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Preliminary Diagnosis of Coronary Artery Disease from Human Heart Sounds: A Signal Processing Prospective

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ABSTRACT

Coronary artery disease (CAD) is becoming the top cause of mortality worldwide. The major concern over CAD is its minimal preliminary symptoms arriving out of blocked coronary arteries. To enable early detection of underlying CAD heart sounds could be considered as potential indicators. Recent past studies give strong evidence for the same. This paper focuses on exploring the possibility of using spectral and Spectro temporal techniques to analyze heart sounds to detect coronary artery disease. Recording of heart sounds is done using electronic stethoscope 3M Littmann 3200. After verifying the fidelity of electronic stethoscope, spectral and Spectro temporal techniques are used to extract the features of heart sounds. The results from spectral analysis of heart sounds were utilized as a commencement point for Spectro-temporal feature analysis. Band wise spectral kurtosis is computed for after taking Stockwell transform for 10-400 Hz range. After experimentation, it was observed that band 3 (169-253 Hz) discriminated CAD and non-CAD heart sounds with linear separability. Minimum distance classifier has provided the classification accuracy of 95.64%. Therefore, preliminary diagnosis of Coronary artery Disease can be carried even in remote areas without costly equipment using this approach and provides major breakthrough for early diagnosis and prevention of mortalities for this dreaded ailment.

Key words: Coronary Artery Disease, Digital Recording, Electronic Stethoscope, Minimum Distance Classifier Stockwell Transform.

1. INTRODUCTION

The main objective of this work is to study the applications of signal processing techniques for preliminary detection of Coronary artery disease (CAD) from human cardiac sounds. Telemedicine is an emerging topic in the field of healthcare. In developing countries like India where patients to medico ratio are impecunious, telemedicine applications if applied efficaciously can immensely benefit the rural population. Due to recent advances in technology and widespread perforation of cellular network, it is now possible to auscultate fundamental human body sounds and send the recording to a healthcare server for analysis and diagnosis report generation. Traditionally doctor uses heart and lung auscultation sound to obtain an initial diagnosis of any underlying abnormality. This approach is still utilized by many medicos but there are following concerns over this approach

1. Preliminary diagnosis from auscultation by the doctor is subjective and depends mainly on his experience and cognizance skill.
2. For neophyte doctor, it is very arduous to diagnose from human body acoustics due to unavailability of any objective reference.
3. In developing countries like India, there is a severe shortage of trained medical practitioners. According to the report published by the Medical Council of India (MCI), India has one doctor for every 1681 persons which is much below the 1:1000 ratio prescribed by WHO [1].

Considering these factors, it is urgently necessary to address the issues through the development of simple, low cost and non-invasive procedure to preliminary detect major health related diseases. The objective of this research work is to study the application of signal processing methods to aid early detection of Coronary artery disease (CAD) from the human body sounds acquired with the electronic stethoscope.

Coronary artery disease (CAD) or Ischemic heart disease or in common terminology heart attack is becoming a major health concern globally. Coronary artery disease is the condition of the heart where at least one coronary artery has a diameter reduction of 30% [2]. It is observed that worldwide approximately 17.5 million deaths are happening due to coronary artery disease which is 31 % of all deaths in the world [3], in India, there are estimated 4.5 million people suffering from CAD [4]. The above facts directly lead to the conclusions that diseases related to the heart are on the top for mortality, globally as well as in India.

The major difficulties in efficacious treatment of these diseases arise due to the tardy diagnosis. In India, people generally have the proclivity to evade visits towards medicos and in the initial phase of disease occurrence, they generally rely on OTC (over the counter) medicines. In rural India, situations like unavailability of medicos and distant hospitals additionally lead to the reluctance of the population to pursue treatment for healthcare except in chronic pain cases. Additionally, symptoms of heart cognate diseases such as CAD generally appear tardy so patient residing in the remote rural areas customarily do not get adequate time for diagnosis and treatment. As early diagnosis of these diseases could be life preserving, it is consequential to develop a system which is not only a simple and non-invasive, but will additionally correctly provide a road map to the prospective patients for more categorical diagnosis and efficacious treatment. Recent advances in human body sound auscultation and signal processing has opened up new opportunities for the researchers to analyze human body sounds for objective analysis and classification. This research work is an effort in this direction involving the study of the different signal processing methods for human body acoustics analysis. These methods can be then utilized in telemedicine applications.

For analyzing heart sound, *Phonocardiography* is a popular term among medical researchers and this work is generally employed in the detection of heart sound murmurs originating from valvular diseases. Although, analysis of heart signals such as ECG was classical idea and ample literature is available in this domain with continuously evolving signal and image processing techniques [5-9], the low accuracy of ECG itself is an issue. The detection of coronary artery diseases from heart sounds is quite a popular topic among researchers during the last decade. The philosophy behind this work traces back to 1967 [10], but due to non-availability of congruous technology, gamut research could not be performed at that time. The underlying theoretical foundations could be found in [10,24]. There are in fact, very few researchers, who are currently working towards the analysis of heart sounds for detection CAD with the avail of the electronic stethoscope. The paper is divided into nine sections. Section 2 discusses some previous work related to heart sound analysis, Section 3 describes objectives of the paper, Section 4 explains the data and methods utilized in this study like, recording of heart sounds and preprocessing, Section 5 explores some spectral features for heart sound analysis, followed by section 6, which is dedicated to analysis of heart sounds using Stockwell transform. Section 7 presents results followed by section 8 which is dedicated to discussion. Finally the paper is concluded in section 9.

2. RELATED WORKS

The work done in this field can be summarized as under:
Thomas JL et al. [25] describes detection CAD based on analysis of cardiac sounds using CAD score system. They carried out frequency domain analysis and obtained AUC was 0.72. CAD score combined with clinical parameters has given the AUC of 0.82.
Winther Set al. [26] studied the detection of coronary stenosis using frequency power ratio, principal component analysis, auto mutual information, and fourth heart sound amplitude. The archived accuracy in this study was 82%. The studies prove the potential of acoustic features in detecting coronary artery disease.
A recent study by Winther S et al. [27] included 1675 subjects for studying the detection of CAD from heart sounds using acoustic features. An algorithm developed in [26] was employed and AUC of 58.1% was archived. Considering the inclusiveness of a large number of subjects, the obtained AUC proves to be a good indicator of the potential of using acoustic features in the diagnosis of coronary artery disease.

S. E. Schmidt et al. [28] investigated various spectral and signal complexity features for identification of coronary artery disease from heart sounds. Total of 133 subjects was included in the study, which consists of 70 non-CAD and 63 CAD patients. 3M Littmann E4000 electronic stethoscope was used for heart sound recording. The recording site was left fourth intercostals space on the patient's chest. To obtain features from low and high-frequency bands, the signal was filtered in different bands as; 25-250 Hz (low-frequency band), 25-1000 Hz (wideband), 50-500 Hz, 125-750 Hz and 250-1000 Hz (High-frequency band). The spectral and signal complexity-based features were extracted. The spectral features culled in this study were Auto-Regressive (AR) model, Instantaneous Frequency and Amplitude (IFA) and power in octave bands (1/3 octave filter). The signal complexity features involved sample entropy, simplicity, spectral entropy, and simple complexity. The Area under the curve (AUC) obtained from multivariate classifier (based on Quadratic discriminate analysis QDA) for all the features was compared with k fold cross-validation. The authors concluded that the amplitude of the first-order pole in a sixth order AR model for 25-250 Hz band (low-frequency band) can discriminate CAD and non-CAD heart sounds with AUC of 0.71%. This study indicates that, along with high frequency, the low-frequency features can also be considered as potential discrimination parameters for the relegation of CAD and non-CAD heart sounds.

Makaryus Amgad N. et al. [29] investigated the diagnostic utility of Cardiac Sonospectrographic Analyzer (CSA) to detect coronary artery disease. CSA (SonoMedia model 3.0, SonoMedia Inc, Vienna, Virginia) is kind of digital stethoscope which can record heart sounds with simultaneous ECG synchronization, so the automatic diastole segmentation is easily performed. 161 subjects, referred for coronary angiography were used in the study. The band-wise spectral analysis of heart sounds was carried out using SonoMedia acoustic analysis software for 400-2700 Hz frequency band. The authors had reported a significant difference in the energy in a specific frequency band (The authors have termed it as Microbruits). The conducted study achieved sensitivity and specificity of 89.5% and 57.7% respectively.

S. E. Schmidt et al. [30] investigated the effect of noise in the detection of coronary artery disease with an electronic stethoscope. A total of 633 recordings were taken from 140 subjects using 3M Littmann Electronic stethoscope E4000 model. The recording site was left fourth intercostals space on the patient's chest. In this study the same method as in [28] was employed for feature extraction. The authors had reported the drop in the accuracy of classification with the inclusion of noisy recordings in the analysis. The sensitivity of classification in terms of area under receiver operating characteristics (AUC) curve was compared against inclusion and exclusion of noisy recordings. The sensitivity of the AR pole corresponding to 25-100 Hz drops from AUC of 0.70 to 0.57 whereas the sensitivity of best discriminating AR pole (25-250 Hz) drops from AUC of 0.73 to 0.70 with the addition of noisy recordings. The study concluded that the lower frequency features are more robust against noise than features from higher frequency bands.

S. E. Schmidt et al. [31] studied the relationship between autoregressive model and signal entropy for analysis of cardiac sounds. Total 50 subjects were analyzed and sixth order autoregressive pole was used as the discriminating criterion for CAD and non-CAD sound. AUC of 0.765 was obtained for the AR pole and 0.762 for sample entropy. The Spearman correlation between the two measures was 0.92. As the AUC for both the feature set is nearly same, it was concluded that, along with parametric approach such as AR model, spectral features can also be considered differentiating both said category of heart sounds.

M. Akay et al. [32] described the dynamics of diastolic heart sounds caused by a narrowed coronary artery. Total 40 subjects, of whom 30 correspond to CAD and 10 to non-CAD categories, were included in the study. Thinklabs ds32a electronic stethoscope was used to record heart sounds with a sampling frequency of 4000 Hz at left fourth intercostal space. From each recording 15 diastolic segments were selected which were normalized with respect to mean energy and subsequently filtered with fifth-order Butterworth bandpass filter in 60-500 Hz band. To determine the non-linearity in diastolic heart sounds, approximate entropy was calculated for each recording. The study had obtained the sensitivity of 77% and specificity of 80% with an overall accuracy of 78%. The authors had also used spectral analysis thereby calculating mean power ratio (the power above 130 Hz to power below 130 Hz) for both categories of heart sounds. The reported sensitivity and specificity for spectral analysis was 67% and 70% respectively.

D. Gauthier et al. [33] conducted a spectral analysis of heart sounds associated with coronary occlusions. Thinklabs ds32a electronic stethoscope was utilized to record the heart sounds of normal and abnormal subjects with a sampling frequency of 4000 Hz. Total of 34 subjects of each category was considered for the analysis. 12 segments of diastole were extracted from each recording. The energy normalization was performed to account for sound attenuation effect due to physical differences between patients. The segments were filtered between 60 and 500 Hz using the fifth-order Butterworth filter. The spectral analysis was performed using 512-point FFT. The ratio of spectral energy above 130 Hz to spectral energy below 130 Hz was then calculated for each recording. The authors concluded that the diastolic segment recorded from abnormal subjects has more energy components in the range of 130-300 Hz than their normal counterparts. With the optimal threshold detection ratio as 1.5, a sensitivity of 71% and specificity of 83% was reported in the study.

S. E. Schmidt et al. [34] described a method to detect coronary artery disease using an electronic stethoscope. Bedside recordings were done from left fourth intercostal space on the chest of 50 patients using the 3M Littmann Electronic stethoscope model E4000 with a sampling frequency of 4000 Hz. Each recording was 8 seconds long which corresponds to the capacity of the stethoscope. The audio files were converted to 8 kHz '.wav' format through 3M Littmann sound analysis software before analysis. Manual segmentation of the diastolic period was performed by observing time domain heart sound waveform. Total of 373 diastoles from 50 subjects was identified for analysis. The diastolic segments were bandpass filtered between 240 Hz to 1500 Hz. The authors had divided the diastolic segments into non-overlapping sub-segments of 50 ms duration. The noisy segments were identified and removed by conducting stationery and variance analysis. Auto-regressive (AR) model was employed as a feature extraction tool. The study reports maximum classification accuracy of 82%, with 86.2% sensitivity and 76.2% specificity using optimal threshold as a discriminating parameter.

The major strengths of previous work related to heart sound analysis for detection CAD include automatic segmentation [28] and a good level of accuracy i.e AUC of 78.5%. The major weaknesses related to heart sounds analysis for detection of sounds incldess the use of 3M Littmann E4000 and Thinklabs one s32, which doesn't have ambient noise reduction mechanism. Furthermore, non-utilization of spectro-temporal approach for feature extraction could be termed as the lacunas in the previous work related to heart sound analysis for detection of CAD. Also, there is no study involving a high-risk group of Indian subjects. So, to address the above thirst areas, following objectives were formed and are given in the next section.

3. OBJECTIVE

When Taking into the account the current studies, there is need to utilize existing signal processing techniques for human heart sound analysis for classification of CAD and non-CAD sounds. As the mortality due to CAD is increasing significantly globally and especially in India, it is necessary to study heart sounds specifically for Indian population. Previous studies of heart sound for detection of CAD mainly utilized spectral features. However, as heart sound is basically a non-stationary signal and therefore there exists need to investigate Spectro-temporal features for robust classification of CAD and non-CAD heart sounds.

The main objective of this work is to explore the Spectro temporal techniques which were not used earlier for the said purpose to analyze and classify the CAD and non-CAD heart sounds. This will lead to some explored dimensions of heart sounds in terms of frequency domain characteristics. Simultaneously it is desired to improve the classification accuracy.

4. DATA AND METHODS

4.1 Heart Sound Recording

The study related to heart sounds recording and performance of recording method utilized are been published in our earlier work [35-38].

5. STUDY OF POSSIBLE FEATURES FOR HEART SOUNDS ANALYSIS

The study of feature identification related to heart sounds associated with CAD was published in our previous paper [39]. For keeping the continuity of discussion intact, the brief review of that study is presented here.

As the basis of this study is the evidence that diastolic cycle of heart sounds contains minute murmurs, the important aspect is to segment the diastoles from the combined cardiac cycle using either automatic segmentation or using manual methods. In this study to avoid any errors in segmentation manual method has opted. The duration between S2-S1 represents the diastole period of heart sounds. '*Wavedit*' software was used to do the task. The details of the recording setup and related procedure could be found in our previous work [39].

Total 267 diastoles were extracted, out of which Non-CAD count was 129 and the remaining 138 counts belong to CAD heart sounds. Following features were extracted for each diastole. The brief of these features [40] is given in the next section,

Energy

Normalized energy of signal $x(n)$ with length L is given as

$$E_n = \frac{1}{L}\sum_{n=1}^{L}\left|x(n)\right|^2 \quad (1)$$

Entropy of Energy

It is actually a representation of changes in the energy of the signal. The more the changes the more will be entropy. It is given as

$$\hat{\mathrm{H}} = -\sum_{j=1}^{k} e_j * \log_2(e_j) \quad (2)$$

Where e_j is energy in the subframe.

Spectral Centroid

Considering spectrum as a geometrical shape, its center of gravity can be calculated as

$$SC = \frac{\sum_{k=1}^{L} kX(k)}{\sum_{k=1}^{L} X(k)} \quad (3)$$

Spectral Spread

To know how much spectrum spread, its second moment is calculated and the formula for same is represented as

$$SS = \frac{\sum_{k=1}^{L}(k-C)^2 X(k)}{\sum_{k=1}^{f_L} X(k)} \quad (4)$$

For normalization of spectral spread, it is divided by a factor of f_s/2.i.e the maximum frequency of the recorded signal.

Spectral Entropy

It's just like energy entropy except it is calculated for spectrum rather than time domain signal.

Spectral Entropy is defined as

$$\hat{H}_F = -\sum_{f=0}^{f_L-1} n_f \log_2 n_f \quad (5)$$

Where n_f is the ratio of sub-band energy to the total energy

$$n_f = \frac{E_{fsub}}{E_f} \quad (6)$$

Spectral Roll-off

To know how fast, the spectrum after a certain frequency is declining, spectral roll-off is calculated. It is defined as

$$\sum_{k=1}^{m} X_i(k) = C\sum_{k=1}^{f_L} X_i(k) \quad (7)$$

Where C is used to set the threshold for declination. In our case, it was chosen as 0.999. Narrower spectrum provides less roll off where wider spectrum provides more roll off.

Out of all the features, spectral centroid and spectral roll-off had shown promising discrimination ability. The bar plot showing these values is given in Fig. 1 and 2.

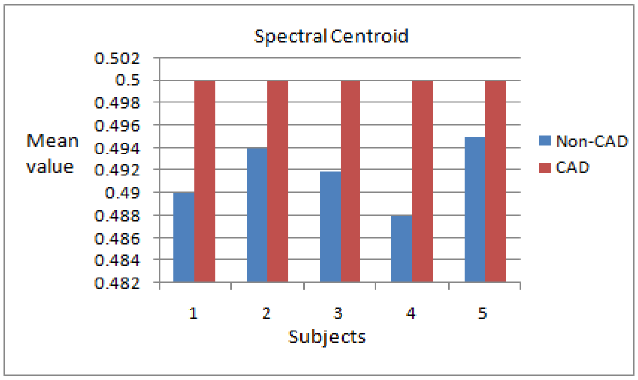


Figure 1: Scatter. Spectral Centroid for CAD Vs Non-CAD Plot of Spectral Kurtosis from Band 1 to Band

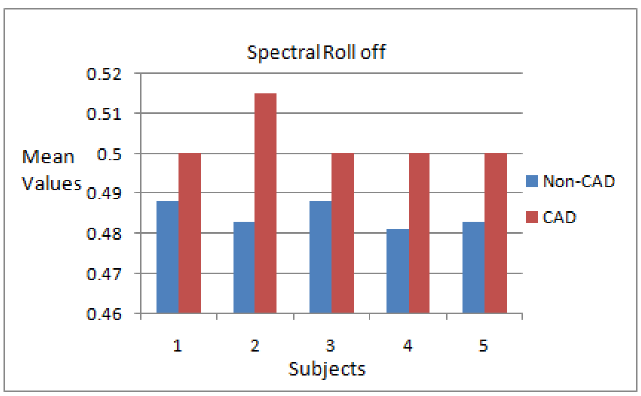


Figure 2: Scatter. Spectral Roll off for CAD Vs Non-CAD

Due to the promising results from spectral centroid and spectral roll off, it has been decided to go with spectral analysis with the multiresolution approach. The discrimination based on spectral roll off and spectral centroid clearly suggests a significant difference in higher frequency components of both categories of heart sounds. Here the definition of high frequency is not a rigid one, previous studies differ in definition of higher frequency from heart sounds perspective. Hereby 'high frequency' we are referring to the band between 100 Hz to 800 Hz. The next section concentrates on the band of interest (100-800 Hz) to analyze heart sounds associated with CAD.

6. STUDY SPECTRO-TEMPORAL FEATURE EXTRACTION BY S-TRANSFORM

R.G Stockwell [41] introduced a transform in 1996 which uses Spectro temporal approach for analysis of non-stationary signals. It is actually an extension of STFT and Wavelet transform in a sense that the basic function consists of sine and cosine signals with variable width Gaussian window. For a signal *x(t)* it is defined as [42-43]

$$S(\tau, f)=\int_{-\infty}^{+\infty} x(t)\left(\frac{|f|}{2\pi}\right) e^{\frac{-(\tau-t)^2 f^2}{2}} e^{-i2\pi ft}\,dt \qquad (8)$$

$\left(\frac{|f|}{2\pi}\right) e^{\frac{-(\tau-t)^2 f^2}{2}}$, is the variable width Gaussian window.

The discrete version of the above equation may be represented by the following equation.

$$H\left[\frac{n}{NT}\right]=\frac{1}{N}\sum_{k=0}^{N-1} h[kT]\, e^{\frac{-j2\pi nk}{N}} \qquad (9)$$

Here $h[kT]$ is a discrete time series to be transformed.

In equation 9, to achieve the orthogonality, the Fourier transform of each basis vector is divided into N number of vectors by taking elementary products and subsequently it is shifted by N times such that the localized summation of all the vectors will result in original basis vectors.

Frequency Sampling

In the case of the Wavelet transform, scaling has been defined loosely and generally, it uses octave scaling, which in turn, result in oversampling at lower frequencies and under sampling at higher frequencies. In discrete S-transform, sampling space is sampled identically so there is no issue of over and under sampling.

Signal Reconstruction

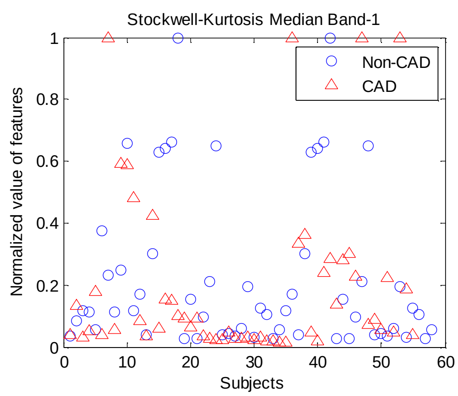
In general, sinusoidal signal is represented as

$$x(t)=A\cos\left(2\pi f(t)t\right)+\phi(t) \qquad (10)$$

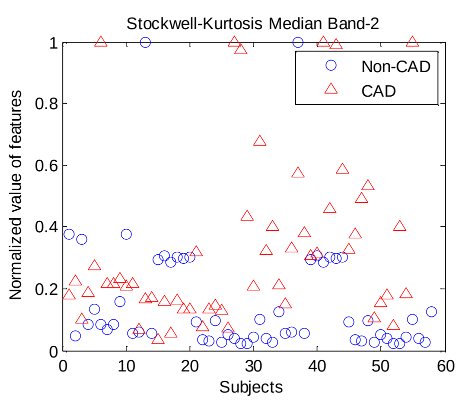
where *A(t)*,*f(t)* and *φ(t)* represents amplitude, frequency and phase of signal *x(t)* at time *t*. As S-Transform provides absolutely referenced phase information and frequency invariant amplitude, the signal can be extracted and reconstructed at any moment *t*, with the corresponding combination of *A(t)*, *f(t)* and *φ(t)*. In the case of Wavelet transform it is not possible because Wavelet only provides local phase information (local to scaling function).

This work involves the localization of S transform of each cycle of heart sounds representing the particular subject. The minimum and maximum frequencies are chosen for analysis are 10 Hz to 850 Hz and the complete bandwidth is 840 Hz and it is divided into ten bands thereby resulting in a band of 84 Hz.

For each band, various basic statistical (such as Mean, Median, Minimum, Maximum and Standard Deviation), as well as higher order statistical (such as Skewness and Kurtosis) features, were computed. These features were computed for magnitude and phase of the Stockwell transform. By observing the scatter plots for all the computed features, it was decided to opt for spectral kurtosis because of its linear separability. In the early studies [44,46], it has been proved that the statistical features such as Kurtosis combined with Spectro temporal techniques like S transform is an efficient approach for the analysis of non-stationary signals.
Kurtosis is a measure of the "peakedness" of a distribution. That is, the higher the kurtosis, the more the distribution is spread out from the mean. Hence for obtained S matrix, mean of only magnitude (after taking kurtosis) is computed whereas the phase information was kept intact. In future studies, the phase plot may be included to get more insight into heart sounds. In this work, seven random diastoles were selected from each heart sound. To get rid of any unbounded outlier, median value among seven diastoles was selected. The resultant vector consists of band wise kurtosis for each subject. Fig. 3 shows the scatter plot representing spectral kurtosis for each band for CAD and Non CAD subjects.



(a)



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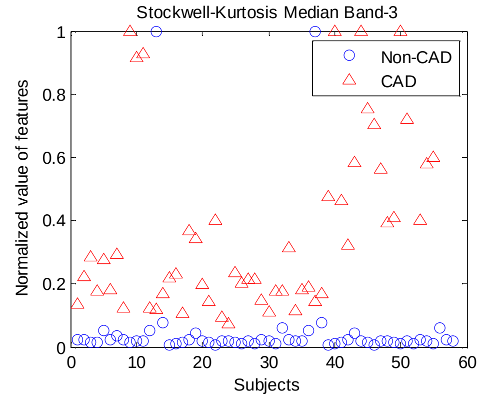

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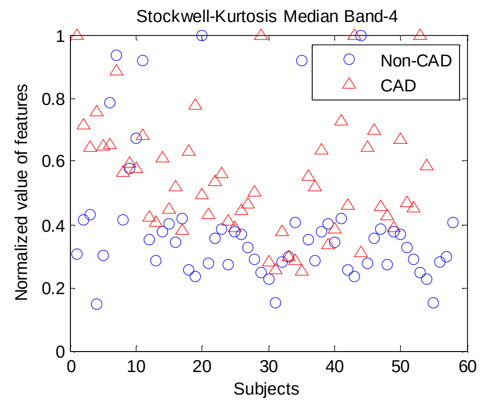

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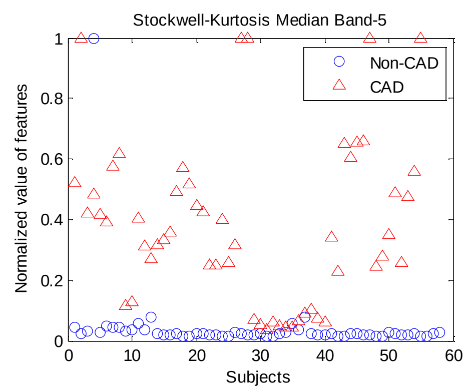

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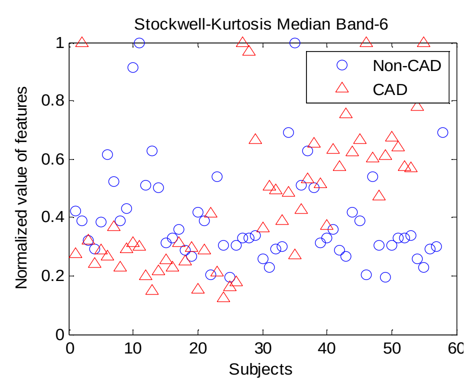

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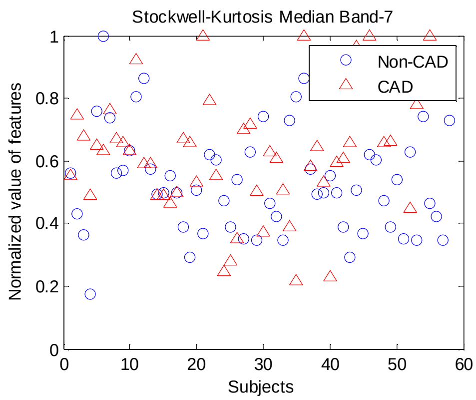
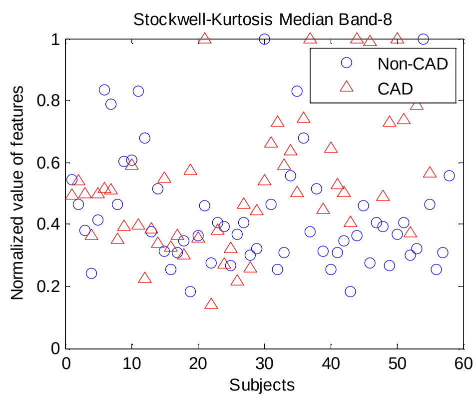
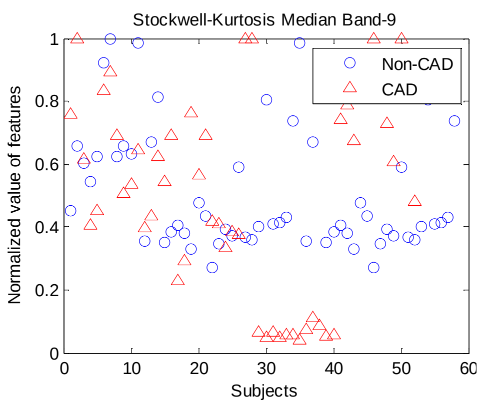


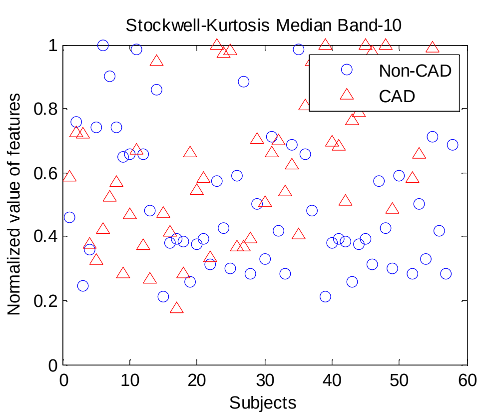
(g)



(h)



(i)



(j)

Figure 3(a)-(j): Scatter Plot of Spectral Kurtosis from Band 1 to Band

7. CLASSIFICATION AND RESULTS

From scattering plots shown in Fig. 3, it is evident that only band 3 (169-252 Hz) and band 5 (336-420 Hz) shows linear separability. Out of these two bands, band 3 is more linearly separable than band 5 (there is overlapping of 12 CAD subjects with non-CAD subjects in band 5). So, to keep the classification simple and computationally efficient, a simple threshold-based approach is employed (A simple variant of minimum distance classifier with Euclidian distance). First 20 samples from both normal and CAD category were used to train a simple minimum distance classifier with the mean of each class as a prototype. To calculate threshold, two means m_1 and m_2 of two classes were averaged and the corresponding threshold value is calculated and the computed value of the threshold is 0.0745.

With this threshold, the classification performance is as under:

True positive (TP) = 54.
False positive (FP) = 04.
True negative (TN) = 54.
False negative (FN) = 01.

$$Sensitivity = \frac{TP}{TP + FN} \times 100 = 98.18\%$$

$$Specificity = \frac{TN}{TN + FP} \times 100 = 93.10\%$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 = 95.57\%$$

To summarize, the flow chart describing the methodology for CAD detection from heart sounds is shown in Fig. 4.

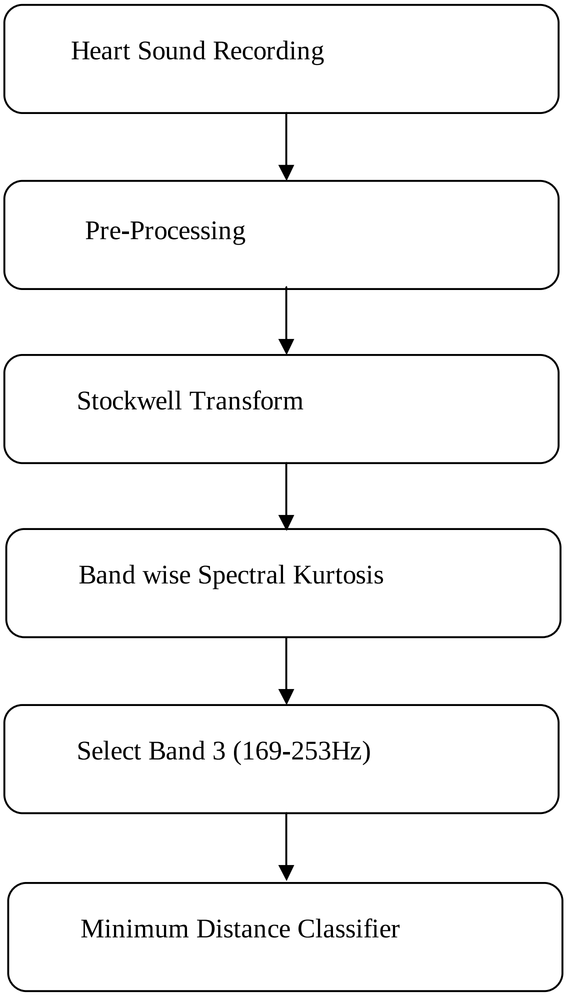


Figure 4: Flow chart of the complete methodology

8. DISCUSSION

The results presented in section 6 clearly provides the evidence of diastolic murmurs in heart sounds, indicative of coronary artery disease. The Stockwell transform and band-wise kurtosis which is indicator of peakedness in frequency distribution suggest the strong possibility of CAD heart sounds in the frequency band of 169-253 Hz. This could be termed as band of interest in regard to CAD heart sounds. The finding is also in accordance with the previous studies [32,33], where frequencies of the said heart sounds were analyzed.

9. CONCLUSION

After a detailed study of literature and recent advances in signal processing, several signal processing techniques were studied and implemented to analyze human. heart sounds for detection of Coronary Artery Disease, a novel approach of Stockwell transform is utilized which yielded good results. The sensitivity, specificity, and accuracy obtained by this approach is 98.18%, 93.10% and 95.57% respectively which is higher than that obtained by previous researchers. These results are very encouraging and this work can be easily incorporated for telemedicine application.

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