

Survey of Different Methodologies Used in Phonocardiogram Signal Analysis

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ABSTRACT

Heart sounds give us information about the state of the heart. Heart diseases can be detected at an earlier stage by analyzing the heart sounds. In this paper, detailed discussion of various methodologies that have been used earlier to analyze the heart sounds has been carried out. Comparison has been done on the basis of methodology used and the performance achieved.

Keywords

Heart sounds, Systolic, Diastolic, Murmurs

1. INTRODUCTION

The technique of listening to heart sounds using stethoscope is called cardiac auscultation. Abnormalities in the heart sounds start appearing much earlier than the symptoms. Therefore, this technique can be used to detect various heart disorders at an earlier stage. The graphic recording of heart sounds is known as phonocardiogram (PCG). PCG signal is generated due to mechanical activity of heart, blood flow, vibration of chamber valves, opening and closing of valves. It is mainly recorded using electronic stethoscope and the signal is displayed on the computer screen. The heart sounds usually occur at the time of closure of major heart valves [1]. With each heart beat, normal heart produces two distinct sounds- often described as 'lub-dub' [1]. The first heart sound (lub), also known as S1, is caused by the closure of atrioventricular valves. When the blood from atria flows to ventricles, these valves allow unidirectional blood flow i.e. from atria to ventricles and block the reverse blood flow back to atria from ventricles. The second heart sound (dub), also known as S2, is caused due to closure of semilunar valves. These valves release blood into the pulmonary and systemic circulation systems and prevent backflow of blood. Third (S3) and fourth (S4) heart sounds are rare heart sound which are not normally audible but may be visible on the graphic recording. S3 is caused due to rushing of blood from atria to ventricles. S4 is produced when blood is forced into stiff or enlarged ventricle. S1 and S2 are called Fundamental Heart Sounds (FHS).

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 systole and the region between S2 and starting of S1 of next heart sound cycle is called diastole. Sometimes we may hear unusual sound during the heartbeat cycle. They may be whooshing or swishing noise. These are called murmurs. They are generally high-frequency, noise like sounds that are produced as a result of turbulent blood flow [2]. Intensity, frequency content, split information, time relations, location of murmurs etc. are some of the features of PCG signal which can be helpful in detecting heart valve diseases, if any, and the condition of the functioning of heart. We may classify heart murmurs as systolic murmur, diastolic murmur or continuous

murmur. Murmurs which occur in systole are called systolic murmurs and which occur in diastole are called as diastolic murmurs. Murmurs which occur continuously throughout the cardiac cycle are known as continuous murmurs. Diastolic murmurs, which occur during diastole, are mostly associated with ventricular relaxation and filling as they originate after S2 i.e. second heart sound. The cause of occurrence of such murmurs may be due to aortic or pulmonic valve regurgitation or by mitral or tricuspid valve stenosis. Systolic murmurs, which occur during diastole i.e. between S1 and S2, are associated with mechanical systolic and ventricular ejection or regurgitation across the atrio-ventricular valves [3]. Many studies classify different heart diseases based on the PCG signal.

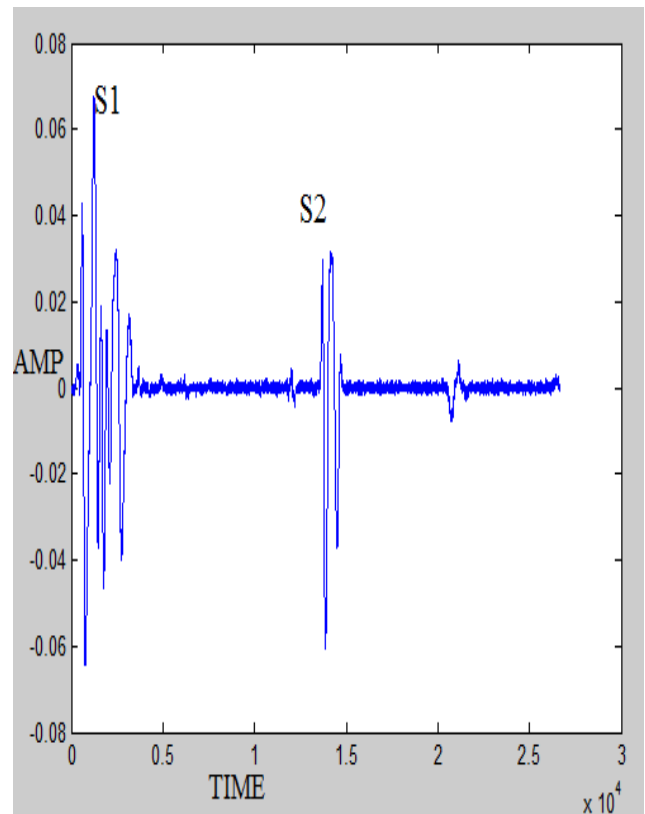


Figure 1: A normal PCG signal showing S1 and S2 heart components.

2. COMPARISON

Different methodologies used to analyze the phonocardiogram signal have been compared which include discrete wavelet transform, Continuous wavelet transform, Hilbert transfer, Short term Fourier transform etc. and a comparison table has been made.

Table 1. Comparison table of different methodologies used in studies.

Year	Methodology	Contributions	Performance achieved	ECG gating used	Comments
2005	Short Time Fourier Transform (STFT) [4]	Detection of heart sounds (S1 & S2) and systolic murmur.	100%- S1 97%- S2	Yes	20-70% of systolic segment was selected for murmur detection analysis.
2006	Cardiac Sound Characteristic Waveform (CSCW) [5]	Arrhythmia, Mitral Stenosis, Aortic Regurgitation		No	Adaptive Threshold Value was calculated using Fuzzy C-Means.
2007	Phonospectrogram [6]	Characterization of innocent murmurs in children	90%- Sensitivity 91%- Specificity	No	Innocent murmurs have lower frequencies and frequency spectrum with more harmonic structure as compared to pathological murmurs.
2008	Fuzzy clustering [3]	Location/ detection of systolic murmur.	80%- Detection 73%- Sensitivity 100%- Specificity	No	An amplitude and frequency invariant signal characteristic has been proposed to distinguish cardiac murmur.
2011	Discrete Wavelet Transform [7]	High noise robustness	92%- Noise-free 90%- with white noise and 10 dB SNR and for impulse noise up to 0.3s duration.	No	No segmentation used.
2011	Adaptive Singular Spectrum Analysis (ASSA) [8]	Extraction of different types of murmur signal.	Correlation between separated components, heart sound and murmur signal	No	Two sounds are separated perfectly even if they are temporally overlapped over a region.
2011	Digital Subtraction Phonocardiography [9,10]	Murmurgram	Visual differences	Yes	Normal murmurgram is fairly flat and low in intensity
2011	CSP (Color Spectrographic Phonocardiography) [11]	Distinguish pathological and innocent murmurs in children	Visual differences	Yes	Pathological systolic murmurs have lower frequency and shorter duration than innocent systolic murmurs
2011	Hilbert Transfer Envelope [12]	Classification of normal and abnormal PCG signals	Accuracy-91.3%	No	Energy of each segment (0.01s time) is calculated and energy plot is obtained.
2012	CWT (Continuous Wavelet Transform) [13]	Scalogram	Visual differences	No	Temporal and frequency rates are considered to quantify the differences between various PCG signals.
2012	Wavelet Packet transform [14]	Distinguish normal, mitral stenosis, mitral regurgitation, aortic stenosis, and aortic regurgitation	Accuracy- 96.94%	No	Wavelet packet entropy was used to calculate or generate features from PCG recordings which are discriminative in nature.
2013	Improved EMD (Empirical Mode Decomposition) [15]	PCG signal denoising and extraction of 1 st and 2 nd heart sounds	S1- 100% S2- 99.48% overall accuracy- 99.74%	No	Signal is decomposed into several different frequency bands from high frequencies to low frequencies.
2013	Wavelet Packet transform [16]	Distinguish normal heart sound, mitral regurgitation, aortic regurgitation and aortic stenosis.	Accuracy- 97.56%	Yes	Multi-level basis selection (MLBS) was proposed so that the most informative bases of a wavelet packet decomposition tree is preserved.
2013	Feature extraction in time domain, frequency domain and statistical features[17]	A new feature, mean12, is proposed which is the maximum of the mean in systolic and diastolic regions.	Bayes Net- 91.6667% Naïve Bayes-93.33% SGD-91.6667% Logit boost-88.3333%	No	Classification of normal and abnormal heart sounds is done.

3. DISCUSSION

In 2005, Seiger *et al* used STFT for detection of first and second heart sounds (S1 & S2). Also, for murmur analysis he used 20-70% of the systolic segment as heart signals S1 and S2

sometimes partially overlap systolic murmur [4]. In 2006, Jiang *et al* proposed analytical model which was based on single DOF. Characteristic waveforms were extracted using this model from heart sounds to detect heart disorders. The diagnostic parameters [T1, T2, T11, T12] were obtained by

FCM clustering method. For cardiac sound characteristic waveform (CSCW) scattergram and histogram were plotted for [T1, T2] and [T11, T12] [5]. In 2007, Noponen *et al* differentiated innocent murmurs and pathological murmurs using phono-spectrographic analysis. The study showed that innocent murmurs are characterized by lower frequency and have a frequency spectrum with more harmonic structure as compared to pathological cases [6]. In 2008, Nigam *et al* proposed a method to locate systolic murmurs in the PCG signal based on their visual simplicity which is independent of their absolute amplitude and frequency characteristics. Fuzzy clustering approach was used and it showed that number of fuzzy clusters can be used to determine presence of cardiac murmurs. The degree of membership of simplicity value in clusters was used to locate systolic murmurs. The accuracy achieved in detecting systolic murmurs was 80% [3]. In 2011, Yuenyoung *et al* proposed an algorithm in which cardiac cycles were extracted from heart sounds with different heart rates. Using this algorithm there was no need to label the individual Fundamental Heart Sounds (FHS) for extraction of individual heart cycles. Discrete wavelet transform was used for feature extraction of cardiac sounds and classification was done using neural network bagging predictors [7]. In 2011, Sanei *et al* used Adaptive Singular Spectrum Analysis (ASSA) to separate murmurs from the recorded heart sounds. The major advantage of this technique is in perfectly separating the two sounds even in temporally overlapped regions [8]. In 2011 Akbari *et al* proposed new analytical technique known as Digital Subtraction Phonocardiography (DSP). It is based on the principle that the murmurs are random in nature but the FHS are deterministic in nature. A murmurgram was constructed by simply taking the difference between the acoustic emissions of two successive heart beats. It was found that the murmurgram should be flat between the FHS for normal cases but it is not the case with abnormal cases [9, 10]. In 2011, Sarbandi *et al* proposed a new technique known as Color Spectrographic Phonocardiography (CSP). It was used to detect and characterize heart murmurs [11]. In 2011, Xiao-Juan *et al* extracted S3, S4, the first split and the second split and relocated the starting and ending of S1 and S2. It was based on the slopes of envelop of Hilbert Transfer Envelope after energy segmentation. In this research the overall accuracy of 91.95% was achieved for features extraction. 25 significant clinical features were introduced and SVM classifier was used for classification. The overall accuracy of 91.3% was achieved in case of classification. The result showed that features including clinical signification is of signification for enhancing the accurate rate of Phonocardiogram classification [12]. In 2012, Debbal *et al* used Continuous Wavelet Transform (CWT) to study normal and abnormal Phonocardiogram (PCG) signals. Features in time-frequency domain were extracted and their scalograms exhibited noticeable morphological differences in terms of duration and spectral composition of sounds [13]. In 2012, Safara *et al* introduced new entropy to analyze heart sounds and it was shown that it was feasible to use this entropy in classification of five types of heart sounds and murmurs. The heart sounds considered for classification consisted of one normal heart sound and four common murmurs: Aortic regurgitation, Mitral regurgitation, Aortic stenosis, and Mitral stenosis. Heart sound analysis was done by wavelet packet transform. To derive various feature vectors the entropy was calculated. Five types of classification were performed and the accuracy of the generated features was evaluated. The best results were achieved using Bayes Net as a classifier with an accuracy of 96.94%. The results showed that the proposed wavelet packet entropy was effective for heart sounds classification [14]. In 2013, Sun *et al* combined Improved EMD

(Empirical Mode Decomposition) and Shannon energy envelope algorithm for extraction of S1 and S2 components and achieved a high accuracy of 99.74% [15]. In 2013, Safara *et al* proposed multi-level basis selection (MLBS) so that the most informative bases of the wavelet packet transform decomposition tree is preserved. It was done by removing the less informative bases. In order to do this three exclusion criteria was applied i.e. frequency range, noise frequency, and energy threshold. Classification of normal heart sound signal and three kinds of murmur signals (mitral regurgitation, aortic regurgitation and aortic stenosis) is done in this study. The results of MLBS were compared with single-level basis selection (SLBS), local discriminant basis (LDB) and best basis selection (BBS) and it was found out that using MLBS higher accuracy of 97.56% was achieved [16]. In 2013, Singh *et al* proposed a new feature, mean12, which is the maximum of the mean in systolic and diastolic region to classify signal into two classes i.e. normal and murmur signal. 23 features in time domain, frequency domain, statistical and cepstrum were extracted and out of all the features only 5 optimal features were selected for classification. Four different classifiers were used and the accuracies were calculated. Also, 5 fold cross validation was used. The classifiers used were Bayes Net, Naïve Bayes, SGD and Logit boost and the accuracies achieved were 91.6667%, 93.3333%, 91.6667% and 88.3333% respectively. Highest accuracy of 93.3333% was achieved using the Naïve Bayes classifier [17].

4. CONCLUSION

In this paper various methodologies which have been used in analyzing the phonocardiogram signal have been compared. Performance of each methodology has also compared. Maximum accuracy of 99.74% was achieved by Shannon energy envelop algorithm in extraction of S1 and S2 heart sound components. Due to the denoising of the signal the results achieved were better. Wavelet based PCG signal analysis achieved accuracy of 90% - 97.56% [7, 13, 14, 16].

5. FUTURE SCOPE

3 class classification of the phonocardiogram signal can be done i.e. normal signal, systolic murmur signal and diastolic murmur signal. Hybrid classifier can also be used for classification with higher accuracy.

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