Efficient ECG Signal Conditioning Techniques using Variable Step Size Least Mean Fourth Algorithms

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***Abstract*—obtaining an artifact free signal is an important task in making a successful diagnosis using Electro Cardiograph (ECG) signal. Several techniques were proposed in the literature with varying degree of accuracy. In this paper some efficient signal conditioning techniques to remove the artifact from ECG signals are presented. The proposed techniques are derived from basic higher order technique known as of Least Mean Fourth (LMF) algorithm.All the techniques are evaluated using MIT-BIH arrhythmia database. The SNR performance of the techniques is calculated and is compared with Normalized Least Mean square (NLMS) algorithm. From the SNR measurements obtained variable XE-NLMF was found to be exhibiting the superior performance over the NLMS and the other techniques and on an average the SNR values of variable XE-NLMF in case of PLI, BW,MA and EM artifacts are 10.7800dB, 8.5950dB, 9.0703dB, 8.3210dB which are better than their counterparts. The convergence characteristics of all these techniques measured have further shown the suitability of the Variable XE-NLMF technique over the other in using at real time situations**

Keyword - Electro Cardio Graph, Artifact, Least Mean Fourth Algorithm, Noise Cancellation.

I. INTRODUCTION

Remote Diagnostics is playing a vital role in modern day health care. It basically involves wireless transmission of medical data and is meant for outpatient care in hospitals. But at the same time challenges arise in the form of handling the signal against the artifact and operating environment. Great amount of work was carried out in the past to develop an ideal system to meet the constraints needed to tackle the real time situations [1]-[2], [4]-[8]. For instance in [4] Shuang Song*et.al* proposed a power efficient amplifier to amplify the ECG signals. The system is implemented on a 0.18µm CMOS technology. It uses multichannel power supply with optimized circuitry along with the low power amplifier to achieve better performance. Similarly in [5] a power efficient loss less encoder has been proposed and it is implemented at 0.18 µm CMOS technology. It uses a two stage Huffman encoder in addition to an adaptive predictor for lossless encoding of the data

The current work concentrates on removing the artifact from the ECG signal. From the reports of WHO [9] it is observed that majority of deaths are due to the heart related issues and the ECG is a fundamental technique to identify the problems in heart. The flow of Electrocardiograph(ECG) based analysis can be as shown in the Fig.1. Artifact removal is the first pre-processing task in ECG analysis. Successful removal helps to identify the arrhythmia accurately. This is usually followed by the target segment identification and monitoring and data analysis. Arrhythmias are the abnormal rhythms that gives us the information about the cardiac health and which need to be monitored. Some examples are Bardycardia, Tachycardia and ventricular fibrillation. These are identified by means of monitoring the onset, duration and the amplitude of the segment (P,Q,R, S and T). However the signal degradation is inevitable due to the physiological, non-physiological reasons and during transmission. Basically the signals obtained from a transducer will in general have low strength and will be low in frequency. At this stage it is necessary to amplify the signal reducing the impact of noise on signal. These artifacts will affect the detection of arrhythmia greatly by corrupting the amplitude and timing information in the original signal. So extraction of signal into its pure form needs to be done before. Due to the inherent non stationary of the data and noise the adaptive algorithms are found to be suitable in denoising these signals. At the same time it is also possible to use non adaptive algorithms [12]-[16].These basically involves independent component analysis, Empirical Mod Decompositionand wavelet techniques. LMS filtering can be regarded as a fundamental method in adaptive filtering technique. It is computationally easy but has a relatively low performance over standard LMF algorithm. Researchers have worked in denoising the signal using LMS [10], [11]. In [10] Rahman et.al has used the LMS based filter for the effective noise cancellation in ECG signal. The LMS is computationally easy but it has poor performance at low SNR.

In adapting a technique to filter the signal the convergence rate the technique is offering, steady state error and the complexity are the important factors. This is because faster convergence rate means that the technique is able to track the signal changes effectively and low steady state error indicates the closeness of the solution to the actual signal characteristics. So in our present work we would like to investigate the performance of the LMF in case of various artifacts keeping in view of the performance of variable XE-NLMF algorithm and Standard MIT BIH arrhythmia database was used to evaluate these techniques.

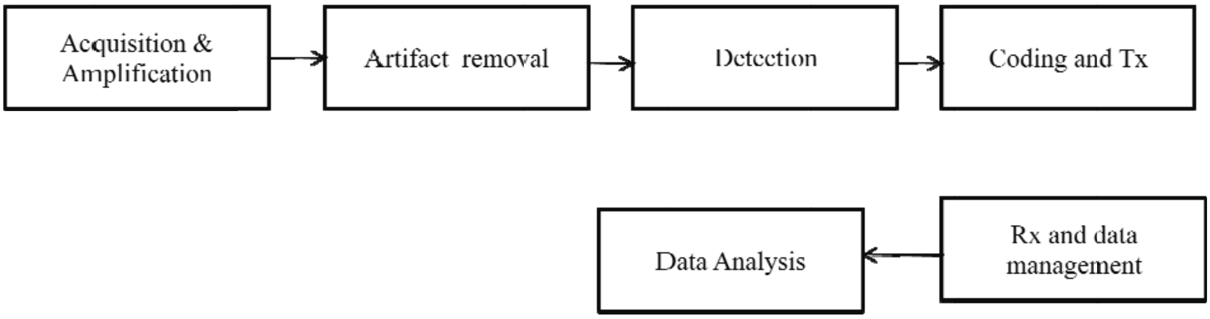

Fig.1. Flow of ECG based Analysis

II. SIGNAL CONDITIONING TECHNIQUES

In the present paper in order to filter the ECG we are using the LMF algorithm. It possesses fast convergence when the error is high and it reduces when the error decreases. Unlike LMS the LMF algorithm offers better performance at low SNR if weights are initialized nearer to optimum value. Similarly one of the advantages of LMF over the LMS is its faster convergence at low SNR conditions. But the stability of the algorithm depends on input signal power, noise power, weight initialization vector and regressor statistics [18]-[21]. LMF works best under non Gaussian environments like uniform, sine etc. However the performance in Gaussian environments is improvised in later work. In order to overcome the above said drawbacks of LMF many variants to LMF have been proposed. A combination of both LMS and LMF have used in [22] to get the benefit of both of the algorithms. This algorithm switches between the two based on some threshold logic. Similarly the normalized versions are introduced. A normalized LMF enjoys the advantages of LMF in addition to the stability resulting from the normalization. It is obtained by normalizing the step size with respect to the signal and noise power. This helps to recover the signal in low SNR conditions with good convergence rate. This advantage is observed in the performance parameters measured.

The basic adaptive filter structure is as shown in the Fig.2. Here the ECG signal corrupted with the artifact is given as desired input to the filter and it is denoted as d. Artifact that corrupted the signal is denoted as P_1. Similarly the input to the filter is a random signal R which is assumed to be statistically correlated with P_1. The basic idea in these algorithms is to find the difference between the desired and the output of the filter and to minimize it, this results in increased signal to noise ratio (SNR). Here the error is denoted as e. So e = d-R*W. Where W is the weight vector of the filter and μ is the step size.

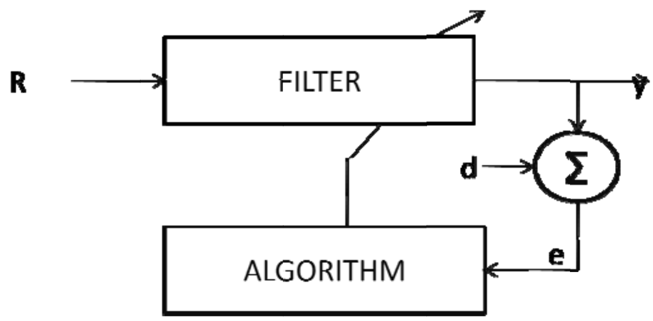

Fig.2. Adaptive Filter

By minimizing the fourth ordered error the SNR of filter output will increase. The resulting weight update equation of LMF can be written as [17]

$$W_{k+1} = W_k + \mu e_k^3 R_k \tag{1}$$

As mentioned earlier this algorithm has different stability issues. To overcome it normalization is performed. The idea behind the normalization is to normalize the step size with respect to the signal power. It facilitates the filter to have faster convergence while reducing the error. The basic equations for LMF normalization can be taken from the work of Eweda in [25].Here the step size is normalized with respect to the fourth ordered regressor. The weight update equation of this algorithm is as below.

$$W_{k+1} = W_k + \frac{\mu e_k^3 R_k}{\delta + \max(R_k)^4} \tag{2}$$

In general in addition to the even powered signal in the denominator of the equation it is customary to place a very small value δ to prevent the system from becoming unstable when the signal approaches zero. As a whole these terms are making the filter to be a variable step size. But the above equation has disadvantages in terms of its stability depending on the signal power. So in this paper we would like to use the contribution made by Chan et.al in [23] for normalization. Here both the signal and error power are used in normalization along with a mixed power parameter α which manages the convergence rate maintaining the stability. The EMSE performance clearly indicated the improvement of it over the NLMF. It is called as XE-NLMF and its weight update equation can be written as[23],Where X denotes the signal and E denotes the error

$$W_{k+1} = W_k + \frac{\mu e_k^3 R_k}{\delta + (1-\alpha)R_k^2 + \alpha e_k^2} \tag{3}$$

Where, δ is a small constant used to avoid the system from becoming unstable when the input is approaching zero. Also α is usually unity. In order to overcome the dependency on the mixing parameter in [24] a variable XE-NLMF algorithm was proposed. Here α value is varied according to the step size. The weight update equation in this algorithm is [24]

$$W_{k+1} = W_k + \frac{\mu e_k^3 R_k}{\delta + (1-\alpha_k)R_k^2 + \alpha_k e_k^2} \tag{4}$$

The above equation conveys that as long as the error is small the mixed term will be small and the steady state error will be small and if the error is more, then the mixed term parameter will tend towards unity[24] thereby stability is achieved. In order to observe the efficiency of the LMF over LMS the normalized LMS algorithm is used. The weight update equation of the NLMS is

$$W_{k+1} = W_k + \frac{\mu e_k R_k}{\delta + \max(R_k)^2} \tag{5}$$

III. CONVERGENCE CHARACTERSTICS

An algorithm is said to be converging if it is able to track the changes in the signal by suppressing the noise. It is well known that convergence is controlled by the step size. Because if the step size is low then convergence will be low and it will not be able to track the rapid changes in the signal, on other hand if the step size is large then the algorithm will converge faster tracking the signal changes. Faster convergence rate is desirable characteristic of any algorithm with the lowest possible steady state error. In filtering an ECG signal with arrhythmia it is necessary to track the sudden changes in the signal which are more rapid in certain arrhythmia cases.

The noise arises during the transmission and also during the acquisition. To meet the high throughput requirement and low margin for the steady state error, it is necessary that the algorithm converge faster in a reliable manner. But the error that arises due to these noises makes the algorithm to update the step size with larger value ending up with the large approximation error and low convergence rate. As stated in [19] the LMF will surely diverge in case of such large change in step size. During the initialization the error will be usually high and the convergence rate will be more and in the later stages it slows down and the error reaches its steady state value.

However it is not the case with the normalized LMF. From the analysis made in [24], it is clear that the variable XE-NLMF is able to handle the noises that occur during the transmission and artifacts. It is the parameter α that actually controls convergence. When the error is large then α will tend towards unity and the convergence will be fast. Similarly if the error is small then α will be small and convergence will be slow making the step size small. This actually occurs when the filter is reaching the steady state. The convergence curves results from plotting the EMSE over several iterations. Here the ECG signal corrupted with the artifact is taken as input and step size, mixed parameter is held constant. Fig.3a shows the convergence characteristics of the XE-NLMF over various values of α. We can see that the EMSE is reducing over iterations and more specifically over the change in α value. It conveys that as α is increasing error term is weighted more and as a result the noise is effectively suppressed. Similarly in Fig.3bthe performance of several of filters is shown. Here a good change

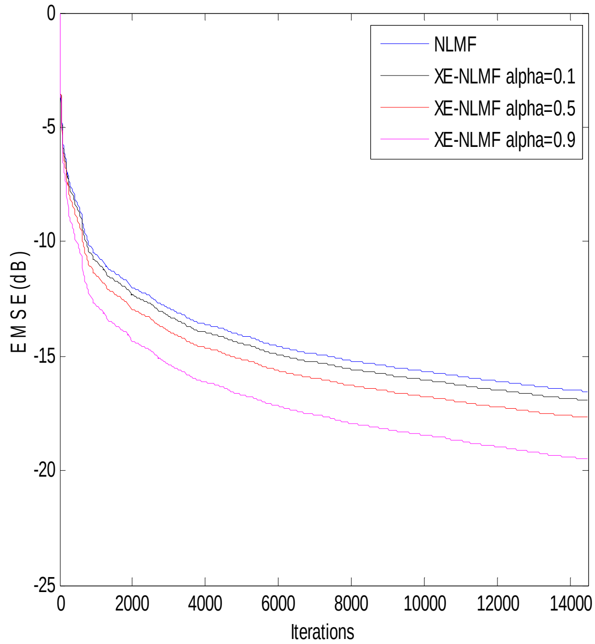

Fig.3a Convergence Curves Of XE-NLMF with various value of α

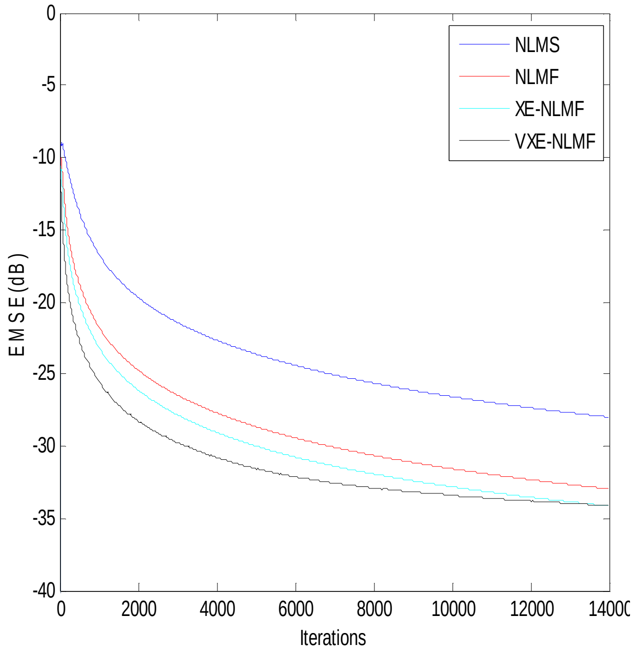

Fig. 3b.Comparison of Convergence Curves

in performance can be seen from the NLMS to the NLMF case and the EMSE is reduced at faster pace compared to NLMS and the steady state error is considerably less compared to NLMS. The steady state error is the difference between the EMSE and zero. This shows the good tracking performance of the LMF at low SNR. We can observe a much more rapid fall of EMSE in case of variable XE-NLMF with a low steady state error, proving it as a suitable technique in tightly time bound usage. A much more clear understanding about the LMF family can be seen in Fig.3c. Here the superiority of variable XE-NLMF can be seen over the other two techniques.

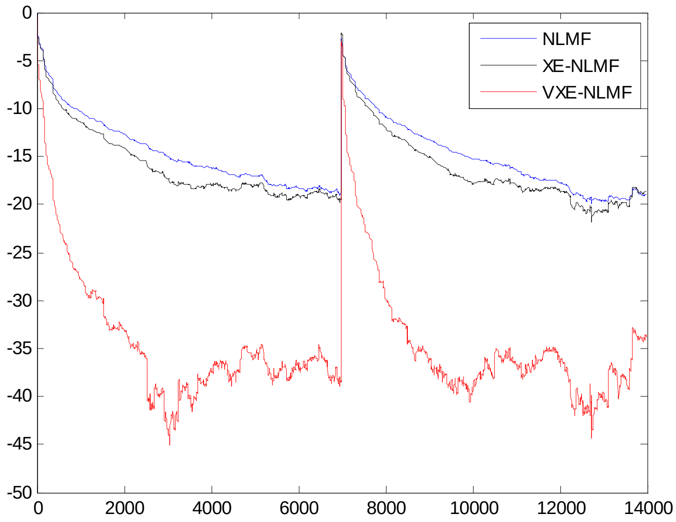

Fig. 3c.Convergence Characteristics of LMF family

IV. EVALUATION OF NOISE CANCELLERS

All the above algorithms along with the NLMS are tested with the help of MIT arrhythmia database. It is obtained from 47 healthy subjects including both men and woman. All the artifacts i.e., Motion artifact, Muscle artifact and Baseline wander are taken from the MIT database itself. These artifacts are collected from the 18 healthy subjects and are sampled at 128Hz. Fig.4 shows the ECG signal corrupted with all the four types of artifacts.

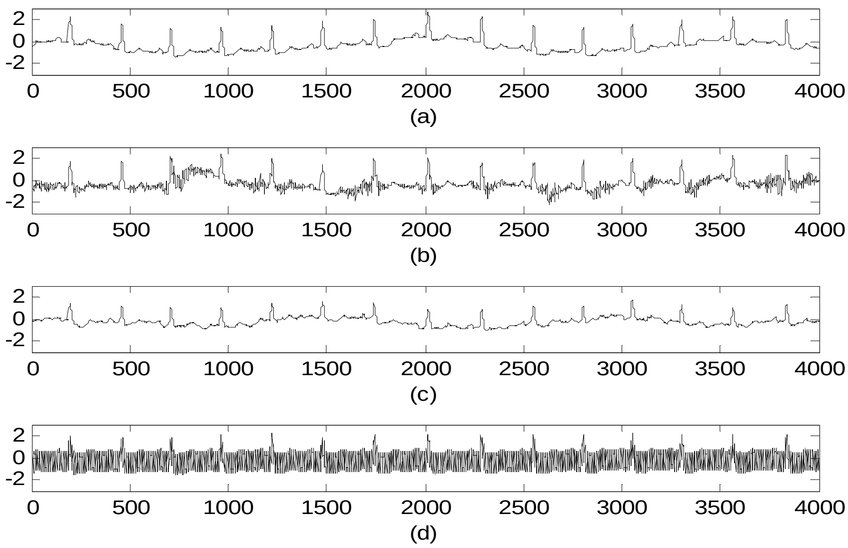

Fig.4. ECG signal Contaminated with a) Base Line Wandering, b) Muscle artifact, c) Electrode Motion artifact and d)Power Line Interference

A. Power Line Interference Cancellation

Power line interference was derived with 1mv amplitude, centred at 60Hz and was sampled at 360Hz from a noise generator. The PLI noise generated is given as reference input and the corrupted signal is given as the desired input.Fig.5 shows the output of the different filters. Here the change in performance can be seen from the NLMS to the variable XE-NLMF case. Similarly Fig.6shows the spectrum of output of the noise cancellers. The SNR measurements are taken for the records and are tabulated as shown in the Table. From the measurements we observe that variable XE-NLMF has a relatively high performance over NLMS. This is also evident from the Fig.5 here an improvement over NLMS is observed. The averaged values of SNR of all the four filter techniques NLMS, NLMF, XE-NLMF and variable XE-NLMF are 7.8392dB, 10.2136dB, 10.7558dB and 7.780dB respectively.

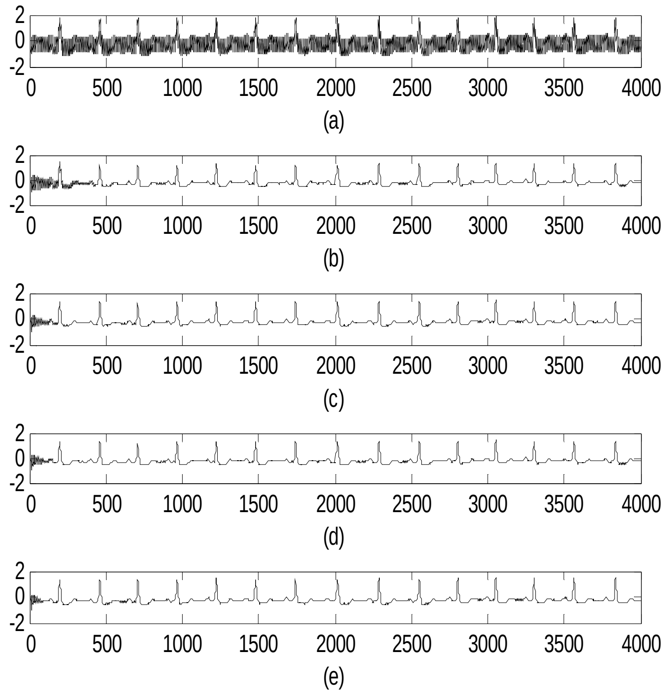

Fig.5. Results of PLI Cancellation using a) Noisy ECG, b) NLMS, c)NLMF, d)XE-NLMF, e) Variable XE-NLMF

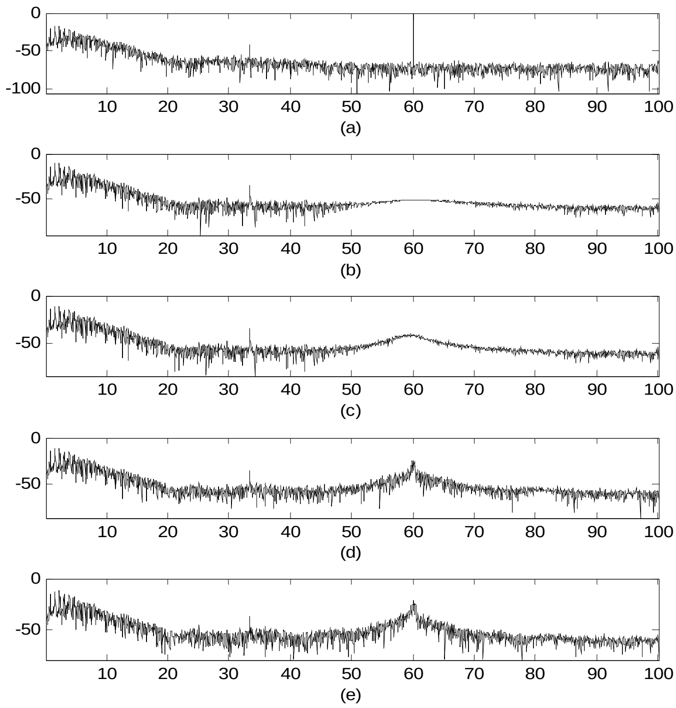

Fig.6. Frequency Spectrum of output of PLI Cancellation using a) Noisy ECG, b) NLMS, c) NLMF, d) XE-NLMF, e) Variable XE-NLMF

B. Base Line Wander Removal

Here the signal corrupted with the base line wander was used as a desired signal and the noise taken from the database is used as the reference to the adaptive filter. The outputs of all the four techniques are as shown in the Fig.7. The residual base line wander noise can be seen in the figure. There exists little or much noise in variable XE-NLMF over the techniques. A good improvement can be seen in terms of change in irregular signal pattern and also from the SNR measurements in the table. The SNR values of the filters NLMS, NLMF, XE-NLMF and variable XE-NLMF are 6.5979dB, 7.621dB, 8.207dB, 8.595dB respectively.

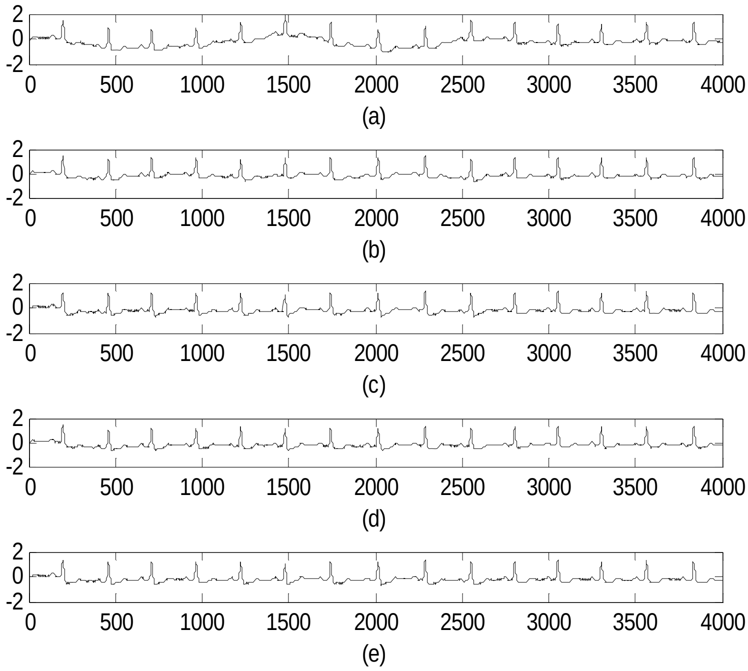

Fig.7. Results of Base Line Wander Cancellation using a) Noisy ECG, b)NLMS, c) NLMF, d) XE-NLMF, e) Variable XE-NLMF

C. Muscle Artifact Cancellation

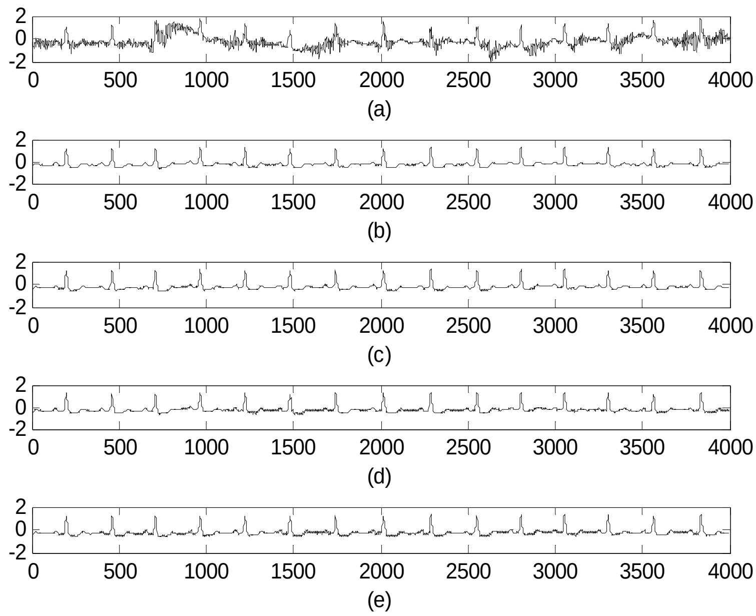

Fig.8. Results of MA Cancellation using a) Noisy ECG, b) NLMS, c) NLMF, d) XE-NLMF, e) Variable XE-NLMF

In this experiment the Muscle noise taken from the database is given as the reference to the adaptive filter. Similarly the ECG records which are corrupted by the Muscle artifact are taken as the desired input to the adaptive filter. The performance of the all the filter techniques can be seen in Fig.8. Traces of noise exist in all the four types of techniques and severity reduced considerably as we come to the case of variable XE-NLMF. The SNR measurements of these filters are 6.9526dB, 7.64093, 8.4247dB, 9.0703dB respectively.

D. Electrode Motion Artifact Cancellation

In this experiment the real time motion artifacts taken from the database is given as the reference to the adaptive filter. Similarly the ECG signal corrupted with the motion artifact is taken as desired input to the adaptive filter. The output of these filters can be seen in Fig.9. Usually the motion artifact introduces the spurious drifts in the signal and adds random noise. This is evident to us from Fig. 9a. A gradual change in this drift can be seen in terms of the amplitude from the NLMS to the variable XE-NLMF filter. The SNR performances of these filters are 7.0914dB, 7.505dB, 7.9741dB, 8.321dB are indicating a significant change in performance.

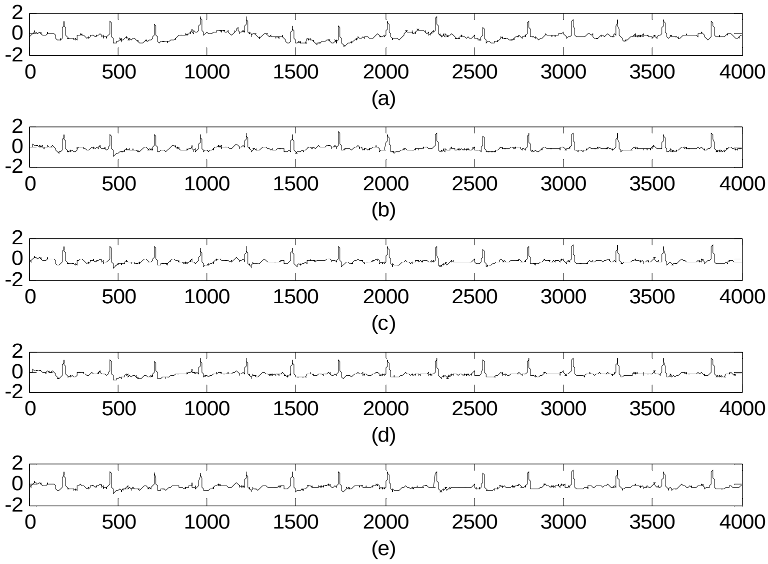

Fig.9. Results of MA Cancellation using a)Noisy ECG, b) NLMS, c) NLMF, d) XE-NLMF, e) Variable XE-NLMF

Table I. SNRI performance of various algorithms for ECG enhancement

Noise Type	Record Number	NLMS	NLMF	XENLMF	VXENLMF
PLI	100	7.8868	10.7769	10.9467	11.7797
	101	7.8193	10.7491	10.9282	11.325
	102	7.8762	10.4698	10.733	11.7496
	103	7.8010	7.7194	9.9277	7.6855
	104	7.8867	11.2273	11.4015	11.2948
	105	7.7654	10.3391	10.5981	10.8460
	Average	7.8392	10.2136	10.7558	10.7800
BW	100	6.3896	7.5622	8.4514	8.9511
	101	6.2955	7.2845	8.1185	8.6516
	102	7.5789	7.9298	8.6790	9.0992
	103	7.3000	7.5486	8.1667	8.4291
	104	7.2637	7.5679	7.6848	7.8941
	105	7.0282	7.8330	8.1436	8.5467
	Average	6.9759	7.6210	8.2073	8.5950
MA	100	6.8942	7.7382	8.4845	8.9357
	101	6.4678	7.1425	8.5638	8.8714
	102	6.7839	7.2891	8.4672	9.6718
	103	7.3673	7.9851	8.2367	8.9267
	104	7.1289	7.7856	8.0135	8.7348
	105	7.0738	7.9051	8.7829	9.2816
	Average	6.9526	7.6409	8.4247	9.0703
EM	100	6.8189	7.6094	8.4037	8.6478
	101	6.6087	7.0499	7.7498	8.1881
	102	7.3564	7.7018	7.9715	8.5654
	103	7.5497	7.8285	8.1361	8.3853
	104	6.8048	7.0709	7.5223	7.7453
	105	7.4103	7.7698	8.0615	8.3970
	Average	7.0914	7.5050	7.9741	8.3210

V. CONCLUSION

In the present paper some adaptive noise cancellers based on LMF algorithm were investigated to denoise the ECG signal. All the four techniques are evaluated using the MIT BIH database. In order to show the efficiency of the proposed method the (NLMS) Normalized Least Mean Fourth algorithm was used. From the SNR performance shown in the Table I and form the convergence curves it is clear that variable XENLMF shows a good performance over the other techniques and it's usage in real time ECG signal denoising with tight timing constraints and can be met with reasonable degree of accuracy even in low SNR conditions.

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