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Performance Comparison of Adaptive Filter Algorithms for ECG Signal Enhancement

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***ABSTRACT*— In this paper various adaptive filter based algorithms that can be applied to ECG signal in order to remove various artefacts from them are presented. The goal of the paper is to show the comparison based on signal to noise ratios of all the adaptive filter algorithms used for the analysis of ECG signals with Power line Interference. Simulation studies shows that the proposed novel algorithms like NLMS and DLMS based adaptive systems present better performances compared to existing realizations LMS, SRLMS and NSRLMS based procedures in terms of signal to noise ratio**.

***Keywords*—ECG, Adaptive filter Algorithms, LMS, NLMS, DLMS, SRLMS, NSRLMS.**

I. INTRODUCTION

The electrocardiogram (ECG) is a graphical representation of the cardiac activity and it is widely used for the diagnosis of heart diseases. Several noises contaminate the ECG signal while recording, the predominant artefacts present in the ECG signal are Power-line Interference (PLI), Baseline Wander (BW), Muscle Artefacts (MA) and Motion Artefacts (EM). In this paper Power-line Interference is considered for SNR simulations. The goal for ECG signal enhancement is to separate the valid signal components from the undesired artefact, so as to present an ECG that facilitates easy and accurate interpretation.

In general these methods can be categorized in to non adaptive and adaptive filtering. The non adaptive filtering approaches mainly include IIR filter, FIR filter and notch filter. Adaptive filtering techniques are the popular approaches for the processing and analysis of the ECG signals. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals.

Power-line interference (PLI) is a significant source of noise during bio-potential measurements. It degrades the signal quality and overwhelms tiny features that may be critical for clinical monitoring and diagnosis [1]. In most existing PLI suppression methods, it is assumed that 1) the PLI is already present in the input ECG signal, 2) the number of harmonics is known (usually a single sinusoid), and 3) the frequencies of the narrowband harmonics or the statistics of them are known. But these assumptions are often unrealistic in real-world applications [1].

In this study we propose all the adaptive filter algorithms, filter updating equations which provide a base for the SNR results.

This paper is organized as follow: Section I gives the introduction of the ECG signal and power-line interference noise that affects the ECG. Section II helps to understand the background of adaptive filter algorithms with their equations of the related work. This section also explains the basic adaptive filter structure used for primitive LMS algorithm, which forms a base for all the other improved algorithms. Section III shows the simulation results and performance of the proposed techniques and at last section IV concludes the paper and followed by the references.

II. PROPOSED IMPLEMENTATION

Consider a LMS adaptive filter structure of length L, depicted in Fig. 1, that takes an input sequence x(n) and updates the weights as

$$w(n + 1) = w(n) + \mu\, x(n)\, e(n), \qquad (1)$$

Where w(n) is the tap weight vector at the nth index x(n) =

$$[x(n)\ x(n-1) \cdot \cdot x(n-L+1)] \ (2)$$

With x(n) is the input vector

$$e(n) = d(n)-w(n)\, x(n)$$

with d(n) being the so-called desired response available during initial training period and μ being the step size [11].

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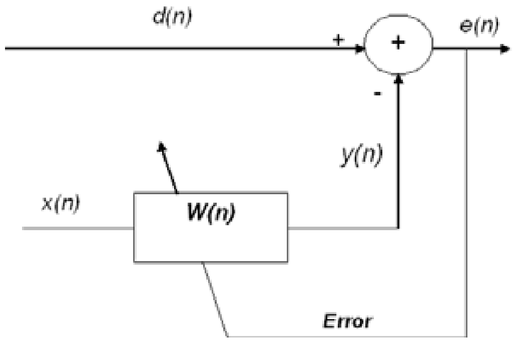

Fig. 1. Adaptive filter structure

Normalized LMS (NLMS) algorithm is another class of adaptive algorithm used to train the coefficients of the adaptive filter [12]. This algorithm takes into account variation in the signal level at the filter output and selecting the normalized step size parameter that results in a stable as well as fast converging algorithm.

The weight update relation of NLMS can be expressed as,

$$\mathbf{w}(n + 1) = \mathbf{w}(n) + \mu(n)\, \mathbf{x}(n)\, e(n) \quad (3)$$

with variable step size parameter $\mu(n)$, $x(n)$ being the input vector, $e(n)$ is the error.

Another weight update relation for NLMS algorithm is as follows

$$\mathbf{w}(n + 1) = \mathbf{w}(n) + [\, \mu / (p+ x^t(n)\, \Phi(n)\,]\, \mathbf{x}(n)\, e(n) \quad (4)$$

The variable step can be written as,

$$\mu(n) = \mu / p + x^t(n)\, x(n) \quad (5)$$

Here μ is fixed convergence factor to control mal adjustment. The parameter p is set to avoid denominator being too small and step size parameter too big.

Among the two adaptive algorithms presented above, the SA has a convergence rate and a steady-state error that are slightly inferior to those of the LMS algorithm for the same parameter setting. But, the computational complexity of SA is much less compared to LMS algorithm [11]. The advantage of the NLMS algorithm is that the step size can be chosen independent of the input signal power and the number of tap weights. Hence the NLMS algorithm has a convergence rate and a steady state error better than LMS algorithm. On the other hand some additional computations are required to compute $\mu(n)$ [12].

In order to cope with both the complexity and convergence issues without any restrictive tradeoff we proposed a normalized signed LMS algorithm (NSLMS) for removal of noise from ECG signal.

The weight update relation of NSLMS can be expressed as,

$$\mathbf{w}(n + 1) = \mathbf{w}(n) + \mu(n)\, \mathbf{x}(n)\mathrm{sgn}\{e(n)\} \quad (4)$$

with sgn being the sign term which reduces computational complexity [12].

III. SIMULATION RESULTS

To show that NSRLMS algorithm is really effective in clinical situations, the method has been validated using several ECG recordings with a wide variety of wave morphologies from MIT-BIH arrhythmia database. We used the benchmark MIT-BIH arrhythmia database ECG recordings as the reference for our work and real noise is obtained from MIT-BIH [11].

To demonstrate power line interference (PLI) cancellation we have chosen MIT-BIH record number 103, record number 105 and record number 106. The input to the filter is ECG signal corresponds to the data 105 corrupted with synthetic PLI with amplitude 1mv and frequency 60Hz, sampled at 200Hz [10]. In the simulation we provide the input ECG database number, Order of the filter, Step size, amplitude of the interference signal proportional to the intensity of the interference signal and initial phase angle of power line interference signal.

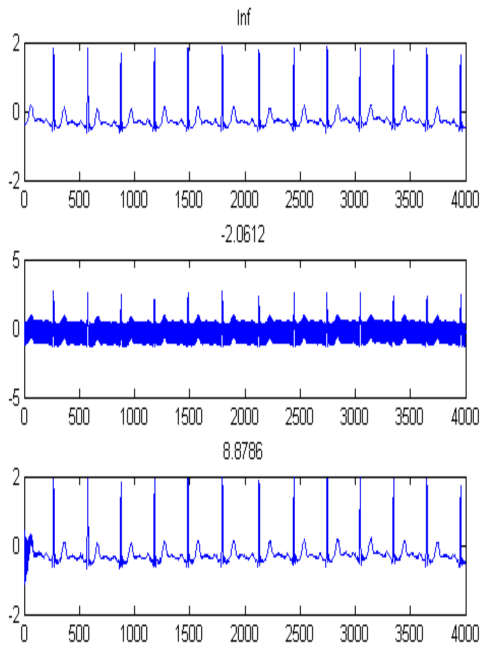

Figure. 2. Typical filtering Results of Power-line Interference (a) Original ECG Signal (b) ECG Signal with 60hz noise (c) Recovered ECG Signal using Sign Repressor LMS Algorithm.

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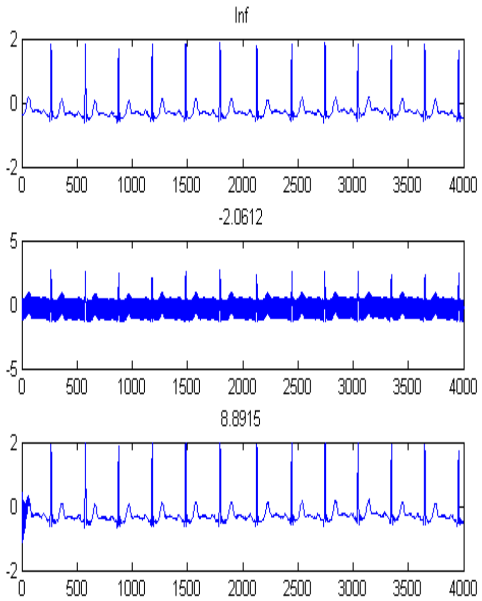

Figure. 3. Typical filtering Results of Power-line Interference (a) Original ECG Signal (b) ECG Signal with 60hz noise (c) Recovered ECG Signal using Normalized Sign Repressor LMS Algorithm.

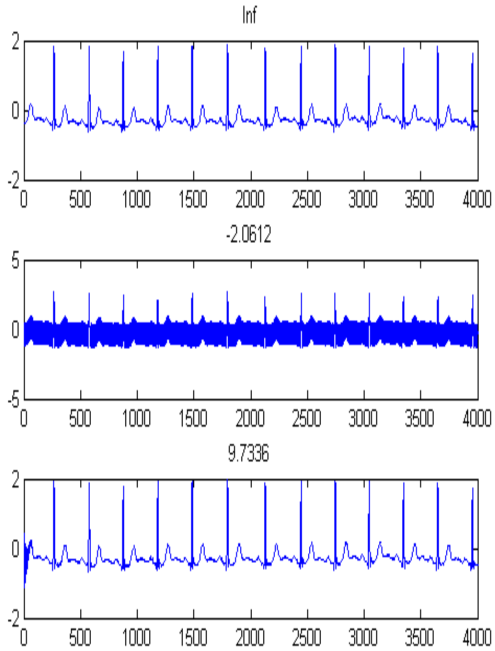

Figure. 4. Typical filtering Results of Power-line Interference (a) Original ECG Signal (b) ECG Signal with 60hz noise (c) Recovered ECG Signal using LMS Algorithm.

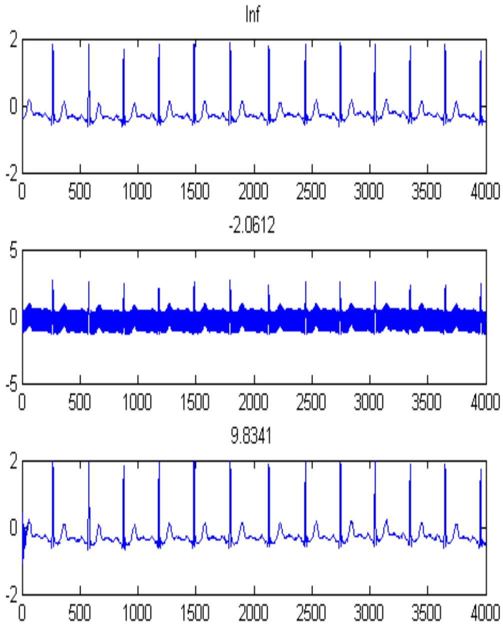

Figure. 5. Typical filtering Results of Power-line Interference (a) Original ECG Signal (b) ECG Signal with 60hz noise (c) Recovered ECG Signal using Normalized LMS Algorithm.

Figures 2,3,4 and 5 reflects the diagrams of ECG signal in cleaned, noisy and recovered condition.

First graph shows the original ECG signal with infinity SNR. Second graph shows the ECG signal with 60Hz PLI noise with a SNR of -2.0612. Third graph shows the cleaned ECG signal at filter output.

By comparing first and last graph in all the figures it is seen that the signals are replica of each other, which means that the ECG signal obtained after filtering is the perfect approximation of the clean ECG signal. This also shows the efficiency of adaptive filter algorithms.

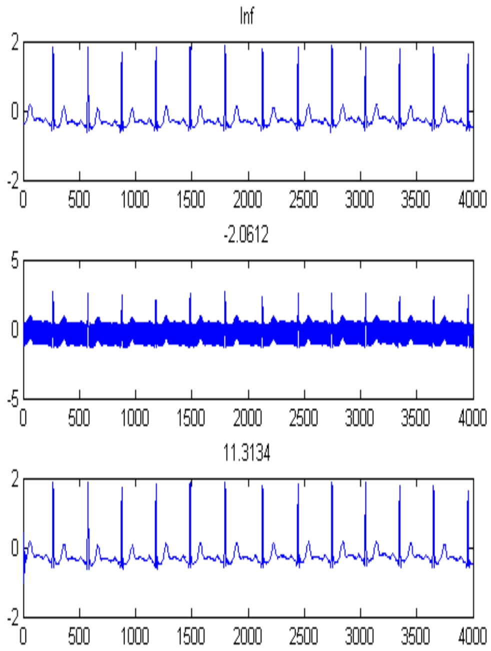

Figure. 6. Typical filtering Results of Power-line Interference (a) Original ECG Signal (b) ECG Signal with 60hz noise (c) Recovered ECG Signal using Differential LMS Algorithm.

Above Figure shows that the signal to noise ratio in the original ECG signal is infinity because of noise being zero. In the next two figures we can evaluate the signal to noise ratio improvement given in the table.

TABLE I

PERFORMANCE COMPARISION of SRLMS, NSRLMS, LMS, NLMS and DLMS ALGORITHMS for POWER-LINE INTERFERENCE

Algorithm	SNR before filtering	SNR after filtering	SNR Improvement
SRLMS	-2.0612	8.8786	6.8174
NSRLMS	-2.0612	8.8915	6.8303
LMS	-2.0612	9.7336	7.7124
NLMS	-2.0612	9.8341	7.7729
DLMS	-2.0612	11.3134	9.2522

Above table shows the comparison of all the adaptive filter algorithms considered, that are SRLMS, NSRLMS, LMS, NLMS and DLMS. This performance comparison is based on signal to noise ratios. It is shown from the table that the basic algorithm like SRLMS produces an SNR which is less compared with NSRLMS, which means that normalizing improves the SNR. Same is the case with LMS and NLMS also. Whereas the highest SNR is obtained with DLMS algorithm but the drawback with this algorithm is computational complexity is very high.

IV. **CONCLUSION**

In this paper performance comparison of all the adaptive filter algorithms used to remove the Power-line Interference from the ECG signal after its enhancement is presented. From the simulation results it is shown that the output SNR values for the algorithms are obtained and compared with each other, with reference to Power-line Interference Noise and we can see that the approach of using adaptive filter algorithms for ECG signal enhancement provide a better realization than non-adaptive structures. This paper also shows that ECG signal enhancement gives a clear picture, how easily we can evaluate a noisy ECG signal, a clean ECG signal and prevent the original signal being contaminated from PLI. The proposed weight updating equations for NLMS and NSLMS boost up the speed over respective LMS algorithm based realization. Also the computational complexity is reduced with the proposed formula which is in fact also useful for wireless biotelemetry ECG realizations.

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Biography

Syed Ateequr Rehman, obtained BE(ECE) from ghousia college of engineering, Mtech(DEC) from AMC college. His area of research is DSP and Image processing. He has published 2 papers in national conference.

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