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Letters

# An adaptive filtering approach for electrocardiogram (ECG) signal noise reduction using neural networks

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ABSTRACT

Electrocardiogram (ECG) signals have been widely used in clinical studies to detect heart diseases. However, ECG signals are often contaminated with noise such as baseline drift, electrode motion artifacts, power-line interference, muscle contraction noise, etc. Conventional methods for ECG noise removal do not yield satisfactory results due to the non-stationary nature of the associated noise sources and their spectral overlap with desired ECG signals.

In this paper, an adaptive filtering approach based on discrete wavelet transform and artificial neural network is proposed for ECG signal noise reduction. This new approach combines the multi-resolution property of wavelet decomposition and the adaptive learning ability of artificial neural networks, and fits well with ECG signal processing applications. Computer simulation results demonstrate that this proposed approach can successfully remove a wide range of noise with significant improvement on SNR (signal-to-noise ratio).



## 1. Introduction

The electrocardiogram (ECG) signal is generated by the rhythmic contractions of human heart. It represents the electrical activity of heart muscles, and provides a very effective way to detect heart diseases in clinical studies. Fig. 1 shows a typical ECG waveform of one cardiac cycle which consists of a P-wave, a QRS-complex, and a T-wave [1].

In general, ECG signals are measured by surface electrodes that are placed on patients and are often corrupted with various types of noise, including baseline drift (also termed the baseline wander noise), motion artifacts, electrode contact, muscle contraction, power-line interference, instrumental noise, and electrosurgical noise, etc. [2]. The drift of the baseline with respiration (i.e., baseline wander noise) can be modeled as a non-stationary sinusoidal signal of time-varying amplitude and frequency of respiration. That is, the effect of baseline drift can be considered as an amplitude modulation to the ECG signal. It is reported that the amplitude of ECG signals may vary up to 50% with baseline noise [2]. Power-line interference is another source of noise that often appears in ECG signals that consists of a 60 Hz (or 50 Hz in some countries) sinusoid and its harmonics. The electrode motion and muscle contraction artifacts are two commonly encountered noise sources in ECG signal measurements. They are usually considered to be most difficult to suppress (especially the electrode motion artifact that mimics the appearance of ectopic beats) due to their spectral overlap with desired ECG signals. The motion artifact (also termed electrode motion noise) is the noise associated with the changes in electrode-skin impedance, usually caused by the movement of electrodes or human subject. The muscle contraction noise may appear as additional "bursts" in ECG signals, and usually can be modeled as a zero-mean, band-limited Gaussian noise ([3]).

ECG noise removal is very important for an accurate clinical diagnosis. An ECG signal contaminated with noise may mislead the doctor and result in misdiagnosis. However, due to the time-varying and non-stationary nature of the ECG noise, especially its spectral overlap with the signal, ECG noise removal can be a very difficult and complex process.

The traditional approaches for ECG signal noise reduction include low-pass filters [4] and filter banks [5,6]. However, these methods may introduce additional artifacts to the signal, especially on the QRS-complex. Another class of ECG noise reduction algorithms combines ECG signal modeling and filtering together, such as [7,8,9,24,27]. Various modeling techniques are employed, such as the extended Kalman filters [7], a mean shift algorithm [8], state vectors with time delay [24], and empirical mode decomposition (EMD) [9,27]. Typically, these algorithms are studied only for cases where the ECG signal is contaminated either by white noise or one (or two) other types of noise separately; the effect of combined noise is usually not considered and not all artifacts are included.

As a powerful tool for multi-resolution signal analysis [25,26], wavelet transform (with thresholding) has become a viable

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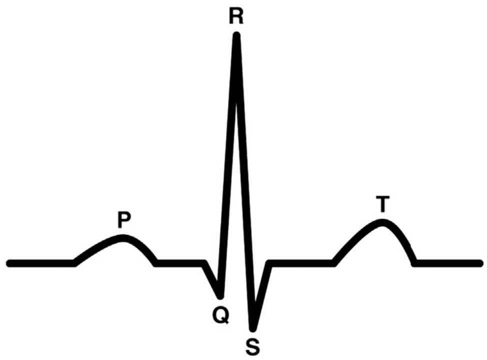


**Fig. 1.** A typical ECG signal [1].

technique for ECG signal noise reduction [10,11]. In [12], a new modified wavelet transform termed "multi-adaptive bionic wavelet transform" (MABWT) was proposed. It is shown that this method yields a small SNR (signal-to-noise ratio) improvement over the traditional wavelet transform; however, similar to [8], only Gaussian noise and baseline wander noise are considered.

Recently, artificial neural networks (ANN) have also been applied to ECG signal processing. Currently, most of the neural network applications are concentrated on the ECG signal classification and pattern recognition, such as [13,14]. For noise reduction, a method was discussed in [15] where ECG signals are modeled using nonlinear series expansion (such as power series or Chebyshev polynomials) and a FLANN (functional link artificial neural network) is employed to remove the Gaussian and baseline wander noise.

An approach for ECG signal noise removal based on wavelet neural network (WNN, [16]) is investigated in [17]. It is shown in [17] that WNN can successfully remove white noise; however, more complicated situations (such as baseline drift, electrode contact artifact, muscle contraction noise, etc.) are not considered.

In this paper, a novel adaptive filtering approach based on wavelet transform and artificial neural networks is investigated for ECG signal noise reduction. This new approach combines the multi-resolution nature of wavelet transform and the adaptive learning and nonlinear mapping properties of artificial neural networks, and fits well with the ECG application. The neural network employed in this approach not only performs the inverse wavelet transform (IWT) for signal reconstruction, but also serves as a nonlinear adaptive filter to further reduce noise. Note that in the conventional wavelet transform approach, the value of threshold is usually application dependent and difficult to determine. In the proposed approach, this function is performed by an artificial neural network in a self-learning and adaptive manner. Besides, this approach also eliminates the need to calculate the inverse wavelet transform that is required in conventional methods, making the overall signal processing system more efficient. In addition, unlike most of the previous algorithms which only consider white noise and/or one (or two) other artifacts, the proposed approach is tested on various noise and artifacts, including power-line interference, baseline wander noise, electrode motion artifact, muscle contraction artifact, and white noise. Furthermore, the effectiveness of this approach is also demonstrated by reducing the "combined noise" that includes all the above noises in ECG signals.

The remaining parts of this paper are organized as follows. A brief summary on wavelet transform is given in the next section; then the proposed adaptive filtering approach is discussed in detail in Section 3. In Section 4, five different types of noise that are often associated with ECG signals are removed individually, and the "combined noise" is considered and filtered. The final section concludes the paper and discusses the direction for future works.

## 2. The wavelet transform

Wavelet transform provides a way to represent signals in both time and frequency. In wavelet transform, various wavelets are generated from a single basic wavelet $\psi(t)$ known as the mother wavelet. Two important parameters are defined: the scale (or dilation) factor $s$ and the translation (or shift) factor $\tau$. The shifted and dilated versions of the mother wavelet can be expressed as

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{|S|}}\psi\left(\frac{t-\tau}{s}\right) \tag{1}$$

The wavelet transform of a signal $x(t)$ with mother wavelet function $\psi(t)$ can then be written as

$$T(s,\tau) = \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \tag{2}$$

The asterisk represents the complex conjugate of the wavelet function that is used in the transform. In fact, wavelet transform can be considered as the cross-correlation of a signal with a set of wavelets of various "widths".

The discrete wavelet transform (DWT) is based on sub-band coding and yields the fast computation of wavelet transform coefficients. The family of discrete wavelets can be written as

$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t-n) \tag{3}$$

where $m$ and $n$ are integers for indices. The DWT of a signal can be considered as passing the signal through a series of high-pass (HPF) and low-pass (LPF) filters, as shown in Fig. 2, where "↓" represents the downsampling (subsampling) operator [28].

Most of the current wavelet denoising approaches employ various shrinkage techniques based on the idea of thresholding the wavelet coefficients. Let $x(t)$ be the noisy signal; $T$ and $T^{-1}$ be the wavelet and inverse wavelet transform, respectively. We can write the wavelet coefficients $w$ as

$$w = \mathrm{T}(\mathrm{x}) \tag{4}$$

Two different types of thresholding approaches can be found in the literature: hard thresholding (i.e., delete the wavelet coefficients that are smaller than the threshold and keep all the other ones unchanged) and soft thresholding (i.e., also delete the wavelet coefficients that are below the threshold, but scale all the other ones based on certain rules) [29]. Let $D$ be the thresholding operator and $\lambda$ be the threshold, we have

$$z = D(w,\lambda) \tag{5}$$

where $z$ is the wavelet coefficients after thresholding. The filtered signal can then be reconstructed using inverse wavelet transform

$$y = T^{-1}(z) \tag{6}$$

Though wavelet shrinkage (thresholding) is a viable technique for noise reduction, the value of threshold is usually application dependent and difficult to determine in practice. In addition, the inverse wavelet transform must be performed to reconstruct the filtered signal, adding an extra computational cost to the

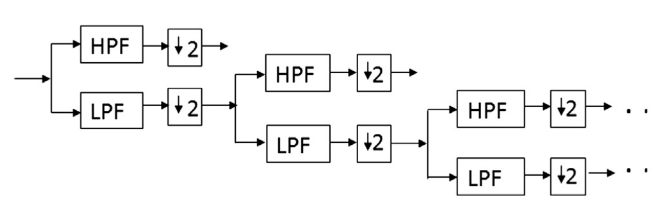


**Fig. 2.** The discrete wavelet transform and filter banks [28].

algorithm. In the following section, an approach based on wavelet transform and artificial neural network is proposed, in which wavelet transform is employed to decompose the signal and the neural network performs both nonlinear filtering and the inverse wavelet transform.

## 3. The proposed approach using wavelet transform and artificial neural networks

In this section, the proposed adaptive filtering technique based on wavelet transform and artificial neural network is presented. The overall system block diagram for neural network training is shown in Fig. 3.

During training, DWT is employed to decompose the noisy ECG signal into wavelet coefficients. The Daubechies wavelet is one of the most commonly used orthogonal basis sets for discrete wavelet transform and has been successfully applied to ECG signal feature extraction [18]. In this work, Daubechies 4-tap wavelet (D4) is employed.

Once the wavelet transform coefficients are obtained, sub-band thresholding is then performed on these coefficients. This thresholding step serves two purposes: it discards high frequency noise and also performs feature extraction of the ECG signal to provide the inputs to the neural network. As a result, there will be less unnecessary information for the neural network to process. Note that after this initial filtering, the remaining coefficients still contain the information on both ECG signal and its associated noise. In other words, certain types of noise, especially the ones whose spectra overlap with the desired ECG signal spectrum, still exist and are represented by these coefficients. A neural network is then employed as the final filtering process to further remove the remaining noise that are "embedded" in DWT coefficients, using its adaptive learning and fault tolerance properties. In the meantime, the neural network effectively performs an "inverse discrete wavelet transform (IDWT)" at the output. That is, the inputs of neural network are DWT coefficients while the output of neural network is the filtered ECG signal in time domain. During training, the neural network compares its output with a pre-recorded noise-free ECG signal and the error signal is used to update the weights of neural network. That is, the following objective function is minimized:

$$J = \frac{1}{2N}\sum_{i=1}^{N}[e(i)]^2 = \frac{1}{2N}\sum_{i=1}^{N}[d(i)-y(i)]^2 \tag{7}$$

where $d$ is the desired output and $y$ is the output of neural network; $e$ is the output error; $N$ is the total number of outputs. The weights of neural network are updated with the back-propagation algorithm [19]:

$$W(k+1) = W(k) + \eta\frac{\partial J}{\partial W} \tag{8}$$

where $\eta$ is the learning/training rate.

To speed up neural network learning and improve its performance, normalization and de-normalization are performed to pre- and post-process the ECG signal so that it is within the interval of $[-1, +1]$. The signal normalization can be written as

$$x_{norm}(t) = 2\left(\frac{x(t)-\hat{x}_{\min}}{\hat{x}_{\max}-\hat{x}_{\min}}\right)-1 \tag{9}$$

where $x(t)$ is the amplitude of signal and $x_{norm}(t)$ is the amplitude of normalized signal, respectively; $\hat{x}_{\max}$ and $\hat{x}_{\min}$ are the maximum and minimum values, respectively, of the noisy signal during the training phase (Fig. 3), or the estimated maximum and minimum values of the input signal during the testing phase (Fig. 4). After normalization, wavelet transform is then performed to extract wavelet coefficients of the signal

$$w = T(x_{norm}(t)) \tag{10}$$

As described at the beginning of this section, the subset of the above wavelet coefficients (64 "approximation coefficients") is chosen as the input of neural network. For the output of neural network, de-normalization is performed:

$$y_1(t) = \frac{(y(t)+1)(\hat{y}_{\max}-\hat{y}_{\min})}{2} + \hat{y}_{\min} \tag{11}$$

where $y(t)$ is the output of neural network (before de-normalization) and $y_1(t)$ is the final result (filtered signal) after de-normalization.

Once the neural network is fully trained, the performance of the overall system can be tested with a new noisy ECG signal as its input. The system output is the filtered ECG signal, as shown in Fig. 4.

## 4. Simulation results

In this section, the proposed wavelet-neural network approach is applied to ECG signal noise reduction. Both training and testing data are taken from the actual measurements in MIT–BIH (Massachusetts Institute of Technology–Beth Israel Hospital) database [20,21].

The noise-free ECG signals are taken from [20]. Each signal in the above database is a 2-lead recording with the resolution of 11 bits per sample. Five different types of noise are considered in this paper; they are baseline wander, electrode motion artifact, muscle contraction, white noise, and 60 Hz power-line interference. Data for the first three types of noise (i.e., baseline wander, electrode motion artifact, and muscle contraction) are taken from [21], where the noise data are obtained using a Holter recorder and standard electrodes for ambulatory ECG monitoring on a human subject. The remaining two noise data (i.e., white noise and power-line interference) are generated using Matlab. The first 4000 samples from a patient (with noise added) are used for neural network training. After training, the next 4000 samples (also with noise) can be used for testing.

A "clean", noise-free ECG signal is shown in Fig. 5 (record 220 of [20]). To demonstrate the effectiveness of the proposed approach, the network is trained and tested to remove one type of noise at a time first (Figs. 6–10). By doing so, one can closely examine the performance of neural network to each noise type to determine whether it meets the performance criteria. Next, we consider the situation when all five types of noise are presented in the ECG signal for medical diagnosis. Similar to the above five cases with individual noise, the weights of neural network are initialized at random; the network is then trained and tested using the signal with "combined" noise (Fig. 11).

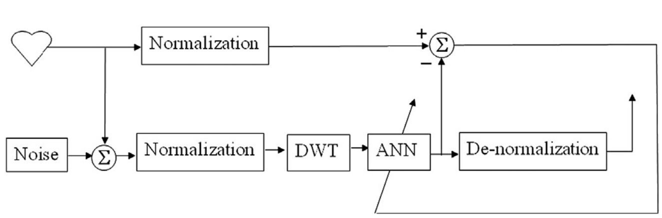


**Fig. 3.** The neural network training scheme.

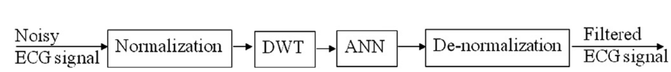


**Fig. 4.** The neural network testing mode.

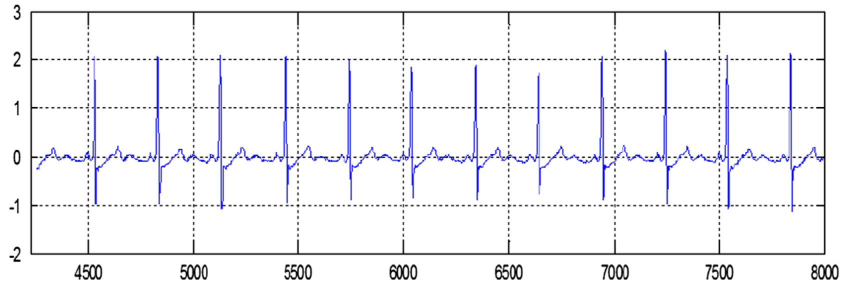


**Fig. 5.** Noise-free ECG signal.

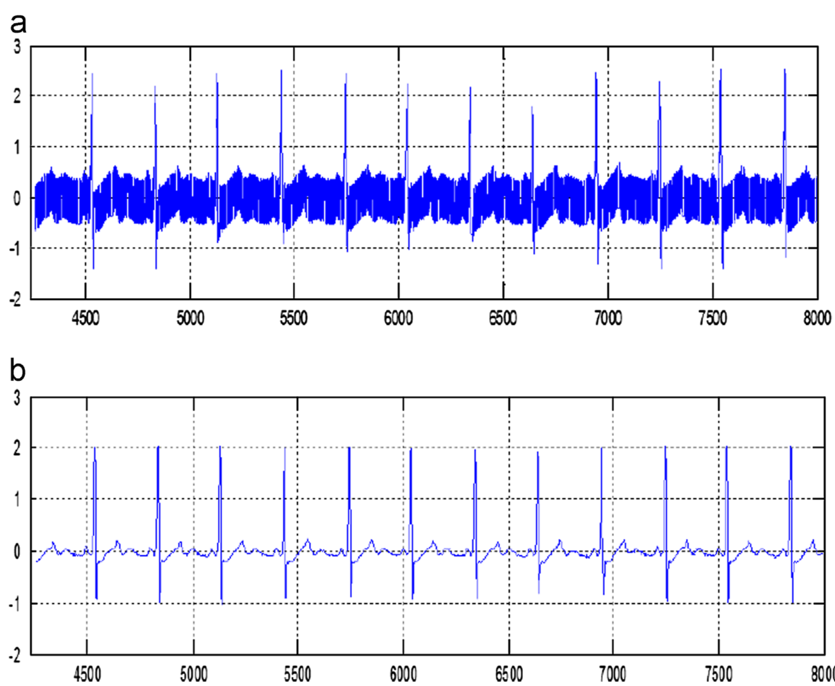


**Fig. 6.** The 60 Hz power-line interference removal. (a) Signal with power-line interference and (b) signal after filtering.

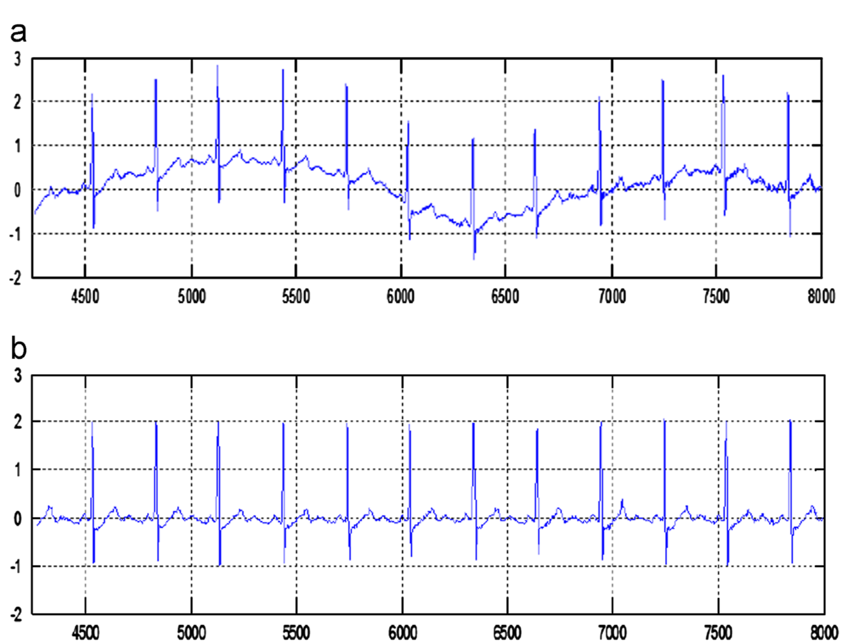


**Fig. 7.** Baseline wander noise removal. (a) Signal with baseline wander noise and (b) signal after filtering.

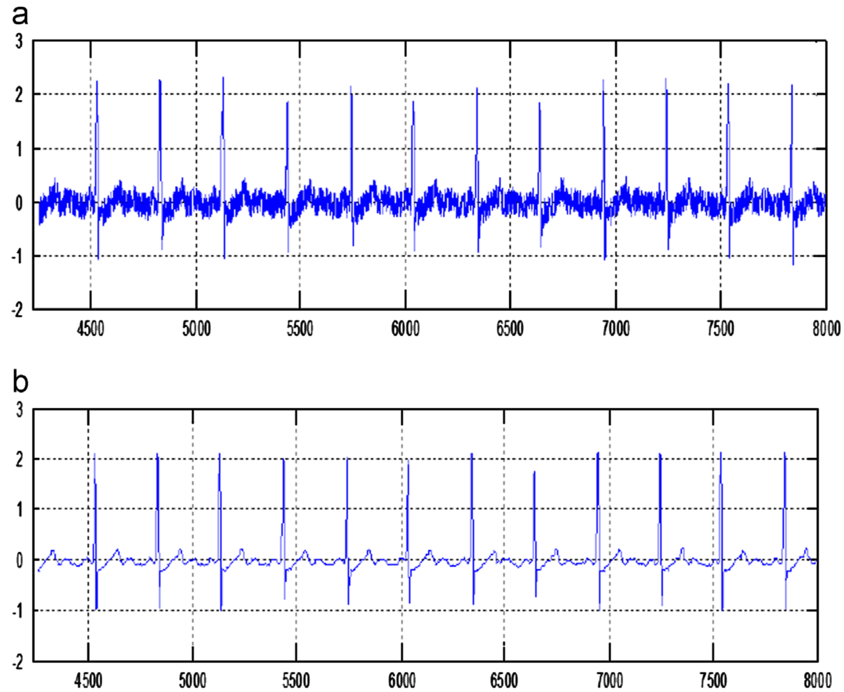


**Fig. 8.** White noise removal. (a) Signal with white noise and (b) signal after filtering.

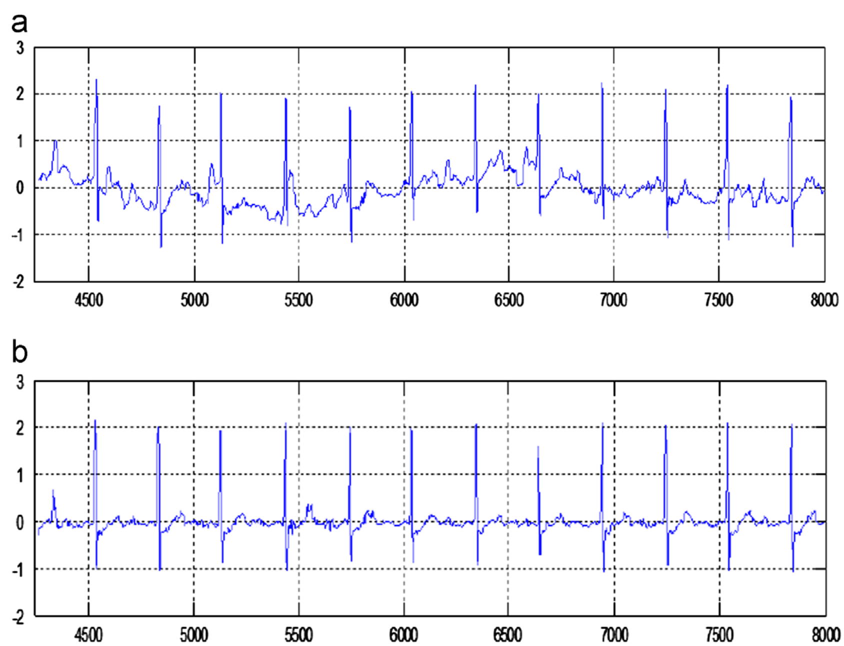


**Fig. 9.** Electrode motion artifact removal. (a) Signal with electrode motion artifact and (b) signal after filtering.

The neural network employed in the proposed approach is a multi-layer feed-forward neural network with 64 inputs (must be in the power of 2 for DWT). The number of hidden layers and the number of hidden neurons are chosen based on a series of trial and error experiments. There are two hidden layers; the first hidden layer contains 56 hidden neurons and the second one contains 12 hidden neurons. Hyperbolic tangent function is employed as the nonlinear activation function for each neuron:

$$f(x)=\frac{1-e^{-ax}}{1+e^{-ax}} \tag{12}$$

where $a$ is a constant parameter ($a>0$). In our simulation, we choose $a=1$.

### 4.1. Removal of individual noise

We start with the removal of the power-line interference that consists of the 60 Hz signal with its harmonics. Fig. 6(a) shows the contaminated signal; and (b) shows that our proposed wavelet-neural network algorithm (described in Section 3) can successfully remove this stationary, predictable noise.

Next, we consider the baseline wander noise. As shown in Fig. 7(a), the drift of the baseline with respiration can be modeled as a non-stationary sinusoidal signal with the frequency of respiration, which usually ranges from 0.15 to 0.3 Hz ([22]). This frequency is generally lower than the frequency resolution of DWT in this application; thus the neural network performs as an

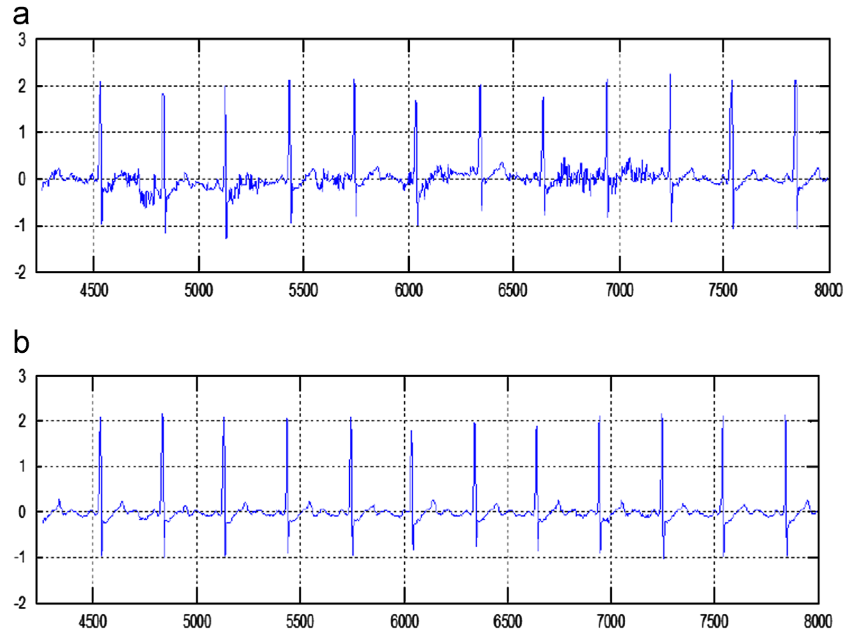


**Fig. 10.** Muscle contraction artifact removal. (a) Signal with muscle contraction artifact and (b) signal after filtering.

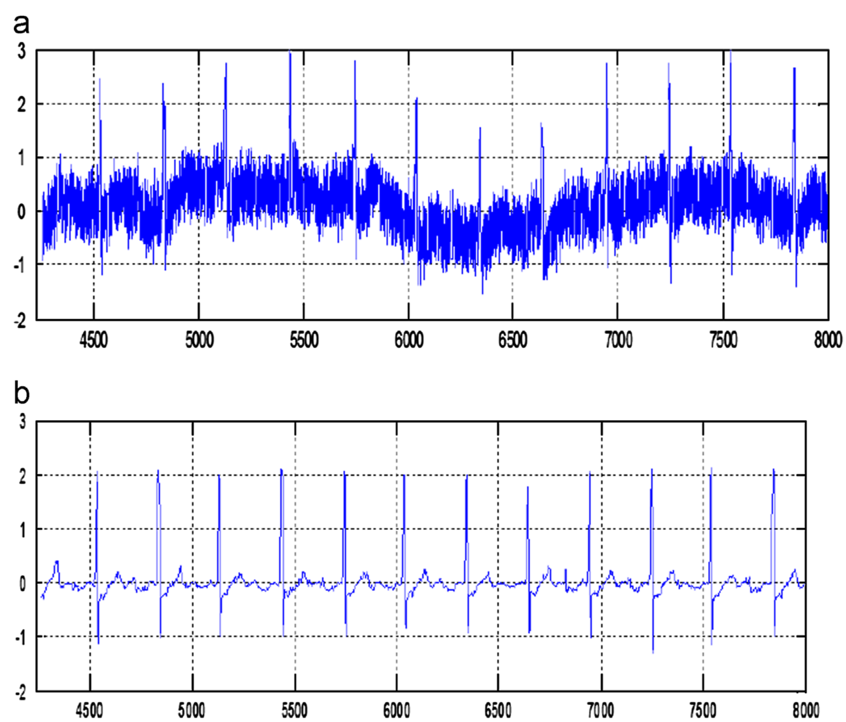


**Fig. 11.** Combined noise removal. (a) Signal with combined noise and (b) signal after filtering.

adaptive filter to remove the noise. The filtered signal is shown in Fig. 7(b).

The proposed approach also performs well to remove white noise, as shown in Fig. 8. This can be attributed to the fact that both DWT thresholding and artificial neural networks are efficient tools for random noise reduction.

Figs. 9 and 10 demonstrate the result of electrode motion artifact removal and the result of muscle contraction noise removal, respectively. Though these two types of noise are very difficult to eliminate due to their spectral overlap with the desired ECG signal, simulation results show that the proposed approach still performs very successfully.

All the above results are summarized in Table 1, where the signal-to-noise ratios (SNRs) of the contaminated signal and the filtered signal are calculated and compared. SNR is commonly expressed in decibels (dB):

$$SNR = 10 \log\left(\frac{S}{N}\right) \tag{13}$$

where $S$ is the power of the signal and $N$ is the power of the noise. Note that $S$ and $N$ are not calculated directly as in other typical signal processing applications, due to the complications of ECG signals described in [23]. Based on the method suggested in [23], a "windowing" algorithm is employed where $S$ is considered as a

**Table 1**
Individual noise removal summary.

| Noise | SNR (dB) pre-filter | SNR (dB) post-filter | SNR (dB) improvement |
|---|---|---|---|
| Baseline wander | 19.18 | 30.74 | 11.56 |
| Electrode motion artifact | 15.65 | 25.29 | 9.64 |
| Muscle contraction | 22.90 | 28.09 | 5.19 |
| 60 Hz power line | 10.95 | 33.31 | 22.36 |
| Random noise | 17.69 | 29.49 | 11.80 |
| Average SNR improvement (dB) | | | 12.11 |

**Table 2**
Combined noise removal summary.

| Noise | SNR (dB) post-filter | SNR (dB) improvement |
|---|---|---|
| Traditional filter groups | 16.24 | 6.52 |
| DWT filtering | 10.22 | 0.5 |
| Proposed approach | 25.43 | 15.72 |
| SNR (dB) pre-filter=9.72 dB | | |

function of QRS amplitude and $N$ is defined as a measurement of frequency-weighted noise power. To determine $S$, the peak-to-peak amplitude of the signal is measured with a 100 ms time window around each QRS-complex; then the mean of these measurements are used to obtain an estimate of signal power.

As shown in Table 1, the proposed adaptive filtering approach can successfully reduce various types of noise and improve the signal-to-noise ratio. The SNR improvement on power-line interference is the most significant one (22.36 dB); the SNR improvement on baseline wander and white noise is moderate (11.56 dB and 11.80 dB, respectively); the SNR improvements on electrode motion and muscle contraction artifact are the two lowest ones, but are still acceptable (9.64 dB and 5.19 dB). The average SNR improvement is 12.11 dB.

### 4.2. Removal of "combined" noise

The simulation results in Section 4.1 show that the proposed method is able to reduce noise with significant SNR improvement on each of the five different noise types. In the following, the performance of the proposed approach is tested when all the noise sources are combined and added to the ECG signal, which is usually the case of reality. Unlike the traditional filter bank method which employs several filters to reduce noises in different frequency bands, only one neural network is needed to filter the "combined noise" in our approach.

Fig. 11(a) shows the corrupted ECG signal with all five types of noise, i.e., power-line interference, baseline wander, white noise, electrode motion artifact, and muscle contraction noise. The proposed wavelet-neural network approach is tested on 10 sets of noisy ECG signals, with an average SNR of 9.72 dB. A typical filtered signal is shown in Fig. 11(b). For the post-filter SNR improvement of the 10 test runs, the maximum value (best case) is 16.46 dB, the minimum improvement is 14.40 dB, the average is 15.72 dB and the standard deviation is 0.65 dB. Apparently, a well-trained neural network with wavelet decomposition can effectively filter out the combined noise. The SNR improvement is even better than the average SNR improvement when each type of noise is applied and removed separately.

### 4.3. Comparison with other methods

The performance of the proposed approach is further compared with two other filtering methods for the case of combined noise, as shown in Table 2. The first method employs the design of a traditional filter group to remove noise from ECG signal. The four traditional filters employed in this paper include a low-pass filter (with a cut-off frequency of 90 Hz), a high-pass filter (with a cut-off frequency of 0.5 Hz), a notch filter at 60 Hz (to remove power-line interference), and a fifth-order averaging filter to smooth the overall signal. All four filters are connected in cascaded form. A SNR improvement of 6.52 dB is obtained, which is much lower than the SNR improvement of the proposed approach (15.72 dB).

Another approach listed in Table 2 for comparison uses DWT to decompose the signal and eliminate high-frequency noise; neural network is not included. In other words, the 64 coefficients (which were the inputs of neural network) are now used to reconstruct the signal directly using IDWT (inverse discrete wavelet transform) without the neural network. Computer simulation results show that only a small SNR improvement (0.5 dB) is obtained, indicating that this method is not effective for ECG noise reduction.

## 5. Conclusions

An adaptive filtering approach based on discrete wavelet transform and artificial neural networks is investigated in this paper. The approach combines wavelet transform and artificial neural network in a novel way to achieve noise reduction: the wavelet transform decomposes ECG signals and performs initial filtering, while the neural network implements an inverse transform and nonlinear adaptive filtering to further reduce noise. Since no additional inverse wavelet transform is needed, the algorithm is very efficient. Computer simulation results show this approach can successfully remove various noise and artifacts in ECG signals with significant SNR improvement over other algorithms which are typically limited to remove only one or two types of noise. Future work will include more testing on the proposed approach to further study and evaluate its performance.

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