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Gait and Postural Analysis in Healthy Young Adults and People with Parkinson's Disease

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By

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Claremont Graduate University and California State University Long Beach

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Aisha Chen as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in Engineering and Industrial Applied Mathematics.

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Abstract

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Postural analysis is the study of how the position of the body in any mode interacts with internal and external forces. This type of analysis is typically used to assess potential abnormalities in the balance control system and to understand how the balance control system changes with time. However, compared to other medical fields of study, postural analysis is relatively new [1]. In fact, although widely used in clinical and research studies, postural assessment methods are scientifically inaccurate, and some data collection methods are relatively expensive. A better understanding of the human balance control system could lead to more accurate and less expensive postural assessment techniques.

The human balance control system must continuously act because the human body is an inherently unstable system. In fact, gait and balance impairments lead to loss of mobility, falls, and a diminished quality of life. Advanced age, orthopedic and neurological conditions affect overall balance control, which leads to gait and balance impairment [1, 2]. In fact, disability, falls and increased mortality are all associated with insufficient balance control during gait and postural support [2].The ability to maintain stability is dependent on executing postural movements to control the temporal and spatial change in the center of mass of the body [3]. The inability to maintain this stability, results in falls and fall related injuries.

Although the risk of falling increases with age and neurological condition, there is some risk of falling for adults of all ages and circumstance [4]. In fact, falling is one of the leading causes of accidental death in the United States [5]. In 2015, the total medical cost of falls older adults was $31.9 billion, and of that total $637 million of that cost was due to death [5]. One of the main causes of falls is a trip, which accounts for 35-53% of all falls and is responsible for 12-22% of hip fractures [6]. Therefore, an understanding of the postural instability that leads to a trip could lead to prevention of a significant portion of falls, which

would ultimately lead to a decrease in the cost associated with falls. Nonetheless, there are many other factors that can contribute to an individual falling, and a better understanding of the postural control system can lead to an understanding of how to prevent recurring falls.

Traditionally, gait initiation and reaction to postural perturbation can be observed in order to evaluate the potential an individual has to fall [7, 8, 9]. In addition, analysis of standing upright posture allows for a better understanding of the overall balance control system and the ability to identify strategies the human body uses to maintain upright posture [10, 11, 12]. Kinematic, kinetic, and electromyographic signals have all previously been used to identify strategies the body can use to main posture, initiate movement, or recover from a perturbation. Each signal offers information about the balance control system, which could ultimately lead to a better understanding of postural stability.

While several studies have focused on kinetic and electromyographic (EMG) signals in order to analyze posture during perturbation, there a very few studies that have added kinematic information as a factor [8, 13]. In contrast, there have been several studies that have used kinetic and kinematic signals or kinematic and electromyographic signals in order to analyze gait initiation but there have been only a few studies that have used all three signals [14, 15]. Lastly, most studies focus on kinetic information in order to analyze standing posture, but few studies use both kinetic and electromyographic information[7, 11]. The main purpose of this study is to analysis an appropriate basis for stereotypical gait and posture. A secondary purpose is to analyze how that basis can be applied to gait and postural analysis of people with Parkinson's disorder.

Dedication

Gait and posture are of particular importance to living independently. I can recall a time before my grandmother passed when she was no longer able to walk as long or as far as she could in the previous year. I remember her tenacity in insisting she could still get around on her own and refusing to use some of the walking aids my mother and uncle persistently asked her to use. When I would come home to visit her she would climb up the stair to see me, even though she knew I would prefer her to safely wait for me to see her. I would then promptly insist that she let me assist her back down to her living quarters, and she would insist that she would be able to make it using the railing. Her persistence reinforced the notion that independence of movement was important to quality of living.

Acknowledgements

I would like to first thank my advisor Dr. Shadnaz Asgrari who orginally suggested this project to me. I am very grateful for all of her advise and guidance throughout this process. I would also like to thank Dr. Vennila Krishnan who has also been with me throughout most of this process. Thank you to Dr. Chugunova, Dr. Nadim, and Dr. Daniels for agreeing to be on my dissertation committee. Thank you everyone who has helped me with data collection: Pouye Sedighian, Trevor Frosig, Sandhya Selvaraj, Nia, Mary Alice Wintz, Jennifer Scales, and Sabrina Vujas.

To both my mom, who is with me, and dad (rest in peace), thank you for always encouraging me to pursue knowledge. To my Heavenly Father, thank you for giving me the strength and persistence to finish this. Finally, to anyone who has given me encouragement for this project in any way thank you.

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Chapter 1

Introduction

Postural analysis is the study of how the position of the body in any mode interacts with internal and external forces. This type of analysis is typically used to assess potential abnormalities in the balance control system and to understand how the balance control system changes with time. Although widely used in clinical and research studies, postural assessment methods are scientifically inaccurate, and some data collection methods are relatively expensive. A better understanding of the human balance control system could lead to more accurate and less expensive postural assessment techniques. This is a review a commonly used practices in analysis of quiet standing, postural perturbation, and gait initiation.

1.1 Quiet Standing

Quiet standing is the act of standing in one place without moving, which is complicated by the human body being a multi-link inverted pendulum [16]. This causes difficulty in preventing postural sway, because the balance control system must continuously act. However, the central nervous system solves this challenge by continuously stabilizing the center of mass by using sensorimotor coordination, which involves muscle contractions that can be seen using electromyography [16, 17, 10]. One way to measure efficiency of the balance control system is to look at postural sway, which can be identified by changes in the body's center of mass (COM)[16]. Stable quiet standing is achieved when the area of projected COM displacement is significantly smaller compared to the area of the supporting contour of the feet [16]. In

addition, studies have shown that center of pressure (COP) data such as amplitude, area, and root mean square (RMS) of the COP displacement can identify reduced ability to recover balance in neurological populations [18, 10, 11].

Since quiet standing involves relaying information to and from the CNS and it has already been shown that the main signal for the balance control system comes from vision, some studies have focused on secondary sensory conveyors. In particular, studies have shown that light fingertip contact ($< 1N$) can lead to a decrease in overall postural sway when visual information is not available [16, 17, 19]. According to previous studies, significant reduction of body sway at the smallest possible force of finger contact must be a result of feedback from proprioceptive means rather than as a result of the mechanical support provided by the contact itself [16, 19, 20]. Overall, studies have identified the motor mechanisms of balance during quiet standing, but more information of how COP displacement and electromyographic activity could lead to a better understanding of the balance control system.

1.2 Postural Perturbation

A perturbation is a sudden deviation from normal gait or standing posture, which acts as a destabilizing force and results in a displacement of the body's center of mass (COM) [21]. These perturbation can occur internally (by the individual) or externally (by the environment) [21]. While perturbations happen in daily life, healthy young individuals are more likely to recover balance from a perturbation than elderly people or people with neuromuscular disorders such as Parkinson's (PD). Therefore, some studies investigate balance recovery during perturbation to understand the difference in the balance control system between these two groups.

According to prevoius studies, there are two main strategies to restoring balance after a perturbation: feedforward control (or anticipatory postural adjustments, APA) and feedback control (or compensatory postural adjustments, CPA) [21, 22, 23, 24]. Previous studies have shown that a delay and/or diminishing occurs in APAs for elderly people and people with neurological conditions, such as Parkinson's [22, 25, 26, 27]. Therefore, methods that could

strengthen APAs during perturbations could lead to an increase in overall stability.

Specifically, when a standing person with eyes closed receives a perturbation, providing an additional support can significantly enhance the stability [21]. While studies have focused on the instability within muscles, overall stability can be determined from ground reaction forces (GRFs) [21, 28]. In addition, if stability is increased due to additional support, then the motor mechanisms behind that increased stability can help to identify the decrease in stability seen in neurlogical populations.

1.3 Gait Initiation

Gait initiation is the transition between the steady states of standing and walking[29, 30, 31, 32, 33, 34]. The transitional period is broken down into two main phases: anticipatory postural adjustments (APAs) and execution phase[29, 32, 33, 6, 35]. Gait Initiation marks the end of APAs and the beginning of the execution phase, which ultimately leads to heel-off then toe-off of the reference limb1,4,9. APAs are necessary in order to achieve balance and movement while walking[33, 34]. Impairment of APAs can lead to imbalance during gait initiation, which sometimes can result in sudden falls[31, 33, 6]. In fact, participants with neurological conditions, such as Parkinson's disease (PD) tend to have higher incidence rate of falls compared to healthy participants[36, 37]. An accurate and a reliable gait initiation onset detection method is essential for a precise evaluation of both APAs and the execution phase. Gait initiation in PD is complicated by neural disruption in the basal ganglia[30, 38]. Some symptoms of PD include freezing of gait and postural instability, which leads to falls, fear of falling, and physical injuries[36, 39, 40]. Specifically, freezing of gait refers to an absence or reduction of movement during any point of the gait cycle; however, it tends to occur during postural transitions, including during gait initiation[36, 40]. Therefore, analysis of gait initiation is of particular interest within this population as well as in any neurologically impaired population.

Onset Detection Methods

Over the last decade, several methods of gait onset detection have been proposed using different types of data including electromyography[41], COP [42, 29, 32, 35, 43], and center of mass [15, 44]. However, despite the substantial importance of reliability and accuracy of the gait onset detection for the correct assessment of gait initiation performance, these methods - especially those based on COP data - have been poorly standardized [29, 45, 41, 15, 44].

While several studies have used two [32, 6, 43] or three [35, 46] times of standard deviation of COP displacement from baseline to detect the onset of gait initiation, the authors in [34] applied a threshold equivalent to 10% of maximal COP velocity to calculate the onset. Nevertheless, many studies commonly use the tedious visual inspection of COP velocity or displacement to obtain the gait onset when the chosen algorithm fails to detect the correct onset [15, 35, 47]. Evaluation of both reliability and accuracy of the gait onset detection algorithms can address these issues and help with standardization of the gait onset detection methods. Despite such a need, there exists a lack of existing literature regarding the accuracy of onset detection algorithms. As for the reliability analysis, in a recent study, Sousa et al. have tested the reliability of two algorithms - one employing 2-standard deviations of COP displacement from the baseline to detect the onset and the other one using 5% of the first peak of COP displacement as the threshold to obtain the onset[29]. The result of this study revealed that the displacement baseline-method had higher reliability than the maximal displacement-based method.

Additional Load

The process of gait initiation is innately unstable due to the transition of posture into a single-leg stance and the simultaneous production of momentum to take a step with the swing leg [48]. This transient state is marked by anticipatory postural adjustments (APAs), which result in a deviation from the steady state of quiet standing [49, 14]. APAs are then followed by the execution phase (EP), resulting in in steady state walking [50]. Impaired and inadequate APAs are shown to be associated with an increased risk of falling [6].

The center of pressure (COP) response and its reliability during gait initiation has al-

ready been well documented [49, 51, 45]. From the literature, we know that additional load negatively affects dynamic balance during walking [52], the duration of APA during gait initiation [50], and postural control during quiet standing [53]. However, to the best of the authors knowledge, the effect of additional load on COP stability during the APA or EP phase of gait initiation has not been studied yet. This work is aimed at investigating the role of additional weight on COP stability and muscle activation (latency) during gait initiation. We hypothesized that additional load would cause earlier muscle activation and lower COP stability.

1.3.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) have been used to map gait measurements onto COM data [54, 55]. Since gait initiation is inherently unstable, understanding how other gait measurements coordinate with COM measurements can lead to a better understanding of the balance control system. In particular, gait patterns are accommodated in people with neurological conditions such as Parkinson's. For example, the relative EMG signal amplitude in the tibialis anterior in subjects with Parkinson's shows inconsistency during gait initiation. ANNs can be used to map the EMG signal to the COM data in order to understand how the change in activity relates to the overall gait output.

1.4 EMG Normalization

Regarding gait and perturbation studies that use EMG data, normalization of EMG signals is a crucial step that helps rule out confounding errors in interpretation [56]. Currently there exist several methods for normalization [57, 58, 24]. While several studies have looked at the effect of different normalization techniques during walking, to the best of our knowledge no study has investigated the effect of these techniques on gait initiation or perturbation [57, 58]. EMG signals can be a valuable tool for investigating muscle activity. However, to properly quantify EMG data an appropriate normalization technique is needed for subject to subject comparison [56].

Chapter 2

A Comparison of EMG Normalization Techniques in Gait Initiation and Perturbation Studies

2.1 Introduction

Electromyography (EMG) shows the electrical activity in the muscles and is a commly used tool in gait and postural studies. In particular, surface EMGs are commonly used because of thier accesibility and ease of use. The normalization of EMG signals is a crucial step that helps rule out confounding errors in interpretation and allows for comparison of in-group subject-to-subject muscle activity [56]. Since normalization is an essential step in gait and postural studies, the criterion for normalization should be considered carefully [56].

Currently there exist several methods for EMG normalization; however, the most effective technique for normalization is unknown [57, 58, 24, 59]. In particular, a study on the spatial variabilty of the muscle activity found using the peak EMG value during the stance phase of walking or using the maximal volutary contractions reduced the spatial variablity of the soleus muscle compared to unnormalized EMGs[59]. The study also noted that using the peak value was more effective at reducing the variability compared to using the maximal voluntary contractions[59]. However, it should be noted that only male subjects were used in

this study[59]. This results show promise for the peak EMG value during the stance phase; however, another study suggest using the maximum value obtained during walking trials gave significantly different muscle forces than those obtained using the maximal voluntary contraction method[57]. However, it should be noted that only two healthy subjects were used to estimate significance[57].

While several studies have looked at the effect of different normalization techniques during walking, this study seeks to investigate the effect of these techniques on gait initiation and perturbation [57, 58, 59]. Specifically, the aim of this investigation is to compare dynamic versus static peak EMG normalization techniques. We hypothesize that calculating the peak using dynamic data will lead to a larger maximum EMG compared to using static calculation.

2.2 Materials and Methods

2.2.1 Experimental Protocol

For this study 10 healthy right leg dominant subjects (5 female, 5 male) consented to participate in an investigation of gait initiation and perturbation. Surface EMG markers were attached to 10 muscles unilaterally on the right side of the subject (soleus (SOL), erector spinae lateralis (ESL), gluteus medius (GMED), tibialis anterior (TA), biceps femoris (BF), external obliques (EO), vastus medialis (VM), medial gastrocnemius (GM), rectus femoris (RF), rectus abdominis (RA)).

To get the static maximal contractions for the respective muscle the subjects pushed and pulled a fixed bar with maximal effort for 5 seconds each to collect the static peak contraction value for the muscles that opposed the action [24]. The subjects then stood on an AMTI force plate and were perturbed with a pendulum (3% body weight) at the shoulder level in front and back directions with both eyes open and closed at random sequence intervals for a total of 60 perturbations. The accelerometer was placed on the subjects' right knee. The subjects then stood on a force platform and commenced gait initiation starting with the right leg at a self-selected speed with and without 15% body weight added around the pelvis for a total of 30 gait initiations.

2.2.2 Data Analysis

After data was collected, the EMG signal was rectified and filtered using a Butterworth band pass filter (10-50Hz). The data was then segmented and integrated. The integrated data was then normalized using two methods: (1) dynamically - using the peak EMG value during walking trials and (2) statically - using the peak EMG value during the static peak contraction collection [60, 59]. Finally, the maximum integrated EMG (IEMG) from each normalization method was calculated for each muscle by taking the maximum value across all trials.

2.2.3 Statistics

The difference between the static and the dynamic methods were then compared using a t-test between normalization methods ($p < 0.05$) Statistical analysis was performed using Matlab R2016.

2.3 Results

The standard t-test gave significant values during perturbation for integrated EMGs for all muscles except the GM and BF. Specifically, the integrated EMGs were significanlty higher using the dynamic method. Similarly, during gati initiation all muscles except ESL were significantly higher with the dynamic approach. Table 2.1 shows the result of the t-test for both pertubation and gait initiation trials, and figure 2.1 shows the peak integrated EMG values calculated for both methods.

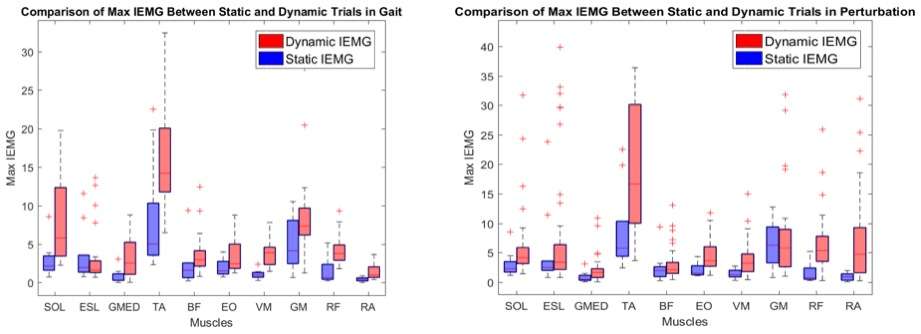

Figure 2.1: Bar Plot of Max IEMG between Static and Dynamic Trials

Table 2.1: Results of t-tests for Perturbation (Pert) and Gait Initiation (GI) Experiments

Muscle:	SOL	ESL	GMED	TA	BF	EO	VM	GM	RF	RA
Pert:	0.0013	0.0008	0.0012	0	0.1769	0	0	0.1052	0	0
GI:	0.0001	0.5599	0.0004	0	0.0209	0.0013	0	0.0088	0	0.0002

2.4 Discussion

The results show that during both gait initiation and perturbation dynamic versus static calculation of maximal muscle contraction lead to significant differences in the peak value for several muscles. For the two normalization methods tested, dynamic calculation lead to higher values compared to static calculation. The higher integrated EMG for both conditions may be due to an inability to reach the same muscle activity in the static trials. This finding has important implications considering the selection of a normalization method. Specifically, these findings corroborate those from a previous study [57]

These results may not be generalized to other age groups, and there should be additional considerations for persons with muscle disorders or neurological conditions that effect muscle activation. This study could benefit by considering bilateral muscle activity, since previous studies have shown inhomogenous muscle activities in some conditions[61]. Furthermore, this study could benefit from considering the maximal voluntary contractions method of normalization since it is considered the gold standard for EMG normalization[57, 59]. Since

most muscles had a higher peak value with the dynamic approach for both experiments, we would recommend using this approach for both gait initiation and perturbation.

Chapter 3

The Effect of Vision Compared to Unilateral Additional Support on Stability After a Perturbation

3.1 Introduction

The central nervous system (CNS) regulates postural control by integrating information from the vestibular, proprioceptive, and visual systems [62]. When a perturbation or disturbance of balance occurs, each system detects the change in balance and an output response to correct the balance is generated based on the sum of the signals received from each system [62]. Specifically, the CNS uses anticipatory postural adjustments (APAs) and compensatory postural adjustments (CPAs) to restore balance [8, 63, 64]. APAs are initiated prior to the perturbation and are based on the perceived effects that the perturbation may have on the balance control system [8, 63, 64]. CPAs are initiated after the perturbation and serve to restore the body's position after a perturbation [8, 63, 64]. In particular, a past study has shown that decreased visual acuity leads to a decrease in anticipatory postural adjustments [64].

However, there are some common situations that may occur that suddenly decrease the visual systems' input into the CNS. For example, a sudden power outage during the

night would lead to a lack of visual acuity. A previous study has already shown that using a walker, which would provide bilateral support showed a CPA response similar to those shown with vision [21]. That same study, showed that in conditions where vision is available, visual information overruled simultaneously available proprioceptive information [21]. While studies have focused on the the response seen in muscle activation, actual output response can be determined from ground reaction forces [21, 28, 65]. We hypothesize that with unilateral support when no visual information is available, CPA response should be similar to those seen when visual information is available. This study aims to provide further evidence for improved stability due to additional support when vision is limited.

3.2 Materials and Methods

3.2.1 Experimental Protocol

15 healthy young, right-legged adults (7 females, 8 males; age 21.9 ± 3.2 years) consented to participate in this study. Surface EMG electrodes were attached to the following 10 muscles: soleus (SOL), erector spinae lateralis (ESL), gluteus medius (GMED), tibialis anterior (TA), biceps femoris (BF), external obliques (EO), vastus medialis (VM), medial gastrocnemius (GM), rectus femoris (RF), rectus abdominis (RA). An accelerometer was attached to the left clavicle. The subject stood on a force platform while a perturbation to the shoulder via a swing pendulum was applied during standing [21] under the following conditions: eyes open (EO), eyes closed (EC), and eyes closed while holding a grip force transducer on a stable adjustable table (ECG).

3.2.2 Data Analysis

All data was processed using MATLAB R2012a. The EMG signals were first filtered with a bandpass filter with cut-off frequencies 10-500Hz [14, 51]. The signals were then rectified and low pass filtered with cut-off frequency 50Hz[21]. EMG onset was defined as the moment the signal was greater than 2 standard deviations from the mean calculated from baseline. In the case that the threshold method failed to produce an onset, the EMG signal was

visually inspected for an onset. The onset (t_0) was determined as the time in which the accelerometer data deviated 10% from the mean. Finally, muscle latencies were defined as the time difference between EMG onset and t_0. Similarly, ground reactions were filtered using a 20Hz Butterworth low pass filter. The center of pressure (COP) was then calculated and divided into two sections: anticipatory (APA), which was defined as the COP from 250ms before $t0$ until $t0$ and compensatory (CPA), which was defined as the COP from $t0$ to 250ms after t_0. Time domain features were then calculated in both sections for COP and included: root mean square (RMS), mean distance from center, mean velocity, approximate entropy (apEn), total excursion area (Area), total displacement (TD). All features were averaged across trials for each subject.

3.2.3 Statistics

A one-way ANOVA was used to determine if there was a significant difference between conditions for each feature. When a significant difference ($p < 0.05$) was found post hoc analysis with Bonferroni correction was used to compare conditions.

3.3 Results

A significant difference between conditions was found for the following muscle latencies: TA, BF, VM, RF, and RA (Table 3.1). Post hoc analysis revealed that for all muscles, latency was significantly lower for the EO condition compared to both EC and ECG (Figure 3.1). However, there was no significant difference for muscle latency between EC and ECG. During CPA, a significant difference was seen for the total excursion area, total displacement, mean distance, and approximate entropy of COP data. Specifically, total displacement, total excursion area, mean distance, and approximate entropy were all significantly larger for EC compared to either EO or ECG. No significant difference was found between the three conditions during APA (table 3.2, figure 3.2).

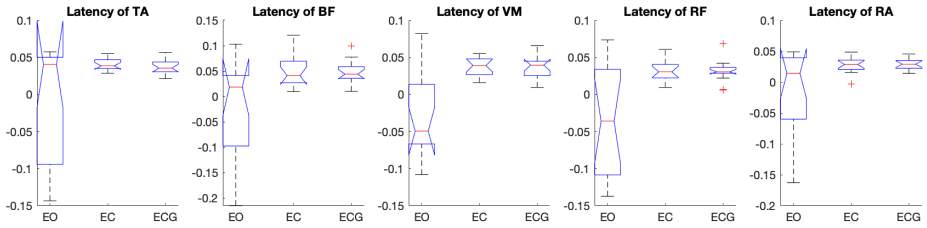

Figure 3.1: This shows a boxplot for each of the muscle latencies ($p < 0.05$)

Table 3.1: ANOVA Results for Muscle Latencies after a Perturbation

Muscles	p-Values
SOL	0.553
ESL	0.972
GM	0.239
TA	0.020
BF	0.001
EO	0.596
VM	0.000
GMED	0.119
RF	0.000
RA	0.014

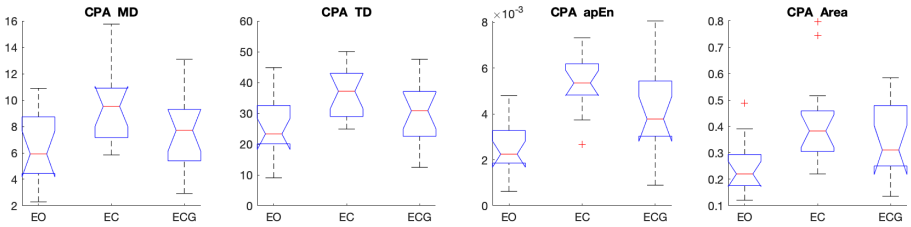

Figure 3.2: This shows a boxplot for each of the significant COP features ($p < 0.05$)

3.4 Discussion

The goal of this study was to examine the role of unilateral support and vision on balance regulation after a perturbation. We were also interested in the response seen in information from the ground reaction forces. We hypothesized that additional support would show a similar response in CPAs as seen when visual information is available.

Table 3.2: ANOVA Results for Center of Pressure Features for Anticipatory Postural Adjustments (APA) and Compensatory Postural Adjustments (CPA)

Feature	APA	CPA
MD	0.298	0.027
rms_{AP}	0.869	0.754
rms_{ML}	0.481	0.651
MV	0.721	0.193
MF	0.997	0.366
TP	0.861	0.641
PF	0.882	0.286
f50	0.354	0.77
f75	0.768	0.794
HE	0.44	0.619
TD	0.219	0.01
apEn	0.083	0
Area	0.137	0.003

3.4.1 The Role of Additional Support

The addition of unilateral additional support showed a reduction of CPAs even though the muscle latencies show that APAs were negligible. Specifically, the COP response showed no significant difference between the condition with vision and the condition with no vision and unilateral additional support. This result is similar to those found in previous studies[21, 8, 64]. Specifically, when vision is not available APAs are not generated, which can we see in our muscle latencies[21, 8, 64]. However, when vision is not available and additional support is available, then CPAs show a reduction of the COP response. These results suggest that when vision is not available using unilateral additional support can be a valuable strategy to improve postural control.

Chapter 4

The Effect of Light Touch on Stability During Quiet Standing

4.1 Introduction

Human beings employ multiple strategies to maintain body balance in standing position. Specifically, the central nervous system (CNS) receives signals from visual, vestibular, and proprioceptive systems and uses that input to output appropriate corrective responses[62]. In particular, light touch can be used as a proprioceptive means of maintaining balance [19, 66]. Light touch has been defined as a force no greater than 1N that gives a non-supportive fingertip contact with another stable object[19, 67, 68, 69]. Other studies have shown that light touch increases postural stability[17, 19, 70, 67, 69, 66, 71]. The Hurst's exponent is a measure of long-term memory of a time series[72, 73]. We hypothesize that traditional analysis will not be able to quantify the subtle changes that occur during standing. The main objective of this study is to use the Hurst's exponent to quantify the subtle changes that occur with light touch compared to without light touch.

4.2 Materials and Methods

To achieve this goal, ground reaction forces from a force plate (AMTI) were collected from 15 healthy adults during quiet standing under the following conditions: eyes open while lightly

touching a force sensor (EOLT), eyes closed while lightly touching a force sensor (ECLT), eyes open without light touch (EO), eyes closed without light touch (EC). Three 30-second trials were collected from each condition, and light touch was defined as any force less than 1 Newton. Ground reaction force data was first filter using a 20Hz low-pass filter. The filtered data was then used to calculate the center of pressure (COP). The Hurst's exponent (HE) was then estimated by first taking the first derivative of the COP and then using dispersional analysis on the differentiated COP, and then calculating the coefficient of a polynomial of degree 1 using the MATLAB built-in function polyfit() to a log-log plot[74]. The following features were also calculated: root mean square, mean distance from center, mean velocity, approximate entropy, total excursion area, total displacement.

4.3 Results

ANOVA results revealed that only HE was significantly different between conditions. Post-hoc analysis showed that the HE for ECLT was significantly closer to 1 than the HE for EC ($p = 0.0006$) and EO ($p < 0.000001$) (see Table 4.1 and Figure 4.1).

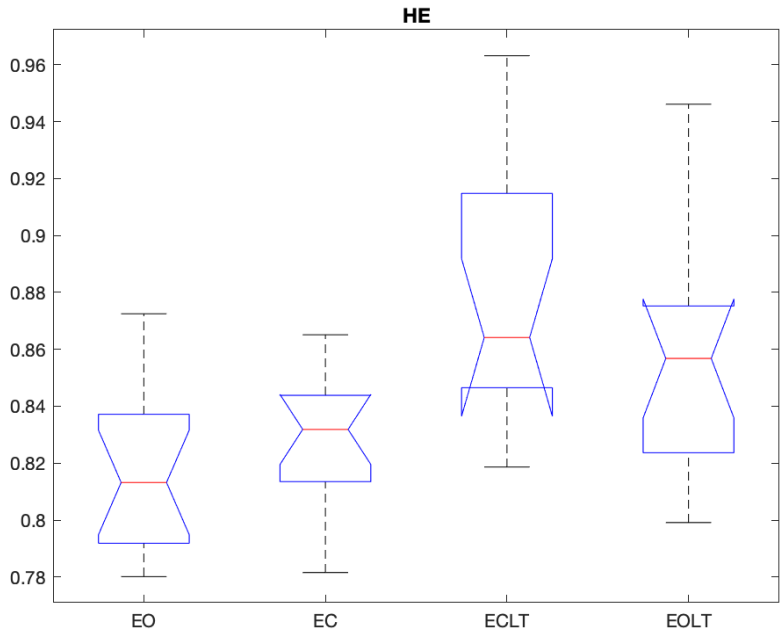

Figure 4.1: This shows a boxplot for each of the significant COP features ($p < 0.05$)

Table 4.1: ANOVA Results for Center of Pressure Features for Vision and Touch Conditions

Feature	p-value
MD	0.274269
rms_{ML}	0.999247
rms_{AP}	0.877062
MV	0.149532
MF	0.825123
TP	0.985715
PF	0.954709
f50	0.475318
f75	0.995399
HE	1.35E-05
TD	0.612056
apEn	0.148704
Area	0.590554

4.4 Discussion

We hypothesized that traditional analysis would not be able to quantify the subtle changes that occur in standing. The results show that only the Hurst's exponent differentiated the differences between light touch and no light touch. These results are in agreement with findings from previous studies[19, 72]. We conclude that compared to traditional analysis, HE analysis could discriminate the subtle postural changes associated with the displacement of COP in healthy adults. This parameter could potentially be employed to discriminate the postural changes associated with aging process and with neurological disorders.

Chapter 5

Accuracy & Reliability of Onset Detection Algorithms in Gait Initiation for Healthy Controls and Participants with Parkinson's Disease

5.1 Introduction

Gait initiation is the transition between the quasi-static state of standing and the dynamic state of walking[34, 30, 33, 31, 29, 32]. This transitional period is broken down into two main phases: the postural phase and the execution phase. In the postural phase, the anticipatory postural adjustments (APAs) for balance and moving is achieved via the displacement of center of pressure (COP) in the posterior direction (by inhibition of soleus and bilateral gastrocnemius and the activation of tibialis anterior) and in the lateral direction (by preloading of the leading foot by hip abductors)[34, 75, 76, 77]. On the other hand, the execution phase begins with the unloading of the swing foot, which is followed by the unloading of stance foot[78, 42]. The motor program for APA is controlled through a stable mechanism in central nervous system to manage the inherent instability of upright bipedalism during gait initiation5. The impairment of APAs can lead to imbalance and sudden falls during gait initiation[33, 31, 6].

Thus patients with neurological conditions such as Parkinson's disease (PD) or stroke tend to have higher incidence rate of falls compared to healthy participants[36, 37, 39, 40]. In fact, gait initiation in PD is complicated by neural disruption in the basal ganglia[30, 38]. Freezing of gait – a common symptom of PD defined as an absence or reduction of movement – tends to occur during any point of the gait cycle, especially gait initiation[37, 40, 45]. Analysis of gait initiation can help with better understanding of motor control system and its impairment/degradation in the patient/older populations. Gait initiation analysis can also assist with the development of rehabilitation programs or interventions for neurologically impaired population in a more efficient manner[29]. Accurate and reliable detection of the onset of gait initiation is a pre-requisite for correct assessment of gait. For example, the values of various quantitative measures of gait initiation including displacement of COP during APA are dependent on the correct measurement or detection of the gait onset[29]. Over the last decade, several methods of gait onset detection have been proposed using different types of data including electromyography[41], COP[34, 29, 32, 35, 43], and center of mass[15, 44]. However, despite the substantial importance of reliability and accuracy of the gait onset detection for the correct assessment of gait initiation performance, these methods - especially those based on COP data - have been poorly standardized[29, 45, 41, 15, 44]. While several studies have used two[32, 6, 43] or three[35, 46] times of standard deviation of COP displacement from baseline to detect the onset of gait initiation, the authors in 1 applied a threshold equivalent to 10% of maximal COP velocity to calculate the onset. Nevertheless, many studies commonly use the tedious visual inspection of COP velocity or displacement to obtain the gait onset when the chosen algorithm fails to detect the correct onset[35, 43, 47]. Evaluation of both reliability and accuracy of the gait onset detection algorithms can address these issues and help with standardization of the gait onset detection methods. Despite such a need, to the best of our knowledge, no study has ever evaluated the accuracy of existing onset detection algorithms. As for the reliability analysis, in a recent study, Sousa et al. have tested the reliability of two algorithms - one employing 2-standard deviations of COP displacement from the baseline to detect the onset and the other one using 5% of the first peak of COP displacement as the threshold to obtain the onset[29]. The result of this study revealed that the displacement baseline-method had higher reliability

than the maximal displacement-based method. To our knowledge, no other study on reliability analysis of gait onset detection has been published. In response to the existing need for the standardization of gait onset detection methods, in this study we investigated both the reliability and accuracy of three gait onset detection algorithms using COP data: The first and second algorithms were a velocity baseline-based method (Method 2) and a velocity extrema-based method (Method 3)[34], respectively. The reliability and accuracy of these algorithms were obtained and then compared with those of the displacement baseline-based method (Method 1), which had showed high reliability in the work of Sousa et al.[29]. Given that the COP velocity is derivative of COP displacement and consequently more sensitive to the changes in the signal, we hypothesize that the velocity-based detection methods (Method 2 and Method 3) will be more accurate and reliable than COP displacement baseline-based method (Method 1).

5.2 Materials and Methods

Participants: 16 healthy right leg dominant participants (7 females), age (22.1 ± 3.1) and 3 participants with Parkinson's disease (2 females), age (68.7 ± 7.7) consented to participate in our study. All participants were required to be able to follow instructions and walk independently (with or without any aid or orthosis) for at least 10 meters without rest, have no pacemaker, no shoulder dislocation, no pain or sensory disturbances that may interfere with their daily activities and should have no known auditory pathology. The experiment was approved by the institutional review board at California State University, Long Beach. Before participation in the study, participants with PD took a Montreal Cognitive Assessment (MOCA) test to assess their cognitive ability and were required to have a score above 24 to participate in the study[79]. Data Acquisition: Participants were instructed to stand on a force plate and given a verbal cue to initiate gait with their dominant leg. (Figure 5.1) shows a schematic of positions of feet during the experiment: starting on force plate 1, using force plate 2 as a marker for the initial swing position and ending after force plate 2. Participants performed 10 trials of gait initiation. Ground reaction forces (GRFs) were recorded with sampling frequency of 2000Hz. Initial Data Processing: The COP signals in the mediolat-

eral direction (COP_ML) and anterior-posterior direction (COP_AP) were calculated from the GRFs for each trial using the following equations:

$$COP_{ML} = -(M_y + F_z \times z_0)/F_z$$

$$COP_{AP} = (M_x - F_y \times z_0)/F_z$$

where M_x and M_y are the moments around the mediolateral and anterior-posterior directions respectively. F_z, F_y and F_x are the forces in the z, mediolateral and anterior-posterior directions respectively, and z_0 is the plate thickness. The COP signals were filtered using a second order Butterworth low-pass filter with cut-off frequency of 20Hz. To get a zero-phase distortion, after filtering the data in the forward direction, the filtered sequence was reversed and ran back through the filter[80]. Baseline data was defined as the first second of the trial during which the subject was standing. Gait Onset Detection Algorithms: For Method 1, the onset detection threshold was calculated as three times the standard deviation greater (less) than the mean of baseline COP displacement in ML (AP) direction. For Method 2, the threshold was calculated as three times the standard deviation greater (less) than the mean of baseline COP velocity in ML (AP) direction. For Method 3, the threshold was calculated as 10% of the peak (trough) of COP velocity in ML (AP) direction. For all algorithms, onset was determined as the first instance (after the baseline) in which the COP signal (displacement or velocity) in the AP (ML) direction was above (below) the threshold for at least 50ms (average electromechanical delay) to exclude variations unrelated to gait initiation[29, 81] (Figure 5.2). The onset was also detected visually at the base of a significant deviation from initial COP for each trial. COP displacement during the postural phase (Δ_{COP}) was calculated as

$$\Delta_{COP} = |COP(t_0) - COP(t_{RHO})|$$

where t_0 is the onset time of gait initiation and t_{RHO} is the heel-off moment for the right foot, i.e. when the maximum peak (minimum trough) of COP data in ML (AP) direction occurs. Statistical Analysis: Statistical analysis was performed in Matlab R2017b (Math-

Works, Inc, Natick, MA). The relative (intrasession) reliability and absolute reliability of each algorithm were evaluated. For relative reliability, we calculated the degree of absolute agreement among measurements of Δ_{COP} through a two-way random effect model[82]. For this purpose, intra-class correlation coefficients (ICC) type (2,k) of Δ_{COP} and their 95% confidence interval were obtained[45, 83, 84, 85]. Then the following ranges were used to report the degree of ICC reliability[29]: 0–0.25 = very low correlation; 0.26–0.49= low correlation; 0.5–0.69 = moderate correlation; 0.7–0.89 = high correlation; and 0.9–1 = very high correlation. To evaluate the statistical difference between intrasession reliabilities, t-statistic was employed following the application of Fisher's Z transformation[29]. To measure absolute reliability, we calculated the coefficient of variation (CV) for Δ_{COP} of each subject as[29, 85]:

$$CV = SD/Mean,$$

where Mean and SD are the average and standard deviation of data (Δ_{COP}) across all trials for each subject. Paired samples t-test was used to compare Δ_{COP} and CV between the methods and between ML and AP directions within each method. Unpaired t-test was used to compare the results between healthy and PD subjects. A probability of less than 0.05 was used to indicate statistical significance. To measure accuracy of the algorithms, the onset detection error of each algorithm relative to that of visual inspection was calculated as:

$$\Delta t = |t_0(visual) - t_0(algorithm)|$$

A Wilcoxon rank-sum test was done on Δt (due to non-Gaussian distribution) to measure the significance of the difference between the accuracy of the three algorithms. We also calculated the normalized histograms of onset detection error for each algorithm and used the area under the normalized histogram for error values smaller or equal to 50 ms, as another quantitative measure to compare the accuracy of the three algorithms.

5.3 Results

With respect to reliability, all three algorithms had high to very high intrasession reliability; however, the onset of the velocity baseline-based method (Method 2) and the velocity extrema-based method (Method 3) showed significantly better absolute reliability than the displacement baseline-based method (Method 1) in healthy controls. Figure 5.2 shows example selections of each algorithm. For healthy subjects, significant differences of Δ_{COP} between all the methods were observed in both ML and AP directions (Table 5.1). In fact, paired t-test analyses revealed that the calculated COP displacement by Method 1, Visual, Method 2 and Method 3 were in increasing order (significantly), respectively. We also observe that regardless of the method, the COP displacement in AP direction was significantly greater than that of ML direction. For the PD subjects, while Method 1 achieved the lowest COP displacement among the methods (ML: p=0.02, AP: p=10-4), the other three methods (Method 2, Method 3 and Visual Selection) showed no significant difference (ML: p=0.08, AP: p=0.26). Similar to healthy subjects, the COP displacement of PD subjects in AP direction was significantly greater than that of ML direction, regardless of the employed onset detection method. Comparison of the Δ_{COP} of healthy and PD subjects revealed that COP displacement of PD subjects were significantly lower than those of healthy subjects in both ML and AP directions for all the methods: SDD (p=10-4 and p=10-5), SDV (p=10-4 and p=10-8), EXV (p=10-3 and p=10-8), Visual (p=10-5 and p=10-7). For healthy participants, all four methods (including Visual) showed high correlation in the ML direction and very high correlation in the AP direction (except for Method 1 which showed high intrasession reliability) (Table 2). However, no significant difference between AP and ML intrasession reliabilities were observed for any of the methods (Method 1: p=0.70, Method 2: p=0.17, Method 3: p=0.34, Visual: p=0.33). Interestingly, no significant difference among the intrasession reliabilities of all four methods were also observed for healthy subjects (ML: p=0.40, AP: p=0.05). For PD participants, all four methods showed high intrasession reliability in both ML and AP directions, except for Method 3 in ML direction and Visual in AP direction which demonstrated a very high correlation. Similar to healthy participants, no significant difference between AP and ML intrasession reliabilities were observed for any of

the methods (Method 1: p=0.42, Method 2: p=0.67, Method 3: p=0.38, Visual: p=0.47). Furthermore, no significant difference among the intrasession reliabilities of all four methods were also observed for PD subjects (ML: p=0.10, AP: p=0.54). Finally, the comparison of ICC values of healthy to those of PD subjects revealed no significant difference for any of the methods and in any directions. According to the absolute reliability analyses for the methods, the onset detection in the AP direction using Method 2 and Method 3 showed the most reliability (Table 5.3). Paired sample t-test showed that CV values in ML direction were significantly greater than those of AP direction for Method 1 (p=0.007), Method 2 (p=0.04). However, for Method 3 and Visual selection, there were no significant differences between the CV values of ML and AP directions (p=0.08 and p=0.20, respectively). The ANOVA revealed that for healthy subjects there were significant differences between the CV of methods in the ML direction (p=0.01). Specifically, while CV values of Visual selection and Method 3 revealed no significant differences (p=0.12), both methods showed significantly smaller CV values relative to Method 2 (p=0.03). Among all four methods, Method 1 showed the highest values of CV (p=0.001). Similarly, in the AP direction, ANOVA revealed significant differences in CV values of all methods (p=0.03). However, further analysis showed that only Method 1 had significantly higher CV values than the other three methods (p=0.008), and in fact, the difference between absolute reliability of the other three methods were not statistically significant. For PD participants, the CV values in the ML and AP directions showed no statistically significant difference for any of the methods: Method 1 (p=0.09), Method 2 (p=0.13), Method 3 (p=0.15), Visual (p=0.14). Furthermore, the ANOVA revealed no significant difference in the CV values of among the four methods in ML (p=0.26) or AP (p=0.11) directions. An unpaired t-test between the CV values of healthy and those of PD subjects revealed no significant difference for any of the methods and in any directions other than the following: For Visual selection (Method 3), CV values of PD subjects were significantly larger than healthy subjects in ML (AP) direction with p=0.02 (p=0.01).

For both healthy and PD subjects, Method 2 has the highest accuracy in both the AP and ML direction. All three algorithms were able to detect the gait onset close to that of the visual inspection (difference being less than 100 ms), but the onset of the velocity baseline-based method (Method 2) seems to be closer to that of visual inspection relative to the other

two methods (Figure 5.3). In addition, the area under the histogram measure shows how often (on average) each algorithm can estimate the gait initiation onset with an error less than or equal to 50 ms (Figure 5.4). Note that the more accurate the algorithm, the higher values of normalized histogram for smaller values of error. Thus, an algorithm with a higher area under the histogram will be more accurate. Based on this interpretation, the results showed that for an estimated error equal or less than 50 ms, Method 2 is the most accurate algorithm for gait onset detection in both healthy and PD subjects with an overall accuracy equal or greater than 0.76 (Method 1: 0.37, Method 2: 0.53). If the upper bound for the estimated error is increased to 200 ms, the overall accuracy of Method 1, Method 2 and Method 3 would increase to 0.63, 0.80 and 0.70, respectively (Table 5.4). For healthy adults, the Wilcoxon rank-sum test revealed that in the ML direction, the estimated error of Method 2 was significantly lower than that of Method 1 (p=10-10) and Method 3 (p=0.01). Between Method 1 and Method 3, the latter showed significantly lower estimation error. Similarly, in the AP direction, Method 2 showed significantly lower estimation error than the other two algorithms (Method 1: p=10-19, Method 3: p=10-6). For participants with PD, the Wilcoxon rank-sum test revealed that in the ML direction, Method 2 had significantly lower estimation error than that of Method 1 (p=0.02). However, there was no significant difference between Method 2 and Method 3 (p=0.26) or between Method 1 and Method 3 (p=0.52). Similarly, in the AP direction, Method 2 had significantly lower estimation error than that of Method 1 (p=10-4). However, there was no significant difference between Method 2 and Method 3 (p=0.23) or between Method 3 and Method 1 (p=0.1). Finally, the comparison of error values between healthy and PD subjects revealed that the estimation error of Method 2 in healthy and PD subjects were not significantly different for both ML (p=0.21) and AP (p=0.05) directions. However, Method 1 and Method 3 performed worse in PD subjects for AP direction (p=10-4) and ML direction (p=0.01), respectively.

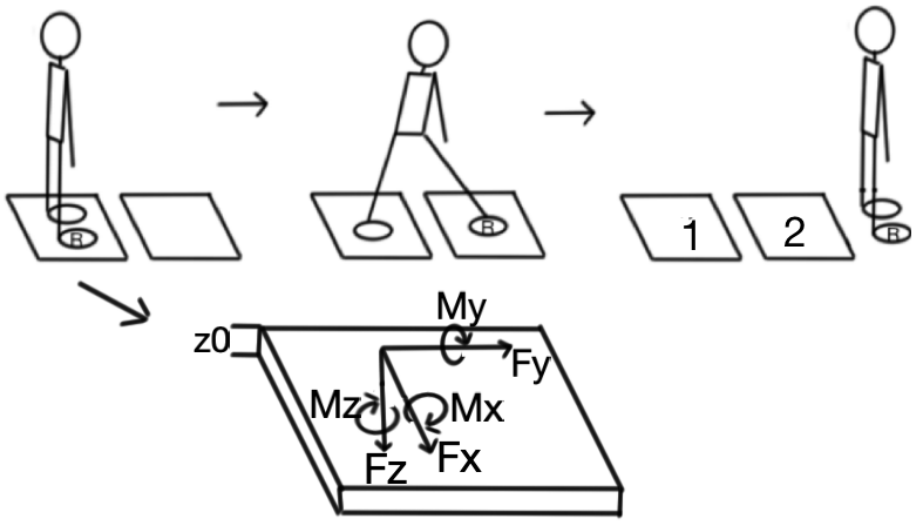

Figure 5.1: Schematic of positions on force plate during gait initiation. 'R' denotes the Right foot.

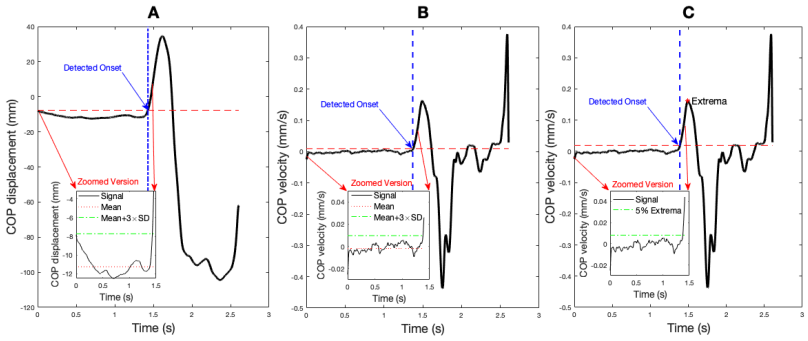

Figure 5.2: Sample threshold and onset detection values: (A) displacement baseline-based method (Method 1); (B) velocity baseline-based method (Method 2); (C) velocity extrema method (Method 3).

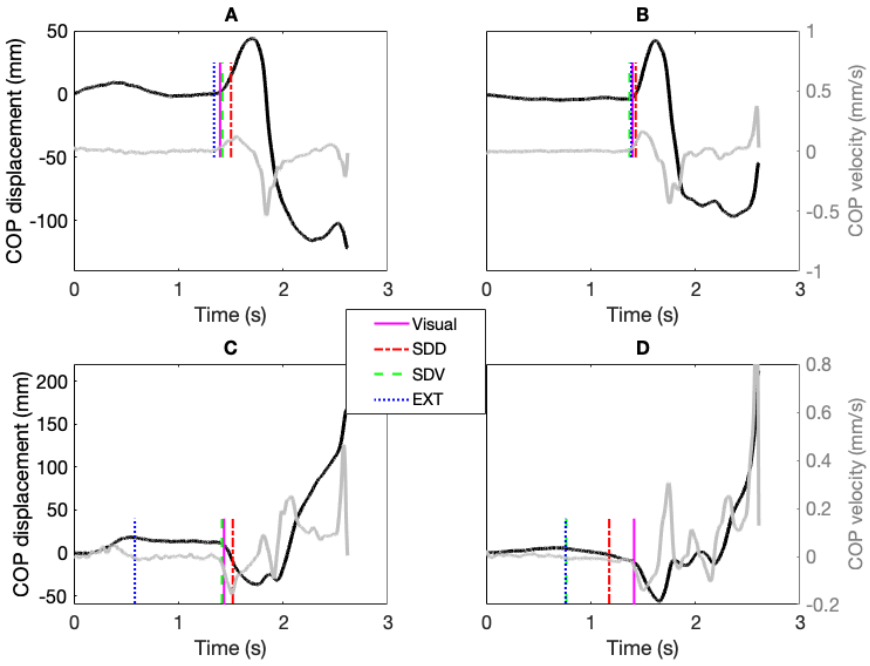

Figure 5.3: Sample displacement and velocity of COP in a representative healthy young adult and a participant with PD: (A) COP-ML direction in healthy; (B) COP-ML direction in PD; (C) COP-AP direction in healthy; (D) COP-AP direction in PD.

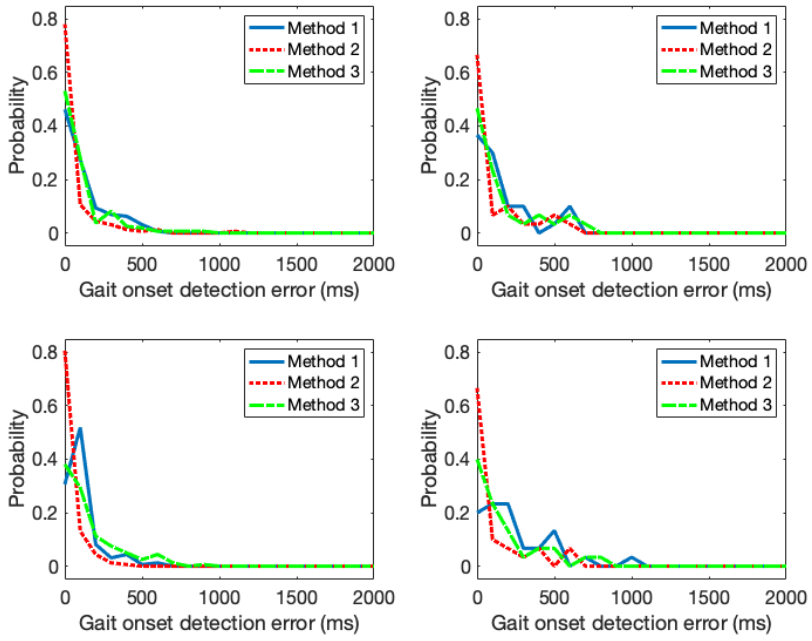

Figure 5.4: Normalized histogram of gait onset detection errors for three algorithms in healthy and PD patient groups (A) using COP-ML data in healthy; (B) using COP-ML data in PD; (C) using COP-AP data in healthy; (D) using COP-AP data in PD.

Table 5.1: Calculated COP displacement (Δ_{COP}) values as mean $\pm$ SD (in cm) using different methods. * indicates significant results

		Method 1	Method 2	Method 3	Visual	p-value between the methods
Healthy	ML	3.79 ± 1.89	4.68 ± 1.62	4.84 ± 1.53	4.60 ± 1.42	10^{-8}*
	p-value between ML and AP	$p = 10^{-8}$*	$p = 10^{-22}$*	$p = 10^{-25}$*	$p = 10^{-21}$*	
	AP	4.79 ± 1.66	6.79 ± 1.66	7.08 ± 1.99	6.59 ± 1.89	10^{-27}*
PD	ML	2.66 ± 2.47	3.58 ± 2.67	4.20 ± 2.54	3.33 ± 1.86	0.04*
	p-value between ML and AP	$p = 0.03$*	$p = 0.006$*	$p = 0.02$*	$p = 0.003$*	
	AP	3.28 ± 1.70	4.72 ± 1.93	4.85 ± 1.99	4.55 ± 1.71	0.004*

Table 5.2: Intrasession reliability (ICC(2,k)) as mean (95% confidence interval) using different methods. * indicates significant results

		Method 1	Method 2	Method 3	Visual	p-value between the methods
Healthy	ML	0.83 (0.67,0.93)	0.85 (0.70,0.94)	0.87 (0.75,0.95)	0.88 (0.78,0.95)	0.4
	p-value between ML and AP	$p = 0.7$	$p = 0.17$	$p = 0.27$	$p = 0.33$	
	AP	0.8 (0.61,0.92)	0.92 (0.84,0.97)	0.92 (0.85,0.97)	0.93 (0.86,0.97)	0.06
PD	ML	0.71 (0.31,0.99)	0.81 (0.22,1)	0.94 (0.79,1)	0.83 (0.24,1)	0.1
	p-value between ML and AP	$p = 0.42$	$p = 0.67$	$p = 0.38$	$p = 0.47$	
	AP	0.85 (0.29,1)	0.87 (0.41,1)	0.89 (0.53,1)	0.90 (0.58,1)	0.54

Table 5.3: Absolute reliability (CV) values as mean ± SD using different methods. * indicates significant results

		Method 1	Method 2	Method 3	Visual	p-value between the methods
Healthy	ML	0.44 ± 0.31	0.27 ± 0.18	0.23 ± 0.14	0.22 ± 0.12	0.01*
	p-value between ML and AP	$p = 0.007$*	$p = 0.04$*	$p = 0.08$	$p = 0.20$	
	AP	0.29 ± 0.18	0.20 ± 0.07	0.19 ± 0.07	0.20 ± 0.08	0.04*
PD	ML	0.72 ± 0.15	0.48 ± 0.27	0.33 ± 0.12	0.40 ± 0.19	0.15
	p-value between ML and AP	$p = 0.09$	$p = 0.13$	$p = 0.19$	$p = 0.14$	
	AP	0.47 ± 0.14	0.28 ± 0.10	0.30 ± 0.08	0.26 ± 0.06	0.11

Table 5.4: Calculated areas under the normalized histograms of three algorithms for errors less than or equal to 50ms

	Healthy		PD	
	ML	AP	ML	AP
Method 1	0.57	0.59	0.47	0.37
Method 2	0.83	0.86	0.67	0.67
Method 3	0.81	0.73	0.53	0.53

5.4 Discussion

Employment of an accurate and reliable gait onset detection algorithm is a necessary step for correct gait analysis. However, gait onset detection algorithms have been poorly standardized[29, 41, 15, 44] In response to this need, this study evaluated the reliability and accuracy of three algorithmic methods in both healthy and PD subjects: a COP displacement-based algorithm (Method 1), a COP velocity-based algorithm (Method 2) and a COP velocity-extrema algorithm (Method 3). Our results revealed that all three algorithms have high or very high

intrasession reliability in both ML and AP directions and for both healthy and PD subjects. In fact, the analysis showed that there was no significant difference between intrasession reliability of the any of the algorithms and that of the Visual method. These high values of intrasession reliability corroborate that gait initiation is the result of some stereotyped patterns of activity[29, 86]. These results are also consistent with the observation that COP displacement achieves high reliability even in upright standing of PD subjects, even though PD subjects present a decreased COP displacement backwards and towards the swing leg compared to the healthy individuals[87]. With respect to absolute reliability, Method 1 showed the lowest reliability among the methods in both ML and AP directions for healthy subjects. The differences of absolute reliability for Method 2, Method 3 and Visual selection were not statistically significant in healthy subjects. For PD subjects, no significant differences were observed between the absolute reliability of the methods. However, the results of CV analysis for PD subjects should be interpreted with caution, because in contrast to ICC rendering one value per trial and for each subject, CV has only one value per subject. Given the low number of PD participants in this study, the obtained CV analysis results may not be valid for PD subjects.

Our results also indicated that, regardless of the algorithm used, the COP displacement in the AP direction was significantly greater than that of the ML direction for both healthy and PD subjects. This observation is consistent with those of [42, 35, 43, 88] and could be explained by the fact that at gait initiation, the COP displacement backward would be more substantial to produce the sufficient moments to propel the body center of mass forward in the intended direction of stepping[43]. We also observed that COP displacements of PD subjects in both ML and AP directions were significantly smaller than those of healthy subjects, corroborating that the under-scaled voluntary movement in PD patients is present during the preparation phase[43, 89] and emphasizing on the role of the basal ganglia in 'energizing' muscle activation for appropriate magnitude of scaling for particular tasks[42, 90]. Our results also showed that among the three algorithms, Method 1 (Method 3) achieved the smallest (largest) COP displacement values. This can be explained by the fact that Method 1 is a COP displacement baseline-based detection method while Method 3 is COP velocity extrema-based method. Thus, Method 1 is more sensitive to the baseline variation (i.e.

swaying in quiet standing) and has an onset later than that of Method 3. Since Method 1 (Method 3) has the latest (earliest) onset among the three algorithms, it presents the smallest (largest) COP displacement during postural phase of gait initiation.

With respect to algorithm accuracy, in healthy subjects, Method 1 achieved the lowest accuracy while Method 2 proved to be the most accurate one (in both ML and AP directions). In PD subjects, Method 1 still performed as the least accurate one, however, no significant differences were observed between the performance of Method 1 and Method 3. This observation in PD subjects could be explained by the fact that COP displacement signal is dampened in PD relative to healthy individuals11 . As both Method 1 and Method 3 detect the onset based on the changes in COP velocity signal, their difference in the location of the detected onset was diminished by the dampened COP due to pathophysiology of PD. In contrast, Method 1 finds the onset based on the COP displacement during quite standing. PD subjects have increased body sway (in both ML and AP directions) [91]. The increased body sway can result in a higher threshold value for the onset detection in Method 1. Consequently, the onset of Method 1 in PD subjects will still be significantly later than those detected by Method 2 and Method 3. Our results also indicated that Method 2 was the only algorithm whose accuracy did not significantly downgrade for PD subjects. So, in conclusion, Method 3 seemed to be the most accurate algorithm. To our knowledge, this is the first study evaluating both reliability and accuracy of gait onset detection algorithms using COP data. All three algorithms had high intrasession reliability. But Method 2 and Method 3 showed better absolute reliability than Method 1. From an accuracy point of view, Method 1 outperformed the other two algorithms. Therefore, this study recommends using the Method 2 algorithm for accurate and reliable gait onset detection.

Chapter 6

Analysis of Stability during Gait Initiation with Additional Load

6.1 Introduction

Gait initiation is a voluntary internal perturbation from upright stance leading to a steady state gait cycle [49]. The process of gait initiation is innately unstable due to the transition of posture into a single-leg stance and the simultaneous production of momentum to take a step with the swing leg [48]. This transient state is marked by anticipatory postural adjustments (APAs), which result in a deviation from the steady state of quiet standing [49, 14]. APAs are then followed by the execution phase (EP), resulting in in steady state walking [76]. Impaired and inadequate APAs are shown to be associated with an increased risk of falling [6]. The center of pressure (COP) response and its reliability during gait initiation has already been well documented [49, 51, 45]. From the literature, we know that additional load negatively affects dynamic balance during walking [52], the duration of APA during gait initiation [76], and postural control during quiet standing [53]. However, to the best of the authors' knowledge, the effect of additional load on COP stability during the APA or EP phase of gait initiation has not been studied yet. This work is aimed at investigating the role of additional weight on COP stability and muscle activation (latency) during gait initiation for healthy young adults and older adults with Parkinson's disease. We hypothesized that additional load would cause earlier muscle activation and lower COP stability.

6.2 Materials and Methods

6.2.1 Protocol

Fifteen healthy subjects (7 females, 8 males; age 21.9 ± 3.2 years; weight 142.6 ± 29.0) and two older adults with Parkinson's disease (2 females; age 68.7 ± 7.7) consented to participate in this study. Subjects were all right-leg dominated (leg-dominance defined as the same side as the foot a soccer ball would be kicked with) and had no known neurological or musculoskeletal disorders. This study was approved by the institutional review board at California State University Long Beach. All participants were informed of the step-by-step process before being accepted as a volunteer. Electromyography (EMG) signals were captured using disposable self-adhesive electrodes, which were applied unilaterally (on the right side) to the following muscles: soleus (SOL), lateral erector spinae (ESL), gastrocnemius (GM), tibialis anterior (TA), biceps femoris (BF), external obliques (EO), vastus medialis (VM), gluteus medius (GMED), rectus femoris (RF), rectus abdominus (RA). Center of pressure (COP) was calculated using the ground reaction forces (GRFs) from two consecutive forceplates. Using the command go, subjects were asked to stand on a forceplate and initiate walking as quickly as possible with their right leg. Subjects were instructed to complete one gait cycle and terminate walking with both feet together past both forceplates (see Figure 5.1). There was a total of 15 trials of gait initiation for each of the following conditions: subjects performing gait initiation normally (GI), subjects performing gait initiation with 15% body weight added around the pelvis (GIW). Weight was added symmetrically in 3lb increments using an MiR Champion Belt around the center of the waist.

6.2.2 Data Analysis

After data was collected GRF signals were low-pass filtered with a 4th order Butterworth filter with frequency 20Hz [45]. The COP was then calculated. The onset (t0) of gait was defined as the time that the absolute value of first derivative of COP was greater than 2 standard deviations from the mean. The COP was then segmented into two-time epochs: APA (-250ms to t0) and EP (t0 to heel-off) [76]. Segmented data was then linearly nor-

malized to 250ms [92]. Each time-normalized COP was then used to calculate the following features: total power (TP), mean distance (MD), root mean square (rms) for AP and ML directions, mean velocity (MV), mean frequency (MF), median frequency (f50), 75th percentile of frequency (f75), Hurst exponent (HE), and confidence ellipse area (Area) [92].

EMG signals were filtered with a bandpass filter with cut-off frequencies 10-500Hz [14, 51]. The signals were then rectified and filtered using a moving average filter with a window size of 50ms. EMG onset was defined as the moment the signal was greater than 2 standard deviations from the mean calculated from baseline (the first 50ms of trial when subject was standing). Finally, muscle latencies were defined as the time difference between EMG onset and t_0.

6.2.3 Statistics

Each feature was checked for normality using the Kolmogorov-Smirnov test. The effects between GI and GIW of additional load were evaluated using a paired t-test (for normally distributed features) or a rank sum test (for non-normally distributed features). $p < 0.05$ was chosen for statistical significance. Statistical analysis was performed using Matlab R2016a.

6.3 Results

The standard t-test for all muscle latencies, MV, and APA duration showed no significant differences between GI and GIW (with $p > 0.05$) (see Table 6.1). The results of the paired t-test for all COP features during APA and EP are displayed in (Table 6.2). We found significant differences in the following: 1) for healthy subjects during APA, the mean distance, the absolute value of the mean velocity, total displacement and approximate entropy were significantly higher for GI compared to GIW (Figure 6.1, 6.2) for subjects with Parkinson's during APA, the absolute value of the mean velocity, total power, approximate entropy, and area were significantly higher for GI compared to GIW (Figure 6.2, 6.3) for subjects with Parkinson's during EP, the 75th percentile frequency and approximate entropy were significantly higher for GIW compared to GI (Figure 6.3) for subjects with Parkinson's during EP, Hurst's exponent was significantly higher for GI compared to GIW (Figure 3). These results

show a decrease in the pre-paratory phase of gait initiation. Lastly, there was no significant difference found in the maximum values of COP for either subject group.

Table 6.1: Maximum value paired t-test (or rank sum) results between GI and GIW

Feature	**Healthy**	**Parkinson's**
AP	0.5072	0.1989
ML	0.9181	0.7648
R	0.7086	0.7615

Table 6.2: APA and EP paired t-test (or rank sum test) results between GI and GIW. * indicates significant results

	Healthy		**Parkinson's**	
Feature	**APA p-Value**	**EP p-Value**	**APA p-Value**	**EP p-Value**
MD	0.0410*	0.2488	0.6372	0.1577
rms-AP	0.5508	0.2485	0.1404	0.1004
rms-ML	0.6363	0.2983	0.7758	0.1847
MV	0.0150*	0.6648	$< 0.0001*$	0.9552
MF	0.8208	0.6961	0.1574	0.0883
TP	0.5411	0.314	$< 0.0001*$	0.1302
f50	0.8357	0.1529	0.3503	0.6601
f75	0.5746	0.8882	0.8685	0.0205*
HE	0.6907	0.4193	$< 0.0001*$	$< 0.0001*$
TD	0.0075*	0.2508	0.6846	0.1212
apEn	0.0013*	0.1286	$< 0.0001*$	$< 0.0001*$
Area	0.2174	0.2359	$< 0.0001*$	0.1989

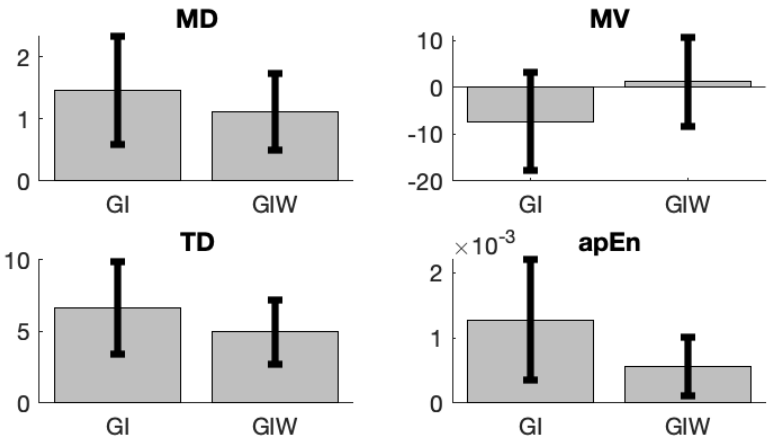

Figure 6.1: Bar plots showing mean ± standard deviation of significant features for healthy young adults during the APA phase

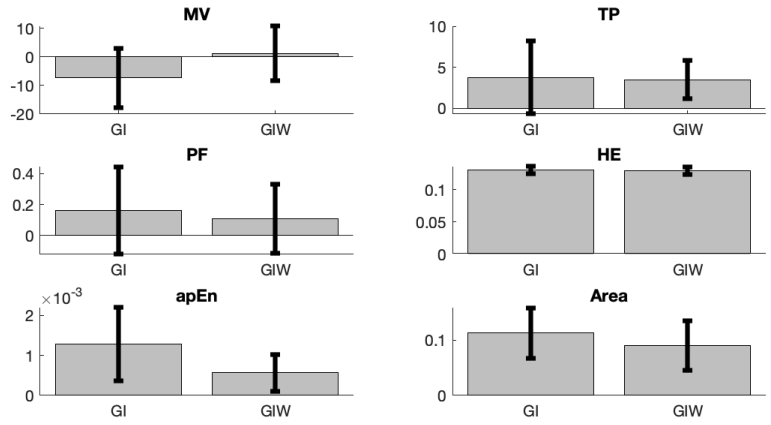

Figure 6.2: Bar plots showing mean ± standard deviation of significant features for older adults with Parkinson's during the APA phase

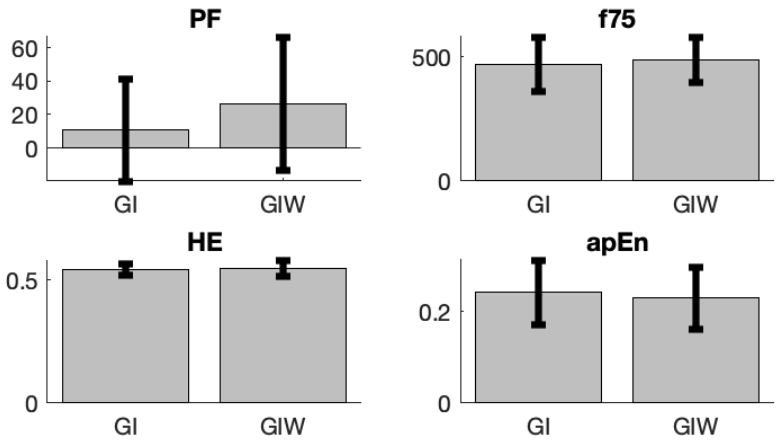

Figure 6.3: Bar plots showing mean ± standard deviation of significant features for older adults with Parkinson's during the EP phase

6.4 Discussion

During the EP phase there were no significant differences in the mean velocity with respect to GI and GIW for either subject group suggesting that the subjects generated similar speed in both conditions during that phase. However, during the APA phase both subject groups had a significant difference with respect to GI and GIW. Specifically, GI had a higher mean velocity than GIW. The results showed that our hypothesis was not supported. For healthy subjects, the additional load had a significant lower mean distance, total power, and approximate entropy during APA indicating a decrease in the transfer of weight before movement. According to studies, higher values of mean distance, total displacement and approximate entropy signify an increase in the COP trajectory, and consequently instability [10, 42]. Similarly, for subjects with Parkinson's, during the APA phase, additional load significantly de-creased the mean velocity, total power, approximate entropy, and area. Lastly, during the EP phase, for subjects with Parkinson's the additional load significantly in-creased the 75th percentile frequency, the approximate entropy, and the Hurst's exponent and significantly decreased the approximate entropy. The increase in the peak frequency and the 75th percentile frequency, shows an increase in the frequency of oscillation, and consequently instability [10, 42]. This reveals that the load positively affected stability during the APA

phase for both subject groups and negatively affected stability during the EP phase for subjects with Parkinson's [10, 73, 72]. This study highlights the resulting instability due to additional load during the EP of gait initiation. One previous study found that additional load did not have a significant effect on the velocity during heel-off but did influence the overall duration of APA [76]. The current study extended the previous result related to the velocity not only to APA, but also to EP. In addition, our study revealed some features that indicate a positive impact on the stability during the APA phase, while some features indicate a negative impact during EP. While some studies have suggested the use of additional load during therapy [72, 93], it is important to keep in mind the negative effects of additional load on stability during the execution phase of gait initiation.

6.4.1 Conclusion

In conclusion, during gait initiation with additional weight, both healthy young adults and older adults with Parkinson's show increased stability in some COP features during anticipatory postural adjustments. However, during the execution phase of gait initiation with additional weight, older adults with Parkinson's show decreased stability in some COP features. These findings reveal that when additional load is used during gait initiation, further precaution should be taken for older adults with Parkinson's during the execution phase.

Chapter 7

An Artificial Neural Network Model for the Generation of Muscle Activation Patterns During Gait Initiation

7.1 Introduction

Gait initiation is a voluntary internal perturbation from upright stance leading to a steady state gait cycle [49]. The process of gait initiation is innately unstable due to the transition of posture into a single-leg stance and the simultaneous production of momentum to take a step with the swing leg [48]. In fact, gait initiation is the gait phase in which most falls occur [94, 88]. Therefore, an understanding of the balance control system during gait initiation could lead to prevention of a significant portion of falls. The production of muscle activation patterns during gait initiation involves relaying information to and from the central nervous system from different sensory inputs. Understanding the relationship between these inputs and muscle activation could lead to a better understanding of the balance control system. However, it is a challenge to completely characterize the many inputs involved. A simpler model can use kinematic and center of pressure (COP) response values to predict muscle

activations [54]. The purpose of this study is to demonstrate the ability of an ANN model to map the kinematic and COP response during gait initiation to the muscle activations needed for successful gait initiation. Artificial Neural Networks (ANNs) have been used to map gait measurements onto kinematic and COP data [54, 55, 78]. This study uses a model similar to [5] and verifies viability of the ANN model across healthy subjects. Furthermore, this study seeks to validate the viability of the ANN model for mapping gait measurements in a subject with Parkinson's.

7.2 Materials and Methods

7.2.1 Experimental Protocol

Fifteen healthy subjects (7 females, 8 males; age 21.9 ± 3.2 years; weight 64.5 ± 13.2 kg) and one subject with Parkinson's (male, age 60, weight 79.2kg) consented to participate in this study. Subjects were all right-leg dominated (leg-dominance defined as the same side as the foot a soccer ball would be kicked with) and had no known neurological or musculoskeletal disorders. All participants were informed of the step-by-step process before being accepted as a volunteer. A total of 25 Vicon placement markers and 6 Vicon placement arrays were placed on the subject, and the kinematic data were collected with infrared cameras using VICON Nexus 1.51. Unilateral markers were placed on the C7, sternal end of the right clavicle, and the L5/S1. Bilateral markers were placed on the anterior portion of the acromion, the most superior aspect of the iliac crest, the posterior superior iliac spine, the superior anterior aspect of the greater trochanter, the most prominent aspect of the medial and lateral femoral epicondyle, the most prominent aspect of the medial and lateral malleoli, the metatarsal head of the greater toe and 5th digit, and the most distal aspect of the 2nd toe. Bilateral arrays were placed on the thighs, shins, and ankles. Electromyography (EMG) signals were captured using disposable self-adhesive electrodes, which were applied unilaterally (on the right side) to the following muscles: soleus (SOL), lateral erector spinae (ESL), gastrocnemius (GM), tibialis anterior (TA), biceps femoris (BF), external obliques (EO), vastus medialis (VM), gluteus medius (GMED), rectus femoris (RF), rectus abdominus

(RA). Center of pressure (COP) was calculated using the ground reaction forces (GRFs) from two consecutive forceplates. Using the command go, subjects were asked to stand on a forceplate and initiate walking as quickly as possible with their right leg. Subjects were instructed to complete one gait cycle and terminate walking with both feet together past both forceplates. There was a total of 10 trials of gait initiation for each subject. EMG, GRF, and kinematic data were captured simultaneously using the VICON system. The EMG and GRF data were captured at 2000Hz while the kinematic data were captured at 100Hz.

7.2.2 Data Analysis

After data were collected, the center of motion (COM), right ankle angle, left ankle angle, right hip angle, left hip angle, right knee angle, and left knee angle were calculated from the kinematic data using Visual 3D. Each kinematic component was calculated in the x, y, and z plane. GRF signals were low-pass filtered with a 4th order Butterworth filter with frequency 20Hz [45]. The COP was then calculated using teh following equations:

$$COP_{ML} = -(M_y + F_z \times z_0)/F_z$$

$$COP_{AP} = (M_x - F_y \times z_0)/F_z$$

EMG signals were filtered with a bandpass filter with cut-off frequencies 10-500Hz [14, 85]. The signals were then rectified and filtered using a lowpass filter with frequency 50Hz. The EMG signal was then normalized using the largest EMG output across all trials for each muscle and for each subject. COP and kinematic components were normalized by subtracting the lowest value across all trials and dividing the result by the maximum value across all data for each component and for each subject. Finally, the normalized COP and EMG data were down-sampled to 100Hz. Only three seconds of data were further processed. The first second and the last segment of each data vector were not processed.

7.2.3 Neural Network Model

This study used a neural network model after [54] with the following modifications: there were 21 input units, 14 hidden units and 10 output units. The output vector consists of the muscle activations of the SOL, ESL, GM, TA, BF, EO, VM, GMED, RF, RA. The input units consisted of the kinematic components and the COP in the ML and AP direction. Since, the input and output data were time varying a series of input and output vectors were used where each vector pair was the matching data of a single time step [5]. The neural network was then trained and tested using the neural network toolbox in MATLAB R2018a. The data was dividing using 80% for training, 10% for validation and 10% for testing.

7.2.4 Network Assessment

The network model was assessed on its ability to predict the muscle activations on separate gait initiation trials. The root mean square (RMS) difference between the actual and predicted muscle activation was chosen to measure degree of error in the magnitude and the correlation was chosen to capture how well the network modeled the phasic profile [54, 45, 85]. The average and standard deviation of the RMS and correlation value were calculated for each muscle for both healthy subjects and the subject with PD. A t-test was used to evaluate if there was difference between trials for each muscle for every subject.

7.3 Results

The muscle activation time histories predicted by the model showed low RMS error and low to high correlation values. For healthy adults, the RMS error values ranged from 0.02 to 0.11 and the correlation values ranged from 0.07 to 0.96. Standard deviation and mean values across healthy subjects for each muscle are depicted in (Table 7.1). For the subject with Parkinson's, the RMS error values ranged from 0.02 to 0.11 and the correlation values ranged from 0.14 to 0.91.

Table 7.1: RMS Error and Correlation

Muscle	**RMS error**		**Correlation**	
	Healthy	***PD***	***Healthy***	***PD***
SOL	0.05±0.01	0.07±0.01	0.83±0.06	0.78±0.07
ESL	0.06±0.01	0.05±0.01	0.79±0.09	0.81±0.05
GM	0.06±0.02	0.07±0.01	0.78±0.16	0.82±0.06
TA	0.06±0.01	0.04±0.01	0.79±0.09	0.79±0.07
BF	0.05±0.01	0.03±0.00	0.80±0.07	0.73±0.11
EO	0.07±0.02	0.06±0.01	0.75±0.08	0.81±0.05
VM	0.05±0.02	0.03±0.00	0.77±0.09	0.78±0.09
GMED	0.05±0.01	0.05±0.01	0.80±0.09	0.81±0.08
RF	0.05±0.01	0.06±0.01	0.79±0.08	0.58±0.06
RA	0.06±0.02	0.07±0.01	0.75±0.09	0.53±0.19

A t-test revealed that there was a significant difference RMS error and correlation values between trials for all muscle and across all subjects. For healthy adults, the correlation was high for most trials with 49.4% of the trials with a correlation above 0.80, 70.9% with a correlation above 0.75, and 84.2% with a correlation above 0.7. The weakest results were obtained from the RA. These low correlation values correspond with low activation of the RA during gait initiation. Also, the RMS value was low for most trials with 98.6% of the trials having an RMS value less than 0.10 [54]. For the subject with Parkinson's, 39% of the trials with a correlation above 0.80, 59% with a correlation above 0.75, and 75% with a correlation above 0.7. The weakest results were obtained from the RA. These low correlation values correspond with low activation of the RA during gait initiation. Also, the RMS value was low for most trials with 100% of the trials having an RMS value less than 0.10 [54]. (Table 7.2) displays the percentage of trials with a correlation above 0.8 for each muscle.

Table 7.2: Muscle Correlation Percentage

Muscle	**Percent Greater than 0.8**		**Percent Greater than 0.75**	
	Healthy	***PD***	***Healthy***	***PD***
SOL	73.30%	40%	91.10%	70%
ESL	51.10%	60%	70.00%	90%
GM	53.30%	70%	77.80%	90%
TA	48.90%	30%	74.40%	70%
BF	46.70%	10%	82.20%	50%
EO	33.30%	80%	52.20%	80%
VM	45.60%	50%	65.60%	60%
GMED	58.90%	50%	75.60%	70%
RF	52.20%	0%	72.20%	0%
RA	31.10%	0%	47.80%	10%

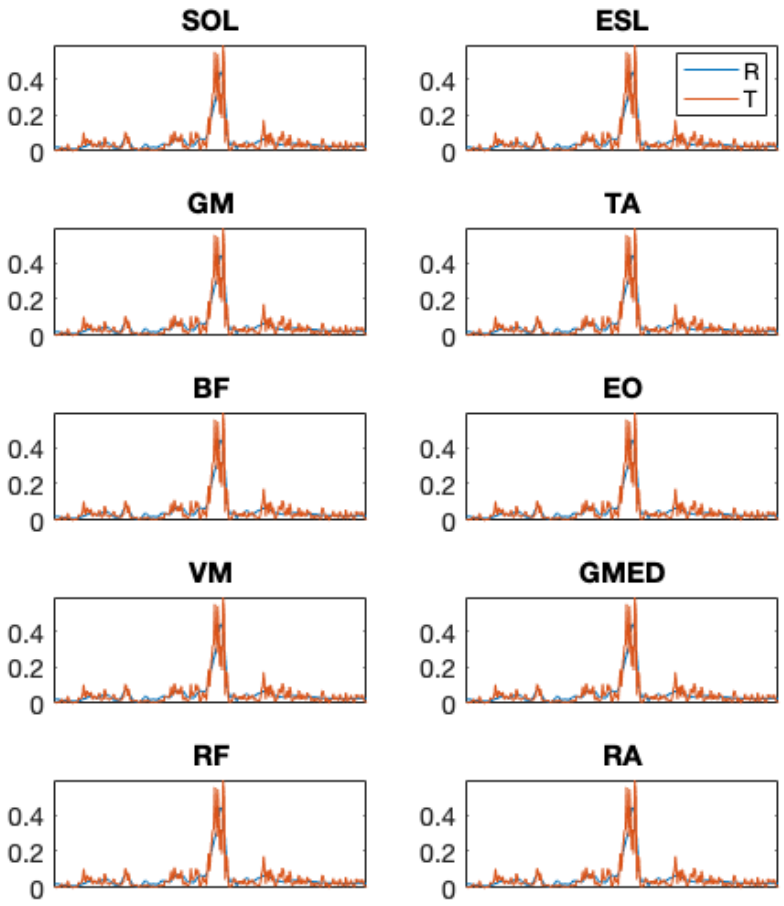

Figure 7.1: Sample Muscle Activation patterns predicted by the model. T represents the target muscle activation pattern and R represents the model's output.

7.4 Discussion

The results of the models have demonstrated the feasibility of ANNs to model the kinematic movement plan and COP response during gait initiation to the muscle activation patterns. A model similar to [54] was used to verify viability of that ANN model across healthy subjects and to validate the viability of that model for a subject with Parkinson's. Overall, the high correlation values and low RMS values are strong indicators for the model's ability to map the gait movement patterns onto the muscle activation patterns. However, there exists

variability between each trial and differences do exist between the predicted behavior and muscle activation patterns. Specifically, errors in the level of activation during gait initiation can have a significant effect on successful gait initiation. In fact, the difference between the correlation and RMS values in each trial suggests a more robust model is needed to successfully map kinematic and COP response data to muscle activation patterns during gait initiation.

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