Penerbit Akademia Baru

Journal of Advanced Research in Computing and Applications

Journal homepage: www.akademiabaru.com/arca.html
ISSN: 2462-1927

Computer-Aided Model for Abnormality Detection in Biomedical ECG Signals

Open Access

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ARTICLE INFO

Article history:
Received 18 October 2017
Received in revised form 12 December 2017
Accepted 3 March 2017
Available online 3 April 2018

Keywords:
Electrocardiogram (ECG), wavelet transform, QRS complex, feature extraction, arrhythmia

ABSTRACT

The paper introduces a new model that integrates the wavelet packet transform and ECG signal feature extraction for effect abnormality detection in ECG signals. It presents a brief description of ECG signal and its characteristics. At first, Wavelet decomposition is used for analyzing ECG signals, and extracting some features in order to increase the reliability of QRS detection. Then, major components of the ECG signal such as P wave, QRS complex and T wave have been detected to extract some features. Finally, the beats have been classified to detect the cardiac problems known as arrhythmia including tachycardia and bradycardia. Some recordings of the MIT-BIH Arrhythmia Database have been used.

1. Introduction

In recent years, Biomedical engineering is the combination of engineering principles and design concepts with biology and medicine. The Electrocardiogram (ECG) signal is one of the most important biological signals used to diagnose heart diseases. It is a representation of the electrical activity of the heart muscle from different angles as it changes with time [1]. Electrodes are placed on different parts of a patient's limbs and chest to record the signal. ECG varies from person to person due to the difference in position, size and anatomy of the heart, age, relatively body weight, chest configuration and various other factors [2, 6]. The ECG signal is characterized by a cyclic occurrence of patterns at different frequency range. It consists of five peaks labeled by the letters P wave, QRS complex and T wave as shown in Figure 1 [2, 3, 11]. The most important information in the ECG signal are concentrated in these waves. Based on the analysis of ECG signal, doctors can correctly diagnose human heart diseases such as ventricular fibrillation, arrhythmia and atria abnormality. The components of an ECG signal have been briefly summarized. P wave is the first short upward movement of the ECG tracing. It indicates that the atria are contracting, pumping blood into the ventricles. The QRS complex, normally beginning with a downward deflection, Q; a

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larger upwards deflection, a peak (R); and then a downwards S wave. The QRS complex represents ventricular depolarization and contraction [12]. T wave is normally a modest upwards waveform representing ventricular re-polarization.

The deviations in the normal electrical patterns indicate various cardiac disorders. Heart rate frequency is very important health status information. The frequency measurement is used in many medical or sport applications like stress tests or life treating situation prediction. Heart rate frequency can be detected d from ECG signal by many methods and algorithms. Many algorithms for heart rate detection are based on QRS complex detection and hear rate is computed like distance between QRS complexes. The earlier method of ECG signal analysis was based on time domain method. But this is not always sufficient to study all the features of ECG signals. So, the frequency representation of a signal is required. To accomplish this, FFT (Fast Fourier Transform) technique is applied. But the unavoidable limitation of this FFT is that the technique failed to provide the information regarding the exact location of frequency components in time. In this paper, the next Section, Section 2, discusses the related work that was earlier proposed in literature for ECG feature extraction. Section 3 explains the proposed model. Section 4 illustrates experimental results. Section 5 concludes the paper.

Fig. 1. A Typical ECG Signal

2. Literature Review

A lot of work from early time has been done to study ECG feature extraction and lots of advanced techniques have been proposed for accurate ECG feature extraction. Some of the used techniques are summarized and explained in this section.

P. G. Patel, *et al.*, [15] studied the Pan Tompkins Algorithm (efficient method for ECG Signal Analysis) which is simple and has good accuracy and less computation time. MIT database are used for analyzing the ECG signals. The peak detection is very important in diagnosis arrhythmia which is proved as tachycardia, bradycardia, asystole, second degree AV block. The results show that from detected QRS peaks, arrhythmia which are based on increase or decrease in the number of QRS peak, absence of QRS peak can be diagnosed.

A novel approach for ECG features extraction by Castro *et al.*, [16]. Their proposed paper presents an algorithm based on the wavelet transform for feature extraction from an electrocardiogram (ECG) signal and recognition of abnormal heartbeats. Since wavelet transforms can be localized both in the frequency and time domains. They developed a method for choosing an optimal mother wavelet from a set of orthogonal and bi-orthogonal wavelet filter bank by means of the best correlation with the ECG signal. The foremost step of their approach is to denoise the ECG signal by a soft or hard threshold with limitation of 99.99 reconstructs ability and then each PQRST cycle is decomposed into a coefficients vector by the optimal wavelet function. The coefficients, approximations of the last scale level and the details of the all levels, are used for the ECG analyzed. They divided the coefficients of each cycle into three segments that are related to P-wave, QRS complex, and T-wave. The summation of the values from these segments provided the feature vectors of single cycles.

Afahoum *et al*., [17] has analyzed the work dealing with classification problem of four different arrhythmia: NSR – normal sinus rhythm, AF-atrial fibrillation, ventricular fibrillation (VT) and ventricular tachycardia (VT), RPS. Nonlinear dynamical behavior of the ECG arrhythmia used to identify the cardiac arrhythmia. This algorithm shows that sensitivity and specificity are within range of 87.7 -100%. The classification accuracy is 100% for VF arrhythmia.

Mahmoodabadi *et al*., [18] described an approach for ECG feature extraction which utilizes Daubechies Wavelets transform. They had developed and evaluated an electrocardiogram (ECG) feature extraction system based on the multi-resolution wavelet transform. The wavelet filter with scaling function further intimately similar to the shape of the ECG signal achieved better detection. The foremost step of their approach was to de-noise the ECG signal by removing the equivalent wavelet coefficients at higher scales. Then, QRS complexes are detected and each one complex is used to trace the peaks of the individual waves, including onsets and offsets of the P and T waves which are present in one cardiac cycle. Their proposed approach for ECG feature extraction achieved sensitivity of 99.18% and a positive predictivity of 98%.

3. Proposed Model

The shape of ECG conveys very useful hidden information in its structure. ECG signal should be processed to extract important information. In our proposed model, the process of ECG analysis is divided into a number stages as shown in figure 2.

Fig. 2. Proposed Model Architecture

3.1 Pre-processing

The Pre-processing of an ECG signal is performed for the removal of noise associated with the ECG signal. ECG signal mainly contains noises of different types such as Powerline Interference, Baseline Wandering and Muscle Noise.

One of the common problems in ECG signal processing is baseline wander removal which is a common noise in ECG signal. Baseline wander is a low-frequency component caused by the interactions between the electrodes and the skin of the patient [13]. This is due to offset voltages in the electrodes, respiration, and body movement. This can cause problems in the analysis of the ECG waveform. In this paper, Baseline have been removed in order to obtain good ECG signal noise free. Examples of ECG signal as shown in Figure 3.

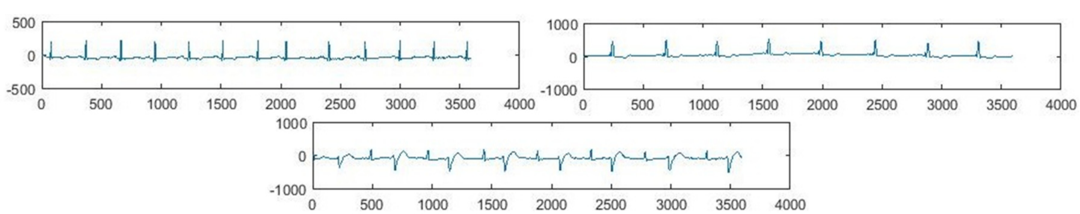

Fig. 3. ECG Signal

3.2 Wavelet Packet Transform

The wavelet transform has a huge number of applications in science, engineering, mathematics, and computer science. It is a time-scale representation that has been used in signal compression and the detection of ECG characteristic points also. The Wavelet transformation decomposes the signal into a number of scales related to frequency components and analyses each scale with a certain resolution. The advantages of wavelet method are possibility of receiving good quality signal for beat to beat analysis and possibility of having high quality signal.

The wavelet transformation is based on a set of analyzing wavelets allowing the decomposition of ECG signal in a set of coefficients. Each analyzing wavelet has its own time duration, time location and frequency band. The wavelet coefficient resulting from the wavelet transformation corresponds to a measurement of the ECG components in this time segment and frequency band. Daubechies wavelet of order 4 (db4) have selected the. This is because it is similar in shape to QRS complexes and their energy spectra are concentrated around low frequencies. It also gives details more accurately than other wavelet families. ECG signals have been decomposed into the details D1-D4 [4]. Selecting the number of decomposition levels is depended on the frequency of the ECG signal. Here is example for Wavelet decomposition of ECG signal as in figure 4.

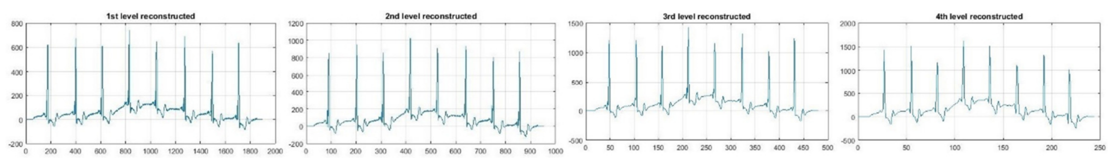

Fig. 4. Wavelet Packet Decomposition

3.3 PQRST Detection

The QRS complex is a name for the combination of three of the graphical deflections seen on a typical ECG signal. It is the most striking waveform within the ECG, caused by ventricular depolarization of the human heart. It is seen as three closely related waves on the ECG (Q, R and S wave). The normal duration (interval) of the QRS complex is between 0.08 and 0.10 seconds. A QRS duration of greater than 0.12 seconds is considered abnormal. In case of noisy signal not every QRS complex contains a Q wave, an R wave, and an S wave. After removing the noise from the ECG signal, the maximum peaks at the signal which represent the R-peaks have been found. However, some of the peaks are very close to each other, the R-peaks have been specified using threshold to remove unwanted peaks. Then, the minimum value in a window of the R location-20 to the R location-2has been selected to can find the locations of the Q-waves. Next, peak detection on the actual signal has been performed and used logical indexing by applying window of R location+2 to the R location+20to find the locations of the S-waves.

The P-waves represent atrial depolarization. In sinus rhythm, there should be a P-wave preceding each QRS complex. The normal duration (interval) of the P wave is less than 0.12 seconds. The window for the P-wave is selected by starting from R location-80 to the R location-15.
The T-wave represents the voltage repolarization influence after ventricular depolarization. Repolarization is lower than depolarization, as a result the T wave is more spread out and has a lower amplitude (height) than the QRS wave. It comes after ST segment having the same direction with QRS complex, whose width is about 0.05-0.25 seconds. The window for the T-wave is selected by starting from R location+25 to the R location+140.

P and T waves exist in one R-R interval, P-waves are present nearer to the 2nd R-peak in one R-R interval, and T waves lie next to the 1st R-peak. The particular P and T peak location is selected by taking the highest value in their respective windows. The following figure shows that the PQRST successfully detected in the ECG signal.

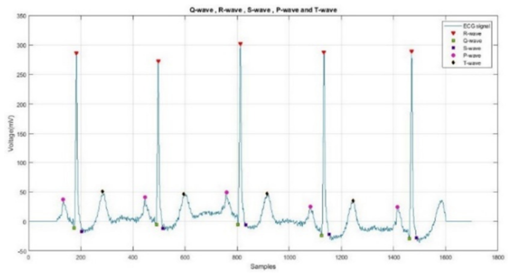

Fig. 5. PQRST

3.4 Feature Extraction

The purpose of the Feature Extraction process is to select and extract diagnostic information from the original ECG signal. Also finds few properties as possible within ECG signal that would allow successful abnormality detection. In this paper, for feature extraction stage, Wavelet Packet Transform has been used to extract features.

3.4.1 RR Interval

RR Interval is the average difference between R-peaks. Feature as RR interval (used medically as an indicator of Ventricular Heart Rate) metrics are generated from the deflection positional information. To determine RR interval two R peaks in consecutive beats is calculated and their difference is computed using the following formula:

$$RR(i) = RLoc\ (i+1) - RLoc\ (i) \quad (1)$$

where RLoc denotes R peak locations.

3.4.2 PR Interval

PR interval is the average difference between R peak location and P peak location, denoted by PR, is calculated using the following formula:

$$PR(i) = RLoc\ (i) - PLoc\ (i) \quad (2)$$

where RLoc denotes R peak locations and PLoc denotes P peak locations.

3.4.3 QRS Interval

QRS duration is calculated using the following formula:

$$QRS(i) = (SLoc\ (i) + x) - (QLoc\ (i) - x) \quad (3)$$

where Sloc and Qloc denote S and Q peak locations respectively, x denotes immediate 5 ms, these samples are added to Sloc and are subtracted from Qloc because QRS duration is defined from start of Q peak till end of S peak.

3.4.4 Heart Rate

The Heart Rate is depending on the RR interval, the RR interval has been used to calculate the heart rate as in the following equation [14]:

$$\text{Heart Rate} = \frac{60}{\text{RR interval}} \ \text{beats per minute} \qquad (4)$$

3.5 Beat Classification

ECG beat classification plays an important role in the timely diagnosis of the critical heart case. Beats were classified into two different classes as normal beats and abnormal beats.

3.5.1 Normal heart rhythm

In normal ECG, T wave is of positive amplitude but in abnormal ECG, the T wave can be inverted having negative amplitude. Example of Normal Heart Rhythm shown in figure 6.
Normal heart rate is 60-100 beats/min.

3.5.2 Abnormal heart rhythm

Abnormalities in the QRS complex indicate problems in the ventricles or ventricular conduction. There are various abnormal heart rhythms ECG signals as follows:

3.5.2.1 Sinus Bradycardia

Bradycardia is a term to describe the heart beating more slowly than normal. Sinus bradycardia can occur in well-conditioned athletes and during sleep relaxation. In the case of athletes, the heart muscle is tremendously strong and efficient at pumping blood, therefore, less contraction needed [5]. During deep relaxation, the body is at rest and requires less oxygen consumption than during normal activity which allows the heart rate to slow. However, sinus bradycardia can also occur as a result of heart disease or as a reaction to medication and when there is a normal sinus P wave preceding every QRS complex. A sinus rhythm of less than 60 beats per minute is called sinus bradycardia.

3.5.2.2 Sinus Tachycardia

Sinus tachycardia is sinus rhythm with a rate above 100 beats per minute (BPM). It is an example of a supraventricular rhythm. In sinus tachycardia the sinus node fires between 100 and 180 beats per minute, faster than normal [6]. Most often sinus tachycardia is caused by an increase in the body's demand for oxygen, such as during exercise, stress, infection, blood loss and hyperthyroidism. Inappropriate sinus tachycardia can result from Fever, Congestive heart failure, Bleeding, Anemia. Inappropriate sinus tachycardia is rare. It can also express an effort of the heart to compensate for a reduced stroke volume, as occurs during cardiomyopathy.

Fig. 6. Normal Heart Rhythm

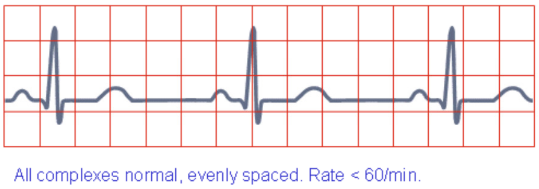

Fig. 7. Sinus Bradycardia

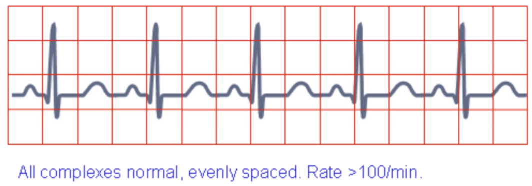

Fig.8. Sinus Tachycardia

4. Experimental Results

4.1 Data Collection

ECG signals required for analysis are chosen from MIT-BIH Arrhythmia Database. A lot of continuous ECG dataset of patients have been collected which is a *.mat file from healthy volunteers and patients with different heart diseases.

The Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) arrhythmia database is a well-established source of ECG data for researchers studying ECG classification techniques [3]. It contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmia that would not be well-represented in a small random sample. The sampling frequency of the ECG signals in this database is 360Hz. The length of data is 10 seconds.

4.2 Performance Measures

Two parameters are calculated to evaluate the detection performance which are sensitivity and specificity. Sensitivity measures the accuracy in detection while specificity gives an indication of rejection of false detections. These two parameters are calculated using the following equations:

$$Sensitivity = S_C = \frac{TP}{TP+FN} \tag{5}$$

$$Specificity = S_P = \frac{TP}{TP+FP} \tag{6}$$

where, TP, FP, FN denote for true positive, false positive and false negative respectively. True positive is that tests positive for a condition and is positive. False positive is that tests positive but is negative. False negative is that tests negative but is positive. The final result of detection is provided in Table 1.

In Table 2, the performance of the proposed model is compared with other work for the Sensitivity and Specificity Calculation of PQRST detection.

Table 1
Sensitivity and Specificity Calculation of PQRST detection on MIT-BIH arrhythmia database

Arrhythmia	**Sensitivity (%)**					**Specificity (%)**				
	P	**Q**	**R**	**S**	**T**	**P**	**Q**	**R**	**S**	**T**
Normal Heart Rhythm	97.5	100	100	100	95	99	100	100	100	70
Sinus Bradycardia	96	100	100	100	94	85	100	100	100	80
Sinus Tachycardia	93.5	100	100	100	92.5	79	100	100	100	82
Average	**95.6**	**100**	**100**	**100**	**93.8**	**87.6**	**100**	**100**	**100**	**77.3**

Table 2
Sensitivity and Specificity compared with previous work

Existing Approaches	**Sensitivity (%)**	**Specificity (%)**
Proposed Model	97.8	93
M. Umer *et al*. [13]	96.9	92.59
Mahmoodabadi *et al*. [18]	99.18	98

5. Conclusion

ECG signals required for analysis are collected from MIT-BIH Arrhythmia Database. This paper consists of two phases after the preprocessing of the signal: the feature extraction phase and the classification phase. The first phase based on WT for the detection of PQRST waves. In the second phase, R-peak detection is considered as one of the important criteria for accurate feature extraction. Once the R-peaks have been identified, RR intervals and the number of beats per minute have been calculated. Then, PR interval and QRS interval have also been calculated. These features help doctors to monitor patients efficiently and therefore improve correct clinical diagnoses. Then the beats have been classified into normal and abnormal beats. The abnormal heart rhythm ECG signals which have been discussed in this paper are Sinus bradycardia and Sinus tachycardia.

By comparing results of the proposed algorithm with M. Umer *et al*. [13], it is observed that the proposed model had an improvement in the sensitivity and specificity values. Moreover, the proposed algorithm is also easier to implement while Castro et al. [16] is complex and require large computation time.

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