# Facial Controlled Wheelchair Using Multi-layer Perceptron in Time Frequency Domain

Jamal Ahmed, Abdul Majid, Idress Riaz, Sarah Bano , M. Anas & M.Ghazaal

***Abstract*—Non-invasive Electroencephalography (EEG) based Brain Computer Interfaces (BCIs) is a growing technology which provides a possibility for intuitive operation comprising a multi-degree of freedom for upper extremity prosthesis. In this paper, we investigate bio signal classification concerns. Understanding bio signals and perform any action on behalf of it is a difficult task to accomplish. This method comprises of classification, feature extraction of EEG signals and objective was to make process as simple as possible. In this trial we first collected the patterns of four different types of facial activities namely right smirk, left smirk, eye blink and neutral activity. Firstly Samples were preprocessed. Wavelet decomposition is used to extract features from signal and IEMG and MAV are used to make feature vectors. Multilayer perceptron (MLP) and Support vector machines are used for classification. Results suggest that MLP can perform classification task at high accuracy. Our proposed model facilitates patient who are suffering from severe muscle injury and disability. They can freely move around by means of facial muscles regardless of any assistance.**

***Keywords:* BCI, Electencephlography, Motor Neurons Disease, Artificial Neural Network, Multi-Layer Perceptron. IEMG, MAV, SVM**

## I. INTRODUCTION

IN this era of modern world, everything becomes digital. Brain computer interface is one of the emerging technologies of this modern era. BCI was although invented in 1924 by Hans Berger when he discovered the electrical activity of the human brain. A BCI is a combination of techniques for recording brain activity, extracting and processing signals, and translating aspects of the signals into computer commands, which are fed back to the user [1-4].

In this research paper we proposed a model as shown in Fig. 1 to work on Brain signals for the sake of charity for those people who are physically disabled, patients who cannot move their hand or legs with their intentions due to paralyzed or frozen body. These kinds of patients can be helped by various methods. Tool which we have used is Emotiv epoch+ which follows all international standards. Brain computer interface can be used to help such kind of patients. Clinical reports pointed out that approximately 50 % of patients, including paralyzed people are not able to control Electric wheel chair by conventional methods Specially MND patient [5,6]. In this context brain controlled wheel chair is the mobility aid, especially suitable for patients who are paralyzed and cannot control the wheelchairs.

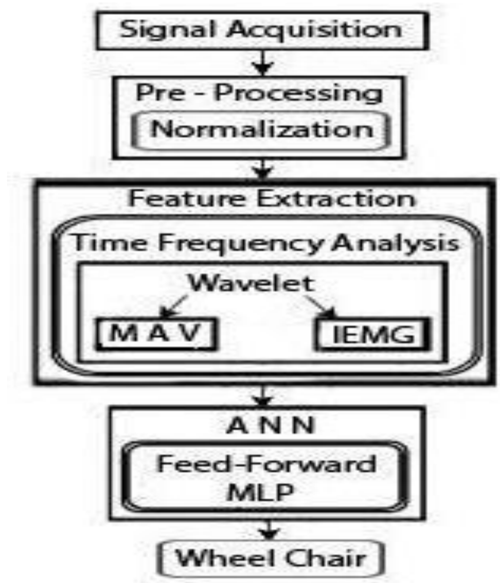


Fig.1: Proposed model for facial controlled wheelchair

There have several studies on controlling wheel chair from brain signal without any manual control [6-9].

To use EEG signal it needs to be filtered from noise which is in this case high frequency EEG signal and also needed to be classified so that the computer can understand it and perform some task on behalf of it. For this purpose we have first collected the signal from brain for four types of activities, i.e. eye blink, left smirk, right smirk and a neutral activity. These signals are acquired using Emotive EPOC Plus Neuro-headset [10] as shown in Fig. 2.

Fig.2: 14 channel Emotiv Epoch Plus headset

## II. PROPOSED MODEL

Patients suffering with Motor Cortex dysfunctioning or sever muscle injures make them liable to others; from eating food to locomotion they are totally dependent. BCI technology is strongest contender to make them self-dependent again. Brain controlled wheel chair is one step to restore patient movement [8][9].Follwing is the explanation of our proposed model

### *A. Data Acquisition:*

Signal acquisition was accomplished by Emotive Epoch Plus, real data set collected from different subjects have been used for this purpose. It is non-invasive device having low cost with very high reputation amongst the high grade research level equipment and the signals acquired by it are highly reliable and sufficient for most of the applications [11-14]. It measures neural activity of the subject with 14 electrodes placed according to the international 10-20 system assisted by Emotiv's graphical user interface known as test bench [10] displays signal as its recorded. The collected data is divided into four classes, class A represent "neutral expression", class B is for "eye blink", class C and class D represent '"left smirk" and ''right smirk'' respectively. Each class contains training data of total 40 seconds captured in the interval of 10 seconds. In every trial new data needed as bio signal varies due to numerous reasons such as tiredness, pain, excitement.

Emotiv headset is made to cover complete EEG signal spectrum but signals of facial muscle movement and eye movement detect with high amplitude and power on frontal electrode which are AF3, AF4, F7 and F8 Each electrode provide 1024 samples per 10 seconds providing data matrix of 1024x4, we recorded total of 40 seconds of data in one trial which consist of 1024x16.

### *B. Pre – Processing:*

To reducing the noise levels in this signal, narrow notch filter of 50Hz is used to remove power frequency interference. Normalization of the signal is done so every signal lie between 0 to 1 this reduce the complexity because each electrode's data has values according to channel spacing set in test bench.

### *C. Wavelet:*

Wavelet Transform is an effective way of representing the time - frequency domain element of the signal. The most important point of WT is that at high frequencies it gives precise information of time and at low frequencies it gives precise frequency information of the signal. In time-frequency analysis Fast Fourier Transform is widely used, but they are not good against non-stationary signals wavelet is specifically appropriate for the non-stationary signals *[15, 16]*. There are two forms of wavelet analysis, i.e. discrete wavelet transforms and continuous wavelet transforms.

- *Continuous Wavelet Transform:*

When the signal x (t) is convolutes with the wavelets function ψs (t) the continuous wavelets is formed

$$CWT_x^{\varphi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\varphi^{\cdot}\left(\frac{t-\tau}{s}\right) dt \quad \textbf{(1)}$$

The above equation is the CWT where ψs (t) is the wider and advance version of wavelet function.

$$\varphi_{\tau,s(t)} = \frac{1}{\sqrt{s}}\varphi\left(\frac{t-\tau}{s}\right) \quad \textbf{(2)}$$

Where **t** is the time parameter, **τ** is the shift parameter and **s** is the scale parameter. Ψτ,s (t) has zero mean which was given in the following equation.

$$\int_{-\infty}^{+\infty} \varphi_{\tau,s(t)dt=0} \quad \textbf{(3)}$$

The significant projecting part of continuous wavelet analysis is the preference of the particular wavelet function Ψτ,s (t). Amid other wavelets functions the Morlet wavelets function is being chosen because it is adeptly fixed in the frequency domain. In accordance to the comparison of the other wavelets the Morlet wavelet function has the identical shape to the signal to be analyzed. *Some reaches. [17,18]*

- *Discrete Wavelet Transform:*

For the division of the signal into rough approximation and brief information at non-identical frequency band to determine the essential feature of signal the discrete wavelet transform is utilized. The DWT is divided into two kinds of stamp function that is scaling function related for low pass filter and wavelets function related to high pass filter. The division of the signal into non identical frequency is achieved by continuous high pass and low pass filtering of primordial signal researches using DWT [15, 16, 19].as presented in Fig.3,

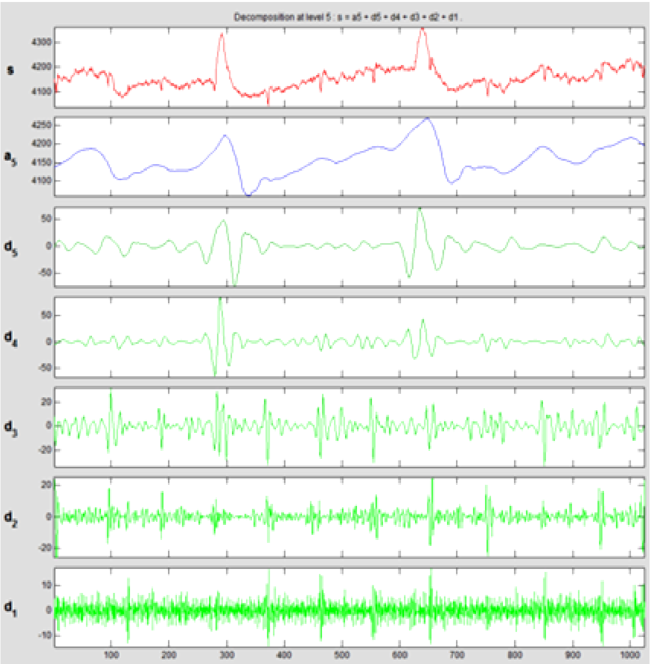

Fig.3: Show the 5 level decomposition of eye blink signal from d1 to d5 and the approximated signal a5.

DWT is fast, more practical then CWT, gives less redundant data. Our research covers DWT, filtered and normalized signal divided into sub bands which is known asoutput which was counted by MSE (mean squared value). The training algorithm RP (Resilient back propagation) is used. It is the network training function which is used to initialized the weight and biases fortuitously. The number of data points in the training sets, the number of weights and biases in the networks, and the error goal can be determine by above discussed training parameter. When it is reached to maximum number of epoch the training process stopped and goal is attained.

Decomposition levels the level that defines the feature of the signal is used for creating feature vectors with MAV and IEMG [19].

*D. Classification:*

In order to choose the most appropriate classifier for a given set of features, the properties and limitations of the available classifiers must be known.

Neural Networks (NN) are the category of classifiers widely used in BCI research (see, e.g., [43] [44). To compare the results of our model we also test SVM classifier considered as the best binary classifier although it can be used as multi classifier with help of one Vs. one strategy.

- *ANN Feed Forward Multi-Layer Perceptron:*

An artificial neural network is computational method based on biological neuronal network of brain. It is widely used in researches for biological signal .A neural network is consisting of nodes and arrow. The fundamental underlying design of ANN includes number of nodes to choose how to set the weight between the nodes, training the network and evaluating the results.

Weight change from any unit ‘j’ to unit ‘k’ by gradient descent i.e. weight change by small increment in negative direction to gradient.

$$\Delta w = w - w_{old} \qquad \textbf{(4)}$$

$$\Delta w = -n\frac{\vartheta\epsilon}{\vartheta w} = +n\,\delta\, x \qquad \textbf{(5)}$$

The weight change from input layer unit ‘i’ to hidden layer ‘j’ is:

$$\Delta w_{ij} = n\,\delta_j x_i \qquad \textbf{(6)}$$

Where, $\delta_{k=o_j(1-o_j)\sum_k w_{jk}\delta_k}$

The weight change from the hidden layer unit ‘j’ to output layer unit ‘k’ is:

$$\Delta w_{jk} = n\,\delta_k\, o_j \qquad \textbf{(7)}$$

Where, $\delta_k = (y_{target,k} - y_k)y_k(1 - y_k)$

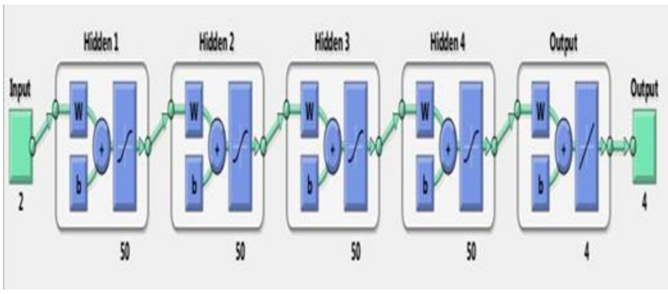


Fig .4: Feed forward multilayer perceptron structure containing 3 elements 1. Input layer 2. Hidden Layer 3. Output layer

The basic part of feed forward Neural Network is that the output is known from the beginning. The constantly adjustment of weights and biases took place to form the output which is imminent to the anticipated value of the output which was counted by MSE (mean squared value). The training algorithm RP (Resilient back propagation) is used. It is the network training function which is used to initialized the weight and biases fortuitously. The number of data points in the training sets, the number of weight and biases in the networks, and the error goal can be determine by above discussed training parameter. When it is reached to maximum number of epoch the training process stopped and goal is attained.

Feed forward MLP structure consist of one input layer with two nodes, four hidden layers with fifty neurons each and one output layer with four nodes as shown in Fig.4.

- *Support Vector Machines:*

Support vector machines considered as a fundamental supervised machine learning technique that has attracted a lot of researchers. Moreover, SVM is considered among the best classifiers,

$$w^T . x_i + b \ \geq 1 \,, for\ all\ x_i \ \in P$$
$$w^T . x_i + b \ \leq 1 \,, for\ all\ x_i \ \in N$$

With the decision rule given by:

$$f_{w,b}(x) = sign(w^T . w_i + b) \qquad \textbf{(8)}$$

Where, **W** is termed the weight vector, **b** the bias (**- b** or is termed the threshold), $x_i$ is an observation and **P** and **N** present respectively positive and negative data. When it is possible to linearly separate two classes, an optimum separating hyper plane can be found by minimizing the squared norm of the separating hyper plane. The minimization can be set up as a convex quadratic programming (QP) problem:

$$\frac{\min 1}{2}\left|\left|w\right|\right|^2 + C\ \sum_{i=1}^{m} \varepsilon_i \ , subjected\ to\ \ y_i(w.x_i + b) \geq 1 - \ \varepsilon_{i\,,}\varepsilon_i \geq 0\ for\ i = 1,..,m \qquad \textbf{(9)}$$

With the class of the observation, the number of observations and the dimension number. Fig.5 shows the optimal hyper plane relative to the decision function

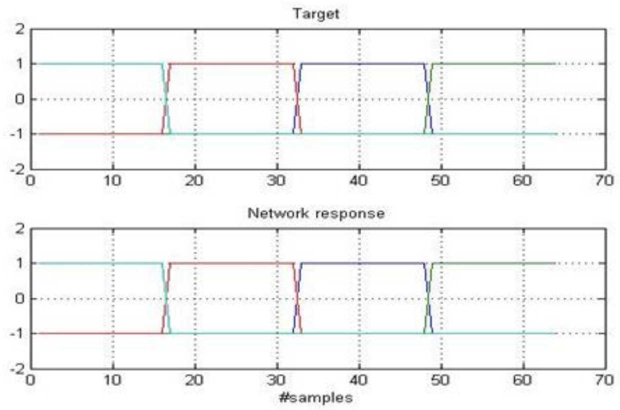


Fig.5 NN perfect network response in comparison to the assign targets.

- *One Vs. One:*

The “one against one” strategy, also known as “pairwise coupling”, “all pairs” or “round robin”, consists in constructing one SVM for each pair of classes. Usually, classification of an unknown pattern is done according to the maximum voting, where each SVM votes for one class.

## III. Result and Analysis:

### A. *Wavelet Results:*

Daubechies wavelet family is used for analysis in current study, extensive tests on Daubechies wavelets orders db4 and db5 with decomposition levels D5 results suggests that db5 is giving better classification results as shown in Table I. It is concluded in our tests that db5 is the most effective Daubechies wavelet order for our purpose; also compare db5 results with db4.

### B. *ANN Results:*

Feed Forward Multi-layer Perceptron is the work horse of the Matlab’s neural network toolbox. With training function “trainrp” which is very fast and achieve 1000 epochs in few seconds we set parameters limits like validation check, mean squared value (MSE) and gradient in such a way that it reaches 1000 epochs. We also tested neural network with different combinations of layers and different numbers of neurons in a layer given in Table II. Our neural network provides maximum 100% accuracy with configured parameters.

Table I*:* Classifications results of NN (4 hidden layers) and SVM along with Decomposition level.

| Db4 | | | Db5 | | |
|---|---|---|---|---|---|
| level | Classification Results | | level | Classification Results | |
| | NN | SVM | | NN | SVM |
| D4 | 91% | 50.00% | D4 | 92.4% | 68.75% |
| D5 | 96% | 81.25% | D5 | 99% | 81.25% |

Table II. Number of hidden layers and time taken to reach 1000 epoch.

| Number of Layers | Classification Accuracy. | Time taken to reach 1000 epochs |
|---|---|---|
| 4 layers with 50 neurons each | 40-60% | 0.5 to 1 sec |
| 2 layers with 50 neurons each | 50-78 % | 1 to 2 sec |
| 3 layer with 50 neurons each | 60-86% | 3 to 4 sec |
| 4 layers with 50 neurons each | 80-100% | 5 to 6 sec |

Table III. Real time trial results for NN and SVM classifier

| Number of Layers | Classification Accuracy | Targeted task | Output | |
|---|---|---|---|---|
| | | | NN | SVM |
| class A | Neutral | Stay | 100% | 87% |
| class B | Eye Blink | Forward | 88% | 50% |
| class C | Left Smirk | Rotate left | 65% | 20% |
| class D | Right Smirk | Rotate Right | 69% | 35% |

### C. *SVM Result:*

Support vector Machine algorithm known as the best binary classification algorithm although can converted into multi classification algorithm where each multiple binary classification provides the same results as multi classifier and results in the fair classification accuracy utilizing around 0.5 second which is very less as compare to the NN; classification results in Table I .

### D. *Overall Results:*

Trained classifier given quasi real time data and integrated with electric wheelchair, the test results were averagely acceptable as subject was fairly trained, test contains 10 trails in 10 days each time classifier trained with new data, subject had 10 chances to perform each given task, the cumulated results NN and SVM for successful and failed attempt shown in Table III.

## IV. Conclusion:

In our proposed research subject we presented a methodology for wheel chair control using EEG. Presented method utilizes Feed Forward Multilayer Perceptron as a classifier along with wavelet for Time-Frequency analysis facilitating in Feature extraction for the neural network.

Significance of this model is the low cost consumer grade device Emotiv-Epoc Plus. Which requires less than 5 minutes to get fully functional in comparison with traditional EEG recording device needing an hour to set up? Our object was to create a system that require very short interval of time to reach it operational state. We successfully achieved our research objective and presented a model that requires 5 to 10 minutes to setup up.

It is evident from results that time frequency analysis using wavelet order db5 has given fruitful results. On the other hand classification with NN results shows four different accuracy levels. For 1st layer accuracy is unacceptable. While 2 and 3 layer gives around 78% and 86% maximum accuracy with delay time 2 & 4 seconds. Lastly 4$^{th}$ layer has around 99% accuracy with a latency of 5-6 seconds. Therefore we can say that it is a slight tradeoff between successful classification and latency induced for controlling of a wheel chair. In addition SVM multilayer classifier with one vs. one strategy gives acceptable offline classification around 80% to 90% consuming very little time of 0.8 to 1 second but while online trails its accuracy training was not up to the standard as NN. Hence a wheelchair can be successfully controlled by facial expressions.

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## AUTHORS:


**Jamal Ahmed, Abdul Majid, Idress Riaz, Sarah Bano, Muhammad Anas**
FEST Department
Main Campus, Iqra University, Pakistan

**Muhammad Ghazaal,** mgsyed@iqra.edu.pk
FEST Department
Main Campus, Iqra University, Pakistan