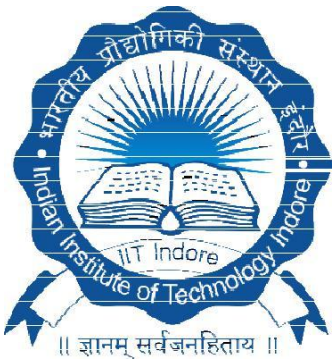
DETECTION OF ATRIAL FIBRILLATION IN ELECTROCARDIOGRAM SIGNALS USING TUNABLE-Q WAVELET TRANSFORM

M.Tech. Thesis

By
SATYARTHA SHARMA



DISCIPLINE OF ELECTRICAL ENGINEERING
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DETECTION OF ATRIAL FIBRILLATION IN ELECTROCARDIOGRAM SIGNALS USING TUNABLE-Q WAVELET TRANSFORM

A THESIS

Submitted in partial fulfillment of the requirements for the award of the degree of

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled "**DETECTION OF ATRIAL FIBRILLATION IN ELECTROCARDIOGRAM SIGNALS USING TUNABLE-Q WAVELET TRANSFORM"** in the partial fulfillment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** with specialization in **COMMUNICATION AND SIGNAL PROCESSING** and submitted in the **DISCIPLINE OF ELECTRICAL ENGINEERING** at **Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from JULY 2015 to JUNE 2016 under the supervision of Dr. Ram Bilas Pachori, Associate Professor, Discipline of Electrical Engineering, IIT Indore.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Signature of the student with date
(SATYARTHA SHARMA)

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Signature of the Supervisor with date
DR. RAM BILAS PACHORI

SATYARTHA SHARMA has successfully given his M.Tech. Oral Examination held on **29-06-2016**.

Signature of Supervisor of M.Tech. Thesis
Date:

Convener, DPGC
Date:

Signature of PSPC Member
Date:

Signature of PSPC Member
Date:

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SATYARTHA SHARMA

M.Tech. (Communication and Signal Processing)

Discipline of Electrical Engineering

IIT Indore

Dedicated

to

My Family

Abstract

This work introduces the application of wavelet entropy for detection of episodes of atrial fibrillation (AF), from electrocardiogram (ECG) recording. AF is a common cardiac arrhythmia which is often asymptomatic and shows very brief episodes. Early detection of AF will improve the treatment of it and will reduce the risk of death and strokes in patients. In the present work after getting the RR segment we apply tunable Q wavelet transform (TQWT) and then calculate the wavelet entropy of that RR segment. We repeat this process for different values of Q. In the presence of AF the complexity of signal increases which results in higher value of wavelet entropy. Thus on the basis of value of wavelet entropy we decide the presence or absence of AF in a beat. This method provides a good discriminant ability of 93.44% which have been compared with previous work. This method is capable of detecting very brief episodes of AF, which are hardly of few beats in length. This method can be implemented in ECG monitoring system, it can help clinicians in early detection of AF and to gain sufficient knowledge of causes that results in arrhythmia.

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CHAPTER 1

Introduction

Human heart is a very delicate organ supplying nutrients and oxygen to every organ through blood. Any damage to the heart may cause a serious disease, which may prove to be fatal in some cases. Our heart beats 72 times in a minute and any major alteration in the pulse rate is termed as arrhythmia [1]. During arrhythmia, the heart can pulsate too quick, too moderate, or with a sporadic mood. Atrial Fibrillation (AF) is one of the common kinds of arrhythmia. AF is the condition which causes upper two chambers of the heart called atria to fibrillate (contract quickly and unpredictably). Normally, when blood pools in the atria it is further pumped into ventricles, but in AF it is not pumped totally into ventricles. Hence, heart's upper and lower chambers do not co-operate as they ought to [1, 2]. The AF can enhance the threat of stroke. In some individuals, AF can result in heart attack, particularly if the heart rate is exceptionally fast. AF may occur seldom or from time to time, or it might turn into a progressing or long haul heart issue that goes on for a considerable length of time [2].

AF is the commonest cardiovascular arrhythmia in clinical routine, with an expected pervasiveness of 1.5%–2% of all the inclusive community in the developed world [3]. More than 6 million individuals in Europe and 3 million individuals in the United States of America (USA) suffer at present from this arrhythmia [3]. It is expected that number will become two times in the following 50 years [4].

AF itself is not a life-threatening condition, but it influences the blood flow and hence may lead to development of thrombus inside the atrium [3]. This may increase the risk of heart strokes and heart failure by five times and three times respectively as compared to a normal and healthy person [3]. People who are already infected by any heart disease are more susceptible to AF. An early identification of AF may help with reducing this risk by re-establishing ordinary heart rate or by enhancing the blood flow with the help of antithrombotic treatment [5, 6]. The treatment of AF can be done using rate control and rhythm control mechanism [5]. In rate control mechanism electro-cardioversion is applied. This is the process in which an electric shock is sent

across the chest so as to disrupt the atrial irregular activity and resume normal functioning of atria [7].

The main characteristic of AF is the absence of P-wave before QRS complex in an electrocardiogram (ECG) signal or replacement of P-wave with a random wave which is of saw-tooth shape [8]. In order to detect AF episodes we need to extract atrial activity from ECG signal which may include extracting RR segment, delta RR segment (difference between successive RR segment) or P-wave [9, 10].

The early identification may likewise include outstanding advantages for health care administrations around the world [11]. However detection of AF in early stages is not an easy task, as its initial episodes are very brief (few beats in length) [5]. Moreover, current AF identification is carried out by looking out for ordinary side effects for example, dyspnea (shortness of breath), chest pain, dizziness and palpitations [12], however not each and every patient displays these signs. Indeed 90% of AF episodes are asymptomatic [13]. Similarly previous works also describes the poor correlation of symptoms and AF [14, 15], thus the computer aided AF diagnosis system ready to be implanted into continuous monitoring system poses a challenge [16].

1.1 Types of AF

Depending on the duration of the AF episodes and the time taken to develop it, AF can be broadly classified into three main types described below [5]:

1.1.1 Paroxysmal AF

Paroxysmal AF is the condition in which AF terminates abruptly on its own and retain hardly for a week, usually it lasts for 24 hours. Its occurrence and duration of episodes increases with time [5].

1.1.2 Persistent AF

In case of persistent AF abnormality in heart rhythm lasts for more than a week [5]. In this case arrhythmia can be reverted with the help of medical treatment [5].

1.1.3 Permanent AF

Permanent AF is the condition in which arrhythmia lasts for more than one year [5]. In this case abnormality in heart rate is permanent and it cannot be reverted and heart rate is controlled with the help of medication [5]. The paroxysmal AF and the persistent AF may change to the permanent AF with time if not treated. The flow of AF is shown in Figure 1.1.

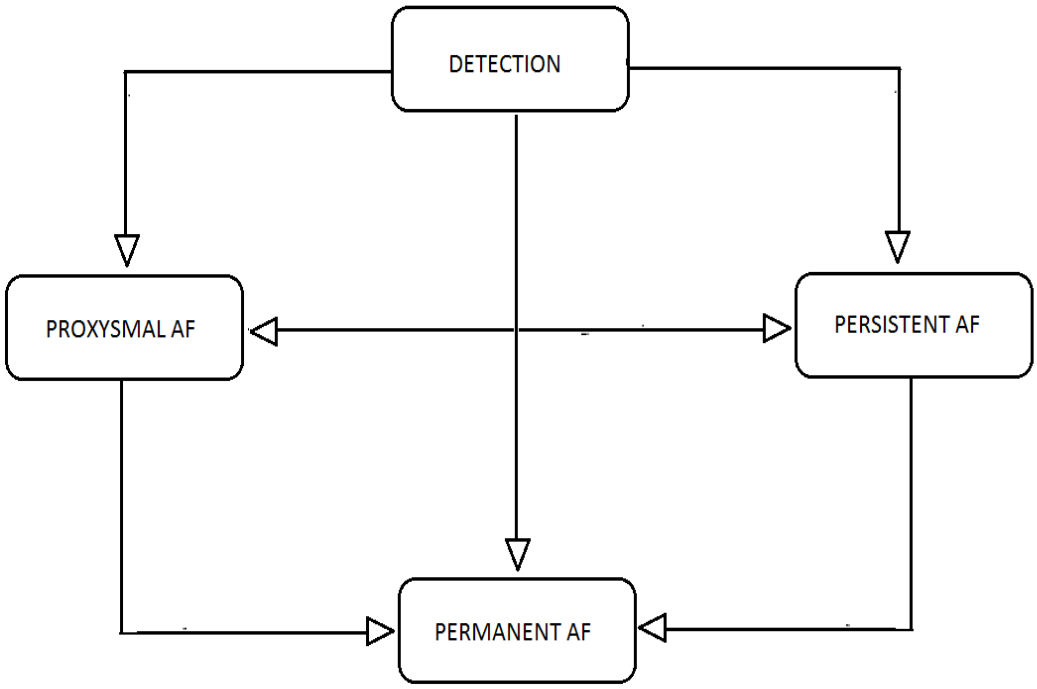


Figure 1.1: Flow of AF [3]

1.2 Signs and symptoms of AF

AF causes rapid contraction of the atrial chambers of heart than normal and because of this rapid contraction ventricles do not contain enough blood to pump through body and lungs, which in turn causes different symptoms, such as: palpitation, dyspnea, weakness, chest pain, fainting and fatigue [17]. Heart stroke and Heart failure are the two major consequences of AF. In case of

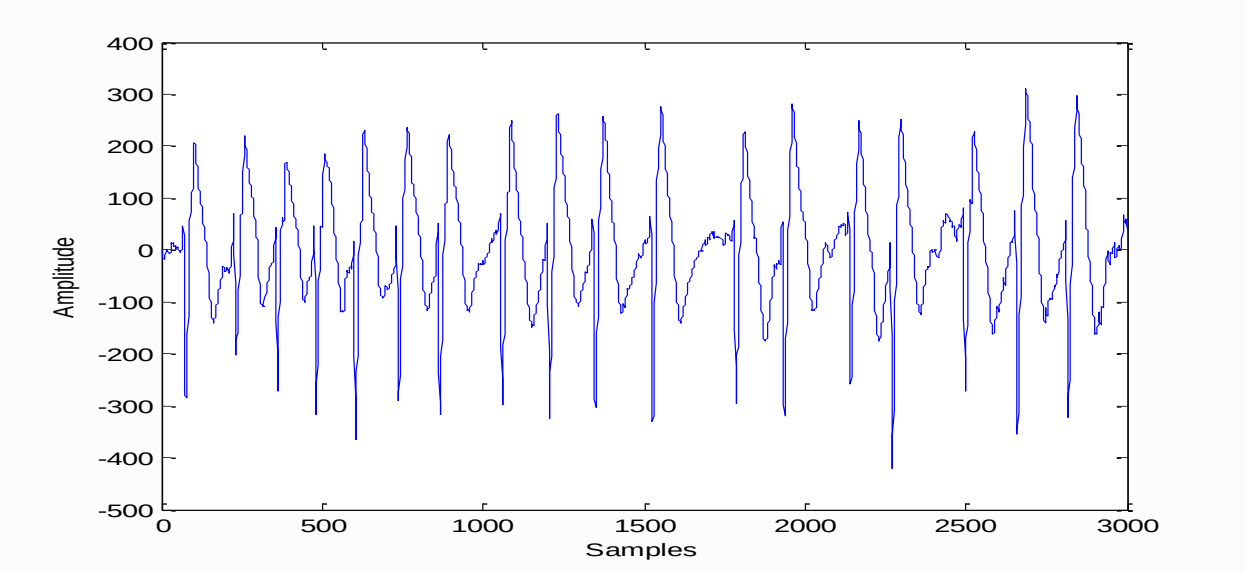
AF detection family history plays an important role as it can be genetically transmitted. AF generally affects the older ones but effects can also be seen in young individuals [17, 18].

Depending on the population survey carried out by Fuster et al. in [3] different age groups were found to have different pervasiveness for AF. According to this population survey the individuals below 60 years of age have 10% chances of having AF or only 10% people below 60 years of age were found to be affected by AF. 20% people between 60 to 70 years were suffering from AF and around 40% of individuals above 70 years were suffering from this. Most importantly these people had no signs and symptoms denoting the presence of AF and lead a very normal life ignorantly. This population survey conveys that AF is mostly present in the higher age group and this is the permanent type of AF which had developed through their lifetime.

1.3 Electrocardiogram

ECG is the recording of the heart's electrical activity which is properly calibrated to record them [19]. ECG signals provide information about the heart rate and any abnormalities, if present. ECG signals are recorded with the help of electrodes, which are placed on arms, legs and chest. In ECG signals every heart beat is made up of mainly P-wave followed by QRS complex, and T-wave. Each of these wave shows a different electrical activity of heart in its single beat [19]. Depolarization of right and left atria is shown by P-wave. It always has a positive polarity, and its period is less than 120 milliseconds [20]. The spectral characteristic of a normal P wave is below 10–15 Hz [19]. P-wave maintains a very low value of amplitude. Depolarization of right and left ventricle is represented by QRS complex, which lasts for 70- 110 milliseconds [20]. R wave has the highest amplitude in ECG recording. Frequency spectrum of QRS complex is in the range of 10-40 Hertz. The T-wave represents the ventricular repolarization, it lasts for about 300 milliseconds. In case of rapid heartbeats T-wave becomes narrow and shifts closer to the QRS complex [20].

In case of AF beats the P-wave is absent or replaced by random waves. The ECG recording showing the AF and normal episodes are shown in the Figure 1.2. These signals are taken from MIT BIH database.



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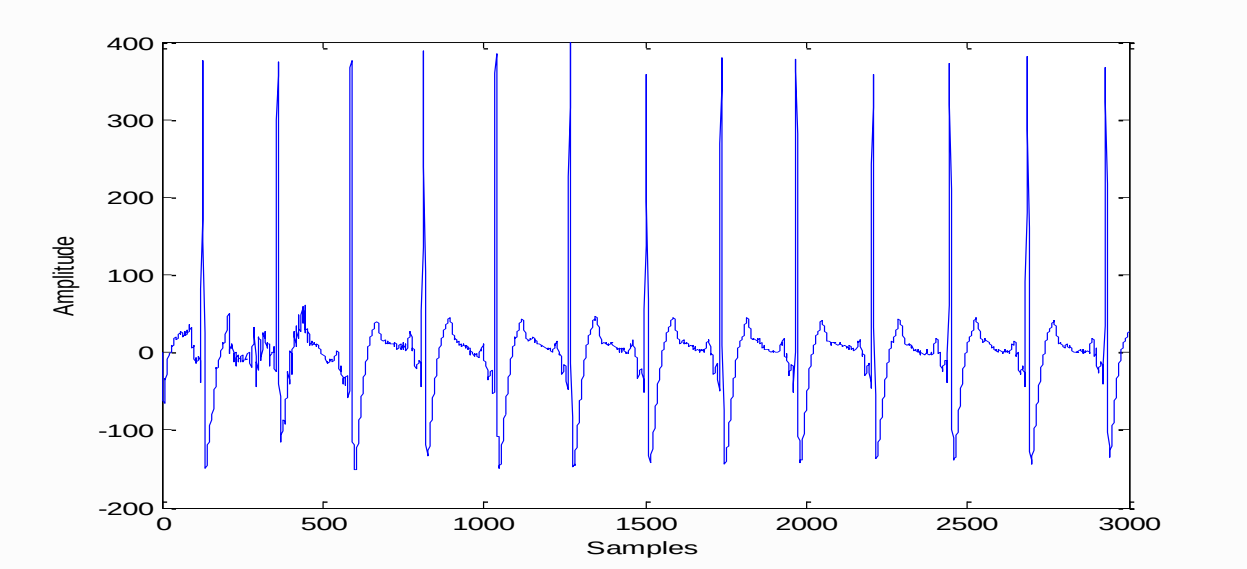


(b)

Figure 1.2: (a) ECG recording showing AF episodes. (b) ECG recording showing normal episodes.

AF distorts the normal ECG signal as it affects the P-wave of a heartbeat [9]. In presence of AF, P-wave is either absent or distorted. Presence of AF in ECG signal increases its complexity. Frequent monitoring is required to detect the asymptomatic AF [9].

1.4 Related work

Ladavich et al [21] proposed a method for detection of AF from ECG signals and the method is called as P-wave absence (PWA) method. They extracted features from P-wave of ECG signals and fed them as input to expectation maximization algorithm and hence create Gaussian Mixture Model (GMM) of feature space of P-wave. This model identifies the absence of P-wave in ECG signals and hence detects AF. Laburu et al [22] studied nine different types of AF detection algorithms from literature under different conditions. They showed that the method using analysis of irregular RR segments gave highest specificity and sensitivity. Zhang et al [23] showed that there are two main strategies to control AF: rate control and rhythm control. In rate control the target is to control the rate of ventricular contraction in spite of AF and rhythm control aims at restoring the sinus rhythm. Tateno et al [24] studied the detection of AF based on RR segment, delta RR segments and their density histogram. Delta RR segment refers to the difference between two consecutive RR segments. They also showed that Kolmogorov-Smirnov test with RR segment gave better specificity and sensitivity. They classified the ECG signal as AF affected if the density histogram of RR segment and delta RR segment were not found significantly different.

Dash et al [25] showed a method of AF detection based on complexity, variability and randomness of RR segment. They used root mean square of delta RR segment with turning point ratio and Shannon entropy to characterize arrhythmia. They also used Receiver Operating Characteristics (ROC) plots to achieve better specificity and sensitivity. Huang et al [26] have proposed a new method to detect transition between sinus rhythm and AF based on delta RR segment's density histogram and detecting peaks from this histogram curve which represents AF events. Further they were used to classify its types.

Rodenas et al [27] used discrete wavelet transform to extract feature like wavelet entropy and relative energies from P-waves, extracted from the ECG signals of affected patients to detect the episodes of AF. Christov et al [28, 29] studied the presence of atrial activity and ventricular arrhythmia by detecting P-wave in ECG signal using sequential analysis. Stridth and Sornmo [30, 31] extracted and studied the variation in waveform shape and fibrillation frequency in case of AF patients. On the basis of time frequency distribution analysis of AF subjects they

characterized AF. Cerutti et al [32] also studied RR segment of normal sinus rhythm subjects and AF subjects. They derived parameters using conditional entropy and autoregressive methods.

Ozbay et al [33] have done arrhythmia classification using multilayered perceptron combined with back propagation algorithm and compared them with fuzzy clustering neural network architecture. Sadik et al [7] applied welch and wavelet method for extracting features and ECG signals preprocessing. They used logarithmic sigmoid neurons for making Levenberg-Marquart network using back propagation feature.

In the present work Tunable-Q Wavelet Transform (TQWT) [34] is applied on RR segments, extracted from ECG signals. The coefficients obtained are used to calculate relative energy of each level, and corresponding wavelet entropy of every RR segment to detect AF. The proposed methodology is also shown in form of flow diagram in Figure 1.3.

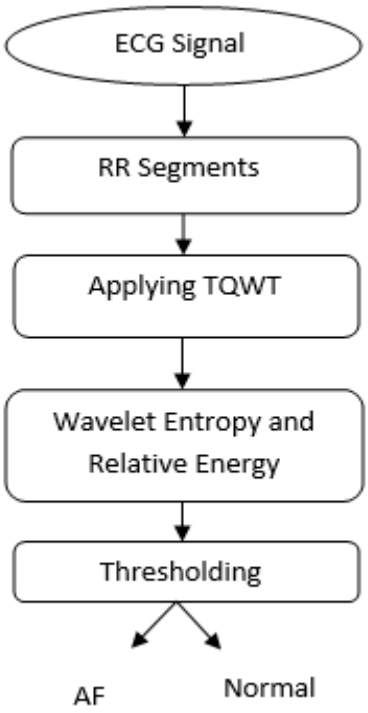


Figure 1.3: Flow of present methodology

1.5 Thesis organization

The rest of the thesis is organized as follows:

A detailed description of the proposed methodology is presented in chapter 2, which includes brief review of wavelet transform, TQWT, wavelet entropy and quasi ROC. Chapter 3 represents the experimental results and discussion followed by chapter 4 which include the conclusion and scope of future work.

CHAPTER 2

Methodology

This chapter will give an overview of the method and the techniques used in the data processing of the present work. Data preprocessing (removal of noise), extraction of the useful data content and then feature extraction from these data contents are described in detail in this chapter.

2.1 Data acquisition and preprocessing

For execution of proposed work, the dataset of MIT BIH AF was utilized. Which is available from Physionet [35] and this has been used frequently in previous work for the AF detection [21, 25, 26, 36, 37, 38, 39]. This data set comprises of 23 fully annotated ECG signal of 10 hours length and these recordings were done from patients affected by Permanent AF. Sampling frequency of signal is 250 Hz with a resolution of 12 bit over a span of ±10 mV.

In the data set used each ECG recording consisted of two leads, but the one which represented a higher value of P-waves were considered for analysis. In the case when both leads are showing same P-wave amplitude, they were manually inspected and the one with less noise was considered, because in case of ambulatory recordings noise is a nuisance artifact [40]. Generally the recorded ECG data contains noise within it that has some high frequency parts and some low frequency parts which results in power line interference and baseline wandering respectively. ECG signal is corrupted with the presence of noise which in turn results in less accurate feature extraction and classification. Thus for the improvement of later analysis signal is first preprocessed and a bidirectional high-pass filter of 0.5 Hz frequency was used to remove baseline wandering. An eighth order bidirectional Infinite Impulse Response (IIR) low-pass filter of 50 Hz frequency was used to reduce power line interference.

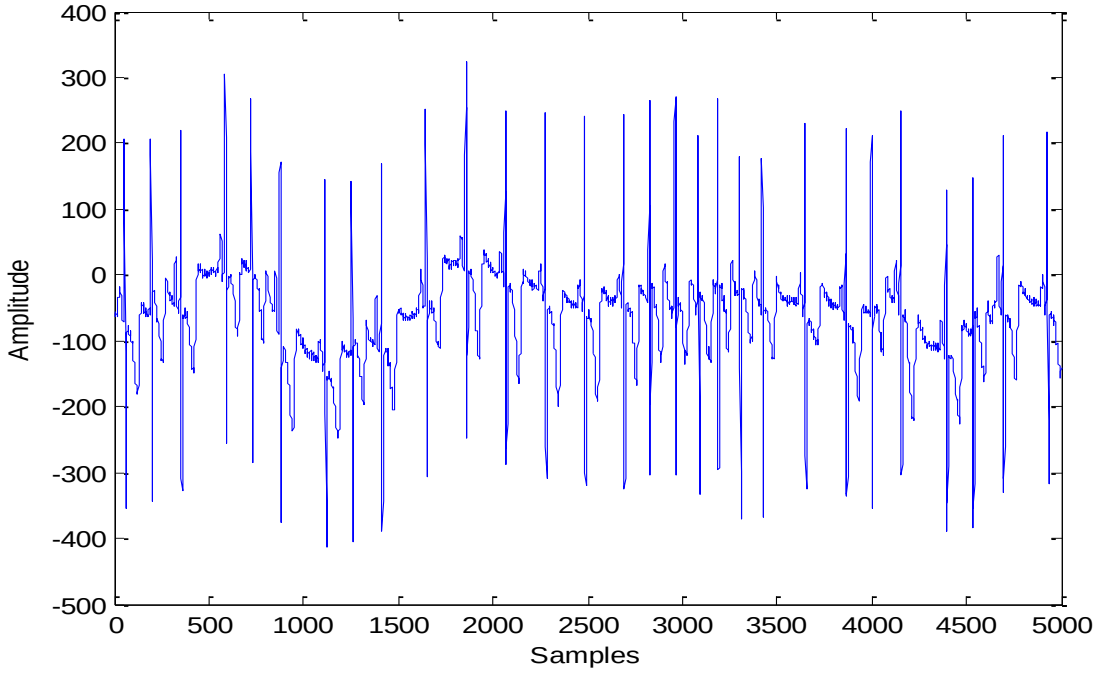
2.1.1 Baseline wandering:

In case of baseline wandering heart beat morphology is changed and these changes in beat morphology do not have a cardiac origin, it mainly affects the ST segment of a heartbeat [41]. Respiration, change in electrode impedances and increased body movement are the main causes of baseline wandering in most of the ECG signals [41]. In the presence of baseline wandering the analysis of ECG data is not easy, thus it is necessary to remove baseline wandering from ECG data for its faithful evaluation. Baseline wandering has a frequency content which is below the range of 0.5 Hz. Frequency content of baseline wandering increases with the increased body movement.

The most crucial consideration in case of designing a high pass filter for removal of baseline wandering is to decide the cut off frequency of high pass filter, the cut off frequency should be chosen such that it maximize the removal of baseline wandering and minimizes the risk of losing useful information in an ECG signal. Generally the slowest heart beat is analyzed to find out the lowest possible frequency. Heart rate can be 40 beats/minute in case of bradycardia, it clearly indicates that 0.67 Hz is the lowest possible frequency in the ECG signal [42]. As the heart rate fluctuates from beat to beat we choose a lower cut off frequency of 0.5 Hz, because if we select a high cut off frequency then the output of high pass filter will have some unwanted components which will distort the information within the ECG signals. The Figure 2.1 shows the ECG signal before and after removal of baseline wander. Figure 2.1 (a) signal is also taken from MIT BIH database for AF.

2.1.2 Power line interference:

Power line interference is one of the most common artifacts that contaminate the ECG recordings. Interference voltage in case of power line interference may have a frequency of 50 Hz which makes it easily recognizable. Such interference in ECG signals makes the analysis and interpretation difficult, because in such cases representation of low amplitude waveforms is not reliable and specious waveforms can be introduced [43]. A strong disturbing signal due to disconnected electrodes is the main reason of 50 Hz interference. Electromagnetic interferences due to power lines results in tracing of poor quality.



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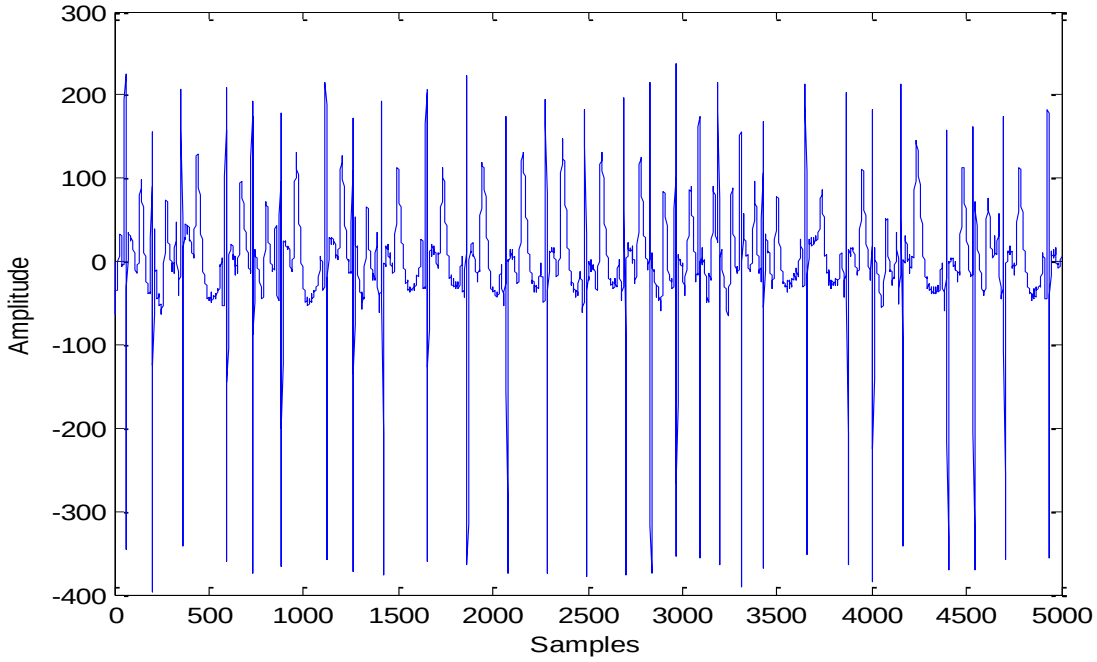


(b)

Figure 2.1: ECG recording (a) with baseline wander (b) without baseline wander

Electrical equipment draw heavy power line current, this may also result in power line interference in recorded ECG signals. An eighth order bidirectional IIR low-pass filter of 50 Hz frequency may be used to reduce power line interference. While filtering power line interferences the extent of influence of QRS complexes on output of the filter is a major concern. The filter should not introduce any distortion in the signal and its performance should be estimated by means of simulated signals [44].

After removing baseline wandering and power line interference from the signal, RR segments were extracted. Extraction of RR segments from ECG signals is shown in Figure 2.2 and the extracted RR segments are shown in Figure 2.3.

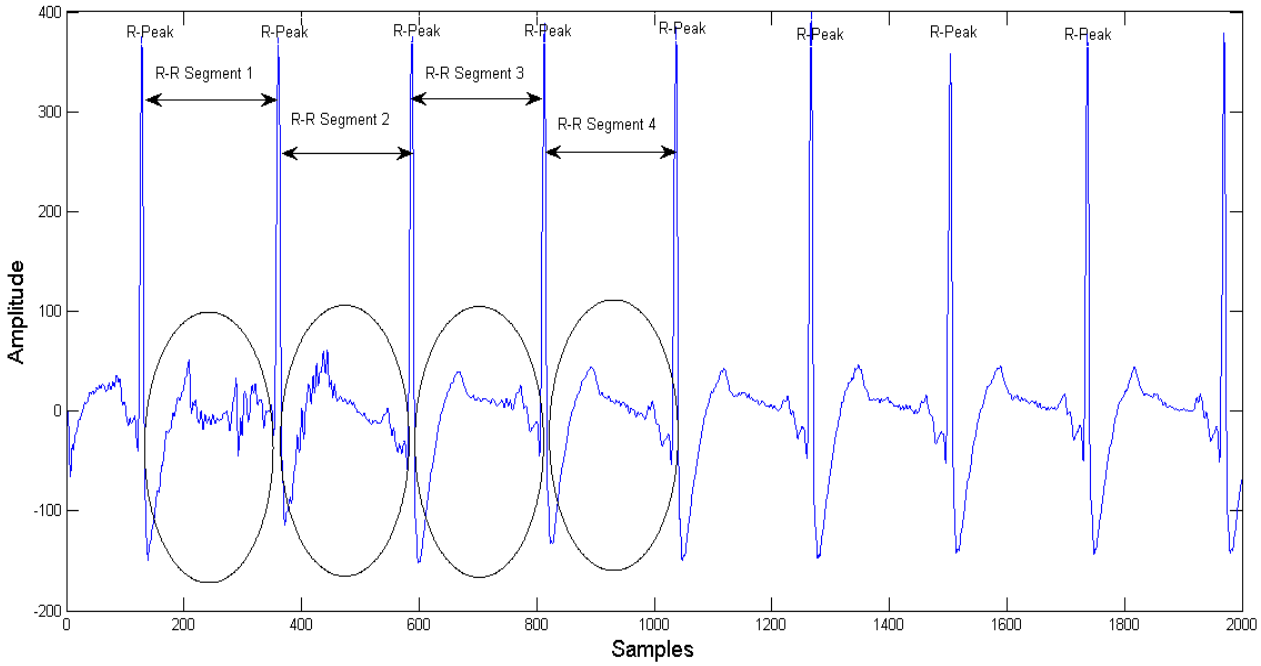
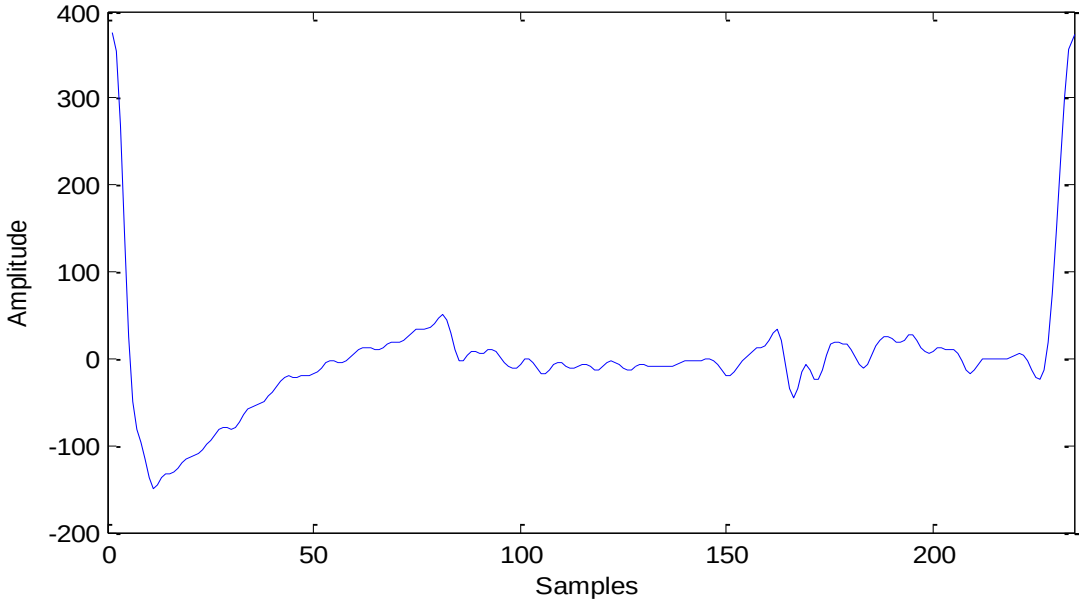


Figure 2.2: Extracting RR segments from the ECG recording.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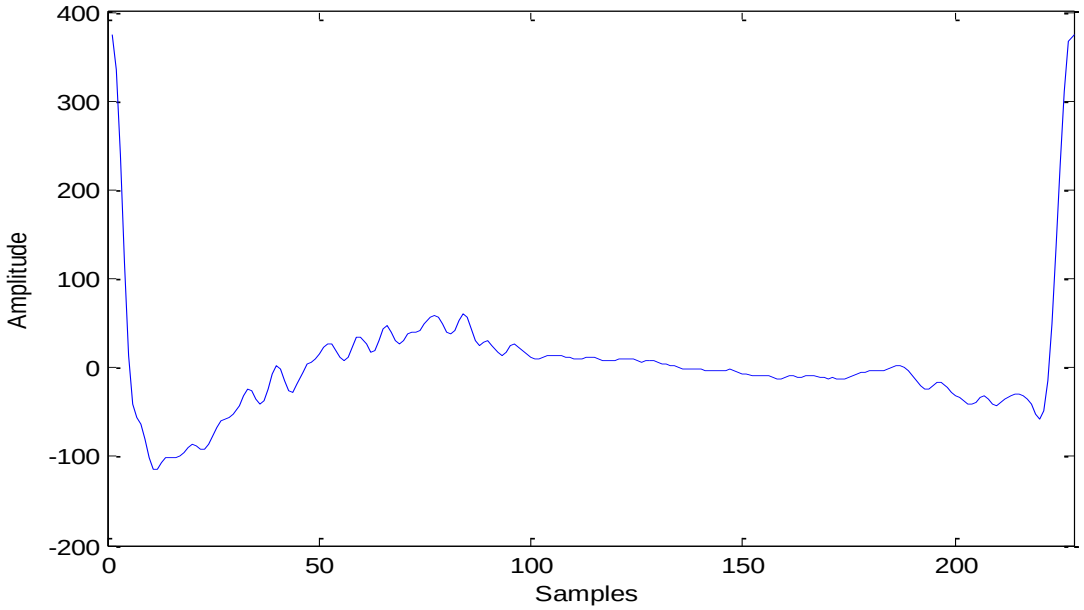
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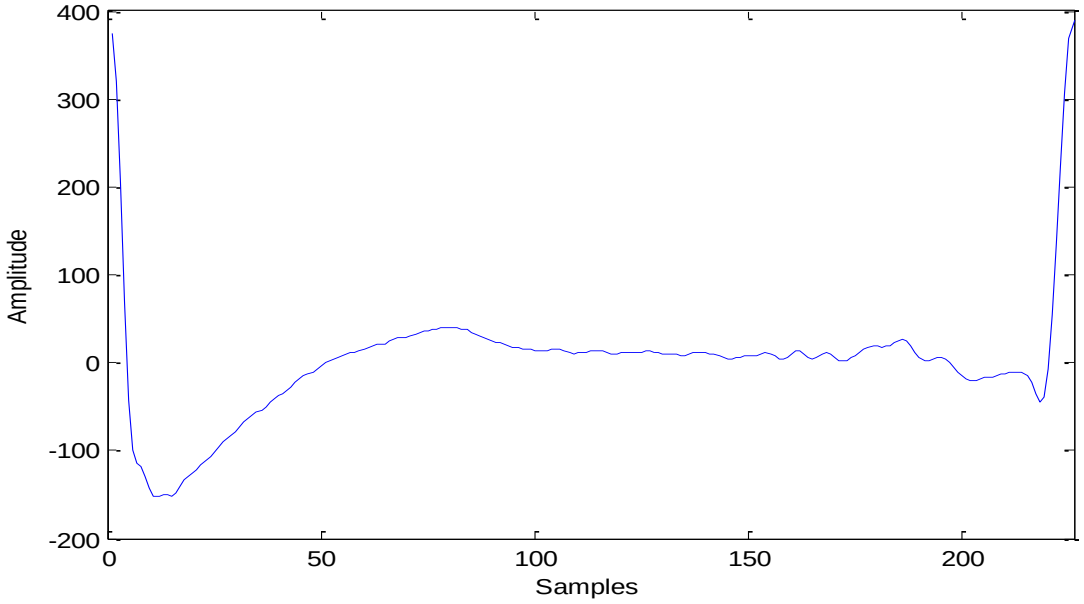

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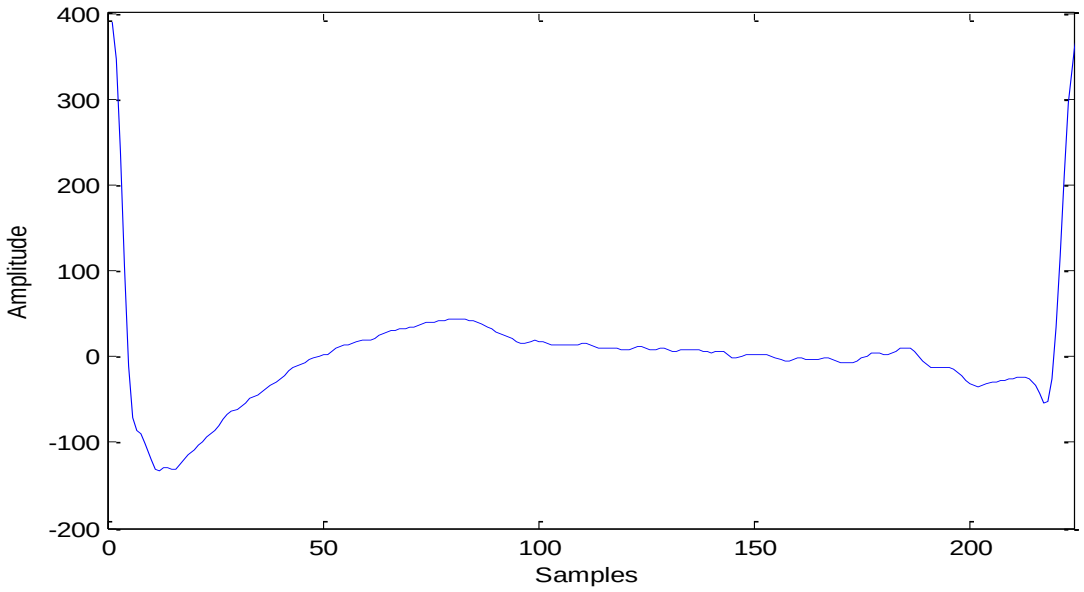


(d)

Figure 2.3: (a) RR Segment 1 (b) RR Segment 2 (c) RR Segment 3 (d) RR Segment 4

2.2 Wavelet transform

The wavelet transform characterizes signal in form of combination of dilated and translated versions of another signal which is called as mother wavelet [27].

$$\vartheta_{x,y}(t) = |x|^{-\frac{1}{2}}\vartheta\left(\frac{t-y}{x}\right) \quad (2.1)$$

Here, t is time and $\vartheta_{x,y}(t)$ is family of mother wavelet. Hence, continuous wavelet transform of a signal d(t) is expressed as:

$$CWT(x,y) = |x|^{-1/2}\int_{-\infty}^{\infty} d(t)\vartheta^*\left(\frac{t-y}{x}\right)dt \quad (2.2)$$

The sampled version of continuous wavelet transform is called discrete wavelet transform. Any signal is considered to have maximum amount of information in low frequency, and high frequency content is considered to give small details of the signal. In case of wavelet analysis we consider signal as combination of low frequency and high frequency components or coefficients. Low frequency components are called as approximation and high frequency components are called details [45]. Discrete wavelet transform decomposes the signal into approximation and detailed coefficients. These coefficients represent different frequency bands.

Discrete wavelet transform is used to decompose ECG signals and extract features from decomposed signal coefficients [46]. Discrete wavelet transform uses low pass and high pass filters and the signal thus obtained from low pass filter is further fed to a series of low pass and high pass filters depending on the number of decomposition levels [46].

Rodenas et al [27] used discrete wavelet transform to detect episodes of AF by extracting P-wave form ECG signals. In the present work we present the analysis of normal and AF signals using TQWT which has some advantages over discrete wavelet transform with a variable quality factor (Q). The Q factor can be changed and adjusted accordingly [34]. Here we present the effect of Q factor in analyzing the AF episodes in ECG signals. The basic understanding of TQWT is given in the next section.

2.3 Tunable-Q wavelet transform

The TQWT is a method employed for studying non-stationary oscillatory signals [34]. It has three easily adjustable parameters: redundancy factor (r), quality factor (Q) and number of sub band decomposition levels denoted by K. It is found that for lower Q values the frequency response of a signal is wider and as Q value is increased the frequency response becomes narrow. During high Q values underlying wavelets have more oscillations [34, 47].

For every level in TQWT the signal of sampling frequency f is passed through a high pass and low pass filter. The signal is decomposed into a low frequency sub band signal with sampling frequency of δf and high frequency sub band signal with sampling frequency of εf. δ denotes the low pass scaling parameter and ε denotes the high pass scaling parameter [48, 49, 50]. Figure 2.4 and Figure 2.5 depicts the diagrammatical representation of TQWT of signal d(t) for single level and K level decomposition respectively.

The RR segment for the normal and AF beat is shown in Figure 2.6 and the detail coefficients of different levels obtained after TQWT decomposition of RR segment are shown in Figure 2.7.

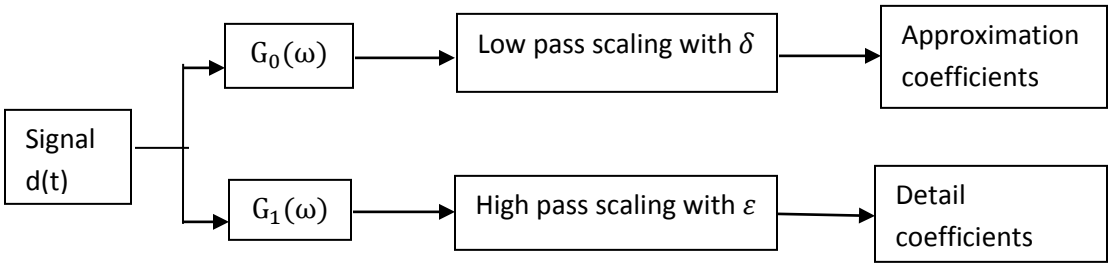


Figure 2.4: Diagrammatically representing TQWT of signal d(t) for K=1 (single level).

The frequency response of high pass and low pass sub band signal after K stages are expressed as ${G_0}^K(\omega)$ and ${G_1}^K(\omega)$ [34].

$$G_0{}^K(\omega) = \begin{cases} \prod_{n=0}^{K-1} G_0\left(\frac{\omega}{\delta^n}\right), & |\omega| \leq \delta^K\pi \\ 0, & \delta^K\pi < |\omega| \leq \pi \end{cases} \quad (2.3)$$

And,

$$G_1{}^K(\omega) = \begin{cases} G_1(\omega/\delta^{K-1}) \prod_{n=0}^{K-2} G_0\left(\frac{\omega}{\delta^n}\right), & \text{for } (1-\varepsilon)\delta^{K-1}\pi < |\omega| \leq \delta^{K-1}\pi \\ 0, & \text{for other } \omega \in [-\pi, \pi] \end{cases} \quad (2.4)$$

Where $G_0(\omega)$ and $G_1(\omega)$ are low pass and high pass filters given by [34]:

$$G_0(\omega) = \varphi\left(\frac{\omega+(\varepsilon-1)\pi}{\delta+\varepsilon-1}\right) \quad (2.5)$$

And,

$$G_1(\omega) = \emptyset\left(\frac{\delta\pi-\omega}{\delta+\varepsilon-1}\right) \quad (2.6)$$

Here $\emptyset(\omega)$ signifies Daubechies filters. Its frequency response is given as:

$$\emptyset(\omega) = 0.5\,[(1+\cos\omega) - \sqrt{2-\cos\omega}\,], \quad \text{for } |\omega| \leq \pi \quad (2.7)$$

Values of redundancy factor (r) and quality factor (Q) in terms of δ and ε is given by:

$$r = \frac{\varepsilon}{1-\delta} \quad \text{and} \quad Q = \frac{2-\epsilon}{\epsilon} \quad (2.8)$$

If the number of levels up to which the signal is to be decomposed is suppose K then, number of sub bands obtained are K+1 arranged in the form of cell array [34].

$$W = \{w_1,\ w_2,\ w_3 \ldots\ldots\ldots\ w_K,\ w_{K+1}\} \quad (2.9)$$

Here, w_{K+1} is the lowest frequency signal component and (w_1, w_2, $w_3 \ldots\ldots\ldots w_K$) are all high frequency signal components. In other words, w_{K+1} is the approximation coefficient and (w_1, w_2, $w_3 \ldots\ldots\ldots w_K$) are detail coefficients.

The block diagram of TQWT for K number of stages is shown in Figure 2.5.

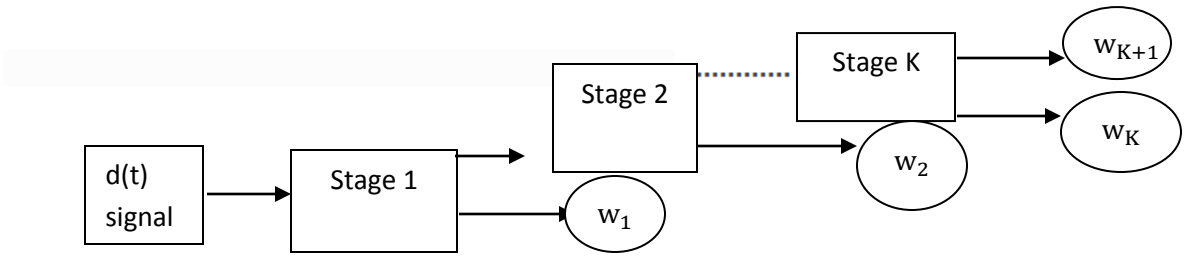


Figure 2.5: TQWT with K number of stages.

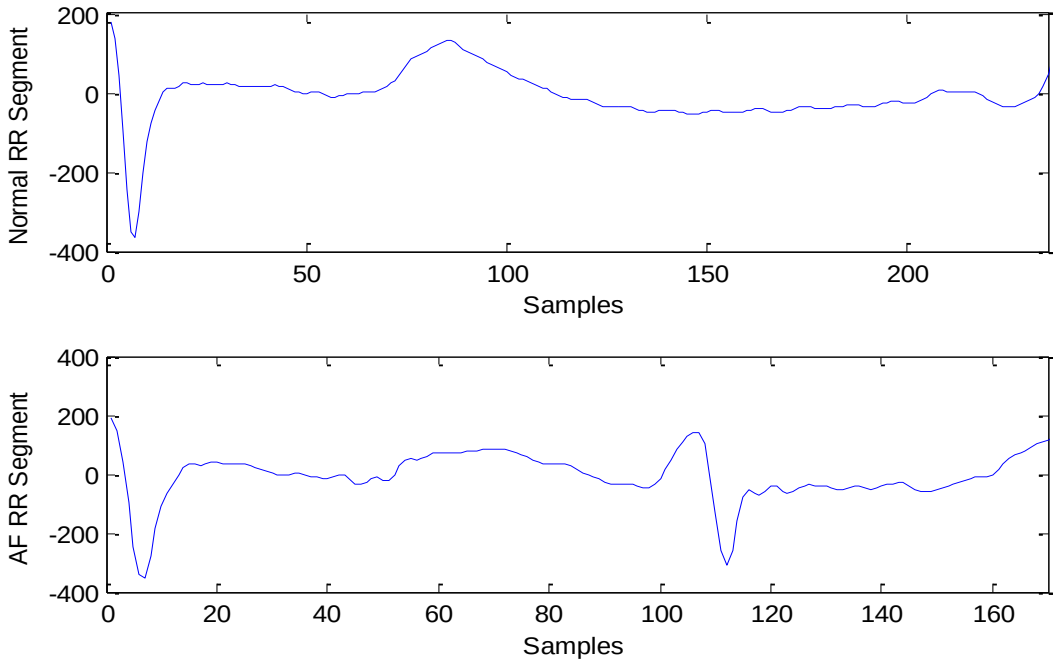
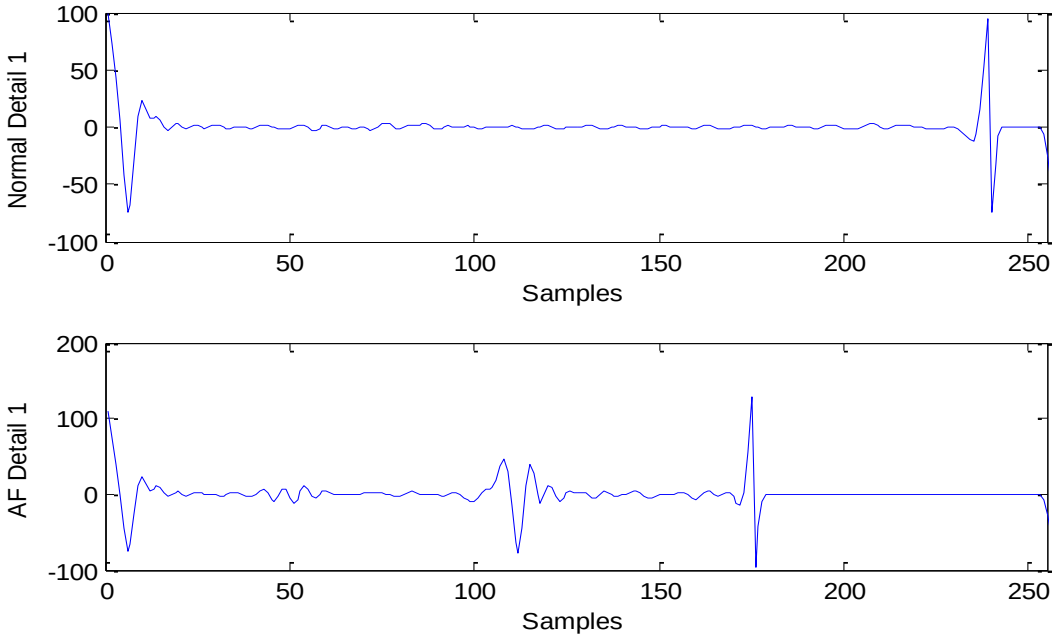
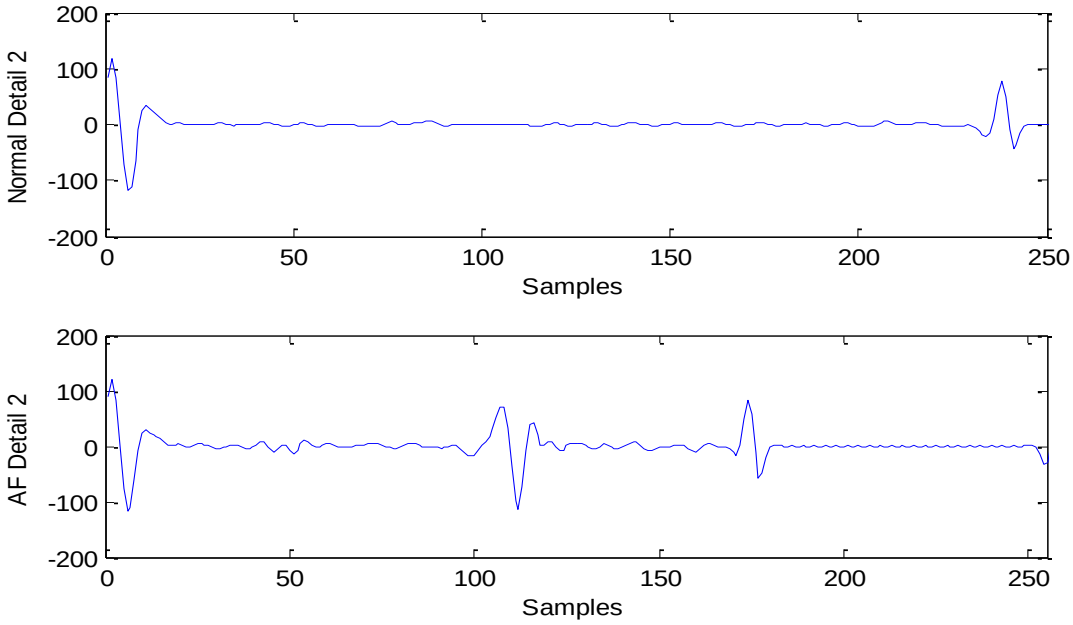


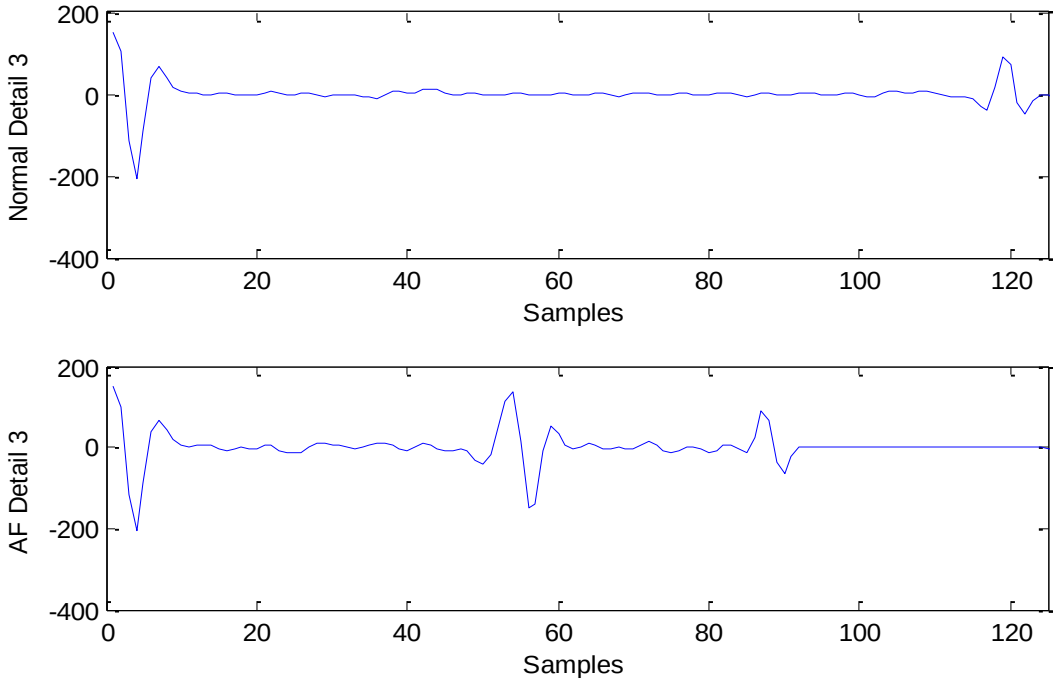
Figure 2.6: RR segment of normal and AF ECG signals


Normal Detail 1
100
50
0
-50
-100
0
50
100
150
200
250
Samples
AF Detail 1
200
100
0
-100
0
50
100
150
200
250
Samples

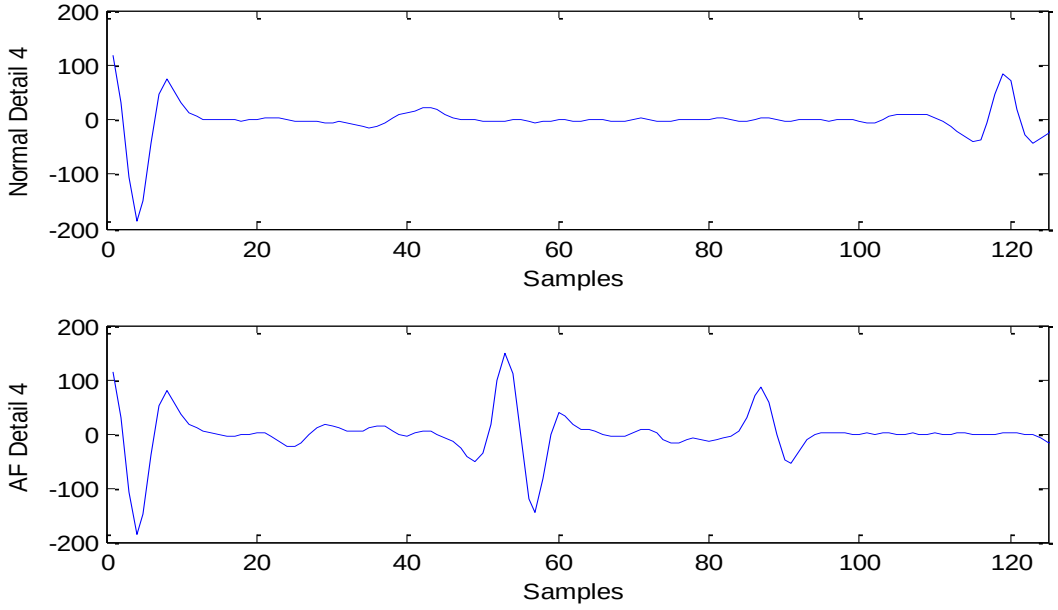
(a)


Normal Detail 2
200
100
0
-100
-200
0
50
100
150
200
250
Samples
AF Detail 2
200
100
0
-100
-200
0
50
100
150
200
250
Samples

(b)



(c)



(d)

Figure 2.7: Four level TQWT based decomposition of (a) Detail 1 coefficients (b) Detail 2 coefficients (c) Detail 3 coefficients (d) Detail 4 coefficients of normal and AF RR segments

2.4 Wavelet entropy

Amount of information carried by a random process can be estimated with the help of entropy. Since last few years entropy has been playing a very important role in case of biomedical signal analysis. In fact various entropy based measurements have given a great capability to uncover valuable information of diseases which are still a clinical challenge like schizophrenia [51], Alzheimer [52] and AF [53]. Wavelet entropy may be able to reveal more useful information which is principally associated with hidden mechanism that cannot be evaluated by clinicians in an exploratory examination, in this way it not only increases the knowledge of the disease but also improves their diagnosis and treatment [54, 55]. Wavelet entropy has been proved as a useful tool in determination of important clinical events from Electroencephalogram (EEG) [56, 57] and ECG [58] signals. In the present work we will use wavelet entropy for the detection of AF in ECG signals.

Very useful results are shown by wavelet entropy, because it joins entropy and wavelet decomposition to enhance its strength to artifacts, noise and non-stationary nature [56]. Wavelet entropy gives an estimation about the complexity of the signal. If d(n) is analyzed signal and $\vartheta_{j,k}(n)$ is the wavelet function then correlation between d(n) and $\vartheta_{j,k}(n)$ can be interpreted as wavelet coefficients c(j, k) [27].

$$c\ (j,\ k) = \sum_{n=1}^{M} d(n)\vartheta_{j,k}(n) \tag{2.10}$$

Here, M represents the length of d(n). There is no redundant information in these wavelet coefficients, thus the original signal can be completely reconstructed if the orthogonal function is used as the mother wavelet [59].

At each analyzed scale the signal energy can be directly estimated by using the coefficients c(j, k) [27]. Thus the relative energy for scale j can be represented as [27]:

$$E_j = \frac{\sum_{k=1}^{p_j} c(j,k)^2}{\sum_{j=1}^{N}\sum_{k=1}^{p_j} c(j,k)^2} \tag{2.11}$$

p_j and N here are used to represent the length of c(j,k) and the number of decomposition levels respectively, therefore by using Shannon entropy the wavelet entropy for this distribution can be defined as [27]:

$$WE = -\sum_{j=1}^{N} E_j \log_2(E_j) \quad (2.12)$$

Degree of complexity of the signal is measured by wavelet entropy. Thus for a well-organized signal , a very low value of wavelet entropy will be there, on the other hand for a disorganized or complex signal wavelet entropy will have a higher value.

2.5 Quasi ROC

ROC curve analysis is an efficient and simple tool to determine the performance of a classifier. For computation of an ROC curve we must have the knowledge of probability distribution function (pdf) or a probability score [60], with the help of which an instance would be classified in the two classes. A probability score or pdf may not be available all the time for a classifier, in such cases thresholding is used because the probability score does not work which is important to generate an ROC curve [60]. In the present work due to small size of data set and lack of knowledge of probability we have used the concept of quasi ROC or qROC [61]. With the help of qROC curve we can determine the efficiency of a classifier without any knowledge of pdf or probability score within it.

For generating a qROC curve, AF detection is classified in two classes, one is positive and the other is negative. These two classes are further classified in four sub classes, which are True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). If actual AF is detected then this type of detection is true positive but if AF is detected for a normal signal then this type of detection is termed as false positive detection. In the same way when a normal signal is detected correctly, it is termed as true negative and in the case when a normal signal is detected for AF signal, it is called as false negative detection. In qROC True Positive Rate (TPR) is taken on the Y-axis and False Positive Rate (FPR) is taken on the x-axis. TPR and FPR can be formulated as shown below [61]:

$$\text{FPR} = 1 - \text{specificity} = 1 - \frac{\text{TN}}{\text{TN+FP}} \tag{2.13}$$

$$\text{TPR} = \text{sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \tag{2.14}$$

Following steps are followed to generate the qROC [60]:

Step 1: Arrange FPR in ascending order.

Step 2: Repeated FPR values are arranged according to increasing value of corresponding TPR.

Step 3: Denote the lowest value of TPR as L_{TPR}.

Step 4: Denote the highest value of FPR as H_{FPR}.

Step 5: (0, 0) is considered as the point of origin.

Step 6: (1, 1) is considered as point of termination.

Step 7: qROC curve is generated by connecting the following points: (0, 0), $(0, L_{TPR})$, (H_{FPR}, L_{TPR}), $(H_{FPR}, 1)$ and (1, 1).

For better performance of a classifier the area under the qROC curve should be close to unity [61]. The classification accuracy is calculated with the help of equation 2.15 [62].

$$\text{Classification accuracy} = \frac{\text{TN+TP}}{\text{TN+TP+FN+FP}} \tag{2.15}$$

CHAPTER 3

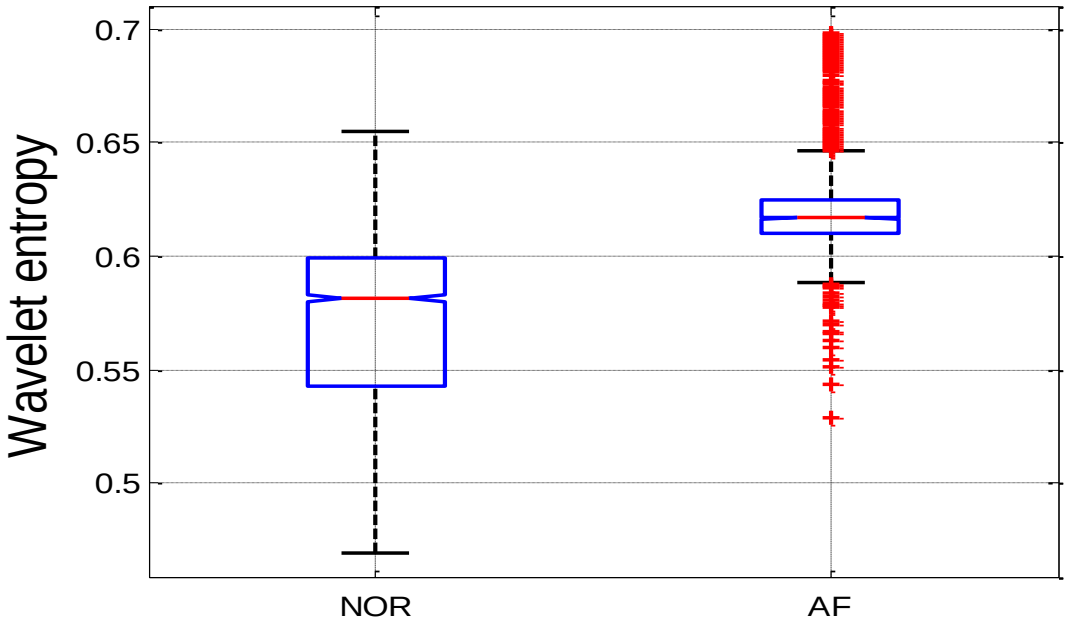
Results and Discussion

This chapter includes the results obtained after applying the above said methodology to the AF dataset. This chapter includes the boxplots, graphs and the tables showing results and the comparison of the present method to the previous methods. Later, discussion section provides the details explanation of the results.

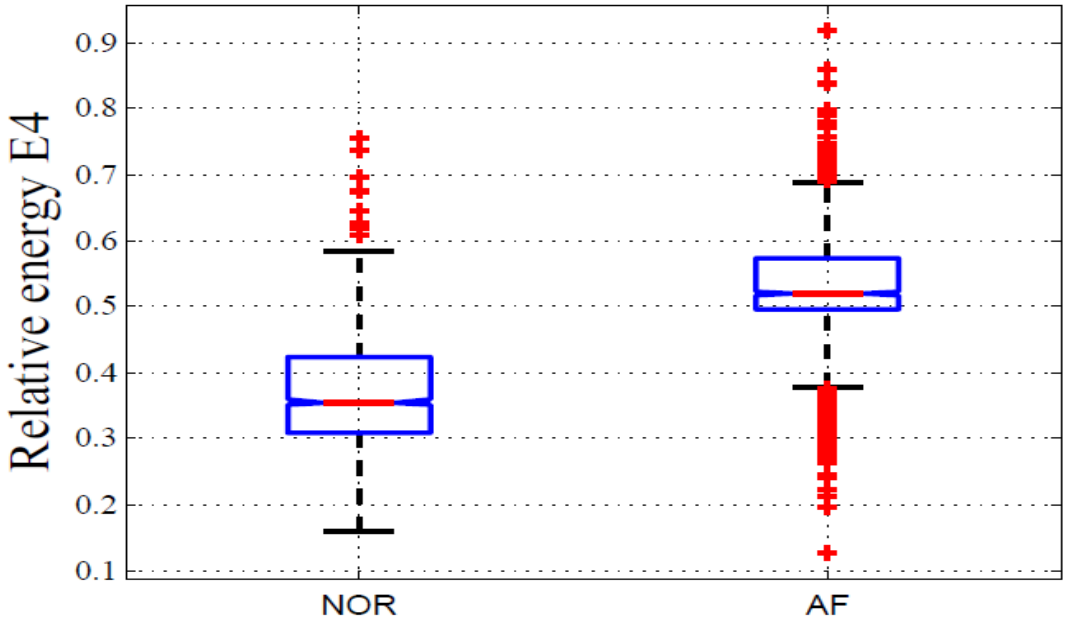
3.1 Results

We have 9 signals which contain both normal and AF episodes out of which 5 are used as learning set and 4 signals are used for test set. The wavelet entropy for learning set is computed using TQWT for parameters Q, r, J. The threshold giving maximum area under the curve is considered to be an optimum threshold for computing classification accuracies for learning and test sets. It should be noted that these thresholds determined for learning set are used for the test signal set for computing classification accuracy.

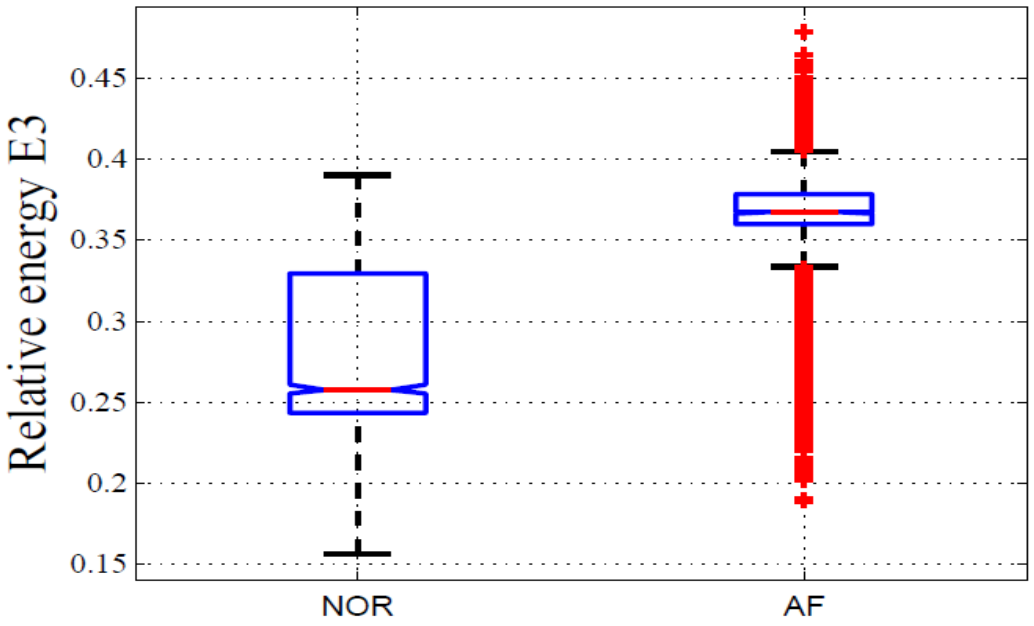
The similar process is repeated for learning and test set signals by changing the Q factor each time. The Q factor is varied from 1 to 10 and the optimum threshold is derived from learning set. This optimum threshold is applied to the test set for analyzing the effectiveness of this method to detect AF episodes from ECG signals. Kruskal-Wallis statistical test [63] is also applied to the normal and AF episodes to check statistical significance of wavelet entropy and relative energies features. Figure 3.1 shows the box plots obtained from Kruskal-Wallis statistical test of wavelet entropy and relative energies for Q=10, r=3 and J=4. The obtained probability (p) values for Kruskal-Wallis statistical test measures the statistical significance between two classes. The p value provides better statistical significance of two classes for $p < 0.05$.


Wavelet entropy
0.7
0.65
0.6
0.55
0.5
NOR
AF

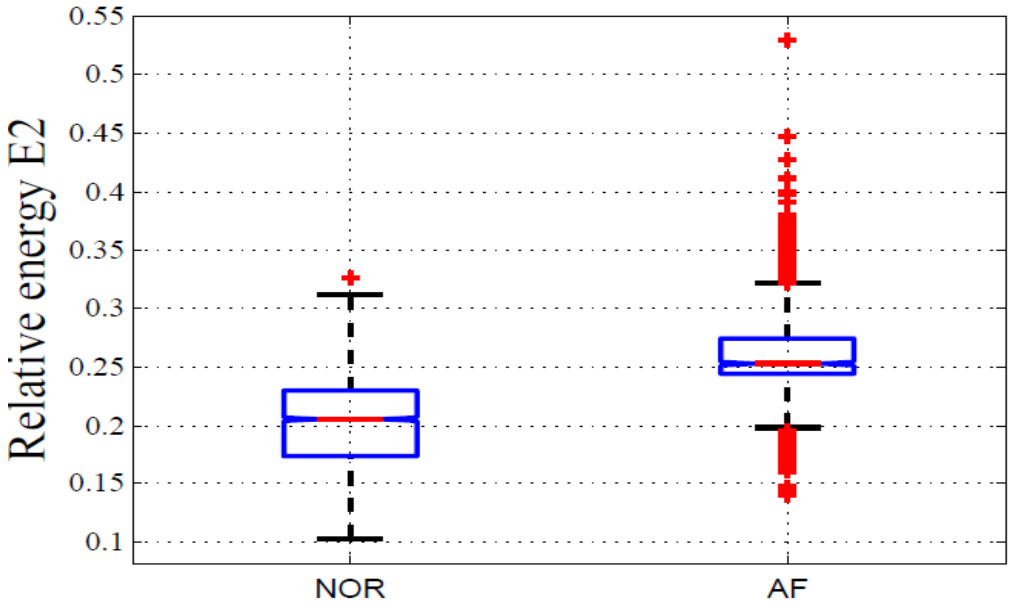
(a)


Relative energy E4
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
NOR
AF

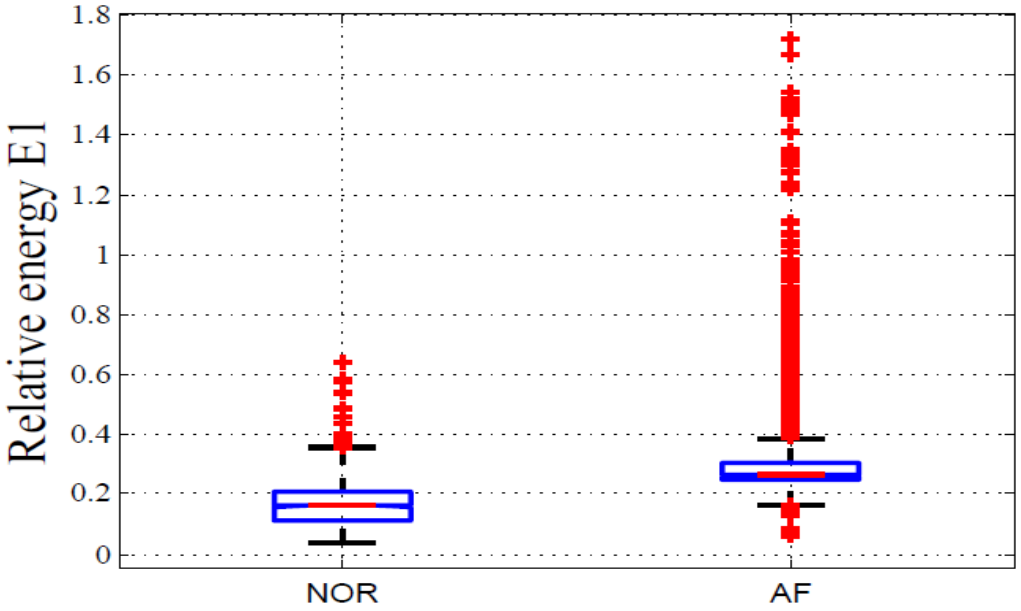
(b)


Relative energy E3
0.45
0.4
0.35
0.3
0.25
0.2
0.15
NOR
AF

(c)


Relative energy E2
0.55
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
NOR
AF

(d)



(e)

Figure 3.1: Boxplots for (a) Wavelet entropy (p =2.2e-8) (b) Relative energy E4 (p = 5.6e-9) (c) Relative energy E3 (p =7.8e-8) (d) Relative energy E2 (p =3.7e-6) and (e) Relative energy E1 (p= 6.2e-5) for Q=10.

NOR class shown in the box plots contain normal ECG beats and AF class contains the beats affected from AF. Relative energy E4, Relative energy E3, Relative energy E2 and Relative energy E1 represents the energies in the fourth level, third level, second level and first level of decomposition respectively. Quasi ROC curve of wavelet entropy for learning set with Q=10 is shown in the Figure 3.2 with TPR = 0.8025 and FPR = 0.2932, which results in 94.2093 % accuracy.

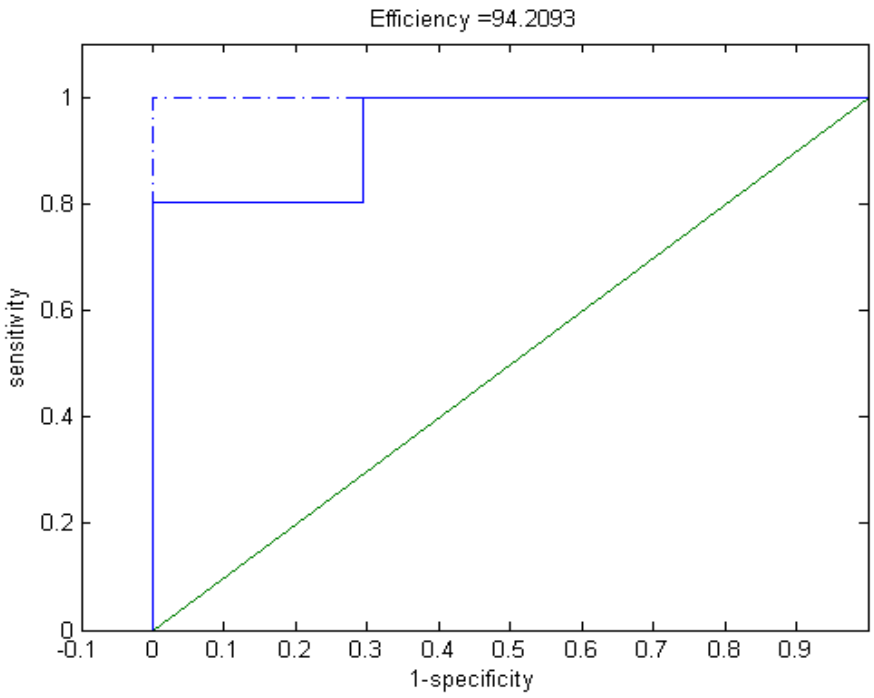


Figure 3.2: Plot of Quasi ROC for Q=10.

Learning and test set accuracies for different values of Q varying from 1 to 10 are shown in Tables 3.1 and 3.2 respectively. Figures 3.3, 3.4, 3.5, 3.6 and 3.7 show the variation of wavelet entropy and relative energies respectively, with the varying Q of TQWT (Q varying from 1 to 10) in graphical form. The graphs shows the variations between the two above said entities for learning set (solid line) as well as test set (dotted line) and the deviation of test set accuracy for their corresponding learning set.

Table 3.1: Learning set accuracies (in %) of the features for different values of Q- factor

Q-values	Wavelet entropy	Relative energy E4	Relative energy E3	Relative energy E2	Relative energy E1
Q=1	91.18	90.19	90.39	90.99	91.04
Q=2	91.27	90.49	90.25	90.78	87.26
Q=3	91.31	91.02	91.34	91.56	91.45
Q=4	91.61	92.47	91.48	91.10	91.03
Q=5	91.77	92.53	91.87	93.85	91.46
Q=6	92.31	92.42	92.05	92.47	91.99
Q=7	93.68	92.97	91.54	93.09	93.24
Q=8	93.56	93.18	93.65	90.26	89.59
Q=9	93.77	92.55	94.03	92.69	93.98
Q=10	94.2093	93.44	94.12	93.58	94.01

Table 3.2: Test set accuracies (in %) of the features for different values of Q-factor

Q-values	Wavelet entropy	Relative energy E4	Relative energy E3	Relative energy E2	Relative energy E1
Q=1	90.82	90.71	90.60	88.53	90.01
Q=2	91.05	90.25	90.88	90.02	89.20
Q=3	91.33	91.52	91.03	91.14	90.71
Q=4	91.35	91.13	91.97	91.43	92.56
Q=5	92.08	90.72	90.90	91.12	91.49
Q=6	92.71	92.90	92.70	93.09	92.30
Q=7	92.98	93.01	92.74	93.12	92.88
Q=8	93.11	93.42	92.82	93.11	93.29
Q=9	93.39	93.40	92.99	93.21	93.33
Q=10	93.44	93.25	92.89	93.32	93.37

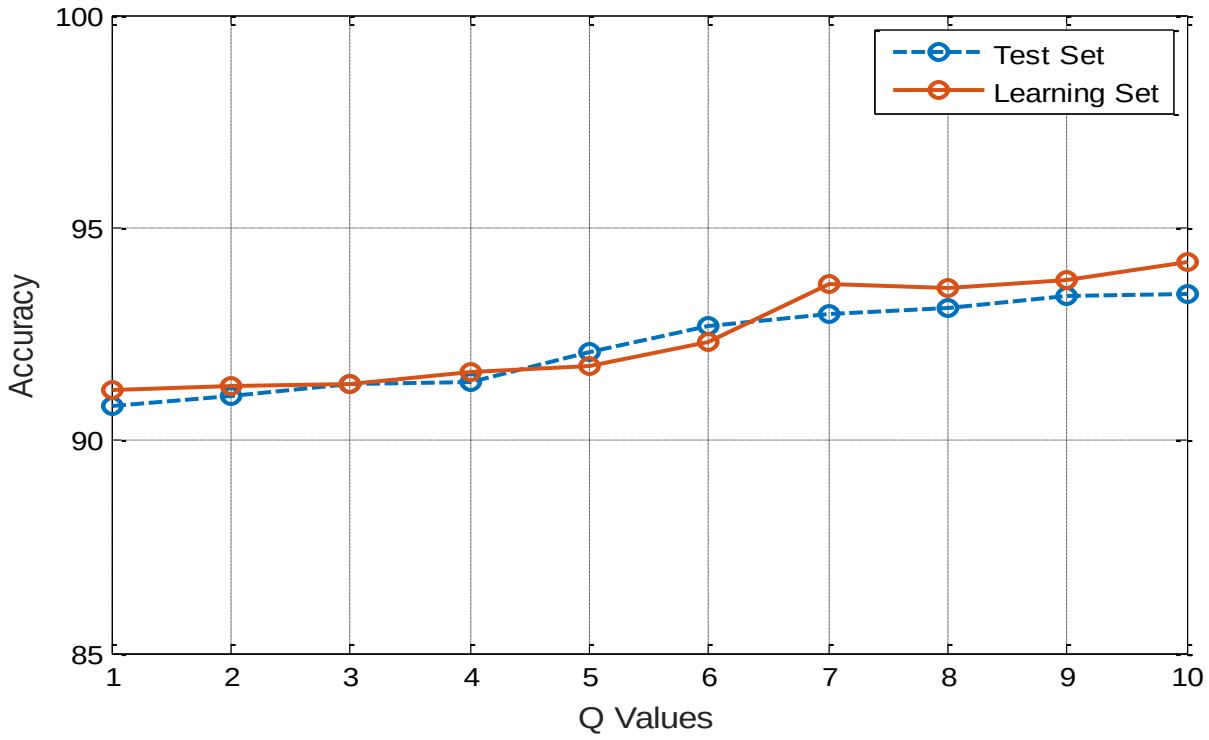


Figure 3.3: Graphical plot of accuracy values of wavelet entropy for different Q-values.

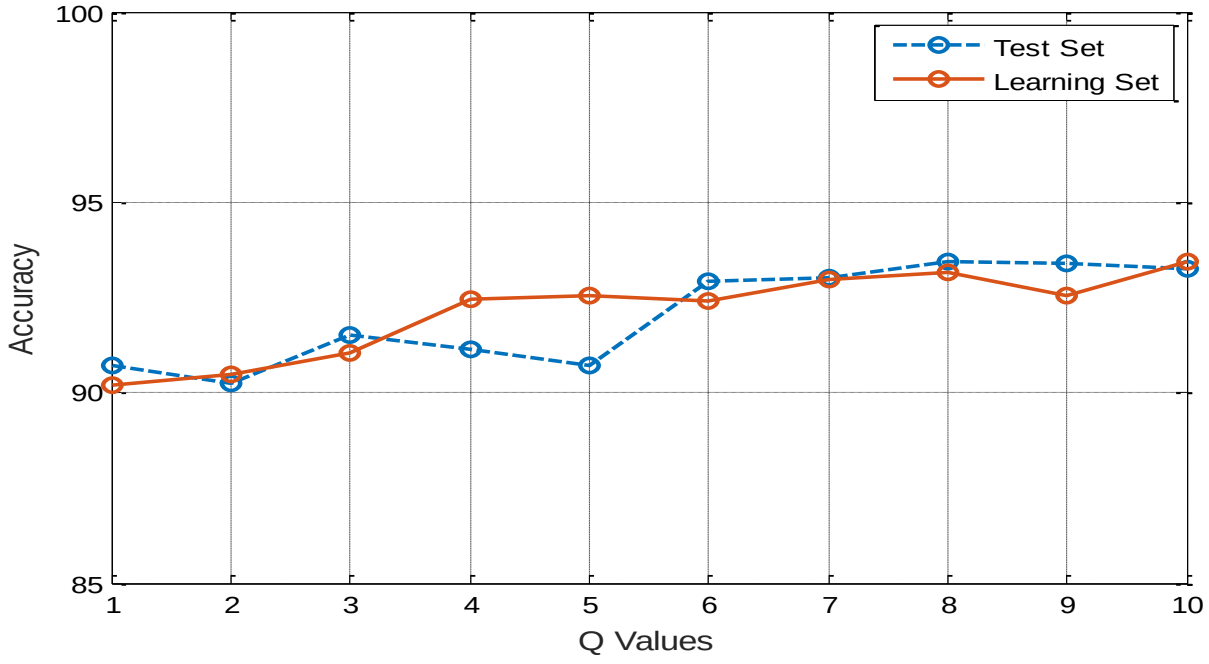


Figure 3.4: Graphical plot of accuracy values of relative energy E4 for different Q-values.

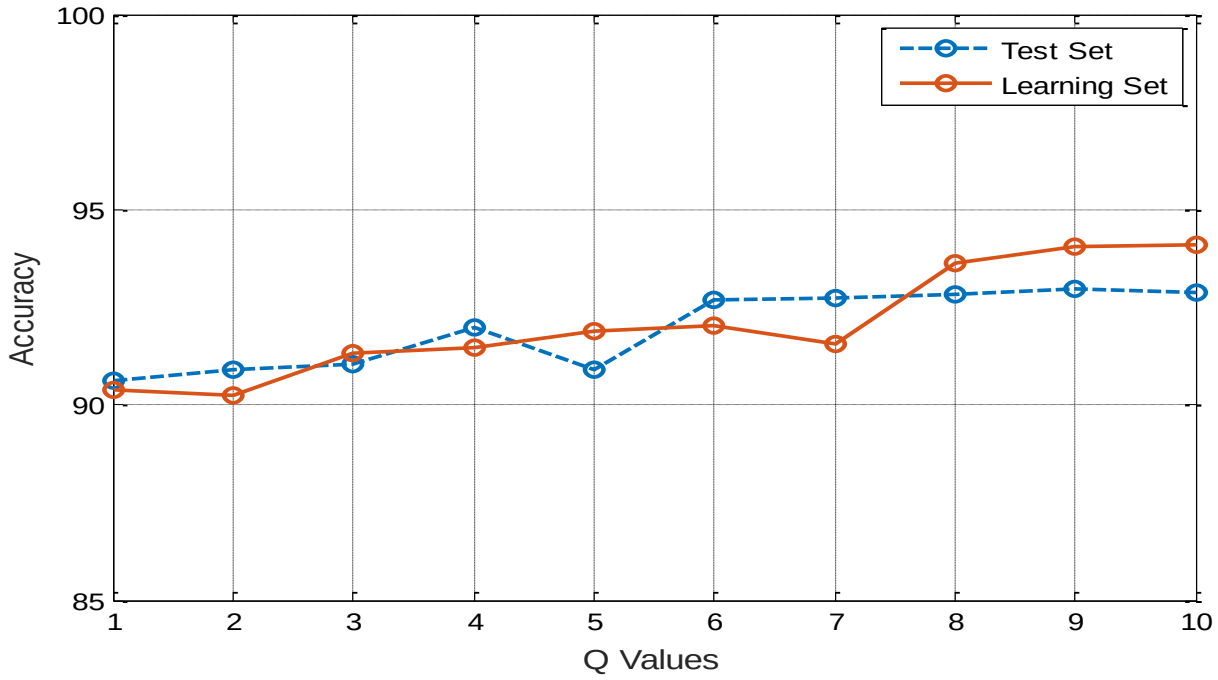


Figure 3.5: Graphical plot of accuracy values of relative energy E3 for different Q-values.

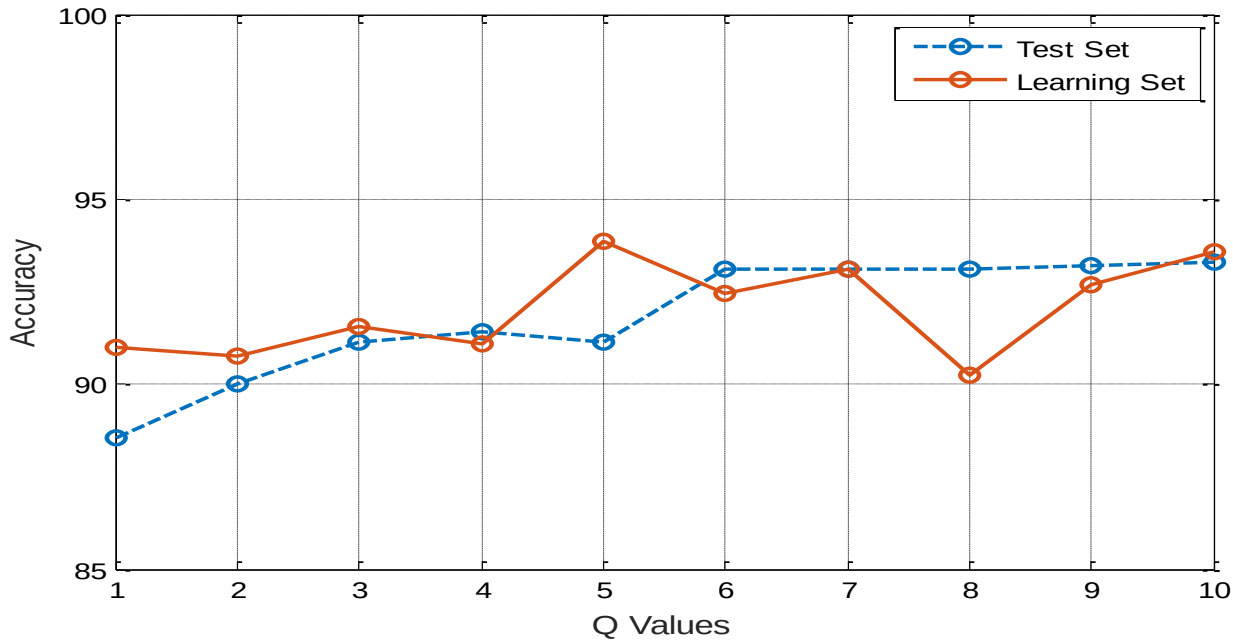


Figure 3.6: Graphical plot of accuracy values of relative energy E2 for different Q-values.

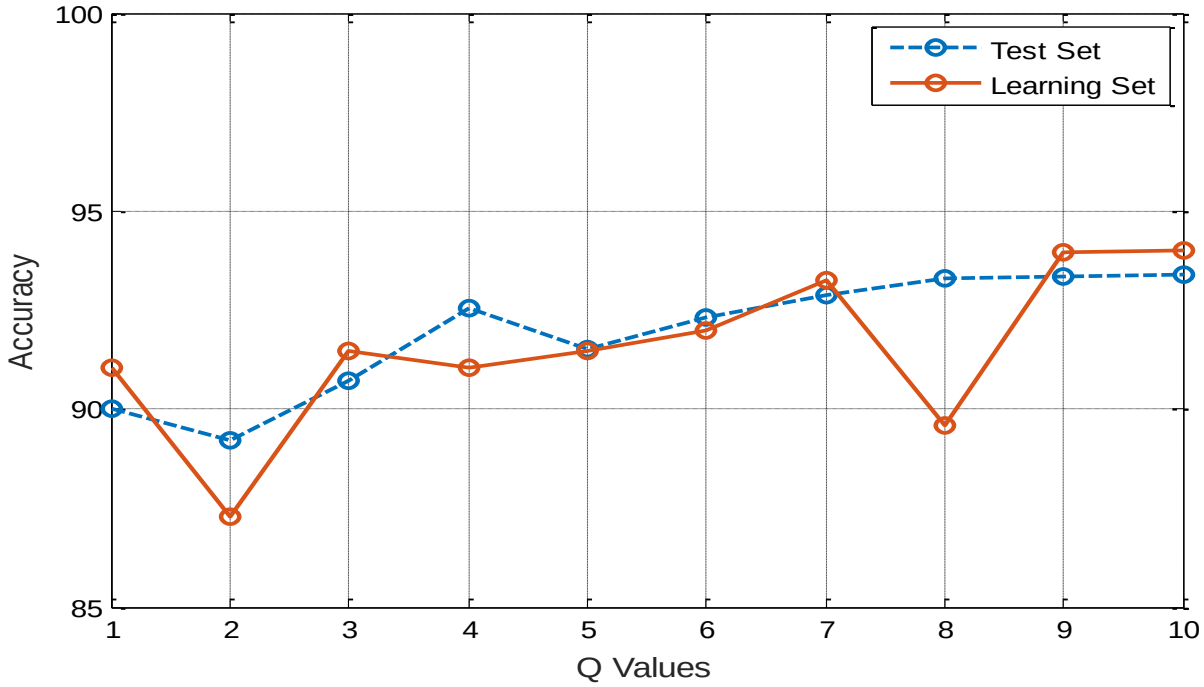


Figure 3.7: Graphical plot of accuracy values of relative energy E1 for different Q-values.

3.2 Discussion

This method is compared with the previous methods used by various authors along with the accuracies, and the method used by then in Table 3.3. Slocum et al. [64] created a remainder ECG signal by cancelling the QRST activity and they found a significant difference between the ower of normal and AF rhythm in the remainder ECG. Their test has an accuracy of 68.3 %. Babaeizadeh et al. [65] studied the RR segment patterns of normal and AF beats. The AF beats show more random segment than normal beat. They used Markov modelling approach and calculated a Markov score corresponding to each RR segment. This score measures the likelihood of AF RR segment and normal RR segment. Based on this score they were able to detect AF with an accuracy of 94.40 %. Lake and Moorman [66] used the delta RR segment. They computed confident entropy and density histogram by varying the tolerance matching parameter. The combination of extracted delta RR segment and the sample entropy was able to detect AF with a delay of 12 beats and resulted in an accuracy of 96.20 %.

Zhou et al. [67] devised a method using RR segments and computing Shannon entropy by recursive algorithm. They performed it on different datasets including long term AF, MIT BIH AF and MIT BIH arrythmia with accuracy of 96.05 %, 97.67 % and 91.46 % respectively. Ladavich et al. [21] extracted nine features through statistical analysis of P-wave. These features were given to the input of expectation maximization algorithm to form GMM and hence identifies the absence of P-wave with an accuracy of 93.22 %. Rodenas et al. [27] used the wavelet entropy feature to automatically detect AF. They extracted median TQ segment from ECG signals and compute wavelet entropy from these extracted segments. They were able to detect AF with a minimum delay of 5 beats with an accuracy of 95.28 %.

The present work has used TQWT for the very first time to detect the episodes of AF in ECG signal by extracting the RR segments. Wavelet entropy and relative energies are calculated using TQWT coefficients. Wavelet entropy is used as it has recently shown great ability to measure the degree of randomness of signal and hence is proved to be a powerful tool for the identification of AF episodes. The variation of accuracy on changing the Q-parameter can be seen from Figure 3.3 for learning set and test set depicted by solid line and dotted line respectively. In case of wavelet entropy the accuracy increased from 90.82 % for Q=1 to 93.44 % for Q=10. The accuracy curve against Q-values in Figure 3.3 obtains saturation with a very slight increase in accuracy values for the higher values of Q. On increasing Q values beyond 10 the accuracy starts to decrease. The similar kind of trend is observed for relative energies at different levels. The deviation of test set accuracy values from the learning set is found to be small within the range of ± 1 %.

Table 3.3: Comparison of proposed method with previous work on same data set

Algorithm	Accuracy	Methodology
Slocum et al. [64]	62.80 %	QRST cancellation
Babaeizadeh et al. [65]	94.40 %	Analysis of RR segment signal
Lake and moorman [66]	96.10 %	Analysis of delta RR signal and their density histogram
Zhou et al. [67]	97.67 %	Analysis of RR segment signal with extraction of shannon entropy
Ladavich et al. [21]	93.22 %	P-wave analysis using gaussian mixture model
Rodenas et al. [27]	95.28 %	Analysing median TQ segment and wavelet entropy
Present work	Maximum 93.44% at Q=10	TQWT at different Q-values and extracting wavelet entropy and relative energies

CHAPTER 4

Conclusion and Future scope

This chapter includes the conclusion of present work and the future scope.

4.1 Conclusion

This method has proved that wavelet entropy is an efficient tool to differentiate between normal heart beat and beat affected by AF. TQWT has been used in this work which proves that for different values of Q, we get different discriminant ability. Efficiency of this work increases as the value of Q increases up to a certain limit and then it saturates. In this method accuracy of wavelet entropy varies from 90.82% for Q=1 to 93.44% for Q=10, which is comparable with the previous work done for AF detection. This method has the ability to detect very brief episodes of AF which are hardly of few beats in length. This method can be integrated in the monitoring system, so that the clinicians would be able to detect very brief episodes of AF, which occurs mostly at the initial stages of it.

4.2 Future scope

This method can be studied for multiclass classification, wherein ECG signals affected by other heart issues and arrhythmias would be considered as separate classes. In this way the clinicians would be able to able to know the exact type of arrhythmia patient is suffering from, so that a better medical treatment can be provided. It should be studied on the larger data sets before applying for the clinical purpose. It can also be studied for classification of other biomedical signals like EEG, Electromyogram (EMG) signals corresponding to normal and abnormal cases.

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