# Classification of heart sounds associated with murmur for diagnosis of cardiac valve disorders

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**Background:** Nowadays, cardiovascular diseases have been a major cause of death in the world. The heart sound is still used as a primary tool for screening and diagnosing many pathological conditions of the human heart. The abnormality in the heart sounds starts appearing much earlier than the symptoms of the disease.

**Methods:** In this paper, the Phonocardiography signal has been studied and classified into three classes, namely normal signal, murmur signal and extra sound signal. A total of 15 features from different domains have been extracted and then reduced to 7 features. The features have been selected on the basis of correlation based feature selection (CFS) technique. The selected features are used to classify the signal into the predefined classes using multi-class support vector machine (SVM) classifier. The performance of the proposed denoising algorithm is evaluated using the signal to noise ratio (SNR), percentage root means square difference, and root mean square error.

**Results:** The experimental result shows that the 4$^{th}$ level of decomposition for the Db10 wavelets gives the highest SNR values when using the soft and hard thresholding. The overall accuracy, sensitivity and specificity of the developed algorithm is 97.96%, 97.92% and 98.0% respectively.

**Conclusions:** The algorithms presented in this research require only electronic stethoscope as input signal unlike other methods which require electrocardiogram (ECG) gating and the proposed method delivered a considerable improved result for detection heart valve-related diseases.

**Keywords:** Auscultation; discrete wavelets transform (DWT); heart sound; phonocardiography (PCG); support vector machine (SVM)

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## Introduction

Heart diseases are the main health problem and a primary cause of fatality all over the world. Phonocardiography (PCG), tracing of sounds produced by electronic stethoscope, is a tool that leads to valuable PCG information about the heart status and can be a great tool to identify abnormalities of heart early. Cardiovascular disorders (CVDs) are the number one causes of death worldwide and more people die annually due to CVDs than from any other causes (1). A lot of studies show the proportion of deaths due to non-communicable diseases under the age of 70 years while cardiovascular diseases assume the highest proportion of deaths among the non-communicable diseases (51.45%), followed by cancers and chronic respiratory diseases. All broad indications derived from a range of developing countries indicate an increasing burden imposed by cardiovascular diseases (1,2).

CVDs are broad terms that can affect both heart valve and the heart muscle itself. In auscultation technique, a stethoscope is used for heart sound analysis to diagnose the human heart generated by muscle contractions and closure of the heart valves which produces vibrations audible as sounds and murmurs, which can be analyzed by qualified cardiologists (3). The existence of murmur in PCG recording is often related to heart valve diseases. Heart diseases include; heart failure, coronary artery disease, hypertension, cardiomyopathy, valve defects, and arrhythmia. The current study is concerned only with heart valve defects. There are two general types of cardiac valve defects: Valvular stenosis results from a narrowing of the valve orifice that is usually caused by a thickening and increased rigidity of the valve leaflets, often accompanied by calcification. When this occurs, the valve does not open completely as blood flows across it. Valvular insufficiency results from the valve leaflets not completely sealing when the valve is closed so that regurgitation of blood occurs (backward flow of blood) into the proximal chamber (4).

The heart sounds are still an essential tool for screening and diagnosing many pathological conditions of the human heart, which is compound sound of mechanical vibration, and involves different parts of the heart. Traditional auscultation technique using stethoscope requires intensive training and experience of the physician for proper diagnosis of cardiac valve disorder. In contemporary that, the storage of records for future references is not possible with conventional auscultation (5). This is the driving force of this study to move forward automatic auscultation using electronic stethoscopes. In the current study PCG will be used for heart condition monitoring which finds its roots in auscultation. There is difficulty in performing conventional heart sound diagnosis. The main issues are difficulty of obtaining high quality signals, the differences in hearing sensitivity of each person and the vast amount of experience to master heart auscultation skills (3). Murmurs are caused by blood turbulence having a capacity of producing sounds that can be heard using a stethoscope. The murmurs can be termed as indicators of various heart valve problems (6). The problem causing murmurs in adults could be congenital or developed with time. As heart sounds and murmurs have very less overlap with human audibility range, the minute details that can be missed during auscultation can be best viewed and taken care of with the help of PCG.

Many researchers have been proposed different methods on how heart diseases can be diagnosed. So far, an intelligent algorithm based on PCG signal analysis (7), a new analytical technique called digital subtraction phonocardiography (DSP) (8), which is based on the principle that the murmurs are random in nature, measuring entropy to analyze heart sounds (9) and a new feature called mean 12 was proposed, which is the maximum of the mean in the systolic and diastolic region to classify signals into two classes, i.e., normal and murmur signal (10). The aim of this work is to develop a system for classification of heart sounds associated with murmur for diagnosis of cardiac valve disorder by using discrete wavelet transform (DWT) and multi-class support vector machine (SVM) learning algorithm. Therefore, PCG signal is investigated in time, frequency and statistical domain. Additional features were also introduced to increase the efficiency and accuracy of the proposed method.

## Methods

The proposed methodology used in this research to classify heart sounds into predefined classes consists of five stages, i.e., signal acquisition, preprocessing, feature extraction, feature reduction, and classification as shown in *Figure 1*.

### *Datasets*

The PCG signal acquisition can be done using electronic stethoscopes which respond to the sound waves identically to the traditional acoustic stethoscope with the changes in electric field replacing the changes in air pressure. The PASCAL Classifying Heart Sounds Challenge dataset (11) is the first large publicly available heart sound dataset. We used the PASCAL heart sound dataset for this study, which was collected using a digital stethoscope. In this study, a dataset recorded from heart sound having 300 signals was used out of which 150 are normal signals, 100 are murmur signals and 50 are extra sounds. The particular heart sounds are best heard at auscultation sites which are decided on the basis of their area of origin. The data base used for this study was recorded from aortic area, on the patients' right side of the sternum. This research has been approved by Jimma University Institutional Review Board (IRB: 36/2019) and the study was conducted in accordance with the Declaration of Helsinki (as revise in 2013).

### *Wavelet-based preprocessing of PCG signals*

PCG signal is a typical biomedical signal, which is non-stationary and capable of exposed to strong background

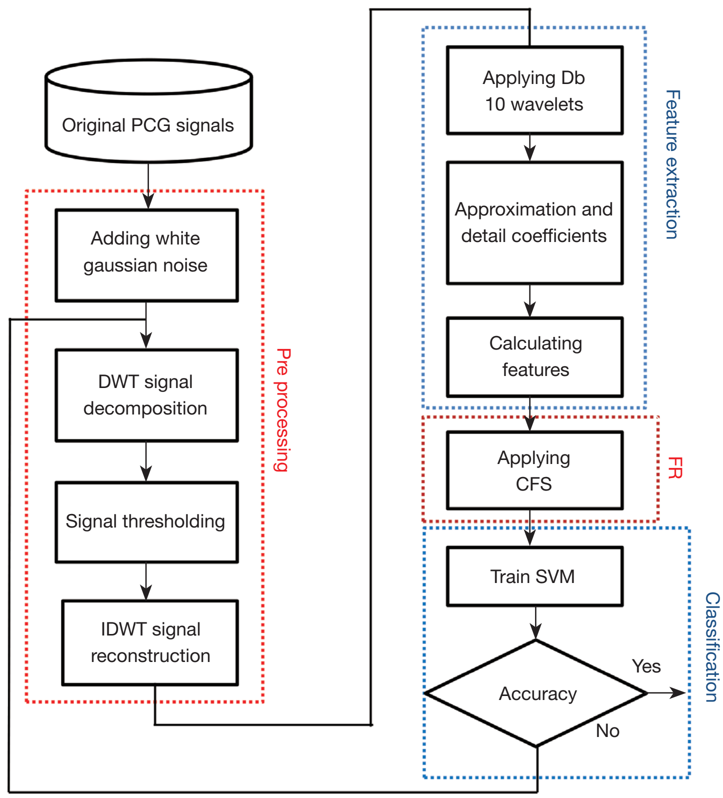


**Figure 1** The general methodology of the research: signal acquisition, pre-processing, feature extraction, feature selection and classification. PCG, phonocardiography; DWT, discrete wavelet transform; IDWT, inverse discrete wavelet transform; CFS, correlation based feature selection; FR, feature reduction; SVM, support vector machine.

noises. In the process of collecting HS signals, it is vulnerable to external acoustic signals and electrical noise interference, friction caused by breathing or body movement (12). The objective of this wavelet-based denoising technique is to recover a signal with less noise than the original signal by using an appropriate wavelet function and a suitable thresholding method. In this study, four different wavelet families (Daubechies, Symlets, Coiflets and Discrete Meyer) and two wavelet function from each family were applied for PCG signal denoising. For thresholding the two most common methods of thresholding signals, soft and hard are used and also four different threshold selection rules were applied in this study to investigate their performance in PCG signal denoising (10,13).

(I) Rigrsure: the threshold is selected using the principle of Stein's unbiased risk estimate (SURE) quadrature loss function.
(II) Sqtwolog: the threshold is fixed at that yielding minimax performance multiplied by a small factor proportional to log (length(s)), usually $\sqrt{2\log\left(length(s)\right)}$.
(III) Heursure: the threshold is selected using a mixture of the first two methods.
(IV) Minimax: the fixed threshold is chosen to yield minimax performance for the mean-square error against an ideal procedure. All of them are included in the MATLAB software toolbox.

DWT is basically used to analyze the signal by splitting the given signal into its detail (high frequency) coefficients and approximation (low frequency) coefficients. Such splitting process is called signal decomposition. Therefore, DWT is used to decompose the lung sound signals into two parts such as high frequency and low frequency components by employing successive high pass and low pass filtering operations. During DWT based signal decomposition, the signal is passed through a series of high pass filters to analyze the high frequency components of the signal and

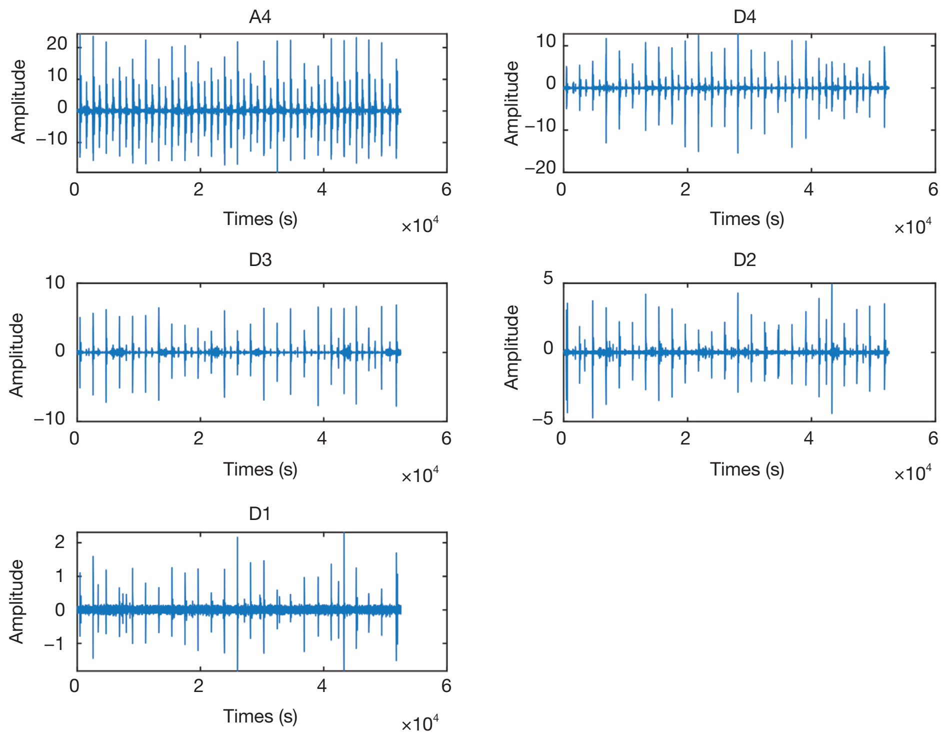


**Figure 2** Wavelet coefficients. A4, approximation coefficient; D1, denoised detailed coefficient of first level; D2, denoised detailed coefficient of second level; D3, denoised detailed coefficient of third level; D4, denoised detailed coefficient of fourth level.

low pass filters to analyze the low frequency components of the signal as shown in *Figure 2*. After the denoising process, the performance can be measured by comparing the denoised signal with the original signal. Numerous studies have been made on heart sound signals containing the desired level of white Gaussian noise to measure the performance of denoising algorithms by calculating the signal to noise ratio (SNR). The SNR is a traditional parameter for measuring the amount of noise present in a signal. The root-mean-square error and percentage root-mean-square difference are also used to evaluate the performance of denoising algorithms (13,14). The SNR, RMSE, and PRD can be formulated as in Eqs. [1-3].

$$\mathrm{SNR}_{db} = 10\log_{10}\frac{\sum_{N=0}^{N-1} S(n)^2}{\left(S(n)-s'(n)^2\right)} \qquad [1]$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{N=0}^{N-1}\left(S(n)-s'(n)^2\right)} \qquad [2]$$

$$\mathrm{PRD} = \sqrt{\frac{\sum_{N=0}^{N-1}\left(S(n)-s'(n)^2\right)}{\sum_{N=0}^{N-1} S(n)^2}} \qquad [3]$$

Where $s(n)$ is the original signal and $s'(n)$ is the denoised signal.

### *Feature extraction*

The DWT was used to extract characteristics from a signal on various scales proceeding with successive high pass and low pass filtering. The wavelet coefficients are the successive continuation of the approximation and detail coefficients. The basic feature extraction procedure consists of decomposing the signal using DWT into N levels using filtering and decimation to obtain the approximation and detailed coefficients and extracting the features from the DWT coefficients as shown in *Table 1*.

The various steps involved in the feature extraction algorithm are summarized as follows:

(I) The Heart sound signals decomposed into six detail sub bands using DWT. The subbands are the details (high-frequency band coefficients) and the approximation (low frequency band coefficients).

(II) The approximation coefficients are further decomposed using DWT to extract information

**Table 1** List of features extracted for classification

| No. | Feature | Feature domain | Feature source |
|---|---|---|---|
| 1 | Maximum frequency | Frequency | (15) |
| 2 | Dynamic range | Frequency | (15) |
| 3 | Total harmonic distortion | Frequency | (16) |
| 4 | Maximum amplitude | Time | (16) |
| 5 | Power | Time | (16) |
| 6 | Mean | Statistical | (17) |
| 7 | Standard deviation | Statistical | (14) |
| 8 | Variance | Statistical | (18) |
| 9 | Skewness | Statistical | (19) |
| 10 | Kurtosis | Statistical | (20) |
| 11 | Root mean square | Time | (19) |
| 12 | Bandwidth | Frequency | (21) |
| 13 | Cepstrum peak amplitude | Cepstrum | (14) |
| 14 | Mid-frequency | Frequency | New |
| 15 | Average frequency | Frequency | New |

from the subband of detail coefficients. In this study Daubechies wavelet (Db10) was implemented to do four levels of decomposition.

(III) All the four level of detail band coefficients have been taken for further analysis and processes.

(IV) Four detail sub bands of the frequency vector (in radians/sample) are extracted for using periodogram function in Matlab.

(V) After decomposition, signals are reconstructed using Inverse DWT.

(VI) The features are computed either by using syntax or by implementing the formula. They are mean, variance, standard deviation, kurtosis, skewness, root mean square, total harmonic distortion, bandwidth, dynamic range, maximum amplitude, cepstrum peak amplitude, power, average frequency, maximum frequency, and mid frequency.

(VII) At last, the extracted features for all the heart sound classes were tabulated in feature table for classification.

The extracted features from the signal including their source are as shown in *Table 1*. Thus, the extracted features for the three classes of HS signals are tabulated and analyzed for classification.

***Feature reduction***

In this phase, best features are selected out of all the extracted features which can do classification with higher accuracy. There are various methods for feature reduction process. Some of them are principal component analysis, box plot method, fisher's Discriminant Ratio and correlation-based feature selection (CFS). Here in this study, CFS algorithm was employed to select the best subsets of relevant features which have been used for classification. Correlation-based heuristic evaluation function has been used to evaluate the rank of the feature subset (22).

The implementation of CFS used in the experiment is based on forward selection with an appropriate correlation measure and a heuristic search strategy. CFS's feature subset evaluation function is shown in Eq. [4].

$$\mathrm{Ms} = \frac{k r_{cf}}{\sqrt{k + k(k-1) r_{ff}}} \quad [4]$$

Where Ms= the heuristic "merit" of a feature subset s containing k features.

$r_{cf}$= The mean feature-class correlation.

$r_{ff}$ = The average feature-feature inter-correlation.

The acceptance of a feature will depend on the extent

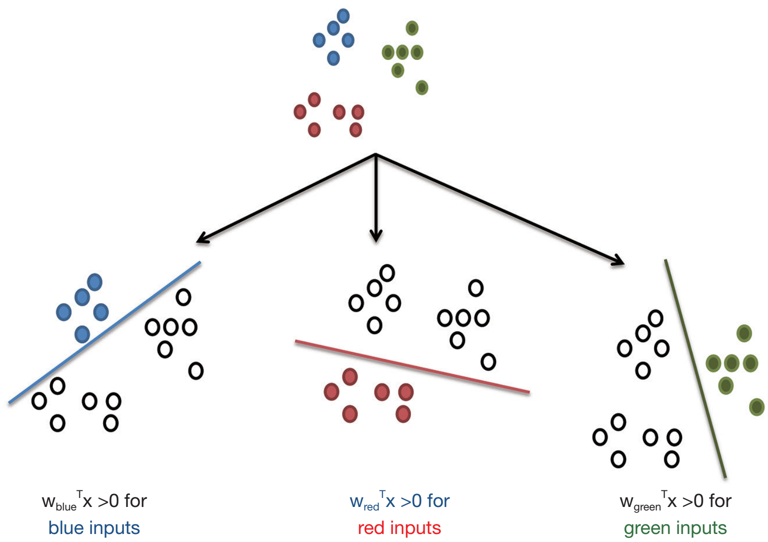


**Figure 3** Visualizing one-*vs.*-all multi-classification of SVM for three classes. W, represent binary classifier; $^T$x, values of elements; SVM, support vector machine.

to which it predicts classes in areas of the instance space which is not already predicted by other extracted features. CFS calculates feature-feature correlations using forward selection and then searches the feature subset space. The subset with the highest merit as measured by Eq. [4] found during the search is used to reduce the dimensionality of the data. It is important to note that the general concept of CFS does not depend on anyone module. A more sophisticated method of measuring correlation may make discretization unnecessary. Similarly, any possible search strategy may be used with CFS.

### *Classification*

SVM classifier was originally designed for binary classification problems. However, real-world problems often require discrimination for more than two categories. Thus, multi-class pattern recognition has a wide range of applications including optical character recognition, intrusion detection, speech recognition, and bioinformatics (23). In practice, the multi-class classification problems are commonly decomposed into a series of binary problems such that the standard SVM can be directly applied.

The learning methodology for classification is defined in the following way. Let's given a dataset D = $\{x_i, y_i\}$, here the need is to specify a learning algorithm that takes D to construct a function that can predict y given x. Finally, it finds a predictor that does well on the training data and has low generalization error. The input $x^2 < n$ is represented by their feature vectors, whereas the output $y^2\{1,2,\ldots,k\}$ is classes that represent domain specific labels. It decomposes into K binary classification tasks due to class $k$ and constructs a binary classification task as Positive examples (elements of D with label k) and negative examples (all other elements of D). Finally, it trains K binary classifiers $w_1, w_2, \cdots w_k$ using any learning algorithm to make a decision by the winner takes all principles which is argma $x_i w_i^T x$ (24).

From the full dataset, as shown in *Figure 3* the winner takes all values to construct three binary classifiers, one for each class predict the right answers. But only the correct label will have a positive score. In this study, one-*vs.*-all multi-classification is selected as it is easy to learn and use any binary classifier learning algorithm.

### *Statistical analysis*

A correlation based analysis was done on data to evaluate the rank of the feature subset. The implementation of correlation based analysis used in the experiments is based on forward selection with an appropriate correlation measure and a heuristic search strategy.

## Results

In this study, the PCG signals were studied and classified into three classes which is normal signal, murmur signal and

**Table 2** SNR results obtained when denoising the heart sound signals using different wavelet functions at different level of decomposition with soft and hard thresholding methods using Rigrsure threshold selection rule

| Wavelet type | Level 3 | | Level 4 | | Level 5 | | Level 6 | |
|---|---|---|---|---|---|---|---|---|
| | Soft | Hard | Soft | Hard | Soft | Hard | Soft | Hard |
| Db5 | 11.0130 | 10.9492 | 13.6971 | 13.7023 | 14.7013 | 14.6126 | 8.6228 | 8.5790 |
| Db10 | 10.9935 | 10.8748 | 15.4307 | 15.6019 | 13.8640 | 13.9565 | 9.0519 | 9.0421 |
| Sym5 | 11.0357 | 11.0521 | 14.7928 | 14.2736 | 13.8969 | 13.7673 | 8.7134 | 8.7020 |
| Sym6 | 10.9267 | 10.9575 | 14.4862 | 14.3950 | 13.6277 | 13.6422 | 9.2143 | 9.1888 |
| Coif3 | 10.9859 | 10.9606 | 14.5283 | 14.5062 | 13.8659 | 13.8216 | 9.0621 | 9.0716 |
| Coif5 | 10.9597 | 11.1185 | 15.0288 | 15.0281 | 13.8573 | 13.9143 | 9.1598 | 9.1339 |
| DM wavelets | 11.0522 | 10.9872 | 15.2460 | 15.3563 | 13.9473 | 13.7343 | 9.4293 | 9.4629 |

SNR, signal to noise ratio; Db, Daubechies; Sym, Symlet; Coi, Coiflet; DM, Discrete Meyer.

**Table 3** SNR, RMSE, and PRD values of the four threshold selection rules for denoising some heart sound signals using Db10 wavelet function at 4$^{th}$ level decomposition with soft thresholding method

| Threshold parameters | Soft | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Heursure | | | Rigrsure | | | Minimax | | | Sqtwolog | | |
| | SNR | RMSE | PRD% | SNR | RMSE | PRD% | SNR | RMSE | PRD% | SNR | RMSE | PRD% |
| Normal | 14.957 | 0.011 | 17.9 | 14.99 | 0.011 | 17.95 | 15.01 | 0.011 | 17.7 | 14.89 | 0.011 | 17.89 |
| Murmur | 7.9908 | 0.013 | 39.9 | 7.98 | 0.013 | 40.22 | 7.969 | 0.013 | 40 | 7.97 | 0.013 | 39.96 |
| Extra HS | 13.03 | 0.04 | 22.3 | 13.07 | 0.04 | 22.42 | 12.99 | 0.04 | 22.4 | 11.7 | 0.04 | 22.08 |

SNR, signal to noise ratio; RMSE, root mean square error; PRD, percentage root means square difference; Db, Daubechies; HS, heart sound.

extra sound signal. Many features in time domain, frequency domain and statistical domains have been extracted and the best features were selected for the classification using Multi SVM which is illustrated in *Tables 2,3*. Two new features mid-frequency and average frequency were introduced in this research for the classification of the PCG signals. The study also presents the application of discreet wavelet transform method to PCG signal noise elimination which is examined at different levels and the Db10 wavelets at the 4$^{th}$ level of decomposition offer the maximum SNR and minimum RMSE for HS. In this work classification method is proposed to separate normal and abnormal heart sound signals associated with murmur without getting into the tedious process of segmenting fundamental heart sounds using ECG gating. Thus, it will have a good potential to help researchers who need to study heart diseases identification based on heart sounds (classifying normal heart sounds from pathological murmur) and also applicable for the development of portable devices.

The accuracy of the developed algorithms for classification of HS in to three classes can be further increased by incorporating different types of machine learning techniques or other hybrid classifiers on a larger dataset. The case of continuous murmurs and its types are not included in this study which can be included for classification in further studies.

## Discussion

The work performed in preprocessing is to determine the most suitable parameters for a discrete wavelet based denoising of the lung sound signals which involves the three important steps such as decomposition, to denoise heart sound signals to insight excellent ability to inform physicians about heart related problems. This is by adding white noise to the original signals and applying different types of wavelet thresholding techniques to remove the noise from the PCG signals, with four threshold selection

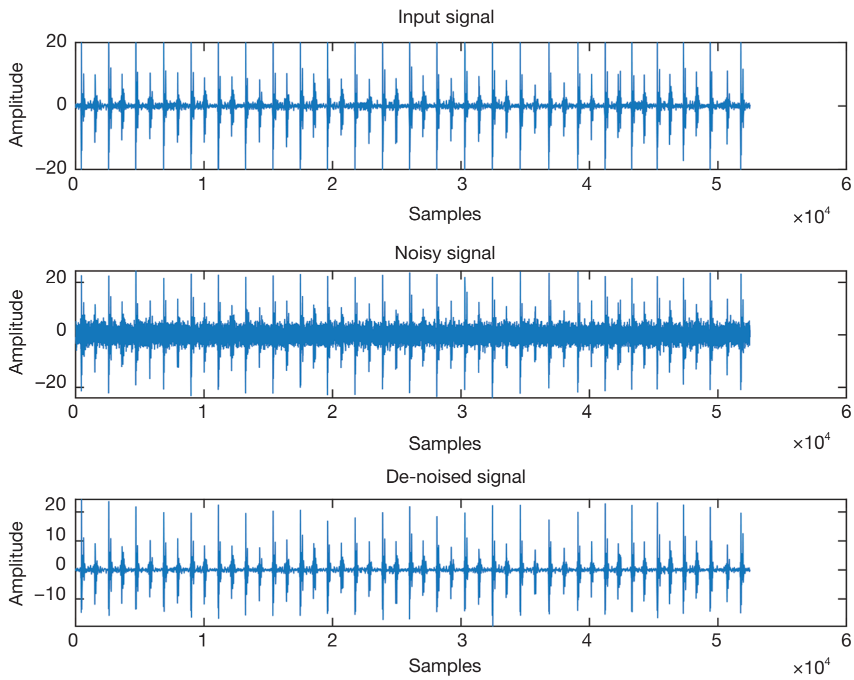


**Figure 4** Denoising of heart sound signal using Db10 wavelets at 4$^{th}$ level with soft thresholding. Db, Daubechies.

rules (Rigrsure, Sqtwolog, Heursure, and Minimax) to analyze the resulting denoising performance of PCG signal and denoising the lung sound signals using the selected wavelet function. After applying a threshold at each level of the original signal, the effects of noise on PCG signals were removed. Finally, the denoised signal was reconstructed using Inverse DWT.

The presented algorithm is tested using four types of wavelet families, i.e., Daubechies wavelet family, Symlets wavelet family, Coiflets wavelet family and discrete meyer wavelet family with two wavelet function. The tested PCG signals were contaminated by white noise added at SNR =5 dB as an initial value to test the performance of the proposed technique for noise elimination. *Figure 1* shows the wavelet coefficients of the heart sound signal, whereas *Figures 4,5* show the effect of the Sym6 and Db10 wavelets on denoising the normal heart sound signal using the 4$^{th}$ level of decomposition. *Figure 6* shows a spectrogram representation of how the frequency content of a signal changes with time after in the process of denoising PCG signals. To study the effect of the two thresholding types *Table 2* presents the SNR results when denoising normal, murmur and extra heart sound signals using different wavelet families.

According to *Table 2*, the SNR results for the different wavelet functions were calculated at different level of decomposition from 3$^{rd}$ to 6$^{th}$ level of decomposition According to the SNR value analysis, the results were found by applying Rigrsure threshold selection rule with soft and hard thresholding methods. From *Table 2*, it is clear that the level of decomposition and the thresholding method could affect the performance or the SNR values of the wavelet function. Based on the result shown in *Table 2*, the 4$^{th}$ level of decomposition for the discrete Meyer and Db10 wavelets shows the highest SNR values when using the soft and hard thresholding. The SNR values using Db10 are 15.4307 and 15.6019, compared with 15.3563 and 15.2460 when using the discrete Meyer wavelets for soft and hard thresholding respectively.

The wavelet function particularly Db10 function gives the highest SNR value with soft thresholding method. The SNR value of Db10 at 4$^{th}$ level of decomposition with soft thresholding method was 15.4307. This is the highest SNR value as compared to the other wavelet functions SNR values. Thus, Db10 wavelet function with 4$^{th}$ level decomposition is used for preprocessing this study. To study the effect of the four thresholding rules, several experiments were done using selected wavelet families for denoising of HS signals based on selected optimal threshold parameters. Therefore, in this research, Rigrsure was found

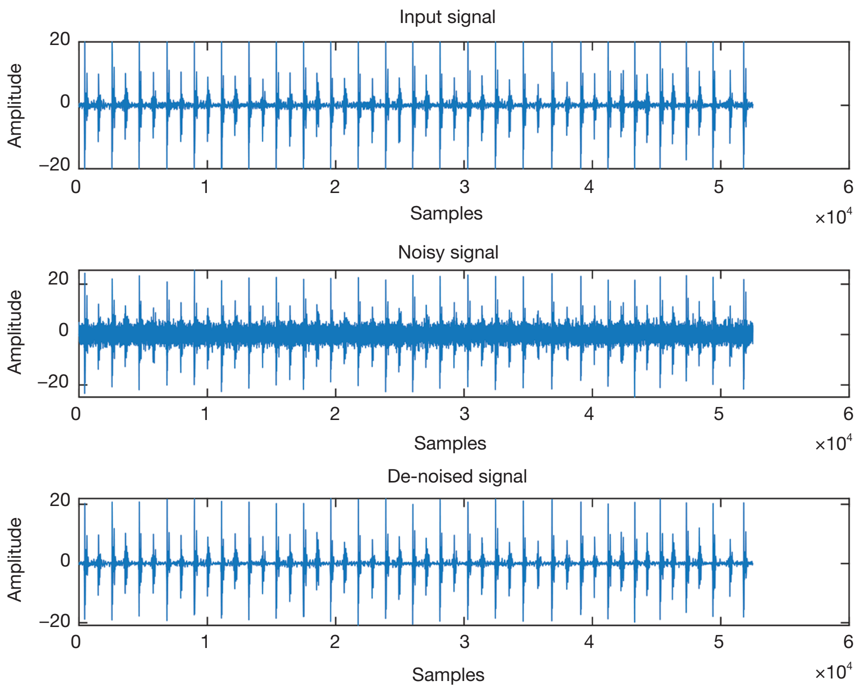


**Figure 5** Denoising of heart sound signal using Sym6 wavelets at 4th level with soft thresholding. Sym, Symlet.

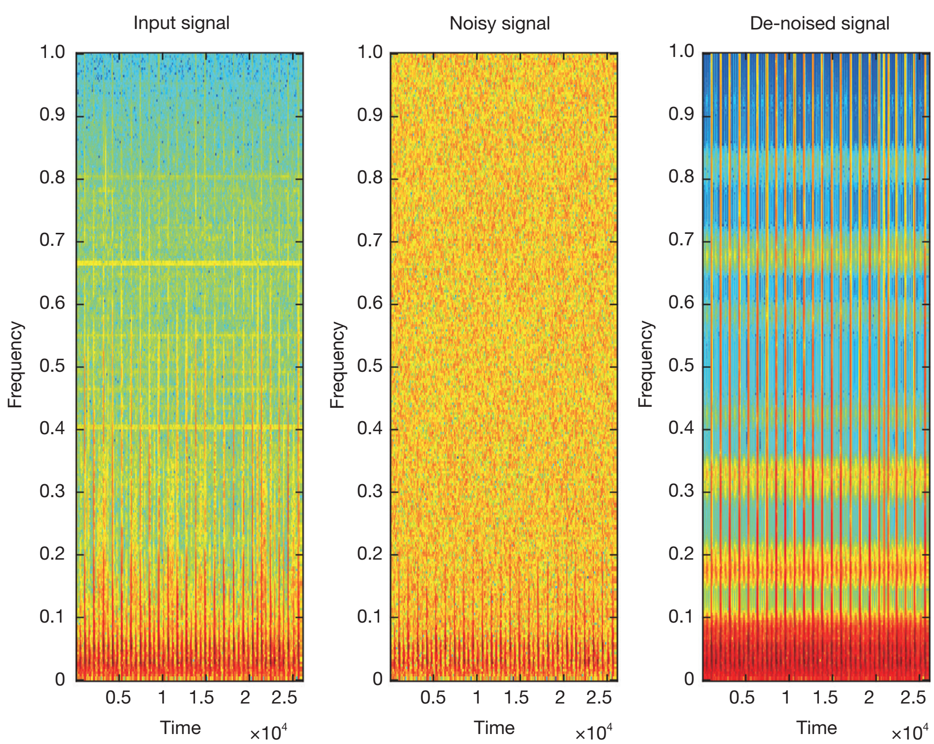


**Figure 6** Spectrograms of PCG signals: original/input lung sound signal (left), noisy lung sound signal (middle), and denoised lung sound signal (right). PCG, phonocardiography.

 

**Table 4** List of features using CFS feature ranking method

| Rank | Feature | Feature domain |
|---|---|---|
| 1 | Mean | Statistical |
| 2 | Standard deviation | Statistical |
| 3 | RMS | Time |
| 4 | Dynamic range | Frequency |
| 5 | Peak amplitude | Time |
| 6 | Total power | Time |
| 7 | Maximum frequency | Frequency |

CFS, correlation based feature selection; RMS, root mean square.

the best threshold selection rule for the best denoising of the lung sound signals using Db10 wavelet function with soft thresholding method. *Table 2* presents the performance in terms of Threshold parameters which are SNR, RMSE, and PRD when denoising normal, murmur and extra sound PCG signals.

From *Table 3*, it is clearly shown that the Rigrsure and Sqtwolog selection rules perform better than the other thresholding types. From this table, it is clearly shown that the performance (SNR, RMSE, and PRD values) of Db10 wavelet function with soft thresholding method was different for the four threshold selection rules. According to the result shown in *Table 2*, the highest SNR values of Db10 wavelet function were observed in using Rigrsure threshold selection rule. The result indicates that Rigrsure threshold selection rule gave the maximum performance of the selected wavelet function for denoising of heart sound signals of normal and extra subjects, shown in *Table 3*.

Due to the difficulties of analyzing non stationary heart sound signals in the time domain, HS signals in the frequency domain were provide in *Figure 6*, presents spectrograms for the noisy and denoised PCG signals to show the clarity of the heart sound components obtained after applying the proposed denoising algorithm. In the denoised PCG signal spectrogram, the heart sounds are clear.

The spectrograms in *Figure 4* are used to show the clarity of lung sound segments obtained after applying the selected algorithm. After applying Db10 wavelet function at $4^{th}$ level with soft thresholding method using Rigrsure threshold selection rule, thus it is observed that the heart sounds are clear in the denoised PCG signal spectrogram, shown in *Figure 6*.

After the HS signal is preprocessed features have been extracted in different domains i.e., time domain, frequency domain, and statistical domain. A total of 15 features have been extracted for 300 signals, and new features mid frequency and average frequency are also introduced in this study. Several MATLAB built-in functions and formulas were used to calculate the 15 features. Then features are reduced to a few features which are further used for classification. This is done in order to reduce the dimensionality, redundancy and computational load the developed algorithm. The features that have been reduced using CFS and those selected features with higher CFS values are shown in *Table 4*.

In this study, 300 heart sound signals were used and divided into 202 signals (100 normal signals 70 murmur signals and 32 extra sound signals) for training and 98 signals (50 normal signals and 30 murmur signals and 18 extra sound signals) for testing. Based on the result shown in *Table 5* out of the 50 normal HS signals 49 was classified correctly and 1 normal HS signal was classified wrongly as a murmur signal. Out of 18 extra sound signals, 17 were classified correctly as extra sound signals and 1 extra sound signal was classified as a normal signal. All the 30 murmur HS signals were classified correctly.

The 98%, 100%, and 94.4% were the classification performance of a developed system for normal, murmur and extra sound classes respectively. 1 signal (2%) from normal and 1 signal (5.6%) from extra sound class were misclassified into murmur and normal respectively and all of the murmur classes were correctly classified as shown in *Table 4*. The overall accuracy of the developed algorithm was 97.96% with a Sensitivity of 97.92 % and a Specificity of 98.0%, which gives better classification performance of a system when it is compared with previously conducted research as summarized in *Table 5*.

Based on the result in *Table 6*, it is clear that the presented algorithm achieved better classification accuracy than the compared studies, which might lead to a more reliable diagnosis. To conclude, this developed algorithm is fully automated and robust enough for the classification of the three classes of heart sound signals.

## Conclusions

In this study, the characteristic features of HS for detection of heart valve related diseases were investigated and analyzed. The algorithms presented in this study were time efficient, simple, and require only electronic stethoscope as input signal unlike other methods which require ECG

**Table 5** Evaluation metrics for classification using multiclass SVM algorithm

| Class | Normal | Murmur | Extra sound | Total (100%) | |
|---|---|---|---|---|---|
| | | | | Correctly | Incorrectly |
| Normal | 49 | 1 | 0 | 98% | 2% |
| Murmur | 0 | 30 | 0 | 100% | 0% |
| Extra sound | 1 | 0 | 17 | 94.4% | 5.6% |
| Total (%) | | | | | |
| Correctly | 98% | 96.8% | 100% | 97.96% | |
| Incorrectly | 2% | 3.2% | 0% | 2.04% | |

SVM, support vector machine.

**Table 6** Comparison between the proposed method and the previous methodologies

| Author | Database | Methods | Results |
|---|---|---|---|
| Mandeep Singh [2013] | PASCAL dataset | Naïve Bayes classifier | Accuracy 93.33% |
| Elsa Ferreira [2013] | PASCAL dataset | Decision tree classification algorithm | Accuracy 76.33% |
| N. R. Sujit [2016] | PASCAL dataset | Regression tree | Accuracy 78.33% |
| Zichun Tong [2015] | PASCAL dataset | Hilbert transform + SVM | Accuracy 90.5% |
| Mohammed Nabih-Ali [2017] | PASCAL dataset | DWT and ANN | Accuracy 97% |
| The proposed system | PASCAL dataset | DWT and SVM | Accuracy 97.96% |

SVM, support vector machine; DWT, discrete wavelets transform; ANN, artificial neural network.

gating. The proposed algorithm for detection of murmur signals is useful to detect mainly valve-related diseases and other congenital abnormalities.

Hear sound signals are still capable of indicating the heart fatality at an earlier stage which can be very helpful in preventing causality due to cardiac problems. This work presents the application of the wavelet transform method to PCG signal analysis. Comparison of the results obtained using different wavelet families-based signal Denoising technique gives the resolution differences among them. Since the noise level is one of the most important parameters in wavelet denoising, it was examined at different levels and the Db10 wavelets at the 4th level of decomposition offered the maximum SNR and minimum RMSE for heart sound.

The PCG signals were studied and classified into three classes, namely normal signal, murmur signal and extra sound signal. Different types of features in time, frequency and statistical domains have been extracted and the best features were selected for the classification using Multi SVM. Two new features; mid-frequency and average frequency were introduced for classification of the HS signals. Finally using 7 optimal features and Multi SVM classifier an accuracy of 97.96% was achieved and this can lead to a more reliable diagnosis. The proposed method delivered a considerable improved result for classification of most common hears value diseases as normal, abnormal or healthy.

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## Footnote

*Conflicts of Interest*: All authors have completed the ICMJE uniform disclosure form (available at https://ht.amegroups.com/article/view/10.21037/ht-21-23/coif). The authors have no conflicts of interest to declare.

*Ethical Statement*: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. This research has been approved by Jimma University Institutional Review Board (IRB: 36/2019) and the study was conducted in accordance with the Declaration of Helsinki (as revise in 2013).



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