Electrocardiogram Signal Denoising Technique Based on Genetic Algorithm and Wavelet Theory

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Abstract. This paper proposes a wavelet denoising technique for ECG signals. In this technique, GA is integrated with the wavelet theory to optimally search the wavelet denoising parameters in order to maximize the ECG denoising efficiency. The efficiency of this technique is evaluated using Mean Square Error (MSE) and Signal to Noise Ratio (SNR). The experimental results show that this integration using GA has a better performance than the other wavelet thresholding algorithms and is more accurate. The quality of the denoising ECG signal is more suitable for the clinical diagnosis. Several real-world datasets have been tried using the proposed GA-based technique. Compared with other reported denoising methods, the proposed GA-based denoising technique improves the denoising efficiency. Therefore the wavelet denoising based on Genetic Algorithm is very efficient for medical applications.
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1 Introduction

The electrocardiogram (ECG) is a time-varying signal reflecting the ionic current flow which causes the cardiac fibers to contract and subsequently relax. The ECG signal contains an important amount of information that can be exploited in different manners. When an electrocardiogram is recorded, it would be contaminated with noise and artifacts. Extraction of pure cardiological indices from noisy measurements has been one of the major concerns of biomedical signal processing and need reliable signal processing techniques to preserve the diagnostic information of the recorded signal [1].

Developing techniques to get the ECG signal clear without noise has been of interest. ECG signal is one of the biosignals that is considered as a non-stationary signal and needs a hard work to process. An efficient technique for such a non-stationary signal processing is the wavelet transform. [2-5]. One of the most important applications of wavelets is removal of noise from signals called denoising accomplished by thresholding wavelet coefficients in order to separate signal from noise. However, conventional denoising fails for signals with low signal-to-noise ratio (SNR).

Thresholding is used in wavelet domain to smooth out or to remove some coefficients of wavelet transform subsignals of the measured signal. The denoising method that applies thresholding in wavelet domain has been proposed by Donoho as a powerful method [7-9].

Methods based on shrinkage of wavelet coefficients are very popular for estimation of biological signals. Most ECG signal denoising algorithms are based on Donoho's Universal theory [1, 5, 6, 10-12]. Omid Sayadi et al. [1] have proposed a technique to remove noise from the ECG using a daptive wavelet transform, named bionic wavelet transform. Daniel Novak et al. [13] have proposed a denoising technique based on adaptive wavelet method using a detection algorithm for different noise level as pre-processing. B. N. Singh et al. [14] have proposed a selection procedure of mother wavelet basis functions applied for denoising of the ECG signal in wavelet domain.

Good selection of wavelet denoising parameters, such as wavelet function, decomposition levels, threshold function (method), and threshold selection rules is critical to the success of signal denoising. Usually these parameters selected empirically which leads to low denoing performance. So the contribution of this paper is to introduce an evolutionary optimization method based on the Genetic Algorithm to search the wavelet denoising parameters in order to realize the optimal ECG signal denoising efficiency.

The rest of the paper is organized as follows. The proposed wavelet denoising technique is described in Section 2. A brief review of WT and wavelet denoising using Donoho's method are provided in Section 3. Section 4 describes the GA-based parameter optimization. In Section 5, the experimental and results of the proposed work are discussed. Finally conclusions and future work are given in Section.

2 The proposed wavelet denoising technique based on genetic algorithm.

This section presents the proposed wavelet denoising methodology that maximizes the denoising performance of the ECG signals corrupted by standard white Gaussian noise. The GA was used, for the purposes of this paper, to search for the optimum wavelet denoising parameters for ECG signal denoising problems. The proposed wavelet denoising method can be summarized as follows: see Fig. 1

- Input the proper wavelet thresholding denoising parametrs for ECG signal; and construct the objective functions, including MSE;
- Optimize the wavelet denoising parameters using GA; when the Termination Criteria Satisfied is reached, according to the denoising performance, select the optimal denoising parameters;

– Perform a 1D discrete wavelet transform for the noisy ECG signal to get the noisy wavelet coefficients
– Threshold the coefficients in ECG signal with the optimal thresholds, and get the modified new ECG components;
– Reconstruct the denoised ECG.

The next two sections give a brief account about the discrete wavelet transformation; the wavelet denoising principle, and the integration of genetic algorithm with wavelet theory for building the proposed ECG wavelet denoising technique.

3 ECG signal denoising based on wavelet analysis

ECG signal is one of the biosignals that is considered as a non-stationary signal and needs a hard work to denoising [12]. An efficient technique for such a non-stationary signal processing is the wavelet transform. Wavelet theory has already proven its ability in splitting signal and noise in wavelet domain [13] and the wavelet denoising method is well established as a technique for removing noise from signals.

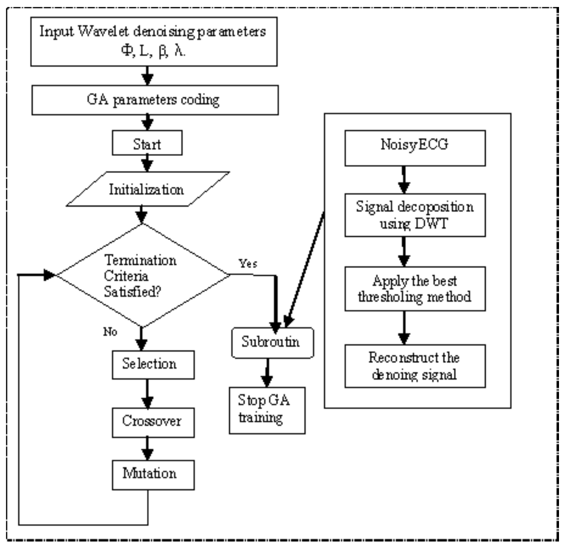

Fig. 1. The proposed wavelet denoising technique based on Genetic Algorithm.

3.1 The wavelet denoising principle

The wavelet transform is a time-scale representation technique, which describes a signal by using the correlation with translation and dilation of a function called mother wavelet [13]. The wavelet transform represents a signal as a sum of wavelets with different locations and scales. In this paper; the Donoho's method is applied to the discrete wavelet transform DWT. The definition of a discrete wavelet transform is given by [14].

$$C(a,b) = \sum_{n \in Z} s(n) g_{j,k}(n) \qquad (1)$$

Where s(n) is the input signal C(a,b) are dyadic wavelet coefficients

$a = 2^j, b = k2^j, j \in N, k \in Z$, a is a dilation (scale), b is translation and $g_{j,k}(n) = 2^{j/2} g(2^j n - k)$ is discrete wavelet

When the signal is decomposed to a certain level using wavelet transform (WT), a set of wavelet coefficients is correlated to the high frequency subbands and the other wavelet coefficients is correlated to low frequency subbands [15]. The selection of a suitable level depends on the signal and the experience. Often the level is chosen based on a desired low-pass cutoff frequency. The high frequency subbands consist of the details in the data set. If these details are small enough, they might be omitted without substantially affecting the main features of the data set. In addition, these small details are often associated with noise; therefore, by setting these coefficients to zero, we are essentially killing the noise. This becomes the basic concept behind thresholding; set all frequency subband coefficients those are less than a particular threshold to zero and use these coefficients in an IDWT to reconstruct the data set [10, 11]. The first method of wavelet-based de-noising is proposed by Donoho and Johnstone [7-9], which is carried out by thresholding wavelet coefficients. Two types of thresholding functions are more popular, Hard thresholding and Soft thresholding [7-9]. The 'hard' and 'soft' thresholding functions are defined as [16]:

$$\text{Hard } thresholding = \begin{cases} 0, & \text{if } |d_{jk}| \leq \delta, \\ d_{jk}, & \text{if } |d_{jk}| < \delta \end{cases} \qquad (2)$$

$$\text{Soft } thresholding = \begin{cases} 0, & \text{if } |d_{jk}| \leq \delta, \\ d_{jk} - T, & \text{if } |d_{jk}| < \delta \\ d_{jk} + T, & \text{if } |d_{jk}| < -\delta \end{cases} \qquad (3)$$

The thresholding is based on a value δ that is used to compare with all the detailed coefficients. Generally, the threshold value δ to be applied in the wavelet domain is the product of the standard deviation of the noise amplitude σ and a factor δ_0 that depends on the length N of the data sample: $\delta = \sigma\delta_0$. There are mainly four threshold selection rules [16], Table 1 summaries them.

Table 1. Summaries the four threshold selection rules

Thresholding Rule	Description
Rule 1: Rigrsure	Threshold is selected using the principle of Stein's Unbiased Risk Estimate (SURE).
Rule 2: Sqtwolog	Fixed form threshold yielding minimax performance multiplied by a small factor proportional to log (length(s)). It is usually equal to sqrt (2* log (length (s)))
Rule 3: Heursure	Threshold is selected using a mixture of first two methods.
Rule 4: Minimaxi	Selected using the minimax principle. It uses a fixed threshold chosen to yield minimax performance for mean square error against an ideal procedure.

The choice of thresholding functions and threshold values plays an important role in the global performance of a wavelet processor for noise reduction. Threshold selection rules are based on the underlying model. Given a measured signal s(n) with a Gaussian white noise N(0,1):

$$s(n) = f(n) + \sigma e(n) \qquad (4)$$

where f(n) is the original signal and e is the noise, σ is the strength of the noise, and time n is equally spaced.

The basic idea of the wavelet-based denoising procedure is summarized in Fig. 2.

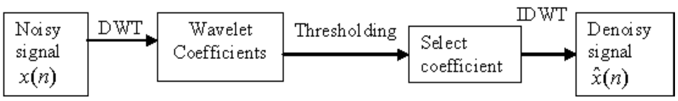

Fig. 2. The wavelet denoising procedure.

3.2 Wavelet denoising parameters

It is clear from the above subsections that the wavelet denoising performance of the ECG signal is conditioned by four processing parameters named "wavelet denoising parameters", including: (1) the type of wavelet basis function Φ, (2) the decomposition level L, (3) thresholding function β, and (4) threshold selection rules λ. Selection of a suitable wavelet denoising parameters is critical for the success of ECG signal denoising in wavelet domain. Because there is currently no known method to calculate which combination of the above wavelet denoising parameters gives best denoise signal. Therefore, in this denoising method the genetic algorithm has been used to select the optimal parameters which lead to maximize the denoising performance.

4 Genetic algorithm approach

To achieve good denoising, Genetic Algorithm (GA) is introduced and applied to optimize the wavelet denoising parameters for denoising the ECG signals. Genetic algorithms constitute an optimization technique based on Darwinian principle of 'survival of the fittest paradigm found in nature [17]. The GA uses three fundamental operators termed (1) selection (Reproduction.), (2) crossover and (3) mutation to evolve global optimized network parameters [17, 18]. GA works with a set of candidate solutions called a population. Based on the principle of 'survival of the fittest', the GA obtains the optimal solution after a series of iterative computations on it's operators: the reproduction, the crossover, and the mutation. The size of the population and the probability rates for crossover and mutation are called the control parameters of the GA. GA generates successive populations of alternate solutions that are represented by a chromosome, i.e. a solution to the problem, until acceptable results are obtained based on the fitness function. The fundamentals of traditional GAs are well covered in [18-20].

The fitness function has to provide some measure of the GA's performance in a particular environment, and assesses the quality of a solution in the evaluation step. The objectives of denoising are to effectively suppress the noises and restore the original ECG signal. A common goal of optimization in ECG denoising is to minimize the mean square error (MSE) between the original ECG signal and the denoisy version of this ECG signal, so the MSE has choosen as the fitness function. Given an original signal *x(n)*, consisting of N samples, and a reconstructed approximation to this signal, $\hat{x}(n)$, the mean square error is given by [5]:

$$MSE = \frac{1}{N}\sum_{n=1}^{N}[s(n) - \hat{s}(n)]^2 \qquad (5)$$

5 Experimental study and results

To evaluate the denoising efficiency of the proposed technique, several real world datasets were downloaded from the MIT-BIH database [21]. Each of the ECG records has the following specifications: signal length is 650,000 samples, sampling rate is 360 Hz, resolution is 11 bits over a 10 mV range, and bit rate is 3960 bps. These data sets have been frequently used as benchmarks to compare the performance of different denoising methods in the literature. The ECG datasets were contaminated with additive white Gaussian noise of different values of standard deviation (σ). The noise is randomly generated and added linearly to the original ECG signal.

Parameters listed above are usually selected empirically in practical application. To guide the selection of these parameters besides experience, GA is proposed in this paper to optimize the entire set of denoising parameters.

Table 2. The ranges of the parameters to be optimized.

Wavelet Denoising parameters	Range
The type of wavelet basis function	Daubechies(1-22), Symlet (1-22), Biorthogonal (bior) (1-5), and Coiflet (1-15).
Thresholding function	soft, hard.
Decomposition level	(1-10).
Thresholding selection rule	Heursure, Rigsure, sqtwolog, and Minimax

In this work; the GA parameters are chosen after extensive studies: A steady-state GA with a single population of 150 individuals was evolved for 30 generations using a crossover rate of 80 percent and a replacement rate of 90 percent. The optimal wavelet denoising parameters obtained by the GA are given in table 3.

Table 3. The optimal wavelet denoising parameters obtained by the GA.

Wavelet denoising parameters	Value
Wavelet function	db8
Decoposition levle	4
Threshold selection rule	Hard
Thresholding function	HEUSURE

The mean squared error MSE and the signal-to-noise ratio SNR are used as measure of denoising performance. MSE is used as the GA's performance and the SNR was calculated for the denoising signal and the clean signal. The MSE is calculated from eqn. (5) and the SNR (in dB) is given below [6]:

$$SNR = 10log_{10}\{\sum_{n=1}^{N}[x(n)]^2/\sum_{n=1}^{N}[x(n)-\hat{x}(n)]^2\}$$

For the wavelet denoising parameters obtained by the GA based on the fitness function, the experiment is conducted on 50 numbers of ECG signals. The average values of MSE and SNR are calculated for the signal before and after the denoising. Table 4 shows the denoising results of ECG signal obtained using the proposed technique for Input SNR: 0-35 dB. The original, the noisy, and the denoised signals obtained using the proposed technique are shown in Fig. 3. For a noisy signal of input SNR =15 dB, a MSE of 44.87 and output SNR of 23.85 are obtained on denoising using the proposed technique. The higher the SNR, the less noise there is. Fig. 4-a shows the relation between SNR before and after denoising. The SNR after denoising appear to be relatively linear. We also computed the mean square errors (MSE) between the original data and the denoised data, and the results are shown in Fig. 4-b. The MSE plot confirms that the proposed denoising technique smooths too much when the noise level is low. Less MSE indicates efficient denoising of the original signal.

For denoising performance evaluation, we define the SNR improvement achieved by the wavelet denoising technique to be the value of the system output SNR (in dB) minus the input SNR (in dB). Fig. 4-c shows the relation between the SNR improvement and the input SNR, it can be seen that less SNR improvement is achieved for high SNR conditions. This is, of course, understandable. When SNR increases, the ECG signal becomes less noisy, so there is less noise to be reduced. If SNR approaches infinity, the a posteriori SNR would be the same as the a priori SNR. In all the conditions, we see that the a posteriori SNR is always greater than the corresponding a priori SNR.

Tables 4. The of denoising the ECG signals for different input SNR.

Input SNR (dB)	**Output SNR (dB)**	**Improvement SNR**	**MSE**
0	15	15	0.5
5	18	13	0.48
10	22	12	0.42
15	25	10	0.37
20	29	9	0.36
25	33	8	0.35
30	35	5	0.35

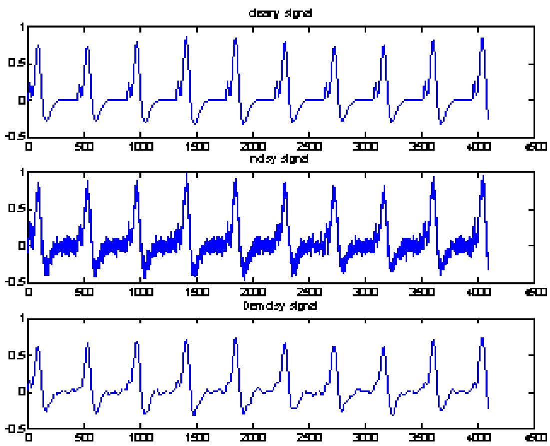

Fig. 3. (a) Original signal. (b) The corrupted ECG with noise at SNR 6:8 dB. (c) The denoised ECG signal resulting from the proposed technique (wavelet function, thresholding function=, thresholding selection rule=, decomposition level =) with SNR = 11:58 dB).

In this study, the SNR obtained from the proposed wavelet denoising technique based on GA are compared to other reported denoising techniques; wavelet based techniques [6, 10, 12], adaptive filtering approach [22], Nonlinear Baysian Filter, and Kaman filtering [23]. These techniques are applied to the same database. For comparison, the SNR improvements versus different input SNRs, achieved over the ECG signals are claculated. The results of the SNR improvements calculated over ECG signals are extremely sensitive to the noise level. Table 5 shows the SNR for several common techniques applied to our dataset. The result provides a comparative study of effectiveness of the proposed technique over other denoising techniques used in the ECG signal denoising.

Table 5. The SNR for several common techniques applied to our dataset.the compared with the SNR obtained by the proposed GA based denoising technique.

Denoising Approach	**SNR (dB)**
wavelet based techniques [6]	30
wavelet based techniques [10]	30
adaptive filtering technique [23]	28
Nonlinear Baysian Filter [23]	27
Wavelet based Thresholding [12]	25
Our proposed technique	33

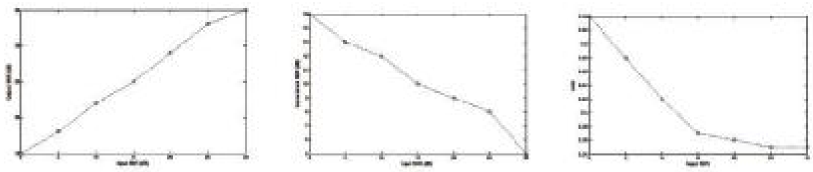

Fig. 4. a - The dependence of the output SNR of the input SNR; b- MSE with SNR; c - the SNR improvement with SNR.

6 Conclusion and future work

In this paper an off-line wavelet denoising technique for ECG signals is proposed based on genetic algorithm and wavelet theory. Selection of wavelet denosing parameters is critical to the success of wavelet denoising for the ECG signal. To guide the selection of these parameters besides experience, genetic algorithm is proposed to optimize the entire set of wavelet denoising parameters resulting in efficient ECG signal denoising and best denoising performance. The proposed noise elimination technique using wavelet denoising and Genetic Algorithm retains the necessary diagnostics information contained in the original ECG signal and has potential application in data acquisition medical systems. This result is of great help in denoising of ECG signals using Wavelet theory because the computational effort required is markedly reduced.

From the results obtained, we can show that the denoising of a signal depends on the optimum value of level of decomposition, suitable forms of wavelet family and thresholding techniques. This varies for different kinds of input signals. Genetic algorithm is a powerful tool to play the rule of parameters selection and optimization.

The proposed denoising technique is used as pre-processing technique for the analysis and classification ECG signal. The future work is to extent this system to classify and analysis the ECG signal then build the full system on FPGA chip for real time applications.

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