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Detection of Murmur from Time Domain Features of Heart Sounds – an Investigation

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ABSTRACT--- Automated identification of valve disorders from heart sounds is a competent task in cardiology. Time domain features like variance (μ), standard deviation (SD), entropy (E), peak amplitude (PA), RMS, crest factor (CRF), impulse factor (IF), shape factor (SHF), energy and clearance factor (CLF) are extensively used in Artificial Intelligence (AI) to reflect the physical attributes of signals. Time domain features are analytically simple and easy to compute. In this paper, the reliability of employing time domain features for the detection of murmur from heart sound is investigated. It is found that energy of the signal is able to detect the murmur from PCG signal with an accuracy of 98.87 %, sensitivity of 99.70 % and specificity of 98.09 %.

Index Terms— energy, heart abnormality, murmur, PCG signal, statistical significance, type of heart signal, time domain features.

I. INTRODUCTION

The feature extraction is the primary step involved in any artificial intelligence system. Signal processing techniques employed for extracting the features plays an important role in systems meant for automated analysis. This mainly involves fault diagnosis of mechanical/electrical systems using their vibration data, detection of diseases by analyzing various biological signals etc., From the features, extracted via suitable signal processing techniques, problems can be detected, accurately traced and even their type can be recognized. Moreover, the features selected via the appropriate feature extraction technique should be statistically significant and computationally efficient. The features extracted will be of time domain, frequency domain or Time–Frequency (TF) domain. Out of these, time domain features are simpler and computationally viable than features in transformed domain because they do not involve complex domain transformation.

A few methods that incorporates time domain features to identify problems of numerous sectors are presented in the literature. For diagnosing bearing defect, Hu et al. [1] proposed a method by utilizing the ensemble averaging of the largest amplitude impact transients of bearing vibration data. The proposed method was able to differentiate normal or faulty bearing with 91.20% accuracy. Carrasco et al. [2] introduced a method for predicting the solar activity by using the relationship between the solar maximum amplitude and max–max cycle length of solar cycle. Selamtzis et al. [3] introduced a method to detect the dysphonia by computing the sample entropy of excerpted vowels of 31 different subjects (accuracy 89%). Li et al. [4] put forth a method to obtain the failure probability in structural reliability analysis via the maximum entropy of the random samples. To improve the input image recognition performance, Shi et al. [5] computed the entropy orthogonality loss of the penultimate layer of the convolutional neural networks (CNN). Wang et al. [6] proposed a system by considering the mean value of RR intervals, the standard deviation of RR intervals and the square root of mean squared differences of successive RR intervals of the Electrocardiograph (ECG) signal to investigate the heart rate changes. The features were input into the support vector machine (SVM) classifier and reported a mean sensitivity, specificity and accuracy of 91.31%, 90.04% and 90.95%, respectively. Rapalis et al. [7] proposed a technique for estimating the blood pressure and heart beat variability. For estimating the blood pressure variability, standard deviation of normal-to-normal (NN) and RR interval, square root of mean squared differences of NN intervals of the ECG signal was utilized. The heart beat variability was estimated by measuring the pulse arrival time of ECG and photoplethysmogram (PPG) signal by hilbert transform after preprocessing and amplitude normalization. Ibrahim et al. [8] explored a technique to help in the diagnosis of epilepsy and autism spectrum disorder (ASD) by estimating the shannon entropy of the preprocessed electroencephalography (EEG) signal. The features were given into various classifiers and reported a classification accuracy of 94.6%. Wang et al. [9] proposed a scheme for the diagnosis of epilepsy by estimating the Teager energy operator of EEG signal. Ma et al. [10] introduced a technique to detect the roller element bearing fault using the Teager energy operator of the intrinsic mode functions (IMF) of the preprocessed bearing vibration data. Khan and Ali [11] presented a procedure for the detection of seizure by analyzing the preprocessed EEG signal. The ratio of signal energy concentrated along the time axis and the frequency axis with the total signal energy was estimated and were given as input into the SVM classifier (Accuracy 98.25%). Mahapatra and Horio [12] proposed a system for the classification of interictal and ictal EEG. Initially, the empirical mode decomposition (EMD) was employed for decomposition of EEG into IMFs. The RMS frequency of the IMFs after hilbert transform was estimated and used as

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feature. The method reported an accuracy of 99.91%. Silva and Scotti [13] investigated that, the mean and RMS values of the current could be used to characterize current in the modeling of arc welding bead geometries. The first pixel-based just noticeable difference (JND) algorithm proposed by Jakhetiya et al. [14], the contrast sensitivity was measured via RMS contrast of the input image. Wang et al. [15] used the time-dependent shape factor for evaluating the flow rate of a stress-sensitive fractured reservoir. The value of the shape factor was derived by solving the nonlinear pressure diffusivity equation for matrix-fracture transfer flow using the combination of the Boltzmann transform, the separation variable method and the method of power series. Choi et al. [16] computed shape factors of different holographic images for the estimation of effective density of cohesive sediment. To examine the status of power systems, Kim and Russell [17] suggested a method by assessing the crest factor of the current and the voltage waveforms. Fu et al. [18] utilized the crest factor of the vibration data to diagnose bearing fault. The method offered by Arun et al. [19], crest factor, impulse factor, shape factor and clearance factor of the vibration data were evaluated for the fault diagnosis of bearing system.

In most of the literatures, the statistical significance, separability and the inter-class variability of the features were not examined or tested. To detect the problem, majority of the literatures utilized numerous classifiers along with features rather than using the fundamental time domain features. Neural networks or classifiers are needed in environments, where in feature space, the features are less statistically significant. Moreover, a scheme with classifiers may wane the system performance and furthermore the complexity will be expanded. None of the papers discussed in the literature have addressed the time domain features to detect the murmur from the heart sound. Hence a technique by utilizing time domain features may be employed to detect the murmur.

In this paper, the reliability of employing the time domain features for the detection of murmur from heart sound by inspecting their statistical significance and the separability offered among them is studied. The features used are variance (µ), standard deviation (SD), entropy (E), peak amplitude (PA), RMS, crest factor (CRF), impulse factor (IF), shape factor (SHF), energy and clearance factor (CLF). These features are tested on the phonocardiogram (PCG) signal availed from the two common public heart sound data bases namely pascal heart sounds challenge database and physionet heart sound database.

The highlights of this study are i) The statistical significance of all the time domain features are tested and the separability offered by them to distinguish normal/murmur is evaluated. ii) It is fairly simple as the scheme used only fundamental time domain features. Besides, the computational complexity of the technique is less than that of other techniques that incorporates classifiers.

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 differentiate normal or murmur is analyzed.

I. METHODOLOGY

The schematic of the steps involved in the computation of time domain features and feature evaluation is presented in fig.1.

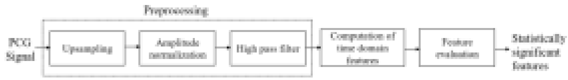

Figure 1: schematic of the experimental design

Before computing the time domain features, the PCG signal is preprocessed. This involves 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 10 Hz. The feature evaluation is carried out after extracting the time domain features. The time domain features like variance, standard deviation, entropy, peak amplitude, RMS, crest factor, impulse factor, shape factor, energy and clearance factor of the preprocessed signal is estimated to test their ability to detect the presence of murmur in the heart signal. Moreover, their statistical significance is also evaluated.

The up sampled PCG signal after normalization is given as

$$X_n(t)=\frac{\mathbf{X_i}(t)}{\max|\mathbf{X_i}(t)|} \quad (1)$$

where ‘Xi(t)’ is the PCG signal, sampled at a rate ‘1/fs’ and contains ‘N’ samples, 1≤n≤N.To regulate the amplitude of heart signal, the samples are normalized to a range between -1 and +1 as in (1). The mathematical formulation of the time domain features used in this papers are as follows,

The variance of the preprocessed PCG signal (C0) with zero shift is given as

$$C_0=\frac{1}{N}\sum_{t=1}^{N}\left(Xp_t-\mu\left(Xp_t\right)\right)^2 \quad (2)$$

where ‘µ (Xpt)’ is the mean value of the preprocessed signal ‘Xpt’ given by,

$$\mu\left(X_{pt}\right)=\frac{1}{N}\sum_{t=1}^{N} Xp_t \quad (3)$$

The mathematical representation of standard deviation is

$$\text{Standard deviation (SD)} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(Xp_t-\mu\left(Xp_t\right)\right)^2} \quad (4)$$

For a discrete signal represented with M quantization levels,

$$\text{Entropy (E)} = -\log\sum_{t=1}^{M} P\left(Q_t\right)\log_2\left(P\left(Q_t\right)\right) \quad (5)$$

$$\text{Peak amplitude } (X_{Peak}) = \text{Max}\left(\left|Xp_t\right|\right) \quad (6)$$

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$$\text{Root Mean Square value (RMS)} = \sqrt{\frac{1}{N}\left(\sum_{t=1}^{N}\left(Xpt^2\right)\right)} \quad (7)$$

$$\text{Crest factor (CRF)} = \frac{Y_{Peak}}{RMS} \quad (8)$$

$$\text{Impulse factor (IF)} = \frac{Y_{Peak}}{\mu(X_{pt})} \quad (9)$$

$$\text{Shape factor (SHF)} = \frac{RMS}{\mu(Xp_t)} \quad (10)$$

$$\text{Energy} = \frac{\left[\sum_{t=1}^{N}\sqrt{|(Xp_t)|}\right]^2}{N} \quad (11)$$

$$\text{Clearance factor (CLF)} = \frac{X_{Peak}}{\text{Energy}} \quad (12)$$

The proposed technique used two common public heart sound data bases namely pascal heart sounds challenge database (Pascal HSDB) [20] and physionet heart sound database (Physionet HSDB) [21]. The Pascal HSDB consists dataset A and dataset B. The former has been collected from the general public using 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 KHz) in the dataset B varies from 1 second to 30 seconds. The Physionet HSDB recordings were collected from various contributors round the globe, gathered at either a medical or nonmedical environment, from both healthy people and pathological patients. This data set consists 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 holds only one PCG lead. All the recordings were provided as .wav format.

The method is tested on a total of 400 records. Out of these, 340 records from dataset E of Physionet HSDB (dataset 1) and 60 records from dataset B of Pascal HSDB (dataset 2). Out of the 60 records of dataset 2, 30 records are normal and 30 records are murmur. The 340 records of dataset 1 consist 170 records each from normal and murmur category. The signals are selected in such a way that each records have sample length more than 8 seconds and are upsampled by a factor 2 ie; the sampling frequency 'fs' of the first dataset is 8 KHz and that of the second dataset is 4 KHz. The frequency components less than 10 Hz are eliminated by a high pass filter with cut off frequency 10 Hz.

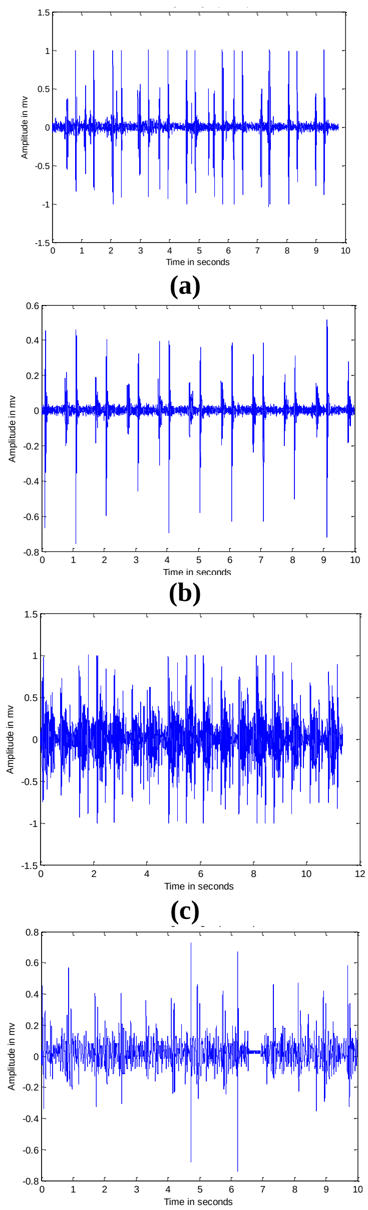
The wave shape of heart signal corresponding to normal and murmur acquired from two data set are shown in fig. 2 (a) – fig. 2. (d).

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 that of normal heart sound. By observing fig.2 (a) and (c), the average amplitude of normal heart signal (fig.2 (a)) is comparatively smaller than that of murmur (fig.2 (c)).

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®.

II. RESULTS

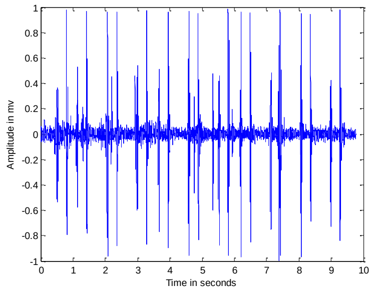
As stated earlier, variance (μ), standard deviation (SD), entropy (E), peak amplitude (PA), RMS, crest factor (CRF), impulse factor (IF), shape factor (SHF), energy and clearance factor (CLF) of the preprocessed PCG signal are estimated on the PCG signal collected from dataset 1 and dataset 2 to evaluate their ability to differentiate normal and murmur. The wave pattern of the PCG signal after preprocessing is presented in fig.3 (a – d).



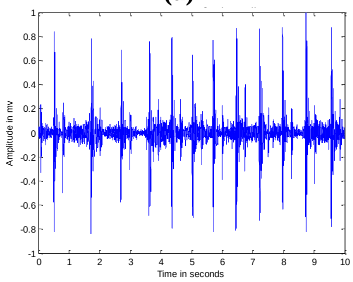
(d)

Figure 2: Wave shape of normal heart sound and murmur (a)normal heart sound (dataset 1)

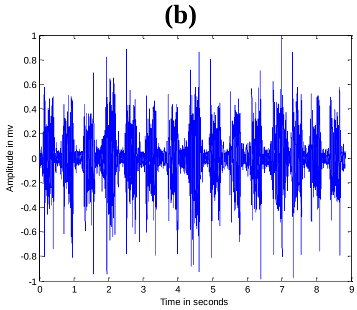
(b) normal heart sound (dataset 2) (c) Murmur (dataset 1) (d) Murmur (dataset 2)



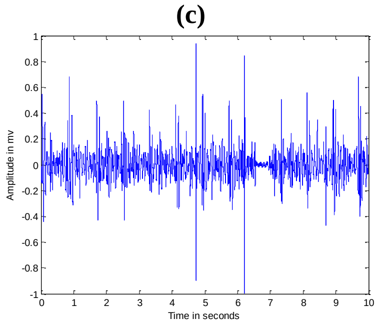
(a)



(b)



(c)



(d)

Figure 3: Wave shape of preprocessed heart signal (a) normal (dataset 1) (b) normal (dataset 2) (c) Murmur (dataset 1) (d) Murmur (dataset 2)

The wave shape of normal heart sound (fig.3 (a-b)) and murmur (fig.3(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.3 (a-b)) is less random and their average amplitude is comparatively lesser than the wave shape of murmur. By observing fig.3 (a) and (c), the average amplitude of murmur (fig.3 (c)) is comparatively larger than that of normal heart signal (fig.3 (a)).

The range and numerical values of all the features extracted from the signal corresponding to normal and murmur is presented` in Table 1. From Table 1, It is observed that, for dataset1, the range of normal signal are 2.0531 to 4.4399,0.0003 to 0.0571,0.0179 to 0.2390,0.0581 to 1.2092,0.0179 to 0.2390,3.2509 to 28.3916, -8.6473E+19 to 4.8092E+20, -6.6799E+18 to 4.739E+19, 1290.8124 to 5225.9 and 0.0001 to 0.0038 for E, μ, SD, PA, RMS, CRF, IF, SHF, energy and CLF, respectively. The values of range of murmur for the above said features of dataset1 are 0.5853 to 4.3883,0.0009 to 0.0479,0.0293 to 0.2188, 0.9103 to 1.0701,0.0293 to 0.2188,4.5639 to 34.509, -3.4087E+19 to 3.2661E+20, -4.2759E+18 to 1.7819E+19,4669.7 to 13216.8 and 0.0001 to 0.0233, respectively. range of features (normal) like entropy, variance, standard deviation, peak amplitude, RMS, crest factor, impulse factor, shape factor, energy and clearance factor of dataset 2 are 2.8762 to 3.7716,0.0048 to 0.0373,0.0692 to 0.1931,0.99 to 1.05,0.0692 to 0.1931,5.4421 to 14.4447, -4.9478E+19 to 4.5166E+18, -9.0917E+18 to 3.1269E+17,1360.1 to 5496.9 and 0.0001 to 0.0007, respectively. For the same dataset the above said features (murmur) ranging from 2.9793 to 4.5904,0.0036 to 0.1226,0.0599 to 0.3502,0.9947 to1.0522,0.0599 to 0.3502,2.9266 to 16.7458, -8.4823E+18 to 3.062E+20, -2.81E+18 to 4.809E+19,5118.5 to 26217 and 0.00003 to 0.0007, correspondingly.

The numerical values of the features shown in table.1 are listed as follows. The numerical value of entropy of dataset 1 is 3.4553 ± 0.4297 (normal), 3.5747 ± 0.4834 (murmur) and that of dataset 2 is 3.3126±0.2029 (normal) and 3.6693±0.4465 (murmur), respectively. In the case of variance, the numerical value of dataset1 is 0.0164 ± 0.0092 (normal), 0.0170 ± 0.0096 (murmur) and that of dataset 2 is 0.0136 ± 0.0071(normal) and 0.0287 ± 0.0285 (murmur), respectively. For standard deviation, the numerical value of normal signal and murmur of dataset 1 is 0.1219 ± 0.0373 and 0.1244 ± 0.0380, respectively. For dataset 2, values of SD are 0.1125 ± 0.0285(normal) and 0.1505 ± 0.0707(murmur). The numerical value of peak voltage of normal and murmur of dataset 1 is 0.9701 ± 0.1504 and 0.9965 ± 0.0230, respectively and that of dataset 2 is 1.01± 0.01 and1.0095 ± 0.013. The numerical values of the RMS are same as that of SD. For dataset 1, the numerical values relate to crest factor and impulse factor of normal and murmur are 8.7428 ± 3.1440, 9.1436 ± 3.8556 and 4.1354E+18 ± 3.9012E+19, 5.7229E+18 ± 2.7999E+19, respectively. For dataset 2 the numerical values are 4.1354E+18 ± 3.9012E+19, 5.7229E+18 ± 2.7999E+19 and 9.5904 ± 2.2399, 8.3007 ± 3.2665, accordingly. The numerical value (dataset 1) relate to shape factor and energy are 4.0481E+17 ± 3.8620E+18,4.217E+17 ± 2.23477E+18 and 2127.4343 ± 681.3786, 7503.0338 ± 1795.7697 for normal and murmur, respectively. For the second dataset the numerical values of shape factor and energy are -6.99198E+17 ± 1.66578E+18,2.94238E+18 ± 8.8127E+18 and 2777.50 ± 964.36, 9136.69 ± 3579.73 for normal and murmur, respectively. For clearance factor, the numerical values correspond to normal and murmur of dataset 2 are 0.0004 ± 0.0001 and 0.0002 ± 0.000, respectively.

As far as the numerical values of features of murmur is considered, they are confined to a wide range compared to that of normal heart sound. That means, the numerical values of all the features of normal heart signal is less than that of the murmur. These clearly outward differences among the magnitude and the range of features extracted from the signal relate to normal as well as murmur justify the potential of the time domain features.

The statistical significance of all the features is evaluated for their ability to differentiate normal and murmur via 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 entropy, Peak Voltage, energy and clearance factor for both datasets. But the 'H' value correspond to peak voltage is contradictory for two datasets. The 'H' values are computed for a default significance level of 5%. Energy and clearance factor correspond to normal and murmur of dataset 1 differ with a 'P' value of 1.32x10-74 and 2.01x10-04 and that of dataset 2 are 1.50x10-74 and 2.02x10-04, respectively. It can be inferred that; out of the ten features, energy and clearance factor are statistically more significant than others.

Table 1: Numerical values and range of features of normal heart sound and murmur

Sl no	Features	Type	Dataset 1		Dataset 2	
			Range	Numerical value	Range	Numerical value
1	Entropy	Normal	2.0531 to 4.4399	3.4553 ± 0.4297	2.8762 to 3.7716	3.3126±0.2029
		Murmur	0.5853 to 4.3883	3.5747 ± 0.4834	2.9793 to 4.5904	3.6693±0.4465
2	Variance	Normal	0.0003 to 0.0571	0.0164 ± 0.0092	0.0048 to 0.0373	0.0136 ± 0.0071
		Murmur	0.0009 to 0.0479	0.0170 ± 0.0096	0.0036 to 0.1226	0.0287 ± 0.0285
3	Standard Deviation	Normal	0.0179 to 0.2390	0.1219 ± 0.0373	0.0692 to 0.1931	0.1125 ± 0.0285
		Murmur	0.0293 to 0.2188	0.1244 ± 0.0380	0.0599 to 0.3502	0.1505 ± 0.0707
4	Peak Voltage	Normal	0.0581 to 1.2092	0.9701 ± 0.1504	0.99 to 1.05	1.01± 0.01
		Murmur	0.9103 to 1.0701	0.9965 ± 0.0230	0.9947 to1.0522	1.0095 ± 0.0131
5	RMS	Normal	0.0179 to 0.2390	0.1219 ± 0.0373	0.0692 to 0.1931	0.1125 ± 0.0285
		Murmur	0.0293 to 0.2188	0.1244 ± 0.0380	0.0599 to 0.3502	0.1505 ± 0.0707
6	Crest Factor	Normal	3.2509 to 28.3916	8.7428 ± 3.1440	5.4421 to 14.4447	9.5904 ± 2.2399
		Murmur	4.5639 to 34.509	9.1436 ± 3.8556	2.9266 to 16.7458	8.3007 ± 3.2665
7	Impulse Factor	Normal	-8.6473E+19 to 4.8092E+20	4.1354E+18 ± 3.9012E+19	-4.9478E+19 to 4.5166E+18	-4.20499E+18 ± 9.33693E+18
		Murmur	-3.4087E+19 to 3.2661E+20	5.7229E+18 ± 2.7999E+19	-8.4823E+18 to 3.062E+20	1.95959E+19 ± 5.60344E+19
8	Shape Factor	Normal	-6.6799E+18 to 4.739E+19	4.0481E+17 ± 3.8620E+18	-9.0917E+18 to 3.1269E+17	-6.99198E+17 ± 1.66578E+18
		Murmur	-4.2759E+18 to 1.7819E+19	4.217E+17 ± 2.23477E+18	-2.81E+18 to 4.809E+19	2.94238E+18 ± 8.8127E+18
9	Energy	Normal	1290.8124 to 5225.9	2127.4343 ± 681.3786	1360.1 to 5496.9	2777.50 ± 964.36
		Murmur	4669.7 to 13216.8	7503.0338 ± 1795.7697	5118.5 to 26217	9136.69 ± 3579.73
10	Clearance Factor	Normal	0.0001 to 0.0038	0.0007 ± 0.0004	0.0001 to 0.0007	0.0004 ± 0.0001
		Murmur	0.0001 to 0.0233	0.0008 ± 0.0017	0.00003 to 0.0007	0.0002 ± 0.0001

Table 2: Kolmogorov-Smirnov Test - 'H' and 'P' values of features of heart signal corresponding to normal and murmur

Sl no.	Features	Dataset1		Dataset 2	
		Chi Square value (H)	Probability value (P)	Chi- Square value (H)	Probability value (P)
1	Entropy	1	5.05E-04	1	0.0046
2	Variance	0	0.5934	0	0.055
3	Standard Deviation	0	0.5934	0	0.055
4	Peak Voltage	1	2.01E-04	0	0.2003
5	RMS	0	0.5038	0	0.055
6	Crest Factor	0	0.686	0	0.0259
7	Impulse Factor	0	0.0455	0	0.2003
8	Shape Factor	0	0.1069	0	0.055
9	**Energy**	**1**	**1.32E-74**	**1**	**1.50E-13**
10	Clearance Factor	1	2.01E-04	1	2.02E-04

As already mentioned, histogram is employed to qualitatively assess the separability offered by the features. The histogram of all the features relate to normal heart

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sound and murmur of dataset 1 and dataset 2 are shown in fig. 6(a)-(d).

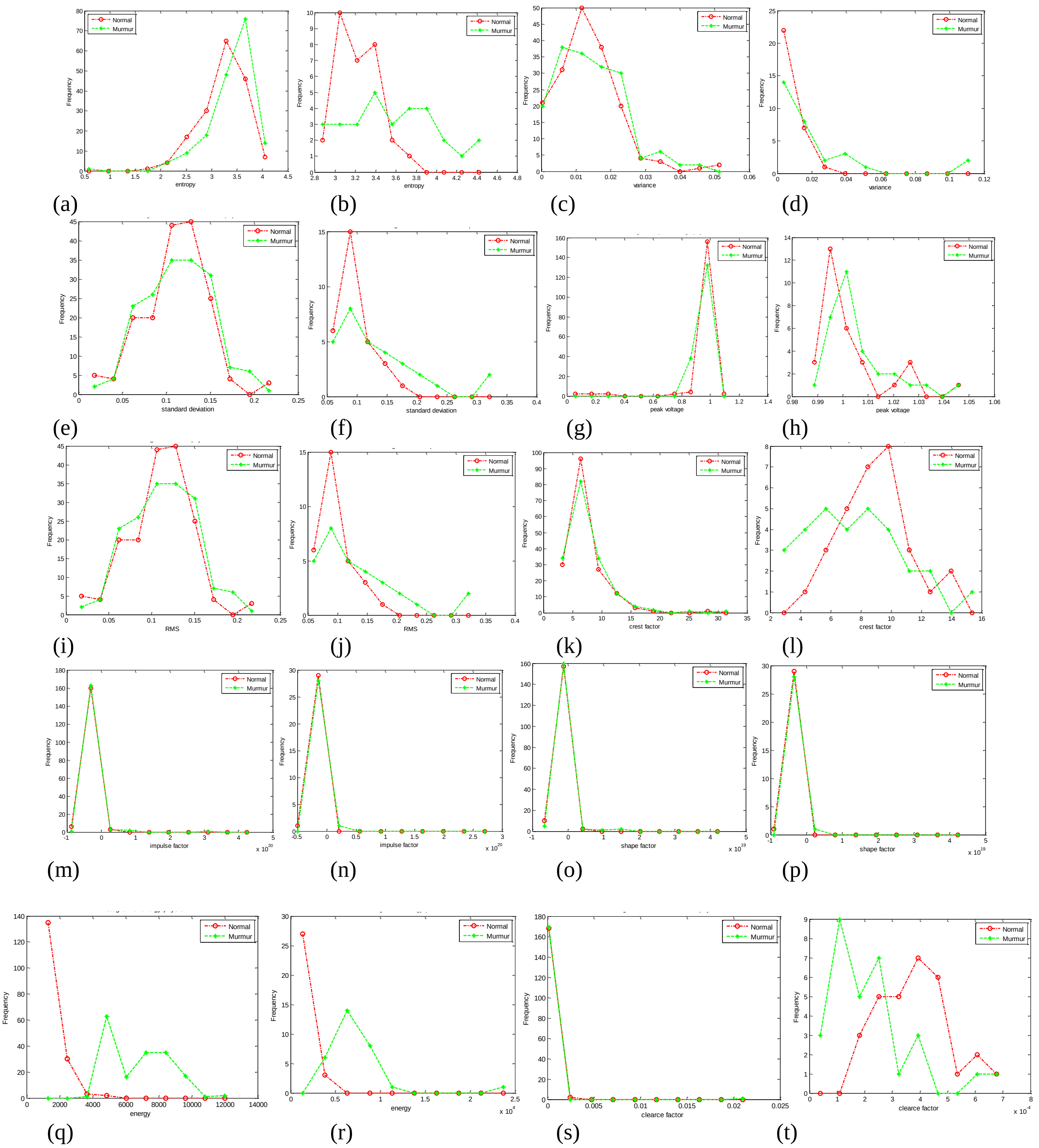

Figure 6: The histogram of features of normal heart sound and murmur. Fig. 6(a, c, e, g, i, k, m, o, q, s) for dataset 1 and Fig.6(b, d, f, h, j, l, n, p, r, t) for datset2.

In the histogram shown in fig. 6, except the histogram of energy (fig. 6 (q)-(r)), all other histograms show overlap among that of normal and murmur. In the histogram of energy (fig. 6 (q)-(r)), the histogram corresponding to normal heart signal is lying sufficiently apart spatially from the histogram analogous to murmur. But in all other histograms, the separability among normal and murmur is very less. That means, energy feature offers very minimal overlap and also offer very good separability among normal and murmur. Hence, energy can be used to effectively distinguish normal and abnormal heart signal than all other features used in this paper. The performance parameters like sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and accuracy of all the features to classify normal/murmur are also calculated for the two datasets and are shown in Table.3.

By observing the values of performance parameters of all the evaluated features, the energy feature is effectively distinguishing normal or murmur than all other features. The sensitivity, specificity, PPV, NPV and accuracy offered by this feature to differentiate

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normal/murmur is 99.41% for dataset 1. The same feature offers 100 % sensitivity, 96.77 % specificity, 98.33 % accuracy, 96.77 % PPV and 100 % NPV for dataset 2. Hence, a method by using energy as a feature to detect the presence of murmur from heart signal definitely has its own significance.

Sl No:	Features	Sensitivity (%)		Specificity (%)		Accuracy (%)		PPV (%)		NPV(%)	
		Dataset1	Dataset2	Dataset1	Dataset2	Dataset1	Dataset2	Dataset1	Dataset2	Dataset1	Dataset2
1	Entropy	61.17	76.67	59.41	63.33	60.29	70	60.11	67.64	60.47	73.07
2	Variance	45	56	60	70	52.64	63.33	53.10	65.38	52.30	61.76
3	Standard Deviation	46.47	56.66	58.82	70	52.64	63.33	53.02	65.38	52.35	61.76
4	Peak Voltage	35.88	73.33	71.17	53.33	53.52	63.33	55.45	61.11	52.60	66.67
5	RMS	46.47	56.66	58.82	70	52.64	63.33	53.02	65.38	52.35	61.76
6	Crest Factor	47.64	70	56.47	60	52.05	65	52.25	63.63	51.89	66.67
7	Impulse Factor	48.23	96.67	88.23	60	68.23	78.33	80.39	70.73	63.02	94.73
8	Shape Factor	70.58	50	41.17	76.67	55.88	63.33	54.54	68.18	58.33	60.52
9	**Energy**	**99.41**	**100**	**99.41**	**96.67**	**99.41**	**98.33**	**99.41**	**96.77**	**99.41**	**100**
10	Clearance Factor	24.11	73.33	67.05	80	55.58	76.67	42.27	78.57	46.91	75

Table 3: Performance parameters of time domain features

II. CONCLUSIONS

The reliability of employing time domain features for the detection of murmur from heart sound was investigated in this paper. It has found that, out of the features examined, energy was useful to detect the murmur from PCG signal with an average accuracy, sensitivity and specificity of 98.87 %, 99.70 % and 98.09 %, respectively. The technique by utilizing energy as a feature may overcome the problems associated with the manual auscultation. The scope of the ability of time domain features to discriminate the phenotypes of murmur can also be explored as a future expansion.

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