ECG Arrhythmia Classification Using Simple Reconstructed Phase Space Approach

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Abstract

ECG arrhythmias such as ventricular and atrial arrhythmias are one of the common causes of death. These abnormalities of the heart activity may cause an immediate death or cause a damage of the heart. In this paper, an arrhythmia classification algorithm is presented. The proposed method uses the nonlinear dynamical signal processing techniques to analyze the ECG signal in time domain. The classification algorithm is based upon the distribution of the attractor in the reconstructed phase space (RPS). The behavior of the ECG signal in the reconstructed phase space is used to determine the classification features of the whole classifier. To evaluate the performance of the presented classification algorithm, data sets are selected from the MIT database. Two groups of data, learning and testing datasets, are used to design and test the proposed algorithm. A classification sensitivity and specificity of 100% are used to fine tune the parameters of the selected features using the learning dataset. Forty five signals are used to test the proposed approach resulting in 85.7-100% sensitivity and 86.7-100% specificity are obtained respectively.

1. Introduction

THE ELECTROCARDIOGRAM (ECG) is the graphical representation of the electrical activity generated by the heart [1]. The first stage of the heart beat begins when the sino-atrial node (SA) depolarizes. SA node, located in the right atrium, is the pacemaker of the heart, depolarizing in regular time interval to ensure proper pacing. Then the electrical signal moves rapidly through the heart muscle with normal rhythmicity. If the electrical system of the heart does not properly function, the hart's rhythm becomes abnormal due to the firing in the SA node or the transmission of the signal throughout the heart muscle. These abnormalities can be monitored using changes in the ECG recording whether in its behavior or rate. Reconstructed phase space can easily differentiate these behavior differences depending on the signal distribution. Quantitative classification of cardiac arrhythmia is an important tool in ICU and CCU that enables online monitoring of the cardiac activities that require special algorithms for detection and prediction [2]. There are several methods used to detect cardiac arrhythmia depending on heart rate variability [3], spectral analysis, time-frequency distribution [2], [4-6], and nonlinear signal processing techniques [3], [7-11]

R Acharya, *et al*. [3] presents a classification algorithm of heart arrhythmias depending on the heart rate variability (HRV) signals. Linear and nonlinear parameters are calculated to differentiate the different types of arrhythmias; the linear parameters are estimated in the time domain and frequency domain; the nonlinear parameters also are calculated to specify correlation dimension (CD), largest Lyapunov exponent (LLE) and approximation entropy (ApEn). Also the phase space plots are obtained to differentiate the different types of arrhythmias from the shape (behavior) of the phase space. L. Khadra, *et al*.[2] present a high order spectral analysis algorithm to classify different types of heart arrhythmias such as AF, VT and VF. The method used was bispectral analysis technique. F.M.Roberts, *et al.* [7] obtain the reconstructed phase space for using the ECG leads II and VI by plotting them against each other for four different types of arrhythmias using 100 features extracted from the RPS and used as input to artificial neural network (ANN) classifiers. R.J.Povinelli, *et al.*[8] use the reconstructed phase space for different types of arrhythmias by using ECG leads II and VI for different segment time intervals from 0.5 -3.0 seconds using 101 features (attractors) extracted from the reconstructed phase space. R.J.Povinelli, *et al.* [9] use distribution models as statistical representations over multi-dimensional reconstructed phase space both nonparametric distributions based on binning and occurrence counts and parametric distributions based on Gaussian Mixture Model (GMM) are used. F. M. Roberts, *et al.* [10] filter different types of heart arrhythmias into four sub-bands: 0.5-5, 5-10, 10-20 and 20-32 Hz. A phase space is constructed with embedding dimension of three and a time lag of 20. R. J. Povinelli , *et al.* [11] use the phase space to classify four different ECG rhythms by using the global false nearest-neighbor technique to calculate RPS dimension and build Gaussian Mixture Models (GMM) for each signal class from the reconstructed phase spaceType the introduction here.

2. Methods

This work is dealing with classification problem of four different types of heart arrhythmias; normal sinus rhythm (NSR), atrial fibrillation (AF), ventricular fibrillation (VF) and ventricular tachycardia (VT), depending on their distribution in the reconstructed phase space. In previous work [7]-[11], as mentioned above, the RPS was used in cardiac arrhythmias classification, at least 100 features were extracted from the RPS to distingue each rhythm, while only three classification parameters are used in this proposed classification algorithm.

A two–dimensional phase space plot may explain the structure which is hidden in the dynamics. In such a plot each data point is plotted versus the value sampled at a chosen fixed time delay earlier. The formal basis of this simple tool lies in the concept of phase space reconstruction. Each point in the RPS is calculated as follows

$$\mathrm{x}_n = [x_{n-(d-1)\tau} \;\; \ldots\ldots \;\; x_{n-\tau} \;\; x_n \;\;]$$

For $n = (1 + (d-1)\tau).....N$

Where N is the dimension of the time series, τ is the delay time and d is the embedding dimension. Then the entire phase space is generated by

$$\mathrm{X} = \begin{bmatrix} x_1 & x_{1+\tau} & \cdots & x_{1+(d-1)\tau} \\ x_2 & x_{2+\tau} & \cdots & x_{2+(d-1)\tau} \\ \vdots & \ddots & & \vdots \\ x_{N-(d-1)\tau} & x_{N-(d-2)\tau} & \cdots & x_N \end{bmatrix}$$

In phase space reconstruction, different time series fill different subset in the phase space; this subset is called an attractor. In other words, there are different patterns or trajectories in the RPS that are produced by the trajectory matrix, these different geometrical distributions are used to characterize different time series in the RPS.

2.1. Analysis of ECG signal

2.1.1. Data and pre-processing

The datasets are chosen from MIT-database which is available at PhysioNet website [12]. Different datasets are selected, each dataset represents different type of heart arrhythmia; MIT-BIH Normal Sinus Rhythm Database (NSRDB) for normal sinus rhythm, CU Ventricular Tachyarrhythmia Database (CUDB) for ventricular tachycardia, AF Termination Challenge Database (AFTDB) and MIT-BIH Atrial Fibrillation Database (AFDB) for atrial fibrillation, and MIT-BIH Malignant Ventricular Ectopy Database (VFDB) for ventricular fibrillation arrhythmia. In order to create a database for the classifier implemented in this research, the records are divides into two groups:

Group I (learning set) contains 40 records, these records are divided into four categories, each category has 10 records which represents one type of heart arrhythmia. Each record has 5 seconds time duration. This group of data is used for building the classifier.

Group II (test set) contains 45 records; 14 records for normal sinus rhythm (NSR), 15 records for atrial fibrillation (AF), 8 records for ventricular tachycardia (VT) and 8 records for ventricular fibrillation (VF). This dataset is used for testing the classification process.

The proposed algorithm uses small segments of waveform, each waveform consists of 5 seconds tracing. A 250 Hz sampling frequency is used for all the datasets, so the data is re-sampled to 250 Hz. From the nature of the ECG signals coming from different individuals and different recording periods for the same individuals, it is obvious that these signals have different amplitudes and base lines. These variations are due to the muscle artifacts and the power line interferences. In order to correct these effects, the data must be adjusted to have standard statistical parameters. The mean of the signal is calculated and subtracted so that the signal is zero meaned. Next, the signal is divided by the standard deviation to give a unit variance.

2.1.2. Phase space reconstruction

To reconstruct the phase space for the data, the time lag and the embedding dimension should be determined. The time lag can be determined by using the first minimum of the automutual information function method, the first zero crossing of the autocorrelation [13], or empirically to obtain maximum classification accuracy. The dimension can be selected using the false nearest neighbors, Cao's method [14], or empirically. To reconstruct the phase space for the ECG signals the following steps are performed

The first minimum of the automutual information function is calculated for each time series.

A histogram of the calculated time lags is drawn, and the peak value is chosen as the time lag.

An embedding dimension of 2 is chosen empirically to achieve maximum classification accuracy.

A two-dimensional RPS is plotted for all arrhythmias using the obtained time lag.

The set shows three peaks at 19, 21 and 22. Therefore, a time lag of 19 is chosen.

2.1.3. Features extraction

Features extracted from the reconstructed phase space are depending on the distribution of the data in the phase space to follow the transmission of the ECG signal in the heart muscle, in other words, these features are depending on the geometric structure of the attractor in the reconstructed phase space. Three boxes are chosen in the RPS to extract such features as follows:

Three distinguished boxes (***a***, ***b*** and ***c***) are determined depending on data density distribution in the phase space, where

a is the box in the RPS centered at zero with –0.5 and 0.5 edges,

b is the box in the RPS bounded by $\{ X \leq -1.2, -0.5 \leq X + \tau \leq 0 \}$

and

c is the box bounded by $\{ X + \tau \leq -0.2 \}$

The percentages of the number of points bounded by the three areas (*P(a)*,*P(b)*, and *P(c)*) are calculated with respect to the whole number of points in the RPS.

A classification rules are generated depending upon the distribution of the arrhythmias bounded by these boxes.

The reconstructed phase spaces were initially created for the learning dataset. Each type of ECG arrhythmia is found to occupy a distinguished geometrical distribution in the RPSDescribe your methods here.

3. Results

Figure 1 shows the overall classification algorithm based on the selected threshold values of the predefined classification parameters. The threshold values of 31.27%, 0.63% and 54.22% for *P(a)*, *P(b)* and *P(c)* respectively are chosen for the whole classification process. The false positive (FP) is defined as the number of misclassified signals, and the false negative (FN) is the number of signals that are classified as a part of group when they are not. Sensitivity is defined as the ability of the classifier to classify a certain signal as being a part of the group it actually belongs to. Specificity refers to the ability of the classifier to correctly rule out signals that do not belong to the group [2]. Table 1 shows the results of the sensitivity and specificity of the classification algorithm using data in group II which contains 45 waveforms. While for the learning data the sensitivity and specificity were 100%.

The classification algorithm is tested using different embedding dimension, lag time and different signal duration. For different time lag it concludes that the over all accuracy of the classification algorithm remains approximately constant over the region with time lag of 9-19 units, which is 91.1%. This behavior is obtained because the attractors in the reconstructed phase space reserve there dynamical behavior in this region, while the overall accuracy below and above this range is decreasing.

The results for time duration less than and equal to 5 seconds show that the sensitivity and specificity increase while increasing the signal duration, however, in some types of arrhythmias sensitivity and specificity remain constant regardless of the time duration which indicates that the classification process do not completely depend on the time duration of the classified signal. This result indicates that the nonlinear dynamical characteristics of the ECG signal do not completely lost when reducing the time duration. This conclusion goes in line with what was obtained in [8]. Table 2 shows the sensitivity and specificity for the test dataset versus different signal duration. The results of the classification accuracy for test data versus the embedding dimension show that the overall accuracy remains constant for embedding dimension of 2 to 6 which is 91.1%. Using other values will decrease the obtained accuracy. It can be concluded that the reconstructed phase space is to be topologically equivalent to the original state space of the system when the embedding dimension is suitable, in our experiments dimension of 2-6 seems suitable.

4. Discussion and conclusions

The method presented in this paper deals with the nonlinear dynamical behavior of the ECG arrhythmias, which is used to identify the cardiac arrhythmias. The method used here is different from the previous approaches that used the reconstructed phase space in arrhythmias classification which used many classification parameters [7-11]. Since heartbeats depend on other bodily events such as hormone and chemical levels, it can be modeled as a nonlinear system. The nonlinearity in the behavior of such a system can be captured by the RPS that contains state variables and relationships between state variables that provide greater differentiability across classes than the original state variable by itself [2, 9].

Comparison between different methods that were used in cardiac arrhythmia classifications and the proposed approach shows that the sensitivity and specificity for the proposed algorithm are within the range of 85.7-100% and 86.7-100% respectively. These results outperform those results that are provided in [7-8]. The classification accuracy is 100% for VF arrhythmia which is the most dangerous type among other arrhythmias. Other research groups achieved a 100% accuracy only for the normal case, and the classification accuracy provided by other researchers for classifying VF arrhythmia were 91.7% [2], 96.5% [9], 88% [8] and 95.1% [7].

The simplicity of the algorithm can be helpful for the real time implementation of the classification algorithm to decrease the time needed both in classification itself and in providing the suitable therapy to the patients. Future work is needed to increase the classification accuracy of the proposed algorithm; this may be done by combining this method with other classification methods.

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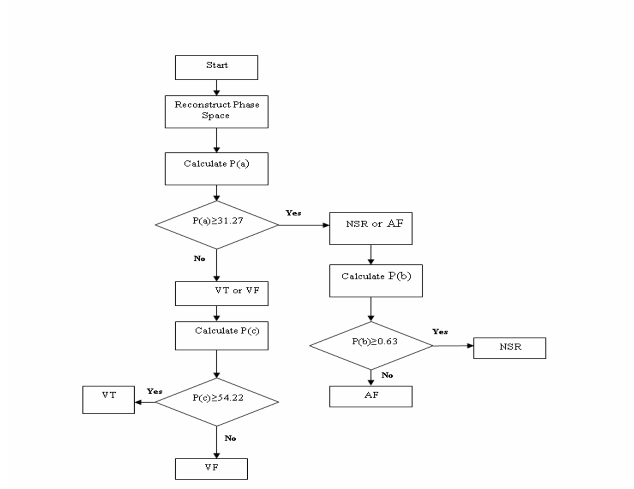

Fig. 1 The overall classification algorithm

Table 1: Sensitivity and specificity of the classification algorithm for the test group

	FP	FN	Sensitivity %	Specificity %
NSR	2	1	85.7	92.9
AF	1	2	93.3	86.7
VT	1	0	87.5	100
VF	0	1	100	87.5

Table 2: Sensitivity and specificity of the classification algorithm versus signal duration (test dataset)

Duration (s)	Sensitivity %	Specificity %
1	57.1-100	73.3-100
2	50-100	66.7-92.9
3	64.3-100	75-92.9
4	71.4-100	75-92.9

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