An Efficient System for the Detection of Arrhythmic Segments in ECG Recordings based on non-Linear Features of the RR Interval Signal

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Abstract

In this paper we explore the RR interval signal to detect arrhythmic segments in electrocardiograms (ECG) using non-linear analysis. Initially, the RR interval signal is extracted and it is segmented into small segments. Linear (standard deviation), spectral (total energy) and non-linear (approximated entropy and normalized entropy) characteristics are extracted for each segment. Time-frequency analysis is used for the calculation of the total energy. These characteristics are fed into a neural network to classify each segment as normal or arrhythmic.

The proposed approach is validated using the MIT-BIH database for various segment sizes (32, 64, 128, 256 and 512 RR intervals). The method results in high sensitivity and specificity (85% sensitivity and 92% specificity) for arrhythmic segment detection.

1. Introduction

An arrhythmia is a collective term for any cardiac rhythm that deviates from normal sinus rhythm. Arrhythmia may be due to a disturbance in impulse formation or conduction, or both. Thus, arrhythmia is a general term for abnormal impulse formation or conduction, but not a synonym for irregular heart activity. Impulse formation may be sinus or ectopic, the rhythm regular or irregular and the heart rate fast, normal or slow [1].

Automatic arrhythmia detection and discrimination from the normal heart activity is an important task in clinical cardiology. Several methods have been proposed in the literature for automated arrhythmia detection and/or classification [4-16]. Most of the studies are based on the analysis of the ECG signal, initially extracting the features of ECG, which are used for the detection and/or classification of arrhythmias. Another common approach is to analyze the signal using known signal processing techniques, without using any type of medical knowledge. Sequential hypothesis testing algorithm [2], time-domain analysis [3], threshold-crossing intervals [4], neural networks [5-7], multiway sequential hypothesis testing [8], time-frequency analysis [9], multifractal analysis [10], fuzzy adaptive resonance theory mapping [11], sequential detection algorithm [12], wavelet analysis [13], complexity measure [14], wavelet analysis combined with radial basis neural networks [15] and non-linear dynamical modeling [16] are methods which belong to this type of approach. In all cases, the methods address the detection of only a few types of arrhythmia.

Physiological systems are non-linear and dynamical in nature. Therefore, non-linear dynamic analysis could be a powerful tool to reveal characteristics and mechanisms in biological systems [17]. Approximate Entropy (ApEn) is a non-linear statistic that can be used as a measure to quantify the complexity of a signal [18]. ApEn have been extensively used for the analysis of the heart rate variability and the RR interval signal [19-21]. For some systems the entropy does not only depend on the structure of the system, which generates the time-series, but also on the system's energy. For this reason, it has been suggested to normalize the Shannon entropy of a time-series by its time average energy (power) [22]. This quantity is called normalized entropy (NormEn).

In this paper we propose an arrhythmic segment detection method based on the non-linear analysis of the RR interval signal. Initially, the RR interval signal is extracted from ECG recordings and it is segmented into small segments. Linear (standard deviation), spectral (total energy) and non-linear (approximated entropy and normalized entropy) characteristics are extracted for each segment. Time-frequency analysis is used for the calculation of the total energy and the power of the segment, used for the NormEn calculation. These characteristics are fed into a neural network, which classifies the segment as normal or arrhythmic.

2. Materials and methods

The proposed method includes three stages: (a) preprocessing, (b) feature extraction and (c) arrhythmic segment detection.

2.1. Method

In the first stage, QRS detection is performed on the ECG recordings and the RR interval signal is constructed. The signal is segmented into small segments. In the second stage 4 features are extracted from each segment: standard deviation, total energy, ApEn and NormEn. The calculation of ApEn is based on a method proposed in [18]. The parameters m and r needed for the calculation of ApEn are set to m = 2 and r = 20% of the standard deviation of the segment, as proposed in [20]. NormEn was calculated as:

$$\text{NormEn} = \frac{\text{Entropy}}{\text{Power}},$$

where Entropy is the Shannon Entropy defined as:

$$\text{Entropy} = -\sum_{i=1}^{M} \frac{N_i}{N} \log_2(P_i),$$

where N is the segment length (i.e. number of RR intervals in the segment), M the total possible values of an RR interval, N_i the number of appearances of value i (i.e. length of an RR interval) in the segment and P_i the probability of appearance of value i in all segments. P_i is calculated as:

$$P_i = \frac{\#\text{ of appearances of value i in all segments}}{\text{length of all segments}}.$$

The energy of the segment is calculated using Smoothed Pseudo Wigner-Ville distribution (SPWV),

$$SPWV_x(t,v) = \int_{-\infty}^{+\infty} h(\tau) \int_{-\infty}^{+\infty} g(s-t)x(s+\tau/2)x^*(s-\tau/2)ds\ e^{-j2\pi\omega\tau}d\tau,$$

where x is the signal, x^* is the complex conjugate of the signal, g is a time smoothing window and h is a frequency smoothing window in the time domain. To avoid marginal problems in the segments, the calculation of the time-frequency plane was made before the segmentation of the RR interval signal. The energy of the segment is defined as the integration of $SPWV_x$ over the time-frequency plane:

$$\text{Energy} = \int_{-\infty}^{+\infty} \int_{\text{segment}} SPWV_x(t,v)\ dt\ dv.$$

The power of the segment, used for the calculation of the NormEn, is defined as the ratio of the energy and the segment duration (i.e. the sum of the duration of all RR intervals in the segment):

$$\text{Power} = \frac{\text{Energy}}{\text{segment duration}}.$$

The features extracted from stage b are used to train a back propagation neural network (stage c). The chosen architecture of the neural network contains: 4 inputs, one hidden layer with 20 neurons and one output, being a real number in the interval [0,1]. The final decision (normal or arrhythmic) was made using a threshold 0.5 (i.e. if the neural network's output is less or equal to 0.5 then the segment is considered normal, otherwise arrhythmic). Different RR interval segment sizes are used, with 32, 64, 128, 256 and 512 RR intervals. 20% of the RR interval segments, for each segment size, are used for the training of the neural network and the rest 80% for testing. The training of the neural network ends if the sum of the square errors for all segments is less than 0.001 or the maximum number of training epochs is reached (2.000 epochs).

2.2. Dataset

The MIT-BIH arrhythmia database is used for the training and testing of the proposed method [23]. The database beat and rhythm annotation was used to determine if an RR interval segment is arrhythmic or normal. The annotation of the second beat of the RR interval (i.e. the beat containing the second R wave) was used to annotate the RR interval. An RR interval segment is annotated arrhythmic or normal according to the following rules: (i) if an RR interval is annotated as N, L, R, P, f, p or Q and the rhythm is annotated as (N, (IVR, (B, (T, (P or (PREX [23] then it is considered normal, otherwise it is considered arrhythmic, and (ii) if there are less or equal than n arrhythmic RR intervals in an RR interval segment then it is considered normal, otherwise it is considered arrhythmic. Several values were used for n: 0, 1, 2 and 3 RR intervals and 5%, 10% and 15% of the segment length (i.e. for 128 RR interval segment 6, 13 and 19, which are 5%, 10% and 15% of 128, also used as n values).

3. Results

The sensitivity and specificity for arrhythmic segment detection are defined as follows:

$$\text{Sensitivity} = \frac{\#\text{ of segments correctly classified as arrhythmic}}{\text{total \# of arrhythmic segments}}$$

$$\text{Specificity} = \frac{\#\text{ of segments correctly classified as normal}}{\text{total \# of normal segments}}$$

Results in terms of sensitivity and specificity are obtained for different RR interval segment sizes (32, 64, 128, 256 and 512) and values of n (0, 1, 2 and 3 RR intervals and 5%, 10% and 15% of the segment length). The results are presented in Table 1. The best results for sensitivity and specificity are obtained for small segment length (16 and 32 RR intervals): 89.59% and 85.73%, respectively, for segment length 16 RR intervals and n = 0 RR intervals, 85.28% and 91.79%, respectively, for segment length 16 RR intervals and n = 3 RR intervals and 86.55% and 81.06%, respectively, for segment length 32 RR intervals and n = 0 RR intervals.

Receiver operating characteristic (ROC) curves are computed for all segment sizes and n values. Selected ROC curves are shown in Fig. 1. The area under curve (AUC) marker is calculated. Selected results are presented in Table 2.

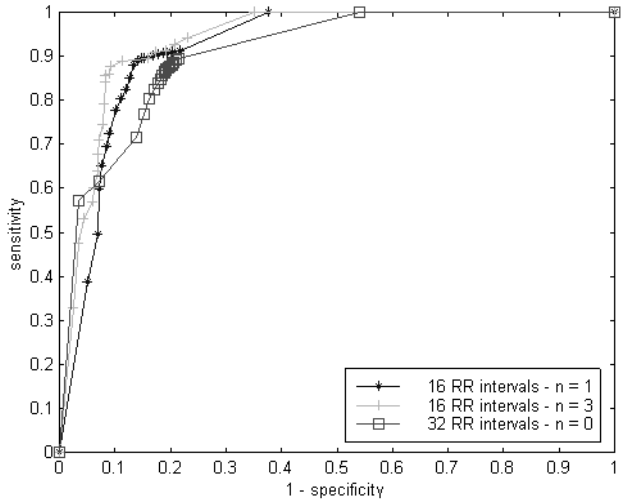

Figure 1. Selected ROC curves for different segment sizes and n values.

Table 2. AUC marker.

segment length	n	AUC
16 RR intervals	0	91.95%
	1	91.80%
	2	92.51%
	3	93.61%
32 RR intervals	0	90.72%
	1	89.43%
	2	88.74%
64 RR intervals	0	84.09%
	1	83.26%
	2	84.14%

Table 1. Sensitivity and specificity for arrhythmic RR interval segment detection, for segment size 32, 64, 128, 256 and 512 and n values 0, 1, 2, 3 RR intervals and 5%, 10% and 15% of the segment length.

segment length	n	Sensitivity	Specificity
16 RR intervals			
	0	89.59%	85.73%
	1	88.05%	86.68%
	2	86.22%	88.76%
	3	85.28%	91.79%
32 RR intervals			
	0	86.55%	81.06%
	1	84.43%	82.28%
	2	81.74%	84.69%
	3	78.78%	88.68%
	15% (5)	61.41%	89.98%
64 RR intervals			
	0	83.09%	76.71%
	1	80.26%	78.46%
	2	77.14%	83.76%
	3	74.89%	84.28%
	10% (6)	66.55%	86.69%
	15% (10)	53.46%	100%
128 RR intervals			
	0	75.68%	70.69%
	1	73.02%	71.00%
	2	69.57%	72.68%
	3	68.38%	73.89%
	5% (6)	65.90%	78.29%
	10% (13)	63.69%	87.34%
	15% (19)	55.00%	92.56%
256 RR intervals			
	0	77.95%	65.13%
	1	74.84%	69.46%
	2	72.95%	72.50%
	3	71.45%	75.15%
	5% (13)	65.10%	85.00%
	10% (26)	55.81%	86.96%
	15% (39)	50.28%	89.90%
512 RR intervals			
	0	85.45%	53.33%
	1	85.57%	53.84%
	2	77.57%	55.56%
	3	74.29%	56.36%
	5% (26)	65.47%	65.56%
	10% (51)	53.59%	74.19%
	15% (77)	50.33%	88.49%

4. Discussion and conclusions

We have proposed an approach to detect arrhythmic segments in ECG recordings, using the RR interval signal, which can be easily extracted. Non-linear features are used for the classification of arrhythmic segments. The method is limited to detect only the arrhythmic segments that contain certain types of arrhythmia that disturb the RR interval signal.

The results for sensitivity and specificity indicate that the detection is better when small segments (16 and 32 RR intervals) are used. This can be easily explained because if the RR interval segment contains few arrhythmic RR intervals and it is very large, it is more difficult to be detected. Also the value of n determines the detail of the detection; if n has small value then the RR interval segment is classified as arrhythmic for even few arrhythmic classified RR intervals in it. It is clear that as the n value increases the results for sensitivity decrease but specificity increases, meaning that less, but more accurate, arrhythmic segments are detected.

The method is advantageous, compared to other approaches in the literature because: (a) it uses only the RR interval signal, which can be extracted with high accuracy even for noisy or complicated ECG recordings; (b) it performs in real time, and it is limited only by the segment length (i.e. the 16 RR interval length must be completed before the detection starts); (c) it is not limited to only few types of arrhythmias but detects all types included in the MIT-BIH arrhythmia database.

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