ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

Sultan ASLAN

CATEGORIZATION OF NORMAL AND ABNORMAL HEART RYHTMS FROM PHONOCARDIOGRAM SIGNALS

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

ADANA, 2020

ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

CATEGORIZATION OF NORMAL AND ABNORMAL HEART RHYTHMS FROM PHONOCARDIOGRAM SIGNALS

Sultan ASLAN

MSc THESIS

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

We certify that the thesis titled above was reviewed and approved for the award of degree of the Master of Science by the board of jury on -/-/2020.

……	……..	……
Assoc. Prof. Dr. Sami ARICA	Assist. Prof. Dr. Ercan AVŞAR	Assist. Prof. Dr. Abdurrahman ÖZBEYAZ
SUPERVISOR	MEMBER	MEMBER

This MSc Thesis is written at the Department of Institute of Natural And Applied Sciences of Çukurova University.
Registration Number:

Prof. Dr. Mustafa GÖK Director
Institute of Natural and Applied Sciences

This study supported by Çukurova University Scientific Research Projects Unit.
Project No:

ABSTRACT

MSc. THESIS

CATEGORİZATİON OF NORMAL AND ABNORMAL HEART RHYTHMS FROM PHONOCARDİOGRAM SİGNALS

Sultan ASLAN

ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES
DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

Supervisor : Assoc. Prof. Dr. Sami ARICA
Year: 2020, Page:63
Jury : Assoc. Prof. Dr. Sami ARICA
: Assist. Prof. Dr. Ercan AVŞAR
: Assist. Prof. Dr. Abdurrahman ÖZBEYAZ

The phonocardiogram is based on recording the mechanical sounds of the heart, especially the sounds of the heart valves, and subsequent analysis. It provides an objective assessment of the cardiovascular system, which is vital for human life. In this thesis, the classification and analysis of normal and abnormal heart sounds obtained from the PCG signal was investigated. The data was obtained from challenge 2016 Physio-net database which consisted of two groups; A and B. Phonocardiogram signals was first decomposed into S1, S2 and S4 waves. Then bursts in each wave were segmented, and average power and dominant frequency were calculated from the segments of these signals. A simple linear Bayesian classifier was used to categorize heart sounds. The average accuracy of group A and B was obtained as 61% and 48% respectively. It was observed that the method fails for group B. However, the result for A was promising.

Key Words: Phonocardiogram; heart sounds; dominant frequency; classification.

ÖZ

YÜKSEK LİSANS TEZİ

FONOKARDIYOGRAM SINYALLERINDEN NORMAL VE ANORMAL KALP RITIMLERININ SINIFLANDIRILMASI

Sultan ASLAN

ÇUKUROVA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ
ELEKTRİK-ELEKTRONİK MÜHENDİSLİĞİ BÖLÜMÜ

Danışman : Doç. Dr. Sami ARICA
Yıl: 2020, Sayfa: 63
Jüri : Doç. Dr. Sami ARICA
: Dr. Öğr. Üyesi Ercan AVŞAR
: Dr. Öğr. Üyesi Abdurrahman ÖZBEYAZ

Fonokardiyogram, kalbin mekanik seslerini, özellikle kalp kapakçıklarının seslerini kaydetmeye ve sonraki analize dayanır. İnsan yaşamı için hayati önem taşıyan kardiyovasküler sistemin objektif bir değerlendirmesini sağlar. Bu tezde, PCG sinyalinden elde edilen normal ve anormal kalp seslerinin sınıflandırılması ve analizi araştırılmıştır. Veriler, iki gruptan oluşan A ve B; 2016 Physio-net veri tabanından elde edildi. Fonokardiyogram sinyalleri ilk olarak S1, S2 ve S4 dalgalarına ayrıştırıldı. Daha sonra her dalgadaki patlamalar bölümlere ayrıldı ve bu sinyallerin bölümlerinden ortalama güç ve baskın frekans hesaplandı. Kalp seslerini kategorize etmek için basit bir doğrusal Bayes sınıflandırıcısı kullanıldı. Grup A ve B'nin ortalama doğruluğu sırasıyla %61 ve %48 olarak elde edildi. B grubu için yöntemin başarısız olduğu gözlendi. Ancak A için sonuç umut vericidir.

Anahtar Kelimeler: Fonokardiyogram; kalp sesleri; baskın frekans; sınıflandırma.

EXTENDED ABSTRACT

Sounds formed as a result of changes in the opening and closing of the heart valves (mechanical movements) and the movement of blood in the cardiovascular system during the work of the heart are called heart sounds. These sounds and vibrations recorded on the chest via a microphone are defined as Phonocardiogram (PCG) signals. The heard heart sounds are formed by the flow of blood entering and exiting the heart and the movements of the heart valves formed according to this flow. The sounds formed by the blood flow are meaningful and are listened to by physicians through a stethoscope. This is called auscultation. Auscultation is an inexpensive, effective, easy-to-apply, harmless diagnostic tool for the patient and the most common diagnostic method used worldwide. Sounds different from normal can be a symptom of any disease. For this reason, the heart sounds that are listened from the body with a stethoscope are interpreted by the experts and used in the diagnosis. Heart sounds are very complicated. For this reason, these sounds must be interpreted correctly and reliably for diagnosis. Defining and interpreting the findings obtained from auscultation depends on the expertise of the physician. Despite these advantages of auscultation, this process also has many limitations and disadvantages. Deficiencies in diagnostic skills cause serious consequences for some patients to suffer from serious heart conditions or even carry a risk of death.

Recently, developments in the fields of engineering, computer and electronics have overcome these limitations, making it possible to listen and analyze sounds in a more reliable and better quality in digital environments. Accordingly, computerized analysis of heart sounds with numerical signal processing algorithms can help diagnose the disease. In addition, thanks to computer-aided methods, physicians can interact with their colleagues for diagnosis and diagnosis via the internet, even if they do not work in the same environment. Digitally recorded sounds can be stored for a long time and used for

the pathological changes of the patient.

In this thesis, challenge 2016 data obtained from Physio-net physiological signal source is used. The database includes recordings from subjects, heart sounds collected from healthy individuals and patients with various conditions. Classification and analysis of normal and abnormal heart sounds obtained from PCG signal were performed. The algorithm of the thesis consists of sample reduction, decomposition, feature extraction and classification sections. Bayesian classifier was used to categorize heart sounds. It is divided into waves and the average power and dominant frequency is calculated from the segmented explosion of these signals. This approach appears to be important for detecting some abnormalities in the heart rhythm.

ACKNOWLEDGEMENTS

I would like to express my deep gratitude to my thesis supervisor Assist. Prof. Dr. Sami ARICA for his excellent guidance, support and patience. I wish to thank my parents for their support and encouragement throughout my study.

CONTEXT **PAGE**

LIST OF FIGURES **PAGE**

LIST OF TABLES **PAGE**

LIST OF ABBREVIATIONS

PCG	: Phonocardiogram
ECG	: Electrocardiogram
CPR	: Cardiopulmonary resuscitation
DFT	: Discrete fourier transform
IDFT	: Inverse discrete fourier transform
RMS	: Root mean square

1. INTRODUCTION

Cardiovascular diseases are among the diseases that seriously threaten human health. Therefore, heart sound analysis has become a basic need for physicians. Listening with a stethoscope is a primary method used by physicians to differentiate their cardiac systems through normal and abnormal heart sounds 1(Sinha, R.K., Aggarwal, Y., and Das, B.N., 2007). However, the method of listening with a stethoscope has many limitations. The ability of the physician to interpret different heart sounds depends on experience and skill (Kandaswamy et al., 2004). Due to these difficulties, listening with a stethoscope, that is, auscultation, is insufficient in the examination of heart abnormalities. For this reason, methods that examine biological signs, which give important information about the work of the heart, such as electrocardiogram and phonocardiogram, are used. ECG informs about the operation of the electrical conduction system of the heart. But PCG is used to study the mechanical movements of the heart (Novey, 1996).

This thesis is organized as follows. In the first chapter, PCG is defined and explained. The second chapter covers previous studies on the classification of heart sounds from phonocardiogram signals. In the third chapter, the algorithm of the thesis is explained. Then the results are provided. Also, the results are interpreted and finalized.

1.1. Structure of Heart

The heart is vitally one of the most important organs in our body. It provides the oxygen needed by the tissues to be pumped throughout the body. The functioning mechanism of the heart is an important pattern showing the electrical and mechanical power working together. Cardiopulmonary resuscitation (CPR) is an important part of medical emergencies. Because it is not possible for the body to maintain its continuity without working out.

The heart consists of four chambers. These chambers consist of two atria and two larger structures, the ventricle. The atrium, located on the right side of the heart, receives oxygen-poor blood in the body through vena cava superior and inferior. The blood that passes to the right ventricle by opening the valves is sent to the lung through the pulmonary artery. The blood sent to the lung becomes rich in oxygen through the agency of the circulation in the lung here. The oxygen-rich blood is brought to the left atrium through the pulmonary veins, and then the blood that enters the ventricle is pumped from here to the aorta. Thus, the oxygen need of the body is met. The heart here acts as a pump between the lung and the body (Martin and Lily, 2006)

Cardiac cycles consist of systole and diastole. During this pumping, the passive relaxation of the heart while taking blood from the body and lungs is called diastole. When the pressure in the atrium filled in the diastole exceeds the pressure of the ventricle, the AV valve (tricuspid on the left and the mitral on the right) is opened and the ventricular filling is completed. When the ventricular pressure passes through the atrium, the AV valve closes again.

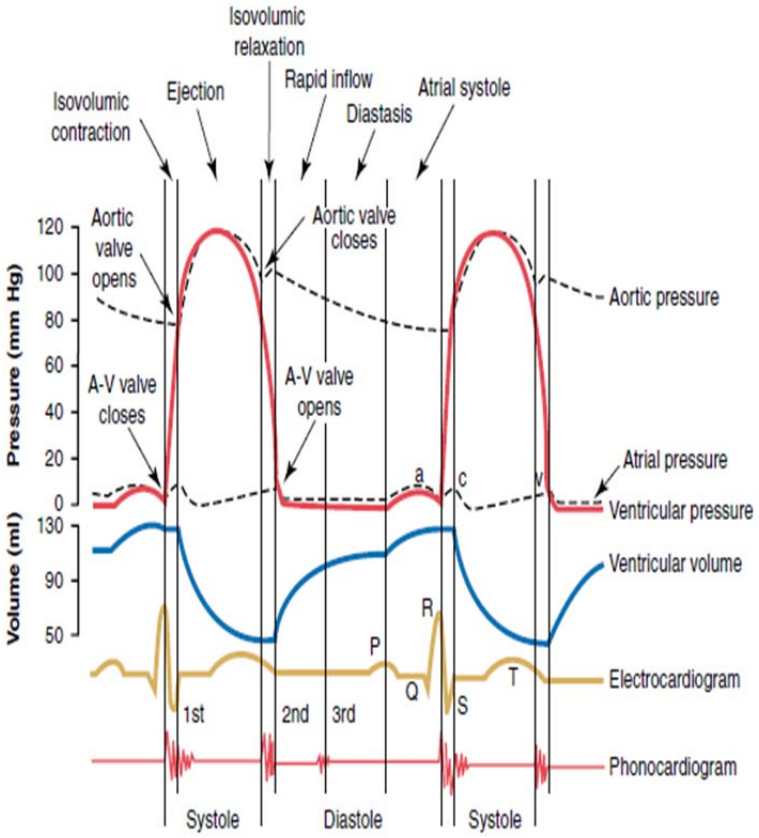

Figure 1.1. Volume pressure cardiac cycle ECG and PCG (Hall, 2015)

The electrical activity in the heart starts from the SA node and is transmitted to the AV node and then to the purkinje fibers and spreads to the whole heart.

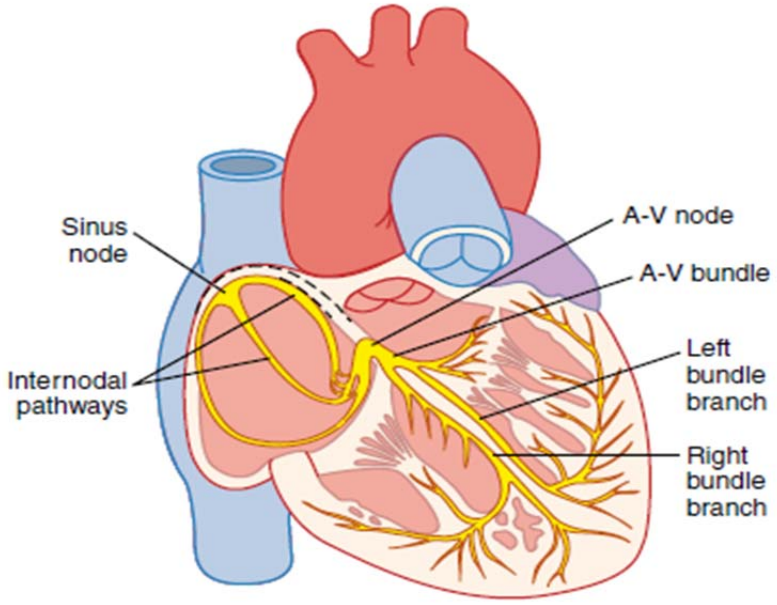

Figure 1.2. Electrical system model of the heart (Hall, 2015)

This electrical stimulation occurs during the depolarization phase of the action potential that occurs here and the systole phase of the heart by contracting the heart muscle (Chowdhury et. Al, 2013). Repolarization corresponds to diastole. When the pressure of the ventricles contracted in systole exceeds the pressure of the aorta and pulmonary artery, the seminar valves located there are opened and blood is pumped. Decreased blood in the ventricles causes the pressure to drop. When the aortic and pulmonary artery pressure exceeds the ventricular pressure, the seminar valves are closed. While diastole forms 2/3 of the heart's temporal cycle, 1/3 forms systole. This is due to the feeding of cardiac muscle cells in diastole. Any pathology in the mechanical or electrical system of the heart causes disruption of the heart's pump function, which poses a vital risk.

1.2. Heart Sounds

The mechanical movements of the heart produce audible sounds. These sounds are called heart sounds. When listening to the heart with a stethoscope, it cannot be heard that the valves open (Balogh, 2012). Because the opening, which is a relatively slow event, does not sound. However, vibrations caused by sudden pressure differences that develop when the heart valves are closed from the leaf valves and the surrounding fluids make sounds emitted in all directions in the chest. When the ventricles contract, a sound is first created by closing the AV valves. This vibration with a low frequency and a relatively long duration is known as the first heart sound (S1). At the end of systole, when the aortic and pulmonary valves close, a relatively rapid impact sound is heard, because these valves close fast and everything around vibrates for a short time, this sound is known as the second heart sound (S2) (Vermarien, 2006).

The first heart sound, S1, is the sound of the AV valve that closes at the end of the diastole at the end of the systole to pass the pressure created by the blood filled to the ventricles into the atria. The duration of the S1 sound is 0.15 sec and its frequency is in the range of 25-45 HZ. S2 is formed when the pulmonary and aortic valves open during systole are closed when the pressure in the aorta and pulmonary artery exceeds the ventricular pressure. The duration of the S2 sound is 0.12 sec and its frequency is in the range of 50-70 HZ. S3 is the sound created by the blood rapidly filling from the artery to the ventricle by opening the AV valve at the beginning of the diastole. Although S3 is accepted as pathological in some cases, it can be seen physiologically in newborns and children. The duration of the S3 sound is 0.10 sec and the frequency is 30 HZ. The fourth heart sound, S4, is the sound of the blood filled into the ventricle during the contraction of the arthritis towards the end of the diastole. It is generally not considered a natural sound. It is a disease finding. The duration of the S4 sound is 0.08 sec and the frequency is below 20 HZ.

In this study, the sounds of s1, s2 and s4 were examined. The reason for not examining the S3 heart sound was not included in our thesis because the frequency range of the S3 sound is in the frequency range of S1 and the sound of S3 is not a specific finding of any disease.

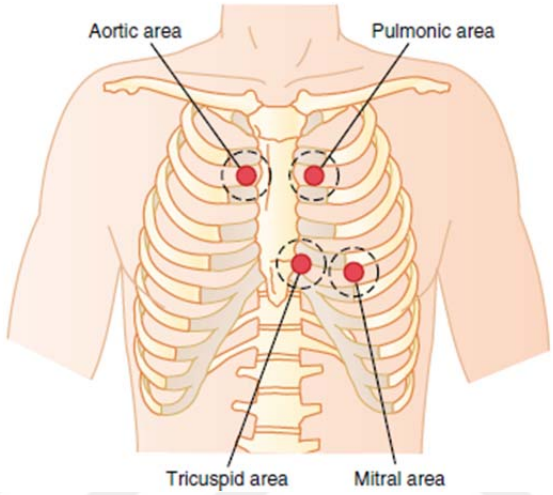

Figure 1.3. Auscultation areas where heart sounds are best heard (Hall, 2015)

1.3. Phonocardiogram

The ability of the blood circulation system to perform its functions in the body depends on the healthy functioning of the system components. The work of the heart, which is the most important part of this system, is very important for human life. Considering that heart diseases constitute a large part of human deaths; Learning about the work of the heart, diagnosing heart diseases that may occur before it is late is an important part of modern medicine. Depending on the development of technology, new methods are developed to get the most information in the shortest time without performing surgical intervention. The most commonly used methods, such as electrocardiograms and phonocardiograms, are methods of examining biological signals that provide important information about

the functioning of the heart. The electrocardiogram (ECG) is a large electrical amplitude signal resulting from simultaneous contraction of the heart muscles (Yazgan and Korürek, 1996). It provides information about the functioning of the heart's electrical conduction system and can be detected from the body. The sounds that occur as a result of the mechanical movements of the heart valves during the work of the heart and the changes that occur during the movement of the blood in the cardiovascular system are called heart sounds (Moukadem, 2012).

PCG and auscultation are noninvasive, low cost and essential for the diagnosis of certain heart diseases. PCG and auscultation are noninvasive, low cost and essential for the diagnosis of certain heart diseases. Auscultation is an inexpensive, effective, easy to apply, harmless diagnostic tool for the patient and the most common diagnostic method used in the world. Auscultation not only provides useful information to physicians regarding the function and condition of the organ being listened to but also increases the interaction between the patient and the physician (Spieth and Zhang., 2011). Despite the advantages of auscultation, this process also has many limitations and disadvantages. The fact that the human ear is not very sensitive to sounds under a certain frequency is also considered among the disadvantages of auscultation (Sovijarvi et al., 2000). When a special microphone is placed on the chest wall that can receive low frequency sound, heart sounds can be enlarged and printed with a high speed printing device, and this printable recording is called a phonocardiogram. PCG examines the sounds that occur during the mechanical work of the heart to obtain signs (Chernecky and Berger, 2008). Transforming heart sounds into a biomedical signal, usually referred to as phonocardiogram (PCG), enabling the usage of signal processing and data analysis techniques to obtain a quantitative understanding of the heart sounds (Emmanuel, 2012).

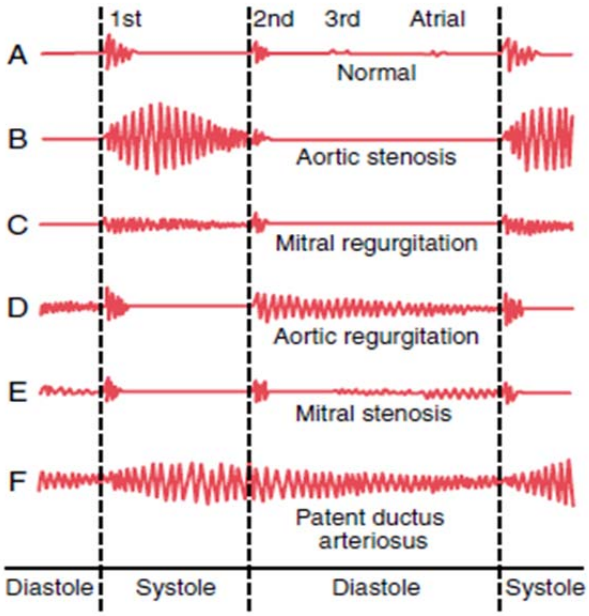

Figure 1.4. Phonocardiograms from normal and abnormal hearts (Hall, 2015)

The purpose of using phonocardiogram in medicine is changes in s1 and s2 sounds of the finding of various heart valve diseases. These diseases caused by regurgitation or stenosis of the valve cause changes in the frequency of these sounds as seen in figures b, c, d, e and f. Observing these changes in the phonocardiogram enables the diagnosis of the disease.

2. PREVIOUS STUDIES

Biomedical sounds are generally non-periodic signs. Although heart sounds are a bit closer to being periodic than other sound signals, there are also important changes in the periodicity of individuals heart sounds. These features make the analysis of biomedical sounds a difficult task (Marshall and Boussakta, 2007).

With technological advances, researching heart sounds has been an exciting field of study for years. There are many researches and studies in this field. These studies were generally examined under three basic groups. The first group is the work done to record sound signals and create a database (Yi & Caiming, 2006). The second group is filtering studies to separate sounds from various noises (Mastorocostas et al, 2004), and the third group is the work done for the analysis, processing and classification of heart sounds, which will constitute a large part of these studies. (Li and Du, 2005) (Icer and Gengeç, 2014).

The studies falling into the second groud can be summerized as follows. Heart sounds often have undesirable components from sounds such as environmental noise, breath sounds, lung sounds, and muscle movements. Due to the extremely unstable, complex nature and frequency characteristics of the heart sound signals, proper filtering operations must be performed to minimize noise before effective heart sound identification (Choi & Jiang, 2010). In years of studies for filtering heart sound signals, bandpass, low and high pass filters and wavelet based filters have been used. Amiri et.al. were determined that the fundamental frequency spectra of the first (S1) and second (S2) heart sounds were around 200 Hz and applied the 3rd order butterworth band filter on the heart sounds and obtained the frequency range of 50 Hz-2000 Hz (Amiri and Armano, 2013). By using a digital bandpass filter with a frequency range of 20-250 Hz, it was ensured that continuous heart sounds were removed from unnecessary components before analysis (Amit et al., 2009). Since that normal and abnormal heart sounds have a

distribution in the frequency range of 50-700 Hz, higher frequencies have no clinical significance for diagnosis and analysis, Gupta et al., reduced the frequency components above 750 Hz to a minimum by designing a low-pass Chebyshev type filter (Gupta et al, 2005).

Wang et al (2014) stated that the environmental noises interfering with the heart sounds consist of complex and unpredictable high frequency components. These researchers stated that their heart sounds were usually in the range of 0-300 Hz, and they filltered phonocardiogram signal with a the low pass filter in order to purify the sounds from high frequency unnecessary components. They argued that in some cases the low-pass filter would not be very effective for reducing noise, so in the next step, they applied wavelet soft thresholds to the sounds to filter out the heart sounds.

The literature about classification of phonocardiogram is summerzied at this satage. The loudness of the sound heard by the ear is called the intensity of the sound. The intensity of the sound depends on the amplitude and energy of the vibrations. The sound quality, called timbre, depends on the frequencies that make up a particular sound. Thanks to the timbre, the examiner can detect different sounds and diagnose the disease. Sound acquires this unique feature as a result of the complex vibrations caused by overlapping the side vibrations in proportion to the carrier bit vibration (Howell, 2006). Determining these characteristic features is an important step in the classification of sounds. The classification accuracy of sounds can vary depending on the sound characteristics extracted with the selected analysis methods. So for an accurate classification analysis of sound signals and feature extraction phase is a very important step. Classification of heart sounds is a challenging task that mainly depends on segmentation of heart sounds and derivation of features using segmented samples. Classification success of heart diseases depends on correct determination of S1 and S2 segments. Discrete Wavelet Transform (DWT) and Mel-Frequency Cepstral Coefficients (MFCC) were used as solutions to clean basic heart sounds from noisy data (Çelebi,2017).

In order to determine the S1-S2 locations, the heart rate and systole time interval were determined using signal autocorrelation. With this developed algorithm, S1 and S2 sounds were detected with 98.19% accuracy and 98.52% sensitivity on normal heart sounds without disease information, while the study on abnormal heart sounds was detected with 94.31% precision and 96.92% sensitivity. Ten different distinguishing features were extracted for each sound region from the segmented heart sounds. Aortic Stenosis, Mitral Insufficiency, Aortic Insufficiency, Mitral Stenosis and Normal heart sound signals were identified with the help of supervised classifiers.

Segmentation of heart sound signals is one of the frequently used approach to extract features. S1 and S2 voices were segmented using the resampled energy method and the contribution of the segment to the segmentation performance was examined. Three different heart sounds such as normal, murmur and extrasystole were collectef amd Artificial Neural Networks were used to classify these sounds. In order to compare the obtained results, two classifications were made for segmented and non-segmented sounds. As a result of the classification studies, the average overall accuracy of the classification was 84% in the non-segmented artificial neural network study, and the average overall classification accuracy was 88.6% in the segmented S1-S2 sounds artificial neural network study. Thus, the segmentation of heart sounds increased the classification accuracy by about 4.6% (Deperlioğlu, 2018).

Research by Singh et.al. for PCG classification provided by PhysioNet / CinC Challenge 2016 has focused on improving the accuracy of the classification model. By eliminating segmentation steps using multiple area features, an automatic heart sound classification results in precision. This study is based on homomorphic envelogram, Mel Frequency Sepstral Coefficient, power spectral density and multi-domain feature extraction. The extracted features are trained using a 5-fold cross validation method based on a community enhancement algorithm of over 100 independent iterations. Their proposed designs were

evaluated using publicly available data sets published in the PhysioNet / Computers in Cardiology Challenge 2016. Using this model, an accuracy of 92.47% was obtained with an improved sensitivity of 94.08% and a specificity of 91.95% (Singh and Majumder, 2020).

As can be seen from the studies conducted, different methods are used for the analysis and classification of heart sounds. All methods give different results and their accuracy is varied. Previous studies give us different ideas and show the advantages and disadvantages of the methods used.

The classification of heart sounds is still at an evolving stage when it comes to practice. Using the latest technology, mobile phones can also be used as an electronic stethoscope and digital phonocardiogram signals can be easily obtained, recorded and transmitted to a cardiologist for further analysis. In the diagnosis of cardiovascular diseases, early diagnosis and diagnosis is important with vital technology and applied methods. In this thesis, similar to the studies described above, a study was conducted on the data obtained from the database. A plain algorithm was developped to correctly classify heart sounds as normal or abnormal. The phonocardiogram signal was divided into physological waves and the average power and dominant frequency were calculated from the bursts of these signals and the therefore features were extracted. A simple linear was used to classify normal and abnormal heart sounds. The results were reported.

3. MATERIAL AND METHOD

3.1. Data

Signal processing and data analysis using Heart Sound Recordings are commonly used methods in biomedical research. For this purpose, Physionet.org, which is supported by many institutions, can be downloaded from physionet.org/challenge/2016 of the database created in 2016 to create a large database and encourage researchers worldwide to work on the classification of normal and abnormal.

The challenge 2016 data obtained from the physio-net physiological signal resource has been employed (Liu et al, 2016). The database includes recordings taken from subjects, heart sounds collected from both healthy people and patients with a variety of conditions (Clifford et al, 2016). It consists of six groups of data; A, B, C, D, E, and, F. Only A and B groups were analyzed. Because C, D and E have an insufficient number of attempts. The number of normal and abnormal records in F is quite different, so the data is unstable.

The algorithm written in the Matlab R2017b program consists of 3 stages; sample reduction, decomposition of S1, S2 and S3 waves, feature extraction and classification. The block diagram of the algorithm is given in Figure 3.1.

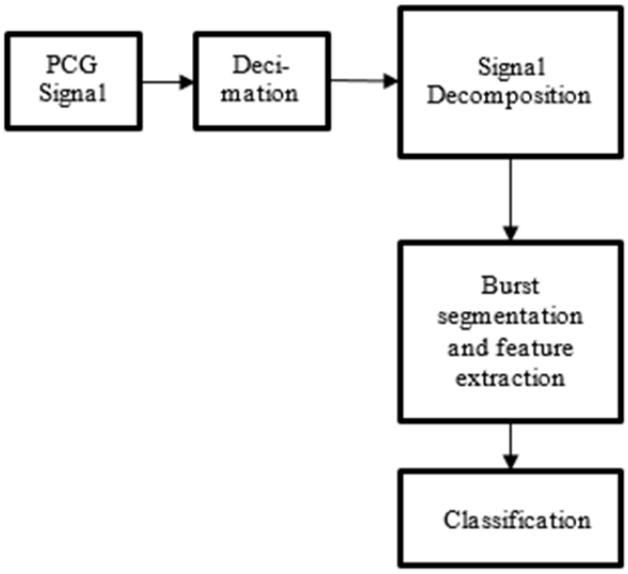

Figure 3.1. Block diagram of algorithm

3.2. Sample Reduction

The sampling frequency of the PCG data is Fs = 2000 Hz. PCG signals have bandwidths of 0-70 Hz. 2000 Hz is a very high sampling frequency for this frequency band. Sampling rate was decreased to 175 Hz to reduce computation cost. This is done by cascading employing four decimators as shown in Figure 3.2. The decimator is a half-band low-pass filter followed with a down-sampler with resampling rate 2. The cascade of four decimators eliminates designing a relatively narrow band low pass filter. The filters in the stages were equivalent and were fifth-order low-pass Butterworth filters with relative bandwidth of 0.35 (35% of the full band). The relative band of the filters was set to 0.35 instead of 0.5 (half band) in order to avoid aliasing which may occur in case of non-ideal filters The Butterworth filter had a flat frequency response due to its characteristics. Consequently, the resultant signal frequency range was limited to frequency band [0, 87.5] Hz.

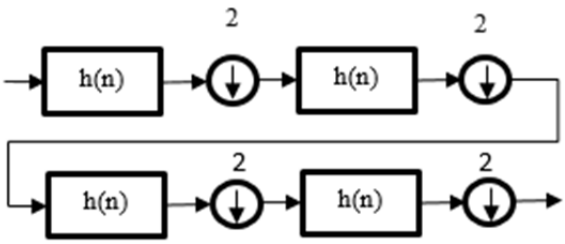

Figure 3.2**.** Sampling rate reduction

3.3. Decomposition of S1, S2 and S4 Waves

The signal frequency range that occurs after the sampling rate is reduced is divided into here basic frequency. In this thesis, the sounds of S1, S2 and S4 are examined.

The signal frequency range that occurs after the sampling rate is reduced is divided into 3 basic frequencies. There are four basic heart sounds, but since the frequency range of the S3 sound is within the frequencies of the 1st and 2nd heart sounds, in this thesis, the sounds of s1, s2 and s4 are examined. The signal is divided into 3 basic frequency bands; [0, 20], [25, 45] and [50, 70], which are called S1, S2 and S4 waves. First the discrete Fourier transform is computed at number of points twice the length of the signal. The frequency bands are separated in the frequency domain by multiplying the transform coefficients with the hamming window centered at mid-points of these bands and then computing the inverse Fourier transform. This approach is illustrated in Figure 3.3.

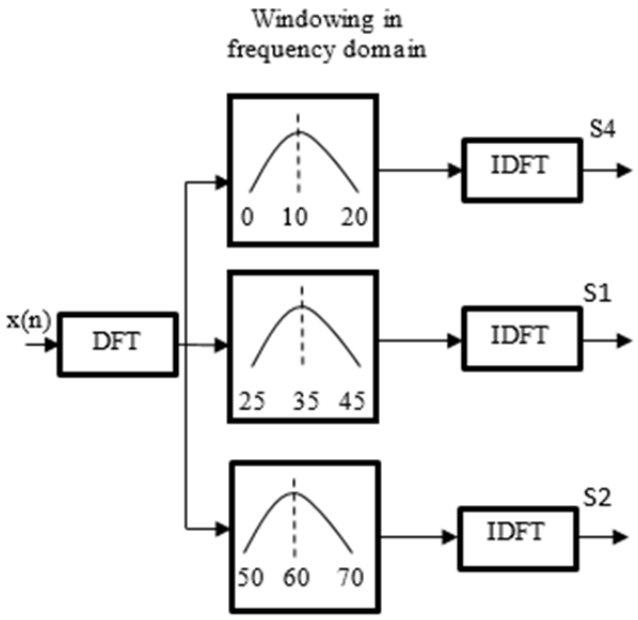

Figure 3.3. Decomposition S1, S2 and S4 waves

3.3.1. Discrete Fourier Transform

A discrete fourier transform estimates the fourier transform of a function from a finite number of its sampled points. The dft has symmetry properties almost exactly the same as the continuous fourier transform.

Unlike some theoretically defined sequences, Fourier transforms of actual sequences cannot be calculated. Therefore, it is not appropriate to use Fourier transform for numerical signals. An analogue representation of the frequency and the need for an infinite number of samples are the main reasons for this inconvenience. Because of these difficulties, considering the importance of Fourier transform in signal processing, it is necessary to define a more feasible transformation.

Therefore, discrete fourier transform is used. Discrete Fourier Transform (DFT) is defined on a discrete series x[n] as below:

$$X(K) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi kn/N} \quad (3.1)$$

(K = 0, 1...N, N-1)

3.3.2. Inverse Discrete Fourier Transform

Just like DFT is used to convert a signal from time to frequency domain, Inverse Discrete Fourier Transform (IDFT) is used as an inverse process by converting a signal from frequency to time domain. IDFT is defined as

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(K) e^{j2\pi kn/N} \quad (3.2)$$

(n = 0, 1...N, N-1)

3.3.3. Hamming Window

The signals are divided into pieces containing certain number of samples before processing. Each of these parts is called a window. Window functions are functions that multiply signal segments. With these functions, the central parts of the signal parts are highlighted. The parts near the beginning and end of the windows are deflated. This reduces the spectral leakage.

3.4. Feature Extraction and Classification

As a next features from each sub-bands are extracted. The bursts in each wave are detected and are segmented. The method used to determine a burst is summarized in the following. The root-mean square (RMS) and the dominant frequency in each burst are computed. The averages of the RMS and dominant frequency in each wave are concatenated and serves as feature vector. The natural logarithm of attributes of the feature vector are computed to improve the categorization performance.

Algorithm to segment bursts;

$\hat{y}_1(n) = H\big(x(n)\big)$, where H is the Hilbert transform operator (3.3)

$\hat{y}_2(n) = H\big(-x(n)\big)$ (3.4)

$z_1(n) = \sqrt{\hat{y}_1^2(n) + x^2(n)}$ (3.5)

$z_2(n) = \sqrt{\hat{y}_2^2(n) + x^2(n)}$ (3.6)

$z\,(n) = \frac{z_1(n) + z_2(n)}{2}$ (3.7)

$b\,(n) = z(n) > t$, where threshold (3.8)

$t = \frac{1}{m}\sum_{n=1}^{m} z\,(n)$ (3.9)

In here, $b\,(n)$ specify burst regions. The value 0 stands for no burst and 1 indicates position of burst sample.

To compute dominant frequency of each burst the Eigen method of subspace frequency estimation techniques has been preferred. The pseudo power spectrum has been obtained assuming that the signal has two complex conjugate frequencies. The dominant frequency corresponds to the position of a peak of the spectrum.

As it is widely known that the RMS of i-th burst

$x\_i\ (n)$ is $\sqrt{\frac{1}{L}\sum_{n=1}^{L} x_i^2\,(n)}$, (3.10)

where L is total number of samples of the burst signal (Tang et al. 2016) (see Figure 3.4).

The number of train samples for group A was 88 normal and 88 abnormal type and the test samples was 29 normal and the 29 abnormal categories. Similarly, for group B, the number of train was been taken to be 78 normal and 78 abnormal class samples and the number of train records has been 26 normal and

29 abnormal type samples. The training and testing data has been chosen randomly and the classification process was repeated 250 times. The Linear Bayes classifier has been used as classifier This classifier is a simple and the most widely known classifier.

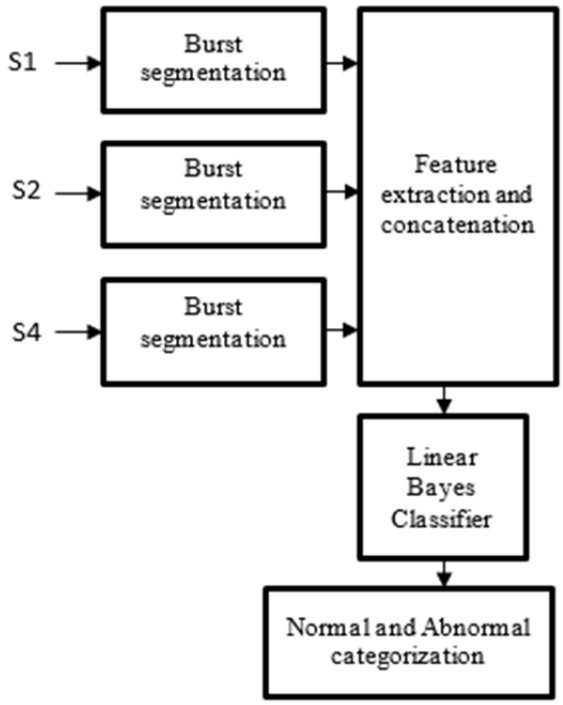

Figure 3.4. Feature extraction and classification

4. FINDINGS AND DISCUSSIONS

The database contains recordings from subjects, heart sounds collected from both healthy people and patients with various conditions. Group A consists of 117 normal and 292 abnormal types of PCG recordings, group B contains 386 normal and 104 abnormal numbers of trials. The PCG signals from the normal and abnormal heart sounds of the A and B groups were examined and the detected S1, S2 and S4 waves and segmented wave bursts are shown in figures. Accuracy, specificity and sensitivity rates of A, B groups are shown in Table 1. It is observed that the method is more unsuccessful for group B than group A. However, the results for A are promising. The reason for this poor accuracy for group B may be that the features used do not adequately represent categories.

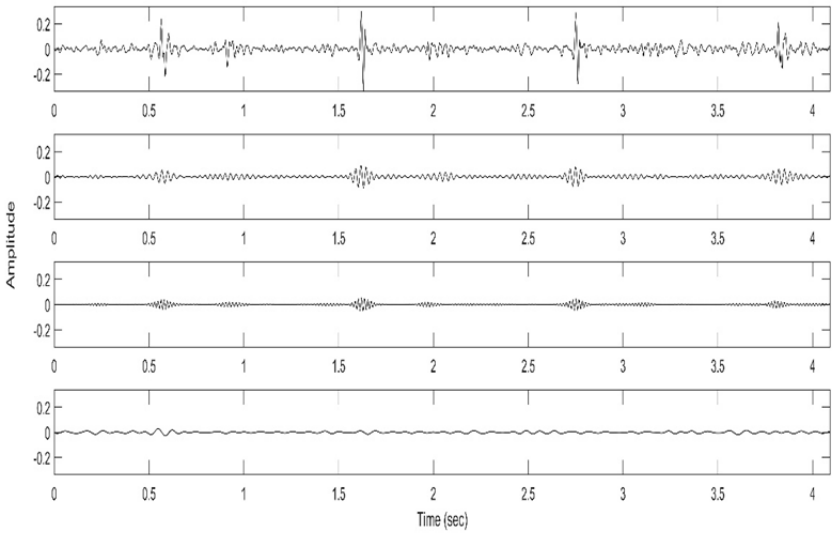

Figure 4.1. Original signal normal A

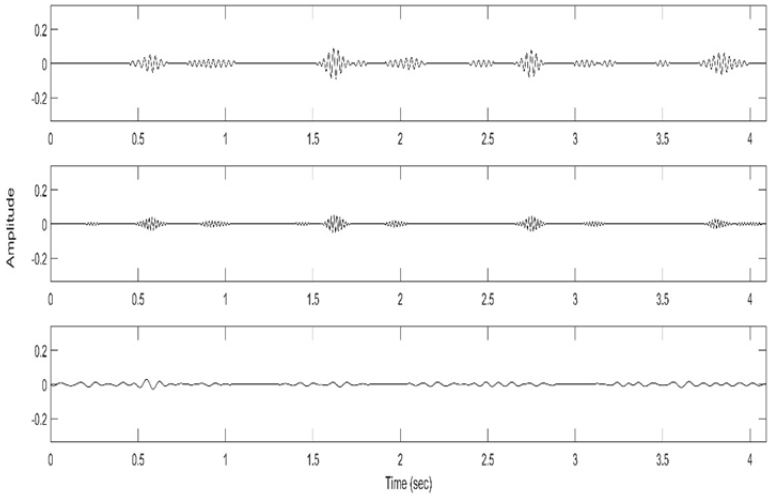

Figure 4.2. Segmentation signal normal A

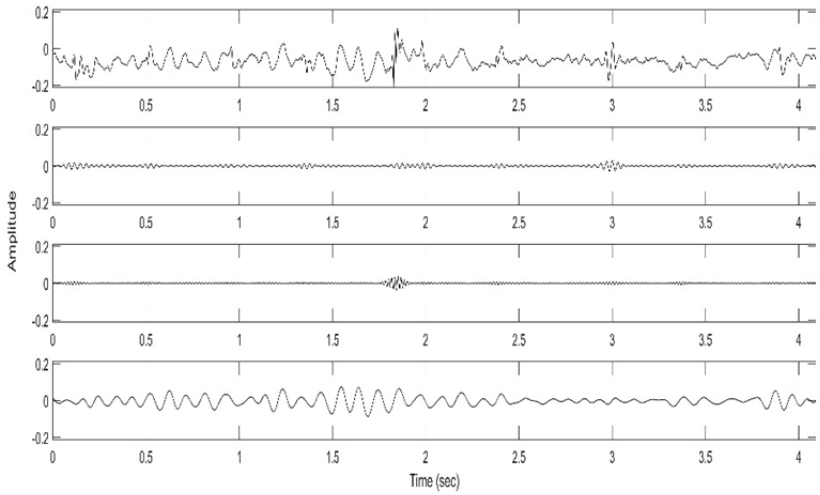

Figure 4.3. Original signal normal B

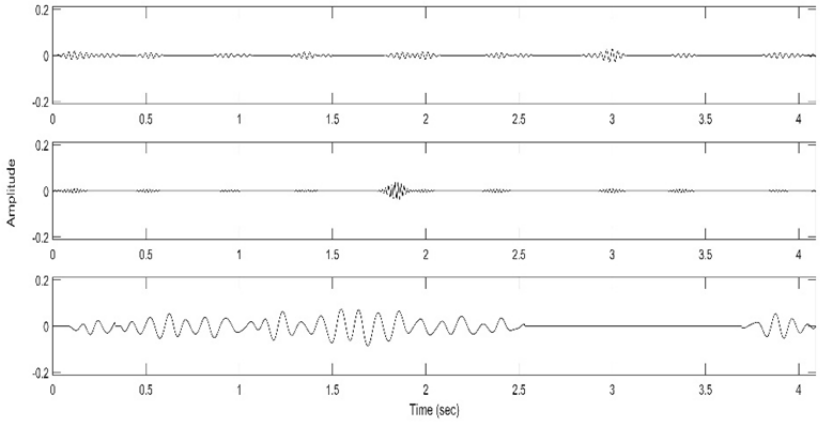

Figure 4.4. Segmentation signal normal B

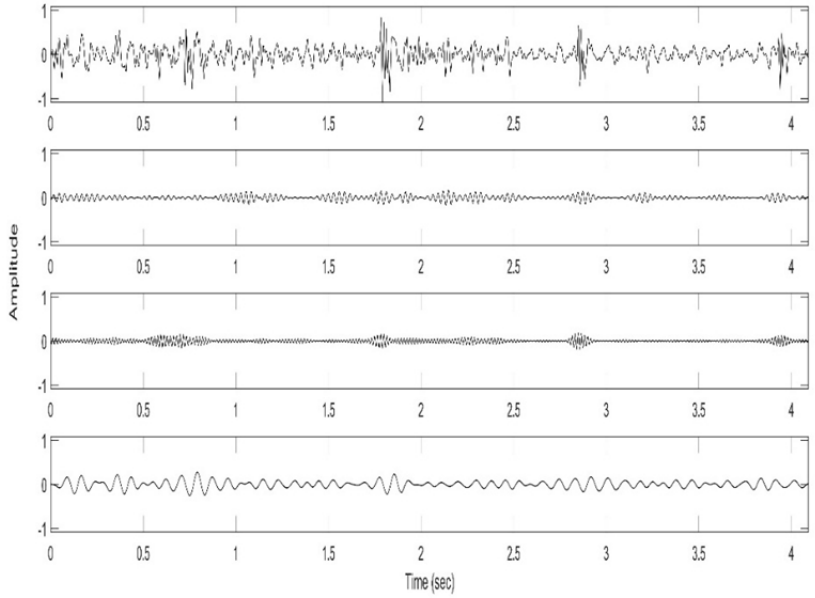

Figure 4.5. Original signal abnormal A

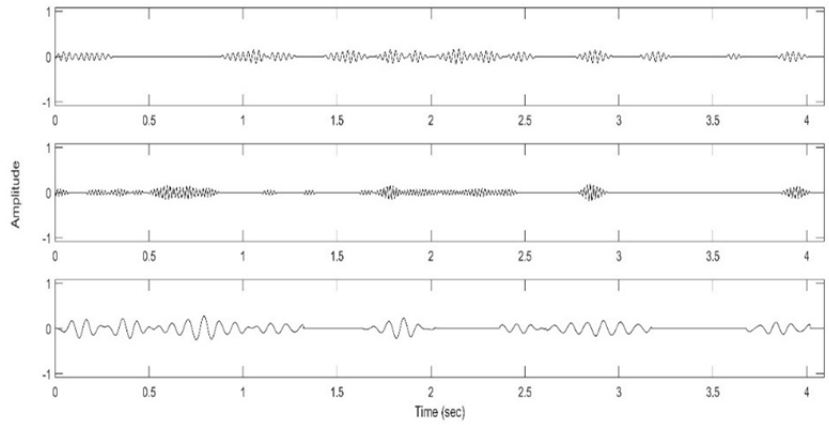

Figure 4.6. Segmentation signal abnormal A

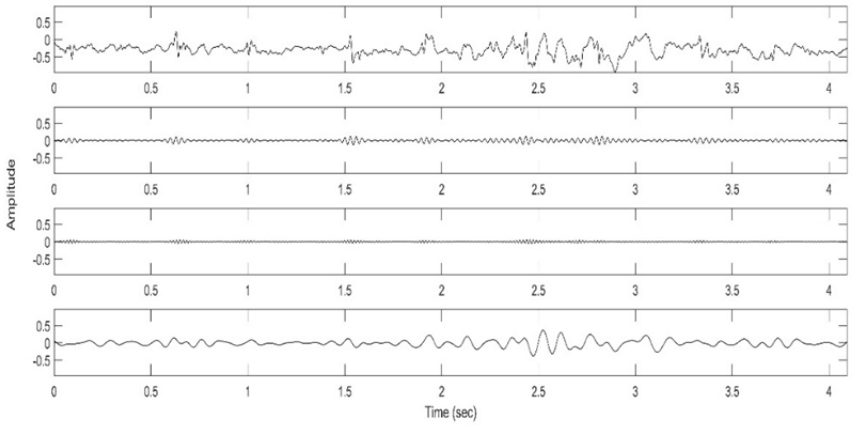

Figure 4.7. Original signal abnormal B

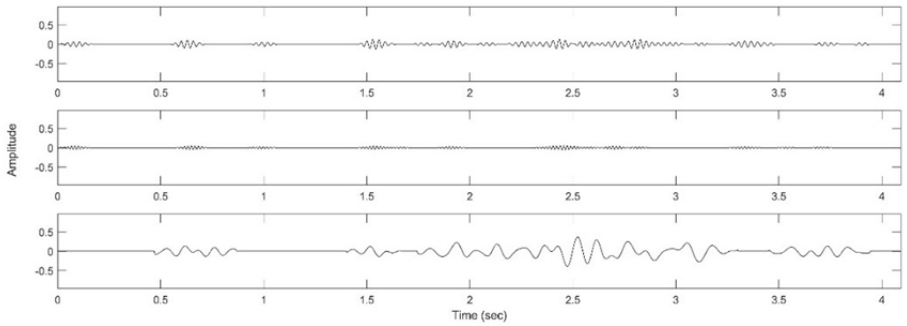

Figure 4.8. Segmentation signal abnormal B

Table 4.1. The Average Results of 250 Times Categorization Attempt

	Accuracy	Specificity	Sensitivity
A	61%	60%	61%
B	48%	49%	48%

5. RESULTS AND SUGGESTIONS

In this study, cardiac sound records collected from clinical or non-clinical settings are classified as normal and abnormal with an algorithm developed. Data from A and B groups obtained from PhysioNet / Computers in Cardiology Challenge 2016 database were categorized and average performances were obtained. First phonocardiogram signal was decomposed into S1, S2 and S4 bands and then sound bursts were segmented in these bands. Root mean square and dominant frequencies were computed from each segments. In toal six atributes constituted a feature vector and fed to a linear Bayes classifier. In this way, it is aimed to diagnose an unhealty subject from heart sounds .

This results was obtained bu using half of data for training and the other half for training. The training and testing data has been chosen randomly and the classification process has been repeated 250 times. The average of the acuricies for group A and be B were obtained as 61% and 48% respectively. The results of the study for group A suggest that it might support physicians to segment and determine normal and abnormal in phonocardiogram data if it is improved. However, the algorithm has failed to achieve the desired success for the type of abnormality in group B.

It is observed that higher success rates have been achieved in previous studies because more complex feature extraction and better classifier utulized. In this study, the performance can be improved by using other linear and non-lineear classifiers and if more than half of the data is employed for training even though basic attributes were utulized. In order to make a more accurate judgment, more PCG data should be used and the method should be tested. Taking all these comments into account, this method can also be adapted to identify certain heart diseases.

6. REFERENCES

Amiri, A. M. and Armano, G., 2013, "Heart sound analysis for diagnosis of heart diseases in newborns", APCBEE Procedia 7, 109-116.

Amit, G., Gavriely, N. and Intrator, N., 2009, "Cluster analysis and classification of heart sounds, Biomedical Signal Processing and Control", 4, 26-36.

Balogh, A.T., 2012 "Analysis of the heart sounds and murmurs of fetuses and preterm infants," Ph.D. dissertation, Pazmany Peter Catholic University.

Chernecky C.C., Berger B.J., 2008, "Laboratory Tests and Diagnostic Procedures", St. Louis, Philadelphia, Page 1232.

Choi, S. and Jiang, Z., 2010, "Cardiac sound murmurs classification with autoregressive spectral analysis and multi-support vector machine technique", Computers in Biology and Medicine, 40, 8-20.

Chowdhury T.M., Sakib M.N., and Rafsanjani H.MD., 2013, "Phonocardiography and analysis using standard deviation profile", Electrical and Electronic Engineering Islamic University of Technology.

Clifford G.D., Liu C., Moody B., Springer D., Silva I., Li Q., and Mark R.G., 2016 "Classification of Normal/Abnormal Heart Sound Recordings: thePhysioNet/Computing in Cardiology Challenge 2016", Computing in Cardiology, 43:609-612.

Çelebi G., 2017, "Segmentation and Classification of Heart Sound Phonocardiogram signals Obtained by Digital Stethoscope" Hacettepe Üniversitesi.

Deperlioğlu, Ö., 2018, "Classification of segmented heart sounds with Artificial Neural Networks", International Journal of Applied Mathematics Electronics and Computers.

Emmanuel B.S., 2012, "A review of signal processing techniques for heart sound analysis in clinical diagnosis, Journal of Medical Engineering & Technology", Volume 36, pp 303-307.

Gupta, C. N., Palaniappan, R., Rajan, S., Swaminathan, S., Krishnan, S. M., 2005 "Segmentation and classification of heart sounds", Electrical and Computer Engineering, Canadian Conference on, 1674-1677.

Hall J.E., 2015 "Guyton and Hall Textbook of Medical Physiology", Elsevier, Page 1168.

Howel, D. C. J., 2006, "Signs of respiratory disease: lung sounds", Oxford: Academic Press, pp 35-41.

İçer, S., and Gengeç, Ş., 2014, "Classification and analysis of non-stationary characteristics of crackle and rhonchus lung adventitious sounds", Digital Signal Processing, 28, 18-27.

Kandaswamy, A., Kumar, C., Ramanathan, R., Jayaraman, S., and Malmurugan, G., 2004. "Neural classification of lung sounds using wavelet coefficients", Computers in Biology and Medicine, Jul., Volume 34, Pages 523–537.

Li, Z., and Du, M., 2005, HHT based lung sound crackle detection and classification in:Proc. IEEE International Symposium on Intelligent Signal Processing and Communication Systems 385-388.

Liu C., Springer D., Li Q., Moody B., Juan RA., Chorro FJ, Castells., Roig JM., Silva I., Johnson AE., Syed Z., Schmidt SE., Papadaniil CD., Hadjileontiadis L., Naseri H., Mouka-dem A., Dieterlen A., Brandt C., Tang H., Samieinasab M., Samieinasab MR., Sameni R., Mark RG., Clifford GD., 2016. "An open access database for the evaluation of heart sound algorithms", Physiological Measurement.

Mastorocostas, P. A. and Constantinos, S. H., 2004, "A dynamic Fuzzy-Neural Filter for the analysis of lung sounds", in: Proc. IEEE International Conference on Systems Man and Cybernetics, 2231-2236.

Marshall, A., and Boussakta, S., 2007, "Signal analysis of medical acoustic sounds with applications to chest medicine", Journal of the Franklin Institute, 344, 230-242.

Martin N., and Lily L.S., 2006, “The Cardiac Cycle : Mechanisms of Heart Sounds and Murmurs”, pp 29-45

Marshall, A., and Boussakta, S., 2007, “Signal analysis of medical acoustic sounds with applications to chest medicine”, Journal of the Franklin Institute, 344, 230-242.

Moukadem A., Dieterlen A., and Brandt C., 2012 Phonocardiogram Signal Processing Module for Auto-Diagnosis and Telemedicine Applications.

Novey, Donald W., 1996. The Guide To Heart Sounds, Hekimler Yayın Birliği, Ankara, p73.

Singh S.A and Majumder S., 2020, “Short unsegmented PCG classification based on ensemble classifier”, Turkish Journal of Electrical Engineering & Computer Sciences Tubitak.

Sinha, R.K., Aggarwal, Y., and Das, B.N., 2007. “Backpropagation Artificial Neural Network Classifier to Detect Changes in Heart Sound due to Mitral Valve Regurgitation”. Journal of Medical Systems, Jun., Volume 31, Pages 205–209.

Sovijarvi, A. R. A., Vanderschoot, J. and Earis, J. E., 2000, “Standardization of computerised respiratory sound analysis”, Eur. Respir. Rev., 10 (77), 585.

Spieth, P. M., and Zhang H., 2011, “Analyzing lung crackle sounds: stethoscopes and Beyond”, Intensive Care Med, 37, 1238-1239.

Tang H., Li T., Qiu T., and Park Y., 2016. “Fetal Heart Rate Monitoring from Phonocardiograph Signal Using Repetition Frequency of Heart Sounds”, Journal of Electrical and Computer Engineering, p6.

Vermarien, H., 2006 “Phonocardiography,” in Encyclopedia of Medical Devices and Instrumentation, J. G. Webster, Ed. Hoboken, New Jersey: John Wiley & Sons, Volume 5, pp. 278–290.

Wang, Y., Wenzao, L., Zhou, J., Li, X. and Pu, Y., 2014, “Identification of the normal and abnormal heart sounds using wavelet-time entropy features based on OMS-WPD”, Future Generation Computer Systems, 37, 488–495.

Yi, L., and Caiming, Z., 2006, A new feature extraction method based on feature integration, in: Proc. IEEE ICICIC’06, 3, 170-173.

RESUME

Sultan Aslan was born in Mersin in 1991. She received BSc. Degree in Electronics Engineering Department from Toros University, Mersin in 2016.

APPENDIX

APPENDIX

APPENDIX- THE ALGORITHMS USED IN THE THESIS WORK

Abnormal A

```
clear
close all

listing = dir('C:\Users\binhan aslan\Desktop\training A\ABNORMAL A\*.wav');
% listing = dir('*.wav');
fls = {listing.name};
N = length(listing);
% FV = zeros(N, 12);
FV = zeros(N, 6);
GROUP = ones(N, 1);

[b, a] = butter(5, 0.35);

L = 1024;

for n = 1:N

[x, Fs] = audioread(cat(2, 'C:\Users\binhan aslan\Desktop\training
A\ABNORMAL A\', fls{n}));



x = filtfilt(b, a, x);
x = x(1:2:end);
x = filtfilt(b, a, x);
```

```
x = x(1:2:end);
x = filtfilt(b, a, x);
x = x(1:2:end);
% x = filtfilt(b, a, x);
% x = x(1:2:end);

K = 8;

Fs = Fs / K;

x = x(1: L);
tm = (0:L - 1)/Fs;
% plot(tm, x); title('Original Signal'); xlim([tm(1) tm(end)])

% L = length(x);


% S1 : 32, 34
% S2 : 33, 35, 36
% S4 : 31

% M = 2^(ceil(log2(L)));
M = 2*L;
X = fft(x, M);

df = Fs/M;

% n = 0,1,2,...,M - 1
% M - 1 - n = M - 1, M - 2,...,1,0
```

```
% M - n = M, M - 1,...,1
FA = [25 45 35; 50 70 60; df 20 10];
B = round(FA/df);
F = FA(:, 3);
u = zeros(1, M);
u(B(1, 1) + 1: B(1, 2) + 1) = hamming(B(1, 2) - B(1, 1) + 1);
u(M - B(1, 2) + 1: M - B(1, 1) + 1) = hamming(B(1, 2) - B(1, 1) + 1);
v = zeros(1, M);
v(B(2, 1) + 1: B(2, 2) + 1) = hamming(B(2, 2) - B(2, 1) + 1);
v(M - B(2, 2) + 1: M - B(2, 1) + 1) = hamming(B(2, 2) - B(2, 1) + 1);
w = zeros(1, M);
w(B(3, 1) + 1: B(3, 2) + 1) = hamming(B(3, 2) - B(3, 1) + 1);
w(M - B(3, 2) + 1: M - B(3, 1) + 1) = hamming(B(3, 2) - B(3, 1) + 1);
X(1) = 0;

if iscolumn(X)
   X = X.';
end



y = zeros(3, M);

y(1, :) = ifft(u .* X);
y(2, :) = ifft(v .* X);
y(3, :) = ifft(w .* X);

y = real(y);
```

```
% figure(2)
% subplot(4,1,1); plot(tm, x); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
% title('Original signal');
% subplot(4,1,2); plot(tm, y(1, 1:L)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
% title('S1');
% subplot(4,1,3); plot(tm, y(2, 1:L)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
% title('S2');
%
% subplot(4,1,4); plot(tm, y(3, 1:L)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
% title('S4');
%
% close all

orsig = zeros(3, L);
parsig = zeros(3, L);
for t = 1:3
p = y(t, 1:L);
% [m, b] = mask(p);
[m, bmsk, wa, wb] = maskk(p, F(t), Fs);
subplot(311); plot(tm, p);
subplot(312); plot(tm, m);
subplot(313); plot(tm, bmsk); ylim([-0.5 1.5])
orsig(t, :) = p;
parsig (t, :) = m;
% [y, w, wa, wb] = promin(x, Fs);
K = length(wa);
```

```
RMS = zeros(1, K);
FRQ = zeros(1, K);
FRQSS = zeros(1, K);
for k = 1:K
burst = y(wa(k):wb(k));
RMS(k) = sqrt(mean(burst.^2));
A = fft(burst);
L2 = length(A);
K2 = ceil(L2 / 2);
B = abs(A);
FRQ(k) = sum(B(1:K2) .* (0:K2 - 1))/ sum(B(1:K2))*Fs/L2;
[S, w] = peig(x, 2, [], Fs,  'half');
[~, m] = max(S);
FRQSS(k) = w(m);
end

% FV(n, 4*t - 3) = mean(RMS);
% FV(n, 4*t - 2) = std(RMS);
% FV(n, 4*t - 1) = mean(FRQSS);
% FV(n, 4*t) = std(FRQSS);

FV(n, 2*t - 1) = mean(RMS);
FV(n, 2*t) = mean(FRQSS);

end
```

```
figure(1);
subplot(4,1,1); plot(tm, x); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
subplot(4,1,2); plot(tm, orsig(1, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(4,1,3); plot(tm, orsig(2, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(4,1,4); plot(tm, orsig(3, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])

figure(2);
subplot(3,1,1); plot(tm, parsig(1, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(3,1,2); plot(tm, parsig(2, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(3,1,3); plot(tm, parsig(3, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
end

FVA=FV;

save('abnormala.mat','FVA')
```

Normal A

```
clear
close all

listing = dir('C:\Users\binhan  aslan\Desktop\training A\NORMAL A\*.wav');
% listing = dir('*.wav');
fls = {listing.name};
```

```
N = length(listing);
% FV = zeros(N, 12);
FV = zeros(N, 6);
GROUP = ones(N, 1);

[b, a] = butter(5, 0.35);

L = 1024;

for n = 1:N

[x, Fs] = audioread(cat(2, 'C:\Users\binhan  aslan\Desktop\training A\NORMAL
A\', fls{n}));



x = filtfilt(b, a, x);
x = x(1:2:end);
x = filtfilt(b, a, x);
x = x(1:2:end);
x = filtfilt(b, a, x);
x = x(1:2:end);
% x = filtfilt(b, a, x);
% x = x(1:2:end);

K = 8;

Fs = Fs / K;

x = x(1: L);
```

```
tm = (0:L - 1)/Fs;
% plot(tm, x); title('Original Signal'); xlim([tm(1) tm(end)])

% L = length(x);


% S1 : 32, 34
% S2 : 33, 35, 36
% S4 : 31

% M = 2^(ceil(log2(L)));
M = 2*L;
X = fft(x, M);

df = Fs/M;

% n = 0,1,2,...,M - 1
% M - 1 - n = M - 1, M - 2,...,1,0
% M - n = M, M - 1,...,1

FA = [25 45 35; 50 70 60; df 20 10];
B = round(FA/df);
F = FA(:, 3);
u = zeros(1, M);
u(B(1, 1) + 1: B(1, 2) + 1) = hamming(B(1, 2) - B(1, 1) + 1);
u(M - B(1, 2) + 1: M - B(1, 1) + 1) = hamming(B(1, 2) - B(1, 1) + 1);
v = zeros(1, M);
v(B(2, 1) + 1: B(2, 2) + 1) = hamming(B(2, 2) - B(2, 1) + 1);
v(M - B(2, 2) + 1: M - B(2, 1) + 1) = hamming(B(2, 2) - B(2, 1) + 1);
```

```
w = zeros(1, M);
w(B(3, 1) + 1: B(3, 2) + 1) = hamming(B(3, 2) - B(3, 1) + 1);
w(M - B(3, 2) + 1: M - B(3, 1) + 1) = hamming(B(3, 2) - B(3, 1) + 1);
X(1) = 0;

if iscolumn(X)
   X = X.';
end


y = zeros(3, M);

y(1, :) = ifft(u .* X);
y(2, :) = ifft(v .* X);
y(3, :) = ifft(w .* X);

y = real(y);



% figure(2)
% subplot(4,1,1); plot(tm, x); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
% title('Original signal');
% subplot(4,1,2); plot(tm, y(1, 1:L)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
% title('S1');
% subplot(4,1,3); plot(tm, y(2, 1:L)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
% title('S2');
%
```

```
% subplot(4,1,4); plot(tm, y(3, 1:L)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
% title('S4');
%
% close all

orsig = zeros(3, L);
parsig = zeros(3, L);
for t = 1:3
p = y(t, 1:L);
% [m, b] = mask(p);
[m, bmsk, wa, wb] = maskk(p, F(t), Fs);
subplot(311); plot(tm, p);
subplot(312); plot(tm, m);
subplot(313); plot(tm, bmsk); ylim([-0.5 1.5])
orsig(t, :) = p;
parsig (t, :) = m;
% [y, w, wa, wb] = promin(x, Fs);


K = length(wa);
RMS = zeros(1, K);
FRQ = zeros(1, K);
FRQSS = zeros(1, K);
for k = 1:K
burst = y(wa(k):wb(k));
RMS(k) = sqrt(mean(burst.^2));
A = fft(burst);
L2 = length(A);
```

```
K2 = ceil(L2 / 2);
B = abs(A);
FRQ(k) = sum(B(1:K2) .* (0:K2 - 1))/ sum(B(1:K2))*Fs/L2;
[S, w] = peig(x, 2, [], Fs,  'half');
[~, m] = max(S);
FRQSS(k) = w(m);
end

% FV(n, 4*t - 3) = mean(RMS);
% FV(n, 4*t - 2) = std(RMS);
% FV(n, 4*t - 1) = mean(FRQSS);
% FV(n, 4*t) = std(FRQSS);

FV(n, 2*t - 1) = mean(RMS);
FV(n, 2*t) = mean(FRQSS);

end

figure(1);
subplot(4,1,1); plot(tm, x); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
subplot(4,1,2); plot(tm, orsig(1, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(4,1,3); plot(tm, orsig(2, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(4,1,4); plot(tm, orsig(3, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
```

```
figure(2);
subplot(3,1,1); plot(tm, parsig(1, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(3,1,2); plot(tm, parsig(2, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(3,1,3); plot(tm, parsig(3, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
end

FVNA = FV;

save('normala.mat','FVNA')
```

ABNORMAL B

```
clear
close all

listing = dir('C:\Users\binhan  aslan\Desktop\training B\ABNORMAL B\*.wav');
% listing = dir('*.wav');
fls = {listing.name};
N = length(listing);
% FV = zeros(N, 12);
FV = zeros(N, 6);
GROUP = ones(N, 1);

[b, a] = butter(5, 0.35);

L = 1024;

for n = 1:N

[x, Fs] = audioread(cat(2, 'C:\Users\binhan  aslan\Desktop\training
B\ABNORMAL B\', fls{n}));



x = filtfilt(b, a, x);
x = x(1:2:end);
x = filtfilt(b, a, x);
x = x(1:2:end);
x = filtfilt(b, a, x);
x = x(1:2:end);
```

```
% x = filtfilt(b, a, x);
% x = x(1:2:end);

K = 8;

Fs = Fs / K;

x = x(1: L);
tm = (0:L - 1)/Fs;
% plot(tm, x); title('Original Signal'); xlim([tm(1) tm(end)])

% L = length(x);



% S1 : 32, 34
% S2 : 33, 35, 36
% S4 : 31

% M = 2^(ceil(log2(L)));
M = 2*L;
X = fft(x, M);

df = Fs/M;

% n = 0,1,2,...,M - 1
% M - 1 - n = M - 1, M - 2,...,1,0
% M - n = M, M - 1,...,1
```

```
FA = [25 45 35; 50 70 60; df 20 10];
B = round(FA/df);
F = FA(:, 3);
u = zeros(1, M);
u(B(1, 1) + 1: B(1, 2) + 1) = hamming(B(1, 2) - B(1, 1) + 1);
u(M - B(1, 2) + 1: M - B(1, 1) + 1) = hamming(B(1, 2) - B(1, 1) + 1);
v = zeros(1, M);
v(B(2, 1) + 1: B(2, 2) + 1) = hamming(B(2, 2) - B(2, 1) + 1);
v(M - B(2, 2) + 1: M - B(2, 1) + 1) = hamming(B(2, 2) - B(2, 1) + 1);
w = zeros(1, M);
w(B(3, 1) + 1: B(3, 2) + 1) = hamming(B(3, 2) - B(3, 1) + 1);
w(M - B(3, 2) + 1: M - B(3, 1) + 1) = hamming(B(3, 2) - B(3, 1) + 1);
X(1) = 0;

if iscolumn(X)
   X = X.';
end



y = zeros(3, M);

y(1, :) = ifft(u .* X);
y(2, :) = ifft(v .* X);
y(3, :) = ifft(w .* X);

y = real(y);
```

```
figure(2)
subplot(4,1,1); plot(tm, x); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
title('Original signal');
subplot(4,1,2); plot(tm, y(1, 1:L)); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
title('S1');
subplot(4,1,3); plot(tm, y(2, 1:L)); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
title('S2');

subplot(4,1,4); plot(tm, y(3, 1:L)); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
title('S4');

% close all

orsig = zeros(3, L);
parsig = zeros(3, L);
for t = 1:3
p = y(t, 1:L);
% [m, b] = mask(p);
[m, bmsk, wa, wb] = maskk(p, F(t), Fs);
subplot(311); plot(tm, p);
subplot(312); plot(tm, m);
subplot(313); plot(tm, bmsk); ylim([-0.5 1.5])
orsig(t, :) = p;
parsig (t, :) = m;
% [y, w, wa, wb] = promin(x, Fs);


K = length(wa);
RMS = zeros(1, K);
```

```
FRQ = zeros(1, K);
FRQSS = zeros(1, K);
for k = 1:K
burst = y(wa(k):wb(k));
RMS(k) = sqrt(mean(burst.^2));
A = fft(burst);
L2 = length(A);
K2 = ceil(L2 / 2);
B = abs(A);
FRQ(k) = sum(B(1:K2) .* (0:K2 - 1))/ sum(B(1:K2))*Fs/L2;
[S, w] = peig(x, 2, [], Fs,  'half');
[~, m] = max(S);
FRQSS(k) = w(m);
end

% FV(n, 4*t - 3) = mean(RMS);
% FV(n, 4*t - 2) = std(RMS);
% FV(n, 4*t - 1) = mean(FRQSS);
% FV(n, 4*t) = std(FRQSS);

FV(n, 2*t - 1) = mean(RMS);
FV(n, 2*t) = mean(FRQSS);

end
```

```
figure(1);
subplot(4,1,1); plot(tm, x); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
subplot(4,1,2); plot(tm, orsig(1, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(4,1,3); plot(tm, orsig(2, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(4,1,4); plot(tm, orsig(3, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])

figure(2);
subplot(3,1,1); plot(tm, parsig(1, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(3,1,2); plot(tm, parsig(2, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(3,1,3); plot(tm, parsig(3, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
end

FVB = FV;

save('abnormalb.mat','FVB')
```

NORMAL B

```
clear
close all

listing = dir('C:\Users\binhan  aslan\Desktop\training B\NORMAL B\*.wav');
% listing = dir('*.wav');
fls = {listing.name};
N = length(listing);
% FV = zeros(N, 12);
FV = zeros(N, 6);
GROUP = ones(N, 1);

[b, a] = butter(5, 0.35);

L = 1024;

for n = 1:N

[x, Fs] = audioread(cat(2, 'C:\Users\binhan  aslan\Desktop\training B\NORMAL
B\', fls{n}));



x = filtfilt(b, a, x);
x = x(1:2:end);
x = filtfilt(b, a, x);
x = x(1:2:end);
x = filtfilt(b, a, x);
x = x(1:2:end);
```

```
% x = filtfil          ÖÖ                    t(b, a, x);
% x = x(1:2:end);

K = 8;

Fs = Fs / K;

x = x(1: L);
tm = (0:L - 1)/Fs;
% plot(tm, x); title('Original Signal'); xlim([tm(1) tm(end)])

% L = length(x);



% S1 : 32, 34
% S2 : 33, 35, 36
% S4 : 31

% M = 2^(ceil(log2(L)));
M = 2*L;
X = fft(x, M);

df = Fs/M;

% n = 0,1,2,...,M - 1
% M - 1 - n = M - 1, M - 2,...,1,0
% M - n = M, M - 1,...,1

FA = [25 45 35; 50 70 60; df 20 10];
```

```
B = round(FA/df);
F = FA(:, 3);
u = zeros(1, M);
u(B(1, 1) + 1: B(1, 2) + 1) = hamming(B(1, 2) - B(1, 1) + 1);
u(M - B(1, 2) + 1: M - B(1, 1) + 1) = hamming(B(1, 2) - B(1, 1) + 1);
v = zeros(1, M);
v(B(2, 1) + 1: B(2, 2) + 1) = hamming(B(2, 2) - B(2, 1) + 1);
v(M - B(2, 2) + 1: M - B(2, 1) + 1) = hamming(B(2, 2) - B(2, 1) + 1);
w = zeros(1, M);
w(B(3, 1) + 1: B(3, 2) + 1) = hamming(B(3, 2) - B(3, 1) + 1);
w(M - B(3, 2) + 1: M - B(3, 1) + 1) = hamming(B(3, 2) - B(3, 1) + 1);
X(1) = 0;

if iscolumn(X)
    X = X.';
end



y = zeros(3, M);

y(1, :) = ifft(u .* X);
y(2, :) = ifft(v .* X);
y(3, :) = ifft(w .* X);

y = real(y);

% figure(2)
% subplot(4,1,1); plot(tm, x); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
% title('Original signal');
```

```
% subplot(4,1,2); plot(tm, y(1, 1:L)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
% title('S1');
% subplot(4,1,3); plot(tm, y(2, 1:L)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
% title('S2');
%
% subplot(4,1,4); plot(tm, y(3, 1:L)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
% title('S4');
%
% close all

orsig = zeros(3, L);
parsig = zeros(3, L);
for t = 1:3
p = y(t, 1:L);
% [m, b] = mask(p);
[m, bmsk, wa, wb] = maskk(p, F(t), Fs);
subplot(311); plot(tm, p);
subplot(312); plot(tm, m);
subplot(313); plot(tm, bmsk); ylim([-0.5 1.5])
orsig(t, :) = p;
parsig (t, :) = m;
% [y, w, wa, wb] = promin(x, Fs);

K = length(wa);
RMS = zeros(1, K);
FRQ = zeros(1, K);
```

```
FRQSS = zeros(1, K);
for k = 1:K
burst = y(wa(k):wb(k));
RMS(k) = sqrt(mean(burst.^2));
A = fft(burst);
L2 = length(A);
K2 = ceil(L2 / 2);
B = abs(A);
FRQ(k) = sum(B(1:K2) .* (0:K2 - 1))/ sum(B(1:K2))*Fs/L2;
[S, w] = peig(x, 2, [], Fs,  'half');
[~, m] = max(S);
FRQSS(k) = w(m);
end

% FV(n, 4*t - 3) = mean(RMS);
% FV(n, 4*t - 2) = std(RMS);
% FV(n, 4*t - 1) = mean(FRQSS);
% FV(n, 4*t) = std(FRQSS);

FV(n, 2*t - 1) = mean(RMS);
FV(n, 2*t) = mean(FRQSS);

end

figure(1);
subplot(4,1,1); plot(tm, x); axis([tm(1) tm(end) -max(abs(x)) max(abs(x))])
subplot(4,1,2); plot(tm, orsig(1, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
```

```
subplot(4,1,3); plot(tm, orsig(2, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(4,1,4); plot(tm, orsig(3, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])

figure(2);
subplot(3,1,1); plot(tm, parsig(1, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(3,1,2); plot(tm, parsig(2, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
subplot(3,1,3); plot(tm, parsig(3, :)); axis([tm(1) tm(end) -max(abs(x))
max(abs(x))])
end

FVNB = FV;

save('normalb.mat','FVNB')
```

CATEGG A

```
clear

load abnormala.mat
load normala.mat
K = 10;
% A = 7;
% B = 3;
A = 5;
B = K - A;
succ = zeros(1, 100);
sen = zeros(1, 100);
spc = zeros(1, 100);
for u = 1:100

k = randperm(K);
m = k(1:A);
k = randperm(K);
n = k(1:A);
r = 1:K;
trn = [FVA(m,:); FVNA(n,:)];
tst = [FVA(setdiff(r, m),:); FVNA(setdiff(r, n),:)];
trnlb = [2*ones(A,1); ones(A,1)];
tstlb = [2*ones(B,1); ones(B,1)];

mdl = fitcdiscr(trn, trnlb);
clss = predict(mdl, tst);
```

```
e = clss == tstlb;

sen(u) = sum(and(e, tstlb == 1)) / sum(tstlb == 1);
spc(u) = sum(and(e, tstlb == 2)) / sum(tstlb == 2);
succ(u) = sum(e)/(2*B);

end

sc = mean(succ)*100;
sn = mean(sen)*100;
sp = mean(spc)*100;

disp(sc);



% c = classify(tst,trn,trnlb);
% e  = c == tstlb;
% suc = sum(e)/(2*B);
% disp(suc);
```

CATEGG B

```
clear

load abnormalb.mat
load normalb.mat
K = 10;
% A = 7;
% B = 3;
A = 5;
B = K - A;
succ = zeros(1, 100);
sen = zeros(1, 100);
spc = zeros(1, 100);
for u = 1:100

k = randperm(K);
m = k(1:A);
k = randperm(K);
n = k(1:A);
r = 1:K;
trn = [FVB(m,:); FVNB(n,:)];
tst = [FVB(setdiff(r, m),:); FVNB(setdiff(r, n),:)];
trnlb = [2*ones(A,1); ones(A,1)];
tstlb = [2*ones(B,1); ones(B,1)];

mdl = fitcdiscr(trn, trnlb);
clss = predict(mdl, tst);
```

```
e = clss == tstlb;

sen(u) = sum(and(e, tstlb == 1)) / sum(tstlb == 1);
spc(u) = sum(and(e, tstlb == 2)) / sum(tstlb == 2);
succ(u) = sum(e)/(2*B);

end

sc = mean(succ)*100;
sn = mean(sen)*100;
sp = mean(spc)*100;

disp(sc);



% c = classify(tst,trn,trnlb);
% e  = c == tstlb;
% suc = sum(e)/(2*B);
% disp(suc);
```