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Extraction of ECG Features in Time and Frequency Domains

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Annotation: Electrocardiogram (ECG) analysis plays an important role in the diagnosis and monitoring of various cardiovascular conditions. An electrocardiogram records the electrical signals in the heart. It's a common and painless test used to quickly detect heart problems and monitor the heart's health. ECG is mainly generated by the SA node. The SA node, also known as the sinus node, represents a crescent-like shaped cluster of myositis divided by connective tissue, spreading over a few square millimeters. It is located at the junction of the crista terminals in the upper wall of the right atrium and the opening of the superior vena cava.

An electrocardiogram is a painless, noninvasive way to help diagnose many common heart problems. A health care provider might use an electrocardiogram to determine or detect: irregular heart rhythms (arrhythmias), if blocked or narrowed arteries in the heart (coronary artery disease) are causing chest pain and a heart attack, whether you have had a previous heart attack, or how well certain heart disease treatments, such as a pacemaker, are working.

The extraction of ECG features in both time and frequency domains have been widely studied to provide valuable insights into the disease diagnosis. This research aims to present a comprehensive review of the methods and techniques used for the extraction of ECG features in these domains.

In the time domain, ECG features are derived

from the temporal characteristics of the ECG waveform. Commonly extracted features include P,Q,R,S,T values, and ST segment morphology. These features provide valuable information about the regularity and conduction abnormalities of the heart. Various methods, such as peak detection algorithms, and statistical analysis, have been employed to accurately extract time-domain features.

In the frequency domain, ECG signals are transformed into the spectral domain using techniques like the Fourier transform. The resulting frequency components can reveal abnormalities associated with arrhythmias, including changes in power distribution. Power spectral analysis, spectrogram analysis techniques are commonly used for extracting frequency-domain features.

The extraction of ECG features in both the time and frequency domains offers valuable insights into the cardiac system's functioning and aids in the diagnosis and management of cardiovascular disorders, this research aims to contribute to the advancement of ECG analysis and foster future research in the field of cardiovascular medicine.

Keywords: ECG, electrocardiogram, cardiovascular, muscle, rhythmically, MATLAB, heart rhythm.

1.1. Introduction:

The heart is a muscle that pumps blood throughout the body, and contracts rhythmically. The atrial sine node, which functions as a natural pacemaker, initiates this contraction, which then spreads to the rest of the muscle. There is a pattern to the way that this electrical pulse spreads. This action causes fluctuations in the skin's surface's electrical potential by producing electric currents on the body's surface. Electrodes and proper tools can be used to record or measure these signals, known as an electrocardiogram (ECG).

The electrocardiogram (ECG) signal has been an indicator of human health. It is the graphical representation of the electrical activity of the heart muscles occurring due to their contraction and relaxation. A single cardiac cycle is labeled using different waves: P, Q, R, S, and T. The location and amplitudes of these waves are used primarily in ECG analysis during medical practices. It helps to predict the onset of cardiovascular diseases, irregularities in heart rhythm, stress levels, human emotions, and so on. A standardized ECG signal is represented via twelve leads, each calculated using a set of limb and chest leads. Conventionally, the ECG waves were visually observed and analyzed by an expert. The evaluation includes detecting any subtle change in the time series information that takes in morphological details such as the RR interval, QT segment, ST segment, QRS complex, and their statistical variations. Unfortunately, it is not always possible

to track the minute changes in the morphological parameters (intervals, peaks, and waves) of the ECG signal [1].

The ECG feature extraction system provides fundamental features (amplitudes and intervals) to be used in subsequent automatic analysis. In recent times, a number of techniques have been proposed to detect these features. The previously proposed method of ECG signal analysis was based on time domain method. But this is not always adequate to study all the features of ECG signals. Therefore the frequency representation of a signal is required. The deviations in the normal electrical patterns indicate various cardiac disorders. Cardiac cells, in the normal state are electrically polarized [2].

The time-domain analysis gives the best time resolution but no frequency information. Consequently, the frequency domain analysis provides the best frequency resolution without time-related details. A proper time-frequency technique can overcome the disadvantage of one-dimensional analysis and provide signal information in the time and frequency domain. Some of the most widely used time-frequency analysis methods have been discussed in this section.

The decomposition of the time-series data into another domain, frequency or timefrequency, is used for easy analysis. **Fourier transform** (FT) is the most widely employed method for frequency analysis. The technique uses the sinusoidal basis function to represent a time series signal in the frequency domain. The amplitudes of the measured sinusoids at different frequencies form a spectrum. It is one of the transformation methods that has changed the world of signal processing and have diverse application in feature extraction, denoising, and so on. However, FT does not have any information in the time domain [3].

1.2. Previous work

ECG Classification Based on Time and Frequency Domain Features Using Random Forests:

Martin Kropf , Dieter Hayn , Günter Schreier

They present a combined method of classical signal analysis and machine learning algorithms for the automated classification of 1-lead ECG recordings, To classify ECG recordings into the four classes as defined for the Challenge (normal, suspicious to AF, suspicious to other arrhythmia, noise) they used MATLAB. and a set of algorithms for detection of beats, wave point detection on detected beats, quality evaluation of the detection, averaging of beats, beat classification, rhythm classification and many more. A variety of features are extracted from both time and frequency domain etc. as input features for the classifier [4].

Time and Frequency Exploration of ECG Signal:

Govind Sharan Yadav, Shubham Yadav, Prachi, In April (2013)

They confirm, use of time and frequency domain analysis can be very useful to identify the exact multicomponent structure of these biological signals. In this paper they have analyzed the ECG signal in time domain and calculated various statistical parameters and the study of different plots were done. Then They headed on the frequency analysis where the power spectral density is calculated using Welch method [5].

Advanced Time-Frequency Methods for ECG Waves Recognition:

Ala'a Zyout, Hiam Alquran, Wan Azani Mustafa, Ali Mohammad Alqudah, In December 2022

They study the performance of two different spectrum representations, iris-spectrogram and scalogram, for different ECG beat waves in terms of recognition of normal, tachycardia, and bradycardia classes. These two different spectra are then sent to two different deep convolutional neural networks (CNN), i.e., Resnet101 and Shuffle Net, for deep feature extraction and classification. The results show that the best accuracy for detection of beats rhythm was using ResNet101 and scalogram of T-wave with an accuracy of 98.3%, while accuracy was 94.4% for

detection using iris-spectrogram using also ResNet101 and QRS-Wave. Finally, based on these results They note that using deep features from time-frequency representation using one wave of ECG beat They can accurately detect basic rhythms such as normal, tachycardia, and bradycardia [6].

Time Frequency Analysis of ECG Signal Using Ramanujan Fourier Transform:

Dr CR PRASANTH, Mrs Neena Uthaman, In November 2021

The objective of this report is to automatically detect the cardiac problems in ECG signal. Recently developed digital signal processing technique is used in this report for the detection of cardiac problems. Hence, they develop a method for analysis of heartbeats to detect cardiac abnormalities in ECG signals. ECG generated waveforms are used to find patterns of irregularities in cardiac cycles in patients. In many cases, irregularities evolve over an extended period of time that requires continuous monitoring. However, this requires compression of ECG signals. The practical importance of ECG data compression has become evident in many aspects of computerized electrocardiography. Various ECG compression methods are discussed [7]. Aims of this study are Analysis the Electrocardiogram signals (Normal & Abnormal), also to Extraction Features of this signals in Time-Domain by using a special code in "**MATLAB**" also to Extraction Features of this signals in frequency-Domain by using a special code in "**MATLAB**" , also aims to Create a special program to compare the incoming signal with the characteristics of the existing normal and abnormal signal, and discover if that signal is normal or abnormal, know the type of this abnormal signal if is similar to someone‟s characteristics of the abnormal signals.

Materials and Methods

The methodology for this study is designed to ensure the effective extraction and analysis of ECG features in both the time and frequency domains. This research employs a structured approach, beginning with data acquisition, where ECG signals are collected from a reliable database or real-time recording devices. Preprocessing is then applied to filter noise and artifacts, using techniques such as baseline correction and high-pass filtering. Feature extraction is performed by analyzing time-domain characteristics, including P, Q, R, S, and T wave morphology, and intervals such as RR, QT, and ST segments. Additionally, frequency-domain analysis is conducted using Fourier and wavelet transforms to capture power spectral density and frequency distribution patterns. Machine learning algorithms, such as Random Forest and deep learning-based models, are implemented to enhance classification and pattern recognition. Statistical validation techniques, including mean, variance, and standard deviation calculations, are applied to assess the reliability of extracted features. The results are benchmarked against existing methods to ensure accuracy and robustness. The methodology also incorporates a comparative study of normal and abnormal ECG signals, identifying key variations linked to cardiovascular diseases. Ethical considerations, including patient data privacy and compliance with medical research standards, are strictly adhered to. This approach enables a comprehensive understanding of ECG signal characteristics, paving the way for improved diagnostic tools and automated detection systems in medical applications. The proposed methodology is designed to contribute to advancements in cardiovascular research by refining ECG feature extraction techniques and integrating machine learning for enhanced diagnostic accuracy.

CHAPTER TWO Theoretical Background

2.1. Structure of the Heart:

The heart is a muscle consisting of four hollow chambers. It is a double pump: the left part works at a higher pressure, while the right part works on a lower pressure.

Electrophysiological sense, it is actually two chambered. As per the "dual-chamber". „biatrial chamber‟ and „bi-ventricular chamber‟**.**

The Right heart pumps blood into the *pulmonary circulation* (i.e. the lungs).

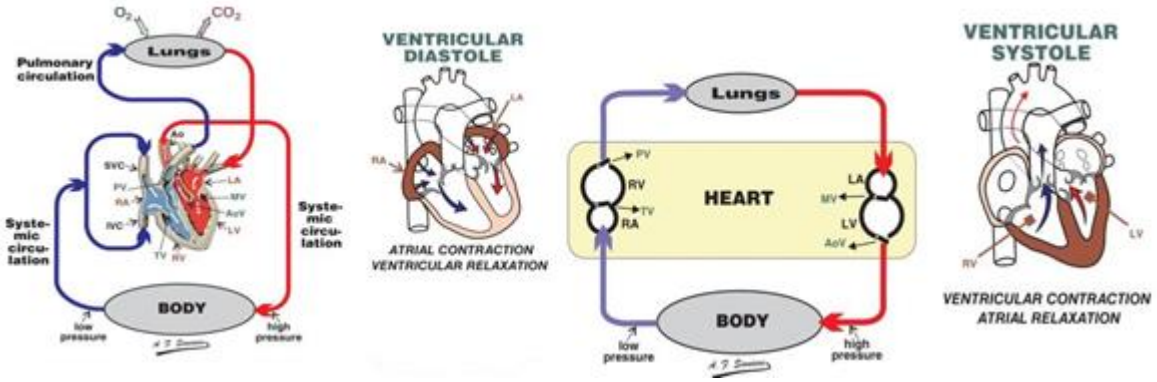
The Left heart drives blood through the *systemic circulation* (i.e. the rest of the body).

The blood flowing into the aorta is further distributed throughout the body where it releases oxygen to the cells and collects carbon dioxide from them.

The cardiac cycle consists of two primary phases:

VENTRICULAR DIASTOLE is a period of myocardial relaxation when the ventricles are filled with blood.

VENTRICULAR SYSTOLE is the period of contraction when the blood is forced out of the ventricles into the arterial tree.



(A)VENTRICULAR DIASTOLE **Figure 2.1 (B)** VENTRICULAR SYSTOLE

2.2. Electrocardiogram (ECG):

Is the recording of the electrical activity generated during and after activation of the various parts of the heart. It is detected by electrodes attached to the skin. ECG is a device that graphically records the tiny electrical activities of the heart‟s rhythm. It records the activity of the heart in a specific period of time via the use of electrodes placed on the body of a patient. It became widely used in clinics for heart disease diagnoses. The ECG signals are recorded by electrodes placed on the surface of the limb and chest to detect the changes in electrical potential difference during the polarization and depolarization of the myocardial fibers [1].

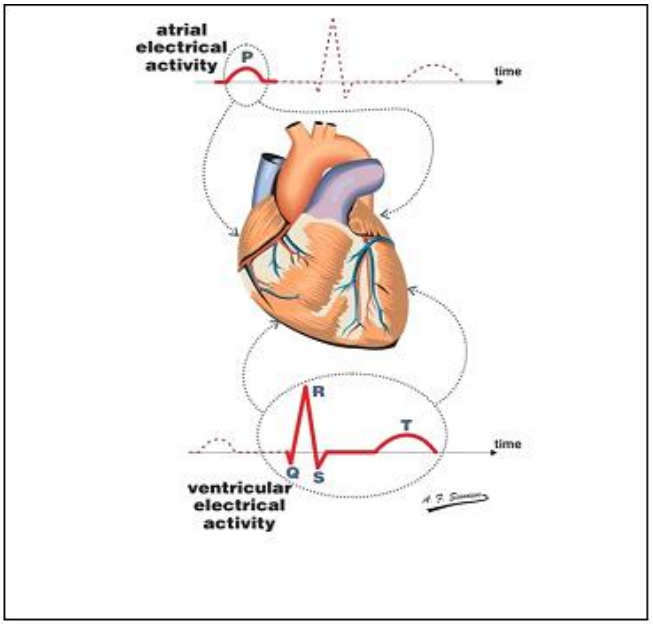


Figure 2.2 ECG Signal

2.3 Electrodes: The electrodes in ECG divided into Three groups

2.3.1. Standard leads according to Einthoven:

- ✓ Bipolar leads: since the measurement occurs between two electrodes attached to the body
- ✓ Limb leads: or extremity leads since the electrodes are connected to the extremities.

Einthoven's law

If : VLA is the potential at the left arm (LA)

If : VRA is the potential at the right arm (RA)

VLL is the potential at the left leg (LL)

Lead I = VLA − VRA , Lead II = VLL − VRA , Lead III = VLL – VLA

lead I + lead III = lead II

2.3.2. The augmented leads :

- ✓ Limb leads: because the exploring electrode is connected to a leg or an arm.
- ✓ Unipolar leads: since only one exploring electrode is used and the negative pole of the ECG machine is connected to the reference point.
- ✓ Frontal plane: leads like leads I, II and III.

The lead axis for any particular augmented lead is a straight line drawn between the reference voltage point at the center of the heart and its extremity electrode.

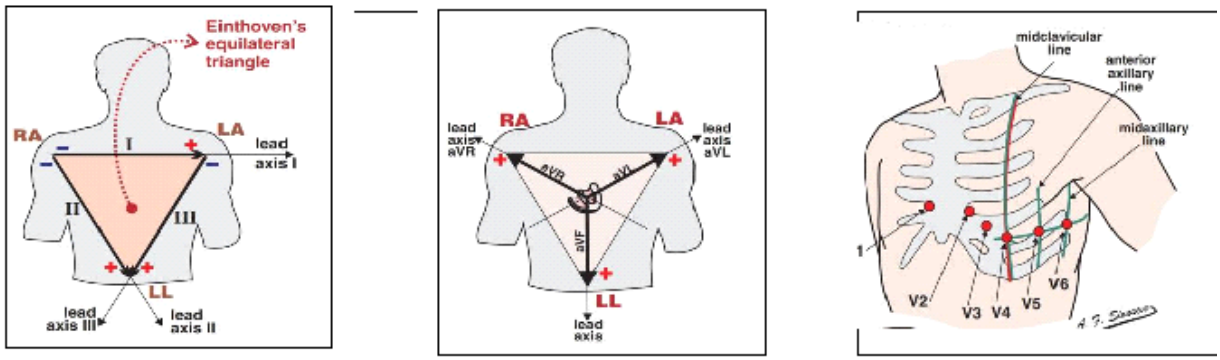
So if: VLA is the potential at the left arm (LA)

VRA is the potential at the right arm (RA)

VLL is the potential at the left leg (LL) aVR + aVL + aVF = 0

2.3.3. The Wilson leads

- ➢ Unipolar leads : since the measurement occurs with only one exploring or probing electrode (the negative pole of the ECG machine is connected to the central terminal; the reference point Vct acts as a zero potential)
- ➢ Chest leads or precordial leads: since the electrodes are placed on the chest around the heart [1].



(A) Einthoven leads (B) augmented leads (C) Wilson leads

Figure 2.3. The Electrodes

2.4. THE ORIGIN OF THE ECG:

- **Initial phase**, depolarization takes place in the interventricular septum, the paraseptal and anteroseptal zones of the left and right ventricles. The initial heart vector VI is directed to the right, anteriorly and slightly superiorly or inferiorly.
- During the **Main phase ventricular depolarization,** occurs in the anterolateral and slightly later in the posterolateral regions. The main heart vector VM is directed to the left, posteriorly and inferiorly.
- **Ventricular depolarization ends,** in the posterobasal zone of the left ventricle, the upper part of the interventricular septum and finally the outflow tract of the right ventricle. The terminal heart vector VT is directed backwards and upwards and may be directed to the left or to the right [8].

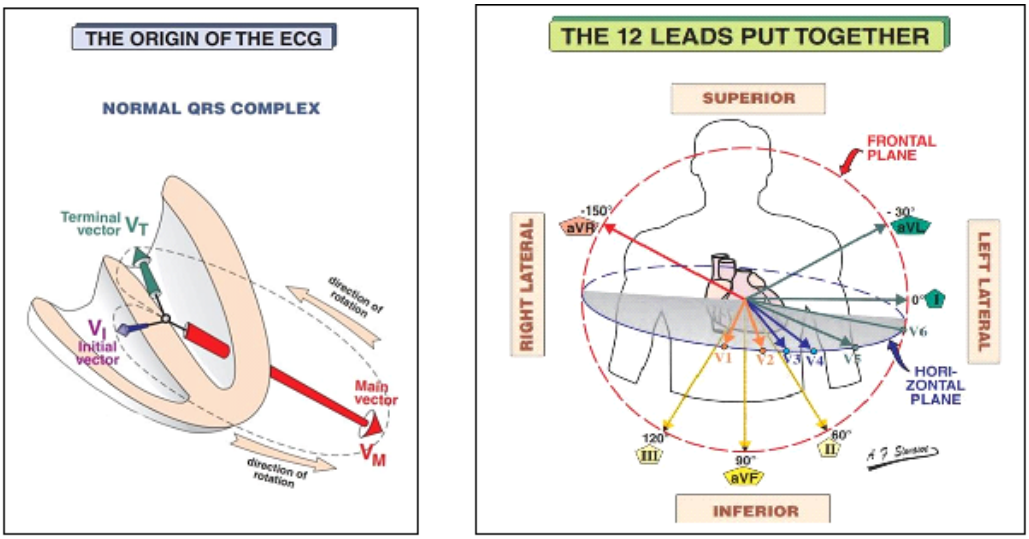


Figure 2.4 THE ORIGIN OF THE ECG

2.5. Electrocardiogram Signal Section:

- Only electrical activity can be seen.
- Atrial repolarization is not seen in the ECG.
- The depolarization of sinus node, AV node, His bundle and bundle branches is not marked on the normal ECG because they do not contain sufficient cells to produce a voltage that can be measured on the skin of the body.
- An obvious **U** wave is seldom seen on a normal ECG.
- **Normal P Wave**: The P wave is a small rounded wave produced by atrial depolarization. In fact, it reflects the sum of right and left atrial. (0.25 mV) in height, (0.10 sec) in width.
- **Normal QRS Complex**: The QRS complex is the major positive deflection on the ECG produced by ventricular depolarization. In fact, it represents the timing and sequence of synchronized depolarization of the right and left ventricles.
- **Normal T Wave**: The T wave is a large rounded wave produced by the rapid phase of ventricular repolarization. The normal amplitude 5 mm in the limb leads and 10 mm in the precordial leads [1].

2.6. Intervals and Segments

- **PR interval**: The PR interval begins at the onset of the P wave and ends at the onset of the QRS complex. This interval represents the time taken by the cardiac impulse to reach the ventricles starting from the sinus node and high right atrium. Normal values are between 0.12 and 0.20 s ;
- **RR interval**: The RR interval starts at the peak of one R wave to the peak of the next R wave. This measurement is useful in calculating the heart rate.
- **QT interval**: The QT interval represents the duration from depolarization to repolarization of the ventricles.
- **QRS complex**: The QRS complex represents the duration of ventricular depolarization. The short duration of the QRS complex indicates that ventricular depolarization normally occurs very rapidly (0.06 to 0.10 s). The deflections are still termed QRS complexes even if one or more of the 3 waves (Q, R, S) are not visible. Hence the traditional use of the term RR interval to indicate the time between two QRS complexes regardless of their configurations.
- **ST segment**: The ST segment begins at the endpoint of the S wave and ends at the onset of the T wave, lasting 0.08 to 0.12 s. During the ST segment, the atria are relaxed and the ventricles are contracting. Electrical activity is not visible so that the ST segment is normally isoelectric [1].

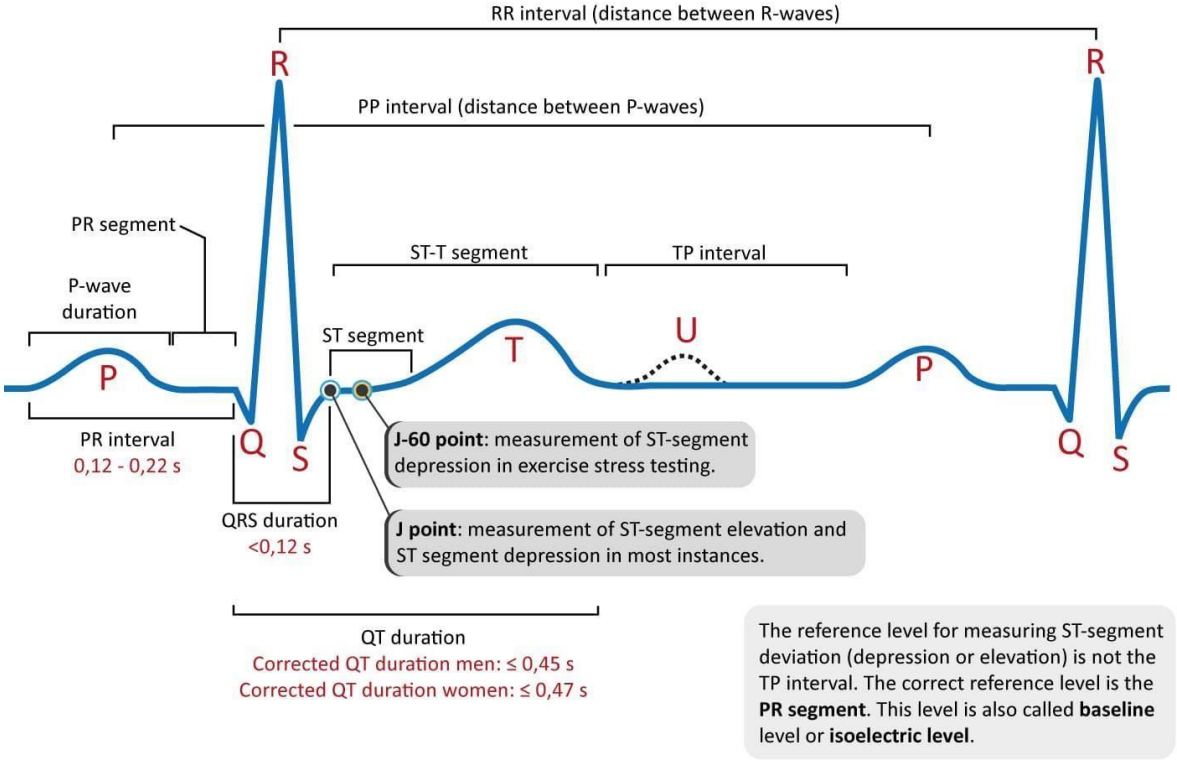


Figure 2.6 About Intervals and Segments

2.7. About Abnormal Signal:

- ✓ Bragada Syndrome
- ✓ Ventricular Tachycardia
- ✓ Right Bundle Brunch Block
- ✓ ST Elevation
- ✓ Cardiac Dysrhythmia

- ✓ Repolarization
- ✓ Sinus Bradycardia
- ✓ ST Depression
- ✓ Lift Bundle Brunch Block

The ST segment: physiology, normal appearance, ST depression & ST elevation:

- ➢ The ST segment corresponds to the plateau phase of the action potential. The ST segment extends from the J point to the onset of the T- wave. Because of the long duration of the plateau phase most contractile cells are in this phase at the same time so, the ST segment is flat and isoelectric
- ➢ Displacement of the ST segment is of fundamental importance, particularly in acute myocardial ischemia. Because myocardial ischemia affects a limited area and disturbs the cells' membrane potential (during phase 2), it engenders electrical potential difference in the myocardium. The electrical potential difference exists between ischemic and normal myocardium and it results in displacement of the ST segment. The ST segment may be displaced upwards (ST segment elevation) or downwards (ST segment depression). The term ST segment deviation refers to elevation and depression of the ST segment. The magnitude of ST segment deviation is measured as the height difference (in millimeters) between the J point and the PR segment.
- ➢ ST segment and the T-wave are electro physiologically related. so, any changes in the ST segment are frequently accompanied by T-wave changes.
- ➢ The normal ST segment is Flat and isoelectric. The translation from ST segment to T-wave is smooth, and not abrupt [9].

Primary and secondary ST-T Changes:

Primary ST-T changes are caused by abnormal repolarization. This is seen in ischemia, electrolyte disorders (calcium, potassium), tachycardia, increased sympathetic tone, drug side effects etc.

Secondary ST-T changes occur when abnormal depolarization causes abnormal repolarization. This is seen in bundle branch blocks (left and right bundle branch block), pre-excitation, ventricular hypertrophy, premature ventricular complexes, pacemaker stimulated beats etc. In each of these conditions the depolarization is abnormal and this affects the repolarization so that it cannot be carried out normally.

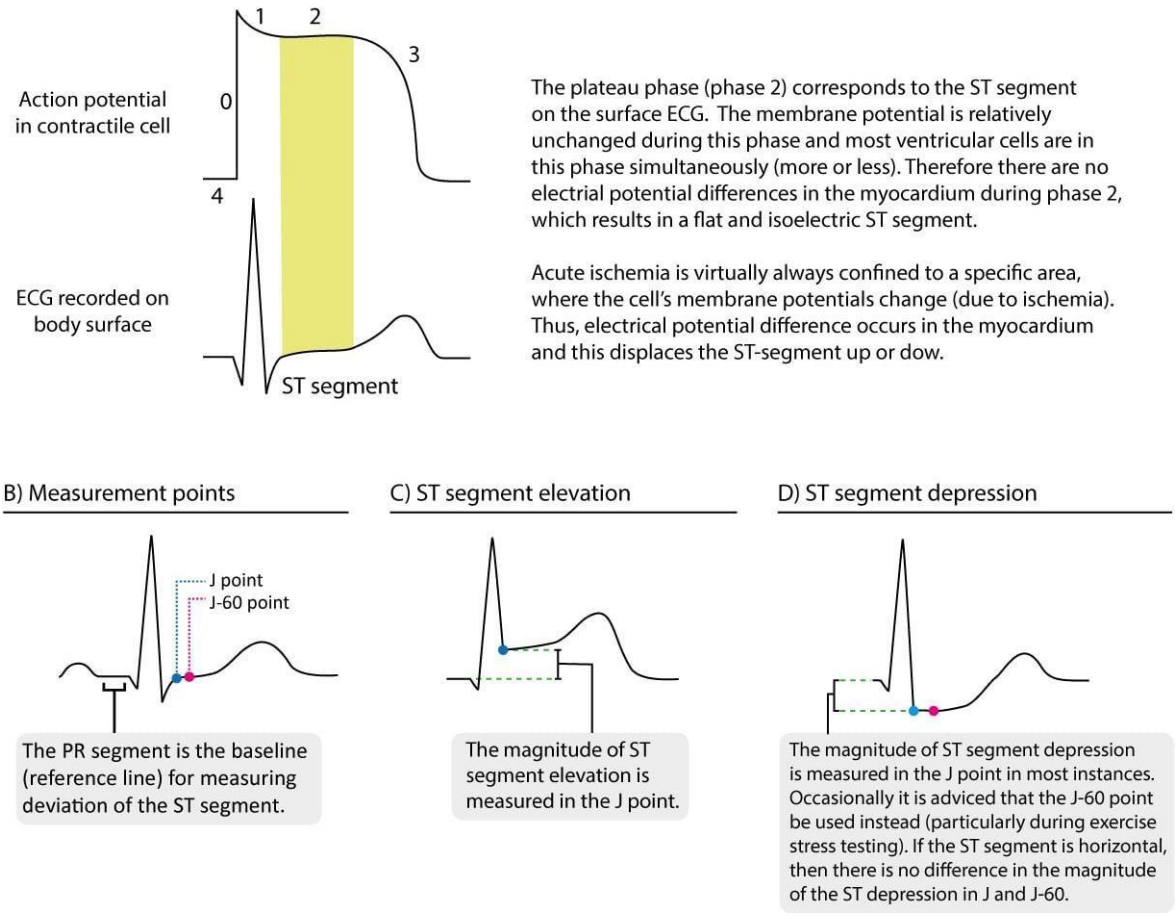


Figure 2.7 The ST segment

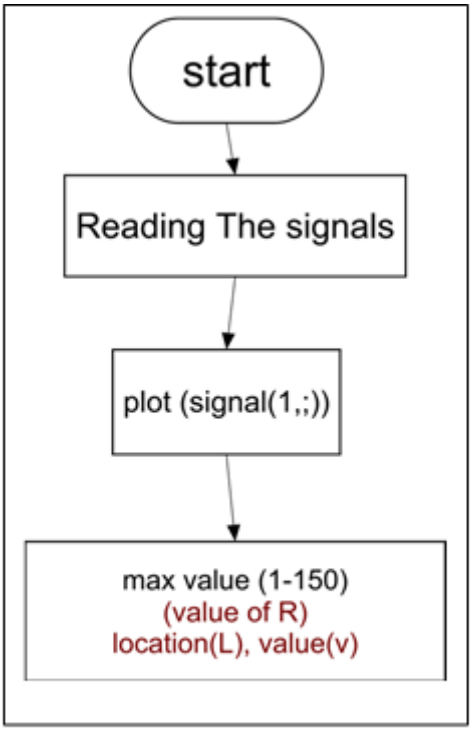


Figure 3.1 R Wave

3. ECG Feature Extraction

3.1. steps of features extraction

in this step we proposed an algorithm. The ultimate goal of this algorithm is to replace human intervention in ECG interpretation especially when a large number of ECGs is required to be analyzed for medical or research purposes.

Often the first and foremost stage is the detection of the R waves because they are distinct with their sharp deflection which makes them easy to be detected. Other waves detection normally follows this stage. R Waves are the sharp high positive deflections succeeding the P waves. Due to its distinct morphology and high frequency content, the R wave is easier to detect than other waves. Successful R wave localization simplifies other waves detection. The proposed algorithm to detect R waves in temporal domain processing adopts the following procedure. First it finds all peaks in the ECG signal, then the peaks are arranged in descending order. Next the amplitude value of the highest peak among the peaks is found.

S. wave is the negative deflection that succeeds R wave directly. A search area is set for the detection of S waves in every R-R interval. The area is defined as the period beginning from the first R wave and ending at point N which is determined for each ECG signal independently as it is defined as a percentage. However, the percentage is set conveniently on trial-and-error basis.

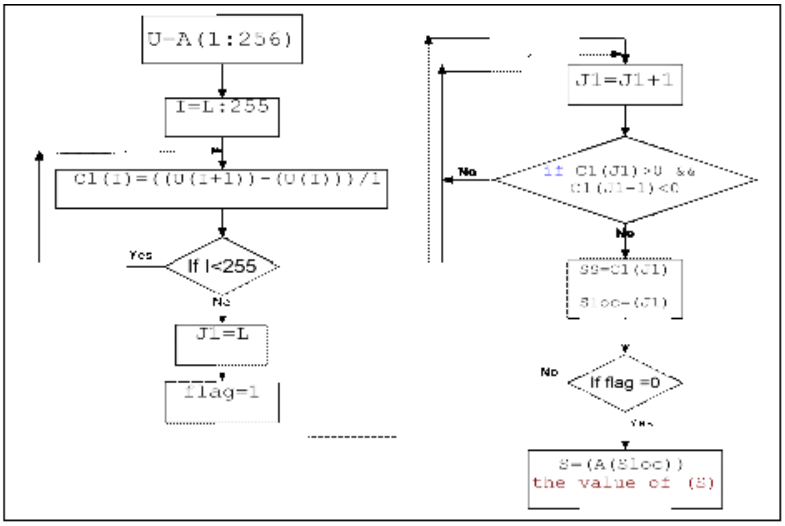


Figure 3.2 S Wave

T. Waves are the first positive deflections after QRS wave complexes. A search area is set in every R-R interval for the detection of T waves. The area is defined as the period beginning at M samples after the first R wave and ending at M samples before the second R wave in every R-R cycle. M is determined for each ECG signal independently. The percentage is obtained based on trial-and-error method. We used M=12% of the respective R-R interval. Defining search areas not only aids for the correct detection of a wave but also reduces the burden of processing unnecessary samples as well it avoids searching areas that does not contain a particular wave [4].

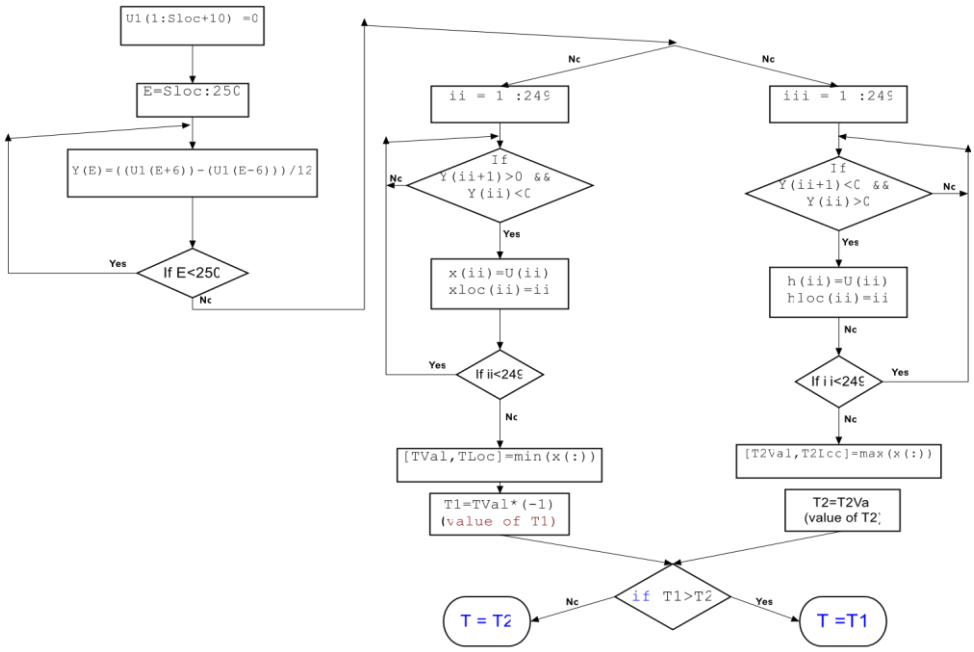


Figure 3.3 T Wave

P wave is the first positive deflection on the ECG. We detected the P waves by setting a search area behind every R wave, it starts almost from the point 2M samples away from the T wave peak of the previous cycle to exclude the T wave itself from being processed and extends until M/4 samples before the R wave to exclude the R wave itself from being processed, then the P wave is located by finding the maximum amplitude within the search area.

A Q Wave is the negative deflection that precedes an R wave directly. Detection of Q waves is attained by setting a search area that always starts from the R wave and extends backward to the P wave in every R-R interval. The minimum amplitude point in the search area of the respective cycle is attributed to the Q wave [5].

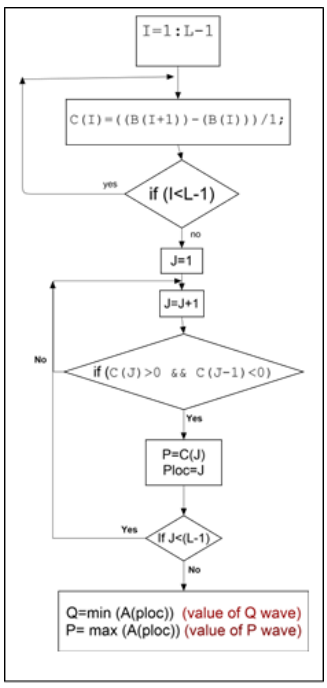


Figure 3.4 ***P&Q Wave***

4-Results

As a result of applying the program mentioned in the third chapter on a set of normal signs and abnormal signs for several diseases (ST-depression, ST-Elevation, Right Bundle Branch Block, Left Bundle Branch Block), results were obtained that match the true values, by 90%. Also, the value of ST-segment was calculated, whether it was in the case of increasing or decreasing from the normal limit, as it will help us determine the type of abnormal ST-segment.

4.1. Results in Time Domain

Compare the true value with the values that extracted from the program

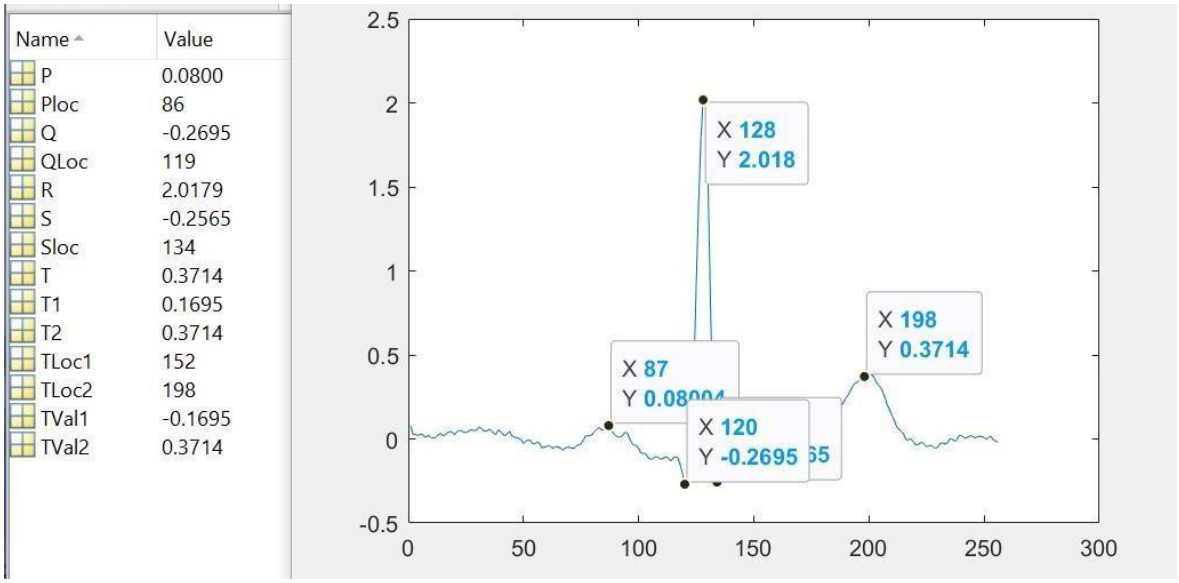


Figure 4.1 The peaks of Normal signal

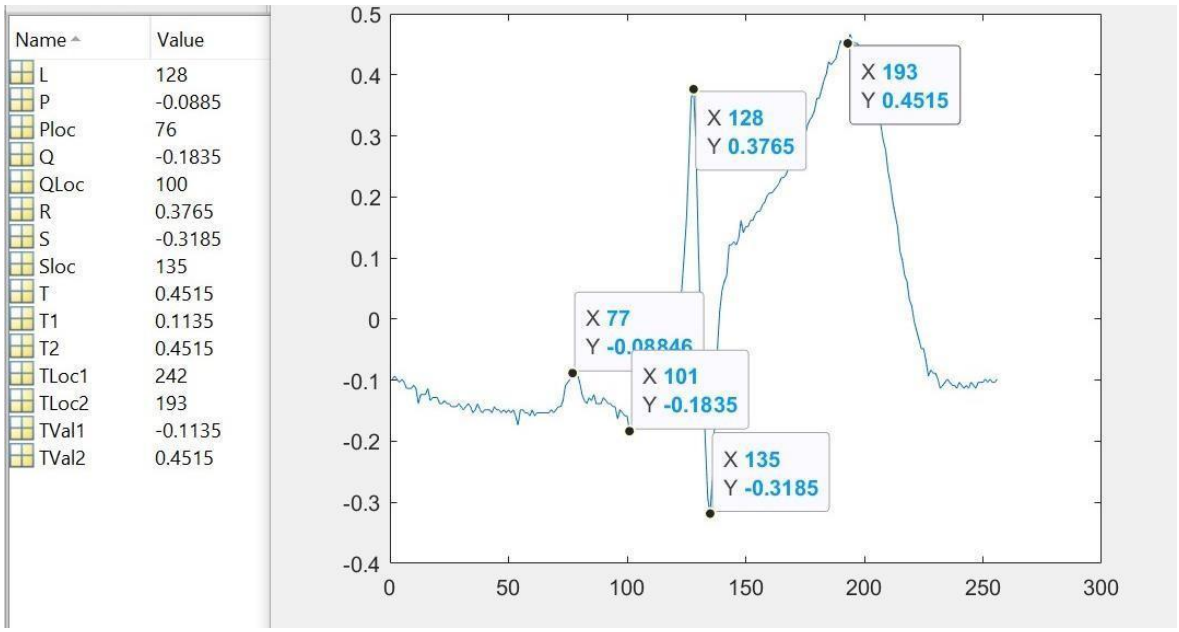


Figure 4.2 The peaks of Abnormal ST-Elevation signal

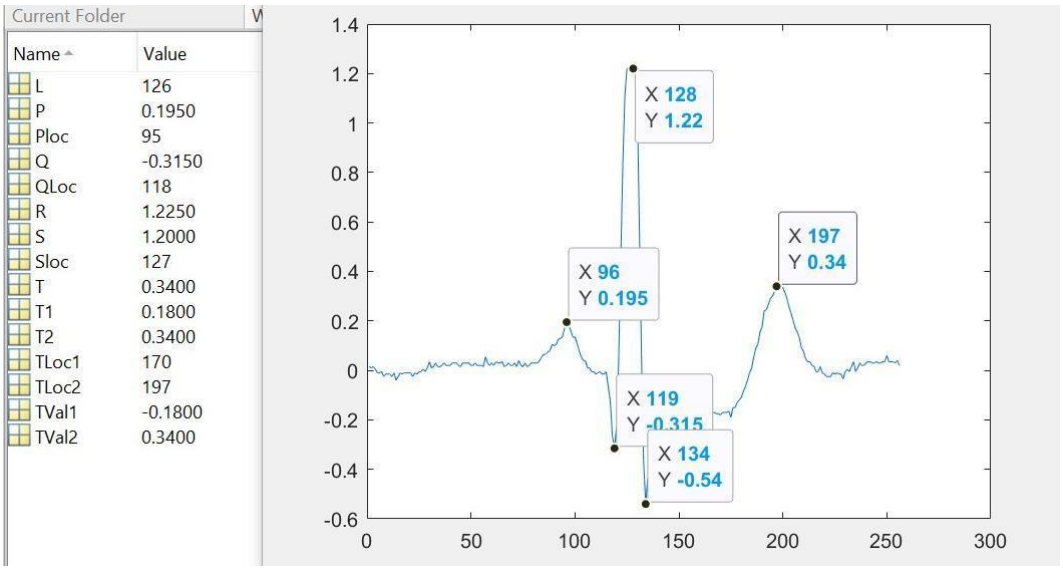


Figure 4.3 The peaks of Abnormal ST- depression signal

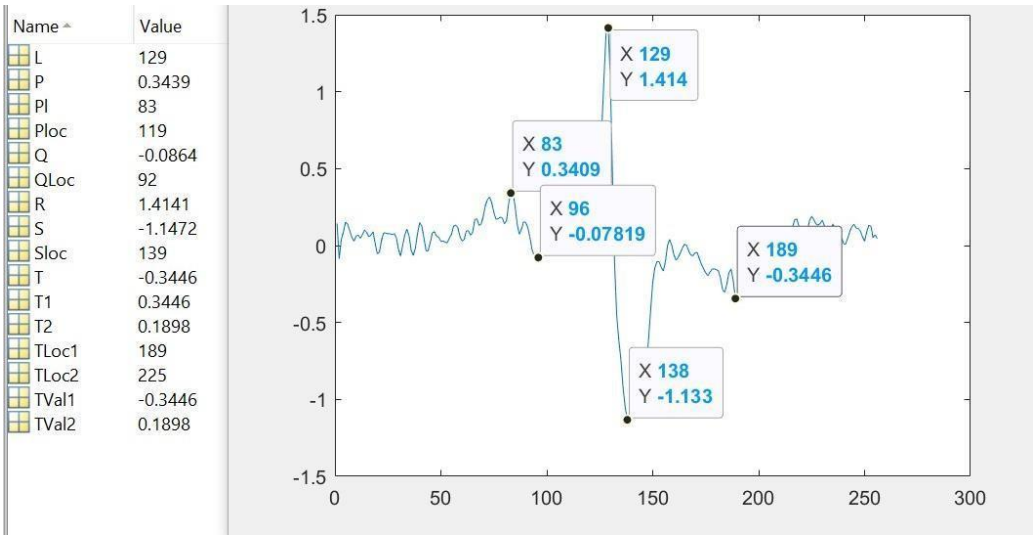


Figure 4.4 The peaks of Abnormal RBBB signal

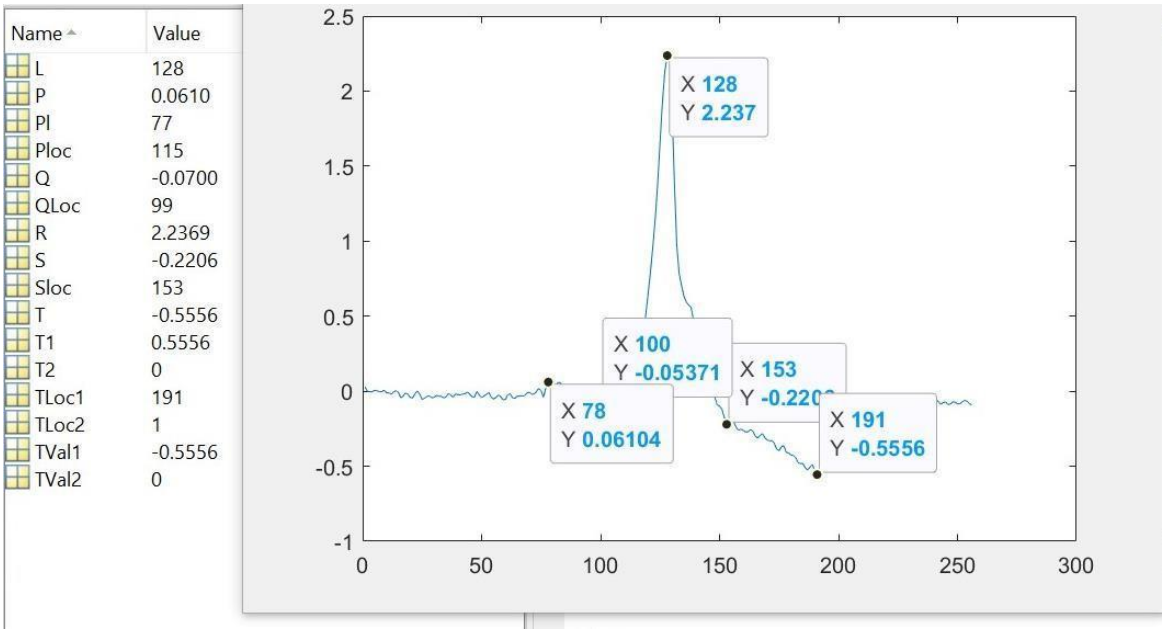


Figure 4.5 The peaks of Abnormal LBBB signal

We take Samples for 15 different patients with the same disease, and the Average and Variance for each type of abnormal signals were taken for all patients and compared with the true signal. The tables below show the values in detail:

Table 4.1 The Average Value of peaks

Average	P	Q	R	S	T	ST-segment
Normal signals	0.0112	-0.3459	2.006	-0.294	0.365	-0.18425597
ST_DEB signals	0.1625	-0.237	1.182	-0.917	0.373	-0.26051275
ST_ELE signals	-0.092	-0.177	0.392	-0.356	0.493	0.043065762
RBBB signals	0.3165	-0.113	1.386	-1.174	-0.446	0.108279601
LBBB signals	0.0702	-0.06	2.246	-0.211	-0.387	-0.56949215

Table 4.2 The Variance value of peaks

Variance	P	Q	R	S	T	ST-Segment
Normal signals	0.00151	0.002543	0.00569	0.000597	3.32E-05	4.99E-06
ST_DE signals	0.001189	0.001189	0.001189	0.001189	0.001169	7.977E-11
ST_ELE signals	3.15E-05	3.15E-05	3.20E-05	0.000266	3.60E-33	1.19E-08
LBBB signals	0.003407	0.003406	0.003407	0.003406	0.176373	0.0059835
RBBB signals	0.00947	0.009464	0.00947	0.00947	8.62E-05	1.761E-05

4.1. Results in Frequency Domain

Statistics have been made for 15 patients for each type of abnormal signals. This statistic includes extracting signal values in the segment of frequency and extracting:

1. Average values
2. Variance values
3. Median values
4. Standard Deviation values

1. Average of PSD values: The arithmetic average is one of the types of statistical measures, and it is calculated by calculating the sum of observations in one variable, and then we divide the result by the sum of the number of observations for this type of variable. The arithmetic mean takes all values into account when performing calculations

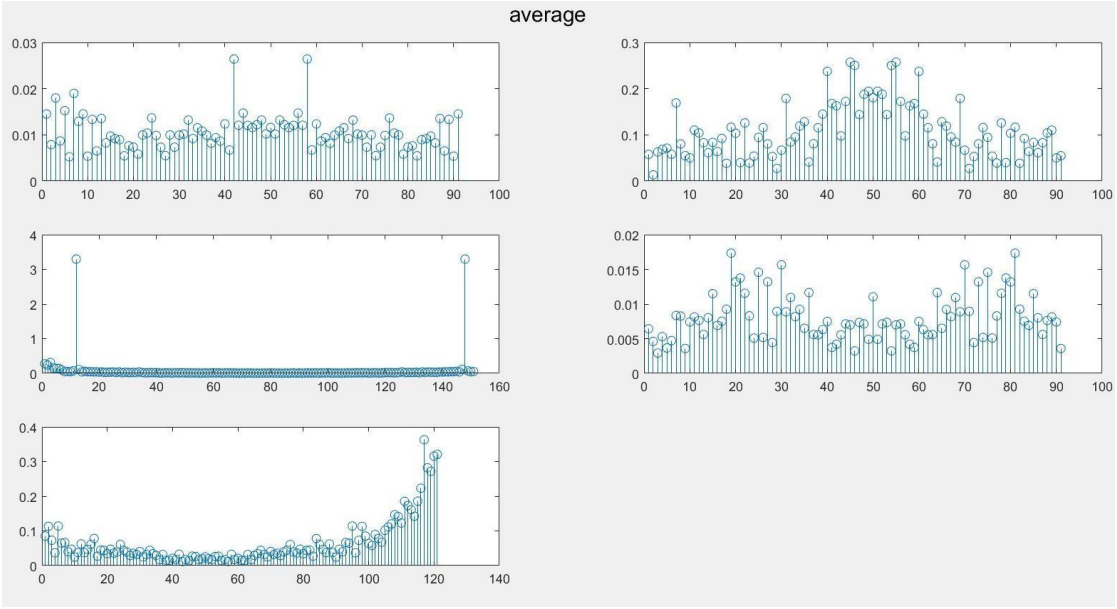


Figure 4.6 the Average of values 2.

2-Standard Deviation of PSD values: The use of all signs in the given distribution. It gives us the average and the deviations from it. Its value becomes larger when the distribution of signs becomes inhomogeneous. The only way to develop a statistic that satisfies these requirements is to find the distance between each score and the mean, and sum these distances. The distance between the marks and the mean is called the deviation. The measure of dispersion depends on these deviations. The value of these deviations increases whenever the distribution of the marks is not homogeneous

5.1. Conclusion

The extraction of ECG features in the time and frequency domains has been extensively studied and serves as a valuable tool for understanding cardiac function, diagnosing cardiovascular disorders, and monitoring patient health. Time-domain features capture waveform morphology and intervals, while frequency-domain features analyze the power distribution across different frequency bands. Various algorithms and techniques have been developed to extract these features, but challenges related to noise, variability, and signal characteristics persist.

Future research should focus on advancing feature extraction techniques by leveraging advanced computational methods, integrating multimodal data, validating in clinical settings, and enabling real-time monitoring. Techniques such as machine learning, deep learning, and nonlinear analysis show promise for improving accuracy and robustness. Personalized feature extraction, explain ability, and interpretation of results are also critical for enhancing the clinical relevance and acceptance of automated systems.

Ultimately, advancements in ECG feature extraction techniques in both the time and frequency domains is important in cardiovascular diagnosis, risk stratification, and personalized patient care. Continued research and innovation in this field will contribute to the development of reliable, efficient, and clinically relevant tools for the analysis of ECG signals.

5.2. Future Works

Future work in the field of ECG feature extraction in time and frequency domains can focus on several promising directions:

1. Advanced Machine Learning Techniques: Exploit the potential of deep learning approaches, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for ECG feature extraction. These techniques have shown success in various domains and could potentially improve the accuracy and robustness of feature extraction from ECG signals.
2. Real-Time Monitoring and Wearable Devices: Develop real-time ECG feature extraction algorithms that can be implemented in wearable devices or mobile applications for continuous monitoring of cardiac health. This can enable early detection of arrhythmias, ischemia, and other cardiac abnormalities, facilitating timely intervention and improving patient outcomes.
3. Contextual Information Integration: Incorporate contextual information, such as patient medical history, medication profiles, and environmental factors, into the feature extraction process. This can help personalize the analysis and improve the understanding of the impact of contextual factors on ECG patterns and cardiac health.
4. Personalized Feature Extraction: Develop methods for personalized feature extraction that account for individual variations in ECG signals due to factors such as age, sex, body composition, and cardiac pathologies. This can lead to more accurate and personalized diagnostic tools that consider the unique characteristics of each patient.

Overall, future work in ECG feature extraction should aim to leverage advanced computational techniques, incorporate multimodal data, validate in clinical settings, and focus on real-time monitoring and clinical translation. By addressing these areas, researchers can contribute to the development of more accurate, reliable, and clinically relevant ECG analysis tools, ultimately improving cardiovascular disease diagnosis, management, and patient care.

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