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SNR IMPROVEMENT FOR EVOKED POTENTIAL ESTIMATION USING WAVELET TRANSFORM TECHNIQUES

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ABSTRACT

Digital Signal Processing uses mathematical analysis and algorithms to extract information hidden in signals derived from sensors[1]. The Biomedical Signal contaminated by noise and artifcats. The problem of estimating one signal from another is one of the most important in signal processing[9]. In many applications, the desired signal is not available or observable directly. Instead the observable signal is a degraded version of the original signal. The signal estimation problem[12] is to recover in the best way possible , the desired signal from its degraded replica. In this case, the desired signal may be corrupted by strong additive noise, such as weak evoked brain potentials measured against the strong background of on going EEG (ElectroEncephalogram) Signals.

***Wavelet transform** technique of estimation improves the SNR by a large amount in almost one sweep of EP. The two different wavelet transforms such as Daubechies wavelet transform and Bi – Orthogonal wavelet transform have 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 Daubechies wavelet transform and 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, Daubechies, Evoked Potential, Ensemble Averaging, SNR.

I. INTRODUCTION

The brain is the most complex structure in the well known universe. The brain dominate 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[2]. 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.

1.1 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[3] 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.

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.

1.2 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 2reversals 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]

1.3 Earlier Methods

During the analysis of real biomedical signals it can almost always be seen noise that distorts the signal. The presence of interference is associated with the specific acquisition of these signals. For example in the case of bioelectric signals, disturbances may come from the hardware retrieves those signals, the power line or the bioelectric activity of body cells. The bioelectric signals, which are widely used in most fields of biomedicine, are generated by nerve cells or muscle cells. The electric field propagates through the tissue and can be acquired from the body surface, eliminating the potential need to invade the bio medical system. However, using surface electrodes results in high amplitude of noise and the noise should be suppressed to extract a priori desired information.

There are many approaches to the noise reduction problem while preserving the variability of the desired signal morphology. One of the possible methods of noise attenuation is low-pass filtering such as arithmetic mean. The classical band-pass filtering is very simple method but also very ineffective because the frequency characteristics of signal and noise significantly overlap. The methods of noise attenuation are ensemble averaging techniques and based on transforming the input space of signal and creating a new space with the help of wavelet transform. In the case of repeatable biomedical signals, another possible method of noise attenuation is the synchronized averaging. The method assumes that the biomedical signal is quasi-cyclic and the noise is additive, independent and with zero mean.

Weighted averaging techniques gave the best signal-to-noise ratios when compare with ensemble averaging technique. By considering the statistical parameters like standard deviation should be considered for changing weight of the each sample. Two EP samples have been considered for the analysis. Weighted averages of brain evoked potentials (EP's) are obtained by weighting each single EP sweep prior to averaging. These weights are shown to maximize the signal-to-noise ratio (SNR) of the resulting average if they satisfy a generalized eigenvalue problem involving the correlation matrices of the underlying signal and noise components.

A parametric method of identification of event-related (or evoked) potentials on a single-trial basis through an AR, MA and ARMA algorithm is implemented. The basic estimation of the information contained in the single trial is taken from an average carried out on a sufficient number of trials, while the noise sources are EEG. The simulations as well as the experimental results confirm the capability of the model of drastically improving the S/N (signal-to-noise) ratio in each single trial and satisfactorily identifying the contributions of signal and noise to the overall recording.

Adaptive filters have been widely utilized in applications that include channel equalization, echo cancellation, radar, linear prediction, spectral analysis and system identification [9]. Here the discussion is about the use of adaptive filters for adaptive noise cancellation for Evoked Potentials. The implementation of the Wiener theory for adaptive noise cancellation requires infinite filter weights to minimize the output error. To make the Wiener solution realizable, a finite number of filter weights must be used. That is, adaptive filters must assume the Wiener filter as an FIR filter.

Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where one[10] [11] want more precise low frequency information, and shorter regions where one want high frequency information.

In this paper ensemble averaging technique and wavelet transform techniques have been implemented for improving the output SNR values.

II. METHODS

2.1 Ensemble Averaging Technique

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 ($i = 1, 2,\ldots, n$) 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

2.1.1 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.

2.2 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].

2.2.1 Daubechies Wavelets Approximation

Non-linear approximation is obtained by thresholding low amplitude wavelet coefficients.

This defines the best M-terms approximation fM of f:

fM=∑|⟨f,ψj,n⟩|>T⟨f,ψj,n⟩ψj,n.

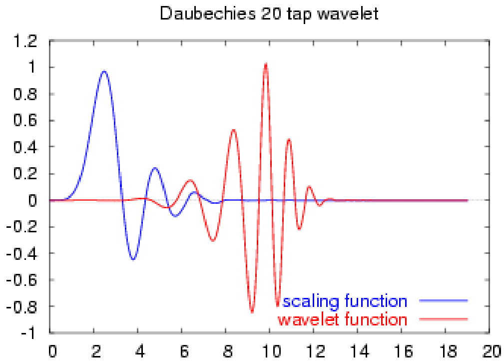


Fig. 2.1 The Shape of a Wavelet

A wavelet coefficient is an inner product dj[n]=⟨f,ψj,n⟩ with a wavelet atom ψj,n.

A wavelet atom ψj0,n0 can be computed by applying the inverse wavelet transform to coefficients {dj[n]}j,n such that

dj[n] = 1 if j=j0 and n=n0,

0 otherwise.

2.2.2 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

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

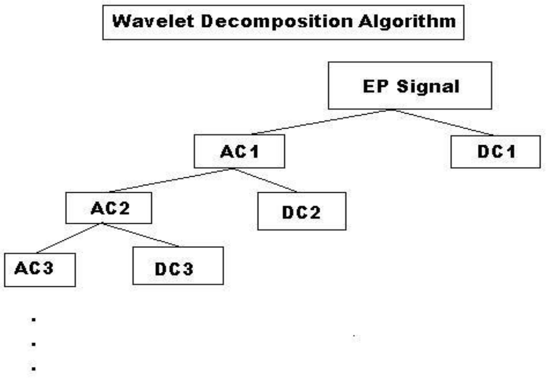
$$\tilde{b}_n = (-1)^n a_{M-1-n} \qquad (n = 0, \dots, N-1)$$

2.3 Algorithm for Wavelet Transform Technique

1. Decompose the signal by applying the discrete wavelet transform[7] 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[7][8].

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.



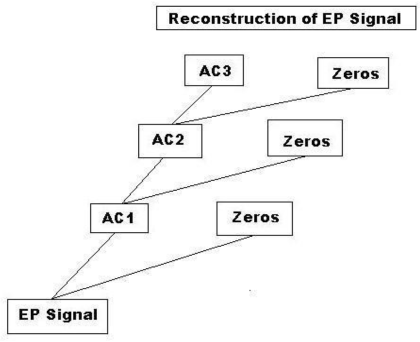


Fig. 2.2 Decomposition of EP Signal **Fig. 2.3 Reconstruction of EP Signal**

III. RESULTS

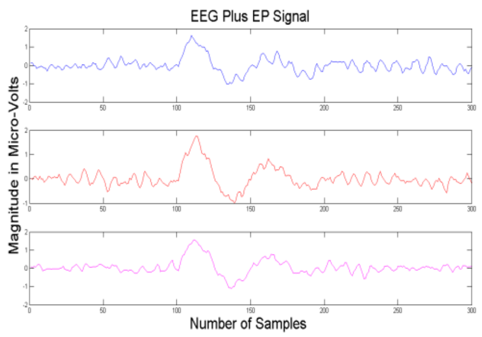


Fig. 3.1 EEG plus EP Signal

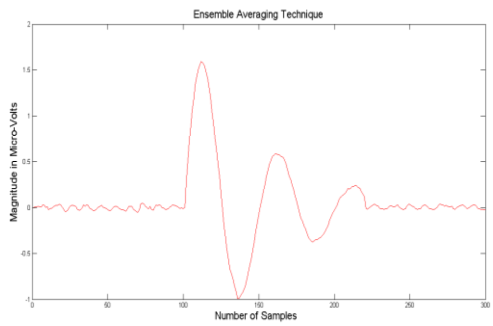


Fig 3.2 Ensemble Averaging Output

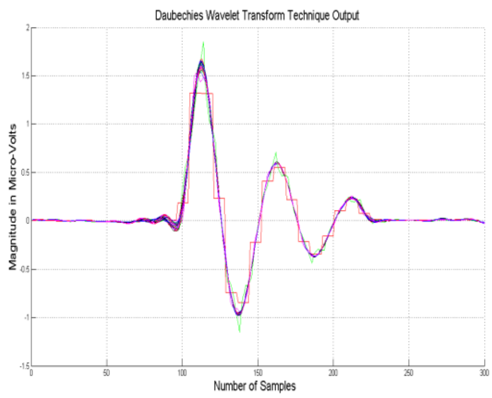


Fig. 3.3 Daubechies Wavelet Transform Output

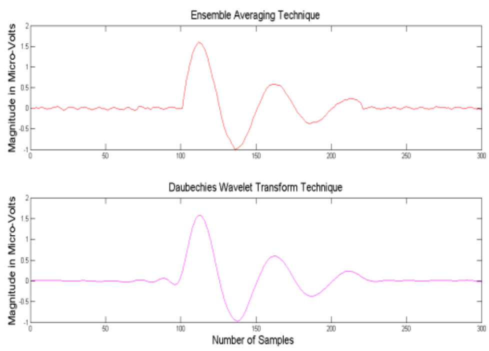


Fig.3.4 Ensemble Averaging and Daubechies Wavelet Transform Output

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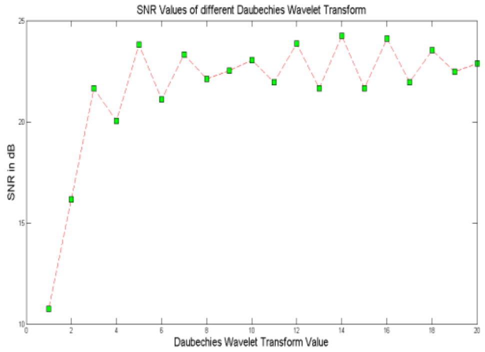


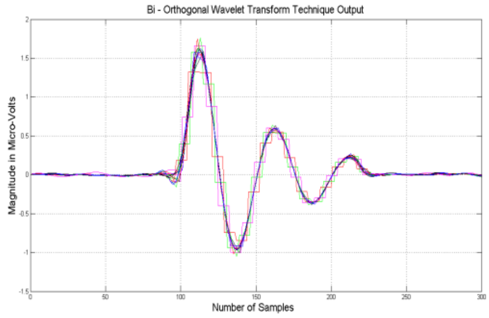
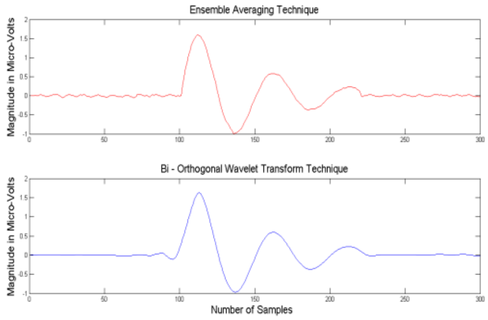


Fig. 3.5 Output SNRs vs Daubechies Values Fig. 3.6 Bi – orthogonal Wavelet Transform Output



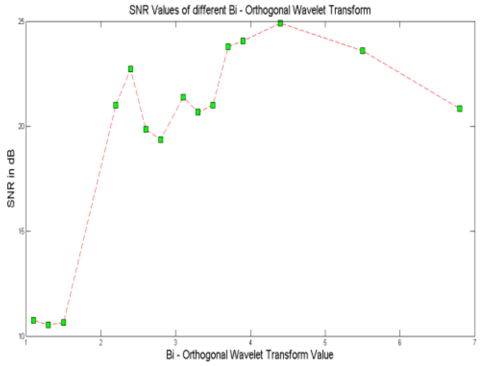


Fig.3.7 Ensemble Averaging and Bi – orthogonal Wavelet Transform Output

Fig. 3.8 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 Daubechies Wavelet Transform Technique of SNR Table for EP

Daubechies Value	SNR in dB
db1	10.7477
db2	16.1588
db3	21.6576
db4	20.0363
db5	23.8056
db6	21.1091
db7	23.3163
db8	22.1091
db9	22.5339
db10	23.0505
db11	21.9618
db12	23.8590
db13	21.6615
db14	24.2534
db15	21.6659
db16	24.1004
db17	21.9520
db18	23.5450
db19	22.4692
db20	22.8903

Table 3.2 Daubechies 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

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3.1 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.1, sweep no.16 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 narrates 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, there are two different wavelet transforms have been used. Each 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 Daubechies wavelets are used in the algorithm and the corresponding SNR values are tabulated in the table 3.2. Table 3.2 shows the different Daubechies wavelets and the corresponding SNR values are tabulated for the EP Data From the tables highest SNR values are obtained and corresponding Daubechies wavelet is highlighted. This signifies the maximum SNR is obtained if the corresponding Daubechies wavelet is used. The wavelet transform is most useful in decomposing and reconstructing the any signal, can also be data compression algorithms. Fig. 3.3 shows output waveform of different Daubechies values used in obtaining the output waveforms. Some output waveform are 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 Daubechies 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. Fig 3.5 shows the output SNR plots of Daubechies wavelet transform technique. In this figure, different Daubechies 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 Daubechies wavelet transform value equal to db14 and is highlighted in table 3.2 as well.

In Fig 3.7 Bi – Orthogonal wavelet transform output waveform is shown and as mentioned earlier this waveform is compared with Ensemble averaging technique output waveform. Different output waveforms for different Bi – Orthogonal wavelet transform functions are shown in Fig 3.6. Here, also some of the Bi – Orthogonal wavelet transform functions will not give the desired output. It is evident that Bior 4.4 function will give the better SNR in comparison with the other functions and is shown in Fig 3.8. Table 3.3 shows that tabulated output SNR values with that of Bi – orthogonal function values

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 $\sqrt{m}$. 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 Daubechies wavelet and Bi – orthogonal wavelet transform improves SNR in the results obtained and is more suitable for EEG and EP signal estimation.

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