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Noise Removal of ECG Signals using RLS Adaptive Algorithm

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Abstract*— Noise reduction in ECG signal is an important task for the biomedical field. Different Adaptive filtering algorithms are evolving rapidly in biomedical science to remove the noise by an appreciable amount. The main objective of this paper is to develop Some of the feasible solutions to develop an adaptive algorithm to remove the contaminating signal and to obtain original ECG .We propose RLS Method (Recursive Least Square) to remove noise from ECG Signal Based on three modulation technique BPSK(Binary Phase Shift Keying),QPSK(Quadrature Phase Shift Keying),8-QAM(Quadrature Amplitude Modulation) ,Since RLS system simulation shows best result on noise reduction with BPSK modulation technique in terms of the signal to noise ratio(SNR) and bit error rate(BER) on MATLAB .

Index Terms*— Digital signal, Noise Removal, RLS (Recursive Least Square),SNR(signal to noise ratio),BER(bit error rate) BPSK(Binary Phase Shift Keying),QPSK(Quadrature Phase Shift Keying),8-QAM(Quadrature Amplitude Modulation).

I. INTRODUCTION

The ECG signal, measured with an electrocardiograph, is a biomedical electrical signal occurring on the surface of the body due to the contraction and relaxation of the heart.

ECG Waves and Intervals

A typical ECG tracing of the cardiac cycle (heartbeat) consists of a P wave, a QRS complex, a T wave, and a U wave, which is normally invisible in 50 to 75% of ECGs because it is hidden by the T wave and upcoming new P wave. The baseline of the electrocardiogram (the flat horizontal segments) is measured as the portion of the tracing following the T wave and preceding the next P wave and the segment between the P wave and the following QRS complex (PR segment). In a normal healthy heart, the baseline is equivalent to the isoelectric line (0mV) and represents the periods in the cardiac cycle when there are no currents flowing towards either the positive or negative ends of the ECG leads. However, in a diseased heart the baseline may be elevated (e.g. cardiac ischemia) or epressed (e.g. myocardial infarction) relative to the isoelectric line due to injury currents flowing during the TP and PR intervals when the ventricles are at rest. The ST segment typically remains close to the isoelectric line as this is the period when the ventricles are fully depolarised and thus no currents can flow in the ECG leads. Since most ECG recordings do not indicate where the 0mV line is, baseline depression often gives the appearance of an elevation of the ST segment and conversely baseline elevation gives the appearance of depression of the ST segment.

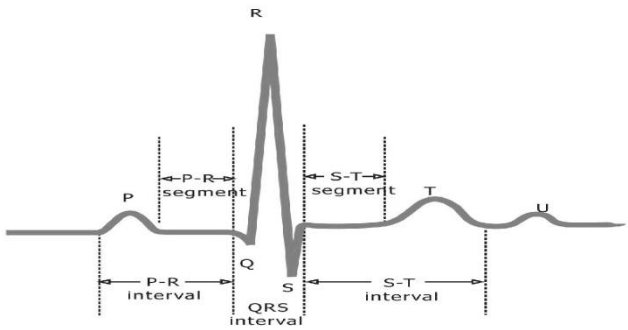

Fig 1: Normal ECG Signal

This signal represents an extremely important measure for doctors, as it provides vital information about a patient's cardiac condition and general health. Generally, the frequency band of the ECG signal is 0.05 to 100Hz. inside the heart there is a specialized electrical conducting system that ensures the heart to expand and contract**.** ECG is commonly recorded with a noise caused by power line interference, electrode noise, Muscle Artifacts (MA), high frequency noise, random body movements and respiration. Different types of digital filters are used to remove signal components from unwanted frequency ranges. It is difficult to apply filters with fixed coefficients to reduce Biomedical Signal noises, because human behavior is not exact known depending on the time.

The Noises in ECG Signal

The common noise sources are:

- Baseline wander and ECG amplitude modulation with respiration
- Power line interference
- Muscle contraction noise
- Electrosurgical noise
- Motion artifacts
- Noise due to variation of electrode skin contact impedance
- Noise generated by electronic devices used in signal processing circuits

Adaptive filter technique is required to overcome this problem. Adaptive filters are considered to reduce the ECG signal noises like PLI and, high frequency noise, electrode noise, body noise (muscle artefact), Base Line Interference. Adaptive filters are designed using different algorithms like least mean square (LMS), recursive least mean square (RLS), normalized least mean squares (NLMS), etc. Least-squares algorithms aim at the minimization of the sum of the squares of the difference between the desired signal and the model filter output when new samples of the incoming signals are received at every iteration, the solution for the least-squares problem can be computed in recursive form resulting in the recursive least-squares (RLS) algorithms.

The goal for ECG signal enhancement is to separate the valid signal components from the undesired artifacts, so as to present an ECG that facilitates easy and accurate interpretation. The basic idea for the adaptive filter is to predict the amount of noise in the primary signal and then subtract that noise from it. The prediction is based on filtering the reference signal, which contains a solid reference of the noise present in the primary signal.

The noise in the reference signal is filtered to compensate for the amplitude, phase and time delay and then subtracted from the primary signal. This filtered noise is the system's prediction of the noise portion of the primary signal. The resulting signal is called error signal and it presents the output of the system. Ideally, the resulting error signal would be only the desired portion of the primary signal. In this paper we present a RLS algorithm to remove

The artefacts from ECG using channel estimation with different modulation technique namely BPS, QPSK and 8-QAM. This algorithm enjoys less computational complexity and good filtering capability. To study the performance of the proposed algorithm effectively remove the noise from the ECG signal, we carried out simulations on MIT-BIH database for different artifacts.

OFDM (Orthogonal Frequency Division Multiplexing) system has been recognized as one of the most popular and competitive technique in a wireless environment nowadays. The performance is calculated in terms of Bit Error Rate (BER) versus the Signal to Noise Ratio (SNR).

The Recursive least squares (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squarescost function relating to the input signals. This is in contrast to other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity. Suppose that a signal d (n) is transmitted over an echoes, noisy channel that causes it to be received as

$$x(n) = \sum_{k=0}^{q} b_n(k) d(n-k) + v(n)$$

…………….. (1)

Where $v(n)$ represents additive noise. We will attempt to recover the desired signal $d(n)$ by use of a $p+1$:

$$\hat{d}(n) = \sum_{k=0}^{p} w_n(k) x(n-k) = \mathbf{w}_n^T \mathbf{x}_n$$

………………(2)

where

$$\mathbf{x}_n = [x(n) \quad x(n-1) \quad \ldots \quad x(n-p)]^T$$

is the vector containing the p most recent samples of $x(n)$. We estimate the parameters of the filter $\mathbf{W}$, and at each time n we refer to the new least squares estimate by $\mathbf{W_n}$. As time evolves, we would like to avoid completely redoing the least squares algorithm to find the new estimate for $\mathbf{W}_{n+1}$, in terms of $\mathbf{W}_n$.

The benefit of the RLS algorithm is that there is no need to invert matrices, thereby saving computational power. Another advantage is that it provides intuition behind such results as the Kalman filter.

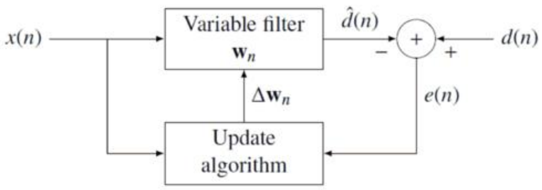

Fig 2. RLS adaptive filtering

The error implicitly depends on the filter coefficients through the estimate $\hat{d}(n)$:

$e(n) = d(n) - \hat{d}(n)$

The weighted least squares error function C—the cost function we desire to minimize—being a function of e(n) is therefore also dependent on the filter coefficients:

$$C(\mathbf{w_n}) = \sum_{i=0}^{n} \lambda^{n-i} e^2(i)$$
………………..(3)

Where $0 < \lambda \leq 1$ is the "forgetting factor" which gives exponentially less weight to older error samples?

The RLS algorithm for a *p*-th order RLS filter can be summarized as

Parameters: $p =$ filter order

$\lambda =$ forgetting factor

$\delta =$ value to initialize

Initialization: $\mathbf{w}(n) = 0$,

$x(k) = 0, k = -p, \ldots, -1$,

$\mathbf{P}(0) = \delta^{-1} I$ where I is the identity matrix of rank $p + 1$

Computation: For $n = 1, 2, \ldots$

$$\mathbf{x}(n) = \begin{bmatrix} x(n) \\ x(n-1) \\ \vdots \\ x(n-p) \end{bmatrix}$$
……………..(4)

$$\alpha(n) = d(n) - \mathbf{x}^T(n)\mathbf{w}(n-1)$$
$$\mathbf{g}(n) = \mathbf{P}(n-1)\mathbf{x}^*(n)\left\{\lambda + \mathbf{x}^T(n)\mathbf{P}(n-1)\mathbf{x}^*(n)\right\}^{-1}$$
$$\mathbf{P}(n) = \lambda^{-1}\mathbf{P}(n-1) - \mathbf{g}(n)\mathbf{x}^T(n)\lambda^{-1}\mathbf{P}(n-1)$$
$$\mathbf{w}(n) = \mathbf{w}(n-1) + \alpha(n)\mathbf{g}(n)$$

II. IMPLEMENTATION

This system is divided into two phases first is the training phase and the second is the testing phase. The training phase is as follows. Firstly the channel estimator (CE) is created using LMS technique or the RMS technique. The CE is inputted with the original signal and the noisy signal then the coefficient is calculated that is the weight by which the denoised signal will be produced. The following figure shows the training phase.

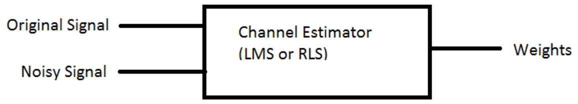

Figure 3. Training Phase of the CE

The testing phase is as follows. The analog signal is taken as the input. The signal is then converted to the binary form. The binary signal is then inputted to the OFDM block where the high bit rate signal is normalized and a low bit rate signal is generated. The low rate signal is then passed over a channel (Tx is the signal which is given as the input to the channel). The channel can use AWGN (Additive white Gaussian noise), Rayleigh, Rician or AWCN + Raylein. The output is termed as Tx|. All these processes were at the senders end.

The signal received Tx|is then again send to the OFDM block and again the high bit rate signal is generated from the low bits which were send to minimize the noise effect like power line interference, electrode noise,muscluer noise,high frequency noise. on the signal. The signals are then send to the Channel Estimator (CE). Here the channel estimator estimates the error by plotting BER to SNR ratio. Where SNR stands for signal to noise ratio and BER is ((T-R)/T)*100. Now the plots are multiplied with the weights and a plot is created. If there is distance between the resulting steps the plots are changed and thus we get the resulting output. This output is again sent to the decimal to analog converter and the resulting output is found. The following figure shows the block diagram of the testing phase.

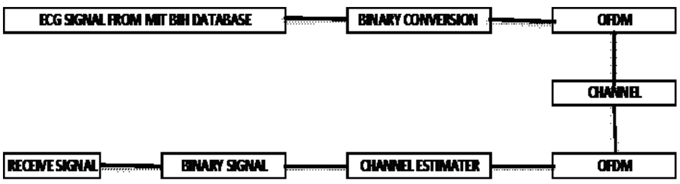

Figure 4. The Testing Phase of Channel Estimator

In this methodology we use three different modulation technique namely binary phase shift keying, quadrature phase shift keying and 8- quadrature amplitude modulation

Result shows that binary phase shift keying method is most efficient in parameter of SNR Vs BER execution of performance process the ECG signal is acquired from MIT BIH Arrhythmia data base.Ressult shown in table is taken as average result of bit error rate of signal in which SNR ranges from 10 to 15.then finally showing result in parameter of bit error rate with SNR for the noises present in ECG signal like power line interference, electrode noise, Muscle Artefacts (body noise),,high frequency noise.

III. RESULTS

In this paper different noise removal from the ECG signals have been performed... Table 1 shows the result of different noise removal from ECG signal using BPSK, QPSK and 8-QAM. We have simulated the noises in terms of signal to noise ratio(SNR) versus bit error rate(BER).Fig 5 and 6 shows the performance of the BPSK,QPSK and 8-QAM modulation scheme. Figure 7 shows GUI of the RLS system .In figure 5 and 6 the graph is plotted among different modulation scheme, BPSK shows lower BER means it is the most efficient method comparing other method.

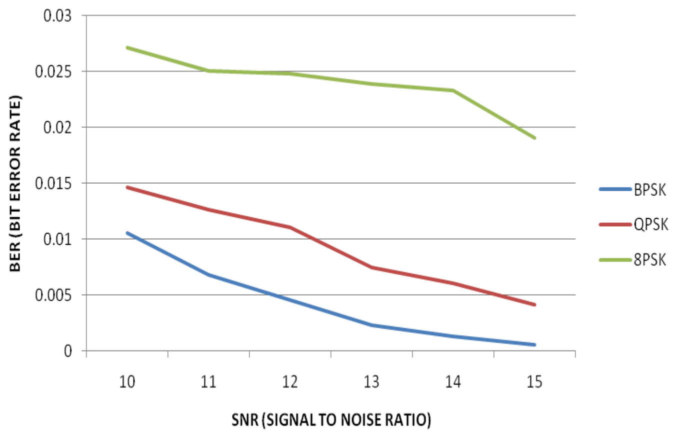

Fig .5:- SNR VS BER for PLI in RLS Algorithm

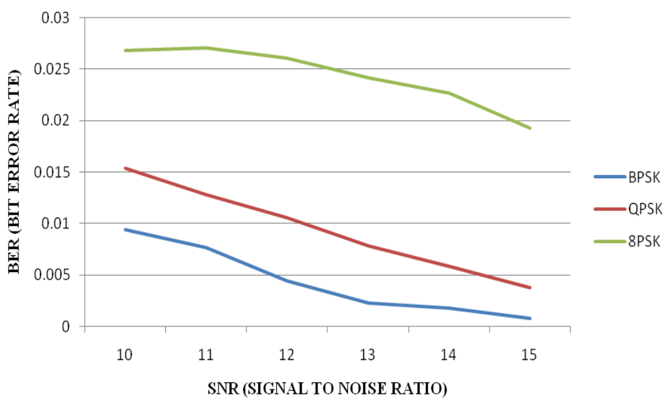

Fig 6:-SNR VS BER for High Frequency Noise in RLS Algorithm

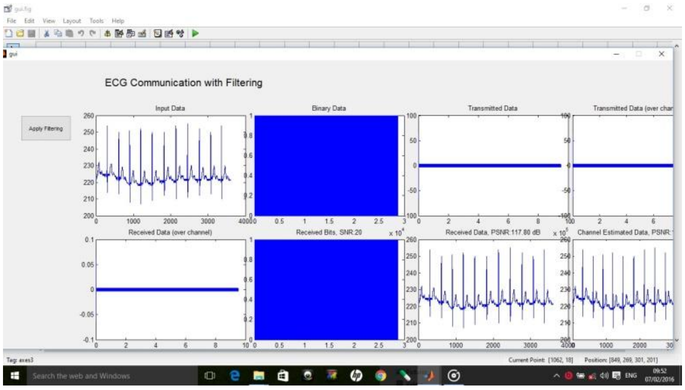

Fig 7:-GUI interface of RLS system

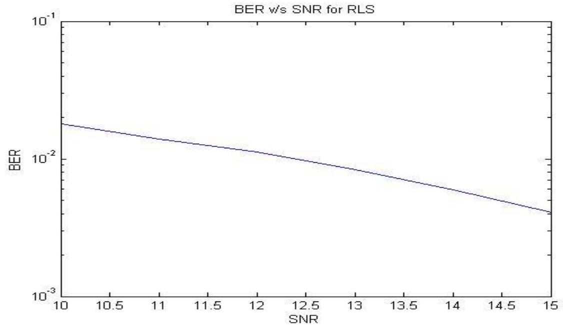

Fig 8:- Plot for SNR vs. BER of RLS algorithm for BPSK

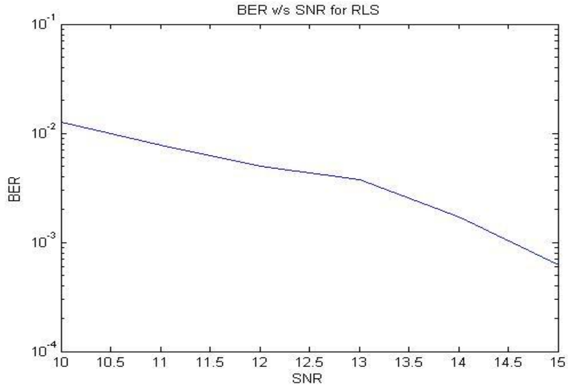

Fig 9:- Plot for SNR vs. BER of RLS algorithm for QPSK

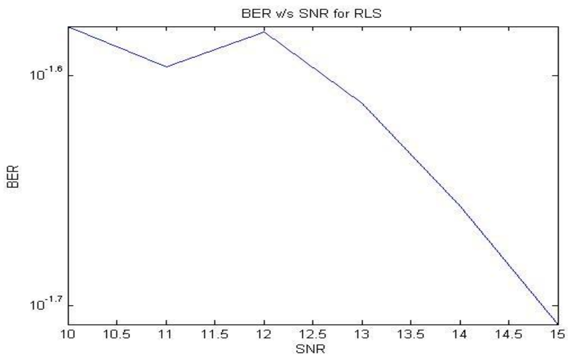

Fig 10:- Plot for SNR vs. BER of RLS algorithm for 8-QAM

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Table: - SNR VS BER Calculation for RLS Algorithm

MIT-BIH SAMPLE 230								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
BPSK	10-15	0.00436644	10-15	0.000000647	10-15	0.000000647	10-15	0.004376466
QPSK	10-15	0.009376297	10-15	0.000000647	10-15	0.000000647	10-15	0.009364951
8-QAM	10-15	0.023864566	10-15	0.000000647	10-15	0.000000647	10-15	0.024308011
MIT-BIH SAMPLE 228								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
BPSK	10-15	0.005855887	10-15	0.00000064	10-15	0.00000064	10-15	0.006387841
QPSK	10-15	0.009603609	10-15	0.00000064	10-15	0.00000064	10-15	0.009533291
8-QAM	10-15	0.009422553	10-15	0.00000064	10-15	0.00000064	10-15	0.024004074
MIT-BIH SAMPLE 124								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
BPSK	10-15	0.00448062	10-15	0.00000064	10-15	0.00000064	10-15	0.004019616
QPSK	10-15	0.009673099	10-15	0.00000064	10-15	0.00000064	10-15	0.009966645
8-QAM	10-15	0.023887116	10-15	0.00000064	10-15	0.00000064	10-15	0.024126646
MIT-BIH SAMPLE 122								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
BPSK	10-15	0.004165385	10-15	0.000000638	10-15	0.000000638	10-15	0.004213678
QPSK	10-15	0.009943056	10-15	0.000000638	10-15	0.000000638	10-15	0.009867134
8-QAM	10-15	0.023599809	10-15	0.000000638	10-15	0.000000638	10-15	0.02292241
MIT-BIH SAMPLE100								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
	10-15	0.00533703	10-15	0.000000651	10-15	0.000000651	10-15	0.005397642
	10-15	0.010117819	10-15	0.000000651	10-15	0.000000651	10-15	0.010179086
	10-15	0.023659091	10-15	0.000000651	10-15	0.000000651	10-15	0.010179086
MIT-BIH SAMPLE 101								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
BPSK	10-15	0.004226465	10-15	0.00000063	10-15	0.00000063	10-15	0.004391263
QPSK	10-15	0.009909173	10-15	0.00000063	10-15	0.00000063	10-15	0.010274364
8-QAM	10-15	0.024386636	10-15	0.00000063	10-15	0.00000063	10-15	0.024071457
MIT-BIH SAMPLE 210								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
BPSK	10-15	0.005865318	10-15	0.000000621	10-15	0.000000621	10-15	0.005852011
QPSK	10-15	0.009914543	10-15	0.000000621	10-15	0.000000621	10-15	0.010283705
8-QAM	10-15	0.023978091	10-15	0.000000621	10-15	0.000000621	10-15	0.024179085
MIT-BIH SAMPLE 213								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
BPSK	10-15	0.00419267	10-15	0.000000645	10-15	0.000000645	10-15	0.004102089
QPSK	10-15	0.009947278	10-15	0.000000645	10-15	0.000000645	10-15	0.00989913
8-QAM	10-15	0.023860021	10-15	0.000000645	10-15	0.000000645	10-15	0.023321786
MIT-BIH SAMPLE 215								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
BPSK	10-15	0.006195973	10-15	0.000000626	10-15	0.000000626	10-15	0.005924053
QPSK	10-15	0.009480754	10-15	0.000000626	10-15	0.000000626	10-15	0.009542907
8-QAM	10-15	0.024109582	10-15	0.000000626	10-15	0.000000626	10-15	0.024230988
MIT-BIH SAMPLE 219								
	PLI		HEART BEAT		ELECTROD NOISE		HIGH REQUENCY	
	SNR	BER	SNR	BER	SNR	BER	SNR	BER
BPSK	10-15	0.004383921	10-15	0.00000062	10-15	0.00000062	10-15	0.004526977
QPSK	10-15	0.009719469	10-15	0.00000062	10-15	0.00000062	10-15	0.009806563
8-QAM	10-15	0.023439525	10-15	0.00000062	10-15	0.00000062	10-15	0.024319594

IV. CONCLUSION

According to the simulation parameters, we can conclude that RLS Method(Recursive Least Square) to remove noise from ECG Signal Based on three modulation technique BPSK(Binary Phase Shift Keying),QPSK(Quadrature Phase Shift Keying),8-QAM(Quadrature Amplitude Modulation) shows best result on noise reduction with BPSK modulation technique in terms of the signal to noise ratio(SNR) versus bit error rate(BER) because bit error rate is low for BPSK ,noises present in ECG signal like power line interference, electrode noise, Muscle Artifacts (MA),,high frequency noise.

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