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Research Article

Parkinson’s Disease Detection Based on Signal Processing Algorithms and Machine Learning

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Abstract

There is more interest in the speech model applications for analysis of Parkinson’s diseases to predictively construct tele diagnosis and telemonitoring models. This motivated us to use a relatively large database of voice samples having different types of vowel phonations, compiled from a series of verbal trials for people suffering from Parkinson's disease. Two main problems are observed in learning from a dataset of this type that contains multiple discourse registration by subject: a) How to foresee such different kinds vowel samples in the diagnosis of Parkinson's disease (PD)? b) How aptly the main inclination and dispersal the metrics can be used as representatives of all example recordings of a subject? This article examines the multiple types of vowel samples collected from PD patients and healthy subjects and utlize state-of-the-art signal processing algorithms like Perceptual Linear Prediction (PLP) and ReAlitive SpecTrAl PLP (RASTA-PLP) for feature extraction purposes. The extracted set of features are classified using SVM model with four different types of kernels. Results show that our algorithm performs 74% accurately.

1. Introduction

Parkinson's disease (PD) is a nervous system disease that yields some or total damage of speech, conduct, intellectual and other roles of the body [1]. It is generally observed in the elderly and causes motor and speech impairments [3]. PD comes the second biggest neurological healthiness problem in the elderly people and it is projected that around ten-million individuals all over the world are perturbed by this disease [4], [5]. In particular, PD is usually found in one person out of one hundred people over 60 years old. At present, PD is incurable [6], [7]. Though, there are some drugs to reduce its effects. PD is typically detected and treated with intrusive methods [8]. Hence, it complexes the diagnosis and treatment of bereaved patients of the disease.

In this study, the use of subject speech data should assist in the development of a non-invasive diagnosis. There are important examples of this type of studies on Alzheimer's disease and PD around the world. PM-based studies focus on symptoms like slow movement, weak balance, tremors or toughness of certain parts of the body [9] - [12] but mainly voice problems. The chief cause for the acceptance of the diagnosis of PD speech disorders is that remote diagnosis and remote monitoring systems using voice signals are inexpensive and easy self-use [7], [13]. Thus, such a system not only reduces the disadvantages and the cost of the physical appointments of the patients to the medical clinic, but also allow timely detection of the disease and in addition to the reduction in the load of medical staff [7], [13] - [15]. People with parkinsonism (PWP) also have speech disorders such as dysphonia (faulty voice), hypophonia (low volume), monotonous (low tonal amplitude) and dysarthria (problem with joint sounds or syllables). In spite of the presence of a lot of studies to diagnose and monitor PD based on these deficiencies. these studies rely on basic diagnostics of the voice. the troubles. Speech disorders can be scaled simply by

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acoustic techniques using non periodic vibrations in the vocal sound.

With regard to disabilities, Little et al. [7] analyzed the phases of PD by measuring dysphonia produced by the disease. They showed that samples of supported vowel "a" phonation were achieved from 31 patients. 23 out of 31 patients were found to be suffering from PD. Then, the measurements of dysphonia were extracted from phonations to detect scale of PD by telemonitoring. Speech data is used by Tsanas et al. [16] to predict inclination to evolution of PD. They took out voice functions using from six thousand samples of forty-two PWP and found the suitable features. Some subsets of the features are then scaled to UPDRS (Unified Parkinson's Disease Rating Scale) by dint of reversion and sorting techniques. In [14], the author adopts a choice of a measure of dysphonia subsets and uses support vector machines (SVM) in order to differentiate two hundred and sixty-three samples pertaining to forty-three subjects [14]. Algorithms for nonlinear examination of speech can be mixed used with typical PD measures such as UPDRS. In [15], the use of nonlinear methods voice examination algorithms with pending UPDRS scales 6,000 records of 42 PWP resulted in a slightly different result estimate of the UPDRS of clinicians estimates. Both UPDRS and H & Y are considered for learning the arithmetical connection amid the 2 metrics and observe an enhancement in the estimation of H & Y [17].

Recent advances in artificial intelligence (AI) shows that many methods have been developed based on optimization and AI techniques for PD detection [18-21], cancer detection [22,23], heart failure dertection [24-28], mortality prediction [29,30] and other communication and industrial applications [31-34]. The author in [35] applied a selection of characteristics based on information technique along with the permutation assessment to evaluate the significance and the numerical implication of the relationships between characteristics and the score of PD, have introduced the designated functions to SVM in order to construct a classification prototype and used a (LOSO) technique to avoid prejudice. Most of the literature utilize SVM to differentiate vigorous subjects from PWP [35][7][36][47][48][49] along with the achievement of the diagnostic system is scaled with ROC lines, false and true positive rate [37]. We aim to design a computerized database gathering, storing and investigation system to make simpler the procedure of finding and treatment of PD. Information from demographic data, voice recordings, health history, and the evolution of the PM of every subject is attained and kept. Then the collected voice records are analyzed and a series features are obtained from it. The datasets of speech used in PD detection usually contains on several discourse recordings by subject [38]. So, the dataset gathered in this experiment have many speech samples by subject, for example vowels, figures, words and small sentences. In this article, we also equate the success of alternatives cross-validation schemes which can be deployed with such datasets in a classification algorithm designed for the detection of PD. K adjacent neighbor (k-NN) and SVM are used and assessed the achievement of models in the discrimination of sound subjects with PD under their correctness, specific, sensitive and Matthews Correlation Coefficient (MCC).

This article is composed in the following organization: Section II describes the data, the procurement methods and the set of collected voice samples. Section III provides details about the signal processing algoirthms and feature extraction methods. In Section IV, the experimental results are outlined. Section V concludes the study.

2. Data Acquisition

The data acquired for this study belong to twenty nine PWP (nine women, twenty men) and thirty healthy people (ten woman, twenty men). The database was collected after the approval of ethical review board of Lady Reading Hospital (Medical Teaching Institution), Pakistan. The database was collected from 160 subjects (60 PD patients and 100 age matched healthy subjects). The ages of the PD group of patients range from 43 to 88 with mean 68.3 and standard deviation of 10.4 while the ages of the healthy group of subjects range from 45 to 86 with mean 61.3 and standard deviation of 8.7. The data collection process was carried out using smart phone. The phone was kept at a distance of 10 cm from each subject during recording of the voice phonations. Each subject was asked to pronounce sustained phonations ``a", ``o" and ``u". The speech samples are nominated by neurologists from a set conversation movement to produce an additional influential sound of PWP [39]. After gathering the above data set with more forms of voice recordings and execution of our tests, in accordance with the results obtained, we gather a self-governing test set from 10 healthy subject and 10 PD patients through the doctor's exam procedure with the same settings. The test set contains on patients from PD having ages in the range of 40 and 80. We utilized the dataset as an autonomous test set in order to authenticate the outcomes we have found on our dataset of several audio recordings.

3. The Methodology Followed

In this section, we discuss the signal processing methods that have been utilized for the purpose of feature extraction from the voice signals. Two types of algorithms have been utilized i.e. Perceptual Linear Prediction (PLP) and ReAlitive SpecTrAl PLP (RASTA-PLP). The working of PLP algorithm is briefly discussed as follows:

3.1. PLP Algorithm

In order to compute PLP, speech signal should be characterized by doing short time spectral analysis.

3.1.1 Spectral Analysis

At first signal breaks are reduced & ends are smoothening in order to connect with the beginnings [40]. Hamming window was used to taper the signal to zero in the start & end of each frame [41]. Here Hamming window length is represented by N with a length about 20 ms. FFT is used to convert time domain into the frequency of each frame of N samples.

The square STSS (short-term speech spectrum) real & imaginary components is utilized in computing the STPS (short-term power spectrum) [42]

$P(\omega)=\mathrm{Re}[S(\omega)]^2+\mathrm{Im}[S(\omega)]^2$

3.1.2. Critical-band Spectral Resolution

The following equations are used to wrap the STPS (short-term power spectrum) along with its frequency axis.

$$\Omega(\omega) = 6\ln\left\{\frac{\omega}{1200\pi} + \sqrt{\left[\left(\frac{\omega}{1200\pi}\right)^2 + 1\right]}\right\} \tag{1}$$

$$\Omega(f) = 6\ln\left\{\frac{f}{600} + \sqrt{\left[\left(\frac{f}{600}\right)^2 + 1\right]}\right\} \tag{2}$$

$$\Omega(f) = 6\sinh^{-1}\left(\frac{f}{600}\right) \tag{3}$$

Here f denotes the frequency in hertz whereas ω is used to represent the angular frequency in [rad/s].

Hynek Hermansky [43] approximation is used to convolve the resulting perverted power with the power spectrum of the simulated critical-band masking curve Ψ (Ω).

$$\Psi(\Omega) = \begin{cases} 0 & for \quad \Omega < -1,3 \\ 10^{2,5(\Omega+0,5)} & for \quad -1,3 \le \Omega \le -0,5 \\ 1 & for \quad -0,5 < \Omega < 0,5 \\ 10^{-1,0(\Omega,-0,5)} & for \quad 0,5 \le \Omega \le 2,5 \\ 0 & for \quad \Omega > 2,5 \end{cases} \tag{4}$$

The following equation is employed in which the discrete convolution of Ψ (Ω) with P (ω) are utilized for producing the samples of the critical-band power spectrum.

$$\theta(\Omega_i) = \sum_{\Omega,-1,3}^{2,5} P(\Omega - \Omega_i)\Psi(\Omega) \tag{5}$$

The spectral resolution of θ (Ω) can be reduced via convolving the broad critical-band masking curve Ψ (Ω) and the short-term power spectrum P (ω) [45]

3.1.3. Equal-loudness Pre-emphasis

The next phase is the pre emphazization of samples Θ[Ω(ω)] using the (SELC) simulated equal-loudness curve, by applying the following equation [44]:

$$\Xi[\Omega(\omega)] = E(\omega) \times \Theta[\Omega(\omega)] \tag{6}$$

Here, E (1) is the proximity of unequal sensitivity by use of the human ear at diverse frequencies. The estimate used in this study was adopted by Hermansky [45] and this was previously suggested by cossel [46] shown below in equation.

$$\mathrm{E}(\omega) = \frac{(\omega^2+56,8\times10^6)\omega^4}{(\omega^2+6,3\times10^6)^2\times(\omega^2+0,38\times10^9)} \tag{7}$$

$$E(f) = \left[\frac{f^2}{f^2+1,6\times10^5}\right]^2 \times \left[\frac{f^2+1,44\times10^6}{f^2+9,6\times10^6}\right] \tag{8}$$

3.1.4. Intensity-loudness Power Law

At the end before all-pole modeling is CRAC (cubic root amplitude compression). The following equation is close to the law of human hearing power and mimics the nonlinear relationship between the emphasization of sound and its professed loudness [45].

$$\Phi(\Omega) = \Xi(\Omega)^{0,33} \tag{9}$$

3.1.5. Auto Regressive Modelling

At this stage, po (Ω) occurs through the spectrum of the all-pole model, using the automated imaging method of near-auto compass modeling [45]. [The auto regressive coefficients are then changed to the cepstral coefficient of the all-pool model [45].

3.1.6. Liftering

The final step involves lubricating the cepstral coefficient, using the equation 6, to make it more similar by using (L = 0.6).

3.2. RASTA-PLP Algorithm

The major aim is to increase the robustness of PLP. Following are the essential steps of computing RASTA-PLP.
Calculate the critical-band color resolution in the same way as PLP.
- Estimate the temporary derivative of the log deduction band spectrum using the regression line through five consecutive spectral values.
- Nonlinear processing can be done in this domain.

Reorganize the critical band temporary derivative of the logs using the first-order unlimited continuity response system.
- In agreement with conventional PLP, add a curve equal to the equation and multiply the power law by 0.3 to 0.33 to heat.
- Take the inverse logarithm of this relative log spectrum, and retrieve the corresponding audio spectrum.

Following the traditional PLP technique, formulate an all-pole model of this spectrum.

4. Results

4.1. Obtained Results Using PLP

Tables 1 shows the obtained outcomes of classification for the four different SVM models with different types of kernelss after retrieving the PLP Cepstral coefficients from the voice samples. SVM with RBF kernel outperformed the other constructed classification systems based on SVM with other types of kernel as shown in table I. Here 74% of highest accuracy is achieved by utilizing the 10 cepstral coefficients of the PLP. In addition, the model obtained the maximum MCC (0.304), PE (0.488), and specificity (77%) values. Results explored that 23 PD patients were properly classified whereas 7 PD patients were misclassified. Similarly, 24 healthy subjects were detected correctly whereas 6 of them were not detected correctly. Compared to other methods presented in literuate, the PD detection performance obrained under the PLP algorithm are promising.

Table 1. SVM Classification accuracies using PLP-BEST accuracy was obtained using the RBF Kernel.

Kernel	Acc	Sens	Spec	MCC
RBF	74	70	77	0.304
LIN	58	90	90	0.200
POL	72	80	60	0.300
MLP	68	70	65	0.245

5.2. Obtained Results using RASTA-PLP

Tables 2 shows the classification results. The maximum accuracy (68%) was attained using SVM model with MLP kernel. Whereas the highest MCC (0.208), PE (0.32), and specificity (70%) values are also obtained. Results also explored that 20 PD patients were accurately classified whereas 9 PD patients were misclassified.

Table 2. SVM Classification accuracies using RASTA-PLP BEST accuracy was obtained using the MLP Kernel

Kernel	Acc	Sens	Spec	MCC
RBF	64	76.66	58	0.202
LIN	51	66.66	50	0.159
POL	45	80	12	0.124
MLP	68	66.66	70	0.208

It is clearly observed that highest classification accuracy of 74% was achieved using PLP based features extraction and SVM model developed with RBF kernel, followed by RASTA-PLP with 68% of classification accuracy obtained under SVM model with MLP kernel. Although the results obtained are reasonbay good. However, there is still need of further work to improve the classification accuracy. In future work, our aim is to develop and explore high accuracy algorithms.

5. Conclusion

Recent interest in vocal pattern study applications of PD for the construction of predictive tele diagnosis and telemonitoring models motivated us to collect a large scale of vocal samples having different types of vowel phonations. In this study, we applied two state-of-the-art signal processing algoirhtms i.e. Perceptual Linear Prediction (PLP) and ReAlitive SpecTrAl PLP (RASTA-PLP) for feature extraction purposes and SVM model with four different types of kernels for classification task. It was observed that highest classification accuracy of 74% was achieved using PLP based features extraction and SVM model developed with RBF kernel, followed by RASTA-PLP with 68% of classification accuracy obtained under SVM model with MLP kernel.

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