Stationary wavelet transform based ECG signal denoising method

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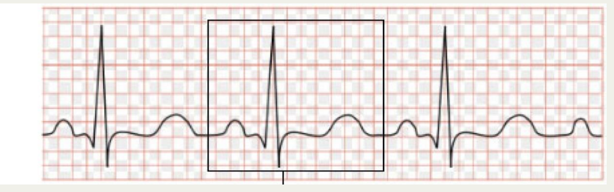
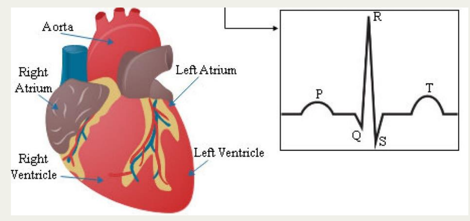
Abstract

Electrocardiogram (ECG) signals are used to diagnose cardiovascular diseases. During ECG signalacquisition, various noises like power line interference, baseline wandering, motion artifacts, and elec-tromyogram noise corrupt the ECG signal. As an ECG signal is non-stationary, removing these noisesfrom the recorded ECG signal is quite tricky. In this paper, along with the proposed denoising techniqueusing stationary wavelet transform, various denoising techniques like lowpass filtering, highpassfiltering, empirical mode decomposition, Fourier decomposition method, discrete wavelet transformare studied to denoise an ECG signal corrupted with noise. Signal-to-noise ratio, percentage root-mean-square difference, and root mean square error are used to compare the ECG signal denoisingperformance. The experimental result showed that the proposed stationary wavelet transform basedECG denoising technique outperformed the other ECG denoising techniques as more ECG signalcomponents are preserved than other denoising algorithms.

Introduction

Cardiovascular disease (CVDs) refers to various problems with heart or blood vessels, including heart attacks, heart failure, and stroke. According to the world health organization survey, nearly eighteen million human beings lose their lives each year . CVDs mainly occur because of the accumulation of plaque inside arteries, making the walls thicken and reducing the arteries' available cross-section area. As a result, to bring the blood flow to typical rates, the heart needs to pump more blood per unit time. The primary investigation and diagnosis of CVDs are generally made with an ECG monitor.





The heart's conduction system controls the generation and propagation of electrical signals that cause the heart muscle to contract and the heart to pump blood.
This electrical activity is measured by placing electrodes at specific points on the human body. The measured electrical activity from electrodes forms a composite recording in the form of a graph famously known as ECG. In most cases, ECG signals are not clean as noises and artifacts corrupt these signals. The primary sources of noise are poor contact between electrodes and skin, incorrect positioning of electrodes, activities of various muscles in the body, respiration, surrounding electrical equipment, and electronic devices used by the machine itself.
Therefore, it is necessary to remove noises and artifacts so ECG features can be examined efficiently and correctly.

Methodology

The following is a description of the proposed and other denoising techniques.

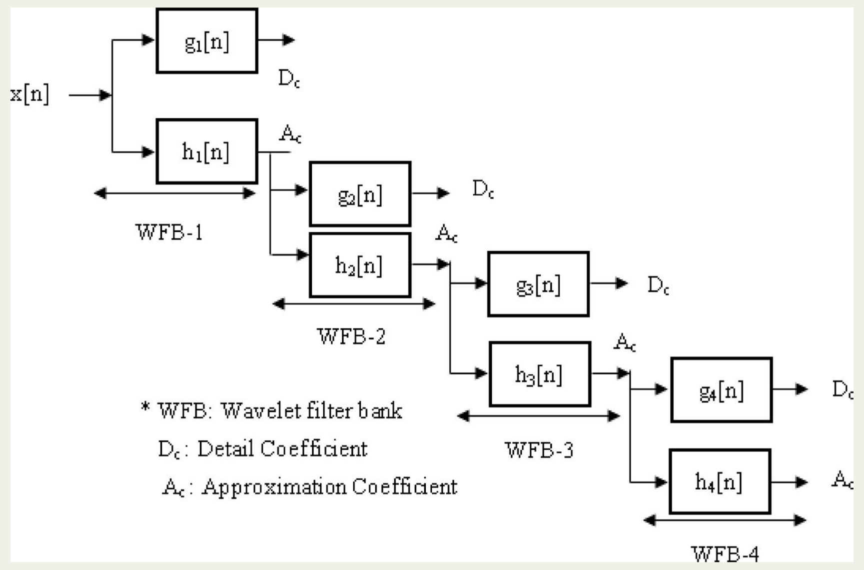
1. **Lowpass Filter and Highpass Filter**: lowpass filter and highpass filter with a cutoff frequency of 0.5 Hz–40 Hz are used in the present work as the energy of the ECG signal (P-wave, QRS complex, and T-wave) lie in 0.5 Hz–40 Hz frequency range.

2. **Discrete Wavelet Transform**: In DWT, the ECG signal is subsampled at each level, and simultaneously, the detail coefficients are subjected to denoising thresholds. Adaptive thresholding is most suitable for ECG signal denoising . In the present work, biorthogonal 3.1 wavelet transform with adaptive thresholding is used to decompose the noisy ECG signal.

3. **Empirical Mode Decomposition Technique**: EMD is employed on the noisy ECG signal. In the pre-processing stage, the data is normalized. Then, EMD decomposes a non-stationary time series into a finite number of intrinsic mode functions, which are monocomponent non-stationary signals. A total of six IMFs and residue components are achieved by employing EMD.

4. **Fourier Decomposition Method**: A noisy ECG signal is decomposed into a set of monocomponent non-stationary signals by dividing the signal's complete bandwidth into an equal number of frequency bands. These monocomponent non-stationary signal frequency bands are known as Fourier intrinsic band functions (FIBFs). After determining FIBFs, various parameters like SNR, PRD, and MSE of each FIBF are computed. Eight FIBFs are extracted from the noisy ECG signal, and the output of the 8th FIBF is the denoised ECG signal.

5. **Stationary Wavelet Transform**: After the pre-processing, the input ECG signal is subjected to a series of a lowpass filter and highpass filter to reject the frequency band as per the Nyquist criterion. This method does not perform any sub-sampling or decimation. The approximate coefficients are outputs of lowpass filters (hi[n]), and detail coefficients are the outputs of highpass filters (gi[n]).



$$A_{c_{b+1,k}} = \int_{-\infty}^{\infty} 2^{-\frac{b+1}{2}}\, x(t)\, \emptyset^*\left(\frac{t-b}{2^{b+1}}\right) dt = \sum h[a]\, C_{b,k+2^b a}$$

$$D_{c_{b+1,k}} = \int_{-\infty}^{\infty} 2^{-\frac{b+1}{2}}\, x(t)\, \psi^*\left(\frac{t-b}{2^{b+1}}\right) dt = \sum g[a]\, C_{b,k+2^b a}$$

Here, "b" is the translation parameter ,and "k" scaling parameter.

Evaluation methods

Various ECG denoising techniques, namely, lowpass filter, highpass filter, DWT, EMD, FMD, and SWT, are evaluated using four ECG databases. The four ECG databases used in this work are the MIT BIH Arrhythmia database, MIT-BIH Noise Stress Test database, Physionet PTB Diagnostic ECG Database, and QT database.
SNR, PRD, and RMSE are the parameters used in this study.

Signal to noise ratio (SNR)

$$SNR = 10 \times \log_{10} \frac{\sum_{k=1}^{N} (y(k) - x(k))^2}{\sum_{k=1}^{N} (\hat{x}(k) - x(k))^2}$$

Percentage-root-mean-square difference (PRD)

$$\text{PRD} = 100 \times \sqrt{\frac{\sum_{n=1}^{N} (x(k) - \hat{x}(k))^2}{\sum_{n=1}^{N} x^2(k)}}$$

Root-mean-square-error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (\hat{x}(k) - x(k))^2}$$

Results

In this section, the experiment through various ECG denoising techniques, namely, lowpass filter, highpass filter, DWT, EMD, FMD, and SWT, are evaluated using four ECG databases. The four ECG databases used in this work are the MIT BIH Arrhythmia database, MIT-BIH Noise Stress Test database, Physionet PTB Diagnostic ECG Database, and QT database.

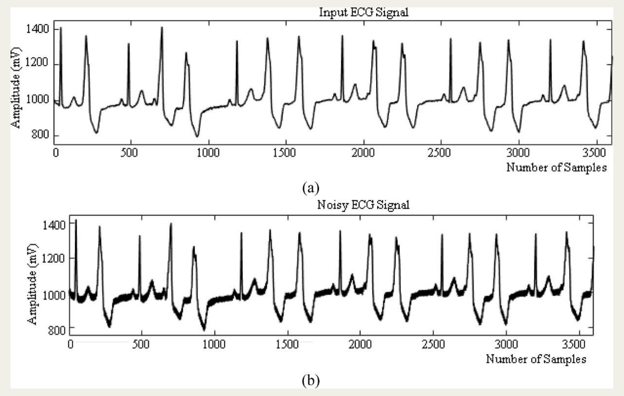


Fig. 1. (a) Input ECG Signal (208 series of data from physionet.org), (b) ECG signal corrupted with noise.

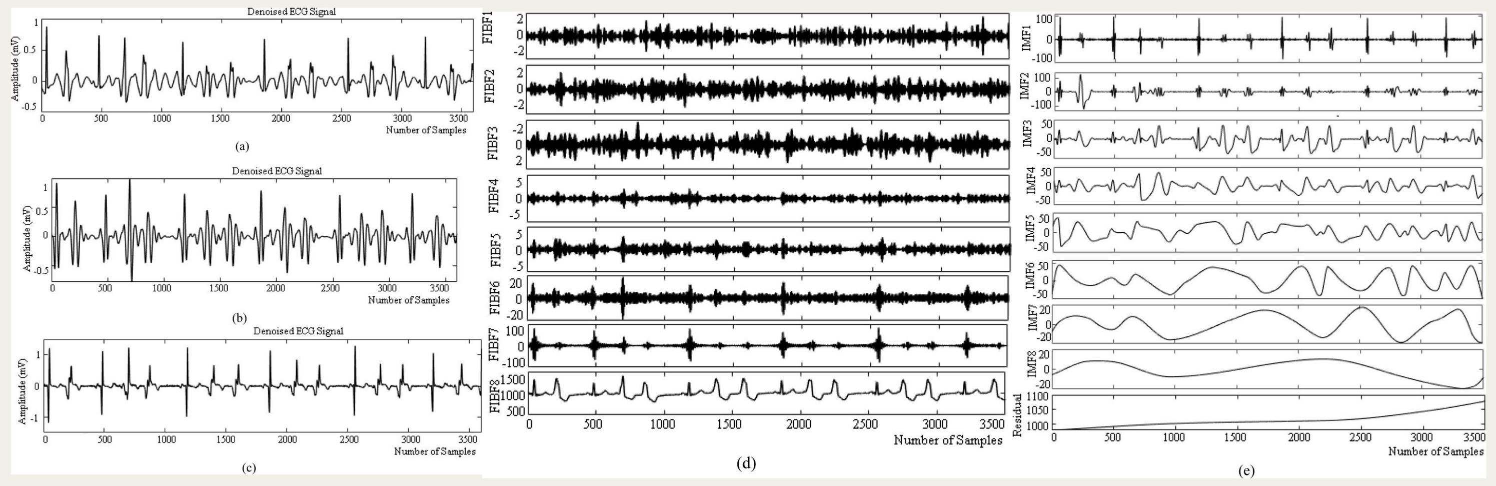
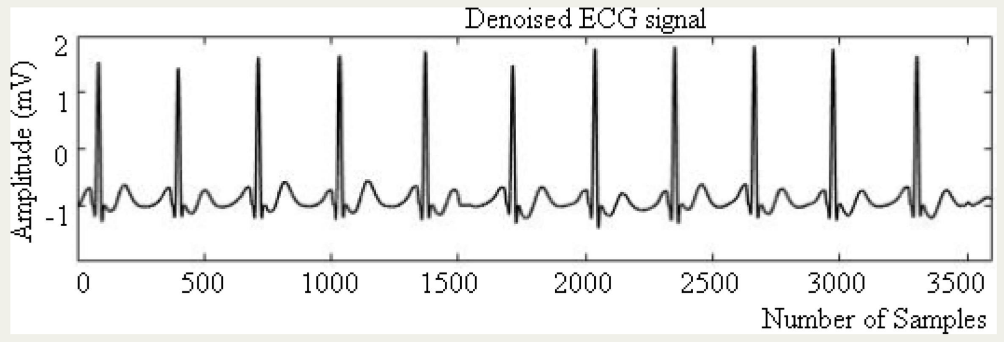


Fig. 2. ECG signal denoised using (a) a lowpass filter, (b) highpass filter, (c) discrete wavelet transform, (d) Fourier decomposition method (FIBF8 is denoised ECGsignal), (e) Empirical decomposition method and corresponding IMFs and residuals.

The denoising performance of the stationary wavelet transform based ECG denoising technique is shown in the picture. It is observed from a picture that the use of a stationary wavelet transform produces a clean ECG signal. Hence, the most considerable SNR improvement of the denoising algorithm is achieved.



Conclusion

In this paper, **a comparison between different ECG denoising techniques is performed** to understand the numerically efficient denoising technique.
All the ECG denoising techniques discussed above are compared on different input and output performance evaluation parameters: SNR, PRD, and RMSE.

SWT showed better results by **providing maximum SNR and minimum PRD, RMSE** when compared to other ECG denoising techniques. **These results proved that the denoised signal obtained is of very high quality** and is least deviated from the original signal.

SWT is an **efficien**t and **potential denoising method** that can easily suppress noises like powerline interference and baseline wandering from a corrupted ECG signal. **SWT is one of the best approaches** which is used for non-stationary signals in **real-time applications**.