Unified Parkinson's Disease Rating Scale Rest Tremor Score Estimation Using the Fundamental Frequency

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Abstract: Parkinson's disease (PD) is a chronic, progressive and neurodegenerative disease that affects more than 10 million people worldwide. One of the cardinal symptoms of this disease is tremor, which is characterized as an involuntary, oscillatory movement of a body part. The tremor associated with PD can be divided into rest tremor, postural tremor, and kinetic tremor and is characterized as a regular and asymmetric tremor. Emerging methods involve the use of data from inertial sensors to measure, analyze and quantify tremor and other symptoms of PD. In this publication, a method for the monitoring of rest tremor scores is explored. This method is based on the number of windows in a signal with a fundamental frequency within the rest tremor frequency band and has potential to be applied as a support for monitoring this symptom. This method had a 87.88% success rate for predicting rest tremor scores on the X axis of a 4 hour accelerometer signal, establishing promising results that will be further explored in future work.

1 INTRODUCTION

Parkinson's disease (PD) is a chronic, progressive, and neurodegenerative disorder (de Oliveira Andrade et al., 2020). In addition to affecting more than 10 million people worldwide, making it the second most common neurodegenerative disorder, PD is the fastest growing neurological disease, being estimated that 12 million people will be diagnosed by 2010 (Shawen et al., 2020; Burq et al., 2022). This disorder can cause patients to feel several motor and non-motor symptoms, with the cardinal symptoms being bradykinesia, rigidity, and tremor (de Oliveira Andrade et al., 2020; Huo et al., 2020).

Tremor is considered the most common movement disorder and is characterized as an involuntary, oscillatory movement of a body part. The tremor associated with PD is characterized as a regular asymmetrical tremor and can be rest tremor, postural tremor, or kinetic tremor. This symptom usually manifests itself at rest and at the onset of the disease tends to affect the hands (Zajki-Zechmeister et al., 2020).

Due to the heterogeneity of PD, accurate monitoring and assessment of symptoms is extremely important for the continuous selection of the most adequate treatment plan, as the disease progresses and the severity of symptoms increases (Huo et al., 2020; Smid et al., 2022). However, the golden standard method to evaluate PD and its symptoms, the Unified Parkinson's Disease Rating Scale (UPDRS) (Goetz et al., 2008), requires a professional to perform the evaluation, leading to a low degree of objectivity, impartiality, and sensitivity (de Oliveira Andrade et al., 2020). This method has a high within-subject variability and low test-retest reliability. Moreover, the physical exams performed in the clinical evaluation provide only a small sample of PD symptoms, which may not accurately represent those symptoms outside the clinic (Burq et al., 2022).

Researchers have shown the feasibility of using data from inertial sensors, such as accelerometers and gyroscopes, to measure, analyze, and quantify tremor and other motor signs of PD, with accuracies from existing trials exceeding 85% for the detection of tremor and bradykinesia (Burq et al., 2022; Shawen et al., 2020). From these sensors, accelerometers are con-

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sidered the minimum necessary sensor for the characterization of human activity, despite it not being clear if this sensor alone is enough to characterize PD symptoms and improve disease detection (Huo et al., 2020).

These sensors are cost-efficient, widely available, and don't rely on the interpretation of an experienced professional, making them less subjective. Nonetheless, due to their potential time-consuming measurements and complexity, most of these devices are not currently used for clinical or home monitoring (Zajki-Zechmeister et al., 2020; Smid et al., 2022). Moreover, their implementation in continuous in-the-wild monitoring is limited by the battery life and memory capacity of the sensor devices, which may lead to intermittent usage and inconsistent positioning (Shawen et al., 2020). Another challenge lies in the distinction between symptoms, like tremor, and normal daily activities in signals collected in uncontrolled living conditions due to noise (San-Segundo et al., 2020).

There is currently a lack of established methods/models for the correlation of PD symptoms' sensor data with UPDRS scores and no commercial systems to complement clinical assessment of symptoms (Huo et al., 2020; San-Segundo et al., 2020). Methods to evaluate PD can generally be divided into two categories. One being machine learning models that can use sensor data and features (typically from the time and/or frequency domains) from that data to detect the presence and severity of symptoms (Shawen et al., 2020; San-Segundo et al., 2020). The other methods involve the correlation of sensor data with PD symptoms through the creation of methods based on the physical and physiological characteristics of symptoms (Huo et al., 2020).

Regarding the use of the fundamental frequency for the assessment of tremor in current literature, in (Kuosmanen et al., 2020), the authors use the fundamental frequency, extracted from the periodograms obtained through the Welch's method, to categorize game sessions, during which data was collected, as types of tremor. In (Bazgir et al., 2018), a short-time Fourier transform (STFT) was implemented and the fundamental frequency, along with other five frequency domain features, were extracted. Four classifiers were tested to estimate hand tremor and Naive Bayesian achieved the highest accuracies of 89% and almost 90% before and after feature selection, respectively. The fundamental frequency was one of the most discriminative features. In (Pierleoni et al., 2019), a system, including a data collection device and two detection and classification for tremor and freezing of gait, was developed. In this system, the authors extract several frequency domain feature, including the fundamental frequency, and define their own parameter to estimate tremor severity using these features. This system achieved an accuracy of 97.7% for tremor. Moreover, the fundamental frequency is one of the most commonly extracted features for the analysis of voice changes in PD(Amato et al., 2023).

In this paper, a simple method with a low computational cost for the estimation of UPRDS rest tremor scores based on the number of windows with a fundamental frequency between 3 and 6 Hz is explored. Firstly, the dataset used and the steps to apply this method, including the preprocessing, feature extraction, and analysis of the data, are explored in the methods in section 2. Then the results are presented and discussed in sections 3 and 4, respectively. This last section also includes a brief discussion of the dataset and the periodograms obtained with the Welch's method.

2 METHODS

In this section, the dataset and the method proposed and implemented to estimate the rest tremor score attributed to each individual using the UPDRS are presented.

2.1 Dataset

Due to a lack of time and resources needed to collect a dataset of tremor data, an open-source dataset collected by the authors of (Adams et al., 2021) was used for the implementation of this framework. This dataset contains accelerometer data from 34 individuals, 17 people with Parkinson's disease (PwPD) and 17 HC, collected at a sampling rate of 31.25 Hz using 5 lightweight MC 10 BioStamp RC sensors, placed on the trunk, left and right anterior thighs, and left and right anterior forearms. The data collection began during a UPDRS clinical evaluation, performed during the ON and OFF states of medication, and lasted around two days.

Only the data collected from the anterior forearms was used, since the study was focused on tremor from the upper extremities. Additionally, for the individuals with ID 7 and ID 60, the dataset only contains files from the sensor on the right forearm. This dataset also contained demographic data, annotations from the UPDRS evaluations, and clinical assessment data, which includes the scores attributed to the rest tremor of each individual during the evaluation. Demographic data and the rest tremor score given to the anterior forearms of each individual during the ON medication state are presented in table 1.

Table 1: Demographic and clinical data during the ON medication state of individuals in the dataset.

ID	Group	Gender	Age	RT score	
				left	right
5	Control	F	74	0	0
6	PD	M	73	2	0
7	Control	F	52	0	0
8	Control	F	77	0	0
10	PD	F	72	0	2
12	PD	F	64	1	1
13	PD	F	60	0	0
14	Control	F	56	0	0
15	PD	M	65	0	1
16	Control	F	62	0	0
17	PD	M	74	0	3
18	Control	F	66	0	0
20	Control	F	68	0	0
22	Control	M	68	0	0
23	PD	F	68	0	2
24	PD	M	62	0	0
25	PD	F	72	0	1
27	Control	F	54	0	0
30	Control	F	68	0	0
33	PD	M	46	0	0
35	PD	M	67	2	0
36	PD	M	69	3	0
38	PD	M	78	1	0
39	Control	F	74	0	0
40	PD	F	75	1	0
41	Control	M	75	0	0
42	PD	M	84	0	0
43	Control	F	69	0	0
44	PD	F	63	0	0
45	Control	M	64	0	0
58	Control	M	39	0	0
60	Control	F	65	0	0
62	Control	F	56	0	0
63	PD	M	37	0	1

The study focused on the evaluation of rest tremor in-the-wild with free-living conditions. Other types of tremor, like postural tremor or kinetic tremor, were not evaluated since the dataset only contains the UPDRS scores attributed during the clinical evaluation for this type of tremor.

From each forearm of each subject, a time period of four hours was selected from the respective data file. This interval starts five minutes after the end of the clinical evaluation, known through the timestamps in the annotations. Thus giving a five minute time margin to guarantee no data from the clinical evaluation is included in the selected data. Since the evaluation ended on the ON medication state, the patient is considered to be in that state for the selected four hours. The rest tremor scores attributed to the subjects for that medication state are shown in table 1.

2.2 Preprocessing

Firstly, the magnitude of the accelerometer signal for the selected interval was calculated with the square root of the sum of squares of each axis. Given that the dataset has a sampling frequency of 31.25 Hz, no downsampling step was implemented.

A 4^{th} order high-pass Butterworth filter with a cut-off frequency of 0.5 Hz was applied to the axes and the magnitude vector to remove the effects of gravitational acceleration and low-frequency noise.

Lastly, the axes and magnitude vector of the selected data were segmented into 10 second windows, with no overlap. This 10 second interval allows the averaging of periodograms of segments from these windows performed for the Welch's method. Due to the averaging of periodograms, the lack of overlap between the windows is also important for the correct implementation of the Welch's method. This method is better described in subsection 2.3.

2.3 Feature Extraction

The features extracted in this study belonged to the frequency domain or time domain. These features were extracted from each of the axes and the magnitude vector and are shown in table 2.

Table 2: Features extracted from the frequency and time domains.

Domain	Features
Frequency	AUC, pv, F0, F50, SF50, and $\|F50 - F0\|$
Time	RMS, range, mean, variance, skewness, and kurtosis

The frequency domain features were extracted from the PSD. The PSD was estimated using the Welch's method, which is used to determine the power contained in a signal's frequency components (Kuosmanen et al., 2020). To apply this method, the data from each 10 second window was divided into four 2.5 second segments with an overlap of 50%. Afterwards the periodogram of each segment was calculated and all the periodograms in each 10 second window were averaged (Welch, 1967). The periodograms are briefly explored in section 4.2.

The frequency domain features extracted from the averaged periodograms were the area under the curve (AUC) between the frequencies of 3 and 6 Hz, peak

value (pv), fundamental frequency (F0), central frequency (F50), frequency dispersion (SF50), and the absolute value of the difference between F50 and F0 ($|F50 - F0|$). These features were the same as the features extracted by (Kuosmanen et al., 2020). The AUC was computed between the frequencies of 3 Hz and 6 Hz using the trapezoidal rule. This feature was calculated between these frequencies to determine the power of the signal in the interval corresponding to the rest tremor frequencies. The features extracted from this domain are described in table 3. The time domain features extracted were the root mean square (RMS), range, mean, variance, skewness, and kurtosis. Despite extracting features from both the frequency and time domains, only features from the frequency domain were explored in this study.

2.4 Data Analysis

Since rest tremor is normally observed in the between the frequencies of 3 and 6 Hz, the windows where the fundamental frequency (F0) is in that frequency band were selected. It can be assumed that the selected windows contain the features when, if present, rest tremor is the dominant type of tremor.

We noticed an increase in the amount of windows with F0 between 3 and 6 Hz as the scores increased. For this reason, the data was analyzed regarding the number of windows that were selected in the 4 hour time interval, previously selected in the preprocessing. That number of windows was then correlated to the UPDRS rest tremor score. After that number was counted for X, Y, and Z axes and the magnitude of both forearms of each subject, the mean of the three axes was calculated. The 4 hour intervals were divided into two intervals of 2 hours and four intervals of 1 hours and the same analysis was also performed for those intervals.

The values of the number of windows that correspond to each tremor score were defined and are presented in table 4. The values for the intervals of 2 hours and 1 hour were adapted from the values for the 4 hour interval. Since no subject in this dataset had a rest tremor score of 4 from the clinical evaluation, this score was excluded from the analysis.

The number of windows can be divided by 200, 100, and 50 for the 4, 2, and 1 hour intervals, respectively, to get the final UPDRS score prediction, since these values represent the number of windows in each interval corresponding to a score for their respective time interval, like shown in table 4. The values obtained from this division were rounded down to get the final score prediction.

3 RESULTS

In this section the results obtained for the data analysis method proposed to estimate the rest tremor score attributed to subjects during a UPDRS clinical evaluation are presented.

The increase of the number of windows with the increase in rest tremor score can be verified in table 5. This table displays, for the X axis of the 4 hour interval, the number of instances when the data from a forearm of any subject was attributed each score (Nº samples), the mean number of windows, and the mean predicted score, before rounding the prediction values, for each real score. For the samples that were evaluated, the mean number of windows increases with the increase of the real rest tremor score, for all scores except score 3. Furthermore, the same increase can be seen in the mean prediction value, except for score 3. Excluding this last score, all mean values for both the number of windows and the prediction are within the established values for a correct prediction.

Table 6 contains the results for the UPDRS rest tremor scores predictions with the number of windows with F0 between 3 Hz and 6 Hz for patient 6. This table does not include the final rounded prediction values that were obtained through the division of the number of windows by 200.

The tremor scores rounded down predictions and the rest tremor from the clinical evaluation for patient 6 in the 4 hour time period are shown in table 7. In this case, all predictions failed for the right forearm and the only failed prediction for the left forearm was in the Y axis.

This method's success rate was determined based on the percentage of times the prediction was correct. The success rates for the X, Y, and Z axes, the magnitude, and the mean in the 4, 2, and 1 hour time intervals are shown in table 8. The X axis had the highest success rate for the 4 and 2 hour time intervals and the Z axis had the highest success rate for the 1 hour interval. Despite this, the difference between the success rate of these axes for the later time interval was only 0.38%. Furthermore, the X axis had the overall highest success rate for the 4 hour interval, with 87.88%. Predictions using the magnitude vector failed most of the time, with the magnitude having the worst success rate for every interval. The second worst success rate in every interval was obtained by the Y axis. The mean number of windows in all axes had a higher success rate than the Z axis in the 4 hour interval, however the X and Z axes had a higher success rate for both the 2 and 1 hour intervals.

Table 3: Features extracted from the periodograms and theirs description (Kuosmanen et al., 2020).

Feature	Description
AUC	Total power of the signal.
pv	Maximum value of the PSD.
F0	Frequency of maximum power. Can be used to determine the dominant tremor type in a window, according to the type of tremor frequency band it belongs to.
F50	Central point where the periodograms are divided into two equal parts.
SF50	Width of the frequency band centered in F50 that contains 68% of the total power.
$\|F50 - F0\|$	Absolute value of the difference between F50 and F0.
tip	Calculated by dividing pv by SF50.

Table 4: UPDRS scores and the corresponding number of windows for the 4,2, and 1 hour intervals.

UPDRS score	Number of windows		
	4 hours	2 hours	1 hour
0	< 200	< 100	< 50
1	200 - 400	100 - 200	50 - 100
2	400 - 600	200 - 300	100 - 150
3	> 600	300 - 400	150 - 200

Table 5: Number of samples, mean number of windows and mean predictions for each real score in the X axis with the 4 hour time interval.

Real score	Nº samples	Mean	
		Nº windows	Prediction
0	53	114.472	0.572
1	7	225.429	1.127
2	4	463.25	2.316
3	2	442.5	2.212

4 DISCUSSION

4.1 Dataset

Firstly, we discuss how the characteristics of this dataset might have influenced the results.

The majority of the dataset is composed of subjects who were given a rest tremor score of 0 the UPDRS clinical evaluation. Furthermore, the dataset contains only seven instances where rest tremors was attributed a score of 1, four instances where it was attributed a rest tremor score of 2 and two instances where it was attributed a rest tremor score of 3. As such, there are few samples of data where rest tremor has a higher score of 3 or 4.

The authors of (Channa et al., 2021) consider a sampling frequency of 100 Hz sufficient to measure motor features related to PD due to the frequency of tremor in the upper extremities being lower than 13 Hz. Nonetheless, despite some authors using higher sampling frequencies, many studies consider a sampling frequency of 50 Hz adequate for the detection of human activity with an accelerometer (San-Segundo et al., 2020; Kuosmanen et al., 2020; Sigcha et al., 2021). However, the sampling frequency of this dataset is 31.25 Hz, being lower than what is typically used in other studies.

4.2 Welch's Periodograms

A brief visual analysis, presented in this subsection, was performed on the PSD plots obtained from the Welch's method. The plots show the periodogram of all windows in the respective axes or magnitude.

The periodograms from the left forearm of patient 5 (HC group; UPDRS rest tremor score 0 for left and 0 for right) are shown in figure 1. The majority of peaks in these periodograms are between 0 and 3 Hz, which is typically not associated with PD's tremor. The authors of (Kuosmanen et al., 2020) considered that dyskinesia is observed in this frequency band, in (San-Segundo et al., 2020) this frequency band is associated with normal human movement, and in (Shcherbak et al., 2023) the frequency band between 1 and 3 Hz is associated with bradykinesia. In addition, when subjects from the PD group have a UPDRS rest tremor score 0, their periodograms have similarities with the periodograms of subjects from the HC group.

Figure 2 shows the periodograms from the right forearm of patient 12 (PD group; UPDRS rest tremor score 1 for left and 1 for right), where more plots with peaks in the rest tremor frequency band between 3 and 6 Hz can be seen, especially on the Y axis.

In figures 3 and 4, the periodograms of the right forearm of patient 17 (PD group; UPDRS rest tremor score 0 for left and 3 for right) and the left forearm of patient 36 (PD group; UPDRS rest tremor score 3 for left and 0 for right), respectively, are shown. It was noted that, for the two instances of UPDRS rest tremor score 3, the periodogram displayed distinctive peaks in the rest tremor, postural tremor, and kinetic tremor frequency bands. In the existing literature, dif-

Table 6: Analysis and prediction performed on the data on both forearms of patient 6 for the 4 hour time period.

ID	Number of windows					Prediction				
	X	Y	Z	Magnitude	Mean	X	Y	Z	Magnitude	Mean
P6_left	537	297	488	436	440.67	2.68	1.48	2.44	2.18	2.20
P6_right	263	213	239	317	238.33	1.32	1.065	1.195	1.585	1.19

Table 7: Predicted and real UPDRS rest tremor scores for patient 6 in a 4 hour time period.

ID	UPDRS score	Prediction				
		X	Y	Z	Mag	Mean
P6_left	2	2	1	2	2	2
P6_right	0	1	1	1	1	1

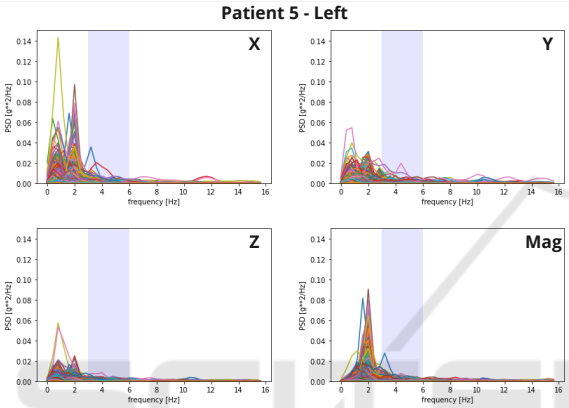

Figure 1: Welch's periodogram for the X, Y, and Z axes and magnitude (Mag) from the left forearm of patient 5.

ferent authors tend to use different frequency bands for the types of tremor, despite using similar values. The frequency bands considered for this study were between 3 and 6 Hz for rest tremor, between 6 and 9 Hz for postural tremor, and between 9 and 12 Hz for kinetic tremor.

Some of the plots from data associated with a tremor score 2 had similar peaks in the tremor frequency bands, like in figure 5. Since no periodograms from subjects of the HC group, who only had scores of 0, had similar peaks, these types of plots could be associated with PwPD and/or a higher UPDRS rest tremor score.

All graphs in this subsection have the same PSD axis scale, except for the periodograms of patient 36, shown in figure 4. This was because the bigger scale used for patient 36, whose periodograms, especially on the Y axis, had peaks with higher PSD values, didn't allow the peaks in the periodograms of other patients to be visible.

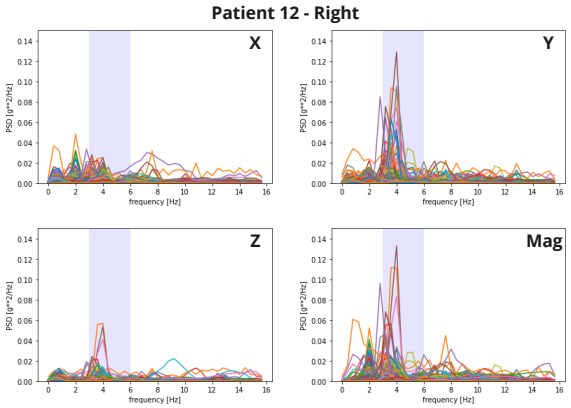

Figure 2: Welch's periodogram for the X, Y, and Z axes and magnitude (Mag) from the right forearm of patient 12.

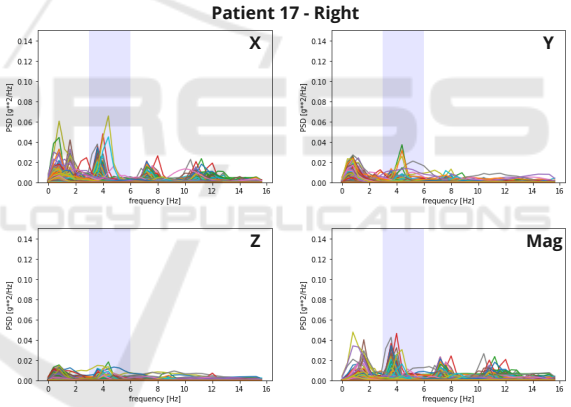

Figure 3: Welch's periodogram for the X, Y, and Z axes and magnitude (Mag) from the right forearm of patient 17.

4.3 Data Analysis

For this dataset and the data that was evaluated, the X axis achieved the best results in the prediction of UPDRS rest tremor scores with the proposed method.

The discrepancies in the mean number of windows and mean prediction for the real score 3 in table 5 can be due to the low amount of samples for this score. Furthermore, for the two instances where the data was associated with a UPDRS rest tremor score 3, this method classified one instance correctly and failed in the other, predicting a rest tremor score 1. This may explain the lower mean number of windows and mean prediction than expected.

In table 7, all predictions failed for the right fore-

Table 8: Success rate for all axes, the magnitude and the mean of the number of windows in the 4, 2, and 1 hour intervals.

Interval	Success rate				
	X	Y	Z	Magnitude	Mean
4	**87.88%**	71.21%	81.82%	34.85%	83.33%
2	82.58%	59.09%	81.82%	37.88%	78.79%
1	77.27%	59.09%	77.65%	39.39%	74.24%

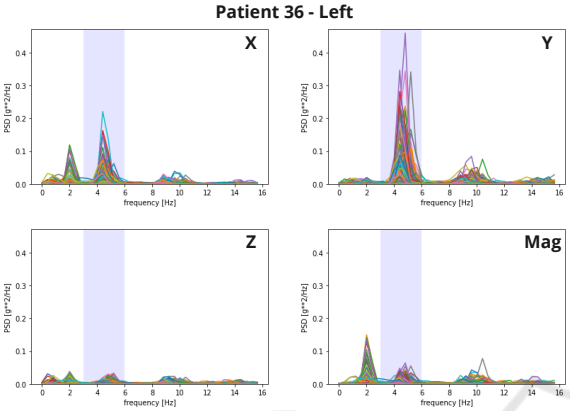

Figure 4: Welch's periodogram for the X, Y, and Z axes and magnitude (Mag) from the left forearm of patient 36.

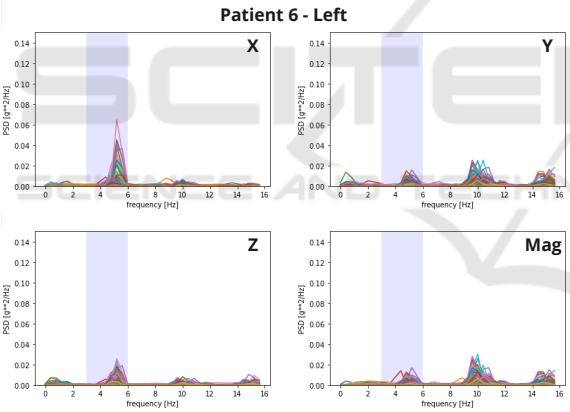

Figure 5: Welch's periodogram for the X, Y, and Z axes and magnitude (Mag) from the left forearm of patient 6.

arm. It is possible that, since the amplitude of tremor and consequently its tremor score can vary during the day, no tremor was present during the evaluation, but it was present during the 4 hour time period that was evaluated. Moreover, another possibility is that noise in the signal might have affected these predictions.

The prediction values were rounded down to obtain the final score predictions, however the analysis of the values with decimals allows us to know how close the prediction was to the limit between scores and by how much it failed. If all windows for the X axis in the 4 hour time period (which had the highest success rate) that failed the prediction by less than 0.1 were discarded, the success rate would increase to 92.06%. Nonetheless, discarding only the windows with a failed prediction is not feasible in the implementation of this method in a real setting where it is not known which predictions are correct or incorrect. If all windows within 0.1 of the limit between scores were discarded and their prediction was marked as inconclusive between the two scores they are closest to, a success rate of 91.23% would be achieved. Furthermore, the indication of which scores the inconclusive prediction is in between could be helpful in a clinical setting, helping the specialist know what were the closest scores to the prediction. For example, windows with values between 0.9 and 1, including these values would be discarded and marked as inconclusive between the scores 0 and 1.

It is important to note that tremor may not be constantly present and its amplitude can vary during the day. As such, the connection between the number of windows with F0 within 3 and 6 Hz and the UPDRS rest tremor score could lie in a potential connection between the rest tremor amplitude (referred to as rest tremor score in this study) and the constancy of rest tremor. This possible connection should be further explored in future work. The results in this study may have also been affected by noise, due to evaluation in free-living and in-the-wild conditions, and the low number of samples for the UPDRS rest tremor scores 2 and 3. The number of window intervals corresponding to which score were loosely established to explore this method and could be improved in future work. However, the method shows promising results, which could be further improved by refining the number of windows intervals corresponding to each rest tremor score, as previously mentioned, and other parts of the method.

5 CONCLUSIONS

This study is focused on the rest tremor associated with Parkinson's disease and the estimation of its rest tremor score according to the UPDRS using data from accelerometers. In this paper we explore a method based on the number of windows in a signal where the fundamental frequency (F0) is in the rest tremor frequency band, indicating that, when present, the dom-

inant type of tremor is the rest tremor. This method to estimate the rest tremor scores had promising results and has a low computational cost. After being further explored and refined, this method has the potential of being implemented for the clinical support of rest tremor evaluation, helping monitor rest tremor and the progression of the disease by providing data for follow-up consultations. This method is limited by the use of tremor scores given during the clinical evaluation in a controlled environment as labels for data collected in free-living, which can lead to some data being incorrectly labeled. Thus, the method should be tested with other datasets to verify its results and with sensor data collected during the clinical evaluations, helping validate the method to be applied in a controlled environment. Moreover, the results shown the capability of this feature in the assessment of tremor and its use with classical machine learning or deep learning models for this task should be further explored.

REFERENCES

Adams, J. L., Dinesh, K., Snyder, C. W., Xiong, M., Tarolli, C. G., Sharma, S., Dorsey, E. R., and Sharma, G. (2021). A real-world study of wearable sensors in parkinson's disease. *npj Parkinson's Disease*, 7(1):106.

Amato, F., Saggio, G., Cesarini, V., Olmo, G., and Costantini, G. (2023). Machine learning-and statistical-based voice analysis of parkinson's disease patients: A survey. *Expert Systems with Applications*, 219:119651.

Bazgir, O., Habibi, S. A. H., Palma, L., Pierleoni, P., and Nafees, S. (2018). A classification system for assessment and home monitoring of tremor in patients with parkinson's disease. *Journal of Medical Signals & Sensors*, 8(2):65–72.

Burq, M., Rainaldi, E., Ho, K. C., Chen, C., Bloem, B. R., Evers, L. J. W., Helmich, R. C., Myers, L., Marks, W. J., and Kapur, R. (2022). Virtual exam for parkinson's disease enables frequent and reliable remote measurements of motor function. *npj Digital Medicine*, 5(1). Cited by: 6; All Open Access, Gold Open Access, Green Open Access.

Channa, A., Ifrim, R.-C., Popescu, D., and Popescu, N. (2021). A-wear bracelet for detection of hand tremor and bradykinesia in parkinson's patients. *Sensors*, 21(3):981.

de Oliveira Andrade, A., Paixao, A. P. S., Cabral, A. M., Rabelo, A. G., Luiz, L. M. D., Dionísio, V. C., Vieira, M. F., Pereira, J. M., Rueda, A., Krishnan, S., et al. (2020). Task-specific tremor quantification in a clinical setting for parkinson's disease. *Journal of Medical and Biological Engineering*, 40(6):821–850.

Goetz, C. G., Tilley, B. C., Shaftman, S. R., Stebbins, G. T., Fahn, S., Martinez-Martin, P., Poewe, W., Sampaio, C., Stern, M. B., Dodel, R., et al. (2008). Movement disorder society-sponsored revision of the unified parkinson's disease rating scale (mds-updrs): scale presentation and clinimetric testing results. *Movement disorders: official journal of the Movement Disorder Society*, 23(15):2129–2170.

Huo, W., Angeles, P., Tai, Y. F., Pavese, N., Wilson, S., Hu, M. T., and Vaidyanathan, R. (2020). A heterogeneous sensing suite for multisymptom quantification of parkinson's disease. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28(6):1397–1406.

Kuosmanen, E., Wolling, F., Vega, J., Kan, V., Nishiyama, Y., Harper, S., Van Laerhoven, K., Hosio, S., Ferreira, D., et al. (2020). Smartphone-based monitoring of parkinson disease: quasi-experimental study to quantify hand tremor severity and medication effectiveness. *JMIR mHealth and uHealth*, 8(11):e21543.

Pierleoni, P., Belli, A., Bazgir, O., Maurizi, L., Paniccia, M., and Palma, L. (2019). A smart inertial system for 24h monitoring and classification of tremor and freezing of gait in parkinson's disease. *IEEE Sensors Journal*, 19(23):11612–11623.

San-Segundo, R., Zhang, A., Cebulla, A., Panev, S., Tabor, G., Stebbins, K., Massa, R. E., Whitford, A., De la Torre, F., and Hodgins, J. (2020). Parkinson's disease tremor detection in the wild using wearable accelerometers. *Sensors*, 20(20):5817.

Shawen, N., O'Brien, M. K., Venkatesan, S., Lonini, L., Simuni, T., Hamilton, J. L., Ghaffari, R., Rogers, J. A., and Jayaraman, A. (2020). Role of data measurement characteristics in the accurate detection of parkinson's disease symptoms using wearable sensors. *Journal of neuroengineering and rehabilitation*, 17(1):1–14.

Shcherbak, A., Kovalenko, E., and Somov, A. (2023). Detection and classification of early stages of parkinson's disease through wearable sensors and machine learning. *IEEE Transactions on Instrumentation and Measurement*, 72:1–9.

Sigcha, L., Pavón, I., Costa, N., Costa, S., Gago, M., Arezes, P., López, J. M., and De Arcas, G. (2021). Automatic resting tremor assessment in parkinson's disease using smartwatches and multitask convolutional neural networks. *Sensors*, 21(1):291.

Smid, A., Elting, J. W. J., van Dijk, J. M. C., Otten, B., Oterdoom, D. M., Tamasi, K., Heida, T., van Laar, T., and Drost, G. (2022). Intraoperative quantification of mds-updrs tremor measurements using 3d accelerometry: A pilot study. *Journal of Clinical Medicine*, 11(9):2275.

Welch, P. (1967). The use of fast fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. *IEEE Transactions on audio and electroacoustics*, 15(2):70–73.

Zajki-Zechmeister, T., Kögl, M., Kalsberger, K., Franthal, S., Homayoon, N., Katschnig-Winter, P., Wenzel, K., Zajki-Zechmeister, L., and Schwingenschuh, P. (2020). Quantification of tremor severity with a mobile tremor pen. *Heliyon*, 6(8):e04702.