Speech Processing Algorithm For Detection Of Parkinson's Disease

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Abstract

The brief survey on detection of Parkinson's Disease (PD) by speech impairment gives an overview of the major technological perspective and appreciated the fundamental progress of PD detection .Here we compute the dysphonia measures from sustained vowels and the feature selection algorithms are used to select the features and then classify the PD by Back-Propagation learning algorithm based on Levenberg-Marquardt Back-propagation algorithm and have used an existing database consisting of 195 samples computing 132 dysphonia measures and these measures can perform and give out the best-art results, reaching the maximum of overall classification accuracy using only 22 features, where the selected measures represent the PD in male and Female Separately.

Keywords: *Data acquisition, Feature Selection, Parkinson's Disease (PD), Classification, Levenberg Marquardt (LM).*

1. Introduction

Parkinson's Disease is a progressive neurodegenerative [1], condition resulting from the death of the dopamine containing cells of the substantia nigra. People with PD classically present with the symptoms and signs associated with parkinsonism, namely poverty of movement, slowness of movements with total neuronal loss in substantia nigra , Rigidity and as well as other brain structures, reported incident rates varies in ranges due to most important factor of PD i.e., Age [1]. Neurological disorders are effecting people's lives at an epidemic rate worldwide amongst which PD is one such disease. Parkinsonism can also be caused by drugs and less common conditions such as the multiple cerebral infarct, and also degenerative conditions such as progressive-supranuclear-palsy (PSP) and multiple-system-atrophy (MSA).

Although PD is predominantly the movement disorder and other impairments frequently develop here including psychiatric problems such as depression and dementia. Autonomic disturbances and pain later ensured and condition progresses to cause significant disability and handicap with impaired quality of life for the affected person. Family and careers may also be affected indirectly.PD is been defined as a progressive neurological condition, estimated to affect 100–180 per 100,000 of the population (6–11 people per 6,000 of the general population in the UK)* and has an annual incidence of 4–20 per 100,000 and a rising prevalence with age and a higher prevalence and incidence of PD in males and females [4]. Consequently, the features extracted by conventional analysis methods characterize the combined effect of the excitation signal and vocal tract. In several important applications of speech processing, including speech analysis, speaker recognition, and speech coding, it is advantageous both to extract features of the vocal tract and also, separately, features of the excitation signal.

This entails the blind deconvolution of the vocal tract transfer function and its input excitation signal since neither is observable individually. Such a deconvolution enables separate feature sets to be extracted for the excitation and the vocal tract in each analysis frame. These separate feature sets provide significantly more accurate analysis and modelling of speech [3].Speech signal processing algorithms offer an objective, potentially reliable method for assessing general voice disorders. In the context of PD, speech signals have been used to separate PWP and healthy controls (people with no PD symptoms) [1], [5], with very encouraging results. The study here uses Back-propagation learning algorithm based on Levenberg Macquardt algorithm [8] and feature selection algorithms[1] and feature extractions [1] and our work is an attempt to detect the PD in male and female using an existing data with 22 features and training the neural models separately for male and female which can give effective results with higher level of accuracy.

2. Related Work

Recently, a wide range of speech signal processing algorithms (dysphonia measures) aiming to predict PD symptom severity using speech signals have been introduced. In the base paper, we test how accurately these novel algorithms can be used to discriminate PD subjects from healthy controls. In total, we compute 132 dysphonia [1] measures from sustained vowels. Then,we select four parsimonious subsets of these dysphonia measures using four feature selection algorithms, and map these feature subsets to a binary classification response using two statistical classifiers: random forests and support vector machines.We use an existing database consisting of 263 samples from 43 subjects, and demonstrate that these new dysphonia measures can outperform state-of-the-art results, reaching almost 99% overall classification accuracy using only ten dysphonia features. This paper measures only ten features and not able to detect PD based on gender [1].In other related study, the Multi-Layer Perceptron (MLP)with Back-Propagation learning algorithm are used to classify to effective diagnosis Parkinsons disease(PD).It's a challenging problem for Medical community and it was characterized by tremor, PD occurs due to the loss of dopamine in the brains thalamic region that results in involuntary or oscillatory movement in the body and the feature selection algorithm along with biomedical test valued the diagnose Parkinson disease.Clinical diagnosis is done mostly by doctor's expertise and experience.But still cases are reported of wrong diagnosis and treatment. Patients are asked to take number of tests for diagnosis.In many cases,not all the tests contribute towards effective diagnosis of a disease.

Our work is to classify the presence of Parkinson disease with reduced number of attributes.Original,22 attributes are involved in classify.We use Information Gain to determine the attributes which reduced the number of attributes which is need to be taken from patients.The Artificial neural networks is used to classify the diagnosis of patients.Twenty-Two attributes are reduced to sixteen attributes.The accuracy is in training data set is 82.051% and in the validation data set is 83.333% [2]. There is another study which present the Dynamic Programming Projected Phase-Slope Algorithm (DYPSA) for automatic estimation of glottal closure instants (GCIs) in voiced speech. Accurate estimation of GCIs is an important tool that can be applied to a wide range of speech processing tasks including speech analysis, synthesis and coding. DYPSA is automatic and operates using the speech signal alone without the need for an EGG signal. The algorithm employs the phase-slope function and a novel phase-slope projection technique for estimating GCI candidates from the speech signal. The most likely candidates are then selected using a dynamic programming technique to minimize a cost function that we define. We review and evaluate three existing methods of GCI estimation and compare the new DYPSA algorithm to them. Results are presented for the APLAWD and SAM databases for which 95.7% and 93.1% of GCIs are correctly identified [3].And also a study describes, Dysphonia measures used were signal processing algorithms that offer an objective method for characterizing voice disorders from recorded speech signals. This related paper studied the disordered voices of people with Parkinson's disease (PD). Here, we demonstrate a simple logarithmic transformation of these dysphonia measures which can significantly enhance their potential for identifying subtle changes in PD symptoms. This gives the superiority of log-transformed measures which is reflected in feature selection results using Bayesian Least Absolute Shrinkage and Selection Operator (LASSO) linear regression. The related study about the Marquardt algorithm for nonlinear least squares is presented and is incorporated into the backpropagation algorithm for training feedforward neural networks. The algorithm is tested on several function approximation problems, and is compared with a conjugate gradient algorithm and a variable learning rate algorithm. It is found that the Marquardt algorithm is much more efficient than either of the other techniques when the network contains no more than a few hundred weights.[10]
We demonstrate the effectiveness of this enhancement in the emerging application of automated characterization of PD symptom progression from voice signals, rated on the Unified Parkinson's Disease Rating Scale (UPDRS), the gold standard clinical metric for PD. Using the least-squares-regression shows that UPDRS can be accurately predicted to within six points of the clinicians' observations[5].

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3. Proposed System

The aim of this study is to analyze and train the speech signals, extract the features, train the neural models separately based on male and female genders and attempt to classify PD (PD versus healthy control and then PD in male and female) and also shown in figure 1 below.

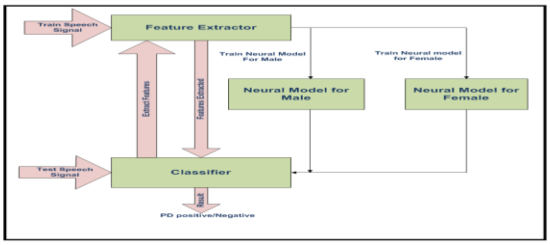

Figure 1. Software Architecture for Detection of Parkinson's Disease.

The network used is a two-layer feed-forward network as illustrated in Figure 2. The two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (newfit), can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. After a few experimental run, the number of neurons in the hidden layers was set to 15.

Figure 2. Two-layer feed-forward network

3.1Date Acquisition

The data is been acquired as follows :

3.1.1. Source

The dataset was collected from UCI learning Machine Repository were we found the dataset which was created by Max Little of the University of Oxford, in collaboration with the National Centre for Voice and Speech, Denver, Colorado, who recorded the speech signals.

3.1.2.Data Set Information

This dataset is composed of a range of voice measurements from 40 people, 19 with Parkinson's disease (PD). The given column in the table is a particular voice measure, and each row corresponds one of 195 voice recording from these individuals . The main aim of the data is to discriminate healthy people from those with PD, according to "status" column which is set to 0 for healthy and 1 for PD.

3.1.3 Attribute Information

This study reviewed the literature and used the following 22 variables as explanatory variables given in Table 1. [2]Before building models,the data set were randomly split into two subsets,55 %(n=105) of the the data for training set and 40 %(n=88) of the data validation set and we use the Table 2. [1] for detailed description of attributes.

Attribute	Description
MDVP:Fo(Hz)	Average vocal fundamental frequency
MDVP:Fhi(Hz)	Maximum vocal fundamental frequency
MDVP:Flo(Hz)	Minimum vocal fundamental frequency
MDVP:Jitter(%) MDVP:Jitter(Abs) MDVP:RAP MDVP:PPQ Jitter:DDP	Several measures of variation in fundamental frequency
MDVP:Shimmer MDVP:Shimmer(dB) Shimmer:APQ3 Shimmer:APQ5 MDVP:APQ Shimmer:DDA	Several measures
RPDE D2	Two nonlinear dynamical complexity measures
DFA	Signal fractal scaling exponent
spread1 spread2 PPE	Three nonlinear measures of fundamental frequency variation
NHR HNR	Two measures of ratio of noise to tonal components in the voice
Concept Class	Healthy,Sick

Table 1. Patients Data set based on PD [2]

Family of dysphonia measures	Brief description	Number of measures
Jitter variants	F0 perturbation	30
Shimmer variants	Amplitude perturbation	21
Harmonics to noise ratio (HNR) and noise to harmonics ratio (NHR)	Signal to noise, and noise to signal ratios	4
Glottis quotient (GQ)	Vocal fold cycle duration changes	3
Recurrence period density entropy (RPDE)	Uncertainty in estimation of fundamental frequency	1
Detrended fluctuation analysis (DFA)	Stochastic self-similarity of turbulent noise	1
Pitch period entropy (PPE)	Inefficiency of F0 control	1
Glottal to noise excitation (GNE)	Extent of noise in speech using energy and nonlinear energy concepts	6
Vocal fold excitation ratio (VFER)	Extent of noise in speech using energy, nonlinear energy, and entropy concepts	9
Empirical mode decomposition excitation ratio (EMD-ER)	Signal to noise ratios using EMD-based energy, nonlinear energy and entropy	6
Mel Frequency Cepstral Coefficients (MFCC)	Amplitude and spectral fluctuations	42
F0-related measures	Summary statistics of F0, Differences from expected F0 in age- and sex- matched controls, variations in F0	8

Algorithmic expressions for the 132 measures summarized here are described in detail in Tsanas *et al*. [1]. F0 refers to fundamental frequency estimates.

Table 2. Breakdown of 132 Dysphonia measures which is been used in this study [1].

3.2 Feature Extraction

An additional information from physical models of voice production mechanisms, for example to improve the accuracy of jitter, shimmer and HNR estimates using glottal source signals obtained from the voice recordings.

For males, the most important features appear to be the mid-range MFCCs, DFA, and VFERNSR,TKEO. The MFCCs have traditionally appeared in speaker identification applications and have only relatively recently been introduced in the study of dysphonias [1]; our findings strongly support their use for monitoring Parkinson‟s disease symptom progression. This finding indicates that it is probably necessary to focus on formant resonances, as well as F0 and amplitude. That DFA is consistently selected verifies that increased turbulent noise is a feature of male PD voices. VFERNSR, TKEO being selected indicates that it is interesting to look at different frequency bands and determine signal to noise ratios in these bands; in particular, our experiments suggest that it may be useful to characterize frequencies above 2.5 kHz as „noise‟, and frequencies below this as „signal‟, in order to define signal to noise ratios .

For females, we note that in addition to MFCCs, F0-related measures are often selected. This perhaps stems from the physiological observation that normal vibrato is exacerbated in low fundamental frequency voices (that is, males) [12]. Although robust dysphonia measures to normal vibrato have been proposed (higher order jitter measures, PPE), we speculate that these approaches can only guard against low physiological tremor.

This could suggest that vocal vibrato in females might be effectively removed using these robust vibrato-removal approaches, whereas the (comparatively larger) vibrato in males may not. Thus, robust F0 perturbation measures could indicate vocal pathology in females which might be otherwise overshadowed in males due to increased normal vibrato.

3.3 Feature Classification

For features Classification we have used a well known classifier namely Back propagation learning algorithm based on Levenberg-Marquardt-algorithm(LM) [8]. The application of Levenberg-Marquardt to neural network training is very efficient. This algorithm has been shown to be the fastest method for training moderate sized feed-forward neural networks (up to several hundred weights). It also has an efficient implementation in MATLAB software, since the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB environment .

The network trainlm [8] can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate the Jacobian jX of performance with respect to the weight and bias variables X. Each variable is adjusted according to Levenberg-Marquardt equation,

jj = jX * jX
je = jX * E
dX = -(jj+I*mu) / je ………………..…………….[8]

where E is all errors and I is the identity matrix. The adaptive value mu is increased until the change results in a reduced performance value.The Mean Square Error (MSE) and Regression (R) values for the Training, Validation and Testing.[9]

	MSE	R
Training	2.25880e-4	0.902515
Validation	8.83702e-5	1.000000
Testing	6.15467e-4	1.000000

Table 3. Sample MSE and R values for taining, testing and validation. [9]

The Table 3. is observed that the value of R is closest to 1 indicating the accurate prediction. When the data set was trained in Levenberg – Marquardt algorithms the performance obtained was in 9 epochs. Levenberg – Marquardt algorithm (LM) is the most widely used optimization algorithm. LM algorithm is an iterative technique that locates a local minimum of a multivariate function that is expressed as the sum of squares of several non-linear, real-valued functions. It has become a standard technique for non linear least-square problems, widely adopted in various disciplines for dealing data-fitting applications.[9]

4. Results

The Result here is been evaluated by using the Levenberg Macquardt Back-propagation learning algorithm whish is efficient and the Figure 3 shows the accuracy for training set comparing the existing and proposed attributes then the Figure 4 shows the accuracy of the testing set similarly comparing the existing and propsed attributes. The Table 4 gives out the result of all 22 attributes for both the training and testing set. The Figure 5, indicates that the parkinson’s disease is been detected and it shows that Male suffer more from PD compare to Female.

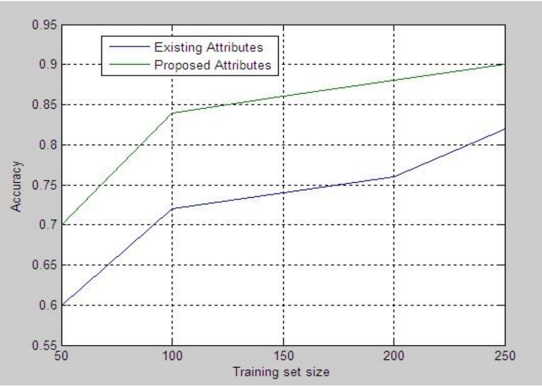

Figure 3. Accuracy for Training set.

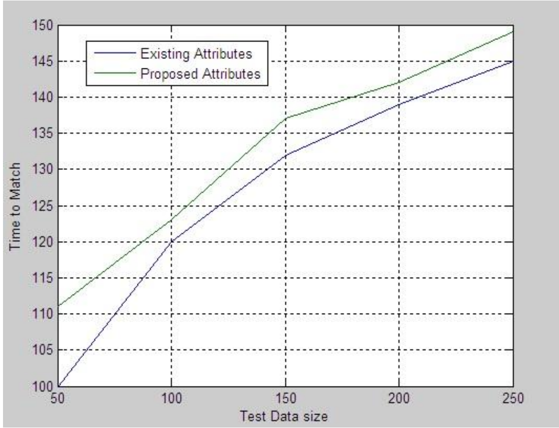

Figure 4. Accuracy for Testing Set

Features	Training	Testing
22	92.535%	86.799%

Table 4. Accuracy of ANN classifier Based on all 22 Features.

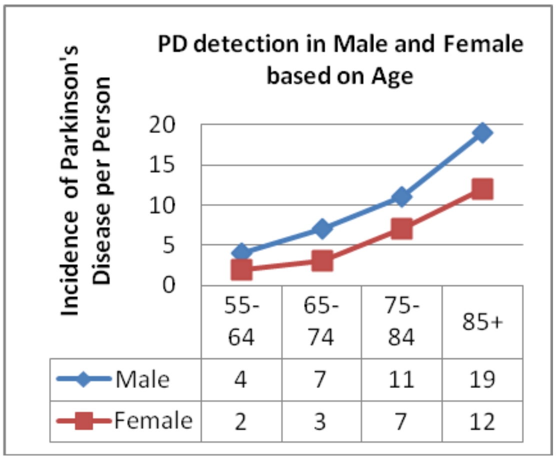

Figure 5. Parkinson's Disease in male and female based on age

5. Conclusion

This paper aimed to evaluate the artificial neural network in detecting Parkinson's Disease based on gender. The feedforward backpropagation neural network with supervised learning is proposed to diagnose the disease. The reliability of the proposed neural network method depends on data collected from the patients and experts opinion. Backpropagation learning algorithm is used to train the feedforward neural network to perform a given task based on Levenberg-Marquardt algorithm and gives out best performance and also analyzed that Levernberg-Marquardt algorithm gives the best performance in the detection of parkison's disease compared to any other backpropogation algorithm. The proposed diagnosis based on neural network showed significant results in identifying the Parkinson's disease in both Male and Female.The further research would be better if done with new data set with different features and evaluate more accuracy.

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