

Research Article**RLS adaptive algorithm efficient performance used to enhance the quality of ECG signals in Telecardiology****Golbahar Zandkarimi^{1*} and Hossein Makari²**¹Dept. of Electrical Engineering, Islamic Azad University (IAU),
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ABSTRACT

When the signal electrocardiogram (ECG) taken from an individual, the signal should be processed before to write the analyst to decide about the signal, because the signal can be affected by various artificial cases. Noise cancellation corrupted signals in multiple applications; adaptive filters play an important role. Several stylized effects that usually occur in the signal obtained ECG are physiological and non-physiological noise (which is the main source of power line interference), muscle artifact, baseline noise and electrode motion artifact. Adaptive algorithm is a minimum mean square (LMS), provides a low convergence rate, so that for rapid convergence rate and noise reduction algorithms in this paper Recursive Least Square efficient, eliminate to power line noise and interference the intended muscle. For additional validation signal, and high signal-to-noise ratio (SNR), fast convergence rate was obtained using the RLS adaptive algorithm LMS in exchange for additional calculations.

Keywords: adaptive algorithms, algorithms RLS, SNR, artifacts, convergence rate.

1. INTRODUCTION

When the biological signal is achieved from the human body several artifact clearly strongly influenced the frequency and changes amplitude of the signal [1]. James and colleagues study the interference problem in the ECG signal in the article [2]. Among the biological signals, ECG signals plays an important role and provides functions of the heart: Some of them are former intelligence from a heart attack, effects on the heart, reducing the oxygen supply to the heart and spread of abnormal electrical impulses in the heart. ECG signal is a series of waves of electrical activity caused by the non-polar body and re-polarization of the cell electrolyte changes. When the signals measured in the clinical laboratory, affected by different parasites and due to this parasite, change the main features of the signal. Net ECG signal degradation include various types of noise that interfere with power line (Power) (PLI), measuring instruments noise, noise caused by the movement of the electrode (EM), respiratory

noise and noise caused by artificial muscle (MA). When the transmission of ECG signals from a remote site to a diagnostic center, through [3] system Telecardiology signal is done for signal analysis, additional channel noise and electromagnetic interference is added to pure signal. One of the applications in mobile wireless ECG system is Telecardiology [4-5]. Mobile wireless system is shown in the form of a block diagram in Figure 1. In this system, the ECG signal is a bioelectrical signal and an outpatient clinic used to know heart condition. Mobile wireless ECG monitoring is used for arrhythmia detection. During ECG signals using electrodes placed on the body, the ECG signal is multiple artifacts. Sometimes the GSM modem connected to its antenna used to transmit stored signals. Expert can be detected in the data received in real time and analyze the signal to make the right decisions and guidelines for action on the patient to the ambulance offer. When the transmission of signals for

analysis, channel noise should be taken into account and removed at the receiver side. Better diagnosis of the patient's ECG signal and the signal with high accuracy reduction through noise using various different techniques during its acquisition and transfer. We can use Adaptive and non-adaptive filters to reduce signal noise [6-10]. The most dominant technique for removing noise signal is adaptive filters. Adaptive algorithms that are used to adjust the filter coefficients are in such a way that decrease the error signal based on the method of least squares mean square. In the article [7], Yvzal Biswas et al used two adaptive filters such as LMS and LMS normally to remove noise. To illustrate better simulation results in terms of different performance parameters such as power spectral density (PSD), spectroscopy, frequency spectrum and convergence were compared. Pradeep Kumar et al in the article [8] effectively suppress noise ECG using wavelet threshold and empirical mode decomposition methods. In the article [11] Dhar and colleagues have provided, efficient method for removing high frequency noise

interference and the Power of Digital Signal electrocardiogram (ECG). Prime contaminated ECG signal passes through a low pass filter Butterworth to high-frequency noise that is selected so that they experimentally reduced. To remove power line interference, improved IIR notch filter is used. Thakur and colleagues [12] LMS adaptive filter to eliminate repetitive motion artifacts on ECG signal is applied. Recently, Gowri and colleagues [13-14] LMS algorithms with variable step size and the dead zone leaky LMS to reduce the noise in ECG signals are used. LMS and RLS algorithms normally used for extraction of fetal ECG in the article [15] is used, and they have proven to be more noise than the RLS method eliminates the LMS algorithm. R. Naumann et al. [16] RLS algorithm spatial mode to eliminate noise PLI was no noise reference. When the input signal is random, the algorithm least mean square (LMS) obtained good output, but when the input signal is deterministic, algorithms Recursive Least Square (RLS) brings better results than the LMS algorithm.

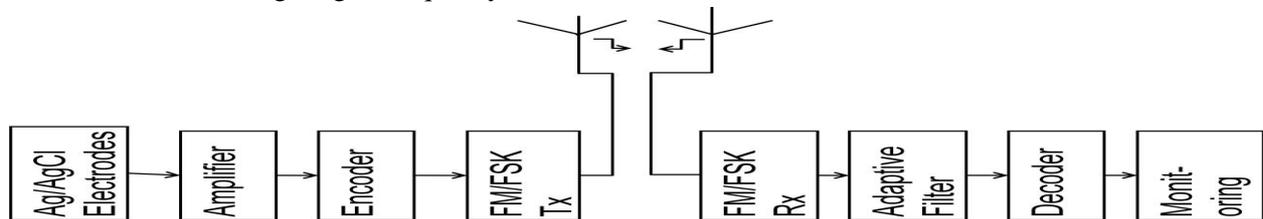


Figure 1. Mobile wireless system

In this article we have proposed efficiencies RLS algorithm back (after - RLS) and additional validation to obtain a better quality signal, the signal is first broken and then algorithm LMS algorithm RLS (LMS-RLS) passed. The analysis results show that the algorithm -RLS and LMS-RLS algorithm better result in comparison with RLS and LMS signal-to-noise ratio (SNR) and brings about rapid convergence rate. Rest of the paper is organized as follows. In the second, amounts to an update of an RLS adaptive filtering techniques are discussed. The simulation results are discussed in section 3. Finally, in Section 4 concludes the paper is done.

2. RLS efficient algorithms for improving signal quality

Over the last decade's adaptive filtering have vital role in removing jamming signals that ruined. General adaptive filter structure is shown in Figure 2.



2. Adaptive filter structure

In the figure, the signal $d(s)$ with artificial noise and noise channel are as the main entrance. Input $X(s)$ reference is given to other input and output filter:

$y(s) = X^T(s)W(s)$ Can be adapted to obtain the output error using adaptive weight based on the signal $e(s)$. Vector weight $W(s) = [w_0(s) w_1(s) \dots w_{L-1}(s)]^T$ For the length L , the initial iteration is assumed to be zero. If LMS be an adaptive algorithm, then the equation updates to its weight shifting $W(s+1) = W(s) + \mu e(s) X(s)$ In which $X(s) = [x(s) x(s-1) \dots x(s-L+1)]$ And the error signal output $e(s) = d(s) - y(s)$. Step size of (μ) that controls the error signal is between 0 and $\lambda_{max} / 1$, where λ_{max} is the maximum amount Eigen autocorrelation function input. According to the dependency factor in the algorithm LMS, slow convergence rate varies throughout the sampling period. So to improve the quick convergence rate and the highest remove noise from the signal above the expected, we used the RLS algorithm. In this algorithm, RLS, error signals were found using the least squares method [17], through increased convergence speed and the LMS algorithm using mean-squared error signal is found through the convergence occurs slowly. RLS algorithm least squares cost function for error is as follows:

$$(2) \quad J(s) = \sum_{j=0}^s e(j)^2$$

Here λ represents exponential factor, which is chosen between 0 and 1, for good removing value λ noise is chosen close to one. Full back weight vector obtained by using

(3) $W(s) = \lambda P(s) R_{dx}(s-1) + d(s) P(s) X^*(s)$, In which R_{DX} is certain amount of cross-correlation between the desired signal and input signal data. $P(s)$ is Reverse cross-correlation function. $P(s)$ with $P(s) = \delta^{-1} I$ is initialized, where δ is a small amount and I , matrix matched selected as during times. RLS prediction of an updated weight is a simple mathematical equation is as follows:

$$(4) \quad W(s) = W(s-1) + e1(s)g(s),$$

Where $e1(s)$ is error estimation, which determines as follows:

$$(5) \quad e1(s) = d(s) - W^T(s-1)X(s).$$

$$(6) \quad g(s) = \frac{R^{-1}(s-1)X(s)}{X^T(s)R^{-1}(s-1)X(s)}$$

And improved RLS posterior Simple Weight equation is determined by the following equation:

$$W(s) = W(s-1) + a e(s)g(s),$$

Where in that with a random selection of 'A' with a value between 1 and 2, shows with a better result in the removal of elected 1.6 noise compared with RLS. The error signal is called the posterior error signal and determined as follows:

$$(8) \quad e(s) = d(s) - W^T(s)X(s).$$

In comparison (5) to (8), in (8) equation error signal is calculated after the update equation weight shifting. So comparison RLS posterior with RLS priori, shows fast convergence rate and a high ratio of signal to noise.

To improve the signal-to-noise and better the further and faster convergence rate, in this article, double validation signal is analyzed. That the final residual LMS weight vector is taken as a vector of initial weight for RLS algorithm. ECG signal spoiled for the first time in the algorithm LMS (1), then the entire repetition of remaining weight vector signal is given, initial weight vector length (L) is equal to zero, and this weight vector is the vector of initial weight RLS algorithm (4). Because of this additional validation, signal noise in the output signal can reduce better than all the above algorithms. We call this algorithm as LMS-RLS algorithm pointed out. The convergence properties for different adaptive algorithms are shown in Figure 3.

RLS LMS algorithm to converge faster rate compared to the remainder algorithms, which has additional complexities. Also, we can see that the improved algorithm posterior RLS is slightly faster than convergence RLS algorithm.

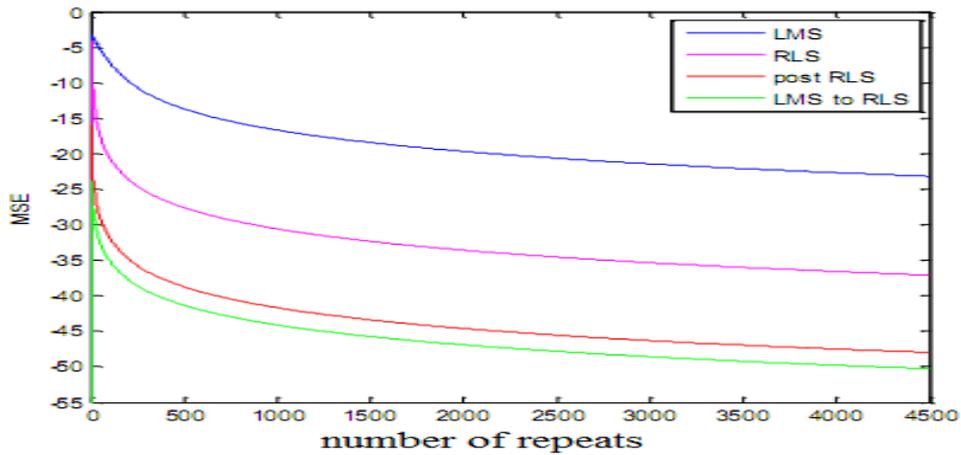


Figure 3. The convergence properties for different algorithms

3. Simulation results discussed

Previously derived by analyzing different algorithms, adaptive algorithms that are used for ECG signals, is the best algorithms to eliminate noise. Net ECG signal physionet MIT-BIG were collected from the database. In this database, 47 ECG signal is generally available. Some of these signals were collected from men and some women. These signals were sampled with a resolution of 360Hz and bit 11 mV 10 in the area. Of these 47 cases, 15 records at random from the database and added parasites were collected and then the input signal was sent for the adaptive filter as shown in Figure 2. The sample was collected in 4500. After using measuring devices for signal acquisition ECG, power line noise interference automatically signal ECG, along with added tools and the noise signal transmission, channel noise was also added. This noise is completely subverted the original ECG signal, so they should be removed using adaptive algorithms mentioned above. As shown in Figure 4 (a) ECG signal with PLI and random noise has been destroyed. PLI was sampled at a frequency of 200Hz. Added random noise here was 0.001, the amount of μ for LMS algorithm, RLS algorithm at a rate of 0.0001 to the 0.04 and δ was chosen. From Figure 4 (b-e) observed that the small remaining noise in the LMS algorithm, but using RLS algorithm this noise is almost reduced. The posterior forms of samples in the x-axis and the y axis is shown. Functional features were drawn for the record number of 104. To analyze the

performance of different algorithms, signal-to-noise ratio (SNR) for removing noise shown in Table 1 were PLI. In Table 1, we see that LMS-RLS algorithm reduces the noise compared to other algorithms show, with dB SNR 16.5693 next rank posterior RLS algorithm is related to the SNR of 16.3514 dB. Artificial Noise real muscle of noise stress MIT-BIH database was collected. Overall MA noises noise compared with other artificial effects of higher frequency. The noise was pure MA ECG signal and adaptive filter was applied. The MA artificial noise is added to the ECG signal in Figure 5 (A) is shown. In Figure 5 (b-e) can be seen that using the LMS algorithm MA noise is small, but with different noise algorithms RLS better MA reduced. As Table 2 shows the different algorithms adaptive noise suppression MA, from the table analysis, algorithm validation double LMS-RLS, SNR of 10.0606 dB offers, then RLS dB SNR 7.6339 is posterior. For better analysis, these algorithms were used to remove noise in speech signal recordings for Czech cross. Figure 6 (a) is a speech signal and the noise filled 6 (b) -6 (e) show signals after removing noises. From this graph, we can see that RLS algorithm shows improved SNR higher than the overall noise removal algorithm LMSRLS. As shown in Table 3, the functional parameters that were calculated such as mean squared error (MSE), MSE too (EMSE) and peak SNR ((PSNR for different matching algorithms. From Table 3, View the LMS-RLS algorithm leads to high PSNR

(54.4121dB) and low MSE ($8.1466e-06$) compared with the rest of the algorithms.

4. CONCLUSION

This article focused mainly to reduce the effects of artificial muscle power line noise interference on line using different RLS adaptive filters. Different matching algorithms that were used in this article include LMS, RLS, RLS rear and signal for additional validation, we LMS-RLS algorithm was derived. To analyze the performance of the signal, SNR, MSE, MSE and

peak SNR is calculated extra. Based on the above analysis, better noise reduction algorithm LMSRLS compared with the rest of the computational complexity of algorithms that are created. Somehow reduce the complexity of RLS algorithms to remove distortion-back also lead to better output. In this paper, the noise using LMS-RLS algorithms for computational complexity is greatly reduced, to strengthen it in the future, may perform reduced calculations using different matching algorithms to reduce signal noise better ECG.

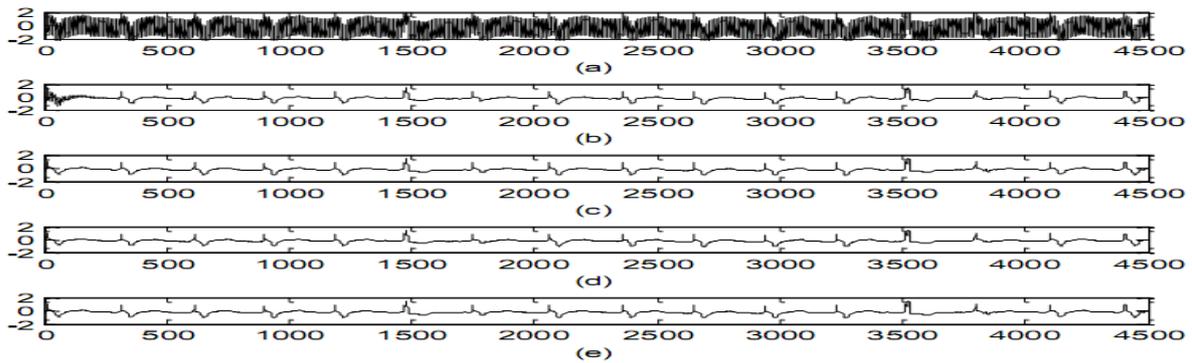


Figure 4: (a) ECG signal degraded by noise PLI, noise reduction using (b) algorithm LMS (c) algorithm RLS (d) RLS posterior and (e) LMS algorithm to RLS

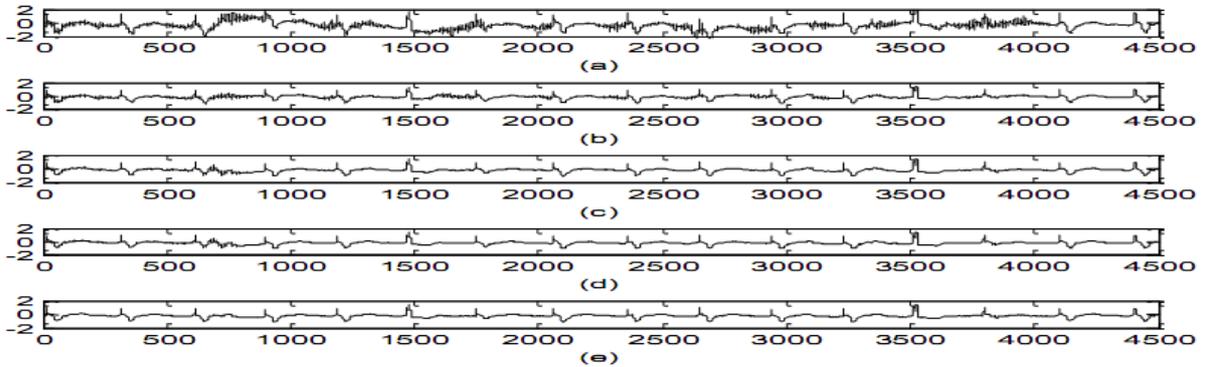


Figure 5: (a) ECG signal degraded by artificial muscles noise, noise reduction using (b) algorithm LMS (c) algorithm RLS (d) RLS posterior and (e) LMS algorithm to RLS

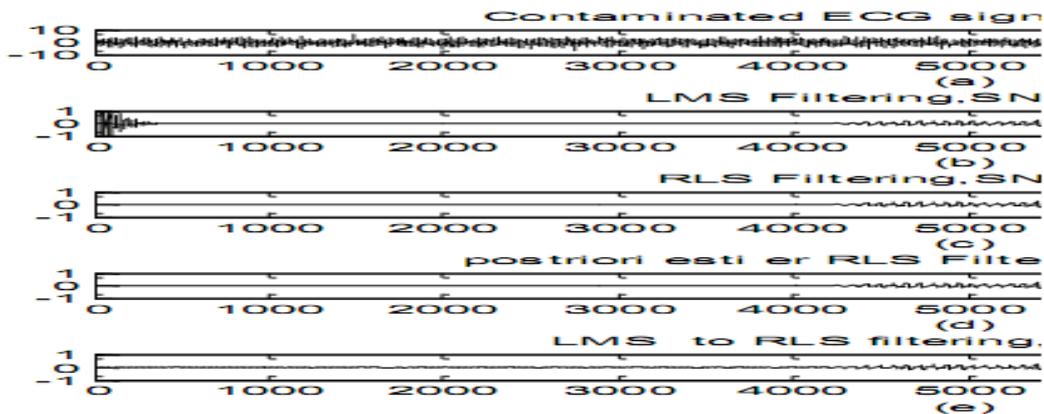


Figure 6: (a) speech signal degraded by random noise, noise reduction using (b) algorithm LMS (c) algorithm RLS (d) RLS posterior and (e) LMS algorithm to RLS

Table 1: measure the performance of different adaptive filters for noise removal in ECG signal PLI

Parasites	Rec · No.	SNR after Parasites	SNR after filtering			
			LMS	RLS	RLs posterior	LMS- RLS
PLI	100	- 2.9 263	8.79 09	14.0 215	17.44 84	17.62 33
	102	- 3.8 874	7.83 98	13.0 06	15.79 99	16.20 66
	104	- 3.1 062	8.62 85	14.1 022	18.74 34	19.77 74
	111	- 4.3	7.36	12.4	16.08	16.15

		7	64	53	03	41
114	- 5.2 854	6.47 83	11.6 619	15.81 38	15.93 31	
202	- 4.7 304	6.99 93	11.9 064	15.06 74	15.12 85	
207	- 2.9 976	8.68 81	13.6 314	15.95 16	16.12 45	
208	- 1.1 358	10.2 58	13.8 652	14.74 39	14.77 79	
209	- 4.1 455	7.54 44	12.2 165	14.58 24	14.61 67	
210	- 3.9 608	7.77 73	12.9 942	17.05 97	17.16 76	
214	- 1.6 192	10.0 47	15.2 547	18.70 26	18.89 04	
222	- 5.9 639	5.81 41	11.3 304	17.46 24	17.81 69	
228	- 3.6 45	8.04 39	12.9 201	15.27 25	15.39 44	
233	- 0.5 181	10.9 75	15.3 004	16.53 62	16.88 86	
234	- 3.0 692	8.61 16	13.4 66	16.00 68	16.03 99	
Average		8.25 75	13.2 086	16.35 14	16.56 93	

Table 2: Measure the performance of adaptive filters to remove noise AM ECG signal

Parasites	Rec. No.	SNR after filtering			
		LMS	RLS	Post-RLS	LMS-RLS
MA	100	3.8171	5.4971	5.6844	11.5618
	102	4.341	6.4641	6.9149	13.0312
	104	4.5039	7.41	7.5176	14.156
	111	4.9041	7.6491	7.7184	12.1946
	114	3.8085	5.2855	5.566	7.9896
	202	5.0316	7.9039	8.1363	4.9579
	207	3.3087	6.5924	6.7399	6.3964
	208	5.1171	8.234	8.4956	13.9413
	209	4.9295	8.0095	8.1228	13.5261
	210	5.4417	7.7423	7.8068	12.0156
	214	5.2143	9.9076	10.1657	11.3899
	222	4.6927	6.2755	6.4342	6.8678
	228	4.1109	5.4246	5.5977	8.3105
	233	4.6907	9.1423	9.4519	9.1617
	234	5.0585	10.035	10.1566	5.4099
	Average	4.5980	7.4382	7.6339	10.0606

Table 3: MSE, MSE added and the peak SNR adaptive filters for noise removal in ECG signal PLI

Algorithm	Record Number	MSE	EMSEss (dB)	PSNR (dB)
LMS	102	0.0022	-44.4963	26.1254
	104	0.0022	-42.8362	30.0090
RLS	102	1.7613e-04	-66.1370	37.1418
	104	1.7579e-04	-65.4815	41.0720
Rls posterior	102	1.9485e-05	-61.0597	46.7031
	104	1.4339e-05	-60.8412	51.9567
LMS TO RLS	102	1.4665e-05	-61.1651	47.9371
	104	8.1466e-06	-63.1446	54.4121

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