Heart sound segmentation using PCG signals

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March,2019

DECLARATION

I certify that this research work titled “Heart sound segmentation “is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

Signature of Student

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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. The thesis is also according to the format given by the university.

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ABSTRACT

Cardiac auscultation is a method used to listen heart sound. Condition of the heart can be predicted with cardiac auscultation because heart generates a specific rhythm of sound and any changes in the rhythm of the heart sound may be due to abnormalities of heart. Auscultation is an easy way to diagnose heart abnormalities; however, it needs training and years of physician's experience to diagnose heart and identify any heart abnormalities. With years of experience it is still difficult to analyse heart sound. The ability to automatically identify abnormalities or at least support physician decision is relevant to ease the reach of medical diagnosis using mobile or Digi-scope. The phonocardiogram PCG signal are collected with the help of mobile or electronic stethoscope. Heart beat detection is very important in these signals for segmentation of fundamental heart sound. Finding heart rhythm in PCG signals is a challenging task due to the presence of noise i.e. external environmental noise or internal body noise. Another challenging task is segmentation of S1 and S2 heart sound. This thesis presents a novel approach for segmentation of S1 and S2 heart sounds by using some of heart sounds temporal and spectral features. Total of four features are extracted from these signals, in which two features are temporal feature and two are its spectral feature. K-mean clustering algorithm is used for segmentation of S1 and S2 on the bases of these features. PASCAL PCG heart sound dataset is used for testing our algorithm. Our method differentiates between S1 and S2 heart sounds to great extent and also improves the results.

Keywords— *Heart sound segmentation, PCG, spectral centroid, variation coefficient.*

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Chapter 1 : INTRODUCTION

1.1. Background

According to world health organization, 32% humans died of heart disease in 2015 in the world, which are 97.5 million people. 80 percent of death happened in low or middle-income countries where people have limited access to diagnosis and treatment. The situation in Pakistan is not good. In Pakistan, 40% of total deaths are due to heart disease. Deaths due to cardiovascular disease (CVDs) have reached about 200,000 per year[2].

Major causes of cardiovascular disease like heart attack and stroke are alcohol, smoking, hypertension, obesity etc. Therefor risk of CVDs can be minimized by changing daily routine one example is a person need to exercise for avoiding obesity and hypertension which we mentioned above, is major cause of heart problems. CVDs are also related to age, risk of cardiovascular disease increase with age.

To effectively deal with the aforementioned problem, CVDs need to be diagnosed at early stages. For this purpose, many systems for health care are going to shift from curative care to preventative care strategies. Therefore preventative healthcare i.e. cost controlling is believed the solution to health problems. It can be achieved by early diagnosis. Early diagnosis is possible with long-term telemonitoring and avoids critical life situation as well as expensive and aggressive treatment.Nowadays treatment and diagnosis solution in hazard environment which are able to assist doctors effectively, are increasingly in demand. To reduce the interference in daily life routine the reduction of intrusiveness and invasiveness of these systems is important. Another purpose of the system to diagnose a patient on regular bases and make it easy or help physician to diagnose patent.

1.2. Motivation

Heart sound is a valuable source of diagnosis heart and it provides information about the state of heart. Listening to the sound generated by heart thought stethoscope is called auscultation. Nowadays diagnosis of different heart disease like heart attack, angina, stroke etc depends upon complex methods like magnetic resonance imaging (MRI), ECG etc.

Figure 1.1 cardiac MRI [84]

The uses of these methods are increased due to its goods precision of heart diagnosis. In spite of these qualities, these methods of diagnosis are quite complex, their equipment is bulky and also the equipment and method are expensive.

1.3. Diagnostic value of auscultation

Experience physician detects heart abnormalities by listening to the sound and analyze the sequence of its beats and murmurs. In fact, 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. presences if some heart sound components and temporal information between heart sound events and morphological characteristics. Generation of heart sound and its source from the heart will be explained in the next chapter in detail. A preliminary introduction is given here in order to show the relationship between some component of heart sound and their diagnostic value.

Phonocardiogram is a graphical representation of sound waves generated by a functional heart. Auscultation of heat is a widely used method for identification of heart valves disorder, heart lesion and heart failure [kernath and Thornton]. There is two major heart sounds i.e. S1 and S2. The S1 heart sound is generated when atrioventricular valve close is systole phase of heart [Abbas 2009]. The S1 sound is low pitched and dull sound. The sound can be heard through the chest as it is transmitted to the chest from the ventricles. The sound is produced due to the closure of the atrioventricular valves at the start of a ventricular contraction. The S2 heart sound has a high pitch and sharper in quality as compared to S1 and it can be heard all over the precordium. It is produced to by the closure of the semilunar valves. There are also two other sounds besides of S1 and S2 i.e. S3, S4. The S3 (third hear the sound) is generated from the sudden halt in the movement of the ventricle in response filling in pre-diastole. This sound can normally be heard in child and young people. S4 heart sound is caused by sudden halt of the ventricle in response to filling in early systole as a result of atrial contraction.

The most common heart abnormal component in heart sound is a heart murmur. A murmur can be observed in between S1 and S2 or between S2 and S1 heart sounds. On the basis of its occurrence murmur is having two types, one is called systolic murmur and the other is diastolic murmur. Systolic murmur occurs between systole and diastole and diastolic murmur occur in between diastole and systole. Murmur usually have a low frequency as compare to S1 and S2. A heart murmur is created due to abnormalities in heart valves.

Myocardial relaxation and contraction are directed by intracellular recycling of calcium ions. Therefore, the timings of the basic cardiac function are related to the health of cardiac cells, which determine its ability to suppress blood delivery according to metabolic requirements of the organs. The timing of the left ventricle is another important aspect because it is ventricle function that controls the flow of blood in the circulation. Hear sound can be applied to measure the systolic intervals and the 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.[Fan et al].

1.4. Socioeconomic impacts

It is evident from the above words that heart sound is an important sound signal which identifies heart function and supports heart diagnosis. Therefore a computer-aided auscultation system help diagnosis of different cardiac abnormalities. Heart sound can be acquired from electronic devices digiscope or smartphone and analyzed for heart abnormalities.

Figure 1.2 electronic stethoscope [85]

In addition, the patient can check their heart condition or can be monitored from their home for the purpose to reduce their frequent visits to the hospital. This technique can be used in remote health care system which is known as telemedicine or telehealth. Telehealth brings improvements in the quality of life by offering socioeconomics advantages.

1.5. Personal medical care

Heart sound signals analysis have scope in personal health care. Personal health care is a new trend of health care provided to the patient to tailor diagnosis, home care, prevention and lifestyle services. In the healthcare system function of different systems of the body are monitored using vital signal regular analysis of patent at home. The signal generating from the respective organ in a system provides information to their functionality i.e. lungs sounds during respiration, heart sound during circulation of blood etc. A new concept of portable devices to acquire these vital signals is adopted which may be wearable garments with embedded sensors. It registers information from the signals while performing daily routine works.

As we mention before that cardiovascular disease are deadly and its connection to different factors i.e. aging, high blood pressure etc. in order to support a health system is crucial to being developed. Electrocardiogram knew as ECG and PCG(recorded sound of heart with a digital stethoscope) are among those signals which are widely used for cardiovascular disease diagnosis as shown in Figure 1.3. Photoplethysmogram (PPG) impedance cardiogram(ICG) is another type of signals is also modalities to diagnose heart disease as shown in Figure1.3 and 1.4 respectivily, but these are less common. Third generation health system can be implemented for heart due to the potential for heart sound. PHealth system will be able to provide continuous feedback to the user.

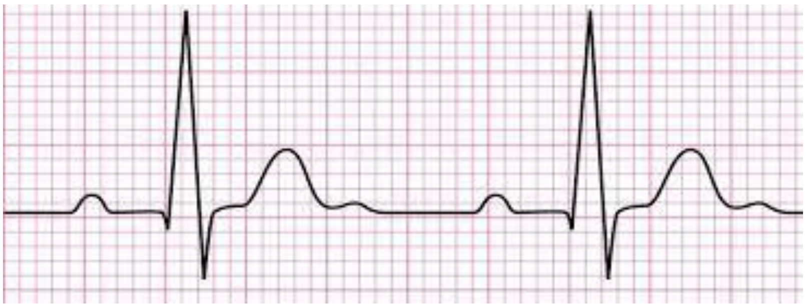

Figure 1.3 ECG Signal Sample [86]

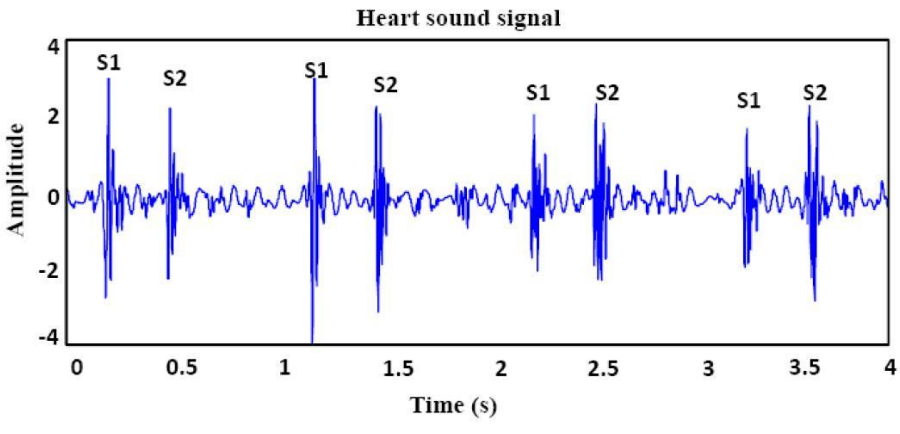

Figure 1.4 PCG Signal Sample [87]

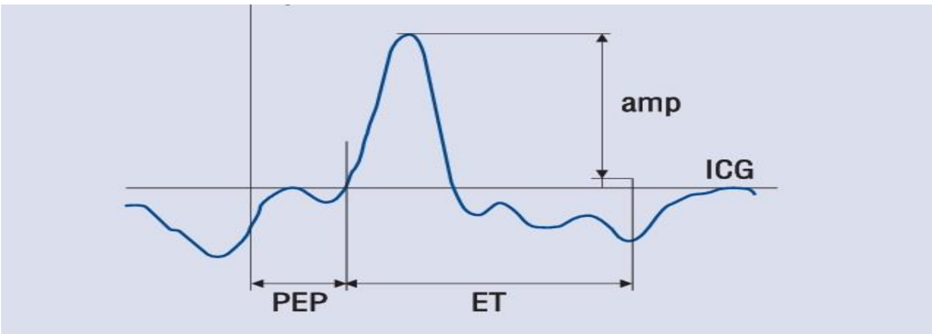

Figure 1.5 ICG signal [88]

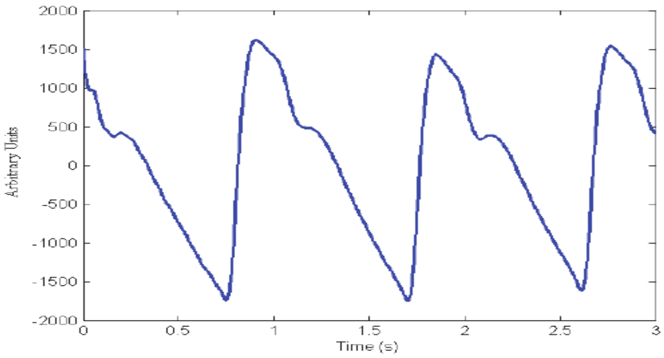

Figure 1.6 PPG signal [89]

1.6. Training medical professionals

In practical auscultation based diagnosis medical professional is less interested. Many new medical professionals don't know how to use a stethoscope properly. Nowadays auscultation is not considered needful technique as many advanced methods and machine are available i.e. ECG, pulmonary arteriography, MRI etc are available. As we know that the major advantage of auscultation on these methods is cost. That's why it is necessary for the medical professional to strengthen assessment on the basis of auscultation for patient diagnosis. That's why Computer-aided auscultation can play role in training and teaching medical professional with the new methods. A system based Computer-aided auscultation help reduce the auscultation proficiency gap between distinct skill levels student. Error in cardiac diagnosis can be reduced by providing training based on a vast range of heart sounds using computer-aided auscultation system.

1.7. Objectives

It is important to enhance and promote cost-effective and non colossal technique for medical examination of heart by exploring heart sound. Heart sound contains valuable information about the heart so it is important for heart diagnosis to extract this information using data processing technique. The technique for heart sound analysis comprises several task i.e. denoising, sound extraction etc.

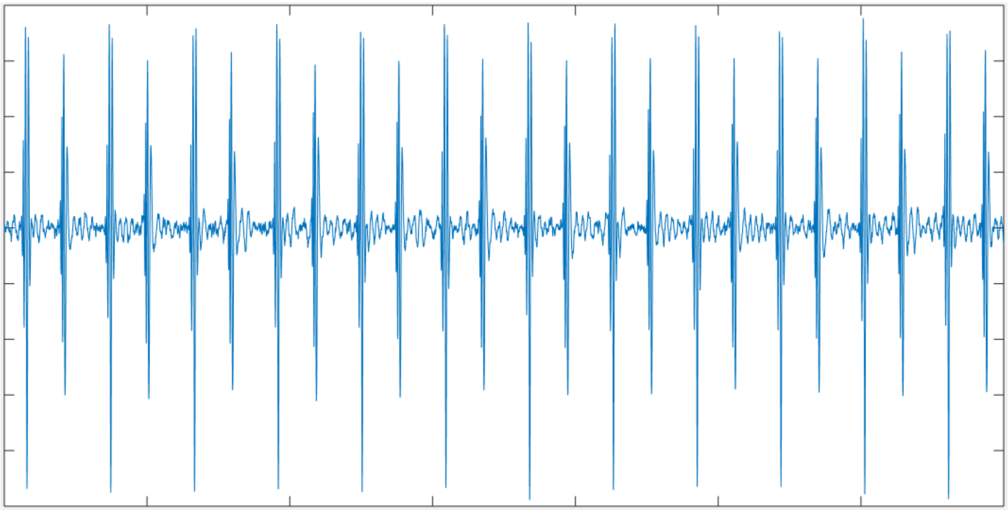

Figure 1.7 Example of Normal Heart sound

Heart sound is very diffecult to be free of noise. PCG is an acoustic signal ,its acquisition is likely to interface with different noise sources and its is diffecult to avoid until it is recorded in a completely sielint room but still there is chances of noise due to other internal body sounds like lungs sound during respiration. Recorded heart sound signal may include heart sound, noise from external sources and noise from internal sources. Noise have a broad range of charecteristics ovelaping over heart sound charecteristics that can effect diagnosis features of heart sounds. Our main objective is removel or reduction of noise that are recorded with the heart sound signal to enhance the diagnosis method.

After cleaning heart sound from noise the next task is localization of heart sound to identify its components i.e. S1 and S2. The following tasks are needed to be performed for segmentation.

- Smoothing of the heart sound signals.
- Identifing peaks of the smoothed heart sound records.
- Segmenting peaks to locate heart sound components i.e. S1 and S2

1.8. Main contribution

Our major contribution of this thesis in relation to heart sound analysis problem are listed in this section. Two problems are coped with the help of signal processing and machine learning technique. Heart sound signal contaminated with noise generated due to internal and external noise sources is the first problem.

Our goal is to develop an approach to reduce the noise with less complex and less computation. The second problem which is tackled here is segmentation problem. A novel approach is developed for this problem by segmenting S1 and S2 heart sounds through clustering with a well known clustering algorithm. This clustering algorithm is applied on features that are extracted from each peak in both spectral and temporal domain.

1.9. Thesis outline:

In **chapter 2** Origin of heart sound are explained. It discusses structure of heart its chambers, valves and heart cycle phases.

In **chapter 3** cardiac auscultation are discussed. The chapter comprises explanation of dataset we used in our thesis and introduction to fundamental heart sound.

Chapter 4 presents detail review of the techniques used, analysis and the research done in this area.

Chapter 5 comprise complete and detail explanation of the propose methodology. It shows that how the problem is tackled and how the aforementioned objective is achieved.

Chapter 6 explains the results in detail. It presents the results of the proposed methodology and conclusion of the thesis.

Chapter 2 : ORIGIN OF HEART SOUND

The sound generated during beating of heart for the flow of blood within chambers and vessels through values is called heart sound. The turbulence created by the flow of blood and closing of valves can be reflected by the heart sound, that can be heard with a stethoscope. Different heart disease can be diagnosed through auscultation by understanding heart structure and the origin of the cardiac sound. In this chapter we will study heart sound, its function, structure, auscultation, and relationship of auscultation with heart function.

2.1. Introduction

The sound generated due to mechanical activity of the heart is known as PCG while the signal generated due to electrical activity is called ECG. In this chapter, we will describe briefly the origin of heart sound and ECG signals. As we mentioned above heart sound generated due to closing and opening of heart valves and turbulence flow of blood in hear and vessels and it occurs in a specific rhythm to the sound generated is in a rhythm. Any abnormalities in heart generate some extra sound or change heart sound rhythm. Sounds of different quality and pitch are generated from that heart having prosthetic valves.

2.2. Heart Structure

Cardiovascular system, which is also known as the circulatory system, is a system that conducts blood in most living organisms. The circulatory system of a human allows about 5 later of blood, to distribute nutrients and transport oxygen from the lung to different parts of the body and deoxygenated blood to heart as shown in the Figure 2.1. The blood also contains elements that help in fighting disease, stabilize pH and temperature of the body.

Circulatory systems comprise a muscular organ known as heart, blood vessels, and blood. The heart is located in middle mediastinum. It has strong muscular walls named myocardium. Pericardium a double membrane sac is surrounded the heart. The heart lies in between vertebral column and rib cartilage. At the upper side of the heart, vessels are attached i.e. inferior vena cava, superior vena cava, pulmonary vein, pulmonary artery, and aorta.

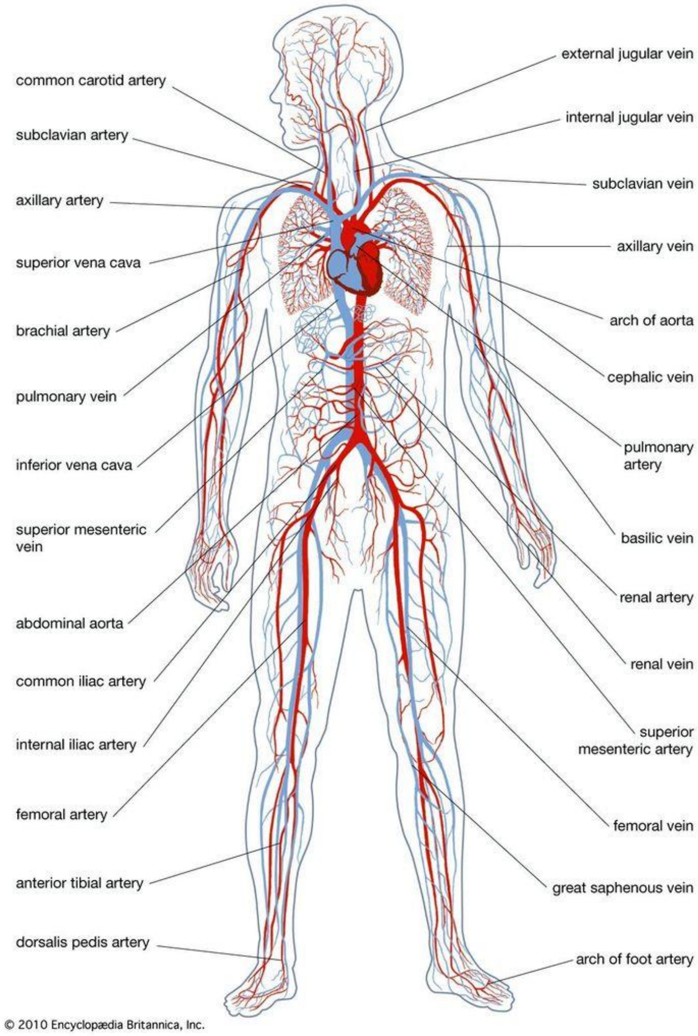

Figure 2.1 Human circulatory system [90]

The weight of a normal healthy and average human heart is 259 to 300 grams. Heart circulates blood with the help of blood vessels within the whole body. Heart work as a pump, collecting deoxygenated blood from all parts of the body and oxygenated blood from lungs then transport that oxygenated blood collected from lungs to different parts of the body and deoxygenated blood into lungs. This is why the accurate operation of the heart is important.

2.3. Heart Chambers

The human heart is a strong muscular organ, nonstop pump blood throughout the whole life. The heart has four chambers that are separated by four valves. During pumping of the heart, blood flows from one chamber to another through valves. These valves don’t allow the blood to go back. The two upper chambers are called atria which is also called receiving chambers the lower two chamber are ventricles also known as discharging chambers. Atria are smaller in size then ventricular as shown in figure.

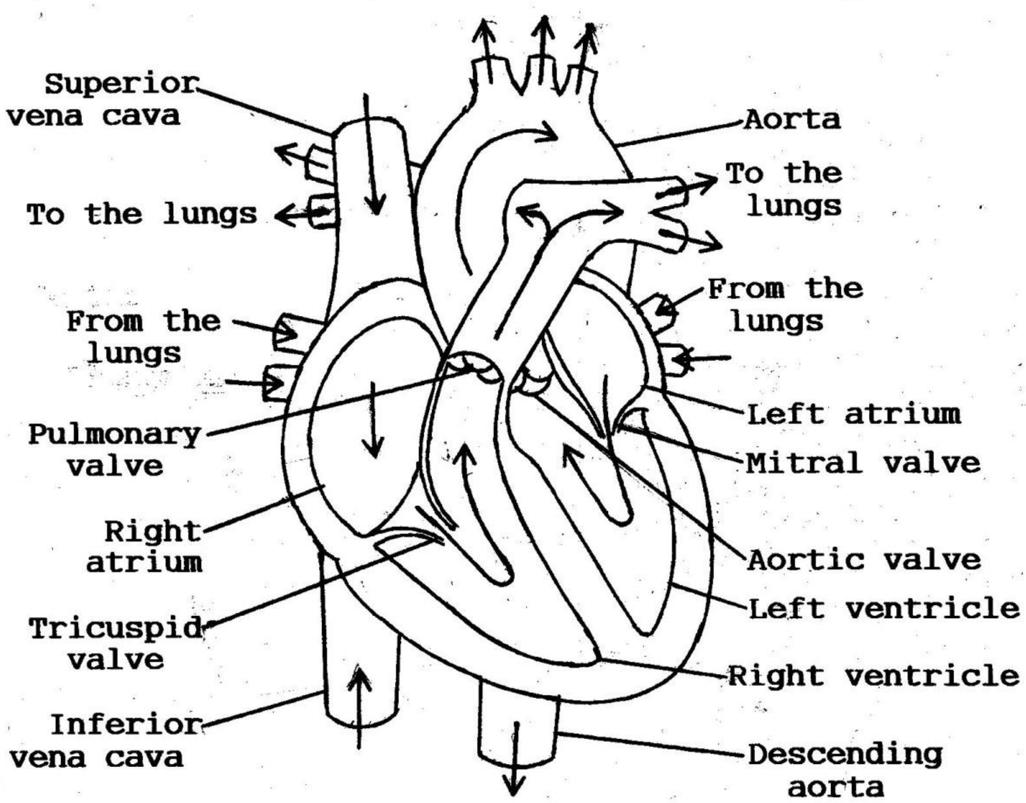

Figure 2.2 Human heart anatomy [91]

Heat function is to provide oxygenated blood received from lungs to all parts of the body and supply deoxygenated blood received from different part of the body to lungs. The heart consists of four chambers and four valves to perform its function. Blood is forced from one chamber to another through valves during the pumping process.

2.4. Heart cycle phases

There are two phases of heart's pumping cycle: systole and diastole. Blood move into the heart through atria, atria at the lift side receive oxygenated blood from lungs where oxygen are collected by blood hemoglobin within lungs, while the right atria collect deoxygenated blood from different parts of the body. Both atriums contract, the valve between atria and ventricles open and blood moves from atria to the ventricle. Due to closing and opening of these valves between atria and ventricles an audible sound is produce called lub. Ventricular muscle contracts and deoxygenated blood moves to the pulmonary trunk that opens to lungs and aorta on the left side distributes oxygenated blood to different parts of the body. In this phase, no blood goes back to atria as a valve between atria and ventricle remains closed while valves between left ventricle and aorta, and value between the right ventricle and pulmonary trunk opened. These values produced another audible sound which is called dub. As the heart repeats the whole process again and again so it produced the repeated sound of lub dub.

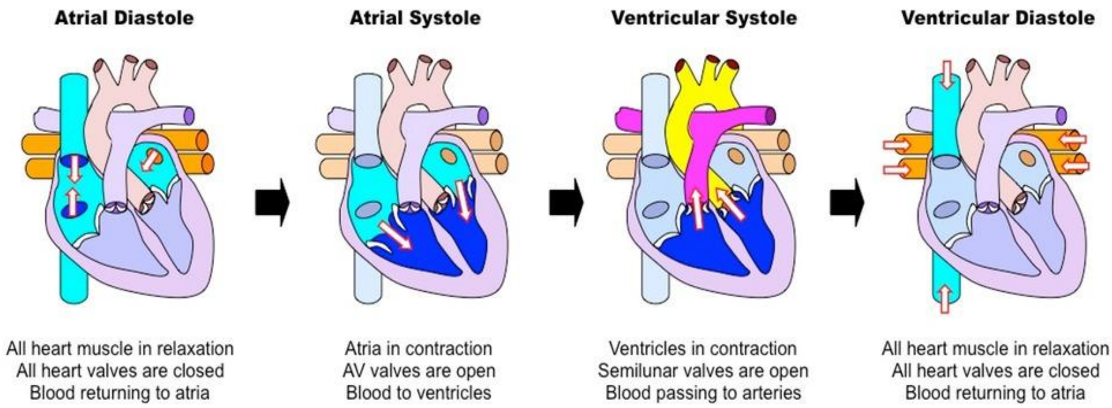

Figure 2.3 heart cycle of a healthy human [92]

2.5. Heart valve

In the heart function, cardiac valve plays an important role. A healthy human heart comprises four valves as we mentioned above. Atrioventricular valves i.e. tricuspid and mitral have three and two cusps respectively. Aortic and pulmonary known as semilunar valves has three cusps. The shape of the cusps in semilunar valves prevent prolapse and these valves have no chordate tendineae. A fibrous skeleton separates atrium from ventricles. The atrioventricular valves are connected through the chordate tendineae and papillary muscles to the ventricular wall.

2.5.1. Artificial heart valves

There are other kinds of valves which we called artificial or prosthetic valves. These valves are used in the place of abnormal valves. A substantial development in the prosthetic valves is made since 1952. In this year for the first time mechanical prosthetic valve was developed.

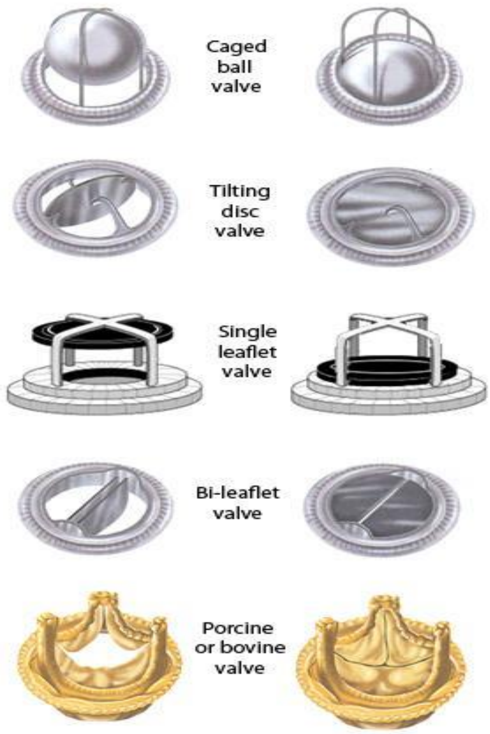

Figure 2.4 Prosthetic heart valves [93]

The first mechanical prosthetic valve was named caged-ball valve, that was implanted to suppress an aortic insufficiency. The valve consist of a ball within a cage as shown in figure 2.2. After the implementation of the caged-ball valve, development in prosthetic valves. Some of the prosthetic valves are shown in figure 2.2. There are two types of prosthetic valves mechanic valves and bioprosthetic valves also known as tissue-based valves. Sence these valves are made of synthetic material so there is more possibility of problems i.e.infection and tissue growth.

2.6. Heart conduction system

The heart is muscular pumping organ. Conductivity, contractibility, and lusitropy are the properties of the heat muscles. Heart muscles are capable to conduct electric impulses. Electric activities take place in the heart muscles like nerves of our body. These electric activities are composed of two events depolarization and repolarization that's happening with the pumping of the heart.

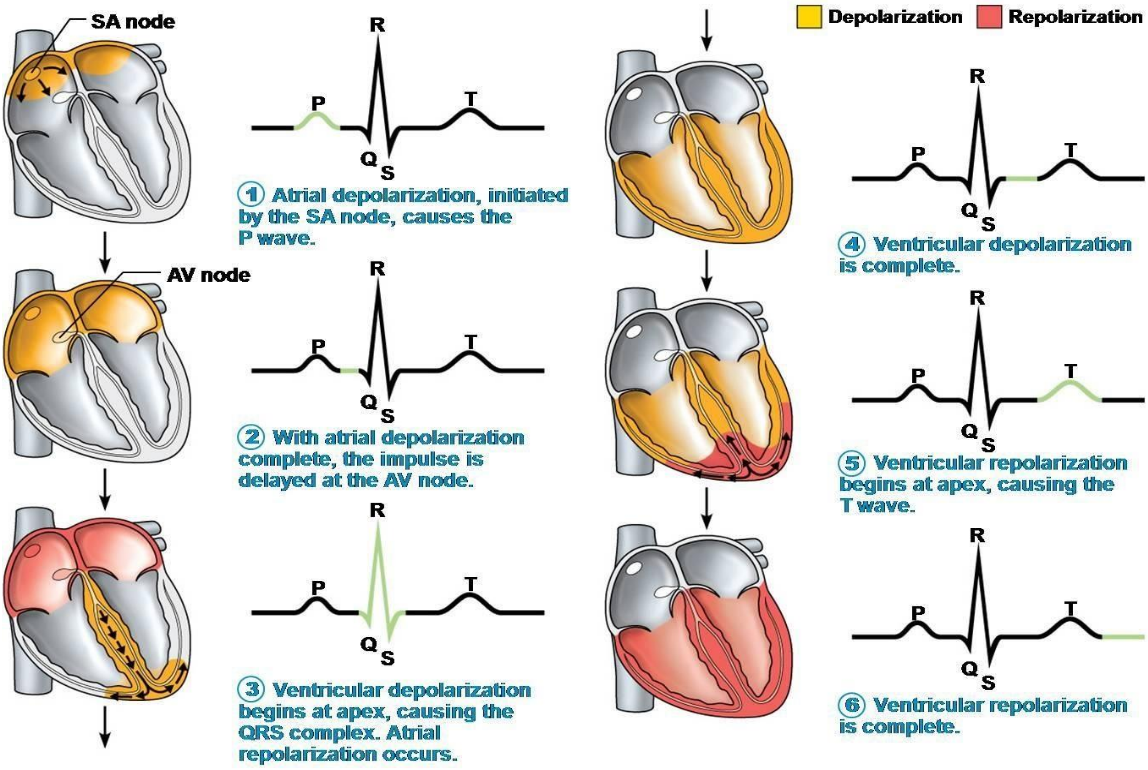

Figure 2.5 Depolarization and Apolarization events in Heart cycle [95]

An impulse generated by the sinoatrial node which spreads through atria and stimulates its muscles due to this stimulation the atria contract. Ventricles and atria are isolated from each other electrically. Electrical impulse generates for ventricle are in a little in delay, as a result, the atria are emptied into the ventricle when impulse generates for atria and atria contracts. Ventricle muscle contracts as a result of stimulus spread on ventricle muscles. Stimulus throughout the heart is conducted in steps. This electric impulses can be analyzed with the help of a technique called electrocardiogram ECG. From ECG, the status of the heart can be evaluated. ECG provides a graph for different electrical phases of heart in one cycles. One single cycle is segmented into five waves i.e. P, Q, R, S, T as shown in the figure 2.2. Every wave show stimulus at a specific part of heart’s muscles and indicates the functionality of the heart.

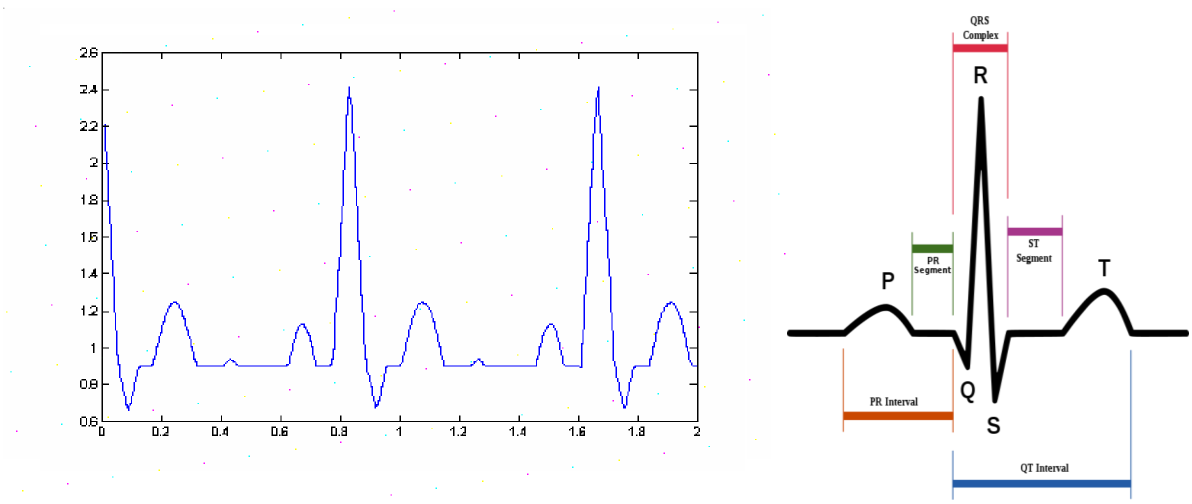

Figure 2.6 ECG Signals of a healthy Heart [96]

In a heart cycle atria and ventricles contracts and relax and this process repeats in sequence. The contraction and relaxation of both atria and ventricle are different in phase. Overall there is two phases of heart one is called systole and the other is known as diastole. In systole blood from the heart are transported to different parts of the body while in diastole phase the heart sucks the blood from different from the body.

Technically in systole, the blood is pumped into pulmonary arteries and aorta from the ventricle. Its starts with the closing of triculsid valve after that the ventricle contract which force the semilunar to open and the blood rush from ventricle. The movement of blood is very rapid due to ventriclar and aortic pressure and a large volume of blood are ejected. This pressure then gradually decrease with the flow of blood from aorta periphery this whole precess can be analize with ECG, while in diastole the blood is moved into ventricles from atria. This phase starts with the clossing of similunar valves and opening of atrioventricular valves. The ventricle starts filling with blood rapidly that flows from atria and from the lungs.

2.7. Heart sound

The main reason for heart sound is the flow of blood within heart chambers, and between body and heart. This flow of blood is regulated by heart valves and its muscles that direct blood within the heart chambers and also between the heart and the body. Two sounds can be heard as a result and is known as S1 heart sound and S2 heart sound.

2.7.1. S1 heart sound

S1 sound is generated in the systole phase of the heart. The tricuspid and mitral valves, in combine together is known as atrioventricular valves are closed. A tension is created in the ventricular muscles due to the rise of pressure in the ventricle that produces S1 sound. So the main reason for S1 sound generation is the closure of tricuspid and mitral valves.

2.7.2. S2 heart sound

S2 sound can be heard after a small time period from S1 sound. S2 sound produced during diastole phase as a result of the closure of aortic and pulmonary valves. Some experiment shows that S1 sound has low frequency then S2 heart sound. S2 heart sound frequency range from 10-400 Hz while S1 frequency ranges from 10 to 150 Hz. Figure 2.3 shows S1 and S2 heart sound.

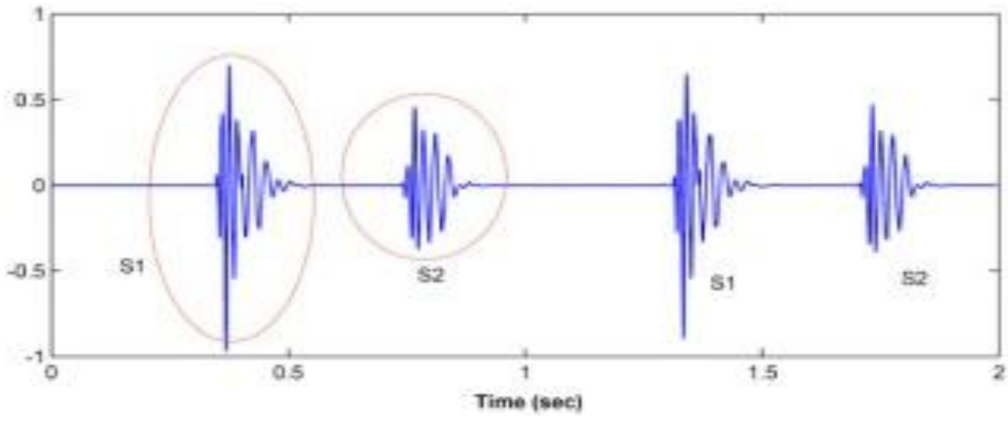

Figure 2.7 S1 and S2 heart sound in PCG signal [87]

2.7.3. Other heart sounds

Some extra heart sounds, murmurs, or change in heart sound rhythms can be heard from an abnormal heart. Murmur sounds emerge due turbulent flow of blood. The reason for turbulent flow is any deficiency in heart valves that have no ability to completely block blood from going back. These sounds can be heard in systolic or in diastolic of the heart cycle as shown in figure 2.8. This sound can also occur in both systolic and diastolic phase. Murmur sound may be of short duration or may be of long duration base on cardiac condition. Murmur sound can occur at a different position in heart sound signals. Murmur founds between S1 and S2 are called systolic murmur. Thay is normally considered as innocent murmur but with other anomalies, this murmur can be pathologic. Its severity depends on its length, not on its loudness. This sound is produced due to the backward flow of blood from the ventricle through the tricuspid or mitral valve. This sound can also be as a reason of forward flow of blood across the aortic or pulmonary valve. Diastolic murmurs are the roaring or wooshing sound between S2 and S1 or it may start with S2. Diastolic murmurs are all pathologic. Some murmur start with the end of S1 and continue in diastole, such kind of murmur is called continuous murmur.

2.8. Prosthetic valve sound

Above we duscessed about sounds produced by valves of heart. It is also necessary to talk about sounds of heart having prosthetic valves. We mention in previous section that abnormal heart valves can be replaced with prosthetic valves. These valves can be biological or mechanical depend on patient heart status. Sound of these heart are different from normal heart and depend upon the type of valves and the position of replacement.

2.8.1. Sound of mechanical valve

Commonely known mechanical valves are caged-ball, bileaflet and tilting disk. The sound generating from these valves are due to opening and closing of valves. The sound produces during closing event show differenet charecteristics which depends on the architecture of these valves. For example caged ball valves have a ball that's move freely with in a cage as shown in the figure 2.8.

The caged ball produce a high frequency and high amplitude sound with short duration. During opening the ball move to the other side of the cage and produces a loud sound while in closing phase the ball moves towards the heart and and produce a little show sound then the opening one. The bileaflet disk is comprise two ssmilunar leaflet based on a cicular swing ring thats open in the center. When the valves close it produces a loud sound with high frequency. As compare to caged ball it produce a loud sound during closing.

The third type of mechanical valve which is also known as tilting disk valve have lens shaped and floating disks based on a circular ring that can tilt from 60 to 80 degrees. Its genereates high frequency and loud sound in both opening and closing condition. The sound in closing pahse of this valve is also louder in then cagged ball valves. The main problems with these valves are thrombosis which cause immobilization of the disks and blockage.

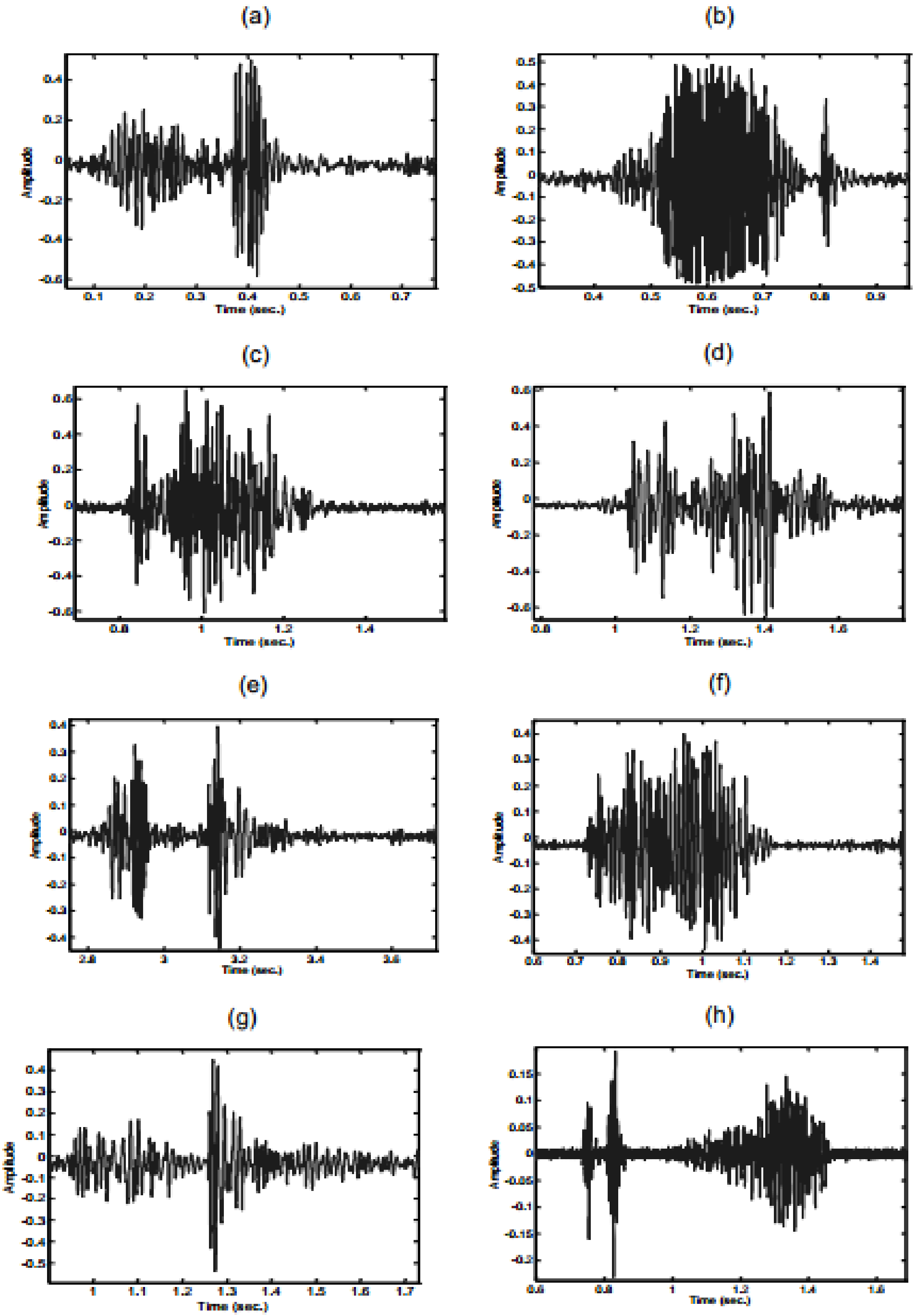

Figure 2.8 Systolic murmurs from (a) to (f) and diastolic murmurs in (g) and (h) [32]

2.8.2. Sound of Biological valve

The other kind of valves that are mostly used as a replacement of heart valves are biological valves that are also known as bioprosthetic valve. These valves are tissue valves. Based on their manufacturing material these valves are of three type allograft homologous and hererologous. Allograft are obtained from the fascia lata of the pulmonary valve. Homologous are obtained from corpse or matter and hererologous are from bovine aortic valve or vine pericardium. Sounds produce by these valves are same as sounds of natural heart valves.

Chapter 3 : CARDIAC AUSCULTATION

3.1. Introduction

Listening to heart sound with some equipment like stethoscope is called Cardiac auscultation or auscultation. When the heart sound is recorded, the recorded sound is called phonocardiogram (PCG). These sounds can be recorded through a digital stethoscope, a digi-scope or it can also be recorded through an iPhone.

There are different methods and tool which help a Doctor to diagnose heart abnormalities, includes ECG (electrocardiography), echocardiography, CT (computed tomography), MRI (magnetic resonance imagining) etc. However, these methods are costly, complex and need expensive and bulky setup. Therefore, Doctors try to prevent the aforementioned methods and prefer to use easy and less expensive methods for diagnosis. Cardiac auscultation is a simplest, cheapest and is there for a widely used method for heart diagnosis.

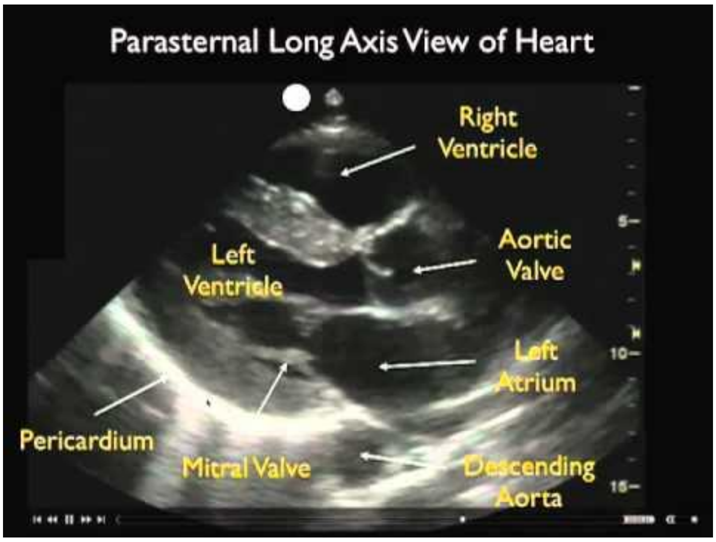

Figure 3.1 Echocardiography [97]

Hearing of heart sound and identification of any abnormality of heart from that sound is a difficult task. Cardiac auscultation needs expertise and proper training to diagnose any abnormalities in heart properly. Even with years of experience, it is still difficult to interpret the sound correctly in many cases there is a strong possibility of wrong interpretation. It on the record the about 80% of interpretation done by a doctor using auscultation are actually wrong [10]. Cardiac auscultation analysis is normally not conclusive and this is the reason the error rates are reported so high.

As mentioned above that auscultation analysis results are difficult to conclude. If such an approach is developed that help in concluding correct results for auscultation analysis will help in avoiding some expensive and hurtful methods. Such an approach will help in health budget of a country, mainly third world countries. This system will help people of those areas who have no access or where there are no availabilities of complex test like MRI, CT scan etc for diagnosis of cardiovascular disease. We can get recorded heart sound with the help of digital stethoscope or smartphones so a computer-aided tool is needed that effectively analyses these sounds and provide details of cardiovascular disease risks.

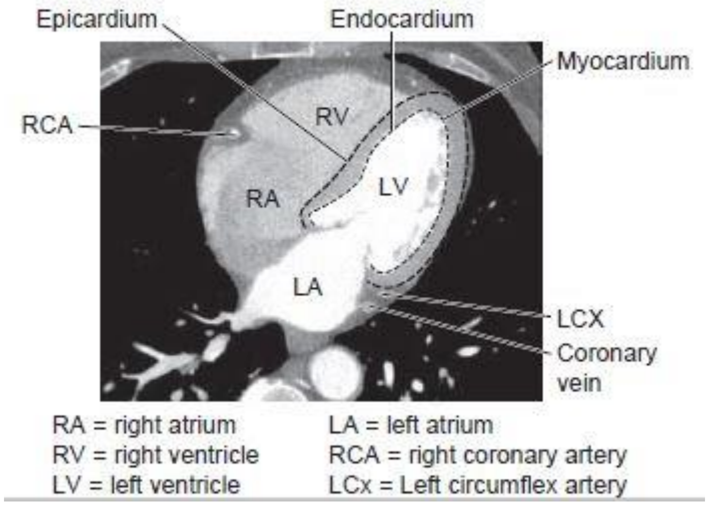

Figure 3.2 Cardiac CT scan [98]

Different methods and algorithms of machine learning and signal processing are used for identification and detection of cardiovascular diseases. Most of these methods involve segmentation, feature extraction, and classification while some classify the sounds without segmentation by extracting time or frequency features from the sound signal. A lot of work has already been done in classification while segmentation part remained unnoticed. According to Bentley if segmentation challenge is solved then the classification challenge is much easier.

3.2. Fundamental Heart sound

Heartbeat has a specific sound of lub and dub. Any extra sound like murmur or any changes of rhythm in lub dub sound might because of abnormalities in the heart. So, it's important to identify the position or location of sound lub (S1) and dub S2 for diagnosing heart abnormalities. Segmentation of heart sound is the localization of S1 and S2 sound within PCG.

These heart sound recorded may have noise that may be sound of lungs that aree produced with respiration, white noise, sounds produced due to movement or rubbing of the stethoscope with skin and some outside environmental noises. Extracting heartbeats or identification of fundamental heart sounds is difficult within one cardiac cycle so enough cycles are needed for analysis. Due to increase in cycles, the complexity of the algorithms will also increase as it has to correctly detect as many cardiac cycles as possible. It also needs a strong algorithm which is capable of identifying heart beats within this noisy sound in order to do a reliable diagnosis

3.3. PASCAL heart sound dataset

This section presents a detail discussion on a Heart sound dataset which is widely used in the area of biomedical signal processing and machine learning for validation and evaluation of segmentation and classification results in computer aided diagnosis.

PASCAL heart sound datasets are acquired from two different sources i.e. Dataset A from general public via the istethoscope pro iPhone app and Dataset B from a clinic trial in hospitals using the digital stethoscope Digi scope.

Dataset A contain 176 files in .wav as well as in .aif format. Dataset A is subcategorized into normal, murmur, Extraheart and artifact. Normal contain 31 sound files of normal heart, murmur contain 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 .aiff file format. Normal, murmur and extrasystole are subcategory of Dataset B. Among 656 sound files of dataset, 320 belongs to normal category ,95 to murmur and 46 files to extrasystole category. A test dataset of 195 sound files named Bunlabledtest is sub dataset of dataset B.

These sound files are different in length, minimum length is 1 second and maximum 30 second. Some of these sounds' files are clipped to reduce noise. More domain specific knowledge about the above mention categories of sounds are given below.

3.3.1. Normal

There are normal, healthy heart sounds in this category. These files might contain different kind of noises in the background like traffic and radios. These may contain noises in the last second of the sound due to removing of device from the body. Some other noises like sound of lungs during inhaling and exhaling of air or brushing the microphone against skin or cloths. There is a clear pattern of lub and dub in normal heart sound. Time between lub and dub is shorter as compare to the time between dub and lub. Lub sound is called S1 and dub sound is called S2 heart sound in medicine. Dataset A and Dataset B, both contain normal category.

3.3.2. Murmur

In this category there are heart sound having roaring, rumbling, wooshing, turbulent fluid noise in one of the two temporary location i.e. between S1 and S2 or Between S2 and S1. This can be a symptom of abnormal heart, even with serious disorder. The main problem in here is that it confuses untrained people about the position of murmur in the heart sound. Murmur may happen in between S1 and S2 or S2 and S1. But not on S1 or S2. Both Dataset A and B contain murmur category

3.3.3. Extra heart sound

Extra heart sound can be easily identified. Extra heart sound has additional heart sound that might be S1 or S2 e.g. S1-S1-S2 or S1-S2-S2. These types of heart sound may not be a sign of any heart disease. But in some condition, it is very vital sign of heart disease and its early detection is necessary for a person health. Extra heart sound cannot be detected by ultrasound accurately therefor it needs to be detected with some other method. Only Dataset A contain this category.

3.3.4. Artifact

Artifact Category possess a large amount of different sounds that include echoes, feedback squeals, speech, music and noises. Heart sounds is difficult to detect in this type of sounds. Therefore, it is important to distinguish this category from the other category for the reason that someone gathering heart sound data are instructed to try again. Only dataset A comprise this category

3.3.5. Extrasystole

Extrasystole can be identified due to there out of rhythm heart sound. This sound involves extra or skipped heart sound e.g. lub dub lub dub dub or lub lub dud lub dub etc. there is no regular pattern of heart sound in extrasystole. some time it's a sign of heart disease but normally it is not a sign of any heart disease and it is very common in children. Extraheart sound category is only in dataset B.

Chapter 4 : LITERATURE REVIEW

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 cardio vascular disorders (CVDs). Strictly speaking in the perspective of this thesis work, we are mainly concerned with preprocessing of PCG signals and segmentation of hearts sounds into S1 and S2. In the preprocessing step, noise and artifacts are normally eradicated from the PCG signals by making use of different digital signal processing algorithms whereas a set of pattern recognition and machine learning techniques are mainly used for segmentation of heart sounds into S1 and S2. This chapter discuss in detail different state of the art techniques presented in the literature so far.

Heart sound segmentation is defined as detection and separation of cardiac cycles with the intent of identifying heartbeats. The different energy distribution associated to heart murmurs represents different medical conditions, to detect the temporal locations of such events compared to regular cardiac cycle it is of utmost importance to have a good segmentation algorithm.

The heart of a mammal comprises of four different chambers, symmetrically detached into two sides. The sequential contraction of these chambers, in association with four unidirectional valves, successfully pushes blood in one direction. The contraction results in two perceptible sounds, specifically the first heart sound (S1) and the second heart sound (S2), also sometimes defined as the 'lub' and the 'dub' (or 'dup') [10]. Cardiac cycle is then defined as the interval from one S1 to the next. As a result, every cardiac cycle also comprises an S2 peak which splits the cardiac cycle into two sub-intervals: The time between S1 and the subsequent S2 is termed as a systolic period, while the interval between an S2 and the upcoming S1 is refer to as a diastolic period [6]. Summing up, a cardiac cycle entails an S1 peak, a systolic period, an S2 peak, and a diastolic period in the specified order. Naturally, the systolic period of a given cardiac cycle has a shorter length than its diastolic period.

The recording of a heart sound might contain other sounds, some of which (for example, S_3 and S_4) are almost not audible without amplification. Though, the heart sounds S_1 and S_2 are the only that are usually articulated in any phonocardiogram, that is why they are unanimously used by every segmentation algorithm. There are a number of challenges that maps the segmentation as a non-trivial task. Primarily, heart sound recordings are extremely affected by different noise sources such as electrical and mechanical; spanning but not limited to reservation caused by internal tissues, sharps peaks generated by stethoscope unexpected moments, abnormalities in the heart and so on [32], thus assumptions made on a certain dataset might not hold for another. Since S1 and S2 have different frequencies for every patient and even in different cycle also the accompanying noise may occur at any frequency band thus leads to the failure of any attempt to remove noise by separating S_1 and S_2 sounds in their frequency bands [10].

Despite the fact that a number of attempts have been made to remove lung sounds from these recordings [32], design of a reliable technique for the elimination of the noises in phonocardiograms which is capable to clearly expressing S_1 and S_2 sounds, is still an open problem for research. Consequently, segmentation algorithms attempt to employ techniques definite to the features of the heart sound signal, with dependence on core assumptions obtained from medical observations [6, 15, 17, 23–26, 29–32]. In literature a number of attempts have been made to devise a technique, for classification of the heart sound, independent of segmentation [22], more robust performance for these techniques have been reported when used on segmented data [11]. Which means that heart sound segmentation still remains to be a 'bottleneck' for the performance of many algorithms proposed for heart disease detection and classification.

Another challenge in this field of research is that the datasets on which most of the methods listed in the literature have been tested were preprocessed and curated exclusively and are kept private. which means that there is no guarantee that a similar performance would be expected from a method that is tested on a given dataset when applied another dataset. A proper comparison and unification of these techniques on a mutual reliable dataset is missing.

Over the last two decades cardiac cycle segmentation problem is extensively studied by a number of researchers. Two significant approaches in this domain are ECG based segmentation and PCG segmentation. PCG segmentation algorithm uses the heart sound waveform as input as opposed to ECG based segmentation which uses the electrocardiogram signal to segment the phonocardiogram.

4.1. ECG segmentation

A number of methods have been reported in the literature for the segmentation of the heart sound using electrocardiogram signal as reference. ECG based segmentation, where we look for measuring the electrical activity, has a definitive advantage that it is not affected by heart murmurs, which might be congenital or develop later and are not electrical events, makes it the most attractive choice for industrial applications. In the presence of strong abnormal sounds, the PCG envelop might not be strongly correlated with the cardiac activities [28]. The sensitivity of PCG to these abnormal sounds degrades its performance as compared to ECG based segmentation algorithm.

Available the ECG and PCG recording at the same time, ECG segmentation starts segmenting the ECG signal first [47]. To locate the R waves a QRS detection algorithm for instance, the Tompkins method [12], is applied on the ECG signal. A temporal correlation between the R waves and S1 sounds is usually observed, from this it can be inferred that the S1 sound in the PCG signal must be somewhere in close vicinity of R waves in the ECG signal [21]. Another technique reported in [16, 17] known as “ECG gating” involves searching for S1 signal in the predefined neighbourhood of R wave and then looking for the S2 peak somewhere in-between.

Such type of ECG segmentation algorithms has a number of advantages for instance, the ECG waveform is insensitive to presence of the murmurs and thus has no effect on the performance of the algorithms [10]. Compared to PCG signal the segmentation of ECG signals is well studied and is relatively easier additionally the reported accuracies for the ECG segmentation algorithms is high as compared to PCG segmentation algorithm. However, to carry out these types of segmentation ECG signal needs to be recorder along with the PCG in the first place. Keeping our objective in mind, that is to minimize the cost and increase the availability by reducing the hardware required, this approach seems to be in appropriate. To operate ECG-aided segmentation algorithms a precise temporal alignment of PCG and ECG signals is necessary, because the segmentation obtained in one needs to be mapped onto the other, for this we need synchronous operation of two independent systems one for recording of PCG and the other for ECG is needed, which with good temporal precision is non-trivial to achieve. Even if ECG signal is segmented properly, S1 and S2 sounds are still looked up on the PCG signal. Specifically, the presence of strong murmurs highly affects the location of S2. From this point onward, we permanently turn our attention towards PCG segmentation algorithms.

4.2. PCG segmentation

Unlike ECG waveform to achieve segmentation, PCG waveform do not need any secondary external signals. Rather, segmentation itself is achieved directly on the PCG waveform. The performance of PCG segmentation algorithm is affected by the heart abnormalities as the 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. Even though S1 and S2 are assumed to be highly audible, their amplitudes might change significantly, to the point of disappearance in the presence of certain abnormalities. Finally, S1 and S2 peaks do not seem to have fixed frequencies, but rather present themselves within different frequency bands in two separate cardiac cycles. Literature for instance [6, 23, 25, 29, 31, 32] 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.

Groch at el [27] proposed one of the earliest solutions for heart sound segmentation that was dependent on only the PCG signal. The main idea of the approach was to threshold the absolute value envelogram of the signal after it was passed through a band-pass filter. The proposed solution was defined to be easy and can be implemented using only analog circuits, in [29] the idea was extended and refined. The suggested methodology consists of several different steps, and inspired many other papers in the field in terms of the approach to be taken towards the solution of the problem. To discuss the research, work available on this technique in a unified way, a slightly enhanced approach is used to describe the methodology of the algorithm as below,

STEP 0: Preprocessing
STEP 1: Time-frequency transformation
STEP 2: Transformation to a non-negative domain
STEP 3: Envelope detection
STEP 4: Picking up peaks
STEP 5: Rejection and merging of extra peaks

A number of heart sound segmentation algorithms presented in the literature for instance [6, 11, 13, 15–19, 23, 25, 27–32] follow this general approach with variation in each step. Other approaches include matching pursuit method [10], SAX-based multiresolution motif discovery [48] and Mel-cepstrum analysis [22].

Step 0 pre-processing

The pre-processing further consists of two steps,

i- Resampling of original recording
ii- Normalization of original recording

In literature sampling of heart sound recording and its normalization has been carried out at different frequency rates. Usually the resampling of the original heart sound recording is done at a sampling frequency of 2000Hz or 4000Hz. Table 3.1 gives information about the decimation scheme applied in several papers. For instance, Lang at el has worked with the heart sound recording having a sampling frequency f_s =11025 Hz. Before normalization of the signal frequency of the recording was decimated f_s =2205Hz.

Before down sampling of the signal, required to remove the redundant information from the signal, it is passed through a Type I low pass Chebyshev filter having a cutoff frequency of 882Hz. This cut off frequency is selected as the clinical of the signal lies in the frequency range of 50-700 Hz [23].

The signal can be normalized using the following mathematical relationship

$$x_{norm}(t) = \frac{x(t) - \mu}{\delta},$$

Where μ and δ represents the mean and standard deviation for the signal x(t) respectively [19]. However, Gupta at el latter on reported that this normalization scheme has a negative impact on the performance of the algorithm [23], to carry out normalization of the signal he used the following relation,

$$x_{norm}(t) = \frac{x(t)}{\max\limits_{t \in R} |x(t)|},$$

This will limit the value of $x_{norm}(t)$ within the range [-1, 1].

In this study we will use Pascal heart sound classification challenge dataset [1], these signals have a sampling frequency of 44100Hz. For Step 0 preprocessing we will decimate the signal first to a frequency f_s=4410Hz. At the start we were to receive annotated heart sounds recorded by the $3M^{TM}$ Littmann electronic stethoscope, for which the down sampling frequency was set at 4000Hz [18]. These signals were then normalized and used as is.

STEP 1: Time-frequency transformation

Usually, a considerable amount of irrelevant information and noise is contained in the heart sound signal. Therefore, time frequency transformation technique is employed by several researchers to transform the original signal in to a signal where certain useful bands of the frequency are considered. At the beginning in the papers for instance [29] the step of selection or suppression of a certain frequency band was not employed. To suppress the irrelevant frequency bands Vepa [11] and Delgado-Trejos et al. [13] have used short time Fourier transform. Based on the observation that the S1 and S2 peaks are present at a frequency band of 45 Hz, Strunic et al. [15] used this band for segmentation to obtain the spectrogram of the signal. Livanos et al. [25] compared S-transform with STFT and Morlet wavelet. in order to eliminate lung sounds Mondal et al. [32] proposed the use of Hilbert transform and Heron's formula.

Based on the observation that D4, Morlet and Meyer wavelets are optimal for the analysis of heart sound, a number of researchers [6, 17-19, 30] has preferred wavelet transform. As S1 and S2 sounds most often express themselves at different frequencies which might not be contained in a single wavelet band, thus a number of wavelet bands are considered in parallel at once [6, 30].

In the proposed work, four different wavelet bands such as d7, d6, d5 and a5 corresponding to the frequency bands 128 fs, 64 fs , 64 fs , 32 fs , 32 fs , 16 fs , 0, 32 fs respectively will be considered. For fs = 4096 Hz, these frequency bands correspond to 32-64 Hz, 64-128 Hz, 128-256 Hz and 0-128 Hz respectively. Our application transforms any signal into a sampling frequency of either 4000 Hz or 4410 Hz, as a result the frequency ranges will almost have the same boundaries.

Step 2: Transformation for a nonnegative domain

In case of normal heart sound activities, the signals such as S1 and S2 will have amplitude similar to that of the modulated signals [23]. This leads to the requirement of extracting signal envelope for further analysis, for which the signal first needs to be 'rectified' into the nonnegative y-axis (Step 2). For mapping the original signal to the non-negative domain, Liang et al. [29] tried four different equations, as shown in Figure 3.2 and mathematically given as

Absolute value: $E = |x|$

Energy (square): $E = x^2$

Shannon entropy: E $= -|x|log|x|$-|x|log|x|

Shannon energy: $E = -x^2 log x^2$

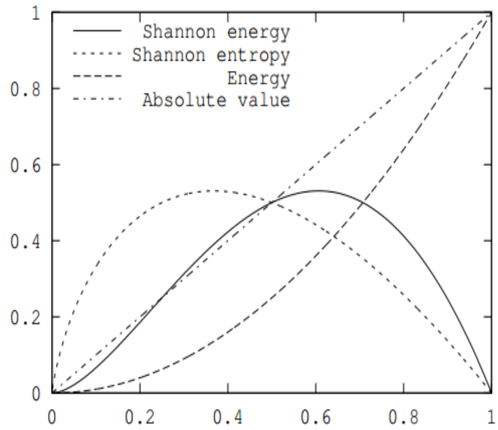

Figure 4.1 Non-negative transforms

Shannon energy is used by most of the future application such as [17, 18, 29, 30, 49] as it attenuates high and low intensity signals, by emphasizes the medium energy signal more efficiently, to suppress the noise. This property although is shared by Shannon entropy which further accentuates the low intensity noise [49].

Step 3 Envelope detection

When the rectification and time-frequency transformation (also known as energy calculation at this stage) is carried out the temporal location at which threshold is exceeded by the amplitude can be detected [26]. However, for such an operation the signal still need to be smoothed further; as redundant peaks might be caused by the fluctuations around the threshold especially because of noise.

In order to make the signal smooth and get rid of the noise, the signal envelope is calculated in this step. The envelogram approach where a tumbling time windows of 20 ms length, with 10 ms overlaps used to average the rectified signal is employed by Liang et al. [29]. The windows with 20 ms length correspond to N = ⌊t · fs⌉ = ⌊0.02 s · 2205 Hz⌉ = ⌊44.1⌉ = 44 samples. It must be noted down that in the original paper step 2 and step 3 are considered as a single step as given

$$E_s = -\frac{1}{N}\sum_{i=1}^{N} x_{norm}^2(i).\, log x_{norm}^2(i)$$

Where x_{norm} represents the decimated and normalized signal obtained in step 0. The specific approach has also been employed by other researchers [18, 32].

Another approach has been used by [20,23] where they have employed a homomorphic filter onto the signal. Since a trend similar to the amplitude modulated signal is shown heart sound recording, thus it can be considered as output of the product of a low-frequency message signal LF (t) (which we want to obtain) and a high-frequency carrier signal HF (t) [23]. The original signal then is f(t) = HF (t) ·LF (t). Taking log on both sides will result in

$$\log\big(f(t)\big) = \log\big(HF(t)\big) + \log\big(LF(t)\big)$$

Let consider that we have a low pass filter (LPF) having capability to completely suppress all the signal above the cutoff frequency. When the signal f(t) is passed through this LPF the resulting signal will only consist of LF(t). Then the homomorphic filter is defined as

$$e^{LPF\{\log(f(t))\}} = e^{LPF\{\log\left(HF(t)\right)+\log(LF(t))\}}$$

$$= e^{\log(LFP\{HF(t)\})+\log(LFP\{LF(t)\})}$$

$$= e^{\log\left(LF(t)\right)}$$

$$= LF(t)$$

The basic assumption in this method is that f(t) is defined i.e. f(t)>0 for all time t. A number of tests were carried out to check the credibility of both the methods and it was found that both the mentioned methods performed very well, therefor we proceeded with the envelogram method.

Step 4: Picking up peaks:

In order to pick a peak as a candidate when the envelope is obtained a threshold is applied on to the signal. If an interval exceeds this threshold it is considered as a peak candidate. The centre of the peak is the highest point in the interval. The width of the interval where the highest point is considered the peak width.

Since the threshold criterion in [29] is not given explicitly however from figures in that paper it can be depicted that slightly different thresholds between 0.75 and 0.8 are used. Mean of the envelope can be used as a method to automatically select a threshold. Gupta et al. used 35% of the maximum peak as the threshold value instead [23]. Hedayioglu [6] presented a mathematical relation for the selection of threshold given as

$$thr = 0.5(\max_{t \in R} E_s(t) + \min_{t \in R} E_s(t))$$

Step 5: Rejection and merging of extra peaks

Not necessarily all the candidate peaks be meaningful, neither we can make assumption that every peak we have selected is a relevant or a desired peak. A technique proposed by Liang et al [29], to merge the extraneous peaks that someone might have obtained during the thresholding step, is described as follow,

1. Calculate the intervals between the adjacent peaks
2. Using these intervals calculate *high-level time limit and Low-level time limits*.
3. An extra or a redundant peak is present if the interval is less than low-level time limit.
    - If the largest splinted time interval is observed to be 50 ms, then if two peaks appears within 50 ms of each other it is considered to be because of a split heart

sound. We will select the first peak if its energy is not *too small* as compared to the second one

- Else the second one will be selected.

4. If the interval is more than the *high-level time limit* it means that the peak was too weak to be detected, to handle the problem the threshold limit is reduced by a certain amount and the process is repeated.

In the above set of rules there are three uncertainties written in italic. Most importantly high-level and low level time limits are not defined explicitly. We consider that these values are obtained as follow,

$$Low - level\ time\ limit = \mu - c_1\sigma$$

$$High - level\ time\ limit = \mu - c_2\sigma$$

the term μ and σ represents the mean of the interval and standard deviation respectively, mathematically defined as,

$$\mu = \frac{1}{N}\sum_{i=1}^{N-1} p_{i+1} - p_i$$

$$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N-1}[(c - p_i) - \mu]^2$$

The variables $P = \{p_1, p_2, \dots, p_N\}$ represents the peaks temporal locations with the assumption that $p_i < p_j$ if $i < j$ that is all the peaks are sorted. The same assumption is also made by Hedayioglu [6].

In the elimination process the expression “not too small” is another uncertainty.

When all the peaks are inside a reliable limit, the algorithm then determines which peaks are S1 and which are S2. Since the diastolic periods usually lasts longer than systolic period, thus the approach is to select widest interval and label it as diastolic. Any peak that occurs between a systolic and diastolic is defined as S1 and vice versa.

An algorithm similar to that of Liang et al is implemented by Gupta et al in [23] is given as follow

1- Peaks closer than 80 ms to each other are combined into a single one.
2- Calculate the mean peak width.
3- Peaks with width less than half the mean peak width are considered as noise and are rejected.
4- If the width of a peak is more than 120 ms they are limited to 120 ms.

To eliminate those peaks that might be because of the presence of murmurs, Haghighi-Mood and Torry [28] proposed an intermediate step where a morphological transform is applied to the signal. Their basic assumption is that peaks that are because of murmurs are more likely to have greater width as compared to S1 and S2 peaks which are sharp and thus based on the width of the peaks they are either suppressed or are allowed to pass. If -25dB is the threshold value and if the sorted set of peaks above this value is given by $P = \{p_1, p_2, \dots, p_N\}$ $then$

$$E_{ms}(k) = \begin{cases} E_s(k) - 0.5[E_s(p_i - l)] & for\ p_i - l \le k \le p_i + l \\ 0 & other\ wise \end{cases}$$

After passing the signal through a low pass filter for suppressing the peaks because of noise, K-mean clustering is used to determine S1 and S2 sounds. With the basic assumption that a systolic period is always shorter than a diastolic period Hedayioglu further simplified this step; If the number of detected S1 peaks equals that of S2 then the interval set should be easily separated into systolic and diastolic intervals by the median of all the intervals. When labelling of each interval is carried out any peak that comes a priori of a systolic period is S1, and vice versa.

Ricke et al in [35] proposed yet another novel approach for heart sound segmentation using Hidden Markov Model (HMM) which is a famous supervised learning algorithm. Since this approach works on the prior information extracted from heart sounds. Hence, as a pre-processing steps Shannon energy envelope and other spectral features using Mel-spaced filter banks from each heart cycle are computed beforehand. The proposed method is reported to be a simple method in order to obtain spectral properties of heart sounds via a set of triangular filter bank through the signal spectrum.

4.3. Approach for noise detection

Noise and artifacts are inevitable part of signals which are added to the original signals during recording due to environment and ambient interference. For example, while recording heart sounds using sensor-based stethoscope, all types of acoustic signals are recorded and it is difficult to distinguish heart sound from other due to a vast range of spectral characteristics. All of these contaminating signals results in false diagnosis of cardio vascular diseases. That is why it is important to detect an inadequate signal acquisition problem and pre-process such insufficient signals in order to get sufficient information about heart.

In order to remedy the problem of noise and unwanted artifacts in heart sounds, two main strategies are normally practiced. i.e. (i) identify the position of noisy and non-cardiac sounds and eliminate that portion of the signal and you will have pure heart sounds, or (ii) suppress/ cancel out noise from the whole signal and there you are left with heart sound only. The later approach for noise detection and elimination is normally practiced in the literature. [50]-[55]. These methods which are widely used in the literature normally use different filtering techniques and algorithms like adaptive noise cancellation and blind source separation etc. Noise detection approaches followed in the literature during heart sound acquisition using computer assisted electronic stethoscope can be classified into two sets of algorithms, i.e. Algorithms which use an auxiliary reference signal and the other set of algorithms do not use such reference signals. In the former approaches, an auxiliary signal is also recorded while recording heart sounds. One such example is that of ECG signal which is widely used biomedical signal for extracting information about the length of heart cycles and locating S1 and S2 heart sound components. [56],[57],[58]. In the later approaches, different distinguishing characteristics of the cardiac cycle is extracted from heart signals.

4.3.1. Multi-Channel Signal Approaches

In this class of approaches, two different types of signals are demonstrated and are used alongside the heart sounds in order to make the noise removal process easy and simple. These signals are the ECG signals, the acquisition of which is carried out using gel-based electrodes, and the second type of sounds are artifacts caused by environment. Carvalho et al [56] for the first time used ECG signals as a reference for identification of noise in heart sounds. The idea behind this approach is to find the correlation between the power spectral density (PSD) of each cycle of the heart sound and the reference heart sound PSD. It is a three step process i.e. (i) Identify heart cycle, (ii) Identify reference sound, and (iii) correlate the PSD of heart cycle and reference sound. ECG is used for the determination of heart cycles by identification of consecutive Q components in the ECG. After that, a reference sound is identified from the first ten heart cycles using correlation of each heart cycle's PSD and PSD of the remaining heart cycles. The reference cycle is chosen on the basis of average PSD which is largest among the 10 heart cycles. The effectiveness of this approach is reported in identification of different types of noise i.e. cough, stethoscope movement, environmental artifacts and speech sounds. Another approach is that of Paul et al [57], which is mainly used for speech recognition and is adapted for noise reduction in heart sounds. Their approach is based on spectral domain minimum mean squared error estimation. In this approach, the estimation of noise spectrum is carried out using a direct decision mechanism and needs no reference signal at all. This approach minimizes the effect of white noise from heart sounds. Let suppose we have $x(t)$ as our desired neat and clean heart sound. Additive white noise $n(t)$ is mixed with heart sound and we have $y(t) = x(t) + n(t)$ as the signal acquired from the sensor. Heart sound signal $x(t)$ is obtained using spectral domain estimation of noise. The magnitude of Fourier transform for the clean heart sound signal is find as:

$$X(f) = G(f)Y(f) \tag{1.1}$$

where $G(f)$ in the above equation is Wiener filter gain and can be given as

$$G(f) = \frac{SNR_{priori}}{1+SNR_{priori}} \quad (1.2)$$

In the above equation, SNR_{priori} is computed on the basis of original clean heart signal i.e. $X(f)$ and noise spectrum $N(f)$ and is termed as Apriori signal-to-noise ratio. ECG is not only used in identification of S1 and S2 heart sounds but it is also used in localizinhe S3 and S4 sounds by identification of QRS-complex and T-wave. Moreover, spectral peaks in the heart sounds can also be searches which are aligned with this location which help in identification of these events.

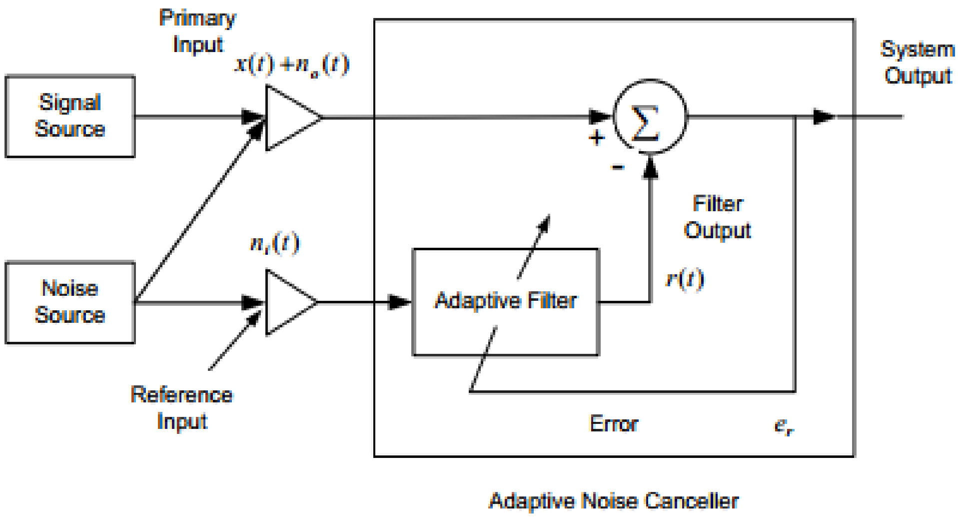

Figure 4.2 Adaptive noise cancellation in multi-channel signal approach

Another approach for noise detection and removal make use of additional sensor which captures noise with heart sound. Spectral subtraction of ambient noise from the acquired signal is carried out in order to eliminate unwanted signal. Let us suppose we have $x(t)$ as our heart sound signal, $n_o(t)$ is white noise which is added with heart sound. $n_i(t)$ is the reference signal i.e. noise signal. The correlation of noise signals i.e. $n_o(t)$ and $n_i(t)$ is assumed as shown in Fig 4.2. The phenomena are that Adaptive Noise Canceller block receives the reference noise signal and adaptively filter it. The result is then subtracted from the original signal and the relative error is calculated as follow:

$$e_r = x(t) + n_o(t) - r(t)$$

The minimum mean square error estimation can now be calculated as follow:

$$E\ (e_r^2) = E(x(t)^2) + E((n_o(t) - r(t))\ ^2)$$

It is evident from the above equation that expectation minimization of the power signal is not affected. So, the part of error signal i.e. $(n_o(t) - r(t))\ ^2$ is minimized in order to minimize the expected error (e_r^2) and cancel out noise from the heart sound signal. The expectation minimization is carried out using the following equation,

$$min\ E\ (e_r^2) = E(x(t)^2) + min\ E((n_o(t) - r(t))\ ^2)$$

In the above equation, the term $r(t)$ which is the filter output of the adaptive filter is the best least square estimation of the noise $n_o(t)$. Now it is quite evident that by changing the adaptive filter results in minimizing the total output power and give promising estimated signal for the input signal and reference signal as well. The mechanism of action for noise cancellation is that two microphones are introduced to the signal acquisition setup. One microphone is attached to the stethoscope in order to acquire heart sounds and the second one is used for acquiring the noise artifacts caused due to environment. This way, contaminated sounds are subtracted from the noisy sounds using the above mentioned ANC method. Due to the promising results this method gives, many other authors have also used this method as a preprocessing step in their medical signal processing tasks. [54] [59] [61].

4.3.2. Single Channel Approaches

In Single Channel approaches for heart sound, different physiological and acoustic properties of the heart sounds are considered which give an insight and in-depth understanding for developing proper techniques for noise detection and removal.

It is a matter of common observation that noise removal in heart sounds is considered as a de-noising process and noise is suppressed in the recorded heart sounds using digital filtering. An extensive amount of work is done by different authors in this area using their novel techniques for filtering and noise reduction. For example, Liang et al make use of an eighth order Chebyshev type I low pass filter having cutoff frequency at 882Hz for noise removal. [62] Hurtig et al in [63], on the other hand make use of a fifth order Butterworth band pass filter with cutoff frequencies between 5Hz and 250Hz. Although these are very straight away methods and work fine for removal of additive white noise however these simple methods give no promising results in such cases where the frequencies of noise lie in the pass band. Sornmo et al in [64] used another method which is known as ensemble averaging, in which they hypothesized that the fluctuations in signals occurs in some periodic fashion. So they divided the signal into segments and found maximum likelihood estimator by averaging sample of each segment. They argued that an additive, independent and Gaussian noise $n_i(t)$ is additively added to the clean signal $x(t)$ and results in the contaminated signal $y_i(t) = x(t) + n_i(t)$. The estimated signal can then be calculated as follow;

$$\hat{x}(t) = \frac{1}{M}\sum_{i=1}^{M} y_i(t)$$

Where M represents the number of samples in each segment and $\hat{x}(t)$ is the estimation of original signal. Moreover, $\hat{x}(t)$ can also be calculated as in a recursive manner as follow;

$$\hat{x}_M(t) = \hat{t}_M(t)\frac{1}{M}(y_i(t) - \hat{x}_{M-1}(t))$$

In the above equation, $\frac{1}{M}$ act as the controlling factor for the update of new segment averaging ensemble. However, Gustfsson reported in [16] that it can be adjusted in such a way that it should take higher values for more recent samples as compared to less one which would take smaller values. Another approach of adaptive line enhancement (ALE) is proposed by

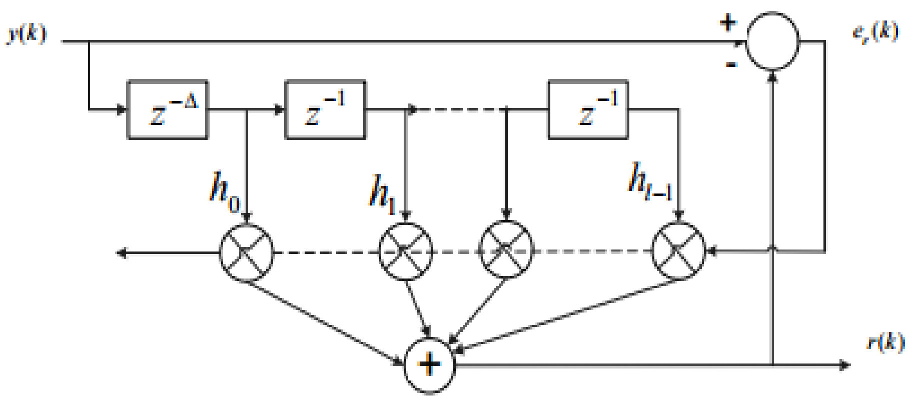

Figure 4.3. Taped delay adaptive line enhancement filter model

Tinati et al in [66] as depicted in the Fig 1.2. in which delay blocks are kept in a series fashion and correlation between signals and delayed signals is calculated which eliminates the noise.

Another noise removal technique which is extensively used in one dimensional and multi-dimensional signals e.g. images is the wavelet decomposition. This approach is significant in situations where the signal is transient and poses higher amplitude as compared to that of the noise. The basic philosophy behind wavelet decomposition is that the original signal is successively decomposed into lower frequency bands until it reaches a certain depth, then thresholding is applied and the signal is reconstructed in order to get the noise free signal. Many authors have used this approach for noise removal from heart sounds. [67]-[69]. Khan et al in [70] proposed noise removal technique based on multi-scale product of wavelet coefficients and tried to find a trade-off between information loss and time complexity for linear adaptive filtering and time-frequency based adaptive filtering techniques.

4.4. Heart Sound Segmentation

Segmentation is one of the most important, sensitive and interesting tasks in heart sound analysis after noise removal. Segmentation is carried out in two parts i.e. delimitation and recognition. In the former part, the onset and offset of the signals are identified where as in the later part, components of the heart sound i.e. S1, S2 and murmur are recognized. There exist two main classes of approaches in the literature for heart sound segmentation i.e. segmentation with and without an auxiliary signal. The former set of approaches needs less processing steps as these approaches consider markers which coincide with the main heart sound. On contrary to these approaches, segmentation without auxiliary signal make use of a sliding window approach for locating the main heart sound. Detail discussion and state of the art are presented in the following sub sections.

4.4.1. Approaches with an Auxiliary Signal

It is a matter of fact that signal profiles of S1 and S2 heart sound are different from murmur. So, if one can precisely identify S1 and S2 heart sounds then it is not difficult to identify murmur as well with proper processing steps. It is observed that heart sounds with murmur in systolic or diastolic cycle produce complex signals as compared to normal heart sounds. Such cases need a reference signal for efficient segmentation of heart sounds. That is why majority of the multichannel signals based heart sound segmentation approaches consider peak detection more as compared to duration.

Wilton et al for the very first time made use of ECG signals for computer assisted cardiac assessment [71]. El-Segaier et al carried out S1 and S2 heart sound detection by merely using ECG signals. They used to search the signal intensity above a pre-defined threshold values in a single heart beat i.e. (interval 0.05-0-2R-R) in order to identify S1 whereas for the detection of S2 sound, they searched within the interval of 0.6R-R after T-wave. In order to identify murmur, they used to find the highest peak point in between S1 and S2. [72]. Carvalho et al in [56] used almost the same approach where they made use of the fractal dimension of variance for determining S1 and S2 and segment out these sounds using R-peak and T-wave gating mechanism by polling. Barschdorff et al proposed their novel approach of using a multi sensor signal. In their method, they used to measure five different synchronized signals namely ECG, ear pulse, Doppler, Ultrasonic blood flow and heart sounds. Identification of S1 and S2 sounds was carried out by information extracted from either of the signals.

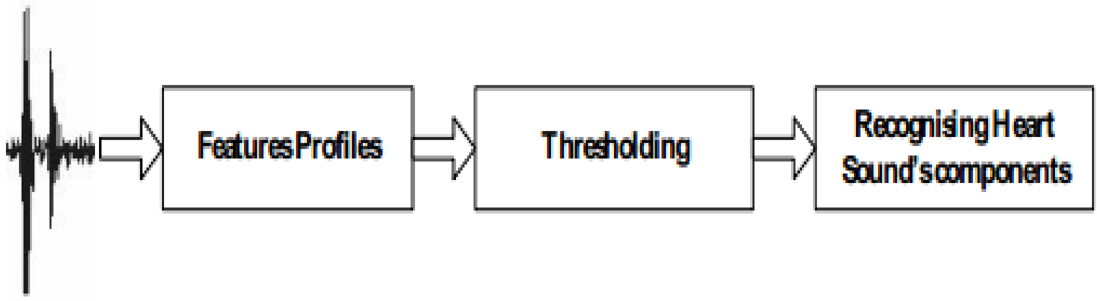

Figure 4.4 Steps for heart sound segmentation

4.4.2. Approaches with Heart Sound Signals

Identification of S1 and S2 heart sounds by the adding a synchronized signal leads to a potential hardware and time complexity of the system thus make it less user friendly and practically odd for applications. In order to avoid these bottlenecks in heart sound segmentation, various methods are proposed in the literature which not only do the same heart sound segmentation task efficiently, rather save the hardware cost and reduce the time complexity as well. These types of methods are based on machine learning approaches which consider cardiac acoustic signals solo and perform operations on this data. Since machine learning approaches can be broadly classified as supervised and un-supervised techniques, so as in the case of heart sound segmentation both classes of techniques are used. The mechanism of action for Un-supervised approaches is same as depicted in Fig 1.3. On contrary, the supervised approaches make use of features extraction from heart signal profiles and then perform machine learning classifier for segmentation of heart acoustics into S1 and S2.

i. Unsupervised Approaches

After performing the very first noise removal step, features set in the time and/or frequency domain are extracted from the clean heart sound signal for segmentation. These are then fed to an unsupervised classifier which distinguish heart sounds from rest of the signal due to the periodic nature of cardiac acoustics along with consideration of other characteristics i.e. frequency range of heart sounds and intensity etc.

In this regard, Liang et al in their proposed method tried to extract features from heart sound signal using Shanon energy because of its ability to highlight medium frequency sounds i.e. S1 and S2. [62]. The peaks related to S1 and S2 are identified using adaptive threshold average normalized Shanon energy. The basic philosophy behind their proposed method is that they find the larger interval between two consecutive diastolic cycles, reason being diastolic intervals are a bit larger than systolic intervals. The same approach was employed by other researchers as well later in [73]-[75]. Wang et al computed the Shannon energy from the heart sounds signals directly whereas Nazeran et al made use of the wavelet decomposition up-to the depth of 6 levels where they assume that the effect of external noise and environmental artifacts is minimum.

Yadollahi et al in their novel approach introduced the concept of computation of Shanon and

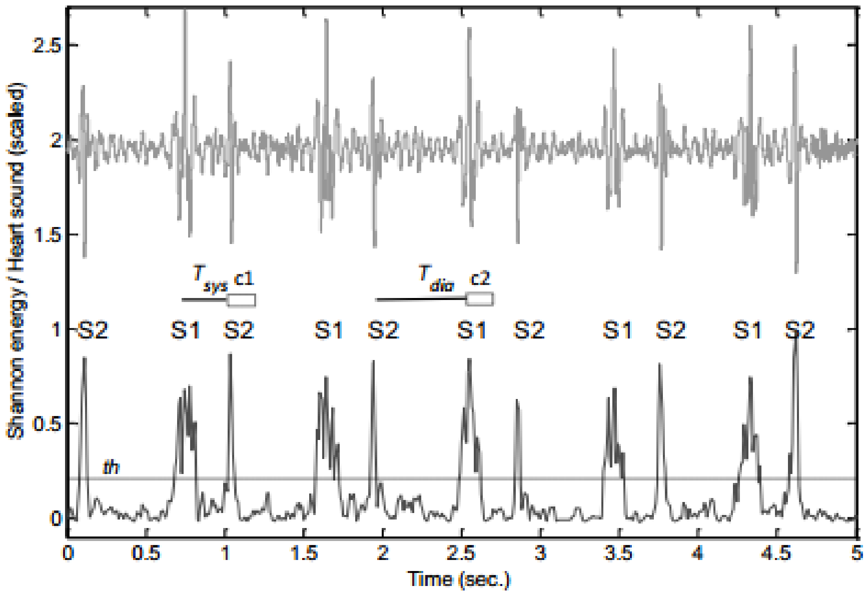

Figure 4.5 Heart sounds segmentation using Liang's envelogram method

Renyi entropy and used a kernel based entropy estimation approach is used for computing probability density distribution using the following equations.

$$H(p) = -\sum_{i=1}^{N} P_i \log P_i$$

P_i in the above equation represents the series of samples probability of heart sounds and N is the total number of cycles.

$$H_{\alpha}^{Re}(p) = \frac{1}{1-\alpha} \sum_{i=1}^{N} p_i^{\alpha} \tag{1.9}$$

Where α represent a real number. Entropy will be high when $\alpha > 1$ and so as the probability and vice versa. Heart sounds are localized in the presence of lung sounds by thresholding different values of entropy computed. The thresholding of Shanon entropy resulted in more accurate heart sound localization as compared to Renyi entropy. Moreover, it was also found that Renyi entropy is more prone to noise and environmental artifacts as compared to Shanon entropy. Hasfjord in [76] proposed a method which make use of different fractal techniques and reported a dissimilar degree of complexity for main heart sound, murmur, noise and unwanted signal components. The fractal techniques used by this author are continuous box counting methods, variance, Hegushi and information methods. The author reported that variance and Hegushi based complexity curve give promising results in discrimination of heart sounds into S1, S2 and murmur.

Yet another approach in the class of unsupervised approaches for heart sound segmentation is that of using temporal features of the cardiac acoustic signals. However, the absence of frequency intensity values in the power spectral density (which corresponds to the temporal information of the signal) leads the researchers to consider time-frequency features for heart sound segmentation. For example, Liang et al introduced a time-frequency analysis approach which segment out S1 and S2 sounds based on the quantification of spectrogram. Similarly, the short time Fourier transform (STFT) is yet another approach for time-frequency analysis of a signal. However, the main bottleneck of STFT is its inability to capture high resolution frequency components in a signal due to fixed size of the window. In order to overcome the aforesaid problems, many authors have proposed their novel approaches which make use of the wavelet transform (WT). [77]-[80]. The wavelet transforms make use of a shift and scale parameters for capturing the signal components of interest in any signal as follow.

$$CWT(c,d) = \frac{1}{\sqrt{c}} \int \psi \left(\frac{t-d}{c} \right) x(t) dt$$

Where c, d in the above equation are scale and shift parameters respectively. Whereas ψ represent the mother wavelet (window function). A variety of mother wavelets are discussed in the literature, the choice of using a particular wavelet function is based on the resemblance of waveform with mother wavelet output. Kumar et al in [81] proposed yet another novel approach which combines the Shanon energy in the wavelet domain to Mel-frequency spectral coefficients (MFSC) and reported a more efficient heart sound segmentation into S1 and S2. Nigam et al in [82] proposed yet another novel approach in which they consider heart as a dynamic system and the heart sound segmentation is performed on the basis of its dynamic complexity. Although the authors reported the simplicity of their approach as shown in the figure below, however no S1 and S2 heart sound segmentation in the presence of murmur is reported.

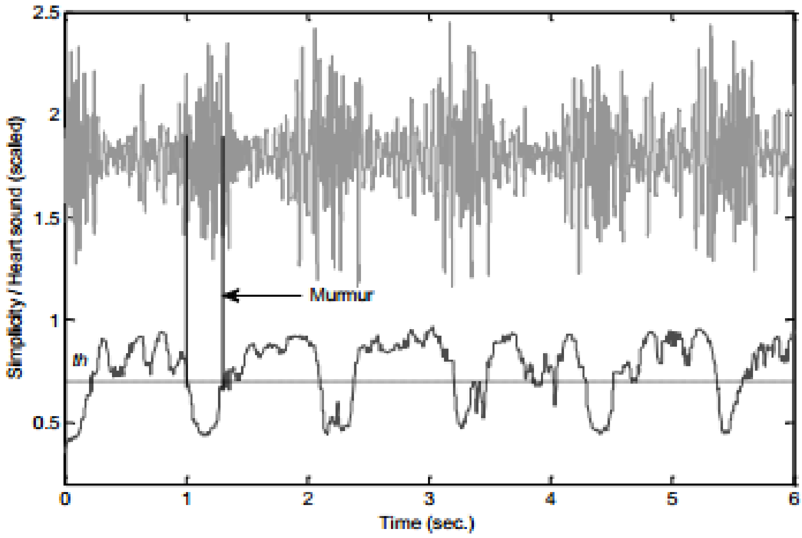

Figure 4.6 Heart sound segmentation [82]

ii. Supervised Approaches

In the supervised learning paradigm, heart sound segmentation into S1 and S2 is carried out in a typical machine learning approach which normally includes the steps like features extraction, features selection and training followed by training the classifier e.g. ANN, SVM, GMM, WN etc. Reed et al in [83] proposed their neural network-based feature extraction approach for S1 and S2 heart sounds signals from their wavelet decomposition. They modeled the cardiac system as a liner time-varying system with different time invariant responses. The idea is they consider valve closure event as input to the system whereas the sound components heard from the thorax is considered as output. S1 and S2 heart sounds are the output which are produced as a result of impulse generation by the Mitral and Tricuspid valves, and the Aortic and Pulmonary valves respectively. In order to characterize the system response, the following steps are taken as (i) Estimate the relative amplitude and time of input impulses, (ii) Estimate the transfer function for S1 and S2 in the frequency domain. An interesting point is that S1 and S2 sounds are computed for both normal heart sounds and those with some abnormalities. Both sets of S1 and S2 are then compared and used to train a neural network-based classifier.

Chapter 5 : PROPOSED METHODOLOGY

This chapter explain the approach we developed for localization of S1 and S2 heart sounds within the PCG. Our main goal about which we are concern is methods related to reduction or cancelation of noise from the heart sounds, identification of heart sound and segmentation of heart sound into fundamental (S1 and S2) heart sound. Figure 1 shows the flow of our method.

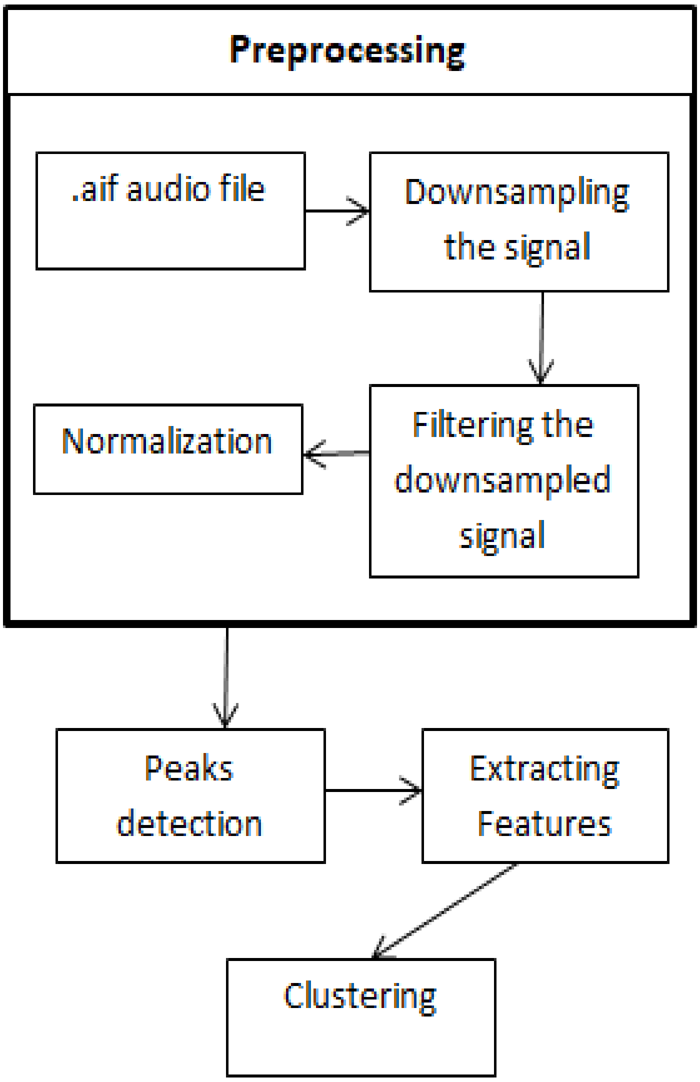

Figure 5.1 Flow chart of Segmentation Methodology

5.1. Pre-processing

Heart sounds with duration of three seconds or less than three seconds are eliminated. These sounds files in the targeted dataset are recording of heart sounds contaminated with noise. It is better to clean or reduce the noise from the audio sound.

PCG audio files are initially pre-processed before localizing or segmenting S1 and S2 heart sounds [3]. Down sampling, filtering and normalization are three steps involved in pre-processing.

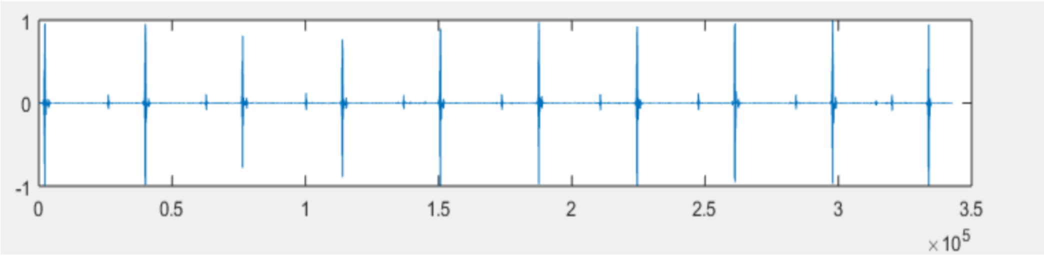

Figure 5.2 201106151236.aif file from normal category of PASCAL dataset

To avoid some computation these audio files are down sampled with the factor of 2, using decimate function of Mat lab (MATLAB, 2015b). Information of heart sound are mostly present in low frequencies while noise on the other hand can be located in the higher frequencies. Therefore, the down sampled signals are filtered with Butterworth bandpass filter of order 6 with cut-off frequency from 25 Hz to 900 Hz to reduce noise which is shown in the fig 2.

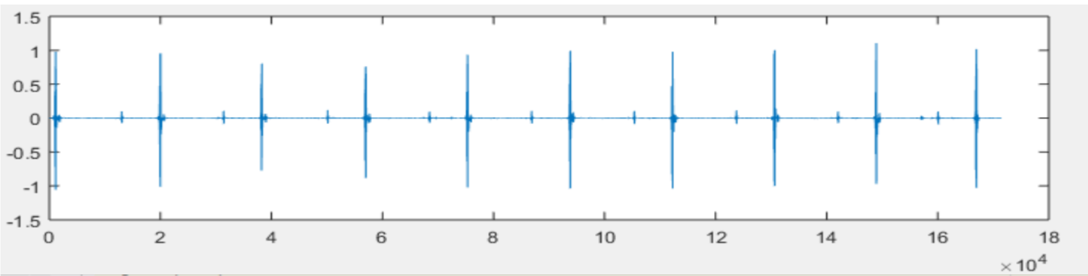

Figure 5.3 down sampled 201106151236.aif normal heart sound signal

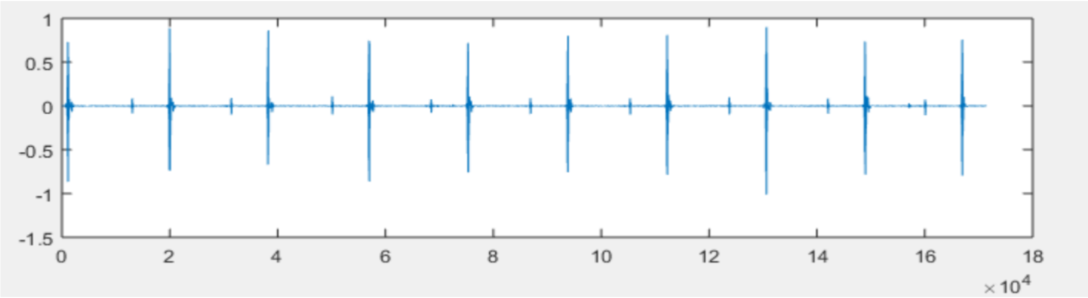

Figure 5.4 filtered with Butterworth lowpass filter of order 6

Then, the signal is normalized with absolute maximum normalization as shown in the fig 2. This brings all the signals to a common range of -1 to 1. Normalization is done in two steps, finding extreme absolute value is first step and in second step the signal is divided by maximum value.

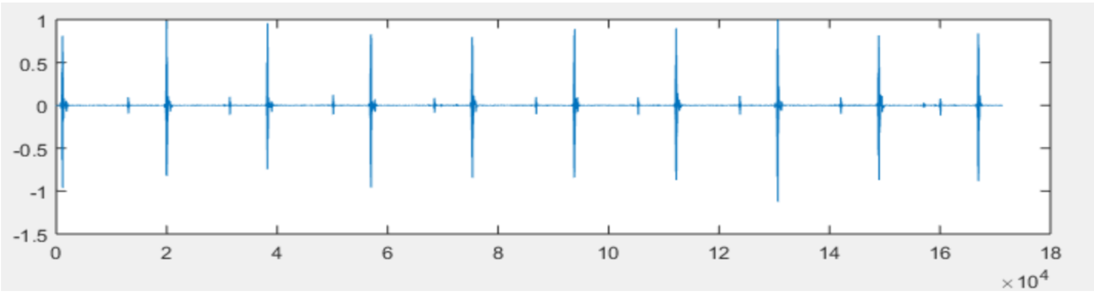

Figure 5.5 absolute maximum normalization of the above processed signal

5.2. Peak detection

Shannon Energy is a powerful technique for extraction of envelope from heart sounds. It helps in split and tooted peaks. It works best in localization of various components in PCG signals. This method converts nonlinear combination of signal into some linear combination of signals. Therefore, Shannon energy is calculated in order to smoothen the pre-processed signal which will help next in finding peaks. Shannon energy has been depicted in the following equation [5].

$$Shannon\ Energy = -x^2\ (t)\ log\ x^2(t) \tag{5.1}$$

Shannon energy for each file is calculated as average Shannon energy. The average Shannon energy is calculated in continuous 0.02 samples per second window with 0.01 samples per second overlap.

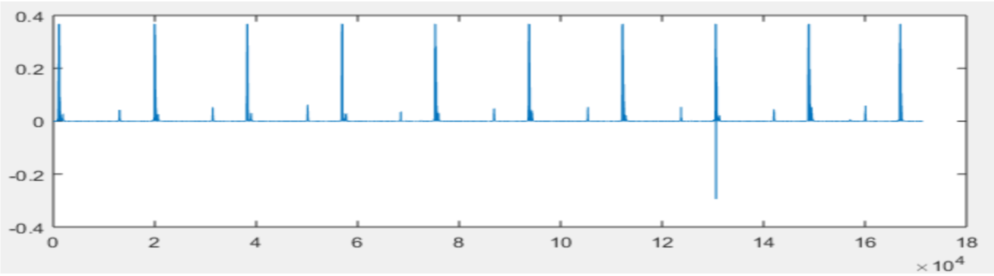

Figure 5.6 Shannon energy of the processed signal

The average Shannon energy can be represented as follow.

$$E = -\frac{1}{N}\sum_{n=1}^{\infty} x^2\ (i) log x^2(i) \tag{5.2}$$

Where x(t) is the processed signal and N is length of the windows which is in this case 0.02 samples per second. In the last, average Shannon energy is calculated of every window in the processed sample is then normalized. Normalized Shannon energy of the processed signal can be calculated as fallow.

$$P(t) = \frac{E(t)-ME(t)}{SE(t)} \tag{5.3}$$

Where E (t) is average Shannon energy calculated of window number "t" of size 0.02 sample per second while ME (t) and SE (t) are mean energy and standard deviation of E(t), respectively. P (t) is the normalized average Shannon energy which is also called Shannon Envelope.

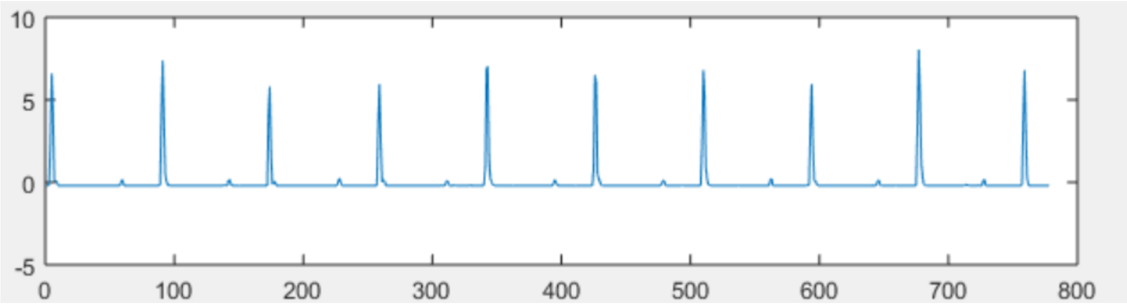

Figure 5.7 Normalized average Shannon energy of the processed signal

Shannon envelope as shown in the fig 3 smoothen the sound signal and make peaks prominent. Fundamental heart sound peaks are selected on the basis of amplitude thresholding and peaks gap thresholding after calculating Shannon envelope by using a predefined and open source function. Extra peaks with amplitude smaller than threshold are eliminated and those peaks are also rejected whose in-between gaps are smaller than the defined threshold.

After identifying or selecting fundamental heart sound peaks, now it needs to distinguish in between these peaks to analysis the rhythm of heart sound. From that rhythm of heart sounds abnormalities of heart can be identified. The peak selected may be S1 or S2. For this purpose, a novel approach is used to distinguish S1 (lub) and S2 (Dub) heart sounds within selected peaks.

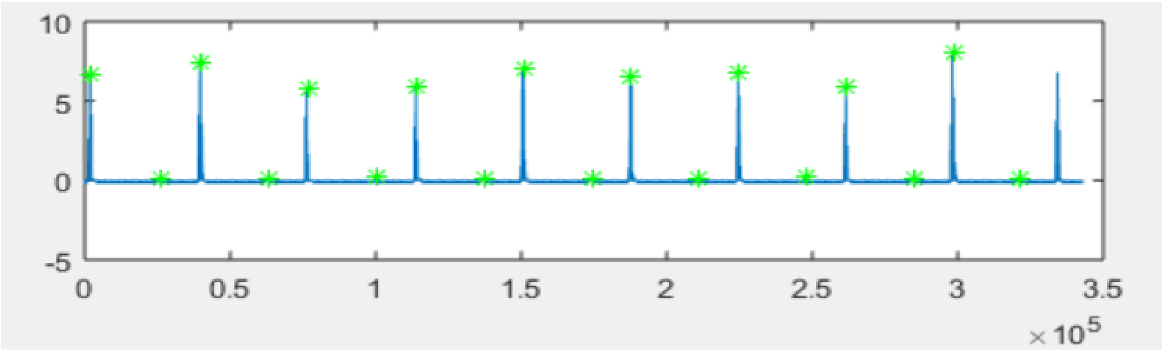

Figure 5.8 Fundamental heart sound peaks

5.3. Feature Extraction

Among these peaks, S1 (lab) and S2 (dub) peaks are to be segmented out. For this purpose, features are extracted from both time and frequency domains of the Shannon envelope, in this paper. We extract four features, half of these features are from time domain and the other half is from frequency domain.

Temporal features are as follows:

1. **Peak value:** Amplitude value of the peak.
2. **Peak Gap:** Gap between two successive peaks [6].

Whereas Spectral features are:

1. **Spectral centroid**
2. **Variation coefficient**

The two temporal features, Peak values and peak gaps are calculated from the peaks of the processed signal while spectral centroid and variation coefficients are calculated with our special method.

Some samples are selected before peak sample and the same number of samples after the peak position are selected from the signal obtained after preprocessing phase. Also including sample at peak position. Power Spectral Density (PSD) is calculated for the selected section of the signal for spectral feature extraction [7]. PSD can be calculated with the help of the following equation.

$$P(w) = \sum_{-\infty}^{\infty} r_y[n] e^{-jwn} \quad (5.4)$$

Where $r_y[n]$ is autocorrelation of the selected region of the signal which can be define as E(y[m]y[m]*), let y[m] is the selected region of the pre-processed signal. The two spectral features are extracted from here.

The first spectral feature Spectral feature extracted is spectral centroid. Spectral centroid can be calculated as follow.

$$C = \frac{\sum wP(w)}{\sum P(w)} \qquad (5.5)$$

P (w) is the amplitude of w^{th} frequency bin in the spectrum. During our studies we analyse that variation coefficient of S1 and S2 was different from one another. Variation coefficient can be calculated as:

$$\sigma^2 = \frac{\sum (w-C)^2 P(w)}{\sum P(w)} \qquad (5.6)$$

Whereas C in spectral centroid which we calculated in the previous equation.

5.3. Clustering

We have extracted four features of each peak, that helps us in identification of S1 (lub) sound peak and S2 (dub) sound peak. There are different machine learning techniques for classification and segmentation that can be used to segment out S1 heart sound and S2 heart sound.

The best approach we find in our case in K-mean clustering algorithm. K-mean clustering algorithm gives good result as compere to some other clustering and classification algorithms. It almost successfully identifies S1 and S2 heart sound peaks with the help of features extracted as shown in figure 5.9.

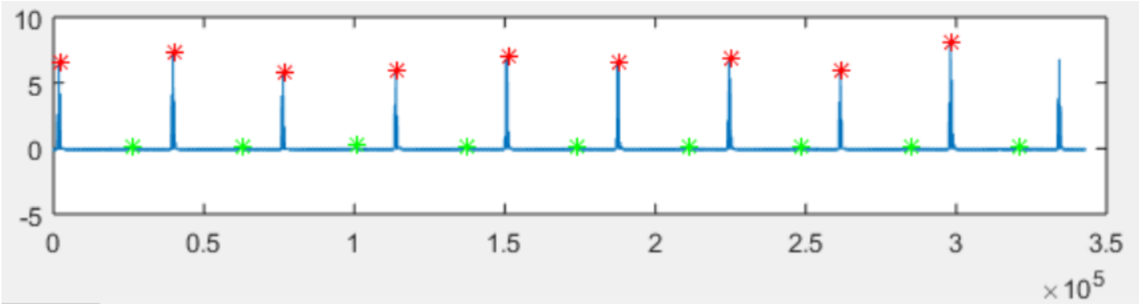

Figure 5.9 S1 and S2 segmented heart sounds

Green dots show S2 (dub) heart sound and red dots show S1(lub heart sound). 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.

Chapter 6 : RESULTS AND CONCLUTION

We evaluate the results of our approach with the provided training data of Dataset A and Dataset B. This set contains annotated data of the normal heart sound category from Dataset A and B. The annotated data help improve our approach by comparing our method's results and required results.

We also evaluate our results for test dataset and the calculated error of test set A and test set B are shown in table 1 and table 2 respectively.

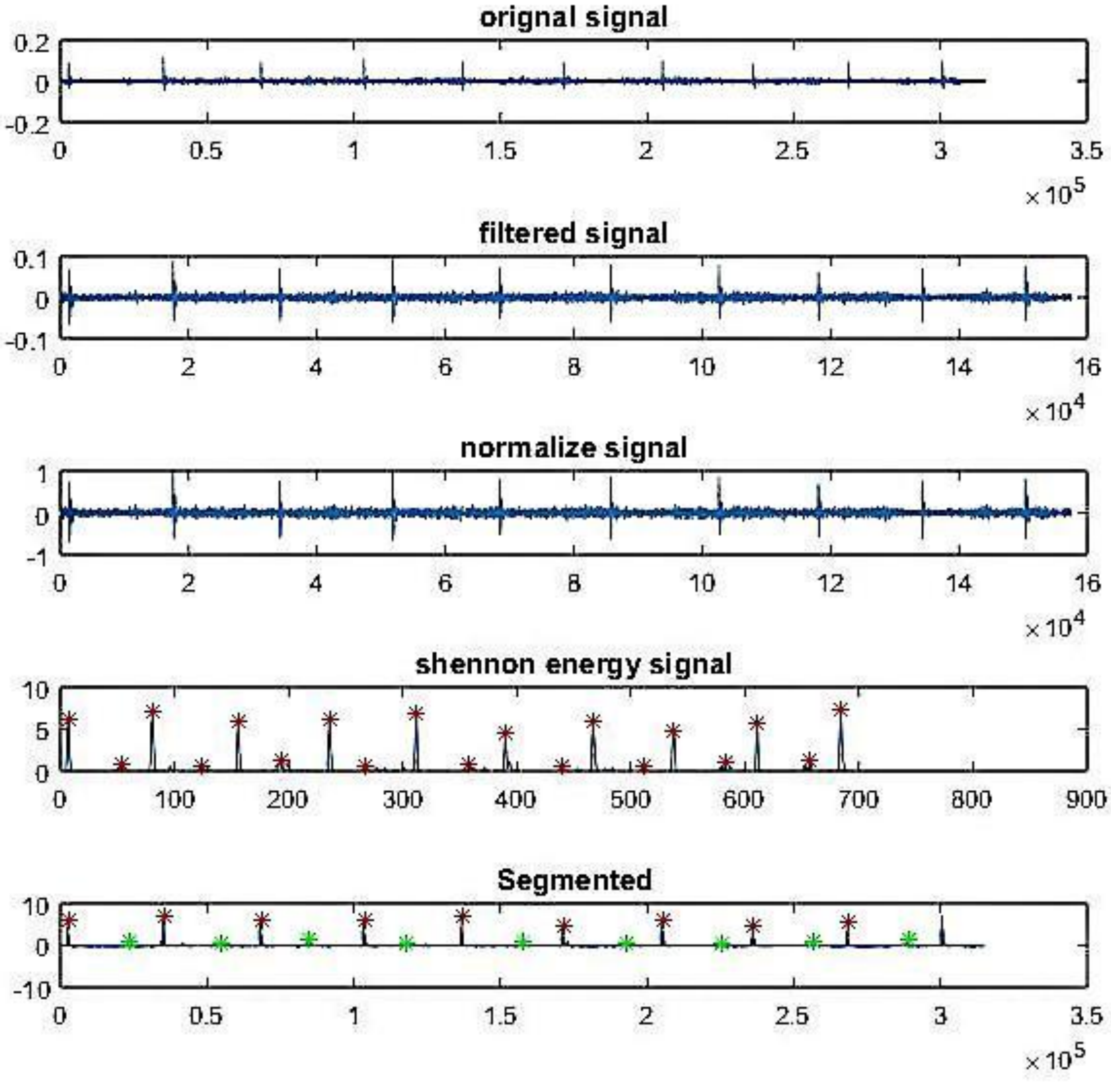

Figure 6.1 201102081152.aif file from normal category of PASCAL dataset

In figure 6.1, we can see the results of our applied methods for detection of peaks and localization of S1 and S2 heart sounds within the PCG audio file 201102081152.aif. The file 201102081152.aif is selected from the normal category of dataset A. In the first plot, we have the original heart sound signal, whereas, second plot shows signal filtered with Butterworth filter. The third is plot of normalized filtered signal, normalized by absolute maximum normalization while in the fourth plot we can see Shannon energy signal of the processed heart sound signal and in the last we have plot of segmented S1 and S2 heart sound peaks. Green peaks in the last plot represent S1 heart sound while red peaks indicate S2 heart sound.

6.1. Result of Dataset A

In table 1 we depict the segmentation results for the audio files from the category of normal in dataset A. We can see the total numbers of heartbeats in the second column of the table and the third column shows average error for each sound sample which is measure in sample for precision, while the total error of Dataset A is 853188.3002.

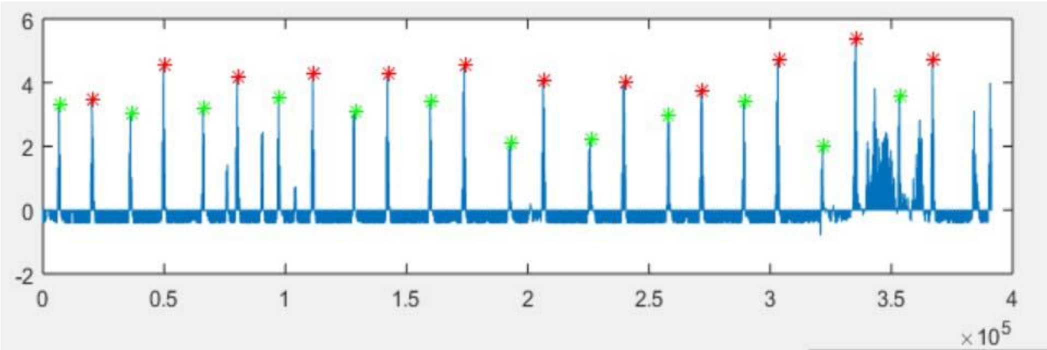

Figure 6.2 201101070538.aif file from dataset A of PASCAL

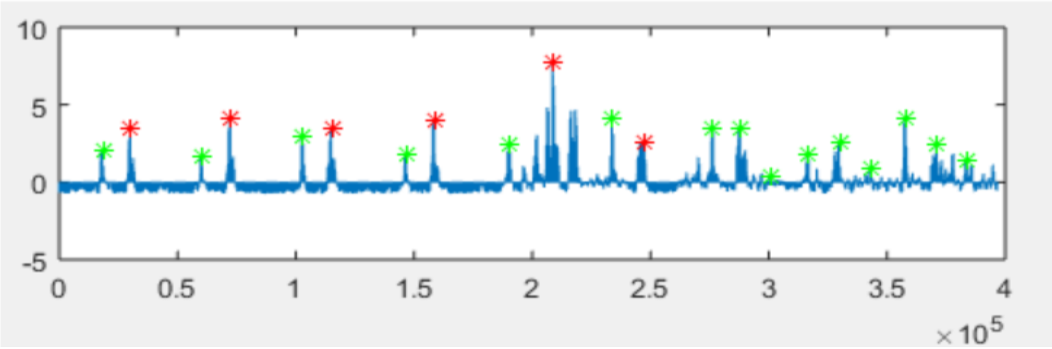

Figure 6.3 201101151127.aif file from dataset A of PASCAL

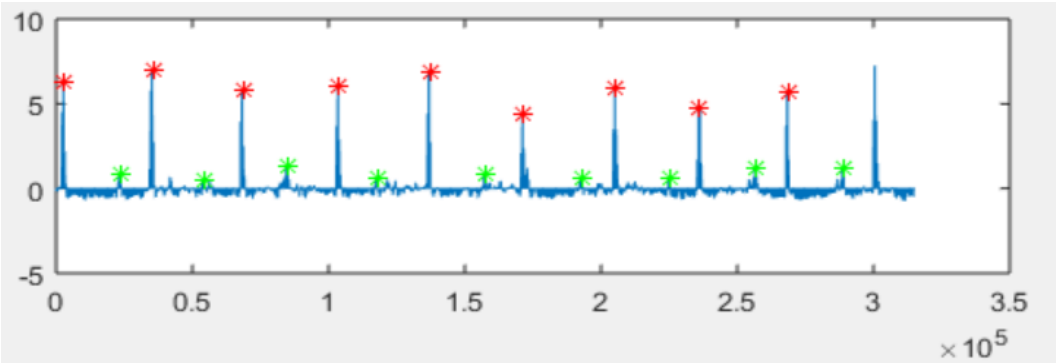

Figure 6.4 201102081152.aif file from dataset A of PASCAL

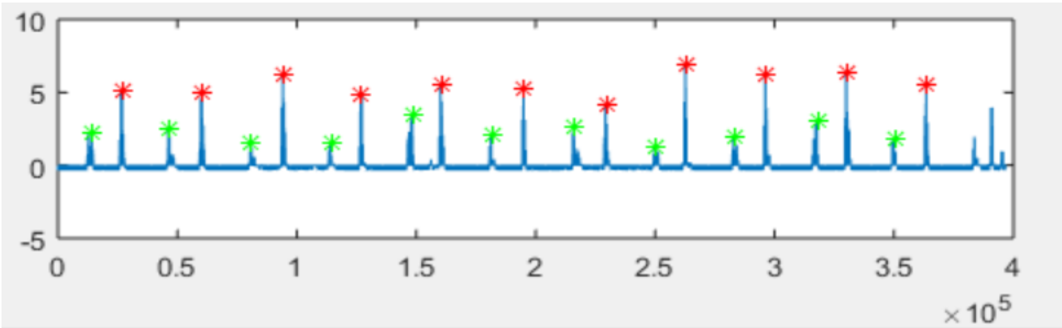

Figure 6.5 201102201230.aif file from dataset A of PASCAL

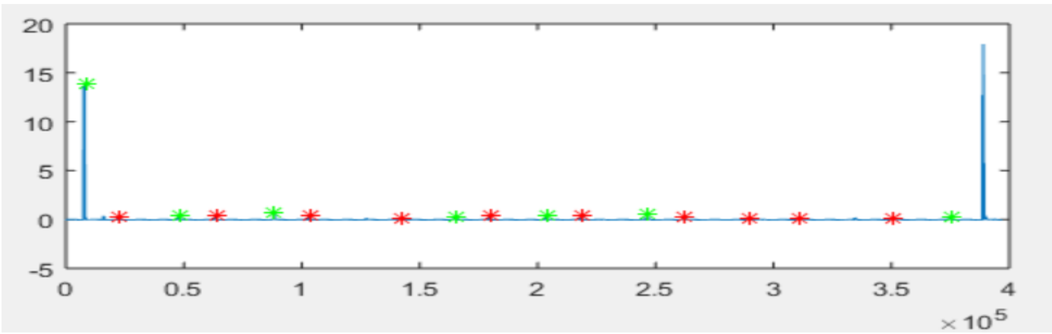

Figure 6.6 201102270940.aif file from dataset A of PASCAL

Table 6.1 Result of dataset A

File Name	Total of Heartbeat	Average Error
201101070538.aif	11.5	15719.26087
201101151127.aif	8	109283.8125
201102081152.aif	6	153499.1667
201102201230.aif	11	584.2727273
201102270940.aif	9.5	189061.1053
201103101140.aif	9.5	20782.73684
201103140135.aif	7.5	48645.73333
201103170121.aif	9.5	35623.84211
201104122156.aif	11	182462.1818
201106151236.aif	9.5	43708.52632

6.2. Results of dataset B

Table 2 presents the segmentation results for audio files, which is from the normal category of Data set B. Column 2 in the table shows total heart beats identified while the third column shows average error. The total error of dataset B is 20346.0474.

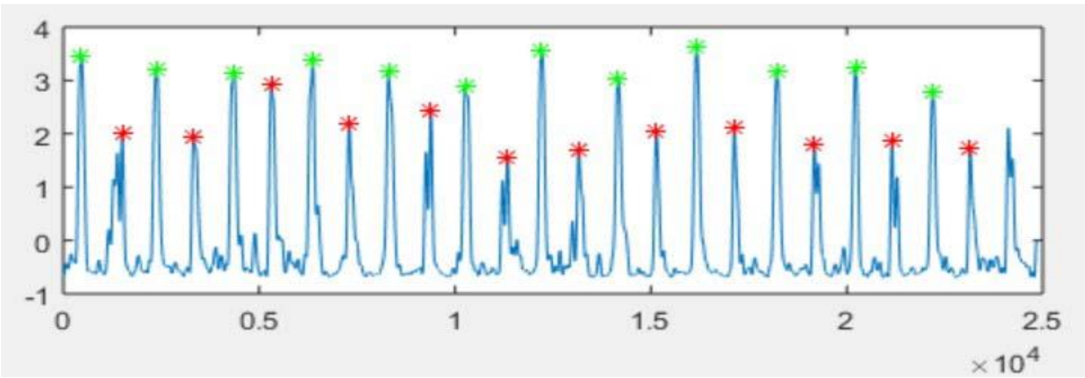

Figure 6.7 103_1305031931979_B.aiff file from dataset B of PASCAL

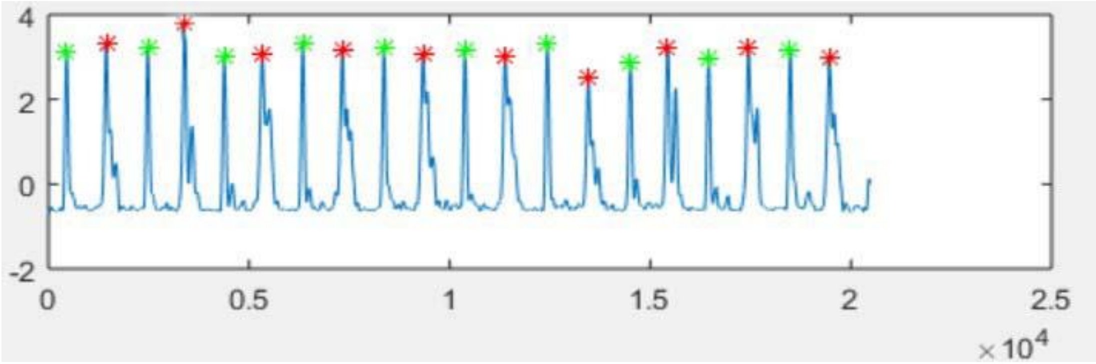

Figure 6.8 103_1305031931979_D2.aiff file from dataset B of PASCAL

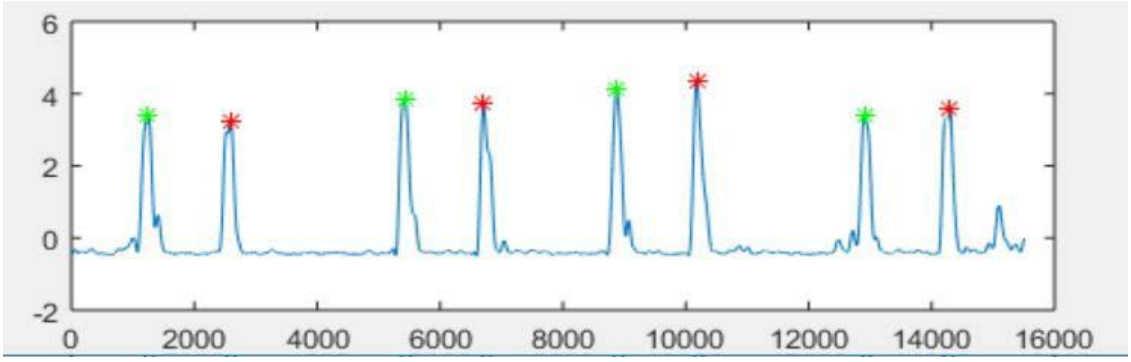

Figure 6.9 106_1306776721273_B1.aiff file from dataset B of PASCAL

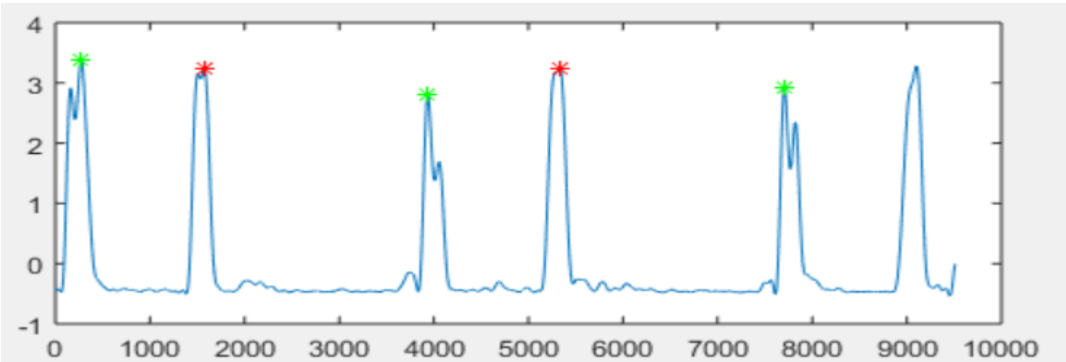

Figure 6.10 106_1306776721273_C2.aiff file from dataset B of PASCAL

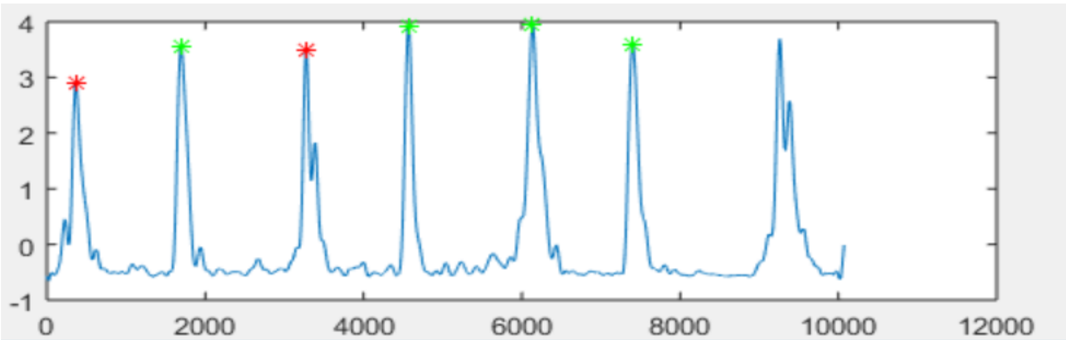

Figure 6.11 106_1306776721273_D1.aiff file from dataset B of PASCAL

Table 6.2 Results of Dataset B

File Name	Heartbeat	Average Error
103_1305031931979_B.aiff	12	4196.791667
103_1305031931979_D2.aiff	8	4842.375
106_1306776721273_B1.aiff	4	6808.125
106_1306776721273_C2.aiff	2.5	1783
106_1306776721273_D1.aiff	3	4202.166667
106_1306776721273_D2.aiff	7.5	2770.866667
107_1305654946865_C1.aiff	7.5	3378.8
126_1306777102824_B.aiff	8	5458.6875
126_1306777102824_C.aiff	5	1464.6
133_1306759619127_A.aiff	4.5	7763.333333
134_1306428161797_C2.aiff	2.5	2122.2
137_1306764999211_C.aiff	15	660.1333333
140_1306519735121_B.aiff	11	62.95454545
146_1306778707532_B.aiff	17.5	534.0285714
146_1306778707532_D3.aiff	3	14
147_1306523973811_A.aiff	3.5	38.57142857

148_1306768801551_D2.aiff	7	793.3571429
151_1306779785624_D.aiff	4.5	89.66666667
154_1306935608852_B1.aiff	4.5	47.22222222
159_1307018640315_B1.aiff	5	1989.9
159_1307018640315_B2.aiff	3	48.16666667
167_1307111318050_A.aiff	13	2075.5
167_1307111318050_C.aiff	2.5	381
172_1307971284351_B1.aiff	2.5	2371.8
175_1307987962616_B1.aiff	2.5	30
175_1307987962616_D.aiff	7.5	1918
179_1307990076841_B.aiff	16	2340.375
181_1308052613891_D.aiff	3	77.33333333
184_1308073010307_D.aiff	19.5	12157.76923
190_1308076920011_D.aiff	3.5	67.57142857

We can see that the error in dataset B is much better than Dataset A. This might be due to the reason that the Data of dataset B are collected with a digital statoscope in a quite environment of a hospital by expert physician however Dataset A are collected by person with less or no experience in rough condition on a smart phone.

Table 3 shows results of the three finalists and the results of our methodology for both of the datasets A and B.

Table 6.3 Total error found by three Finalists and by proposed methodology

	Dataset A	Dataset B
ISEP/IPP Portugal	4219736.5	72242.8
CS UCL	3394378.8	75569.8
SLAC Stanford	1243640	76444.4
Our Methodology	799370.6384	70488.2954

Chapter 7: CONCLUSION AND FUTURE WORK

7.1. Conclusion

This thesis presents a novel technique for segmentation of S1 and S2 heart sounds, which is the first challenge of "PASCAL Classify Heart Sound Challenge" [1]. In this work we created an improved segmentation approach by selecting two features in time domain and two features in frequency domain. Feature selection for clustering or segmentation involves these steps. First the sound signals are de noised and normalized. Shannon envelop of the processed signal are calculated. Extra peaks are rejected by peak amplitude thresholding and time in between two successive peak thresholding. In the last four features are extracted from every peak. Our proposed algorithm successfully differentiates between S1 and S2 heart sounds to a great extent while at this stage the two finalists could not achieve substantial success [3] [4]. We also reduced the total error of the Dataset A and Dataset B.

7.2. Future work

We still look forward to completely differentiate between the two heart sounds and to reduce the error. Our next aim is to agree the second challenge of "PASCAL Classify Heart Sound Challenge" [1] and develop an approach for classification of heart sounds. Major application of this approach is in the area of telemedicine and affordable as it is easy, cost efficient and non-colossal health care.

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