International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 1, January 2013)

Analysis of Finger Movements Using EEG Signal

C.Vigneshwari[1], V.Vimala[2], S.Vaira Vignesh[3], G.Sumithra[4]
Electronics and Communication Engineering, Madras Institute of Technology, India

***Abstract*--The purpose of this work is to analyse the electroencephalogram (EEG) signals of left and right hand finger movements, an application of Brain-Computer Interface (BCI). Discrete Wavelet Transform is used for Feature extraction, which separates Alpha and Beta band of frequencies of EEG Signal. Various noises pose a major problem in recognizing the EEG signal. Random noise is generally difficult to be removed using typical filtering methods. Ten features which include both time domain and frequency domain are evaluated in a noisy environment, for various Signal-to-Noise ratios. Then features with low percentage error are computed as the best features that can tolerate with the random noise and there is no need for any exclusive noise removal algorithm. The work can be further extended by using these features for classification of different finger movements.**

***Keywords*-- Brain Computer Interface (BCI), Electroencephalogram (EEG), Discrete Wavelet Transform(DWT)**

I. Introduction

EEG signals are easily recorded and processed with inexpensive equipment and hence they are the most popular way of interpreting the brain activities in the realm of non-invasive Brain Computer Interface (BCI). EEG signals are rather well studied and there is evidence that these signals can be used for artificial hand movements [9]. The main motivation of BCI today is to develop replacement communication and control means for severely disabled people, especially those who have lost all voluntary muscle control.

Although the EEG is an imperfect, distorted indicator of brain activity, it remains nonetheless its direct consequence. Also, it is based on a much simpler technology and is characterized by much smaller time constants when compared to other non-invasive approached such as MEG, PET and fMRI [9].

As it is possible to process digitized EEG signals on a computer, the temptation was great to use EEG as a direct communication channel from the brain to the real world. The last ten years have witnessed a tremendous development in the area of BCI research.

The brain electrical activity and review methods and procedures aiming at detecting and interpreting EEG signals for the purpose of command and control in a multimedia environment is used to learn about Brain Computer Interface [9].

Wavelet analysis and its application to neuroelectric waveforms such as the EEG and Event related potentials (ERP) are used in Feature Extraction [10]. Wavelet techniques can optimize the analysis of such non-stationary signals by providing excellent join time-frequency resolution [10]. Feature extraction is done from the alpha and beta bands as they contain more information about finger movements [7].

The paper is organised as follows: the next section describes the building block of BCI and the EEG data acquisition. Section III describes the feature extraction method. The simulation results are given in Section IV followed by conclusion in Section V.

II. Parts Of BCI And Data Acquisition

A basic building block of brain computer interface systems is shown in the Figure 1 and they are Signal Acquisition (EEG), Signal Processing: Feature Extraction and Classification, Output.

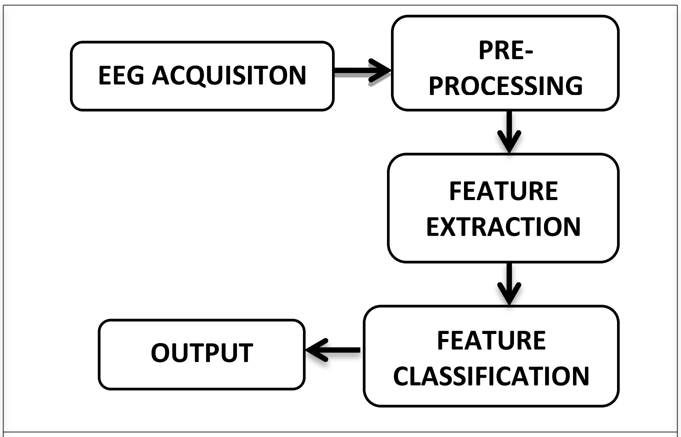

Figure.1. Block Diagram of BCI

A. Data acquisition

The datasets used in this work consists of open and close of right and left hand finger movement of EEG signal recorded when eyes of the subjects are closed. The datasets are in Matlab mat format. Each column represents one electrode

International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 1, January 2013)

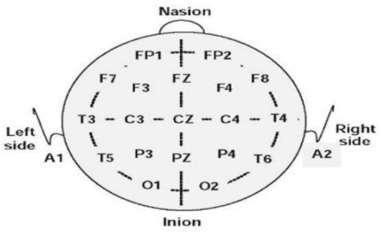

Figure.2. Placement of Electrodes

This datasets consists of three trials of each Left Hand Finger Close(LHFC), Left Hand Finger Open(LHFO), Right Hand Finger Close(RHFC) and Right Hand Finger Open(RHFO) movements as well as one trial of imagined-left hand and right hand of finger close and open movements. A previous study has shown that channels C3 and C4 contain most of the important information for this particular application and thus datasets of Channel C3 and C4 are used in this work. The EEG dataset was downloaded from the website [1].

B. Pre-processing

Various noises pose a major problem in recognizing the Electro-encephalography (EEG) signal. Hence, methods to remove noise become most significant in EEG signal analysis. Removal of White Gaussian noise (WGN) is difficult using typical filtering and solutions to remove WGN are limited. In addition, noise removal is an important step before performing feature extraction.

Major types of noise, artifact and interference in recorded EEG signal are electrode noise, electrode and cable motion artifice, AC power line interference and other noise sources such as broad band noise from electronic instrument. The interferences of random noise that fall in EEG dominant frequency energy are difficult to be removed using normal methods.

WGN is used to represent the random noise in EEG signal analysis. Though there are different methods for its removal, still WGN cannot be removed one hundred percent and sometimes some important part of EEG signals are removed with noise even if we use adaptive filter algorithm. Thus the selections of features are such that it has tolerance to WGN and there is no necessity for any WGN removal algorithms.

III. FEATURE EXTRACTION

The original EEG signal is a time domain signal and the signal energy distribution is scattered. The signal features are buried away in the noise. In order to extract the features, the EEG signal is analyzed to give a description of the signal energy as a function of time or/and frequency. Based on previous studies, features extracted in frequency domain are one of the best to recognize the mental tasks based on EEG signals.

A number of feature extraction methods have been proposed in the literature to represent EEG signals, such as wavelet transform, power spectra and adaptive autoregressive (AAR). Wavelet transform is used as it has been found to provide a good way to visualize and decompose EEG signals into measurable component events. Also compared to Fourier Transform, Wavelet Transform have both time and frequency resolution and also better when compared to Short Time Fourier Transform.

A. Wavelet transform

The Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. In CWT, the signals are analyzed using a set of basis functions which relate to each other by simple scaling and translation [8]. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cut-off frequencies at different scales.

The CWT maps a one-dimensional time signal to a two-dimensional time-scale joint representation. The time bandwidth product of the CWT output is the square of tat of the signal. For most applications, however, the goal of signal processing is to represent the signal efficiently with fewer parameters. The use of the DWT can reduce the time bandwidth product of the wavelet transform output.

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by upsampling and downsampling (subsampling) operations.

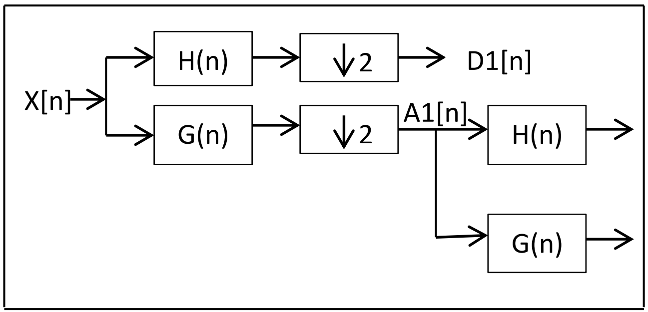

Figure.3. Wavelet decomposition tree

IJETAE
EXPLORING RESEARCH AND INNOVATIONS

International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 1, January 2013)

The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal as shown in Figure 3. This is called the Mallat algorithm or Mallat-tree decomposition [8]. Its significance is in the manner that it connects the continuous-time mutiresolution to discrete-time filters. In the Figure 3, the signal is denoted by the sequence X[n], where n is an integer. The low pass filter is denoted by G(n) while the high pass filter is denoted by H(n). At each level, the high pass filter produces detail information, D[n], while the low pass filter associated with scaling function produces coarse approximations, A[n].

B. Time and frequency domain features

1) Integrated EEG:

Integrated EEG (IEEG) is calculated as the summation of the absolute values of the EEG signal amplitude. Generally, IEEG is used as an onset index to detect the muscle activity that in turn produces a control command for assistive control device. It is related to the EEG signal sequence firing point, which can be expressed as,

$$\boldsymbol{IEEG} = \sum_{i=1}^{N} |\boldsymbol{X_n}| \qquad (1)$$

Where N denotes the length of the signal and x_n represents the EEG signal in a segment.

2) Mean Absolute Value:

Mean Absolute Value (MAV) is similar to average rectified value (ARV). It can be calculated using the moving average of full-wave rectified EEG. In other words, it is calculated by taking the average of the absolute value of EEG signal. It is an easy way for detection of muscle contraction levels. It is defined as

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_n| \qquad \textbf{(2)}$$

3) Modified Mean Absolute Value 1:

Modified Mean Absolute Value 1 (MMAV1) is an extension of MAV using weighting window function w_n. It is shown as

$$MMAV1 = \frac{1}{N}\sum_{i=1}^{N} w_n|x_n| \qquad \textbf{(3)}$$

$$w_n = \begin{cases} 1, & 0.25N \le n \le 0.75N \\ 0.5, & \text{Otherwise} \end{cases}$$

4) Modified Mean Absolute Value 2:

Modified Mean Absolute Value 2 (MMAV2) is similar to MMAV1. However, the smooth window is improved in this method using continuous weighting window function w_n. It is given by

$$MMAV2 = \frac{1}{N}\sum_{i=1}^{N} w_n|x_n| \qquad \textbf{(4)}$$

$$w_n = \begin{cases} 1, & 0.25N \le n \le 0.75N \\ 4n/N, & 0.25N > n \\ 4(n-N)/N, & 0.75 < n \end{cases}$$

5) Simple Square Integral:

Simple Square Integral (SSI) uses the energy of the EEG signal as a feature. It can be expressed as

$$SSI = \sum_{n=1}^{N} |x_n|^2 \qquad \textbf{(5)}$$

6) Variance:

Variance of EEG (VAR) uses the power of the EEG signal as a feature. Generally, the variance is the mean value of the square of the deviation of that variable. However, mean of EEG signal is close to zero. Hence, variance of EEG can be calculated by

$$VAR = \frac{1}{N-1}\sum_{n=1}^{N} {x_n}^2 \qquad \textbf{(6)}$$

7) Root Mean Square:

Root Mean Square (RMS) is modeled as amplitude modulated Gaussian random process whose RMS is related to the constant force and non-fatiguing contraction. It relates to standard deviation, which can be expressed as

$$\text{RMS}= \sqrt{\frac{1}{N}\sum_{n=1}^{N} {x_n}^2} \qquad \textbf{(7)}$$

Clancy et al. experimentally found that the processing of MAV feature is equal to or better in theory and experiment than RMS processing. Furthermore, the measured index of power property that remained in RMS feature is more advantage than MAV feature.

8) Waveform Length:

Waveform length (WL) is the cumulative length of the waveform over the time segment. WL is related to the waveform amplitude, frequency and time. It is given by

$$\text{WL}= \sum_{n=1}^{N-1} |x_{n+1} - x_n| \qquad \textbf{(8)}$$

9) Zero Crossing:

Zero crossing (ZC) is the number of times that the amplitude value of EEG signal crosses the zero y-axis. In EEG feature, the threshold condition is used to abstain from the background noise. This feature provides an approximate estimation of frequency domain properties.

It can be formulated as

$$ZC = \sum_{n=1}^{N-1} sgn(x_n \times x_{n-1}) \cap |x_n - x_{n-1}| \geq Threshold \quad (9)$$

$$sgn(x) = \begin{cases} 1, x \geq Threshold \\ 0, \ \ otherwise \end{cases}$$

10) Slope Sign Change:

Slope Sign Change (SSC) is similar to ZC. It is another method to represent the frequency information of EEG signal. The number of changes between positive and negative slope among three consecutive segments are performed with the threshold function for avoiding the interference in EEG signal. The calculation is defined as

$$\sum_{n=2}^{N-1}\left[f\left[(x_n - x_{n-1})\times(x_n - x_{n+1})\right]\right] \qquad \textbf{(10)}$$

$$f(x) = \begin{cases} 1, x \geq Threshold \\ 0, \ \ Otherwise \end{cases}$$

11) Mean Absolute Deviation:

To find the total variability of the data sets of the EEG signal amplitude, Mean Absolute Deviation is used. The calculation is defined as

$$MAD = \frac{\sum_{n=1}^{N} |x_n - \overline{X}|}{N} \qquad (11)$$

IV. EXPERIMENTAL RESULTS

The EEG signal is analysed using the MATLAB version 7.8.0.347 (R2009a). As explained before, the signal is first low pass filtered to 0-64 Hz by butterworth filter using Signal Processing Toolbox in MATLAB. The filtered signal for Left Hand Finger Open is shown in Figure 4. Here, the x-axis is time in seconds and y-axis is Amplitude in microvolt. Similarly, for each movement it has been simulated.

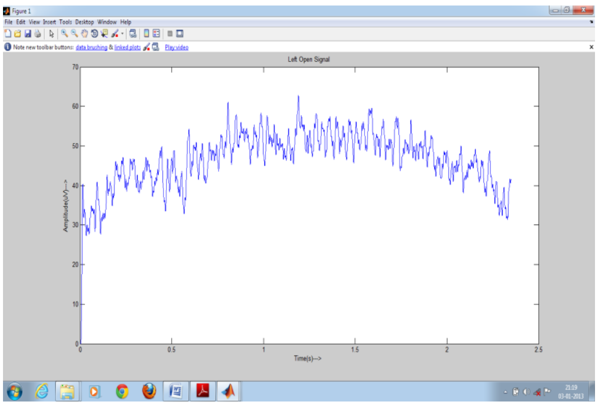

Figure.4. Left Hand Fingers Open signal

On applying Discrete Wavelet Transform (DWT) to this filtered signal, second and third level coefficients of decomposition will give the Beta [16-32 Hz] and Alpha [8-16 Hz] band of frequencies. The different levels of decomposition of the filtered signal are shown in Figure 5 and 6 for LHFO signal. Here, the x-axis is Time in milliseconds and y-axis is amplitude in microvolt. Similarly, for other movements also decomposition using DWT is done.

The Percentage Error (*PE*) is used to evaluate the quality of the robust of WGN of EEG features, as in

$$PE = \left| \frac{feature_{clean} - feature_{noise}}{feature_{clean}} \right| \times 100\% \qquad \textbf{(12)}$$

Where $feature_{clean}$ denotes the feature vector of the original EEG signal and $feature_{noise}$ represents the feature vector of the noisy EEG signal.

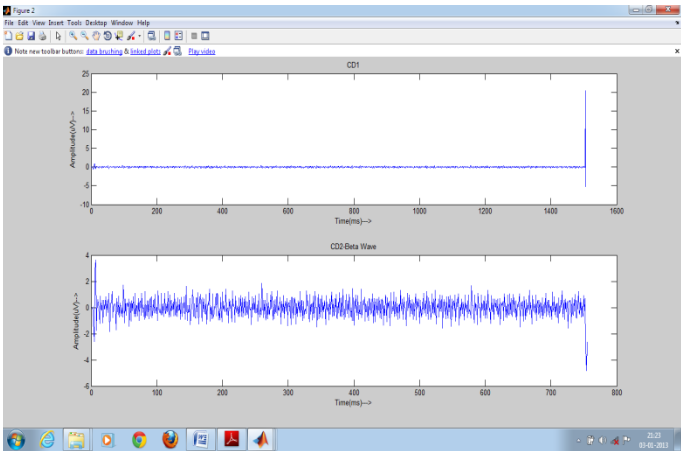

Figure.5. DWT of the LHFO signal with CD1 and CD2

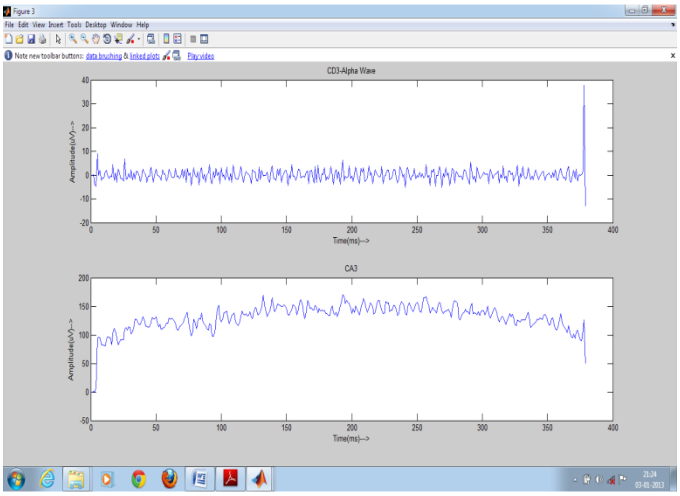

Figure.5. DWT of the LHFO signal with CD3 and CA3

International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 1, January 2013)

WGN at different level is added to the original EEG signal. The performance of the methods is the best when *PE* is the smallest value. We calculated average *PE* for each movement in the dataset. Therefore, we calculated for two channels for each feature and noise level was varied from 20 to 0 dB *SNR* in dataset. Moreover, WGN was added 10 times in each noise level to confirm the results. *SNR* is calculated by

$$SNR = 10log_{10}\left(\frac{P_{clean}}{P_{noise}}\right) \qquad \textbf{(13)}$$

Where P_{clean} is power of the original EEG signal and P_{noise} is power of WGN. The robust features should have the small value of *PE* and still have maximum classification accuracy. Thus a graph is plotted for percentage error for each time domain feature and thus the features that have small PE are chosen as best feature that can be used for classification. The graph that is plotted is shown in Figure 7 with x-axis as SNR in dB and y-axis as PE in %.

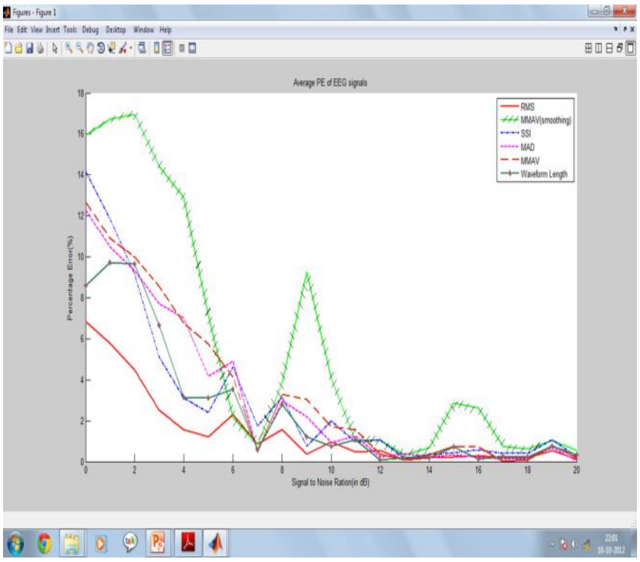

Figure.7. Plot of PE of Different Features

In the Figure 7, the Percentage Error of time domain features computed using EEG signal amplitude demonstrates that RMS, Waveform length, Simple Square Integral and Modified Mean absolute values results in powerful performance in robust noise tolerance than the other features. Hence these four features are used to represent the features in this group. In frequency domain, the features that are used are Zero Crossing and Slope Sign Change. In Table 1 and Table 2, the calculated values of these six best features which has low percentage error for each movement i.e. Left Open, Left Close, Right Open, Right Close are computed and tabulated.

Each movement will have value nearer to these tabulated values. So, it can be classified based on these values.

Table.1
Best Features Extracted From Alpha Band

Features	Left Open	Left Close	Right Open	Right Close
RMS	2982.99	3014.1	1796.2	1640.8
WL	984.72	1008.45	940.19	874.0
MMAV	1.5848	1.6529	1.5815	1.469
SSI	2982.9	3014.1	1796.2	1640.8
ZC	374	375	113	360
SSC	52	61	176	365

Table.2
Best Features Extracted From Beta Band

Features	Left Open	Left Close	Right Open	Right Close
RMS	0.5773	0.5892	0.5589	0.5211
WL	535.57	540.44	523.56	509.77
MMAV	0.3231	0.3268	0.3157	0.3101
SSI	251.62	262.18	235.91	205.01
ZC	744	754	277	344
SSC	742	748	561	218

Thus these six features in time and frequency domain are used for the efficient classification of the EEG signals in the presence of WGN also. These Six features can be fed to the Classifier for classification of Different Finger Movements.

V. CONCLUSION

The objective of this work is to analyse the EEG signals for various finger movements in particular Left and Right hand fingers open and close are focused. The Alpha and Beta band of EEG signal are extracted from the original signal using Discrete Wavelet Transform. Nine features in Time domain and two features in Frequency domain were tested. Results showed that Root Mean Square, Simple Square Integral, Waveform Length, Modified Mean absolute Value in the time domain showed low Percentage Error. In Frequency domain, Zero Crossing and Slope Sign Change are calculated for both Alpha and Beta band. These six features in frequency and time domain are thus the best features comparing with others in the quality of the robustness of EEG features with White Gaussian Noise. These six features can be fed to the classifier for further classification of different finger movements which are used in the application of artificial upper limb.

International Journal of Emerging Technology and Advanced Engineering
Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 3, Issue 1, January 2013)

Acknowledgement

We thank Brain Computer Interface research at National University of Sciences and Technology (NUST) Pakistan for providing Project BCI - EEG motor activity data set [1] which is very helpful for us.

REFERENCES

[1] http://sites.google.com/site/projectbci/

[2] Arnaud Delorme and Scott Makeig, EEG Changes Accompanying Learned Regulation of 12 Hz EEG Activity, IEEE transactions on neural systems and rehabilitation engineering, vol. 11, no. 2, June 2003.

[3] D.Lee Fugal, Conceptual Wavelets in Digital Signal Processing, 2009 space and signals technologies, LLC.

[4] Darvishi S., Al-Ani A. "Brain-computer interface analysis using continuous wavelet transform and adaptive neuro-fuzzy classifier", Proceedings of the 29th International Annual Conference IEEE Engineering, Medicine and Biology Society, August 2007, pp. 3220- 3223.

[5] Ericka Janet Rechy-Ramirez and Huosheng Hu , Stages for Developing Control Systems using EMG and EEG Signals: A survey TECHNICAL REPORT: CES-513 ISSN 1744-8050, June 9, 2011.

[6] Jessy Parokaran Varghese, Analysis of EEG Signals For EEG-based Brain-Computer Interface, July 2009.

[7] Ozan Gunaydin, Mehmed Ozkan. Design of a Brain Computer Interface System based on Electroencephalogram (EEG). Proceedings of the 4th European DSP in Education and Research Conference.

[8] Robi Polikar, The Wavelet Tutorial, http://users.rowan.edu/~polikar/WAVELETS / WTpart1.html

[9] T.Ebrahimi, J.M. Vesin and G.Garcia. Brain-computer interface in multimedia communication. IEEE Signal Processing Magazine, vol.20,pp 14-24, 2003.

[10] V.J.Samar, A.Bopardikar, R.Rao and K.Swartz. Wavelet analysis of neuroelectric waveforms: a conceptual tutorial. Brain Language. Vol.66, pp.7-60, 1999.