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Efficient Adaptive Filtering Method to Reconstruct the Cardiac Signal

C. Himabindu, T. Gowri, P. Rajesh Kumar,D.V.Rama Koti Reddy

Abstract— This paper introduces a Decorrelation based modified robust Variable Step Size adaptive algorithm (DMRVSS) to improve the quality of an electrocardiogram (ECG). An ECG signal is a graphical representation of the sequence of depolarization and repolarization of heart. In some emergency situations the ECG signal needs to be transmitted to the clinic from the ambulance. During the transmission the tiny features of the ECG signal may 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. In that moment the doctor may give the wrong diagnosis to the patient. So the electrocardiogram (ECG) signal is necessary to be pre-processed. In this paper we are going to present various adaptive filtering methods based on a Decorrelation based modified robust Variable Step Size adaptive algorithm (DMRVSS). Here the main goal is to eliminate the affect of PLI and BW artifacts using Variable Step Size Least Mean Squares (DMRVSS-LMS), VSS-Normalized LMS (DMRVSS-NLMS) and variable step size sign based LMS algorithms and to decide which can give the best results with less computational complexity.

Index Terms— A Decorrelation based modified robust Variable Step Size adaptive algorithm and comparision using SNR, MSE calculations.

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1 Introduction

An electrocardiogram (ECG) is used to measure the heart rate of a patient. 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 basically consists of P, Q, R, S and T waves. An ECG signal may get affected by various artifacts like Power Line Interference (PLI), Baseline Wander (BW), Electrode Motion artifact (EM) and Muscle artifact (MA) etc due to various reasons. These artifacts occur mostly due to power line variations, lose contacts of the electrodes and unwanted movements of the patient etc. This artifact affected ECG signal 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 filters which consists of constant filter weights. But, to implement a wiener filter in hardware or software will be easy. An adaptive filter can give more accurate results compared to wiener filter because of its adaptive filter weights. The least mean squares (LMS), Normalized LMS (NLMS), Sign-Regressor LMS (SR-LMS), Sign LMS (S-LMS) and Sign-Sign LMS (SS-LMS) are already implemented [2]-[5]. A Decorrelation based modified robust Variable Step Size adaptive algorithm is applied to all these five adaptive algorithms to eliminate both PLI and BW artifacts in ECG

2 Adaptive Algorithm

2.1 *Least Mean Squares (LMS) algorithm*

In Adaptive filtering, the filter weights (coefficients) will change over time which leads to obtain minimum error in each iteration. The following Fig 1 shows a basic adaptive filter structure.

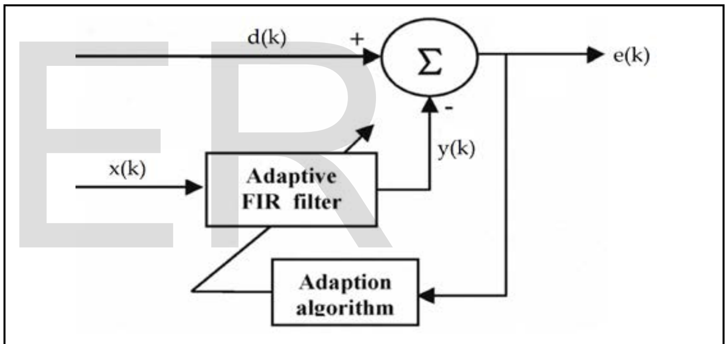

Fig. 1: Adaptive filter structure

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

The input vector representation is given by $x(k) = [x(k), x(k-1), \ldots\ldots x(k-N-1)]$

$$x(k) = d(k) + n(k) \tag{1}$$

The LMS algorithm is a linear adaptive algorithm which, in general, consists of two basic processes [6]; 1. A filtering process- 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- the automatic adjustment of filter parameters in accordance with the estimation error. The output of a filter can be obtained as

$$y(k) = \hat{w}^H(k)x(k) \tag{2}$$

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

$$e(k) = d(k) - y(k) \tag{3}$$

The tap-weight adaptation can be obtained as

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

Where μ is the constant step size and it has to be chosen in

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between 0 and $2/\lambda_{max}$, λ is an eigen value in auto correlation matrix of input vector $x(k)$.

2.2 The Proposed a Decorrelation based modified robust Variable Step Size adaptive algorithm

2.2.1 *Decorrelation based modified robust Variable Step Size Least Mean Squares algorithm (DMRVSS-LMS)*

The conventional variable step size algorithm has good tracking ability but poor anti-noise ability. The RVSS algorithm has good anti-noise ability but tracking ability is poor.

In order to overcome the difficulties in conventional variable step size algorithms like poor tracking ability and anti-noise ability, a new decorrelation based modified robust modified variable step size algorithm has been proposed now.

The output of a filter can be obtained as

$$y(k) = \widehat{w}^H(k)x(k) \quad (5)$$

The error signal 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

$$\widehat{w}(k+1) = \widehat{w}(k) + \mu(k)x(k)e^*(k) \quad (6)$$

Where the variable step size update equation for the filter coefficient is given by

$$\mu(k+1) = \begin{cases} \mu_{max}; if\ \mu(k+1) > \mu_{max} \\ \mu_{min}; if\ \mu(k+1) < \mu_{min} \\ \alpha\mu(k) + \gamma\varphi(k)^2 \end{cases} \quad (7)$$

Where α, γ are positive constants which ranges from 0 to 1 and to get good result we should chose the value of γ is close to 1. when the initial value of $\mu(k)$ is large then it gives fast convergence rate so that it can give optimum lower MSE.

In (7), $\varphi(k)$ is a control signal to control the adaptation process by using squared of the time average estimate of autocorrelation of the present error signal $e(k)$ and the past one $e(k-1)$ [7]. The estimated control signal can be expressed as

$$\varphi(k+1) = \big(1-\beta(k)\big)\varphi(k) + \beta(k)e(k)e(k-1) \quad (8)$$

Where $\beta(k)$ is a control parameter. Initially the value of $\varphi^2(k)$ is large, resulting $\mu(k)$ also large. As we approach the optimum, the error signal approaches to zero, that the control signal also approaches to zero. This will result a small value of step size.

The control parameter $\beta(k)$ can be written as

$$\beta(k+1) = \begin{cases} \beta_{max};\ if\ \beta(k+1) > \beta_{max} \\ \beta_{min};\ if\ \beta(k+1) < \beta_{min} \\ \eta\beta(k) + \lambda e(k)^2 \end{cases}$$

Where the constant values η, λ are ranges from 0 to 1($\eta < 1, \lambda > 0$).

2.2.2 *Decorrelation based modified robust Variable Step Size Normalized LMS algorithm(DMRVSS-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

$$\delta\widehat{w}(k+1) = \widehat{w}(k+1) - \widehat{w}(k)$$

$$= \frac{\mu(k)}{\|x(k)\|^2}x(k)e^*(k)$$

Where $\mu(k)$ is a variable step size parameter. Equivalently, we write

$$\widehat{w}(k+1) = \widehat{w}(k) + \frac{\mu(k)}{\|x(k)\|^2}x(k)e^*(k) \quad (9)$$

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 [8]. Setting

$$\tilde{\mu} = \frac{\mu(k)}{\|x(k)\|^2} \quad (10)$$

We may view the NLMS filter as an LMS filter with a time varying step size parameter [8]. The NLMS filter introduces a problem of its own, namely that when the tap-input vector $x(k)$ is small, numerical difficulties may arise because then we have to divide by a small value for the squared norm$\|x(k)\|^2$. To overcome this problem, we modify the recursion of (9) slightly to produce

$$\widehat{w}(k+1) = \widehat{w}(k) + \frac{\mu(k)}{\delta+\|x(k)\|^2}x(k)e^*(k) \quad (11)$$

Where δ is a positive constant ($\delta > 0$) and $\mu(k)$ is variable step size as in (7).

2.2.3 *Decorrelation based modified robust Variable Step Size Signed Regressor LMS algorithm (VSS-SRLMS)*

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

$$y(k) = w^t(k)x(k) \quad (12)$$

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

$$w(k+1) = w(k) + \mu(k)sgn\{x(k)\}e(k) \quad (13)$$

Where $\mu(k)$variable step is size as in (7) and $sgn(z)$ is a signum function [9] which can be defined as follows

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

Because of the replacement of $x(k)$ 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.

2.2.4 *Decorrelation based modified robust Variable Step Size Sign LMS algorithm (DMRVSS-SLMS)*

This algorithm is obtained from conventional LMS recursion by replacing $e(k)$ by its sign. This leads to the following recursion [10]:

$$w(k+1) = w(k) + \mu(k)x(k)sgn\{e(k)\} \quad (14)$$

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Where $\mu(k)$ is variable step size as in (5).

2.2.5 *Decorrelation based modified robust Variable Step Size Sign Sign algorithm (DMRVSS-SSLMS)*

This can be obtained by combining SRLMS and SLMS resulting in the following recursion [10]:

$$w(k+1) = w(k) + \mu(k)sgn\{x(k)\}sgn\{e(k)\} \qquad (15)$$

Where $sgn\{.\}$ 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 and $\mu(k)$is variable step size as in (7).However the sign and sign-sign are both slower than the LMS algorithm.

3 Simulation Results

The proposed Novel variable step size adaptive algorithm based on decorrelation was implemented in MATLAB to eliminate both Power Line Interference and Baseline Wander artifacts in ECG signal. The ECG signal was collected from MIT-BIH arrhythmia database and it consists of 48 half-hour excerpts of two-channel ambulatory ECG recordings [11]. The ECG recordings are obtained from 47 subjects studied bi BIH arrhythmia laboratory and collected from a mixed population of inpatients (about 60%) and outpatients (about 40%). The PLI artifact 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 a low frequency noise it will be in range from 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 be chosen manually. The proposed Novel variable step size algorithm based on decorrelation (DEMRVSS) is applied to basic adaptive filtering algorithms and signed based LMS algorithms which can give the improved results compared to conventional constant step size adaptive algorithms.

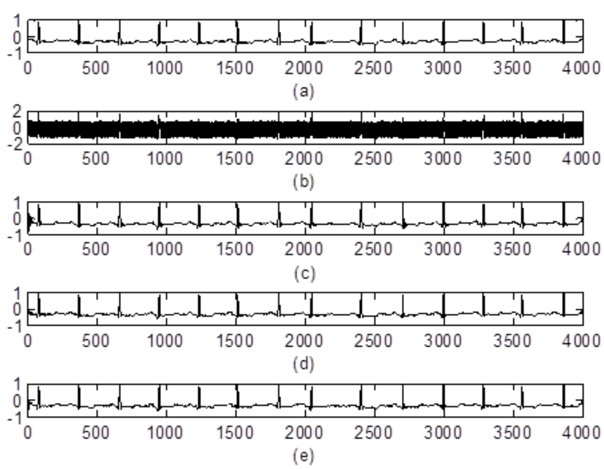

Fig. 2. (a) Original ECG, (b) PLI corrupted ECG, (c) PLI eliminated ECG using LMS, (d) PLI eliminated ECG using VSS-LMS, (e) PLI eliminated ECG using VSS-NLMS

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. *For all figures x-axis is number of samples and y-axis is amplitude of signal.

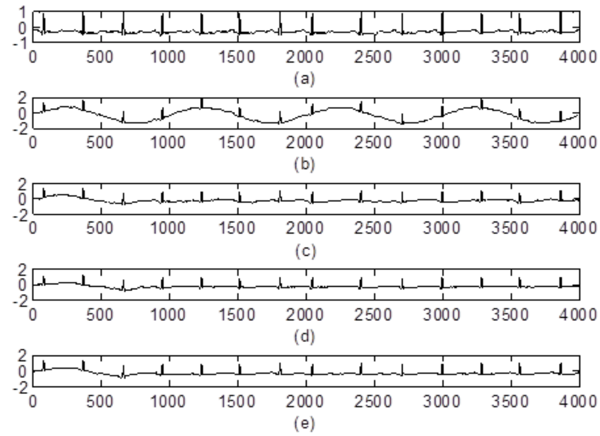

Fig. 3. (a) Original ECG, (b) BW corrupted ECG, (c) BW eliminated ECG using LMS, (d) BW eliminated ECG using VSS-LMS, (e) BW eliminated ECG using VSS-NLMS

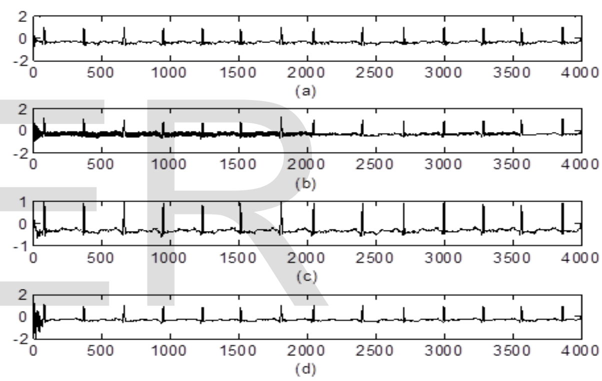

Fig. 4. (a) PLI eliminated ECG using SR-LMS, (b) PLI eliminated ECG using S-LMS, (c) PLI eliminated ECG using VSS-SRLMS, (d) PLI eliminated ECG using VSS-SLMS

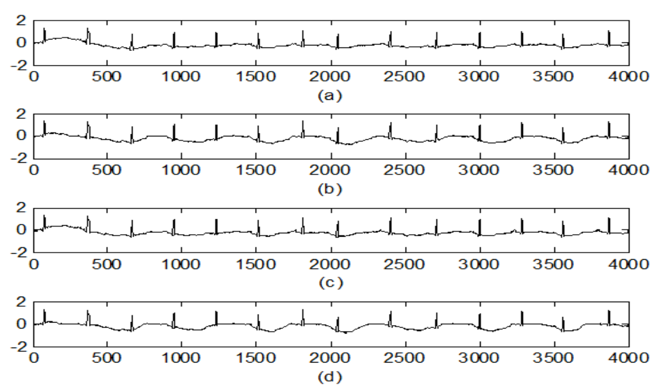

Fig. 5. (a) BW eliminated ECG using SR-LMS, (b) BW eliminated ECG using S-LMS, (c) BW eliminated ECG using VSS-SRLMS, (d) BW eliminated ECG using VSS-SLMS

TABLE 1
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	2.4340	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

In constant step size adaptive algorithms the normalized LMS algorithm gives the best results when compared to other algorithms and it is clear from the TABLE 1. These algorithms were compared based on their signal to noise ratios and mean square errors.

The TABLE 2 illustrates the list of SNR and MSE values for

TABLE 2
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
DMRVSS-LMS	12.3847	0.000371	2.5260	0.0407
DMRVSS-NLMS	12.2992	0.000389	2.5193	0.0408
DMRVSS-SRLMS	11.1653	0.000699	2.4797	0.0416
DMRVSS-SLMS	5.6090	0.0098	1.3159	0.0711
DMRVSS-SSLMS	2.6443	0.0386	1.1639	0.0763

all the variable step size adaptive algorithms. The variable step size LMS algorithm gives the better results compared to other algorithms.

4 CONCLUSION

The variable step size algorithms can give better results compared to conventional constant step size algorithms. The variable step size LMS algorithm can give most appropriate results compared to other algorithms in both the elimination of 60Hz PLI artifact and 0.5Hz BW artifact in ECG signal. This variable step size algorithm will work better for the elimination of PLI artifact than BW artifact.

REFERENCES

[1] Leslie Cromwell, Fred J. Weibell, Erich A. Pfeiffer "Biomedical instrumentation and Measurements", 2nd edition, Chapter 6, pp. 105-169, 2010.

[2] Thumbur Gowri, Injeti Sowmya, Zia Ur Rahman, Rama koti Reddy Dodda, "Adaptive Power Line Interference Removal from Cardiac signals using Leaky based Normalized Higher order Filtering Techniques", IEEE First International Conference on Artificial Intelligence, Modeling & Simulation, pp. 259-263, 2013.

[3] Thumbur Gowri, P. Rajesh Kumar, D. V. Rama Koti Reddy, "An Efficient Variable Step size Least Mean Square Adaptive Algorithm used to enhance the quality of electrocardiogram Signal", Advances in Signal Processing and Intelligent Recognition Systems, Published by Springer Switzerland, Advances in Intelligent Systems and computing, Volume 264, pp. 463-475, 2014.

[4] Mohammad Zia Ur Rahman, Rafi Ahamed Shaik D V Rama Koti Reddy, "Baseline wander and Power line interference elimination from Cardiac Signals using Error Nonlinearity LMS Algorithm", International Conference on Systems in Medicine and Biology, December16-18, 2010.

[5] Lin Bai, Qinye Yin, "A modified nlms algorithm for adaptive noise cancellation" IEEE on Intelligent Networks and Network Security, pp. 3726-3729, 2010.

[6] Simon Haykin, Adaptive filter theory, 4th ed. Pearson Education, pp. 231-278, 2002.

[7] Jianhua Li, Jing LiC, "A Novel Variable Step Size LMS Algorithm Based on Decorrelation" IEEE 3rd International Congress on Image and Signal Processing, pp. 3291-3294, 2010.

[8] Bernard widrow, Samuel D. stearns, "Adaptive signal processing", pp. 99-109.

[9] Baby Paul, P. Mythili, "ECG Noise Removal using GA tuned Sign-Data Least Mean Square Algorithm", IEEE International Conference on Advanced Communication Control and Computing Technologies (ICACCCT), pp. 100-103, August 23-25, 2012.

[10] A. Bhavani sankar, D. Kumar, K. Seethalakshmi, "Performance study of various adaptive algorithms for noise cancellation in Respiratory signals", Signal processing: An international journal (SPIJ), volume (4), issue (5), pp. 267-278, 2011.

[11] www.physionet.org.