Wheel Chair Control With EEG Signal using Multilayer Perceptron Neural Network

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***Abstract*— in this paper we have designed a Brain Computer Interface using EEG signals. This paper presents an approach to classify EEG Signals by implementing Multilayer Perceptron Neural Network (MLPNN) and back propagation algorithm. Feature extraction of the signal is done using wavelet transformation. The EEG signal acquisition is done through non-invasive International 10/20 system. The input sample consists of five mental tasks that are mapped to motions of wheel chair prototype. It is a small robot driven by micro-controller Atmega 16 and stepper motors. In this paper we identify the parts of the brain with maximum EEG activity with respect to the mental tasks. The system results in 68.75% accuracy in real-time operations. There is no significant time lag. The reason for low accuracy is discussed; major one identified as small number of samples for training and testing.**

Keywords—Artificial Neural Networks, Multilayer Perceptron, Back propagation algorithm, Wavelet transformation, EEG Signal acquisition, 10/20 System, Bascom, Matlab, Machine Learning, Brain Computer Interface

I. INTRODUCTION

Our research is motivated by a desire to help the paralyzed and injured people to control their movements using the brain. Along with mobility, we hope to bring about a sense of independence to people with motor disabilities. In this paper we have designed a Brain Computer Interface using EEG signals. This paper presents an approach to classify EEG Signals by implementing Multilayer Perceptron Neural Network (MLPNN) and back propagation algorithm. The EEG signal acquisition is done through non-invasive International 10/20 system. The input sample consists of five mental tasks as follows: Complex arithmetic calculation, Simple arithmetic calculation, imagining rotation, imagining right hand movement and relaxed state. The 5 classes are mapped to 4 motions of the wheel-chair prototype: forward movement, backward movement, left rotation, right rotation and a stop command. Feature extraction of the signal is done using wavelet transformation bearing in mind that the signal is non-stationary. MLPNN has 2 hidden layers with sigmoid nodes. Number of nodes in the input layer is decided dynamically depending on the output of the wavelet transformation, i.e. wavelet coefficients. The output layer has 5 binary nodes each indicating the five classes.

The wheel-chair prototype is driven by micro-controller Atmega 16 and stepper motors. Micro-controller is programmed using Bascom and feature extraction and classification is implemented in MATLAB. The process is explained in Fig. 1.

In this paper we identify the parts of the brain with maximum activity for the specified tasks, for ex. Rotation task has maximum activity in f4 electrode region (right side of the frontal lobe). The system results in 68.75% accuracy in real-time operations. There is no significant time lag. The reason for low accuracy is discussed; major one identified as small number of samples for training and testing. The system can be made robust and tested better with more number of data samples.

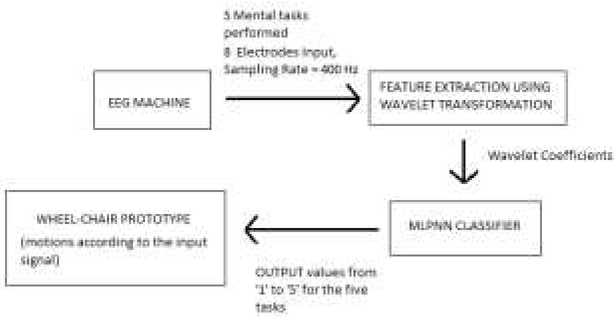

Fig. 1. Block Diagram of the classification process

II. SIGNAL ACQUISITION

A. International 10-20 System Setup

EEG signal acquisition is done non-invasively using International 10-20 system. The acquisition is done by placing electrodes on the scalp using conductive gel or paste to reduce impedance. Electrodes are placed at points that are 10% and 20% of inion-nasion distance. In Fig. 2, the letters F, T, C, P, and O stand for Frontal, Temporal, Central, Parietal and

Occipital. Even numbers (2 and 4) refer to the right hemisphere and odd numbers (1 and 3) refer to the left hemisphere.

EEG machine uses differential amplifier to produce each channel activity. The setup in which electrodes are connected is called montages. We have used Common Reference Montage with M1 and M2 as common reference and channels are as follows: F3-M1, C3-M1, P3-M1, O1-M1, F4-M2, C4-M2, P4-M2 and O2-M2. EEG recorded is the gross neural activity between two electrodes placed on the scalp.

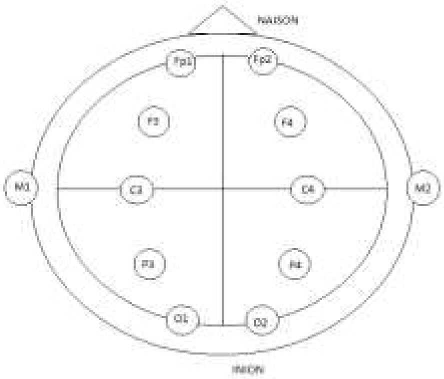

Fig. 2. 10-20 International System Electrode Setup

B. *Mental Task Recording*

The input data set consist of one subject. Subject has 5 mental tasks to perform. Each task has 50 samples of one second each. Sampling rate is 400Hz; therefore the maximum frequency component that can be present is 200Hz. In Fig. 4, we can also see a peak at 50 Hz due to the fact that electricity is supplied at 50Hz in India, which interferes with the EEG Signal.

Subject was laid on a bed with eyes closed, Fig 3. Following tasks were performed:

1. Complex Arithmetic Calculations (ARTH C): Multiplication of two digit numbers.
2. Simple Arithmetic Calculations (ARTH S): Multiplication of single digit numbers.
3. Imagining Rotation (ROTATION): A rotating object graphic is first displayed to the subject on a screen, then the same rotation is imagined.
4. Imagining Right Hand Movement (MOVE): Right hand of the subject is imagined to move in the upward direction.
5. Relax (RELAX): Brain is in relaxed state.

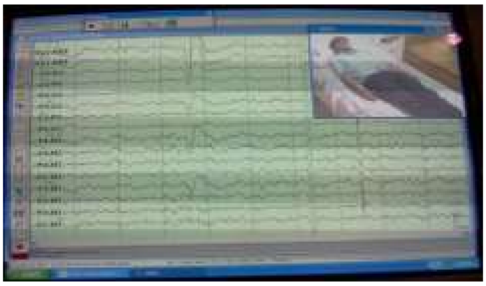

Fig. 3. EEG Acquisition

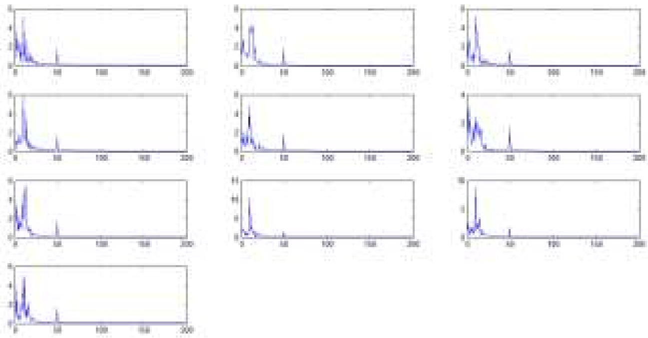

Fig. 4. Frequency bands of 10 samples of brain in relaxed states

C. *EEG Signal Frequency Bands*

The EEG Signal is divided into four major frequency bands as shown in Table I. All the tasks were assumed to affect the signal in alpha range only.

Fourier transform of every sample of all five classes are calculated for all electrodes. The maximum frequency component for each sample is taken and average for each class is calculated. Fig. 5 shows average of the maximum frequency component. We observe the areas of the brain with relatively more significant EEG activity for each task.

TABLE I. EEG SINGAL ACTIVITY AND THEIR FREQUENCY BANDS

EEG activity	***Frequency Range(Hz)***
Alpha (α)	8 – 13
Beta (β)	14 – 30
Theta (θ)	4 – 7
Delta (δ)	< 3

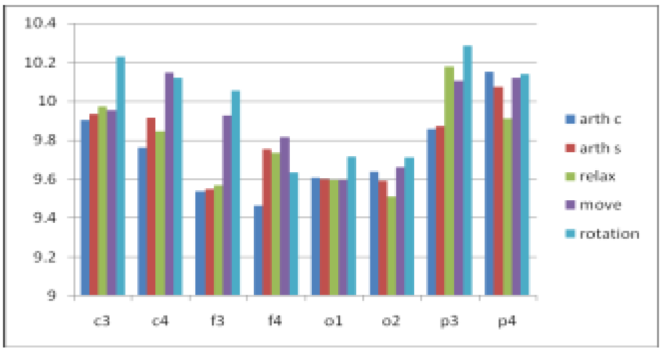

Fig. 5. Average Maximum Frequency Component for each class

III. FEATURE EXTRACTION

Feature extraction is required to extract relevant information from the huge input dataset. Input data of a sample consists of around 800 sample points. These are converted into 17-27 wavelet coefficients.

Fourier transform are not suitable for non-stationary signals (whose frequency change with time) [3]. Fourier Transform simply presents the frequency components in the signal, but have no information at what instances these frequencies occur. Wavelet transform is capable of providing time and frequency information simultaneously.

Wavelet transform is not discussed extensively in this paper. The idea and use is borrowed from [1] and implemented in our process as feature extraction.

Biorthogonal 3.7 wavelet is used as mother wavelet. In Fig. 6 we can see frequency component range of detailed coefficients at fifth level of transformation is 6.25 to 12Hz, which is approximately the alpha range. The same is shown in Fig. 8. These coefficients are passed through MLPNN.

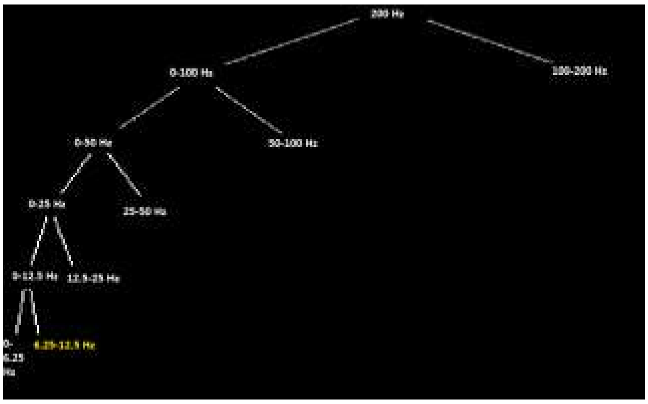

Fig. 6. Wavelet Tree

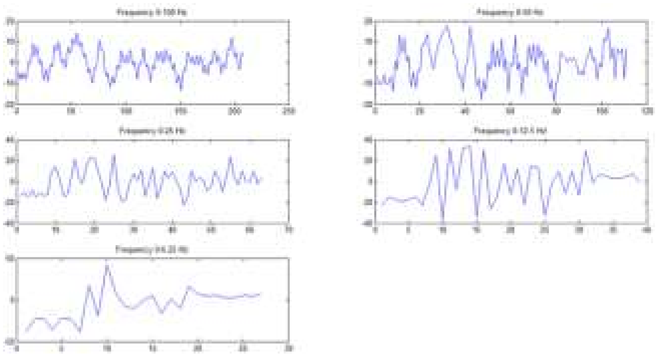

Fig. 7. Approximate Wavelet Coefficients

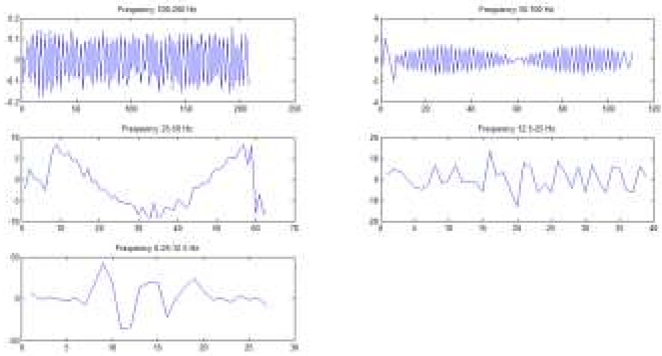

Fig. 8. Detailed Wavelet Coefficients

IV. CLASSIFICATION

We are using MLPNN with two hidden layers. The weights are trained by Back Propagation algorithm. Wavelet coefficients extracted in feature extraction are fed to the neural network as input. The output from MLPNN is further fed to the wheel-chair prototype.

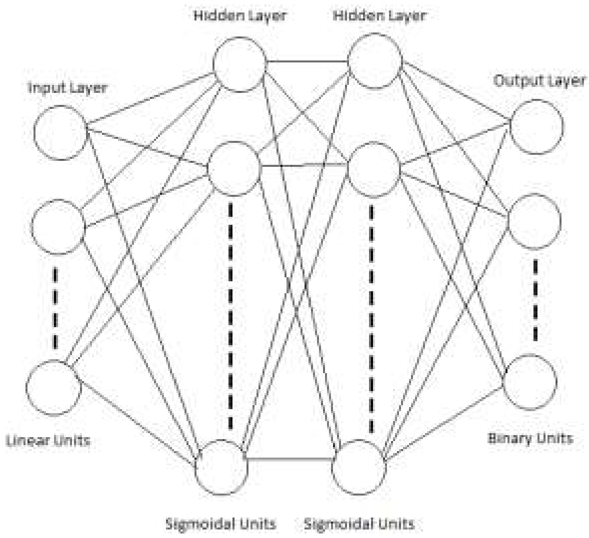

Fig. 9. MLPNN Network

A. *Multi-Layer Perceptron Neural Network (MLPNN)*

Artificial Neural Network (ANN), inspired by biological nervous system is composed of layers of large number of nodes or processing units. The processing unit consists of two parts -a summing part and an activation function. Summing part receives weighted input values and computes the sum known as activation value. The output of the node is determined by the activation function which generally is linear, sigmoid or binary. The weights on connecting links determine the output. The error between the expected output and computed output is used to update the weights through any of the various learning laws. The weights combined forms a weight vector which when computed with input vector to give output vector. [4]

MLPNN is a feed-forward neural network with multiple layers. The architecture is shown in Fig. 9. Designed network for this research has:

1. One input layer with linear function as activation function.
2. The number of nodes in input layer is equal to the number of wavelet coefficients obtained from wavelet transformation.
3. Two hidden layers are used with activation function as sigmoid functions. The number of nodes in hidden layers is equal to number of nodes in input layer.
4. Output layer has five nodes with binary activation function.
5. Learning Parameter is 0.01.

B. Back Propogation Algorithm

The below algorithm is discussed in [2]. Let us assume the below structure of the MLPNN,

$$x^0 \xrightarrow{W^1, b^1} x^1 \xrightarrow{W^2, b^2} \cdots \xrightarrow{W^L, b^L} x^L \tag{1}$$

Where X^l is the l^{th} layer where l=0, 1…L. X^l has n_l number of nodes. W^l is the weight matrix of size n_{l-1} x n_l. b_l is the bias vector.

Back Propagation consists of following steps:

1. Forward Pass: The input vector x^0 is transformed into output vector x^L, by evaluating the equation:

$$x_i^l = f(u_i^l) = f\left(\sum_{j=1}^{n_{l-1}} W_{ij}^l x_j^{l-1} + b_i^l\right) \tag{2}$$

2. Error Computation: The difference between the desired output d and actual output x^L is computed.

$$\delta_i^L = f'(u_i^L)(d_i - x_i^L) \tag{3}$$

3. Backward Pass: The error signal at the output units is propagated backwards through the entire network, by evaluating,

$$\delta_j^{l-1} = f'(u_j^{l-1}) \sum_{i=1}^{n_l} \delta_i^l W_{ij}^l \tag{4}$$

4. Learning updates: The weights and biases are updated using the results of forward and backward passes,

$$\Delta W_{ij}^l = \eta \delta_i^l x_j^{l-1} \tag{5}$$

$$\Delta b_i^l = \eta \delta_i^l \tag{6}$$

These are evaluated for l = 1 to L.

C. Implementation

We have taken 40 samples of each task for training the MLPNN. The rest 10 are for testing. The MLPNN is trained re-iteratively with these samples. The input class and the output are mapped as shown in Table II.

TABLE II. INPUT CLASS – OUTPUT LAYER MAPPING

Input Class	*Output Layer MLPNN*
ARTH C	{**1**,-1,-1,-1,-1}
ARTH S	{-1,**1**,-1,-1,-1}
RELAX	{-1,-1,**1**,-1,-1}
MOVE	{-1,-1,-1,-1,1}
ROTATION	{-1,-1,-1,-1,**1**}

V. HARDWARE IMPLEMENTATION

Wheel-Chair prototype consists of Atmega 16 microcontroller and stepper motors as shown in Fig. 10. Atmega 16 is serially connected to MATLAB. IC Max232 is used for interfacing microcontroller and RS232 of the computer/laptop. L293D ICs are used to interface microcontroller and motors. Two power supplies are used, 5V to microcontroller and 12V to stepper motors. The microcontroller is programmed using Bascom. The program instructs microcontroller to drive motors in various directions according to the serial input which are ASCII values from 1 to 5.

TABLE III. MAPPING OF MLPNN OUTPUT, MICROCONTROLLER INPUT AND ROBOT MOTION

Input Class	*MLPNN Output*	*Microcontroller Input*	*Robot Motion*
ARTH C	{**1**,-1,-1,-1,-1}	1	Forward
ARTH S	{-1,**1**,-1,-1,-1}	2	Backward
RELAX	{-1,-1,**1**,-1,-1}	3	Stop
MOVE	{-1,-1,-1,-1,1}	4	Right Rotation
ROTATION	{-1,-1,-1,-1,**1**}	5	Left Rotation

Fig. 10. Wheel-Chair Prototype

VI. Results And Conculsion

MLPNN classifier is tested with accuracy of 68.75%. The low accuracy is attributed to small number of data samples for training and testing. It is also realized that a temporal data is being classified by a static classifier (MLPNN).

It was noted during trials that number of hidden layer or the number of nodes in hidden layer is not proportional to the efficiency of the classifier.

An increase in efficiency of the classifier was noted when the hidden layer nodes were changed to sigmoidal from binary activation function.

Fig. 5 shows the regions with maximum activity in the brain. Maximum activity is seen in parietal and central region. Minimum activity is seen in occipital region.

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References

[1] Neep Hazarika Jean Zhu Chen Ah Chung Tsoi Alex Sergejew, "Classification of EEG Signals Using the Wavelet Transform" ELSEVIER Singal Processing, vol. 59, pp. 61-72, May 1997.

[2] S. Seung, "Multilayer perceptrons and backpropagation Learning", 9.641 Lecture 4: September 17, 2002.

[3] Rodrigo Quian Quiroga, "Quantative Analysis of EEG Signals: Time-frequency methods and Chaos Theory", Institute of Phsiology - Medical University Lubeck, Institute of Signal Processing – Medical University Lubeck, 1998. Available:http://www.vis.caltech.edu/~rodri/papers/thesis.pdf

[4] B.Yegnanarayana," Artificial Neural Network", Prentice-Hall of India Private Limited, India, February 2001