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A SURVEY ON ELECTROENCEPHALOGRAPHY SIGNAL CLASSIFICATION TECHNIQUES FOR BCI APPLICATIONS

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ABSTRACT

In this paper, we present two new methods for the Electroencephalography signal analysis and those are Empirical Mode Decomposition and Ensemble Empirical Mode Decomposition and their comparison is done as to find the better efficient signal analysis technique. And the signals are classified into seizure and non-seizure signals by applying neural network classifier which is easier to implement and more efficient as well.

I. INTRODUCTION

A chronical disorder of the nervous system will be termed as Epilepsy and if a bulk of neurons undergo some synchronized eruptible changes then is will be noted that the person is a seizure person. Sometimes it is also called that an ictal activity is taking place. We very well know that Electroencephalography, popularly known as EEG signals are the set of signals which consists of the recordings of the activities of the human brain. In this paper, different EEG signals are taken and these signals are first to be analyzed using two different signal analysis techniques i.e. Empirical Mode Decomposition and Ensemble Empirical Mode Decomposition and then the classification of these signals are to be done using neural network as in to determine whether the applied signal is seizure or non-seizure.

A. EEG based BCI (Brain Computer Interface) System

In *Fig (1)* the general model of EEG based BCI system is shown where initially we take the signals from the database or real time data acquisition from the electrodes can be done and these signals will be preprocessed and then segmented where Empirical Mode Decomposition or Ensemble Empirical Mode Decomposition theory is applied for the signal analysis by which the features are extracted and then a neural classifier is applied for the detection of the seizure and non-seizure signals.

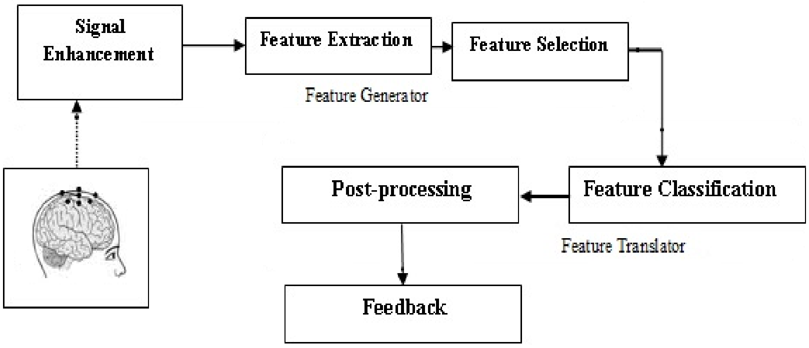

Fig 1: General model of EEG based BCI system

So in this paper first we deal with the two types of signal analysis techniques ,Empirical Mode Decomposition or Ensemble Empirical Mode Decomposition in part II. And then types of Neural Networks used to classify the given EEG data into seizure and non-seizure EEG signals are dealt in part III. And finally we conclude with the conclusion in part IV which decides which among the two signal analysis technique is better.

II. SIGNAL ANALYSIS TECHNIQUES

2.1 Empirical Mode Decomposition

Empirical Mode Decomposition is a unique technique wherein we can break down a particular EEG signal without leaving the time domain. It can be compared with other methods of analysis, for example Fourier Transforms and wavelet decomposition of EEG signals. This could be done to analyze the natural signals which will be more often non-linear and non stationary.

If there are formations of orthogonal basis for the actual/original signals then those functions will be filtered out by the EMD filters. And these functions are named as Intrinsic Mode Functions also known as IMF's and these are enough to elaborate about a signal even if they are not orthogonal.

Now an EEG signal which will be decomposed into functions will all be in time domain and also will be of same length as that of the original signal. This will allow for regulating the frequency in time to be preserved. Acquiring IMF's from the real signals is necessary because natural processes usually have multiple causes and each of which happens at specific intervals. This type of data is seen in EMD analysis and absent in Wavelet decomposition signal analysis and Fourier signal analysis.

Intrinsic Mode Functions: An IMF has to fulfill two main requirements and those are as follows -

1) The number of extrema as well as zero crossings must either match up or vary at most by one ,in the whole dataset .
2) The envelope's mean value defined by the local maxima as well as local minima should at any point be zero.

Hilbert Spectral Analysis: Hilbert Spectral Analysis is a procedure for inspecting each IMF's instantaneous frequency as functions of time. And finally we get the Hilbert Spectrum which will be a frequency time distribution of signal energy and it finally allows for the detection of localized features in an EEG signal.

2.1.1General steps for Implementation

In EMD a given data of an EEG signal can be reduced into a collection of IMF's and to these obtained IMF's the Hilbert transform can be applied. A simple oscillatory mode is a counterpart to simple harmonic function is what an IMF actually represents. Along the time axis the IMF will be having variable frequency and amplitude instead of constant frequency and amplitude.

2.1.2 Sifting process

A data adaptive algorithm was suggested by Huang in order, to extract a sinusoidal wave or frequency from the given signal ***x***. Firstly ,the detection of local extrema is to be done as shown in *Fig 2(a)*. Then interpolate the obtained local maxima and local minima and generate two functions called upper and lower envelope functions. See *Fig 2(b)*. Then the average of the two is to be taken which will produce a lower frequency component than the actual/original signal. See *Fig 2(c)*. Thirdly, there is a need to subtract the envelope mean from the actual/original signal *x* through which a highly oscillated signal pattern is obtained. See *Fig 2(d)*.

Now the oscillating wave could be treated as the IMF only if it satisfies the two conditions and they are

a) The number of zero crossings as well as extrema should differ by one in the whole dataset.

b) The envelope's mean value defined by local maxima as well as local minima should be zero at any point.

If in case the above declared conditions of IMF's are not satisfied then the same procedure is applied to the obtained residue signal as shown in the *Fig 2(d), 2(e) and 2(f)* until the above conditions match up.

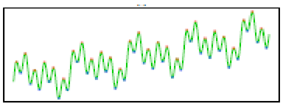

Fig 2a

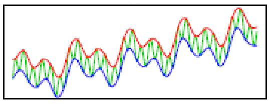

Fig 2b

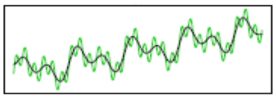

Fig 2c

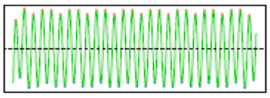

Fig 2d

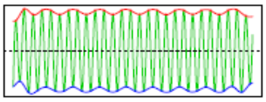

Fig 2e

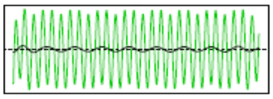

Fig 2f

2.1.3 Stopping Rule

When the copies of sifting procedure becomes more than the maximum number of sifts which was predefined ,the sifting process stops. The sifting process stops even when all the conditions of IMF's are satisfied by the signal.

There are two types of stop rule and they type 1 and type 2. In type 1 ,the sifting process stops when the tolerance level would go higher than the absolute value of IMF $\boldsymbol{h_i}$, $\boldsymbol{h_i(t)<tol}$. And in type 2 the sifting process stops when the changes in the consecutive candidate IMF's is within the tolerance level.

$$\sum_t \left(\frac{h_i(t) - h_{i-1}(t)}{h_{i-1}(t)} \right)^2 < \text{to1} \text{ --------- } (1)$$

- **Ensemble Empirical Mode Decomposition (EEMD)**

There comes another approach for EEG signal processing that is EEMD. Here an ensemble of white noise added signal is to be sifted and here mean will be considered as the ultimate result. Also that finite ,not infinitesimal ,amplitude white noise is important to enforce the ensemble to exhaust all possible solutions in the sifting process. And with this the different scale signals will combine to form proper IMF's as obeyed by the dyadic filter banks. Here all data are the blend of signal and noise. Let's consider a recorded EEG signal $x(t)$ and let $s(t)$ and $n(t)$ be the true signal and noise respectively as seen in *equation (2)*

$$x(t) = s(t)+ n(t) \text{ -----(2)}$$

From the separate observations the data will be collected and each of them will be having different noise as in to improve the accuracy of measurements. Now a white noise will be added to the signal $x(t)$ which is considered as the possible random noise that would be confronted in the measurement process ,as shown in the *equation (3)*. Therefore the i^{th} artificial observation will be given as below

$$x\ (t) = x(t)+ w\ (t) \text{ ----(3)}$$

In the case of only one observation, one of the multiple-observation ensembles is resembled by adding different copies of white noise, $w_i(t)$, to that single observation as given in Equation (3). A smaller signal to noise ratio will be generated after the addition of noise ,yet the added white noise will give a uniform reference scale distribution to facilitate the EMD so that the low SNR does not affect the decomposition method instead should enhance it in order to nullify the mode mixing. Now let's see how an EEG signal will be decomposed using EEMD method.

a) The white noise series is to be added to the targeted data.
b) The data will be decomposed with added white noise into IMF's.
c) With different white noise series steps 1 and 2 is to be repeated.
d) Obtain the means or ensemble of corresponding IMF's of the decomposition as the ultimate result.

Here the chances of occurrence of mode mixing will be reduced since the added white noise series would cancel each other and also the mean IMF's stays within the dyadic filter windows.

Assume an EEG data to be there and if the EEMD decomposition is to take place with the added noise signal of amplitude of 0.1 standard deviation of the original data for a single trial then the result is that there will be a perfect extraction of the low frequency component as the high frequency components could be hidden or concealed in noise. The high frequency intermittent signal may occur as the number of ensemble members increases. There is an improvement in the capability of extracting the signals from the given EEG data using EEMD analysis. Therefore EEMD method is more efficient than the normal EMD technique.

III. CLASSIFICATION OF THE EEG SIGNALS USING NEURAL NETWORKS

3.1 Types of Neural Networks used to classify the given EEG data into seizure and non-seizure EEG signals

As we know that the given EEG dataset will be consisting information about the electrical activity of the human brain, characterizing the complex human brain dynamics. Now if the eventual work is to detect whether the input signal is seizure or non seizure signal then that particular signal will have to be decomposed into IMF's using any of the techniques that is EMD or EEMD. Then we need to classify these obtained signals into seizure and non-seizure

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by using the neural network classifier. There are many other classifiers like Support Vector Machine classifier ,but classification is a bit tedious here when compared to neural network classifier. The two types of neural network classifiers are as follows-

Multilayer Perceptron Neural Network Model: It has three layers that is output layer ,hidden layer and input layer. The input layer will be having a set of predictor variable values from (x1……xp). And each variable ranges from -1 to +1. And these variables will be given to the hidden layer neurons. A constant input of 1 which is called as bias is fed to each of the hidden layers which are to be multiplied with the weights and to be added to the sum going into the neuron. Now let's consider hidden layer, wherein the values which comes as the output of the hidden neurons will be multiplied with the weight ***(w_{ji})*** and then these weighted values result's are added together giving a merged value ***u_j***. The weighted sum ***(u_j)*** is then inserted to the transfer function ***(σ)*** which gives a value ***(h_j)*** as the outcome. Outputs from the hidden layer are then distributed to the last layer that is the output layer. Then let's consider the output layer ,wherein weight ***(w_{kj})*** is considered and it is to be multiplied with all the outcomes of the hidden layer and then these resulting weighted values are taken into account and which are added together and finally a merged value ***(v_j)*** is obtained which is to be inserted into the transfer function ***(σ)*** and we get ***(y_k)*** as the outcome value. These obtained y values are treated as the eventual output of the network. See *Fig (3)*

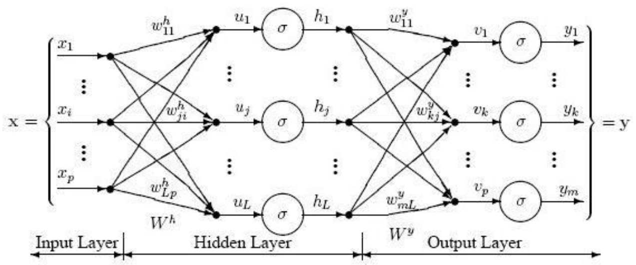

Fig 3: Three layer Perceptron network

Probabilistic Neural Network: A probabilistic neural network (PNN) is mainly a classifier which depicts any input pattern to a number of classifications and could be enforced into a more general function approximator. A supervised training set is used here which produces the probability density functions (PDF's) within the pattern layer. A PNN deals with the implementation of a statistical algorithm called kernel discriminant analysis in which the operations are organized into a multilayered feed forward network with four layers called as Input layer ,Pattern layer ,Summation layer and Output layer as shown in the *Figure (4).*

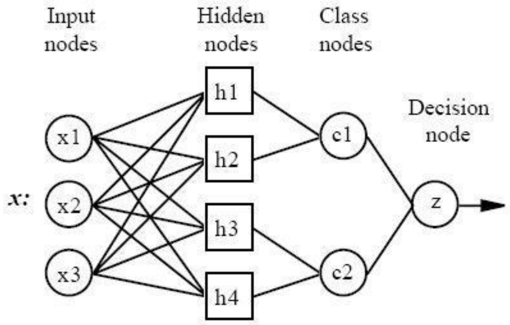

Fig 4: A PNN Architecture

In PNN networks there are four layers and those are: **1. Input layer**: As shown in architecture ,there are three nodes here and those are (x1,x2,x3). For every variable predictor there is one neuron in the input layer. And then for the case of categorical variables (N-1) neurons are used where N stands for the the number of categories. Input neuron adopts the range of the values by subtracting the median and dividing by the Inter quartile range or also called as IQR. Then input neurons insert the obtained values to the hidden layer neurons.**2. Hidden layer**: As shown in the architecture ,there are three hidden nodes and those are (h1,h2,h3). For every variable predictor there is one neuron in the input layer. Here, this layer which usually has one neuron for each case in the training EEG dataset. Neuron accumulates the values of the predictor variables along with the target value for the case. From the neuron's center point the Euclidean distance is to be calculated with the help of hidden neuron and later there is a need to apply the Radial Basis Function Kernel function (RBF) using the value of sigma. Evaluated value is passed to the neurons in the pattern layer. **3. Pattern layer or Summation layer:** As per the architecture c1 and c2 are the class nodes. In PNN network ,each class of the target variable has one pattern neuron. The actual target class of each training case is accumulated with each hidden neuron; the weighted value coming out of a hidden neuron is inserted only to the pattern neuron that corresponds to the hidden neuron's type. Pattern neurons add the values for the class they represent. **4. Decision layer:** As per the architecture z is the decision node. In PNN network the decision layer compares the weighted votes for each target class stored in the pattern layer and in order to predict target class the largest vote is used.

IV. CONCLUSION

We can conclude by saying that Ensemble Empirical Mode Decomposition is better than Empirical Mode Decomposition because in EEMD segregation of the signals can be done into different scales without mode mixing. And in time frequency scale a dyadic reference frame will be constructed due to the addition of white noise. Estimation of the zero mean of the noise done here helps to deduct the noise background once its work is done of providing uniformly distributed frame of scales in the time domain data analysis.

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