Heart Sounds Segmentation and Classification

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Thesis Supervisor

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Declaration

I certify that this research work titled "**Heart Sounds Segmentation and Classification"** is my own work. The work has not been submitted elsewhere for assessment. The material used from other sources, has been properly acknowledged / referred.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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Copyright Statement

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ABSTRACT

Heart valves, responsible for correct pumping of blood to entire body generate certain sounds during its functionality called as heart sounds. Listening and interpretation of these sounds using stethoscope is known as auscultation. Heart sounds commonly known as phonocardiogram signal provide valuable information for correct identification of any heart disease, if interpreted correctly. These sounds though audible but need an extensive practice and skills to be correctly understood. Any illness of heart valves like murmurs though appear in these sounds but are very difficult to be correctly identified by the cardiologist. These murmurs are even further having many types. Phonocardiogram signals can be utilized more efficiently by the cardiologists and medical officers when they are converted into some easily interpretable form rather through a conventional stethoscope. This research work is carried out with an aim to segment the heart sounds by identify the correct locations of first and second heart sounds and classify them to identify any illness of heart valves. Correct identification of S1 and S2 is an important but less addressed issue of segmentation problem. By correctly segmenting the phonocardiogram signal into its subparts any illness can easily be isolated, detected and classified. To undertake the segmentation task I have used the effectiveness of k-means clustering which is used to segregate and label the heart sounds as S1 and S2 sounds. For correct classification of illness I have used a novel feature set by combing the temporal and frequency domain characteristics. All distinct features from both the domains are made part of feature vector for classification purpose. To test the effectiveness of my method, I used PASCAL Classifying Heart Sounds Challenge 2011(PASCAL-CHSC2011) dataset and successfully obtained improved results for segmentation, identification and classification problem than any of the challenge participants.

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CHAPTER I: Introduction

According to the World Health Organization heart disease is one of the leading causes of human deaths in the world. To be more specific heart failure, coronary heart diseases and heart valve disorders or cardiovascular diseases (CVDs) are leading among all the heart diseases [1]. Heart sounds reflect most of the heart valve disorders and can be detected through its detailed analysis. Abnormalities appear in heart sounds much before the pathological symptoms start appearing. Any method which can help to detect early signs of heart disease could therefore have a significant impact on health of human beings. In medical science analysis of heart sounds is known as auscultation. Despite remarkable advances in imaging technologies for heart diagnosis, clinical evaluation of cardiac defects by auscultation is still a main diagnostic method for discovering heart disease. In experienced hands, this method is effective, reliable, and cheap.

There are two types of heart sounds, high-frequency transients associated with the abrupt terminal checking of closing or opening valves and low-frequency sounds related to early and late diastolic ventricular filling events. High frequency sounds are further distributed in S1 and S2 sounds and low frequency sounds in S3 and S4. Mitral and tricuspid valve closing sounds (M1 and T1), nonejection sounds, and opening snaps are related to closing and opening of the atrioventricular valves are known as S1 sounds. Aortic and pulmonary valve closure sounds (A2 and P2) and early valvular ejection sounds are related to closing and opening of semilunar valves are known as S2 sounds. Low-frequency sounds include the physiologic and pathologic third heart sound (S3) associated with early ventricular filling events, and presystolic, atrial, or fourth heart sounds (S4) associated with late diastolic events resulting from the atrial contribution to ventricular filling [2]. Thus a heart sound has four primary parts, S1 and S2 as major sounds with high amplitude and frequency as compared to S3 and S4 which are minor sounds with lower amplitude and frequency as shown in Figure 1.

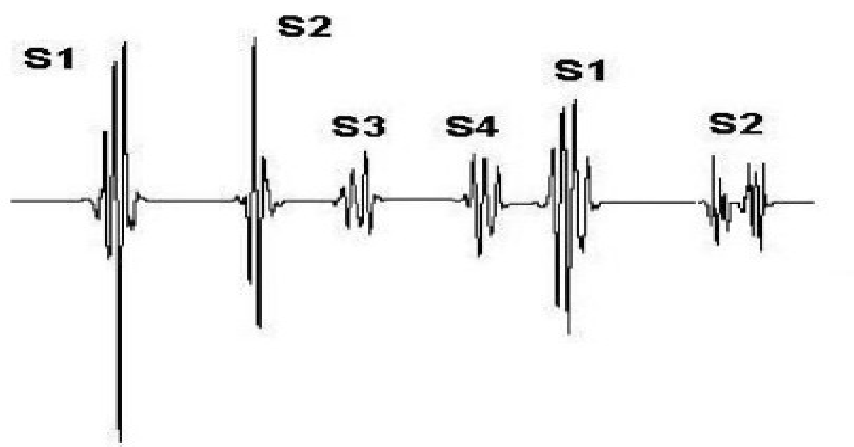

Figure 1: Internal parts of a NORMAL heart sound [3]

Hence, most researchers restrict themselves to S1 and S2. Using the cardiac cycle (S1–S2–S1), any illness of heart valves can be detected effectively from heart sounds. These artifacts will appear as high frequency peaks anywhere between S1 and S2 or between S2 and S1, as shown in Figure 2, where a high frequency murmur is visible between S1 and S2. [2] [4]

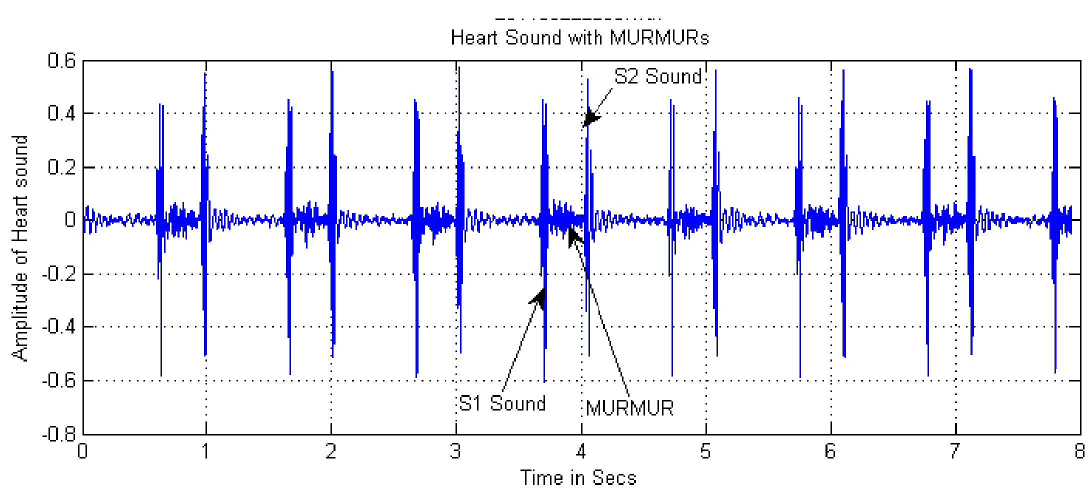

Figure 2: Input heart sound with MURMUR, different parts are indicated

With the established fact that a cardiac cycle (S1–S2–S1) can clearly depict the health of a heart, a sequential approach for analysis starts with the correct labeling of S1 and S2 sounds followed by their location identification. If a sound is correctly labeled for its S1 and S2 parts, further selection and rejection processes will be correct and diagnosis basing on this set of information would be accurate. Though very effective, auscultation using stethoscope still needs an extensive amount of practice by a skilled cardiologist. Any system which assist the cardiologists in this diagnosis would be extremely helpful and improve the chances of early and correct identification of disease. Although with the emergence of computer assisted analysis, this field of medical science has progressed a lot yet correct identification of S1 and S2 and precise classification of illness of heart are still the most challenging and unexplored areas of machine learning [2].

There have been numerous efforts to address this problem and lot of literature is available on the subject. One of such efforts is the conduct of PASCAL heart sound challenge 2011 (CLASSIFYING HEART SOUNDS CHALLENGE2011) organized by a team duly sponsored by PASCAL [1]. Main aim of this challenge was to develop an algorithm which can correctly segment and classify the heart sounds on a standard dataset. This challenge was open entry for all in the world. Segmentation, training and classification has to be done using a standard dataset. Availability of a good dataset is always a bench mark and a testing standard for the efficiency of classifiers. This research is based on the datasets provided for the challenge thus taking on the most challenging problem using slandered set of data files. I have presented a novel technique for the detection, segmentation and classification of heart sounds. Segmentation problem is addressed using a clustering technique and for classification problem I have used a hybrid feature vector which effectively explored the distinct nature of frequency and time domain of heart sounds. Details of segmentation and classification are given in chapter 4 “Methodology”. A brief description of PASCAL heart sound classification challenge is given in chapter 3. Datasets are discussed in chapter 5 whereas results are discussed in chapter 6.

CHAPTER II: Background and Literature Review

Analysis of heart sounds started with the emergence of field of machine learning and thus has a long history however with the emergence of modern computers; research in this field has gained a significant importance. There is a large list of researchers who has presented their work and put-in acknowledge able efforts in this field [1-33]. Despite of its importance this filed is still a challenging and unexplored area of machine learning. Being an important aspect of human health worldwide efforts are always remained in progress to improve upon the existing procedures with more and more challenging and standard environments. Due to non linear and non stationary nature of heart sounds its analysis are extremely challenging. Mainly researchers focus on the time and frequency domain analysis either independently or as a hybrid model [5] [6] [7] [8] [9]. Despite of an extensive research trends with more advanced methods still satisfactory results which can be marked as a yardstick are lacking.

There could be many possible fields and areas to distribute the contributions of the researchers; however I have divided this sec in two different aspects. Basing on the tasks performed there could be following areas.

- Classification tasks [10] [11] [12] [13] [14] [15] [16]
- Segmentation tasks [5] [6] [7] [17] [18] [8] [19] [20] [21]
- Feature extraction methods [10] [11] [12] [8] [19] [13] [15] [22] [9]

Basing on the techniques this sec could be further divided on following sub parts

- Envelope extraction methods [23] [17] [19]
- Analysis methods [5] [6] [24] [25] [26]
- Energy Signatures [23] [22] [27] [16] [19] [5] [6]
- Clustering based methods [25] [18]

A detail summary of literature review as discussed in next paragraphs is summarized in the **Table 1 below.**

Table 1: Summary of literature review

Title of Publication	Problem Area Addressed	Source	Key Points / Techniques used	Year
Improving Classification Accuracy of Heart Sound Signals Using Hierarchical MLP Network	Classification of Heart sounds, Feature extraction	Journal	Cross Correlation, Frequency Power spectrum	2014
Heart Sound Segmentation Techniques: A Survey	Comparison on Segmentation Techniques	Conf	Wavelet, Entropy, Recurrence time statistics, Shannon Energy	2014
Heart Sounds Classification using Feature Extraction of Phonocardiography Signal	Classification of Heart sounds, Feature extraction	Journal	Murmurs, Feature extraction, Naïve Bayes, Bayes Net classifier, PASCAL Challenge Dataset	2013
A robust heart sounds segmentation module based on S-transform	Segmentation of Heart sounds	Journal	S-Transform, Shannon energy	2013
Automated Diagnosis of Cardiac Abnormalities using Heart Sounds	Classification of abnormalities, Feature extraction	Conf	Wavelet, MIR tool box, RMS Energy Curve	2013
Segmentation of cardiac sound signals by removing murmurs using constrained tunable-Q wavelet transform	Segmentation of Heart sounds	Journal	Q Wavelet, TQWT, CSCW	2013
Segmentation of Heart Sound Using Double-threshold	Segmentation of Heart sounds	Conf	Hamming Window, HHT, Envelope extraction	2013

Exploring the Stationary Wavelet Transform Detail Coefficients for Detection and Identification of the S1 and S2 Heart Sounds	Segmentation and Labeling of Heart sounds	Conf	Stationary WT, Clustering, PASCAL Challenge Dataset	2013
Heart Sound Segmentation of Pediatric Auscultations Using Wavelet Analysis	Segmentation of Heart sounds, Feature Extraction	Conf	Time, Frequency domain, Wavelet, PASCAL Challenge Dataset	2013
Towards a Time-Feature Independent Phonocardiogram Segmentation	Segmentation of Heart sounds, Feature Extraction	Conf	SWT, Shannon Energy, Envelope	2013
Heart Sounds Classification Based on SVD and SVM Technique	Classification of Heart sounds, Feature extraction	Journal	SVD, SVM	2013
Cardiac disorder classification by heart sound signals using murmur likelihood and hidden Markov model state likelihood	Segmentation and Classification of HS	Journal	Murmur Likelihood, HMM State Likelihood, MFCC features	2012
Cardiac sound murmurs classification with autoregressive spectral analysis and multi-support vector machine technique	Classification of Murmurs	Journal	NAR-PSD, Morphological characteristics, PSD Characteristics	2012
Segmentation of heart sounds based on dynamic clustering	Segmentation of Heart sounds	Journal	Instantaneous Cycle frequency, Weighted density Function	2012

A Biomedical System Based on Artificial Neural Network and Principal Component Analysis for Diagnosis of the Heart Valve Diseases	Classification of Heart sounds, Feature extraction	Journal	DFT for feature extraction	2012
Matrix decomposition based feature extraction for murmur classification	Classification of Murmurs, Feature Extraction	Journal	CWT, CVD, QR decomposition, Shannon energy, Ginni index	2012
An adaptive singular spectrum analysis approach to murmur detection from heart sounds	Classification of Murmurs	Journal	Singular Spectrum Analysis, Decomposition & Reconstruction	2011
Automatic phonocardiograph signal analysis for detecting heart valve disorders	Segmentation and Classification of HS	Journal	Auto correlation, STFT, Discrete Cosine Transform	2011
Choice of the wavelet analyzing in the phonocardiogram signal analysis	Comparison study on use of PWT & DWT	Journal	Orthogonal, Bi-Orthogonal	2010
Feature Integration For Heart Sound Biometrics	Feature Integration	Conf	Temporal Shape, Spectral shape, Cepstral Coefficient, GMM super Vector	2010
Detection of valvular heart disorders using wavelet packet decomposition and support vector machine	Segmentation of Heart Disease	Journal	SVM, WPT	2008

Comparison of envelope extraction algorithms for cardiac sound signal segmentation	Comparison on Segmentation Techniques	Journal	CSCW, Envelope extraction, Hilbert transform, Shannon Energy	2008
Time-frequency analysis of the first and the second heartbeat sounds.	Comparison study on Segmentation methods	Journal	Spectrogram, Wavelet, FT, WT, STFT	2007
EEG signal classification using wavelet feature extraction and a mixture of expert model	Classification of HS	Journal	Wavelet, Supervised Learning	2007
Neural network classification of homomorphic segmented heart sounds	Segmentation of Heart sounds, Feature Extraction	Journal	k-means, Homographic Filtering	2007
A cardiac sound characteristic waveform method for in home heart disorder monitoring with electric stethoscope	Segmentation of Heart sounds	Journal	Spectrogram, Eardrum Model Simulation, FCM clustering, CSCW	2006
Feature Extraction for Systolic Heart Murmur Classification	Classification of Heart sounds, Feature extraction	Journal	Shannon Energy, Wavelets	2006
Classification of heart sounds using an artificial neural network	Segmentation and Classification of HS	Journal	2 Periods Window, Wavelets	2003
Heart Sound Segmentation Algorithm Based on Heart Sound Envelolgram	Segmentation of Heart sounds	Journal	Shannon Energy	1997

2.1 Classification tasks

Harun Uğuz [4] proposed a classification system, in which he relied upon DFT and Burg AR method for feature extraction. Due to digitized nature of signal, DFT is preferred on Fourier transform for feature extraction. For classification task they use 3- layered "MLP feed-forward neural network with back-propagation algorithm" For experimental results they select 120 subjects which were equally distributed among three classes named as normal, mitral stenosis and pulmonary stenosis. Mohd Zubir Suboh et.al in their paper proposed a hierarchical MLP network could which significantly increase the classification accuracy when tried to classify the heart sounds [5]. Mandeep Singh and Amandeep Cheema while using the PASCAL competition dataset proposed a method which uses Electrocardiogram (ECG) gating to classify normal and abnormal heart sound signals with murmurs. They did not attempt the segmenting and extracted the features directly [6]. At time previous history of the patients is helpful as proposed by [7]. They have augmented the medical information of patient already stored with heart sounds to detect the abnormalities. They used wavelet for de-noising of heart sounds. For feature extraction, they used MATLAB tool box "MIR". Their approach is based on a standard length signal of 10S to avoid missing of any special characteristics which can assist in detection process. Although this paper is written with an aim to help and assist the cardiologist but yet they have ignored the very important fact that what if heart sound is of very small duration or it contains abnormalities other than murmurs. Shape comparison through gives an idea about the murmur but is not very effective tool in analyzing or classification of abnormalities.

Qiongmin et.al [8] implemented a classification method using SVM s classifier and SVD as feature generation tool. SVD is used to decompose the HS as a 1st step. Using 2 main singular values as features, SVM is used to classify between normal and abnormal sounds. Multi SVM with NR-PSD curve as a feed is also a technique as used by [9]. They capture morphological characteristics of the power spectral density characteristics in frequency domain and use Fmax and Fwidth as features. As an intermediate step they use SVM to identify the cardiac sounds. For disease verification and discrimination between the murmurs, a multi-SVM module was generated consisting of 6 SVM modules. They used the accuracies of all the SVM modules to decide about the abnormality and classification among six heart disorders. Few reserchers [10], [11] aimed on the murmur classification to isolate the innocent murmurs from that of the organic murmurs. Statistical properties of data incorporated with A- prior knowledge is a technique use by [11] while basing on spectral analysis. Wen Chung kao et.al. [12] in their setup used STFT to extract the signal characteristics in which Fourier coefficients are calculated in an overlapping window. These coefficients represent time-varying frequency characteristics and thus can be used in 2-D space. For classification purpose they made use of SVM with adaptive feature selection and claimed successful results. Wavelet transforms and modular neural network architecture for supervised learning is another choice to classify the EEG signal as used by [13].

2.2 Segmentation Tasks

Wen Chung kao et.al. [12] in their paper presented a complete setup for computer analysis from segmentation to classification. They include auto correction for predicting the cycle time of a heart beat and made use of STFT, the discrete cosine transform, and adaptive feature selection techniques for a final feature set. As a 1st step of their recognition cycle they predicted the cycle duration of a heart beat through auto correlation. Ali Moukadem et al [15] discussed, S-transform based segmentation of heart sounds. They propped a segmentation model with three main blocks basing on the characteristics of S1, S2 peaks and their locations. For distinguishing the S1 and S2 sound they used a feature extraction technique basing on the singular value decomposition of the S-matrix from S-Transform. To detect the boundaries of S1 and S2 sounds, a window width optimization algorithm is employed for the energy concentrations of the localized heart sounds. They tried to maximize the distance between the heart sounds and back ground noise. Which is further thresholded and peak is detected.

Tunable wavelet transform as used by [15] is another technique used for segmentation. Decomposition and reconstruction of Heart sound using TQWT removes murmurs from cardiac sound signals if constrained suitably. The motivation behind this was to reconstruct a murmur free cardiac sound signal from which an envelope based on CSCW is be extracted after removing low energy components. Once envelop is extracted, then its locations are used to map the locations of S1 and S2 in actual HS. TQWT is a flexible form of discrete wavelet transform and is effective in analysis of oscillatory signals. Gupta et al [19] Presented an homographic filtering and K-means based method for segmentation of heart sounds as S1 systole S2 diastole parts. For segmentation process K-means clustering is applied on the gaps and basing on the smaller and larger gaps peaks are segmented. Stationary wavelet transform based technique [21] to segment the HS into S1 and S2 parts instead of using threshold methods is an alternate option. Heart sound segmentation basing on stationary WT are discussed by [22] in which boundaries of HS are located and noise and other artifacts are disposed off. Shannon energy is the selected technique to extract envelop, when calculated for the reconstructed parts. Features like averaged Shannon energy and Teager energy with amplitude and widths of pulses are selected.

2.3 Feature Extraction

Ishanka S. Perera et.al [7] in their classification method, after going through all the verification checks extracted the features which include, S1 and S2 boundary values, location of S1 and S2 peaks i.e. X, Y coordinates, intermediate gap values, RMs energy value. With this set of features wave shape of abnormalities were extracted and compared with already saved such shapes. Yuerong Chen et.al [10] used continuous wavelet transform instead of discreet wavelet. Output matrix of CWT is used for feature extraction after being processed with CVD and QR decomposition. Feature generation is achieved with Shannon entropy and Gini index. Finally suitable features are selected using sequential forward floating selection algorithm to achieve the maximum average accuracy when classified as 10-fold cross validation using CART algorithm. Christer Ahlstrom et al [14] proposed a feature extraction method for classification of systolic heart murmurs. They employed a set of analysis techniques such as Shannon energy, wavelets, fractal dimensions and recurrence quantification analysis to extract 207 features from a phonocardiography signals. Out of these features, a multi-domain subset consisting of 14 features was derived with Pudil's sequential floating forward selection method. Feature integration framework as used by [18] selects best features from the different classification setups and output is a biometric system of unique heart sounds. They investigated many feature extraction methods but found linear frequency band cepstral coefficients and GMM super vector feature extraction methods to be the most promising methods. Gupta et al [19] Presented a homographic filtering and K-means based method for segmentation of heart sounds as S1 systole S2 diastole parts. Feature vector is extracted using dubieties -2 wavelet coefficients with decomposition level 2. Suboh et al [5] while discussing the effectiveness of improvised and standard MLP in hierarchical form, stated a feature generation technique using cross-correlation method. Heart sound segmentation basing on stationary WT are discussed by [22] in which boundaries of HS are located and noise and other artifacts are disposed off. Shannon energy is the selected technique to extract envelop, when calculated for the reconstructed parts. Features like averaged Shannon energy and Teager energy with amplitude and widths of pulses are selected.

2.4 Labeling of Peaks

Correct labeling of peaks as S1 and S2 is always an important phase of ant segmentation / classification method. Researchers always try to do it as accurate as possible. Christer Ahlstrom et al [14] while classification of systolic heart murmurs used ECG gating to correctly label S1 and S2 peaks. They used the knowledge that "S1 in certain time window is after R- wave and S2 is after T- peak of the ECG signal. Many researchers classify the peak as S1 and S2 basing on fact that systolic period is shorter than diastolic period. Ishanka S. Perera et.al [7] in their classification method, once found a sequence of continuous matches for both tall and short peaks they calculate the gaps between adjacent tall and short peak and classify the peak as S1 and S2 basing on fact mentioned above. Chen Jie and Hou Hailiang [16] employed a hamming windows for noise removal and filtering purpose. Once filtered, they use improved Hilbert hung transform to calculate the envelop of HS. Finally a double threshold method is applied to determine the time gap or width of peaks. Segmentation is achieved using the physiology of Heart sounds and the relationship time gaps between the peaks.

2.5 Envelope extraction

CSCW is one of the common techniques used by researchers to extract the envelope of Heart sounds as used by [15]. They had the motivation to reconstruct a murmur free cardiac sound signal from which an envelope based on CSCW is be extracted after removing low energy components. Chen Jie and Hou Hailiang [16] employed a hamming windows for noise removal and filtering purpose. Once filtered, they use improved Hilbert hung transform to calculate envelop of HS. Gupta et al [19] Presented a homographic filtering and K-means based method for segmentation of heart sounds as S1 systole S2 diastole parts. Homographic filtering is used to extract envelop for peaks detection. Heart sound segmentation basing on stationary WT are discussed by [22] in which boundaries of HS are located and noise and other artifacts are disposed off. Shannon energy is the selected technique to extract envelop, when calculated for the reconstructed parts. Features like averaged Shannon energy and Teager energy with amplitude and widths of pulses are selected.

2.6 Energy Signatures

Ishanka S. Perera et.al [7] in their classification method utilized RMS energy curve to enhance the visibility of S1 and S2 peaks. They used a technique called as tall peak / short peak identification which focus on charging the resolutions of the heart beat to finding an exact match. Yuerong Chen et.al [10] in their classification method used Shannon entropy and Gini index for feature generation. Christer Ahlstrom et al [16] proposed a feature extraction method for classification of systolic heart murmurs. They employed Shannon energy to extract the HS envelope and then marked the S1 and S2 with the help of a time window using an ECG gating. Ali Moukadem et al [15] in their segmentation method used S-transform to calculate the local spectrum of the healthy sounds, subsequently its Shannon energy is calculated.

2.7 Analysis Techniques

Yuerong Chen et.al [10] while classifying murmur used continuous wavelet transform instead of discreet wavelet. Decomposition and reconstructions is a popular analysis technique. Like wavelets, SSA in its basic shape consists of decomposition and re-construction parts as used by [11]. They aimed and utilized the separatbility property of this method which describes how well different components can be separated from each other. Their approach is good and certainly provides an opening for future work. Ali Moukadem et al [15] in their segmentation method used S-transform to calculate the local spectrum of the healthy sounds, subsequently its Shannon energy is calculated. Chen Jie and Hou Hailiang [16] employed a hamming windows for noise removal and filtering purpose. A comparative study [20] for spectrogram, wavelet and winger distribution when used for the analysis of phonocardiogram signals Spectrogram and STFT failed to detect the internal components of S1 and S2. Likewise winger distribution is also exposed. WT and FT can detect them but FT gives no information on time gap between them.

2.8 k-means Clustering

Clustering is very effective and flexible method which can be used in multiple ways. Gupta et al [19] Presented a homographic filtering and K-means based method for segmentation of heart sounds as S1 systole S2 diastole parts. Homographic filtering is used to extract envelop for peaks detection. Extra peaks removed and a conditioned signal is used to calculate the gaps between the peaks. K-means clustering is used to identify a single cardiac cycles. For segmentation process K-means clustering is applied on the gaps and basing on the smaller and larger gaps peaks are segmented.

CHAPTER III: Classifying Heart Sounds Challenge

3.1 Motivation

As already mentioned cardiac vascular diseases are the leading cause of death in the world. According to the statistic of world health organization for the year 2004 CVDs caused 17.1 million people to die which is around 29% of the total deaths in that year. To a further break down around 7.2 million people among them died due to coronary heart disease. Thus any system which can reduce or help to reduce this ratio either directly detecting the signs of heart disease or help to do so, would be of great value leaving significant impacts on the health of world globally. ***Classifying Heart Sounds Challenge*** as sponsored by ***PASCAL*** was organized to produce a method which can do exactly the same. To be more specific it targeted the option of 1st level of screening of cardiac pathologies either in a hospital by a doctor using a digital stethoscope or by the patient itself in home using a mobile device. Technically speaking ***Classifying Heart Sounds Challenge*** problem is a typical problem of machine learning which invites the researchers for a classification task of sound signal where distinguishing between classes of interest is non-trial. Data sets for the challenge is generated in the real world environments thus have extensive amount of noise from radio signals to traffic sounds. Symptoms of heart are closely resemble to each other and thus are extremely difficult to separate. Success in classifying such subtle and challenging sounds requires the classifiers which are extremely robust. [1] [31] [32]

A progressing country like Pakistan significantly lags such facilities which can be employed as initial screening or diagnosis aids. These facilities even do not exist in major hospitals like AFIC, PIC etc. Auscultation of heart sounds is very effective, efficient and precise if properly incorporated. With computer aided setup can be used as a continuous monitoring tool or as a helping aid in 1st aid centers, or even in the wards for general medical officer in addition to assist the cardiologist. This area is under extensive development in progressive countries as a smart application of either computer or iPhone. For better results detection of peaks and correct labeling of sounds is extremely important and plays a vital role in further diagnosis. Though this is very significant area of medical science, yet it is somewhat unexplored application of machine learning. ***Classifying Heart Sounds Challenge*** is not only an effort in this context but a reference for undertaking any future tasks using the challenge datasets. ***Classifying Heart Sounds Challenge*** can be discussed as under.

3.2 Task Overview

Classifying Heart Sounds Challenge was distributed in two sub parts named as segmentation and classification challenge. Details of both the challenges are discussed in subsequent sections. Data files for this challenge were gathered from two sources with following characteristics: -

- Using iStethoscope as a pro iPhone application, sound files collected form general public is contained in a dataset named as "Dataset A"

- Using digital stethoscope Digiscope, sound files are collected from a clinic trial in hospitals are contained in a dataset named as "Dataset B".

3.2.1 HS Segmentation, (Challenge – 1)

Segmentation challenge was to be performed on the data files from normal category, and it has to produce a method that can identify and mark the S1 and S2 sound components within the given data files. Both the datasets A and B contains Normal category files. Some of the sound files with exact location of S1 and S2 were provided by the organizers for learning purpose of the designed method. Testing of the procedure has to be carried out on unlabelled category. The results are to be in the lines with the pattern provided by the organizers. Segmentation challenge aimed to produce a method which can give the locations of sound components of heart sounds in which number of audio samples to be used as measuring units. Any deviation from the exact locations would be marked as error and thus needed to be minimized. [1]

3.2.2 Heart Sound Classification (Challenge – 2)

Aim of this part is to produce a method which can carry out beat classification of real heart sound to detect any illness of heart valves. For this part both the datasets are given with different classes of disease to be identified. For dataset A, four categories were to be classified named as:-

- Normal Heart Sounds
- Heart Sound with Murmurs
- Heart Sound containing an Extra Heart Sound
- Heart Sounds with samples of Artifact

For data set B, there are three classes named as:-

- Normal Heart Sounds
- Heart Sound with Murmurs
- Heart Sound containing an Extra Systole

Both the challenges were two be dealt as an independent challenge and were open to world for participation either in both or any of the one. Segmentation task is considered relatively difficult and any method which successfully addressed the segmentation part would easily solve the classification part. Any method able to segment and/or classify the given sets of unlabelled data in both categories (Dataset A and Dataset B) with better results than the others would be the winner. To test the efficiency and results an evalution sheet was provided by the organizers with certain calculating parameters [1]. Details of this evaluation sheet are discussed in next part.

3.2.3 Evaluation Scripts

Full details of evaluation scripts along with the metrics and the testing procedures used to measure the effectiveness of the methods were provided.

Evaluation Measures Challenge – 1

Testing procedure for this challenge is the deviation from the actual location of HS and is measured with an error calculated with Equation 1.

$$\delta_k = \frac{\sum_{i=1}^{\frac{Nt}{2}} (|RS1_i - TS1_i|) + (|RS2_i - TS2_i|)}{N_k}$$

$$\delta = \sum_{k=1}^{i} \delta_k$$

Equation 1

Where ∂k means the average distance of the "k-th" sound clip in a dataset. ∂ is the total error; Nk is the total number of S1 and S2 in the k-th sound clip; RS1i(RS2i) indicates the real location of S1(S2) of the i-th heat beat and TS1i(TS2i) indicates the calculated location of S1(S2) of the i-th heat beat. j is the total of all the sound clips in the specific dataset. Few fields from the locked evaluation excel sheet are given in Table 2. These values are deviations of detected peaks from actual locations for calculating error as given in Table 3

Table 2: Fields from the evaluation sheet, showing the calculated positions of S1 & S2

Sound Files	S1	S2	S1	S2	S1
201101070538.aif	2200	11880	38720	50160	79200
201101151127.aif	1320	14520	36960	84040	97240
201102081152.aif		9240	43560	51480	60720
201102201230.aif	25520	39600	73480	87560	120560
201102270940.aif	18480	32120	61160	74360	101640
201103101140.aif	18040	31240	58520	70400	96800
201103140135.aif	16720	30800	55880	69080	92840
201103170121.aif		9240	14520	18040	20240
201104122156.aif	6160	13640	38720	63360	88880
201106151236.aif	20680	34760	66880	86240	99440

Table 3: Calculated Error using the evaluation sheet

Name of sound file	No of Heartbeat	Average Error
201101070538.aif	11.5	44151.87
201101151127.aif	7.5	151423.4
201102081152.aif	11	206686.8
201102201230.aif	11.5	50411.3
201102270940.aif	10	193358.1
201103101140.aif	10.5	37371.43
201103140135.aif	9	10770.89
201103170121.aif	10.5	71852.05
201104122156.aif	11	215902.2
201106151236.aif	10	30834.5
Total Error		**1012762**

Evaluation Measures Challenge – 2

To calculate the effectiveness of classification method, three metrics were to be calculated from the *tp, fp, tn* and *fn* values. For Dataset A we required to calculate:

- Precision
- Youden's Index
- F-score

For Dataset B, we required to calculate:

- Precision
- Youden's Index
- Discriminant Power

Precision. It provides us with the positive predictive value i.e the proportion of samples that belong in category $\boldsymbol{c}$ that are correctly placed in category $\boldsymbol{c}$.

$$\boldsymbol{precision = \frac{tp}{tp + fp}} \quad \textbf{Equation 2}$$

Youden's Index has traditionally been used to compare diagnostic abilities of two tests, by evaluating the algorithm's ability to avoid failure. In Dataset A, we are to evaluate the Youden's Index of the Artifact category. In Dataset B we have to calculate the Youden's Index of problematic heartbeats (Murmur and Extra systole categories combined). Mathematical expression for calculating Youden's index is given in Equation 3

$$\boldsymbol{\gamma = sensitivity - (1 - specificity)} \quad \textbf{Equation 3}$$

where sensitivity $= \frac{\text{tp}}{\text{tp+fn}}$ and $specificity = \frac{tn}{fp+tn}$

F-score (Dataset A only): The F-score is evenly balanced when $\boldsymbol{\beta = 1}$. This metric favors precision when $\boldsymbol{\beta} > 1$ and specificity otherwise. I use $\boldsymbol{\beta = 0.9}$ and evaluate the F-score of problematic heartbeats in Dataset A (Murmur and Extra Heart Sound categories combined) using Equation 4

$$F = \frac{(\beta^2 + 1) * precision * sensitivity}{\beta^2 * precision + sensitvity} \quad \textbf{Equation 4}$$

Discriminant Power (Dataset B only) evaluates how well an algorithm distinguishes between positive and negative examples. The algorithm is a poor discriminant if DP < 1, limited if DP < 2, fair if DP < 3, and good in other cases. Here I calculate the Discriminant power of problematic heartbeats (Murmur and Extra systole categories combined) using Equation 5

$$DP = \frac{\sqrt{3}}{\pi}(\log X + \log Y) \quad \textbf{Equation 5}$$

where X = sensitivity / (1-sensitivity), and Y = specificity / (1-specificity)

CHAPTER IV: METHODOLOGY

As discussed in the chapter III, I have used the datasets of ***Classifying Heart Sounds Challenge*** thus my methods must follow the templates given by the organizers for training, testing and results verification. ***Classifying Heart Sounds Challenge*** focused on segmentation and classification task as separate challenges and so I did for results verifications. In this chapter I shall describe my methodology for correctly detection, segmentation and identification of S1 and S2 sounds and classification of HS illness. Details of my approach along with a novel technique for feature vector generation are also discussed in length. A systematic flow of approach is given in figure below.

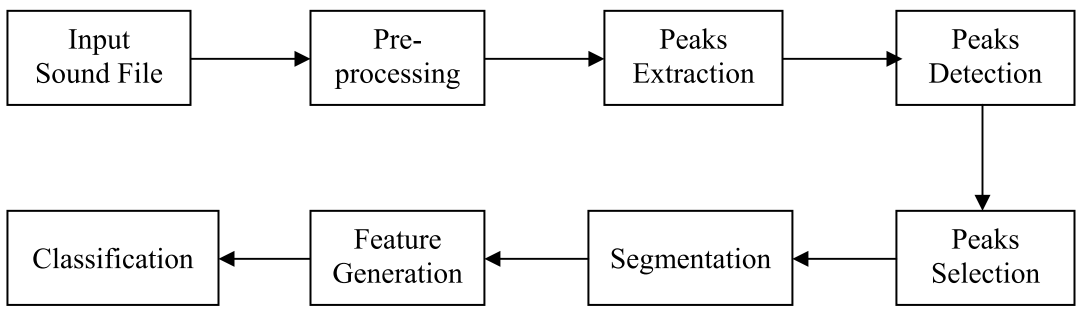

Figure 3: Systematic and sequential flow of methodology used in this research

As dictated by the organizers of ***Classifying Heart Sounds Challenge***, datasets used for this research were recorded in different environment with different characteristics and sampled at different rate, thus required robust algorithms to handle it. My methodology handles all these issues with significant improved results [32] [31]. A detail of each process and sub process used in the implementation is discussed as a separate section below.

4.1 Preprocessing

As discussed earlier datasets are recorded in actual environments with digital stethoscope during a clinical trial in hospitals labeled as “Dataset B” and with iStehthoscope pro-iPhone application in the field from general public labeled as “Dataset A”. Both of these datasets include considerable amount of environment, traffic, sensor rubbing against body or any considerable medium noise, thus has to be pre-processed. Preprocessing is achieved in two steps called as decimation and filtering steps.

4.1.1 Decimation

Dataset A which is recorded using iStehthoscope as a pro-iPhone application is sampled at 44,100 Hz and dataset B, recorded using digital stethoscope is sampled at 4,000 Hz. Maximum valuable information pertaining to the health of heart sound is contained within 800 Hz of band and thus minimum sampling rate required to retain all information should sampled minimum at 1.6 kHz. Down sampling of both datasets is achieved with this threshold in mind.

Decimation of Dataset A:- Dataset A is sampled at 44.1 kHz and has to be decimated by a factor of 20 so that a signal at 2.2 kHz can be achieved for further processing [23]. I used MATLAB's built in decimation function in two steps. In 1st step, decimation with a factor of 5 is achieved and in 2nd step a further decimation with a factor of 4 is achieved. As per instructions of decimate function, for better results when factor is greater than 13 it should be broken up into factors and call decimate several times. By default decimate function resample data at lower rate after low-pass filtering with a Chebyshev type 1 low pass filter with cutoff frequency to be calculated as 0.8 *(FS/2)/R. Here R is the decimation factor used to down sample the data.

Decimation of Dataset B: - Dataset B is sampled at 4 kHz and is decimated by a factor of 2 to get a signal at 2 kHz which is around the frequency required for further processing.

4.1.2 Filtering

Sound files being recorded in real world environments have significant amount of noises and must be filtered to have the information being clear of every contamination. Once decimated, the signal is filtered with a Chebyshev band pass type 1 filter of order 8 [23]. First band pass / lower limit frequency of the filter is Set at 100 Hz and second pass band

/ higher limit frequency at 882 Hz with pass band ripple at 1 db. These limits effectively cover the range of required frequency band. For dataset a sampling frequency is 2205 Hz whereas for dataset B it is set at 2000 Hz. This filtering effectively removes all the noise contents and thus a clear signal is available for further analysis.

4.1.3 Normalization

As the HS were varied extensively in nature therefore has to be normalized. Once down sampled and filtered, signal is normalized to absolute maximum value of the signal using the following equation [23]. There were certain other options available for normalization but preferred to use the maximum absolute value so that no information is suppressed.

4.2 Envelope Extraction and Peaks Detection

There is a wide range of techniques available to analyses the pre-processed signal in time and frequency domains [5] [6] [24] [25] [26]. If we critically analyses the characteristics of heart sounds in time and frequency domain, we found a lot of distinct nature in both time and frequency domain however time domain offers somewhat more distinct nature of parameters ideal for analysis. I selected time domain characteristics for further analysis of heart sounds. Peaks Extraction section can be further divided in to subsections. Details of these sections are discussed in succeeding paragraphs.

4.2.1 Energy Signatures

Peaks extraction / detection process starts with as envelop extraction to get the peaks (S1 and S2) of the heart sounds. There is several possible ways which offer envelope extraction from the input heart sound few of them are: -

- Envelogram [23] [19] [27]
- Wavelet decomposition and reconstruction [5] [30]
- AR Modeling
- Envelogram estimation using Hilbert transform. [27] [17]

From the above mentioned techniques I used envelogram using Shannon energy method [23]. Shannon energy is used to calculate the envelop values. Other candidates are Shannon entropy, absolute energy values and square energy values. A comparison of all these methods is given below in Figure 4 [23].

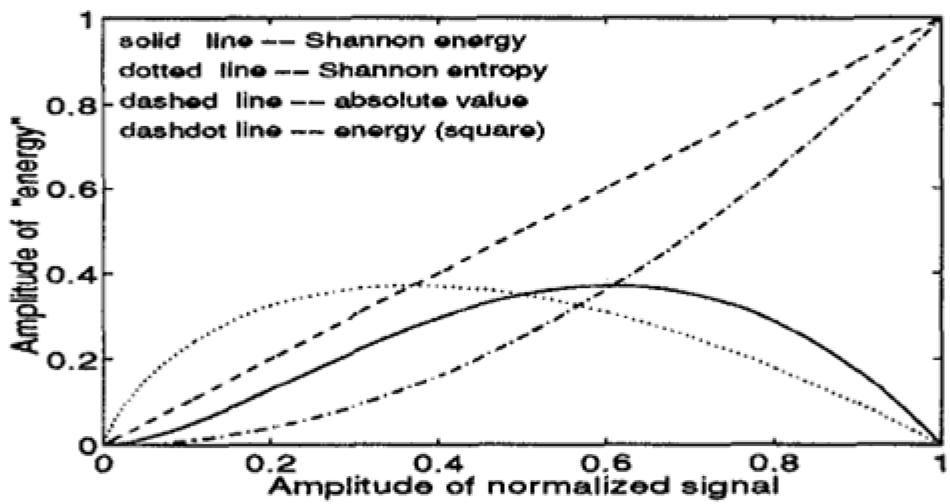

Figure 4: The comparison of different envelope methods

Shannon energy of the filtered, decimated and normalized heart sound is calculated in a continuous, sliding window of size 20 m sec (0.02 sec). Sliding step of window is 10 m sec thus giving an overlap of 10 m sec in each step. In each step energy of all samples under the window are calculated, summed and saved as a single sample (window energy value) for subsequent calculations. Mathematical equation of these energy calculations is given below in Equation 6.

$$E_S = -\frac{1}{N} + \sum_{i=1}^{\mathrm{N}} \mathrm{x}^2_{\mathrm{norm}}(\mathrm{i}) \,.\, \log \mathrm{x}^2_{\mathrm{norm}}(\mathrm{i})$$ **Equation 6**

By the physiology of Heart sounds, it is clear that any part of Heart sound (S1, S2) does not have a frequency which is not covered in the resolution of window. Thus there is no possibility that any useful information is missed during energy calculation. Frequency range of S1 is 10-200 Hz and that of S2 is 10-410 Hz, which are effectively falling in the range of this window/sliding step sequence. In order to achieve a valid value for each window location, sound values of all samples under window are averaged over the total samples in the entire signal. By running an iterative calculation the entire signal is passed through the window and a resultant matrix of energies is formed.

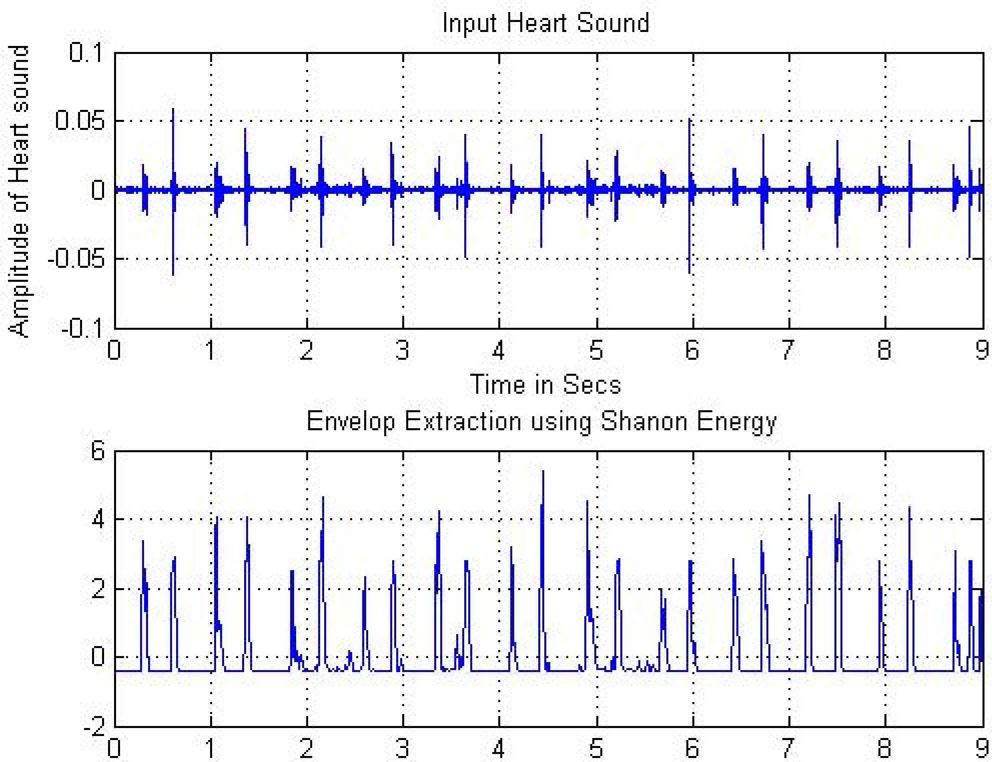

Figure 5 Envelope extraction results used Shannon energy for a normal heart sound

4.2.2 Peaks Detection

Once the entire signal is processed for energy calculation and calculated energies are stored as matrix, an envelope extraction technique is used to identify the peaks from the energy signatures. Envelop extraction is implemented on the normalized average energy values using a simple concept of finding local maxima and minima values. Outcome of this part would be that all the maxima points are marked as peaks and minima points as the depths. These detected maxima points are known as peaks and it has to undergo further selection rejection criteria to segregate the valid peaks and reject the invalid peaks. This subsequent procedure is discussed under peaks selection and segmentation sections respectively.

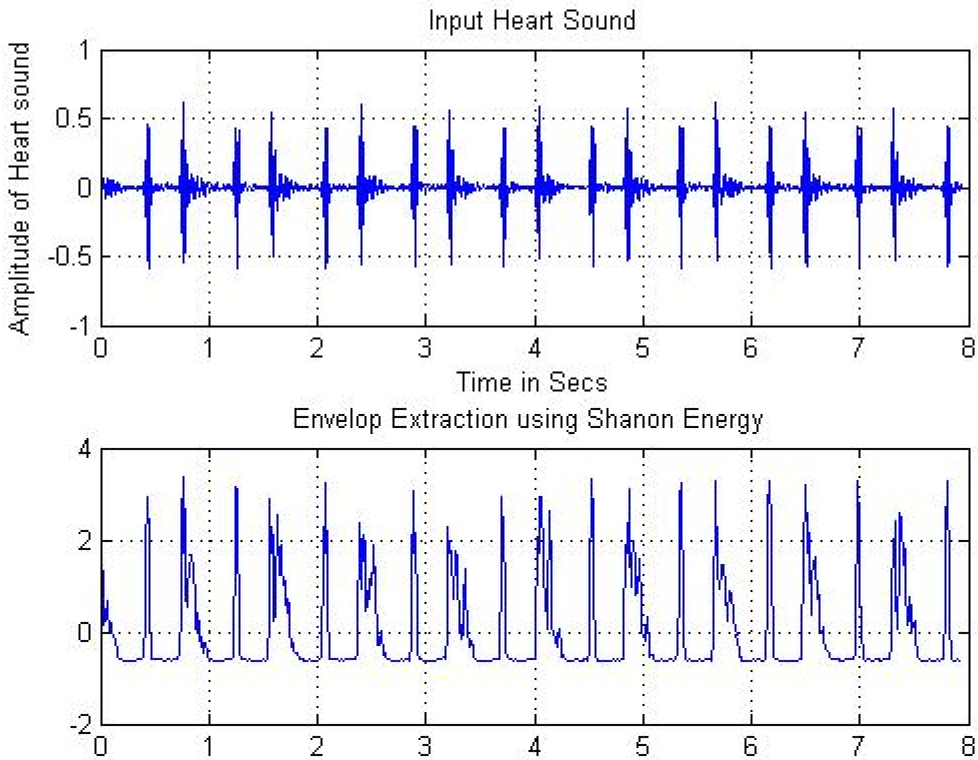

Figure 6: Envelope extraction using Shannon energy for a heart sound with MURMURs

4.3 Coarse Peaks Selection

Peaks detected in the previous section have to undergo few selection and rejection steps before it is being segmented. Due to noise, improper placement of recording medium or any other reason there may be some split in peaks, irregular in amplitude. These sound samples generally appear as peaks after being detected by the peaks detection process. These peaks may appear as adjacent peaks to the actual peak or may appear as a very low amplitude peak in the overall results. In order to address all such possibilities a peak selection algorithm is implemented in a series of sub steps as described in following algorithm.

Take detected sounds as input

Discard all the peaks which are with negative amplitude (Output-1)

Identify the pair of peaks within 50 ms from each other

Select one out of them basing on amplitude value

If 2^{nd} peak is larger by 30% value from 1^{st}

select it as valid

Otherwise

select 1^{st} peak as valid

Discard all the left out peaks and use the selected ones as output (Output-2)

Carry out amplitude thresholding using a flexible technique (Output-3)

Carry out selection rejection procedure for peaks not within 50 ms from each other (Output-4)

Verification run of the final selected peaks to address any missed or extra peak

Output the selected sequence for further processing

Figure 7: Algorithm for selection rejection criteria of detected heart sound peaks

Descriptive details for functioning of theses subparts / steps are given in following paragraphs which clearly highlight all the details and operations of each step.

4.3.1 Dealing Peaks with Negative Amplitude

After envelope extraction, peaks are detected using a local maxima and local mina comparison setup. All the maxima values which are apart from its neighbors by certain time gap are selected regardless of its magnitude. There is a possibility that few peaks with negative value may also be detected and marked as peaks. This section isolate all such possibilities by simply running a magnitude comparison with “0” amplitude value. This is going to be the 1^{st} step and all the peaks with amplitude below zero value are rejected. These peaks may appear due to noise contents left unfiltered and contributed in the formation of some peaks. MATLAB code to do so is appended below for reference.

```
L = length(Peaks_detected);
Peaks_value = (Peaks_detected(L+1 : 2*L))';
Peaks_loc = (Peaks_detected(1 : L))';
Indices = find(Peaks_value > 0 );
Peaks_loc = Peaks_loc(Indices);
Peaks_value = Peaks_value(Indices);
Peaks_detected  = [(Peaks_loc) (Peaks_value)];
```

Figure 8: MATLAB implementation of Step-1, "Discarding the peaks with negative amplitudes"

4.3.2 Dealing Adjacent Peaks with Gap < 50 ms

Physiology of heart sounds says that min gap between any two adjacent peaks cannot be less than 50 ms and for any such pair one is valid and other is its split part. Thus after selecting all valid peaks which are with positive amplitude undergoes a testing mechanism basing on time gap between them. Any two adjacent peaks occurring within 50 ms from each other are assumed to be the parts of a single heart sound and one peak is selected and the other one is rejected basing on the amplitude of both the peaks. Pseudo code to implement this algorithm is given in Figure 9.

4.3.3 Selection Basing on Amplitude Threshold

In practical life there could be instances where the signals may not be recorded properly or may be corrupted with noise. There could be few parts or the entire signal which have this type of characteristics. If the entire signal is not properly recorded its effect can easily be removed as the energy value are normalized but if few peaks are effected they may be considered as week or irrelevant ones and has to be sorted out. Peaks with small amplitudes can be easily removed by comparing with some threshold on amplitude. This amplitude threshold has to be very carefully selected, as higher amplitude threshold may cause to lose some valid peaks where as too low threshold may result in selection of some unwanted peaks and thus overloading the subsequent verification process as shown in Figure 10.

```
Get peaks selected after step-1 as input
          Find the no of peaks
          loop on no of peaks
          begin
                    if gap between two adjacent peaks < 50 ms
                              check the amplitudes ratio of both peaks 1st /2nd
                              if  ratio > 30%
                                        discard 1st peak
                              else
                                        discard 2nd peaks
                    else
                              go to next iteration
          end

Save the selected peaks
```

Figure 9: Pseudo code for operational functionality of step-2 implemented to select / rejects the peaks which are 50 ms from each other

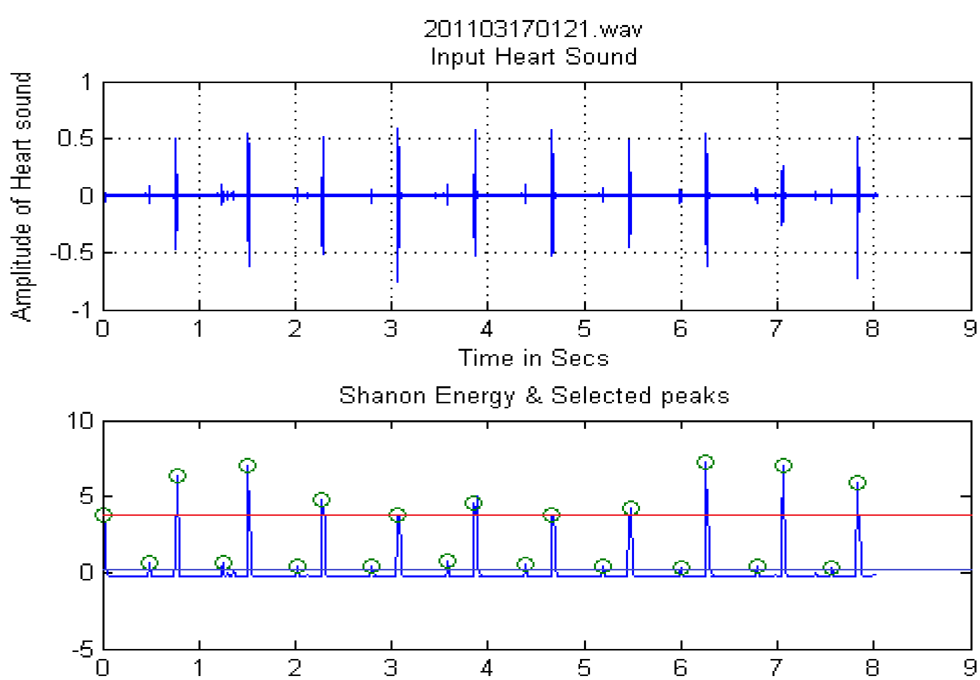

Figure 10: Effect of thresholds on selection and rejection of peaks

I use a technique which is quite simple, effective and flexible to tune itself with the input sound signals. Sequential flow / steps involved in this selection are as given in Figure 10 as a flow chart.

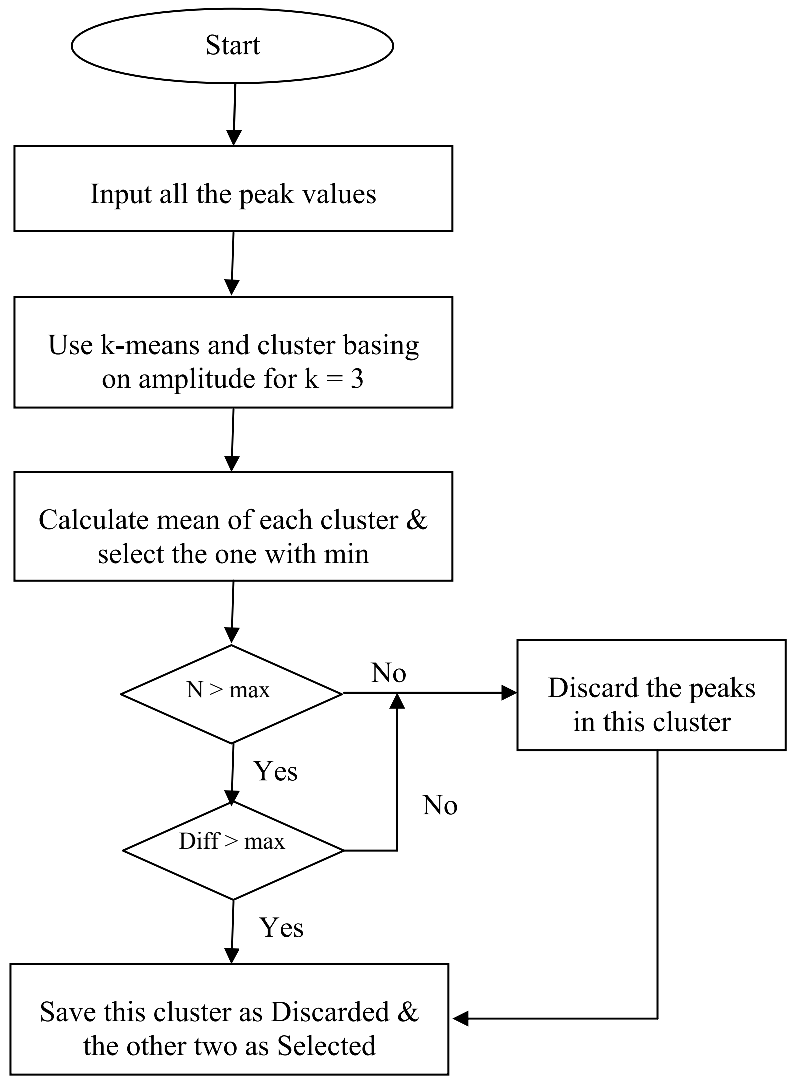

Figure 11: Flow chart to implement the process based on amplitude threshold

4.4 *Fine Peaks Selection*

In the previous section peaks selection was made for those peaks which are either very low in amplitude, distorted due to noise and all those which are split due to any reason. In this section all those peaks which are at a distance greater than 50 ms from each other will be tested for selection and rejection purpose. Physiology says that the gaps between the peaks should be consistent for systolic and diastole periods. Basing on this parameter all the gaps are checked for consistency with reference to its neighbor intervals and a merger between the gaps by discarding a peak or interpolation from the previously discarded peaks is achieved.

For this selection / rejection check, an algorithm is implementation which will check the intermediate gaps and identify the fact whether the peak is valid or not. To start with this part, a reference gap is generated and every other gap is compared with this reference gap. Decision is made and reference gap is updated for next peak in queue. Two very important factors which will directly affect the efficiency and correctness of the procedure are selection of reference gap and start point from where this verification step has to start. A wrong start point or incorrect reference gap in the beginning means that the entire subsequent process is going to be wrongly accessed. I have opted for a much effective and simple procedure for this part which is based on clustering the gaps between the peaks. The entire process is sub divided in following steps:-

- Calculate the gaps between all the peaks
- Cluster the gaps using k-means with k =3
- Use each cluster values (gaps) and run the start point candidate test, as given in next section, whose output will be a group of 3 alternate peaks passing the test according to algorithm given in Figure 12
- From the available start point candidates (a group of 3 peaks), select the best one basing on the standard deviation of each group

- Use the intermediate 2 gaps to construct a group of 5 gaps. Select its central member (gap) as a start point for verification run.

- Use the gaps of the selected group as the valid reference gaps and keep on updating the reference gaps using running average mechanism.

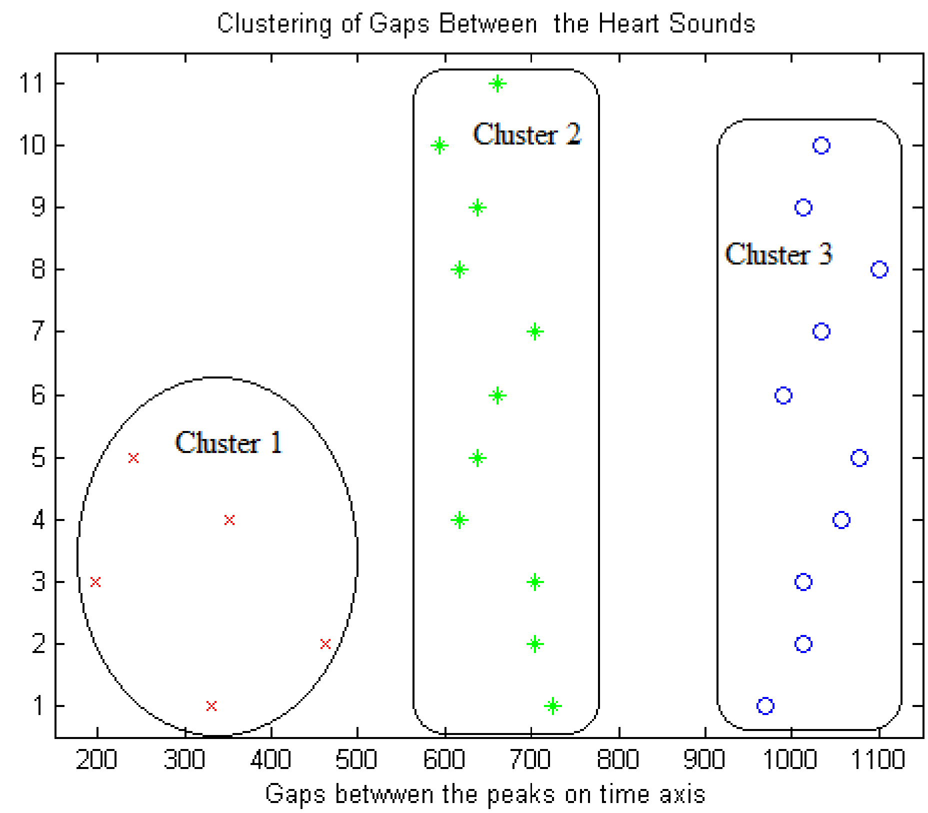

Figure 12: Clustering basing on the gaps between the peaks for start point selection

Once the start point is identified and valid reference gaps are marked following selection rejection procedure as given in Figure 13 is run twice for each sound file, initially from start point towards end and finally from start point towards beginning.

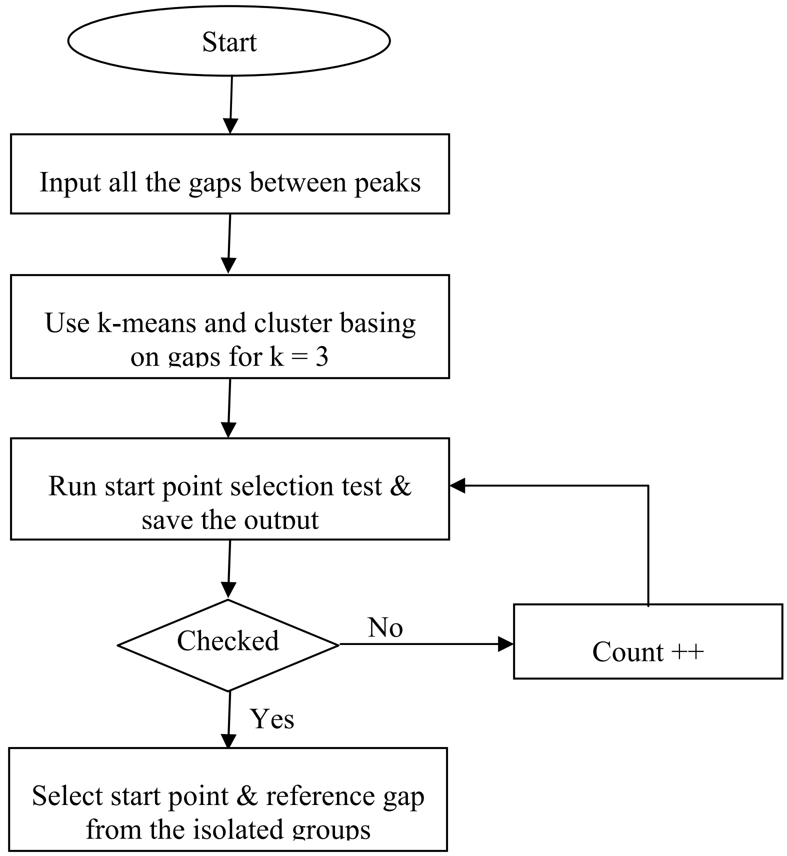

Figure 13: Flow chart for the internal operation of the fine selection criteria

4.4.1 Start Point Selection

This is the most crucial and critical part of this chunk of code. Being the launching pad of entire verification process this part is very significant. Effectiveness of k-mean clustering is used to implement this part. After successfully running the k-means we had three clusters mainly having the gaps closely related with each other. Physiological knowledge of heart sound says that gaps against all systole periods would be of almost same size and that of diastole would be of same size. Furthermore both of these type would differ from each other in their gap lengths. This means that our clusters would form in such a way that one cluster would have all the valid gaps for one type and 2nd cluster would have the gaps of other type. Outliers or irrelevant gaps would be in 3rd cluster. Output of these clusters is used one by one as an input to this algorithm. Basing on its input this part will find 3x consecutive alternate peaks. All possible instances of such occurrences are recorded and saved for further processing. The aim behind this segregation is that if we found 3 valid alternate peaks, surely there will be two valid peaks within them. This makes a group of 5x valid peaks. All such groups once found we may select the best one with maximum co-relation with each other. A sequential flow of this part is given in flow graph below as Figure 14.

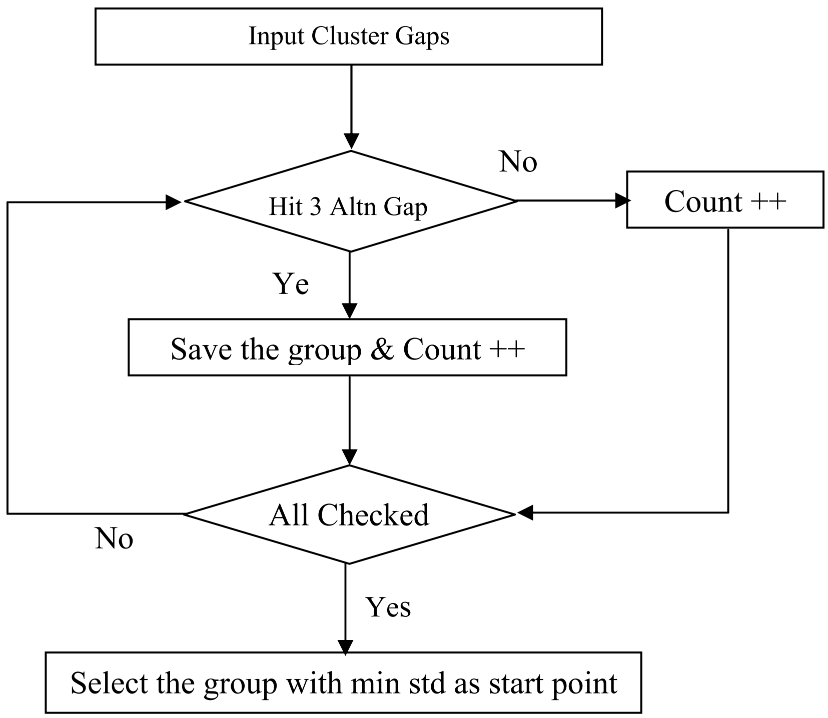

Figure 14: Start point selection criteria from the cluster values

4.4.2 Selection/Rejection Basing on Start Point

This part is further distributed in two subparts for those peaks which does not meet the selection criteria and has to be either rejected or some interpolation is needed. Task performed by these subparts are narrated below

- Merging of two adjacent peaks if the gaps between them are less than that of its alternate neighbors.

- An interpolation of additional peak is need if the gap between the two peaks is much larger than that of its alternate neighbors.

During the merging part it rechecks the gap achieved after merging and re-verifies it for validity. If it qualify the test, this merging task remained intact otherwise a reversal is taken. Similarly for interpolation part it checks the peaks already discarded during the threshold part and fits it if it qualifies the test. This part also ensures that no peaks are rejected wrongly on the bases of threshold. Both of these blocks are given below as a separate flow graphs in Figure 15 and 16. In case of interpolation it is run multiple times and continues till no further interpolation is required. No missing peak is interpolated virtually as missing peak can be an indication of heart value sickness which has to be identified and marked accordingly.

4.4.3 Confirmation Run

After finalization the peak selection steps, a final confirmation run is mandatory to identify and remove any wrongly missed or interpolated peaks. This confirmation test is very similar to the verification steps explained earlier except few differences. For this confirmation run start point is selected in a different way. This time all the consecutive available peaks are compared with that of selected in step-2 (***Dealing Adjacent Peaks with Gap < 50 ms***) and a patch with maximum length is selected for start point and reference gap generation. After the availability of start point and reference gaps, all discarded peaks are also used additionally as an input along with the selected peaks. This time the algorithm looks for all gaps including and excluding the discarded peaks and finalizes the selection process. Final output of this part is considered and used as sequence of all valid selected peaks and are ready to undergo segmentation phase.

Output for this part is plotted in Figure 17, in which selected peaks are marked with small circles for two different sound files, one with normal input and other with murmurs in it. Detected peaks show the effectiveness of adopted algorithm.

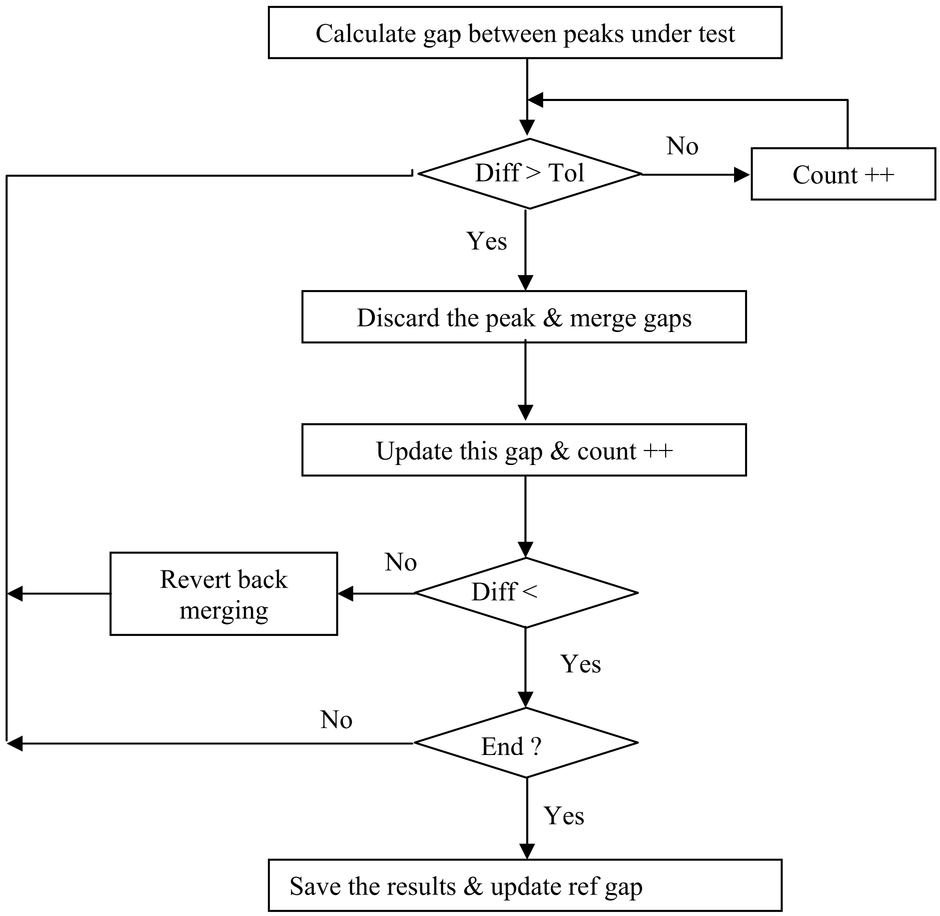

Figure 15: Flow graph for implementation part used for merging of peaks

4.5 Segmentation

Once all the peaks have been selected they can be segmented to get the desired results. Segmentation part is implemented with two sub parts.

- Labeling is process in which all the peaks are identified as S1 or S2
- Location identification is the process in which location of all peaks has to be determined.

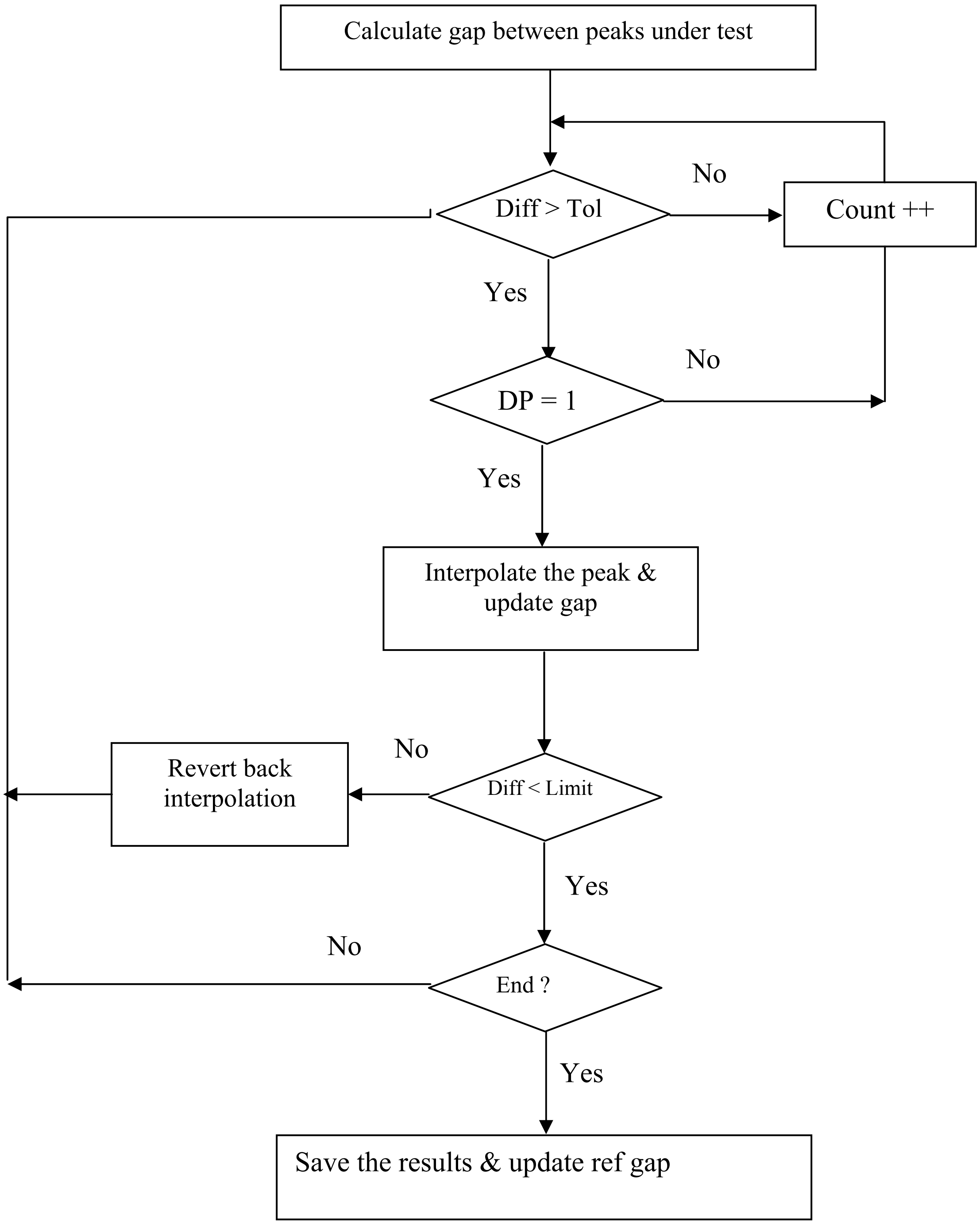

Figure 16: Flow graph for implementation part used for interpolation of peaks

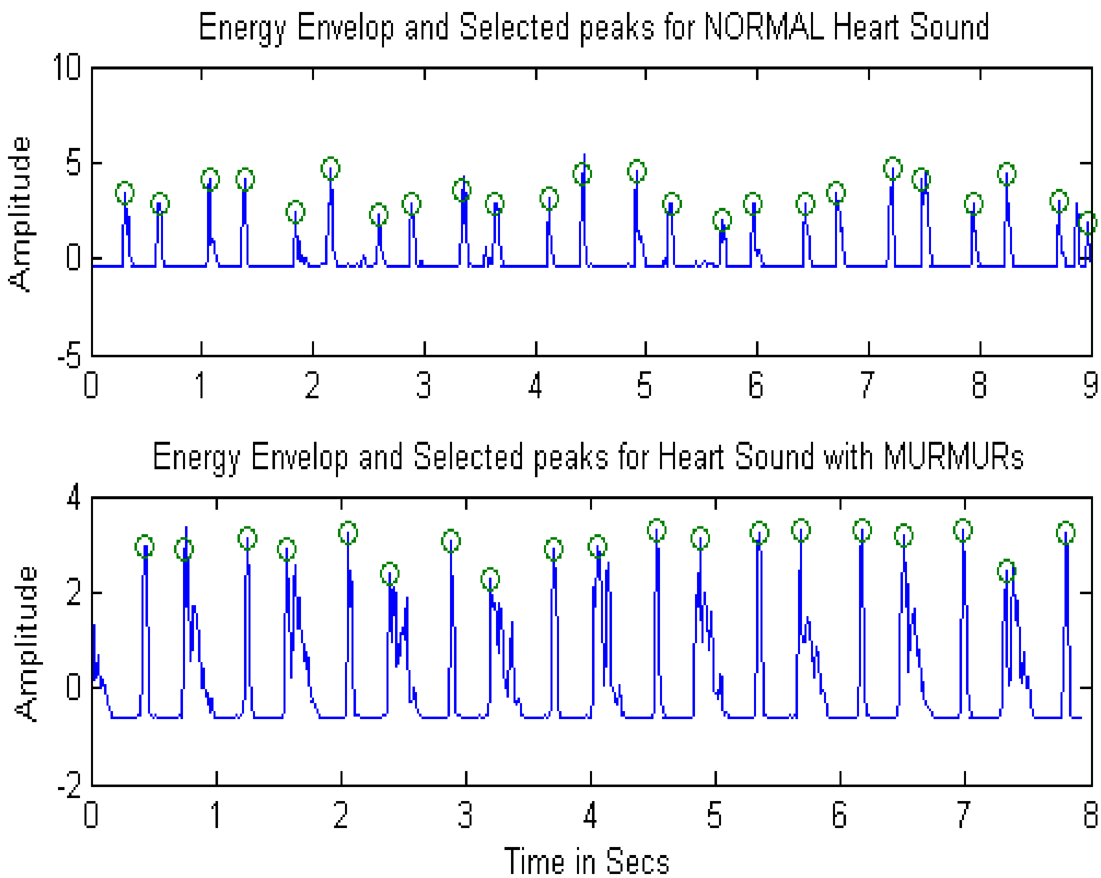

Figure 17: Plot of output file after successful segmentation and selection steps

4.5.1 Labeling

All selected peaks have to be labeled correctly as S1 and S2. Physiology of Heart sounds offers distinct features on time axis which clearly distinguish S1 and S2 peaks from each other and that is "diastole period is larger than systole period". But this feature is not always a unanimous choice to label peaks as S1 and S2 as the gaps between the peaks keep on charging with pulse rate. A very common practice in this regard is based on the fact that diastole gap is larger than systole gap. Researches select the longest gap, mark it as diastole period and assign the peaks on its left as S1 and on right as S2. This could be misleading especially if due to some reason, you missed a peak and both the gaps are shown as combined gap. I used another effective method for this process. All the gaps are clustered in such a way that we get the odd and even gaps. Mean value of these gaps are calculated and used to decide about the systole and diastole periods the gaps with greater mean value is considered as the diastole periods and peak are marked as S1 and S2 accordingly. Most of the time researches use 1st peak either as S1 or S2 due to ineffectiveness of any robust technique which can resolve this issue, however my approach has not only resolved this issue but also has open a new era to consider upon. Once the peaks are correctly labeled the subsequent processing is extremely precise and correct.

4.5.2 Location Identification

Correctly labeled peaks will undergo the last segmentation step and that is to find the location of each peak on the time axis number of samples as its unit. We already had all the information related to interval gaps, boundary locations and only required to be managed in the way it's required for results compilation.

4.6 Features Extraction

Analysis of time and frequency domain offer many features which can be explored and critically analyzed for selection as feature set of classification part. Out of all such features, some offer very distinctive features which if correctly extracted can be very helpful in classification. Both of the domains through offer a good set of features yet they fail on certain extreme cases if used independently. If used together, they offer a very flexible solution with considerable improvements in results. I used a hybrid feature set for classification purpose. After correctly segmenting the peaks, I had a valid set of gaps between adjacent peaks which serves as a source for generation of feature set. Correct positions of each peak, gaps between each peak, labels of each peaks and peak boundaries are used as valuable information for selection of features. With the boundary location, I determine the pulse widths of each peak at a certain threshold value. Each cardiac cycle (S1----S2--------S1) can be broken down in four distinct parts named a S1 peak, Systole period, S2 peak and diastole period as given in Figure 18. I used these parts as three distinct feature candidates by using both peaks individually and combining the gaps together as one feature.

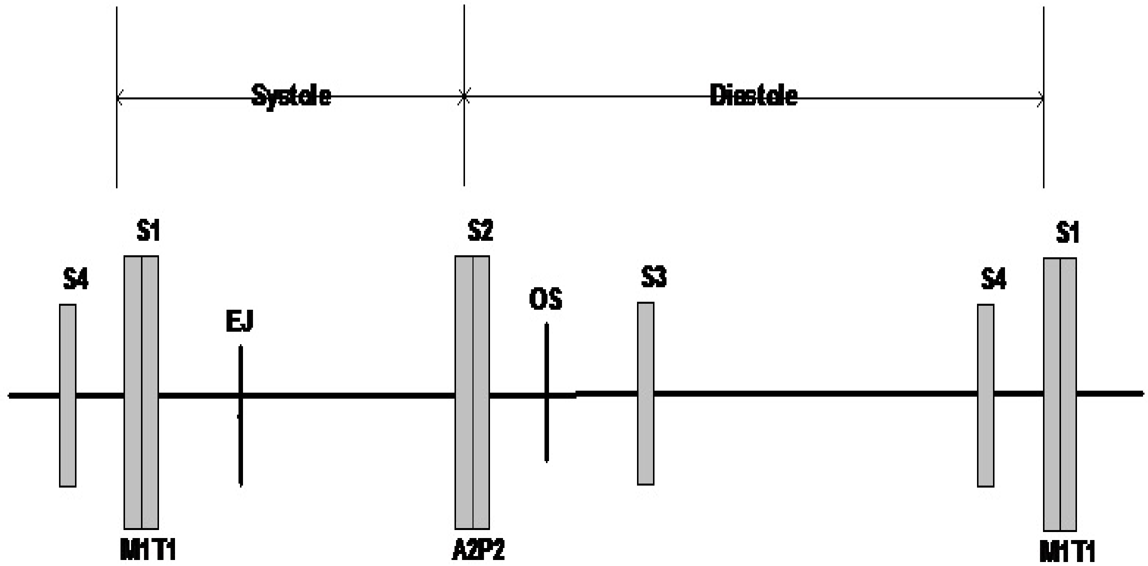

Figure 18: Parts of heart sounds used for feature extraction (Time domain) [2]

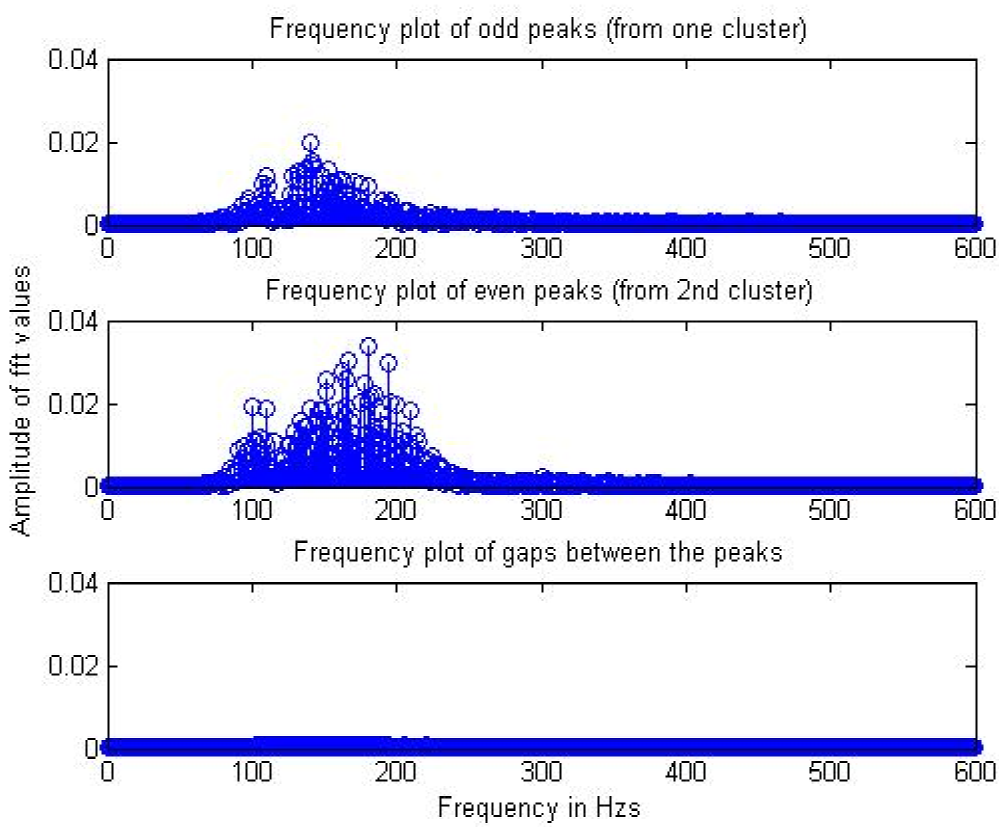

Figure 19: Frequency plot of even peaks, odd peaks and gaps between all these peaks of a "NORMAL" heart sound

Pulse widths are used to generate the features in frequency domain. Fourier transform of peaks, gaps between peaks are calculated for range of frequencies from 10-600 HZs and feature set is generated. Frequency response of a normal heart sound and a sound with murmurs are shown in Figure 19 and Figure 20 to highlight the uniqueness of both the peaks in frequency domain from each other and also from gaps. Any abnormality in heart valves will appear in the systole or diastole interval as clear in the figures, so this interval is included as a feature for classification purpose. Figure 19 and 20 indicates the differences in all these parts especially the appearance of murmurs.

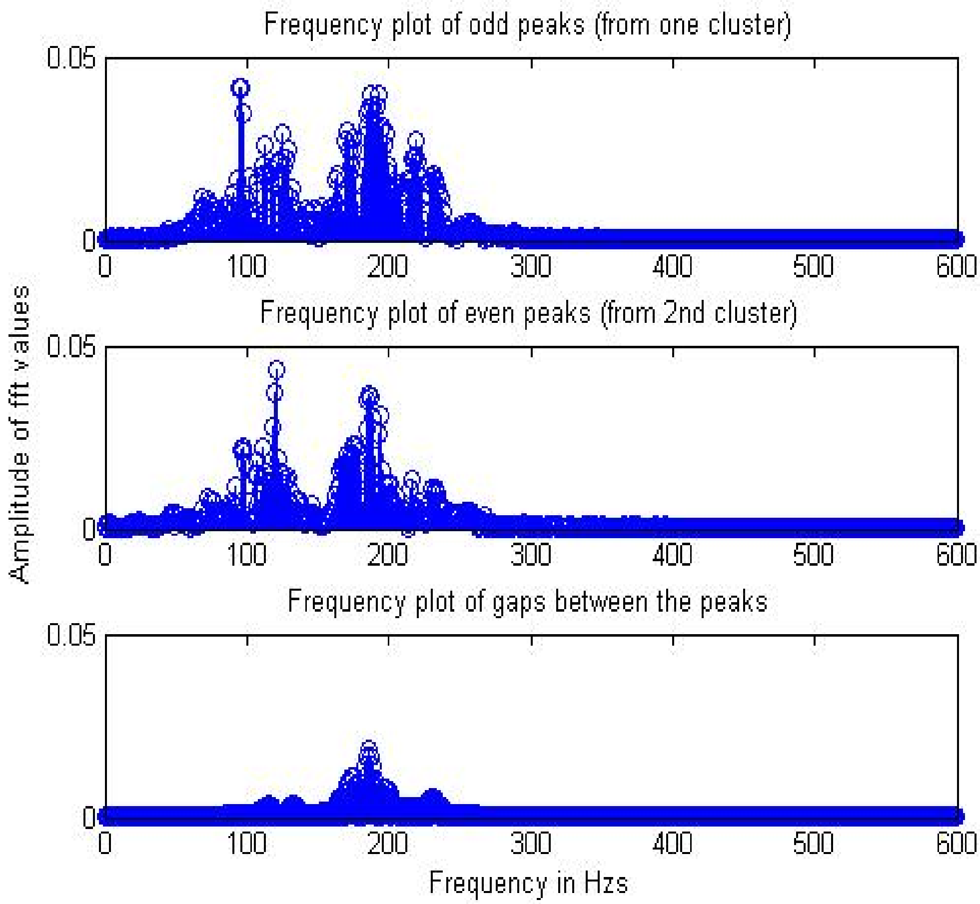

Figure 20: Frequency plot of even peaks, odd peaks and gaps between all these peaks of a heart sound with "MURMURs"

There could be many possible characteristics which can serve as features but the features I sleeted for the classification task are a mix of time and frequency domain. Summary of these features is given in table below: -

Table 4: Description of feature vector used for classification of heart sounds

Name	Description
RSO	stddev of odd gaps/stddev of all gaps
RSE	stddev of Even gaps/stddev of all gaps
RMO	mean of odd gaps/mean of all gaps
RME	mean of even gaps/mean of all gaps
Rmed	Median of max 3 gaps / mean of all gaps
RFO	FFT values of odd peaks / FFT values of total signal
RFE	FFT values of Even peaks / FFT values of total signal
RFG	FFT values of gaps / FFT values of total signal

Pulse widths in time domain though are district and have a potential to be used as feature set, yet it does not improve the results very much. I included the pulse widths in time domain at different thresholds but the results does not improve rather in some cases it degrade the results one of the possible reasons for this is that it changes very sharply with the change of pulse rate. Statistical features as evident from the table are very effective due to its steady response to the changes in input samples.

I have used a feature set of 14 features in which the frequency domain features are used in multiple ways. I divided the frequency band in 3 frequency bands as, from 0-200 Hz, from 200-400 Hz and bands 400-600 Hz. For each group of peaks (even and odd) fast Fourier transform of all these frequency bands are calculated and used to generate the features. Additionally one such set is generated for gaps (by combining both types i.e. from S1-S2 and S2-S1). Frequency response of gaps is an important part as any abnormality like murmur will always occurs in these gaps. This will give in total 9 features in frequency domain when calculated using its statistical values. Additionally another feature is added which is based on the energy values above certain threshold this feature is also useful as illness generally occur at low value peaks thus can be isolated with the help of this feature. Details of parameters used for generation of feature set are as under:-

- Ratio of Standard deviation of all the odd gaps (representing either systole or diastole interval) with standard deviation of all the gaps (both systole and diastole periods) is calculated and used as feature in time domain

- Ratio of Standard deviation of all the even gaps (representing either systole or diastole interval) with standard deviation of all the gaps (both systole and diastole periods) is calculated and used as feature in time domain

- Ratio of mean of all the odd gaps (representing either systole or diastole interval) with mean of all the gaps (both systole and diastole periods) is calculated and used as feature in time domain

- Ratio of mean of all the even gaps (representing either systole or diastole interval) with mean of all the gaps (both systole and diastole periods) is calculated and used as feature in time domain

- 3 Gaps with maximum length are determined and its median value is used as feature in time domain

- Ratio of frequency response (using ***fft)*** of all odd peaks (assuming it will either be S1 or S2 peak) with frequency response (using ***fft)*** of entire signal is used to generate 3 features in frequency domain

    - For frequency range from 10-200 Hz

    - For frequency range from 200-400 Hz

- For frequency range from 400-600 Hz

- Ratio of frequency response (using ***fft)*** of all even peaks (assuming it will either be S1 or S2 peak) with frequency response (using ***fft)*** of entire signal is used to generate 3 features in frequency domain
  - For frequency range from 10-200 Hz
  - For frequency range from 200-400 Hz
  - For frequency range from 400-600 Hz

- Ratio of frequency response (using ***fft)*** of all the gaps (assuming any illness will either occupy systole or diastole period and thus will be catered for) with frequency response (using ***fft)*** of entire signal is used to generate 3 features in frequency domain
  - For frequency range from 10-200 Hz
  - For frequency range from 200-400 Hz
  - For frequency range from 400-600 Hz

4.7 Classification

Basing on the feature vector constructed (consisting of temporal locations and frequency response), classification of the sound files is carried out. As already described in dataset section, classification task is run for 4 classes in dataset A and for 3 classes in dataset B. Heart sounds files were distributed in normal, murmur, artifact, and extra heart sound categories in dataset A, for dataset B the classes were categorized as normal, murmur and extra systole. If a strong feature set is used and feed to even an inefficient classifier it many produce good results, but a weak feature set even if feed to a very good classifier may not give very satisfied results. I have tried many classifiers and archived a satisfactory response from each one. As the heart sounds are of non stationary nature I used 2 classifiers for final classification tasks. The classifiers used for my classification task are JL48 and MLP. Both the classifiers gave a set of very encouraging results for datasets. Detailed results are mentioned in results section, however for a comparison it is worth mentioning that I have achieved a success rate which is better than all the participants of ***Classifying Heart Sounds Challenge*** and have not yet further improved upon by any other, researches by now. For classification task, I used the 10 fold cross valid action option of classier and used the generated confusion matrix and relevant details to compile the results. The results are compiled and formatted in the format was asked by the organizers of ***Classifying Heart Sounds Challenge***, for clear comparison and assessment of my results.

CHAPTER V: Data Sets

Datasets selected for any machine learning problem are very important as the efficiency of any method can only be tested with a good quality dataset. For a dataset to be of a very good quality, it must have the samples representing the actual environment. Prior the conduct of ***Classifying Heart Sounds Challenge***, there was no dataset which can be refer as standard. All the existing dataset for heart sounds were exclusively designed for some specific application. Organizers of ***Classifying Heart Sounds Challenge*** provided a standard dataset for the researchers of machine language work in the field of heart sound auscultations. Contrary to the other available datasets for HS analysis, challenge's datasets are of varying lengths thus are more like real one. Each file may be of 1 sec length min or it may be as long as of 30 s. Few sound files are provided after clipping to reduce any excessive noise and to provide the salient fragment of the sound. As the clinical knowledge of HS dictate maximum information is contained within the lower frequency parts of the HS. To be more specific we can say that filtering with a low pass filter at 195Hz will significantly have the desired information contained in Heart Sounds. The organizers also provided information about these basic physiological characteristics of HS and also highlighted the importance of FFT if applied. Basing on the useful information obtained from FFT of these HS related to volume and frequency over time, domain specific knowledge of different categories as provided by them is given below.

5.1 Normal Category

This category contains files which are healthy and normal in nature. There is the possibility of noise due to rubbing of sensor against the body while it is being removed. They may contain back ground noise like radios are traffic sounds. In addition to those random noises generated due to breathing, rubbing of microphone with body or cloths, may occasionally be part of this sounds. Physiology of HS says that a normal heart sound has a clear lub dub, lub dub pattern audible with stethoscope. More over mostly the time duration from lub to dub is less than dub to lub, provided that heart beat is less than 140 beats per minute. In the medical science this lub dub, lub dub, would be interpreted as S1

S2, S1S2. Excluding the outliers mostly we have the pulse rate between 60 pulse per minute to 100 pulse per minute. For this challenge we may have samples beyond these limits. While giving the description for normal category of dataset B they specifically warned that it may contain substantial amount of background noise.

5.2 Murmur Category

Murmur is the type of illness in the sounds which appear as if there is “whooshing, roaring, rumbling or turbulent fluid” noise in one of the temporal locations. It may be during systole period or it may be during diastole period. Physiology of heart sounds say that murmur can only occur between S1 to S2 or between S2 to S1 intervals but can’t suppress any of these sounds (S1 and S2). These are of many type some are innocent and some are serious. They appear in addition to lub, dub sound. Following figure shows a pictorial view where these murmurs are shown with asterisk* at the locations they may appears. Murmurs category of dataset B has noisy murmur data as well with background noise or distortion.

5.3 Extra heart Sound Category – Dataset -A

Extra heart sound may not be a disease itself but its appearance in heart sound may be a sign of disease. They may look like “lub lub dub” or “lub dub -dub”. Due to its apparent nature, they can be identified. Detection of this category is important as it may assist in diagnosing the disease. More over this is such type of symptom which cannot be detected by ultrasound. Any method which helps in detection of this category is of great deal for the health of human. Temporal description of these sounds can be considered as shown below with asterisk “*”.

lub……..dub…*******… lub……..dub…*******… lub……..dub…*******…lub

OR

lub…*******…dub…….. lub…*******…dub…….. lub…*******…dub…….. lub

5.4 Artifact Category Dataset -A

This is not a heart sound but can be assumed a sound which includes feedback squeals and echoes, speech, music and noise. This category may be thought of a one having wide range of different sounds. These are usually very less or no discernable heart sounds which mean temporal periodicity for such sound is either very low or will be at frequencies below 195 Hz. Due to this characteristic this sound is very different from other sounds The organizers has kept this deliberately to provide guidance to the staff recording and collecting this data that they may have to do it again. This is an important argument to support the correct detection of this sound as for the provision of any automated computer assisted setup this will ensure that sounds are recorded properly.

5.5 Extra systole Category Dataset- B

Extra systole sound may appear occasionally due to the out of rhythm action of heart. This out of rhythmic characteristic is an important feature which makes it very much detectable. Its appearance may be thought of as “lub-lub dub” or “lub dub-dub”. Though looks similar to extra heart sound category of data set “A”, but actually not the same as it is not rhythmic in nature and is not occur regularly. This sound may not be a sign of any disease itself and may happen normally in adults. It can be a common feature of children heart sounds. It cannot be ignored straight away as in some situation it can be caused by some of heart diseases. Its early detection may help in an effective treatment of disease. Temporal location for extra systole is given in figure below.

CHAPTER VI: RESULTS

Organizers of ***Classifying Heart Sounds Challenge*** provided an evaluation sheet for verification of results and accessing the efficiency of segmentation and classification algorithms. I have used the same evaluation sheet for a comparison.

6.1 Segmentation results

Target for the segmentation part was to correctly identify the peak locations on time axis and then label them correctly as S1 or S2. Difference between the correct position and the identified position is marked as error. More deviation from actual location means more error, similarly incorrect labeling will also count for an error. A validation set with correct locations of peaks has been made available for error calculation and procedure evaluation by the organizer of ***Classifying Heart Sounds Challenge***.

Table 5: Average error comparison for segmentation problem

Sound file	**Proppposed**	**Challenge Results**		
		Participant 1	**Participant 2**	**Participant 3**
201101070538.aif	15867	15324.8	41308.8	43380.56
201101151127.aif	170853.9	516698	166513.4	211373.76
201102081152.aif	156046.8	156064.2	179655.2	113710
201102201230.aif	17218.0	88952.8	17465.0	17118.69
201102270940.aif	199342.1	1445703.5	488124.4	1445798.5
201103101140.aif	36243.8	374151.6	53111.3	71534.77
201103140135.aif	25715.6	314072.2	63606.7	314214.6
201103170121.aif	64602.5	299314.2	2522.7	299207.54
201104122156.aif	196946.4	640841.8	186624.5	509360.4
201106151236.aif	43849.7	368613.5	44708.6	368680
Total Error	**926685.9**	**4219736.6**	**1243640.7**	**3394378.82**

For the files provided in validation set I have shown our results in Table 5, which are much better than the participants of the challenge. These are shown as average error values for segmentation problem of the proposed methodology in-comparison with the three participants of the ***Classifying Heart Sounds Challenge***

6.2 Classification Results

The classification results of the proposed methodology in comparison with the two of the participants of the challenge (Participant 1 and Participant 3) are given in Table 6.

Table 6: Results comparison for classification problem

Description	**Proposed Methodology**		**Participant 1**		**Participant 2**
	MLP	**J48**	**MLP**	**J48**	
Precision of Normal	0.688	0.611	0.35	0.25	0.458
Precision of Murmur	0.788	0.765	0.67	0.47	0.3125
Precision of Extra sound	0.571	0.417	0.18	0.27	0.1127
Precision of Artifact	0.972	0.875	0.92	0.71	0.5833
Artifact Sensitivity	0.921	0.921	0.69	0.63	0.4375
Artifact Specificity	0.988	0.94	0.44	0.39	0.444
Heart problem Detection Sensitivity	0.835	0.89	0.45	0.55	–
Heart problem Detection Precision	0.835	0.8	0.43	0.4	–
Youden Index of Artifact	0.909	0.862	0.13	0.01	-0.09
F-Score of Heart problem Detection	0.835	0.473	0.2	0.2	0.1396
Total Precision	**3.019**	**2.668**	**2.12**	**1.71**	**1.4668**

The matrices used to evaluate the effectiveness of the classification methodology are precision per class, the F-score of heart problem detection and Youden's Index of artifact category. These matrices are generated from the confusion matrices of both the classifiers using the scripts provided by the challenge organizers. For heart problem detection we used normal category heart sounds as one class and all other categories as the second class. Descriptive details and calculation parameters are according to the

CHSC2011rules. The total precision value using proposed methodology in comparison with other contributors of the challenge shows its effectiveness. The results achieved are much better than any of the contributors of the CHSC2011.

CHAPTER VII: Conclusions and Future Work

In this research document, I have presented an algorithm for the classification of heart sounds using a standard dataset developed for PASCAL Challenge CHSC2011. I have proposed a novel clustering based solution for identification of S1 and S2 heart sound (segmentation) without any external reference. This was one of the problems that is none of the participants of the challenge managed to address. Despite of varying nature of input heart signals I achieved a good performance for the correct detection and identification of S1 and S2 sounds in the signal. Combined feature set of temporal and frequency domain provided a good accuracy in classification of heart sounds into 'normal', 'murmur', 'extra sound' and 'artifact'.

Future Work

As identification of heart sounds is of extreme importance which directly improves upon the classification accuracy following areas can be further explored in this regard

- Use of Split characteristics of S2 sounds for labeling of S1 and S2 sounds
- Use of lower bound gaps of both the systole and diastole gaps for using it as a parameter in segmentation of sounds.
- Development of some application which is in a form easily interpretable by the Cardiologists.
- A bed monitoring system can be developed especially for kids which can be used as an early diagnosis aid.

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