



SPECIAL ISSUE PAPER

# Diagnosis of Parkinson's disease from electroencephalography signals using linear and self-similarity features

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## Abstract

An early stage detection of Parkinson's disease (PD) is crucial for its appropriate treatment. The quality of life degrades with the advancement of the disease. In this paper, we propose a natural (time) domain technique for the diagnosis of PD. The proposed technique eliminates the need for transformation of the signal to other domains by extracting the feature of electroencephalography signals in the time domain. We hypothesize that two inter-channel similarity features, correlation coefficients and linear predictive coefficients, are able to detect the PD signals automatically using support vector machines classifier with third degree polynomial kernel. A progressive feature addition analysis is employed using selected features obtained based on the feature ranking and principal component analysis techniques. The proposed approach is able to achieve a maximum accuracy of  $99.1 \pm 0.1\%$ . The presented computer-aided diagnosis system can act as an assistive tool to confirm the finding of PD by the clinicians.

## KEYWORDS

correlation coefficients, electroencephalogram (EEG), linear predictive coefficients, Parkinson's disease, SVM

## 1 | INTRODUCTION

Parkinson's disease (PD) is one of the most pervasive, devastating neurodegenerative disorder worldwide (WHO, 2006). In this disorder, the neurons are unable to secrete a chemical compound called dopamine, which serves as a communicator between brain and body parts. This leads to both motor and nonmotor symptoms like stiffness in muscles, blank expressions, shaking of hands, change in voice, posture, mood, gait instability, asymmetric resting, slowed movements, and so on. These symptoms are mild in the initial stage and become severe with time. Although the cause of PD in most of the cases is unknown, the cause in some of the cases is found to be an environmental or genetic mutation of LRRK2 gene (Li, Tan, & Yu, 2014; Bhat, Acharya, Hagiwara, Dadmehr, & Adeli, 2018). With more than 10 million people diagnosed worldwide, the incidence of PD is found to be more in men as compared with women. A detailed review report on the prevalence of PD can be obtained in the work by Pringsheim, Jette, Frolikis, and Steeves (2014).

The diagnosis of PD based on the plausible symptoms and clinical findings is a difficult task especially during the onset of PD. The accuracy based on clinical diagnosis is poor and requires expert intervention and multiple assessments for confirmation. Machine learning methods have

been successfully applied to problems in the fields like congestive heart failure (Bhurane, Sharma, San-Tan, & Acharya, 2019; Sharma, Bhurane, & Acharya, 2018), arrhythmia detection (Pławiak & Acharya, 2019; Sharma & Acharya, 2019; Sharma, Tan, & Acharya (2018, 2019)), hepatocellular carcinoma (Książek, Abdar, Acharya, & Pławiak, 2019), sleep disorders (Sharma, Agarwal, & Acharya, 2018; Sharma, Raval, & Acharya, 2019; Sharma, Goyal, Achuth, & Acharya, 2018), and epilepsy identification (Sharma & Pachori, 2017; Sharma, Pachori, & Acharya, 2017; Sharma & Shah, 2019). A computer-aided diagnosis can not only act as an alternative tool to identify PD but can also help the neurologists to confirm their findings. For this, we have used electroencephalography (EEG) signals that act as a simple and convenient measure to identify the neural activity in the PD patients.

The main contributions of this work are as follows:

- We propose a natural (time) domain approach for the diagnosis of PD patients based on inter-channel self-similar features. We have extracted linear prediction and correlation coefficients from the EEG signals. As the features are extracted in the natural domain, the approach completely eliminates the need for domain transformations.
- A progressive inclusion of features based on feature ranking and principal component analysis (PCA) is also employed. Partial set of features, which are vital to attain maximum performance, have been identified.
- The approach is validated on the EEG data obtained from 20 PD patients and 20 normal controls. The presented approach is able to achieve a maximum accuracy of  $99.1 \pm 0.1\%$  accuracy.

The main motivation to undertake this research is to explore the usage of linear and self-similar features for the diagnosis of PD. To the best of authors' knowledge, this is the very first work of applying these linear and self similar features in the natural domain (time) for the diagnosis of PD using EEG signals.

## 2 | RELATED WORKS

The works on the diagnosis of PD can be classified based on the type of signal used for the diagnosis. Major progress have been made on computer-aided PD detection using 1D biological signals like voice, speech, gait (Tsanas, Little, McSharry, Spielman, & Ramig, 2012; Little, McSharry, Hunter, Spielman, & Ramig, 2009; Sakar & Kursun, 2010; Zuo, Wang, Liu, & Chen, 2013; Chen et al., 2013; Ma, Ouyang, Chen, & Zhao, 2014; Hariharan, Polat, & Sindhu, 2014), 2D signals like images obtained from handwritten tasks from the subjects, or spatial-temporal gait signals (Hass et al., 2012; Roggendorf et al., 2012; Jeon, Han, Yi, Jeon, & Park, 2008; Zijlmans et al., 1996; Wahid, Begg, Hass, Halgamuge, & Ackland, 2015; Joshi, Khajuria, & Joshi, 2017). Recently, a feature selection algorithm for the identification of PD based on modified Grey Wolf Optimization was presented by Sharma et al. (2019). An optimized crow search algorithm was presented by Gupta et al. (2018), where three different classifiers were employed for efficient diagnosis of PD. An enhanced probabilistic neural network-based work was employed by Hirschauer et al. (2015) for PD diagnosis. A brief survey on computer-assisted PD diagnosis till 2017 is available in the review article by Pereira et al. (2018). Further, a survey and analysis of clinical diagnosis of PD is available in the work by Rizzo et al. (2016).

Several studies have also been reported analysing the statistics, change in the EEG patterns, and power spectrum of EEG for PD patients (He et al., 2017; Klassen et al., 2011; Soikkeli, Partanen, Soininen, Paakkonen, & Riekkinen, 1991; Yuvaraj et al., 2015; Rajamanickam et al., 2014). A very few work has been reported in the diagnosis of PD using EEG signals (Yuvaraj, Rajendra Acharya, & Hagiwara, 2018; Han, Wang, Yi, & Che, 2013; Liu et al., 2017; Oh et al., 2018). In Yuvaraj et al. (2018), a set of higher-order spectra features was used to determine the PD diagnostic index. In Han et al. (2013), changes in the EEG dynamics were identified as a biomarker of PD. A sample entropy-based features in wavelet domain were used by Liu et al. (2017). In another study, optimal centre constructive covering algorithm method was used to detect the PD subjects automatically. The work presented by Oh et al. (2018) explores the use of convolutional neural networks for classification of normal and PD EEG signals.

Unlike the existing techniques, in this work, we use simple time-domain, inter-channel, self-similar features of EEG signals. The details of the work are described in the subsequent sections.

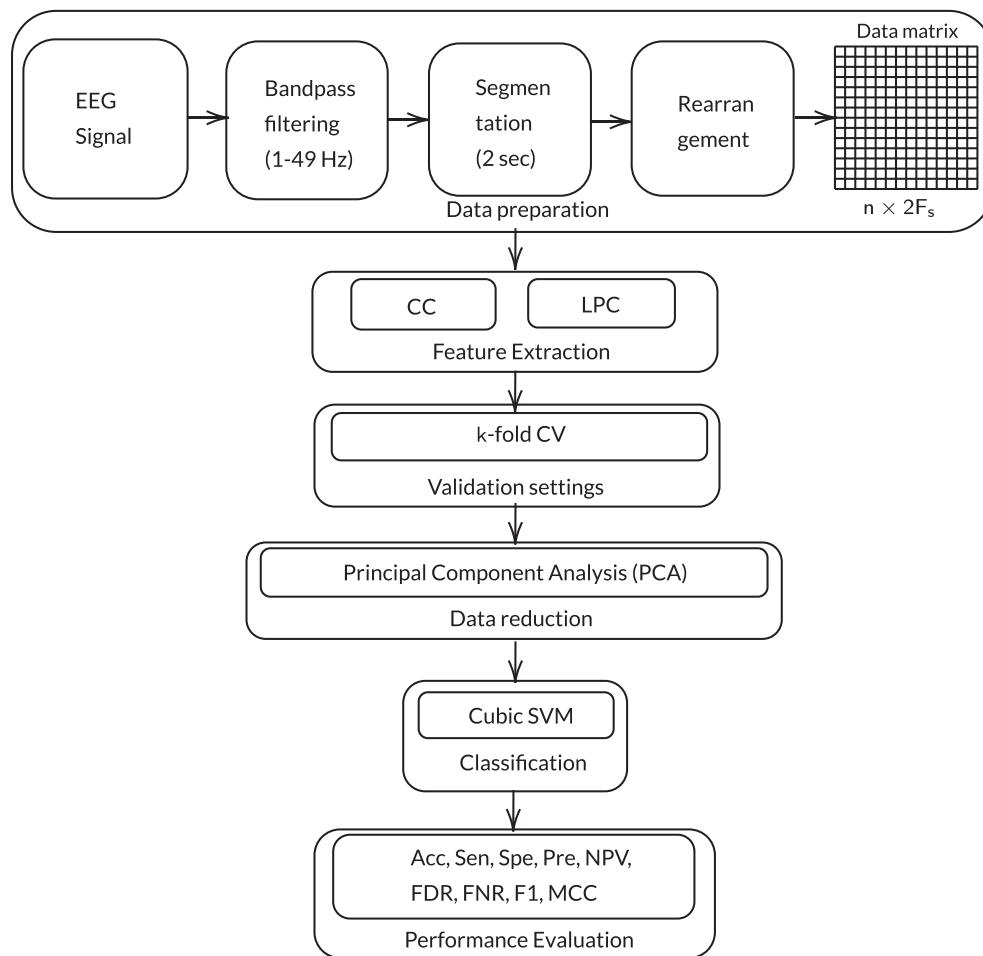
## 3 | MATERIALS AND METHODS

### 3.1 | Database used

In this paper, the EEG signals recorded from 20 normal and 20 PD subjects at Hospital University Kebangsaan Malaysia are used. The patients ranging in the age group of 45 and 65 years were considered for this study. Each EEG was recorded from 14 channels at a sampling rate of  $F_s = 128$  Hz. The EEG signals were recorded for 5 min in eyes-closed resting state to attain a state of relaxed wakefulness. The more details about participant characteristics can be found in Yuvaraj et al. (2016) and Oh et al. (2018).

### 3.2 | Proposed approach

Our approach is outlined in the block diagram shown in Figure 1.



**FIGURE 1** Block diagram for proposed approach

### 3.2.1 | Data preparation

An EEG signal is segmented into chunks of 2 s duration. The segmented signals were preprocessed by filtering them through a sixth order Butterworth band-pass filter in order to retain the frequencies in the band 1–49 Hz. The amplitude values greater than  $100\mu\text{V}$  were thresholded in order to remove the eye-blinking artifacts. Finally, a set of artifact-free epochs (1588 normal and 1571 PD) was obtained (Yuvaraj et al., 2018; Oh et al., 2018). This process was applied to the signals obtained from all the 14 channels (AF3, AF4, F3, F4, F5, F6, F7, F8, T7, T8, P7, P8, O1, and O2.). Thus, each EEG signal is represented as a data matrix of size  $n \times 2F_s$  (14 × 256 in our experiments). A sample of 14-channel normal controls and PD patients EEG signals is shown in Figure 2.

### 3.2.2 | Feature extraction

We have represented the EEG signals using linear predictive coefficients (LPC) and correlation coefficients (CC). We have chosen these features as both of these features are linear and can represent the self similarity in the data acquired from different EEG channels. The details of the feature extraction stage are given below:

#### Linear predictive coefficients

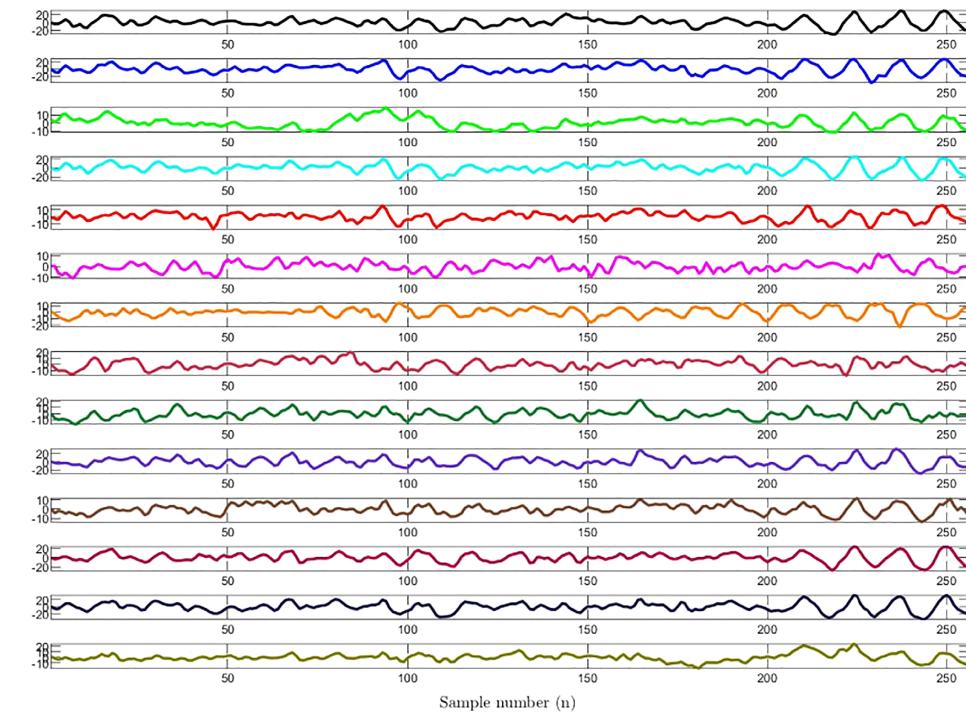
LPCs are widely used for signal representation and analysis (O'Shaughnessy, 1988). The LPC model finds its applications in audio codecs, speech recognition, synthesis, compression, and secured communication. The LPC are used to approximate the given signal  $x[n]$  using a linear combination of its past values as,

$$\hat{x}[n] = \sum_{k=0}^p a[k]x[n-k], \quad (1)$$

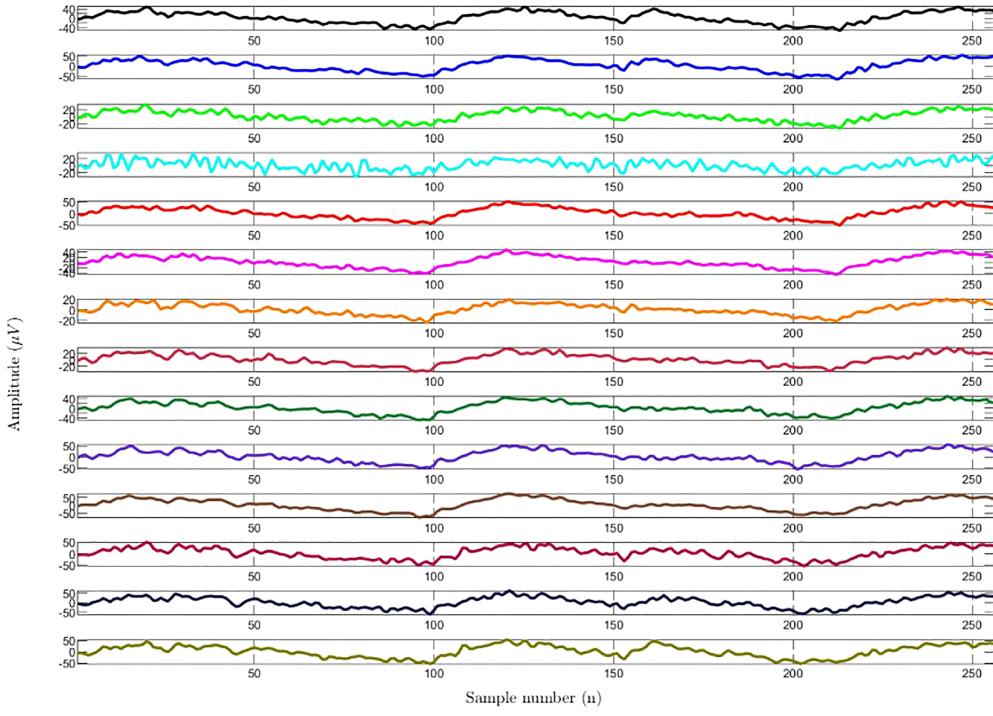
where,  $\hat{x}[n]$  is the approximated signal,  $p$  is the order of approximation and  $a[k]$  are the predictor coefficients that are determined by minimizing the mean-squared error between  $x[n]$  and  $\hat{x}[n]$  given by,

$$E = \sum_{vn} (x[n] - \hat{x}[n]). \quad (2)$$

This gives a set of equations that can be solved using autocorrelation or covariance method. A matrix obtained from this process can be used to find the coefficients  $a_k$ .



(a) A sample of 14-channel EEG signal for normal control.



(b) A sample of 14-channel EEG signal for Parkinson's disease

**FIGURE 2** Sample electroencephalography (EEG) recordings from the database used. The signals are sequentially plotted from all the 14 channels (AF3, AF4, F3, F4, F5, F6, F7, F8, T7, T8, P7, P8, O1, and O2)

### Correlation coefficients

The idea of CC was first conceived by Francis Galton as a measure of linear relationship between two variables (Galton, 1889; Kendall, Stuart, & Ord, 1987). Mathematically, the correlation coefficient between two  $L$ -length vectors  $\mathbf{x}$  and  $\mathbf{y}$  is given by,

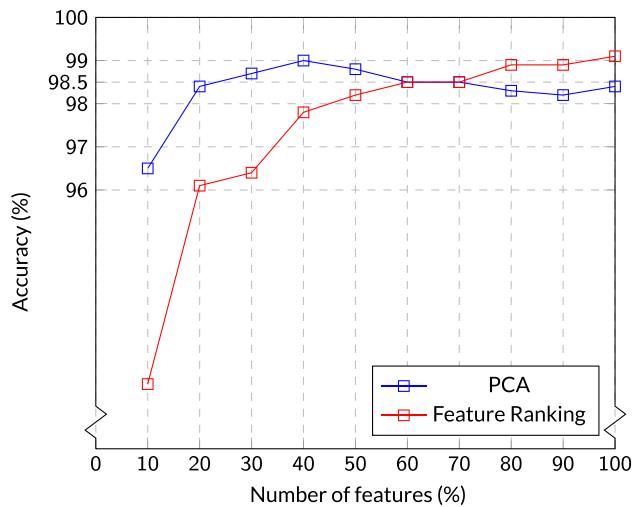
$$\rho_{xy} = \frac{1}{L} \sum \left( \left( \frac{\mathbf{x} - \mu_x}{\sigma_x} \right) \left( \frac{\mathbf{y} - \mu_y}{\sigma_y} \right) \right). \quad (3)$$

The matrix of correlation coefficients is a set of linear regression coefficients of one variable over the other and vice versa.

$$\mathbf{R} = \begin{pmatrix} \rho_{xx} & \rho_{xy} \\ \rho_{yx} & \rho_{yy} \end{pmatrix}.$$

$$R_{n \times n} = \begin{pmatrix} 1 & \rho_{12} & \rho_{13} & \dots & \rho_{1n} \\ \rho_{21} & 1 & \rho_{23} & \dots & \rho_{2n} \\ \rho_{31} & \rho_{32} & 1 & \dots & \rho_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \rho_{n1} & \rho_{n2} & \rho_{n3} & \dots & 1 \end{pmatrix} \Rightarrow f = \begin{pmatrix} \rho_{12} \\ \rho_{13} \\ \rho_{23} \\ \vdots \\ \rho_{1n} \\ \rho_{2n} \\ \rho_{3n} \\ \vdots \\ \rho_{(n-1)n} \end{pmatrix}$$

**FIGURE 3** Correlation coefficient feature extraction. Total  $\frac{n(n-1)}{2}$  features are extracted that are further subjected to feature ranking



**FIGURE 4** Accuracy (%) versus number of features obtained using principal component analysis (PCA) and feature ranking technique with support vector machine (SVM) classifier

As  $\rho_{xy} = \rho_{yx}$ , CC matrix is symmetric. Further, the principal diagonal has the maximum normalized value of 1. Therefore, the complete CC coefficients can be represented using a strictly lower or upper triangular matrix coefficients.

We calculated the CC of an  $n$ -channel EEG signal by treating each channel as a variable resulting in an  $n \times n$  matrix. The unique coefficients are rearranged to form a feature vector as shown in Figure 3. In total, we have extracted  $\frac{n(n-1)}{2}$  CC features. To avoid the redundancy, all the features are subjected to feature ranking.

### 3.2.3 | Feature ranking and dominance

The extracted features may not be in the order of their significance. For this purpose, all the features are ranked using an independent evaluation criterion, Student's t test (STUDENT, 1908), which tests the hypothesis based on sample means. We have ranked the features as per the value obtained from two-sample t test with pooled variance estimate. The performance of the classifier has gradually improved with the addition of features based on their ranks. This is shown in red line plot in Figure 4. In our experiments, we have chosen top 40 features as we were able to obtain maximum accuracy using these features.

The ranked features are analysed for their dominance. The dominance simply signify the percentage of contribution by these features to attain the maximum accuracy. As can be observed from Table 1 that both features are contributing significantly to attain the highest classification performance.

### 3.2.4 | Selecting principal components

The extracted feature matrix may contain redundant features. In order to identify important features, the popular data reduction technique, PCA is applied to the feature matrix (Shlens, 2003). This is an optional step and gives an additional flexibility to choose the number of prominent features. Data with or without PCA can be directly applied to the classifier learner, and the results are given in the next section. The effect of applying PCA is shown in the blue line plot in Figure 4.

### 3.2.5 | Classification

In this step, the extracted feature matrix is prepared for the validation settings. In our experiments, we have chosen 10 – fold and leave-one-out cross validation (CV) techniques. As a trade-off between the SVM complexity (degree) and accuracy of classifying the normal and PD EEG signals,

**TABLE 1** Dominance of features post feature ranking

# features (%)	Dominance (%)	
	CC	LPC
10	69.23	30.77
20	69.23	30.77
30	46.15	53.85
40	61.54	38.46
50	69.23	30.77
60	61.54	38.46
70	53.85	46.15
80	46.15	53.85
90	38.46	61.54
100	46.15	53.85

Abbreviations: CC, correlation coefficients; LPC, linear predictive coefficients.

**TABLE 2** Effect on classification accuracy due to changes in SVM parameters for 10-fold CV

Sr. No.	SVM Parameters		
	Box Constraint level	Kernel Scale	Accuracy (%)
1	1	1	99.1
2		2	98.7
3		3	98.9
4		4	98.9
5		5	98.9
6	2	1	98.4
7		2	98.7
8		3	98.9
9		4	98.9
10		5	98.9
11	3	1	98.5
12		2	98.6
13		3	98.9
14		4	99.0
15		5	98.9
16	4	1	98.5
17		2	98.6
18		3	98.9
19		4	99.0
10		5	99.0
21	5	1	98.5
22		2	98.6
23		3	98.9
24		4	98.9
25		5	99.0

Abbreviations: CV, cross validation; SVM, support vector machine.

we have used an with cubic kernel  $d = 3$ . This can be achieved by mapping the features on kernel (Cortes & Vapnik, 1995; Hearst, 1998),

$$K(x, y) = \left( \sum_{j=1}^n x_j y_j + c \right)^d, \quad (4)$$

where  $(x, y)$  denote feature vectors and  $c$  is a positive constant. The SVM parameters like box constraint and kernel scale were manually varied from 1 to 5 in steps of 1. We have obtained consistent average accuracy of 98.8% and highest accuracy of 99.10% for the box constraint and kernel scale values as 1. The variations in SVM parameters and the corresponding accuracies obtained for 10-fold CV are tabulated in Table 2. The data can be classified into two classes based on the sign of a function given by,

$$H = \sum_{j=1}^n w_j K(x, s_j) + b,$$

where,  $w_j$ ,  $s_j$ , and  $b$  are the weights, support vectors, and bias respectively.

### 3.2.6 | Performance evaluation

To measure the efficacy of the proposed algorithm, the confusion matrix, receiver operating characteristics (ROC), and eight different parameters namely accuracy, sensitivity, specificity, precision, false positive rate, false negative rate, F1 score, and Matthews correlation coefficient (Goutte & Gaussier, 2005; Matthews, 1975) are calculated.

## 4 | RESULTS AND DISCUSSION

The performance of the proposed two linear and self similar features (CC and LPC) is shown in Table 3. The individual and combined accuracy obtained for CC- and LPC-based features are given in Table 4. A maximum accuracy of 99.1% was recorded with the proposed method. The progressive performance of applying PCA is shown in Figure 4. The plot shows the overall accuracy of the extracted features with respect to the number of features used for classification. Our experiments were executed on MATLAB 2017B platform installed on a laptop with 16 Gb RAM and Intel's sixth generation i7 processor. The time complexity of the proposed method in terms of the training time and prediction rate is listed in Table 5. Further, the confusion matrices along with the ROC curves for 10-fold and leave-one-out CV settings are shown in Figures 5 and 6. It can be seen that the ROC is able to achieve nearly maximum area under the curve (AUC = 1) whereas for leave-one-out, the AUC = 0.9986 with the false positive rate of < 0.01.

The extracted linear, self similarity features are found to be highly competitive in representing the EEG signals for normal and PD patients. The summary of the comparison with the related competitive techniques is shown in Table 6. The cumulative performance shown in Figure 4 shows

Measure	Value	
	10-fold	Leave-one-out
Accuracy	0.9908	0.9899
Sensitivity	0.9887	0.9912
Specificity	0.9930	0.9886
Precision	0.9930	0.9887
False positive rate	0.0070	0.0114
False negative rate	0.0113	0.0088
F1 score	0.9908	0.9899
Matthews correlation coefficient	0.9816	0.9797

TABLE 3 Performance measures obtained for the proposed approach

Sr. No.	Feature	Maximum Individual Accuracy (%)		Combined Accuracy (%)	
		10-fold	Leave-one-out	10-fold	Leave-one-out
1	CC	97.6 ± 0.1	97.8 ± 0.1	99.1 ± 0.1	98.99 ± 0.1
2	LPC	96.3 ± 0.1	96.14 ± 0.1		

TABLE 4 Individual and combined accuracy obtained for proposed features

Settings	Training time (sec)	Prediction rate (obs/sec)	Average feature extraction time per signal (mSec)
Without PCA	3.60	28000	0.45
With PCA (35%)	4.40	9700	0.45

TABLE 5 Time complexity for the proposed approach for 10-fold CV

Abbreviations: CV, cross validation; PCA, principal component analysis.

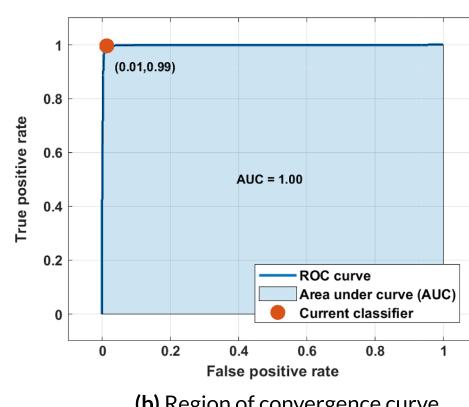
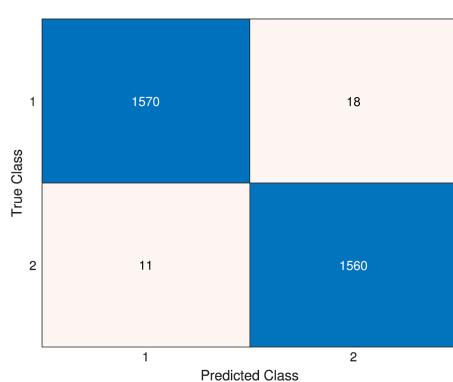
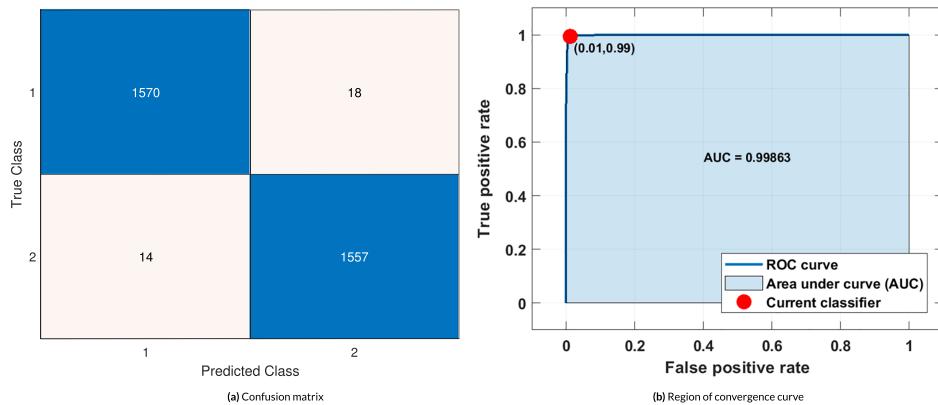


FIGURE 5 Confusion matrix and region of convergence obtained for the proposed approach using 10-fold cross validation (CV)

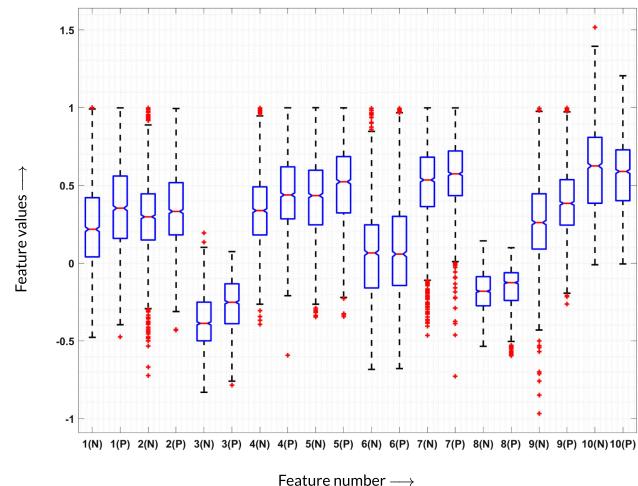


**FIGURE 6** Confusion matrix and region of convergence obtained for the proposed approach using leave-one-out cross validation (CV)

**TABLE 6** Summary of comparison for automated detection of PD using EEG signals

Author	Year	Validation	Duration	Approach	Performance (%)
Yuvaraj et al. (2018)	2016	10-fold CV	2 sec	Higher-order spectra features	Acc: 99.62 Sen: 100.00 Spe: 99.25
(Oh et al., 2018)	2018	10-fold CV	2 sec	13-layer Deep CNN	Acc: 88.25 Sen: 84.71 Spe: 91.77
This work	2019	10-fold CV	2 sec	LPC + CC	Acc: 99.08 Sen: 98.87 Spe: 99.30

Abbreviations: CC, correlation coefficients; CV, cross validation; EEG, electroencephalography; LPC, linear predictive coefficients; PD, Parkinson's disease.



**FIGURE 7** Box plots of top 10 features for normal (N) and Parkinson's disease (PD; P) signals

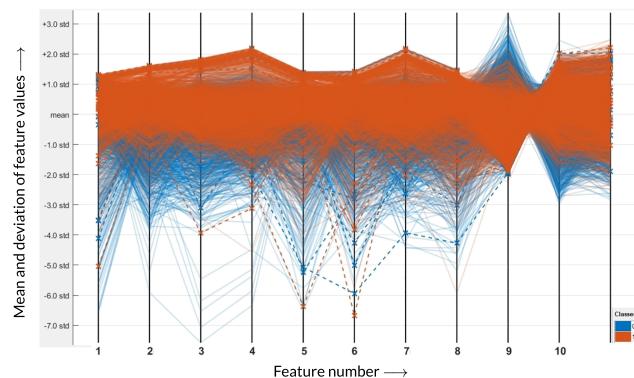
that partial set of features (35% of the principal components) are able to achieve a maximum accuracy, whereas it takes around 80% of the top ranked features are able to attain the maximum accuracy. The distinction of the top 10 features between the two groups can be observed in the box plots of Figure 7. The median notch in the interquartile range distinguishes the normal and PD classes. Further, the parallel coordinate plot in Figure 8 for top 10 features also indicates the amount of overlap and separation between the two classes. The top ranked feature values have lesser deviation for normal subjects whereas a significant deviation is observed for PD patients, thus indicating a variation in the self-similarity pattern in EEG signals for PD patients.

The salient features of this proposed approach are as follows.

- The proposed set of features are defined in the time domain and therefore eliminating the need for any sort of domain transformation.
- For achieving maximum accuracy, merely 35% of total principal coefficients are used.
- The combination of inter-channel LPC and CC features are able to achieve a maximum accuracy of  $99.1 \pm 0.1\%$ .
- The feature extraction does not require any data dependent parameters.
- Unlike deep learning techniques in which the data accuracy is dependent on large number of data, the proposed method can achieve higher accuracy with fewer features.

The proposed approach however has a few limitations including the following:

- High training time of SVM that increases with decrease in the number of features.
- The trade-off between the complexity of SVM kernel and accuracy makes the optimal choice of selecting a kernel a difficult task.



**FIGURE 8** Parallel coordinate plots for top 10 ranked features of normal (blue) and Parkinson's disease (PD; orange) class

- Although PCA can be used in order to satisfy the memory requirements for computing the training model, it adds to the complexity of the overall system.
- In contrast with the deep learning algorithms where the data are fed directly to the learning algorithms, the proposed approach requires essential stages like feature extraction and data labelling.

The feature extraction being executed in the time domain is quicker to implement unlike the approaches presented in Yuvaraj et al. (2018) and Oh et al. (2018), which used complex spectral features or deep learning procedures. The presented model can act as an effective alternative for the diagnosis of PD.

## 5 | CONCLUSIONS

Identification of specific features for the diagnosis of PD using EEG with minimal complexity is a challenge. In this work, we have used two linear and self-similar features for the classification of normal and PD EEG signals. The features are extracted in the time-domain, thus eliminating the need for complex transformations or specialized filter design techniques. For classification, we have employed SVM classifier with cubic kernel. The proposed approach is found to be competitive with the state-of-the-art diagnosis techniques, which uses EEG signals for the diagnosis of PD. Both the features, LPC and CC, are found to be contributing significantly to attain maximum achievable accuracy. Our results show that the maximum accuracy of 99.1% is achieved using these features. Further, it is observed that just 35% of the total features are able to achieve the maximum accuracy. The proposed approach can not only act as an alternative tool for the diagnosis of PD but may also help in distinguishing other neurological disorders and can help the neurologist to confirm his findings. In this study, we have used only 20 normal and 20 PD patients. We hypothesize a similar performance for a large set of data too. Recently, Sharma et al. (2018; 2018; 2018; 2017; 2017) have designed novel wavelet filter banks for the analysis of physiological signals including EEG. In future, the study can be extended for detection of PD using the wavelet-based features. Also, the proposed method can be effectively applied to problems from other fields like congestive heart failure, arrhythmia detection, hepatocellular carcinoma detection, estimating the state of positive displacement pump (Pławiak, 2014), and so on.

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