pattern, hence detecting abnormal gait.



(a) Sensors Data **(b) Graphical Representation**

Figure 13. Screenshots of android based data collection

We also have a patient log system as shown in figure 14(a). Each user needs to enter their biographical information before start collecting data from the shoe. Figure 14(b) shows a corresponding graph of four insole sensors for a test subject.



(a) Users Log **(b) Graphical Representation**

Figure 14. Screenshots of android based data collection

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 less than 26μA at sleep mode, 3mA at connected situation and 30mA during data collection.

To test the power consumption of smartphone battery during data collection, we monitor the power states continuously for two hours for the following two scenarios: (1) the phone runs with Bluetooth communication for data collections (2) the iPhone runs with Wi-Fi communication and continuously collects insole data for abnormal gait pattern identification. Figure 15 presents the two curves of battery level states versus time during the time period of two hours or 120 minutes. It is observed that the battery usage while using Wi-Fi communication is much higher than that of our proposed Bluetooth communication.

Low energy consumption is expected to be in Bluetooth wireless technology systems. With this technology our algorithm of selecting the target device assures minimal consumption of power. It provides a unique solution for portable, battery-powered products that demand a part of the power use of existing Bluetooth solutions. This is especially important in the medical product industry, where patients are encouraged to be mobile but need constant monitoring in real time.

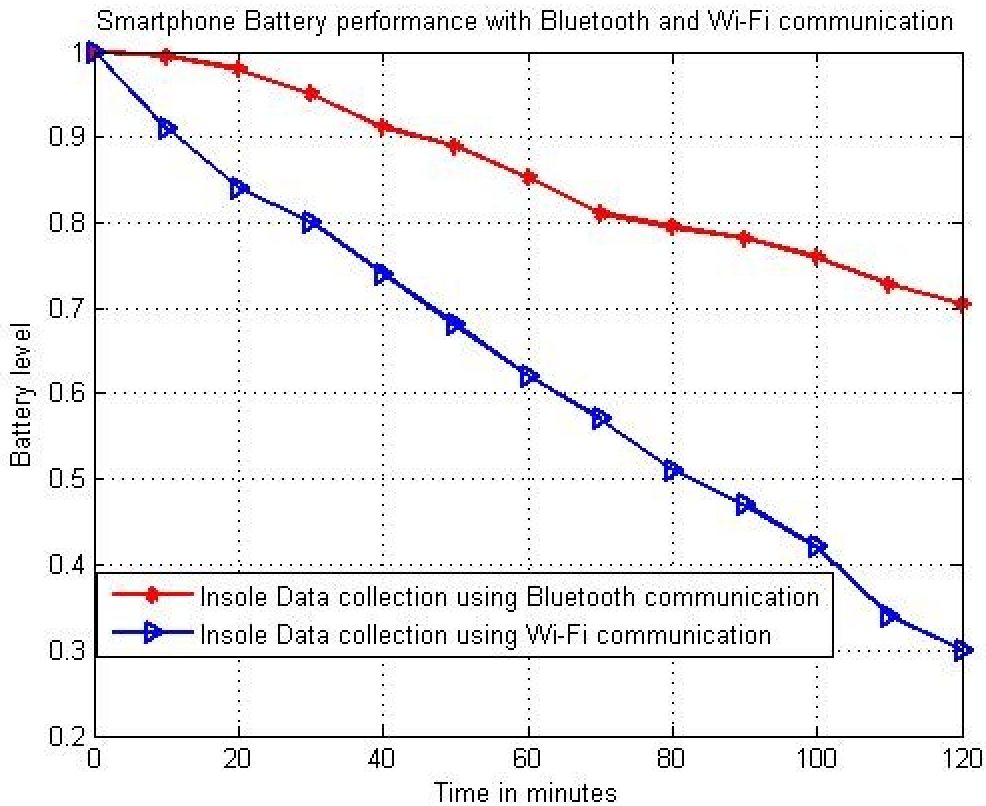


Figure 15. Blue curve presents the battery levels when the data collected using Wi-Fi communication and red curve presents the battery levels when data collected using Bluetooth communication

CHAPTER 7 CONCLUSION

7.1 Summary of Thesis

In this thesis we presented a smartphone- and smart-shoe-based human gait recognition system with low energy Bluetooth communication. This design was used to collect different gait data. Our approach, LPcomS, presents how our application can establish a low power communication between smart-shoe and smartphone for continuous data collection. These records that have been tailored for individual patient can make a positive impact in treatment procedure and help caregivers to identify abnormal gait pattern quickly and efficiently. This work, however provides a solid conceptual and demonstrable result for a low energy gait analysis system.

7.2 Contributions of Thesis

First and foremost, it has developed and validated a low cost smart-shoe with insole pressure sensors for automatic gait monitoring. Also, it has developed a Wi-Fi communication network between smartphone and smart-shoe for collecting shoe sensor data using smartphone. But the battery consumption is high while using Wi-Fi communication for data collection. Then we have developed a low energy Bluetooth communication system for collecting insole pressure from shoe sensors. This thesis has also gathered personalized biographic information (age, weight and gender) upon automatic gait monitoring. An SQLite database has been created to save the user's personal information. Finally, a generic frame work for low energy communication between smartphone and smart-shoe has been proposed for further study.

7.3 Impacts of Work

This work's most obvious impact will be on the quality of life for users able to utilize this low energy communication system for smart monitoring. As LPcomS was designed with a remote monitoring context in mind, users will be able to ensure they are receiving adequate care from their doctors while maintaining their daily lives. It will also allow doctors to receive daily, or more frequent, gait data on their users, allowing them to more accurately predict incident at home. Furthermore, as this is a system designed with mobile health in mind, it is a system that could easily be adapted to a world where the majority of people have access to a cell phone. Not all of these phones are capable of communicating with IoT, but it is obvious that cellphone ownership is a growing, global trend, so it is not unreasonable to assume that access to phones with that capability is also growing. Thus, LPcomS could potentially improve the smartphone battery life and will provide gait information to the caregiver for a long period of time. Long term, this method will hopefully be able to be adapted to a real time gait monitoring system that could potentially be put into hospitals and intensive care units to give doctors real time gait updates, which again would allow for even more responsive care.

7.4 Future Work

In continuation of this work, several aspects could be investigated. The most important are the inclusion of a generic frame work for the communication with Android and iPhone platform. Also, the inclusion of biographic information within the algorithm could improve the efficient battery usage during data collections. Finally, any way of taking this method and putting it in the hands of medical personnel should be looked at, whether it be simple remote monitoring, which could easily be done with the current mechanism, or as a possible real time gait monitor. Anything that could possibly aid medical personnel in reducing the fall of their patients should be investigated in order to help improve the quality of life of everyone in having some kind of gait abnormality.

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Appendix A: Definitions

Internet of Things (IoT)	Internet of Things (IoT) is a proposed advance of the Internet in which everyday objects have network connectivity and permitting them to send and receive data.
Bluetooth® Smart	*Bluetooth*® Smart is the intelligent and power-friendly version of Bluetooth wireless technology. Bluetooth smart makes it perfect for the devices needing to run off a tiny battery for long periods
Bluetooth Core	*Bluetooth*® wireless technology is a global wireless standard which enables simple, secure connectivity for an increasing range of devices and serves as the backbone for the Internet of Things (IoT).
Energy Harvesting	Energy Harvesting is the process by which **energy** is derived from external sources captured, and stored for small, wireless autonomous devices.

Appendix B: Hardware Components

B .1 Bluetooth Module and Battery Holder

B. 1.1 Flexiforce Pressure Sensor

Sparkfun Part # SEN-08712 ROHS

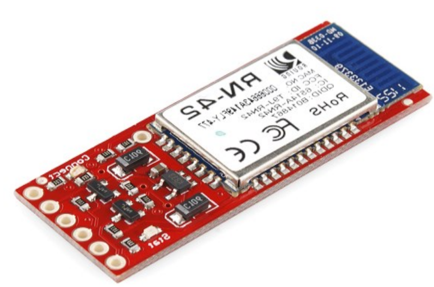
https://www.sparkfun.com/products/8712

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

B. 1.2 Class 2 Module

Sparkfun Part # WRL-10938 ROHS

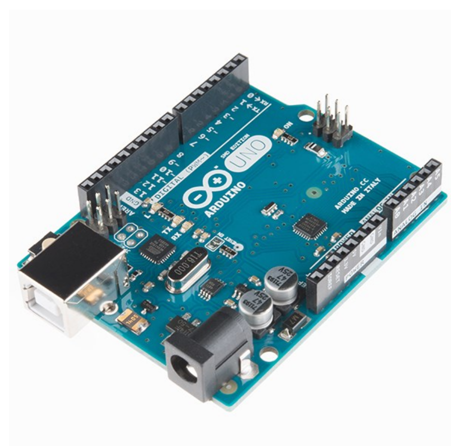
https://www.sparkfun.com/products/10938



- Small radio - 0.15x0.6x1.9"
- Very robust link both in integrity and transmission distance (18m)

- Hardy frequency hopping scheme - operates in harsh RF environments like WiFi, 802.11g, and Zigbee
- Encrypted connection
- Frequency: 2.402~2.480 GHz
- Operating Voltage: 3.3V-6V
- Operating Temperature: -40 ~ +70C
- Built-in antenna

B. 1.3 Arduino Uno



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

B.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)