International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-2, December 2019

Performance Analysis of Adaptive Filters with various Wavelets for Noise Removal in EEG Signals

M. Purnachandra Rao, E. Srinivasa Reddy

Abstract: ***Noise removal from recorded EEG signal is most essential for better analysis of brain disorders. During recoding 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].

Revised Manuscript Received on December 30, 2019.
***** Correspondence Author
M. Purnachandra Rao*, Research Scholar, Department of CSE, Acharya Nagarjuna University, Guntur, Andhra Pradesh, India.
E. Srinivasa Reddy, Research Supervisor, Department of CSE, Acharya Nagarjuna University, Guntur, Andhra Pradesh, India.

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 signalsMuhammad Tahir Akhtar 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 solutionVVKDV Prasad et al[10] proposed a new filter based on thresolding 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 thresolding filters.Geeta 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:

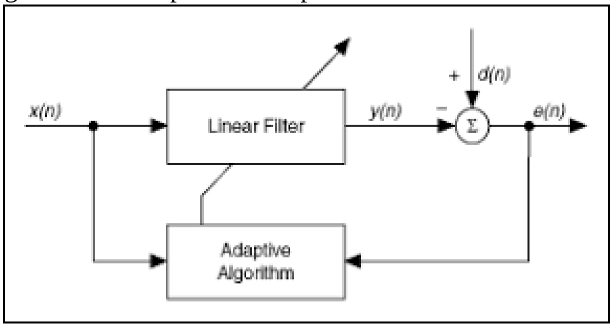

Fig 1: General Adaptive Filter Algorithm

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 μ is step size whose value between 0 and 1.This step size μ 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 β 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^n 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.

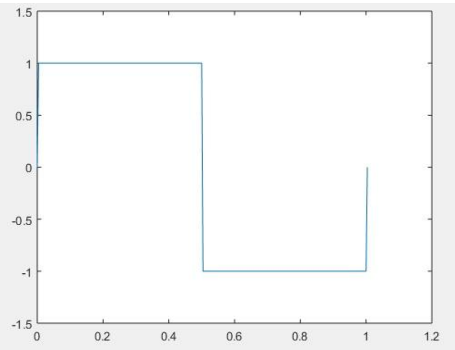

Figure 2: Haar wavelet

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 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.

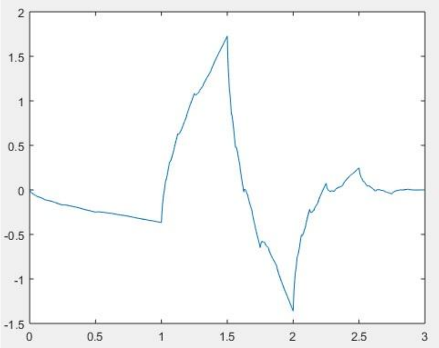

Figure 3: Daubechies Wavelet

c) Coiflets Wavelet: These are discovered by Ingrid Daubechies at the request of Ronald Coifman. These wavelets are belonging to orthogonal wavelet family. For both scaling and wavelet functions these have high number of vanishing moments when supported compactly.

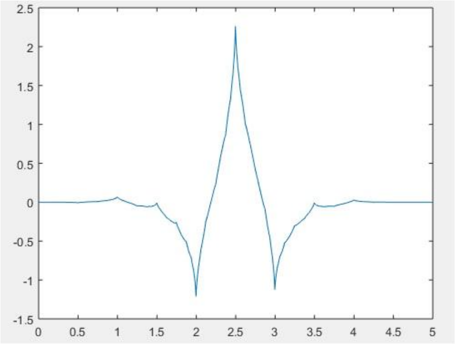

Figure 4: Coiflets Wavelet

d) Symlets Wavelet: These are modified versions of Daubechies wavelets with increased symmetry. Except symmetry property, these wavelets are very similar to Daubechies wavelets. The names of the family are written as symN where N is the order of the wavelet.

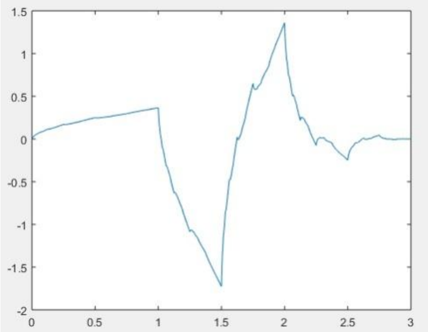

Figure 5: Symlet Wavelet

V. PROPOSED ALGORITHM:

The following notations have been used for proposed algorithm

Z(n): Convolution matrix for input signal X(n).
Y(n): Desired signal
C(n): Normalization Constant
E(n): Error signal
W(n): Weight Coefficient matrix
O(n): Output of the filter
μ: Step size
h: 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.

$$Z(n) = \mathrm{conv}(X,h)$$

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

$$C(n) = Z(n) * Z(n) + 0.0001$$

Step 3: Calculation of error using previous weight coefficients

$$E(n) = Z(n) – W(n) * Z(n)$$

Step 4: update weight coefficient matrix as

$$W(n)= W(n-1) + \mu/ C(n) * Z(n) * E(n)$$

Step 5: Calculation of filter output

$$O(n) = W(n) * Z(n)$$

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.

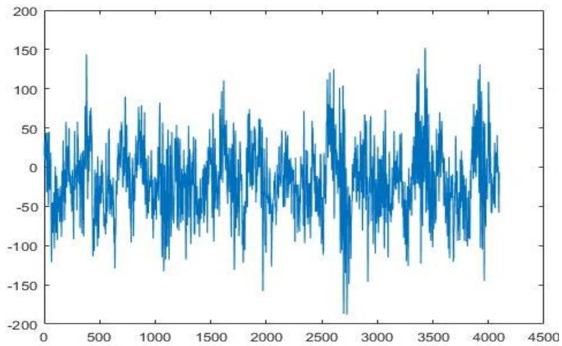

Figure 6: Pure EEG signal taken from public EEG database

The following table shows the result of filter with Haar wavelet

Table 1: MSE and SNR analysis of Haar wavelet

Sno	Step value	Haar wavelet	
		MSE	**SNR**
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

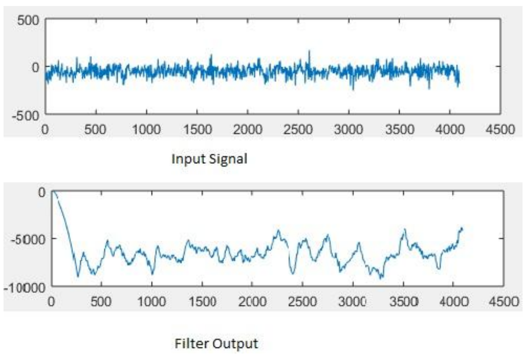

Figure 7: Noisy input signal and Filter Output signal

The following table shows the result of filter with Daubachies wavelet

Table 2: MSE and SNR analysis of Db2 wavelet

Sno	Step value	Db2	
		MSE	**SNR**
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

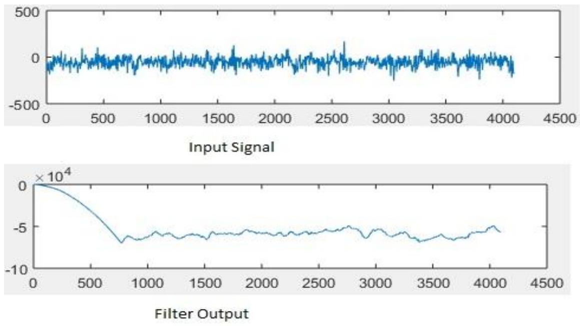

Figure 8: Noisy input signal and Filter Output signal

The following table shows the result of filter with Coiflets wavelet

Table 3: MSE and SNR analysis of Coif1 wavelet

Sno	Step value	Coif1	
		MSE	**SNR**
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

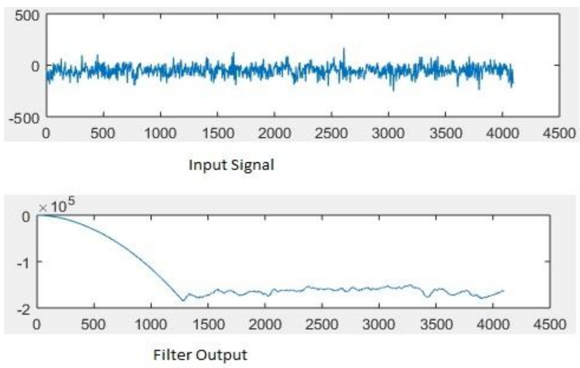

Figure 9: Noisy input signal and Filter Output signal

The following table shows the result of filter with Symlets wavelet

International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-2, December 2019

Table 4: MSE and SNR analysis of sym2 wavelet

Sno	Step value	Sym2	
		MSE	SNR
1	0.1	0.2496	73.8299
2	0.2	0.0061	75.4443
3	0.3	7.3306e-4	76.3620
4	0.4	2.0225e-4	76.9212
5	0.5	8.9048e-5	77.2775
6	0.6	5.1797e-5	77.5128
7	0.7	4.8121e-5	77.5448
8	0.8	1.1252e-4	77.1759
9	0.9	0.001	76.2219

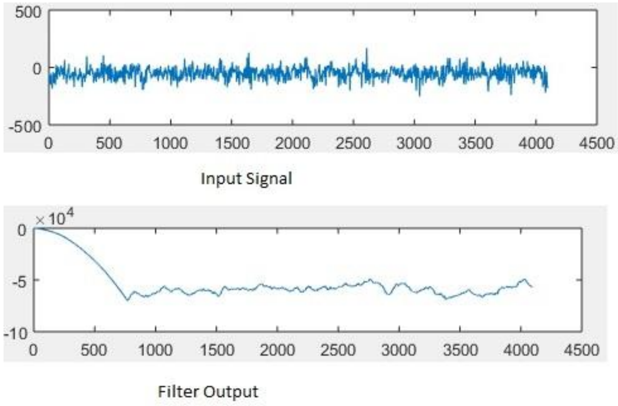

Figure 10: Noisy input signal and Filter Output signal

a) **The following table shows the previous result of wavelets for denoising EEG signals**

Table 5: Previous Performance of Wavelets for denoising the 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**

Table 6: MSE and SNR analysis of filter after various wavelets decomposition at level 1

Sno	Step value	Haar		Db1		Sym2		Coif1	
		MSE	SNR	MSE	SNR	MSE	SNR	MSE	SNR
1	0.1	0.2491	73.8306	0.2496	73.8298	0.2496	73.8299	0.249	73.8309
2	0.2	0.0061	75.4447	0.006	75.4467	0.0061	75.4443	0.0061	75.4444
3	0.3	7.31E-04	76.363	7.34E-	76.3615	7.33E-04	76.362	7.31E-04	76.3632
4	0.4	2.02E-04	76.9211	2.03E-	76.9202	2.02E-04	76.9212	2.03E-04	76.919
5	0.5	8.87E-05	77.2792	8.89E-	77.2781	8.90E-05	77.2775	8.89E-05	77.2782
6	0.6	5.02E+00	77.5129	5.22E-	77.5096	5.18E-05	77.5128	5.20E-05	77.5111
7	0.7	4.08E+00	77.5463	4.76E-	77.5491	4.81E-05	77.5448	4.76E-05	77.5499
8	0.8	1.13E-04	77.1757	1.12E-	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**

Table 7: MSE and SNR analysis of filter after various wavelets decomposition at level 2

Sno	Step value	Haar		Db2		Sym2		Coif1	
		MSE	SNR	MSE	SNR	MSE	SNR	MSE	SNR
1	0.1	2.06E+03	69.9138	107.4486	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
3	0.3	35.516	71.6767	0.1904	73.9475	0.191	73.9461	8.52E-07	79.2969
4	0.4	13.976	72.0817	0.0326	74.714	0.0327	74.7126	5.55E-07	79.4827
5	0.5	7.7047	72.3403	0.0083	75.3095	0.0083	75.30659	3.89E-07	79.6368
6	0.6	5.1806	72.5127		75.7544	0.003	75.751	2.85E-07	79.772
7	0.7	4.4376	72.5799	0.005	75.5318	0.005	75.5298	2.24E-07	79.8762
8	0.8	5.7206	72.4696	0.0314	74.7295	0.0313	74.7314	2.06E-07	79.9141
9	0.9	13.4432	72.0986	0.4158	73.6083	0.4156	73.6084	1.00E-06	79.2265
10	1	1.7215	72.9912	0.157	74.0311	0.1591	74.0255	8.08E+04	68.3197

VII. CONCLUSION:

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.

REFERENCES:

1. GiuseppinaInuso, Wavelet-ICA methodology for efficient artifact removal from Electroencephalograhic recordings, *Proceedings of International Joint Conference on Neural Networks*, Orlando, Florida, USA, August 12 – 17, 2007.
2. Mrs V Baby Deepa, Dr. P. Thangaraj, Dr. S Chitra, Investigating the performance improvement by sampling techniques in EEG data, *International Journal on Computer Science and Engineering*, Vol. 2, Jun, 2010, pp: 2025 – 2028.
3. G He P, Wilson G, Russel C: "Removal of artifacts from electro-encephalogram by adaptive
4. filtering", Medical & biological engineering & computing 2004; 42(3); 407-12.
5. M. Surya Prakash and Rafi Ahamed Shaik, "Low-Area and High-Throughput Architecture for an Adaptive Filter Using Distributed Arithmetic", *IEEE Transactions onCircuits and Systems*, Vol. 69, No. 11, pp. 781-785, November 2013
6. Rajesh Mehra and Swapna Devi, "Effcient Hardware Co-Simulation of Down Convertor for Wireless Communication Systems", International Journal of VLSI Design & Communication Systems (VLSICS), Vol 1. No. 2, pp. 13-21, June 2010.
7. Raj Kumari, Dr. Rajesh Mehra and Lalita Sharma "Effective Adaptive Noise Cancellaer Desing Using Normalized LMS", *IEEE conference on NextGeneration Computing Technologies, pp. 571-575, September 2015.*
8. Xueli Wu, Zizhong Tan, Jianhua Zhang and Wei Li, "Dual Adaptive Noise Cancellation Method Based on Least Mean M-Estimate of Noise", IEEE Conference on Intelligent Control and Automation", China, pp. 5741-5746, July 2014.
9. Muhammad Tahir Akhta et al, "Focal Artifact Removal From Ongoing EEG-A Hybrid Approach Based on Spatially –Constained ICA and Wavelet Denoising ", 31st Annual International Signal Conference of the IEEE EMBS Minneapolis, Minnesota, USA, September 2-6, 2009
10. Jeena Joy, Salice Peter et al, "Denoising Using Soft Thresholding ", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, vol 2, issue 3, pp. 1027 -1031, March 2013
11. V.V.K.D.V. Prasad et al, " A New Wavelet Packet Based Method for Denoising of Biological Signals", Interantional Journal of Research in Computer and Communication Technology, vol 2, issue 10, pp. 1056 -1062, October 2013.
12. Geeta Kaushik et al., "Biomedical Signal Analysis through Wavelets: A Review", International Journal of Advanced Research in Computer Science and Software Engineering, vol 2, issue 9, pp. 422 – 428, September, 2012
13. Priyanka Khatwani, Archana Tiwari, " A Survey on Different Noise Removal Techniques of EEG Signals", International Journal of Advanced Research in Computer and Communication Engineering vol. 2, issue 2, pp. 1091 -95, February 2013
14. Hsu-Chang Huang and Junghsi Lee, " A New Variable Step-size NLMS algorithm and Its Performance Analysis", IEEE Transactions On Signal Processing, Vol. 60, No. 4, April 2012
15. S. C. Chan, Y. J. Chu and Z. G. Shang., "ANew Variable Regularized Transform Domain NLMS Adaptive Filtering Algorithm – Acoustic Applications and Performance Analysis", *IEEE Transactions on Audio, Speech, and Language Processing*, Vol. 2 No. 4, pp. 868-878, 2013.

ABOUT AUTHORS

Mudigonda Purnachandra Rao, M. Tech(CSE), is working as Assistant Professor in the department of computer science in Hindu College of Engineering and Technology, Amaravathi road, Guntur. He has 19 years of teaching experience and contributing several activities. His National and International publications are less than 3.

Prof. E. Srinivasa Reddy is working as Dean in ANU College of Engineering. He has 30 years of teaching experience and 12 years of research experience. He published more than 150 journal papers, 6 Text books and 15 chapters. Until now 16 students are awarded Ph.D under his guidance. His areas of interests are Machine Learning, Image Processing and Deep Learning.