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Evoked Potential Detection using LMS Adaptive Wiener Filter and Wavelet Transform

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Abstract: ***Signal Processing utilizes scientific investigation and calculations to separate data concealed in signal got from different types of sensors. The Biomedical Signals are defiled by commotion and artifacts. In numerous applications, the ideal signal is not accessible or recognizable straightforwardly. The signal assessment issue is to recuperate in the most ideal manner conceivable, the ideal signal from its debased copy. When obtaining EEG (Electroencephalogram) evoked potentials from scalp electrodes, background activity and other noise is added to the signal. The Wavelet Transform system of estimation surpasses the SNR(Signal to Noise Ratio) by a huge value in just about one sweep of EP(Evoked Potential). The two diverse wavelet Transform systems, Daubechies wavelet transform and Biorthogonal wavelet transform have been discussed in this paper to improve SNR.***

Keywords : Bi – Orthogonal, Daubechies, Evoked Potential, Ensemble Averaging, LMS and SNR

I. INTRODUCTION

The brain is the ultimate perplexing structure in this outstanding universe. The brain commands numerous exceptionally particular component parts each related with explicit functionalities. The brain electrical movement, that happens regarding an extraneous Impetus(sound-related, visual or somatosensory), is called Evoked Potential (EP).If the perceptive examination is applicable to a subjective movement, then the reaction signal is regularly called as event-related-potential (ERP). EPs are significant indicative devices in examination of physiological and psychological circumstances of the subject. The split up of the EP (the signal) and the continuous EEG (the noise) in the estimations have been appealing focuses in this paper. This needs utilization of incredible Bio – Medical Digital Signal Processing techniques and a few methods have been proposed for this reason[4].

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A. Visual Evoked Potential (VEP)

Evoked potential (EP) establish a generally new technique for clinical neurophysiology permitting functional assessment of the neural framework. Such non-obtrusive strategies give data about the utilitarian conditions of various expanse inside the nervous system. Evoked potentials are particularly valuable in the recognition of subclinical brokenness.

The main acknowledgment of Visual Evoked Potential (VEP) corresponds with the disclosure of EEG. It was observed that electrical activity of the brain is modified when an escalated light stimulus is applied. By the introduction of computerized averaging techniques and due to the very low potentials popularity of this method grew very high.

B. Earlier Methods

During the investigation of genuine biomedical signals it can generally be seen that noise misaligns the signal. Arithmetic mean is one among the many methods for noise attenuation using low pass filtering technique. The conventional band-pass filtering is a highly unambiguous method but also very ineffective because the frequency characteristics of signal and noise significantly overlap.

In Weighted averaging technique, the weight of each sample is changed considering standard deviation, a statistical parameter. Two EP samples have been considered for the analysis. Each signal to be averaged is assigned a weight in this Technique before averaging to obtain weighted averages of brain evoked potential and these weights maximize the SNR of the resulting average if certain criterion is met.

In this context adaptive noise cancellation for Evoked Potentials using adaptive filtering is dealt[2]. Wavelet analysis: a windowing technique with variable sized regions. We get more accurate low frequency information from long time intervals and higher frequency information from shorter regions by the use of Wavelet Analysis[7].

II. METHODS

A. Ensemble Averaging Technique

The Ensemble Averaging Technique is the most commonly used technique for determining Evoked Potential estimate. Ensemble averaging is the process of creating multiple models and combining them to produce a desired output by averaging the successive sets of data that are collected starting from the same data point for collecting data from the repeated signal, as opposed to creating just one model.

The following attributes of signal and noise contribute to Signal averaging.

- Repetitive signals are considered
- The noise must be unrelated with the signal and random in nature.
- Accurate Knowledge of the temporal position of each signal sample is a must

SNR increases as the number of trials under consideration for averaging is more.

1) Algorithm for Ensemble Averaging Technique

- Various memory locations store the various ensemble data
- Include the main position estimations of the considerable number of exhibits and store it in first position of another cluster, similarly all the position esteems are to be included and stored
- Dividing by trials quantity, the average is calculated
- A plot of Signal to Noise Ratio array elements is obtained by evaluating SNR for each sweep and stow them in arrays

B. Wavelet Transform Technique

Wavelet transform have evoked extensive enthusiasm for the signal processing domain. They have discovered applications in a few regions, for example, speech coding, edge identification, information confinement, derivation of criteria for acknowledgment and analysis and so forth since wavelets give an approach to speak to a signal on different degrees of resolution, they are helpful tool for investigation of information and modification of information[5].

1) Daubechies Wavelets Approximation

Thresholding low potential wavelet coefficients results in Non-linear approximation. The M-terms approximation is defined as

$$fM = \sum |f, \psi j, n| > T(f, \psi j, n)\psi j, n. \quad (1)$$

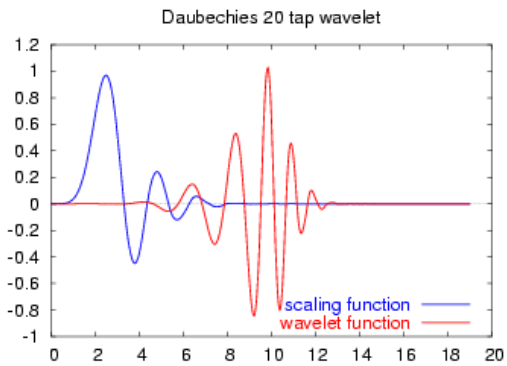

Fig. 2.1 The shape of a Wavelet

2) Biorthogonal wavelet

A Wavelet Transform where in the related wavelet transform is invertible however not really symmetrical is the Biorthogonal wavelet. More degrees of freedom can be achieved by Biorthogonal wavelet when compared to orthogonal wavelets. Symmetric wavelet functions can be constructed by One additional degree of freedom.

In the Biorthogonal case, there are two scaling functions, which may generate different multiresolution analyses, and accordingly two different wavelet functions φ, φ' . The scaling sequences a, a' may differ[6]. The following biorthogonality conditions must be met by the scaling sequences

$$\sum_{n \in Z} a_n a'_{n+2m} = 2 * \partial_{m,o} \quad (2)$$

Then the wavelet sequences can be determined as

$$b_n = (-1)^{n'} a_{M-1-n} \quad (n=0,1,\ldots..,N-1) \quad (3)$$

$$b'_n = (-1)^{n} a_{M-1-n} \quad (n=0,1,\ldots..,N-1) \quad (4)$$

C. Algorithm for Wavelet Transform Technique

- Decay the signal by administering the discrete wavelet transform and is as appears in Fig.2.1
- Expel the high recurrence signal for example the detailed coefficients and hold the low recurrence signal for example approximation coefficients
- Reproduce the Evoked Potential signal by applying inverse wavelet transform of disintegrated signal and appears as shown in Fig.2.2
- Make every single detailed coefficient to zero, while applying inverse wavelet transform
- Find the throughput Signal to Noise Ratio for various trials

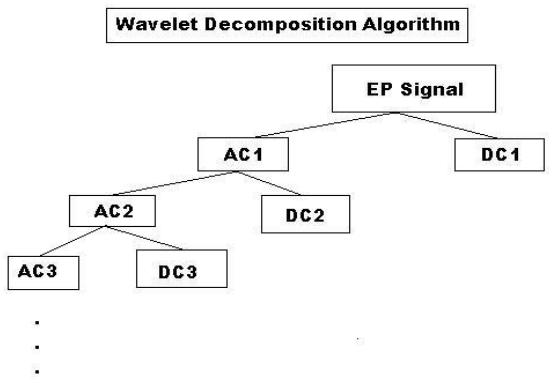

Fig. 2.2 Decomposition of EP Signal

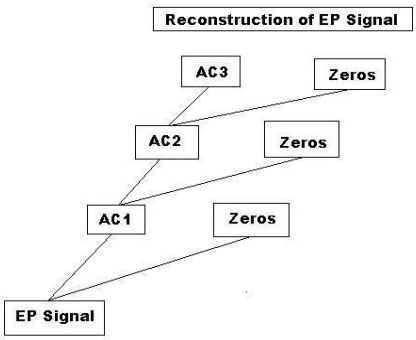

Fig. 2.3 Reconstruction of EP Signal.

D. Adaptive Noise Cancelling with the LMS Adaptation Algorithm

It is evident that the optimal filter weight cannot be comprehended if there isn't previous knowledge available about the reference signal vector $\underline{P}$ and the input correlation matrix R. For this reason, an alternative iterative solution for the Wiener FIR filtering. In this solution the term $\partial\varepsilon(\omega(n))/\partial\omega$ is replaced with an instantaneous gradient by dropping the expectation operator

$$\frac{\partial\varepsilon(\omega(n))}{\partial\omega} = 2E\left[e(n)\frac{\partial e(n)}{\partial\underline{\omega}}\right] = -2E[e(n)\underline{r}(n)] = -2e(n)\underline{r}(n) \quad (5)$$

Where

$$\partial e(n)/\partial\underline{\omega} = \partial(s(n) - \underline{\omega}^T\underline{r}(n))/\partial\underline{\omega} = -\partial\underline{\omega}^T\underline{r}(n)/\partial\underline{\omega} = -\underline{r}(n) \quad (6)$$

The filter weights can then be updated by combining above equations

$$\underline{\omega}(n+1) = \underline{\omega}(n) + 2\mu e(n)\underline{r}(n) \quad (7)$$

E. *LMS adaptive Wiener filter Algorithm*

The below steps is for the adaptive noise canceling algorithm (based on LMS).

Step 1. Calculate the adaptive FIR filter output, $v(n)$ as

$$v(n) = \sum_{m=0}^{M} \omega_m(n) r(n-m) \quad (8)$$

Where M represents the filter order

Step 2. Estimate the error, e(n), for the current time, n,

$$e(n) = s(n) - v(n) \approx x(n) \quad (9)$$

Step 3. Update the filter weights, $\omega_m(n)$, using the gradient-descent LMS algorithm:

$$\omega_m(n+1) = \omega_m(n) + 2\mu e(n) r(n-m) \quad (10)$$

for $0 \le m \le M$

Step 4. Go to next time instant:
$n \rightarrow n + 1$

The convergence parameter, μ, must be positive and should satisfy the following:

$$0 < \mu < \frac{1}{R} \quad (11)$$

$$0 < \mu < \frac{1}{\lambda_{\max}} \quad (12)$$

Where $\lambda_{\max}$ represents the maximum Eigen value of the autocorrelation matrix R. ho ever, in practice, the value of R is not known and the value of parameter **μ** must be chosen heuristically. While a small value of **μ** may guarantee convergence, caution should be taken against excessively small values which promote very slow convergence. In contrast, choosing a large **μ** increases the speed of convergence at the expense of noisy convergence[1].

III. RESULTS

Here, Counterfeit information has been considered for examination and it appears in Fig.3.1, which shows three distinct trials of information considered at trial no.20, trial no.40 and trial no.60 individually. Each trial consists 300 inspects, 60 alike trials of information have been considered for the investigation. Just three trials of information appears in the underneath figure.

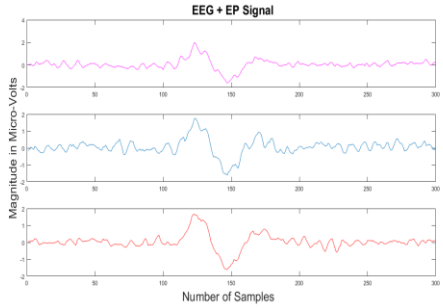

Fig 3.1 EEG plus EP Signal

For the Ensemble averaging procedure, 60 alike trials of information is considered in getting the yield and to ascertain SNR values.

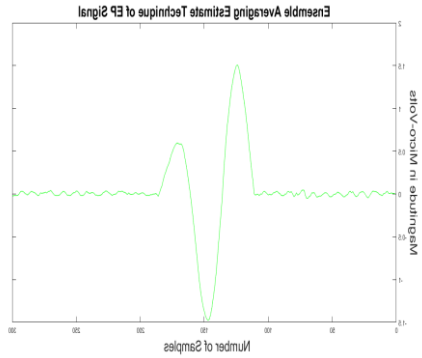

Fig 3.2 Ensemble Averaging Output Signal

Fig 3.2 demonstrates the yield waveform of Ensemble averaging procedure. In this figure, it depicts about the reiterative signals are averaged out to feature EP signal. Table 3.1 demonstrates that as progressively count of trials are considered, SNR upgrades by a part of practically square base of number of trials. The Signal to Noise Ratio (SNR) to number of sweeps is as shown in fig 3.3.

Table 3.1 Ensemble Averaging Technique SNR for Various Trials

Data	Number of Trials	Ensemble Averaging Technique SNR in dB
1	10	16.1dB
2	20	17.73 dB
3	40	20.58 dB
4	60	22.78 dB

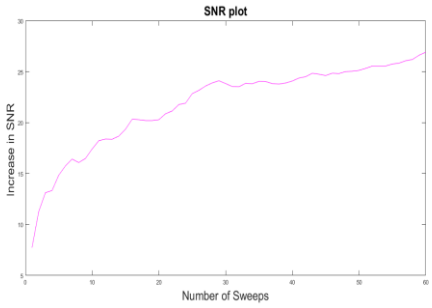

Fig 3.3 Signal to Noise Ratio (SNR) plot

Various plots of LMS adaptive Wiener filter are discussed below. Fig 3.4 shows the result plots obtained for +5dB input SNR. This figure has in subplots of the corrupted signal, estimated signal and the output signal. Initially the original signal has been corrupted by +5dB noise, it considers to be the Input SNR of +5dB. Fig 3.5 shows the plots obtained for 0 dB input SNR, similarly, Fig 3.6 shows the result for the -5 dB Input SNR.

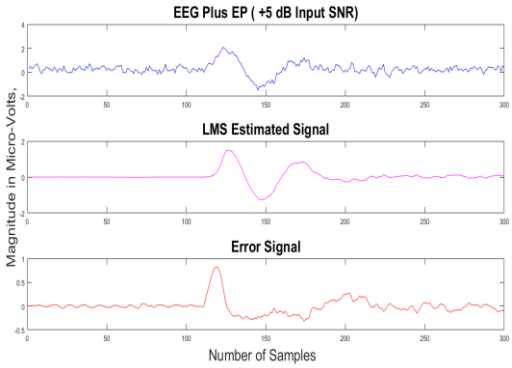

Fig 3.4 LMS algorithm output for +5dB Input SNR

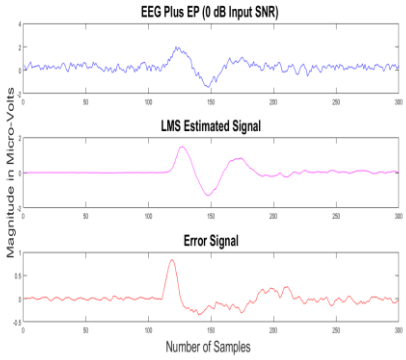

Fig 3.5 LMS algorithm output for +0dB Input SNR

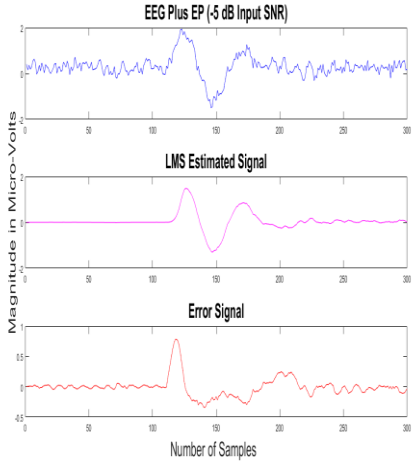

Fig 3.6 LMS algorithm output for -5dB Input SNR

In Fig.3.7 comparing results acquired by the Daubechies Wavelet Transform calculation. The distinctive Daubechies wavelets are utilized in the calculation and the comparing SNR qualities are arranged in the table 3.2 for the EP Data.

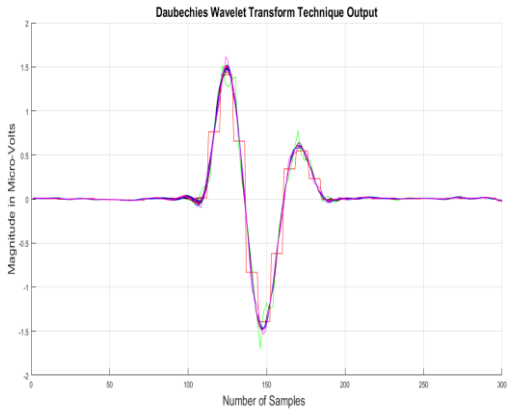

Fig 3.7 Daubechies Wavelet Transform Output Signal

Table 3.2 SNR values of various Daubechies Wavelet Transform Technique

Daubechies Value	SNR in dB
db1	10.8487
db2	16.2598
db3	21.7586
db4	20.1373
db5	23.9066
db6	21.2101
db7	23.4173
db8	22.2101
db9	22.6349
db10	23.1515
db11	22.0628

db12	23.96
db13	21.7625
db14	24.3544
db15	21.7669
db16	24.2014
db17	22.053
db18	23.646
db19	22.5702
db20	22.9913

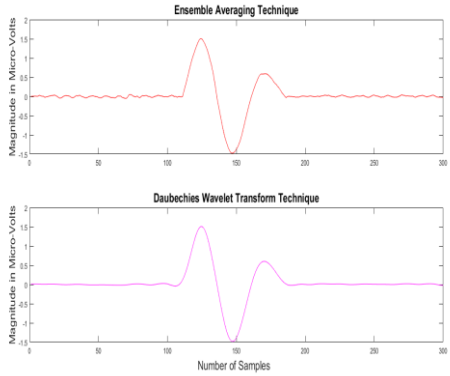

Fig.3.8 Ensemble Averaging and Daubechies wavelet Transform Output Signal

Fig 3.9 demonstrates the yield SNR plots of Daubechies wavelet transform strategy. Here, distinctive Daubechies wavelet change values have been plotted along the X–pivot and yield SNR values along Y–pivot.

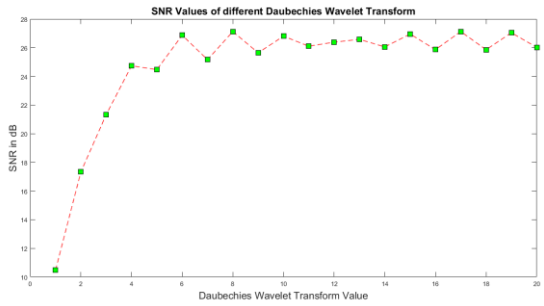

Fig. 3.9 Output SNRs vs Daubechies Values

Distinctive yield waveforms for various Bi – Orthogonal wavelet transform capacities are as appearing in Fig 3.10. Ensemble averaging & Bi-Orthogonal Wavelet Transform technique output waveform is as shown in fig. 3.11 and similarly fig. 3.12 shows the output is compared with original EP signal. Here, additionally a portion of the Bi – Orthogonal wavelet transform capacities won't provide ideal yield. From Fig 3.13 it's apparent that Bior 4.4 capacity provides a good SNR in examination with different capacities. Table 3.3 demonstrates that the organized yield SNR values compared with that of Bi – symmetrical capacity values.

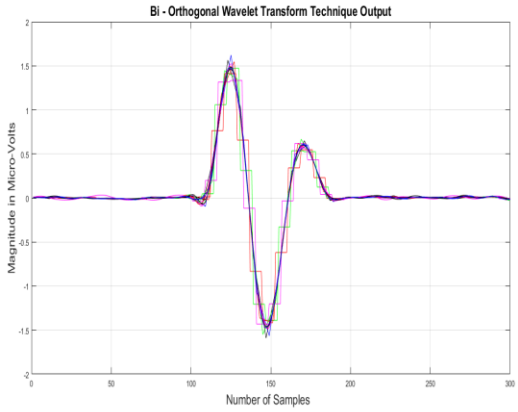

Fig. 3.10 Bi – orthogonal Wavelet Transform Output Signals

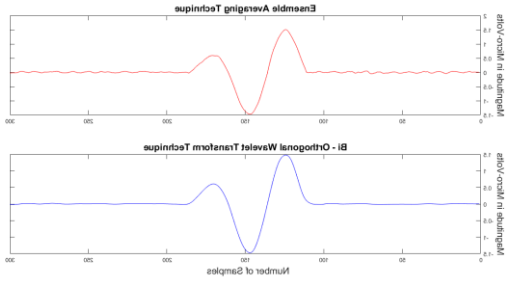

Fig.3.11 Comparison of Ensemble Averaging and Bi – orthogonal Wavelet Transform Output Signal

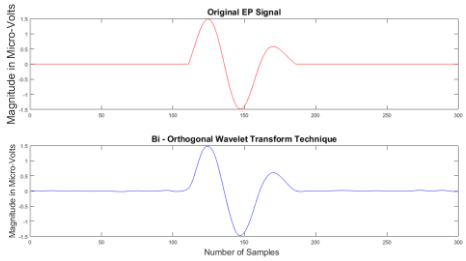

Fig.3.12 Comparison of Original EP signal and Bi – orthogonal Wavelet Transform Output Signal

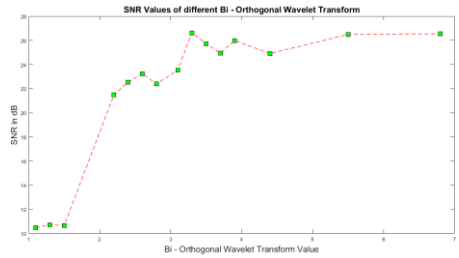

Fig. 3.13 Output SNRs vs Bi – orthogonal values

Table 3.3 Bi – Orthogonal Wavelet Transform Technique of SNR Table for EP

Bi – Orthogonal Values	SNR in dB
Bior 1.1	10.8577

Bior 1.3	10.6546
Bior 1.5	10.7602
Bior 2.2	21.0938
Bior 2.4	22.819
Bior 2.6	19.9706
Bior 2.8	19.4607
Bior 3.1	21.499
Bior 3.3	20.7682
Bior 3.5	21.1186
Bior 3.7	23.9016
Bior 3.9	24.161
Bior 4.4	25.0155
Bior 5.5	23.6933
Bior 6.8	20.9504

IV. CONCLUSION

Ensemble Averaging Technique suffers from the drawback of requirement of several thousands of sweep count, which are then averaged to measure the EP over several minutes causing undue motion artifact in some cases like infant patients. Reducing the acquisition time of EP measurement is thus very desirable.

Wavelet-based signal processing has turned out to be regular in the signal handling domain in the course of recent years. Significant utilizations of wavelets is expulsion of unwanted signals from biomedical signals and is known as assessment which is cultivated by Thresholding wavelet coefficients so as to separate data from noise[6]. The calculation to assess EP Signal dependent on wavelet transform demonstrates the potential of the wavelet transform, particularly for handling time-differing biomedical signals. The intensity of wavelet transform lies in its multi resolution data investigation which describes a signal in detail. In this paper Daubechies wavelet and Bi – orthogonal wavelet transform upgrades SNR in the outcomes acquired and is increasingly appropriate for EEG and EP signal estimation.

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