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MOTION ARTIFACT CANCELLATION IN AMBULATORY ECG MEASUREMENT SYSTEM FOR THE DETECTION OF CARDIAC DISEASES

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Abstract- In this work, a simple and efficient artifact cancellation in ambulatory ECG using adaptive filter is designed for the detection of different cardiac diseases like bradycardia, tachycardia, left ventricular hypertrophy and right ventricular hypertrophy. Our work is focused on extraction of noise free ECG signal and the real-time implementation of artifacts removal techniques. As ECG signal is very sensitive in nature, and even if small noise mixed with original signal the various characteristics of the signal changes, data corrupted with noise must either filtered or discarded, filtering is important issue for design consideration of real-time ECG measurement systems. Here we have implemented different adaptive filtering algorithms (LMS-Least Mean Square, RLS-Recursive Least Squares) using virtual instrumentation technique to minimize the noisy components and to analyze different cardiac diseases like bradycardia, tachycardia, left ventricular hypertrophy and right ventricular hypertrophy. Finally the overall performance of LMS and RLS algorithm is also compared according to the error signal generated by the techniques.

Keywords-Ambulatory ECG; Adaptive filter; Virtual Instrumentation; Artifacts; Cardiac Disease; Arrhythmia; Bradycardia; Tachycardia; Left and Right Hypertrophy.

INTRODUCTION

Electrocardiograph (ECG) is a transthoracic interpretation of the electrical activity of the heart over time captured and externally recorded by skin electrodes. It is a noninvasive recording produced by an electrocardiography device. ECG is very significant to diagnose the heart disease such as myocardial ischemia, arrhythmia and cardiac infarction. Recently, ECG is used on purpose to keep good health as well as to diagnose the heart disease [1]. The oxygen demand in the cardiac muscle is different according to the body condition.

The ECG works mostly by detecting and amplifying the tiny electrical changes on the skin that are caused when the heart muscle "depolarizes" during each heart beat [9]. At rest, each heart muscle cell has a charge across its outer wall, or cell membrane. Reducing this charge towards zero is called de-polarization, which activates the mechanisms in the cell that cause it to contract [2]. During each heartbeat a healthy heart will have an orderly progression of a wave of depolarization that is triggered by the cells in the sinoatrial node, spreads out through the atrium, passes through "intrinsic conduction pathways" and then spreads all over the ventricles. This is detected as tiny rises and falls in the voltage between two electrodes placed either side of the heart which is displayed as a wavy line either on a screen or on paper. This display indicates the overall rhythm of the heart and weaknesses in different parts of the heart muscle [6]. The purpose of the study discussed herein was to develop a continuous healthcare system offering greater convenience in vital signal monitoring in our daily life. To achieve this purpose, we have developed a system that monitors ECG, a data rich signal with comprehensive use in monitoring a person's health. Further, this system was applied with adaptive signal processing to enable continued signal measuring while the subject carries on their normal daily routine, freeing the subject from the static constraints of conventional vital signal measuring processes undergone in medical institutions [3].

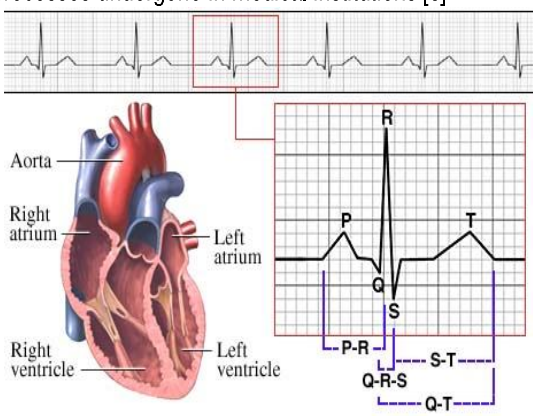

Fig. 1- Normal QRS complex and intervals in two ECG pulses

ECG signal is a type of electrical signal generated as myocardial tissues making up the heart constrict and relax under the regulation of the heart's impulse conduction system. Specifically, the waveform derived from measuring these types of electrical and biological electric generation using external leads is ECG [5]. Generally, ECG consists of a P wave, a QRS complex, and a T wave. P wave is formed as the atria constrict QRS complex forms as the ventricles constrict, and T wave is formed as the ventricles relax. The wave that forms as the astria relax virtually overlaps entirely with the wave generated with the constriction of the ventricles and is therefore ignored. "Figure 1" shows an example of ECG waveform and the various parameters that can be derived from ECG waveform for use in diagnosis and health monitoring. Normal ECG signals carry a virtually consistent cycle and generate a regular rhythm.

The heart signals from the electrodes are very low level signals. To collect correct samples of the raw electrode signals a highly sensitive, high CMRR and high slew rate amplifier is required. In this work, we have designed a high sensitive differential amplifier and a high gain amplifier as shown in figure 1. The output of the amplifier stage is directly connected to a National Instruments DAQ card for the acquisition and adaptive signal processing of the raw data.

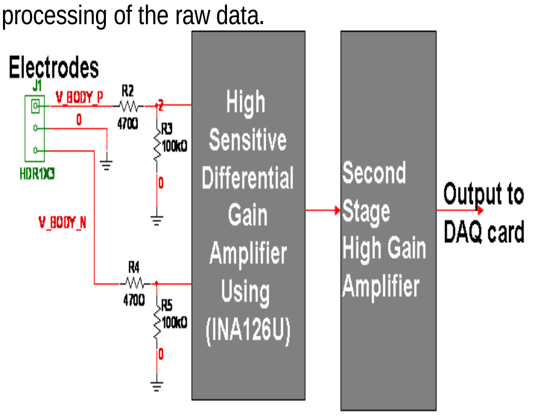

Fig. 2- Basic circuit connections required for data acquisition.

ECG bandwidth between 0.05Hz and 100Hz is used for general diagnosis applications, and ECG bandwidth between 0.05Hz and 35Hz is used for patient monitoring or healthcare purposes. These ECG bandwidths, however, can overlap with other elements such as the 60Hz power supply noise, baseline wandering due to respiration, high frequency noises originating from various electronic devices and equipments, motion artifact from changes in skin-to-lead impedance brought on subject movement, and EMG signal of muscle tissue movements [4]. Filter set comprising of a high pass filter, a low pass filter, and a notch filter is the most commonly used method of canceling noise elements embedded in the ECG signal.

An adaptive filter is required when either the fixed specifications are unknown or the specifications cannot be satisfied by time-invariant filters [1]. Strictly speaking an adaptive filter is a nonlinear filter since its characteristics are dependent on the input signal and consequently the homogeneity and additivity conditions are not satisfied. In an ECG signal the motion artifacts are usually not fixed specifications. That's why adaptive filters are usually implemented for the reduction of motion artifacts and other undesired noisy components in the usual ECG signal.

ADAPTIVE FILTER

Discrete-time (or digital) filters are ubiquitous in today's signal processing applications. Filters are used to achieve desired spectral characteristics of a signal, to reject unwanted signals, like noise or interferers, to reduce the bit rate in signal transmission, etc. The notion of making filters adaptive, i.e., to alter parameters (coefficients) of a filter according to some algorithm, tackles the problems that we might not in advance know, e.g., the characteristics of the signal, or of the unwanted signal, or of a systems influence on the signal that we like to compensate. Adaptive filters can adjust to unknown environment and even track signal or system characteristics varying over time [3]. In a transversal filter of length N, as depicted in figure 3, at each time n the output sample y[n] is computed by a weighted sum of the current and delayed input samples x[n], x[n − 1], ...

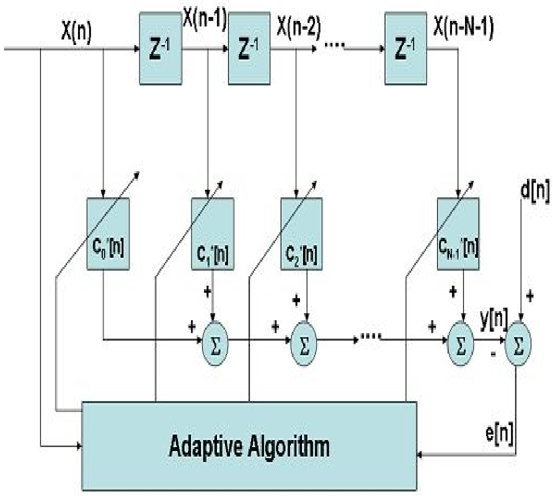

Fig. 3- General Block Diagram of Adaptive Filter

Here the output signal y[n] is expressed as the weighted sum of input signal.

$$y[n] = \sum_{k=0}^{N-1} c_k^*[n]\,x[n-k] \qquad (1)$$

Here, the $C_K[n]$ are time dependent filter coefficients (we use the complex conjugated coefficients $C^*_K[n]$, so that the derivation of the adaption algorithm is valid for complex signals, too) [7]. This equation re-written in vector form, using $X[n] = [x[n], x[n-1] \ldots x[n-N+1]^T$ The tap-input vector at time n, $C[n] = [C_0[n], C_1[n] \ldots C_{N-1}[n]]^T$ the coefficient vector at time n, is

$$\mathbf{y[n] = c^H[n] \times X[n]} \qquad (2)$$

Both x[n] and c[n] are column vectors of length N, $C^H[n] = (C^*)^T[n]$ is the hermitian of vector c[n] (each element is conjugated *, and the column vector is transposed T into a row vector). In the special case of the coefficients C[n] not depending on time n: C[n] = C the transversal filter structure is an FIR filter of length N [8]. Here, we will, however, focus on the case that the filter coefficients are variable, and are adapted by an adaptation algorithm.

2.1. *The LMS Adaptation Algorithm*

The LMS (least mean squares) algorithm is an approximation of the steepest descent algorithm which uses an instantaneous estimate of the gradient vector of a cost function [9]. The estimate of the gradient is based on sample values of the tap-input vector and an error signal. The algorithm iterates over each coefficient in the filter, moving it in the direction of the approximated gradient [15]. 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 [9].

$$\mathbf{e[n] = d[n] - c^H[n] \times X[n]} \qquad (3)$$

A schematic of the learning setup is depicted in figure 4.

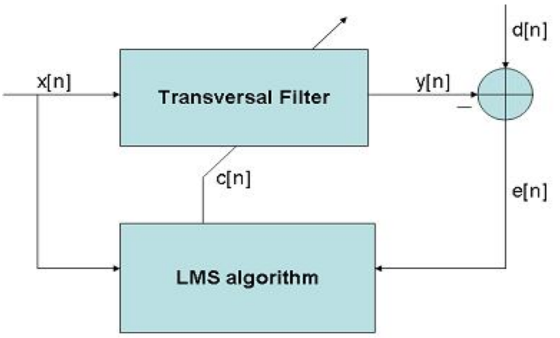

Fig. 4- LMS Algorithm Based Adaptive Filter Block Diagram

The task 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 (thus the name) [16]. The squared error and its expected value are (for simplicity of notation and perception we drop the dependence of all variables on time n [8].

$$e^2 = \left(d - \mathrm{c}^\mathsf{H}\mathrm{x}\right)^2 = d^2 - 2d\,\mathrm{c}^\mathsf{H}\mathrm{x} + \mathrm{c}^\mathsf{H}\mathrm{x}\,\mathrm{x}^\mathsf{H}\mathrm{c} \qquad (4)$$

$$\begin{aligned} \mathrm{E}(e^2) &= \mathrm{E}(d^2) - \mathrm{E}(2d\,\mathrm{c}^\mathsf{H}\mathrm{x}) + \mathrm{E}(\mathrm{c}^\mathsf{H}\mathrm{x}\,\mathrm{x}^\mathsf{H}\mathrm{c}) \\ &= \mathrm{E}(d^2) - \mathrm{c}^\mathsf{H}\,2\,\mathrm{E}(d\mathrm{x}) + \mathrm{c}^\mathsf{H}\ \mathrm{E}(\mathrm{x}\,\mathrm{x}^\mathsf{H})\,\mathrm{c} \end{aligned} \qquad (5)$$

Note, that the squared error e^2 is a quadratic function of the coefficient vector C, and thus has only one (global) minimum (and no other (local) minima), that theoretically could be found if the correct expected values in eq (5) were known. The gradient descent approach demands that the position on the error surface according to the current coefficients should be moved into the direction of the 'steepest descent', i.e., in the direction of the negative gradient of the cost function J = E (e^2) with respect to the coefficient vector [7].

$$-\nabla_\mathbf{c} J = 2\,\mathrm{E}(d\,\mathrm{x}) - 2\,\mathrm{E}(\mathrm{x}\,\mathrm{x}^\mathsf{H})\mathrm{c}. \qquad (6)$$

The expected values in this equation, E (d x) = p, the cross-correlation vector between the desired output signal and the tap-input vector, and E (xx^H) = R, the auto-correlation matrix of the tap-input vector, would usually be estimated using a large number of samples from d and x. In the LMS algorithm, however, a very short-term estimate is used by only taking into account the current samples: E (dx) ≈ dx, and E (xx^H) ≈ xx^H, leading to an update equation for the filter coefficients

$$\begin{aligned} \mathbf{c}^{\text{new}} &= \mathbf{c}^{\text{old}} + \mu/2\ \left(-\nabla_\mathbf{c} J(\mathbf{c})\right) \\ &= \mathbf{c}^{\text{old}} + \mu\ \mathbf{x}\ (d - \mathbf{x}^\mathsf{H}\mathbf{c}) \\ &= \mathbf{c}^{\text{old}} + \mu\ \mathbf{x}\ e^*. \end{aligned}$$

Here, we introduced the 'step-size' parameter μ, which controls the distance we move along the error surface [9]. In the LMS algorithm the update of the coefficients, is performed at every time instant n,

$$\mathbf{c}[n+1] = \mathbf{c}[n] + \mu\, e^*[n]\, \mathbf{x}[n]. \qquad (8)$$

2.1.1. *Choice of step-size*

The 'step-size' parameter μ introduced in eq.7 controls how far we move along the error function surface at each update step. "μ" certainly has to be chosen μ > 0 (otherwise we would move the coefficient vector in a direction towards larger squared error). Also, μ should not be too large, since in the LMS algorithm we use a local approximation of p and R in the computation of the gradient of the cost function, and thus the cost function at each time instant may differ from an accurate global cost function [12].

Furthermore, too large a step-size causes the LMS algorithm to be instable, i.e., the coefficients do not converge to fixed values but oscillate [13]. Closer analysis [1] reveals, that the upper bound for μ for stable behavior of the LMS algorithm depends on the largest eigenvalue μ_{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

$$\mu < \frac{2}{\lambda_{\max}}. \qquad (9)$$

Since we still do not want to compute an estimate of R and its eigenvalue, we first approximate μ_{max} ≈ tr(R) (tr(R) is the trace of matrix R, i.e., the sum of the elements on its diagonal), and then – in the same way as we approximated the expected values in the cost function –tr(R) ≈ $||x[n]||^2$, the tap-input power at the current time n. Hence, the upper bound for μ for stable behavior depends on the signal power [14].

Summary of the LMS algorithm

- Filter operation: $y[n] = c^H[n]x[n]$
- Error calculation: $e[n] = d[n] - y[n]$ where d[n] is the desired output
- Coefficient adaptation: $c[n+1] = c[n] + \mu\, e^*[n]\, x[n]$

2.2. *The RLS Adaptation Algorithm*

The other class of adaptive filtering techniques studied in this thesis is known as Recursive Least Squares (RLS) algorithms. These algorithms attempt to minimize the cost function in equation 10.

Where k=1 is the time at which the RLS algorithm commences and lambda is a small positive constant very close to, but smaller than 1. With values of lambda <1 more importance is given to the most recent error estimates and thus the more recent input samples, this results in a scheme that places more emphasis on recent samples of observed data and tends to forget the past samples [9].

$$J[n] = \sum_{i=1}^{n} \rho^{n-i} |e[i,n]|^2, \qquad (10)$$

Unlike the LMS algorithm and its derivatives, the RLS algorithm directly considers the values of previous error estimations. RLS algorithms are known for excellent performance when working in time varying environments [10]. These advantages come with the cost of an increased computational complexity and some stability problems. The block diagram of the RLS algorithm is shown in the following figure.

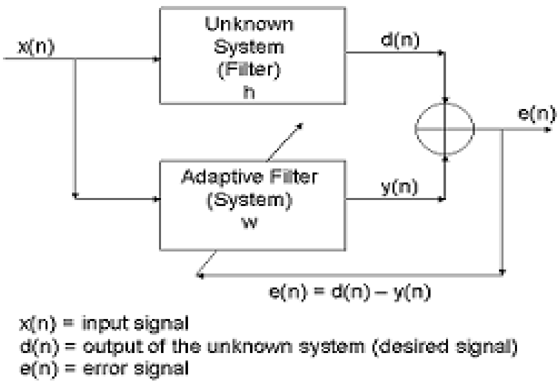

Fig. 5- RLS Algorithm Based Adaptive Filter Block Diagram

2.3. *Comparison of the LMS and RLS Adaptive Filter Algorithms*

a. If LMS algorithms represent the simplest and most easily applied adaptive algorithms, the recursive least squares (RLS) algorithms represents increased complexity, computational cost, and fidelity. In performance, RLS approaches the Kalman filter in adaptive filtering applications, at somewhat reduced required throughput in the signal processor.

b. Compared to the LMS algorithm, the RLS approach offers faster convergence and smaller error with respect to the unknown system, at the expense of requiring more computations.

c. In contrast to the least mean squares algorithm, from which it can be derived, the RLS adaptive algorithm minimizes the total squared error between the desired signal and the output from the unknown system.

d. The signal paths and identifications are the same whether the filter uses RLS or LMS. The difference lies in the adapting portion.

e. One interesting input option that applies to RLS algorithms is not present in the LMS processes — a forgetting factor, λ, that determines how the algorithm treats past data input to the algorithm.

f. When the LMS algorithm looks at the error to minimize, it considers only the current error value. In the RLS method, the error considered is the total error from the beginning to the current data point.

g. Said another way, the RLS algorithm has infinite memory — all error data is given the same consideration in the total error. In cases where the error value might come from a spurious input data point or points, the forgetting factor lets the RLS algorithm reduce the value of older error data by multiplying the old data by the forgetting factor.

h. Since $0 \leq \lambda < 1$, applying the factor is equivalent to weighting the older error. When $\lambda = 1$, all previous error is considered of equal weight in the total error. As λ approaches zero, the past errors play a smaller role in the total. For example, when $\lambda = 0.9$, the RLS algorithm multiplies an error value from 50 samples in the past by an attenuation factor of $0.9^{50} = 5.15 \times 10^{-3}$, considerably deemphasizing the influence of the past error on the current total error.

RESULTS AND DISCUSSION

In the present work, we have taken 1500 samples of noisy ECG data and the data were tested with both types of adaptive filtering methods (LMS adaptation algorithm and RLS adaptation algorithm). The reference signal was also taken as 1500 sample. The algorithms were developed using LabView and the noisy ECG signal was rectified using both types of adaptive technique.

3.1. ECG Results With LMS Algorithm

Using LMS adaptive noise cancellation technique we have take 1500 sample of noisy ECG signal as the input signal and another 1500 samples of reference ECG signal. Both the signals were taken as the input signals and we have found out the noise free ECG signal and the error signal from the adaptive filter. Figure-6 shows a noisy ECG signal taken as input signal for the LMS algorithm based adaptive filter.

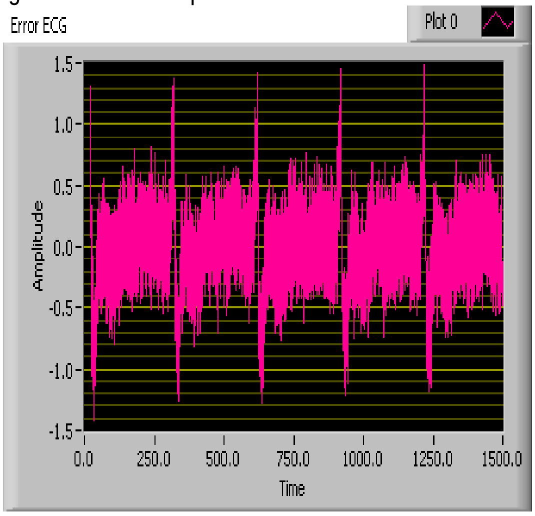

Fig. 6- Noisy ECG signal taken as input signal for LMS adaptive filter

In the figure 7, a reference ECG signal is also taken for the adaptive system. The final output (figure 8) shows the fast converge output of the LMS algorithm based adaptive filter. The error signal is also plotted in the figure 9. We can see from the error signal that the converge output and error signal for the LMS algorithm based adaptive filter is comparable with RLS algorithm based adaptive filtering technique.

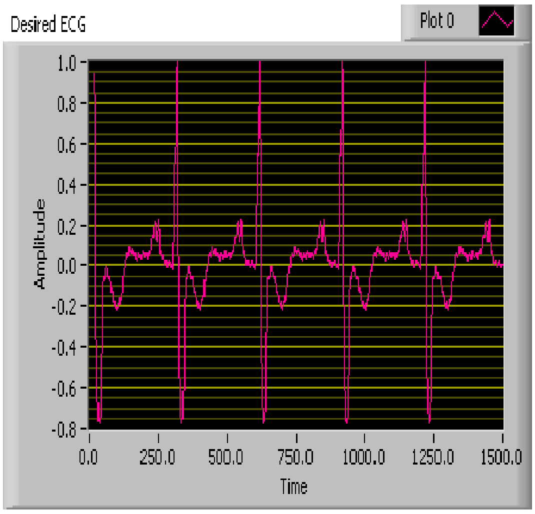

Fig. 7- Reference ECG signal (LMS based adaptive filter)

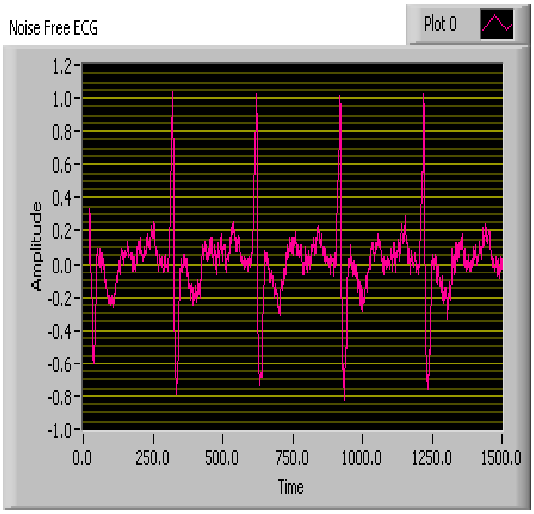

Fig. 8- Filtered ECG signal from the LMS based adaptive filter

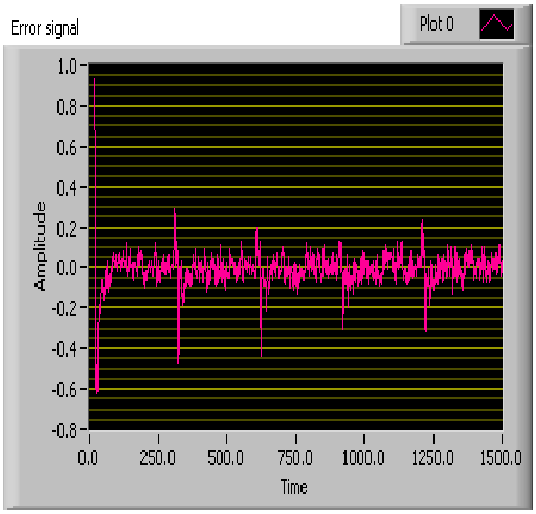

Fig. 9- Error signal plotted for LMS based adaptive filter

3.2. ECG Results With RLS Algorithm

Again an RLS algorithm based adaptive filtering technique was also developed and 1500 samples of same ECG signal was taken as input signal for the filter. We have plotted the noisy ECG signal (Figure 10), reference ECG signal (figure 11), Filtered ECG signal (figure 12) and the noise signal (figure 13). We can compare the results of LMS based adaptive technique and RLS based adaptive technique that the error signal in the case of RLS method converges more quickly as compared to LMS algorithm based technique. Also the output of the noise free ECG signal form RLS technique is more clearly visible as compared to LMS based technique.

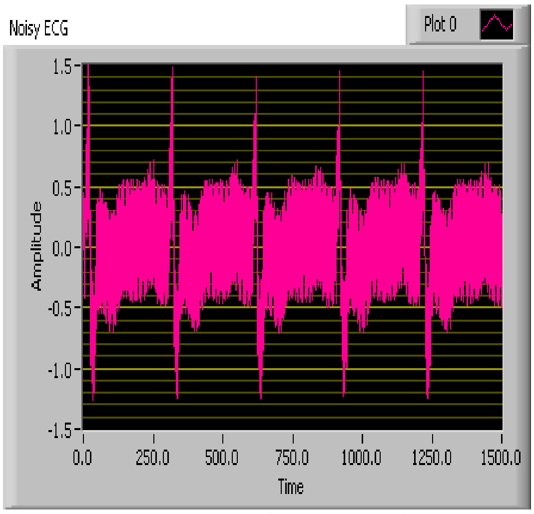

Fig. 10- Noisy ECG signal taken as input signal for RLS adaptive filter

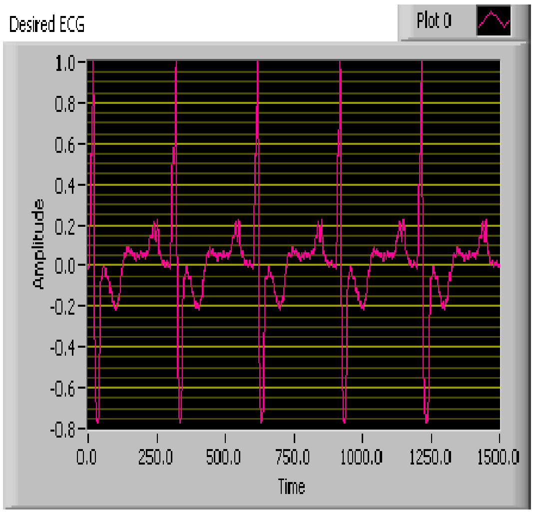

Fig. 11- Reference ECG signal (RLS based adaptive filter)

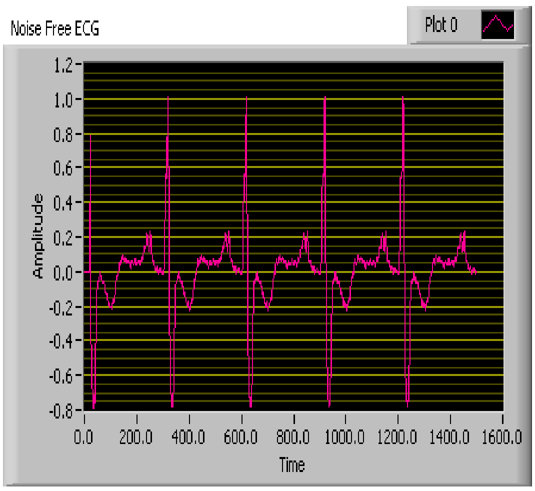

Fig. 12- Filtered ECG signal from the RLS based adaptive filter

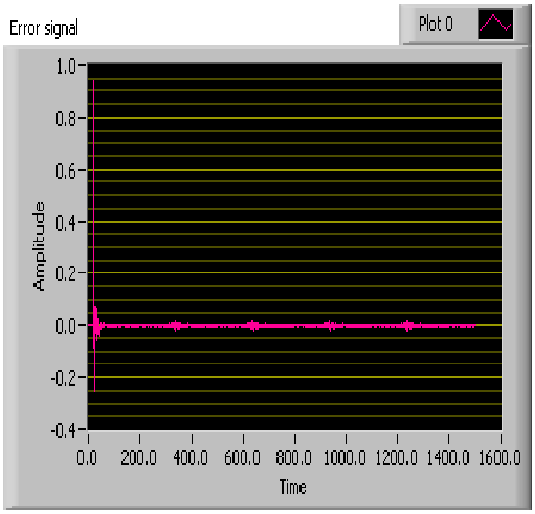

Fig. 13- Error signal plotted for RLS based adaptive filter

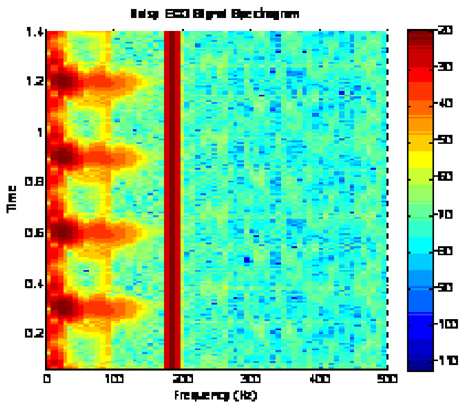

Fig. 14- Spectrogram of Noisy ECG Signal

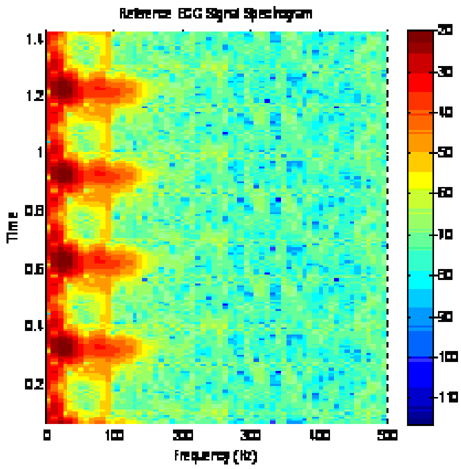

Fig. 15- Spectrogram of Reference ECG Signal for Adaptive filter

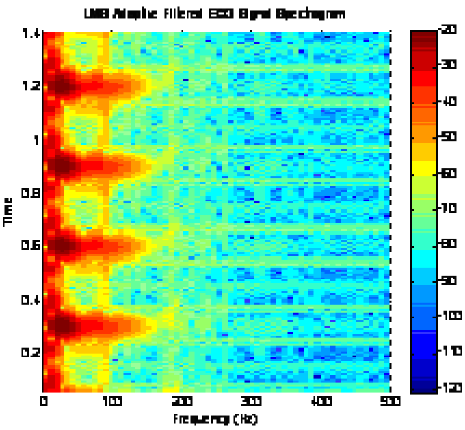

Fig. 16- Spectrogram of LMS algorithm based adaptive filter ECG output

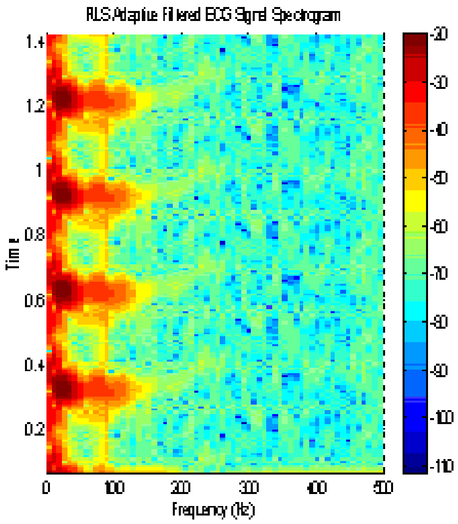

Fig. 17- Spectrogram of RLS algorithm based adaptive filter ECG output

From the above figures, figure-14 is the spectrogram of noisy ECG signal of 1500 samples of data. Figure-15 shows the spectrogram of reference ECG signal used for adaptive filter reference input. In the figure-14, we cab observe that the raw ECG signal contains many noisy components (frequencies). The figure-16 shows LMS algorithm based adaptive filter output, where the noisy components are removed. The figure-17 show RLS algorithm based adaptive filtering technique, where the filtered signal quite equivalent to the reference input and the noisy components are better removed as compared to LMS based filtering technique.

CONCLUSION

ECG is one of the major diagnosis methods for every heart disease. In this paper we have presented a new approach for noise cancellation in raw ECG signal using LMS (Least Mean Square) algorithm based adaptive filtering and RLS (Recursive Least Squares) algorithm based adaptive technique. Both the techniques are having its own advantages and disadvantages. From the filtered ECG signal we have found that RLS (Recursive Least Squares) algorithm is having better convergence as compared to LMS. We have observed that the filtered ECG signal using RLS method is more equivalent to the corresponding reference ECG signal. The main theme of this method is to find out the actual ECG pulses from the raw noisy signal and the filtered ECG signal can easily be passed to a suitable detection algorithm for better analysis of arrhythmia like bradycardia, tachycardia; abnormalities like left ventricular hypertrophy, right ventricular hypertrophy.

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