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Current methods in electrocardiogram characterization

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ABSTRACT

The Electrocardiogram (ECG) is the P-QRS-T wave depicting the cardiac activity of the heart. The subtle changes in the electric potential patterns of repolarization and depolarization are indicative of the disease afflicting the patient. These clinical time domain features of the ECG waveform can be used in cardiac health diagnosis. Due to the presence of noise and minute morphological parameter values, it is very difficult to identify the ECG classes accurately by the naked eye. Various computer aided cardiac diagnosis (CACD) systems, analysis methods, challenges addressed and the future of cardiovascular disease screening are reviewed in this paper. Methods developed for time domain, frequency transform domain, and time-frequency domain analysis, such as the wavelet transform, cannot by themselves represent the inherent distinguishing features accurately. Hence, nonlinear methods which can capture the small variations in the ECG signal and provide improved accuracy in the presence of noise are discussed in greater detail in this review. A CACD system exploiting these nonlinear features can help clinicians to diagnose cardiovascular disease more accurately.

Contents

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1. Introduction

The cardiovascular disease (CVD) poses an epidemic to the world [1]. In the olden days, the deaths were occurring mainly due to infectious diseases and malnutrition. Increased intake of fat, obesity, physical inactivity, diabetes mellitus, smoking, consumption of alcohol, etc. have contributed to the increase in cardiovascular diseases [2]. While epidemic of CVD is receding in several high income countries, low and middle income nations have seen a rise in the occurrence, where 82% of CVD deaths occur in both genders equally [3,4].

According to a recently published (2013) report, the adjusted populations attributable to cardiovascular disease mortality are 40.6% for high blood pressure, 11.9% for insufficient physical exercise, 13.2% for poorly balanced diet, 13.7% for smoking and 88% for abnormal glucose levels [5]. Despite the health awareness and progress in cardiovascular healthcare management, 21.3% of men and 16.7% of women of Americans more than 18 years old continue to smoke cigarette [5]. In 2011, it is reported that about 18.1% of students between grade nine and twelve used to smoke cigarette [5]. The youth population of age less than 18 years who engage themselves in no regular physical activity is high [5]. It is reported that 17.7% of girls and 10% of boys between 9 and 12 grades have not had moderate to vigorous physical exercise of more than 60 min [5]. In 2009, mortality rate due to CVD is 236.1 per 100,000 population [5]. It is 281.4, 190.4, 387.0 and 267.9 per 100,000 population for white males, white females, black males and black females respectively [5].

Arrhythmia is a cardiac condition caused by the abnormal electrical activity of the heart. Every arrhythmia is not life threatening and is caused due to chaotic electrical activity. The main cause for the arrhythmias may be cardiovascular disease. Few cardiac arrhythmias like ventricular flutter and ventricular fibrillation may cause sudden death, hemodynamic collapse and cardiac arrest [5–7]. Cardiac arrhythmias usually happen in people having disease such as cardiomyopathy, hypertension and coronary artery disease. They may cause due to either or both defects in the impulse conduction or its formation [1]. The heart beat may be too fast, too slow, and may be regular or irregular. Depending on the region of origin in the heart, arrhythmia is broadly classified as supraventricular or ventricular arrhythmia. Different types of arrhythmias generally have different generating mechanisms in the heart, have clinically different implications and require different management. There is a strong scientific basis for the mechanism of origin and clinical interaction between many types of arrhythmia, say for example atrial flutter and atrial fibrillation [2,8]. It is common to find patients with primary atrial fibrillation experiencing atrial flutter and vice versa [2,8].

The electrocardiogram (ECG) is the noninvasive method to detect various arrhythmias. It is very important to detect and diagnose fatal arrhythmias accurately as early as possible, as they can cause sudden cardiac death. Arrhythmias like atrial fibrillation increase the possibility of having stroke and thromboembolic events [9]. Physicians face difficulty in the diagnosis of arrhythmias due to their unknown mechanisms, complex nature, and clinical interrelations. Consequently visual inspection may lead to misdiagnosis and inaccurate classification [10,11]. ECG is generated as a result of sum of the depolarization potential of millions of cardiac cells. The cardiac abnormality can be diagnosed using the ECG wave. However, its amplitude and frequency components are very subtle to detect accurately and consistently for a clinician using manual method. Hence, a computer-aided diagnosis of ECG screening will help the clinicians to significantly manage the cardiovascular diseases [12,13]. Also visual inspection of ECG analysis is tedious and time consuming even for an expert cardiologist. It is reported that the usage of computer software to diagnose the ECG classes is cost effective and significantly improves diagnostic accuracy and patient healing outcomes [14,15].

One cycle of the electrical activity of heart is called an ECG beat. Ectopic beats result due to the defects in conduction and/or formation of impulse. One of the open source ECG databases is the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database [16]. The Association for the Advancement of Medical Instrumentation (AAMI) proposes combining all different types of beats into five classes [17]. Table 1 shows the ANSI/AAMI EC57:1998 standard of classification of arrhythmia beats [17]. This standard classifies the ECG beats into five classes. The classes are non-ectopic beats (N), fusion beats (F), supraventricular ectopic beats (S), ventricular ectopic beats (V) and unknown beats (U). The non-ectopic beats consist of normal beats, left bundle branch block (LBBB), atrial escape beat (AE), right bundle branch block (RBBB), and nodal (junctional) escape beats (NE). Other beats present in each class are shown in Table 1.

Section 2 of this paper discusses the ECG pre-processing and QRS complex detection, and Section 3 explains various methods of ECG analysis. Different methods for computer aided recognition of

Table 1
MIT-BIH arrhythmia beats classification per ANSI/AAMI EC57:1998 standard database [17].

Non-ectopic beat (N)	Supraventricular ectopic beat (S)	Ventricular ectopic beat (V)	Fusion beat (F)	Unknown beat (Q)
Normal	Aberrated Atrial Premature (aAP)	Ventricular Escape (VE)	Fusion of Ventricular and Normal (fVN)	unclassifiable (U)
Right Bundle Branch Block (LBBB)	Atrial Premature (AP)	Premature Ventricular Contraction (PVC)		Paced
Left Bundle Branch Block (RBBB)	Supraventricular Premature (SP)			fusion of Paced and Normal (fPN)
Nodal (junctional) Escape (NE)	Nodal (junctional) Premature (NP)			
Atrial Escape (AE)				

ECG beat and computer aided diagnosis of ECG disorders are presented in Sections 4 and 5 respectively. Limitations of current methods are presented in Section 6. Future directions and applications of ECG in mobile healthcare and telecare are described in Sections 7 and 8, respectively. Finally, the paper concludes in Section 9.

2. ECG Preprocessing and QRS complex detection

The quality of ECG beat classification depends on the preprocessing stage. The frequencies of the noise and artifacts may interfere with the frequency band of the ECG. Sources of noises are contact noise, muscle artifacts, power line interference, baseline drift, data collecting device noise, electrosurgical noise, quantization noise, aliasing and signal processing artifacts such as Gibbs oscillations [18] (due to finite windowing effects). Luo and Johnston [19] presented a review on different methods of ECG preprocessing for noise and artifact elimination and baseline removal [19]. Addison [20] described wavelet transform and its application to ECG analysis [20]. Automated QRS peak detection helps us to detect the heart rate signals. There are many automated QRS detection algorithms like signal derivatives [21], digital filters [22], multi-scale or multi resolution approach [23,24], filter banks [25], mathematical morphology [31], neural networks [26,27], Hilbert transform [34], learning vector quantization [28], matched filters [32], hidden Markov model [29], adaptive filters [30], length and energy transform [35], genetic algorithms [33] and syntactic approaches [36]. Kohler et al. discussed most of the QRS detection algorithms until 2002 [37]. A simple QRS detection algorithm based on low pass, high pass filtering and thresholding proposed by Pan and Tompkins is widely used in different applications [38]. Recently Pal and Mitra presented a method based on empirical mode decomposition (EMD) for detection of QRS complex in ECG [39].

3. Methods of ECG analysis

Clinical assessment of ECG is performed by measuring various amplitudes and corresponding positions of different peaks such as P, QRS, T and U waves. Based on the clinical acumen, cardiologists interpret the changes in the amplitude and positions of ECG waveform. The changes in the amplitude are in milli-volts and the duration is in milli-seconds. These subtle changes are difficult to decipher by the naked eye. Hence it is necessary to design a CACD system for detecting the abnormalities using the minute changes in the amplitude and durations of ECG. Fig. 1 shows a typical normal and Premature Ventricular Contraction (PVC) beat.

MIT BIH arrhythmia database [16] is the most widely used database for analysis of ECG, where the signals are sampled at 360 Hz. The ECG signal analysis methods can be broadly divided into the following: (i) time based, (ii) frequency based, (iii) time–frequency based, and (iv) nonlinear methods. They are briefly discussed in the following sections.

3.1. Time based methods of ECG analysis

Linear prediction [40], principal component analysis (PCA) [41], linear discriminant analysis (LDA) [41] and independent component analysis (ICA) [42] have been used for ECG analysis. LDA is basically a statistical learning method, which can be used as a classifier itself. However some authors have used the LDA components as features for subsequent pattern identification [132]. The LDA method learns from the data to get the LDA components and these components are used for pattern recognition.

3.1.1. Linear prediction

Linear prediction [40] assumes that a given signal at the current instance of time can be predicted from its past values through a weighted linear function. If $x(n)$ is the given signal and $a(k), k=1,2,\ldots,p$, are p weights of the past p time instances, the amplitude of the predicted signal is given by

$$\hat{x}(n) = \sum_{k=1}^{p} a(k)x(n-k) \tag{1}$$

where the prediction error is $e(n) = x(n) - \hat{x}(n)$, which indicates the portion of the signal that cannot be predicted by the model.

The coefficients of linear prediction $a(k)$ can be used as features for the pattern identification. Kang-Ping and Chang [43] used a prediction order of two for fast arrhythmia detection and showed a sensitivity of 92% in the detection of PVC beat using the MIT-BIH

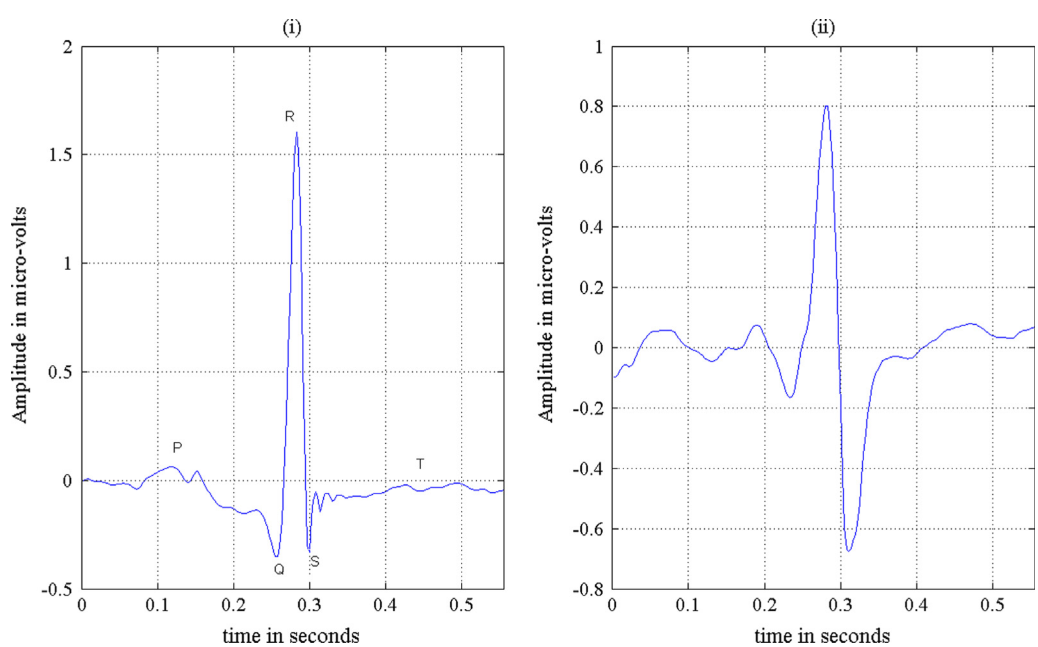

Fig. 1. Typical ECG beat: (i) normal and (ii) PVC.

arrhythmia database. More recently Martis et al. [44] used linear prediction coefficients and Gaussian mixture model (GMM) to classify two cardiac abnormalities, i.e., arrhythmia beats and ischemia beats with 94.29% accuracy [44].

3.1.2. Principal component analysis (PCA)

It is a linear dimensionality reduction method which computes the directions of highest variability in descending order and projects the data onto them [41,45,46]. It uses eigenvectors of covariance matrix as the basis vectors in the directions of maximum variability. Eigenvectors and eigenvalues are computed using eigenvalue decomposition of covariance matrix. In order to select the number of principal components, a threshold on total variability of the data is used.

The PCA algorithm projects the data into the directions of maximum variability and reduces the number of dimensions [41,47,179]. The reduced number of components is well represented but may not provide the best possible discrimination for classification by a classifier. Polat and Güneş [48] detect arrhythmia beats using a combination of least square support vector machine, a differential expert system method [48,49]. They report an accuracy of 96.86%, 100% and 100% using 50–50%, 70–30% and 80–20% training-test dataset, respectively, employing the MIT-BIH arrhythmia database. Martis et al. [44] report an accuracy of 94.29% using a Gaussian mixture model coupled with principal components of error signal of the linear prediction model [44]. Martis et al. [50] used the principal components of discrete wavelet transform (DWT) coefficients for arrhythmia detection and reported a 95.60% classification accuracy. The same group [51] reported a classification accuracy of 98.11% using the principal components of time domain signal as well as the principal components of DWT coefficients of the ECG beat.

3.1.3. Linear discriminant analysis (LDA)

It is a dimensionality reduction method which provides the highest possible discrimination among various classes [41,52]. The within class covariance matrix represents the scatter within the class which is defined as

$$\mathbf{S}_W = \sum_{k=1}^{K} \sum_{n \in C_k} (\mathbf{x}_n - \mathbf{m}_k)(\mathbf{x}_n - \mathbf{m}_k)^T \tag{2}$$

where $\mathbf{m}_k = (1/N_k)\sum_{n \in C_k} \mathbf{x}_n$, N_k is the number of patterns in class C_k, $\mathbf{x}_n$ is the data vector, $\mathbf{m}_k$ is the mean vector of the kth class and K is the total number of classes present in the dataset. The between class covariance matrix is defined as

$$\mathbf{S}_B = \sum_{k=1}^{K} N_k(\mathbf{m}_k - \mathbf{m})(\mathbf{m}_k - \mathbf{m})^T \tag{3}$$

where, $\mathbf{m} = (1/N)\sum_{n=1}^{N} \mathbf{x}_n = (1/N)\sum_{n=1}^{N} N_k \mathbf{m}_k$ and $\mathbf{m}$ is the global mean of the data. The total covariance of the data is given by

$$\mathbf{S}_T = \mathbf{S}_W + \mathbf{S}_B \tag{4}$$

From $\mathbf{S}_W$ and $\mathbf{S}_B$ the projection matrix (direction matrix) $\mathbf{W}$ is to be derived on which the data needs to be projected for the final representation and is given by

$$\mathbf{W} = \arg\max_W \{(\mathbf{W}\mathbf{S}_W\mathbf{W}^T)^{-1}(\mathbf{W}\mathbf{S}_B\mathbf{W}^T)\} \tag{5}$$

Using $\mathbf{W}$, the LDA coefficients are computed as

$$\mathbf{y} = \mathbf{W}^T\mathbf{x} \tag{6}$$

The coefficients in vector $\mathbf{y}$ which has a smaller dimension than the original data is used as inputs to an automated classifier.

Yeh et al. present classification of normal, LBBB, right RBBB, PVC and atrial premature contraction (APC) ECG beats using the coefficients of LDA with an accuracy of 98.97%, 91.07%, 95.09%, 92.63% and 84.68%, respectively [53].

3.1.4. Independent component analysis (ICA)

It is a nonlinear method of dimensionality reduction. This method assumes that the signal which we are observing is formed by the linear mixing of source components. If $\mathbf{x}$ is the n dimensional mixture signal and $\mathbf{s}$ is the n dimensional source signal. (It is assumed that the number of independent components is equal to the number of source components.) Let $\mathbf{A}$ be the weight vector with elements a_i, the ICA model is represented mathematically as

$$\mathbf{x} = \mathbf{A}\mathbf{s} = \sum_{i=1}^{n} a_i s_i \tag{7}$$

The source signal is represented mathematically in terms of mixed signal as

$$\mathbf{s} = \mathbf{W}\mathbf{x} \tag{8}$$

where $\mathbf{A}$ and $\mathbf{W}$ are the inverses of each other. In the ICA approach a method is needed to solve the weights (elements of $\mathbf{A}$). There are many methods to solve this problem. The FastICA [42,54,55] algorithm is a fast and efficient implementation of ICA algorithm. In this algorithm, the data is centered by subtracting mean from it and whitened by transforming the data distribution into Gaussian. An iterative method is used to evaluate the weights. The weight matrix consisting of the weights of the source signals can be used as features for pattern identification of ECG beats.

Yu and Chou [57] integrated ICA with an error back propagation neural network [56,57] for ECG beat discrimination and presented a beat recognition accuracy of 98% for eight ECG classes (normal, paced beat, ventricular flutter, ventricular escape beat, LBBB, RBBB, APC and PVC) from MIT BIH arrhythmia database [57].

3.2. Frequency based methods of ECG analysis

The time domain methods provide good visualization of the data, but the minute variations in the amplitude and frequency of ECG are not very well represented. Many methods such as [57] report high classification accuracy, they are tested on noise free conditions. In real scenario, there will be noise, baseline wander and artifacts. There is a need to explore the information from these noisy data. In order to explore such a hidden information in the data, different frequency domain methods such as the Fourier transform and the power spectral density (PSD) [58] methods are explored. The Fourier transform of a discrete time sampled signal $x(n)$ is given by

$$\mathbf{X}(f) = \sum_{n=0}^{N} x(n)e^{-j2\pi fn} \tag{9}$$

where N is the length of the signal window in number of discrete time samples. $\mathbf{X}(f)$ is the Fourier transform of $x(n)$. From the Fourier transform, the power spectral density (PSD) is defined by

$$\mathbf{P_{xx}}(f) = \frac{1}{N}|\mathbf{X}(f)|^2 \tag{10}$$

The PSD estimated by Eq. (10) is the basis for non-parameteric estimation of PSD. The plot of PSD versus frequency is called the periodogram. The PSD appears to vary randomly about an average spectrum for different records of a signal. Numerous techniques have been proposed subsequently to summarize PSD in a meaningful way noting the variance in PSD estimation.

Modified versions of periodogram have been proposed. Most of them perform a window operation on the time domain signal with an aim of smoothing the edges. This operation can bring down the edge amplitudes in the periodogram. (They are also called sidelobes in signal processing terminology.)

Welch method [58,59] of PSD computation averages the periodograms from overlapped and windowed segments. Let us assume that signal $x(n)$ of length N samples is used to obtain periodograms of K overlapping segments of length M . The periodogram is evaluated after windowing each segment. The ith segment is given by

$$x_i(n) = x(n+iD), \quad n = 0, 1\ldots, M-1; \; i = 0, 1, \ldots, K-1 \tag{11}$$

where D is the overlap. For half overlap, $D = N/2$ and for no overlap $D = N$. For the ith window segment, the periodogram is given by

$$P_{XX}^{(i)}(f) = \frac{1}{NU}\left|\sum_{n=0}^{N-1} w(n)x_i(n)e^{-j2\pi fn}\right|^2 \tag{12}$$

where U is the power in the window function $w(n)$ and is defined as

$$U = \frac{1}{N}\sum_{n=0}^{N-1} w^2(n) \tag{13}$$

Average of K periodograms obtained from windowed and overlapped segments of the signal yields the Welch power spectrum defined as

$$P_{XX}^{W}(f) = \frac{1}{K}\sum_{i=0}^{K-1} P_{XX}^{(i)}(f) \tag{14}$$

The parametric methods of spectrum estimation include autoregressive (AR) method, moving average (MA) method and auto regressive moving average (ARMA) method. These methods assume a functional form for the power spectra and the parameters of these functional forms are estimated. According to spectral factorization theorem, the rational power spectral density can be factored as [58,59]

$$\overline{P}_{XX}(f) = \left|\frac{B}{A}\right| P_{XX}(f) \tag{15}$$

where $A = 1 + a_1 z^{-1} + \cdots\cdots\cdots\cdots + a_n z^{-1}$; $B = 1 + b_1 z^{-1} + \cdots\cdots\cdots\cdots + b_m z^{-1}$; $P_{XX}(f)$ is the actual estimate of PSD and $\overline{P}_{XX}(f)$ is the parametric estimate of PSD. $A = 1$, for autoregressive (AR) and $B = 1$ for moving average (MA) model.

Fig. 2 depicts the typical AR spectrum of a normal and PVC beat. It can be observed from the figure that the normal ECG has two peaks in the spectrum, whereas the PVC beat has one peak in the frequency domain. This information can be used to discriminate the two types of beats.

Using power spectral density features, Khazee and Ebrahimzadeh [60] classified normal and four arrhythmia (LBBB, RBBB, APC and PVC) beats [60]. They used genetic algorithm [61–63] to search for the best parameters of a support vector machine (SVM) classifier [64,65] and reported the highest classification accuracy of 96%.

4. Nonlinear methods of ECG analysis

4.1. Time-frequency based methods of ECG analysis

The Fourier transform is a technique used to analyze the global frequency of a given signal. It provides good frequency resolution but cannot provide good temporal localization [66]. In wavelet transform, the frequency resolution may be compromised to some extent to increase the temporal resolution. In the wavelet transform, the inverse of frequency called the scale is used. The wavelet transform provides multiple resolutions, known as multiresolution analysis. Wavelet transform can provide discrimination between two different signals with the same spectrum magnitude (absolute amplitude of frequency spectrum) [67–70,176–178,180].

The translation and the dilation of basis function (mother wavelet) yield the full spectrum of wavelet coefficients at every scale. The basis function at scale a and translation b is given by [67,71,72]

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{16}$$

The discrete wavelet transform (DWT) is obtained when the wavelet transform is sampled on a dyadic grid. The basis function is defined as

$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n) \tag{17}$$

where m is the dilation (or the scale) and n is the translation. The wavelet function given by Eq. (17) is associated with the high frequencies, termed as details of the signal. Detail coefficients of the DWT of the signal, using the translation and the dilation of the basis function, are given by the inner product of the signal at

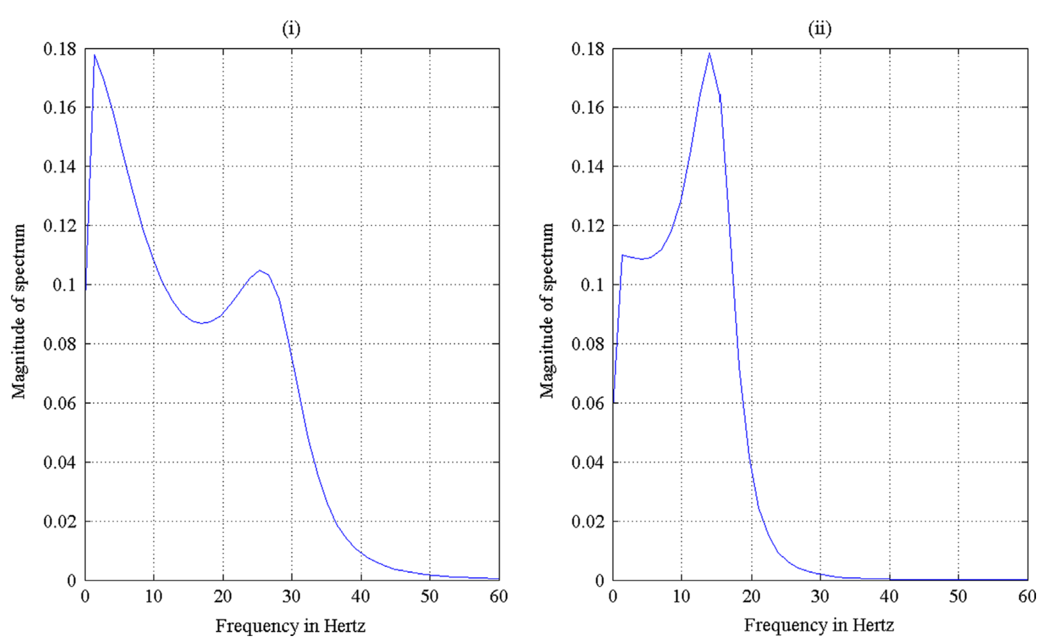

Fig. 2. Results of AR spectra for typical ECG signal: (i) normal and (ii) PVC.

a given m and n

$$T_{m,n} = \int_{t=-\infty}^{\infty} x(t)\psi_{m,n}(t)\,dt \tag{18}$$

There is a scaling function related to the low frequency content of the signal, which is orthogonal to the wavelet function. The scaling function provides the approximation coefficients of the DWT and is given by

$$S_{m,n} = \int_{t=-\infty}^{\infty} x(t)\phi_{m,n}(t)\,dt \tag{19}$$

where

$$\phi_{m,n} = 2^{-m/2}\phi(2^{-m}t-n) \tag{20}$$

and

$$\int_{t=-\infty}^{\infty} \phi_{0,0}(t)\,dt = 1 \tag{21}$$

In the first level of decomposition of DWT, a given signal is decomposed into approximation and detail coefficients. Approximation coefficients are further decomposed into next level detail and approximate coefficients. In each and every level, approximation coefficients are further decomposed into detail and approximate coefficients in the next level. Each level, either the approximation or the detail, is called a sub-band [71,73].

Martis et al. [74] decompose the ECG signal up to four levels using a few (in total 54) available basis functions. From these 54 basis functions, finite impulse response (FIR) approximation of Mayer wavelet provided the highest classification accuracy due to the similarity of basis function with ECG signal morphology. The large number of DWT sub-band coefficients can create a high dimensionality problem for accurate classification but it can be reduced using PCA.

Martis et al. used the principal components of DWT coefficients for the classification of normal and arrhythmia beats of ECG and reported accuracies of 95.60% and 96.88% for two classes and five classes respectively [50–52]. Shyu et al. used wavelet transform and fuzzy neural network [75–77] for classification of normal and arrhythmia beats in ECG and reported an accuracy of 99.79% in detecting PVC beats [78]. Engin [79] used coefficients of autoregressive model, higher order cumulants and variances of wavelet transform as features and classified the ECG beats using fuzzy hybrid neural network [80–85] with an accuracy of 93.5%. Qibin and Liqing [86] classified six types of ECG beats using coefficients of wavelet transform and autoregressive model with an accuracy of 99.68%. Minhas and Arif [87] used wavelet transform features of QRS complex of the ECG and instantaneous R–R interval to classify six types of heart beats and reported 95% accuracy at 10 dB of signal to noise ratio.

The frequency and time–frequency (wavelet) domain methods can capture the rhythmic oscillations present in the signals. However the nonlinear and phase interrelationships among different frequency components are not well captured by these methods [88]. The biological systems are inherently nonlinear and non-stationary in nature [89–92]. So nonlinear methods can capture the hidden information and the nonlinear interrelationships among different parameters. The most widely used current nonlinear methods are higher order spectra cumulants, higher order poly-spectra, recurrence quantification analysis (RQA) and Hilbert Huang transform.

In wavelet transform, the translation of a given basis function is a linear operation. But the dilation operation is a nonlinear operation. Therefore the wavelet transform is a nonlinear method.

4.2. Higher order cumulants

Higher order spectra (HOS) is a tool for the analysis of nonlinear, non-stationary and non-Gaussian signals [74,93]. The first two order statistics are not sufficient to represent nonlinear systems since they make use of higher order correlations. The HOS can model the nonlinearity, deviations from Gaussian, and phase interrelationships between different frequency components. Another advantage of HOS is that it filters Gaussian noise, because Gaussian process is characterized by first two order statistics. The HOS of Gaussian process is identical to zero.

Higher order cumulants are derived from higher order moments. They represent the deviations from Gaussianity, and can model the nonlinear dynamical nature of ECG signals. Suppose that $x(n)$ is a discrete time stationary signal and its moments up to order n do exist. Then the n th order moment function is defined by [93]

$$m_n^X(\tau_1, \tau_2, \ldots, \tau_{n-1}) = E[x(n)x(n+\tau_1)\cdots x(n+\tau_{n-1})] \tag{22}$$

The moment function described by Eq. (22) depends only on the time lags, $\tau_1, \tau_2, \ldots \tau_{n-1}, \tau_i = 0, \pm 1, \pm 2, \ldots$ for all i. The 2nd order moment $m_2^X(\tau_1)$ is the autocorrelation sequence of $x(n)$, whereas $m_3^X(\tau_1, \tau_2)$ and $m_4^X(\tau_1, \tau_2, \tau_3)$ are the moment functions of 3rd and 4th orders, respectively and $E[\bullet]$ is the statistical expectation operator. Using the nth order moment, the nth order cumulant can be computed as [93]

$$C_n^X(\tau_1, \tau_2, \ldots, \tau_{n-1}) = m_n^X(\tau_1, \tau_2, \ldots, \tau_{n-1}) - m_n^G(\tau_1, \tau_2, \ldots, \tau_{n-1}) \tag{23}$$

where $m_n^X(\tau_1, \tau_2, \ldots, \tau_{n-1})$ is the nth order moment function and $m_n^G(\tau_1, \tau_2, \ldots, \tau_{n-1})$ is the nth order moment of equivalent Gaussian process. Using the moments, the first four order cumulants for a zero mean process are given by [93]

$$\begin{aligned}
C_1^X &= m_1^X \\
C_2^X(\tau_1) &= m_2^X(\tau_1) \\
C_3^X(\tau_1, \tau_2) &= m_3^X(\tau_1, \tau_2) \\
C_4^X(\tau_1, \tau_2, \tau_3) &= m_4^X(\tau_1, \tau_2, \tau_3) - m_2^X(\tau_1)m_2^X(\tau_2-\tau_3) \\
&\quad - m_2^X(\tau_2)m_2^X(\tau_3-\tau_1) - m_2^X(\tau_3)m_2^X(\tau_1-\tau_2)
\end{aligned} \tag{24}$$

Figs. 3 and 4 show the 1) magnitude and 2) contour of typical normal and PVC beats, respectively in the form of a 3rd order cumulant. The variables τ_1 and τ_2 are the time lags or time differences along the horizontal and vertical axes as provided by Eq. (24). These plots are unique for a given cardiac condition. Using these plots one can distinguish different beats and classify different cardiac disorders.

Using HOS cumulants of DWT coefficients, Martis et al. [74] classify normal and abnormal ECG beats with an accuracy of 98.4% [74]. Same group classified normal, APC, PVC, RBBB, and LBBB classes using HOS features (bispectrum) with an average accuracy of 93.48% [94]. Ying-Hsiang [95] used higher order statistics and Hermite basis function decomposition for ECG beat classification [102]. Based on their experiments, they conclude that the Hermite basis function decomposition provides more accurate results than higher order statistics. Park et al. [97] used higher order statistics of DWT sub-bands for ECG beat classification and reported an accuracy of 97.5%. Yu and Chen [98] presented ECG beat classification which the authors claim to be noise-tolerant based on higher order statistics (HOS) of sub-band components.

4.3. Higher order spectra

A third-order statistics called the bispectrum can be used for the analysis of ECG signals. The bispectrum $B(f_1, f_2)$ of the ECG signal is the Fourier transform of the third order correlation, given

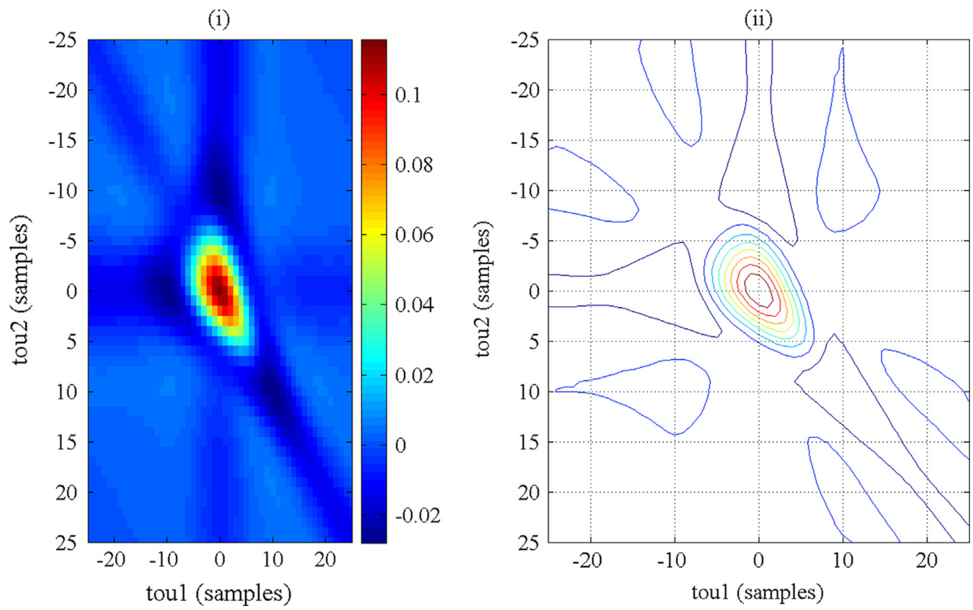

Fig. 3. 3rd order cumulant plot of normal ECG signal: (i) magnitude plot and (ii) its contour.

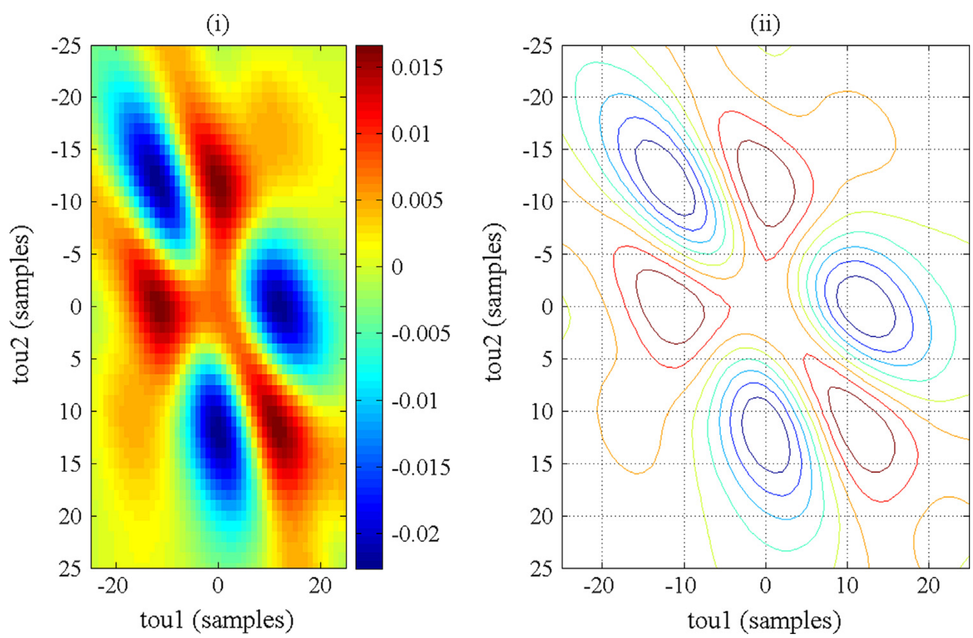

Fig. 4. 3rd order cumulant plot of PVC ECG signal: (i) magnitude plot and (ii) its contour.

by the averaged biperiodogram as [99]

$$B(f_1, f_2) = E[X(f_1)X(f_2)X^*(f_1+f_2)] \quad (25)$$

where $X(f)$ represents the Fourier transform of the ECG signal $x(n)$, star (*) represents complex conjugation operator and $E[\bullet]$ is the ensemble average operator. The bispectrum $B(f_1, f_2)$ is normalized to obtain the bicoherence as [93]

$$B_{norm}(f_1, f_2) = \frac{E[X(f_1)X(f_2)X^*(f_1+f_2)]}{\sqrt{P(f_1)P(f_2)P(f_1+f_2)}} \quad (26)$$

where $P(f)$ is the power spectral density of the ECG signal.

Figs. 5 and 6 show (i) magnitude and (ii) contour of typical normal and PVC ECG beats of bispectrum respectively. In the plots the horizontal and vertical axes are the frequency variables whose units are radians per second. Both frequencies are equally important, and the bispectrum is symmetric with respect to the frequency variables f_1 and f_2. These plots are unique for a given cardiac condition.

Martis et al. [94] presented unique HOS plots for five different classes of ECG beats. They have used the principal components of bispectrum to classify the five types (normal, LBBB, APC, PVC, and RBBB) of ECG beats and reported an accuracy of 93.48% [94]. They used higher order spectra cumulants of 2nd, 3rd and 4th orders for the classification of ECG beats using fuzzy hybrid neural network model [100]. The accuracies reported in [94,100] are lower than other methods such as wavelets. However the dataset used differs in each study.

4.4. Recurrence plot (RP)

It is a two dimensional plot depicting the states of recurrences and non-stationarity in the time series [101]. The plot can be used to interpret the hidden periodicities present in the time series

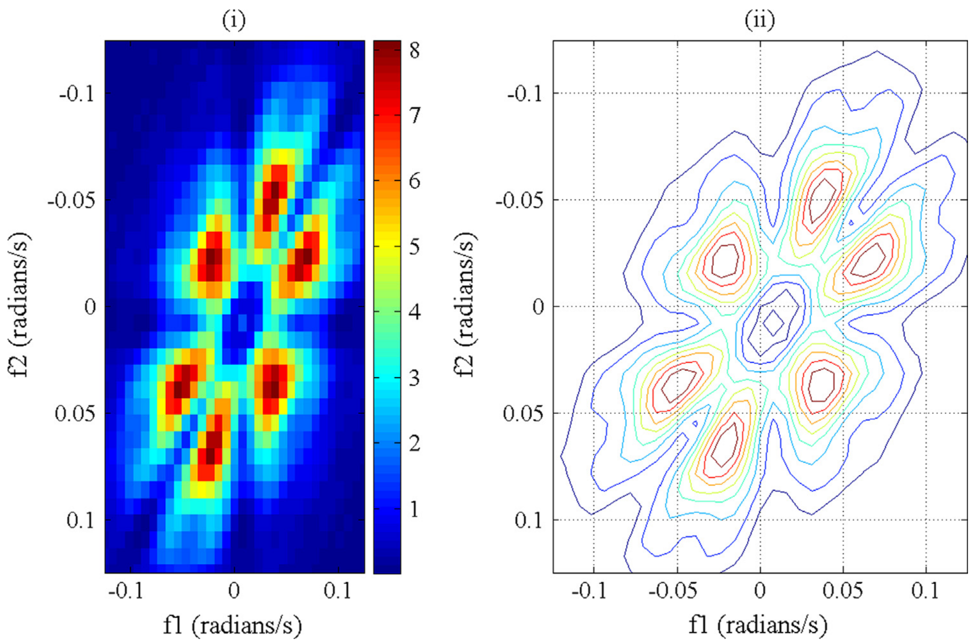

Fig. 5. Bispectrum of normal ECG signal: (i) magnitude and (ii) its contour.

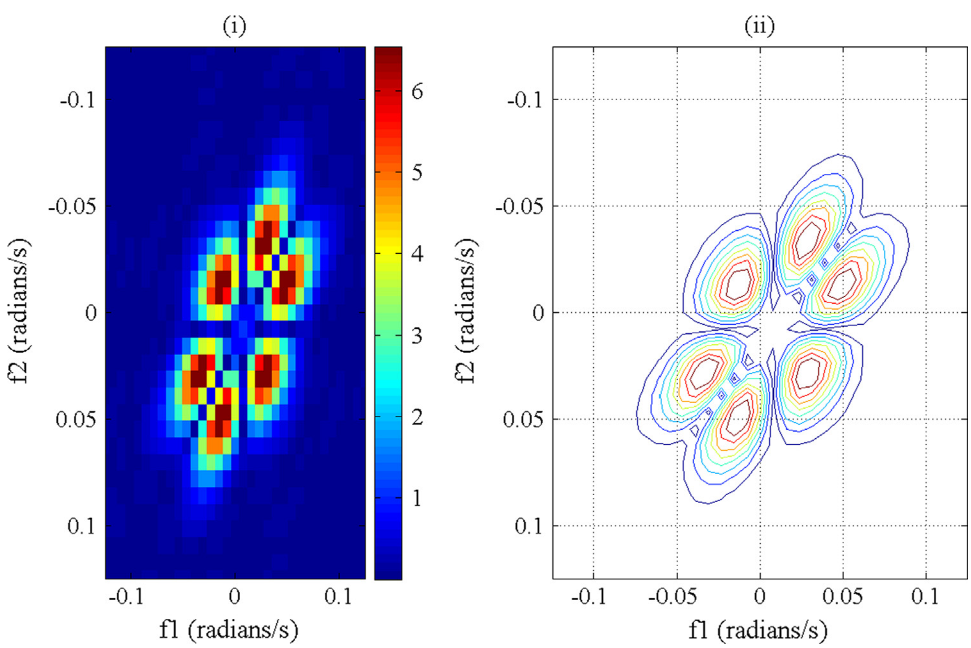

Fig. 6. Bispectrum of PVC ECG signal: (i) magnitude and (ii) its contour.

otherwise unnoticeable. The recurrence takes place when the gap between two states i and j falls less than a predefined fixed value ε. Let x_i and x_j be two points on the orbit in an m dimensional space. When x_j is very near to x_i in distance, a recurrence is said to have occurred and a dot is placed at (i,j) location. In the diagonal $(i=j)$ direction, the plot is symmetric because if x_j is near x_i then x_i is equally near x_j . Hence, this RP is a patch of dots on a square of $N \times N$ size. It can also be visualized as a white and black dot image in a time lag space with black dot indicating the occurrence of recurrence [101]. Figs. 7 and 8 depict the typical RP of normal and PVC beats respectively.

The RP provides a good visual representation of the signal. From this plot a number of numeric quantities can be derived and used as features for pattern classification of ECG signals. These numeric quantities are obtained from a so-called recurrence quantification analysis (RQA) [101]. These RQA parameters measure the nonlinearity and complexity of the system. Mean diagonal length, longest diagonal line, longest vertical line, recurrence rate, determinism, entropy, linearity, trapping time, and recurrence time parameters derived from recurrence plot representation can indicate the nonlinearity of the signal [101].

4.5. *Hilbert–Huang transform (empirical mode decomposition)*

This technique expands a given ECG signal into a few number of intrinsic mode functions (IMFs) to yield the instantaneous frequency [102]. Instantaneous magnitude and its frequency are obtained from the IMFs. Subsequently the Hilbert transform can be applied to every intrinsic mode to track instantaneous frequencies and its magnitude. Empirical mode decomposition (EMD) is

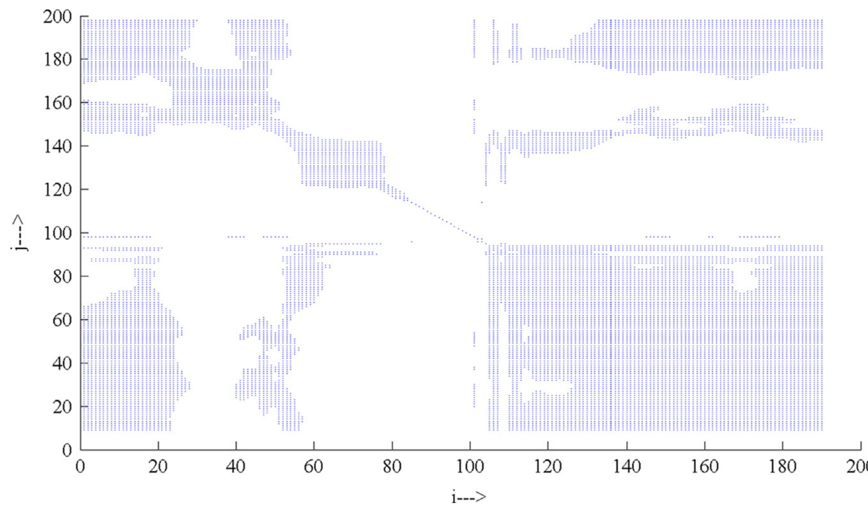

Fig. 7. The typical RP of normal ECG beat.

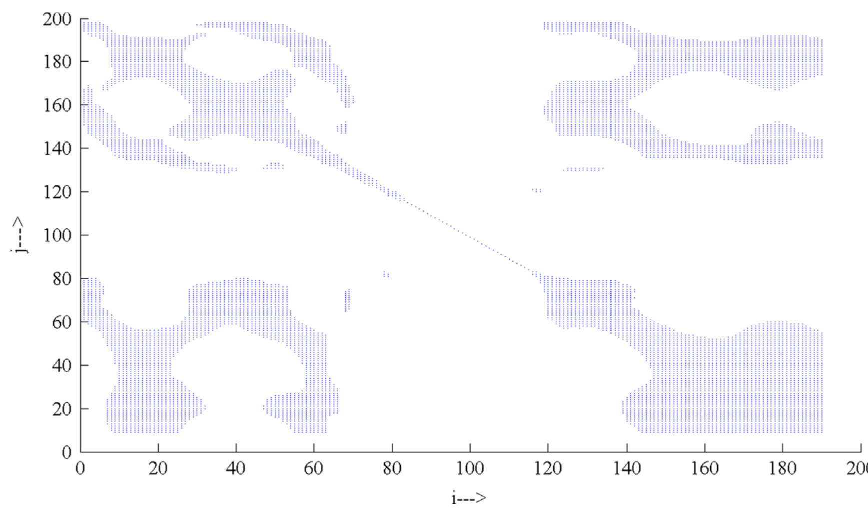

Fig. 8. The typical RP of PVC beat.

a nonlinear, adaptive and easily implementable method depicting the subtle fluctuations in the signal. The IMFs are amplitude and frequency modulated waves.

Let $x(t)$ be the given ECG signal, and identify the local extrema (both maxima and minima) on it. The local extrema are connected by two different cubic splines to yield upper envelope $x_u(t)$ and lower envelope $x_l(t)$. The mean of the lower and upper envelopes at every point is computed as

$$m_1(t) = \frac{x_u(t) + x_l(t)}{2} \tag{27}$$

The first IMF is derived as

$$h_1(t) = x(t) - m_l(t) \tag{28}$$

In order to compute second IMF, $h_1(t)$ is considered as the signal, its upper and lower envelopes are computed to get the next IMF and the procedure is iterated. The procedure is repeated up to when the normalized standard deviation (NSD) between successive IMFs is less than 0.2 or 0.3. The NSD is given by

$$NSD = \frac{\sum_{t=0}^{T} |h_{(k-1)}(t) - h_k(t)|}{h_{(k-1)}^2(t)} \tag{29}$$

The EMD method provides a proper rotation of the frequency and it is a conceptual advantage among other time–frequency methods [95,96]. It has a few drawbacks. It requires a threshold to stop the iterations. The threshold value of 0.2 or 0.3 on NSD is empirical. When this value is smaller the reconstruction error (the process of getting back the original signal from the IMF using EMD representation) is less. Figs. 9 and 10 show the first five IMFs of normal and PVC beats respectively.

5. Computer aided recognition of ECG beats

Hultgren et al. [103] reported a computerized system for arrhythmia monitoring to provide beat-to-beat analysis of cardiac rhythm and QRS morphology. They showed that computer aided diagnosis can improve accuracy compared with manual screening. Govrin et al. [104] used a cross correlation-based approach for computerized arrhythmia detection using the ECG signal. The beats are detected by computing the cross correlation between the template and successive ECG waveforms. They computed RR, PP and PR intervals of each beat accurately for various arrhythmias. Coast et al. [105] used the hidden Markov model for modeling various segments of ECG signal. They classified normal, ventricular ectopic and supraventricular ectopic beats. Thakor et al. [106] presented a multi-way sequential hypothesis testing algorithm for simultaneous discrimination of supraventricular tachycardia and normal sinus rhythm.

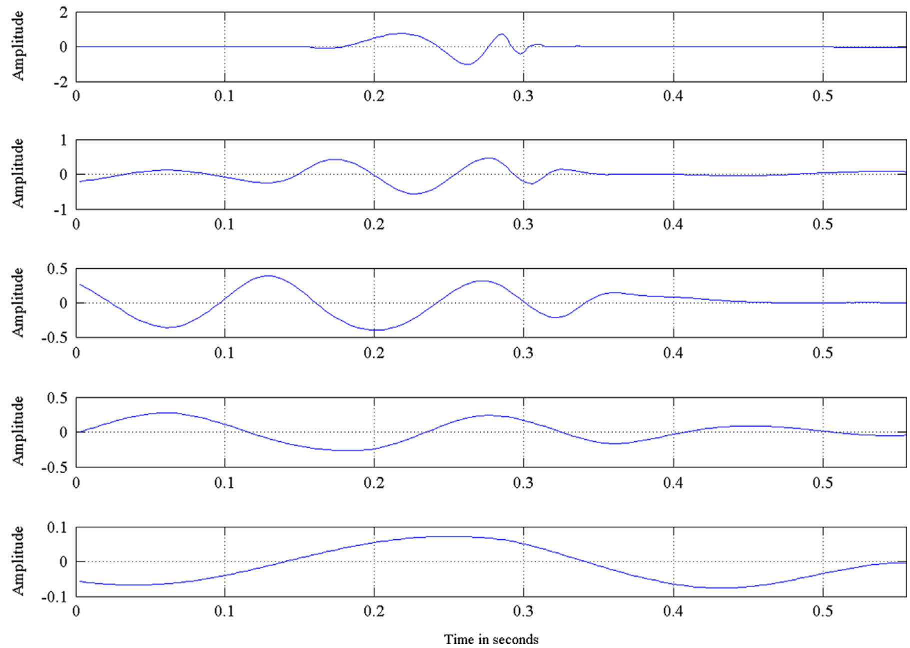

Fig. 9. The first five IMFs of normal ECG beat.

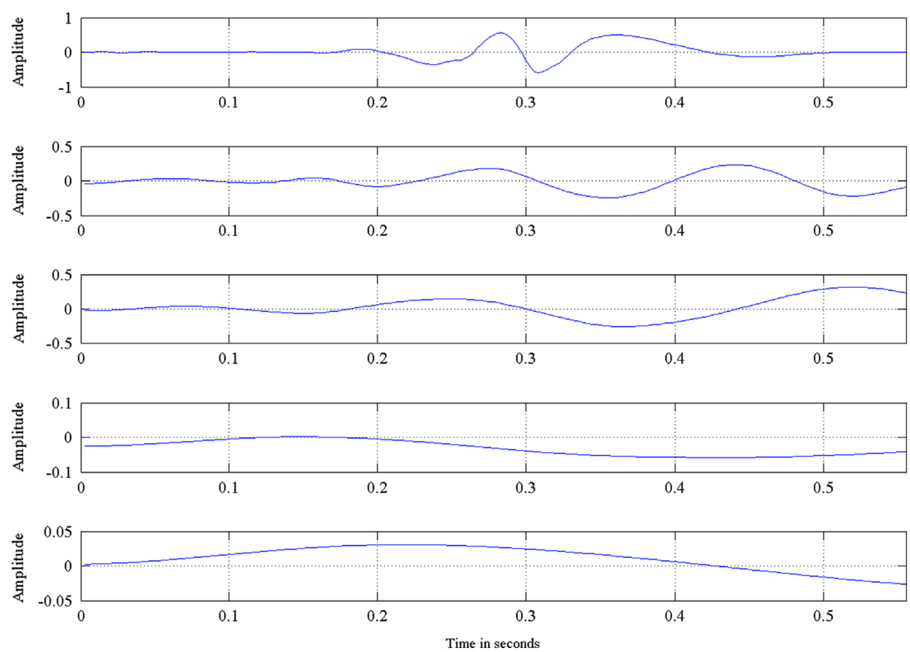

Fig. 10. The first five IMFs of PVC beat.

Hu et al. [123] present an approach based on the mixture of experts for the classification of normal, fusion, ventricular ectopic and supraventricular ectopic ECG beats and reported an accuracy of 94%. He uses entire MIT BIH arrhythmia database for the study and performs normal and abnormal classification. He uses both global expert and local expert methods. He also uses mixture of experts method which uses both local and global experts. He reports sensitivity and specificity of 63.50% and 83.50% respectively with global expert classifier, sensitivity and specificity of 78.61% and 98.03% respectively with local expert classifier and sensitivity and specificity of 82.60% and 97.10% respectively with mixture of experts classifier. Lagerholm et al. [124] used the Hermite function decomposition of ECG beats to classify 25 types of beats in arrhythmia and reported an accuracy of 98.51% using self-organizing map. He classifies normal, LBBB, RBBB, APC, abberated atrial premature beat, normal (junctional) premature beat, supraventricular premature beat, PVC, fusion of ventricular and normal beat, ventricular flutter wave beat, atrial escape beat, nodal (junctional) escape beat, ventricular escape beat, paced beat, fusion of paced and normal beat and unclassifiable beat with 98.99%, 99.83%, 98.66%, 91.25%, 96.61%, 79.66%, 0%, 97.85%, 87.31%, 90.46%, 0%, 82.58%, 97.05%, 97.69%, 90.75% and 100% respectively. Osowski and Linh [125] used the higher order statistics features to discriminate seven ECG classes using a hybrid fuzzy neural network and reported an accuracy of 96.06%. They used 4035 and 3150 beats for training and testing of the classifier (in total 7185 beats) respectively. They achieved rate of misclassification of 2.24%, 3.29%, 1.67%, 4.19%, 2.25%, 0%, 16.36% respectively with normal, LBBB, RBBB, APC, PVC, ventricular flutter wave and ventricular escape beats and with the learning (training) set of the database. Similarly they achieved rate of misclassification of 1.9%, 3%, 6%, 8.67%, 3.43%, 5.5%, 10% respectively with normal, LBBB, RBBB, APC, PVC, ventricular flutter wave and ventricular escape beats and with testing set of the database. The average rate of misclassification on learning set is 2.55% and that of testing set is 3.94%. de Chazal and Reilly [126] use a semi-automated method where the system can be partially trained automatically and remaining beats are manually chosen to classify the supra ventricular ectopic and ventricular ectopic beats with an accuracy of 95.9% and 99.4%, respectively. He uses local and global classifier methods to classify the data correctly. Using local classifier, he achieves 94.29%, 87.71%, 94.33% 73.97% and 0% accuracy for normal, supraventricular ectopic beats, ventricular ectopic beats, fusion beats and unclassifiable beats respectively. Using global classifier supraventricular ectopic beats are classified with sensitivity, positive predictive value and false prediction rate of 87.7%, 47% and 3.8% respectively. Similarly using the global classifier, the ventricular ectopic beats are classified with sensitivity, positive predictive value and false prediction rate of 94.3%, 96.2% and 0.2% respectively. In this study all the beats in the entire MIT BIH arrhythmia database are used. Inan et al. [128] use a neural network-based classifier and wavelet transform features and timing information to classify PVC, normal and other beats with an accuracy of 95.16%. He uses 93,281 ECG beats from the 40 files of MIT BIH arrhythmia database comprising normal, PVC and other classes. Normal beats are classified with sensitivity and positive predictive value of 98.33% and 97.58% respectively. Similarly the PVC beats are classified with sensitivity and positive predictive value of 82.57% and 93.42% respectively. Similarly the other beats are detected with sensitivity and positive predictive value of 86.76% and 94.59% respectively. Jiang and Seong Kong [127] use Hermite transform coefficients with the *R*–*R* interval features coupled with a block-based neural network for classification of ECG beats and report an accuracy of 96.6% for five types of beats as recommended by AAMI. They classify all the beats present in the entire MIT BIH arrhythmia database. The normal, supraventricular ectopic beats, ventricular ectopic beats, fusion beats and unclassifiable beats are classified with 98.72%, 50.57%, 86.60%, 35.78% and 0% accuracy respectively.

Ubeyli [107] classified normal, ventricular tachyarrhythmia, atrial fibrillation, and congestive heart failure using an adaptive neuro fuzzy inference system. Yu and Chen [108] classified ECG beats using the higher order spectra of DWT sub-band components. They report a classification in the range of 91–97.5% depending on the signal to noise ratio. Ince et al. [129] used temporal features and wavelet transform to discriminate five classes defined by AAMI. They classified supra ventricular ectopic beats and ventricular ectopic beats with an accuracy of 98.3% and 97.4%, respectively. They use 44 files without paced beats in the entire MIT BIH arrhythmia database. With training and testing datasets they classified normal, supraventricular ectopic beats, ventricular ectopic beats, fusion and unclassifiable beats with 97.81%, 63.02%, 84.64%, 60.64% and 7.14% respectively. Using testing dataset alone the normal, supraventricular ectopic beats, ventricular ectopic beats, fusion beats and unclassifiable beats are classified with 97.04%, 62.11%, 83.44%, 61.36% and 0% respectively. Dutta et al. [109] used a combination of cross correlation and least-square SVM to extract features from ECG and reported an accuracy of 95.51–96.12%. Faezipour et al. [110] presented a patient adaptive cardiac profiling. The authors claim an accuracy of 99.6% in detecting the normal ECG beats and 99.4% accuracy in identifying abnormal beats. Oresko et al. [111] presented a smartphone-based wearable cardiovascular real time disease detection platform able to acquire data in real time, and display the features and classification results. Sayadi et al. [130] use a wave-based Bayesian framework for detection of premature ventricular contractions. They classified normal, PVC and other possible beats with an accuracy of 99.1%. They detected normal beats with sensitivity and positive predictive value of 99.66% and 91.38% respectively. Similarly the PVC beats are detected with sensitivity and positive predictive value of 98.77% and 97.47% respectively. Similarly the other beats are classified with sensitivity and positive predictive value of 96.54% and 98.81% respectively.

Karimifard and Ahmadian [112] modeled the HOS cumulants of ECG beats by Hermitian basis functions to classify normal, PVC, APC, LBBB and RBBB using one-nearest neighbor classifier. They reported specificity of 99.6% and sensitivity of 98.6% over 9367 ECG beats. Kutlu and Kuntalp [113] classify five types of ECG beats defined by AAMI standard using a combination of HOS, morphological, Fourier transform and HOS of wavelet packet coefficients. These features are selected using wrapper type feature selection algorithm and classified using k-nearest neighbor algorithm with an average accuracy of 85.6%, sensitivity of 95.5% and specificity of 99.5%. Liu et al. [114] proposed an ECG signal analysis method comprising baseline drift filtering using dominant high pass filter, noise elimination, R wave detection, prediction of heart rate and classification on an application specific integrated circuit with 0.18 μm CMOS technology. Chen and Yu [115] used a non-linear correlation-based filter for removal of redundant features prior to feature selection process. They evaluate the discriminability and redundancy of the retained features quantitatively and report an accuracy of 96.34% using eight features. Kutlu and Kuntalp [116] used higher order statistics of wavelet packet decomposition [119,120] for ECG beat recognition and reported average sensitivity of 90%, selectivity of 92% and specificity of 98%. Citi et al. [121] proposed a technique for the identification of erroneous beats in the ECG signal with low signal quality. They assumed the length of next *R*–*R* interval following a time varying inverse Gaussian probability distribution motivated by the physiology. They designed an automated identification and correction technique for erroneous and arrhythmic beats based on their probability model.

Martis et al. [131] use principal components of ECG signal to classify normal, RBBB, LBBB, APC and PVC ECG beats with an accuracy of 98.11%. They reported sensitivity, specificity and PPV during classification as 99.90%, 99.10% and 99.61% respectively. They used 34,989 ECG beats from the MIT BIH arrhythmia database. Using principal components of HOS bispectrum the same group reported an accuracy of 93.5% for five classes [94]. They report sensitivity, specificity and PPV of 99.27%, 98.31% and 99.33% respectively in the classification of normal and abnormal beats. Martis et al. [132] classify the AAMI recommended beats using DWT and ICA, and present a classification accuracy of 99.3%. In this study all the beats from the entire MIT BIH database are used. They reported sensitivity, specificity and PPV during classification as 97.97%, 99.83% and 99.21% respectively. Also the AAMI recommended ECG classes are classified with an accuracy of 99.52% using principal components of discrete cosine transform coefficients of ECG [133]. In this study all the beats from the entire MIT BIH arrhythmia database are used. They reported sensitivity, specificity and PPV during classification as 98.69%, 99.91% and 99.58% respectively. Martis et al. [175] classify the principal components of cumulants and report 94.52% of accuracy in classifying five beat types. They obtain sensitivity, specificity and PPV of 98.61%, 98.41% and 99.36% respectively. Shandilya et al. [174] designed a novel nonlinear dynamical signal characterization method for successful defibrillation of ventricular fibrillation.

Table 2 presents a compilation of studies conducted on automated detection of ECG beats using MIT-BIH database.

Table 2
Overview of studies conducted on automated detection of ECG beats using MIT BIH database.

Literature	Features	Classifier	Classes	Accuracy (%)
Linear Methods				
Hu et al. [123]	Temporal features	Mixture of experts	2	94.0
Lagerholm et al. [124]	Hermite function expansion coefficients	Self-organizing map	25	98.51
de Chazal and Reilly [126]	Morphology and RR interval	Linear discriminant	5	85.9
Inan et al. [128]	DWT and timing interval	Neural network	2	95.2
Jiang and Kong [127]	Hermite function parameters and RR interval	Block based NN	5	96.6
Ince et al. [129]	DWT+PCA	Multidimensional particle swarm optimization	5	95.58
Sayadi et al. [130]	Innovation sequence of extended Kalman filter	Bayesian filtering	2	99.1
Martis et al. [131]	PCA	SVM with RBF kernel	5	98.11
Martis et al. [132]	DWT+PCA	Probabilistic neural network (PNN)	5	99.28
Martis et al. [133]	DCT+PCA	PNN	5	99.52
Nonlinear methods				
Osowski and Linh [125]	HOS representation	Hybrid fuzzy NN	7	96.06
Martis et al. [94]	Bispectrum+PCA	SVM with RBF kernel	5	93.48
Martis et al. [175]	Cumulant+PCA	NN	5	94.52

6. Computer aided diagnosis of cardiac disorders

García et al. [134] describe a ST-T complex (repolarization phase of the cardiac cycle) changes detector using the root mean square differences between ST segment and average pattern segment using the European ST-T database and report a sensitivity of 85% in detecting deviations in ST segment and changes in ST-T complex. Chen [135] presents a total least squares based Prony modeling algorithm to distinguish ventricular fibrillation (VF), ventricular tachycardia (VT) and supra-ventricular tachycardia (SVT) and showed a detection accuracy of 95.2%, 96.0% and 97.7% for SVT, VF and VT, respectively, using the MIT-BIH database. Wang et al. [136] suggest different nonlinear measures such as correlation dimension to be used as features to differentiate normal and coronary artery disease (CAD) using 12 lead ECG signals. They provide distinct non-overlapping range of values for correlation dimension for both healthy and CAD subjects. Tatara and Cinar [137] propose combining statistical methods with artificial intelligence tools for interpreting the ECG signal. Garcia et al. [138] propose a remote server-based telemedicine system to aid in diagnosis using the Internet. The system uses simple signal processing tools on a web browser window. The authors suggested its potential application in remote rural locations. Addison et al. [139] detected coordinated atrial activity in the surface ECG of anaesthetized and ventricular fibrillation-induced pigs using continuous wavelet transform with a Morlet basis function. The authors suggested it as a new phenomenon invisible in normal ECG.

Gacek and Pedrycz [140] describe an ECG segmentation method using genetic algorithm. Chazal et al. [141] detected the obstructive sleep apnea from the ECG signals and reported an overall 100% classification accuracy. Vai et al. [142] used a beat sequence filter as a pre-processing method to preserve within class variability of ECG beats and wavelet transform to detect ventricular late potentials. Shyu et al. [143] used fuzzy neural network coupled with wavelet transform to identify PVC from the Holter ECG monitoring and reported an accuracy of 99.79% using computationally simple methodology. Osowski et al. [144] proposed using higher order statistics and Hermite characterization of QRS complexes and reported an accuracy of 94.57% based on a database of 6690 ECG beats. Hadzievski et al. [145] present a mobile ECG trans-telephonic system consisting of a stationary diagnostic calibration center and a mobile ECG device with electrodes. The mobile unit records a three-lead ECG and transmits it to the stationary unit, where a twelve-lead ECG is reconstructed.

Özbay et al. [146] use a fuzzy clustering neural network architecture to classify ten different arrhythmias namely normal, LBBB, paced beat, RBBB, sinus bradycardia, ventricular tachycardia, sinus arrhythmia, atrial flutter, atrial fibrillation, and atrial premature contraction and report an accuracy of 99.9%. Kutlu and Kuntalp [147] use a diverse set of features based on HOS, Fourier transform, WPD coefficients to discriminate five ECG beats suggested by Association for Advancement of Medical Instrumentation (AAMI) with sensitivity, selectivity and specificity of 85.5%, 95.4%, 99.5% respectively. Ros et al. [148] detect the paroxysmal atrial fibrillation using time domain features and K Nearest Neighbor (KNN) for classification and report an accuracy of 80%. Andreão et al. [149] classify the ECG signals into normal and Ischemic using incremental Hidden Markov Model (HMM) with a sensitivity of 86% and positive predictivity of 85%.

7. Limitations of the current methods

The clinical features of ECG, time domain amplitude, the peaks (P, QRS complex, T and U) and their durations provide vital information about the behavior of the heart. Subtle changes in these peaks and their positions however cannot be clearly deciphered by the naked eye. The time domain features cannot provide high discrimination among different normal and abnormal beats. In order to increase the discrimination among classes, various transform domains need to be used. The Fourier transform used for PSD estimation provides global signal frequency, but does not provide time resolution.

Two different ECG signals with a similar magnitude spectrum can be discriminated in the wavelet domain due to the compromise in frequency resolution and increase in time resolution. The challenge lies in the choice of the optimal wavelet basis function. There is no hypothesis to define a best basis function for a given signal. In the case of ECG signals the optimal basis function should lead to maximize the discrimination among the classes. Martis et al. [74] conducted an exhaustive experimentation to select the best basis function by using 54 different basis functions to classify the normal and abnormal ECG beats. They proposed that the Mayer wavelet function provided the highest classification accuracy.

Linear models are used based on the presumption that the ECG signal and noise are present in different parts of the frequency spectrum. When they occupy the same band of frequencies, the linear models are unable to represent these random processes. Hence the ECG signal, which is inherently nonlinear and non-stationary in nature, necessitates the use of nonlinear models for its representation and analysis.

The limitations of non-linear methods are the following: (i) They are computationally intensive. (ii) These sets of methods do not follow the principle of superposition and hence additivity and homogeneity principles are not followed by these methods. (iii) Symmetry and reflection properties are not followed. Linear shift invariance is not true for these non-linear systems.

8. Future direction of ECG analysis

The amplitude peaks provide the vital information about the behavior of the heart. However these minute changes in these peaks and their positions cannot be clearly deciphered by the naked eye. In signal processing terminology, these time domain features cannot provide high discrimination among different normal and abnormal beats [150–153]. In this review a few widely used effective nonlinear methods based on chaos theory, higher order spectra, HOS cumulants, RQA and EMD are reviewed. Higher order spectra are insensitive to noise and hence provide robust performance [154].

The linear methods provide good classification accuracy [131]. But these experiments are performed in the noise free ECG data using MIT BIH arrhythmia database. Noise is always present in the ECG signals due to power line interference, muscle tremor and movement electrodes, baseline drift due to respiration and abdomen movement, etc. These linear methods may not yield the same highest accuracy in the presence of noise [131]. Hence, the nonlinear methods in general perform well even under noisy conditions [131].

The normal and abnormal ECG beats can be classified using heart rate signal [150,151,155–159]. Rhythm disturbance is manifested in the form of heart rate interval variability. Also the heart rate intervals can be merged with the ECG morphology features for classification. Various nonlinear features are used on the plaque images to classify cardiac diseases [160–165]. Different methods follow different pre-processing methods, feature extraction techniques and classifiers. For a given pre-processing method, the combination of features to be extracted that will provide the highest accuracy for a given classifier needs to be studied.

Acharya et al. [160] proposed an index using different extracted features to classify symptomatic and asymptomatic plaques.

8.1. *ECG in mobile healthcare and telecare*

Apart from the methods and algorithmic improvements in ECG analysis, there is still room for improvement in terms of its applications. The focus in cardiac healthcare is changing from being hospital centric where the doctor is entirely in charge of the patient's health to patient centric where the patient takes responsibility for his/her health. Mobile healthcare (m-health) is a technology where the physiological parameters such as ECG are recorded using a Smart phone. Recorded ECG signals are analyzed by embedded algorithms of these Holter-like devices connected to the patient [166–168]. In case of an emergency, the patient's condition can be readily reported to the critical care unit. This helps to save the patient's life by reducing the waiting time before he is attended to [169–172].

Sankar and Adeli [122] invented Heart saver, a low-cost mobile medical device for real time monitoring of cardiac health, capable of detecting atrial fibrillation, myocardial infarction and atrio-ventricular block and proposed it for mass screening of cardiac health.

A major challenge is the development of an efficient decision support system (DSS) to analyze a huge amount of remotely acquired ECG data to aid in decision-making and informing patients as fast as possible for the severity of disease and treatment options. There is an urgent need for such a DSS in cardiac telecare. However, such a DSS requires the use of a huge database of diverse chronic cardiac diseases to train the classifiers. Rare abnormal beats may be present only for short durations. Fatal arrhythmias such as ventricular fibrillation and flutter must be instantly detected. Therefore, there is also a need for monitoring ECGs through wearable electrodes which are linked through a web-based system to the central hospital system for immediate screening of the ECG beats and intervention by doctors [173]. This system must be cost effective, and be affordable to the patient. Various high performance computing algorithms may be needed to improve the accuracy of cardiac health monitoring. The tremendous surge in silicon chip technology has allowed miniaturization of ECG devices and pacemakers. These miniaturized data acquisition systems, embedded with high performance computing algorithms for ECG analysis and decision making, and coupled with low power consumption and low cost, will make cardiac monitoring practical and affordable in the near future. Platforms such as C, C++, enterprise Java and dot.NET technologies can make the real time implementation of DSS practical and useful in clinical practice. The patient will be able to get the expert advice from his doctor remotely. Such systems must perform with near zero false positives to save the screening time for normal cases and allow the clinicians to focus only on the abnormal beats. Using such DSS, various other physiological signals can also be simultaneously monitored and used as an adjunct tool by the physicians.

9. Conclusions

The ECG contains different noise components like baseline wander, power line interference, muscle and movement artefacts, and electrode contact noise. But in most of the articles which are reviewed in the survey, the linear methods have provided a good performance. However there are not much work performed to study the classification performance in the presence of natural noise processes. In summary there is a need for testing both linear and non-linear methods on noisy data. This is a gap in the literature which needs to be supported in the future. However the authors intuition is that these non-linear methods may provide a good performance on noisy data than linear methods. There are studies to support some nonlinear methods such as higher order spectra are noise immune and robust in the presence of noise. Unique bispectrum, bicoherence and RP plots for each ECG class can be proposed. These plots can be used to find the efficacy of drugs and cardiac health. The signatures extracted from these plots will be unique and characterize the particular class. These features coupled with robust classifier can yield an accurate CAD system. The performance of the system can be improved by using a combination of linear and nonlinear domain features coupled with robust classifiers.

Conflict of interest statement

There are no said and potential conflicts of interests in conjunction with the submission of this paper.

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