International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
Volume 2 Issue 4, pp : 256-259 1 April 2013

Classification of EEG Signals under Different Mental Tasks Using Wavelet Transform and Neural Network with One Step Secant Algorithm

Dipti Upadhyay
Department of Applied Mechanics, Motilal Nehru National Institute of Technology, Allahabad, India
2006upadhyay@gmail.com

Abstract—The ability to effectively classify electroencephalograms (EEG) is the foundation for building usable Brain-Computer Interfaces. In this presented work EEG signals were used to extract the information and classify with different mental task. EEG data was collected from a source[1]. This data contains recording of 5 subjects in different mental task conditions (Resting, math, letter composition, geometric figure rotation task). EEG Signals were pre-processed and filtered. EOG artifacts were removed by visual inspection. For classification of these mental tasks wavelet was used to extract the features. Second order Daubechies mother wavelet has been used to get the wavelet coefficients for the selected EEG epochs. Mean, maximum, minimum and standard deviations values of wavelet coefficients for the EEG epochs were selected as inputs for the training the network and to classify mental tasks. The ANN architecture trained with one step secant method used in present study shows overall very good results of classification. This architecture of ANN was also found effectively differentiating the EEG from different mental tasks conditions Resting (98%) multiplication (92%), Letter composition (92%) and rotation (96%).

Keywords— ***EEG signals; Wavelet; Neural Network; one step secant method***

I. INTRODUCTION

The electroencephalogram represents the bioelectric potential generated by the neural activity of the brain. The work presented here has a goal—to extract information from EEG signals and classify these EEG signal so that mental states can be discriminated and serve as a mode of communication for a paralyzed person. Brain Computer interfaces (BCIs) is as Neural-Prostheses. It is technological interfaces between a machine (usually a computer) and the brain of a user.

Feature extraction and classification methods are playing important role in any BCI system. Since any misclassification and error may cause a wrong signal. To make decision about the classification method, it is essential to know what the features are, what is their application and in which way they may help classification. . A better classification result is also reported by combining adaptive radial-basis function (ARBF) and AAR especially with PCA and LDA as classifiers [6]. For classification and analyzing EEG signals different method have been proposed ,namely, neural networks [7], statistical methods [8], autoregressive model [9][10], mixture of densities approach [11], independent component analysis [12], time-frequency analysis [13], Bayes quadratic, Hidden Markov Model, and Linear Discriminant Analysis(LDA)[14].

II. MATERIALS AND METHODS

A. *EEG Data collection*

The data was obtained from a source[1].There were 7 subjects. Subjects performed five trials of each task. The EEG recorded over 7 channels with electrodes positioned at C3, C4, O1, O2, P3, P4 and EOG according to the 10-20 system of electrode placement left eye[2]. The four tasks are:

The base line task- the subjects were asked to relax in this task.

The letter task- the subjects were instructed to mentally compose a letter to a friend or relative without vocalizing.

The math task- the subjects were given multiplication problems, such as 49 times 78, and were asked to solve them without vocalizing or making any other physical movements.

The geometric figure rotation- the subjects were asked to visualize a particular three-dimensional block figure being rotated about an axis.

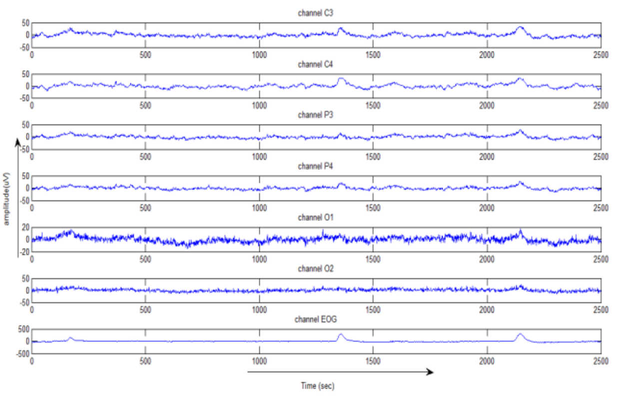


Figure 1 : EEG signal under Baseline task

B. *Signal Preprocessing*

The mean and any linear trend in the data were removed before multiplying the signal with a window. Hamming window was used. Band Pass filter was used with 1Hz low cut off frequency and 35Hz high cut off frequency. The objective of filtering is to improve the quality of a signal.

International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
Volume 2 Issue 4, pp : 256-259 1 April 2013

C. Analysis of EEG Signals

The frequency content of EEG signal provides useful information than time domain representation. The wavelet transform gives us multi-resolution description of a nonstationary signal. EEG is non stationary signal hence wavelet is suited for EEG signals [5]. At high frequencies it represents a good time resolution and for low frequencies it represents better frequency resolution. This multi-scale feature of the Wavelet allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The procedure of multiresolution decomposition of a signal x[n] is schematically shown in Fig.2.

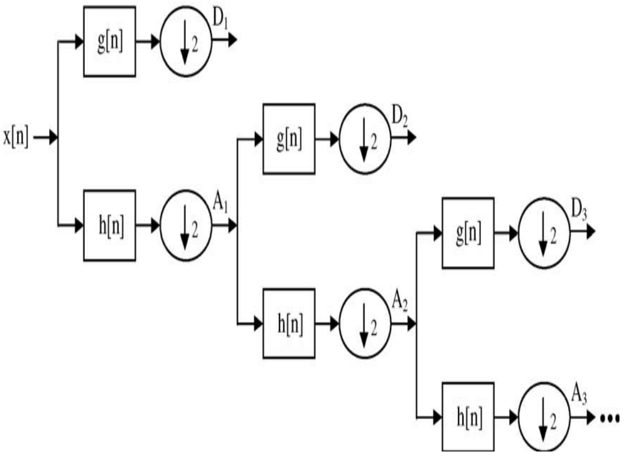


Figure 2: Subband decomposition of discrete wavelet transform implementation; g[n] is the high-pass filter, h[n] is the low-pass filter [3]

The wavelet coefficients were computed using daubechies wavelet of order 2 because its smoothing features are more suitable to detect changes in EEG signal. In the present study, the EEG signals were decomposed into details D1-D4 and one approximation A4. The decomposition of the signal leads to a set of coefficients called wavelet coefficient. Down sampled outputs of high pass filters produces detail wavelet coefficient (D1) and that of low pass filters produces approximation wavelet coefficients(A1).

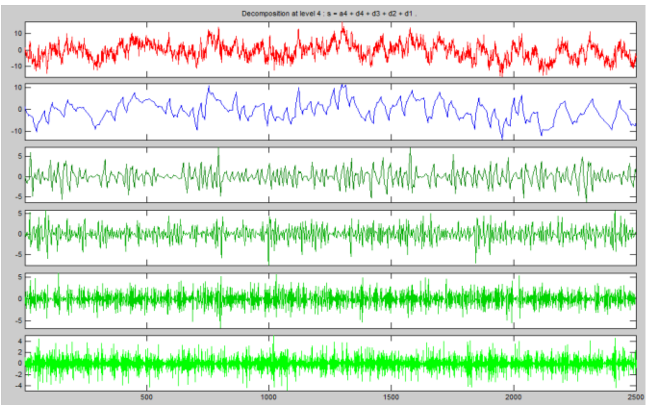


Figure3: Wavelet Decomposition of EEG Signal at different levels

D. Classification Methodology

The classifier proposed for classification of the EEG signals was implemented by MATLAB software package (MATLAB with neural networks toolbox). The One-Step-Secant (OSS) is an approach to bridge the gap between the conjugate gradient algorithm and the quasi-Newton (secant) approach. The OSS approach doesn't store the complete Hessian matrix; it assumes that at each iteration the previous Hessian was the identity matrix. This also has the advantage that the new search direction can be calculated without computing a matrix inverse . To evaluate the performance of the classifier, classifier was trained by 60% of total data set called training sets and remaining 40% of total data set used as testing sets. The test set were created in the same way as training set and they were formed from the EEG signals that were not used for training. The test sets were used to measure the performance of the network after the training.

There are one input layer, two hidden layers and one output layer. The Specifications for the neural network employed for the classification of EEG signals are given in Table I.

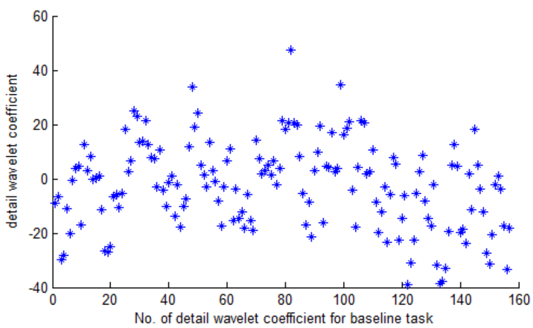
TABLE I
NETWORK DESIGN AND SPECIFICATIONS

S.No.	Parameters	Value
1.	Type of network	Feed forward
2.	No. of Neurons in the first hidden layer	15
3.	No. of Neurons in the second hidden layer	10
4.	Performance function	MSE
5.	Training Function	TRAINOSS
6.	Activation Function in the hidden layers	Tan – Sigmoid
7.	Activation Function in the output layer	Linear
8.	Maximum no. of epochs	3000
9.	Goal	0.00000001
10.	Maximum step	100

III. RESULTS AND DISCUSSIONS

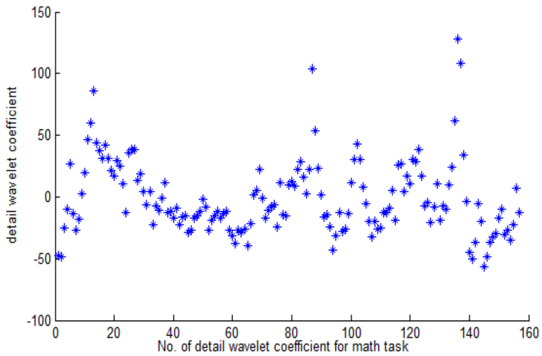
A. Feature Extraction

The detailed wavelet coefficients of EEG segments under different mental task condition at the fourth decomposition level is shown in the following figures.

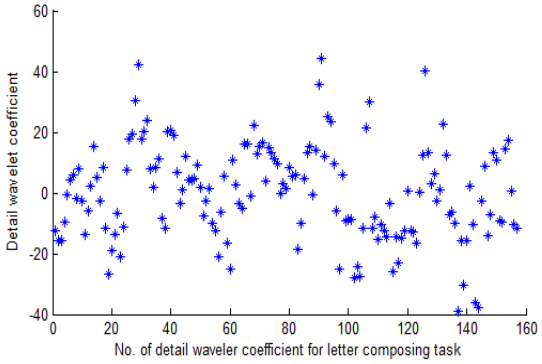


(a)

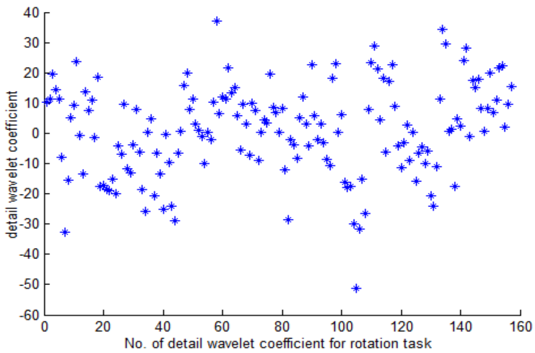
International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
Volume 2 Issue 4, pp : 256-259 1 April 2013



(b)



(c)



(d)

Figure 4: (a),(b),(c) and (d) Plots for Discrete wavelet coefficients for baseline task, math task, letter composition task and rotation task respectively

The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency band. Therefore, the computed detail and approximation wavelet coefficients of the EEG signals were used as the feature vectors representing the signals.
There are no. of wavelet coefficients. In order to reduce the dimensionality of the feature vectors, statistics over the set of the wavelet coefficients were used. The following statistical features were used to represent the time-frequency distribution of the EEG signals:
(i) Maximum of the wavelet coefficients in each subband.
(ii) Minimum of the wavelet coefficients in each subband.
(iii) Mean of the wavelet coefficients in each subband.
(iv) Standard deviation of the wavelet coefficients in each subband.
These feature vectors, which were calculated for the D1–D4 and A4 frequency bands.

B. Classification

The neural networks performance in our classification process is evaluated by means of Mean Squared Error. The MSE is computed by taking the differences between the target and the actual neural network output, squaring them and averaging over all classes and internal validation samples. As the neural network is iteratively trained, the MSE should drop to some small, stable value. Each neural network has its MSE plotted independently. The Training graph between the number of epochs and error performance is shown as in Fig 5.

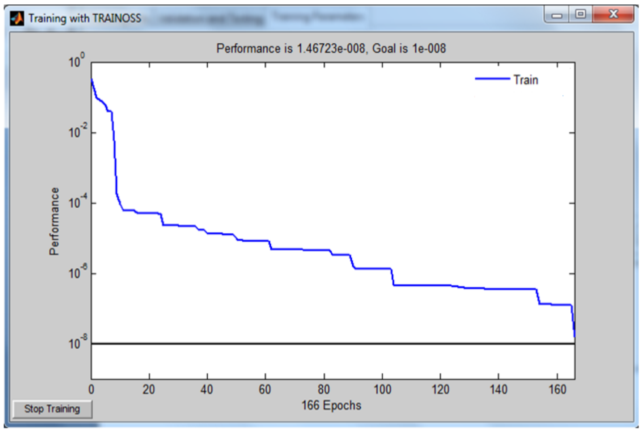


Figure 5: Network training graph

C. Classification Accuracy

The classification accuracy has been calculated as total number of task identified correctly divided by total number of tasks presented from testing set. The percentage accuracy of classification achieved using one step secant algorithm is found to be good and well suited for BCI applications.

TABLE II

CLASSIFICATION ACCURACY

Name of Mental Tasks	**Classification Accuracy**
Baseline Task	98%
Multiplication Task	92%
Letter Composing Task	92%
Rotation Task	96%

IV. CONCLUSIONS

The visual inspection of the four classes of EEG signal does not provide much information. Feature extraction was done using discrete wavelet transform. EEG signals were decomposed upto level four using daubechies wavelet of order 2. Wavelet coefficients were computed. Mean, maximum, minimum and standard deviations of the wavelet coefficient were estimated. These wavelet feature vectors were serve as input to classify EEG mental tasks using neural network. For classification back propagation feed forward with one step secant algorithm was employed. This trained neural network gave good performance at 166 epoch. The percentage of classification accuracy of network was found 92% to 98%. Finally the EEG signals was successfully classified.

ACKNOWLEDGMENT

The author thanks the management of Motilal Nehru National Institute of Technology, Allahabad for providing the necessary facilities to undertake the above work.

REFERENCES

I. http://www.cs.colostate.edu/~anderson

II. [The "10-20 System" of Electrode Placement. http://faculty.washington.edu/chudler/1020.html

III. [İnan Güler, Elif Derya Übeyli, (2005) "Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients", Journal of Neuroscience Methods, Vol. 148, Issue 2, 30 October, 113-121.

IV. [http://www.mathworks.in/help/toolbox/wavelet/gs/f3-998390.html

V. [Elif Derya Übeyli,(2009), "Statistics over Features: EEG signals analysis", Computers in Biology and Medicine, Vol. 39, Issue 8, 733-741.

VI. [Jeybalan V., Samraj A.,Chu Kiong A.(2008), "Motor Imaginary Signal Classification using Adaptive Recursive Bandpass Filter and Adaptive Autoregressive Models for Brain Machine Interface Designs," International Journal of Biological and Medical Sciences.

VII. [Qiu W., Fung K. S. M., Chan F. H. Y., Lam F. K., Poon P. W. F., and Hamernik R. P. (2002), "Adaptive filtering of evoked potentials with Radial-Basis-Functions neural network prefilter," IEEE Trans. Biomed. Eng., vol. 49, 225-212.

VIII. [Borisoff J. F., Mason S. J., Bashashati A., and Birch G. E.(2002),"Brain-Computer Interface design for asynchronous control applications: improvements to the LF-ASD asynchronous brain switch," IEEE Trans. Biomed. Eng., vol. 51, June,.985-993.

IX. [Peters B. O., Pfurscheller G., and Flyvjberg H.(2001). "Automaticdifferentiation of multichannel EEG signals,"IEEE Trans. Biomed. Eng., vol. 48 (1), Jan. 111-16.

X. [Coyle D., Prasad G., and McGinnity T. M.(2005) "A time-series prediction approach for feature extraction in a Brain-Computer Interface," IEEETrans. Neur. Syst. Rehabil. Eng.,vol. 13, Dec, 461-467.

XI. [Bigan C., Ungureanu C., Strungaru R., and Lazarescu V.(2002),"Mixture of Densities Approach for EEG Signals Source Separation," in Proc. 2nd European Medical&Biological Engineering Conference, Vienna, Austria, December,604-605.

XII. [Jung T. P., Making S., Westerfield M., Townsend J., Courchesne E., Sejnowski T. J., (2001)."Analysis and visualization of singletrial event-related potentials," Human Brain Mapping, vol. 14, Nov. 166-185.2001.

XIII. [Bostanov V.,(2004). "BCI Competition 2003-Data sets Ib and IIb,"Feature extraction from Event-Related brain potentials with the continuous wavelet transform and t-Value scalogram,"IEEE Trans. Biomed. Eng., vol. 51, June. 1057-1061.

XIV. [Piotr Olejniczak (2006), "Neurophysiologic basis of EEG", Journal of Clinical Neurophysiology, vol.23, 186-189.