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Enhancement of ECG Signal

Hend Fat'hy
Modern academy for Engineering and Technology

Eman Mohamed, PhD
Modern academy for Engineering and Technology

Ashraf Mohamed, PhD
October University forModern Sciences and Arts

Wagdy Anis, PhD
Ain Shams University

ABSTRACT
An Electrocardiogram (ECG) signal is a recording of the electrical activity of heart. It considered as an important source of vital diagnostic information. ECG signal is exposed to different types of noise. These noises change the nature of the ECG signal and provide difficulties on its analysis.

The one long Least Mean Squares (LMS) adaptive filter is an algorithm used to reduce the noise effect on the ECG signal. This algorithm is widely used in adaptive filter applications due to its simplicity and low computational complexity, but it suffers from low convergence speed.

This paper proposes to improve the one long LMS adaptive filter convergence speed using the multiple sub-adaptive filters proposed algorithm where simulations show that at MSE of 0.04 the required number of iterations are saved by about $4.3*10^4$ times compared to the one long LMS adaptive filter. Also comparison between them is performed in terms of Signal to Noise Ratio (SNR) against the step size (μ). It is found that the proposed algorithm provides improvement in the SNR by 5 dB at μ=o.2.

The ECG samples are recorded from MIT-BIH database and an additive white Gaussian noise (AWGN) is added to the signal to examine the proposed technique and 2011a Mat lab platform is used to simulate these results.

General terms
ECG, Adaptive filter, one long LMS

Keywords
ECG, Adaptive filter, Noise reduction, one long LMS, multiple sub-filter, SNR and MSE

1. INTRODUCTION
The ECG signal is a diagnostic tool that graphically measures and records the electrical activity of heart in details[1]. ECG signal is used in the extraction of vital characteristics. ECG signal amplitude lies between 0.01 to 3 mv and its frequency ranges from 0.5 to 100 Hz[2]. It consists of three pulses p-wave, QRS complex and T-wave as represented in figure1.

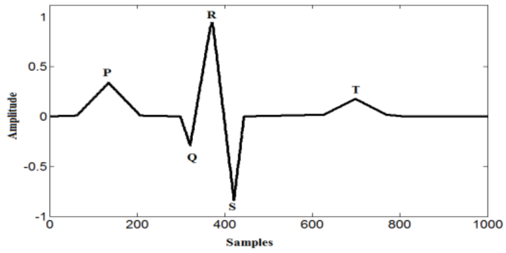

Figure 1 ECG signal

ECG signal suffer from different types of noise such as Power Line Interference (PLI), Base Line Wander (BW)andElectromyography (EMG). PLI generated when an ECG machine is poorly grounded andits frequency value is 60 HZ and its multiples[3]. BW occurs due to Patient movement, dirty lead wires/electrodes, loose electrodes, respiration and perspiration. Its frequencyis lower than0.5 HZ. EMG generated from muscles, it change from person to person and it is nearly has the same range of ECG signal frequency[4].It is important to produce ECG signal without noise in order to provide accurate diagnostic.

Adaptive filter techniques are suitable for filtering the EGG signal as it is random in nature[2].

2. ADAPTIVE FILTER
Adaptive filter algorithms are widely used for different applications such as noise cancellation, acoustic Echo cancellation, signal prediction and Channel equalization[5]. These filtersare self-designing digital filter as their coefficients are varying with time in order to minimize the error signal[6] .This error signal is the difference between desired signal and the filter output signal as;[5].

$$e\,(n) = d\,(n) - y(n) \qquad (1)$$

Where, X (n) is the input signal , y (n) is the output signal, d(n) is the desired signal and e(n) is the error signal .This error signal used to control the adaptive filter algorithm in order to update the filter coefficients[7] as illustrated inFigure 2.

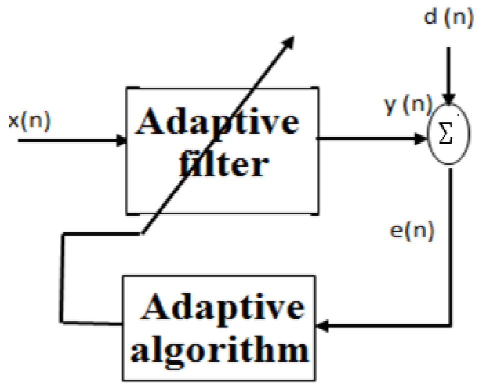

Figure 2 block diagram of adaptive filter.

Least Mean Square error (LMS), Normalized Least Mean Square error (NLMS), Recursive Least Mean Square error (RLS) and state-Space Recursive Least Mean Square error (SSRLS) are examples of adaptive filter algorithms[8]. These algorithms are different from each other by the relation which used to update the filter coefficients.The performance is evaluated according to:

- **Convergence speed:** This is determined by the number of iterations required for an algorithm to reach its desired MSE value[9].

- **Misadjustment:** The misadjustment is a dimensionless measure of the difference between the optimal performance and the actual performance of the LMS algorithm[10].
- **Computational requirements:** it is related to number of operations required to perform complete iteration of the algorithm and amount of memory needed to store the required data[11].
- **Numerical Robustness:** An adaptive filter algorithm is robust when its digital implementation using finite-word- length operation is stable[12].

The preferred adaptive filter algorithm should be robust, simple computations with higher convergence speed and small misadjustment. The stability and convergence speed are the most important parameters used to evaluate the adaptive algorithms[13].

3. LMSADAPTIVE FILTER

LMS is widely used adaptive filter due to its simplicity, low computational complexity and stability[14]. The coefficients of this filter are updated using the following formula:

$$\mathrm{W}(n+1) = \mathrm{w}(n) + \mu e(n) x(n) \qquad (2)$$

Where $\mathrm{w}(n) = [\mathrm{w}_0(n), \mathrm{w}_1(n),, \ldots, \mathrm{w}_P(n)]^T$ the filter coefficients vector and P is is the filter order. This filter is updated at each iteration, and it is effected by pervious filter coefficients vector , step size(μ) and calculated error signal [3].The range of step size is 0≤μ<1 LMS output vector is controlled using filter coefficients vector as following[15]:

$$y(n) = w(n)^T x(n) \qquad (3)$$

LMS is a slow convergence speed filter, as it takes high time or needs large number of iterations in order to calculate the optimum filter coefficients that reduce MSE signal.

If fast convergence is desired, one should choose a large step size according to the stability limits[13].

The one long LMS adaptive filter is evaluated using 2011a Matlab platform. Figure 3 (a) represents the desired ECG signal for a normal patient. If EMG noise applied to this signal it will look like Figure 3 (b). EMG noise is equivalent to 10 dB AWGN. Figure 3 (c) illustrates the ECG signal after one long LMS filter with μ=0.2 and $P = 10$.

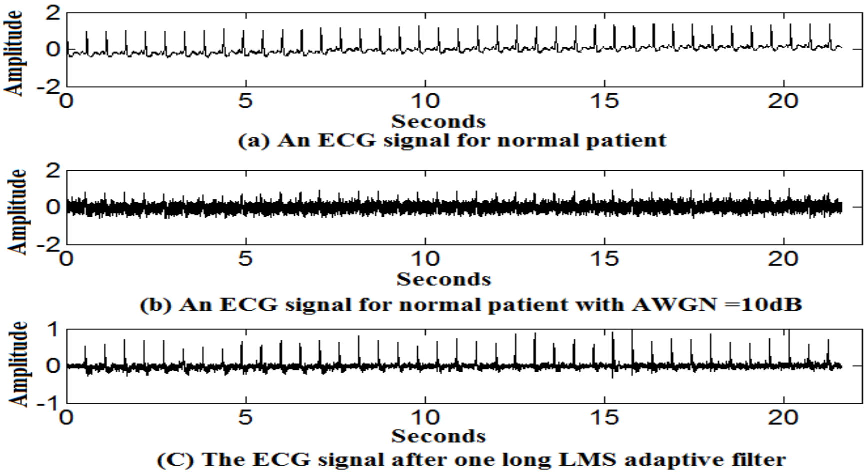

Figure 3the result of one long LMS for noisy ECG signal with input SNR 10dB

AWGN is the basic noise model[16]. AWGN is used as noise source for ECG signal to examine the one long LMS algorithm and the proposed technique .AWGN is generated by Matlab code with SNR 10 dB.The noisy ECG signal is presented in figure 3 (b). This signal used as input to one long LMS adaptive filter algorithm and its SNR before filtering is equal to -3.684 dB. Figure 3 (c) represent the output of filter with SNR =2.4302 dB so, noisy ECG signal is enhanced by 6.11 dB.

4. PROPOSED TECHNIQUE

This paper proposed a multiple sub-adaptive filter to increase convergence speed of one long LMS adaptive filter[17]. This technique based on; decompose the one long LMS adaptive filter into three cascaded low order filters as shown in Figure 4. The filter order of three sub-filters is 2, 6 and 2 respectively.

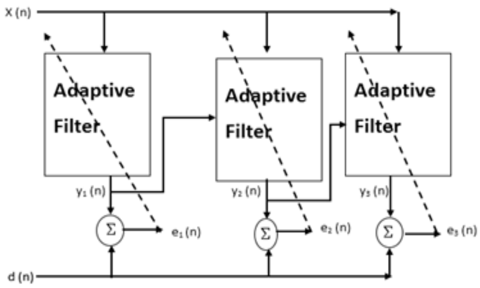

Figure 4the block diagram of the proposed technique

The operation of this filter based on, applying input signal to 1st sub-filter. The output of this filter is filtered by 2nd sub-filter. Finally, the 2nd filtered signal applied to 3rdsub-filter in order to reduce its noise as:

$$y_1(n) = w_1(n)^T x(n) \qquad (4)$$

$$e_1(n) = d(n) - y_1(n) \qquad (5)$$

$$w_1(n+1) = w_1(n) + \mu e_1(n)\, x(n) \qquad (6)$$

$$y_2\ (n)\ = w_2\ (n)^T y_1(n) \qquad (7)$$

$$e_2\ (n)\ =\ d\ (n) - y_2\ (n) \qquad (8)$$

$$w_2\ (n+1)\ = w_2\ (n)\ +\ \mu e_2\ (n)\ x(n) \quad (9)$$

$$y_3\ (n)\ =\ w_3\ (n)^T y_2\ (n) \qquad (10)$$

$$e3\ (n)\ =\ d\ (n) - y3(n) \qquad (11)$$

$$w_3(n+1) = w_3(n) + \mu e_3\ (n)\ x(n) (12)$$

The multiple sub-adaptive filtersalgorithm is evaluated using 2011a Matlab platform. Figure 5 (a) represents the desired ECG signal for a normal patient. Figure 5 (b) represent AWGN added to ECG signal with SNR = 10 dB. Figure 5 (c) illustrates the output of first sub filter LMS filter , Figure 5 (d) illustrates the output of second sub filter LMS filter and Figure 5 (e) illustrates the output of third sub filter LMS withμ=0.2.

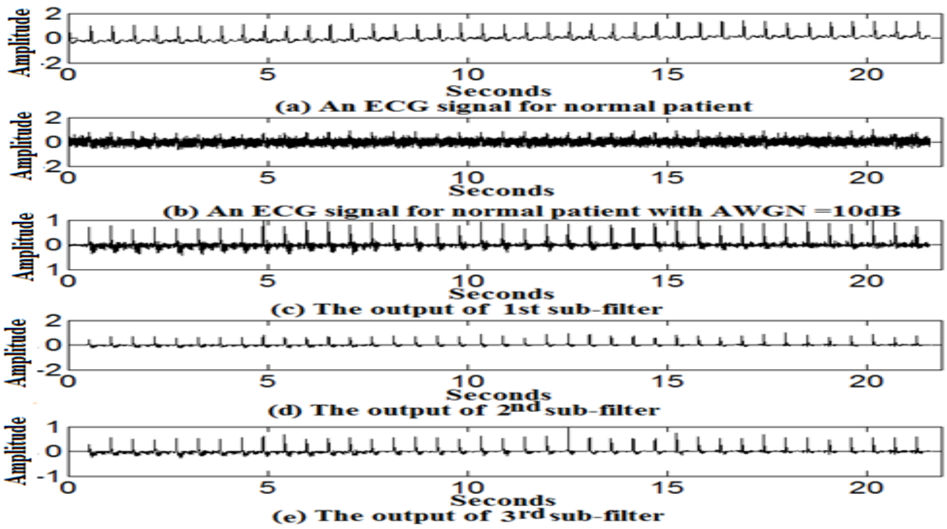

Figure 5 the results of proposed technique

Noisy ECG signal as in figure 5 (b) used as input to first 1st sub-filter algorithm with SNR before filtering = -3.684 dB. Figure 5 (c) represent the output of first 1st sub-filter with SNR =4.1163 dB so, noisy ECG signal is enhanced by 7.8003 dB. Figure 5 (d)represents the output of second 2nd sub-filter with SNR= 6.5478 dB so, noisy ECG signal is enhanced by 10.2318 dB. Figure 5 (e)represent the output of third 3rd sub-filter with SNR = 7.4269 dB so, noisy ECG signal is enhanced by 11.1109 dB.

From Figure 3 and Figure 5, the three multiple sub- adaptive LMS filter provides higher improvement in terms of SNR than one long LMS adaptive filter by 5 dB.

5. EVALUATION OF THE PROPOSED TECHNIQUE

The one long LMS adaptive filter and proposed multiple sub-adaptive filter are evaluated and examine using the data base of ECG signal is used from MIT-BIH data base of patient (100) from physio bank ATM[18]. The sampling frequency of the recorded samples is 1000 Hz. AWGN of 10 dB is added to the signal to examine the one long LMS adaptive filter and proposed technique. The tested signal consists of 22000 samples.

This paper aimed to design an adaptive filter with fast convergence speed and provide higher SNR.The convergence speed depends on the length of filter and step size μ[19]. In this paper the filter length is fixed and different values of μ is used.

To evaluate performance of the proposed technique comparison between one long LMS adaptive filter and proposed technique is applied in terms of different values of μ and SNR with fixed filter length p=10 for both one long LMS and proposed technique as illustrated in figure(6).

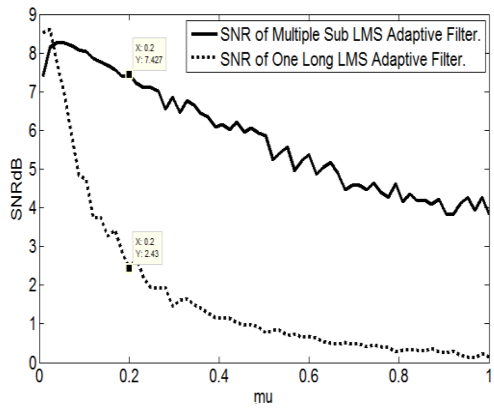

Figure 6a comparison between proposed technique and One Long LMS adaptive filters in terms of SNR for different mu

As shown in figure 6 it is Cleary that the proposed technique has SNR higher than the one long LMS algorithm for different values of step size μ.Also the ECG signal for a sick Patient is used to evaluate the difference between one long LMS adaptive filter and the proposed technique.

Figure 7 a represents the desired ECG signal for a Sick patient. This signal applied to AWGN of 10 dB SNR so, its calculated SNR is -3.4414 dB as presented in Figure 7 (b). Figure 7 (c) illustrates the output of one long LMS filter with μ=0.2 and filter order P=10. The calculated SNR of this filtered signal is 4.6781 dB. This means that one long LMS adaptive filter enhance SNR of ECG signal by 8.1195 dB.

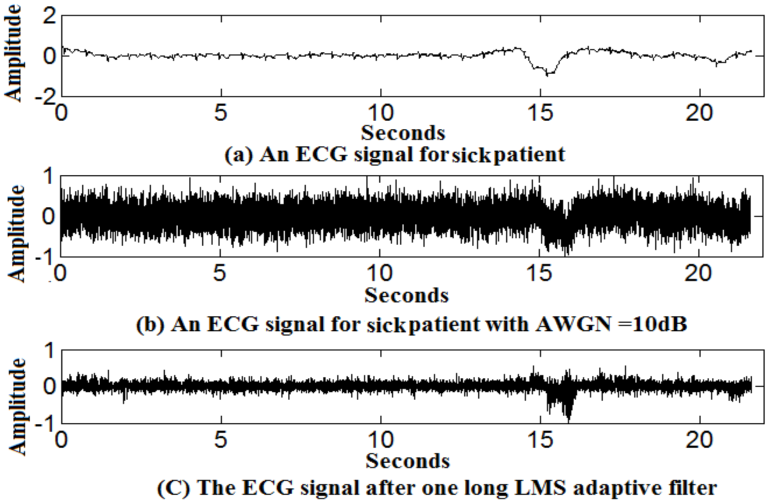

Figure 7 the result of one long LMS for noisy ECG signal with input SNR 10dB

Also this desired ECG signal and Noisy signal are applied to the proposed technique. Figure 8 (a) illustrates the output of first sub-filter with μ=0.2 and filter order p=2 with SNR=3.8518 dB. The first sub-filter enhances ECG by 7.2932 dB. Figure 8 (b) illustrates the output of second sub- filter with filter order p=6 with SNR=3.7990.the second sub-filter enhance ECG by 7.2403 dB. Figure 8 (c) illustrates the output of third sub-filter withSNR=5.8851 dB. The third sub-filter enhances the ECGsignal by9.3265 dB.

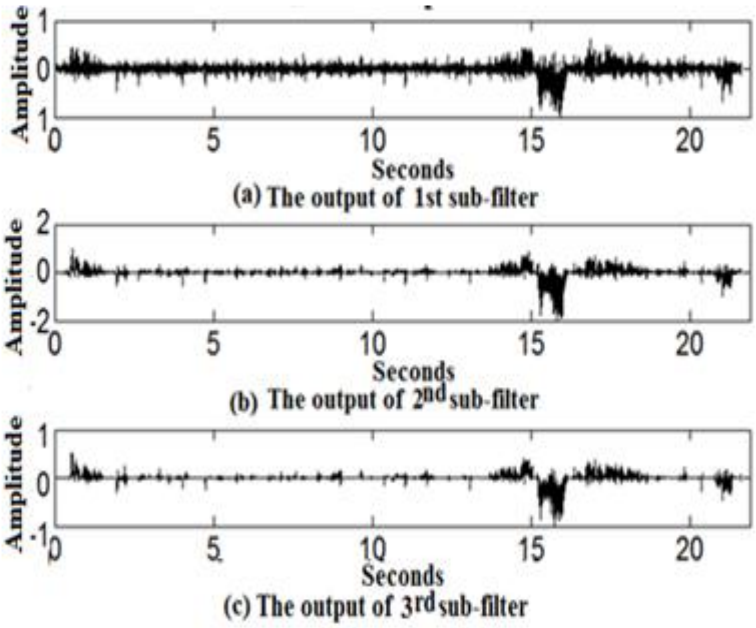

Figure 8 the output of the proposed technique

From figure 7 and figure 8, the three multiple sub-adaptive LMS filter provide higher improvement in terms of SNR than one long LMS adaptive filter by 1.207 dB.

For normal patient and sick patient, the proposed technique has higher improvement in SNR than one long LMS adaptive filter as illustrates in table 1 and table 2 respectively.

Table 1 record of SNR for normal patient

Step size(μ)	SNR					Improvement in SNR	
	SNR before filter	SNR for one long LMS	SNR of 1st sub-filter	SNR of 2nd sub-filter	SNR of 3rd sub-filter	One long LMS	3 sub - LMS
0.096	-3.684	4.7932	4.7005	7.5825	8.0291	8.48	11.71
0.2	-3.684	2.4302	4.1163	6.5478	7.4269	6.11	11.11

Table 2 record of SNR for sick patient

Step size(μ)	SNR					SNR improvement	
	SNR before filter	SNR for one long LMS	SNR of 1st sub-filter	SNR of 2nd sub-filter	SNR of 3rd sub-filter	One long LMS	3 sub-LMS
0.096	-3.4414	6.0676	4.2750	5.3101	7.3267	9.51	10.8
0.2	-3.4414	4.6781	3.8518	3.7990	5.8851	8.12	9.33

To examine the convergence speed number of iterations with MSE is plotted to compare between one long LMS adaptive filter and proposed technique. Figure 9 illustrates that comparison at certain value of μ=0.2. At MSE=0.04 the number of iteration required by proposed technique is 1.54*104 but number of iteration required by one long LMS adaptive filter is 4.68*104. The proposed technique is converge to its MSE faster thanone long LMS filter by 3.14*104times.

It is obvious that the proposed technique is higher than one long LMS adaptive filter in terms of MSE for largest number of iterations.

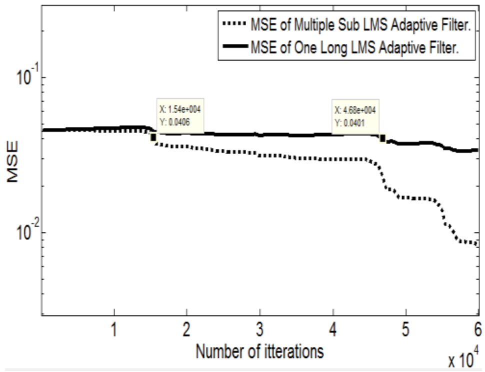

Figure 9a comparison between proposed technique and One Long LMS adaptive filters in terms of MSE for different number of iterations

6. CONCLUSION

This Paper proposes to filter ECG signal to enhance it. Anew technique for multiple sub-filters is introduced. This proposed technique provides higher SNR than one long LMS adaptive filter. Also, it provides higher convergence speed. Using different types of adaptive filter algorithms will be suggested to increase the quality of ECG signal.

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