

Classification of Electroencephalogram Using Wavelet Transform and Neural Network

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Abstract: *Electroencephalogram (EEG) being a non-stationary signal its analysis using the Fourier Transform (FT) and Short Time Fourier Transform (STFT) is limited to a selection of window in which signal remains stationary. In this paper we will classify the Electroencephalogram (EEG) using Wavelet Transform (WT) and Feed Forward Neural Network. The database of Sleep EEG and Epileptic EEG are obtained from the www.physionet.org in the EDF (European Data File) file. The various features of EEG are obtained using WT these feature namely are delta, theta, alpha and beta. Any one of features described is dominant during a particular stages of sleep or when patient is alert, however with the age of patient, feature distribution with condition of patient may change i.e. dominant feature during particular stage of sleep is not same for different age group of patients. The feature vector obtained is given as input to Feed forward Neural Network (FFNN) for classification. Hence alertness level of a patient can be classified as sleep, drowsy and alert.*

Keywords: EDF(European Data File), EDFbrowser Electro-encephalogram, Feed Forward Neural Network, Fourier Transform(FT), physioorg.net, Polyman, STFT, WT.

1. Introduction

The electroencephalogram (EEG) is an electrical voltage signal picked up along a scalp on which the brain's functionality has strong impact. Hence EEG is most often used to diagnose epilepsy, which causes obvious abnormalities in EEG readings [13].

EEG being a non-stationary signal, the Fourier Transform (FT) cannot be used for EEG analysis, even if we apply Fast Fourier Transform (FFT) to the segments(either overlapping or non-overlapping) of an EEG signal, the frequency spectrum is observed to vary over time. Many attempts have been made for analysis of the non-stationary signal and found that Wavelet Transform (WT) is versatile tool for this. WT act as a mathematical microscope with varying window size, small window size for a high frequency signal and large for a low frequency signal.

A Wavelet is a waveform/signal of short duration that has an average value of zero. Basically there are two types of wavelets viz. mother wavelet (wavelet) and father wavelet (scaling function). Let $\psi(t)$ be the wavelet then (1) and (2) shows the basic property of mother wavelet and father wavelet respectively.

$$\int_{-\infty}^{\infty} \psi(t) dt = 0 \quad (1) \quad \alpha + \beta = \chi. \quad (1)$$

$$\int_{-\infty}^{\infty} \psi(t) dt = 1 \quad (2) \quad \alpha + \beta = \chi. \quad (2)$$

It is roughly said that the father wavelets are suitable for representing the smooth or low frequency constituents of a signal and the mother wavelets appropriate for representing the detail or high frequency components of a signal [8]. Using a mother wavelet $\psi(t)$, dilation and translation captures the signals (functions) f in $L^2(\mathbb{R})$. $L^2(\mathbb{R})$ is space of functions which has finite L_2 norm. In general L_p norm is defined as,

$$L_p = \left\{ \int_{-\infty}^{+\infty} |f(x)|^p dx \right\}^{1/p} \quad (3)$$

Space $L^2(\mathbb{R})$ implies that if we take any linear combination of the functions in the space and we get function present in the same space. Any function in space $L^2(\mathbb{R})$ can be

uniquely represented by $\psi(t)$ and its translates which are orthogonal (i.e. if we multiply $\psi(t)$ and its translates and integrate result will be zero) to each other. If we substitute $p = 2$ in (3) we obtained the L_2 norm which is same as the expression for energy of signal. Hence finite energy non-stationary signal can be expressed in terms of dilates and translates of $\psi(t)$ i.e. mother wavelet or simply wavelet.

There are many orthogonal wavelets such as Haar, Meyer and Shannon. Using the Daubechies Wavelet which is also orthogonal wavelet we can extract the features of EEG. EEG signal mainly characterized by the rhythms viz. delta (0-4 Hz), theta (4-7 Hz), alpha (7-12 Hz) and beta (>12 Hz) signals. As WT has the feature of Multi Resolution Analysis (MRA) i.e. expressing the given signal by dilates and translates of a wavelet function at multiple scale but at one particular scale(of interest depends on the characteristic of signal being analyzed) at a time. So selecting appropriate scale for taking the WT of segmented EEG for feature extraction then these feature are given to the Feed Forward Neural Network (FFNN) for classification. Since dominant EEG rhythm gives the alertness level of patient such as sleep, drowsy and alert. In section II we segment the sleep EEG signal obtained from www.physionet.org and in subsequent section III we discuss feature extraction using Discrete Wavelet Transform (DWT) and then in section IV we discuss the classifier using FFNN.

2. Sleep eeg segmentaion

The database file of EEG was downloaded from physionet.org that has an .edf file format. The EEG was obtained from the normal female patient during sleep with a sampling frequency of 100 Hz; the age of patient was 33 year when EEG was recorded. For viewing the downloaded EEG signal the Polyman or EDFbrowser software can be used. The short duration EEG in .edf file format can be read in MATLAB environment using the readEDF function, but long duration EEG should be first of all viewed in EDFbrowser that has feature of converting EDF to ASCII (.txt) then this .txt with delimiter can be read in MATLAB.

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Since recording was of 20 hour hence 20(number of hour) x 3600 (number of seconds per hour) x 100(samples per second) =7200000 number of samples in the recording. For extracting a feature we must segment the long duration EEG signal. Figure 1 and Figure 2 shows the segmented EEG taken at Fpz and Oz position in 10-20 system of EEG acquisition.

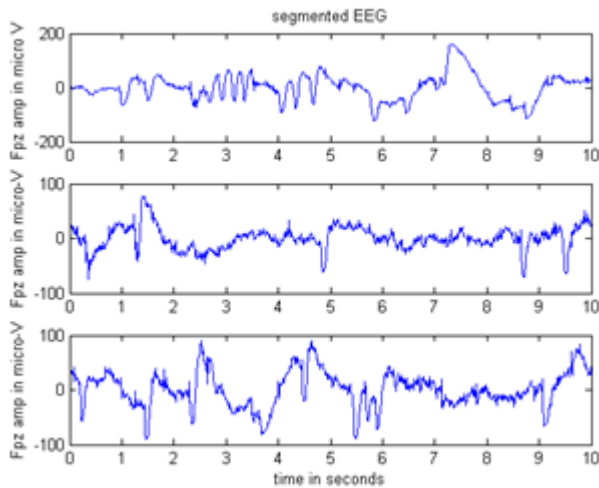


Figure 1: Segmented EEG (a) EEG segment of first 10 seconds taken at Fpz-Cz position in 10-20 system (b) EEG segment of next 10 seconds (c) EEG segment of next 10 seconds.

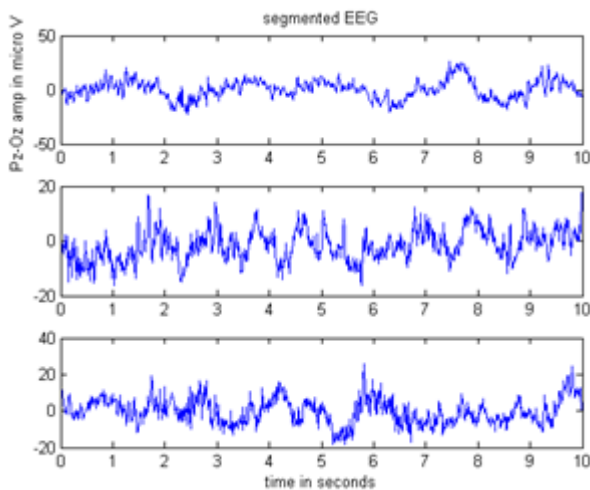


Figure 2: Segmented EEG (a) EEG segment of first 10 seconds taken at Pz-Oz position in 10-20 system (b) EEG segment of next 10 seconds (c) EEG segment of next 10 seconds.

3. Feature extraction using wavelet transform

The dilates and translates of basic wavelet $\psi(t)$ gives the WT, hence if we have the dilation variable as 'd' and translation variable as 'l' then (4) gives the basic expression of WT.

$$W_{d,l}(f(t)) = \frac{1}{|d|^{1/2}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-l}{d}\right) dt \quad (4)$$

Where $d, l \in \mathbb{R}$ is set of Real Number. With $d \neq 0$. If a wavelet is dilated with $d = 2^m$ i.e. dyadic operation and translated with $l = k * 2^m$ then it is known as DWT. For each one of the orthogonal wavelets there is an analysis and a synthesis filter bank associated with them which can use for signal analysis and then followed by sub sampling operation yields wavelet co-efficient. Signal decomposition

performed by a pyramidal algorithm is interpreting wavelets as pass-band filters.[S7help.pdf] The filter bank consist of low pass filter and high pass filter for each level of decomposition. Figure (3) shows the pyramidal analysis filter bank structure.

The DWT of sleep EEG was taken at different scales, the scale vector = [1 2 4 8] was used and then percentage energy of approximation wavelet coefficient was calculated and found that at scale of four, the wavelet coefficient has maximum energy, Hence these coefficient are arranged in a matrix. In this matrix has each column is feature vector corresponding to the delta, theta, alpha and beta. The extracted feature are plotted in Fig 4.

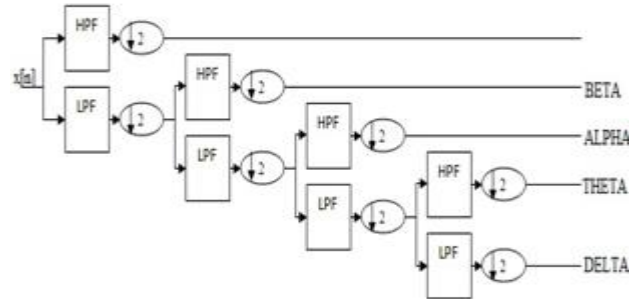


Figure 3: A pyramidal analysis filter bank structure with sub sampling by factor two for extracting the features of EEG .

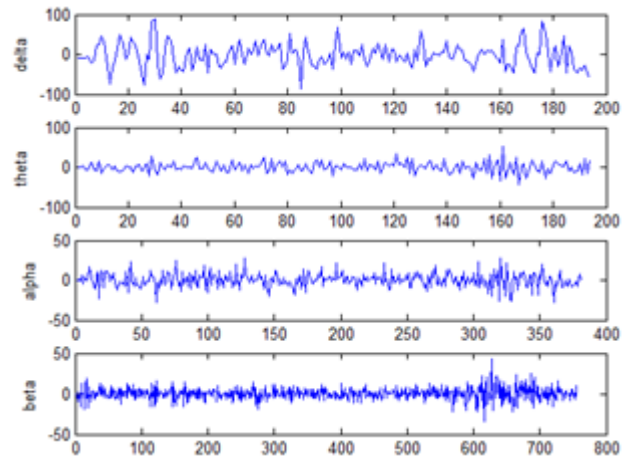


Figure 4: Segmented EEG (a) EEG segment of first 10 seconds taken at Pz-Oz position in 10-20 system (b) EEG segment of next 10 seconds (c) EEG segment of next 10 seconds.

4. Classification of EEG using neural network

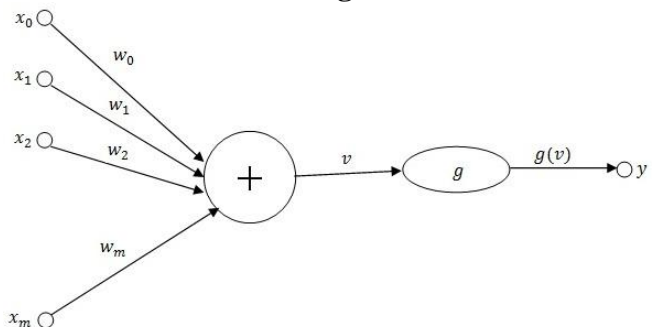


Figure 5:The mathematical model of an artificial neuron. An Artificial Neural Network (ANN) is a computational model inspired by a biological neuron [14]. The fundamental

building block in an ANN is the mathematical model of an artificial neuron as shown in Fig 5. The three basic components of the artificial neuron are:

1. The synapses or connecting links that provide weights, w_j , to the input values, x_j for $j=1, \dots, m$;
2. An adder that sums the weighted input values to compute the input to the activation function

$$v = w_0 + \sum_{j=1}^m w_j x_j \quad (5)$$

Where w_0 is called the bias is a numerical value associated with the neuron. It is convenient to think of the bias as the weight for an input x_0 whose value is always equal to one, so that

$$v = \sum_{j=0}^m w_j x_j \quad (6)$$

3. An activation function g that maps v to $g(v)$ the output value of the neuron. This function is a monotone function.

These weights w_j can be adjusted in accordance with the criteria for an error ϵ . The criteria for an error can be either minimum mean square or mean square error. An error is calculated by subtracting the target \hat{y} from the output y .

$$\epsilon = y - \hat{y} \quad (7)$$

Hence weight vector can be updated for further output calculation. This process of updating the weight vector is called the Learning, which is accomplished through special training algorithms. The frequently used dynamic updating algorithm for the neural net version of linear regression is known as the Widrow-Hoff rule or the least-mean-square (LMS) algorithm. Other learning algorithms are gradient descent and backpropagation.

The classifier for EEG classification is designed using multilayer feed forward neural network (MFFNN). MFFNN may contain two or more layers. A simple two-layer MFFNN consists of an input layer with the number of nodes (artificial neuron) equal to the number of features to be classified and output layer with the number of nodes equal to the number of desired classes. But these simple two-layer MFFNNs are only suitable for linear problems. For nonlinear problems hidden layers are used in between input layer and output layer.

Depending on the complexity of the problem to be classified the required number of hidden layers differs. Three layer architecture of MFFNN is adequate to classify features of the sleep EEG. Unfortunately there is no clear theory for choosing the number of nodes in each hidden layer or indeed the number of layers. The common practice is to use trial and error, although there are schemes for combining optimization methods such as genetic algorithms with network training for these parameters [14].

Training algorithms are an integral part of ANN model development [3]. The gradient descent with adaptive learning rate back-propagation is used for updating the weights and bias values. This training algorithm belongs to the supervised learning algorithm hence target vectors are also to be given to the classifier. Gradient descent is an iterative minimization method. The gradient of the error function always shows in the direction of the steepest ascent of the error function.

$$w_{t+1} = w_t + \Delta w, \Delta w = -\eta \frac{\delta E(w)^T}{\delta w} \quad (8)$$

Where η is a learning rate and $E(w)$ is a expected value of squared error ϵ^2 , error is defined in (7).

The extracted features of EEG are vectors of different rhythms viz. delta, theta, alpha and beta. Since these four different feature vectors are acting as input to the classifier hence input layer of MFFNN has the four nodes. Alertness levels of patient are namely alert, drowsy and sleep so the output layer of MFFNN has the three nodes. Based on monitoring the variation of error and time required for training the network the optimal number of nodes in the hidden layer was found as 15.

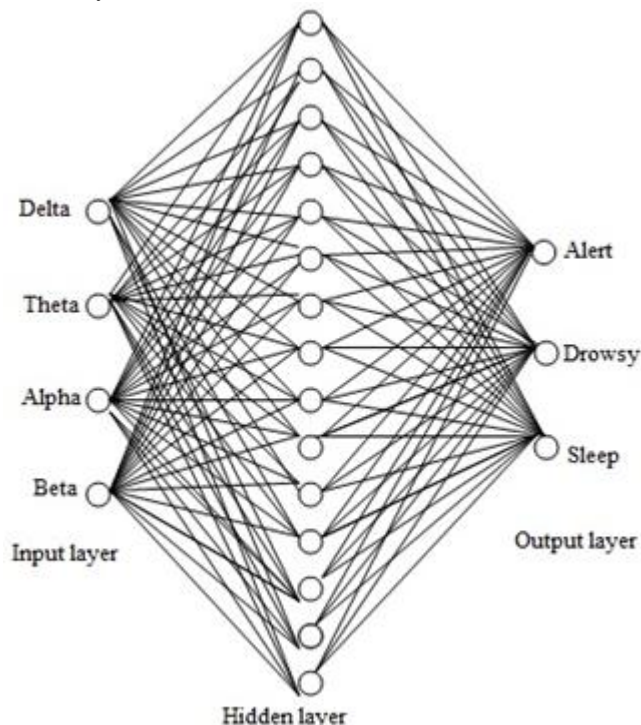


Figure 6: The Architecture of ANN used for classifying the sleep EEG into alertness level of the subject

5. Result

Table 1: Classification of alertness level of subject using sleep eeg

Classes of EEG segment Input EEG Description	Class 'Alert'	Class 'Drowsy'	Class 'Sleep'
Sleep EEG	5%	16%	79% (Since only Sleep EEG was the input)

In this study, the long EEG recordings were segmented into many segments then WT was operated on them which in turn yields features such as alpha, beta, theta and delta. These feature vectors are applied to MFFNN. For classification purpose MFFNN employing gradient descent with back-propagation algorithm was used.

The classification efficiency, which is defined as the percentage ratio of the number of EEG signals correctly classified to the total number of EEG signals considered for classification, also depends on the type of wavelet chosen for the application. When the segments of sleep EEG was used for alertness level classification it is found that 79 % segment was correctly classified as they belongs to the class

'Sleep'. During early segments of EEG, subject may be either in early stages of sleep or in drowsy state and these segments was of short duration hence less number of segments belongs to class 'Drowsy' ultimately account for 16 %. The five percent segments were incorrectly classified which shows Alert state of subject.

6. Conclusion

The work demonstrates the uses of wavelet transform and NN for a given non-stationary signal classification. The method can be used for epileptic seizure detection. The method can also be for brain-computer interface (BCI) for computer-assisted EEG diagnostics. The BCIs can be developed controlling of computers by people who are disabled. As they think about what they want the computer to do, their thinking will be classified based on their EEG waves and the computer will automatically execute the corresponding instructions. Accurate EEG wave classification is critical for computers to issue the correct instructions. The capability of WT to analyze different scales of neural rhythms is found to be a powerful tool for analyzing small-scale oscillations of the brain signals. However, to utilize this mathematical microscope effectively, the best suitable wavelet basis function has to be identified for the particular application. However the gradient descent algorithm employed for learning suffer from the problem of finding the local minima.

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