Analysis of Cardiac Beats using Higher Order Spectra

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***Abstract*— For early diagnosis of the heart failures, the electrocardiography (ECG) is the most common method because of its simplicity and cost. Computer based analysis of ECG provides reliable and efficient tools in diagnostics of arrhythmias. With this objective there are lots of studies on automatic and semi-automatic ECG analysis. Like many biosignals, ECG signals are nonlinear in nature, higher order spectral analysis (HOS) is known to be a very good tool for the analysis of nonlinear systems producing good noise immunity. Thus in this study, HOS analysis of ECG signals of normal heart rate, right bundle branch block, paced beat, left bundle block branch and atrial premature beats have been studied in order to reveal the complex dynamics of ECG signals using the tools of nonlinear systems theory. Some of the general characteristics for each of these classes in the bispectrum and bicoherence plot for visual observation have been presented. For the extraction of R-R intervals, well known Pan-Tompkins algorithm has been used and three higher order statistical parameters of skewness, kurtosis and variance from these features have been computed. These features with statistical parameters fed into artificial neural network classifier (ANN) and obtained an average accuracy of 94.9%.**

***Keywords*— ECG, HOS, Bispectrum, Bicoherence, Pan Tompkins**

I. INTRODUCTION

Human computer technology has an important role in structuring biological systems. The explosive growth of high performance computing techniques in recent years, with regard to the development of good and accurate models of biological systems, has contributed significantly to new approaches of fundamental problems of modeling linear and nonlinear behaviors of biological systems.

A complex system like cardiovascular system cannot be linear in nature and by considering it as a nonlinear system, can lead to better understanding of the system dynamics. The progress made in the field using measures of chaos has attracted the scientific community to apply these tools in studying physiological systems, and ECG is no exception.

Recently, the nonlinear techniques have been used to analyze physiological signals: heart rate, nerve activity, renal blood flow, arterial pressure, EEG and respiratory signals [1]. To investigate the time-varying spectral characteristics of the underlying process, most of the methods often begin by computing the time variation of the common statistical properties of the process [2-4]. However, these methods all assume that piecewise first-order or second-order stationarity is satisfied for each segment of the observation after segmentation.

In practice, many medical signals show significant nonlinear and non-Gaussian characteristics, such as the presence of nonlinear effects of phase coupling among the signal frequency component [5,6,7,8]. The methods based on lower order statistics or spectral analysis fail to deal with the nonlinearity and non-Gaussianity of the processes, but higher-order spectral techniques (HOS) allow us to effectively process these signals to obtain their higher order statistics.

HOS have been applied to many applications such as in 1D pattern recognition [9], chaotic signal characterization [10], array signal processing [11], telecommunication [12], ultrasound image processing [13], detection of mines from sonar images [14], study of machine faults [15], speaker verification [16], recognition of viruses from electron microscopic images [17], termite detection [18], analysis of bio signals like the ECG [19] and identification of cardiac ischemia [20]. Rama et al in his work has identified the difference between cardiac ischemia and the normal heart rate beat. In which he found the higher order statistical parameters of the normal and compare it with the ischemic patient, and conclude that the phase correlation of a normal person is low while that of ischemic person is high. In [21], five classes or cardiac arrhythmia using HOS features (bispectrum) have been classified with an average accuracy of 93.48%. The recent methods used in ECG analysis are summarized in [22].

The use of nonlinear features motivated by higher order spectra has been reported to be a promising approach to analyze the non-linear characteristics of the bio signals. Thus, in this work, the applications of higher order spectra (HOS) for ECG signals have been discussed. The ECG signals of MIT-BIH database with normal, right bundle branch block (Rbbb), left bundle branch block (Lbbb), paced beat and atrial premature beats (Apb) have been classified by the artificial neural networks using features from higher order cumulants such as skewness, curtosis and variance. The preprocessing and R-R interval extraction of the ECG waves have implemented by Pan-Tompkins algorithm. Additionally, the bispectrum plots of the normal and arrhythmic heart beats are demonstrated and interpreted. After a brief introduction of electrocardiography and arrhythmias in Section 2, higher order spectral methods will be explained. Then, in Section 4

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experiments and system design will be introduced. Finally the results and conclusions will be given.

II. ELECTROCARDIOGRAPHY AND ARRYTHMIAS

The human heart is at the center of the cardiovascular system, which is responsible for oxygenating blood and delivering it to different parts of the human body. Electrodes placed on the body's surface can detect electrical activity, which occurs in the heart. The recording of these electrical events comprises an electrocardiogram. Comparison of the information obtained from electrodes, placed in different positions on the body, enables electrical activity to be monitored and so the performance of different areas of cardiac tissue [23]. There are four chambers in the heart that is left atrium, right atrium, left ventricle, right ventricle and several sinoatrial and atrioventricular node [24].

The electrical sequence of the heart is initiated by the sinoatrial node of the heart (SA node) which determines the frequency of the heart signal. The initiation of the signal at the SA node starts a sequence of electrical activity that passes through the left atrium, right atrium, and the AV node simultaneously. The right atrium is the first to depolarize as it is closer to the pacemaker (SA node), resulting in a contraction of the right atrium slightly before the left atrium (P wave). The impulse is delayed at the AV node so that ventricles expand and fill up with blood (PR interval). Thereafter, the impulse passes through the Bundle of His and the Purkinje fibers which triggers ventricular contraction (depolarization) (QRS complex), pumping blood either to the lungs (small blood circulation) or out to the body (large blood circulation). There-polarization of atria happens concurrently with ventricular depolarization. Ventricular re-polarization (Twave) is the last event in the sequence of electrical activity [25].

The symptoms of a cardiac disease can be obtained by thorough study of the origin, property and iso-electric lines of the major waves or deflections of the P,Q,R,S and T waves. Fig 1 below shows normal ECG wave and its segment [26].

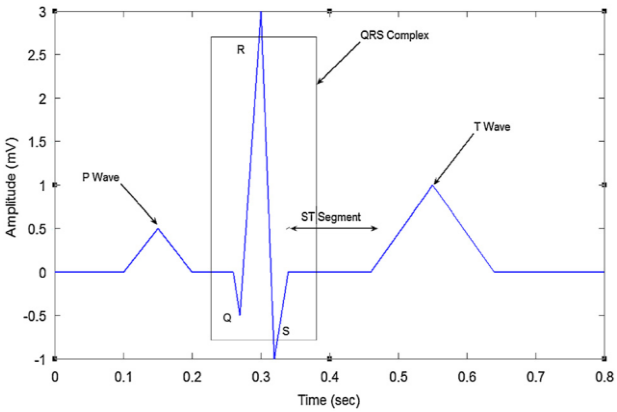


Fig. 1. A healthy human ECG with major cardiac waves and segments indicated [28].

In this study, five different arrhythmias which are very important especially for early detection of cardiac problems are considered. Two branch block arrhythmias known as right bundle branch block (Rbbb) and left bundle branch block (Lbbb) occurs when one bundle branch is blocked: Electrical impulse will travel through intact branch and stimulate ventricle supplied by that branch. Ventricle affected by blocked or defective bundle branch is activated indirectly. There is a delay caused by this alternate route QRS complex will represent widening beyond usual time interval of 0.12 sec. Classified as either complete (QRS measures 0.12 sec or greater) or incomplete blocks (QRS measures between 0.10 and 0.11 second). The paced beat is the artificial beat form from the device called pacemaker. A pacemaker is a treatment for dangerously slow heart beats. Slow heart beats can be the result of metabolic abnormalities or occur as a result of blocked arteries to the heart's conduction system. These conditions can often be treated and a normal heart beat will resume. Slow heart beats can also be a side effect of certain medications in which case discontinuation of the medicine or a reduction in dose may correct the problem. It can be characterized in ECG by a large peak after QRS complex [27]. The last arrhythmia is atrial premature beat (Apb) which occur when an area of the heart becomes irritable enough to produce a spurious action potential at a time between normal beats. The action potential spreads across the myocardium in much the same manner as the regular discharge. Beats occurring at improper times are called ectopic beats. If it results in atrial contraction, then it is an atrial premature contraction (APC), and if in the ventricle, a ventricular premature contraction (VPC), and both the two can be referred to as atria premature beats.

III. HIGHER ORDER SPECTRA TECHNIQUES

The Higher order spectra are defined to be spectral representation of higher order cumulants of a random process. Higher order spectra (HOS) techniques were first applied to real signal processing problems in 1970s, and since then it is continued to expand into different fields such as plasma physics, optics, speech and biomedicine. The estimation of power spectrum of discrete-time deterministic or stochastic signals is one of the most fundamental and useful tools in digital signal processing. In power spectral estimation, the signal under consideration is processed in such a way that the distribution of power among its frequency components is estimated. As such, phase relations between frequency components are suppressed.

Let $X(n)$ is real, discrete time random process. Moments can be obtained from the coefficients of the Taylor's series expansion of the moment generating function about the origin, t=0. For zero mean discrete time signal, moments and cumulants are defined as [29]:

$$m_2(\tau) = E[X(n)X(n+\tau)] \quad (1)$$

$$m_3(\tau_1, \tau_2) = E[X(n)X(n+\tau_1)X(n+\tau_2)] \quad (2)$$

$$m_4(\tau_1, \tau_2, \tau_3) = E[X(n)X(n+\tau_1)X(n+\tau_2)X(n+\tau_3)] \quad (3)$$

where $E[\cdot]$ is defined is the expectation operator, i and j are the time lag parameters.

The cumulant generating function is defined as the logarithm of the moment generating function. The cumulants are define as

$$c_2(\tau) = m_2(\tau) \tag{4}$$

$$c_3(\tau_1, \tau_2) = m_3(\tau_1, \tau_2) \tag{5}$$

$$c_4(\tau_1, \tau_2, \tau_3) = m_4(\tau_1, \tau_2, \tau_3) - m_2(\tau_1)m_2(\tau_3 - \tau_2) \tag{6}$$
$$-m_2(\tau_2)m_2(\tau_3 - \tau_1) - m_2(\tau_3)m_2(\tau_2 - \tau_1)$$

The zero-lag cumulants have special names: $c_2(0)$ is the variance and is denoted by σ^2; it is the measure of the spread of the data from the mean. $c_3(0,0)$ is known as skewness and it is a measure of the asymmetry of the processes. It is denoted by Υ_{3x}. For symmetric distribution skewness is identically zero. $c_4(0,0,0)$ is denoted by Υ_{4x} and called as kurtosis. It is related to the degree of flatness of a distribution near its center [30]. For Gaussian distribution, the value of kurtosis is 3. The values of more than 3 are indicating that the probability density function (PDF) is more peaked around its center than a Gaussian distribution.

The method used for estimating the second-order spectrum or power spectrum can easily be extended to obtaining frequency domain counterparts of higher order cumulants. Hence the bispectrum is the frequency domain representation of the third-order cumulant and it is represented as

$$B(f_1, f_2) = E[X(f_1)X(f_2)X^*(f_1 + f_2)] \tag{7}$$

where X(f) denotes Fourier transform of a segment of a single realization of a stationary and ergodic random process.

The bispectral estimates of bispectrum are asymptotically unbiased and the variance of the estimator depends on the second-order spectral properties [31].

Since the estimates depends on signal energies in the bifrequency, the variance of the estimate will be higher at a frequency where the energy is high and lower where the energy is low. This causes a serious problem in the estimation. This unsatisfactory property can be resolved in so many ways. One of which is the normalization. Hence, bicoherence is the normalization of the bispectrum to get a new measure whose variance is independent of the signal energy. The bicoherence is represented as

$$Bic(f_1, f_2) = \left| \frac{B(f_1, f_2)}{\sqrt{P(f_1)P(f_2)P(f_1 + f_2)}} \right|^2 \tag{8}$$

where P(f) is the power spectrum [32].

IV. DATA ACQUISITION AND PROCESSING

A. ECG Data Acquisition

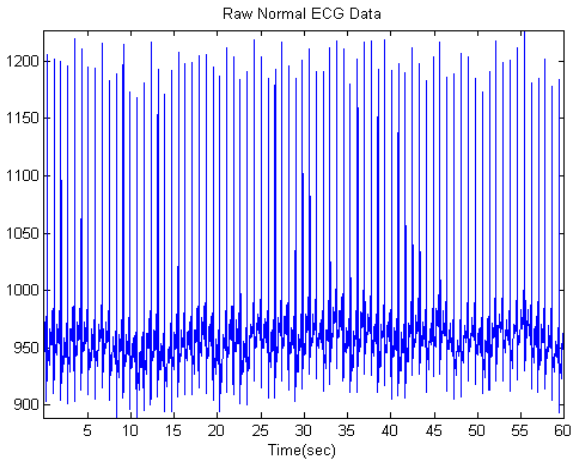
In this study, the source of the ECG data used for training and testing is MIT-BIH Arrhythmia database from Physionet website [33]. The database contains 48 recordings of both routinely clinical waveforms and some complex arrhythmias sampled at 360Hz of 30 min durations selected from 24 hr recording with two channels obtained from 47 patients [34]. Only one channel of 1 min long for each record is used in this work.

B. Preprocessing

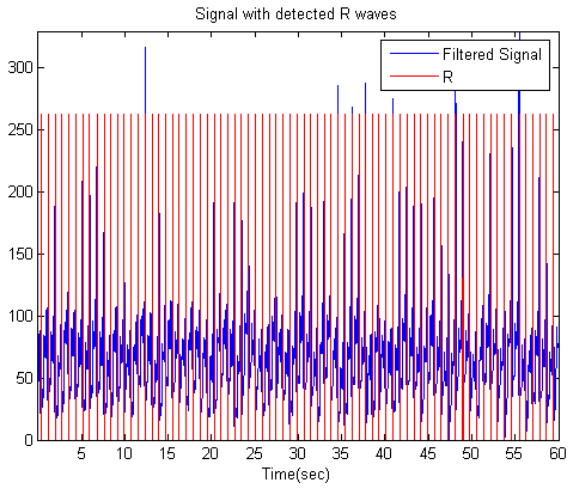
Preprocessing step involves removal of noise from sources such as electrode contact noise, baseline drift, muscle contraction, power line interference and motion artifacts. Also QRS detection [35] was carried out in this stage. A well-known and acceptable Pan Tompkins algorithm is employed as a real time QRS detection algorithm based on the analysis of slope, amplitude and width of QRS complexes [36]. The steps of preprocessing are given as

- Removing DC component
- Removing high frequency noise (low pass filter)
- Removing low frequency noise (high pass filter)
- Removing power line interference (comb filter)
- Derivative operation
- Squaring operation
- Integrator
- Thresholding
- Search procedure for R-peaks

One sample of the original normal ECG recording and preprocessed ECG wave with detected R waves are shown in Fig. 2. The red lines in Fig.2.b point the detected R waves. In the feature calculation R-R intervals are taken into account.



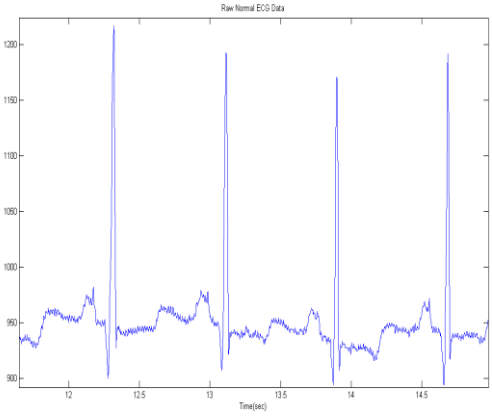
(a)



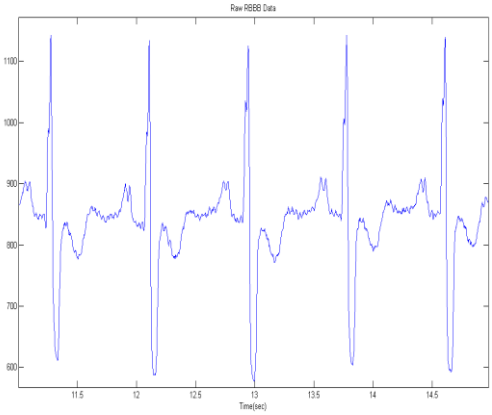
(b)

Fig. 2.(a) Original Normal ECG for 1 minute signal, (b) preprocessed ECG signal

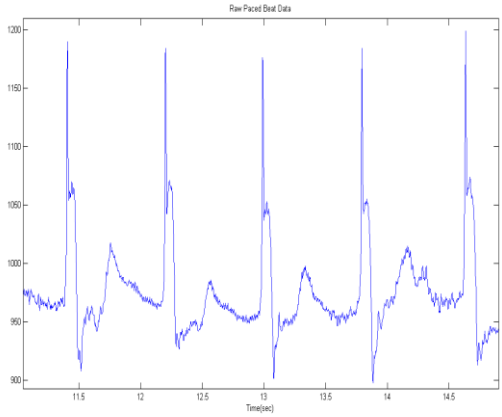
In Fig.3, a few beats from normal ECG and the arrhythmias considered in this study are demonstrated.



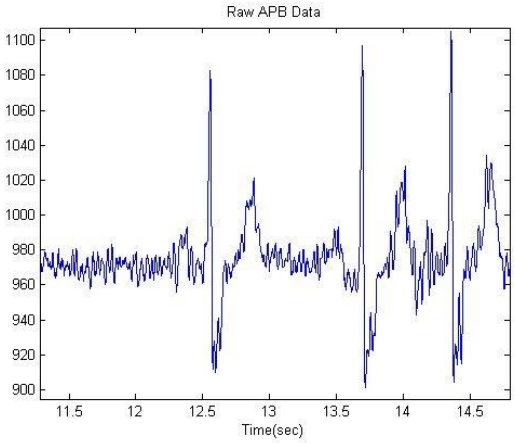
(a)



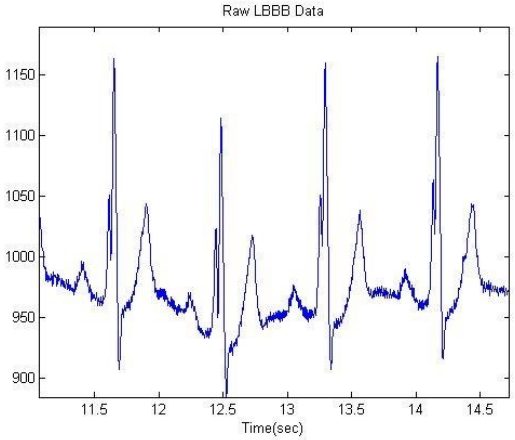
(b)



(c)



(d)



(e)

Fig. 3. Raw ECG waveforms for (a) normal, (b) Rbbb, (c) paced, (d) Apb and (e) Lbbb.

C. Feature selection

Selecting and extracting useful and most informative features in ECG pattern recognition and classification is one of the most important tasks which makes the classifier to

perform accurately. In this work, 200 samples have been extracted starting from detected R-peaks, which corresponds to R-T interval for feature extraction. The feature vector is constructed depending on the number of R-peaks in each ECG record which is between 60-90 per record. Then higher order statistical features are calculated. It is possible to extract and define hidden information contain in the ECG using higher order statistics parameters which have been applied successfully to extract features for good classification. There are a lot of studies which used first and second order statistics and gained a significant result. However, when it comes to nonlinearity of a signal, higher order statistics is more suitable because the signal can be examined properly unlike second order statistics. In the first and second order statistics we have mean and variance while higher order statistics contain higher order moments (m3,m4,…) and cumulants (c1,c2, …) which is the non-linear combination of higher order moments.

D. Artificial Neural Networks

The artificial neural networks (ANN) are the structures inspired by human nervous system. They mimic learning the input-output relations behavior, by using some predefined algorithms. The simplest and most common ANN structure is multi layer feedforward neural network with backpropagation learning which is illustrated in Fig. 4.

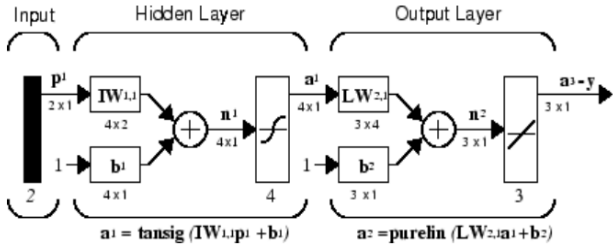


Fig. 4. a. Multi layer feedforward neural network [37]

For function approximation or system modelling, after the selection of system structure, number of layers, number of neurons in each layer, ANN is fed with training samples and weights are determined according to the learning algorithm. The basic backpropagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient). This is the direction in which the performance function is decreasing most rapidly. In this study, ANN with one hidden layer containing 15 neurons of Matlab Neural Networks toolbox is used for its simplicity. The number of hidden neurons is selected heuristically. The learning algorithm is the Levenberg-Marquardt algorithm, which is the fastest method for training moderate sized feed-forward neural network [37].

V. RESULTS AND DISSCUSSION

The ECG signal was analyzed using different higher order spectra (also known as polyspectra) that are spectral representation of higher order moments or cumulants of a signal. In particular, this work studied the features related to the third order statistics of the signal, namely the bispectrum and bicoherence (normalized bispectrum), and then the skewness, kurtosis and variance related to these higher order statistics were computed.

The classification performance is considered in terms of sensitivity, specificity, positive predictive value, and accuracy. The used measures are defined as

$$Sensitivity = \frac{TP}{TP + FN} \quad (9)$$

$$Specificity = \frac{TN}{TN + FP} \quad (10)$$

$$Positive\ Predictive\ Value = \frac{TP}{TP + FP} \quad (11)$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (12)$$

where TP is True Positive and TN is True Negative (correctly identified), FP is False Positive (incorrectly identified), FN is False Negative (incorrectly rejected) [38].

A. Performance Analysis for Higher Order Statistical Parameters

In this paper, ECG signal from MIT-BIH database were used for training and testing. ECG records were downloaded as .mat files and distributed randomly for classification of normal, paced, rbbb, lbbb and apb beats. 1729 ECG beats were obtained and the higher order statistics parameters of skewness, kurtosis and variance of each sample were also computed and used as features. These features are fed to artificial neural network and approximately 70% is used for training and the remaining is used for validation and testing. After training the actual testing samples were loaded and tested using created training network.

Table 1 below depicts the performance for higher order statistical parameters

TABLE I
PERFORMANCE MEASURES FOR HOS FEATURES

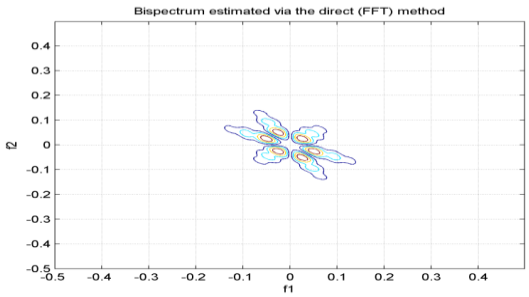
ECG Beat Class	Sensitivity (%)	Specificity (%)	Pos. Pred. Value (%)	Accuracy (%)
Normal	99.0	96.0	84.9	97.0
Rbbb	99.3	100	100	99.8
Paced	76.5	92.0	88.2	91.4
Lbbb	73.0	93.0	70.2	88.6
Apb	94.3	98.9	93.4	97.9
Average (%)	**88.4**	**96.2**	**87.3**	**94.9**

As it can be observed from Table 1, the statistical features gives an acceptable accuracy with relatively low sensitivity of 88.4% and positive prediction value of 87.3%.

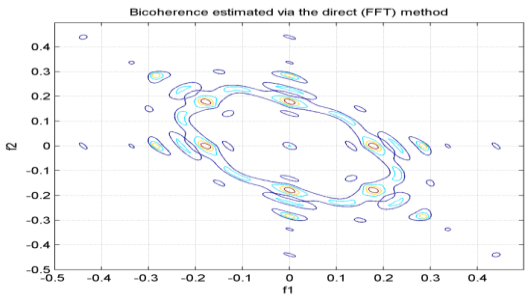
B. Bispectrum and Bicoherence Plots

The bispectrum and bicoherence were computed using HOSA toolbox of Matlab with the FFT window size of 512, wind size of 1 which is the same size as the various signals

size, segment size of 18 for each of the five signals and 50% overlap which is 128 were used and the corresponding bicoherence values were computed. The resulting bispectrum magnitude plots for various types of diseases are shown in the figures below.



(a)



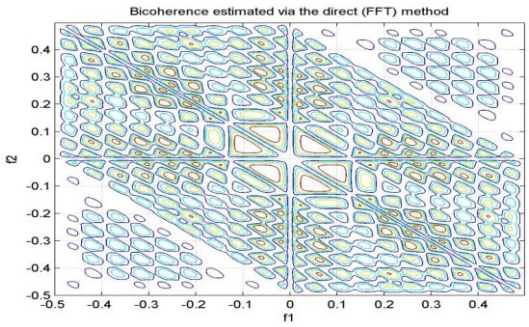
(b)

Fig. 5. a. Bispectrum, b. Bicoherence plot for normal beat

For the normal cases, the bispectrum magnitude plot exhibit peaks at lower frequencies Fig 5(a). The heart rate is varying continuously between 60-80 beats per minute (bpm). The bicoherence values appear to be scattered throughout the bi-frequency plane in a random manner except for a few peaks that are narrow-band.



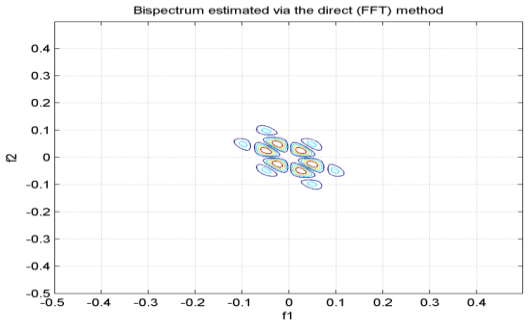
(a)



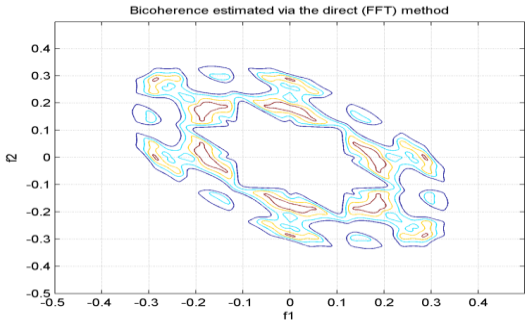
(b)

Fig. 6. a. Bispectrum, b. Bicoherence plot for rbbb beat

In the case of the Right bundle branch block (Fig.6), the most of the peaks in the plots are at high frequency. The bicoherence values appear to be congested at the centre of the bifrequency plane and are more structured compared to normal.



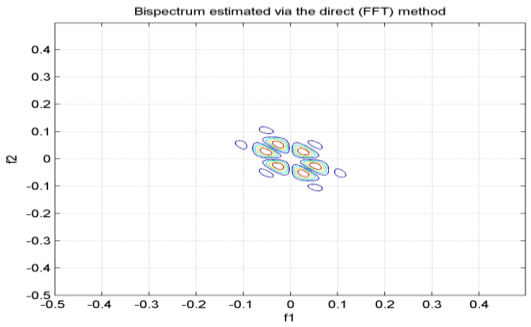
(a)



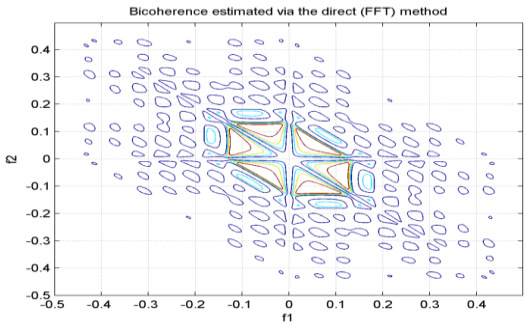
(b)

Fig. 7. a. Bispectrum, b. Bicoherence plot for paced beat

In the paced beat, shown in Fig.7, the bispectrum magnitude plot exhibits peaks at lower frequency just as in normal beat. Sometimes the A-V node fails to send electrical signals rhythmically to the ventricles, which make the heart rate to remain low and even lead to complete heart block. The bicoherence plot indicates a spreading in the bifrequency plane with more peaks crowded at low frequency.



(a)



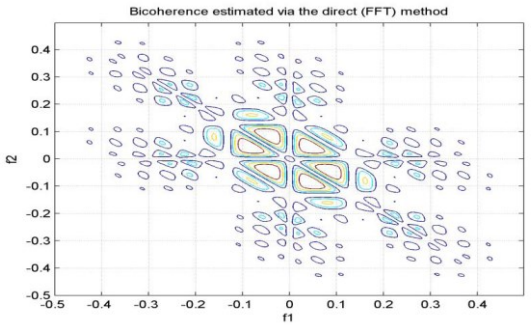
(b)

Fig. 8. a. Bispectrum, b. Bicoherence plot for lbbb beat

In the case of the left bundle branch block, the bispectrum shows peaks at higher frequencies, since the heart rate variation in Lbbb is high as illustrated in Fig.8. The bicoherence plot indicates more structure than the normal case.



(a)



(b)

Fig. 9. a. Bispectrum, b. Bicoherence plot for Apb beat

For the atrial premature beat (Fig.9), since the beats are premature and is very close to the normal it exhibit peaks at lower frequencies in the bispectrum. In the bicoherence most of the values are scattered also as in normal.

From Fig. 5 through 9, it is observed that there are differences between the normal and other arrythmias presented in the plots which possibly can be used in the identification of the arrhythmia.

VI. CONCLUSION

The automatic diagnosis of cardiovascular diseases using ECG processing is an emergent area of the biomedical signal processing, because of the importance of the early diagnosis in treatment and the difficulties of the evaluation of the long records by the experts. Since the ECG waveform is nonlinear in nature, it is suitable to use methods developed for the nonlinear systems. Thus, in this study higher order statistical measures such as skewness, kurtosis, variance have been used to classify five different ECG beat classes. It has been observed for only 1 minute of recording and the average of three parameters statistical parameters are sufficient for classification. Also, the bispectrum and bicoherence plots are demonstrated to show that there are obvious differences between different types of heart beats. It is the concern of the future studies to extract new features from bispectrum and bicoherence values.

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