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ORIGINAL CONTRIBUTION

ECG Signal Analysis and Arrhythmia Detection using Wavelet Transform

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Abstract Electrocardiogram (ECG) is used to record the electrical activity of the heart. The ECG signal being non-stationary in nature, makes the analysis and interpretation of the signal very difficult. Hence accurate analysis of ECG signal with a powerful tool like discrete wavelet transform (DWT) becomes imperative. In this paper, ECG signal is denoised to remove the artifacts and analyzed using Wavelet Transform to detect the QRS complex and arrhythmia. This work is implemented in MATLAB software for MIT/BIH Arrhythmia database and yields the sensitivity of 99.85 %, positive predictivity of 99.92 % and detection error rate of 0.221 % with wavelet transform. It is also inferred that DWT outperforms principle component analysis technique in detection of ECG signal.

Keywords Electrocardiogram · Discrete wavelet transform (DWT) · Denoising · QRS detection · Arrhythmia

Introduction

Long term recordings and continuous monitoring of ECG signals can be used to diagnose cardiac abnormality present [1, 2]. Electrocardiograph machine is used to obtain ECG signal by capturing the signal through electrodes placed on specific locations on skin of the human body [3]. It is an illustration of the bioelectrical activity of heart formed through cyclical contractions and relaxations of the human heart muscles [4, 5]. Apart from detecting cardiovascular diseases, ECG is also used to examine breathing pattern or any kind of mental stress. It also reveals the identity of the person [6].

Heartbeat patterns changes considerably with time and varying physical conditions for same individual [7]. A single normal cardiac cycle of ECG signal shown in Fig. 1 [8], comprises of the P-QRS-T waves. It defines the features as time intervals and amplitudes [9]. P wave occurs due to atrial depolarization, QRS complex due to ventricular depolarization and T wave due to ventricular repolarization [10]. QRS complex is the most significant and distinctive feature of ECG used to indicate the presence of cardiac cycle [11]. After T, U wave is a small rounded upright wave representing repolarization of Purkinje fibers. The intervals that occur in ECG wave are PR Interval and QT Interval. PR interval is measured from beginning of P wave to start of QRS complex. It measures travel time of depolarization wave from atria to ventricles. QT interval is beginning of QRS complex to end of T wave. It reflects total ventricular activity [12].

A 24 h ECG recording consists of more than 100,000 heartbeats that may take long hours to diagnose cardiac diseases by visual inspection and still some essential information may be missed. Monitoring of long ECG recordings can incorrectly interpret the signal. Therefore automated tools are needed to analyze the large amount of data collected [13]. Various methods have been developed to analyze ECG signal in past years. In 1985, Pan and Tompkins [14] presented an algorithm to detect QRS complex using slope, amplitude and width information. Afonso et al. [15] showed a multirate processing algorithm in that incorporates filter banks for ECG beat detection. In [16], Bert-Uwe et al. discussed various methods of derivative based algorithms, digital filters based algorithms, neural networks based

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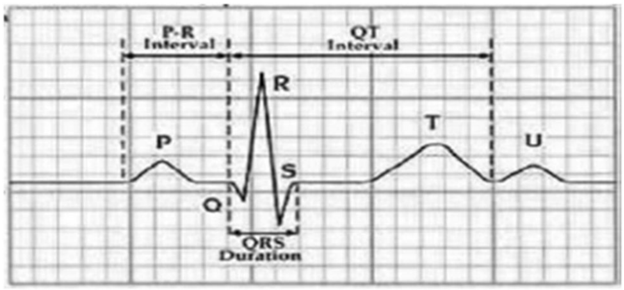


Fig. 1 Normal ECG waveform [8]

approach, adaptive filters and hidden Markov models for QRS detection. Another technique of continuous wavelet transform (CWT) is proposed in [17]. In [18], Ince et al. proposed a patient specific classifier for accurate detection of ECG heartbeat patterns. TI-DWT and PCA signal processing tools are used for feature extraction scheme. In [19], Slimane and Naït-Ali developed a new signal analysis technique called empirical mode decomposition (EMD) method which includes the decomposition of signal into finite number of intrinsic mode functions (IMF). In [20], difference operation method (DOM) was proposed for quick detection of QRS complex by Ganesan et al. Bolton and Westphal first described the use of Hilbert transform in ECG signal analysis [21]. Sharma et al. [22] denoised ECG signal with digital filters. Another powerful tool for analysis of ECG signal is Short Time Fourier Transform (STFT) which provides both time and frequency information but has a fixed time window for all frequencies [23].

In this paper, discrete wavelet transform (DWT) and PCA are used to analyze and detect ECG signal. The type of arrhythmia has also been detected on the basis of heart rate and wave characteristics.

Materials and Methods

Principal Component Analysis (PCA)

The concept of principal component analysis (PCA) includes the reduction of the dimensionality of a data set by converting data set into principal components (PCs). The components are uncorrelated and only first few components are retained that reflects the variation present in original data [24].

The generalized steps to find the PCA are shown in Fig. 2.

Wavelet Transform

A wavelet is similar to any other waveform, but it is a small wave of limited duration whose average value is zero [26]. Its characteristic features are scale and position that are useful in analyzing variations in signals and images [27]. Wavelet Transform is two-dimensional in time and frequency that allows analysis of data in both domains simultaneously. A time–frequency graphical representation of ECG signal is provided by wavelet transform at different scales with different resolutions [28]. The wavelet transform of signal x (t) is defined by Eq. (1) [29]:

$$W_a x(b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\Psi\left(\frac{t-b}{a}\right) dt \quad (1)$$

where a is the dilation parameter, $b =$ translation parameter.

Wavelet transform is classified as discrete wavelet transforms (DWTs) and continuous wavelet transforms (CWTs).

Discrete Wavelet Transform (DWT)

In recent years, signal processing is done using DWT. It proves to be beneficial as it provides good time resolution at high frequency and good frequency resolution at low frequency. The two-level wavelet decomposition of a signal x (n) is proceeded as illustrated in Fig. 3. The input signal is convoluted with designed filters (low and high pass) to produce the decomposed signal. Filtered signal is then down sampled by two. The decomposition process uses a high-pass filter g (n) and a low-pass filter h (n). The first level decomposition results in detail D1 and approximation A1 coefficients using high-pass and low-pass filters, respectively. The process continues as approximation A1

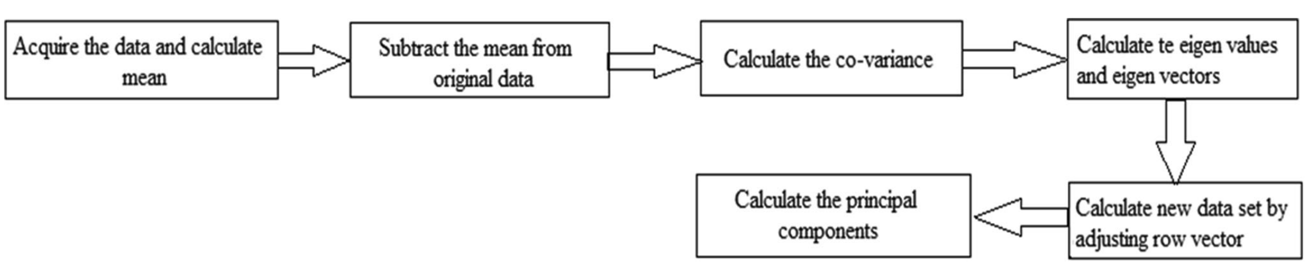


Fig. 2 General steps to find PCA [25]

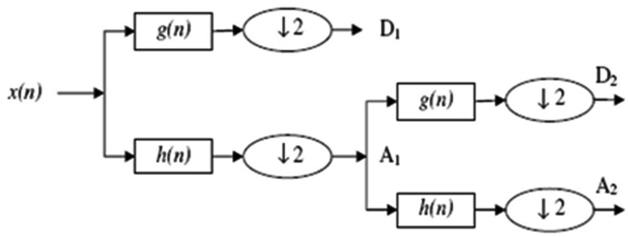


Fig. 3 Two-level decomposition with DWT

coefficient of first level decomposition is further decomposed in second level using the same filters [30].

DWT is expressed by Eq. (2) [31]:

$$W(j,k) = \sum_j \sum_k x(k)\, e^{-\frac{j}{2}} \Psi\left(2^{-j} n - k\right) \qquad (2)$$

where Ψ (t) is a time function with finite energy and fast decay called the mother wavelet.

Methodology

In this paper, ECG signal has been analyzed to detect the QRS complex and R-wave and Arrhythmia has been detected on the basis of heart rate. The detection is done using methods of wavelet transform and PCA. Various steps/stages of detection process with DWT and PCA are shown in Fig. 4a, b, respectively.

Results and Discussion

The first stage is pre-processing stage. ECG signal gets degraded due to various noises as power line interference (50 Hz), muscle artifact, baseline wandering while recording ECG, so extraction of correct information from the signal becomes difficult [32].

The baseline drift is the most significant noise, introduced in the signal due to coughing, breathing which cause a larger movement of chest. Hence it is needed to be removed first. The baseline drift is removed by smoothing the data using a moving average filter. After denoising, the signal is decomposed using PCA. Then the beats are detected as depicted in Table 1. MIT/BIH arrhythmia database has been used for analysis [33].

When ECG signal is analyzed using DWT, all noises are to be cleared off as done in PCA. Hence the first step is to remove baseline drift. It is done using the smooth filter with an odd span. Figure 5a, b show the original ECG signal and signal with baseline drift removed, respectively. Although the sample is of 30 min duration but for simplification it is shown for 10 s.

Then signal is decomposed using DWT and the detail and approximation coefficients are extracted. The other noises present in the signal are removed through global thresholding with db6 wavelet as depicted in Fig. 6.

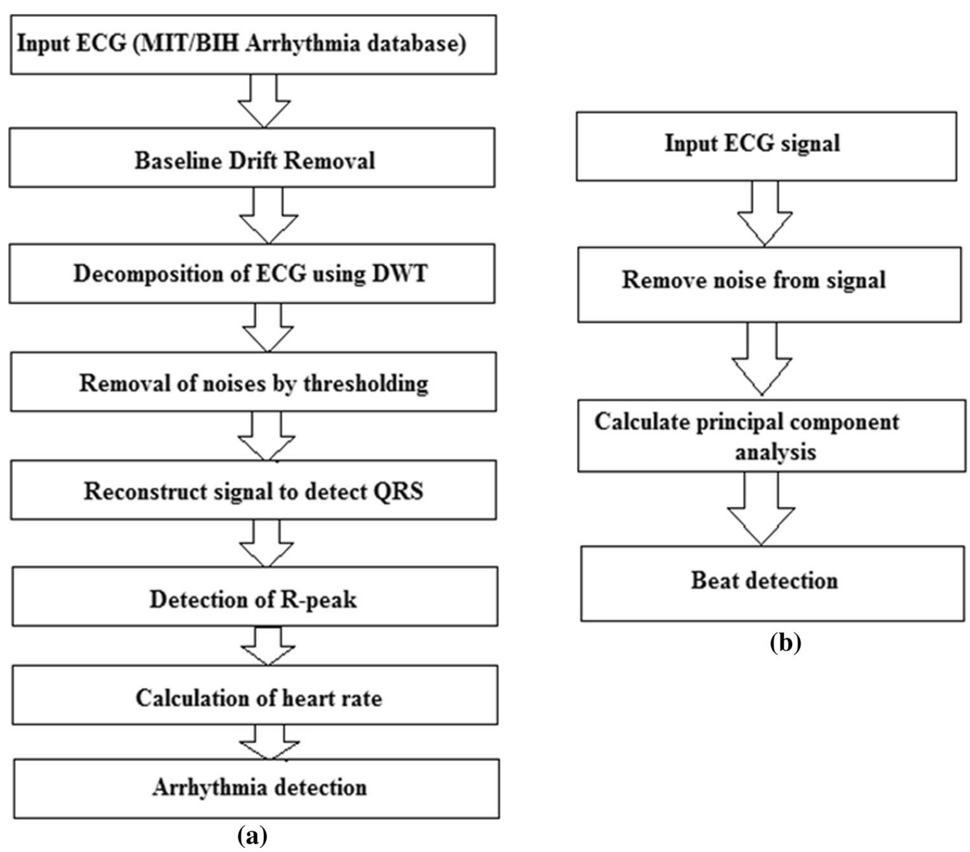


Fig. 4 Flowchart showing the stages of detection for **a** DWT and **b** PCA

Table 1 Beat detection for PCA

Sample	Total beats	Detected beats
100	2273	2263
101	1872	1858
103	2084	2077
112	2539	2538
113	1795	1787
115	1953	1950
117	1535	1534
122	2476	2475
123	1518	1513
Overall	18,045	17,995

After denoising, the next step is QRS complex detection which forms the basis for wave detection. QRS complex varies according to age and gender of the person. QRS complex is detected by reconstructing specific detail coefficients of d1–d5 and approximation coefficient a5. Figure 7 shows detected QRS complex and its zoomed view.

After QRS complex, beats are detected in ECG signal for DWT as depicted in Table 2. Table 2 shows that the beats detected with DWT are 18,005 for the same number of six samples which were earlier used with PCA. It is apparent from the table that DWT proved to be better than PCA since beats detected for PCA are less than that for DWT.

Performance Parameters

After QRS complex detection next step is to detect the R-wave, that is, the largest amplitude wave among other waves present in the signal. So it is easily identified. R-wave is detected by the squaring the detected wave of previous stage. All the waves above certain specified threshold are considered as R-wave and rest all are ignored. Figure 8 shows detected R-wave.

The performance parameters used for R-peak detection are sensitivity (Se), positive predictivity (P +) and detection error rate (DER). These are shown by the Eqs. (3), (4) and (5):

$$\mathrm{Se} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \times 100\% \tag{3}$$

$$\mathrm{P}+ = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \times 100\% \tag{4}$$

$$\mathrm{DER} = \frac{\mathrm{FP} + \mathrm{FN}}{\mathrm{TP}} \times 100\% \tag{5}$$

where TP is the true positive (correct detection of R-peak); FN is the false negative (undetected R-peak); and FP is the false positive (misdetections)

Table 2 shows beat detection performance for MIT/BIH Arrhythmia database. It can be seen from the results that 99.85 % sensitivity, 99.92 % positive predictivity and 0.221 % detection error rate is achieved when ECG analysis is done with DWT.

Detection of Arrhythmia

Any kind of disturbance in the rate, regularity or transmission of the electrical impulses through heart depicts the abnormal electrical activity of the heart leading to cardiac arrhythmias. Some types of arrhythmias are life threatening but exist for a short term whereas other types appear less frequently and characterizes a long-term threat without proper treatment [35]. The last stage is to calculate the heart rate and detect arrhythmia on basis of calculated heart rate and its characteristics. It is defined as the count that how many times heart beats in 1 min and measured in beats

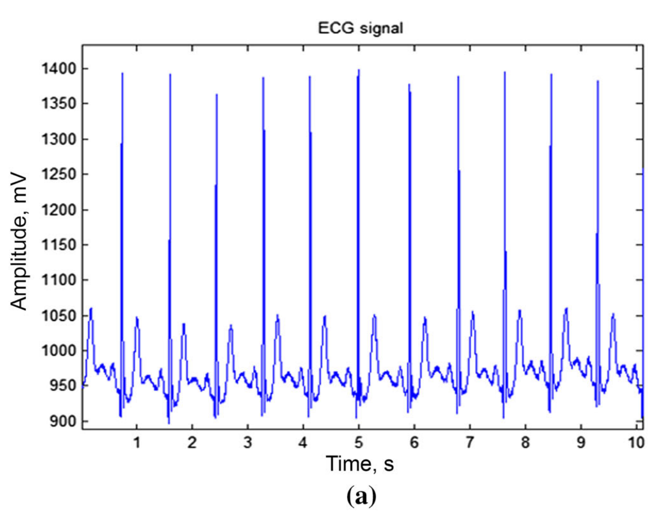


Fig. 5 **a** Original signal, **b** removed baseline drift of sample 103

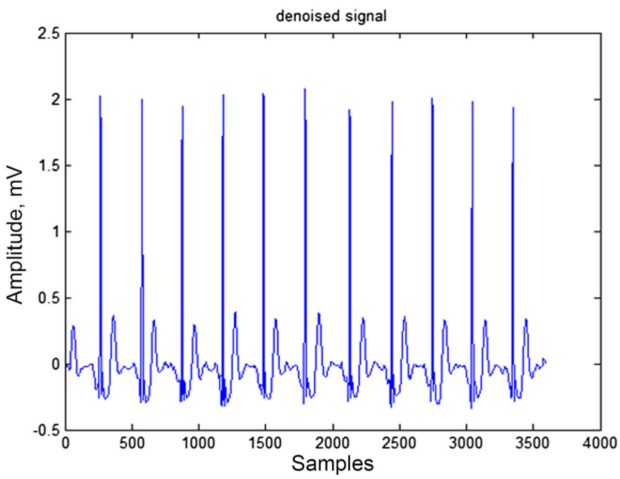


Fig. 6 Denoised signal of sample number 103 with DWT [34]

per minute (bpm). It is the ratio of 60 and average RR-interval where RR-interval is the distance between two adjacent QRS-peaks. Table 3 shows the types of arrhythmia detected.

The original samples along with type of arrhythmia detected are shown below:

Sample No. 106 (Female, Age 24)

Figure 9 depicts original signal and corresponding ventricular bigeminy detected in sample no. 106.

Sample No. 109 (Male, Age 64)

Figure 10 shows multiform PVC detected for the sample number 109 alongwith original ECG signal.

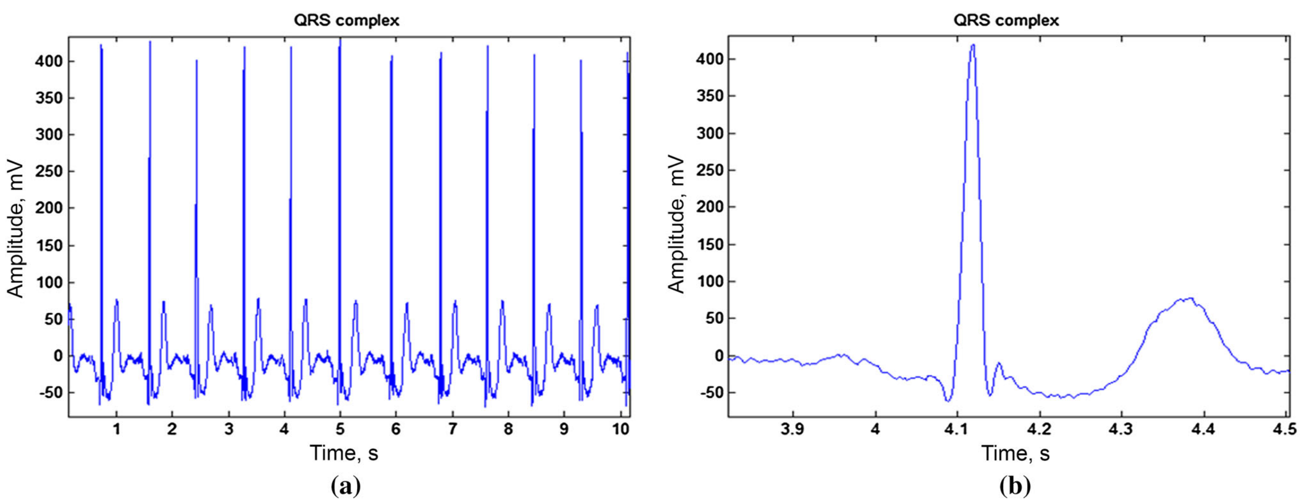


Fig. 7 **a** Detected QRS complex, **b** its wider view of sample 103

Table 2 Beat detection performance evaluated for MIT/BIH Arrhythmia database

Sample	Total beats	Detected beats	TP	FP	FN	Se, %	P+, %	DER, %
100	2273	2264	2264	0	9	99.6	100	0.397
101	1872	1860	1865	5	7	99.6	99.7	0.693
103	2084	2079	2084	5	0	100	99.7	0.239
112	2539	2538	2538	0	1	99.9	100	0.039
113	1795	1788	1789	1	6	99.6	99.9	0.391
115	1953	1950	1953	3	0	100	99.8	0.153
117	1535	1535	1535	0	0	100	100	0
122	2476	2476	2476	0	0	100	100	0
123	1518	1515	1515	0	3	99.8	100	0.198
Overall	18,045	18,005	18,019	14	26	99.85	99.92	0.221

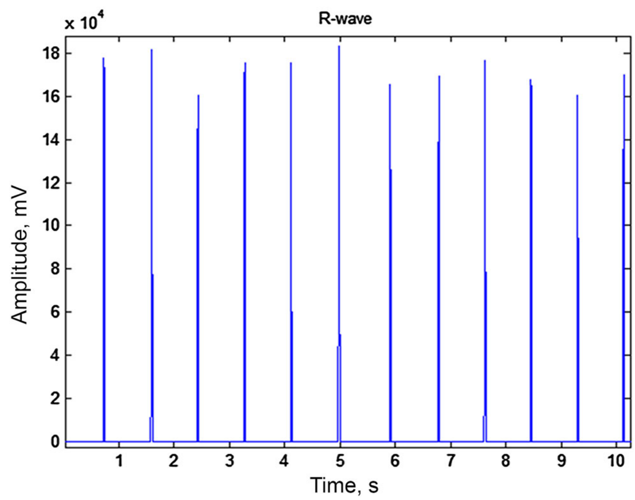


Fig. 8 Detected R-wave

Sample No. 124 (Male, Age 77)

Figure 11 demonstrates original signal and bradycardia detected in ECG sample number 124.

Sample No. 200 (Male, Age 64)

Figure 12 shows original signal and corresponding tachycardia detected in sample number 200.

Sample No. 203 (Male, Age 43)

Figure 13 illustrates original signal and Atrial flutter detected in sample number 203.

Table 3 Arrhythmia detected

Sample	Heart rate, bpm	Characteristics	Arrhythmia detected
106 (Female, age 24)	60	Continuous alteration of long and short beats	Ventricular bigeminy
109 (Male, age 64)	82	PVC is a skipped beat	Multiform premature ventricular contraction (PVC)
124 (Male, age 77)	50	Heart rate is <60 bpm	Bradycardia
200 (Male, age 64)	106	Heart rate is more than 100 bpm	Tachycardia
203 (Male, age 43)	120	Heart rate is more than 100 bpm and fluttering waves occur in the signal	Atrial flutter

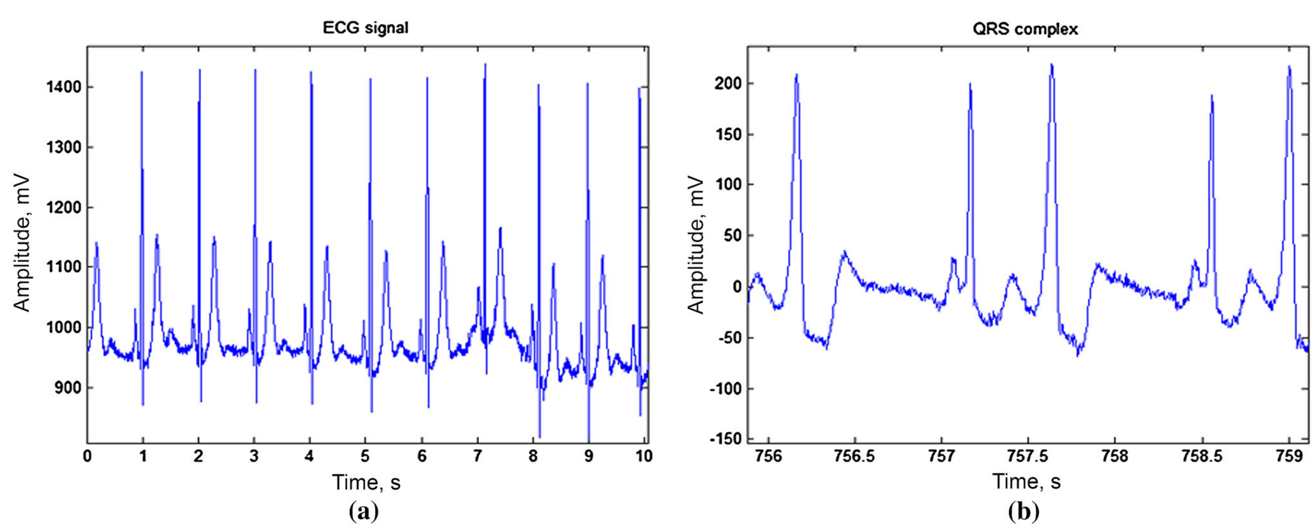
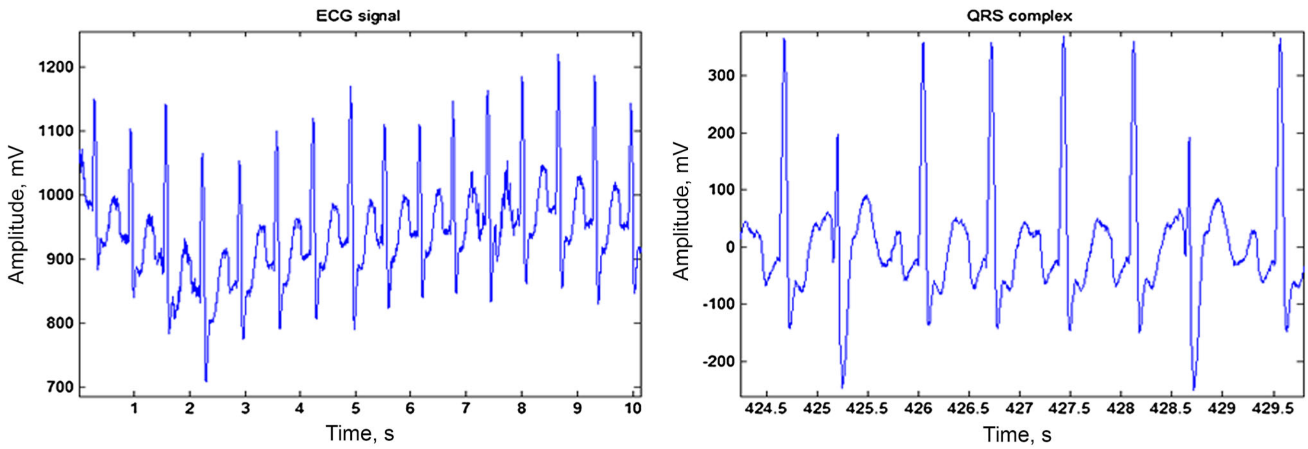
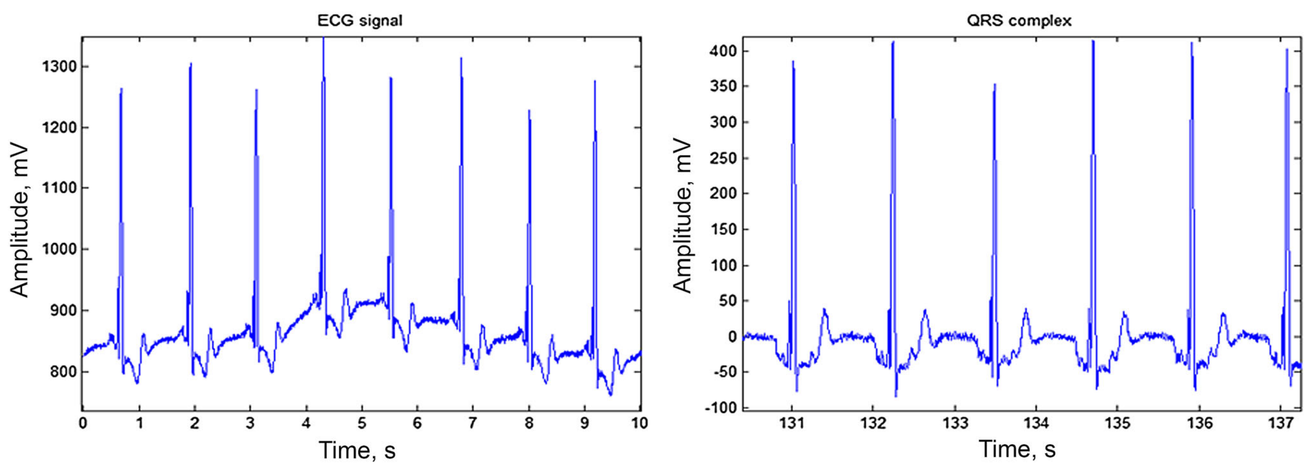


Fig. 9 **a** Original signal, **b** detected ventricular bigeminy (sample number 106)



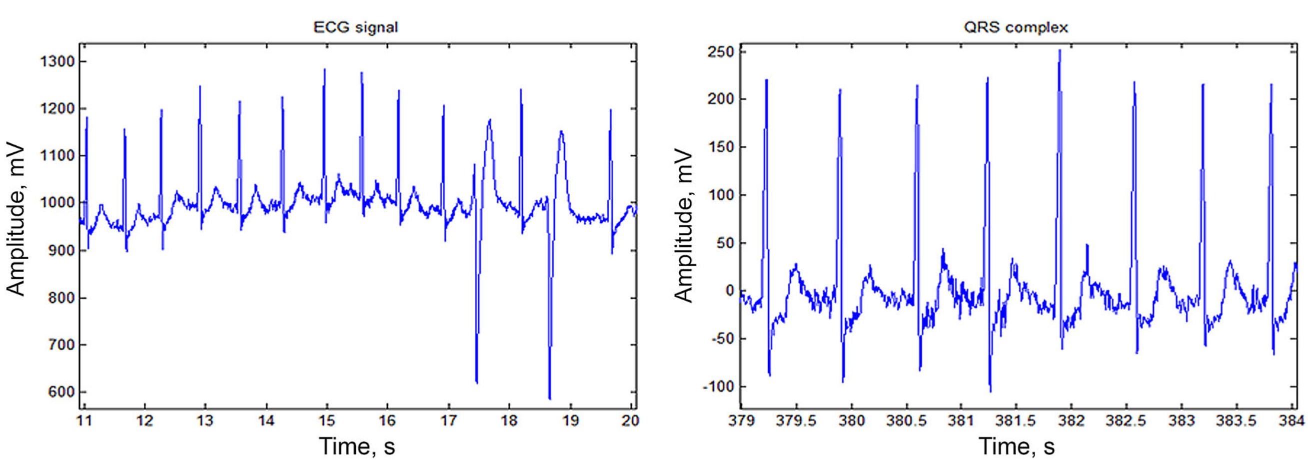
(a) (b)

Fig. 10 **a** Original signal, **b** detected multiform PVC (sample number 109)



(a) (b)

Fig. 11 **a** Original signal, **b** detected Bradycardia (sample number 124)



(a) (b)

Fig. 12 **a** Original signal, **b** detected Tachycardia (sample number 200)

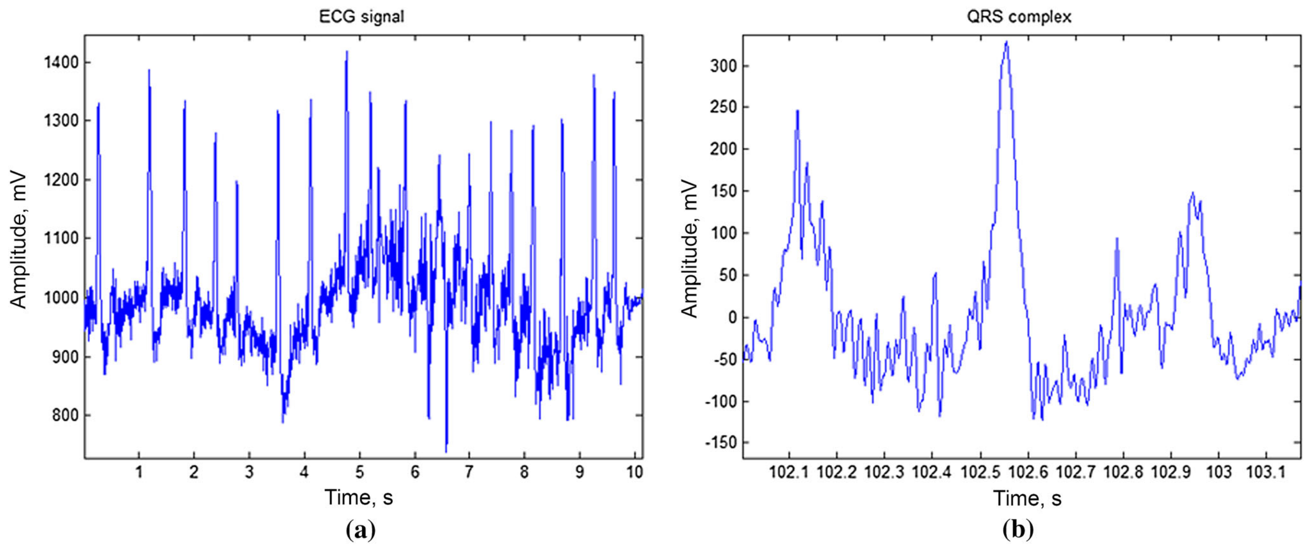


Fig. 13 **a** Original signal, **b** detected Atrial flutter (sample number 203)

Conclusion

In this paper, ECG signal is analyzed through PCA and DWT. It is clear from the results that wavelet transform is better than PCA in terms of beats detected. In DWT, the first stage of denoising is done through process of thresholding. Further, detection of QRS complex is the significant part of ECG signal analysis. It is correctly detected using reconstruction of detail and approximation coefficients and then R-wave is detected. The parameters used to analyze the performance of beat detection achieve 99.85 % Se, 99.92 % P+ and DER of 0.221 %. Finally Arrhythmia is detected on basis of heart rate and the disorders or abnormalities like ventricular bigeminy, multiform PVC, Bradycardia, Tachycardia and Atrial flutter are identified.

In future, this work can be extended for classification of various kinds of abnormalities with a classifier and feature extraction methodology could be improved.

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