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A novel adaptive noise cancellation method based on minimization of error entropy for electrocardiogram denoising

Zahraa Mousa Saad[1], Nsaif Jasim Al-Chaabawi[2], Saif Al_Deen H. Hassan[3]
[1]Department of Economy, College of Administration and Economics, University of Misan, Amarah, Iraq
[2]Department of Petroleum, College of Engineering, University of Misan, Amarah, Iraq
[3]Electronic Computing Center, University of Misan, Amarah, Iraq

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ABSTRACT

In this paper, we use an adaptive method that conforms to the error entropy criterion in order to eliminate noise from cardiac signals electrocardiogram (ECG). In previous works, the mean squared error (MSE) criterion has been used to adaptive noise cancelation of ECG signals, which only has the ability to minimize the second moment of error. The MSE criterion only works optimally on systems with Gaussian noise and stationary signals, so this is not suitable for ECG signals that are non-stationary and have non-Gaussian noise. In contrast, the use of error entropy-based algorithms like minimum error entropy (MEE) is very useful in ECG noise cancelation. The results of the proposed algorithm indicate a significant advantage in terms of signal-to-noise ratio (SNR) and convergence value compared to the algorithm based on MSE criteria.

Corresponding Author:

Nsaif Jasim Al-Chaabawi
Department of Petroleum, College of Engineering, University of Misan
62001, Misan, Amarah, Iraq
Email: nsf_jsm@uomisan.edu.iq

1. INTRODUCTION

Electrocardiogram (ECG) is among the most important diagnostic methods for initial recognition of cardiac disorders. Thus, having a high-quality ECG signal is essential for accurate diagnosis and treatment of cardiac disorders. Numerous artifacts exist in the medical environment which their impacts on ECG signal quality is negative during signal recording. To improve ECG signals quality, removing these artifacts from them is an important issue. Some of these artifacts belong to environmental sources and others are related to biological resources. The most common high-amplitude ECG noises include: electrode motion (EM), baseline wander (BW), power line interference (PLI), and muscle artifacts the majority of these noises [1], [2] are non-Gaussian, highly non-stationary in time, and colored.

There are different strategies to remove these artifacts, which can be divided into two different classes, including adaptive and nonadaptive methods [3]–[9]. Since the ECG signals have a dynamic and non-linear nature, applying filters with constant coefficients in order to eliminate biomedical signal artifacts will not be perfect [10]. Consequently, using adaptive techniques have more advantages compared to non-adaptive ones, since adaptive filtering techniques have the ability to track dynamic variations of the signals.

The user should specify a parametric mapper filter that is either linear or non-linear, an optimality measure, and an algorithm to weight adaptation based on adaptive filtering. Mean-squared error (MSE) criterion is a widely used criterion among designers. The least mean square (LMS) method introduced by Widrow [11] is also among the finest methods used for weight adaptations based on MSE. The performance of the LMS algorithm has been improved by a number of revised algorithms, which are reported in [12], [13].

Other methods use the normalized least-mean-square (NLMS) algorithm, which reduces step size to reach the global minimum [14], the NLMS algorithm with variable step size and faster convergence [15], and the sign algorithm, which lowers processing costs [16]. Although the MSE criterion is frequently used in filter adaptation, it can only take into account the second-order statistics of the mistake. Despite this shortcoming, it is obvious why second-order statistics are emphasized as the optimality criterion for adaptive filtering applications for three key reasons: i) analytical tractability, ii) the presumption that second-order statistics can adequately explain real-world random occurrences, and iii) the abundance of effective adaptive algorithms are the first two. The central limit theorem emphasizes that the Gaussian probability density function (PDF), which is only governed by first- and second-order statistics, is used to describe various real-life aberrations affecting the desired signals. The aberrations that taint the ECG records, however, include non-Gaussian distributions, as is evident from the analysis of the ECG signals. Therefore, it is necessary to employ criteria that consider both higher order statistical behavior of systems and signals as well as second-order statistics when evaluating systems and signals.

Entropy [17]–[21] is a more universal adaptive filtering criterion since it quantifies the average information intrinsic in a given PDF. The MSE can be expanded if information is used as an optimality criterion. The major reason is that it is a function of PDF itself, whereas by MSE only the second order statistics of the PDF is considered. In an adaptive filter, when the entropy is minimized, all moments of the error PDF are constrained, compared to the MSE minimization, which constraints only the second-order statistics.

In this study, the ECG signal is cleaned of noise and artifacts using an adaptive filter with an error entropy criterion. The error entropy between the main input and the reference input is reduced using this technique. The algorithm employed for this is known as minimum error entropy - adaptive noise canceller (MEE-ANC), and it updates the adaptive filter weights by minimizing error entropy in order to provide a denoised ECG signal. The calculation of the error entropy, which is a function of the error PDF, is a key component of this approach. Since no assumptions are made here regarding the PDF of the ECG anomalies, the suggested structure is based on a combination of a nonparametric PDF estimator and a technique to compute entropy. The Parzen window approach is crucial for the former [22]. For the latter, the quadratic form of a more general form of entropy measure, i.e. α-Renyi's entropy [23], has been utilized as a measure of the entropy instead of the classic entropy definition introduced by Shannon.

Results show that the proposed MEE based adaptive algorithm outperforms the conventional LMS algorithm, which uses MSE criterion, to cancel each of four main categories of ECG artifacts, i.e., PLI, BW, EM and MA. The MEE algorithm is described in section 2 of the following. First, we define the -order Renyi's entropy of error in our experiments by treating the error as the random variable. Following that, the Parzen windowing process is used to represent the error probability density function. We then offer the error entropy measurement. The adaptive noise canceller system is covered in section 3. Additionally, we'll look into the analytical relationships between our methodology and the traditional LMS method according to the MEE measure. The effectiveness of LMS and MEE-based techniques is contrasted in section 4 in terms of their capacity to simulate away four significant forms of disturbances that taint ECG signals. Finally, section 5 expresses the conclusion.

2. MINIMUM ERROR ENTROPY ALGORITHM

Assume that e is the random variable representing the error that the adaptive system generates as a result of the discrepancy between the desired and actual outputs. The goal of the adaptive filtering structure is e minimization. The following equation [23] will be used to calculate the e's -order Renyi's entropy:

$$H_\alpha(e) = \frac{1}{1-\alpha} \log \int f^\alpha(e)\, de \tag{1}$$

where $f(e)$ represents the error random variable's probability density function. Based on the following formula, we utilize Renyi's quadratic entropy (i.e., =2) as a measure of entropy in our experiments:

$$H_2(e) = -\log \int f^2(e)\, de \tag{2}$$

Equations (1) and (2) show that the PDF of the provided random variable must be determined before the entropy of the random variable can be calculated. Our non-parametric adaptive method works under the premise that the error's PDF is unknown. Additionally, the adaptive filter processes each data sample separately. As a result, we require a PDF estimator to calculate the probability density function for the samples of incoming data. A useful tool for this is the Parzen windowing technique, which may be acquired as:

$$\hat{f}(e) = \frac{1}{N}\sum_{i=1}^{N} k_\sigma\,(e - e(i)) \tag{3}$$

where $k(e)$ and σ denote Kernel function and the size of Kernel, respectively. Also, $\{e(1), e(2), \ldots, e(N)\}$ show error samples. For the Parzen window, various Kernel functions are used. For the sake of simplicity, we will be using the multidimensional Gaussian function with radially symmetric σ^2. Thus, the following equations are used to estimate Renyi's quadratic entropy for error samples:

$$\hat{H}_2(e) = -\log \int_{-\infty}^{+\infty} \left(\frac{1}{N}\sum_{i=1}^{N} G_\sigma(e - e(i))\right)^2 de \tag{4}$$

$$\hat{H}_2(e) = -\log \frac{1}{N^2} \int_{-\infty}^{+\infty} \left(\sum_{i=1}^{N}\sum_{j=1}^{N} G_\sigma(e - e(j)) G_\sigma(e - e(i))\right) de$$

$$\hat{H}_2(e) = -\log \frac{1}{N^2} \left(\sum_{i=1}^{N}\sum_{j=1}^{N} \int_{-\infty}^{+\infty} G_\sigma(e - e(j)) G_\sigma(e - e(i))\right) de$$

where the kernel function with a Gaussian core is $G_\sigma(.)$. Remember that the integral of the product of the two original Gaussian functions is computed using the sum of their variances to determine the value of the Gaussian determined at the point where the arguments diverge. Consequently, $\hat{H}_2(e)$ can be expressed as (5).

$$\hat{H}_2(e) = -\log\left(\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} G_{\sigma\sqrt{2}}(e(j) - e(i))\right) \tag{5}$$

The phrase that is inside log operator is defined as information potential (IP), and can be obtained from the incoming samples using Gaussian kernels as,

$$\hat{V}_2(e) = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} G_{\sigma\sqrt{2}}(e(j) - e(i)) \tag{6}$$

accordingly, for error random variable, we can obtain entropy:

$$\hat{H}_2(e) = -\log\left(\hat{V}_2(e)\right) \tag{7}$$

since the log is a monotonic function, it is evident from (7) that minimizing Renyi's quadratic entropy is equivalent to increasing the information potential. The suggested adaptive noise canceller uses this expression of error entropy in the following section.

3. THE PRESENTED ADAPTIVE NOISE CANCELLER SYSTEM

Figure 1 shows the flowchart of the presented adaptive noise canceller structure using adaptive filtering. In this Figure 1, $x(n)$ denotes the reference input with length N and $d(n)$ expresses the desired input. For utilizing above system to remove noise from ECG signal, an ECG signal, $s_1(n)$ that is corrupted with noise $P_1(n)$, is exerted to the adaptive filter as the desired input $d(n)$. A noise signal, $P_2(n)$, which is generated by another noise source is exerted as the reference input, $x(n)$. This noise is assumed to be correlated to $P_1(n)$. Besides, signal and noise are supposed to be uncorrelated. Then, the output error is obtained as:

$$e(n) = [s_1(n) + P_1(n)] - y(n) \tag{8}$$

where the filter output is shown by $y(n) = \boldsymbol{W}^T(n)\boldsymbol{X}(n)$. A shown in (8), $\boldsymbol{W}(n) = [w_0(n)\ w_1(n) \ldots\ w_{L-1}(n)]$ denotes the filter input vector, and $\boldsymbol{X}(n) = [x_0(n)\ x_1(n) \ldots\ x_{L-1}(n)]$ means the filter coefficients weight vector (in *n*th time index). The following will demonstrate how, because the ECG signal and both noises are uncorrelated, reducing e(n) using either the MSE or MEE measure results in the contamination noise in the ECG signal ($P_1(n)$) being similar to y(n). Therefore, in our study, the desired denoised ECG signal is created using the output error signal, e(n).

In the following subsections, we first provide an explanation of the basic LMS approach for adaptive noise canceller (LMS-ANC), which is utilized as the benchmark. The MEE-trained adaptive filter for noise canceller (MEE-ANC) is explained after that.

3.1. Adaptive noise canseller based on LMS

The usual adaptive LMS technique can iteratively decrease the mean squared error between the principal input if the filter coefficients are adjusted. The reference input is a recorded noise signal that is correlated with the primary input, which is a noisy ECG signal. The LMS is one of the simplest adaptive structures based on the MSE criterion. The LMS algorithm has many uses because of its stability and ease of use with signal statistics.

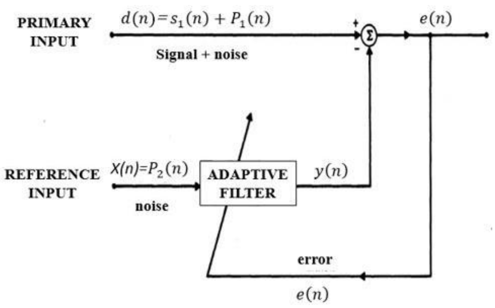


Figure 1. Adaptive noise cancellation structure

The following is how MSE is obtained in the proposed adaptive noise canceller system, which is shown in Figure 1:

$$E[e^2(n)] = E[s_1(n)^2] + E[(p_1(n) - y(n))^2] + 2E\big[s_1(n).\big(p_1(n) - y(n)\big)\big] \tag{9}$$

since $s_1(n)$ will be uncorrelated with both $p_1(n)$ and $y(n)$, as a result:

$$E[e^2(n)] = E[s_1(n)^2] + E[(p_1(n) - y(n))^2] \tag{10}$$

the problem is to adapt the filter coefficients through minimizing the MSE. Accordingly, there is no effect on the primitive signal $s_1(n)$, and the following equation is satisfied:

$$MIN\ E[e^2(n)] = E[s_1(n)^2] + MIN\ E[(p_1(n) - y(n))^2] \tag{11}$$

the following formula will be used to update the filter coefficients in order to reduce MSE adaptively based on the preceding equation about the LMS methodology:

$$\boldsymbol{W}(n+1) = \boldsymbol{W}(n) + \mu.\nabla E[e^2(n)] \tag{12}$$

in which $\nabla E[e^2(n)] = \boldsymbol{X}(n)e(n)$, therefore:

$$\boldsymbol{W}(n+1)\ = \boldsymbol{W}(n) + \mu\boldsymbol{X}(n)e(n) \tag{13}$$

in which the parameter μ shows the size of step.

It should be noted that (11) states that if the error's mean square is decreased, the best least-squares estimate of signal $s_1(n)$ is obtained in the filter output. This shows that the created error signal shares second-order characteristics with the original ECG signal. The LMS-based approach can extract as much information as is practical from the error signal because it only uses the first and second order statistics of the error signal $e(n)$ with a Gaussian distribution to describe it. The quality of the reconstructed ECG signal is therefore appropriate. However, the artifacts that have higher order statistics, i.e., non-Gaussian distributions, are what contaminate the ECG recordings. Since this higher order statistic is not considered in the LMS method, it would not be capable to remove ECG artifacts entirely. So, deployment of the MEE criterion will be presented in order to updating the adaptive noise canceller (ANC) weights.

3.2. MEE-based ANC system

The filter coefficients in the provided adaptive noise canceller system will be adjusted in accordance with the error entropy criterion minimization in order to reconstruct the ECG signal. This criterion is used to develop the equations required to update the active noise control/cancelation (ANC) weight vector W. As shown in (8)'s definition of error leads to the following calculation of error entropy (14).

$$H[e] = H[s_1 + p_1 - y] \tag{14}$$

Assume X and Y denote two independent variables randomly. Generally, an equality relation for the entropy of summation of two random variables does not exist, but by supposing independency of them, the following inequality is satisfied:

$$\max\{H(X), H(Y)\} \leq H(X+Y) \leq H(X) + H(Y) \quad (15)$$

by employing the above inequality and also if it is imagined that signal and noise are independent, the following inequality is written for (14):

$$H(s_1) \leq H(e) \leq H(s_1) + H(p_1 - y) \quad (16)$$

adapting the filter coefficients according to MEE, leads to minimizing the entropy of error, $H(e)$. Since it has no effect on the primitive signal, $s_1(n)$, the following inequality can be obtained regarding (16):

$$H(s_1) \leq \min\{H(e)\} \leq H(s_1) + \min\{H(p_1 - y)\} \quad (17)$$

if $\min\{H(p_1 - y)\}$ approaches zero, then:

$$\min\{H(e)\} \approx H(s_1) \quad (18)$$

by decreasing the entropy of error in a filter output, the best minimum entropy estimate of the signal $s_1(n)$ is obtained. This technique lowers the entropy of the incorrect signal, $e(n)$. If the error entropy is kept as low as possible, all error distribution moments will be minimized. The cause of it is because entropy is a PDF function. Therefore, since non-Gaussian disturbances in ECG signals have higher order statistics, this approach is advantageous for them.

As shown in (7), to minimize the error entropy, it is sufficient to maximize the information potential. For online training methods used in the adaptive filters, IP should be estimated iteratively. To do so, the stochastic information gradient (SIG) can be used as:

$$\hat{V}_2(e(n)) \approx \frac{1}{L}\sum_{i=n-L}^{n-1} G_{\sigma\sqrt{2}}(e(n) - e(i)) \quad (19)$$

where, for $n - L \leq i \leq n$, $e(i) = d(i) - \boldsymbol{W}^T(n)\boldsymbol{X}(i)$ in equation (19), the most recent L samples at time n are used for the summing. The coefficients are updated by implementing the MEE-SIG approach [24] using the following equation in order to adaptively reduce the entropy of the error signal $e(n)$:

$$\boldsymbol{W}(n+1) = \boldsymbol{W}(n) + \mu.\nabla V(e(n)) \quad (20)$$

in which the IP gradient will be computed as (21).

$$\nabla V(e(n)) = \frac{1}{2\sigma^2 L}\sum_{i=n-L}^{n-1} G_{\sigma\sqrt{2}}(e(n) - e(i))\{e(n) - e(i)\}\{\boldsymbol{X}(n) - \boldsymbol{X}(i)\} \quad (21)$$

It should be noted that the LMS method is a peer of the MEE-SIG adaptive filter in the group of adaptive filters in accordance with the MSE measure [23]. This filter builds adaptive systems in accordance with the MEE measure. The efficiency of the MEE-ANC filter will next be compared to that of the LMS-ANC filter using simulations.

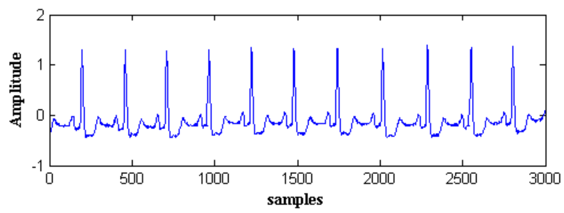
4. THE RESULTS OF SIMULATION

We implement the benchmark LMS-ANC method and the proposed MEE-ANC methodology using MATLAB®. This study uses a variety of ECG recordings from the MIT-BIH arrhythmia database (MITDB) with a range of wave shapes to show how well the suggested approach works as a noise canceller [25]. 48 two-channel ambulatory ECG recordings from 47 research participants at the BIH Arrhythmia Laboratory are included in this collection along with detailed comments. Based on this database, the adaptive filter's principal input, d(n), is the original ECG signal that has been damaged by noise. PLI, BW, EM, and MA are four significant noise types that are inherent in recorded ECG signals and are regarded as the reference signal x(n) (see Figure 1), which should be subtracted from the noisy ECG signal. The MIT-BIH normal sinus rhythm database (NSTDB) will be used to retrieve the BW, MA, and EM noise samples [26]. Without using any harmonics, simulations produce the PLI noise. The signal to noise ratio at the adaptive filter input is taken to be 1.25 dB for the aforementioned situations. The signal-to-noise ratio improvement (SNRI) is determined by comparing the input and output SNR, and the obtained findings are compared with those of the LMS-ANC algorithm in order to assess the effectiveness of the provided approach. For the LMS method and the MEE method, the step-size (μ) parameter is regarded as 0.01 and 1, respectively.

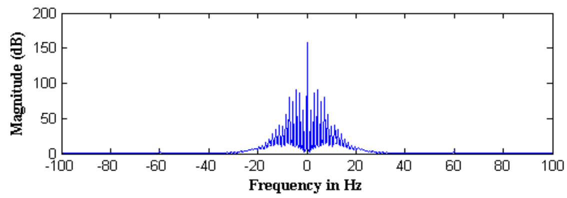
In our computations, we use 10,000 samples of the ECG signals. Table 1 gives the effectiveness comparison of applying MEE-ANC and LMS-ANC methods over five various ECG records in terms of SNRI (dB). As can be seen, MEE-ANC method has far better efficiency in eliminating all of above-mentioned noises. In the following, the denoising performance of the proposed algorithm is discussed in the presence of each of the noises in more detail, separately. All figures in this work have been plotted for first 3,000 so that the results can be seen more clearly. Besides, for all the figures, x-axis and y-axis indicate the samples number and the signals magnitude, respectively. Figure 2 shows the clean ECG signal, taken from data 105, before adding noise. In this regard, Figure 2(a) indicates the signal in the time domain and Figure 2(b) depicts its frequency spectrum.

Table 1. Comparison of LMS- and MEE-based algorithms in terms of SNR improvement (dBs)

Noise	PLI		BW		MA		EM	
Rec. no.	LMS	MEE	LMS	MEE	LMS	MEE	LMS	MEE
100	13.86	18.09	6.65	20.51	9.10	15.59	7.66	16.33
101	13.76	16.26	6.68	16.72	9.58	16.97	8.89	14.16
102	12.91	13.47	7.59	14.55	9.77	16.72	8.29	14.79
103	13.83	16.42	10.72	14.14	11.63	11.91	11.11	19.18
104	13.45	15.24	11.35	15.37	10.10	15.87	10.95	21.03
105	14.42	21.86	10.80	12.78	12.95	22.27	12.23	16.64
average	13.705	16.89	8.967	15.678	10.51	16.555	9.855	17.02



(a)



(b)

Figure 2. ECG signal and its frequency spectrum (data 105 taken from the MIT-BIH database) (a) magnitude in the time domain and (b) magnitude in the frequency domain

4.1. Adaptive power line interference cancellation

PLI, which is brought on by electric power lines, is viewed as high frequency noise when compared to the frequency content of the ECG signal. To get rid of this noise, a synthetic PLI with a 1 mV range is employed as the reference signal. Additionally, the main input of the adaptive filter is an ECG signal with synthetic PLI at a frequency of 60 Hz. Figure 3 displays the outcomes of noise removal using LMS- and MEE-based algorithms, in which Figures 3(a) and 3(b) illustrate the raw signal and the noisy one, respectively. Furthermore, Figures 3(c) and 3(d) the obtained results for each algorithm. The average SNR improvement for the MEE technique is 16.89 dB, as opposed to 13,705 dB for the conventional LMS approach, as shown in Table 1. In order to show the convergence characteristics of LMS and MEE approaches, we exhibit the difference between signals, which comprises the clean and reconstructed signals acquired by both methods in Figure 4, where Figure 4(a) illustrates the elimination results for LMS algorithm and Figure 4(b) illustrates the elimination results for MEE algorithm. As can be seen, the MEE method speeds up convergence while also reducing steady state error. The frequency spectrum for MEE and LMS algorithms, both before and after filtering, is shown in Figure 5. In this regard, Figure 5(a) shows the signal contaminated with 60 Hz PLI, Figure 5(b) illustrates its frequency spectrum after filtering by MEE, and Figure 5(c) shows its frequency spectrum after filtering by LMS.

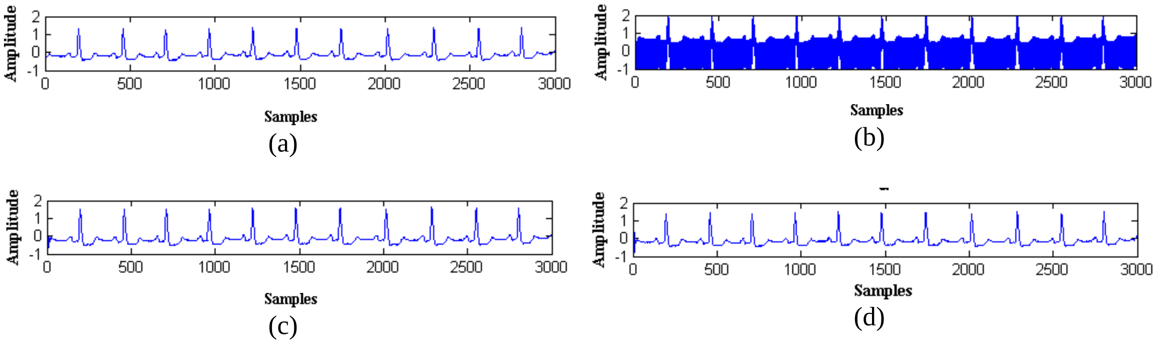


Figure 3. PLI elimination results (a) original ECG, (b) noisy ECG, (c) recovered by LMS algorithm, and (d) recovered by MEE algorithm

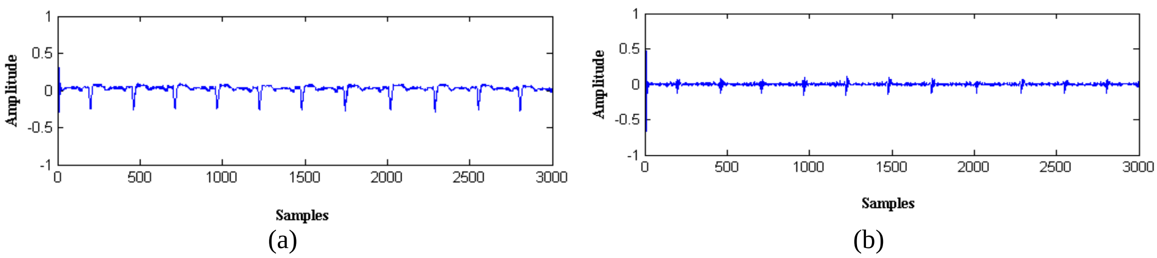


Figure 4. The difference signals between original and reconstructed signals (a) PLI elimination results for LMS algorithm, and (b) PLI elimination results for MEE algorithm

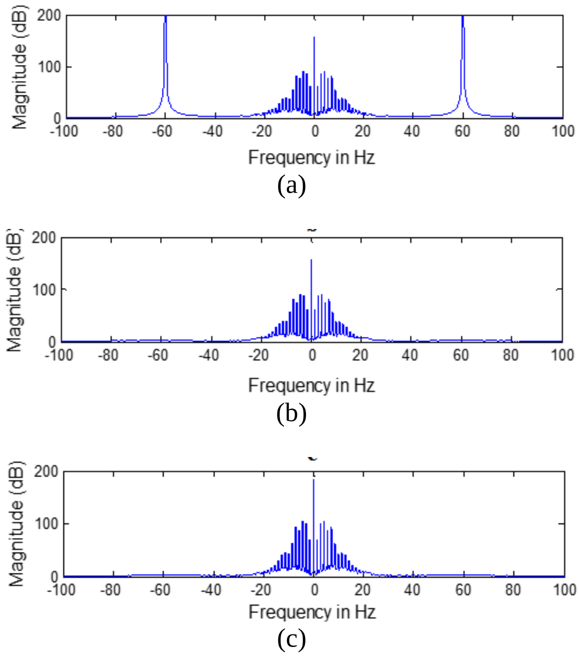
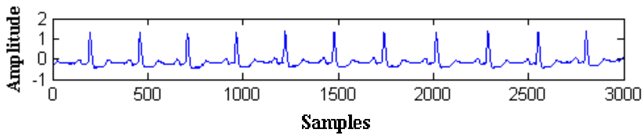


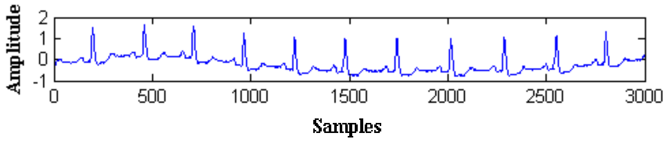
Figure 5. The frequency spectrum of the ECG signal, both before and after filtering (a) frequency spectrum corrupted with PLI at a frequency of 60 Hz, (b) frequency spectrum after filtering by MEE, and (c) frequency spectrum after filtering by LMS

4.2. Adaptive Baseline wander reduction

Baseline wandering of the ECG signal is a result of factors such patient movement, respiration, and contact between the electrodes and skin. ECG signal that has been tampered with using BW is used as the main input to get rid of this noise. As seen in picture 1, real BW is also provided as the reference signal x(n). Figure 6 shows the outcomes of the noise removal. The average SNR improvement for MEE is 15,678 dB, compared to 8.967 dB for traditional LMS. Figure 7 also shows the signals that differ. Figure 7(a) shows that when non-Gaussian noise is present, some BW will be remined in the filter output after LMS filtering as shown in Figure 7(b), demonstrating the inadequacy of the MSE criterion.



(a)



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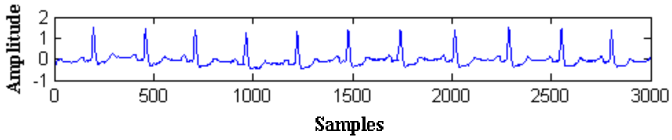

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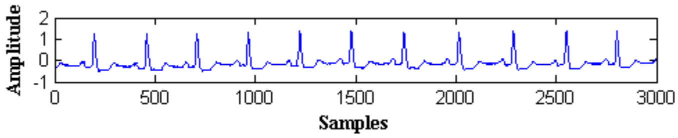
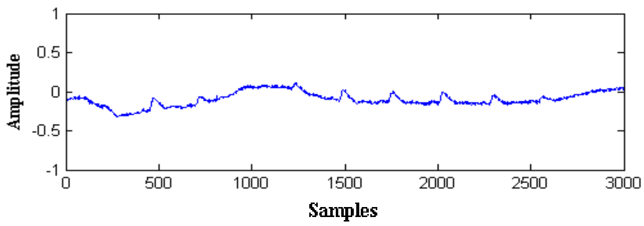
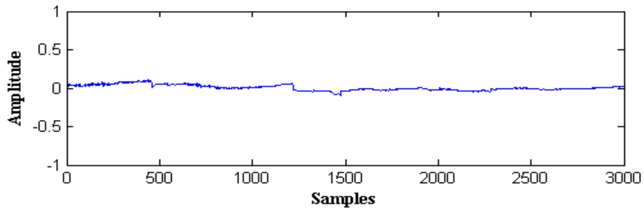


(d)

Figure 6. BW elimination results (a) original ECG, (b) noisy ECG, (c) recovered by LMS algorithm, and (d) recovered by MEE algorithm



(a)



(b)

Figure 7. The difference signals between original and reconstructed signals (a) BW elimination results for LMS algorithm and (b) BW elimination results for MEE algorithm

4.3. Adaptive motion artifacts elimination

Electrode motion (EM) artifact is a result of changes in the electrode-skin junction's impedance or shifts in the potential of the skin brought on by stretching of the skin. This artifact overlaps the ECG signal in the frequency domain because EM has a similar wave shape to ECG, including P, QRS, and T waves. Therefore, band-pass filtering is insufficient to get rid of this artifact. The noise removal process utilizing LMS and MEE algorithms is shown in Figure 8. In this regard, Figures 8(a) and 8(b) depict the raw signal and its noisy version. Moreover, Figure 8(b) shows the recovered signal using LMS and Figure 8(c) indicates the recovered signal using MEE. According to the findings of the simulation, the average SNR improvement for the MEE algorithm is 17.02 dB, compared to 9.855 dB for the LMS algorithm. Additionally, Figure 9 shows the difference signals, where Figure 9(a) indicates the obtained results using the LMS algorithm, and Figure 9(b) indicates the obtained results using the MEE algorithm.

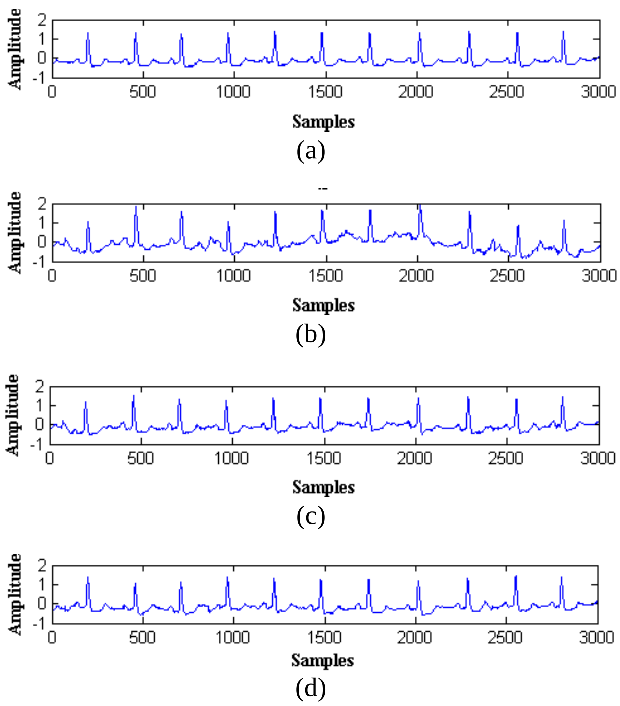


Figure 8. EM elimination results (a) original ECG, (b) noisy ECG, (c) recovered by LMS algorithm, and (d) recovered by MEE algorithm

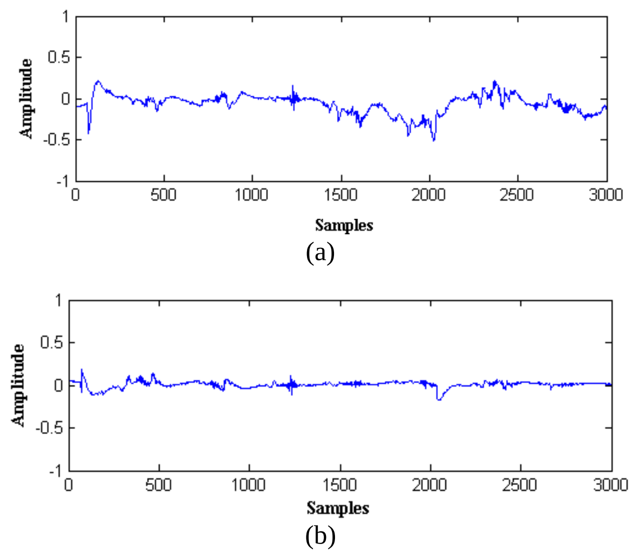


Figure 9. The difference signals between original and reconstructed signals (a) EM elimination results for LMS algorithm and (b) EM elimination results for MEE algorithm

4.4. Adaptive muscle artifacts elimination

The presence of MA is caused by muscle contractions around the electrodes. MA has a broad bandwidth which sometimes overlaps with the ECG signal. Due to this, simple low-pass filtering is not adequate to suppress this artifact. Figure 10 indicates the filtering results for MA removal by LMS- and MEE-based algorithms. Figures 10(a) and 10(b) show the original and noisy signals, respectively. Figures 10(c) demonstrates that the restored signal using LMS algorithm has a very low quality. On the other hand, Figure 10(d) demonstrates that the reconstructed signal by MEE algorithm has the desired quality. This observation is emphasized in Figure 11, which shows the difference signals for MEE and LMS algorithms. As can be seen in Figure 11(a), the error rate for the LMS algorithm is relatively large, while the MEE algorithm has shown a fast rate of convergence and little steady state error based on Figure 11(b). The average SNR enhancement for the MEE and LMS algorithms, according to simulation findings, is 16,555 dB and 10.51 dB, respectively. These findings show that the MEE algorithm can track even in the presence of non-stationary non-Gaussian disturbances.

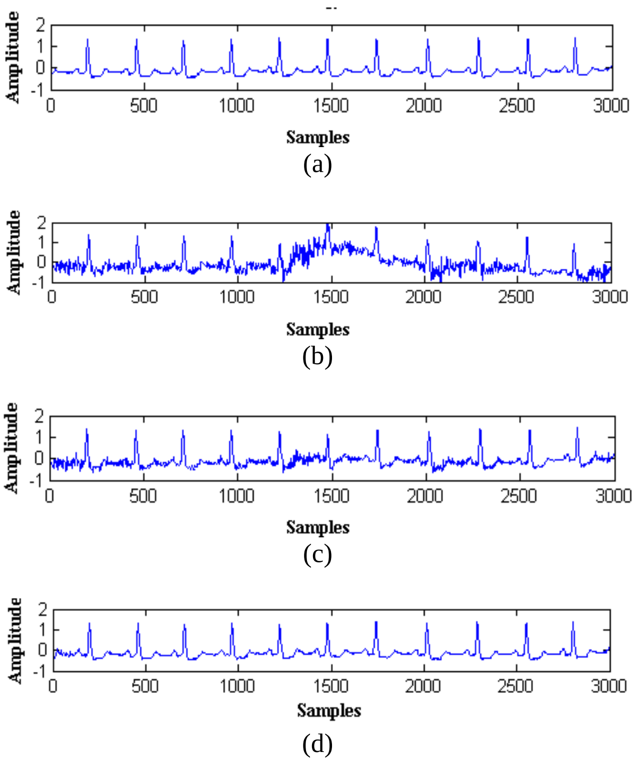


Figure 10. MA elimination results: (a) original ECG, (b) noisy ECG, (c) recovered by LMS algorithm, and (d) recovered by MEE algorithm

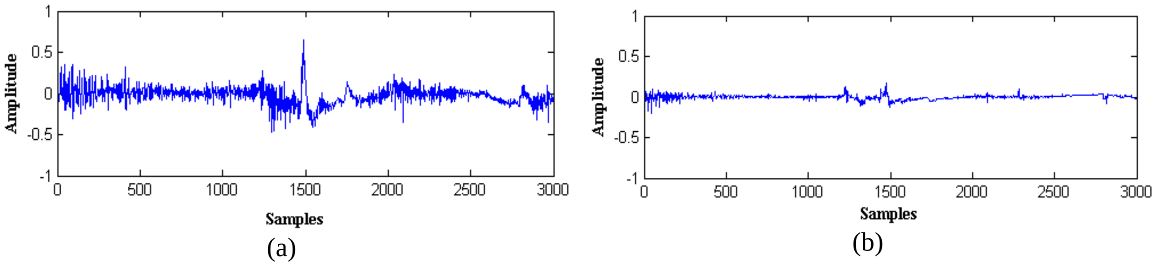


Figure 11. The difference signals between original and reconstructed signals: (a) MA elimination results for LMS algorithm and (b) MA elimination results for MEE algorithm

5. CONCLUSION

The minimal error entropy criterion, an information-theoretic criterion, is used in this study to support the proposal of an adaptive noise cancelling algorithm. The Renyi's quadratic entropy is taken into account as the information measure in this case. To estimate this measure from the input ECG signal on a sample-by-sample basis, an adaptive formulation is used. Since this measure is directly derived from an estimate of the error PDF, all data pertaining to the error distribution are considered in the process of minimizing it. In contrast, the well-known MSE criterion simply takes into account the second-order statistics of the error distribution. When denoising an ECG signal, where noises are often non-Gaussian, this is beneficial. The effectiveness of the suggested approach is evaluated using real ECG signals that are noisy and have different artifacts. According to simulation data, this strategy is superior than the LMS adaptive approach for the four primary types of disturbances present in recorded ECG signals.

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BIOGRAPHIES OF AUTHORS

Zahraa Mousa Saad was born in 1987, in Al-Amarah, Iraq. She received the Bachelor's degree in Information Technology/Software Engineering from Imam Jaafar Al-Sadiq University, Baghdad, Iraq in 2009. She received the Master's degree in Computer Engineering/Software Engineering from Imam Reza International University, Mashhad, Iran. 2020. Currently a Ph.D. student studying software engineering/Computer Engineering College at the Islamic Azad University, Isfahan, Iran. She worked as an engineer at Al-Faw Engineering and Architecture Company, Iraq in 2009, and then worked as an engineer at Al-Rafidain Bank, Iraq in 2010, and then worked as an engineer at Misan University in the same year. After that, he became responsible for the Engineering Division in the College of Administration and Economics from 2016- 2019. Currently, she is an engineer in the Division of Quality Assurance and Academic Performance of the same university. She can be contacted at email: zahraa.m.s@uomisan.edu.iq.

Nsaif Jasim Al-Chaabawi was born in Amarah, Iraq, in 1983. He received the B.Sc. degree in Electrical and Electronic Engineering/Computer Technologies from the Technical College, Baghdad, Iraq, in 2006, and the M.Sc. degree in Electronic Communication and Computer Engineering from Nottingham University, Nottingham, UK, in 2016. In 2017, he joined the Department of Electrical Engineering, University of Misan, as a Lecturer, and in 2018 became a Head of the Systems and Software Division at the Computer Center at the University of Misan. Since December 2018, he has been with the Department of Petroleum Engineering. His current research interests include communication technology, E-learning and power quality. He can be contacted at email: nsf_jsm@uomisan.edu.iq.

Saif Al_Deen H. Hassan was born in Salahuddin, in January 1991. He received the B.Sc. degree in computer science from the University of Basrah, in 2014 and the M.Sc. degree in Computer Science in Artificial intelligence specialty Modern University for Business and Science 2021. He is currently a lecturer with College of Administration and Economics, Department of Economy, University of Misan. Previously, he was in Supervisor at EarthLink Telecom Company. He can be contacted at email: saif_aldeen@uomisan.edu.iq.