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Arrhythmia Classification Approach Based On Features Extracted From 1Dand 2D Discrete Cosine Transforms On ECG Signals

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Abstract: *Any disturbance in the activity of heart can cause irregular heart rhythm known as cardiac arrhythmia. Electrocardiogram (ECG) is one of the most promising tools for classification of different types of arrhythmia, which is necessary until it goes fatal and causes loss of life. For ECG arrhythmia classification, a wide range of signal processing techniques extracting features from time, frequency domains have been reported in the literature. Since, ECG is a non stationary signal; frequency analysis can perform better than the conventional time analysis methods. But, development of a multi class arrhythmia classification method, which is simple yet effective, is still a challenging task. In this thesis, 1-D Discrete cosines transform (DCT) and 2-D DCT is proposed to form feature vectors. Each of the feature vector is fed to a Euclidean distance based classifier to classified different types of ECG arrhythmia .Simulations are carried out to evaluate the performance of the proposed method in terms of accuracy. It is shown that the propose method using 2-D DCT can perform better than 1-D-DCT thus providing superior efficacy.*

Keywords: *Arrhythmia, Electrocardiogram, Heartbeat.*

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I Introduction

The term arrhythmia suggests abnormalities in the heart rate, although it is commonly used to refer to changes in the shape of the heart wave. The electrocardiogram (ECG) is the most important bio-signal, if properly analyzed, provides key information about the electrical activity of the heart. Life threatening situation, signaled by the occurrence of premature ventricular (PVC), ventricular fibrillation (VF) or other serious arrhythmias, can often be reversed if detected in time for proper treatment. However, ECG being a non-stationary signal, the irregularities may not be periodic and may not show up all the time, but would manifest at certain irregular intervals during the day. So continuous ECG monitoring permits observation of cardiac variation over an extended period of time, either at the bedside or when patients are ambulatory, providing more information to physicians. Thus, continuous monitoring increases the understanding of patient's circumstances and allows more reliable diagnosis of cardiac abnormalities. Detection of abnormal ECG single is a critical step in administering aid to patients. Often, patients are hooked up to cardiac monitors in hospital continuously. This requires continuous monitoring by the physicians. Since clinical observation of ECG can take long hours and can be very tedious, the cardiac intensive care unit has been incorporated hospitals in order to improve the chances of survival of and to treat patients suffering traumatic episodes of heart diseases.

1.1 Objective of the Study:

The objectives of this study are:

1. To develop a set of feature vector based on 1-D Discrete cosine transform (DCT) of ECG signals.
2. To derive another set of feature vector based on 2 -D Discrete cosine transform (DCT) of ECG signals.
3. To investigate the performance of the proposed feature sets for the classification of five types of arrhythmia using ECG signals available from the MIT-BIH arrhythmia database.

1.1 The Heart Anatomy

The heart contains four chambers that is right atrium, left atrium, right ventricle, left ventricle and several atrioventricular and sinoatrial node as shown in the Fig. 1.1. The two upper chambers are called the left and right atria, while the lower two chambers are called the left and right ventricles. The atria are attached to the ventricles by fibrous, non-conductive tissue that keeps the ventricles electrically isolated from the atria. The right atrium and the right ventricle together from a pump to the circulate blood to the lungs. Oxygen poor blood is received through large veins called the superior and inferior vena cava and flows into the right atrium. The right ventricle then pumps the blood to the lungs where the blood is oxygenated. Similarly the left atrium and the left ventricle together form a pump to circulate oxygen-enriched blood received from the lungs to the rest of the body. In heart Sino-atrial (S-A) node spontaneously generates regular electrical impulse, which then spread through the conduction system of the heart and initiate contraction of the myocardium. Propagation of an electrical impulse through excitable tissue is achieved through a process called depolarization. Depolarization of the heart muscles collectively generates a strong ionic current. This current flows through the resistive body tissue generating a voltage drop. Similarly, ventricular depolarization results in the spreading of the electrical impulse throughout the ventricular myocardium.

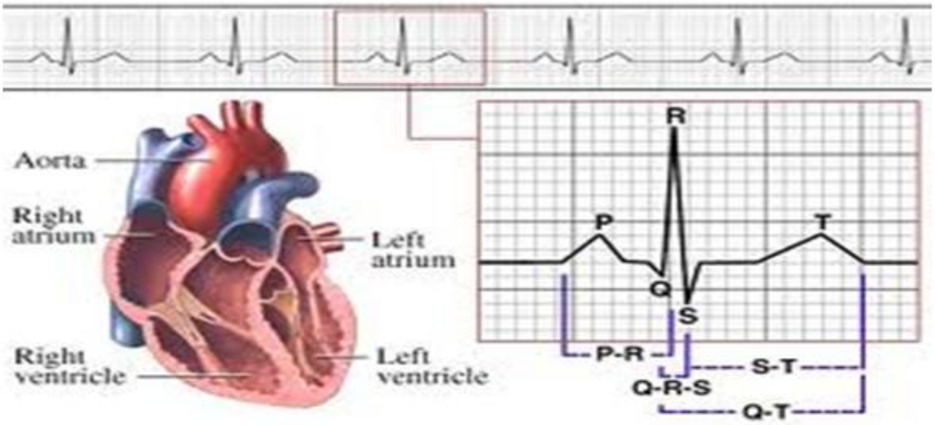


Fig. 1.1 A diagrammatic structure of human heart

1.2 Electrocardiogram

Electrocardiogram (ECG) is a diagnosis tool that reported the electrical activity of heart recorded by skin electrode. The morphology and heart rate reflects the cardiac health of human heartbeat. It is a noninvasive technique that means this signal is measured on the surface of human body, which is used in identification of the heart diseases. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of cardiac arrhythmia, which could be detected by analysis of the recorded ECG waveform. The amplitude and duration of the P-QRS-T wave contains useful information about the nature of disease afflicting the heart. The electrical wave is due to depolarization and repolarization of Na+ and K+ ions in the blood. The ECG signal provides the following information of a human heart .

- Heart position and its relative chamber size
- Impulse origin and propagation
- Heart rhythm and conduction disturbance
- Extent and location of myocardial ischemia
- Changes in electrolyte concentrations
- Drug-effects on the heart.

ECG does not effort data on cardiac contraction or pumping function.

1.3 ECG Waves and Interval

1.3.1 P Wave

P wave represents the sequential activation of the right and left atria, and it is common to see notched or biphasic P waves of right and left atrial activation. It is very difficult to analyze P waves with a high signal-to-noise ratio in ECG signal.A clear P wave before the QRS complex represents sinus rhythm. Absence or P waves may suggest atrail fibrillation, sinus node arrest, junctional rhythm or ventricular rhythm.

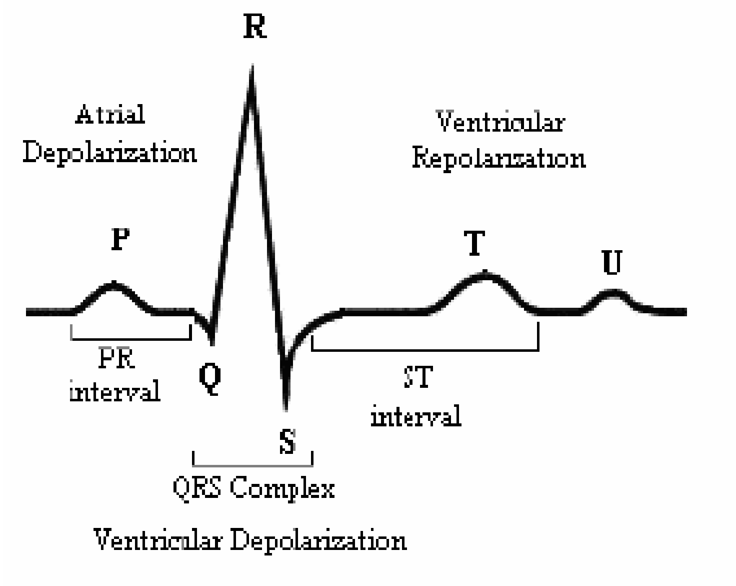


Fig 1.2 Normal ECE waveform

1.3.2 PR Segment

The PR segment connects the P wave and the QRS complex. The impulse vector is from the AV node to the bundle of His to the bundle branches and then to the Purkinje fibers. This electrical activity does not produce a contraction directly and is mercy travelling down towards the ventricular and this show up flat on the ECG. The Pr interval is more clinically relevant than Pr segment to any abnormality.

1.3.3 PR Interval

The Pr interval is measured from the beginning of the first part the QRs complex. It includes time for atrail depolarization, conduction through the AV node, and conduction through the His-Purkinje system. Disruption at any point can prolong the PR interval. The length of the PR interval changes with heart rate. Long PR interval suggests 1st degree atrioventicular block whereas varying PR interval implies Mobitz type I atrioventicular block or multifocal atrio tachycardia.

1.3.4 QRS complex

The QRS complex is the largest voltage deflection of approximately 10-20 mV but may vary in size depending on age, and gender. The QRS represents the simultaneous activation of the right and left ventricles, although most of the QRS waveform is derived from the larger left ventricular musculature. Duration of the QRS complex indicates the time for the ventricles to depolarize and may give information about conduction problems. Wide QRS complex indicates right or left bundle branch block, ventricular flutter or fibrillation etc.

1.3.5 T wave

T wave represents ventricular repolarization. The interval from the beginning of the QRS complex to the apex of the T wave is referred to as the absolute refractory period. Tall T wave may suggest left bundle branch block, ventricular hyper trophy, hyperkalemia, stroke whereas small, flattened or inverted T wave implies myocardial ischemia, myocarditis, anxiety, certain drugs, right bundle branch block, hypokalemia etc.

1.3.6 ST Segment

The ST segment occurs after ventricular depolarization has ended and before repolarization has begun. The ST segment is usually isoelectric and has a slight upward concavity. It is always measured from the J point, where the QRS and ST segments Elevation of ST segment implies myocardial ischemia, acute MI, LBBB, left ventricular hypertrophy, hyperkalemia, hypothermia whereas depression of ST segment may suggest myocardial ischemia, acute posterior MI, LBBB, RBBB etc.

1.3.7 ST Interval

The ST interval is measured from the J point to the end of the T wave.

1.3.8 QT Interval

The QT interval consists of the QRS complex (representing only a brief part of the interval), along with the ST segment and T wave, which constitutes the majority of the duration. The QT interval is used primary as a measure of membrane repolarization. Since the QT interval varies with heart rate, the QT interval is "corrected" QTc) to make comparisons between ECG beats. A prolonged QT interval is a risk factor for ventricular tachyarrhythmias and sudden death. Short QT interval may suggest hypercalcemia, hypomagnesemia, Graves' disease etc.

1.3.9 U wave

The U wave is hypothesized to be caused by the repolarization of the interventricular septum. Their amplitude is normally one-third of the following T wave and even more often completely absent. It may be seen following the T wave and can make interpretation of the QT interval especially difficult. This is associated with metabolic disturbances, typically hypokalemia, hypomag-nesemia and ischemia.

1.4 Chest (Precordial) ECG leads

- V1: 4th intercostals space, right sternal edge.
- V2: 4th intercostals space, left sternal edge.
- V3: Between the 2nd and 4th electrodes.
- V4: 5th intercostals in the midclavicular line.
- V5: On 5th rib, anterior axillary line.
- V6: In the midaxillary line.

To make recordings with the chest leads the three limb leads are connected to form and indifferent electrode with high resistances. The chest leads mainly detect potential vectors directed towards the back. These vectors are hardly detectable in the frontal plane. Since the mean QRS vector is usually directed downwards and towards the left back region, the QRS vector recorded by leads V1-V3 are usually negative, while those detected by V5 and V6 are positive. In leads V1 and V2, QRS= -ve because, the chest electrode in these leads is nearer to the base of the heart, which is the direction of eletronegativity during most of the ventricular depolarization process. In leads V4, V5, V6, QRS= +ve because, the chest electrode in these leads is nearer the heart apex, which is the direction of electropositivity during most of depolarization.

1.5 Arrhythmias in ECG Signal

The normal rhythm of the heart where there is no disease or disorder in the morphology of ECG signals is called normal sinus rhythm (NSR) shown in Fig 1.5(a). The heart rate of NSR is generally characterized by 60-100 beats per minute. The regularly of the R-R interval varies slightly with the breathing cycle. The source of the rhythm is the sino-atrial node. This is the normal parameker of the heart. When the heart rate increases above 100 beats per minute, the rhythm is known as sinus tachycardia. This is not an arrhythmia but a normal response of the heart which demand for higher blood circulations. Arrhythmias may be easily understood by categorizing them in the following manner:

1. Left bundle branch block beat (LBBB)
2. Right bundle branch block beat (RBBB)
3. Premature ventricular contraction (PVC)
4. Atrial premature contraction (APC)
5. Paced beat (PB)

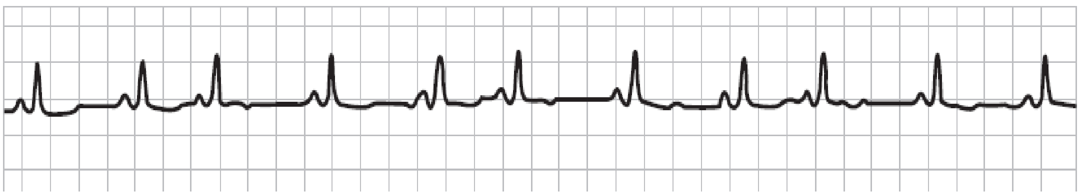


Fig. 1.5 (a) Normal sinus rhythm has regular, repeating waveforms of P, QRS, T waves and stable time segments between the waves.

1.5.1 Left Bundle Branch Block (LBBB)

The left bundle branch will prevent the electrical impulses from the A-V node from depolarizing the left ventricular myocardium in the normal way. For LBBB, the right ventricle is depolarized primarily; generating an electrical wave front that eventually spreads to the left ventricular myocardium causing the myocardium to depolarize.This type of arrhythmia arises from the S-A node of heart. As the electrical impulse is generated from the normal pacemaker, the characteristic feature of these arrhythmias is that P-wave morphology of the ECG is normal. These arrhythmias are the following types: Sinus Arrhythmia, Sinus Bradycardia, and Sinus arrest etc shown in Fig. 1.5(b).

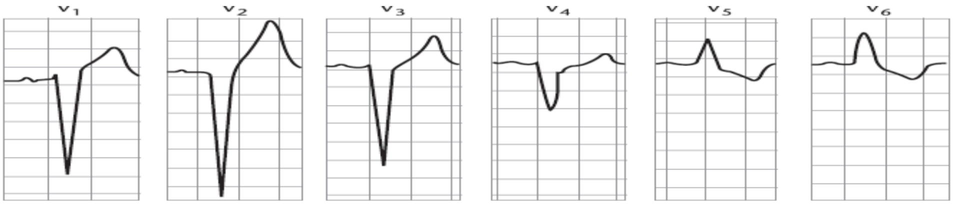


Fig. 1.5 (b) Left bundle branch block (LBBB).

1.5.2 Right Bundle Branch Block (RBBB)

When the right bundle branch is blocked, the electrical impulse from the AV node is not able propagate to the Purkinje network to depolarize the right ventricular myocardium. Instead, the impulse propagates in a convoluted manner through the left ventricular myocardium to reach the right ventricular myocardium. Since propagation through the myocardium is much slower than through the specialized conducting tissue, the QRS-complex becomes widened. The morphology of the QRS complex also changes and takes on a bizarre appearance because of the different direction of depolarization shown in Fig. 1.5(c).

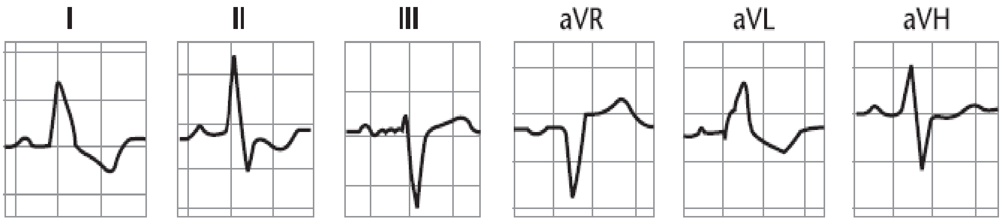


Fig. 1.5 (c) Right bundle branch block (RBBB).

1.5.3 Premature Ventricular Contractions (PVC)

In PVC the abnormality is originated from ventricles. PVCs usually do not depolarize the atria or the S-A node and hence the morphology of P-waves maintains their underlying rhythm and occurs at the expected time. PVCs may occur anywhere in the heart beat cycle. PVCs are described as isolated if they occur singly, and as couplets if two consecutive PVCs occur shown in Fig. 1.5(d).

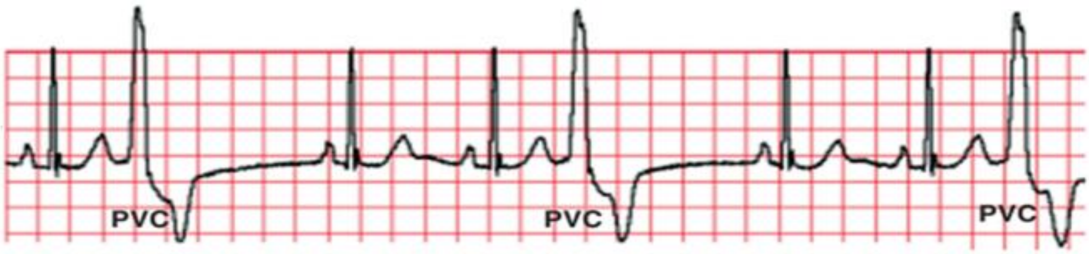


Fig. 1.5 (d) premature ventricular contraction (V).

1.5.4 Atrial Premature Contraction (APC)

When the ectopic beat originates in the atria, it leads to a premature atrial beat, also known as an atrial premature contraction (APC) shown in Fig. 1.5(e). When it originates in the ventricles, it leads to a premature ventricular beat or ventricular premature contraction (VPC)

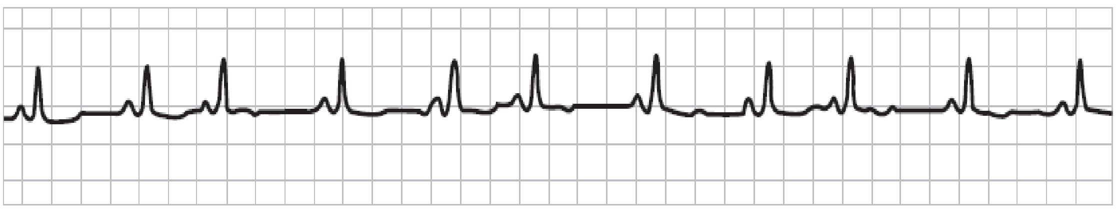


Fig. 1.5 (e) Atrial premature contractions (APC).

1.5.5 Paced Beat (PB)

Hearts implanted with an artificial pacemaker will generally beat around 60 to 70 beats per minute depending on the setting of the artificial pacemaker. The pacing electrode is commonly attached to the apex of the right ventricular cavity (ventricular pacemaker) or the right atrium (atrial pacemaker), or both (dual chamber pacemaker). The artificial pacemaker produces a narrow, often biphasic spike. A pacemaker lead positioned in an atrium produces a pacemaker spike followed by a P -wave. A pacemaker lead positioned in a ventricle produces a pacemaker spike followed by a wide, bizarre QRS-complex sometimes it is also called pacemaker rhythm shown in Fig. 1.5(f).

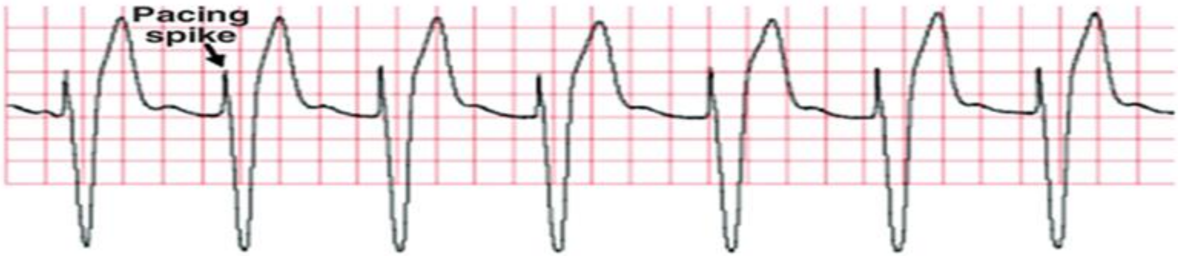


Fig. 1.5 (f) Paced beat (PB).

1.6 Importance of ECG Arrhythmia Classification

Modern era of medical science is facilitated by computer aided feature extraction and disease diagnostics in which various signal processing techniques have been utilized in extracting different kinds of features from the ECG signals. The objective of computer aided digital signal processing of ECG signal is to reduce the time taken by the cardiologists in interpreting the results. Due to the large member of patient in intensive care units, the need for continuous observation of them and the high possibility of the analyst missing the vital information by visual analysis, over the years researchers have developed a variety of relatively effective signal processing techniques in time or frequency in order to classify ECG arrhythmia accurately. However, the problem of classifying different type of ECG arrhythmia still poses a challenge to the area of signal processing. In a particular arrhythmia condition, morphological changes occur in different sections of normal ECG beat and such changes vary detail characteristics of each arrhythmia through signal processing techniques into a feature vector capable of correctly classifying among different types of ECG arrhythmia is a difficult task. Complexity and ease of implementation of the cardiac arrhythmia classification methods is also of concern in real life applications. The overall goal of arrhythmia classification technique is to find a simple yet effective method capable of performing the classification task with greater accuracy.

II Proposed Method For ECG Arrhythmia Classification

2.1 Introduction

Designing a feature set which is capable of extracting distinguishable information to classify different classes of arrhythmia from mixture of normal and abnormal ECG signals is not an easy task. The proposed ECG based arrhythmia classification method consists of some major steps, namely, feature extraction and classification. In the classification, we consider five classes of arrhythmia data, namely Left bundle branch block beat (LBBB), Right bundle branch block beat (RBBB), Premature ventricular contraction (PVC), Atrial premature contraction (APC), and Paced beat (PB). For the purpose of classifying arrhythmia, a training database is needed to be prepared consisting of template ECG signals of different classes. The classification task is based on comparing a test ECG signal with template data. It is obvious that considering ECG signals themselves would require extensive computations for the purpose of comparison. Thus, instead of utilizing the ECG signals, some characteristic features are extracted for preparing the template. It is to be noted that extracted features. Therefore, the main focus of this thesis is to develop an effective feature extraction algorithm. The block diagram of the proposed method is shown in Figure: 2.1

Training & Testing

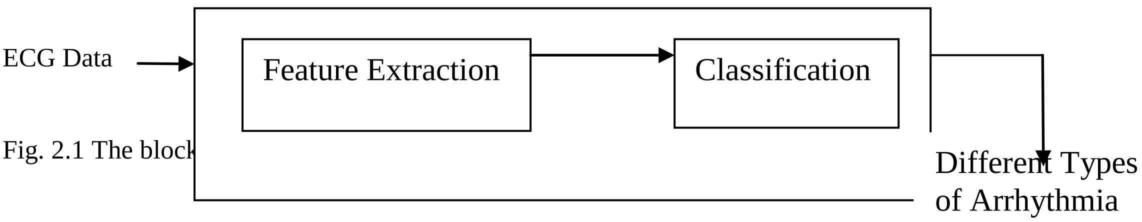


Fig. 2.1 The block

2.2 Feature selection

Two types of features are proposed for ECG arrhythmia classification base on1-D DCT and 2-D DCT. In this section 1-D DCT and 2-D DCT are described separately.

2.2.1 Discrete cosine transform

A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. Formally, the discrete cosine transform is a linear invertible function $f : \mathbb{R}^N \rightarrow \mathbb{R}^N$ (where $\mathbb{R}$ denotes the set of real numbers), or equivalently an invertible N × N square matrix. There are several variants of the DCT with slightly modified definitions. The N real numbers x_0... x_{N-1} is transformed into the N real numbers X_0...X_{N-1} according to one of the formulas.

In particular, as seen from fig 2.2, DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), where in some variants the input and output data are shifted by half a sample. There are eight standard DCT variants, of which four are common.

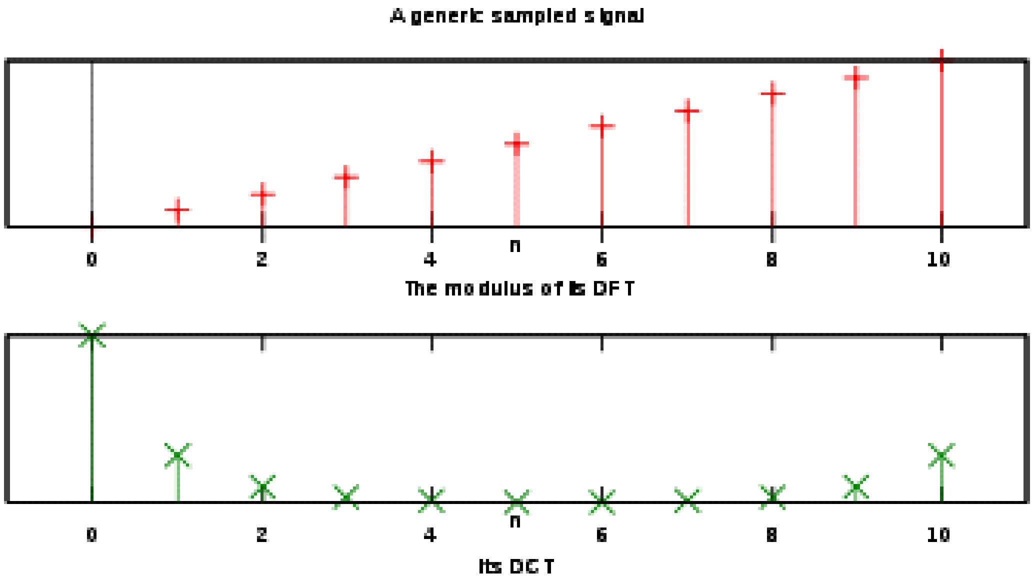


Fig 2.2 A typical example of DFT and its DCT

2.2.2 Applications of DCT

DCTs are important to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical in these applications: for compression, it turns out that cosine functions are much more efficient (as described below, fewer functions are needed to approximate a typical signal), whereas for differential equations the cosines express a particular choice of boundary conditions. A related transform, the modified discrete cosine transform, or MDCT (based on the DCT-IV), is used in AAC, Vorbis, WMA, and MP3 audio compression. DCTs are also widely employed in solving partial differential equations by spectral methods, where the different variants of the DCT correspond to slightly different even/odd boundary conditions at the two ends of the array. DCTs are also closely related to Chebyshev polynomials, and fast DCT algorithms (below) are used in Chebyshev approximation of arbitrary functions by series of Chebyshev polynomials, for example in Clenshaw–Curtis quadrature. The DCT, and in particular the DCT-II, is often used in signal and image processing, especially for lossy data compression, because it has a strong "energy compaction" property most of the signal information tends to be concentrated in a few low-frequency components of the DCT, approaching the Karhunen-Loève transform (which is optimal in the decorrelation sense) for signals based on certain limits of Markov processes.

2.2.3 1-D Discrete cosine transforms (DCT)

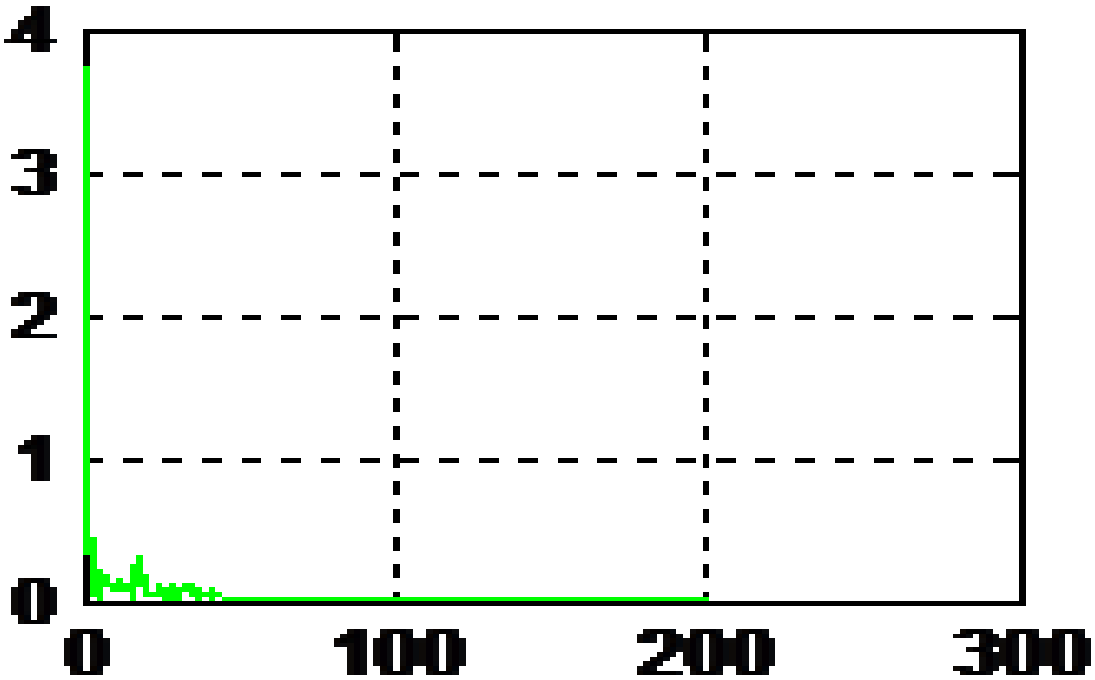
The equation for 1-D (DCT) is

$$X_k = \frac{1}{2}(x_0 + (-1)^k x_{N-1}) + \sum_{n=1}^{N-2} x_n \cos\left[\frac{\pi}{N-1} nk\right], k = 0, \ldots, N-1. \qquad (2.1)$$

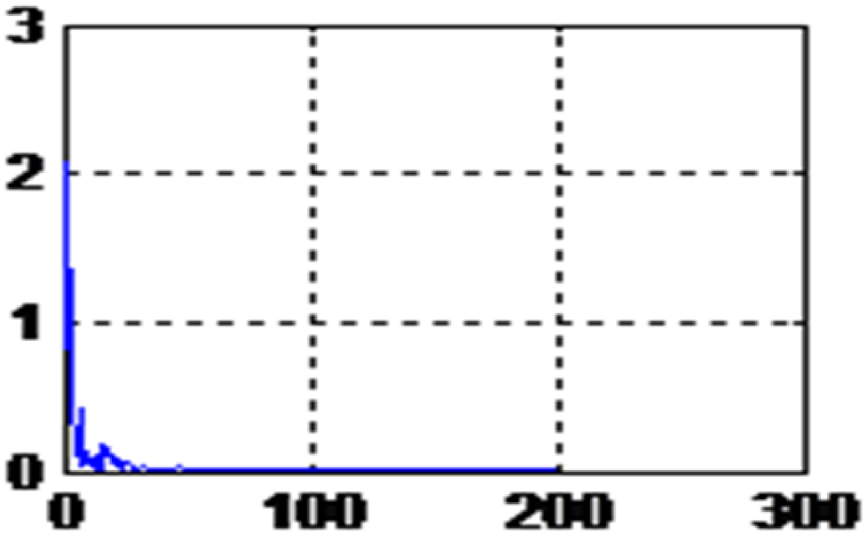
some authors further multiply the x_0 and x_{N-1} terms by $\sqrt{2}$, and correspondingly multiply the X_0 and X_{N-1} terms by $1/\sqrt{2}$. This makes the 1-D (DCT) matrix orthogonal, if one further multiplies by an overall scale factor of $\sqrt{2/(N-1)}$, but breaks the direct correspondence with a real-even DFT. The 1-D (DCT) is exactly equivalent (up to an overall scale factor of 2), to a DFT of 2N – 2 real numbers with even symmetry.

For example, a 1-D (DCT) of N=5 real numbers abcde is exactly equivalent to a DFT of eight real numbers abcdedcb (even symmetry), divided by two. Note, however, that the 1-D (DCT) is not defined for N less than 2. (All other DCT types are defined for any positive N). Thus, the 1-D (DCT) corresponds to the boundary conditions: x_n is even around n=0 and even around n=N-1; similarly for X_k. In math lab implementation , Y = DCT(X) returns the discrete cosine transform of X .The vector Y is the same size as X and contains the discrete cosine transform coefficients = DCT (X, N) pads or truncates the vector X to length N before transforming. If X is a matrix, the DCT operation is applied to each.

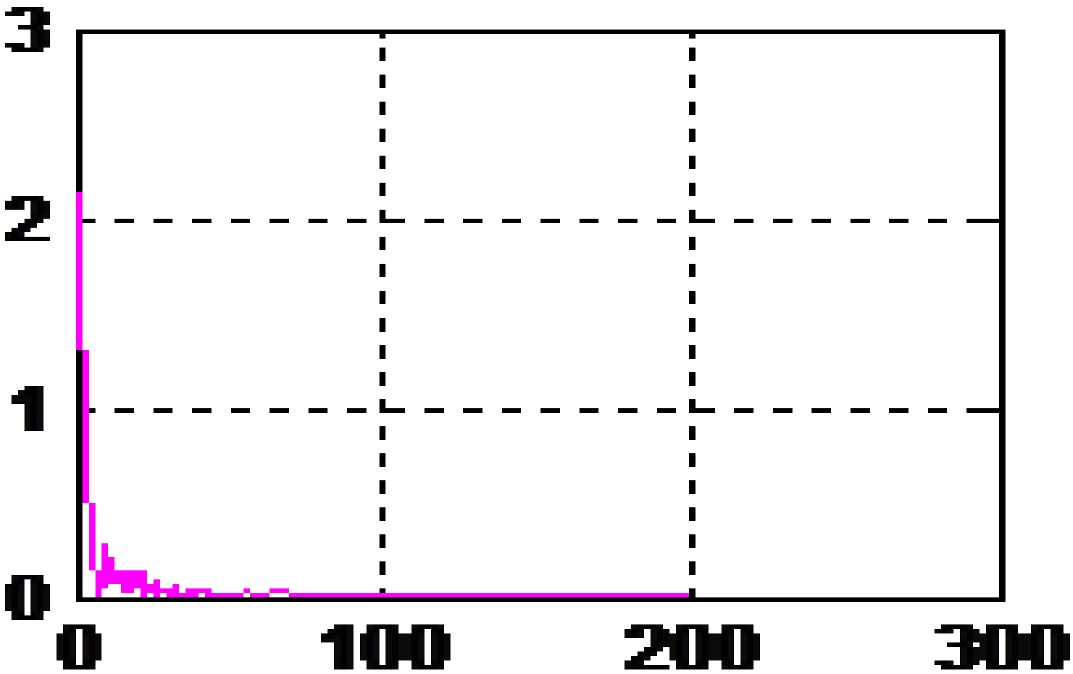
The following figures represent 1-D DCT plots for normal ECG and five types of ECG Arrhythmia.



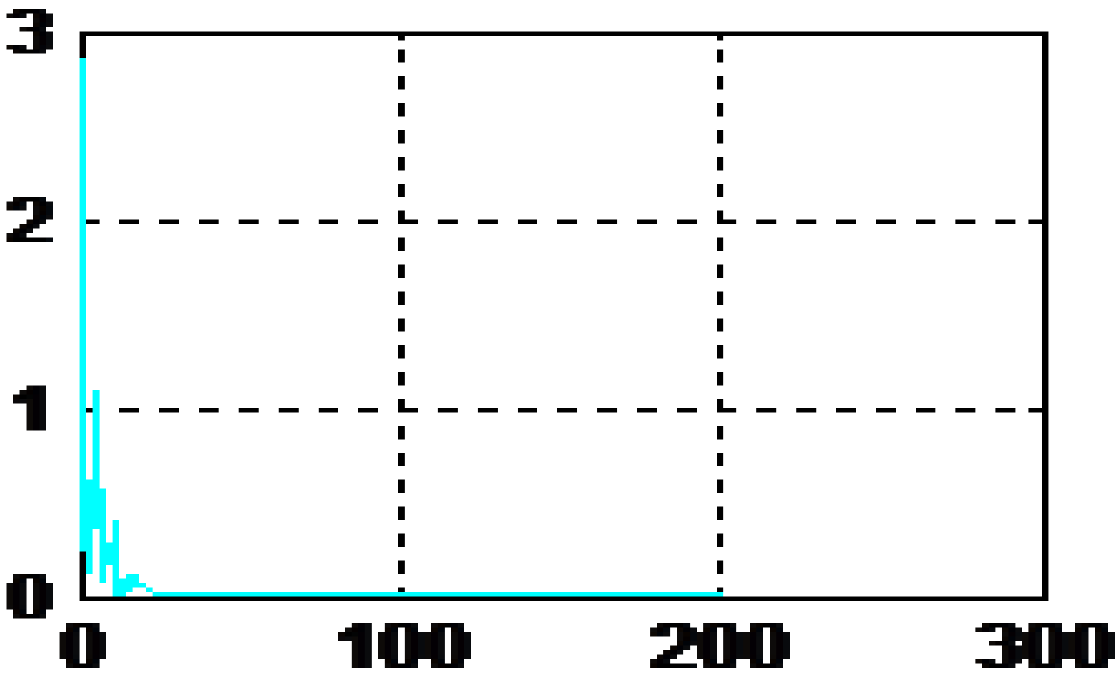
(a) Normal (N)



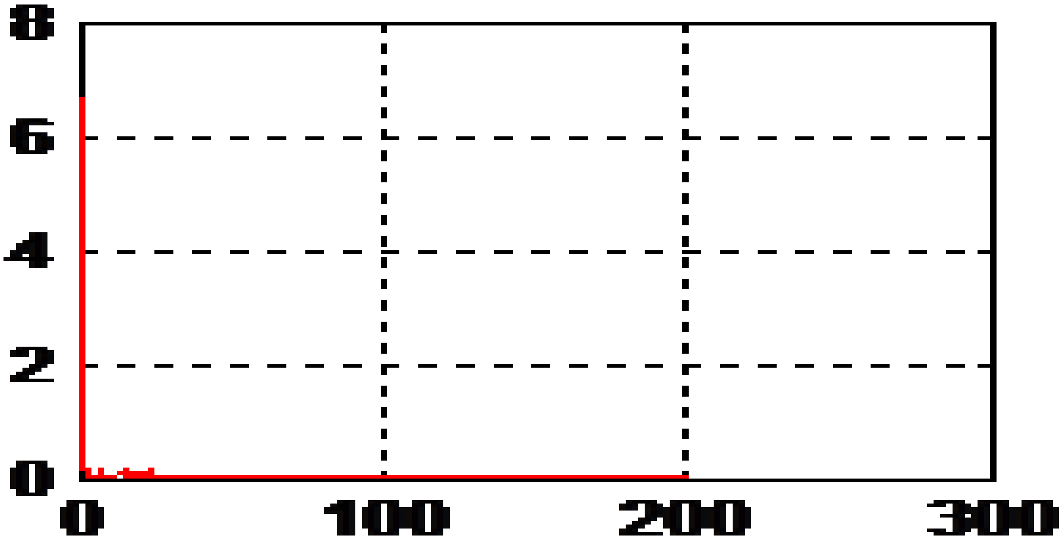
(b) Left bundle branch block (LBBB)



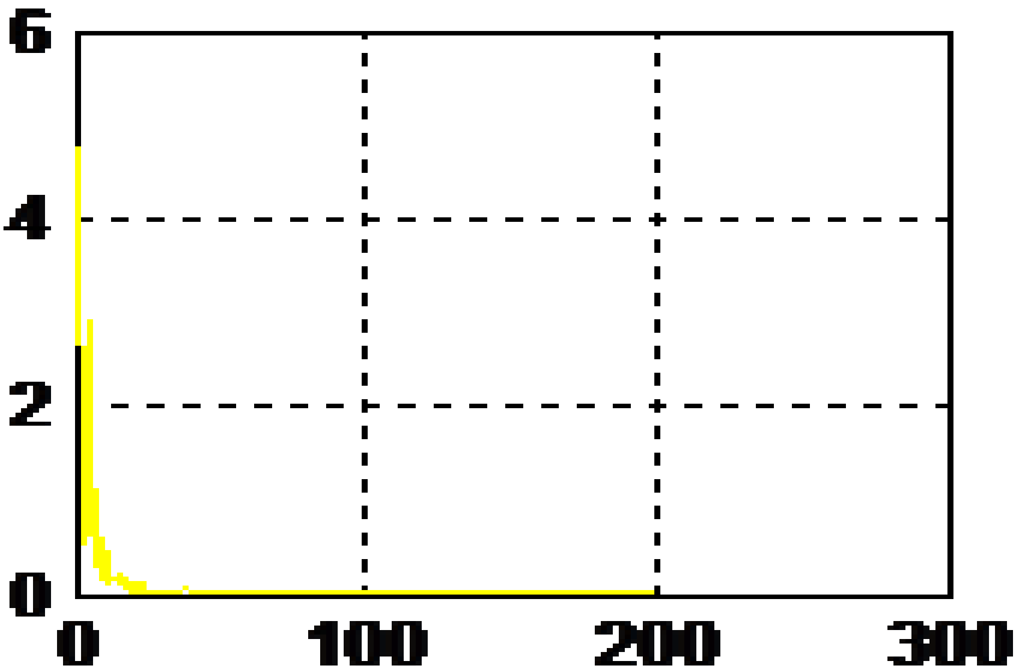
(c) Right bundle branch block beat (RBBB)



(d) Premature ventricular contraction (PVC)



(e) Atrial premature contraction (APC)



(f) Paced beat (PB)

Figure 2.3 plots of 1-D (DCT) (a) Normal (N), (b) Left bundle branch block (LBBB), (c) Right bundle branch block (RBBB), (d) premature ventricular contraction (PVC), (e) Atrial premature contraction (APC), and (f) Paced beat (PB).

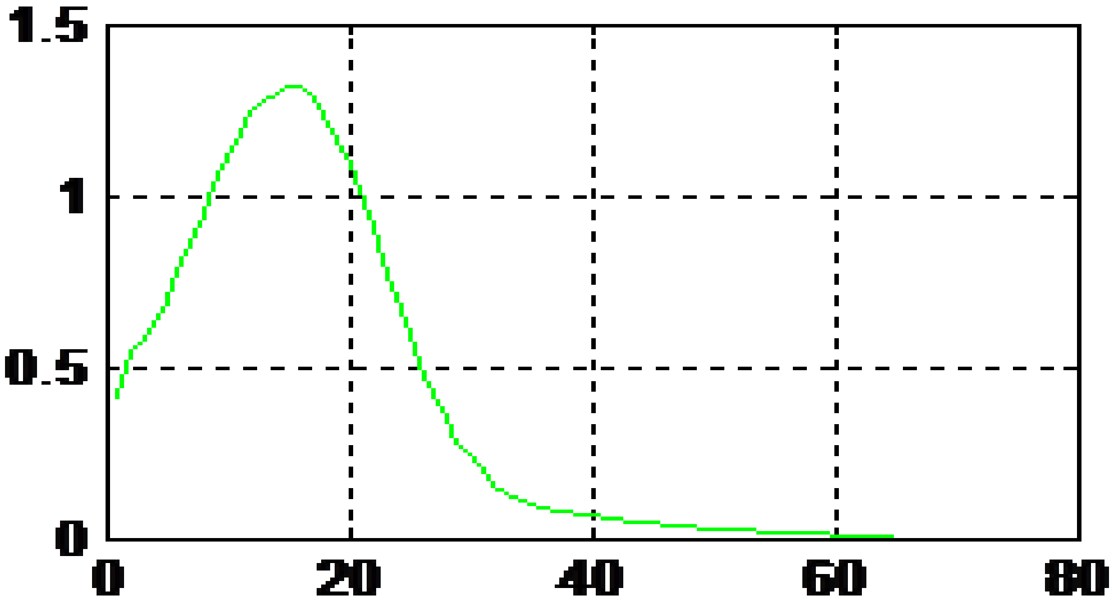
From these figures, it is found that Peaks and the amplitude values of 1-D DCT are different for different types of ECG arrhythmia. Thus 1-D DCT can be used for different types of ECG arrhythmia classification.

2.2.4 2-D Discrete cosine transforms (DCT)

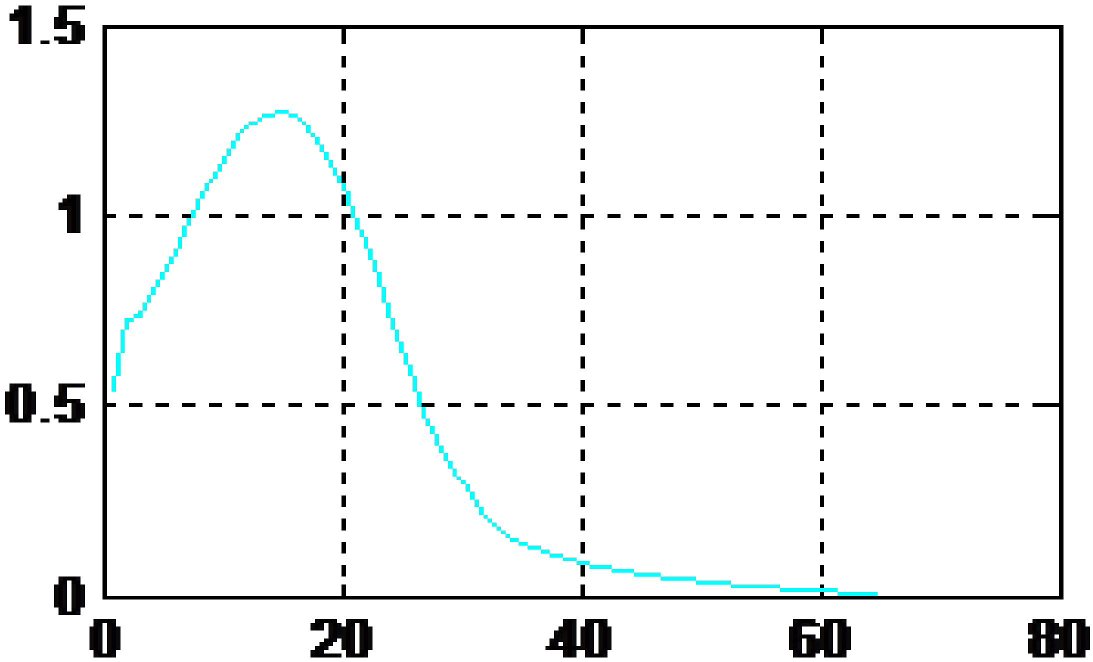
The equation for 2-D (DCT) is

$$X_k = \sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{N}\left(n + \frac{1}{2}\right)k\right], k = 0, \ldots, N-1 \qquad (2.2)$$

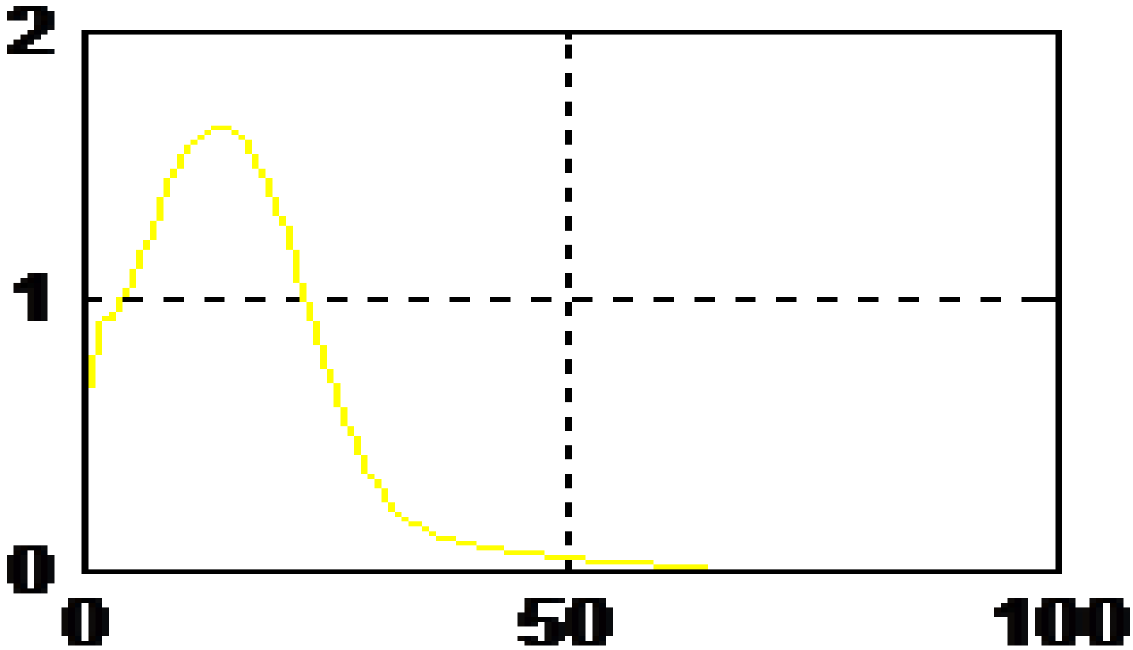
This transform is exactly equivalent (up to an overall scale factor of 2) to a DFT of 4N real inputs of even symmetry where the even-indexed elements are zero. That is, it is half of the DFT of the 4N in puts y_n, where $y_{2n=0}$, y2n+1 = x_{nfor} $0 \leq n < N$, $y_{2N\,=\,0}$, and $y_{4N\,-\,n} = y_n$ for $0 < n < 2N$. Some authors further multiply the X_0 term by $1/\sqrt{2}$ and multiply the resulting matrix by an overall scale factor of $\sqrt{2/N}$. This makes the 2-D (DCT) matrix orthogonal, but breaks the direct correspondence with a real-even DFT of half-shifted input. The 2-D (DCT) implies the boundary conditions: x_n is even around n=-1/2 and even around n=N-1/2; X_k is even around k=0 and odd around k=N. In matlab implementation, the 2-D (DCT) function computes the two dimensional discrete cosine transform (DCT) of an image. For example B = DCT2 (A) returns the discrete cosine transform of A. The matrixes B is the same size as A and contains the discrete cosine transformcoefficients. B = DCT2 (A, [M N]) or B = DCT2 (A, M, N) pads the matrix A with zeros size M-by-N before transforming. If M or N is smaller than the corresponding dimension of A, DCT2 truncates. The following figures represent mean value of 2-D DCT plots for normal ECG and five types of ECG arrhythmia.



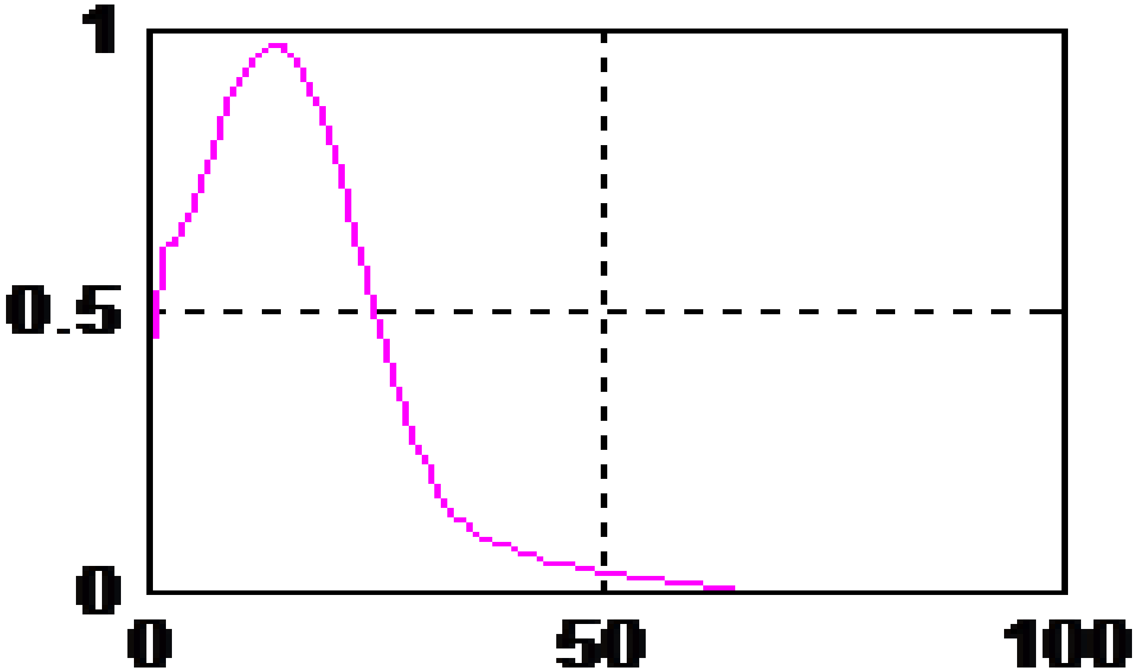
(a) Normal (N)



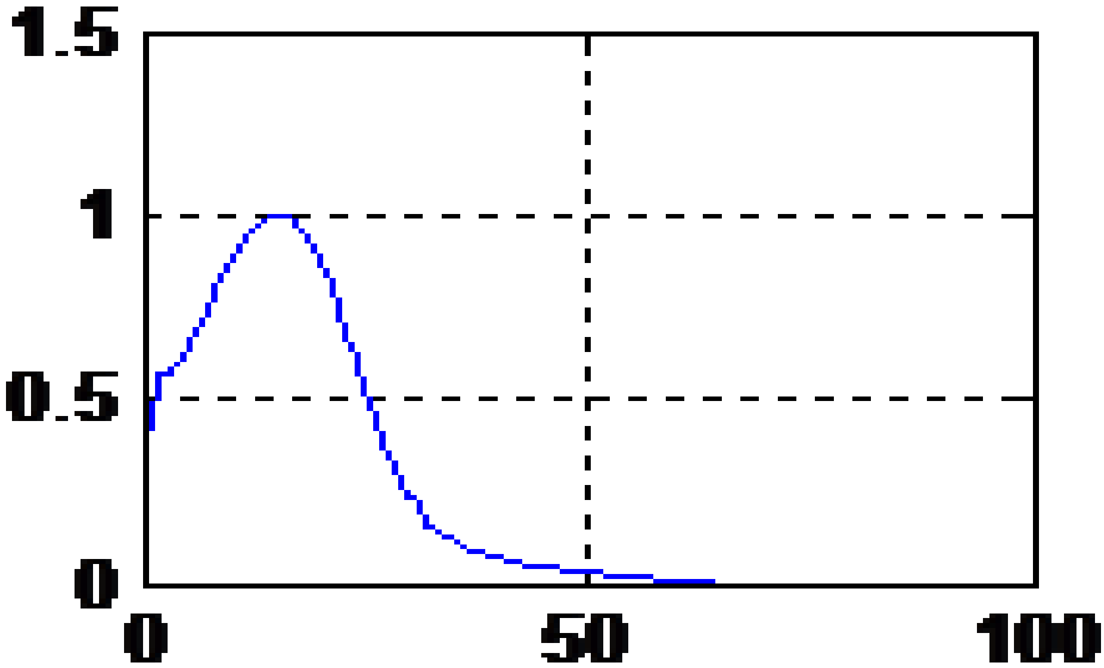
(b) Left bundle branch Block (LBBB)



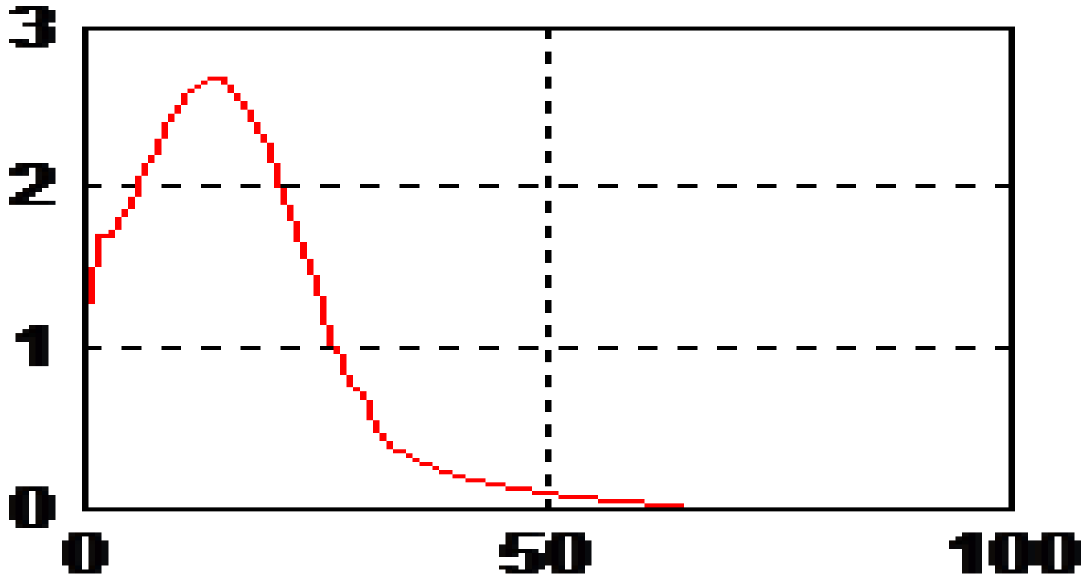
(c) Right bundle branch block beat (RBBB)



(d) Premature ventricular contraction (PVC)



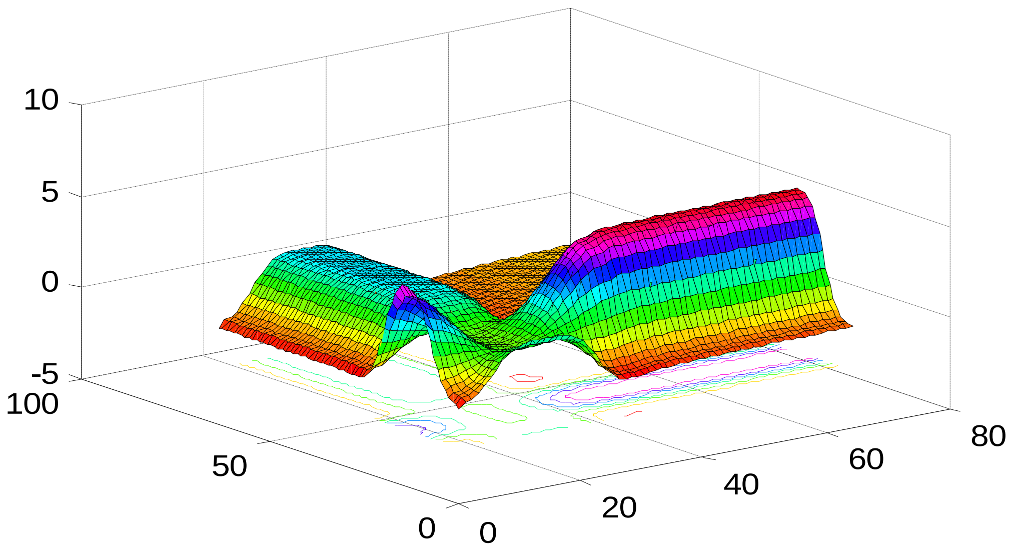
(e)Atrial premature contraction (APC)



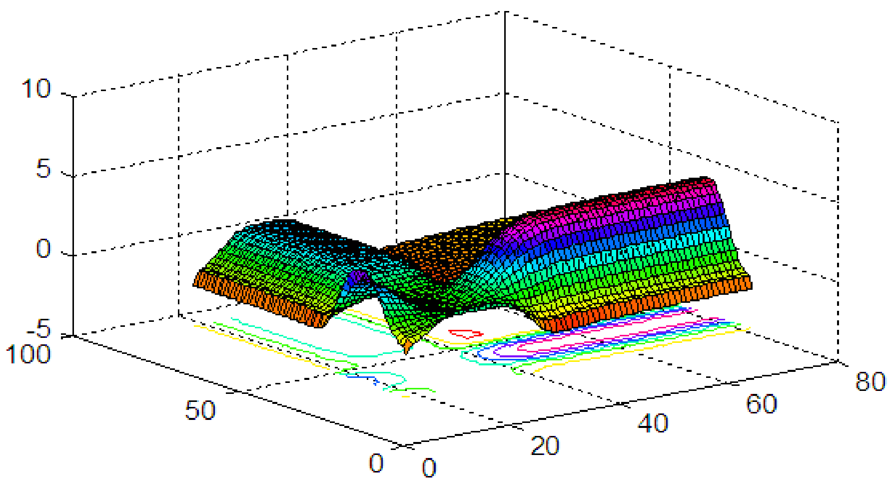
(f) Paced beat (PB)

Figure 2.4 plots mean value of 2-D (DCT) (a) Normal (N), (b) Left bundle branch block (LBBB), (c) Right bundle branch block (RBBB), (d) premature ventricular contraction (PVC), (e)Atrial premature contraction (APC), and (f) Paced beat (PB).

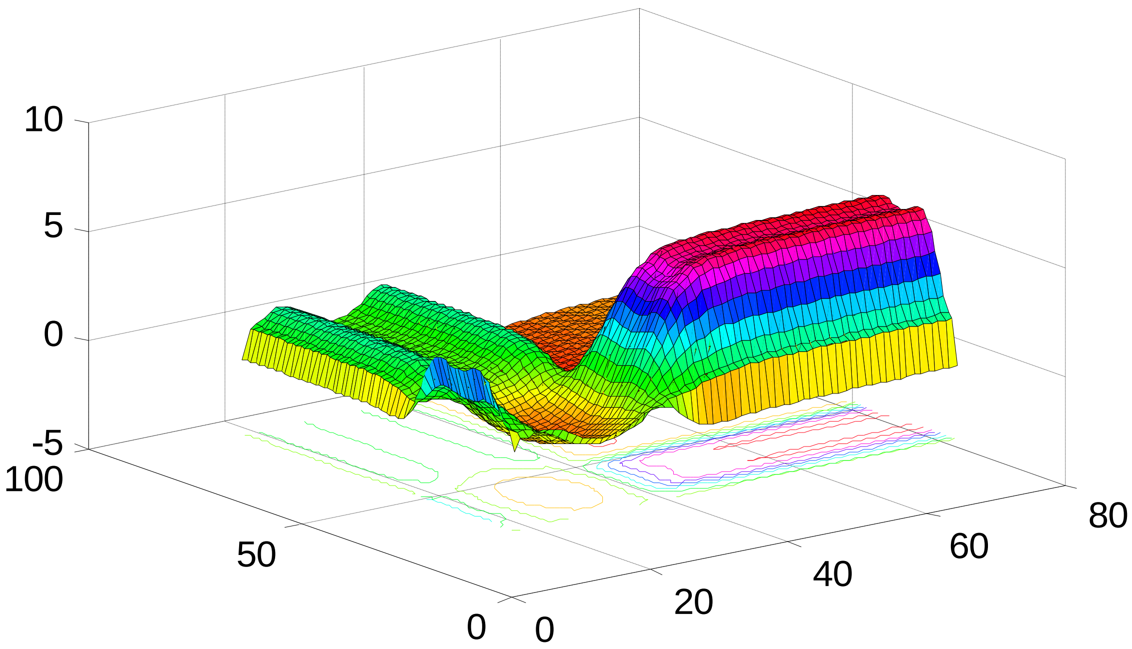
The following figures represent surface plots of 2-D DCT for normal ECG and five types of ECG arrhythmia.



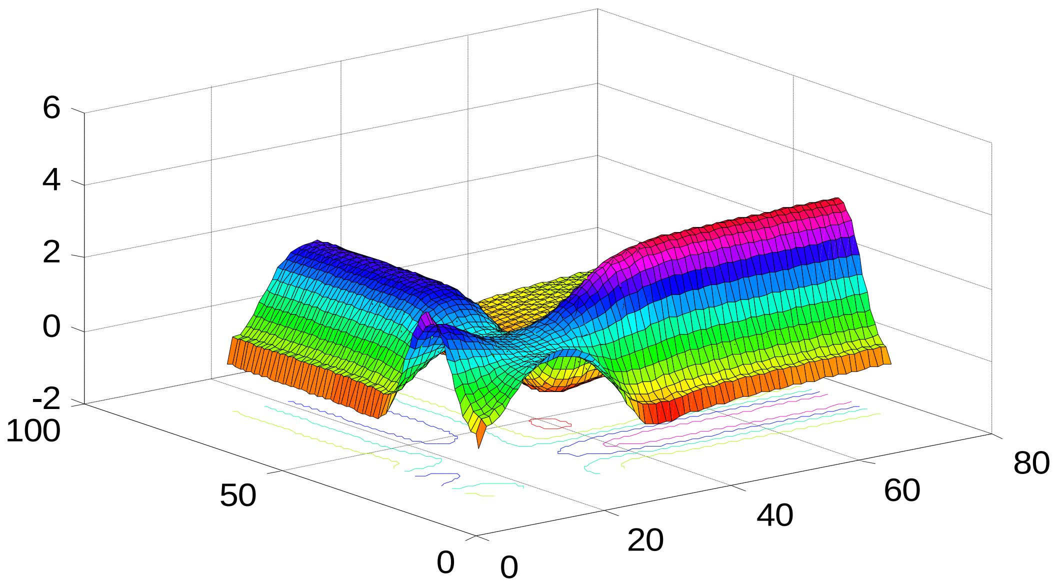
(a) Normal (N)



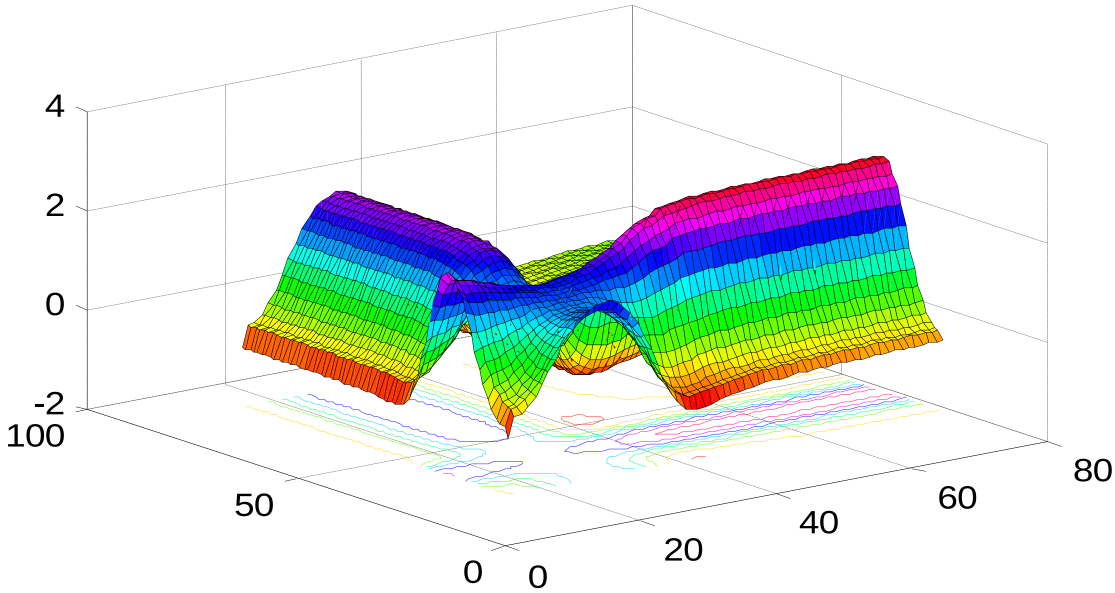
(b) Left bundle branch block (LBBB)



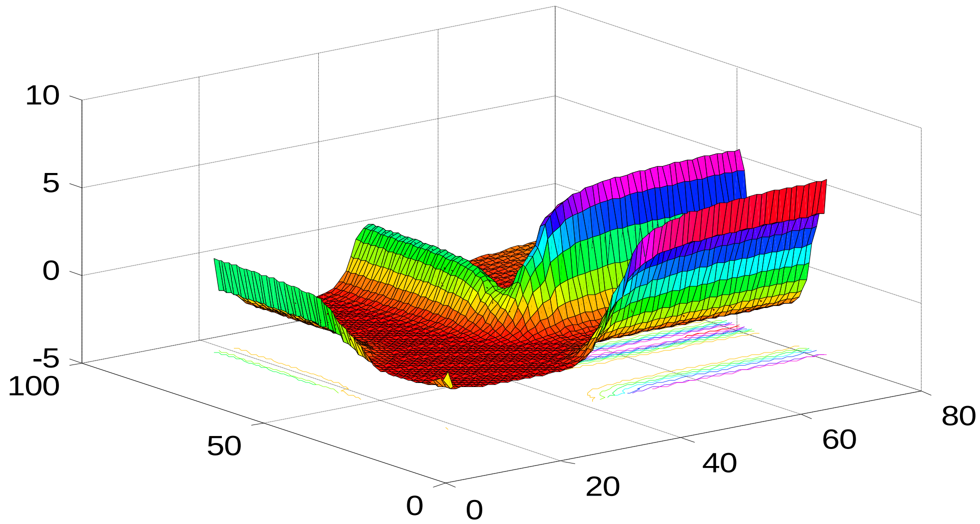
(c) Right bundle branch block (RBBB)



(d) Premature ventricular contraction (PVC)



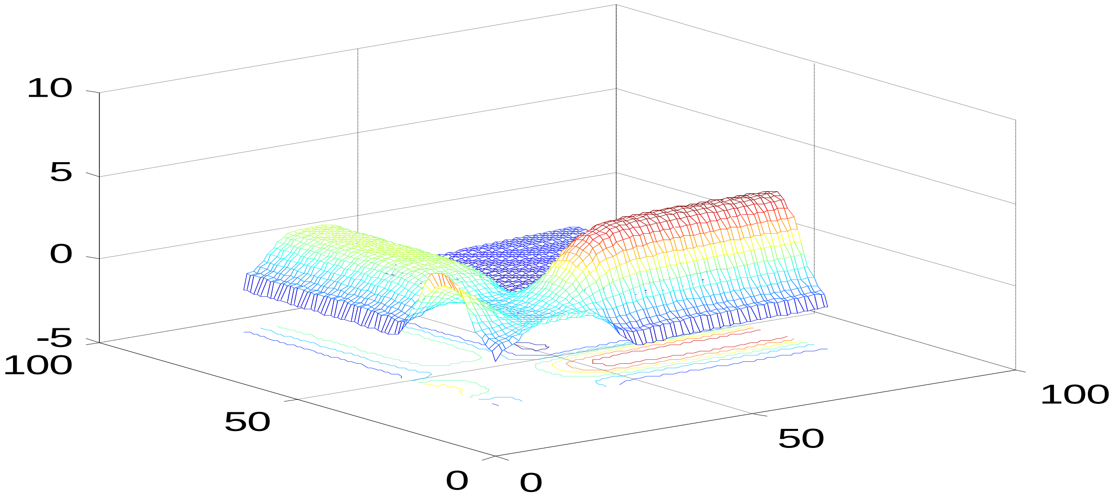
(e) Atrial premature contraction (APC)



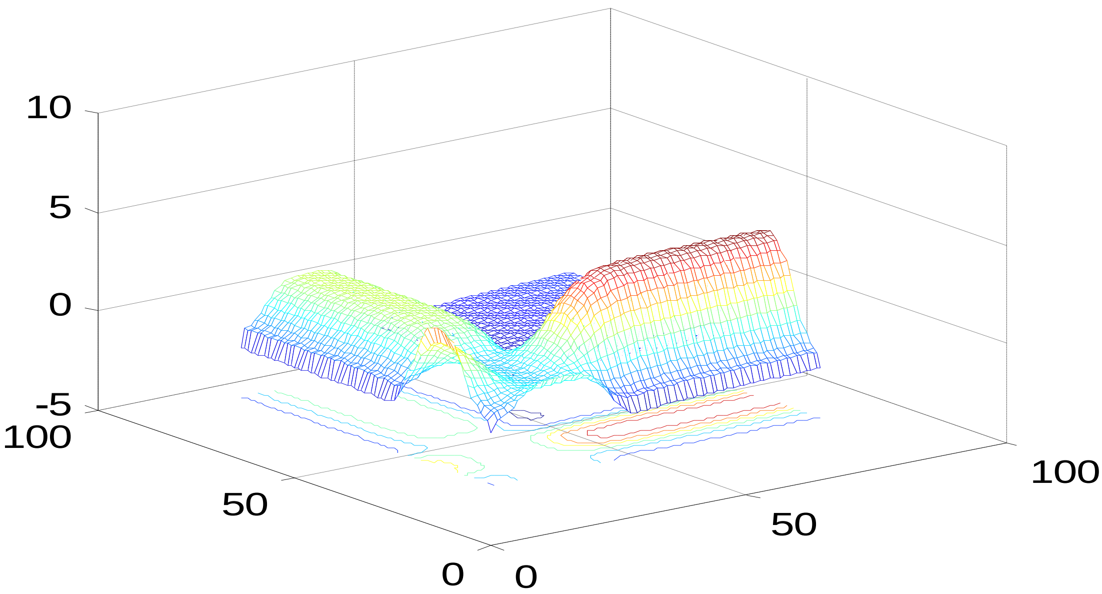
(f) Paced beat (PB).

Figure 2.5 surfaces plots of 2-D (DCT) (a) Normal (N), (b) Left bundle branch block (LBBB), (c) Right bundle branch block (RBBB), (d) premature ventricular contraction (PVC), (e) Atrial premature contraction (APC), and (f) Paced beat (PB).

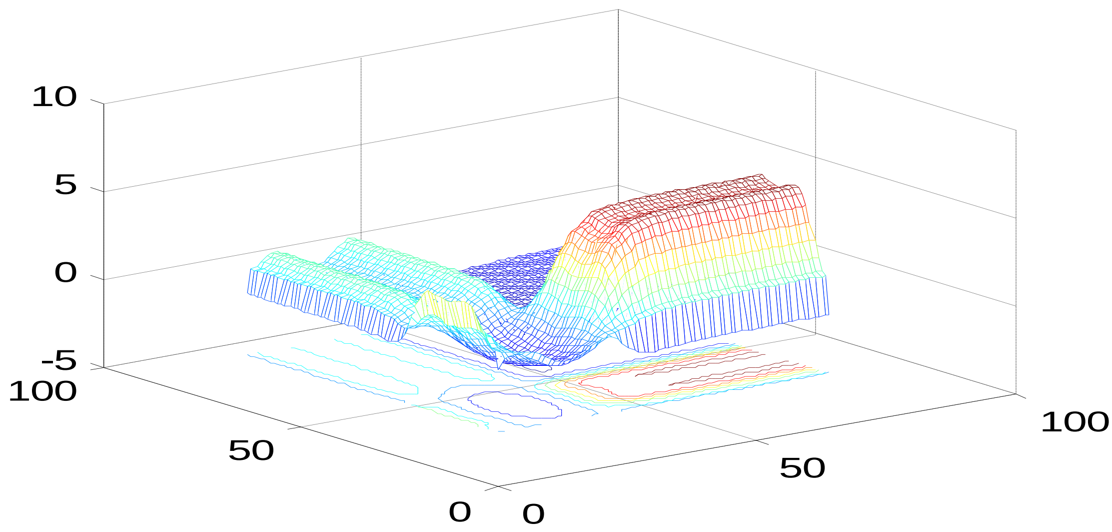
The following figures represent mesh plots of 2-D DCT for normal ECG and five types of ECG arrhythmia.



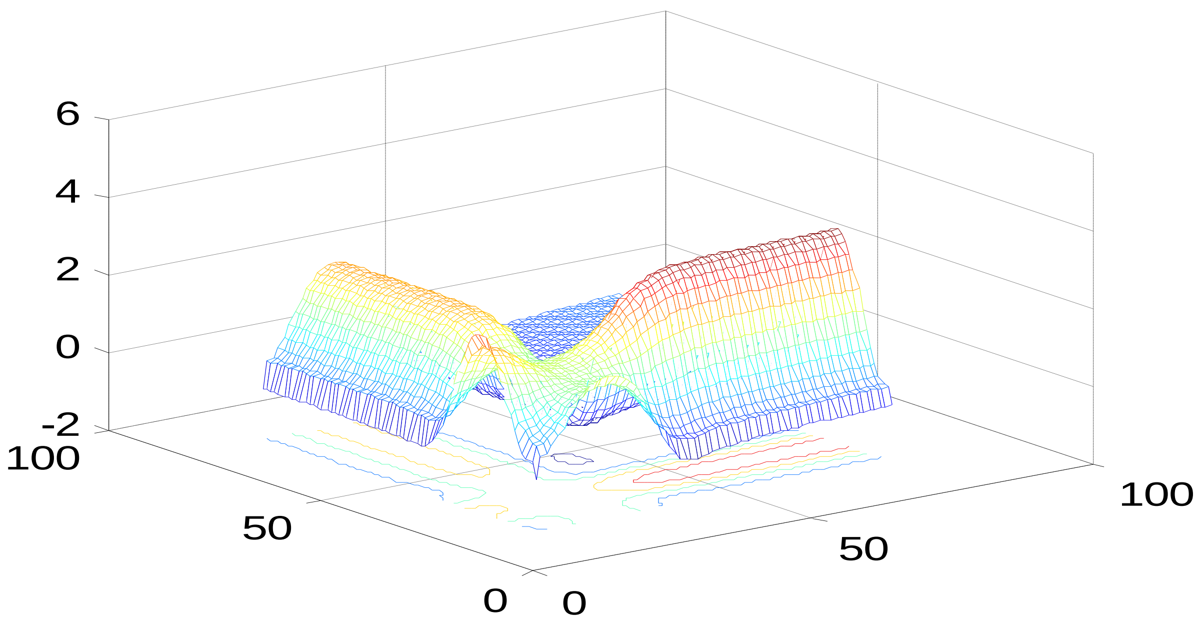
(a) Normal (N)



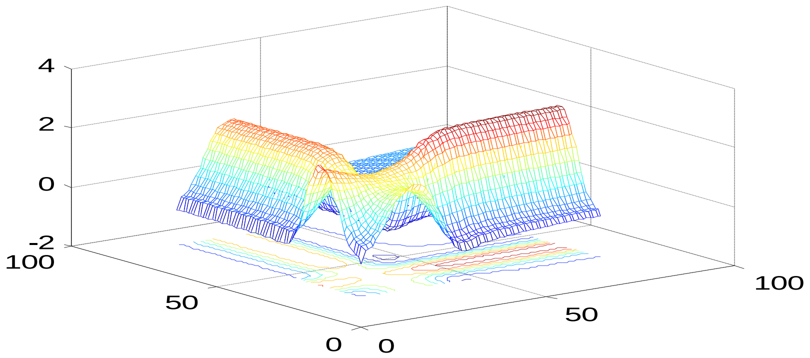
(b) Left bundle branch block (LBBB)



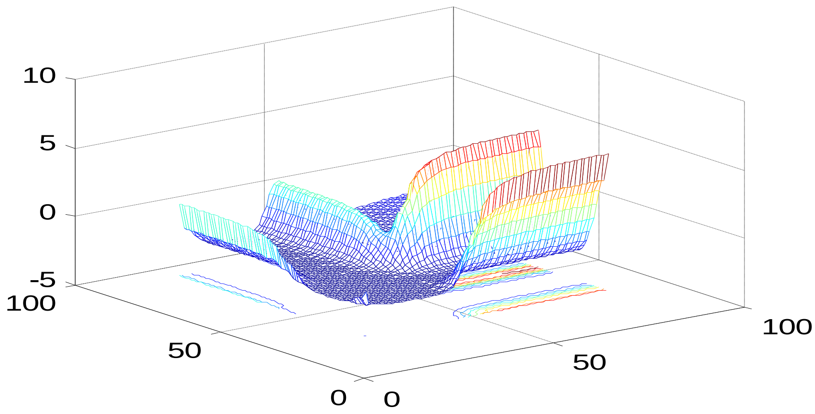
(c) Right bundle branch block (RBBB)



(d) Premature ventricular contraction (PVC)



(e) Atrial premature contraction (APC)



(f) Paced beat (PB).

Figure2.6 mesh plots of 2-D (DCT) (a) Normal (N), (b) Left bundle branch block (LBBB), (c) Right bundle branch block (RBBB), (d) premature ventricular contraction (PVC), (e) Atrial premature contraction (APC), and (f) Paced beat (PB).

From these figures, it is found that Peaks and the amplitude values of 2-D DCT are different for different types of ECG arrhythmia. Thus 2-D DCT can be used for different types of ECG arrhythmia classification. The difference is prominent for more coefficients in case of 2-D DCT compare to 1-D DCT. This difference is more visible from surface and mesh plots. Thus it is more reasonable to use 2-D DCT for classifying different types of ECG arrhythmia.

2.3 Classification

In the proposed method the classification task is carried out based on the Euclidean distances between feature vector of the training ECG and the feature vectors of the testing ECG. Given the N-dimensional feature vector for the f-th training ECG belonging to class z arrhythmia is $\{\alpha_{zf}(1), \alpha_{zf}(2) \ldots \alpha_{zf}(N)\}$ and a V-the test ECG with a feature vector

$\{\beta_z(1)\ \beta_z, (2) \ldots \beta_z(N)\}$, Euclidean distance is measured between the test ECG v & the training ECG f belonging to class z as

$$ED_{zf}^{v} = \sqrt{\sum_{t=1}^{N} |\alpha_{zf}(i) - \beta v(i)|^2} \quad (2.3)$$

Where α_{fz} (i) is testing feature vector and βv (i) is training feature vector

Considering total v training ECG beats belonging to class z arrhythmia, minimum Euclidean distance is obtained from

$$ED_{z}^{u} = \min_{f=1}^{u} ED_{zf}^{u} \qquad (2.4)$$

Therefore, test ECG beat will be classified as z class arrhythmia among P number of classes if it satisfies the condition

$$\underset{z}{\overset{u}{\mathrm{ED}}} < ED_g,\ \forall z \neq g, \text{and}, \forall g \in 1,2,\ldots,P.$$

In this thesis, we are interested to handle a six-class problem (P = 6) i.e. to discriminate among six classes from the mixture of normal ECG and five classes of arrhythmia as mentioned before.

III Conclusion

In this chapter, 1-D DCT and 2-D DCT are used to form feature vectors. Each of the feature vectors is fed to a Euclidean distance Based classifier to classified different types of ECG arrhythmia.

Simulation Results and Performance Evaluation

3.1 Introduction

Performance evaluation of the proposed methods for classifying five types of ECG arrhythmia plus normal ECG is an important task.

3.2 Database

In the proposed method, we have employed MIT-BIH (Massachusetts Institute of Technology - Boston Beth Israel Hospital) arrhythmia database. The ECG recordings are sampled at 360 samples per seconds per channel with 11-bit resolution over a 10 mV range. But normal beats are frequently difficult to discern in the lower signal of each ECG record, on the other hand, normal QRS complexes are usually prominent in the upper signal. Thus the ECG records of upper signal namely modified limb II (MLII) are used in this work, from which the heartbeat waveform is extracted by taking 50 samples before the R peak and 150 samples after the R peak thus forming 201 samples of ECG beat. From the database ,we have Considered normal ECG beats (N) and that belonging to five types of arrhythmia, namely Left bundle branch block beat (LBBR), Right bundle branch block (RBBB), atrial premature beat (APB), premature ventricular contraction (PVC), and Paced beat (PB). For each class, 25 beats are considered resulting in a total 147 ECG beats. Out of these ECG beats, approximately 40% are selected for training and the remaining is left for testing or validating the classifiers.

3.3 Performance Parameter

Performance of the proposed method is evaluated in terms of accuracy defined as the ratio of number of beats correctly classified to the number total beats used for testing.

3.4 Simulation Results

Classification accuracy for 1-D DCT is 48% and that for 2-D DCT is 80%. So classifying ECG arrhythmia based on feature extracted from 2-D (DCT) performs better than 1-D DCT.

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