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Wavelet Subband Dependent Thresholding for Denoising of Phonocardiographic Signals

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***Abstract*—In this paper a wavelet transform based optimum subband thresholding algorithm is proposed. This algorithm is used for denoising of heart sound signals that are highly corrupted by noise. The proposed algorithm applies signal dependent optimum thresholding to all the subbands of the signal. The algorithm is tested against different noise densities of the Phonocardiogram signal (PCG) . Experimental results demonstrate that our proposed algorithm can obtain better performances in terms of minimized value of mean square error (MSE). The most significant feature of the denoised signal obtained by this algorithm is that it can be used for accurate diagnosis of cardiovascular diseases.**

***Keywords*—Denoising, Heartsound, Mean Square Error, Phonocardiography, Thresholding, Wavelet.**

I. INTRODUCTION

Heart auscultation is a fundamental technique for non-invasive and low-cost diagnosis of cardiac disease. In this technique stethoscope is used to record the sounds produced by heart. Phonocardiography is an advanced form of auscultation. It is the graphical recording of heart sounds, which provides clinically useful information not obtainable with other methods. The processing and analysis of PCG signals allows detection of cardiac anomalies. The main disadvantage of this technique is that, at the time of acquisition, the signals get contaminated by noises [1], [2], [3]. Due to this reason the diagnostic result of PCG techniques are not very accurate. Hence a robust signal processing technique is required for denoising of PCG records so as to facilitate the accurate analysis of the signal.

Several techniques have been reported in the literature for denoising of PCG signals. Paul et al. (2006) developed method for single channel noise reduction of heart sound recordings using spectral domain minimum-mean squared error (MMSE) estimation [1]. Zhao et al. (2009) proposed a novel de-noising method for heart sound signal using improved thresholding function in wavelet domain [2]. Vikhe et al. (2009) used discrete wavelet transform (DWT) for denoising and finding split between Aortic valve closure (A2) and Pulmonic valve closure (P2) in PCG signals [3]. Boutana et al. (2011) proposed a technique that automatically selects the most appropriate Intrinsic Mode Functions achieving for denoising of heart sound signals based on Elementary movement detector (EMD) and Euclidean measure [4]. A novel wavelet-based denoising method using two-channel signal recording and an adaptive cross-channel coefficient thresholding technique was presented [11]. All these studies have come to a common conclusion that it is practically difficult to remove noise from the PCG signals. Additionally, any step towards fine denoising of the signal may result in loss of information of diagnostic importance.

The above discussed studies have also come to a common conclusion that the PCG signal is non-stationary and non-deterministic in nature. The Wavelet Transform (WT) has been found particularly useful for the analysis of non-stationary signals because of its ability to localize in both time and frequency [5]. The key feature of WT is that it uses short windows at high frequencies and long windows at low frequencies [6].

This paper introduces a novel technique for denoising of PCG signals. In this technique a WT based decomposition in which thresholding and reconstruction is adopted. To achieve the above mentioned technique, DWT based multi-resolution analysis is used. The PCG signals were decomposed into five levels using fifth order coiflets wavelet. The decomposed coefficients are thresholded using an effective and adaptive thresholding technique. The thresholded coefficients are then reconstructed, to get the denoised version of PCG signal. The experimental results demonstrate that our method can obtain better performances in terms of decrement in Mean Square Error (MSE). The proposed technique can be used as advanced pre-processing stage in phonocardiographic diagnostic systems.

The rest of the paper is organized as follows. Section II discuss about the Discrete Wavelet Transform, characterstics and the use of it in the proposed technique. Then proposed theoretical concepts are revealed in Section IV . In section V, we verify the performance of the proposed method through several experiments with the comparison between pre MSE and post MSE. Conclusion is drawn in section VI.

II. REVIEW OF WAVELET TRANSFORM

The WT [9] is a two-dimensional timescale processing method for non-stationary signals with adequate scale values and shifting in time. It is capable of representing signals indifferent resolutions by dilating and compressing its basis functions [10]. The main advantage of the WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies. A WT in which the wavelets are discretely sampled is known as the DWT. It gives the multi-resolution description of signal which is very useful in analyzing real-time signal [5]. In DWT, the original signal is decomposed into approximation and detail coefficients at the first stage while in the remaining stages the decomposition is performed on the approximation coefficients only as shown in Fig.1, which leads to the achievement of the multi-resolution analysis (MRA).

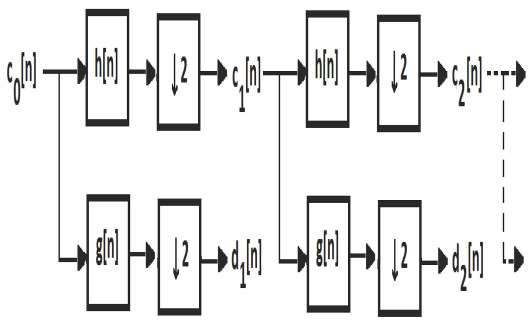

Fig. 1. Multi-level wavelet decomposition tree.

Here $c_0[n]$ denotes the signal which is being decomposed and $h[n]$ and $g[n]$ denotes response of low pass filter and high pass filter respectively. Here $c_i[n]$ and $d_i[n]$ denotes approximation and detail coefficient respectively. For reconstruction purposes at each level, after upsampling, approximation and decomposition coefficients are convolved with a low-pass and high-pass filter respectively. The reconstruction of the signal from the wavelet coefficients, as shown in Fig. 2.

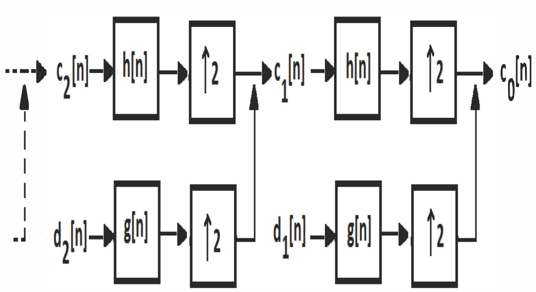

Fig. 2. Multi-level wavelet reconstruction tree.

Effective implementation of WT is based on selection and choice of wavelet family, mother wavelet and its filter order. There exists a wide variety of wavelets families. Some of these are Daubechies wavelet, Coiflets wavelet, Biorthogonal wavelet, Symlets wavelet, Morlet wavelet, Discrete Meyer wavelet and Haar wavelet. These families are used to transform the signals from one domain to another domain. They are implemented by using different ordered quadratic filters. After carring extensive experiments it is found that the presented work is suited best with the fifth order Coiflets wavelet (coif5) for analysis of PCG signals [7]. Fifth order filter is used as it gives better experimental results than other various order filters. This family is characterized by its highest number of vanishing moments. The general characteristics of this family are that it is:

- Compactly supported
- Orthogonal
- And their members are near to symmetry.

III. DATABSE

The sound materials used were recorded using a wireless data acquisition system [12]. The signals were sampled at a frequency of 8000Hz and with a 16-bit accuracy. Total 65 recording (including 10 normal, 40 abnormal and 5 fetal) were acquired from people ranging from 16-40 age groups. The whole process was carried in presence of an experienced cardiologist. The abnormal signal consists of recording from heart patients of ventricular septal defect, pulmonary valve stenosis, Mitral Regurgitation, Aortic Stenosis and Tricuspid Regurgitation.

IV. PROPOSED ALGORITHM

The overview of the proposed technique is shown in Fig. 3. After the wavelet decomposition of the PCG signals upto five levels, the noise can further be removed by wavelet denoising technique. This process retains the decomposition coefficients containing signal and removes those associated with the noise. The efficiency of denoising technique greatly depends on the choice of threshold parameter. If the threshold level is too small, too much noise will be retained. On the contrary, if the threshold level is too high, some information contained in the signal will be lost. Thus an optimum subband thresholding is used for different levels of decomposition. For optimum subband thresholding, soft thresholding is adopted [8] as hard thresholding would be too vigourous and may cause loss of diagnoistic informations. In soft thresholding, coefficients above level (λ) are also modified, they are reduced by particular value of the threshold and coefficients below level

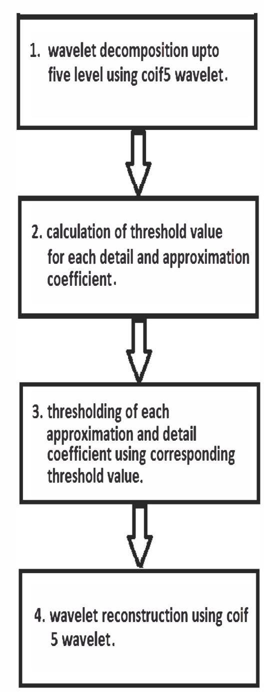

Fig. 3. Block Diagram of Proposed Algorithm.

(λ) are reduced to zero where λ can be calculated using equation (2).

$$Y_{j,k}^{soft} = \begin{cases} Y_{j,k} - \lambda, & \forall Y_{j,k} \geq \lambda \\ 0, & \forall \mid Y_{j,k} \mid < \lambda \\ Y_{j,k} + \lambda, & \forall Y_{j,k} < -\lambda \end{cases} \tag{1}$$

Here $Y_{j,k}$ denotes the coefficient value which is being thresholded and $Y_{j,k}^{soft}$ denotes the coefficient value after thresholding.
The magnitude of the wavelet coefficients vary with the decomposition level. Therefore, if all the coefficients are thresholded with same value, there are significant chances of loss of information in the resultant signal. Thus to overcome this problem, the value of threshold for each approximation and detail coefficients are calculated by determining their standard deviation and substituting it into the equation (2).

$$\lambda(k, m, n, \sigma) = \ k * m * \sigma * (2 * log(n))^{1/2} \tag{2}$$

Where, $0 < k < 1$ and $0 < m < 1$, σ is standard deviation given by equation 3 and n is number of samples [8].

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3}$$

Here σ denotes standard deviation of a vector X having N number of elements and denotes a sample value of vector x and denotes mean of the elements of vector x and $\bar{x}$ denotes mean of the elements of vector x.
In the presented work the values of k and m used are 0.8 and 0.9 respectively for detailed coefficients and for approximation coefficients it is 0.4 and 0.5 respectively (Fig. 10). After carrying out extensive experiments we found that the above mentioned value of k and m gives better results as compared to the other values of$k$ and m as shown in Table 1 and Table 2. The values of k and m used in detail coefficients are greater than that used in approximation coefficient, as the approximation coefficients contain most part of the heart signal as shown in Fig. 8. So we have to maintain a low threshold level to prevent signal content. The detail coefficients contain most of the noise so high threshold level is maintained by taking the values of k and m high. After thresholding we recovered the signal using wavelet reconstruction.

The experiments are carried out on a normal original PCG signal, at different noise level, as shown in Fig. 4 and its frequency spectrum is shown in Fig. 7. This signal is added with white Gaussian noise to form the noisy signal, whose waveform is shown in Fig. 5. The noisy PCG signal is then fed to the developed algorithm for denoising. These signals are then decomposed to five levels using fifth order coiflets wavelet up to five levels as shown in Fig. 1. The thresholding is applied to each decomposed coefficients based on the value calculated through equation (1). The thresholded coefficients are then used for reconstruction of the denoised version of the signal as shown in Fig. 4. The waveform of reconstructed PCG signal is shown in Fig. 6 and its frequency spectrum is shown in Fig. 8.

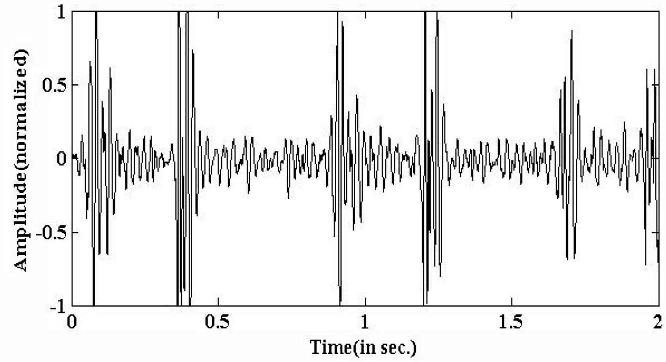

Fig. 4. Waveform of a PCG signal without noise.

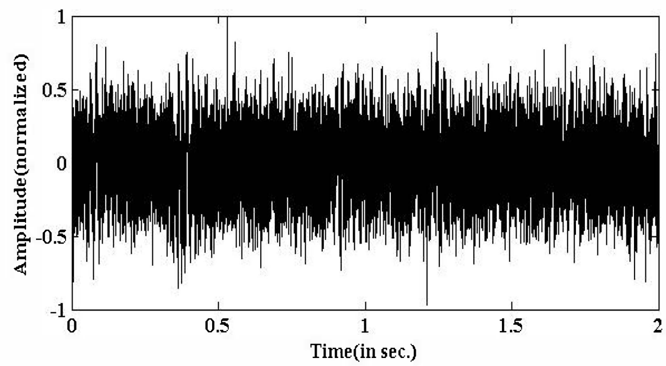

Fig. 5. Waveform of noisy PCG signal.

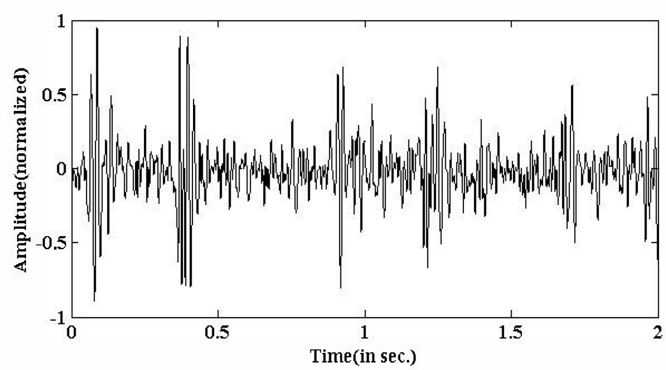

Fig. 6. Waveform of denoised PCG signals.

V. Simulation Results

The performance of the proposed algorithm is assessed by comparing the Mean square error (MSE) of signals before and after denoising. It can be obtained using following expression.

$$MSE = \frac{1}{n}\sum_{i=1}^{i=n}(y - y')^2 \tag{4}$$

where y is a signal of n predictions and y is the signal containing true values . Pre MSE and Post MSE denotes the

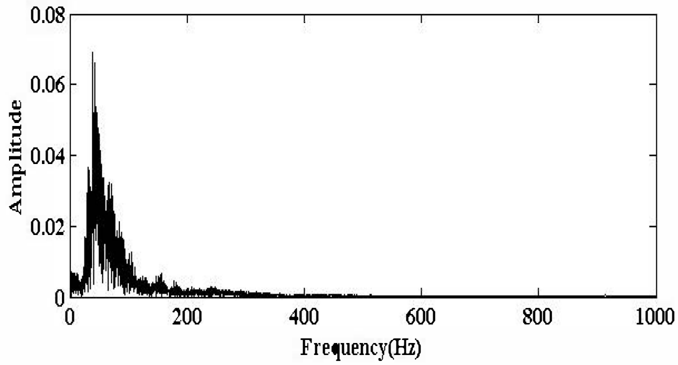

Fig. 7. Frequency spectrum of normal PCG signal(without noise).

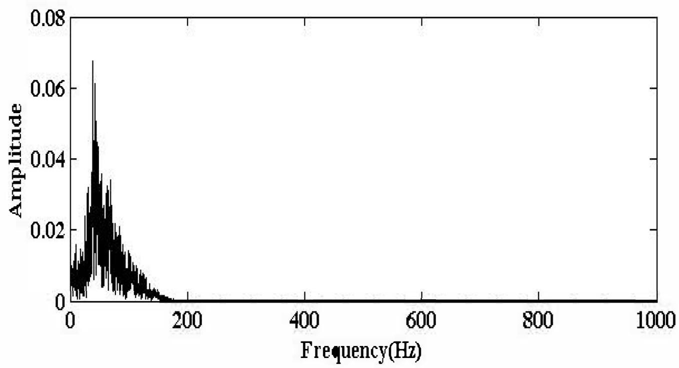

Fig. 8. Frequency spectrum of denoised PCG signal.

mean square error of noisy and denoised signal respectively with respect to the original signal.
The results of this comparison are depicted by using Table 1 and Table 2. And the graphical comparison between Pre MSE and Post MSE is shown in Fig 10.
From Fig. 10 it is clear that we get minimum MSE for k and m value 0.4 and 0.5 respectively for approximation coefficient and 0.8 and 0.9 for detail coefficient respectively.

VI. CONCLUSION

In this Paper, a new algorithm is proposed for removal of noise from PCG signals. The performance of the algorithm has been tested by adding white gaussian noise to a PCG signal

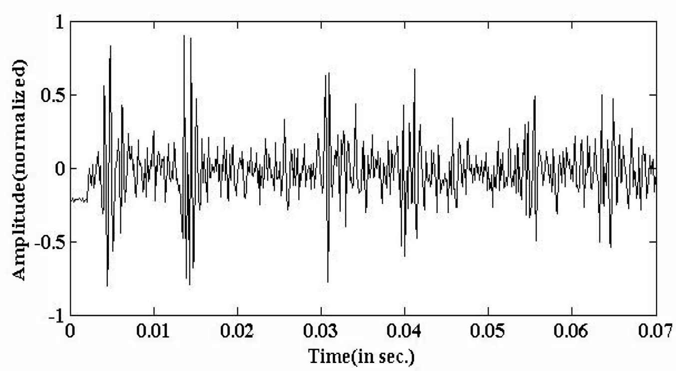

Fig. 9. Waveform of approximation coefficient after 5 level decomposition(before thresholding).

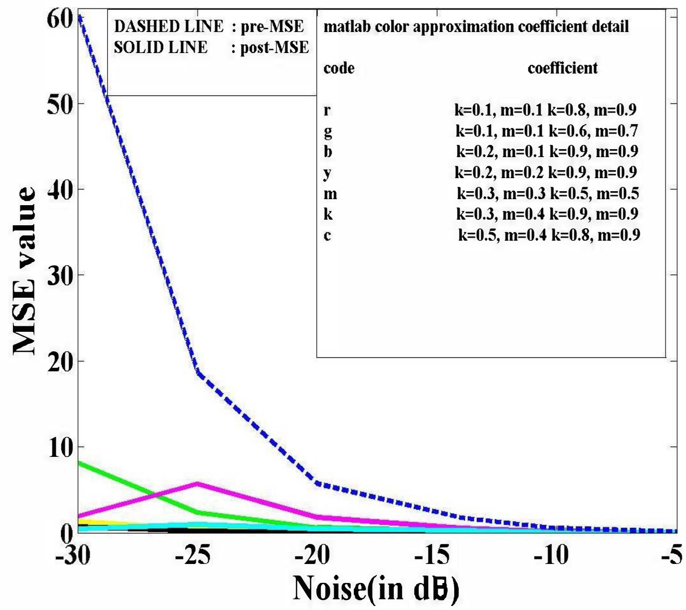

Fig. 10. Pre and Post MSE vs. noise level graph for different values of k and m.

. The results show that the proposed algorithm can decrease MSE of the PCG signals to a very high extent. This algorithm will find its application in denoising the PCG signals those are randomly corrupted during transmission for distant diagnosis.

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Serial No.	Approximation coefficient		Detail coefficient		Noise Level					
	k	m	k	m	-30		-25		-20	
					Pre_MSE	Post_MSE	Pre_MSE	Post_MSE	Pre_MSE	Post_MSE
1	0.1	0.1	0.8	0.9	60.60187	1.496061	18.65949	0.500435	5.721154	0.148886
2	0.1	0.1	0.6	0.7	60.53982	8.13183	18.80884	2.320034	5.743752	0.626664
3	0.2	0.1	0.9	0.9	61.04933	1.581737	18.83154	0.452881	5.684629	0.127573
4	0.2	0.2	0.9	0.9	60.79698	1.297721	18.75294	0.378124	5.830882	0.114023
5	0.3	0.3	0.5	0.5	60.59609	18.98203	18.89541	5.695721	5.772161	1.793929
6	0.3	0.4	0.9	0.9	61.69249	0.683711	18.64634	0.178894	5.839228	0.064402
7	0.3	0.4	0.8	0.8	60.2846	1.253498	19.18681	0.384192	5.693787	0.093946
8	0.3	0.4	0.6	0.6	60.5897	9.953008	18.91039	2.937995	5.746092	0.909758

Table 1. Pre MSE and Post MSE for different value of k and m at different noise level (in dB)

Serial No.	Approximation coefficient		Detail coefficient		Noise Level					
	k	m	k	m	-15		-10		-5	
					Pre_MSE	Post_MSE	Pre_MSE	Post_MSE	Pre_MSE	Post_MSE
1	0.1	0.1	0.8	0.9	1.748558	0.046569	0.518967	0.518967	0.156005	0.005949
2	0.1	0.1	0.6	0.7	1.715083	0.216105	0.518844	0.068701	0.155742	0.018981
3	0.2	0.1	0.9	0.9	1.746512	0.043445	0.520127	0.012401	0.157435	0.005361
4	0.2	0.2	0.9	0.9	1.773154	0.036954	0.525194	0.012091	0.155669	0.005264
5	0.3	0.3	0.5	0.5	1.721565	0.523693	0.525261	0.16162	0.158011	0.048901
6	0.3	0.4	0.9	0.9	1.743315	0.019495	0.527981	0.010999	0.157455	0.009507
7	0.3	0.4	0.8	0.8	1.705825	0.042843	0.537624	0.013194	0.156777	0.010328
8	0.3	0.4	0.6	0.6	1.719172	0.310724	0.521391	0.0889	0.158066	0.030121
9	0.5	0.4	0.8	0.9	1.739584	0.026412	0.525368	0.016753	0.158376	0.016021

Table 2. Pre MSE and Post MSE for different value of k and m at different noise level (in dB)