International Journal of communication and computer Technologies, ISSN: 2278-9723

Available at http://www.ijccts.org

An Improved Approach of DWT and ANC Algorithm for Removal of ECG Artifacts

Received: 02-08-2016, **Revised:** 13-10-2016, **Accepted:** 23-11-2016, **Published online:** 19-12-2016

[1]P.Nandhini, [2]G.Vijayasharathy, [3]N.S. Kokila, [4]S. Kousalya, [5]T. Kousika

[1]Assistant Professor, [2,3,4,5]Student, Department of ECE, AVS College of Technology

***Abstract*- The electrocardiogram is the recording of the electrical potential of heart beat. The analysis of ECG signal plays a vital role in the detection of cardiac abnormalities. The ECG signals are often contaminated by noise from diverse sources. Noises that commonly disturb the basic electrocardiogram are power line interference, baseline wander, electrode motion. These noises can be classified according to their frequency content. It is essential to remove these disturbances in ECG signal to improve accuracy and reliability. Different types of adaptive algorithms have been proposed to remove these noises. In adaptive filter technique the filter coefficients can be varied to track the dynamic variations of the signals. The algorithms are Least Mean Square (LMS), Normalized Least Mean Square (NLMS) and Sign-Sign Least Mean Square (SSLMS). The new model is arrived to remove various noises by combining Discrete Wavelet Transform (DWT) and Adaptive Noise Cancellation technique (ANC). The Wavelet is used to form approximate and detail coefficients. ECG signal is obtained from MIT-BIH arrhythmia database. Denoising of ECG is performed by combining DWT and ANC technique.**

***Keywords*— Adaptive Noise Cancellation (ANC), Discrete Wavelet Transform (DWT), Least Mean Square (LMS), Normalized Least Mean Square (NLMS), Sign Sign LMS (SSLMS), Electrocardiogram (ECG).**

I. INTRODUCTION

An Electrocardiogram is an electrical activation of heart. The new model has proposed the QRS Detection algorithm to remove various noises in ECG signal [1]. Baseline wandering and background noise are removed from original ECG signal by a mathematical morphological method. Then the multipixel modulus accumulation is employed to act as a low-pass filter to enhance the QRS complex and improve the signal-to-noise ratio. The performance of the algorithm is evaluated with standard MIT-BIH arrhythmia database. High detection rate and high speed demonstrate the effectiveness of the proposed detector. An ocular artifact (OA) removed by combination of independent component analysis and wavelet. This technique is used to reduce noise which is utilized for detection and removal of OA [2]. The new investigation is arrived in the study of cardiovascular and other complex biomedical signals. It is entirely based on the resources such as Physiobank, PhysioToolkit and PhysioNet [3]. The model in [4] is based on discrete wavelet transformation (DWT) and adaptive noise

cancellation (ANC) technique to remove ocular artifacts (OA) from electroencephalograms (EEG). It is able to eliminate OAs in the low-frequency band even when their frequency is overlapping with that of the EEG signal. The most important step of this model is to construct a reference signal using DWT. From the analysis as a whole, the tracking performance of RLS algorithm is good than Independent Component Analysis method.

Jessica Arbona and Christopher Brady (2011) proposed a technique for Active noise cancellation using LMS and RLS [5]. Both speech and ultrasound data were used to verify the system. MATLAB/Simulink was used to design and test a LMS and RLS. The LMS algorithm was chosen to be implemented in hardware because of the inverse matrix calculations in RLS filters are difficult to perform on embedded system. In [6] Least Mean Square (LMS), Normalized Least Mean Square (NLMS) and Error Nonlinear Least Mean Square (ENLMS) based adaptive filters algorithm are used to analyze the ECG signals. Approximate and detailed coefficients are formed by using wavelet method. The original signal is compressed and reconstructed based on approximate and detail coefficient using four type of wavelets (haar, db10, sym8 and dmey). From the analysis, it is clear that these algorithms remove the noise efficiently present in the ECG signal. In [7], the mean and mean-square convergence behaviors of the deficient length LMS algorithm have been analyzed for stationary Gaussian inputs. In [8], various adaptive filters are used to remove the noises in ECG signal. In [9], by combining ICA and wavelet, Ocular artifacts in EEG is removed. In [10], family of adaptive filters with desirable decorrelation properties has been proposed. The proposed novel IC classifier is a combination of a modified probabilistic multiclass Support Vector Machine (SVM). From the analysis, better performance of the proposed method is mainly due to its higher accuracy on EEG ICs as compared to the standard SVM.

This method has a better tradeoff between removing artifacts and preserving inherent brain activities [11].

II.DISCRETE WAVELET TRANSFORM

Discrete Wavelet Transform (DWT) is a multiresolution scheme for input signals. It does not change the information content present in the signal. The discrete wavelet transform (DWT) provides a time-frequency representation of the signal. It was developed to overcome the short coming of the Short Time Fourier Transform. Comparing with other wavelet transforms, an advantage it has over Fourier transforms is temporal resolution, i.e., it captures both frequency and location information (time location).

The DWT is used for signal coding, to represent a discrete signal in a more redundant form, often as a preconditioning for data compression. Some of the wavelets are Haar, Daubechies, Symlets and Coiflets. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application.

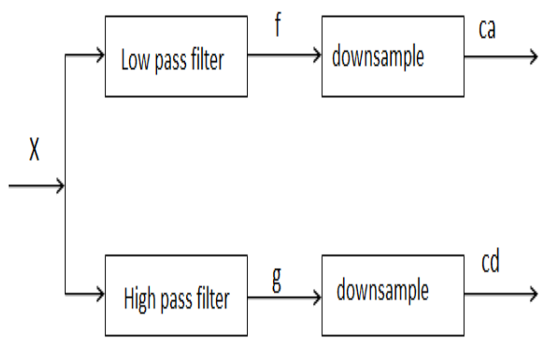

Fig 1: Discrete Wavelet Transform

Initially, input signal 'X' is convolved with the low pass and high pass filters. Then, down sampling the convolution result by 2 to get the coefficients called an approximation coefficient (which is denoted by ca) and detail coefficient (which is denoted by cd). The Daubechies is used as the wavelet in DWT.

III.ADAPTIVE NOISE CANCELLATION

The ECG is a signal which records the electrical activity of heart. Measurement of ECG may be corrupted by various types of noise. The noises are Power line interference, Baseline wander noise and Motion artifacts. These artifacts strongly affects the ST segment, degrades the signal quality, frequency resolution, produces large amplitude signals in ECG that can resemble PQRST waveforms and masks tiny features that are important for clinical monitoring and diagnosis. Cancelation of these artifacts in ECG signals is an important task for better diagnosis, for which adaptive filter is used.

In adaptive filters, the weight vectors are updated by an adaptive algorithm to minimize the cost function. The main function of this filter is to adapt the coefficients of FIR filters to match closely to the response of an unknown system.

The Proposed model is based on combining the discrete wavelet transformation (DWT) and adaptive noise cancellation (ANC). DWT is used to detect the artifacts region and then select the correct threshold to remove the interference. A particularly novel feature of the new model is the use of DWT to construct an Artifact reference signal, using the three lowest frequency wavelet coefficients of the ECGs. The proposed methods have an improved performance with respect to the recovery of true ECG signals and also have a better tracking performance. Because it requires only single channel sources, it is well suited for use in portable environments where constraints with respect to acceptable wearable sensor attachments usually dictate single channel devices.

IV.PROPOSED LEAST MEAN SQUARE FILTER

The Least Mean Square (LMS) algorithm is a class of adaptive filter, used to imitate closely a desired filter by finding the filter coefficients that relate to give the least mean squares of the error signal i.e., the difference between the desired and the actual signal. The recorded ECG signals are contaminated by Artifacts; this contamination is considered to be an additive noise within the ECG signal.

The recorded ECG signal is given in equation (1)

$$ECG_{rec}(t)=ECG_{true}(t)+k.Artifacts(t) \qquad (1)$$

Where

$ECG_{rec}(t)$ is recorded ECG signal,

$ECG_{true}(t)$ is ECG signal due to cardiac activity and without interference,

k.Artifacts(t) is artifacts during ECG recording.

The $ECG_{true}(t)$ is recovered from $ECG_{rec}(t)$ by removing k.Artifacts(t) efficiently. The proposed LMS algorithm figure as shown in Fig 2.

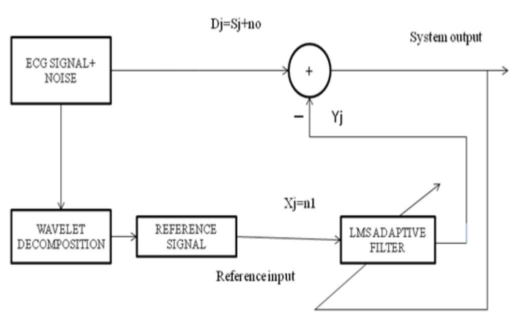

Fig 2: Proposed LMS filter using wavelet

The Steps for the proposed method for LMS as follows

- Decompose

Wavelet decomposition is applied to expand the contaminated ECG signal to get the coefficients for wavelets. There are several possible mother wavelet functions. Daubechies 4 family is efficient to remove to noises. So, the Daubechies 4 wavelet is used as the mother wavelet function for DWT. Compute the wavelet decomposition for the noisy ECG signal at level N.

- Threshold detail coefficient

According to minimum risk values, threshold detail coefficients are computed. For each level from 1 to *N*, a threshold is selected and soft thresholding is applied. The wavelet coefficient resulting from the wavelet transformation corresponds to a measurement of the ECG components in this time segment and frequency band. The coefficient equation is given in equation (2) and (3)

$$\text{Approximate coefficient(ca)} = \frac{s_i + s_{i+1}}{2} \qquad (2)$$

$$\text{detail coefficient (cd)} = \frac{s_i - s_{i-1}}{2} \qquad (3)$$

where s_i = element in the signal and
i = time index.

- Apply wavelet reconstruction to the new wavelet coefficients for constructing the reference signal.
- Now, LMS algorithm is applied to the contaminated ECG with the constructed reference signal as an input to remove the artifacts.

Thus, the proposed method that combines the DWT and LMS algorithm is used to remove the various noises in contaminated ECG signal.

V. PROPOSED NORMALIZED LMS ALGORITHM

Normalized LMS (NLMS) is an LMS adaptive algorithm in which the input vector to the filter is normalized. This normalization results in smaller step size values than the conventional LMS. The normalized algorithm usually converges faster than the LMS algorithm. The proposed NLMS algorithm figure as shown in Fig. 3.

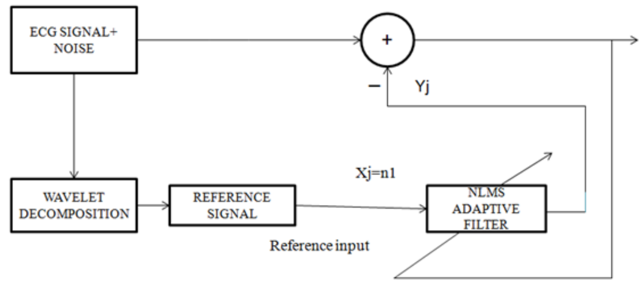

Fig 3: Proposed NLMS filter using wavelet

Similar to the proposed LMS filter, the same steps is used for both NLMS and SSLMS algorithm.

V. PROPOSED SIGN SIGN ALGORITHM

In this algorithm, the signum function is applied in the weight update equation to both error signal and input signal. The proposed SSLMS algorithm figure as shown in Fig.4

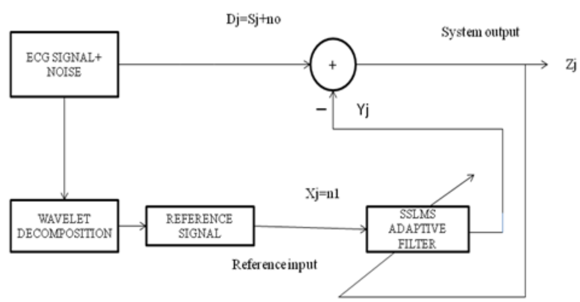

Fig 4: Proposed SSLMS filter using wavelet

VII.RESULTS AND DISCUSSION

The ECG signal used for analysis is obtained from MIT-BIH Arrhythmia database. This database was the first generally available set of standard test material for evaluation of arrhythmia detectors. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979.

Twenty-three recordings were chosen at random from a set of 4000 samples 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. ECG signal (100.mat) considered for the analysis measuring number of samples along the X-axis and amplitude (in mV) along the Y-axis.

The approximate and detailed coefficients for the baseline wander noise is shown the below Fig 5.

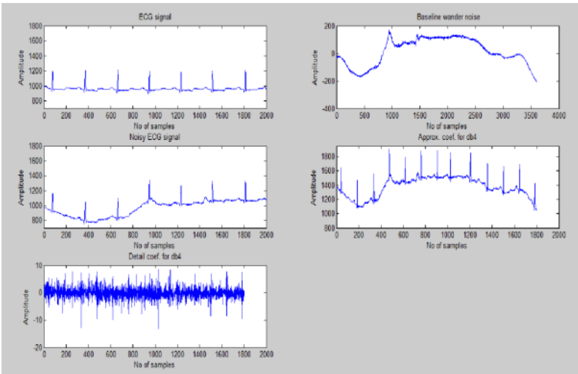

Fig. 5. Coefficients for Baseline Wander

The approximate and detailed coefficients for the powerline noise is shown the below Fig 6.

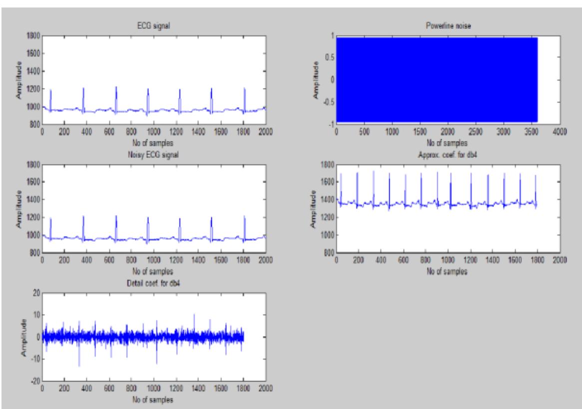

Fig. 6. Coefficients for Powerline noise

The approximate and detailed coefficients for electrode motion is shown the below Fig 7.

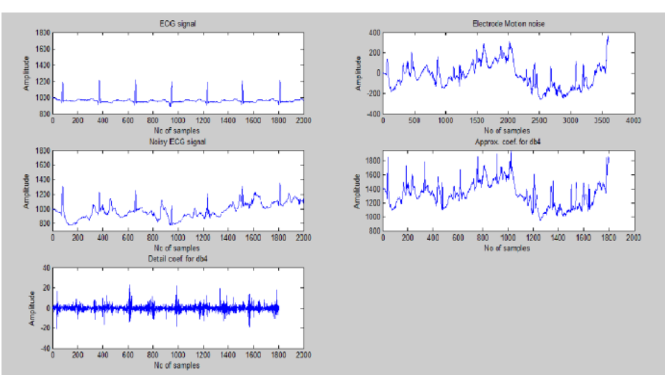

Fig. 7. Coefficients for Electrode motion

An 8-tap LMS filter designed in MATLAB Simulink is shown in Fig.8.,

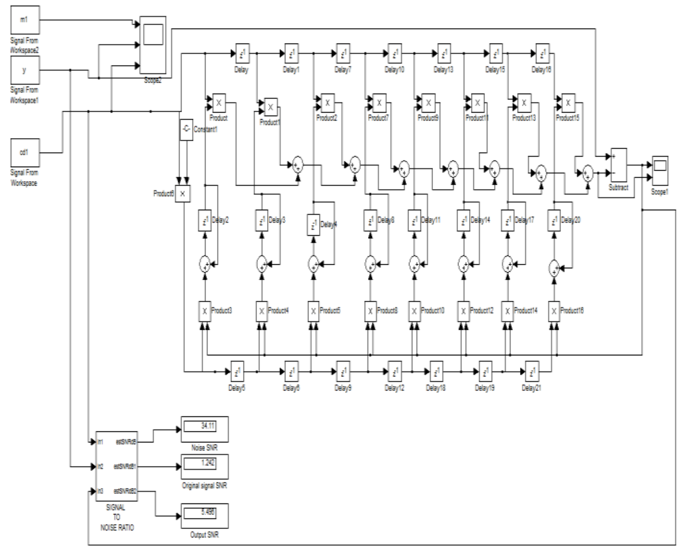

Fig. 8. 8-tap LMS filter

The ECG signal obtained from the BIT-MIH database. The denoised ECG signal is obtained as output after passing the into the LMS filter. The baseline wander noise along with ECG and denoised ECG signal is shown in Fig 9.

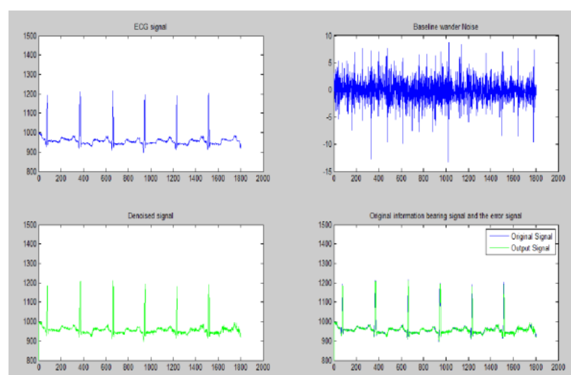

Fig. 9: Denoised ECG signal for LMS filter

The output of baseline wander along with ECG signal after passing through the SSLMS algorithm is shown in the Fig 10.

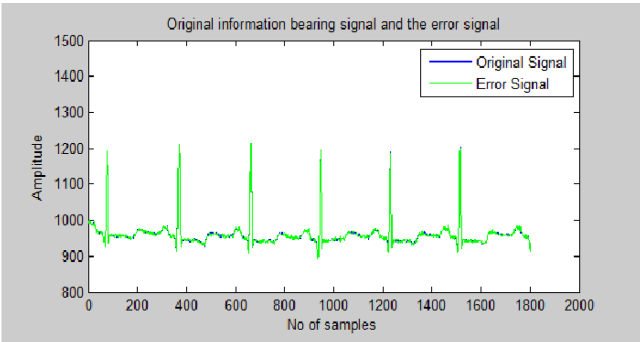

Fig. 10: Denoised ECG signal for SSLMS filter

The output of baseline wander along with ECG signal after passing through the NLMS algorithm is shown in the Fig 11.

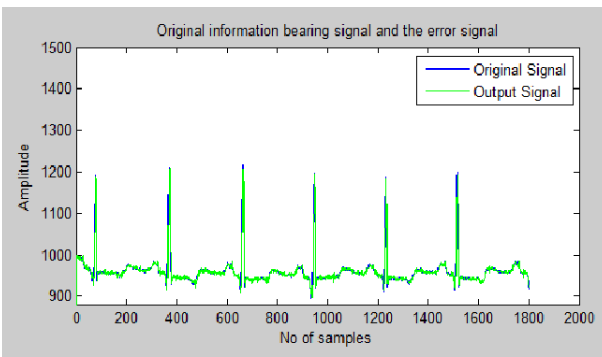

Fig. 11: Denoised ECG signal for NLMS filter

The LMS filter used for denoising ECG signal is simulated for various recordings to remove various noise. The algorithms are tested for various dataset and its Signal to noise Ratio is shown in Table I.

TABLE I
Performance of LMS filter for removal of various Noise

NOISES	RECORD NO: 100	RECORD NO: 105	RECORD NO: 108	RECORD NO: 214
POWERLINE INTERFERNCE	26.80	31.60	26.61	33.58
ELECTRODE MOTION	21.56	25.87	21.37	28.59
BASELINE WANDER	25.49	29.98	25.16	32.54

The graphical representation of Signal to Noise Ratio for LMS Algorithm is shown in Fig 12 .The X-axis taken for various Database Records and Y-axis is for SNR value for various Noises, from this graph the Baseline noise and Powerline noise removed effectively

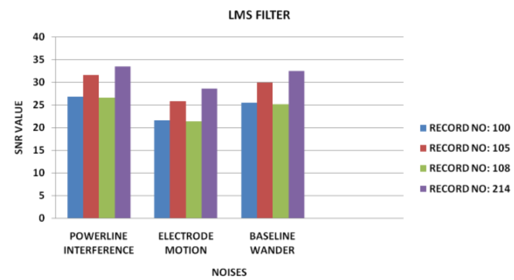

Fig 12.Graphical Representation for LMS filter

The NLMS filter used for denoising ECG signal is simulated for various recordings to remove various noise and their corresponding SNR are obtained as shown in Table II. Graphical representation for NLMS is shown in Fig 13.

TABLE II
Performance of NLMS filter for removal of various Noise

NOISES	RECORD NO: 100	RECORD NO: 105	RECORD NO: 108	RECORD NO: 214
POWERLINE INTERFERNCE	26.80	30.81	26.36	33.64
ELECTRODE MOTION	21.75	25.74	21.31	28.5
BASELINE WANDER	25.46	29.97	25.16	32.55

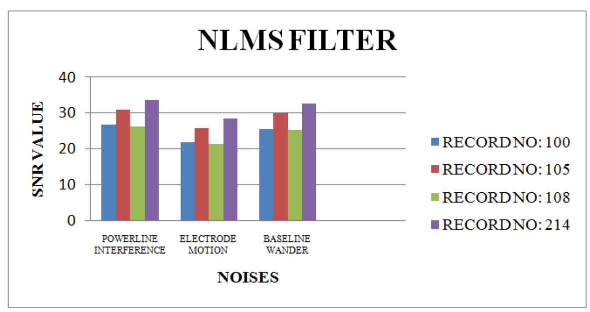

Fig 13.Graphical Representation for NLMS filter

The SSLMS filter used for denoising ECG signal is simulated for various recordings to remove various noise and their corresponding SNR are obtained as shown in Table III. Graphical representation for SSLMS is shown in Fig 14.

TABLE III
Performance of SSLMS filter for removal of various Noise

NOISES	RECORD NO: 100	RECORD NO: 105	RECORD NO: 108	RECORD NO: 214
POWERLINE INTERFERNCE	24.94	30.90	24.10	33.28
ELECTRODE MOTION	19.63	25.19	19.03	28.21
BASELINE WANDER	23.60	29.27	22.75	31.95

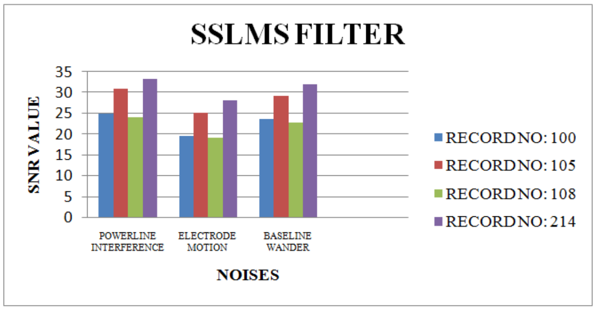

Fig 14.Graphical Representation for SSLMS filter

Daubechies (db4) used as the wavelet in DWT. In LMS, NLMS and SSLMS algorithms which proved to have better performance in recovering true ECG signal and Daubechies wavelet plays a vital role in removing the noises in ECG signal.

VII. CONCLUSION

The combination of DWT and various ANC techniques is used to remove the various noises in contaminated ECG signal. Daubechies wavelet plays a vital role in removing the noises in ECG signal. For de-noising ECG signal obtained from the MIT-BIH database, LMS, NLMS, SSLMS algorithm is simulated using MATLAB. From the simulation results the LMS, NLMS, SSLMS algorithm produces a signal to noise ratio which proved to have better performance in recovering true ECG signal.

REFERENCES

[1] Chris F. Zhang and Tae-Wuk Bae (2012), ‘‘VLSI Friendly ECG QRS Complex Detector for Body Sensor Networks’’, IEEE journal on emerging and selected topics in circuits and systems, Vol. 2, no. 1.

[2] Ghandeharion.H and Ahmadi-Noubari (2009), ‘‘Detection and removal of ocular artifacts using independent component analysis and wavelets’’, IEEE EMBS Conf. Neural Eng., Antalya, Turkey.

[3] Goldberger. A. L, Amaral. L. A. N, Glass.L, Hausdorff.J.M, Ivanov. P. C, and Stanley (2000), ‘‘Physiobank, Physiotoolkit, and Physionet: Components of a new research resource for complex physiologic signals’’, Circulation, vol. 101, no. 23, pp. e215–e220.

[4] Hong Peng, Bin Hu, Qiuxia Shi, Martyn Ratcliffe, Qinglin Zhao, Yanbing Qi, and Guoping Gao (2013), ‘‘Removal of Ocular Artifacts in EEG—An Improved Approach Combining DWT and ANC for Portable Applications’’,IEEE JOURNAL of biomedical and Health informatics, Vol. 17, no. 3.

[5] Jessica Arbona and Christopher Brady (2011), ‘‘Active noise cancellation’’, IEEE Int. Symp. Circuits and Syst., pp. 677–680.

[6] Karthiga Mohanan, Tharini.C (2012), ‘‘Adaptive Noise Cancelers and Wavelet transform analysis of ECG signal for remote patient monitoring’’, International International Conference on Computing and Control Engineering (ICCCE).

[7] Mayyas.K (2005), ‘‘Performance analysis of the deficient length LMS adaptive algorithm’’, IEEE Trans. Signal Process., vol. 53, no. 8, pp. 2727–2734.

[8] Muhammad Zia Ur Rahman, Member, IEEE, Rafi Ahamed Shaik, Member, IEEE, and Rama Koti Reddy.D.V (2012), ‘‘Efficient and simplified adaptive noise cancelers for ECG sensor based remote health monitoring’’, IEEE Sensors Journal, Vol. 12, no. 3.

[9] Romo-Vazquez, Ranta.R, Louis-Dorr, and Maquin.D (2007), ‘‘Ocular artifacts removal in scalp EEG: Combining ICA and wavelet denoising’’, Int.Conf. Physics in Signal and Image Process.,Mulhouse, France.

[10] Rupp.M (1998), ‘‘A family of adaptive filter algorithms with decorrelating properties’’, IEEE Trans. Signal Process., vol. 46, no. 3, pp. 771–775.

[11] Yun Shao, Kai-Quan Shen, Chong Jin Ong, Member, IEEE, E.P.V. Wilder-Smith, and Xiao-Ping Li (2009), ‘‘Automatic EEG Artifact Removal:A Weighted Support Vector Machine Approach With Error Correction’’, IEEE Transactions on biomedical engineering, Vol. 56, no. 2.