Heart Diseases diagnosis using intelligent algorithm based on PCG signal analysis

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Abstract: - This paper presents an intelligent algorithm for heart diseases diagnosis using phonocardiogram (PCG). The proposed technique consists of four stages; data acquisition, pre-processing, feature extraction and classification. PASCAL heart sound database is used in this research. The second stage concerns with removing noise and artifacts from the PCG signals. Feature extraction stage is carried out using discrete wavelet transform (DWT). Finally, artificial neural network (ANN) have been used for classification stage with an overall accuracy 97%.

Key-Words: - Heart Diseases – Phonocardiogram (PCG) – Feature Extraction – Discrete Wavelet Transform (DWT) – Artificial Neural Network (ANN)

1 Introduction

Cardiovascular disorders (CVDs) Heart diseases are broad terms that can affecting both vasculature and the heart muscle itself [1]. CVDs remains the first cause of mortality globally, responsible for 17.5 million people die annually [2]. More than 75% of CVDs deaths occur in middle and low income countries [2].

The heart sounds still the primary tool for screening and diagnosing many pathological conditions of the human heart. Using auscultation technique which was invented and defined by Laennec for heart sound analysis is still insufficient. The reason of insufficiency reported by Avendano-Valencia et al., [3-4] being due to the human ear limitation and subjective of the analyst and the discriminatory skills that can take many years to acquire.

Phonocardiography (PCG) is the one of non-invasive technique to diagnose condition of human heart generated by muscle contractions and closure of the heart valves produces vibrations audible as sounds and murmurs, which can be analyzed by qualified cardiologists [5].

The PCG recording consist of four heart sound components (S1, S2, S3 and S4). The first and second heart sound (S1 and S2) can be heard from the normal heart. They are produced by the closure and opening of the normal valves. For the abnormal heart, a third and a fourth sound (S3 and S4) may also exist in addition to (S1) and (S2) [6]. These abnormal sounds are called murmurs. The existing of murmur in PCG recording is often related to heart valve disease. The four heart sounds (S1, S2, S3 and S4) are shown is Fig. 1.

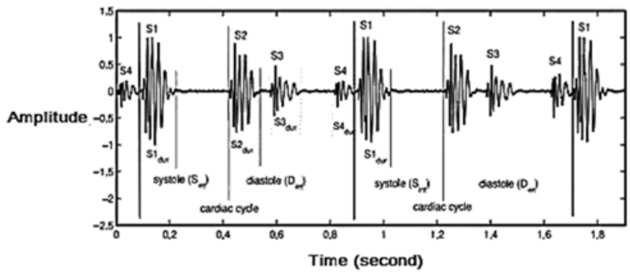

Fig. 1 PCG Heart sound signal

A major challenge, facing healthcare organizations (hospitals, medical centers) is the provision of quality services at affordable costs. Quality service implies diagnosing patients correctly and administering treatments that are effective [7].

The objective of this paper is to present an algorithm to integrate the clinical decision support with computer-based patient records could reduce medical errors, enhance patient safety, decrease unwanted practice variation, and improve patient outcome.

This paper is organized as follows. Section 2 presents the proposed machine learning techniques and the aspects of data acquisition, pre-processing, feature extraction and classification processes. In section 3, experimental results are shown. Finally, Section 4 concludes the paper and proposes future research work.

2 Proposed Methodology

A methodology of a heart diseases diagnosis system usually mimics that of a pattern recognition system. Thus, it can be broken down into four main processes, namely; (1) data acquisition, (2) pre-processing; (3) feature extraction and (4) classification (subject identification). Fig. (2) shows the proposed methodology for heart diseases diagnosis.

The experiments were carried out on the platform of core i3 with 3 G memory running under windows 10 64 bit. The proposed algorithms were developed using MATLAB 2014b wavelet toolbox.

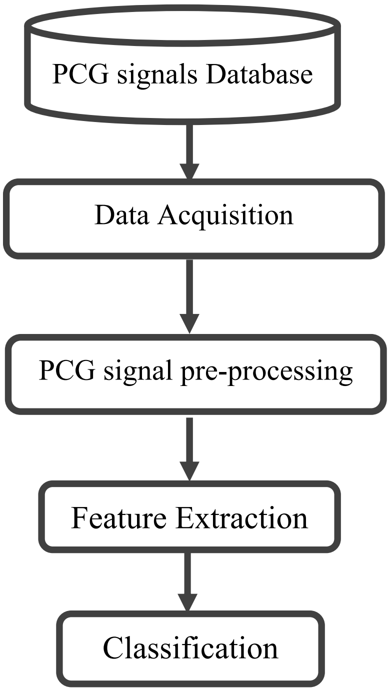

Fig. 2 Proposed methodology

2.1 Data acquisition

Datasets were collected from PASCAL heart sound database [8]. A data base of 170 heart sound signals was created and divided into 121 signals (24 normal signals and 97 abnormal signals) for training and 49 signals (10 normal signals and 39 abnormal signals).

The acoustic audio files have varying lengths, between 1 second and 30 seconds. Mainly the most information in heart sounds is enclosed in the low frequency components, having noise in the higher frequencies.

2.2 Signal pre-processing

PCG signals usually suffers from noise like electromagnetic interference from surrounding environment, power frequency interference, electrical signal interference with human body and lung sounds. These various noise components make the diagnosis of PCG records difficult or in some cases is impossible.

DWT which is a series of high-pass and low-pass filters shows a superior performance in signal denoising due to its properties such as multi-resolution and windowing technique.

Noises in PCG signals was removed using DWT family called Daubechies wavelet family of order ten (Db 10) with the fourth level of decomposition. Fig. (3) shows the noisy PCG signal and fig. (4) shows the denoised PCG signal.

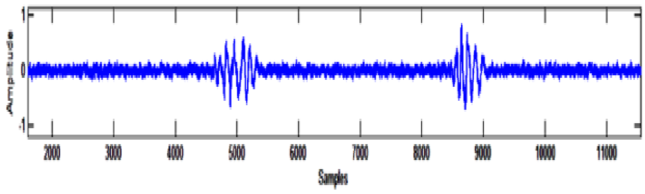

Fig. 3 Noisy PCG signal

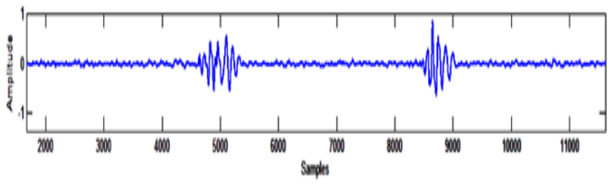

Fig. 4 Denoised PCG signal

2.2 Feature Extraction

Feature extraction is one of the most important steps of heart sound classification systems [9]. Time – frequency domain wavelet based feature extraction technique has been successfully used to extract important features from non-stationary heart sound signals for heart diseases classification.

The spectrum of heart sound signals is divided into sub-bands (tree structure was used) to extract the most meaningful information from normal and abnormal heart sounds.

Daubechies wavelet with 4^{th} order (Db4) with 10^{th} level of decomposition is used for determining wavelet coefficients from the PCG signals. DWT decomposes the signal into approximation

(Approximate coefficients (A) – low frequency coefficients of signal) and detail (Detail coefficients (D) – high frequency part components of signal).

2.3 Classification

The classification process of the artificial neural network begins with sum of multiplication of weights and inputs plus bias at the neuron, if the sum is positive then only output elements fires. Otherwise it doesn't fire. The artificial neural network is an adaptive system, in other words, the system adopting itself and changes the system weights during the operation [10].

The proposed neural network architecture consists of three layers input layer, hidden layer and output layer. The feature vector extracted from the PCG signal with size 44 features is used as an input to the proposed neural network to classify it into 2 classes (normal and abnormal).

Levenverg-Marquardt back propagation algorithm is used for neural network training, sigmoid activation function, momentum constant equal 0.7, learning rate 0.9 and number of epochs 1000 iterations. Table 1 shows the parameters used for training the neural network classifier.

Table 1 Proposed Neural network training parameters

Network Type	Feed-forward back propagation
No. of layers	3 layers: input, hidden and output layers
Activation function	Sigmoid activation function
Training algorithm	Levenverg-Marquardt back propagation
No. of epochs	1000
Accuracy	97%
Momentum constant	0.7
Learning rate	0.9

For 170 heart sound signals was created and divided into 121 signals (24 normal signals and 97 abnormal signals) for training and 49 signals (10 normal signals and 39 abnormal signals) the neural network classifier misclassified one signal achieving an accuracy of 97%.

Finally, table 2 shows a comparison between our proposed algorithm results with the previous methodologies results to see the efficiency of the proposed methodology.

Table 2 Comparison between our proposed methodology and previous proposed methodologies

Author	***Database***	***Methods***	***Results***
Cota Navin 2007 [11]	Dataset of 41 volunteers	Db 2 and ANN.	Accuracy 97.01
Zümray Dokur 2008 [12]	14 heart sounds	DWT , ISOM and Kohonen's ANN	ISOM accuracy 95%, Kohonen's accuracy 70%
Resul Das 2009 [13]	215 signals	DWT and ANN	Accuracy 97.4%
Wen-Chung Kao 2011 [14]	44 of heart sounds	2-D Discrete Fourier Transform	Accuracy 94.79%
Sivagowry 2013 [15]	14 signals	ANN	Accuracy 80%
Juan. Guillermo 2014 [16]	17 training signals	CWT and ANN	Accuracy 76.08%
Ana Gavrovska 2013 [17]	164 pediatric patients	Multifractal spectrum	Accuracy 95%
HaoDong Yao. 2015 [18]	60 heart sound signals	DWT and ANN	Accuracy 96%
E. J. Harfash (2016) [19]		MFCC Eigen vector	Accuracy 86%
Imani Maryam (2016) [20]	98 PCG signals	Max likelihood classifier with Gaussian distribution + SVM with polynomial kernel	Accuracy 81.49%
Our proposed System	170 signals	DWT and ANN	Accuracy 97%

DWT: Discrete wavelet transform
ANN: Artificial neural network
CWT: Continuous wavelet transform
ISOM: Incremental self-organizing map
MFCC: Mel-frequency Cepstrum coefficients

From Table 2, it is clear that our proposed algorithm reached better classification accuracy than the compared studies.

4 Conclusion

This paper proposed an algorithm for heart diseases diagnosis based on PCG signals. The proposed algorithm consists of four stages: data acquisition, pre-processing, feature extraction and classification. PASCAl PCG signal databased was used for training and testing the proposed algorithm. We applied DWT noise elimination and feature extraction stages and neural network is used for PCG signals classification.

A feature vector of size 44 features is formed using DWT used as an input to the classifier for training and testing. ANN is trained using the obtained features. The results showed accuracy of 97% for PASCAL heart sound database.

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