Performance Analysis Of Dwt Based Denoising Of Vibration Signals: A Case Study Of Heart Sound Signals

Ravindra Manohar Potdar

Bhilai Institute of Technology, Durg, India potdar.bit@gmail.com

Arun Kumar

Bhilai Institute of Technology, Durg, India arun.kumar@bitdurg.ac.in

Ramesh Kumar

Govt. Polytechnic, Simdega, Jharkhand, India rk_bitd@rediffmail.com

Abstract – Discrete Wavelet Transform (DWT) is a very powerful and effective technique to remove in-band noises corrupting any sounds arising out of vibrations. Phonocardiogram, being the record of the sounds generated by heart due to its electro-mechanical activities carry information regarding the status of cardiovascular system. Hence, the noises corrupting the PCG are required to be removed. The efficacy of denoising process largely depends upon the choices of proper Mother Wavelet (MWT) function, the number of decomposition level (DL)and the Thresholding Function (TF) applied after decomposition. The present work aims at optimal selection of the type of MWT, DL and TF to obtain lowest values of Mean Square Error (MSE) and Root Mean Square Error (RMSE). Five different types of orthogonal MWT, DL up to 10 and seven TFs are applied for analysis of performance of the denoiser.

The performances of every combination are compared through exhaustive experiments performed in the MATLAB environment. After analyzing the results obtained, it was observed that sym20 as the MWT with a DL of 10 with a soft TF namely Bayes Soft in removing noises from PCG.

Keywords – Denoising, DWT, MSE, PCG, RMSE, Vibration Signal

I. INTRODUCTION

Phonocardiogram signal is of interest for condition based monitoring of cardiovascular functions and the physiological status of the heart. Heart is considered as an electro-mechanically initiated pump with two stages and four chambers. The main job of the heart is to circulate blood throughout the body to supply energy for their functioning using oxygenated blood and at the same time to collect the impure blood from the organs. The vessels associated with the heart are responsible for carrying the blood. The flow of blood is controlled through the valves instilled in the heart. The pressure built inside the heart due to its rhythmic contraction and expansion controls the opening and closing of the heart valves. Such phases of the heart are commonly known as systolic and diastolic phase. Sound is created during any mechanical activity so as the heart also creates sound. The frequency may or may not be in the audible range. The sound created due to functioning of the heart normally falls in the audio range of frequency and hence is audible by using an acoustic arrangement called the stethoscope. To monitor the activities occurring in the cardiovascular system, physicians often take the help of stethoscope to hear the sounds generated by the heart. This is the cheapest method of monitoring and diagnosis in a non-invasive manner for any disorder occurring in the cardiovascular system. However, this technique being very much subjective solely depends upon the skill, experience and expertise of the concerned physicians for accurate diagnosis. Hence, to avoid any medico-legal litigation, the physicians normally refer the patient for costly diagnostic tests involving automated techniques. The major hindrance in feeling the heart sound captured by stethoscope is that it does not support visual display. Phonocardiogram (PCG), which is an electronic record of the heart sound signal (HSS), helps to obtain audio-visual record of the heart sound signal with graphical display. Thus, PCG can be exploited for enhancing the efficacy of the diagnostic system as well as can be effectively used for training, experimentation and future record purposes [1].

Heart sound signals lying in the audio frequency range are due to closing and opening of the heart valves due to pressure variations inside the heart chambers, vibration arising in the heart walls and flow of blood through the vessels attached to heart. Such audible sounds are marked as heart sounds and heart murmurs. Both of them are important from the diagnostic point of view. Primarily there are two heart sounds marked as S1 (First sound) and S2 (Second sound). Apart from these two sounds sometimes additional sounds marked as S3 (Third sound) and S4 (Fourth sound) also arise during activities of the heart. Normally these heart sounds fall in the lower band of frequency of HSS frequency band. Heart murmurs are those types of sounds which occur either during systole phase or diastole phase or during both the phases. Heart murmurs are broadly classified into two categories: innocent murmurs and pathological murmurs. Innocent murmurs are normal murmurs whereas pathological murmurs are caused due to presence of some sort of defects in the cardiovascular system [2].

The electronic record of HSS is called PCG. Such records are useful in Automated Computerized Auscultation (ACA) in monitoring the functioning of the heart to assist the physicians to diagnose accurately. Unfortunately, during acquisition of HSS, the signal is corrupted by noise due to external as well as internal sources. Some of the noises lie in the same frequency band as that of the HSS. Hence, for accurate decision to be taken based on the acquired signal, it is to be made free from any noise. Here comes the need of a denoiser that can remove the noise part contained in the signal without any loss of information carried by the signal.

The information contained in a time series signal is not readily observable. Moreover, PCG is a non-stationery and irregular type of signal. Hence, denoising technique using transformation of the original signal in frequency domain, time domain and time-frequency domain is most suitable. Fourier transform (FT) is a well-known and widely used transformation technique to convert any signal in time domain into frequency domain. Unfortunately, FT cannot be used in the case of a non-stationery signal due to its variation in frequency components in an irregular manner with time. Short Time FT (STFT) is an alternative of FT that is employed for non-stationery signals to denoise. STFT decomposes the signal in time-frequency domain using windowing technique where a time window of short duration is utilized to extract a small portion of the signal in time and FT is applied on that portion. The window is then shifted sequentially to cover the whole duration of the signal. Use of wider window enhances the frequency resolution but reduces the time resolution; on the other hand, narrower window improves the time resolution but degrades the frequency resolution. This restricts the wide use of STFT. Variable window size is a better alternative to address the fixed size window problem. Such technique is known as Wavelet Transform (WT). Discrete Wavelet Transform (DWT) is a variant of WT. A time domain signal is decomposed in different frequency bands to determine detail and approximate coefficients using suitable filter banks comprised of high pass filter (HPF) and low pass filter (LPF). Thereafter using suitable thresholding techniques looking into the nature of the noise, the signal is denoised and finally the denoised signal is reconstructed using Inverse DWT (IDWT). DWT is a suitable means to denoise non-stationery signals [3].

A wavelet is considered a small part of a wave with its amplitude starting from zero then increases to reach a maximum value and again diminishes back to zero. The uniqueness of wavelets is that a single function called scaling function that is the solution of a linear renormalization group equation is required to generate wavelets by combination of translations and scaling. Scaling functions having a fractal like structure demand a different approach for numerical analysis [4].

DWT is a type of transformation of a signal that disintegrates the signal into sets of time series coefficients in the corresponding frequency bands. The converse of DWT is Inverse DWT (IDWT) that reconstructs the signal into its original form by manipulating the coefficients obtained during disintegration. The wavelets primarily localize features of the signal to different scales preserving the important features of the signal. Wavelet coefficients with relatively smaller amplitudes arise due to the noise part corrupting the signal. Such coefficients with smaller amplitudes do not contribute to the signal quality and can be effectively removed without any compromise with the signal quality. After removing these small valued features using thresholding technique the signal can be reconstructed applying Inverse DWT [3].

Mother wavelets (MWT) are nothing but transformation functions from which Daughter Wavelets can be extracted through scaling and translation. An MWT is a windowed function that is slided along the time-series signal for the whole duration of the signal in smaller window duration. The MWT function is multiplied by the part of the signal under consideration which is covered by the window. To obtain the wavelet coefficients, this is integrated over the whole time duration of the window. The width of this window is technically called the support of the window [5].

Decomposition of the signal under consideration to obtain the wavelet coefficients termed as Approximation coefficients and Detail coefficients is accomplished by employing DWT filter bank. In the subsequent stage, thresholding is carried out to remove the portions of the signal contributed by noise and finally the original signal is reconstructed or synthesized by IDWT filter bank [6]. The filters in the filter bank are LPF and HPF type. The performance of the noise removal process effective ly depends upon the type of MWT selected, the number of Decomposition Level (DL) and the Thresholding Function (TF).

Selection of the type of MWT, the TF and DL are of prime importance leading to best performance of the denoising process. They can be suitably selected by carrying out rigorous experiments with adequate number of combinations of these factors [7]. Generally the metrics used for performance evaluation of denoisers are Signal to Noise Ratio (SNR) and Root Mean Square Error (RMSE).

II. LITERATURE REVIEW

Due to the nature of heart sound characteristics and associated acquisition process, the HSS contains lot of noises. Hence, it is of prime importance that during the preprocessing of the signal, the PCG must be denoised properly so that information contained in the signal does not get lost in noise leading to wrong diagnosis. The following paragraphs provide a brief review of works reported by previous researchers in this direction. L T Hall et. al. (2000) [8] demonstrated a solution for denoising the PCG signal using wavelets and made a comparison between its performance with that of conventional Fourier transform based decomposition. They concluded that due to fewer numbers of coefficients being handled in wavelet-based decomposition it exhibited superiority in denoising with lesser operational complexity. Moreover, they also commented that background noise could be drasticall y reduced by using thresholding operation. Jawerth and Sweldens (1994) [9] investigated four different models of denoising HSS using FFT, Square and LPF, Hilbert Transform and Wavelet based decomposition. They pointed out that although the four models provided clear segmentation of cardiac cycle yet the wavelet based method provided most accurate results in detecting abnormalities in function of the heart. Williams (1997) [10] explored the extraction of TF features of PCG signal highlighting the choice of wavelet detail of both Packet Wavelet Transform (PWT) and DWT. They observed that the morphology of internal components is much more affected by PWT than by DWT. They suggested that db10 is the most suitable MWT for appreciable performance in providing information regarding the clicks and murmurs. Arafat (2003) [11] used Coif-5 as the MWT for denoising the PCG signal. In order to optimize the performance of the traditional DWT method, they combined an adaptive thresholding technique, a nonlinear intermediate function method and a generic algorithm. Their proposed technique showed an improvement in denoising performance by eliminating the out-of-band noises and removing the lower detail level coefficients. Ali et al. (2017) [12] examined the effect of types of MWT and DL on the noise removal performances. They posted the conclusion that db10 wavelet and discrete Meyer wavelet with DL of four provided the highest value of SNR and the minimum RMSE during denoising operation. Zheng et al. (2017) [13] presented a denoising model combining the modified Singular Value Decomposition (SVD) and Compressed Sensing (CS). They pointed out that the proposed model of denoising maintains the morphological characteristics of the PCG. They concluded that compared to conventional techniques such as DWT and Empirical Mode Decomposition (EMD), the proposed model provided higher SNR value maintaining the highest correlation with the original PCG. Mondal et al. (2018) [14] denoised the PCG signal using a combination of DWT framework and SVD. They selected the most abundant nodes in the wavelet tree and suppressed the noise part from PCG corresponding to the selected nodes by employing SVD. Deng and Han (2018) [15] in their work presented a denoising model based on adaptive denoising algorithm. They reported that the adaptive denoising algorithm exhibited better denoising performance compared to the standard denoising algorithms. Zhang et. al. (2020) [16] applied DWT based denoising for weak signals obtained from underwater targets using a newly proposed thresholding function to overcome the shortcomings of hard and soft thresholding functions. They reported a better denoising effect in terms of SNR and RMSE using the proposed method of thresholding.

III. MATERIALS AND METHODS

The denoising capability of a DWT based denoiser depends largely upon the proper detection of the MWT function, suitable number of DL and the nature of TF. However, there is no mathematical relationship to optimize the selection. Hence the performances of different combinations of mother wavelet, number of decomposition level and thresholding function are compared on the basis of performance metrics like SNR and RMSE for optimal performance. The coding for conducting the experiments as suggested is done under MATLAB environment. The materials and the theoretical backgrounds of the methods adopted for such comparison are discussed in the following paragraphs.

A. Datasets used

Physionet [17] is a reliable source for datasets of PCG signals for monitoring purpose. .wav format is used to store the datasets. Sampling frequency of 2 KHz is used to record the PCG signal with duration varying between 5 seconds and 120 seconds from adults and children in clinical environment.

Out of 3153 samples available in the dataset, 665 samples are abnormal type marked as 1 and the rest are normal type PCG marked as -1. In the present work, -1 and 1 are replaced by 1 and 0 respectively for the sake of convenience.

B. DWT Based Denoising

DWT exhibits Multi Resolution Analysis (MRA) capability [18] and hence is suitable for the extraction of discriminant multi-scale features. Also the features present at high and low frequency spectrums of the signal are preserved and thus the peaks and valleys present in the spectra remain intact [19]. DWT effectively segregates the detail and approximation coefficients in the form of fine-scale and coarse-scale information contained in the signal under consideration. From these coefficients, the multi-scale features of the signal under consideration can be mined without any loss of information contained in the signal.

A short portion of a signal represented in the time domain in which the energy is concentrated is known as wavelet function with its energy preserved. Such signals with small duration are often termed as “Mother Wavelet” from which “Daughter Wavelets” can be derived by scaling and dilation mechanism. Wavelet transform is a mathematical transformation tool used for better understanding, interpretation and effective processing of a signal particularly non-stationary type like PCG.

Inner products, like Fourier analysis, may be used to decompose any signal using this collection of orthogonal sample data. FT and WT differ in that FT decomposes the signal in the frequency domain only, while using shifting and scaling capabilities of WT, it can decompose the signal in frequency as well as time scale [10]. Based on the scaling and translation techniques, WT are classified as Continuous WT (CWT) and Discrete WT (DWT). DWT has been proved to the most powerful transformation tool in analyzing and processing non-stationery signals. The mother wavelets utilized in DWT vary from those used in CWT [20].

DWT divides the signal into various sub-bands in different frequency ranges with their high and low frequency components at each band. By inspecting the output of the filters at different levels, the signal may be detailed. This method is known as wavelet decomposition, and it is a relatively new contribution to multiscale signal processing applications. The Wavelet Filter emphasizes a signal in the appropriate spatial frequency domain or details it. Constellation of Low Pass Filter (LPF) and High Pass Filter (HPF) forms the filter bank used in DWT based decomposition of a signal. The filter bank is used to expand or compress a segment of the signal lying within a specific frequency range. This filter bank generates the approximation and detail coefficients of a signal at various frequencies of interest in the spatial domain. Wavelet Packet Decomposition (WPD) is the decomposition of a signal for detailed study using wavelet packets. WT gives approximation and detail components at each level of breakdown. These approximate components are then further decomposed to produce additional approximate and detailed components. As a result, complex components of the signal under examination are acquired at each level of decomposition. The number of levels is limited by the amount of signal information needed in the frequency domain. WPD is a very accurate signal analysis approach that focuses on abstracting information in the signal at higher frequency ranges. Because the signal of non-stationery nature is usually investigated in a time-frequency domain differentiating the noise signal and information bearing signal at different frequencies of interest, DWT is more suitable for this purpose. Noise is represented as a continuous high-frequency signal across the time span in this methodology, making its detection simpler than using Fourier analysis. The following paragraphs will discuss each of the three essential processes of DWT de-noising: (i) Decomposition by DWT filter bank, (ii) Thresholding, and (iii) Reconstruction by IDWT filter bank [21].

C. Decomposition of HSS using DWT filter bank

To decompose a non-stationery signal for denoising using DWT, the signal under consideration needs to be analyzed at various frequency levels to highlight the signal components at those frequencies, digital filter banks are applied [22]. Convolution and WT are the major functions need to be performed for the implementation of a digital filter bank.

WT exhibits superiority in localizing the signal in frequency as well as spatial domains, DWT becomes an obvious choice for the detection and cancellation of the noise part embedded in HSS. Convolution between the impulse coefficients of the selected MWT and the signal is used to perform filtering operation. Down sampling by base-2 of the signal is performed after the convolution operation yielding the coefficients and more particularly the outputs of LPF generates Approximation coefficients whereas the HPFs generate Detail Coefficients. The basic unit is explained through a self-explanatory diagram presented in Fig. (1) below:

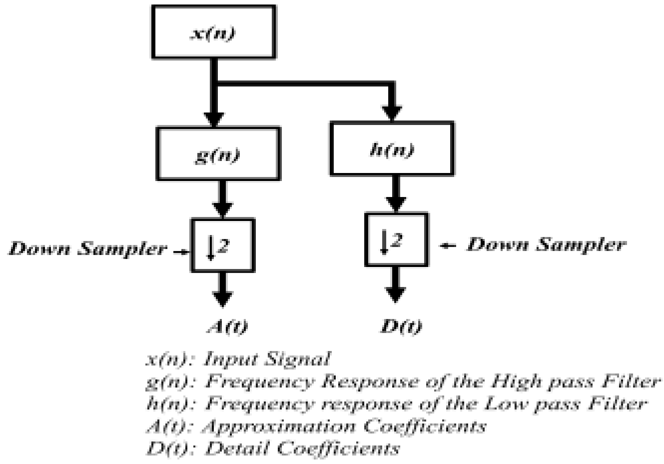

Figure 1. Basic Unit of Digital Filter Bank

Such basic units are cascaded to create a filter bank for signal decomposition for better frequency resolution in the form of detail coefficients at each level. The outputs of the HPF are represented as Detail coefficients and are restricted to coarser scale whereas the outputs of LPF, known as Approximation coefficients, are observed at finer scale. The approximation coefficients are used as the input to the following level, and these approximation coefficients are separated further into approximation and detail parts repeatedly, called Decomposition Level (DL). The resolution coefficients will increase as the number of DL increases. When using DWT, the frequency resolution rises as the DL increases, but the time resolution drops. The number of DL to be used is determined by the resolution requirement. Fig. (2) depicts the whole structure of the digital filter bank's decomposition tree, with D_1, D_2,.... D_n denoting the associated detail coefficients at each level whereas A_1, A_2,.... A_n are the corresponding approximation coefficients.

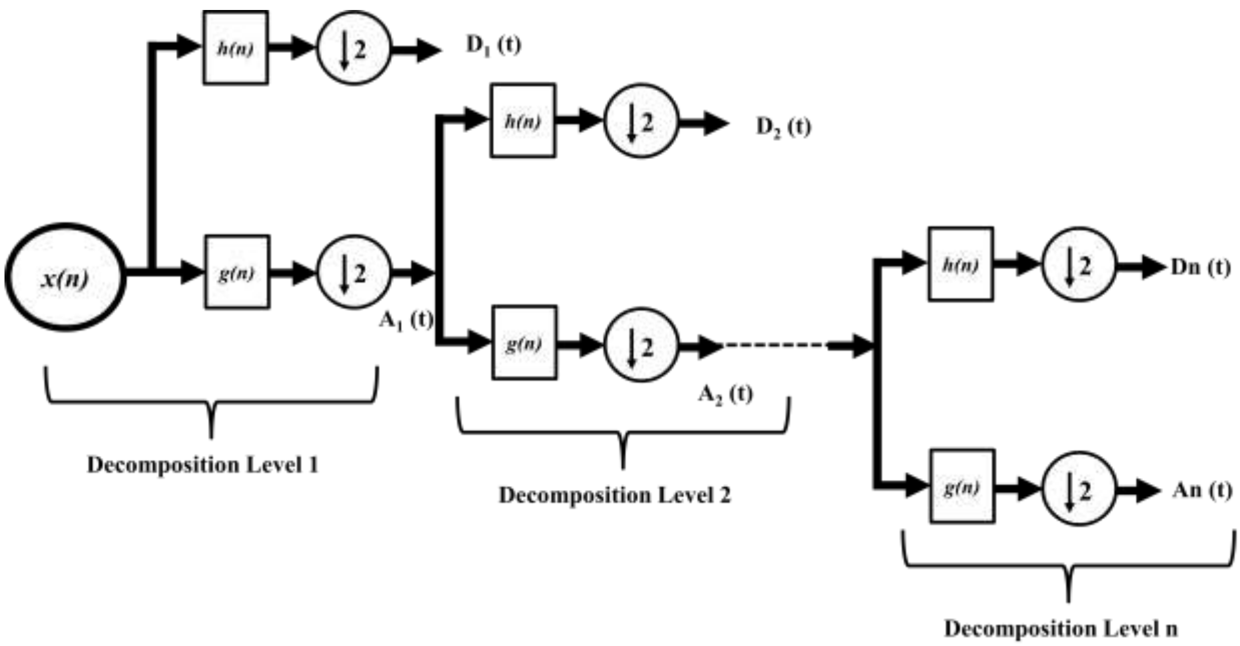

Figure 2. Block Diagram of the Filter Bank Implemented

The decomposed signal is then examined to determine the existence of different frequencies at different points of time, and the signal may subsequently be changed to eliminate noise at high frequencies by a process called thresholding. In MRA, the signal is composed of two parts: a smooth ("coarse") component that reflects the signal's essential characteristics (approximation signal) and a detailed ("fine") portion that represents the signal's details [23]. In this paper, MATLAB scripts were developed to create a filter bank and, lastly, to reduce noise.

D. Thresholding

Thresholding is a non-linear operation performed on the coefficients of the decomposed signal to remove the noise portion embedded in a signal bi amplitude scaling. A threshold value is decided depending on the nature of the signal and the requirement for the purpose. The amplitude of the signal at a particular frequency will be adjudged acceptable or not depends upon the threshold value of the Thresholding Function (TF). Normally the noise portion in the signal is found either in the higher band of the frequency or in the lower band. Hence the coefficients obtained through DWT based decomposition solely contain the noise signal corrupting the signal. In case of PCG, it is observed that the noise present in the signal lie in the higher band of frequencies and to eliminate them thresholding can be effectively applied. Proper selection of thresholding function as well as threshold parameter plays an important role in removing the noise [24].

Depending on how the selected coefficients are pulled down to zero, the TFs are categorized into two types: Hard TF and Soft TF. In Hard TF, the coefficients are equated to zero if they are less than the threshold level are equated to zero whereas the coefficients having values more than the threshold level are retained. As there appears a step change in the transfer function of Hard TF, it may sometime cause oscillation. On the other hand, in Soft TF, the transfer function does not exhibit any sharp transition and are more suitable for denoising purpose [3] as is clear from Fig. (3). Thus Soft TF provides a better continuity. ‘rigrsure’ [25], ‘heursure’ [26], ‘sqtwolog’ [27], and ‘minimaxi’ [27] are the most common types of Soft TF used for denoising PCG signal.

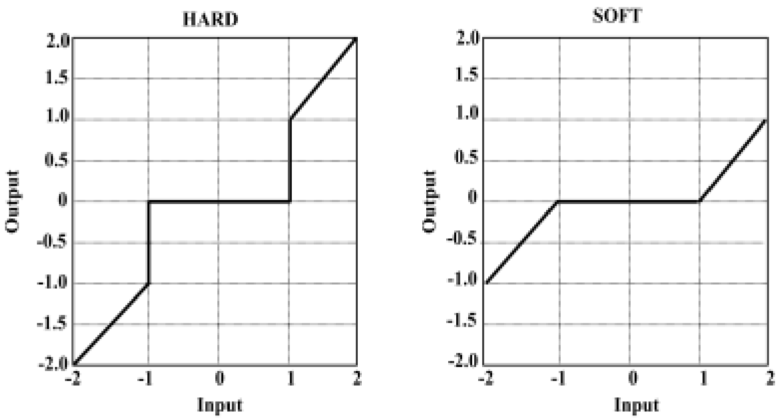

Fig.3: Thresholding Functions

Selection of the thresholding value greatly influences the processing of reducing the noise part from the signal maintaining the major information contained in the signal. A large value of threshold may lead to curbing of important information contained in the signal whereas a very small threshold value may not be efficient to make the signal noise free. As such there is no mathematical relationship [25] for the selection of the threshold value and hence a trial and error method based on rigorous experiments have been adopted.

E. Reconstruction of HSS using IDWT Filter Bank

After cleaning the noise from the signal using decomposition technique applying DWT, it needs to be reclaimed to make it noise free signal. This process is known as reconstruction alias synthesis. The inverse of DWT is used for this purpose. Technically, it is termed as IDWT synthesis. The qualities of the signal remain intact during synthesizing from its sampled values [28].

During reconstruction, the detail coefficients and approximation coefficients obtained at the outputs of the thresholder are first up-sampled by two by adding zero in the middle of the sampled signals synthetically boost the sampling rate. These original samples are then passed through HPF and LPF. The outputs of the filters are then added as many number of DL as done during decomposition.

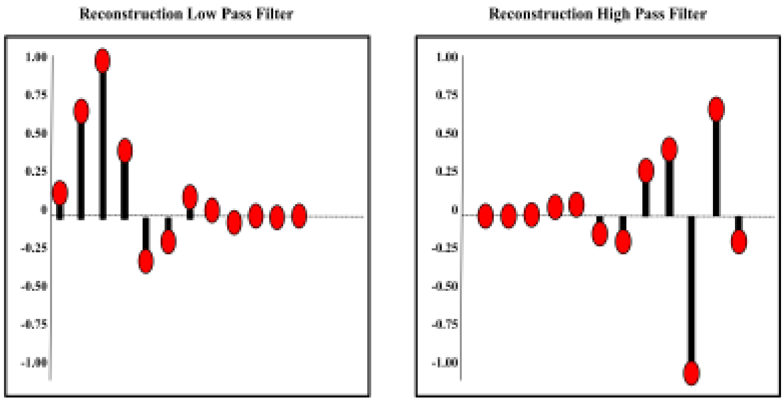

Figure. 4. Typical outputs of reconstruction LPF and HPF

The work flow of denoising thus include (i) decomposition by DWT to obtain the detail and approximation coefficients, (ii) thresholding of the coefficients to remove the noise part through proper selection of the threshold value, and finally to (iii) reconstruct the signal under consideration using IDWT. The block diagrammatic representation of the process is presented in Fig. (5) below, where x(n) and y(n) are the signals corrupted by noise and signal free from noise respectively.

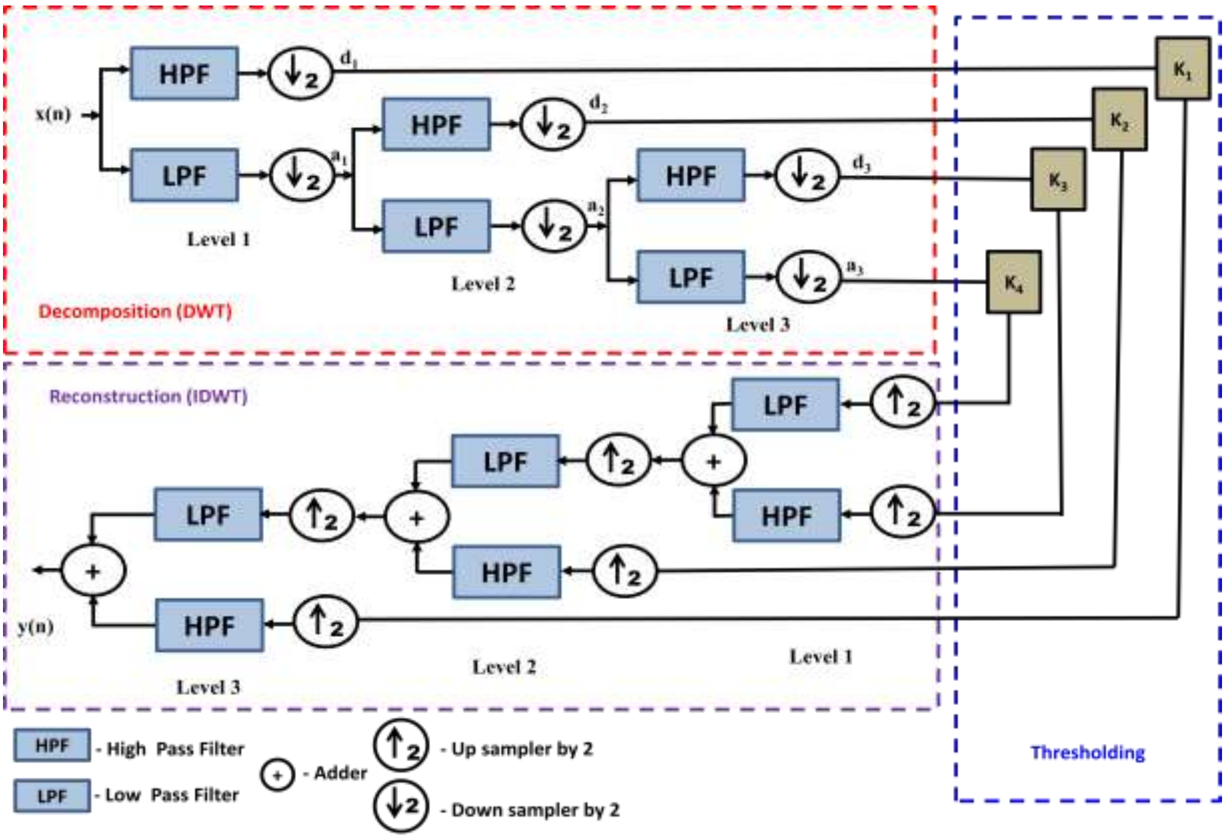

Figure 5: Block diagram of DWT based decomposition and IDWT based reconstruction for denoising HSS

F. Mother Wavelets under Consideration

In order to optimize the selection of the suitable MWT, experiments are performed using five different types of wavelet families including Daubechies (db), Coiflets (coif), Symlets (sym), Biorthogonal (bior), and Reverse Biorthogonal (rbio) wavelet families.

The nature of the wavelets are guided by few characteristics of the MWT such as the scaling function, orthogonality nature, symmetry or irregularity, the length of the support and number of vanishing moments in it. Hence selection of the MWT for the denoising purpose using DWT technique is of prime importance. In order to maintain the energy and entropy of the signal under consideration for denoising, orthogonal or bi-orthogonal MWT are used so that after denoising the important information in the signal remain intact.

A collection of orthogonal MWT is contained in Dahbechis (db) family. Vanishing moments are at maximum for some given length of support is the main characteristics of db family wavelets. db families have orthogonal and compact support abilities. The scaling function corresponding to each MWT is also known as Father Wavelet that generates an orthogonal MRA. In the db wavelet family, the duration of the support is always double to that of the vanishing moments. The db MWTs are not symmetric. Symlets (sym) MWT family is very close to db family but having the major difference that it is an asymmetric type of wavelet. It is very compact, orthogonal and type continuous. It is very much suitable for retaining the energy and entropy of the signal under consideration for noise removal. Coiflets (coif) family of wavelets is more symmetrical compared to db family. Its computational overhead is higher than that of the db family of MWT. Biorthogonal (Bior) MWT families of wavelets are characterized by the property of linear phase, which is favorable for signal synthesis purpose. Designing biorthogonal wavelets allows additional degrees of freedom than orthogonal wavelets. Reverse biorthogonal (rbior) wavelet family is obtained from biorthogonal wavelet pairs.

G. Parameters to Measure the Performance of the Denoiser

To deal with the optimization problem, twenty-two PCG signals from open sources are considered. The PCG signals considered are of different nature and types containing normal as well as abnormal arising out of various defects in the functioning of the heart. Orthogonal MWT like db, coif, sym, bior, and rbio are used with varying DL. For thresholding purpose seven different types of soft TF are used. The parameters used to measure the performance of the denoiser are Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE). A value of 16 – 24 dB of SNR marks a satisfactory performance for PCG denoiser [28]. The SNR in dB is calculated as per the following formula:

$$\mathrm{SNR} = 10\log_{10}\left[\frac{\frac{1}{\mathrm{N}}\sum_{\mathrm{n}=1}^{\mathrm{N}}\left(\mathrm{x_a}(\mathrm{n})\right)^2}{\frac{1}{\mathrm{N}}\sum_{\mathrm{n}=1}^{\mathrm{N}}\left(\mathrm{x_a}(\mathrm{n})-\mathrm{y}(\mathrm{n})\right)^2}\right]$$

The issue concerned to sample size can be avoided by using RMSE. Values of RMSE lie between 0 and 1. A value of RMSE less than 0.08 is considered to be satisfactory good fit for a PCG denoiser [22]. RMSE is calculated according to the following formula:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{n}=1}^{\mathrm{N}}[\mathrm{x_a}(\mathrm{n})-\mathrm{y}(\mathrm{n})]^2}$$

Where

N = Time length of the signal

$x_a(n)$ = Acquired PCG signal corrupted with noise

y(n) = Denoised PCG signal

IV. RESULTS

Rigorous experiments in MATLAB environment are conducted using 73 MWT consisting of 20 from db family, 20 from sym family, 5 from coif family, 14 from rbio family and 14 from bior family. The DL is varied from 1 to 10 for decomposing the signal into detail and approximation coefficients. Soft TFs like Minimax, Universal, Block James Stein, Bayes Mean, Bayes Median, Bayes Soft and Sure threshold are applied for the thresholding purpose. The results in terms of SNR and RMSE are presented in tabular form as shown below.

Table#1 exhibits the values of SNR obtained for various types of TFs used as discussed earlier for different MWTs. A single PCG signal out of 22 PCG signals obtained from open data source was considered for performing the experiments. Only the best performances in terms of SNR are tabulated for presentation. The best performances are highlighted. For example, in row 1 of Table 1, TF used is Minimax, DL varies between 1 to 10 and all the MWTs selected are applied out of which db20 provided the best result at DL6.

TABLE 1 SNR FOR VARIOUS COMBINATION OF MWT, DL AND TF

Sl. No.	**Type of TF**	**MWT**	**DL 1**	**DL 2**	**DL 3**	**DL 4**	**DL 5**	**DL 6**	**DL 7**	**DL 8**	**DL 9**	**DL 10**
1	Minimaxi	db20	5.00	8.00	11.02	14.01	17.01	19.70	16.09	13.78	13.06	13.04
2	Universal Threshold	sym20	5.01	8.03	11.03	14.04	17.07	19.78	15.25	12.66	11.89	11.88
3	Block JS	rbio5.5	4.91	7.93	10.98	14.00	17.00	18.83	19.67	20.06	20.21	20.23
4	Bayes Soft	sym20	5.00	8.00	11.01	14.02	17.00	19.70	20.53	20.81	20.97	**21.12**
5	Bayes Mean	db19	5.00	8.01	11.00	14.03	17.03	19.73	20.17	20.17	20.17	20.20
6	Bayes Median	sym18	5.00	8.01	11.02	14.05	17.06	19.73	20.50	20.81	20.96	21.07
7	SURE (Steins Unbiased Estimate of Risk)	sym20	5.01	8.02	11.02	14.04	17.04	19.74	20.48	20.68	20.80	20.96

From the data obtained through experiments and tabulated in Table 1, it is evident that as far as the SNR is concerned, the best performance is provided by the combination of sym 20 as MWT with DL= 10 and Bayes Soft as the TF.

Table 2 provides the characteristics of the PCG signals used for the experiments conducted for the purpose of comparison.

TABLE 2 THE LIST OF PCG SIGNALS USED

ID No.	**Types of PCG signals**	**ID No.**	**Types of PCG signals**
PCG # 1	S1 & S2 (Normal)	PCG # 12	S3 and holo systolic murmur
PCG # 2	S1 (Split)	PCG # 13	Mitral opening snap and dystolic murmur
PCG # 3	S4 (Gallop)	PCG # 14	S1 & S2 Aortic (Normal)
PCG # 4	Click (Midsystolic)	PCG # 15	Aortic Stenosis
PCG # 5	S3 (Gallop)	PCG # 16	Aortic early diastolic murmur
PCG # 6	Murmur (Early systolic)	PCG # 17	Aortic stenosis and regurgitation
PCG # 7	Murmur (Mid systolic)	PCG # 18	N single S1 pulmonic
PCG # 8	Murmur (Late systolic)	PCG # 19	Split S2 persistent pulmonic
PCG # 9	Murmur (Holo systolic)	PCG # 20	Pulmonic split S2 sp
PCG # 10	Systolic click with late systolic murmur	PCG # 21	Ejection systolic murmur S2 splitting
PCG # 11	S4 and late systolic murmur	PCG # 22	Ejection systolic murmur S2 split pulmonic

The next experiment conducted is to check the denoising performances based on average value of SNR for the best combinations of the MWT, DL and the thresholding functions for all the PCG signals as shown in Table#3. The combinations that produce the best result (as per Table 1) are applied.

TABLE 3 AVERAGE VALUES OF SNR FOR VARIOUS COMBINATIONS OF MWT, DL AND TF
(Only the best results obtained are presented)

Sl. No.	Types of PCG signals	Minimaxi TF (MWT: db20) (DL=6)	Universal TF (MWT: sym20) (DL=6)	Block JS TF (MWT: rbio5.5) (DL=10)	Bayes Mean TF (MWT: db19) (DL=10)	Bayes Median TF (MWT: sym18) (DL=10)	Bayes soft TF (MWT: sym 20) (DL=10)	SURE TF (MWT: sym20) (DL=10)
1	PCG # 1	20.090	20.02	23.22	24.23	21.86	23.56	23.45
2	PCG # 2	20.100	20.04	22.79	23.57	21.70	23.07	23.17
3	PCG # 3	19.720	20.02	22.54	23.64	21.50	23.14	22.98
4	PCG # 4	19.210	20.04	22.62	23.85	21.34	23.21	23.08
5	PCG # 5	19.500	20.02	22.40	23.42	21.24	23.32	22.91
6	PCG # 6	17.670	20.02	20.63	21.93	20.65	21.7	21.82
7	PCG # 7	14.820	15.83	19.36	19.59	17.89	19.17	19.54
8	PCG # 8	19.140	18.85	20.70	21.09	19.78	20.59	21.25
9	PCG # 9	16.250	17.02	19.33	19.66	17.90	18.98	19.72
10	PCG # 10	18.740	19.71	21.81	23.03	20.75	22.85	22.39
11	PCG # 11	16.860	18.38	19.96	20.35	18.93	19.88	20.30
12	PCG # 12	15.420	16.75	19.34	19.45	17.82	18.98	19.50
13	PCG # 13	18.110	20.01	21.22	22.11	20.22	21.96	21.90
14	PCG # 14	21.400	20.04	23.91	24.24	22.26	24.06	23.87
15	PCG # 15	16.240	19.71	21.07	21.88	20.67	21.88	21.38
16	PCG # 16	20.110	19.93	23.35	24.35	21.76	24.24	23.57
17	PCG # 17	15.810	18.99	19.92	20.66	19.74	20.05	20.39
18	PCG # 18	21.340	20.05	23.90	24.23	22.27	24.08	23.86
19	PCG # 19	19.100	20.00	22.18	22.99	21.17	22.89	22.51
20	PCG # 20	20.040	20.00	23.11	23.69	21.60	23.12	23.15
21	PCG # 21	18.730	19.98	21.31	22.28	20.72	21.94	21.98
22	PCG # 22	16.090	19.71	20.21	21.10	20.20	21.06	20.94
AVERAGE SNR		17.41	18.386	19.324	21.585	20.544	**21.988**	20.544

It is observed from the Table 3, that an average value of SNR of 21.988 is obtained. This average value of SNR being the highest it is inferred that the combination of sym20 MWT, DL = 10 and Bayes Soft as the TF yield the best result.

Next performance is to check the average value of RMSE. All the 22 PCG signals are considered as test inputs. The combinations that produce the best result for SNR (as per Table#1) are applied. The results obtained are tabulated in Table 4.

TABLE 4 AVERAGE VALUES OF RMSE FOR VARIOUS COMBINATIONS OF MWT, DL AND TF
(Only the best results obtained are presented)

Sl. No.	Types of PCG signals	Minimaxi TF (MWT: db20) (DL=6)	Universal TF (MWT: sym20) (DL=6)	Block JS TF (MWT: rbio5.5) (DL=10)	Bayes Mean TF (MWT: sym18) (DL=10)	Bayes Median TF (MWT: db19) (DL=10)	Bayes soft TF (MWT: sym 20) (DL=10)	SURE TF (MWT: sym20) (DL=10)
1	PCG # 1	0.013	0.013	0.009	0.008	0.011	0.008	0.009
2	PCG # 2	0.017	0.017	0.013	0.012	0.014	0.012	0.012
3	PCG # 3	0.019	0.018	0.014	0.012	0.015	0.012	0.013
4	PCG # 4	0.017	0.016	0.012	0.010	0.014	0.010	0.011
5	PCG # 5	0.020	0.019	0.015	0.013	0.017	0.013	0.014
6	PCG # 6	0.020	0.015	0.014	0.012	0.014	0.012	0.012
7	PCG # 7	0.029	0.026	0.017	0.018	0.021	0.017	0.017
8	PCG # 8	0.019	0.020	0.016	0.016	0.018	0.015	0.015
9	PCG # 9	0.030	0.027	0.021	0.022	0.024	0.020	0.020
10	PCG # 10	0.018	0.016	0.013	0.011	0.015	0.011	0.012
11	PCG # 11	0.023	0.019	0.016	0.016	0.018	0.015	0.015
12	PCG # 12	0.026	0.023	0.017	0.017	0.020	0.017	0.016
13	PCG # 13	0.015	0.012	0.010	0.009	0.012	0.009	0.010
14	PCG # 14	0.017	0.020	0.013	0.013	0.016	0.012	0.013
15	PCG # 15	0.021	0.014	0.012	0.011	0.013	0.011	0.012
16	PCG # 16	0.013	0.014	0.009	0.008	0.011	0.008	0.009
17	PCG # 17	0.022	0.015	0.014	0.013	0.014	0.013	0.013
18	PCG # 18	0.017	0.020	0.013	0.013	0.016	0.012	0.013
19	PCG # 19	0.020	0.018	0.014	0.013	0.016	0.013	0.014
20	PCG # 20	0.017	0.017	0.012	0.012	0.015	0.011	0.012
21	PCG # 21	0.019	0.017	0.014	0.013	0.015	0.013	0.013
22	PCG # 22	0.030	0.020	0.019	0.017	0.019	0.017	0.017
AVERAGE RMSE		0.0201	0.0180	0.0139	0.0132	0.0157	**0.0128**	0.0133

It is observed from Table 4 that the lowest value of RMSE of 0.0128 is obtained for the combination including sym20 as MWT with 10 decomposition Level and Bayes Soft as the TF. Hence as far as RMSE is concerned this combination is the most suitable combination.

V. CONCLUSIONS

Denoising of PCG signal is an essential requirement for developing and automatic computerized analysis of HSS to monitor the status of the heart as well as cardio vascular system. During acquisition of PCG signal various types of noises including internal as well external noises corrupt the HSS. DWT is an effective and efficient tool to denoise the PCG signal. The problem faced to denoise the signal using DWT is the proper selection of WT, DL and TF. An optimization thus is required to select the best combination of them. Exhaustive experiments are performed under MATLAB® (2019a) environment to denoise 22 PCG signals with varieties types of abnormalities obtained from open source as mentioned earlier. It is concluded from the results obtained that a wavelet having higher oscillations in its mother wavelet are more effective in denoising anon-stationery signal compared to its counterpart having lesser oscillations. Though the computational complexity of the denoiser increases while using a MWT with higher oscillations yet the performance of the denoiser enhances as far as SNR and PSNR are considered. It is observed that for the lower values of DL, the performance of the denoiser increase with the increase of number of DL but it becomes almost constant beyond a DL of 10. Thus in all practical cases the DL can be extended up to 10 for effective denoising After comparison of performances of PCG denoiser with 73 various MWT, varying DL and 7 soft types of TF, it is finally concluded that sym20 (MWT), 10 Decomposition level and Bayes' soft TF yielded the best result in terms of SNR and RMSE. This combination is suggested as the best performer to denoise PCG signals.

REFERENCES

[1] Bickley, L. S., & Szilagyi, P. G. The Cardiovascular System, A Guide to Physical Examination and History Taking. 9h Ed., Lippincott Williams & Wilkins, Philadelphia, 2017.

[2] Waider W, Craige E. (1975) First Heart Sound and Ejection Sounds: Echocardiographic and Phonocardiographic Correlation with Valvular Events. Am J Cardiol., **35**(3):346-56

[3] G. Luo, D. Zhang (2012) Advances in Wavelet Theory and Their Applications in Engineering, Physics and Technology, Edited by Dumitru Baleanu, Published by InTech, Janeza Trdine 9, 51000 Rijeka, Croatia.

[4] G. Strang (1989) Wavelets and Dilation Equations: A Brief Introduction, SIAM Review, **31**(4), pp. 614–627.

[5] H. Liang and I. Hartimo (1998) A heart sound feature extraction algorithm based on Wavelet decomposition and reconstruction, Proc. 20th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. **3**(3), pp. 1539–1542

[6] Belmecheri, M.Z., Ahfir, M. and Kale (2018) Automatic Heart Sounds Segmentation based on the Correlation Coefficients Matrix for Similar Cardiac Cycles Identification, Biomedical Signal Processing and Control, vol. 43, pp. 300-310

[7] Dyah Kurniawati Agustika Sumarna Sumarna Agus Purwanto Juli Astono (2019) Optimization of Denoising Technique of Phonocardiography Signal By Using Discrete Wavelet Transform, Proceedings of the International Conference of Science and Technology for the Internet of Things, DOI: 10.4108/eai.19-10-2018.2281369 ICSTI, EAI,

[8] L.T. Hall , J.L. Maplea , J. Agzarianb , D. Abbotta (2000) Sensor system for heart sound biomonitor, Microelectronics Journal, **31**, pp. 583–592

[9] B. Jawerth and W. Sweldens (1994) An overview of wavelet based multiresolution analyses, SIAM Rev., **36**(3), pp. 377–412

[10] William J.Williams (1997), Time-frequency and wavelets in Biomedical Signal Processing. Edited by Metin Akay. IEEE Press Series in BME. Pp. 3-8

[11] Arafat, S.M.A. (2003) Uncertainty Modeling for Classification and Analysis of Medical Signals. Ph.D. Thesis, University of Missouri-Columbia: Columbia, MO, USA.

[12] Nabih-Ali, M. , El-Dahshan, E. and Yahia, A. (2017) Heart Diseases Diagnosis Using Intelligent Algorithm Based on PCG Signal Analysis. Circuits and Systems, **8**, pp. 184-190. doi: 10.4236/cs.2017.87012.

[13] Y. Zheng, X. Guo, H. Jiang, and B. Zhou (2017) An innovative multilevel singular value decomposition and compressed sensing based framework for noise removal from heart sounds, Biomedical Signal Processing & Control, **38**, pp. 34–43.

[14] A. Mondal, I. Saxena, H. Tang, and P. Banerjee (2018), A noise reduction technique based on nonlinear kernel function for heart sound analysis, IEEE Journal of Biomedical and Health Informatics, **22**(3), pp. 775–784.

[15] S. W. Deng and J. Q. Han (2018) Adaptive overlapping-group sparse denoising for heart sound signals, Biomedical Signal Processing and Control, **40**, pp. 49–57.

[16] Ning Zhang, Pengfei Lin and Lei Xu (2019), Application of Weak Signal Denoising Based on Improved Wavelet Threshold, IOP Conference series (ICMAE 2019): Materials Science and Engineering, 751 (2020), doi: 10.1088/1757-899X/751/1/012173

[17] Liu C, Springer D, Li Q, Moody B, Juan RA, Chorro FJ, Castells F, Roig JM, Silva I, Johnson AE, Syed Z, Schmidt SE, Papadaniil CD, Hadjileontiadis L, Naseri H, Moukadem A, Dieterlen A, Brandt C, Tang H, Samieinasab M, Samieinasab MR, Sameni R, Mark RG, Clifford GD (2016) An open access database for the evaluation of heart sound algorithms. Physiol Meas. **37**(12), pp. 2181-2213

[18] Editor(s): Stéphane Mallat (2019), A Wavelet Tour of Signal Processing (Second Edition), Academic Press, pp. 612-628, https://doi.org/10.1016/B978-012466606-1/50016-7.

[19] V.S. Chourasia, A.K. Tiwari, R. Gangopadhyay (2014) A novel approach for phonocardiographic signals processing to make possible fetal heart rate evaluations, Digit. Signal Process. **30** (2014) 165–183

[20] Ed.: Dumitru Baleanu (2012), Advances in Wavelet Theory and Their Applications in Engineering, Physics and Technology, Published by InTech, Janeza Trdine 9, 51000 Rijeka, Croatia.

[21] D. Mehr and N. J. Dabanloo (2017), Diagnosis of Aortic Valve Stenosis Based on PCG Signal Using Wavelet Packet Decomposition (WPD) and Parametric Models, IEEE Conference on Computing in Cardiology, **44**, pp. 1 – 4.

[22] K. P. Soman and K. I. Ramachandran (2004) Insight into wavelets: From Theory to Practice, Prentice-Hall, pp. 15-72.

[23] The wavelet tutorial by **Robipolikar**. https://cseweb.ucsd.edu/~baden/Doc/wavelets/polikar_wavelets.pdf

[24] F. Liu, Y. Wang, Y. Wang (2012) Research and implementation of heart sound denoising, Phys. Proc. **25** pp. 777–785.

[25] S.R. Messer, J. Agzarian, D. Abbott (2001) Optimal wavelet denoising for phonocardiograms, Microelectron. J. **32** (12) pp. 931–941.

[26] K. Agrawal, A. Jha, S. Sharma, A. Kumar, V. Chourasia (2013) Wavelet sub-band dependent thresholding for denoising of phonocardiographic signals, in: Signal Processing: Algorithms, Architectures, Arrangements, and Applications(SPA), pp. 158–162

[27] D. Gradolewski, G. Redlarski (2014) Wavelet-based denoising method for real phonocardiography signal recorded by mobile devices in noisy environment, Comput. Biol. Med. **52** pp. 119–129

[28] H. Naseri, M. Homaeinezhad, H. Pourkhajeh (2013) Noise/spike detection in phonocardiogram signal as a cyclic random process with non-stationary period interval, Comput. Biol. Med. **43** (9) pp.1205–1213