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Research Article – Electronics and Telecommunication

Detection of pathological heart murmurs by feature extraction of phonocardiogram signals

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Abstract

Cardiac auscultation can be perceived as method of determining the human heart condition by listening to the heart sounds. These heart sounds contain vital information related to a person's heart condition. Any departure from the normal cardiac auscultation readings in terms of presence of additional heart sounds is indicative of an unhealthy heart. The use of Phonocardiogram (PCG)signals (i.e. the electronic recording of heart sounds) completely dismisses the limitation of relying solely on the physician's hearing ability. At the same time, they provide with a high-fidelity representation of the heart sounds in the most cost-effective way as compared to the methods like Electrocardiogram (ECG). In this paper, a method of detection of heart ailments by extracting the features of PCG signals is proposed. The normal heart sounds, gallop rhythms and the most common pathological murmurs have been used for analysis. By analyzing these signals, early detection and diagnosis of heart diseases can be done reliably. This will not only confirm health and longevity by early diagnosis and pin-pointed prognosis, but will also be economically suitable for those who can hardly afford tests like ECG. It can also be practicable in the case of infants wherein the other non-invasive diagnosis techniques like ECG fail.

Key words: Cardiac auscultation, Phonocardiogram signals, feature extraction, heart sounds, pathological murmurs, gallop rhythms

Introduction

Heart sounds can be classified as normal (or fundamental heart sounds) and abnormal heart sounds (or murmurs). The normal sounds are termed as S1 and S2. S1 or the First heart sound forms the "lub" of the "lub-dub" sound and is caused by the abrupt block of reverse blood flow due to the closure of the tricuspid and mitral valves at the beginning of the systole. S2 or the Second heart sound which forms the "dub" of the "lub-dub" sound is caused by the sudden block of the blood flow due to the closure of the aortic and pulmonic valves at the beginning of the ventricular diastole. S3 and S4 are called extra heart sounds or gallop rhythms. The heart murmurs can be classified as innocent or pathological. Innocent murmurs originate through normal flow patterns with no structural or anatomic abnormalities of the heart or vessels while the pathological murmurs created by abnormal flow patterns in the heart and vessels resulting from congenital heart abnormalities, valve disease, or other acquired conditions. The pathological murmurs can be further classified as Systolic and Diastolic murmurs. The systolic murmurs studied include: (i)Aortic valve stenosis; (ii) Stenosis of Bicuspid aortic valve; (iii) Mitral regurgitation; (iv) Pulmonary valve stenosis; (iv) Tricuspid valve regurgitation; (v) Hypertrophic obstructive cardiomyopathy; (vi) Atrial septal defect; Ventricular septal defect (VSD); and (ix) Flow murmur. The diastolic murmurs analyzed are: (i) Aortic valve regurgitation; (ii) Mitral stenosis; (iii)

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Tricuspid valve stenosis; and (iv) Pulmonary valve regurgitation.

This paper intends to propose an economical and easy-to-use yet accurate heart diagnosis methodology to minimize the toll of deaths due to undiagnosed heart diseases, especially for the rural poor. The work aims to propose a method to classify normal and abnormal heart sound signals having murmurs without involving complex pre-processing techniques like the segmentation of the heart sounds into systoles and diastoles. This has been achieved by suggesting a large set of features of normal heart sounds extracted in the time, frequency and the statistical domain. This set of features can then be used to detect a cardiac pathology by supervised training techniques using classifiers like Artificial Neural Networks(ANN), Support Vector Machines(SVN), k-Nearest neighbors (k-NN), to name a few.

Murmurs Studied

In this paper, only the most commonly occurring pathological murmurs along with the normal and extra heart sounds have been studied viz.

2.1 Early Systolic Murmur

Early systolic murmurs begin with the first sound and peak in the first third of systole. Early murmurs have the greatest intensity in the early part of the cycle. Common causes are a small ventricular septal defect (VSD), or the innocent murmurs of childhood. The early systolic murmur of a small VSD stops before mid-systole because as ejection continues and the ventricular size decreases, the small defect is sealed shut causing the murmur to soften or cease. This murmur is characteristic of the type of children's VSD which may disappear with age.

2.2 Late Systolic Murmur

LSM is a high-frequency and (usually) crescendo murmur that starts after S1 and extends to or through S2.

2.3 Diastolic Rumble

Diastolic heart murmurs are heart murmurs heard during diastole. Diastolic murmurs start at or after S2 and end before or at S1.These have a rumbling character. Many involve stenosis of the atrioventricular valves or regurgitation of the semilunar valves.

2.4 Opening Snap

It is associated with mitral stenosis. The first heart sound is increased in intensity while the second heart sound is normal. An opening snap is present after the second heart sound. The low-pitched rumbling murmur starts after the opening snap and lasts until mid-diastole.

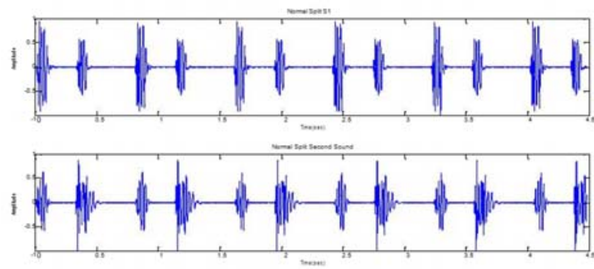

Fig. 1 First & Second Heart Sounds

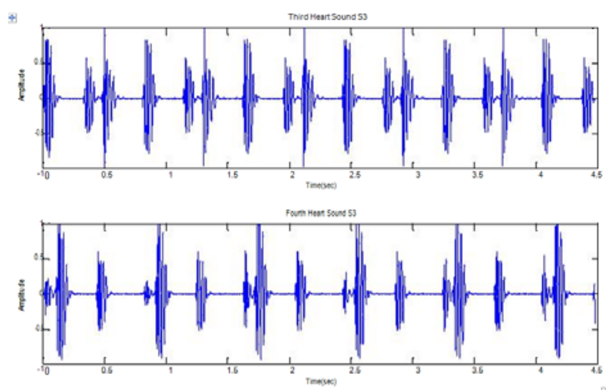

Fig. 2 Third &Fourth Heart Sound

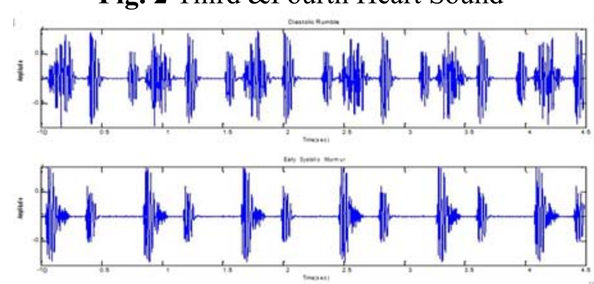

Fig. 3 Diastolic Rumble & Early Systolic murmur

2.5 Ejection Click

Ejection clicks are high-pitched sounds that occur at the moment of maximal opening of the aortic or pulmonary valves. They are heard just after the first heart sound. The sounds occur in the presence of a dilated aorta or pulmonary artery or in the presence of a bicuspid or flexible stenotic aortic or pulmonary valve. Ejection clicks may also be called ejection sounds. The diastolic correlate of the ejection click is the opening snap, which occurs at maximal opening of a flexibly stenotic mitral or tricuspid valve.

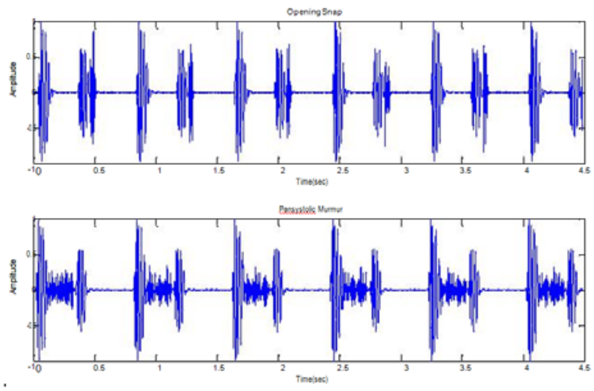

Fig. 4 Opening Snap & Pansystolic Murmur

2.6 Pansystolic Murmur

Pansystolic (Holosystolic) murmurs start at S1 and extends up to S2. They are usually due to regurgitation in cases such as mitral regurgitation, tricuspid regurgitation, or ventricular septal defect (VSD).

Description of features

The fundamental heart sounds (S1 and S2), the extra heart sounds (S3 and S4) and all the other murmurs mentioned above have been studied and their most distinguishing characteristics in terms of periodicity, pitch, loudness, duration, associated auscultation point, presence of clicks etc. have been found. Based on the observations made, a set of features have been proposed. Since the recordings of heart sounds have been obtained from multiple sources, all of them have been subjected to normalization prior to the feature analysis and extraction. After the extraction of features of each kind of heart sound (both normal and murmur), a safe range of feature values for each type has been tabulated.

It can be postulated that if a PCG recording contains any of the features that fall in the unsafe range, meaning that if any pathological heart murmur can be heard during cardiac auscultation, the associated heart can be considered as unhealthy. This means that the same feature extraction algorithm can be applied to the entire heart sound recording (without any segmentation into systolic and diastolic portions) and a decision regarding the presence or absence of a heart anomaly can, thus, be made.

3.1. Feature Extraction

In this study, a set of 20 features from time domain, frequency domain and statistical domain were extracted that could possess the ability to discriminate among the healthy and murmur PCG signals. The PCG signals have been normalized and considered in their entirety, without fragmenting into systolic and diastolic portions, for extraction of their features. In this project the analysis is based on the PCG signals procured from the recordings of 3M^{TM} Littmann ® stethoscope[6].The features are enlisted in the Table 1.The features extracted have been described below:

3.1.1 Maxima

It represents the frequency at which the peak amplitude occurs. Since the murmurs and normal signals vary in amplitude and frequency, it can be treated as a potential feature.

Table 1. List of features extracted

#	Feature	Domain
1.	Maxima	Frequency
2.	Total power	Time
3.	Zero Crossing Rate	Time
4.	Total Harmonic Distortion	Frequency
5.	Peak Amplitude	Time
6.	Kurtosis	Statistical
7.	Skewness	Statistical
8.	Mean	Statistical
9.	Standard Deviation	Statistical
10.	Linear correlation coefficient	Time
11.	Autocorrelation	Time
12.	Correlation(FFT)	
13.	Spectral Centroid	Frequency
14.	Cepstrum	Frequency
15.	Spectral Roll-off	Frequency
16.	Spectral flux	Frequency
17.	Variance	Statistical
18.	Q Factor	Frequency
19.	3 dB Bandwidth	Frequency
20.	Energy Entropy	Statistical

3.1.2 Total Power

It shows the total power of the signal. The murmur is a higher amplitude signal and hence is expected to have a higher value of this feature. [6]

3.1.3 Zero Crossing Rate

The ZCR is the rate of sign-changes along a signal, i.e., the rate at which the signal changes from positive to negative or back. A larger value of ZCR is expected for murmur signals. [6]

3.1.4 Total harmonic Distortion

It is the measurement of the harmonic distortion present in the signal and is defined as the ratio of the sum of the powers of all harmonic components to the power of the fundamental frequency. A comparatively higher THD is expected for murmur signals. [6]

3.1.5 Peak Amplitude

It shows the peak value of the signal. The murmur and normal signals vary in amplitude so this feature had potential. A higher Peak amplitude values are expected for murmur signals as compared to normal signals. [6]

3.1.6 Kurtosis

It indicates the outlier-prone propensity of a distribution. It is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution.

3.1.7 Skewness

It is indicative of the degree of asymmetry of the auscultation data outside the mean value. It is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, data set, is symmetric if it looks the same to the left and right of the center point.

3.1.8 Mean

It indicates the central tendency of the auscultation data distribution.

3.1.9 Standard Deviation

It indicates how much the data varies from the mean value on both sides.

3.1.10 Linear Correlation Coefficient

It can be calculated as the covariance of the two variables divided by their standard deviations.

3.1.11 Autocorrelation

It can be defined as the correlation of a PCG signal with a delayed copy of itself as a function of delay. Informally, it is the similarity between PCG recording observations as a function of the time lag between them.

3.1.12 Correlation (FFT)

It is, basically, the calculation of correlation of auscultation data in the frequency domain by using Fast Fourier Transform.

3.1.13 Spectral Centroid

The spectral centroid is a measure used in digital signal processing to characterize a spectrum. It indicates where the "center of mass" of the spectrum is. Perceptually, it has a robust connection with the impression of "brightness" of a sound. [1]

3.1.14 Cepstrum

It is calculated by taking the Inverse Fourier Transform (IFT) of the logarithm of the estimated spectrum of the signal.

3.1.15 Spectral Roll-off

Spectral roll off point is defined as the Nth percentile of the power spectral distribution, where N is usually 85% or 95%. The roll off point is the frequency below which the N% of the magnitude distribution is concentrated. [3]

3.1.16 Spectral flux

It is a measure of how quickly the power spectrum of a signal is changing, calculated by comparing the power spectrum for one frame against the power spectrum from the previous frame. [4]

3.1.17 Variance

It is the expectation of the squared deviation of a random variable from its mean, and it informally measures how far a set of numbers are spread out from their mean.

3.1.18 Q Factor

Physically speaking, Q is 2π times the ratio of the total energy stored divided by the energy lost in a single cycle or equivalently the ratio of the stored energy to the energy dissipated over one radian of the oscillation. [5]. It is a dimensionless parameter that compares the exponential time constant τ for decay of an oscillating physical system's amplitude to its oscillation period. Equivalently, it compares the frequency at which a system oscillates to the rate at which it dissipates its energy.

Table 3. Comparison of Feature values for trend analysis

Feature	Normal Heart Sound	Extra Heart sound	Murmurs
Peak amplitude	0.6887	0.69085	0.74175
Peak frequency	42.8104	44.5805	47.5804
Total power	4.29E-07	4.21E-07	4.44E-07
Total harmonic distortion	10.986	12.763	14.497
Zero Crossing rate	0.085141	0.0763045	0.0675
Time-period	0.80515	0.8075	0.8043
Kurtosis	9.2338	8.2896	8.69545
Skewness	-0.12315	0.09365	0.03525
Mean	0.0016	0.00145	0.00205
Variance	0.02135	0.02355	0.0279

Table 4. Feature values (Calculated after normalization)

Features Heart sound	Peak Amplitude	Peak Frequency	Total Power	Total Harmonic Distortion	Zero Crossing Rate(ZCR)	Time Period	Kurtosis	Skewness	Mean	Variance
S1	0.7520	46.0945	5.484e-07	15.945	0.078651	0.8	9.5415	-0.0532	0.0021	0.0271
S2	0.6234	39.5336	3.088e-07	6.0277	0.091631	0.8103	8.9261	-0.1931	0.0011	0.0156
S3	0.6020	45.7581	3.358e-07	8.85	0.070034	0.8066	7.0795	0.0724	0.0011	0.0185
S4	0.7797	43.4029	5.052e-07	16.676	0.082575	0.8084	9.4997	0.1149	0.0018	0.0286
ESM	0.7759	43.4025	2.741e-07	16.173	0.078826	0.8032	9.9902	0.1361	0.0018	0.0275
LSM	0.7751	43.4026	4.832e-07	14.261	0.095303	0.8034	10.3509	0.1196	0.0019	0.0249
DR	0.7462	67.4595	3.379e-07	15.151	0.069725	0.8081	5.4311	0.0025	0.0022	0.0394
OS	0.7214	43.7392	5.172e-07	16.543	0.066879	0.8035	8.4393	-0.0261	0.0021	0.0270
EC	0.7220	43.7395	4.903e-07	13.372	0.059086	0.8075	9.0860	-0.0128	0.0021	0.0242
PSM	0.7099	43.7393	5.634e-07	11.482	0.035779	0.8002	8.8752	-0.0078	0.0022	0.0245

3.1.19 3 dB Bandwidth

It is defined as the frequency at which the magnitude of the PCG recording falls 3dB below its maximum value.

3.1.20 Energy Entropy

Entropy (or an entropy-based feature) can be computed from any finite set of values, e.g. a parametric vector, a discrete spectral density estimate, or directly from a segment of the PCG signal. [7]

3.2. Feature Selection

Among the 20 features extracted, only 10 features of the time, frequency and statistical domains have been selected. This has been done to reduce the redundancy of feature values and the computational overheads which enhance the suitability of the data for classification using methods like ANN. In this work, the auscultation data has been classified into 2 sets and then subjected to Feature Reduction by Fisher's Discriminant Ratio (FDR). The features displaying higher values of FDR have been selected [2]. The selected features are (i) Maxima; (ii) Peak amplitude; (iii) Total power; (iv) Total harmonic distortion; (v) Zero crossing rate; (iv) Time-period; (v) Kurtosis; (vi) Skewness; (vii) Mean and (viii) Variance.

Table 2. List of abbreviations used

Abbreviation	Heart Sound
S1	First Heart sound
S2	Second Heart sound
S3	Third Heart sound
S4	Fourth Heart sound
ESM	Early Systolic murmur
LSM	Late Systolic murmur
DR	Diastolic Rumble
OS	Opening Snap
EC	Ejection Click
PSM	Pansystolic murmur

4. Results & Conclusion

Among various features analyzed, the ones tabulated were found to be the best for distinguishing the various normal and abnormal heart sounds. As expected, the peak amplitude of the S4 was the highest. The Diastolic Rumble has the highest peak frequency. Owing to the rumbling nature of the diastolic rumble, it has the maximum average power content. S4, if present, has the maximum Total Harmonic Distortion, followed by Opening Snap. The random clicking nature lends it this fluctuating effect. S2, as can be analyzed from the plot as well as the calculations done exhibits the maximum zero crossing rate. The time-period of the heart sounds was found to be nearly equal.

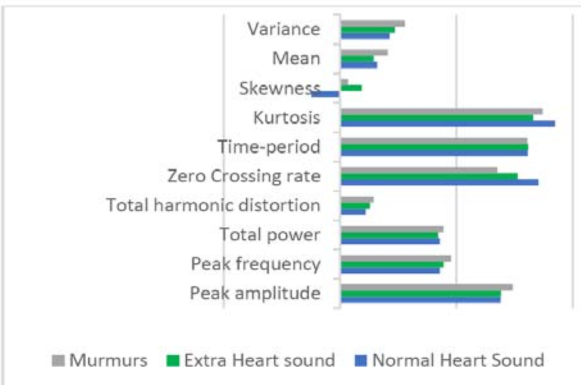

Fig. 5 Comparison of feature values (Not to scale)

Thus, the features listed out can be used as inputs to a classifier for classifying the recorded PCG sounds as healthy or unhealthy. This can be done by using supervised machine learning tools like Artificial Neural networks, support Vector Machines, K-NN, Fuzzy K-NN etc.

The paper analyzes only the most common murmur types and is based on the assumption that classification of heart sounds in the future will be based on the presence or absence of the features, calculated for the test PCG recording, within the reference limits. If the given auscultation recording contains any feature value that falls in the unhealthy range, it must contain a heart abnormality or a pathological murmur. The values of the features extracted have been shown in Table 3.

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