SPECTRAL ANALYSIS OF ECG SIGNALS FOR PRE-DIAGNOSIS OF HEART DISEASES

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ABSTRACT

SPECTRAL ANALYSIS OF ECG SIGNALS FOR PRE-DIAGNOSIS OF HEART DISEASES

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In this thesis we used the three cases for diagnosis of the heart attacks. The first case is healthy persons, second case is non healthy persons and the last one is unknown persons. For detection of them we used the correlation and auto correlation between the cases. For the simulation results we used the MATLAB programming languages. For diagnosis we used two statistical method. The first one is to take only one dice (assuming that this selected dice is a perfect representative of the remaining dice) and throw it many times (multiplying the time axis, to get time average). The second is to throw all dice or some of the dice at the same time (multiplying the event axis, to get ensemble average). The question is how many times should the experiment be repeated along time axis in the first case and how many dice thrown at a time in the second case so that we arrive at a result well approximated to the ones to get a result within 98 % confidence interval the minimum number that an experiment should be performed.

Keywords: ECG signal, signal processing, spectral analysis, heart diseases.

ÖZ

KALP HASTALIKLARININ ÖN TANISI İÇİN EKG SİNYALLERİNİN SPEKTRAL ANALİZİ

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Bu tezde üç olgu kalp krizi tanısı için kullanılmıştır. Birinci vaka sağlıklı kişiler, ikinci vaka sağlıksız kişiler ve sonuncusu bilinmeyen kişiler. Onların tespiti için olgular arasındaki korelasyon ve otomatik korelasyon kullanıldı. Simülasyon sonuçları için MATLAB programlama dillerini kullandık. Teşhis için iki istatistiksel yöntem kullandık. Birincisi, sadece bir zar atmaktır (bu zarların, kalan zarların mükemmel bir temsilcisi olduğunu varsayarsak) ve bir çok kez atın (zaman ortalamasını elde etmek için zaman ekseni ile çarpılır). İkincisi, tüm zarları veya zarların bir kısmını aynı anda atmaktır (topluluk ortalamasını elde etmek için olay eksenini çarparak). Soru, ilk davada zaman ekseni boyunca kaç kez tekrarlanmalı ve ikinci durumda bir defada kaç zar atılmalı, böylece% 98 güven içinde bir sonuç elde etmek için sonuçlara yaklaştığımız soru gelmelidir. aralık bir denemenin yapılması gereken minimum sayıdır.

AnahtarKelimeler: EKG sinyali, sinyal işleme, spektral analiz, kalp hastalıkları.

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TABLE OF CONTENTS

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

ECG	Electrocardiography
MIS	Myocardial ISchemia
PTB	Physikalisch-Technische Bundesanstalt
SVM	Support Vector Machines
KNN	K-Nearest Neighbor
PSD	Power Spectral Density
SD	Spectral Density

CHAPTER I
INTRODUCTION

Electrocardiogram (ECG) is the recording of the electrical potentials that are generated from electric currents radiating from the heart throughout the heart rhythmical work and perceived from certain points on the body surface. Analysis and interpretation of ECG signals are among the methods used to determine heart diseases. ECG signals are of great value for the diagnosis of many cardiac diseases. Therefore, interpretation of ECG signals is of paramount importance [1].

1.1.Background

Nowadays, one of the most dangerous diseases in the world is one of heart disease, and every day it takes the life of a lot of winter. In every period of life, heart health has become the most important issue of health field.

Because of the importance of heart function, it is of utmost importance to solve heart health problems. As well as being in many places in the field of health, early diagnosis is also an underestimation in the treatment of heart diseases. Electrocardiography (ECG) is the most common and most effective method for the early diagnosis of heart diseases.

This method was designed to *examine* the function of the heart muscle and neural transmission system, heart enlargement, heart enlargement, reduction in blood flow to the heart, new or old heart damage, can provide important information about heart rhythm problems and various cardiac and pericardial diseases.

An ECG signal; *P, Q, R, S and T* are the sine signals from the given waves, *ST and PR* segments and *RR, QT and PR* intervals. In a normal ECG signal, *the* waves *P, Q, R, S, T* occur in a certain sequence and intervals. The formation of the waves in this order and *spacing* can change the parameters such as the shape, duration, *ST*

segment, *RR interval* comprising. Abnormalities in these parameters provide information about heart problems, either alone or in combination with other tests. For example, when the *RR interval is* abnormal, it indicates that the heart has rhythm disturbance. *ST segment* depression or elevation Myocardial Infarction or Myocardial Ischemia signs of disease [2].

Studies and literature have shown that ECG alone is not sufficient for the definitive diagnosis of a cardiac condition, besides it is absolutely necessary to make further investigations. However, ECG signals carry invaluable information for diagnosis. For this reason, correct interpretation of ECG is very important.

The most common cases where ECG can be diagnosed are; Rhythms, Disorders in the Activation Series, Growth or Growth in the Wall of Atria and Ventricles, Myocardial Infarction and Ischemia, etc. under the main headings such as. Doctors determine this diagnosis in the light of the ECG chart. However, it may be necessary to evaluate multiple ECG indications to establish a diagnosis. These processes are processes that require time and attention. Errors caused by the carelessness of doctors can lead to misdiagnosis and to avoid important details. With this study, it is aimed to find solutions to these problems and to enable the doctors to gain time.

The study focused on the diagnosis of myocardial infarction. By using the least number of parameters, a model was developed to help doctors diagnose faster and earlier. This classification allows doctors to diagnose faster and with fewer mistakes.

The normal ECG signal consists of the waves labeled P, Q, R, S, and T, which are placed on the base level in the resting state of the heart. Sometimes, after a T wave, there may also be a small U wave. The part called the P wave is the result of contraction of the atrium. The PQ interval indicates the time of the transmission of the feeling. The QRST wave is called the ventricular complex. QRS means ventricular depolarization. Transmission disturbances in his bundle and his arms lead to changes in the QRS wave. An example of an ECG signal is shown in figure 1.1.

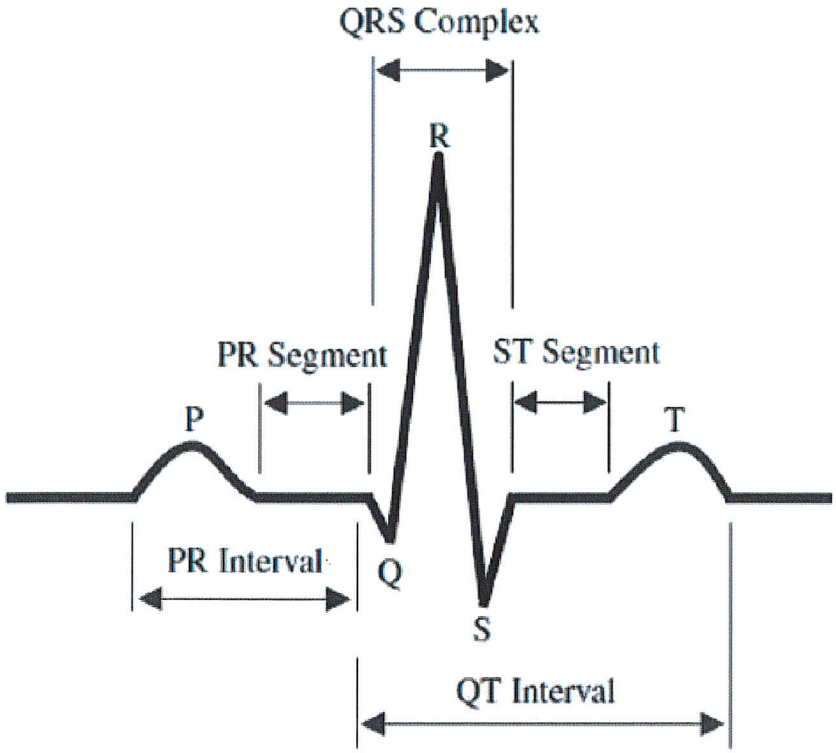


Figure 1. 1. ECG signal sample

1.2.Electrocardiography

ECG is the process of printing the electrical activity of the heart on special paper. ECG mainly shows electrical events and does not give information about mechanical events. The ECG is recorded on a paper that is usually twisted to 25 mm in rotation speed.

On this ECG paper there are small squares of 1x1 mm and large squares of 5x5 mm. An ECG signal; wave, segment, and interval. Waves *P, Q, R, S, T are the* waves. This is the first time that waves have been described [3].

We can classify cases that can be diagnosed by ECG in the most general way as follows.

A. Rhythm and transmission disorders

B. Calbin (myocardium) blood supply

a. Ischemia (not enough blood)

b. Lesion (harm)

c. Necrosis

C. The state of the heart muscle (hypertrophy)

D. Blood ion imbalances

1.3.Normal ECG Signal

Care must be taken when interpreting an ECG specimen as normal or pathologic. The definition of a normal ECG is different for each individual. Also, the normal ECG does not mean that there is no heart disease in that person. Similarly, a person with a pathologically interpreted ECG may not have any heart disease. The following is a summary of normal ECG findings for different derivations, while Figure 1.3 shows an example of a normal ECG.

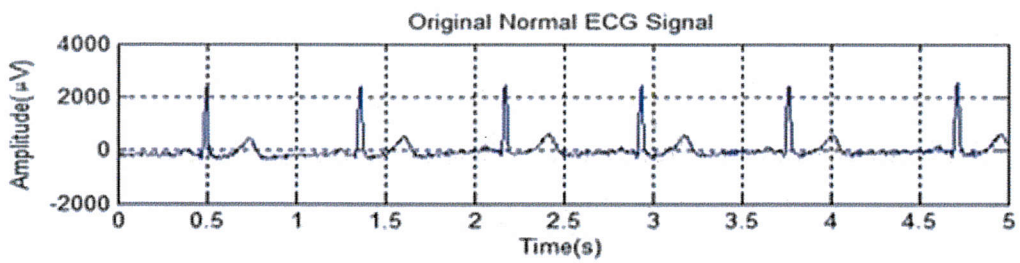


Figure 1. 2. Normal ECG signal

Derivation I: P wave is usually positive. A small q wave can be seen, but the main deflection is R wave. Then a small wave of s might come. T wave is positive and it is smaller than R wave.

Derivation II: The P wave is usually positive and most pronounced in this derivation. There may be a small q-wave, but the main deflection is R-wave. Then a small wave of s might come. The QRS complex in this derivation is similar to I and III. T wave is positive.

Derivation III: P wave may be positive but it is usually biphasic or negative. Mostly there is Q wave and sometimes it can be very deep. Generally R wave is seen, but occasionally QS complex can be encountered. The T wave can be positive or negative.

Derivation aVR: P wave is negative. The QRS deflection is generally negative. T wave is also negative.

Derivation aVL: I derivation, but the P wave may be negative or biphasic. There is usually a small q wave, but the main deflection is R wave. The T wave is usually positive, but can also be negative or biphasic. Negative T waves are observed especially if the P wave is negative and the QRS amplitude is low.

Derivation aVF: P wave is usually positive. A small q wave can be seen. R wave is usually there. The T wave can be positive, negative, or biphasic.

Derivation V1: P wave is biphasic. Generally no q-wave is seen. In rare cases, however, the QS complex may be encountered. Usually a small r wave is followed by a large S wave. Sometimes the rSr 'complex can be seen. The T wave can be positive or negative.

Derivation V2: Similar to V1 derivation. P wave is usually biphasic. Mostly no q-wave. A large r wave follows a small r wave. The T wave can be positive or negative.

Derivation V3: P wave is usually positive. Q wave is not seen. The R wave and the amplitude of the S wave are close together. T wave positive and high amplitude.

Derivation V4: P wave positive. A small q wave follows a large R wave and a small s wave. T wave positive and high amplitude.

Derivation V5: Similar to V4 derivation. P wave is positive. Usually a small q wave follows a large R wave and a small s wave. T wave positive and high amplitude.

Derivation V6: Similar to V4 and V5 leads. P wave is positive. Usually a small q wave follows a large R wave and a small s wave. T wave positive and high amplitude.

1.4.Diseases

Myocardial Infarction (MI); Ischemic necrosis of the heart muscle. That is, the result of insufficiency of the coronary blood circulation in a certain region is the death of the heart tissue in that region. Myocardial infarction is often due to constriction or occlusion of coronary vessels resulting in atherosclerosis. Myocardial infarction manifests itself as a severe, compressive pain in the middle of the chest by 80%. If it is 20%, pain does not occur. Painful myocardial infarction is more common in people with elderly or diabetes [4].

Myocardial Ischemia (MIS); can be defined as oxygen deprivation resulting from decreased tissue perfusion [5]. MIS with symptoms such as weakness, sweating, vomiting and difficulty breathing are more common in people with diabetes and in the elderly.

1.5.Diagnostic conditions with ECG signal

a) **Cardiac arrhythmias:**

Normal heart rhythm loss of heartbeats. Examples are atrium and ventricul fibrillations, flutter, tachycardia, bradycardia, and many other rhythm disorders.

b) **Myocardial ischemia:**

The myocardium is deficient in oxygenation as a result of the narrowing of the heart-feeding vessels or the reduction of the oxygen content of the blood that feeds the heart tissue in secondary conditions.

c) **Myocardial infarction:**

Congestion of the feeding vessels to the heart muscles is the result of damage to that region (necrosis formation).

d) **Ectopic beats, premature contractions:**

Heartbeats created by a stimulus point shifted from one pacemaker point to another.

e) **Atrial and ventricular hypertrophy:**

The ear and ventricular muscle growth.

f) **Pericarditis:**

Inflammation of the heart muscle.

g) **Electricity from the atrium and ventricle**:

Delay of transmission of impulses.

h) **Digitalis and antiarrhythmic agents:**

The effect of drugs on the heart determination.

i) **Electrolyte:**

Especially in the presence of potassium.

j) **Heart attack.**

The heartbeat is to stop the heart.

ECG is a laboratory test and is not a sufficient benchmark for the diagnosis of heart disease. In rare cases, a person with a heart condition may have a normal ECG or a normal person may have an abnormal ECG. Based on some abnormalities in

the ECG alone, it can not be judged that people are heart disease, nor can it be judged based on a normal ECG that a person is not heart disease. The ECG is always interpreted under the umbrella of other relevant clinical conditions [6].

Today, by analyzing ECG signals in computer environment, detailed ECG analysis and interpretation softwares have been developed which facilitate the physician's work and give the same result at the same rate as the diagnosis of the physician.

The ECG analysis and interpretation software mainly analyze time domain and some frequency domain parameters. Literature scans reveal that there are very few articles compared with those using time and frequency domain analysis of ECG signals by the autocorrelation analysis of cardiac arrhythmias to identify the need for studying this issue.

Many different scenes such as geophysical, geological, seismic, radar, sonar, underwater acoustics and electronics are utilized in the "time slip region" and the

correlation functions in this region (autocorrelation and cross-correlation functions), which are different from each other such as time and frequency regions. A research to be done in such a context would be obvious if the possible benefits of correlation functions, which find this wide application area and provide many benefits, are also considered in the processing and analysis of medical signals.

In studies that have been reported in the literature, autocorrelation analysis of ECG signals distinguishes ventricular fibrillation, a fatal arrhythmia, from ventricular tachycardia and other sinus arrhythmias [7, 8].

CHAPTER II
LITERATURE REVIEW

Many investigators have done different studies to detect ST segment changes and myocardial infarction. Relevant information will be given to the work done in this section.

2.1.Literature review

C. Papaloukas et al. Have found ischemic segmentation in their work by performing noise reduction, feature extraction, rule-based classification, and floating window classification. The study was tested in the European ST-T database and the sensitivity and positive predictive value were given as 93.8% and 78.5%, respectively [9].

Bin Liu and others have developed a new method of describing the ECG signal as PolyECG-S by adapting the polynomial from the 20th. Physikalisch-Technische Bundesanstalt (PTB) was chosen as the database for the study. The ECG signals in this database are standard 12-lead and have a sampling frequency of 1000 Hz.

A total of 148 ST segment changes and 52 healthy data were selected from the database. The accuracy of detecting random mycardic infarction using the J48 and Naive Bayes classification algorithms, one of the Decision Trees algorithms, was the highest 94.4% [10].

Themis P. Exarchos et al., selected 1 hour of the data for the selected number of e0104 in the European ST-T database, ie 2 hours, ie the total number of data, e0103, e0105, e0108, e0113, e0114, e0147, e0159, e0162 and e0206. Because of this selection, 86384 heart beats were labeled as normal or ischemic. The proposed method is performed in three main steps: feature extraction, feature extraction, rule generation and classification. In the feature extraction phase, the QRS complex of the ECG signal was first determined. Then, four morphological features were created on this complex, namely ST segment field, ST segment deviation, ST segment gradient, T wave

amplitude. A tree classification algorithm, CT-disc, has been used to decompose the attribute. Using rule-based classification algorithms, sensitivity to detect ischemic beat was 87% and specificity was 93% [11].

L. N. Sharma and others performed wavelet-transform-based feature extraction in their work. ECG signal; With the help of the Pan Tompkins algorithm, wavelet transform is applied after determining the R peaks. Multi-scale energy values and eigenvalues of multi-scale covariance matrices are used as attributes from the values obtained as a result of wavelet transform. The PTB database was used in the study. The accuracy, specificity and sensitivity of detecting myocardial infarction using Support Vector Machines (SVM) and K-Nearest Neighbor (KNN) classifiers were given as 96%, 93% and 99% respectively [12].

Xiaoying Tang and others in their studies using the Hidden Markov Model on QRS complexes selected from the Long-Term ST database; they have performed attribute extraction. Sensitivity to detect myocardial ischemia and positive predictive value were given as 89% and 85%, respectively [13]. Similarly, A.Smrdel and colleagues performed feature extraction on QRS complexes using the Hidden Markov Model during the feature extraction stage. In study, when 86 ECG recordings are used 24 hours of protocol B in Long Term ST database; the sensitivity of detecting ischemia was 78.9% and the positive predictive value was 80.7%. Sensitivity and positive predictive values were found to be 81.3% and 89.2%, respectively, when using the European ST-T database in the study [14].

Yorgos Goletsis et al. Have provided the detection of myocardial ischemia using multiple criteria via QRS complexes. These criteria are ST segment deviations, ST segment gradient, T wave amplitude and the age of the patient. Twenty ischemic ST segment sections and 20 ischemic T wave segments from the European ST-T database were used in the study. These sections contain a total of 86,384 beats. We then used genetic algorithms to detect the sensitivity and specificity of detecting myocardial ischemia by 91% [15].

Al-Fahaum et al. Randomly selected 14 diseased ECG signals from the European ST-T database and 24 random normal ECG signals from the MIT-BIH Arrhythmia database. High-frequency analysis techniques such as twin-spectrum analysis and

quadratic phase matching were applied to ECG signals and the mean sensitivity and positive predictive value were found to be 100% and 93.33%, respectively [16].

P. Ranjith et al. They started by applying wavelet transforms to the ECG signals they received from the European ST-T database. Then, using the coefficients obtained as the wavelet transform, R peak, the starting and ending points of the QRS complex, and the T and P wave are characteristic points of the ECG signal. Sensitivity to detect myocardial ischemia and positive predictive value were 87.5% and 93.3%, respectively [17].

Amit Kumar and others in their studies; firstly R-R range and ST segment were found by taking advantage of wavelet transform. In the next step, the isoelectric reference was found and the isolated energy was calculated. At the latest stage, myocardial ischemia was detected by setting threshold values. A total of 43,876 ST-segments were selected from the data of e0103, e0104, e0105, e0108, e0113, e0114, e0147, e0159, e0162, e0206 selected from the European ST-T database. The mean sensitivity for detection of myocardial ischemia was 98.12% specificity and 98.16% [18].

R Correa and others; They used 2 different databases. 52 healthy ECG data were selected from the PTB database. 51 databases of ischemic patients were obtained from the database created by Charleston Area Medical Center. Butterworth filter is used as pre-processing in the study. The vector cardiographic parameters were used in the extraction of the attribute. Classification with linear discriminant analysis (LDA) revealed sensitivity and specificity for detection of myocardial ischemia as 99.5% and 99.4%, respectively [19]. The same parameters were used in the other studies they carried out in 2014. In these studies, a database of patients with 80 myocardial ischemic history in the Charleston Area Medical Center was used. They used Linear Discriminant Analysis method in classification stage. Sensitivity to detect myocardial ischemia is 90.5% and specificity is 92.6% [20].

L Dranca and colleagues have performed many features such as ST amplitude, ST segment gradient, QRS complex duration, and heart rate. These attributes are used; Bagged Trees, Random Forest, Naive Bayes, and Multilayer Artificial Neural Networks. The best results were obtained by Bagged Trees method. Long term ST database and European ST-T database were used in the study. Sensitivity and positive

predictive values for the ischemia detection in the Long Term database were 93.97% and 74.91%, respectively, and for the European ST-T database, sensitivity and positive predictive values were 83.33% and 77.31%, respectively [21].

Mingfang Xu et al. Have identified the ST segment by morphological classification. 1) Filtering with 0.05-45 Hz banding 2) Finding R peak points 3) Removing ECG pulses with nonrandom RR intervals 4) Finding start and end points of ST segment 5) Finding baseline 6) Rule-based morphological classification steps have been performed for each ST segment. A total of 17,314 heart beats were taken from the European ST-T database. The accuracy of training and test myocardial ischemia detection was given as 91.8% and 90.1% [22].

In Costas Papaloukas et al. Studies, initially the isolated line, QRS complex, ST segment and T wave in the ECG were excluded. The heartbeats were then classified as negative ST trend, positive ST trend and T wave inverse, T wave fluctuation, and negative T wave amplitude. They selected ECG data from the European STT database. This database contains 90 ECG recordings and 589 ST episodes obtained from these records and 393 T episodes. ST segment detection sensitivity and positive predictive values were 92.0% and 93.77%, respectively [23].

E. S. Jayachandran et al. Have applied wavelike transformations to these pulses after determining their heart beats in their work. ECG data were obtained from the National Institute of Technology Calicut center in Hindustan. These ECG records are 2282 normal and 718 pulses containing myocardial ischemia. The recommended method of detecting myocardial ischemia was 95% [24].

Jinho Park et al. First removed their baseline deviation using wavelet transform in their work. Then they found QRS complexes using wavelet transform. They have defined 3 different attributes for each heart beat.

These are the area between the QRS complex and the T peak, the normalization of the values from the QRS complex to the zero voltage point, and the slope from the starting point to the end point of the QRS complex. The performance evaluation of the proposed method was performed with core density estimation and DVM. 90 ECG records from European ST-T database are used in the study. These records contain a total of 367 ischemic ST episodes. The sensitivity and specificity of finding the

ischemic ST segment using core density estimation were 93.39% and 91.12%, respectively; When DVM is used these values are 94.1% and 92.3% respectively [25].

Miha Amon and others aimed to find the ischemic ST segment in their studies. The proposed method has benefited from orthogonal transformations.

Karhunen-Loeveve transformation and Legendre Polynomial-based transformations. The performance evaluation of the study was conducted using 1130 ischemic ST segments selected from the Long-Term ST database and 234 non-ischemic ST segments. In the classification stage, Decision Tree, Quadratic Discriminant Analysis and DVM algorithms are used. The best classification results were found by choosing k = 3 in the K-EYK algorithm. The classification accuracy, sensitivity and specificity were found to be 90%, 91% and 85%, respectively, using the attributes obtained from the Karhunen-Loeveve transformation. When using Legendre polynomial-based transformations, these values are 82%, 85% and 75% [26].

U. Rajendra Acharya and others aimed to detect myocardial infarction in their studies. First they applied Discrete Wavelet Transforms to their heartbeats.

Then, using these transformation coefficients, they determined 12 different facial features. These attributes are; approximate entropy, signal energy, fuzzy entropy, Kolmogrov-Sinai, permutation, Renyi, Shannon, Tsallis and Wavelet entropy, proportional fracture size, Kolmogrov complexity and the greatest Lyapunov superstructure. A total of 485,753 ischemic heart beats and 125,652 normal heart beats from the PTB database were selected. The accuracy of detecting myocardial infarction was 98.8%, 99.45%, and 96.27%, respectively, in sensitivity and specificity [27].

Muhammad Arif and others performed myocardial infarction classification using T wave amplitude, Q wave amplitude and ST segment level deviation features in the study. 20,160 heart beats from the PTB database were used. There are 10 subgroups of myocardial infarction: Anterior, Anterior-Lateral, Anterior-Septal, Inferior, Inferior-Lateral, Inferior-Posterior, Inferior-Posterior-Lateral, Lateral, Posterior and Posterior-Lateral. Sensitivity, specificity, and accuracy were 90%, 90%, and 98.3%, respectively [28].

In the thesis study, methods based on time-frequency transforms have been developed to detect ST segment elevations or falls in the range of ECG R-R. Unlike the studies

in the literature, a large database was created using the MIT-BIH Arrhythmia, European ST-T and Long Term ST databases in the proposed methods. In addition, different classification techniques are used in the performance evaluation than in the literature, and the performance evaluation results of the proposed methods are based on many studies.

2.2.Databases

ECT records from the MIT-BIH Arrhythmia database, the European ST-Tandem database and the Longterm ST database are used in the studies conducted. These databases can be accessed at http://www.physionet.org/ [29].

From the MIT-BIH Arrhythmia database, 46 ECG recordings with V1, V2, V4 and V5 derivations, each of 30 minutes each, were selected. ECG signals have a sampling frequency of 360 Hz. This database contains records of different arrhythmia types and healthy ECG signals.

From the European ST-T database, 70 ECG recordings with lead times V1, V2, V3, V4 and V5, each of 2 hours each, were selected. The records were taken from 70 men aged between 30 and 84 and 7 men between 55 and 71 years old. These ECG signals have a sampling frequency of 250 Hz. This database contains ECG records with ST segment depression or elevation.

In the selected Long Term ST database as the other database, the ECG recordings are from 21 to 24 hours and have a sampling frequency of 250 Hz. The recordings are taken from 17 different people whose age and gender are different. 21 ECGs with V2, V3, V4, V5 and V6 derivations In this database, ischemic ST segments, non-ischemic ST segments and ST segment changes due to the patient's movement are labeled by specialist doctors.

Ischemic ST segments were selected from the Long-Term ST database in thesis studies. In the database there are three different protocols to express ST segment falls or elevations: sta, stb, and stc. The schematic representation of these protocols is given in Figure 1.20. Here, R: local reference and GR: global reference ST reference is derived by subtracting ST reference from ST level.

CHAPTER III
SPECTRAL ANALYSIS OF ECG SIGNALS

3.1.Spectral Density

The time series x(t) of the power spectrum defines the distribution of the frequency components that cause this signal $S_{xx}(f)$. According to the Fourier analysis, any physical signal can be decomposed into different frequencies, or can be transformed into frequency spectra over a continuous sequence. The statistical mean of a given signal or any signal types (including noise) is analyzed according to the frequency components it contains. This is also called the spectrum [30].

The spectral energy density can be measured when the energy of the signal is concentrated in a limited time interval, especially when the total energy is limited. The more commonly used name, spectral power density (briefly the power spectrum), is applied as long as the signal is present, or is applied for an indefinite time period at a high amount during a certain time period (especially during the hopping period). Spectral power density (PSD) is related to the distribution of spectral energy, and each unit can be found at a time. Because the total energy of such a signal is usually infinite all the time. The integration or integration of the spectral components (for the physical process) or the variance (for the statistical process) of the spectral components is obtained by integrating the time interval of $x^2(t)$ is equivalent to the value obtained, just as Parseval's theory states [30].

Following figure shows the spectral density of a fluorescent lamp as an optical wavelength function. The vertices indicated by the arrows indicate atomic transformations.

A physical process spectrum x(t) usually carries the necessary information about the nature of x. For example, the pitch of a musical instrument (the thickness or fineness of each of the voices forming a musical piece) can be determined instantly by spectral analysis. The color of the light source can be determined by the extremely high

frequency fluctuation of the electric field of the electromagnetic waves E(t). As in the Fourier transform, it is possible to obtain the spectrum from the time series and to obtain the Fourier analysis-based approximations. In most cases time values are not used specifically. For example, a light-scattering prism is used in the spectrograph to obtain the light spectrum, or when an audio is perceived by the auditory perception receptors of the inner ear (each is sensitive to a certain frequency), it creates an effect along these receptors [31].

However, this article focuses on situations that are known to the time series (least statistical perception) or directly measurable (such as microfunting of any computer). The power spectrum is very important in the statistical signaling process and the statistical study as much as it is in the branches of physics and engineering. Typically, this process is time dependent, but spatial data separated into spatial frequencies can be discussed [32].

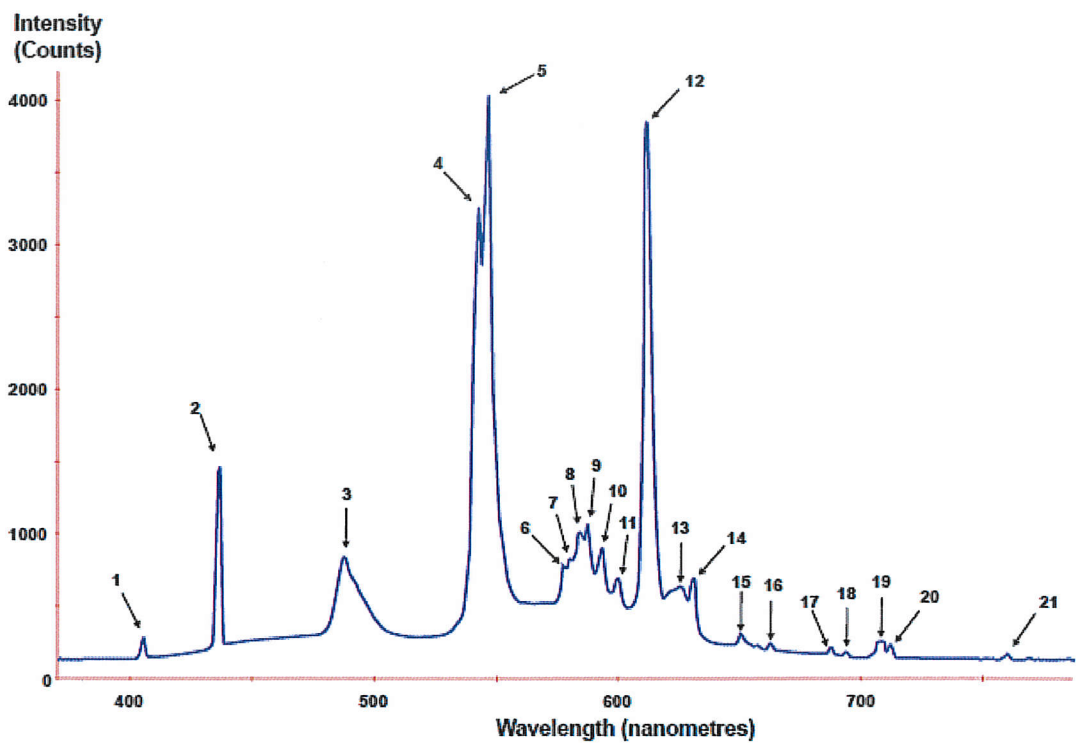


Figure 3. 1. Fluorescent lighting spectrum with emission peaks numbered

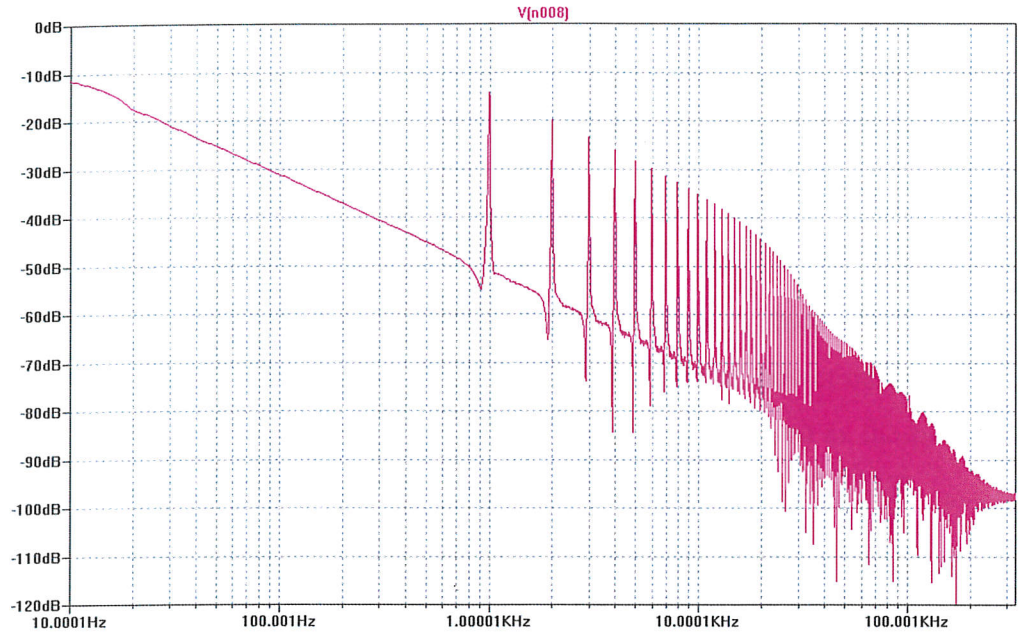


Figure 3. 2. Power density spectrum of a signal

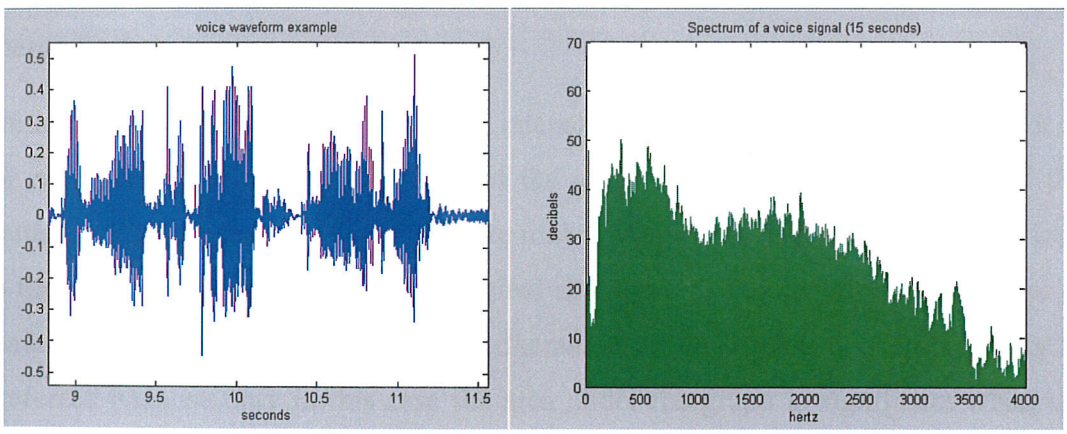


Figure 3. 3. The auditory power spectrum (spectrum) (right) that emanates from the sound wave formation (on the left) that occurs over a period of time.

Each of the signals that can be shown as amplitude varies depending on the time and there is an appropriate frequency spectrum. These are the light (perceived as color), musical notes (perceived as perceived), radio / television (as determined by frequency, or sometimes wave length) and even the Earth's regular turn. When these signals are analyzed as a frequency spectrum form, they are turned on and off with the underlying production of the received signals or the underlying process. In some cases, the

apparent peak of the frequency spectrum may correspond to the sine wave component. Some waves may correspond to the fundamental peaks of the harmonic motion. The periodic signal that it indicates may not be in the form of a sinus curve. A stable spectrum may exhibit a developed narrow frequency range, which corresponds to resonance frequency ranges usually have zero power as produced in the rice filter [32].

In physics, the signal can be some kind of wave, such as an electromagnetic wave, an acoustic wave, or a vibration of a mechanism. The spectral power density (PSD) of a signal defines the frequency function of the frequency function as the power signal. The spectral power density is expressed in watts per hertz (W / Hz) [33].

When a signal is expressed only in terms of voltage, there is no specific power connected to a particular severity in this case. The power is simply calculated by the signal's luminance. Because this is always proportional to the actual power the signal gives to the impedance. One uses V2 Hz-1 (frequency squared frequency) as the unit for the spectral power density, while the other uses V^2 s Hz-1 (frequency squared times frequency) for the spectral energy density, although there is no specified power or energy [34].

Sometimes one may encounter spectral intensity, which is equal to the square root of the spectral power density. The unit of the intensity of the spectral density of the voltage signal is used as V $Hz^{-1/2}$ (square root of voltage times frequency). Variations in the spectral intensity (SI) of the original spectrum will be directly proportional to variations in the signal level. But mathematically, the spectral power density is preferred because only in this case the area under the graph is significant when the actual power is used entirely in the frequency or the specified band gap [35].

For the acceleration of the spectral power density in random vibration analysis, a formula of 2 Hz-1 (square frequency of gravity acceleration) is often used.

Mathematically, there is no need to use physical dimensions for signals or arguments. In the ensuing discussions, the meaning of x(t) will remain unspecified. But the argument will be assumed to be time o [36].

3.2.Spectral Power Density

Spectral Power Density is the spectral energy density described above is suitable for transient waves (such as pulse-signals) and Fourier-transformed signals are generally found. For continuous signals over time, for example, one must be specified as a power spectral density (PSD) we can see how the power of the signal or time series is distributed over a certain frequency, as in the previous example. Power is a physical force or more often it is identified with the frame of the signal and also facilitates the abstract signals.) (or on another independent equation) and use an analogy with the electrical signals (suggesting that for the first of the two, the similarity or similarity between two different things is the same for the other) (even among other physical processes). Even if something in the system does not contain any physical force, it traditionally coincides with the power spectrum. If any of the x (t) forms a subsequent physical voltage source and the end portions have a resistance of 1 ohm the instantaneous distributed power in resistance is expressed as x^2 watt.

The mean power P of the signal over a whole time interval is given by P mean time: x(t)

$$P = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} x(t)^2 \, dt$$

For example, in stationary processes there may be limited power, despite the presence of infinite energy. The energy is then integrated and the stationary signal is continuous in infinite time. We can not use the spectral energy density in this way as in the cases mentioned above [38].

The calculation of any signal when controlling the frequency components of any signal x(t) is similar to an ordinary Fourier Transform $\hat{x}(\omega)$. However, most of the Fourier Transform related signals never existed. This complexity of yesterday's intermittent Fourier transforms $\hat{x}_T(\omega)$ works better. In the Fourier transform, the signal is only integrated in the closed range [0, T] [39].

$$\hat{x}_T(\omega) = \frac{1}{\sqrt{T}} \int_0^T x(t) e^{-i\omega t} \, dt$$

Spectral power density after

$$S_{xx}(\omega) = \lim_{T\to\infty} \mathbf{E}\left[|\hat{x}_T(\omega)|^2\right]$$

The value in E specifies the expected value. The elimination passes a function as follows.

$$\mathbf{E}\left[|\hat{x}_T(\omega)|^2\right] = \mathbf{E}\left[\frac{1}{T}\int_0^T x^*(t)e^{i\omega t}\,dt \int_0^T x(t')e^{-i\omega t'}\,dt'\right] = \frac{1}{T}\int_0^T\int_0^T \mathbf{E}\left[x^*(t)x(t')\right] e^{i\omega(t-t')}\,dt\,dt'$$

In the latter case $\Delta t = t - t'$ can be changed with variables in random / stationary random processes and the limit of integration approaches infinitely. The resulting spectral power density (which is the relationship between successive values of the error term in the multiple regression analysis) function of this signal becomes Fourier's transformations, $S_{xx}(\omega)$ statistic definition of the autocorrelation in the fonction $\gamma(\tau) = \langle X(t)X^*(t+\tau)\rangle$ (or more generally when X (t) is a complex value $\gamma(\tau) = \langle X(t)X(t+\tau)\rangle$

where $\gamma(\tau)$ is integrable in all conditions:

$$S_{xx}(\omega) = \int_{-\infty}^{\infty} \gamma(\tau)\, e^{-i\omega\tau}\, d\tau = \hat{\gamma}(\omega)$$

Most authors describe the spectral power density with this formula [40].

You can use $[f_1, f_2]$ or $[\omega_1, \omega_2]$ can be calculated by taking the integral of the power frequency range. $S_{xx}(-\omega) = S_{xx}(\omega)$ power positive and negative frequencies. It is calculated with the fold in the form shown below. The smallest factors are dependent on the used sum.

$$P_{\text{bandlimited}} = 2\int_{f_1}^{f_2} S_{xx}(2\pi f)\,df = \frac{1}{\pi}\int_{\omega_1}^{\omega_2} S_{xx}(\omega)d\omega$$

More generally, similar techniques can be used in estimating time-varying spectral intensities. In this case, we can not say that the cut-off Fourier transformation approaches infinite limit of T in the above-mentioned limited time interval (0, T). This

causes low spectral coverage and low resolution. low frequencies are not tried as examples and the frequencies cause the coefficients of 1 / T to not be an integer. The estimated spectral power density using a single time sequence will be very loud, but this can be mitigated. If the expected value (in the above equation) is used, the short-time spectra can be made by evaluating x (t) at a specific time interval to address statistical unity using large numbers (or infinite) [41].

This definition of spectral power density can be generalized as discrete time x_n. Above is limited to $1 \leq n \leq N$ We have specified a signal sample for $T = N\Delta t$. Then a single spectral power density can be obtained by extrapolation from the integration for estimation.

$$\tilde{S}_{xx}(\omega) = \frac{(\Delta t)^2}{T}\left|\sum_{n=1}^{N} x_n e^{-i\omega n}\right|^2$$

Previously, we could obtain the actual spectral power density N (and thus T) forever, and the expected value is formally applied. In the real World implementation, one would typically use one more accurate estimate of theoretical spectral The intensity of the measured spectral power is sometimes called a periodogram (spectral density estimate). The periodogram combines the correct spectral power density with the number of estimated values while the mean time interval approaches infinity [42].

If the two signals affect the spectral power density, the cross spectral density can be calculated in a similar way. For the spectral power density to be related to autocorrelation, the cross spectral density is related to the cross correlation.

Cross-correlation is the calculation of the similarities of interdependent delays of two serial functions in the signaling process. (.) is also known as a dot product or an inter-product product.

3.3.Prediction

Estimation of spectral intensity is the estimation of the spectral intensities of random signals from a set of time samples. Depending on what is known about the signal, estimation techniques include parametric and nonparametric statistical approaches and

may be based on time domain or frequency domain analysis. For example, common parametric technical observations follow autographed mode. The indication of an ordinary process type in autogressive, statistical and signaling processes. For example, it defines the precise variable time period in nature. Non-parametric technique is periodogram [43].

Spectral density is often estimated using Fourier variable techniques. The Welch method is also one of them. The Welch method is an improved version of the standard periodogram spectrum (tafy) estimation method. This method reduces the noise power of the estimated power spectrum by reducing the net frequency. However, other techniques (eg: the maximum entropy method) are used.

3.4.Linked Concepts

The spectral center of gravity of any signal is the midpoint of the spectral density function. (It is frekans that divide the distribution into two peaks) [44].

Instead of dividing the spectral edge frequency of a signal into two separate parts, the previous concept is an expanded rate.

Spectral density is a frequency dependent function, not a time dependent function. However, the spectral density of a small-spaced signal can be calculated and the time-dependent graph of the interval can be plotted. Such charts are called spectograms. Such techniques are a kind of spectral analysis technique based on the Fourier short-time transformations and the principle of small waves.

The spectrum usually refers to the spectral power density. As mentioned above, the scattered signal content is depicted along the frequency. It should not be confused with the transmission function of the frequency (which includes the actual or imaginary phase of the frequency function type). The graph of the frequency response for transmission functions (eg: Bode diagram) is drawn in two different ways. The first is intensity-frequency and the second is phase-frequency graphs (real and imaginary parts of the less used transmission function). The impulse response (at time interval) h(t), spectral intensity intensity alone can not be recovered without phase function. they are Fourier transformations, but there is no symmetry (also for autocorrelation)

that will force the fourier transformation to its true value. Spectral phase and phase noise can be looked at for extra information [45].

3.5.Electrical engineering

The use of the power spectrum and concept of a signal is based on electrical engineering. Especially in electronic communication systems, these are radio communications, radars and related systems. In addition, there is passive remote sensing technology. Spectrum analyzers, called electronic instruments, were used to observe and measure the power spectra (spectra) of the signals.

The spectrum analyzers measure the value of short-time Fourier transforms of the input signal. If the signal is analyzed, the short-time Fourier transform, which is a fixed / stationary process, allows the spectral power density of the signal to be estimated at its best estimate [46].

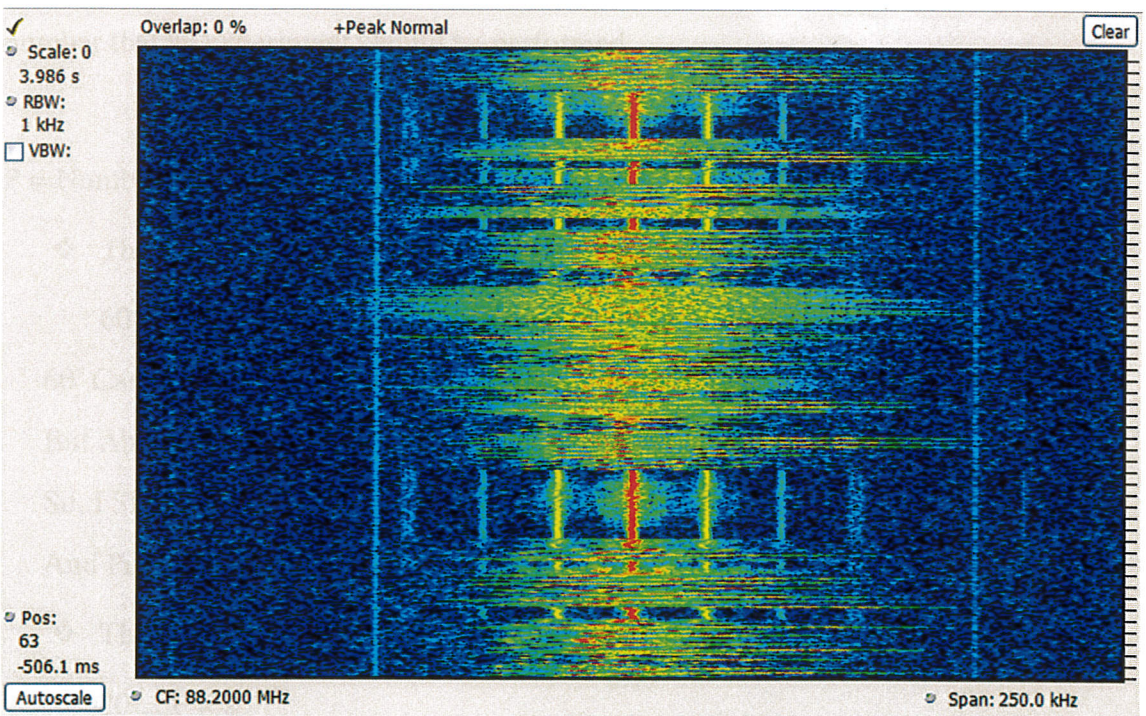


Figure 3. 4. The frequency spectrum of the FM radio signal in the horizontal plane and time is increasing in the vertical plane.

CHAPTER IV
SIMULATION RESULT AND DISCUSSION

4.1.Proposed work

The first one is to take only one dice (assuming that this selected dice is a perfect representative of the remaining dice) and throw it many times (multiplying the time axis, to get time average). The second is to throw all dice or some of the dice at the same time (multiplying the event axis, to get ensemble average). The question is how many times should the experiment be repeated along time axis in the first case and how many dice thrown at a time in the second case so that we arrive at a result well approximated to the ones to get a result within 98 % confidence interval the minimum number that an experiment should be performed

P = Number Of Cases

- The Inverse Of Probability Of That Particular Event $\times 10 = \frac{1}{P} \times 10 =$ 60 ... P = 6

60 Cases ... For The Dice.

But About My Case ... Healthy and Unhealthy Persons

So, I Should Take 20 Cases.

And Put 2 Rather Than P and Change 60 To 20

- The Inverse Of Probability Of That Particular Event $\times 10 = \frac{1}{P} \times 10 =$ 20 ... P = 2

X Values Only For Sampling.

I Will Use Only Y Values To Put It By Matlab And To Find The Average.

For Normal person:

6.434211 ... After Adding.

0.1949760909090909 ... After Dividing.

.....

For Abnormal person:

5.671053 ... After Adding.

0.1718500909090909 ... After Dividing.

.....

For X?

6.5358671 ... After Adding.

0.1980565787878788 ... After Dividing. .....

From My Results I Found That The Person " X?" His Health Is Very Good.

From 20 Cases ... I Get (19) Cases For Normal And (1) Case For Abnormal

So, The Rate Is 98% ... He Is Healthy Pearson.

4.2.Correlation

In probability and statistics, the correlation indicates the strength and direction of a linear relationship and proportionality between two statistical variables. It is considered that two quantitative variables are correlated when the values of one of them vary systematically with respect to the homonymous values of the other: if we have two variables (A and B) there is correlation between them if the values of A decrease also do so those of B and vice versa. The correlation between two variables does not imply, by itself, any causal relationship.

The relationship between two quantitative variables is represented by the line of best fit, drawn from the point cloud. The main elementary components of an adjustment line and, therefore, of a correlation, are strength, meaning and form:

- The extreme force according to the case, measures the degree to which the line represents the cloud of points: if the cloud is narrow and elongated, it is represented by a straight line, which indicates that the relationship is strong; If the point cloud has an elliptical or circular trend, the relationship is weak.

- The sense measures the variation of the values of B with respect to A: if when growing the values of A do those of B, the relation is direct (positive slope); if the values of A decrease in those of B, the relation is inverse (negative slope).
- The shape establishes the type of line that defines the best fit: the straight line, the monotonic curve or the non-monotonic curve.

There are several coefficients that measure the degree of correlation, adapted to the nature of the data. The best known is the Pearson correlation coefficient (actually introduced by Francis Galton), which is obtained by dividing the covariance of two variables by the product of its standard deviations. Other coefficients are:

- Spearman correlation coefficient
- Kendall correlation
- Canonical correlation
- Intraclass Correlation Coefficient
- Biserial Correlation Coefficient
- Poliserial Correlation
- Tetracoustic correlation
- Polychoric Correlation
- Kendall correlation
- Jaspen correlation
- Correlation of Fechner

4.3.Autocorrelation

In figure 4.1, the Autocorrelation description is illustrated. Above plot of a series of 100 random numbers concealing a sine function. Below: The sine function revealed in a correlogram produced by autocorrelation.

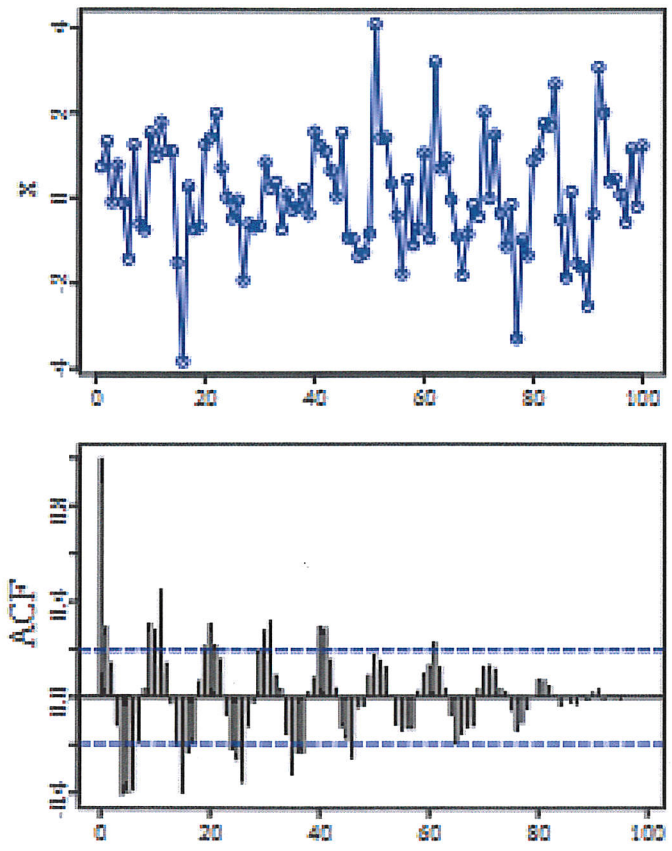


Figure 4. 1. Autocorrelation description

Visual comparison of convolution, cross-correlation and autocorrelation.

Autocorrelation, also known as serial correlation, is the correlation of a signal with a delayed copy of itself as a function of delay. Informally, it is the similarity between observations as a function of the time lag between them. The analysis of autocorrelation is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal obscured by noise, or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. It is often used in signal processing for analyzing functions or series of values, such as time domain signals.

Unit root processes, trend stationary processes, autoregressive processes, and moving average processes are specific forms of processes with autocorrelation.

Autocorrelation measures the similarity of a signal with its time shifted copy. It was defined earlier for an energy signal, repeated here as

$$R_x(\tau)=\int_{-\infty}^{\infty} x(t)x^*(t-\tau)dt=\int_{-\infty}^{\infty} x(t)x^*(t+\tau)dt$$

means that we have to shift x(t) over the whole interval of overlap by and amount τ and perform integration over t .

By taking x(t) to be (a single) rectangular function, whose mathematical expression, we illustrate in following figure graphically the sliding of

$$x^*(t-\tau)=x(t-\tau)$$

against x(t).

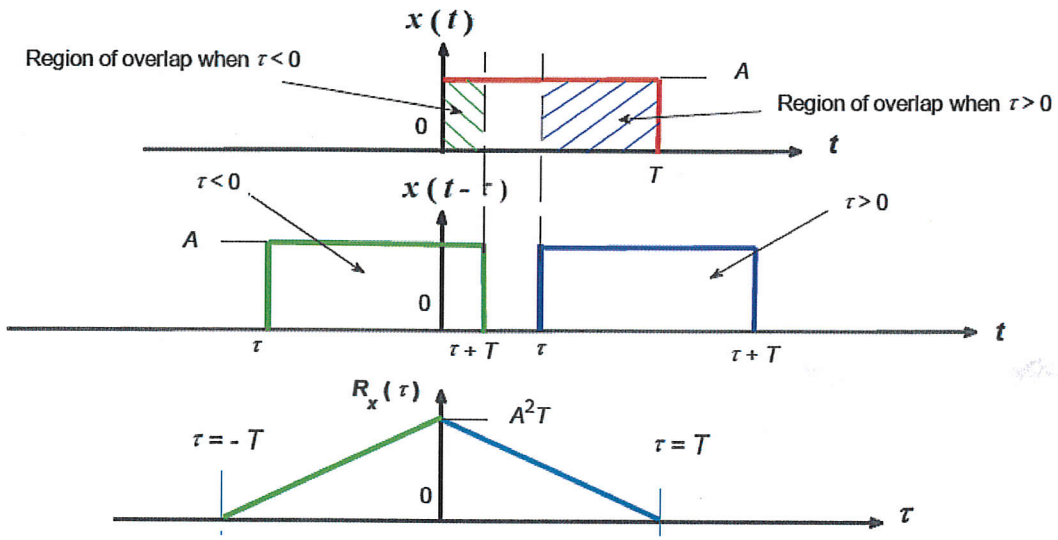


Figure 4. 2. Graphical illustration of computation of autocorrelation function of a single rectangular pulse.

4.4.Cross correlation

In statistics, the term cross-correlation is sometimes used to refer to the covariance cov (X, Y) between two random vectors X and Y. In signal processing, cross-correlation (or sometimes called "cross-covariance") is a measure of the similarity between two signals, often used to find relevant features in an unknown signal by comparing it with a known one. It is a function of the relative time between the signals, sometimes it is also called the displaced scalar product, and it has applications in pattern recognition and in cryptanalysis.

4.5.Statistical

Statistics is a branch of mathematics and a tool that studies uses and analyzes from a representative sample of data, which seeks to explain the correlations and dependencies of a physical or natural phenomenon, occurrence in random or conditional.

It is transversal to a wide variety of disciplines, from physics to social sciences, from health sciences to quality control. In addition, it is used in business areas or government institutions since its main objective is to describe the set of data obtained for decision making or to make generalizations about the observed characteristics.

Nowadays, statistics is a science that is responsible for studying a specific population through the collection, collection and interpretation of data. In the same way, it is also considered a special technique suitable for the quantitative study of mass or collective phenomena.

The statistic is divided into two main areas:

Descriptive statistics: It is dedicated to the description, visualization and summary of data originated from the phenomena of study. The data can be summarized numerically or graphically. Its objective is to organize and describe the characteristics of a set of data with the purpose of facilitating its application, generally with the support of graphs, tables or numerical measurements.

Basic examples of statistical parameters are: the mean and the standard deviation.

Graphic examples are: histogram, population pyramid, pie chart, among others.

Inferential statistics: It is dedicated to the generation of models, inferences and predictions associated with the phenomena in question taking into account the randomness of the observations. It is used to model patterns in the data and extract inferences about the population under study. These inferences may take the form of answers to yes / no questions (hypothesis testing), estimates of numerical characteristics (estimation), forecasts of future observations, descriptions of association (correlation) or modeling of relations between variables (regression analysis) . Other modeling techniques include analysis of variance, time series and

data mining. Its objective is to obtain useful conclusions to make deductions about the totality of all the observations made, based on the numerical information.

Both branches (descriptive and inferential) comprise the applied statistics, but the inferential statistics, on the other hand, is divided into parametric statistics and non-parametric statistics.

There is also a discipline called mathematical statistics, which refers to the theoretical basis of the subject. The word "statistics" also refers to the result of applying statistical logarithms to a set of data, such as economic statistics, criminal statistics, and so on.

4.6.Matlab code for implementation

```
clear;clc;clf reset;warning off MATLAB:divideByZero;close
all
x1 = [-0.0131579
0
0
0
0.0526316
0.0263158
0
0
-0.0657895
0.0394737
0.171053
0.342105
0.526316
0.657895
0.828947
1
0.815789
0.684211
0.526316
0.328947
0.171053
0.0394737
-0.0131579
0
0
0.0394737
0.131579
0.118421
0.0263158
```

```
0
0
0
0
]; %%%% Sample values of normal person
x2 = [0
0
0
0.0526316
0
0
-0.0657895
0.0657895
0.171053
0.289474
0.473684
0.618421
0.763158
0.973684
0.802632
0.644737
0.513158
0.342105
0.171053
0
-0.184211
-0.171053
-0.118421
-0.0131579
0.0657895
0.144737
0.105263
0.0263158
0
0
0
0
0
]; %%%% Sample values of sick person
x = [-0.0131579
0
0.03123
0
0.0526316
0.0263158
0
0
-0.0657895
0.0394737
0.171053
```

```
0.342105
0.526316
0.657895
0.828947
1
0.815789
0.684311
0.5263167
0.3283477
0.1710537
0.0394737
-0.0139579
0
0
0.0884737
0.1315797
0.118421
0.0263158
0.0087654
0
0
0
]; %%%% Sample values of uknown person

xx1 = xcorr(x,x1,'coeff');xx2 = xcorr(x,x2,'coeff');
%xx1 = xx1/sum(xx1);xx2 = xx2/sum(xx2);
xx1int = sum(xx1);%/sqrt(sum(xx1)*sum(xx2));
xx2int = sum(xx2);%/sqrt(sum(xx1)*sum(xx2));
mx = max(xx1int, xx2int);
[xx1int/mx; xx2int/mx]
figure(6)
plot(0:length(xx1) - 1,xx1,'-k','LineWidth',3);hold on;
plot(0:length(xx2) - 1,xx2,'--r','LineWidth',3);hold off;
set(gcf,'Color','w');

xlabel('\it\tau\rm\bf (in
msec)','FontSize',16,'FontWeight','bold');
ylabel('\itR_x \rm\bf (\it \tau\rm\bf
)','FontSize',16,'FontWeight','bold');set(gca,'FontSize',
16)
%axis ([min(tau/1e-3) max(tau/1e-3)*1.0
min(RxMatlab)*1.05 max(RxMatlab)*1.05]);
```

The result of this code is shown in following figure.

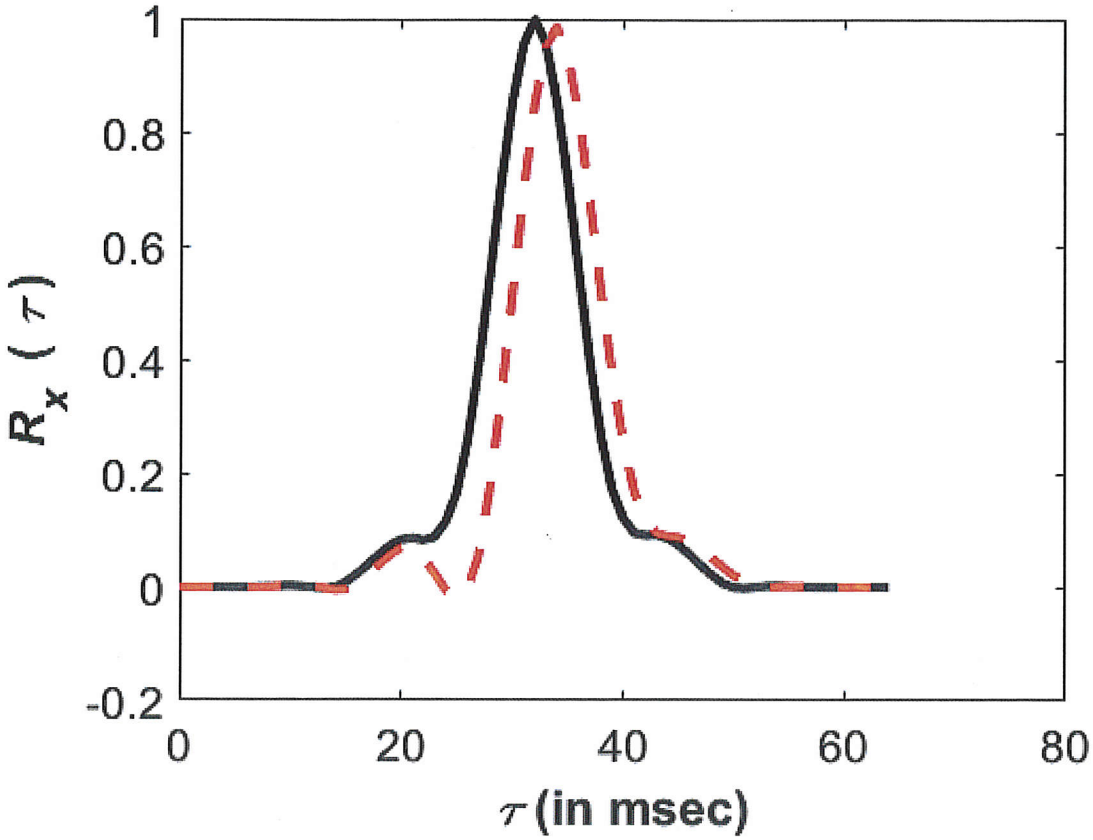
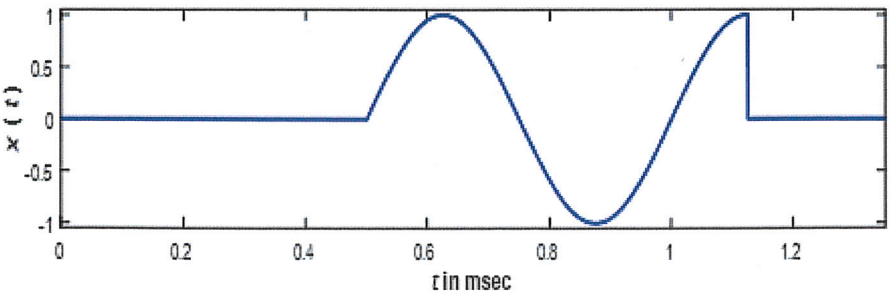
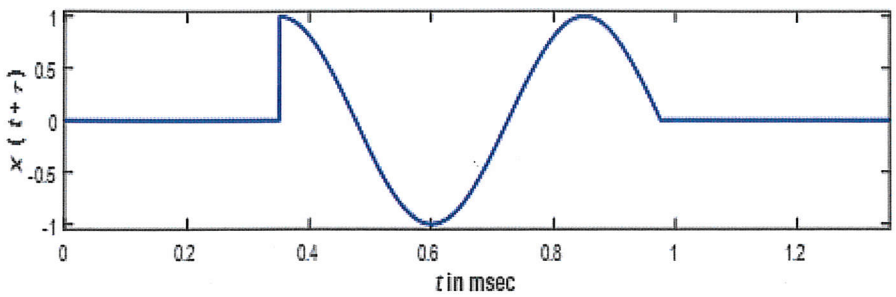


Figure 4. 3. Correlation between normal and abnormal with unknown signal

As seen in this figure the red one show about the correlation between abnormal (x2) and unknown signal (x). The black one shows the correlation between normal (x1) and unknown signal (x).



(a)



(b)

Figure 4. 4. a) Time domain signal, b) time shifted and flipped signal

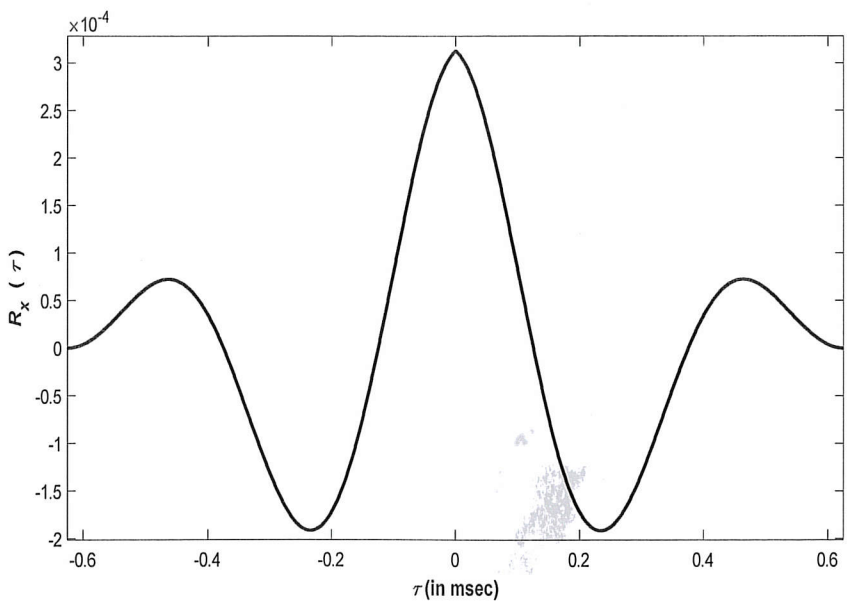


Figure 4. 5. Autocorrelation for the signal of figure 4.2.

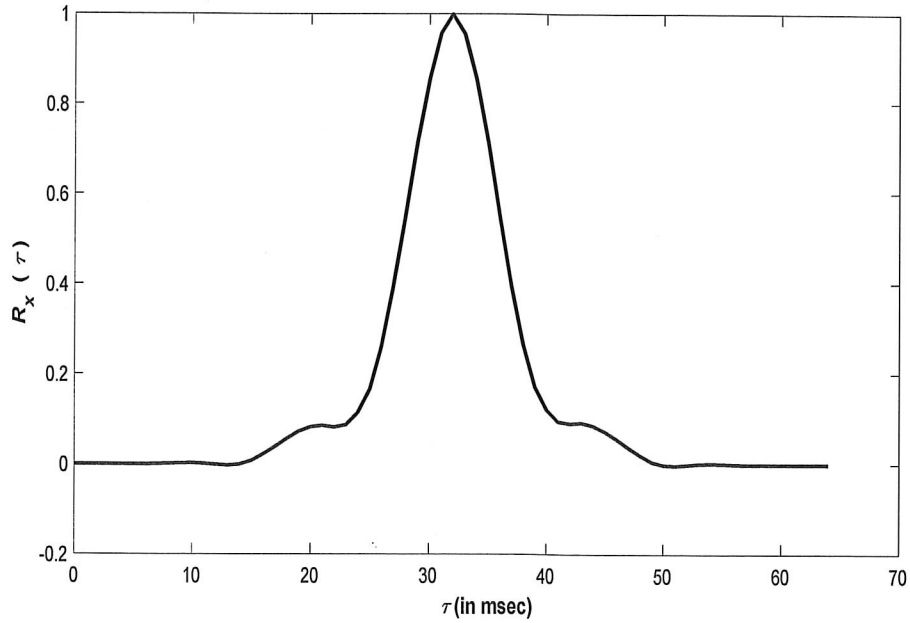


Figure 4. 6. Autocorrelation for normal signal (x with x1 signal)

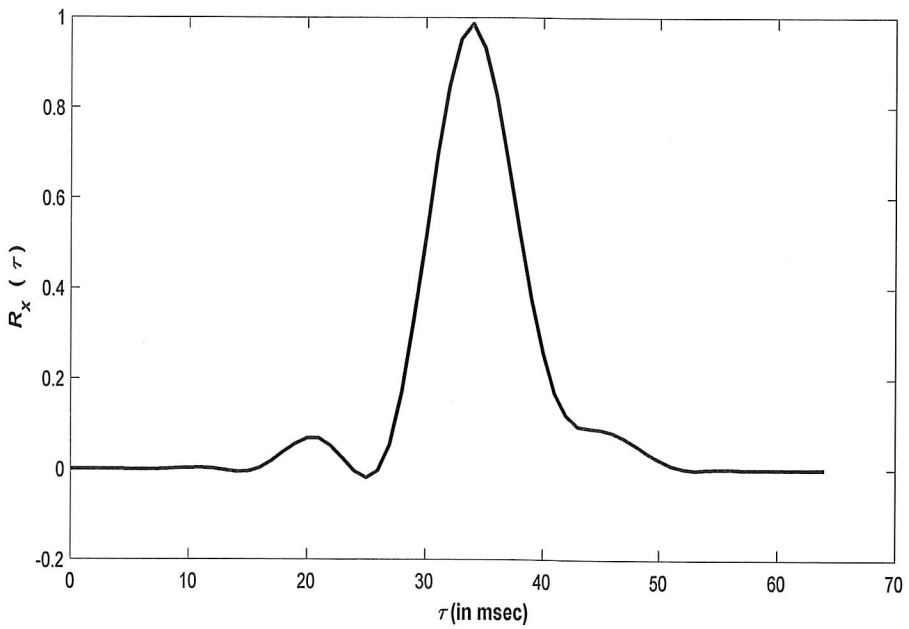


Figure 4. 7. Correlation for abnormal signal (x with x2 signal)

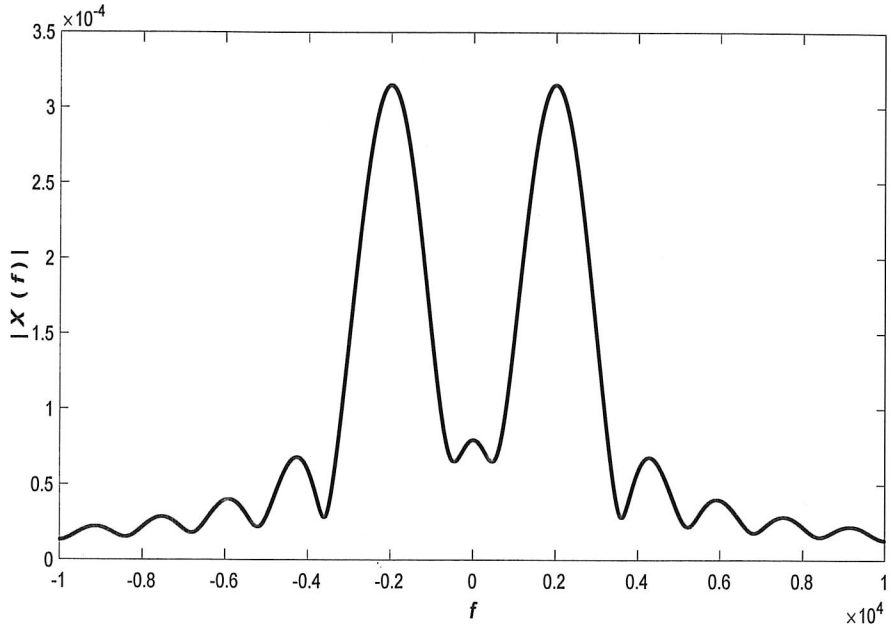


Figure 4. 8. Spectral of signal

The Fourier transform of the original signal is shown in figure 4.8.

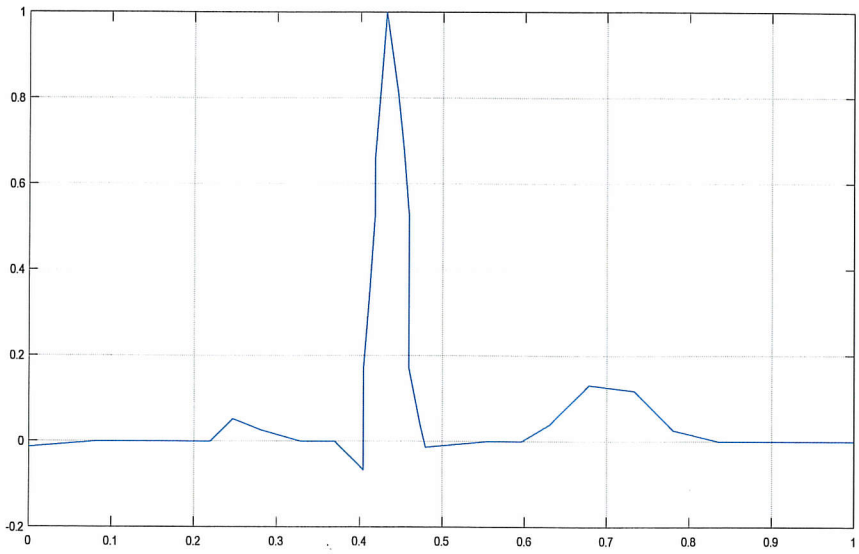


Figure 4. 9. Normal heart signal

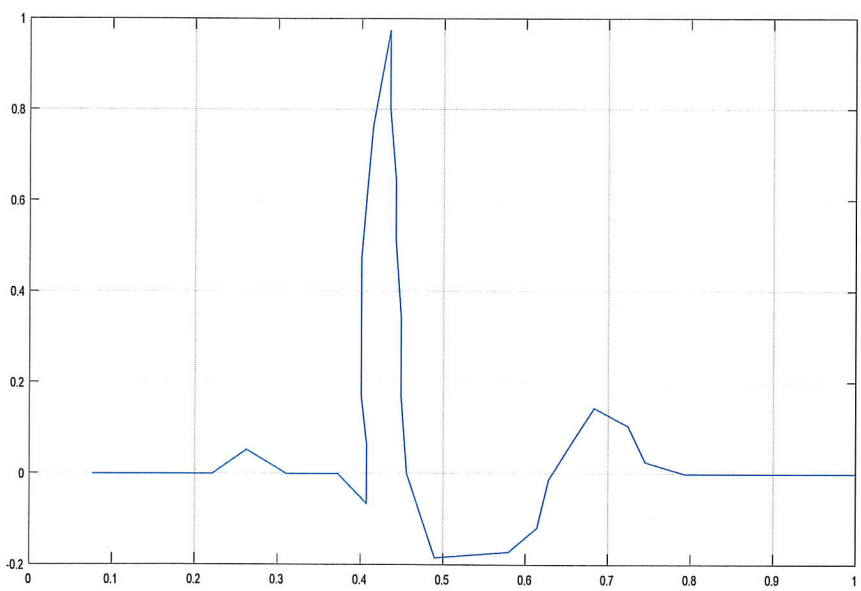
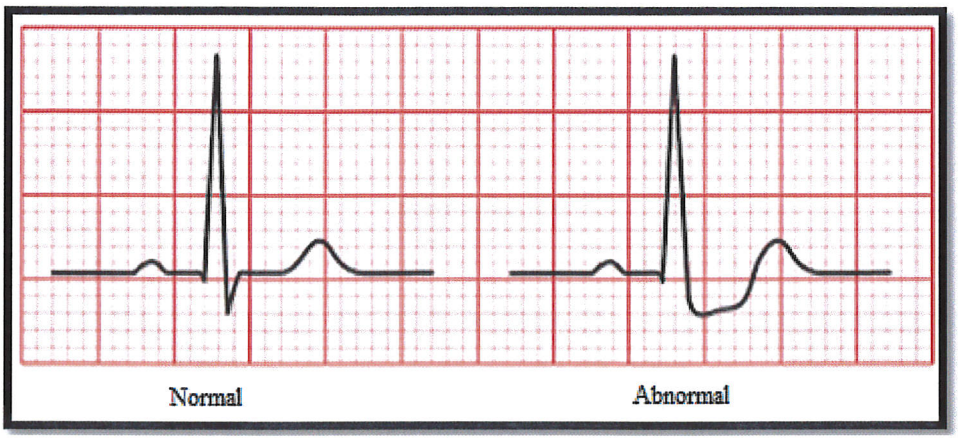
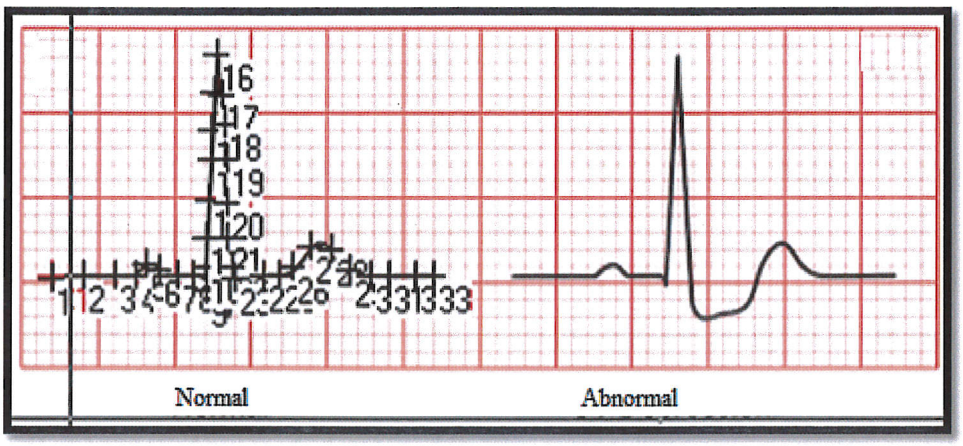


Figure 4. 10. Abnormal heart signal





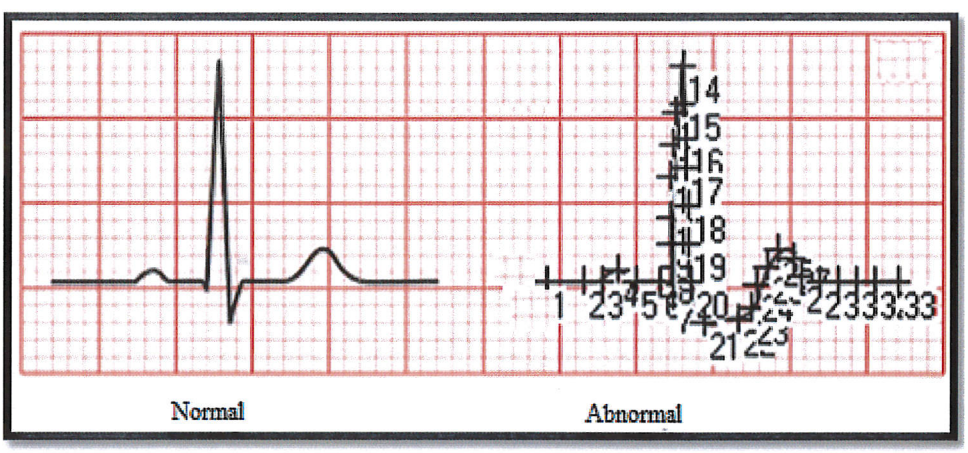


Figure 4. 11. Normal and Abnormal heart signal

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APPENDICES A
CURRICULUM VITAE

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