Heart Sound Analysis for Detection of Cardiovascular Diseases (CVDs) Through Segmentation

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Abstract— Abnormalities in human heart can be detected by listening to heart sound. This process is known as cardiac auscultation. The heart generates a specific rhythm through which the condition of the heart can be determined. Changes in this rhythm might be due to the **abnormalities** of the heart. These abnormalities can be diagnosed via cardiac auscultation. Heart doctors or physicians needs to be very experienced and accurate in listening and identifying heart sound as there are many other noises accompanied by it, like lungs sound or internal noise or some external noise. This research work proposes a mechanism to automatically record and analyze heart sound in which phonocardiogram PCG signals are collected with the help of mobile or electronic stethoscope. PASCAL PCG heart sound dataset is used for testing of proposed methodology and initial testing revealed a total error rate of 835188 and 20346 for Dataset A and B respectively.

Index Terms— PCG, Heart sound segmentation, variation coefficient, spectral centroid.

1 Introduction

HEART sound is a key source of diagnosing some of the life-threatening diseases related with heart. It provides a detailed insight about the state of heart. Cardiac auscultation is the process of listening to the sound generated by heart through stethoscope. During contemporary times, diagnosis of different heart diseases like heart attack, angina, stroke, etc. are dependent upon costly and complex methods like magnetic resonance imaging (MRI), CT angiography, etc. The uses of these methods have recently increased due to their tremendous precision in diagnosing heart related diseases. Despite the availability of these quality methods, their modes of diagnosis entail extreme complexity, the equipment is bulky and come at a cost that cannot be afforded by a vast majority of people. There is a critical need to enhance and promote cost-effective and non-colossal technique for medical examination of heart by precise analysis of heart sound.

Experienced doctors distinguish between a normal healthy heart and an abnormal heart by listening to the sound of heart and break down the succession of its murmurs and beats. Many heart abnormalities can be diagnosed by auscultation method. Diagnostic information might be extracted from the automatic heart sound analysis from two main sets of features i.e. presence of some heart sound components and temporal information between heart sound events and morphological characteristics. Figure 1 illustrates the morphology of human heart and blood flow in it.

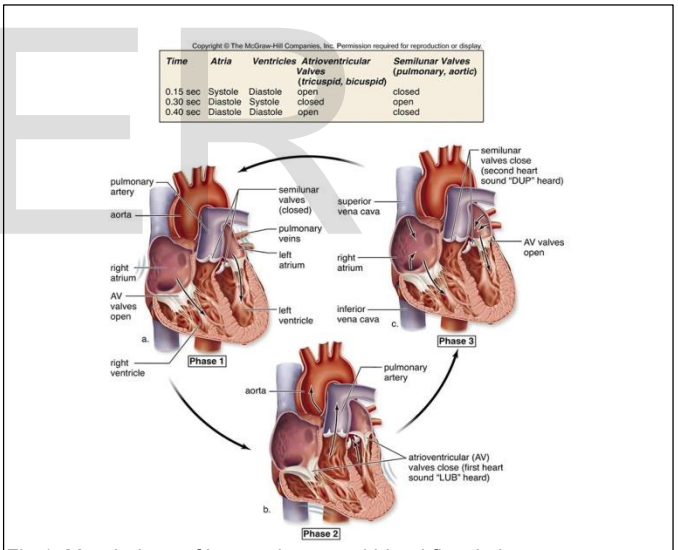

Fig.1. Morphology of human heart and blood flow in it.

Phonocardiogram is a graphical representation of sound waves generated by a functional heart. Auscultation of heart is a widely used method for identification of heart valves disorder, heart lesion and heart failure [1]. There are two major heart sounds i.e. *S1* and *S2*. The *S1* heart sound is generated when atrioventricular valve closes. It is the systole phase of heart [2]. *S1* is low-pitched and dull sound. The heart sounds can be heard through the chest as the ventricles transmits it to the chest. When the atrioventricular valves close due to ventricular contraction, it produces sound. S2 sound is sharper and have high pitch than the S1 sound and can be heard over the precordium.

The closure of semilunar valves produces S2 sound. There are also two other sounds besides of S1 and S2 i.e. S3

sound and S4 sound. The S3 heart sound or the third heart sound is produced as a result of sudden pause in the ventricular movement in response filling in pre-diastole. This sound can normally be heard in children and young people. The S4 heart sound is produced due the abrupt pause in the ventricular movement in response filling in early systole due to atrial contraction.

The most common heart abnormal component in heart sound is a heart murmur. A murmur can be observed in between S2 sounds and S1 sounds or between S1 sounds and S2 sounds. On the basis of its occurrence, murmur has two types, the systolic murmur which is produced in between systole and diastole and the diastolic murmur which is produced between diastole and systole. Murmurs usually have a low frequency as compare to S1 sounds and S2 sounds. A heart murmur occurs due to abnormalities in heart valves.

The flow of the blood in the circulation is controlled by the left ventricle therefore it timing is another important aspect here. These heart sounds are used in measuring the systolic interval and ejection time of left ventricle. In systole, heart sound changes with a change in blood amount in the heart, hypovolemia can be detected from these changes in heart sound [8].

2 Related Works

In the domain of Computer Assisted Diagnosis (CAD) systems, a number of digital signal processing algorithms and pattern recognition techniques are widely used for analysis of heart sounds in order to diagnose different cardiovascular disorders (CVDs). The emphasis of this research is upon segmentation of PCG waveform; therefore, we will be discussing some prominent works in this domain and the limitations of each of these works.

PCG waveform does not need any secondary external signals, it achieves segmentation directly. The performance of PCG segmentation algorithm is affected by the heart abnormalities as they make themselves dominant on the heart sound. Using the PCG segmentation algorithm we do not need synchronization, installation and acquisition of any external module such as an electrocardiogram thus making it the most desirable approach to the problem i.e. to reduce the cost. Because of the highly organic nature of the heart sound signal, finding a constant factor in them is very difficult. Most of the time a deviation in the temporal length of every systolic and diastolic period is observed. Besides the fact that S1 and S2 are highly audible, their amplitudes changes to a high extent and reaches the point of disappearance when certain abnormalities are present. Thus, S1 and S2 frequencies are not fixed but rather having different frequencies in two different cardiac cycles. Literature for instance [5] [7] [10] [11] [12] have general approaches for the PCG segmentation however the limitations of the PCG signals discussed above the hinders the performance of such general approach of PCG segmentation, these limitations opens up a new area of research where the researchers needs to develop a rather unique algorithm for segmentation of heart sound. Figure 2 illustrates the segmentation of heart sound.

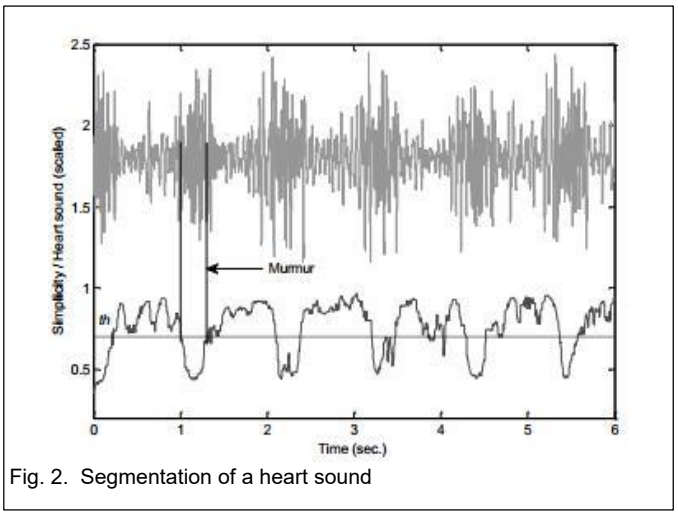

Fig. 2. Segmentation of a heart sound

Groch et al. [8] proposed one of the earliest solutions for segmentation of heart sounds that only depends on the PCG signal. The main idea of the approach was to pass the signal through a band-pass filter and then threshold it. The proposed solution was defined to be simple and can be implemented using only analog circuits, in [9] the idea was extended and refined. The suggested methodology consists of several different steps and this same approach was used by other researchers in this field in search of a solution to the problem.

3 Implementation

3.1 Dataset Acquisition

PASCAL heart sound datasets are acquired from two different sources i.e. the General Public via Istethoscope pro iPhone app, it provides Dataset A, while the clinical trials in hospitals using the digital stethoscope or digi-scope provides Dataset B.

Dataset A contains 176 files in .wav as well as in .aif format. Dataset A is subcategorized into normal, murmur, extraheart and artifact. Normal contains 31 sound files of normal heart, murmur contains 34 files of murmur heart sound, extraheart contains 19 files of extraheart sound and artifact comprised 40 sound files of artifact. There is another category of 52 unknown sound file in Dataset A with name "Aunlabledtest" is a test dataset.

Dataset B comprises 656 files both in .wav and .aif file format. Normal, murmur and extra systole are subcategory of Dataset B. among 656 sound files of dataset, 320 belongs to normal category ,95 to murmur and 46 files to extra systole category. A test dataset of 195 sound files named "Bunlabledtest" is sub dataset of dataset B.

These sound files are different in length. The minimum length is 1 second and maximum 30 second. Some of these sounds' files are clipped to reduce noise.

3.2 Signal Pre-processing

This step involves elimination of heart sound of duration less than three seconds. The sound files of heart sounds recordings, provided in the dataset, are contaminated with noise. This noise needs to be removed in order to get better accuracy or results. As a pre-processing measure, the PCG signal are down-sampled, filtered and normalized before localization or segmentation into S1 and S2 heart sounds [1]. Figure 3 shows sound signal of normal category.

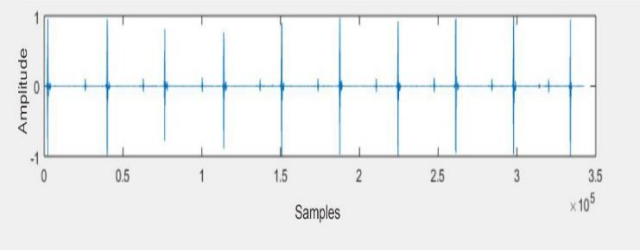

Fig. 3. Illustration of a sound signal from normal category of PASCAL dataset

3.3 Peak Detection

The next step involves detection of peaks in the PCG signal. To achieve this, we adopt the equation of Shannon Energy, which is a powerful technique to detect and extract the envelope from the heart sounds. It is also the best technique for localization of components in PCG signal. The non-linear combination of signals is converted into linear combination, which helps in smoothening the pre-processed signal and makes it easy to detect or find peaks. The equation for the Shannon Energy is as under [4].

$$Shannon\ Energy\ = -x^2\ (t)\ log\ x^2(t) \quad (1)$$

The average Shannon energy can be equated as:

$$E\ = -\frac{1}{N}\sum_{n=1}^{\infty} x^2(t) log x^2(t) \quad (2)$$

Where x(t) is the processed signal and N is windows length, 0.02 samples per second, in this case. Finally, the average Shannon energy calculated for every window was normalized. The equation for the normalization of Shannon energy is stated as under:

$$P(t)\ =\ \frac{E(t) - ME(t)}{SE(t)} \quad (3)$$

Where E(t) denotes the average Shannon energy at 0.02 samples per second for windows number 't'. ME(t) is the mean energy while SE(t) is the standard deviation of E(t). P(t) is the Shannon envelop or the normalized average Shannon energy.

After selection of the basic heart sounds peaks, the next step involved analyzing the rhythm of heart sound by distinguishing between the detected peaks. The heart abnormalities can be identified by this analysis. The selected peaks may either be S1(lub) or S2(dub) [4]. Figure 4 demonstrates the fundamental heart sound peaks.

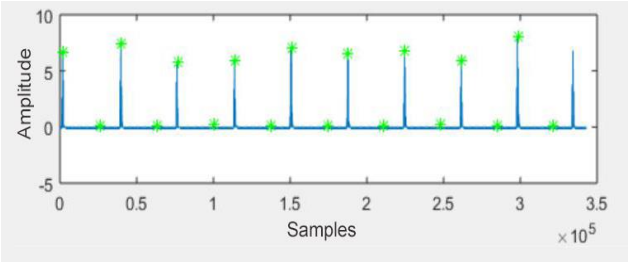

Fig. 4. Fundamental heart sound peaks

3.4 Feature Extraction

After successful detection of fundamental peaks, the next step involves segmenting out S1 and S2. The Shannon Envelope was then processed for feature extraction in terms of both time and frequency domains. Four features were extracted in total, half were from time domain while the remaining half were from frequency domain.

The two temporal features or time domain features are Peak Value and Peak Gap while the two spectral features or frequency domain features are Spectral Centroid and Variation Co-efficient [4].

We calculated the first two features, peak gaps and peak values from the processed signal's peaks whereas for the other two features we used a special method. We selected some samples pre peak position and selected equal numbers post peak position, from the filtered signal in the pre-processing step. The sample at peak position was also included. After this, the Power Spectral Density (PSD) was computed to extract spectral features from the selected peaks or samples [6]. The equation used to achieve this is as under:

$$P(w)\ = -\sum_{-\infty}^{\infty} r_y[n] e^{-jwn}\, s \quad (4)$$

Where $r_y[n]$ is autocorrelation of the signal for the selected region and defined as E(y[m]y[m]*), let y[m] be the region selected from the pre-processed signal. The spectral centroid and variation co-efficient were extracted from here. The equation used for the spectral centroid was:

$$C\ =\ \frac{\sum wP(w)}{\sum P(w)} \quad (5)$$

P(w) is the amplitude of w^{th} frequency. During the course of this methodology, it was found that the variation co-efficient of S1 and S2 are different from each other. The variation co-efficient was calculated as:

$$\sigma^2\ =\ \frac{\sum (w-C)^2 P(w)}{\sum P(w)} \quad (6)$$

Whereas C is spectral centroid obtained from the equation (5).

3.5 Clustering

After extracting the four required features, the primary objective was to recognize S1 and S2 peaks. The S1 heart sound and S2 heart sound, were segmented out. Various machine learning techniques are used to achieve this. K-Mean clustering is one of the best clustering techniques used for this purpose [2]. K-Mean clustering is also best suited for

this research. According to [2] K-Mean clustering algorithm provides good results as compared to other algorithms. K-mean clustering identifies S1 and S2 most precisely and efficiently. The features extracted are shown in figure 5.

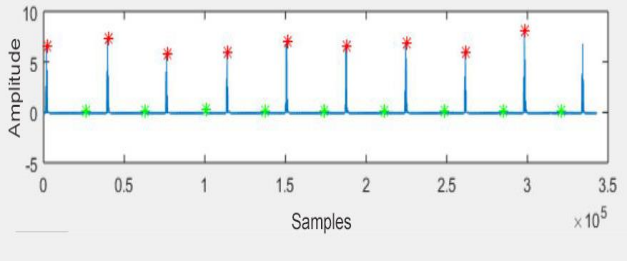

Fig. 5. Segmentation of S1 and S2 components.

Green dots indicate S2 (dub) heart sound and red dots indicate S1(lub) heart sounds. This identification clearly shows us that the selected signal is sound of a normal healthy person and that is also mentioned in the dataset as it is selected from normal heart sound category of well-known PASCAL PCG heart sound dataset. Figure 6 demonstrates the methodology adopted to pursue this research work.

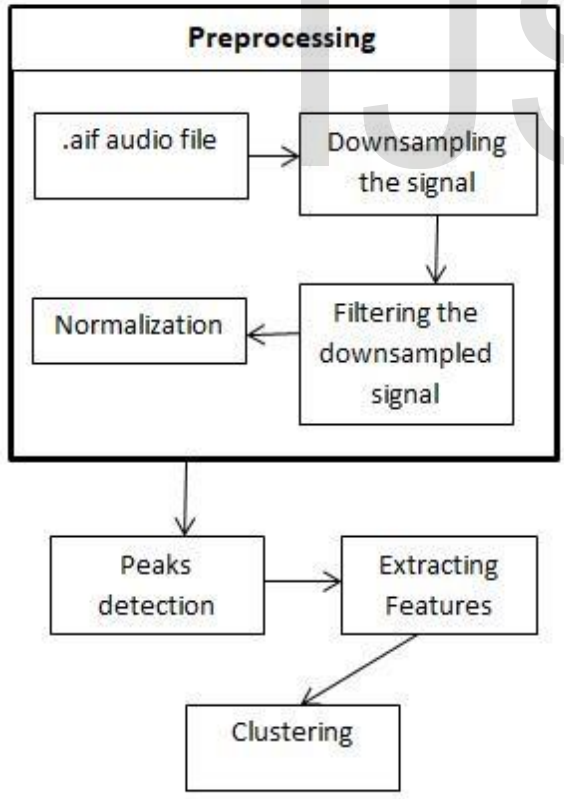

Fig. 6. Detailed flow chart of the methodology adopted.

4 Evaluation

The results of the methodology are eventually evaluated with the available Dataset A and Dataset B. These annotated datasets contained data of normal heart sounds and abnormal heart sounds. The results were compared with the ground-trothed data provided in the aforementioned datasets and helped in evaluation of the proposed methodology.

5 Results And Discussions

Table 1 provides an in-depth overview of the results obtained from the segmentation for the normal category audio files in dataset A. The total number of heart beats are displayed in the second column while the average error measured in samples per precision is displayed in the third column. The total error of Dataset A was 853188.3002.

Table 2 provides a detailed overview of the results obtained from segmentation for Dataset B. These are also normal category audio files. The total heartbeats are identified, and the average error is shown in table 2. The total error in dataset B is relatively much lesser than that of dataset A, 20346.0474 to be exact.0

TABLE 1

SEGMENTATION RESULTS OBTAINED FROM DATASET A

File Name (.aif)	Total of Heartbeat	Average Error
1070538	11.5	15719.26087
1151127	7.5	117933.4
2081152	9	171266.1111
2201230	11	584.2727273
1070538	11.5	15719.26087
2270940	9.5	189061.1053
3101140	9.5	20782.73684
3140135	7.5	73441.6
3170121	9.5	38229.10526
4122156	11	182462.1818
6151236	9.5	43708.52632

TABLE 2

SEGMENTATION RESULTS OBTAINED FROM DATASET B

File Name (.aiff)	Heartbeat	Average Error
31931979_B	12.5	88.48
31931979_D2	10	38.75
6721273_B1	4	46.875
6721273_C2	3	60
6721273_D1	3.5	117.2857143
6721273_D2	7.5	2770.866667
4946865_C1	7.5	1623.866667
7102824_B	8.5	3239.823529

7102824_C	5	1464.6
1306759619127_A	4	61.625
1306428161797_C2	2.5	55.8
1306764999211_C	15	40.13333333
1306519735121_B	11.5	2325.956522
8707532_B	18	4246.305556
8707532_D3	3	14
1306523973811_A	4	246
1306768801551_D2	8	56.9375
9785624_D	4.5	89.66666667
1306935608852_B1	4.5	47.22222222
1307018640315_B1	6	27.75
1307018640315_B2	3	48.16666667
1307111318050_A	13	62.03846154
1307111318050_C	3	249.6666667
71284351_B1	3.5	66.71428571
87962616_B1	2.5	30
87962616_D	7	2521.142857
90076841_B	16	496.375
52613891_D	3	77.33333333
73010307_D	26.5	65.09433962
76920011_D	3.5	67.57142857
31931979_B	12.5	88.48
31931979_D2	10	38.75
6721273_B1	4	46.875
6721273_C2	3	60
6721273_D1	3.5	117.2857143
6721273_D2	7.5	2770.866667
4946865_C1	7.5	1623.866667
7102824_B	8.5	3239.823529
7102824_C	5	1464.6
1306759619127_A	4	61.625
1306428161797_C2	2.5	55.8

After the comparison, it is obvious that the average error in Dataset A is much more than that in set B. this might the fact that the dataset A has been recorded using some mobile devices while that in dataset B is recorded with a digital stethoscope in a quite environment in the hospital. The other possibility is that the recordings are done by inexperience in case of data set A. Table 3 illustrates the total error, the three final values obtained and the total error found in the proposed methodology in this study for both datasets.

TABLE 3

RESULT COMPARISON OF DATASET A AND B

	Dataset A	Dataset B
ISEP/IPP Portugal	4219736.5	72242.8
CS UCL	3394378.8	75569.8
SLAC Stanford	1243640	76444.4
Proposed Methodology	835188.3002	20346.4742

6 CONCLUSION AND FUTURE WORK

The proposed methodology aimed at providing cost-efficient and precise method for early detection of cardiovascular diseases by contributing to "PASCAL Classify Heart Sound Challenge" [2]. Evaluation indicated that the proposed methodology performed better than the finalists of the challenge [1] [3]. The total error for the Dataset A and Dataset B was reduced significantly. Keeping all these factors under consideration, we conclude that the proposed methodology for early detection of cardiovascular diseases is a far more feasible option than several costly methods available in the field of healthcare.

However, in future, several amendments can be done to this work to make it more efficient and accurate by further improving the algorithm used for segmentation and feature extraction.

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