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Utilizing SimEMG to Evaluate the Effectiveness of Adaptive Filters in Removing EMG Contamination from ECG Recordings

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Abstract. The noise in electrocardiographic (ECG) recordings can significantly affect their medical interpretation, especially when the electromyographic (EMG) noise overlaps with the QRS complex, making it difficult to remove. Typically, noise-removal methods are evaluated using algorithms tested on artificially contaminated signals created by adding noise to noise-free ECG recordings. In this context, the SimEMG database containing EMG-noise-free and EMG-contaminated ECG signals is used. The paper uses SimEMG database to evaluate the effectiveness of adaptive filters based on an adaptive noise cancellation in removing real EMG contaminants, as well as other noise artifacts, from the ECG recorded signals. The evaluation is made by computing the Signal to Noise Ratio (SNR) of the ECG signal compared to the contaminant EMG and other noise before and after adaptive filtering. Different filtering algorithms, step sizes, and filter lengths are investigated. The obtained results indicate the effectiveness of the used method in removing the EMG artifacts and enhancing the ECG signal, achieving an improvement of above 3 dB at a certain value of the filter length and step size.

Keywords: Adaptive filters, Electrocardiogram, ECG, Electromyogram, EMG, SimEMG, SNR

Uporaba SimEMG za oceno učinkovitosti prilagodljivih filtrov pri odstranjevanju šuma EMG s posnetkov EKG

Šum v elektrokardiografskih (EKG) posnetkih lahko pomembno vpliva na njihovo medicinsko interpretacijo, zlasti kadar se elektromiografski (EMG) šum prekriva s kompleksom QRS, zaradi česar ga je težko odstraniti. Običajno se metode za odstranjevanje šuma ocenjujejo z uporabo algoritmov, preizkušenih na umetno popačenih signalih, ki so generirani z dodajanjem šuma posnetkom EKG. Na tej osnovi je bila uporabljena baza podatkov SimEMG, ki vsebuje signale EKG brez EMG in popačene z EMG. Vrednotenje je bilo opravljeno z izračunom razmerja med signalom in šumom (SNR) signala EKG v primerjavi s popačenim EMG in drugim šumom pred prilagodljivim filtriranjem in po njem. Raziskali smo različne algoritme filtriranja, velikosti korakov in dolžine filtrov. Dobljeni rezultati kažejo na učinkovitost uporabljene metode, pri čemer smo dosegli izboljšave za več kot 3 dB pri določenih vrednostih dolžine filtra in velikosti koraka.

1 INTRODUCTION

Electrocardiogram(ECG) is a medical test that records the electrical activity of an individual cardiac. The activity usually generates a small electric current that spreads through the human body. It is a fundamental tool in medical diagnosis, as it provides an invaluable insight into the human cardiac health.

Unfortunately, the accuracy of the ECG recordings is usually questionable due to the noise contamination. The Electromyographic (EMG) interference, power line interface(PLI) and baseline wander(BW) are among the most effective ones. These artifacts can significantly reduce the quality of the recorded signals and the accuracy of the diagnosis. This impact on heartbeat detection methods and relevant information gathering is noticeable [1]. Removing the EMG signals and other contaminants from the ECG recordings while keeping the distortion level as low as possible results in a better diagnostics of relevant information [2].

To minimize the contamination and low quality issues in the ECG signals and to improve the diagnostic accuracy, numerous research papers have been published. Their main goal is to eliminate a wide range of interference signals and increase the signal quality. The proposed denoising methods may involve specific filters to address various types of the noise [3], or might include multiple filter types [4]. More advanced methods have also been utilized to develop reliable ECG denoisers, particularly for the wearable devices [5], [6].

Our research is based on several papers summarizing the up-to-date methods. The authors in [7], [8] review the noise removal techniques in the ECG signals. Oza-

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ydin and Ahmad [9] conduct a comprehensive analysis to evaluate the effectiveness of the existing methods to remove the noise and artifacts from the ECG signals, especially BLI. They provide a comparative analysis of the performance and relative merits of various methods. Velusamy et al. [10] review the current state-of-the-art support systems for various medical decisions to prevent cardiac diseases. The systems are based on pre-processing (ECG signal denoising), feature extraction, and classification methods for cardiac disease diagnosis.

In our research, we investigate the use of adaptive filter techniques to effectively remove the EMG signals as well as other contaminated artifacts based on an adaptive noise cancellation model. Unlike other filters, adaptive filters adjust their weight dynamically to track the time-varying noise. Our method holds the potential to improve the cardiac diagnosis by obtaining a clean ECG signal. It is theoretically suitable for real-time processing because of its low computational complexity which makes it more appropriate for the carry-on and wearable ECG recorders.

The rest of the paper is organized as follows. Section 2 reviews the most relevant work on the topic with a focus on the last two years. Section 3 analyses the theoretical background of the topic. Section 4 presents our proposed method. Section 5 comments and discusses the obtained results. Section 6 shows the conclusion of our research.

2 RELATED WORK

ECG signal recording comes with the following contamination problem. EMG interference resulting from muscle contraction, is considered as the most significant one since it overlaps with the recorded ECG signal in certain frequency bands. Eliminating it as well as other artifacts from the ECG signals has been investigated by many scholars who claim their proposed methods are more efficient than others. In this section, we describe some of the related research performed in the last two years. [11] utilizes a moving average (MA) filter as part of the ECG pre-processing stage to eliminate the noise and spikes while preserving the original ECG signal representation. The filter which is based on the Matlab and Vivado software demonstrates a powerful noise cancellation by attenuating different types of the noise. Balasubramanian et al. [12] use swarm intelligence approaches to improve adaptive hybrid filters and empirical wavelet transforms (EWTs) to remove the contaminated noise from the ECG signals.

For the recordings to be evaluated, Elouaham et al. [13] propose EWT as an effective denoising method. The EWT method effectively eliminates noise while preserving the main signal information. Hossain et al. [14] employ a variable frequency complex demodulation (VFCDM) algorithm providing a high-resolution time-frequency analysis to denoise the ECG signals in various noisy states.

Similarly, [15] designs several filtering approaches to eliminate the EMG noise and baseline wander present in the ECG signals. Assali et al.[16] present an automatic ECG filtering method using a support vector machine (SVM) to select from three different denoising methods: discrete wavelet transform (DWT), empirical mode decomposition (EMD), and extended Kalman filter (EKF).

There are also some other methods used to remove the noise and EMG artifacts from the recorded ECG. The most utilized ones use the adaptive filter. [17] utilizes the Reptile Search Algorithm (RSA) to obtain the optimal adaptive filter weight to minimize the error signal. The filter method performs better than other ones while maintaining the main cardiac data in the signal. Kose et al. [18], [19] use a structure consisting of adaptive filters to remove the motion artifact noise, baseline wander noise, and muscle noise from the ECG signal based on various adaptive filter algorithms.

To eliminate different types of the noise in the ECG signals, Manickam et al. [20] utilize a variable leaky least mean square (VLLMS) adaptive filter. Chen et al. [21] present an adaptive periodic segment matrix concept as an effective way of extracting the ECG signal in a noisy environment. Seeni et al [22] introduce a novel filter design i.e an AdaptIIR filter to remove the contaminated noise and improving the Signal to Noise Ratio(SNR) value.

Sometimes, removing the noise from the ECG signal may not be enough. This can be solved by improving the recording itself. [23] investigates the ECG signal enhancement using different filters (linear, non-linear, and adaptive). The investigation which considers SNR and MSE as its main metrics shows that an adaptive median filter ensure an optimal performance in terms of the noise reduction and signal enhancement.

Other researchers attempt to separate the ECG signal from the EMG or sEMG(surface EMG). The goal is different. It is to obtain a clear EMG signal for specific diagnoses. For instance, Wang et al. [24] use a fully convolutional networks (FCN) to eliminate undesired ECG signals from single-channel sEMG interference. Esposito et al.[25] apply feed-forward comb (FFC) filters to remove the noise and artifacts from the EMG signal.[26] illustrates the state of the art of sEMG advances, limitations, and future goals in employing sEMG to monitor patients with a respiratory failure. Lu Wei et al.[27] use an improved multi-layer wavelet transform to remove the ECG noise from the sEMG signals. Their method consists of several steps with the aim to discriminate the ECG from the sEMG signals. Their results indicate the validity of the proposed method not only in removing the ECG signals from the contaminated sEMG signals but also in improving the quality of sEMG signals. Mohamed et al. [28] and

[29] present an automated method to detect and remove the ECG noise from the sEMG signals based on a fuzzy inference system (FIS). Their method is evaluated using several metrics shows its superiority over other methods in terms of enhancing the SNR (signal to noise ratio) levels. [30]presents a novel approach known as SDEMG(a score-based diffusion model for the sEMG) signal as an effective method for EMG denoising. It is evaluated by conducting an experiment to reduce the noise in the sEMG signals utilizing a non-invasive adaptive prosthetic database from the MIT-BIH Normal Sinus Rhythm Database[31]. The obtained results prove that SDEMG produces high-quality sEMG signals. More details on this types of papers can be found in Boyer et al.[32] where they review the current methods to reduce the noise and artifacts in the EMG signals with a special emphasis laid on methods enabling a full reconstruction of the EMG signal without losing the information.

Almost all the above researchers use the MIT-BIH Arrhythmia Database [31] to evaluate their methods since it has been so far the only one freely available. However, recently, other databases have been provided, even though their intended usages might be different. The authors in [33] publish SimEMG which is the first available dataset that records the ECG signal with and without the EMG artifacts. This database can be used to evaluate and compare ECG denoising methods. Kim et al. [34]provide two databases containing the ECG and EMG signals to be used as an alternative method of the user recognition. This kind of recognition might be considered the next generation of recognition since the current methods based on face and fingerprint are very limited.

3 Theoretical Background

3.1 Adaptive Filters Overview

Adaptive filters are a class of the digital filters able to change and adjust their coefficients over time in response to the input signals. In other filters, the coefficients are fixed, unlike in adaptive filters where the coefficients vary over time to optimize the performance based on certain criteria. They have a wide range of applications, such as adaptive noise cancellation, system identification, equalization, and system prediction. More details about the architectures suitable for each application can be found in [35], [36].

There are several algorithms in adaptive filters that can be used to adjust the filter weight and achieve the optimization goal, such as:

3.1.1 LMS: The Least Mean Square (LMS) algorithm is the fundamental algorithm for the adaptive filters. It is a simple and effective method to adjust the filter weight in order to minimize the error signal, the difference between the desired and the actual signals. The weight update equation in the LMS algorithm is [35], [36]:

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

where $w(n)$ and $w(n+1)$ are the filter coefficients at the current time sample n and the next one $n+1$, μ is the step size, $e(n)$ is the error signal at the time sample n, and $x(n)$ is the input signal at the time sample n.

The LMS algorithm starts by calculating the error signal. Then, it updates the filter weights based on the obtained error signal(see Equation 1). The process of the error computation and weight adjustment is repeated iteratively until converging to an optimal response.

3.1.2 NLMS: The Normalized Least Mean Square (NLMS) improves LMS algorithm. It is a better algorithm in terms of convergence speed. The working principle is similar to the LMS algorithm. However, the weight update equation here is a little different, as shown in [35], [36]:

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

where $||x(n)||^2$ is the norm square of the input signal.

NLMS algorithm has a faster convergence speed compared to the LMS algorithm. It is very sensitive to the variation in step size μ.

3.1.3 LLMS: In certain cases, the stability condition can not be achieved using LMS algorithm without choosing a suitable learning rate that guarantees it. To solve this problem, an alternative algorithm called LLMS (Leaky LMS) is introduced. It guarantees the stability requirements and overcomes the slow convergence of the LMS algorithm [37].The working principle is similar to LMS and NLMS algorithms. However, the weight update equation is different [37]:

$$w(n+1) = (1 - \gamma * \mu)w(n) + \mu * e(n) * x(n) \tag{3}$$

where γ is a very small positive number ($\gamma << 1$) known as the leaky factor which guarantees the stability condition.

Besides NLMS and LLMS, there are other versions of the LMS algorithm, such as the signs LMS and NLMS, and VLLMS. They all operate on the same principle, but their weight update equations are different. Their main goal is to address the problems and limitations of LMS and NLMS.

3.1.4 RLS: Recursive Least Square (RLS) is a powerful adaptive filtering algorithm that efficiently finds the appropriate filter coefficients that minimize the weighted linear least squares of the cost function, which is the difference between the desired and actual outputs [35]. Compared to LMS, RLS has a faster convergence speed and a higher computational-complexity. The working principle and the weight updates in the RLS algorithm are different from those in LMS and NLMS. It also includes more complex mathematics and linear algebra.

3.2 Adaptive Filters Standards

In adaptive filters, there are four common filtering standards(see Figures 1-4). The intended purpose of using each one is different.

For instance, the main goal of using the system identification approach(see Figure 1), is to find an approximate model of an unknown system. The unknown system and adaptive filters are connected in parallel, and both are stimulated by the same primary input. When the output error signal is reduced, the adaptive filter equates the desired model for the unknown system [36].

In the inverse modeling diagram presented in Figure 2, the goal is to reverse the operation of the unknown system [36]. This diagram is usually utilized in communication systems, especially in the signal enhancement and channel equalization.

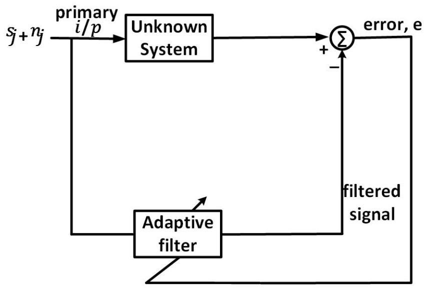

Figure 1. System identification based on the adaptive filter.

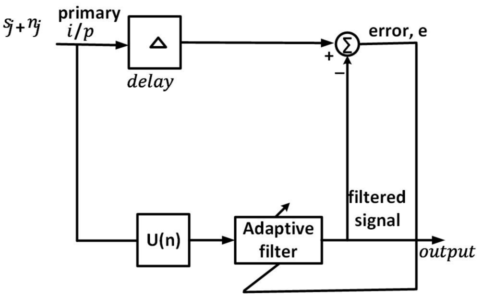

Figure 2. Inverse modeling based on the adaptive filter.

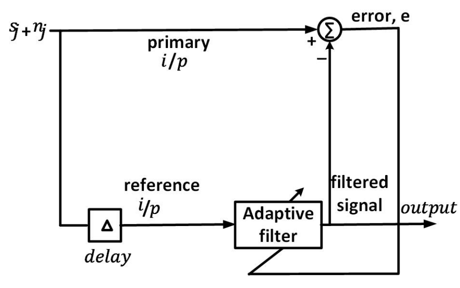

Figure 3. System prediction based on the adaptive filter.

In the adaptive system prediction diagram shown in Figure 3, the main role of the adaptive filter is to find the best possible output based on an instantaneous input signal [36]. The model is widely utilized in speech processing applications.

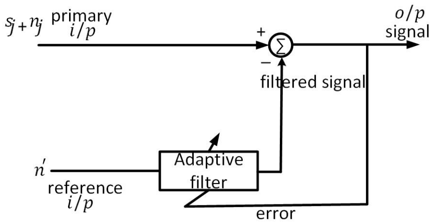

Figure 4. Noise cancellation based on the adaptive filter.

The adaptive noise cancellation (ANC) diagram [36], depicted in Figure 4, is more efficient in removing the noise and disturbance signals as the name implies.

3.3 Available Databases

The ECG signals, as well as their contaminated noise, can be simulated using various software. Nonetheless, a real-time evaluation and examination of any proposed denoising method can be conducted using several available databases. Some databases are described below.

3.3.1 MIT-BIH: The MIT-BIH Arrhythmia Database [31] is the first freely available dataset. It has been widely used for research on cardiac dynamics at approximately 500 sites worldwide since 1980 [38]. The database has played a significant role in conducting research and investigations, stimulating manufacturers of arrhythmia analyzers to compete based on an objectively measurable performance. [38] reviews the history of the database, illustrates its contents, describes the learning outcomes from it, and highlights some of the latest projects that utilizes it. The MIT-BIH database can be accessed at https://www.physionet.org/content/mitdb/1.0.0/.

3.3.2 Brno University of Technology ECG Quality Database (BUT QDB): The BUT QDB database was created by a group of cardiologists at the Brno University of Technology, Department of Biomedical Engineering [39]. It evaluates the quality of the ECG signals. The database contains 18 recordings of single-lead ECGs associated with three-axis accelerometer data, collected from 15 people (six male, and nine female). Their ages ranged between 21 and 83 years. The recordings were taken between August 2018 and October 2019. During the recording period, the participants were asked to live their ordinary lives as the data were collected using a mobile ECG and accelerometer with a sampling frequency of 100 Hz for accelerometer signals and 1,000 Hz for ECG signals [39]. BUT QDB can be accessed at https://physionet.org/content/butqdb/1.0.0/.

3.3.3 CSU_MBDB1 and CSU_MBDB2: CSU_MBDB1 and CSU_MBDB2 are two databases presented in [34]. They contain recorded ECG and EMG signals under different scenarios. The physiological signals are recorded in several sessions from 36 and 58 individuals respectively, with a more than 24 hours time interval between the sessions. They are used for user recognition and to overcome the limitations of the currently used face and fingerprint-based user recognition methods. They can be accessed at http:/www.chosun.ac.kr/riit.

3.3.4 SimEMG: The database was presented by Atanasoski et al. [33] in 2023. It contains a total of 147 recordings, 37 of them are noise-free, and 110 of them are noise-contaminated. SimEMG is recommended to evaluate various ECG denoising methods due to the absence of a standardized database. It is the first dataset with simultaneously recorded ECG signals with and without the EMG noise allowing for direct comparison and evaluation. The data are recorded by a novel acquisition technique which enables a direct recording of the EMG-noise-free and contaminated ECG signals. The database can be accessed at https://drive.google.com/file/d/ 128EFArKpYfFMk-cIrvzadP8h EKlk8shKt/view?usp=share$_link$.

4 Proposed Methodology

Among the above configuration standards of the adaptive filter, adaptive noise cancellation and adaptive system prediction are the most suitable ones to remove the noise and artifacts from the ECG recordings [19]. Since our goal is to denoise the ECG signals and evaluate the effectiveness of the denoiser and make it technically suitable for wearable devices, we use the adaptive noise cancellation model. Figure 5 shows a flowchart of the proposed method. The loaded contaminated ECG signal serves as the main input for the adaptive filter. It undergoes a series of procedures to reduce the noise level and enhance the ECG signal itself. Except for the RLS algorithm, all other algorithms can be used based on this flowchart. The only change that we must be aware of is the weight update equations.

5 Results and Discussion

The results obtained by using the proposed method are shown in Figures 6-17. The contaminated and reference ECG signals are taken from the SimEMG database by Atanasoski et al. [33]. It is used to evaluate the effectiveness of the proposed method in removing the EMG artifacts. Compared to other databases, the SimEMG is more recent. As shown in figures, the proposed method is very effective in removing the EMG signals, as well as other noise and artifacts. The improved SNR evaluates the effectiveness of the utilized adaptive filtering algorithms and represents the difference between the output and input SNR.

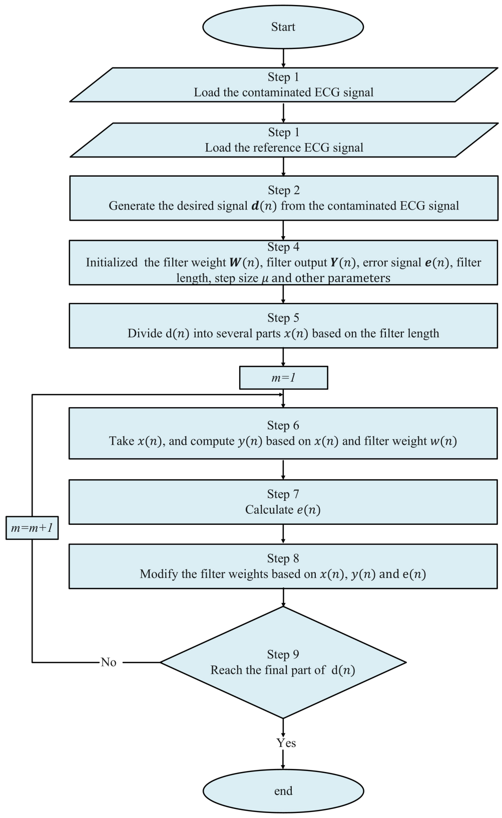

Figure 5. Proposed method.

Different step sizes(μ), filter lengths(L) and three adaptive filtering algorithms (LMS, NLMS,LLMS) are investigated. The results show that shorter filters ensure a better SNR improvement but the computation time to clean the whole signal is longer. The step size guarantees the convergence of the used algorithm without being too large to distort the output signal (see Table 1). The best results are achieved in the LMS algorithm at the step size of $\mu = 1e-5$, whereas the best results are achieved in NLMS and LLMS algorithms at the step size of $\mu = 1e-2$. LMS algorithm doesn't converge at the step size of $\mu < 1e-5$, whereas the NLMS and LLMS algorithms distort the output signal at the step size of $\mu > 1e-3$.

6 Conclusion and future work

The SimEMG database by Atanasoski et al. [33] is used to evaluate the effectiveness of adaptive filters in removing the EMG contaminants and other noise artifacts from the recorded ECG signals. An adaptive noise cancellation diagram is used, as it is more commonly applied in such task. The evaluation criteria involve computing the SNR of the ECG signals compared to the contaminating EMG and other noise, both before and after adaptive filtering. Different filtering algorithms, step sizes and filter lengths are investigated. The results

Table 1. SNR improvement based on various algorithms for different step sizes and filter lengths.

Algorithm	**LMS**		**NLMS**		**LLMS**	
$\mu =$	**L=15**	**L=25**	**L=15**	**L=25**	**L=15**	**L=25**
1e-1	NC	NC	2.25351	2.09728	2.2133	2.09728
1e-2	NC	NC	3.10923	2.99236	3.10923	2.99236
1e-3	NC	NC	1.6505	0.2986	1.6505	0.2986
1e-4	NC	NC	- 0.0871	-0.6791	-0.0871	-0.6791
1e-5	3.65105	3.74902	0.2448	-0.1540	0.2448	-0.1540
1e-6	3.16894	3.15809	0.2911	-0.1035	0.2911	-0.1035
1e-7	0.6229	0.7822	0.2958	-0.0985	0.2958	-0.0985

NC means No Convergence was achieved based on these inputs

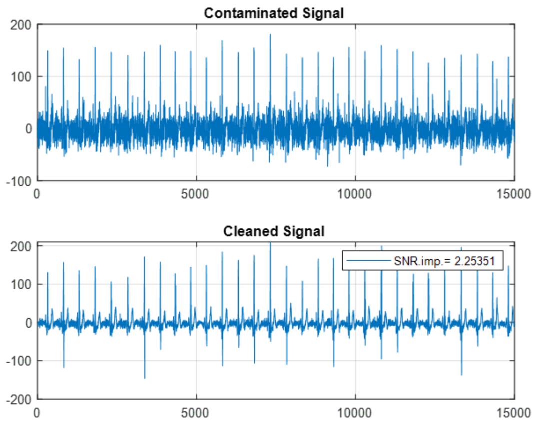

Figure 6. NLMS, filter length=15,μ=1e-1, SNR.imp=2.25351 dB.

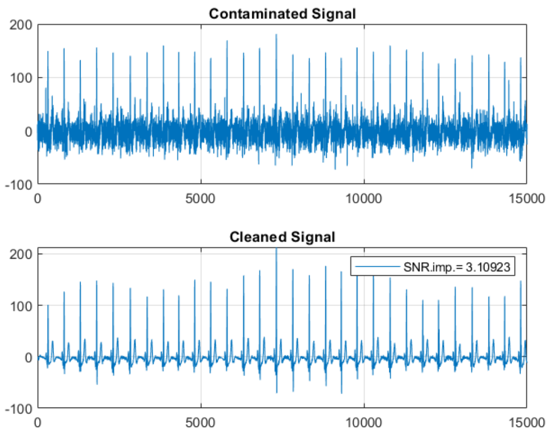

Figure 7. NLMS, filter length=15, μ=1e-2, SNR.imp= 3.10923 dB.

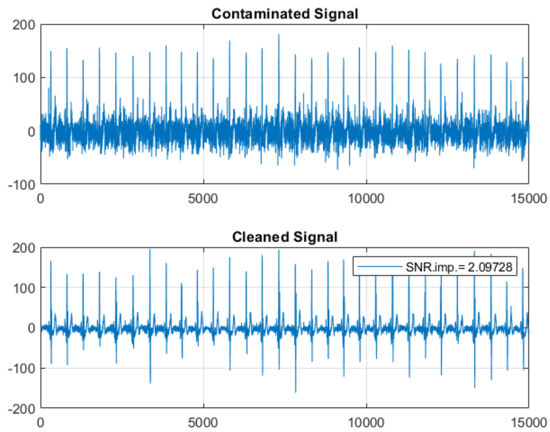

Figure 8. NLMS, filter length=25, μ=1e-1, SNR.imp= 2.09728dB.

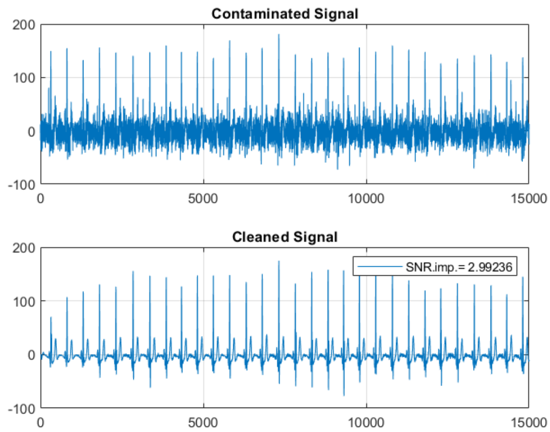

Figure 9. NLMS, filter length=25, μ=1e-2, SNR.imp=2.99236 dB.)

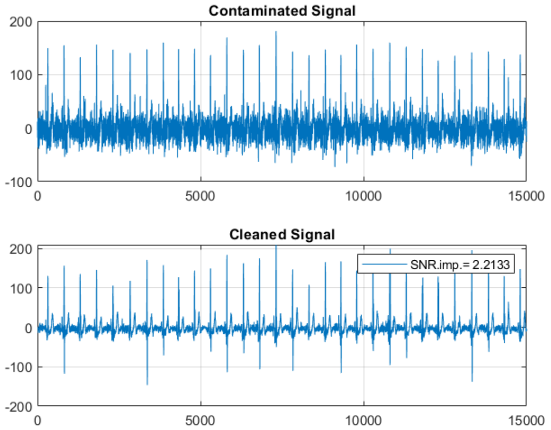

Figure 10. LLMS, filter length=15,μ =1e-1, SNR.imp=2.2133 dB.

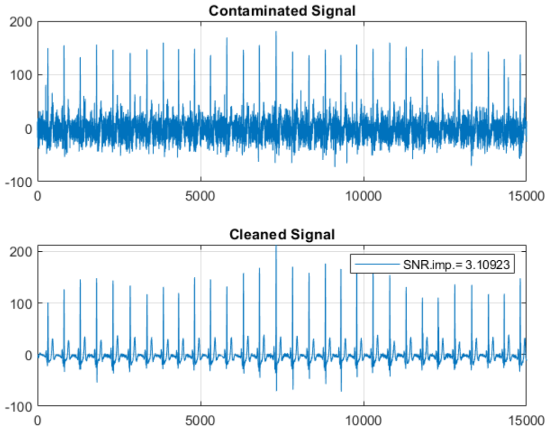

Figure 11. LLMS, filter length=15,μ =1e-2, SNR.imp=3.10923 dB.

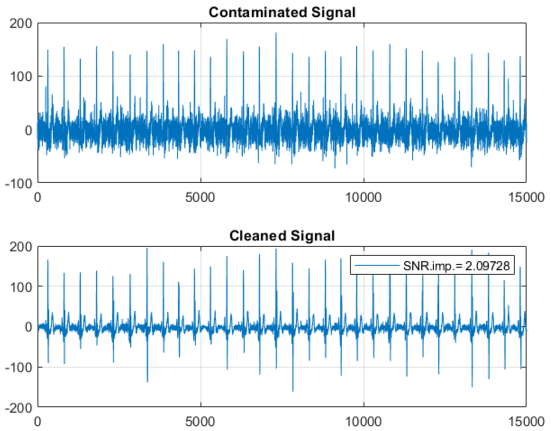

Figure 12. LLMS, filter length=25,μ =1e-1, SNR.imp=2.09728 dB.

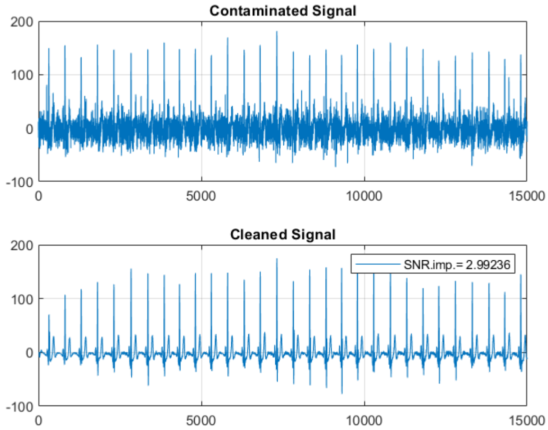

Figure 13. LLMS, filter length=25,μ =1e-2, SNR.imp=2.99236 dB

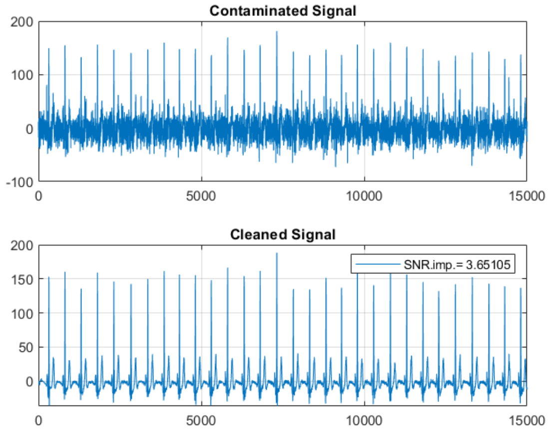

Figure 14. LMS, filter length=15,μ =1e-5, SNR.imp=3.65105 dB.

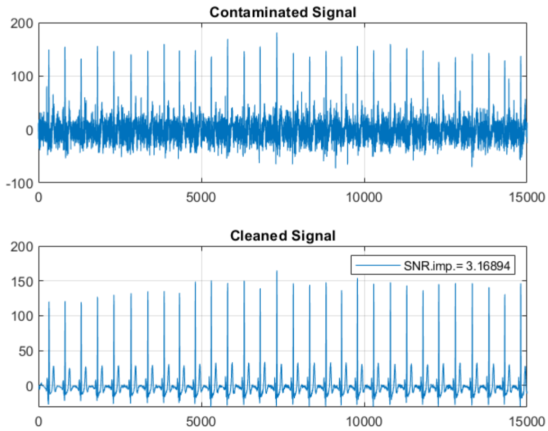

Figure 15. LMS, filter length=15, μ =1e-6, SNR.imp=3.16894 dB.

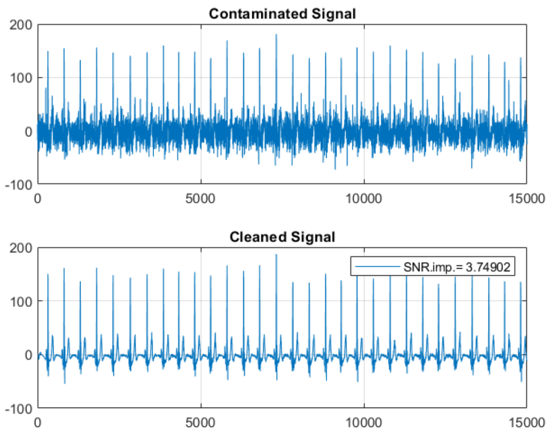

Figure 16. LMS, filter length=25,μ =1e-5, SNR.imp=3.74902 dB.

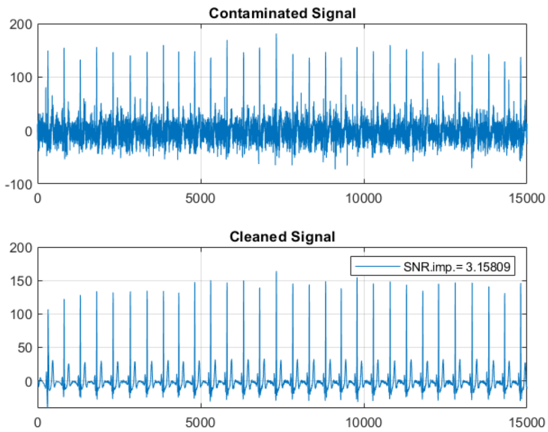

Figure 17. LMS, filter length=25,μ =1e-6, SNR.imp=3.15809 dB.

illustrate the effectiveness of the used method. They show an enhancement in the ECG signal with an improvement above 3dB at specific step sizes and filter lengths.

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