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Predicting termination of atrial fibrillation based on the structure and quantification of the recurrence plot

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Abstract

Predicting the spontaneous termination of the atrial fibrillation (AF) leads to not only better understanding of mechanisms of the arrhythmia but also the improved treatment of the sustained AF. A novel method is proposed to characterize the AF based on structure and the quantification of the recurrence plot (RP) to predict the termination of the AF. The RP of the electrocardiogram (ECG) signal is firstly obtained and eleven features are extracted to characterize its three basic patterns. Then the sequential forward search (SFS) algorithm and Davies–Bouldin criterion are utilized to select the feature subset which can predict the AF termination effectively. Finally, the multilayer perceptron (MLP) neural network is applied to predict the AF termination. An AF database which includes one training set and two testing sets (A and B) of Holter ECG recordings is studied. Experiment results show that 97% of testing set A and 95% of testing set B are correctly classified. It demonstrates that this algorithm has the ability to predict the spontaneous termination of the AF effectively. © 2008 IPEM. Published by Elsevier Ltd. All rights reserved.

Keywords: Atrial fibrillation; Termination; Prediction; Recurrence plot; Feature selection; Electrocardiogram

1. Introduction

The atrial fibrillation (AF) is a commonly encountered cardiac disorder in clinical practice, which occurs in up to 10% of individuals older than 70 years of age [\[1\].](#page--1-0) The AF can be subdivided into three different forms: the paroxysmal AF, the persistent AF, and the permanent AF. Evidence suggests that the paroxysmal AF is a precursor to the development of the persistent AF which requires external electrical intervention to allow its termination [\[2\]. T](#page--1-0)he risks of the sustained AF are serious which include strokes and myocardial infarctions caused by the formation of blood clots within stagnant volumes in the atria [\[1\]. T](#page--1-0)hus it is important to discriminate between the paroxysmal AF and the persistent AF and predict whether the paroxysmal AF is likely to terminate spontaneously or be sustained. By identifying the termination of the AF, not only better understanding of the mechanism of the arrhythmia but also more effective therapy can be achieved. The appropriate intervention may terminate the AF by predicting the AF maintenance. Vice versa, the unnecessary therapeutic intervention may be avoided and risks for patients can be minimized if the AF is predicted that it can terminate spontaneously.

Several algorithms for the characterization of the AF have been proposed including cross-correlation [\[3,4\],](#page--1-0) frequency analysis [\[5–8\].](#page--1-0) Wave-morphology analysis [\[9\],](#page--1-0) linear prediction [\[10\],](#page--1-0) non-linear or statistical analysis [\[11–14\]](#page--1-0) and time-frequency analysis [\[14–16\]](#page--1-0) are also proposed.

The focus of this paper is to predict the spontaneous termination of the AF based on the structure and quantification of the recurrence plot (RP) of ECG signals from a non-linear point of view. The original motivation for this work was the Computers in Cardiology Challenge in 2004 [\[17\]. T](#page--1-0)he RP was initially designed to graphically display distance correlations and non-stationarity in time series [\[18\].](#page--1-0) No mathematical assumptions regarding the data and the generating systems constrain the construction of the recurrence plot, thus this tool is particularly suitable for the analysis of physiological signals which are often non-stationary.

In this study, eleven features are extracted to identify three basic patterns of the RP, namely, the pattern along the main (45◦) diagonal, the pattern along the 135◦ diagonal and

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the square-like pattern. The sequential forward search (SFS) algorithm and Davies–Bouldin criterion are then utilized for the feature selection to predict the termination of the AF effectively. Finally, a multilayer perceptron (MLP) neural network is applied to predict the termination of the AF. Experiment results demonstrate that the new algorithm described in the study can be implemented and provide an accurate prediction for the spontaneous termination of the AF.

2. Database

The 2004 Computers in Cardiology/PhysioNet Challenge database [\[17\]](#page--1-0) is an open competition with the goal of developing automated methods to predict the spontaneous termination of the AF. It consists of 80 two-channel ECG recordings. The database contains three AF types with different termination properties: non-terminating (labeled N, meaning that the AF episode continues at least 1 h after the end of the recordings), soon-terminating (labeled S, meaning that the AF episode terminates within 1 min after the end of the recordings) and immediately terminating (labeled T, meaning that the AF episode terminates within 1 s after the end of the recordings). Each recording has 1 min length. All signals are extracted from 20 to 24 h Holter recordings from patients with paroxysmal AF and digitized at 128 Hz, with 16 bits/sample and $5 \mu V$ resolution.

The database has been divided into a training data set and two testing data sets (A and B). The training data set contains 30 recordings with 10 recordings for each type. The testing data set A contains 30 recordings. It is known that half recordings are N and half are T. The testing data set B contains 20 recordings with 10 S recordings and 10 T recordings. For example, Fig. 1 shows three different types of AF signals in the training data set.

In this paper, all data are split into 4 s segments for the analysis, so it consists of 15 segments for each 1 min record-

Fig. 1. A segment of non-terminating (N), soon-terminating (S) and immediately terminating (T) AF signals in the training data set.

ing. For each segment, it is processed using a Butterworth filter to reduce baseline wander. The band stop frequencies are set at 0.25 and 40 Hz. Following this, the QRST complexes are canceled using the averaging technique [\[19\]](#page--1-0) to obtain atrial waveforms. The Challenge dataset has already contained the QRST complex annotation. All the complexes within a fixed length of window are aligned by their R points and averaged to construct a median complex. The window length is set as 100 ms with 30 ms preceded the R point and 70 ms followed the R point. The remainder atrial activity is obtained by subtracting the median complex from every ventricular complex. In order to demonstrate that the components of the atrial fibrillation are not cancelled, power spectrum of the remainder signals is analyzed with the discrete Fourier transform. If the frequency with the maximum power falls between 5 and 9 Hz, it is considered that the remainder signals include the atrial activity. Results show that 99.7% of the total signal segments in the database include the atrial activity after the QRST cancellation. It can be inferred that the averaging technique achieves a high performance for the QRST cancellation.

3. Methods

3.1. State space reconstruction

For a time series s_i ($i = 1, 2, ..., N$), it is embedded to a high-dimensional space with the time-delay embedding technique [\[20\]](#page--1-0) and a trajectory matrix is obtained

$$
X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_M \end{bmatrix} = \begin{bmatrix} s_1 & s_{1+\tau} & \dots & s_{1+(d-1)\tau} \\ s_2 & s_{2+\tau} & \dots & s_{2+(d-1)\tau} \\ \vdots & \vdots & \ddots & \vdots \\ s_{N-(d-1)\tau} & s_{N-(d-2)\tau} & \dots & s_N \end{bmatrix}
$$
(1)

where *d* is the embedding dimension and τ is the delay time. Each row vector in the matrix $x_j = (s_j, s_{j+\tau}, \ldots, s_{j+(d-1)\tau})$, $j = 1, 2, \ldots, M$ ($M = N - (d - 1)\tau$) represents a *d*-dimensional trajectory point in the reconstructed state space. For each signal in the training data set, d and τ are calculated using the false nearest neighbor (FNN) method and autocorrelation method respectively [\[21\].](#page--1-0) The mean values of them are taken as the final embedding dimension and delay time respectively. Thus signals are embedded into 3 dimensional reconstructed state space with a lag of 70 sample points.

3.2. Recurrence plot

After the state space reconstruction, the RP of a signal can be obtained. The RP is a two-dimensional representation technique. It is $M \times M$ arrays whose element can be Download English Version:

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