Research Article

Optimal Parameter Selection for DWT based PCG Denoising

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ABSTRACT
Analysis of PCG signals helps in diagnosis of cardio vascular disorder non-invasively. PCG signals are non-stationery in nature and hence time-frequency analysis of PCG is the most suitable means for analysis to determine the basic features of it. However, the PCG signals need to be denoised before feature extraction process and DWT proves to be most suitable for this purpose. During acquisition of HSS technically known as PCG various types of noises and artifacts contaminate the signal of interest. Hence denoising of the signal is inevitable before proceeding for diagnosis. DWT has been proved to be a powerful and handy tool along with thresholding for this purpose. However, the main challenge lies in the fact of selection of the suitable MWT with required number of DL and the type of thresholding function. The present work deals with the optimization of the selection process using varieties of MWT with varying DL and thresholding functions. Rigorous experiments have been conducted using codes in MATLAB environment to select the suitable MWT, DL and thresholding function. After optimization, the selected MWT, DL and Thresholding function have been applied on 22 PCG signals obtained from open data source and the performance of the process has been measured in terms of SNR and RMSE. It has been observed from the extensive experiments using different combination that sym20 wavelet with 10 decomposition level along with Bayesian Soft thresholding function provide the best result in denoising the applied PCG signals. The database used is that of MHSDB available at www.med.umich.edu/Irc/psb/heartsounds/index.htm provided by the University of Michigan Health System.

Keywords: PCG, Denoising, DWT, Decomposition level, Thresholding function, SNR, RMSE

Abbreviations used:

ASF	Adaptive Smoothing Filters	**HSS**	Heart Sound Signals
AV	Atrioventricular	**ICA**	Independent Component Analysis
BLW	Baseline Wander	**IDWT**	Inverse Discrete Wavelet Transform
BSS	Blind source separation (BSS)	**LPF**	Low Pass Filter
CAD	Computer Aided Diagnosis	**MHSDB**	Michigan Heart Sound Data Base
CVD	Cardio Vascular Disorder	**MRA**	Multi Resolution Analysis
CVS	Cardio Vascular System	**MWT**	Mother Wavelet
CWT	Continuous Wavelet Transform	**PCG**	Phonocardiogram
DFT	Discrete Fourier Transform	**RMSE**	Root Mean Square Error
DL	Decomposition Level	**SNR**	Signal to Noise Ratio
DWT	Discrete Wavelet Transform	**TF**	Thresholding Function
EMD	Empirical Mode Decomposition	**WAF**	wavelet adaptive filter
FT	Fourier Transform	**WPD**	Wavelet Packet Decomposition
HPF	High Pass Filter	**WT**	Wavelet Transform

I. INTRODUCTION

Computer Aided Diagnosis (CAD) boosts the potentials of physicians for more truthful and prompt diagnosis. Automatic diagnosis systems are developed to offer the physicians with more information and suggestions to the physicians to ease the diagnostic process. Diagnosis based on Heart Sound Signals (HSS) is an important indicator for detection of Cardio Vascular Disorder (CVD). Thus recording, processing, analysis and abstraction of HSS play an important role in automatic diagnosis of an early indication of CVD. Phonocardiography deals with the technique of generating phonocardiogram (PCG) signal depicting the nature of HSS for better understanding of the functioning of the Cardio Vascular System (CVS). Hence in order to develop an effective and efficient system for clinical diagnostic related to CVS, a good knowledge about the nature of HSS is very much required. Heart is the life line of the CVS to supply energies to various organs of the body with blood as the carrier for their proper functioning. Blood also takes away the waste product and gets itself purified in the lungs.

Normally the heart is oriented on the slight left side of the chest. Its size is about the fist of the person concerned and weighs between 200 to 450 grams **[1].** The pumping action of the heart is accomplished by various types of muscles attached to it. As the heart is engaged in circulation of fluid (blood) hence it is obvious that sounds will be generated during the circulation and control of blood flow in and out of various chambers in the heart.

Moreover, vibrations created in the walls of the heart during the flow of blood also generate some mechanical sounds. All these sounds put together are called HSS and an electronic record of such signals is known as PCG. A typical HSS during a cardiac cycle contains four major sounds named as S1, S2, S3 and S4 apart from various types of murmurs. The first sound (S1) is caused due to initiation of left ventricular contraction, abrupt tension on the AV valve at its closure and turbulent flow of blood into the great vessels. It has the longest duration (100 msec – 160 msec) with a frequency range of 10 Hz to 150 Hz. S2, the second heart sound is caused due to the closure of aortic valve, closure of pulmonary valve and sudden reversal of blood flow. Its duration typically is 60 msec to 100 msec. it is of higher frequencies than S1. The source of sound heard as the third sound (S3) is due to rapid ventricular filling during early diastole. It is observed as low frequency transient. The fourth sound (S4) occurs at the end of the diastole due to atrial contraction. Pathological heart murmurs occur due to high rate of blood flow through normal and abnormal orifices at the heart valves, blood flow into a dilated chamber, and flow reversal of blood due to defects in heart valves. Innocent heart murmurs are observed due to circulation of blood through the heart chambers and valves or blood vessels attached to heart. Murmurs occur between S1 and S2 is called systolic murmurs and that occurring between S2 and S1 is called diastolic murmurs **[2]**.

The HSS, i.e., the signal obtained from PCG has an edge over the sound obtained through clinical stethoscopes since, the PCG can be recorded and analyzed using signal processing systems and many more information can be extracted from them. PCG carries important physiological indications related to cardiovascular system. Significant diagnostic information can be obtained using computer aided diagnostic techniques and with the intervention of experienced clinical staff. Such information can be analyzed for an early diagnosis of functioning of the cardiovascular system **[1]**. Moreover compared to recording of other pathological signals related to cardiovascular system, PCG is more convenient, low cost and low maintenance requirements.

To record the heart sound properly for audio-visual display and storage in electrical form, the clinical stethoscope is modified by the placement of a sensor to pick up the heart sound while the stethoscope is placed on the auscultation areas over the chest. The signal acquired by the sensor is then amplified and make it compatible to the display and storage systems.

Frequency band of HSS typically remains in the range 10Hz – 250 Hz. Also their amplitudes are very low and hence are very susceptible to noise. Noise contamination is a major problem while capturing the HSS using electronic circuitry **[3]**. Many sources of noise can contaminate the PCG; some of which are internal like lung sounds, movement of the subject etc. while some of them are external like improper contact between the body surface and the recording device, various electronic noises inherent to the circuits and semiconductor devices under use, power line interference, improper matching circuits, design flaws of the circuits etc.

The noise picked up by the acquisition system causes misleading results during analysis of the HSS. Hence it is of utmost importance that the noise to be removed as far as possible before analyzing the HSS to come to any decision regarding the well being of the CVS. Traditionally the noise can be removed by utilizing suitable filters with appropriate pass band and stop band. But the problem with the use of filters is that the HSS share the same frequency band of the noise. Hence more careful and efficient techniques need to be adopted for denoising purposes. Another suitable technique to remove the noise is the use of frequency analysis of the HSS and then appropriate tool is to be applied to make the HSS noise free. However, transformation of HSS only in frequency domain will not be sufficient to remove the noise since the signal under consideration is of non-stationery type. Hence a method of transformation in time as well as frequency domain is adopted. Thus Wavelet Transform is an efficient alternative. As the further analysis of HSS to be accomplished using digital systems, DWT has been proved to be the best and suitable choice **[4]**.

Wavelet transform, a mathematical tool, is used very often whenever a signal of non-stationery nature is required to be analyzed both in time as well as frequency domain. The wavelets are used to decompose a signal into a single function called mother wavelet. DWT is a type of wavelet transform that utilizes a discrete set of wavelet functions and translations based on some predefined rules. DWT transforms the signal in mutually orthogonal set of wavelets in time and frequency domain at the same time which differentiates DWT from Continuous Wavelet Transform (CWT). DWT finds its wide application in processing biomedical signals. A time domain signal of finite length can be decomposed in different frequency bands to obtain the detail and approximation coefficients **[5].**

The wavelet approach of denoising is based on 'Decomposition' through multilevel filter bank rather 'filtering' by a single filter. Wavelets are capable of reconstructing the original signal free from noise by using Inverse DWT (IDWT) transform operation. Also they do not introduce any phase shift in the signal; hence signal after reconstruction (synthesis) remains intact. Time-frequency localization can be achieved using wavelet, thus most of the energy content of the signal remains confined in a finite time interval. A good number of wavelet functions and associated algorithms are available for implementation. Wavelets have Multi Resolution Analysis (MRA) capability. Wavelet filter banks are capable of generating lower level coefficients even from the higher level coefficients **[6]**. Due to the features of DWT mentioned above, they can be proved to be an efficient and effective means to denoise a non-stationery signal.

Decomposition (analysis), thresholding and reconstruction (synthesis) are the main stages of denoising a signal using DWT. To retrieve the noise free signal after denoising, orthogonal wavelet functions are to be chosen since they conserve the energy content of the signal **[7]**. Decomposition stage decides the coefficients of the low and high frequencies using the outputs of the filters of the filter bank. Thresholding is used to eliminate the values of the signal beyond the threshold thus actually removing the noise content in the signal. Reconstruction is the process of reclaiming back the original signal which is free from noise.

The key factors behind the success of effective noise removal depend on the following factors:

- Selection of the Mother Wavelet (MWT)
- Choosing the number of Decomposition Level (DL)
- Selection of Thresholding Function (TF)

In order to obtain the best performance of the denoising process of the PCG signal, the above key factors need to be optimized **[8]**. The optimization will be done through experiments to be performed in MATLAB environment. The results obtained during the experiments are to be carefully observed based on the evaluation parameter under consideration like Signal to Noise Ratio (SNR) and Root Mean Square Error (RMSE). Adequate number of MWT, DL and TF are used to optimize the technique and components of denoising process.

II. THEORETICAL BACKGROUND

2.1 Baseline Wander Removal

Any signal when recorded and measured must have a reference with respect to which the measurements are done. Such a level or line of reference is known as baseline. Normally this line must be a straight line in nature. It is also known as isoelectric line. Whenever a drift in the baseline occurs due to incorporation of noise in the acquisition system, the baseline does not remain fixed and keeps on varying its level. Such a behavior is known as Baseline Wander (BLW). BLW severely limits the decision making process based on PCG records. The drift or wandering of the baseline can be caused by external noises during acquisition of the signal. The sources may include all or some of the artifacts like movement of the patient during acquisition, breathing sound, loose coupling between the sensing element and the points of auscultations etc. Normally such noises are of very low frequency and drift the baseline of the signal in an irregular manner. The presence of baseline drift effectively changes the amplitudes of the peaks exhibited by the signal and hence proper measurements of the peak amplitudes cannot be achieved. Thus wandering of the baseline degrades the signal quality and makes it difficult in decision making. Thus BLW creates mystifying data while measuring the parameters of the HSS **[9]**.

Removal of BLW is one of the primary steps in preprocessing the PCG signal. A high pass filter can be used to block the low frequency components in the signal causing baseline drift, however, cut-off frequency and phase response characteristics are the main considerations in designing such filters. Linear filters can be used to avoid the issue of phase distortion in such cases. Thus use of digital filters is another choice to remove such drift of the baseline. Better control over the cut-off frequency can be achieved by using time variant filters. Also wavelet adaptive filter (WAF) in the category of multirate system wavelet transform can also be utilized to remove the BLW of the PCG. Another filter known as empirical mode decomposition (EMD) can also be adopted to get rid of the drift in baseline. BLW can also be removed by using a cascaded structure of adaptive smoothing filters (ASF) consisting of a notch filter to eliminate the DC components present in the PCG followed by a comb filter. Blind source separation (BSS) and in particular independent component analysis (ICA) can also be an alternative for this operation. ASF with a higher window length of 2.2 sec with an iteration number equal to 5 has been employed in the current work for the removal of BLW. Following figure (Fig. 1) exhibits the visual quality of the signal before and after the removal of BLW **[10]**.

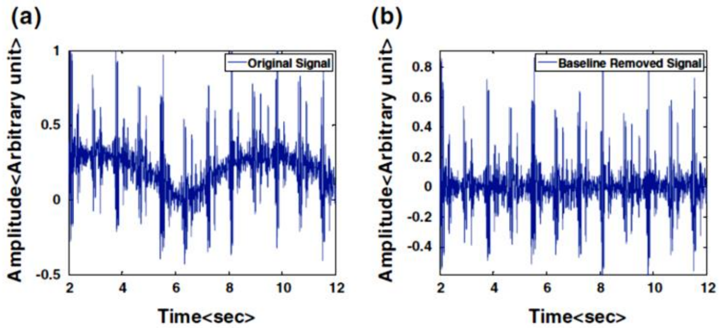

Fig. 1: (a) PCG signal before BLW removal, (b) PCG signal before BLW removal

2.2 Normalization

Normalization of a signal is a technique to change the range of the signal by increasing or decreasing the sampled values of the signal by multiplying the signal by a predefined factor based on a mathematical function. Normalization and standardization are often used as synonymous; however, these two are different processing methods. Normalization scales the amplitude of the given signal to acquire values between 0 and 1 or between -1

and 1 whereas standardization converts the signal amplitude in such a way that the standard deviation turns out to be 1 and mean becomes 0. The aim of the normalization of a signal lies in the fact that normalization of a signal removes redundancy of amplitude data so that storage of the data occupies less space at the same time less data are to be handled for processing. Normalization can be done both in time as well as in amplitude domain.
In the present work amplitude normalization is employed since amplitude is of more importance than frequency for further processing. Each sample of the given signal is divided by the maximum of absolute value of signal. Thus the signal range can be limited between -1 and 1. Initially the sampled signal from the original signal are collected into a fixed-size window and then they are normalized according to the predefined formula and then the window slides by a fixed amount in the time domain to normalize the samples lying in the next window. This is known as sliding window normalization technique. Thus the window keeps on sliding until the whole range of the signal in time domain is covered. It is not practical to observe the dynamic range of the signal after acquisition of the signal during every observation. Hence without the prior knowledge of the amplitude limits, amplitude thresholding cannot be employed.

$$x_n(t) = \frac{x(t)}{\mathrm{Max}(|x(\tau)|)}\ , \quad \text{such that } t - \frac{l}{2} < \tau < t + \frac{l}{2}$$

Where, l is the length of the sliding window, x(t) is the original signal recorded by stethoscope after removing the baseline wandering and $x_n(t)$ is the normalized signal.
The following figure (Fig. 2)depicts the visual representation of the signal after normalization using the technique as discussed. The normalization has been applied after removing the baseline wandering of the original signal **[11]**.

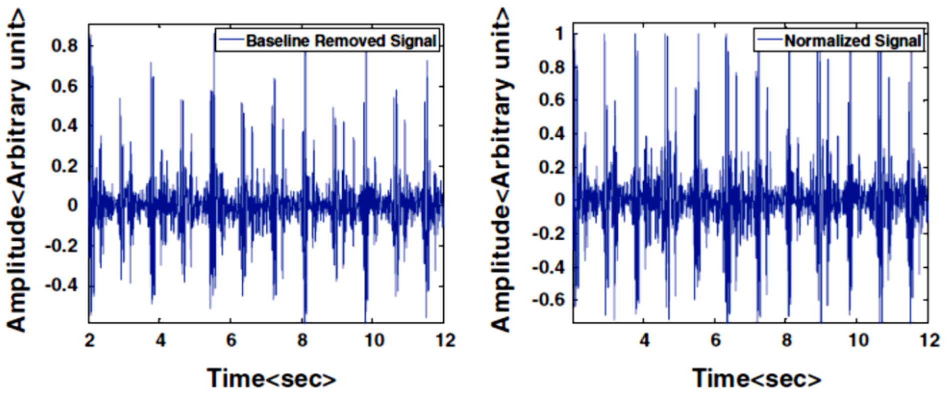

Fig. 2: Visual display of PCG signal after normalization

2.3 DWT Based Denoising

A wavelet is a small part of the signal located in time with concentrated amount of energy for better understanding, processing and analysis of signals. A wavelet transform is a type of linear transformation of a signal in time – frequency domain using mathematical function called wavelet function. The original transformation function is called “mother wavelet” and is used to generate “daughter functions” from mother wavelet by applying scaling and dilation on the mother wavelet. As in the case of Fourier analysis, inner products can be applied on this set of orthogonal sample data to decompose any signal. FT and WT are different in the sense that FT decomposes the signal only in the frequency domain whereas WT decomposes the signal both in time as well as frequency domain usinf shifting and scaling properties of WT **[12]**. WT is superior to FT since time information is not lost when moving to the frequency domain. Depending upon how wavelet transforms treat scale and translation, it is divided into two categories: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). DWT proves to be a very powerful means in signal processing applications especially for non-stationery signals like biomedical signals the type of mother wavelets used in DWT are different from that of CWT **[6]**.
DWT decomposes the signal into sub-bands or levels covering different frequency ranges so that each level simultaneously splits the signal into high and low frequency components. Thus detailing of the signal can be obtained by checking the output of the filters at various levels. This particular technique is called wavelet decomposition technique, a more recent addition to multiscale signal processing applications. The Wavelet Filter is used for detailing of a signal, i.e. to highlight the signal in the desired spatial frequency domain. Filter bank is a collection of filters, mainly Low Pass Filter (LPF) and High Pass Filter (HPF) to emphasize or deemphasize certain portion of the signal in a selected frequency region with certain mutual and individual characteristics either with a common input or with a common output summation. Digital filter bank of DWT provides the approximate and detail components of a signal at various desired frequencies in the spatial domain. Decomposition of a signal for detail analysis using wavelet packets is called Wavelet Packet Decomposition

(WPD). At each level of decomposition, the wavelet transform provides approximate components and detail components. Such approximate components are further transformed to get new approximate components and detail components. Thus at every levels of decomposition, detail components of the signal under consideration are obtained. Number of levels is restricted depending upon the detailing of the signal required in the frequency domain. WPD is very accurate technique in analyzing the signal with the predominance of abstracting the information in the signal at higher frequency ranges. The wavelets approach is more appropriate due to the fact that the signal will be studied using a "dual" frequency-time representation, which allows separating noise frequencies from valuable signal frequencies. Under this approach, noise will be represented as a consistent high frequency signal in the entire time scope and so its identification will be easier than using Fourier analysis. DWT de-noising is performed in three basic steps: (i) analysis decomposition DWT filter bank, (ii) thresholding and (iii) synthesis reconstruction IDWT filter bank **[13]** which will be dicsussed separately in the subsequent paragraphs. Each mother wavelets lead to four different filters, two of them (LPF and HPF) will be used for decomposition purposes and the other two (LPF and HPF) will be used for reconstruction purposes. Thus to sum up it can be inferred that DWT is an operation that receives a signal as an input (a vector of data) and decomposes it in its frequential components. By this description, it may be confused with the also very important DFT (Discrete Fourier Transform) but the DWT has its tricks. First, DFT has a fixed frequency resolution (e.g.: It can separate frequential components lineally along the whole frequency range), on the other hand, DWT can separate frequential components with an increasing frequency resolution as the frequency increases. This means that at bigger frequencies, the number of components that can be distinguished is larger.

2.3.1 Decomposition of HSS using DWT filter bank

A filter bank is a constellation of filters used to separate a signal into sub-signals (wavelets) consisting various frequency bands within the entire range of the signal frequency. In order to analyze the signal contaminated either by external interference, internal noise of the system under measurement or external noise generated from the acquisition system, the signal must be decomposed at various frequency levels to emphasize the frequency components under consideration. Such separation or decomposition of the signal can be achieved using filter banks **[14]**. The major operations performed to implement digital filter bank are: (i) Convolution and (ii) Wavelet transform analysis. As the localization capabilities in time and frequency domain is better for wavelet transform analysis compared to direct filtering of the signal in terms of noise detection and reduced signal distortion, wavelet transform is the natural choice for noise detection and removal from HSS. The filtering operation is implemented by convolving the impulse coefficients of the chosen wavelet function and the input signal. Upon convolution, the output of the filters after down sampling by base 2 will be termed as coefficients and more specifically, the output of LPF is called 'Approximation coefficients' and that of HPF are termed as 'Detail coefficients'. The basic unit of a digital filter to decompose the signal is as shown in Fig. (3) below. As has been depicted through the figure, the signal is applied as input simultaneously to a LPF with impulse response g[n] and a HPF with impulse response h[n].

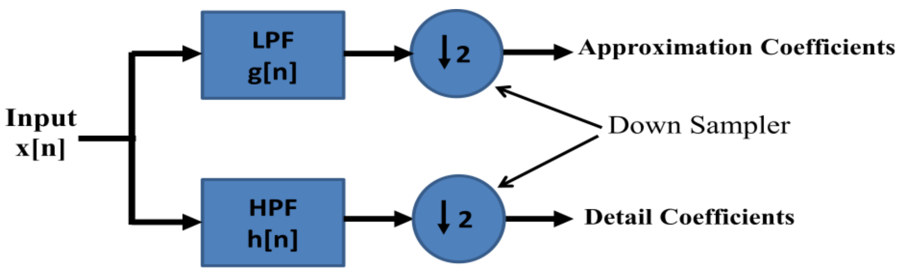

Figure (3): Basic unit of digital filter bank

Basic units as shown above can be cascaded to implement the filter bank for the decomposition of the signal so that at each level the detail coefficients can be obtained with higher frequency resolution. The low pass representations of the signal are the approximation coefficients whereas the wavelet coefficients correspond to the detail coefficients at each level of decomposition. The detail coefficients of a noisy signal are often such that the coefficients of the signal are confined to coarser scales, while those of the noise are observed in finer scales. At the subsequent level, the approximation coefficients will act as the input and again this approximation coefficient will be divided into approximation part and detail part at the next level. Thus more the number of levels more will be the resolution coefficients. Using DWT, as the level increases, the frequency resolution increases whereas the time resolution decreases. The number of levels to be employed depends on the requirement of resolution. The whole scheme of decomposition tree of the digital filter bank has been shown in figure (4) where d_1, d_2, …. d_n represent the corresponding detail coefficients at each level.

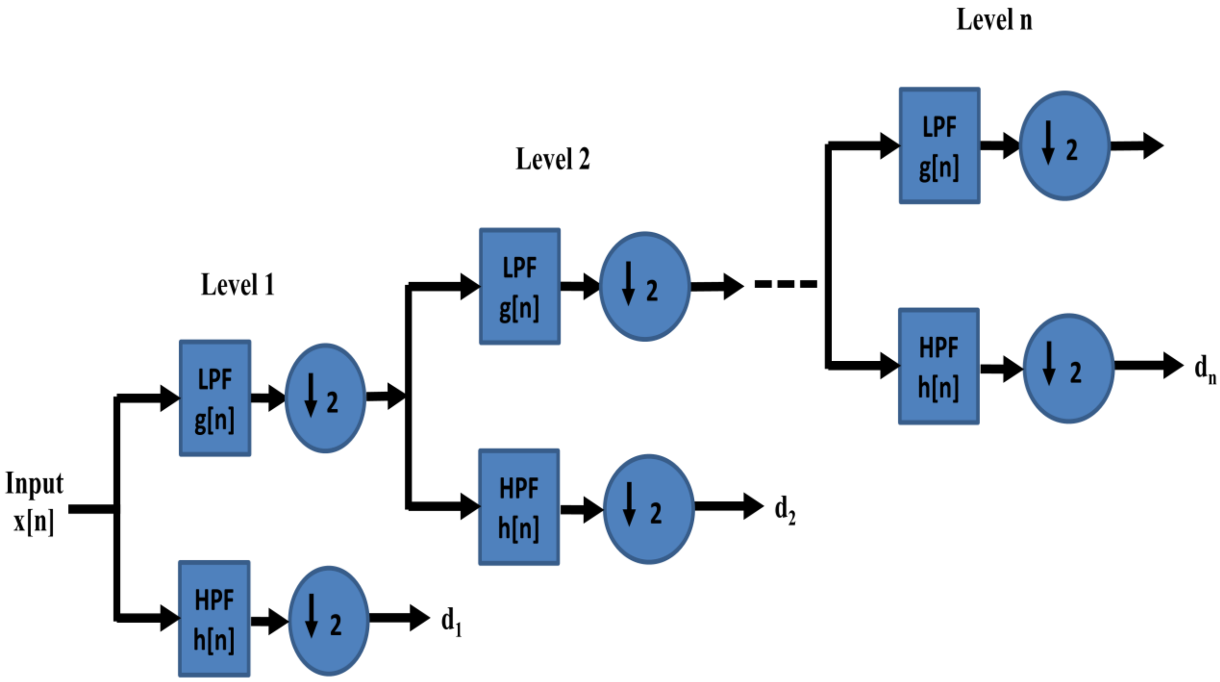

Figure (4): Block diagram of the filter bank implemented

The decomposed signal then can be analyzed to find out the presence of various frequencies at various instants of time and hence can be modified accordingly to remove the noise appearing at high frequencies. In Multi Resolution Analysis (MRA), the signal can be viewed as the sum of a smooth ("coarse") part—reflects main features of the signal (approximation signal) and a detailed ("fine") part—faster fluctuations represent the details of the signal **[15]**. In the present work MATLAB codes have been developed to implement filter bank and finally to remove the noise.

2.3.2 Thresholding

Thresholding is the next stage for denoising a non-stationery signal like PCG after wavelet decomposition using DWT. It is a non-linear processing technique that operates on one of the coefficients after decomposition using wavelet transform at a time. Threshold is a specific value, to be decided according to the type and nature of the thresholding function, in the amplitude scale of the signal so that the signal occupies a specific value depending on whether it is greater than or less than the threshold value. Various algorithms are in use for implementing thresholding operation.

In most of the cases, the useful part of the signal is present either in the lower part of the frequency band of the range of frequency in which the signal varies or the variation of the signal is very smooth. On the other hand, the unwanted pat of the signal in the form of noise either appears in the higher frequency region or varies randomly. Hence a signal with the above features when decomposed using DWT technique, the noise part of the signal appear in the higher frequency band which can be eliminated using thresholding process. Hence to denoise any non-stationery signal like PCG, the following processes are adopted: the signal is first decomposed into detail coefficients and approximation coefficients using filter banks of wavelet function, properly choosing the threshold level and thresholding function to quantify the high frequency components of the wavelet decomposition and reconstruction of the signal using IDWT to make the signal free from noises **[16]**.

There are good numbers of thresholding techniques but in PCG denoising widely used thresholding estimation techniques used are: 'rigrsure' **[17]**, 'heursure' **[18]**, 'sqtwolog' **[19]**, and 'minimaxi' **[20]**. Based on the nature of shrinking of the coefficients to zero, threshold functions can be categorized into two types: Hard Thresholding function and Soft Thresholding function which are adopted extensively for the denoising purpose of PCG signals **[21]**. In hard threshold function, the decomposition coefficients those are less than the threshold level are set to zero and retains the coefficients those are higher than the threshold value thus maintaining the local properties of the signal. However, this causes a discontinuity in the reconstructed signal and makes it oscillating. In soft thresholding, coefficients lower than the threshold level, are replaced by zero while the other coefficients get shrank by the threshold level. The shrinkage of the wavelet coefficients using soft threshold function reduces the effect of singularities and transients that cannot be resolved by hard thresholding which produces higher SNR value than the soft threshold function **[6]**.

As is clear from the above discussion, soft thresholding function exhibits a much better continuity but provides a constant deviation as is clear from the characteristics of the thresholding functions (Fig. 5) shown below.

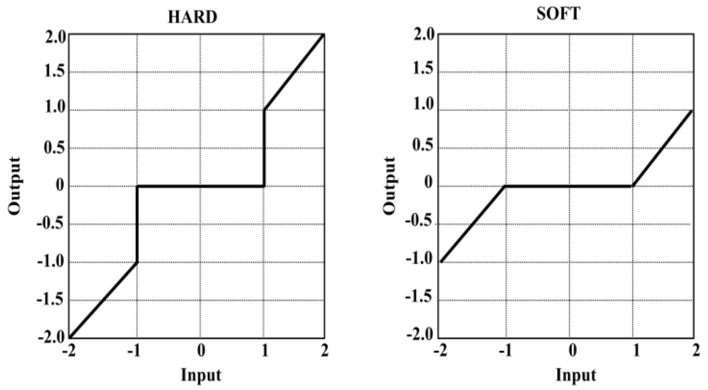

Fig.5: Thresholding Functions

A judicious selection of threshold value affects the DWT based denoising process largely, since a lower value of threshold may not be effective to curb the noise from the signal whereas a large value of threshold may adversely affect the signal components **[22]**, hence a trial and error method has been adopted to choose the suitable threshold level looking into the noise level and signal level of interest.

2.3.3 Reconstruction of HSS using IDWT filter bank

Signal reconstruction is a process of forming the signal back from its samples taken at equal intervals without any loss of information contained in the original signal. The words reconstruction and synthesis of a signal are used interchangeably. Synthesis is a process to assemble the original signal from equally spaced samples without any deformation of the original signal. After denoising the PCG using DWT filter bank analysis and thresholding, the reconstruction of the outputs of the thresholding units can be done to get back the noise free PCG signal. IDWT is a synthesis process to reconstruct the original signal from the approximation coefficients and detail coefficients after thresholding using the same wavelet function and level of decomposition as used during analysis process **[23]**.

During reconstruction, the detail coefficients and approximation coefficients obtained at the outputs of the thresholding unit are first upsampled by two by adding zero in the middle of the sample signals in order to artificially enhance the sampling rate. These samples are then allowed to pass through high pass and low pass synthesis filters and then added together. This process is repeated for same number of processing steps using the same wavelet function as has been done in decomposition process.

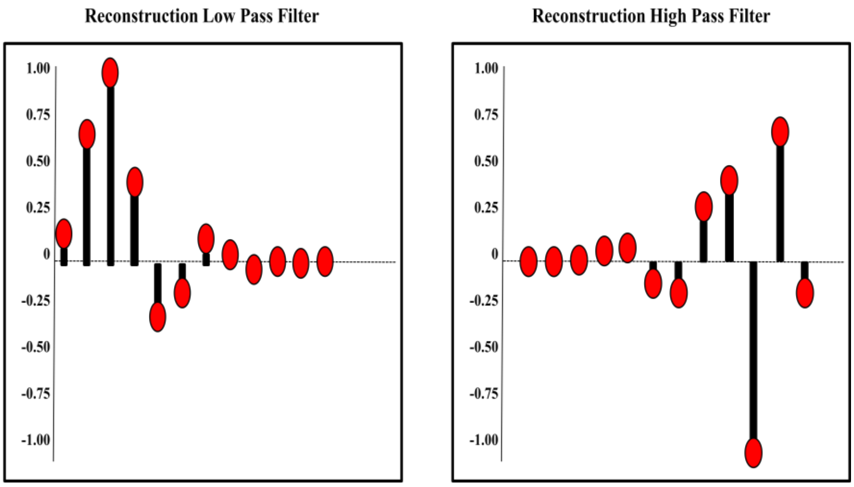

Figure. 6. Typical outputs of reconstruction LPF and HPF

Hence to conclude, the denoising of HSS includes DWT Decomposition to obtain the approximation coefficients and detail coefficients, thresholding to compress the data by selecting a suitable thresholding function and thresholding level and finally IDWT synthesis to reconstruct the original signal after freeing it from embedded noise. A detail block diagram of the whole denoising process consists of Decomposition using DWT, Thresholding and Reconstruction using IDWT techniques is presented below (Fig. 7) where x(n) is the HSS signal obtained after baseline wander removal and normalization and y(n) is the HSS after denoising:

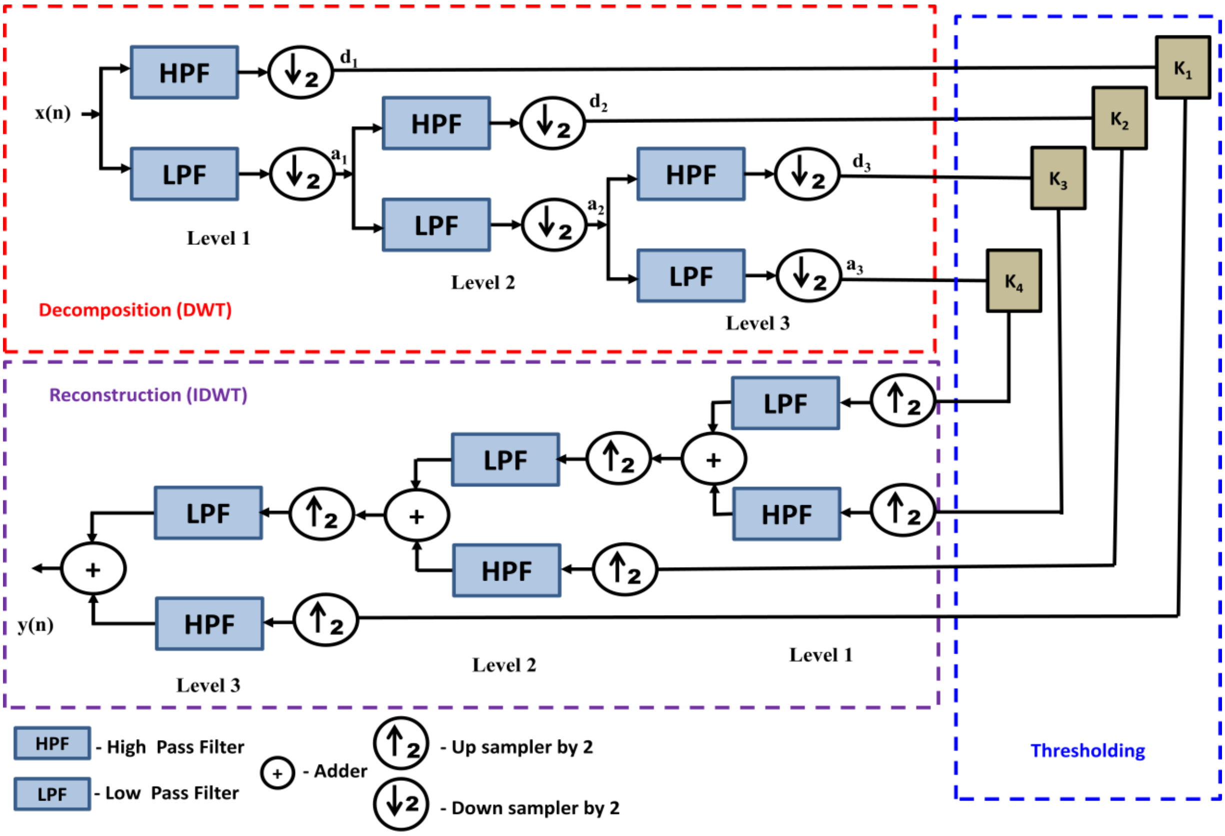

Figure 7: Block diagram of DWT based decomposition and IDWT based reconstruction for denoising HSS

III. RESULTS AND DISCUSSIONS

It has been observed and reported by various researchers that DWT is a suitable technique for denoising of PCG signals. The procedure of the signal denoising based on DWT consists of three steps; decomposition of the signal, thresholding and reconstruction of the signal. As the decomposition and reconstruction process of the signal employ the same MWT and number of DL, the main challenge to obtain the best performance of the denoiser largely depends upon the factors like (i) selection of the suitable MWT, (ii) optimization of the number of DL and (ii) type of thresholding function being adopted. However, researchers have yet to establish the type of MWT and the DL that can yield the best performance for denoising PCG signal. The present work is centered on Daubechies (db), Coiflets (coif), Symlets (sym), Biorthogonal (bior), Reverse Biorthogonal (rbio) MWT families used for analysis of non-stationery type of signals like PCG. Empirical or visual observations can be used for the selection of suitable MWT along with prior knowledge and experiences **[24]**. There are two types of thresholding techniques in use: Hard thresholding and Soft thresholding for the purpose of denoising PCG signals. The most known threshold selection algorithms are minimax, universal and rigorous sure (rigresure) threshold estimation techniques **[25]**.

In order to optimize the MWT and DL, 22 PCG signals of different nature obtained from the open source mentioned earlier have been denoised by using various types of orthonormal MWT with varying DL and seven types of soft thresholding functions. The performances of the MWT and related DL considered in the experiments performed are evaluated based on the following performance metrics: Signal-to-Noise Ratio (SNR), and Root Mean Square Error (RMSE).

SNR is used to compare the performances of the denoising system. A value of 16 – 24 dB signifies a good performance in PCG denoising system **[22]**. The formula used for obtaining the SNR in dB is as under:

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

Where

$N =$ Length of a signal

$xa(n) =$ Actual PCG signal (With Noise)

$y(n) =$ Denoised PCG signal (after DWT denoising)

RMSE is used to avoid the issues concerning sample size. Values of RMSE range from 0 to 1. A value of RMSE below 0.08 is now considered to be a good fit for a denoising system **[22]**. The following formula has been used in the present work for the calculation of RMSE:

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

The results obtained after exhaustive experiments performed using a total of 73 MWT out of which 20 in Daubechies (db), 20 in Symlets (Sym), 5 in Coiflets (Coif), 14 in Biorthogonal (Bior) and 14 in Reverse Biorthogonal (rbio) families of MWT with decomposition levels varying from 1 to 10 and considering seven TFs namely Minimax, Universal, Block James Stein, Bayes Mean, Bayes Median, Bayes Soft and Sure threshold in soft thresholding domain are presented in the following Tables {1-3} to draw the final conclusions. The best performances of the denoising operations have been observed for different TF and at different DL are presented in the following table (Table 1) considering a single PCG signal obtained from the open database as mentioned earlier.

Table 1: Comparison of SNR values obtained using various Thresholding functions and MWT at various DL

Type of TF	MWT	DL 1	DL 2	DL 3	DL 4	DL 5	DL 6	DL 7	DL 8	DL 9	DL 10
Minimaxi	db20	4.0061	7.0104	10.0274	13.0208	16.0190	18.7075	15.1010	12.7870	12.0665	12.0542
Universal Threshold	sym20	4.0194	7.0350	10.0379	13.0512	16.0795	18.7945	14.2645	11.6652	10.9009	10.8883
Block JS	rbio5.5	3.9166	6.9399	9.9856	13.0107	16.0058	17.8444	18.6775	19.0698	19.2182	19.2392
Bayes Mean	sym20	4.0068	7.0103	10.0204	13.0301	16.0087	18.7146	19.5434	19.8222	19.9778	**20.1290**
Bayes Soft	db19	4.0087	7.0160	10.0126	13.0350	16.0395	18.7438	19.1806	19.1806	19.1806	19.2144
Bayes Median	sym18	4.0119	7.0216	10.0300	13.0585	16.0664	18.7398	19.5060	19.8150	19.9742	20.0792
SURE (Steins Unbiased Estimate of Risk)	sym20	4.0152	7.0262	10.0309	13.0512	16.0508	18.7481	19.4886	19.6943	19.8090	19.9717

From the above table it is observed that the highest SNR is obtained while the PCG signals are denoised using the combination of sym 20 MWT at DL = 10 and Bayes Mean as the thresholding function. The next experiment conducted is to check the denoising performances of the best combinations of the MWT, DL and the thresholding functions for 22 PCG signals obtained from open data source and to obtain the average values of SNR and RMSE.

Table (2): SNR values with respect to depth of decomposition and threshold functions (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: sym 20) (DL=10)	Bayes Median TF (MWT: sym18) (DL=10)	Bayes soft TF (MWT: db19) (DL=10)	SURE TF (MWT: sym20) (DL=10)
1	Normal s1& s2	19.1091	19.0431	22.2438	23.2476	23.0765	20.8827	22.4716
2	Split s1	19.1247	19.0551	21.8080	22.5912	22.6572	20.7231	22.1940
3	s4 gallop	18.7374	19.0382	21.5605	22.6561	22.6427	20.5162	21.9978
4	Midsystolic click	18.2332	19.0636	21.6362	22.8724	22.8118	20.3645	22.0988
5	s3 gallop	18.5168	19.0434	21.4187	22.4419	22.3425	20.2600	21.9289
6	Early systolic murmur	16.6888	19.0446	19.6473	20.9539	20.7222	19.6688	20.8385
7	Mid systolic murmur	13.8438	14.8542	18.3768	18.6147	18.1876	16.9118	18.5628

8	Late systolic murmur	18.1584	17.8701	19.7205	20.1079	19.6063	18.8002	20.2737
9	Holo systolic murmur	15.2650	16.0367	18.3534	18.6806	18.0044	16.9229	18.7425
10	Systolic click with late systolic murmur	17.7598	18.7293	20.8253	22.0486	21.8656	19.7651	21.4087
11	s4 and late systolic murmur	15.8798	17.3950	18.9790	19.3681	18.9010	17.9508	19.3210
12	s3 and holo systolic murmur	14.4415	15.7706	18.3563	18.4719	17.9987	16.8374	18.5178
13	Mitral opening snap and dystolic murmur	17.1254	19.0287	20.2384	21.1250	20.9787	19.2358	20.9192
14	Normal s1 & s2 aortic	20.4169	19.0570	22.9344	23.2623	23.0765	21.2752	22.8887
15	Aortic stenosis	15.2649	18.7288	20.092	20.8977	20.8981	19.6943	20.4028
16	Aortic early diastolic murmur	19.1316	18.9522	22.3732	23.3657	23.2631	20.7767	22.5933
17	Aortic stenosis and regurgitation	14.8282	18.0114	18.9355	19.6824	19.5895	18.7566	19.4104
18	N single s1 pulmonic	20.3568	19.0674	22.9240	23.249	23.0972	21.2865	22.8792
19	Split s2 persistent pulmonic	18.1159	19.0162	21.1979	22.0058	21.9094	20.1874	21.5270
20	Pulmonic split s2 sp	19.0613	19.0244	22.1285	22.7072	22.4688	20.6176	22.1681
21	Ejection systolic murmur s2 splitting	17.7545	19.0035	20.3284	21.2990	20.9646	19.7368	21.0003
22	Ejection systolic murmurs2 split pulmonic	15.1141	18.7305	19.2294	20.1202	20.0787	19.2179	19.9598
AVERAGE SNR		**17.40581**	**18.34382**	**20.60489**	**21.35315**	**21.14278**	**19.5631**	**21.0047**

Table (3): RMSE values with respect to depth of decomposition and threshold functions (only the best results obtained are presented)

Sl. No.	Types of PCG signals	Minimaxi TF (MWT: db20) (DL=7)	Universal TF (MWT: sym20) (DL=6)	Block JS TF (MWT: rbio5.5) (DL=10)	Bayes Mean TF (MWT: sym 20) (DL=10)	Bayes Median TF (MWT: sym18) (DL=10)	Bayes soft TF (MWT: db19) (DL=10)	SURE TF (MWT: sym20) (DL=10)
1	Normal s1& s2	0.0132	0.0133	0.0092	0.0082	0.0083	0.0107	0.0089
2	Split s1	0.0173	0.0174	0.0127	0.0116	0.0115	0.0144	0.0121
3	s4 gallop	0.0187	0.018	0.0135	0.0119	0.0119	0.0152	0.0128
4	Midsystolic click	0.0174	0.0158	0.0118	0.0102	0.0103	0.0136	0.0112
5	s3 gallop	0.0204	0.0192	0.0146	0.013	0.0131	0.0167	0.0138
6	Early systolic murmur	0.0198	0.0151	0.0141	0.0121	0.0124	0.0140	0.0123
7	Mid systolic murmur	0.0292	0.0260	0.0173	0.0168	0.0177	0.0205	0.0169
8	Late systolic murmur	0.0193	0.0200	0.0161	0.0154	0.0164	0.0179	0.0151
9	Holo systolic murmur	0.0295	0.0270	0.0207	0.0199	0.0216	0.0244	0.0198
10	Systolic click with late systolic murmur	0.0183	0.0164	0.0129	0.0112	0.0114	0.0145	0.012
11	s4 and late systolic murmur	0.0229	0.0192	0.016	0.0153	0.0162	0.018	0.0154
12	s3 and holo systolic murmur	0.0263	0.0225	0.0167	0.0165	0.0174	0.0199	0.0164
13	Mitral opening snap and dystolic murmur	0.0147	0.0118	0.0103	0.0093	0.0094	0.0115	0.0095
14	Normal s1 & s2 aortic	0.0172	0.0201	0.0128	0.0124	0.0126	0.0155	0.0129
15	Aortic stenosis	0.0210	0.0141	0.012	0.0110	0.011	0.0126	0.0116
16	Aortic early diastolic murmur	0.0133	0.0136	0.0091	0.0082	0.0083	0.011	0.0089

17	Aortic stenosis and regurgitation	0.0222	0.0154	0.0138	0.0127	0.0128	0.0141	0.0131
18	N single s1 pulmonic	0.0173	0.0200	0.0129	0.0124	0.0126	0.0155	0.0129
19	Split s2 persistent pulmonic	0.0200	0.0180	0.0140	0.0128	0.0129	0.0157	0.0135
20	Pulmonic split s2 sp	0.0173	0.0174	0.0122	0.0114	0.0117	0.0145	0.0121
21	Ejection systolic murmur s2 splitting	0.0191	0.0166	0.0142	0.0127	0.0132	0.0152	0.0132
22	Ejection systolic murmurs2 split pulmonic	0.0303	0.0200	0.0189	0.0170	0.0171	0.0189	0.0174
AVERAGE RMSE		**0.0202**	**0.0180**	**0.0139**	**0.0128**	**0.0131**	**0.0156**	**0.0132**

The above two tables (Table 2 & 3) confirmed the conclusion that the combination comprised on sym 20 as the MWT with 10 Decomposition Level and Bayes Soft as the thresholding function yielded the best result in denoising the PCG signal. Hence this combination can be very effectively used for the denoising purpose of PCG signal for further processing.

IV. CONCLUSIONS

In order to optimize the selection of Mother wavelet type, number of decomposition level and the thresholding function for denoising PCG signal, available from open source mentioned earlier, rigorous experiments have been conducted under MATLAB® (2019a) platform. It is noteworthy to mention that the MWT with higher oscillation provide better results. In the present work symlet wavelet with higher oscillations in its mother wavelet produces better result compared to other wavelets with fewer oscillations. Though the computational complexity increases with the increase of number of oscillations, yet the performance of the denosier enhances as far as SNR and RMSE are concerned. The performance of the denoiser have been found to be better with the increase in the number of decomposition levels in most of the cases but decomposition level with more than 10 provides almost flat performances. Hence an optimum value of 10 as the number of decomposition level can be set for the denoiser. Thus the optimized performance for the purpose of denoising the PCG signals a combination of sym 20 as the MWT with 10 DL and Bayes Soft as the thresholding function can be obtained.

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