Quantitative Measurement of Motor Symptoms in Parkinson's Disease: A Study with Full-body Motion Capture Data

Samarjit Das[1], Laura Trutoiu[1], Akihiko Murai[2], Dunbar Alcindor[3], Michael Oh[3], Fernando De la Torre[1] and Jessica Hodgins[1]

Abstract— **Recent advancements in the portability and affordability of optical motion capture systems have opened the doors to various clinical applications. In this paper, we look into the potential use of motion capture data for the quantitative analysis of motor symptoms in Parkinson's Disease (PD). The standard of care, human observer-based assessments of the motor symptoms, can be very subjective and are often inadequate for tracking mild symptoms. Motion capture systems, on the other hand, can potentially provide more objective and quantitative assessments. In this pilot study, we perform full-body motion capture of Parkinson's patients with deep brain stimulator off-drugs and with stimulators on and off. Our experimental results indicate that the quantitative measure on spatio-temporal statistics learnt from the motion capture data reveal distinctive differences between mild and severe symptoms. We used a Support Vector Machine (SVM) classifier for discriminating mild vs. severe symptoms with an average accuracy of approximately 90%. Finally, we conclude that motion capture technology could potentially be an accurate, reliable and effective tool for statistical data mining on motor symptoms related to PD. This would enable us to devise more effective ways to track the progression of neurodegenerative movement disorders.**

Index Terms— **Parkinson's Disease (PD), movement disorder, motion capture (mocap), Support Vector Machine (SVM), deep brain stimulation (DBS), biomechanics and robotics**

I. Introduction

Parkinson's Disease (PD) is a progressive neurodegenerative movement disorder effecting about 3% of the population over 65 years [1]. In advanced stages, it severely effects the normal lives of the patients with predominant symptoms such as motor disability, tremors, dyskinesia, freezing and postural instability [1], [2]. Several drug therapies and surgical interventions (e.g. deep drain stimulation or DBS) have been developed to treat the disease. One of the major problems with PD is the progressive nature of the disease. Unfortunately, in many of the patients, the progressive deterioration continues in spite of drug therapy or even surgical interventions. Therefore it is very important to keep track of the progression of the disease over time and change the course of treatment if necessary. The Unified Parkinson's Disease Rating Scale (UPDRS) was developed as a comprehensive scale to incorporate multiple elements that can help assess and monitor various aspects of PD including motor disability and motor impairments. The inherent problem with the current UPDRS is the reliance on a human observer for the severity assessments. Understandably, this judgement can be subjective and inadequate for tracking the progression of mild symptoms. More objective and quantitative measures [6] of the PD motor symptoms might improve clinical decision making. In recent years, several researchers have addressed the problem of quantitative assessment of motor symptoms using wearable sensors like accelerometers [1], [2], [3]. Some other works developed quantitative measures for a few standard motor tests e.g. finger tapping [4], [5] and gait [7]. Quantitative measures on the test-retest reliability of PD motor tests were given in [8], [9]. In [8], the reliability score of the UPDRS motor component was found to be about 0.90. These approaches, however, were not designed to be adapted for precise quantitative analysis of individual symptoms over a wide range of motor tasks.

Accelerometers have limitations when used for computing precise motion because they measure the proper acceleration w.r.t the local reference frame of the accelerometer itself (not necessarily the same as the coordinate acceleration). Optical motion capture systems can provide highly accurate data for full body movements. Motion capture systems have not been widely used in PD research due to their high cost and lack of portability. However, recent advancements in portability and affordability have made various clinical applications possible [10]. With that goal in mind, in this pilot study, we perform full-body motion capture of Parkinson's patients with deep brain stimulators (DBS). To the best of our knowledge, there have been very few studies with high fidelity motion capture systems for PD related motor assessments [11], [12], [13].

In the current study, we have designed and computed various features that provide quantitative measures on the severity of PD symptoms. We have also trained and tested Support Vector Machine (SVM) classifiers for discriminating across mild vs. severe symptoms as well as on vs. off states of the DBS. These analysis techniques could potentially be applied to the motion data history of PD patients to quantify the progression of disease symptoms.

II. Methods

In this section, we first discuss the motion capture data acquisition methods for various motor tasks. This discussion is followed by a brief overview of the feature computation techniques. Then we describe the design and implementation of the support vector machine classifier for discriminating mild vs. severe symptoms.

[1]The Robotics Institute, School of Computer Science, Carnegie Mellon University, Pittsburgh, PA 15213, USA. [2]Disney Research Pittsburgh, Pittsburgh, PA 15213, USA. [3]Department of Neurosurgery, Allegheny General Hospital, Pittsburgh, PA 15212, USA. This work was supported by NSF.

a) Action tremor b) Gait c) Leg agility d) Postural stability

Fig. 1. In this figure, four frames of the motion capture session are shown. The subjects went through various motor tests: a) action tremor, b) gait, c) leg agility and d) postural stability. All the patients wore a body leotard with 60 reflective markers attached to it and performed various motor tasks. A trained clinician was monitoring them and assigning the scores for various motor components.

A. Data Collection for Various Motor Tasks

For full body motion capture, we used a commercially available system from Vicon [14]. The system consisted of 16 infrared cameras, each capable of recording at 120 Hz with images of 1000×1000 pixels resolution. A set of 60 14mm retro-reflective markers were used to capture the motion of the full body excluding the fingers and face. The subjects were asked to perform various motor tasks as described below and their motion data was recorded as 3D trajectories of the 60 marker points.

The motion capture protocol was designed to adapt and replicate the UPDRS motor impairment tests. Each subject went through a six stage motion capture session performing different motor tasks. The UPDRS motor components included in our experiments were action tremor, tremor at rest, hand pronate and supinate, leg agility, gait and postural stability. A few video frames from the capture session are shown in Fig. 1. Each motor task was assigned a UPDRS score by a trained professional depending on the severity of the symptoms. The scores ranged from 0 (minimal) to 4 (severe). In our experiments, we consider the scores from 0 to 2 as mild and 3 to 4 as severe.

B. Feature Extraction

Feature extraction is the most important step in the quantitative analysis of PD motor symptoms. Essentially, we would like to single out computational measures that reflect the differences between a mild and a severe symptom. In other words, the feature extraction should be performed in such a way that the UPDRS scores are discriminable in the corresponding feature space.

For each motor task, we analyze a relevant set of 3D marker trajectories for computing the features. First, let us define some generic features. They are aimed at quantifying tremor-related symptoms and can be quite useful for analyzing motor tasks affected by tremor. The frequency of PD related tremors tend to be of the order of 4 Hz or higher. Hence, the temporal data on 3D marker trajectories was high-pass filtered (4 Hz cut-off) as a preprocessing step for this feature. We define, $V_{hp}(x)$ as the maximum amplitude variations in the signal x after high-pass filtering. It can be given as : $V_{hp}(x) = max(h \circledast x) - min(h \circledast x)$, where h is the impulse response of the high-pass filter and $\circledast$ denotes convolution. PD symptoms are also associated with random involuntary movements of the body parts and those movements occur at a range of frequencies. The frequency domain entropy can reveal the extent of randomness in the involuntary movements. The frequency domain entropy of a signal x is given as

$$H_F(x) = \sum_f -p(X_f)\log p(X_f) \text{ where, } p(X_f) = \frac{||X_f||^2}{\sum_f ||X_f||^2}$$

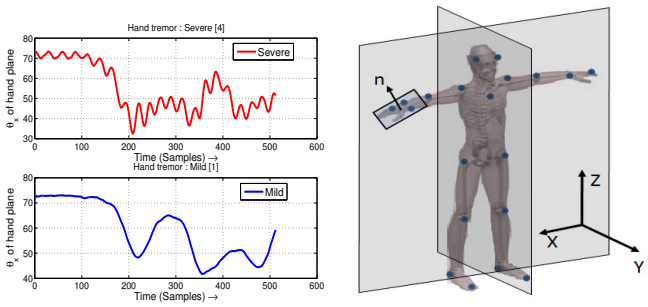
where X_f is the Fourier transform of x computed at frequency f and $||.||$ denotes the ℓ_2 norm. The effects of PD symptoms (particularly, tremor related) are also reflected in the high frequency energy content of the features associated with various body joints. Note that the feature $V_{hp}(x)$ gives the severity of tremors even if they are not persistent throughout the task and only occur in short time intervals. For measuring the extent of persistent PD tremor, we define the feature $E_r(x)$, the high frequency energy content of the signal x. It is the percentage of residual energy of x beyond a certain cut-off frequency (here, 4 Hz). It is given as, $E_r(x) \triangleq 100 \sum_i \tilde{x}_i^2 / \sum_i x_i^2$, where, $\tilde{x}$ is the high-pass filtered version of the signal x.

The motor task associated with the action tremor (AT) test involves successive taping of the nose with the finger. In this case, the severity of PD symptoms correlates with the amplitude and frequency of the tremor associated with the hand and elbow movements. Hence, we chose to use the following feature vector for action tremor:

$$F_{AT} \triangleq [V_p(\theta_x), V_p(\theta_y), V_p(\theta_z), E_r(\theta_{EL}), H_F(\theta_x), H_F(\theta_y), H_F(\theta_z)]^T$$

where θ_x, θ_y and θ_z are the angles made by the normal $\mathbf{n}$ (shown in Fig. 2) with the axes and θ_{EL} is the elbow angle. For tremor at rest, we use all the above features other than frequency domain entropy. This is because the hand/leg movements are quite restricted in this particular test.

For hand pronate-supinate tasks, the high frequency shaking of the axis of hand rotation leads to difficulty in performing the task when severe symptoms are present. The axis of rotation was roughly aligned to the y-axis and correspondingly, $E_r(\theta_y)$ gave a quantitative measure of the high frequency wobbling of the axis of rotation. This particular feature was found to correlate with the level of difficulty in performing the task. The motor task associated with leg agility involved tapping the ground with the left/right heel



a) Tremor effects on θ_x b) Front facing markers

Fig. 2. Fig. 2a demonstrates the effect of severe tremor symptoms on θ_x i.e. the angle made by the normal $\mathbf{n}$ with the x-axis (shown in Fig. 2b).

in rapid succession. The severity of the symptoms correlate with the maximum amplitude associated with heel tapping. Also, the level of difficulty increases as the high frequency energy content at the knee position increases. Thus the descriptive features for the leg agility task was given as : $F_{LA} \triangleq [\max(z_{hl}), E_r(z_{kn})]^T$ where z_{hl} and z_{kn} are the signals associated with the heel and knee heights from the ground.

The gait sequences showed that as the severity of the symptoms increase, the walking speed seemed to decrease and the subjects tended to take slow but wider steps (often with smaller step lengths). Hence, we used *mean speed* and *mean step width* as the features corresponding to the gait component of the motor tests.

As the severity of PD related symptoms increase, postural stability is likely to decrease. During the postural stability test, the subject was gently pushed backwards and the process of pose recovery was observed. We used *maximum heel deviation* w.r.t the initial position and the *body angle variance* as two of the basic features to reflect the time and effort required in the recovery process. Two other features that we also looked at were the trajectories of the center of mass (COM) and center of pressure (COP) of the body during the trials. As we will see in the results section, reduced postural stability leads to larger variations in both trajectories during severe symptoms. The COP and COM were computed by fitting musculoskeletal models to the motion capture data. Further details can be found in [15].

C. SVM : Mild vs. Severe Symptom Classifier

The features computed for various motor tasks can be used in a binary classification framework for discriminating mild vs. severe symptoms. We train a support vector machine (SVM) for each motor task as follows. Let n different trials of a particular motor task are associated with the feature vectors $\{\mathbf{x}_i\}_{1\leq i\leq n}$. The corresponding class labels are assigned as : $y_i = -1$ if $\mathbf{x}_i$ corresponds to the UPDRS scores from 0 to 2 (mild symptoms) and $y_i = +1$ otherwise (severe symptoms with scores from 3 to 4). While training, we solve the following standard linear SVM optimization problem,

$$\min_{\mathbf{w},\mathbf{b}} ||\mathbf{w}||^2 + C\sum_{i=1}^{n} \zeta_i \text{ such that } y_i(\mathbf{w}.\mathbf{x}_i + \mathbf{b}) \geq 1 - \zeta_i,\ \ \zeta_i \geq 0$$

where $\mathbf{w}$ is the SVM weight vector, $\mathbf{b}$ is the offset to the classifying hyperplane and C is the weighting parameter for the slack variables ζ_i's of the soft margin classifier. A test feature vector $\mathbf{x}_{test}$ could be assigned as mild or severe as follows. If $\mathbf{w}.\mathbf{x}_{test} + \mathbf{b} \leq 0$ assign as mild or else assign as severe. We also implemented some other nonlinear variants of the support vector machine such as SVM with polynomial and Gaussian kernels.

III. Experiments and Results

We performed full body motion capture of six subjects. Four of them (three male and one female) were diagnosed with PD and two (male) were healthy with no PD symptoms. The study was reviewed by an institutional review board and all the subjects provided their informed consent. All of the four PD patients had undergone sub-thalamic deep brain stimulator (DBS) implantation by the same surgeon. Their age range was 51 to 67 years with a mean age of 58 years. Average disease duration was 11 years with a range of 8 to 16 years. The patients received their last dose of anti-PD medications 12 hours prior to the motion capture session.

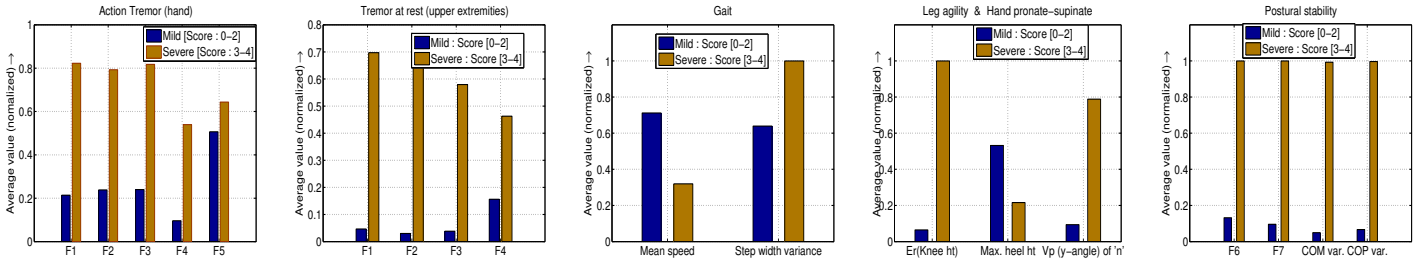
For each PD patient, there were two phases of motion capture. Each phase had six different stages corresponding to the six motor tasks mentioned earlier. For each motor task, we recorded the motion capture data and the corresponding UPDRS score assigned by the trained clinician. In the first phase, the patients went through all the motor tasks with their deep brain stimulator switched 'on'. After that their deep brain stimulators were switched off and following a short break, they went through a second phase of the capture session performing similar tasks as the first phase. In both phases, the UPDRS scores ranged from 0 (minimal) to 4 (severe) depending on the observed severity of the symptoms. In particular, for tremor related symptoms, the severity seemed to depend on whether their stimulator was turned on or off. Further details about the effects of DBS on tremor symptoms can be found in [16].

TABLE I

Features vs. UPDRS score correlation

Task	Feature	Correlation
Action tremor	Average of $V_p(\theta_x), V_p(\theta_y), V_p(\theta_z)$	0.77
	Residual Energy of θ_{EL} : $E_r(\theta_{EL})$	0.75
Tremor at rest	Average of $V_p(\theta_x), V_p(\theta_y), V_p(\theta_z)$	0.86
	Residual Energy of θ_{EL} : $E_r(\theta_{EL})$	0.34
Hand Pro-Sup	Rotation axis tremor $V_p(\theta_y)$	0.92
Leg agility	Amp. of heel tapping : $\max(z_{hl})$	-0.42
	HF energy content (knee) : $E_r(z_{kn})$	0.73
Gait	Mean speed over the sequence	-0.51
	Mean Step width over the sequence	0.67
Postural stability	Variance of Center of Mass (COM)	0.95
	Variance of Center of Pressure (COP)	0.93
	Max. heel deviation w.r.t init pos.	0.90
	Body angle variance	0.94

In Fig. 3, we compare the relative values of various features for different motor tasks averaged across mild (score 0-2) and severe (score 3-4) cases over all the subjects. There is a clear discrimination between the mild and the severe symptoms. The center of mass (COM) trajectories of the body for the mild and severe cases of postural stability are plotted in Fig. 4a (for a single subject). The severe symptoms with reduced postural stability led to larger variability in

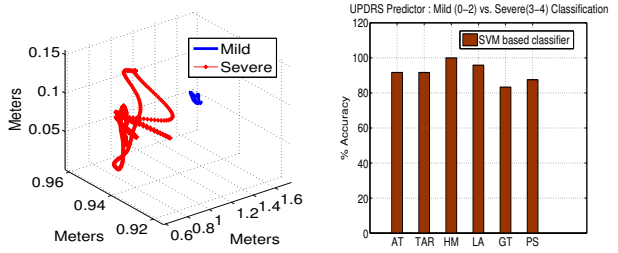


a) Action tremor b) Tremor at rest c) Gait d) Leg ag. & Hand P/S e) Postural stability

Fig. 3. In Fig. 3a through 3e, we demonstrate the quantitative differences between mild and severe symptoms for different features across the motor tasks. The feature values are normalized to the unit range due to the various ranges of variations across different features. The features appearing in the bar plots are as follows : F_1, F_2, F_3 represent $V_p(\theta_x)$, $V_p(\theta_y)$ and $V_p(\theta_z)$ respectively. F_4, F_5 represents $E_r(\theta_{EL})$ and the average entropy over $\theta_{x,y,z}$ respectively. Maximum heel deviation and body angle variances are represented by F_6 and F_7 respectively. It can be seen that there is a clear discrimination between the mild and the severe symptoms.

the COM trajectory compared to the mild case. Similar patterns were observed across other subjects as well. The corresponding quantitative comparisons can be found in the bar plot (Fig. 3e). We also computed the correlation of the features with each UPDRS score ranging from 0 to 4 (not just mild (0-2) vs. severe (3-4)). The results are given in Table. I. This gives a quantitative measure on the sensitivity of the features for subtle changes in symptoms and would be useful for designing better features.

The SVM classifier's performance for discriminating mild vs. severe symptoms across various motor tasks is shown in Fig. 4b. All the classifiers go through leave one out cross validation tests i.e. we train the classifier on all but one subject and use the motion capture data from the left out subject for testing. The average classification accuracy over all the subjects were 91.7% for action tremor and tremor at rest, 100% for hand pronate-supinate, 95.8% for leg agility, 83% for gait and 88% for postural stability. SVMs with a nonlinear kernel also showed similar performance characteristics. The average accuracy for discriminating on vs. off states of the DBS were as follows: 80% for action tremor, 91.67% for tremor at rest, 88.33% for hand pronate-supinate and 70% for leg agility. Gait and postural stability did not reflect the DBS state (on vs. off SVM classifiers had low accuracy). This failure is most likely due to the fact that the DBS primarily affects tremor related symptoms. In fact, people with severe gait/postural disturbances are not even considered to be fit for the DBS implantation as it might actually worsen the postural stability and freezing [16].



a) COM trajectories b) SVM classification

Fig. 4. Fig. 4a plots the trajectories of the center of mass (COM) of the body for mild and severe symptoms of postural stability. In Fig. 4b, we give the performance evaluation of the SVM classifiers for discriminating mild vs. severe symptoms (AT: action tremor, TAR: tremor at rest, HM: hand movement (pronate-supinate), LA: leg agility, GT: gait and PS: postural stability).

IV. Conclusion and Future Directions

In this paper, we have performed full body motion capture of Parkinson's patients with deep brain stimulators. We have demonstrated that the spatio-temporal features computed from the motion capture data gives a quantitative measure of the severity of PD symptoms across various motor components of the UPDRS. We leverage this property of the features to train SVM classifiers for discriminating between mild vs. severe symptoms. In future work, these analysis techniques could potentially be extended for reliable, quantitative tracking of disease progression.

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