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Comparative Analysis of SNR Improvement for Evoked Potential Estimation Using Different Wavelet Transforms

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Abstract *: Digital Signal Processing uses mathematical analysis and algorithms to extract information hidden in signals derived from sensors. The Biomedical Signal contaminated by noise and artifacts[1]. The problem of estimating one signal from another is one of the most important in signal processing[5]. 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 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. The brain receives the information from and sends command signals to all parts of the body. The EEG has very complex pattern, which is difficult to recognize as compared to ECG (ElectroCardiogram) Signals*

Evoked potentials (EP) are often defined to be potentials that are caused by the electrical activity in central nervous system after a stimulation of the sensorial system. In the analysis of evoked potentials the fundamental problem is to extract information about the potential from measurements that contain also on-going background electroencephalogram (EEG).The most widely used tool for the analysis of evoked potentials has been the averaging of the measurements over an ensemble of trials. This is the optimal way to improve the signal-to-noise ratio when the underlying model for the observations is that the evoked potential is a deterministic signal in independent additive background noise of zero mean. However, it has been evident that the nature of evoked potentials is more or less stochastic. In particular, the latencies and the amplitudes of the peaks in the potentials can have stochastic variation between repetitions of the stimuli. Currently the goal in the analysis of the evoked potentials is to obtain best possible estimates for single potentials. The most common approach to this estimation is to form an estimator (filter)[2] with which the unwanted contribution of the EEG can be filtered out from the evoked potential using different wavelet transforms.

Keywords: EEG, EP, SNR, Ensemble Averaging, Daubechies, Haar, Bi – orthogonal, Wavelet Transform

1. Introduction

The work presented in this paper is to improve the Signal to noise ratio (SNR) of the EP estimation using wavelet transform. A comparative analysis is being made with the results of the various wavelet transforms. Conventional method of estimating EP is ensemble averaging technique, which improves the SNR, But the main disadvantage of the Ensemble averaging technique is that it needs more number of sweeps of data. The patient will undergo by receiving more number of stimulus depending on types of stimulus. The stimulus can be visual stimulus, auditory stimulus and somato sensory stimulus.

2.0 Methodology

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, the signal waveforms directly sum together. On the other hand, the uncorrelated noise averages out time. Thus, the signal – to – Noise **(SNR)** is improved[1].

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[1]. 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.

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

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

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

Where **m** is number of sweeps

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

A **wavelet** is a wave-like oscillation with an amplitude that begins at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "reverse, shift, multiply and integrate" technique called convolution, with portions of a known signal to extract information from the unknown signal[3][7].

2.2.1 Wavelets

A wavelet is an oscillatory function with a mean of zero and finite energy, of which there are many, such as derivatives of Gaussian functions, the selection of a particular function is based upon criteria set by the use of the function e.g. de-noising seismic signals, compressing music, etc. Each individual function is known as a mother wavelet and compressed and dilated versions of this mother are used throughout the wavelet analysis process.

Second derivative of Gaussian (mother wavelet)

$$\psi(t) = (1-t^2)e^{-t^2/2} \quad (8)$$

Compressed or dilated versions of mother

$$\psi\left(\frac{t-b}{a}\right) = \left[1-\left(\frac{t-b}{a}\right)^2\right]e^{-\frac{1}{2}[(t-b)/a]^2} \quad (9)$$

Thus, the result is a probe which can move throughout the signal at different frequencies to produce a wavelet transform.

2.2.2 Wavelet Transform

The wavelet transform is so chosen, it must be used as a probe to separate the signal frequencies within that signal. The continuous wavelet transform is defined as;

$$T(a,b) = w(a)\int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \quad (10)$$

or as an inner product

$$T(a,b) = \left\langle x, \psi_{a,b}\right\rangle \quad (11)$$

$w(a)$ 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. The same analysis is applicable to Discrete wavelet transform (DWT)[3].

2.2.3 Thresholding

Once the decomposition of the signal has been performed and the transform has been created it is clearly possible to alter any wavelet coefficients. After decomposition two types of coefficients are existing, one is detailed coefficients, which represents the high frequency signals and another one is approximate coefficients, which represents the low frequency signals. Estimating of wavelet coefficients is performed by removing the smaller coefficients in the difference terms. In these terms are the detailed coefficients which can often be removed without making a large difference to the overall structure. Two types of thresholding are used to estimating the signal in noisy environment and are as follows..

1. Hard Thresholding

A difference term is treated as follows:

$d = 0$ if $|d| < \lambda$ and otherwise is not touched.

2. Soft Thresholding

As above but all other values for which $d > \lambda$ have the following operation done to them:

$d \leftarrow \mathrm{sgn}(d)(|d| - \lambda)$

This repositions the remainder of the coefficients. The literature suggests that λ is best set to $\frac{\sigma\sqrt{2\ln n}}{\sqrt{n}}$. The standard deviation σ is taken over all the difference terms. 'n' is the number of difference terms[7]. The choice of threshold is critical and one method is to base the threshold on the noise of the system, as in the universal threshold;

$$\lambda_U = (2\ln N)^{1/2}\sigma$$

Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or *mother*) wavelet[6].

Different wavelet transforms which are used for the analysis are as follows forth

- Daubechies wavelet transform
- Biorthogonal wavelet transform
- Coiflets wavelet transform
- Symlets wavelet transform

2.2.4 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.

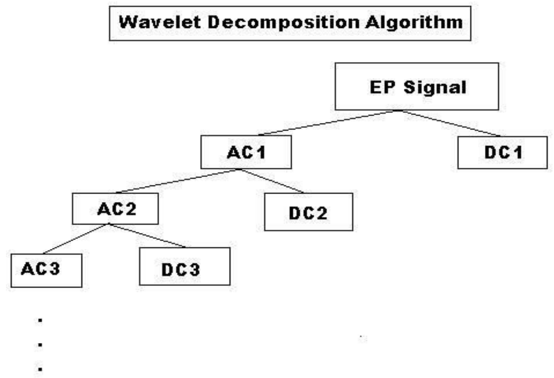

Fig. 2.1 Decomposition of EP Signal

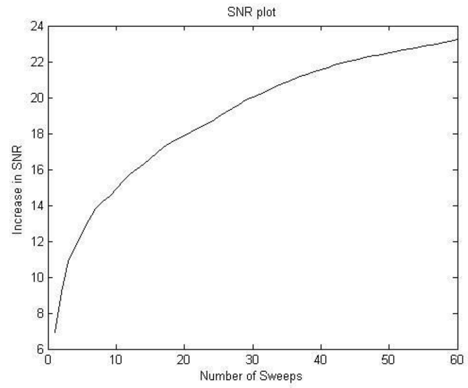

Fig.3.2 Ensemble average & wavelet output

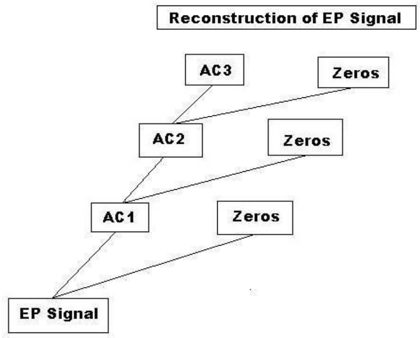

Fig. 2.2 Reconstruction of EP Signal.

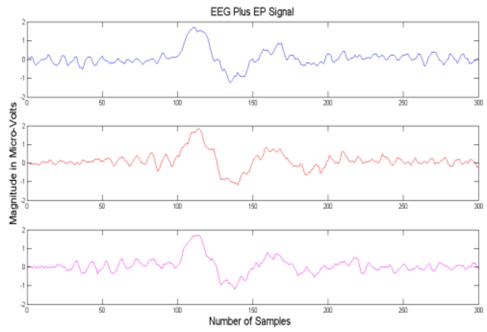

Fig 3.3SNR Plot vs Number of sweeps

3.0 Results

3.1 Output waveforms

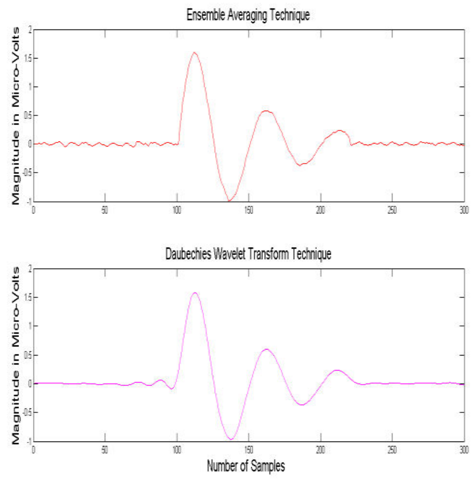

Fig.3.4 Ensemble Average Technique and Daubechies wavelet transform results

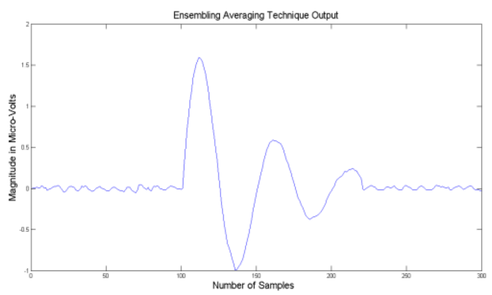

Fig.3.1 EEG plus EP Signal

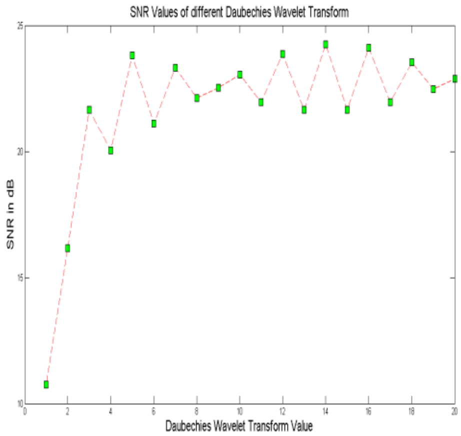

Fig.3.5 Output SNR Plot of Daubechies Wavelet Transform

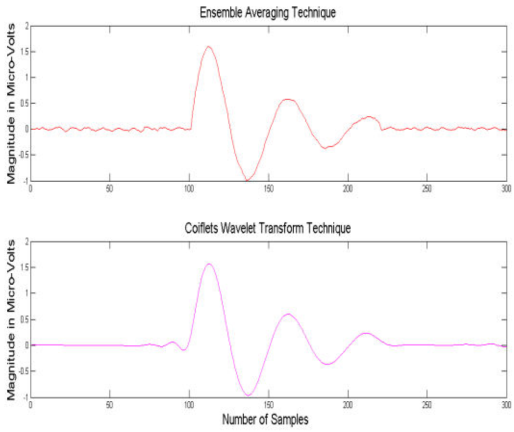

Fig 3.6 Output Plots of Ensemble Average Technique and Coiflet Wavelet Transform

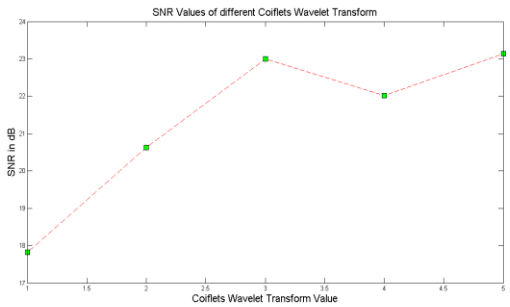

Fig 3.7 Output SNR Plot of Coiflet Wavelet Transform

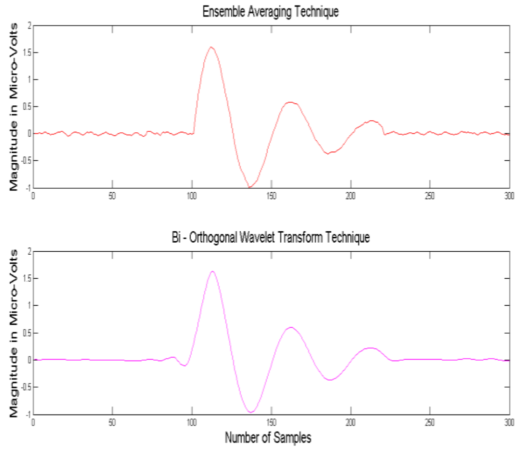

Fig 3.8 Output Plots of Ensemble Average Technique and Bi – orthogonal Wavelet Transform

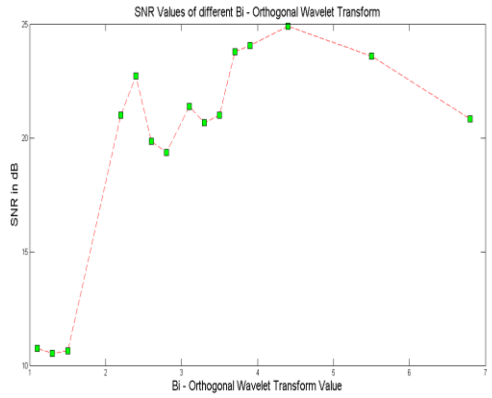

Fig 3.9 Output SNR Plot of Bi – orthogonal Wavelet Transform

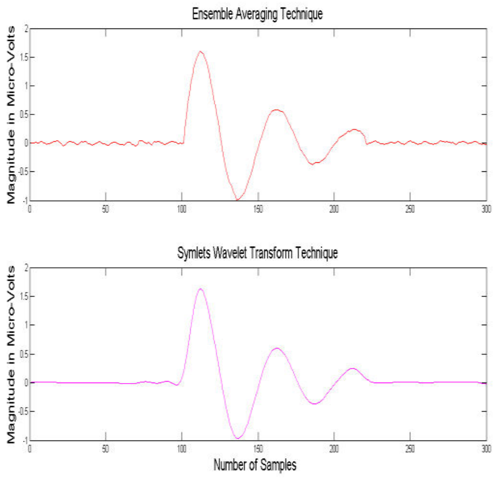

Fig 3.10 Output Plots of Ensemble Average Technique and Symlet Wavelet Transform

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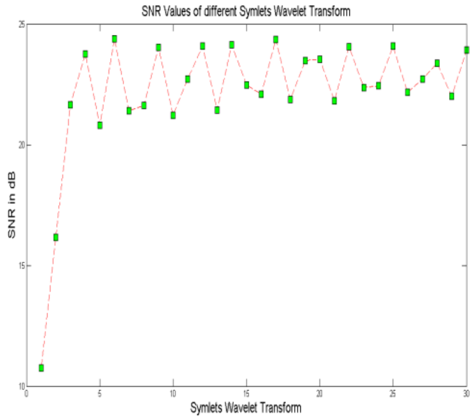

Fig 3.11 Output SNR Plot of Symlet Wavelet Transform

Table 3.1 SNR Comparison Table for Ensemble Averaging Technique

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 SNR Comparison Table for Daubechies Wavelet Transform

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 3.3 SNR Comparison Table for Bi – Orthogonal Wavelet Transform

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

3.2 Interpretation of Results

In this paper the synthetic signals are generated with 300 samples in length. The signals generated are evoked potential signal and random signals, and the two signals are being added, these signals are considered in this paper for the comparative analysis. Fig 3.1 shows the three sweeps of data , actually, total 60 sweeps of such data have been used in the process of estimation. The first technique used one is conventional ensemble averaging technique, Fig 3.2 shows the result of ensemble averaging technique. Comparing the sweeps of data in fig 3.1 and fig 3.2 , fig 3.2 sweep of data is having less noise when compare with the corrupted. This shows ensemble averaging techniques improves the quality of the signal being estimated and also improves the SNR of the signal. Fig 3.2 shows the SNR plot of various numbers of sweeps of data being considered. In this figure, it shows that as more number of sweeps of data are being considered, SNR also improves. But in this technique, main disadvantage is that, more number of sweeps are required. Table 3.1 shows that the more number of sweeps being averaged, SNR improvement is observed. To overcome this problem, wavelet transform technique is implemented. In this technique, single sweep of data is enough to estimate the EP signal. Four different wavelet transforms have been used for the analysis on this data. Fig 3.4 shows the output waveforms of ensemble averaging technique and Daubechies wavelet transform technique. From the figure it shows that the wave form is smoother, almost all high frequency signals have been removed when in comparison with ensemble averaging technique.

Hard thresholding technique is implemented in wavelet transform technique. Fig 3.5 shows that the SNR plots of various resolutions of Daubechies wavelet transform. Similarly Fig 3.6 shows the output of coiflet wavelet transform technique and Fig 3.7 shows the SNR plot of various resolutions of Coiflet wavelet transform. Fig 3.8 shows and Fig 3.10 shows the output for Bi – orthogonal wavelet transform technique and Symlet wavelet transform technique respectively. From the table 3.2, it shows SNR value of 24.2534 dB is obtained for db14 using Daubechies wavelet transform. Similarly table 3.3 shows that 24.9055 dB is obtained for the Bior4.4 using Bi – orthogonal wavelet transform

4.0 Conclusion

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 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. Amongst all the different wavelet transforms used, Daubechies and Bi – orthogonal wavelet transform gives more SNR when compared to other wavelet transforms. These wavelet transforms are most applicable for estimating Evoked potential signals in a noisy environment.

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