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# A noise removal methodology for effective ecg enhancement in heart disease prediction & analysis

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***Abstract*---**An electrocardiogram (ECG) measures the electrical activity of the heart by placing various terminals on the body. The heart cannot pump blood properly due to electrical anomalies, resulting in insufficient blood supply to the body and brain. As a result, ECGs are vital in determining the condition of cardiovascular patients. An ECG signal may be debased by various clamours, for example, power line interference, standard meandering, anode contact disturbance, movement antiquities, muscle contraction, instrumentation noise caused by the electronic device, and so forth. So, to overcome such issues, this paper brings an effective proportionate linear Mean Square algorithm (PLMS) for its improved version of LMS and progresses the adaptive tracking phenomenon and provides superior performance. Using the proposed algorithm, the adaptive filter works more efficiently and consumes less power. As a result, the signal-to-noise ratio and MSE are high and hence computational complexity is greatly reduced. Therefore, it can effectively monitor patients with heart-related problems.

***Keywords*---**Adaptive filter, Electrocardiogram, Linear Mean Square, Noise removal, Proportionate LMS.

## Introduction

The electrical activity of the heart muscles is measured by Electrocardiograms (ECGs) in biomedical applications. ECG signals are generally measured by using surface electrodes on different parts of the body. They can be corrupted by much noise, including baseline drift, motion artefacts, muscle contractions, power-line


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interference, and so on [1]. When these noises are present in the ECG, it could lead to a misdiagnosis. For an accurate diagnosis, these noises must be eliminated. The ECG noise has a non-stationary and time-varying nature, making it difficult to remove. Monitors for portable ECG devices are miniaturized, low-cost, and low-power. The performance of these devices requires the use of signal conditioning to extract and amplify very low-level signals from noisy environments [2]. Normal conditions cause interference between the high-frequency signals and the QRS components. As a result, it will be difficult for clinicians to interpret ECG signal parameters. To handle non-stationary signals, a filter needs to be designed so that it can change its coefficients or weights according to the requirements. For ECG signal analysis, several filtering techniques have been employed, including adaptive and non-adaptive methods [3]. The adaptive filter has become a crucial component of Digital Signal Processing (DSP) and digital communications. Despite the availability of numerous adaptive algorithms, the Least Mean Square (LMS) algorithm has gained popularity due to its simplicity (Figure 1).

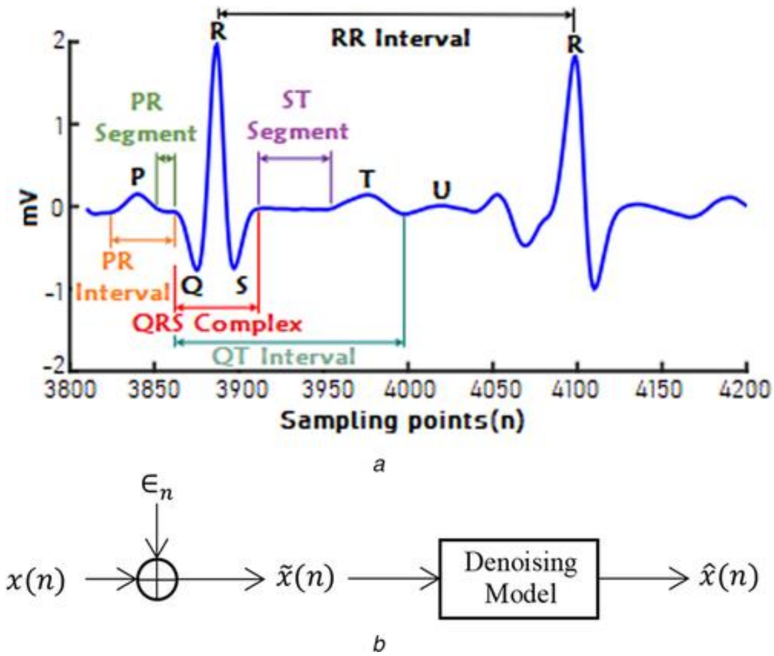


Figure 1. ECG signals and their respective conventional architecture of noise removal using LMS

The LMS algorithm (figure 2) is unusable in real-time applications because of its weak tracking ability [4-6]. Although the recursive least square algorithm converges quicker than LMS-based techniques, it has a larger computational complexity. The Normalised LMS (NLMS) algorithm was done to enhance tracking capability and resolution. Variable step-size algorithms are proposed because adaptive filtering performance is influenced by the step size. In the previous versions, the adaptive algorithms' application was restricted by their high computational requirements. Complex circuits can now be implemented on a single chip because of advancements in very large-scale integration (VLSI) technology [8-10].

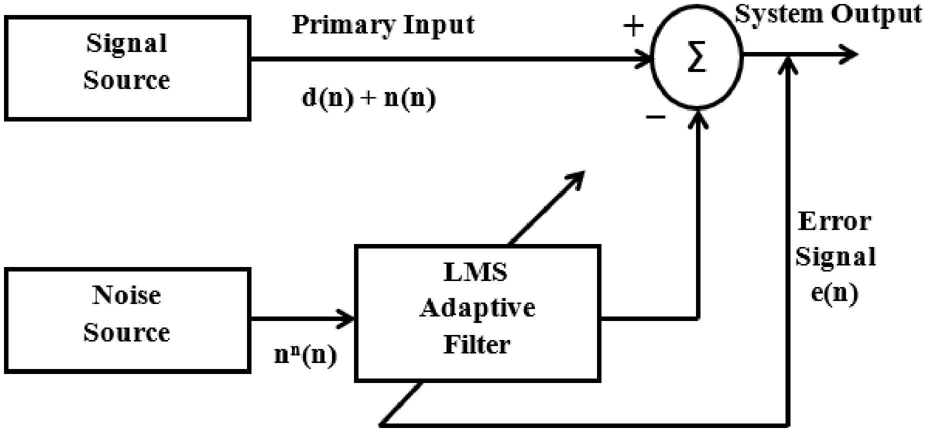

Figure 2. Conventional LMS algorithm model for noise removal

Studies in the field of biomedical signal processing have presented adaptive solutions based on the LMS algorithm [11-16]. A dynamic noise cancellation filter is defined by Widrow et al. [17]. According to Thakor and Zhu, a modified recurrent filter can be applied to ambulatory ECG data to facilitate the detection of arrhythmias by collecting the impulse response of normal QRS complexes. The LMS algorithm's standard inputs are deterministic functions specified by a collection of orthonormal basis functions that are regularly extended and truncated. According to those papers, LMS works on an "immediate" basis, meaning that the weight vector is updated every time a sample is taken within the event, based on an estimation of the immediate gradients. According to a new study, a steady-state evaluation of the LMS algorithm with predictable reference inputs showed that the constant-state weight vector is skewed and thus the adaptive approach does not approach Wiener's solution. In this study, we introduce the Proportionate LMS algorithm, an enhanced variant of the LMS algorithm for reducing noise and improving cardiac ECG signals.

### *Key highlights*

This paper focuses on bringing an effective noise cancellation model for ECG. Following are the main objectives followed for the same.

- Developing a noise removal model for better ECG enhancement.
- Model is developed by proposing an improved version of the LMS algorithm i.e., the Proportionate LMS algorithm.
- Since there are so many difficulties in noise removal and also in regular LMS algorithm, an effective and improved version is required for overcoming.
- Experimental results state the proposed system has greater performance on various measures.

### Organization of the paper

As we already came across an overview of ECG and its way to noise removal using LMS in part 1, the remainder of the paper consists of part 2, depicting the literature review, part three explaining the methodology, part 4 illustrating the Performance evaluation and finally summing up with a conclusion in part 5.

**Literature Review**

Using actual ECG signals, Manju and Sneha (2020) [18] investigated filters to denoise several types of noise. The Wiener filter and this Kalman filter are used to remove the sounds. Performance properties such as Mean Square Error (MSE), Percentage Root Mean Square Difference (PRD), Signal to Noise Ratio (SNR), Power Spectral Density (PSD), Spectrogram, and Magnitude Spectrum are used to compare the simulated results. It is shown in simulations that the Wiener filter provides excellent denoising of ECG signals. Based on the self-correcting leaky normalized least square algorithm SC-LNLMS with a variety of step sizes and leakage coefficients, it needs to pass through a noise cancellation algorithm based on the leaky normalized least square algorithm using multiple stages and adjusting both step sizes and leakage coefficients. A new adaptive filter has been proposed by Khiter et al. (2020) [19] for removing EMG noise from corrupted ECG signals. Noise Stress Test database (NSTDB) and MITBIH Arrhythmia database (no noise) were used in the experiment.

Using either a Discrete Fourier Transform (DFT) or Discrete Cosine Transform (DCT), Singhal et al. (2020) [20] analyzed the signal. To identify and inhibit key DFT/DCT coefficients related to BW and PLI, we use an optimal FDM design based on a zero-phase filtering method. We verified the efficiency of our technique using the MIT-BIH Arrhythmia Database. Simulated results indicate that the proposed method outperforms existing state-of-the-art solutions at various levels of Signal to Noise Ratio (SNR).

Chartatterjee et al. (2020) [21] explored the workflow and design ideas employed by each method and categorized them into distinct methods so that they can be compared and developed for mutual advancement in modern ECG denoising methods. Using the MITBIH databases, PTB, QT, and other databases, they have compared ECG denoising strategies based on root-mean-square error, per cent-root-mean-square difference, and signal-to-noise ratio improvement. Several algorithms are suitable for additive white noise reduction including WaveletVBE, EMDMAF, GAN2, GSSSA, more recent MPEKF, DLSR, and AKF. Muscle artefacts can be effectively removed using GAN1, new MPEKF, DLSR, and AKF.

To eliminate these three noise sources, Kose et al. (2020) [22] designed a descendent architecture based on adaptive filters (i.e., motion artefact noise, baseline wander noise and muscle noise). There have been two methods of adaptive filtering developed: Least Mean Square (LMS) and Recursive Least Square (RLS). In evaluating the performance of these filters, several fidelity parameters have been observed, including Mean Square Error (MSE), normalized root mean Square Error (NRMSE), signal-to-noise ratio (SNR), and the Percentage Root Mean Square Difference (PRD), and Maximum Error (ME). A novel attenuation background subtraction approach is presented by Nagasiricha & Prasad (2020) [23]. Adaptive filters are used in this research to eliminate noise using an Extended Squirrel Search (ESS) method. We have developed adaptive Least Mean Square (LMS) and adaptive Recursive Least Square (RLS) filters for noise reduction using an ESS. This new algorithm outperforms others. The Signal-to-Noise Ratio (SNR) measured in decibels, the Maximum Error (ME), the Mean Square Error (MSE), the standard deviation and the mean value difference are all used as performance indicators.

## Methodology

### *Linear Mean Square Algorithm*

This algorithm is an approximation of the steepest descent algorithm. The idea behind LMS filters is to use the steepest descent algorithm to minimize a cost function by finding the filter weights w(n). A Cost function is the mean square error which is minimized by the LMS algorithm [24]. Cost function which is denoted by C(n) can be written as:

$$C(n) = E\{|e(n)^2|\}\ C(n) = E\{|e(n)|^2\} \tag{1}$$

The ECG signal, s is the original uncontaminated input signal. The desired output signal x is the contaminated ECG signal. The adaptive filter will do its best to reproduce this contaminated signal only if the original 50Hz noise source v is known. Therefore, it can only reproduce the part of x which is known as t, that is linearly correlated with v. The adaptive filter will also attempt to mimic the noise source so that the output of the adaptive filter y will be close to the contaminated noise t. Therefore, in this way, the error signal will be close to the original uncontaminated signal ECG signal s. Now (s+t) is the primary input signal e and v be the reference signal (Figure3).

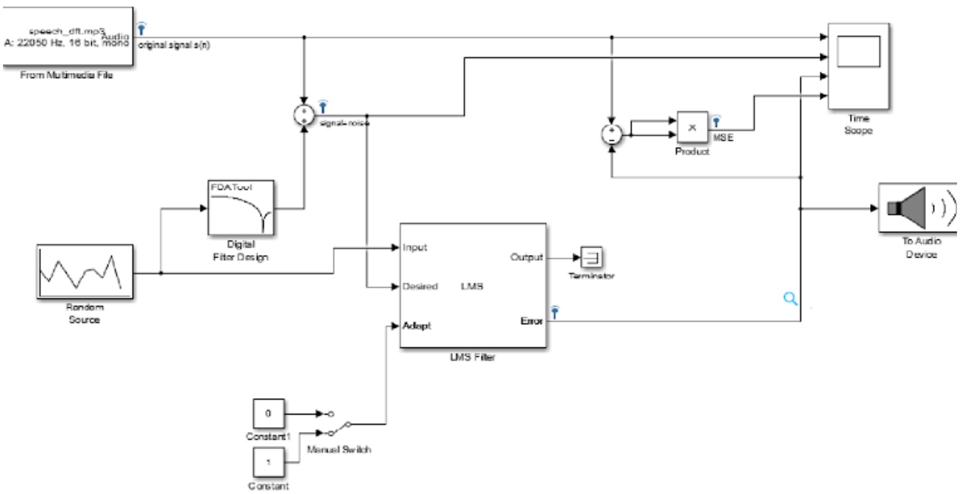


Figure 3. Real time system for LMS

The output of the adaptive filter is y and the error is e, the Mean Square Error (MSE) is given as [2]:

$$e = s + t - y$$
$$e^2 = ((s+t) - y)^2 = (s+t)^2 + y^2 - 2(s+t)y = (t-y)^2 + s^2 \tag{2}$$

Signal and noise are uncorrelated, so their product will be zero. Therefore MSE is:

$$[e^2]_{\min} = E[(t-y)^2]_{\min} + E[s^2] \tag{3}$$

Adapting the filter to minimize the error energy will not affect the signal energy which we obtained after squaring the equation (7) and minimum error energy is obtained from equation (9). E(e-s)2 are also minimized since (e-s) = (t-y). So, we can say that minimizing the total output energy is the same as minimising the noise energy. Minimizing the MSE in a filter, error is the best least square estimate of the signal s, or in other words, an adaptive filter extracts the signal from the noised signal by minimizing the MSE between the reference and primary inputs [25]. The filter weight update equation of the LMS algorithm which helps in minimizing the error is:

$$w(n+1)w(n) + 2\mu e(n)v(n) \quad (4)$$

Here, w(n) is the current weight value vector, and μ is an appropriate step size or convergence factor which is 0<μ<0.2 for the convergence speed and overall behaviour. If the step size is large, then the coefficients fluctuate widely and the LMS algorithm experience a gradient noise amplification problem. In the case of LMS, step size should be less but because of less μ, the rate of convergence is slow. To increase the rate of convergence, the use of PLMS came into the picture.

***Proposed System: PLMS-Sign***

The Proportionate LMS (PLMS) algorithm is an improved version of LMS and improves the adaptive tracking phenomenon and provides superior performance. PLMS also reduces the MSE in the progression of filtering. PLMS is the famous family of sparse adaptive algorithms that exhibits an improved convergence rate than LMS. The proportionate mechanism is driven by a gain matrix, G(n) [26].

$$w(n + 1) = w(n) + \mu\ G(n)\ x(n)\ e(n) \quad (5)$$

Here μ is the step size parameter, e(n) = d(n)−xT(n)w(n) is the estimated error and the gain matrix G(n) computation is the same for all proportionate algorithms. The G(n), allots the efficiency of the estimation to all the coefficients of the filter in equal proportion. It indicates that the extra estimations energy is allocated to the tap weights of the operating filter and minimum estimation energy to the tap weights, which are inoperative. This type of allocation leads to fast convergence in contrast to conventional methods [27-30]. The diagonal values of the G(n) change rapidly with time, thus the recursive computations of the input data vector are stopped. In this process, the vector- matrix-vector multiplications should be performed for every instance and this becomes more complex. Thus it is not suitable for health care monitoring. This mechanism can be modified by eliminating the normalization scheme which leads to the Proportionate LMS algorithm (PLMS). The real representation is shown below:
The estimated weight vector can be written in terms of real and imaginary parts wˆ = wˆ R +jwˆ I, where wˆ R and wˆ I are vectors of length L consisting of the real and imaginary components of wˆ, respectively. Motivated by the derivation of the Normalized Least Mean Square (NLMS) algorithm let us consider the following minimization problem.

$$\min_{\hat{w}}{}^{+}(\hat{w}_R^+ - \hat{w}_R)^T M_R^{-1}(\hat{w}_R^+ - \hat{w}_R)$$
$$+(\hat{w}_I^+ - \hat{w}_I)^T M_l^{-1}(\hat{w}_l^+ - \hat{w}_I)$$

such that

$$d = \mathrm{x}^H \hat{\mathrm{w}}^+ \quad (6)$$

where MR and MI are real-valued, non-negative, diagonal matrices, which have the property that Tr[MR] = Tr[MI ] = L. The method of Lagrange multipliers will be used to cast this constrained minimization problem into one of unconstrained minimization. Before performing this step the following definitions are introduced to aid in the derivation. Let

$$\hat{\omega} = \begin{bmatrix} \hat{\mathrm{w}}_R \\ \hat{\mathrm{w}}_I \end{bmatrix} \mathrm{M} = \begin{bmatrix} \mathrm{M}_R & 0 \\ 0 & \mathrm{M}_I \end{bmatrix} \quad (7)$$

The following form of xHwˆ will also be employed

$$\mathrm{x}^H \hat{\mathrm{w}} = \mathrm{x}_R^T \hat{\mathrm{w}}_R + \mathrm{x}_l^T \hat{\mathrm{w}}_I + j\mathrm{x}_R^T \hat{\mathrm{w}}_I - j\mathrm{x}_l^T \hat{\mathrm{w}}_R$$
$$= [\mathrm{x}_R^T, \mathrm{x}_I^T] \begin{bmatrix} \hat{\mathrm{w}}_R \\ \hat{\mathrm{w}}_I \end{bmatrix} + j[-\mathrm{x}_I^T, \mathrm{x}_R^T] \begin{bmatrix} \hat{\mathrm{w}}_R \\ \hat{\mathrm{w}}_I \end{bmatrix}$$
$$= [\mathrm{x}^H, j\mathrm{x}^H] \begin{bmatrix} \hat{\mathrm{w}}_R \\ \hat{\mathrm{w}}_I \end{bmatrix}$$
$$= [\mathrm{x}^H, j\mathrm{x}^H \mid \hat{\omega}. \quad (8)$$

Using these definitions the minimization problem can be rewritten as:

$$J(\hat{\omega}^+) = (\hat{\omega}^+ - \hat{\omega})^T \mathrm{M}^{-1} (\hat{\omega}^+ - \hat{\omega})$$
$$+\lambda(d - [\mathrm{x}^H, j\mathrm{x}^H \mid \hat{\omega}) + \lambda^*(d^* - [\mathbf{x}^T, -j\mathbf{x}^T]\hat{\omega}). \quad (9)$$

Next, taking the derivative of J(ωˆ +) with respect to ωˆ + and setting the result to zero yields

$$\frac{\partial J(\hat{\omega}^+)}{\partial \hat{\omega}^+} = 2\mathbf{M}^{-1}(\hat{\omega}^+ - \hat{\omega}) - \lambda \begin{bmatrix} \mathbf{x}^* \\ j\mathbf{x}^* \end{bmatrix} - \lambda^* \begin{bmatrix} \mathbf{x} \\ -j\mathbf{x} \end{bmatrix} = 0. \quad (10)$$

Multiplying (5) from the left by M and rearranging terms allows us to write

$$2(\hat{\omega}^+ - \dot{\omega}) = \lambda \mathrm{M} \begin{bmatrix} \mathrm{x}^* \\ j\mathrm{x}^* \end{bmatrix} + \lambda^* \mathrm{M} \begin{bmatrix} \mathrm{x} \\ -j\mathrm{x} \end{bmatrix}. \quad (11)$$

Next, we employ the relationships given by [xH, jxH](ωˆ +−ωˆ ) = e and [xT , −jxT ](ωˆ + −ωˆ ) = e∗ to form the following linear system of equations.

$$2\begin{bmatrix} e^* \\ e \end{bmatrix} = \begin{bmatrix} \mathrm{x}^H(\mathrm{M}_R + \mathrm{M}_l)\mathrm{x} & \mathrm{x}^T(\mathrm{M}_R - \mathrm{M}_l)\mathrm{x} \\ \mathrm{x}^H(\mathrm{M}_R - \mathrm{M}_l)\mathrm{x}^* & \mathrm{x}^H(\mathrm{M}_R + \mathrm{M}_l)\mathrm{x} \end{bmatrix} \begin{bmatrix} \lambda \\ \lambda^* \end{bmatrix} \quad (12)$$

It is straightforward to invert the matrix given in (7) which allows us to find

$$\lambda = 2\frac{\mathrm{x}^H(\mathrm{M}_R+\mathrm{M}_l)\mathrm{x}e^* - \mathrm{x}^T(\mathrm{M}_R-\mathrm{M}_l)\mathrm{x}e}{[\mathrm{x}^H(\mathrm{M}_R+\mathrm{M}_I)\mathrm{x}]^2 - |\mathrm{x}^T(\mathrm{M}_R-\mathrm{M}_t)\mathrm{x}|^2}. \quad (13)$$

Returning our attention to (6) this equation can be rewritten as:

$$2(\dot{\omega}^+ - \dot{\omega}) = \lambda \begin{bmatrix} \mathrm{M}_R x^* \\ j\mathrm{M}_1 \mathrm{x}^* \end{bmatrix} + \lambda^* \begin{bmatrix} \mathrm{M}_R \mathrm{x} \\ -\mathrm{M}\mathrm{M}_1 \mathrm{x} \end{bmatrix} \quad (14)$$

Using the definition in (2) allows us to write

$$2(\hat{w}_R^+ - \dot{w}_R) = \lambda \mathrm{M}_R \mathrm{x}^* + \lambda' \mathrm{M}_R \mathrm{X}$$
$$2(\hat{w}_l^+ - \hat{w}_I) = j\lambda M_l x^* - j\lambda^* M_I x$$

(15)

Next using (10) and (8), we form

$$\bar{w}^{\top} - \bar{w} = (\bar{w}_R^{\top} - \bar{w}_R) + j(\bar{w}_I^{\top} - \bar{w}_I)$$
$$= \frac{\lambda}{2} M_R x^* + \frac{\lambda^*}{2} M_R x - \frac{\lambda}{2} M_I x^* + \frac{\lambda^*}{2} M_I x$$
$$= \frac{\lambda}{2} (M_R - M_I) x^* + \frac{\lambda^*}{2} (M_R + M_I) x$$
$$= \frac{[x^H (M_R + M_I) x e^* - x^T (M_R - M_I) x e]}{[x^H (M_R + M_I) x]^2 - |x^T (M_R - M_I) x|^2} (M_R - M_I) x^*$$
$$+ \frac{[x^H (M_R + M_I) x e - x^H (M_R - M_I) x^* e^*]}{[x^H (M_R + M_I) x]^2 - |x^T (M_R - M_I) x|^2} (M_R + M_I) x.$$

(16)

The overall generalized algorithm is shown below in Figure 4.

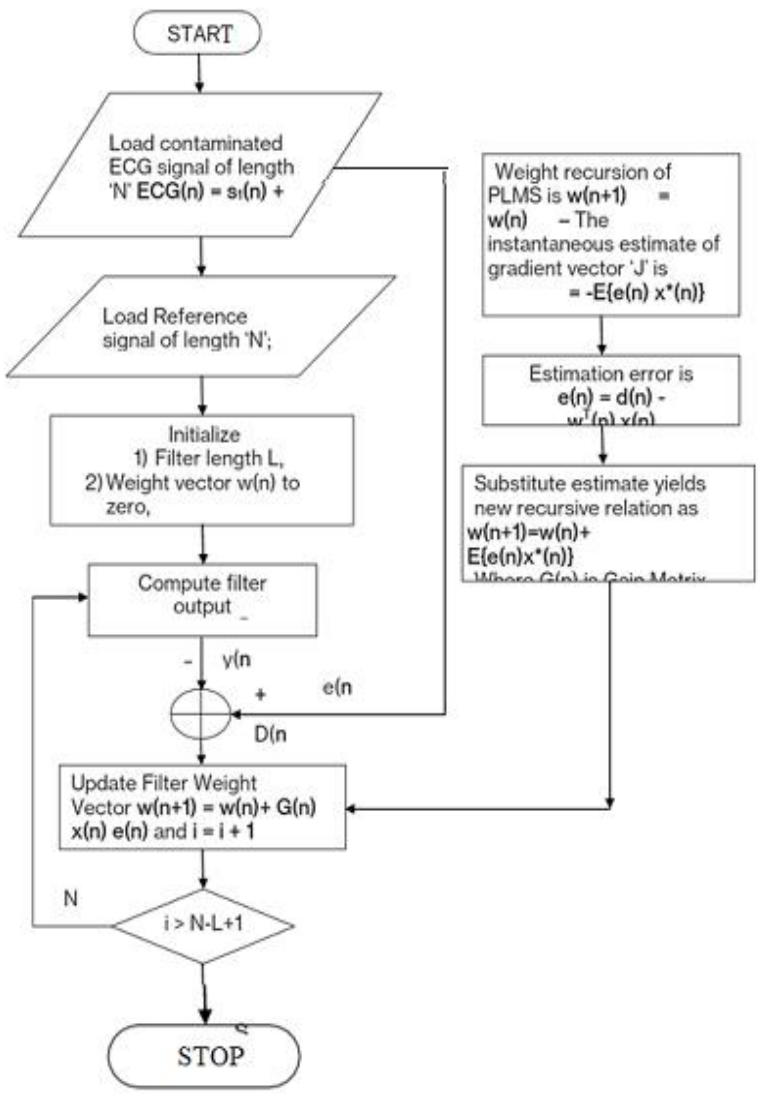


Figure 4. PLMS for better noise cancellation of ECG

***Sign based PLMS***

To minimize the computational burden of the LMS method, we use SRA, SA and SSA adaptive methods to realize hybrid versions of PLMS and sign-based algorithms. PLMS algorithm is a basic type of the higher-order adaptive filter. The combination of PLMS with SRA, SA and SSA gives Sign Regressor Proportionate LMS (SRPLMS), Signed Proportionate LMS (SPLMS) and Sign Sign Proportionate LMS (SSPLMS) respectively [29-35].

**Performance Analysis**

For the implementation of adaptive algorithms and error minimization, data collected is raw ECG recorded data of different subjects like 100, 101, 108, 113, 114, 117, 118, 205 etc. from Physionet-bank, MIT-BIH arrhythmia database, with sampling frequency 360Hz over a period of just 10 seconds but we select one patient (record # 101) to analyze the data and to get required results. Similarly, it can also be done for other patients.

***Noise1: Power Line Interface (PLI)***

The 50Hz power-line interference is added to an original ECG signal collected from the physionet and gets the noisy signal. This corrupted/noisy signal is taken as the desired signal and the signal coming from the noise source is applied as a reference signal which is linearly correlated with the noise signal but uncorrelated with the original ECG signal. Finally, by subtracting the reference signal from the noise signal, PLI is removed using LMS and PLMS Algorithms. Table 1 depicts the overall analysis of LMS and PLMS over MSE, SNR and RMSE. Figure 5 depicts the graphical representation of LMS and PLMS under MSE, SNR and RMSE.

Table 1
Overall analysis for PLI Noise

| Algorithm | Records | MSE | SNR | RMSE |
|---|---|---|---|---|
| LMS | 100 | 0.013 | 0.94 | 0.153 |
| | 101 | 0.0135 | 0.943 | 0.154 |
| | 108 | 0.0137 | 0.942 | 0.156 |
| | 113 | 0.0138 | 0.946 | 0.153 |
| | 114 | 0.0132 | 0.945 | 0.152 |
| | 117 | 0.0131 | 0.941 | 0.153 |
| | 118 | 0.0136 | 0.933 | 0.157 |
| | 205 | 0.0135 | 0.948 | 0.154 |
| PLMS | 100 | 0.021 | 0.97 | 0.147 |
| | 101 | 0.022 | 0.98 | 0.142 |
| | 108 | 0.016 | 0.94 | 0.141 |
| | 113 | 0.017 | 0.95 | 0.139 |
| | 114 | 0.015 | 0.96 | 0.142 |
| | 117 | 0.015 | 0.97 | 0.146 |
| | 118 | 0.016 | 0.95 | 0.146 |
| | 205 | 0.017 | 0.94 | 0.144 |

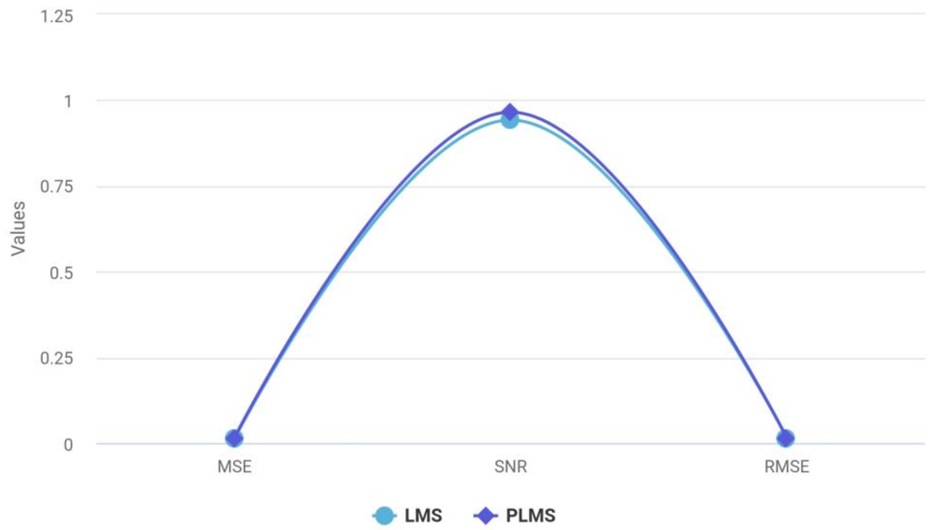


Figure 5. The overall analysis of LMS and PLMS under PLI noise removal

***Noise2: Baseline Wander (BW)***

BW noise is a low-frequency noise which occurs because of respiration. The frequency taken for this signal is 0.5Hz. Because of this noise, the original ECG signal drifts from its baseline and the noise is added to the original as a sinusoidal signal with a 0.5 Hz frequency. From the figures, it can be seen that the results shown by LMS and PLMS look the same. So it is not possible to analyze by only seeing which algorithm converges faster. But in Baseline Wandering noise convergence takes place only if the step size is $\mu$=0.000000001 for the LMS algorithm and $\mu$ = 0.000001 for the PLMS algorithm otherwise it keeps on diverging. So, the PLMS algorithm is better for BW noise because only in this case convergence is obtained. Table 2 depicts the overall analysis under BW over MSE, SNR and RMSE measures. Figure 6 depicts a graphical representation of LMS and PLMS under various measures.

Table 2
Overall analysis under BW noise

| Algorithm | Records | MSE | SNR | RMSE |
|---|---|---|---|---|
| LMS | 100 | 0.023 | 0.93 | 0.133 |
| | 101 | 0.024 | 0.933 | 0.134 |
| | 108 | 0.026 | 0.932 | 0.136 |
| | 113 | 0.022 | 0.936 | 0.133 |
| | 114 | 0.021 | 0.935 | 0.132 |
| | 117 | 0.020 | 0.931 | 0.133 |
| | 118 | 0.021 | 0.933 | 0.137 |
| | 205 | 0.023 | 0.938 | 0.134 |
| PLMS | 100 | 0.031 | 0.957 | 0.157 |
| | 101 | 0.022 | 0.958 | 0.152 |
| | 108 | 0.016 | 0.954 | 0.141 |

| | | | | |
|---|---|---|---|---|
| | 113 | 0.027 | 0.955 | 0.139 |
| | 114 | 0.025 | 0.956 | 0.152 |
| | 117 | 0.015 | 0.957 | 0.146 |
| | 118 | 0.016 | 0.955 | 0.146 |
| | 205 | 0.014 | 0.956 | 0.144 |

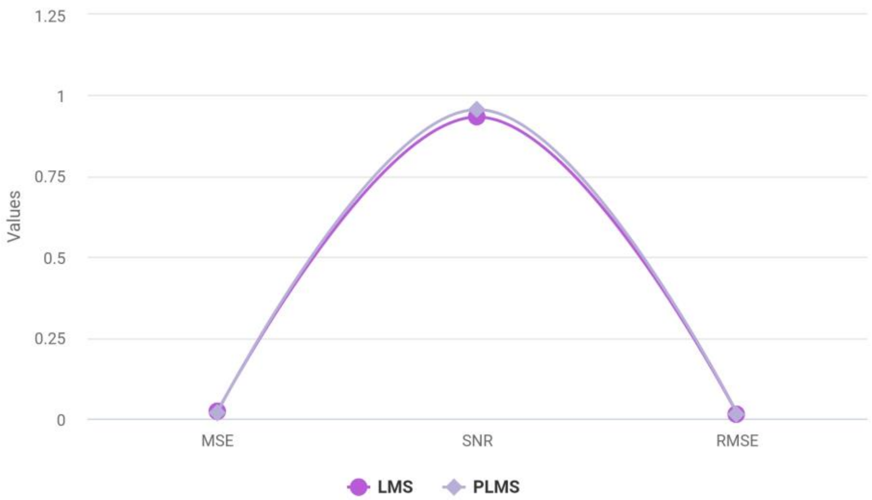


Figure 6. Overall analysis under LMS and PLMS on BW noise

***Noise3: Muscle Contraction Noise (MCN)***

Muscle contraction noise occurs due to the contraction of muscles beside the heart muscles. In other words, this noise occurs due to the generation of artificial mili-volt level potential. This noise is insignificant usually because it is induced in the patient's body randomly. This noise is a very small or negligible noise with a very small range. To obtain the simulation results by adding this noise to the ECG signal, a random signal is used. The maximum level of noise is formed if the amplitude of the random signal added to the original ECG is±50% of the uncorrupted ECG signal. Table 3 depicts the overall analysis under MSE, SNR and RMSE. Figure 7 depicts the graphical representation of LMS and PLMS under various measures.

Table 3
Overall analysis for MC noise

| Algorithm | Records | MSE | SNR | RMSE |
|---|---|---|---|---|
| LMS | 100 | 0.033 | 0.93 | 0.123 |
| | 101 | 0.034 | 0.953 | 0.124 |
| | 108 | 0.036 | 0.952 | 0.126 |
| | 113 | 0.032 | 0.956 | 0.123 |
| | 114 | 0.031 | 0.955 | 0.122 |
| | 117 | 0.020 | 0.941 | 0.123 |
| | 118 | 0.021 | 0.943 | 0.127 |
| | 205 | 0.033 | 0.948 | 0.124 |
| PLMS | 100 | 0.041 | 0.967 | 0.147 |

| | | | | |
|---|---|---|---|---|
| | 101 | 0.042 | 0.968 | 0.142 |
| | 108 | 0.036 | 0.964 | 0.141 |
| | 113 | 0.037 | 0.965 | 0.149 |
| | 114 | 0.035 | 0.966 | 0.142 |
| | 117 | 0.025 | 0.957 | 0.146 |
| | 118 | 0.026 | 0.955 | 0.146 |
| | 205 | 0.024 | 0.966 | 0.144 |

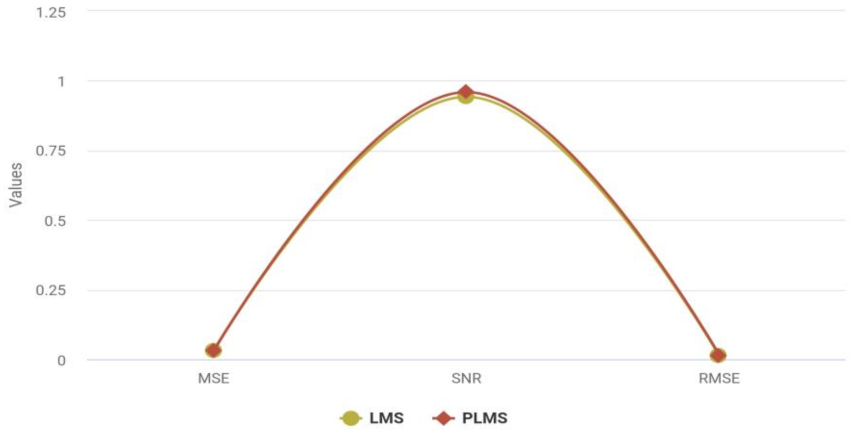


Figure 7 Overall analysis of MC noise removal for LMS and PLMS

## Conclusion

This paper presents an effective and improved LMS algorithm for better ECG enhancement. This paper brings an improved LMS i.e., a Proportionate LMS algorithm for bringing such high convergence compared to conventional LMS algorithm. Since its sign is based on PLMS, it also gives an add on to that PLMS in an even more effective way. Experimental results are conducted over 3 noises such as PLI, BW and MC over various medical records collected from the database. This paper will be also helpful for other research specialists to dig deep and understand the stages and bring an integrated approach for better ECG enhancement.

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