

Detection of Murmur from Non-Stationarity of Heart Sounds

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<http://dx.doi.org/10.13005/bpj/1721>

(Received: 13 March 2019; accepted: 13 May 2019)

Early diagnosis of heart diseases bears a major role in saving lives. Presence of spurious extra-frequency components, termed as murmurs within the phonocardiography record may be indicative of valvular disorders like stenosis, lesions or regurgitation. It is difficult to identify the subtitle spectral components of murmurs through subjective audition. In this paper, a technique is proposed to detect the presence of murmur from the heart signal by analyzing their non-stationarity behavior by using autocorrelation based features namely, Standard Error (SE) of Auto-Correlation Function (ACF) and absolute deviation of SE from the reciprocal of the square root of number of samples ($\hat{\alpha}$). The selected features corresponding to normal and murmur differ with a 'P' value of 1.80×10^{-14} (dataset 1) and 2.20×10^{-76} (dataset 2) for SE and $\hat{\alpha}$, respectively. It is found that SE and $\hat{\alpha}$ could effectively distinguish normal and murmur with 100% accuracy, sensitivity, and specificity.

Keywords: Autocorrelation, heart abnormality, murmur, non-stationarity, PCG signal, type of heart signal, time domain features.

Cardiovascular diseases (CVDs) are one of the major causes of death worldwide. As per the report of world health organization, the annual death rate due to CVDs is more than from any other diseases [1]. In 2015, around 17.7 million people died because of CVDs. Of these deaths, an estimated 7.4 million were due to coronary heart disease. Hence, early detection and diagnosis of heart diseases play a major role in saving lives. Presence of spurious extra-frequency components, termed as murmurs within the phonocardiography (PCG) records, or heard

during the routine auscultation with steth, may be indicative of valvular disorders like stenosis, lesions or regurgitation. But it is difficult to detect the presence of murmur in the heart signal through subjective audition. Hence an automated method to detect the presence of murmur in the heart sound has its own importance to find out the heart abnormalities.

Few methods dealing with the computerized detection and characterization of heart murmurs are available in the literature [2-18]. Kang *et al.* [2] developed a system for automatic

identification of Still's murmur in children with a sensitivity of 84-94% and a specificity of 91-99%. They used time domain features (average Shannon energy and envelope detection) and frequency domain features (spectral width and peak frequency) of S1 and S2 heart sounds. These features were given as input to Support Vector Machine (SVM) classifier. S.W. Deng and J. Q. Han [3] proposed a method based on the autocorrelation features like Sub-band autocorrelation function. These features were extracted from the sub-band envelopes derived from the sub-band coefficients of PCG signals obtained using Discrete Wavelet Transform (DWT). Finally using diffusion maps, these features were fused to get unified features and they were given into the SVM classifier (Accuracy 91 %).

Chen *et al.* [4] used a continuous wavelet transform to distinguish organic and innocent murmurs. Singular value decomposition and QR(Q is an orthogonal matrix and R is an upper triangular matrix) decomposition were applied on the time-frequency matrix, obtained from continuous wavelet transforms for feature extraction. Shannon entropy and the Gini index were further computed on the decomposition results and were taken as features. To reduce the number of features and the computational complexity, Sequential Forward Floating Selection (SFFS) was used as a feature selection algorithm. Classification accuracy of 90% was reported for regression tree based classification scheme.

Safara *et al.* [5] used wavelet packet entropy to discern stenosis and regurgitation of mitral and aortic valves (Bay's Net classifier 96% accuracy). Choi *et al.* [6] used features like maximum peak frequency, the position index of the wavelet packet coefficient corresponding to the maximum peak frequency and the ratios of the wavelet energy and entropy of PCG signal (99.78% specificity and 99.43% sensitivity). In the method suggested by V. N. Varghees and K. I. Ramachandran, [7] initially the PCG signal was decomposed by Empirical Wavelet Transform (EWT). The heart sound/murmur detection was done by Shannon entropy and instantaneous phase after discriminating them using mode boundary frequency and maximum absolute amplitude. The evaluation results showed that the system had an accuracy of 91.92%. To extract S1 and S2 heart

sounds G. Eslamizadeh and R. Barati [8] applied Continuous Wavelet Transform (CWT) with Morlet wavelet function to PCG signal. To detect the murmur, an algorithm was also proposed to extract features such as maximum amplitude values from consecutive S1 and S2 and vice versa. These features were normalized and input into Artificial Neural Network (ANN) classifier (average success rate of 94 %). Guillermo *et al.* [9] introduced a system based on radial wavelet neural network with Kalman learning. At first, by using CWT, the PCG signal was segmented to get S1 and S2 heart sounds. As a feature extraction method, a total of 9 relative divisions made recursively upon each division generated on a symmetric way by considering previous S1's and S2's. From each division, a maximum and minimum amplitude point were taken and considered a feature. Thus a total of 18 features were obtained. These selected features were input into a Radial Wavelet Neural Network (RWNN) with Kalman learning. The system was able to differentiate normal and murmur with a success rate of 98.04%.

Safara *et al.* [10] proposed a technique termed as Multi-Level Basis Selection (MLBS) to preserve the most informative bases of a wavelet packet decomposition tree by removing less informative bases by applying three exclusion criteria: frequency range, noise frequency, and energy threshold. MLBS achieved an accuracy of 97.56%. Hamidi *et al.* [11] suggested two methods for heart abnormality detection using PCG signal. In the first method curve fitting of the heart, signal was performed after preprocessing and filtering. The power spectrum of the curve fitted signal was computed and used it as a feature. In the second method, the signal was divided into equal parts and fractal dimension was computed for each part. The resultant signal was considered as the second feature. These two features were input into K-Nearest Neighbors (KNN) classifier. Average accuracy of 90 % was reported. Bozkurt *et al.* [12] proposed a system using Mel-frequency Cepstral Coefficient (MFCC), Mel-spectrogram and sub-band envelopes of the PCG signal for paediatric heart abnormality detection with 84.5% sensitivity, 78.50% specificity, and 81.5% accuracy. The features were directly inputted into the Convolutional Neural Network (CNN) classifier. Thiyagaraja *et al.* [13] prototyped a smartphone

based electronic stethoscope that can record, process and detect heart sounds. In their system, S1 and S2 heart sounds were extracted using peak detection method after preprocessing. By using this S1 and S2 heart sounds, a classification model utilizing the MFCC and Hidden Markov Model (HMM) were introduced to detect normal/murmur (Accuracy of 92.68%).

The features used by Zheng *et al.* [14] include the energy fraction of the first and the second heart sounds (S1–S2EF), energy fraction of heart murmur (HMEF), the maximum energy fraction of heart sound frequency sub-band (HSEFmax), sample entropy of the first and the second heart sound component (S1–S2sampen) and sample entropy of heart murmur component (HMsampen). The heart sounds after denoising, normalized signals were decomposed into wavelet

packets. The features were calculated from the reconstructed selective frequency components of the signals. It was reported that the SVM classifier discriminated heart murmurs with an accuracy of 97.17%, a specificity of 98.55% and a sensitivity of 93.48%.

Choi *et al.* [15] illustrated a method based on a multi-Gaussian fitting algorithm of the cardiac spectral curve. The spectral autoregressive Power Spectral Density (aPSD) curve was estimated from the cardiac sounds noise-canceled by the wavelet decomposition. 5-GaPSD was approximated by a five-Gaussian model consisting of five Gaussian peaks, P1 to P5. The spectral profiles, the maximum frequency, the amplitude, the half-width, the area portion and the loss of area, of five Gaussian peaks, were investigated and compared for segmenting the spectral information of normal heart sound and regurgitation murmurs. Redlarski *et al.* [16] used Linear Predictive Coding (LPC) Coefficients as feature input to a composite classifier made of SVM and modified cuckoo search, to separate innocent murmur (S1, S2, S3, and S4) and organic murmur (Accuracy 93%). Zhang *et al.* [17] used scaled spectrogram after dimensionality reduction with partial least squares regression as feature input to SVM classifier to distinguish heart murmur from extrasystole and controls (Precision 91%). Another method proposed by Zhang *et al.* [18], spectrograms of the heart signal were scaled to a fixed size after preprocessing and dimensionality reduction. Then the scaled spectrograms were concatenated as a three-way tensor and decomposed using Tucker-2 decomposition method. The decomposed information has given in to SVM (Accuracy 76 %).

In most of the literature, the statistical significance, separability and the inter-class variability of the features were not investigated or tested. To distinguish the normal/murmur, most of the literature used various classifiers along with various features rather than using the fundamental time, frequency or time-frequency

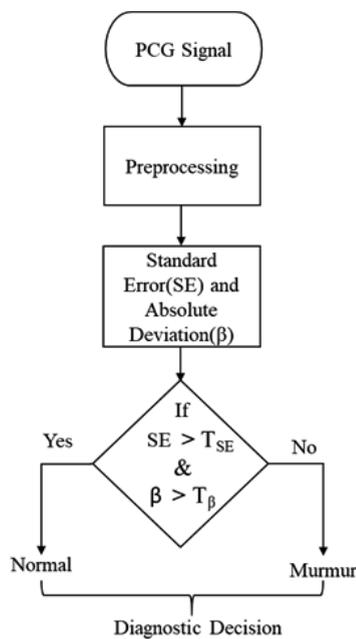


Fig. 1. Schematic of the stages incorporated in the computation of the temporal features and feature evaluation

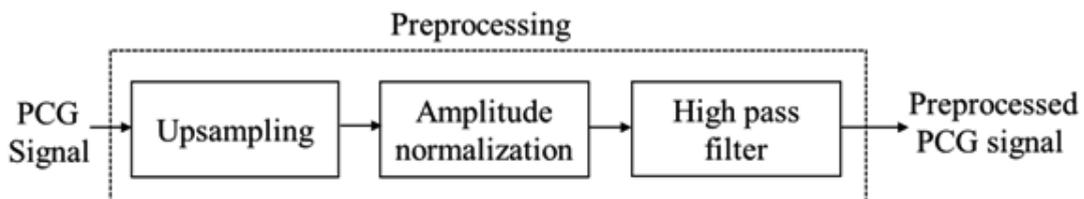


Fig. 2. Schematic of the steps incorporated in the preprocessing

domain features. Neural networks or classifiers are essential in conditions, where in feature space, the features are less statistically significant. Moreover, a system with classifiers may deteriorate the system performance and also the system complexity will be increased. The works presented in literature failed to differentiate the normal and murmur with cent percentage sensitivity, septicity, and accuracy. Usually, the pattern of the heart signal of a normal heart is stationary. When extra frequency components like murmurs isinterfered in the heart sound, the non-stationarity of the resultant signal will be increased. That means PCG measurements of an abnormal heart will be highly nonstationary. Moreover, the normal heart signal is less stationary than the heart signal interfered with a murmur.

Hence, the objective of this paper is to design a technique by using the time domain features such as the autocorrelation based features such as Standard Error (SE) of Auto-Correlation Function (ACF) and absolute deviation of SE from the reciprocal of the square root of number of samples (\hat{a}) to detect the Murmurs from Non-Stationarity of heart sound. The highlights of the proposed technique are i) The method is able to identify the presence of murmur in the heart signal with 100 % sensitivity, septicity, and accuracy. ii) It is quite simple as the method used only fundamental time domain features. Moreover, the computational complexity of the technique is also very less.

The analysis, mathematical formulation of features and the details of the dataset used are furnished in section 2. In section 3, the statistical significance and separability offered by the features to distinguish normal or murmur is analyzed. In section 4, discussion with the existing methods is included.

METHODOLOGY

The methodology adopted in the method to detect the presence of murmur from the non-stationarity of the heart sound is discussed in this section.

The schematic of the stages involved in the computation of autocorrelation based features and feature evaluation is presented in fig.1.

Before computing the autocorrelation based features, the PCG signal is preprocessed.

The block schematic of the steps involved in the preprocessing is illustrated in fig.2. After extracting the autocorrelation based features like SE and \hat{a} , a threshold is set up for accurately classifying the heart signal. If SE is greater than the threshold T_{SE} and \hat{a} is greater than that of $T_{\hat{a}}$, the heart signal belongs to normal else it is murmur. Where T_{SE} and $T_{\hat{a}}$ are the threshold for SE and \hat{a} , respectively.

The preprocessing (fig.2) of the PCG signal includes upsampling of the signal by a factor 2 to achieve adequate sampling rate, the amplitude normalization between -1 and +1 and the high pass filter to remove the frequency components below 10Hz. The time domain features like SE and \hat{a} of the preprocessed signal is estimated to test their ability to differentiate normal heart sound and murmur. Besides, their statistical significance is also evaluated.

The upsampled PCG signal after normalization is given as

$$X_n(t) = \frac{Xi(t)}{\max|Xi(t)|} \quad \dots(1)$$

where 'Xi(t)' is the PCG signal, sampled at a rate '1/fs' and contains 'N' samples, '1d'nd'N. To regulate the amplitude of heart signal, the samples are normalized to a range between -1 and +1 as in (1).

As already stated, PCG measurements of an abnormal heart will be highly nonstationary. That means the murmur may more non-stationary than the normal heart signal. The properties of the autocorrelation of heart signal are employed in this paper. Autocorrelation is extensively used to measure non-stationarity of a signal. The autocorrelation based features can be used to quantify the change in non-stationarity of the heart signal. Box et.al [19] proposed that SE of the ACF can be used to estimate the randomness or non-stationarity behavior of a signal. It was also stated that, as the signal becomes more random, the value of SE moves nearer to the reciprocal of the square root of the number of samples in the signal. The SE of the sample autocorrelation function can be denoted as

$$SE = \sqrt{\frac{1}{N} \left(1 + 2 \sum_{j=1}^q (r_j^2) \right)} \quad \dots(2)$$

where 'N' is the total number of samples, 'q' is the lag beyond which the theoretical ACF is effectually become 0 and 'r_j' is the SACF function. When the series becomes completely random, SE reduces to 1/√N [19]

The SACF 'r_k' at lag 'k' is

$$r_k = \frac{C_k}{C_0} \quad \dots(3)$$

where 'C₀' and 'C_k' are the variance (with zero shift) and covariance of the signal, respectively.

$$C_0 = \frac{1}{N} \sum_{t=1}^N (X_t - \mu(X_t))^2 \quad \dots(4)$$

Where 'X_t' is the heart signal after preprocessing and its mean is given by 'μ (X_t)'

$$\mu(X_t) = \frac{1}{N} \sum_{t=1}^N X_t \quad \dots(5)$$

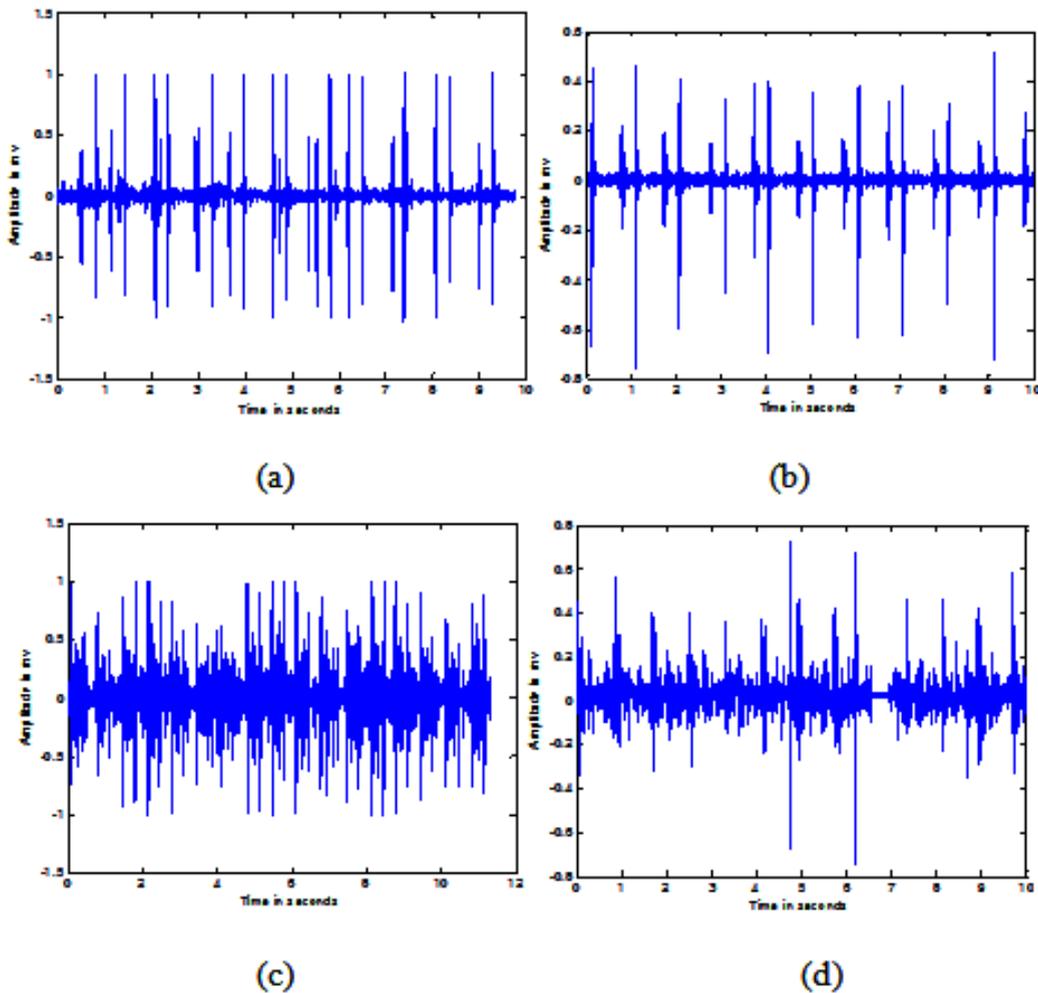


Fig. 3. Wave shape of normal heart sound and murmur (a) normal heart sound (dataset 1) (b) normal heart sound (dataset 2) (c) Murmur (dataset 1) (d) Murmur (dataset 2)

$$C_k = \frac{1}{N-1} \sum_{t=1}^{N-k} (X_t - \mu(X_t))(X_{(t+k)} - \mu(X_t)) \dots(6)$$

where 'X_(t+k)' is the shifted version of the signal 'X_t' and given k=0,1,2K.

The mathematical representation of the absolute deviation of SE from the reciprocal of the square root of the number of samples (â) is given as,

$$\beta = \frac{1}{\sqrt{N}} - SE \dots(7)$$

$$\beta = \frac{1}{\sqrt{N}} \sqrt{\frac{1}{N} \left(1 + 2 \sum_{j=1}^{N-1} \left(\frac{\frac{1}{N-1} \sum_{t=1}^{N-k} (X_t - \mu(X_t))(X_{(t+k)} - \mu(X_t))}{\frac{1}{N} \sum_{t=1}^N (X_t - \mu(X_t))^2} \right)^2 \right)} \dots(8)$$

The proposed technique used two common public heart sound databases namely pascal heart sounds challenge database (Pascal HSDB) [20] and physionet heart sound database (Physionet HSDB) [21]. The Pascal HSDB consists of dataset A and dataset B. The former has been collected from the general public using the iStethoscope Pro iPhone app and later from a clinical trial in hospitals via digital stethoscope DigiScope. The duration of recorded '.wav' files (sampling frequency 4

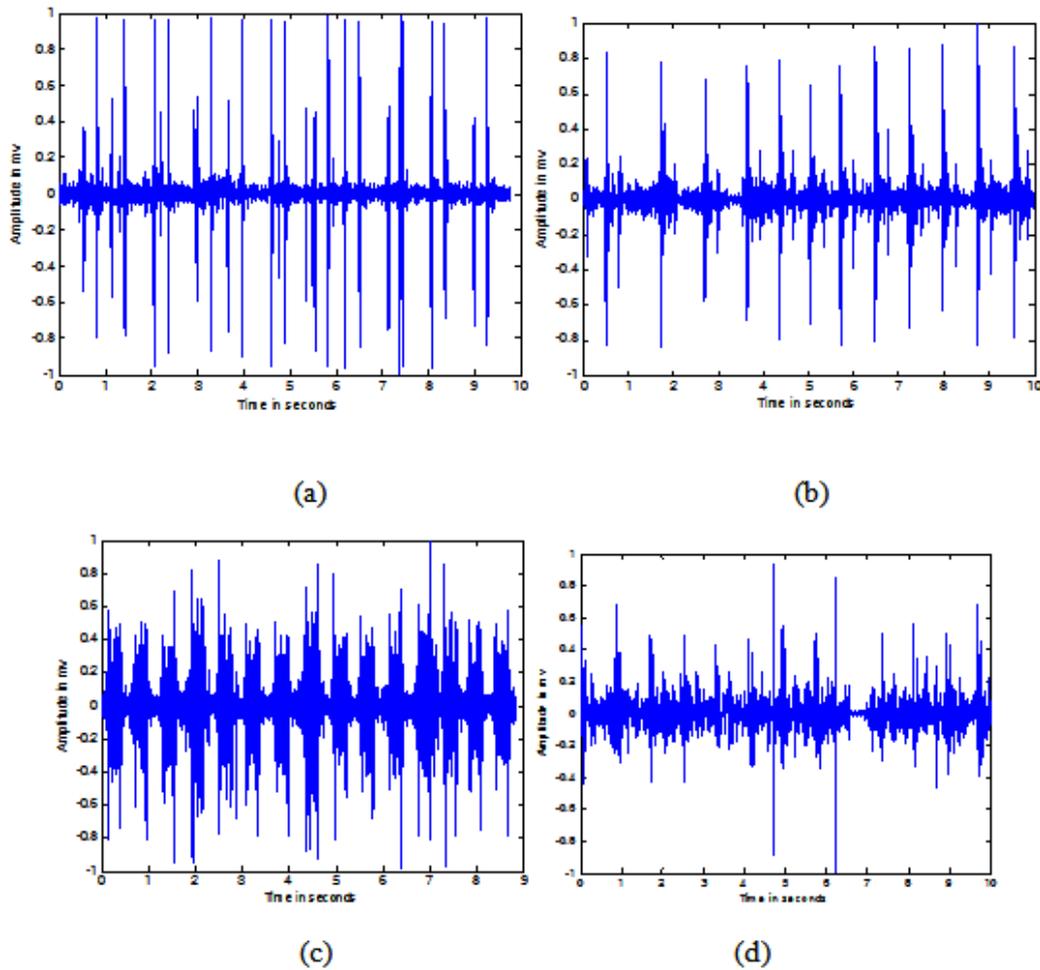


Fig. 4. Wave shape of preprocessed heart signal (a)normal(dataset 1) (b) normal(dataset 2) (c) Murmur (dataset 1) (d) Murmur (dataset 2)

KHz) in the dataset B varies from 1 second to 30 seconds. The Physionet HSDB recordings were collected from various contributors around the globe, gathered at either a medical or nonmedical environment, from both healthy people and pathological patients. This data set consists of five training databases (A to E) comprising a total heart sound recording of 3,126 samples with a duration from 5 to 120 seconds. All records were resampled to 2 KHz and hold only one PCG lead. All the recordings were provided as .wav format.

The proposed method is tested on 400 records. Out of these, 60 records from dataset B of PascalHSDB (dataset 1) and 340 records from dataset E of Physionet HSDB (dataset 2). Out of

the 60 records of dataset 1, 30 records are normal and 30 records are murmur. The 340 records of dataset 2 consist of 170 records each from normal and murmur category. The signals are selected in such a way that each record have sample length more than 8 seconds and are upsampled by a factor 2 ie; the sampling frequency ‘fs’ of the first dataset is 8KHz and that of the second dataset is 4KHz. The frequency components less than 10Hz are eliminated by a high pass filter with a cut off frequency 10Hz.

The wave shape of heart signal corresponding to normal and murmur acquired from two data set are shown in fig. 3 (a) – fig. 3. (d).

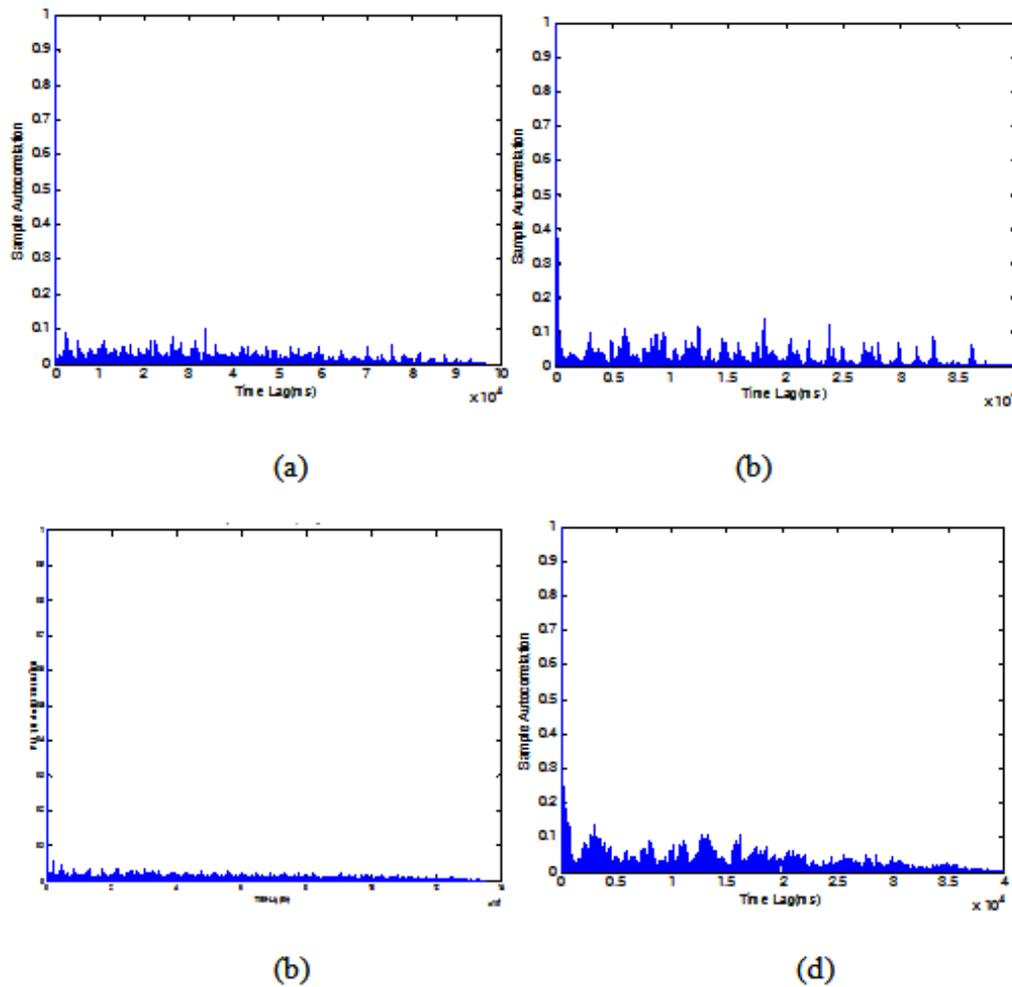


Fig. 5. ACF of normal heart sound and murmur (a) normal heart sound(dataset 1)(b) normal heart sound(dataset 2) (c) Murmur (dataset 1) (d) Murmur (dataset 2)

The wave pattern of normal heart sound and murmur are entirely different from each other. They differ in terms of their amplitude and randomness characteristics. For example, the wave pattern of heart signal corresponding to murmur is more random and their average amplitude is

comparatively higher than the wave pattern of the normal heart sound. By observing fig.3 (a) and (c), the average amplitude of normal heart signal (fig.3 (a)) is comparatively smaller than that of the murmur (fig.3 (c)).

Table 1. Numerical values and Range of features of Normal heart sound and Murmur

SI no	Features	Type of Heart Signal	Range	Dataset 1 Numerical value	Dataset 2 Range	Dataset 2 Numerical value
1	Standard Error (SE)	Normal	0.0701 to 0.0878	0.0776 ± 0.0042	0.2384 to 0.351	0.2677 ± 0.0120
		Murmur	0.0262 to 0.0439	0.0337 ± 0.0042	0.0303 to 0.2124	0.0481 ± 0.0173
2	Absolute deviation ($\hat{\alpha}$)	Normal	0.0674 to 0.0851	0.0749 ± 0.0042	0.2371 to 0.3467	0.2634 ± 0.0120
		Murmur	0.0233 to 0.0402	0.0301 ± 0.0040	0.0253 to 0.2074	0.0431 ± 0.0173

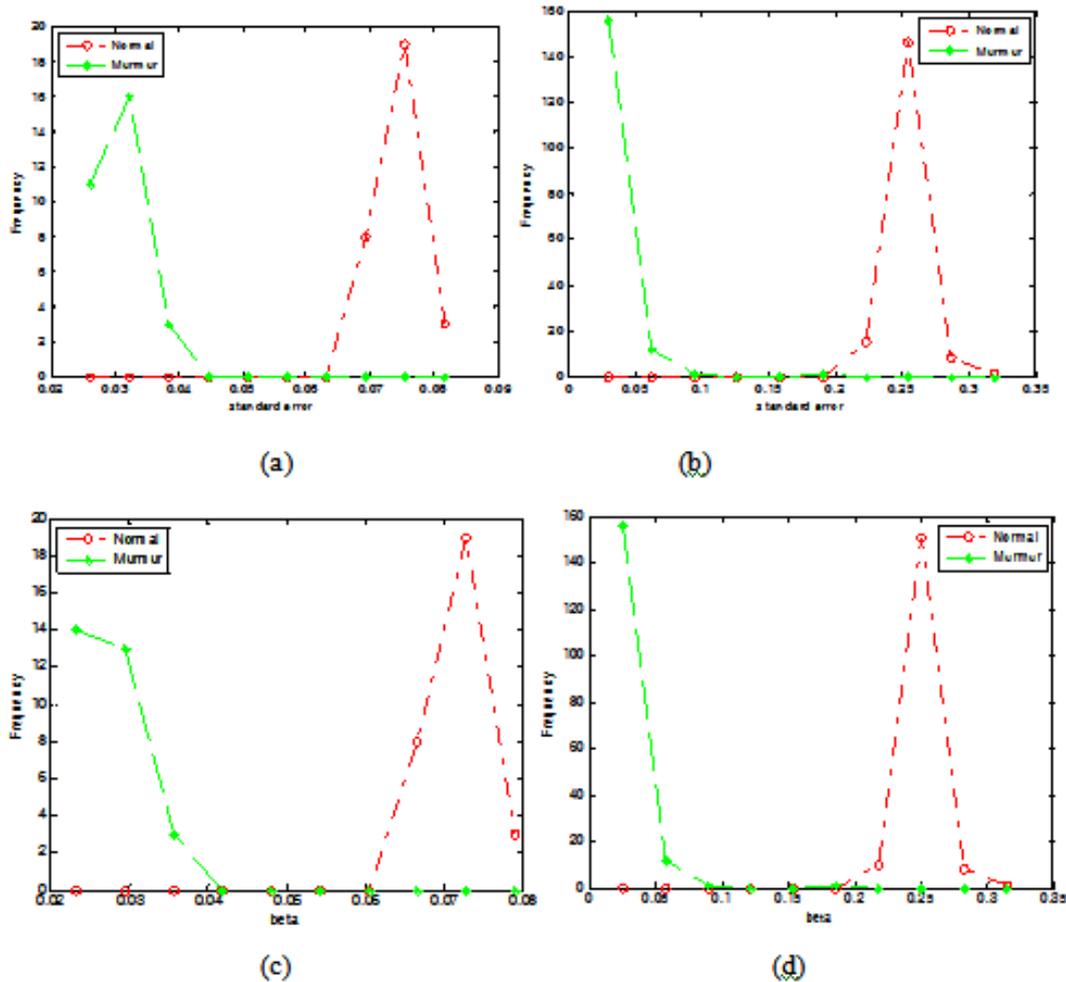


Fig. 6. The histogram of features of normal heart sound and murmur (a) Standard error (dataset 1) (b) Standard error (dataset 2) (c) Beta (dataset 1) (d) Beta (dataset 2)

The statistical significance of the features is tested for their ability to distinguish normal and murmur via Kolmogorov–Smirnov test. The Histogram is used to qualitatively evaluate the separability offered by the features. Both feature extraction and their statistical evaluation are performed in Matlab®.

RESULTS

As stated earlier, Standard Error (SE) of Auto-Correlation Function and absolute deviation of SE from the reciprocal of the square root of a number of samples ($\hat{\alpha}$) of the preprocessed signal are utilized as features. The wave pattern of the PCG signal after preprocessing is presented in fig.4(a – d).

The wave shape of normal heart sound (fig.4 (a-b)) and murmur (fig.4(c-d)) shows certain dissimilarity in their pattern. They vary in terms of their amplitude and randomness. That means,

the wave shape of preprocessed heart signal corresponding to normal (fig.4 (a-b)) is less random and their average amplitude is comparatively lesser than the wave shape of murmur. By observing fig.4 (a) and (c), the average amplitude of murmur (fig.4 (c)) is comparatively larger than that of normal heart signal (fig.4 (a)).

The pattern of normalized ACF of normal heart sound and murmur of dataset 1 and dataset 2 is shown in fig. 5(a)–(d).

It is clear that the pattern of the autocorrelation of the normal heart signal (fig. 5 a-b) and that of the murmur (fig. 5 c-d) of dataset 1 and dataset 2 differ significantly. This highlights the possibility of ACF of heart signal to be used to distinguish the type of heart signal like normal and murmur. In this paper, the time domain features like SE of Auto-Correlation Function and $\hat{\alpha}$ are estimated on the PCG signal collected from dataset 1 and dataset 2 to evaluate their ability to differentiate normal and murmur. The range and

Table 2. Kolmogorov-Smirnov Test 'H' and 'P' values of features of heart signal corresponding to Normal and Murmur

Sl no	Features	Dataset1		Dataset2	
		Chi-Square value (H)	Probability value (P)	Chi-Square value (H)	Probability value (P)
1	Standard Error(SE)	1	1.80 x10-14	1	2.20 x10-76
2	Absolute deviation (?)	1	1.80 x10-14	1	2.20 x10-76

Table 3. Range of features of Normal heart sound and Murmur

Sl. No	Features	Type of Signal	Dataset 1	Dataset 2
1	Standard Error (SE)	Normal	0.0701 to 0.0878	0.2384 to 0.351
		Murmur	0.0262 to 0.0439	0.0303 to 0.2124
2	Absolute deviation (?)	Normal	0.0674 to 0.0851	0.2371 to 0.3467
		Murmur	0.0233 to 0.0402	0.0253 to 0.2074

Table 4. Performance parameters of SE and β

Parameters	Standard Error (SE)		Absolute deviation (β)	
	Dataset 1	Dataset 2	Dataset 1	Dataset 2
Sensitivity	100%	100%	100%	100%
Specificity	100%	100%	100%	100%
Accuracy	100%	100%	100%	100%
PPV	100%	100%	100%	100%
NPV	100%	100%	100%	100%

Table 5. List of certain previously reported studies on detection of a murmur

Sl No	Method used (Reporter & Year)	Features Used	Classifier	Dataset	Se (%)	Sp (%)	Acc (%)
1	Time Frequency Bozkurt et al.,2018	Mel-frequency cepstral coefficient (MFCC), mel-spectrogram	SVM	University of Crete HSDB and Physionet HSDB	84.5	78.5	81.5
2	Frequency Domain Hamidiet al. ,2018	Curve fitting and power spectrum	KNN	Pascal HSDB and Physionet HSDB	–	–	90
3	Time Domain Thiyagarajaet al.,2018	Peak detection	Not Used	Experimental setup	–	–	92.6
4	Time and Frequency Vargheeset al. ,2017	Mode boundary frequency and maximum absolute amplitude	Not Used	Pascal HSDB and Physionet HSDB	–	–	91.9
5	Time Frequency Eslamizadehet al.,2017	CWT and maximum amplitude	ANN	Pascal HSDB	–	–	94
6	Time and Frequency Kang et al. ,2017	Average Shannon energy and envelope detection width and peak frequency	SVM	The murmur library	94	99	–
7	Time-Frequency Zhang et al. ,2017	Scaled spectrogram with tensor decomposition	SVM	Pascal HSDB	–	–	76
8	Time-Frequency Zhang et al. ,2017	Scaled spectrogram and partial least squares regression	SVM	Pascal HSDB	–	–	90
9	Time Domain Deng et al. ,2016	Autocorrelation (Sub-band ACF feature)	SVM	Pascal HSDB	–	–	91
10	Time and Time-Frequency Zheng et al.,2015	Energy fraction, sample entropy and wavelet packets	SVM	unknown	93.5	98.6	97.1
11	Time-Frequency Guillermo et al.,2015	Maximum and minimum amplitude	RWNN	Experimental setup	–	–	98
12	Frequency Domain Choi et al.,2014	Wavelet decomposition	Not Used	Not mentioned	–	–	–
13	Frequency Domain Redlarskiet al.,2014	Linear Predictive Coding (LPC) Coefficients	SVM	Littmann HSDB	–	–	93
14	Time-Frequency Safaraet al.,2013	Wavelet packet decomposition	SVM	Experimental setup	–	–	97.5
15	Time Frequency (Chen et al.,2012)	CWT, Shannon entropy and the Gini index	SFFS	Earson HSDB	94	83	90
16	Time-Frequency (Safaraet al.,2012)	Wavelet packet entropy	Bay's net	unknown	–	–	96
17	Time-Frequency Choi et al.,2011	Wavelet packet coefficient	Not Used	unknown	99.4	99.7	–
18	Time Domain Proposed System	SE and absolute deviation	Not Used	Pascal HSDB and Physionet HSDB	100	100	100

numerical values of SE and \hat{a} extracted from the signal corresponding to normal and the murmur is presented in Table 1.

From Table 1 it is observed that, for dataset 1, the standard error and absolute deviation of normal signal ranging from 0.0701 to 0.0878 and 0.0674 to 0.0851, respectively. The SE and \hat{a} of dataset 2 of normal signal ranging from 0.2384 to 0.351 and 0.2371 to 0.3467, respectively. For murmur, the feature ranging from 0.0262 to 0.0439 and 0.0233 to 0.0402 for SE and \hat{a} , respectively for dataset 1 and 0.0303 to 0.2124 and 0.0253 to 0.2074 for SE and \hat{a} , respectively for dataset 2.

The numerical value of SE of dataset 1 is 0.0776 ± 0.0042 (normal), 0.0337 ± 0.0042 (murmur) and that of dataset 2 is 0.2677 ± 0.0120 (normal) and 0.0481 ± 0.0173 (murmur), respectively. In the case of \hat{a} of dataset 2, its numerical value is 0.2634 ± 0.0120 (normal) and 0.0431 ± 0.0173 (murmur), respectively. It can be inferred that the numerical values of SE and \hat{a} of PCG signal corresponding to normal heart sound are significantly greater than that of murmur for both datasets.

As far as the range of features of murmur is considered, they are confined to a narrow range compared to that of the normal heart sound. As mentioned earlier, the heart signal of an abnormal heart will be highly nonstationary. That is, when the signal becomes more random (murmur), the value of SE moves closer to the reciprocal of the square root of the number of samples in the signal. As the signal becomes more random, the value of SE moves nearer to the reciprocal of the square root of the number of samples of the signal. These clearly apparent distinctions between the magnitude and the range of feature values extracted from the signal corresponding to normal as well as murmur justify the potential of the time domain features, particularly the autocorrelation based features.

The statistical significance of SE and \hat{a} are tested for their capability to differentiate normal and murmur using Kolmogorov–Smirnov test. The ‘H’ and ‘P’ values of these features of dataset 1 and 2 are presented in Table 2.

The Chi-Square values (H) obtained from the Kolmogorov-Smirnov Test (table 1) is ‘1’ for both SE and \hat{a} . The ‘H’ values are computed for a default significance level of 5%. SE and \hat{a} corresponding to normal and murmur of both

dataset 1 and dataset 2 differ with a ‘P’ value of 1.80×10^{-14} and 2.20×10^{-76} , respectively. It can be inferred that the above two features are statistically more significant.

The histogram of features specifically SE and \hat{a} of normal heart sound and murmur of dataset 1 and dataset 2 are shown in fig. 6(a)-(d).

In the histogram of SE of dataset 1 (fig. 6(a)) and that of dataset 2 (fig. 6(b)), there is no overlap exists among the histogram of normal and murmur. Similarly, in the histogram of \hat{a} of dataset 1 (fig. 6(c)) and that of dataset 2 (fig. 6(d)), there is no overlap occurs between the histogram of normal and murmur. Besides, the histogram of SE (fig. 6(a)-(b)) and that of \hat{a} (fig. 6(c)-(d)), the histogram corresponding to normal heart signal is lying sufficiently apart spatially from the histogram corresponding to murmur. That means, there is no overlap between the features of normal and murmur and also they offer very good separability among them. Hence, SE and \hat{a} can be used to effectively distinguish normal and abnormal heart signal.

The range of features of normal heart sound and murmur are given in Table 3. The range of SE of dataset 1 of the normal signal is 0.0701 to 0.0878 and that murmur is 0.0262 to 0.0439. In the case of absolute deviation, the normal signal ranges from 0.0674 to 0.0851 and murmur from 0.0233 to 0.0402. For the second dataset, the normal signal is varying from 0.2384 to 0.351 and murmur from 0.0303 to 0.2124 for the feature SE. For the same dataset, the absolute deviation (\hat{a}) of the normal signal ranging from 0.2371 to 0.3467 and that of murmur is lies between 0.0253 to 0.2074.

As stated earlier, there is no overlap exists among the range of normal and murmur of two features (SE and \hat{a}) of dataset 1 and dataset 2. Therefore, these two features are useful to effectively classify the normal and murmur. Using the range values of the selected feature of normal and murmur, a threshold (T_{SE} and $T_{\hat{a}}$) is set for dataset 1 and dataset 2. Where T_{SE} and $T_{\hat{a}}$ are the threshold for SE and \hat{a} , respectively. To get better classification accuracy, the threshold level is selected in such a way that, it is the average of the minimum value of murmur and the maximum value of the normal signal. Hence the threshold levels obtained by using the range shown in Table 3 is listed as follows. For first dataset, the thresholds are $0.057(T_{SE})$ and $0.054(T_{\hat{a}})$, respectively. For

second dataset the thresholds are $0.1322(T_{SE})$ and $0.2254 (T_{\hat{a}})$, respectively. That means for the first dataset if T_{SE} specifically above 0.057, the signal is normal and if it goes just below 0.057, the signal is murmur. If $T_{\hat{a}}$ is exactly below 0.054, the signal is murmur and if it is just above 0.054, the signal is normal. For the second dataset, if T_{SE} above 0.2254 the signal is normal and if it is below 0.2254, the signal is murmur. When $T_{\hat{a}}$ goes just above 0.1322, the signal is normal and if it is just below 0.1322 the signal is murmur. So it can be inferred that the features namely, standard error and absolute deviation of SE from the reciprocal of the square root of a number of samples of the heart signal can be effectively useful to differentiate the normal and murmur signal.

The performance parameters like sensitivity, specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV) and accuracy of the features (SE and \hat{a}) to distinguish the normal/murmur are also computed for the two datasets and are presented in Table 4.

For both dataset, the two features namely, SE and \hat{a} are capable to discriminate normal or murmur heart signal with 100 % sensitivity, specificity, PPV, NPV, and accuracy.

DISCUSSIONS

Table 5 presents several related studies formerly reported on the detection of murmur from the PCG records (arranged by publication year). As already discussed, most of the literature presented in the table. 5 failed to address the heart signal discrimination by using fundamental features. Most of the methods used either combination of fundamental features or used classifiers. Moreover, in all the below reported cases, 100% sensitivity, specificity, and accuracy was not achieved for categorizing normal or murmur.

Compared to the methods presented in table 5, we proposed a technique to detect heart sound and also to differentiate them as normal or murmur by using time domain features, exclusively autocorrelation features such as SE and \hat{a} by utilizing the PCG records collected from two publicly available databases namely, Pascal HSDB and Physionet HSDB. The two features are successfully tested on the two datasets, statistically evaluated and separability among the features

is examined. The technique offered an efficient performance (100% sensitivity, specificity, PPV, NPV, and accuracy) to differentiate normal/murmur heart signal. Hence, the proposed technique could be an effective study for the state-of-the-art methods available in the literature.

CONCLUSIONS

A technique for the detection of heart murmur from the non-stationarity of the heart signal, via autocorrelation based features like Standard Error (SE) of Auto-Correlation Function (ACF) and absolute deviation of SE from the reciprocal of the square root of a number of samples (\hat{a}), was proposed in this paper. It was inferred that PCG measurements of murmur is highly nonstationary than that of normal heart signal. The features were statistically evaluated and the separability offered them was assessed on the PCG records collected from Pascal HSDB and Physionet HSDB. The proposed system by using the fundamental time domain features was able to detect the murmur with 100% accuracy, sensitivity and specificity without incorporating any complex classifiers. The method overcomes the problems associated with manual auscultation. The scope of the methods to characterize the Phenotypes of the murmur can be investigated as a future deviation.

ACKNOWLEDGMENT

The authors would like to thank the people behind the Pascal heart sound database and Physionet heart sound database for providing the required PCG signals to test the proposed system.

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