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Gait and tremor assessment for patients with Parkinson's disease using wearable sensors ☆

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Abstract

Typically, subjects with Parkinson's disease (PD) display instances of tremor at an early stage of the disease and later on develop gait impairments and postural instability. In this research, we have investigated the effect of using both gait and tremor features for an early detection and monitoring of PD. Various features were extracted from the data collected from the wearable sensors and further analyzed using statistical analysis and machine learning techniques to find the most significant features that would best distinguish between the two groups: subjects with PD and healthy control subjects. The analysis of our results shows that the features of step distance, stance and swing phases, heel and normalized heel forces contributed more significantly to achieving a better classification between the two groups in comparison with other features. Moreover, the tremor analysis based on the frequency-domain characteristics of the signal including amplitude, power distribution, frequency dispersion, and median frequency was carried out to identify PD tremor from atypical Parkinsonism tremor.

Keywords: Gait and tremor features; Linear discriminant analysis; Parkinson's disease; Wearable sensors

1. Introduction

Parkinson's disease (PD) is ranked the second most common neurodegenerative disease next to Alzheimer's disease. Parkinson Disease Foundation [1] estimates that nearly 7–10 million people worldwide suffer from PD. Deterioration of dopamine-producing neurons in the brain is the primary cause of PD, where dopamine is an essential neurotransmitter that controls both smooth and coordinated muscle function [1]. The main motor symptoms of PD include tremor at rest, bradykinesia, rigidity, and impairment of postural balance [2].

The diagnosis of PD can be difficult especially in its early stages and currently, there are no specific tests or biomarkers available to diagnose PD. Mostly, the current diagnosis is based on subjective measures derived from visual observations by clinicians/ neurologists to generate a score from UPDRS. Typically, a neurologist analyzes the patient's complete medical history and performs numerous clinical assessments to confirm the presence of PD in that subject [1,3]. Sometimes, it might take up to a year to diagnose PD after careful consideration of the subject's neurological history and clinical assessments. Moreover, due to lack of objective measures, there is also a high possibility of misdiagnosing PD. It has been found that the rate of misdiagnosis of PD is around 25%, and approximately 40% of PD cases are overlooked for other neurological disorders [1,3]. According to experts, the diagnosis of PD requires the presence of one or more of the four main PD motor symptoms. The progress of PD symptoms varies from one subject to another. For example, resting tremor occurs in only 70% of PD patients during the onset of the disease, while others might develop gait disturbances or even action tremor during their initial stages of PD [1,3]. So, an early and accurate diagnosis of PD is required for better treatment and for more efficiently control the effects of the symptoms.

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Over time, many types of research have evolved on developing a PD monitoring system, using different types of sensors, feature sets and analysis methods. Few among the many wearable sensors used in acquiring the bio-signals include accelerometers, force sensors, gyroscopes and magnetometers [4]. Patel et al. [5] worked on developing a system that measures the severity of tremor, bradykinesia (slowness of movement) and dyskinesia (motor fluctuations) using a wearable sensor platform. The resting tremor occurs during the early stages of PD and also is an essential criterion to diagnose the PD, where accelerometers are widely used to detect and record its occurrences [6,7]. Salarian et al. [8] proposed an algorithm to detect and quantify tremor and compared the measured tremor amplitude to the corresponding UPDRS score. Further, Edwards and Beuter [9] utilized tremor characteristics such as the amplitude, frequency and spectral power to identify PD tremor. Then, they combined the characteristics into a single variable to identify a PD from abnormal tremor effectively [9]. Additionally, it is vital to monitor the gait impairments in patients, to detect PD at an early stage. In the experiments conducted by Salarian et al. [10], they concluded that the stride velocity, stride length and swing time of Parkinsonian patients were lower in comparison to healthy control subjects. On the contrary, the stance time in Parkinson's patients was higher than that of healthy subjects. Additionally, Okuno et al. obtained similar results [11] using a force sensor worn by the subjects. Further, Tahir and Manap [12] extracted basic, kinetic and kinematic features based on force measurement. Then, through statistical analysis, it was found that step length, walking speed and VGRF were among the significant features that would differentiate a Parkinson's patient from healthy control subject [12]. Barth et al. [13] extracted various gait features and were classified using multiple classifiers, and their individual performances were studied. Among the classifiers used, LDA (Linear Discriminant Analysis) provided the best classification accuracy. In [14] Frenkel-Toledo et al. studied the relationship between the walking speed and gait variability in PD and healthy control subjects. Also, the investigators had performed statistical analysis (t-test) to compare the two groups. From the results, it was concluded that the patients with PD had an increased variability of stride time and swing time as compared to healthy control subjects.

The goal of this research is to analyze the features exhibited by subjects with PD during the initial phase of the disease, which would enable us to detect the presence of PD at its onset. In this study, we extracted kinetic and spatiotemporal features using data from an online database (Physionet) and found a set that best discriminates between subjects with PD (H&Y stages 2, 2.5 and 3) and healthy subjects. Also, tremor features were extracted and we performed various analyses using advanced signal processing and machine learning techniques on the extracted tremor and gait parameters to compare and distinguish between subjects with PD and healthy subjects. Majority of the studies either utilize gait or tremor features for PD monitoring. Here, we have investigated the use of both gait and tremor features and analyzed their impact on early detection and monitoring of PD.

2. Data collection

For the gait analysis, data from the Physionet online database [15] was utilized, consisting of readings from the experiments conducted on 93 patients with idiopathic PD (mean age: 66.3 years) with moderate disease severity (H & Y Stage 2–3) and 73 healthy controls, sampled at a rate of 100 Hz. The database comprises of 3 different experiments conducted by Frenkel-Toledo et al. (Group 'Si') [14], Hausdorff et al. (Group 'Ju') [16] and Yogev et al. (Group 'Ga') [17]. The forces imparted by the heel, below toe (metatarsophalangeal joint) and toe regions of the foot were analyzed. To reduce the influence of subject's body weight on the forces, the force values were normalized to the percentage of their body weight. For the tremor analysis, data from the Physionet database was utilized, resulting from the experiments conducted on a group of 16 patients with PD [18]. The patients were under minimum medications at the time of study to induce tremor and the data were recorded for a time period of 60 secs (depending on the duration of tremor occurrence in subjects) and sampled at 100 Hz.

3. Feature extraction

3.1. Gait characteristics

A gait cycle begins at the point of heel strike called as initial contact, marking the beginning of a stance phase. The stance phase ends at the toe-off period, and the swing phase terminates at the next heel strike event. The stance and swing periods of a healthy control subject varies from that of a PD patient. The stance and swing phase values are essential in identifying the individuals with PD from the healthy subjects [19]. Other spatiotemporal parameters include the step length, the linear distance in the plane of progression between two successive points of foot floor contact of the opposite feet. Also, step time is the time interval between the successive instant of foot floor contact of the opposite feet. The last feature is the kinetic feature that mainly focuses on the force acting on the ground during initial contact and toe-off positions [20].

3.2. Gait detection algorithm

Initially, the raw force data was filtered using a Chebyshev type II high pass filter with a cut-off frequency 0.8 Hz to remove noises arising from the changes in orientation of the subject's body and other factors during measurement. The filtered data was used for extracting various gait features using the peak detection and pulse duration measuring techniques. The threshold values of the gait detection algorithm were tuned to individual subjects. From the peak detection algorithm, various kinetic features including the heel, below toe, and toe forces, and their normalized values were obtained. The pulse duration algorithm was developed to extract different spatial and temporal features including the step distance, stance and swing phases, and stride time.

In Fig. 1, the force readings are plotted against time for the left foot of the subject. From the plot, points P1–P4 are marked

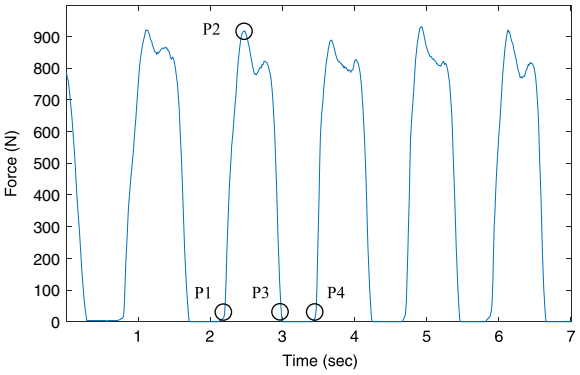

Fig. 1. Force readings plotted against time for a patient with PD. Points P1 to P4 denote one gait cycle.

to denote one gait cycle. The time period between P1 and P4 defines the stride time. Additionally, time taken to reach from position P1 to P3 is the stance period. In the same way, the time taken from point P3 to P4 is defined as the swing period. Hence, the swing/stance ratio can be calculated.

Further, the extracted gait features were used to train the classifier and the accuracy rate of classification was obtained as the output.

3.3. Tremor characteristics

There are two different types of tremor that occur in humans: the pathological and physiological tremor [21]. Pathological tremors may occur due to central nervous system and peripheral nervous system disorders. The relevant example of a pathological tremor is the parkinsonian tremor, which is further classified into rest, postural and kinetic tremors. To elaborate, the rest tremor occurs when the body performs no voluntary action, postural tremor occurs while holding a body part such as the arm, leg against gravity without any movement and kinetic tremor can be seen when the subject performs any particular task such as finger-to-nose test, or writing. However, the PD tremor mostly occurs at rest, oscillating at a frequency of 4–6 Hz [21].

In comparison to a PD tremor, a physiological tremor is typically present in all humans and is considered as an artifact. It usually occurs at a frequency of 8–12 Hz and sometimes at even higher frequency depending on the position of measurement [21]. Also, tremors caused by atypical Parkinsonism resemble PD tremors and occur due to various factors including the usage of certain drugs, vascular problems, Progressive Supranuclear Palsy (PSP), Multiple System Atrophy (MSA), Dementia with Lewy bodies (DLB) and others [3]. The various tremor features [22,23] in the frequency domain that would help us in detecting a PD tremor include the amplitude, power distribution, frequency dispersion and median frequency.

4. Data analysis and results

4.1. Statistical analysis

The statistical analysis was done using the Minitab®17.2.1 [24]. It was observed that the features extracted from the left and right foot were highly correlated for all the study group subjects, hence force data from the left foot alone had been used for analysis purposes. One-way analysis of variance (ANOVA) test was used to determine if there are any significant differences between the mean values of the two groups (PD and healthy control) and the results are presented in Table 1. It was performed with a 95% confidence interval, observations with a p-value ≤ 0.05 are deemed to be of significance.

The gait parameters under investigation are the step distance, stride time, stance and swing phases, heel, metatarsophalangeal joint (below toe), and toe forces, and the normalized values of the heel, below toe, and toe forces. From Table 1, it is evident that PD patients from all the three groups have shorter average step distance, with a slightly higher average stride time than a healthy control subject. Also, the patients with PD have reduced average swing phase compared to healthy control subjects, and an increase in the average stance phase. Further, we can notice that the vertical force imparted by the heel region of the foot and the normalized heel force are higher in healthy subjects compared to the PD patients, thus indicating better stability and control. Since the vertical force indicates body control stability, this proves that the healthy control subjects participated in the study had better body control compared to PD patients.

4.2. Ground reaction force (GRF) plot

In Fig. 2(a), the ground reaction force value of a healthy subject has been plotted against the % of the gait cycle. From the plot, two peaks are generated in a gait cycle and the first peak occurs when the heel strikes the floor followed by the second one at the toe-off period, produced by the push-off force from the ground. During the early stages of PD, the force values at the initial contact and toe-off phases are reduced. Also, in the later stages, the force plot is characterized by a single narrow peak [25] as seen in Fig. 2(b). It occurs due to the difference in the anatomy of walking between a patient with PD and a healthy subject.

In a normal gait, the heel strikes the ground first followed by the toe which is called as heel-to-toe walking. In contrast, the PD gait is characterized by a flat foot strike: where the entire foot is planted on the ground, simultaneously. Also, during the later stages, the toe touches the ground before the heel called as the toe-to-heel walking [26].

4.3. Pattern classification using LDA

Pattern classification was performed in Matlab [27]. The Linear Discriminant Analysis (LDA) classifier was used to study the performance of the extracted gait parameters. The algorithm and its specifications have been chosen based on its better performance in comparison to other algorithms including the Support Vector Machine (SVM) and Artificial Neural Network (ANN). A total of 40 observations was used per group for classification purpose, distributed as 20 observations each between PD and healthy control subjects.

The five-fold cross-validation method was used, that partitions the data into five sets or folds. Then for each fold,

Table 1
Mean, standard deviation and p-value for gait features from groups 'Si', 'Ju' and 'Ga'.

Gait feature	Group 'Si'			Group 'Ju'			Group 'Ga'		
	Healthy subject	PD subject	ANOVA p-value ≤ 0.05, significant difference	Healthy subject	PD subject	ANOVA p-value ≤ 0.05, significant difference	Healthy subject	PD subject	ANOVA p-value ≤ 0.05, significant difference
	Mean ± SD	Mean ± SD		Mean ± SD	Mean ± SD		Mean ± SD	Mean ± SD	
Step distance (m)	0.70 ± 0.04	0.58 ± 0.07	<0.001	0.679 ± 0.06	0.498 ± 0.09	<0.001	0.676 ± 0.084	0.467 ± 0.079	<0.001
Stride time (sec)	1.05 ± 0.06	1.16 ± 0.08	<0.001	1.106 ± 0.087	1.131 ± 0.163	0.537	1.127 ± 0.083	1.240 ± 0.269	0.098
Stance phase (%)	64.49 ± 2.35	65.74 ± 2.16	0.088	64.08 ± 1.453	66.61 ± 2.477	<0.001	63.66 ± 1.955	69.05 ± 4.481	<0.001
Swing phase (%)	34.42 ± 2.51	33.32 ± 2.07	0.141	35.90 ± 1.454	33.27 ± 2.741	<0.001	35.54 ± 1.894	29.80 ± 4.191	<0.001
Heel force (N)	351.35 ± 83.62	229.03 ± 86.20	<0.001	348.13 ± 80.30	227.98 ± 88.5	<0.001	315.0 ± 94.28	230.8 ± 102.1	0.015
Below toe force (N)	287.92 ± 95.14	295.58 ± 87.71	0.793	248.25 ± 50.92	235.38 ± 65.32	0.491	267.8 ± 71.46	249.9 ± 54.68	0.403
Toe force (N)	171.91 ± 84.35	167.00 ± 72.11	0.844	169.27 ± 68.19	173.15 ± 81.71	0.871	187.7 ± 88.36	152.9 ± 51.35	0.157
Normalized force for heel (% body weight)	51.83 ± 11.42	34.79 ± 11.38	<0.001	52.15 ± 13.79	32.58 ± 12.09	<0.001	45.20 ± 12.82	31.77 ± 11.65	0.003
Normalized force for below toe (% body weight)	40.08 ± 10.32	42.93 ± 8.85	0.361	36.6 ± 7.25	34.48 ± 10.22	0.454	41.39 ± 10.13	36.43 ± 10.63	0.173
Normalized force for toe (% body weight)	25.67 ± 11.77	25.66 ± 10.04	0.999	25.04 ± 9.98	25.88 ± 13.26	0.823	28.75 ± 12.41	23.03 ± 8.25	0.129

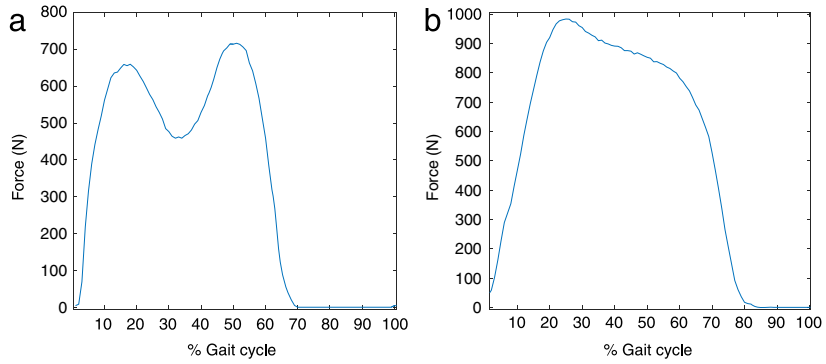

Fig. 2. (a) The vertical ground reaction force acting on a group 'Ga' healthy control subject during the gait cycle. (b) The vertical ground reaction force acting on a PD patient from the group 'Ga'.

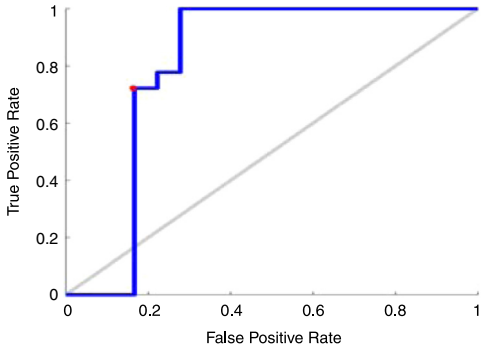

Fig. 3. ROC curve plotted using all the gait features for PD and control group.

it trains a model and assesses its performance. Further, it calculates the average test error over all the folds [28]. The rate of accuracy for the average values of the parameters including the step distance, stance and swing phase, heel and normalized heel forces have outperformed the other features. Hence, these features display a substantial difference between the PD and healthy control groups.

Moreover, the accuracy rate when all the features were combined is around 87.5% for the subjects in group 'Si', 90.0% and 83.3% for the subjects in groups 'Ju' and 'Ga' respectively. We decided to group the most distinct features: step distance, stance phase, swing phase, heel and normalized heel force together and an accuracy rate of 90.0% was achieved for the 'Si' group, followed by 92.5% and 92.25% for the 'Ju' and 'Ga' groups, respectively. On the other hand, the remaining less distinguishable features including the stride time, below toe force, toe force and normalized forces of the below toe and toe regions, combined had a lower accuracy rate.

In Fig. 3, we can see the ROC plot between the PD and control subjects utilizing all the gait features. A ROC curve plots between the values of true positive rate (sensitivity) to the false positive rate (1-specificity). In the plot below, we chose an optimal cut-off point that best balances between sensitivity and specificity. In the ROC curve, the point at which the sensitivity is at 0.72 and the specificity is 0.81 is taken as the optimal value by the classifier. Also, the area under the curve was achieved as 96%, which quantifies the overall ability of the algorithm to distinguish between a subject with PD and healthy subject.

4.4. Tremor analysis

The time domain signal is transformed to the frequency domain using the Fast Fourier Transform (FFT) [29]. Prior to performing the transform, all signals were high-pass filtered with a cutoff frequency of 0.5 Hz (2nd order Butterworth filter) to remove low frequency noise due to respiratory and cardiac oscillations. Also, the signal's spectral density denoting the amount of signal present per unit of bandwidth is plotted to obtain the power of the signal. The tremor characteristics that was observed to provide differentiation between a PD tremor and tremors due to atypical Parkinsonism [30] are as follows,

(1) Amplitude

The peak RMS (root mean square) value is defined as the square root of the mean of all the input-squared value and is found out to be 0.0749. It is also called as the average mean power of the signal, which is useful to compare with other atypical tremors that typically has a low amplitude value.

(2) Power distribution

The peak amplitude was measured between the 4–6 Hz interval where a single large peak can be seen. In a typical PD tremor, a large amount of power is concentrated in the region between 4–6 Hz contributing to a significant peak in the region, as seen in Fig. 4. The amount of power distributed in the 4–6 Hz range is 0.0561, i.e., around 91.92% of the total power in the spectrum.

(3) Frequency dispersion

The Power Spectral Density (PSD) estimate of the input signal displays the distribution of power at various frequencies. The PSD plot before applying windowing technique consists of spectral leakages. Some of the windows mostly used include the Rectangular (flat-top), Hamming, and Hann and are chosen based on the application. In our case, we require a window to enhance the frequency resolution and to reduce the spectral leakage, where a Hann window would be ideal [29]. Moreover, the dispersed frequency value was measured to be around 15.418 π milli-rads/sample, consisting of 68% of the spectrum power with a narrow bandwidth, which is typical in a PD tremor.

(4) Median frequency

In Fig. 5, the PSD with a reduced spectral leakage and increased resolution can be seen after applying the Hann window of 500 samples length. The median frequency is the

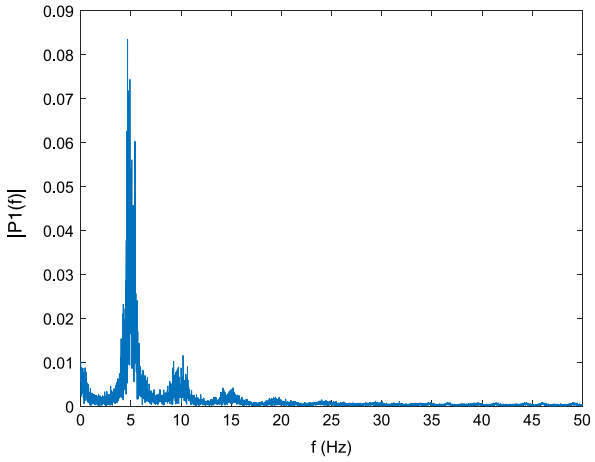

Fig. 4. Plot displaying the FFT output of the input time-domain signal and the amplitude of the signal is plotted in a single-sided spectrum.

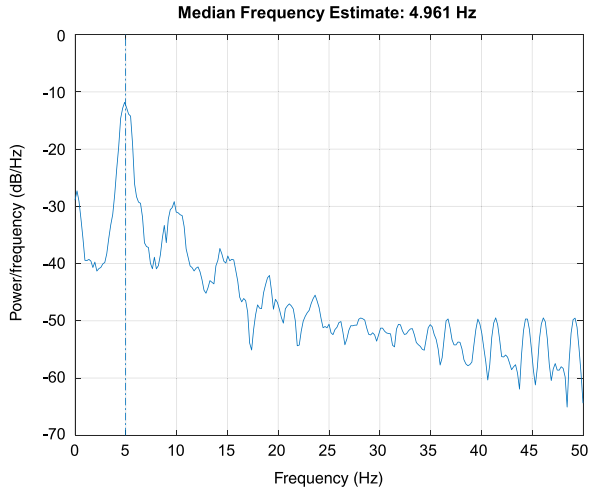

Fig. 5. The Power Spectral Density (PSD) estimate of the signal using Hann window length of 500 samples is displayed. It also specifies the median frequency of the signal.

point where the power is equally divided between the upper and lower parts of the spectrum, was determined to be of value 4.96 Hz. Moreover, from the plot, it is evident that the median frequency coincides with the single large peak in the spectrum, and a similar spectrum is mostly seen in PD subjects.

5. Discussion

Various aspects of the motor symptoms that are displayed by subjects with PD were individually investigated in this work:

(a) Gait features comprising of (i) spatiotemporal parameters including the step distance, stride time, stance and swing phases and (ii) kinetic parameters inclusive of heel force, below toe force, toe force and the normalized values of the heel, below toe and toe forces.

(b) Frequency-domain characteristics of the tremor signal including the amplitude, power distribution, frequency dispersion, and median frequency.

The hypothesis of this research is that both the tremor and gait features are vital in designing a monitoring system to detect PD at its onset and track its progression. In this research, an algorithm was developed to extract different gait and tremor features and was analyzed to obtain the most significant features that would best differentiate a subject with PD from a healthy subject. As a result, specific gait features including step distance, stance and swing phases, heel and normalized heel forces were found to be more significant than others for discrimination. In the tremor analysis, the results across all the 16 PD subject's data were comparable, and all the frequency based characteristics discussed were essential in identifying a PD tremor from tremors due to atypical Parkinsonism.

In the available online databases, the gait and tremor data are from different patients collected at different labs. However, in order to develop an integrated monitoring and management system for PD, it is critical that we have a more unified clinical data collection using multiple sensors from the same subjects. The integration of accelerometers for tremor monitoring and force/pressure sensors for gait monitoring and an improved algorithm need to be developed into a single tool to facilitate the clinician's decision in diagnosing and managing PD. Moreover, by individually studying the gait pattern of PD patients, it could assist the therapists or clinicians in the process of designing physical therapy and other rehabilitation programs. Also, falls are commonly seen in PD patients due to postural instability and knowledge of the postural balance of the patients while walking could be useful to manage them better.

6. Conclusion

Individuals with PD display tremor occurrences and gait impairments during the various stages of the disease. Due to lack of objective measures in diagnosing PD and high rate of misdiagnosis, an early and accurate diagnosis of PD is needed for better treatment and to control the effects of the symptoms more efficiently. Here, we have studied the role of motor symptoms to detect PD in its early stages and the potential for being a biomarker for an early diagnosis of PD. It is expected to act as a supplemental testing method to the standard methods used in hospitals.

In this research, we have investigated the effect of using both gait and tremor features for an early detection and monitoring of PD. Various features were extracted from the data collected from the wearable sensors and further analyzed using statistical analysis and machine learning techniques to find the most significant features that would best distinguish between the two groups: subjects with PD and healthy control subjects. From the results, it was observed that a set of gait features including step distance, stance and swing phases, heel and normalized heel forces provided better performance (feature discrimination) than others. An average accuracy rate of 86.9% was obtained in classifying between a PD patient and healthy control subject. Similarly, tremor analysis was conducted where we extracted the frequency-domain characteristics of the signal to identify a PD tremor from the tremors due to atypical Parkinsonism. A subject with PD had a large peak at the frequency between 4–6 Hz, and around 91.92% of the total power in the spectrum was concentrated within this band. A narrow bandwidth was

observed in the power spectrum with a median value falling in the 4 to 6 Hz region. This provides the differentiation between a PD tremor and other tremors due to atypical Parkinsonism occurring outside this frequency band.

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