

APPLICATION OF LINEAR STOCHASTIC MODELS IN THE  
INVESTIGATION OF THE EFFECTS OF PARKINSON'S DISEASE ON THE  
COP TIME SERIES

BY

Chandrashekara Kaushik Gandur Balagangadhara

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\_\_\_\_\_  
Dr. Carl W. Luchies, Chairperson

\_\_\_\_\_  
Dr. Sara Wilson

\_\_\_\_\_  
Dr. Huazhen Fang

Date Defended: \_\_\_\_\_

The Thesis Committee for Chandrashekara Kaushik Gandur Balagangadhara certifies  
that this is the approved Version of the following thesis:

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Dr. Carl W. Luchies, Chairperson

Date Approved:

## *Abstract*

The primary objective of this study was to use linear stochastic modeling approach to investigate parameters which may be sensitive enough to detect and quantify the changes in postural instability (PI) related to the progression in Parkinson's disease (PD). Data collected in a previous study were analyzed in the current study. Participants with mild PD (n=13), moderate PD (n=10) and age range match healthy controls (HC, n=21) were instructed to stand in a comfortable self-selected natural stance on a force platform in both eyes open (EO) and eyes closed (EC) conditions. The foot-floor reaction forces were used to calculate the center of pressure (COP) time series. This COP time series was fitted by two different linear stochastic models: 1) an autoregressive (AR), and 2) an autoregressive moving average (ARMA) model. The postural control system was modeled as an inverted pendulum to describe pure body mechanics and a proportional, derivative and integral (PID) strategy was assumed for balance regulation. Swiftiness, damping and stiffness parameters were extracted from the AR model. Natural frequency and damping ratio were extracted from the ARMA model.

The statistical analysis (ANOVA) of these parameters revealed significant differences in stiffness and swiftiness parameters between the HC and moderate PD population in the EO condition. These three parameters showed trends with progression of PD. The swiftiness parameter showed decreasing mean values as PD severity increased, indicating that PD caused slower reactions to small deviations from equilibrium when compared to healthy controls. The mild and moderate PD, compared to HC, demonstrated by higher mean values of stiffness, suggesting a more rigid control strategy. The analysis of damping parameter revealed that the PD, compared to HC, may have a reduced ability to attenuate sway velocity during quiet stance as indicated by lower mean values of damping parameter and damping ratio. The natural frequency did not show significant trends in EO condition, but revealed an increasing trend with progression of PD. This could indicate that the PD could have larger number of deviations of COP from equilibrium. The analysis of effect of condition (EO, EC) revealed significant differences in all the five parameters. The stiffness, damping parameter and damping ratio had higher mean values for EO, compared to the EC condition, indicating the vital role that the visual feedback plays in detecting small perturbations from equilibrium leading to a better posture regulation in EO condition. The swiftiness parameter and natural frequency indicated higher mean values in EC, compared to the

EO condition, suggesting that the various sensory cues might be weighted differently in EO and EC conditions.

Future studies should investigate the sensitivity of these calculated parameters to changes in PI in PD using a larger sample size and longer duration of trials. Also the variations in these parameters in response to dynamic tasks such as gait initiation and balance recovery should be considered in future studies.

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## CHAPTER ONE: INTRODUCTION

### *Background and motivation.*

Postural Instability (PI) is one of the most debilitating challenges in Parkinson's disease (PD) due to the associated increase in falls, fractures, nursing home placements and loss of confidence in PD patients. This disease in North America alone is estimated to affect around 1.5 million people [1, 2]. There is no current treatment to slow or halt the neurodegenerative progression of this disease. The total deaths resulting from PD in 2013 alone was estimated to be around 103,000 [3]. Falls related to PD are severe and lead to hip fractures and other injuries. These sustained injuries after a fall can have significant impact on the person's mobility, lifestyle and confidence. Therefore it is important to understand the changes in postural control with the progression of PD.

Analyzing the whole body center of pressure (COP) is one of the most commonly employed methods for studying postural dynamics. Several studies in the past have explored postural sway and its control related to the central nervous system through using different task conditions such as balance recovery and gait initiation [4, 5, 6], movable platforms to evoke perturbation [7, 8], multisensory fusion methods [9, 10, 11, 12] and quiet stance approaches [13, 14, 15, 16, 17]. While these past studies have helped describe human postural control, the timing of the onset of PI and its subsequent changes with PD progression related to the COP time series remains unclear. A thorough understanding of the changes in the COP time series with increasing PD severity could result in sensitive measures which could not only help in early clinical diagnosis of PI, but can also indicate its subsequent progression in PD.

The oscillating behavior inherent in the COP measure even during quiet standing presents a unique challenge in analyzing the postural dynamics. Therefore the study of the COP time series by traditional averaged COP measures alone may be insufficient. Using linear stochastic models and its parameters could present a more in depth understanding of the changes in the COP time series in terms of physical parameters. These physical measures can also help improve understanding of the differences in the control strategies adopted between healthy controls, mild

PD and moderate PD subjects. Lastly these measures in the long run could help in early PI detection and its subsequent progression with PD.

***Specific aims.***

The analysis of COP time series data by using linear stochastic models have been proven to yield physical parameters which could potentially be used for assessing the ability to maintain posture [18]. Motivated by this fact, the current study aimed at calculating various physical parameters by fitting two different linear stochastic models to the COP time series data collected during postural sway (quasi-static quiet stance). These calculated parameters were then used for analyzing the changes in the COP time series associated with increasing PD severity. It was hypothesized that some parameters would be able to represent differences in control strategy adopted by the three groups (healthy controls, mild PD and moderate PD) in two different conditions (eyes open (EO) and eyes closed (EC)).

***Thesis content.*** This work is organized into four chapters. Chapter 1 consists of an introduction to the area of study. Chapter 2 consists of extensive background and literature review concerning the relevant works published. Chapter 3 consists of the current study in the form of a manuscript reporting the background, methods and results of the analysis using the linear stochastic models applied to COP time series. Chapter 4 consists of a brief summary of this study, conclusion and future work.

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## **CHAPTER TWO: BACKGROUND**

### ***Significance of Parkinson's disease***

Parkinson's disease (PD) is a neurodegenerative progressive disorder that affects the motor control system, causing postural instability (PI), slowed movement, rigidity, tremors and subsequently an increase in fall risk in the affected population. The motor related symptoms of PD result from death of cells which are responsible for the production of dopamine in the central portion of the brain called substantia nigra. Postural instability (PI) is one of the most debilitating challenges in PD because it causes an increase in falls, which results in fractures, nursing home placements and loss of confidence in PD patients. In North America alone it is estimated to affect around 1.5 million people [1, 2]. The severity of PD symptoms worsen with disease duration. There is no treatment to slow or halt the neurodegenerative progression of this disease. In 2013 alone PD was the cause for approximately 103,000 deaths [3]. Hence there is a need to understand PI and determine parameters which are sensitive to detect the onset and the progression of PI in PD. Early detection of PI can help clinicians to better assist and provide the necessary therapy for prevention of falls and fall related consequences.

### ***Postural Instability***

Postural control is maintained by the central nervous system with the help of proprioceptive, vestibular, loco motor system and integrated visual feedback [5]. The death of the neurons caused as PD progresses leads to impairment of postural control and equilibrium. It is estimated that approximately 60-70% of the neurons in the substantia nigra are lost at the onset of clinically significant PD symptoms [6]. The study of postural control can be done using three parameters namely the base of support (BOS), center of pressure (COP) and center of mass (COM). The base of support (BOS) is basically characterized by the area of the surface supporting the body. In the

case of quiet standing, the BOS is the area circumscribed by the feet. The COP is a dynamic measure which indicates the point of application of the ground reaction force vector of the body obtained from a force platform. The COM of the body is the point location at which the entire mass of the system is concentrated. The most commonly used measure for balance and gait studies is the COP. The location of the COP at any point in time for the human body during quiet standing should be within the area defined by the BOS. In healthy populations the central nervous system makes use of the various sensory systems and ensures that the COP does not move outside of the base of support [7]. The estimation of the COP position in the anterior-posterior direction is done by using the following equation:

$$COP = \sqrt{\left(-\frac{M_y + F_x * d_z}{F_z}\right)^2 + \left(\frac{M_x - F_y * d_z}{F_z}\right)^2}.$$

Within this equation,  $F_x$  and  $F_y$  are the forces acting in the anterior-posterior (AP) and medial-lateral (ML) directions parallel to the top surface of the force plates,  $F_z$  is the force acting in the perpendicular direction to the top surface of force plates,  $M_x$  and  $M_y$  are the moments acting in the AP and ML directions parallel to the top of the force plates,  $d_z$  is the distance below the force plate top surface where the reference origin is located. The location of the net force vector applied by the body on the force platform depends on the foot placement and the control of the muscles producing moments about the joints of the body controlling posture (e.g. ankle, knee, hip, etc.).

The information about the movement of head in space is provided by the vestibular system which has organs located in the inner ear. The information about the pain, touch, pressure, temperature and proprioception are provided by the skin and deep pressure sensors in the human body [4, 8]. For healthy gait and postural control, all the above mentioned signals must be appropriately

utilized to compensate for deviations from the equilibrium by the central nervous system. PD impairs this process and thus eventually results in PI symptoms.

Since the COP is a non-stationary measure, the oscillating behavior of the body sway is irregular and stochastic by nature [5]. Hence the study of postural sway by traditional statistical analysis methods alone may be insufficient. Therefore it is useful to analyze the output COP data using model based analysis methods that consider the brain as the controller. It is also beneficial if a description of PI can be characterized in terms of physical parameters such as stiffness or damping in order to help in PI detection and subsequent progression in PD.

#### *Previous methods used to analyze postural dynamics*

***Disturbance Mechanisms.*** In order to accurately detect postural dynamics, a reliable and reproducible method is necessary. Several methods have been implemented in various studies and are described in the following paragraphs.

To study the COP response to visually induced postural sway, several movable platform methods have been used to assess the effects of vestibular impairments or aging [9, 10]. In these studies a moving posture platform with an embedded force plate and a controlled visual field were utilized to assess the effects of surface translation and vision on the whole body COP. The visual field was controlled using a frontal wall and two lateral walls encompassing the entire visual periphery of the subject. Participants stood on a force platform driven sinusoidally by a servo motor at a certain frequency and a peak to peak amplitude displacement. The COP response was recorded with the platform stationary and then later made to move at a predetermined frequency for the rest of trial duration. The output COP data [see [11] for detailed description of COP estimation] were analyzed with various spectral analysis methods such as discrete Fourier transform and several statistical measures such as average frequency, average frequency at each time and the standard deviation in

frequency at each time. Statistical analysis revealed that there was time dependent and frequency dependent differences between the healthy and patients with vestibular impairment during visual perturbation. However there were no significant differences in the average frequency of sway and the spread about the frequency during quiet standing. Also there were differences in relative energy levels of sway prior to the stimulus [9]. In the study assessing young versus elderly subjects [10], there were no relative significant differences in the COP response except that the elderly showed a greater overall sway during quiet standing.

***Induced stimulus or vibration methods.*** These methods use external devices capable of producing stimulus at the required frequency and amplitude in order to instigate postural sway [5, 36]. In an induced vibration postural sway study by Johansson et al., participants stood on a force platform and a stimulus was applied through a device attached to the calf muscles. The application of the stimulus frequency was done pseudo randomly. The sagittal perturbation and the corresponding posture control was modeled based on the “ankle strategy”. The system was then described using an inverted pendulum to explain pure body mechanics with a proportional integral derivative (PID) control model to investigate balance regulation. The proportional ( $k$ ), derivative ( $\eta$ ) and integral ( $p$ ) coefficients were determined from an auto regressive moving average (ARMA) model transfer function denominator. The normalized form of the transfer function derived from the inverted pendulum dynamics results in three output parameters namely swiftness, stiffness and damping. These parameters are used to quantitatively describe the postural sway in terms of one swiftness parameter and two stability parameters (stiffness and damping). They showed that these parameters could be potentially used to describe the human postural control.



**Multisensory fusion methods.** In order to better understand the stochastic structure of postural sway, several multisensory fusion methods have been employed [12, 13, 14, 15]. In a study by Kiemel et al., [12] the effect of four sensory conditions namely light touch, vision, light touch and vision, and neither touch nor vision on postural sway was explored. A visual display capable of displaying the computer generated whole field patterns consisting of random dots was placed in front of the subject during quiet stance. A horizontal touch plate was placed at the hip level of the subject on which the subject would place the tip of the finger. A sensor which is used to track the position of the body center of mass was attached to the hip of the subject. The sensor data in the ML direction were measured using an ultrasound position tracking system. An auto regressive moving average ( $n, n$ ) (ARMA ( $n, n$ )) model was used to fit the ML data using the maximum likelihood method based on a predefined probability density function. The Eigen values and the coefficients were calculated by defining an auto covariance function. The significant findings of this study showed that the properties of postural sway would largely change if all sensory information related to velocity were eliminated.

Jeka et al. [14] sought to understand the effects of changing contact forces at the finger tip of the subject on postural sway. Subjects stood on a force platform and a touch plate is placed at the hip level of the subject. The torque generated by a servo motor was used to oscillate the touch plate parallel to the front plane of the subject at various predetermined frequencies and a linear second order model was fitted to the output data. This study showed that postural control parameters are not fixed but vary depending on the moving frame of reference and that the spatial position and velocity information are provided by the somatosensory system.

*Stationary quiet stance approach.* Several different approaches have been used to study the control strategy adopted by the human body during quiet standing in both eyes open and closed conditions [16, 17, 18, 37, 38, 39]. Didier et al. [16] used fractal analysis methods such as detrended fluctuation analysis (DFA), stabilogram diffusion analysis (SDA) and spectral analysis methods to understand the persistent and anti-persistent correlations in the postural sway data. An auto regressive first order model (AR (1)) model was fitted to the COP velocity data. The study results suggest that the COP velocity is usually bounded between upper and lower limits and that the control action is activated based on the velocity data crossing a certain threshold value. Further, they demonstrated that DFA analysis on the velocity data revealed a crossover that was previously not visible with DFA applied to position data. However, the results also show that the conclusions drawn from such analysis methods are strongly dependent on the specific algorithms and procedure used for the analysis.

Sabatini et al., [17] used a fractional autoregressive integrated moving average (FARIMA) model to fit COP data from quiet standing (postural sway). They showed that postural sway could be modeled as a self-similar, random walk process with anti-persistent correlation obtained by summing the non-Gaussian random variables. The correlation between these variables is shaped by the linear time invariant (LTI) low pass filter at small time lags. Several quantitative parameters were introduced, namely strength of stochastic driving, root mean square value of time differenced COP motion, damping ratio, DC gain, natural frequency of the filter and an anti-persistent magnitude or factor called the Hurst exponent [see 19 or 20 for description of Hurst exponent]. They also argue that the healthy subject groups can be divided into two separate groups depending

on the sensory cues adopted by the particular subject (i.e. some healthy subjects rely more on visual feedback and some others rely on non-visual feedback such as touch or feel ).

### ***Previous methods used for COP data analysis***

***Sway parameters and statistical analysis methods.*** In addition to looking at the influence of different postural sway tasks and the effects of age or vestibular function, several studies have assessed biomechanical tasks in order to understand how motor control and balance are affected by neurophysiological diseases. Specifically, to study the effect of Parkinson's disease (PD) on balance recovery and postural sway, several traditional statistical analysis methods has been employed. These studies involve extracting several biomechanical parameters in both quasi-static (quiet standing) and dynamic tasks (such as gait initiation or balance recovery) and then used to detect the onset of PI prior to clinical presentation and also to check if these measures persist with PD progression [7, 18, 20, 21]. In studies by McVey et al. and King et al. [7, 21], they investigated the differences in balance recovery strategy between healthy young versus healthy elderly [21] and healthy controls versus mild parkinsonian subjects [7]. Both studies utilized a backward pull and release strategy to study the COP response in balance recovery. Several measures related to kinematic, temporal and kinetic parameters were extracted from the response. Specifically, step length, step height, ankle angle, reaction time, weight shift time, step duration etc. were extracted to determine if group differences (i.e. young versus old or healthy versus PD) were present in the balance recovery response.

Stylianou et al. [20] assessed whole body COP quiet standing (postural sway) to extract the Hurst exponent [see 19 or 22 for details on Hurst exponent] in addition to postural sway parameters that characterized the overall COP trace. Several differences in the output measures related to the COP were found between the healthy controls and PD groups in both ML and AP directions.

Barnds et al [18] analyzed COP data using principal component analysis (PCA) in order to determine if a combination of traditional postural sway COP measures could differentiate preclinical PI and its changes with PD progression. Correlation matrix PCA models with COP and clinical parameter inputs were utilized for selection of sensitive parameters in analyzing the PI between healthy, mild and moderate PD subjects. The resultant PCA models were able to significantly differentiate both preclinical onset of PI as well as changes with increasing clinical disease progression.

However, a significant drawback of averaging the COP measures as argued by Newel et al. [26] is that averaged measures can conceal the underlying control principles for the observed postural dynamics. Hence emphasis is laid on the time series approaches.

***Fractal analysis techniques.*** One of the challenges in dealing with COP data is its property as a non-stationary signal (i.e. frequency content changes with time). In order to deal with this, several fractal analysis techniques such as de-trended fluctuation analysis (DFA) and stabilogram diffusion analysis (SDA) have been applied to analyze COP postural sway data [16]. Both SDA and DFA are used for characterizing the serial correlation properties in the time series data. They depend mainly on the diffusion properties of a time series and are based on a scaling law [see 16 for details]. The SDA mainly calculates the mean variance of COP sway displacement relative to the time interval. A bi-logarithmic diffusion plot is generated and the slope of which is used to assess the correlations. DFA is also similar to SDA except that the time series is first integrated and the mean standard deviation of this integrated series is determined as a function of time interval. Then a parameter such as the average absolute maximal velocity (AAMV) is calculated

to show the empirical threshold for the postural sway. Delignières et al [16] suggested that postural control is mainly based on COP velocity and that the control system (brain) regulates the posture once the COP velocity attains a value beyond a certain threshold value. However other studies [24, 25] have asserted that when the above methods are applied to COP data (i.e. DFA and SDA), the postural sway control is based on position rather than velocity. They showed that sway displacements are unchecked until the displacements exceed a certain predetermined threshold value. Therefore the conclusions drawn from the above techniques are largely dependent on the particular properties of algorithms and the procedures used.

***Wavelet analysis techniques.*** Wavelet analysis is used to study the postural sway by decomposing the COP signal into multiple time scales. Two different variations of the wavelet analysis are commonly used, namely continuous wavelet transform (CWT) and discrete wavelet transform (DWT) [see [33] for details]. The CWT expresses the signal in terms of wavelet coefficients for a certain time scale and time shift. However this requires large computational resources. Therefore DWT is often employed. The DWT involves repeated filtering of the signal using two different filters. The DWT decomposes a signal into two constituent signals, namely, an approximation signal and a detail signal. The approximation signal is obtained by passing the signal through a low pass filter and the detail component of the signal is obtained by passing the signal through a high pass filter. These filters are derived from the wavelet function and a scaling function [see [34] appendix for details on wavelet transforms]. The obtained approximation signals are further decomposed into approximate and detail components. This process is done iteratively until a set of approximation signals are obtained at different scales along with a final gross approximation of the signal. Chagdes et al. [32] used DWT to assess the COP during quiet postural sway. After

applying the DWT, the energy content at different time scales was calculated and several parameters such as average energy percentage, average energy percentage change in both eyes open and eyes closed conditions were calculated. The study results suggested that the vision controls postural sway at lower frequencies.

***System identification approaches.*** Parametric system identification methods have been employed by several studies to understand PI [5, 12, 13, 27, 37, 40]. The basic principle behind these methods is that a COP time series data is fitted to parametric models such as autoregressive (AR), autoregressive moving average (ARMA), or autoregressive integrated moving average (ARIMA) models (see [28] for detail descriptions of such models) of a certain order. This order is either determined by using auto correlation (ACF) and partial auto correlation plots (PACF) or by using several information criterions available such as Akaike's information criterion (AIC) [30], Bayesian information criterion (BIC) [29] or by using maximum likelihood methods after defining a probability density function. These model parameters are then used to identify differences in the postural sway time series data.

Johansson et al., [5] applied both non parametric and parametric identification methods. For the non-parametric approach, methods such as auto spectrum analysis, cross spectrum analysis and coherence analysis were used. In the parametric system identification approach, an ARMA system of third order was fitted to the data and three parameters namely swiftness, stiffness and damping were determined from the ARMA model transfer function denominator by assuming inverted pendulum dynamics. A PID control strategy was assumed for postural control. They showed that these three parameters identified from the ARMA model transfer function could be potentially used for the assessment of postural sway.

Specifically, Kiemel et al. [12] used an ARMA ( $n, n$ ) model to fit postural sway data by application of a maximum likelihood estimation technique. This technique involves defining a likelihood function based on the product of conditional probability densities. The best order for the model is determined by subjecting the models to a pairwise maximum likelihood ratio test at a significance level of 0.05. Once the order is identified, an auto covariance function is defined. The eigenvalues and coefficients of the auto covariance functions were used to define certain parameters such as slow decay fraction, eigen frequency, slow decay parameter etc.

Jeka et al. [13] also used a parametric identification method by fitting an ARMA ( $n, n-1$ ) model to the COP data to obtain measures of postural sway in different experimental conditions (fixed, foam, sway). The method of maximum likelihood was employed for fitting the parameters to the model. Again an auto covariance function was defined and the eigenvalues and coefficients were used to define certain parameters such as eigen frequency, damping, slow decay rate etc.

Kowalczyk et al. [27] also employed an ARMA modelling approach to study of postural sway. In this study, the postural sway data was generated from a linear time invariant system (LTI) and non-linear models of human balance. The outputs of these processes were then analyzed using the ARMA models. Also, the power spectrum obtained from experimental data (quiet postural sway) was fitted by using ARMA models of low order. This order was determined by application of Akaike's information criterion (AIC), where a lower AIC value reflects a better fit model [30]. [31]. The study results suggest that both intermittent (switched) systems and linear continuous systems can be modeled using the ARMA model approach.

#### ***A brief description of AR and ARMA models***

Generally in order to study the behavior of a system from the measured output data, it is beneficial to identify a parametric model for the system. Using the identified model, several parameters can be calculated which can be used to understand a particular process. There are several models used

to describe a random or stochastic process. For example, auto regressive (AR), moving average (MA), auto regressive moving average (ARMA), auto regressive integrated moving average (ARIMA), and Box Jenkins models are commonly used. The details of these models can be found in references [28], [31] and [36]. Two of the above mentioned models (AR and ARMA) that are used in the current study will be explained briefly in the following section.

*Auto regressive (AR) model.* An auto regressive (AR) process is a parametric description of a random process which assumes that the output of a stochastic system depends linearly on its own previous states or values. The general difference equation of an AR ( $n$ ) process where ' $n$ ' represents the order of the process is as follows:

$$y(t) + a_1y(t - 1) + a_2y(t - 2) + \dots + a_ny(t - n) = e(t) \quad (2.1)$$

Where,

$y(t)$  is the output of the process at a time 't'.

$a_1, a_2, a_3, \dots, a_n$  are the auto regressive (AR) coefficient terms.

$e(t)$  is the white noise term.

Rewriting the above equation using the back shift operator we get:

$$y(t) + a_1q^{-1}y(t) + a_2q^{-2}y(t) + \dots + a_nq^{-n}y(t) = e(t). \quad (2.2)$$

Using the following substitution in equation (2.2):

$$A(q) = 1 + a_1q^{-1} + a_2q^{-2} + \dots + a_nq^{-n}$$

The equation becomes:



$$A(q)y(t) = e(t) \quad (2.3)$$

Equation (2.3) gives the general representation of the AR ( $n$ ) model. Here  $A(n)$  terms are called auto regressive (AR) terms. Thus from equation (2.3) it can be seen that an AR ( $n$ ) model can be viewed as an all pole system with white noise as its input. In the study that is the subject of this thesis, there was no externally applied stimulation or signal during the data collection process (quiet postural sway). Hence we do not have a particular mathematical description of the input. Thus an AR ( $n$ ) model with white noise as the input was used for the first method of the study.

*Auto regressive moving average (ARMA) model.* A parametric model which depends on not only the previous states of the system but also on the previous shocks or errors is termed as an ARMA ( $n, m$ ) process. Where ' $n$ ' and ' $m$ ' are the orders of auto regressive (AR) and moving average (MA) terms respectively. The difference equation of an ARMA ( $n, m$ ) model is given below:

$$y(t) + a_1y(t - 1) + a_2y(t - 2) + \dots + a_ny(t - n) = c_1e(t - 1) + c_2e(t - 2) + \dots + c_me(t - m) + e(t). \quad (2.4)$$

In which:

$y(t)$  is the output of the system at time 't',

$a_1, a_2, a_3, \dots, a_n$  are the auto regressive (AR) coefficient terms,

$c_1, c_2, c_3, \dots, c_n$  are the moving average (MA) coefficient terms, and

$e(t)$  is the white noise term.

Rewriting the above equation by employing the back shift operator we get:

$$y(t) + a_1q^{-1}y(t) + a_2q^{-2}y(t) + \dots + a_nq^{-n}y(t) = e(t) + c_1q^{-1}e(t) + c_2q^{-2}e(t) + \dots + c_mq^{-m}e(t). \quad (2.5)$$

Using the following substitutions in equation (2.5):

$$A(q) = 1 + a_1q^{-1} + a_2q^{-2} + \dots + a_nq^{-n}$$

$$C(q) = 1 + c_1q^{-1} + c_2q^{-2} + \dots + c_mq^{-m}$$

We get:

$$A(q)y(t) = C(q)e(t) \quad (2.6)$$

It can be seen from equation (2.6) that the ARMA ( $n, m$ ) process provides adequate freedom for describing the process in terms of the previous outputs or states and the disturbance term. For this study an ARMA (2, 1) model was used to study characteristics of postural sway in terms of modal properties of the ARMA system such as damping ratio and natural frequency. The method used for estimation of ARMA parameters is the prediction error (PE) method [see [28] chapter 7 for detailed description of PE methods]. The main principle behind the PE methods is estimating the error obtained by comparing the observed data and the model output. This error obtained is then minimized by defining a quadratic norm. This iterative procedure is done till the error is less than a set tolerance value or if sufficient improvement is not observed from one step to the next.

***Significance of the current study.*** Currently, there is an unmet need in PD research to better characterize the onset and progression of PI with PD progression. A robust method that can accurately detect the onset of PI and can quantify the progression of PI in terms of physical parameters could be used to help delay the onset of falls and reduce fall risk through the use of an intervention. An accurate screening method could not only help clinicians better assist in reduction

of falls in PD patients but also could help the clinicians to determine whether a treatment prescribed has had a positive or negative impact on the patients motor functions. While past studies have helped describe human postural control, the timing of the onset of PI and its subsequent progression related to the COP time series remains unclear. Hence a method which can quantify and indicate the changes in COP time series in terms of physical parameters is necessary. Therefore the current pilot study is aimed at evaluating a method in which the long term goal is to potentially quantify and aid in understanding the changes in COP time series between healthy controls and a range of PD severities. The results from this study could also help to improve our understanding in whether linear system identification methods can be used to extract parameters that are sensitive to the clinical progression of PD.

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## CHAPTER THREE: STUDY

**Background.** Postural instability (PI) increases with Parkinson's disease (PD) progression. Quantifying PI with PD progression remains an unmet need. We applied system identification methods to the center of pressure (COP) time series data and utilized model parameters to quantify the changes in PI. We hypothesized that the stiffness and natural frequency parameters would increase, while damping and swiftness parameters would decrease with PD progression.

**Methods.** Postural sway was previously measured using force plates in healthy controls (HC, n=21), participants with mild PD (n=13) and moderate PD (n=10) in both eyes open (EO) and closed (EC) conditions. The COP data were used in the current study to fit an auto regressive (AR) model and an auto regressive moving average (ARMA) model. We extracted damping, swiftness and stiffness (AR); and damping ratio and natural frequency (ARMA). ANOVA was used to investigate the effects of group (HC, Mild-PD, Moderate-PD) and condition (EO, EC).

**Results.** AR model: Damping and swiftness decreased and stiffness increased with PD progression. No condition effects were found in the damping and swiftness parameters. Within the EO condition, the stiffness parameter was significantly different between HC and moderate PD, but not between mild and moderate PD. Within the EC condition, no group effects were found.

ARMA model: Damping ratio and natural frequency showed no significant group effects, although the condition effect was significant. EO, compared to EC, had a larger damping ratio and a smaller natural frequency.

**Conclusions.** Increase in stiffness and swiftness parameter values from HC to mild PD, and from mild to moderate PD suggests that the PD may results in a higher ankle joint rigidity and offer slower response to small deviations from equilibrium. The decrease in damping with PD progression suggests that there is a decrease in the ability of the controller to attenuate sway velocity. The natural frequency and damping ratio parameters obtained through ARMA model indicate a larger and faster deviations of COP measure from equilibrium and a decreased ability to provide adequate damping to perturbations in mild and moderate PD, compared to HC. The significant differences in the parameters based on condition (EO vs EC) indicates that the visual feedback plays a crucial role in balance regulation by detecting the fine deviations from



equilibrium which could aid in attenuation of body sway in EO condition. Future studies with longer duration of trials and larger group sample size could help in better understanding of the effect of PD progression in terms of the calculated parameters.

### ***1. Introduction***

Parkinson's disease is a neurodegenerative disorder which affects the motor control functions of the human body. The prominent effects of this disease are postural instability (PI), tremors, slowed movement, and increased rigidity, resulting in an increase fall risk. In North America alone approximately 1.5 million people are diagnosed with PD [1, 2]. Human posture is maintained by the central nervous system with the help of feedback systems such as proprioceptive, loco motor, vestibular system and visual. The death of the dopamine producing neurons caused by PD leads to impairment of postural control and equilibrium. It is estimated that approximately 60-70% of the neurons in the substantia nigra are lost at the onset of clinically significant PD symptoms [3]. The early detection of PI and its subsequent development with PD progression is one of the most significant unmet challenges and an ongoing need in PD. A sensitive quantitative assessment in detection and progression of PI with disease progression will help reduce fall risk by enabling clinicians to implement fall reducing therapies before the first fall occurs.

The study of PI is commonly assessed through analyzing the whole body center of pressure (COP) time series. One important challenge in the study of PI is understanding the oscillating behavior of the system during quiet stance. This COP oscillating behavior is irregular and stochastic by nature. Hence to better understand postural dynamics and the correlations between biological and control variables responsible for PI, it is beneficial to apply model based identification methods to the COP time series.

Numerous experimental methods have been applied for studying postural control. Several disturbance mechanisms such as moving platforms and visual surround methods [4, 5] have been employed to evoke perturbations in body sway to study the time varying characteristics of postural sway. Multisensory fusion techniques [6, 7, 8, 9] have been applied to study the effect of different sensory conditions such as touch, vision, etc. on postural control. Johansson et al. [10] used a vibration or induced stimulus on calf muscles during quiet standing to identify feedback parameters useful in maintaining postural control. They showed that postural sway can be modeled as a linear third order stochastic system. Several studies [16, 17, 18] also utilized a quiet stationary

stance to analyze the COP displacement and velocity to understand the postural dynamics during postural sway.

Different analysis methods have been employed for analyzing COP displacement and velocity. Traditional statistical analysis and sway parameter approaches (i.e. discrete COP measures: sway path length, sway path range) [13, 14, 15, 16] have been employed to understand the COP behavior in both quiet standing (postural sway) and dynamic tasks such as gait initiation. Techniques such as Principal Component Analysis (PCA) and Hurst exponent analysis, along with calculation of postural sway parameters, are used to determine biomechanical markers aimed at helping with detection and progression of PI in PD. One drawback of averaging the COP measures, as argued by Newell et al. [17], is that averaging could conceal the underlying control principles of the observed postural dynamics. Therefore, several fractal analysis techniques have been applied such as detrended fluctuation analysis (DFA) and stabilogram diffusion analysis (SDA) [18, 19, 20]. Both SDA and DFA characterize the serial correlation properties in the time series data. They depend mainly on the diffusion properties of a time series and are based on a specific scaling law. Didier et al. [11] indicates that the conclusions drawn from DFA and SDA are largely dependent on the particular properties of the algorithms and procedures used.

Wavelet analysis techniques have been employed to decompose the COP time series signals into multiple time scales in order to study postural sway [21, 22]. Chagdes et al. [21] applied discrete wavelet transform (DWT) techniques to decompose the COP signal into different time scales and energy content at such time scales. System identification methods have been used to analyze postural sway data [10, 6, 7, 23]. Johansson et al. [10] showed that postural sway can be modeled by a linear third order stochastic system. Kiemel et al. [6] and Jeka et al. [7] used linear stochastic models to fit the COP data to study the effect of various sensory conditions and the sensory information fusion from various modalities for upright stance. Kowalczyk et al. [23] used system identification methods to show that both intermittent (switched) systems and linear continuous systems can be modeled using the auto regressive moving average (ARMA) modelling approach. The current study applies the linear stochastic modelling approach to study changes in COP time series associated with PD. The current study investigates the COP time series during postural sway through modeling the postural control system in terms of an inverted pendulum model with torsional spring and viscous damping [10]. The approach is similar to that used by Johansson et

al. [10] in order to identify feedback parameters useful in evaluating posture control in young healthy subjects.

Toward this goal, we fit two different models, an auto regressive (AR) and an auto regressive moving average (ARMA) model, to the COP times series data. The Laplace transform method is used for input/output transfer function analysis. The coefficients of the two models are estimated by application of the prediction error (PE) method. The models are selected based on best fit percentage and test of autocorrelation of residuals. From the AR model transfer function denominator, three parameters namely stiffness, swiftness and damping are extracted by comparing it with the derived inverted pendulum dynamics. From the ARMA model poles, the damping and natural frequency are calculated. Group (healthy, mild PD and moderate PD) and condition (EO or EC) effects are investigated using the ANOVA analysis (MATLAB, Natick, MA, USA). The obtained results are also compared with the similar previous studies published. Finally a power analysis on select parameters is done to demonstrate the required sample size for the application of these two models for studying COP time series changes with PD progression.

## ***2. Methods***

***2.1. Subjects.*** The participant's demographic details and methods used have been explained in detail in previously published work [13, 14, 15]. A brief description is given here. Twenty one age-range matched healthy controls (mean age  $66 \pm 7.5$  years), thirteen subjects with mild PD (mean age  $62 \pm 8.2$  years) and ten subjects with moderate PD (mean age  $68 \pm 3.9$  years) participated in this study after providing written consent as approved by the University's institution review board. The PD patients were recruited from the Kansas University Medical Center Parkinson's disease and movement disorders clinic. PD patients had their diagnosis confirmed by a movement disorder specialist. They could stand without external help and had no significant depression, dementia or any other neurological disorders unrelated to PD. The PD patients were asked to maintain their regular medication for the experiment. The healthy subjects did not have any significant head trauma, neurological disease or any musculoskeletal impairments. Table 3.1 shows the details of the subjects for this study.

***2.2. Tasks.*** Participants were instructed to stand in a comfortable self-selected natural stance on a force platform with their arms in a relaxed position at their sides. A total of 6 trials were conducted

in both eyes open (EO) and eyes closed (EC) conditions (3 trials per condition) in a random order. The duration of each trial was 30 seconds. During the eyes open (EO) trials the participants were asked to focus on a fixed target six feet in front of them.

**2.3. Experimental setup and data collection.** The foot/floor reactions were collected using a six channel AMTI force plates (Advanced Mechanical Technology Inc., Watertown, MA, USA). Data collection was done at 1000 Hz using a 16 bit A/D data acquisition system (National Instruments, Austin, TX, USA). Video recording of the trials were also done to verify task compliance of each participant.

**2.4. Modelling of postural control system.** The postural control system was modelled using inverted pendulum dynamics in the anterior-posterior (AP) direction [10]. The human postural control system is often modelled using two different approaches, an ankle strategy and the hip strategy [24]. The ankle strategy involves the application of a balancing torque by the leg muscles about the ankle joint to maintain balance. The hip strategy uses the hips and knee muscles to stabilize the body. The hip strategy is usually utilized when COP leaves the base of support (BOS) as the result of an external balance perturbation. In the current study no external balance perturbations were introduced, so the COP was maintained within the BOS, resulting in an ankle strategy being sufficient to counteract the small perturbations from equilibrium during quiet standing. Therefore a single link inverted pendulum model including the ankle strategy was used for the model (Figure 3.1).

The human postural control system during quiet standing is characterized by small perturbations from equilibrium [25]. This is represented by a disturbing torque term ( $T_d$ ) with equilibrium for the inverted pendulum at an angle of  $\Theta = 0$  degrees. Therefore, an active correction or balancing torque ( $T_{bal}$ ) acting at the ankle joint is needed to restore the system to its equilibrium point. The balance control system is also assumed to have a damping ( $\eta$ ) and a stiffness ( $k$ ) to help counteract the small perturbations from equilibrium.

The detailed model assumptions can be found in [10]. A summary of the most relevant model assumptions are provided here. The balancing torque ( $T_{bal}$ ) is assumed to be regulated by a proportional, derivative and integral control strategy (PID). It is assumed that either an internal or external disturbing torque ( $T_d$ ) is acting on the system to destabilize it. The transfer function

derivation adopted here is based on Laplace transform similar to Johansson et al. [10], with the primary difference being the absence of the input stimulus to the calf muscles in our model. The simplified form of the transfer function model derived is shown below:

$$\frac{T_{bal}(s)}{T_d(s)} = - \frac{(\eta s^2 + (k + \frac{g}{l})s + \rho)}{s^3 + \eta s^2 + ks + \rho} \quad (3.1)$$

The derivation of equation (3.1) can be found in the appendix A.1. It can be inferred from equation (3.1) that the description of postural control system can be given in terms of three coefficients:  $k$ ,  $\eta$  and  $\rho$ , describing the controller properties. The proportional constant ( $k$ ) represents the balancing torque related to the angular position error signal. The derivative ( $\eta$ ) and integral ( $\rho$ ) constants represents the derivative and integral of this angular position error signal, respectively. Hence the derivative term ( $\eta$ ) controls the damping of the system and the integral term ( $\rho$ ) controls the angular position steady state error of the system.

Naturally a good system will have higher values of spring effect ( $k$ ) and the dashpot effect ( $\eta$ ). The normalization done with respect to swiftness parameter ( $f$ ) as done by [10] gives:

$$\frac{T_{bal}(s)}{T_d(s)} = - \frac{(\eta (\frac{s}{f})^2 + (k + \frac{g}{l}) \frac{s}{f} + 1)}{(\frac{s}{f})^3 + \eta (\frac{s}{f})^2 + k (\frac{s}{f}) + 1} \quad (3.2)$$

In which:

$$\text{Swiftness } (f) = \sqrt[3]{\rho} \text{ (rad/sec)} \quad (3.3)$$

$$\text{Stiffness } (K) = \frac{k}{f^2} \quad (3.4)$$

$$\text{Damping } (P) = \frac{\rho}{f} \quad (3.5)$$

From equation (3.2) three parameters can be extracted namely, swiftness (rad/sec), stiffness (dimensionless) and damping (dimensionless). The swiftness term represents the largest angular frequency component of the disturbance for which the identified model provides adequate correction and the damping and stiffness are dimensionless quantities which are not related to swiftness parameter.

**2.5. Analysis.** The data were down sampled to 50 Hz and a low pass, zero phase shift, 4<sup>th</sup> order Butterworth filter with a cut off frequency of 10 Hz was applied. The resulting 50 Hz COP signal represents a time step of 0.02 seconds. Using a relatively higher time step reduces the effect of low amplitude and high frequency components in the postural sway trajectories [7]. The data was processed and analyzed using MATLAB (Mathworks, Natick, MA, USA). A typical COP AP displacement time series is as shown in figure 3.13. Two linear stochastic models are used to fit the COP time series data, namely an auto regressive model (AR) and an auto regressive moving average (ARMA) model. From this point forward, for the purpose of convenience, we will refer to the AR model as model 1 and ARMA model as model 2.

**2.5.1. Model 1.** The difference equation of an AR ( $n$ ) model is given as follows:

$$y(t) + a_1y(t - 1) + a_2y(t - 2) + \dots + a_ny(t - n) = e(t) \quad (3.6)$$

Using the backshift operator we can write:

$$A(q)y(t) = e(t) \quad (3.7)$$

Where,

$$A(q) = 1 + a_1q^{-1} + a_2q^{-2} + \dots + a_nq^{-n} \quad (3.8)$$

Where  $a_i$  are the autoregressive coefficient terms,  $e(t)$  is the white noise term, and  $y(t)$  is the output of the model at time 't'. For each subject, the COP time series data from all three trials were used to fit the AR ( $n$ ) model, treating each trial as an individual experiment for each subject. The prediction error (PE) method was used for fitting the model to time series data. This method involves the estimation of one step ahead prediction of the model and comparing it with the observed experiment output data to determine the error in prediction. Then this error is minimized by defining a quadratic norm. The prediction error is given as,

$$y(t, \theta) = y(t) - \phi^T(t, \theta) \quad (3.9)$$

Where,

$\phi(t, \theta)$  is the vector of regressors for the respective models.

The least squares criterion used is a quadratic function in  $\theta$ . It is shown below,

$$V_N(\theta, z^N) = \frac{1}{N} \sum_{t=1}^N \frac{1}{2} [y(t) - \phi^T(t, \theta)]^2 \quad (3.10)$$

The minimization of  $V_N(\theta, z^N)$  gives the desired least squares estimate (See [26] chapter 7 for detailed description of PE methods). Models of order one to five were fitted to the COP time series data. The best fit percentages for one step ahead prediction were calculated. Models of order three and higher gave good fit percentages (>95 %). The AIC [31] values were calculated for each of these models. The orders 3, 4 and 5 give larger negative AIC values than models of order 1 and 2 and the values did not change by a large margin between model orders 3, 4 and 5. A test of autocorrelation of residuals was done on the models. The residuals show that the 3<sup>rd</sup>, 4<sup>th</sup> and 5<sup>th</sup> order models describe the data well when compared to 1<sup>st</sup> and 2<sup>nd</sup> order models. The model with the smallest order which has the best fit for COP time series data was a 3<sup>rd</sup> order model. Hence the selected model is an AR (3) model. The one step ahead prediction and the best fit percentage of the 3<sup>rd</sup> order model for trial 1 of the healthy subject #1 in EO condition is as shown in figure 3.2. The autocorrelation of residuals is shown in figure 3.3. Also an important factor affecting the order selection in our study is the fact that an AR (3) model has a transfer function denominator in the form of a cubic polynomial. When the discrete AR (3) model is converted to a continuous time form, the coefficients of the polynomial can be compared directly to the constants  $k$ ,  $\eta$  and  $\rho$ . Hence this facilitates the extraction of the three parameters namely damping ( $P$ ), stiffness ( $K$ ) and swiftness ( $f$ ).

**2.5.2. Model 2.** The second model fitted to the time series data is the ARMA ( $n, n-1$ ). The difference equation for an ARMA ( $n, n-1$ ) is given below in equation (3.9):

$$y(t) + a_1y(t-1) + a_2y(t-2) + \dots + a_ny(t-n) = c_1e(t-1) + c_2e(t-2) + \dots + c_{n-1}e(t-(n-1)) + e(t) \quad (3.11)$$

Using the backshift operator we can write:

$$A(q)y(t) = C(q)e(t) \quad (3.12)$$

Where,

$$A(q) = 1 + a_1q^{-1} + a_2q^{-2} + \dots + a_nq^{-n} \quad (3.13)$$

$$C(q) = 1 + c_1q^{-1} + c_2q^{-2} + \dots + c_{n-1}q^{-(n-1)} \quad (3.14)$$

Equation (3.12) gives the general representation of an ARMA ( $n, m$ ) model. Here  $A(q)$  and  $C(q)$  are the autoregressive and the moving average coefficients, respectively. In this study, models of orders 'n' from 1 to 5 were fitted to the COP time series data. The model of least order which fit the COP time series data satisfactorily was a 2<sup>nd</sup> order model ( $n = 2$ ). Our main model validation criterion was the best fit percentage. Hence an ARMA (2, 1) model was used for the analysis. The one step ahead prediction and the best fit percentage are as shown in figure 3.4. The autocorrelation of residuals is shown in figure 3.5. Using the transfer function poles of the ARMA (2, 1) model, the natural frequency ( $w_0$ ) and damping ratio ( $\zeta$ ) are calculated for each subject.

**2.5.3. Statistical analysis.** For both AR (3) and the ARMA (2, 1) models, three way Analysis of variances (ANOVA) was used to investigate the effects of group (healthy controls, Mild PD and Moderate PD), condition (eyes open, eyes closed) and group-by-condition on each parameter. Significance was defined as  $p < 0.05$  for all tests. A Post-Hoc Tukey Kramer test was performed to identify the group(s) responsible for any significant main effect in group. If trends existed that missed significance, a power analysis was performed to determine the number of samples needed for group differentiation. Due to the pilot nature of this study, in all the identified parameters (Swiftness, Stiffness, Damping, Damping ratio and Natural frequency) a standard value of the overall group 'mean  $\pm 3$ \*Standard Deviation' was used to identify and remove the outliers before the statistical analysis. All statistical analyses were done using "Statistics and Machine Learning Toolbox" (MATLAB, Mathworks, Natick, MA, USA).

### 3. Results

The results based on condition factor and group factor separately are presented in this section. The group\*condition factor was not significant for any of the parameters analyzed, therefore it will not be considered further.



**3.1. Model 1.** The parameters that were extracted from the AR (3) model are the swiftness ( $f$ ), stiffness ( $K$ ) and damping ( $P$ ). The results of the statistical analysis of these three parameters are presented in the following sections.

**3.1.1. Swiftness ( $f$ ).** The Swiftness parameter tends to decrease with PD progression, with a significant difference ( $P < 0.05$ ) between HC and moderate PD, but no significant differences between HC-to-mild PD and mild-to-moderate PD in EO condition. There were no significant group differences in swiftness parameter in the EC condition. The effect of condition was significant ( $P < 0.01$ ), with the swiftness parameter being higher for the EO, compared to the EC condition. The means and standard deviations of the swiftness parameter for the three groups are shown in figure 3.6. The power analysis indicates that a sample size of 34 would help to accurately assess the sensitivity of swiftness parameter in distinguishing the mild and moderate PD in the EO condition.

**3.1.2. Damping ( $P$ ).** The damping parameter showed a decreasing trend with PD progression with no significant group differences. The condition effect was significant ( $P < 0.01$ ) for the damping parameter, which was higher in EO, compared to EC condition. The means and standard deviations of damping parameter for healthy controls, mild and moderate PD subjects are shown in figure 3.7.

**3.1.3. Stiffness ( $K$ ).** The stiffness parameter trended towards higher values with PD progression. The effect of group was significant ( $P < 0.05$ ), with stiffness values of moderate PD being higher than HC, but no significant difference were found between HC to mild PD and between mild PD to moderate PD. The effect of condition was significant ( $P < 0.01$ ), with the stiffness in EO being larger than EC condition. Table 3.2, 3.3 and 3.4 show the values of swiftness parameter ( $f$ ), damping parameter ( $P$ ) and the stiffness parameter ( $K$ ) along with their means and standard deviations for the three groups in both EO and EC conditions. The means and standard deviations of the stiffness parameter for HC, mild and moderate PD subjects are shown in figure 3.8. The power analysis suggests that a sample size of 80 would help to accurately assess the sensitivity of stiffness parameter in differentiating the mild and moderate PD groups in EO condition.

The comparison of the three extracted parameters for EO versus EC trials are shown in figure 3.9. The means and standard deviation values for the swiftness, damping and stiffness parameters are given in table 3.2.

**3.2. Model 2 results.** Using the poles of the identified ARMA (2, 1) transfer function, natural frequency and damping ratio were calculated. The statistical analysis of these two parameters are presented in the following paragraphs.

**3.2.1. Natural frequency ( $w_0$ ).** The natural frequency showed no significant group differences in both EO and EC conditions, with an increasing trend shown in the EC condition only. The condition effects were significant ( $P < 0.01$ ) for natural frequency with a higher mean value in EC, compared to EO condition. The means and standard deviations of natural frequency for healthy controls, mild and moderate PD subjects are shown in figure 3.10.

**3.2.2. Damping ratio ( $\zeta$ ).** The damping ratio did not show any significant group differences in both EO and EC conditions. The condition effect was significant ( $P < 0.01$ ) with higher values in EO, compared to EC condition. The means and standard deviations of damping ratio for HC, mild and moderate PD subjects are shown in figure 3.11. The mean values of natural frequency and damping ratio for EO versus EC conditions for the total population are shown in figure 3.12.

## **4. Discussion**

**4.1. Model 1 results discussion.** The swiftness and damping parameter values obtained from HC in our study were comparable to the values published for HC by Johansson et al [10]. The stiffness parameter values obtained in our study for HC are slightly higher than that obtained Johansson et al. This may be due to the fact that the age groups of the HC subjects were significantly different between the two studies. Our HC group are older compared to young HC group who participated in the Johansson study. Secondly, there was no application of external stimulus in our study to evoke perturbation. Johansson used pseudorandom application of controlled vibrations to the calf muscles during upright stance.

**4.1.1. Swiftness parameter ( $f$ ).** The swiftness parameter is basically extracted from the integral constant of the PID control model. The swiftness is described as the parameter which governs the rapid compensation for small deviations from the equilibrium position of the subject [10]. The higher the value of swiftness, the faster the subject is able to react to perturbations from equilibrium. Our results show that the HC have a higher swiftness parameter mean value in both the EO and EC condition, compared to the mild and moderate PD groups. The significantly higher swiftness of HC, compared to moderate PD in the EO condition, could indicate that the control system of healthy subjects is able to integrate the signals received from the different sensory sources (visual, proprioception etc.) faster and offer a quicker response or compensation for the small perturbation or deviations from the equilibrium. The lower mean value of swiftness in the mild and moderate PD groups, compared to HC, could be due to the loss of the ability of the control system to compensate or eliminate the bias action of the angular position of the system with respect to equilibrium.

Higher mean values of the swiftness parameter in the EC condition, compared to the EO condition, suggests that the absence of visual feedback effects the compensative action in a way which causes the other senses to become more dominant contributors to alerting the control system of small deviations. Sabatini [12] suggests that the groups of subjects may depend differently on visual feedback, and the various sensory cues are weighted differently for various subjects. Some subject may be more dependent on the visual feedback and the other subjects may be largely dependent on other sensory information sources independent of visual feedback. Therefore in providing the sensory information regarding the small deviations from the equilibrium, the proprioceptive and other sensory cues might be weighted more heavily compared to visual feedback. This could explain the higher values of swiftness parameter even in the absence of visual feedback in EC, compared to the EO condition.

**4.1.2. Damping parameter ( $P$ ).** The decreasing trend in mean values of the damping parameter from HC to mild to moderate PD could indicate that progression of PD is related to decreases in the ability of the control system to provide necessary attenuation of sway velocity. A higher damping parameter value indicates a better ability of the system to attenuate the sway velocity in HC. In the PD group, there could be decreased ability of the control system to regulate muscle

activity at the ankle joint which is required to provide necessary damping when deviations from equilibrium are detected. The observed differences in the means of the damping parameters across groups were not statistically significant. However, a power analysis done on the damping parameter suggests that an accurate assessment could be made with higher sample size (approximately, 190 for healthy controls to mild PD and 260 for mild to moderate PD in EO condition).

The means of the damping parameter between the total populations in EO and EC conditions were significantly different. Larger mean values of the damping parameter in EO, compared to the EC condition, suggests that the visual feedback information could be aiding in attenuation of the rate change in position. The proprioceptive, visual and tactile sensors of the body are taught to rely more on velocity information rather than position [7, 8, 11]. Hence it can be hypothesized that when the visual feedback is eliminated, one of the sensory cues sensitive to changes in sway velocity is absent or not available for the control system, and thus can lead to a decrease in the ability to provide adequate damping of sway velocity during quiet standing in the EC condition. In the previous study by Barnds et al. [13] done on healthy controls, mild PD and moderate PD subjects, the PD group, compared to the healthy controls, showed a greater mean sway speed. This also supports our inference that PD progression may affect the ability of the control system to provide adequate attenuation in sway velocity.

**4.1.3. Stiffness parameter ( $K$ ).** The stiffness parameter showed increasing trends between the HC, mild and moderate PD groups in both EO and EC conditions. The higher the value of stiffness, the smaller are the deviations from equilibrium [10]. Thus, the higher stiffness could indicate a more rigid control strategy. Higher values of stiffness in mild and moderate PD groups, compared to HC, may be due to higher rigidity of muscle fibers. A study done by Jaroslaw et al. [27] showed that PD subjects have a higher muscle passive stiffness when compared to HC measured by the application of Myotonometry. Carpenter *et al.* [28] showed that the PD patients had a decreased trunk rotation and smaller ankle torques when subjected to rotational perturbations, indicating that the PD subjects may have a higher muscle stiffness. Our results also show that the PD groups, compared to HC, could tend to adopt a more rigid control strategy due to the higher values of stiffness.

When comparing the effects of condition (EO versus EC), the results show that the mean value of the stiffness parameter is higher for the EO, compared to the EC condition. This could be due to the fact that in the EO condition, the participants were focused on a fixed target. This visual fixation could have led the control system to adopt a stiffer strategy. Sabatini et al. [12] suggests that the main aim of the control system in EO condition is to stabilize the head movement in space. Hence in our study we can hypothesize that the task restriction placed on the participants could have led to the higher values of stiffness in EO, compared to the EC condition (where in EC the movement of the head was not controlled). Carpenter et al. [29] suggested that the visual feedback could play an important role in increasing the ankle stiffness when balance confidence is compromised. Therefore it can also be said that the heightened awareness in EO condition due to available feedback led to decreased movement away from equilibrium. However the current higher mean value in stiffness for EO, compared to the EC condition, could be one of the limitations of our study which did not control the head position in space during EC trials.

**4.2. Model 2 results discussion.** The natural frequency values obtained for the EC condition were comparable to the undamped natural frequency values obtained by Winter et al. [30] in the EC condition with 100% width stance. But the natural frequency values obtained for EO condition were less than that calculated by Winter et al. [30] in 100% width stance EO condition. This may be due to the difference in experiment protocol in EO condition. In the Winter study, it is unclear whether the participants in EO condition were asked to focus on a fixed target when in quiet stance. But in our study the participants were focused on a fixed target in EO condition. The damping ratio values obtained in our study for HC are comparable to that obtained for HC by Sabatini et al. [12] in EO and EC conditions obtained by non-Gaussian FARIMA stochastic model during quiet standing.

**4.2.1. Natural frequency ( $w_0$ ).** The increasing trend in mean values of  $w_0$  in the EC condition with PD progression could indicate that the COP oscillates with higher frequencies for the PD groups, compared to HC. The absence of significant effect of the group factor could suggest that  $w_0$  may not be sensitive to changes in PI with PD progression. However the significantly higher values of mean  $w_0$  for the total population between the EO and EC condition could indicate the prominent role of visual feedback in regulating the COP sway. In the EC condition, the absence

of visual sensory information may lead to higher dependence on proprioceptive muscle feedback at the ankle joint. This could result in a larger and faster sway of the COP from the equilibrium position.

**4.2.2. Damping ratio ( $\zeta$ ).** The damping ratio in both EO and EC conditions did not show any significant differences across the three groups. However the significantly higher value of  $\zeta$  in EO, compared to the EC condition, could indicate that the visual sensory information plays a vital role in attenuating the sway velocity. The previous study [13] between the EO and EC conditions using the PCA measures of COP indicate a higher mean peak sway speed value for EC than for EO condition. This again supports the results in our current study where the mean  $\zeta$  values are lower for the EC condition allowing for a larger sway velocity.

This study has a few limitations. The simple linear stochastic models and analysis based on inverted pendulum dynamics do not describe the effect of various forms of sensory information on the PI in PD. The quiet stance approach used in the current study does not challenge the postural control system and hence it cannot give insights into the changes in these parameters during an active task such as responding to a small postural perturbation without a change in the base of support (BOS), or during tasks requiring a change in the BOS such as gait initiation and taking a step in response to a large balance disturbance. The sample size used for this study is small and a need for larger sample sizes is shown by the preliminary power analysis done on the extracted parameters.

**Conclusions.** This study was aimed at using system identification methods to understand the changes in COP time series data with progression of PI in PD. This was accomplished by fitting two different linear stochastic models to the COP time series data. The statistical analysis on the extracted parameters revealed the following. First, the decreasing trend in the swiftness parameter with PD progression could indicate the slower compensation for small deviations from equilibrium in the mild and moderate PD population. Second, the smaller mean values of damping in the PD group, compared to the HC, may indicate the loss in ability of the controller to provide adequate attenuation of sway velocity in PD. Third, the increasing mean stiffness values with PD progression could indicate that the mild and moderate PD patients could offer a higher ankle joint

rigidity when compared to HC. Last, the natural frequency and damping ratio analysis results may indicate larger and faster deviations of COP from the equilibrium and a reduced ability of the controller to provide necessary damping of sway velocity in the mild and moderate PD groups.

Overall the following features of the current study are worthy of mention. The study gave an interpretation of the changes in PI with the severity of PD in terms of swiftness, damping and stiffness parameter with swiftness and stiffness parameter able to differentiate between HC and moderate PD groups. The extracted parameters showed that they could serve as potential measures of the changes in COP time series with PD progression. Future studies should further investigate the changes in the above mentioned parameters with a larger sample size and longer duration of trials in order to accurately determine the sensitivity of these parameters in characterizing PI with PD progression. Also studies should be performed with these parameters as applied to dynamic or balance recovery tasks such as gait initiation or the backward pull test in order to examine the behavior of these parameters in a dynamic task environment.

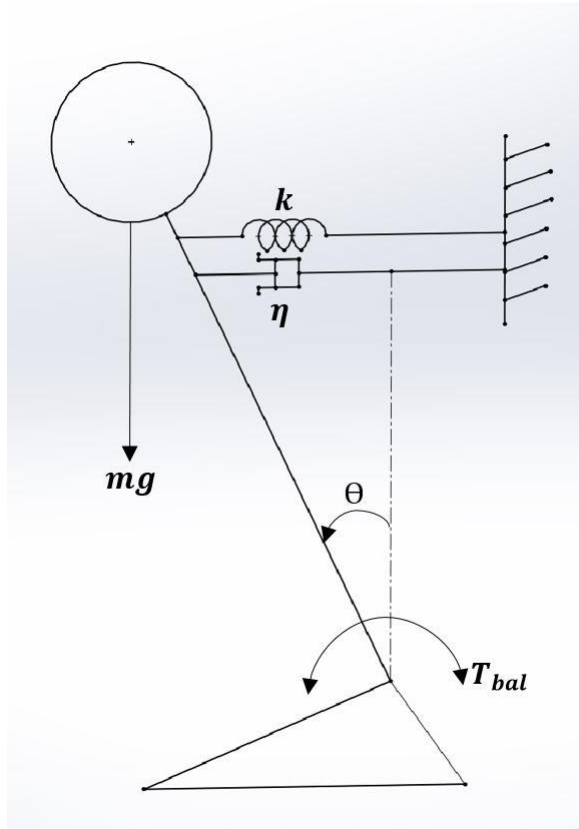
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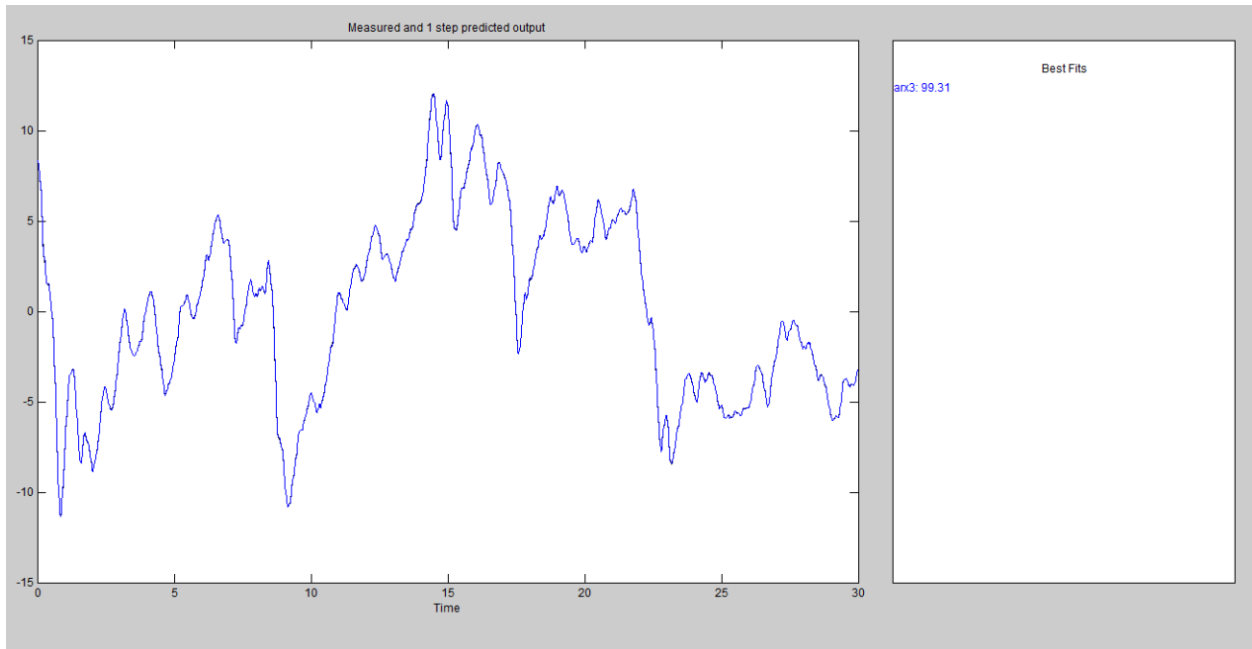


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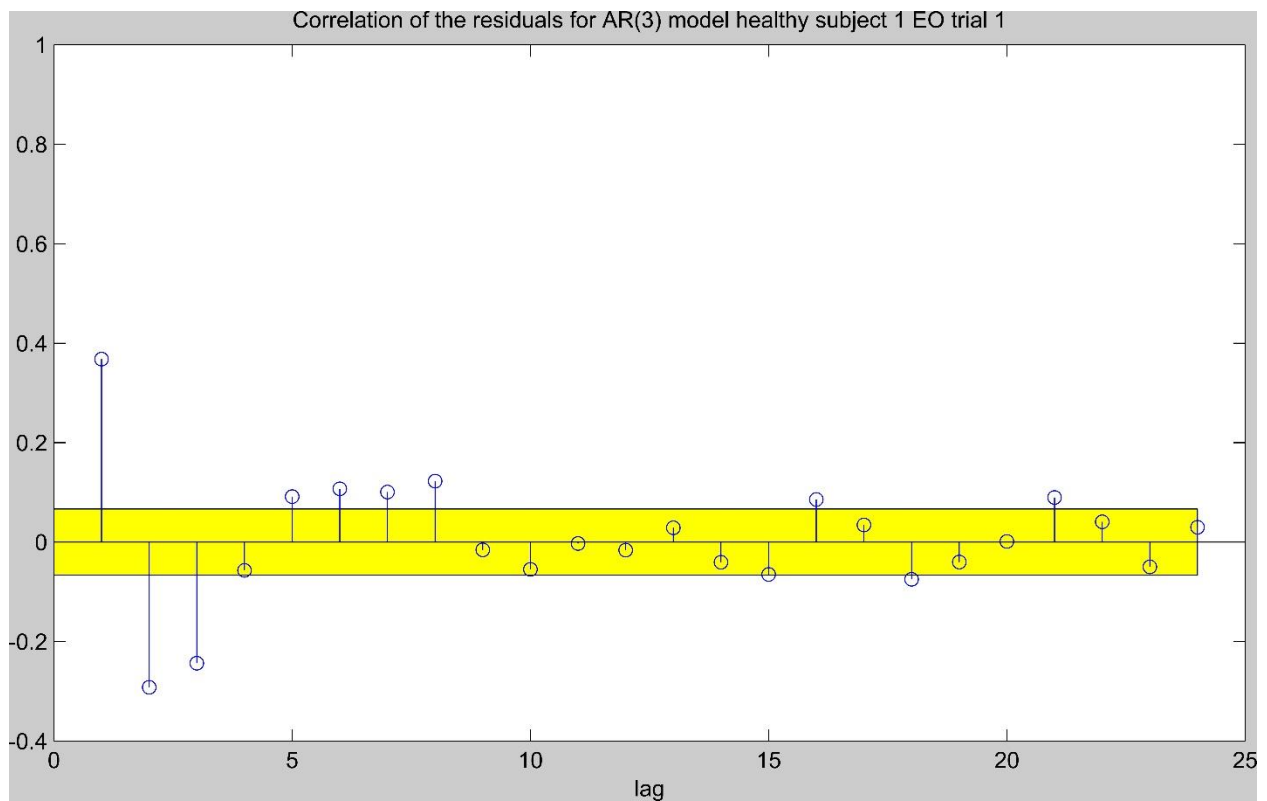
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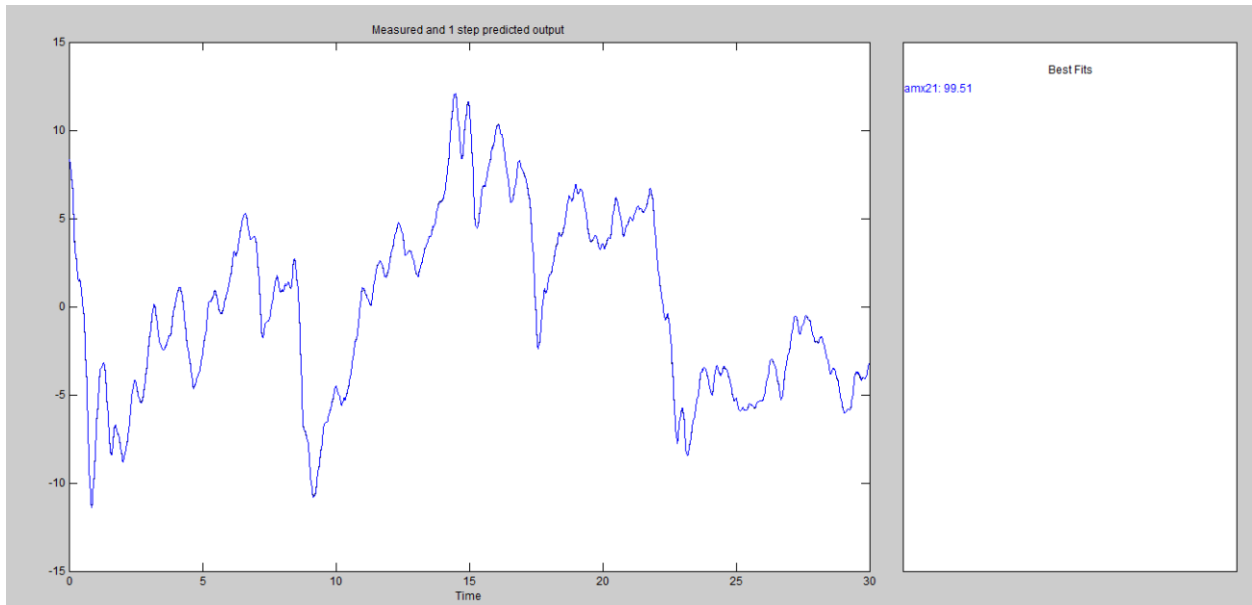
**Figure 3. 1. Schematic of the inverted pendulum model for posture control during upright stance**



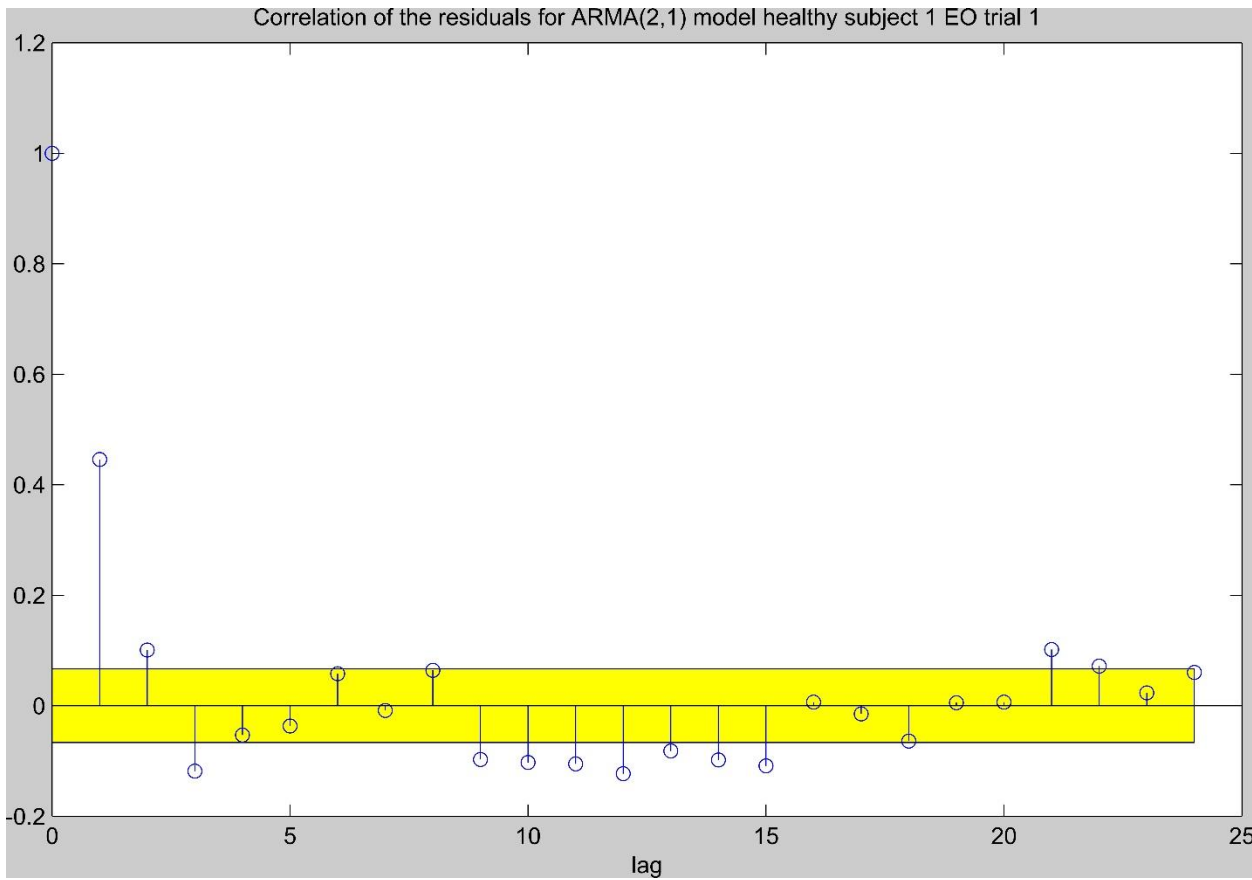
**Figure 3. 2. One step ahead prediction of the AR (3) model for healthy subject 1 EO trial 1**



**Figure 3. 3Autocorrelation of residuals of the AR (3) model for healthy subject 1 EO trial 1. The yellow region indicates the 99% confidence interval.**



**Figure 3. 4. One step ahead prediction of the ARMA (2, 1) model for healthy subject 1 EO trial 1**



**Figure 3. 5. Autocorrelation of residuals of the ARMA (2, 1) model for healthy subject 1 EO trial 1. The yellow region highlighted indicates 99% confidence interval.**

**Table 3. 1. Mean  $\pm$  SD, Demographic for Parkinsonian subjects and healthy controls**

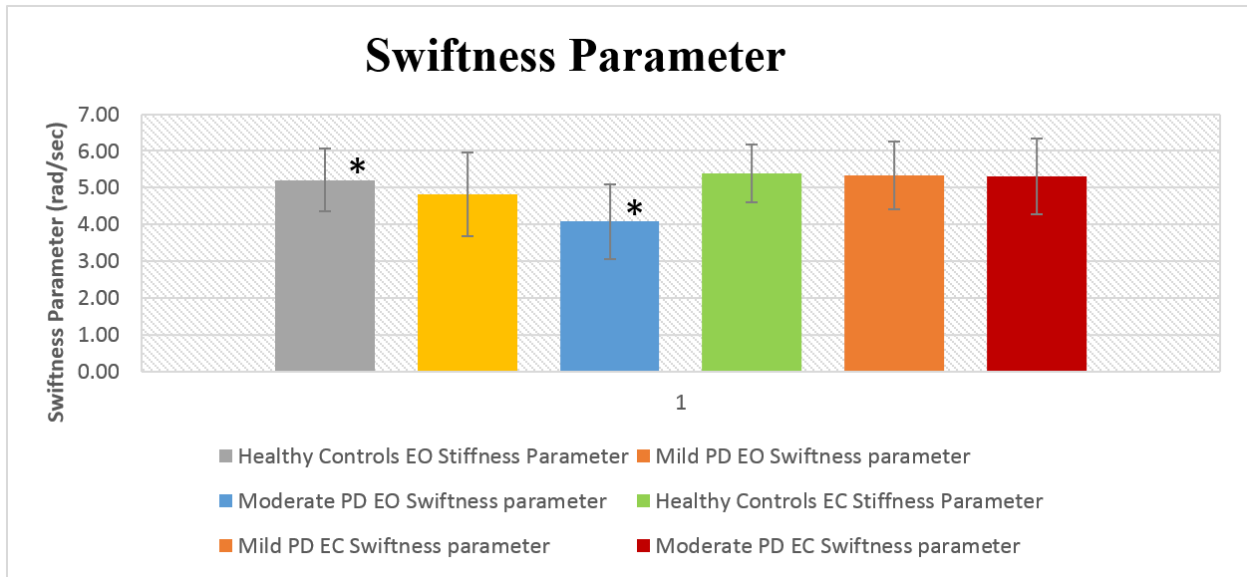
	Gender		Age (years) $\pm$ SD	Height (m) $\pm$ S.D	Weight (kg)
	Male	Female			
<b>Healthy controls</b>	15	8	66 $\pm$ 8	1.71 $\pm$ .08	79 $\pm$ 28
<b>Mild PD</b>	7	6	65 $\pm$ 7	1.70 $\pm$ .09	85 $\pm$ 17
<b>Moderate PD</b>	8	2	62 $\pm$ 8	1.67 $\pm$ .08	74 $\pm$ 11
<b>Total PD subjects</b>	17	8	68 $\pm$ 4	1.73 $\pm$ .10	95 $\pm$ 15

SD - Standard Deviation

**Table 3. 2. Mean  $\pm$  Standard Deviations of extracted parameters from model 1 and model 2 for healthy controls, mild and moderate PD subjects**

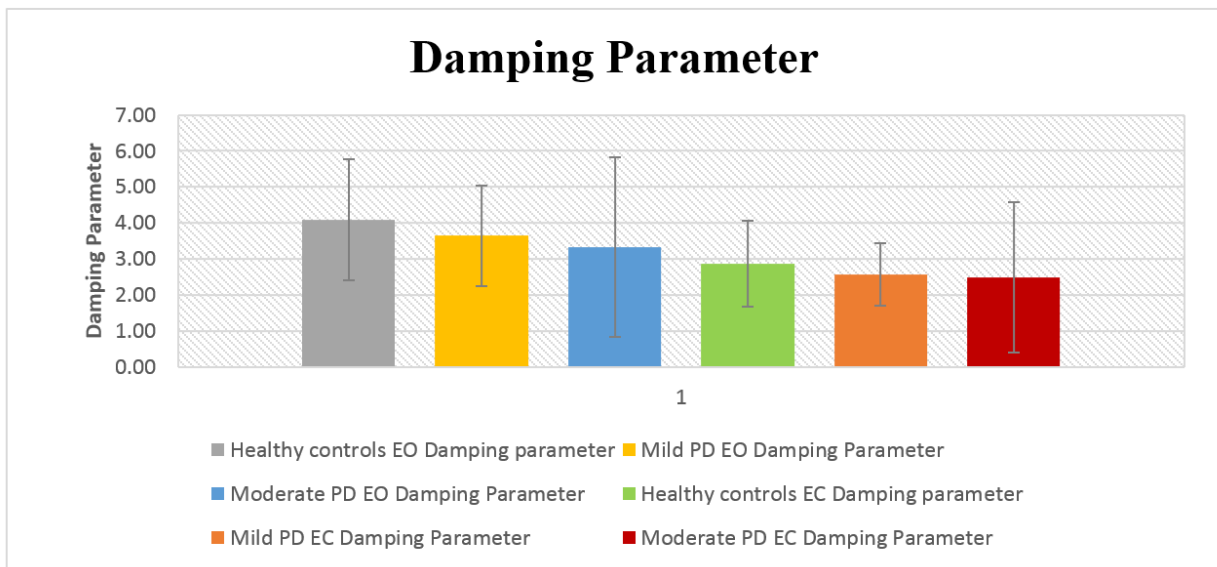
	Healthy controls		Mild PD subjects		Moderate PD subjects	
	EO	EC	EO	EC	EO	EC
<b>Swiftness parameter*</b> (rad/sec)	5.21 $\pm$ 0.85	5.39 $\pm$ 0.79	4.83 $\pm$ 1.14	5.33 $\pm$ 0.92	4.09 $\pm$ 1.01	5.31 $\pm$ 1.03
<b>Damping parameter*</b>	4.08 $\pm$ 1.68	2.88 $\pm$ 1.19	3.64 $\pm$ 1.39	2.57 $\pm$ 0.87	3.33 $\pm$ 2.49	2.50 $\pm$ 2.10
<b>Stiffness parameter*</b>	11.98 $\pm$ 7.07	8.71 $\pm$ 3.27	17.14 $\pm$ 16.16	9.89 $\pm$ 5.84	23.75 $\pm$ 18.29	13.00 $\pm$ 6.42
<b>Natural frequency**</b> (Hz)	0.39 $\pm$ 0.18	0.51 $\pm$ 0.18	0.36 $\pm$ 0.23	0.56 $\pm$ 0.18	0.33 $\pm$ 0.17	0.58 $\pm$ 0.39
<b>Damping ratio**</b>	0.72 $\pm$ 0.24	0.54 $\pm$ 0.31	0.70 $\pm$ 0.38	0.47 $\pm$ 0.26	0.74 $\pm$ 0.25	0.60 $\pm$ 0.34

EO – Eyes open condition, EC – Eyes closed condition, \* - Model 1, \*\* - Model



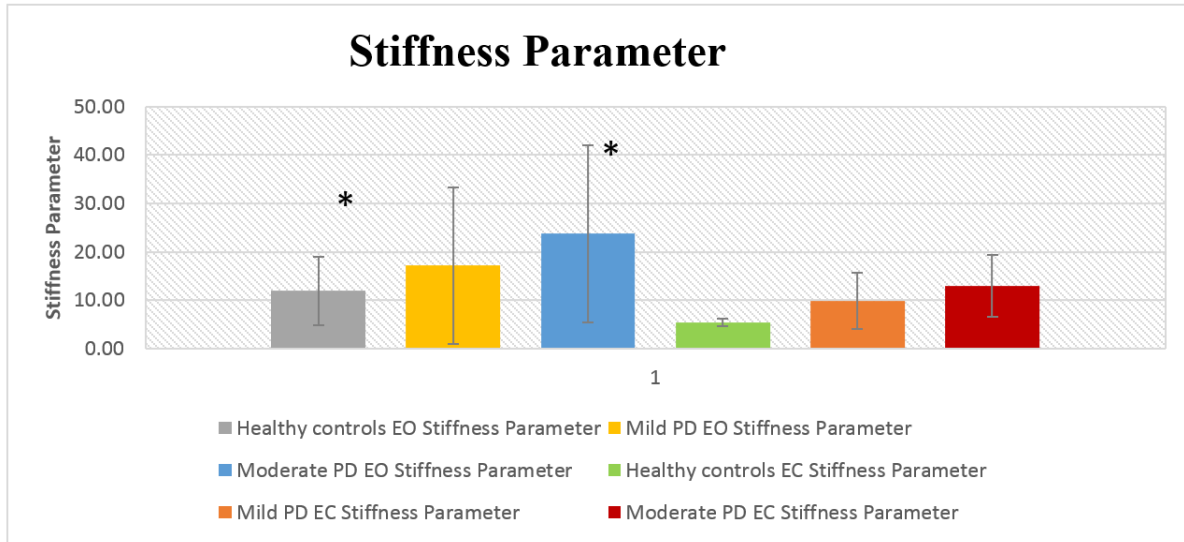
\*- Significant difference ( $P < 0.05$ )

**Figure 3. 6. Mean values of swiftness parameter for healthy controls, mild and moderate PD.**



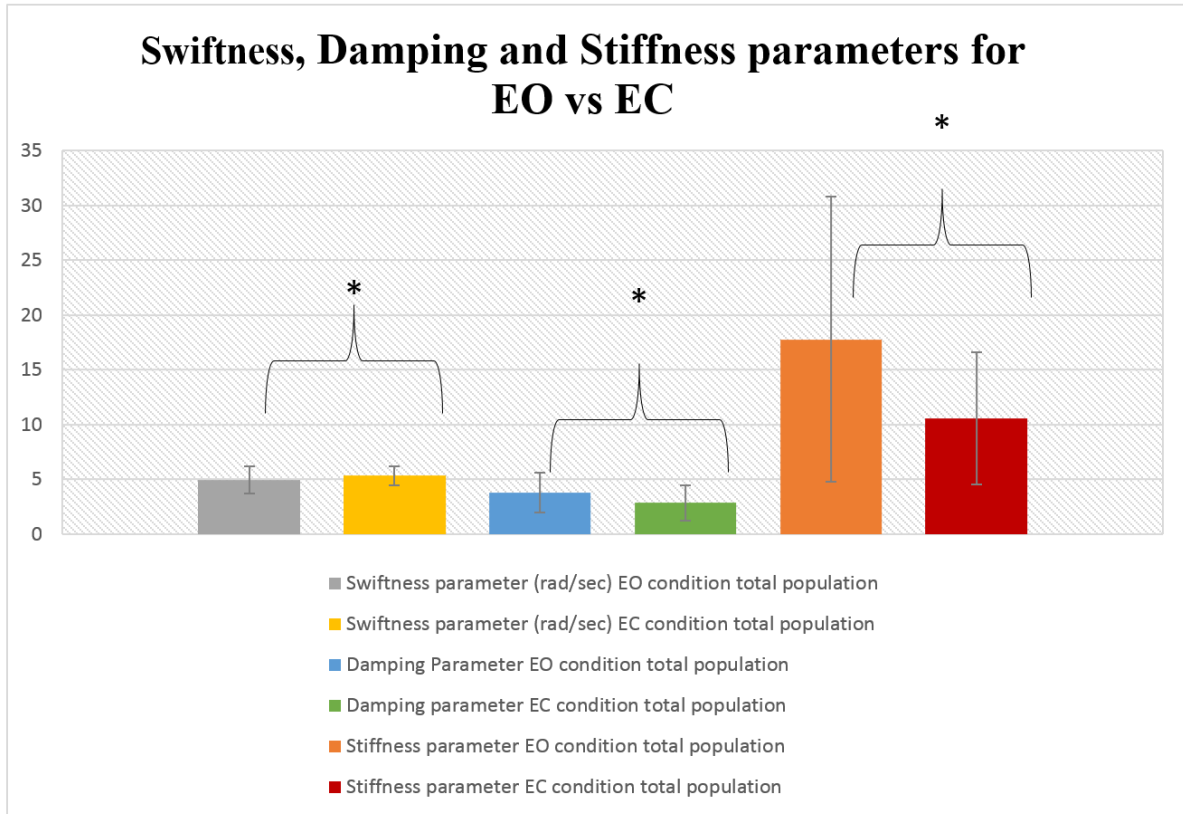
**Figure 3. 7. Mean values of damping parameter for healthy controls, mild and moderate PD.**





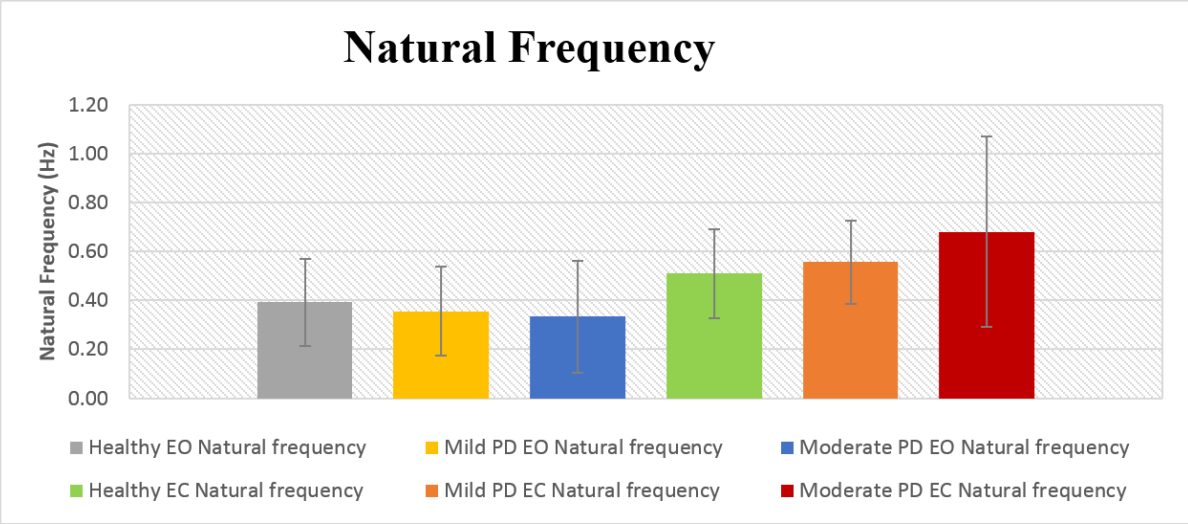
\*- Significant difference ( $P < 0.05$ )

**Figure 3. 8. Mean values of stiffness parameter for healthy controls, mild and moderate PD.**

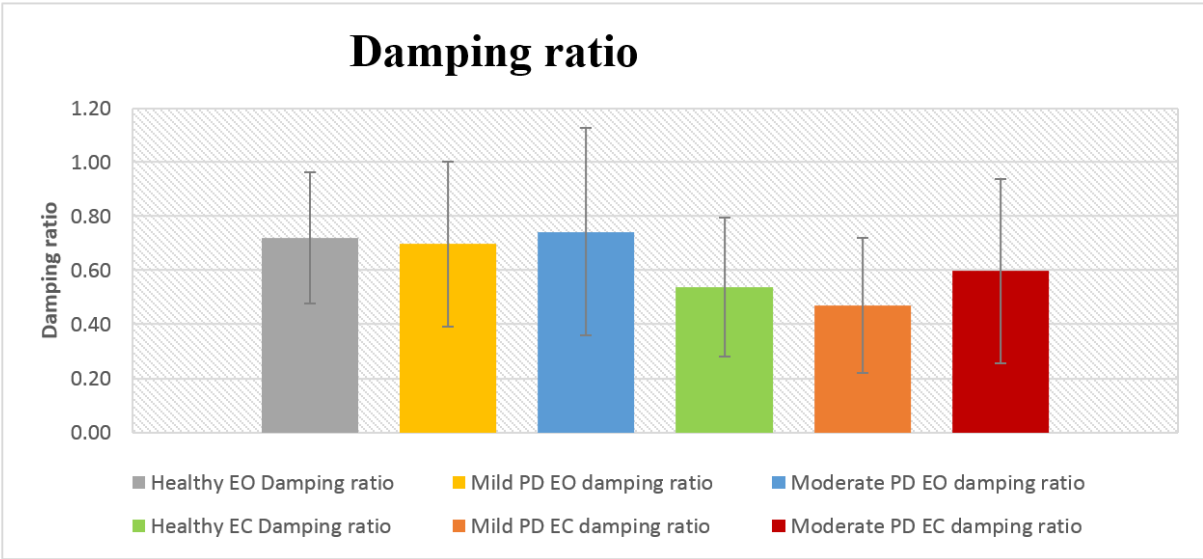


\*- Significant difference ( $P < 0.05$ )

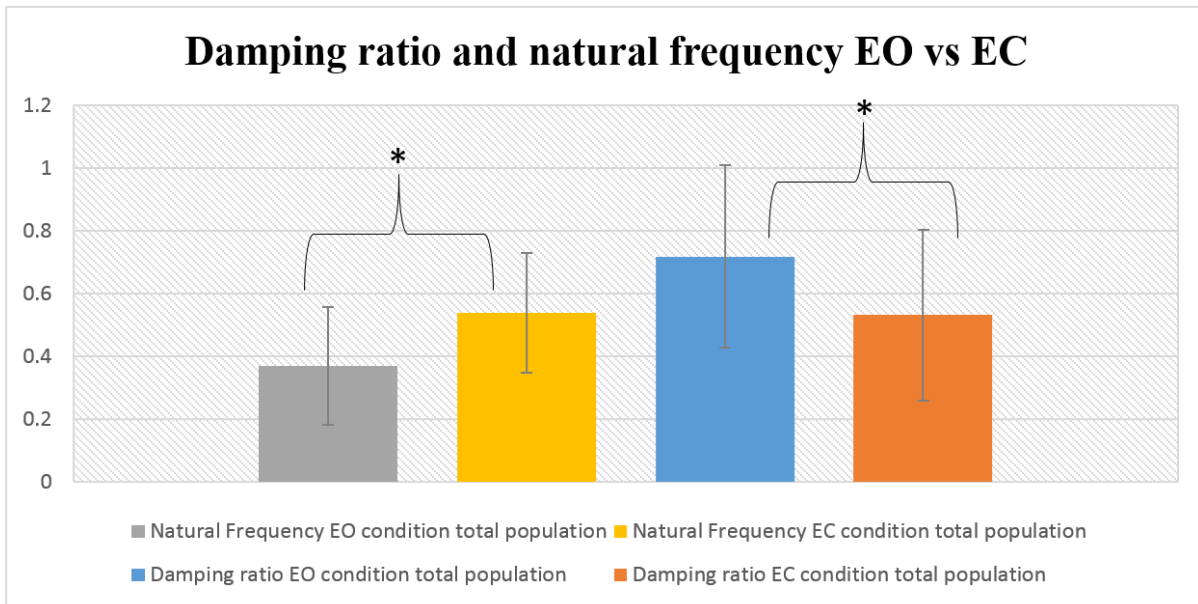
**Figure 3. 9. Mean values of swiftness, damping and stiffness for healthy controls, mild and moderate PD.**



**Figure 3. 10. Mean values of Natural frequency for healthy controls, mild and moderate PD.**

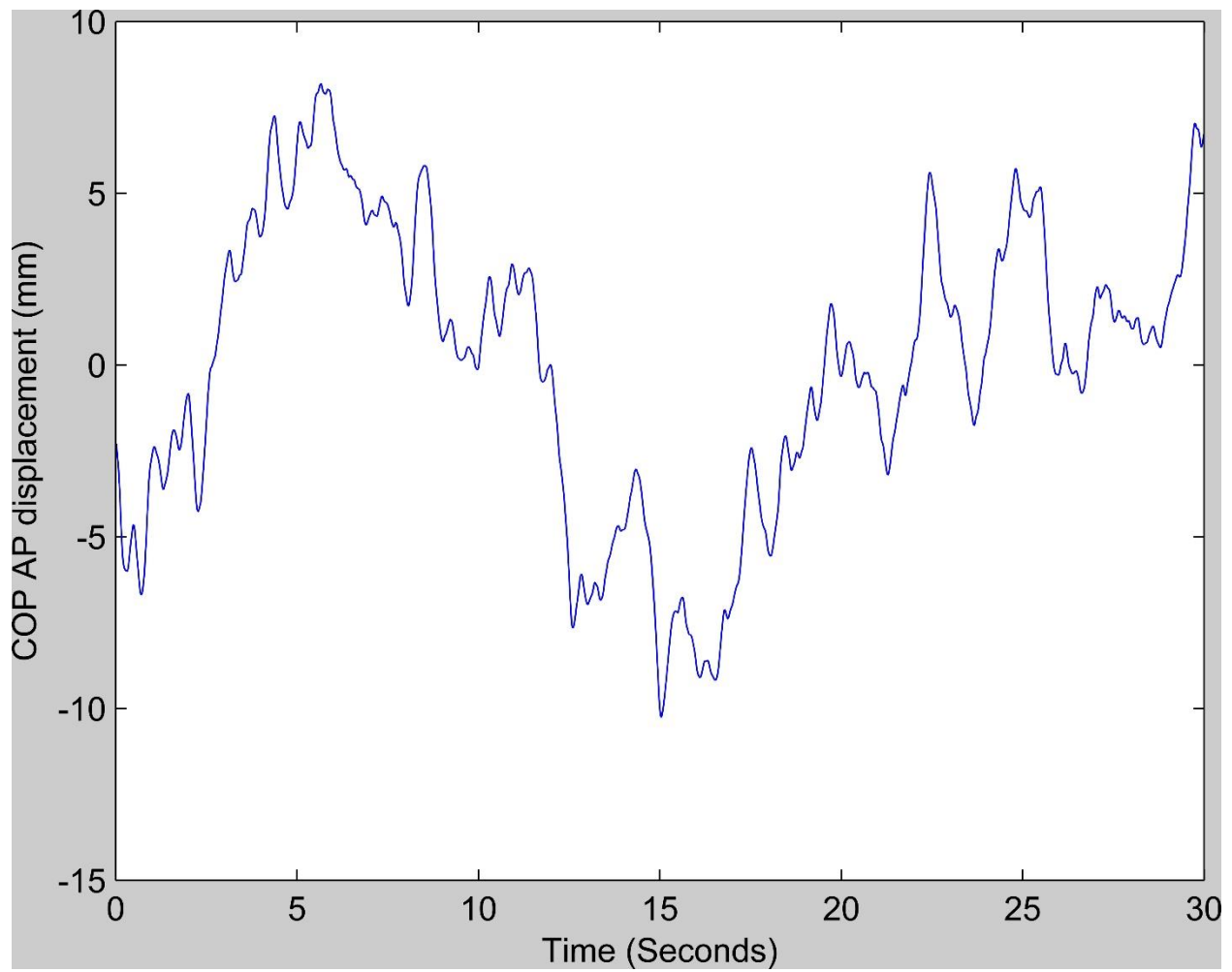


**Figure 3. 11. Mean values of damping for healthy controls, mild and moderate PD.**



\*- Significant difference ( $P < 0.05$ )

**Figure 3. 12. Mean values of damping for healthy controls, mild and moderate PD.**



**Figure 3. 13. A typical detrended COP AP time series data for healthy subject 5 trial 1 in EO condition**

## CHAPTER FOUR: SUMMARY

### *Summary of study*

The primary goal of this study was to investigate the changes in COP time series data with severity of PD. Twenty one healthy controls, thirteen mild PD and ten moderate PD subjects were asked to stand in a comfortable stationary stance with their arms at their sides on a force platform. The COP displacement was later calculated using the force and moments extracted from the force platform. This COP time series was fitted by two different linear stochastic models namely an AR (3) system (model 1) and an ARMA (2, 1) (model 2) system. Using the coefficients of the identified model 1, three parameters were calculated namely swiftness, damping and stiffness. There were significant differences in the mean values in swiftness and stiffness parameter between the healthy and moderate PD population in EO condition. There was an increasing trend with mean stiffness values from healthy to mild to moderate PD. The mean swiftness values showed a decreasing trend with the severity of PD. The values of damping parameter did not show any significant differences between the three groups but did show a decreasing trend with progression of PD. As a total population the three parameters were significantly different between the EO and EC conditions.

The statistical analysis of stiffness parameter revealed that the subjects with mild and moderate PD could adopt a more rigid control strategy when compared to healthy controls. The analysis of damping parameter showed that PD (mild and moderate PD) may cause a reduced ability to provide necessary damping of sway velocity. Swiftness parameter analysis revealed that the healthy controls could have a better ability to integrate the information from various sensory cues and react faster to small deviations from the equilibrium.

The parameters calculated from the model 2 were natural frequency and damping ratio. The two parameters did not show any significant differences across the three groups. However the mean natural frequency values showed an increasing trend in EC condition between the three groups. The damping ratio did not show any particular trends across the three groups. As a total population, the mean values for natural frequency and damping ratio were significantly different between EO and EC conditions. The natural frequency tended to increase with absence of visual feedback indicating that the visual feedback could play a vital role in sensing small perturbations from the equilibrium position. Damping ratio showed a significantly lower value for EC when

compared to EO condition. This indicated that the absence of visual sensory information could make the control system less sensitive to deviations from equilibrium leading to lower damping of sway velocity.

### ***Conclusions and recommendations***

This study revealed several trends indicating sensitiveness of the calculated physical parameters to changes in COP time series with severity of PD. The higher mean values of stiffness parameter indicated a more rigid control strategy in mild and moderate PD subjects, compared to healthy controls. Higher mean values of swiftness parameter revealed that the PD may result in a slower reaction to deviations from equilibrium. The lower values of damping parameter and damping ratio in mild and moderate PD, compared to healthy controls, could represent the loss of ability to provide necessary attenuation of sway velocity with progression of PD. The higher values of natural frequency in EO, compared to EC, for mild and moderate PD could mean a larger number of deviations from equilibrium in PD subjects. The power analysis done on these subjects revealed that with larger sample size, several of the parameters analyzed could potentially differentiate the three groups with significant accuracy in the EO condition. Hence future studies with larger sample sizes and longer duration of trials is need to accurately assess the sensitiveness of these calculated parameters to changes in COP time series with PD progression.

### ***Study limitations***

While the study showed trends in the calculated parameters between the healthy controls, mild and moderate PD, due to a small sample size used in this pilot study it is difficult to assess the sensitivity of these parameters with changes in COP time series with clinical PD progression. The short trial duration of 30 seconds used in our pilot study could be too short, hence future studies should include longer duration of trials. Lastly the experimental procedure used is that of quasi-static quiet stance which does not challenge the postural control system by a significant margin. Hence it is difficult to determine the effects of various sensory information on the postural control system in response to dynamic tasks.

### *Future studies*

A logical next step for future studies would be to consider a larger sample size. Having longer duration of each trial would possibly give insights into modelling the long term control strategy used by the central nervous system. Application of the linear stochastic methods used in this study on COP time series obtained through tasks such as gait initiation, backward pull and release strategy, moving platform methods etc. could reveal the changes in these parameters in response to these dynamic tasks.

This study also revealed that the identified parameters are sensitive to the presence or absence of visual feedback. Our study showed that the calculated parameters are more sensitive in the EO condition rather than EC condition. This could have a significant impact in assessing the presence of PI and its subsequent progression in PD. Hence further investigation with experiments designed to challenge the postural control system using variations in visual feedback could reveal the effectiveness of this method in analyzing the influence of visual feedback on posture regulation.



## APPENDICES

### *Appendix A: Details of modelling and analysis*

#### *A.1. Transfer function description of inverted pendulum model*

The method of transfer function analysis used here is that of Laplace transforms. The detail description of this transfer function model is already presented in the previously published work by Johansson et al. 1988<sup>[1]</sup>. The main difference between our study and theirs is that there is no external stimulus vibration applied to calf muscles in our study to evoke perturbation. The figure 3.1 gives the schematic of an inverted pendulum model. It is assumed that the environment tries to apply a disturbing torque ( $T_d$ ) on the system. To compensate for this a balancing torque ( $T_{bal}$ ) is assumed to be applied by the controller using a PID control strategy. The description of the proportional, derivative and integral constants are as given below:

**Proportional constant:** The proportional term is assumed to compensate for the gravitational term as well as provide necessary correction in deviation angle ( $\Theta$ ). The form assumed by the proportional term becomes:

$$\mathbf{P:} \quad -mgl \sin\theta(t) - kJ \theta(t)$$

Where  $k$  is the proportional constant.

**Integral constant:** The form assumed by the integral constant is as shown below:

$$\mathbf{I:} \quad -\rho J \int_{t_0}^t \theta(t) dt$$

**Derivative constant:** The form assumed by the derivative constant is as shown below:

$$\mathbf{D:} \quad -\eta J \dot{\theta}(t)$$

Where  $\eta$  is the derivative constant.

The balancing torque then becomes:

$$T_{bal}(t) = -mgl \sin\theta(t) - kJ \theta(t) - \rho J \int_{t_0}^t \theta(t) dt - \eta J \dot{\theta}(t) \quad (\mathbf{A1.1})$$

The net torque acting at the joint is,

$$\tau_{net} = J \ddot{\theta}(t) \quad (\mathbf{A1.2})$$

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<sup>[1]</sup> Johansson, R., M. Magnusson, and M. Akesson. "Identification of Human Postural Dynamics." IEEE Transactions on Biomedical Engineering, 1988, 858-69.

Where,

$J$  – Angular moment of inertia

$\ddot{\Theta}(t)$  – Angular acceleration

Also the torque applied by the gravity can be written as,

$$\tau_{net} = mgl \sin\theta(t) \quad (\text{A1.3})$$

Here  $l$  is the length of the pendulum.

For equilibrium the equation (A1.2) and (A1.3) must be equal. Therefore,

$$J\ddot{\Theta}(t) = mgl \sin\theta(t) \quad (\text{A1.4})$$

The complete equation for the pendulum which includes  $T_d$  and  $T_{bal}$  can be written as,

$$J\ddot{\Theta}(t) = mgl \sin\theta(t) + T_{bal}(t) + T_d(t) \quad (\text{A1.5})$$

Substituting for  $T_{bal}(t)$  from equation (A1.1) into the equation (A1.5). We get,

$$J\ddot{\Theta}(t) = mgl \sin\theta(t) - mgl \sin\theta(t) - kJ\theta(t) - \rho J \int_{t_0}^t \theta(t) dt - \eta J \dot{\Theta}(t) + T_d(t)$$

Reduces to,

$$J\ddot{\Theta}(t) = -kJ\theta(t) - \rho J \int_{t_0}^t \theta(t) dt - \eta J \dot{\Theta}(t) + T_d(t) \quad (\text{A1.6})$$

Taking Laplace transform on both sides we get,

$$Js^2\theta(s) = -kJ\theta(s) - \frac{\rho J\theta(s)}{s} - \eta Js\theta(s) + T_d(s) \quad (\text{A1.7})$$

Simplifying,

$$\frac{\theta(s)}{T_d(s)} = \frac{s\left(\frac{1}{J}\right)}{s^3 + \eta s^2 + ks + \rho} \quad (\text{A1.8})$$

At the equilibrium point i.e. at  $\theta \approx 0$ . We can approximate the  $\sin\theta \approx \theta$ .

Therefore the equation (A1.5) can be written as,

$$J\ddot{\Theta}(t) = mgl\theta(t) + T_{bal}(t) + T_d(t)$$

Applying Laplace transform we get,

$$Js^2\theta(s) = mgl\theta(s) + T_{bal}(s) + T_d(s)$$

Rearranging we get,

$$T_{bal}(s) = (Js^2 - mgl)\theta(s) - T_d(s) \quad (\text{A1.9})$$

Substituting equation (A1.8) in equation (A1.9) we get,

$$T_{bal}(s) = (Js^2 - mgl) \left( \frac{s \left( \frac{1}{J} \right) T_d(s)}{s^3 + \eta s^2 + ks + \rho} \right) - T_d(s) \quad (\text{A1.10})$$

Simplifying we get the final transfer function,

$$\frac{T_{bal}(s)}{T_d(s)} = \frac{\eta s^2 + \left( k + \frac{g}{l} \right) s + \rho}{s^3 + \eta s^2 + ks + \rho} \quad (\text{A1.11})$$

Equation (A1.11) gives the inverted pendulum transfer function used for this study. For model 1 analysis the denominator of the equation (A1.11) can be compared to the denominator of the AR (3) model transfer function in continuous form. For example the denominator of AR (3) model transfer function in continuous form obtained for healthy subject 1 in EO condition is,

$$A(s) = s^3 + 18.58 s^2 + 210 s + 113.3 \quad (\text{A1.12})$$

It can be seen from equation (A1.12) that the coefficients can be compared to the three parameters from the transfer function denominator ( $\eta, k, \rho$ ). For instance, from the equation (A1.12) the three constants are,

$$\eta = 18.58$$

$$k = 210$$

$$\rho = 113.3$$

From the above constants the swiftness ( $f$ ), damping parameter ( $P$ ) and stiffness parameter ( $K$ ) are calculated as shown below,

$$\text{Swiftness, } f = \sqrt[3]{113.3} = 4.838 \text{ rad/sec}$$

$$\text{Damping parameter, } P = \frac{18.58}{4.838} = 3.8404$$

$$\text{Stiffness parameter, } K = \frac{210}{(4.838)^2} = 8.971$$

These above three parameters are used for analyzing the postural control system.

**A1.2. Fit percentage of the model.** The fit percentage for the identified models using the measured data is calculated by using the following equation:

$$\mathbf{Fit \% = \left(1 - \frac{|y - \hat{y}|}{|y - \bar{y}|}\right) * 100} \quad \mathbf{(A1.13)}$$

Where,

$y$  – Observed experimental output at a time ‘t’.

$\hat{y}$  – Model output obtained by the identified system at time ‘t’.

$\bar{y}$  – Mean of the observed experimental data for the entire trial duration.

**A.2. Model 2 analysis.** The determination of natural frequency ( $\mathbf{w_o}$ ) and damping ratio ( $\mathbf{\zeta}$ ) was done as follows:

For a second order transfer function the standard form is written as,

$$\frac{X(s)}{U(s)} = \frac{G \cdot w_o^2}{s^2 + 2 s w_o \zeta + w_o^2} \quad \mathbf{(A1.14)}$$

The transfer function denominator obtained from ARMA (2, 1) model has the same form as the denominator of the equation (A1.14). For instance the denominator of the transfer function obtained from the ARMA (2, 1) model identified for healthy subject 1 in EO condition is,

$$s^2 + 3.012 s + 6.136 \quad \mathbf{(A1.15)}$$

From this we get,

$$w_o = \sqrt{6.136} = 2.477 \text{ rad/sec}$$

$$\text{Or } w_o = 0.39 \text{ Hz}$$

For damping ratio we get,

$$2 w_o \zeta = 3.012 \quad \mathbf{(A1.16)}$$

Hence simplifying we get,

$$\zeta = 0.6079$$

These two parameters are used for analyzing the COP time series data using the ARMA (2, 1) model.

*Appendix B. Tables*

**Table B.1. Swiftness, stiffness and damping parameters extracted from AR (3) model for healthy controls in EO condition.**

<b>Subject number</b>	<b>Swiftness, <math>f</math> (rad/sec)</b>	<b>Stiffness parameter (<math>K</math>)</b>	<b>Damping parameter (<math>P</math>)</b>
1	4.84	8.97	3.84
2	4.32	23.12	4.06
3	4.54	11.74	4.65
4	4.09	14.00	4.11
5	3.79	11.17	4.33
6	5.31	9.63	2.37
7	5.98	9.17	2.39
8	4.87	8.30	1.88
9	5.28	8.20	3.26
10	7.16	7.19	5.15
11	4.90	33.24	8.75
12	4.39	10.41	6.22
13	5.14	8.38	2.31
14	5.89	14.37	6.32
15	4.44	26.55	2.87
16	6.20	7.59	5.34
17	6.28	5.93	2.03
18	5.48	8.56	2.96
19	5.43	7.75	4.09
20	6.24	7.39	4.86
21	4.80	9.90	3.98
<b>Mean</b>	<b>5.21</b>	<b>11.98</b>	<b>4.08</b>
<b>Standard Deviation (SD)</b>	<b>0.85</b>	<b>7.07</b>	<b>1.68</b>

**Table B.2. Swiftness, stiffness and damping parameters extracted from AR (3) model for Mild PD subjects in EO condition.**

Subject number	Swiftness, $f$ (rad/sec)	Stiffness parameter ( $K$ )	Damping parameter ( $P$ )
1	3.66	12.61	3.84
2	5.24	5.51	1.49
3	2.88	65.06	3.14
4	5.19	6.65	2.74
5	4.86	8.58	3.04
6	5.95	10.99	5.60
7	4.89	7.83	2.39
8	4.22	10.26	4.74
9	4.20	28.89	2.07
10	4.44	28.39	5.93
11	7.60	12.00	3.93
12	5.23	13.84	5.26
13	4.40	12.24	3.17
<b>Mean</b>	<b>4.83</b>	<b>17.14</b>	<b>3.64</b>
<b>Standard Deviation (SD)</b>	<b>1.14</b>	<b>16.16</b>	<b>1.39</b>

**Table B.3. Swiftness, stiffness and damping parameters extracted from AR (3) model for Moderate PD subjects in EO condition.**

Subject number	Swiftness, $f$ (rad/sec)	Stiffness parameter ( $K$ )	Damping parameter ( $P$ )
1	3.2334	54.73	3.16
2	4.5502	4.29	1.36
3	5.8047	5.17	2.10
4	4.8582	9.59	7.65
5	3.5343	9.53	0.43
6	4.6944	34.07	7.41
7	3.6029	23.30	2.08
8	4.119	27.70	2.41
9	2.4053	45.36	1.88
10			4.80
<b>Mean</b>	<b>4.09</b>	<b>23.75</b>	<b>3.33</b>
<b>Standard Deviation (SD)</b>	<b>1.01</b>	<b>18.29</b>	<b>2.49</b>

**Table B.4. Swiftness, stiffness and damping parameters extracted from AR (3) model for healthy controls in EC condition.**

<b>Subject number</b>	<b>Swiftness, <math>f</math> (rad/sec)</b>	<b>Stiffness parameter (<math>K</math>)</b>	<b>Damping parameter (<math>P</math>)</b>
1	4.98	7.93	2.33
2	5.27	15.84	2.94
3	5.88	4.63	2.61
4	4.08	13.47	2.26
5	4.84	7.49	3.98
6	4.70	12.92	2.33
7	6.25	5.59	1.95
8	4.75	6.83	1.33
9	5.95	6.41	2.08
10	6.26	8.20	5.00
11	4.19	7.17	4.55
12	4.68	5.11	1.50
13	6.58	13.97	5.38
14	5.25	11.35	1.76
15	6.06	4.63	2.98
16	6.66	7.22	1.88
17	5.11	8.39	2.18
18	5.29	10.00	3.40
19	5.90	7.21	4.41
20	6.14	9.92	2.75
21	4.44		
<b>Mean</b>	<b>5.39</b>	<b>8.71</b>	<b>2.88</b>
<b>Standard Deviation (SD)</b>	<b>0.79</b>	<b>3.27</b>	<b>1.19</b>



**Table B.5. Swiftness, stiffness and damping parameters extracted from AR (3) model for Mild PD subjects in EC condition.**

<b>Subject number</b>	<b>Swiftness, <math>f</math> (rad/sec)</b>	<b>Stiffness parameter (<math>K</math>)</b>	<b>Damping parameter (<math>P</math>)</b>
1	4.23	9.90	2.68
2	6.19	4.09	0.98
3	4.74	23.60	1.49
4	4.61	7.93	2.01
5	5.59	6.12	2.31
6	5.92	5.58	3.74
7	5.37	6.36	1.87
8	4.81	5.07	3.31
9	4.42	18.67	2.51
10	6.16	13.01	4.01
11	7.50	5.11	2.89
12	4.78	11.03	3.19
13	4.98	12.05	2.41
<b>Mean</b>	<b>5.33</b>	<b>9.89</b>	<b>2.57</b>
<b>Standard Deviation (SD)</b>	<b>0.92</b>	<b>5.84</b>	<b>0.87</b>

**Table 3.7. Swiftness, stiffness and damping parameters extracted from AR (3) model for Moderate PD subjects in EC condition.**

<b>Subject number</b>	<b>Swiftness, <math>f</math> (rad/sec)</b>	<b>Stiffness parameter (<math>K</math>)</b>	<b>Damping parameter (<math>P</math>)</b>
1	6.47	12.47	2.11
2	5.52	4.34	0.76
3	5.02	8.39	2.00
4	4.03	10.35	7.16
5	7.40	14.29	0.45
6	4.28	15.05	5.33
7	5.55	14.41	1.69
8	4.37	6.09	2.03
9	5.01	26.72	1.51
10	5.44	17.88	1.92
<b>Mean</b>	<b>5.31</b>	<b>13.00</b>	<b>2.50</b>
<b>Standard Deviation (SD)</b>	<b>1.03</b>	<b>6.42</b>	<b>2.10</b>

**Table B.6. Natural frequency and damping ratio extracted from ARMA (2, 1) model for  
Healthy controls in EO condition.**

<b>Subject number</b>	<b>Natural frequency (Hz)</b>	<b>Damping ratio</b>
1	0.39	0.61
2	0.16	1.00
3	0.34	0.83
4	0.32	0.86
5	0.30	0.61
6	0.56	0.46
7	0.62	0.54
8	0.57	0.32
9	0.48	0.48
10	0.52	0.94
11	0.04	1.00
12	0.29	0.99
13	0.55	0.39
14	0.11	1.00
15	0.18	1.00
16	0.28	1.00
17	0.72	0.33
18	0.52	0.59
19	0.43	0.68
20	0.47	0.81
21	0.40	0.69
<b>Mean</b>	<b><i>0.39</i></b>	<b><i>0.72</i></b>
<b>Standard Deviation (SD)</b>	<b><i>0.18</i></b>	<b><i>0.24</i></b>

**Table B.7. Natural frequency and damping ratio extracted from ARMA (2, 1) model for Mild PD controls in EO condition.**

<b>Subject number</b>	<b>Natural frequency (Hz)</b>	<b>Damping ratio</b>
1	0.30	0.58
2	0.70	0.17
3	0.15	1.00
4	0.51	0.35
5	0.44	0.47
6	0.20	1.00
7	0.52	0.32
8	0.32	0.65
9	0.52	0.93
10	0.07	1.00
11	0.31	1.00
12	0.18	1.00
13	0.42	0.58
<b>Mean</b>	<b>0.36</b>	<b>0.70</b>
<b>Standard Deviation (SD)</b>	<b>0.18</b>	<b>0.31</b>

**Table 3.10. Natural frequency and damping ratio extracted from ARMA (2, 1) model for Moderate PD controls in EO condition.**

<b>Subject number</b>	<b>Natural frequency (Hz)</b>	<b>Damping ratio</b>
1	0.10	1.00
2	0.62	0.11
3	0.64	0.24
4	0.12	1.00
5	0.05	0.22
6	0.53	1.00
7	0.37	0.94
8	0.38	0.91
9	0.18	1.00
10		1.00
<b>Mean</b>	<b>0.33</b>	<b>0.74</b>
<b>Standard Deviation (SD)</b>	<b>0.23</b>	<b>0.38</b>

**Table B.8. Natural frequency and damping ratio extracted from ARMA (2, 1) model for Healthy controls in EC condition.**

<b>Subject number</b>	<b>Natural frequency (Hz)</b>	<b>Damping ratio</b>
1	0.54	0.35
2	0.51	0.93
3	0.58	0.28
4	0.44	0.49
5	0.38	0.54
6	0.46	0.59
7	0.70	0.30
8	0.64	0.20
9	0.66	0.32
10	0.46	0.88
11	0.04	1.00
12	0.33	0.63
13	0.86	0.22
14	0.16	1.00
15	0.69	0.56
16	0.62	0.40
17	0.59	0.30
18	0.59	0.38
19	0.53	0.73
20	0.47	0.75
21	0.44	0.44
<b>Mean</b>	<b>0.51</b>	<b>0.54</b>
<b>Standard Deviation (SD)</b>	<b>0.18</b>	<b>0.26</b>

**Table B.9. Natural frequency and damping ratio extracted from ARMA (2, 1) model for Mild PD controls in EC condition.**

<b>Subject number</b>	<b>Natural frequency (Hz)</b>	<b>Damping ratio</b>
1	0.42	0.41
2	1.00	0.11
3	0.63	0.75
4	0.52	0.28
5	0.61	0.29
6	0.51	0.44
7	0.64	0.24
8	0.43	0.28
9	0.49	0.72
10	0.33	1.00
11	0.72	0.42
12	0.43	0.63
13	0.52	0.56
<b>Mean</b>	<b>0.56</b>	<b>0.47</b>
<b>Standard Deviation (SD)</b>	<b>0.17</b>	<b>0.25</b>

**Table B.10. Natural frequency and damping ratio extracted from ARMA (2, 1) model for Moderate PD controls in EC condition.**

<b>Subject number</b>	<b>Natural frequency (Hz)</b>	<b>Damping ratio</b>
1	0.68	0.72
2	1.00	0.08
3	0.59	0.31
4	0.21	1.00
5	1.58	0.39
6	0.25	1.00
7	0.71	0.55
8	0.50	0.20
9	0.65	0.93
10	0.62	0.79
<b>Mean</b>	<b>0.68</b>	<b>0.60</b>
<b>Standard Deviation (SD)</b>	<b>0.39</b>	<b>0.34</b>

**Table B.11. ANOVA results of swiftness parameter**

Analysis of Variance					
Source	Sum Sq.	d. f.	Mean Sq.	F	Prob>F
Group	4.767	2	2.38349	2.74	0.0707
Condition	7.899	1	7.89898	9.07	0.0035
Group*Condition	3.4802	2	1.74008	2	0.1421
Error	70.506	81	0.87044		
Total	83.8375	86			

Constrained (Type III) sums of squares.

**Table B.12. ANOVA results of damping parameter**

Analysis of Variance					
Source	Sum Sq.	d. f.	Mean Sq.	F	Prob>F
Group	5.022	2	2.5108	0.96	0.3863
Condition	21.422	1	21.4223	8.21	0.0053
Group*Condition	0.463	2	0.2313	0.09	0.9153
Error	211.335	81	2.6091		
Total	242.457	86			

Constrained (Type III) sums of squares.

**Table B.13. ANOVA results of stiffness parameter**

Analysis of Variance					
Source	Sum Sq.	d. f.	Mean Sq.	F	Prob>F
Group	842.09	2	421.044	4.32	0.0165
Condition	977.97	1	977.968	10.04	0.0022
Group*Condition	193.35	2	96.674	0.99	0.3751
Error	7791.1	80	97.389		
Total	9569.08	85			

Constrained (Type III) sums of squares.



**Table B.14. ANOVA results of natural frequency**

Analysis of Variance					
Source	Sum Sq.	d. f.	Mean Sq.	F	Prob>F
Group	0.00069	2	0.00035	0.01	0.9906
Condition	0.67768	1	0.67768	18.57	0
Group*Condition	0.06228	2	0.03114	0.85	0.4298
Error	2.91871	80	0.03648		
Total	3.60068	85			

Constrained (Type III) sums of squares.

**Table B.15. ANOVA results of damping ratio**

Analysis of Variance					
Source	Sum Sq.	d. f.	Mean Sq.	F	Prob>F
Group	0.0857	2	0.04285	0.52	0.5957
Condition	0.68123	1	0.68123	8.29	0.0051
Group*Condition	0.01926	2	0.00963	0.12	0.8896
Error	6.74003	82	0.0822		
Total	7.61254	87			

Constrained (Type III) sums of squares.

**Table B.16. Power analysis results representing the number of sample required in EO condition**

	Healthy controls - mild PD	Mild PD - Moderate PD
Swiftness parameter	67	34
Stiffness parameter	27	80
Damping parameter	190	260
Natural frequency	313	17
Damping ratio	1399	592

**Table B.17. Power analysis results representing the number of sample required in EC condition**

	<b>Healthy controls - mild PD</b>	<b>Mild PD - Moderate PD</b>
<b>Swiftness parameter</b>	2026	19913
<b>Stiffness parameter</b>	328	48
<b>Damping parameter</b>	414	1810
<b>Natural frequency</b>	194	27
<b>Damping ratio</b>	194	53

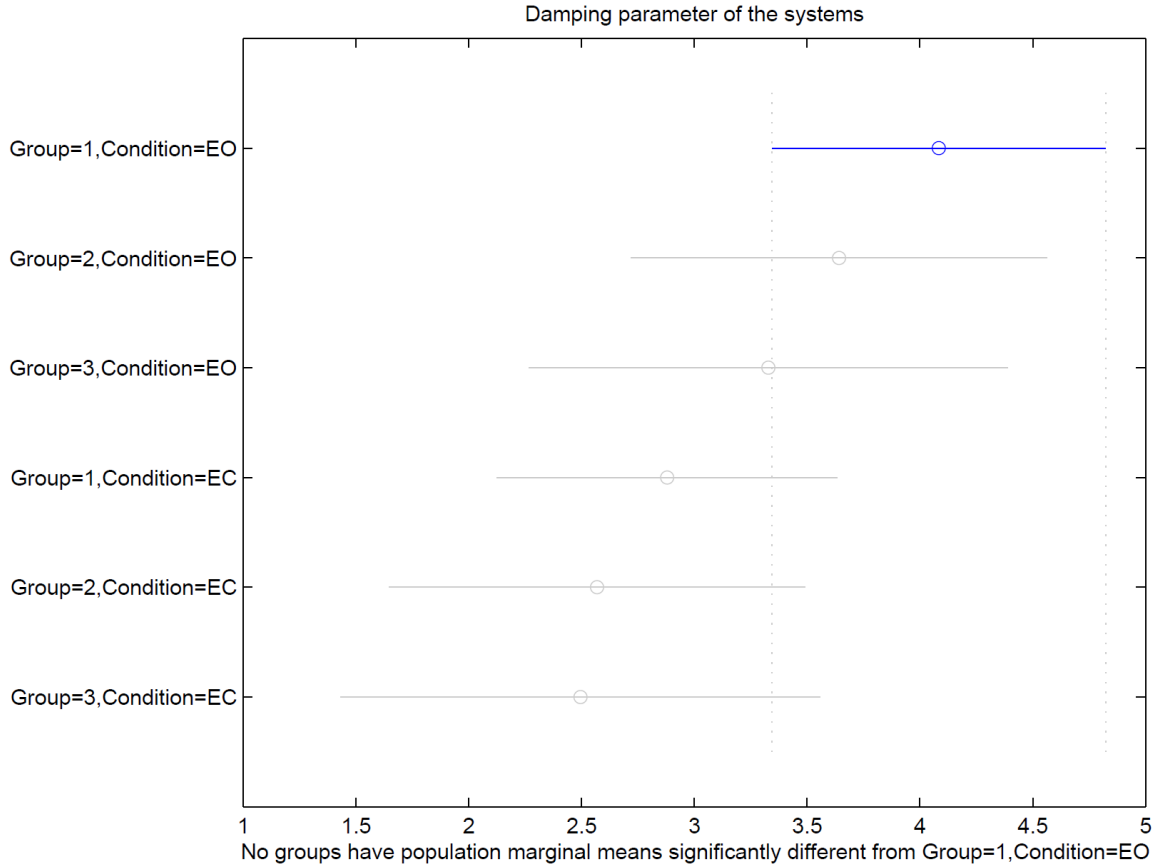
**Table B.18. Akaike's final prediction error for the two models**

Subject number	Model 1 (AR (3))		Model 2 (ARMA (2,1))	
	EO	EC	EO	EC
1	1.94E-03	2.49E-03	1.51E-03	2.33E-03
2	2.41E-03	3.25E-03	1.86E-03	2.64E-03
3	1.07E-03	1.37E-03	7.67E-04	1.11E-03
4	1.42E-03	2.07E-03	1.20E-03	2.24E-03
5	1.00E-03	9.42E-04	8.26E-04	7.31E-04
6	2.00E-03	4.11E-03	1.69E-03	3.69E-03
7	1.84E-03	2.29E-03	1.54E-03	2.06E-03
8	1.81E-03	4.38E-03	1.93E-03	5.79E-03
9	1.20E-03	1.86E-03	8.79E-04	1.58E-03
10	4.86E-03	5.72E-03	3.15E-03	3.64E-03
11	5.10E-03	4.80E-03	3.14E-03	3.04E-03
12	1.69E-03	2.01E-03	1.29E-03	1.61E-03
13	1.94E-03	5.89E-03	1.75E-03	5.66E-03
14	2.33E-03	2.56E-03	1.53E-03	1.72E-03
15	3.33E-03	1.02E-02	2.85E-03	9.13E-03
16	9.96E-04	1.43E-03	7.73E-04	1.14E-03
17	1.68E-03	2.59E-03	1.53E-03	2.60E-03
18	1.38E-03	2.18E-03	1.12E-03	1.97E-03
19	1.64E-03	3.53E-03	1.22E-03	2.41E-03
20	1.81E-03	2.02E-03	1.23E-03	1.41E-03
21	2.56E-03	3.93E-03	2.01E-03	3.47E-03
22	1.58E-03	2.09E-03	1.35E-03	1.96E-03
23	4.37E-03	1.54E-02	4.86E-03	2.02E-02
24	6.47E-03	1.60E-02	6.60E-03	1.92E-02
25	2.26E-03	3.11E-03	1.86E-03	3.14E-03
26	3.02E-03	5.80E-03	2.36E-03	4.63E-03
27	1.77E-03	2.37E-03	1.19E-03	1.76E-03
28	6.33E-03	1.60E-02	5.25E-03	1.43E-02
29	1.86E-03	2.34E-03	1.33E-03	1.83E-03
30	2.47E-03	2.92E-03	2.66E-03	2.64E-03
31	1.63E-03	1.62E-03	1.11E-03	1.12E-03
32	1.03E-02	2.07E-02	6.66E-03	1.43E-02
33	4.77E-03	5.71E-03	3.26E-03	4.66E-03
34	3.80E-03	3.94E-03	3.06E-03	3.34E-03
35	6.60E-03	5.69E-02	6.25E-03	4.23E-02
36	3.34E-03	1.78E-02	4.76E-03	3.17E-02
37	3.71E-03	1.36E-02	3.05E-03	1.21E-02
38	1.71E-03	2.12E-03	1.32E-03	1.56E-03
39	4.51E-02	4.21E-02	8.82E-02	9.97E-02

<b>40</b>	1.81E-03	2.64E-03	1.14E-03	1.68E-03
<b>41</b>	4.81E-03	1.13E-02	4.75E-03	1.09E-02
<b>42</b>	1.23E-02	1.01E-02	1.29E-02	1.03E-02
<b>43</b>	1.21E-02	2.09E-02	1.37E-02	2.39E-02
<b>44</b>	6.09E-03	1.14E-02	5.23E-03	1.04E-02

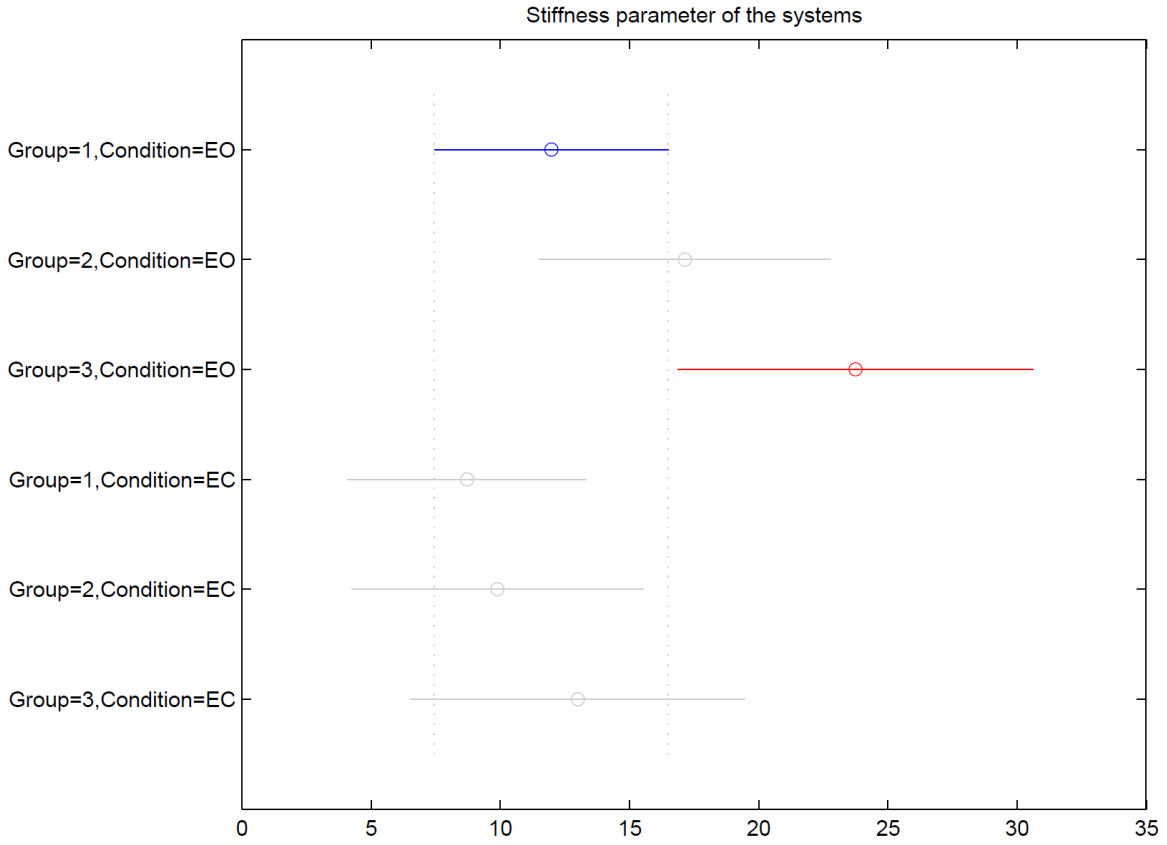
### Appendix C. Figures

The following figures from figure C.1 to C.11 represent the Post-Hoc Tukey Kramer results graphically.



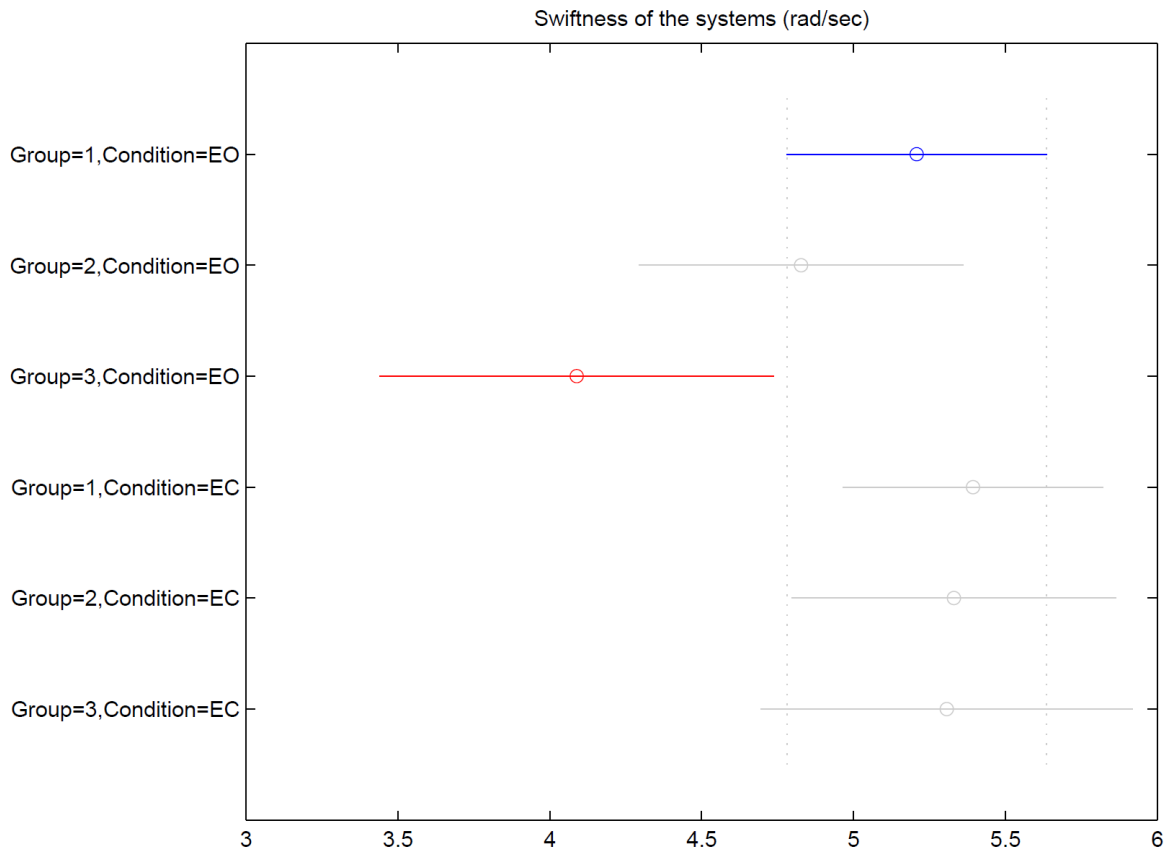
Group 1 - Healthy controls, Group 2 - Mild PD, Group 3 - Moderate PD

**Figure C.1. Post Hoc Tukey Kramer test results for damping parameter represented graphically**



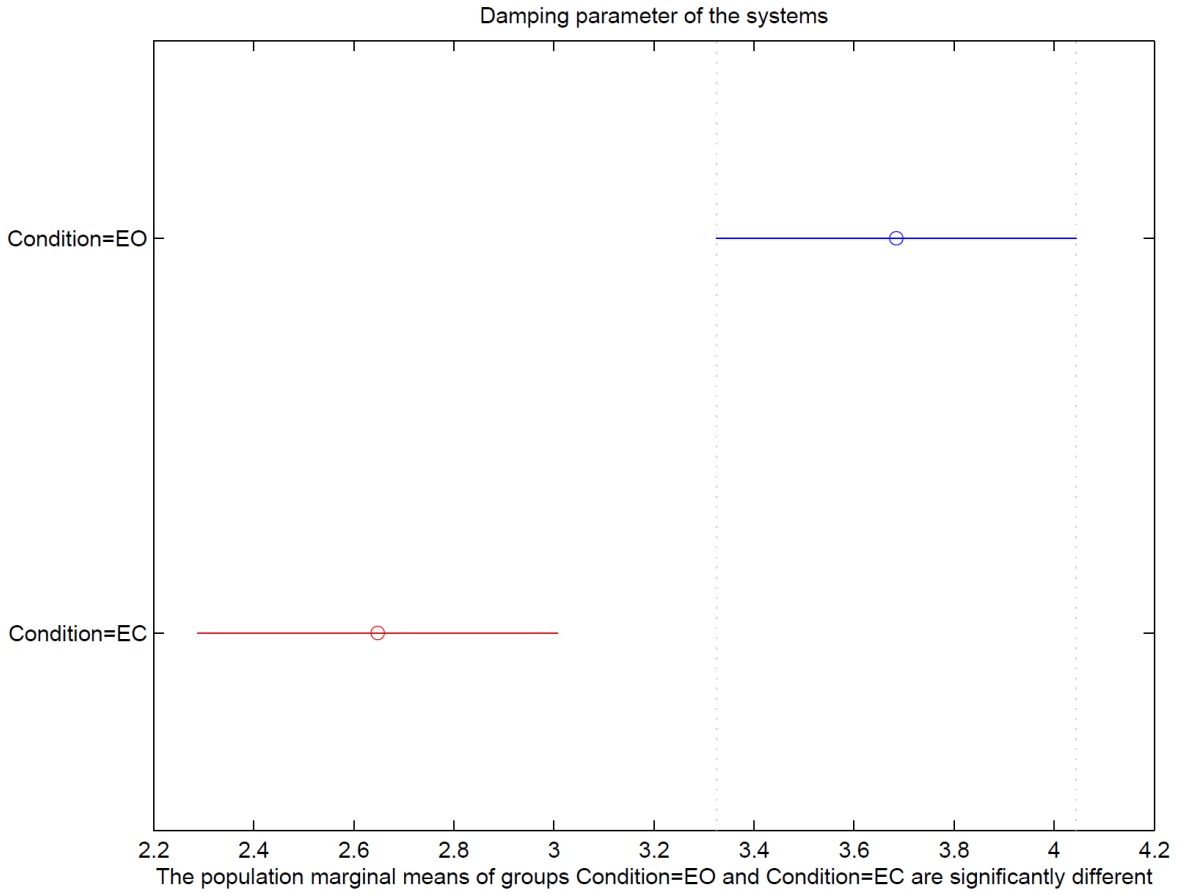
Group 1- Healthy controls, Group 2 - Mild PD, Group 3 - Moderate PD

**Figure C.2. Post Hoc Tukey Kramer test results for stiffness parameter represented graphically**

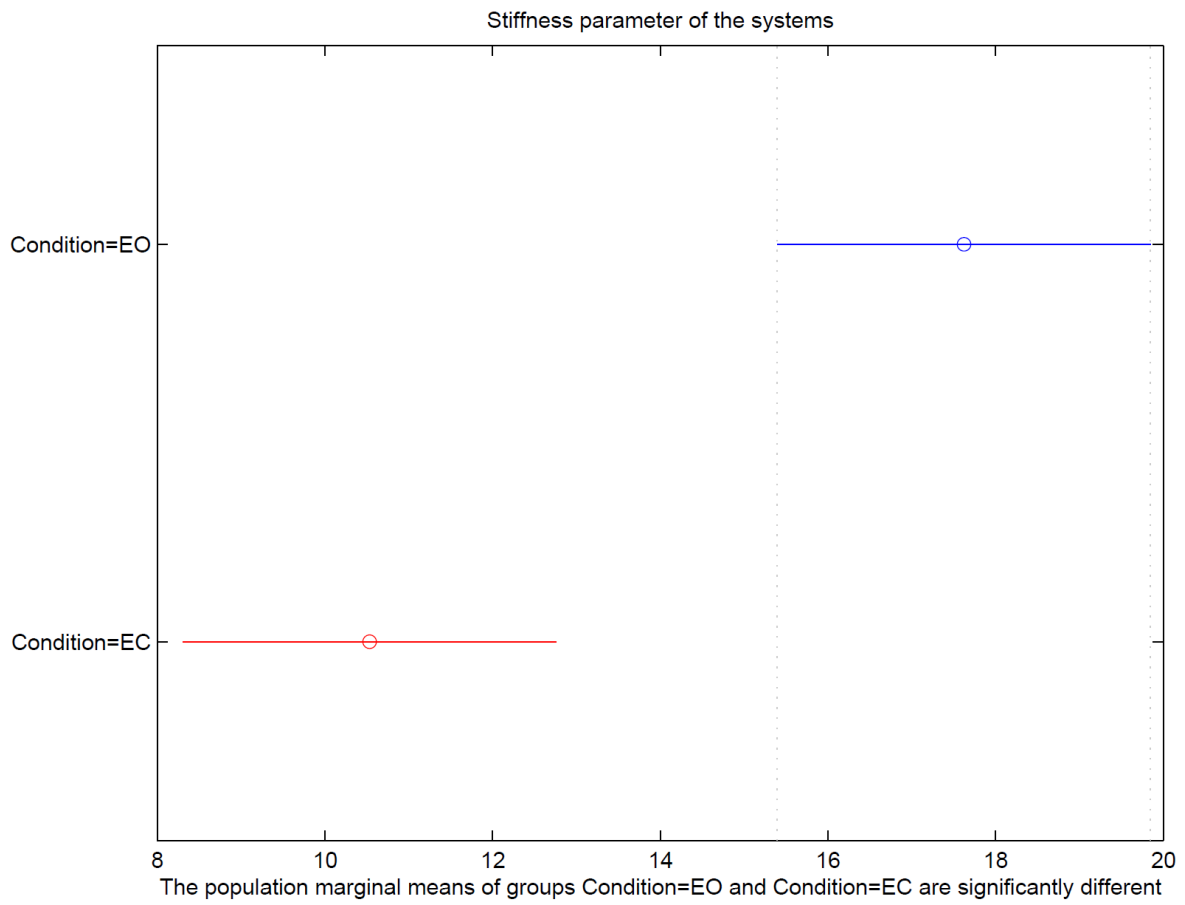


**Figure C.3. Post Hoc Tukey Kramer test results for swiftness parameter represented graphically**

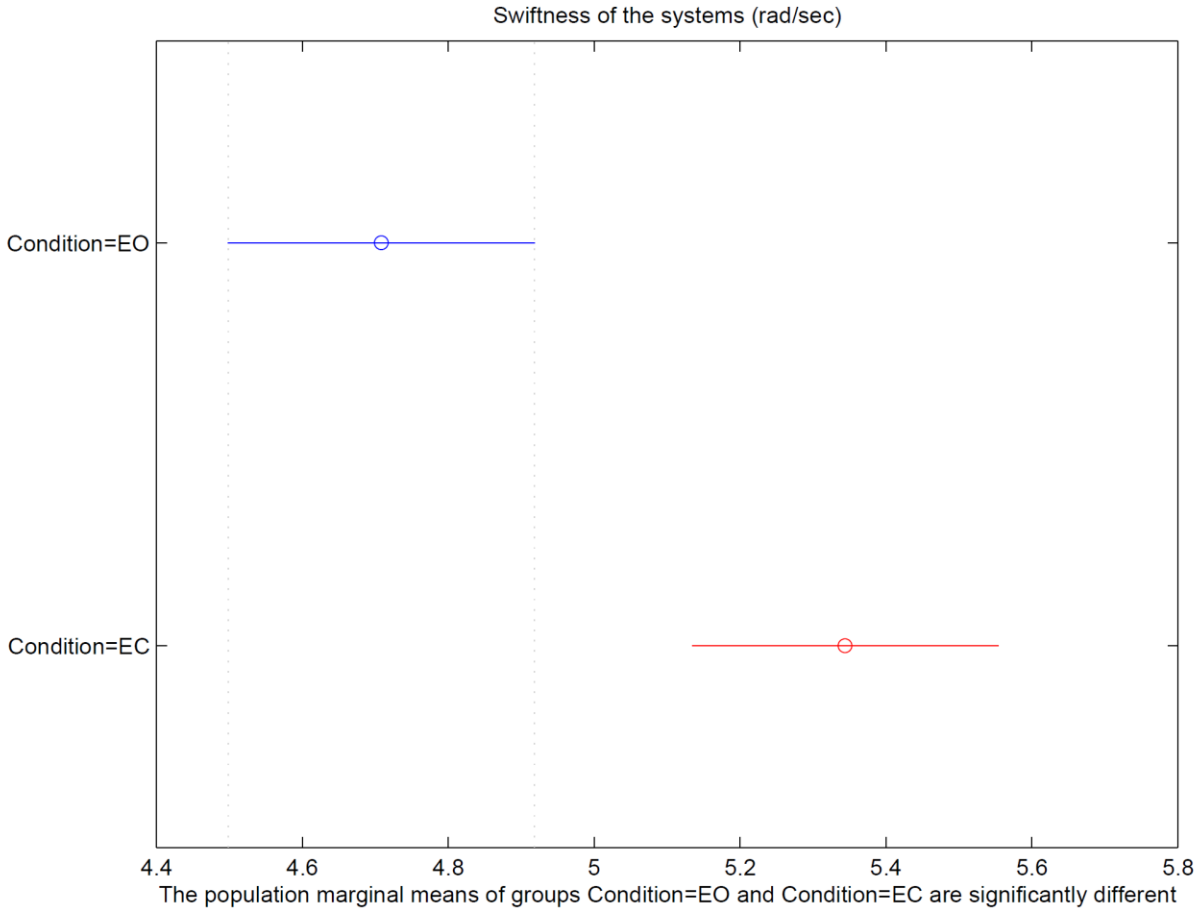




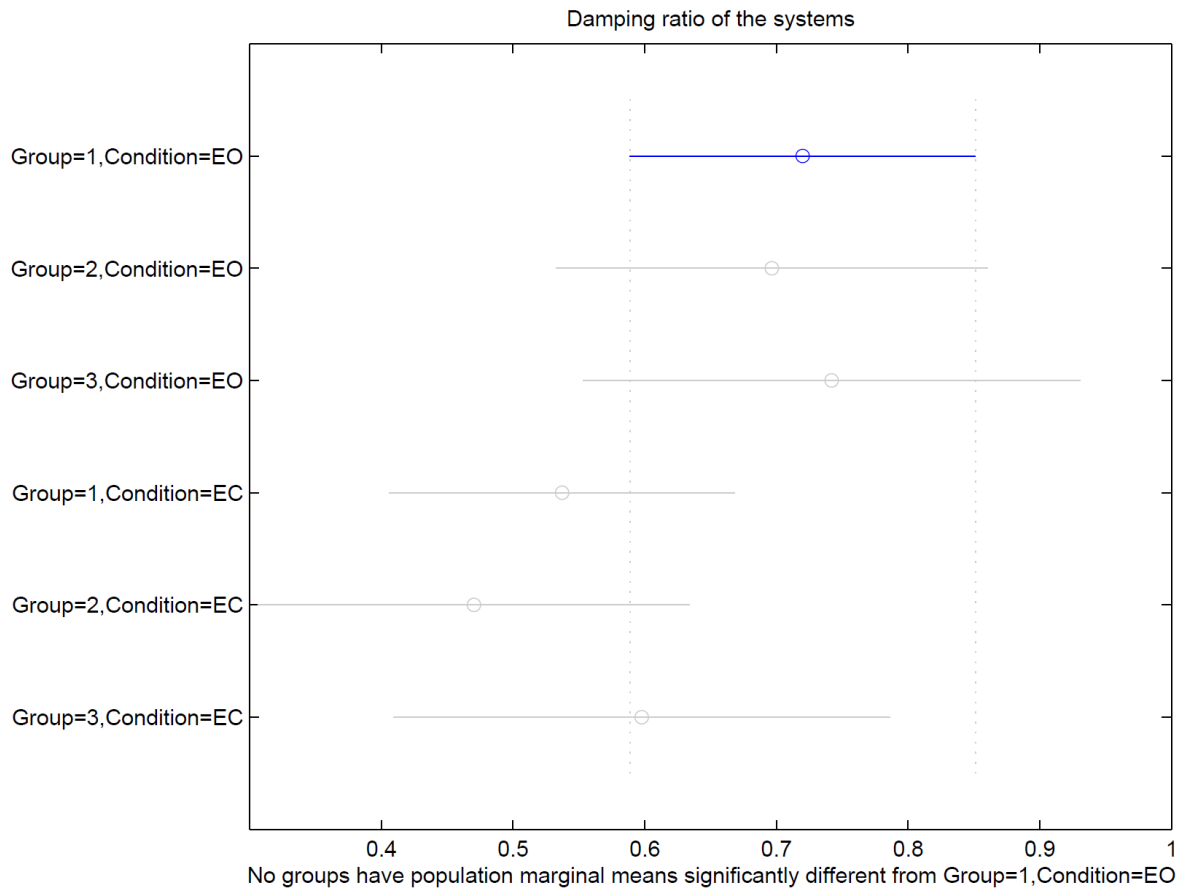
**Figure C.4. Post Hoc Tukey Kramer test results for damping parameter represented graphically between EO and EC conditions for total population**



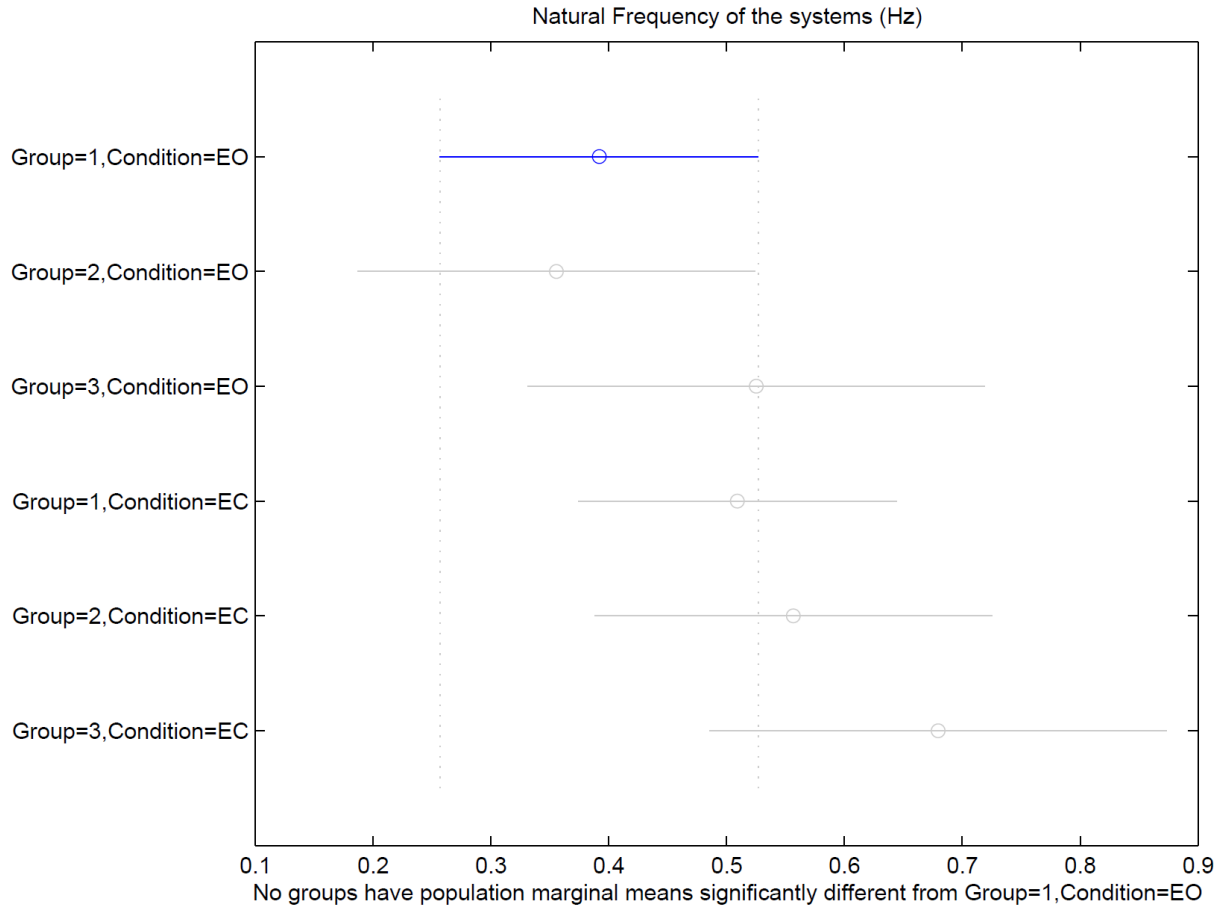
**Figure C.5. Post Hoc Tukey Karmer test results for stiffness parameter represented graphically between EO and EC conditions for total population**



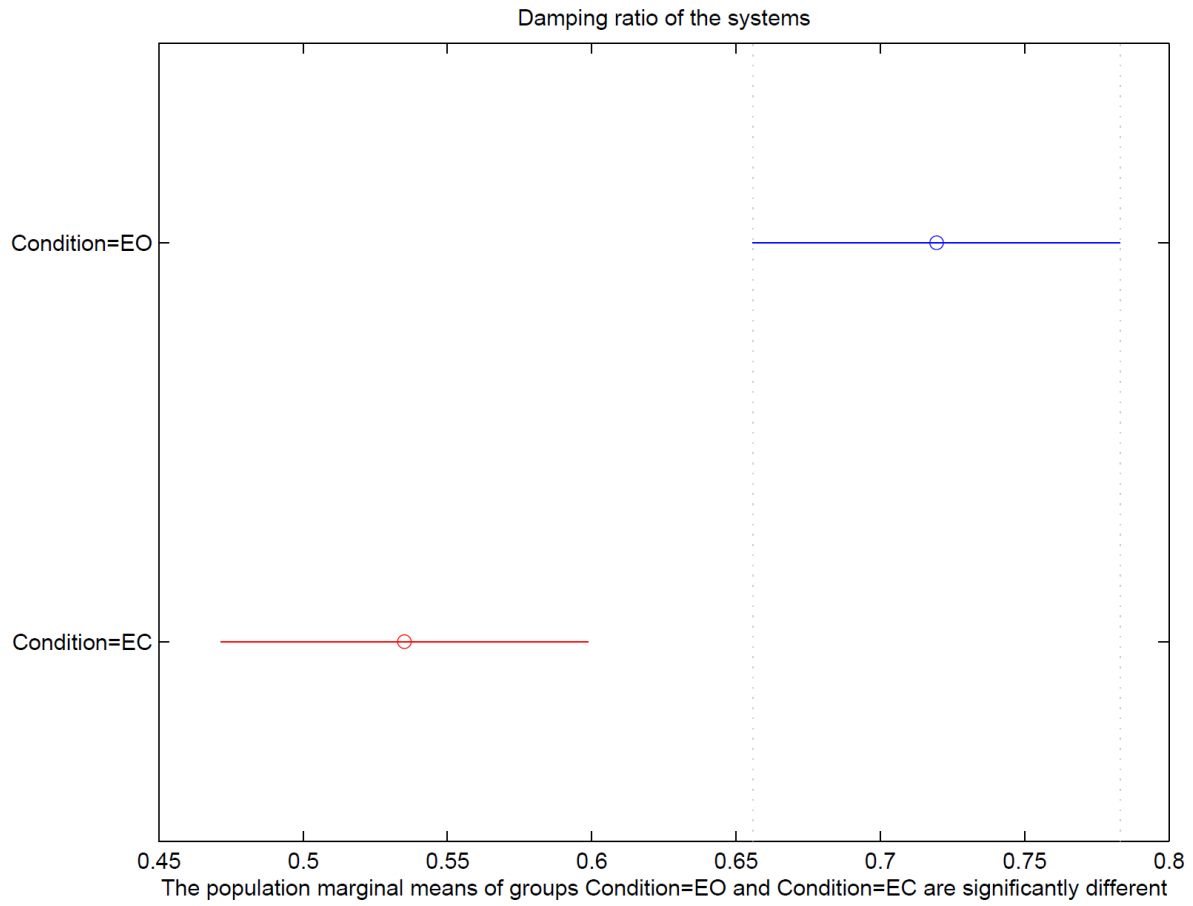
**Figure C.6. Post Hoc Tukey Kramer test results for swiftness parameter represented graphically**



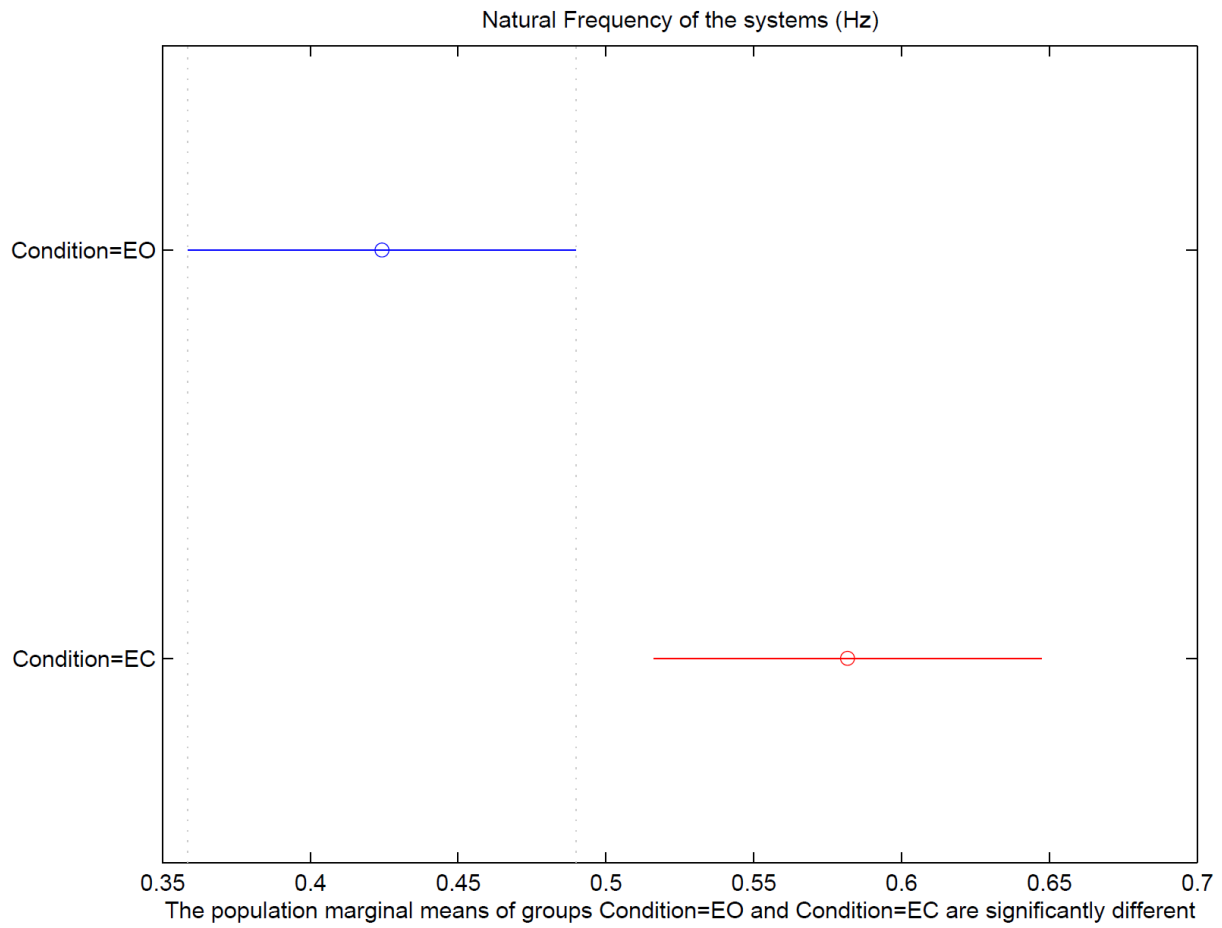
**Figure C.7. Post Hoc Tukey Karmar test results for damping ratio represented graphically**



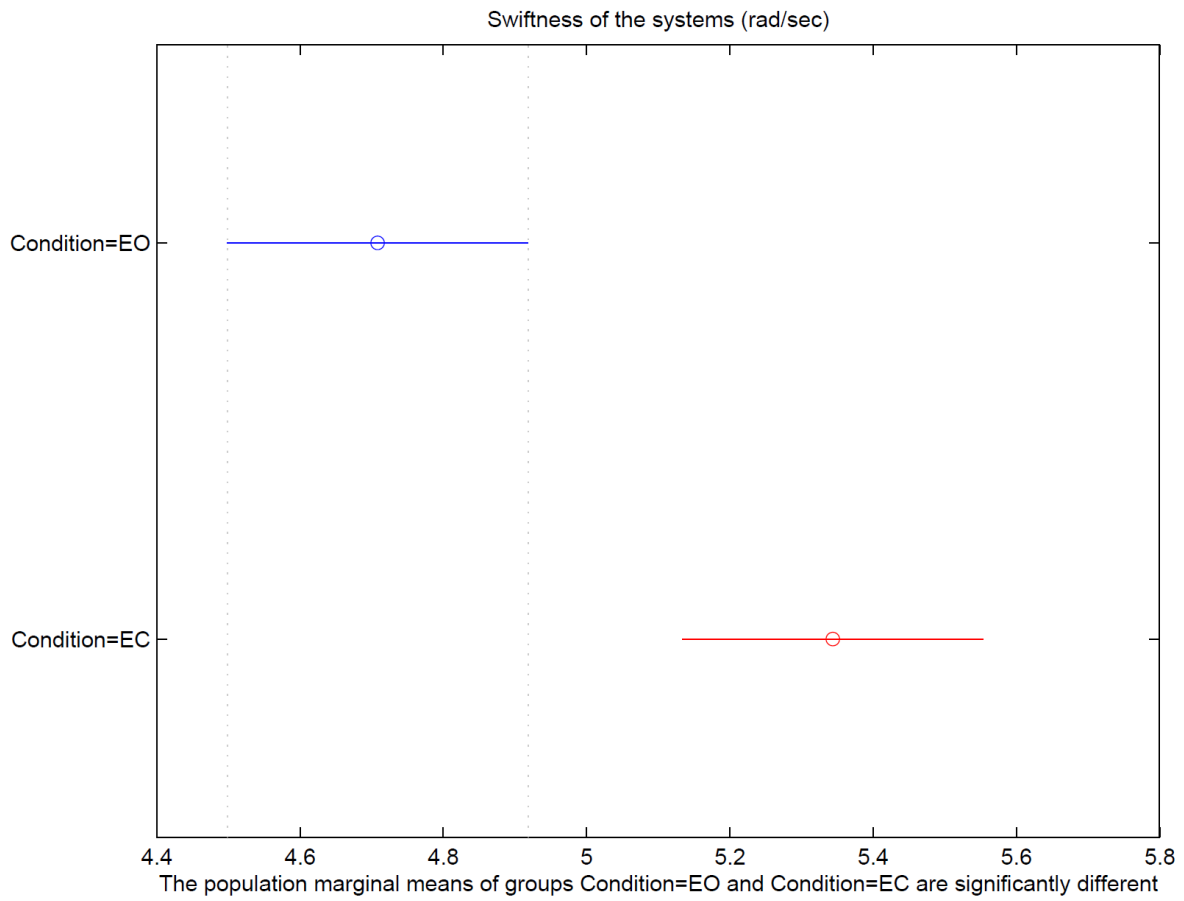
**Figure C.8. Post Hoc Tukey Karmar test results for natural frequency represented graphically**



**Figure C.9. Post Hoc Tukey Karter test results for damping ratio represented graphically between EO and EC conditions for total population**



**Figure C.10. Post Hoc Tukey Kramer test results for natural frequency represented graphically between EO and EC conditions for total population**



**Figure C.11. Post Hoc Tukey Kramer test results for swiftness parameter represented graphically between EO and EC conditions for total population**



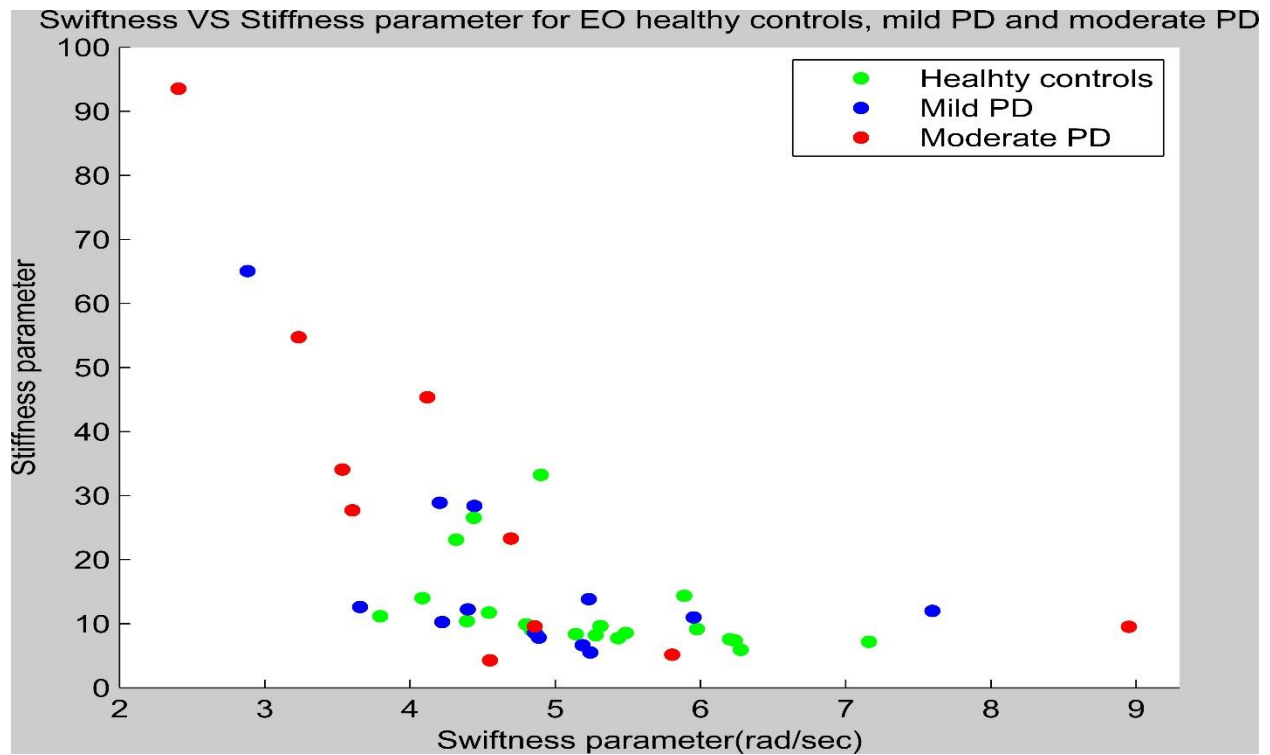


Figure C.12. Scatter plot for stiffness vs swiftness parameter (EO)

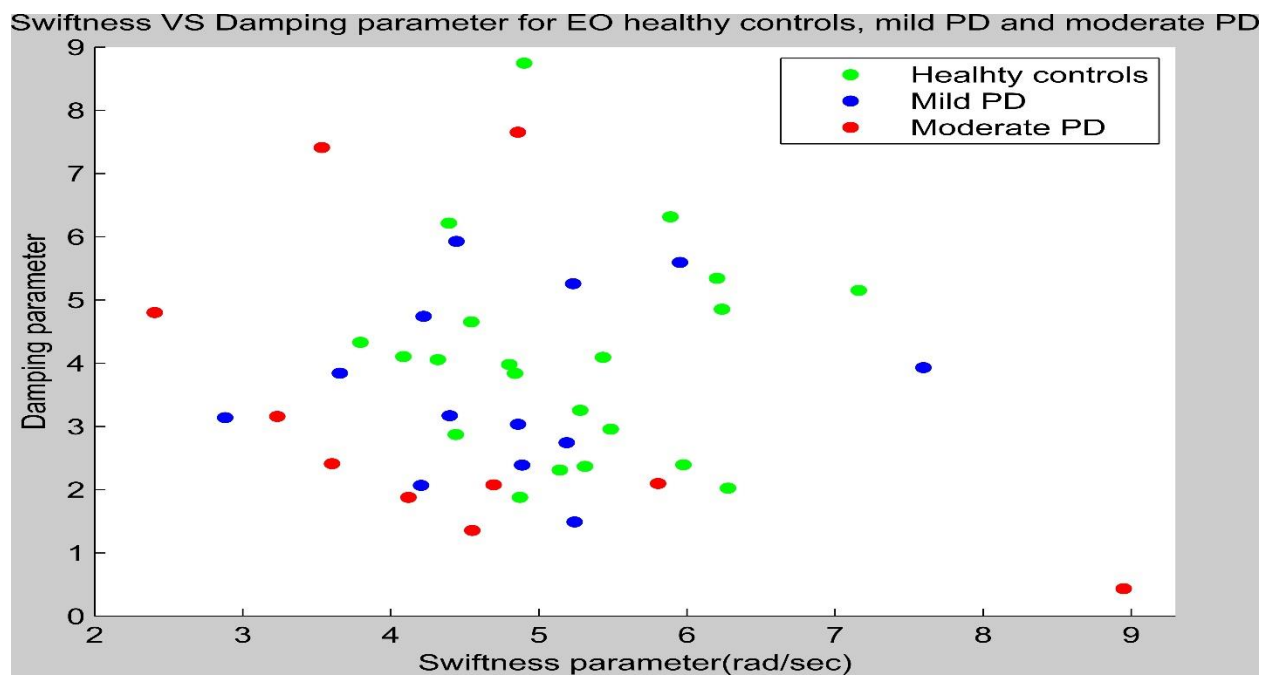


Figure C.13. Scatter plot for damping vs swiftness parameter (EO)

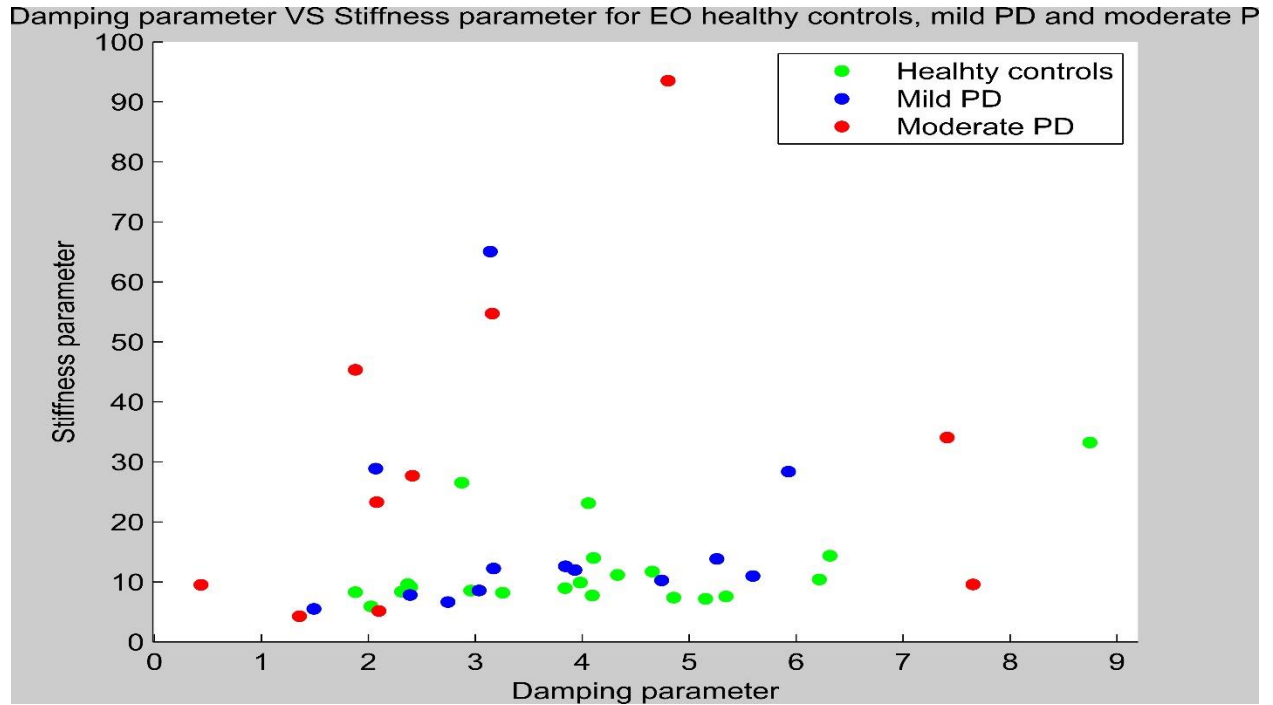


Figure C.14. Scatter plot for stiffness vs damping parameter (EO)

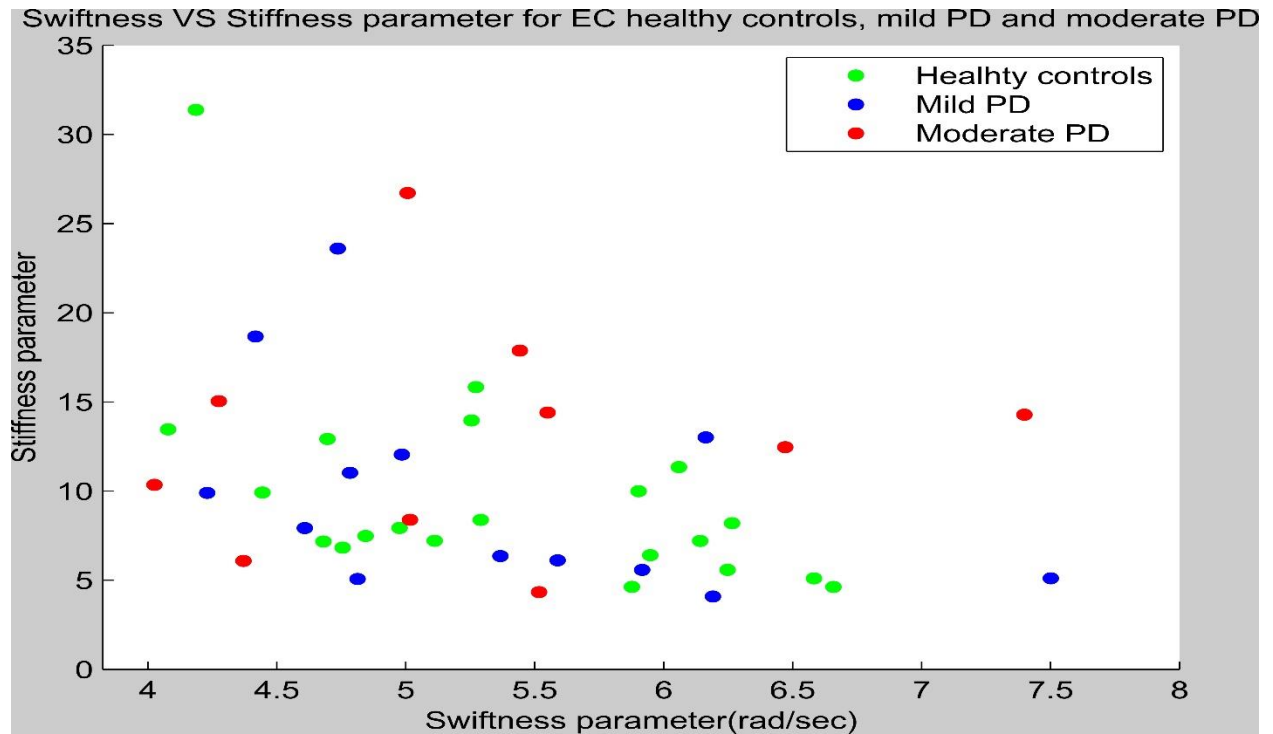


Figure C.15. Scatter plot for stiffness vs swiftness parameter (EC)

Swiftness VS Damping parameter for EC healthy controls, mild PD and moderate PD

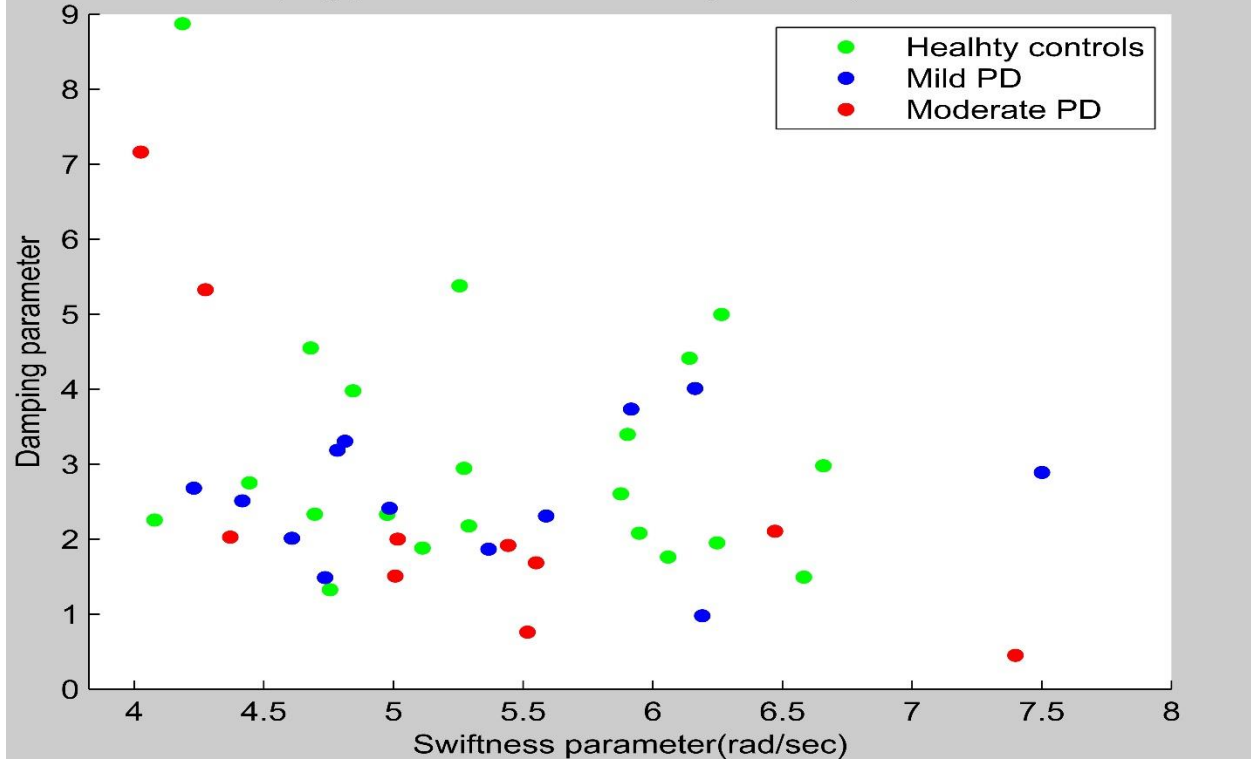


Figure C.16. Scatter plot for damping vs swiftness parameter (EC)

Damping parameter VS Stiffness parameter for EC healthy controls, mild PD and moderate P

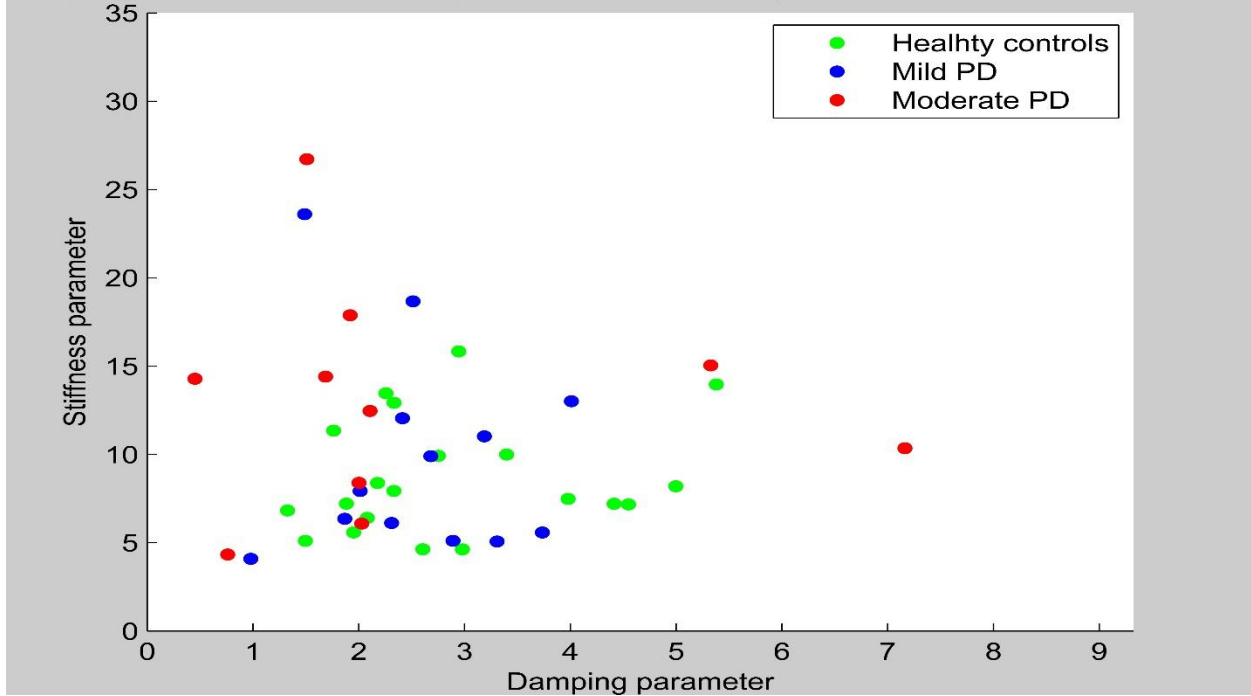
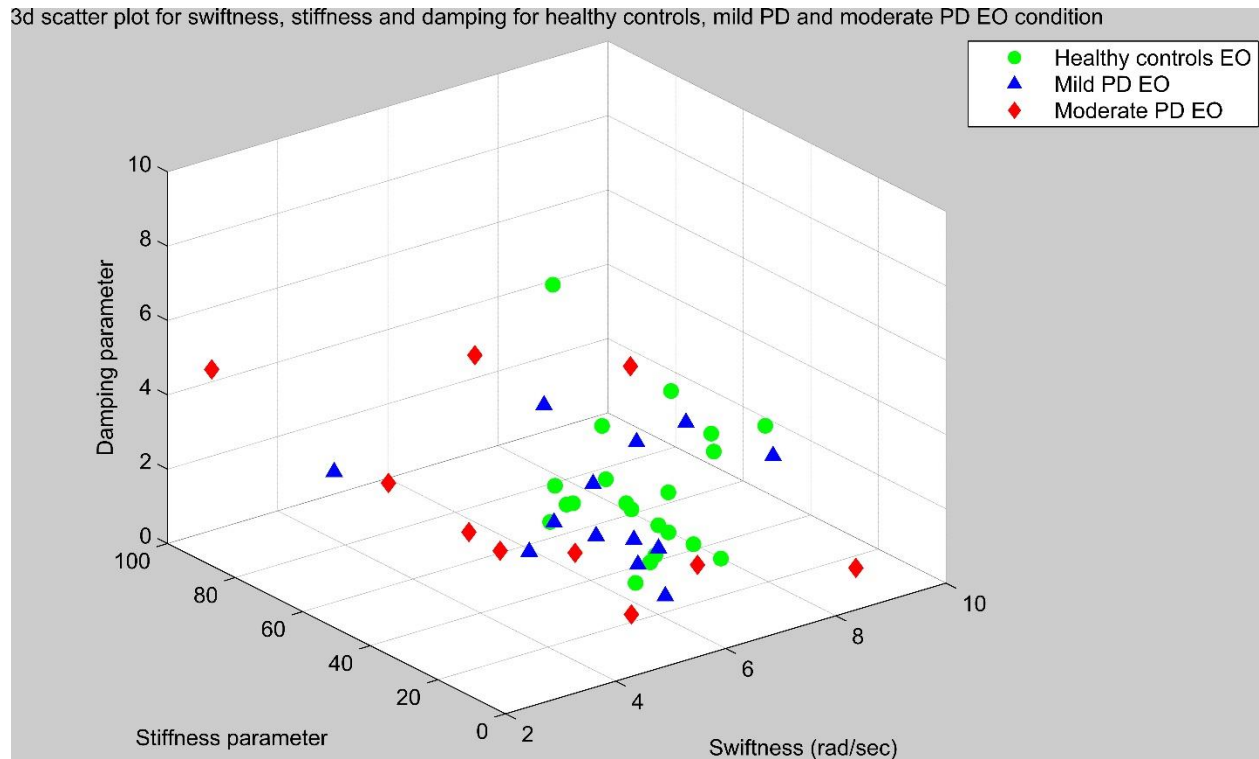
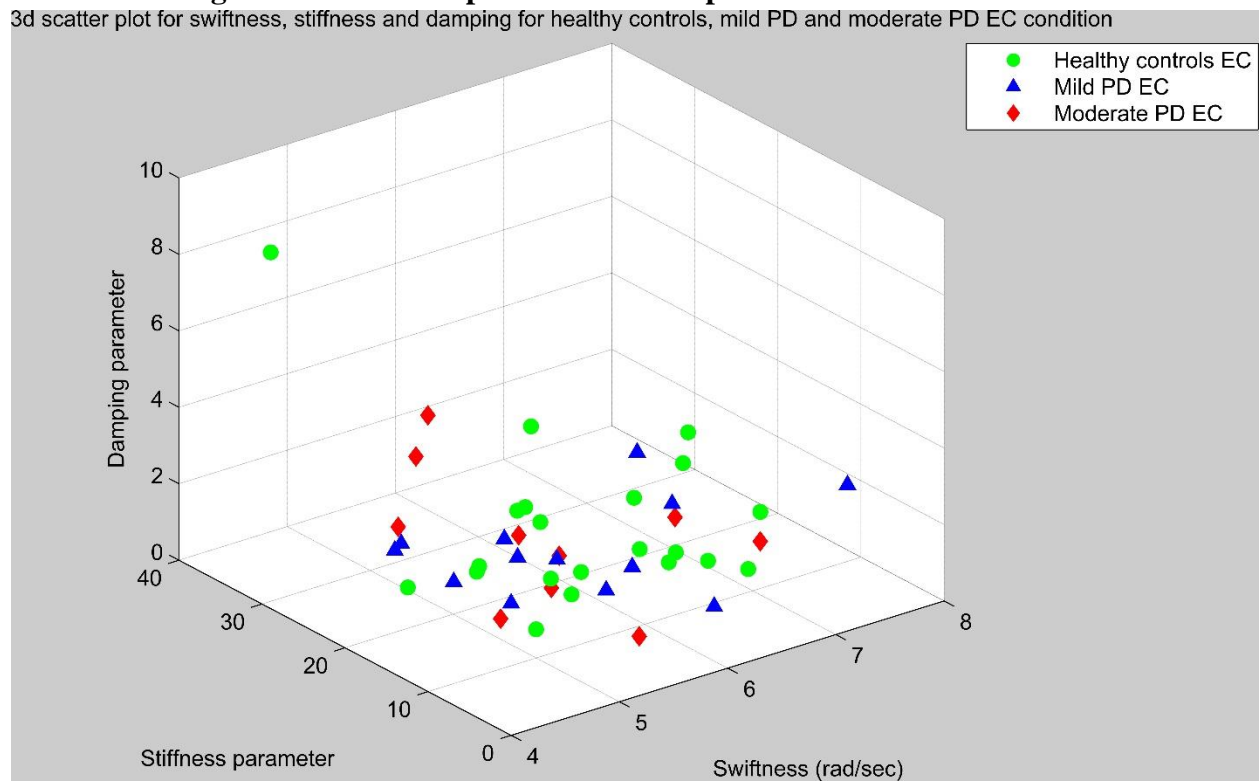


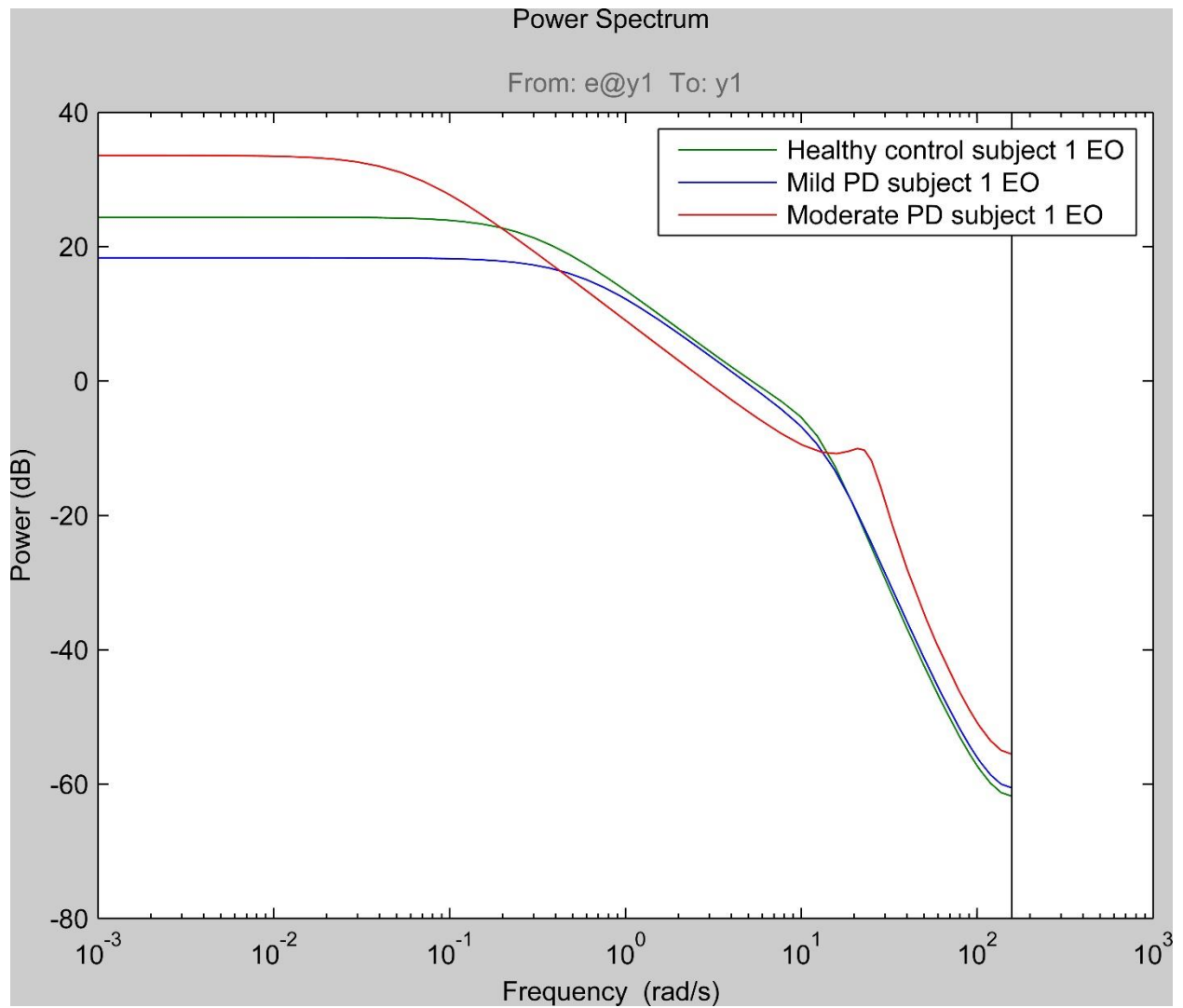
Figure C.17. Scatter plot for stiffness vs damping parameter (EC)



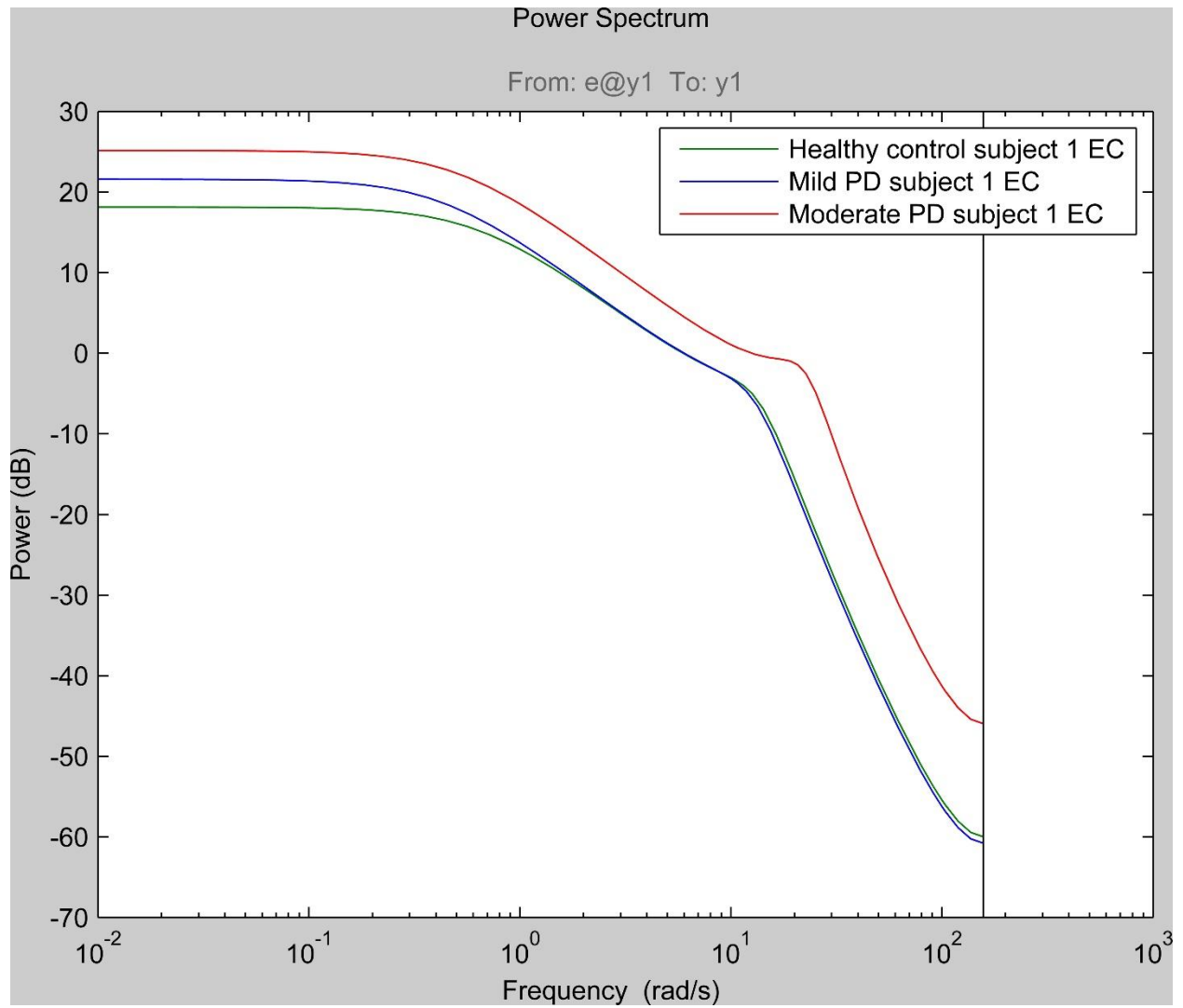
**Figure C.18. Scatter plot for the three parameters in EO condition**



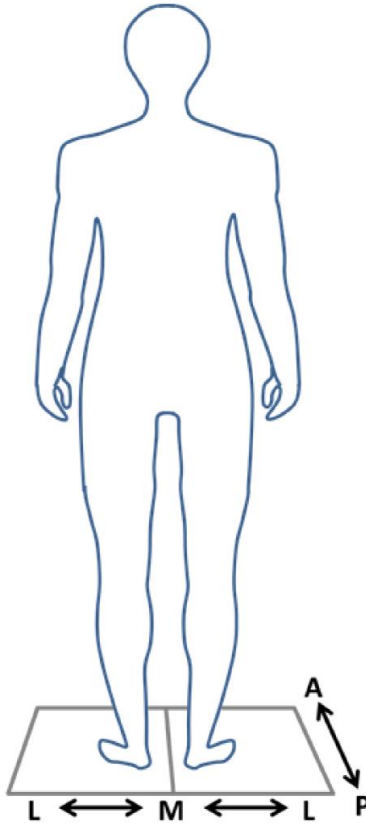
**Figure C.19. Scatter plot for the three parameters in EC condition**



**Figure C.20. Typical output power spectrum of AR (3) models for healthy control, mild PD and moderate PD subjects in EO condition**



**Figure C.21. Typical output power spectrum of AR (3) models for healthy, mild PD and moderate PD subjects in EC condition**



**Figure C.22. Schematic of the experimental setup for postural sway study. This figure represents a subject standing on a force plate setup used for data recording. Reprinted from “Biomechanical markers as indicators of postural instability progression in Parkinson’s disease” (p. 105, appendix), by Barnds, Annaria. N. 2015, The university of Kansas, Reprinted with permission.**

### ***Appendix D. COP calculations***

The following are the parameters obtained from the force plate:

1. Forces ( $F_x, F_y, F_z$ )
2. Moments ( $M_x, M_y, M_z$ ).

The couple for two force vectors acting in the opposite directions in a non-collinear manner is calculated by using the following equation,

$$\mathbf{M} = \mathbf{r} \cdot \mathbf{F}$$

Where,

$r$  - A vector connecting the lines of action of the two force vectors.

$F$  - The second force vector.

Moment of force is calculated as follows,

$$\mathbf{M}_o = \mathbf{r} \cdot \mathbf{F}$$

Where,

$r$  - The vector connecting the origin of the line of action of the force vector

$F$  - The force vector

The total moment about the axis normal to the x, y and z-axis of the force plate is given by,

$$M_x = -F_z \cdot y + F_y \cdot dz + T_x$$

$$M_y = -F_z \cdot x + F_x \cdot dz + T_y$$

$$M_z = -F_x \cdot y + F_y \cdot x + T_z$$

Where,

$dz$  - The distance below the top surface of the force plate below which the origin is located



As the subjects just stand on the force plate, there are no  $T_x$ , and  $T_y$  torques acting. Hence the equations for the  $COP_x$  and  $COP_y$  can be simplified into the following,

$$COP_x = \left( -\frac{M_y + F_x * d_z}{F_z} \right)$$

$$COP_y = \left( \frac{M_x - F_y * d_z}{F_z} \right)$$

Therefore the  $COP$  equation becomes,

$$COP = \sqrt{\left( -\frac{M_y + F_x * d_z}{F_z} \right)^2 + \left( \frac{M_x - F_y * d_z}{F_z} \right)^2}$$

## ***Appendix E. MATLAB codes for the study***

### ***E.1. Code 1. Program for analysis using the AR (3) modelling approach (Model 1).***

```
%Program to analyze the COP time series data in AP direction using the AR
%modelling approach
%Author: Chandrashekara Kaushik Gandur Balagangadhara
clc;
clear all;
close all;
cd('C:\Kaushik\Research\Data\COP_Data_100Hz');      %Set the directory
containing the data
%%
% EYES OPEN CONDITION DATA
%Analysis for eyes open condition
%Healthy controls year 1
data_struc1{1,1} = load('1_1001_EO1.mat');
data_struc1{2,1} = load('1_1001_EO2.mat');
data_struc1{3,1} = load('1_1001_EO3.mat');
data_struc1{1,2} = load('1_1003_EO1.mat');
data_struc1{2,2} = load('1_1003_EO2.mat');
data_struc1{3,2} = load('1_1003_EO3.mat');
data_struc1{1,3} = load('1_1006_EO1.mat');
data_struc1{2,3} = load('1_1006_EO2.mat');
data_struc1{3,3} = load('1_1006_EO3.mat');
data_struc1{1,4} = load('1_1007_EO1.mat');
data_struc1{2,4} = load('1_1007_EO2.mat');
data_struc1{3,4} = load('1_1007_EO3.mat');
data_struc1{1,5} = load('1_1008_EO1.mat');
data_struc1{2,5} = load('1_1008_EO2.mat');
data_struc1{3,5} = load('1_1008_EO3.mat');
data_struc1{1,6} = load('1_1009_EO1.mat');
data_struc1{2,6} = load('1_1009_EO2.mat');
data_struc1{3,6} = load('1_1009_EO3.mat');
data_struc1{1,7} = load('1_1010_EO1.mat');
data_struc1{2,7} = load('1_1010_EO2.mat');
data_struc1{3,7} = load('1_1010_EO3.mat');
data_struc1{1,8} = load('1_1011_EO1.mat');
data_struc1{2,8} = load('1_1011_EO2.mat');
data_struc1{3,8} = load('1_1011_EO3.mat');
data_struc1{1,9} = load('1_1012_EO1.mat');
data_struc1{2,9} = load('1_1012_EO2.mat');
data_struc1{3,9} = load('1_1012_EO3.mat');
data_struc1{1,10} = load('1_1013_EO1.mat');
data_struc1{2,10} = load('1_1013_EO2.mat');
data_struc1{3,10} = load('1_1013_EO3.mat');
data_struc1{1,11} = load('1_1014_EO1.mat');
data_struc1{2,11} = load('1_1014_EO2.mat');
data_struc1{3,11} = load('1_1014_EO3.mat');

%Healthy year 2
data_struc1{1,12} = load('2_1001_EO1.mat');
data_struc1{2,12} = load('2_1001_EO2.mat');
data_struc1{3,12} = load('2_1001_EO3.mat');
data_struc1{1,13} = load('2_1002_EO1.mat');
data_struc1{2,13} = load('2_1002_EO2.mat');
data_struc1{3,13} = load('2_1002_EO3.mat');
```

```

data_struc1{1,14} = load('2_1003_EO1.mat');
data_struc1{2,14} = load('2_1003_EO2.mat');
data_struc1{3,14} = load('2_1003_EO3.mat');
data_struc1{1,15} = load('2_1004_EO1.mat');
data_struc1{2,15} = load('2_1004_EO2.mat');
data_struc1{3,15} = load('2_1004_EO3.mat');
data_struc1{1,16} = load('2_1005_EO1.mat');
data_struc1{2,16} = load('2_1005_EO2.mat');
data_struc1{3,16} = load('2_1005_EO3.mat');
data_struc1{1,17} = load('2_1006_EO1.mat');
data_struc1{2,17} = load('2_1006_EO2.mat');
data_struc1{3,17} = load('2_1006_EO3.mat');
data_struc1{1,18} = load('2_1007_EO1.mat');
data_struc1{2,18} = load('2_1007_EO2.mat');
data_struc1{3,18} = load('2_1007_EO3.mat');
data_struc1{1,19} = load('2_1008_EO1.mat');
data_struc1{2,19} = load('2_1008_EO2.mat');
data_struc1{3,19} = load('2_1008_EO3.mat');
data_struc1{1,20} = load('2_1009_EO1.mat');
data_struc1{2,20} = load('2_1009_EO2.mat');
data_struc1{3,20} = load('2_1009_EO3.mat');
data_struc1{1,21} = load('2_1010_EO1.mat');
data_struc1{2,21} = load('2_1010_EO2.mat');
data_struc1{3,21} = load('2_1010_EO3.mat');

```

#### %Load Mild PD data

```

data_struc1{1,22} = load('1_3001_EO1.mat');
data_struc1{2,22} = load('1_3001_EO2.mat');
data_struc1{3,22} = load('1_3001_EO3.mat');
data_struc1{1,23} = load('1_3002_EO1.mat');
data_struc1{2,23} = load('1_3002_EO2.mat');
data_struc1{3,23} = load('1_3002_EO3.mat');
data_struc1{1,24} = load('1_3003_EO1.mat');
data_struc1{2,24} = load('1_3003_EO2.mat');
data_struc1{3,24} = load('1_3003_EO3.mat');
data_struc1{1,25} = load('1_3004_EO1.mat');
data_struc1{2,25} = load('1_3004_EO2.mat');
data_struc1{3,25} = load('1_3004_EO3.mat');
data_struc1{1,26} = load('1_3005_EO1.mat');
data_struc1{2,26} = load('1_3005_EO2.mat');
data_struc1{3,26} = load('1_3005_EO3.mat');
data_struc1{1,27} = load('1_3006_EO1.mat');
data_struc1{2,27} = load('1_3006_EO2.mat');
data_struc1{3,27} = load('1_3006_EO3.mat');
data_struc1{1,28} = load('1_3008_EO1.mat');
data_struc1{2,28} = load('1_3008_EO2.mat');
data_struc1{3,28} = load('1_3008_EO3.mat');
data_struc1{1,29} = load('1_3009_EO1.mat');
data_struc1{2,29} = load('1_3009_EO2.mat');
data_struc1{3,29} = load('1_3009_EO3.mat');
data_struc1{1,30} = load('1_3010_EO1.mat');
data_struc1{2,30} = load('1_3010_EO2.mat');
data_struc1{3,30} = load('1_3010_EO3.mat');
data_struc1{1,31} = load('1_3011_EO1.mat');
data_struc1{2,31} = load('1_3011_EO2.mat');
data_struc1{3,31} = load('1_3011_EO3.mat');
data_struc1{1,32} = load('1_3013_EO1.mat');

```

```

data_struc1{2,32} = load('1_3013_EO2.mat');
data_struc1{3,32} = load('1_3013_EO3.mat');
data_struc1{1,33} = load('1_3014_EO1.mat');
data_struc1{2,33} = load('1_3014_EO2.mat');
data_struc1{3,33} = load('1_3014_EO3.mat');
data_struc1{1,34} = load('2_4009_EO1.mat');
data_struc1{2,34} = load('2_4009_EO2.mat');
data_struc1{3,34} = load('2_4009_EO3.mat');

```

```

%Moderate PD data

```

```

data_struc1{1,35} = load('2_4001_EO1.mat');
data_struc1{2,35} = load('2_4001_EO2.mat');
data_struc1{3,35} = load('2_4001_EO3.mat');
data_struc1{1,36} = load('2_4002_EO1.mat');
data_struc1{2,36} = load('2_4002_EO2.mat');
data_struc1{3,36} = load('2_4002_EO3.mat');
data_struc1{1,37} = load('2_4004_EO1.mat');
data_struc1{2,37} = load('2_4004_EO2.mat');
data_struc1{3,37} = load('2_4004_EO3.mat');
data_struc1{1,38} = load('2_4005_EO1.mat');
data_struc1{2,38} = load('2_4005_EO2.mat');
data_struc1{3,38} = load('2_4005_EO3.mat');
data_struc1{1,39} = load('2_4006_EO1.mat');
data_struc1{2,39} = load('2_4006_EO2.mat');
data_struc1{3,39} = load('2_4006_EO3.mat');
data_struc1{1,40} = load('2_4007_EO1.mat');
data_struc1{2,40} = load('2_4007_EO2.mat');
data_struc1{3,40} = load('2_4007_EO3.mat');
data_struc1{1,41} = load('2_4008_EO1.mat');
data_struc1{2,41} = load('2_4008_EO2.mat');
data_struc1{3,41} = load('2_4008_EO3.mat');
data_struc1{1,42} = load('2_4012_EO1.mat');
data_struc1{2,42} = load('2_4012_EO2.mat');
data_struc1{3,42} = load('2_4012_EO3.mat');
data_struc1{1,43} = load('2_4010_EO1.mat');
data_struc1{2,43} = load('2_4010_EO2.mat');
data_struc1{3,43} = load('2_4010_EO3.mat');
data_struc1{1,44} = load('2_4010_EO1.mat');
data_struc1{2,44} = load('2_4011_EO2.mat');
data_struc1{3,44} = load('2_4011_EO3.mat');

```

```

%%

```

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```

% EYES CLOSED CONDITION DATA

```

```

data_struc2{1,1} = load('1_1001_EC1.mat');
data_struc2{2,1} = load('1_1001_EC2.mat');
data_struc2{3,1} = load('1_1001_EC3.mat');
data_struc2{1,2} = load('1_1003_EC1.mat');
data_struc2{2,2} = load('1_1003_EC2.mat');
data_struc2{3,2} = load('1_1003_EC3.mat');
data_struc2{1,3} = load('1_1006_EC1.mat');
data_struc2{2,3} = load('1_1006_EC2.mat');
data_struc2{3,3} = load('1_1006_EC3.mat');
data_struc2{1,4} = load('1_1007_EC1.mat');
data_struc2{2,4} = load('1_1007_EC2.mat');
data_struc2{3,4} = load('1_1007_EC3.mat');

```

```

data_struc2{1,5} = load('1_1008_EC1.mat');
data_struc2{2,5} = load('1_1008_EC2.mat');
data_struc2{3,5} = load('1_1008_EC3.mat');
data_struc2{1,6} = load('1_1009_EC1.mat');
data_struc2{2,6} = load('1_1009_EC2.mat');
data_struc2{3,6} = load('1_1009_EC3.mat');
data_struc2{1,7} = load('1_1010_EC1.mat');
data_struc2{2,7} = load('1_1010_EC2.mat');
data_struc2{3,7} = load('1_1010_EC3.mat');
data_struc2{1,8} = load('1_1011_EC1.mat');
data_struc2{2,8} = load('1_1011_EC2.mat');
data_struc2{3,8} = load('1_1011_EC3.mat');
data_struc2{1,9} = load('1_1012_EC1.mat');
data_struc2{2,9} = load('1_1012_EC2.mat');
data_struc2{3,9} = load('1_1012_EC3.mat');
data_struc2{1,10} = load('1_1013_EC1.mat');
data_struc2{2,10} = load('1_1013_EC2.mat');
data_struc2{3,10} = load('1_1013_EC3.mat');
data_struc2{1,11} = load('1_1014_EC1.mat');
data_struc2{2,11} = load('1_1014_EC2.mat');
data_struc2{3,11} = load('1_1014_EC3.mat');

```

```

%Healthy year 2

```

```

data_struc2{1,12} = load('2_1001_EC1.mat');
data_struc2{2,12} = load('2_1001_EC2.mat');
data_struc2{3,12} = load('2_1001_EC3.mat');
data_struc2{1,13} = load('2_1002_EC1.mat');
data_struc2{2,13} = load('2_1002_EC2.mat');
data_struc2{3,13} = load('2_1002_EC3.mat');
data_struc2{1,14} = load('2_1003_EC1.mat');
data_struc2{2,14} = load('2_1003_EC2.mat');
data_struc2{3,14} = load('2_1003_EC3.mat');
data_struc2{1,15} = load('2_1004_EC1.mat');
data_struc2{2,15} = load('2_1004_EC2.mat');
data_struc2{3,15} = load('2_1004_EC3.mat');
data_struc2{1,16} = load('2_1005_EC1.mat');
data_struc2{2,16} = load('2_1005_EC2.mat');
data_struc2{3,16} = load('2_1005_EC3.mat');
data_struc2{1,17} = load('2_1006_EC1.mat');
data_struc2{2,17} = load('2_1006_EC2.mat');
data_struc2{3,17} = load('2_1006_EC3.mat');
data_struc2{1,18} = load('2_1007_EC1.mat');
data_struc2{2,18} = load('2_1007_EC2.mat');
data_struc2{3,18} = load('2_1007_EC3.mat');
data_struc2{1,19} = load('2_1008_EC1.mat');
data_struc2{2,19} = load('2_1008_EC2.mat');
data_struc2{3,19} = load('2_1008_EC3.mat');
data_struc2{1,20} = load('2_1009_EC1.mat');
data_struc2{2,20} = load('2_1009_EC2.mat');
data_struc2{3,20} = load('2_1009_EC3.mat');
data_struc2{1,21} = load('2_1010_EC1.mat');
data_struc2{2,21} = load('2_1010_EC2.mat');
data_struc2{3,21} = load('2_1010_EC3.mat');

```

```

%Load Mild PD data

```

```

data_struc2{1,22} = load('1_3001_EC1.mat');

```

```

data_struc2{2,22} = load('1_3001_EC2.mat');
data_struc2{3,22} = load('1_3001_EC3.mat');
data_struc2{1,23} = load('1_3002_EC1.mat');
data_struc2{2,23} = load('1_3002_EC2.mat');
data_struc2{3,23} = load('1_3002_EC3.mat');
data_struc2{1,24} = load('1_3003_EC1.mat');
data_struc2{2,24} = load('1_3003_EC2.mat');
data_struc2{3,24} = load('1_3003_EC3.mat');
data_struc2{1,25} = load('1_3004_EC1.mat');
data_struc2{2,25} = load('1_3004_EC2.mat');
data_struc2{3,25} = load('1_3004_EC3.mat');
data_struc2{1,26} = load('1_3005_EC1.mat');
data_struc2{2,26} = load('1_3005_EC2.mat');
data_struc2{3,26} = load('1_3005_EC3.mat');
data_struc2{1,27} = load('1_3006_EC1.mat');
data_struc2{2,27} = load('1_3006_EC2.mat');
data_struc2{3,27} = load('1_3006_EC3.mat');
data_struc2{1,28} = load('1_3008_EC1.mat');
data_struc2{2,28} = load('1_3008_EC2.mat');
data_struc2{3,28} = load('1_3008_EC3.mat');
data_struc2{1,29} = load('1_3009_EC1.mat');
data_struc2{2,29} = load('1_3009_EC2.mat');
data_struc2{3,29} = load('1_3009_EC3.mat');
data_struc2{1,30} = load('1_3010_EC1.mat');
data_struc2{2,30} = load('1_3010_EC2.mat');
data_struc2{3,30} = load('1_3010_EC3.mat');
data_struc2{1,31} = load('1_3011_EC1.mat');
data_struc2{2,31} = load('1_3011_EC2.mat');
data_struc2{3,31} = load('1_3011_EC3.mat');
data_struc2{1,32} = load('1_3013_EC1.mat');
data_struc2{2,32} = load('1_3013_EC2.mat');
data_struc2{3,32} = load('1_3013_EC3.mat');
data_struc2{1,33} = load('1_3014_EC1.mat');
data_struc2{2,33} = load('1_3014_EC2.mat');
data_struc2{3,33} = load('1_3014_EC3.mat');
data_struc2{1,34} = load('2_4009_EC1.mat');
data_struc2{2,34} = load('2_4009_EC2.mat');
data_struc2{3,34} = load('2_4009_EC3.mat');

```

```

%Moderate PD data

```

```

data_struc2{1,35} = load('2_4001_EC1.mat');
data_struc2{2,35} = load('2_4001_EC2.mat');
data_struc2{3,35} = load('2_4001_EC3.mat');
data_struc2{1,36} = load('2_4002_EC1.mat');
data_struc2{2,36} = load('2_4002_EC2.mat');
data_struc2{3,36} = load('2_4002_EC3.mat');
data_struc2{1,37} = load('2_4004_EC1.mat');
data_struc2{2,37} = load('2_4004_EC2.mat');
data_struc2{3,37} = load('2_4004_EC3.mat');
data_struc2{1,38} = load('2_4005_EC1.mat');
data_struc2{2,38} = load('2_4005_EC2.mat');
data_struc2{3,38} = load('2_4005_EC3.mat');
data_struc2{1,39} = load('2_4006_EC1.mat');
data_struc2{2,39} = load('2_4006_EC2.mat');
data_struc2{3,39} = load('2_4006_EC3.mat');
data_struc2{1,40} = load('2_4007_EC1.mat');
data_struc2{2,40} = load('2_4007_EC2.mat');

```

```

data_struc2{3,40} = load('2_4007_EC3.mat');
data_struc2{1,41} = load('2_4008_EC1.mat');
data_struc2{2,41} = load('2_4008_EC2.mat');
data_struc2{3,41} = load('2_4008_EC3.mat');
data_struc2{1,42} = load('2_4012_EC1.mat');
data_struc2{2,42} = load('2_4012_EC2.mat');
data_struc2{3,42} = load('2_4012_EC3.mat');
data_struc2{1,43} = load('2_4010_EC1.mat');
data_struc2{2,43} = load('2_4010_EC2.mat');
data_struc2{3,43} = load('2_4010_EC3.mat');
data_struc2{1,44} = load('2_4010_EC1.mat');
data_struc2{2,44} = load('2_4011_EC2.mat');
data_struc2{3,44} = load('2_4011_EC3.mat');

%Load EO data
for i = 1:44
    for j = 1:3
        data1{j,i} = data_struc1{j,i}.dt_COPAP_COPML; %Store the data in
the a cell named 'data1' for EO condition
        t_EO{j,i} = data1{j,i}(:,1); %Store time data for
EO condition
        AP_EO{j,i} = data1{j,i}(:,2); %Anterior-Posterior
EO data
        ML_EO{j,i} = data1{j,i}(:,3); %Medio-Lateral EO
data
    end
end

%Load EC data
for i = 1:44
    for j = 1:3
        data2{j,i} = data_struc2{j,i}.dt_COPAP_COPML; %Store the data in
the a cell named 'data1' for EC condition
        t_EC{j,i} = data2{j,i}(:,1); %Store time data for
EC condition
        AP_EC{j,i} = data2{j,i}(:,2); %Anterior-Posterior
EC data
        ML_EC{j,i} = data2{j,i}(:,3); %Medio-Lateral EC
data
    end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%
%Filter the data AP direction EO data

for i = 1:44
    for j = 1:3
        [xfiltered_EO{j,i},yfiltered_EO{j,i}] = LPF(100,
30,AP_EO{j,i}(:,1),ML_EO{j,i}(:,1)); %Filter the AP and ML data for EO
condition
    end
end

```

```

        detrendedsig_AP_EO{j,i} = detrend(xfiltered_EO{j,i});
%Detrend the AP COP time series data in the EO condition
    end
end

for i = 1:44
    for j = 1:3
        detrendedsig_AP_EO{j,i} = downsample(detrendedsig_AP_EO{j,i},2);
%Downsample the detrended signal for EO condition from 100Hz to 50Hz
    end
end

%Filter the data AP direction EC data

for i = 1:44
    for j = 1:3
        [xfiltered_EC{j,i},yfiltered_EC{j,i}] = LPF(100,
30,AP_EC{j,i}(:,1),ML_EC{j,i}(:,1)); %Filter the AP and ML data for EC
condition
        detrendedsig_AP_EC{j,i} = detrend(xfiltered_EC{j,i});
%Detrend the AP COP time series data in the EC condition
    end
end

for i = 1:44
    for j = 1:3
        detrendedsig_AP_EC{j,i} = downsample(detrendedsig_AP_EC{j,i},2);
%Downsample the detrended signal for EC condition from 100Hz to 50Hz
    end
end

%%
%Merge the three trials for AP data EO

Position_Final_EO = cell(1,44);
%Create a cell of size 1*44 for storing time series data (EO trials)
for i = 1:44
    for j = 1:3
        Position_AP_EO{j,i} = iddata(detrendedsig_AP_EO{j,i},[],0.02);
%Store the time series data trials in the form of separate experiments (EO
trials)
    end
end

%Merge the three trials for AP data EC

Position_Final_EC = cell(1,44);
%Create a cell of size 1*44 for storing time series data (EC trials)
for i = 1:44
    for j = 1:3
        Position_AP_EC{j,i} = iddata(detrendedsig_AP_EC{j,i},[],0.02);
%Store the time series data trials in the form of separate experiments (EC
trials)
    end
end
end

```



```

%%
%AP data EO & EC
for i = 1:44
    Position_Final_EO{1,i} =
merge(getexp(Position_AP_EO{1,i},1),getexp(Position_AP_EO{2,i},1),getexp(Posi
tion_AP_EO{3,i},1)); %Store the data in the form of three columns for the
different trials (EO)
    Position_Final_EC{1,i} =
merge(getexp(Position_AP_EC{1,i},1),getexp(Position_AP_EC{2,i},1),getexp(Posi
tion_AP_EC{3,i},1)); %Store the data in the form of three columns for the
different trials (EC)
end

%%
%System identification for position data using
%arma system for AP direction
for i = 1:44
    for o = 1:4
%This is only used for determining the best order for the system. (i.e.
replace the order of the system in the next line with the variable 'o' and
run the loop. find AIC and determine the best model.
        Opt = armaxOptions;
%Set the options for prediction error method
        armasysp_EO{1,i} = armax(Position_Final_EO{1,i},[3 0], Opt);
%System identification using an AR(3) model for EO data
        tfarmap_EO{1,i} = tf(armasysp_EO{1,i}.c,armasysp_EO{1,i}.a,0.02);
%Transfer function form of the identified model for EO condition
        z_EO{1,i} = d2c(armasysp_EO{1,i});
%Convert the transfer function from discrete to continuous form using 'ZOH'
method for EO data
        AIC_EO(1,i) = aic(armasysp_EO{1,i});
%Calculate the AIC values for EO data models identified

        Opt = armaxOptions;
%Set the options for prediction error method
        armasysp_EC{1,i} = armax(Position_Final_EC{1,i},[3 0], Opt);
%System identification using an AR(3) model for EC data
        tfarmap_EC{1,i} = tf(armasysp_EC{1,i}.c,armasysp_EC{1,i}.a,0.02);
%Transfer function form of the identified model for EC condition
        z_EC{1,i} = d2c(armasysp_EC{1,i});
%Convert the transfer function from discrete to continuous form using 'ZOH'
method for EC data
        AIC_EC(1,i) = aic(armasysp_EC{1,i});
%Calculate the AIC values for EC data models identified
    end
end

%%
%Akaike's final prediction error for the two models
for i = 1:44
    ak_EO(i,1) = fpe(armasysp_EO{1,i});
%Calculate the final prediction errors for the ARMA models identified using
EO COP AP data

```

```

    ak_EC(i,1) = fpe(armasysp_EC{1,i});
%Calculate the final prediction errors for the ARMA models identified using
EC COP AP data
end
%%
%Storing the coefficients
for i = 1:44
    eta_EO{1,i} = z_EO{1,i}.A(1,2);
%Extract the 'eta' coefficients from the TF denominators of the identified
models for EO condition
    k_EO{1,i} = z_EO{1,i}.A(1,3);
%Extract the 'k' coefficients from the TF denominators of the identified
models for EO condition
    rho_EO{1,i} = z_EO{1,i}.A(1,4);
%Extract the 'rho' coefficients from the TF denominators of the identified
models for EO condition
end

for i = 1:44
    eta_EC{1,i} = z_EC{1,i}.A(1,2);
%Extract the 'eta' coefficients from the TF denominators of the identified
models for EC condition
    k_EC{1,i} = z_EC{1,i}.A(1,3);
%Extract the 'k' coefficients from the TF denominators of the identified
models for EC condition
    rho_EC{1,i} = z_EC{1,i}.A(1,4);
%Extract the 'rho' coefficients from the TF denominators of the identified
models for EC condition
end
%%
%Coefficients for EO condition
w_EO = cell(1,44); %Create a cell for storing
w values in EO condition
for i = 1:44
w_EO{1,i} = (nthroot(rho_EO{1,i},3)); %w(omega) gives the
swiftness (rad/sec) for EO condition models
w_new_EO{1,i} = (nthroot(rho_EO{1,i},3));
end

%Coefficients for EC condition
w_EC = cell(1,44); %Create a cell for storing
w values in EC condition
for i = 1:44
w_EC{1,i} = (nthroot(rho_EC{1,i},3)); %w_EC(omega) gives the
swiftness (rad/sec) for EC condition models
w_new_EC{1,i} = (nthroot(rho_EC{1,i},3));
end

w_EO = cell2mat(w_EO); %Cell to matrix conversion
for swiftness EO condition
w_EC = cell2mat(w_EC); %Cell to matrix conversion
for swiftness EC condition

%%
%Stiffness and damping for EO data
for i = 1:length(w_EO)

```

```

st_EO{1,i} = ((k_EO{1,i})/((w_EO(1,i))^2));           %Stiffness coefficient
in EO condition

d_EO{1,i} = ((eta_EO{1,i})/(w_EO(1,i)));           %Damping coefficient in
EO condition

end

%Stiffness and damping for EC data
for i = 1:length(w_EC)
st_EC{1,i} = ((k_EC{1,i})/((w_EC(1,i))^2));           %Stiffness coefficient
in EC condition

d_EC{1,i} = ((eta_EC{1,i})/(w_EC(1,i)));           %Damping coefficient in
EC condition

end

%%
%Compressing the data coefficients into one single matrix
%Exclude the values which have values more or less than mean+-(3*SD)
M = mean(w_EO)+(3*std(w_EO));           %Calculate the value of
mean + 3*S.D, EO trials
deletethese = (w_EO >= M);           %Create a matrix which
alots '1's to those values whic are > mean + 3* S.D, EO trials
W1 = w_EO(~deletethese);           %Update the matrix W1
%%
M = mean(w_EC)+(3*std(w_EC));           %Calculate the value of
mean + 3*S.D, EC trials
deletethese = (w_EC >= M);           %Create a matrix which
alots '1's to those values whic are > mean + 3* S.D, EC trials
W1_EC = w_EC(~deletethese);           %Update the matrix W1_EC
%%
% d_EO = cell2mat(d_EO);           %Cell to matrix
conversion for d_EO
% d_EC = cell2mat(d_EC);           %Cell to matrix
conversion for d_EC
M = mean(d_EO)+(3*std(d_EO));           %Calculate the value of
mean + 3*S.D, EO trials
deletethese = (d_EO >= M);           %Create a matrix which
alots '1's to those values whic are > mean + 3* S.D, EO trials
d1 = d_EO(~deletethese);           %Update the matrix d1_EO
and store it in d1
%%
M = mean(d_EC)+(3*std(d_EC));           %Calculate the value of
mean + 3*S.D, EC trials
deletethese = (d_EC >= M);           %Create a matrix which
alots '1's to those values whic are > mean + 3* S.D, EC trials
d1_EC = d_EC(~deletethese);           %Update the matrix d1_EC
%%
st_EO = cell2mat(st_EO);           %Cell to matrix
conversion for st_EO
st_EC = cell2mat(st_EC);           %Cell to matrix
conversion for st_EC
M = mean(st_EO)+(3*std(st_EO));           %Calculate the value of
mean + 3*S.D, EO trials

```

```

    deletethese = (st_EO >= M); %Create a matrix which
alots '1's to those values which are > mean + 3* S.D, EO trials
    s1 = st_EO(~deletethese); %Update the matrix s1_EO
    %%
    M = mean(st_EC)+(3*std(st_EC)); %Calculate the value of
mean + 3*S.D, EO trials
    deletethese = (st_EC >= M); %Create a matrix which
alots '1's to those values which are > mean + 3* S.D, EC trials
    s1_EC = st_EC(~deletethese); %Update the matrix s1_EC

%%
W = W1'; %Put the swiftness values
into a column matrix for EO condition
W(44:87) = W1_EC'; %Update the swiftness
values into a column matrix for EC condition
%%
STF = s1'; %Put the stiffness values
into a column matrix for EO condition
STF(44:86) = s1_EC'; %Put the stiffness values
into a column matrix for EC condition
%%
DAMP = d1'; %Put the damping values
into a column matrix for EO condition
DAMP(45:87) = d1_EC'; %Put the damping values
into a column matrix for EC condition
%%
W = cell2mat(W); %Cell to matrix
conversion of 'W'
STF = cell2mat(STF); %Cell to matrix
conversion of 'STF'
DAMP = cell2mat(DAMP); %Cell to matrix
conversion of 'DAMP'

M = mean(w_EO)-(3*std(w_EO)); %Calculate the value of
mean + 3*S.D, EO trials
    deletethese = (w_EO <= M); %Create a matrix which
alots '1's to those values which are > mean + 3* S.D, EO trials
    W1 = w_EO(~deletethese); %Update the matrix W1
    %%
    M = mean(w_EC)-(3*std(w_EC)); %Calculate the value of
mean + 3*S.D, EC trials
    deletethese = (w_EC <= M); %Create a matrix which
alots '1's to those values which are > mean + 3* S.D, EC trials
    W1_EC = w_EC(~deletethese); %Update the matrix W1_EC
    %%
    M = mean(d_EO)-(3*std(d_EO)); %Calculate the value of
mean + 3*S.D, EO trials
    deletethese = (d_EO <= M); %Create a matrix which
alots '1's to those values which are > mean + 3* S.D, EO trials
    d1 = d_EO(~deletethese); %Update the matrix d1_EO
and store it in d1
    %%
    M = mean(d_EC)-(3*std(d_EC)); %Calculate the value of
mean + 3*S.D, EC trials
    deletethese = (d_EC <= M); %Create a matrix which
alots '1's to those values which are > mean + 3* S.D, EC trials

```





```

close all;
%%
figure(6);
cD = multcompare(statsD, 'Dimension', [1 2]);
%Post-hoc Tukey Kramer test for damping parameter
title('Damping parameter of the systems');
filename = sprintf('Damping_Parameter_Post_Hoc.pdf');
%Save the Post-Hoc results figure in PDF format
print(figure(6), filename, '-dpdf');
close all;

%%
%Power analysis
%Find the means and standard deviations for the three parameters
w_h_EO = mean(W(1:21));
w_mild_EO = mean(W(22:34));
w_moderate_EO = mean(W(35:43));

w_h_EC = mean(W(44:64));
w_mild_EC = mean(W(65:77));
w_moderate_EC = mean(W(78:87));

st_h_EO = mean((STF(1:21)));
st_mild_EO = mean((STF(22:34)));
st_moderate_EO = mean((STF(35:43)));

st_h_EC = mean((STF(44:63)));
st_mild_EC = mean((STF(64:76)));
st_moderate_EC = mean((STF(77:86)));

d_h_EO = mean((DAMP(1:21)));
d_mild_EO = mean((DAMP(22:34)));
d_moderate_EO = mean((DAMP(35:44)));

d_h_EC = mean((DAMP(45:64)));
d_mild_EC = mean((DAMP(65:77)));
d_moderate_EC = mean((DAMP(78:87)));

n_h_mild_swift = sampsizepwr('t', [w_h_EO std(w_EO(1:21))], [w_mild_EO
std(w_mild_EO)], 0.95) %Power analysis using both means and S.D 's of
the healthy - mild PD data EO condition (Swiftness parameter)
n_h_mild_stiff = sampsizepwr('t', [st_h_EO std((st_EO(1:21)))], [st_mild_EO
std(st_mild_EO)], 0.95) %Power analysis using both means and S.D 's of the
healthy - mild PD data EO condition (Stiffness parameter)
n_h_mild_damp = sampsizepwr('t', [d_h_EO std((d_EO(1:21)))], [d_mild_EO
std(d_mild_EO)], 0.95) %Power analysis using both means and S.D 's of
the healthy - mild PD data EO condition (Damping parameter)

n_h_mm_swift = sampsizepwr('t', [w_mild_EO std(w_EO(22:34))], [w_moderate_EO
std(w_moderate_EO)], 0.95) %Power analysis using both means and S.D 's
of the mild - moderate PD data EO condition (Swiftness parameter)
n_h_mm_stiff = sampsizepwr('t', [st_mild_EO
std((st_EO(22:34)))], [st_moderate_EO std(st_moderate_EO)], 0.95) %Power

```

```

analysis using both means and S.D 's of the mild - moderate PD data EO
condition (Stiffness parameter)
n_h_mm_damp = sampsizepwr('t',[d_mild_EO std((d_EO(22:34)))],[d_moderate_EO
std(d_moderate_EO)],0.95)      %Power analysis using both means and S.D 's
of the mild - moderate PD data EO condition (Damping parameter)

%%
n_h_mild_swift = sampsizepwr('t',[w_h_EC std(w_EC(1:21))],[w_mild_EC
std(w_mild_EC)],0.95)      %Power analysis using both means and S.D 's of
the healthy - mild PD data EC condition (Swiftiness parameter)
n_h_mild_stiff = sampsizepwr('t',[st_h_EC std((st_EC(1:21)))],[st_mild_EC
std(st_mild_EC)],0.95)      %Power analysis using both means and S.D 's of the
healthy - mild PD data EC condition (Stiffness parameter)
n_h_mild_damp = sampsizepwr('t',[d_h_EC std((d_EC(1:21)))],[d_mild_EC
std(d_mild_EC)],0.95)      %Power analysis using both means and S.D 's of
the healthy - mild PD data EC condition (Damping parameter)

%%
n_h_mm_swift = sampsizepwr('t',[w_mild_EC std(w_EC(22:34))],[w_moderate_EC
std(w_moderate_EC)],0.95)      %Power analysis using both means and S.D 's
of the mild - moderate PD data EC condition (Swiftiness parameter)
n_h_mm_stiff = sampsizepwr('t',[st_mild_EC
std((st_EC(22:34)))],[st_moderate_EC std(st_moderate_EC)],0.95) %Power
analysis using both means and S.D 's of the mild - moderate PD data EC
condition (Stiffness parameter)
n_h_mm_damp = sampsizepwr('t',[d_mild_EC std((d_EC(22:34)))],[d_moderate_EC
std(d_moderate_EC)],0.95)      %Power analysis using both means and S.D 's
of the mild - moderate PD data EC condition (Damping parameter)

%%
%Scatter plots of the three parameters
cd('C:\Kaushik\Research\MATLAB_KAUSHIK\Kaushik_Combined_Analysis\Individual
Analysis\LATEST ANALYSIS\LATEST RESULTS\Scatter Plots');

%Scatter plots of the three parameters for EO condition
group1 =
[1;1;1;1;1;1;1;1;1;1;1;1;1;1;1;1;1;1;1;2;2;2;2;2;2;2;2;2;2;2;2;2;2;3;3;3;3;
3;3;3;3;3;3];

figure(1);
gscatter(W(1:44),STF(1:44),group1,'gbr')
title('Swiftness VS Stiffness parameter for EO healthy controls, mild PD and
moderate PD');
xlabel('Swiftness parameter(rad/sec)');
ylabel('Stiffness parameter');
legend('Healthy controls', 'Mild PD', 'Moderate PD');
export_fig figure(1) -jpg -r1000 -q100;

%%
figure(2);
gscatter(W(1:44),DAMP(1:44),group1,'gbr')
title('Swiftness VS Damping parameter for EO healthy controls, mild PD and
moderate PD');
xlabel('Swiftness parameter(rad/sec)');
ylabel('Damping parameter');
legend('Healthy controls', 'Mild PD', 'Moderate PD');

```



```

export_fig figure(2) -jpg -r1000 -q100;

%%
figure(3);
gscatter(DAMP(1:44),STF(1:44),group1,'gbr')
title('Damping parameter VS Stiffness parameter for EO healthy controls, mild
PD and moderate PD');
xlabel('Damping parameter');
ylabel('Stiffness parameter');
legend('Healthy controls', 'Mild PD', 'Moderate PD');
export_fig figure(3) -jpg -r1000 -q100;
close all;

%%
% Scatter plots for EC condition
figure(4);
gscatter(W(45:88),STF(45:88),group1,'gbr')
title('Swiftness VS Stiffness parameter for EC healthy controls, mild PD and
moderate PD');
xlabel('Swiftness parameter(rad/sec)');
ylabel('Stiffness parameter');
legend('Healthy controls', 'Mild PD', 'Moderate PD');
export_fig figure(4) -jpg -r1000 -q100;

%%
figure(5);
gscatter(W(45:88),DAMP(45:88),group1,'gbr')
title('Swiftness VS Damping parameter for EC healthy controls, mild PD and
moderate PD');
xlabel('Swiftness parameter(rad/sec)');
ylabel('Damping parameter');
legend('Healthy controls', 'Mild PD', 'Moderate PD');
export_fig figure(5) -jpg -r1000 -q100;

%%
figure(6);
gscatter(DAMP(45:88),STF(45:88),group1,'gbr')
title('Damping parameter VS Stiffness parameter for EC healthy controls, mild
PD and moderate PD');
xlabel('Damping parameter');
ylabel('Stiffness parameter');
legend('Healthy controls', 'Mild PD', 'Moderate PD');
export_fig figure(6) -jpg -r1000 -q100;
close all;

%%
%3d scatter plot EO condition
figure(7);
S = repmat([50],numel(W(1:21)),1);
C = repmat([1],numel(W(1:21)),1);
scatter3(W(1:21),STF(1:21),DAMP(1:21),S,C,'og','filled');
hold on;

S1 = repmat([50],numel(W(22:34)),1);
C1 = repmat([2],numel(W(22:34)),1);
scatter3(W(22:34),STF(22:34),DAMP(22:34),S1,C1,'^b','filled');

```

```

S3 = repmat([50],numel(W(35:44)),1);
C3 = repmat([3],numel(W(35:44)),1);
scatter3(W(35:44),STF(35:44),DAMP(35:44),S3,C3,'dr','filled');

title('3d scatter plot for swiftness, stiffness and damping for healthy
controls, mild PD and moderate PD EO condition');
xlabel('Swiftness (rad/sec)');
ylabel('Stiffness parameter');
zlabel('Damping parameter');
legend('Healthy controls EO', 'Mild PD EO', 'Moderate PD EO');
%%
export_fig figure(7) -jpg -r1000 -q100;

%%
%3d scatter plot EC condition
figure(8);
S4 = repmat([50],numel(W(45:65)),1);
C4 = repmat([1],numel(W(45:65)),1);
scatter3(W(45:65),STF(45:65),DAMP(45:65),S4,C4,'og','filled');
hold on;

S5 = repmat([50],numel(W(66:78)),1);
C5 = repmat([2],numel(W(66:78)),1);
scatter3(W(66:78),STF(66:78),DAMP(66:78),S5,C5,'^b','filled');

S6 = repmat([50],numel(W(79:88)),1);
C6 = repmat([3],numel(W(79:88)),1);
scatter3(W(79:88),STF(79:88),DAMP(79:88),S6,C6,'dr','filled');

title('3d scatter plot for swiftness, stiffness and damping for healthy
controls, mild PD and moderate PD EC condition');
xlabel('Swiftness (rad/sec)');
ylabel('Stiffness parameter');
zlabel('Damping parameter');
legend('Healthy controls EC', 'Mild PD EC', 'Moderate PD EC');
hold off;
%%
export_fig figure(8) -jpg -r1000 -q100;
cd('C:\Kaushik\Research\Thesis\Chandrashekar_Thesis\Figures');
%%
e=resid(armasysp_EO{1,1},detrendedsig_AP_EO{1,1},0.95)
%Calculate the auto correlation of residuals of the fitted model
title('Correlation of the residuals for AR(3) model healthy subject 1 EO
trial 1');

%END OF CODE%

```

## ***E.2. Code 2. Program for analysis using the ARMA (2, 1) modelling approach (Model 2).***

```
%Program to analyze the COP time series data in AP direction using the ARMA
%modelling approach
%Author: Chandrashekara Kaushik Gandur Balagangadhara
clc;
clear all;
close all;
cd('C:\Kaushik\Research\Data\COP_Data_100Hz');      %Set the directory
containing the data
%%
% EYES OPEN CONDITION DATA
%Analysis for eyes open condition
%Healthy controls year 1
%Load the data from the respective directory.
data_struc1{1,1} = load('1_1001_EO1.mat');
data_struc1{2,1} = load('1_1001_EO2.mat');
data_struc1{3,1} = load('1_1001_EO3.mat');
data_struc1{1,2} = load('1_1003_EO1.mat');
data_struc1{2,2} = load('1_1003_EO2.mat');
data_struc1{3,2} = load('1_1003_EO3.mat');
data_struc1{1,3} = load('1_1006_EO1.mat');
data_struc1{2,3} = load('1_1006_EO2.mat');
data_struc1{3,3} = load('1_1006_EO3.mat');
data_struc1{1,4} = load('1_1007_EO1.mat');
data_struc1{2,4} = load('1_1007_EO2.mat');
data_struc1{3,4} = load('1_1007_EO3.mat');
data_struc1{1,5} = load('1_1008_EO1.mat');
data_struc1{2,5} = load('1_1008_EO2.mat');
data_struc1{3,5} = load('1_1008_EO3.mat');
data_struc1{1,6} = load('1_1009_EO1.mat');
data_struc1{2,6} = load('1_1009_EO2.mat');
data_struc1{3,6} = load('1_1009_EO3.mat');
data_struc1{1,7} = load('1_1010_EO1.mat');
data_struc1{2,7} = load('1_1010_EO2.mat');
data_struc1{3,7} = load('1_1010_EO3.mat');
data_struc1{1,8} = load('1_1011_EO1.mat');
data_struc1{2,8} = load('1_1011_EO2.mat');
data_struc1{3,8} = load('1_1011_EO3.mat');
data_struc1{1,9} = load('1_1012_EO1.mat');
data_struc1{2,9} = load('1_1012_EO2.mat');
data_struc1{3,9} = load('1_1012_EO3.mat');
data_struc1{1,10} = load('1_1013_EO1.mat');
data_struc1{2,10} = load('1_1013_EO2.mat');
data_struc1{3,10} = load('1_1013_EO3.mat');
data_struc1{1,11} = load('1_1014_EO1.mat');
data_struc1{2,11} = load('1_1014_EO2.mat');
data_struc1{3,11} = load('1_1014_EO3.mat');

%Healthy year 2
data_struc1{1,12} = load('2_1001_EO1.mat');
data_struc1{2,12} = load('2_1001_EO2.mat');
data_struc1{3,12} = load('2_1001_EO3.mat');
data_struc1{1,13} = load('2_1002_EO1.mat');
```

```

data_struc1{2,13} = load('2_1002_EO2.mat');
data_struc1{3,13} = load('2_1002_EO3.mat');
data_struc1{1,14} = load('2_1003_EO1.mat');
data_struc1{2,14} = load('2_1003_EO2.mat');
data_struc1{3,14} = load('2_1003_EO3.mat');
data_struc1{1,15} = load('2_1004_EO1.mat');
data_struc1{2,15} = load('2_1004_EO2.mat');
data_struc1{3,15} = load('2_1004_EO3.mat');
data_struc1{1,16} = load('2_1005_EO1.mat');
data_struc1{2,16} = load('2_1005_EO2.mat');
data_struc1{3,16} = load('2_1005_EO3.mat');
data_struc1{1,17} = load('2_1006_EO1.mat');
data_struc1{2,17} = load('2_1006_EO2.mat');
data_struc1{3,17} = load('2_1006_EO3.mat');
data_struc1{1,18} = load('2_1007_EO1.mat');
data_struc1{2,18} = load('2_1007_EO2.mat');
data_struc1{3,18} = load('2_1007_EO3.mat');
data_struc1{1,19} = load('2_1008_EO1.mat');
data_struc1{2,19} = load('2_1008_EO2.mat');
data_struc1{3,19} = load('2_1008_EO3.mat');
data_struc1{1,20} = load('2_1009_EO1.mat');
data_struc1{2,20} = load('2_1009_EO2.mat');
data_struc1{3,20} = load('2_1009_EO3.mat');
data_struc1{1,21} = load('2_1010_EO1.mat');
data_struc1{2,21} = load('2_1010_EO2.mat');
data_struc1{3,21} = load('2_1010_EO3.mat');

```

`%Load Mild PD data`

```

data_struc1{1,22} = load('1_3001_EO1.mat');
data_struc1{2,22} = load('1_3001_EO2.mat');
data_struc1{3,22} = load('1_3001_EO3.mat');
data_struc1{1,23} = load('1_3002_EO1.mat');
data_struc1{2,23} = load('1_3002_EO2.mat');
data_struc1{3,23} = load('1_3002_EO3.mat');
data_struc1{1,24} = load('1_3003_EO1.mat');
data_struc1{2,24} = load('1_3003_EO2.mat');
data_struc1{3,24} = load('1_3003_EO3.mat');
data_struc1{1,25} = load('1_3004_EO1.mat');
data_struc1{2,25} = load('1_3004_EO2.mat');
data_struc1{3,25} = load('1_3004_EO3.mat');
data_struc1{1,26} = load('1_3005_EO1.mat');
data_struc1{2,26} = load('1_3005_EO2.mat');
data_struc1{3,26} = load('1_3005_EO3.mat');
data_struc1{1,27} = load('1_3006_EO1.mat');
data_struc1{2,27} = load('1_3006_EO2.mat');
data_struc1{3,27} = load('1_3006_EO3.mat');
data_struc1{1,28} = load('1_3008_EO1.mat');
data_struc1{2,28} = load('1_3008_EO2.mat');
data_struc1{3,28} = load('1_3008_EO3.mat');
data_struc1{1,29} = load('1_3009_EO1.mat');
data_struc1{2,29} = load('1_3009_EO2.mat');
data_struc1{3,29} = load('1_3009_EO3.mat');
data_struc1{1,30} = load('1_3010_EO1.mat');
data_struc1{2,30} = load('1_3010_EO2.mat');
data_struc1{3,30} = load('1_3010_EO3.mat');
data_struc1{1,31} = load('1_3011_EO1.mat');
data_struc1{2,31} = load('1_3011_EO2.mat');

```

```

data_struc1{3,31} = load('1_3011_EO3.mat');
data_struc1{1,32} = load('1_3013_EO1.mat');
data_struc1{2,32} = load('1_3013_EO2.mat');
data_struc1{3,32} = load('1_3013_EO3.mat');
data_struc1{1,33} = load('1_3014_EO1.mat');
data_struc1{2,33} = load('1_3014_EO2.mat');
data_struc1{3,33} = load('1_3014_EO3.mat');
data_struc1{1,34} = load('2_4009_EO1.mat');
data_struc1{2,34} = load('2_4009_EO2.mat');
data_struc1{3,34} = load('2_4009_EO3.mat');

```

```

%Moderate PD data

```

```

data_struc1{1,35} = load('2_4001_EO1.mat');
data_struc1{2,35} = load('2_4001_EO2.mat');
data_struc1{3,35} = load('2_4001_EO3.mat');
data_struc1{1,36} = load('2_4002_EO1.mat');
data_struc1{2,36} = load('2_4002_EO2.mat');
data_struc1{3,36} = load('2_4002_EO3.mat');
data_struc1{1,37} = load('2_4004_EO1.mat');
data_struc1{2,37} = load('2_4004_EO2.mat');
data_struc1{3,37} = load('2_4004_EO3.mat');
data_struc1{1,38} = load('2_4005_EO1.mat');
data_struc1{2,38} = load('2_4005_EO2.mat');
data_struc1{3,38} = load('2_4005_EO3.mat');
data_struc1{1,39} = load('2_4006_EO1.mat');
data_struc1{2,39} = load('2_4006_EO2.mat');
data_struc1{3,39} = load('2_4006_EO3.mat');
data_struc1{1,40} = load('2_4007_EO1.mat');
data_struc1{2,40} = load('2_4007_EO2.mat');
data_struc1{3,40} = load('2_4007_EO3.mat');
data_struc1{1,41} = load('2_4008_EO1.mat');
data_struc1{2,41} = load('2_4008_EO2.mat');
data_struc1{3,41} = load('2_4008_EO3.mat');
data_struc1{1,42} = load('2_4012_EO1.mat');
data_struc1{2,42} = load('2_4012_EO2.mat');
data_struc1{3,42} = load('2_4012_EO3.mat');
data_struc1{1,43} = load('2_4010_EO1.mat');
data_struc1{2,43} = load('2_4010_EO2.mat');
data_struc1{3,43} = load('2_4010_EO3.mat');
data_struc1{1,44} = load('2_4010_EO1.mat');
data_struc1{2,44} = load('2_4011_EO2.mat');
data_struc1{3,44} = load('2_4011_EO3.mat');

```

```

%%

```

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```

% EYES CLOSED CONDITION DATA

```

```

data_struc2{1,1} = load('1_1001_EC1.mat');
data_struc2{2,1} = load('1_1001_EC2.mat');
data_struc2{3,1} = load('1_1001_EC3.mat');
data_struc2{1,2} = load('1_1003_EC1.mat');
data_struc2{2,2} = load('1_1003_EC2.mat');
data_struc2{3,2} = load('1_1003_EC3.mat');
data_struc2{1,3} = load('1_1006_EC1.mat');
data_struc2{2,3} = load('1_1006_EC2.mat');
data_struc2{3,3} = load('1_1006_EC3.mat');
data_struc2{1,4} = load('1_1007_EC1.mat');

```

```

data_struc2{2,4} = load('1_1007_EC2.mat');
data_struc2{3,4} = load('1_1007_EC3.mat');
data_struc2{1,5} = load('1_1008_EC1.mat');
data_struc2{2,5} = load('1_1008_EC2.mat');
data_struc2{3,5} = load('1_1008_EC3.mat');
data_struc2{1,6} = load('1_1009_EC1.mat');
data_struc2{2,6} = load('1_1009_EC2.mat');
data_struc2{3,6} = load('1_1009_EC3.mat');
data_struc2{1,7} = load('1_1010_EC1.mat');
data_struc2{2,7} = load('1_1010_EC2.mat');
data_struc2{3,7} = load('1_1010_EC3.mat');
data_struc2{1,8} = load('1_1011_EC1.mat');
data_struc2{2,8} = load('1_1011_EC2.mat');
data_struc2{3,8} = load('1_1011_EC3.mat');
data_struc2{1,9} = load('1_1012_EC1.mat');
data_struc2{2,9} = load('1_1012_EC2.mat');
data_struc2{3,9} = load('1_1012_EC3.mat');
data_struc2{1,10} = load('1_1013_EC1.mat');
data_struc2{2,10} = load('1_1013_EC2.mat');
data_struc2{3,10} = load('1_1013_EC3.mat');
data_struc2{1,11} = load('1_1014_EC1.mat');
data_struc2{2,11} = load('1_1014_EC2.mat');
data_struc2{3,11} = load('1_1014_EC3.mat');

```

```

%Healthy year 2

```

```

data_struc2{1,12} = load('2_1001_EC1.mat');
data_struc2{2,12} = load('2_1001_EC2.mat');
data_struc2{3,12} = load('2_1001_EC3.mat');
data_struc2{1,13} = load('2_1002_EC1.mat');
data_struc2{2,13} = load('2_1002_EC2.mat');
data_struc2{3,13} = load('2_1002_EC3.mat');
data_struc2{1,14} = load('2_1003_EC1.mat');
data_struc2{2,14} = load('2_1003_EC2.mat');
data_struc2{3,14} = load('2_1003_EC3.mat');
data_struc2{1,15} = load('2_1004_EC1.mat');
data_struc2{2,15} = load('2_1004_EC2.mat');
data_struc2{3,15} = load('2_1004_EC3.mat');
data_struc2{1,16} = load('2_1005_EC1.mat');
data_struc2{2,16} = load('2_1005_EC2.mat');
data_struc2{3,16} = load('2_1005_EC3.mat');
data_struc2{1,17} = load('2_1006_EC1.mat');
data_struc2{2,17} = load('2_1006_EC2.mat');
data_struc2{3,17} = load('2_1006_EC3.mat');
data_struc2{1,18} = load('2_1007_EC1.mat');
data_struc2{2,18} = load('2_1007_EC2.mat');
data_struc2{3,18} = load('2_1007_EC3.mat');
data_struc2{1,19} = load('2_1008_EC1.mat');
data_struc2{2,19} = load('2_1008_EC2.mat');
data_struc2{3,19} = load('2_1008_EC3.mat');
data_struc2{1,20} = load('2_1009_EC1.mat');
data_struc2{2,20} = load('2_1009_EC2.mat');
data_struc2{3,20} = load('2_1009_EC3.mat');
data_struc2{1,21} = load('2_1010_EC1.mat');
data_struc2{2,21} = load('2_1010_EC2.mat');
data_struc2{3,21} = load('2_1010_EC3.mat');

```

```

%Load Mild PD data
data_struc2{1,22} = load('1_3001_EC1.mat');
data_struc2{2,22} = load('1_3001_EC2.mat');
data_struc2{3,22} = load('1_3001_EC3.mat');
data_struc2{1,23} = load('1_3002_EC1.mat');
data_struc2{2,23} = load('1_3002_EC2.mat');
data_struc2{3,23} = load('1_3002_EC3.mat');
data_struc2{1,24} = load('1_3003_EC1.mat');
data_struc2{2,24} = load('1_3003_EC2.mat');
data_struc2{3,24} = load('1_3003_EC3.mat');
data_struc2{1,25} = load('1_3004_EC1.mat');
data_struc2{2,25} = load('1_3004_EC2.mat');
data_struc2{3,25} = load('1_3004_EC3.mat');
data_struc2{1,26} = load('1_3005_EC1.mat');
data_struc2{2,26} = load('1_3005_EC2.mat');
data_struc2{3,26} = load('1_3005_EC3.mat');
data_struc2{1,27} = load('1_3006_EC1.mat');
data_struc2{2,27} = load('1_3006_EC2.mat');
data_struc2{3,27} = load('1_3006_EC3.mat');
data_struc2{1,28} = load('1_3008_EC1.mat');
data_struc2{2,28} = load('1_3008_EC2.mat');
data_struc2{3,28} = load('1_3008_EC3.mat');
data_struc2{1,29} = load('1_3009_EC1.mat');
data_struc2{2,29} = load('1_3009_EC2.mat');
data_struc2{3,29} = load('1_3009_EC3.mat');
data_struc2{1,30} = load('1_3010_EC1.mat');
data_struc2{2,30} = load('1_3010_EC2.mat');
data_struc2{3,30} = load('1_3010_EC3.mat');
data_struc2{1,31} = load('1_3011_EC1.mat');
data_struc2{2,31} = load('1_3011_EC2.mat');
data_struc2{3,31} = load('1_3011_EC3.mat');
data_struc2{1,32} = load('1_3013_EC1.mat');
data_struc2{2,32} = load('1_3013_EC2.mat');
data_struc2{3,32} = load('1_3013_EC3.mat');
data_struc2{1,33} = load('1_3014_EC1.mat');
data_struc2{2,33} = load('1_3014_EC2.mat');
data_struc2{3,33} = load('1_3014_EC3.mat');
data_struc2{1,34} = load('2_4009_EC1.mat');
data_struc2{2,34} = load('2_4009_EC2.mat');
data_struc2{3,34} = load('2_4009_EC3.mat');

```

```

%Moderate PD data
data_struc2{1,35} = load('2_4001_EC1.mat');
data_struc2{2,35} = load('2_4001_EC2.mat');
data_struc2{3,35} = load('2_4001_EC3.mat');
data_struc2{1,36} = load('2_4002_EC1.mat');
data_struc2{2,36} = load('2_4002_EC2.mat');
data_struc2{3,36} = load('2_4002_EC3.mat');
data_struc2{1,37} = load('2_4004_EC1.mat');
data_struc2{2,37} = load('2_4004_EC2.mat');
data_struc2{3,37} = load('2_4004_EC3.mat');
data_struc2{1,38} = load('2_4005_EC1.mat');
data_struc2{2,38} = load('2_4005_EC2.mat');
data_struc2{3,38} = load('2_4005_EC3.mat');
data_struc2{1,39} = load('2_4006_EC1.mat');
data_struc2{2,39} = load('2_4006_EC2.mat');
data_struc2{3,39} = load('2_4006_EC3.mat');

```

```

data_struc2{1,40} = load('2_4007_EC1.mat');
data_struc2{2,40} = load('2_4007_EC2.mat');
data_struc2{3,40} = load('2_4007_EC3.mat');
data_struc2{1,41} = load('2_4008_EC1.mat');
data_struc2{2,41} = load('2_4008_EC2.mat');
data_struc2{3,41} = load('2_4008_EC3.mat');
data_struc2{1,42} = load('2_4012_EC1.mat');
data_struc2{2,42} = load('2_4012_EC2.mat');
data_struc2{3,42} = load('2_4012_EC3.mat');
data_struc2{1,43} = load('2_4010_EC1.mat');
data_struc2{2,43} = load('2_4010_EC2.mat');
data_struc2{3,43} = load('2_4010_EC3.mat');
data_struc2{1,44} = load('2_4010_EC1.mat');
data_struc2{2,44} = load('2_4011_EC2.mat');
data_struc2{3,44} = load('2_4011_EC3.mat');

%Load EO data
for i = 1:44
    for j = 1:3
        data1{j,i} = data_struc1{j,i}.dt_COPAP_COPML; %Store the data in
the a cell named 'data1' for EO condition
        t_EO{j,i} = data1{j,i}(:,1); %Store time data for
EO condition
        AP_EO{j,i} = data1{j,i}(:,2); %Anterior-Posterior
EO data
        ML_EO{j,i} = data1{j,i}(:,3); %Medio-Lateral EO
data
    end
end

%Load EC data
for i = 1:44
    for j = 1:3
        data2{j,i} = data_struc2{j,i}.dt_COPAP_COPML; %Store the data in
the a cell named 'data1' for EC condition
        t_EC{j,i} = data2{j,i}(:,1); %Store time data for
EC condition
        AP_EC{j,i} = data2{j,i}(:,2); %Anterior-Posterior
EC data
        ML_EC{j,i} = data2{j,i}(:,3); %Medio-Lateral EC
data
    end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%
%Filter the data AP direction EO data

for i = 1:44
    for j = 1:3

```



```

        [xfiltered_EO{j,i},yfiltered_EO{j,i}] = LPF(100,
30,AP_EO{j,i}(:,1),ML_EO{j,i}(:,1)); %Filter the AP and ML data for EO
condition
        detrendedsig_AP_EO{j,i} = detrend(xfiltered_EO{j,i});
%Detrend the AP COP time series data in the EO condition
    end
end

for i = 1:44
    for j = 1:3
        detrendedsig_AP_EO{j,i} = downsample(detrendedsig_AP_EO{j,i},2);
%Downsample the detrended signal for EO condition from 100Hz to 50Hz
    end
end

%Filter the data AP direction EC data

for i = 1:44
    for j = 1:3
        [xfiltered_EC{j,i},yfiltered_EC{j,i}] = LPF(100,
30,AP_EC{j,i}(:,1),ML_EC{j,i}(:,1)); %Filter the AP and ML data for EC
condition
        detrendedsig_AP_EC{j,i} = detrend(xfiltered_EC{j,i});
%Detrend the AP COP time series data in the EC condition
    end
end

for i = 1:44
    for j = 1:3
        detrendedsig_AP_EC{j,i} = downsample(detrendedsig_AP_EC{j,i},2);
%Downsample the detrended signal for EC condition from 100Hz to 50Hz
    end
end

%%
%Merge the three trials for AP data EO

Position_Final_EO = cell(1,44);
%Create a cell of size 1*44 for storing time series data (EO trials)
for i = 1:44
    for j = 1:3
        Position_AP_EO{j,i} = iddata(detrendedsig_AP_EO{j,i},[],0.02);
%Store the time series data trials in the form of separate experiments (EO
trials)
    end
end

%Merge the three trials for AP data EC

Position_Final_EC = cell(1,44);
%Create a cell of size 1*44 for storing time series data (EC trials)
for i = 1:44
    for j = 1:3

```

```

        Position_AP_EC{j,i} = iddata(detrendedsig_AP_EC{j,i}, [], 0.02);
%Store the time series data trials in the form of separate experiments (EC
trials)
    end
end

%%
%AP data EO & EC
for i = 1:44
    Position_Final_EO{1,i} =
merge(getexp(Position_AP_EO{1,i},1),getexp(Position_AP_EO{2,i},1),getexp(Posi
tion_AP_EO{3,i},1)); %Store the data in the form of three columns for the
different trials (EO)
    Position_Final_EC{1,i} =
merge(getexp(Position_AP_EC{1,i},1),getexp(Position_AP_EC{2,i},1),getexp(Posi
tion_AP_EC{3,i},1)); %Store the data in the form of three columns for the
different trials (EC)
end

%%
%System identification for position data using
%arma system for AP direction
for i = 1:44
    for o = 1:5
%This is only used for determining the best order for the system. (i.e.
replace the order of the system in the next line with the variable 'o' and
run the loop. find AIC and determine the best model.
        Opt = armaxOptions;
%Set the options for prediction error method
        armasysp_EO{1,i} = armax(Position_Final_EO{1,i}, [2 1], Opt);
%System identification using an ARMA (2,1) model
        tfarmap_EO{1,i} = tf(armasysp_EO{1,i}.c,armasysp_EO{1,i}.a,0.02);
%Transfer function of the identified model for EO condition
        z_EO{1,i} = d2c(armasysp_EO{1,i});
%Convert the transfer function from discrete to continuous form using 'ZOH'
method

        Opt = armaxOptions;
%Set the options for prediction error method
        armasysp_EC{1,i} = armax(Position_Final_EC{1,i}, [2 1], Opt);
%System identification using an ARMA (2,1) model
        tfarmap_EC{1,i} = tf(armasysp_EC{1,i}.c,armasysp_EC{1,i}.a,0.02);
%Transfer function of the identified model for EC condition
        z_EC{1,i} = d2c(armasysp_EC{1,i});
%Convert the transfer function from discrete to continuous form using 'ZOH'
method
    end
end

%%
%Akaike's final prediction error for the two models
for i = 1:44

```

```

    ak_EO(i,1) = fpe(armasysp_EO{1,i});
%Calculate the final prediction errors for the ARMA models identified using
EO COP AP data
    ak_EC(i,1) = fpe(armasysp_EC{1,i});
%Calculate the final prediction errors for the ARMA models identified using
EC COP AP data
end

%%
for i = 1:44
    %     dtfarmap{1,i} = d2c(tfarmap_EO{1,i});
    %     den{1,i} = pole(tfarmap_EO{1,i});
    %     R_EO{1,i} = den{1,i};
    [Wn_EO{1,i},zetan_EO{1,i}] = damp(tfarmap_EO{1,i});
%Calculate the natural frequency and damping ratio of the poles of TF
identified for EO trials
    [Wn_EC{1,i},zetan_EC{1,i}] = damp(tfarmap_EC{1,i});
%Calculate the natural frequency and damping ratio of the poles of TF
identified for EC trials

end

%%
%Getting the characteristic equation
for i = 1:44
    %     for j = 1:10
    %         M_EC{1,i} = min((R_EC{1,i}));
    %         if min((R_EC{1,i}(j,1)))== M_EC{1,i}
    %             Selected_eigen_EC{1,i} = R_EC{1,i}(j,1)
    %         end
    %     end
    %     end

    w_EO{1,i} = (Wn_EO{1,i}(1,1))/(2*pi);
%Convert Natural frequency from rad/sec to Hz
    zeta_EO{1,i} = zetan_EO{1,i}(1,1);
%Store the damping ration caluclated in 'zeta_EO' cell for EO trials
    w_EC{1,i} = (Wn_EC{1,i}(1,1))/(2*pi);
%Convert Natural frequency from rad/sec to Hz
    zeta_EC{1,i} = zetan_EC{1,i}(1,1);
%Store the damping ration caluclated in 'zeta_EC' cell for EC trials

end

%%
for i = 1:44
    w_EO{1,i} = (Wn_EO{1,i}(1,1))/(2*pi);
%Convert Natural frequency from rad/sec to Hz
    zeta_EO{1,i} = zetan_EO{1,i}(1,1);
%Store the damping ration caluclated in 'zeta_EO' cell for EO trials
    w_EC{1,i} = (Wn_EC{1,i}(1,1))/(2*pi);
%Convert Natural frequency from rad/sec to Hz
    zeta_EC{1,i} = zetan_EC{1,i}(1,1);
%Store the damping ration caluclated in 'zeta_EC' cell for EC trials

end

```

```

%%
%Exclude the values which have values more or less than mean+- (3*SD)
w_EO = cell2mat(w_EO);
%Convert the cell to matrix for W_EO, EO trials
w_EC = cell2mat(w_EC);
%Convert the cell to matrix for W_EC, EC trials
%%
M = mean(w_EO)+(3*std(w_EO));
%Calculate the value of mean + 3*S.D, EO trials
deletethese = (w_EO >= M);
%Create a matrix which alots '1's to those values whic are > mean + 3* S.D,
EO trials
W1 = w_EO(~deletethese);
%Update the matrix W1
%%
M = mean(w_EC)+(3*std(w_EC));
%Calculate the value of mean + 3*S.D, EC trials
deletethese = (w_EC >= M);
%Create a matrix which alots '1's to those values whic are > mean + 3* S.D,
EC trials
W1_EC = w_EC(~deletethese);
%Update the matrix W1_EC
%%
zeta_EO = cell2mat(zeta_EO);
%Cell to matrix conversion of damping ratio matrix for EO condition
zeta_EC = cell2mat(zeta_EC);
%Cell to matrix conversion of damping ratio matrix for EC condition
M = mean(zeta_EO)+(3*std(zeta_EO));
%Calculate and store the value for mean + 3* S.D, EO condition
deletethese = (zeta_EO >= M);
%Create a matrix which alots '1's to those values whic are > mean + 3* S.D,
EO trials
d1 = zeta_EO(~deletethese);
%Update the matrix d1
%%
M = mean(zeta_EC)+(3*std(zeta_EC));
%Calculate and store the value for mean + 3* S.D, EC condition
deletethese = (zeta_EC >= M);
%Create a matrix which alots '1's to those values whic are > mean + 3* S.D,
EC trials
d1_EC = zeta_EC(~deletethese);
%Update the matrix d1_EC
%%
%For values lower than mean -3* S.D
M = mean(w_EO)-(3*std(w_EO));
%Calculate the value of mean - 3*S.D, EO trials
deletethese = (w_EO <= M);
%Create a matrix which alots '1's to those values whic are < mean - 3* S.D,
EO trials
W1 = w_EO(~deletethese);
%Update the matrix W1
%%
M = mean(w_EC)-(3*std(w_EC));
%Calculate the value of mean - 3*S.D, EO trials

```





```

cW = multcompare(statsS, 'Dimension', [1 2]);
%Post-Hoc Tukey Kramer test on the stats matrix obtained from ANOVA analysis
for EC condition
title('Damping ratio of the systems');
%Save the results figure in PDF format
filename = sprintf('Damping_ratio_Post_Hoc.pdf');
%Give it a file name and save figure
close all;
print(figure(4), filename, '-dpdf');
%Give it a file name and save figure
close all;

%%
cd('C:\Kaushik\Research\Thesis\Chandrashekara_Thesis\Figures');
%Set directory
e = resid(armasysp_EO{1,1}, detrendedsig_AP_EO{1,1}, 0.95);
%Calculate the auto correlation of residuals of the fitted model
title('Correlation of the residuals for ARMA(2,1) model healthy subject 1 EO
trial 1');

%%
%Power analysis for a 't' test to determine the sample size for the current
%study
n_h_mild_w_EO = sampsizepwr('t', [mean(w_EO(1:21))
std(w_EO(1:21))], [mean(w_EO(22:34)) std(w_EO(22:34))], 0.95)
%Power analysis using both means and S.D 's of the healthy - mild PD data EO
condition (natural frequency)
n_mild_mod_EO = sampsizepwr('t', [mean(w_EO(22:34))
std(w_EO(22:34))], [mean(w_EO(35:44)) std(w_EO(35:44))], 0.95)
%Power analysis using both means and S.D 's of the mild - moderate PD data EO
condition(natural frequency)
n_h_mild_d_EO = sampsizepwr('t', [mean(zeta_EO(1:21))
std(zeta_EO(1:21))], [mean(zeta_EO(22:34)) std(zeta_EO(22:34))], 0.95)
%Power analysis using both means and S.D 's of the healthy - mild PD data EO
condition (Damping ratio)
n_mild_mod_d_EO = sampsizepwr('t', [mean(zeta_EO(22:34))
std(zeta_EO(22:34))], [mean(zeta_EO(35:44)) std(zeta_EO(35:44))], 0.95)
%Power analysis using both means and S.D 's of the mild - moderate PD data EO
condition(Damping ratio)

%%
n_h_mild_w_EC = sampsizepwr('t', [mean(w_EC(1:21))
std(w_EC(1:21))], [mean(w_EC(22:34)) std(w_EC(22:34))], 0.95)
%Power analysis using both means and S.D 's of the healthy - mild PD data EC
condition (natural frequency)
n_mild_mod_EC = sampsizepwr('t', [mean(w_EC(22:34))
std(w_EC(22:34))], [mean(w_EC(35:44)) std(w_EC(35:44))], 0.95)
%Power analysis using both means and S.D 's of the mild - moderate PD data EC
condition(natural frequency)
n_h_mild_d_EC = sampsizepwr('t', [mean(zeta_EC(1:21))
std(zeta_EC(1:21))], [mean(zeta_EC(22:34)) std(zeta_EC(22:34))], 0.95)
%Power analysis using both means and S.D 's of the healthy - mild PD data EC
condition (Damping ratio)
n_mild_mod_d_EC = sampsizepwr('t', [mean(zeta_EC(22:34))
std(zeta_EC(22:34))], [mean(zeta_EC(35:44)) std(zeta_EC(35:44))], 0.95)

```

%Power analysis using both means and S.D 's of the mild - moderate PD data EC  
condition(Damping ratio)

%END OF CODE%



### ***Appendix F. Recruitment and Testing Materials***

The details on documentation, scripts, experimental protocol and setup used for this study can be found in the appendix of previous works <sup>[2, 3]</sup>.

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[2] McVey, Molly A. 2007. "Effect of Parkinson's Disease on the Step Response to a Backwards Pull." Order No. 1447172, University of Kansas. <http://search.proquest.com/docview/304833964?accountid=14556>.

[3] Barnds, Annaria. N. "Biomechanical markers as indicators of postural instability progression in Parkinson's disease", unpublished thesis, 2015, University of Kansas

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