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EEG Mental Tasks Classification Using Neural Networks

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Abstract— BCI (Brain Computer Interface) is the method of communication between neural activity of the human brain and an external device. The activity of the brain can be interpreted in terms of an EEG (Electroencephalogram) signal. This paper aims at classifying mental tasks by processing the EEG signal recordings recorded using sensors place on the scalp according to the Ten-Twenty Electrode system, performing wavelet decomposition and classifying it using different recurrent neural networks. The neural networks were trained and tested for all the five tasks and for combination of two task pairs. The accuracy of classification during comparison for all five tasks was found to be 82.33% and average accuracy for two task pairs was 99.5%.

Index Terms— Brain computer interface (BCI), Electroencephalogram (EEG), Mental tasks, Wavelet decomposition, Resilient backpropagation network, Scaled conjugate gradient network, Ten-Twenty electrode system.

1 Introduction

A Brain Computer Interface (BCI) is a means of communicating with the external world without the general established methods of the brain's external pathways and peripheral nerves. Thus BCI systems play a crucial role for people with severe disabilities and neuro-muscular disorders. These systems make use of the cognitive and sensory abilities of a person to derive information and restore communication with the external world. There are two different types of BCIs - Invasive BCIs and Non-Invasive BCIs. Among the two, non-invasive BCIs use the Electroencephalogram (EEG) signals recorded by various sensors strategically placed on the scalp to record neural activity. Brain development and learning are unique to each individual and hence no BCI system can be developed that works for all users, right from the start. As a result, achieving high level of accuracy in a BCI involves a process of integration and requires training of brain activity in a predetermined method.

The EEG signal measured with the help of electrodes on the scalp consists of summation of thousands of neurons fired simultaneously. As a consequence, the magnitude of the EEG signal is less dependent on the total neural activity of the brain. The focus is instead on how synchronous that activity is. In this paper, features are extracted for five mental tasks using wavelet transform. These features were then used to train the neural net to perform accurate classification of all five tasks as well as task combination pairs. The output of this BCI can then be used to translate into a two way conversion mode to control external devices. It can serve as a communication channel for patients with neuro-muscular disorders or movement impairments.

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2 Methodology

The methodology consists of experimental dataset, feature extraction, neural networks and classification using neural network toolbox.

2.1 Experimental Data

The EEG dataset used for this study was obtained by Keirn and Aunon [2], [3]. This dataset was formed by recording EEG signals from seven subjects. A 10-20 system of electrode placement was used and the electrodes namely C3, C4, P3, P4, O1 and O2 recorded the neural activity of the subjects and two reference electrodes A1, A2 were used to record the eye blink artifacts. These electrodes were connected to amplifiers and were bandpass filtered from 0.1-100 Hz. Sampling rate of 250 Hz was chosen. A total of five tasks performed by the seven subjects were analyzed. The five tasks performed were:

1. *Baseline Task*: In this task the subject was made to relax under normal conditions and not think of anything. This task is used as a base for comparison with other tasks.
2. *Problem solving*: The subject is given any mathematical problem such as multiplication and he solves it mentally without any physical action.
3. *Figure Rotation*: The subject is shown a 3D object and is asked to perform rotation mentally about a particular axis.
4. *Letter composing*: In this case the subject is asked to compose a letter to a friend mentally without any vocal or written action.
5. *Visual counting*: This task involves the subject to visualize a blackboard and numbers appearing on it one after the other. The subject has to mentally count these numbers.

The signals were recorded for duration of 10 seconds for each task. Each of the trial resulted in a total of 2500 samples per trial. The subjects attended two sessions and in each session the task was repeated five times. Thus a total of 10 trials per

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task were performed.

2.2 Feature Extraction

Feature Extraction is an essential step towards classification because it defines the given class of data with optimal number of samples, thus reducing the dimensionality of the original data. In this paper wavelet transform was used for the process of extracting features. Other researchers have used Autoregressive models [4], Independent Component Analysis (ICA), Principle Component Analysis (PCA) for the purpose of feature extraction [5].

The Wavelet Transform provides a more flexible way of time-frequency representation of a signal by allowing the use of variable sized windows. Due to this, the wavelet transform gives accurate frequency information at low frequencies and accurate time information at high frequencies [6]. This makes the WT suitable for analysis of irregular data patterns, such as impulses occurring at various time instances.

Additionally, the Wavelet Transform provides multi-resolution description of non-stationary signals like the EEG. Discrete Wavelet transform (dwt) was computed using the following formula:

For a given EEG signal f(n), having dilation parameter $a=1/2^s$ and translation parameter as $b=k/2^s$ where k, s $\in$ Z; the dwt is given as

$$DWT\left(\frac{k}{2^s},\frac{1}{2^s}\right) = 2^{\frac{s}{2}} \sum_n f(n)\,\varphi(2^s n - k) \quad (1)$$

The wavelet tree decomposition of experimental data into 4 levels and their corresponding frequency ranges are as shown in fig.1.

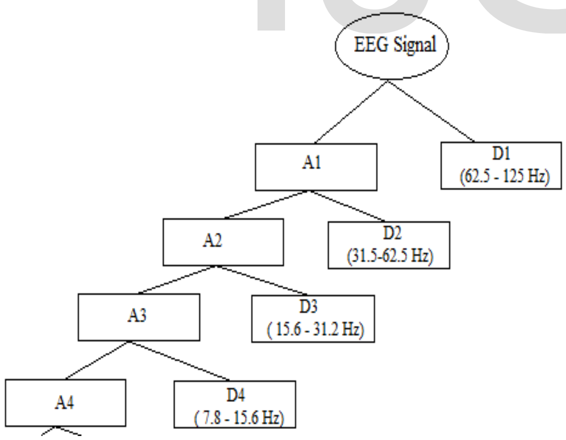

Fig. 1. Wavelet tree decomposition of EEG into four levels and their respective frequency ranges.

In this paper the EEG signals procured from six electrodes for five mental tasks are considered. The eye blink artifacts were not removed and are considered as a part of the signal feature. The samples from each trail were divided into half second segments to effectively decompose the data and retain information of the recordings. This method helps in reducing the dimensionality of the data without having to perform complex approximations later [7]. In this research, mother wavelets like haar, db2, db3, db4, db5, db6, db7, db8, db9, db10, sym4, sym5, sym6, sym7, sym8, sym9 and sym10 were used for a comparative study. The power spectrum, energy, variance, energy, and mean of the signal are extracted as features. Energy provided the best results hence energy was selected as the feature. Four details and one approximation were selected and 2500 samples were decomposed into 36 samples. Discrete wavelet energy is computed for half second segments of EEG data. For each of these segments, signals are decomposed into approximation and details.

The feature extractions algorithm uses the following procedure: X= sample data of 10 seconds. X is partitioned into 0.5 second windows. Perform wavelet transform on each window. Repeat the above steps foe each trial.

Thirty-six features are extracted for each subject per task pair combination per trial. The features extracted for ten such trials are used to train and test the neural network.

2.3 Neural Networks

The main aim of pattern recognition algorithms is to classify signals of interest into the correct class among a group of specified classes or tasks. These signals of interest are EEG signals and the problem objective is to classify them into one of the five tasks performed. For this purpose, artificial neural networks were selected.

In this paper two algorithms are used for performing classification of five mental tasks namely – scaled conjugate gradient algorithm and resilient backpropagation algorithm.

1) *Scaled Conjugate Gradient* (SCG) *algorithm* – It's a second order conjugate algorithm which helps in minimizing the goal functions of several variables. It uses a step size scaling mechanism which makes it faster than other second order algorithms by avoiding line search per learning iteration.
2) *Resilient Backpropagation Algorithm* – The main advantage of using this algorithm is to eliminate the harmful effects of partial derivatives encountered in other algorithms like the steepest descent algorithms. It uses the sign of the derivatives to determine the weight change; whereas the magnitude is determined by a separate update value. As a result, the algorithm becomes transparent and has a powerful adaption process having the advantage of effective computation with respect to storage consumption and time [8].

2.4 Classification using Neural Network Toolbox in MATLAB

In order to carry out classification using the MATLAB toolbox the network, activation function, weights and biases are initialized [9]. The data is divided randomly into three parts: 75% training, 15% validation and 15% testing. Subsequently the result simulated by the network was tested against the measured input data and the error rate was calculated. The final validation was then carried out with the individual data. Different MATLAB commands were used to generate the network and also the test results.

In this paper, a feedforward neural network with one hidden layer consisting of 10 neurons was implemented. Number of neurons in the output layer was 5 for all task combinations and 2 for only two task combination pairs. There were 36 input neurons present.

The fig.2 below represents the network implemented.

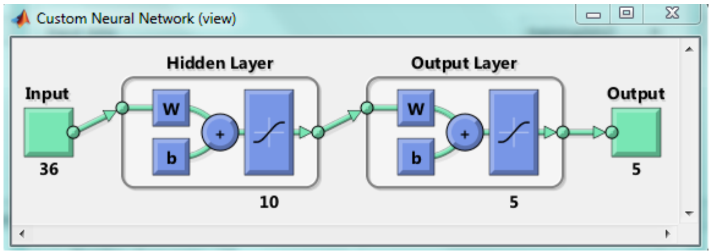

Fig. 2. Neural network architecture for classification of five tasks.

3 Results

Neural network was formed and trained using nntraintool GUI in MATLAB. Data was divided randomly into training, validation and testing using dividerand command.
The analysis of the results obtained indicated that maximum accuracy of classification was achieved using db4 wavelet for scaled conjugate gradient algorithm as well as resilient back-propagation algorithm for subject 1 and subject 2. In case of subject 1 it reached 90.4% accuracy using resilient backpropagation and for subject 2 it was 86.6%; these results were obtained for all five mental tasks combination.

Table 1
Percentage Accuracy of all five tasks using mother wavelets and two training algorithms

	Subject 1		Subject 2	
Mother wavelet	Scaled Conjugate Gradient algorithm	Resilient back-propagation	Scaled Conjugate Gradient algorithm	Resilient back-propagation
Name	Accuracy (%)	Accuracy (%)	Accuracy (%)	Accuracy (%)
db2	72	75	66.7	72
db3	32	35	70.7	71
db4	88.8	90.4	85.4	86.6
db5	62.7	60	78.3	79
db6	84	83	77.3	72
db7	85.3	87	80	78
db8	65.3	67	68	69.5
db9	69.3	70.7	84	85
db10	78.7	78.9	73	75.5
sym4	64	66.8	65.6	65.5
sym5	58.7	66.5	65.3	69.2
sym6	50.7	55.5	76	75.5
sym7	82.7	88	72	75.5
sym8	76	80.5	85.20	84
sym9	77.3	75.6	66.7	69
sym10	58.7	55.5	64	70.2
haar	73.3	70.5	70.8	71.5

The confusion plots of results obtained are shown in fig.3a and fig.3b. They indicate the percentage of correctly classified EEG data based on the training algorithm used for developing the network.

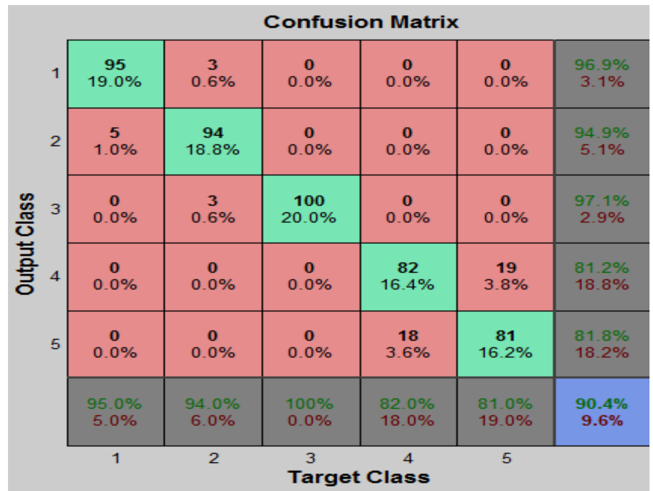

Fig. 3a. Output for subject 1-'db4-rprop'

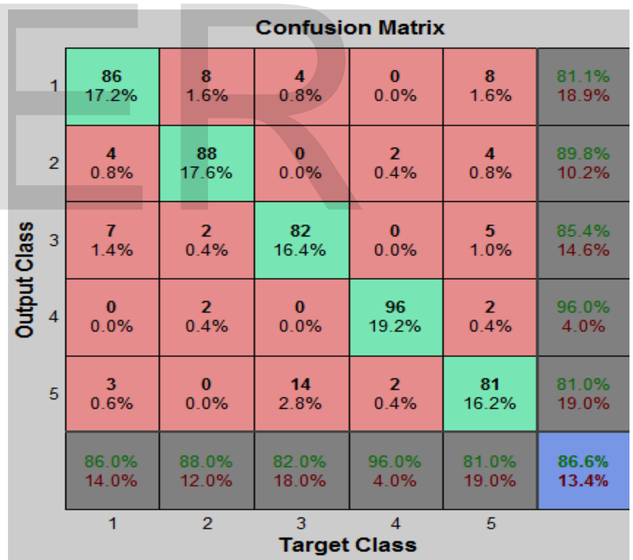

Fig. 3b. Output of subject 2-'db4-rprop'

The neural networks were also trained for two task combination pairs for subject 1 and 2. The classification accuracy obtained for two task pairs is higher than that for all five tasks. For this classification only db4 wavelet was used and energy was selected as a feature. The best task combination pair was task 1 and task 4(Baseline and Figure rotation). It showed almost 100% accuracy for both subjects 1 and 2.

The minimum error rate was achieved by resilient backpropagation algorithm. Beside the good performance, it is one of the fastest functions in pattern recognition. Acceptable performances were observed for scaled conjugate gradient algorithm but with a higher number of iterations.

Task combinations:
Task 1: Baseline
Task 2: Multiplication
Task 3: Letter- Composing
Task 4: Rotation
Task 5: Counting

Table 2
Percentage accuracy of db4 mother wavelet for different task pairs using two training algorithms

	Task(1,2) Accuracy (%)	Task(1,3) Accuracy (%)	Task(1,4) Accuracy (%)	Task(1,5) Accuracy (%)
Subject1 SCG	94.5	92.5	97.5	96.5
Subject1 rprop	97.5	99.5	100	99.5
Subject2 SCG	96	90.5	95.5	93.5
Subject2 rprop	97	91	99	98.5

The receiver operating characteristics for five task classification for subject 1 is shown in fig.4.

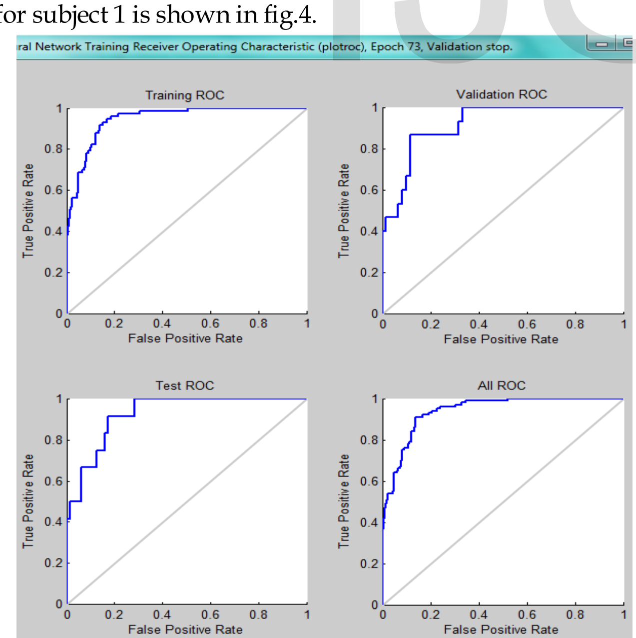

Fig. 4. Receiver Operating Characteristics.

4 Conclusion

The main aim of the project was to develop the framework of a BCI system such that provided with appropriate inputs it can correctly classify mental tasks within a particular error limit.

The analysis of different wavelet bases showed that daubechies wavelet (db4) proved to be the best discrete wavelet function which can be used to extract EEG features. Furthermore, a comparative study of two neural networks i.e. Scaled Conjugate Gradient algorithm and Resilient Backpropagation algorithm concluded that resilient backpropagation was best in terms of accuracy as well as rate of convergence.

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