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Research Article

Muscular Artifacts Removal in Electro Cardio Gram by Combining Discrete Wavelet Transform and Adaptive Noise Cancellation

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Abstract: Filtering the noise present in ECG signal by using adaptive algorithms is the aim of the study. The electrocardiogram (ECG) is the recording of the electrical potential of heart beat. A stationary noise that is commonly found to disturb the basic electrocardiogram is power line interference. It is essential to reduce such disturbance in order to improve accuracy and reliability. The denoising of electrocardiogram signals is a challenging fact as it is difficult to apply filters with fixed coefficients. Adaptive filtering techniques can be used in which the filter coefficients can be varied to track the dynamic variations of the signal. The model is based on combined approach of Discrete Wavelet Transform (DWT) and Adaptive Noise Cancellation filter (ANC). A new model is constructed using DWT for reference signal. Denoising is performed by applying ECG signal obtained from MIT-BIH arrhythmia database and the modelled reference signal using LMS and SSLMS filters. The results show that the new model demonstrates an improved performance with respect to the recovery of true ECG signals and also has a better tracking performance.

Keywords: Adaptive Noise Cancellation (ANC), Electrocardiogram (ECG), Least Mean Square (LMS), Sign Sign LMS (SSLMS)

INTRODUCTION

An Electrocardiogram represents electrical activation of heart. It is the record of the electrical potentials produced by the heart. The electrical wave is generated by depolarization and repolarisation of certain cells in the blood. Meher and Park (2013) said that Electrocardiography (ECG) is a tool that is widely used to understand the function of the heart. The activity of the heart is represented by electrocardiographic signals. The ECG is acquired by placing electrodes on the skin of the patient. The ECG signal and heart rate reflects cardiac health of human heart. Wu *et al*. (2009) said clinical environment, various types of artifacts are encountered during acquisition of the ECG signal. The most common encountered artifacts are Power line interference, Baseline Drift, Instrumentation noise generated by electronic devices, Motion artifacts, Electrosurgical Noise, Electrode contact noise. These noises degrade the quality of signal, frequency resolution and thereby strongly affect the morphology of ECG signal containing important information. Therefore, it is essential to reduce disturbances in ECG signal and improve the accuracy and reliability for better diagnosis. Adaptive filtering is the most widely used technique for de-noising of ECG. The Least Mean Square (LMS) and Recursive Least Squares (RLS) algorithm are well known algorithms used in adaptive filtering. In literature various filtering techniques have been presented for ECG analysis. Karthiga and Tharini (2012) analyzed adaptive filter and wavelet transform for noise cancellation in ECG. The input and the desired response signals are properly chosen in such a way that the filter output is the best least squared estimate of the original ECG signal. The signals were compressed and reconstructed using four types of wavelets. From the simulated results, it is clear that these algorithms remove the noise efficiently present in the ECG signal. Dhubkarya and Katara (2013) have analyzed that the adaptive filters are attractive to work in real-time and non-real time environments. This study emphasis on the performance comparison of MATLAB simulation and DSP Processor implementation of an adaptive filter for LMS and NLMS Algorithms and the performance is analyzed based on the SNR improvement. Various modifications to the LMS algorithm are proposed by Olmos *et al*. (2002) and Li *et al*. (2009).

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Rahman *et al*. (2011) proposed several computationally less complex adaptive LMS algorithms have been proposed. The complexity of the adaptive algorithm such as LMS can be reduced by using sign based algorithms namely sign algorithm, sign-sign algorithm and sign regressor algorithm. These algorithms require less multiplication compared to conventional algorithm thus exhibits good filtering capability and reduction in computational complexity. Singh and Tiwari (2006) have proposed wavelet based ECG signal denoising. The experimental results have revealed that the Daubechies mother wavelet of order 8 to be the most appropriate wavelet basis function for the denoising application. Kaushik and Sinha (2012) introduced a new model by combining DWT and ANC technique to remove artifacts from EEG. It is able to eliminate the artifacts in the low frequency band even when their frequency is overlapping with that of the EEG signal. A wireless biotelemetry application such as de-noising ECG signals with computationally less complex adaptive filters becomes essential. In order to analyze the performance of the filter structures which removes artifacts from ECG signal, simulations where carried out on signals obtained from MIT-BIH database. The simulation results show that the SSLMS algorithm is used to obtain convergence with reduced complexity than conventional LMS adaptive algorithm.

DISCRETE WAVELET TRANSFORM

Discrete Wavelet Transform (DWT) is a multiresolution scheme for input signals. In numerical analysis and functional analysis, a DWT is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, an advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time). The input signal x (n) is decomposed into two sets of coefficients called approximation coefficients (denoted by ca) and detail coefficients (denoted by cd). The types of wavelets are Daubechies Wavelets: dbN, Symlet Wavelets: symN, Haar wavelet: haar, Coiflet Wavelets: coifN.). These coefficients are obtained by convolving the input signal with a low-pass filter (for ca) or a high-pass filter (for cd) and then down sampling the convolution result by 2.

The size of ca and cd is half of the size of the input signal for Periodic extention mode and half of the sum of the input signal's size and the filter's size for Zero-padded extention mode. DWT (discrete in scale and shift and continuous in time) is successfully implemented as analog filter bank in biomedical signal processing. Figure 1 is commonly used DWT diagram for low pass and high pass filter.

Adaptive noise cancellation: The Electrocardiogram (ECG) is a signal which records the electrical activity of heart and is an important diagnostic tool for assessing heart function. Measurement of ECG may be corrupted by many sorts of noise. The ones of primary interest are Power line interference, Baseline wander noise, Motion artifacts and Muscle 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.

An adaptive filter is a filter whose coefficients are adjusted in a way to optimize a cost function or to satisfy some predetermined optimization criterion. The main purpose of this filter is to change (adapt) the coefficients of an FIR filter to matches closely as possible to the response of an unknown system. Figure 2 shows the general structure of an adaptive filter which serves as a foundation for particular adaptive filter realizations.

This filter that self-adjusts its transfer functions according to an optimization algorithm driven by an error signal. Because of the complexity of optimization algorithms, most of the adaptive filters are digital filters. A non-adaptive filter has a static transfer function. The adaptive filter uses feedback in the form of error signal to refine its transfer function to match the changing parameters. It finds its application in adaptive noise cancellation, system identification, frequency tracking and channel equalization.

Least mean square filter: The LMS algorithm is a method to estimate gradient vector with instantaneous value. It changes the filter tap weights so that

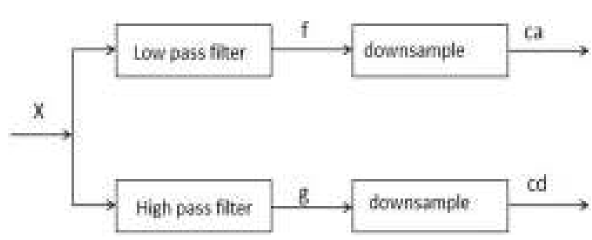

Fig. 1: Discrete wavelet transform

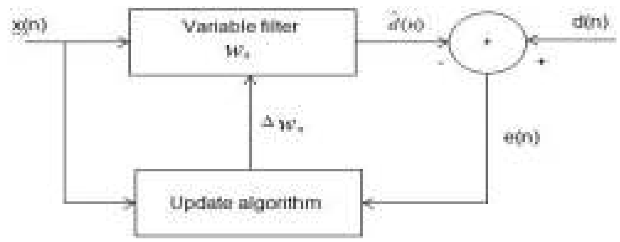

Fig. 2: Adaptive filter structure

e(n) is minimized in the mean- square sense. It is a stochastic gradient descent method in which the filter weights are only adapted based on the error at the current time. The LMS algorithm is most commonly used adaptive algorithm because of its simplicity and a reasonable performance. Since it is an iterative algorithm it can be used in a highly time-varying signal environment. It has a stable and robust performance against different signal conditions. However, many high-performance DSP systems, including LMS adaptive filters, may be implemented using Field Programmable Gate Arrays (FPGAs) due to some of their attractive advantages.

The LMS adaptive filter enjoys a number of advantages over other adaptive algorithms, such as robust behaviour when implemented in finite-precision hardware, well understood convergence behaviour and computational simplicity for most situations as compared to least square methods. An input random process be x(n) and FIR filter weight be $(w_0, w_1, \ldots w_{n-1})$. The filter output will be $y(n) = w^T x(n)$ and the error signal is as follows:

$$e(n) = d(n) - y(n)$$

where, d(n) is the desired output:

$$W(n+1) = w(n)+2*\mu*x(n)*e(n) \quad (1)$$

where, μ is the step-size parameter and controls the convergence characteristics of the LMS algorithm. The weight updation is shown in Eq. (1). The LMS adaptive filter enjoys a number of advantages over the other adaptive filter algorithms, such as the robust behaviour when implemented in finite-precision hardware, well understood convergence behaviour and computational simplicity for most situations as compared to least square methods. For biomedical applications sign based algorithms are suitable in which large signal to noise ratios with less computational complexity can be achieved. Sign based algorithms differ from the conventional LMS adaptive algorithms by utilizing signum function in the weight updation equation.
The equation is given by (2):

$$W(n+1) = w(n)+2*\mu*\text{sgn}\{e(n)\}*\text{sgn}\{x(n)\} \quad (2)$$

By introducing such signum functions in the weight update equation, the computational complexity reduces without affecting the signal quality.

METHODOLOGY

In this method, 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 Eq. (4):

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

where,
$ECG_{rec}(t)$ = Recorded ECG signal
$ECG_{true}(t)$ = ECG signal due to cardiac activity and without interference
k.Artifacts (t) = Artifacts during ECG recording

The ECG_{true} (t) is recovered from ECG_{rec} (t) by removing k. Artifacts (t) efficiently. The proposed ANC algorithm figure is shown in Fig. 3.
The Steps using DWT and ANC are as follows:

Decompose: Wavelet decomposition is applied to expand the contaminated ECG signal to get the wavelet coefficients. There are several possible mother wavelet functions such as daubechies, coiflet, symlet. Daubechies 4 family is efficient to remove the artifacts. So, the Daubechies 4 wavelet is used as the mother wavelet function for DWT. Compute the wavelet decomposition for the contaminated 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 coefficient equation is given in Eq. (3) and (4):

$$\text{Approximate coefficient} = \frac{s_i+s_{i+1}}{2} \quad (3)$$

$$\text{Detail coefficient} = \frac{s_i-s_{i-1}}{2} \quad (4)$$

where,
s_i = The element in the signal
i = The time index

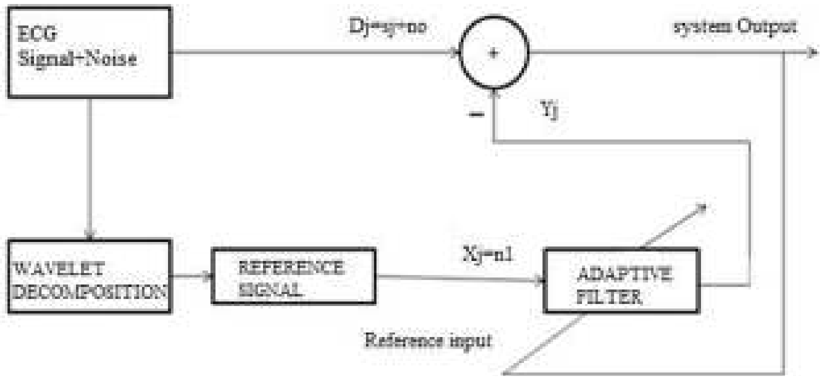

Fig. 3: Block diagram combining DWT and ANC filter

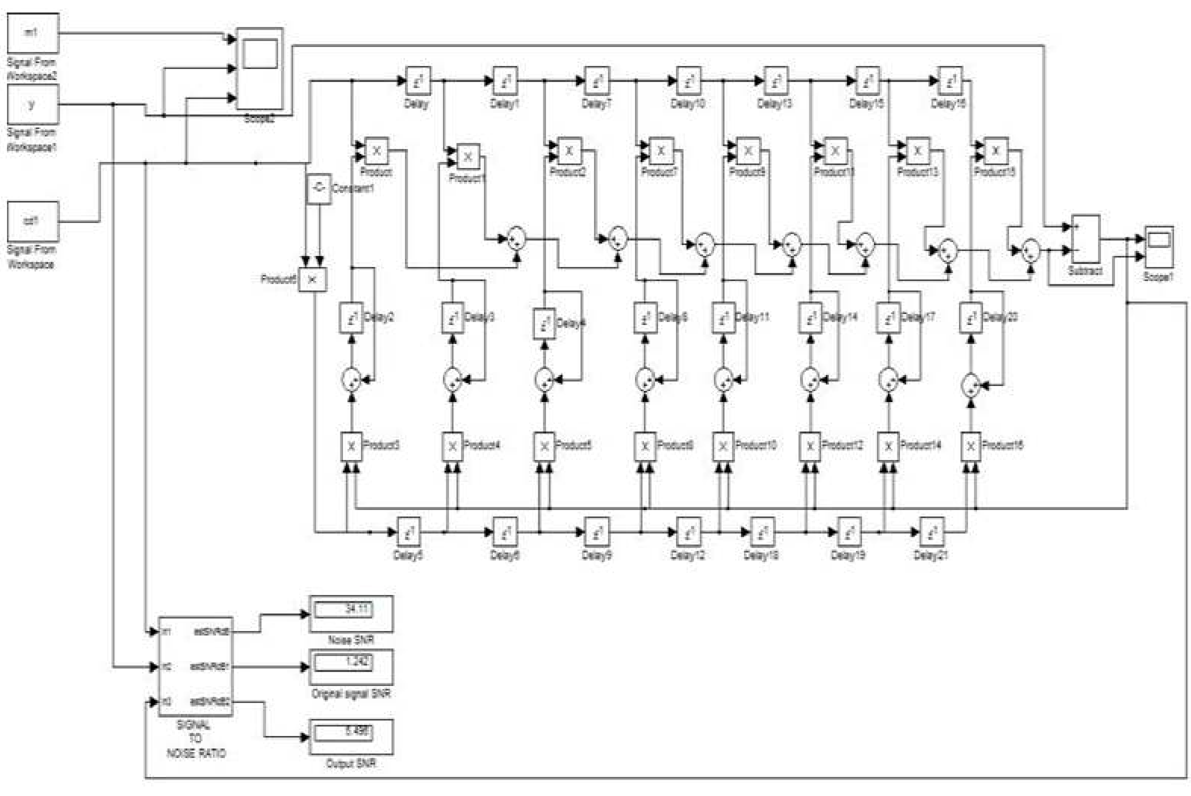

Fig. 4: 8-tap LMS filter

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

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-h 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.

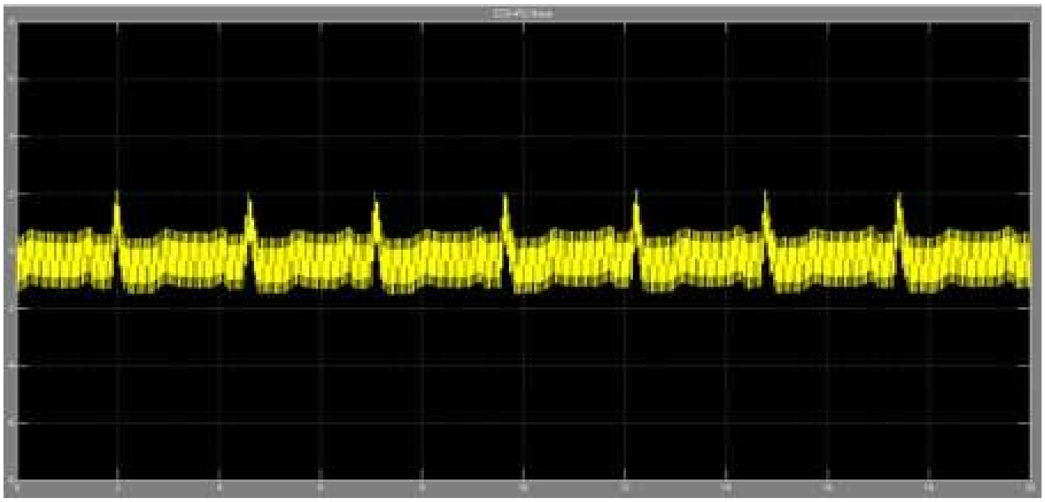

Fig. 5: Noisy ECG signal

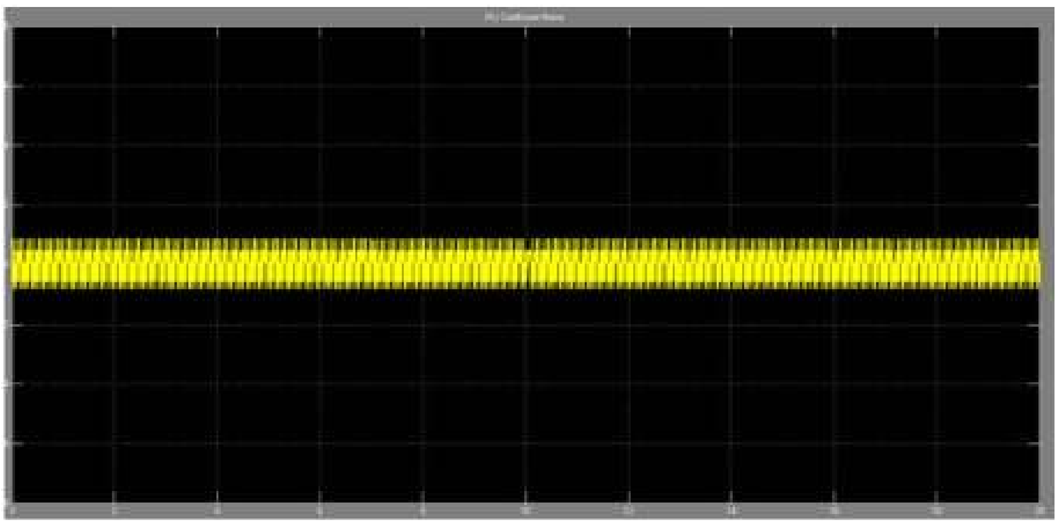

Fig. 6: Detailed coefficient

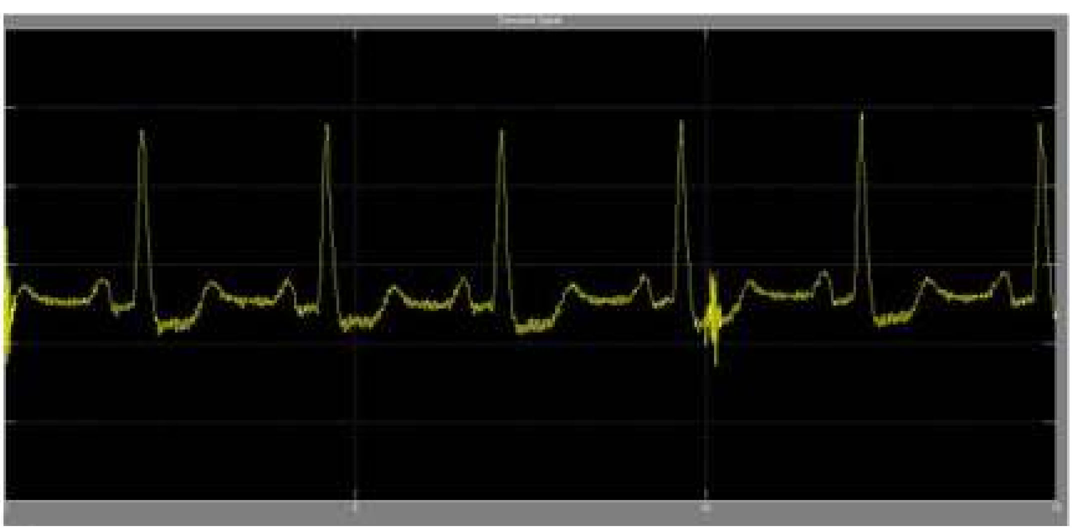

Fig. 7: Denoised ECG signal for LMS filter

An 8-tap LMS filter designed in MATLAB Simulink is shown in Fig. 4. The ECG signal along with Power line noise is shown in Fig. 5. The detailed coefficients for Noisy ECG signal is shown in Fig. 6. The denoised ECG signal obtained from the LMS filter is shown in Fig. 7.

The computational complexity of the conventional LMS can be reduced by introducing signum functions in its weight update equation. The multiplication required for SSLMS filter is less compared to LMS filter. It is suggested that stability analysis of SSLMS be carried out to place bounds on the choice of step-size parameter to achieve stable performance in a given application.

Furthermore, convergence analysis be carried out to obtain a deeper insight into the potentials of the filter. Thus, SSLMS algorithm is used to obtain convergence with reduced complexity. The sign-sign algorithm in which signum function is applied both to the input signal as well as the error signal.

The 8-Tap SSLMS filter is shown in Fig. 8 with Noisy ECG and modelled reference signal is given as input to SSLMS filter. The denoised ECG signal obtained from the SSLMS filter is shown in Fig. 9.

From the Table 1 it is seen that the Daubechies wavelet produce better SNR than the other wavelet for step size 0.01. So, daubechies wavelet is taken as mother wavelet function.

The algorithms are tested for various dataset and its Signal to noise Ratio is shown in Table 2. The average SNR improvement for various algorithms is 5.843dB and 5.228dB for LMS and SSLMS algorithms respectively.

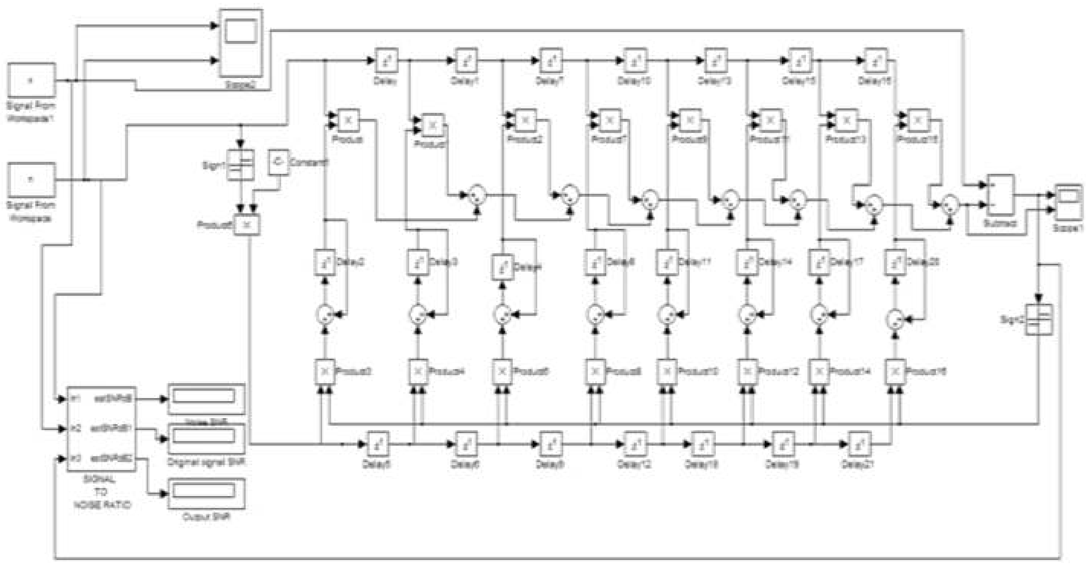

Fig. 8: 8-tap SSLMS filter

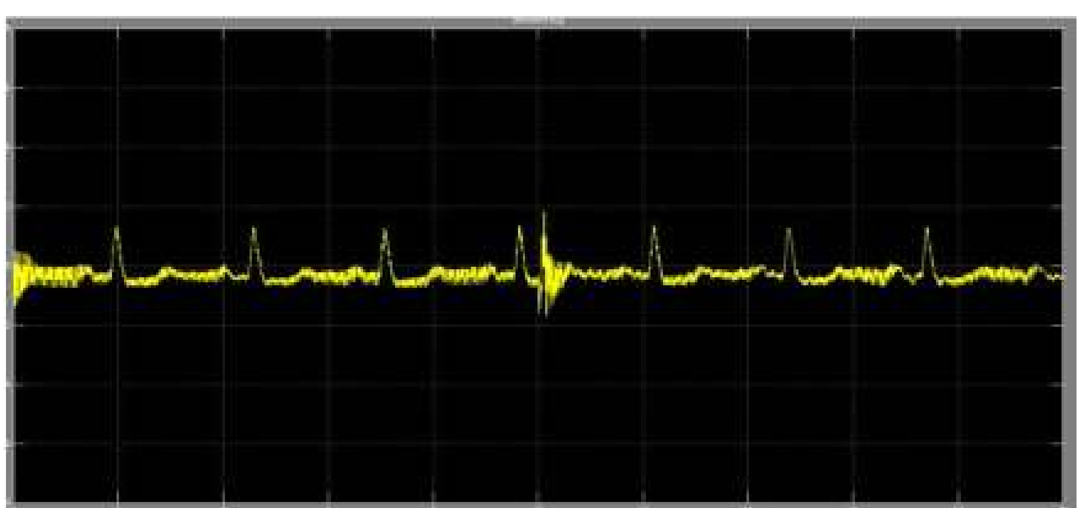

Fig. 9: Denoised ECG signal for SSLMS filter

Table 1: SNR improvement of db4 for PLI cancellation (μ = 0.01)

Noise	Rec. No	SNR before filtering	Daubechies		Coiflet		Symlet	
			8.13	7.01	5.97	6.62	7.90	6.66
PLI	100	1.88	8.13	7.01	5.97	6.62	7.90	6.66
	105	2.01	7.42	6.87	6.3	5.53	7.22	6.18
	108	2.09	7.72	8.46	6.16	6.94	6.85	8.22
	200	1.65	6.78	6.62	6.05	5.12	6.61	6.36
	203	1.24	5.51	5.27	4.23	4.94	5.38	4.78
	228	2.31	9.64	8.64	8.95	8.12	9.08	8.10
	Avg	1.86	7.50	7.14	6.27	6.21	7.17	6.72

Table 2: SNR improvement of various algorithms for PLI cancellation (μ = 0.01)

			LMS		SSLMS	
Noise	Rec. No	SNR before filtering	SNR after filtering	SNR imp	SNR after filtering	SNR Imp
PLI	100	1.883	7.442	5.559	7.024	5.141
	105	2.018	8.223	6.205	7.013	4.995
	108	2.092	8.569	6.477	7.723	5.631
	200	1.652	6.811	5.159	6.625	4.973
	203	1.242	5.496	4.254	5.27	4.028
	228	2.313	9.717	7.404	8.815	6.502
	Avg	1.95	7.709	5.843	7.078	5.228

In both cases, SNR after filtering is improved. The computations required for weight updation are reduced due to the sign function present in the filter. Thus, the computation complexity is reduced in SSLMS algorithm than LMS algorithm.

CONCLUSION

An adaptive filter is a filter whose coefficients are adjusted in a way to optimize a cost function and to minimize the sum of the squares of the difference between the desired signal and the filter output. These filters that self adjusts its transfer function according to an optimization algorithm driven by an error signal. The combination of DWT and various ANC techniques is used to remove the various noises in contaminated ECG signal. For de-noising ECG signal obtained from the MIT-BIH database, LMS, SSLMS algorithm is simulated using MATLAB. From the simulation results the LMS, SSLMS algorithm produces a signal to noise ratio which proved to have better performance in recovering true ECG signal and the computation complexity is reduced in SSLMS algorithm than LMS algorithm. In future, the sign based algorithms along with DWT will be analyzed for various noises present in ECG signal.

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