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Classification of EEG signals using Empirical Mode decomposition and Neural networks

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Abstract— The brain is the central part of the human nervous system and is highly complex organ. The problems related to brain activities are analyzed and the diagnosis is carried out with the help of classification of normal and abnormal signals produced by the brain activity. Several methods were proposed for the classification of the EEG normal and abnormal waves which are non stationary waves. The classification of seizure (abnormal) and non-seizure (normal) signals is very important in the diagnosis of problems related to brain and some physiological disorders. This paper presents a method to classify the EEG signals with the help of Empirical mode decomposition which produces intrinsic mode functions (IMFs) and they can be considered as amplitude and frequency modulated (AM-FM) signals. The Hilbert transformation of IMFs helps to represent the signals in analytical form. The two bandwidths, namely amplitude modulated bandwidth and frequency modulated bandwidth calculated from the analytic IMFs, have been used as input to artificial neural networks (ANN) for classifying normal and abnormal EEG signals. Available EEG signals are used to show the effectiveness of the proposed method.

Keywords—Seizure, nonseizure, EMD, EEG, IMFs, feature extraction, back propogation.

I. INTRODUCTION

One extensively used test of the electric activity is Electroencephalography. Electroencephalography is the technique used in the measurement of the electrical signals which are produced by the brain. The brain signals are recorded from the electrodes placed on the scalp or, in some cases, on the cortex of the patient. The results of this recording are known as an electroencephalogram (EEG), which reflects the electrical activity of multitude of neural populations in the brain. Electroencephalogram (EEG) is a highly complex signal, containing a lot of information about the human brain function and neurological disorders. It is a test used to assess brain damage, epilepsy and other problems, Sometimes it is used to assess brain death also. In short, EEG can be considered as a test to detect the abnormalities in the electrical activity of the brain.

In this work we are using Empirical mode decomposition (EMD) method for classification of electroencephalogram (EEG) signals. In this work we mainly are concentrating on classification of theta waves. In this work we are taking the recorded sample waves of theta category and analyzing the waves with respect to its normality and abnormality. The frequency range of theta waves is about 3.5 -7.5 Hz. Some consider Theta to be from 4 – 8 Hz. Theta wave is normal in the healthy adult EEG in the waking state. Theta is more well-known and considered very normal in the raw EEG's of children & people between the age group 10-19 unless they are suffering from disease or any disorders. Theta wave recorded from the adults at the scalp surface is normal because of early stages of drowsiness. During day dreaming also theta waves may be seen. If the Theta activity is excess in the raw EEG's of waking adults then it is considered as abnormal condition. This condition can represent too little oxygen uptake. Some Spike and slow wave kind of complexes that occur in seizure disorder condition can often occur in the frequency range of theta. More Theta activity is often seen in conditions like Attention Deficit Hyperactivity Disorder (ADHD), Head injuries or brain lesions, Learning disabilities and certain neurological disorders.

A. Brain Computer Interface

A Brain computer interface (BCI) is an arrangement in which a link between human brain and the computer system through which both communicates is setup. In 1924 Hans Berger invented the process of recording of electrical activity of human brain, from then Brain–computer interface (BCIs) started and also it helped for the development of electroencephalography (EEG). In 1924 Berger by analyzing EEG signals he could spot oscillatory action in the brain, such a wave what he saw for the first time has the frequency 8-12 Hz and it is named as Berger's wave or alpha wave. The changes in the EEG signals can be observed only when there is psychological activity of the brain. The Brain computer interface (BCI) system tracks such changes and converts it into a control signal and these signals can be used in different applications like motion of a wheel chair, video games etc.
A Brain computer interface is a communication and control system that does not depend in any way on the brain's normal neuromuscular output channels. The user's intent is conveyed by brain signals (such as EEG) rather than by peripheral nerves and muscles, and these brain signals do not depend for their generation on neuromuscular activity. Furthermore, as a communication and control system, a Brain computer interface creates a real-time communication between the patient or person and the external world. The user receives feedback reflecting the outcome of the BCI's operation, and that feedback can affect the user's subsequent intent and its expression in brain signals. Figure 1 shows the typical arrangement of Brain computer interface. In the figure we can see the representation of how the signals are processed and features are extracted and classified with the help of different blocks.

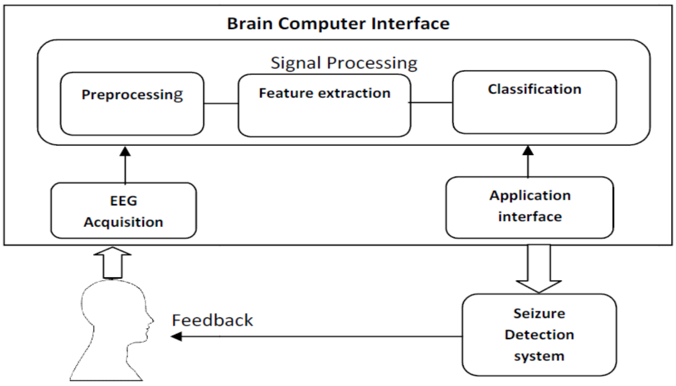

Figure 1. Block diagram representation of Brain computer interface (BCI)

C. Electroencephalogram (EEG)

Electroencephalography (EEG) is a technique used in measuring the electrical activity of the brain. The electrical activity is continuous in human brain. The brain never rests. When one is unconscious also the brain remains active. To a great extent of the time, the brain waves are unequal and no common pattern can be observed. There are four major types of continuous rhythmic EEG waves: alpha, beta, delta and theta. The other waves include gamma and sensory motor rhythm (SMR). Figure 2 shows the types of EEG waves.

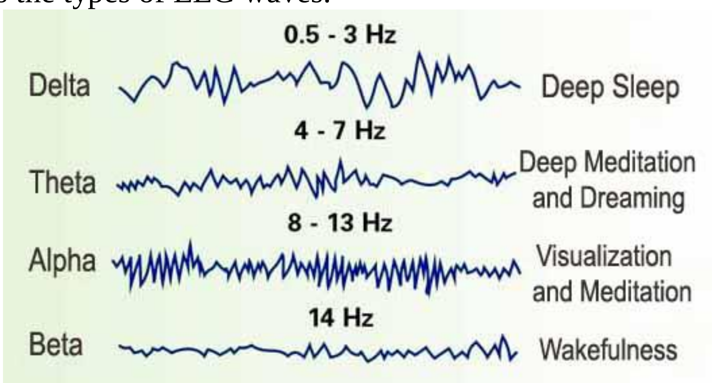

Figure 2. Types of EEG waves

The goal of the classification is to assign class labels to the features extracted from the observations of a set of data in a specific problem. An algorithm that implements classification, particularly in an existing implementation, is known as a classifier. Classifiers are able to learn how to identify the class of a feature vector thanks to training sets. These sets are composed of feature vectors labeled with their classes of belonging. The Neural networks and Support vector machines are the well known classifiers.

II. LITERATURE REVIEW

This section presents the literature review carried out on the topics like Brain Computer Interface (BCI), basics of Electroencephalogram (EEG), Empirical Mode Decomposition (EMD), and Artificial Neural networks.

2.1 Brain computer interface

In the reference paper [1] they have presented a motor imaginary based BCI system. The input signal to the BCI system used in this method is the patient's left and right wrist imagery during which the EEG data is recorded. The results what they obtained imply that the proposed technique has the possible for the classification of psychological tasks in BCI scheme. In their work, EEG data recorded in an offline BCI experimental setting presents two classes which correspond to the left wrist and the right wrist motor imageries.

In this paper [2] they have briefly explained the recent development of BCI technologies from the perspective of industrial robotics and offered the estimation of the new BCI viable products. Then they have discussed the possible applications of commercial BCIs to industrial robot scheme.

In This paper [3] they have discussed in detail the application of independent component analysis (ICA) way of dealing with the problem to propose a new EEG based BCI for normal control of "prosthetic hand grasp".

2.2 Empirical Mode Decomposition

In This paper [4] the authors presented the use of EMD for EEG signal analysis. The EMD splits or decays an EEG signal into finite set of signals called as IMFs. The IMFs can be represented analytically by the use of Hilbert transform. In this paper they have proposed that to separate normal and seizure EEG signals the feature used is the area considered starting the draw of the analytic IMFs, which have circular type in complex plane. The differentiation of EEG signals using this method showed good performance.

In this paper [5] they have presented a technique for the study of electroencephalogram (EEG) waves which has the possible to differentiate between ictal and seizure-free intracranial EEG data collections. This is achieved by studying common frequency components in multichannel EEG data collection, by means of the multivariate empirical mode decomposition (MEMD) method.

In this paper [6] the authors presented a real-time performance of an EMD-based signal improvement method. The projected execution is used for separating noise, for reducing muscle artifacts, and for removing drift of EEG signals in a usual manner and in real-time.

2.3 Artificial Neural Networks

In this paper [7] the authors have proposed an automatic EEG recognition system which is based on neural networks and which uses Feed forward ANN containing sliding window scheme for template recognition. The event classifier used in this analysis [18] was neural network based model. The result of an event based on the data of the matching EEG signal can be predicted using ANN. Experiments were carried out to authenticate this method by the use of classifier to differentiate whether the persons positioned their fingers into cold or hot water. The results were effective and this approach can be used in other fields.

They have concluded in this paper [8] that the use of ANN was the best method for post-classifying the EEG data which is collected from BCI system. The multilayered perceptron (MLP) NN was also suitable for distinguishing EEG waves when body parts experience unlike temperature [8]. The objective of this investigation [9] was to judge against the utilization of Artificial neural systems (ANN) with shrouded class examination and logistic relapse to perceive for whom a crisp, intellectual behavioral system to the treatment of low back agony is pointed or contra-showed.

III. METHODOLOGY

A. Empirical Mode Decomposition

In this section, the principles and detail steps of Empirical Mode Decomposition (EMD), including definitions of IMFs will be elaborated.

The EMD was firstly proposed by Huang *et al*. as an efficient method for non-stationary and nonlinear signal analysis. The decomposition is based on the simple assumption that any data is consisting of dissimilar simple intrinsic modes of oscillations. Every intrinsic mode, linear or nonlinear, shows a simple fluctuation, which will have the equal number of extrema and zero-crossings. Also, the oscillation will also be symmetric regarding the "local mean." At any time, the information may have lots of different parallel modes of oscillations, one superimposing on the others. The outcome is the final complex data. All of these oscillatory modes is represented by an intrinsic mode functions (IMFs).

Intrinsic Mode functions

The goal of the Empirical Mode Decomposition (EMD) technique [10] is to decay the nonlinear and non-stationary signal $x(t)$ into a sum of intrinsic mode functions (IMFs). Every IMF satisfies two necessary conditions:

- In the entire data set, the number of extrema and the number of zero crossings must be the equal or differ at most by one.
- At any position, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

To implement this method, a signal $x(t)$ is decomposed into IMF by the following steps:

1. Detect the extrema (maxima and minima) of the dataset $x(t)$.
2. Generate the upper and lower envelopes $e_m(t)$ and $e_l(t)$, correspondingly, by connecting the maxima and minima separately with cubic spline interpolation.
3. Find out the local mean as $a(t) = \frac{[e_m(t) + e_l(t)]}{2}$.
4. Remove the detail $h_1(t) = x(t) - a(t)$.
5. Decide whether $h_1(t)$ is an IMF or not by inspecting the two basic conditions as described above.
6. Repeat steps (1) to (4) and end when an IMF $h_1(t)$ is obtained.

Once the first IMF is derived, define $c_1(t) = h_1(t)$, which the smallest temporal scale is in $x(t)$. To determine the the rest of the IMFs, generate the residue $r_1(t) = x(t) - c_1(t)$, the residue can be treated as the new signal and repeat the above illustrated process until the final residue is a constant or a function from which no further IMFs can be derived. At the end of the decomposition, the original signal $x(t)$ is represented as

$$x(t) = \sum_{m=1}^{M} c_m(t) + r_M(t) \tag{1}$$

where M is the number of IMFs, $c_m(t)$ is the mth IMF, and $r_M(t)$ is the final residue. Each IMF in (1) is assumed to yield a meaningful local frequency, and different IMFs do not exhibit the same frequency at the same time. Then, (1) can be written as

$$x(t) \approx \sum_{m=1}^{M} A_m(t) \cos[\phi_m(t)]. \tag{2}$$

Hilbert Transform

It has been proposed that the Hilbert transform should be applied on all IMFs obtained by EMD method [19]. The analytic signal of any real IMF $c(t)$ is defined as

$$z(t) = c(t) + jc_H(t) \tag{3}$$

where the Hilbert transform of $c(t)$ is given by $c_H(t) = c(t) * \frac{1}{\pi t}$. Equation (3) can be written as

$$z(t) = A(t)e^{j\phi(t)} \tag{4}$$

The analytic signal amplitude $A(t)$ and instantaneous phase $\varphi(t)$ can be defined as follows:

$$A(t) = \sqrt{c^2(t) + c_H^2};\ \phi(t) = \arctan\left[\frac{c_H(t)}{c(t)}\right]. \tag{5}$$

The instantaneous frequency of the analytic IMF $z(t)$ is given by

$$\omega(t) = \frac{d\phi(t)}{dt} \tag{6}$$

The signal $x(t)$ given in (2) can be expressed in a Fourier-like representation as

$$x(t) \approx \Re\left\{\sum_{m=1}^{M} A_m(t)e^{j\phi_m(t)}\right\} \tag{7}$$

where the index m refers to mth IMF and $\Re\{.\}$ denotes the real part of a complex quantity.

***AM* and *FM* Bandwidths**

The information of the signal could be a measure of the spread in frequencies for the period of the signal. The information measure will not provide us info, whether or not the spread of frequencies is due to deviation from the typical frequency or attributable to amendment in amplitude or combination of each.

It is obvious that the bandwidth of the signal has two parts, one depending on the amplitude and therefore the different counting only on the phase. Therefore, the bandwidth owing to AM (B_{AM}) and therefore the bandwidth owing to FM (B_{FM}) are outlined as

$$B_{AM}^2 = \frac{1}{E}\int\left(\frac{dA(t)}{dt}\right)^2 dt \tag{8}$$

$$B_{FM}^2 = \frac{1}{E}\int\left(\frac{d\phi(t)}{dt} - (\omega)\right)^2 A^2(t)dt \tag{9}$$

The overall bandwidth of analytic IMF z(t) is expressed as

$$B = \sqrt{B_{AM}^2 - B_{FM}^2} \tag{10}$$

B. Multilayer perceptron neural network (MLPNN) for classification.

The Multi layer perceptron (MLP) is the most general form of neural network. MLPs are feed-forward networks of simple processing units with at least ONE “hidden” layer .This kind of neural network is called as a supervised network because it needs a preferred output so as to learn. The target of this type of network is to make a model that properly maps the input to the output using old statistics so that the representation can then be used to create the output when the desired output is unidentified.

The general form of an MLPNN is a fully connected one where each node or neuron in a given layer is connected to all nodes or neurons in the previous layer through some connecting weights. Each node, in its most general form, comprises two functions: integration function and activation function. The integration function integrates or summates all the weighted inputs at the given node to produce an aggregated input for the activation function.

The Back propogation algorithm

The backpropagation algorithm trains a given feed-forward multilayer neural network for a given set of input patterns with known classifications. When each entry of the sample set is presented to the network, the network examines its output response to the sample input pattern. The output response is then compared to the known and desired output and the error value is calculated. Based on the error, the connection weights are adjusted. The backpropagation algorithm is based on *Widrow-Hoff delta learning rule* in which the weight adjustment is done through *mean square error* of the output response to the sample input. The set of these sample patterns are repeatedly presented to the network until the error value is minimized.

Back propagation algorithm was initially formulated by Werbos (1974) which was later adapted by Rumelhart and McClelland (1986).

IV EXPERIMENTAL RESULTS

The EMD method decomposes the non stationary signal into group of AM and FM components called IMFs. Figure 3 shows the plot of the sample EEG signal which can be plotted using EEGLAB.

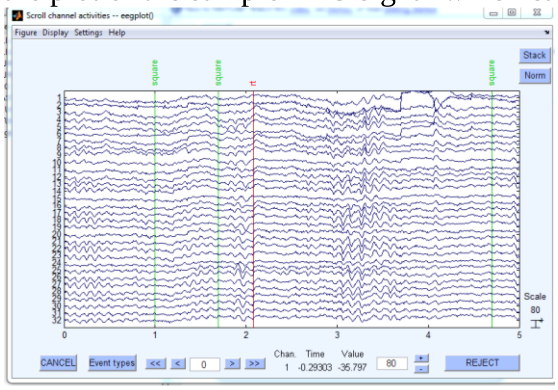

Figure 3 Plot of sample channel EEG data

New EEG data is imported or existing data is loaded into the EEGLAB. The EEG data can be plotted using ‘Plot’ option and the pop up window will display the plot of the EEG data as shown in the above figure 4.2. Here the text field which explains the present data set can be viewed, edited and saved as an element of that dataset. A text editing window pops up when the option Edit→about this dataset which permits the user to edit a depiction of the present dataset.

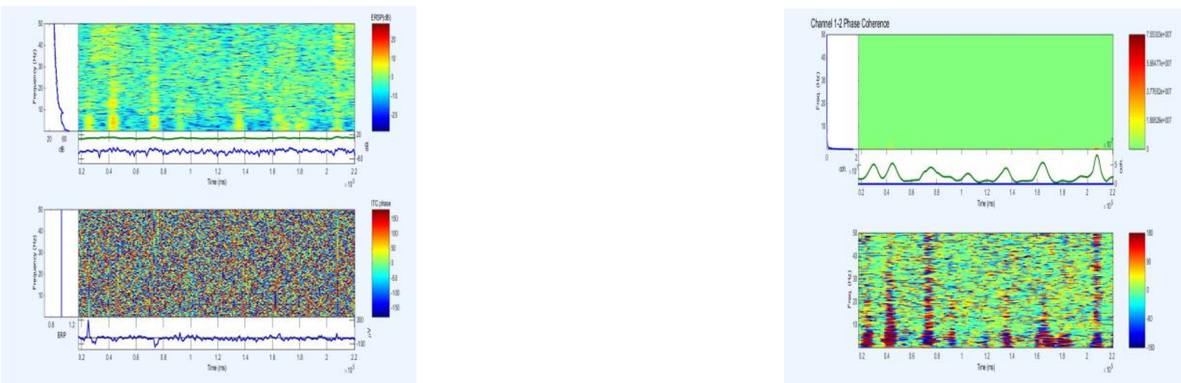

Figure 4 Time-Frequency plot and cross coherence plot

Figure 4.6 depicts the Time-Frequency plot of the selected EEG data. Time/frequency study characterizes variations in the spectral content of the information considered as a total of windowed sinusoidal functions or wavelets. To notice short-lived event related spectral variations and inter-trail coherence actions in epoched EEGLAB datasets, select Plot→Time frequency transforms → Channel time−frequency.

Table I *p*- values of the bandwidth features of the IMFs used in the experiment

Feature	IMF_a	IMF_b	IMF_c	IMF_d	IMF_e	IMF_f	IMF_g	IMF_h
B_{AM}	0	0	0	10^{-8}	0.1495	0.1798	0.2142	0.6354
B_{FM}	0	0	0	0	10^{-9}	0.0510	0.2895	0.3896

V. CONCLUSION

The Empirical Mode Decomposition (EMD) is a very useful scheme to decompose EEG signal into group of IMFs. These IMFs can be represented in the form of Amplitude and Frequency modulated bandwidths. These bandwidth parameters B_{AM} and B_{FM} of the IMFs can be used as features for the classification of epileptic and non-epileptic EEG signals. The classification performance can be tested using the better classifier like Neural Networks.

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