Abstract: Noise removal from recorded EEG signal is most essential for better analysis of brain disorders. During recording time, EEG signals are usually contaminated by various noise and distortions due to several artifacts. These noisy EEG signals may lead to wrong diagnosis of brain disorders. There are several techniques available to remove the noise from EEG signals. But these techniques are unable to remove the noise completely. However, they can minimize the noise in EEG signals so that the physicians can predict brain disorders. This work presents to minimize the noise by Discrete Wavelet Transform Methods using haar, db2, symlet and coiflet wavelets. EEG original signals from public EEG database are used for experimentation and wavelet transformations, are applied by using Matlab code. The filters performance is measured and analyzed on the basis of performance parameters like SNR and MSE which are calculated for various step sizes of signal and filter orders. Wavelet analysis techniques shows better performance when compared to others.

Keywords: EEG, Adaptive filters, NLMS, haar, sym2, db2, coif1, SNR and MSE.

I. INTRODUCTION

The entire nervous system of human being is connected to the brain. In order to predict the neurological disorders, the physicians are usually take electric pulses form the brain. Electroencephalogram(EEG) signal is widely used for recoding the brain pulses. So, physicians use these EEG signals to diagnosis the neurological disorders. The frequencies of EEG signals vary with respect to the different neurological waves like beta, theta, delta and gamma waves. These waves are analyzed to detect the normal and abnormal disorders in human brain by the physicians[1]. During the recording time of EEG signals, various noise signals may arise and may affect the quality of original EEG signal. Noise can arise due to internal and external sources. The internal sources include muscular activity (EMG), heart movement (ECG) and eye movement (EOG) etc. The external sources include the cell phone signals, electromagnetic waves and other disturbances in the surroundings [2] [3].

Adaptive filters are widely used in various signal processing applications. These are two types of adaptive filters like Finite Impulse Response (FIR) filters and Infinite Impulse Response filters. Generally FIR filters update their coefficients by using minimization criterion. These FIR filters produce output as a weighted sum of current and previous input samples [4]. In the process of noise cancellation, the signal with noise is passed through the filter which produces the output signal that is noise free. Actually adaptive filters use the negative feedback to remove the noise by adjusting the coefficient values [5]. In order to adapt to changes in the signal characteristics, the filter coefficients keep on changing with time. The number of parameters and type of parameters to be adjusted can be specified after selection of specific adaptive filter. For this DSP have made much advancement in improving speed, space and power consumption. This is the reason for adaptive filtering algorithms to become more practical and necessary for forthcoming of communications [6]. It is not required the prior knowledge of noise and signal characteristics in adaptive process. Even we have FIR and IIR filters for use, FIR filter is mostly used for adaptive filtering. Because FIR provides adjustable zeros, as it is free from the problems of stability [7].

II. LITERATURE SURVEY:

Electroencephalography(EEG) signals helps to study the brain disorders. But these signals are contaminated by different artifacts leading to noise. The analysis of signals become difficult by this contamination of noise. So appropriate analysis is required for removal of noise from the signal. Various techniques have been proposed because of different types of signals and noise. From this literature survey, it can be concluded that using wavelets in adaptive filtering may give better results for denoising EEG signals. Muhammad Tahir Akhtiar et al [8] suggested a framework based on ICA and wavelet denoising to get clean EEG signal. He employed a concept of spatially contrained ICA to extract artifact from EEG signals. Jeena Joy et al [9] presented a comparative study for different techniques to denoise the EEG signals. The discrete wavelet transformation can give a joint time frequency representation of signal and suitable for both stationary and non-stationary signals. Discrete wavelet transform supports multi resolutional properties and provides a better solution. VVKDV Prasad et al [10] proposed a new filter based on thresholding for denoising EEG signals using wavelet packets. Wavelet packets have been found to be effective in noise removal of signals. The methods for denoising signals based on wavelets employ hard and soft thresholding filters.

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Kaushik et al[11] concludes that one of the most important applications of wavelets is to denoise the biomedical signals and denoising is accomplished by thresholding wavelet coefficients in order to separate the signal from noise. Priyanka Khatwani et al[12] studied various techniques that can be used to denoise the EEG signals and concluded that wavelet method of denoising is the best for enhancement of quality of the signal.

III. ADAPTIVE FILTER ALGORITHMS:

The adaptive filter algorithms involve the changing filter parameters over time to adapt to changing signal characteristics. Every time signal passed through the filter, the adaptive filter coefficients modify themselves to achieve desired result such as removing noise from input signal. The adaptive algorithm provides impulse response of filter and weights are adjusted by adaptive control mechanism. There are number of algorithms available to remove noise. Selection of algorithm depends on type of application that what type of error signal to be removed. Block diagram of General Adaptive Filter algorithm with inputs and outputs:

Fig 1: General Adaptive Filter Algorithm

The principle of adaptive filter is shown in the above diagram. x(n) is input signal to filter, w(n) is weight vector whose values are estimated from adaptive algorithm. d(n) is desired signal and y(n) is estimated value of desired signal that is used to find the error signal e(n). The error signal and filter input signal are used to update the weight vector w(n) for the filter.

i) Least Mean Square Algorithm (LMS):

This algorithm changes the filter weight vector values so that error signal e(n) is minimized in mean square sense. The mathematical description of this algorithm is given as

\[ y(n) = w(n) * x(n) \]
\[ e(n) = d(n) - y(n) \]
\[ w(n+1) = w(n) + \mu * e(n) * x(n) \]

where x(n) is input signal, w(n) is value of weight at time n, \( w(n+1) \) is new weight value at time \((n+1)\) and \( \mu \) is step size whose value between 0 and 1. This step size parameter changes the length of coefficient of adaptive filter. The smaller the parameter the maximum the convergence time to adapt the coefficients where as large value of this parameter causes the algorithm to adapt coefficients with minimum convergence time, so that minimizing the error rate of adaptive filter. However selection of acceptable level of step size is critical for the algorithm

ii) Normalized Least Mean Square Algorithm (NLMS):

Because LMS algorithm has some limitations such as instability, i.e. the change order of filter value results change of rate of convergence. Thus NLMS is evolved to overcome these limitations [13]. This NLMS eliminates the limitations by normalizing the power of the input signal. But in case of NLMS minimal disturbance is imposed during the change of iteration for which the weight vector w(n) should be changed so as to get minimum error is obtained in output signal [14]. The step size takes the form of

\[ \mu = \beta / ||x(n)||^2 \]

where \( \beta \) is normalized step size whose value lie in between 0 and 1. This change in step size gives improved rate of convergence and diminishes the noise amplification problem.

IV. WAVELET TRANSFORM

Wavelets are mathematical functions with finite length and are oscillatory in nature. Wavelets are having wide range of applications in signal processing like noise reduction, signal compression. These wavelets have been preferred in noise reduction because they preserve the signal characteristics while minimizing the noise from the signal. Generally wavelets are chosen to preprocess the signal because whose shapes resemble the signal. Discrete Wavelet Transform (DWT) is one type of wavelet transforms which is based on two functions, namely scaling function and wavelet function. In this work we use 4 wavelets, namely Haar, Daubechies, Symlet and Coiflet wavelets.

a) Haar wavelet: This wavelet is discovered by Alfred Haar. This is simplest wavelet used for DWT. It acts as prototype for all other wavelets. For the given input of 2^i values, this wavelet transform may be considered to pair up input values, storing difference and passing eh sum. This process will be repeated recursively and pairing up the sums to the next scale.

b) Daubechies wavelet: These are a family of wavelets. The names of family are written as dbN, where N is order of wavelet, or the number of vanishing moments and db is surname of the wavelet. These wavelets are discovered by

Figure 2: Haar wavelet
Ingrid Daubechies. This Daubechies wavelets are defined by computing the running averages and differences through scalar products with scaling signals and wavelets. These wavelets use overlapping windows, so they are useful in noise removal for EEG signal.

Figure 3: Daubechies Wavelet

In the proposed algorithm, traditional NLMS has been modified with the following steps.

Step 1: Convolution matrix for the given input signal X(n) is computed with the help of wavelet h.

\[ Z(n) = \text{conv}(X,h) \]

Step 2: Normalization constant can be calculated by using convolution matrix as

\[ C(n) = Z(n) \ast Z(n) + 0.0001 \]

Step 3: Calculation of error using previous weight coefficients

\[ E(n) = Z(n) - W(n) \ast Z(n) \]

Step 4: update weight coefficient matrix as

\[ W(n) = W(n-1) + \mu \ast \frac{C(n) \ast Z(n) \ast E(n)}{C(n) \ast Z(n) + 0.0001} \]

Step 5: Calculation of filter output

\[ O(n) = W(n) \ast Z(n) \]

The above algorithm is tested with Matlab code to find out the result for various wavelets.

VI. RESULTS AND DISCUSSIONS:

In this work pure EEG signal from public EEG database is used and some random noise is added to it. The above algorithm is implemented and tested to estimate performance in minimizing the noise by altering wavelet for convolution of input signal. For different values of stepsize optimum values of SNR and MSE are estimated.
The following table shows the result of filter with Haar wavelet

| Sno | Step value | Haar wavelet |
|-----|------------|--------------|
| 1   | 0.1        | 0.2491       | 73.8306      |
| 2   | 0.2        | 0.0061       | 75.4447      |
| 3   | 0.3        | 7.3135e-4    | 76.3630      |
| 4   | 0.4        | 2.0228e-4    | 76.9211      |
| 5   | 0.5        | 8.8695e-5    | 77.2792      |
| 6   | 0.6        | 501780e-5    | 77.5129      |
| 7   | 0.7        | 407954e-5    | 77.5463      |
| 8   | 0.8        | 1.1255e-4    | 77.1757      |
| 9   | 0.9        | 0.001        | 76.2219      |

Figure 7: Noisy input signal and Filter Output signal

The following table shows the result of filter with Daubachies wavelet

| Sno | Step value | Db2          |
|-----|------------|--------------|
| 1   | 0.1        | 0.2496       | 73.8298      |
| 2   | 0.2        | 0.0060       | 75.4467      |
| 3   | 0.3        | 7.3381e-4    | 76.3615      |
| 4   | 0.4        | 2.0272e-4    | 76.9202      |
| 5   | 0.5        | 8.8917e-5    | 77.2781      |
| 6   | 0.6        | 5.2174e-5    | 77.5096      |
| 7   | 0.7        | 4.764e-5     | 77.5491      |
| 8   | 0.8        | 1.1239e-4    | 77.1764      |
| 9   | 0.9        | 0.001        | 76.2225      |

Figure 8: Noisy input signal and Filter Output signal

The following table shows the result of filter with Coiflets wavelet

| Sno | Step value | Coif1        |
|-----|------------|--------------|
| 1   | 0.1        | 0.249        | 73.8309      |
| 2   | 0.2        | 0.0061       | 75.4444      |
| 3   | 0.3        | 7.3087e-4    | 76.3632      |
| 4   | 0.4        | 2.0329e-4    | 76.9190      |
| 5   | 0.5        | 8.8897e-5    | 77.2782      |
| 6   | 0.6        | 5.2002e-5    | 77.5111      |
| 7   | 0.7        | 4.7559e-5    | 77.5499      |
| 8   | 0.8        | 1.1153e-4    | 77.1797      |
| 9   | 0.9        | 0.001        | 76.2221      |

Figure 9: Noisy input signal and Filter Output signal

The following table shows the result of filter with Symlets wavelet

| Sno | Step value | Sym2         |
|-----|------------|--------------|
| 1   | 0.1        | 0.2496       | 73.8299      |
a) The following table shows the previous result of wavelets for denoising EEG signals

| S.No | Author | Method | Parameter | Value |
|------|--------|--------|-----------|-------|
| 1    | Lanlan Yu | Wavelet Decomposition | SNR | 38.96 |
| 2    | Suyi Li | Wavelet Decomposition | SNR | 4.493 |
| 3    | Girisha Garg | Wavelet Decomposition | SNR | 26.872 |
| 4    | Janett Walters – Williams | Wavelet Decomposition | MSE | 1.00E+03 |

b) The following table shows the results of filter with wavelets decomposition at level 1

| Sno | Step value | Haar | Db1 | Sym2 | Coif1 |
|-----|------------|------|-----|------|-------|
|     | MSE        | SNR  | MSE | SNR  | MSE  | SNR  |
| 1   | 0.1        | 0.2491| 73.8306 | 0.2496| 73.8298 | 0.2496| 73.8299 | 0.2497| 73.8309 |
| 2   | 0.2        | 0.0061| 75.4447 | 0.0061| 75.4447 | 0.0061| 75.4447 | 0.0061| 75.4444 |
| 3   | 0.3        | 7.31E-04| 76.3636 | 7.34E-04| 76.3615 | 7.33E-04| 76.3627 | 7.31E-04| 76.3630 |
| 4   | 0.4        | 2.02E-04| 76.9211 | 2.03E-04| 76.9202 | 2.02E-04| 76.9212 | 2.03E-04| 76.9191 |
| 5   | 0.5        | 8.87E-04| 77.2792 | 8.89E-04| 77.2781 | 8.90E-05| 77.2775 | 8.89E-05| 77.2782 |
| 6   | 0.6        | 5.02E+00| 77.5129 | 5.22E-04| 77.5096 | 5.18E-05| 77.5128 | 5.20E-05| 77.5121 |
| 7   | 0.7        | 4.08E+00| 77.5463 | 4.76E-04| 77.5491 | 4.81E-05| 77.5448 | 4.76E-05| 77.5499 |
| 8   | 0.8        | 1.13E+00| 77.1757 | 1.12E-04| 77.1764 | 1.13E-04| 77.1759 | 1.12E-04| 77.1797 |
| 9   | 0.9        | 0.001 | 76.2219 | 0.001 | 76.2225 | 0.001 | 76.2219 | 0.001 | 76.2221 |
| 10  | 1          | 743   | 70.3561 | 754   | 70.3492 | 5.39E+04| 68.4953 | 3.59E+05| 67.6715 |

c) The following table shows the results of filter with wavelets decomposition at level 2

| Sno | Step value | Haar | Db1 | Sym2 | Coif1 |
|-----|------------|------|-----|------|-------|
|     | MSE        | SNR  | MSE | SNR  | MSE  | SNR  |
| 1   | 0.1        | 2.06E+03| 69.9138 | 107.4846 | 71.1959 | 107.6198 | 71.1952 | 7.17E-04| 76.3713 |
| 2   | 0.2        | 165   | 71.0089 | 2.2814 | 72.8689 | 2.2867 | 72.8679 | 5.87E-06| 78.4586 |
Performance Analysis of Adaptive Filters with various Wavelets for Noise Removal in EEG Signals

From the above tables 5, 6 and 7, by comparing the experimental results of various wavelets decompositions at level 1 and level 2, we have observed that level 1 results are better than level 2 in achieve maximum value for SNR and least value for MSE.

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