

# Wavelet Based Feature Extraction Scheme of Electroencephalogram

Mr. C. E. Mohan Kumar<sup>1</sup>, Mr. S. V. Dharani Kumar<sup>2</sup>

Assistant Professor, GRT Institute of Engineering & Technology, Tamilnadu, India<sup>1,2</sup>

**Abstract-** The Electroencephalograph (EEG) signals is one of the most widely used in the bioinformatics field due to its rich information about human tasks. The Electroencephalogram is a neuronal activity that represents the electrical activity of the brain. The uses of EEG signals in the field of Brain computer Interface (BCI) have obtained a lot of interest with diverse applications ranging from medicine to entertainment. BCI is designed using EEG signals where the subjects have to think of only a single mental task. The specific features of EEG are used as input to Visual Evoked Potential (VEP) based Brain-computer Interface or self paced BCIs (SBCI) for communication and control purposes. This work proposes scheme to extract feature vectors using wavelet transform as alternative to the commonly used Discrete Fourier Transform (DFT). Brain Computer Interface is a direct connection between the brain and a computer, without using any of the brains natural output pathways. Visually-evoked Potentials extracted from the electroencephalographic activity in the visual cortex recorded from the overlying scalp. Wavelets are powerful candidates for decomposition, feature extraction, and classification of non-stationary EEG signals for BCI applications. Wavelet Transform (WT) is superior to Discrete Fourier Transform due to its high localization in time and frequency domain. The main objective of Wavelet Transform usage is to localize the artifact component.

**Index Terms:** Electro-Encephalogram (EEG), Brain-Computer Interface (BCI), Wavelet Transform (WT), Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), Short time Fourier transform (STFT), visually Evoked Potential (VEP),

**Discrete Fourier Transform (DFT), Multi-resolution Analysis (MRA).**

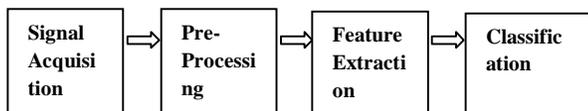
## I. INTRODUCTION

A Brain Computer Interface (BCI) or Brain Machine Interface (BMI) has been proposed as an alternative communication pathway, bypassing the normal cortical-muscular pathway. BCI is a system that provides a neural interface to substitute for the loss of normal neuronal-muscular outputs by enabling individuals to interact with their environment through brain signals rather than muscles. Most BCI research is aimed towards developing tools for patients with severe motor disabilities and paralyzes. This group of potential users could particularly benefit from BCI technology, since output pathways that are normally employed by the brain can no longer be used. Brain Computer Interface is also referred to as Enhanced form of neuro-prosthetic support system was conceived as communication interface between machines (usually a computer) and the brain of a user. They should permit the use to perform a certain task, usually without implementing any motor action. This implies that neural impulses generated by the user's brain are detected, elaborated and utilized by the machines approximately in real time, to perform definite tasks.

Electroencephalograph (EEG) represents complex irregular signals that may provide information about underlying neural activities in the brain. Electroencephalograms are recordings of the tiny electrical potentials (generally less than 300 $\mu$ V) produced by the brain. The brain waves recorded from the scalp have small amplitudes of approximately 100 $\mu$ V. The frequencies of these brain waves range from 0.5 to 100Hz, and their characteristics are highly dependent on the degree of activity of the cerebral cortex. The EEG spectrum contains some characteristic

waveforms that fall primarily within four frequency bands: delta (1-4Hz), theta (4-8Hz), alpha (8-13Hz), and beta (13-30Hz).

The first step in BCI systems is the data collection and filtering, the filters are designed in such a way not to introduce any change or distortion to the signals. High pass filter with a cut-off frequency of usually less than 0.5Hz are used to remove the disturbing very low frequency components such as those of breathing. On the other hand, high frequency noise is mitigated by using low pass filter with a cut-off frequency of approximately 40-70Hz. BCI is composed of signal collection and processing, pattern identification and control systems.



**Fig.1.** The Block diagram of the BCI work

Fig.1. illustrates the part of the work. The EEG signals are collected and represented using special filters by the method of signal acquisition, then the acquired signal is preprocessed where the artifact component (undesired component) is removed from the desired components, then the EEG feature are extracted from the feature vector using several methods and finally those features are classified depending on the frequencies for mental task they represent.

There are few new concepts in the design of EEG measurement systems like miniaturized, battery-powered front-end close to patient, with fiber optic data transfer to the signal processing PC. A group of most important authors in the field of non-invasive BCIs gave the list of goals important for future progresses of these systems. Future progress will depend on:

- Identification of those signals, whether evoked potential, spontaneous rhythms, or neuronal firing rates, that user are best able to control.
- Development of training methods for helping users to gain and maintain that control.
- Delineation of the best algorithms for translating these signals into device commands.
- Attention to eliminate if artifacts as electro-myographic and electro-oculographic activity.
- Adoption of precise and objective procedures for evaluating BCI performance.

## II. FEATURE EXTRACTION

Feature extraction methodologies analyze signals to extract the most prominent features that are representative of the various classes of signals. The main aim of feature extraction is to obtain the further information's from the raw signal. The neuron is the basic structural and functional unit of nervous system. The brain's electrical charge is maintained by billions of neurons. Neurons are electrically charged (or "polarized") by membrane transport proteins that pump ions across their membranes. Neurons are constantly exchanging ions with the extracellular milieu, for example to maintain resting potential and to propagate action potentials. Ions of like charge repel each other, and when many ions are pushed out of many neurons at the same time, they can push their neighbors, who push their neighbors, and so on, in a wave. This process is known as volume conduction. When the wave of ions reaches the electrodes on the scalp, they can push or pull electrons on the metal on the electrodes.

Since metal conducts the push and pull of electrons easily, the difference in push or voltage between any two electrodes can be measured by a voltmeter. Recording these voltages over time gives us the EEG. From the extracted feature the artifacts components are removed by preprocessing stage then this feature is given as input to the classifier and the classified signal is given to the some of the applications like wheel chair, computer cursor movements etc., Since the features have very small amplitude range special amplifier and booster circuits are used to enhance the strength of signals.

A Special form of dimensionality reduction in image processing is transforming the external stimulus or sensations into the set of features in the surface of brain. To enable brain-computer interface construction an efficient method of feature extraction from EEG signal is needed. This paper proposes a feature extraction method based on higher order statistics calculated for the details of discrete wavelet transform (DWT) of EEG signal. Limiting the number of electrodes is supposed to simplify the use of the interface and reduce the cost of the EEG signal amplifier. This would also facilitate the analysis, processing and classification of signals. The methods reinforce the non-stationary EEG concept and

call for the necessity of extracting more information to understand the brain signals and its dynamics.

### III. METHODOLOGY

Time-domain wavelets are simple oscillating amplitude functions of time. So are the sine and cosine waves of Fourier analysis. However, unlike sine and cosine waves which are precisely localized in frequency but extend infinitely in time (sines and cosines have definite single frequencies, e.g., 40Hz, constant for all time); wavelets are relatively localized in both time and frequency.

They have large fluctuating amplitudes during a restricted time period and are very low amplitude or zero amplitude outside of that time range. That is, wavelets are said to be “supported” over a restricted domain of time if the bulk of their energy is restricted to that time period and are said to be “compactly” supported if all of their energy is restricted to a specific domain of time.

In this paper, the non-parametric method of feature extraction based on multi-resolution analysis of Wavelet Transform (WT) is introduced. The EEG signal is non-stationary, time domain signal and the signal energy distribution is scattered. The signal features are buried away in the noise. In order extract the features, the EEG signal is analyzed to give a description of the EEG energy as the function of time or/and frequency. The joint time-frequency resolution obtained by WT makes it as a good candidate for the extraction of details as well as approximations of the signal which cannot be obtained either by Fast Fourier Transform (FFT) or by Short Time Fourier Transform (STFT). The non-stationary nature of EEG signals is to expand them onto basis functions created by expanding, contracting and shifting a single prototype function ( $\Psi_{a,b}$ , the mother wavelet), specifically selected for the signal under consideration. The mother wavelet function  $\Psi_{a,b}(t)$  is given as

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right)$$

Where  $a, b \in \mathbb{R}$ ,  $a > 0$ , and  $\mathbb{R}$  is the wavelet space. Parameters ‘a’ and ‘b’ are the scaling factor and shifting factor respectively. The only limitation for choosing a prototype function as mother wavelet is to satisfy the admissibility condition.

$$C_{\omega} = \int_{-\infty}^{\infty} |\Psi(\omega)| \frac{|\Psi(\omega)|^2}{\omega} d\omega < \infty$$

Where  $\Psi(\omega)$  is the Fourier transform of  $\Psi_{a,b}(t)$ . The wavelet function has been chosen due to their near optimal time-frequency localization properties.

The CWT is not very efficient since localization of artifact components in time and frequency is not possible and also it consumes more time. The information it displays at closely spaced scales or at closely spaced time points is highly correlated and therefore unnecessarily redundant for many analytic purposes. It is also time consuming to compute directly. Although the CWT has some advantages, there are many applications where a more efficient and computationally simpler wavelet analysis is desirable. Such an analysis, known as the Discrete Wavelet transforms. Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. Wavelets are obtained from a single prototype wavelet  $y(t)$  called mother wavelet by dilations and shifting.

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right)$$

Where  $a$  is the dyadic scaling parameter and  $b$  is the dyadic shifting parameter.

#### A. Wavelet Analysis

Wavelet analysis refers to a growing class of signal processing techniques and transforms that use wavelets and related functions called wavelet packets to efficiently measure and manipulate such non-stationary signals. These detail functions can isolate all scales of waveform structure, from the largest to the smallest pattern of variation in time and space that is available in the neuro-electric data set. Consequently, wavelet analysis provides flexible control over the resolution with which neuro-electric components and events can be localized in time, space, and scale.

The set of wavelet functions is usually derived from the initial (mother) wavelet  $h(t)$  which is dilated by value  $a = 2^m$ , translated by constant  $b = k 2^m$  and normalized so that

$$h_{m,k}(t) = \frac{1}{\sqrt{a}} h\left(\frac{t-b}{a}\right) = \frac{1}{\sqrt{2^m}} h(2^{-m}t - k)$$

For integer values of m, k and the initial wavelet defined either by the solution of a dilation equation or by an analytical expression. Both continuous and discrete signals can be then approximated in the way similar to Fourier series and discrete Fourier transform. In case of a sequence  $\{x(n)\}_{n=0}^{N-1}$  having  $N = 2^s$  values it is possible to evaluate its expansion.

$$x(n) = a_0 + \sum_{m=0}^{s-1} \sum_{k=0}^{2^{s-m-1}} a_{2^{s-m-1}+k} h(2^{-m}n - k)$$

Wavelet transform coefficients can be organized in a matrix T with its nonzero forming a triangle structure with each its row corresponding to a separate dilation coefficient m. The set of  $N = 2^s$  decomposition coefficients  $\{a(j)\}_{j=0}^{N-1}$  of the wavelet transform is defined in the way formally close to the Fourier transform but owing to the general definition of wavelet functions they can carry different information using the orthogonal set of wavelet functions they are moreover closely related to the signal energy.

The initial wavelet can be considered as a pass-band filter and in most cases half-band filter covering the normalized frequency band (0.25, 0.5). Wavelet dilation by the factor  $a = 2^m$  corresponds to a pass-band compression. This general property can be demonstrated for the harmonic wavelet function and the corresponding scaling function by expressions.

$$h(t) = \frac{1}{j\Pi/2t} (e^{j\Pi t} - e^{j\Pi/2t})$$

$$l(t) = \frac{1}{\Pi/2t} (e^{j\Pi/2t} - 1)$$

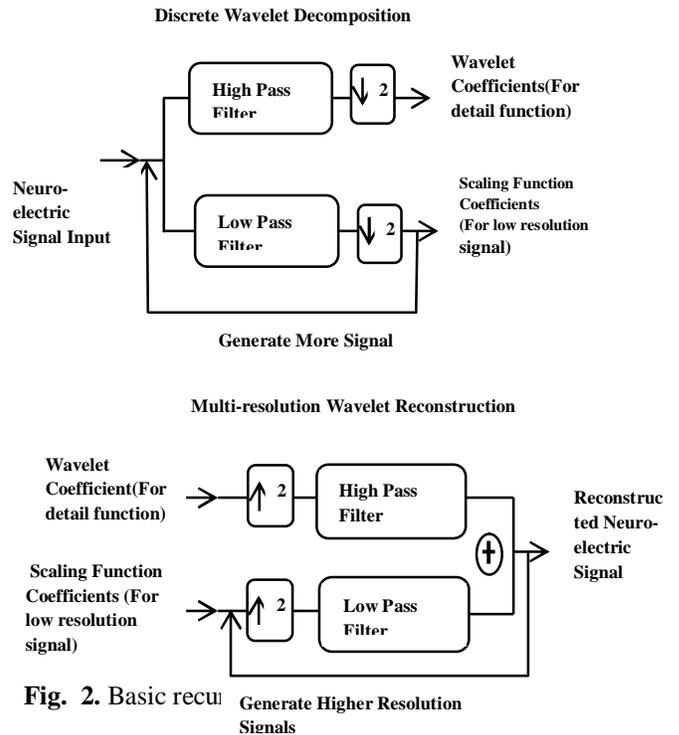
As both these functions are modified by the scaling index  $m = 0, 1, \dots$  the wavelet is dilated and its spectrum compressed resulting in time and frequency domain representation presented in. Similar approach can be also applied for other wavelet functions defined in either analytical or recurrent form.

The set of wavelets define a special filter bank which can be used for signal component analysis and resulting wavelet transform coefficients can be further applied as signal features for its classification. Signal

decomposition performed by a pyramidal algorithm using the fast Fourier transform.

**B. Decomposition**

The output of Wavelet transformed Signals are having two Co-Efficient called as Approximate Co-Efficient and Detail Co-Efficient. The Approximation Co-Efficient corresponds to Low frequency Component and the Detail Co-Efficient corresponds to High frequency Component of a Wavelet. This process is called Signal Decomposition



**Fig. 2.** Basic recursive algorithm to generate higher resolution signals

At the beginning of a DWT computation, a neuro-electric waveform like EEG containing n samples is run through the high and low pass filters. The output each filter is a series of n wavelet coefficients. Every other coefficient is discarded from the series, leaving n/2 coefficients for each filter output. This process of discarding alternate coefficients is known as down sampling and is indicated in the figure by the downward pointing arrow and adjacent “2” symbol.

The output of the high pass filter is the set of DWT wavelet coefficients associated with all of the discrete wavelets at the smallest single scale available for the particular digitized neuro-electric waveform that



wavelet transform adopts the variable window length which can deal with the non-stationary signal with a variable frequency rate. Hence the wavelet based feature extraction is considered as the best when compared with any other based transform based feature extraction. Mathematical basis of the wavelet transform has also proved that EEG analysis based on wavelet transform coefficients can be used very efficiently for the estimation of EEG features.

## VI. FUTURE WORK

Further work suggestions include finding the best combination of channels in the case of space-time-frequency analysis for specific task.

Also one of our suggestions for the future is building the hardware model for the EEG feature extraction and classification system using the Field Programmable Gate Array (FPGA)

## REFERENCES

- [1] Ale` sProch´ azk, Jarom´ irKukal, "Wavelet Transform use for Feature Extraction and EEG Signal Segments Classification", Institute of Chemical and Control Engineering.
- [2] Maan M. Shaker, "EEG Waves Classifier using Wavelet Transform and Fourier Transform", International Journal of Biological and Life Sciences 1:2 2005.
- [3] G.Saravana Kumar, Dr. S. Ravi, "Feature Extraction Scheme for Brain-Computer Interface using Wavelet Transform", International Journal of Research and Reviews in Computer Science (IJRRCS), Vol.2, No.1, March 2011, pp.242-246.
- [4] Abdul- Bary Raoquf Suleiman, Toka Abdul- Hamed Fathei, "Features Extraction Techniques of EEG signal for BCI Applications", Computer and Information Engineering Department.
- [5] Luis Fernando Nicolas-Alonso, Jaime Gomez-Gil, "Brain Computer Interfaces, a Review", Department of Signal Theory, Communications and Telemetric Engineering, University of Valladolid, 31 January 2012, pp.1211-1273
- [6] Febo Cincotti, Donatella Mattia, Fabio Aloise, Simon Bufalari, Laura Astolfi, Fabrizio De Vico Fallani, Andrea Tocci, Luigi Bianchi, Maria Grazia Marciani, Shangkai Gao, Jose Millan, Fabio Babiloni, "High resolution EEG techniques for brain-computer interface applications".
- [7] Kenji Kanasaku, "Brain-Machine Interfaces for Persons with Disabilities", Systems Neuroscience Section, Department of Rehabilitation for Brain Functions, Research Institute of National Rehabilitation Center for Persons with Disabilities (NCRD), pp.19-33.
- [8] Nikhil Ramachandran, A.K. Chellappa, "Feature Extraction from EEG using Wavelets: Spike Detection Algorithm".
- [9] Mai S. Mabrouk, "Non- Invasive EEG-based BCI system for Left or Right Hand Movement ", Majlesi Journal of Electrical Engineering, Vol. 5, No. 3, September 2011, pp.46-52.
- [10] Onder aydemir, Temel Kayikcioglu, "Wavelet Transform Based Classification of Invasive Brain Computer Interface Data", Radio Engineering, Vol. 20, no.1, April 2011, pp.31-38.
- [11] Ayhan,T; Seker, S, " BCI modeling using Discrete Wavelet Transform", Innovations in intelligent Systems and Applications (INISTA), 2011 International Symposium on 15-18 June 2011, pp.268-271.
- [12] Mamatha, M.N.; Ramachandran, S.; Chandrasekaran, M, "BCI- A communication for physically challenged people", Communication Software and Networks (ICCSN), 2011 IEEE 3rd International Conference on 27-29 May 2011, pp.464- 468.
- [13] Murugappan, Nagarajan Ramachandran, Yaacob Sazali, "Classification of human emotion from EEG using discrete wavelet transform", J. Biomedical Science and Engineering, 2010, 3, pp.390-396.
- [14] Ali S. Almejrad, "Human Emotions Detection using Brain Wave Signals: A Challenging", European Journal of Scientific Research, Vol.44 No.4 (2010), pp.640-659.
- [15] Azim, M.R; Amin, M.S.; Haque, S.A., Ambia, M.N.; Shoeb, M.A, "Feature extraction using EEG waves", Signal processing (ICSPS), 2010 2nd international conference on 5-7 July 2010, V3 701-705.
- [16] Dietmar Dietrich, Roland Lang,Dietmar Bruckner, eorge Fodor, Brit Muller, "Limitations , Possibilities and Implications of Brain-computer Interfaces", 2010, pp.722-726.
- [17] Haider Hussein Alwasiti, Ishak Aris and Adznan Jantan, "Brain Computer Interface Design and Applications: Challenges and Future", World applied science journal 11(7): pp. 819-825, 2010.
- [18] Mohammad Reza Nazari Kousarrizi, Abdolreza Asadi Ghanbari, Mohammad Teshnehlab, Mahdi Aliyari Shorehdeli, Ali Gharaviri, "Feature Extraction and Classification of EEG Signals Using Wavelet Transform", SVM and Artificial Neural Networks for Brain Computer Interfaces", 2009 International Joint Conference on Bioinformatics, Systems Biology and Intelligent Computing.
- [19] Aihua Zhang, Bin Yang, Ling Huang, "Feature Extraction of EEG Signals Using Power Spectral Entropy", 2008 international conference on biomedical engineering and informatics.
- [20] Omerhodzic, S. Avdakovic, A. Nuhanovic, K. Dizdarevic, "energy Distribution of EEG Signals: EEG Signal Wavelet-Neural Network Classifier", International Journal of Biological and Life Sciences 6:4 2010.