

Effective Reconstruction of the Cardiac Signal Using Adaptive Noise Cancellers



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Abstract : An electrocardiogram (ECG) is a graphical representation of the sequence of myocardial depolarization and repolarization. In some emergency cases the ECG signal can be obtained in the ambulance itself and it has to be transmitted to the clinic. During the transmission the tiny features of the ECG signal are masked due to channel noise. In addition to these the signal may get disturbed by some artifacts like power line interference (PLI), base line wander (BW), muscle artifacts (MA), and electrode motion artifacts (EM) etc.. These artifacts strongly affect the ST segment of the signal and degrade the signal quality. In this situation the doctor may give the wrong diagnosis to the patient. So the electrocardiogram (ECG) signal needs to be pre-processed. In this paper we are going to present various adaptive noise cancellers (ANC) based on variable step-sized algorithm. Adaptive filter is a primary method to filter the ECG signal. Here the main interest is to reduce the affect of PLI and BW artifacts using different algorithms like Variable Step Size Least Mean Squares (VSS-LMS), VSS-Normalized LMS (VSS-NLMS), VSS Signed Regressor LMS (VSS-SRLMS), VSS Signed LMS (VSS-SLMS) and VSS Sign-Sign LMS (VSS-SSLMS) to decide which can give the good results with less computational complexity.

Key words : A new variable step size algorithm with error nonlinearity and SNR, MSE calculations for them.

INTRODUCTION

An electrocardiogram is useful in measurement of heart rate. It is an electrical wave generated by depolarization and repolarization of certain cells due to movements of Na⁺ and K⁺ ions in the blood. This ECG signal consists of P, Q, R, S and T waves. Mostly the ST segment of ECG signal will be affected by various artifacts like Power Line Interference, Baseline Wander, Electrode Motion artifact and Muscle artifact etc. These artifacts occur mostly due to power line variations, lose contacts of the electrodes and unwanted movements of the patient etc. Due to these artifacts the signal may get affected severely and it will cause the doctor may give wrong diagnosis to the patient [1]. So in order to pre-process the signal we may use filtering methods for example wiener filter which consists of constant filter weights. But, to implement the wiener filter we need to know the statistical characteristics of the input signal. An adaptive filter can give more accurate results compared to wiener filter because of its adaptive filter weights. The least mean squares (LMS) algorithm is more popular because of its simplicity, but the drawback is its convergence rate is very slow. In addition to this Normalized LMS (NLMS),

Sign-Regressor LMS (SR-LMS), Sign LMS (S-LMS) and Sign-Sign LMS (SS-LMS) are already implemented [2]-[3]. In this paper we are going to propose a new variable step size algorithm with error nonlinearity. The aim is to find out the best algorithm among those five algorithms with variable step size.

ADAPTIVE ALGORITHM

Least Mean Squares (LMS) algorithm

Adaptive filtering involves the change of filter weights (coefficients) over time which leads to the minimization of error in every iteration. The following Fig 1 shows an adaptive filter structure.

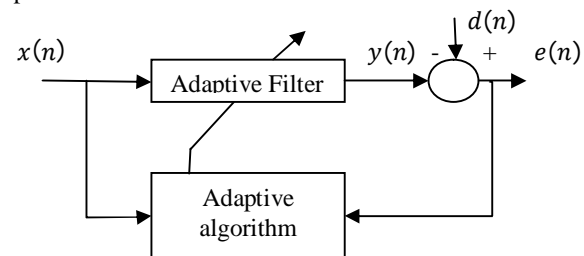


Fig 1: Adaptive filter structure

Here $x(n)$ is an input signal, $y(n)$ is an output signal, $e(n)$ is an error signal and $d(n)$ is a desired signal. The input signal is corrupted by noise $v(n)$. In other words, it is the sum of desired signal $d(n)$ and noise $v(n)$, as mentioned in (1).

The input vector representation is given by

$$x(n) = [x(n), x(n-1), \dots, x(n-N+1)]$$

$$x(n) = d(n) + v(n) \quad (1)$$

The LMS algorithm is a linear adaptive algorithm which, in general, consists of two basic processes [4]; 1. A filtering process which involves, computing the output of a linear filter in response to the input signal and generating an error by comparing the output with the desired signal. 2. An adaptive process which involves the automatic adjustment of filter parameters in accordance with the estimation error. The output of a filter can be obtained as

$$y(n) = \hat{w}^H(n)x(n) \quad (2)$$

The estimation of error can be generated by comparing the output signal with the desired signal and it can be written as

$$e(n) = d(n) - y(n) \quad (3)$$

The tap-weight adaptation can be obtained as

$$\hat{w}(n+1) = \hat{w}(n) + \mu x(n)e^*(n) \quad (4)$$

Where μ is the constant step size and it has to be chosen in between 0 and $2/\lambda_{max}$, λ is an eigen value in auto correlation matrix of input vector $x(n)$.

THE PROPOSED NEW VARIABLE STEP SIZE ALGORITHM

A. Variable Step Size Least Mean Squares algorithm (VSS-LMS)

The output of a filter can be obtained as

$$y(n) = \hat{w}^H(n)x(n)$$

The estimation of error can be generated by comparing the output signal with the desired signal. The tap-weight adaptation can be obtained using least mean squares algorithm as

$$\hat{w}(n+1) = \hat{w}(n) + \mu(n)x(n)e^*(n)$$

Where $\mu(n)$ is a variable step size, this can be obtained by using a new variable step size algorithm.

In the new variable step size proposed algorithm, the variable step size is inversely proportional to the error vector. The length of the error vector is equal to the instantaneous number of iterations [5]. Thus, the weight update equation of the new variable step size algorithm becomes

$$w(n+1) = w(n) + \frac{\mu}{1+\mu\|e(n)\|^2} e(n)x(n) \quad (5)$$

The new variable step size may be considered as a variable step size algorithm in which a variable step size $\mu(n)$ is given by

$$\mu(n) = \frac{\mu}{1 + \mu\|e(n)\|^2}$$

This can be rewrite as

$$\mu(n) = \frac{1}{\frac{1}{\mu} + \|e(n)\|^2} \quad (6)$$

When $\|e(n)\|^2 \gg \frac{1}{\mu}$, $\mu(n)$ becomes independent of μ . So the (5) can be modified as

$$w(n+1) = w(n) + \frac{\mu}{1+\mu e(n)^2} e(n)x(n)$$

Where $e(n)$ is an instantaneous error value at n^{th} iteration and it is appropriate for the stationary environment.

B. Variable Step Size Normalized LMS algorithm (VSS-NLMS)

The normalized LMS algorithm is similar to LMS algorithm but differ only in the way in which the weight controller is mechanized. We define the change in weight vector in each iteration as

$$\begin{aligned} \delta \hat{w}(n+1) &= \hat{w}(n+1) - \hat{w}(n) \\ &= \frac{\mu}{\|x(n)\|^2} x(n)e^*(n) \end{aligned}$$

Equivalently, we write

$$\hat{w}(n+1) = \hat{w}(n) + \frac{\mu}{\|x(n)\|^2} x(n)e^*(n) \quad (7)$$

The adaptation constant μ for the NLMS filter is dimensionless, where as the adaptation constant μ for the LMS filter has the dimension of inverse power [6]. Setting

$$\mu = \frac{\mu}{\|x(n)\|^2}$$

We may view the NLMS filter as an LMS filter with a time varying step size parameter [6]. The NLMS filter introduces a problem of its own, namely that when the tap-input vector $x(n)$ is small, numerical difficulties may arise

because then we have to divide by a small value for the squared norm $\|x(n)\|^2$. To overcome this problem, we modify the recursion of (7) slightly to produce

$$\hat{w}(n+1) = \hat{w}(n) + \frac{\mu(n)}{\delta + \|x(n)\|^2} x(n)e^*(n)$$

Where δ is a positive constant ($\delta > 0$) and $\mu(n) = \frac{\mu}{1+\mu e(n)^2}$.

C. Variable Step Size Signed-Regressor algorithm (VSS-SRLMS)

The signed regressor algorithm is obtained from the conventional LMS recursion by replacing the tap-input vector $x(n)$ with the vector $\text{sgn}\{x(n)\}$. Consider a signed regressor LMS based adaptive filter that processes an input signal $x(n)$ and generates the output $x(n)$ as per the following:

$$y(n) = w^t(n)x(n)$$

Where $w(n) = [w_0(n), w_1(n), \dots, w_{N-1}(n)]^t$ is an N^{th} order filter. The adaptive filter coefficients are updated by the signed regressor LMS algorithm as,

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

Where $\text{sgn}(x)$ is a signum function [7] which can be defined as follows

$$\text{sgn}(x) = \begin{cases} -1 & \text{if } x < 0 \\ 0 & \text{if } x = 0 \\ 1 & \text{if } x > 0 \end{cases}$$

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

D. Variable Step Size Sign algorithm (VSS-SLMS)

This algorithm is obtained from conventional LMS recursion by replacing $e(n)$ by its sign. This leads to the following recursion [8]:

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

E. Variable Step Size Sign-Sign algorithm (VSS-SSLMS)

This can be obtained by combining SRLMS and SLMS resulting in the following recursion [8]:

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

Where $\text{sgn}\{\cdot\}$ is well known signum function, $e(n)$ is the error signal. The sequence $d(n)$ is the so-called desired response available during initial training period. However the sign and sign-sign are both slower than the LMS algorithm.

SIMULATION RESULTS

The variable step size adaptive algorithms are used to eliminate the Power Line Interference, Baseline Wander artifacts in ECG signal. The ECG signal was collected from MIT-BIH arrhythmia database [9]. The ECG recordings are obtained from 47 subjects collected by from a mixed population of inpatients (about 60%) and outpatients (about 40%) studied by the BIH Arrhythmia Laboratory. The PLI artifact is due to power variations, this can be considered as a high frequency noise and in this paper it is taken as 60Hz. In the same manner the BW artifact is nothing but low frequency noise it will be in range of 0 to 0.5Hz. In this paper we consider the BW noise as 0.5Hz. In conventional

method the step size is fixed and it has to choose manually that, which value is suitable in order to get the best results but, the proposed variable step size algorithm is based on its error nonlinearity and it is applied to conventional and signed based LMS algorithms which can give the best results than conventional adaptive algorithms. The obtained results by using VSS-LMS, VSS-NLMS algorithms are shown in Fig 2, Fig 3. In similar the obtained results for sign based variable step size algorithms are shown in Fig 4, Fig 5.

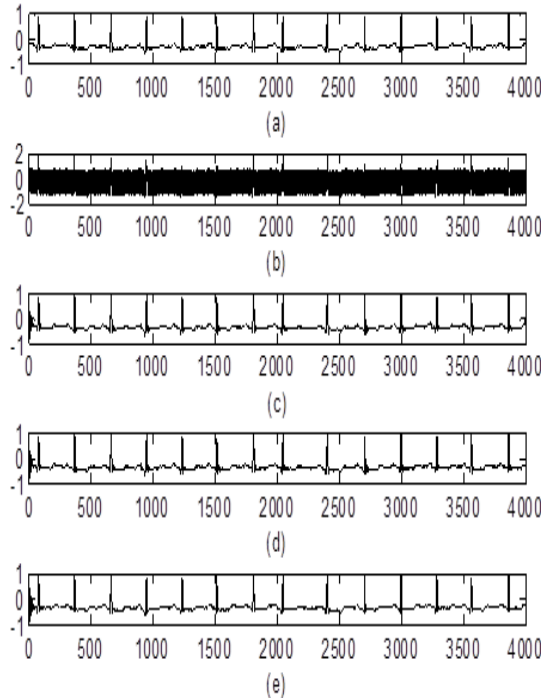


Fig 2: (a) Original ECG, (b) PLI corrupted ECG, (c) PLI eliminated ECG using LMS, (d) PLI eliminated ECG using VSS-LMS, (e) PLI eliminated ECG using VSS-NLMS

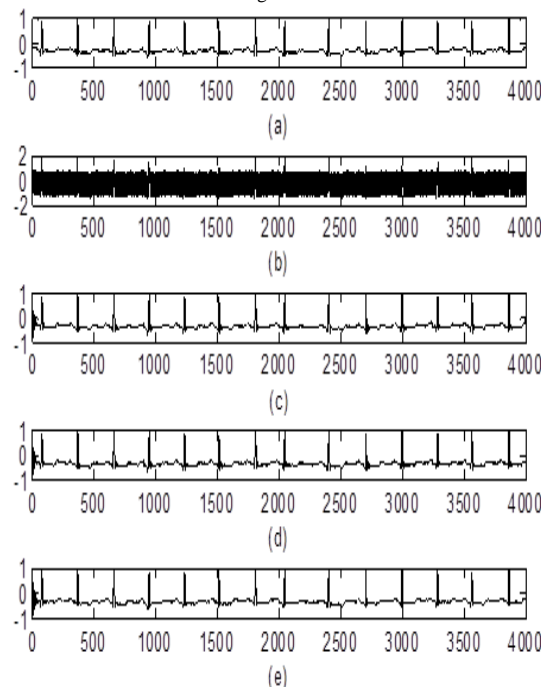


Fig 3: (a) Original ECG, (b) BW corrupted ECG, (c) BW eliminated ECG using LMS, (d) BW eliminated ECG using VSS-LMS, (e) BW eliminated ECG using VSS-NLMS

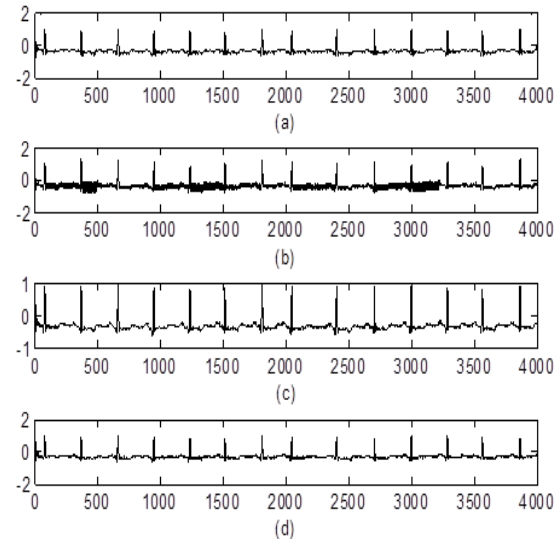


Fig 4: (a) PLI eliminated ECG using SR-LMS, (b) PLI eliminated ECG using S-LMS, (c) PLI eliminated ECG using VSS-SRLMS, (d) PLI eliminated ECG using VSS-SLMS

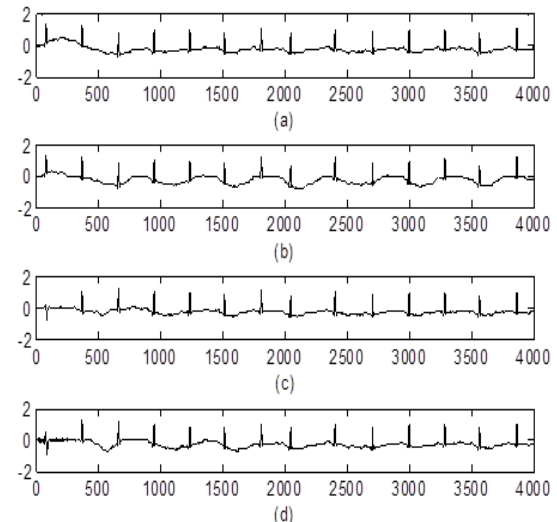


Fig 5: (a) BW eliminated ECG using SR-LMS, (b) BW eliminated ECG using S-LMS, (c) BW eliminated ECG using VSS-SRLMS, (d) BW eliminated ECG using VSS-SLMS

In constant step size algorithms the normalized LMS algorithm gives the best results when compared to other algorithms and it is clear from the Table I. These algorithms were compared based on their signal to noise ratios and mean square errors.

Table I: comparison of SNR and MSE values for different adaptive algorithms

Name of the algorithm	SNR for PLI eliminated signal	MSE for PLI eliminated signal	SNR for BW eliminated signal	MSE for BW eliminated signal
LMS	8.7905	0.0023	2.4057	0.0431
NLMS	8.9357	0.0021	2.4540	0.0412
SRLMS	2.9274	0.0339	2.5132	0.0410
SLMS	2.1214	0.0491	1.5274	0.0645
SSLMS	1.6405	0.0612	1.4438	0.0671

The table II illustrates the SNR and MSE values for all the variable step size algorithms. From the Table II we know that the variable step size LMS algorithm gives the better results compared to other algorithms.

Table II: comparison of SNR and MSE values for different variable step size adaptive algorithms

Name of the algorithm	SNR for PLI eliminated signal	MSE for PLI eliminated signal	SNR for BW eliminated signal	MSE for BW eliminated signal
VSSLMS	11.7228	0.000589	3.9920	0.0207
VSSNLMS	10.0661	0.0013	2.9976	0.0328
VSS-SRLMS	10.0086	0.00139	2.7835	0.0362
VSS-SLMS	7.2757	0.0046	2.8453	0.0352
VSS-SSLMS	2.9967	0.0328	1.5913	0.0626

CONCLUSION

The ECG signal may get disturbed by some artifacts like power line interference (PLI), base line wander (BW), muscle artifacts (MA), and electrode motion artifacts (EM) etc,. The main concentration is to eliminate PLI and BW artifacts in ECG signal. From this work we can decide that the variable step size algorithms can give better results compared to conventional constant step size algorithms. Among all these variable step size algorithms the variable step size LMS algorithm can give most appropriate results compared to other algorithms.

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