A new Cepstral-based biomarker of reward positivity evaluated in Parkinson's disease detection

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Abstract
Parkinson's disease (PD) is one of the central nervous system disorders that affect dopaminergic neurons in the substantia nigra, leading to impairments in midbrain dopaminergic functions. The development of efficient detection is required to control the impairments. In previous PD detection works, either the detection cost or complexity is high or the robustness of the method to clinical parameters or individual differences is low. This article provides a reliable PD detection method proposing a new marker of reward positivity using a Cepstral decomposition of electroencephalogram (EEG) signals discriminating oscillation and excitation components and providing amplitude and phase information while minimizing the number of analyzed coefficients. Cepstral analysis has been used for extracting a more effective representation of spectral information of the quasi-periodic signals using source-filter separation. The capability of this method has been evaluated using 28 patients on both ON and OFF medication states and 28 healthy control individuals during the reinforcement-learning task. It has achieved an average accuracy rate of 99.79% by minimizing the real Cepstrum coefficients to 250 from 4000 ones. It has also obtained satisfactory results on medication states and frontal channels (85% channel reduction) indicating the efficiency, robustness, and cost-effectiveness of the method.

Keywords
Neurodegenerative disease, reinforcement-learning task, Cepstrum analysis, automatic diagnosis, EEG signal processing, machine learning.

1. Introduction

Parkinson's disease (PD) is one of the most common progressive disorders of the central nervous system and its cause is still unknown [1]. PD is the result of the loss of dopaminergic neurons in the substantia nigra [2]. PD causes motor and non-motor symptoms in patients[3], and as a neurological disease with no specific treatment [2], impacts the quality of their daily life. Consequently, the development of a reliable and clinical detection method can play an essential role in slowing down the progression of the disease, providing better control strategies, and improving the quality of patient's life.

In recent years, various neuroimaging techniques such as electroencephalography (EEG), magnetic resonance imaging, positron emission tomography and single-photon emission computerized tomography have been used individually or simultaneously for the detection of neurological diseases [4,5]. Some of the mentioned tools may not be recommended for widespread and frequent uses due to their high cost and, sometimes invasiveness, or radiation exposure [4]. Out of them, EEG is an electrophysiological monitoring tool that records the electrical activity of the brain with high time resolution [4]. It can provide low-cost and non-invasive information about the pathology of PD, supporting physicians in diagnosing the patients [6]. Hence, PD detection using EEG signals with high test-retest capabilities has attracted the attention of researchers [4]. Recently, a large number of studies have been conducted on PD detection based on EEG pattern recognition techniques [7-22]. In this regard, various linear and nonlinear features, such as entropy [9, 11, 14, 21,22], fractal dimension [21], Hurst exponent [15, 21], , Fisher information analysis [21], partial directed coherence [19], Hjorth parameters [10, 11, 13, 15, 21], Holo-Hilbert spectrum [8], wavelet transform [9,15], common spatial pattern-based features [7], aspirin pattern-based features [17], power [11, 12, 18, 20-22], and higher order statistical features [16] have been extracted from the EEG signals. In state-of-the-art works, either the computational cost or complexity is high or the robustness of the method to clinical parameters or individual differences is low. EEG signals are composed of PD-relevant and irrelevant variability of the brain activity [23]. An efficient feature extraction step, as a main part of the pattern recognition process, not only should provide useful information about the pathology of the disease but also should be insensitive to irrelevant information and noises. To extract PD-relevant information, it is better to separate the informative components from irrelevant ones. It has been shown that EEG signals can be modeled as a convolution of the oscillation and the excitation function which is too hard to deconvolve in the time domain. In addition, EEG signals have a non-stationary and non-linear nature [24], therefore the use of nonlinear decomposition methods, such as Cepstrum analysis can be more compatible with EEG signals. Cepstrum analysis as a homomorphic transformation

can simply separate different components from each other by changing the nonlinear relationship between them into linear ones [25, 26]. It can also offer clean and compact frequency information of the signal using a small number of Cepstral coefficients, which is promising for clinical and practical applications [27]. These considerations have motivated this study, in which the benefits of Cepstrum analysis have been employed for the decomposition of EEG signals. The study aims to present a new signal processing method for extracting more relevant frequency information of the EEG signals using Cepstrum analysis. This technique has been successfully employed in cognitive workload estimation [26], speech recognition [28], EEG classification [29] and EMG classification [30]. However, to the best of our knowledge, its application for PD detection using EEG signals is novel.

Currently, most existing works have investigated the potential of rest EEG signals for PD detection [3-27]. However, fewer studies have explored the effect of cognitive impairments such as reward positivity changes in automatic PD detection [28, 29]. However, this paper has evaluated the performance of the proposed method using EEG signals of PD patients and healthy control (HC) individuals performing the reinforcement learning task. It has been shown that PD and dopamine-driven processes are directly associated with each other and dopamine is a key element of the reward system. Consequently, PD can affect the reward processing function such as reward positivity and the evaluation of the performance of the reward system can be one of the appropriate ways to better identify the symptoms of the disease [28, 29]. In this regard, the use of reinforcement learning task that challenges the performance of the reward system may better reveal PD-related impairments and enhance the detection performance [29]. However, few studies have explored these types of cognitive tasks for automatic PD detection using pattern recognition of the EEG signals [28, 29]. Hence, in this research, a set of Cepstral-based features have been extracted from EEG signals during the reinforcement-learning task to provide new reward positivity markers for PD detection.

The main contributions of this paper are:

a. An efficient and robust PD detection method based on the homomorphic filtering of EEG signals has been proposed to decompose excitation and oscillation components of EEG signals providing a clean and compact frequency representation.
b. The proposed Cepstral-based features have been evaluated using EEG signals recorded during reinforcement-learning tasks to quantify alterations in reward positivity function for PD detection.
c. The roles of amplitude and phase information of EEG signals in PD detection have been investigated and compared in the forms of real and complex Cepstral coefficients.
d. In a comparative study, the effects of EEG channels on different brain areas and medication conditions have been explored on the performance to evaluate the possibility of channel reduction or the robustness of the results.

The rest of this paper is organized as follows: Section 2 describes in detail materials and methods. In Section 3, extensive experiments are performed to evaluate the proposed method. Finally, discussion and conclusions are summarized in Section 4, and Section 5, respectively.

2. Materials and Methods

The schematic diagram of the proposed PD detection approach is demonstrated in Fig.1. As illustrated in the figure, the method consists of preprocessing step, homomorphic filtering of EEG segments using Cepstrum analysis, statistical feature extraction, and a classification stage. A detailed description of the role of each processing step has discussed in its corresponding subsections.

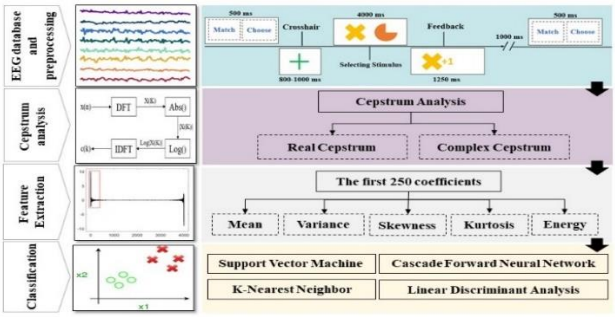

Fig. 1. The schematic diagram of the proposed approach

2.1. EEG database and preprocessing

The EEG dataset used in this study is available on www.predictsite.com; Accession #d007 [28, 30]. A total 54 subjects, 28 PD patients (17 males and 11 females) and 28 HC individuals (17 males and 11 females), were participated in this dataset. The clinical and demographic characteristics and neuropsychological questionnaires and assessments that all participants filled out are shown in Table I [28]. According to Table I, Participants with PD were similar to the control group in whole demographic or neuropsychological measurement, except that they had higher depression scores [28]. Healthy people visited the lab once, whereas PD patients visited the lab twice, seven days apart: once with taking medication and the other with skipping medication for 15 hours [28]. Hence, there were two medication states: PDON (referred to the patients on medication status) and PDOFF (referred to the patients without the medication).

Table I. Participant Demographic Information

Demographic features	Parkinson's disease (11F/17M)		
	Mean	SD	Range
Age	69.75	8.59	49-83
Yrs Ed[a]	17.25	3.24	12-24
Yrs Ed parents	12.49	3.82	1-20
MMSE[b]	28.64	1.06	27-30
NAART[c]	45.04	10.20	16-55
BDI[d]	7.64	5.23	0-21
UPDRS[e] ON	22.14	10.15	5-40
UPDRS OFF	23.79	8.71	10-41
LED[f]	703	440	60-1796
Years since Dx[g]	5.54	4.18	1-20
Demographic features	Healthy controls (11F/17M)		
	Mean	SD	Range
Age	69.21	9.23	48-84
Yrs Ed[a]	16.63	3.13	12-24
Yrs Ed parents	12.37	3.41	4-20
MMSE[b]	28.82	1.02	27-30

NAART[c]	47.00	7.36	21-58

[a] Yrs Ed: Years of Education, [b]MMSE=Mini Mental State Exam, [c]NAART=North American Adult Reading Test, [d]BDI=Beck Depression Inventory, [e]UPDRS=United Parkinson's Disease Rating Scale (motor), [f]LED=L-Dopa equivalence dose, [g]Dx=Parkinson's diagnosis.

In this database, EEG data were recorded using the Brain Vision System with 64 electrodes during the reinforcement learning task [28]. The signals were digitized at a sampling rate of 500 Hz and filtered using a 0.01-100 Hz band pass filter [28]. CPz and FPz were considered as reference electrode and ground one, respectively [28]. CPz was reconstructed by computation of the average reference. Vertical electrooculogram was also recorded using two electrodes. Blink activity was eliminated using Independent Component Analysis in EEGLAB [31]. Then, FT9, FT10, TP9, and TP10 electrodes were removed due to invalidity [28]. A 60 Hz notch filter was also applied to signals to remove line frequency.

In this database, a reinforcement learning task was performed during the data recording. In this task, participants were asked to select one of the free-choice or match modes. In each mode, there were four stimuli with easy or hard reinforcement rates. In each trial of the free-choice mode, the participants could select either one of the two stimuli. However, in the matching mode, they had to select the stimulus with a box around it [28]. Depending on performance, between three and five training blocks were presented. In each block, participants were required to perform 20 presentations of each stimulus pair. At the beginning of each trial, an instruction screen (''choose" or ''match") was displayed for 500 ms followed by a crosshair for 800–1000 ms. The crosshair was replaced with the stimulus pairs, which were presented for a maximum of 4000 ms. On the other hand, participants had 4000 ms to make a choice; otherwise ''No Response Detected" was displayed [28]. In this study, reward positivity-related EEG signals, which are around reward feedback screen onset have been selected for further analysis to capture all events [28]. It is defined as 6000 ms prior to 2000 ms after reward feedback screen onset [28]. Overall, the recorded data of 60 pre-processed EEG channels, containing 8-seconds (4000 samples) segments, have been used for feature extraction. On the other hand, the number of epochs for the three groups of HC, PDOFF, and PDON are 3640, 3500, and 3551, respectively.

2.2. Feature extraction based on Cepstrum analysis

Preliminary study has demonstrated that the pathological PD samples have shown a symptom-specific alteration in reward positivity amplitudes [28]. However, there exist some reward-positivity-related events that distinguish people with PD from matched HC, such as condition differences in reward surprise, higher value for volitional outcomes, or diminished reward positivity amplitudes [28, 32, 33]. To discriminate the specific reward positivity events from the rest directly and explore the role of reward positivity changes in PD, a novel application of Cepstrum analysis has been considered in this study. This method has been employed to derive intrinsic periodicity and frequency distribution of reward positivity-related events in PD using a small number of oscillation components of EEG signals. Cepstrum is a nonlinear decomposition method that allows the non-linear and non-stationary pattern of the EEG signals to be quantified well [34]. This technique has been defined first time by Bogert et al. in the audio processing field [35]. Compactness, source-filter separation, and orthogonally are some of the positive points of this method [34]. Cepstrum as a homomorphic filter is capable of separating the oscillation and excitation components of a signal by converting the convolution operator into a sum [36], leading to choosing the a more informative component set for feature extraction. These considerations motivate our choice of this method for PD detection. The Cepstrum transform is defined as the inverse Fourier transform of the log spectrum [36]. This technique can be explained as follows:

If it is assumed that the pre-processed EEG signal $x[n]$ is resulting from the convolution between oscillation function $x_1[n]$ and excitation function $x_2[n]$ as follows:

$$x[n] = x_1[n] * x_2[n] \tag{1}$$

frequency domain as follows [37]:

$$X[e^{j\omega}] = F\{x[n]\} = X_1[e^{j\omega}]X_2[e^{j\omega}] \tag{2}$$

by taking logarithm of $X[f]$, according to the product rule of logarithm, product of Fourier transforms switches to sum of their logs as [37]:

$$\log X[e^{j\omega}] = \log X_1[e^{j\omega}] + \log X_2[e^{j\omega}] \tag{3}$$

finally, by applying inverse Fourier transform as linear filtering, we will have [37]:

$$\begin{aligned} C[k] &= F^{-1}\{\log|X([e^{j\omega}]|\} \\ &= F^{-1}\{\log|X_1[e^{j\omega}]|\} + F^{-1}\{\log|X_2[e^{j\omega}]|\} \end{aligned} \tag{4}$$

where k is an independent variable of Cepstrum which is known as quefrency. There are two different types of Cepstral coefficients namely complex and real. The first type contains both amplitude and phase information of the signal. The mathematical definition of complex Cepstrum of signal $x[n]$ is as follows [34]:

$$C_c[k] = \frac{1}{2\pi}\int_{-\pi}^{\pi} \log\{X(e^{j\omega})\}e^{j\omega n}d\omega \tag{5}$$

where $X(e^{j\omega})$ and $\log(X(e^{j\omega}))$ respectively denote the discrete Fourier transform and complex logarithm which are given by following mathematical statements:

$$X(e^{j\omega}) = \sum_{n=-\infty}^{n=\infty} x[n]e^{(-j\omega n)} \tag{6}$$

$$\log\{X(e^{j\omega})\} = \log|X(e^{j\omega})| + j\arg\{X(e^{j\omega})\} \tag{7}$$

The real Cepstral coefficient contains amplitude information and its usage is more common in EEG signal processing [38]. It can also be expressed as [34]:

$$C_r[k] = \frac{1}{2\pi}\int_{-\pi}^{\pi} \log|X(e^{j\omega})|e^{j\omega n}d\omega \tag{8}$$

The obtained $C_r[k]$ and $C_c[k]$ coefficients are vectors with real values if x[n] is real [36]. Fig. 2 and Fig. 3 represent the complex and real Cepstrum coefficients extracted from one epoch of the pre-processed EEG signals across three HC, PDON, and PDOFF groups. In this study, to better verify the effectiveness of the amplitude and phase information for PD detection, features extracted from real

and complex coefficients have been explored and compared separately.

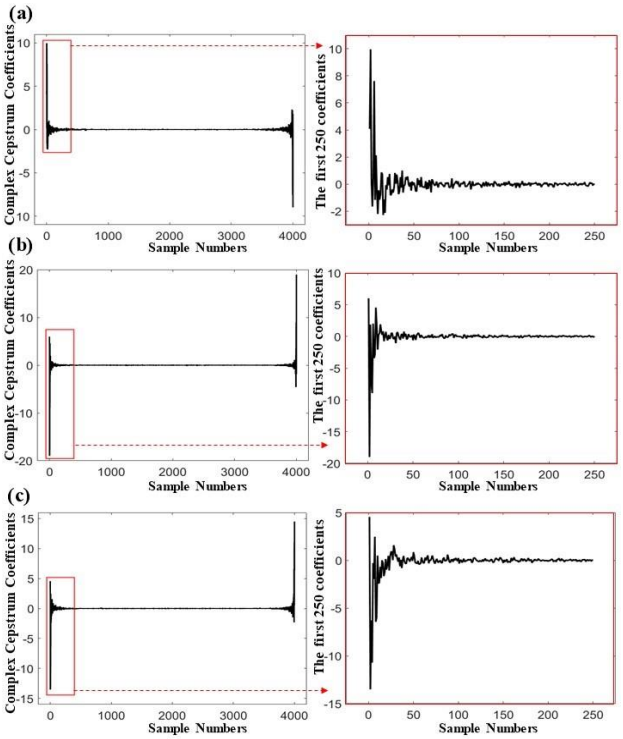

Fig. 2. Complex Cepstrum coefficients and their low-quefrency components of one epoch of (a) a PDOFF (b) a PDON, and (c) a HC subjects

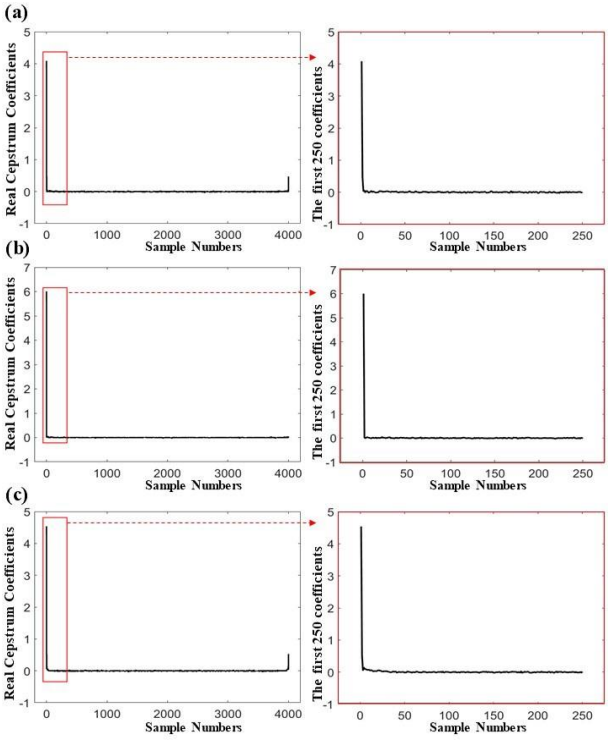

Fig. 3. Real Cepstrum coefficients and their low-quefrency components of one epoch of (a) a PDOFF (b) a PDON, and (c) a HC subjects

As can be seen from these figures, the calculated Cepstral coefficients can represent the overall energy distribution in the quefrency domain. There exist some differences in amplitude and distribution of Cepstral coefficients, especially in low-quefrency components. It has been shown that low-quefrency components of Cepstrum analysis include information about the oscillation function (action potential in EEG signals [39]) and high-quefrency ones contain information about the excitation one [40]. To further explore the role of reward positivity-related changes in amplitude and distribution changes of Cepstral coefficients, in this study, statistical features have been extracted from the first 250 coefficients. They have quantified the changes that occurred in the oscillation function. For this purpose, five statistical features, such as means, variance, skewness, kurtosis, and energy, have been extracted due to low computational complexity and their capability in quantification of asymmetry, flatness, and explanation of the shape of probability distribution. The mathematical formula of these features, namely means, variance, skewness, kurtosis, and energy can be expressed as follows:

$$m = \frac{1}{N}\sum_{k=1}^{N} C[k] \tag{9}$$

$$\sigma^2 = \frac{1}{N}\sum_{k=1}^{N} (C[k]-m)^2 \tag{10}$$

$$S = \frac{\frac{1}{N}\sum_{k=1}^{N} (C[k]-m)^3}{\left[\sqrt{\frac{1}{N}\sum_{k=1}^{N} (C[k]-m)^2}\right]^3} \tag{11}$$

$$K = \frac{\frac{1}{N}\sum_{k=1}^{N} (C[k]-m)^4}{\left[\frac{1}{N}\sum_{k=1}^{N} (C[k]-m)^2\right]^2} \tag{12}$$

$$E = \sum_{k=1}^{N} \left|C[k]\right|^2 \tag{13}$$

2.3. Classification

Up to now, several supervised learning approaches have been used to discriminate PD patients from HC individuals using EEG signals [8-24, 41]. Among the classification approaches, support vector machine (SVM) and K-nearest neighbour (KNN) have been employed in this study, given their superior performance and their frequent use in PD detection. Furthermore, the performance of two other classifiers including cascade forward neural network (CFNN) and linear discriminate analysis (LDA) has been explored to handle high dimensional, time-dependent patterns and nonlinear data relationship modeling.

2.3.1 Support vector machine (SVM)

SVM is a well-known supervised learning algorithm in pattern recognition that was introduced by Vapnik [42]. The objective of this algorithm is to find an optimal hyperplane for categorizing samples and assigning the right label to the given unlabeled data [43]. This classifier is successfully implemented in both linear and nonlinear patterns of data [43, 44]. The ability of SVM to provide a trade-off between training error and modeling complication has resulted in better generalization performance compared to other classifiers [45]. In PD detection field

as well as cognitive disorder detection [46], this technique has shown the capability of providing outstanding performance [8, 10, 12, 16, 20, 21, 23, 41]. Consequently, in this paper, a model of SVM with radial basis function kernel has been established to evaluate the discriminative power of quefrency patterns of features between HC and PD patients.

2.3.2 K-nearest neighbour (KNN)

KNN is one of the simplest machine-learning algorithms that is frequently used in PD detection [8, 10, 12, 21]. It is based on the distance metrics and classifies unlabeled data based on similarity to its neighbours [47]. For this purpose, the distance between unseen data and all the training data is calculated using different distances [48]. After sorting the samples based on the calculated distance values, the K minimum values are determined and the label of the unknown data is selected according to the majority voting technique [48]. In this work, a KNN classifier with Euclidean distance and K=1 has been used for the classification of EEG signals.

2.3.3 Cascade forward neural network (CFNN)

Artificial Neural Networks (ANN) are biological-inspired systems that are employed for data processing [49]. These Networks are made neurons, which are stacked in layers. According to the connection between neurons, different architectures of ANN are built. CFNN is one of the general types of ANN in which the input layer is attached to both hidden and output layers [50]. The advantage of this method is that it offers an improvement in the accuracy of nonlinear and time-dependent data modeling by combining the linear and nonlinear connections [50]. In this study, a CFNN model composed of one hidden layer with 10 neurons has been developed to address the nonlinear and time-varying nature of EEG signals. This model has been trained using the Levenberg-Marquardt algorithm along with tan-sigmoid and linear functions as transfer functions of the hidden layer and output layer, respectively.

2.3.4 Linear discriminate analysis (LDA)

The last classifier that has been tried is built on LDA. It is a simple and frequently used trainable system that is specifically designed to extract the linear combinations of features for discriminating different classes of events or dimensionality reduction [51]. LDA can easily handle the data unbalanced problems [52]. This classifier promises maximal separation by maximizing between-class variance and minimizing within-class variance in any particular data set [51]. Hence, this method as a basic classifier has been used in this study to evaluate the performance of the proposed Cepstral features.

In this study, to evaluate the generalization performance of these classifiers, 5-fold cross-validation technique is utilized. Furthermore, to explore the robustness of the detection method, in several other experiments, different feature sets including real and complex Cepstrum and the fusion of them have been used for training and testing procedures, separately. The effect of medication states (ON vs. OFF) on the detection performance has also been evaluated in three classification tasks, including HC vs. PDOFF, HC vs. PDON, and HC vs PD (ON+OFF).

3. Results

Table II presents the performance of the proposed method across real and complex Cepstrum coefficients, as well as different classifiers. Since, one of the effective classification approaches used for disease detection is "Naïve Bayesian"; the performance of the proposed method using this classifier has also been evaluated and reported in this Table. The average values of accuracy achieved by the proposed system using SVM, KNN, CFNN, and LDA are 99.7%, 99.6%, 99.5%, and 98.6% respectively. It is calculated as $Acc. = \frac{TP + TN}{TP + TN + FP + FN}$ [53]. These results confirm the effectiveness of the proposed Cepstral-based features of reward positivity in EEG signals and their application for PD detection.

To compare the importance of amplitude and phase information in PD detection using reward positivity-related features, a smaller number of features extracted from real and complex coefficients have been tested. The difference between the results denotes that real Cepstrum-based feature set has achieved outstanding performance in PD detection using all the classifiers. Whereas, the use of complex feature set has decreased the detection accuracies. Fusion of real and complex feature sets has also affected SVM and KNN classifiers. However, it has no significant impact on LDA and CFNN indicating performance robustness of these classifiers. These results confirm that change occurring due to reward positivity functions can be effectively captured by only evaluating the amplitude oscillations, which are quantified using a limited number of real coefficients reducing computational complexity.

Medication state as an affecting factor may lead to ease symptoms and decrease PD detection performance. Hence, correctly diagnosis of patients with different medication states is an important feature from clinical point of view. In other words, a system with high robustness is preferred for PD detection. For such a reason, a comparative analysis between two medication states has also been performed and the obtained results have demonstrated that the average values of accuracy achieved by the system using SVM across ON and OFF states are 99.74% and 99.90% respectively. The average values obtained by all the states are 99.79%. Hence, there is no significant difference in performance metrics between ON and OFF states, revealing the robustness of the proposed PD detection algorithm against the medication state.

Table II. PD detection performance using the proposed Cepstral features across real and complex coefficients and different classifiers.

Feature	Classification	Classifier / Performance metrics				
		SVM	KNN	CFNN	LDA	Naive Bayesian

		Real Cepstrum		Complex Cepstrum		Fusion of real and complex Cepstrum	
		HC vs. PDON	HC vs. PDOFF	HC vs. PDON	HC vs. PDOFF	HC vs. PDON	HC vs. PDOFF
Acc.[a]	HC vs. PD	99.7	99.9	66.3	58.0	58.7	58.3
Sen.[b]		99.6	99.8	99.1	61.6	61.7	58.6
Spe.[c]		99.8	100	2.8	54.6	55.7	58.1
Pre.[d]		99.7	100	66.3	56.9	57.6	57.3
F1.[e]		99.6	99.9	79.5	59.1	59.5	57.9
Acc.	HC vs. PD	99.5	99.8	60.5	54.7	55.0	55.1
Sen.		99.7	99.8	72	55.7	56.7	56.3
Spe.		99.4	99.7	37.3	53.7	53.4	54.0
Pre.		99.3	99.6	68.9	53.9	54.2	54.0
F1.		99.5	99.7	70.4	54.8	55.4	55.1
Acc.	HC vs. PDON	99.3	99.6	70.4	62.5	99.3	99.7
Sen.		99.9	99.8	92.2	61.3	99.3	99.8
Spe.		98.8	99.5	28.2	63.6	99.2	99.6
Pre.		98.7	99.4	71.3	62.1	99.1	99.5
F1.		99.3	99.6	80.4	61.7	99.2	99.6
Acc.	HC vs. PDOFF	99.5	99.6	68.7	59.3	99.5	99.5
Sen.		99.4	99.7	93.3	61.8	99.4	99.6
Spe.		99.6	99.6	21	56.7	99.5	99.5
Pre.		99.5	99.5	69.5	58.2	99.4	99.4
F1.		99.4	99.6	79.7	59.9	99.4	99.5
Acc.	HC vs. PD	98.8	99.6	66.9	54.3	61.0	60.9
Sen.		77.1	82.6	93.4	93.2	89.6	91.6
Spe.		64.6	60.2	15.5	16.2	33.1	31.3
Pre.		68.0	66.6	68.1	52.0	56.7	56.2
F1.		72.3	73.5	78.8	66.8	69.4	69.6

[a] Accuracy,[b] Sensitivity,[c] Specificity,[d] Precision,[e] F_measure or F1_score

To investigate the possibility of channel reduction for clinical application, the performance of each channel has also been explored separately. The aim is to select the most informative channels and minimize the number of analyzed EEG signals for computational complexity reduction. For this purpose, each EEG channel has been evaluated using all real Cepstrum-based features, and the 10 best obtained accuracies are reported in Table III. According to the Table, four channels namely 'F2', 'AF4', 'Fz', and 'F7' are more significant in terms of 83.67, 80.97%, 80.45%, and 80.32% accuracy, respectively. It demonstrates more efficiency of frontal channels in reward positivity-related feature extraction for PD detection, which is consistent with a recent study [29].

Table III. SVM classification accuracy using real Cepstral-based features across EEG channels

Channel	Performance		
	Acc.	Sen.	Spe.
'AF4'	80.9	78.4	83.3
'Fz'	80.4	83.6	77.3
'F2'	83.8	86.7	81.1
'F3'	77.4	77.5	77.4
'F6'	76.4	75.3	77.4

'F7'	80.3	79.8	80.7
'FC1'	78.6	76.2	80.9
'FC5'	77.6	78.9	76.4
'FT8'	78.4	80.4	67.5
'CP3'	76.1	77.4	89.7

Finally, to evaluate the distribution of informative EEG channels and features, the effect of different features and combinations of them (26 combinations) have been examined in six brain areas. Fig. 4 represents the accuracy rates of all possible combinations. Furthermore, the obtained experimental results of single features and the three best combinations of them are reported in Table IV. As can be seen from these results, the features extracted from the frontal lobe have performed the best, which is promising from the practical point of view [29]. Furthermore, the presence of energy and kurtosis features in all combinations has increased the detection results. Therefore, such a system enables the use of a small number of channels and features leading to a more cost-effective PD detection method.

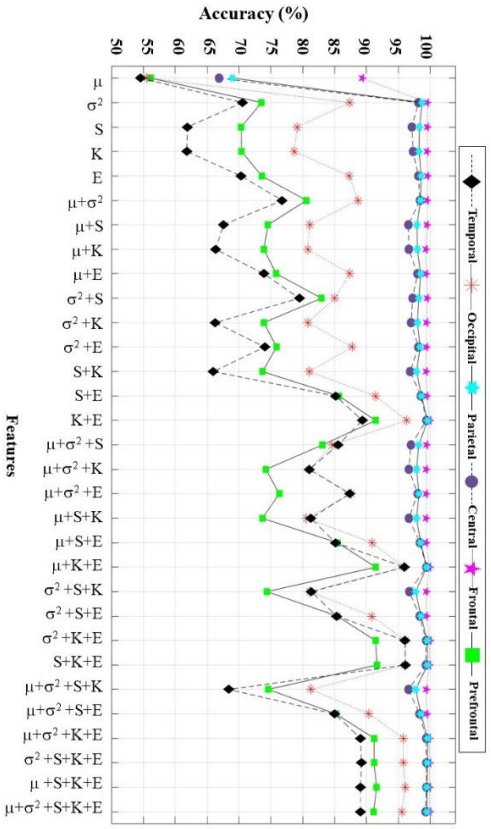

Fig. 4. Plots of test accuracies versus Cepstral-based features across different brain areas

Table IV. PD detection performance using different Cepstral features evalauted on several brain areas

Brain regions	Classification metrics	Features							
		Mean	Variance	Skewness	Kurtosis	Energy	$\mu+K^6+E^7$	S^8+K+E	$\mu+S+K+E$
Prefrontal[1]	Acc (%)	56.1	73.5	70.3	70.4	73.5	91.4	91.6	91.5
	Sen (%)	56.3	68.5	62.9	62.0	69.7	91.1	91.3	91.4
	Spe (%)	55.9	78.2	77.5	78.4	77.2	91.7	91.9	91.7
Frontal[2]	Acc (%)	**89.3**	**99.5**	**99.5**	**99.5**	**99.5**	**99.8**	**99.85**	**99.8**
	Sen (%)	89.8	99.5	99.5	99.5	99.5	99.79	99.7	99.7
	Spe (%)	88.8	99.5	99.4	99.5	99.6	99.9	99.9	99.9
Central[3]	Acc (%)	66.8	98.1	97.1	97.2	98.1	99.3	99.3	99.3
	Sen (%)	62.9	97.1	96.9	96.9	97.2	99.3	99.2	99.3
	Spe (%)	70.6	99.0	97.3	97.5	98.9	99.4	99.3	99.3
Parietal[4]	Acc (%)	68.9	98.7	98.2	98.2	98.5	99.4	99.5	99.4
	Sen (%)	66.1	98.3	98.1	98.1	98.2	99.4	99.5	99.4
	Spe (%)	71.7	99.1	98.4	98.2	98.9	99.4	99.5	99.4
Occipital[5]	Acc (%)	55.5	87.3	79.1	78.6	87.3	95.8	96.0	96.0
	Sen (%)	46.2	83.7	75.7	74.5	83.5	95.1	95.3	95.5
	Spe (%)	64.5	90.9	82.4	82.5	90.9	96.5	96.7	96.5
Temporal[6]	Acc (%)	54.5	70.5	61.9	61.8	70.3	95.9	96.0	89.0
	Sen (%)	45.9	63.7	54.6	56.2	64.9	95.3	95.4	88.6

Spe (%)	62.8	77.0	68.9	67.2	75.4	96.5	96.6	89.3

[1] Prefrontal: 'FP1','FP2'
[2] Frontal: 'Fz', 'F1', 'F2', 'F3', 'F4', 'F5', 'F6', 'F7', 'F8'
[3] Central: 'Cz', 'C1', 'C2', 'C3', 'C4', 'C5', 'C6'
[4] Parietal: 'Pz', 'P1', 'P2', 'P3', 'P4', 'P5', 'P6', 'P7', 'P8'
[5] Occipital: 'Oz', 'O1', 'O2'
[6] Temporal: 'T7', 'T8'
[7] K: Kurtosis, [8] S: Skewness, [9] E: Energy

4. Discussion

The major aim of this paper is to develop a novel efficient and robust but cost-effective method with enhanced detection performance by extracting reward positivity-related EEG symptoms of PD. For this purpose, this article has used the Cepstrum transform for discriminating oscillation and excitation components of EEG signals to better quantify alteration in reward positivity of PD patients. Based on this technique, a compact representation of these components has been proposed, and a discriminated model has been introduced to describe the action potential of EEG signals using a small number of quefrency coefficients. In addition, this study has analyzed the role of amplitude and phase information of EEG signals on PD detection from the perspective of real and complex Cepstrum coefficients. The obtained results have shown outstanding performance of the proposed method and a better estimation of the reward positivity state of PD using the features extracted from real Cepstral coefficients. This result consequently reveals more importance of amplitude information of EEG signals compared with phase information in PD diagnosis.

It is worth noticing that providing a trade-off between computational complexity and reliable robust performance of PD detection is important from the clinical point of view. For such a reason, the possibility of reducing the number of EEG channels or required features while providing a high ability of discrimination has been assessed in this study. The results have suggested that the proposed system can offer robust performance while reducing the number of required EEG channels and features from 60 to 9 (in the frontal lobe) from 5 to 2, respectively. It may be attributed to the ability of the Cepstrum analysis to remove irrelevant PD-related components by deconvolution of oscillation and excitation components, selecting more related information and consequently providing clean and compact frequency information of EEG signals. To date, various PD detection methods have been proposed using EEG signal analysis techniques. Table V represents a comparison between the proposed method and other existing machine-learning-based PD detection algorithms. It is obvious from the table that the accuracy of this study is superior to all other methods. It can be attributed to the presence of different sources of variability in EEG signals and the ability of Cepstrum analysis to discriminate different components of signals and to overcome deconvolved noises. In addition, due to the role of reward positivity in the dopamine-driven learning process [28], the extraction of EEG markers of reward positivity can improve PD detection performance [29]. The proposed Cepstral features of reward positivity also offer a compact representation of clean spectral frequency bands reducing computational complexity. On the other hand, the merits of the proposed PD detection method in terms of computational complexity are as follows: (1) a small set of Cepstral coefficients instead of all EEG samples has been used for feature extraction, (2) a limited number of statistical features with low computational complexity has been employed, (3) simple classification methods, such as KNN, have been utilized, and (4) finally the proposed method has achieved outstanding detection performance using a few or limited channels of EEG signals. This method was also robust against medication status and has been able to maintain accuracy despite the feature and channel reduction which is promising for clinical applications.

Table V. Comparative results of PD detection achieved by previous EEG-based studies.

Refrence	Year / State	Features	Classifier	Accuracy
[9]	2023/Rest	Flexible Analytic Wavelet Transform and entropy features	SVM, KNN, Random Forest, Logistics, Radial Basis Function	99
[10]	2023/Task	Hjorth parameters	SVM, KNN, Random Forest	89.56
[11]	2023/Rest	Mean, Standard deviation, Entropy, Hjorth parameters, Power Spectrum, Energy	SVM, KNN, Extra tree, Random Forest	97.5
[12]	2023/Rest	Power spectral density	SVM, KNN, Logistic Regression, Decision tree	72.2
[14]	2023/Rest	Sample entropy of frequency bands and Budget based feature selection	Logistic Regression	76
[7]	2022/Rest	Common spatial pattern-based features	SVM, KNN, Discriminant Analysis, Random Forest	99
[7]	2022/Rest	Holo-Hilbert spectral analysis	SVM, KNN, Decision tree, Gentle adaptive boosting, Logit boost, Bagging, Naive Bayes	90

[13]	2022/Rest	Hjorth parameters	Gradient boosting decision tree	89.3
[16]	2022/Rest	Higher-order statistical features	Bagged trees ensemble classifier	99.11
[15]	2021/Rest	Tunable Q Wavelet Transform	SVM, KNN, ANN, Random Forest, least-square SVM	97.65
[17]	2021/Rest	Aspirin pattern-based features	KNN	93.57
[20]	2021/Rest	Power Spectrum	SVM	87.54
[21]	2021/Rest	Fractal dimension, Hjorth parameters, Hurst exponent, Sample entropy, Fisher information analysis, Power spectral density	ANN	88.19
[18]	2020/Rest	Power spectral density	Linear predictive coding	85.70
[19]	2020/Task	Partial directed coherence	SVM, J48, Random tree, Random Forest, neural network, Naive bayes, Extreme learning machine	99.22
[54]	2021/Task	Walsh-Hadamard-based features	SVM, KNN	99.9
Proposed method	Task	Cepstrum Analysis	SVM, KNN, LDA, CFNN	99.9

5. Conclusion

This work brings insights from reliable PD detection and efficient biomarkers of reward positivity into Parkinsonian EEG signal analysis. This research further confirms that alteration in reward positivity can be considered a suitable biomarker of PD and provide a new set of Cepstral-based features to identify PD-related changes from the EEG signals. To explore the best system for PD detection the following experiments have been performed. (1) Comparative analysis between amplitude and phase information for PD detection using real and complex Cepstral coefficient (2) analyses of the most proper set of features, EEG channels, and brain lobes for PD detection using Cepstral-based features, (3) analyses of the effects of the medication states on the detection performance and (4) comparison with other EEG-based PD detection method. The results have suggested that kurtosis and energy features extracted from real Cepstral analysis are effective EEG indices of the reward-positivity during a reinforcement-learning task for PD detection. It is worth noting that the best detection performance of the proposed technique relies on capturing amplitude oscillations of the EEG signals that are associated with action potential. Finally, the development of a cost-effective method for the processing procedure by using a small number of coefficients, reducing the number of channels and features, and overcoming the convolutional noises by the homomorphic capability of Cepstrum analysis are the main advantages of this method. Evaluating the proposed method using another EEG database can be future work.

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Data availability statement

Data will be made available on reasonable request.

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