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Performance Analysis of Adaptive Filters for Denoising of ECG Signals

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ABSTRACT: Electrocardiogram (ECG) can help to diagnose range of diseases including heart arrhythmias, heart enlargement, heart inflammation (pericarditis or myocarditis) and coronary heart disease. ECG consists of noise which is non stationary that affects the reliability of ECG waveform. In this paper an adaptive filter for denoising ECG signal based on Least Mean Squares (LMS), Normalized Least Mean Square (NLMS), Affine Projection LMS (APA-LMS) and Recursive least Squares algorithm (RLS) is presented with experimental results and the results are found to be encouraging. The performances of these algorithms are compared in terms of various parameters such as SNR, PSNR, MSE and SD. To validate the proposed methods, real time recorded data from the MIT-BIH database is used. RLS algorithm is found to exhibit lower MSE, and higher SNR compared to other algorithms. Therefore the results demonstrate superior performance of adaptive RLS filter for denoising of ECG signal.

KEYWORDS: ECG, LMS, NLMS, RLS, APA-LMS, MSE, Interference, SNR and denoising

I. INTRODUCTION

As an adaptive filter do not require any signal statistical characteristics, it is considered as a primary method to filter noise and interference in ECG signals [1]. In recent years a remarkable improvement has been shown by medical research in areas of tumour detection, haemophilia, venereal diseases etc. Cardiac syndrome is considered to be one of the prominent focused areas of medical research. This area remains an open challenge to avoid maximum threats occurring to human life despite of many achievements [2]. ECG is considered as the most effective tool developed for cardiac analysis which provides a detailed profile of the electrical impulses that causes the cardiac fibres to expand and contract. As ECG signal is very sensitive there might be a possibility of interference of different types of noises corrupting the ECG signal thereby changing the real amplitude and duration [3]. To effectively process these ECG signals for proper diagnosis, denoising of ECG signal is essential [4-5]. ECG is used for the detection of sudden death syndromes and different heart diseases. ECG is a composite signal, where different heart activities result in generation of its components. Factors which affect in the improper diagnosis of ECG are the artifacts and noises introduced during its extraction [6]. One cycle of ECG signal corresponds to different phases of heart activities. Conventionally an ECG signal is labelled with peaks P, Q, R, S and T as in Fig.1. The P and T waves are low frequency components i.e. 5-9 Hz, while QRS is at high frequency of 10-40 Hz [7, 8]. The ECG signal enhancement results in presentation of an ECG signal which provides accurate and easy interpretation by separating invalid signal components from undesired artifacts.

ECG signals are subjected to various types of noises, which lie in different frequency ranges. These include persistent noises, which reside in a variety of frequency bands such as low frequency range (Base Line Wander), mid frequency range (Power Line Interference) and high frequency range (Electromyography) signals and burst noises, which appear for very short duration (electro-surgical noise) [9].

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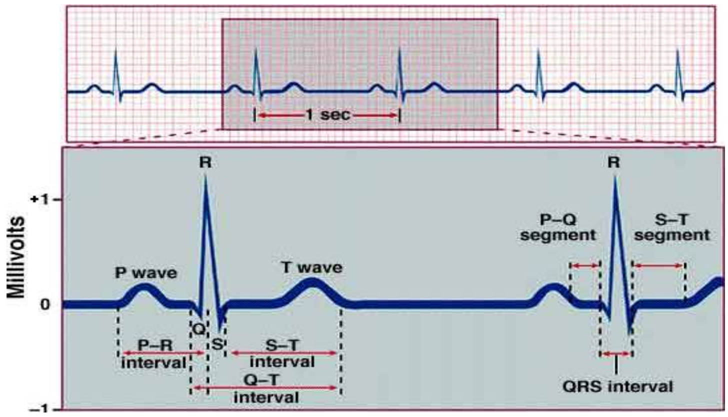

Fig 1. Components of normal ECG waveform [10]

ECG signals are easily corrupted by unwanted interference and noise. This is considered as one of the most serious problem resulting during the acquisition and recording of ECG signals. Many denoising algorithms are developed such as Discrete Cosine transform (DCT), SG smoothing, DWT, LMS, RLS. Many other techniques such as principle component analysis, independent component analysis and neural networks have also been used to extract noise free ECG signal from a noisy ECG which involves statistical analysis. These denoising algorithms should improve SNR to obtain clean and readily observable ECG recording, and preserve the original shape without introducing distortions in low amplitude ST-segment and P, T waves.

II. RELATED WORK

Verulkar et. al., (2012) used various filters such as Adaptive Volterra filter, FIR filter, Nyquist filter and IIR Notch filter for PLI (Power Line Interference) reduction [11]. The results show that IIR Notch filter gives a noise free output. In [12] a comparison between LMS, NLMS, and RLS algorithm is done to mitigate the power line interference. The performance of the algorithms is analyzed based on MSE (Mean Square Error) and SNR (Signal to Noise Ratio). The results show that, in comparison with LMS and NLMS algorithm, RLS algorithm exhibits high speed of convergence as well as low steady state error. Ahmad et. al., (2013) described the comparison of adaptive filters based on LMS and RLS algorithm which are implemented for cancellation of motion artifact noise in ECG signals [13]. Results show that adaptive filter using RLS algorithm gives best performance based on performance parameters MSE and SNR. The aim of this paper is to investigate and compare the performance of different adaptive filter algorithms in detail for ECG signal denoising. The methods used here for denoising of ECG signals are presented in the next section.

III. PROPOSED ALGORITHM

ECG signal is taken from MIT-BIH database with 2500 samples per second and amplitude 1.3 mV [14]. Random noise is generated using MATLAB with SNR of 5 dB and is added to this recorded ECG signal to get the desired mixed signal. The parameters to be considered in the implementation of any FIR filter are filter order, cut-off frequency, and window type. Here the filter order determines the width of the transition band. The combination of the three basic processes of adaptive filters i.e. given an input signal ECG signal compute the output with filtering process, comparing output with desired response and generating estimation error and finally adjusting filter coefficients depending on estimation error constitutes a feedback loop as shown in Fig. 2 [15]. Where $x(n)$ is input signal, $n(n)$ is noise signal, $d(n)$ is the desired ECG signal, $y(n)$ is the response of the filter and $w(n)$ are the filter coefficients. The error signal is obtained by subtracting $d(n)$ from $y(n)$

$$e(n) = d(n) - y(n) \tag{1}$$

For all the adaptive filter algorithms, the filter length is chosen to be 16 taps, i.e the number of coefficients of the HPF (FIR filter) is set to 16 with normalized cut-off frequency 0.5 Hz resulting in the desired ECG signal $d(n)$. Cut-off frequency (which enables a noise free ECG to be extracted by a FIR filter) above 0.5 Hz is found to give distorted ECG

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signal. Changing the behavior of the ECG signal in time by self-modifying frequency response is considered to be the main property of an adaptive filter [16].

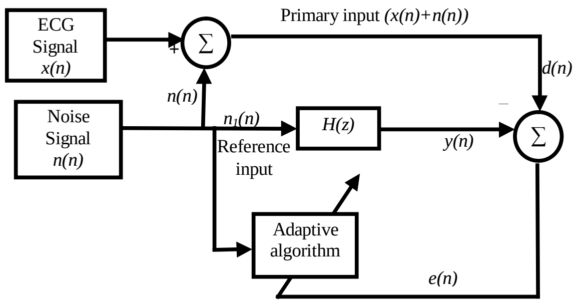

Fig 2. Basic principle of adaptive filter [17]

In all the applications of noise and interference cancellation an ECG signal is corrupted with uncorrelated interference and it is desired to recover the original ECG signal from the observed noisy ECG. The primary input is a combination of ECG signal and noise i.e. $d(n)=x(n)+n(n)$. The reference input $n_1(n)$ which is correlated with $n(n)$ is filtered by an adaptive filter to produce output $y(n)$. The adaptive filter coefficients are adjusted so that $y(n)$ is as close as possible to the interference at the primary input $n(n)$. $H(z)$ is the frequency response of FIR filter, i.e.

$$H(Z)=\frac{\sqrt{1-\alpha^2}}{1-\alpha\cdot Z^{-1}} \qquad (2)$$

Where $|\alpha|<1$, is a correlation parameter which controls the spectral property of reference signal $n_1(n)$. For $\alpha=0$, $n(n)=n_1(n)$ and as α increases the difference between $n(n)$ and $n_1(n)$ increases and as a result the eigen value spread of reference signal also increases. The reference signal so obtained is used to calculate the filter coefficient through an adaptive filter of length 2500 samples per second such that

$$y(n)=\sum_{i=0}^{N-i} w_n(i)x(n-i)=a_n^T w_n \qquad (3)$$

Where w_n is the coefficient vector of the filter, a_n is the estimated reference input vector and $y(n)$ is the estimated reference signal.

A. LMS ALGORITHM

One of the simplest algorithms based on steepest descent method with an adaptive structure is LMS (Least Mean Square) algorithm [16]. In this algorithm the statistics of the signal are estimated continuously, as a result adaptive filters with LMS algorithm show good performance for processing and analysis of ECG signal corrupted by noise and interference [18]. The main feature that attracts the use of LMS algorithm is low in computational complexity, unbiased convolution and stable behavior [19]. LMS algorithm minimizes the cost function $E\left\{|e(n)|^2\right\}$, where $e(n)$ is the error signal. In Fig. 2, the primary input signal is ECG signal corrupted by noise, reference signal contains noise alone, $y(n)$ is the filtered output, $d(n)$ is the desired ECG signal, and $e(n)$ is the error signal. The filtered reference noise signal is subtracted from the primary input to produce the system output which is considered to be the best least squares estimate of the primary signal. Depending on the error signal the LMS adaptive filter updates the weight of the filter to obtain denoised ECG [20]. The LMS algorithm produces the least mean square of this error signal $e(n)$ by changing the filter tap weight $w(n)$. The iterative nature of LMS filter's coefficient update gives a smooth response of instantaneous gradient to obtain a more reasonable estimate of true gradient [21]. For each iteration, the three basic operations of LMS algorithm are:
Calculates output signal $y(n)$ from the adaptive filter as

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$$y(n)=\sum_{i=0}^{N-1} w_i(n)x(n-i) \qquad (4)$$

Calculates error signal *e(n)* from the Eq. 1, and finally adjusts the filter coefficients using the equation

$$w(n+1)=w(n)+2\mu e(n)x(n) \qquad (5)$$

where *w(n)* is tap weight vector at 2500 samples, μ is the step size (0.01) which lies in the range $0<\mu<\frac{2}{M*\lambda_{Max}}$, where λ_{Max} is the maximum PSD (Power Spectral Density) of input signal power *x(n)* which is calculated as 0.12 (m^2/Hz), obtained by Fourier transforming the input auto correlation function, and M (16) is the filter length. The step size μ (0<μ<1), also called as convergence factor is introduced so that the filter can be protected from divergence, caused due to the presence of noise in the signal. The step size selected for LMS algorithm is found to have fast convergence and low MSE. The step size is selected such that the filter convergence error is small for all values of n (2500 samples). A large step size can improve convergence speed of resulting adaptive filter, but a large convergence speed may result in large steady state error or cause instability in resulting adaptive filter [1].

B. NLMS ALGORITHM

For every iteration, the step size parameter in LMS algorithm is fixed, which is the primary drawback of LMS algorithm. Therefore understanding the input ECG signal statistics is required prior to adaptive filtering [22-24]. The larger step size fluctuates the coefficient and so LMS algorithm experiences gradient noise amplification problem. To overcome this problem a normalized step size is used which is known as Normalized LMS (NLMS) algorithm [18].
The coefficient updating equation for NLMS algorithm is

$$w(n+1)=w(n)+\frac{\beta}{\|x(n)\|^2}e(n)x(n) \qquad (6)$$

To ensure fast convergence step size (μ) is calculated as

$$\mu(n)=\frac{\beta}{c+\|x(n)\|^2} \qquad (7)$$

where β is normalized step size and c is a small positive constant. The step size is proportional to the inverse of total expected energy of the instantaneous values of the coefficients of the input ECG signal *x(n)*. The step size is normalized by the input signal power. As the noise is a non-stationary signal, NLMS is considered as the algorithm for fast convergence speed for non-stationary input. NLMS algorithm shows greater stability with unknown signals as the step size is based on current input values. From Eq. (7), the convergence rate is directly proportional to the normalized step size or the adaptation constant β (0.008), i.e. this algorithm is independent of input signal power [25].

C. APA-LMS ALGORITHM

An Affine Projection Algorithm (APA) is an extension of NLMS algorithm, and belongs to the family of LMS algorithm with higher order [19]. In the application where the input ECG signal is highly correlated, the APA is considered as a better alternative than NLMS algorithm [26, 27]. One of the drawback associated with NLMS algorithm is during updating of coefficient vector it utilizes only the current signal information. To overcome this, an extension of NLMS algorithm called as APA-LMS algorithm is used which reutilizes both past and current signal information called as data-reusing. In [28], it is already proposed that, to update the weight of current input vector APA algorithm reuses past multiple input vectors. The block diagram of APA-LMS is shown in Fig. 3.

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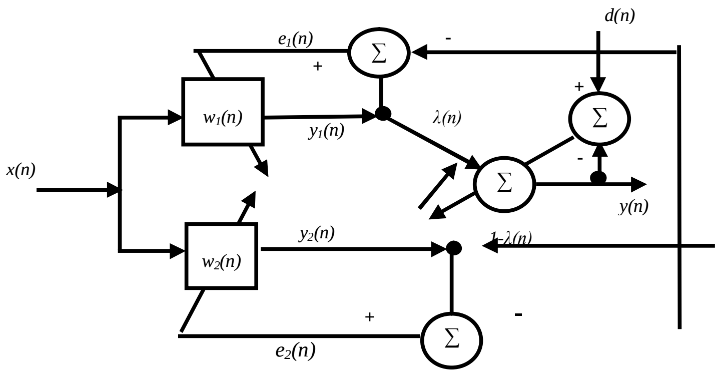

Fig 3. Block diagram of APA-LMS algorithm [29]

The three steps involved in this algorithm are: first we calculate the error vector, then we deduct the normalized error vector. And this normalized vector is used to update the filter coefficients. The updating equations of APA-LMS algorithm for every iteration are given by [30].

$$e(n) = d(n) - x^T(n)w(n) \qquad (8)$$

$$w(n+1) = w(n) - \mu x(n)t(n) \qquad (9)$$

$$\text{Where } t(n) = \left[x^T(n)x(n) + \partial I\right]^{-1} e(n) \qquad (10)$$

where ∂ is the regularization parameter which is employed to avoid the inversion of rank-deficient matrix [$x^T(n)x(n)$]. The output of the filter is given as

$$y(n) = \lambda(n)y_1(n) + \left[1 - \lambda(n)\right]y_2(n) \qquad (11)$$

Where $y_1(n)$ is the output of first LMS filter with step size 0.05, and is the output of second LMS filter with step size 0.005. The step size relation between the two LMS filters is given by μ_1=0.1* μ_2 [31]. Here we assume $\mu_1 > \mu_2$, so that $w_1(n)$ converges faster than $w_2(n)$. The step size parameter controls the stability, convergence rate and estimation error of the algorithm. When the step size is large, the algorithm will converge fast but with an increase of steady state misalignment. But when the step size is small, its convergence is slow with less misalignment. The desired and input signal vectors are given by

$$d(n) = \left[d(n) \quad d(n-1) \cdots \quad d(n-P+1)\right] \qquad (12)$$

d(n) is the signal containing the most recent P (projection order) samples of the reference signal.

$$x(n) = \left[x(n) \quad x(n-1) \cdots \quad x(n-P+1)\right] \qquad (13)$$

where P (10) is the projection order which provides fast convergence, small steady state error and low computational complexity for 2500 samples of ECG signal used. When the Projection order of APA is 1, it is equivalent to NLMS filter. There are three main parameters that control the performance of APA algorithm. The first parameter is the projection order, as projection order increases the convergence rate also increases thereby increasing the computational complexity. The second parameter is the step size μ (0<μ<2) which compromises between the convergence rate and misalignment [1]. The third parameter is regularization parameter (), where large value of regularization parameter results in small step size, slow convergence rate and less misalignment. When highly correlated signals like speech signals, ECG signals are used, APA algorithm has improved convergence rate compared to NLMS algorithm. As the projection order increases, the computational complexity of the APA-LMS algorithm also increases. Selection of high projection order with large step size results in faster convergence with increased estimation error. On the other hand, when low projection order with small step size is selected, it results in low convergence rate with low estimation error [32]. Each tap weight vector updated in NLMS algorithm can be considered as a one-dimensional APA. In APA-LMS algorithm projections can be made in multiple dimensions.

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D. RLS ALGORITHM

Compared to all LMS algorithms, RLS algorithm has a faster convergence speed and do not exhibit eigen value spread problem. It is a method of least squares for automatically adjusting the coefficient of a FIR filter without invoking assumptions on the statistics of input ECG signal. The estimation of RLS algorithm is done by minimizing the sum of squares of instantaneous error values [33]. The reason for faster convergence of this algorithm is, it denoises ECG signal by using inverse correlation matrix of the data assumed to be zero mean and also because it uses all the information contained in input data from, start of adaptation to the present. This improvement is achieved by increasing computational complexity of RLS filter. Inverse correlation matrix is computed directly in RLS algorithm [34]. Due to this feature RLS algorithm does not require any matrix inversion computations. The following equation provides the update coefficient for RLS algorithm [35].

$$w(n+1) = w(n) + e(n)k(n) \tag{14}$$

where k(n) is the gain factor defined by

$$k(n) = \frac{p(n)\cdot x(n)}{\lambda + x^T(n)p(n)x(n)} \tag{15}$$

where λ (1) is the forgetting factor which lies in the range $0 < \lambda \le 1$, and *p(n)* is the inverse correlation matrix of *x(n)* defined as

$$p(n) = \partial^{-1}x(n) \tag{16}$$

where ∂ is the regulation factor which is the initial value of inverse correlation matrix. The parameters that can be adjusted in this algorithm are forgetting factor (λ) and regulation factor (∂). The RLS algorithm uses the following equation to update inverse correlation matrix

$$p(n) = \lambda^{-1}p(n) - \lambda^{-1}k(n)x^T(n)p(n) \tag{17}$$

IV. RESULTS AND DISCUSSION

The simulation results of all the four algorithms LMS, NLMS, APA-LMS and RLS, are used to analyze the given ECG signal quantitatively in noise free signal processing aspect (Fig 4, 5, 6, 7). The performance of all the algorithms is studied in the presence of an external reference signal and compared in terms of MSE, computational complexity and stability. These methods are validated using ECG recording from MIT-BIH arrhythmia database signal with various morphologies. RLS algorithm is shown as an appropriate tool for denoising of ECG signal. The APA algorithm is an intermediate algorithm that lies between NLMS and RLS algorithm. In affine combination of two LMS filters high convergence speed and higher stability is achieved. Therefore, the performance of APA-LMS is superior to LMS and NLMS. The simulation results confirm that the performance of RLS is better than the LMS adaptive algorithms in terms of MSE. When input signal is non-stationary in nature, the RLS algorithm is proved to have the highest convergence speed, less MSE (84.06 dB) and high SNR (23.41 dB) improvement (Table 1), but at the cost of large computational complexity and large memory requirements. Fig. 8 represents the MSE of all the four algorithms, calculated for 500 samples.

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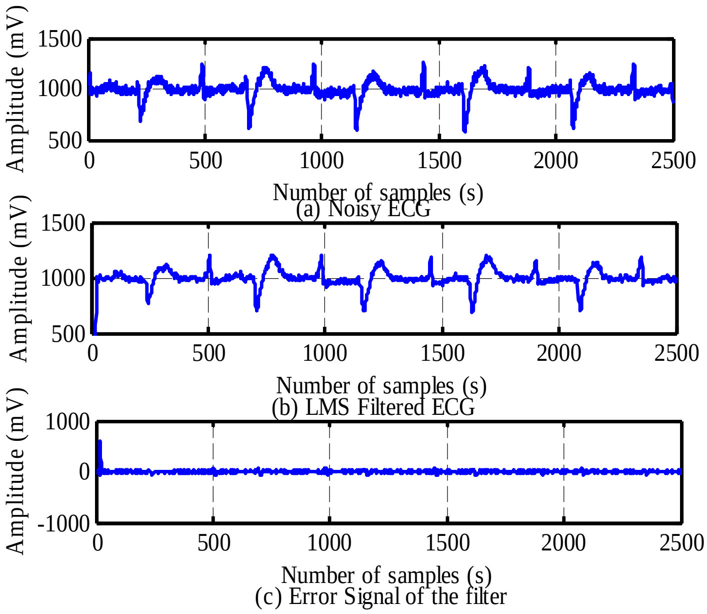

Fig 4. Response of LMS filter (a) Noisy ECG (b) LMS Filtered ECG (c) Error signal of the filter

The LMS filter output *y(n)* and the error of the filter *e(n)* depends on the fixed step size (μ) which is calculated as 0.01. The error signal in Fig 4(c) shows few traces of the signal. The practical implementation of NLMS filter is similar to that of simple LMS filter. The only difference is the way in which the filter coefficients are updated. In NLMS the filter coefficients are updated using Eq. (6). NLMS filter has normalized step size which makes it converge faster than simple LMS. Comparing Fig 4(c) and Fig 5(c) it is clear that the error signal of NLMS converges faster than the LMS filter.
The response of APA-LMS filter is shown in Fig 6. To consider trade-off between convergence speed and minimum MSE an affine combination of two LMS filters is proposed. The output response *y(n)* and the error signal *e(n)* of RLS adaptive filter is shown in Fig. 7. for APA-LMS and 500 samples for RLS respectively.

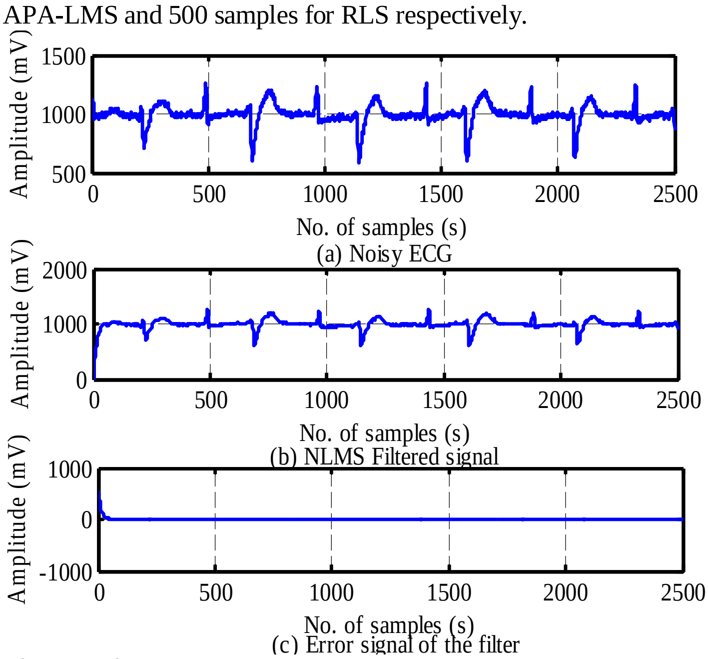

Fig 5. Response of NLMS filter (a) Noisy ECG (b) NLMS Filtered ECG (c) Error signal of the filter

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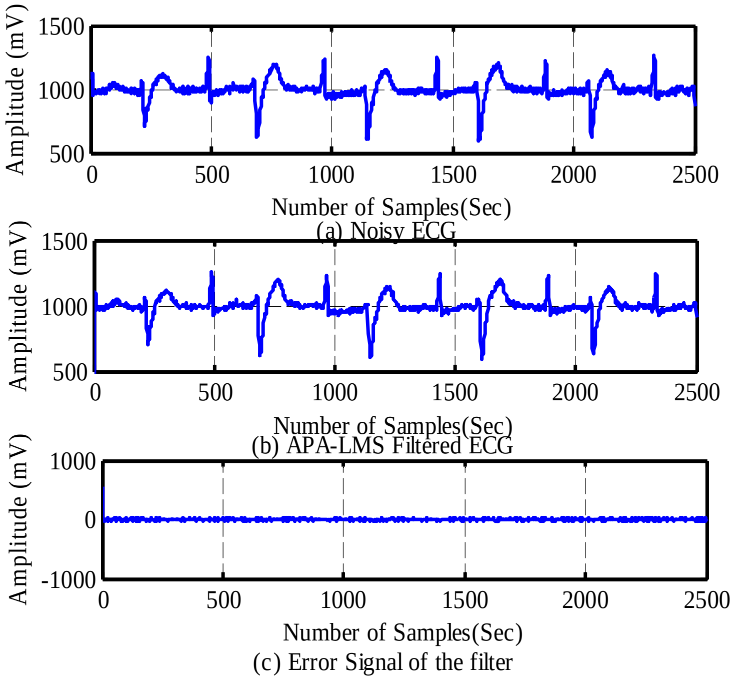

Fig 6. Response of APA-LMS filter (a) Noisy ECG (b) APA-LMS Filtered ECG (c) Error signal of the filter

Comparing the output of all the algorithms from Fig. 4 (b), 5 (b), 6 (b) and 7 (b), the response of simple LMS filter adopts the approximate correct output ECG signal at 1800 samples. NLMS filter adopts at around 1500 samples, 800 samples. This represents that RLS algorithm has fast convergence rate.
In this paper we have shown that the RLS algorithm denoises ECG signal exceptionally better than the other LMS algorithms in terms of SNR, MSE, PSNR and Standard Deviation (SD) as shown in Table.1.

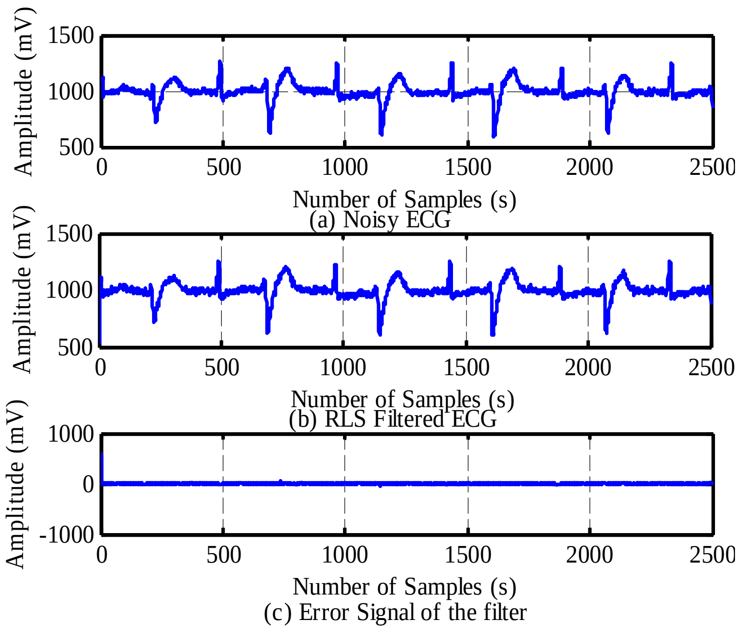

Fig 7. Response of RLS filter (a) Noisy ECG (b) RLS Filtered ECG (c) Error signal of the filter

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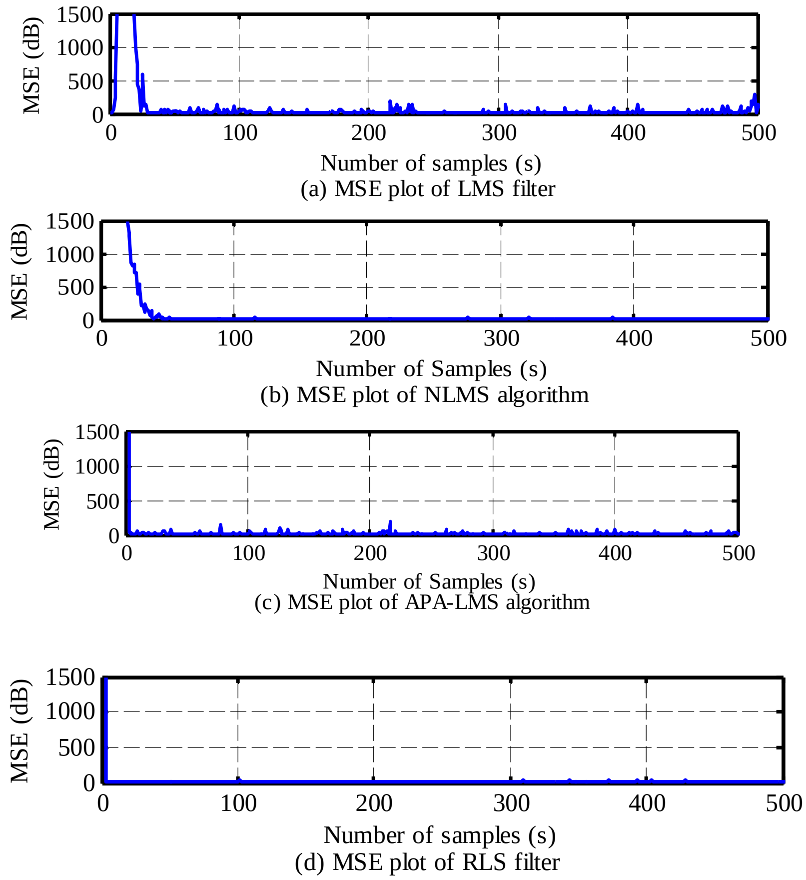

Fig 8. MSE plot of (a) LMS filter (b) NLMS filter (c) APA-LMS filter (d) RLS filter

The performance of these algorithms is compared by these operation parameters. The measure of signal strength relative to background noise is given by the parameter SNR which is measured in dB.
Higher the value of SNR better is the algorithm for denoising of ECG signals. The SNR is calculated using:

$$SNR = 10 * 10\log_{10}\left[\left|\frac{E_{ECGSignal}}{E_{NoiseSignal}}\right|^2\right] \qquad (18)$$

Table 1. Performance analysis for various Adaptive algorithms

Name of the algorithm	**SNR (dB) Before filtering**	**SNR (dB) After filtering**	**MSE (dB)**	**PSNR (dB)**	**SD**
LMS	18.3	20.79	111.37	27.693	110.79
NLMS	18.3	22.22	97.21	28.287	97.21
APA-LMS	18.3	23.31	85.27	28.89	85.27
RLS	18.3	23.41	84.06	29.87	84.87

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The cumulative squared error between filtered and the original image is given by the parameter MSE (Mean Square Error), which measures the average of the squares of the error (convergence error) i.e. the difference between the estimator signal (original ECG signal) and what is estimated (noisy ECG signal) and calculated as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[b(n) - x(n)\right]^2 \tag{19}$$

where n=2500, *b(n)* is original ECG and *x(n)* is noisy ECG. The ratio of maximum possible power of original ECG signal to power of corrupted noise which affects the fidelity of the original ECG signal is given by the parameter PSNR which is calculated using equation

$$PSNR = 10 * \log_{10}\left[\frac{MAX^2}{MSE}\right] \tag{20}$$

where MAX = maximum possible value of ECG signal and MSE is the mean square error. In SNR we calculate how strong the filtered ECG signal is compared to noisy ECG, whereas in PSNR we calculate the signal peak values like R wave (Fig.1), which detects the cardiac problems.

V. CONCLUSION

In this paper various adaptive algorithms such as simple LMS, Normalized LMS, APA-LMS and RLS are used to mitigate noise and interference from ECG signals. Appropriate step size is calculated for each adaptive filter and their performances are examined. By using simple LMS, there is no much improvement in SNR (Table.1). In NLMS the step size parameter is normalized with respect to input signal for better performance. Using NLMS the SNR is calculated as 22.22 dB. Hence NLMS performance is better than LMS. APA-LMS adaptive filter uses two step size parameters with smaller step size (0.05µ) for good steady state response and slow convergence. And by using APA-LMS the SNR has increased from 18.3 dB to 23.3 dB. It has improved performance compared to LMS and NLMS. RLS adaptive filter gives encouraging increase in SNR from 18.3 dB to 23.41 dB. Convergence speed of all the filters is estimated, and the results found are, RLS adaptive filter has less convergence speed (Fig. 8 (d)). That is slower convergence yields better mitigation of noise from the ECG signals. Hence for improving the convergence speed of filters, Recursive Least Squares (RLS) adaptive filtering algorithms are very useful. As RLS has higher computational operations and higher memory requirements, algorithm such as fast RLS (F-RLS), and QR decomposition RLS (QRD-RLS) can also be used to reduce computational requirements which will be invested.

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