ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 8, August 2015

SNR Improvement for Evoked Potential Estimation using Bi – Orthogonal Wavelet Transform

Shailesh M L[1], Dr. Anand Jatti[2], Madhushree K S[3], Siddesh M B[4]

Research Scholar, Pacific University, Udaipur, Rajasthan, Member of IEEE, India[1]

Professor Dept. of Electronics and Instrumentation, R.V.College of Engineering, Bangalore, Karnataka, India[2]

UG Student, Dept of Electronics & Communication Engineering, VTU, Belgaum, Karnataka, India[3]

Assistant Professor, Dept of Electronics & Communication Engineering, VTU, Belgaum, Karnataka, India[4]

Abstract: Biomedical signals are those signals which are generated by the physiological activities of the body, which can be measured & monitored continuously and is an interdisciplinary subject. These signals take on one of the forms of chemical or electrical or acoustics, it can be in the form of continuous or discrete form. It is of utmost importance to study these signals which helps us to know the conditions of the human body. There are different types of biomedical signals, to name a few are Electroencephalogram (ECG), Electroencephalogram (EEG), Electromyography (EMG), Magnetoencephalogram (MEG), Mechanomyogram (MMG) & Electrooculography (EOG) which measure the electrical activities of a particular organ in the human body. Evoked Potentials (EP) or Event Related Potentials (EVP) is the potential developed in the body due to the application of external stimulus.. The stimulus can be visual or auditory or sensual accordingly they are called Visual Evoked Potential (VEP), Auditory Evoked Potential (AEP) & Somato Sensory Evoked Potential (SEP). These evoked potentials are embedded in the EEG signals and have very low amplitude. Extraction of visual evoked potentials (VEPs) from the human brain is generally very difficult due to its poor signal-to-noise ratio (SNR) property. Wavelet transform technique of estimation improves the SNR by a large amount in almost one sweep of EvokedPotential EP. The two different wavelet transforms such as Bi – Orthogonal wavelet transform and this wavelet transform has been used to improve the SNR. SNR comparison is made with the conventional ensemble averaging technique, where this technique requires more number of sweeps to improve the SNR. Comparison is made to understand the best Bi – Orthogonal wavelet transform for estimating the EP signal. In this paper, Visual Evoked Potential signals have been considered for the analysis.

Keywords: Bi – Orthogonal, Evoked Potential, Ensemble Averaging, SNR.

I INTRODUCTION

The brain is the most complex structure in the well known universe. The brain dominates many highly specialized component parts each associated with specific functionalities, i.e., memory and vision. While these parts work united, each part is amenable for a specific function. To analyze the functional status of the brain such as in anesthesia, hypoxia sleep (lack of oxygen) and in certain nervous diseases, i.e., epilepsy, the brain's recordable neuro electric signals, called electroencephalogram (EEG), are processed and analyzed The brain electrical activity, that occurs in connection with an external stimulus (auditory, visual or somatosensory), is called **Evoked Potential** (EP). If the analysis is relevant to a cognitive activity, the response signal is frequently called as either event-related-potential (ERP) or cognitive EP in a wide range of cognitive paradigms. EPs are important diagnostic tools in investigation of physiological and psychological situation of subjects. In general, EPs or ERPs are not recognizable by visual inspection since they are buried in spontaneous Electroencephalogram (EEG) with signal-to-noise ratio (SNR) as low as -5dB considering stimulus-unrelated background EEG as the noise in the measurements. The split up of the EP (the signal) and the ongoing EEG (the noise) in the measurements have been very attractive points in this paper. This needs use of powerful Bio – Medical Digital Signal Processing tools and several methods have been proposed for this purpose.

A Visual Evoked Potential (VEP)

Evoked potentials (EP) constitute a relatively new method of clinical neurophysiology allowing functional evaluation of the neural system. Such non-invasive techniques give information about the functional state of different tracts within the central nervous system, specifically when the clinical signs and the results of neuro imaging methods are either non informative or non-definable. Evoked potentials are very much useful in the detection of subclinical dysfunction.

VEPs provide a sensitive indication of abnormal conduction in the visual pathway. Increases in retino-striate conduction time caused by processes such as demyelination can be detected by measuring the latency of this cortical response. Abnormalities in the amplitude and

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 8, August 2015

waveform of the VEPs may also be caused by the loss of axons in the pathway. VEPs are therefore widely used in the investigation of demyelinating disease, optic neuritis, and other optic neuropathies.
The first recognition of visual evoked potentials (VEP) coincides with the discovery of electroencephalography. It was observed earlier the electrical activity of the brain is altered when an intensive light stimulus is applied. However - since these potentials are of very low amplitude widespread use of the method was made possible only by the introduction of computerized averaging techniques.

B Recording of Visual Evoked Potentials (VEPs)

- VEPs are recorded from the occipital region of the scalp (visual cortex) with reference at the vertex
- The most common stimulation modalities are pattern reversal (about 2 reversals per second) and flashing (about 5…7 flashes per second)
- It lasts up to 300 ms (and beyond)
- The VEP amplitude is up to 20 µV
- The maximun100 stimuli enough for averaging
- The spectral contents or frequency range 1…300 Hz[4]

II METHODLOGY

A Ensemble Averaging Technique

The evoked responses can be quantified by measuring peak amplitudes and latencies, in the millisecond (ms) domain, and they provide numerical data that are quantitative extensions of the neurological examination. The clinical utility of evoked potentials (EPs) is based on their ability to:

- demonstrate abnormal sensory system conduction, when the history and/or neurological examination is equivocal
- reveal subclinical involvement of a sensory system ("silent" lesions), particularly when demyelination is suggested by symptoms and/or signs in another area of the central nervous system
- help define the anatomic distribution and give some insight into pathophysiology of a disease process
- Monitor changes in a patient's neurological status.

Signal averaging is a technique for separating a repetitive signal from noise without introducing signal distortion. Ensemble signal averaging sums a set of time epochs of the signal together with the super imposed random noise. If the epochs are properly aligned, [8] the signal waveforms directly sum together. On the other hand, the uncorrelated noise averages out time. Thus, the signal – to – Noise **(SNR)** is improved.

Signal averaging is based on the following characteristics of the signal and the noise.

1. The signal waveform must be repetitive (although it does not have to be periodic).
2. The noise must be random and uncorrelated with the signal. In this application random means that the noise is not periodic and that it can only be described (e.g. by its mean and variance).
3. The temporal position of each signal waveform must be accurately known.

In this method SNR is improved as more number of sweeps is considered for averaging. The relation below represents that SNR improvement factor. This can be proven mathematically as follows

The input waveform f(t) has a signal portion S(t) and a noise portion N(t). Then

$$f(t) = S(t) + N(t) \qquad (1)$$

Let f(t) be sampled every T seconds. The value of any sample point in the time epoch (i = 1, 2… n) is the sum of the noise component and the signal component.

$$f(iT) = S(iT) + N(iT) \qquad (2)$$

Each sample point is stored in memory. The value stored in memory location i after m repetitions is

$$\sum_{k=1}^{m} f(iT) = \sum_{k=1}^{m} s(iT) + \sum_{k=1}^{m} N(iT) \qquad (3)$$

The signal component for sample point i is the same at each repetition if the signal is stable and the sweeps are aligned together perfectly. Then

$$\sum_{k=1}^{m} S(iT) = m\,S(iT) \qquad (4)$$

The assumptions for this development are that the signal and noise are uncorrelated and that the noise is random with a mean of zero. After many repetitions, N(iT) has an rms value of σn.

$$\sum_{k=1}^{m} N(iT) = \sqrt{(m\,\sigma n^2)} = \sqrt{(m)}\,\sigma n \qquad (5)$$

Taking the ratio of Eqs. (4) and (5) gives the SNR after m repetitions as

$$SNRm = \sqrt{m}\ SNR \qquad (6)$$

Thus, signal averaging improves the SNR by a factor of m

$$SNRm = sqrt\ (m)*SNR \qquad (7)$$

Where **m** is number of sweeps

B Algorithm for Ensemble averaging Technique

1. Take the different ensemble data and store it in different arrays
2. Add the first position values of all the arrays and store it in first position of another array, likewise all the position values are to be added and stored.
3. Calculate the average by dividing it by number of sweeps.
4. For SNR plot calculate the output SNR for each sweep and store it in an array, finally plot the SNR array elements.

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 8, August 2015

C Wavelet Transform Technique

Wavelet transforms have evoked considerable interest in the signal processing community. They have found applications in several areas such as speech coding, edge detection, data compression, extraction of parameters for recognition and diagnostics etc. since wavelets provide a way to represent a signal on various degrees of resolution, they are convenient tool for analysis of data and manipulation of data. Wavelet transform already discussed in the early part of this paper. Next we will see algorithm for EP estimation using Wavelet Transform [5].

D Wavelet Transform Functions

Once the wavelet is chosen it must be used in a signal as a probe to separate the frequencies within that signal, thus producing a transform. The continuous wavelet transform is defined as[7];

$$T(a,b) = w(a)\int_{-\infty}^{\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right)dt \qquad (8)$$

or as an inner product

$$T(a,b) = \left\langle x, \psi_{a,b} \right\rangle \qquad (9)$$

$w(a)$ is a weighting function and $x(t)$ is the signal. The wavelet transform is a convolution of a signal at different translation with a wavelet of various widths. This produces wavelet coefficients at certain locations and scale within the signal.
Time-scale analysis (wavelet) methods have been widely used in the signal processing of biomedical signals. These methods represent the temporal characteristics of a signal by its spectral components in the frequency domain. In this way, important features of the signal can be perceived and analyzed in order to understand or model the physiological system. The analysis of nonstationary signals requires the use of a method which can provide good localization of signal discontinuities. The traditional methods, such as STFT and Gabor methods, fail to localize these phenomena. Furthermore, even for stationary signals, it can sometimes be difficult to choose a good resolution to analyze the signal. The wavelet transform is signal decomposition onto a set of basis functions. These basis functions are obtained by dilations, contractions, and shifts of a unique function called the "wavelet prototype." According to the characteristics of this basis, the wavelets are classified as orthogonal, biorthogonal, or noorthogonal.

E Biorthogonal wavelet

A Biorthogonal wavelet is a wavelet where the associated wavelet transform is invertible but not necessarily orthogonal. Designing Biorthogonal wavelets allows more degrees of freedom than orthogonal wavelets. One additional degree of freedom is the possibility to construct symmetric wavelet functions.
In the Biorthogonal case, there are two scaling functions, which may generate different multiresolutional analyses, and accordingly two different wavelet functions $\psi, \tilde{\psi}$. So the numbers M and N of coefficients in the scaling sequences $a, \tilde{a}$ may differ[6]. The scaling sequences must satisfy the following biorthogonality condition

$$\sum_{n\in\mathbb{Z}} a_n \tilde{a}_{n+2m} = 2 \cdot \delta_{m,0}$$

Then the wavelet sequences can be determined as

$$b_n = (-1)^n \tilde{a}_{M-1-n} \qquad (n = 0, \ldots, N-1)$$
$$\tilde{b}_n = (-1)^n a_{M-1-n} \qquad (n = 0, \ldots, N-1)$$

F Algorithm for Wavelet Transform Technique

1. Decompose the signal by applying the discrete wavelet transform on the signal and is shown in Fig.2.1
2. Remove the high frequency signal i.e. detailed coefficients and retain the low frequency components i.e. approximation coefficients.
3. Reconstruct the EP signal by applying inverse wavelet transform of the decomposed signal and is shown in Fig.2.2
4. Make all detailed coefficients to zero, while applying inverse wavelet transform.
5. Calculate the output SNR for different sweeps.

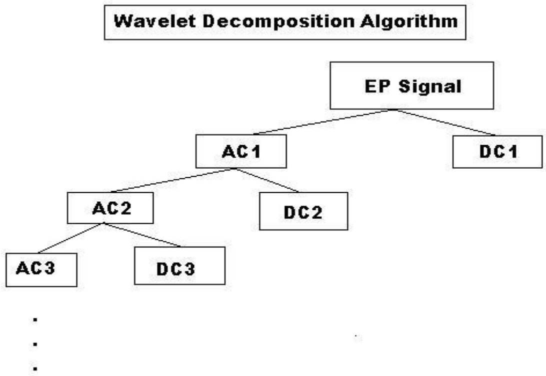

Fig.2.2 Decomposition of EP Signal

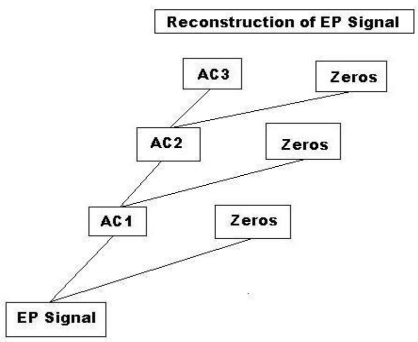

Fig.2.3 Reconstruction of EP Signal.

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

IJARCCE

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 8, August 2015

III. RESULTS

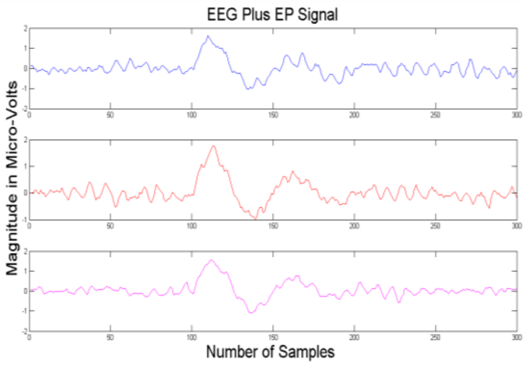

Fig. 3.1 EEG plus EP Signal

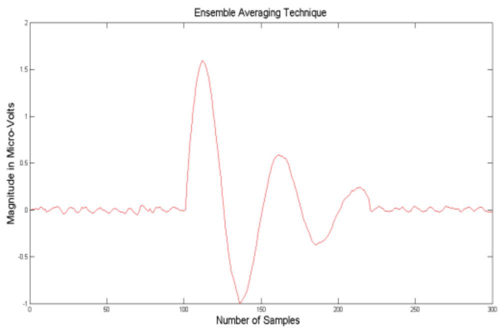

Fig 3.2 Ensemble Averaging Output Signal

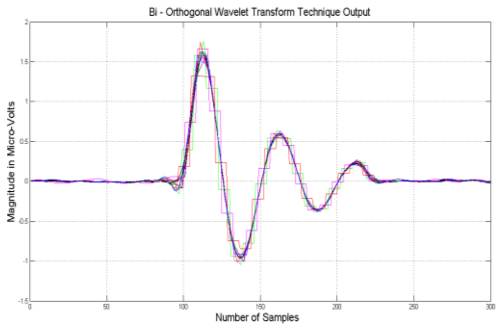

Fig. 3.3 Bi – orthogonal Wavelet Transform Output Signals

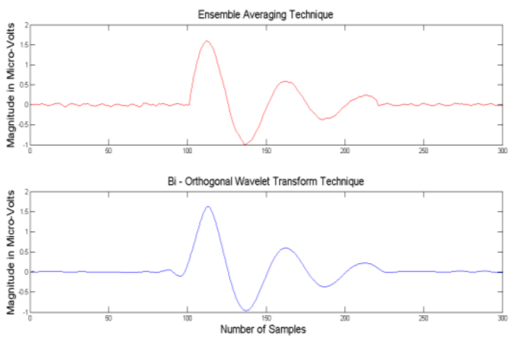

Fig.3.4 Ensemble Averaging and Bi – orthogonal Wavelet Transform Output Signal

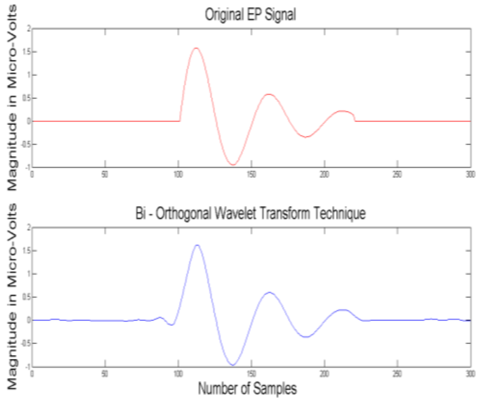

Fig.3.5 Original EP signal and Bi – orthogonal Wavelet Transform Output Signal

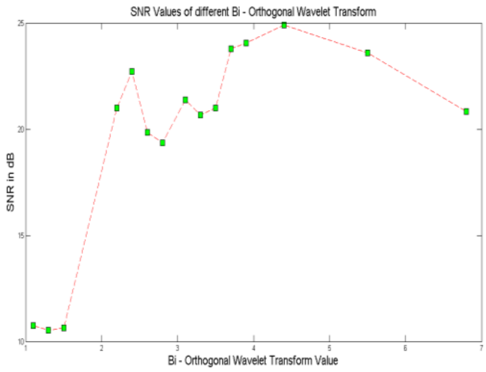

Fig. 3.6 Output SNRs vs Bi – orthogonal Values

Table 3.1 Ensemble Average Technique of SNR Table for EP

Data 1	Number of Sweeps	Ensemble Averaging Technique SNR in dB
#1	10	17.1dB
#2	20	18.63 dB
#3	40	19.48 dB
#4	60	21.28 dB

Table 3.2 Bi – Orthogonal Wavelet Transform Technique of SNR Table for EP

Bi – Orthogonal Values	SNR in dB
Bior 1.1	10.7477
Bior 1.3	10.5446
Bior 1.5	10.6502
Bior 2.2	20.9838
Bior 2.4	22.7090
Bior 2.6	19.8606
Bior 2.8	19.3507
Bior 3.1	21.3890
Bior 3.3	20.6582
Bior 3.5	21.0086
Bior 3.7	23.7916
Bior 3.9	24.0510
Bior 4.4	24.9055
Bior 5.5	23.5833
Bior 6.8	20.8404

Copyright to IJARCCE
DOI 10.17148/IJARCCE.2015.4889

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 8, August 2015

A Interpretation of Results

In this paper, simulated data's have been taken for the analysis and is shown in Fig.3.1 Fig 3.1 shows three different sweeps of data taken at sweep no.20, sweep no.40 and sweep no.60 respectively. One sweep contains 300 samples, 60 such sweeps of data have been taken for the analysis. Only three sweeps of data have shown in Fig 3.1. The simulated signal contains EP and EEG signal and both signals are added to form the contaminated signal. For the Ensemble averaging technique, 60 such sweeps of data have been considered for obtaining the output and also to calculate SNR values. Table 3.1 shows SNR values for different number of sweeps for obtaining the output.

Fig 3.2 shows the output waveform of Ensemble averaging technique. In this figure, it describes about the repetitive signals are almost averaged to highlight EP signal. The strength of the noise signal which is an EEG (back ground signal) reduces as more number of sweeps is considered. Table 3.1 shows that as more number of sweeps is considered, SNR improves by a factor of almost square root of number of sweeps.

In wavelet transform technique of estimating EP signal, only one sweep has been considered for obtaining the output. In this paper, Bi – Orthogonal wavelet transform has been used. Each level of wavelet transform has its own features, but most suitable for denoising or estimation of signals in noisy environment. Three levels of decomposition is processed for each wavelet transform. Hard Thresholding is used for each decomposed signal, since EP signal is low frequency signal and background signal is an EEG signal, which is an high frequency signal. In this method smooth curve is obtained since high frequency components are removed in the process. Fig.3.4 corresponding results obtained by the algorithm. The different Bi – Orthogonal wavelets are used in the algorithm and the corresponding SNR values are tabulated in the table 3.2. Table 3.2 shows the different Bi – Orthogonal wavelets and the corresponding SNR values are tabulated for the EP Data From the tables highest SNR values are obtained and corresponding Bi – Orthogonal wavelet is highlighted. This signifies the maximum SNR is obtained if the corresponding Bi – Orthogonal wavelet is used. The wavelet transform is most useful in decomposing and reconstructing the any biomedical signal, can also be data compression algorithms. Fig. 3.3 shows output waveform of different Bi – Orthogonal values used in obtaining the output waveforms. Some output waveform is degraded version, but most output waveforms are approximated to the desired EP signal. A different color of output waveforms have been plotted and are shown in Fig.3.3. Fig.3.4 shows the output waveform of Ensemble averaging technique and Bi – Orthogonal wavelet transform. In this figure, it is observed that a smooth curve is obtained from initial part of the signal to the end part of the signal in wavelet transform, in Ensemble averaging technique; some noise is present at initial part and end part of the signal. Similarly, Fig 3.5 shows that the Original EP signal (simulated signal) and output waveforms of Bi – Orthogonal wavelet transform technique. In this figure, it is evident that the output waveform of Bi – Orthogonal wavelet transform technique is approximated to the original EP signal. Fig 3.6 shows the output SNR plots of Bi – Orthogonal wavelet transform technique. In this figure, different Bi – Orthogonal wavelet transform values have been plotted along the X – axis and output SNR values along Y – axis. It is observed that maximum SNR is obtained for Bi – Orthogonal wavelet transform value equal to Bior 4.4 and is highlighted in table 3.2 as well.

IV. CONCLUSION

Various estimation methods were studied for EP signals denoising. The signals were estimated using Wavelet method. It is known that signals with higher SNR and low MSE are less noisy signals. By looking at the various evaluation parameters like MSE, SNR calculated by different methods it is concluded that wavelet method gave the best denoising result with its multiresolutional capacities. Wavelet transform analyses the signals in both time and frequency domain and also signals with low noise amplitudes can be removed from the signals by selecting the best wavelet to decompose the signal and reconstruct the signal also improves the SNR.

In the ensemble signal averaging technique, it improves the SNR by a factor of √m. where m is the number of sweeps**.** The main disadvantage of this method is that more number of sweeps of data is required to improve the SNR and which is practically difficult for the subject to receive more number of stimulus and respond equally.

Wavelet-based signal processing has become common place in the signal processing community over the past few years. One of the most important applications of wavelets is removal of noise from biomedical signals and is called de-noising or estimation which is accomplished by thresholding wavelet coefficients in order to separate signal from noise. A biomedical signal is a non-stationary signal whose frequency changes overtime and for the analysis of these signals Wavelet transform is used. Wavelet transform has been a very novel method for the analysis and processing of non-stationary signals such as bio-medical signals in which both time and frequency information is required. The algorithm for estimating EP Signal based on wavelet transform shows the potential of the wavelet transform, especially for processing time-varying biomedical signals. The power of wavelet transform lies in its multi scale information analysis which can characterize a signal very well. In this paper Bi – Orthogonal wavelet transform improves SNR in the results obtained and is more suitable for EEG and EP signal estimation.

V. ACKNOWLEDGEMENT

Foremost, I would like to express my sincere gratitude to my mentor, guide, supervisor and advisor **Dr. Anand Jatti,** Ph.D (VTU), Associate Professor, Department of Electronics and Instrumentation, R.V.College of Engineering, Bangalore for the continuous support

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 8, August 2015

extended during the preparation of this paper. I thank him for all his courtesies, patience, motivation, enthusiasm and immense knowledge extended to me. His guidance helped me throughout the process and producing of this paper

I express heartfelt gratitude to **Ms. Sujitha Vasu,** Sri Venkateshwara International Educational Trust, Bangalore, who supported morally to have the idea of producing this paper and encouraged in all phases of obtaining this useful results.

I also thank my colleagues Prof. **Dr. Shobharani A, Prof. Dr. Prithvi Shekhar, Prof. Renuka Kajur, Prof. Asha C N, Prof. Bhargav N, Prof. I Vijaya Kumar Reddy, Prof. Bhaskar G R, Er. Guru Prasad A G, Er. Vinod Kumar**, who have reviewed my paper work, for all the technical support and extended valuable suggestions during different phases of my producing of this paper.

REFERENCES

[1]. M P Wachovia, G S Rash, P M Quesada, A H Desoky in IEEE Transactions on Biomedical Engineering(2000).Wavelet-based noise removal for biomechanical signals: a comparative study.

[2]. Groseth **GS**, Ashman EJ. Practice parameter: the usefulness of evoked potentials in identifying clinically silent lesions in patients with suspected multiple sclerosis (an evidenced based review). Neurology2000; 54:1720–5. Report of the Quality Standards Subcommittee of the American Academy of Neurology

[3]. **McDonald WI**, Compston A, Egan G, et al. Recommended diagnostic criteria for multiple sclerosis: guidelines from the international panel on the diagnosis of multiple sclerosis. Ann Neurol 2001; 50:121–7. An updated and simplified outline of the diagnostic multiple sclerosis guidelines which plays down the clinical role of evoked potentials.

[4]. L. Hua, Z.G. Zhang, Y.S. Hung, K.D.K. Luk, G.D. Iannetti, Y. Hua, Single-trial detection of somatosensory evoked potentials by probabilistic independent component analysis and wavelet filtering

[5]. Brignell MG. The visual evoked potential. In: Fishman GA, Birch DG, Holder GE, Brignell MG, eds. Electrophysiological testing in disorders of the retina, optic nerve and visual pathway. San Francisco: Foundation of the American Academy of Ophthalmology, 2001:237–9.

[6]. Jenna Joy, Salice Peter, Neetha John, "Denoising Using Soft Thresholding", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering Vol.2, Issue 3, March 2013

[7].Willis.J.Tomkins Bio Medical Digital Signal Processing, PHI Publications

[8].C.Britton Rorabaugh DSP Primer, John Wiley

[9].Stephane Mallat A wavelet tour of signal processing, PHI Publications

[10].Time frequency and wavelets in Biomedical signal processing by Metin Akay (IEEE express)

[11].Sophacles J. Orfanidis Optimum Signal Processing, John Wiley.

[12] Darshan Iyer and George Zouridakis, "Estimation of Brain responses based on Independent Component Analysis and Wavelet Denoising", Technical Report Number UH-CS-05-01 January 23, 2005.