Classification of PCG Signals: A Survey

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ABSTRACT
Heart sounds are multi component non-stationary signals characterized as the normal phonocardiogram (PCG) signals and the pathological PCG signals. PCG is a weak biological signal mixed with strong background noise susceptible to interference from noise. The noise may be added due to various sources. The PCG signal has specific individual characteristics which are considered as a physiological sign in a biometric system. Literatures suggest that the method on time-frequency analysis is known as the trimmed mean spectrogram (TMS). The abnormal murmurs in heart sound can be diagnosed. Another method in time-frequency domain is used in which features are extracted from the TMS containing the distribution of the systolic and diastolic signatures. Probability Neural Networks (PNNs) are used in feature extraction with the acoustic intensities in systole and diastole. These methods can detect accurately the heart disease depending on the applied PCG signal but the result obtained is not optimum. An adaptive neuro-fuzzy inference system (ANFIS) is suggested that can correctly detect the pathological condition of heart.

General Terms
PCG signal classification, ANFIS, Auscultation.

Keywords
PCG signal, Wavelet, Heart Sounds, Phonocardiogram, ANFIS, Time-Frequency analysis etc...

1. INTRODUCTION
When a patient visits the physician for auscultation, a heart murmur is the most common abnormal auscultatory NGs among findings of the physician. The auscultation is a technique in which a stethoscope is used to listen to the sounds of a body. The heart is divided into four chambers namely atrium and ventricles. The upper two chambers are known as atria while the lower two chambers are called as ventricles. Heart muscles squeeze the blood from chamber to chamber. During this squeezing process, the valves help the blood to keep flowing smoothly in and out of the heart. The structural defects of the heart are often reflected in the sounds produced by the heart. As an example, a very important type of abnormal sound is the “murmur”, which is a sound caused by the turbulent flow of blood in the cardiovascular system. In case of murmur, the physician decides if it represents either a pathological or an innocent murmur. The ability of primary care physicians to diagnose a murmur is poor [1-3].

1.1 Phonocardiogram Signal
Heart sounds are weak acoustic signals in range from 10 Hz to 250 Hz [1]. The PCG signals are heart sound signals produced by the vibration of the heart sound and thoraxic systems containing information related to the heart condition. The pitch and timing of a heart sound are very important used in diagnosing various pathological conditions of the heart valves. The analysis of heart sounds using frequency spectra is referred as phonocardiography [4]. The PCG signal of normal case has two distinct activities, the first heart sound s1 and the second heart sound s2; whereas for an abnormal heart, many signal activities between the first and the second heart sound are present. These extraneous activities between s1 and s2 are called as two abnormal sound signals. Wavelet theory is used to find the accurate pathological condition of heart. Generally, multi-resolution decomposition, the thresholding, processing in wavelet domain and the modulus maxima method of the wavelet transform are employed. Several features such as entropy, energy, variance and standard deviation are considered for the detection of heart’s pathological conditions [5]. The cause of abnormal heart murmurs is the congenital heart defects or acquired heart valve diseases. Mitral stenosis, aortic regurgitation, aortic stenosis, mitral regurgitation are among the most common pathological types of murmurs [3]. These can be seen in Fig. 1, Fig. 2, Fig. 3 and Fig. 4.

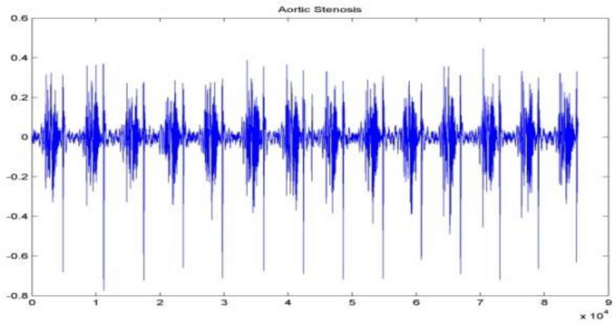

Fig 1: Aortic Stenosis

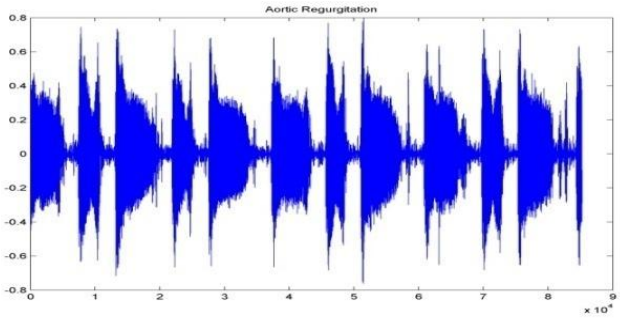

Fig 2: Aortic Regurgitation

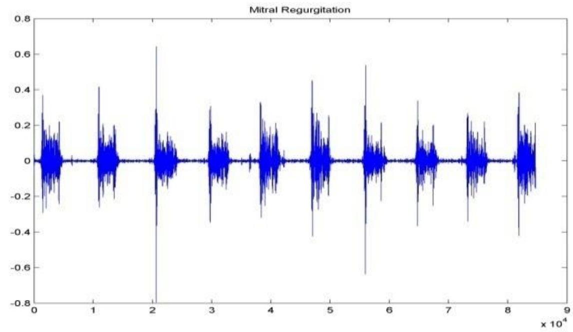

Fig 3: Mitral Regurgitation

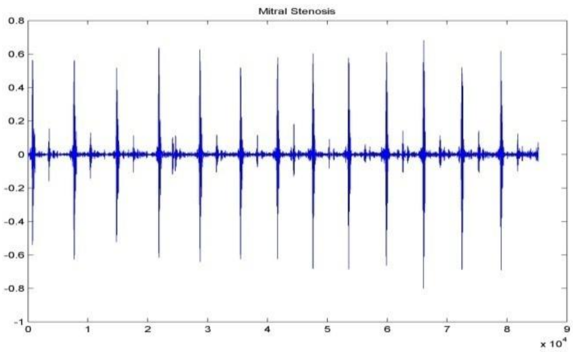

Fig 4: Mitral Stenosis

2. SEVERAL METHODS

Motaleb et al. [2012] proposed a new algorithm, where new features characteristics are extracted from the PCG signals used to develop artificial intelligence algorithms. Using these features, PCG signals of 94 human subjects collected from Texas heart institute and Biosignetics Corporation, were classified using a neural network utilizing Back Propagation Network (BPN) and Radial Basis Function (RBF) network algorithms to assess the diagnosis predictability of the developed algorithm. Total 32 are diagnosed with mitral regurgitation (disease-1), 31 with coarctation of the aorta (disease-2), and 31 with mitral stenosis (disease-3). Out of the 94 signals, 66 were used for training, 5 for validation and 23 for testing.

2.1 Feature Extraction

There are a number of feature extraction algorithms available in current literatures. Linear Frequency Band Cepstral (LFBC), the Heart Sound Segmentation (HSS), the Mel Frequency Cepstrum Coefficients (MFCC) and the Discrete Wavelet Transform (DWT) methods are mainly used. The classification algorithms use wavelet transform and the segmentation algorithms. Normally, four features are extracted namely activity or variance, mobility, complexity or form factor and the number of peaks from the frequency domain plot of the Power Spectral Density (PSD) [6]. The number of peaks can be very large; the raw data may not be suitable for use as inputs to the neural networks. This problem is solved using a grading system depending on the number of peaks for each system which is shown in TABLE-I. The features used are collectively known as Hjorth descriptors.

Table I. Grading system used for the peaks

No. of Peaks	Grading value
0-20	0.1
20-40	0.2
40-60	0.3
60-80	0.4
8-100	0.5
100-120	0.6
120-140	0.7
140-160	0.8
160-180	0.9
180 and above	1.0

2.2 Neural Networks based Classification

Classification is the process of assigning a label to an unknown pattern so that it is categorized into one of several known categories. The neural networks provide a practical, general and robust method for learning discrete-valued, vector-valued or real-valued functions from samples [7]. Two algorithms are studied here.

2.2.1 Back-propagation Network (BPN)

BPN is a feed-forward network consists of three layers, input layer, hidden layer and output layer. For increased complexity of the problem, more number of hidden layers is used. The back-propagated signals are usually modified using the derivative of transfer function and the connection weights that are adjusted using the Delta Rule. The minimum value of mean square error between the actual output layer of the network and the desired output is minimized using the gradient descent algorithm. A sigmoid function is used because of its similarities with the biological neuron. Because of three classes of diseases, a state numerical code is assigned for each disease. The BPN is trained to reproduce the related code at the outputs. The output can be left in decimal form, where the decimal numbers 1, 2, and 3represent the classes, or codes in binary form are used. Binary classification system is used for the output layer in which the outputs are coded in binary form as: code 00, for disease 1; code 01 for disease 2; and code 10 for disease 3.

2.2.2 Radial Basis Function Network (RBF)

RBF is a three-layer network consists of the input layer, the output layer and the hidden layer, where a radial activated function is implemented by each hidden unit in hidden layer. RBF is compared to feed-forward networks in terms of accuracy and shorter computational time. The error between the target and the desired output is minimized using gradient descent algorithm. Radial basis function networks have many uses, it is used as activation functions in ANN and its uses in different field includes function approximation, time series prediction, classification, and system control. An RBF is shown in Fig.5.

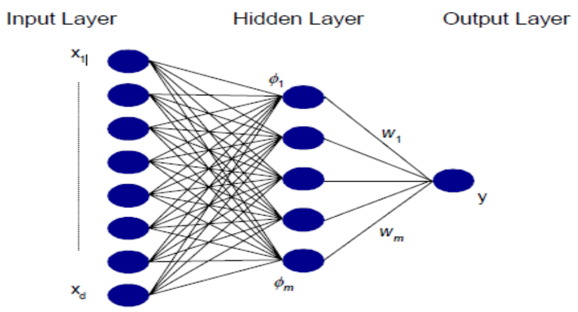

Fig 5: Radial Basis Function Network

Venkatesan et al. [8] has explained the response of the jth-hidden unit which can be expressed as: $Zj = Ø[x - \mu j/\sigma j2]$where Ø is a strictly positive; symmetrical function (kernel) with unique maxima at its center, μ_j and σ_j^2 is the width of the receptive field. The prepossessing was performed using Wavelet transform and four independent feature characteristics of PCG signals are extracted. These features are fed as inputs to two neural networks. The networks were trained using the 66 samples and tested using 23 samples for the three different diseases. The performance of RBF networks is superior as compared to the traditional BPN networks with 98% accuracy compared with 90.8% for the BPN.

Boutana et al. [2010] presented a novel method for the segmentation and identification of normal and pathological PCG signals based on time-frequency analysis [12]. It is possible to detect and characterize abnormal murmur caused by several heart diseases as aortic stenosis, pulmonary stenosis and mitral regurgitation. Useful features were extracted as the main HS components (s1 and s2) and the pathological murmur. The upper bound of the entropy was taken as an appropriate threshold to determine the boundary between signal events. The method was applied on speech signal [9] and PCG signals [10] and may be useful especially in case of abnormal HS containing various murmurs. This method is implemented using four steps discussed below.

Step 1: Time-frequency analysis

The time-frequency representation of the PCG signal is evaluated with the help of the spectrogram. This is very important parameter of the window analysis. The entropy is used as a measurement of the complexity of the signals, which permits to obtain the optimal window length for the analysis.

Step 2: Estimation of RME

The RME is estimated between the main components and the murmurs of the PCG signal [11].

Step 3: Thresholding

This consists of the detection of the ending point of the murmur and the starting point of s1 and s2 component based on a threshold of the RME profile. After detection of a threshold, samples of the RME with values below the threshold (corresponding to sample of the signal in time representation) are considered samples of the main components. This provides the segmentation of the signal which permits the characterization of the main components and the murmur both in time and frequency.

Step 4: Enhancement of time-frequency representation

After the segmentation between the main component and the murmur of the PCG signal, enhancement of the time-frequency representation is applied. A narrow window for the murmur is considered as random event and wide window for main component is considered as quasi-organized event.

Pavlopoulos et al. [2004] discussed about different heart diseases. It considered a typical heart sound signal that corresponds to a heart cycle and consists of four structural components:

a. The first heart sound (s1) which is the closure of the mitral and the tricuspid valve).

b. The systolic phase.

c. The second heart sound (s2) that corresponds to the closure of the aortic and pulmonary valve).

d. The diastolic phase.

The pathological heart sound can occurs in heart as: systolic murmur (SM), diastolic murmur (DM), pro-systolic murmur (PSM) [13]. The heart sound diagnosis problem consists in the diagnosis from heart sound signals and can be found whether the heart is healthy, or not. If it is not healthy, what is the exacted heart disease to be determined? Closure of aortic valve affects the second and that of mitral valve affects the first heart sound. A set of heart sound signals were initially pre-processed in order to detect the cardiac cycles in PCG signal, i.e. to detect s1 and s2, using a Wavelet decomposition method normalized average Shannon Energy and morphological transform. Criteria for this evaluation were the classification Accuracy for the training and testing set. The decision trees can be used with high levels of success for the differentiation between AS and MR.

There is a small subset of the initial features that contain most of the information required for the differentiation. The diagnosis for any new data set is based on this feature's subset. In the specific discrimination problem the fully expanded decision tree structures have similar levels of Generalization and Classification Accuracy for new data in comparison with the Pruned decision tree structures. Increasing the size of the training data sets (more patterns) improves the Classification Accuracy and the general reliability of the system. The general heart sound diagnosis problem can be divided into a number of problems [14] such as: detection of diastolic murmur, systolic murmur, determination of the type of the murmurs (crescendo, decrescendo), determination of the frequency content (low, high, and medium), and detection of arrhythmia and Mid-systolic click of premature ventricular contraction. The partial diagnosis by decision support systems can be combined to produce diagnosis which leads to an integrated decision support system architecture for diagnosis of Heart Sound.

Bung et al. [2000] presented the implementation of a diagnostic system to reduce the number of echocardiograms that are ordered for healthy patients. This system is based on an easy-to-use graphical user interface and designed using MATLAB software and the ANN Toolbox. The ultimate goal of the diagnostic system is to provide physicians with an inexpensive classification tool to use along with auscultation. The classifier may provide helpful guidance in the event that a patient has a heart sound that is somewhat difficult for physicians to diagnose. Three different training target sets are:

a. Normal heart sounds, aortic regurgitation (a type of diastolic murmur denoted as AR), and aortic stenosis (a type of systolic murmur denoted as AS).

b. Normal heart sounds, AR, AS, and mitral regurgitation (a type of systolic murmur, denoted as MR).

c. Innocent (low-grade) AS and pathological (severe) AS.

The design and implementation of the classifier system was described in terms of the following:

a. Types of heart sounds that can be detected.

b. Heart sounds database.

c. Type of data and pre-processing steps used to provide design and test vectors to the ANN classifier.

d. ANN architecture.

The ANN architecture was determined through comparison of preliminary test results. This is achieved with the optimal number of hidden layers and of neurons to use in the input and hidden layers, system complexity were reduced until performance began to degrade. ANN structure is used having 3 hidden layers with 25 neurons in the input and hidden layers. The single frequency component simplifies the analysis of results, but the use of multiple frequency bands in a single ANN system has been left to be explored further. All methods showed a greater performance compared to previous works. Proposed method using adaptive artificial neuro-fuzzy inference system (ANFIS) employs extraction of the features of the signal from the signal using Daubechies wavelet and the features i.e. Entropy, Energy, Variance and Standard Deviation are used as an input to ANFIS. The expected result of proposed method along with some other method is shown in TABLE-II.

Table II. Comparison of proposed method.

Classifier	Sensitivity (%)	Specificity (%)	Total accuracy (%)
Proposed method	100	95.24	98.33
DFT/Burg AR-PCA-ANN[21]	97.44	90.48	95
DFT-ANN [22]	97.29	82.60	91.67

3. CONCLUSION

A survey on several classification techniques of PCG signals is reported in terms of various prepossessing technique, segmentation methods, and classification strategies. The Receiver Operating Characteristic (ROC) curve is shown in Fig. 6 that represents the training in blue color, testing in red and validation data in green for BPN and RBF.

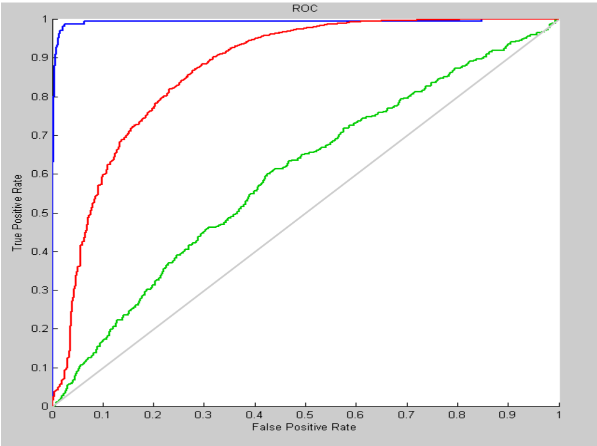

Fig 6: ROC plot for overall data using RBF networks

RBF gives the 98% accuracy compared to 90.8% for the BPN. The performance of RBF is superior compared to the traditional BPN networks. The classification accuracies achieved with pruned decision trees having minimum leaf node support of at least 5%, 10%, 15% and 20%, for all the data schemes. An adaptive method called Artificial Neuro Fuzzy Inference System (ANFIS) can be implemented for the accurate detection of the pathological condition of the heart using PCG signal. Daubechies wavelet can be used for feature extraction and this information to be utilized as an input in ANFIS for the accurate detection of heart disease.

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