CARDIAC BEAT CLASSIFICATION BASED ON WAVELET ANALYSIS OF EMPIRICAL MODE DECOMPOSED ECG SIGNALS

by

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The thesis entitled "**CARDIAC BEAT CLASSIFICATION BASED ON WAVELET ANALYSIS OF EMPIRICAL MODE DECOMPOSED ECG SIGNALS**" submitted by Tasnuva Binte Anowar, Student ID. 0412062254F, Session: April, 2012 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING on March 31, 2019.

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I, do, hereby declare that neither this thesis nor any part of it has been submitted elsewhere for the award of any degree or diploma.

Signature of the candidate

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Dedication

To my daughter

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Abstract

The information of electrocardiograms (ECG) signal is the most important bioelectrical message of human body, which reflects the basic law of heart activity. To improve the efficiency and accuracy of the diagnosis of cardiovascular diseases, it has a very important significance. For ECG beat classification, a wide range of signal processing techniques extracting features from time, frequency and time frequency domains have been reported in the literature. Since, ECG is a nonstationary signal, time frequency analysis can perform better than the conventional time or frequency analysis methods. But, development of a multi-class beat classification method, which is simple yet effective in handling practical conditions such as lack of enough training dataset and random selection of training and testing dataset, is still a challenging task. In the empirical mode decomposition (EMD) domain, the basic functions are directly derived from the original signal without the knowledge of any previous value of the signal.In this thesis, first the intrinsic mode functions (IMFs) are extracted by using the EMD and then the discrete wavelet packet decomposition (WPD) is performed only on the selected dominant IMFs. Both approximate and detail WPD coefficients of the dominant IMF are taken into consideration. It is found that some higher order statistics of these EMD-WPD coefficients corresponding to different beat classes exhibit distinguishing characteristics and these statistical parameters are chosen as the desired features. It is proposed and shown that smoothed three point central difference for an ECG signal namely dECG signal and modified dECG signal can further enhance the level of discrimination as it also includes the effect of P and T waves apart from QRS complex of an ECG beat. Each of the proposed sets of feature when fed to Euclidean distance based k-Nearest Neighbor (k-NN) classifier can classify different cardiac beats with randomly selected training and testing dataset. Simulations are carried out to evaluate the performance of the proposed methods in terms of sensitivity, specificity, selectivity and accuracy. It is shown that the proposed methods outperform the state-of-the-art method with greater effectiveness.

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Abbreviations

ECG	Electrocardiogram
EMD	Empirical Mode Decomposition
IMF	Intrinsic Mode Functions
WPD	Wavelet Packet Decomposition
HOS	Higher Order Statistics
KNN	K-Nearest Neighbor
dECG	Differential Electrocardiogram
GSI	Geometrical Separability Index
BD	Bhattachariyya Distance

Chapter 1

Introduction

The information of electrocardiograms (ECG) signal is the most important bio-electrical message of human body, which reflects the basic law of heart activity. The properly analyzed ECG signal can provide the key information about the electrical activity of the heart. To improve the efficiency and accuracy of the diagnosis of cardiovascular diseases, it has a very important significance. However, ECG signal is a non-linear, non-stationary weak signal with strong randomness, which increases the difficulty of analyzing and processing data. As the irregularities are not always periodic and often do not show up continuously, so continuous ECG monitoring is required to observe the cardiac variations over an extended period of time. It has now gone beyond the capacity of the expert cardiologist to take care of large numbers of cardiac patients efficiently and effectively. Since cardiologists are unlikely to be available to monitor the ECGs of all the patients during all 24 hours in a day, automated monitors programmed to detect abnormal heart rhythms are needed.Therefore, computer-aided feature extraction and analysis of ECG signal for disease diagnosis has become the necessity. Over the past several years, the computerised ECG monitors that provide complete ECG recordings and interpretations have become common. Computerized ECG monitoring and analysis are now carried out with bed side monitors, mobile carts equipped with ECG amplifiers and microcomputers, and portable ECG recorders hooked up via telephone networks. The first step in computer aided diagnosis is the identification and extraction of the features of the ECG signal. Over the years researchers have developed a variety of relatively effective signal processing techniques in time or frequency or time-frequency domain to classify cardiac beats accurately. Although there has been a tremendous amount of improvement in technology and various approaches to the problem, automatic cardiac beat detection and classification with high reliability is still an open research area. Different types of morphological changes occur in different sections of a normal ECG beat in a particular arrhythmia condition, and these changes may vary from beat to beat under the same arrhythmia condition. Thus extracting these characteristics in detail under each arrhythmia condition through signal processing techniques into a feature vector that is capable of correctly classifying among different types of cardiac beat is a difficult task. Thus, in real life applications complexity and ease of implementation of the cardiac beats classification methods is a matter of concern. The overall goal of cardiac beat classification technique is to find a simple and effective method capable of performing the classification with greater sensitivity, specificity, selectivity and accuracy.

In this chapter, we describe about ECG signals and ECG signal interpretation methods, motivation and objective of the thesis to classify cardiac beats. Finally, organization of the thesis is presented for a better clarification.

1.1 The Anatomy of Heart

The heart has four chambers – the right and left atrium and the right and left ventricle. The anatomy of heart is shown in Fig. 1.1. The right side of the heart collects blood from the body and pumps it to the lungs while the left side of the heart receives blood from the lungs and pumps it to the body [1].

Blood flows through the body in the following way [2]:

- Oxygen-rich blood from the lungs enters the left atrium through the pulmonary veins.
- Blood then flows into the left ventricle where it is pumped into the aorta and is distributed to the rest of the body. This blood supplies organs and cells with oxygen and nutrients necessary for metabolism.
- Blood that returns to the heart is depleted of oxygen and carries carbon dioxide, the waste product of metabolism. The blood enters the right atrium though the vena cava, where it is collected and pumped to the right ventricle.
- The right ventricle then pumps blood through the pulmonary artery to the lungs where carbon dioxide is stripped off, oxygen is replaced, and the cycle begins again.

Electrically, the heart can be divided into upper and lower chambers. An electrical impulse is generated in the upper chambers of the heart that causes the atria to squeeze and push blood into the ventricles. There is a short delay to allow the ventricles to fill. The ventricles then contract to pump blood to the body and the lungs.

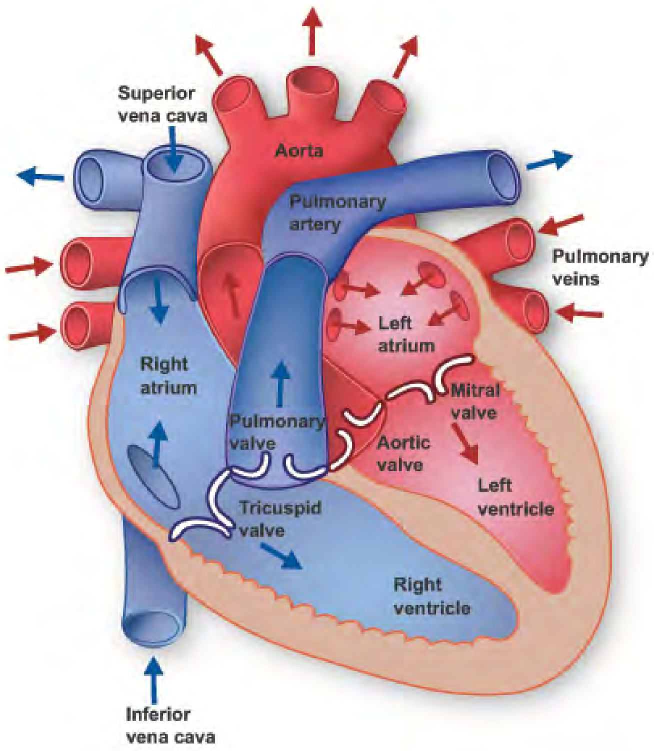


Figure 1.1: Diagram of Human Heart

1.1.1 Heart Conduction System

The heart has its own automatic pacemaker called the sinaoatrial, or SA node, located in the right atrium. The SA node acts independently of the brain to generate electricity for the heart to beat[3].

- Normally, the impulse generated by the SA node runs through the heart's electrical grid and signals the muscle cells in the atria to beat simultaneously, allowing for a coordinated squeeze of the heart. Contraction of the atria pushes blood into the ventricles.

- The electrical signal that was generated in the SA node travels to a junction box between the atria and ventricles (the AV node) where it is delayed for a few milliseconds to allow the ventricles to fill.

- The electrical signal then travels through the ventricles, stimulating those heart muscle cells to contract. Ventricular contraction pumps blood to the body (from the left ventricle) and the lungs (from the right ventricle).
- There is a short pause to allow blood to return to the heart and fill before the electrical cycle repeats itself for the next heartbeat.

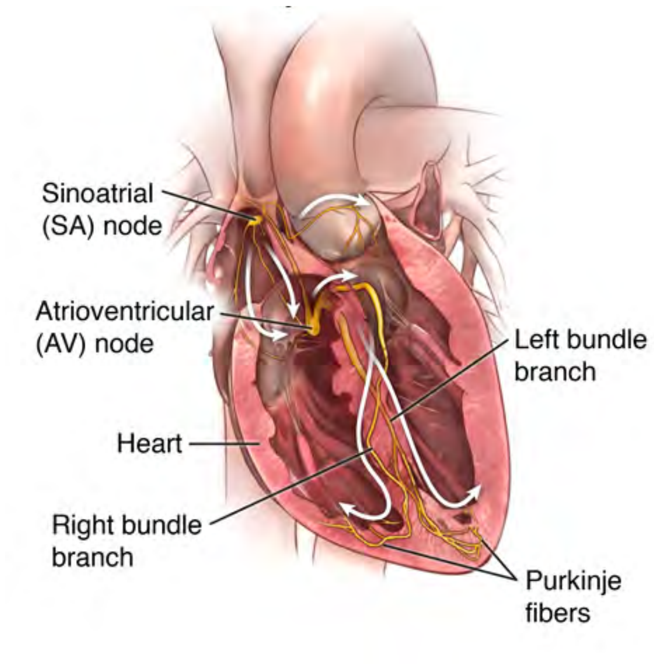


Figure 1.2: Electrical Conduction System of Heart

1.2 ECG Signal

Electrocardiogram (ECG) represents electrical activity of human heart. The heart is a muscle that contracts in a rhythmical manner, pumping blood throughout the body. A heart consists of two pumps (right and left) and each pump has two chambers (upper and lower). The upper chamber is call atrium and the lower chamber is called ventricle. The right pump circulates blood from other parts of the body to the lung and the left pump circulates blood from the lung to the rest of the body. This contraction has its beginning at the atrial sine node that acts as a natural pacemaker, and propagates through the rest of the muscle. This electrical signal propagation follows a pattern. As a result of this activity, electrical currents are generated on the surface of the body, provoking variations in the electrical potential of the skin surface. These signals can be captured or measured with the aid of electrodes and appropriate equipment.

The difference of electrical potential between the points marked by the electrodes on the skin, usually is enhanced with the aid of an instrumentation (operational) amplifier with optic isolation. In a conventional 12-lead ECG, ten electrodes are placed on the patient's limbs and on the surface of the chest. The overall magnitude of the heart's electrical potential is then measured from twelve different angles ("leads") and is recorded over a period of time (usually ten seconds) [4]. In this way, the overall magnitude and direction of the heart's electrical depolarization is captured at each moment throughout the cardiac cycle. Then, the signal is submitted to a high-pass filter; and as a second stage, submitted to an antialiasing low-pass filter. Finally, it appears in an analogical to digital converter. The graphical registration of this acquisition process is called electrocardiogram (ECG). The normal ECG signal and the ECG acquisition process are shown in Fig. 1.3 and Fig. 1.4 respectively.

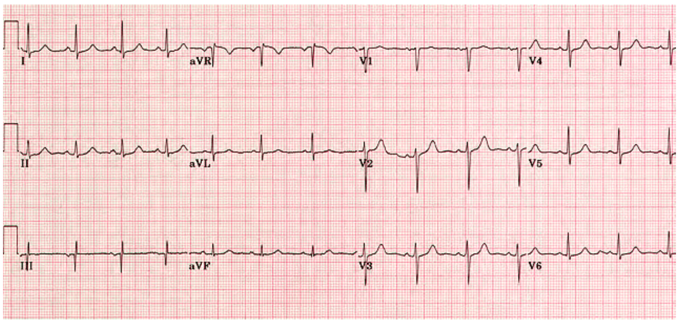


Figure 1.3: The Normal ECG

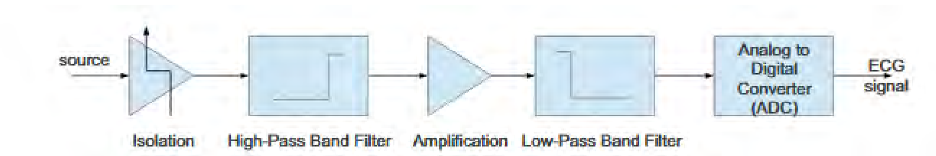


Figure 1.4: ECG Acquisition Process

1.2.1 Significance of Performing ECG

An electrocardiogram is a painless, noninvasive way to help diagnose many common heart problems in people of all ages. Electrocardiogram is done to detect [5]:

- **Heart rate:** Nomally,heart rate can be measured by checking pulse. An ECG may be helpful if pulse is difficult to feel or too fast or too irregular to count accurately. An ECG can help the doctor identify an unusually fast heart rate (tachycardia) or an unusually slow heart rate (bradycardia).

- **Heart Rythm:** An ECG can show heart rhythm irregularities (arrhythmias). These conditions may occur when any part of the heart's electrical system malfunctions. In other cases, medications, such as beta blockers, cocaine, amphetamines, and over-the-counter cold and allergy drugs, can trigger arrhythmias.
- **Heart attack:** An ECG can show evidence of a previous heart attack or one that's in progress. The patterns on the ECG may indicate which part of the heart has been damaged, as well as the extent of the damage.
- **Inadequate blood and oxygen supply to the heart:** An ECG done while anyone's having symptoms that can help doctor determine whether chest pain is caused by reduced blood flow to the heart muscle, such as with the chest pain of unstable angina.
- **Structural abnormalities:** An ECG can provide clues about enlargement of the chambers or walls of the heart, heart defects and other heart problems.

1.2.2 Measurement of ECG

Nowadays, there are many approaches to measurement/ record ECG. The majority of devices used for ECG measurements are in the on-the-person category. Devices on this category normally require the use of some electrodes attached to the skin surface. Examples of such equipments are bed side monitors and holters. Nowadays the standard devices used for heart beat analysis come from this category.

Commonly, 10 electrodes attached to the body are used to form 12 ECG leads, with each lead measuring a specific electrical potential difference. Leads are broken down into three types: limb, augmented limb and precordial or chest. The 12-lead ECG has a total of three limb leads and three augmented limb leads arranged like spokes of a wheel in the coronal plane (vertical), and six precordial leads or chest leads that lie on the perpendicular transverse plane (horizontal).The placements of the electrodes are shown in Fig. 1.5. The electrodes are placed as per Table 1.1.

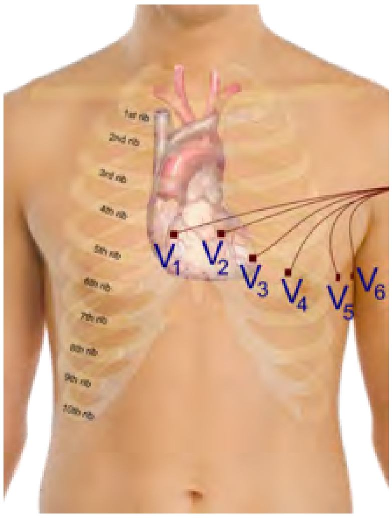


Figure 1.5: Placement of Electrode

Table 1.1: Placement of 10 Electrode

Electrode Name	**Electrode Placement**
RA	On the right arm, avoiding thick muscle
LA	In the same location where RA was placed, but on the left arm
RL	On the right leg, lower end of inner aspect of calf muscle. (Avoid bony prominences)
LL	In the same location where RL was placed, but on the left leg.
V_1	In the fourth intercostal space (between ribs 4 and 5) just to the right of the sternum (breastbone).
V_2	In the fourth intercostal space (between ribs 4 and 5) just to the left of the sternum
V_3	Between leads V_2 and V_4.
V_4	In the fifth intercostal space (between ribs 5 and 6) in the mid-clavicular line.
V_5	Horizontally even with V_4, in the left anterior axillary line.
V_6	Horizontally even with V_4 and V_5 in the mid-axillary line.

1.3 Leads in ECG

In a 12-lead ECG, all leads except the limb leads are unipolar (aVR, aVL, aVF, V_1, V_2, V_3, V_4, V_5, and V_6). The measurement of a voltage requires two contacts and so, electrically, the unipolar leads are measured from the common lead (negative) and the unipolar lead (positive) [6].

1.3.1 Limb Lead

Leads I, II and III are called the limb leads. The electrodes that form these signals are located on the limbs i.e. one on each arm and one on the left leg.

- Lead I is the voltage between the (positive) left arm (LA) electrode and right arm (RA) electrode: I= LA - RA
- Lead II is the voltage between the (positive) left leg (LL) electrode and the right arm (RA) electrode: II= LL – RA
- Lead III is the voltage between the (positive) left leg (LL) electrode and the left arm (LA) electrode: III = LL – LA

1.3.2 Augmented limb leads

Leads aVR, aVL, and aVF are the augmented limb leads. They are derived from the same three electrodes as leads I, II, and III, but they use Goldberger's central terminal as their negative pole. Goldberger's central terminal is a combination of inputs from two limb electrodes, with a different combination for each augmented lead. It is referred to immediately below as "the negative pole".

- Lead augmented vector right (aVR) has the positive electrode on the right arm. The negative pole is a combination of the left arm electrode and the left leg electrode
- Lead augmented vector left (aVL) has the positive electrode on the left arm. The negative pole is a combination of the right arm electrode and the left leg electrode: Equation
- Lead augmented vector foot (aVF) has the positive electrode on the left leg. The negative pole is a combination of the right arm electrode and the left arm electrode: Equation
- Together with leads I, II, and III, augmented limb leads aVR, aVL, and aVF form the basis of the hexaxial reference system, which is used to calculate the heart's electrical axis in the frontal plane.

1.3.3 Precordial leads

The precordial leads lie in the transverse (horizontal) plane, perpendicular to the other six leads. The six precordial electrodes act as the positive poles for the

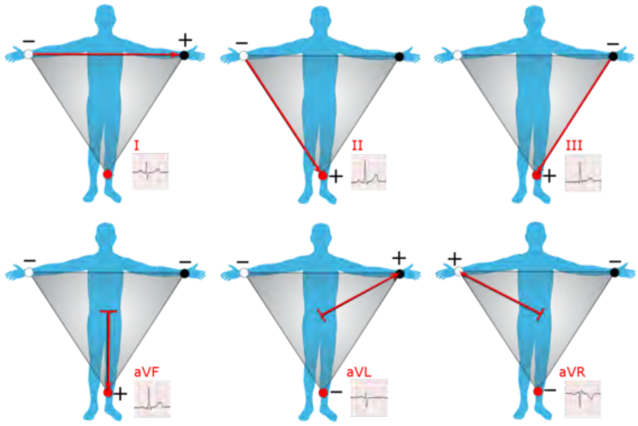


Figure 1.6: The limb leads and augmented limb leads

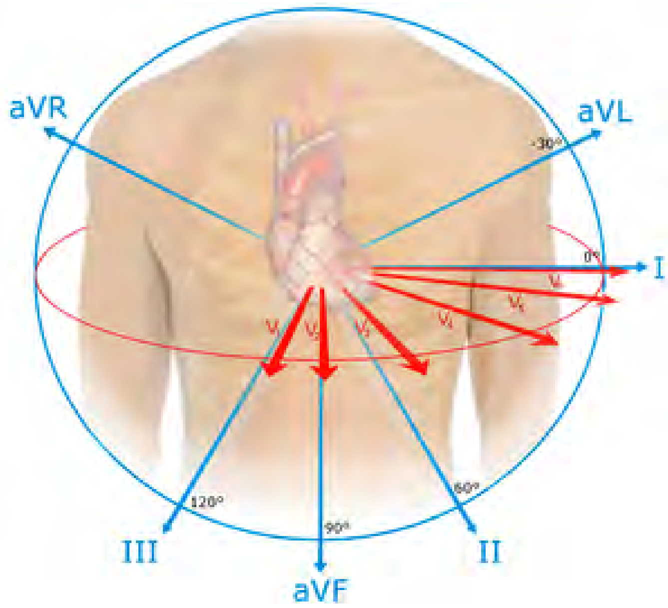


Figure 1.7: Detail View of Augmented Limb Leads

six corresponding precordial leads: (V_1, V_2, V_3, V_4, V_5, and V_6). Wilson's central terminal is used as the negative pole.

1.3.4 Specialized leads

Additional electrodes may rarely be placed to generate other leads for specific diagnostic purposes. Right-sided precordial leads may be used to better study pathology of the right ventricle or for dextrocardia (and are denoted with an R (e.g., V_5R). Posterior leads (V_7 to V_9) may be used to demonstrate the presence of a posterior myocardial infarction.

1.4 Interpretation of ECG Signal

Interpretation of the ECG is ultimately that of pattern recognition. In order to understand the patterns found, it is helpful to understand the theory of what ECGs represent. The theory is rooted in electromagnetic and boils down to the four following points [7]:

- depolarization of the heart toward the positive electrode produces a positive deflection
- depolarization of the heart away from the positive electrode produces a negative deflection
- repolarization of the heart toward the positive electrode produces a negative deflection
- repolarization of the heart away from the positive electrode produces a positive deflection

Thus, the overall direction of depolarization and repolarization produces a vector that produces positive or negative deflection on the ECG depending on which lead it points to. For example, depolarizing from right to left would produce a positive deflection in lead I because the two vectors point in the same direction. In contrast, that same depolarization would produce minimal deflection in V1 and V2 because the vectors are perpendicular and this phenomenon is called isoelectric. Normal rhythm produces four entities a P wave, a QRS complex, a T wave, and a U wave that each have a fairly unique pattern[8].

- The P wave represents atrial depolarization.
- The QRS complex represents ventricular depolarization.
- The T wave represents ventricular repolarization.
- The U wave represents papillary muscle repolarization.

1.5 Significance of Components of an ECG Beat

Normally, the frequency range of an ECG signal is of 0.05 100 Hz and its dynamic range of 1 10 mV. The ECG signal is characterized by five peaks and valleys labeled by the letters P, Q, R, S, T as shown in Fig.1.8. In some cases (especially in infants) we may also find another peak called U. The performance of ECG

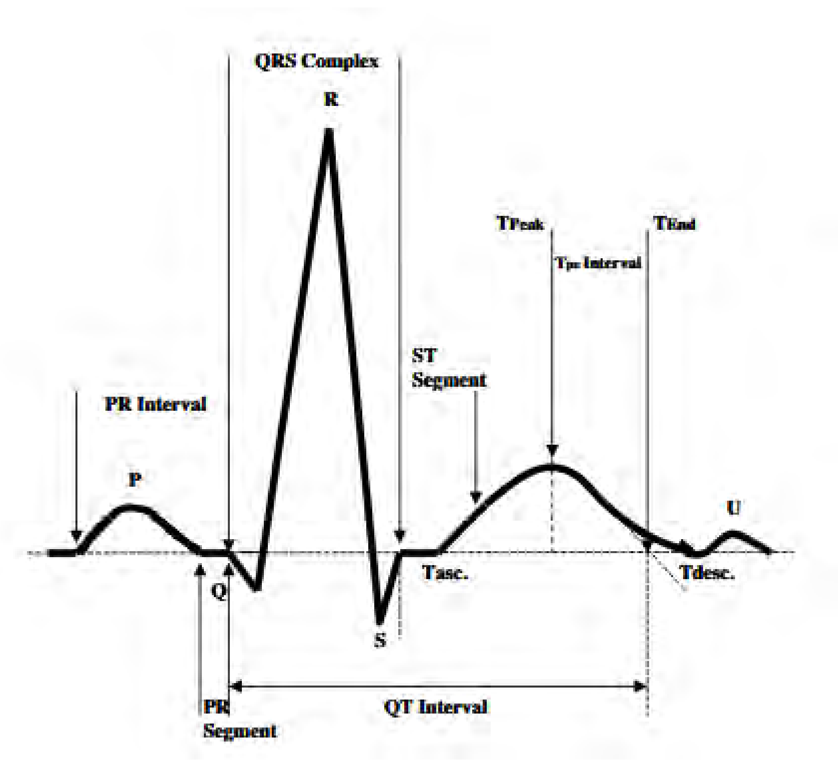


Figure 1.8: Schematic representation of normal ECG waveform

analyzing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T and P waves.

The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified a more detailed examination of ECG signal including the heart rate, the ST segment etc. can be performed.

In the normal sinus rhythm (normal state of the heart) the P-R interval is in the range of 0.12 to 0.2 seconds as shown in Fig.1.8. The QRS interval is from 0.04 to 0.12 seconds. The Q-T interval is less than 0.42 seconds and the normal rate of the heart is from 60 to 100 beats per minute. So, from the recorded shape of the ECG, we can say whether the heart activity is normal or abnormal. The electrocardiogram is a graphic recording or display of the time variant voltages produced by the myocardium during the cardiac cycle. The P-, QRS- and T-waves reflect the rhythmic electrical depolarization and repolarization of the myocardium associated with the contractions of the atria and ventricles. This ECG is used clinically in diagnosing various abnormalities and conditions associated with the heart.

The normal value of heart beat lies in the range of 60 to 100 beats/minute. A slower rate than this is called bradycardia (slow heart rate) and a higher rate is called tachycardia (fast heart rate). If the cycles are not evenly spaced, an arrhythmia may be indicated. If the P-R interval is greater than 0.2 seconds, it may suggest blockage of the AV node. The horizontal segment of this waveform preceding the P-wave is designated as the baseline or the isopotential line. The P-wave represents depolarization of the atrial musculature. The QRS complex is the combined result of the repolarization of the atria and depolarization of the ventricles, which occur almost simultaneously. The T-wave is the wave of ventricular repolarization, where as the U-wave, if present is generally believed to be the result of after potentials in the ventricular muscle. So, the duration amplitude and morphology of the QRS complex is useful in diagnosing cardiac arrhythmias, conduction abnormalities, ventricular hypertrophy, myocardial infection and other disease states. Table 1.2 represents the components of individual ECG beats.

1.6 Signal Processing in ECG Data Interpretation and Beat Classification

Reliable classification of ECG beats based on digital processing of ECG signals is vital in providing suitable and timely treatment to a cardiac patient. Computerized ECG signal interpretation systems are very much needed as they aid a cardiologist in taking crucial decisions while diagnosing abnormal heart rhythms. However, due to corruption of ECG signals with multiple frequency noise and presence of multiple arrhythmic events in a cardiac rhythm, computerized interpretation of abnormal ECG rhythms is a challenging task. Computerized ECG interpretation to classify ECG beats is a process of ECG data acquisition, waveform recognition, measurement of wave parameters and rhythm classification. Substantial progress has been made over the years in improvising techniques for signal conditioning, extraction of relevant wave parameters and rhythm classification. However, many problems and issues, especially those related to detection of long P and T peaks and reliable analysis of multiple arrhythmic events etc., still need to be addressed in a more comprehensive manner to brighten the prospect of commercial automated analysis in mass health care centres.

Although the first attempt to automate ECG analysis by digital computer was made as early as in 1956 by Pipberger and his group [9], but the first industrial ECG processing system came in the market during seventies. Since then many investigative and commercial minicomputer-based and microcomputer based sys-

Table 1.2: Interpretation of ECG Signal Pattern

Feature	**Description**	**Duration**
P wave	The P wave represents depolarization of the atria. Atrial depolarization spreads from the SA node towards the AV node, and from the right atrium to the left atrium.	<80 ms
PR interval	The PR interval is measured from the beginning of the P wave to the beginning of the QRS complex. This interval reflects the time the electrical impulse takes to travel from the sinus node through the AV node.	120 to 200 ms
QRS complex	The QRS complex represents the rapid depolarization of the right and left ventricles. The ventricles have a large muscle mass compared to the atria, so the QRS complex usually has a much larger amplitude than the P wave.	80 to 100 ms
J-point	The J-point is the point at which the QRS complex finishes and the ST segment begins.	
ST segment	The ST segment connects the QRS complex and the T wave; it represents the period when the ventricles are depolarized.	
T wave	The T wave represents the repolarization of the ventricles. It is generally upright in all leads except aVR and lead V_1.	160 ms
Corrected QT interval (QTc)	The QT interval is measured from the beginning of the QRS complex to the end of the T wave. Acceptable ranges vary with heart rate, so it must be corrected to the QTc by dividing by the square root of the RR interval.	<440 ms
U wave	The U wave is hypothesized to be caused by the repolarization of the interventricular septum. It normally has a low amplitude, and even more often is completely absent.	

tem have become common in use. It took considerable time to develop operational computer programs than originally anticipated. However, over last 20 years, research groups have mainly developed the computer programs but in last decade, the development has shifted to industry. Computers can assist a cardiologist in the task of ECG monitoring and interpretation. For example, in a cardiac intensive care unit (CICU), ECGs of several patients must be monitored continuously to detect any life-threatening abnormality that may occur. Various algorithms for the automatic detection of cardiac beats have been developed by different investigators for accurate classification of various types of beats.

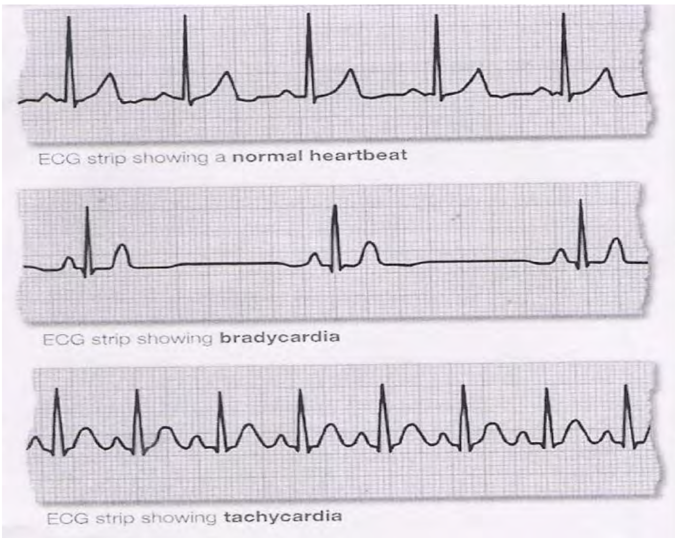


Figure 1.9: Practical ECG Signal Pattern

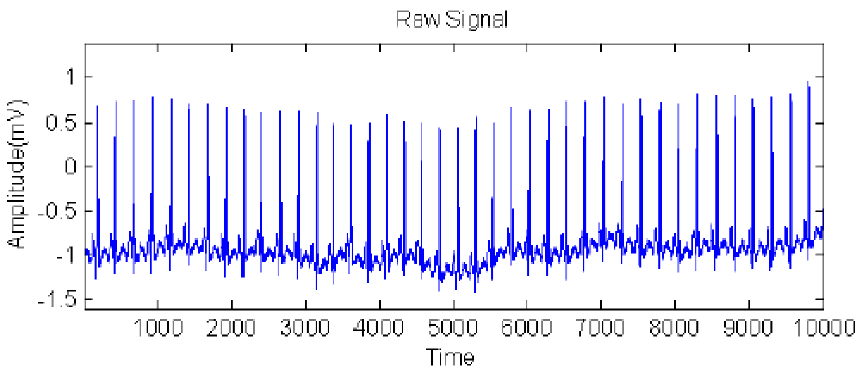


Figure 1.10: Raw ECG Data

The QRS complex is the most prominent feature and its accurate detection forms the basis of extraction of other features and parameters from the ECG signal. There are a number of methods, some of which deal with detection of ECG wave segments, namely P, QRS and T, while others deals with detection of QRS complexes. Transformative Techniques, namely Fourier Transform, Cosine Transform, Pole-zero Transform, Differentiator Transform, Hilbert Transform and Wavelet Transform are being used for the QRS detection. The use of these transforms on ECG signal helps to characterize the signal into energy, slope, or spike spectra, and thereafter, the temporal locations are detected with the help of decision rules like thresholds of amplitude, slope or duration. The real ECG signal is shown in Fig. 1.10.

1.7 Problem Definition

The information of electrocardiograms (ECG) signal is the most important bio-electrical message of human body, which reflects the basic law of heart activity. However, ECG signal is a non-linear, non-stationary weak signal with strong randomness, which increases the difficulty of analyzing and processing data. As a result, computer based automatic ECG beat detection and classification with high reliability is still an open research area. For ECG beat classification, a variety of features and a number of classification methods have been used. The features have been based on higher order statistics [10], wavelet transform [11], Fourier transform [12], principle component analysis [13], Helmit function coefficients [14] and morphological features, such as RR-interval, QRS complex, QRS duration in time, T wave duration in time, P wave flag, and T-wave segment [12]. Moreover, different classifiers based on different systems such ANNs [10, 12], mixture of experts approach [15], fuzzy logic [10], support vector machine [16], k-nearest neighbor [17], and SOM [18, 19], are used. However, the methods used and the number of beat types that are classified show a great deal of variance which makes it very difficult to fairly compare the performances of different algorithms under stringent conditions, such as reduction of training data set and random distribution of training and testing dataset. Thus, development of a proficient method capable of classifying different cardiac beat classes especially when multiclass beats are to be handled is still a challenging task.

1.8 Motivation

In view of above discussions, it is evident that we need to propose and develop an efficient cardiac beat classification method which will be capable of performing effectively in numerous stringent conditions. Due to the randomness of ECG signals, we have moved to exploit discrete wavelet packet decomposition (WPD) operation empirical mode decomposed ECG signals and choose approximate and detail WPD coefficient of dominant IMF for reduced feature set which will make the algorithm more efficient. For an effective feature extraction and classification strategy, we have been motivated to build a statistical model of the discrete wavelet packet decomposition (WPD) empirical mode decomposed ECG signals and feed the modeling parameters to the classifiers for sorting purpose. It is found more functional to make the features from the entire shape of the data class rather than taking discrete parameters which is representing each class in more consistent way and further make the classification procedure effective. Lastly, a classification problem involving several kinds of ECG data is found very limitedly reported in literature. That is why; we have been motivated to propose a cardiac beat classification exploiting higher order statistical features of discrete wavelet packet decomposition (WPD) of empirical mode decomposed ECG signals

1.9 Objective of the Thesis

The objectives of this thesis are:

- To obtain a set of Intrinsic Mode Function (IMF) through empirical mode decomposition (EMD) of ECG signals.
- To select the dominant IMF based on maximum temporal energy criterion.
- To decompose the dominant IMF of ECG signals into approximate and detail wavelet packet decomposition (WPD) coefficients.
- To develop an effective method for ECG arrhythmia classification based on higher order statistical measures of the of dominant IMF of ECG signals.
- To investigate the performance of the proposed feature sets with a simple classifier such as KNN classifier for the detection and classification of five AAMI (Advancement of Medical Instrumentation) cardiac beat classes.

The outcome of this thesis is the development of an ECG based method exploiting higher order statistical measures of the approximate and detail WPD coefficients of the dominant IMF, which is able to classify different cardiac beat classes with greater sensitivity and specificity even in case of reduction of training dataset and random distribution of training and testing dataset.

1.10 Organization of the Thesis

The thesis is organized as follows

- Chapter 1 provides the introduction of the overall thesis
- Chapter 2 presents popular ECG beat classification methods reported in literature
- Chapter 3 describes the proposed method of cardiac beat classification based on wavelet analysis of empirical mode decomposed ECG signals

- Simulation results and quantitative performance analysis are described in Chapter 4 for the proposed method described in chapter 3. Performance of the proposed method is also compared with the state-of-the-art methods

- Finally, in chapter 5, concluding remarks highlighting the contribution of the thesis and suggestions for further investigation are provided.

Chapter 2

Literature Review

2.1 Introduction

A Sudden Cardiac Death (SCD), which happens within one hour of onset of symptoms because of cardiac causes. The health data accumulated from more than 190 countries show heart disease remains the No. 1 global cause of death with 17.3 million deaths each year, according to "Heart Disease and Stroke Statistics from the American Heart Association (AHA). That number is expected to rise to more than 23.6 million by 2030, the report found [20]. As such cardiac beat classification is very essential to the serious patients suffering from different dangerous heart condition. If life threatening problems are detected in time, the patients can be treated timely and saved from sudden death. However, to analyze long ECG records of a patient is a very time consuming job. Therefore, computer aided signal processing techniques have been utilized in order to extract features that are capable of classifying different cardiac beats. Such methods are based on the principle of pattern recognition techniques. There are several methods based on various signal processing techniques reported in the literature for cardiac beat classification based on time or frequency or time-frequency domain. To extract features from ECG, researchers have been reported to use behavioral modeling [21], cross spectral density [22], empirical mode decomposition (EMD) [23], wavelet transform [24- 30], fractal dimension [31-35], artificial neural networks (ANN) [36-38], support vector machines (SVM) [39-40], cluster analysis (CA) method [41], principal component analysis (PCA) [42] and independent component analysis (ICA) [43]. The performance of these methods in classifying different types of cardiac beats are evaluated in terms of different performance evaluation criteria e.g. sensitivity, specificity, selectivity and accuracy. Most of the methods fall under three broad categories: (1) time domain, (2) frequency domain, and (3) time-frequency domain.

The two primary considerations for this detection system are- the type of features to be extracted from the ECG input signal (feature extraction techniques) and the type of analysis techniques to be applied on these extracted features to detect the class (classification techniques).

In the literature, methods that are capable of classifying multi-class cardiac beats in practical conditions like random selection of training and testing dataset have been reported limitedly. In this chapter, literature survey review of the different cardiac beat classification methods used to date are presented.

2.2 Time-Domain Methods

To classify cardiac beats ECG morphology and RR intervals are used for feature extraction in time domain methods. Some recently reported methods overview exploiting time domain features of ECG signals are described here.

Chazal et al. developed a method to classify five different ECG groups: normal beats, VEBs, SVEBs, fusion of normal and VEBs and unknown beat types. In this approach, MIT-BIH arrhythmia database were used. Heart beat fudicial points were manually calculated in this work. This paper derived 4 features on RR intervals, 3 features on heart beat intervals and 8 representations on ECG morphology. This showed that multiple lead configurations can perform better than single lead configurations processing the same feature sets. Beat by beat performance of this study showed the result that 1904 normal beats and 3509 normal beats were misclassified as SVEB and fusion beats respectively. Since fusion beats are the combination of ventricular and normal beats, differentiating normal beats from fusion beats is crucial task [44].

Another approach is to classify the heart beat using the morphological wavelet transform features. Ince et al. proposed an automated patient-specific ECG heart beat classification system based on morphological wavelet transform features and temporal features from the ECG data. In this work, principal component analysis (PCA) were used to reduce the morphological features to a lower-dimensional feature space. Multi-dimensional particle swarm optimization (MD PSO) technique has been proposed to classify. To construct an artificial neural networks (ANNs) optimally, MLPs were designed. In this work, relatively small common and patient-specific training data are used.This classification method can withstand significant inter-patient variations in ECG morphology by deriving the optimal network structure. As such, it can be applicable to any ECG database without any modifications[45].

Another approach to analyze ECG signal is exploiting cluster analysis method. Yeh et al. proposed a method of analyzing ECG signal to classify 5 different types of cardiac beats based on the cluster analysis (CA) method. In analyzing ECG signal for classification, QRS waveform are detected at first and after that qualitative features are selected. In this method no complex computational burden is needed [41].

Time domain methods that are reported in literature can only capture detail information from different aspects of time resolution representation of ECG signals. But, it does not consider any frequency resolution characteristics of an ECG. Since ECG is a non-stationary signal, it has both time and frequency resolution characteristics. To represent ECG signal as a whole, time and frequency characteristics must be considered simultaneously. Only time domain features are not sufficient in order to represent detail characteristics regarding different types of cardiac beats. As a result time domain methods have the the limitations in classifying cardiac beats with different conditions.

2.3 Frequency-Domain Methods

Different frequency domain methods such as fast Fourier transform (FFT), short-time Fourier transform (STFT), auto regressive (AR) models and power spectral density (PSD) are used and reported in literature to classify different cardiac beats.

Lin et al. proposed a method for ECG heartbeat discrimination using grey relational analysis (GRA). Each QRS complexes was converted to a Fourier spectrum from ECG signals. The variations of power spectrum were observed in the range of 0–20 Hz in the frequency domain. To quantify the frequency components among the various ECG beats, GRA is performed to classify the cardiac arrhythmias [46].

Dutta et al. proposed a heartbeat detection method based on Artificial Neural Network (ANN) classifier. In this work all the preprocessed ECG beats are cross-correlated with the normal heartbeats. Thus a cross correlation sequences for every beat is formed. These cross-correlation sequences are then transformed into frequency domain by using Fourier transform to extract final feature vectors from the magnitude and phase cross-spectral density curves. In this study, the Learning Vector Quantization (LVQ) methods based classifiers are employed. Here three different types of beats: normal, Premature Ventricular Contraction (PVC) and other beats are classified.To demonstrate the efficiency of the proposed method, a large testing dataset is validated by classifying them against a small training dataset [47].

Dutta et al. proposed a scheme that utilizes a cross-correlation based approach where the cross-spectral density information in frequency domain is used to extract suitable features. A least square support vector machine (LS-SVM) classifier was developed utilizing the features and ECG beats were classified into three categories: normal beats, PVC beats and other beats. This three-class classification scheme utilized a small training dataset and tested with an large testing dataset[48].

In frequency analysis methods, only frequency domain characteristics of an ECG is considered ignoring time domain features. Thus, it is not sufficient to classify cardiac beats and complete feature extraction.

2.4 Time-Frequency-Domain Methods

As a result of the infinite extent of the Fourier integral, analysis is time averaged. Thus it contains only globally averaged information and so has the potential to obscure transient or location specific features within the signal. This limitation can be partly overcome by introducing a sliding time window of fixed length to localize the analysis in time. This local or short time Fourier transform (STFT) provides a degree of temporal resolution by highlighting changes in spectral response with respect to time. A number of alternative time–frequency methods are now available for signal analysis. Of these, the wavelet transform has emerged over recent years as the most favoured tool by researchers for analysing problematic signals across a wide variety of areas in science, engineering and medicine. It is especially valuable because of its ability to elucidate simultaneously local spectral and temporal information from a signal in a more flexible way than the STFT by employing a window of variable width. Thus wavelet transforms produce a time–frequency decomposition of the signal which separates individual signal components more effectively than the traditional short time Fourier transform (STFT). This flexible temporal–spectral aspect of the transform allows a local scale-dependent spectral analysis of individual signal features. In this way both short duration, high frequency and longer duration, lower frequency information can be captured simultaneously. Hence the method is particularly useful for the analysis of transients, aperiodicity and other non-stationary signal features where, through the interrogation of the transform, subtle changes in signal morphology may be highlighted over the scales of interest. Another key advantage of wavelet techniques is the variety of wavelet functions available, thus allowing the most appropriate to be chosen for the signal under investigation. This is in contrast to Fourier analysis which is restricted to one feature morphology: the sinusoid. In its discrete form using orthogonal wavelet bases, the wavelet transform is particularly useful in signal coding, allowing information within the signal to be localized within a number of pertinent coefficients for compression purposes [49].

Chen et al. has developed feature selectors based on nonlinear correlations in order to select the most effective and least redundant features from an ECG beat classification system based on higher order statistics of subband components and a feed-forward back-propagation neural network, denoted as HOS-DWT-FFBNN. In order to select the most effective and less redundant features, two nonlinear correlation based filters (NCBFs), which apply feature-feature correlation, are employed in this study. The application of NCBFs with prior redundancy reduction further improves the efficiency of the methods with a little reduction in classification rates [50].

Homaeinezhad et al. proposed method that consists of structurally diverse classifiers with a new QRS complex geometrical feature extraction technique. First, the events of the electrocardiogram (ECG) signal are detected and delineated using a robust wavelet-based algorithm. Then, each QRS region and also its corresponding discrete wavelet transform (DWT) are supposed as virtual images and each of them is divided into eight polar sectors. Next, the curve length of each excerpted segment is calculated and is used as the element of the feature space. In this approach six different classifiers namely as SVM, KNN and four MLP-BP neural networks with different topologies were designed and applied. Proposed learning machine was employed to classify 7 arrhythmias belonging to 15 different records [39].

Dewangan et al. developed an artificial neural network (ANN) based classifier. In this work discrete wavelet transform (DWT) is used for preprocessing and feature extraction purposes and neural network designed is used to classify five types of arrhythmias namely Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Paced Beat (PB), Atrial Premature Beat (APB) and First degree AV Block (AVB) beats apart from normal (N) beats. Here optimum feature set is developed and number of hidden layer neurons is utilized to increase the classification performance of the neural network based classifier[51].

Shen et al. proposed a system for cardiac arrhythmia detection in ECGs with adaptive feature selection and modified support vector machines (SVMs). Wavelet transform-based coefficients and signal amplitude/interval parameters are first enumerated as candidates, but only a few specific ones are adaptively selected for the classification of each class pair. A new classifier, which integrates k-means clustering, one-against-one SVMs, and a modified majority voting mechanism, is proposed to further improve the recognition rate for extremely similar classes[40].

Yu et al. proposed an electrocardiogram (ECG) beat classification system based on wavelet transformation and probabilistic neural network (PNN) to discriminate six ECG beat types. The ECG beat signals are first decomposed into components in different subbands using discrete wavelet transformation. Three sets of statistical features of the decomposed signals as well as the AC power and the instantaneous RR interval of the original signal are exploited to characterize the ECG signals. A PNN follows to classify the feature vectors. Only 11 features are required to attain this high accuracy, which is substantially smaller in quantity than that in other methods. These observations prove the effectiveness and efficiency of the proposed method for computer-aided diagnosis of heart diseases based on ECG signals [29].

Mahesh et al. presents a diagnostic system for classification of cardiac arrhythmia from ECG data, using Logistic Model Tree (LMT) classifier. Clinically useful information in the ECG is found in the intervals and amplitudes of the characteristic waves. The amplitude and duration of the characteristic waves of the ECG can be more accurately obtained using Discrete Wavelet Transform (DWT) analysis. Fur27 ther, the non-linear behavior of the cardiac system is well characterized by Heart Rate Variability (HRV). Hence, DWT and HRV techniques have been employed to extract a set of linear (time and frequency domain) and nonlinear characteristic features from the ECG signals. These features are used as input to the LMT classifier to classify 11 different arrhythmias. The system can be deployed for practical use after validation by experts [52].

Wavelet packet decomposition method is an extension of wavelet transform. WPD can divide the whole time-frequency plane whereas classical WT can provide analysis only for low-band frequencies. This multi-resolution capability of WPD allows the decomposition of a signal into a number of scales, each scale representing a particular feature of the signal under study. The top level of the WPD is the time representation of the signal whereas bottom level has better frequency resolution. Thus using WPD, a better frequency resolution can be achieved over WT for the decomposed ECG signal. The advantage of wavelet packet analysis is that it is possible to combine the different levels of decomposition in order to construct the original signal.

Kutla et al. proposed an automatic heart beat recognition system exploiting features extracted from higher order statistics (HOS) of wavelet packet decomposition (WPD) coefficients. First of three stages involves the calculation of wavelet packet coefficients (WPC) for each different ECG beat. Then, feature vectors are extracted by calculating higher order statistics, namely second, third and fourth cumulants of each level of WPC. After applying normalization to all extracted features, final feature set is formed, which is applied as input to the k-NN algorithm based classifier. The proposed method has its ability to handle Gaussian noise which is ineffective since the system is based on cumulants [30].

Chouakri et al. proposed wavelet packet based QRS complex detection algorithm. It consists of a particular combination of two vectors obtained by applying a designed routine of QRS detection process using 'haar' and 'db10' wavelet functions respectively. The QRS complex detection routine is based on the histogram approach where the node with highest number of histogram coefficients are found at center. The remaining least number coefficients reflect the R waves peaks. Following a classical approach based of a calculated fixed threshold, the possible QRS complexes are be determined. The QRS detection complex algorithm has been applied to the whole MIT-BIH arrhythmia Database [53].

Li et al. proposed a method to classify ECG signals using wavelet packet entropy (WPE) and random forests (RF) following the Association for the Advancement of Medical Instrumentation (AAMI) recommendations and the inter-patient scheme. First the ECG signals are decomposed by wavelet packet decomposition (WPD), and then the entropy is calculated from the decomposed coefficients as representative features. After that RF is used to build an ECG classification model [54].

2.5 Other Methods

Yu et al. proposed a novel independent components (ICs) arrangement approach to collaborate with the independent component analysis (ICA) method used for classifying different ECG beat. The ICs extracted by fast ICA algorithm are rearranged according to the L2 norms of the rows of the de-mixing matrix. The efficacy and efficiency of the proposed method and three other general ICs arrangement strategies are studied. Two kinds of classifiers, including probabilistic neural network and support vector machines, are employed to calculate the performance of the proposed method in classifying eight different ECG beat types. The classification results reveal that the proposed ICs arrangement strategy outperforms the other strategies in eliminating the number of features required for the classifiers [55].

Moavenian et al. proposed a novel use of Kernel-Adatron (K-A) training algorithm collaborating with SVM (Support Vector Machine) for classifying six types of ECG arrhythmia plus normal ECG. The proposed pattern classifier is compared with MLP (multi-layered perceptron) using back propagation (BP) learning algorithm. The MLP and SVM training and testing stages were carried out twice. They were first trained only with one ECG lead signal and then a second ECG lead signal was added to the training and testing datasets in order to investigate its influence on training and testing performance and training time for both classifiers. The results designate that SVM in comparison to MLP is much faster in training stage and nearly seven times higher in performance, but MLP generalization ability in terms of mean square error is more than three times less [37].

Castillo et al. described a hybrid intelligent system for classification of cardiac arrhythmias exploiting three methods of classification: Fuzzy KNN, Multi-Layer Perceptron (MLP) Gradient Descent with momentum Back propagation, and MLP Scaled Conjugate Gradient Back propagation. Since the mentioned classifiers capture different knowledge about classification, all of them produced good classification results individually. Finally, a Mamdani type fuzzy inference system was used to aggregate the outputs of the individual classifiers, and a very high classification rate was achieved [38].

2.6 Conclusion

In this chapter, literature survey of the recent state-of-the-art ECG beat classification methods is presented in brief. All the proposed methods have some merits and demerits. In order to handle the practical situations of real life applications such as random selection of training and testing feature set, design of a multi-class cardiac beat classification method is needed that can provide superior performance with greater sensitivity, specificity, selectivity and accuracy. Thus, development of a multi-class cardiac beat classification method, which is simple yet effective in handling practical conditions as mentioned above, is still a challenging task.

Chapter 3

Cardiac Beat Classification Exploiting Wavelet Packet Decomposition of Empirical Mode Decomposed ECG Signals

3.1 Introduction

Designing a feature set, which is capable of extracting distinguishable information to detect and classify cardiac beat class is a difficult task. In the literature, many researchers used a variety of features to represent the ECG signal and a number of classification methods. The features have been based on higher order statistics [10], wavelet transform, Fourier transform, principle component analysis, Helmit function coefficients, morphological features such as RR-interval, QRS complex, QRS duration in time, T wave duration in time, P wave flag, and T-wave segment. Moreover, different classifiers based on different systems such ANNs, mixture of experts approach, fuzzy logic, support vector machine, k-nearest neighbor, and SOM, are used. However, the methods used and the number of arrhythmia types that are classified show a great deal of variance which makes it very difficult to fairly compare the performances of different algorithms. To overcome this difficulty, some standards are recommended for reporting performance results by the Association for the Advancement of Medical Instrumentation (AAMI) [44]. According to AAMI standards, all ECG beats in MIT-BIH database are grouped into five beat classes.

In this chapter, EMD analysis of the ECG signals is performed at first where a set of IMFs is obtained. Instead of using all IMFs resulting from an ECG signal, only dominant IMF is selected based on maximum temporal energy criterion. Next to extract features, discrete wavelet packet decomposition (WPD) is employed on the dominant IMF and both approximate and detail WPD coefficients are utilized. Some higher order statistical measures of the WPD coefficients are used as desired features which are found very efficient in discriminating different types of cardiac beats.

3.2 Proposed Method

The proposed ECG beat classification method consist of some major steps, namely- pre-processing, ECG signal using EMD, dominant IMF Selection, that is obtained from EMD, wavelet packet decomposition of the dominant IMF, feature extraction from WPD coefficient and classification. Firstly, a set of IMFs is obtained through EMD of ECG signals, because EMD is intencontuitive and adaptive, with basic functions directly derived from the signal under test and its computation does not require any previously known value of the signal. Then, the dominant IMF has been selected via analyzing the temporal contents of the resultant IMFs from EMD analysis. To obtain further discriminatory behavior, discrete wavelet packet decomposition (WPD) is employed on the dominant IMF. After considering the temporal energy pattern, the 4th Level detail and approximate WPD coefficients of the selected IMFs are found suitable for feature computation. For further reduction of the dimension of the feature vector, higher order statistics of these coefficients are employed to form the feature vector. Euclidian distance based kNN classifier is found effective for distinguishing and classifying the multiclass cardiac beat classes even in case of reduction of training dataset and random distribution of training and testing dataset. It is shown that the proposed method is capable of producing greater sensitivity, specificity and accuracy in comparison to that obtained by few state-of-the-art methods using the same ECG dataset and classifiers. The simplified block diagram of the proposed method is shown in Fig. 3.1.

3.3 Pre-processing

The ECG consists of three basic waves, P, QRS and T. These waves correspond to the far field induced by specific electrical phenomena on the cardiac surface, namely the atrial depolarization (P wave), the ventricular depolarization (QRS complex), and the ventricular repolarization (T wave). The ECG does not look the same in all the leads of the standard 12 lead system used in clinical practice. The polarity and the shape of the ECG constituent waves are different depending

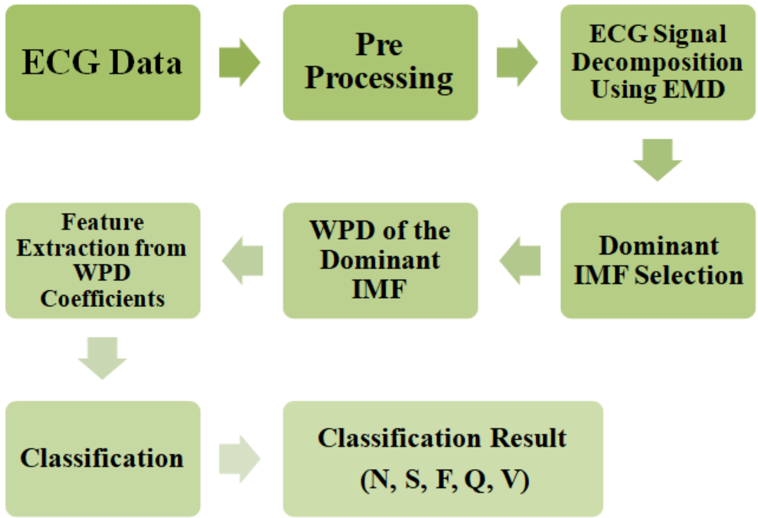


Figure 3.1: Simplified Block Diagram of the Proposed Method

on the lead that is used.
In a normal cardiac cycle, the P wave occurs first, followed by the QRS complex and the T wave. The sections of the ECG between the waves and complexes are called segments. The ECG is characterized by three segments namely the PR segment, the ST segment and the TP segment. The characteristic time periods in the ECG wave are the PR interval, the RT interval, and the R-R interval. Usually ECG signals are contaminated by various kinds of noise.

3.3.1 Noises in ECG Signal

- **Power Line Interference:**Power line interference consists of 60/50 Hz pickup and harmonics that can be modeled as sinusoids and combination of sinusoids. The frequency content of this kind of noise is 60/50 Hz with harmonics and the amplitude is 50% of peak-to-peak ECG amplitude[56].

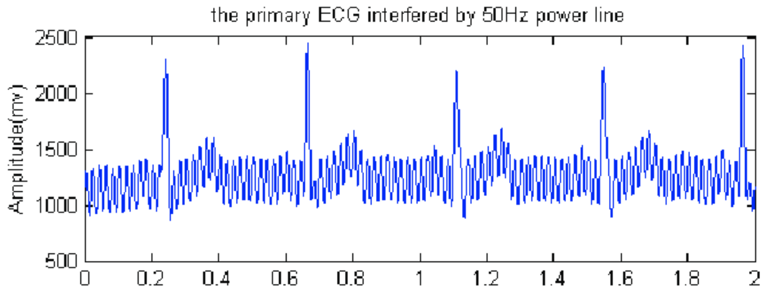


Figure 3.2: Power Line Noise

- **Electrode Contact Noise:** Electrode contact noise is transient interference caused by loss of contact between the electrode and the skin, which can be permanent or intermittent. The switching action can result in large artifacts since the ECG signal is usually capacitively coupled to the system. This type of noise can be modeled as a randomly occurring rapid baseline transition that decays exponentially to the base line and has a superimposed 60 Hz component. The duration of the noise signal is 1 sec and the amplitude is the maximum-recorded output with the frequency of 60 Hz[56].

- **Motion Artifact:** Motion artifacts are transient base line changes in the electrode skin impedance with electrode motion. The shape of the base line disturbance caused by the motion artifacts can be assumed to be a biphasic signal resembling one cycle of a sine wave. The peak amplitude and duration of the artifacts are variables. The duration of this kind of noise signal is 100–500 ms with amplitude of 500% peak-to-peak ECG amplitude[56].

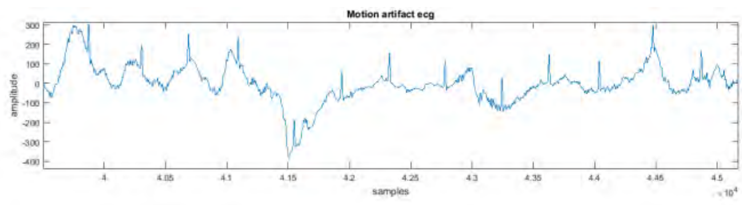


Figure 3.3: Motion Artifacts

- **Muscle Contraction:** Muscle contraction causes generation of artifactual millivolt level potentials. It can be assumed to be transient burst of zero mean band limited Gaussian noise. The variance of the distribution may be estimated from the variation and duration of the bursts. Standard deviation of this kind of noise is 10% of peak-to-peak ECG amplitude with duration of 50 ms and the frequency content being dc to 10 kHz[56].

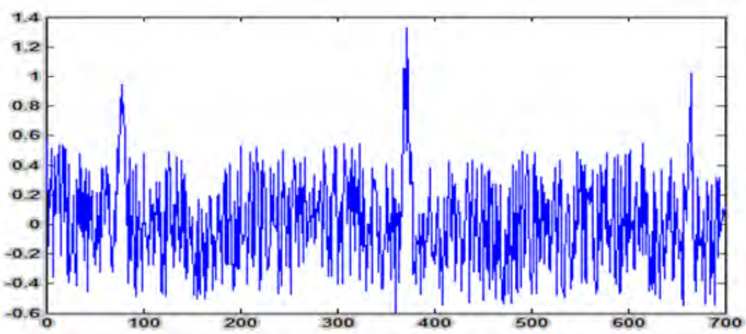


Figure 3.4: Muscle Noise

- **Base Line Wander:** The baseline wander of the ECG signals causes problems in the detection of peaks. For example, due to the wander, the T peak could be higher than R peak, and it is detected as an R peak instead. Low frequency wander of the ECG signal can be caused by respiration or patient movement. The drift of the baseline with respiration can be represented as a sinusoidal component and the frequency of respiration added to the ECG signal. The variation could be reproduced by amplitude modulation of the ECG by the sinusoidal component that is added to the base line. The amplitude variation is 15% of peak-to-peak ECG amplitude and the base line variation is 15% of ECG amplitude at 0.15 to 0.3 Hz[56].

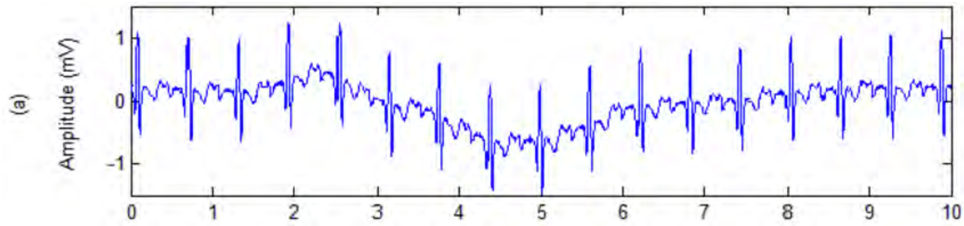


Figure 3.5: Baseline Shift Noise

3.3.2 Filtering

These noise must be removed from ECG before extracting the characteristic features. Noise removal is accomplished by passing the cardiovascular signals through filter whose cutoff frequency is a function of the noise frequency [57].

To eliminate baseline wander, two median filters have been used in this work. First, the first 200 ms of samples were extracted and sorted out in ascending order, then its median was calculated. Then for every 200 ms of samples till the end of the ECG signal, the same procedure was carried out. Now, these samples are fed as input to the 600 ms window median filtering. Later, the median value is evaluated for every 600 ms of samples. Then these median values were subtracted from the original waveform to remove the baseline wander of the ECG signal. Fig. 3.7 shows the result of the baseline wander filter.

3.4 Feature Extraction

3.4.1 Empirical Mode Decomposition of ECG signal

EMD is intuitive and adaptive signal processing technique used for nonlinear, non-stationary time series data, such as ECG. EMD has been reported to behave well

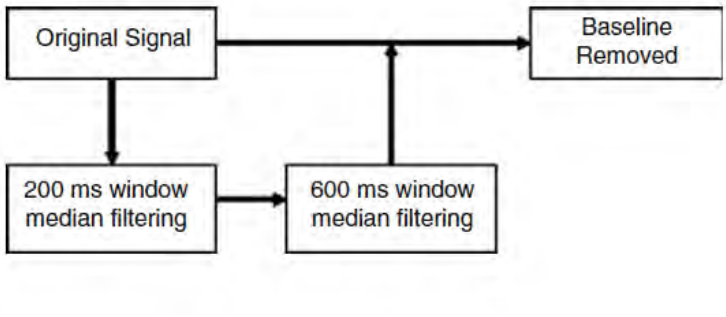
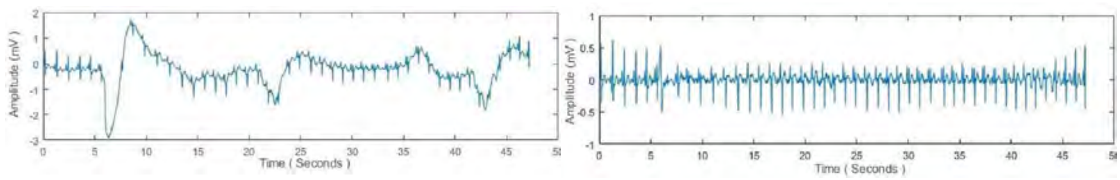


Figure 3.6: Block Diagram for removing baeline wander



(a) ECG Signal with Baseline wander (b) Corrected ECG Signal

Figure 3.7: Results of Filtering Algorithm to Remove the noise

for speech and some other biomedical signal[58]. The basic functions in EMD are derived only from the data signal under consideration. As such, to compute the EMD previously known value of the signal is not required [25]. In EMD process the objective here is to identify the intrinsic oscillatory modes by their characteristic time scales in the signal empirically. Thus the signal is decomposed into intrinsic mode functions (IMFs) [59, 60]. A complex signal is decomposed into a series of stationary and linear IMFs using EMD. Each IMF must satisfy two requirements:

- In the whole data set, the number of local extrema and the number of zero are either equal or differ at most by one.

- At any point, the mean value of the upper envelope defined by the local maxima and the lower envelop that defined by the local minima is zero.

The systematic way to decompose the data into IMFs, known as the ”sifting” process, is described as follows

1. All the local maxima of the ECG data are determined and joined by cubic spline line thus constructing an upper envelope.

2. All the local minima of the ECG data are found and connected by cubic spline line to obtain the lower envelope.

3. The mean m_1 of both the envelopes are calculated and the difference between the input signal $x[n]$ and m_1 is computed as $h_1[n]$

$$h_1[n] = x_1[n] - m_1 \tag{3.1}$$

4. If $h_1[n]$ satisfies the conditions of IMF, then it is the first frequency and amplitude modulated oscillatory mode (IMF) of $x[n]$.

5. If $h_1[n]$ dissatisfies the conditions to be an IMF, it is treated as the data in the second sifting process, where steps 1, 2 and 3 are repeated on $h_1[n]$ to derive the second component $h_2[n]$ as

$$h_2[n] = h_1[n] - m_2 \tag{3.2}$$

where m_2 is the mean of upper and lower envelopes of $h_1[n]$

6. Let after ω cycles of operation, if $h_\omega[n]$, given by

$$h_\omega[n] = h_{\omega-1}[n] - m_\omega \tag{3.3}$$

becomes an IMF, it is designated as $c_1[n]$=$h_\omega[n]$ the first IMF component of the original ECG signal.

7. Subtracting $c_1[n]$ from $x[n]$, $r_1[n]$ is calculated as

$$r_1[n] = x[n] - c_1[n] \tag{3.4}$$

which is treated as the original data for the next cycle for calculating the next IMF.

8. Repeating the above process for L times, L no. of IMFs is obtained along with the final residue $r_L[n]$. A popular stopping criteria for the sifting process is to have the value of standard difference (SD) within a predefined threshold as

$$SD = \sum_{n=-1}^{N} \frac{h_\omega[n] - h_{\omega-1}[n]^2}{h_\omega[n]^2} \tag{3.5}$$

here, ω and $\omega-1$ are index terms indicating two consecutive sifting processes. Thus the decomposition process is stopped since $r_L[n]$ becomes a monotonic function from which no more IMF can be extracted. To this end, for L level of decomposition, the original signal can be reconstructed by the following formula,

$$x[n] = \sum_{k=1}^{L} c_k[n] + r_L[n] \tag{3.6}$$

A typical ECG signal and the resulting IMFs are shown in Fig. 3.8.

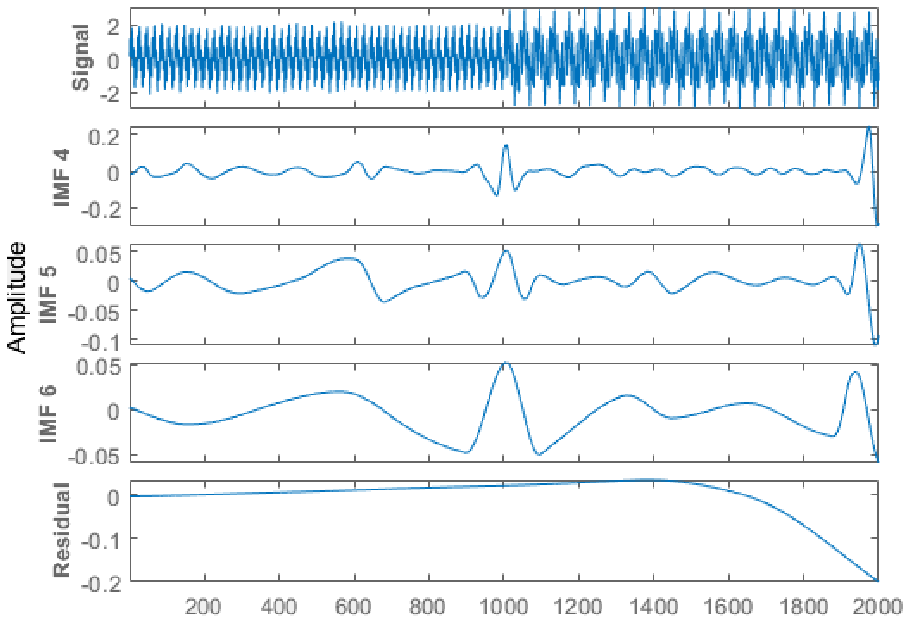


Figure 3.8: Empirical Mode Decomposition of ECG Signal

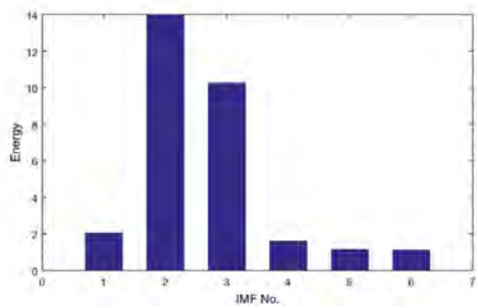
In IMF based ECG beat classification methods, generally all of the extracted IMFs are equally treated, although it is well known that not all of them can uniquely characterize the class they belong to. Moreover, it is obvious that considering all IMFs would increase the size of the feature vector and also would require extensive computations for the purpose of comparison with the training database. Therefore, in the proposed method, we propose to use only the dominant IMF among all the extracted IMFs.

3.4.2 Dominant IMF Selection

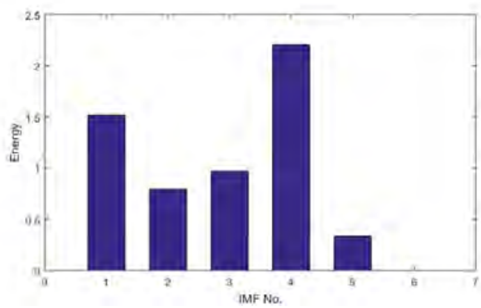
For a particular ECG signal, the selection criteria for the dominant IMF is proposed as to consider the temporal energy content of all the IMFs. Among the IMFs extracted from a particular ECG signal, the IMF with the highest energy content is selected as the dominant IMF. The temporal energy of the dominant IMF is given by

$$E_d = \sum_{t=1}^{N} C_d[t]^2 \tag{3.7}$$

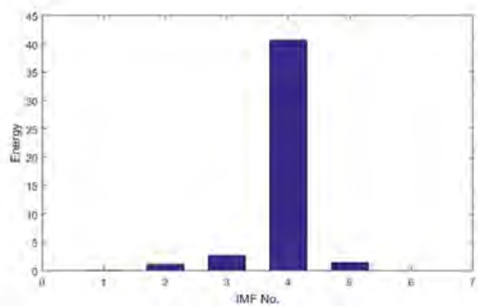
Here N is the length of the IMF and E_d represents the temporal energy of the dominant IMF C_d[n]. Temporal energy patterns of all the IMFs for different ECG beat classes are shown in Fig.3.9. It is observed from Fig. 3.9 that the second IMF contains the highest temporal energy for the N class of ECG beat and hence it is identified as the dominant IMF. It is also seen from Fig. 3.9 that since the fourth IMF contains the highest temporal energy, it is identified as the dominant IMF for the S class of ECG beat. Similarly for F class ECG beat third IMF, for Q class ECG beat fourth IMF and for V class ECG beat second IMF with highest temporal energy has been chosen as shown in the figure. Since using only dominant IMF, it may not be possible to discriminate the cardiac beat classes of ECG effectively, once the dominant IMFs for different ECG data are obtained, these are then used for the further analysis via WPD.



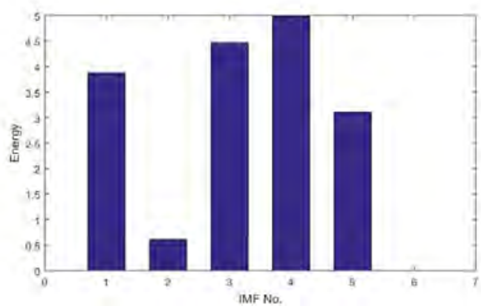
(a) Energy Pattern of IMFs of N Class



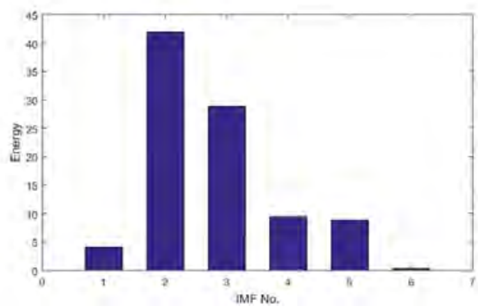
(b) Energy Pattern of IMFs of S Class



(c) Energy Pattern of IMFs of F Class



(d) Energy Pattern of IMFs of Q Class



(e) Energy Pattern of IMFs of V Class

Figure 3.9: Temporal Energy Pattern of IMFs of Five AAMI Cardiac Beat Class

3.4.3 Wavelet Packet Decomposition of the Dominant IMF

3.4.3.1 Wavelet Transform

Discrete wavelet Transform (DWT) is a multi-resolution transform with a very fast implementation. DWT is a lost less linear transformation of a signal or data into coefficients on a basis of mother wavelet functions [16,17]. A family of mother wavelet is available having the energy spectrum concentrated around the low frequencies like the ECG signal as well as better resembling the QRS complex of the ECG signal [61]. Therefore, for the analysis of an ECG signal $x[n]$ at different scales, wavelet transform (DWT) is used in practice. A general equation for the DWT transformed signal is written as [62]

$$Z(a,b) = \sum_{n=-\infty}^{\infty} x[n]\phi_{a,b}[n] \tag{3.8}$$

where, $x[n]$ is the given ECG signal to be transformed and

$$\phi(a,b)[n] = \frac{1}{\sqrt{2}} \times \phi\frac{n-b}{a} \tag{3.9}$$

In DWT, the function represents a window of finite length, where b is a real number known as window translation parameter and a is a positive real number named as dilation or contraction parameter. In discrete wavelet transform (DWT), for analyzing both the low and high frequency components in $x[n]$, it is passed through a series of low-pass and high-pass filter with different cut-off frequencies. This process results in a set of approximate and detail DWT coefficients, respectively. The filtering operations in DWT result in a change in the signal resolution [57]. Thus, DWT decomposes the signal into approximate and detail information thereby helping in analyzing it at different frequency bands with different resolutions. In wavelet analysis, only scale space is decomposed, but wavelet space is not decomposed. This results in a logarithmic frequency resolution, which does not work well for all the signals. By the restriction of Heisenberg's uncertainty principle, the spatial resolution and spectral resolution of high frequency band become poor thus limiting the application of wavelet transform.Fig.3.10 shows the wavelet decomposition tree of wavelet transform.

3.4.3.2 Wavelet Packet Decomposition

In order to overcome the drawback as mentioned above, it is desirable to iterate the high pass wavelet branch as well as the low pass scaling function branch. Such a wavelet decomposition produced by these arbitrary subband trees is known as wavelet packet (WP) decomposition. A method based on the Wavelet Packet Transform is a generalization of the Wavelet Transform based decomposition process that offers a richer range of probabilities for the analysis of signals, namely ECG. In wavelet packet analysis, the wavelet space is also decomposed thus making the higher frequency band decomposition possible. Since, both the approximation

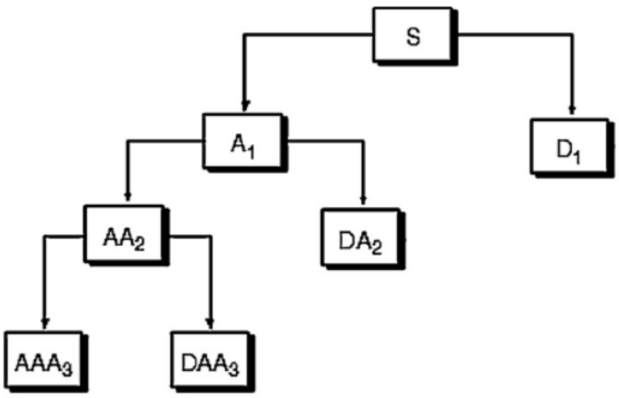


Figure 3.10: Wavelet Transform Decomposition Tree

and the detail coeffecients are decomposed into two parts at each level of decomposition, a complete binary tree with superior frequency localization can be achieved as shown in Fig. 3.11. Thus the wavelet packet transform provides a closer approximation of the dataset, compared to the wavelet transform. Features extracted from these wavelet packet decomposition (WPD) coefficients can efficiently represent the characteristics of the original ECG signal in different details. Therefore, recently WPD has drawn attention of the researchers in ECG pattern recognition [30].

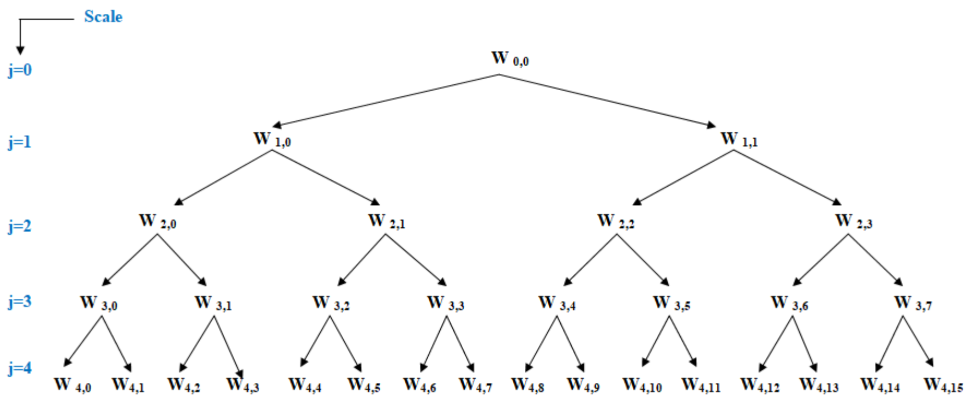
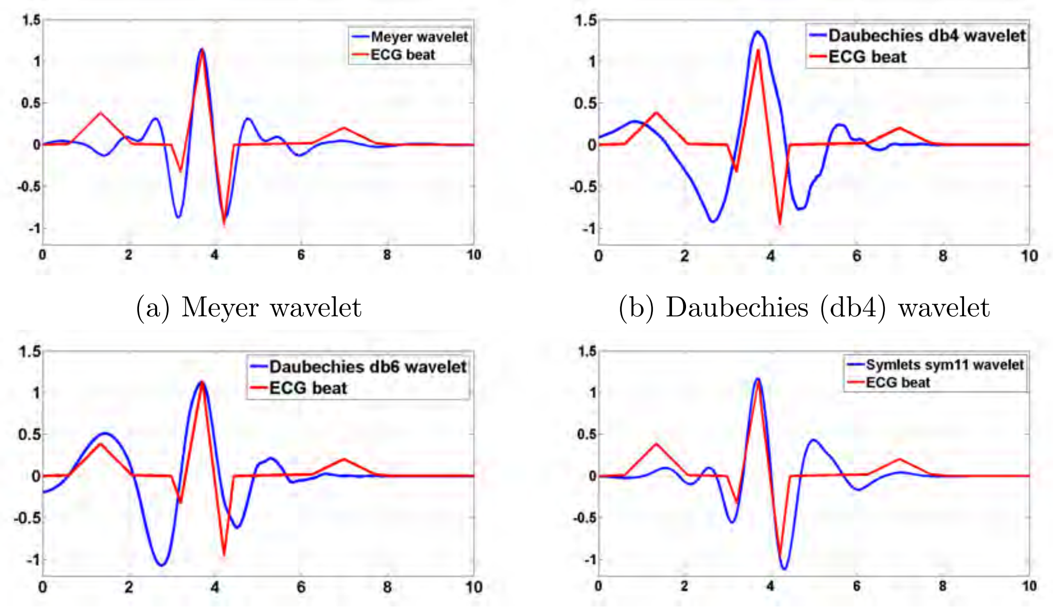


Figure 3.11: Wavelet Packet Decomposition Tree

3.4.3.3 Selection of Mother Wavelet

Selection the mother wavelet in the WPD procedure is very important task. As there is no universal rule that is suggested to select a particular mother wavelet, the selection depends upon the characteristics of the signal to be analyzed. The mother wavelet having similarity or resemblance to the signal being analyzed is usually chosen [63]. There are several wavelet families, namely Harr, Daubechies, Biorthogonal, Coi ets, Symlets, Morlet, Mexican Hat, Meyer etc. and several other real and complex wavelets.

In Fig. 3.12, plots representing the shapes of some mother wavelets are shown. An ECG beat is superimposed on each plot in Fig. 3.12 in order to compare it with the mother wavelet. It is seen from this figure that Symlets (sym11) provides better resemblance to the ECG beat than others. Detail analysis demonstrates that since, for the sym11 wavelet, energy spectrum is mainly concentrated around low frequencies as that in ECG, it is chosen for extracting features in the proposed method of cardiac beat classification[63].



(a) Meyer wavelet

(b) Daubechies (db4) wavelet

(c) Daubechies (db6) wavelet

(d) Symlets (sym11) wavelet

Figure 3.12: Different mother wavelets along with ECG beat: a) Meyer wavelet b) Daubechies (db4) wavelet c) Daubechies (db6) wavelet and d) Symlets (sym11) wavelet.

3.4.3.4 Rationale behind Selection of 4-Level Detail and Approximation coefficients

Since, both the approximation and the detail coefficients are decomposed into two parts at each level of decomposition, a complete binary tree with superior frequency localization can be achieved. Thus the wavelet packet transform provides a closer approximation of the ECG data set. For an ECG signal $x(n)$ of length N, the normalized energy can be found as

$$E = \frac{1}{N}\sum_{n=1}^{N} x^2[n] \tag{3.10}$$

The WPD approximate and detail coefficients are shown in Fig.3.13 and Fig. 3.14. From the figure it is shown that the normalized energy of the sum of detail and approximate WPD coefficients at the 4th level is the highest among that of the WPD coefficients at the other levels. Since, the 4th level WPD coefficients carry the dominant information of ECG signal in terms of normalized energy, so the 4th level detail and approximate WPD coefficients are considered for feature extraction.

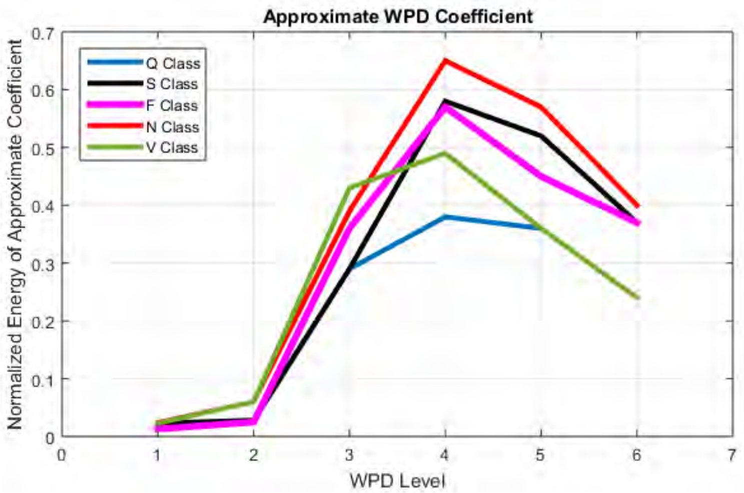


Figure 3.13: WPD Approximate coefficients of the dominant IMFs for AAMI cardiac beat classes

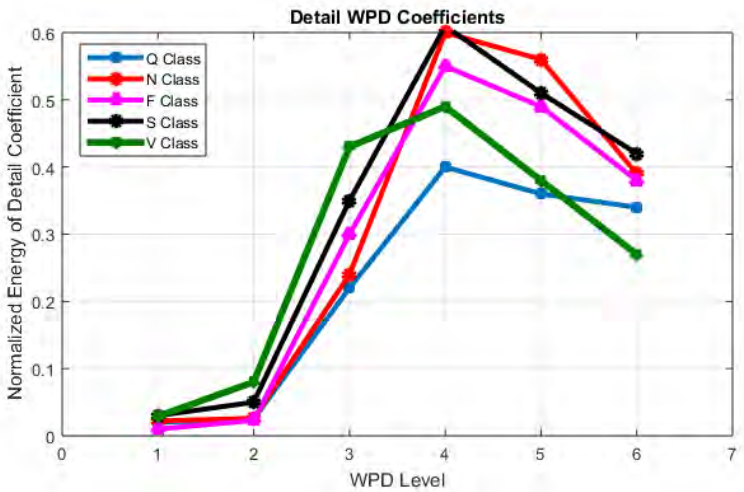


Figure 3.14: WPD Detail coefficients of the dominant IMFs for AAMI cardiac beat classes

3.4.4 Higher Order Statistics of the WPD Coefficients

Features extracted from these WPD coefficients can efficiently represent the characteristics of the original ECG signal in different details. A main difficulty of ECG cardiac beat classification is the search of reliable features which represents ECG beats the best.In recent years the field of HOS has continued its expansion, and applications have been found in fields as diverse as economics, speech, seismic data processing, plasma physics and optics. Higher order statistics (HOS) have been applied successfully to extract features for good classification [64].

HOS measures are extensions of second-order measures (such as the autocorrelation function and power spectrum) to higher orders. The second-order measures work fine if the signal has a Gaussian (Normal) probability density function, but as mentioned above, many real-life signals are non-Gaussian. Higher-order spectra are not sensitive to a Gaussian signal, which can be used to restrain noise, and it can be used to detect a nonlinear signal. The conventional power spectrum density provides information on the second-order properties (i.e., energy) of a signal, whereas the bispectrum can provide information on the signal's third-order properties. In a physical sense, the bispectrum provides insight into the nonlinear coupling between frequencies (as it involves both amplitudes and phases) of a signal compared to the traditional power spectrum density, which gives only the content of different frequencies and their amplitudes in a signal. Traditional correlation and power spectral analysis based on a Fourier transform could not extract useful information from the nonstationary and nonlinear signals, because in principle, a Fourier transform is based on the assumption that the signals are stationary. Higher-order spectra have been proven to be effective in handling nonstationary and nonlinear signals, which are able to capture the characteristic frequencies, identify phase information, and quantify nonlinear properties. When various frequency components in the signal interact with each other due to nonlinear physical phenomena, new combinations of frequencies are generated in the form of the sum, difference, or fraction of the interacting frequencies. Those frequency components are phase-coupled to the primary interacted frequencies. Higher-order spectra use this phase-coupling signature between frequency components to detect nonlinearities.

By using HOS of sub-band signals, it becomes possible to define hidden features embedded in the QRS complex.
Let $X[n]$ is real, discrete time random process. The moments of $X[n]$ are defined

as the coefficients in Taylor series expansion of the moment generating function

$$\phi_x(\omega) = E[\exp(j\omega x)] \tag{3.11}$$

For zero mean discrete time signal, moments and cumulants are defined as:

$$m_2[i] = E[X[n], X[n+i]] \tag{3.12}$$

$$m_3[i,j] = E[X[n], X[n+i].X[n+j]] \tag{3.13}$$

$$m_4[i,j,k] = E[X[n], X[n+i].X[n+j].X[n+k]] \tag{3.14}$$

where E[.] is defined as the expectation operation, X[.] is the random process. The second characteristic function of $X[n]$, defined as:

$$X[\omega] = ln\phi x[\omega] = lnE[exp(j\omega x)] \tag{3.15}$$

is called the cumulant generating function, and the coefficients in its Taylor expansion are the nth-order cumulants of $X[n]$. The cumulants are defined as

$$c_2[i] = m_2[i] \tag{3.16}$$

$$c_3[i,j] = m_3[i,j] \tag{3.17}$$

$$c_4[i,j,k] = m_4[i,j,k] - A - B - C \tag{3.18}$$

where $A = m_2[i]m_2[j-k]$,$B = m_2[j]m_2[k-i]$) and $C = m_2[k]m_2[i-j]$ The second, third and fourth order cumulants are calculated for each beat taking lag 0. The zero-lag cumulants have special names: $c_2(0)$ is the variance and is denoted by σ^2 ; $c_3(0,0)$ and $c_4(0,0,0)$ are denoted by $\gamma_3 x$ and $\gamma_4 x$ known as skewness and kurtosis, respectively.

Finally, the proposed feature vector is formed as follows

$$F = \begin{pmatrix} V_a & S_a & K_a & V_d & S_d & K_d \end{pmatrix} \tag{3.19}$$

where V, S, and K represent the variance, skewness and kurtosis for WPD coefficients of the dominant IMFs of ECG beats. Here subscript a is used for indicating approximate and d for detail WPD coefficients.

3.5 Classification

Once a set of features has been obtained to classify AAMI cardiac beat classes , it is necessary to apply a classification method in order to classify the ECG beat classes. Just as a wide variety of features has been used, an equally varied set of classification methods can be found in the literature. In this work, the k nearest neighbor (KNN) classifier has been used as the classifier.

3.5.1 k-NN Classifier

k-NN classifier was adopted in some literatures for its simplicity fact and wide ranging use in patterns categorization. k-NN classifier is based on learning by analogy[17].It considers a distance function which is computed between the test set and train set of ECG beat classes. The ECG pattern from the test set is classified based on the class labels of k closer ECG patterns. In the proposed method, the Euclidean distance is used. To calculate the distance between A and B, the normalized Euclidean metric is generally used by

$$dist(A, B) = \sqrt{\frac{\sum_{i=1}^{m}(x_i - y_i)^2}{m}} \tag{3.20}$$

In the KNN classifier, it is required to find a suitable value of k for achieving the best classification performance.In the proposed method, the value of k is varied within a large range and it is found that because of the better feature quality, consistent performance is achieved.

3.6 Conclusion

The Electrocardiogram (ECG) is the most important bio-signal which is analyzed for the diagnosis of any heart-related diseases. Conventional time or frequency domain analysis is found inadequate to describe the characteristics of a non-stationary signal such as ECG. Moreover, conventional time-frequency analysis has the limitation of being computationally expensive. In this chapter, we propose to transform the ECG data by wavelet packet decomposition (WPD) in order to get the dominant IMF. The transformed data thus obtained is exploited to formulate a feature vector consisting of higher order statistics of only the 4th level WPD detail and approximation coefficients that can better model the characteristics of the ECG data. The feature vector is fed to Euclidean distance classifier in order to classify the AAMI cardiac beat classes. A number of simulations are carried out using selected number of ECG beats from records of the MIT-BIH (Massachusetts Institute of Technology - Boston's Beth Israel Hospital) arrhythmia database. It is shown that the proposed method based on higher order statistics of WPD detail and approximate coefficient is capable of producing greater accuracy in comparison to that obtained by using a state-of-the-art method of ECG cardiac beat classification using the same classifier and ECG beats.

Chapter 4

Cardiac Beat Classification Exploiting Wavelet Packet Decomposition of dECG and Modified dECG Signals

4.1 Introduction

Modern era of medical science is supported by computer aided feature extraction and disease diagnostics in which various signal processing techniques have been utilized in extracting features from the biomedical signals and analyzes these features. The objective of computer aided digital signal processing of ECG signal is to reduce the time taken by the cardiologists in interpreting the results. A typical ECG wave of a normal heartbeat consists of a P wave, a QRS complex, and a T wave. The P wave represents the se-quential depolarization of the right and left atria. A normal P wave is usually considered to be of low frequency, below 10–15 Hz. The QRS complex corresponds to depolarization of the right and left ventricles. The frequency content of the QRS complex is considerably higher than that of the other ECG waves, and is mostly concentrated in the interval of 10–40 Hz. The T wave reflects ventricular repolarization and extends about 300 milliseconds after the QRS complex. In this chapter, the derivative of electrocardiogram (ECG) signal, which we refer to as dECG, instead of the ECG signal has been used. It is shown that the derivative of the ECG signal (dECG) provides a better estimation for the QRS complex modeling [65]. In view of obtaining robust features, unlike conventional methods that mostly utilize directly the ECG signal, a dECG signal is first modified and then time and wavelet domain features are extracted.

4.2 Proposed dECG Based Method

In this chapter, first, the preprocessing of the ECG signal is done, then, the modified dECG from the ECG signal is derived. Derivative of the ECG signal, namely dECG, has various definitions that are in practice, such as two point first derivative, three point first derivative, smoothed three point central difference and seven point first derivative. Smoothed three point central difference has the advantageous property of providing a more accurate estimation of the QRS complex of the ECG signal [66]. The smoothed three point central difference for an ECG signal $x(n)$, namely dECG signal, can be obtained as

$$y(n) = x(n+1) - x(n-1) \tag{4.1}$$

A dECG signal calculated from equation 4.1 is presented on Fig. 4.1.From the derived ECG Signal (dECG) the features are obtained to classify the AAMI cardiac beat classes.

(a) One Bit of ECG Signal (b) dECG Signal

Figure 4.1: (a) One bit of ECG signal, (b) dECG signal obtained from the ECG beat from (a)

Firstly, a set of IMFs is obtained through EMD of dECG signals.Then, the dominant IMF has been selected via analyzing the temporal contents of the resultant IMFs from EMD analysis. To obtain further discriminatory behavior, discrete wavelet packet decomposition (WPD) is employed on the dominant IMF. After that the 4th Level detail and approximate WPD coefficients of the selected IMFs are obtained for feature computation. For further reduction of the dimension of the feature vector, higher order statistics of these coefficients are employed to form the feature vector. kNN classifier is used for distinguishing and classifying the multiclass cardiac beat classes.The simplified block diagram of the proposed method is shown in Fig. 4.2.

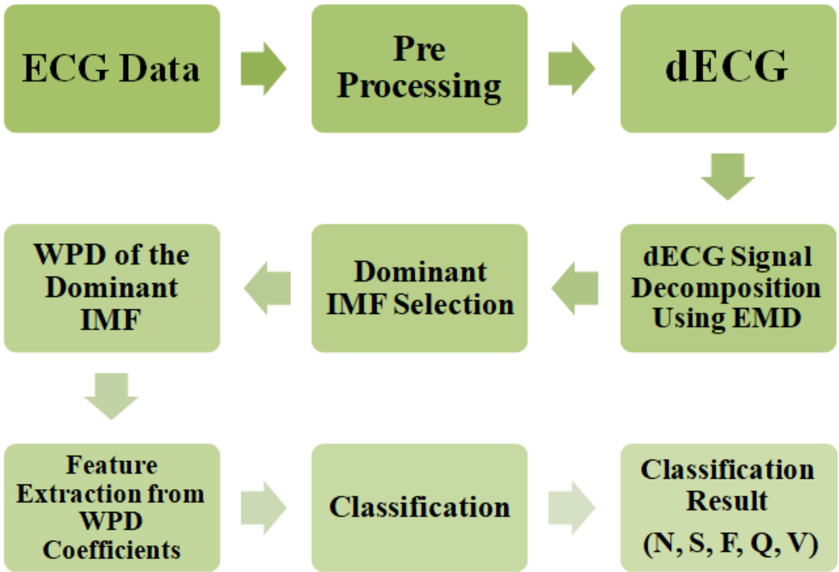


Figure 4.2: Simplified Block Diagram of the Proposed Method using dECG

4.2.1 Feature Extraction

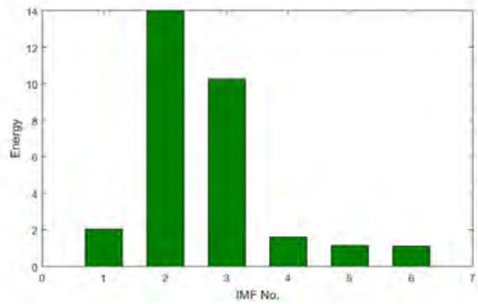
The pre-processed dECG signal $y[n]$, obtained using equation 4.1 is decomposed into a series of stationary and linear IMFs using EMD. A typical dECG signal and the resulting IMFs are shown in Fig. 4.3.

After the selection of the dominant IMF, it is decomposed in the wavelet packet domain. Since, both the approximation and the detail coefficients are decomposed into two parts at each level of decomposition, a complete binary tree with superior frequency localization can be achieved. In this work a 4-level WPD decomposition using Haar wavelet for detail and approximate coefficient extraction have been used.

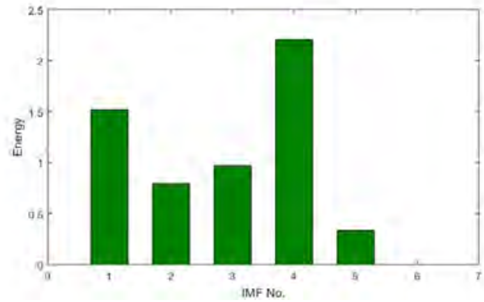
From the WPD coefficients the characteristics of the dECG signal can be represented in different details. In Fig.4.4 and Fig. 4.5, WPD coefficients of the dominant IMFs for AAMI cardiac beat classes are plotted.
In Higher order statistics (HOS) have been applied successfully to extract features for good classification of dECG beats $y[n]$ obtained from equation 4.1. Among different HOS features, in the proposed method, variance, skewness and kurtusis are used for feature extraction. From equation 4.1 the proposed feature vector is formed as

$$F = \begin{pmatrix} V_{ad} & S_{ad} & K_{ad} & V_{dd} & S_{dd} & K_{dd} \end{pmatrix} \tag{4.2}$$

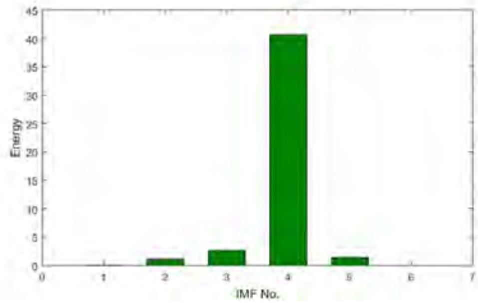
where, V , S, and K represent the variance, skewness and kurtosis for WPD coefficients of the dominant IMFs of dECG beats. Here subscript ad is used for



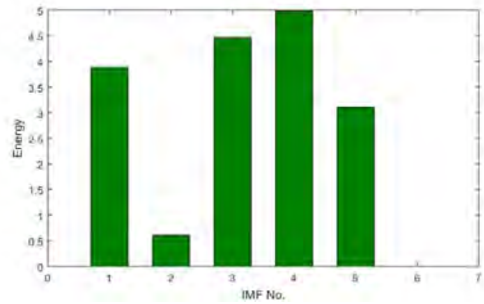
(a) Energy Pattern of IMFs of N Class dECG



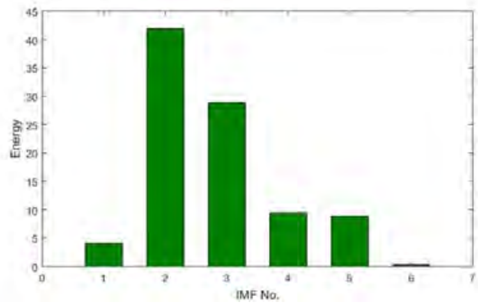
(b) Energy Pattern of IMFs of S Class dECG



(c) Energy Pattern of IMFs of F Class dECG



(d) Energy Pattern of IMFs of Q Class dECG



(e) Energy Pattern of IMFs of V Class dECG

Figure 4.3: Temporal energy pattern of IMFs obtained from dECG

indicating approximate and dd for detail WPD coefficients.

4.2.2 Classification

Once a set of features has been obtained to classify AAMI cardiac beat classes , it is necessary to apply a classification method in order to classify the dECG beat classes. Just as a wide variety of features has been used, an equally varied set of classification methods can be found in the literature. In this work, the k nearest neighborhood (KNN) classifier has been used as the classifier.

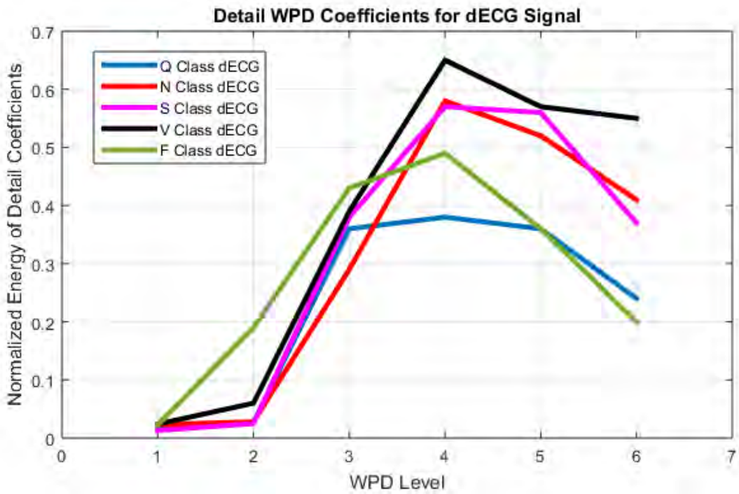


Figure 4.4: WPD Detail coefficients of the dominant IMFs for AAMI cardiac beat classes for dECG signals

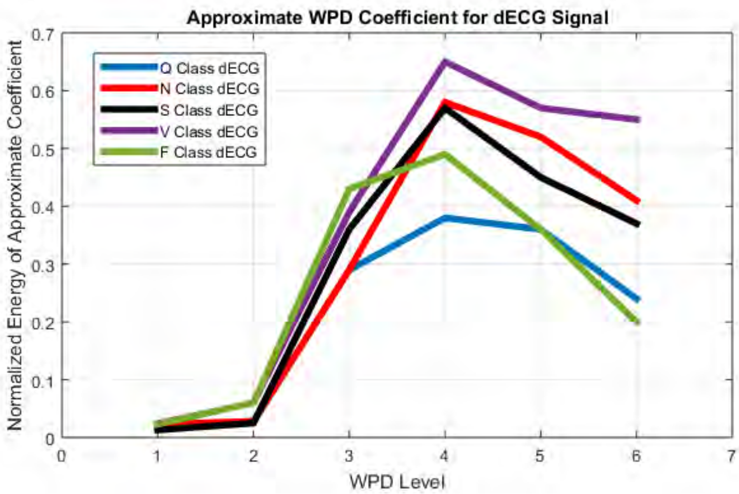


Figure 4.5: WPD Approximate coefficients of the dominant IMFs for AAMI cardiac beat classes for dECG signals

4.3 Proposed Modified dECG Based Method

The purpose of smoothed three point central difference for an ECG signal $x(n)$ named dECG signal is the relative suppression of P and T peaks with respect to the QRS peak, which becomes prominent after the operation. From Fig. 4.6 it is found that the prominent zero crossing in dECG corresponds to the R peak in ECG. As mentioned before, the dECG operation helps in better detection of the QRS complex. A modification in the dECG calculation is proposed as follows[67]

$$y(n) = x(n+1) + x(n) - x(n-1) \tag{4.3}$$

This modified dECG approach offers a good compromise between retaining characteristics of P and T peaks and obtaining a better QRS complex. A modified dECG signal calculated using equation 4.2 is presented on Fig. 4.6. From the modified

Figure 4.6: (a) One bit of ECG signal, (b) dECG signal obtained from the ECG beat from (a), (c) Modified dECG signal for the ECG beat from Fig. (a) and (b)

dECG the features are obtained to classify the AAMI cardiac beat classes. The simplified block diagram of the proposed method is shown in Fig.4.7.

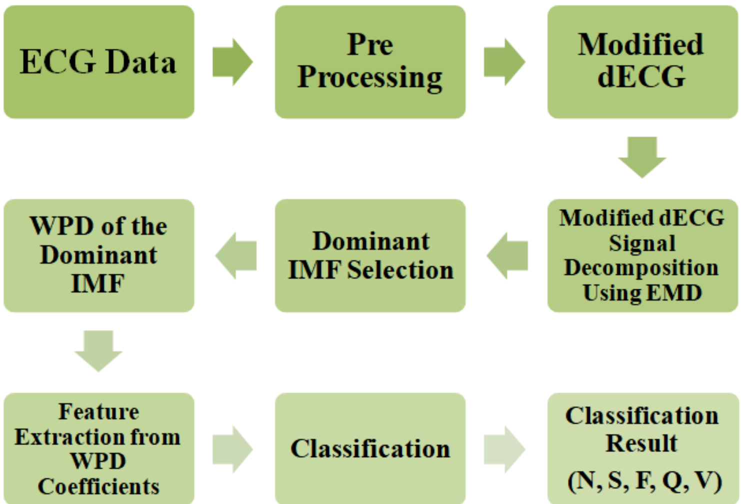
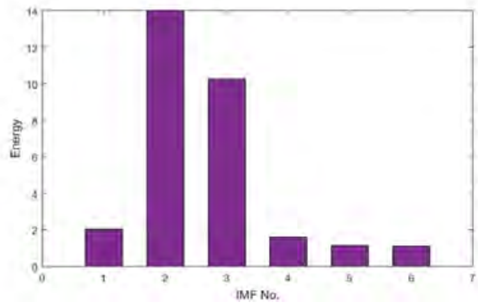


Figure 4.7: Simplified Block Diagram of the Proposed Method using modified dECG

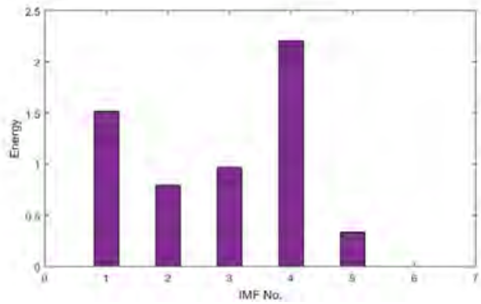
4.3.1 Feature Extraction

The modified dECG signal $y[n]$, obtained using equation 4.2 is decomposed into IMFs. The resulting IMFs are shown in Fig. 4.8

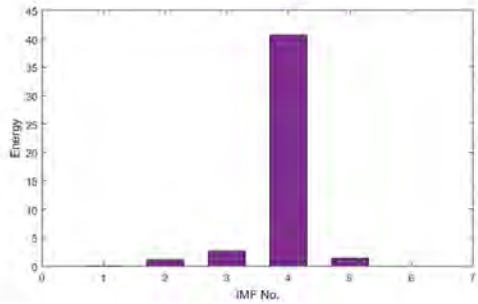
After the selection of the dominant IMF, it is decomposed in the wavelet packet domain. Since, both the approximation and the detail coefficients are decomposed into two parts at each level of decomposition, a complete binary tree with superior frequency localization can be achieved. In this work a 4-level WPD decomposition using Haar wavelet for detail and approximate coefficient extraction have been



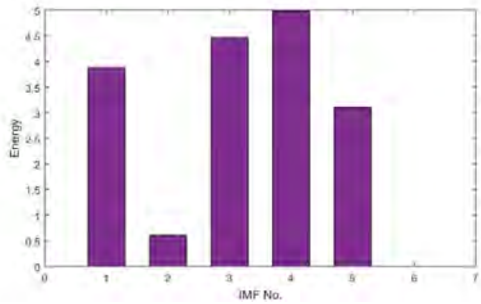
(a) Energy Pattern of IMFs of N Class Modified dECG



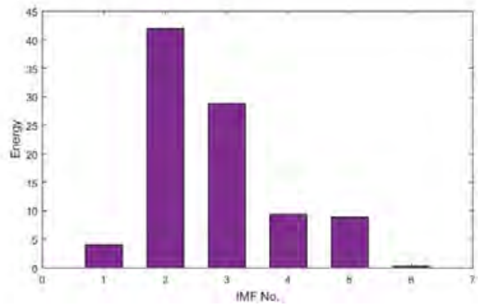
(b) Energy Pattern of IMFs of S Class Modified dECG



(c) Energy Pattern of IMFs of F Class Modified dECG



(d) Energy Pattern of IMFs of Q Class Modified dECG



(e) Energy Pattern of IMFs of V Class Modified dECG

Figure 4.8: Temporal energy pattern of IMFs obtained from Modified dECG

used. In Fig.4.9 and Fig. 4.10, WPD coefficients of the dominant IMFs for AAMI cardiac beat classes are plotted.

From the WPD coefficients the characteristics of the modified dECG signal can be represented in different details. In Higher order statistics (HOS) have been applied successfully to extract features for good classification of modified dECG beats $y[n]$ obtained from equation 4.2.Among different HOS features, in the proposed method, variance, skewness and kurtusis are used for feature extraction.The proposed feature vectors are formed as follows:

$$F = \begin{pmatrix} V_{am} & S_{am} & K_{am} & V_{dm} & S_{dm} & K_{dm} \end{pmatrix} \tag{4.4}$$

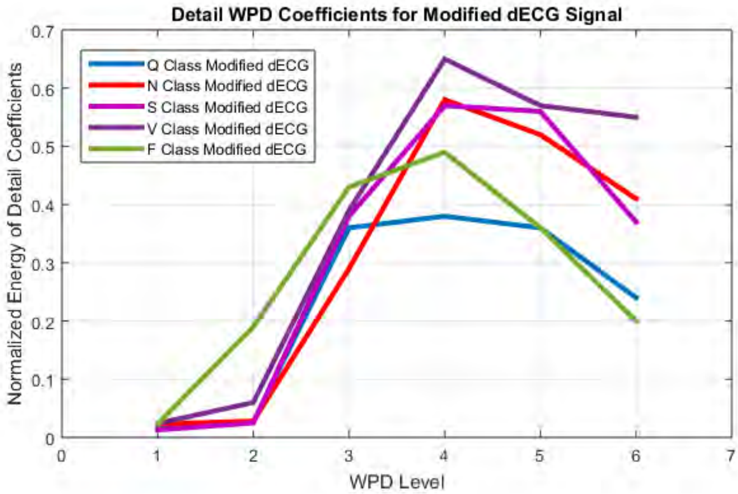


Figure 4.9: WPD Detail coefficients of the dominant IMFs for AAMI cardiac beat classes for Modified dECG signals

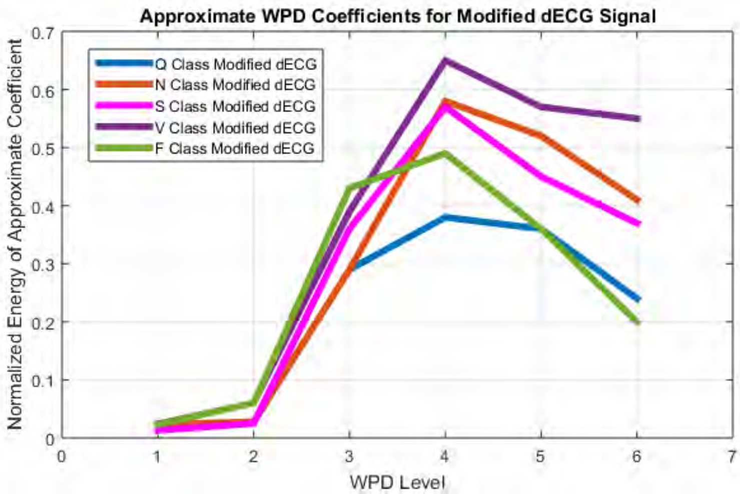


Figure 4.10: WPD Approximate coefficients of the dominant IMFs for AAMI cardiac beat classes for Modified dECG signals

where, V , S, and K represent the variance, skewness and kurtosis for WPD coefficients of the dominant IMFs of modified dECG beats. Here subscript am is used for indicating approximate and dm for detail WPD coefficients.

4.3.2 Classification

Once a set of features has been obtained to classify AAMI cardiac beat classes , it is necessary to apply a classification method in order to classify the dECG and modified dECG beat classes. Just as a wide variety of features has been used, an equally varied set of classification methods can be found in the literature. In this work, the k nearest neighborhood (KNN) classifier has been used as the classifier.

4.4 Conclusion

The Electrocardiogram (ECG) is the most important bio-signal which is analyzed for the diagnosis of any heart-related diseases. Since conventional time or frequency domain analysis is found inadequate to describe the characteristics of a non-stationary signal, such as ECG, in this chapter, we propose to obtain the data from the smoothed three point central difference for an ECG signal named dECG signal and modified dECG signal. In this chapter, the dECG and modified dECG data is transformed by wavelet packet decomposition (WPD) in order to get the dominant IMF. The transformed data thus obtained is exploited to formulate a feature vector consisting of higher order statistics of only the 4th level WPD detail and approximation coefficients that can better model the characteristics of the dECG and modified dECG data. The feature vector is fed to Euclidean distance classifier in order to classify the AAMI cardiac beat classes. A number of simulations are carried out using selected number of ECG beats from records of the MIT-BIH (Massachusetts Institute of Technology - Boston's Beth Israel Hospital) arrhythmia database. It is shown that the proposed method based on higher order statistics of WPD detail and approximate coefficient is capable of producing greater accuracy in comparison to that obtained by using a state-of-the-art method of ECG cardiac beat classification using the same classifier and ECG beats.

Chapter 5

Simulation Results

Performance evaluation of the proposed methods for classifying AAMI cardiac beat classes is an important task. A number of simulations are carried out to evaluate the performance of the proposed methods. Performance of proposed method is compared with a state-of-the-art method for the evaluation purpose.The popular MIT-BIH arrhythmia database is used for extracting different ECG beats for simulation.

5.1 Data Acquisition

In the proposed method, we have employed MIT-BIH (Massachusetts Institute of Technology-Boston's Beth Israel Hospital) arrhythmia database [68]. All ECG data are obtained from this database. The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings are chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings are selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample. The recordings are digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range.

The Association for the Advancement of Medical Instrumentation (AAMI) recommended practice is used to combine the MIT-BIH cardiac beat types into five cardiac beat classes, which are used in all subsequent processing. The AAMI convention is used to combine the beats into five classes of interest: normal beat, left bundle branch block (LBBB), right bundle branch block (RBBB), and atrial escape and nodal junction escape beats belong to class N category; class V contains premature ventricular contraction (PVC) and ventricular escape beats, class S contains atrial premature (AP), aberrated premature (aAP), nodal junction premature (NP), and supraventricular premature (SP) beats, class F contains only fusion of ventricular and normal (fVN) beats, and class Q which is known as unknown beat contains paced beat (P), fusion of paced and normal (fPN) beats, and unclassified beats. Five AAMI cardiac beat classes are shown in Fig. 5.1

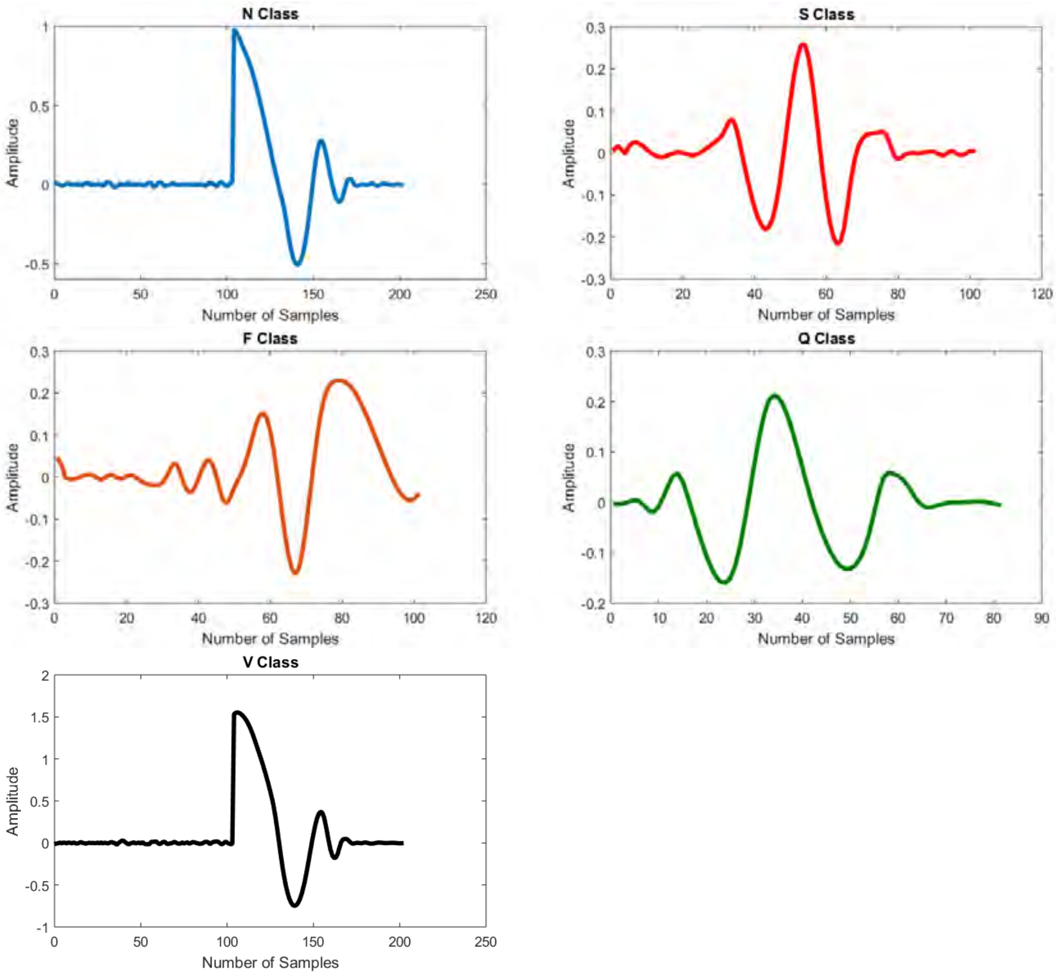


Figure 5.1: Five classes of ECG beat (a) Non-ectopic (N), (b) supraventricular ectopic (S), (c) fusion (F), (d) unknown (Q), and (e) ventricular ectopic (V)

For the purpose of comparison, we have implemented the state-of-the-art methods of [30] and compared those with the proposed method.In Table 5.2, the number of the ECG file that is used from the MIT-BIH database is shown. It is seen from this table that we have employed ECG signals from patients. Here, in every case, 50% of feature data are selected randomly for the purpose of training and testing.

Table 5.1: Mapping of MIT-BIH arrhythmia database heartbeat types to the AAMI heartbeat classes

AAMI heartbeat classes	**MIT-BIH heartbeat classes**
Non-ectopic beats (N)	Normal beat Left bundle branch block beat Right bundle branch block beat Nodal(junctional)escape beat Atrial escape beat
Supraventricular ectopic beats(S)	Aberrated atrial premature beat Premature or ectopic supraventricular beat Atrial premature contraction Nodal (junctional) premature beat
Fusion beats (F)	Fusion of ventricular and normal beat
Ventricular ectopic beats (V)	Ventricular flutter wave Ventricular escape beat Premature ventricular contractione
Unknown beats (Q)	Paced beat Unclassified beat Fusion of paced and normal beat

Table 5.2: AAMI Cardiac beat class and MIT-BIH database file number

AAMI cardiac beat class	**MIT-BIH file**
N	100, 112, 122, 123, 109, 111, 207, 214, 118, 124, 212, 231
S	101, 102, 103, 108
F	108, 200, 205, 208, 210, 213, 215, 219
V	100, 105, 108, 116, 123, 200, 203, 205, 208, 209, 210, 213, 215, 217, 219, 221, 231, 234
Q	102, 104, 107, 217

5.2 Performance Evaluation Criteria

For the performance evaluation of the proposed methods, criteria considered in our simulation study are: 1) Clustering analysis and 2) Confusion matrix. For the purpose of comparison, we use state-of-the-art method [30].

5.2.1 Clustering Analysis

The effectiveness of the proposed feature sets in classifying the AAMI five classes cardiac beat in terms of clusters is justified by the inter-class separability and intraclass compactness of the feature. Among different statistical measures, we employ Geometrical Separability Index (GSI) and Bhattacharya distance (BD) to quantitatively show the cluster-to-cluster distance and cluster dispersion in case of AAMI five class cardiac beats.

5.2.1.1 Geometrical Separability Index

Geometrical Separability Index (GSI) shows the numerical demonstration of inter class distance. Based on the nearest neighbor aptitude measurement, it reports a clue to which degree two classes can be considered as separable or inseparable.
GSI, also known as Thornton's separability index s is defined as the fraction of a set of data points whose classification labels are the same as those of their nearest neighbours. Thus, it is a measure of the degree to which inputs associated with the same output tend to cluster together [69]. It may be written

$$s = \sum_{i=1}^{n} \frac{(f(x_i) + \ f(x_i^{'}) + 1)mod2}{n} \tag{5.1}$$

Where, x′ is the nearest neighbour of x and n is the number of points.
It is intuitively obvious that s will be close to '1' for a set of points in which those with opposite labels exist in tight, well-separated clusters. As the clusters move closer together and points from opposing classes begin to overlap, the index will begin to fall. If the centroids of the clusters coincide, or the points are uniformly distributed in the space without clustering, the nearest neighbour of a point will have no more than a 50% probability of having the same class label as its neighbour, and the separability index will be close to 0.5. A regular intermeshed grid of alternately-labelled points (as would be generated by the exclusive-OR or parity problems) would have s = 0.

5.2.1.2 Bhattachariyya Distance

In statistics, the Bhattacharyya distance measures the similarity of two probability distributions. It is closely related to the Bhattacharyya coefficient which is a measure of the amount of overlap between two statistical samples or populations. The coefficient can be used to determine the relative closeness of the two samples being considered. It is used to measure the separability of classes in classification.

The class with smaller BD value shows strong compactness of its features.
In its simplest formulation, the Bhattacharyya distance between two classes under the normal distribution can be calculated [70] by extracting the mean and variances of two separate distributions or classes:

$$D_B(p,q) = \frac{1}{4}ln\left(\frac{1}{4} + \left(\frac{\sigma_p^2}{\sigma_q^2} + \frac{\sigma_q^2}{\sigma_p^2} + 2\right)\right) + \frac{1}{4}\left(\frac{(\mu_p - \mu_q)^2}{\sigma_p^2 + \sigma_q^2}\right) \tag{5.2}$$

where: $D_B(p,q)$ is the Bhattacharyya distance between p and q distributions or classes,
σ_p^2 is the variance of the p-th distribution,
μ_p is the mean of the p-th distribution, and
p, q are two different distributions.

5.2.2 Confusion Matrix

For the performance evaluation of the proposed method, criteria considered in our simulation study are: 1) Sensitivity 2) Specificity 3) Selectivity and 4) Accuracy. These indices have been calculated from confusion matrix which is a way of showing the assessment result from a classification test.
The columns in the matrix stand for the actual classes to be tested and rows provide the class classified by a method. In particular, any [row, column] entry in the confusion matrix indicates the number of cases from the test database that belongs to the class corresponding to the column but classified as the class corresponding to the row. In Fig. 5.2, a general confusion matrix for five class problem is shown, where TP , FP , FN and TN are represented for class i.

In general, TP_i, true positive for any class i, denotes the number of testing cases, which are correctly classified as class i.
FP_i, false positive for any class i, measures the number of testing cases, which are incorrectly classified as class i.
FN_i, false negative for any class i, measures the number of testing cases, which are incorrectly classified as other than class i.
TN_i, true negative for any class i, denotes the number of testing cases, which are correctly classified as other than class i.
In Fig. 5.2, a general confusion matrix with respect to set N for a five class problem is shown.

Output Class (Detected by the Classifier) \ Actual Class	N	S	F	Q	V
N	TP_N	FP_N	FP_N	FP_N	FP_N
S	FN_N	TN_N	TN_N	TN_N	TN_N
F	FN_N	TN_N	TN_N	TN_N	TN_N
Q	FN_N	TN_N	TN_N	TN_N	TN_N
V	FN_N	TN_N	TN_N	TN_N	TN_N

Figure 5.2: Confusion Matrix for Five Class AAMI beat Class with respect to N Class

5.2.2.1 Sensitivity

Sensitivity refers to the test's ability to correctly detect ill patients who do have the condition. In the example of a medical test used to identify a disease, the sensitivity of the test is the proportion of people who test positive for the disease among those who have the disease. Mathematically, this can be expressed as:

$$\begin{aligned} Sensitivity &= \frac{number\ of\ true\ positives}{numer\ of\ true\ positives + number\ of\ false\ negatives} \\ &= \frac{TP}{TP + FN} \\ &= probability\ of\ positive\ test\ result\ given\ that\ the\ patient\ has\ the\ disease \end{aligned} \tag{5.3}$$

5.2.2.2 Specificity

Specificity relates to the test's ability to correctly reject healthy patients without a condition. In the example of a medical test used to identify a disease, Specificity of a test is the proportion of healthy patients known not to have the disease, who will test negative for it. Mathematically, this can also be written as:

$$\begin{aligned} Specificity &= \frac{number\ of\ true\ negatives}{numer\ of\ true\ negatives + number\ of\ false\ positives} \\ &= \frac{TN}{TN + FP} \\ &= probability\ of\ negative\ test\ result\ given\ that\ the\ patient\ is\ well \end{aligned} \tag{5.4}$$

5.2.2.3 Selectivity

Selectivity relates to the test's ability to correctly reject healthy patients without a condition. In the example of a medical test used to identify a disease, Specificity of a test is the proportion of healthy patients known not to have the disease, who will test negative for it. Mathematically, this can also be written as:

$$\begin{aligned} Selectivity &= \frac{number\ of\ true\ positive}{numer\ of\ true\ positive + number\ of\ false\ positives} \\ &= \frac{TP}{TP + FP} \\ &= probability\ of\ positive\ test\ result\ given\ that\ the\ patient\ is\ well \end{aligned} \tag{5.5}$$

5.2.2.4 Accuracy

Accuracy is one metric for evaluating classification models. Informally, accuracy is the fraction of predictions our model got right. Formally, accuracy has the following definition:

$$Accurracy = \frac{Number\ of\ Correct\ Predictions}{Number\ of\ Total\ Predictions} \tag{5.6}$$

Accuracy can also be calculated in terms of positives and negatives as follows:

$$Accurracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.7}$$

5.3 Performance Comparison of the Proposed Method Using ECG Data

This section presents the results of the proposed method based on HOS obtained from detail and approximate coefficient of WPD using ECG data. All ECG beats mentioned in Table 5.2 are processed for extracting HOS feature vectors. The performance of the proposed method is compared with the method [30] on the basis of the following performance evaluation criteria as described before.

5.3.1 Performance Comparison Using Clustering Analysis

Two statistical measures are utilized in order to show the clustering analysis, where inter-class separability and intra-class compactness of the proposed feature are highlighted. Thornton's separability index or geometric separability index (GSI) is a term that signifies the ability of a particular classification method in separating the clusters of any two classes as well as in reflecting the compactness between the clusters of the same class. The higher GSI value indicates the more separability between two classes under consideration, whereas lower GSI value stands for declaring the two classes as the same class[69].

GSI value of the features of comparison methods and proposed feature set using ECG data are shown in Table 5.3−5.4. In Table 5.4 the GSI index obtained using the proposed method using ECG data for each AAMI beat classes is shown. It is seen from Table 5.4 that each diagonal entry representing the same class has a value zero, whereas each entry other than the diagonal representing two different classes has a value close to one. Such GSI values indicate that the proposed HOS feature extracted from the WPD detail and approximate coefficient is capable of providing high separability between any two different classes as well as yielding high compactness for the same class.

From the Table 5.3−5.4 it is shown that the proposed three approaches show greater separability between any two classes.Thus, the proficiency of projected schemes to offer high separability among five classes in this work is established.

Bhattacharya distance (BD) is another term that signifies the ability of a particular classification method in reflecting the intra-class compactness of clusters of the same class [70]. Among different methods, the method yielding lower BD value indicates more compactness of its feature employed in the inter-patient analysis. BD value of comparison methods and the proposed feature set are shown in Table 5.5.

Table 5.3: Geometrical Separability Index(GSI) of the method in [30]

Classes	N	S	F	Q	V
N	0	0.98	0.9825	0.95	0.9825
S	0.98	0	0.9950	0.9675	1
F	0.9825	0.9950	0	0.9650	0.9950
Q	0.95	0.9675	0.9650	0	0.9475
V	0.9825	1	0.9950	0.9475	0

Table 5.4: Geometrical Separability Index(GSI) of the proposed method using ECG Data

Classes	N	S	F	Q	V
N	0	0.9950	1	1	1
S	0.9950	0	0.9975	1	1
F	1	0.9975	0	1	1
Q	1	1	1	0	1
V	1	1	1	1	0

It is found from the BD values of stated all features in Table 5.5, each entree corresponding to AAMI cardiac beat classes are having a value closing to ‘0’ which further shows the goodness of proposed feature set.

5.3.2 Performance Comparison Using Confusion Matrix

Among 10 iterations of random selection of training and testing datasets, for each iteration, confusion matrix representing the test classes along with the classified classes is obtained and sensitivity, specificity, selectivity and accuracy of each class are determined for the performance comparison. Table 5.6 and 5.7 represent the confusion matrices derived for method in [30] and the proposed method using ECG data respectively. In each table, the diagonal entries stand for the number of cases

Table 5.5: Bhattacharyya Distance(BD) values for method in [30] and the proposed method using ECG data

Class	BD Values (Method in [30])	BD Values (Proposed Method)
N	0.0085	0.0019
S	0.0159	0.0191
F	0.0104	0.0090
Q	0.0118	0.0141
V	0.0204	0.0473

when a particular AAMI cardiac beat class is correctly classified. From Table 5.7, it is found that, the proposed method based on using ECG data is capable of reducing the mis-classification while providing the similar correct classification rate for other classes of beats. For the proposed method and the method in [30], the average sensitivity, specificity, selectivity and accuracy of all AAMI beat classes are summarized in Tables5.8−5.9.

It is evident from Table 5.8 that the method in [30] produce relatively lower values of sensitivity for all five classes, whereas the proposed method using the ECG data yields higher sensitivity even in case of five AAMI beat classes for which the comparison method [30] produces the least sensitivity. Such high values of sensitivity attest the capability of the proposed method using ECG data in successfully classifying five AAMI cardiac beat classes. It can also be seen from Table 5.8 that for all beat classes, the comparison method [30] show lower values of specificity but the specificity is higher, as expected, for the proposed method using ECG data. It is observable that the specificity is much lower in case of Q class while employing the method in [30]. Since for a particular method, a higher specificity indicates a better classification, the proposed method based using ECG data is indeed better in performance. From Table 5.9 that for all beat classes, the comparison method [30] show lower values of selectivity but the selectivity is higher, for the proposed method using ECG data. Since for a particular method, a higher selectivity indicates a better classification, the proposed method based using ECG data is indeed better in performance. As demonstrated from Table 5.9 that the accuracy resulting from the other methods are comparatively lower for all AAMI cardiac beat clases, whereas the proposed method using ECG data is able to result in better classification performance as it gives higher accuracy for different classes considered.

Table 5.6: Confusion Matrix of Method in [30] Over 10 Iteration

	N	**S**	**F**	**Q**	**V**
N	95	5	3	13	1
S	2	93	3	3	0
F	2	1	91	5	0
Q	2	1	1	71	0
V	4	1	1	8	96

Table 5.7: Confusion Matrix of Proposed Method Using ECG data Over 10 Iteration

	N	**S**	**F**	**Q**	**V**
N	103	0	1	0	0
S	1	99	1	0	0
F	0	0	97	0	0
Q	0	0	1	100	0
V	0	0	0	0	98

Table 5.8: Comparison Between Proposed Method Using ECG Data and the Method in [30] in terms of Average Sensitivity(in %) and Average Specificity(in %)

ECG beat Class	**Sensitivity of Method in [30]**	**Sensitivity of Proposed Method Using ECG Data**	**Specificity of Method in [30]**	**Specificity of Proposed Method Using ECG Data**
N	81.2	99.0	97.4	99.8
S	92.1	98.0	98.0	100.0
F	91.9	100.0	98.0	99.3
Q	94.7	99.0	93.2	100.0
V	87.3	100.0	99.7	100.0
Avg	89.4	99.2	97.2	99.8

Table 5.9: Comparison Between Proposed Method Using ECG Data and the Method in [30] in terms of Average Selectivity(in %) and Average Accuracy (in %)

ECG beat Class	**Selectivity of Method in [30]**	**Selectivity of Proposed Method Using ECG Data**	**Accuracy of Method in [30]**	**Accuracy of Proposed Method Using ECG Data**
N	90.5	99.0	93.63	99.6
S	92.1	100.0	96.81	99.6
F	91.9	97.0	96.81	99.4
Q	71.0	100.0	93.43	99.8
V	98.9	100.0	97.01	100.0
Avg	88.9	99.2	95.6	99.7

5.4 Performance Comparison of the Proposed Method Using dECG Data Approach

This section presents the results of the proposed method based on HOS obtained from detail and approximate coefficient of WPD using modified dECG data $y(n)$. The performance of the proposed method is compared with the method [30] on the basis of the following performance evaluation criteria as described before.

5.4.1 Performance Comparison Using Clustering Analysis

GSI value of features of comparison methods and the proposed feature set using dECG data are shown in Table 5.10−5.11. In Table 5.11 the GSI index obtained using the proposed method using modified dECG data for each AAMI beat classes is shown. It is seen from Table 5.11 that each diagonal entry representing the same class has a value zero, whereas each entry other than the diagonal representing two different classes has a value close to one. Such GSI values indicate that the proposed HOS feature extracted from the WPD detail and approximate coefficient is capable of providing high separability between any two different classes as well as yielding high compactness for the same class.
From the Table 5.10−5.11 it is shown that the proposed approaches show greater separability between any two classes.Thus, the proficiency of projected schemes to offer high separability among five classes in this work is established.
BD value of features of comparison methods and the proposed feature set are shown in Table 5.12. It is found from the BD values of stated all features in Table 5.12, each entree corresponding to AAMI cardiac beat classes are having a value closing to '0' which further shows the goodness of proposed feature set.

Table 5.10: Geometrical Separability Index(GSI) of the method in [30]

Classes	**N**	**S**	**F**	**Q**	**V**
N	0	0.98	0.9825	0.95	0.9825
S	0.98	0	0.9950	0.9675	1
F	0.9825	0.9950	0	0.9650	0.9950
Q	0.95	0.9675	0.9650	0	0.9475
V	0.9825	1	0.9950	0.9475	0

Table 5.11: Geometrical Separability Index(GSI) of the proposed method using dECG Data

Classes	**N**	**S**	**F**	**Q**	**V**
N	0	1	1	1	1
S	1	0	1	1	1
F	1	1	0	1	1
Q	1	1	1	0	1
V	1	1	1	1	0

Table 5.12: Bhattacharyya Distance(BD) values for the method in [30] and Proposed Method Using dECG

Class	**BD Values(Method in [30])**	**BD Values(Proposed Method Using dECG)**
N	0.0085	0.0023
S	0.0159	0.0282
F	0.0104	0.0050
Q	0.0118	0.0248
V	0.0204	0.0443

5.4.2 Performance Comparison Using Confusion Matrix

Among 10 iterations of random selection of training and testing datasets, for each iteration, confusion matrix representing the test classes along with the classified classes is obtained and sensitivity, specificity, selectivity and accuracy of each class are determined for the performance comparison. Table 5.13 and 5.14 represent the confusion matrices derived for method in [30] and the proposed method using dECG data respectively. In each table, the diagonal entries stand for the number of cases when a particular AAMI cardiac beat class is correctly classified. From Table 5.14, it is found that, the proposed method based on using dECG data is capable of reducing the mis-classification while providing the similar correct classification rate for other classes of beats.

Table 5.13: Confusion Matrix of Method in [30] Over 10 Iteration

	N	**S**	**F**	**Q**	**V**
N	95	5	3	13	1
S	2	93	3	3	0
F	2	1	91	5	0
Q	2	1	1	71	0
V	4	1	1	8	96

Table 5.14: Confusion Matrix of Proposed Method Using dECG data Over 10 Iteration

	N	**S**	**F**	**Q**	**V**
N	99	0	0	0	0
S	0	101	0	0	0
F	0	0	99	0	0
Q	0	0	0	102	0
V	0	0	0	0	98

For the proposed method and the method in [30], the average sensitivity, specificity, selectivity and accuracy of all AAMI beat classes are summarized in Tables5.15−5.16. It is evident from Table 5.15 that the method in [30] produce relatively lower values of sensitivity for all five classes, whereas the proposed method using the dECG data yields higher sensitivity even in case of five AAMI beat classes for which the comparison method [30] produces the least sensitivity. Such high values of sensitivity attest the capability of the proposed method using dECG data in successfully classifying five AAMI cardiac beat classes. It can be seen from Table 5.15 that for all beat classes, the comparison method [30] show lower values of specificity but the specificity is higher, as expected, for the proposed method using ECG data. Since for a particular method, a higher specificity indicates a better classification, the proposed method based using dECG data is indeed better in performance. From Table 5.16 that for all beat classes, the comparison method [30] show lower values of selectivity but the selectivity is higher, for the proposed method using dECG data. Since for a particular method, a higher selectivity indicates a better classification, the proposed method based using dECG data is indeed better in performance. As demonstrated from Table 5.16 that the accuracy resulting from the other methods are comparatively lower for all AAMI cardiac beat clases, whereas the proposed method using dECG data is able to result in better classification performance as it gives higher accuracy for different classes considered.

5.5 Performance Comparison of the Proposed Method Using Modified dECG Data Approach

This section presents the results of the proposed method based on HOS obtained from detail and approximate coefficient of WPD using modified dECG data $y(n)$. The performance of the proposed method is compared with the method [30] on the basis of the following performance evaluation criteria as described before.

Table 5.15: Comparison Between Proposed Method Using dECG Data and the Method in [30] in terms of Average Sensitivity(in %) and Average Specificity(in %)

ECG beat Class	**Sensitivity of Method in [30]**	**Sensitivity of Proposed Method Using dECG Data**	**Specificity of Method in [30]**	**Specificity of Proposed Method Using dECG Data**
N	81.2	100.0	97.4	100.0
S	92.1	100.0	98.0	100.0
F	91.9	100.0	98.0	100.0
Q	94.7	100.0	93.2	100.0
V	87.3	100.0	99.7	100.0
Avg	89.4	100.0	97.2	100.0

Table 5.16: Comparison Between Proposed Method Using dECG Data and the Method in [30] in terms of Average Selectivity(in %) and Average Accuracy (in %)

ECG beat Class	**Selectivity of Method in [30]**	**Selectivity of Proposed Method Using dECG Data**	**Accuracy of Method in [30]**	**Accuracy of Proposed Method Using dECG Data**
N	90.5	100.0	93.63	100.0
S	92.1	100.0	96.81	100.0
F	91.9	100.0	96.81	100.0
Q	71.0	100.0	93.43	100.0
V	98.9	100.0	97.01	100.0
Avg	88.9	100.0	95.6	100.0

5.5.1 Performance Comparison Using Clustering Analysis

GSI value of features of comparison methods and the proposed feature set using modified dECG data are shown in Table 5.17−5.18. In Table 5.18 the GSI index obtained using the proposed method using modified dECG data for each AAMI beat classes is shown. It is seen from Table 5.18 that each diagonal entry representing the same class has a value zero, whereas each entry other than the diagonal representing two different classes has a value close to one. Such GSI values indicate that the proposed HOS feature extracted from the WPD detail and approximate coefficient is capable of providing high separability between any two different classes as well as yielding high compactness for the same class.
From the Table 5.17−5.18 it is shown that the proposed approach show greater separability between any two classes.Thus, the proficiency of projected schemes to offer high separability among five classes in this work is established.
BD value of features of comparison methods and the proposed feature set are shown in Table 5.19. It is found from the BD values of stated all features in Table 5.19, each entree corresponding to AAMI cardiac beat classes are having a value closing to '0' which further shows the goodness of proposed feature set.

5.5.2 Performance Comparison Using Confusion Matrix

Among 10 iterations of random selection of training and testing datasets, for each iteration, confusion matrix representing the test classes along with the classified classes is obtained and sensitivity, specificity, selectivity and accuracy of each class are determined for the performance comparison. Table 5.20 and 5.21 represent the confusion matrices derived for method in [30] and the proposed method using modified dECG data respectively. In each table, the diagonal entries stand for the number of cases when a particular AAMI cardiac beat class is correctly classified. From Table 5.21, it is found that, the proposed method based on using modified dECG data is capable of reducing the mis-classification while providing the similar correct classification rate for other classes of beats.

Table 5.17: Geometrical Separability Index(GSI) of the method in [30]

Classes	**N**	**S**	**F**	**Q**	**V**
N	0	0.98	0.9825	0.95	0.9825
S	0.98	0	0.9950	0.9675	1
F	0.9825	0.9950	0	0.9650	0.9950
Q	0.95	0.9675	0.9650	0	0.9475
V	0.9825	1	0.9950	0.9475	0

Table 5.18: Geometrical Separability Index(GSI) of the proposed method using modified dECG Data

Classes	**N**	**S**	**F**	**Q**	**V**
N	0	1	1	1	1
S	1	0	1	1	1
F	1	1	0	1	1
Q	1	1	1	0	1
V	1	1	1	1	0

Table 5.19: Bhattacharyya Distance(BD) values for the method in [30] and Proposed Method Using Modified dECG

Class	**BD Values(Method in [30])**	**BD Values(Proposed Method Using Modified dECG)**
N	0.0085	0.0139
S	0.0159	0.0073
F	0.0104	0.0162
Q	0.0118	0.0607
V	0.0204	0.0221

Table 5.20: Confusion Matrix of Method in [30] Over 10 Iteration

	N	**S**	**F**	**Q**	**V**
N	95	5	3	13	1
S	2	93	3	3	0
F	2	1	91	5	0
Q	2	1	1	71	0
V	4	1	1	8	96

Table 5.21: Confusion Matrix of Proposed Method Using Modified dECG data Over 10 Iteration

	N	**S**	**F**	**Q**	**V**
N	104	0	0	0	0
S	0	100	0	0	0
F	0	0	100	0	0
Q	0	0	0	98	0
V	0	0	0	0	98

For the proposed method and the method in [30], the average sensitivity, specificity, selectivity and accuracy of all AAMI beat classes are summarized in Tables5.22−5.23. It is evident from Table 5.22 that the method in [30] produce relatively lower values of sensitivity for all five classes, whereas the proposed method using the modified dECG data yields higher sensitivity even in case of five AAMI beat classes for which the comparison method [30] produces the least sensitivity. Such high values of sensitivity attest the capability of the proposed method using modified dECG data in successfully classifying five AAMI cardiac beat classes. It can be seen from Table 5.22 that for all beat classes, the comparison method [30] show lower values of specificity but the specificity is higher, as expected, for the proposed method using modified ECG data. Since for a particular method, a higher specificity indicates a better classification, the proposed method based using dECG data is indeed better in performance. From Table 5.23 that for all beat classes, the comparison method [30] show lower values of selectivity but the selectivity is higher, for the proposed method using dECG data. Since for a particular method, a higher selectivity indicates a better classification, the proposed method based using modified dECG data is indeed better in performance. As demonstrated from Table 5.23 that the accuracy resulting from the other methods are comparatively lower for all AAMI cardiac beat clases, whereas the proposed method using modified dECG data is able to result in better classification performance as it gives higher accuracy for different classes considered.

5.6 Performance Analysis Among The Proposed Three Approaches

Comparing the GSI values in Tables 5.24,5.25, 5.26, 5.27 we observe that the proposed HOS feature extracted from the EMD-WPD domain using ECG, dECG and modified dECG data is more capable of providing high separability between any two different AAMI cardiac beat classesa as well as yielding high compactness for the same class in comparison to the comparison method in [30].

It is seen from Table5.28 and Figure 5.3, that the proposed three approaches yields lower BD values for some of the cardiac beat classes in comparison to method in [30].

For the confusion matrix derived for each approach, sensitivity, specificity, selectivity and accuracy is determined for all the five AAMI cardiac beat classes. In the Figure 5.4, Figure 5.5, Figure 5.6 and Figure 5.7 the comparative sensitivity, specificity, selectivity and average accuracy of all the approached are illustrated

Table 5.22: Comparison Between Proposed Method Using Modified dECG Data and the Method in [30] in terms of Average Sensitivity(in %) and Average Specificity(in %)

ECG beat Class	**Sensitivity of Method in [30]**	**Sensitivity of Proposed Method Using Modified dECG Data**	**Specificity of Method in [30]**	**Specificity of Proposed Method Using Modified dECG Data**
N	81.2	100.0	97.4	100.0
S	92.1	100.0	98.0	100.0
F	91.9	100.0	98.0	100.0
Q	94.7	100.0	93.2	100.0
V	87.3	100.0	99.7	100.0
Avg	89.4	100.0	97.2	100.0

Table 5.23: Comparison Between Proposed Method Using Modified dECG Data and the Method in [30] in terms of Average Selectivity(in %) and Average Accuracy (in %)

ECG beat Class	**Selectivity of Method in [30]**	**Selectivity of Proposed Method Using Modified dECG Data**	**Accuracy of Method in [30]**	**Accuracy of Proposed Method Using Modified dECG Data**
N	90.5	100.0	93.63	100.0
S	92.1	100.0	96.81	100.0
F	91.9	100.0	96.81	100.0
Q	71.0	100.0	93.43	100.0
V	98.9	100.0	97.01	100.0
Avg	88.9	100.0	95.6	100.0

Table 5.24: Geometrical Separability Index(GSI) of the method in [30]

Classes	**N**	**S**	**F**	**Q**	**V**
N	0	0.98	0.9825	0.95	0.9825
S	0.98	0	0.9950	0.9675	1
F	0.9825	0.9950	0	0.9650	0.9950
Q	0.95	0.9675	0.9650	0	0.9475
V	0.9825	1	0.9950	0.9475	0

Table 5.25: Geometrical Separability Index(GSI) of the proposed method using ECG Data

Classes	N	S	F	Q	V
N	0	0.9950	1	1	1
S	0.9950	0	0.9975	1	1
F	1	0.9975	0	1	1
Q	1	1	1	0	1
V	1	1	1	1	0

Table 5.26: Geometrical Separability Index(GSI) of the proposed method using dECG Data

Classes	N	S	F	Q	V
N	0	1	1	1	1
S	1	0	1	1	1
F	1	1	0	1	1
Q	1	1	1	0	1
V	1	1	1	1	0

Table 5.27: Geometrical Separability Index(GSI) of the proposed method using modified dECG Data

Classes	N	S	F	Q	V
N	0	1	1	1	1
S	1	0	1	1	1
F	1	1	0	1	1
Q	1	1	1	0	1
V	1	1	1	1	0

Table 5.28: Bhattacharyya Distance(BD) values

Class	BD Values of Method in [30]	BD Values of Proposed Method Using ECG	BD Values of Proposed Method Using dECG	BD Values of Proposed Method Using Modofied dECG
N	0.0085	0.0019	0.0023	0.0139
S	0.0159	0.0191	0.0282	0.0073
F	0.0104	0.0090	0.0050	0.0162
Q	0.0118	0.0141	0.0248	0.0607
V	0.0204	0.0473	0.0443	0.0221

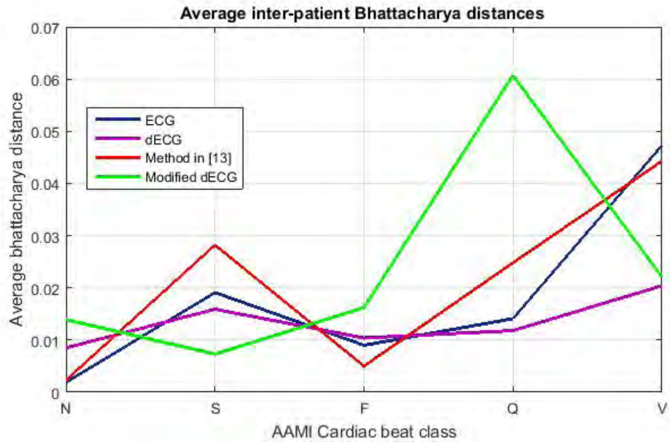


Figure 5.3: Bhattacharyya Distance (BD)Values

respectively.
The total average accuracy of the method in [10] is 98.61% and the total average accuracy of method in [30] is 88.8%. The performance of the proposed method based on HOS features extracted from EMD-WPD domain came quite high with average accuracy of 99.6% for class N, 99.6% for class S and 99.4%, 99.8% and 100% for classes F, Q and class V beat respectively resulting in total average accuracy of 99.2%.
The performance of another proposed method using dECG data came high with average accuracy of 100% for class N, 100% for class S and 100%, 100% and 100% for classes F, Q and class V beat respectively resulting in total average accuracy of 100%.
Finally The performance of another proposed method using modified dECG data came high with average accuracy of 100% for class N, 100% for class S and 100%, 100% and 100% for classes F, Q and class V beat respectively resulting in total average accuracy of 100%. From the Table 5.29 it is shown that the total average accuracy of the proposed three methods is higher than the comparison method of [10] and [30].

5.7 Conclusion

Firstly an empirical mode decomposition based is employed along with Euclidean distance classifier in order to classify five AAMI cardiac beats.In this approach the dominant IMFs obtained from EMD are subjected to WPD analysis. HOS features are selected as feature vectors. Secondly instead of ECG data, The smoothed three point central difference for an ECG signal namely dECG data are used to obtain HOS feature extracted from the EMD-WPD domain in order to classify

Table 5.29: Comparison of Total Average Accuracy(in %) of the Proposed three Methods

Method	Total Average Accuracy
Method in [30]	88.8
Method in [10]	98.61
Proposed Method using ECG data	99.2
Proposed Method using dECG data	100.0
Proposed Method using Modified dECG data	100.0

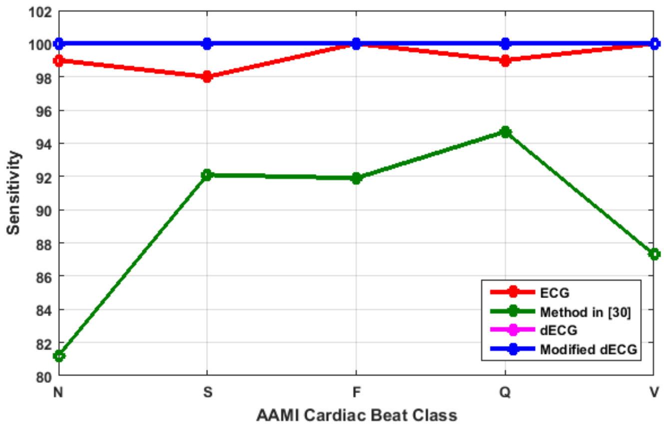


Figure 5.4: Performance Comparison in Terms of Average Sensitivity for the Proposed methods

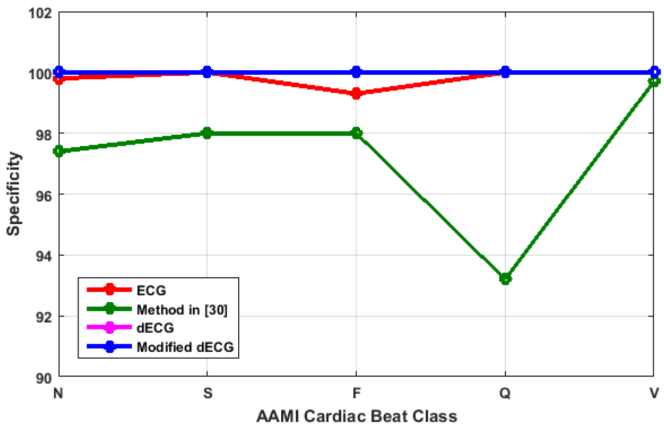


Figure 5.5: Performance Comparison in Terms of Average Specificity for the Proposed methods

the AAMI five beat classes. Finally, a modification in dECG analysis is performed to obtain the signal and classify five AAMI beat classes.Two statistical measures

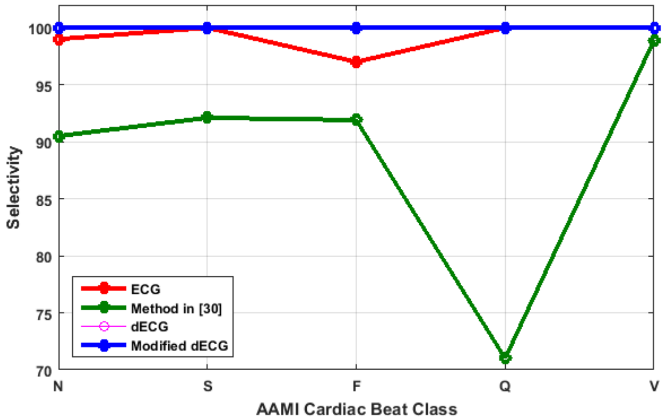


Figure 5.6: Performance Comparison in Terms of Average Selectivity for the Proposed methods

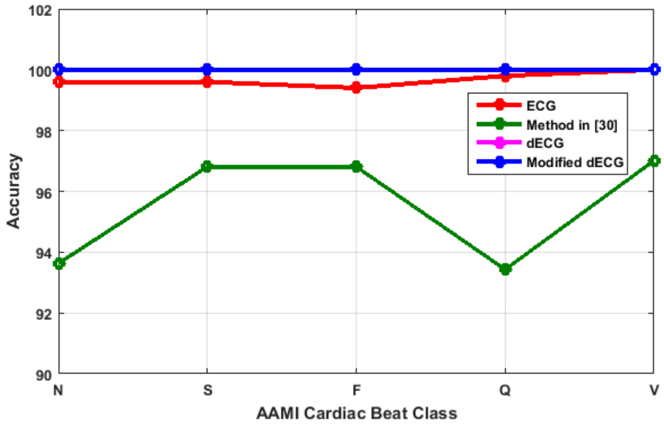


Figure 5.7: Performance Comparison in Terms of Average Accuracy for the Proposed methods

e.g. GSI and BD are utilized in justifying inter-class separability and intra-class compactness of the proposed feature. Average sensitivity, specificity, selectivity and accuracy are calculated from classification performance of 10 iterations, considering random selected training and testing datasets at each stage.

Chapter 6

Conclusion

6.1 Concluding Remarks

It is shown that the use of EMD based decomposed ECG signal for extracting wavelet packet features can provide significantly distinguishable characteristics for different types of cardiac beats. For feature extraction, instead of using all IMFs, use of only dominant IMF not only reduces the computational burden but also avoids inclusion of redundant or less informative data. It is found that the proposed energy based simple selection criterion can consistently identify the dominant IMF. In order to extract discriminative characteristics related to different cardiac beat classes, both approximate and detail coefficients are utilized for feature extraction. Instead of using all WPD coefficients, some statistical parameters are employed on those extracted coefficients which efficiently represent the unique characteristics. It is observed from extensive simulation that the proposed higher order statistical features extracted from EMD-WPD data not only shows better compactness and separability but also provides higher sensitivity, specificity, selectivity and accuracy in distinguishing different cardiac beats even using simple distance based KNN classifier compared to a state-of-the-art method.

6.2 Contribution of this Thesis

The major contributions of this thesis are,

- A set of HOS features is developed exploiting dominant IMFs obtained via empirical mode decomposition (EMD) of ECG signals.
- Another set of HOS features is developed from smoothed three point central difference for an ECG signal namely dECG signal.

- Another set of features is obtained from modification of dECG signal, namely modified dECG.
- Detail simulations have been carried out in order to investigate the performance of the proposed feature sets for the classification of five AAMI cardiac beat class using ECG signals available from the MIT-BIH arrhythmia database, dECG and modified dECG.
- The performance of our proposed method is compared with state-of-the-art method [30]. This is why the comparison method is implemented independently and classification performance has been carried out using the same dataset and the same Euclidian distance classifier.
- Simulation results show that the proposed method is able to classify different types of cardiac beats with greater sensitivity, specificity, selectivity and accuracy even in case of random selection of training and testing dataset.

6.3 Scopes for Future Work

In this thesis, effective and efficient classification methods using ECG, dECG and modified dECG signals exploiting HOS of dominant IMFs in EMD-WPD domain has been built for AAMI five class beat classification. However, there are some scopes for future research as mentioned below:

- In practical cases, where the unknown ECG comes from a different patient whose data is not present in the training dataset, the classification problem is termed as patient independent performance analysis. So, our proposed methods are needed to be fed into patient independent analysis for further justification in handling various practical situations.
- In practical cases, ECG signals are subject to various noises. So, noise analysis can be performed for all the proposed methods in order to verify their performance in noisy environment.
- Available databases other than MIT-BIH arrhythmia database need to be utilized for validating efficacy of our proposed methods.

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