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Low Complexity Adaptive Noise Canceller for Mobile Phones Based Remote Health Monitoring

Jafar Ramadhan Mohammed
Departement of Communication Engineering, College of Electronic Engineering, University of Mosul, Iraq

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ABSTRACT

Mobile phones are gaining acceptance to become an effective tool for remote health monitoring. On one hand, during electrocardiographic (ECG) recording, the presence of various forms of noise is inevitable. On the other hand, algorithms for adaptive noise cancellation must be shared by limited computational power offered by the mobile phones. This paper describes a new adaptive noise canceller scheme, with low computational complexity, for simultaneous cancellation of various forms of noise in ECG signal. The proposed scheme is comprised of two stages. The first stage uses an adaptive notch filters, which are used to eliminate power-line interference from the primary and reference input signals, whereas the other noises are reduced using modified LMS algorithm in the second stage. Low power consumption and lower silicon area are key issues in mobile phones based adaptive noise cancellation. The reduction in complexity is obtained by using log-log LMS algorithm for updating adaptive filters in the proposed scheme. A comprehensive complexity and performance analysis between the proposed and traditional schemes are provided.

Corresponding Author:

Jafar Ramadhan Mohammed,
Departement of Communication Engineering,
College of Electronic Engineering,
University of Mosul,
Mosul, Iraq
Email: mohammedj74@uomosul.edu.iq

1. INTRODUCTION

Telemedicine is a useful tool in prevention or diagnosis of diseases, especially if they are dynamically lethal such as cardiac diseases. In places where access to medical services is time-consuming or infeasible, telemedicine could prove life-saving. Thus, the use of Mobile Phones in remote health monitoring has been of extreme interest during recent years [1-3]. In such case, the mobile phone is utilized as a signal transmitter and receiver by both patient and doctor, as shown in Figure 1. In the receiver side the tiny features of the ECG signal should be very clear for better diagnosis while in the transmitting side during ECG recording, the presence of various types of noises is inevitable. The predominant noises present in the ECG includes: Base-line Wander (BW), Power-Line Interference (PLI), Muscle Artifacts (MA), and Motion Artifacts (EM). These artifacts strongly affects the ST segment, degrades the signal quality, produces large amplitude signals in ECG that can resemble PQRST waveforms, and masks tiny features that are important for diagnosis in the receiver side. Cancellation of these noises in ECG signals before any other processes is an important task for better diagnosis.

One of the first successful approaches to ECG extraction problem was developed by Widrow et al. based on linear adaptive filter [4]. For this approach and some closely related systems theoretical studies for the noise reduction performance of ECG containing BW, PLI, and MA are given in [5]. The widely used adaptive noise canceller consists of two inputs (electrodes) namely, the primary electrode(s) and reference electrode(s). The primary electrode(s) is placed on the abdominal region in order to pick up the ECG signal while the other electrode(s) is placed close to noise source to sense only the background noise. The recent models of Mobile phones are deploying the concept of two-input adaptive noise canceller [6]. Therefore, in this paper more attention has been paid to develop an efficient and simplified adaptive noise canceller for ECG enhancement based on two inputs only that is compatible with recent models of mobile phones. However, the following challenging issues must be addressed for its successful deployment:

- Efficient and simplified two-input adaptive noise canceller capable of dealing with various noises simultaneously: In mobile phones based ECG monitoring, all forms of noise may occur simultaneously and unpredictably. In this situation, the performance of the traditional two-input adaptive noise canceller (ANC) may degrade severely. One of the solutions is by using multi-channel adaptive noise canceller with blind spots (nulls) in the arrival bearing of noise signals. Obviously, the multi-channel ANC involves increased cost in the form of more reference sensors, D/A converters, computational complexity, signal processing power. The modern adaptive noise canceller prefer two-channel [2], over multi-channel ANC due to the low computational complexity provided by the former over the later. To cater this issue we need new and simple two-channel adaptive noise canceller capable to deal effectively with various forms of noise simultaneously. The proposed scheme in this paper is comprised of two stages of adaptive filters. The first stage consist of two adaptive notch filters placed in parallel to estimate and cancel the PLI included in the primary input and reference input signals. The second stage consists of modified adaptive noise canceller which estimates and cancels the other noises present in the noisy ECG signal from the first stage and will provide the required ECG enhancement.
- Low Computational Complexity: The traditional ANC scheme with LMS algorithm is used in telemedicine due to its computational simplicity. However, in mobile phone based ANC further reduction in complexity is required. The reason for this reduction in complexity leads to lower power consumption and low silicon area. Low power consumption is a key issue in mobile phones. Thus far, to the best of the author's knowledge, no effort has been made to reduce the computational complexity of the adaptive noise canceller system, particularly, with limited computational power offered by the mobile phones. The computational complexity can be greatly reduced by using the log-log LMS [7] algorithm for updating the filter coefficients in the proposed scheme. The reduction in complexity is obtained by using values of the reference input data and the output error, quantized to the nearest power of two, to compute the gradient. This eliminates the need for multipliers or shifters in the algorithm's update section. The quantization itself is efficiently realizable in hardware. Thus, this algorithm is similar to the sign-based LMS [8]. However, the complexity of the log-log LMS is lower than that of the sign-based LMS, while its performance is superior to this algorithm [7]. These good advantageous of the log-log LMS making it a good candidate for mobile phone based telemedicine application especially it requires much lower chip area for ASIC implementation.

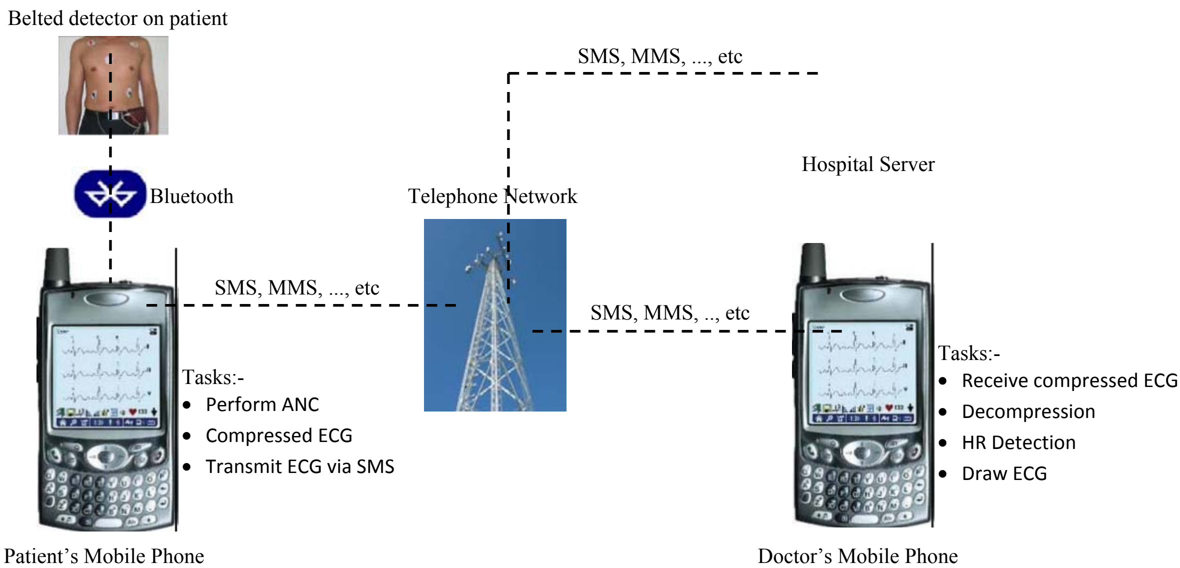

Figure 1. Architecture of a Mobile Phone Based Remote Health Monitoring Including ANC.

The first aim of this paper is to introduce efficient and simplified two-channel adaptive noise canceller system for simultaneous cancellation of various forms of noise. The second aim is to reduce the computational complexity (in terms of power and chip area) of the proposed scheme to cope with limited computational power offered by the mobile phones. This paper is organized as follows. Section 2 introduces the principle of the proposed scheme. The experimental results of the different adaptive noise cancellation schemes using real ECG signal and real noise signals obtained from MIT-BIH database are presented and discussed in Section 3. Conclusions are given in Section 4.

2. THE PROPOSED SCHEME

Figure 2 shows the new proposed adaptive noise cancellation scheme. The primary input and reference input signals of the proposed scheme are given as follows

$$\begin{aligned} x(k) &= ECG(k) + n_P(k) \\ &= ECG(k) + PLI_P(k) + A_P(k) \end{aligned} \tag{1}$$

$$n_R(k) = PLI_R(k) + A_R(k) \tag{2}$$

where $x(k)$ is primary input signal, $ECG(k)$ is clean ECG signal, $n_P(k)$ and $n_R(k)$ represents the noise signals received by primary electrode(s) and reference electrode(s) respectively, $A_P(k) = BW_P(k) + MA_P(k) + EM_P(k)$ and $PLI_P(k)$, $BW_P(k)$, $MA_P(k)$, and $EM_P(k)$ represent the power-line interference, Base-line wonder, Muscle artifacts, and Motion artifacts, respectively.

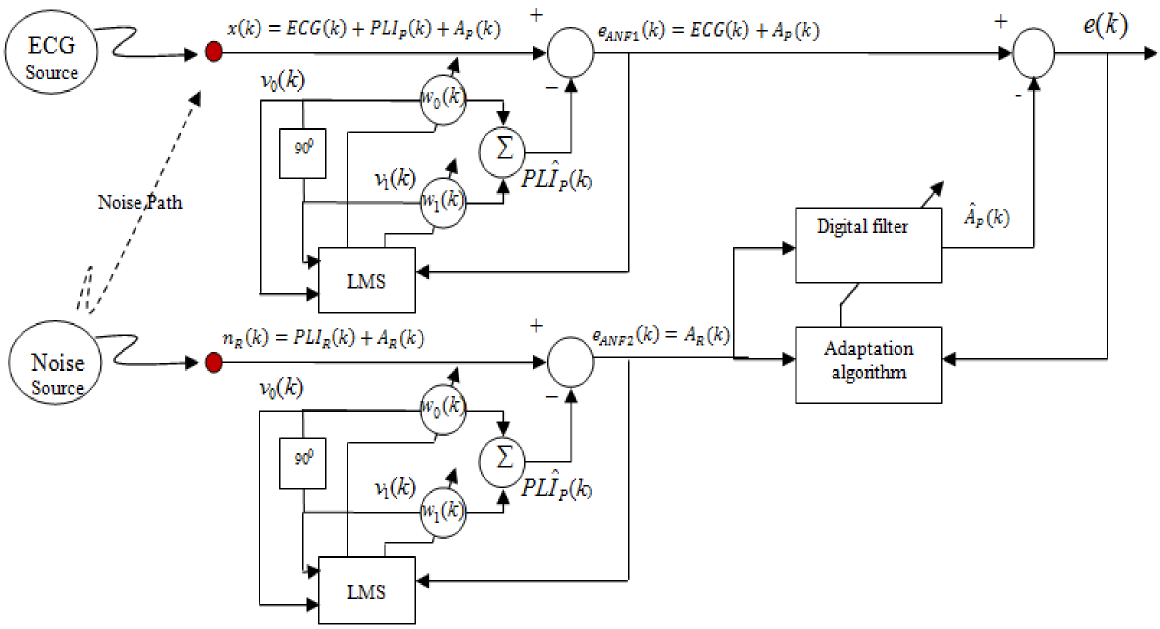

Figure 2. The Proposed Adaptive Noise Cancellation Scheme.

The proposed adaptive noise cancellation scheme shown in Figure 2 consists of two cascade stages. The first stage consists of two adaptive notch filters which are named ANF1 and ANF2 placed in parallel and used for reducing the PLI included in the primary input and reference input signals. This connection gives the advantage of adaptation convergence at same time for both adaptive notch filters (ANF1 and ANF2) if we choose same value of the step size and same number of filter coefficients for both ANFs.

First, the PLI is cancelled by both ANF filters (ANF1 and ANF2). The outputs are just replicas of $x(k) = ECG(k) + A_P(k)$ for ANF1 output and of $A_R(k)$ for ANF2 output.

The second stage in the scheme is used for artifacts cancellation. The $A_R(k)$ is represent the reference input signal to the modified LMS adaptive filter in the second stage, according to the adaptive noise filtering principles, which are explained in section 2.2. The system output $EC\hat{G}(k)$ is the enhanced ECG signal.

2.1. Adaptive Notch Filter

High quality ECG analysis requires the amplitude of the power line interference to be less than 0.5% of the peak-to-peak QRS amplitude [9]. Therefore, the PLI should be removed from the ECG signal before doing any further analysis. An ideal PLI suppression method should remove the PLI, while keeping the ECG signal intact.

The conventional method of cancellation such interference is using a nonadaptive notch filter that is tuned to the frequency of the interference [10]. However, nonadaptive notch filter is suitable for stationary sinusoidal interference (amplitude, frequency and phase are constant), but the PLI encountered in ECG signal measurement is non-stationary in nature, i.e, the amplitude, frequency and phase are varying over time. In order to handle the non-stationary nature of PLI, adaptive notch filter is considered. The details of the adaptive notch filter (ANF) used to reduce PLI in the proposed scheme are explained with the help of the block diagram given in Figure 3.

An adaptive notch filter with only two adaptive weights is shown in Figure 3. The input signal as shown in Figure 3, is represented as

$$v_0(k) = A\cos\left(\frac{2\pi f_0}{F_s}k\right) \tag{3}$$

A 90^o phase shifter is used to produce the quadrature signal

$$v_1(k) = A\, sin\left(\frac{2\pi f_0}{F_s}k\right) \tag{4}$$

The signals $v_0(k)$ and $v_1(k)$ are correlated with $PLI_P(k)$. In addition, the $ECG(k)$ and artifacts $A_P(k)$ are assumed to be uncorrelated with $v_0(k)$ and $v_1(k)$. Thus, if two signals, $v_0(k)$ and $PLI_P(k)$, are correlated, then $PLI_P(k)$ may be estimated by $PL\hat{I}_P(k)$ from $v_0(k)$ and $v_1(k)$.

Estimating $PL\hat{I}_P(k)$ depends on the strategy of how the cost function is to be minimized, be it either least mean squares or recursive least squares [11]. For this paper, the cost function will be minimized based on least mean squares (LMS) algorithm.

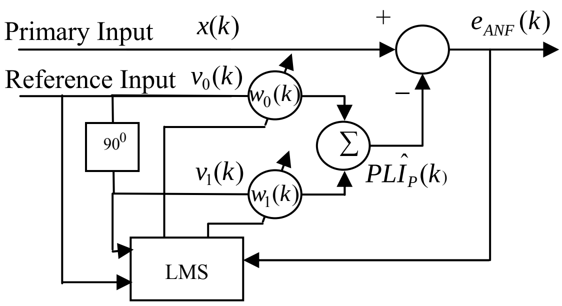

Figure 3. The Adaptive Notch Filter

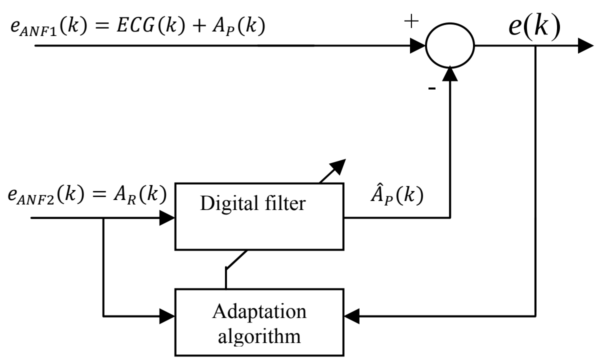

Figure 4. The Adaptive Noise Canceller Filter.

The mean squared error of the ANF1 as shown in Figure 3, is defined as

$$\begin{aligned} E[e^2_{ANF1}(k)] &= E[(ECG(k) + A_P(k) + (PLI_P(k) - PL\hat{I}_P(k)))^2] \\ &= E[ECG(k) + A_P(k)]^2 + 2E[(ECG(k) + A_P(k))(PLI_P(k) - PL\hat{I}_P(k))] + E[(PLI_P(k) - PL\hat{I}_P(k))]^2 \end{aligned} \tag{5}$$

Since ECG signal, PLI and artifacts signals are uncorrelated,

$$E[ECG(k)PLI_P(k)] = 0 \text{ and}$$
$$E[A_P(k)PLI_P(k)] = 0,$$
$$\text{then } 2E[(ECG(k) + A_P(k))(PLI_P(k) - PL\hat{I}_P(k))] = 0 \tag{6}$$

The mean squared error becomes

$$E[e^2_{ANF1}(k)] = E[(ECG(k) + A_P(k))]^2 + E[(PLI_P(k) - PL\hat{I}_P(k))]^2 \tag{7}$$

Minimizing $E[e^2_{ANF1}(k)]$ is equivalent to minimizing $E[(PLI_P(k) - PL\hat{I}_P(k))]^2$. Therefore, this minimization will cause $PL\hat{I}_P(k)$ to be the minimum mean-square estimate of $PLI_P(k)$ [11]. The estimated output of ANF1 filter $PL\hat{I}_P(k)$ which is shown in Figure 3 is given by

$$PL\hat{I}_P(k) = w_o(k)v_o(k) + w_1(k)v_1(k) \tag{8}$$

Where $w_o(k)$ and $w_1(k)$ are two adaptive filter coefficients.
The output (error) signal of ANF1 is given by

$$e_{ANF1}(k) = ECG(k) + A_P(k) \tag{9}$$

Applying the same mathematical analysis to part 2 of Figure 2 above, the input signals of ANF2 are represented as

$$n_R(k) = PLI_R(k) + A_R(k) \tag{10}$$

$$v_0(k) = A\cos\left(\frac{2\pi f_0}{F_s}k\right) \tag{11}$$

Since the signal $v_o(k)$ is correlated with $PLI_R(k)$. In addition, the artifacts $A_R(k)$ is assumed to be uncorrelated with $v_0(k)$, the estimated signal of ANF2 filter, $PL\hat{I}_R(k)$, is given by

$$PL\hat{I}_R(k) = w_o(k)v_o(k) + w_1(k)v_1(k) \tag{12}$$

The output (error) signal of ANF2 is given by

$$e_{ANF2}(k) = A_R(k) \tag{13}$$

2.2. Modified LMS Algorithm

An adaptive noise canceller with LMS algorithm is shown in Figure 4. The output signal y(k) is formed as the weighted sum of a set of input signal samples $e_{ANF2}(k), e_{ANF2}(k-1), \ldots\ldots., e_{ANF2}(k-L+1)$ .Mathematically, the output y(k) is equal to the inner product of the input vector $\mathbf{e}_{\mathbf{ANF2}}(k)$ and the weight vector $\mathbf{w}(k)$

$$y(k) = \mathbf{e}^{\mathbf{T}}_{\mathbf{ANF2}}(k)\mathbf{w}(k) \tag{14}$$

where

$$\mathbf{w}(k) = [w(k), w(k-1), \ldots\ldots\ldots\ldots\ldots, w(k-L+1)] \tag{15}$$

is the weight vector of the adaptive filter. During the adaptation process, the weights are adjusted according to the LMS algorithm [11]. The primary input signal $e_{ANF1}(k)$ which contains the ECG signal, the artifacts $A_P(k)$ as well as residual PLI from output of ANF1. The reference input signal $e_{ANF2}(k)$ contains the artifacts $A_R(k)$ as well as the residual PLI from output of ANF2. The artifacts $A_R(k)$ are correlated with $A_P(k)$ in the primary input signal. A general expression of the output can be obtained as follows

$$e(k) = e_{ANF1}(k) - y(k) = e_{ANF1}(k) - \mathbf{e}^{\mathbf{T}}_{\mathbf{ANF2}}(k)\mathbf{w}(k) \tag{16}$$

The LMS algorithm updates the filter coefficients according to [11]

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu\, \mathbf{e}^{\mathbf{T}}_{\mathbf{ANF2}}(k) e(k) \tag{17}$$

where μ is the step size which controls the convergence speed and the stability of the adaptive filter.

The weight update defined in (17) requires L+1 multiplications and L additions if we multiply $\mu\, e(k)$ outside the loop. In adaptive noise cancellation concept, the noise path has to be modeled by the adaptive filter. The noise path is impulse response from the noise source to the primary input. Since this impulse response can be quite long and highly time-varying due to the movement of the patient body, the adaptive filter will require large number of filter coefficients (high computational complexity). So, we need to develop low complexity adaptive algorithms that can work effectively in mobile phones. There are three simplified versions of the LMS algorithm that significantly reduce the computational complexity [2, 8]. These algorithms are attractive for their assured convergence and robustness against the disturbances in addition to the ease of implementation. The first algorithm called sign-error LMS algorithm and its weight update relation is

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu\, \mathbf{e}_{\mathbf{ANF2}}(k) \operatorname{sgn}[\mathrm{e(k)}] \tag{18}$$

Where

$$\operatorname{sgn}[\mathrm{e(k)}] \equiv \begin{cases} 1, & \mathrm{e(k)} > 0 \\ 0, & \mathrm{e(k)} = 0 \\ -1, & \mathrm{e(k)} < 0 \end{cases} \tag{19}$$

Because of the replacement of *e(k)* by its sign, implementation of this algorithm may be cheaper than the standard LMS algorithm, especially in biotelemetry where these types of algorithms maybe necessary.

The signum operation can be performed on reference input instead of error, and it results in the sign-data LMS algorithm can be expressed as

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu\, \mathrm{e(k)} \operatorname{sgn}[\mathbf{e}_{\mathbf{ANF2}}(k)] \tag{20}$$

Finally, the signum operation can be applied to both error and reference input signals, and it results in the sign-sign LMS algorithm expressed as

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu \operatorname{sgn}[\mathrm{e(k)}] \operatorname{sgn}[\mathbf{e}_{\mathbf{ANF2}}(k)] \tag{21}$$

The computational complexity of these three algorithms is much less compared to the standard LMS algorithm. However, the convergence rates of these signed-based LMS algorithms are much slower than the standard LMS algorithm.

The log-log LMS algorithm [7] is another class of adaptive algorithm used to update the filter coefficients in the proposed scheme. In this algorithm, the reduction in complexity is obtained by using values of the reference input data and the output error, quantized to the nearest power of two, to compute the gradient. This eliminates the need for multipliers or shifters in the algorithms update section. The quantization itself is efficiently realizable in hardware. Moreover, the convergence rate and MSE performance of the log-log LMS algorithm is close to that of the standard LMS algorithm which makes it a suitable algorithm for practical implementation of the adaptive noise canceller based mobile phones.
The weight update relation for log-log LMS algorithm is as follows:

$$\mathbf{w}(k+1) = \mathbf{w}(k) + Q[\mu e(\mathrm{k})]Q[\mathbf{e}_{\mathbf{ANF2}}(k)] \tag{22}$$

Where Q is quantization operation and the values of $Q[\mu e(\mathrm{k})]$ and $Q[\mathbf{e}_{\mathbf{ANF2}}(k)]$ are all powers of two. Therefore, they can be represented in the $\log_2$ domain using fewer numbers of bits (smaller word-length).

2.3. Complexity Analysis

In this section, we show the computational complexity requirements for the proposed scheme. The computational cost is measured in terms of the number of multiplications, additions, power consumption, and silicon area. The results are listed in Table 1, where L is the number of filter coefficients and N is the word-length of the input data. The word-length impacts the complexity (in terms of power and chip area) significantly. Specifically, for log-log LMS algorithm, the word-length is much lower than other algorithms. For example, the nearest power of two quantized representation of a data with a word-length of 128 bits in the $\log_2$ domain requires only 7 bits for the magnitude and one for the sign. The sign-error LMS algorithm uses the signum (polarity) of the error while using full word-length of reference input data. On the other hand, the sign-data LMS algorithm uses the signum of the reference input data and full word-length of error data to update the adaptive filter. Thus, the proposed scheme with sign-error LMS algorithm requires L shifters and 2L+8 full word-length additions. The proposed scheme with sign-data LMS algorithm requires only one shifter but still requires 2L+8 full word-length additions. The sign-sign LMS algorithm eliminates the need for shifter but further worsens the convergence rate. The proposed scheme with log-log LMS algorithm requires L+8 additions at word-length resolution of $\log_2$N per update.

Table 1. Comparison of the Computational Complexity

Algorithm	Mult.	Add.	Shifters	Chip Area
Traditional ANC with standard LMS	2L+1	2L	Nil	L(2N+5N^2)
Proposed ANC with standard LMS*	2L+11	2L+8	Nil	L(2N+5N^2)
Proposed ANC with sign-error LMS*	L+4	2L+8	L	L(2N+8N)
Proposed ANC with sign-data LMS*	L+4	2L+8	1	2LN+8N
Proposed ANC with sign-sign LMS*	L+4	2L+8	Nil	LN+2N
Proposed ANC with log-log LMS*	L+4	L+8	Nil	L(N+N)

* Including the complexity of notch filters and the multiplications that are shown in second column is for computing the adaptive filter output.

The chip areas of multipliers, adders, and shifters are proportional to the word-length (N). Table 1 also compares the chip areas required by the traditional scheme with standard LMS, proposed scheme with standard LMS, proposed scheme with sign-error LMS, proposed scheme with sign-data LMS, proposed scheme with sign-sign LMS, and proposed scheme with log-log LMS algorithms. Among all the algorithms the chip area required by the proposed scheme with log-log LMS algorithm is slightly higher than sign-sign LMS and lower than all other algorithms.

3. EXPREMENTAL RESULTS

The performance of the proposed adaptive noise cancellation scheme with different algorithms were investigated using the actual record of ECG signal under real noise sources and artifacts such as power line interference, base-line wander, muscle artifacts and motion artifacts. These records were taken from the MIT-BIH Arrhythmia database and MIT-BIH Normal Sinus Rhythm database [12]. They were digitized at 360 samples per second per channel with 11-bit resolution over a 10mV range. In all our experiments, we used the first 3600 samples (10 seconds) of the ECG signals and we have considered a dataset of four ECG records: data100, data105, data118, data208 to ensure the consistency of result. Figure 5 shows clean ECG (data 118 of MIT-BIH arrhythmia database), base-line wander (data bm), muscle artifacts (data ma) and motion artifacts (data em). The noisy ECG signal and its spectrogram are shown in Figure 6.

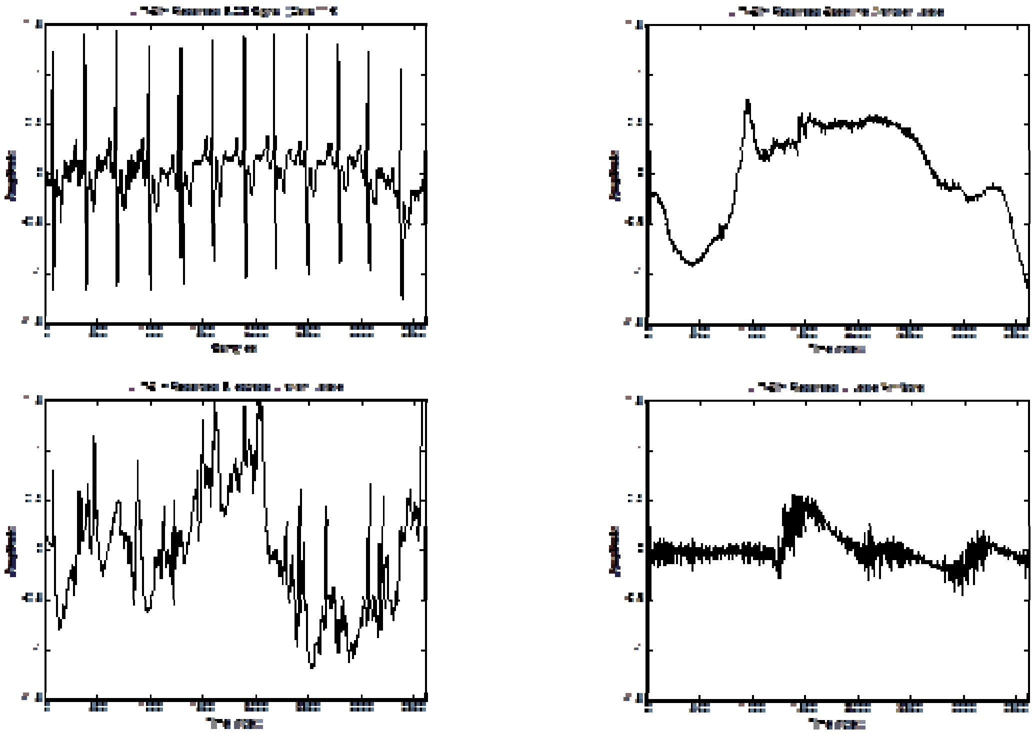

Figure 5. MIT-BIH recorded ECG Signal (data 118) and real noise signals (data bm, data ma, and data em).

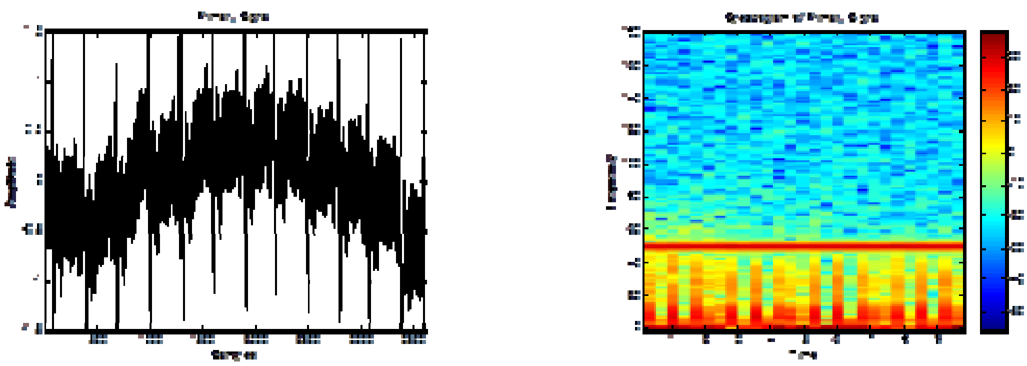

Figure 6. Noisy ECG Signal at Primary Input and its Spectrogram.

First, some experimental results are provided to show the performance of the traditional scheme in the presence of divers forms of noise: PLI, BW, MA, EM, and Gaussian white noise with variance of 0.001. The enhanced ECG signal at the output of the traditional ANC scheme and its spectrogram are shown in Figure 7. Clearly, the conventional scheme is unable to reduce PLI and other noises simultaneously. This misbehavior of the traditional scheme under various forms of noise, particularly wideband and narrowband noise signals, has been also observed in [13].

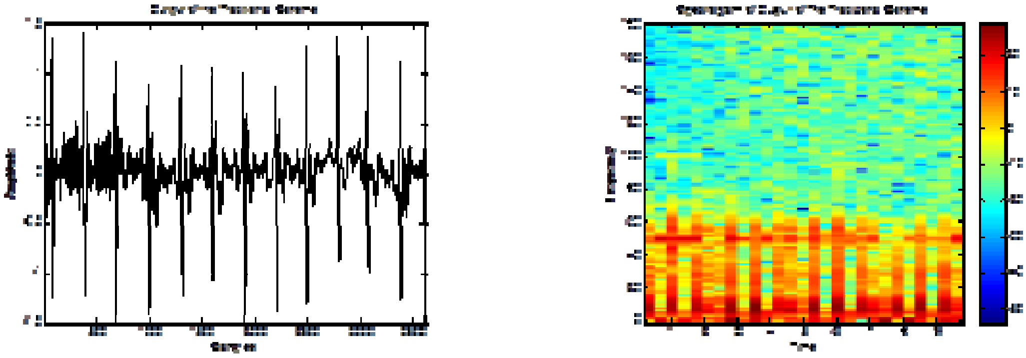

Figure 7. Output of the traditional Scheme and its Spectrogram (step size=0.02, filter length=31 weights, and LMS algorithm).

In our second experiment, we show the importance of adaptive notch filters in first stage of the proposed scheme for cancelling PLI in reference input such that adaptive filter could work effectively. The enhanced ECG signal by the proposed scheme is shown in Figure 8. The improvement in the noise reduction performance provided by the proposed scheme over that of the traditional scheme is evident when this performance in Figure 8 is compared with that of the traditional scheme given in Figure 7. Figure 8 also shows the outputs of the ANF1 and ANF2 in the first stage of the proposed scheme. Note that the reduction of the PLI is done to a high degree.

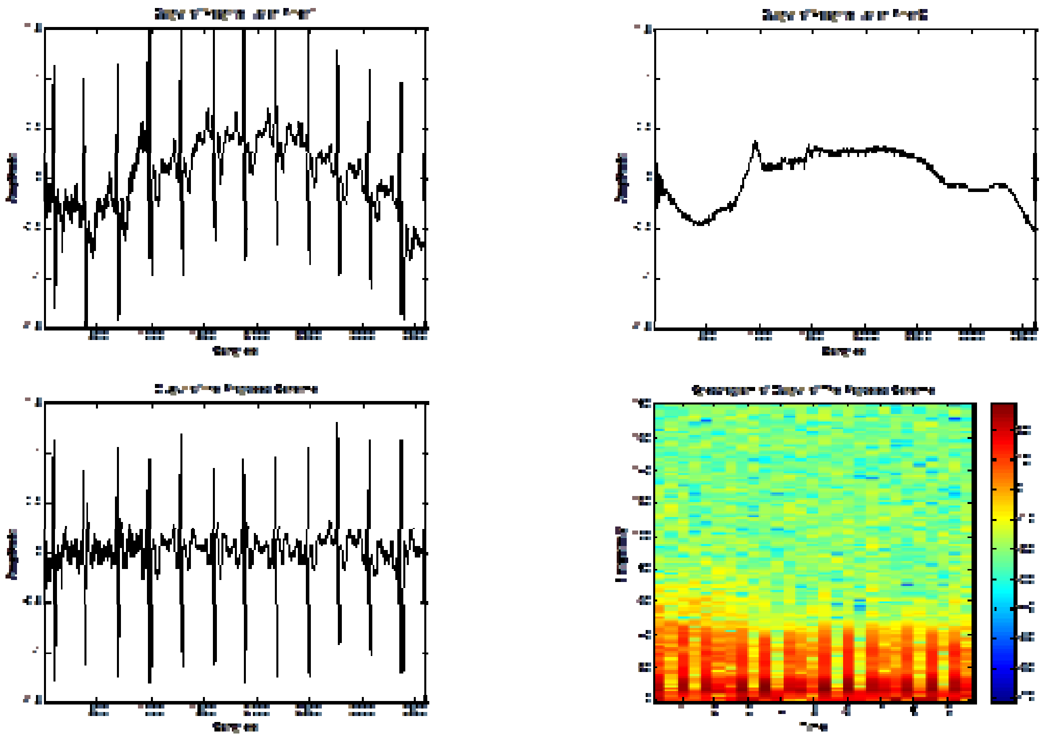

Figure 8. Output of the Proposed Scheme and its Spectrogram (step size and filter length in the second stage are 0.02 and 31 respectively, and LMS algorithm).

Next, the learning curves of various algorithms that maybe used in the proposed scheme are shown in Figure 9. From these curves, it is clear that the proposed scheme with sign-data LMS and with log-log LMS exhibit better performance in terms of both convergence rate and mean square error than other realizations.

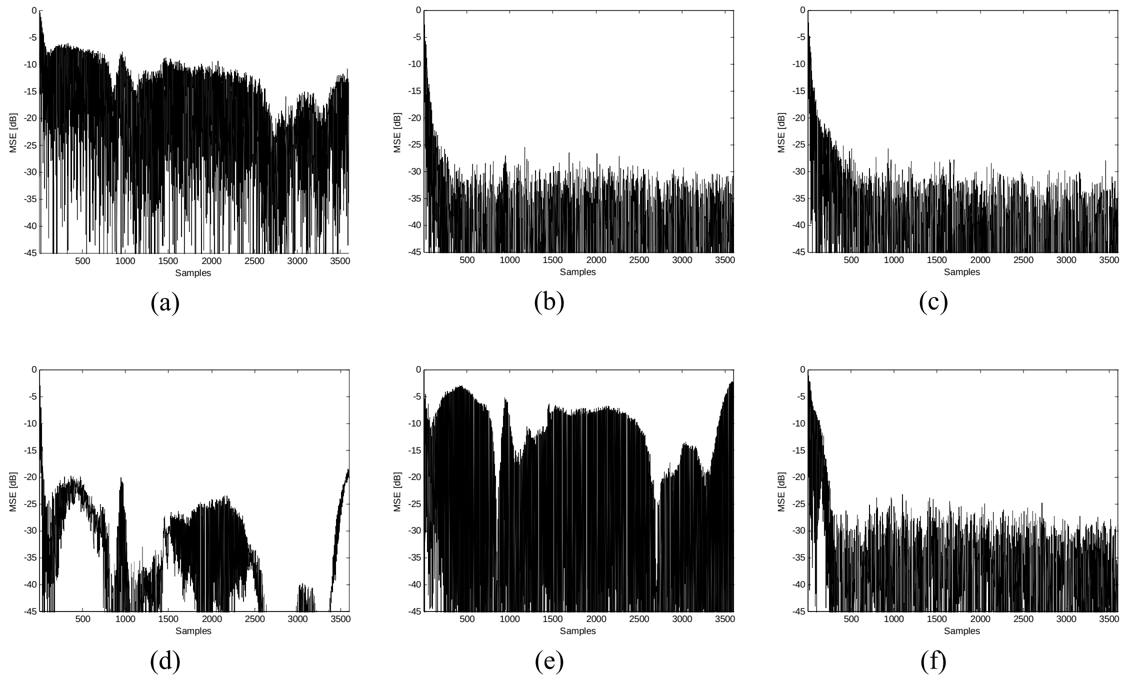

Figure 9. Learning Curves of various algorithms (in all algorithms, step size=0.02, L=31). (a) Traditional Scheme with LMS. (b) Proposed with LMS, (c) Proposed with sign-data LMS, (d) proposed with sign-error LMS, (e) Proposed with sign-sign LMS, (f) Proposed with log-log LMS.

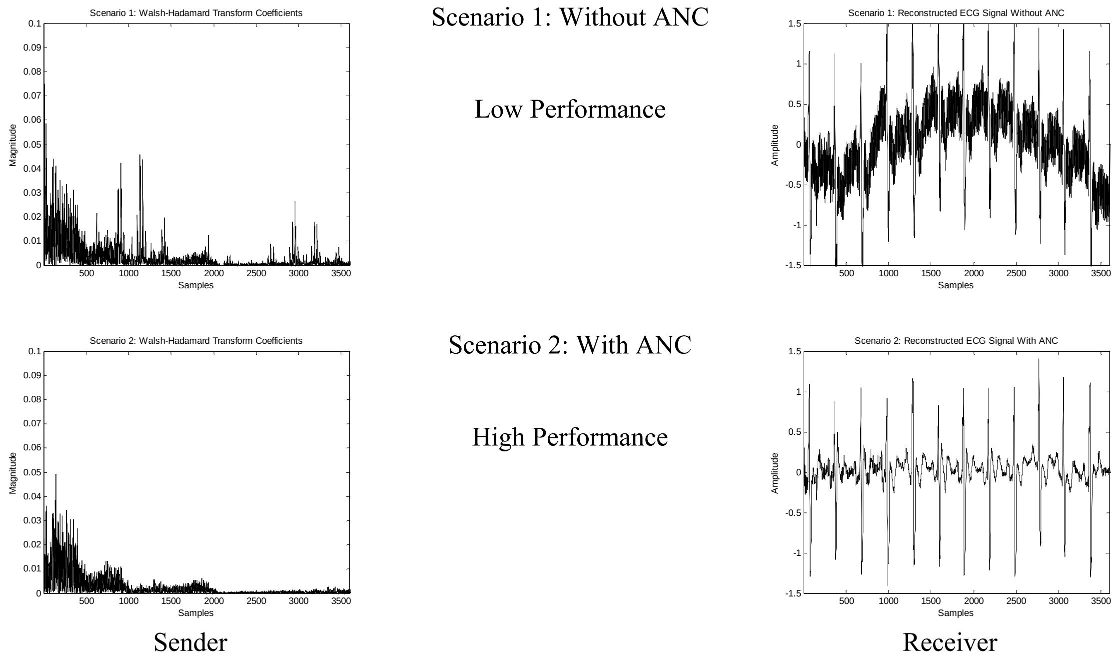

Figure 10. Two Different Scenarios of a Mobile Phone Based Remote Health Monitoring.

Finally, two different scenarios (with and without ANC scheme) are considered in the transmitter side to observe the quality of the received ECG signal in the receiver side. For investigation purposes, we used simple compression like WHT in the transmitter side. WHT is suitable for compression of ECG signals because it offers advantages such as fast computation of Walsh-Hadamard coefficients, less required storage space since it suffices to store only those sequency coefficients with large magnitudes, and fast signal reconstruction. The transmitted and received signals for these two scenarios are shown in Figure 10. Clearly, with ANC (scenario2) most of the compressed signal energy is concentrated at lower sequency values. Thus, only the first 1000 coefficients are stored and used to reconstruct the original transmitted signal. This represents a compression ratio of approximately 4:1. While with scenario 1, estimation about the compressed signal energy is not clear to determine. This leads to loss more ECG data.

4. CONCLUSION

In this paper, an efficient and simplified adaptive noise cancellation scheme for mobile phones has been proposed to reduce various forms of noise during ECG recording. The performance of the proposed scheme is tested on real data for ECG signal with various noises obtained from MIT-BIH database. Simulation results show that the proposed scheme produces results that are significantly favorable than traditional scheme. A comparison of the chip area required by the proposed scheme over that of traditional scheme is given in Table 1. It shows that the proposed scheme with log-log LMS requires lower area for ASIC implementation.

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BIOGRAPHY OF AUTHORS

Jafar Ramadhan Mohammed received the B.Sc. and M.Sc. Degrees in Electronic and Communication Engineering from University of Mosul, IRAQ, in 1998, and 2001, respectively, and the Ph.D. degree in Digital Communication Engineering from Panjab University, INDIA in Nov. 2009. He is currently a Senior Lecturer at University of Mosul, IRAQ. His main research interests are in the area of Adaptive Signal Processing and its application, Adaptive Antenna arrays and Beamforming.