Analyzing Head Pose in Remotely-Collected Videos of People with Parkinson's Disease

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We developed an intelligent web interface that guides users to perform several Parkinson's disease (PD) motion assessment tests in front of their webcam. After gathering data from 329 participants (N=199 with PD, N=130 without PD), we developed a methodology for measuring head motion randomness based on the frequency distribution of the motion. We found PD is associated with significantly higher randomness in side-to-side head motion as measured by the variance and number of large frequency components compared to the age-matched non-PD control group (p=0.001, d=0.13). Additionally, in participants taking levodopa (N=151), the most common drug to treat Parkinson's, the degree of random side-to-side head motion was found to follow an exponential-decay activity model following the time of the last dose taken (r=-0.404, p=6e-5). A logistic regression model for classifying PD vs. non-PD groups identified that higher frequency components are more associated with PD. Our findings could potentially be useful towards objectively quantifying differences in head motions that may be due to either PD or PD medications.

CCS Concepts: • **Human-centered computing** → *Ubiquitous and mobile computing*.

Additional Key Words and Phrases: Parkinson's disease, Head pose, Frequency analysis

ACM Reference Format:
Mohammad Rafayet Ali, Taylan Sen, Qianyi Li, Raina Langevin, Taylor Myers, E. Ray Dorsey, Saloni Sharma, and Ehsan Hoque. 2021. Analyzing Head Pose in Remotely-Collected Videos of People with Parkinson's Disease. *ACM Trans. Comput. Healthcare* 1, 1, Article 1 (January 2021), 13 pages. https://doi.org/10.1145/3459669

1 INTRODUCTION

Parkinson's disease (PD) is a neurological disease which afflicts over 10 million people worldwide [1] and causes over 29,000 deaths every year in the US [2]. PD is a neurodegenerative disorder that affects multiple neurological

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2637-8051/2021/1-ART1 $15.00
https://doi.org/10.1145/3459669

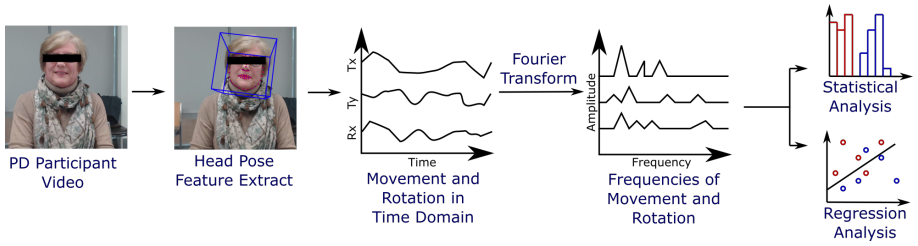


Fig. 1. Computer vision techniques were used to extract head motion and rotation. These signals were then converted into frequency domain in order to analyze the randomness of the movement. Statistical analyses were performed to characterize the differences between participants with and without PD.

systems, particularly the motor system. The behavioral hallmarks of the PD are resting tremor, bradykinesia, rigidity, and impairment to initiate and sustain movements. Unfortunately, there is no cure. While drugs are available to manage symptoms, PD medications do not work equally well for all individuals; when they do work, it is often hard to fine tune the dosage. Their application is further strained by the fact that there is no objective diagnostic test for measuring the severity of symptoms. The existing gold standard technique for assessing PD severity and side effects from medication (MDS-UPDRS) is subjective and requires an examination performed by an expert [3]. Also, the PD symptoms are not visible all the time making it challenging to diagnose.

The most common drug used to treat PD, levodopa, is characterized by "on" and "off" states that do not always follow a specific pattern. Levodopa is rapidly processed by the body (90 minute half-life), making it hard to maintain a stable level in the body [4]. This is aggravated by the fact that too much drug in the body-as well as too little drug-has associated negative side effects. Individuals with PD often try several different strategies to reduce these negative effects, such as experimenting with different dosage levels, taking the drug more often throughout the day, and adding extended time-release versions of the drug. Additionally, it is important to avoid a higher-than-necessary dose, since long-term high-dose use of levodopa is associated with adverse long-term effects [5–7]. In order to determine the most effective medication level and timing strategy to treat an individual's PD, there exists a need for an objective, easily obtainable measure of PD-related motor symptoms and/or PD medication side effects.

Advancement in computer vision has now enabled sensing of subtle movement of face and body with important medical and physiological implications. For example, recent work has shown that it is possible to extract heart rate and beat lengths from subtle head motion [8, 9], measure respiration rate from chest movement [10, 11], detect seizures for patients with epilepsy [12, 13], and even predict cerebral palsy [14]. Automated computer vision techniques may provide a beneficial degree of objectivity in quantifying subtle motion abnormalities that may be due to either PD or side effects from PD medications. Additionally, since more than 89% of older adults in the U.S. have access to the Internet [15], an intelligent web application interface utilizing advanced computer vision techniques is a compelling approach to provide an accessible and objective assessment of PD-related motor symptoms. Such a platform may help mitigate the problems of finding a neurologist, making an appointment, and planning for transportation. Indeed, remote techniques have been investigated in the assessment of PD [16–18]. Independently, head pose has been researched regarding its association with PD [19, 20]. The number of such studies is limited; additionally, whether either of these aspects of PD assessment will be clinically relevant has yet to be determined. In addition, the combined use of remote automated assessment and head pose analysis together, to the best of our knowledge, remains an unexplored domain, and is thus the focus of this paper.

Based on the work of [18], [21] and [22], we developed an intelligent online interface for assessing and quantifying head pose motion abnormalities associated with PD and PD medication side effects; the framework is summarized in Fig. 1. We collected and analyzed 329 videos (PD = 199, non-PD = 130) gathered with an augmented

version of the PARK online PD assessment tool [18]. The online tool guides participants to perform six tasks based on the MDS-UPDRS protocol (i.e., the current gold standard protocol for PD assessment) [3]. The first of these tasks asks the participant to remain at rest with a resting face (with no facial expression) for 10 seconds. We have focused our analysis on head movements during this task. Specifically, we extracted translational head motion in the three dimensions (Tx, Ty, Tz), as well as head rotation about the three axes (Rx, Ry, Rz), for each frame of video (acquired at 15 frames per second) (see Figure 2). We then analyzed the frequency content of each signal using Fourier analysis, noting which frequency components were present. In addition, we investigated the association between head motion and the time PD participants last took their medication.

In summary, our contributions are as follows:

- We developed a next-generation PARK intelligent interface for analyzing head pose and gathered data on N=199 individuals with PD and N=130 without PD.
- We found that individuals with PD had significantly higher random side-to-side head motion (as measured by the variance of large frequency components) compared to the age-matched non-PD control group ($p=0.018$, $d=0.13$).
- In participants taking levodopa (N=151), the degree of random side-to-side head motion was found to follow an exponential decay activity model following the last dose taken ($r=-0.40$, $p=0.0001$).
- In a logistic regression model for classifying the PD vs. non-PD groups, we found that the higher frequency components were predictive of PD, while the lower frequency components were associated with both the PD and non-PD groups.

2 BACKGROUND

In order to provide context to our analysis of head pose motions associated with Parkinson's Disease (PD), we first provide some background with regards to PD and the theories behind its associated motor impairments. We then discuss how PD medications are also associated with their own characteristic motor side-effects.

Parkinson's disease (PD) is a progressive nervous system disorder that causes motor impairments [23], [24] as some of its primary symptoms. In PD, the brain cells that are responsible for producing dopamine stop working normally [25]. Among the many symptoms of PD, motor impairments are commonly characterized by tremor [26], bradykinesia (slowed movement and gait), muscle rigidity, and impaired posture and balance [27]. Although these symptoms can be managed, there is currently no cure for PD. Early diagnosis and medication adjustments according to the disease severity are thus very important in managing the symptoms.

Since PD is characterized by a reduction of dopamine, PD medications aim to increase dopamine levels in the brain ("dopaminergic drugs"). Since dopamine cannot pass the blood-brain barrier, and its serum half-life is on the order of minutes, direct administration of dopamine is not a feasible treatment for PD. The most commonly used PD medication is levodopa (l-dopa), a precursor of dopamine that can be administered orally. Before levodopa can provide a beneficial effect in treating PD symptoms, it must be metabolised in the body into dopamine. Thus, after administering levodopa, a duration of time (45 minutes) is necessary for the activity level to ramp up [4]. The activity of levodopa is associated with characteristic "on" and "off" phases. The decline in activity of levodopa from a peak level follows an exponential decay with a half-life of 1.5 hours (when administered with another drug, carbidopa). The efficacy of levodopa varies substantially across individuals. Additionally, an individual's response to levodopa decreases over the long-term.

Levodopa, unfortunately, also causes several side effects, including its own motor symptom (levodopa-induced dyskinesia), along with headache, nausea, and even toxicity to neuronal cells [28, 29]. Levodopa-induced dyskinesia encompasses non-rhythmic, involuntary, abrupt movements throughout the body including the head [29]. Dyskinesia tends to be associated with the "on" phase of levodopa activity. Conversely, when the effect of

levodopa is wearing off (also known as "off state"), dyskinesia is less visible [30]. Levodopa-induced dyskinesia is often confused with the primary PD symptom of tremor.

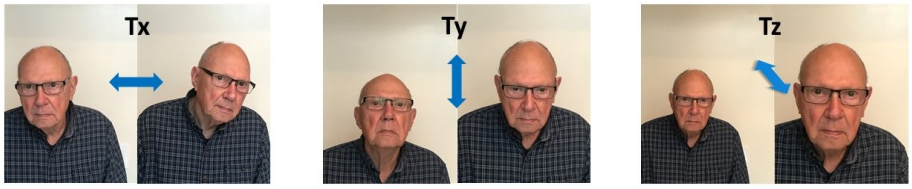
The gold standard for evaluating PD motion disorders, including levodopa-induced dyskinesia, is the expert-administered MDS-UPDRS scoring test. This test involves interviewing the PD patient, asking the nature of motor and non-motor symptoms that they experience. The expert then observes the patient's movements, speech fluency, memory recall and tremor patterns [3]. The trained examiner assigns a value between 0 to 4 indicating the severity of each symptom. This process is subjective and requires an expert examiner that may be difficult for people with PD. Due to these factors, it is difficult to assess whether the patients are responding appropriately to the medication and determine an ideal medication dosage schedule.

3 RELATED WORK

Prior research has attempted to characterize the motion abnormalities associated with PD as well as utilize telemedicine interfaces to treat PD. Computerized analysis has been applied to video and accelerometer/gyroscope data to automatically identify or characterize symptoms of PD. Video analysis and machine learning techniques have specifically been used to detect various symptoms of PD, including freezing of gait, tremor, eye motion, and others [31]. Frauscher et al. [32] analyzed videos of REM sleep from 5 PD participants. In a detailed and systematic video analysis, they showed that the number of motor events were significantly higher in the PD group than the sex- and age-matched control group. Silvia et al. [33] developed a vision-based eye tracker to monitor the pursuit ocular movements in advanced PD. They have shown that the activity in pursuit ocular movements were lower in PD than the control. Orphanidou et al. [34] applied seven different machine-learning techniques on the accelerometer-generated data from 8 PD participants to detect freezing of gait events. Support vector machine with a polynomial kernel was shown to have the best accuracy (over 90%) in predicting the freezing of gait events. Das et al. [35] used multiple-instance learning technique to detect motor symptoms of PD in uncontrolled home environments. Moore et al. [36] used an ankle-mounted sensor to detect the freezing of gait. In a study with 11 participants they were able to detect the freezing of gait event with 89% accuracy.

Some of the research on motion symptoms related to PD have specifically focused on dyskinesia. Manson et al. [37] developed a wearable ambulatory dyskinesia monitor and validated it with 20 participants (PD = 12). They measured the dyskinesia in different settings including walking, eating, drinking, writing and changing clothes. The measure of dyskinesia using the wearable monitor was highly correlated with the abnormal involuntary movement (AIM) and Goetz scales (r = 0.972, 0.951 respectively). Thomas et al. [38] also used a wearable 3D accelerometer and gyroscope sensor to measure levodopa-induced dyskinesia. They asked PD patients to perform different walking tasks while wearing the sensors on four limbs and videotaped them. From the videos, experts rated patients' dyskinesia score and treatment response score. They applied support vector machine on the extracted features from the sensors to predict those expert scores and obtained a 0.70 and 0.47 root mean squared error in predicting treatment response score and dyskinesia score respectively.

Dorsey et al. [22] examined the potential benefit of remote assessment of PD in the context of remote telemedicine, in which a live video communication link was established between patients and physicians [16, 39]. Automated and remote analysis of speech patterns for signs of PD was also investigated by Tsanas et al. [17]. Langevin et al. developed a web application for directing users to perform a set of motion and audio assessment tasks while their video was recorded for facial expression and audio analysis [18]. Ali et al. [21] used the data collected by [18] to detect PD symptoms in hand movements. Smartphone applications have also been researched for PD assessment, for example ParkNosis [40] and PERFORM [41]. Bot et al. [42] used smart-phone sensors to collect high frequency data from individuals with PD and without PD. Zhan et al. [43] developed a smart-phone app HopkinsPD to assess the voice, balance, gait, dexterity, and reaction time of individuals with PD. Chen et al. [44] collected smart-phone sensor data collected from individuals with PD through active tasks and passive



(a) Motion Features. From left to right, Tx = left-right motion, Ty = up-down motion, Tz = forward-backward motion.

(b) Rotation Features. From left to right, Rx = pitch, Ry = yaw, Rz = roll.

Fig. 2. Six types of head movement features.

monitoring to develop machine-learning models to assess postural instability, dexterity, gait, tremor, and voice impairments.

Head motion in particular has been examined by Cole et al., in which PD individuals (N=49) were shown to have increased mediolateral head motion compared with controls (N=34) [19]. Similarly, Franzen et al. investigated differences in neck tone between control subjects (N=15) and individuals with PD (N=15), finding that individuals with PD have significantly higher neck tone which may contribute to reduced performance in balance and walking [20].

To the best of our knowledge, the analysis of head pose motion abnormalities associated with PD has not been investigated with computer vision using an online framework, enabling data collection from individuals across a diverse geography as well as social-economic backgrounds.

4 METHODS

4.1 Intelligent Interface and Head-Pose Feature Extraction

The online automated data gathering framework developed by [18] was modified to also extract head pose. More specifically, after obtaining informed consent from participants, our web application guided participants to perform six tasks from the gold standard PD assessment protocol (MDS-UPDRS). These six tasks include resting facial expression, speech task, finger tapping, opening and closing of fists, postural tremor of hands, and pronation-supination of hands. In the first of these tasks, the participant was directed to remain at rest and maintain a resting face (with no facial expression) for 10 seconds. To isolate involuntary head motion, we focused our analysis on head movements during only this resting task.

Using the OpenFace software [45], we extracted translational head motion in the three dimensions (Tx, Ty, Tz), as well as rotation about the three axes (Rx, Ry, Rz). These signals are extracted at 15 fps sampling rate. Because the videos often captured body motion associated with pressing the mouse or keyboard to start or stop recording, only the middle 80% of the video was used for analysis.

For each of the extracted head pose components (i.e., Tx, Ty, Tz, Rx, Ry, Rz) the Fourier Transform was calculated [46]. For example, shown in Fig. 3 are the resulting middle 80% Tx signal and its Fourier Transform

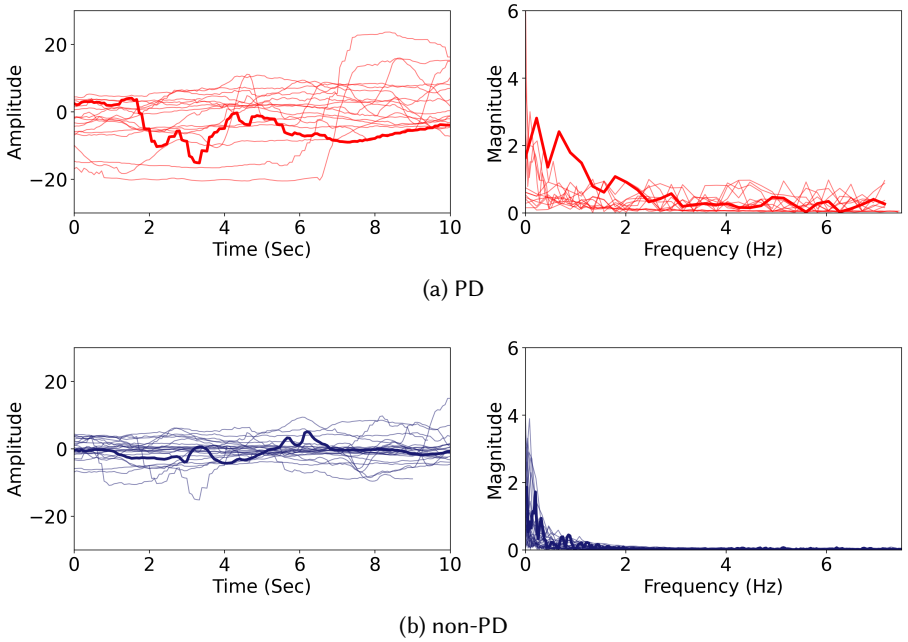


Fig. 3. Overlaid head pose data (Tx) and corresponding Fourier Transforms from the a) PD and b) non-PD groups. The mean is highlighted by bold line. Note the large rapid displacements in the PD sample and the corresponding large number of significant frequency components.

for an individual in the PD group (a) and non-PD control group (b). The magnitudes shown for each frequency represent the absolute value of the real and imaginary components at the given frequency. To avoid analysis of motions that were within the typical noise threshold of a webcam-based video signal, we considered only frequency components that have a magnitude above a noise threshold.

We next evaluated the level of dispersion of the remaining frequency components. We specifically measured this using two different techniques: (i) the count of the number of components, and (ii) the variance of the components. The number of components gives a measure of the complexity of the motion. The number of components is defined as the number of frequencies that has a magnitude greater than a threshold (0.0001). The discrete fast Fourier transform converts the signal into frequency domain with 256 frequency bins. The number of components is then counted by counting those bins with greater than 0.0001 magnitude. Simple periodic motion would be expected to result in only one or two frequency components (i.e. at the frequency of the periodic motion). Alternatively, chaotic motion would be expected to result in a large number of frequency components. An additional measure of motion complexity is the variance of the frequency components. The variance will take into account the frequencies of the components, yielding a larger variance when the resulting frequencies are more spread out over the frequency range.

4.2 Data Collection

Both PD and non-PD group participants were recruited via a combination of online and in-person recruitment. We made several visits to the clinic as well as support group homes to diversify the participant pool. The inclusion criteria were to have a working computer with a working webcam, access to an internet connection (broadband

Table 1. Data set description

	Parkinson's	Non-Parkinson's
N	199	130
Female/Male	82/117	89/41
Age (mean/std)	66.8(8.1)	63.3(5.7)
Country(US/other)	170/29	122/8
Years since diagnosed (mean/std)	8.1(5.9)	

or WiFi), and able to provide informed consent. The exclusion criteria include an inability to carry out study tasks and not being able to provide self-reported PD diagnosis. Participants were offered $50 for completion of the intelligent interface guided tasks as well as an associated survey. The survey asked several demographic questions (gender, age, country) as well as the number of years since PD diagnosis. Additionally, the survey asked what type of medication the participants were taking (if any), and when their medication was last taken. Table 1 shows the total recruitment information.

4.3 Analysis

After gathering data, three types of analyses were performed: (i) statistical significance tests comparing the motion complexity between PD and non-PD groups, (ii) motion complexity vs. time since last levodopa dose, and (iii) PD vs. non-PD classification analysis with a linear model.

For the statistical significance tests, we specifically compared the PD and non-PD groups using each of motion complexity metrics (frequency component count and variance) for each of the head pose motion signals (Tx, Ty, Tz, Rx, Ry, Rz). The nonparametric Mann-Whitney U-test was used for comparison [47], which is appropriate when it cannot be assumed that the data is normally distributed. Additionally, the Cliff's d effect size is used to represent the magnitude of any differences found [48].

Next, in the PD group only, we investigated the association between the motion complexity metrics and the time since last dose. Specifically, we limited our analysis to PD participants who had been taking levodopa for at least two years (N= 151). We measured how the motion complexity metrics (frequency component count and variance) are associated with the time since last dose using a half-life model. In the model, we used a half-life of 90 minutes and a peak activity level of 45 minutes [29]. The model is described in the following equation:

$$\text{motion complexity} \propto e^{0.69(\tau - t_0)/t_{1/2}} \tag{1}$$

where τ is the time since last levodopa dose in minutes, t_0 is the time to peak drug activity, and $t_{1/2}$ is the half-life of levodopa. We then calculated the correlation of this activity level with each of the motion complexity metrics [49].

Finally, we applied logistic regression to classify PD and non-PD participants using binned frequency component counts as input features. The frequency component counts are aggregated into 15 bins in order to avoid data sparsity issues. We used the resulting model to not only estimate classification performance, but to compare the relative weights assigned by the regression model to identify the relative importance of each of the frequency bins in distinguishing the PD and non PD groups. Specifically, logistic regression was run with L1 regularization and 10-fold cross-validation. The ideal hyperparameter (λ) was determined using a grid search with a 90:10 train vs. development set partition. The performance of the logistic regression was evaluated with the F1-score (which is the harmonic mean of precision and recall) [50].

Table 2. Difference in mean number of frequencies between PD and non-PD participants.

Feature	PD mean(sd)	non-PD mean(sd)	p	Effect Size
Tx	**79.52 (56.78)**	**65.12 (44.98)**	**0.01**	**0.28**
Ty	75.88 (50.93)	70.59 (49.14)	0.06	0.11
Tz	100.15 (68.01)	98.34 (100.86)	0.09	0.02
Rx	2.70 (3.29)	3.01 (5.07)	0.27	-0.07
Ry	1.61 (2.59)	1.45 (3.28)	0.05	0.06
Rz	0.80 (1.50)	0.77 (1.92)	0.06	0.02

Table 3. Difference in variance of frequencies between PD and non-PD participants. Mean variances are shown.

Feature	PD mean(sd)	non-PD mean(sd)	p	Effect Size
Tx	**0.05 (0.20)**	**0.03 (0.08)**	**0.001**	**0.13**
Ty	1.37 (1.80)	1.07 (1.58)	0.08	0.18
Tz	3.74 (1.16)	3.60 (1.31)	0.30	0.11
Rx	0.15 (0.78)	0.04 (0.26)	0.21	0.19
Ry	0.04 (0.35)	0.03 (0.21)	0.05	0.03
Rz	0.30 (0.96)	0.27 (1.00)	0.19	0.03

5 RESULTS

In this section, we present the results of the analyses described in the methods section. We first discuss the statistical analysis, followed by the resulting correlations between motion complexity and time since last dose of the half-life model, and ending with the regression analysis.

5.1 Statistical Analysis of PD vs. non-PD groups

Shown in Table 2 is the average number of frequency components in PD and non-PD groups for each of the head pose translational and rotational features. As is represented in the example signals in Fig. 3, we see that the average number of Tx frequency components is higher in the PD group, with a Mann-Whitney U-test p-value of 0.01 and a Cliff's d of 0.31. While this result is suggestive of an association, we must consider the fact that we are performing multiple separate statistical tests; the typical measure of statistical significance (i.e. $p < \alpha$, where $\alpha = 0.05$ for 95% confidence) should factor in the number of tests performed (i.e., Bonferroni correction) [51]. If we use an conservative Bonferroni correction factor of 12 (for 6 * 2 tests), the corresponding significance level becomes $alpha = 0.004$. Each of the other head pose features (Ty, Tz, Rx, Ry, Rz) show less of a difference between the PD and non-PD groups than Tx.

Table 3 shows the average frequency variances of each head pose feature for the PD and non-PD groups. Similar to the number of frequency components measure, the average variance of Tx is larger for the PD group (p=0.001, d=0.13). The significance of this difference is below the Bonferroni-corrected $alpha = 0.004$, indicating a strong association between Tx frequency variance and whether the participant is in the PD vs. non-PD group. While none of the other head pose features had as low a p-value, it is important to note that for all head pose features, the average variance of the frequency components was larger in the PD group (This also suggests that the examples in Fig. 3 are representative of the results).

Table 4. Correlation between the measure of randomness in motion and time of last medication (in minutes) using half-life model.

	Correlation with number of frequencies		Correlation with variance of frequencies	
Feature	Pearson's r	p	Pearson's r	p
Tx	**-0.404**	**0.0001**	**-0.402**	**6e-05**
Ty	-0.234	0.0241	-0.158	0.13
Tz	-0.241	0.02	-0.066	0.53139
Rx	0.03	0.7785	0.07	0.50421
Ry	0.077	0.4617	0.105	0.31792
Rz	-0.026	0.8017	0.022	0.83744

5.2 Motion complexity vs. last dose time

Tables 4 show the correlation of the number of frequency components and frequency variance motion complexity measures with the half-life model in equation 1 for each head pose feature. Most of the correlation coefficients are negative, indicating that in general, the more recently one took medication (while also being longer than the 45 minute t_0 time), the more likely it is that the participant showed higher motion complexity. Similar to how Tx was shown to have the largest motion complexity difference between the PD and non-PD groups, we see that Tx motion complexity is most highly correlated with time since last levodopa dose within PD participants who were taking levodopa. The Tx number of frequency components and frequency variance have respective correlations of $r = -0.404$ and $r = -0.402$ with the half-life model predicted complexity from time since last dose. The associated p-values for each of these motion metric correlations are $p = 10^{-4}$ and $p = 6 \times 10^{-5}$, which are both under the Bonferroni corrected $\alpha = 0.004$ (correction factor = 12). For other features no significant correlation was found.

5.3 Regression Analysis

The logistic regression analysis was most successful (according to F1-score) when using the Tx head pose feature. The average F1-score over the 10-fold cross-validated models was 0.745 (sd = 0.07) when using Tx, yielding the model weights shown in Fig. 4. From Fig. 4 we see that the low frequency bin (0.5 to 1 Hz) is the only feature with a negative weight, indicating that it is more associated with the non-PD group. All higher frequency bins have a positive weight, indicating that they are more associated with the PD group. The highest weight, i.e., the strongest predictor of group membership, is the 3.5 - 4.0 Hz frequency bin count.

6 DISCUSSION

Of the six head pose features collected, the strongest difference between the PD and non-PD group was observed in Tx. This is probably due to multiple factors. First, the Tx an Ty signals are likely to be the least noisy with regards to the computer vision head pose estimation. The noise in Tz is likely higher than Tx and Ty since motion in the dimension towards and away from the camera is only going to result in camera-observed face size differences. Alternatively, any side to side or up and down motion will be observed directly by the camera. Additionally, whereas the Tx and Ty signals only rely upon a face-detection algorithm with a face position discerned from eye and mouth locations, head orientation requires a much more complex calculation involving not only depth information, but also a number of facial landmarks [45]. Second, the way that the head pose extraction software works, the Tx, Ty, and Tz signals represent the position of a face, and not the center of an individual's head. Thus, any time an individual rotates their head while maintaining the same overall position for

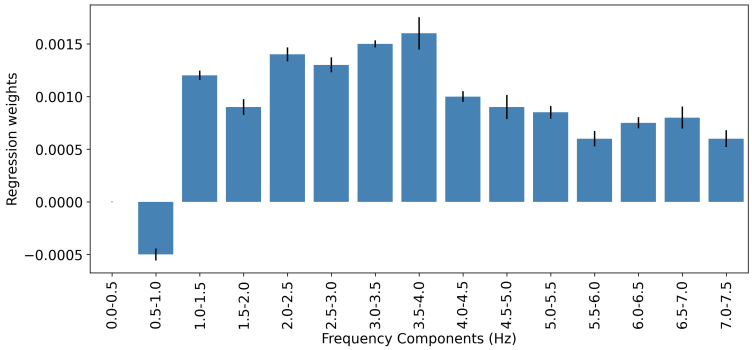


Fig. 4. Logistic Regression model weights for classifying whether the participant is in the PD group (positive class) or non-PD group. Input features are the frequency component counts aggregated into 15 bins.

the center of their head (i.e. their spine), the head pose extraction software will extract a change in translational position with every change in rotation.

The features of frequency component count and frequency component variance provide an objective measure of motion randomness. Since PD participants, especially individuals who are taking levodopa, has an associated higher incidence of involuntary head movement, it is expected that the PD group would have higher frequency component counts and frequency component variances than the non-PD group. The likelihood that this increased level of randomness is associated with levodopa is suggested by the correlation of the level of randomness with the last time that levedopa medication was taken. Effectively, the frequency component count and and frequency component variance may be indirectly measuring levodopa-induced dyskinesia. However, further study should be conducted in which dyskinesia is labeled by experts over time in subjects who have taken levodopa. It should be noted that in our dataset, out of all the participants who were known to be taking levodopa (N=151), many of them (N=26) had been taking it for less than 2 years. In future work it would be useful to see how these features vary over the number of years that individuals with PD have been taking levodopa. It should also be noted that we used only two types of measure of randomness. A potential limitation of our analysis is that we did not analyze the statistical features such as the skewness and kurtosis, or the sample entropy of the spectrum. We believe these features may contain important information on how random the movements are across the 3 directions and 3 rotations. In the future, we plan on analyzing these features in more depth.

The logistic regression model provides further evidence that high-frequency components of motion are more strongly associated with those in PD group vs. non-PD group. Specifically, frequency components near 4Hz region were mostly associated with PD. However, the exponential decay analysis conducted suggests that these differences are due to PD medication rather than a primary symptom of PD itself. In the past, similar observations were made by researchers [52] who found the head movements in the high-frequency range may occur due to levodopa-induced dyskinesia. Additionally, researchers have worked on developing computer vision based machine learning tools to distinguish levodopa-induced dyskinesia and Parkinson's symptoms [53]. However, to gain more confidence further studies needs to be conducted in order to distinguish which motion features are causally related to PD vs. PD medication on a large sample of the population.

A potential limitation of our analysis is that none of the videos are rated by an expert on dyskinesia scale. Since we don't have the information of the patient's medication dosage we can not just select a subset of the participants for getting rated by a expert. In the future, we plan on getting all the videos rated by an expert on both dyskinesia scale and MDS-UPDRS.

The integration of our analysis framework into a web based assessment tool suggests that there may be promise for individuals to objectively monitor their PD and/or PD medication-related motor symptoms. Such a system may enable frequent assessments without in-person clinical visits. Such a tool could be valuable for identifying individuals with motor impairment, which may go undetected by patients and clinicians who see patients infrequently. Also, movements, such as, tremor or dyskinesia, may not be present during episodic examinations. In addition, these movements can be undesirable and disabling to some. Such frequent assessments may enable more efficient fine-tuning of the medication dosage. Also, this type of online PD assessment tool may help in the evaluation of new drugs and treatments for PD.

In the dataset, we do not have information regarding the dosage of levodopa (in milligrams). We also do not have information of the participants' physical characteristics such as body mass index (BMI) which has shown to be associated with levodopa induced dyskinesia as well as Parkinson's severity [54–56]. This is a limitation of our analysis. Also, we do not have participants who have PD but not taking levodopa. While filling out the survey, many participants (N=48) did not mention their medication, which does not conclusively suggests that they are not taking levodopa.

It should be noted that the sample size in this study was limited to 199 participants with PD and the analysis was exploratory in nature (i.e. the hypotheses were formed after data was gathered as opposed to having all hypotheses stated a priori). Finally, while the study was open to participants from all nations, the website was in English only, and a high percentage (85%) of the participants was from the US.

7 CONCLUSION

Parkinson's disease is the fastest-growing neurological disorder. There is a significant shortage of neurologists available worldwide. Automated assessment using computer vision techniques can be very useful for individuals who have no access to a neurologist or are immobile. To achieve an accurate digital assessment, reliable digital biomarkers are necessary. In this paper, we have presented an online interface for characterizing the randomness in the head movement of individuals with and without Parkinson's disease. While our analysis found statistically significant differences, further work is needed before our tool can be deployed for clinical trials. Additionally, our findings support current theories regarding levodopa-induced dyskinesia. We hope these findings will promote further development in objective PD assessment tools and to improve future treatments.

8 ACKNOWLEDGEMENT

This work has been funded by the National Institute of Neurological Disorders and Stroke of the National Institutes of Health under Award Number P50NS108676, grant W911NF-19-1-0029 with the US Defense Advanced Research Projects Agency (DARPA) and the Army Research Office (ARO) and a Google Faculty Award.

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