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Improving Pulse Rating for Electrocardiogram (ECG) Using Recursive Least Square and Low Pass Filter

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ABSTRACT

Electrocardiogram (ECG) records the electrical signals from your heart to check for different heart conditions. Electrodes are normally placed on your chest to record your hearts electrical signal responses, which causes the heart to move or beat. The signals are reflected as waves on an attached monitor. The major issues related to the ECG systems are noise, noise tends to reduce the integrity of the system, most times the noise are being generated by the sound from the heart, which is interfering with the signals. This noise makes it difficult for the physician to get the original results of the pulse rate and sometime could also influence the result which might leads to damages. However, in order to reduce the noise in the ECG signal we used the recursive least square method with a low pass filter in reducing the noise in the ECG signals. This method was carried out based on different heart pulse responses to measure the degree of noise presence at each pulse rates after filtering with recursive least square. The method significantly reduced noise in the signal to as low as 0.5556 % at 32nd order of the filter, when compared to the error rate of the photoplethysmography (PPG) heart rate monitor the results shown that the ECG system with the recursive least square and low pass filter has more integrity in reducing the noise, which promotes a good signal and is better when compared with photoplethysmography (PPG) and an ECG system without the recursive leas square and low pass filter for noise reduction.

KEYWORDS: Least Mean Square, Electrocardiograph, Photoplethysmography, Recursive Least Square, Heart Rate Monitor, Pulse Rate

1.0 INTRODUCTION

Acoustic waves recorded from the chest and backside are referred to as HEART SOUNDS. These are transient signals produced by the vibration of heart valves as they close and open, as well as the vibration of the entire myocardium and adjacent structures. Physicians frequently utilize cardiac auscultation to assess heart valve performance and find anomalies during medical examinations [3]. It's not easy to learn how to perform auscultation, especially in noisy or distracting situations. The impulsive noise or interference alluded to in this paper is characterized by a short time span. Ambient noise, friction between the chest piece and the skin, and lung expiration and inspiration are all common sources of noise and disruption when capturing heart sounds. When there is a lot of noise and disruption, the accuracy of auscultation is questioned. As a result, developing noise and disturbance reduction algorithms to aid physicians and medical students in their work and learning is important. The heartbeat is a set of mechanical processes that occur repeatedly. Although not quite periodic, the repeat is considered quasi-periodic. In a sense, this indicates that the vibration wave records are completely immobile. Even if the recording sites change, quasi-cyclic stationary can be seen. Signal processing techniques in the cycle-frequency domain, such as those found in, have been fully developed in the previous few decades [3]. Few open research has focused on heart sounds in the cycle-frequency domain, to our knowledge. The most recent study to look into the quasi-periodicity of heart sounds in order to separate heart sounds from lung sounds was. The noise of heart sounds is explored in this study through a variety of clinical scenarios. To match the timing of heart sounds from cycle to cycle, linear and nonlinear time scaling are used. The cyclic stationarity of heart sound signals is considerably improved as a result. A unique noise and disturbance reduction method that uses a recursive least square and low pass filter. In prior studies, a variety of approaches for reducing noise have been proposed. Heart sounds were successfully enhanced using adaptive noise cancellation, although an additional reference to the noise signal was necessary [3].

1.1 Problem Statement

To many wrong heart pulse rates has been prescribed to patients by physicians, however this is due to noise presents in the processed signal of the heart rate monitor. The noise tends to reduce the integrity of the heart rate monitor due to the fact that it makes it almost difficult for the real pulse rate to be taken down, this noise are majorly caused by the heart beat sound of the heart or an external noise that is interfering with the pulse signal. This errors occurs both in analogue and digital pulse rate monitors.

1.2 Aim of the Study

The aim of this research work is to improve Pulse Rating for Electrocardiogram (ECG) Using Recursive Least Square and Low Pass Filter

The objectives of this research work are presented as:

i. To identify the noise in the ECG heart signal to be filtered

ii. To evaluate the low pass filter for heart noise reduction

iii. To evaluate the Recursive least square filter for HRM noise cancellation

iv. To simulate the ECG HRM Recursive least square filter system using Simulink

2.0 Literature Review

According to [1] they worked on noise reduction in ECG monitor using FIR they furtherly expressed that The electrocardiogram (ECG) signal is commonly used to assess a person's heart rate and is valuable in cardiac pathology. ECG detects a variety of heart disorders in people. Wearable technology is being used as monitoring devices to obtain the ECG signal directly from the patients. The movement of the patients, on the other hand, will generate noises that will interfere with the ECG findings. To address this issue, it is proposed that a digital filter be constructed and employed to obtain an accurate ECG signal.

According to [2] they proposed a research work on the Using field programmable gate arrays, construct and evaluate a hardware circuit for electronic stethoscopes with cardiac sound cancelling capabilities (FPGAs). To minimize cardiac sound features from breath sounds received via electronic stethoscope pickup, the adaptive line enhancer (ALE) was used as the filtering mechanism. To accomplish near real-time breath sound processing, FPGAs were used to implement the ALE functions in hardware. We feel that such a rollout is unprecedented and critical in the development of a truly useful, stand-alone medical device for outpatient clinics.

According to [3] they expressed that heart sounds are discovered to be quasi-cyclo stationary after an analysis of several clinical scenarios. To improve cyclic stationarity, nonlinear time scaling from cycle to cycle is proposed, where nonlinear time scaling is approximated by a piecewise linear function. To minimize noise and disturbance in the cycle-frequency domain, this paper uses cyclo stationary signal processing approaches. In the context of additive, zero mean noise and disturbance, heart sounds can theoretically be retrieved (perhaps non-Gaussian, nonstationary, or colored).

3.0 Method

3.1 Description of Adaptive RLS Filter for Noise Reduction

A variety of biological applications have made use of adaptive signal processing systems. Both linear and nonlinear adaptive filters use the RLS learning method. Slow adaptation produces the best steady state performance when the adaptive system's input process is (quasi-) stationary. When the input statistics are time-variant (nonstationary), however, a compromise between fast adaptation (required to follow variations in the input process) and slow adaptation yields the best results (necessary to limit the noise in the adaptive process) [4]. The LMS adaptation method is a straightforward and efficient solution for adaptive noise canceling (ANC); but, because of its sluggish convergence and the difficulty in determining the optimum step size, it is not suitable for fast-varying signals [7]. The RLS method is a different approach based on the exact minimizing of the least-squares criterion. Because of its fast convergence, which is nearly an order of magnitude faster than the LMS approach [6], the RLS algorithm as shown in figure 1 has been widely employed in real-time system identification and noise cancellation. The RLS method employs information included in the input data and extends it back to the period when the algorithm was began, which is a key aspect. Upon the receipt of new data, the updated estimate of the tap-weight vector of the filter is generated using the least-squares estimate at time n - 1 [4].

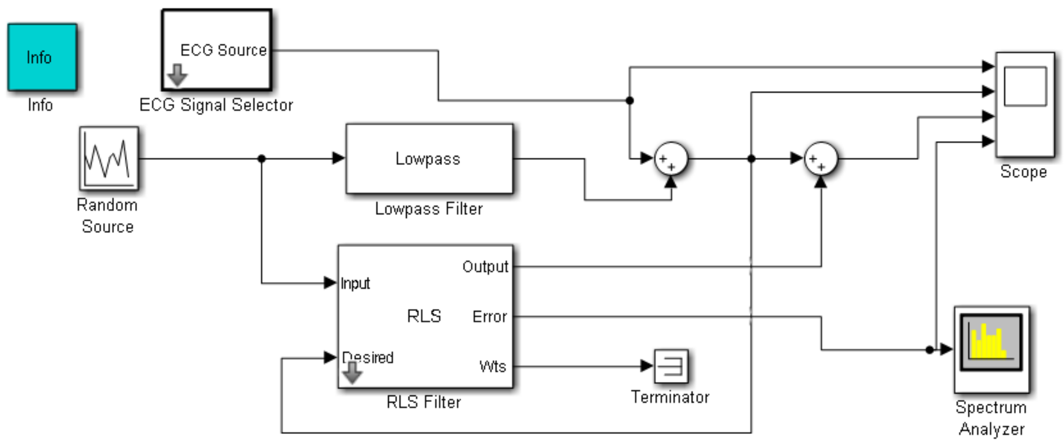

Figure 1: ECG Noise Reduction with Low Pass Filter and RLS

The instantaneous error e [N] can be determined using the following equation in the RLS algorithm derivation:

$$e[N] = x[N] - h[N]z[N] = x[N] - z[\ N]h[n] \tag{3.1}$$

where z[n] is the filter's output, z′[n] is the filter vector's output, and h[N] is the filter parameter, h′[N] is the filter parameter vector, and h[N] is the filter parameter vector. For calculating the filter settings, the RLS algorithm evaluates all accessible data. In a certain sense, the filter should be optimal in terms of all available data [4].

The cost function is minimized.

$$\mathrm{E[N]}=\sum_{k=0}^{N} \lambda^{N-k}\, e^2[k] \tag{3.2}$$

with respect to the filter parameter vector

$$\mathrm{H[N]}=\begin{bmatrix} h_0[N] \\ h_1[N] \\ h_{m-1}[N] \end{bmatrix} \tag{3.3}$$

Where λ is the forgetting factor, recent data is given higher weightage, λ = 1 can be used for stationary cases, λ = 0.99 is effective in tracking local non stationarity, and the minimization problem is Minimize [4].

3.2 Low Pass Digital Filter For Noise Removal

Filter with infinite Impulse Response (IIR) IIR filters are distinguished by their impulse response, which does not become exactly zero past a certain point but continues indefinitely. With contrast, in a finite impulse response (FIR), the impulse response h (t) becomes exactly zero at times t > T for a finite T, indicating that the response is short in duration. Even with IIR systems, the impulse response usually approaches zero in practice and can be ignored after a certain threshold.

$$H(z) = \frac{\sum_{k=0}^{M} b_k z^{-k}}{\sum_{k=0}^{N} a_k z^{-k}} \tag{3.4}$$

Where a_k *and* b_k is the number of zeros, M is the number of poles, and N is the number of filter coefficients. As an output samples, the function demonstrates how IIR's output is dependent on the input preceding it.

3.3 Evaluation of Recursive Least Square Filter

$R_{zz}[N]$ can be written as

$$R_{zz}[N] = \sum_{k=0}^{N-1} \lambda^{N-k}\, z[k]z^{'}[k] + z[N]z^{'}[N]$$

$= \lambda \sum_{k=0}^{N-1} \lambda^{N-1-k} z[k]z'[k] + y[N]z'[N]$

$= \lambda R_{zz}[N-1] + z[N]z'[N]$ (3.5)

This demonstrates that the autocorrelation matrix may be constructed recursively using past values and the current data vector. (Noor,2011) Similarly

$k[N]\frac{p[N-1]z[N]}{\lambda+y'[N]p[N-1]y[N]}$ (3.6)

K[n] The present data vector is also necessary to interpret adaption.

z[n] by K[n]=P[n]y[n] (3.7)

Consider the following to establish the above relationship:

P[N]= $\frac{1}{\lambda}1(p[N-1] - k[N]z'[N]p[N-1])$ (3.8)

multiplying by λ and post-multiplying by y[n] and simplifying we get

$\lambda p[N]z[N] = (p[N-1] - k[N]z[N]p[N-1])z[N]$

= $(p[N-1] - k[N]z'[N]p[N-1]z[N]$

$= \lambda k[N]$ (3.9)

3.4 Operation of the RLS Algorithm

The RLS algorithm was developed as the exact answer to a well-defined estimation issue with a least-squares cost function [4]. The functioning of the RLS algorithm is shown in figure 2:

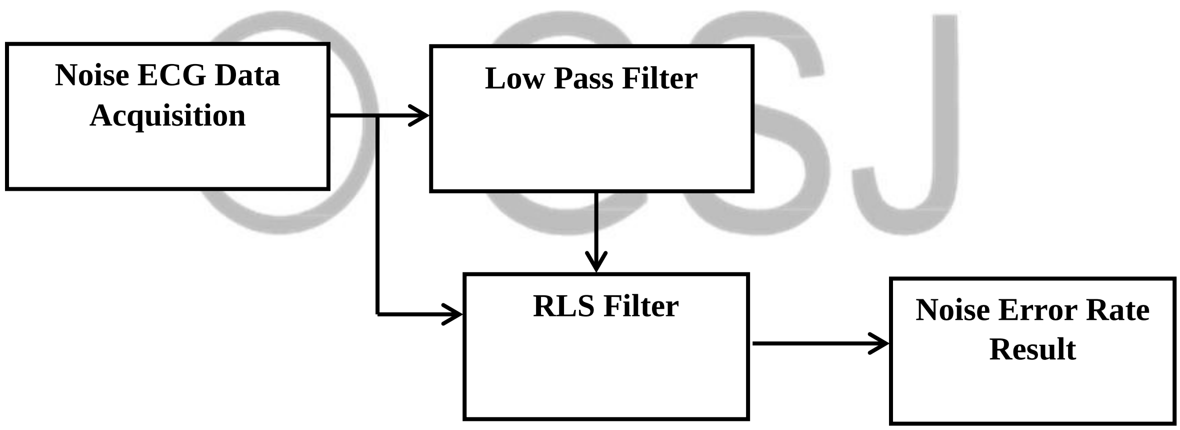

Figure 2: Step or Flow Chart of the Noise cancelation System

For 1 to N= Final

i. Get x[N],z[N]

ii. Get e[N]=x[N]-h'[N-1]z[N] (3.10)

iii. Calculate gain vector

$k[N]\frac{p[N-1]z[N]}{\lambda+z[N]p[N-1]z[N]}$ (3.11)

iv. Update filter parameters

H[n]= h[N-1]+k[N]e[N] (3.12)

v. Update the p matrix

P[N]= $\frac{1}{\lambda}1(p[N-1] - k[N]z'[N]p[N-1])$ (3.13)

End

3.5 ECG Noise signal filtering and Evaluation

The ECG signals were filtered to test the algorithm proposed in this research, and the overall inaccuracy of the signal and the optimal filter order were determined. MATLAB was used to estimate the performance of the suggested filters in this paper, and two types of filters were tested. The standard deviation and mean X were calculated. The average value of a signal is the mean. It may be calculated by multiplying all of the samples together and dividing by N. In mathematical terms, it appears to be like this [4].

$$x = \frac{1}{N}\sum_{i=0}^{N-1} x_i \qquad (3.14)$$

$$std = \left(\frac{1}{N}\sum_{i=0}^{N-1}(x_{i-x})\frac{2}{}\right)^{\frac{1/2}{}} \qquad (3.15)$$

$$x = \frac{1}{N}\sum_{i=0}^{N-1} x_i \qquad (3.16)$$

and represents the sample's n number of elements. Only the divisor n-1 versus n in the two forms of the equation differs [4] [5].

4.0 Recursive Least Square Noise Reduction at ECG 82 BPM Results Presentations

The biopotential created by electrical signals that control the expansion and contraction of the heart chambers was measured using electrocardiography sensors. From the figure 3 we can see the graphical representation of the ECG heart beat rate monitor results, haven known that noise is one of the major factor that prevents the accurate readings of the heart beat rate, but however with the noise cancellation methods using the recursive least square filter, noise has drastically reduced to a lower minimum, the results shows that noise error has been reduced to 0.5556dB. The 82 bpm pulse rate as illustrated from the figure 4 has also shown a normally medical condition of a normal heart pulse rate response appears. However, the heart pulse rate in the ECG heart rate monitor has been improved by reduction of noise in the signal.

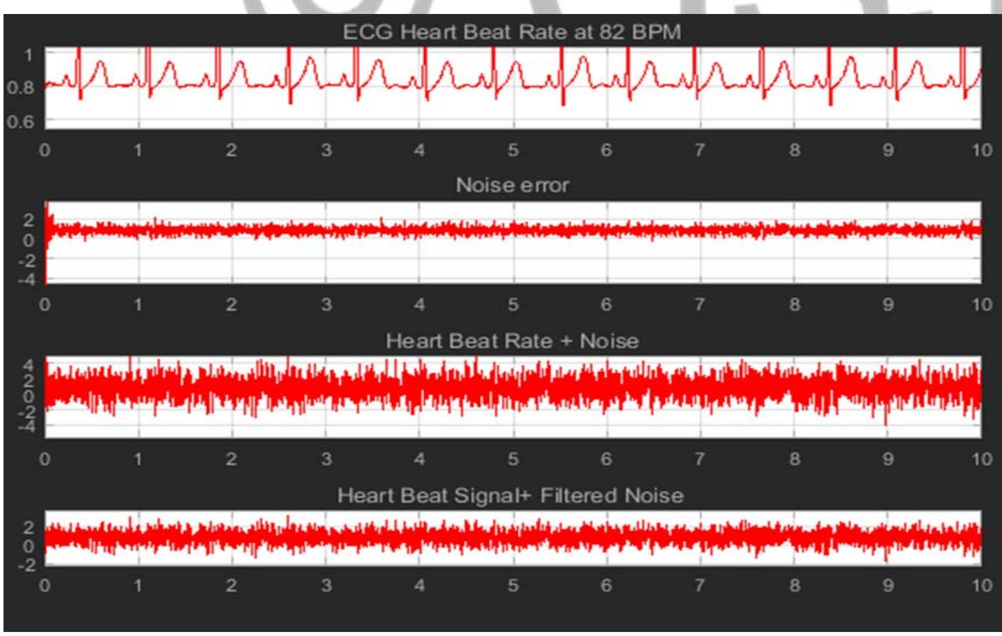

Figure 3: ECG Heart Beat Rate at 82 BPM

4.1 Noise Rate of the Photo plethysmography

Photo plethysmography (PPG) sensors employ light-based technology to detect the rate of blood flow as determined by the heart's pumping motion. This action determines the rate at which a heart pumps but the issues with this hand held devices is instability of the signal generating interferences, and with poor filters when compared to the ECG Machines for heart pulse checking and noise from the figure 4 you can see the rate of noise error at 82 bpm realizes at 1.012 noise error which is almost two times of the electrocardiograph results which is 0.5556. the result shows that the PPG has higher noise than the ECG with a Recursive least square filter.

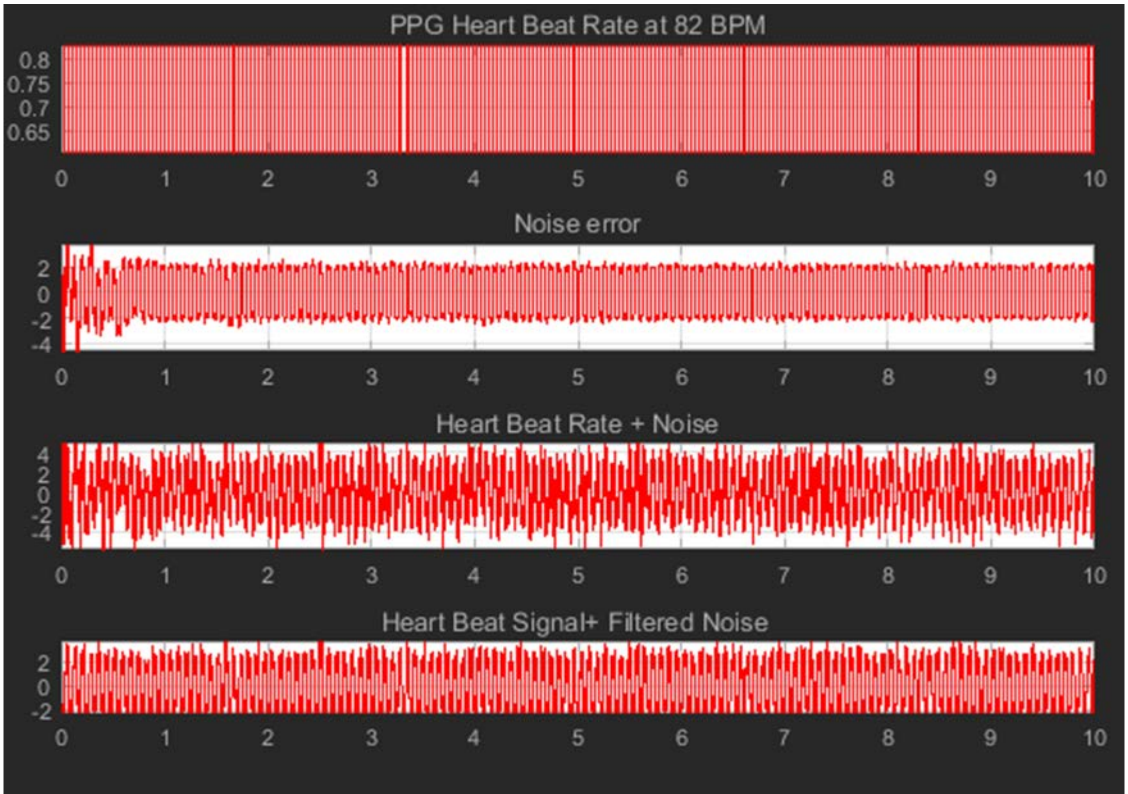

Figure 4: PPG Heart Beat Rate at 82 BPM

4.2 Recursive Least Square Adaptive filter Noise Rate at 45 Bpm ECG

The recursive least square was also used to reduce noise error in the ECG machine at a 45 bpm as shown in figure 5 with a reduced noise rate of 1.079 which is a bit lesser than that of the 82 bpm in figure 6 and 220 bpm in figure 7. This method virtually reduces noise error at any bpm just as shown below in the figures having 220 bpm as the highest heart beat rate here in this research work with a filtered noise error of 0.55556, and the 60 bpm heart beat rate has a filtered noise error at 1.034.

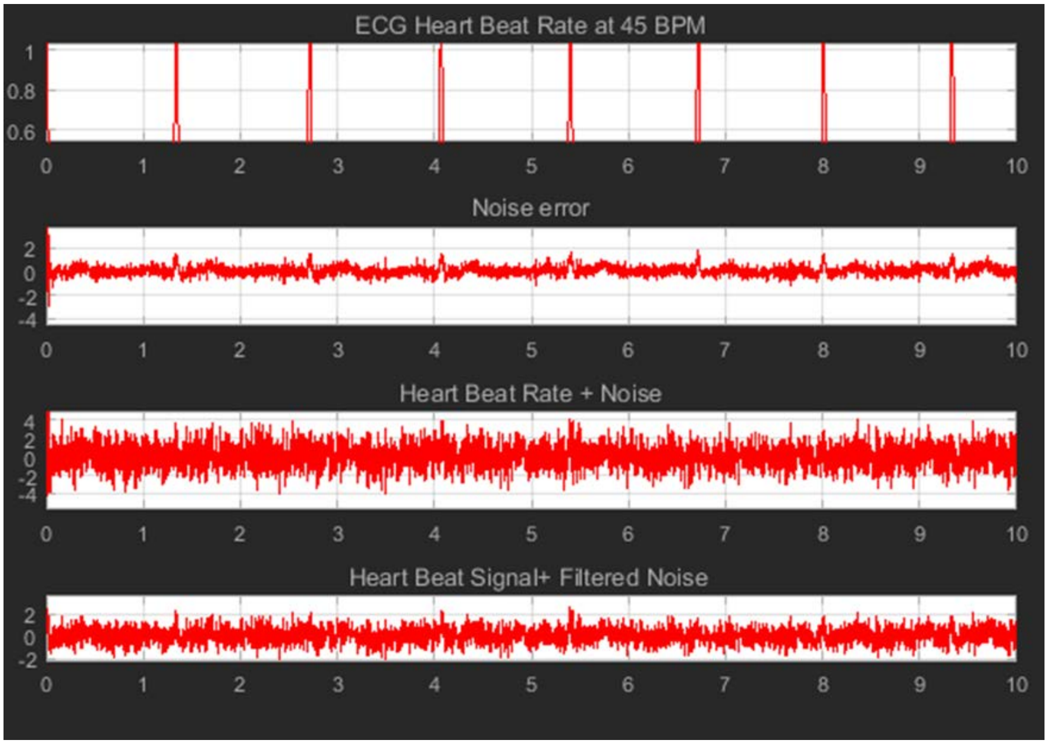

Figure 5 ECG heart beat rate at 45 BPM

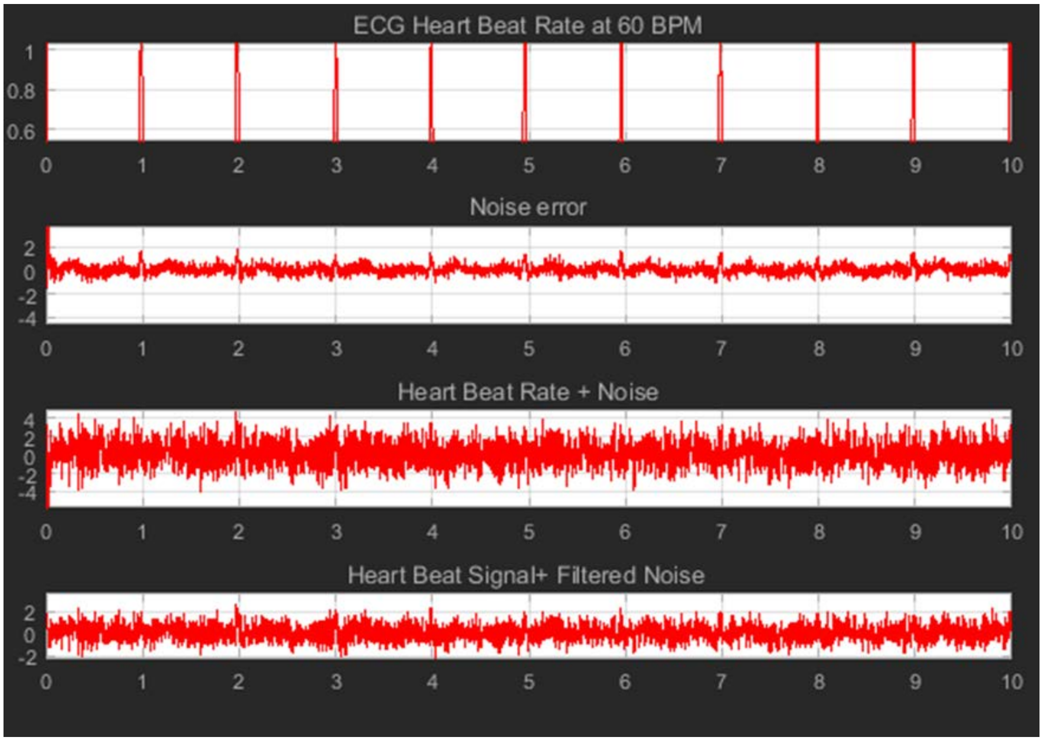

Figure 6 heart beat rate at 60 bpm

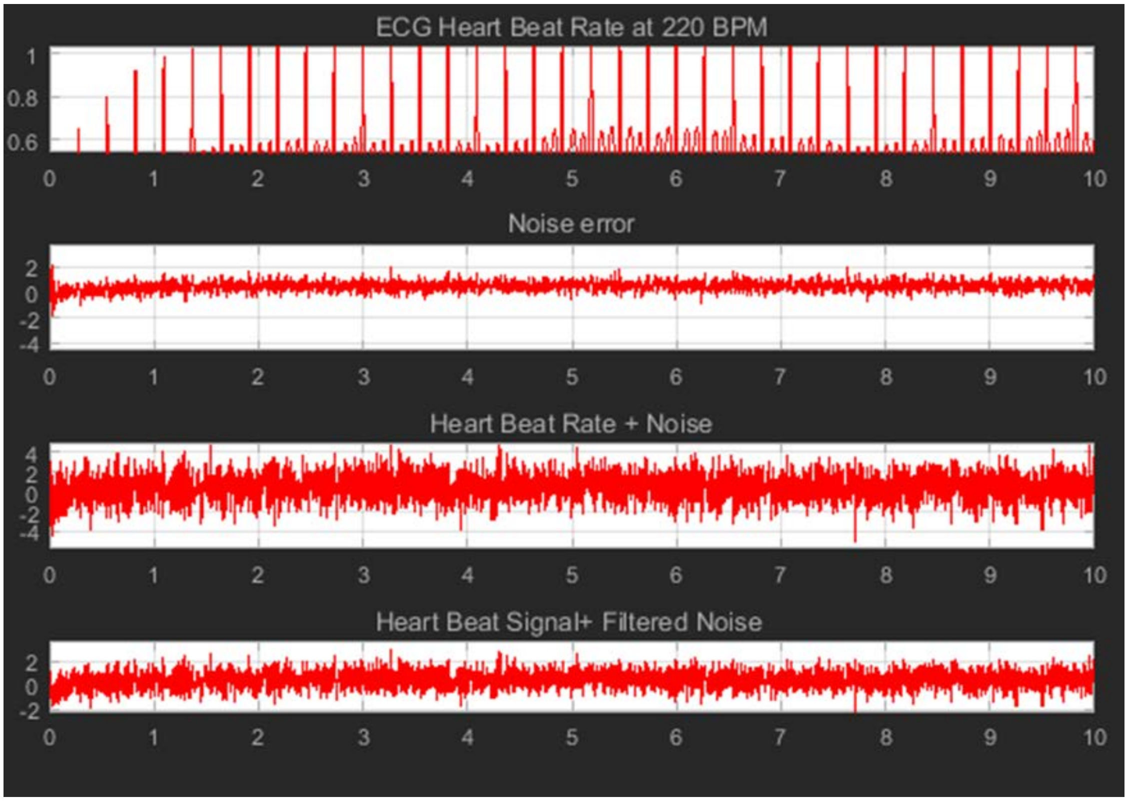

Figure 7: Heart beat rate at 220 bpm

4.3 Noise Rate at 160 BPM ECG Signal

Using the recursive least square filter has actually reduced noise error drastically in the ECG system despite the fact that the pulse rate at 160 bpm is unhealthy but the clarity of the result wasn't hindered by the filter the noise error rate at 160 bpm was reduced to 1.1614 dB which is better, from the figure 8 we can see the heart signal and how noise has prevented the signal to be clearly read, but filtering the signal brought clarity to read the actual signal due to noise reductions.

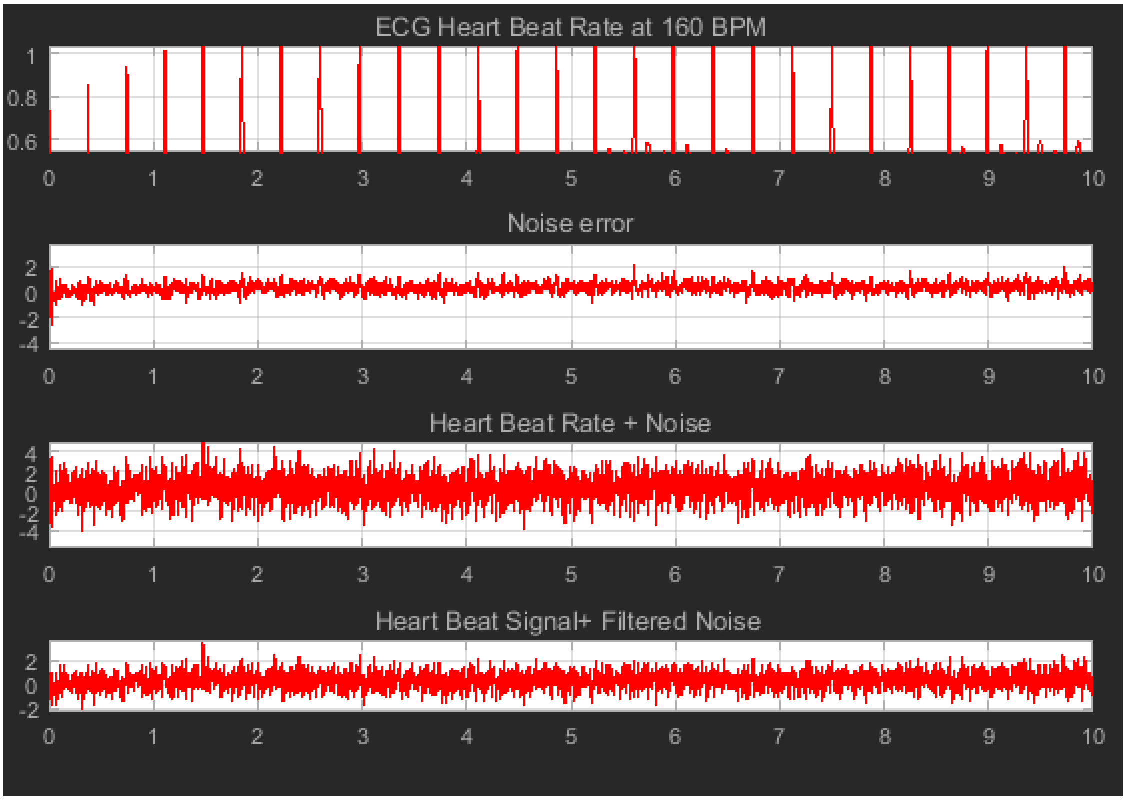

Figure 8 Heart Beat Rate at 160

From the Table 1 the results of the initial noise rate without the RLS filter for the ECG heart rate monitor was obtained through MATLAB/Simulink simulations at different pulse rates and same order of filter 32. The table 1 shows the results of various pulse rates of the ECG and PPG heart rate monitor noise rates.

Order of RLS filter	Initial noise without RLS	ECG Noise Rate with RLS	PPG Noise Rate	Pulse rate
32	2.7691	1.0791	2.1583	45
32	3.0163	1.0844	2.1686	60
32	1.3248	0.5556	1.1112	82
32	2.6541	1.1614	2.3228	160
32	2.5223	1.1723	2.3446	220

4.4 Comparative Results of Noise Rates in Heart Rate Monitors

The results from figure 9 has clearly described the effectiveness of the RLS filter in the ECG monitor, the noise ratio found in the ECG noise is lesser than that of the PPG heart monitor and the results also said that the pulse rate has been improved by reducing the noise signals in the ECG monitor.

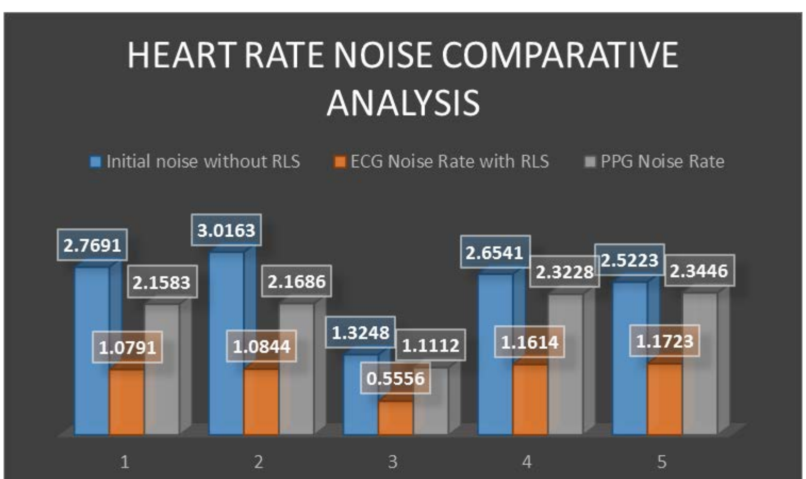

Figure 9 Heart noise comparative analysis

5.0 Conclusion

In the aim of improving pulse rating in a heart beats monitor most especially on the ECG heart monitor, we must consider the major factor which is noise. Noise has actually disrupted the integrity of the ECG system. However, improving the pulse rate of the system will be based on reducing the noise effect. So in this research work we have been able to carry out an analysis of the recursive least mean square and at 32 order to reduce noise in the ECG heart rate monitor. Evaluation process of the recursive least square adaptive filter were carried out in this research work and where the principle of operation of the system was also evaluated. From the result of this research gotten from the Simulink simulations, it was concluded that using recursive least square in filtering noise signal from the ECG system has been proven to be effective, which improved the heart pulse of the ECG system by reducing noise drastically.

From the comparative result analysis we can see that the initial signal without the RLS gave rise t a higher level of noise then followed by the result of the PPG heart rate monitor. However, the ECG with the RLS adaptive filter in addition to the low pass filter at 32 order of the filtering were able to reduce noise to 0.5556 % at 82 BPM.

5.1 Recommendation

In the case of choosing an ECG heart pulse rate monitor system, then i will recommend the ECG system using the RLS adaptive filter for noise cancellation because of it effectiveness and high integrity to give an accurate signal. However, the use of the RLS filter has furtherly improve the pulse rate of the system by reducing noise to 0.5556 % here by making the system to be trust worthy in giving accurate results.

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