

Comparison of Wavelet Types and Thresholding Methods on Wavelet Based Denoising of Heart Sounds

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ABSTRACT

This paper focuses on the denoising of phonocardiogram (PCG) signals by means of discrete wavelet transform (DWT) using different wavelets and noise level estimation methods. The signal obtained by denoising from PCG signal contaminated white noise and the original PCG signal is compared to determine the appropriate parameters for denoising. The comparison is evaluated in terms of signal to noise ratio (SNR) before and after denoising. The results showed that the decomposition level is the most important parameter determining the denoising quality.

Keywords: Discrete Wavelet Transform; Denoising; PCG

1. Introduction

The structural defects of the heart are often reflected on the acoustical vibrations produced as a result of the mechanical action of the heart. The proper analysis of heart sound allows non-invasive detection of coronary artery stenosis, and valve disorders causing the heart murmurs [1]. It is possible a computer aided detection of the abnormalities by means of processing and analyzing of the acoustical vibration [2]. A record of the acoustical vibrations acquired by means of microphones, called phonocardiogram (PCG), consist of the heart sounds and the murmurs. While the heart sounds are produced opening and closing of the heart valves, the murmurs are produced by the turbulence of blood flow.

The heart sounds have low frequency components, and the murmurs are high frequency signals occurring generally between heart sounds. The murmurs can be commonly heard in abnormal cardiovascular cases. The frequency components of a PCG signal may achieve around 1 KHz, which seen particularly in abnormal patient due to the murmurs. On contrary healthy person, the frequency components can exist above 300 Hz in diseased patients. In normal patients, the spectral energy exists in the interval of 100 and 200Hz, and rarely reaches up 300Hz [3].

This noise decreases the performance of visual and computerized analysis. The respiration sounds by lung mechanical actions, patient movement, and improper contacts of microphone to the skin, and external noises from the environments are also added as noise signal into

PCG records. The traditional method to remove the noise from a PCG signal is to use a low or band pass filter with cut off frequencies. However the filtering techniques are able to remove a relevant of the noise, they are incapable if the noise in the band of the signal to be analyzed.

In the present study, we performed the discrete wavelet transform (DWT) to overcome the limitations of the traditional methods. The denoising based on DWT is consist of three steps; decomposition of the signal, thresholding and reconstruction of the signal. Hard and soft thresholding approaches are usually applied to eliminate of small coefficient in denoising process.

In the hard thresholding, the wavelet coefficient below a give value are stetted to zero, while in soft thresholding the wavelet coefficient are reduced be a quantity to the thresh value. The threshold value is the estimation of the noise level, which is generally calculated from the standard derivation of the detail coefficient. The given signal is decomposed on to a set of orthonormal wavelet function that constitutes a wavelet basis. The most known wavelets providing the ortogonality properties are Du-bechies, Symlets, Coiflets and Discrete Meyer to provide reconstruction using the fast algorithms.

The result of the DWT is a multilevel decomposition, in which the signal is decomposed in ‘approximation’ and ‘detail’ coefficients at each level. This is made through a process that is equivalent to low-pass and high passes filtering, respectively [4]. DWT decomposition leads to a tree structure as shown in **Figure 1**, where approximation and detail coefficients are presented.

Here, it is studied on the effects of wavelet types, de-

composition levels, thresholding techniques and noise estimation methods.

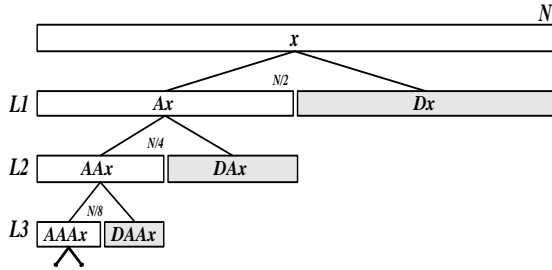


Figure 1. The approximation and the detailed coefficients in the tree structure of the DWT.

2. Methods

2.1. Discrete Wavelet Transform

The wavelet transform is first introduced for the time-frequency analysis of transient continuous signal, and then extended to the theory of multi-resolution wavelet transform using FIR filter approximation. The discrete wavelets $\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n)$ used in multi-resolution analysis constituting an orthonormal basis for $L^2(\mathcal{R})$ [5,6].

$x(t)$ is decomposed an different scale,

$$x(t) = \sum_{m=1}^L \left[\sum_{k=-\infty}^{\infty} D_m(k)\psi_{m,k}(t) + \sum_{k=-\infty}^{\infty} A_L(k)\phi_{L,k}(t) \right] \quad (1)$$

where $\psi_{m,k}(t)$ is discrete analysis wavelet, and $\phi_{L,k}(t)$ is discrete scaling, $D_m(k)$ is the detailed signal at scale 2^m , and $A_L(k)$ is the approximated signal at scale 2^L . $D_m(k)$ and $A_L(k)$ is obtained using the scaling and wavelet filters [4,8].

$$\begin{aligned} h(n) &= 2^{-1/2}\langle\phi(t),\phi(2t-n)\rangle \\ g(n) &= 2^{-1/2}\langle\psi(t),\phi(2t-n)\rangle \\ &= (-1)^n h(1-n) \end{aligned} \quad (2)$$

The wavelet coefficient can be computed by means of a pyramid transfer algorithm. The algorithms refer to a FIR filter bank with low-pass filter h, high-pass filter g, and down sampling by a factor 2 at each stage of the filter bank [6]. **Figure 1** shows the tree structure of DWT decomposition for three levels.

2.2. Threshold Estimation

The main idea of the wavelet denoising to obtain the ideal components of the signal from the noisy signal requires the estimation of the noise level. There are many possible approaches to the estimation of the noise level, and a systematic investigation about their performance [8, 9]. In this work, four different threshold options were

applied to assess their effectiveness.

Rigrisure is adoptive threshold selection using the Stein’s unbiased risk estimation criteria;

$$ThValue = \sigma\sqrt{2\log(N\log_2 N)} \quad (3)$$

where N is the length of the signal, and σ is the standard deviation of the noise. The latter is estimated from the detail coefficient at the first level of signal decomposition; $\sigma = |\text{median}(Dx)|/0.674$

Sqtwolog is defined as the universal threshold;

$$ThValue = \sigma\sqrt{2\log_e(N)} \quad (4)$$

Heursure is the heuristic version that uses a mixture of the previous rules.

Minimaxi is a threshold selection using the minmax principle. A fixed threshold is selected to get the minimum of the maximum mean square error, obtained the worst function in given set, when compared against a ideal procedure.

2.3. Assessments for Comparison

The studies were made on a heart sounds contaminated at a desired SNR level by white Gaussian noise. Measuring the performance of the denoising method by calculation of the residual SNR (SNR) given as;

$$SNR = 10\log_{10} \log_{10} \left(\frac{\sum_{n=0}^{N-1} x[n]^2}{\sum_{n=0}^{N-1} (x[n] - x_{dn}[n])^2} \right) \quad (5)$$

where $x[n]$ is the original signal, $x_{dn}[n]$ is the denoised signal. The comparison between the initial SNR and the result SNR may be used as the performance indicator.

3. Experiments and Results

The assessments were made of the behavior of different mother wavelets and four different threshold estimation techniques in order to find the most reliable parameters for DWT denoising of heart sounds. These have drowned from the most used wavelet families, Daubechies, Symlets, Coiflets, and Discrete Meyer.

The PCG signal was contaminated at SNR=5dB in order to test the performance of the wavelets and the threshold estimation techniques. A normal PCG signal generally contains only two heart sounds, first and second heart sounds. **Figure 2** illustrates a sample PCG signal, the noisy signal, a denoised sample using DWT, and the error between the original and the denoised PCG signals.

The frequency components of a normal PCG signals can be rise up 200 Hz, and the energy of the most significant components concentrates around the frequency band 100 - 150 Hz. The frequency bands of the signal are important in point of the denoising technique using DWT approaches. Because the DWT approaches decomposes

the signal into frequency bands to eliminate the detail components assumed as noise, the decomposition level reflects directly on the frequency components that cause the smoothed version of the signal.

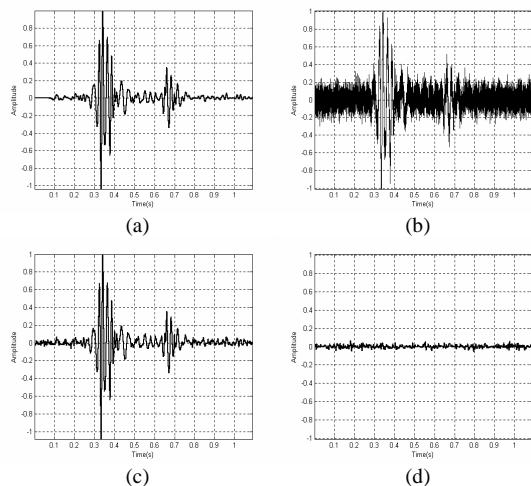


Figure 2. Wavelet denoising of a PCG signal, a) Original signal, b) Noisy signal, c) Denoised signal, d) Error between the original and the denoised signal.

The effected components are related to not only decomposition level but also sampling frequency. The decomposition level, l , influences the frequency bands by dividing the sampling frequency respect to 2^l . In our experiments, choosing $l=5$ causes the proceeding of the denoising process down to 150 Hz due to the sampling frequency is 11.5 Hz.

Therefore, the most important factor determining the SNR level is the depth of the decomposition. **Table 1** presents the SNR results respect to the decomposition level with by using *symlet8* and *rigresure* estimation for hard and soft tresholding. For the both tresholding techniques, it is seen that the highest SNR values obtained when the composition level is 5 due to the reason expressed above.

Table 1. SNR level respect to the depth of decomposition.

Level	Hard	Soft
1	8.1209	7.8843
2	11.1471	10.9218
3	14.3251	14.0031
4	17.2973	16.9275
5	20.1305	19.4396
6	13.2248	13.2472
7	12.1531	9.8726
8	10.8010	8.3255
9	10.4986	8.1632
10	10.4912	8.1593

The other parameters to obtain best SNR level are the

kind of the wavelet and the thresholding rule. **Table 2** presents the SNR levels using different wavelet when the decomposition level is 5. In **Table 2**, there is no significant difference in SNR in terms of wavelet types. Nevertheless, it is attracting that the mother wavelets having high oscillation number produces better SNR results.

Table 2. SNR values respect to wavelet types (*Rigrsure*, level = 5).

Wavelet Type	Hard	Soft
Daubechies2	16.5378	16.5057
Daubechies3	18.9391	18.8353
Daubechies4	19.8138	19.8002
Daubechies5	19.8747	19.7425
Symlet2	16.3487	16.4181
Symlet3	18.5401	18.7874
Symlet4	19.5732	19.8002
Symlet5	19.4795	19.5458
Coiflet1	16.7746	16.7658
Coiflet2	19.4866	19.4501
Coiflet 3	19.7812	19.6252
Discrete Meyer	19.9018	19.7154

It is attracting that the wavelets having higher oscillation frequency gives better SNR results. For example, the symlet wavelet having eight oscillations in its mother wavelet produces better SNR level than the lower ones. The very lower oscillation frequency causes the lower SNR results.

The estimation techniques show the same performance for the level 5 respects to the initial SNR level. For the comparison, the initial SNR level before denoising is increased from 1dB to 30dB, and the result SNR level after denoising is calculated using Equation (5). **Figure 3** presents a comparison of the four noise estimation methods for level 5 and 8 by using *Symlet8*.

We have observed no distinguishing evidence among the noise level estimation methods until level 6. After this level, *rigresure* method has produced better SNR values. And it is observed that *rigresure* preserve the second heart sound in PCG signals while the other methods destroying. This situation is clearly seen in **Figure 4**.

The signal part belonging to second heart sound taking place at around 0.7 s in **Figure 4 (a)** cannot be seen in the other figures. This also proves that the *rigresure* preserve the main characteristic of the signal. Therefore, we can conclude that the *rigresure* is the best noise estimation method.

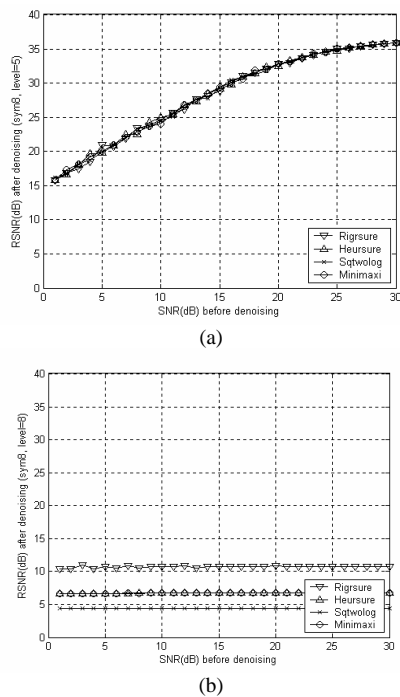


Figure 3. The SNR values after denoising before denoising for level 5 and 8.

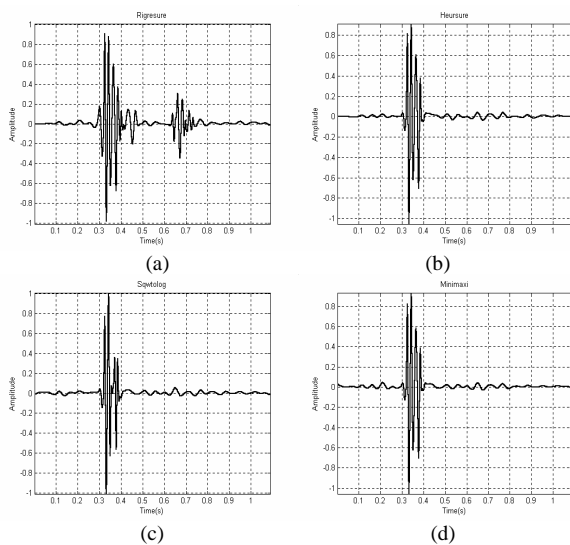


Figure 4. The denoised signal using four different threshold rules at eighth level.

4. Conclusions

The wavelet denoising techniques were studied on a noised PCG signal in this work. The performances of several variations of denoising including thresholding rules and the type of wavelet were compared to produce the best denoising results of the methods.

We conclude that reasonable decomposition level is absolutely depending on the sampling frequency and the

frequency band of the signal. Just in this study, the decomposition level of 5 produced reasonable results because the frequency band of a normal PCG signal is around 150 - 200 Hz and the sampling frequency is 11.5 KHz. Since the noise level method is one of the important parameter in wavelet denoising, it is examined for different levels. We have not seen any noteworthy differences in the methods from level 1 to level 6. After this level, rigrsure method has showed superiority to the other methods in terms of SNR level. Consequently, it is determined that the wavelet type is not very important if the oscillation number is not very low, the decomposition level is absolutely depends on the frequency band of the PCG signal and its sampling frequency, and rigrsure method is best of the noise estimation techniques.

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