

Variable Step Size-Least Mean Squared Algorithm for ECG Signal Denoising Considering Baseline Wander Noise and Cyber Attacks

Md Masud Rana¹, Tamanna Akter² and Ahmed Abdelhadi³

¹Department of Electrical Engineering

The University of Texas at Arlington, Texas, USA

²Department of Electronics and Communication Engineering
Khulna University of Engineering & Technology, Bangladesh

³Department of Engineering Technology

University of Houston, Texas, USA

Email: mmamaraece28@yahoo.com

Abstract—The advancement in the field of information and communication technology explores new paths for healthcare and E-health systems. Generally, the electrocardiographic (ECG) signals are contaminated with different impairments which impose difficulty to analysis and diagnosis the heart diseases. In contrast to the traditional artifacts removal techniques such as wavelet transform, and neural networks, this paper proposes a variable step size-least mean squared (VSS-LMS) algorithm for mitigating noise and cyber attacks in ECG signals. The proposed algorithm is obtained considering tuning parameters and errors, where the step size is adaptively updated based on the signal dynamics. The performances of the proposed approach is demonstrated by using MIT-BIH ECG signals database. It shows that the proposed method can properly remove noises from ECG signals.

Index Terms—Adaptive filtering, electrocardiographic, least mean squared, variable step size-LMS algorithm, noise cancellation.

I. INTRODUCTION

The electrocardiographic (ECG) signal is the main part of human body, and it will need to properly function. Unfortunately, the ECG measurements are incorporated to different noises [1], [2]. In order to design smart patient monitoring centre, the noise from the ECG signal requires remove properly [3]. Driven by this motivation, this paper proposes a variable step size-least mean squared algorithm for mitigating noise and cyber attacks in ECG signals.

There are many different methods and approaches are proposed for removing noises from the ECG signals. Among them, the least mean squared (LMS), normalized LMS, Kalamn filter, and semidefinite programming approaches widely used in the literature [4], [5], [6]. When the ECG signal is vary with time then the aforementioned algorithms can not properly remove noises from the ECG signal [7]. To illustrate, Table 1 shows the detail literature review in terms of design approaches and their advantages and disadvantages. It can be seen that the adaptive and non-adaptive techniques have some advantages and disadvantages over remote health monitoring systems. From the analysis, there is a need of

efficient and valuable ECG remote healthcare systems [8]. For this purpose, we have proposed variable step size-least mean squared algorithm for noise removal in ECG signals. This paper is an extended version of [9], where the standard LMS algorithm is used. The specific contributions are summarized as follows:

- Proposed a variable step size-least mean squared algorithm which can adaptively track and reconstruct ECG signals from noise and cyber attacks. The proposed algorithm is obtained considering tuning parameters and errors, where the step size is adaptively updated based on the signal dynamics.
- Extensive simulation results with different step sizes show that the proposed method can tolerate baseline wander noise and cyber attacks.

Organisation: The rest of this paper is organized as follows. The proposed algorithm is described in Section II. The simulation results and discussions are given in Section III. Conclusions and future work are presented at the end of the paper.

Notation: Bold face lower and upper case letters are used to represent vectors and matrices, respectively; superscripts $\mathbf{x}'$ denotes the transpose of $\mathbf{x}$.

II. PROPOSED VSS-LMS ALGORITHM FOR ECG SIGNALS

The basic structure of the proposed algorithm is described in Fig. 1. Based on the noisy input and desired signal, the error is computed. The error is minimized in each iteration with the adaptive weighting coefficient [20], [21]. The process is continuing until the expected outcome is reached or terminates by user. The followings are the steps for the LMS algorithm [9], [19]:

$$e(n) = d(n) - \mathbf{w}'(n)\mathbf{s}(n). \quad (1)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \mu\mathbf{x}(n)e(n). \quad (2)$$

Here, $e(n)$ is the error signal, $\mathbf{w}(n)$ is the adaptive weight, $\mathbf{x}(n)$ is the noisy ECG signal, $d(n)$ is the desired response,

TABLE I: State-of-the-art literature.

Approach	Advantage	Disadvantage	Ref.
Adaptive Recurrent Filter	Remove noisy signals from repetitive morphology, Appropriate for heart rate measurement and arrhythmia analysis	Create signal distortion, Inappropriate for diagnostic ECG analysis	[10]
Fourier Linear Combiner	Solve frequency mismatch problem created by low frequency noise	System is less sensible in case of slower adaptation	[11]
Adaptive Orthogonal Linear Combiner	Steady-state mean square error is independent of step size	Steady-state mean square error can be negative for truncation error	[12]
Fast Lane Approach	Better prediction for learning step size and signal history length	Hard to implement	[13]
Recursive Least Squares	Higher convergence rate, Lower MSE	Heavy computational complexity	[14]
LMS and Normalized-LMS	Able to remove both stationary and non stationary noise, NLMS converges faster than LMS.	Performance highly depended on step-size parameter	[15]
Variable Tap Length LMS	Provide faster convergence, Smaller steady-state misadjustment error	High computational complexity	[16]
Adaptive Step-size NCLMS Algorithm	Lower excess mean square error, Faster convergence rate.	Higher computational complexity than LMS	[17]
Noise Resilient VSS-LMS Algorithm	Lower steady-state EMSE, Adaptive interference reduction technique.	Lower sensitivity than conventional LMS	[18]

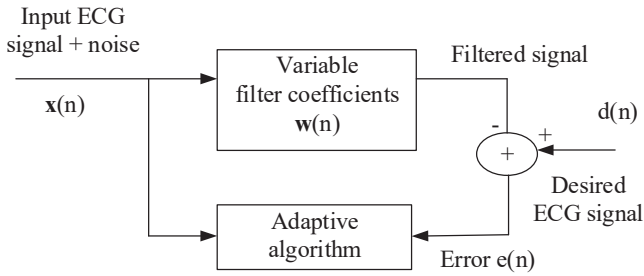


Fig. 1: Proposed algorithmic structure inspired by [9], [19].

and μ is the step size [22]. The considered noise is baseline wander (BW) which is described in [9], [19].

It can be seen that the step size is fixed for LMS algorithm [23], [24]. When the noise and cyber attack is time varying, the LMS can not properly track the ECG signal. Inspired by [9], [19], the variable step size-LMS algorithm is proposed in this paper for ECG signals. The proposed algorithm is described as follows:

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

$$\mu(n+1) = \alpha\mu(n) + \beta|e(n)|^2. \quad (4)$$

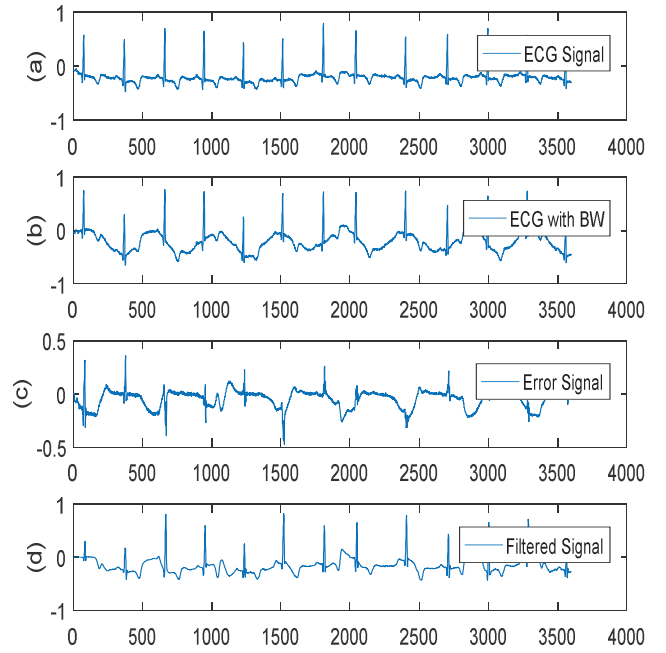


Fig. 2: (a) ECG signal, (b) ECG with baseline wander (BW) noise, (c) Error signal and (d) Reconstructed ECG signal when step size is 0.1.

Here, α and β are the correction coefficients and convergence parameters, respectively [25], [19]. Based on the aforementioned algorithm, the numerical simulation results are demonstrated in the following section.

III. SIMULATION RESULTS AND DISCUSSIONS

After collecting data from the MIT-BIH ECG signal [9], [26], [27], the baseline wander (BW) noise is added into it [28]. The whole simulation process is described in Fig. 1. First of all, the simulation results are presented considering BW noise. Afterwards, the simulation is conducted considering noise and cyber attack in the ECG signals. Considering the BW noise in the input ECG signal, the simulation results are presented in Figs. 2-3 with different step size parameters. It can be seen that the proposed algorithm can properly reconstructed the ECG signal. It is considered that the MIT-BIH ECG signal is collected by sensors which are vulnerable to cyber attack [29]. Considered false data injection attack [30] and BW noise, the simulation results are presented in Figs. 4-5. It can be seen that the proposed algorithm can properly reconstructed the ECG signal.

IV. CONCLUSION AND FUTURE WORK

This paper proposes a VSS-LMS algorithm considering BW and cyber attacks. The proposed algorithm is obtained considering tuning parameters and errors where the step size is adaptively updated based on the signal dynamics. Extensive simulation results illustrate that the presented algorithm can properly handle impairments. Hopefully, this kind of finding

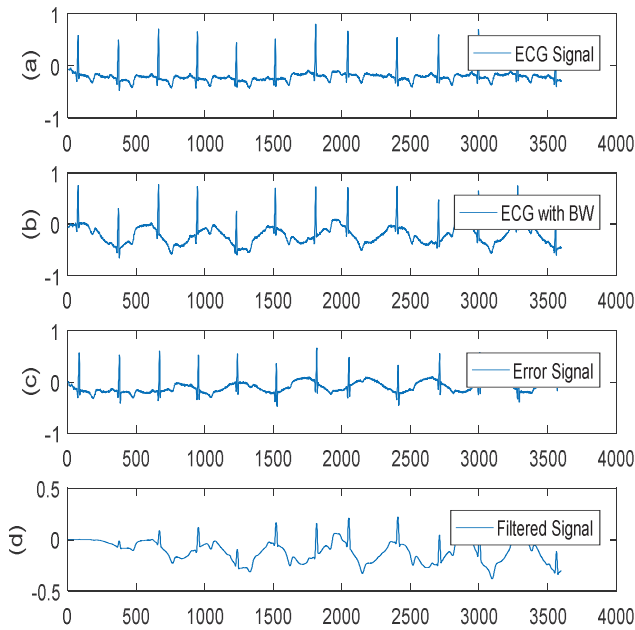


Fig. 3: (a) ECG signal, (b) ECG with baseline wander (BW) noise, (c) Error signal and (d) Reconstructed ECG signal when step size is 0.001.

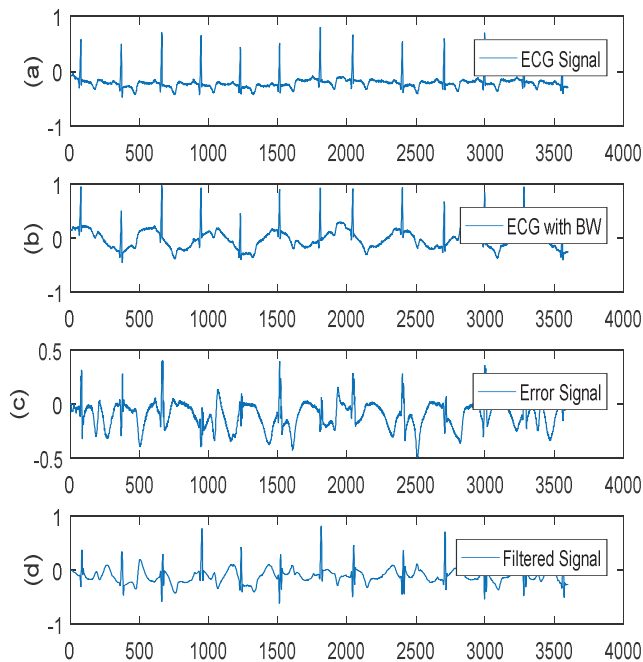


Fig. 4: (a) ECG signal, (b) ECG with baseline wander (BW) noise, (c) Error signal and (d) Reconstructed ECG signal when step size is 0.1 with cyber attack.

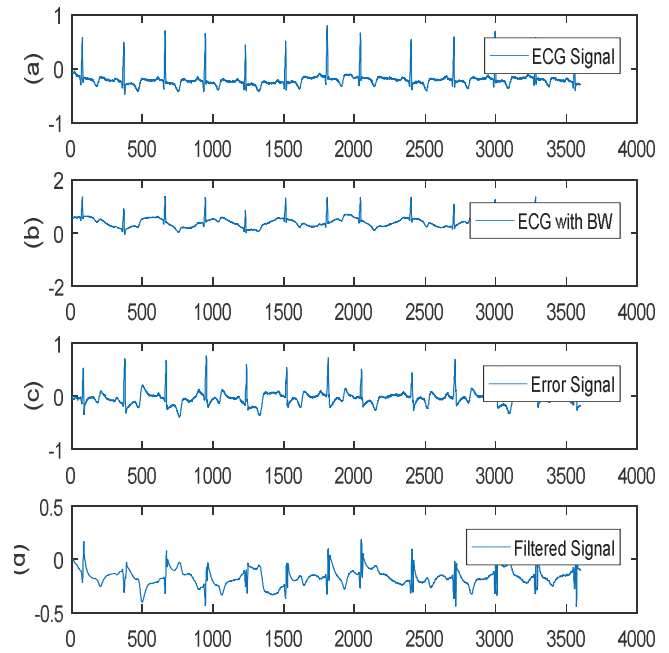


Fig. 5: (a) ECG signal, (b) ECG with baseline wander (BW) noise, (c) Error signal and (d) Reconstructed ECG signal when step size is 0.01 with cyber attack.

and analysis is very important for smart health care design. Considering the normalised LMS algorithm, the proposed algorithm can be extended [31].

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Ahmed Abdelhadi (SM'16) is an Assistant Professor at the University of Houston. Before joining UH, he was a Research Assistant Professor at Virginia Tech. He received his Ph.D. in Electrical and Computer Engineering from the University of Texas at Austin in 2011. He was a member in Wireless Networking and Communications Group (WNCG) and Laboratory of Informatics, Networks and Communications (LINC) group during his Ph.D. In 2012, he joined Bradley Department of Electrical and Computer Engineering and Hume Center for National Security and Technology at Virginia Tech. He was a faculty member of Wireless @ Virginia Tech. His research interests are in the areas of wireless communications and networks, spectrum sharing, cyber physical systems, and security. Dr. Abdelhadi coauthored more than 70 journal and conference papers, and 5 books in these research topics.