

# COMPARATIVE ANALYSIS OF DENOISING THE DIFFERENT ARTIFACTS IN ECG SIGNAL USING DIFFERENT ADAPTIVE ALGORITHMS

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**Abstract:** Now a day's biomedical signal processing having the main problems like in ECG signal effecting noises caused by power line interference, external electromagnetic fields, random body movements and respiration etc. so we have to remove these noises from the ECG signal. For this purpose several methods are there in filters. But it is not possible to apply filters with fixed coefficients to reduce ECG signal noises, because human behavior is varying from time to time. This problem is overcome by Adaptive filter technique. Here we are proposing the different types of adaptive filters to separate the ECG signal from noises like PLI and Base Line Interference. The MATLAB results of simulations are presented. In this we have used Improved Recursive Least Squares (RLS). The ES-RLS algorithm is proposed for removing different noises preserving the low frequency components and tiny features of the ECG. It is designed for the present realization of the input signals. In this least squares method adapted for real time processing of temporal series. The Least-squares algorithm minimize the error from the sum of the squares of the difference between the desired signal and the model filter output. This process is repeats when new samples of the incoming signals are received at every iteration. The error of the least-squares problem can be computed in recursive form resulting in the recursive least-squares (RLS) algorithms. The Improve RLS algorithms are giving the fast convergence performance even when the Eigen value spread of the input signal correlation matrix is large. The RLS algorithms have excellent performance when working in time-varying environments as compared to other algorithms. But the RLS algorithms lead an increased computational complexity and some stability problems, which are not major problems in LMS, NLMS-based algorithms.

**Key words:** ECG Signal, Adaptive Algorithms, PLI, Base Line Interferences.

## I. Introduction:

ECG signal is one of the biomedical signals, which are widely studies and applied in clinic. A normal ECG waveform is usually composed of P wave, QRS complexes, and T wave, and the accurate

detection of them is important to analyze ECG signal [2][3]. However, because ECG signal is very faint, it is extremely easy to interfere by the different noises while gathering and recording. How to suppress noises [6][7] effectively is always an important problem in the detection of ECG signal. Recently, *adaptive filters* have been widely used in signal processing [4][5]. The ECG signal denoising using adaptive algorithm is shown in Fig1.

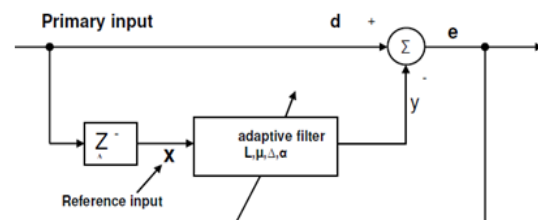


Fig 1: Adaptive filter for noise cancellation

Here the LMS algorithm works on the principle of weight updates when a new sample is arrived, based on updated weight it calculate gradient.

There are some clinical applications where ECG signal is very complex to process by LMS algorithm with less number of taps. In that case the conventional LMS algorithm is inefficient. The LMS algorithm is converted to NLMS (normalized LMS) algorithm by increasing number of taps. Then the NLMS (normalized LMS) algorithm required more computations. But these LMS and NLMS algorithms are slow in convergence because it depends on input signal. However, to improve the convergence speed we went to the RLS (Recursive Least-Squares) algorithm, whose convergence does not depend on the input signal, is the fastest of all conventional adaptive algorithms [10]. The major drawback of the RLS algorithm is its large computational cost. However, fast (small computational cost) RLS

algorithms have been studied recently. In this paper we aim to obtain a faster algorithm by incorporating knowledge of the room impulse response into the RLS algorithm. Unlike the NLMS and projection algorithms, the RLS algorithm does not have a scalar step size. Therefore, the variation characteristics of an ECG signal cannot be reflected directly in the RLS algorithm. Here, we study the RLS algorithm from the viewpoint of the adaptive filter because (a) the RLS algorithm can be regarded as a special version of the adaptive filter and (b) each parameter of the adaptive filter has a physical meaning. Computer simulations demonstrate that this algorithm converges twice as fast as the conventional algorithm. These characteristics may play a vital role in biotelemetry, where extraction of noise free ECG signal for efficient diagnosis and fast computations, high data transfer rate are needed to avoid overlapping of pulses and to resolve ambiguities. To the best of our knowledge, transform domain has not been considered previously within the context of filtering artifacts in ECG signals. In this paper we present an ES-RLS (Exponentially weighted step size RLS) algorithm to remove the artifacts from ECG. This algorithm enjoys less computational complexity and good filtering capability. To study the performance of the proposed algorithm to effectively remove the noise from the ECG signal, we carried out simulations on MIT-BIH database for different artifacts.

## II. The LMS Adaptation Algorithm:

The LMS (least mean squares) algorithm is a noisy approximation of the steepest descent algorithm it works on the principle of weight updates when a new sample is arrived, based on updated weight it calculate gradient. The gradient calculation is unbiased. The calculation of the gradient is based on sample values of the tap-input vector  $w(n)$  where it is random and an error signal. The algorithm iterates over each coefficient in the filter, moving it in the direction of the approximated gradient. For the LMS algorithm it is necessary to have a reference signal  $d[n]$  representing the desired filter output. The difference between the reference signal and the actual output of the transversal filter is the error signal [12].

$$e(n) = d(n) - h(n)x(n) \quad (1)$$

The aim of the LMS algorithm is to find a set of filter coefficients  $c$  that minimizes the expected value of the quadratic error signal, i.e., to achieve

the least mean squared error. The squared error and its expected value are (for simplicity of notation and perception we drop the dependence of all variables on time  $n$ ). In the LMS algorithm, however, a very short-term estimate is used by only taking into account the current samples. Here, we introduced the ‘step-size’ parameter  $\mu$ , which controls the distance we move along the error surface. In the LMS algorithm the update of the coefficients is performed at every time instant ‘ $n$ ’

$$h(t+1) = h(t) + \mu e^*(n)x(n) \quad (2)$$

The ‘step-size’ parameter  $\mu$  introduced in above equation controls how far we move along the error function surface at each update step  $\mu$  certainly has to be chosen  $\mu > 0$  (otherwise we would move the coefficient vector in a direction towards larger squared error). Closer analysis reveals, that the upper bound for  $\mu$  for stable behavior of the LMS algorithm depends on the largest eigenvalue  $\mu_{max}$  of the tap-input auto-correlation matrix  $R$  and thus on the input signal. For stable adaptation behavior the step-size has to be  $\mu = 2/\mu_{max}$ . The main drawbacks of LMS algorithm are steepest descent properties are no longer guaranteed and the instantaneous estimates allow tracking without redesign.

The NLMS algorithm has been developed based on Goodwin and Sin demonstration formula from the constrain optimization problem by the method of Lagrange multipliers, to solve the LMS algorithm drawbacks[9][8]. The NLMS shows improvement over the LMS in convergence rate point of view, while its steady state performance was considerably worse than the LMS because it needs to add some regularization. Never the less, the NLMS is always the favorable choice of algorithm for fast convergence speed and for non-stationary input.

$$h(t+1) = h(t) + \frac{\mu}{x^T(n)x(n)} e^*(n)x(n) \quad (3)$$

Theoretically, the step size ( $\alpha$ ) is varies from 0 to 2 for stable adaptation and, it is always less one unity for NLMS.

## III. The RLS Adaptation Algorithm:

The RLS (recursive least squares) algorithm is based on a deterministic philosophy. It is designed for the present realization of the input signals. In this least squares method adapted for real time processing of temporal series. Here the convergence

speed is not strongly dependent on the input statistics, i.e. convergence is not affected by the eigenvalues[10].

The RLS algorithm calculates autocorrelation matrix of the input vector by using the information from all past input samples (and not only from the current tap-input samples). A weighting factor is used to decrease the influence of input samples from the far past. However the RLS algorithm can be derived from the Kalman filter [1] to recursively solve the least-squares estimation problem. The impulse response variation of covariance matrix is given as

$$Q(k) = (v^{-1} - 1)P_n(n) \quad \text{Where } 0 < v < 1 \quad (4)$$

Using a matrix inversion lemma a recursive update equation for  $P_n(n)$  is

$$P_n(n) = v^{-1}P_n(n-1) + v^{-1}x(n)k(n)$$

With

$$k(n) = \frac{v^{-1}P_n(n-1)x(n)}{1+v^{-1}x^*(n)P_n(n-1)x(n)} \quad (5)$$

Finally, the weights update equation is

$$h(n+1) = h(n) + k(n)e(n) \quad (6)$$

#### IV. Exponentially weighted step size RLS (ES-RLS) algorithm:

The ES-RLS algorithm is derived from the Kalman filter by introducing several assumptions as follows. First, each element of the impulse response variation  $\Delta h(k)$  is assumed to be a statistically independent random variable. As a result, the covariance matrix  $Q(k)$  of the variation  $\Delta h(k)$  becomes a diagonal matrix. Then, for the diagonal component of the matrix  $Q(k)$ . The  $\alpha_0(k)$ , which represents the magnitude of the variation, is assumed to take time-invariant value  $\alpha_0(k)$ .

Based on these assumptions, we set  $Q(k)$  as

$$Q(k) = A = \begin{bmatrix} \alpha_1 & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \alpha_n \end{bmatrix} \quad (7)$$

Where  $\alpha_i = \alpha_0 \gamma^{i-1}$  where  $i=0, 1, 2 \dots L$

$\gamma$  - Exponential attenuation ratio of room impulse responses ( $0 < \gamma < 1$ ). Elements  $\alpha_i$  are time-invariant and decrease exponentially. We introduce  $P_{ES}(n)$  by multiplying with a priori coefficient error covariance matrix  $P_n(n)$  of a filter by  $1/R$ .

$P_{ES}(n) = \frac{P_n(n)}{R}$ , where  $R$  is power of the ambient noise.

Finally we get the following ES-RLS algorithm

$$h(n+1) = h(n) + k(n)e(n) \quad (8)$$

$$\text{And } k(n) = \frac{P_{ES}(n)x(n)}{1+x^T(n)P_n(n)x(n)}$$

$$P_{ES}(n+1) = P_{ES}(n) - k(n)x^T(n)P_{ES}(n) + \frac{A}{R}$$

Where  $A$  is step size matrix and  $P_{ES}$   $L \times L$  matrix. When the value  $A/R$  is large compared to  $P_{ES}(n)$ , the proportion of  $P_{ES}(n)$  in  $P_{ES}(n+1)$  becomes small. In this algorithm,  $A/R$  is added to matrix  $P_{ES}(n)$  at every time step ' $n$ '. These results in fast convergence approximately double the convergence rate of normal RLS [11].

#### V. Simulation results:

To show that RLS algorithms are really effective in critical situations, the method has been validated using several ECG recordings with a wide variety of wave morphologies from MIT-BIH arrhythmia database. Here we are taking the ECG signal as a reference from MIT-BIH database and added the Real noise Normal Sinus Rhythm Database (NSTDB) shown in Fig 2(a). After Applying this noisy ECG signal to Non blind Adaptive algorithms like LMS and NLMS algorithms we get the denoised ECG with in 200 and 90 iterations as output due to the updating the weighting coefficients according to equations(2) and (3). The results has shown in shown in Fig.2(b) and Fig.2(c) correspondingly. But using the blind adaptive algorithms like RLS and proposed ES-RLS gives better denoise signal by updating the coefficients according to equation(6) and (8) with in 50 and 10 iterations, shown in Fig.2(d) and Fig.2(e) respectively. Hence due to the fast convergence nature of ES-RLS algorithm it gives the fastest denoisy signal compared to remaining algorithms. For evaluating the performance of the proposed ES-RLS adaptive filter over existed LMS, NLMS and RLS algorithms considered the SNR improvement after denoising the signal. The similar results that can be obtained by applying the different artifacts to original ECG gives the better SNR ratio.

The ECG signal contaminated with Baseline Wander (BW) noise is applied as primary input to the adaptive filter of Fig.1. The real BW is given as reference signal. The simulation results shown in

Fig.3 indicate the reduction of BW noise gradually.

We use a generated pure ECG signal with electrode motion artifact (EM) added. Where EM is taking by a MIT-BIH database. The ECG signal contaminated with EM is given as input to the adaptive filter. The EM noise is given as reference

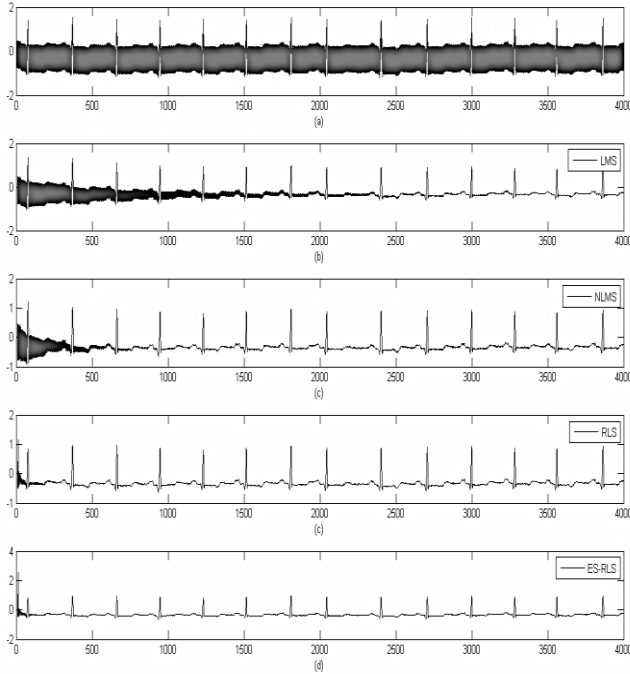


Fig.2:(a)Contaminated ECG signal with real noise,(b) Denoised ECG signal with LMS algorithm (c) Denoised ECG signal with NLMS algorithm,(d) Denoised ECG signal with RLS algorithm(e) Denoised ECG signal with ES-RLS algorithm.

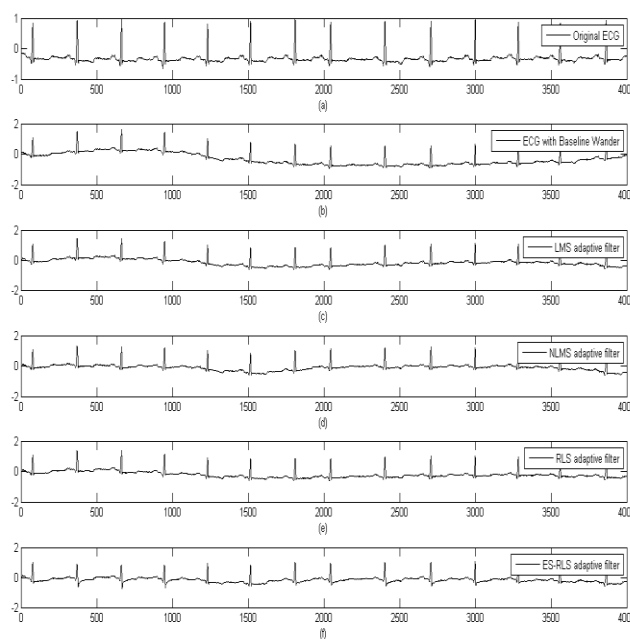


Fig.3:(a)contaminated ECG signal with Baseline Wander,(b)Denoised ECG signal with LMS algorithm,(c) Denoised ECG signal with NLMS algorithm,(d) Denoised ECG signal with RLS algorithm(e) Denoised ECG signal with ES-RLS algorithm.

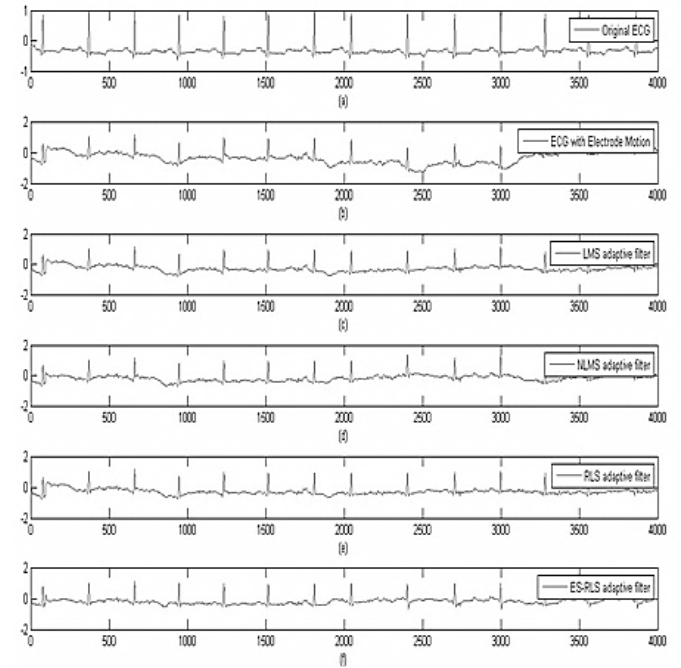


Fig.4 (a)contaminated ECG signal with Electrode Motion,(b)Denoised ECG signal with LMS algorithm,(c) Denoised ECG signal with NLMS algorithm,(d) Denoised ECG signal with RLS algorithm(e) Denoised ECG signal with ES-RLS algorithm.

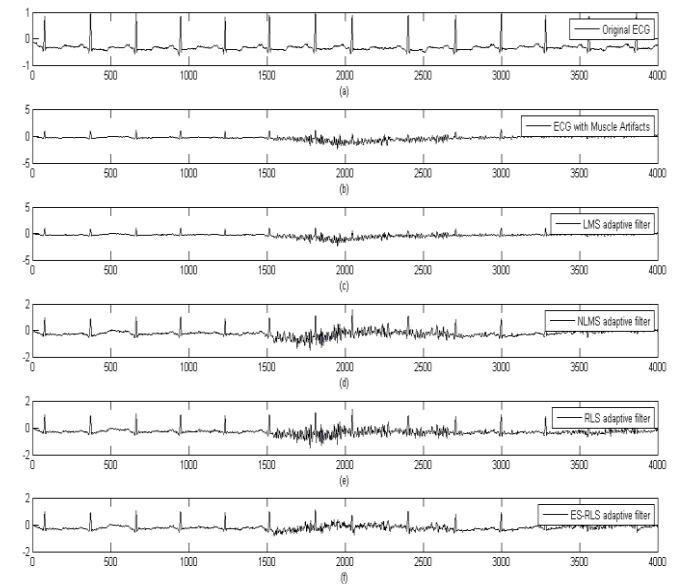


Fig.5:(a)contaminated ECG signal with Muscle Artifacts,(b)Denoised ECG signal with LMS algorithm,(c) Denoised ECG signal with NLMS

algorithm,(d) Denoised ECG signal with RLS algorithm,(e) Denoised ECG signal with ES-RLS algorithm.

signal. Output of the filter is the required to get better resolution ECG signal shown in Fig 4.

In order to observe the filtering performance in the presence of non-stationary noise, muscle artifact (MA) was taken from the MIT-BIH Noise Stress Test Database. These muscle artifacts obscure the ECG and complicate the interpretation of the ECG or even make the interpretation unfeasible. Here the ES-RLS algorithm shows the better results over all previous algorithms as shown in Fig 5.

## VI. Conclusion:

Hence from the above results our proposed adaptive algorithm ES-RLS gives the better results in noise removing from contaminated ECG over nonblind algorithms like LMS, NLMS and blind RLS adaptive algorithms due to the fast convergence rate. In Our simulations, however, it conforms that the SNR of the proposed algorithm gives better result over the other algorithms on denoised ECG signal as shown in Table 1.

Adaptive Algorithm	SNR for EM Artifact (in dB)	SNR for BW Artifact (in dB)	SNR for MA Artifact (in dB)
LMS	5.37	4.68	1.73
NLMS	5.96	5.96	4.31
RLS	6.04	6.15	5.52
ES-RLS	6.83	7.10	6.45

Table 1: SNR values of denoised ECG under different Artifacts for various Adaptive Algorithm.

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