Parkinson's Disease : A Case Study

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Abstract- *In this paper, we tend to gift associate degree assessment of the sensible worth of existing ancient and nonstandard measures for discriminating healthy individuals from individuals with Parkinson's sickness (PD) by detection speech defect. we tend to introduce a brand new measure of speech defect, pitch amount entropy (PPE), that is powerful to several uncontrollable contradictory effects together with creaky acoustic environments and normal, healthy variations in voice frequency In our project uses feed forward neural network classifier to extend the classification performance with having high sensitivity, specificity and accuracy. finally, we discover that nonstandard ways are best ready to separate healthy from metal subjects. the chosen nonstandard ways are sturdy to several uncontrollable variations in acoustic setting and individual subjects, and are so like minded to telemonitoring applications.*

Keyword: Parkinson's sickness,Acoustic environment, speech defect,, telemonitoring.

INTRODUCTION

NEUROLOGICAL disorders, together with Parkinson's malady (PD), Alzheimer's, and brain disorder, deeply have an effect on the lives of patients and their families. PD affects over one thousand people in North America alone . Moreover, associate degree aging population suggests that this range is predicted to rise as studies counsel chop-chop increasing prevalence rates when the age of sixty . In addition to exaggerated social isolation, the monetary burden of metallic element is important and is calculable to rise within the future Currently, there's no cure, though medication is obtainable providing vital alleviation of symptoms, particularly at the first stages of the malady .Most people with Parkinson's (PWP) malady can thus be well obsessed on clinical intervention.

Parkinson could be a disorder and happens owing to lack of dopamine neurons. These dopamine neurons manage all body movements. Parkinson patients have issue in doing all daily routine activities, and even have disturbed vocal fold movements. Victimization voice analysis malady is diagnosed remotely at an early stage with a lot of reliability and economic way.

Diagnosis of Parkinson malady is extremely tough and no diagnostic science laboratory tests are accessible. medical specialty tests and brain scans are done to diagnose it. These strategies are terribly costly and want high level of experience. Some physical identification can even be done however patients are needed to be ascertained for an extended time and this identification provide results once nearly eightieth of dopamine gets terminated.

Concerning seventieth of individuals with Parkinson shows tremor that's most distinguished in hands and fingers. Stiffness within the muscles, slowness of movements and lack of coordination whereas doing daily routine activities also are vital signs of Parkinson. An explicit reason for the death of dopamine isn't renowned. Genetic issue is one amongst the reason for this malady.15% of the patients have their case history. Internal and external toxins scale back the dopamine production. Free radicals also are answerable for the death of dopamine As age will increase the possibilities of occurring this malady additionally will increase.

Voice of the person shows changes at an earlier stage, therefore identification of Parkinson exploitation voice analysis may be done at an earlier stage. Reduced in voice level by approx ten sound unit, whispering, breathiness, tremors, shifting to higher tones are some voice characteristics visible in metallic element voice. This methodology (is extremely) reliable and of very radical low price. Methodology is totally computerized and no medical professionals are needed. because the metallic element patients have problem in clinical visits, during this voice analysis methodology no clinical visits are needed. This methodology may be done telephonically, therefore the telediagnosis of the malady may be done by voice analysis with terribly less prices and efforts. Voice analysis for identification of malady isn't solely restricted to Parkinson however it may be used for several alternative diseases. Voice nodules, Reinke‟ oedema, respiratory disorder can even be diagnosed exploitation this methodology. Numerous classifiers are utilized in such kind of identification. With the assistance of classifiers accuracy and dependability of identification will increase.

The Objective of this project listed below

- The calculation of features.
- The preprocessing of features.
- The application of a classification technique to all possible subsets of features for the discrimination of healthy from disordered subjects, selecting the subset that produces the best classification performance.
- the calculation of features
- To archive more accuracy of system.
- To make system more flexible and robust.

III LITERATURE SURVEY

The paper by Saloni, R.K. Sharma., and A. K. Gupta works occurring this paper show that data processing have nice potential in illness detection for the advancement of medical field. data processing is largely a tool for changing the data into some terribly helpful info. Data processing provides ways in which to extract info rework and gift the info during a helpful format. In this paper, they need used the feature dataset of Parkinson illness. Feature choice and classification is employed to classify healthy and pathological information sets. For feature choice a correlation filter is employed. Fuzzy C means that agglomeration and pattern recognition is applied on elect options for classifying traditional speakers and metallic element speakers Support vector machines builds a model victimisation set of coaching examples, every marked to its class so used for classification.

The paper by Max A.Little make a case for thesensible value of existing ancient and nonstandard measures for discriminating healthy folks from folks with Parkinson's disease(PD) by sleuthing speech defect. He introduce a brand new live of speech defect, pitch amount entropy (PPE), that is strong to several uncontrollable contradictory effects as well as strident acoustic environments and traditional, healthy variations in voice frequency. He collected sustained phonations from thirty one folks, 23 with PD. He then designated 10 extremely unrelated measures, associated an complete search of all potential combos of those measures finds four that together cause overall correct classification performance of ninety one.4%, employing a kernel support vector machine. lastly, He notice that nonstandard strategies together with ancient harmonics-to-noise ratios area unit best ready to separate healthy from metallic element subjects. the chosen nonstandard strategies area unit sturdy to several uncontrollable variations in acoustic setting and individual subjects, and area unit so similar temperament to telemonitoring applications.

The paper by Mohammed Shahbakhi, Danial Taheri Far make a case for a brand new algorithmic rule for designation of Parkinson's malady supported voice analysis. within the beginning, genetic algorithmic rule (GA) is undertaken for choosing optimized features from all extracted options. afterward a network supported support vector machine (SVM) is employed for classification between healthy and folks with Parkinson. The dataset of this analysis consists of a variety of medicine voice signals from thirty one individuals, twenty three with Parkinson's malady and eight healthy individuals. the topics were asked to pronounce letter "A" for three seconds. twenty two linear and non-linear options were extracted from the signals that fourteen options were supported F0 (fundamental frequency or pitch), jitter, shimmer and noise to harmonics magnitude relation, that ar main factors in voice signal. as a result of dynamic in these factors is noticeable for the individuals with Pd, optimized options were elite among them. Of the varied numbers of optimized options, the information classification was investigated. Results show that the classification accuracy p.c of 94.50 per four optimized options, the accuracy p.c of 93.66 per seven optimized options and also the accuracy p.c of 94.22 per nine optimized options, may well be achieved. It may be discovered that the most effective classification accuracy is also achieved victimization Fhi (Hz), Fho (Hz), noise (RAP) and shimmer (APQ5).

SYSTEM ARCHITECTURE

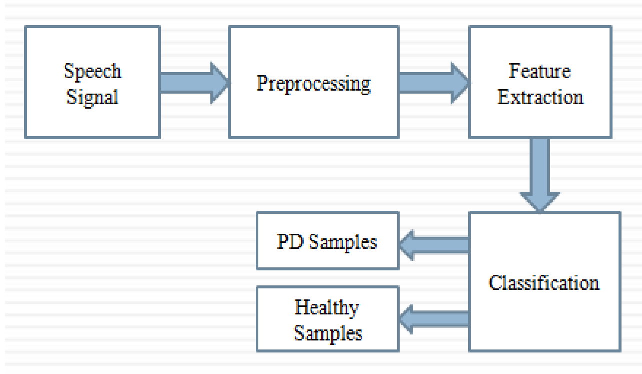

Figure 1: Block diagram of general system

A. Preprocessing:

In order to increase the power of these algorithms in separat-ing healthy from PWP, we discard the second half of each voice signal in calculating these measures. This is because the end of the phonation is dominated by spurious dysphonia caused mainly by lack of lung pressure. Many PWP exhibit similar dysphonia, which otherwise would be conflated with dysphonia caused by natural lack of lung pressure

B. Feature Extraction

This stage involves the application of a representative selection of traditional and nonstandard measurement methods to all the speech signal.

C. Calculation of Traditional Measures

Calculation of the traditional measures was performed using the software Praat [1]. The traditional measures are based on the application of the short-time autocorrelation to successive segments of the signal, with peak picking to determine the frequency of vibration of the vocal folds (F0 or pitch period), and location in time of the beginning of each cycle of vibration of the vocal folds (pitch marks) .

1.JITTER: The jitter and period perturbation measures are derived from the sequence of frequencies for each vocal cycle, by taking successive absolute differences between frequencies of each cycle and averaging over a varying number of cycles, optionally normalizing by the overall average.

$$JITTER(\%) = \frac{1/N \sum_{i=1}^{N-1} |Ti - T_{i-1}|}{1/N \sum_{i=1}^{N} Ti}$$

2.SHIMMER: The shimmer and amplitude perturbation measures are derived from the sequence of maximum extent of the amplitude of the signal within each vocal cycle. The average difference of this sequence is taken as a measure of the deviation between cycle amplitudes.

$$SHIMMER = \frac{1/N \sum_{i=1}^{N-1} |Ai - A_{i-1}|}{1/N \sum_{i=1}^{N} Ai}$$

3.HNR: The noise-to-harmonics (and harmonics-to-noise) ratios are derived from the signal-to-noise estimates from the autocorrelation of each cycle.

Although alternative studies have found applied math relationships between absolute values of F0 and PD-related speech defect, we tend to don't use this as a measure as a result of it's adversely plagued by gender and individual variations. Similarly, though it's ascertained that lower absolute instantaneous sound pressure levels (amplitudes) are related to PD-related speech defect, for sensible reasons, we tend to don't use this as a live as a result of the exactitude standardization needed to obtain reliable estimates of this amount square measure troublesome to attain in remote observance things. Thus, here we tend to square measure deliberately restricted to relative (or perturbative) measures of pitch amount and amplitude since they're a lot of sturdy to uncontrollable environmental and individual variations.Calculation of Nonstandard Measures.

1.D2: The correlation dimension (D2) is calculated by first time-delay embedding the signal to recreate the phase space of the nonlinear dynami-cal system that is proposed to generate the speech signal . In this reconstructed phase space, a geometrically self-similar (fractal) object indicates complex dynamics, which are impli-cated in dysphonia

2.RPDE: The repetition amount density entropy (RPDE) quantifies the extent to that dynamics within the reconstructed space once time-delay embedding is thought of as strictly periodic, i.e., repetition precisely . A continual signal returns to constant purpose within the space once an exact length of your time, known as the repetition amount T. It's been shown that the deviation from cyclicity evaluated by theentropyH of the distribution of those repetition periods P(T)is a smart indicator of general voice disorders, as general voice pathologies cause impairment within the ability to sustain regular vibration of the vocal folds. Dividing through by the entropy of the uniform distribution normalizes the RPDE values (Hnorm) to the vary [0, 1].

3.DFA: DFA may be a measure of the extent of the random self-similarity of the noise within the speech signal. The noise in speech is generally generated by turbulent flow of air through the vocal folds . Such turbulent processes are characterised by a applied mathematics scaling exponent α on a spread of physical scales, which manifests in measured aspects of the dynamics as well as acoustic pressure fields. In some voice disorders, incomplete vocal folds closure ends up in changes during this turbulent "breath" noise, thus the characteristics of the self-similarity of the noise within the speech signal is therefore an indicator of defect of speech [8]. It's found that for general voice disorders, the scaling exponent is larger for dysphonic than healthy subjects [8]. The DFA formula calculates the extent of amplitude variation F(L) of the speech signal over a spread of your time scales L, and therefore the self similarity of the speech signal is quantified by the slope α of a line on a log–log plot of L versus F(L).A simple nonlinear transformation then normalizes these slope values (α norm) to the vary [0, 1] .

4.PPE: All healthy voices exhibit natural pitch (F0) variation characterized by sleek sound and microtremor. speakers with naturally high-pitched voices can have a lot of larger sound and microtremor than those with low-pitched voices, once these variations square measure measured on associate degree cardinal number (in hertz) scale. Therefore, measurements of abnormal speech pitch variation got to take under consideration these 2 necessary effects: healthy, sleek sound and microtremor, and therefore the exponent nature of speech eat utterance (and perception).

These observations counsel that a lot of relevant scale on that to assess abnormal variations in speech pitch is that the perceptually relevant, exponent (tonal) scale, instead of absolutely the frequency scale. To implement these 2 insights algorithmically, we have a tendency to initial get the pitch sequence of the phonations and convert to the exponent half step scale p(t), wherever p is that the half step pitch at time t. we have a tendency to next analyze the roughness of variations during this sequence over and higher than any healthy, sleek variations, by initial removing linear temporal correlations during this half step sequence with a regular linear change of color filter (coefficients of that square measure calculable exploitation linear prediction by the variance technique to provide the relative half step variation sequence r(t).

This filtering impactively flattens the spectrum of the half step statistic and removes the effect of the mean half step (which depends on the individual preferences and gender). Later on, we have a tendency to construct a distinct likelihood distribution of incidence of relative half step variations P(r). Finally, we have a tendency to calculate the entropy of this likelihood distribution, that then characterizes the extent of (non-Gaussian) fluctuations within the sequence of relative half step pitch amount variations. a rise during this entropy live higher reflects the variations over and higher than natural healthy variations in pitch discovered in healthy utterance.

5.MFCC: MFCC is mostly useful tool in speech recognisation process. it is very useful for cough analysis. MFCC involve the estimation of short time power spectra. Mapped to the mel frequency scale and to compute cepstral coefficient.

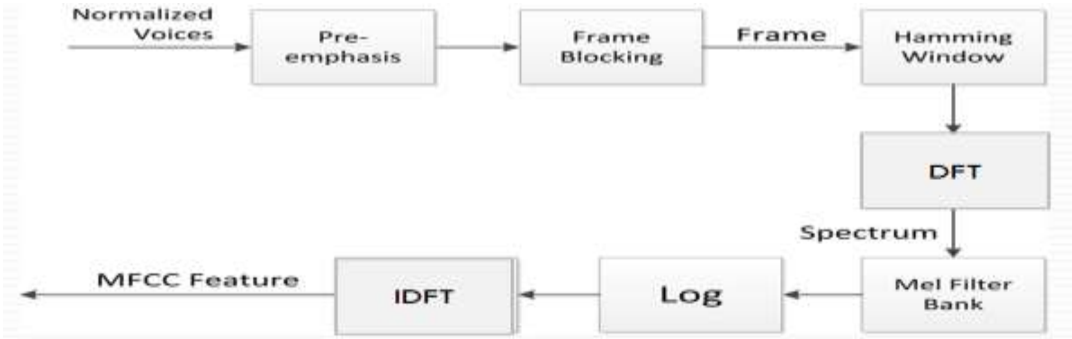

Figure 2: Block diagram of MFCC

Preemphasis

It seems that if we glance at the spectrum for voiced segments like vowels, there's additional energy at the lower frequencies than the upper frequencies. This call energy across frequencies (which is termed spectral tilt) is caused by the character of the speech organ pulse. Boosting the high frequency energy makes info from these higher formants additional on the market to the acoustic model and improves phone detection accuracy.

Windowing

The rectangular window will cause issues, however, as a result of it dead cuts of the signal at its boundaries. These discontinuities produce issues once we do Fourier analysis. For this reason, a lot of common window utilized in MFCC extraction is that the acting window, that shrinks the values of the signal toward zero at the window boundaries, avoiding discontinuities. ensuing step is to extract spectral info for our windowed signal; we'd like to grasp what proportion energy the signal contains at completely different frequency bands. The tool for extracting spectral info for distinct frequency bands for a discrete-time (sampled) signal is that the distinct Fourier rework or DFT.

.Mel filter bank and log

It is less sensitive at higher frequencies, roughly higher than a thousand Hertz. A mel (Stevens et al., 1937; Stevens and Volkmann, 1940) may be a unit of pitch outlined in order that pairs of sounds that area unit perceptually equal in pitch area unit separated by associate degree equal variety of mels. The mapping between frequency in Hertz and therefore the mel scale is linear below a thousand cycle per second and therefore the index higher than a thousand cycle per second. The mel frequencym may be computed from theraw acoustic frequency as follows: mel(f)=1127ln(1+f/700)

Throughout MFCC computation, this intuition is enforced by making a bank of filters that collect energy from every waveband, with ten filters spaced linearly below a thousand cycle per second, and therefore the remaining filters unfold logarithmically higher than a thousand cycle per second. Finally, we have a tendency to take the log of every of the mel spectrum values. generally the human response to amplitude is logarithmic; humans ar less sensitive to slight variations in amplitude at high amplitudes than at low amplitudes. additionally, employing a log makes the feature estimates less sensitive to variations in input

The Cepstrum: Inverse Discrete Fourier Transform

While it would be possible to use the mel spectrum by itself as a feature representation for phone detection, the spectrum also has some problems. For this reason, the next step in MFCC feature extraction is the computation of the cepstrum. The cepstrum has a number of useful processing advantages and also significantly improves phone recognition performance. The cepstrum is more formally defined as the inverse DFT of the log magnitude of the DFT of a signal.

D. Feature Preparation and Classification Stage

Practical exploitation of the information in the measures

calculated before requires us to construct feature vectors from these measures, which can then be subsequently used to discriminate healthy from PWP. classification performance is greatly enhanced by preprocessing of the values of each measure with an appropriate rescaling . Here, we scale each measure such that, over all signals, the measure occupies the numerical range [−1, 1].

1. Support Vector Machines

Support vector machines builds a model victimization set of coaching examples every marked to its class and so used for classification. during this classifier, one hyperplane that represent the most important separation between the 2 categories is chosen. invariably most margin hyperplane is chosen. most margin hyper plane may be a plane from that distance to the closest datum on each aspect is maximized. These nearest information points ar referred to as support vectors. Support vector machine is extremely correct classifiers and sturdy to noise. it's a binary classifier and to try to to a multi-class classification, pair-wise classifications may be used. Cases wherever linear separation isn't attainable kernel functions like polynomial, RBF, sigmoid ar used.

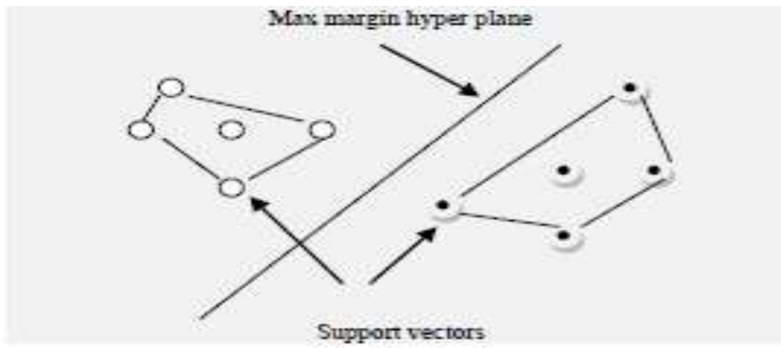

Figure 3: Maximum margin plane and support vectors

2. Artificial Neural Network

An artificial neural network (ANN) is the mirror of biological neural network like brain. An ANN consists of artificial neurons. Connections between neurons have assigned a weight. Every neuron sum all the values it receive and then modifies the value based on its transfer function. So the transfer function translates the input signal to output signal. Following types of transfer functions :

Tansig Transfer Function:

Tan sigmoid transfer function generates output between -1 and +1. The transfer function is represented by following equation

$$B_{k=}\frac{2}{(1+\exp(-2A_{k}))-1}$$

Where Ak is the sum of weighted inputs in kth layer for a neuron.

Logsig Transfer Function:

In the logsigmoid transfer function neuron output is always positive whereas input goes from negative to positive values. The equation is given as

$$B_{k=}\frac{2}{(1+\exp(-A_{k}))}$$

Purelin Transfer Function:

Purelin is a linear function, it generates output same as input. Graph and equation is given below.

$$B_k = A_k$$

In the training process of ANN, the weights of the connections are adjusted, so that the difference between targeted output and predicted output is minimum

6 Types of Artificial Neural Networks Currently Being Used in Machine Learning

- Feedforward Neural Network – Artificial Neuron:
- Radial basis function Neural Network: ...
- Kohonen Self Organizing Neural Network:
- Recurrent Neural Network (RNN) – Long Short Term Memory: ...
- Convolutional Neural Network: ...
- Modular Neural Network:

CONCLUSION

In this paper we studied different types of feature measures and classifiers in order to discriminate healthy persons from Parkinson's affected persons. The selected nonstandard methods are robust to many uncontrollable variations in acoustic environment and individual subjects, and are thus well suited to telemonitoring applications.

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