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Classification of Heart Sound Signals Using Multi- modal Features

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Abstract

Cardiac auscultation is a technique of listening to heart sounds. Any abnormality in the heart sound may indicate some problem in the heart. In this paper, the phonocardiogram (PCG) signal i.e. the digital recording of the heart sounds has been studied and classified into three classes namely normal signal, systolic murmur signal and diastolic murmur signal. Total number of samples used for this study are 144 out of which 60 are normal signals, 45 are diastolic murmur signals and 39 are systolic murmur signals. Various features have been extracted for the classification. A total of 28 features have been extracted and then reduced to 7 most significant features using feature reduction technique. The selected features have been used to classify the signal into various classes using classifiers. The classifiers which have been used in this study are *k-NN (k Nearest Neighbour)*, *fuzzy k-NN* and *Artificial Neural Network (ANN)*. Both *k-NN* and *fuzzy k-NN* as classifiers have the highest accuracy of 99.6%.

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Keywords: Heart Sounds; Classification; Fearture Extraction

1. Introduction

Cardiac auscultation is the foremost basic analysis tool used to evaluate the function of the heart [1]. It is a technique of listening to heart sounds with a stethoscope. The main cause of the generation of heart sounds in blood turbulence. The blood turbulence is mainly caused due to opening and closing of heart valves and also due to fast accelerations and retardations of blood flow in the heart chambers [2]. The digital recording of heart sound is called phonocardiogram (PCG). It is mainly recorded using the electronic stethoscope and the signal is displayed on the computer.

The heart sound comprises of four components: S1, S2, S3 and S4. S1 (lub) and S2 (dub) are called fundamental

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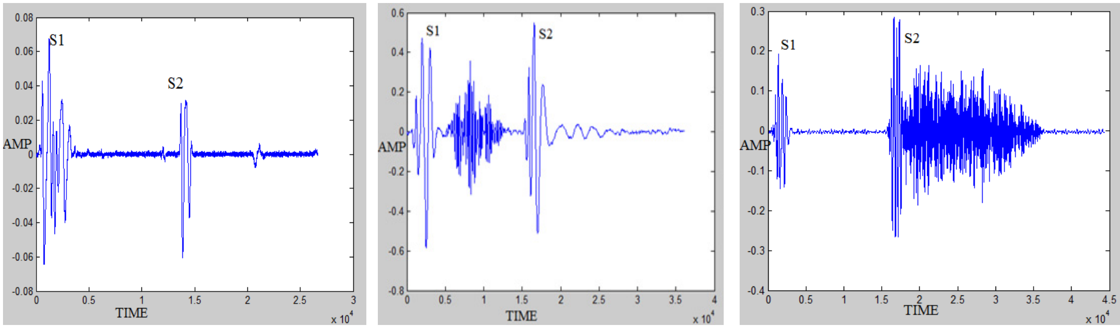
heart sounds (FHS). S1 is caused due to closure of atrioventricular valves. S2 is caused due to closure of semilunar valves. S3 and S4 are rarer heart sounds which are not normally audible and are sometimes visible on the graphical recording i.e. phonocardiogram. The period from beginning of one heart beat to the next one is known as the cardiac cycle. In other words, the interval between start of S1 to start of next S1 is called cardiac cycle. The region between S1 and starting of S2 of same heart cycle is called systolic region and the region between S2 and starting of S1 of next heart sound cycle is called diastolic region. The duration, pitch, shape etc of heart sounds tells or indicates us about the different conditions of the heart. Sometimes unusual sounds appear in the heart sounds which are called murmurs and may indicate some abnormalities in the heart. The murmurs can be classified into systolic murmurs, diastolic murmurs and continuous murmurs based upon their location of occurrence. Murmurs which occur during systolic region are known as systolic murmurs and those occurring during diastolic region are known as diastolic murmurs. Murmurs which occur throughout the cardiac cycle are called continuous murmurs. In this study, the heart sounds have been classified into three classes namely, normal signal, systolic murmur signal and diastolic murmur signal (see figures 1, 2, 3). The systolic murmur may be caused due to stenosis of semilunar valves or regurgitation of the atrioventricular valves and causes of diastolic murmurs include aortic and pulmonary valve regurgitation, and mitral and tricuspid valve rumbles. Previously, various studies have been carried out for classification and feature extraction of the PCG signal.



(a) (b) (c)

Figure 1: (a) A normal PCG signal. (b) PCG signal with systolic murmur. (c) PCG signal with diastolic murmur.

2. Previous work

Many studies have been done on PCG signal so far. The research on this topic decreased with the advent of new techniques like Echocardiography (ECG). But nowadays research in this field has increased again due to improvements in signal processing techniques and new generation personal computers [3]. Researchers have extracted various features in different domains using wavelet transforms, FFT etc and have classified the PCG signal into various classes. Many researchers have done various studies on PCG signal [2, 4-10]. Following are some of the related works done by various researchers.

Nigam *et al* proposed a method in 2008 which was able to locate systolic murmurs in the PCG signals and was based on their visual simplicity. Their absolute amplitude and frequency characteristics were independent of the visual simplicity. The approach used was fuzzy clustering. The accuracy of 80% was achieved in detecting systolic murmurs [11]. In 2010, Ari *et al* classified normal and abnormal heart sounds with least square support vector machine (LSSVM) as a classifier using wavelet based feature set. Results showed that the proposed technique had greater accuracy than standard SVM and classical least square SVM [12]. Choi *et al.* (2010) proposed a novel cardiac sound spectral analysis method using the normalized autoregressive power spectral density (NAR-PSD) curve with the support vector machine (SVM) technique for classifying the cardiac sound murmurs. Also two diagnostic features Fmax and Fwidth were proposed which described the maximum peak of NAR-PSD curve and the frequency width between the crossed points of NAR-PSD curve on a selected threshold value [13]. Akbari *et al*, in 2011, proposed a new analytical technique which he named as Digital Subtraction Phonocardiography (DSP). This technique is based on the principle that the murmurs are random in nature but the Fundamental Heart Sounds (FHS) are deterministic in nature. The difference between the acoustic emissions of two successive heart beats was simply taken and murmurgram was constructed. It was found that for normal cases the murmurgram should be flat between the FHS but for abnormal cases i.e. heart sounds with murmurs this wasn't the case [14, 15]. In 2012, Debbal *et al* used Continuous Wavelet Transform (CWT). He studied normal and abnormal Phonocardiogram signals and extracted features in time-frequency domain and their scalograms were plotted. It was seen that they exhibited noticeable morphological differences in terms of duration and spectral composition of sounds [16]. Safara *et al* proposed multi-level basis selection (MLBS) in 2013. The classification was done between normal heart sound signal and three kinds of murmur signals (mitral regurgitation, aortic regurgitation and aortic stenosis). It was found out that an accuracy of 97.56% was achieved using MLBS [17]. In 2013, Singh *et al* proposed a method to distinguish between normal and abnormal heart sounds based on feature extraction. No ECG gating was used and a new feature 'mean12' i.e. maximum of mean in systolic region and diastolic region was proposed. Classification accuracy was calculated with and without this new feature and it was seen that the accuracy was increased when this feature was used for classification. Highest accuracy of 93.33% was achieved [3].

3. Methodology

As we know that heart sound signal gives us valuable information about the heart condition, the PCG signal is capable of diagnosing various heart diseases at an earlier stage. Therefore, signal processing techniques can be employed to process the PCG signals towards improving the accuracy of diagnosis [18].The various stages that are involved in heart sound analysis are: signal acquisition, feature extraction, feature reduction and classification.

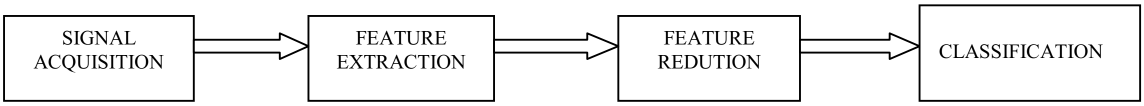


Figure 2: Various steps involved in PCG signal analysis.

3.1 Signal Acquisition

PCG signal is a voice signal which is recorded using the electronic stethoscope. Sometimes preprocessing is done on the acquired signal. The signal may be filtered, normalized, scaled or segmented for further analysis. In this study, the size of dataset is of 144 samples out of which 60 are normal PCG signals, 39 are with systolic murmur and the remaining 45 are with diastolic murmurs. The signals were first divided into individual heart cycles using WavPad Sound editor by NCH Software. The publically available database has been used in the study [19]. This database was recorded during clinic trial in hospitals using the digital stethoscope DigiScope®.

3.2 Feature Extraction

In this stage the parameters which have the potential to discriminate between various classes are calculated from the PCG signal and are further used for classification of the signals. They may be time domain, frequency domain, statistical based parameters. The features that have been used in this study are extracted using MATLAB (R2010b) and Spectrum Analyzers: Spectra Plus SC and Sigview. A total of 28 features are extracted (see Table 1).

Table 1: List of extracted features.

S. No.	Time domain features	S. No.	Frequency domain features	S. No.	Stastical domain features
1	Total power [20]	1	Peak frequency [20]	1	Mean
2	Peak amplitude[21]	2	BW(s) (Spectral)[3]	2	Standard deviation
3	Ta	3	Intermodulation Distortion (IMD)	3	Variance
4	Tb	4	Peak frequency(s) (Spectral)	4	Skewness [20]
5	Zero Crossing Rate (ZCR) [22]	5	Total Harmonic Distortion (THD) [3]	5	Kurtosis [20]
6	ZCR1	6	Q-factor(s) (Spectral)[3]		
7	ZCR2	7	Peak frequency(p) (Peak hold)		
8	RMS	8	BW(p) (Peak hold)[3]		
9	RMS1	9	Q-factor(p) (Peak hold)[3]		
10	RMS2	10	Crest factor		
11	Max1 (proposed)	11	Dynamic range		
12	Max2 (proposed)				

The suffix 1 and 2 used denote the feature value in systolic region and diastolic region respectively. Many different features have been extracted in different studies. Features that have not been used in earlier studies have been explained. RMS is defined as the square-root of mean of square of the waveform. A small variance indicates that the data points tend to be very close to the mean and hence to each other, while a high variance indicates that the data points are very spread out around the mean and from each other. IMD is the amplitude modulation of signals containing two or more different frequencies in a system with nonlinearities. Crest factor is defined as the ratio of peak value to RMS value of a waveform. Higher crest factor indicate peaks. Dynamic range is the ratio of max value to the minimum value in a waveform. Max is the maximum value of the signal. Ta is time in systolic region starting from S1 till the murmur lasts. Tb is time in diastolic region starting from S2 till the murmur lasts.

3.3 Feature Reduction

Feature reduction is the third stage of the methodology used. In this stage out of the extracted features, a few are selected so that misleading and redundant features are removed and it also reduces the dimensionality and computational load. It is one of the important stages so that classification is done properly and with higher accuracy. In this study, features were plotted against each other to see which features are capable of separating the classes. Also, Fisher's Discriminant Ratio (FDR) is calculated between features of two classes. FDR is defined by the following equation:

$$FDR = \frac{|\mu_1 - \mu_2|^2}{\sigma_1^2 + \sigma_2^2} \tag{1}$$

In equation (1), μ and σ represents the *mean* and *standard deviation* of a feature and the subscripts *1* and *2* represent class of the signal. For this study FDR has been calculated between normal-systolic, normal-diastolic and systolic-diastolic signals and those features are selected which have higher value of FDR.

Table 2: Table showing value of FDR ratio calculated for each feature.

S. No.	Feature Name	Normal- Diastolic	Normal- Systolic	Systolic-Diastolic
1	Peak frequency	0.0723	0.7500	0.4124
2	Peak amplitude	0.7842	2.1565	0.4112
3	Total power	0.7380	1.2454	0.0022
4	THD	0.0005	0.0099	0.0054
5	IMD	0.0250	0.0444	0.0004
6	Peak frequency(s)	0.0296	0.3697	0.2898
7	BW(s)	0.0629	0.0726	0.0006
8	Q-factor(s)	0.0032	0.1813	0.4070
9	Peak frequency(p)	0.1505	1.0069	0.2560
10	BW(p)	0.0030	0.4201	0.1777
11	Q-factor(p)	0.1344	0.0016	0.0873
12	Ta	0.0707	13.1090	17.2189
13	Tb	5.9862	0.5120	3.5765
14	Crest factor	3.0335	7.1205	0.8307
15	Dynamic range	0.3169	0.2024	0.0448
16	Mean	0.0069	0.7351	0.4057
17	Standard deviation	1.1625	5.0208	0.3916
18	Variance	0.5692	3.7731	0.2592
19	Skewness	0.0063	0.0004	0.1474
20	Kurtosis	1.5198	1.7497	0.3642
21	ZCR	2.0339	2.1383	0.0122
22	RMS	1.1625	5.0208	0.3916
23	RMS1	0.4519	5.6353	4.8869
24	Max1	0.2117	9.9879	9.4525
25	ZCR1	2.1683	2.6070	0.1518
26	RMS2	1.2155	0.2682	1.0225
27	Max2	1.9291	0.0715	1.8384
28	ZCR2	2.4815	2.2341	0.1007

Table 3.List of features that have been selected for classification after feature reduction stage.

Rank	Feature Name
1	Ta
2	Max1
3	Tb
4	RMS1
5	RMS2
6	Max2
7	Kurtosis

3.4 Classification

The last stage is the classification stage. In this stage the selected features are used to classify the signals into their predefined classes. To classify signals into the three classes namely, normal, systolic and diastolic different classifiers have been used like:

- *k-NN (k nearest neighbours)*
- *Fuzzy k-NN*
- *ANN (Artificial neural network)*

The dataset is divided into training set and the test set. Training set consists of 94 signals and the test set consists of 50 signals. First training of classifier is done using the training set and then testing is done using the test set and the accuracy is calculated. 5 fold cross validation was done to calculate the accuracy for each of the classifier.

4. Results

Different accuracies are obtained using different classifiers. When *k-NN* classifier is used, the value of *k* is varied and different accuracies are obtained which are shown in Figure 4. The 5 fold cross validation has been used to calculate the accuracy at each value of k (see Figure 5 and 6). It is observed that maximum accuracy of 99.6% occurs at *k* = 4. When we use fuzzy *k-NN* classifier the maximum accuracy achieved is of 99.6% at *k*=3 and 4. Also, *ANN* classifier was used with 7 input neurons, one hidden layer with 5 neurons and an output layer with three neurons. Feed-forward Back propagation neural network was used with trainlm as the training function. The transfer function used was Logsig (logarithmic sigmoidal) function. MSE (mean square error) was chosen as the performance function. Accuracy of 98.8% was achieved after 5 fold cross validation using *ANN* as a classifier.

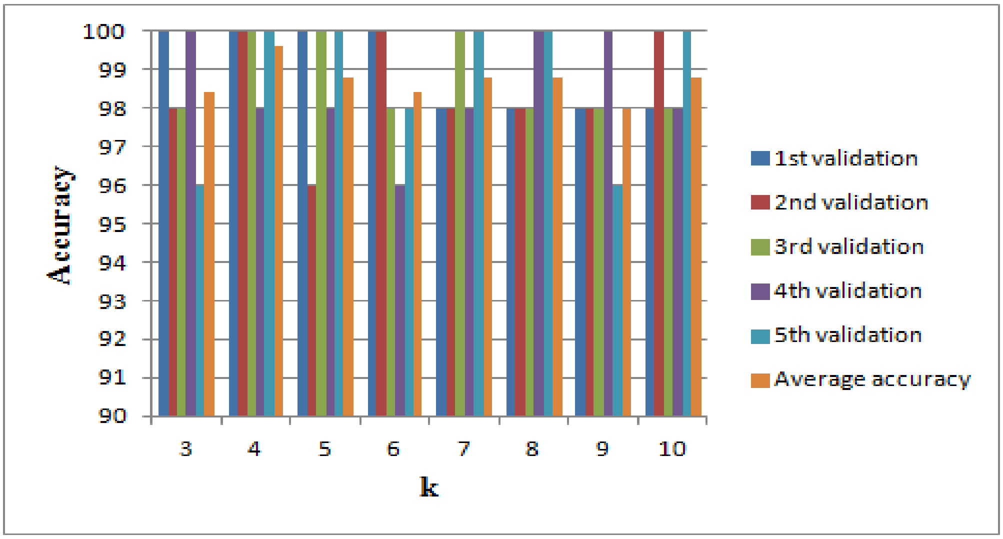


Figure 3: 5 fold validation and average accuracy using k-NN as a classifier.

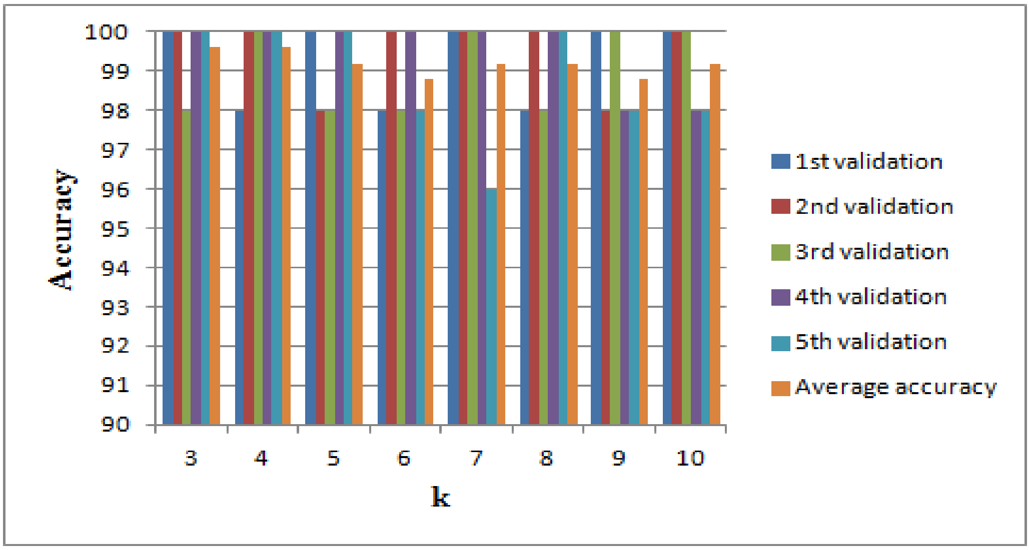


Figure 4: 5 fold validation and average accuracy using fuzzy k-NN as a classifier.

5. Conclusion

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. Research in this area can be very helpful for easy and earlier diagnosis of various heart diseases. In this study, the PCG signals were classified into three classes namely normal, systolic murmur and diastolic murmur signal. Various time domain, frequency domain and statistical features were extracted to classify them into the predefined classes accurately. Two new features, Max1 and Max2, have been proposed in this study for classification of signals with higher accuracy. The highest accuracy of 99.6% was achieved by using *k-NN* and *Fuzzy k-NN* as classifier and 98.8% accuracy was achieved using *ANN* as compared to 93.33% achieved using Naive Bayes classifier in which classification was done into two classes namely normal signal and murmur signal [3].

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