

Signal to Noise Ratio Comparison of LMS and NLMS Adaptive Filter Algorithms for ECG Signal Enhancement and various Artifact removals

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Abstract-- In this paper adaptive filter based algorithms that can be applied to ECG signal in order to remove various artifacts 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 different artifacts. Simulation studies shows that the proposed novel algorithm NLMS based adaptive system present better performances compared to existing realizations LMS based procedures in terms of signal to noise ratios.

Keywords—ECG, Adaptive filter Algorithms, LMS, NLMS, PLI, BWN.

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 artifacts present in the ECG signal are Power-line Interference (PLI) and Baseline Wander (BW), mainly caused by patient breathing, movement, power line interference, bad electrodes and improper electrode site preparation. The low frequency ST segments of ECG signals are strongly affected by these contaminations, which lead to false diagnosis. The extraction of high-resolution ECG signals from recordings contaminated with back ground noise is an important issue to investigate. The goal for ECG signal enhancement is to separate the valid signal components from the undesired artifact, 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. Besides, they modify their behavior according to the input signal. Therefore, they can detect shape variations in the ensemble and thus they can obtain a better signal estimation. The main advantage for going with adaptive filters in order

to cancel various artifacts is to allow the doctors to view the best ECG signal for evaluation.

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.

Baseline fluctuations may be considered a less disturbing event compared to main interferences, but can be more difficult to eliminate or even suppress. The standard first-order high-pass filter of 3.2 sec time constant cannot block most low-frequency baseline drift. It also may bring problems in visual or automatic ECG measurement and interpretation.

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

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

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

Where $w(n)$ is the tap weight vector at the nth index $x(n) = [x(n) x(n-1) \dots x(n-L+1)]$ (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.

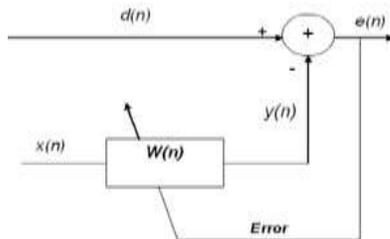


Fig. 1. Adaptive filter structure

Procedure remains the same for all the adaptive filter algorithms, only the filter updating equations differ.

Normalized LMS (NLMS) algorithm is another class of adaptive algorithm used to train the coefficients of the adaptive filter. 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 $\mu(n)$, $\mathbf{x}(n)$ being the input vector, $e(n)$ is the error.

Another weight update relation for NLMS algorithm is as follows

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

The variable step can be written as,

$$\mu(n) = \mu / p + \mathbf{x}^T(n) \mathbf{x}(n) \quad (5)$$

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. 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 $\mu(n)$.

III. SIMULATION RESULTS

To show that NLMS 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. In the simulation we provide the input ECG database number, Order of the filter and step size.

To demonstrate artifact 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 real artifact. The reference signal is synthesized artifact, the output of the filter is recovered signal. The ECG signal of record 105 is corrupted with real artifact.

LMS and NLMS algorithms are applied to clean the ECG signal and the results are shown. The SNR values before and after filtering along with SNR improvements for all the algorithms are also given in table below the simulation results. These results are shown below.

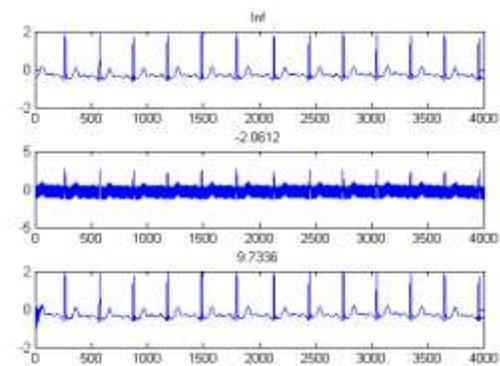


Figure. 2. Typical filtering Results of Power Line Interference (a) Original ECG Signal (b) ECG Signal with PLI noise (c) Recovered ECG Signal using LMS Algorithm.

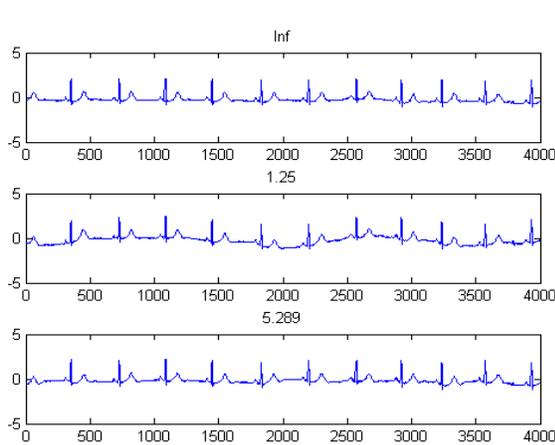


Figure 3. Typical filtering Results of Baseline Wander (a) Original ECG Signal (b) ECG Signal with BWN noise (c) Recovered ECG Signal using LMS Algorithm.

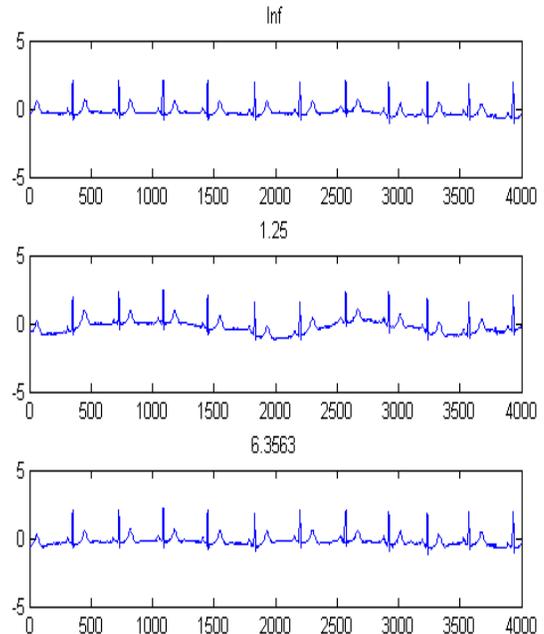


Figure 7. Typical filtering Results of Baseline Wander noise (a) Original ECG Signal (b) ECG Signal with BWN noise (c) Recovered ECG Signal using Normalized LMS Algorithm.

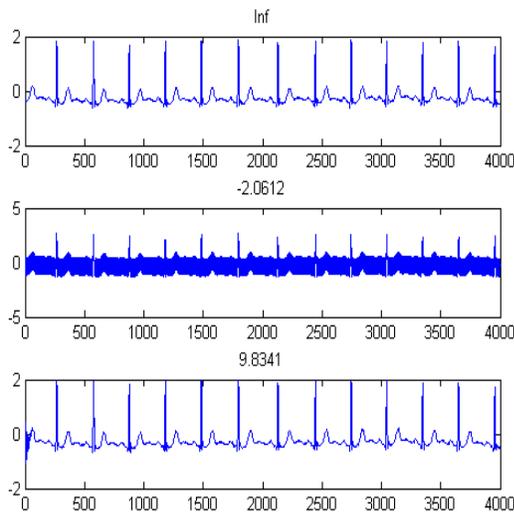


Figure 6. Typical filtering Results of Power Line Interference (a) Original ECG Signal (b) ECG Signal with PLI noise (c) Recovered ECG Signal using Normalized LMS Algorithm.

IV. CONCLUSION

In this paper performance comparison of two adaptive filter algorithms used to remove four different artifacts from the ECG signal after its enhancement is presented. From the simulation results it is shown 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, BWN, EMN and MAN.

The proposed weight updating equations for NLMS 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.

TABLE I

Performance Comparison Of Lms And Nlms Algorithms For Power Line Interference And Baseline Wander

| Algo-rithm | Arti-fact | SNR before filtering | SNR after filtering | SNR Improvement |
|------------|-----------|----------------------|---------------------|-----------------|
| LMS | PLI | -2.0612 | 9.7336 | 7.6724 |
| | BWN | 1.25 | 5.289 | 4.039 |
| NLMS | PLI | -2.0612 | 9.8341 | 7.7729 |
| | BWN | 1.25 | 6.3563 | 5.1063 |

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