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Research Article

Improving the Quality of ECG Signal Using Wavelet Transform and Adaptive Filters

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Abstract: The increasing risk of cardiovascular diseases, stress, high blood pressure, obesity, sleep disorders, and depression causes electrocardiogram (ECG) monitors to be used for diagnosing health. The main objective of this research is to enhance the quality of the ECG signal using wavelet transform and adaptive filters. This research has been made as descriptive-analytic and the method is used in the signal processing stages to calculate the ECG modulation spectrum, the spectral-modulation filtering scheme, and the ECG database from the standard algorithm and performance criteria. The results of the simulation indicate that the conversion of Sym4 and the adaptive filter with the size of 0.0005 and the length of the filter of 25 signals to the noise will be greatly improved to reveal the main features of the ECG signal.

Keywords: ECG signal quality, wavelet, adaptive filter.

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1. Introduction

Different electronic health devices are designed for the elderly in the community and the growing population of these elderly citizens who live alone. This approach arises from the increased interest in personal health care and the growth of cardiovascular diseases. In monitor of a 24hours electrocardiogram (ECG), a data compression method is needed to efficiently use resources and to reduce the time of data transmission. In the telecommunication industry, a compression algorithm for compressing ECG signals has been provided based on selecting the important sub-bands of the wavelet packet transform with the aim of minimizing the data while the quality of the reconstruction signal is desirable. The proposed algorithm consists of four stages for compression and four stages for reconstruction [1]. Wavelet transform, wave compression techniques are suitable for displaying transients, such as sounds recorded in sound or high-frequency components in two-dimensional images (for example, an image of stars in the night sky). This means that the transient elements of a data signal can be represented by a smaller amount of information, unless in case of some other changes including the discrete deformation is more used. The discrete wavelet transform has been successfully used to compress electrocardiographic signals (ECG). In this work, the high correlation between the wavelet coefficients of the signals of successive heart cycles is used by linear prediction [2]. Improvement methods of signal quality of wavelet transform are generally based on a threshold which is rooted in the assumption of energy concentration in a small number of discrete wavelet transform coefficients. The major disadvantage of threshold methods in the ECG signal is to create the distortion in the target signal. For this reason, in recent years, a variety of filters, and especially the adaptive filters, are used to correct wavelet transform coefficients. In the telecommunications industry, a new structure for improving the quality of the ECG signal with the help of using an adaptive and threshold filter on wavelet coefficients has been provided that in this method, instead of threshold, the wavelet coefficients are improved by passing through an adaptive filter. This causes the estimated signal to be largely close to the major signal and the estimate error to be reduced [3]. One of the problems of artisans is the processing of biomedical data (such as electrocardiography) that separates the desirable signal from noises caused by interference of power lines, external electromagnetic fields, interference of high frequency and random and breathing movements. Different types of digital filters are used to remove signal components from undesired frequencies. It is difficult to use constant coefficient filters to reduce random noises. Because the behaviour of the system is not dependent on the specific time. To overcome this problem, an adaptive filter technique is required. Electrocardiogram (ECG) is the most important parameter for controlling cardiac activity. By fully analyzing the shape of the ECG signal, the doctor can detect various types of deviation. In some medical signal applications, useful signals are excelled by various components [4]. To avoid interference of ECG signals, designing a system is needed. To design and achieve a reliable system, there are two issues to consider. The accuracy and processing time should be appropriate. Basically, these methods should be categorized as adaptive and non-adaptive filter. There are some cavities in non-flexible filter or fixed filter. Adaptive filters are used for cancelling noise in different areas. Adaptive filters are capable of responding to their blow, and as a result, there is little information of the signal or information which can be planned for extracting the signal from unwanted information. This will help improve the signal-to-noise ratio. Adaptive filters are for those plans that some of the parameters of the processing operations required are not initially known or cannot be modified [5]. In order to overcome this limitation, algorithms of increasing ECG quality are strongly needed that can act under the broad spectrum of the levels of noise. Typically, two methods were previously investigated to enhance quality; filtering, wavelet contraction. For example, improving the quality of the ECG was performed using multiple repetitions of a moving filter that could have been about 10 dB for noisy signals with a signal-to-noise ratio [5]. A lot of studies have been done on cardiac signals that the Esmaili (2018) analyzed ECG signal in a research by using the features of ECG cardiac signal (morphological and characteristics derived from wavelet transform) and neural network [6] the results show that (25 normal files and 20 non-normal files) of these signals, 64 characteristics are obtained (48 characteristics based on wavelet transform and 16 morphological characteristics) that as inputs in neural network. The result indicated the effectiveness of the algorithm used. Rezai and Khodadadi (2016) investigated the use of an adaptive filter to remove ECG noise from the surface EMG signal [7], and the results show that the fast convergence of the least squared algorithm has made it possible for the proposed filter to effectively remove electrocardiogram noise remove from the surface electromyogram signal. Mohseni et al. (2015) investigated the new method based on the usage of a variety of comparative filters to remove artifacts from the ECG signal in a research [8], and the results of calculations of the signal-to-noise ratio for LMS, EBLMS, ENLMS and ELMS filters respectively 31.557, 3.516, 3.516, 6.830 and 3.038 were obtained. Belgurzi and Elshafiey (2017) investigated fixed-wavelet transforms and adaptive filter for improving the quality of the ECG signal in a research [9], and the results of fixed wavelet showed that an increase in the signal of ECG quality is successfully performed in terms of signal-to-noise ratio. In a study, Tobon and Falk (2016) examined modulation filtering to improve the quality of ECG in a study [10] and the findings obtained showed that the proposed algorithm can be used to improve the quality of wearable ECG monitors even in severe conditions, so it can play a key role in training and monitoring the performance of peak sport. Sehamby and Singh (2016) investigated the elimination of noise by using an adaptive filter in the ECG signal in a study [11], and the ECG signals are weak and easily sensitive to noise and interference. In this research, the implementation of scale of the least squares was presented. Sharma et al. (2015) investigated and designed an adaptive filter for reducing the noise in the ECG in a research [12], and experimental results have shown that rate of convergence increases for small amounts of step. Increasing the risk of cardiovascular disease, stress, high blood pressure, obesity, sleep disorders and depression makes use of portable electrocardiogram monitors (ECG) for diagnosing health, but other parts of the market regarding medical programs are emerging. However, low-cost electromagnetic devices have shown that they are susceptible to numerous artifacts, including muscle contractions, base noises and movement, so the quality of the signal decreases and ultimately prevents heartbeat to change and to analyze it. To overcome this limitation, the algorithms of increasing ECG quality are highly needed which can operate under a broad spectrum of noise levels [13]-[21]. ECG is substantially based on the electrical conductivity of the heart. Normal conduction has started and distributes in a predictable pattern. Deviations from this pattern can be a natural or pathological change. An ECG is not equivalent to the activity of mechanical pump of the heart. For example, electrical activity produces an ECG which needs to pump the blood, but no pulse is felt. Ventricular fibrillation produces an electromagnetic wave, but it is too inefficient to produce the sustained cardiac output. Some rhythms have a good cardiac output, and some have bad heart output. Finally, an echocardiogram model or other anatomical imaging methods is useful in evaluating the mechanical function of the heart. Therefore, in this study, the increase of the quality of the ECG signal will be reviewed by using wavelet transform and adaptive filters.

2. Materials and Method

In the signal processing stages for calculating ECG modulation spectrum, modulation filtering scheme and ECG data base, the standard algorithm and performance criteria are used. The wavelet-based algorithms are the most popular, so here it is used to evaluate the proposed algorithm. A subset of 100 signals, each with 5 levels was used to optimize the parameters of the standard algorithm. It was found that the universal contraction method with soft threshold and a mother wavelet with 8 decomposition levels resulted in the best performance in this subset. Based on above information, the equations for the variables are set.

3. Formulation

In standard algorithm we have the followings.

$$\acute{V} = q_{in} - q_{out} \tag{1}$$

$$\acute{B} = \left(\mu - \frac{q_{in}}{V}\right) B \tag{2}$$

where V is volume, B is biomass, μ is vacuum permeation, and q is signal.

$$\acute{S} = q_{in}(c_{in} - S) - r_1 M_w B \tag{3}$$

where M_w is molar mass, r_1 is rate of absorbance, S is layer concentration, and c_{in} is time of the involved sample (per hour).

4. Wavelet Transform Algorithm

Wavelet transform is an efficient tool for signal processing and is used in many areas such as elimination of images noise, audio and video processing, pattern recognition, image encoding and compression. For this reason, it is important to provide solutions to increase the speed of implementation of the wavelet transform. One of the best solutions is the use of parallel processing. In telecommunications, a new architecture for implementation of a two-dimensional discrete wavelet transform has been provided to be used in image compression. The structure in this research is aimed at reducing the complexity of hardware and software, as well as optimizing the number of consumables and increasing the frequency of work. This implementation includes a processor unit for calculating discrete wavelet transform coefficients and a control unit for controlling data flow in the processor and generating memory address lines and an external memory unit for storing wavelet transform coefficients. The wavelet has some minor benefits over the Fourier transform in reducing the calculations when examining certain frequencies. However, they are rarely more sensitive and in fact, the conventional wavelet is mathematically the same. A short-term Fourier transform using a Gaussian window is called Morelt. The exception, when searching for signals of known form is non-sinusoidal (e.g. heartbeats); in this case, using convergent wavelets can analyze the standards. The function Ψ ∈L^2 (R), wavelet transform is called. This transformation can also be expressed as Hilbert. Hilbert is a complete and comprehensive transformation. Hilbert's base is defined as the function (4):

$$\Psi_{jk}: j.k \in Z \tag{4}$$

$$\Psi_{jk}(x): s^{\frac{j}{2}}\Psi(2^j x - k). \quad j.k \in Z \tag{5}$$

If it is under the internal standard of $L^2(R)$, as bellow:

$$(f.g) = \int_{-\infty}^{+\infty} f(x)g(x)dx \tag{6}$$

$$(\Psi_{jk}.\Psi_{lm}) = \int_{-\infty}^{+\infty} \Psi_{jk}(x)\overline{\Psi_{lm}(x)}dx = \delta_{j1}\,\delta_{km} \tag{7}$$

Where δ_{j1}: Kronecker delta.

$$f(x) = \sum_{j.k=-\infty}^{\infty} c_{jk}\,\Psi_{jk}(x) \tag{8}$$

With the convergence of the above set that seems to be convergence is in it, we reach the objective. Such a representation of "f" is known as a wavelet series. This means that it is a two-dimensional wavelet. The transform of the consistent wavelet of integral transformation is defined in (9):

$$[W_\Psi f](a.b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty} \overline{\Psi\left(\frac{x-b}{a}\right)} f(x)dx \tag{9}$$

Wavelet coefficient of c_{jk} is as (10):

$$c_{jk} = [W_\Psi f](2^{-j}.k2^{-j}) \tag{10}$$

The idea of wavelet transforms is that transformation should only allow to growth for the changes at expansion time, not to the shape. This case affected by selecting the appropriate basis functions that are possible for this task. It is expected that changes in the expansion of time correspond to corresponding frequency analysis of basis function. Based on the uncertainty principle of signal processing, we have:

$$\Delta t\ \Delta\omega \geq \frac{1}{2} \tag{11}$$

where ω is angular frequency, and t is time. In Figs. 1 and 2 we present the basis functions.

A: when the Δt is big:

1. Inappropriate time resolution.
2. Appropriate frequency resolution.
3. Low frequency.

B: when the Δt is small:

1. Appropriate time resolution.
2. Inappropriate frequency resolution.
3. High frequency.

In other words, the basis function of Ψ can be considered as the promissory respond of a system that performance of $x(t)$ is filtered in it. Provides a signal for converting time and frequency related information. Therefore, the wavelet transform contains information that is similar to the short-time Fourier transform but differs from the special features of the wavelet, which are shown at the time of correction in the basis function of analysis frequencies. The difference in time separation of the ascending frequency for Fourier transform and wavelet transform is shown in Fig. 3.

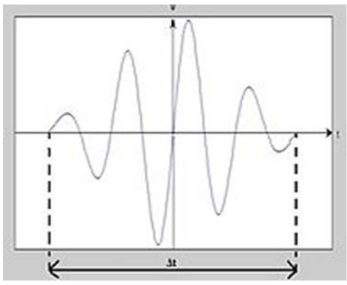

Fig. 1: $\Psi - \Delta t$ curve.

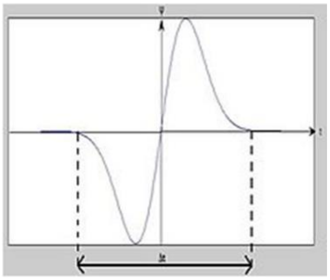

Fig. 2: $\Psi - \Delta t$ curve.

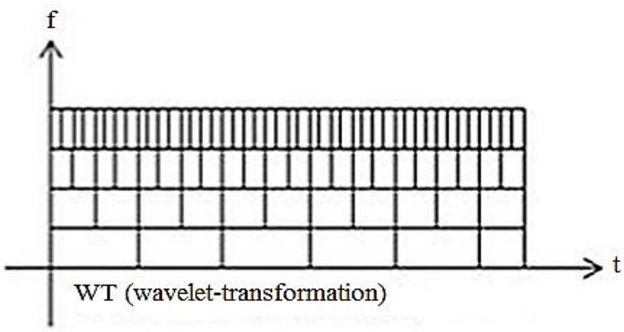

Fig. 3: Wavelet transform.

5. SIMULATION

5.1. Receiving Data

First, we receive the data from the following address, which contains two data sets of 100 and 200. Serial data 100 is randomly selected from 4000 pieces, serial data 200 includes rare, and important arrhythmias that are not well represented by random selection. Each of the data includes three files: Reference, Signals, Header, and Annotations. In Fig. 4, we present the set of ECG data that we used in this paper.

5.2. Using The Database of MIT-BIH in MATLAB

To use the data in the MATLAB software, we downloaded the 100m.mat matrix from the database. The sample frequency is considered 360 Hz, so any beat may range from 441 to 234 samples. The ECG signal is visible after the initial pre-processing and sampling in Fig. 5.

5.3. Noise Signal of ECG

Medical monitoring devices are highly sensitive to biomedical signal recording and require more accurate results for each proper diagnosis. The ECG signal of a healthy person repeats once every 0.8 seconds, which means a very low frequency. The low frequency signal is destroyed by the interference of the 50 Hz sound voltage line; this noise is also the source of interference with the biomedical signal recording. The 50 Hz power line interference frequency is approximately equal to the ECG frequency, so this 50 Hz noise can eliminate the ECG signal output. To simulate an ECG signal contaminated with this noise, we added a 50 Hz noise to the simulated ECG signal, and thus the ECG noise signal is visible in Fig. 6.

Reference annotations	Signals	Header
100.atr	100.dat	100.hea
101.atr	101.dat	101.hea
102.atr	102.dat	102.hea
103.atr	103.dat	103.hea
104.atr	104.dat	104.hea
105.atr	105.dat	105.hea
106.atr	106.dat	106.hea
107.atr	107.dat	107.hea
108.atr	108.dat	108.hea
109.atr	109.dat	109.hea
111.atr	111.dat	111.hea
112.atr	112.dat	112.hea
113.atr	113.dat	113.hea
114.atr	114.dat	114.hea
115.atr	115.dat	115.hea
116.atr	116.dat	116.hea

Fig. 4: Data formats in the MIT-BIH database.

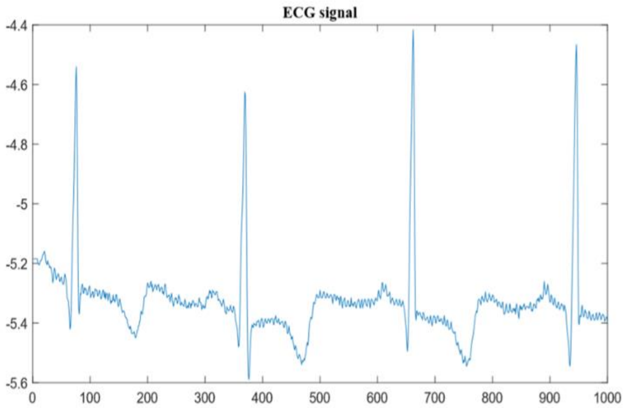

Fig. 5: ECG signal.

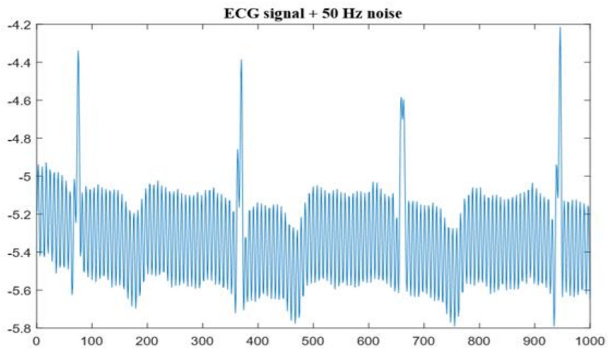

Fig. 6: ECG signal contaminated with50 Hz noise.

5.4. Wavelet Transform

The common problem in recording heart signal is noise and even body and eye movement, which causes error in the recording of signal or its analysis. Noise or artifact can limit the use of ECG signal, and it is necessary to eliminate its effect. In this section, wavelet transform is used to eliminate or reduce of ECG signal noise. Wavelet transform is very practical as a method of time-frequency analysis. Wavelet transform to increase the signal to noise ratio is an effective and efficient method. In this study, wavelet operator has been used at several different levels of analysis to achieve optimal transform for improve the ECG signal noise and extract the feature from this signal. The applied wavelet function is considered on the EGC signal for this research as the following Fig. 7.

ECG signal after applying transform on the wavelet (mentioned above) are visible in the several different levels as the following figures:

Regarding the observed results, after the simulation shown in Figs. 8, 9 and 10, the transformation of the level 3 wavelet from the other surfaces eliminates the noise from the ECG signal by maintaining the feature of the signal well, and desirable wavelet is addressed. In this case, the signal to noise will be equal to 14.4642.

5.5. Design of Adaptive Filter

In this research, least average squares algorithm has been used which has been simulated by taking into account different values for μ and filter length, which are further discussed in more detail.

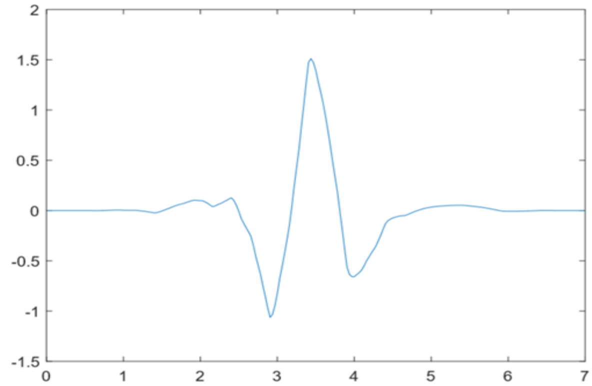

Fig. 7: The applied wavelet function on the ECG signal.

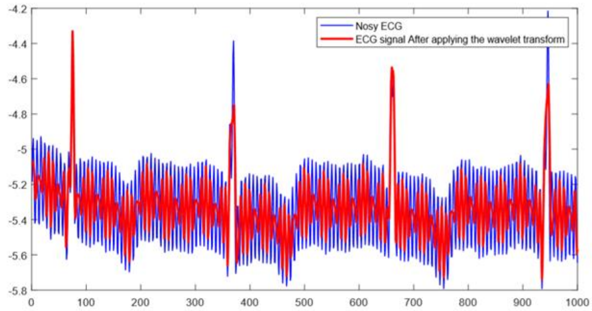

Fig. 8: ECG signal before and after applying transform on wavelet level 2.

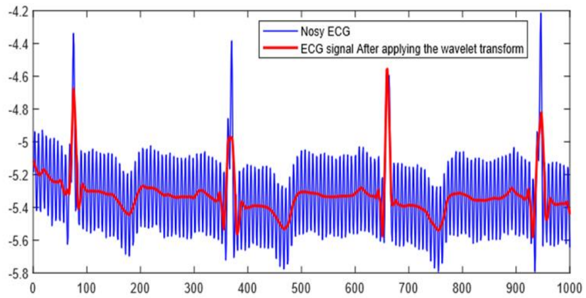

Fig. 9: ECG signal before and after applying transform on wavelet level 3.

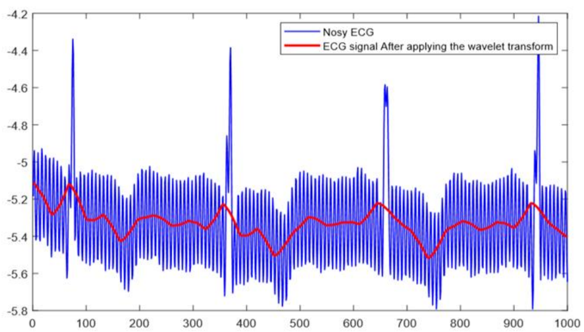

Fig. 10: ECG signal before and after applying transform on wavelet level 5.

1) Results for adaptive filter with μ=0.0005 and filter length of 15 are presented in Fig. 11.

2) Results for adaptive filter with μ=0.0005 and filter length of 20 are presented in Fig. 12.

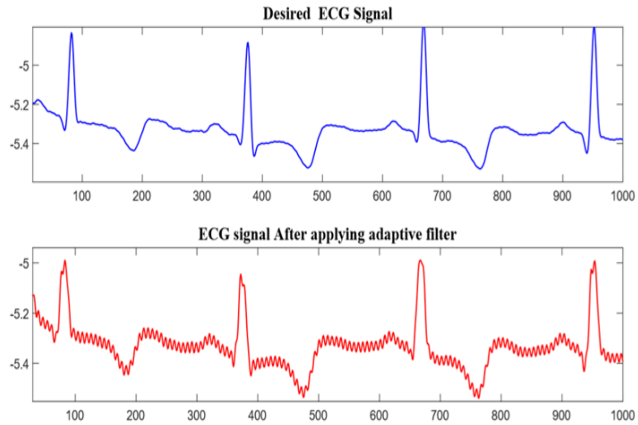

Fig. 11: desirable ECG signal and ECG signal obtained from applying adaptive filter with μ=0.0005 and filter length of 15.

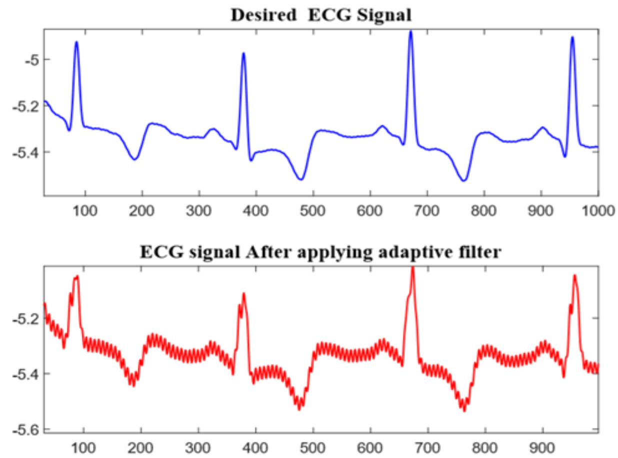

Fig. 12: desirable ECG signal and ECG signal obtained from applying adaptive filter withμ=0.0005 and filter length of 20.

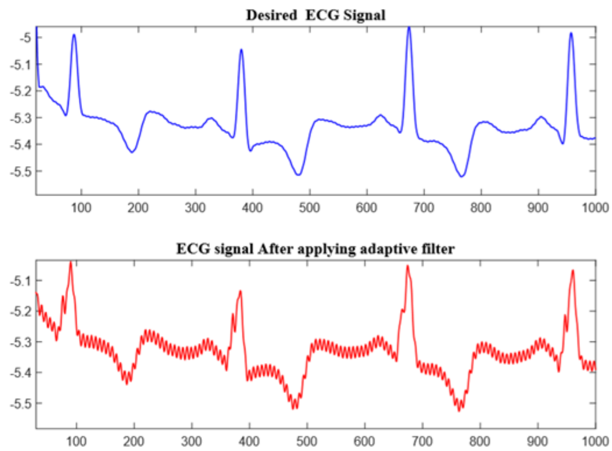

Fig. 13: desirable ECG signal and ECG signal obtained from applying adaptive filter withμ=0.0005 and filter length of 25.

3) Result of adaptive filter with μ=0.0005 and filter length of 25 are presented in Fig. 13.

4) Result of adaptive filter with μ=0.0009 and filter length of 15 are presented in Fig. 14.

5) Result of adaptive filter with μ=0.0009 and filter length of 20 are presented in Fig. 15.

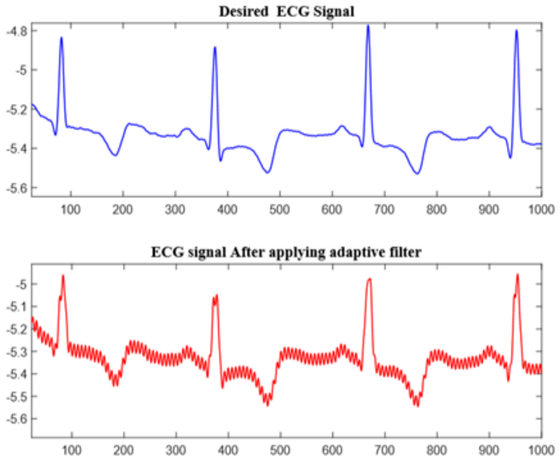

Fig. 14: desirable ECG signal and ECG signal obtained from applying adaptive filter with μ=0.0009 and filter length of 15.

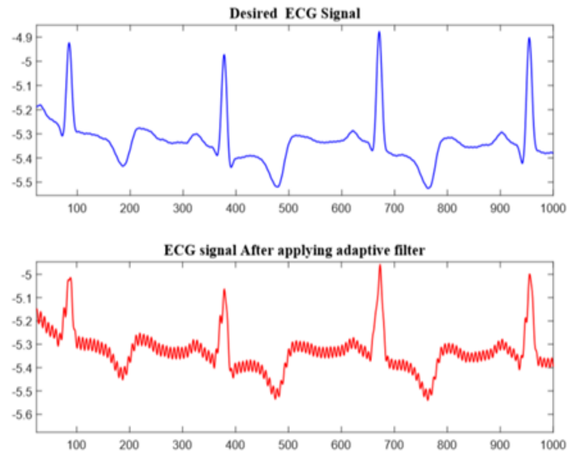

Fig. 15: desirable ECG signal and ECG signal obtained from applying adaptive filter with μ=0.0009 and filter length of 20.

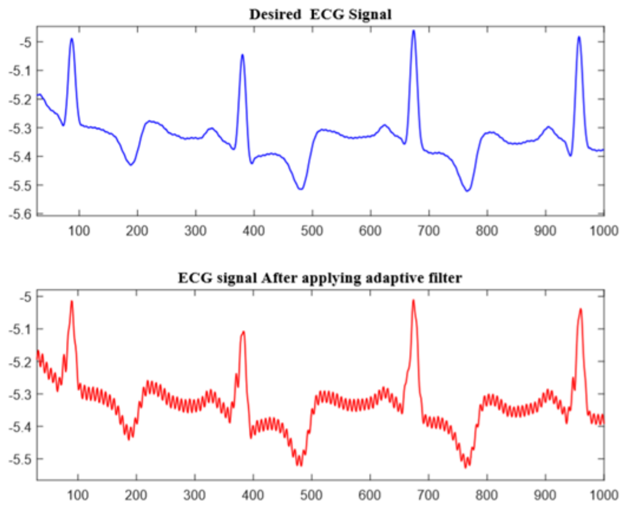

Fig. 16: desirable ECG signal and ECG signal obtained from applying adaptive filter with μ=0.0009 and filter length of 25.

6) Result of adaptive filter with μ=0.0009 and filter length of 25 are presented in Fig. 16.

Table 1: Adaptive filter modes.

Adaptive filter (LMS)	Filtered signal with adaptive filter
μ=0.0005 and filter length of 15	1.2111
μ=0.0005 and filter length of 20	3.5586
μ=0.0005 and filter length of 25	4.5103
μ=0.0005 and filter length of 15	0.377
μ=0.0005 and filter length of 20	3.1193
μ=0.0005 and filter length of 25	4.1828

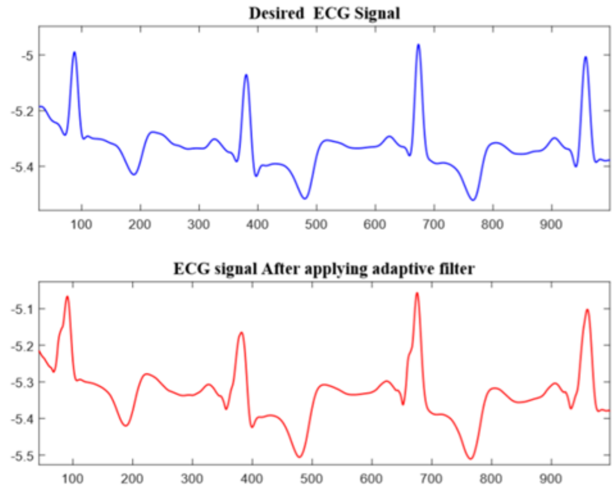

Fig. 17: desirable ECG signal and ECG signal obtained from applying transform on wavelet and adaptive filter with μ=0.0005 and filter length of 25.

5.6. Signal-to-Noise Values for Different Adaptive Filter Modes Materials and Methods

Table 1 presents the various LMS filter modes that we used in this paper.

The results indicate that by increasing the filter length in the adaptive filter, signal-to-noise ratio will be higher. The simulation results after the transformation of wavelet and adaptive filter of μ=0.0005 size of the window 25 will be as follows (see Fig. 17).

5.7. Comparing Results

The results of the simulations indicate that the transformation of the sym4 level 3 wavelet eliminates the noise significantly from the ECG signal and increases the signal to noise. Also, by checking the LMS adaptive filter in different modes with step size (μ) and different filter lengths determined with trial and error that for the size of the step 0.0005 and the filter length of the 25, the signal to noise and signal amplitude would be desirable. In Table 2 we present an explanatory comparison between our findings and the findings of references [22] and [23].

As it is observed in Figs. 18 and 19, the result obtained from stimulation by using mentioned method is more efficient compared to [22] and reduced the noise.

Table 2: Comparison table.

Reference no.	Article title	Release year	Result
[22]	An efficient wavelet transform-based algorithm for reducing power noise from electrocardiogram	2018	It introduces easy and efficient algorithm for suppressing the PLI from the ECG. In summary, the input signal is divided into four wavelet levels, and the resulting coefficients are used to eliminate the estimated PLI from the TQ intervals of the threshold. The ECG denoised signal is then reconstructed by calculating the inverse wavelet transform.
[23]	ECG signal filtering based on CEEMDAN with a minimum time interval range and more accurate statistics for selecting related modes	2018	Enhancement of ECG signal based on collective experimental state of branching with compatibility noise (CEEMDAN) and Statistics Order Order (HOS)

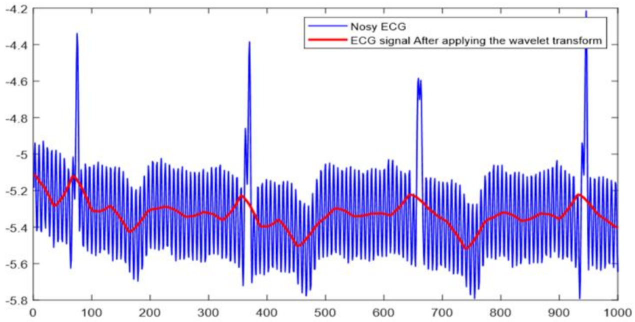

Fig. 18: ECG signal before and after applying the wavelet transform by simulation software.

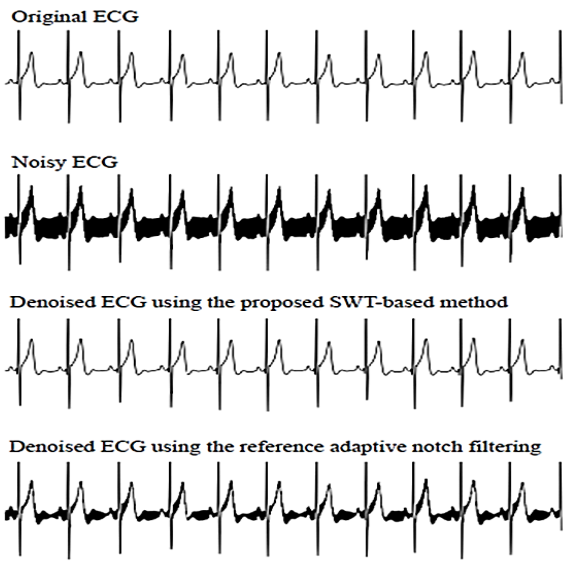

Fig. 19: ECG signal before and after applying noise elimination in [22].

6. Conclusion

The results of the simulations indicate that the transformation of the sym4, level 3 transforms well the noise from the ECG signal and increases the signal to noise. In addition, by checking the LMS adaptive filter in different modes with step size (μ) and different filter lengths was determined by trial and error that step size of 0.0005 and filter length of 25, signal to noise, and signal amplitude will be desirable. In this study, we investigated the performance of digital filters on the ECG signal, and in particular, we applied the adaptive filter and the wavelet transform on an ECG signal that received from the MIT-BIH database. The results of the simulation show that the Sym4 wavelet transform and adaptive filter with step size of 0.0005 and filter length of 25, well improves the signal to noise to the high level and will be able to detect the main features of the ECG signal. In this study, in particular, the wavelet transform and adaptive filter were used to eliminate the noise and extraction of signal features. In this regard, in order to continue the pathway of the researcher, we study more about digital filters such as Kalman filter on the ECG signal.

CRediT Authorship Contribution Statement

Amir Hatamian: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Project administration. **Farzad Farshidi:** Formal Analysis, Project administration, Software, Validation. **Changiz Ghobadi:** Project administration, Supervision, Writing - review & editing. **Javad Nourinia:** Project administration, Supervision, Writing - review & editing. **Ehsan Mostafapour:** Methodology, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

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