Attractor-shape Descriptors for Balance Impairment Assessment in Parkinson’s Disease

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Abstract—In this paper, we propose a computational framework using high-dimensional shape descriptors of reconstructed attractors of center-of-pressure (CoP) tracings collected from subjects with Parkinson’s disease while performing dynamical posture shifts, to quantitatively assess balance impairment. Using a dataset collected from 60 subjects, we demonstrated that the proposed method outperforms traditional methods, such as dynamical shift indices and use of chaotic invariants, in assessment of balance impairment.

I. INTRODUCTION

Parkinson’s disease (PD) is a chronic, progressive and idiopathic disorder of the central nervous system, mainly affecting motor control. In the United States, about one million people are affected by PD [1], and live with no cure. Some of the symptoms include degradation of speech, motor functions, behavior and thought process. These symptoms continue and aggravate over time. It is considered to be the second most common age related neurodegenerative disease, and with aging population worldwide, the incidence of idiopathic PD will only increase [2]. This increasing demand for healthcare and rehabilitation for the elderly calls for efficient management guidelines offering effective assessment of impairment. Of the various motor symptoms in PD, postural stability is the most common symptom [3]–[6] affecting many activities of daily living and is shown to be the leading cause of falls in people with PD.

Most widely, the research studies that investigated the impact of PD on health-related quality of life [7], [8] and balance involved using clinical scores and balance tests that are mainly based on visual evaluation of specified movement tasks by a trained medical personnel. At the most, they included calculation of walking speed, maximum time period for which one can stand quietly without taking a step on various surfaces, how far one can lean without losing balance or take a step. For example, the Unified Parkinson’s Disease Rating Scale (UPDRS) [9] involves subjective clinical observation, has been widely used by clinicians to follow the progression of the disease, especially the severity of the motor impairments, with 0 being least severe and 180 being most severe. Although this clinical scale has been widely used, the number of test items used to evaluate balance control are very less compared to the number of items used to assess various other impairments of the disease. In addition, evaluation based on visual examination may not be sufficient to identify subtle changes in balance. Only a minority of the studies utilized obtained sway measures (using CoP data) during quiet standing and balance perturbations. Given this, developing automated methods to quantitatively assess the level of impairment will be beneficial, and is the motivation for our research to develop a framework for automatic assessment of “quality” of posture shift movement. The goal of this paper is to build a standardized model to effectively assess the level of balance impairment across the subjects in the study. Towards this, we have analyzed postural dynamic shifts dataset from healthy individuals and people with PD while standing on a force platform. Fig. 1 shows an illustration of the real-time feedback paradigm used for data collection while performing dynamic posture shifts.

Organization of the paper: Section 2 mentions recent works on classification of PD and healthy subjects. Section 3 discusses the details of the dynamical posture shifts data collection. Section 4 presents the features that are utilized for classification and prediction of the total UPDRS scores-followed by the analysis of the results of the experiments carried out in Section 5.

Fig. 1. A subject with PD standing on the force platform during dynamic shifts looking at the monitor in front of him (not shown) at his eyes level; (b) The radius of the center and outward targets and distance between the center of starting circle and the target circle were chosen 10% and 30% of subjects limits-of-stability (LoS) to facilitate comparison across subjects; (c) The targets along with typical CoP tracings during dynamic posture shifts of a trial were shown. The sequence of presentation of outward targets were randomized but the presentation of each outer target location was followed by presentation of the center target.

II. RELATED WORK

Mancini and Horak [10], studied the relevance of clinical balance assessment tools to differentiate balance deficits, indicating that the use of wearable sensors and objective
measures of balance will lead to sensitive, specific and responsive clinical balance assessment. Schoneburg et al. [11], described a framework to characterize balance dysfunction using four postural control systems: balance during quiet stance; reactive postural adjustments; anticipatory postural adjustments and dynamic balance control.

Giuberti et al. [12], investigated whether kinematic variables like angular amplitude, speed of thighs’ motion, obtained from a leg agility task, were representative of the UPDRS scores of subjects with PD. Lee and Lim [13], used gait characteristics and wavelet-based features to classify idiopathic PD patients and healthy subjects. Khorasani and Daliri [14], used Hidden Markov Model with Gaussian mixtures to classify gait data collected from healthy and PD impaired subjects, with an accuracy rate of 90.3%. Leddy et al. [15], in their study compared Functional Gait Assessment (FGA) and Balance Evaluation Systems Test (BESTest) over the Berg Balance Scale (BBS), and found both to be reliable and valid for assessing balance in PD subjects. [16], [17] used linear, Gaussian and polynomial kernel support vector machine (SVM) models to classify Minimum foot clearance (MFC) gait patterns into healthy elderly and balance impaired elderly classes. Greene et al. [18] also developed SVM models using standing balance trial information collected from elderly subjects to classify them into subjects with or without a history of falls. However all these methods follow a top-down approach of modeling the dynamics of the performed actions, i.e. they try to approximate the dynamics of the system by attempting to fit a model to the observed data. Non-linear dynamical methods follow a bottom-up approach that estimates the unknown system parameters from the data, using tools from chaos theory. Recent interest has been towards developing automated methods to quantitatively assess the movement quality of stroke survivors to aid in physical therapy treatment [19]–[21].

In this paper, we use non-linear dynamical methods [22] and the attractor-shape features proposed by Venkataramani et al. [23], to model the dynamics of the postural shifts movement and automatically assess PD severity in people, without making any underlying assumptions of the system’s parameters. We test the performance of various features over the Dynamical Posture Shift data.

III. DataSet

A. Subject Characteristics

The dynamical posture shifts dataset utilized for this study were obtained from people with and without PD as a part of a different study [24]. Regarding the dataset obtained from subjects with PD, the data was collected during medication-off state (12 hours after the last dosage of antiparkinsonian medication) from 17 patients (9 female, 8 male) with a mean age of 63.7 ± 4.9 years; ranging from 53 - 72 years with mild to moderate PD according to UK brain bank criteria with Hoehn & Yahr (H&Y) score from 2.5 to 3.0 with a stable medication regimen. Subjects were excluded from the study if they developed any of the following symptoms: dementia as defined by DSM-IV criteria; significant hepatic, renal, cardiovascular, cardiopulmonary, endocrinological issues; significant dyskinesia or on/off fluctuation; freezing-of-gait (FoG) leading to falls; other medical condition which would affect subjects safety or compliance with the study procedures. For healthy individuals, the data was collected from a total of 43 young and elderly subjects with no known neurological or orthopedic disorders. Subjects less than 35 years were assigned to the young category and subjects older than 50 were assigned to the elderly category. 21 of the subjects (12 female, 9 male) fell in the young category (19–32 years) and had a mean age of 23.0 ± 3.8 years. 22 subjects (12 female, 10 male) fell in the elderly category (50-75 years) with a mean age of 62.7 ± 8.5 years at the time of enrollment. The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Boards at Banner Sun Health Research Institute, Sun City, AZ and Arizona State University, Tempe, AZ.

B. Dynamical Posture Shifts Data Collection

First, the subjects were instructed to stand on the force platform with their hands by their side and feet separated by hip-width. All subjects wore comfortable shoes. Once the subjects stood comfortably, the position of their feet on the force plate was traced to maintain consistent placement of the feet across trials. Previously developed LabVIEW-based graphical user interface was utilized to provide real-time visual feedback of the position of the subjects CoP [24]. At the start of the trial, the CoP of the subject was taken as the center of the center target. The subject viewed his/her CoP on the monitor placed in the front of the subject at eye level which provided real-time visual feedback. The goal for the subject is to move their CoP cursor from the center of the starting circle to the target circle and hold the cursor as close as possible to the center of the target circle for 2 seconds. During the course of the trials, the outward targets were displayed in different positions, each separated by an angle of 45°. The distance of the target circle from the center was set to 30% of the distance between the hip and the ankle, which has been demonstrated to be related to the LoS [25]. The radius of the center and target circles was set at 10% of the distance between the hip and the ankle. These facilitate comparison of performance across subjects. The subject was instructed to move their CoP, displayed in a form of red circular cursor, to the target circle position by leaning without lifting their feet off the ground. Once the subject maintained their CoP position as close as possible to the center of the target circle within the target for at least 2 seconds, the current target circle disappeared and the center target appeared which became the new target. If the subject was unable to stay within the target for at least 2 seconds, then the new target appeared automatically in 10 seconds. If the subject stayed inside the target for at least 2 seconds, the target was considered successfully achieved. The five different angles at which the targets presented were 0, 45, 90, 135, and 180 degrees. After reaching towards each
target, the subject came back to the center target position before moving towards the next outward target. Thus, a total of ten targets were provided during the trial- O-0°, O-25°, O-45°, 45°-O, O-90°, 90°-O, O-135°, 135°-O, O-180°, 180°-O, where O represents the origin or center target. During a single trial, 20 targets were presented, i.e. each of the ten targets were presented twice. The sequence of outward targets was randomly presented within and across trials to minimize learning effects or anticipation of the target. A total of five and three trials were performed by healthy subjects and subjects with PD, respectively, with sufficient rest periods in-between. For each trial, the following data were collected at 100Hz: CoP in mediolateral direction; CoP in anteroposterior direction; forces generated in x, y and z directions; and moments generated in x, y and z directions.

IV. FEATURES

A. Stabilogram Postural Indices

For each trial, a two-dimensional stabilogram was obtained from the CoP in the mediolateral and the anteroposterior directions. Many postural indices were calculated from three phases of each target presentation namely, (a) Initiation phase, (b) Movement Phase, and (c) Hold Phase. From the initiation and movement phases, corresponding time taken, path-length, and velocity were obtained [24]. From the hold phase, number of reentries, inaccuracy and unsteadiness (the mean and standard deviation, respectively, of the distances between the center of the target circle and the position of the CoP during the hold phase) were calculated. In addition, the peak velocity of CoP during the entire presentation was calculated.

The peak velocity is defined as the maximum velocity value that is calculated between two adjacent samples, from the time the CoP cursor leaves the starting point and completes the target reach. It is a sensitive measure that can help distinguish people with PD for different deep brain stimulation (DBS) conditions. The peak velocity index can also help distinguish between healthy people and people suffering from PD. Bradykinesia and rigidity of movement is exhibited by people having PD. Healthy people do not exhibit Bradykinesia and therefore show higher peak velocity compared to people with PD.

B. Largest Lyapunov Exponent (LLE)

LLE is a widely used measure of chaos in various engineering applications, including biomechanics to model human movements for applications such as gait analysis [26]. It is a measure of average rate of divergence (or convergence) of initially closely-spaced trajectories over time [27]. The largest Lyapunov exponent is given by

\[ d_j(i) = d_j(0)e^{\lambda_1(i\Delta t)} \]  

where \(d_j(0)\) is the initial separation in the phase space and \(d_j(i)\) is the separation after \(i\) time steps of \(\Delta t\). \(\lambda_1\) is the largest lyapunov exponent principal axes. We use Rosenstein’s algorithm [28] to estimate LLE from real data in our experimental analysis. The parameters of this feature include the embedding dimension \(m\) and the embedding delay \(\tau\). In our experiments, the LLE features were extracted at \(m = 3\) and \(\tau = 5\). We extracted an 8-dimensional feature vector for each trial by using the time-series data, mentioned in Section III-B.

C. D2 Shape Distribution

LLE requires a large number of data samples (of the order of \(10^m \times 30^m\)) for accurate estimation (where \(m\) is a parameter used in the estimation procedure called as the embedding dimension), with typical values of \(m = 3\) and above, corresponding to a minimum of 1000 data samples. A recent approach proposed utilized ideas from shape analysis to achieve better classification and regression results in human activity analysis tasks [23], [29]. Using D2 shape function from [30], the distance between two random vectors of the reconstructed phase space which is defined as

\[ D_{ij} = ||X_i - X_j||_2 \]  

where \(X_i\) and \(X_j\) are embedding vectors in the reconstructed phase space. A set of these distances for randomly chosen embedding vector pairs are computed. From this set, we constructed a histogram by counting the number of samples which fall into each of \(B = 50\) fixed sized bins. The parameters that are required to be estimated include the embedding dimension \(m\) and the embedding delay \(\tau\). We fixed \(m = 3\), and used the first zero-crossing of the auto-correlation function to estimate the value of \(\tau\) [31]. From the time-series information discussed in Section III-B, a 400-dimensional feature vector is obtained for each trial.

V. EXPERIMENTAL ANALYSIS

Our aim in this experiment is two-fold: (a) to classify postural shifts of unimpaired (neurologically normal/healthy) and impaired (PD) subjects, and b) to quantitatively assess the disease severity by utilizing the dynamic postural shifts of healthy subjects and subjects suffering from PD.

We have used the following features in our experiments - (a) stabilogram postural indices, (b) LLE, and (c) D2 shape distribution. Of the various stabilogram indices mentioned earlier, only the peak velocity index was utilized for this study since we found that this index is significantly different between healthy individuals and people with PD, and distinguished the postural shifts performances across different DBS amplitude settings in people with PD [24].

A. Subject Classification Results

A total of 266 posture shift trials were collected, with each of the 17 PD subjects carrying out 3 trials and each of the 43 healthy subjects (21 young and 22 old) carried out 5 trials. The extracted features in section IV were first passed through a k-Nearest Neighbor (k-NN) classifier. 3-class classification was done, with the three classes being PD, OLD and YNG. We took 59 subjects for the training set and 1 subject for the testing set, and performed a round-robin leave-one-subject-out cross-validation to assess the
classifier’s performance. The advantage of using the \( k \)-NN classifier is that it does not have any hidden parameters that require tuning, thereby making it a very transparent technique for comparing different algorithms. We varied the number of neighbors \( k \) from 1, 2, ..., 51. The classification accuracy of the \( k \)-NN classifier over the D2 shape distribution features is higher than LLE and peak velocity index features at all values of \( k \), as seen in Fig.2. The best classification performance for D2 features was found at \( k = 13 \).

We now perform the same experiment using better classifiers like the linear-kernel Support Vector Machine (SVM) classifier. The parameter \( C \) was varied from \( 2^{-9}, 2^{-7}, ..., 2^{15} \). The classification accuracy over the D2 shape features is higher than LLE and peak velocity index features at almost all values of \( C \), as seen in Fig.3. We found the linear-kernel SVM classifier to give best results for \( C = 2^{-5} \). In Table I, we show the classification accuracy of the \( k \)-NN classifier at \( k = 13 \), and the SVM classifier at \( C = 2^{-3} \), after observing a recovery in the SVM’s classification performance over the LLE features. D2 shape distribution features gave the best classification result of 70.30\% using the \( k \)-NN classifier at \( k = 13 \), and 73.68\% using the SVM classifier at \( C = 2^{-5} \). The confusion matrix for the 3-class classification of D2 features using the \( k \)-NN classifier can be seen in Table II and using the SVM classifier in Table III.

![Fig. 2. Classification accuracy of the \( k \)-NN classifier over the D2, LLE and peak velocity index features with \( k \) varying from 1, 2, ..., 51.](image)

![Fig. 3. Classification accuracy of the linear-kernel SVM classifier over the D2, LLE and peak velocity index features with \( C \) varying from \( 2^{-9}, 2^{-7}, ..., 2^{15} \).](image)

![Fig. 4. Comparison between clinical total UPDRS score and the predicted score, obtained using the D2 shape distribution feature, for 17 PD and 43 healthy subjects.](image)

### Table I

<table>
<thead>
<tr>
<th>Feature</th>
<th>( k )-NN (%)</th>
<th>SVM (%)</th>
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<tbody>
<tr>
<td>Peak Velocity Index</td>
<td>50.38</td>
<td>53.01</td>
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<tr>
<td>LLE</td>
<td>47.37</td>
<td>47.37</td>
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<tr>
<td>D2</td>
<td>70.30</td>
<td>71.43</td>
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</table>

### B. PD Severity Assessment

To assess the level of PD severity for the 60 subjects, a linear-kernel SVM regression model [32] was used. Here too, a round-robin leave-one subject-out cross validation was carried out, by considered 59 subjects for the training set and 1 subject for the test set. The parameter \( C \) was

![Table II](image)

<table>
<thead>
<tr>
<th>Feature</th>
<th>True PD</th>
<th>Predicted PD</th>
<th>Predicted OLD</th>
<th>Predicted YNG</th>
</tr>
</thead>
<tbody>
<tr>
<td>True PD</td>
<td>0.61</td>
<td>0.33</td>
<td>0.06</td>
<td></td>
</tr>
<tr>
<td>True OLD</td>
<td>0.03</td>
<td>0.78</td>
<td>0.19</td>
<td></td>
</tr>
<tr>
<td>True YNG</td>
<td>0.01</td>
<td>0.32</td>
<td>0.67</td>
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</table>

![Table III](image)

<table>
<thead>
<tr>
<th>Feature</th>
<th>True PD</th>
<th>Predicted PD</th>
<th>Predicted OLD</th>
<th>Predicted YNG</th>
</tr>
</thead>
<tbody>
<tr>
<td>True PD</td>
<td>0.80</td>
<td>0.16</td>
<td>0.04</td>
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<tr>
<td>True OLD</td>
<td>0.06</td>
<td>0.72</td>
<td>0.22</td>
<td></td>
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<tr>
<td>True YNG</td>
<td>0.01</td>
<td>0.27</td>
<td>0.72</td>
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</table>

### Table IV

<table>
<thead>
<tr>
<th>Feature</th>
<th>Correlation</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak Velocity Index</td>
<td>0.8135</td>
<td>2.8227e^-13</td>
</tr>
<tr>
<td>LLE</td>
<td>0.6449</td>
<td>2.6707e^-108</td>
</tr>
<tr>
<td>D2</td>
<td>0.9090</td>
<td>1.1847e^-22</td>
</tr>
</tbody>
</table>

![Table IV](image)
varied from $2^{-9}, 2^{-7}, \ldots, 2^{15}$. The best regression model was obtained at $C = 10$. Negative predicted scores were forced to zero. Pearson correlation coefficient and p-values were calculated between the clinical and predicted scores, to quantify the performance of the regression model. The correlation coefficient and p-value pairs for all three features, can be seen in Table IV. Fig.4 displays the clinical and predicted total UPDRS scores for all 60 subjects.

VI. CONCLUSION AND DISCUSSION

In this study, we proposed the use of attractor-shape descriptors to assess balance impairment from posture shifts in subjects having PD. We showed the effectiveness of the proposed descriptor by the following experiments: 3-class classification of PD, old and young subjects and prediction of the total UPDRS scores. The results are promising and show that our descriptor can significantly outperform other baseline features. In future, studies can be designed to investigate the potential of the proposed framework to assess disease severity of PD patients at their homes. The dynamic posture shifts data can be collected at the home setup using wearable sensors and these new datasets can also be incorporated to the existing datasets to improve the disease severity assessment.

REFERENCES


