Gait and Tremor Monitoring System for Patients with Parkinson's Disease Using Wearable Sensors

by

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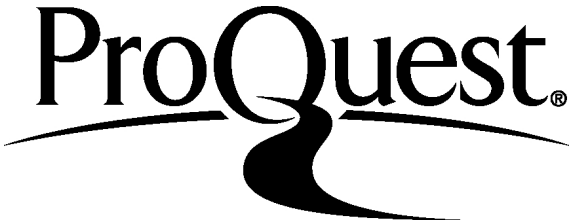

DEDICATION

I dedicate this thesis to my beloved parents, S. Perumal and P. Jayalakshmi.

ACKNOWLEDGMENTS

I would like to thank my advisor Prof. Ravi Sankar for placing trust in my research potential and encouraging me throughout this research. I am also grateful for the opportunity he gave me to work with him, which allowed me to enhance my research skills.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Typically, a Parkinson's disease (PD) patient would display instances of tremor and bradykinesia (slowness of movement) at an early stage of the disease and later develop gait disturbances and postural instability. So, it is important to measure the tremor occurrences in subjects to detect the onset of PD. Also, it is equally essential to monitor the gait impairments that the patient displays, as the order at which the PD symptoms appear in subjects vary from one to another.

The primary goal of this thesis is to develop a monitoring system for PD patients using wearable sensors. To achieve that objective, our work focused first on identifying the most significant features that would best distinguish between PD and normal healthy subjects. Here, the various gait and tremor features were extracted from the raw data collected from the wearable sensors and further analyzed using statistical analysis and pattern classification techniques to pick the most significant features. In statistical analysis, the analysis of variance (ANOVA) test was conducted to differentiate the subjects based on the values of the mean. Further, pattern classification was carried out using the Linear Discriminant Analysis (LDA) algorithm. The analysis of our results shows that the features of heel force, step distance, stance and swing phases contributed more significantly to achieving a better classification between a PD and a normal subject, in comparison with other features. Moreover, the tremor analysis based on the frequency-domain characteristics of the signal including amplitude, power distribution, frequency dispersion, and median frequency was carried out to identify PD tremor from different types of artifacts.

CHAPTER 1:

INTRODUCTION

1.1 Background and Motivation

Computers and electronics have become an integral part of the biomedical signal analysis, aiding from data acquisition to signal processing stages. Also, the introduction of wearable sensors has changed the way we acquire, record and monitor the bio-signals. Numerous products ranging from those that improve the standard of living to monitoring body's vital signs (body temperature, pulse rate, blood pressure, and respiration rate) have been revolutionizing the health care industry. Moreover, with the stepping of tech giants such as Apple, Samsung, Google and others into the world of wearable, it could denote the importance of wearable technologies in improving the quality of life of people.

Earlier, to monitor a person's ECG, an instrument specifically designed to measure the heart's activity with a monitor to display the readings would be essential. Nowadays, a wearable sensor provide us with advantages such as the wireless connectivity, lightweight, and low power consumption. Also, the sensors are multi-dimensional in its purpose, which implies that a single sensor could be used to measure the heart's activity, blood pressure, and also the muscle activity simultaneously [1]. However, its reliability and performance over a period of time are not satisfactory.

Biomedical signal processing has also seen some significant changes over time. Earlier, it was mainly concentrated on removing artifacts, spectral analysis and modelling for signal feature

representation. Recent trends have been toward quantitative or objective analysis of bio-signals. Also, advancements in the practical application of signal processing (digital filter designing, peak detection, feature extraction from signals, and frequency-domain analysis) and machine learning algorithms have provided us an efficient and reliable method for diagnosis, monitoring, and rehabilitation of patients [2-4]. Moreover, these techniques are widely accepted by clinicians and have strengthened the role of engineering in clinical studies.

Figure 1.1 presents wearable sensors that measure the bio-signals from different parts of the human body. All the sensors are connected to a central hub, which acts as a transceiver that connects to a computer through wireless connectivity. Also, it can simultaneously send the measured value from the sensors to the system.

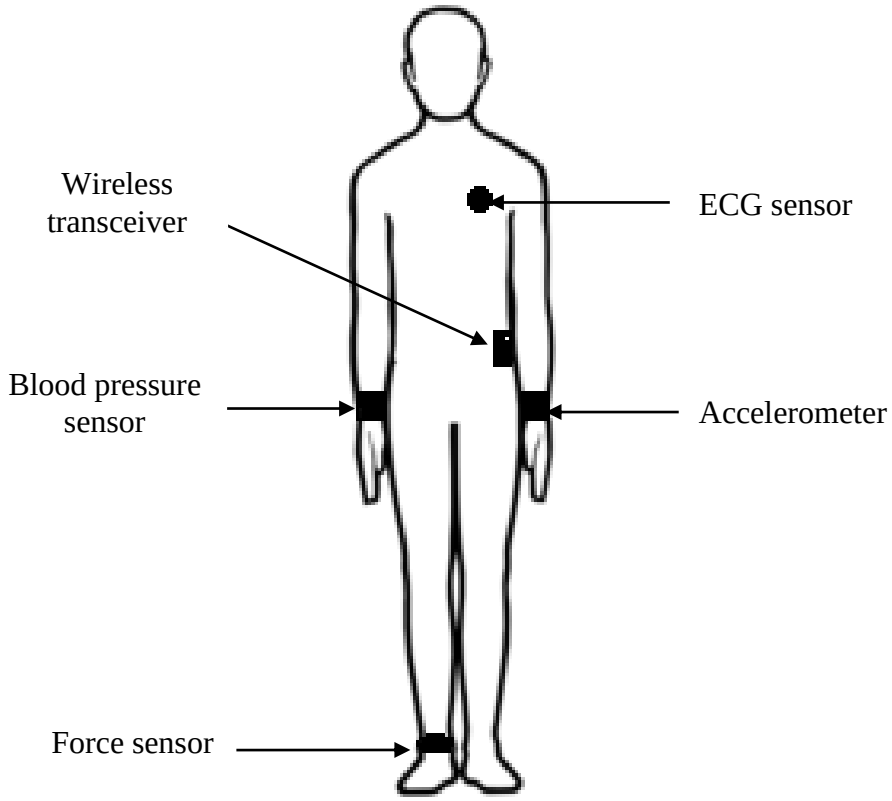

Figure 1.1. Wearable sensors placed at different parts of the body. Adapted from "clker.com" by OCAL, 2012, CC0 public domain.

1.2 Parkinson's Disease: An Overview

Parkinson's disease (PD) is ranked the second most common neurodegenerative disease next to Alzheimer's disease. As identified by Parkinson Disease Foundation [5], nearly 1 million people suffer from PD in the USA alone, and this raises to around 7 to 10 million cases worldwide. PD stands 14th as the most common cause of death in the USA. Deterioration of dopamine-producing neurons in the brain is the primary cause of PD, where Dopamine is an essential neurotransmitter that controls both smooth and coordinated muscle function [5].

The main motor symptoms of PD include tremor at rest, bradykinesia, rigidity, and impairment of postural balance [6]. Resting tremor is a common symptom at an early stage of PD, and it can be seen in 70% of patients approximately. Typically, it occurs at a frequency of 4-6 Hz causing a 'pill rolling' movement of the thumb and index finger. The tremor may also extend to the forearm or even to the elbow and upper arm. Additionally, PD patients also display slowness in performing voluntary movements called as bradykinesia, during the onset of PD. Rigidity is the resistance to passive stretch, and postural instability causes the person to have trouble in walking, turning and balance [6].

Further, postural instability causes instances of freezing of gait (FOG) [7], which is defined as a period where the person would hesitate to move forward or make turns despite the intention to move. The FOG and falls are closely associated with each other, as the PD subjects might experience fall, when they face trouble in maintaining the balance while turning or changing directions. As the FOG episodes are unpredictable, it is also difficult to prevent falls and more appropriately around 38% of patients with PD experience falls each year [7].

Additionally, the gait of a PD patient display features such as stooped posture, hesitation while walking, slow gait, short steps and reduced arm swing, and can be seen during the later

stages of the disease. While, an average person would walk with a straight upright posture, steady and evenly matched steps and arms swinging by his sides [8].

The National Parkinson Foundation claims that typically it requires more than one different method to confirm the presence of PD in subjects. Also, to confirm a PD diagnosis, the subject must display at least 2 of the 4 main motor symptoms, i.e., resting tremor and bradykinesia. Moreover, gait impairments are common in PD patients, who are prone to falls and FOG. It is essential to study the differences between a PD and normal gait that leads to postural instability and falls. Currently, PD cannot be cured, but its symptoms could be controlled by medications and/or by using deep brain stimulation (DBS) treatment [8].

1.3 State of the Art

In this section, a detailed review of the various clinical techniques used for diagnosing PD is provided. In addition, the different applications of wearable sensor technology in monitoring PD symptoms are also discussed. The clinical diagnosis has both its pros and cons, and with the recent developments in wearable sensor technology, it could be supplemental in improving the quality of life for PD patients.

1.3.1 Current Diagnosis

The diagnosis of PD can be difficult especially in its early stages and at present, there is no particular test or biomarker available to diagnose PD. Typically, a neurologist or doctor would require the patient's complete medical history, and also performs numerous clinical assessments to confirm on PD presence in that subject. Additionally, various lab tests and imaging techniques are used to rule out other conditions that may cause Parkinsonism in subjects, which might not

necessarily be due to PD. Moreover, an important diagnostic method includes the subject's response to levodopa therapy. If the subject's symptoms related to PD, respond well to the levodopa therapy then, there is a possibility that the subject might be suffering from PD. However, sometimes doctors feel that the intake of medications might be unnecessary during the premature stage of the disease [5, 8].

Sometimes, it might take up to a year to diagnose PD after careful consideration of the subject's neurological history and clinical assessments. Moreover, there is also a high possibility of misdiagnosing PD for other neurological disorders that show parkinsonism. It has been found that the rate of misdiagnosis of PD is around 25%, and approximately 40% of PD cases are overlooked for other neurological disorders [5, 8]. Also, it is important to note that the progression of symptoms in PD subjects varies from one subject to another. According to experts, the diagnosis of PD requires the presence of one or more of the four main PD motor symptoms. It is because the progress of PD symptoms varies from one subject to another, for example resting tremor occurs in only 70% of PD patients during the onset of the disease. While others might develop gait disturbances or even action tremor during their initial stages of PD [5, 8]. So, an early and accurate diagnosis of PD is required to treat the patients better and also to control the effects of the symptoms more efficiently.

1.3.2 Literature Review

Over time, many types of research have evolved on developing a PD monitoring system, using different types of sensors, feature sets and analysis methods. Few among the many wearable sensors used in acquiring the bio-signals include accelerometers, force sensors, gyroscopes and magnetometers [9]. As a result, numerous gait and tremor features are extracted and analyzed to

find a better approach to the treatment and management of PD symptoms. Initially, PD patients display slowness in performing voluntary movements and tremor at rest, and later develop gait disturbances and postural instability. While, it is important to diagnose the onset of PD in subjects as early as possible, and also it is equally important to predict falls and aid in the rehabilitation of the patients, during the later stages of the disease [10]. For example, Patel *et al.* [11] worked on developing a system that measures the severity of tremor, bradykinesia (slowness of movement) and dyskinesia (motor fluctuations) using a wearable sensor platform. Moreover, the results were analyzed to obtain the most significant features that could assess the severity of the symptoms and dyskinesia reliably.

Firstly, the resting tremor occurs during the early stage in PD patients, it is essential to analyze tremor as the main criterion to diagnose the PD. Several investigators have proposed different methods to measure and analyze the tremor in PD patients, and accelerometers are mostly used to detect and record PD tremor [12, 13]. The measured tremor intensity could aid in early detection of PD, and also for UPDRS (Unified Parkinson's Disease Rating Scale) correlation. For instance, Salarian *et al.* [14] proposed an algorithm to detect and quantify tremor, and compared the measured tremor amplitude to the corresponding UPDRS score. As a result, a high and significant correlation was noticed between the amplitude and UPDRS score. Further, Edwards and Beuter [15] utilized tremor characteristics such as the amplitude, frequency and spectral power to identify PD tremor. Then, they combined the characteristics into a single variable to identify a normal from abnormal tremor effectively [15]. Also, PD tremor is characterized by measuring the relative power between the frequencies 4-6 Hz. It is expected that a significant peak occurs in the region on a power spectral plot for PD patients. Further, a low amplitude value of physiological signal (takes place due to the mechanical reflex and neurogenic oscillations, that are superimposed

on the irregular fluctuations in muscle and limb displacements) at the range of 7-12 Hz can also be observed [16].

On the other hand, it is vital to monitor the gait impairments in patients, to predict falls and aid in the rehabilitation process [17, 18]. Recently, gait analysis is being widely used to predict falls, UPDRS (Unified Parkinson's Disease Rating Scale) correlation, and also to study the gait patterns of a PD patient in contrast to a normal subject. Also, the variation in gait features enables us to group them based on the UPDRS score. In the experiments conducted by Salarian *et al.* [19], they concluded that the stride velocity and stride length of PD patients decreased in comparison to normal subjects. Additionally, the stance time in PD patients was higher than that of healthy subjects. Conversely, the PD patients demonstrated a lower swing time to a normal subject. Additionally, Okuno *et al.* obtained similar results [20] using a force sensor worn by the subjects. Further, Tahir and Manap [21] extracted basic, kinetic and kinematic features based on force measurement. Where, basic features include the stride time, walking speed and step length. Next, kinetic features include the vertical ground reaction forces (VGRF) at heel and toe contact, and the kinematic features include the angle of ankle, knee and hip at heel strike and toe off position. Then, through statistical analysis, it was found that step length, walking speed and VGRF were among the significant features that would differentiate a PD patient from normal subject [21].

Barth *et al.* [22] examined the gait pattern of normal subjects and PD patients in their early and intermediate stages of the disease. The extracted features were classified using different types of classifiers, and their individual performances were studied. Among the classifiers used, LDA (Linear Discriminant Analysis) provided the best classification accuracy. Further, in [23] Frenkel-Toledo *et al.* studied the relationship between the walking speed and gait variability in PD and normal subjects. Also, the investigators had performed statistical analysis (t-test) to compare

the two groups. From the achieved results it was evident that the PD patients had an increased variability of stride time and swing time as compared to normal subjects.

From the above literature, very few have performed experiments using both gait and tremor analysis to predict the presence of PD as well as to prevent falls. By integrating the gait and tremor systems, it could provide us with the tool for early detection and monitoring of PD.

1.4 Research Objectives

Patients with Parkinson's disease (PD) predominantly display resting tremor and slowness of voluntary movement (bradykinesia) at an early stage of the disease and later develop gait disturbances and postural instability. While it is important to diagnose the onset of PD in subjects as early as possible, it is also equally important to aid in their rehabilitation process to improve their quality of life. Currently, the diagnosis process is conducted by clinical examination and confirmed through dopamine response. It requires a series of assessments over a period of time to confirm the presence of PD. The goal of this research is to analyze the features exhibited by PD patients during the initial phase of the disease, which would enable us to detect the presence of PD at its onset. Also, the focus of this research is on studying the gait disturbances in PD that lead to falls and postural instability that has a disastrous impact on the lives of the patients. We had performed various analyses using advanced signal processing and machine learning techniques on the extracted tremor (amplitude, frequency) and gait parameters (speed, stride time and step distance) to compare and distinguish between PD and healthy subjects.

1.5 Thesis Organization

The thesis is comprised of five chapters. Chapter 1 provides a brief introduction to Parkinson's disease, and further discusses the recent development of PD monitoring systems, with the motivation behind this project. In Chapter 2, we have discussed on the various methods used for the acquisition of data (gait and tremor) and also, details on the experimental procedure followed are included in this chapter. Chapter 3 provides an insight into the feature extraction process, which discusses the different types of gait feature to be extracted along with the algorithms used in the process. Also, this chapter focuses on the quantification of tremor process including the details on the different tremor characteristics is provided. Chapter 4 discusses the various statistical and machine learning techniques used on the extracted gait parameters, with the classifier performance results. Further, Chapter 4 also explains the tremor analysis process along with the analysis results. In Chapter 5, the conclusion and future work of the project are included.

CHAPTER 2:

DATA ACQUISITION METHODS

2.1 Gait in Parkinson's Disease

Firstly, in this study the focus has been on the experiment conducted on patients with idiopathic PD (mean age: 66.3 years) with moderate disease severity (H & Y Stage 2–3) and were compared to age and gender matched healthy controls. The system consists of a pair of shoes and a recording unit. Each shoe contains eight load sensors (Ultraflex Computer Dyno Graphy, Infotronic Inc.) that cover the surface of the sole and measure the vertical forces under the foot versus time, and the sampling rate for each of these 16 sensors is 100 Hz. The database [24] comprises of 3 different experiments conducted by Frenkel-Toledo *et al.* [23], Hausdorff *et al.* [25], and Yogev *et al.* [26] which will be discussed in detail below.

2.1.1 Frenkel-Toledo Group Database (Group 'Si')

The medical center located at Tel-Aviv, recruited 36 PD patients ranging between 2 & 2.5 on the Hoehn and Yahr scale (stage of PD). The PD patients were tested against an equally matched group of healthy subjects, w.r.t. age and sample population. The subjects were tested under various experimental setups and conditions. Our focus was on the walking test conducted on a 35 m (meter) walkway, at the subject's comfortable walking speed for a time period of approximately 2 min.

The gait speed of the participants was determined by measuring the avg. time taken to complete 10 m of the total distance. The participant's age, gender, height and weight were collected, and also the Timed Up and Go test was performed to measure the balance and function of lower limbs. The investigators collected the subject's history of falls in the recent year. Also, the severity of the disease in PD patients was measured using the Unified Parkinson's Disease Rating Scale (UPDRS).

2.1.2 Hausdorff and Team Database (Group 'Ju')

The database consists of recordings from the experiment conducted by Hausdorff and his co-investigators, involving 29 PD patients and healthy subjects who had volunteered for this study. The PD subjects were selected if they had a mild to moderate disease severity, ranging from 2-3 on the Hoehn and Yahr scale (H&Y scale). Also, the recruited healthy subjects were verified for being free from neurological, visual and gait disturbances. The subjects were tested under various conditions, but our interest was to analyze the recordings of subjects walking at their usual and comfortable speed. Here, the subjects were instructed to walk for a distance of 100 m on a walkway. Later, the force measurements recorded under each foot were analyzed to extract the different gait features.

2.1.3 Yogev and Co. Database (Group 'Ga')

In this database, clinical trials were conducted using 36 PD patients with a disease severity of 2-3 on the H&Y scale, recruited from the Tel-Aviv Sourasky Medical Center. Also, age-matched 28 healthy subjects had volunteered to participate in the study. The participant's age, gender, height and weight were collected and also the Timed Up and Go test was performed

to measure the balance and function of lower limbs. The investigators also collected the subject's history of falls, and measured the severity of the disease in PD patients using the Unified Parkinson's Disease Rating Scale (UPDRS).

A series of experiments were conducted by the team, which includes a simple walking task to measure the force underneath the foot over a period of time. In which, the subjects were asked to walk for a distance of 25 m at their usual and normal pace for a time period of 2 min. Various gait features were extracted from the force readings, and the gait speed was calculated by measuring the avg. time taken by the subject to complete 8 m of the total distance.

2.2 Tremor Database

Beuter and his team [27] investigated the characteristics of rest tremor in PD patients. In this study, a group of 16 PD patients, under the age of 70 years were recruited. Also, the patients were under minimum medications at the time of study to induce tremor. The tremor was measured using a velocity-transducing laser that is directed at the finger. Moreover, the scattered light, measured in terms of volts is directly proportional to the tremor velocity. The raw output data is processed and converted from volts to mm/sec.

In this experiment, the subjects were under high-frequency deep brain stimulation (DBS) and also were given their medications, except for the initial trial where the subjects had not taken their medications for 12 hours and not under DBS treatment (DBS is a surgical procedure to treat the various PD symptoms – tremor, rigidity, stiffness and others. A neurotransmitter is surgically implanted into patients, and it delivers electrical stimulation to the targeted areas of the brain that controls movement).

We used the readings from the initial trial, which is DBS 'OFF' and medication 'OFF' stage so that we could study the instances of tremor in subjects, and also on their involuntary movements. The readings were obtained from the Physionet database under a free licensing policy [28]. The tremor was recorded for a time period of 60 sec (depending on the duration of tremor occurrence in subjects) and sampled at 100 Hz. The output was plotted on a graph, where a positive value on the velocity axis denotes a finger extension motion and a negative value corresponds to a flexion motion of the finger, which can be seen in Figure 2.1.

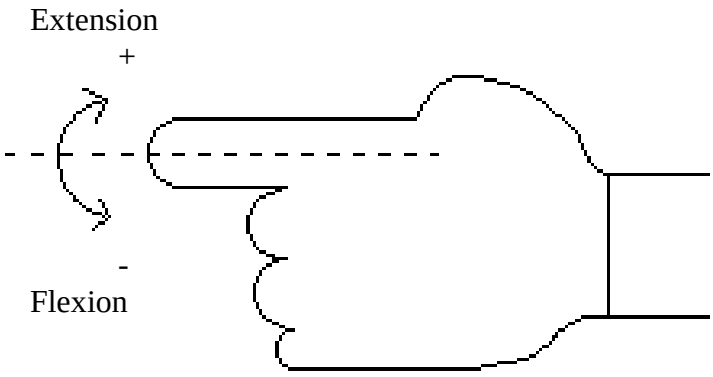

Figure 2.1. Representation of the extension and flexion movements of the finger

CHAPTER 3:

FEATURE EXTRACTION

3.1 Introduction

In this section, the various techniques used to extract features from the force and tremor data available are discussed. The classification result entirely depends on how accurate and reliable are the features extracted. An algorithm was developed to extract the gait features using the force readings obtained from the online database.

3.2 Gait Characteristics

Here, various types of gait parameters were extracted that would contribute in discriminating a PD patient from a normal subject. Several techniques have been used by researchers around the globe, to extract numerous gait features. However, the most significant features were gathered that would provide a better classification between the two groups. Also, an algorithm was coded that runs on a Matlab platform to extract the different gait features.

3.2.1 Different Phases of a Human Gait

The way a human walk varies from person to person but to perform the act of walking, a person must impart enough ground reaction forces using their feet to move forward. Also, a periodic change in each foot's support position is needed to complete a walking step [29].

When a person walks the same cyclic pattern is repeated, which is called as a gait cycle. In Figure 3.1, the various stages of a gait cycle are displayed; initially, it begins at the heel strike period which also marks the beginning of stance phase. Then, during the midstance period the grounded foot passes by the swinging foot. Later, the stance phase ends at the toe off period, also during which the foot accelerates from the ground to enter the swing phase. Further, the foot goes into a midswing period where coincidentally it passes by the foot at midstance position. Finally, the swing phase terminates at the next heel strike event, during which the foot decelerates to stabilize the foot in an attempt to land the heel. The stance and swing periods of a normal subject varies from that of a PD patient. Usually, PD patients have a reduced swing time and by measuring the stance and swing phase of subjects, it could be useful in classifying the PD groups from the normal subjects [29].

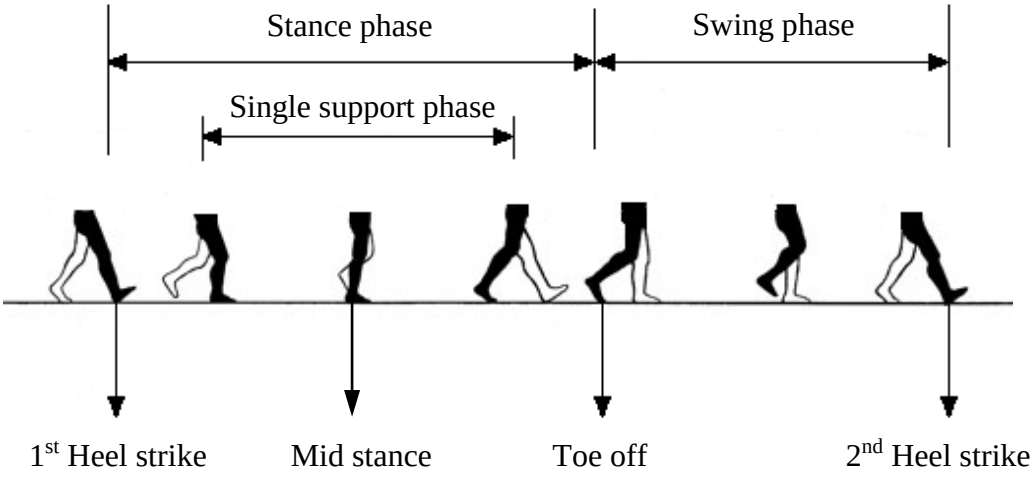

Figure 3.1. Various stages of a gait cycle are displayed. It begins with the 1st heel strike and ends at the next heel strike of the same foot. Reprinted from "http://www.wsiat.on.ca/english/mlo/symptoms_leg.htm#back" by Queen's Printer for Ontario, 2005

3.2.2 Distance Measurements

In Figure 3.2, various distance parameters are displayed, which are useful in studying the gait patterns of subjects. The step length is defined as the linear distance in the plane of progression between two successive points of foot floor contact of the opposite feet, and the distance between two consecutive points of foot contact of the same feet is called as a stride length or a gait cycle. Also, step time is the time interval between successive instant of foot floor contact of the opposite feet, while cadence is measured by counting the number of steps taken per minute. Additionally, walking speed is defined as the distance travelled by the subject per second. The last feature is the kinetic feature that mainly focuses on the force acting on the ground during heel and toe contact positions [30].

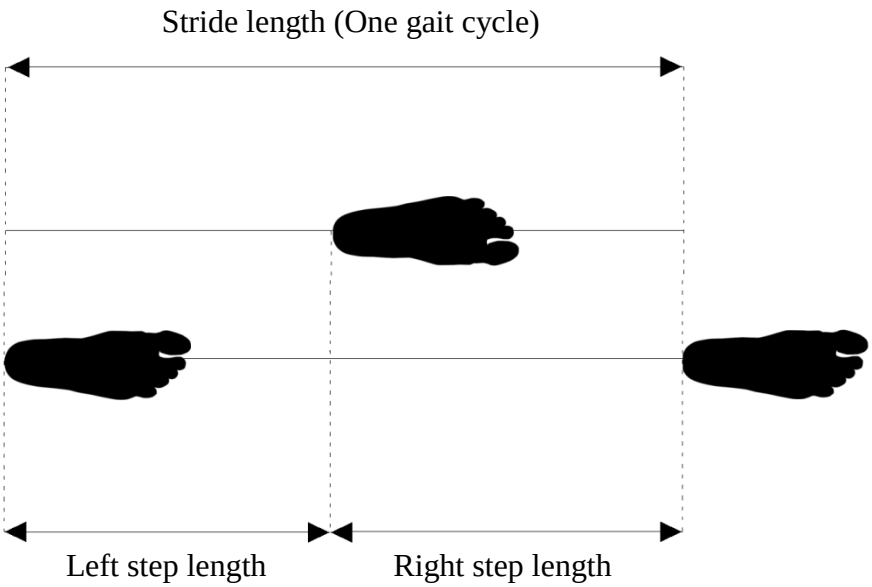

Figure 3.2. Diagram displaying the step and stride lengths of a gait cycle. Adapted from "clker.com" by OCAL, 2010, CC0 public domain

3.2.3 Ground Reaction Force (GRF)

The GRF is the force imparted by the subject walking, on the floor as a function of time. It is measured in Newton (N). In Figure 3.3, the ground reaction force value of a normal subject

from the group ‘Ga’ has been referred to, where the force is plotted against the % of the gait cycle. The force rises to 650 N right after the heel strike period and then, drops to 460 N during the midstance period. After that, at the toe-off period the force value raises up to 720 N to prepare for the swing phase, by gaining enough thrust to push the body forward. Later, during the swing phase the force drops to 0 N, where the foot accelerates forward in the air.

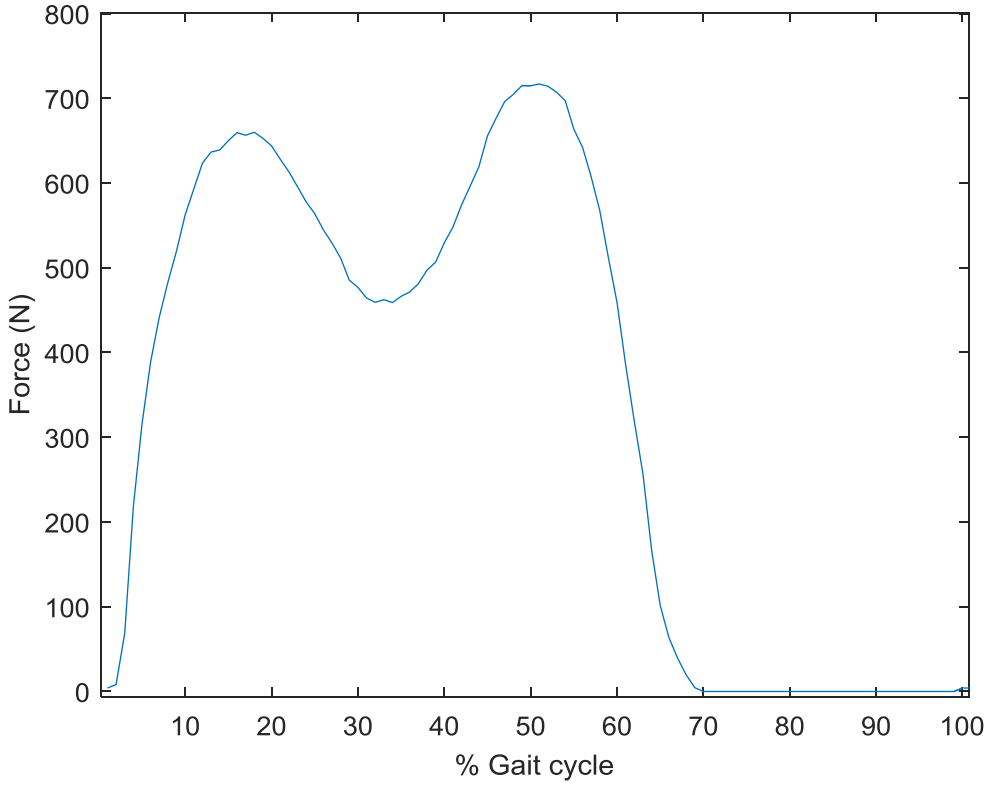

Figure 3.3. The vertical ground reaction force acting on a group ‘Ga’ normal subject during the gait cycle

It can be seen from the above plot that two peaks are generated in a gait cycle. The first peak occurs when the heel strikes the floor and the second one at the toe-off period, which is produced by the push-off force from the ground. During the early stages of PD, the force values for heel contact and toe-off phases are reduced. Also, in the later stages, the force plot is characterized by a single and narrow peak [31, 32] as seen in Figure 3.4. It occurs due to the

difference in anatomy of walking of a PD patient from a healthy subject. Normally, in a normal gait the heel strikes the ground first, followed by the toe which is called as heel-to-toe walking. Whereas, the PD gait is characterised by a flat foot strike: where the entire foot is planted on the ground, simultaneously. Also, during the later stages the toe touches the ground before the heel, called as the toe-to-heel walking [33].

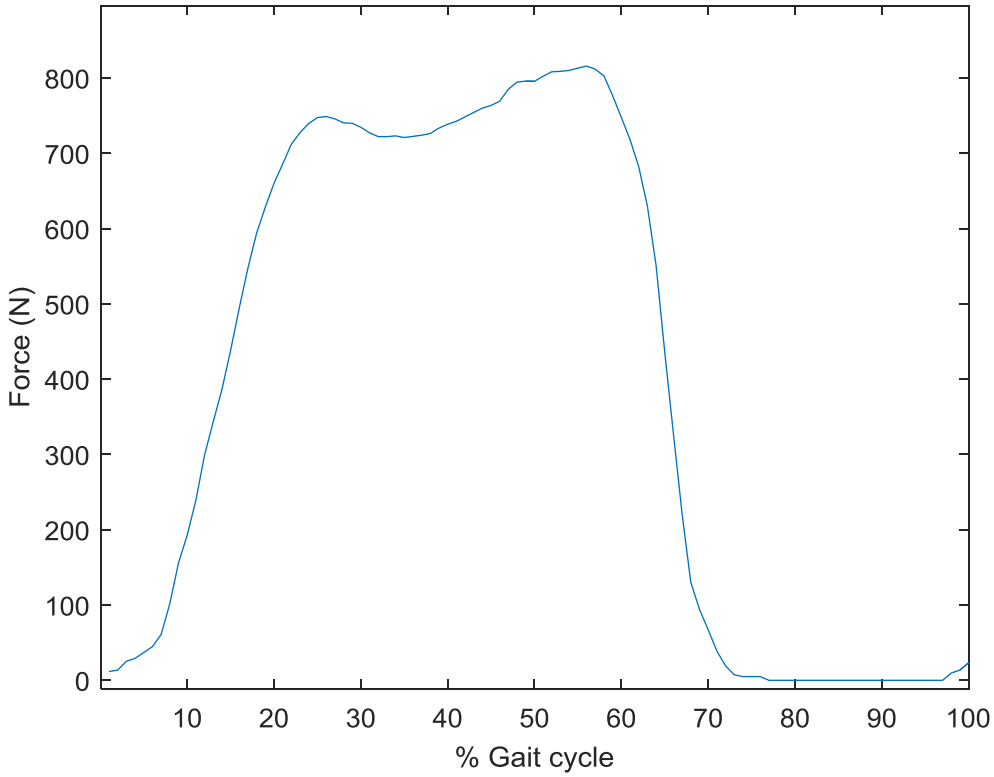

Figure 3.4. The vertical ground reaction force acting on a PD patient from the group 'Ga' during the gait cycle

Additionally, PD patients impart less force at heel strike and it is identified to be related to the severity of the disease, with the value of force decreasing as the disease progresses. Also, the patients with Parkinson's disease tend to apply high pressure to the forefoot regions (toe and

'below toe' areas), in addition to the weight shift near the medial foot regions thus, providing the required postural balance [34].

3.3 Gait Detection Algorithm

In Figure 3.5, the force readings are plotted against time for the left foot of a subject. Various gait features are extracted using peak detection and pulse width estimation techniques. Also, from the plot points P1-P4 marks one gait cycle and the time period between P1 and P4 refers to the corresponding stride time. Additionally, time taken to reach from position P1 to P3 is the stance period. In the same way, the time taken from point P3 to P4 is called as the swing period. Hence, the swing/stance ratio can be calculated from the obtained values.

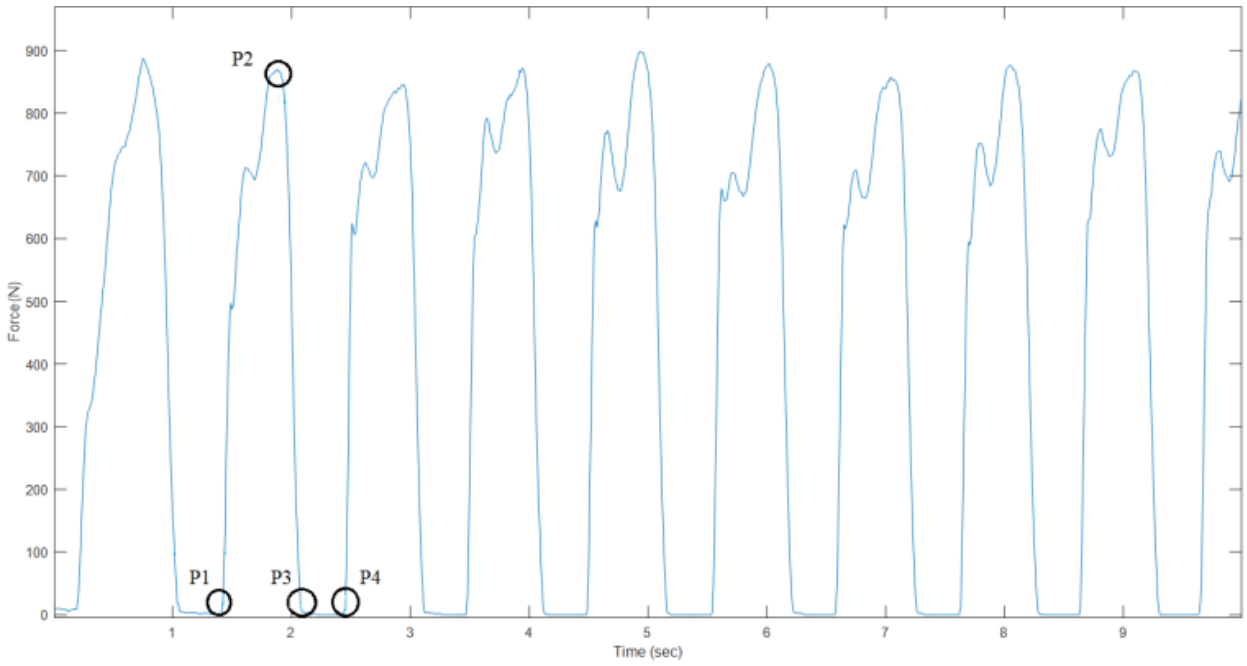

Figure 3.5. Force readings plotted against time for a PD patient's left foot. Points P1 to P4 denotes one gait cycle. Where, P1 is the initial heel contact that marks the beginning of the cycle. P2 is the point of contact where maximum force is exerted by the subject. P3 marks the end of stance period and start of swing period, where the foot is in the air. P4 points the end of swing phase and also the gait cycle.

The walking speed of the subject is evaluated by dividing the total distance covered upon the total time taken during the testing period. It is typically measured in meters per sec, denoting the distance travelled in a second, where the total number of steps is calculated using the peak detecting algorithm, which measures the total number of peaks in the plot corresponding to total steps taken. Similarly, the total number of steps taken by the right foot can be identified. The sum of the steps taken by left and right foot in a minute provides the cadence value. In addition, the total distance divided by the total number of steps taken in the covered area gives the average step length (time remaining constant).

3.4 Quantification of Tremor

Two different types of tremor that occur in humans: the pathological and physiological tremor. They have different characteristics (frequency, oscillation) and reason for their occurrences. Where, the pathological tremors may occur due to central nervous system and peripheral nervous system disorders. The relevant example of a pathological tremor is the parkinsonian tremor, which is further classified into rest, postural and kinetic tremors. To elaborate, the rest tremor occurs when the body performs no voluntary action, postural tremor occurs while holding a body part such as the arm, leg against gravity without any movement and kinetic tremor can be seen when the subject performs any particular task such as finger-to-nose test, or writing. However, the PD tremor mostly occurs at rest, oscillating at a frequency of 4-6 Hz [35].

In comparison to a PD tremor, a physiological tremor (normal tremor) is present in all humans. The limb oscillates at a particular resonance frequency that depends on the stiffness of the muscle and inertia of the arm. The physiological tremor usually occurs at a frequency of 8-12

Hz, and sometimes even higher depending on the position of measurement. So, generally physiological tremor is a high freq. component against a pathological tremor, which tends to occur at low freq. [35].

3.4.1 Tremor Features

The various tremor features [36, 37] in frequency domain that would help us in detecting a PD tremor have been discussed below:

1) Amplitude: It is calculated by taking the root mean square (RMS) value of the input velocity signal, with the mean subtracted. Amplitude is also the standard deviation of the filtered output signal. It is estimated using the power spectral density (PSD) method, which plots the power of the signal to the respective frequency. It uses periodogram spectrum estimates, which is obtained by converting the time series to a frequency domain.
2) Power distribution: In a typical PD tremor, a large amount of power is concentrated in the region between 4-6 Hz contributing to a significant peak in this region. Whereas, the normal physiologic tremor is mainly seen in the 8-12 Hz range, also where a high proportion of power is observed in the absence of any low-frequency pathological tremor (PD tremor).
3) Frequency dispersion: It measures the width of an interval centered at the median frequency that consists of 68% of the spectrum power. In the case of PD, the dispersion bandwidth is small as it has a single large peak. Whereas, physiological tremors being irregular have several peaks thus, display a wider bandwidth.

4) Median frequency: It is the frequency where the power is equally divided between the upper and lower parts of the spectrum. While, for power spectrum with a single peak the median frequency coincides with this peak for PD subjects.

CHAPTER 4:

DATA ANALYSIS AND RESULTS

4.1 Introduction to Statistical Analysis

Various statistical analysis techniques were performed to study the features displayed by a PD subject in comparison to a healthy subject. The statistical analysis was done using the Minitab® 17.2.1 [38] and the results are presented as graphs, plots, and statistical values. Based on the statistical analysis, it was observed that the features of the left foot and right foot for all the study group subjects were highly correlated. Hence, the force data from only the left foot is presented in this thesis for the purpose of discussion. A summary of the data as Mean ± SD (Standard Deviation) for the groups 'Si', 'Ju' and 'Ga' are displayed in Tables 4.1, 4.2 and 4.3, respectively. Here, the mean of a set of data is defined as the ratio between the summations of all the variables in the dataset to the total number of variables in the dataset. The most common measurement of variability is the standard deviation (SD), which is typically the distance between any variable in the dataset to the average.

$$\mathrm{SD} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$$

where, x is any variable in the dataset, $\bar{x}$ is the mean and n is the total number of variables in the dataset. The inter-variability of the features measures the variation between subjects of a group, and is calculated by taking the percentage of the ratio between SD and mean of the corresponding feature of the group. It provides the coefficient of variability that the subject's show within a group.

One-way analysis of variance (ANOVA) test was used to determine if there are any significant differences between the mean values of the two groups (PD and normal). The results are presented in Tables 4.1, 4.2 and 4.3. The basic model is as follows:

$$y_{ab} = \mu + T_b + \in_{ab}$$

where, y_{ab} is the measured value of observation b in group a, μ is the mean value, T_b is the effect of an observation in group b, and $\in_{ab}$ is the random error. The one-way ANOVA typically tests the null hypothesis, which states that there is no significant difference in the mean and are equal to each other:

$$H_0 = \mu_1 = \mu_2 = \mu_3 = \ \ldots \mu_n = \mu$$

where, μ is the mean of a group, and n is the number of groups. However, if the result is a significant value, i.e., ≤ 0.05 (we are using a 95% confidence interval, therefore $\alpha = 0.05$), the ANOVA rejects the null hypothesis. Then, it accepts the alternative hypothesis (H_A), which proves an existence of a significant difference in the mean of the two groups [39, 40].

Moreover, a graphical representation of the results is essential in an analysis process, where box plots are widely used. A box-plot is a diagrammatic method to summarize the results, and it displays the minimum value, lower quartile (bottom 25% of observation), median, upper quartile (75% of the observation), and maximum value. Thus, it is useful to study the distribution of the different variables from a group and compare them to various groups [39, 40].

4.2 Statistical Analysis Results of Gait Parameters

The gait parameters under investigation are the step distance, stride time, stance phase, swing phase, heel force, metatarsophalangeal joint (below toe) force, toe force and the normalized values of heel, below toe, and toe forces. To reduce the influence of subject's body weight on the

forces, the force values are normalized to the percentage of their body weight using the following relation:

$$\text{Normalized Force (\% body weight)} = \frac{\text{Vertical force (N)}}{\text{Body weight (N)}} \text{ X } 100\%$$

The normalized force value indicates the percentage of body weight a subject utilizes when walking. Further, we computed the normalized force percent of the heel, below toe and toe regions individually, which can also be helpful to detect the falling symptom in PD patients. In Tables 4.1, 4.2, and 4.3 statistical results of the test sample from groups 'Si', 'Ju' and 'Ga' are tabulated. It is evident from the results that PD patients from all the three groups have shorter average step distance, with a slightly higher average stride time than a normal subject. Also, the patients with PD have reduced average swing phase compared to normal subjects, and an increase in the average stance phase. Moreover, we can notice that the vertical force imparted by the heel region of the foot is higher in healthy subjects compared to the PD patients, which also leads to a higher normalized heel force in healthy subjects, thus indicating better stability and control. Since the vertical force indicates body control stability, this proves that the normal subjects participated in the study had better body control compared to PD patients.

The ANOVA results provide us with the most significant gait features and are presented as box-plots as shown in Figures 4.1-4.6. The box-plots display the different gait features that have a significant difference in its mean value for PD and normal subjects, included for all the three groups 'Si', 'Ju' and 'Ga'. It also helps to select the features that would yield better classification between a PD and healthy subject in the feature selection process. Further, after the significant features were obtained through ANOVA test, machine learning was performed to classify the subjects based on the patterns exhibited in the dataset.

Table 4.1. Mean, standard deviation and p-value for different gait features extracted from group 'Si'

Gait Feature	**Normal subject**	**PD subject**	**ANOVA p-value ≤ 0.05, significant difference**
	Mean ± SD	***Mean ± SD***	
Step distance (m)	0.70 ± 0.04	0.58 ± 0.07	< 0.001
Stride time (sec)	1.05 ± 0.06	1.16 ± 0.08	< 0.001
Stance phase (%)	64.49 ± 2.35	65.74 ± 2.16	0.088
Swing phase (%)	34.42 ± 2.51	33.32 ± 2.07	0.141
Heel force (N)	351.35 ± 83.62	229.03 ± 86.20	< 0.001
Below toe force (N)	287.92 ± 95.14	295.58 ± 87.71	0.793
Toe force (N)	171.91 ± 84.35	167.00 ± 72.11	0.844
Normalized force for heel (% body weight)	51.83 ± 11.42	34.79 ± 11.38	< 0.001
Normalized force for below toe (% body weight)	40.08 ± 10.32	42.93 ± 8.85	0.361
Normalized force for toe (% body weight)	25.67 ± 11.77	25.66 ± 10.04	0.999

Table 4.2. Mean, standard deviation and p-value for different gait features extracted from group 'Ju'

Gait Feature	**Normal subject**	**PD subject**	**ANOVA p-value ≤ 0.05, significant difference**
	Mean ± SD	***Mean ± SD***	
Step distance (m)	0.679 ± 0.06	0.498 ± 0.09	< 0.001
Stride time (sec)	1.106 ± 0.087	1.131 ± 0.163	0.537
Stance phase (%)	64.08 ± 1.453	66.61 ± 2.477	< 0.001
Swing phase (%)	35.90 ± 1.454	33.27 ± 2.741	0.001
Heel force (N)	348.13 ± 80.30	227.98 ± 88.5	< 0.001
Below toe force (N)	248.25 ± 50.92	235.38 ± 65.32	0.491
Toe force (N)	169.27 ± 68.19	173.15 ± 81.71	0.871
Normalized force for heel (% body weight)	52.15 ± 13.79	32.58 ± 12.09	< 0.001
Normalized force for below toe (% body weight)	36.6 ± 7.25	34.48 ± 10.22	0.454
Normalized force for toe (% body weight)	25.04 ± 9.98	25.88 ± 13.26	0.823

Table 4.3. Mean, standard deviation and p-value for different gait features extracted from group 'Ga'

Gait Feature	**Normal subject**	**PD subject**	**ANOVA p-value ≤ 0.05, significant difference**
	Mean* ± *SD	***Mean* ± *SD***	
Step distance (m)	0.676 ± 0.084	0.467 ± 0.079	< 0.001
Stride time (sec)	1.127 ± 0.083	1.240 ± 0.269	0.098
Stance phase (%)	63.66 ± 1.955	69.05 ± 4.481	< 0.001
Swing phase (%)	35.54 ± 1.894	29.80 ± 4.191	< 0.000
Heel force (N)	315.0 ± 94.28	230.8 ± 102.1	0.015
Below toe force (N)	267.8 ± 71.46	249.9 ± 54.68	0.403
Toe force (N)	187.7 ± 88.36	152.9 ± 51.35	0.157
Normalized force for heel (% body weight)	45.20 ± 12.82	31.77 ± 11.65	0.003
Normalized force for below toe (% body weight)	41.39 ± 10.13	36.43 ± 10.63	0.173
Normalized force for toe (% body weight)	28.75 ± 12.41	23.03 ± 8.25	0.129

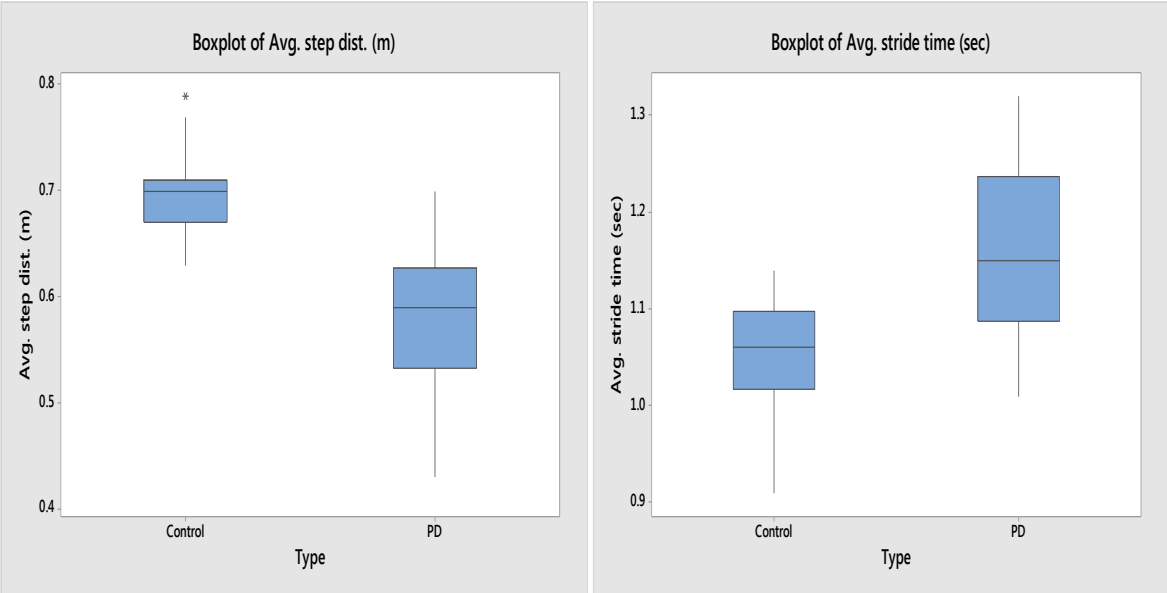

Figure 4.1. Box plots of average step distance and stride time of PD and normal subjects from group 'Si', displaying the mean, range, upper and lower quartile of the two parameters.

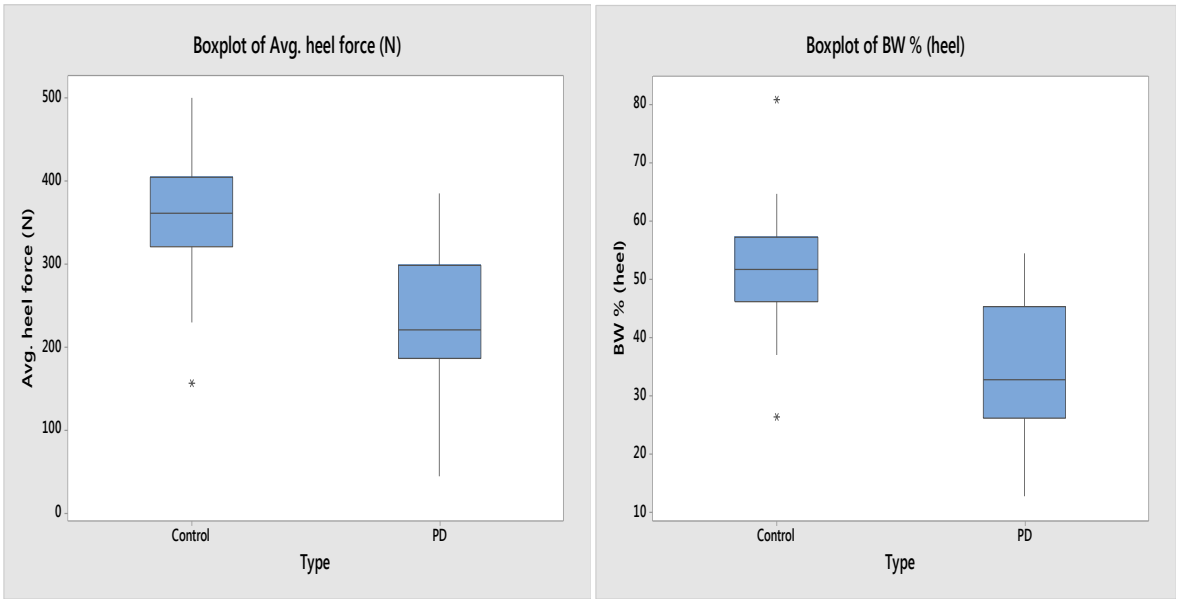

Figure 4.2. Box plots of the average and normalized heel forces of PD and normal subjects from group 'Si', showing the mean, range, upper and lower quartile of the two parameters.

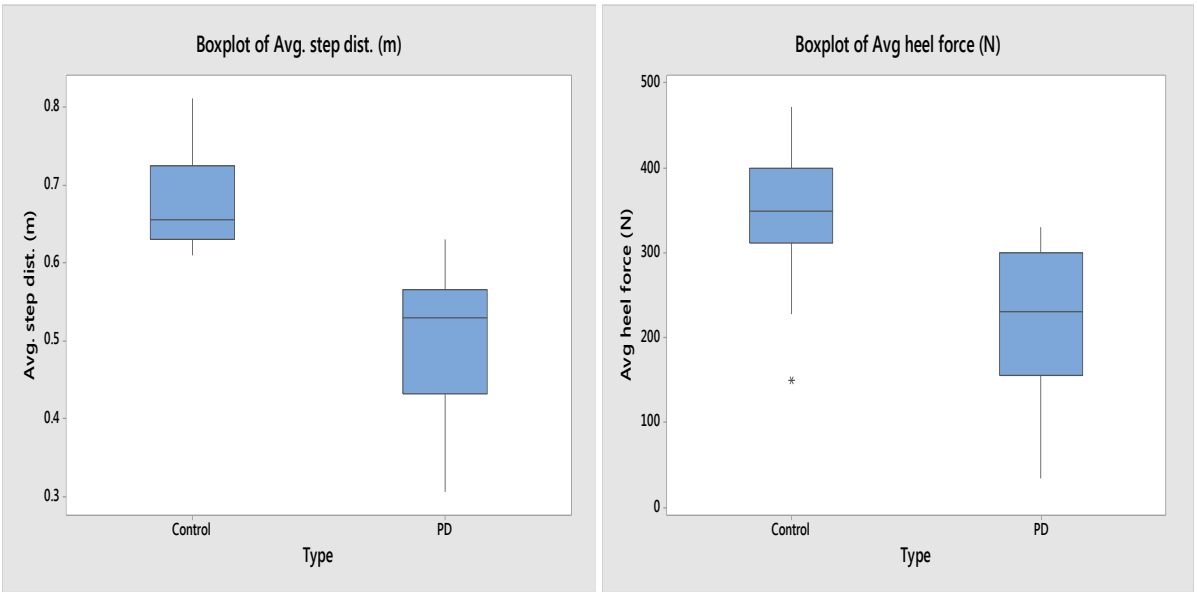

Figure 4.3. Box plots of average step distance and heel force of PD and normal subjects from group 'Ju', displaying the mean, range, upper and lower quartile of the two parameters.

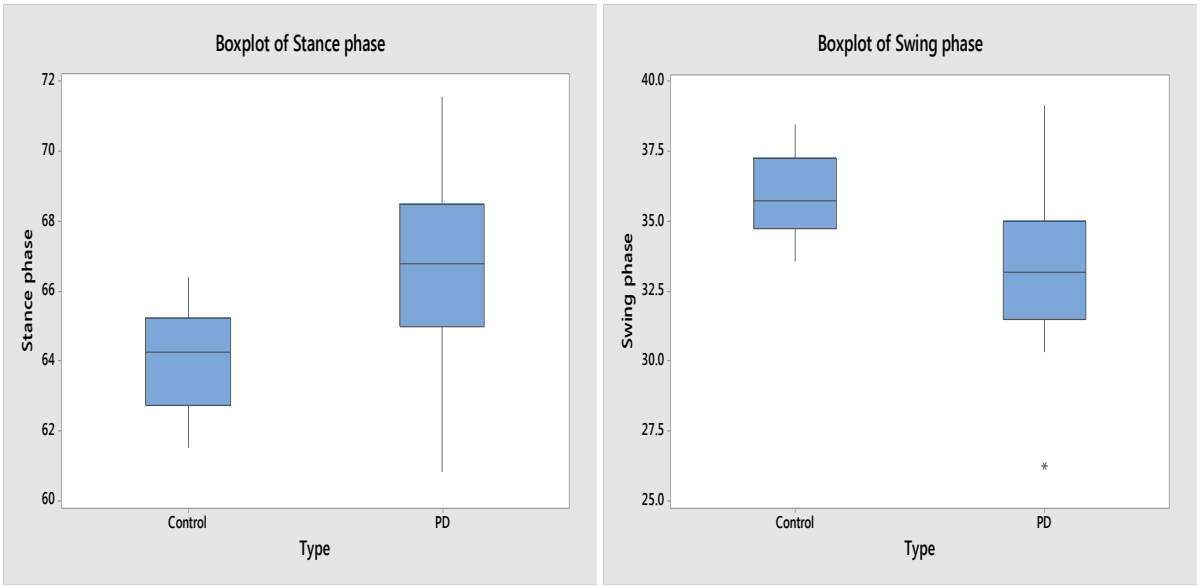

Figure 4.4. Box plots of stance and swing phases of PD and normal subjects from group 'Ju', showing the mean, range, upper and lower quartile of the two parameters.

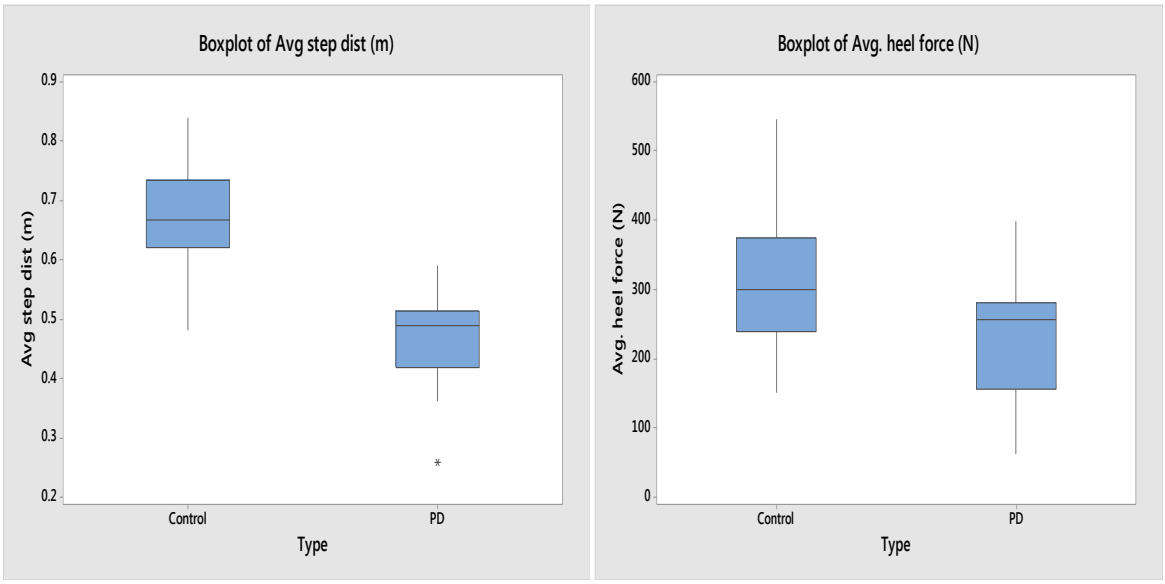

Figure 4.5. Box plots of average step distance and heel force of PD and normal subjects from group 'Ga', displaying the mean, range, upper and lower quartile of the two parameters.

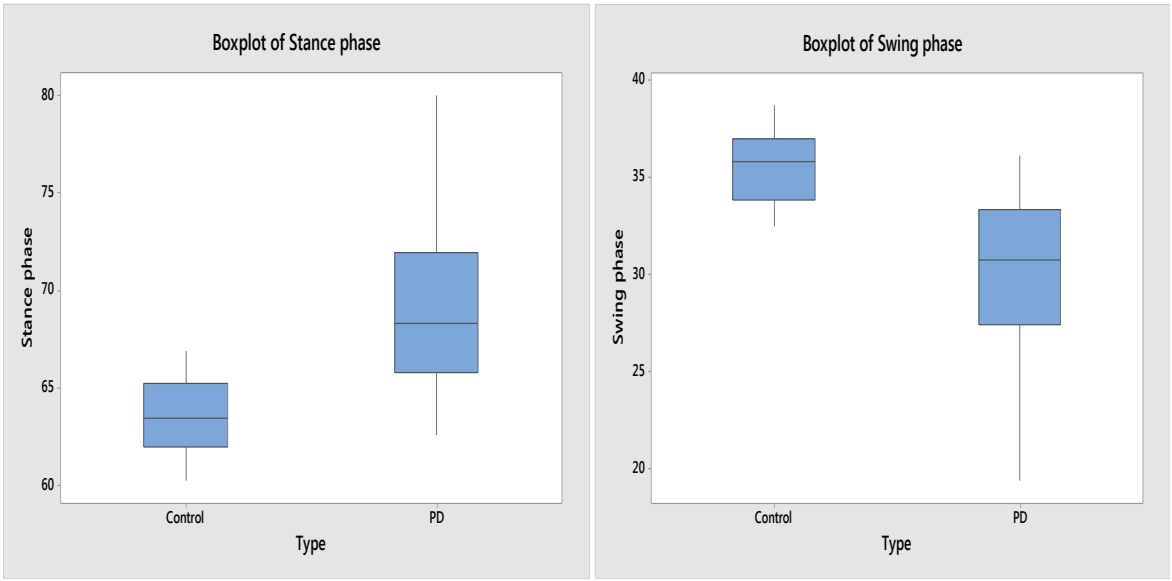

Figure 4.6. Box plots of stance and swing phases of PD and normal subjects from group 'Ga', showing the mean, range, upper and lower quartile of the two parameters.

4.2.1 Comparisons with Current Work

In this section, we are comparing our analysis results with the existing benchmark, i.e. analysis done by the authors of the physionet database [24]: Frenkel-Toledo *et al.* [23], Hausdorff *et al.* [25], and Yogev *et al.* [26]. It is important to note that for our analysis, we had used only the data arising from the subjects performing a walking task at their normal, comfortable speed.

In the benchmark study, student's t-test was performed on data to compare the features of the healthy and PD subjects. An independent model was applied to each gait parameter, where the gait parameter is taken as a dependent variable and their belonging group (PD and healthy) is the independent variable. Also, a 95% confidence interval was used, including a p-value of 0.05 as significant. Moreover, the extracted gait features include the average gait speed, stride length, stride time, and swing time.

In Table 4.4, a comparison chart of the statistical summary of the different gait features is tabulated between the results from our algorithm versus the benchmark algorithm, for the groups 'Si', 'Ju' and 'Ga'. The results were obtained from the published papers [23, 25 & 26] for study purpose only. The gait speed value is taken as a basic reference parameter from the benchmark database to calculate other spatiotemporal characteristics. Also, in this work we had calculated the step distance of the subjects and not the stride length, as they were proportional to each other. However, to perform this comparison, we computed the stride distance value which is the average value of the distance between two consecutive points of foot contact of the same feet. As compared to our developed algorithm, there is less number of features extracted in the benchmark studies, and also our gait feature values are highly correlated to its benchmark.

Table 4.4. A comparison between the statistical results of gait features of this paper versus its benchmark.

Group name	**Gait feature**	**Benchmark algorithm value**		**Our algorithm value**	
		Healthy subject	**PD subject**	**Healthy subject**	**PD subject**
		Mean* ± *SD	***Mean* ± *SD***	***Mean* ± *SD***	***Mean* ± *SD***
‘Si’	Gait speed (m/sec)	1.24 ± 0.18	1.12 ± 0.15	-	-
	Stride distance (m)	1.33 ± 0.11	1.25 ± 0.16	1.41 ± 0.10	1.2 ± 0.12
	Stride time (sec)	1.08 ± 0.09	1.12 ± 0.07	1.05 ± 0.06	1.16 ± 0.08
	Swing time (%)	35.27 ± 1.97	34.45 ± 2.60	34.42 ± 2.51	33.32 ± 2.07
‘Ju’	Gait speed (m/sec)	1.24 ± 0.14	1.00 ± 0.21	-	-
	Stride distance (m)	1.35 ± 0.19	1.06 ± 0.21	1.36 ± 0.11	0.99 ± 0.16
	Stride time (sec)	1.08 ± 0.09	1.08 ± 0.13	1.11 ± 0.087	1.13 ± 0.163
	Swing time (%)	36.3 ± 1.4	33.8 ± 3.3	35.90 ± 1.45	33.27 ± 2.74
‘Ga’	Gait speed (m/sec)	1.31 ± 0.19	1.05 ± 0.23	-	-
	Stride time (sec)	1.07 ± 0.08	1.08 ± 0.15	1.127 ± 0.083	1.240 ± 0.26
	Swing time (%)	38.03 ± 1.35	35.57 ± 2.44	35.54 ± 1.89	29.80 ± 4.19

4.3 Machine Learning Using LDA

In this work, the Linear Discriminant Analysis (LDA) classifier was used to study the performance of the extracted gait parameters. The algorithm and its specifications have been chosen based on its better performance in comparison to other algorithms. A total of 40 observations was used for classification purpose, distributed as 20 observations each between PD and healthy control subjects. The five-fold cross-validation method was used, that partitions the data into five sets or folds. Then for each fold, it trains a model and assesses its performance. Further, it calculates the average test error over all the folds. In general, a discriminant function takes an input x and assigns it to one of the classes k, denoted as C_k. Also, the decision surface is a hyperplane, which is a subspace of one less dimension than the ambient space. The simplest linear discriminant is given by [41, 42],

$$y(x) = W^T x + w_0$$

When, $y(x) \geq 0$, the input x is assigned to class C_1, else C_2. In the equation above, term W is the weight vector and w_0 is the bias. Moreover, in a standard linear classifier, a considerable amount of information is lost due to the overlapping of the data in one dimension. Therefore, we used the Fisher's linear discriminant method to maximize the function to obtain a large separation between the class means. Further, it provides a small variance within the class to minimize the overlapping problem [41, 42]. While, the intra-class variance of the transformed data from class C_k is,

$$S_k^2 = \sum_{n \in C_k} (y_n - m_k)^2$$

where, $y_n = W^T x_n$, and m_k is the mean of classC_k. Also, the Fisher's criteria is defined as the ratio of the inter-class variance to the intra-class variance and is given by,

$$J(w) = \frac{(M_2 - M_1)^2}{S_1^2 + S_2^2}$$

In Figure 4.7, the flow chart of the machine learning process is displayed, which starts by extracting the features from the raw data. Then, the extracted features were trained and tested using a suitable classifier to obtain the performance of the classifier. Later, the ROC curve for the extracted gait features is plotted against the true positive (sensitivity) and false positive (1-specificity) rates. In our test, the outcome can be either positive, i.e., presence of PD or negative, i.e., absence of PD. In that case, the true positive is the situation where the PD subjects are correctly identified with the presence of PD. Then, the false positive denotes that healthy subjects are incorrectly identified as PD patients. Further, the accuracy of classification is calculated by finding the area under the curve [41, 42].

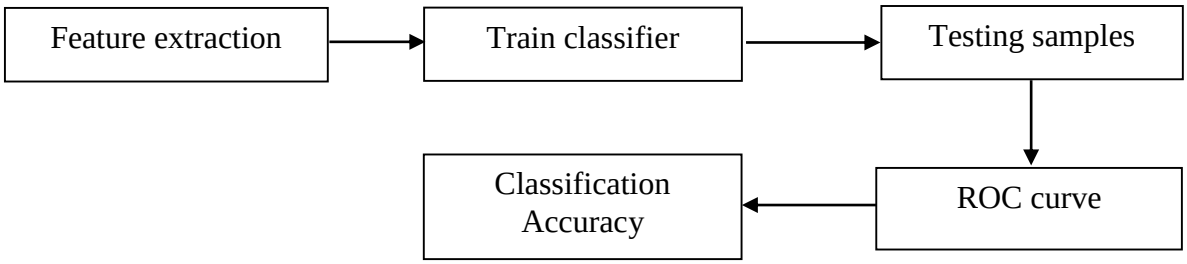

Figure 4.7. Block diagram of the steps involved in the pattern classification process. ROC: receiver operating characteristic.

4.4 LDA Classification Results

In Table 4.4, the classification accuracy of the gait parameters for the groups ‘Si’, ‘Ju’, ‘Ga’ has been tabulated, including the cumulative accuracy of all the gait features combined. The rate of accuracy for the average values of the parameters including the step distance, heel force, stance phase, and swing phase have outperformed the other features. Hence, these features display a substantial difference between the PD and normal groups.

Table 4.5. A comparison between the classification results of various gait features from the 3 group subjects.

Gait feature	Classification accuracy Group "Si" (%)	Classification accuracy Group "Ju" (%)	Classification accuracy Group "Ga" (%)
Step distance (m)	90.0	92.5	94.4
Stride time (sec)	77.5	50.0	52.8
Stance phase (%)	70.0	72.5	77.8
Swing phase (%)	72.5	70.0	86.1
Heel force (N)	77.5	77.5	66.7
Below toe force (N)	27.5	47.5	66.7
Toe force (N)	30.0	30.0	61.1
Normalized force for heel (% body weight)	77.5	80.0	63.9
Normalized force for below toe (% body weight)	52.5	50.0	50.0
Normalized force for toe (% body weight)	40.0	27.5	52.8
Cumulative of all the 10 features	87.5	90.0	83.3

Moreover, the accuracy rate when all the features were combined is around 87.5% for the subjects in group ‘Si’, 90.0% and 83.3% for the subjects in groups ‘Ju’ and ‘Ga’, respectively. We decided to group the most distinct features together, and an accuracy rate of 90.0 % was achieved for the ‘Si’ group, followed by 92.5% and 92.25% for the ‘Ju’ and ‘Ga’ groups, respectively. On the other hand, the remaining less distinguishable features including the normalized forces of the heel, below toe and toe, had an accuracy rate of very less significance.

In Figure 4.8, we can see the ROC plot between the PD and control subjects utilizing all the gait features. An ROC curve plots between the values of true positive rate (sensitivity) to the false positive rate (1-specificity). In the plot below, we chose an optimal cut-off point that best balances between sensitivity and specificity. For a PD group, the point at which the sensitivity is at 0.71 and the specificity is 0.92 is taken as optimal. In a control group, the sensitivity is around 0.67 for a specificity value of 0.7 is considered to be optimal in this case. We can infer that the algorithm performed better in finding a PD from a control subject in comparison to vice-versa. Also, around 7 PD patients are diagnosed correctly, for every single misdiagnosis.

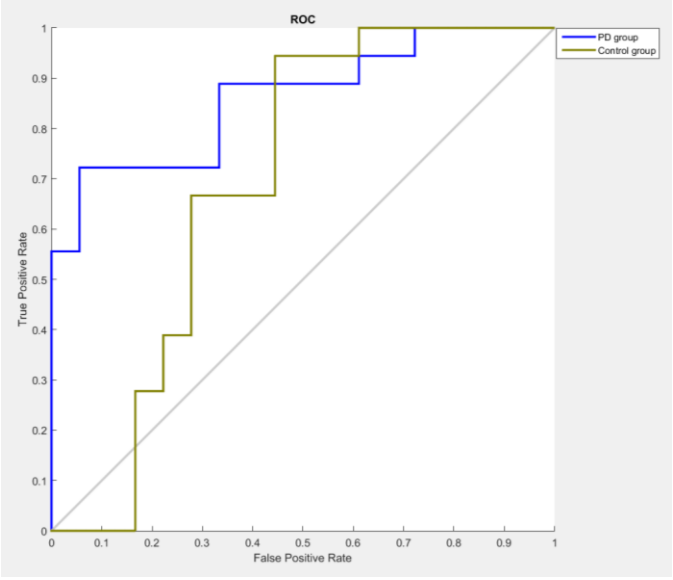

Figure 4.8. ROC curve plotted using all the gait features for PD and control group.

4.5 Tremor Analysis

The input data is obtained from velocity measurements in the time domain and is further converted to digital signal by sampling at 100 Hz. The sampled data taken from [24] consists of tremor readings in subjects with PD. In the digitalization process, the input voltage signal (analog) is converted to the nearest integer value (digital) by quantization process. As very few information can be obtained from the time domain signal, the signal in time domain is transformed to the frequency domain. The signal in the frequency domain consists of useful information such as the amplitude, frequency and phase [43].

The most common and efficient way of converting the time signal to a frequency domain is by using the Fast Fourier Transform (FFT). Firstly, the FFT algorithm decomposes the input time-signal consisting of N samples to N time domain signals of a sample each. Then, it calculates the N frequency spectra w.r.t. the N time domain signals. Finally, all the N spectra are transformed into a single frequency spectrum. Moreover, the horizontal axis of the FFT plot decomposes the signal into N/2 points, containing only the real part (positive side) of the signal. Further, the spectral density describes the amount of signal is present per unit of bandwidth and is also plotted to obtain the power of the signal. In Figure 4.8, the magnitude of the Fourier transformed signal is plotted in a single-sided amplitude spectrum.

4.6 Tremor Results

From the online database, we utilized the tremor data from PD patients to study the various characteristics that could be used to differentiate between a PD tremor and other abnormal tremors. So, the tremor characteristics that could significant in providing the distinct characteristics of PD tremor are discussed below,

4.6.1 Amplitude

The peak RMS (root mean square) value is defined as the square root of the mean of all the input-squared value and is found out to be 0.0749. It is also called as the average mean power of the signal, which is useful to compare with other abnormal tremors that typically has a low amplitude value.

4.6.2 Power Distribution

The peak amplitude was measured between the 4-6 Hz interval where a single large peak can be seen. In a typical PD tremor, a large amount of power is concentrated in the region between 4-6 Hz contributing to a significant peak in the region, as seen in Figure 4.9. The amount of power distributed in the 4-6 Hz range is 0.0561, i.e., around 91.92% of the total power in the spectrum.

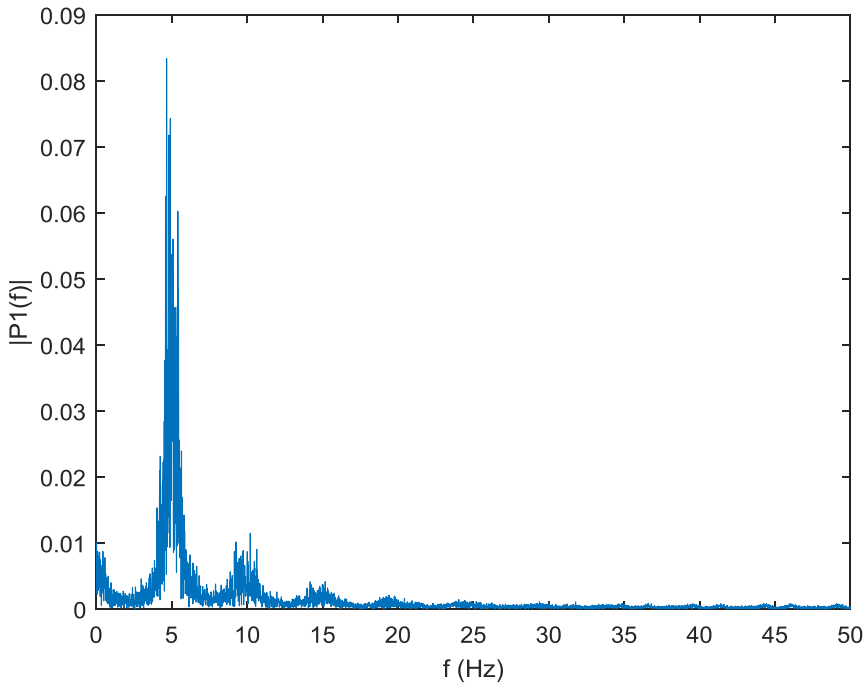

Figure 4.9. Plot displaying the FFT output of the input time-domain signal and the amplitude of the signal is plotted in a single-sided spectrum.

4.6.3 Frequency Dispersion

In Figure 4.10, the Power Spectral Density (PSD) estimate of the input signal is plotted, which displays the distribution of power at various frequencies. Also, it displays the PSD plot before applying windowing technique consisting of spectral leakages. The spectral leakage occurs due to an assumption that the input signals are periodic in nature, and it repeats itself corresponding to the length of the time value. Various windowing techniques were used to neutralize the effect of the spectral leakage. Some of the windows used include the Rectangular (flat-top), Hamming, and Hann and are chosen based on the application. In our case, we require a window to enhance the frequency resolution and to reduce the spectral leakage, where a Hann window would be ideal [43]. Moreover, we measured the dispersed frequency value that consists of 68% of the spectrum power.

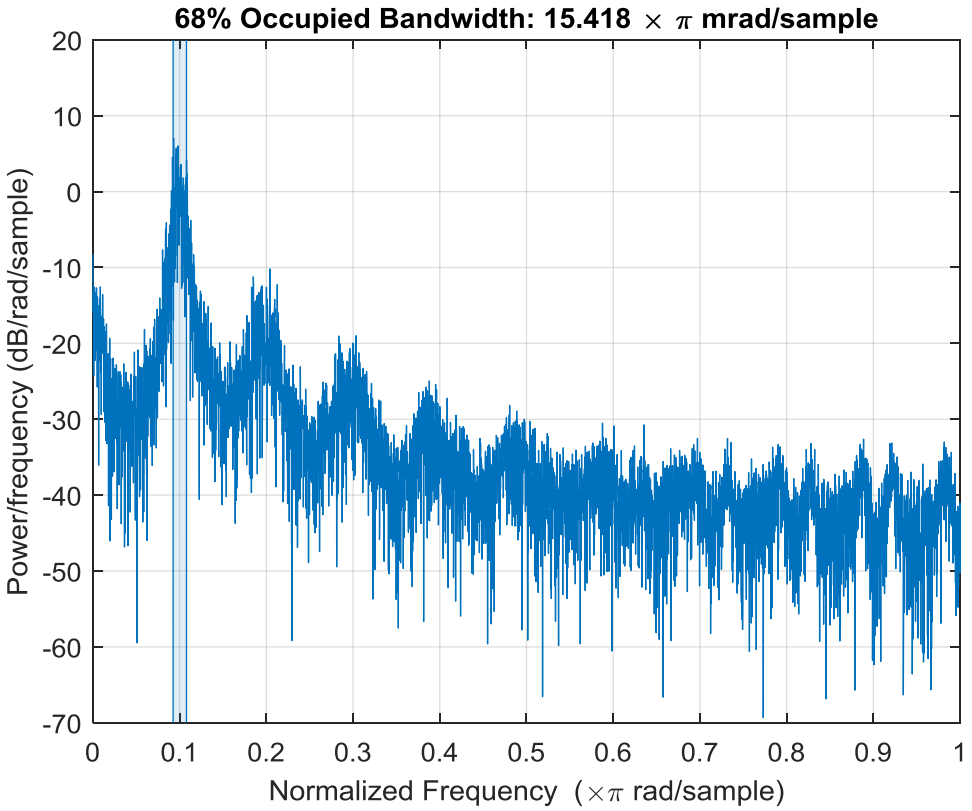

Figure 4.10. The input signal plotted in a normalized frequency value against the spectral power. It also displays the frequency dispersion at 68% of the spectrum power.

A typical PD tremor would have a small and narrow dispersion bandwidth as seen in Figure 4.10. Further, in Figure 4.11 we can see the PSD with a reduced spectral leakage and increased resolution, after applying the Hann window of 500 samples length.

4.6.4 Median Frequency

The median frequency is the point where the power is equally divided between the upper and lower parts of the spectrum, was determined to be of value 4.96 Hz. Moreover, from the plot it is evident that the median frequency coincides with the single large peak in the spectrum, and a similar spectrum is mostly seen in PD subjects.

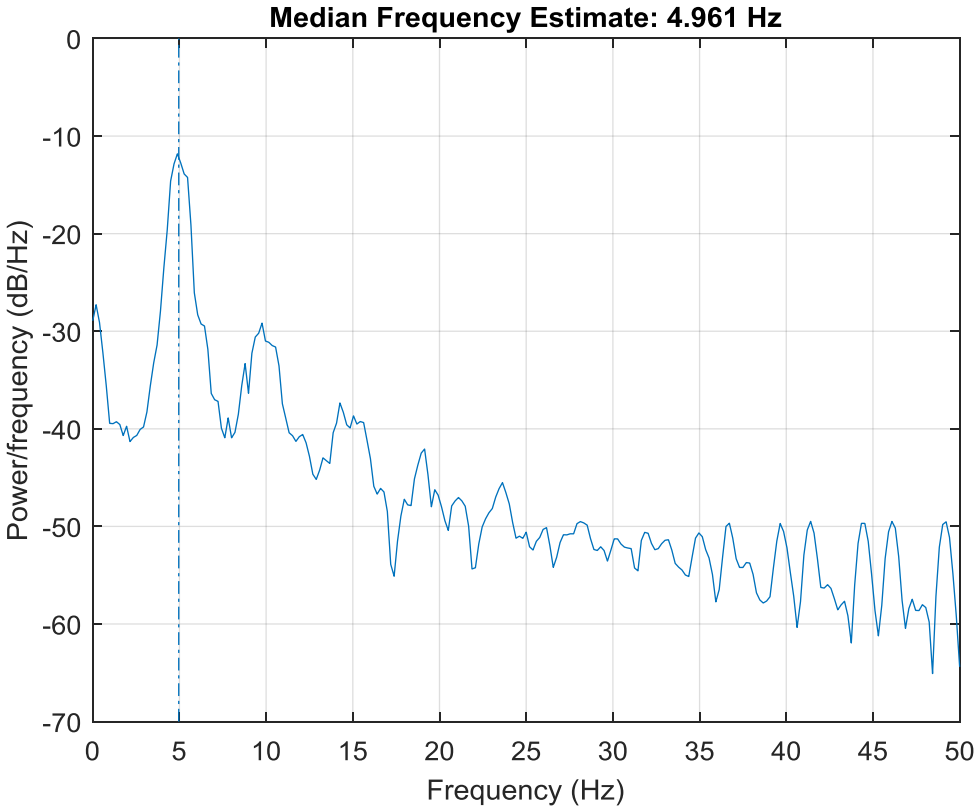

Figure 4.11. The Power Spectral Density (PSD) estimate of the signal using Hann window length of 500 samples is displayed. It also specifies the median frequency of the signal.

CHAPTER 5:

CONCLUSION AND FUTURE WORK

5.1 Conclusion

PD subjects mostly display tremor occurrences and gait impairments during the various stages of the disease. An early and accurate diagnosis of PD is required to control the effects of the symptoms more efficiently. However, clinical diagnosis of PD might take up to a year and also the rate of misdiagnosis is high.

The purpose of this thesis is to develop a monitoring system for patients with PD using wearable sensors. To achieve that objective, our work focused first on determining the most significant gait and tremor features that would best distinguish between PD and normal subjects. Various gait features were extracted from the raw data collected from the force sensors to study the motor characteristics of PD patients. Then, statistical analysis was performed on the gait parameters to recognize the most significant features. Further, LDA classifier was implemented to classify the subjects into two groups (PD and healthy). From the results, it was observed that gait features such as step distance, heel force, stance and swing phases provide better performance (feature discrimination) than other feature parameters. An average accuracy rate of 86.9 % between a PD patient and normal subject was obtained. Similarly, tremor analysis was conducted on the tremor input data, where we extracted the frequency-domain characteristics of the signal: amplitude, power distribution, frequency dispersion, and median frequency to identify a PD tremor

from the artifacts. This research can be supplemental to the clinical evaluation in accurately diagnosing PD at its onset.

5.2 Recommendations for Future Research

The eventual goal is to acquire real-time clinical data by conducting the gait and tremor experiments on PD and healthy subjects, for a better analysis and classification results. Further, the plan is to integrate the tremor and gait monitoring system for an early, accurate diagnosis of PD. Also, from the study it is evident that both the gait and tremor features are critical in diagnosing PD. So, an integrated system will be operating as a logic 'OR' gate, where a high output (presence of PD) appears if one or both of the gate inputs (gait and tremor features) are high. If neither input is high, it results in a low output (absence of PD). Additionally, more distinguishable features would be obtained including the kinematic gait parameters (joint angles), and inter-variability of gait features to provide better performance in separating a PD from a healthy subject.

Next, the developed algorithm would be utilized to extract different gait and tremor features from the real–time clinical data. After extracting the features, the data would be trained using a suitable model and tested for accuracy. Then, a random or a new patient's data would be used to perform the testing, and the algorithm is expected to have the ability to identify the subject as either PD or normal subject that many percentage of times as the accuracy of the model. So, typically the percentage of accuracy denotes the successful rate of the algorithm in predicting the subject's group or class.

Later, our focus is to utilize other feature selection methods such as the principal component analysis (PCA) as a model to study the individual performances of the feature and also to select the most significant features from the others. It would provide us with a high accuracy of

classification and thus, increase the chances of distinguishing a PD from a non-PD subject. Finally, we would look into the possibility of monitoring the occurrences of dyskinesia that occurs during the ‘wearing off’ period of medications. It could help the doctors and patients to understand their pattern of occurrence better and hence manage them more efficiently.

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APPENDIX A: EXTRACTED GAIT FEATURES

Table A1. The gait features extracted from the group 'Si' subjects are tabulated.

Subject no.	Type	H&Y stage	Avg. heel force (N)	Avg. below toe force (N)	Avg. toe force (N)	BW % (heel)	BW % (below toe)	BW % (toe)	Avg. step dist. (m)	Stance %	Swing %	Avg. stride time (sec)
SiPt02	PD	2.5	247.71	211.93	231.49	39.04	38.41	40.33	0.43	69.57	30.25	1.11
SiPt29	PD	2.5	157.49	322.05	99.93	24.05	40.83	11.62	0.54	68.34	31.16	1.32
SiPt39	PD	2	301.96	171.73	60.89	54.45	42.61	15.63	0.47	68.38	31.08	1.07
SiPt31	PD	2	45.13	244.8	164.69	12.88	38.02	23.9	0.51	68.51	30.62	1.14
SiPt10	PD	2	199.95	282.59	203.71	33.51	48.94	31.92	0.56	64.02	35.24	1.23
SiPt36	PD	2	98.01	282.02	124.27	25.71	58.46	24.96	0.51	65.79	33.01	1.06
SiPt12	PD	2	220.59	258.96	201.1	45.86	41.62	39.09	0.59	63.74	35.46	1.21
SiPt37	PD	2.5	187.16	338.83	193.56	28.65	44.41	34.88	0.61	67.26	31.86	1.26
SiPt22	PD	2	328.31	190.19	115.54	51.36	30.45	25.82	0.55	68.27	30.93	1.11
SiPt15	PD	2	126.86	333.3	198.31	22.19	39.22	24.97	0.56	65.63	32.97	1.08
SiPt20	PD	2	338.81	243.95	119.07	50.03	36.64	20.27	0.63	61.76	36.71	1.25
SiPt38	PD	2	205.46	227.96	125.58	32.27	30.52	19.21	0.62	65.65	33.54	1.16
SiPt40	PD	2.5	327.48	451.07	123.16	35.69	52.12	14.01	0.53	66.56	32.26	1.01
SiPt33	PD	2	221.24	462.05	116.79	30.47	57.31	17.22	0.61	63.43	35.92	1.14
SiPt07	PD	2	187.11	273.68	340.12	27.82	41.08	46.11	0.63	64.33	34.86	1.17
SiPt23	PD	2	266.99	274.71	111.36	34.22	34.81	13.27	0.61	62.61	37.28	1.11
SiPt13	PD	2	258.1	487.07	210.68	29.17	61.77	29.14	0.59	66.04	32.85	1.08

Table A1. (Continued)

Subject no.	Type	H&Y stage	Avg. heel force (N)	Avg. below toe force (N)	Avg. toe force (N)	BW % (heel)	BW % (below toe)	BW % (toe)	Avg. step dist. (m)	Stance %	Swing %	Avg. stride time (sec)
SiPt18	PD	2	186.53	290.19	177.89	24.01	35.45	21.55	0.69	65.95	32.81	1.24
SiPt32	PD	2	385.57	342.92	317.68	50.43	46.56	39.28	0.7	64.96	33.29	1.26
SiPt16	PD	2	290.15	221.54	104.22	44.07	39.49	20.17	0.67	64.15	34.46	1.2
SiCo12	Control	0	450.57	241.91	306.57	80.81	42.47	49.19	0.71	65.15	33.97	0.92
SiCo15	Control	0	257.52	215.29	79.27	40.33	26.03	10.82	0.79	66.99	32	1.04
SiCo11	Control	0	500.03	433.41	380.91	63.02	56.33	41.11	0.68	63.76	35.58	0.91
SiCo21	Control	0	333.01	396.81	248.35	37.14	39.84	29.81	0.77	64.97	33.77	1.06
SiCo10	Control	0	397.46	227.15	68.66	57.97	29.64	14.97	0.7	63.04	36.56	0.98
SiCo04	Control	0	357.2	236.51	59.08	53.18	37.24	10.31	0.75	62.52	35.82	1.06
SiCo30	Control	0	461.09	413.05	156.59	57.29	53.66	20.39	0.75	64.53	34.92	1.06
SiCo22	Control	0	413.27	453.04	224.38	49.88	44.62	21.21	0.71	63.94	34.35	1.01
SiCo03	Control	0	317.34	147.05	142.02	52.89	32.34	25.36	0.71	62.35	36.18	1.05
SiCo07	Control	0	156.01	302.87	265.91	26.52	52.51	46.19	0.71	62.26	36.95	1.05
SiCo09	Control	0	372.57	154.51	149.72	51.73	26.54	20.79	0.71	63.38	35.91	1.09
SiCo13	Control	0	337.92	400.85	173.11	56.15	53.39	25.82	0.69	63.81	35.07	1.06
SiCo29	Control	0	376.75	232.11	87.49	48.49	33.49	14.38	0.67	63.11	35.56	1.05
SiCo18	Control	0	229.61	336.22	242.37	46.31	55.79	43.92	0.69	64.11	34.81	1.11
SiCo06	Control	0	353.83	205.12	124.9	64.64	38.31	28.03	0.67	62.74	35.89	1.06
SiCo20	Control	0	406.91	330.87	169.54	45.79	40.11	23.18	0.7	66.42	32.02	1.13
SiCo17	Control	0	232.82	311.07	168.52	N/A	N/A	N/A	0.66	65.16	33.68	1.1
SiCo08	Control	0	332.04	157.81	150.41	48.7	24.49	22.58	0.63	64.32	35.16	1.01
SiCo23	Control	0	375.57	283.21	153.59	47.02	35.71	25.85	0.65	64.5	34.99	1.12
SiCo14	Control	0	365.41	279.6	86.88	57.02	39.17	13.83	0.65	72.9	25.32	1.14

Table A2. The gait features extracted from the group ‘Ju’ subjects are tabulated.

Subject no.	Type	H&Y stage	Avg. heel force (N)	Avg. below toe force (N)	Avg. toe force (N)	BW % (heel)	BW % (below toe)	BW % (toe)	Avg. step dist. (m)	Stance %	Swing %	Avg. stride time (sec)
JuPt18	PD	3	61.46	253.26	192.74	9.63	39.71	30.22	0.306	69.31	30.68	1.67
JuPt21	PD	2.5	266.06	262.58	76.06	36.16	35.68	10.33	0.379	71.56	26.25	1.31
JuPt13	PD	3	35.06	257.04	151.31	5.95	43.67	25.71	0.354	69.66	30.33	1.17
JuPt16	PD	2	220.19	290.92	244.37	35.62	47.07	39.54	0.44	64.29	35.71	1.24
JuPt11	PD	2	278.28	205.78	57.33	35.45	26.22	7.3	0.386	67.92	32.07	0.99
JuPt04	PD	2.5	149.38	351.54	112.79	19.03	44.79	14.37	0.428	68.55	31.44	1.07
JuPt10	PD	3	317.94	131.47	295.69	40.51	16.75	37.67	0.63	67.1	32.89	1.08
JuPt02	PD	2.5	196.04	161.57	112.53	29.38	24.22	16.86	0.47	68.35	31.64	1.04
JuPt14	PD	2	114.56	155.25	138.25	18.53	25.12	22.37	0.581	67.57	32.42	1.28
JuPt24	PD	2.5	320.79	234.07	96.97	43.6	31.81	13.18	0.48	66.66	33.33	1.09
JuPt26	PD	2	231.83	322.58	61.69	28.13	39.14	7.48	0.54	65.3	34.69	1.18
JuPt03	PD	2.5	205.93	231.84	173.92	32.29	36.35	27.27	0.54	65.75	34.24	1.17
JuPt01	PD	2	307.01	269.3	144.05	36.81	32.29	17.27	0.55	63.79	36.2	1.11
JuPt29	PD	2.5	145.82	294.14	214.11	24.36	49.15	35.78	0.54	64.87	35.12	1.08
JuPt12	PD	2.5	231.12	217.51	277.31	42.07	39.59	50.47	0.53	68.51	31.48	1.06
JuPt25	PD	2	231.33	312.86	137.61	34.67	46.89	20.62	0.609	65.87	34.12	1.12
JuPt28	PD	2.5	177.21	424.14	245.74	27.79	66.51	38.53	0.59	66.92	33.07	1.08
JuPt07	PD	3	319.21	265.63	266.18	50.06	41.65	41.74	0.48	63.83	36.16	0.87
JuPt15	PD	2.5	330.58	217.48	295.73	51.05	33.59	45.67	0.53	65.41	34.58	0.99
JuPt17	PD	2.5	279.06	141.41	118.65	37.92	19.21	16.12	0.57	60.83	39.16	1.03

Table A2. (Continued)

Subject no.	Type	H&Y stage	Avg. heel force (N)	Avg. below toe force (N)	Avg. toe force (N)	BW % (heel)	BW % (below toe)	BW % (toe)	Avg. step dist. (m)	Stance %	Swing %	Avg. stride time (sec)
JuCo17	Control	0	399.21	232.18	239.69	67.82	39.44	40.72	0.811	62.95	37.04	1.07
JuCo16	Control	0	465.81	212.32	141.05	57.21	26.07	17.32	0.69	62.64	37.35	0.98
JuCo14	Control	0	329.99	333.09	231.63	37.37	37.72	26.23	0.75	66.4	33.59	1.095
JuCo24	Control	0	229.51	270.12	165.21	32.49	38.24	23.39	0.71	62.28	37.71	1.05
JuCo26	Control	0	307.01	269.3	144.05	44.71	39.21	20.97	0.73	63.79	36.2	1.11
JuCo07	Control	0	351.71	208.98	216.28	61.81	36.73	38.01	0.62	64.54	35.45	0.97
JuCo02	Control	0	400.24	309.61	58.73	50.99	39.45	7.48	0.67	65.91	34.08	1.06
JuCo03	Control	0	344.82	234.26	213.65	58.58	39.81	36.29	0.61	63.12	36.87	1.01
JuCo08	Control	0	440.02	216.92	162.64	69.01	34.01	25.51	0.65	66.09	33.9	1.087
JuCo25	Control	0	472.26	271.62	322.91	56.63	32.57	38.72	0.77	64.33	35.66	1.276
JuCo19	Control	0	336.01	198.74	115.95	58.05	34.33	20.03	0.649	64.18	35.81	1.07
JuCo05	Control	0	285.76	141.84	125.73	56.01	27.81	24.64	0.66	62.39	37.6	1.13
JuCo04	Control	0	357.59	247.15	185.38	45.56	31.49	23.62	0.65	65.39	34.61	1.09
JuCo18	Control	0	347.72	274.48	107.51	60.07	47.42	18.57	0.63	64.73	35.26	1.09
JuCo11	Control	0	150.45	283.54	152.6	21.91	41.29	22.22	0.71	61.51	38.49	1.19
JuCo13	Control	0	406.41	235.35	95.21	57.53	33.32	13.47	0.632	63.97	36.02	1.14
JuCo23	Control	0	228.96	304.19	245.21	26.82	35.64	28.73	0.77	62.29	37.7	1.34
JuCo15	Control	0	391.75	316.91	230.1	71.31	57.68	41.88	0.63	64.68	35.31	1.123
JuCo22	Control	0	343.81	250.21	180.16	46.72	34.01	24.48	0.63	66.13	33.86	1.128
JuCo12	Control	0	373.61	154.26	51.63	62.43	25.77	8.62	0.614	64.41	35.58	1.11

Table A3. The gait features extracted from the group ‘Ga’ subjects are tabulated.

Subject no.	Type	H&Y stage	Avg. heel force (N)	Avg. below toe force (N)	Avg. toe force (N)	BW % (heel)	BW % (below toe)	BW % (toe)	Avg. step dist. (m)	Stance %	Swing %	Avg. stride time (sec)
GaPt03	PD	3	71.97	208.56	155.25	19.84	42.64	28.08	N/A	71.69	27.86	1.995
GaPt07	PD	3	63.33	189.99	109.75	11.3	38.61	25.62	0.455	75.91	23.63	1.52
GaPt09	PD	3	279.89	272.97	98.7	39.96	39.19	18.68	0.444	65.91	31.42	1.014
GaPt17	PD	3	265.36	273.11	128.82	32.89	25.71	18.97	0.425	67.71	31.74	1.169
GaPt21	PD	3	202.13	197.86	166.67	31.86	36.14	26.18	0.59	63.01	33.24	1.039
GaPt23	PD	3	284.83	199.43	105.94	N/A	N/A	N/A	0.26	80.02	19.37	1.749
GaPt04	PD	2.5	264.35	261.83	116.29	N/A	N/A	N/A	0.413	70.09	29.69	1.395
GaPt05	PD	2.5	201.28	348.67	240.59	38.77	66.01	45.6	0.489	64.81	34.46	1.083
GaPt25	PD	2.5	398.1	209.35	303.8	47.89	20.8	26.97	0.553	69.43	28.14	1.00
GaPt28	PD	2.5	168.89	333.43	158.61	19.95	34.19	16.86	0.546	70.18	28.13	1.131
GaPt31	PD	2.5	394.49	247.88	129.73	41.65	32.25	10.59	0.484	68.97	30.18	1.14
GaPt33	PD	2.5	257.87	255.53	160.11	36.42	24.92	25.03	0.51	73.07	26.03	1.274
GaPt20	PD	2	191.77	167.05	145.09	25.04	32.65	14.6	0.405	67.37	31.32	1.152
GaPt13	PD	2	119.27	239.09	163.09	25.08	48.88	30.36	0.363	72.88	26.15	0.988
GaPt22	PD	2	266.43	233.59	131.71	41.63	37.15	19.56	0.498	62.59	36.1	1.254
GaPt06	PD	2	374.43	365.49	116.43	44.35	41.11	15.19	0.489	67.74	31.64	1.158
GaPt18	PD	2	255.82	250.25	125.19	40.35	29.09	19.56	0.51	65.76	33.57	1.146
GaPt15	PD	2	93.54	243.58	196.61	11.28	33.55	26.67	0.517	65.83	33.7	1.107

Table A3. (Continued)

Subject no.	Type	H&Y stage	Avg. heel force (N)	Avg. below toe force (N)	Avg. toe force (N)	BW % (heel)	BW % (below toe)	BW % (toe)	Avg. step dist. (m)	Stance %	Swing %	Avg. stride time (sec)
GaCo04	Control	0	214.57	369.92	126.89	35.49	56.93	28.69	0.734	62.92	35.75	1.254
GaCo11	Control	0	438.95	250.78	52.17	55.66	35.7	8.23	0.768	66.89	32.49	1.035
GaCo12	Control	0	304.22	175.94	117.79	49.81	35.76	23.83	0.698	61.81	34.28	1.025
GaCo15	Control	0	294.14	350.11	244.38	38.68	53.76	42.01	0.711	62.09	37.01	1.059
GaCo16	Control	0	294.37	249.15	224.38	45.4	41	37.31	0.715	66.43	33.15	1.077
GaCo17	Control	0	409.31	275.85	138.11	73.29	43.82	29.17	0.79	60.28	38.74	1.121
GaCo22	Control	0	246.55	298.28	173.89	43.83	40.95	25.42	0.838	65.46	33.31	1.104
GaCo14	Control	0	282.84	283.37	159.5	66.04	58.07	39.33	0.735	60.8	38.13	1.124
GaCo07	Control	0	545.2	221.03	116.82	51.66	30.93	10.51	0.672	63.97	35	1.087
GaCo09	Control	0	241.08	255.35	388.52	41.14	39.55	52.29	0.663	63.48	35.94	1.079
GaCo13	Control	0	333.85	252.81	134.23	48.17	38.89	17.77	0.614	65	34.55	1.008
GaCo10	Control	0	348.82	261.45	281.84	45.66	49.85	39.21	0.624	63.16	36.42	1.071
GaCo06	Control	0	151.76	352.56	263.49	18.01	46.34	34.35	0.653	61.53	36.96	1.167
GaCo01	Control	0	376.97	341.94	122.05	47.45	44.74	18.24	0.657	62.61	35.94	1.262
GaCo03	Control	0	374.63	301.56	173.96	39.84	30.28	20.01	0.653	66.24	33.45	1.277
GaCo02	Control	0	353.45	108.08	103.5	51.22	21.56	16.67	0.578	65.19	34	1.156
GaCo08	Control	0	236.96	324.04	337.01	35	49.44	46.63	0.593	63.5	36.02	1.23
GaCo05	Control	0	222.72	148.68	220.64	27.31	27.45	27.8	0.482	64.51	38.52	1.141

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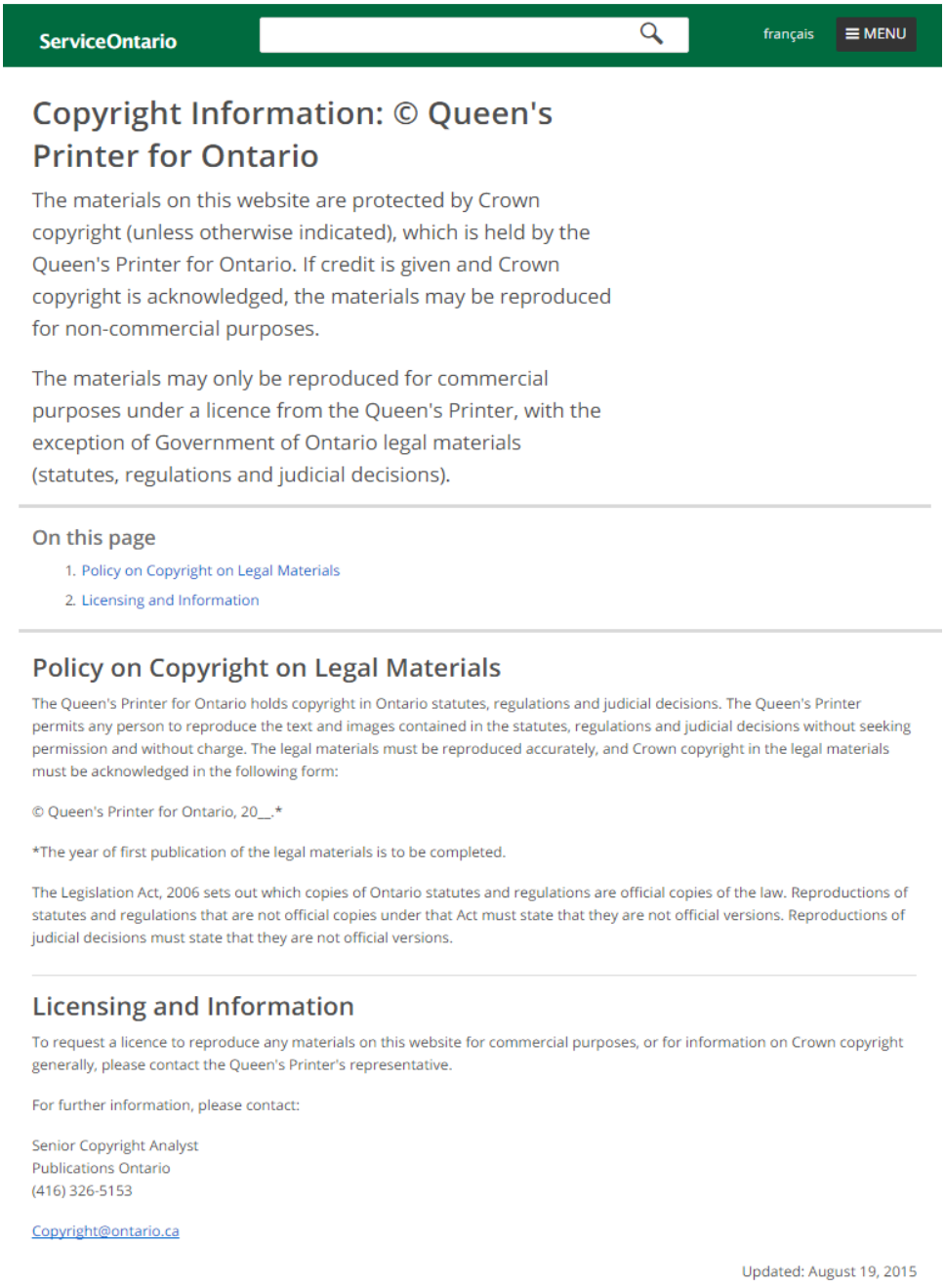

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On this page

1. Policy on Copyright on Legal Materials
2. Licensing and Information

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