Classification of Heart Sounds Associated With Murmur For Diagnosis of Cardiac Valve Disorders

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

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Abstract

Background: Now a day, cardiovascular diseases have been a major cause of death in the world. The heart sound is still the primary tool used 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. In this study, 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 technique. The selected features are used to classify the signal into the predefined classes using multi- class SVM classifier. The performance of the proposed denoising algorithm is evaluated using the signal to noise ratio, percentage root means square difference, and root mean square error. For this work a publically available database for researchers, Partnership Among South Carolina Academic Libraries (PASCAL) and MATLAB 2018a was used to develop the proposed algorithm.

Results: Our experimental result shows that the 4th level of decomposition for the Db10 wavelets shows 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 of 98.0% respectively.

Conclusion: even if the proposed algorithm is useful for murmur detection mainly valve-related diseases and the efficiency of the proposed study is increased, future work will intend to generalize the algorithm by using hybrid classifiers on a larger dataset. Since all experiments used the PASCAL datasets, additional experiments will be needed using new datasets to be implemented using the latest mobile phones which can work as an electronic stethoscope or phonocardiogram. In addition, the case of continuous murmur and types of murmur has been included for classification in further studies.

Keywords: Auscultation, CFS, DWT, Feature extraction, HS, PCG, SVM.

Background

Heart disease is the main health problem and a primary cause of fatality all over the world. Phonocardiography, tracing of sounds produced by digital stethoscope, is a tool that leads to valuable PCG information about the heart function and can be a great tool to identify abnormalities and heart disease early. Cardiovascular disorders (CVD) are the number one causes of death globally and more people die annually from 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 largest proportion of deaths among the non-communicable diseases deaths (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).

Cardiovascular disorders are broad terms that can affect both vasculature and the heart muscle itself. In auscultation technique, a stethoscope is used for heart sound analysis to diagnose the condition of 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: stenosis and insufficiency. 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 is still the primary 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. Conventional auscultation using acoustic stethoscope requires extensive training and experience of the physician for proper diagnosis. Moreover, the storage of records for follow-ups and future references is also not possible with conventional auscultation (5). This is the driving force for this study in order to move towards 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 which is capable of producing a sound that can be heard using a stethoscope. The murmurs can be termed as indicators of various heart problems (6). The problem causing murmurs 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 (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 mean12 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 pathological heart sounds associated with murmur for diagnosis of cardiac valve disorder by using DWT and multi-class support vector machine 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.

Result

In this study, the PCG signals were studied and classified into three classes, namely normal signal, murmur signal and extra sound signal. Many features in time, frequency and statistical domains have been extracted and the best features were selected for the classification using Multi SVM which is illustrated in Tables 2 and 3. Two new features mid-frequency and average frequency were introduced in this study for the classification of the PCG signals. The study also presents the application of the wavelet transform method to PCG signal noise elimination which is examined at different levels and the Db10 wavelets at the 4th 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 having murmurs without getting into the cumbrous 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 presented algorithms can be further increased by incorporating Artificial Intelligence techniques or other hybrid classifiers on a larger dataset. The case of continuous murmurs and its types are not included in the study. So it can be included for classification in further studies.

Discussion

The work performed in preprocessing is to determine the most suitable parameters for a wavelet algorithm to denoise heart sound signals with 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 to remove the noise from the PCG signals, with different thresholding rules (Rigrsure, Sqtwolog, Heursure, and Mini- max) to analyze the resulting denoising performance of PCG signal. 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 IDWT.

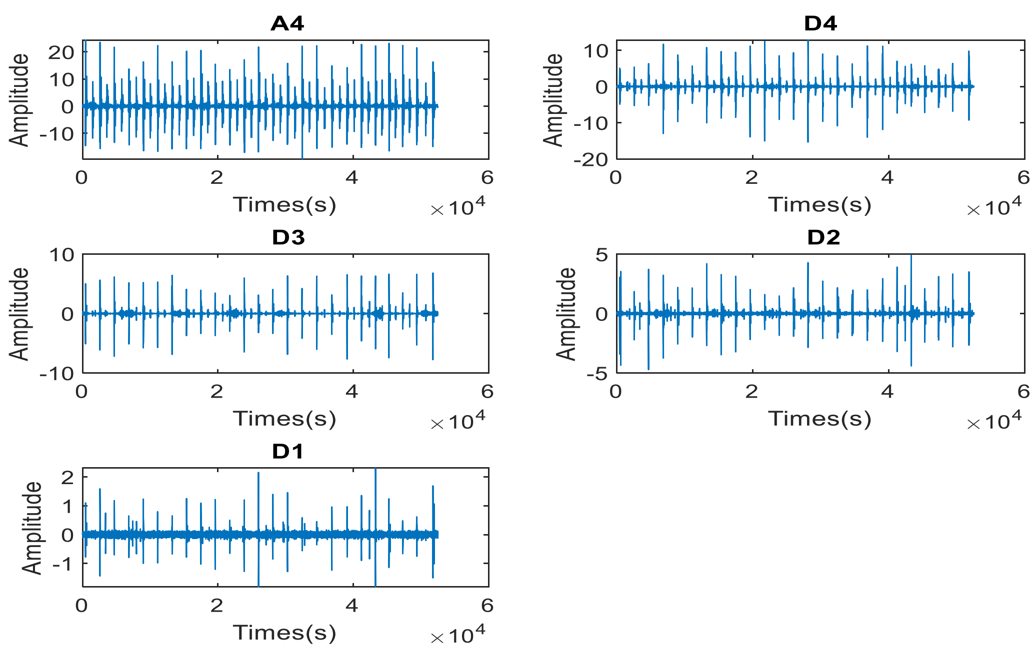

Figure1: Wavelet coefficients: **A4,** approximation coefficient. **D1,** denoised detailed coefficient of first level, **D2,** denoised detailed coefficient of second level, **D3**, denoised detailed coefficient of third level, **D4**, denoised detailed coefficient of fourth level.

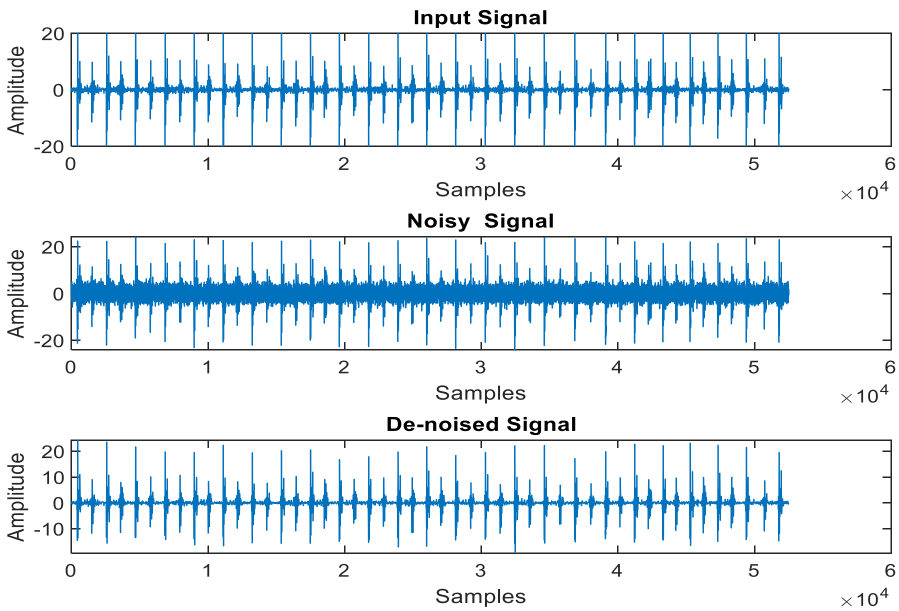

Figure 2: Denoising of PCG signal using Db10 wavelets at 4th level with soft thresholding.

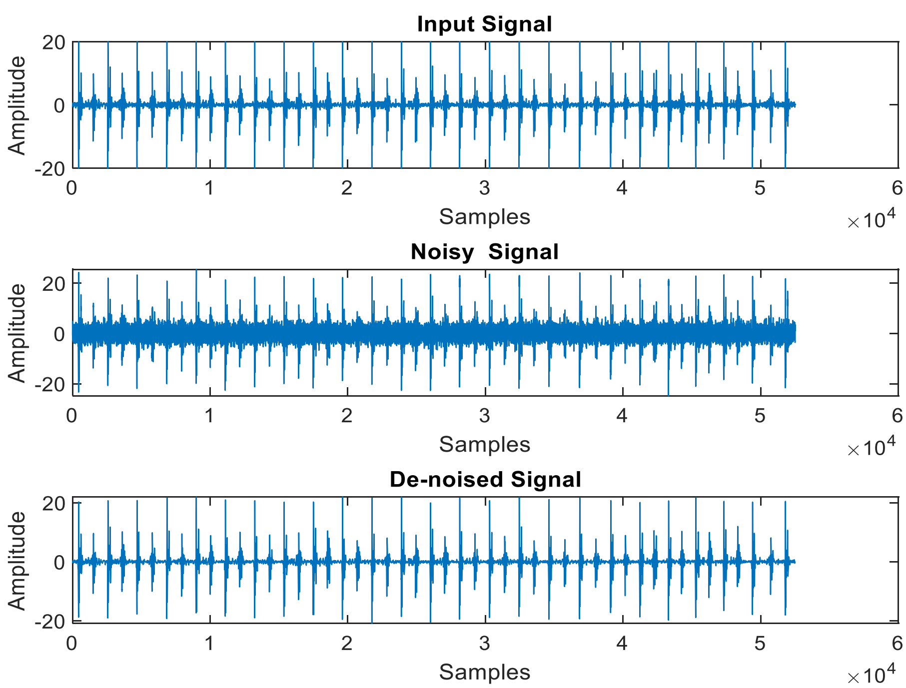

Figure 3: Denoising of PCG signal using Sym6 wavelets at 4th level with soft thresholding.

The algorithm was tested using the most widely used wavelet families, i.e., Daubechies wavelet family, Symlets wavelet family, Coiflets wavelet family and discrete Meyer wavelet family, The tested PCG signals were contaminated by white noise added at SNR = 5 dB as an initial value to test the performance of the proposed technique for noise elimination. Figure 1 shows the wavelet coefficients of the denoised signal, whereas Figures 2 and 3 show the effect of the Sym6 and Db10 wavelets on denoising the normal PCG signal using the 4th level of decomposition. Figure 4 shows a histogram comparing the SNR values obtained when using the different wavelet families with soft and hard thresholding. To study the effect of the two thresholding types Table 1 presents the SNR results when denoising normal, murmur and extra sound PCG signals using different wavelet families.

Table 1. SNR results for denoising PCG signal using different decomposition levels with the 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

Table 1 presents the SNR results using the different wavelet families with different decomposition levels from 3rd to 6th with the Rigrsure threshold selection rule and the two different thresholding types. From

Table1 it is clear that when choosing the wavelet family, the level of decomposition and thresholding type are important parameters affecting the SNR value. According to the SNR value analysis, the 4th level of decomposition for the discrete Meyer and Db10 wavelets shows the highest SNR values when using the soft and hard thresholding. The SNR values using Db10 are 15.4307 and 15.6019, compared with 15.3563 and 15.2460 when using the discrete Meyer wavelets for soft and hard thresholding respectively.

The effect of Db10 wavelets on denoising the PCG signal using the 4th level of decomposition gives better SNR values. Thus Db10 wavelet of 4th level decomposition is used for this work preprocessing analysis. To study the effect of the four thresholding rules, several experiments were done using selected wavelet families. Table 2 presents the performance in terms of SNR, RMSE, and PRD when denoising normal, murmur and extra sound PCG signals using the optimal threshold parameters.

Table2: SNR, RMSE, and PRD values for some heart sound signals using the 4th level of decomposition with the four threshold selection rules and soft thresholding.

Thresholding type	Soft											
Wavelet function	Db10											
Threshold rules	Heursure			Rigrsure			Minimax			Sqtwolog		
Threshold parameters	SNR	RMSE	PRD %	SNR	RMSE	PRD %	SNR	RMSE	PRD %	SNR	RMSE	PRD %
Normal	14.957	0.011	17.9	14.97	0.011	17.85	15.07	0.011	17.7	15	0.011	17.89
Murmur	7.9908	0.013	39.9	7.912	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	22.2	12.99	0.04	22.4	11.7	0.04	22.08

From table2 it is clearly shown that the Rigrsure and Sqtwolog selection rules perform better than the others. But Rigrsure shows the maximum performance for all the wavelet families. These results show that the proposed algorithm using the Db10 families at the 4th level of decomposition gave the maximum SNR, RMSE, and PRD values. It is known that it is difficult to analyze PCG signals in the time domain only. Therefore, Figure 4 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.

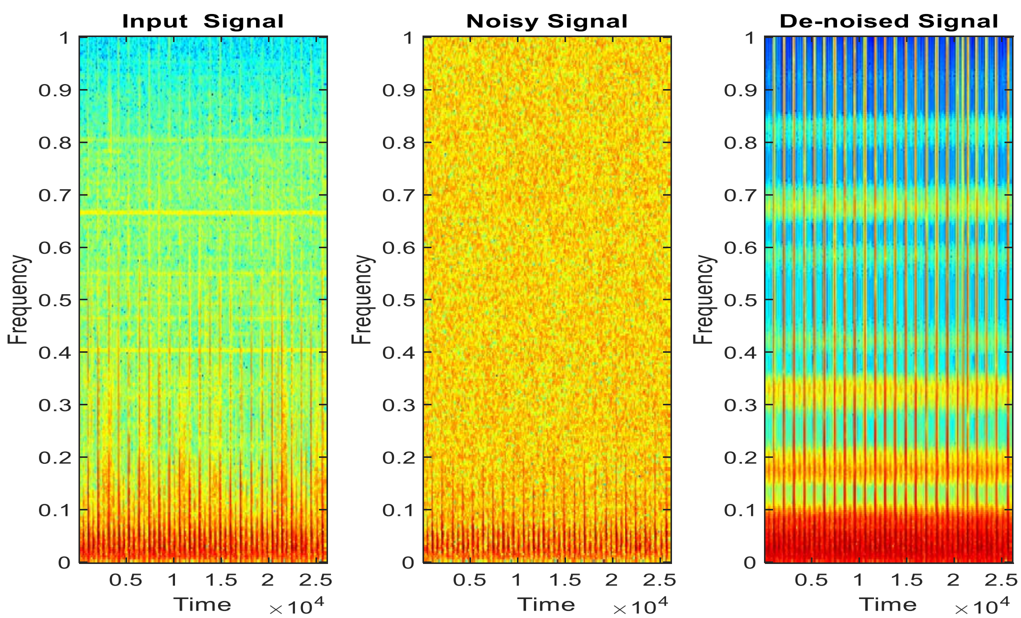

Figure4: PCG signals spectrograms:

After the signal is denoised 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.

The features which are extracted in the feature extraction phase are then 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 features that have been reduced using CFS and those selected features with higher CFS values are shown in Table 3.

Table 3. List of Selected Features for Classification

S.no	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

Selection of only a few significant features reduces the curse of dimensionality and computational time. This means that by simply evaluating the value of signal for the above features, classification of three types of signals can be done. The classification is done using the set of selected feature values. The accuracy is then calculated according to how many test signals are classified correctly and the confusion matrix has also been made according to the classification of test samples.

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. As shown in Table 5 out of the 50 normal signals 49 was classified correctly and 1 normal signal were 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 signals were classified correctly.

Table 4. Evaluation metrics for classification using multiclass SVM algorithm.

Actual Class / Predicted 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%	

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.

Table 5: Comparison between the proposed methodology and previous proposed methodologies.

Author	Database	Methods	Result
Mandeep Singh (2013)	PASCAL dataset	Naïve Bayes classifier	Accuracy 93.33%
Elsa Ferreira (2013)	PASCAL dataset	Decision tree classification algorithm	Accuracy 72.76.33%
N. R. Sujit (2016)	PASCAL dataset	Regression Tree	Accuracy 78.33%
Zichun Tong (2015)	PASCAL dataset	Hilbert Transform + SVM	Accuracy 90.5%
Nabih-Ali (2017)	PASCAL dataset	DWT and ANN	Accuracy 97%
The proposed System	PASCAL dataset	DWT and SVM	Accuracy 97.96%

From Table 5, it is clear that the proposed algorithm achieved better classification ac- curacy 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.

Conclusion

In this study, the characteristic features of PCG for detection of heart valve diseases were investigated and analyzed. The algorithms proposed in this study were time efficient, simple, and require only PCG as input signal unlike other methods which require ECG gating. The proposed algorithm for murmur detection is useful to detect mainly valve-related diseases and other congenital abnormalities.

Research in this area can be very helpful for easy and earlier diagnosis of various heart diseases. PCG signals are capable of indicating the heart problem at an earlier stage which can be very useful in preventing fatality due to heart problems. This work presents the application of the wavelet transform method to PCG signal analysis. Comparison of the results obtained using different wavelet families reveals the resolution differences among them. Since the noise level is one of the most important parameters in wavelet denoising, it was examined at different levels 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. Many 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 PCG 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 can also be implemented using the latest mobile phones with the applications that can work as electronic stethoscope or phonocardiogram which can be used for detecting any abnormalities at an earlier stage.

Methods

The methodology used in this study to classify various heart sounds into predefined classes consists of five stages i.e. Signal acquisition, preprocessing, feature extraction, feature reduction, and classification as shown in Figure 5.

Datasets

The PCG signal acquisition can be done by electronic stethoscopes which respond to the sound waves identically to the conventional acoustic stethoscope with the changes in electric field replacing the changes in air pressure. For this study an electronic database of PCG signals was taken from PASCAL (11). The dataset used was taken from a clinical trial in hospitals using a digital stethoscope from adults. In this study, a dataset recorded from PCG having 300 signals was used out of which 150 are normal signals, 100 are murmur signals and 50 are extra sounds.

Wavelet-based Preprocessing of PCG signals

Heart sound signal is a typical biomedical signal, which is random and has strong background noise. In the process of collecting heart sound signals, it is vulnerable to external acoustic signals and electrical noise interference; particularly , friction caused by subjects breathing or body movement(12). The main idea of the wavelet denoising algorithm is to obtain the essential components of the signal from the noisy one, then threshold the small coefficients considering them to be pure noise. In this research, four different wavelet families (Daubechies, Symlets, Coiflets and Discrete Meyer) were applied for PCG signal denoising.

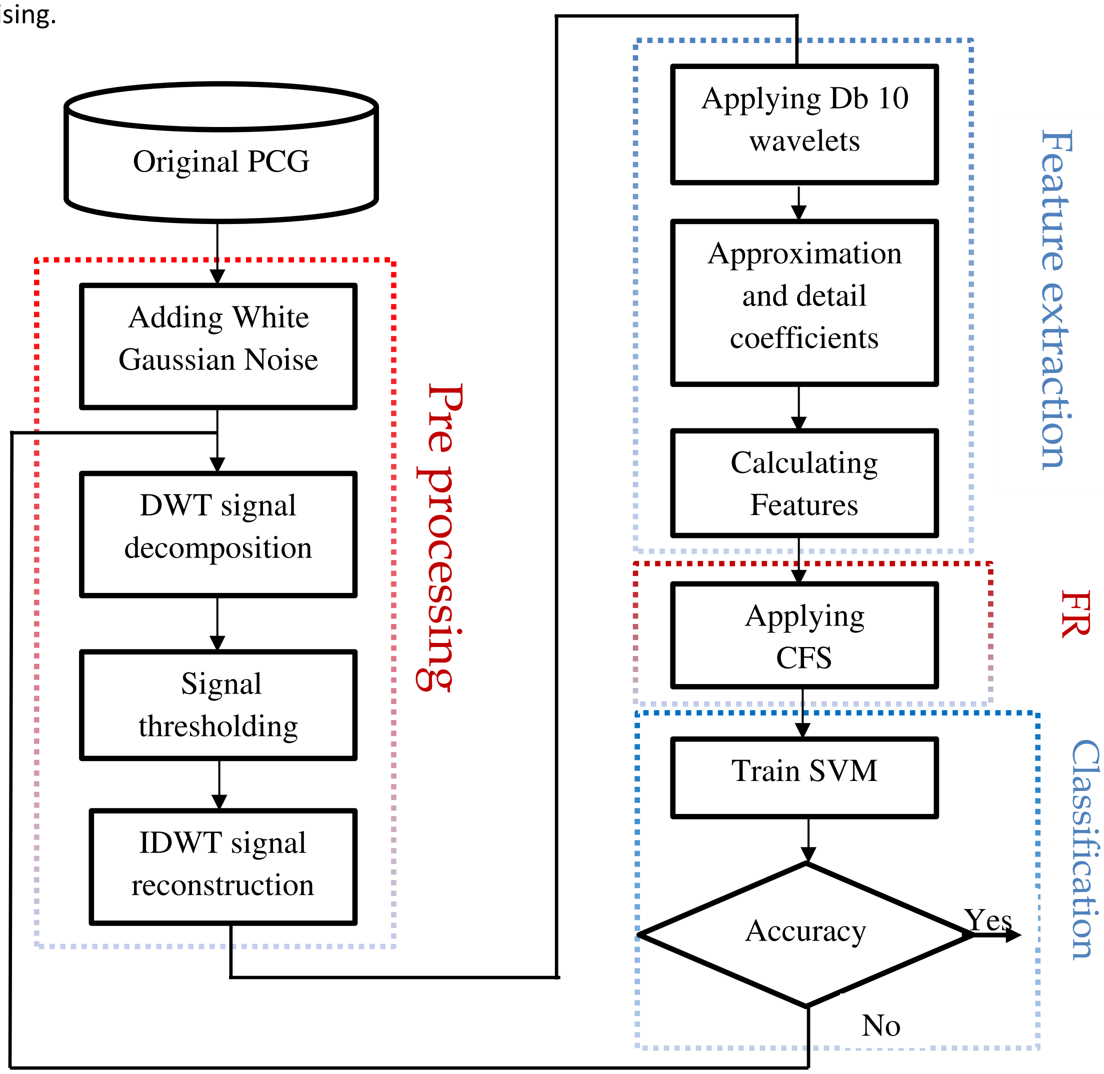

Figure 5: The general methodology of the research project: signal acquisition, pre-processing, feature extraction, feature selection and classification.

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 work to investigate their performance in signal denoising (13).

- Rigrsure: the threshold is selected using the principle of Stein's unbiased risk estimate (SURE) quadrature loss function.
- Sqtwolog: the threshold is fixed at that yielding minimax performance multiplied by a small factor proportional to log (length(s)), usually $\sqrt{2\mathrm{loglength(s)}}$.
- Heursure: the threshold is selected using a mixture of the first two methods.
- 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.

The most suitable way to see the effect of noise added to heart sound signals is to add white Gaussian noise. After the denoising process, the performance can be measured by comparing the denoised signal with the original signal. So many methods have been proposed to measure the performance of denoising algorithms. 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 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 (14). The SNR, RMSE, and PRD can be formulated as follows.

$$\mathrm{SNR}_{db} = 10\log_{1o} \frac{\sum_{n=0}^{N-1} s\,(n)^2}{(s(n)-S'(n)^2)} \text{ ....1}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}\ (s(n)-s'(n)^2)} \text{ ....2}$$

$$\text{PRD} = \sqrt{\frac{\sum_{n=0}^{N-1}\ (s(n)-s'(n)^2)}{\sum_{n=0}^{N-1} s\,(n^2)}} \text{ ....3}$$

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

Feature extraction

The discrete wavelet transform 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 6.

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

1. The HS signal decomposes into four detail subbands using discrete wavelet transform. The subbands are high-frequency detail band coefficients and low-frequency approximation band coefficients.
2. The approximation coefficients are further decomposed using DWT to extract localized information from the subband of detail coefficients. In this work, four levels of decomposition have been done using Daubechies wavelet (db10).
3. For further analysis and processing, all the four-level detail band coefficients have been taken.
4. The frequency vector (in radians/sample) is extracted for four detail subbands using periodogram function in Matlab.
5. After decomposition signals are reconstructed using IDWT.
6. 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.

Table 6. List of features extracted for classification

S. 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	(18)
8	Variance	Statistical	(19)
9	Skewness	Statistical	(20)
10	Kurtosis	Statistical	(21)
11	Root Mean Square	Time	(20)
12	Bandwidth	Frequency	(14)
13	Cepstrum Peak Amplitude	Cepstrum	(18)
14	Mid-frequency	Frequency	New
15	Average Frequency	Frequency	new

The extracted features from the signal including their source are as shown in table 6. Thus, the extracted features for the three classes of HS signals are tabulated and analyzed for classification.

Feature Reduction.

In this phase, the redundant and misleading features have to be reduced and only significant features have to be retained for classification. This reduces the computational cost and makes the algorithm time efficient. The final algorithm is to have a minimum number of features and should have maximum accuracy. So, features are ranked and only the best features are used for classification. The selected features have the potential to discriminate between the three classes of signals namely; normal, murmur and extra sound signals.

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 (PCA), box plot method (BP), fisher's Discriminant Ratio (FDR) 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 experiments is based on forward selection with an appropriate correlation measure and a heuristic search strategy. CFS's feature subset evaluation function is shown as follows:

$$\text{Ms}=\frac{kr_{cf}}{\sqrt{k+k(k-1)r_{ff}}}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$

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 to which it predicts classes in areas of the instance space 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 Equation 4) found during the search is used to reduce the dimensionality of the data. It is important to note that the general concept of correlation-based feature selection 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

Support vector machine 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, Λ w_K using any learning algorithm to make a decision by the winner takes all principles which is argma $\mathrm{x_i}$ $\mathrm{w_i}^{\mathrm{T}}\mathrm{x}$ (24)(25)

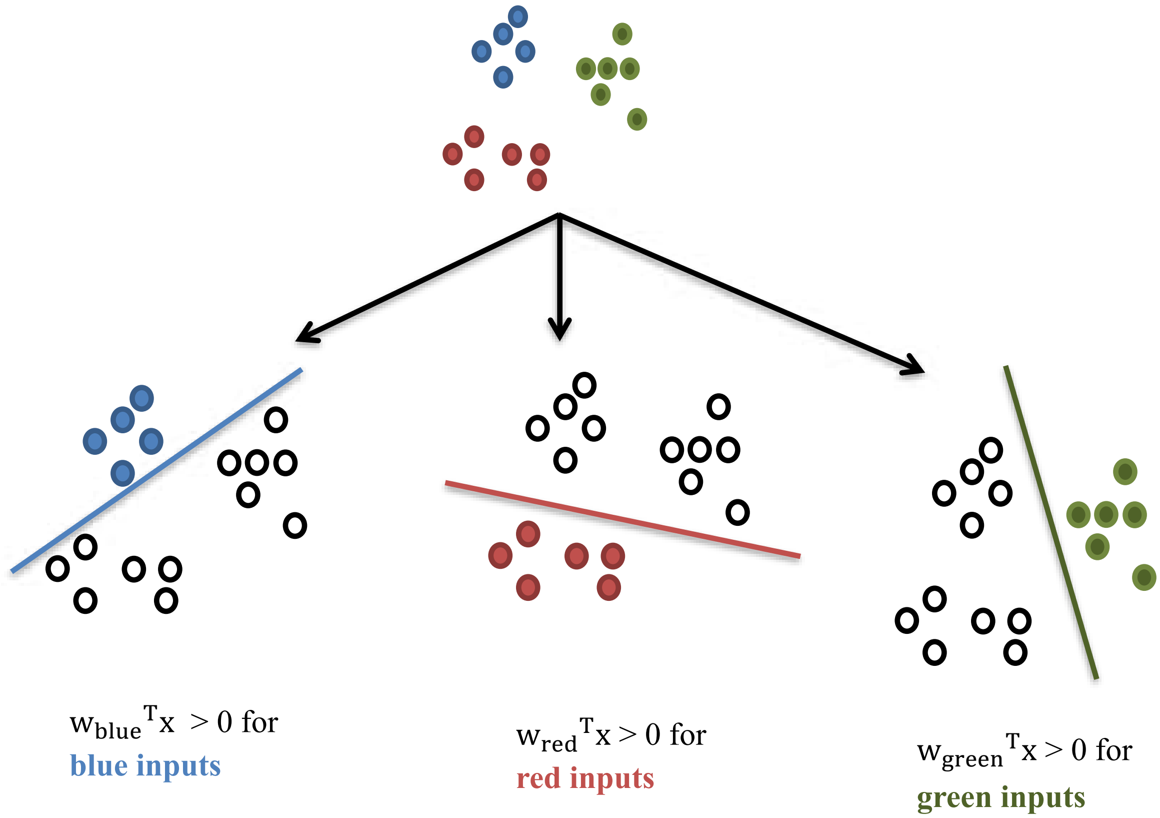

Figure6 Visualizing One-vs-all multi-classification of support SVM for three classes

From the full dataset, construct three binary classifiers, one for each class as shown in Figure6 the winner takes all to predict the right answers, but only the correct label will have a positive score. In this study, this algorithm is selected because it is easy to learn and use any binary classifier learning algorithm.

Aberrations

argmax Arguments of the maxima

CFS Correlation-Based Feature Selection

Coif Coiflets

CVD Cardiovascular Disorder

Db Daubechies

DWT Discrete Wavelet Transform

HS Heart Sound

IDWT Inverse Discrete Wavelet Transform

LS-SVM Least Square Support Vector Machine

MATLAB Matrix Laboratory

MLP-BP Multi-Layer Perceptron Back Propagation

PASCAL Partnership Among South Carolina Academic Libraries

PCG Phonocardiography

RMSE Root Mean Square Error

SNR Signal to Noise Ratio

SVM Support Vector Machine

Sym Symlets

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Not applicable.

Authors' contributions

All authors contributed to the research design of the study. Ahmed Ali Dawud experimented, analyzed the results and drafted the manuscript. Towfik Jemal and Bheema Lingaiah makes Proof read and edited the manuscript. All are approved the final version of the manuscript and agreed to be accountable for all aspects of the work. All authors read and approved the final manuscript.

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Availability of data and materials

The l dataset used for this study was extracted from the original PASCAL dataset.

Link to the original dataset - http://www.peterjbentley.com/heartchallenge/

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors have no any competing interest.

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