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Aortic Stenosis Detection Using Spectral Statistical Features of Heart Sound Signals

S. V. Mahesh Kumar[1,*], P. Dhinakar[2], R. Nishanth[3]

[1]Department of Electronics and Communication Engineering, Amrita College of Engineering and Technology, India
[2]Department of Electronics and Communication Engineering, Bharath Institute of Higher Education and Research, India
[3]Department of Electronics and Communication Engineering, Cochin University College of Engineering Kuttanad, India

Abstract

INTRODUCTION: Aortic stenosis (AS) is a severe complicated heart valve disease. This valve abnormality is a slow-progressive condition and mostly asymptomatic. Hence, there is a need for a rapid non-invasive diagnosis method with minimal feature extraction.
OBJECTIVE: In this paper, we proposed a spectral features-based rapid heart sound signal analysis method to identify the AS stages with minimum number of features.
METHODS: In this study, the heart sound signals were collected from the medical database and transformed into the frequency domain for further spectral feature analysis. We used the windowing technique to conditioning the heart signals before spectral analysis. The spectral statistical features were extracted from the computed frequency spectrum. The range of statistical features was compared for normal, early, and AS sound signals.
RESULTS: In experiments, the normal, early, and delayed AS heart sound signals were used. The normal/unhealthy condition of a heart was identified using the statistical features of the frequency spectrum. The experimental results show the statistical difference between the normal and AS heart sound signal spectrums.
CONCLUSION: The experimental results confirmed that the statistical features derived from the heart sound signal spectrums were varied according to the AS condition. Hence, the spectral statistical features can be considered as rapid predictors of AS.

Keywords: Heart, Aortic stenosis, Heart sound, Frequency spectrum, Statistical features, Early detection.

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1. Introduction

Aortic stenosis (AS) is a frequent and most severe complication in the heart valve[1].This condition narrowing the opening of the aortic valve and restricts the circulation of blood from the left ventricle to the aorta, which can also affect the pressure in the left atrium. If the flow of blood into the aortic valve is shortened or blocked, the heart has to work harder to pump blood to the body[2]. Subsequently, this condition leads to heart muscles damaging. The AS symptoms are such as Angina pectoris[3], lightheadedness, and fatigue. These symptoms indicate that the additional effort for valve opening has exceeded the capacity of the heart to operate normally.

Aortic stenosis is a slow-progressive condition. Many subjects never show symptoms and never need a valve replacement. However, if symptoms occurred or the obstruction is severe, rapid diagnosis and treatment are important[4]. Hence, there is a requirement for a rapid AS diagnosis system. Monitoring for symptoms is sufficient in most cases with asymptomatic AS. The ACC/AHA recommendations[5] prescribed that consecutive diagnosis tests should be conducted regularly for extreme AS, for the moderate condition every one or two years, and for mild conditions every three to five years.

Early finding of AS is through a murmur that is loudest in the right (second) intercostal space and radiated

*Corresponding author. Email: maheshyesvee@gmail.com

to carotid arteries. Physicians can recognize AS in adults with any symptoms followed by systolic murmur. However, for older adults, the murmur is with less intensity and mostly radiated to the apex rather than to carotid arteries. Hence, there is a requirement for a digital analysis system to analyze the heart murmur sound.

In this paper, we proposed a spectral analysis-based feature extraction approach to detect AS. The major objectives of the proposed method are:

(i) To develop a spectral analysis-based approach for heart sound signal analysis.
(ii) To improve the precision of spectral analysis using windowing function-based signal conditioning techniques.
(iii) To identify the early and delayed AS using the range of statistical features derived from the spectral analysis of heart sound signal.
(iv) To compare the range of statistical features of normal, early, and delayed AS heart sound signals.

The AS abnormalities are analyzed using the variations in the spectral features of the heart sound signal. This paper is ordered as follows: The related works are discussed in Section 2. The sequential processing steps of the proposed AS detection method is presented in Section 3. The experimental results are presented in Section 4. Finally, Section 5 concludes the paper.

2. Related Works

Digital recording of the heart sounds with the aid of an electronic stethoscope is known as PCG [6]. The heart sound is caused by the heart’s systole and diastole cycles. It can replicate the physiological information of body mechanisms such as blood vessels, the atria, and ventricles along with their functional conditions.[7]. The fundamental heart sound is classified as first and second heart sounds (known as S1 and S2). S1 arises at the starting of isovolumetric ventricular contraction and S2 arises at the starting of the diastole cycle (when aortic & pulmonic valves closed). The heart sound signals acquired by the PCG is used to find the locations of S1 and S2. It will provide an initial indication about the heart disease, in the procedure of diagnostic investigation. If the heart sound is collected, it could be categorized using computer-aided software techniques, which involves a more precisely defined heart sound duration used for feature extraction[8].

The feature extraction process is used for the conversion of raw high dimensional heart sounds into the low dimension of features using various mathematical transformation approaches to analyze the heart sounds. A smoothed Wigner-Ville distribution (WVD) technique has been used as the state of art feature extraction method in some research works[9]. Few diagnosis systems are also developed to analyze the extracted features. The extracted features are used to train the classification systems[10],[11] used for AS diagnosis. The efficiency of these classification systems depending on the signal analysis and feature extraction method used. Hence, there is a need for an accurate feature extraction signal analysis method.

Recently, numerous mathematical approaches such as Mel frequency cepstrum coefficients (MFCCs) [12],[13] Mel domain filter coefficients (MFSCs)[14], Short-time Fourier transform (STFT) based Spectrograms[15], Discrete wavelet transform (DWT) [16] were used in heart sound signal analysis. Some methods [17], [15] used the combination of MFCC and MFSC for feature extraction from the heart sounds. In deep learning models [18],[19] 1D-Time series signal is preferred as input feature. The observations of the recent feature extraction methods are summarized in Table 1.

Table 1. Review of Recent Works

Reference/ year	Feature analysis method	Observations
[12] 2020	MFCCs	Not a rapid analysis method for repeated heart sounds
[13] 2020	improved MFCC features	It elaborates dynamic characteristics of repeated heart sounds. Not a rapid analysis method.
[14] 2019	MFSCs	Not a rapid analysis method for repeated heart sounds.
[15] 2019	Spectrograms + MFSC + MFCC	More complexity
[16] 2018	Wavelet transform + Hilbert–Huang features	More complexity
[17] 2018	MFCC + MFSC	More complexity
[18] 2020	1D- Time series analysis	Suitable for deep models only
[19] 2019	1D time-series signals + MFCC)	More complexity
This work	Spectrogram+ statistical feature analysis	A rapid method with statistical significance between different stages of AS.

The review of existing methods presented shows that there is a need for a rapid feature analysis method with statistical significance between different stages of AS. Based on the inferences from the literature review, we developed a spectral analysis-based statistical feature extraction method that shows the difference between different stages of AS. Moreover, heart sound effects are typically connected to electromagnetic, power frequency, human body interferences, breathing noises, and lung sound[6]. Hence, signal conditioning is essential before analyzing the signal. For this purpose, we used windowing functions for conditioning the input heart sound signals. The proposed method focused on the analysis of early as well as delayed AS heart sound signals. Hence, it is suitable to detect the AS in its early stage.

3. Methodology

The proposed approach for AS detection is presented in Fig.1. The sequential process starts with the collection of input heart signal from the database. This signal is conditioned by the windowing function. The windowing approaches are used to suppress the discontinuities and spurious frequencies in the frequency domain. The windowing approaches used in this work are given in Equations (1)-(3).

$$\mathrm{HN}(n) = 0.5\left(1 - \cos\left(2\pi \frac{n}{N}\right)\right), 0 \le n \le N \qquad (1)$$

$$\mathrm{HM}(n) = 0.54 - 0.46\cos\left(2\pi \frac{n}{N}\right), 0 \le n \le N \qquad (2)$$

$$\mathrm{B}(n) = 0.42 - 0.5\cos\left(\frac{2\pi n}{L-1}\right) + 0.08\cos\left(\frac{4\pi n}{L-1}\right) \qquad (3)$$

where: $0 \le n \le M - 1$ & M is $N/2$ for N is even & $(N + 1)/2$ if N is odd. In Eqs. (1)-(3) $\mathrm{HN}(n)$ is Hanning widow, $\mathrm{HM}(n)$ is Hamming widow, and $\mathrm{B}(n)$ is the Blackman window.

After signal conditioning, the conditioned signal is involved in spectral analysis. Statistical features are extracted from the spectrum of the conditioned heart signal. Five statistical features such as Mean, Variance, Standard deviation (SD), Skewness, Kurtosis are computed. Along with these statistical features, the sum of the spectrum is also computed. The mean is the fundamental tendency of the heart signal spectrum. A square of the average distance between each frequency information and the mean value is variance. The calculation of the average difference between each frequency level information and the mean is the standard deviation. Skewness is a measure of the asymmetry of a spectrum over its mean value. Kurtosis is a calculation of whether the spectrum information is heavy-tailed or light-tailed in contrast to the normal distribution. These statistical features and sum value are analyzed for the normal, early, and delay AS stages. The statistical differences between AS stages are observed for effective detection of AS.

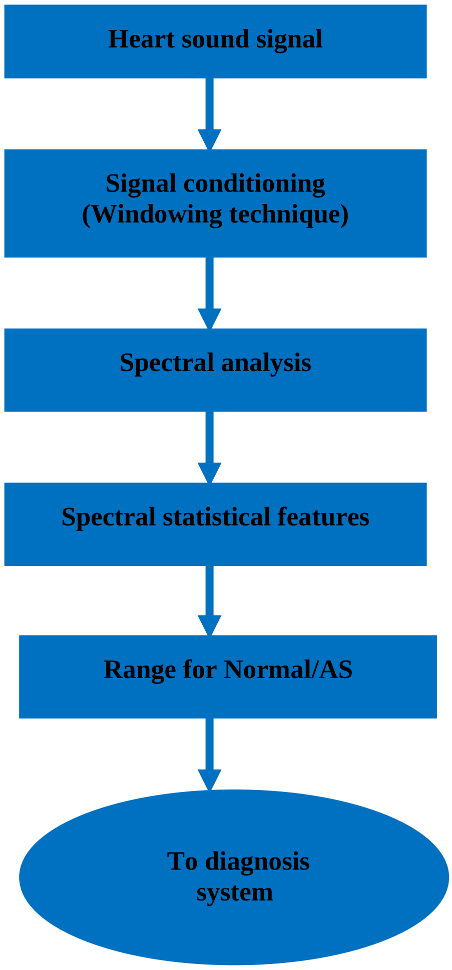
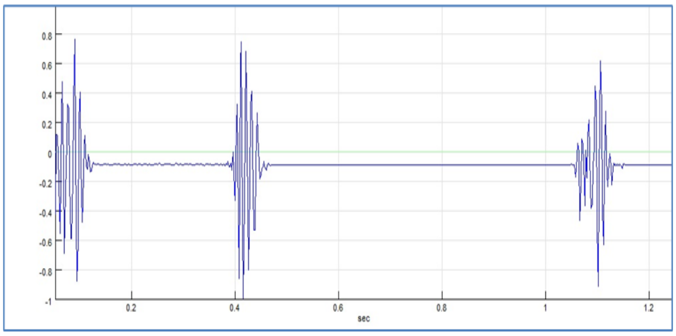


Fig.1. Flow chart of the proposed method

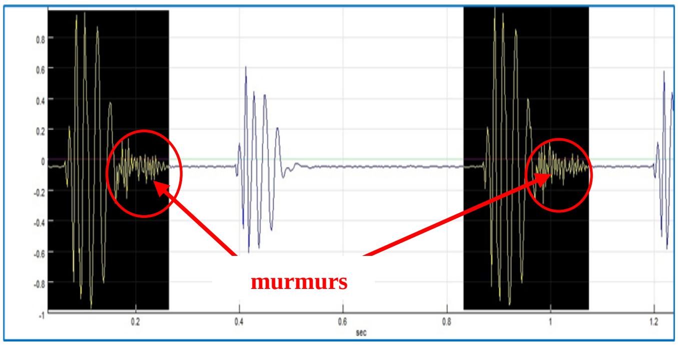
4. Results & Discussions

4.1 Experimental Details

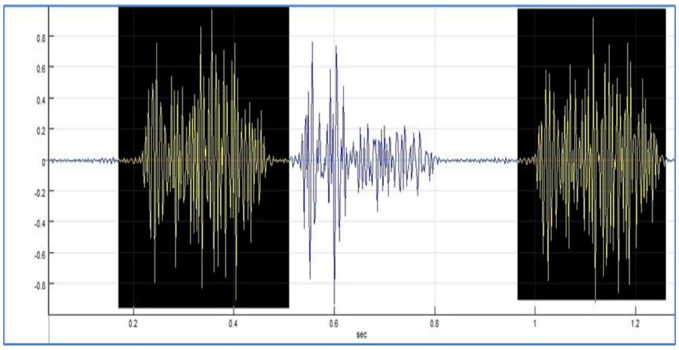
The proposed approach was implemented using the data collected from two sources: source 1 from University of Washington School of Medicine[20], source 2 from Machine learning and dataset community Kaggle[21] These sources contain digital heart sound signals of normal and abnormal (early and delay AS) sound signals. The sound signals were stored as MPEG Audio layer III format (source 1) and WAV format (source 2). The time-domain representation of the collected heart sound signals from data source 1 is shown in Fig.2. Figure 2 shows that the early and delayed AS signals are varied from the normal signal due to murmurs. The increases in the flow through the aortic valve, resulting an improvement in the intensity of the AS-related murmur. The variation due to murmurs is highlighted in Fig.2(b) &(c). Compared with early-stage, delay stage AS shows frequent intensity variations in the sound signal. The time-domain representation of heart sound signals from data source 2 is shown in Fig.3. The normal heart sound signal is shown in Fig.3(a) and murmurs is shown in Fig.3(b). The murmurs cause variations in the heart sound signal.



(a)

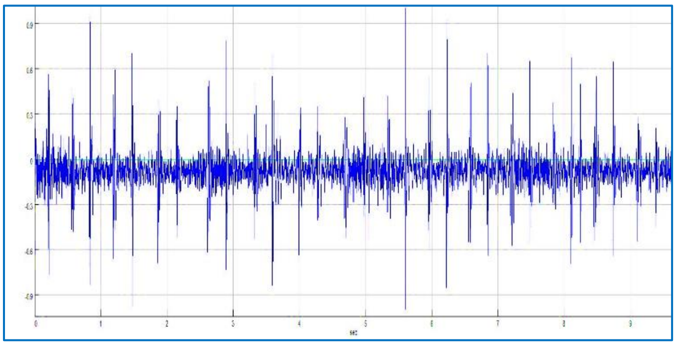


(b)

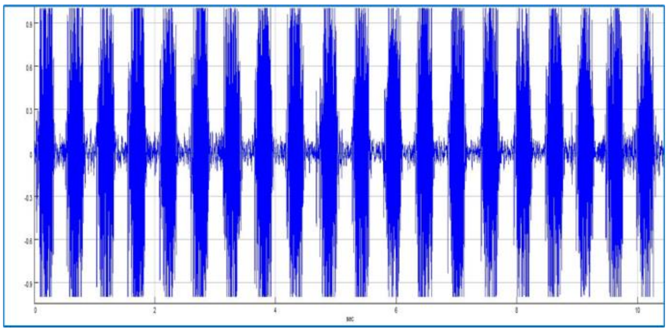


(c)

Fig.2. Sound signals of the heart (MPEG format):(a) Normal, (b) Early AS,(c) Delay AS



(a)

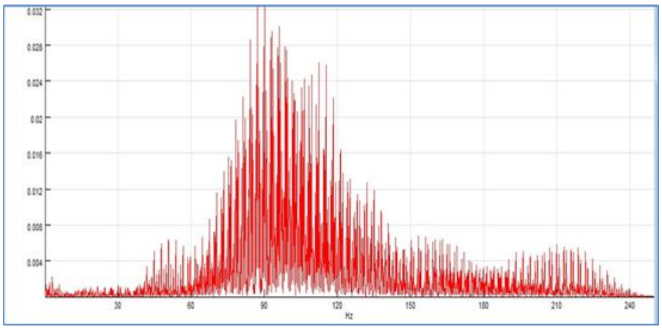


(b)

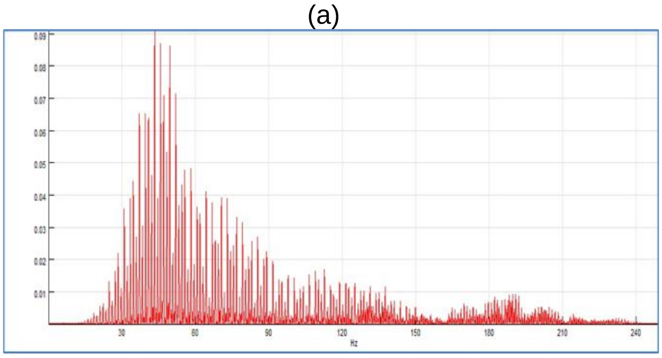
Fig.3. Sound signals of the heart (WAV format): (a) Normal, (b) Murmurs

4.2 Spectral Analysis of Heart Sound Signals

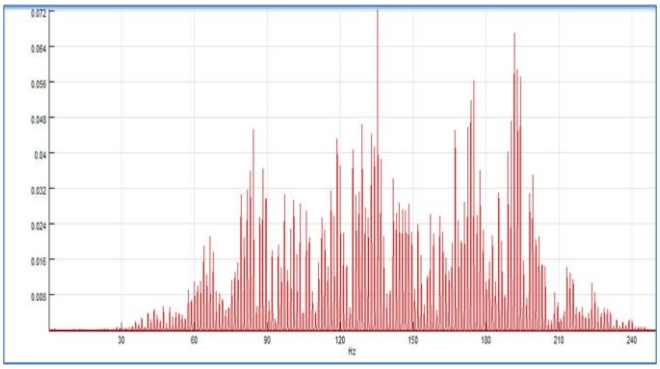
The spectral analysis was performed based on the FFT technique. The spectrogram of normal, early, delay AS stage sound signals (data source 1) are shown in Fig.4. Figure 4(a) show that a gradual distribution over the frequency spectrum. Figures 4(b)&(c) show that the intensity varies at specific frequency ranges due to murmurs. Figures 5(a)&(b) shows the frequency spectrum of normal and murmur sound of sample signal from data source 2. The murmurs caused the intensity variations in the frequency spectrum (shown in fig.5(b)). The computed spectrograms were used as the input for the statistical feature extraction process. In this experiment, the statistical features were extracted from the frequency spectrum of normal, early AS, and delay AS stage sound signals. The extracted features were compared to identify the AS from the statistical features.



(a)

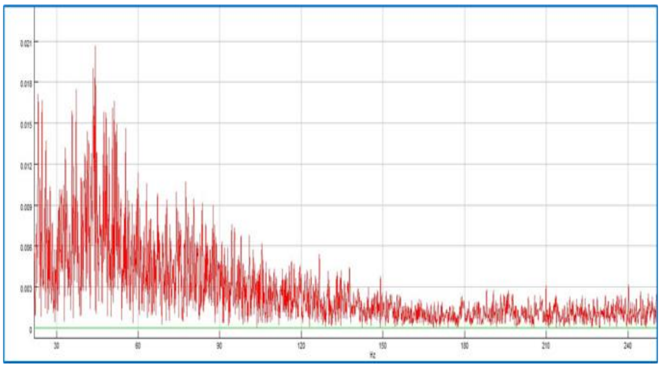


(b)

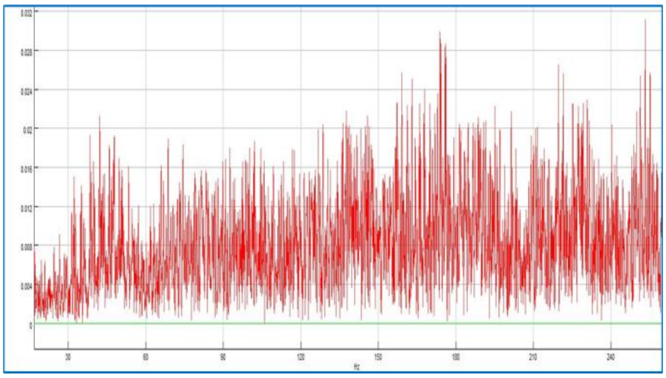


(c)

Fig.4. Spectral analysis of heart signals (MPEG format): (a) Normal, (b) Early AS, (c) Delay AS



(a)



(b)

Fig.5. Spectral analysis of heart signals (WAV): (a) Normal, (b) Murmurs

4.3 Comparison of Spectral Statistical features

The average values of statistical features extracted from the frequency spectrum of normal and AS stages are provided in Table 2. Table 2 shows that the mean, SD, sum values, and variance are gradually increased according to the AS stages. Hence, these features can be used for AS diagnosis system. The skewness and kurtosis values show that the shape of the spectrum varies according to the AS abnormality. Table 3 shows the average values of statistical features extracted from the frequency spectrum of normal and murmur signals. Table 3 shows that normal and murmur signals can be distinguished based on their statistical feature values. The above tables clearly show that the spectral statistical features can be used to differentiate the sound of a normal heart from the abnormal one.

Table 2. Comparison of Spectral statistical features of Normal, Early AS, and Delay AS sound signals (MPEG format)

Features	Normal	Early AS	Delay AS
Mean	0.0026	0.0030	0.0034
Sum	6.4945	7.2990	8.7965
Standard deviation	0.0045	0.0080	0.0090
Variance	2.0811 E^{-05}	6.40183 E^{-05}	8.1492 E^{-05}
Skewness	3.0734	5.6408	3.8866
Kurtosis	10.7406	40.0316	18.2740

Table 3. Comparison of Spectral statistical features of Normal and Murmur sound signals (WAV format)

Features	Normal	Murmurs
Mean	0.0006	0.0008
Sum	11.07	14.04
Standard deviation	0.0020	0.0024
Variance	2.0811 E^{-06}	4.070 E^{-06}
Skewness	4.6248	2.3398
Kurtosis	11.58	4.6108

5. Conclusion

A spectral features-based heart sound signal analysis method was developed in this work. Heart sound signals were collected from the medical database and utilized in spectral feature analysis. Windowing technique was used for signal conditioning of heart signals to attain effective signal analysis outcome. The statistical spectral features extracted from the computed frequency spectrum show that, the features varied according to the AS stages. Hence, the healthy and unhealthy condition of the heart can be identified from the statistical features of the frequency spectrum. Moreover, the experimental result also shows the statistical difference between the early AS and delay AS stages. Hence, the statistical spectral analysis method of heart sounds can be considered as a diagnostic tool of AS.

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