Smart Glasses for Gait Analysis of Parkinson's Disease Patients

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Abstract - **Parkinson's disease (PD) is one of the most common neurodegenerative disorders of the central nervous system, which predominantly affects patients' motor functions, movement, and stability. Monitoring movement in patients with PD is crucial for inferring motor state fluctuations throughout daily life activities, which aids in disease progression analysis and assessing how patients respond to medications over time. In this preliminary study, we examine the possibility of using smart glasses equipped with Inertial Measurement Unit (IMU) sensors for providing objective information on the motor state of PD patients. Data was collected from seven patients with PD with varying levels of symptom severity, who performed a total of 35 trails of the Timed-Up-and-Go (TUG) test while wearing the glasses. We present an IMU-based step-detection algorithm with a potential for continuous monitoring of patients' gait. Furthermore, the analyses reveal patient-specific clusters in the sensor data, suggesting the possibility of developing personalized models for monitoring symptom progression. The findings suggest that smart glasses have the potential for unobtrusive and continuous screening of PD patients' gait, enhancing the medical assessment and treatment.**

Keywords - Parkinson's disease, smart glasses, inertial measurement unit, gait analysis

I. INTRODUCTION

Parkinson's disease (PD) is one of the most common progressive neurological disorders. In the past 25 years, the prevalence of Parkinson's disease has doubled globally. Global estimates in 2019 showed over 8.5 million individuals living with PD. PD predominantly impairs patients' motor abilities but is also associated with a wide variety of non-motor complications, including cognitive impairment, mental health and sleep disorders, sensory disturbances, and other behavioral problems. The severity and frequency of the symptoms usually increase as the disease progresses over time, impacting the patient's mental health and self-esteem, and significantly worsening their quality of life. Gait impairments are considered a good indicator of the progression of the disease, and can provide valuable insight into a patient's overall health, cognitive function, fall risk, and likelihood of institutionalization [1], [2]. Therefore, having efficient and reliable tool for gait monitoring and analysis is crucial for early diagnosis and tracking the progression of PD.

Fortunately, mobile health and behavior monitoring technology has advanced significantly with the availability of small, wearable, low-cost sensors combined with advanced signal processing, machine learning, and information extraction methods [3]. In the PD field, advanced analytics applied to speech (e.g., audio data), gait (e.g., accelerometer data), handwriting (e.g., touchscreen data), and face movements (e.g., video data), have offered great potential for disease monitoring and management [4], [5]. Adopting wearable and smart devices for PD has enabled an understanding of patients' symptoms outside the clinic (e.g., while performing everyday activities). The mobile-health tools also enable clinicians to continuously monitor the response of people with Parkinson's disease to various treatments, opening the opportunity to adapt medications efficiently [6]. Furthermore, recent meta-reviews demonstrate that people with Parkinson's disease want to use digital technologies [6], [7], [8]. Examples of perceived advantages include access to specialists, convenience, and time savings.

However, the meta-reviews also demonstrate that existing digital solutions for PD do not live up to the expectations [9]. One important challenge is acceptance, i.e., in future digital tools for improved care of PD patients should be much more user-friendly than average digital tools, given the motor and cognitive challenges PD patients may face. Another important challenge is personalization. Personalization is essential for PD given the symptoms' unpredictability and high inter-person variability [6], [8]. A third challenge is validation, i.e., the development of PD digital tools must be performed in collaboration with expert medical teams. The digital tools must also be validated against established clinical measures [10], [5].

This study is a step towards addressing the three challenges of the existing digital tools, acceptance, personalization, and validation. We aim to maximize user acceptance by providing a digital solution based on an object that is omnipresent in the life of PD patients, i.e., eyeglasses. The eyeglasses should also enable user-specific data, provided that they are worn daily by the PD patients. The user-specific data provided by the glasses could then

be used for personalized solutions. Finally, aiming towards clinical validation, this study provides initial analysis of data collected in a clinic with actual PD patients while performing a clinically validated protocol, Timed-Up-and-Go (TUG) [11].

II. Background and Related Work

The Timed-Up-and-Go (TUG) test is a clinical tool commonly used for measuring motor dysfunction in PD. The subject stands up from sitting, walks three meters, turns, walks back to the chair, and sits back down. The examiner measures, in seconds, the time taken to complete the task [11]. Total time taken has been shown to correlate with disease severity [12], risk of falls over the next year [13], [14], and response to dopaminergic therapies [15]. The TUG test is limited in that it measures the patient at a single point and is not truly representative of all activities of daily living (ADL). In addition, dopaminergic medications have "on" phases (peak effect) and "off" phases (trough effect), which makes the comparison of TUG testing over time challenging as patients may be in a different part of this cycle [16].

Many studies have looked at wearable devices which can track movements of PD patients without the need for a direct observer. Multiple studies have validated wearable devices during TUG testing and found reliability in measuring the total time taken [17], predicting fall risk, and gait and mobility parameters [18]. Wearable sensors have also been shown to delineate the time taken for specific movements such as the sit-to-stand or stand-to-sit transition [19], gait speed, and turning speed [20]. A study by Weiss et al. [21] measured data from a sensor worn on the lower back for three days and found a significantly improved ability to predict fall risk compared to commonly used clinical scoring measures. Wearable sensors have also been used to measure Freezing Of Gait (FOG) symptoms, i.e., when the patient is unable to initiate movement, over longer time periods [22], [23]. This is important as there may be specific triggers for this, such as walking through a narrow space, which cannot be replicated during a TUG test. Therefore, wearable devices can be used to enhance PD monitoring and aid medication decisions by giving clinicians information about the patient in a wider variety of settings and over a longer time period.

This study aims to assess the feasibility of using smart glasses equipped with an Inertial Measurement Unit (IMU) sensor for monitoring gait in patients with PD as an objective measurement of their motor state. From wearable sensing perspective, the head is a promising position for IMU sensor placement that should provide less noisy sensor data compared to other sensor placements (e.g., wrist/smartwatch). This is because our hands can be involved in a variety of micro and macro tasks (from running to typing on a keyboard). On the other hand, the human body has a natural mechanism to keep the head steady in space when the body is moving in order to maintain a stable visual field [24].

III. Dataset

A total of seven PD patients (four females and three males, with a mean age of 77 ± 7.3 years, range 68–87 years) with different levels of disease symptom severity were recruited. All participants provided written informed consent before participating in the study. For data collection, we used the OCOsense™ smart glasses (Figure 1), developed by Emteq Labs. The smart glasses are equipped with: (i) seven OCO™ sensors that measure skin movement in three dimensions (location indicated by the green rectangles in Figure 1), and (ii) a 9-axis IMU sensor (accelerometer, gyroscope, and magnetometer), including an altimeter (located in the right arm of the glasses frame, indicated by the purple rectangle in Figure 1). The orientation of the inertial sensor in the glasses can be determined by aligning the black dot on the zoomed inertial sensor in Figure 1 and the white dot below the purple rectangle on the glasses frame. This results in the x-axis being vertically oriented (opposite of the gravitational force), the y-axis being aligned with the glasses arm (pointing towards the ear), and the z-axis being the horizontal axis (pointing to the head).

The experimental protocol was based on the Timed-Up-and-Go (TUG) test: the participants sat on a chair, stood up, walked straight for three meters at their normal speed, turned 180° around an obstacle, walked straight back to the chair, did another 180° turn, and finally sat down on the chair. They completed five repetitions of the TUG test, resulting in a total of 35 walking trials in the dataset. All participants were able to perform all trials independently, without an assistive device. The sessions were also recorded with a video camera. The study was reviewed and approved by the NHS research ethics committee, (ref: 18/WM/0205) and took place at Queen Victoria Hospital in East Grinstead, England.

All participants completed two questionnaires: the Freezing of Gait (FOG) Questionnaire and the Parkinson's Disease Questionnaire (PDQ-8). The former includes six questions and is focused on FOG severity and gait impairments over the last week, while the latter includes eight questions about mobility, activities of daily living, emotional well-being, stigma, social support, cognition, communication, and bodily discomfort, and is used to quantify the quality of life among PD patients. Each question was scored between zero and four. A higher score on the FOG questionnaire corresponds to more severe FOG episodes. A higher score for the PDQ-8 questionnaire signifies a poorer quality of life and a more severe form of the disease.

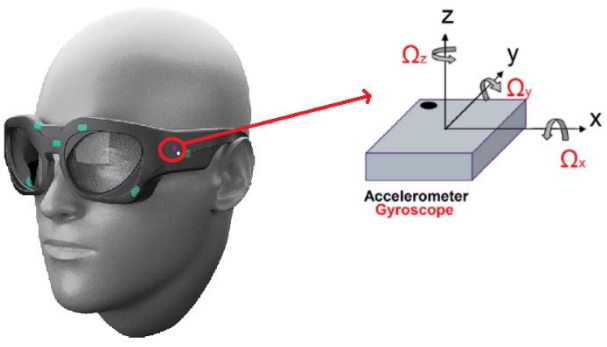

Figure 1. OCOsense™ glasses and the sensors' location. The green rectangles represent the OCO™ sensors, and the purple rectangle represents the 9-axis inertial sensor.

TABLE 1. DEMOGRAPHICS DATA AND QUESTIONNAIRES' SCORES.

ID	Age (Years)	Sex	FOG Score (%)	PDQ-8 Score (%)
1	70	Male	20.8	46.9
2	73	Female	4.2	40.6
3	83	Female	87.5	75.0
4	68	Female	66.7	37.5
5	73	Male	25.0	31.3
6	86	Male	66.7	65.6
7	87	Female	33.3	34.4

The final scores from the questionnaires, alongside the participant demographics, are presented in Table 1. The questionnaire's score for each participant was divided by the total possible score (for each questionnaire separately), and the final scores in the table are given as a percentage out of 100.

IV. SENSOR DATA ANALYSIS

A. *Sensor data preprocessing*

The sensor data was collected using Emteq's OCOsense™ smart-glasses that provided 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer data, all sampled at 50 Hz. To reduce the impact of high-frequency artifacts and preserve the gait information within the signals, a 3rd order Butterworth bandpass filter was applied to the sensor data. It allowed only frequencies within the range of 0.1 to 5 Hz to pass through, effectively filtering out frequencies irrelevant to gait analysis and ensuring that the signals are not impacted by noise. Figure **2** presents an example of a raw acceleration signal recorded during a walking activity, and the same signal after the pre-processing.

B. *Step detection – heathy participants*

We implemented a step detection method that involves analyzing the periodic differences present in the pre-processed accelerometer magnitude data. The peak detection is based on the first order difference of the signal.

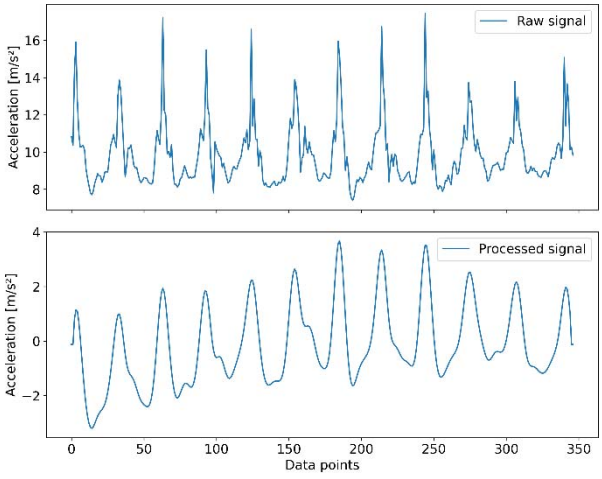

Figure 2. An example of a raw and processed acceleration signal (x-axis).

The algorithm has two parameters, a minimum amplitude threshold above which a data point can be considered as a peak, and a minimum time distance required between two peaks. The detected peaks in the acceleration signal correspond to the moment of highest impact during each step. Similarly, if we invert the acceleration signal and detect the peaks in the inverted signal, we are also able to detect the start and end of each step, or the heel strike and toe off. An example for the step detection algorithm is presented in Figure 3. The figure displays the change in acceleration (represented by the x-axes and measured in meter per second squared). We consider the x-axis to be the most informative for the walking activity because of its orientation (see Figure 1).

Before applying the step-detection method on the data from the PD patients, we performed in-lab testing with data from four healthy participants (with a mean age of 23.3 ± 1.64) following a simple testing scenario. The participants wore the Emteq's OCOsense™ glasses and completed two sessions, in each performing twenty steps at their normal walking pace. Thus, the speed of walking varied between the participants. We evaluated the method using Mean Absolute Percentage Error (MAPE) (1):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{A_i - D_i}{A_i} \right| \quad (1)$$

where n is the number of participants; A_i is the actual number of steps that the *i-th* participant performed; and D_i is the number of detected steps based on the step detection method. This dataset was also used to fine-tune the parameters of the peak detector. The final MAPE score achieved by the method was of 1.3%. This means that error was below one step per participant (on average).

C. *Step detection – PD participants*

The step-detection method was then applied to analyze the number of steps performed by the Parkinson's patients during the five trials of the TUG test. The number of detected steps in each trial for each participant is reported in Table 2. The average number of steps across all participants was 15.9 with a standard deviation of 5.45. The average MAPE in step detection across the participants was 8.1%, which represents an average error of 1.3 steps (out of 16).

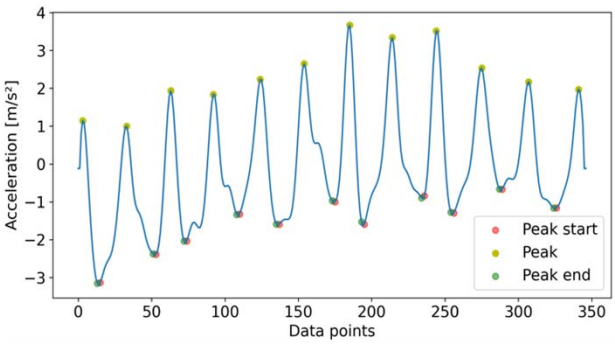

Figure 3. An example of a processed acceleration signal (x-axis) and the detected steps.

TABLE 2. NUMBER OF DETECTED STEPS FOR EACH PARTICIPANT IN FIVE TUG SESSIONS.

ID	S1	S2	S3	S4	S5	FOG	PDQ-8
1	16	16	16	14	14	20.8	46.9
2	11	12	11	10	12	4.2	40.6
3	33	25	24	27	24	87.5	75.0
4	13	13	14	15	14	66.7	37.5
5	11	11	11	11	11	25.0	31.3
6	24	19	19	19	20	66.7	65.6
7	16	13	13	13	13	33.3	34.4

Patients with PD experience changes in their gait, including a decrease in walking speed and reduced step length. This is demonstrated by the number of detected steps required by the patients to complete the TUG test. The results show that participant three, who has the most severe PD symptoms according to the scores of the questionnaires (FOG Score = 87.5, PDQ Score = 75.0), shows notably increased number of steps for completion of the TUG test (26.6 ± 3.1), compared to the rest of the participants. On the other hand, participant five, who is ranked 5th on the FOG Score scale and 7th on the PDQ-8 scale (indicating that this participant is the one with the least severe form of the disease across the dataset), had the lowest number of detected steps, on average (11.0 ± 0.0).

To further determine the strength of the relationship between the questionnaires' scores and the number of detected steps performed during the TUG test, we performed linear regression analysis and obtained the correlation coefficients. These results are depicted in Figure 4.

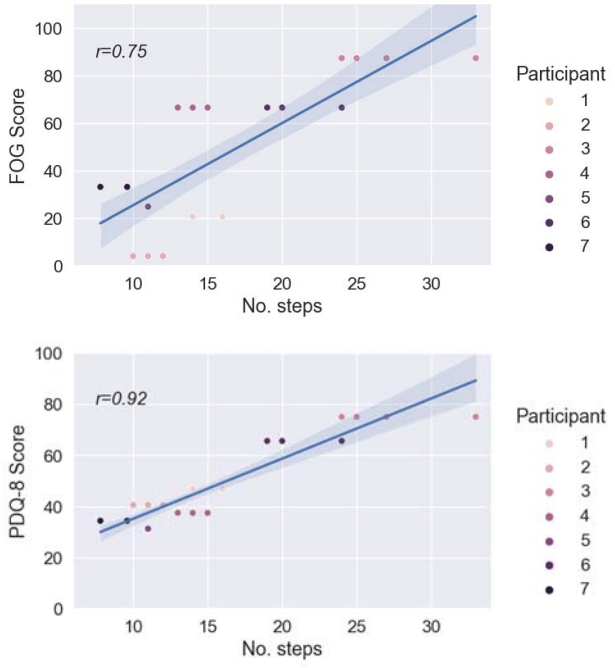

Figure 4. Linear Regression Analysis of the FOG and PDQ-8 Questionnaires Scores versus the number of detected steps performed during the TUG test.

A positive correlation was observed in both tested cases. In general, the results show that the number of detected steps required for completing the TUG test are stronger correlated with the PDQ-8 Score (r=0.92) that the FOG Score (r=0.75). Despite the lower performance of the step detection method on the PD patient dataset compared to the healthy participants dataset, the results still demonstrate a strong correlation between the detected steps and the scores of the PD-specific questionnaires (FOG and PDQ-8). This correlation provides evidence for the potential utility of the step detection method as a tool for monitoring the progression of PD symptoms.

D. Personalized Gait analysis

Next, we explored whether there are intra- and inter-person characteristics in the acceleration signals. The sensor data contains five walking signatures per participants – given that each PD participant performed five repetitions of the TUG test. The resulting walking signatures for each participant are presented in Figure 5. In the figure, each of the horizontal subplots corresponds to data from a single participant, which are further divided into five sessions marked by the vertical gray lines. The x-axis represents the traveled distance (5 x 300 cm), and the y-axis represents the acceleration as measured through the IMU sensor. The walking signature is generated by interpolating the scattered dots, each represent–ting a single step, as detected by the algorithm. The steps (dots) are plotted on the graph based on the distance travelled during each step as determined by assuming a constant walking speed (on the x-axis), and the magnitude of acceleration which they produce (on the y-axis).

We used the dynamic time warping (DTW) algorithm to search for similarities among and within people (intra- and inter-person). The algorithm evaluates the similarity of two time-sequences by using the Euclidian formula to calculate distance. The intra-person distance for a participant was calculated as the average DTW distance between all pairs of walking signatures generated by that participant (one participant has five walking signatures). Similarly, the inter-person distance for a pair of participants was calculated as the average DTW distance between all pairs of walking signatures generated by the two participants (each of them has five signatures), where one item in the pair always belongs to the first participant and the second item belongs to the second participant. The results showed clear examples of contrasting and similar walking signatures. Participants at the opposing ends of the PDQ-8 spectrum (participant three and participant five) had a notable difference in gait, with the lowest similarity value recorded compared to the other pairs of participants. Similarly, the participants with comparable PDQ-8 scores (e.g., participant seven and participant four) had the highest similarity score in the inter-person analysis. In contrast, the intra-person comparison yielded interesting results regarding the participants with high FOG scores. Participants three, four and six had the highest similarity scores. This could be due to their premeditated walking style; a technique used to manage and prevent FOG episodes. A larger dataset is needed to obtain a definitive answer.

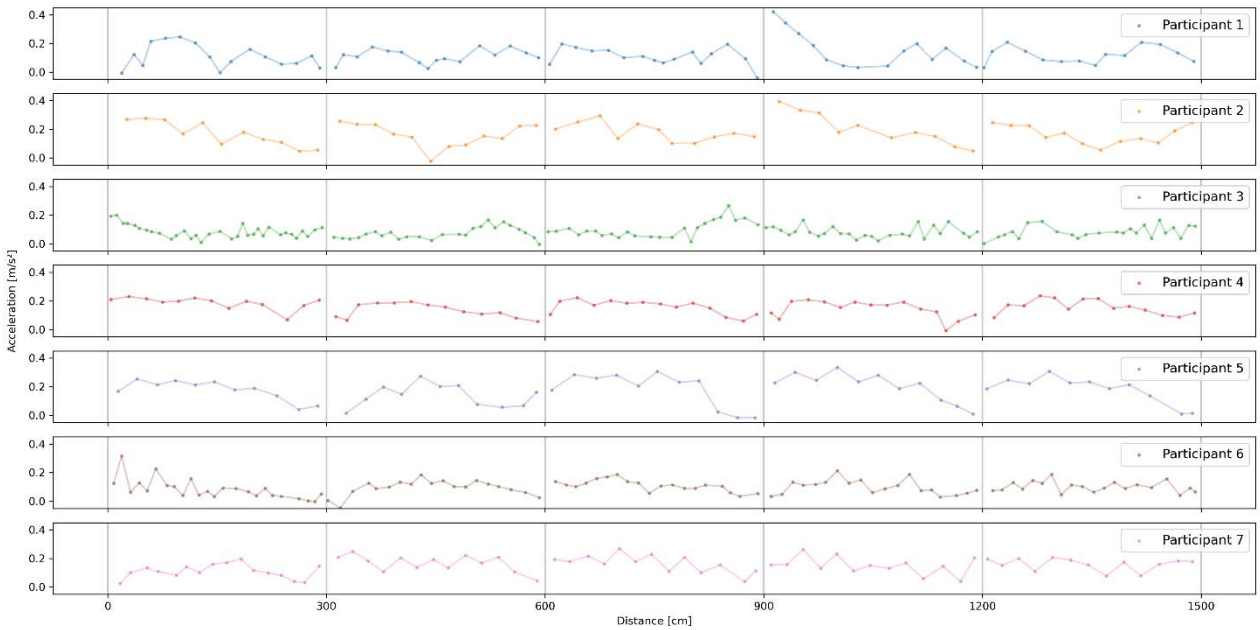

Figure 5. Participant's walking signature, throughout the five sessions. Each horizontal plot represents a single participant, with the grey line dividing the plot into the five separate sessions.

With a view towards real-time machine-learning analysis, we performed additional experiments with segmented data. More specifically, the data was first filtered and then segmented using a sliding window of two seconds and a 50% overlap. We extracted nine general-purpose statistical features from the accelerometer and gyroscope sensor signals, resulting in a total of 72 features. The features included the mean, standard deviation, minimum, maximum, kurtosis, skewness, value range, root mean square, and interquartile range. We conducted the initial analysis in this study with a small number of simple features that are computationally inexpensive in an effort to provide real-time processing on the glasses in the future. The extracted features were then used the with the t-distributed stochastic neighbour embedding (t-SNE) method [25] for visualization, and to determine whether the sensor data recorded from the glasses could reveal additional information about the patients. The method was applied to the feature vectors extracted from the walking segments from the TUG test trials. The result of the t-SNE analysis is shown in Figure 6. The figure shows several distinct clusters of data, highlighting visible differences in walking styles among PD patients.

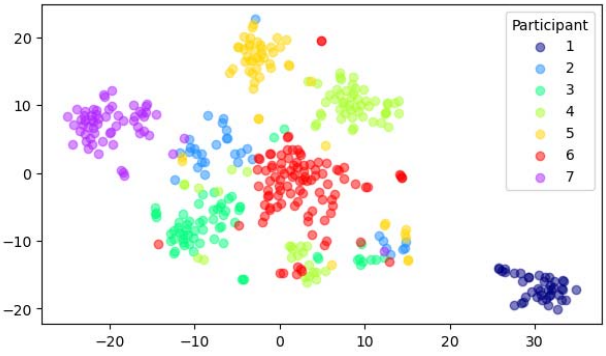

Figure 6. t-SNE visualization of the walking data from the TUG test.

The observed variations in the walking styles could potentially be related to the severity of the PD. While further research with a larger sample size and more diverse patient population is needed to draw definitive conclusions about the uniqueness of each patient's walking style, these findings suggest that the glasses-based data is sufficiently sensitive to be used for the development of personalized models for patient-specific monitoring of symptom progression. Such personalized monitoring could provide valuable information for the management of PD, enabling more targeted interventions based on individual patient needs.

V. Conclusion

In this paper, a preliminary analysis was presented with regards to the ability of Emteq's novel OCOsense™ smart glasses equipped with IMU sensors to provide objective information on the motor state in patients with Parkinson's disease. We used data from seven Parkinson's disease patients with varying levels of the disease's symptoms severity who were performing the Timed-Up-and-Go (TUG) test while wearing the glasses.

Although only a small group of PD patients were examined in the experiment, the analysis suggests that IMU-equipped smart glasses have the potential to provide information about patients' gait and can be used to assess the severity level of Parkinson's disease as measured by two standardized questionnaires. They can therefore be considered as a screening tool that will continuously monitor Parkinson's disease patients' gait and motor activity. Moreover, the analysis of the walking data has shown visible differences walking styles among PD patients, which may also depend on the severity of the disease. This indicates that the glasses-based sensor data is sensitive enough to develop personalized models for patient-specific monitoring of symptom progression.

Some limitations of the presented work are the small number of PD patients in the study and the narrow focus of gait analysis only during the TUG test. While the preliminary results are promising, it is crucial to validate our findings on a larger scale and analyze gait during different activities of daily living. To address these limitations, we are currently undertaking the systematic organization of a large-scale data collection, which aims to compile data from numerous individuals diagnosed with Parkinson's disease. This data collection will also include different positions of the IMU sensors that will enable comparison with our glasses-based approach. Additionally, we plan to add other daily-life activities, including different household and core self-care activities, which will allow us to expand our analysis of gait patterns during day-to-day activities, but also other PD related symptoms that occur during daily living, such as body tremors. Moreover, we intend to conduct a longitudinal study to determine whether data acquired from the glasses could be used to track changes in the disease symptoms over time, which will be beneficial for inferring early disease progression or deterioration.

ACKNOWLEDGMENT

This project was partially supported by the WideHealth project which has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 952279.

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