Computational Tracking of Parkinsonian Motor Fluctuations in a Real-World Setting: a case study

Ainara Carpio Chicote* (a.carpio-chicote22@imperial.ac.uk)
Department of Bioengineering, Imperial College London, London, UK

Julian Jeyasingh-Jacob* (j.jeyasingh-jacob@imperial.ac.uk)
Department of Brain Sciences, Imperial College London, London, UK

Subati Abulikemu* (subati.abulikemu20@imperial.ac.uk)
Department of Brain Sciences, Imperial College London, London, UK

Shlomi Haar (s.haar@imperial.ac.uk)
Department of Brain Sciences, Imperial College London, London, UK

* Ainara Carpio-Chicote, Julian Jeyasingh-Jacob and Subati Abulikemu contributed equally to this work as co-first authors.

Abstract:

Digital biomarkers based on accurate tracking of motor behaviour can provide a cost-effective, objective, and robust measure for Parkinson's Disease progression, changes in care needs, and the effect of interventions. Markerless motion capture technology offers a promising approach for running it in the home. This technology uses depth sensors to capture movement unobtrusively and generate objective and quantifiable movement features. Here we present a 4-month long case study during which the patient visits our lab every month to perform mobility tasks and daily living tasks. Our data suggest accurate tracking of symptom fluctuations during both task types. This is a promising proof-of-concept towards passive tracking in-the-home of Parkinsonian symptom fluctuations.

Keywords: Parkinson's Disease; Markerless motion capture; Real-world neuroscience;

Background

Parkinson's disease (PD) is a neurodegenerative disorder that is characterised by a progressive deterioration of motor function, including fluctuations in symptoms such as tremors, bradykinesia, and rigidity. While medications such as Levodopa can alleviate the symptoms of PD, motor fluctuations can occur as the medication wears off (Parkinson Study Group, 2004), particularly in patients with longer disease duration (Shragg & Quinn, 2000). However, there is currently no accurate method for continuous monitoring of motor symptoms. The standard clinical measure for longitudinal tracking of motor symptoms is the motor examination section of the Unified Parkinson's Disease Rating Scale (UPDRS), which is completed by trained clinicians. However, the infrequency of UPDRS assessments means that motor fluctuations may not be detected promptly. Moreover, less frequent motor symptoms such as freezing of gait may not manifest during UPDRS assessments performed intermittently in a clinic setting.

Previous studies have used wearable devices to measure PD motor fluctuations in home settings (Ramesh & Bilal, 2022; Hassayeni et al., 2021). However, this approach is complicated by the need for multiple wearable sensors for optimal measurement and compliance. Therefore, we employed a full-body tracking markerless motion capture (MMC) approach, which allows for continuous and unobtrusive measurement which is highly suitable for use in real-world settings.

Here we present a case study of a single participant with PD over four monthly visits to the 'Living Lab', a lab space with a studio flat layout, equipped with smart sensors. We focus on the analysis of two primary features obtained from 3D joint position data during standard physical performance tasks versus during daily life activities. These features include shoulder slope and ankle distances, taken frame-by-frame during each task. Our objective was to investigate the influence of symptom fluctuations on motor performance during ADL tasks by analysing the features and their variations.

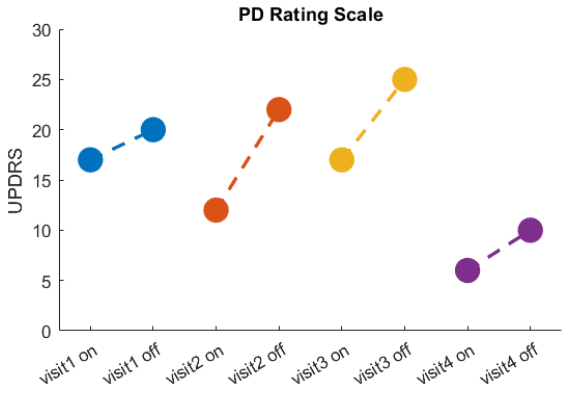

Figure 1: UPDRS motor examination scores of the participant during on and off-medication states over 4 monthly visits.

Methods

Data Collection A patient with PD attended four monthly visits to the living lab. On each visit, they arrived shortly before medication intake. After the medication started to take effect and the participant felt On, the UPDRS was administered by a certified clinician. They then performed the Short Physical Performance Battery (SPPB: https://sppbguide.com/) which includes standard mobility tasks such as walking 4 metres and rising from a chair, followed by the ADL tasks: making tea and toasts. The participant remained in the lab while the medication wore off and repeated the tasks before their next medication intake. During the entire session, we recorded their body movements with six Azure Kinect DK depth cameras and used Microsoft's SDK to extract full skeleton data from each frame at 30Hz.

Data Analysis After defining one of the cameras as the 'main', data from the other cameras were aligned to it in time and space using temporal resampling and transformation matrices. We then merged the information from the different cameras using the level of confidence for each camera in each time frame towards the weighted average. Finally, in a hypothesis-driven approach, we computed different features which an occupational therapist would look at while observing a patient during a clinical assessment. Here we focus on two features: 1) Spine curve area– we quantified it by computing the area between the curvature of the spine and the direct line from the pelvis to the neck, normalised by the length of this line. 2) The front-back distance between the ankles, during walking, its peaks are the step length, but here we look not only at the peaks but the full distribution of those distances.

Results

In each of the visits, the participant indeed showed a fluctuation in their symptoms throughout their medication cycle, as demonstrated by their UPDRS scores taken during the On and Off medication states (*Fig. 1*). The fourth visit was shortly after their medication dosage was increased at clinical review, which might explain the better UPDRS scores and lower fluctuations.

In all visits, during the 4-metre walk task, the spine curve area was higher and more variable while the participant was off medication, suggesting they had a marginally increased stooped posture and oscillated more while walking off medication. A similar trend was evident during the ADL task of making tea (*Fig. 2*).

Similarly, in all visits the ankle distance was longer and more variable while the participant was off medication, suggesting longer and more variable steps (*Fig. 3*). Here on the other hand, during the tea task we see the opposite pattern of smaller distances off medication, with the smallest being in visit 3 when the symptoms were most severe according to the UPDRS scores. This suggests that opposite patterns of this feature occurred during instructed walks compared to spontaneous walks as part of ADL performance.

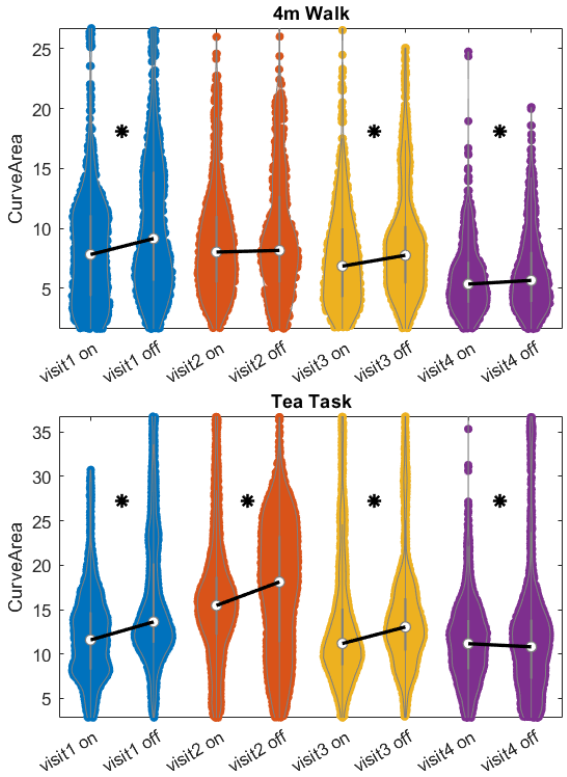

Figure 2: Spine curve area during 4-metre walk (top) and tea task (bottom) for on and off medication states over 4 monthly visits.

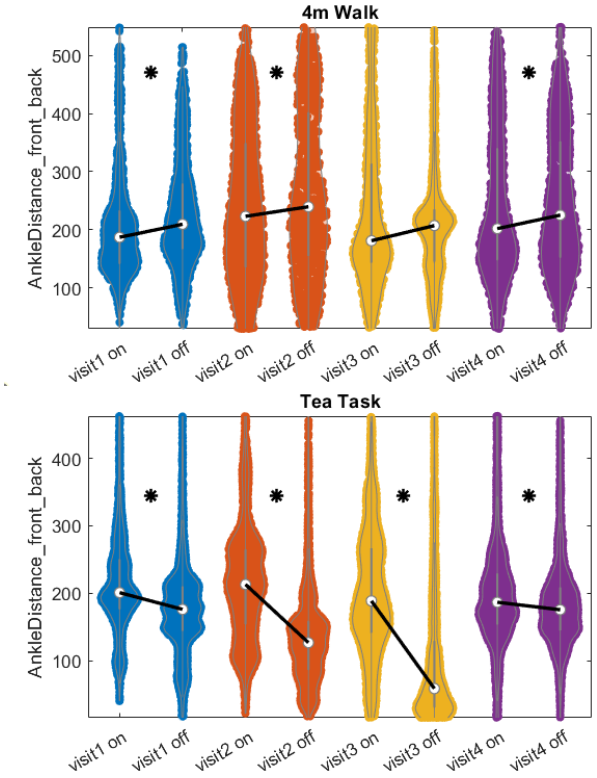

Figure 3: Ankle distance during 4-metre walk (top) and tea task (bottom) for on and off medication states over 4 monthly visits.

Discussion

In this study, we recorded movement and posture with an MMC setup and extracted features that can capture symptom fluctuation. Our preliminary analysis has shown that it is feasible to detect changes in movement and posture attributable to motor fluctuations using our setup. Our findings also demonstrate that fluctuations in motor symptoms and consequently impairments in motor performance can be detected by the identified features during mobility tasks and daily activities in individuals with PD, but the interpretation of the same features might be different in different tasks. Studies with larger sample sizes are required for further evaluation and clinical validation towards the development of digital biomarkers for symptom fluctuations.

Acknowledgments

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References

Hssayeni, M. D., Jimenez-Shahed, J., Burack, M. A., & Ghoraani, B. (2021). Dyskinesia estimation during activities of daily living using wearable motion sensors and deep recurrent networks. *Scientific reports*, *11*(1), 7865.

Parkinson Study Group. (2004). Levodopa and the progression of Parkinson's disease. *New England Journal of Medicine*, *351*(24), 2498-2508.

Ramesh, V., & Bilal, E. (2022). Detecting motor symptom fluctuations in Parkinson's disease with generative adversarial networks. *NPJ digital medicine*, *5*(1), 138.

Schrag, A., & Quinn, N. (2000). Dyskinesias and motor fluctuations in Parkinson's disease: A community-based study, *Brain*, 123 (11), 2297–2305.