GAIT ANALYSIS ON A SMART FLOOR FOR HEALTH MONITORING

by

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Abstract

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Gait analysis is the investigation of an individual pattern of walking. Based on studies in Psychophysics, it has been shown that the human gait contains unique information that is useful for the evaluation of foot and gait pathologies. The goal of this project is to use a floor mounted pressure sensor system capable of measuring a significant number of parameters relevant to gait to predict and detect anomalous behavior. The system consists of an array of pressure sensors mounted under floor tiles and computer hardware responsible for data collection. The method used in this project is unique since most systems that perform similar functions are “on-body” systems using leg attached sensors, body tags or “off-body” systems using vision (camera). Our approach uses floor mounted pressure sensor which are designed to collect data unobtrusively, over long periods of time, and without interfering with gait or inconveniencing the user.

The core of this thesis is aimed at the design of algorithms capable of differentiating parameter values that could be considered normal or abnormal for an individual and from these values draw further conclusions. To achieve this, data obtained from the floor mounted pressure sensor were calibrated and analyzed to extract information about the gait of a user. From this analyzed data, the center of pressure trajectories for each phase of the user’s gait cycle was obtained as well as the user’s

weight, and dynamic characteristics of balance and step impact. With this information we intend to provide a new way for gait analysis, in order to predict fall risk and health issues and to improve elder care by constant monitoring and by reducing the white-coat syndrome that inhibits clinical examinations.

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Chapter 1

Introduction

Human's gait refers to an individual style of walking [1]. According to the Oxford Dictionary, it is defined as a person’s manner of walking. As clear and simple as these definitions are, they do not fully provide us the information about the fundamental facts about the human gait. Fundamentally, it is a particular characteristic of a person that is influenced by a list of an individual’s body feature among which are; an individual’s weight, foot length, height, waist angle, limb length, an individual’s posture combined with characteristic motion and external factors such as floor and foot wear among others [2].

Gait analysis has gained wide interest in the computing field in recent years for use in human identification [3] , biometric authentication, surveillance systems [4], human motion classification [5] and human tracking [6] to mention a few. Formal studies and research of the human gait began largely in 1896 with the invention of the still camera [7], and since then researchers have searched for different areas to look out for and exploit the useful information that can be extracted from the human gait. The use of gait in various fields of science is undoubtedly among other reasons due to the various advantages it has. For example, it has found use in surveillance and tracking because it allows capture and identification of a subject without the subject’s knowledge. This is possible based on studies in Psycho-physics (“the scientific study of the relationship between stimulus and sensation” [8]), it can be concluded that the human gait contains unique information that are useful for person identification [9]. Other fields where gait analysis has been found useful are; in clinical environment, as well as athletics. In the former, measurement of the pressure distribution during gait is useful for the clinical evaluation of foot and gait pathologies [10-13]. Similarly, changes in gait such as slower walking or a more variable stride and rhythm, may be early signs of mental impairments that can develop into Alzheimer's before such changes can be seen on neuropsychological tests [14]. In athletics, gait analysis can be used to improve performance and treatment [15] [16]. These examples illustrate examples of different fields that carry out gait analysis using their favored technique to achieve their tasks.

The question now is how does walking produce unique information for scientific analysis? Walking is a complicated motor act that requires the coordinated movement of the lower-extremity, the trunk and limb, muscles and crossing joints [18]. This coordination is generated by a network of nerve cells referred to as Central pattern generator (CPG) producing a specific and patterned cyclic flow of signals. The patterned flow produced by this CPG is responsible for the human’s ability to hop, swim, run and walk. Other parts that interact with CPG are the Supraspinal, sensory, and neuromodulatory systems, that shape the final motor output. Movement is actuated as a result of the complex interaction between the spinal inter-neurons. Once the pattern flow is generated by the CPG, it is modified by higher cortical and reflexive spinal programs under the control of several supraspinal centers in the brainstem, cerebellum and cortex [19][20]. The Supra-spinal control plays a major role not only in regulating initiated automated motor programs but also in adapting the locomotor patterns to environmental and motivational conditions [21]. From the relationship drawn above, failure or damage of the Supra-spinal control responsible for regulation of interaction with the supra-spinal centers in cerebellum, for example, in the case where Cerebellar ataxia occurs [26], might lead to some gait abnormality.

Based on the conclusion by Baezner, H., et al [22], there exists a strong association between the severity of age-related white matter changes or cerebrovascular disease which primarily affects people who are elderly and the severity of gait and motor compromise. Another disease that can lead to walking dysfunction is Alzheimer’s disease (AD). Previous studies have shown that physical movement abnormalities or dysfunction might predict the onset of dementia (a set of conditions described by a group of symptoms that occur when the brain is damaged by specific diseases.)[17]. However abnormalities are often unlikely be unnoticeable early [23], but are rather diagnosable only in mild and severe cases [24] [25]. Consequently, a person's gait can be instrumental in detecting abnormalities in health early in a known individual due to slight changes in walking pattern or a variation in gait.

Motivation

Despite a rise in the number of health care technology service providers, most of them have been unable to tackle some of the lingering problem such as the white coat syndrome which inhibits clinical examination, or the problem of providing a suitable solution to monitor elderly health in order to detect health changes early on. For example, existing technologies which offer excellent tools have no way to change the users' perspective that they are undergoing an examination when they are about to use their device. This knowledge of being examined by a medical device can produce a psychological effect similar that observed during a doctor's examination (the white coat syndrome). This impairs the ability of the devices to obtain an accurate result. The white coat syndrome has undergone many studies as to why it occurs and enquiries are being made if it should be treated as a regular health condition in the case of white coat induced hypertension [47][48]. According to these studies, this form of psychologically induced hypertension is a situation that can occur in different individuals in different age groups, and is not limited to the elderly. The introduction of monitoring technologies that avoid this white coat syndrome (and thus associated white coat hypertensions) could thus not only result in more accurate medical results but also reduce the medical risks and improve health conditions and outcomes.

Rehabilitation and health monitoring technologies today often suffer from inability to provide in- door monitoring in cases where the users have to have some device attached to their body or have to wear them on their clothes or in the form of gait monitoring shoes. Work in [27][28][37][38][39][41][42] show studies where a shoe or body attached monitoring system is used. These systems however have no way to provide constant and consistent unobtrusive monitoring since the user will have to remove this device, take off this shoes from time to time and will have to remember to recharge them in some cases. In the time period in which, the user has to take off the devices to fulfill other duties or to change them; some significant information might be lost.

User convenience is an integral part of any design and, many of the devices currently in use require a significant amount of effort and involvement from the user and rely heavily on the willingness of the user at any specific time to actually want to use the device. This however, can lead to a biased sensor results where data is obtained only in specific situations and is thus not representative. For example, an individual might get the urge to check there temperature if they feel different, overemphasizing unusual temperature readings, or in the case where users have to put on some specially designed shoes, they might be reluctant to do so when they feel weaker or ill, thus removing the ability of the device to detect changes in health and hence limiting its utility in the detection of the health incidents and trends. One important point to observe here apart from user convenience is that, not all illness gives a noticeable signal to the user in order for them to take an appropriate measure and thus a more regular means of obtaining measurements without the need for the user initiation would be preferable.

To address this, the Smart-Floor, a new way for health monitoring and abnormality detection aims to be used for a wide range of health application for monitoring without inhibiting the user's convenience and without the need for active user intervention to provide measurements. It provides steady, unobstructed data collection and has a design that explicitly tackles the challenges of white coat syndrome and user-introduced measurement bias.

Challenges

Sensor based monitoring or rehabilitation systems often face noise, bias and other limitations. These limitations varies from reliance on battery technology, interference common to wireless technologies[50] and cultural beliefs which associates a stigma with the use of medical devices for home-based clinical monitoring [49].

The design of any sensor based monitoring system must incorporate a reliable method to zero out the noise and bias trade off. There is no unique right way to do this, as different applications might require and prefer a different approach based on the device environment and considerations related to other relevant information into consideration.

Approach

The approach taken here to tackle the existing problems discussed previously is centered on the concept of the Smart Floor and based on its ability to obtain data in an unobtrusive and largely invisible fashion. The technique used to handle the aforementioned challenges in the context of the floor mounted pressure sensor system of the smart floor is mentioned and explained in the later chapter.

Contributions

The emphasis of this thesis is on algorithms that extract important gait parameters in a personalized fashion from the Smart Floor that can then be used to perform health monitoring and anomaly detection. Its main contributions are as follows:

- Based on Smart Floor sensors, it provides algorithms to extract weight
- It introduces a means of segmenting floor pressure signals into gait phases
- It develops a set of algorithms to extract important gait parameters, including step length, step width, step frequency, etc.
- It builds personalized gait parameter models that can be used to monitor walking for changes in pattern characteristics
- With the information extracted from the Smart-Floor, it provides a new way for Gait Analysis.
- Using these contributions, opens up a number of possible areas in health monitoring by monitoring the extracted parameter models. These contributions to such applications include:
    - The basis for a new way for activity recognition
    - The underlying data processing for a technique for estimation of fall prediction risk and changes in health.
    - The foundation for a technology to improve elder care by constant monitoring and by reducing the white-coat syndrome that inhibits clinical examinations of various age groups.

How to Read this thesis

The rest of this thesis is organized as follows. Chapter 2 reviews the related work involving the use of gait in abnormality detection and provides the review of the existing methods. Chapter 3 gives a technical background about gait analysis and discusses notable features about it. Chapter 4 introduces the experimental overview, including tools and procedures involved in data collection, the background and the underlying characteristics of gait, the experiment setup, parameters that are extractable and the possible interpretations. Chapter 5 describes our approach and the analysis techniques used to interpret the data. It presents the methods for the construction of our model and gives a description of the parameter extraction algorithms and all. Chapter 6 shows the experimental results. Finally, Chapter 7 discusses the conclusion and possible future work and expansion of this project.

Chapter 2

Related Works

Over the years, several approaches have been proposed for gait analysis and abnormality detection either for diagnostics useful in clinical examination, for biometrics or for surveillance applications. Determining abnormalities often requires recognizing and modeling an individual's normal gait pattern and trajectory. This approach is often referred to as model based gait recognition. Approaches to gait recognition can be classified into two categories, model-based and model free. Model based methods described for example in [28, 29, 30] construct a model of the observed gait pattern. In vision- based gait analysis for example, a model is built from the observed images with the help of extracted image features to observe and derive the gait trajectories. Results can then be verified by matching with new image data. Model free approaches [31, 32] use a well-defined representation to generalize the whole body motion pattern in the absence of a model. There have been several studies in abnormality detection in gait; the studies are broken down by the choice of the method used:

Abnormality detection in gait using vision based system

One of the methods for gait analysis is vision based gait analysis. There is a vast spectrum of methods that imbibes the use of vision-based system for gait analysis. A comprehensive survey of the recent vision based approaches has been presented in [45, 46]. In vision based approach of motion analysis, Silhouette based gait recognition is one of the most popular method for recognizing moving objects. Veres et al [27] described two types of silhouette, average silhouette obtained by averaging over recorded sequence and the second, the use of differencing operations on silhouettes of a full gait cycle to obtain a differential silhouette. Some statistical analyses tools were performed on this image information to determine the most characteristic information for gait analysis. They concluded that the average silhouette which includes a static component of the head and body has the most important cue. BenAbdelkader et al. [33] imbibed the use of image self-similarity plots of silhouette images and apply pattern matching approach to identify respective individual. Bauckhage et al [34] used a method that allows construction of a robust vector space embedding of the observed silhouette image for automatic detection of abnormal walking pattern. Lee and Grimson [35] divided the silhouette of a walking person into regions by fitting ellipses. Notable features such as the centroid, aspect ratio of the minor and major axis of the ellipse, and the orientation of the axis of the ellipse are being extracted from each of the noted region. In their experiment, 7 regions of the body were considered. This is equivocal to having 7 ellipses that describe the average shape of the body. These features are considered to be robust to noise, thus the phases of all region features are been computed relative to one particular region feature that is "most stable," With the knowledge that a good feature should minimize within class variance and maximize interclass variance and following the assumption that all features are independent from each other, analysis of variance was performed on each feature to perform necessary classification. Collins et al[36] proposed an algorithm based on template matching of 2D body silhouettes extracted from "key" frames through an entire gait cycle sequence. Using Nearest neighbor matching using correlation score, subject classification is performed after comparison is made between key frames and training frames using normalized correlation. Little and Boyd [37] present a method, with the underlying assumption that the image of a moving figure contains image flow information called optical flow that varies spatially and temporally, derives shape of motion and from this data. Based on this, they developed unique features suitable to recognize individual by their gait.

Abnormality detection in gait using body worn tags or markers

Another approach used in gait analysis for detection of anomalous gait is the use of body-worn tags or sensors for activity recognition. In the experiment performed by Luštrek, Mitja, et al [37] with recording s sampled at 10Hz, they varied the number of tags from 1 to 12 and varied the tag coordinates of tags worn on shoulders, elbows, wrists, hips, knees and ankles. Once they collected the data from these locations, they used machine learning algorithms to classify the data and from their classification accuracy they pointed out the level of accuracy to which fall detection or changes in health can be detected with the appropriate locations. Pogorelc et al [38] in their method used body worn tags and wall-mounted sensors. Different from the above, where a brute force method was used to find the best coordinate for tag placement, the tag position are here acquired by the sensors and the resulting time series of position coordinates are analyzed with machine-learning algorithms in order to recognize a specific health problem. The method uses 8 to 12 tags with classification made into: 1) normal, 2) with hemiplegia, 3) with Parkinson's disease, 4) with pain in the back and 5) with pain in the leg. Similar to this, the approach used by Pogorelc et al, [39] used 43 body tags sampled at rate 30Hz. In order to distinguish between seven activities related to military operations. They reported an average classification accuracy of 76.9% using Support Vector Machine (SVM) learning algorithm whose features were the tag coordinates belonging to two postures separated by 1/3 second. [40] proposed a method which is based on transforming joint motion trajectories using wavelets to extract spatio-temporal features which are then fed as input to a vector quantiser to form a self-organising map for classification of walking patterns of individuals with and without pathology. The wavelet - transformed gait characteristics include walking speed and stride length. This approach uses more tags, thus it has high accuracy to detect and distinguish between normal and pathological subjects, males and females, different age ranges, different pathologies and different categories within a specific pathology. It also has high efficiency and reduced noise level. However, the large number of tags and the accuracy required in applying them as well as the need for specific viewing angles in order to identify the tags makes it difficult to apply in real life world scenarios.

Abnormality detection in gait using potable, mobile and custom built sensors

Kong et al [41, 42] used customized shoes with pressure sensors built into their sole called Smart shoe to measure the ground reaction force during gait. The proposed method is based on fuzzy logic and it detects phases in a human gait. In the proposed algorithm, two major abnormalities are detected. In the method proposed by Bamberg et al [43], a sensor suite which include s three orthogonal accelerometers, three orthogonal gyroscopes, four force sensors, two bidirectional bend sensors, two dynamic pressure sensors, as well as electric field height sensors were built into a shoe, which they called the Gait Shoe. Data acquired from these sensors are being wirelessly transmitted to a base station where the sensor output is analyzed. For Diabetes patient monitoring, Morley et al [44] developed an insole based system to measure temperature, humidity and pressure in the shoe in order to predict skin breakdown and also to document the high pressures experienced by patients with diabetes mellitus and peripheral neuropathy.

In contrast to all the methods presented so far, the method presented in this thesis uses Floor Mounted Pressure Sensors (FMPS) which are designed to collect data unobtrusively, and in any walking environment, over long periods of time without interfering with gait or inconveniencing the user. We call it the Smart Floor. The approach is intended to create a system to provide gait analysis outside the common shoe or insole based approach. The Smart Floor system has been designed with components that in no way affect or change the user’s gait. This, in turn allows the presented method to scale more efficiently in real-world problems

Chapter 3

Technical Background

As defined in the earlier chapters, a gait is a person's walking pattern. Since a gait is a repetitive activity, there are several assumptions that could be made about and inferences that can be drawn from its cycle. In addition, there are several parameters that can be extracted from a person's gait. In this chapter, these parameters and other characteristic feature of a gait will be examined.

Gait Cycle

The gait cycle a repetitive walking pattern of an individual during a walking phase, a gait cycle consists of strides and steps. A gait cycle consists of single support and double support phases characterized by having one foot or two feet on the floor. Further classification of a gait cycle is into swing and stance phase. During a gait cycle, a swing and stance for the same leg cannot occur at the same time. A swing, for instance of the left foot is followed by the stance of the same foot. It is important to note that while the right foot is in a stance phase, the left foot swings and interchangeably during the right foot swing phase.

The gait cycle can be historically classified into 6 phases or using a newer classification into 8 phases for an entire gait cycle [51]. These phases are listed in Table 3.1 and illustrated in Figure 3.1;

Table 3.1 Different phases of a gait cycle

Classic Gait Phases	New (Revised) Gait Phases
1. Heel Strike 2. Foot Flat 3. Mid-Stance 4. Heel-Off 5. Toe-Off 6. Mid-Swing	1. Initial contact 2. Loading response 3. Mid stance 4. Terminal stance 5. Pre swing 6. Initial swing 7. Mid swing 8. Late swing

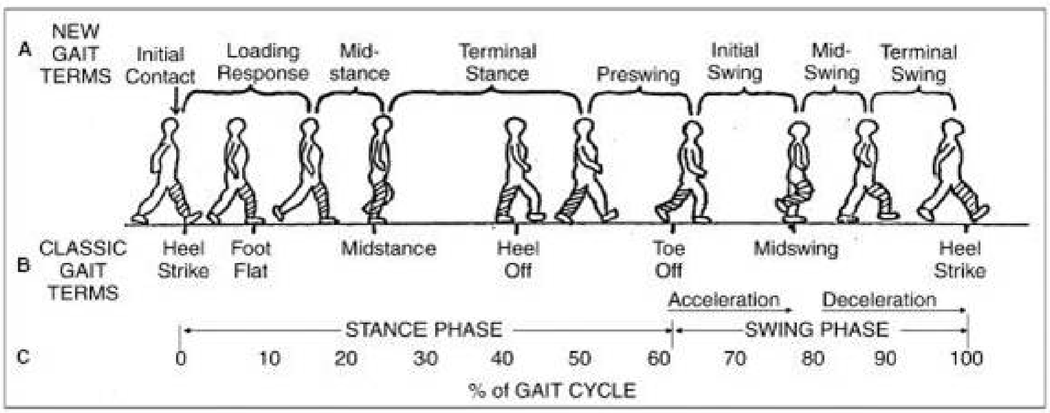

Figure 3.1 Classic and new gait classification in a gait cycle [51]

The Classic gait terms are generally more detailed in the explanation of the transition from one phase to another during a gait cycle. Each phases of the gait cycle can be elaborated as follows:

Heel Strike

This is the point of heel contact with the floor. A heel contact phase is also considered as the beginning of a double support phase of a gait cycle. This can be seen in Figure 3.1 above.

Foot Flat

This is the phase where the entire foot is in contact with the floor. By the beginning of a foot flat phase, 20% of the gait cycle will have been covered.

Mid Stance

This is a phase beginning from the foot flat phase or fore foot loading, here the centre of pressure trajectory under the stance foot moves from the posterior to anterior while the other foot swings. This covers 35% of the entire gait cycle time. At the beginning of this phase, the other foot will be at the toe off point.

Heel off

This is a transition from the mid stance phase to Heel lift. The heel lift occurs when the current foot on the floor just begins to lift off the floor. At this phase the ground reaction force shifts to the anterior of the foot. At this phase 55% of the gait cycle will have been covered.

Toe off

Sometimes it is hard to define the specific point this occurs in a gait cycle; however, it is the part of the cycle that ranges from when the toes just lift off to when it has completely lifted off the floor. Here, the toes lift off the floor completely for the foot in the stance phase. By the end of this phase 60% of the entire gait cycle will have been covered. Just as noted in the mid-stance phase, during this phase the other foot will be in its mid stance phase. This marks the end of the stance phase

Mid Swing

This is the portion of the gait cycle when the foot is in the air. The swing phase consist of the initial, mid and the late swing before the next heel strike which marks the start of a new gait cycle.

Phases in a Gait Cycle

Using the above division of the gait cycle, notable partitions of the gait cycle are into stance and swing phases or into single support and double support phases.

Stance or swing phase

Stance Phase: This is the part of the gait cycle when the foot is in contact with the ground. This phase covers about 60% of the entire gait cycle

Swing Phase: This consists of 40% of a normal gait cycle and it occurs from the toe off of the foot, goes from initial to terminal swing and finally ends at a heel strike.

The relation between the division into stance and swing phases and the classic gait phases is shown in **Error! Reference source not found.** and illustrated in **Error! Reference source not found.**.

Table 3.2 Division of gait classification into phase

Stance Phase	Swing phase
1. Heel Strike 2. Foot Flat 3. Mid-Stance 4. Heel-Off 5. Toe-Off	6. Initial, Mid and Terminal Swing

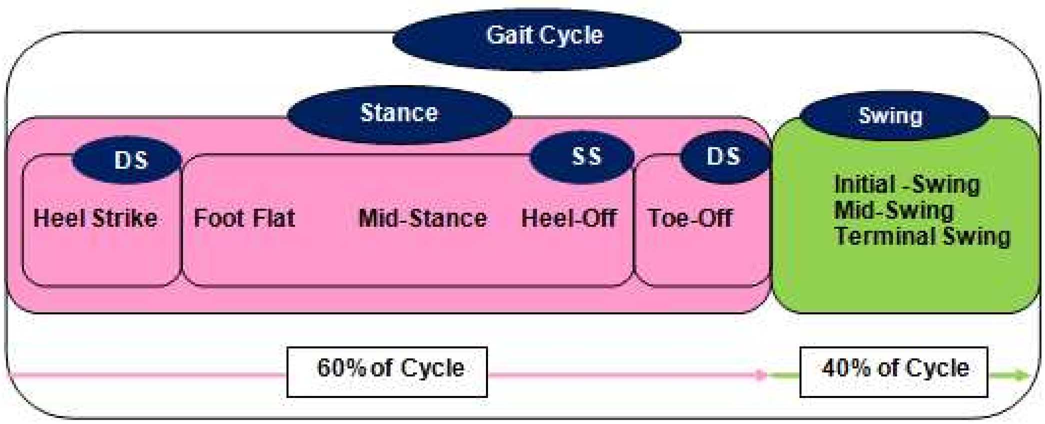

Figure 3.2 Notable Division of a gait cycle and the intersections between different phases

Single Support or Double Support

Double Support

This is the period in a gait cycle when both feet on an individual are on the floor. This happens between heel strike when foot is just making contact with the floor and ends on toe off when the other foot is lifting off the floor.

Single Support

This is period in a gait cycle when only one foot is on the floor. Within one gait cycle, there is a right single support and a left single support.

As shown in the Table 3.2 below, the phases of gait cycle that falls in stance and swing phases are as follows;

Gait Cycle Time Division

The division of the gait cycle into stance and swing phase as well as into single and double support phases also divides the total gait cycle length.

In the partition into swing and stance phases divides the total gait cycle roughly in a ratio of 40%:60% as shown in **Error! Reference source not found.**.

On the other hand, the division into left single stance, double stance, and right single stance phase divides the overall gait cycle at a ratio of 40%:20%:40% as shown in **Error! Reference source not found.**

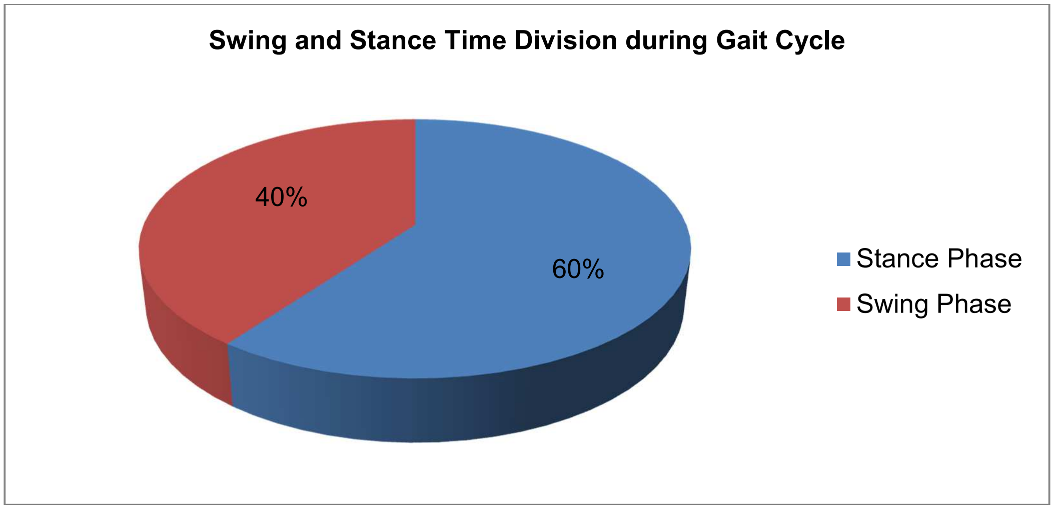

Figure 3.3 Chart showing time division between the stance and swing phase of a gait cycle

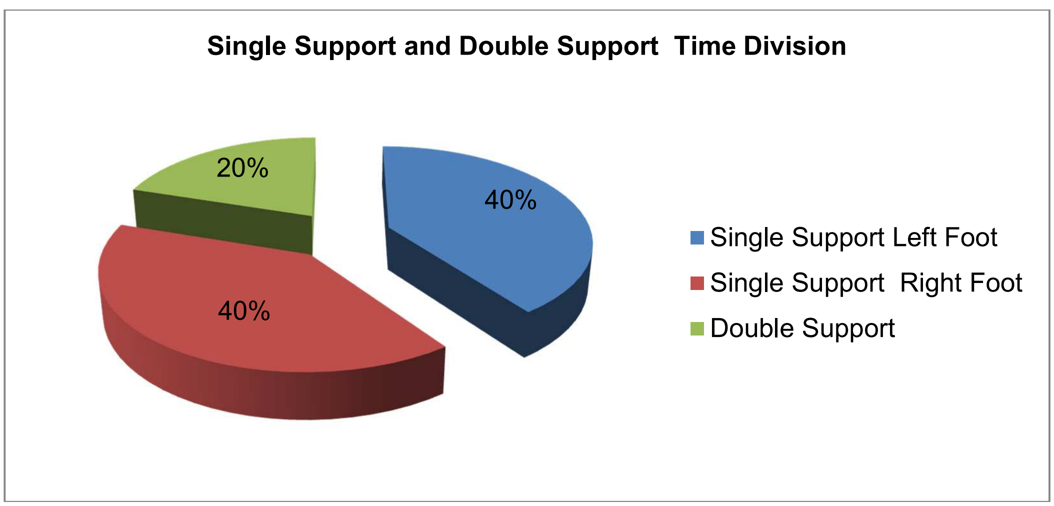

Figure 3.4 Chart showing time division during the double support and single support phase of a gait cycle

Spatial and Temporal Parameters

In gait analysis, there are variables that can be used to measure and represent the overall walking characteristics and performance of an individual. These variables are called the Gait Parameters. They represent aspects of the gait cycle that allow analyzing and characterizing of an individual's walking behavior. These parameters can be classified into Temporal Parameters and Spatial parameters. Spatial gait parameters are related to displacement during the gait and the temporal parameters are related to the time variables.

Spatial gait parameters

Spatial variable include but are not limited to step length, stride length, step width, foot angle or foot angle.

Temporal gait parameters

These variables are used to measure the walking performance in relation to time. They include but are not limited to step time, stride time, stance time, swing time, cadence, single support time, double support time and speed

Some of the most important spatial and temporal parameters of gait are:

Walking speed

This is the displacement from initial position to new position over time taken from initial foot contact to the last observable foot contact point during deceleration before a complete stop.

Step length

The step foot length of the right foot for instance is defined as the distance between the point of the right heel strike and the left heel strike or contact. Likewise for the left foot, the left foot step length is the distance from right heel contact to the next left heel contact.

Step frequency/cadence

This is the number of steps walked in a walking time interval; this is basically how often a step is taken in a walking interval. It is measured in steps per time.

Stride length

The stride is the distance covered in a whole gait cycle, thus the stride length is the length of a whole gait cycle. A stride contains two steps, one for the left and the other for the right foot.

Step width

This is the length of the medio-lateral area between the two feet during each half gait cycle. It can be estimated by measuring the how far apart area farthest from each foot center are for consecutive foots falls.

Double support time

This is the amount of time spent in a double support phase during a gait cycle.

Single support Time

This is the amount of time spent in a single support phase by a foot during a gait cycle.

Stance Time

This is a measure of the time spent before the swing of the foot, a stance time begins from initial heel contact to toe off.

Swing Time

This is the amount of time the foot spends in the air. It begins from toe off and ends at heel strike of the foot.

Chapter 4

Experimental Overview

Hardware

The Smart Floor system consists of an array of pressure sensors mounted under floor tiles that collect data continuously throughout the performed trials and a computer system responsible for data collection. The sensor used is the Tekscan® Flexiforce sensor*s.* The Flexiforce pressure sensor detects and measures pressure applied to sensor detects contact and gives a high level of flexibility in their deployment and integration. The floor board schematics are shown in later chapter

The Flexiforce sensors are available in a variety of force ranges, due to the pressure sensitivity level required by our experiment. The sensors output pressure value equivalent to the force applied by the user.

A custom built computer hardware (see Figure 4.1) was used for data collection from the Flexiforce pressure sensors and for the transfer of the collected data into the centralized storage. Due to the Span of the Floor prototype, four of this hardware was used. Each of them collects data at 40 Hz from 32 connected Flexiforce sensors.

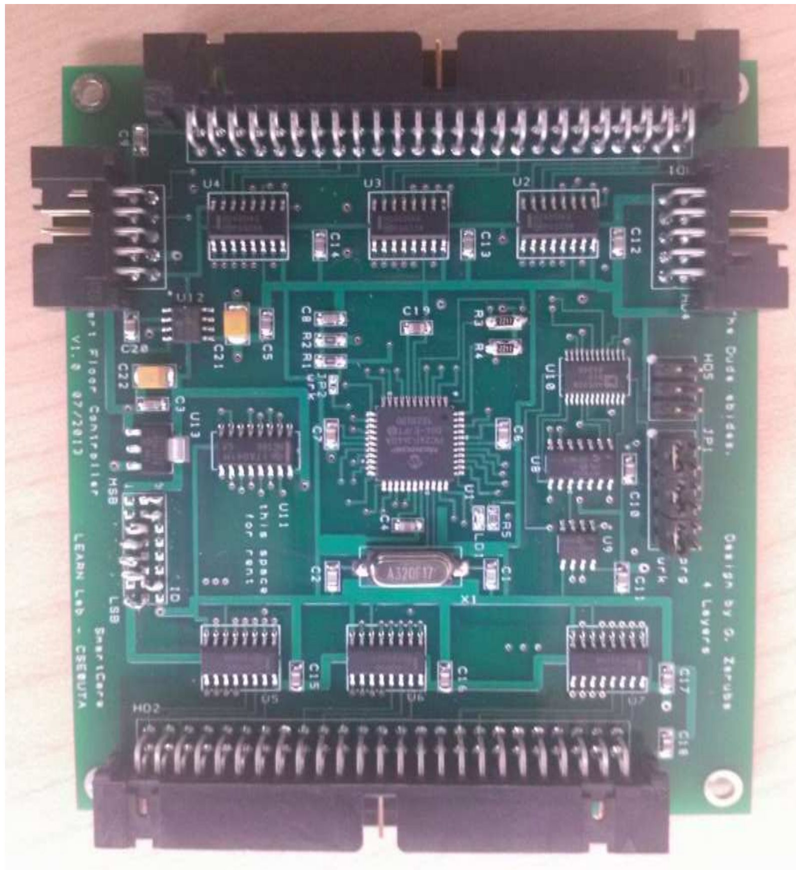

Figure 4.1 Computer hardware used for data collection from sensor

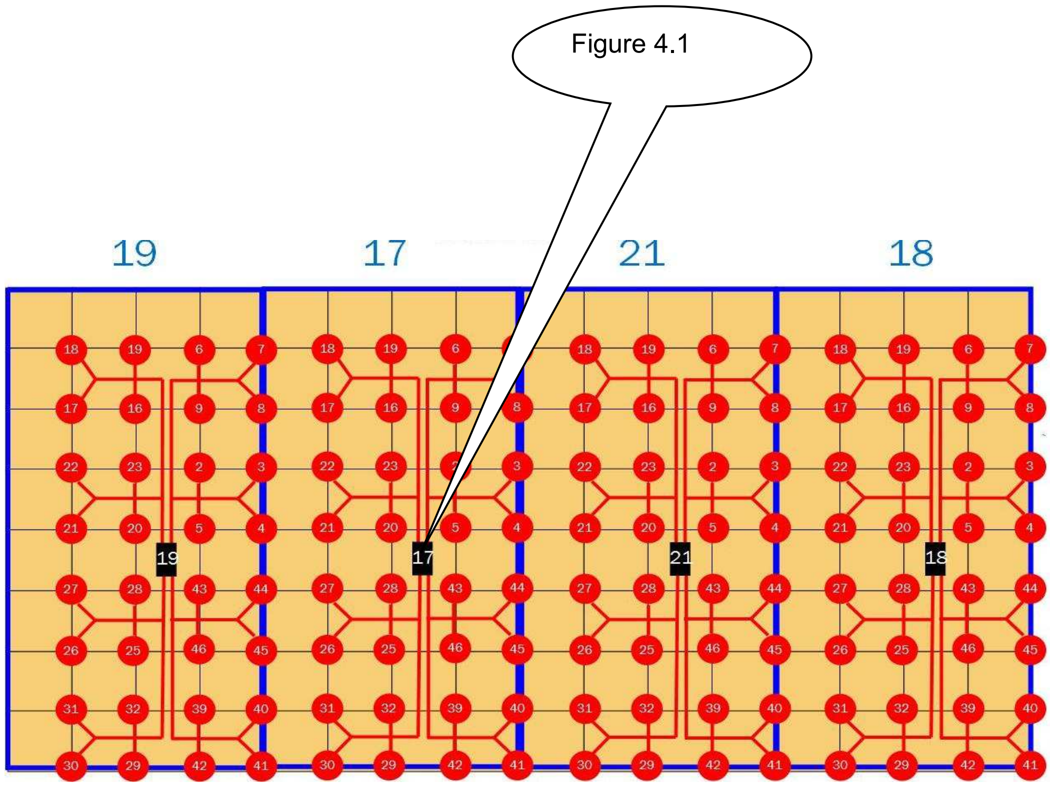

Figure 4.2 Illustration of sensor placement underneath the floor

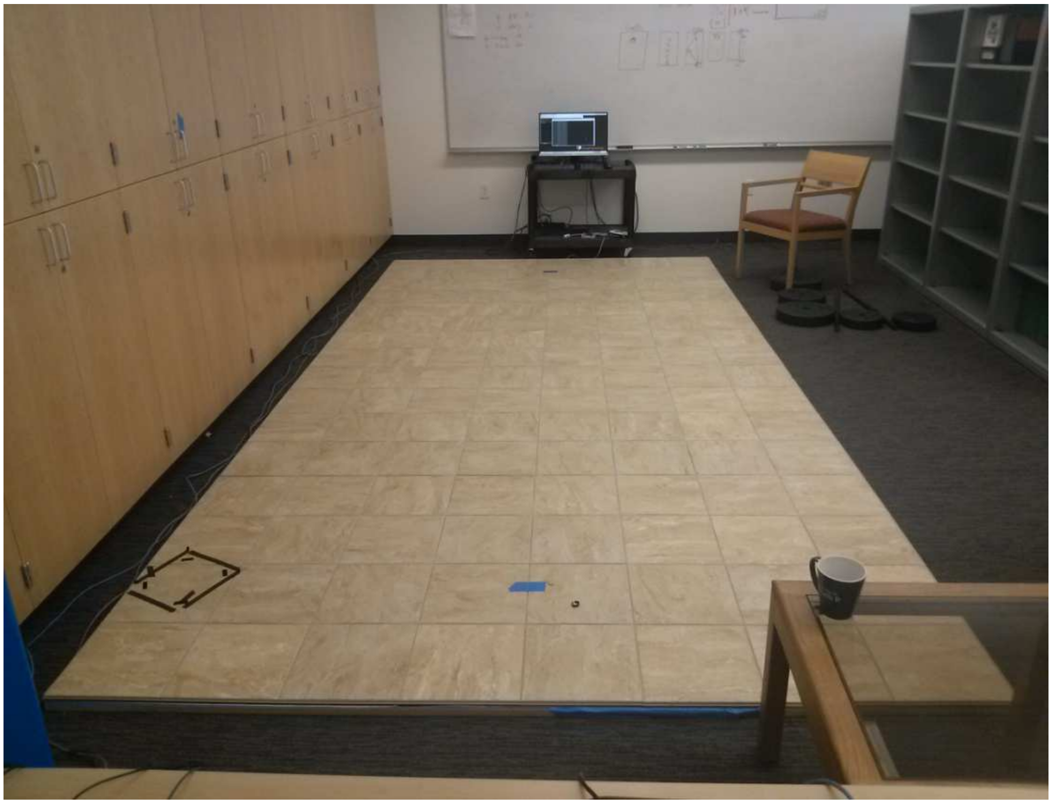
Figure 4.3 Smart floor setup

To allow for cross validation, a Microsoft Kinect 360 was used to record the walking and balancing exercise performed by the user. The data collected from the Kinect was used to segment and match the gait phases with the ones collected and extracted from the pressure sensor data. The data collected from the Kinect camera were sampled at 20Hz-30Hz.

An accelerometer was also used to measure each subject's acceleration data. The Actigraph® wGT3X device that was used to record this data can be worn in 6 different locations; the ankle, thigh, in a pants pocket, on the waist, wrist, or on a lanyard around the neck. Given that our experiment is on gait analysis, we asked the subject's to wear it around their waist. The Actigraph was used to keep track of each subject's linear acceleration and rotational velocities in three dimensions at a rate of 100 Hz.. The data collected is known to have an accuracy level of +/-0.5 % and is initially stored directly into a non-volatile flash memory in the device before manually transferring it to centralized storage

A weighing scale was also included in our experiment to keep track and validate the weight extracted from the floor sensors for the users as they walk across the floor

Software

Data from the Microsoft Kinect was collected using Modified Kinect Explorer D2D, while the Actigraph accelerometer used the Actigraph licenced ActiLife® software. The data collection from the sensor runs on C++ with a gtk widget for the Graphical User Interface. Data Processing was done exclusively with C++ and Matlab. The prediction and analysis program will be presented in the Chapter 5.

Trial Description

All the participant were volunteers and they were first asked to acknowledge and sign a consent form before taking part in the study. After this, each participant performed multiple scripted activities which were designed to generate representative balancing and walking gait data for the subject. In this, one activity was specifically designed to obtain static balancing data while another was performed to obtain a number of continuous gait cycles during a multi-directional walking path. As part of these activities, a Tinetti balance and gait assessment score was also elicited and a corresponding form was filled out by 3 trained investigators to assign appropriate gait and balance scores to each participant. These can later be used to compare automatic gait and balance assessments with the obtained Tinetti scores, which represents the current method of assessment.

Experimental Protocol

Each subject was asked to perform a series of task on the floor. . These started with the standard Tinetti assessment activities and then continued through another set of scripted activities.

Tinetti gait and balance assessment

For the balance Trial and gait assessment , the subject was asked to perform series of tasks following the Tinetti Assessment Tool. These activities were as follows:

- Subject sits down on a chair
- Subject stands up
- Subject is requested to turn 360 degrees
- Subject is nudged while standing.
- Subject walks for a set of steps, turns around, and returns.

Walking Trial

After completing the TInetti assessment activities, the subject walked from the start position to the stop position twice at a steady self-defined normal pace. The subjects then walked to the side of the floor to open a side cabinet from the start position and from there moved to the stop position. The subjects continued by picking up a cup and went back to the start position. Following this, the subjects were instructed by the examiner to stand on one foot for a few seconds for both the left and right foot. Then the subjects picked the cup back up and walked back to the stop position at a slow pace to drop the cup. A complete walking trial lasted for approximately 5 minutes. In total the Consent form filling, weight check procedure, blood pressure check, standing and walking tasks took approximately seventeen minutes for each subject. The different aspects of the walking Trial are illustrated in Figures 4.4–4.10 below:

The walking Trial is illustrated below:

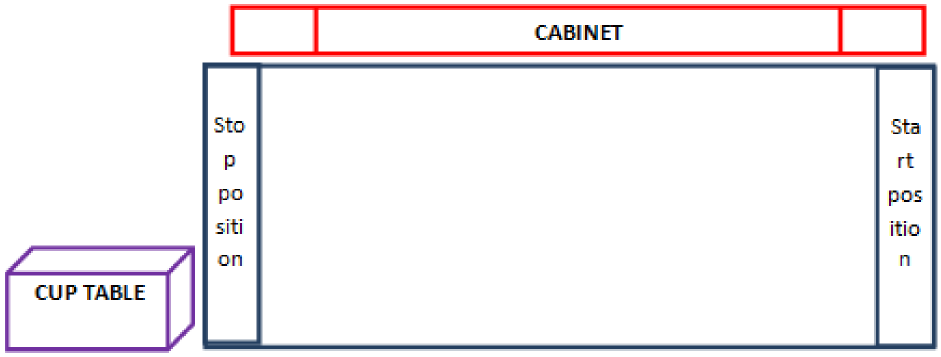

Figure 4.4 Smart Floor Experiment Layout

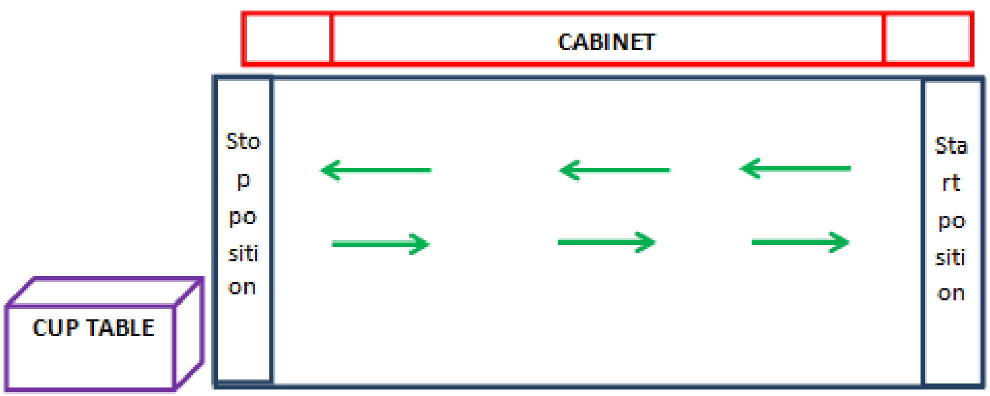

Figure 4.5 Initial Straight Line Walking by the Subject: Performed Twice

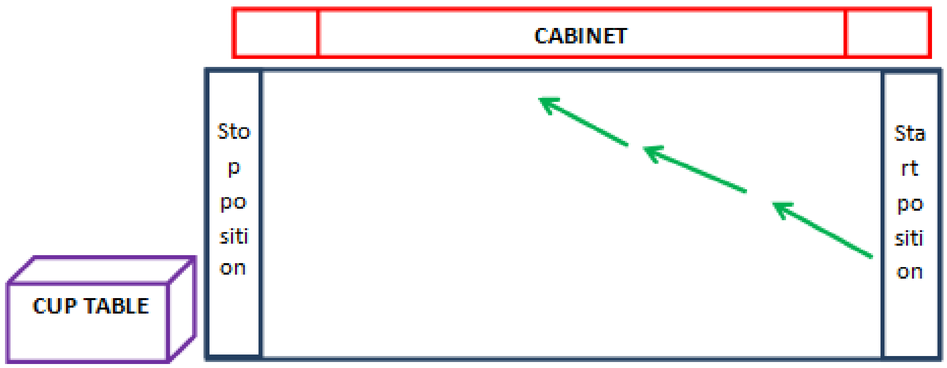

Figure 4.6 Opening Cabinet Door Task by the Subject: Performed Once

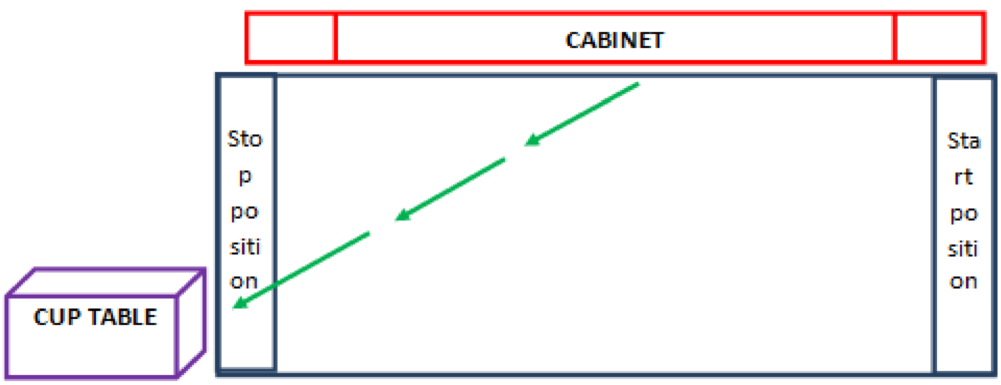

Figure 4.7 Walking from the cabinet to pick up the cup

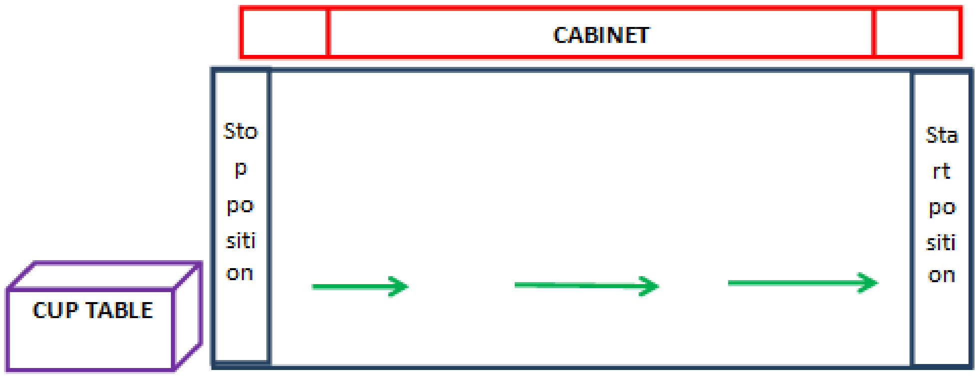

Figure 4.8 Walking back to start position after cup pick up task

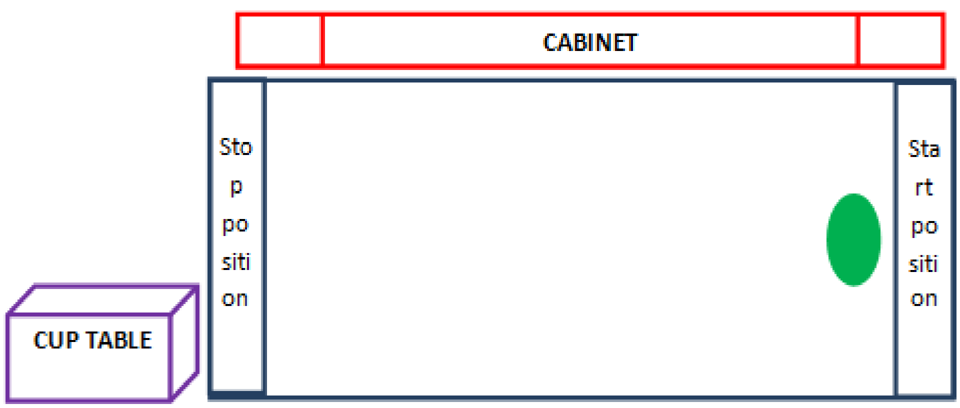

Figure 4.9 Balance on Each Foot Task by the Subject: Performed Once for Each Leg

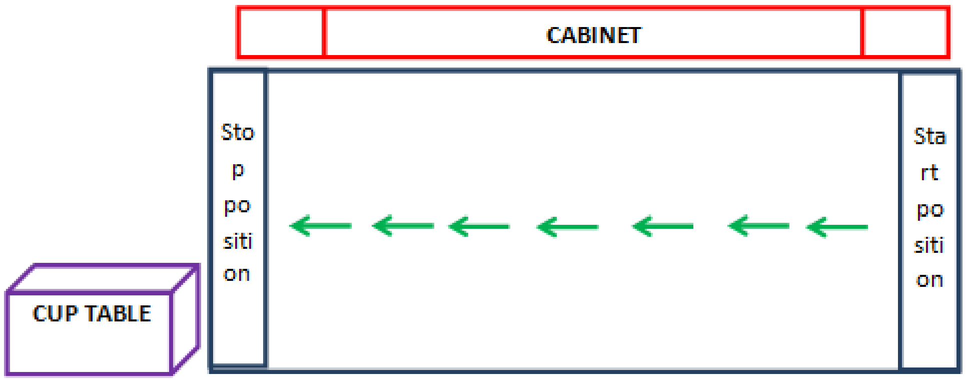

Figure 4.10 Showing Slow walk Task by the Subject

Chapter 5

Parameter Extraction and Algorithms

To extract the spatial and temporal parameters of a gait, the gait line for each individual has to be analyzed. The first step in this analysis is recognition of the double support phase. In this thesis, methods for automatic gait analysis and extraction of parameters, as well as for constructing a model for each subject are developed. To do this, algorithms to extract the weight, the centre of pressure speed, automatic step segmentation, single support and double support phases, stride length, step length extraction, foot separation, right and left foot identification, Step Symmetry assessment and step width extraction have been developed and implemented. Parameters extracted using these methods from each subjects gait dataset include:

- Centre of Pressure (COP)
- Weight
- Centre of pressure speed
- Single support and Double support Detection and Extraction
- Stride length extraction
- Step length extraction
- Foot separation
- Right and left foot.
- Step width
- Step symmetry ratio

Weight

A subject's weight can be best extracted while the subject is standing. Periods of standing in place within the gait dataset for an individual can easily be segmented out by the automatic gait segmentation algorithm. In our experiment, the weight can easily be extracted since we asked each subject to stand still before the walking sections. At this point, the weight of a subject is extracted by summing up the values of the pressure sensors. Thus the weight is a cumulative sum of the Pressure sensor values activated during the frames in which the subject is standing. **Error! Reference source not found.** shows the weight estimate during an entire trial with the initial standing phase used for weight extraction circled in the beginning.

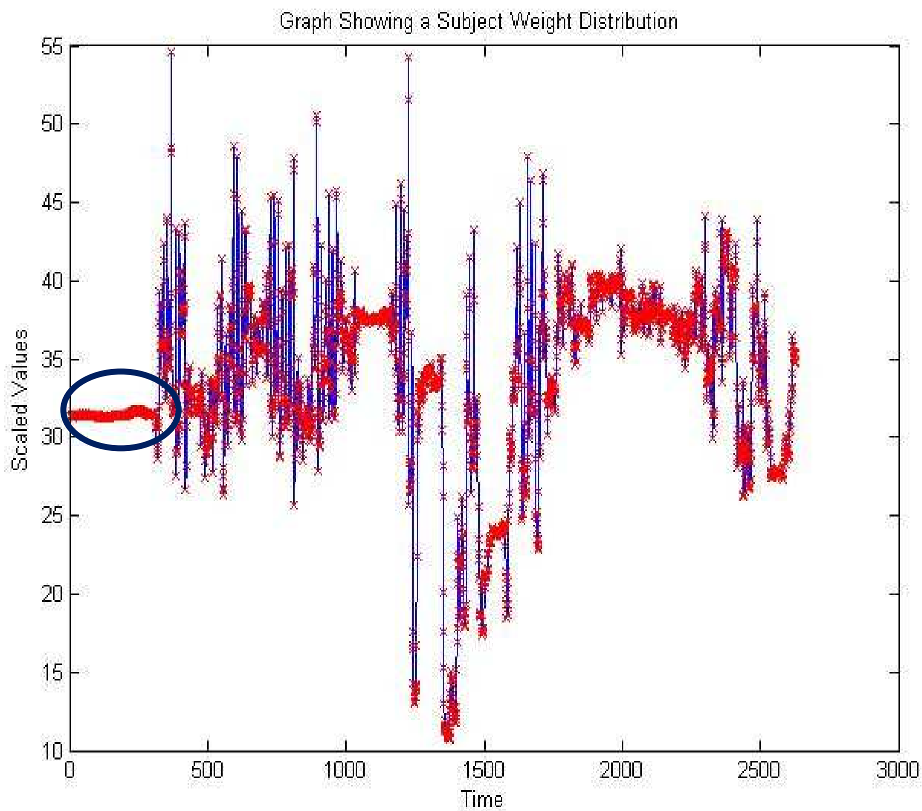

Figure 5.1 Weight estimate over entire experiment with initial standing phase used for weight extraction circled

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Centre of Pressure Speed (COP Speed)

The COP speed is the rate of change of the COP over time. It is directly proportional to the coordinates of the COP. Hence, if the displacement of the COP from its initial position is high, there is an increase in the COP speed and vice versa when there is a low displacement. Let T_N be the time of the last COP point for a subject in their data set, t_i be the i^{th} time step, and $d(x_i, y_i)$ be the corresponding COP coordinate. Using these, the COP speed can be extracted using the algorithm shown in Algorithm 5.1. The resulting COP speed extracted for one subject's experiment is shown in **Error! Reference source not found.**.

Algorithm 5.1 COP Speed Algorithm

1: ***for*** t = 2 to T_N ***do***

2: Obtain the COP coordinate (x_{t-1}, y_{t-1}) at Time t-1

3: Obtain the COP coordinate (x_t, y_t) at Time t

4: Distance: $D = \sqrt{(\mathrm{X}(\mathrm{t}-1) - \mathrm{Y}(\mathrm{t}-1)) + (\mathrm{Y}(\mathrm{t}) - \mathrm{X}(\mathrm{t}))}$

5: Compute change in time (T) = dt = $T_t - T_{t-1}$

6: $COP_{speed} = \frac{D}{dt}$

7: ***end for***

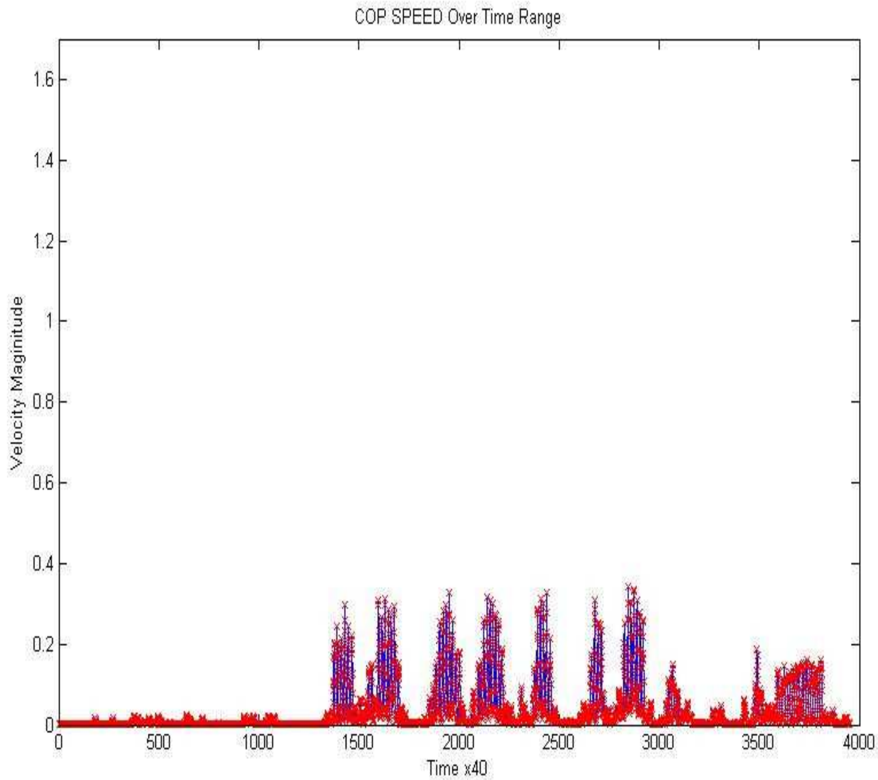


Figure 5.2 Shows the COP speed plot over time for a subject

Double Support (DS) and Single Support (SS) Detection (DS-SD) Algorithm

Segmentation of the walking data into different gait phases is essential for gait parameter extraction. In order to provide more intuition about the double support phase and how the segmentation points at the beginning and end of this phase have been detected, the gait cycle figure in the technical background (**Error! Reference source not found.**) shows these points. Since the double support phase is the part of the gait where the two feet are on the floor, their beginning and end points are characterized by the point of heel strike where the first heel contact is made and the point of toe off where the toe of the other foot is just about to loose contact with the floor. At the former point, a sharp increase will be observed in the centre of pressure value which is the result of the pressure exerted by the heel on initial contact. Another indicator for this point of heel strike is an increase in the COP speed at this point. Ultimately, the heel strike for a foot occurs at the peaks of the COP speed over time. This step is called the DS detection step/ Heel Strike (HS) detection step. The subsequent single support phase starts when the toe lifts off the floor, thus it starts from toe lift off to the next heel contact. Hence, it is of paramount importance to be a be to detect the double support and single support transition points.

In our algorithm, shown in Algorithm 5.2, we first deal with smoothing the COP speed estimates (COPspeed). This is done using an appropriate smoothing algorithm that ensures that the relevant information in the original data is kept. From this operation, we generate an updated version of COPspeed, called COPsmoothspeed. After this (in Line 2), maxima and Minima are detected in the smoothed dataset. The maxima represent the points of highest displacement of the COP which occur during double support while the minima signify the beginning of the single support phases identified by a drop in COP speed. Since one foot is on the floor, the COP only moves from the posterior to anterior part of the foot. As a result, there is little displacement of the COP as it progresses. In Line 3 and 4, the selected maxima and minima are combined and sorted with the knowledge that maxima and minima always alternate. We select the first element of the combined list as the first maximum, resulting in a list called MaxMin. Following this, in Line 5 a max and a min are paired and the difference in their speed and time are found. After doing this for all the pairs, the number of differences found for the speed and time list will be half of the entire MaxMin List. The average of the found speed change and time changes is then computed in Line 6. Setting this average as the threshold in Line 7, the valid Maxima and Minima pairs that correspond to actual walking and are not due to person sway or local, non-walking activities were identified and In Line

8, the Maxima were grouped to a separate list Valid Maxima which signifies the times at which double support starts for a subject. The Valid_Minima list is similarly a corresponding list of all the times at which a single support phase starts for a subject.

The algorithm to segment the double and single support phases is as follows:

Algorithm 5.2 DS-SSD Algorithm

1: Smooth the Computed COP_{speed} Data

- $COP_{smoothspeed}$ = Smooth_Speed(COP_{speed})

2: Select the local Maxima and Minima Times from the smooth speed Data

- Maxima = Select_Maxima ($COP_{smoothspeed}$)
- Minima = Select_Minima ($COP_{smoothspeed}$)

3: Combine the Maxima and Minima: MaxMin

MaxMin = Combine (Maxima, Minima)

4: Sort MaxMin

- MaxMin = Update_MaxMin(MaxMin)

5: Find the difference between successive maxima and minima in speed and time

for i = 2 to N_MaxMin ***do***

(s_i, t_i) = Diff (MaxMin)

6: Calculate the Average of the difference found

- Ave_s_i = Average(s_i)
- Ave_t_i = Average(t_i)

7: Get Rid of Noise and false Maxima and Minima

for i = 1 to N_(s_i, t_i) ***do***

Valid (s_i, t_i) = (s_i, t_i) > (Ave_s_i & Ave_t_i)

8: Select Valid Maxima and Minima

- Valid_Maxima = Maxima with Valid(si, ti)
- Valid_Minima = Minima with Valid(si, ti)

Segmenting Walking and Non Walking Data

Using the DS-SSD Algorithm, the walking segments can be extracted based on the time they occurred. This extraction can be done in two ways. One approach is to feed the time ranges where walking is suspected to the algorithm and the walking time will be extracted into Heel strike and Toe off. An alternative is to feed in the entire data which is a combination of the walking and non-walking data to the algorithm. This gives a list of all the valid Heel strike and Toe off points in the entire data. This is a better approach as it is more automated. However, the results from doing this will need to be further segmented into groups or aggregated into time frames in which walking is performed in a time window so that previous gait cycles obtained in the initial pass are not mixed together with those obtained later. The segmentation of the entire trial is shown in **Error! Reference source not found.** and a more detailed view of the segmentation of one walking pass is shown in **Error! Reference source not found.**

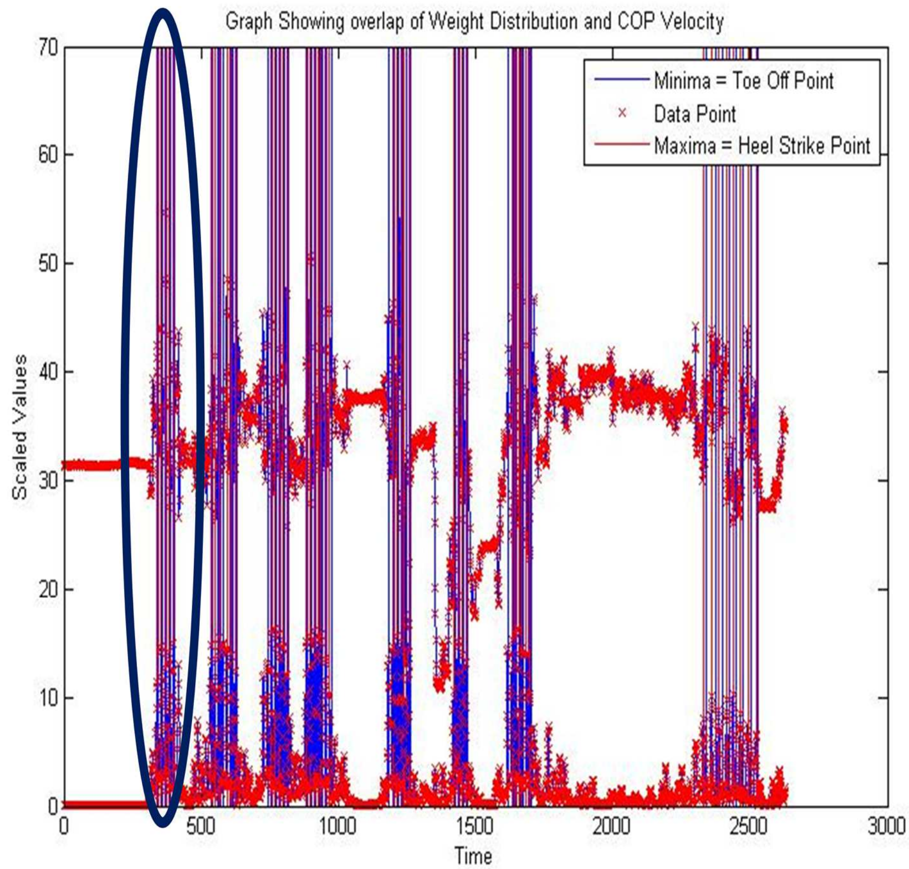


Figure 5.3 Segmented COP Speed Plot Overlayed with Weight distribution

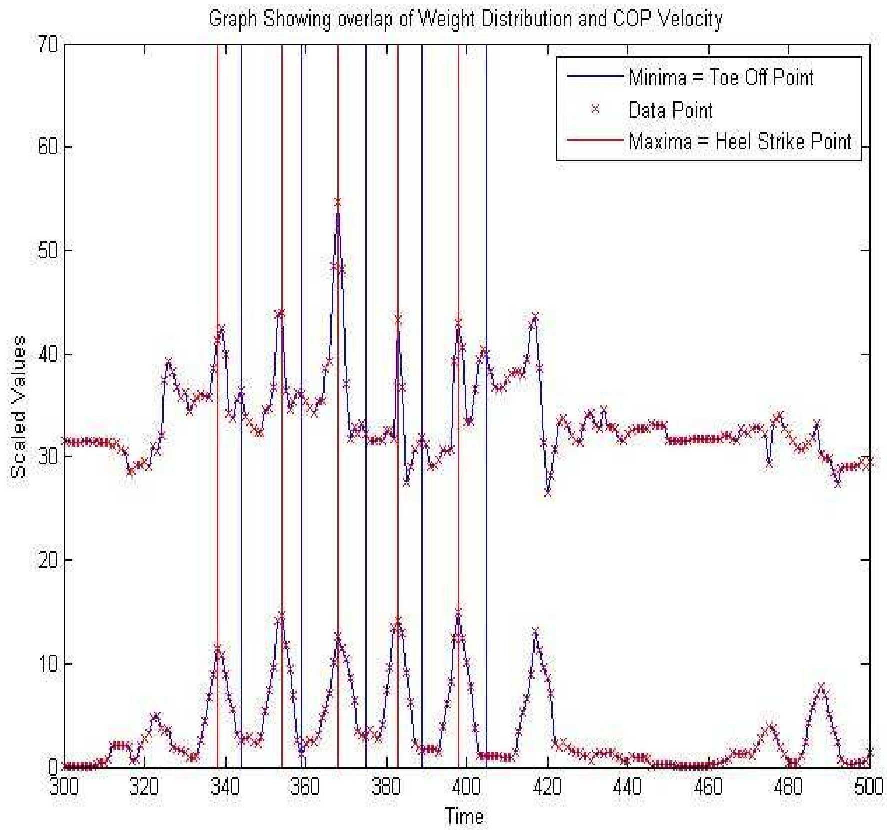


Figure 5.4 One of the Walking Passes With Corresponding Segmentation

Gait Cycle Extraction

Given the segmentation derived previously, it is now possible to extract gait cycles and phases. A gait cycle starts from the beginning of a double support phase and ends at the beginning of the second double support phase after this one. Since the DS-SSD algorithm detects the Heel contact point, the gait cycle for a walking subject can easily be extracted. To get the picture of a gait cycle, it is shown in **Error! Reference source not found.** in the technical background in **Error! Reference source not found.**. For a subject, the gait cycle was extracted using the gait cycle extraction algorithm below in Algorithm 5.3. Let the time window, which is a time range from walk start to walk end for a given frame be represented as TW.

Algorithm 5.3 Gait Cycle Extraction Algorithm

1: ***for*** i = 1 to No of TW ***do***

While (t < end of TW(i) ***) do***

Heel strike $Foot_x$: Identify Double Support point: DS (i)

Heel strike of $Foot_x$: Identify next 2 Double Support point: DS (i+2)

end while

end for

Foot Roll Extraction

Foot roll occurs during the stance phase of a gait cycle. The foot roll pattern can be extracted during the single support phase where it is evident for an individual as the foot COP gait line progresses from the point the toe of the other foot lifts off the floor to the point just before heel strike of the other foot. In essence, one foot's COP progression from posterior to anterior is a representation of the pattern of the foot rolling pattern.

Stride Length Extraction

The stride length extraction becomes straight forward once the gait cycle extraction has been completed. Since the HS points are known, the cadence can easily be found for each gait cycle extracted from the walking data for the subject. The algorithm for this is shown in Algorithm 5.4.

Algorithm 5.4 Stride Length Extraction

1: for each gait cycle (GC) out of TotalGC extracted

for i = 1 to TotalGC ***do***

Get the coordinate (x_t, y_t) at DS (i)

Get the coordinate (x_t, y_t) at DS (i+2)

Find the Stride Length

end for

Step Length Extraction

Step length was extracted using the stride length and the vector of the line connecting the initial point of the gait cycle (the initial heel strike) with the other two heel strike points. Extraction of the step length, L, from the stride length, S, is illustrated below and summarized in Algorithm 5.5.

Stride length = S

Step length = L

Stride Vector = S_Vector = $\begin{pmatrix} X(3) - X(1) \\ Y(3) - Y(1) \end{pmatrix}$

Step Vector = Sp_Vector = $\begin{pmatrix} X(2) - X(1) \\ Y(2) - Y(1) \end{pmatrix}$

L = $\left(\frac{1}{Stride\_Length} . \mathrm{S\_Vector} \right)^{T}$. Sp_Vector

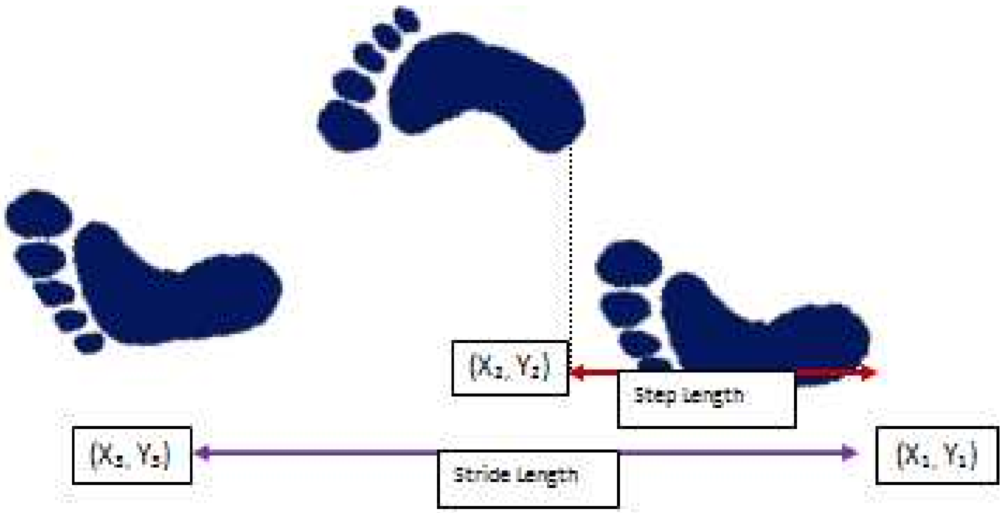


Figure 5.5 Step Length Estimation

Algorithm 5.5 Step Length Extraction Algorithm

1: Find the Stride *Sride_L* using Stride Length Extraction Algorithm

2: Find the Stride Vector:

$$\langle \boldsymbol{S} \rangle = \begin{pmatrix} X(3) - X(1) \\ Y(3) - Y(1) \end{pmatrix}$$

3: Find the Step Vector

$$\langle \boldsymbol{L} \rangle = = \begin{pmatrix} X(2) - X(1) \\ Y(2) - Y(1) \end{pmatrix}$$

4: Compute the Step Length

$$L = \left(\frac{1}{S\_Length} . \langle \boldsymbol{S} \rangle\right)^{T} . \langle \boldsymbol{L} \rangle$$

Foot Separation

Separating the feet into left and right is necessary for recognition of the differences in step length made by the left and right foot during a gait cycle. Determining the foot can again be accomplished using the step vectors and the stride vector in a gait cycle. Using these and considering the stride vector as the walking direction, the foot can be identified based on the side in which the step vector deviates from the stride vector direction. Computing this involves determining the offset of the step vector in the normal direction to the stride direction. This process is summarized in Algorithm 5.6.

Algorithm 5.6 Foot Separation Algorithm

1: Find the Stride Vector:

$$\langle \boldsymbol{S} \rangle = \begin{pmatrix} X(3) - X(1) \\ Y(3) - Y(1) \end{pmatrix}$$

2: Find the Step Vector

$$\langle \boldsymbol{L} \rangle = \begin{pmatrix} X(2) - X(1) \\ Y(2) - Y(1) \end{pmatrix}$$

3: Rotate the Stride Vector 90^0 to obtain Normal Vector

$$\langle \boldsymbol{S} \rangle = \begin{pmatrix} -\,(Y(3) - Y(1)) \\ X(3) - X(1) \end{pmatrix}$$

4: Multiply the Stride Vector and Step Vector

- Detect_Foot = $\langle \boldsymbol{L} \rangle^{T} \cdot \langle \boldsymbol{S} \rangle$

5: Detect if it is < or > 0

- Left Foot ≡ < 0, Right Foot ≡ > 0

Step Symmetry

Once the step length has been obtained and the left and right feet have been identified for a subject, the next step is to obtain the step symmetry which is the ratio of the step length of the left vs. right step cycle. The sum of the step lengths is equivalent to the stride length.

Chapter 6

Experiment and Results

Data Collection

The experiment involves the capturing of walking data using floor mounted pressure sensors. We had 35 volunteer participants from within and outside the academic community. We collected data from 11 males and 24 females with ages ranging from 17 to 72. See Table 6.1 below regarding further information about the participants. From each of this participant we collected both balance and walking data following our experimental protocol described in Chapter 4.

Table 6.1 Subject Information

Subject	**Age**	**Height (in)**	**Weight(lbs)**	**Gender**	**Dominant Foot**
1	58	69	156	Female	Left
2	34	66	186	Female	Left
3	59	63	200	Female	Right
4	69	67	184	Female	Left
5	59	64	189	Male	Right
6	18	72	171	Male	Left
7	51	65	146	Female	Left
8	62	68	215	Female	Left
9	30	70	176	Male	Right
10	49	67	146	Female	Left
11	19	66	191	Male	Left

Table 6.1 - continued

12	66	65	176	Female	Right
13	67	65	170	Female	Left
14	43	66	171	Female	Left
15	42	64	151	Male	Left
16	68	64	144	Female	Left
17	31	63	114	Female	Left
18	29	66	134	Female	Left
19	71	63	153	Female	Left
20	18	64	144	Female	Left
21	25	67	153	Male	Left
22	31	73	224	Male	Left
23	24	63	190	Female	Right
24	31	72	252	Female	Right
25	27	71	220	Male	Left
26	72	62	200	Female	Right
27	24	60	128	Female	Right
28	32	60	128	Female	Right
29	52	63	166	Female	Left
30	25	68	150	Male	Left
31	29	70	148	Male	Right
32	62	69	161	Female	Left
33	60	60	181	Female	Left
34	58	70	164	Male	Left
35	60	57	112	Female	Left

From the entire data collected for each subject we were able to divide the data into two types;

i. The walking data: the part where the subject was walking on the Smart Floor. All subjects were asked to walk as normal as possible during the entire experiment until the last walking phase where they were asked to walk slowly in order to variation from the walking phases exhibited earlier.

ii. The Non-Walking data: The Non-walking data is the segment in the entire data in which the subject is not actively walking but performing other parts of the experimental protocol such as balancing, standing, opening the door, etc.

Floor Calibration

The data obtained from the floor was obtained with approximately pre-calibrated sensors in order to ensure that sensor values in different floor regions are providing pressure information in terms of a uniform measurement unit. There are a total of 128 sensors on the experimental floor. Each sensor can output a value from 0-1023. Since the Tekscan FlexiForce A401 Sensors behave linearly, we can represent each sensor in the standard slope-intercept form of a linear equation: $w = ax + b$,

where

w is the weight in pounds we want to calculate

x is the “raw” output from the sensor (0 – 1023),

a is the x’s coefficient, and b is a constant (offset).

Calibration of the slope and intercept was performed using a set of standard weights that were place on the sensor locations. A linear least square fit was then applied to obtain the calibration parameters for each sensor.

Features Extraction

In order to clearly identify changes in gait pattern for a user walking over the floor, we need to extract the user's gait line and from this gait line perform some pattern distinction. The steps taken for the extraction of walking patterns are presented here.

Using the calibrated sensor data, the Center of Pressure (COP) for each user on the floor was calculated. With the center of pressure, a subject's balance as a measure of postural sway while a person is standing can be measured. Other useful pattern information/parameters that we extracted were the user's weight, dynamic characteristics of balance and step impact, foot roll pattern, step length, step width, cadence, and step velocity. Each of these parameters contains significant information that allows us to identify certain deviations from a user's usual pattern information.

The COP position varies in time along a foot (in single stance where the Cop corresponds approximately to the point of the impact force) and between the feet (in double support where the COP moves between the feet as weight is shifted from one side of the body to the other) during walking and results in what is commonly known as the gait line (the co-ordinates of the progression of the point of application of the vertical ground reaction force). The COP is calculated by weighting each pressure measurement by its magnitude and position so as to be able to resolve all pressures into one point.

Considering the center of pressure's on x coordinate, COP(x,). It can be calculated using the formula:

$$COP(x) = \frac{\sum_i x_i . F_i}{\sum_i F_i}$$

where F_i is the pressure at a sensor location x_i relative to a reference point in the x-direction. Computation of the y position of the COP is performed in the same way.

The extraction module for extracting a user's gait line was written in C++ and MATLAB. This module is divided into three parts:

i. Foot pressure point extraction.

ii. COP extraction.

iii. Gait line extraction.

Foot Pressure point extraction

This module marks the starting point of the analysis and is responsible for identifying pressure sensors that had a value when a user was on the floor. It performs two functions, namely it extracts the pressure sensor value and pressure sensor coordinates. Ultimately, it extracts the pressure map formed by the user when walking on the floor. Data was transmitted at 25Hz which amounts to one pressure reading every 40ms. The information extracted from the Smart Floor every 40ms is referred to as a frame. Activated pressure sensor refers to a sensor that has a value that is above the noise level of the sensor system at a particular frame. When a pressure sensor is activated it gives a value and that value is represented in the Graphical User Interface as a circle in the sensor's location with a radius that is proportional to the sensor reading. Thus, the bigger the radius the higher the pressure value applied to the sensor. **Error!**

Reference source not found. shows an example of the GUI with an activated sensor frame.

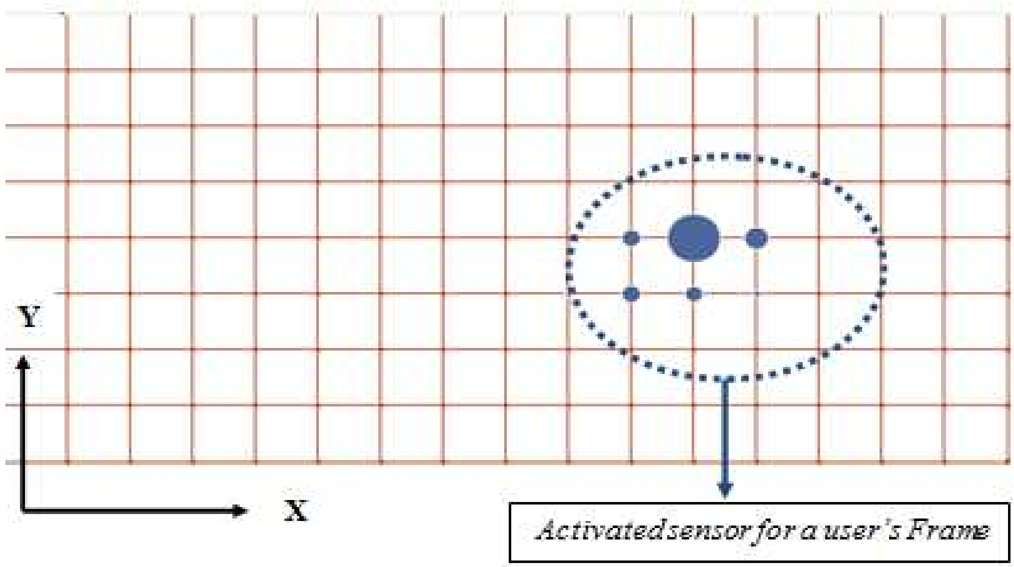


Figure 6.1 An example of frame's activated sensor

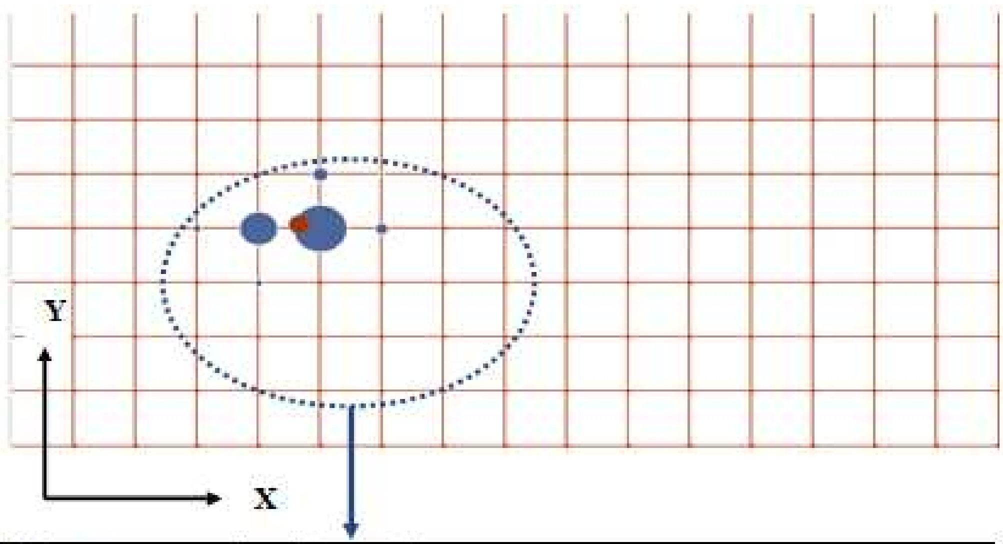
COP extraction

This module is responsible for the extraction of the center of pressure and its value. Given the number of activated sensors at a frame, the center of pressure is computed using the X and Y coordinates and the pressure sensors and the corresponding pressure readings, F(i), in those directions. The position is the average of the activated sensors and thus the COP value computation is computed as

$$COP(X) = \frac{\sum_i x(i).F(i)}{\sum_i F(i)}$$

$$COP(Y) = \frac{\sum_i y(i).F(i)}{\sum_i F(i)}$$

Error! Reference source not found. shows an example of the COP extracted from a set of pressure readings with Table below describing the symbols used in the figure.



Marker	Interpretation
	• An activated sensor for the current frame. • Radius is the amount of force/pressure exacted by user.
	• Centre of Pressure computed based on the Activated sensors • Radius is the COP value

Figure 6.2 An example of an activated sensor with COP

Gait Line Extraction

The center of pressure gait line shows a visual representation of the center of pressure progression during the phases in which the foot is making a contact with the ground. Since the gait line shows the COP progression, it is thus a combined representation of a user's COP over time depending on the number of samples obtained per time step. Here we obtained approximately 40 samples per second. There could be several representations of the gait line. The first representation is for a single step which is from a double support to a second double support and the second is a complete representation for the entire walking period. The software module for the gait line extraction was implemented in Matlab. From this gait line several other parameters can be extracted. This will be elaborated in the results. Using a combination of the frames COP, **Error! Reference source not found.** shows a representation of one subject walking across the Smart Floor.

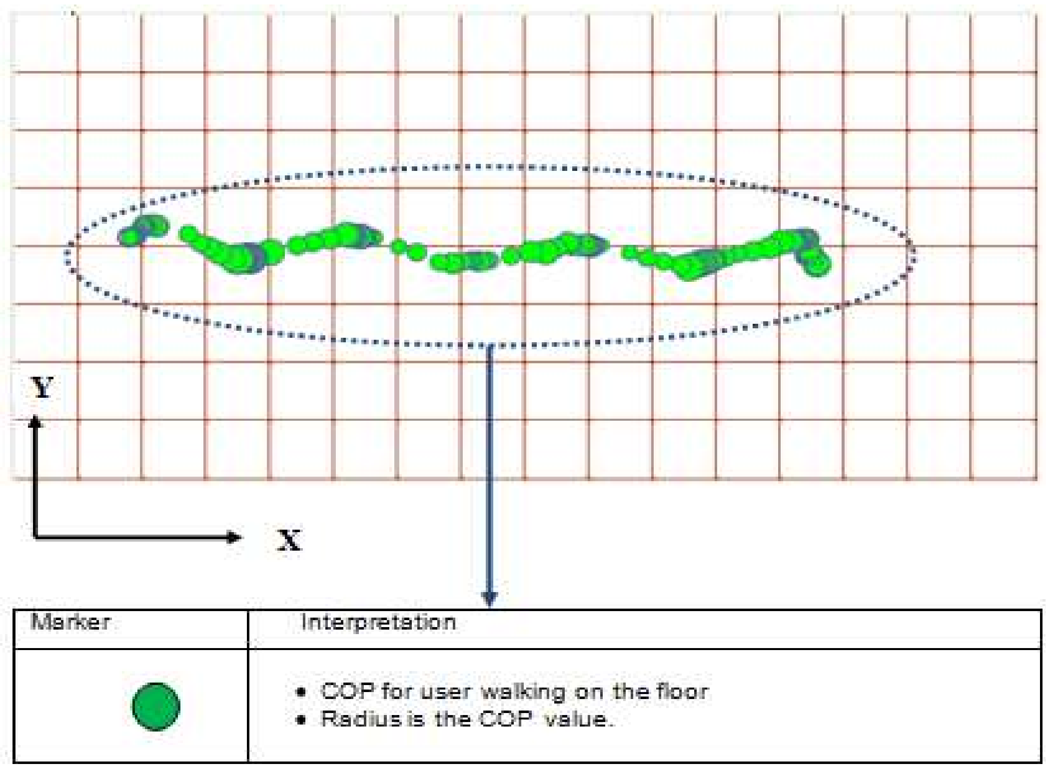


Figure 6.3 An example of a gait line extracted Gait line for Subject walking across the Smart Floor.

Similarly, **Error! Reference source not found.** and **Error! Reference source not found.** show gait line plots for an entire trial, including all parts of the experiment.

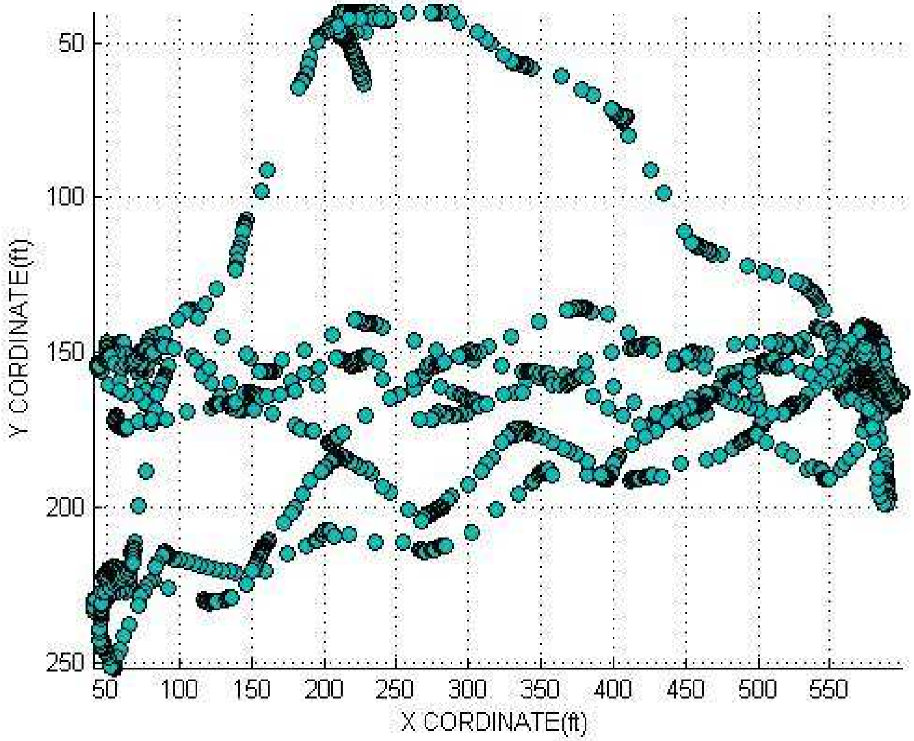


Figure 6.4 A complete gait line 2D plot extracted for a Subject

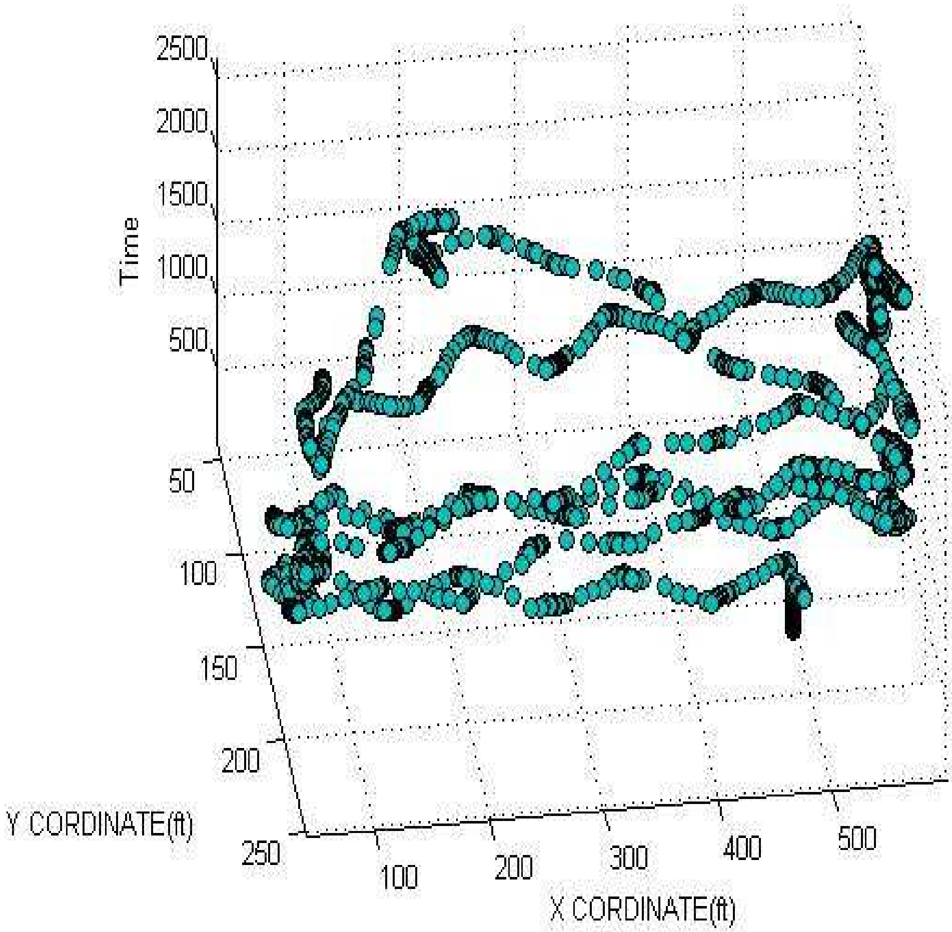


Figure 6.5 A complete gait line 3D plot extracted for a Subject

Experimental Results

Based on the parameters explained in the previous chapters, some relationships have been drawn from them to draw out a pattern that is distinguishable for different individuals during gait.

Using the extraction algorithms explained earlier, observation can be made about parameters that are generic for all subjects and about relationships that do not satisfy the norm for most subjects. The relationship between stride length and COP speed, between stride length and step frequency, and between COP speed and step frequency were determined to be of interest for modeling and and a polynomial equation was derived to model these relationships for some subjects. From these, it can be shown that the relationships follow a particular pattern that varies across individuals. In addition, the choice of this parameter relationship allows to investigate whether individuals' expressly requested slow walking pass falls within the same model relation (and thus looks like other walking passes) or if it falls outside the normal envelope due to participants over-emphasizing the slow walking (thus resulting in "slow motion walking" rather than a regular slow walk). To build this model and test this question, for all data with the exception of the slow walking gait cycle for a subject, the stride length and COP Speed relationships are considered to reflect normal walking with the slow walking data to be tested whether it deviates from their normal walking data.

With the main focus being the stride length and COP Speed here, we were able to draw a relationship using the polynomial regression fit for each subject.

Due to the absence of known abnormal data, we started an analysis of the relationship between the slow and normal walking data in order to check if the same model walking for normal walking as well as slow walking and to see if the model would be able to detect which individuals were walking “abnormally” slow in the slow passage

Deciding on the best model for each subject

As earlier stated, each subject will have a defined model that will represent their parameter relationship for normal walking. So that any deviation from it could be easily noted, we performed some test on the data obtained from each subject to determine the best model for them.

The steps taken to reach a clear conclusion about the preferable model for each subjects as well as to assess whether the slow walking data fits into the same model as the normal walking data, the best model was developed as follows:

Step 1: Split the Data set into two groups:

a. Normal Dataset

b. Combined Dataset Including

i. Normal Walking Dataset

ii. Slow Walking Dataset

Step 2: Select the Normal walking Dataset

Step 3: Since we have only limited data, building a model over this dataset might result in over fitting. To avoid this perform steps A – H below

A. Split the dataset ‘*DS’* into two (training and test) dataset randomly in a preferable ratio where training data is more than the test dataset (ratio 4:1 for instance)

B. Using polynomials of order 1 – 6, create six models 6, ‘ *M6*’, of different complexity for the Training Dataset using best least squares fit.

C. Use these models '*M6'* on the test dataset to determine the root mean squared error (*RMSE*) of '*M6'* on the test data.

D. Perform steps "A-C" above N times where N > 20, resulting in N X 6 RMSE values

E. Find the Mean RMSE for each model in '*M6'* resulting in 6 RMSE values

F. Select the Model '*LM'* with the Lowest Mean RMSE

G. Select the Order O of the Model '*LM*'

H. Finally, Build a new Model '*NM'* in the Order '*O'* above using the Entire Dataset '*DS'*

Step 4: Select the combined dataset

Step 5: Perform step 3, using the selected combined walking dataset

Status: Now, there is a model '*NM'* from the normal walking dataset and a model '*CM'* from the combined dataset

Step 6: Use both models '*NM'* and '*CM'* on the normal walking dataset.

Step 8: Compute the squared residual error of each of the models

Status: There are now two squared errors:

a) SENM(*Squared Error NM*): For the model *'NM'*

b) SECM(*Squared Error CM*): For the model *'CM'*

Step 9: Perform a paired sample t- test using *SENM* and *SECM*

Step 10: State the Hypothesis:

- *Null Hypothesis: Both Models are not significantly different*
- *Alternate Hypothesis: Normal Model is better*
- *Significance Level: 0.1*
- *Two Tailed Test*

Step 11: Based on the result obtained from here, we decide on the model representative of the subject's normal walking dataset.

If we do not reject the null hypothesis, it does mean that the combined model is representative of the entire model. On the other hand, if we do reject the null hypothesis, then the data from the slow walking pass significantly deteriorated the model and thus a combined model is significantly less representative of the normal data as a model built only on known normal walking data. As a result, this would support that for these individuals slow walking was not within their normal range and they thus likely over-emphasized the slow component. As a result, it could also be an indication that the slow walking dataset is not the same as the normal walking dataset for the subject.

Based on the results derived following the process described above, we can show using the t-test that the normal walking data and combined data set for at least some of the subjects does not follow the same model. While this does not consequently mean that one model is better than the other, Occam's razor would indicate that, it is advisable to use a simpler model for the subject. For some subjects, we observed that the combined model, that is the model built from the slow walking data set was equally as good as the Model from the Normal walking data set under those circumstances the combined model is preferable in general as it covers a larger range of the individual's gait patterns. These decisions were made from paired sampled tests of the squared error obtained from the normal data set using each model. The result from the algorithm to decide on the appropriate model for each subject is presented in the table below.

Table 6.2 Table showing the paired sample test results

Subject No	T- Score	Degree of Freedom	P-Value	Accept	T- Value	Accept
1	0.71533	12	0.4669	Null	1.782	Null
2	-1.6085	14	0.13	Null	1.761	Null
3	-4.353	15	0.0006	Alternate	1.753	Alternate
4	-1.0113	9	0.3383	Null	1.833	Null
5	-0.42889	7	0.6809	Null	1.895	Null
6	-1.1251	11	0.2845	Null	1.796	Null
7	-2.3789	13	0.0334	Alternate	1.771	Alternate
8	-0.53694	12	0.6011	Null	1.782	Null
9	-0.10153	10	0.9211	Null	1.812	Null
10	-2.5508	12	0.0254	Alternate	1.782	Alternate
11	-2.0769	15	0.0554	Alternate	1.753	Alternate
12	-1.2673	13	0.2273	Null	1.771	Null
13	-2.274	10	0.0463	Alternate	1.812	Alternate
14	-0.98263	12	0.3452	Null	1.782	Null
15	-4.1752	7	0.0042	Alternate	1.895	Alternate
16	-2.4978	11	0.0296	Alternate	1.796	Alternate
17	-0.16736	13	0.8697	Null	1.771	Null
18	-2.5173	11	0.0286	Alternate	1.796	Alternate
19	1.785	10	0.1046	Null	1.812	Null
20	-2.2841	13	0.0398	Alternate	1.771	Alternate

Table 6.2 - continued

21	-2.1327	11	0.0563	Alternate	1.796	Alternate
22	-0.58799	11	0.5684	Null	1.796	Null
23	-2.1807	10	0.0542	Alternate	1.812	Alternate
24	-1.327	13	0.2073	Null	1.771	Null
25	1.7451	10	0.1116	Null	1.812	Null
26	-0.05603	11	0.9563	Null	1.796	Null
27	-1.4675	10	0.173	Null	1.812	Null
28	-1.1463	11	0.276	Null	1.796	Null

Data Plots Comparing the Use of Normal Model and Combined Model

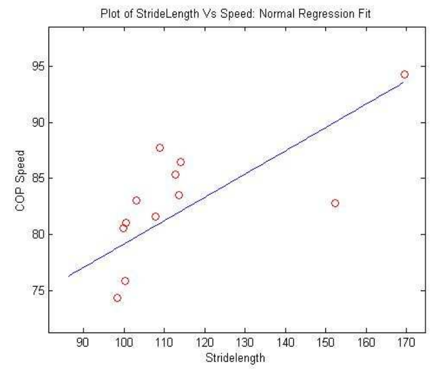
To examine the models and their fit, the polynomial fit models for a number of subjects were visually inspected and compared. In particular, five subjects were selected and their models plotted. The goal here is to show how the regression fits match the recorded points and to demonstrate the differences in the models between individuals.

Subject 1

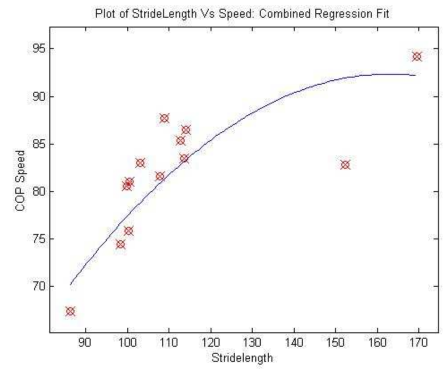
Subject 1 was one of the subjects for whom the two models were not significantly different in terms of being able to describe the normal walking parameters and thus slow walking appeared to follow the pattern of normal walking. **Error! Reference source not found.**3 shows the regression fits for the two models.

Table 6.3 Comparism of the Plot of Normal Model Regression and the combined Model Regression Fit for Subject 1

<table>
<tr><th>Normal Model Regression Fit</th><th>Combined Model Regression Fit</th></tr>
<tr><td>



</td><td>

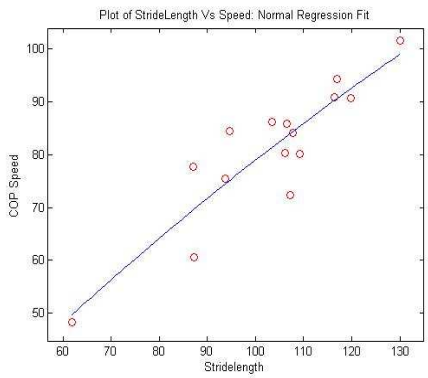
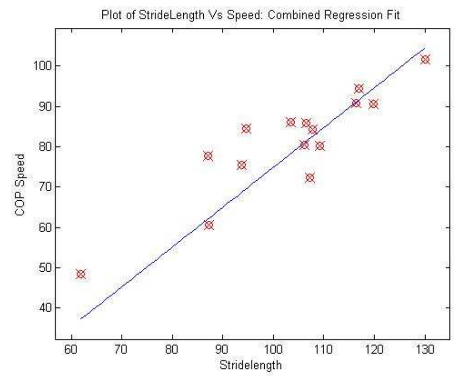


</td></tr>
</table>

Subject 2

Subject 2 was another subject for whom the two models were not significantly different in terms of being able to describe the normal walking parameters and thus slow walking appeared to follow the pattern of normal walking. **Error! Reference source not found.**4 shows the regression fits for the two models.

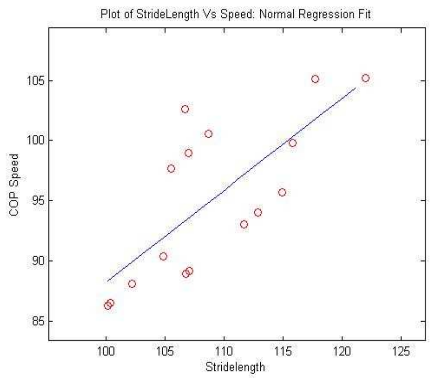
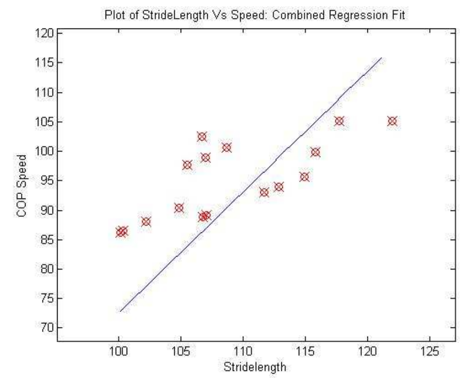
Table 6.4 Comparism of the Plot of Normal Model Regression and the combined Model Regression Fit for Subject 2

Normal Model Regression Fit	Combined Model Regression Fit
	

Subject 3

Subject 3 is the first individual for whom the two models showed significantly different ability to represent the normal walking data and for whom thus the slow walking data did not seem to fit the pattern described by normal walking data. **Error! Reference source not found.**5 shows the regression fits for the two models.

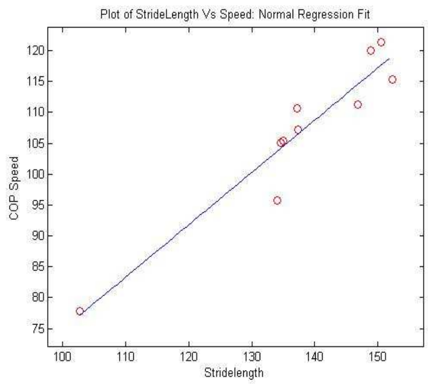
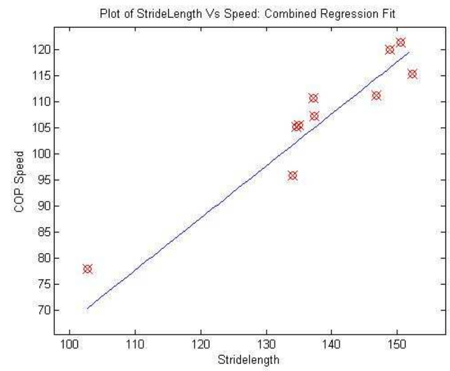
Table 6.5 Comparism of the Plot of Normal Model Regression and the combined Model Regression Fit for Subject 3

Normal Model Regression Fit	Combined Model Regression Fit
	

Subject 4

Subject 4 is again a subject for whom the two models were not significantly different thus slow walking appeared to follow the pattern of normal walking. **Error! Reference source not found.** shows the regression fits for the two models.

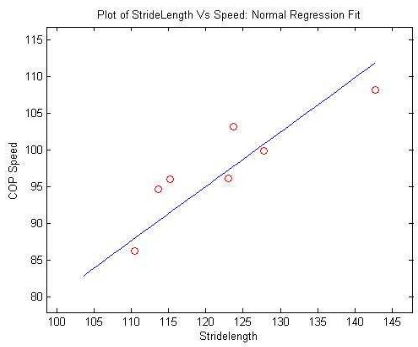
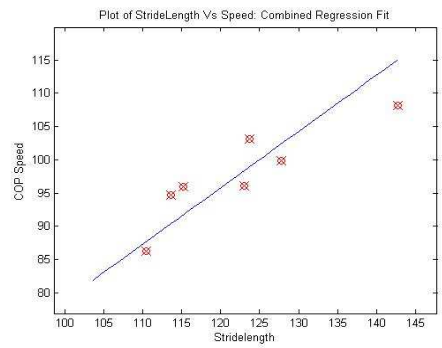
Table 6.6 Comparism of the Plot of Normal Model Regression and the combined Model Regression Fit for Subject 4

Normal Model Regression Fit	Combined Model Regression Fit
	

Subject 5

Subject 5 is also a subject for whom the two models were not significantly different thus slow walking appeared to follow the pattern of normal walking. **Error! Reference source not found.**shows the regression fits for the two models.

Table 6.7 Comparism of the Plot of Normal Model Regression and the combined Model Regression Fit for Subject 5

Normal Model Regression Fit	Combined Model Regression Fit
	

Chapter 7

Conclusion and Future Works

With the further processed data obtained from the Smart Floor, a subject’s Center of Pressure (COP) trajectories was calculated. From a close study of the extracted COP, other dynamic characteristics of balance and step impact necessary for anomalous gait detection were extracted. In this thesis, we were able to recognize and detect differences in a person’s gait based on some of the extracted parameters. We showed formally that separation of gait features is possible using the COP gait line and from it deviations can be observed. A better understanding of center of pressure movement and (pressure distribution) during walking will facilitate clinicians’ assessment and enhance treatment and can provide information about postural control in both normal and pathological situations to further detect anomalous health situations. In future work, we want to further expand our study by analyzing the balance data to extract the level of sway by each subject while taking into account the tile coupling and how these can relate to the subject’s gait. Furthermore, we will precisely recalibrate the floor sensors in this study and also acquire more abnormal gait data in order to have a full software system that analyzes changes in balance and gait patterns.

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