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Denoising of Heart Sound Signals Using Discrete Wavelet Transform

Mohammed Nabih Ali[1] · **EL-Sayed A. El-Dahshan**[1,2] · **Ashraf H. Yahia**[2]

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Abstract Signal denoising remains to be one of the main problems in the field of signal processing. Various signal denoising algorithms using wavelet transforms have been introduced. Wavelets show superior signal denoising performance due to their properties such as multiresolution and windowing. This study focuses on denoising of phonocardiogram (PCG) signals using different families of discrete wavelet transforms, thresholding types and techniques, and signal decomposition levels. In particular, we discuss the effect of the chosen wavelet function and wavelet decomposition level on the efficiency of the denoising algorithm. Denoised signals are compared with the original PCG signal to determine the most suitable parameters (wavelet family, level of decomposition, and thresholding type) for the denoising process. The performance of our algorithm is evaluated using the signal-to-noise ratio, percentage root-mean-square difference, and root-mean-square error. The results show that the level of decomposition and thresholding type are the most important parameters affecting the efficiency of the denoising algorithm. Finally, we compare our results with those from other studies to test and optimize the performance of the proposed algorithm.

Keywords Phonocardiogram (PCG) · Discrete wavelet transform (DWT) · Signal-to-noise ratio (SNR) · Signal denoising

✉ Mohammed Nabih Ali
mnabih@eelu.edu.eg

EL-Sayed A. El-Dahshan
seldahshan@eelu.edu.eg

Ashraf H. Yahia
ayahia@sci.asu.edu.eg

1 Egyptian E-Learning University (EELU), 33 El-Mesaha Street, Eldokki, El-Giza 11261, Egypt

2 Department of Physics, Faculty of Sciences, Ain Shams University, Abbasia, Cairo 11566, Egypt

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1 Introduction

Cardiovascular disorders (CVDs) is a broad term that can refer to diseases affecting the human heart. CVDs are the major cause of death worldwide. Over 17.5 million people died from CVDs in 2016, representing 31 % of all global deaths [15]. According to the latest World Health Organization (WHO) statistics published in May 2016, death due to CVDs in Egypt reached 23.14 % of total deaths [14]. Cardiac auscultation is a useful investigative tool applied by physicians to detect CVDs.

The auscultation technique, which was invented and defined by Laennec [28] as the listening and interpretation of sounds produced by the heart, is considered the oldest noninvasive method providing valuable information about heart valves and heart condition. However, it is found to be highly dependent on clinician experience [28].

Thus, phonocardiography (PCG) is a widely used method for analyzing heart sound signals to provide early warning of heart diseases [30]. Also, PCG provides one of the best graphical representations of heart sounds and murmurs (abnormal heart sounds), documenting the timing of heart sounds and annotating their relative intensities to provide valuable information concerning heart valves. PCG recordings consist of four heart sound components (S1, S2, S3, and S4). The first and second heart sounds (S1 and S2) can be heard from the normal heart, being produced by the closure and opening of normal valves. In an abnormal heart, a third and fourth sound (S3 and S4) may also exist in addition to S1 and S2. S3 occurs just after S2, and S4 occurs just before S1 [28]. These abnormal sounds are called murmurs. The presence of such murmurs in a PCG recording is often related to heart valve disease. These four heart sounds (S1, S2, S3, and S4) are shown in Fig. 1.

Heart sound recordings are often disturbed by various factors and noise, including electromagnetic interference (EMI) from the surrounding environment, power frequency interference, electrical signal interference from the human body, breath sounds, and lung sounds.

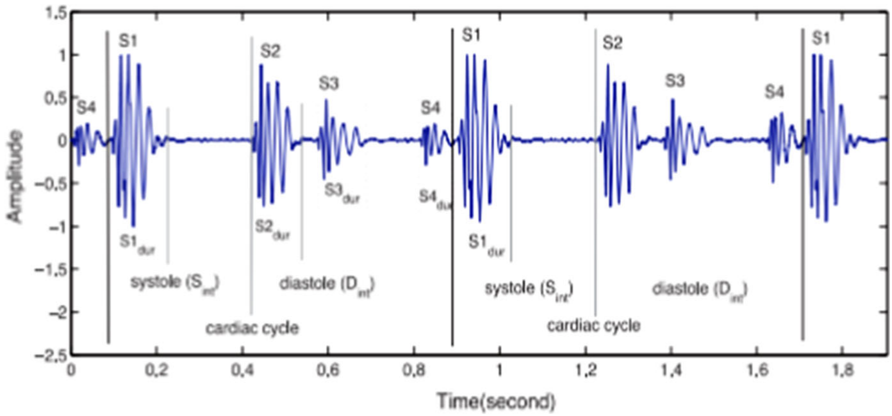

Fig. 1 PCG heart sound signal

These various noise components make diagnosis based on PCG records difficult or, in some cases, impossible. Thus, the main obstacle to developing intelligent automated diagnostic medical systems for analysis of PCG signals is the surrounding disturbance and noise. Accordingly, the research question addressed herein represents an attempt to adapt a denoising algorithm based on discrete wavelet transform for effective reduction and elimination of noise from PCG signals recorded in noisy environments. To achieve this goal, we propose a wavelet denoising algorithm using different families of wavelets, decomposition levels, and thresholding types to give the maximum signal-to-noise ratio (SNR). Also, for generalization, we apply the proposed algorithm to different types of PCG signal and, finally, carry out spectrogram analysis of PCG signals in the frequency domain to illustrate the PCG signal components after applying the proposed denoising algorithm.

The paper is organized as follows: In Sect. 2, a quick survey of related work is presented. Section 3 gives theoretical background on the tools used. In Sect. 4, the methodology used in this research is presented. The experimental results are presented in Sect. 5, and conclusions in Sect. 6.

2 Survey of Related Work on PCG Signal Denoising

To reach firm conclusions and provide suggestions regarding efficient PCG signal denoising algorithms, one must deeply survey and study existing denoising techniques and their performance. This section presents an extensive survey of denoising methods, explains their results, and ends with a conclusion. Table 1 summarizes the most popular denoising methods as well as their features and results.

Various tools and methodologies have been proposed for denoising of heart sound signals. Among all the surveyed methods for PCG signal denoising, the wavelet transform is the most widely used and efficient, because it can analyze signals at different resolutions using the various wavelet families available [10]. From Table 1, it is clear that choosing the most suitable wavelet family with a proper level of decomposition is very important. Also, it is clear that elimination of noise from PCG signals is still under research aiming to determine the optimal wavelet parameters for this application.

3 Brief Overview of Discrete Wavelet Transform

DWT is a linear transformation method that operates on a coefficient vector whose length is an integer power of 2, transforming it to a numerically different vector of the same length [20,21].

The basic idea of DWT for one-dimensional signals is that the signal is split into two parts: a high-frequency component and low-frequency component. This splitting process is called signal decomposition. The edge components of the signal are largely confined to the high-frequency part.

The signal is passed through a series of high-pass filters to analyze the high-frequency components and low-pass filters to analyze the low-frequency components. Filters with different cutoff frequencies are used to analyze the signal at different resolutions. Let us suppose that $s[n]$ is the original signal, spanning the frequency band from 0 to π rad/s. The DWT of a time-domain signal $s[n]$ is defined as

Table 1 Comparison between different methodologies and conclusions of previous studies

Author	Methodology	Results and conclusion
Messer et al. [22]	Hilbert transform	PCG is better than auscultation regarding spectral information analysis
Zhao et al. [33]	Wavelet transform (WT) with thresholding	Thresholding can provide better results when adopting variable parameter values
Vikhe et al. [32]	Discrete wavelet transform (DWT) and continuous wavelet transform (CWT)	Denoising of S2 components A2 and P2 using DWT. Also, frequency components of S1 and S2 are found using CWT
Feng et al. [11]	WT with multiscale decomposition	Contaminated segments of heart sound signals due to noise from respiratory sounds are localized
Song et al. [31]	WT	The proposed approach improves the signal-to-noise ratio
Abdelgham et al. [1]	Short-time Fourier transform (STFT)	The frequency resolution of the resulting spectra is decreased by guaranteeing stationarity
Bai et al. [5]	Mathematical morphological filters	Improved method of signal denoising
Michael et al. [23]	CWT	CWT is useful for characterization of singularities and time–frequency analysis, also providing better signal-to-noise ratio
Anindya et al. [4]	Noise reduction filter based on minimum mean-squared-error estimation in the spectral domain	These techniques can effectively remove various interfering noise sources while retaining critical low-amplitude heart sounds
Olivier et al. [25]	STFT, Gabor transform, and WT	WT is a very promising signal processing tool
Jung Jun et al. [17]	WT for signal analysis	WT can detect S1 and S2
M. S. Obaidat et al. [24]	Wigner distribution, STFT, and WT	WT is the most effective tool for detecting heart sound components

$$W_x(a,b) = \sum_n \frac{1}{\sqrt{a}} s[n]\, \psi^*\left(\frac{n-b}{a}\right), \tag{1}$$

where a and b take only discrete values in the DWT. The index a, commonly chosen as 2^j with $j = 0, 1, 2 \ldots, \log_2(N)$, is called the octave of transformation. When the scale index j increases by one, the discrete mother wavelet function is stretched in the time domain and compressed in the frequency domain by a factor of two. Thus, the frequency resolution doubles with each such scale increase. Next, if the time shifting parameter b is restricted to $k\,2^i$, where k is an integer, this version of the DWT is known as the decimated DWT and can be rewritten as

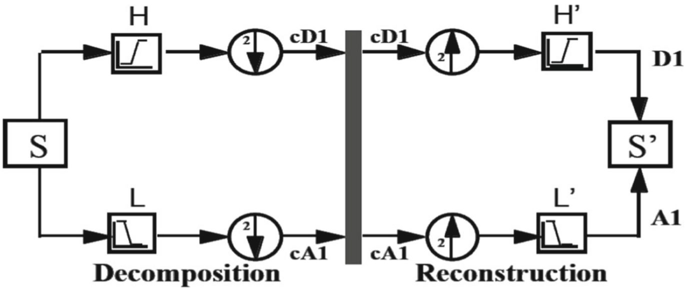

Fig. 2 Signal decomposition and reconstruction of wavelet transform

$$W_{j,k}\left(a,b\right)=\sum_{n}\sqrt{\frac{1}{2^{j}}}s\left[n\right]\psi^{*}\left(2^{-j}n-k\right), \tag{2}$$

where $j=0,1,2\ldots,\log_2\left(N\right), k=l,2,\ldots,N2^{-j}$ and N is the length of the signal $s\left[n\right]$. Note that the number of wavelet coefficients drops to half of those at the next lower scale. Note that, as the scale j decreases, the wavelet becomes more localized in time [8].

The original signal $s\left[n\right]$ is first passed through a half-band high-pass filter $H\left[n\right]$ and a low-pass filter $L\left[n\right]$. After this filtering process, half of the samples can be eliminated, according to Nyquist's rule, since the signal now has highest frequency of $\pi/2$ radians instead of π. The signal can, therefore, be subsampled by 2, simply discarding every second sample. This procedure can be repeated for further decompositions. The outputs of the high-pass and low-pass filters are called the DWT coefficients; these DWT coefficients enable reconstruction of the original signal, a process called the inverse discrete wavelet transform (IDWT). Signal decomposition and reconstruction are shown in Fig. 2. The above procedure is followed in reverse order in the reconstruction process. The signals at every level are upsampled by 2, then passed through the synthesis filters $H'\left[n\right]$, and $L'\left[n\right]$ (high-pass and low-pass, respectively), before being added to each other.

The analysis and synthesis filters are identical to each other, except for time reversal. Here, we use Haar wavelet filters [8]. The outputs of these filters are given by Eqs. (3) and (4).

$$a_{j+1}\left[p\right]=\sum_{n=-\infty}^{\infty}l\left[n-2p\right]a_{j}\left[n\right], \tag{3}$$

$$d_{j+1}\left[p\right]=\sum_{n=-\infty}^{\infty}h\left[n-2p\right]a_{j}\left[n\right]. \tag{4}$$

The elements a_j are used for the next step of the transform, while the elements d_j, called the wavelet coefficients, determine the output of the transform. $L[n]$ and $H[n]$ are the coefficients of the low-pass and high-pass filter, respectively. One can assume that, at scale $j+1$, there is only half the number of a and d elements compared with scale j. The DWT is therefore carried out until only two a_j elements remain in the

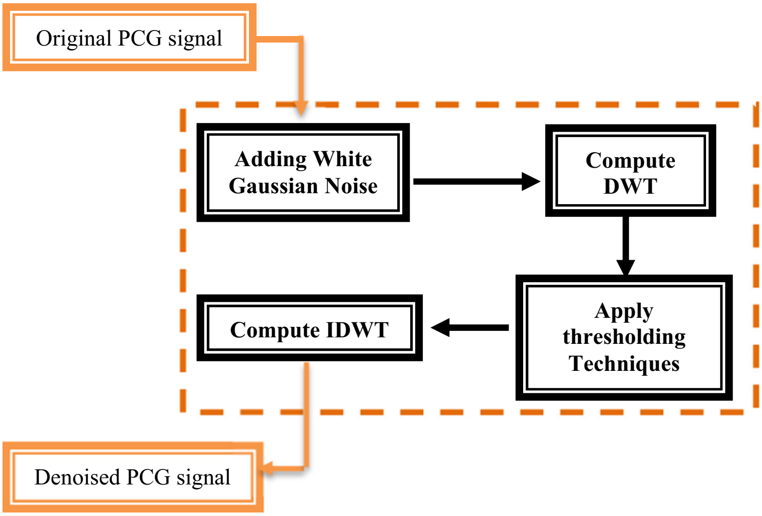

Fig. 3 PCG signal denoising procedure

analyzed signal, being called the scaling function coefficients. The main idea of the wavelet denoising algorithm is to obtain the essential components of the signal from the noisy one then threshold the small coefficients considering them to be pure noise. In the next section, we discuss the wavelet thresholding method.

4 Methodology

The proposed method for denoising PCG signals is divided into four main parts: Adding white Gaussian noise, decomposing the noisy signal in the wavelet coefficients, applying a threshold using a soft or hard method, and finally reconstructing the denoised signal from the remaining coefficients. Figure 3 shows a block diagram for denoising of PCG signals using the DWT and thresholding techniques.

4.1 Database

In this work, the PASCAL heart sound database was used. This database contains normal and abnormal heart sounds that can be used to test the accuracy of proposed denoising algorithms [13].

4.2 White Gaussian Noise

Additive white Gaussian noise (AWGN) contains all frequencies with equal weight or amplitude. The power density and spectrum of white noise are independent of frequency. The occurrence probability of the white level is specified by a Gaussian distribution function [29]. Given a measured signal $s\,(n)$ with white Gaussian noise $N\,(0, 1)$, then

$$s(n) = f(n) + \sigma e(n), \tag{5}$$

where $f(n)$ is the original signal and $e(n)$ is the noise, and σ is the noise strength (standard deviation); in the simplest model, $\sigma = 1$ and the time (n) is equally spaced. The objective of the denoising process is to eliminate the noise part of the signal $s(n)$ in order to recover $f(n)$.

4.3 Signal Decomposition

In this research, different wavelet families (Daubechies, Symlets, Coiflets, and discrete Meyer) were investigated to determine the most suitable wavelet family for PCG signal denoising. The decomposition process was carried out using the MATLAB wavelet toolbox, applying a series of high-pass and low-pass filters to the signal in succession [19]. In the decomposition process, the signal passes through high-pass filters and low-pass filters. The results of this procedure are detailed coefficients corresponding to short-scale, high-frequency elements of the signal, and approximation coefficients corresponding to large-scale, low-frequency elements of the signal. The decomposition process can be carried out using different levels of decomposition.

4.4 Thresholding of Detailed Coefficients

Thresholding is considered to be a simple nonlinear technique, operating on one wavelet coefficient at a time [18]. The two commonest methods for thresholding of signals are soft and hard thresholding, both of which are included in the MATLAB software toolbox. These thresholding methods operate as follows:

- Hard thresholding: elements whose absolute value is less than a threshold value are set to zero;
- Soft thresholding: elements whose absolute value is less than a threshold value are set to zero, then the remaining nonzero coefficients are shrunk towards zero.

Although hard thresholding is the simplest method, soft thresholding produces better results compared with hard thresholding. Hard thresholding may give rise to a discontinuity at λ. Soft and hard thresholding can be formulated as follows (Fig. 4):

$$\text{Hard threshold} = \begin{cases} y = x, & |x| < \lambda \\ y = 0, & |x| \geq \lambda \end{cases} \tag{6}$$

$$\text{Soft threshold } y = \operatorname{sign}(x)\,(|x| - \lambda). \tag{7}$$

4.5 Threshold Selection Rules

The main idea of using wavelets as a signal denoising tool is to obtain the optimal component of the reconstructed denoised signal. This process requires an estimation of the noise level. There are various possible approaches to estimate the noise level and investigate the resulting performance [6–9]. Four different threshold selection rules were applied in this work to investigate their performance in signal denoising:

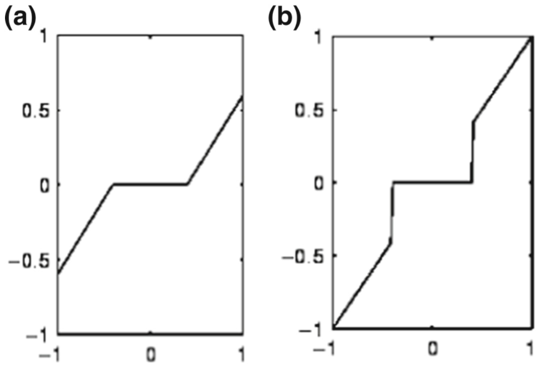

Fig. 4 Different thresholding types **a** Soft thresholding, **b** Hard thresholding

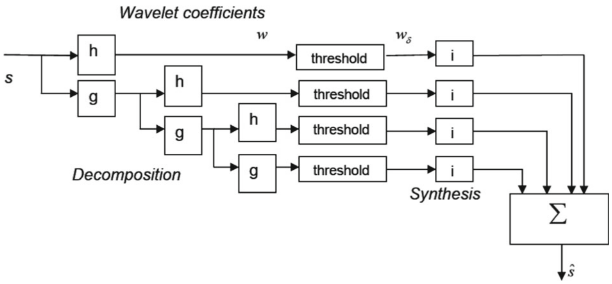

Fig. 5 Model of signal reconstruction using IDWT

- Rigrsure: The threshold is selected using the principle of Stein's unbiased risk estimate (SURE) quadrature loss function.
- Sqtwolog: The threshold is fixed at that yielding minimax performance multiplied by a small factor proportional to log (length (s)), usually $\sqrt{2\text{loglength}\,(s)}$.
- Heursure: The threshold is selected using a mixture of the first two methods.
- Minimaxi: The fixed threshold is chosen to yield minimax performance for the mean-square error against an ideal procedure. The minimax principle is used in statistics to design estimators.

4.6 Signal Reconstruction

In the final step, we need to perform multilevel one-dimensional wavelet reconstruction using either a specific wavelet or specific reconstruction filters h and g. Figure 5 shows a model of the signal reconstruction using inverse discrete wavelet coefficients.

4.7 Performance Estimation

The most suitable way to see the effect of noise added to heart sound signals is to add white Gaussian noise. After the denoising process, the performance can be measured by comparing the denoised signal with the original signal. Many methods have been proposed to measure the performance of denoising algorithms. Numerous studies have been made on heart sound signals containing a desired level of white Gaussian noise to measure the performance of denoising algorithms by calculating the SNR. The SNR is a traditional parameter for measuring the amount of noise present in a signal. The root-mean-square error (RMSE) and percentage root-mean-square difference (PRD) are also used to evaluate the performance of denoising algorithms [16,26,27]. The SNR, RMSE, and PRD can be formulated as follows:

$$\mathrm{SNR_{db}} = 10\log_{10}\frac{\sum_{n=0}^{N-1} s\,(n)^2}{(s\,(n) - s(\widetilde{n})^2)}, \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}(s\,(n) - s(\widetilde{n})^2)}, \tag{9}$$

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=0}^{N-1}(s\,(n) - s(\widetilde{n})^2)}{\sum_{n=0}^{N-1} s(n^2)}}, \tag{10}$$

where $s\,(n)$ is the original signal and $s\,(\widetilde{n})$ is the denoised signal.

5 Experimental Results

We propose herein a new technique to determine the optimal (most suitable) parameters for a wavelet algorithm to denoise heart sound signals with excellent ability to inform physicians about heart-related problems. The algorithm was tested using the most widely used wavelet families, i.e., Daubechies wavelet family from 1st to 10th order, Haar wavelets, Symlets wavelet family from 2nd to 10th order, Coiflets wavelet family from 1st to 5th order, Bior wavelet family, Rbio wavelet family, and discrete Meyer wavelet family. The tested PCG signals were contaminated by white noise added at SNR = 5 dB (as an initial value) to test the performance of the proposed technique for noise elimination. Four levels of decomposition using DWT were applied to remove the noise effectively. For each level of decomposition, we used different types of wavelet thresholding to remove the noise from the PCG signals, i.e., hard and soft thresholding with different thresholding rules (Rigrsure, Sqtwolog, Heursure, and Minimaxi), analyzing the resulting denoising performance of PCG signals. After applying a threshold at each level of the original signal, the effects of noise on PCG signals were removed. Finally, the denoised signal was reconstructed for each level using IDWT. Table 2 presents the SNR results when using the different wavelet families with different decomposition levels from 2nd to 5th with the Rigrsure threshold selection rule and the two different thresholding types, viz. hard and soft.

From Table 2, it is clear that, when choosing the wavelet family, the level of decomposition and thresholding type are important parameters affecting the SNR value. According to the SNR value analysis, the 4th level of decomposition for the discrete Meyer and Db10 wavelets shows the highest SNR values when using the soft and hard thresholding. The SNR values using Db10 are 15.4307 and 15.6019, compared

Table 2 SNR results for denoising PCG signal using different decomposition levels with the Rigrsure threshold selection rule

Wavelet type	Level 2		Level 3		Level 4		Level 5	
	Soft	Hard	Soft	Hard	Soft	Hard	Soft	Hard
Db2	10.8104	11.0108	13.6775	13.3169	12.8815	12.7652	7.0973	7.1026
Db3	10.9232	10.9405	13.7738	13.8241	13.6914	13.5312	8.0247	8.0437
Db4	11.0805	11.0154	13.8069	13.8990	13.9076	14.0201	8.2359	8.3079
Db5	11.0130	10.9492	13.6971	13.7023	14.7013	14.6126	8.6228	8.5790
Db10	10.9935	10.8748	13.8640	13.9565	**15.4307**	**15.6019**	9.0519	9.0421
Haar	10.6341	10.6759	11.6892	11.6815	9.1251	9.1515	4.7769	4.7787
Sym2	10.9045	10.8842	13.6218	13.6170	12.8547	12.9675	7.1039	7.0823
Sym3	10.9669	10.9202	13.7614	13.6657	13.6737	13.6844	8.0327	8.0012
Sym4	10.9689	10.886	13.9557	13.5922	14.1164	14.1754	8.6483	8.6499
Sym5	11.0357	11.0521	13.8969	13.7673	14.7928	14.2736	8.7134	8.7020
Sym6	10.9267	10.9575	13.6277	13.6422	14.4862	14.3950	9.2143	9.1888
Coif1	10.8791	10.9888	13.5948	13.4677	12.8927	12.7739	7.2193	7.2326
Coif2	10.8702	10.9527	13.8477	14.0135	14.0761	14.0436	8.6561	8.6607
Coif3	10.9859	10.9606	13.8659	13.8216	14.5283	14.5062	9.0621	9.0716
Coif5	10.9597	11.1185	13.8573	13.9143	15.0288	15.0281	9.1598	9.1339
Discrete Meyer	11.0522	10.9872	13.9473	13.7343	**15.3563**	**15.2460**	9.4293	9.4629
Bior1.1	10.4745	10.6092	11.6460	11.7274	9.1401	9.1347	4.7772	4.7787
Bior2.4	10.8937	10.7682	13.7009	13.6825	13.9867	13.9224	8.5754	8.5515
Bior3.3	10.2963	10.2488	12.5015	12.3509	13.3449	13.5285	7.9466	7.9030
Rbio1.1	10.6470	10.6001	11.7244	11.7539	9.1851	9.1599	4.7713	4.7890
Rbio2.4	11.0022	10.9648	13.4532	13.4290	13.0265	13.0080	7.1773	7.1723
Rbio3.3	10.2039	10.1117	10.9589	11.1743	6.2374	6.2249	−0.6818	−0.6838
Rbio4.4	10.8499	10.7636	13.6172	13.6703	13.4167	13.5002	7.8675	7.8377

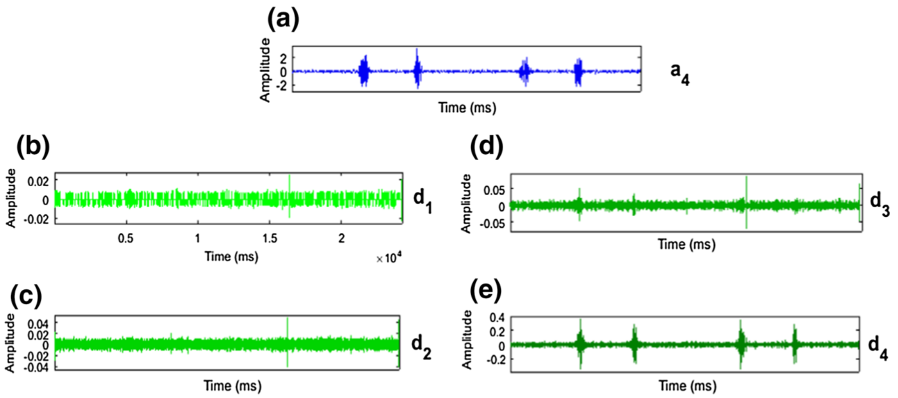

Fig. 6 Wavelet coefficients: **a** nondecimated approximation coefficient, **b** nondecimated denoised detailed coefficient of first level, **c** nondecimated denoised detailed coefficient of second level, **d** nondecimated denoised detailed coefficient of third level, **e** nondecimated denoised detailed coefficient of fourth level

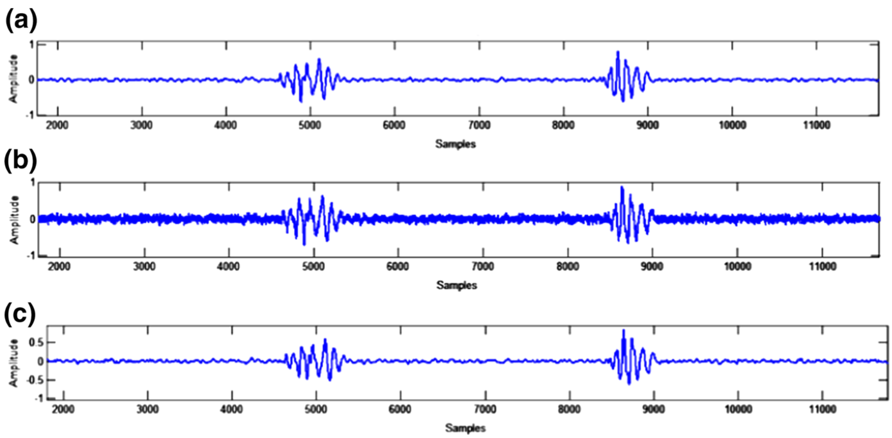

Fig. 7 Denoising of PCG signal using Db10 wavelets at 4th level with soft thresholding: **a** original PCG signal, **b** noisy PCG signal, and **c** denoised PCG signal

with 15.3563 and 15.2460 when using the discrete Meyer wavelets for soft and hard thresholding, respectively. For convenience, Fig. 6 shows the wavelet coefficients of the denoised signal, while Figs. 7 and 8 show the effect of the discrete Meyer and Db10 wavelets on denoising the PCG signal using the 4th level of decomposition. Figure 9 shows a histogram comparing the SNR values obtained when using the different wavelet families with soft and hard thresholding. Also, to study the effect of the four thresholding rules, Table 3 presents the performance in terms of SNR, RMSE, and PRD when denoising normal and abnormal PCG signals using the optimal parameters mentioned in Table 2.

Here, the Heursure and Sqtwolog selection rules perform better than the others. Rigrsure shows the maximum performance for all the wavelet families. These results show that the proposed algorithm using the Db10 and discrete Meyer wavelet families

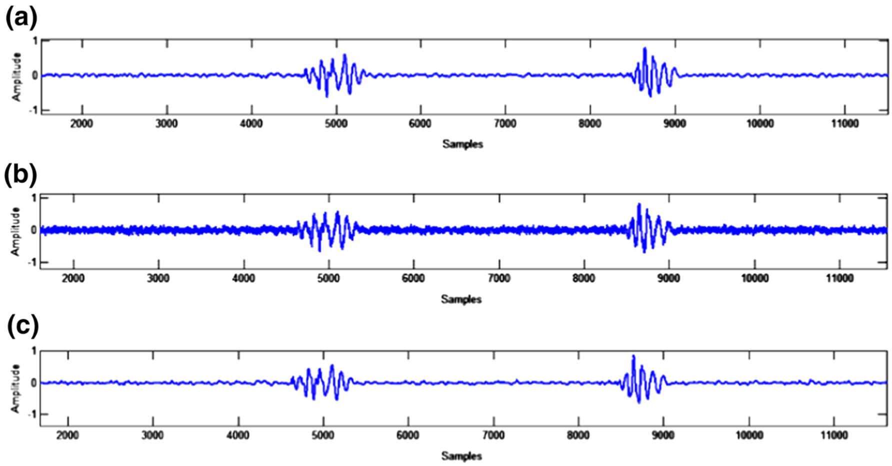

Fig. 8 Denoising of PCG signal using discrete Meyer wavelets at 4th level with soft thresholding: **a** original PCG signal, **b** noisy PCG signal, and **c** denoised PCG signal

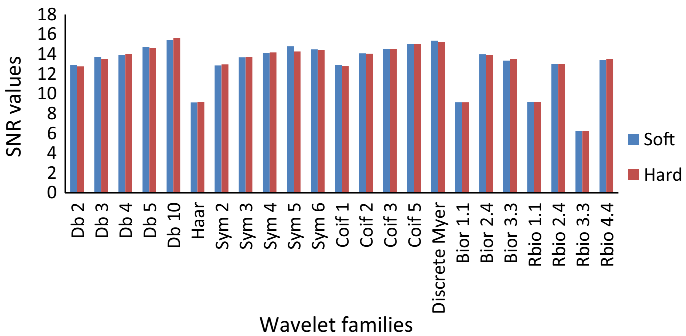

Fig. 9 Comparison of SNR values obtained using different wavelet families with soft and hard thresholding

at the 4th level of decomposition gave the maximum SNR, RMSE, and PRD values. Figure 10 shows the SNR and PRD values obtained for different PCG signals.

It is known that it is difficult to analyze PCG signals in the time domain; so, we provide PCG signals in the frequency domain. Figure 11 presents spectrograms for the noisy and denoised PCG signals to show the clarity of the heart sound components obtained after applying our proposed denoising algorithm. In the denoised PCG signal spectrogram, the heart sounds are clearer.

We also compare our results with denoising methods used in other studies, based on the SNR values. Table 4 illustrates a comparison between our results and those of other denoising methods.

Table 4 shows that our proposed algorithm achieved better SNR values compared with references [2,3,7], coinciding with the results in references [2,3], revealing that

Table 3 SNR, RMSE, and PRD values for some heart sound signals using the 4th level of decomposition with the four threshold selection rules and hard thresholding

Thresholding type	Hard																							
Wavelet function	Db10												Discrete Meyer											
Threshold	Heursure			Rigrsure			Minimaxi			Sqtwolog			Heursure			Rigrsure			Minimaxi			Sqtwolog		
Threshold parameter	SNR	RMSE	PRD%	SNR	RMSE	PRD%	SNR	RMSE	PRD%	SNR	RMSE	PRD%	SNR	RMSE	PRD%	SNR	RMSE	PRD%	SNR	RMSE	PRD%	SNR	RMSE	PRD%
Normal heart sound	14.957	0.011	17.9	14.97	0.011	17.85	15.07	0.011	17.7	15	0.011	17.89	14.91	0.011	17.97	15.44	0.011	16.91	15.36	0.011	17.1	15.14	0.111	17.5
Aortic stenosis	7.9908	0.013	39.9	7.912	0.013	40.22	7.969	0.013	40	7.97	0.013	39.96	7.872	0.013	40.4	7.832	0.013	40.95	7.894	0.013	40.3	7.895	0.013	40.3
Aortic insufficiency	6.7846	0.022	45.8	6.799	0.022	45.72	6.803	0.022	45.7	6.82	0.022	45.6	7.693	0.02	41.24	7.685	0.02	41.28	7.685	0.02	41.3	7.699	0.02	41.2
Mitral stenosis	10.134	0.007	31.1	10.06	0.007	31.39	10.11	0.007	31.2	10.1	0.007	31.34	10.8	0.007	28.83	10.83	0.007	28.74	10.87	0.007	28.6	10.89	0.007	28.5
Mitral regurgitation	1.7159	0.267	82.1	1.717	0.267	82.06	1.718	0.267	82.1	1.71	0.267	82.1	1.553	0.272	83.62	1.564	0.272	83.53	1.567	0.272	83.5	1.564	0.272	83.5
Mitral valve prolapse	6.6591	0.013	46.5	6.641	0.013	46.55	6.638	0.013	46.6	6.66	0.013	46.47	7.804	0.012	40.72	7.816	0.012	40.66	7.797	0.012	40.8	7.803	0.012	40.7
Pulmonary stenosis	7.5781	0.026	41.8	7.577	0.026	41.8	7.535	0.026	42	7.54	0.026	41.96	7.003	0.028	44.65	6.989	0.028	44.73	7.05	0.028	44.4	7.014	0.028	44.6
Atrial septal defect	13.03	0.04	22.3	13.07	0.04	22.2	12.99	0.04	22.4	11.7	0.04	22.08	13.28	0.039	21.68	13.28	0.039	21.67	13.25	0.039	21.8	13.28	0.039	21.7

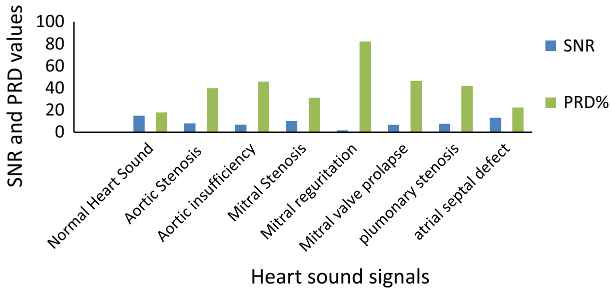

Fig. 10 SNR and PRD for different PCG signals

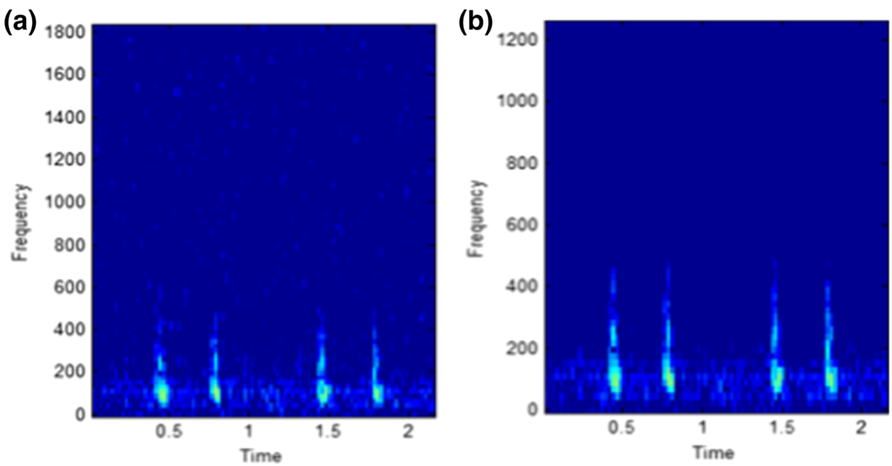

Fig. 11 PCG signal spectrograms: **a** noisy signal, **b** denoised signal

the 4th level of decomposition is the optimal level for signal decomposition. Finally, we conclude that our developed algorithm is fully automated and robust enough for noise removal. In addition, its cost of implementation is much lower compared with other techniques.

6 Conclusions

Wavelet techniques were studied for denoising PCG signals. We varied several parameters of the denoising algorithm, including the thresholding rule and wavelet family, and compared the obtained denoising results. We present the application of the wavelet transform method to PCG signal analysis. Comparison of the results obtained using the different wavelet families reveals the resolution differences among them. Since the noise level is one of the most important parameters in wavelet denoising, it was examined at different levels. We conclude that the Db10 wavelets and discrete Meyer wavelets with 4th level of decomposition give the maximum SNR and minimum RMSE for a standard heart sound. Finally, comparison of our findings with results of

Table 4 Comparison between our proposed wavelet parameters and previously proposed parameters

Study	Wavelet family	Decomposition level	Results
Abhishek et al. [2]	Coif5 and Sym6	3rd and 4th	SNR = 2.7233 and 2.723
Abhishek et al. [3]	Db2	4th	SNR = 7.6556
Feng et al. [12]	Coif wavelet family	8th	
Dawid and Redlarski [7]	Coif5	10th	SNR = 15.3 and 13
Our proposed method	Discrete Meyer and Db10 wavelet families	4th	SNR = 15.4307 and 15.6019

other studies show that our proposed algorithm achieves better SNR values. In future research, we intend to generalize our system to determine the most suitable parameters for real noisy PCG signals. Also, we aim to develop a hardware implementation to perform the proposed denoising algorithm.

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