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Wearable Sensor Configurations for Effective Tremor Assessment in Parkinson's Disease

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***Abstract*—Smartwatches play an increasingly vital role in health monitoring, offering practical solutions for patients to manage their conditions in daily life. This is particularly significant for Parkinson's Disease (PD) patients, as tremors, a notable symptom, significantly impact their quality of life. Our research addresses unanswered questions about the optimal configurations for these devices, considering factors such as the placement of the smartwatch, the type of sensor used (accelerometer vs. gyroscope), and the sampling frequency. Employing a gradient tree-boosting approach, we analyze data from the wrist and ankle sensors of 24 PD subjects engaged in daily living activities. The findings highlight a cost-effective, practical, and resource-friendly configuration: utilizing accelerometer wrist data sampled at 32 Hz demonstrates a robust correlation between the estimations of total tremors (0.82) and rest tremors (0.84) compared to their clinical ground-truth values. This underlines the significant potential of employing smartwatches in a natural environment for clinicians to monitor their patients efficiently, minimizing the necessity for costly, inconvenient in-clinic assessments.**

***Index Terms*—Parkinson's Disease Tremor Monitoring, Wearable Sensor Configurations, Gradient Tree-Boosting Analysis, Machine Learning in Healthcare**

I. Introduction

Smartwatches are increasingly recognized for their significant role in health monitoring, offering practical, day-to-day solutions for managing health conditions. This is particularly relevant for individuals with Parkinson's Disease (PD), a debilitating neurodegenerative condition marked by motor symptoms like tremors and gait difficulties [1]. Tremors are divided into resting, postural, and kinetic. The resting tremor is a tremor that occurs while an individual with PD relaxes their muscles. Postural and kinetic tremors occur when a patient holds a position against gravity and during a patient's voluntary movement, respectively. As these tremor types include voluntary movement, postural and kinetic tremors can be generalized as action tremors. The tremors considerably affect the quality of life of PD patients. However, the current clinical practice of assessing these tremors, primarily through the Unified Parkinson's Disease Rating Scale Part III (UPDRS-III) in clinical settings and during routine-predefined activities [2], provides only a momentary glimpse into the patient's condition, failing to capture the full scope of daily tremor variability [3].

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Our study aims to address this gap by investigating the potential of smartwatches and wearable sensors in continuously monitoring tremors, thus providing a more comprehensive understanding of the condition outside the clinical environment. Earlier studies have explored wearable sensors and machine learning techniques to estimate tremors in individuals with PD [4]–[6]. These methodologies typically provide their estimations during specific tasks outlined in the UPDRS-III, and some involve multiple sensor placements. However, such approaches may not be practical for daily living situations. Recent studies have highlighted the effectiveness of smartwatches in monitoring tremors and motor difficulties in individuals with PD [7], [8]. Apple smartwatches have shown notable promise, utilizing inertial sensor data to monitor PD motor difficulties in real-time [9]. Additionally, software applications like Monipar have been developed to collect movement data from smart devices, assisting in continuously monitoring motor difficulties caused by PD [10]. However, several unanswered questions exist about the optimal configurations for smartwatches and wearable sensors.

To address these questions, this study investigates the optimization of wearable sensor configurations for monitoring tremors in PD patients, focusing on identifying the most effective, cost-efficient, and convenient setup. Central to our research is examining various factors influencing sensor performance, including the placement of the smartwatch (on the wrist or ankle), the type of sensor data used (accelerometer vs. gyroscope), and the sampling frequency. We have explored a range of sensor set combinations, utilizing either an accelerometer, a gyroscope, or both, in different positions, to monitor both resting and total (resting, postural, and kinetic) tremors. Our investigation also expands to the selection of sampling frequencies at 32 and 64 Hz and their effect on accurate tremor estimation. Data was collected from 24 PD patients as they engaged in various activities of daily living (ADL). This comprehensive approach aims to provide a practical and reliable method for assessing tremor severity in a typical day, offering significant potential for improving patient care by enabling physicians to adjust medication based on continuous, real-life tremor data more accurately.

II. Methodology

A. Parkinson's Disease Dataset

Motion data was captured from 24 PD patients [11], [12]. Table I details the subjects' demographics. The data collection

TABLE I
PARKINSON'S' DISEASE DATA PATIENTS DEMOGRAPHICS

Characteristic	Number	Range	Mean $\pm$ STD
Participants	24	–	–
Sex (M, F)	$14, 10$	–	–
Age (years)	–	$[42 - 77]$	58.8 ± 9.5
Disease duration (years)	–	$[3.5 - 17]$	9.9 ± 3.8
Tremor sub-score	–	$[0 - 16]$	1.8 ± 3.3

used protocols approved by the Institutional Review Board (IRB) at Rochester Medical Center, and following the Helsinki Declaration, the subjects signed an informed consent. One tri-axial inertial motion sensor recording accelerometer and gyroscope data was mounted on the most affected wrist, and another was on the most affected ankle of the patient's most affected side at a sampling frequency of 64 Hz. Each patient would then be requested to perform various ADLs (walking, resting, cutting food, drinking, dressing, unpacking groceries, and hygiene). Three to four rounds of ADL were conducted by 15 of the patients [11]. The first round was characterized by performing ADL while the patients were off their medication, confirmed by a neurologist. The second, third, and fourth rounds were conducted when the patients were on medication. The other nine individuals had their movement recorded continuously for two hours [12]. Similar to the other 15, the patients were requested to perform ADL tasks with and without their medication. A specialized neurologist assessed the severity of tremors at each round, assigning scores on a scale ranging from 0, indicating the absence of tremor, to 16, reflecting severe tremor manifestations. The resulting total number of rounds was 91.

B. Data Processing and Features Extraction

The collected rounds of data were segmented into non-overlapping $5s$ windows for all subjects. The tremor score assigned to each round was correlated with the regression score of the corresponding $5s$ data samples. These scores are the ground-truth values utilized in training the machine learning model. The data from each round underwent filtration using a band-pass finite impulse response (FIR) filter featuring a 3 dB cutoff frequency between 0.5 Hz and 15 Hz to eliminate low and high-frequency noises. Afterward, 78 features capturing tremor characteristics were extracted from the accelerometer and gyroscope data within each segmented $5s$ window. The specifics of these features are detailed in [13].

C. eXtreme Gradient Boosting Algorithm

2. The eXtreme Gradient Boosting (XGBoost) is a machine learning implementation of the gradient-boosted decision trees algorithm designed for computational efficiency and performance [14]. The algorithm is a leading tool in the machine learning field used for identifying and classifying PD symptoms [15]. Therefore, the XGBoost methodology was utilized in this study for assigning tremor sub-scores, y^n, to their respective features vector:

$$F^n = [\overrightarrow{f} v_1^n, \overrightarrow{f} v_2^n, ..., \overrightarrow{f} v_w^n], \tag{1}$$

where $\overrightarrow{f} v_w^n; |\overrightarrow{f} v_w^n| = 78$ is the feature vector for one segmented window, w is the number of segmented windows in one round $n; n \in [1, 91]$. The method estimates the output $\hat{y}_t^n$ using ensemble of t weak regressions trees f_i as following:

$$\hat{y}_t^n = \sum_{i=1}^{t} f_i(\overrightarrow{f} v_t^n) \tag{2}$$

The loss function calculates the difference between the estimated tremor score, $\hat{y}_t^n$, and the tremor score, y^n. The loss statistics of the first and second gradients are included within the objective function. The architecture of the proposed XGBoost algorithm can be seen in Fig. 1.

The training and testing of the XGBoost model were conducted through subject-based leave-one-out cross-validation to prevent any data leakage from the training to the testing set. A validation set constituting 20% of the training data was utilized in each fold for hyperparameter optimization. A grid search was conducted to optimize the model's hyperparameters, including the number of estimators, maximum depth, percentage of features per tree, and gamma values. Thereon, the model with the minimum validation mean absolute error (MAE) was selected for testing. The performance during testing was assessed by applying the trained model to the test folds and comparing the predicted scores with the clinical regression scores in the dataset.

III. RESULTS AND DISCUSSION

The algorithm was implemented using the XGBoost Python library. A learning rate of 0.1 was employed, and the algorithm consisted of 170 regression trees. The tree depth varied from 7 to 14 with a step size of 2. The gamma parameter of the algorithm was set to 0.20. Input data for the algorithm comprised combinations of gyroscope and accelerometer vector data for predicting rest and total tremors (both rest and action tremors). The first 34 features, representing wrist data, were segregated and fed into the algorithm to consider wrist sensor data exclusively. The algorithm was trained using 64 Hz and down-sampled 32 Hz versions of the data. Notably, for estimating rest tremors, consideration was restricted to the most affected wrist of the patient by utilizing the wrist sensor data. On the other hand, estimating the total tremors involved utilizing data from both wrist and ankle sensors.

Table II reveals the outcomes of the model's predictions for the rest and total tremor sub-scores in patients with PD. The model demonstrated robust performance across various setup scenarios, yielding a strong average correlation of $r = 0.86 \pm 0.05$ between the estimated and clinically observed total tremor scores and $r = 0.86 \pm 0.01$ for the estimations of rest tremors compared to their documented clinical scores. The model maintained a strong performance when relying solely on the wrist sensor for total tremor estimation, exhibiting a $r =$

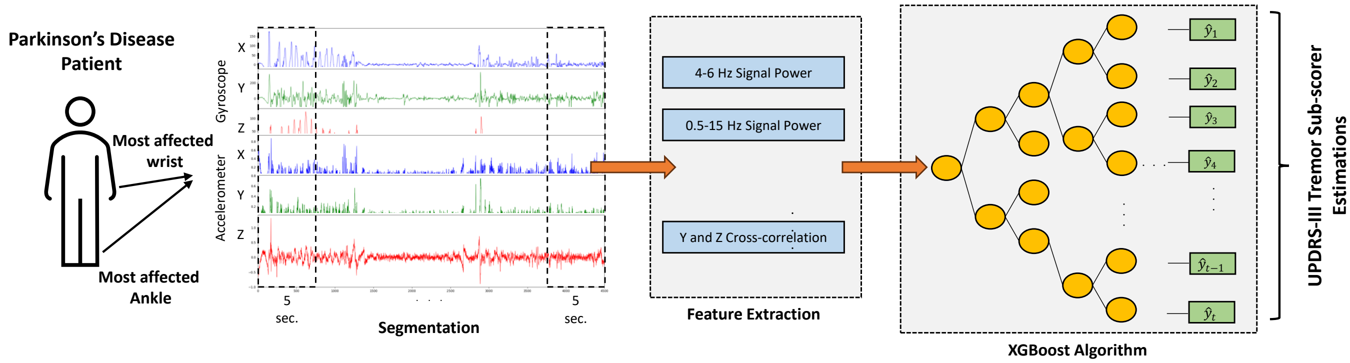

Fig. 1. The sensors are placed on the wrist of the Parkinson's disease patient. The X, Y, and Z vectors are then segmented into $5s$ non-overlapping windows. A set of 34 features is extracted from each window for the wrist; if ankle placements are included, then 78 total features are extracted. These features are inputted into an optimized XGBoost algorithm to estimate the UPDRS-II Tremor sub-scores.

0.81 ± 0.02 correlation. Optimal performance in total tremor estimation was achieved when incorporating gyroscope and accelerometer data from both wrist and ankle sensors, sampled at 64 Hz, resulting in a correlation of $r = 0.92$ with clinically recorded sub-scores. Downsizing the data to 32 Hz resulted in a slight performance reduction, yielding a correlation of $r = 0.91$.

To conduct an in-depth investigation of the impact of sensor placement on the model's performance, we conducted a comparative analysis of the MAE in total tremor estimations across different sensor types and sampling frequencies, as illustrated in Fig. 2. Noticeable enhancements in MAE (0.11 ± 0.08) were observed when utilizing both wrist and ankle placements compared to the sole use of wrist placement at 32 Hz. The difference in MAE is minimal with individual deployment of accelerometer and gyroscope sensors (0.06) but becomes more pronounced when using both sensors concurrently (0.22). At 64 Hz, the MAE exhibits a more substantial variation (0.21 ± 0.03), with the most significant difference observed when employing the gyroscope alone (0.23). These observations indicate that employing a less resource-intensive sampling frequency delivers more consistent results.

Remarkably, the sensor placement on the wrist consistently delivers reliable outcomes across various sensor types and sampling frequency scenarios, exhibiting an MAE of 1.41 ± 0.06. This effect is evident in the marginal difference in MAE of 0.09 ± 0.02 observed when using the wrist sensor alone across three sensor types and sampling frequencies, in contrast to the more significant difference of 0.18 ± 0.06 when both wrist and ankle sensors are employed. Among the sensor types, estimations utilizing accelerometer data displayed the lowest standard deviation across sampling frequencies and sensor placements (0.10), followed by gyroscope data (0.11) and combined data from both sensors (0.12). These findings suggest that accelerometer data for tremor prediction consistently yields reliable results under diverse scenarios.

A comparable trend is observable when the model is trained to estimate rest tremor scores in patients. Fig. 3 illustrates the MAE values of the model across various sensor types

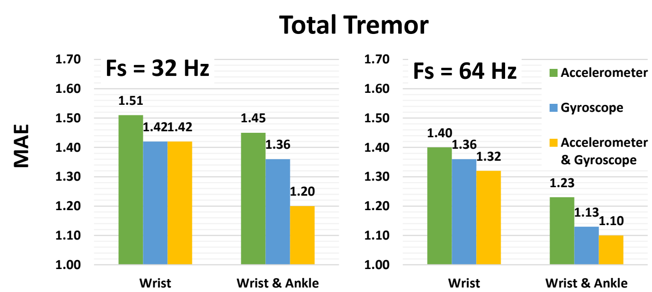

Fig. 2. The proposed model's mean absolute error (MAE) values when estimating the total tremor in Parkinson's disease patients using wrist and ankle wearables.

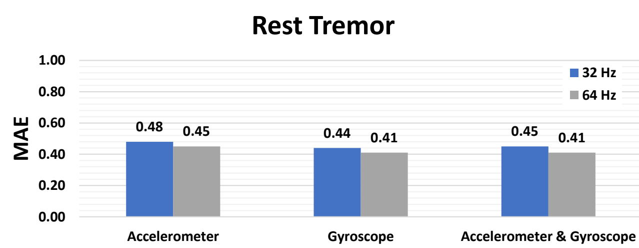

Fig. 3. The model's mean absolute error (MAE) when estimating Parkinson's disease patients' rest tremor using a wrist sensor

and sampling frequency configurations. Despite the lower MAE values when sampling the data at 64 Hz, the observed difference remains negligible (0.03 ± 0.0) across the three sensor types setup. The model's MAE standard deviation was 0.01 across both frequencies when using accelerometer data. This is lower than when utilizing a gyroscope sensor or both sensors, for which the standard deviation was 0.02. These outcomes align with the earlier findings related to total tremor estimation.

The findings from this analysis indicate that the XGBoost model's most consistent performance in estimating total and rest tremors in PD patients is achieved when utilizing data collected and sampled at 32 Hz from a wrist accelerometer

TABLE II
THE RESULTED CORRELATION FOR THE TOTAL AND THE REST TREMORS

Sensor Type	Sampling Frequency (Hz)	Sensor Placement	Total Tremor		Rest Tremor	
			Correlation	p-value	Correlation	p-value
Accelerometer	32	Wrist	0.82	$< 1 \times 10^{-4}$	0.84	$< 1 \times 10^{-4}$
		Wrist & Ankle	0.90	$< 1 \times 10^{-4}$	-	-
	64	Wrist	0.83	$< 1 \times 10^{-4}$	0.86	$< 1 \times 10^{-4}$
		Wrist & Ankle	0.91	$< 1 \times 10^{-4}$	-	-
Gyroscope	32	Wrist	0.79	$< 1 \times 10^{-4}$	0.85	$< 1 \times 10^{-4}$
		Wrist & Ankle	0.87	$< 1 \times 10^{-4}$	-	-
	64	Wrist	0.78	$< 1 \times 10^{-4}$	0.87	$< 1 \times 10^{-4}$
		Wrist & Ankle	0.92	$< 1 \times 10^{-4}$	-	-
Accelerometer & Gyroscope	32	Wrist	0.84	$< 1 \times 10^{-4}$	0.85	$< 1 \times 10^{-4}$
		Wrist & Ankle	0.91	$< 1 \times 10^{-4}$	-	-
	64	Wrist	0.83	$< 1 \times 10^{-4}$	0.87	$< 1 \times 10^{-4}$
		Wrist & Ankle	0.92	$< 1 \times 10^{-4}$	-	-

sensor. A 32 Hz sampling frequency choice is advantageous due to its lower resource demands. Additionally, accelerometer sensors are more cost-effective compared to gyroscopes. The practicality and convenience of wearing a device around the wrist further enhance the feasibility of this approach. Considering these qualities and the potential for further model optimization, it holds significant promise for the reliable and continuous monitoring of individuals with PD as they go about their daily lives.

IV. CONCLUSION

The XGBoost machine learning algorithm was trained on various sensor setup combinations to investigate the potential of employing the widely used wearables and smartwatches in monitoring and estimating UPDRS-III tremor sub-scores in PD patients as they go about their daily living routines. We utilized a segmentation method that segmented 5s non-overlapping windows from gyroscope and accelerometer data. A set of 78 features from wrist and ankle sensors were extracted. The study revealed that a cost-effective, convenient, and less resource-intensive sensor configuration utilizing wrist accelerometer data sampled at 32 Hz could provide reliable estimations of UPDRS-III rest and total tremor sub-scores in PD individuals as they engage in unrestricted daily living activities, demonstrating high consistency. The study revealed that a cost-effective, convenient, and less resource-intensive sensor configuration utilizing wrist accelerometer data sampled at 32 Hz could provide reliable estimations of UPDRS-III rest and total tremor sub-scores in PD individuals as they engage in unrestricted daily living activities, demonstrating high consistency. These results mark a significant step forward in the practical application of commercial wearables for health monitoring. They present a valuable tool for clinicians to gain deeper insights into their patients' conditions outside clinical settings.

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