

Noise Cancellation in ECG Signals using Simplified Adaptive Filtering Techniques

Sushma Patwardhan^{*1}, Harjeet Kaur²

^{*1} Student, ² Associate Professor, Department of E&TC, Indira College of Engineering and Management, Pune, India

Patwardhan.sushma@gmail.com

Abstract

Heart related problems are increasing day by day and ECG signal are very important in diagnosis of heart related problems. There are various artifact which get added in these signals and changes the original signal, therefore there is a need of removal of these artifact from the original. Several signed LMS based adaptive filters, which are computationally superior having multiplier free weight update loops are used for noise cancellation in the ECG signal. The adaptive filters essentially minimizes the mean-squared error between a primary input, which is the noisy ECG, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with ECG in the primary input. In this paper the performance of the signed regressor LMS algorithm is superior than conventional LMS algorithm, the performance of signed LMS and sign-sign LMS based realizations are comparable to that of the LMS based filtering techniques in terms of computational complexity.

Keywords: Adaptive filtering, Artifact, ECG, LMS algorithm, Noise cancellation..

Introduction

Biomedical signal means a collective electrical signal acquired from any organ that represent a physical variable of interest. This signal is normally a function of time and is describable in terms of its amplitude, frequency and phase. Biomedical application using processing techniques is a major area of interest that has been investigated by a large number of scientific researchers. ECG signal is a graphical representation of cardiac activity and it used to measure the various cardiac diseases and abnormalities present in heart. ECG signals are composed of P wave, QRS complex, T wave and any deviation in these parameters indicate abnormalities present in heart. The standard ECG signal is shown in Figure. 1.

The biomedical signal in the present work is the ECG signal and various filtering technique suggested is FIR filter or simply IIR filter. The frequency of ECG signal is between 0.5 Hz-100Hz. This ECG gets corrupted due to various kinds of the artifacts. [1]

1. Power line interference
2. Electrode contact noise.
3. Motion artifacts.
4. Muscle contraction.
5. Base line drift.
6. Instrumentation noise generated by electronic

devices.

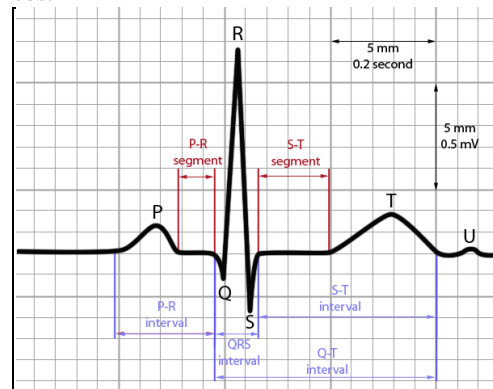


Figure1: An standard ECG waveform

The ECG signal corrupted due to these noises leads to wrong diagnosis. Therefore, to reduce and remove the noises, digital filters are widely used in biomedical signal processing. Analog filters can also be used to remove these noises, but nonlinear phase shift is introduced by them. Digital filters are more accurate and precise than analog filters. [2]- [3] Digital filters are of two kinds:-

1. Finite Impulse Response (FIR),
2. Infinite Impulse Response (IIR).

Several papers have been presented in the area of biomedical signal processing where an adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the ECG and other biomedical 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. Adaptive solution based on the LMS algorithm is suggested. The fundamental principles of adaptive filtering for noise cancellation were described by Widrow et al. [4]. Thakor and Zhu [5] proposed an adaptive recurrent filter to acquire the impulse response of normal QRS complexes, and then applied it for arrhythmia detection in ambulatory ECG recordings. The reference inputs to the LMS algorithm are deterministic functions and are defined by a periodically extended, truncated set of orthonormal basis functions. Complexity reduction of the noise cancellation system, particularly in applications such as wireless biotelemetry system has remained a topic of intense research. To reduce the computational complexity of the adaptive algorithm without affecting the signal quality can be achieved by considering the sign based adaptive algorithms. These algorithms enjoy less computational complexity because of the sign present in the algorithm. In the literature, there exist three versions of the signed LMS algorithm, namely, the signed regressor algorithm, the sign algorithm and the sign-sign algorithm. All these three require only half as many multiplications as in the LMS algorithm, thus making them attractive from practical implementation point of view [6]-[8].

Computationally Efficient Adaptive Filtering Techniques

The electrocardiogram (ECG) is an important tool used for diagnosis of cardiac abnormalities. While examining the patient on-line and want to review the ECG of the patient in real-time, there is a more chance that the ECG signal has been contaminated by noise. The predominant artifacts present in the ECG includes: Base-line Wander (BW), Power-Line Interference (PLI), Muscle Artifacts (MA), and Motion Artifacts (EM). These artifacts strongly affect the ST segment, degrade the signal quality, frequency resolution, produce large amplitude signals in ECG that can resemble PQRST waveforms, and mask tiny features that are important for clinical monitoring, diagnosis. Cancellation of these artifacts in ECG signals is an important task for better diagnosis, we

need to develop an adaptive filter to remove the noise in order to obtain and interpret the ECG data.

Basic Adaptive Filtering Structure

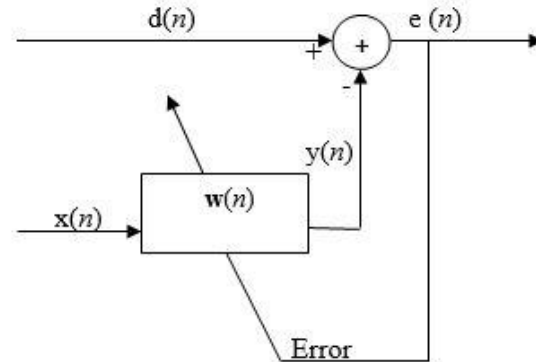


Figure 2: Adaptive Filter Structure

Consider a length L , LMS-based adaptive filter, depicted in Figure 2, that takes an input sequence and updates the weights as

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

where $\mathbf{w}(n) = [w_0(n) \ w_1(n) \ \dots \ w_{L-1}(n)]^t$ is the tap weight vector at the n th index, $\mathbf{x}(n) = [x(n) \ x(n-1) \ \dots \ x(n-L+1)]^t$, error signal $e(n) = d(n) - \mathbf{w}^t(n)\mathbf{x}(n)$, with $d(n)$ being so-called the desired response available during initial training period, and μ denoting so-called step-size parameter.

In order to remove the noise from the ECG signal, the ECG signal $s_1(n)$ corrupted with noise signal is applied as the desired response to the adaptive filter shown in Fig. 1. If the noise signal, possibly recorded from another generator of noise that is correlated in some way with $s_1(n)$ is applied at the input of the filter, i.e., the filter error becomes $e(n)$, where $y(n)$ is the filter output and it is given by

$$y(n) = \mathbf{w}^t(n) \mathbf{x}(n) \quad (2)$$

Now, the mean-squared error (MSE) becomes

$$E[e^2(n)] = E\{[s_1(n) - y(n)]^2\} + E[p_1^2(n)] \quad (3)$$

Since $s_1(n)$ and $p_1(n)$ are uncorrelated, similarly $p_1(n)$ and $y(n)$ are uncorrelated and the last two expectations are zero.

Simplified Adaptive Algorithms

New algorithms that make use of the *signum* (polarity) of either the error or the input signal, or both [9], have been derived from the LMS algorithm for the

simplicity of implementation, enabling a significant reduction in computing time, particularly the time required for “multiply and accumulate” (MAC) operations. These algorithms are attractive for their assured convergence and robustness against the disturbances in addition to the ease of implementation. The most important members of this class of algorithms are: Signed Regressor Algorithm (SRA), Sign Algorithm (SA), and Sign-Sign Algorithm (SSA).

The Signed-Regressor Algorithm (SRLMS):

The signed regressor algorithm is obtained from the conventional LMS recursion by replacing the tap-input vector $x(n)$ with the vector $\text{sgn}\{x(n)\}$. The adaptive filter coefficients are updated by the Signed-regressor LMS algorithm as,

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

Because of the replacement of $x(n)$ by its sign, implementation of this recursion may be cheaper than the conventional LMS recursion, especially in high speed applications such as biotelemetry these types of recursions may be necessary.

The Sign Algorithm (SLMS):

This algorithm is obtained from conventional LMS recursion by replacing $e(n)$ by its sign. This leads to the following recursion:

$$w(n+1) = w(n) + \mu \{x(n)\} \text{sgn}\{e(n)\} \quad (5)$$

The Sign – Sign Algorithm (SSLMS):

This can be obtained by combining signed-regressor and sign recursions, resulting in the following recursion:

$$w(n+1) = w(n) + \mu \text{sgn}\{x(n)\} \text{sgn}\{e(n)\} \quad (6)$$

where $\text{sgn}\{ \cdot \}$ is well known signum function,

$$\text{sgn}\{e(n)\} = \begin{cases} 1 : e(n) > 0 \\ 0 : e(n) = 0 \\ -1 : e(n) < 0 \end{cases} \quad (7)$$

Among the adaptive algorithms presented above, the SRA, SA, and SSA has a convergence rate and a steady-state error that are slightly inferior to those of the LMS algorithm for the same parameter setting because of the sign present in the algorithm, i.e., some residual noise present in the signal, but speed up as the mean square error drops. However, the computational complexity of these algorithms is much less compared to the LMS algorithm.

This can be explained as follows.

Consider the SA, it may be written as

$$w(n+1) = w(n) + \{x(n)\} \frac{e(n)}{|e(n)|} \quad (8)$$

Since $\text{Sgn}[e(n)] = e(n)/|e(n)|$:

This is rearranged as

$$w(n+1) = w(n) + \left[\frac{\mu}{|e(n)|}\right] x(n) e(n) \quad (9)$$

The above equation reveals that the sign algorithm may be thought as an LMS algorithm with a variable step size parameter, μ . The step size parameter increases, on an average, as the sign algorithm converges, since $|e(n)|$ decreases in magnitude. A small $|e(n)|$ leads to an equally small value for μ in the initial portion of the sign algorithm. As a result the algorithm initially converges slowly. However, as the algorithm converges and becomes smaller in magnitude, the step size becomes larger, leads to a faster convergence. Moreover the sign present in the algorithm and setting to a value of power of two, the hardware implementation is highly simplified (shift and add/subtract operation only) [9] [10]

A. Computational Complexity Issues

As the sign-based algorithms are largely free from the MAC operations, the proposed schemes provide elegant means to remove noise from the ECG signal. Table I provides comparative account of different commonly used algorithms and the proposed algorithm in terms of number of operations required.

Table I
A computational complexity comparison table

Algorithm	MAC's	ASC	Divisions	Shifts
LMS	L+1	Nil	Nil	Nil
SRLMS	1	Nil	Nil	Nil
SLMS	L	Nil	Nil	Nil
SSLMS	Nil	L	Nil	Nil

The conventional LMS algorithm requires MAC operations to implement the weight updating (1) on DSP processor. For the SSLMS algorithm, to evaluate from using (4), only add with sign check (ASC) operations are required. But the rate of convergence of this algorithm is very slow. Hence, the SSLMS algorithm alone will not be a suitable candidate for the removal of noise from the ECG signal.

Conclusion

In this paper the problem of noise removal from ECG using Signed LMS based adaptive filtering is presented. For this, the same formats for representing the data as well as the filter coefficients as used for the LMS algorithm were chosen. As a result, the steps related to the filtering remain unchanged. The proposed treatment, however exploits the modifications in the weight update formula for all categories to its advantage and thus pushes up the speed over the respective LMS-based realizations. From the Tables I it is clear that the signed regressor LMS algorithm performs better than LMS in both SNR improvement and computational complexity, hence it is more suitable for wireless biotelemetry ECG systems.[4]

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