Prediction of paroxysmal atrial fibrillation using recurrence plot-based features of the RR-interval signal

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Prediction of paroxysmal atrial fibrillation using recurrence plot-based features of the RR-interval signal

Maryam Mohebbi and Hassan Ghassemian

Biomedical Engineering Department, Faculty of Electrical and Computer Engineering, Tarbiat Modares University, Tehran, Iran

E-mail: ghassemi@modares.ac.ir

Received 3 October 2010, accepted for publication 26 May 2011
Published 27 June 2011
Online at stacks.iop.org/PM/32/1147

Abstract

Atrial fibrillation (AF) is the most common cardiac arrhythmia and increases the risk of stroke. Predicting the onset of paroxysmal AF (PAF), based on noninvasive techniques, is clinically important and can be invaluable in order to avoid useless therapeutic intervention and to minimize risks for the patients. In this paper, we propose an effective PAF predictor which is based on the analysis of the RR-interval signal. This method consists of three steps: preprocessing, feature extraction and classification. In the first step, the QRS complexes are detected from the electrocardiogram (ECG) signal and then the RR-interval signal is extracted. In the next step, the recurrence plot (RP) of the RR-interval signal is obtained and five statistically significant features are extracted to characterize the basic patterns of the RP. These features consist of the recurrence rate, length of longest diagonal segments ($L_{\text{max}}$), average length of the diagonal lines ($L_{\text{mean}}$), entropy, and trapping time. Recurrence quantification analysis can reveal subtle aspects of dynamics not easily appreciated by other methods and exhibits characteristic patterns which are caused by the typical dynamical behavior. In the final step, a support vector machine (SVM)-based classifier is used for PAF prediction. The performance of the proposed method in prediction of PAF episodes was evaluated using the Atrial Fibrillation Prediction Database (AFPDB) which consists of both 30 min ECG recordings that end just prior to the onset of PAF and segments at least 45 min distant from any PAF events. The obtained sensitivity, specificity, positive predictivity and negative predictivity were 97%, 100%, 100%, and 100%.

1 Author to whom any correspondence should be addressed.
96%, respectively. The proposed methodology presents better results than other existing approaches.

Keywords: paroxysmal atrial fibrillation, prediction, recurrence plot, recurrence quantification analysis, RR-interval signal, support vector machines

1. Introduction

Atrial fibrillation (AF) is the most common cardiac arrhythmia and entails an increased risk of thromboembolic events (Feinberg et al 1995). Although AF is not considered a life-threatening arrhythmia, it may severely impact the quality of life and increase the risk of stroke. About 15% of strokes occur in people with AF (Go et al 2001).

Prevention and treatment of AF is still far from satisfactory. The aim of therapy is to prevent stroke and regain sinus rhythm (Al-Khatib et al 2000). Clinically, AF presents itself in different forms. Often it starts as paroxysmal (self-terminating) and becomes more persistent with time. Paroxysmal AF (PAF) is defined as attacks of AF lasting from 2 min to less than 7 days and spontaneously revert to normal sinus rhythm. Permanent AF (non-terminating) is defined as lasting more than 7 days and sinus rhythm cannot be restored or maintained. About 18% of PAF evolve to permanent AF over 4 years (Al-Khatib et al 2000).

Development of accurate predictors of the onset of PAF is clinically important because of the increasing possibility of electrically stabilizing and preventing the onset of atrial arrhythmias with different atrial pacing techniques (Prakash et al 1997). The maintenance of sinus rhythm can lead to decreased symptoms and possibly a decrease in the atrial remodeling that causes increased susceptibility to future episodes of PAF (Prystowsky 2000). In addition, there may be a reduction in the risk of strokes and thromboembolic events.

In recent years, several methods have focused on finding algorithms able to predict PAF by the analysis of surface electrocardiographic (ECG) records. Most of these methods have been evaluated on 30 min ECG segments from the Atrial Fibrillation Prediction Database (AFPDB) and the concept of PAF prediction in the literature, as our proposed method, is to discriminate between ECG segments far from PAF and segments before PAF event. Zong et al (2001) studied the number and timing of premature atrial complexes (PACs) in each segment and found that not only the number of PACs increases in episodes preceding PAF, but also these complexes most occur near the end of these episodes. Thong et al (2004) developed an algorithm based on the number of isolated PACs not followed by a regular RR-interval, runs of atrial bigeminy and trigeminy, and the length of any short run of paroxysmal atrial tachycardia. Their study showed that an increase in activity detected by any of these three criteria is an indication of an imminent episode of PAF. Vikman et al (1999) calculated the approximate entropy (ApEn) and short-term scaling exponent, $\alpha_1$, of heart rate variability (HRV) over 20 min periods and found that a reduced complexity of RR-interval dynamics and altered fractal properties usually precede the onset of PAF as indicated by the decreasing value for ApEn and $\alpha_1$. Chesnokov (2008) combined the complexity and spectral analysis of the 30 min HRV segment from the AFPDB and found that there is a statistically significant increase in the very low frequency (VLF) band, low frequency (LF) band, and high frequency (HF) band for the records immediately before PAF compared to distant ones, but the LF/HF ratio does not discriminate these two groups with statistical significance. He also showed that complexity features such as ApEn, sample entropy (SmEn), and their multiscale versions exhibit smaller values in episodes preceding PAF compared to distant ones.
In recent years, a number of methods have been devised to compute dynamical features from time series (Eckmann and Ruelle 1985). Such features are the information dimension, entropy, Lyapunov exponents, dimension spectrum, etc. Esperer et al (2008) used the Lorenz plot (LP) for the analysis of major cardiac tachyarrhythmias as assessed by 24 h Holter monitoring. They categorized each LP pattern according to its shape and basic geometric parameters and found that the LP method has the potential to significantly improve the accuracy of arrhythmia detection and differentiation, particularly with respect to the supraventricular tachyarrhythmias. Also, they claimed that in patients at risk of paroxysmal atrial arrhythmias, the LP method may prove very useful for online surveillance and risk stratification. Recurrence is a fundamental property of dynamical systems, which can be exploited to characterize the system’s behavior in phase space. A powerful tool for their visualization and analysis called the recurrence plot (RP) was introduced in the late 1980s (Eckmann et al 1987). The information obtained from RPs is often surprising, and not easily obtainable by other methods. The RP is the graphical representation of a binary symmetric square matrix which encodes the times when two states are in close proximity (i.e. neighbors in phase space). Based on such a recurrence matrix, a large and diverse amount of information on the dynamics of the system can be extracted and statistically quantified using recurrence quantification analysis (RQA) (Marwan et al 2009). No mathematical assumptions regarding the data and the generating systems constrain the construction of the RP; thus, this tool is particularly suitable for the analysis of physiological signals which are often non-stationary (Rongrong and Yuanyuan 2008). RPs have been applied in various biological system studies such as neuronal spike trains (Kaluzny and Tarnecki 1993), protein sequence (Zbilut et al 1998, Giuliani et al 2002), analysis of EEG recordings (Pijn et al 1997, Ouyang et al 2008), and classification of ECG abnormalities (El-Atabany et al 2004).

In this paper, an accurate PAF prediction method is proposed in which RQA is used to quantify the RP of the RR-interval signal. These features are based on the recurrence point density and the diagonal and vertical line structures of the RP. We have used five statistically significant features to form an effective feature vector and fed them to a support vector machine (SVM)-based classifier to discriminate the episodes preceding a PAF event from the episodes distant from any PAF event. SVM is a machine-learning technique which has established itself as a powerful tool in many classification problems. Simply stated, the SVM identifies the best separating hyperplane (the plane with maximum margins) between the two classes of the training samples within the feature space by focusing on the training cases placed at the edge of the class descriptors. In this way, not only an optimal hyperplane is fitted, but also less training samples are effectively used; thus, high classification accuracy is achieved with small training sets (Mercier and Lennon 2003). The results show that combining the extracted features and the SVM classifier yields an accurate predictor of PAF attacks.

The layout of the paper is as follows. Section 2 presents the database used for evaluation of the algorithm. Section 3 provides the overall block diagram of the proposed algorithm and the details of each block. Section 4 presents the results of the study. The discussion is presented in section 5. Finally, the conclusions are given in section 6.

2. Database

The RR-interval data used in this work were generated from the archived ECG signals provided by the AFPDB (Physionet AFPDB database). This database consists of both

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30 min ECG segments that end just prior to the onset of PAF and segments at least 45 min distant from any PAF events. Each ECG record consists of two-channel traces from a Holter recording, sampled at 128 Hz and 12-bit resolution. From this database, we have extracted 106 30-min ECG segments from 53 different patients. In other words, we have two ECG segments per patient: one segment contains the ECG immediately preceding an episode of PAF and the other segment contains the ECG during a period that is distant from any episode of PAF.

3. Proposed method

The goal of this study is to develop an effective algorithm for predicting the onset of PAF. A block diagram of the proposed method is demonstrated in figure 1. As seen, it comprises three steps: (1) preprocessing of an ECG signal and RR-interval signal extraction, (2) feature extraction including the RP-based features of the RR-interval signal to characterize patterns which are caused by the typical dynamical behavior, and (3) SVM-based classification. In the following, each block is described in more detail.

3.1. Preprocessing

The aim of the preprocessing stage is to extract the RR-intervals from the ECG signals within the database. It must be noted that the analyzed segments of this database are in sinus rhythm which may contaminate with the ectopic beats. Figures 2(a) and (b) show the last 20 s of an episode preceding PAF (record P10) and an episode far from PAF (record P09) of the AFPDB, respectively. We will show later that these can be effectively differentiated from a nonlinear point of view. In general, preprocessing can be affected by many interfering signals contaminating the ECG signal such as the 50 Hz power line interference, the interferences from EMG signals, and the baseline wandering. Therefore, in the preprocessing stage, these interfering noises are eliminated first by means of a 5–15 Hz band pass filter. Next, in order to detect the R peaks of the ECG, the Hamilton and Tompkins algorithm (Pan and Tompkins 1985, Hamilton and Tompkins 1986) is employed. The RR-interval signal is then constructed by measuring the time intervals between the successive R peaks.

Since ectopic beats and other artifacts are known to have a serious impact on the results of the RR-interval analysis, we have edited the RR-interval signal to handle the ectopic beats and artifacts. To this end, we have used the method recommended by Kamath and Fallen (1995) in which the RR-interval segments with the duration of less than 80% of the duration of the previous normal beat have been regarded as ectopic beats. After detection of the ectopic beats, we have replaced the non-normal RR-intervals with new cubic spline interpolated RR-intervals (Lippman et al 1994).
3.2. Feature extraction

In this step, we attempt to extract the features from the RR-interval signal which can be used as good markers for the prediction of PAF.

3.2.1. Recurrence plot. The first step in the analysis of a signal using RP theory is the reconstruction of the phase space of the signal. A frequently used method for the reconstruction is the time-delay method (Takens 1981). In this approach a time series \( s_i (i = 1, 2, \ldots, N) \) of length \( N \) is embedded into an \( m \)-dimensional space with the time-delay (\( \tau \)) technique:

\[
x_i = [s_i \ s_{i+\tau} \ \cdots \ s_{i+(m-1)\tau}] \quad i = 1, 2, \ldots, N - (m - 1)\tau.
\]

For the analysis, both embedding parameters, the dimension \( m \) and the delay \( \tau \), have to be chosen appropriately. Different approaches for the estimation of the smallest sufficient embedding dimension (e.g. the false nearest-neighbors algorithm (Kennel et al 1992)), as well as for an appropriate time delay (e.g. the auto-correlation function, the mutual information function (Fraser and Swinney 1986)) have been proposed. The false nearest-neighbors algorithm identifies the number of 'false nearest neighbors', points that appear to be nearest neighbors because the embedding dimension is too small, of every point in the phase space.
When the number of false nearest neighbors drops to zero, we have embedded the time series into proper dimensional space (Kennel et al. 1992). For discontinuous signals such as RR-intervals extracted from the continuous ECG signals, the delay is best set to 1 (Zbilut and Webber 1992). The explanations about setting the appropriate values for embedding parameters in our proposed method will be presented at the end of this section.

After the state space reconstruction, the RP of a signal can be obtained. In this step the $M \times M$ recurrence matrix, the elements of which can be calculated using the following equation, is derived:

$$R_{i,j} = \Theta(\varepsilon - \|x_i - x_j\|) \quad i, j = 1, 2, \ldots, M,$$

where $M = N - (m - 1)\tau$, $\varepsilon$ is a threshold distance, $\| \cdot \|$ is the norm (e.g. the Euclidean norm), and $\Theta(x)$ is the Heaviside function. This means that, if two phase space vectors $x_i$ and $x_j$ are sufficiently close together then $R_{i,j} = 1$; otherwise $R_{i,j} = 0$.

The RP is obtained by plotting the recurrence matrix. This means if the distance between $x_i$ and $x_j$ is less than $\varepsilon$, then a dot is placed at $(i, j)$ in the RP. A crucial parameter of a RP is the threshold $\varepsilon$. Therefore, special attention has to be paid for its choice. If $\varepsilon$ is chosen too small, there may be almost no recurrence points and we cannot learn anything about the recurrence structure of the underlying system. On the other hand, if $\varepsilon$ is chosen too large, almost every point is a neighbor of every other point, which leads to a lot of artifacts. A too large $\varepsilon$ also includes points into the neighborhood which are simple consecutive points on the trajectory (Marwan et al. 2007). Several criteria for the choice of the cutoff distance $\varepsilon$ have been proposed (Matassini et al. 2002, Thiel et al. 2002). One approach uses a fixed number of neighbors, $N_n$, for every point of the trajectory, called the fixed amount of nearest neighbors (FAN) (Eckmann et al. 1987). In this approach, the cutoff distance, $\varepsilon_i$, changes for each state $x_i$ to ensure that all columns of the RP have the same recurrence density. Using this neighborhood criterion, $\varepsilon_i$ can be adjusted in such a way that the recurrence rate (REC) has a fixed predetermined value (i.e. $\text{REC} = N_n/N$) (Marwan et al. 2007).

In this study, each 30 min RR-interval signal from the AFPDB is split into 5 min segments for the analysis, so there are six segments for each recording. Figures 3 and 4 show the extracted RPs of an episode far from PAF (record P05) and an episode before PAF (record P02), respectively. The optimum value for embedding dimension, based on the criteria of the percentage of false nearest neighbors being less than 1%, is $m = 7$ for the proper state space reconstruction of the RR-interval segments. The value of delay, $\tau$, is set to 1 and no points in the RR-interval data are skipped for the state space reconstruction.

### 3.2.2. Quantification of the RP

The RQA, which measures the recurrence point density and the diagonal and vertical line structures of the RP, makes it possible to identify and quantify the transitions between periodic, laminar, and chaotic states before PAF attacks, therefore facilitating the possible prediction of PAF (Webber and Zbilut 1994). In this study, seven features were extracted from the RP of each 5 min segment of each record to characterize different patterns. The related features are as follows.

- **Recurrence rate (REC).** Quantifies the percentage of recurrent points. The more periodic the signal dynamics, the higher the REC value:

$$\text{REC} = \frac{1}{M^2} \sum_{i,j=1}^{M} R_{i,j},$$

where $M$ is the dimension of the recurrence matrix.
Figure 3. RPs of various 5 min segments of the episode far from PAF (record P05). The first to the sixth 5 min segments of the episode are shown in (a) to (f).
Figure 4. RPs of various 5 min segments of the episode before PAF (record P02). The first to the sixth 5 min segments of the episode are shown in (a) to (f).
• **Determinism (DET).** Measures the proportion of recurrent points forming diagonal line structures (of at least length \( l_{\text{min}} \)):

\[
\text{DET} = \frac{\sum_{l=l_{\text{min}}}^{l_{\text{max}}} l p(l)}{\sum_{i,j} R_{i,j}},
\]

where \( p(l) \) is the number of diagonal structures whose length is \( l \). Here, \( l_{\text{min}} = 2 \) is used. Processes with stochastic behavior cause none or very short diagonals, whereas deterministic processes cause longer diagonals and less single, isolated recurrence points (Zbilut and Webber 1992).

• **\( L_{\text{max}} \).** Measures the length of the longest diagonal line segment in the RP, excluding the main diagonal line. This is a very important recurrence variable because it is inversely related to the largest positive Lyapunov exponent (Eckmann et al 1987). Positive Lyapunov exponents gauge the rate at which trajectories diverge and are the hallmark for dynamic chaos. Thus, the shorter the \( L_{\text{max}} \), the more chaotic (less stable) the signal.

• **\( L_{\text{mean}} \).** Measures the average length of the diagonal lines whose lengths exceed the certain threshold \( l_{\text{min}} \):

\[
L_{\text{mean}} = \frac{\sum_{l=l_{\text{min}}}^{l_{\text{max}}} l p(l)}{\sum_{i,j} p(l)},
\]

where \( p(l) \) is the number of diagonal structures whose length is \( l \). \( L_{\text{mean}} \) represents the average time at which two segments of the trajectory are close to each other and can be interpreted as the mean prediction time (Marwan et al 2007).

• **Entropy (ENTR).** The Shannon entropy of the distribution of the length of diagonal segments:

\[
\text{ENTR} = - \sum_{l=l_{\text{max}}}^{l_{\text{min}}} P(l) \ln P(l),
\]

where \( P(l) \) is the probability density of the diagonal structure whose length is \( l \) and it is defined as \( p(l)/\sum p(l) \). ENTR reflects the complexity of the RP in respect of the diagonal lines.

• **Laminarity (LAM).** Analogous to DET except that it measures the percentage of recurrent points comprising vertical line structures (of at least length \( v_{\text{min}} \)) rather than diagonal line structures:

\[
\text{LAM} = \frac{\sum_{v=v_{\text{min}}}^{v_{\text{max}}} v p(v)}{\sum_{i,j} R_{i,j}},
\]

where \( p(v) \) is the number of vertical structures whose length is \( v \). Here, \( v_{\text{min}} = 2 \) is used. LAM represents the occurrence of laminar states in the system without describing the length of these laminar phases. LAM will decrease if the RP consists of more single recurrence points than vertical structures.

• **Trapping time (TT).** Measures the average length of vertical structures:

\[
\text{TT} = \frac{\sum_{v=v_{\text{min}}}^{v_{\text{max}}} v p(v)}{\sum_{v=v_{\text{min}}}^{v_{\text{max}}} p(v)},
\]

where \( p(v) \) is the number of diagonal structures whose length is \( v \). Here, \( v_{\text{min}} = 2 \) is used. TT estimates the mean time at which the system will abide at a specific state or how long the state will be trapped.

The various patterns of the RP for different signals and more explanations about our extracted features have been presented by means of a didactic figure in the appendix.
3.3. Classification

The next step is the classification of the RR-interval episodes by considering the extracted features. Different classification methods have been used for AF classification and prediction in the past (Chesnokov 2008, Lynn and Chiang 2001, Mohammadzadeh-Asl et al. 2008, Hickey and Heneghan 2002, Mohebbi and Ghassemian 2008, Kara and Okandan 2007). In this work, the SVM classifier is used for classifying the episodes before PAF and far from PAF.

Given a training set \((x_i, y_i), i = 1, 2, \ldots, l\), where \(x_i \in \mathbb{R}^n\) and \(y_i \in \{-1, 1\}\), the traditional SVM algorithm is summarized as the following optimization problem:

\[
\min_{w, b, \xi} \left\{ \frac{1}{2} w^T w + C \left( \sum_{i=1}^{l} \xi_i \right) \right\}
\]

subject to : \(y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i \), \(\xi_i > 0 \forall i\),

where \(\phi(x)\) is a nonlinear function that maps \(x\) into a higher dimensional space (Wang et al. 2005). \(w\), \(b\), and \(\xi_i\) are the weight vector, bias, and slack variable, respectively. \(C\) is a constant and determined \textit{a priori}. Searching for the optimal hyperplane in (9) is a quadratic programming problem which can be solved by constructing a Lagrangian and transforming it into a dual maximization problem of the function \(Q(\alpha)\), defined as follows:

\[
\max Q(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j)
\]

subject to : \(\sum_{i=1}^{l} \alpha_i y_i = 0\); \(0 \leq \alpha_i \leq C\) for \(i = 1, 2, \ldots, l\),

where \(K(x_i, x_j) = \phi(x_i)^T \phi(x_j)\) is the kernel function and \(\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_l)\) is the vector of nonnegative Lagrange multipliers.

Assuming that the optimum values of the Lagrange multipliers are denoted as \(\alpha_{o,i}(i = 1, 2, \ldots, l)\), it is then possible to determine the corresponding optimum value of the linear weight vector \(w_o\) and the optimal hyperplane as in (11) and (12), respectively:

\[
w_o = \sum_{i=1}^{l} \alpha_{o,i} y_i \phi(x_i),
\]

\[
\sum_{i=1}^{l} \alpha_{o,i} y_i K(x_i, x_i) + b = 0.
\]

The decision function can be written as

\[
f(x) = \text{sign} \left( \sum_{i=1}^{l} \alpha_{o,i} y_i K(x_i, x_i) + b \right).
\]

In this work, the radial basis function is used as the kernel function and the parameters—kernel width \(\sigma\) and regularization constant \(C\)—were experimentally defined to achieve the best classification result.

4. Results

As can be seen from figures 3 and 4, the RPs of the first 15 min of both records of far from PAF and before PAF (figures 3 and 4(a)–(c)) include many isolated recurrence points, and
the diagonal and vertical lines have short lengths. The same patterns can be seen in the last 15 min of the record far from PAF (figures 3(d)–(f)). But in the record before PAF, as we are near the end of record, we see some square-like patterns in the RPs, and the lengths of diagonal and vertical lines become longer than those in previous minutes (figures 4(d)–(f)). In order to characterize these distinct patterns, we extracted the earlier-mentioned features from the RPs of the fourth, fifth, and last 5 min of each episode and considered the average value of each parameter to form the feature vector.

For statistical significance tests, all of the extracted features were tested with ANOVA (analysis of variance) to determine whether there was statistical difference between the features extracted from PAF episodes and non-PAF episodes. We considered statistically significant difference with $p$-values less than 0.01. The mean and standard deviation of each feature among the episodes before PAF (PAF episodes) and episodes far from PAF (non-PAF episodes) of the training set of the AFPDB are shown in table 1. We found that there is statistical difference in the recurrence rate, $L_{\text{max}}$, $L_{\text{mean}}$, entropy, and trapping time features, but determinism and laminarity do not discriminate these two groups with statistical significance. Therefore, we used five features with statistically significant discrimination, excluding the determinism and laminarity from the total seven aformentioned features to form a suitable feature vector. As seen, the features related to the episodes before PAF exhibit higher values than episodes far from PAF.

To evaluate our proposed method, the five features with statistically significant discrimination were extracted from the AFPDB. We used 50 ECG segments to train the SVM classifier and 56 segments to test the algorithm. The training and test sets belong to different subjects and there is no overlapping between the two sets.

To optimize the learning cost and the prediction performance, the SVM classifier parameters, kernel width $\sigma$, and regularization constant $C$ must be chosen effectively. For this purpose, we have divided the training data into train and validation sets. The optimum values of the parameters are chosen such that the smallest error on validation dataset is achieved. The optimum values of parameters are achieved as 0.5 and 10 for $\sigma$ and $C$, respectively.

To evaluate the performance of the proposed method, four measures are used as follows:

Sensitivity ($\%$) = \[ \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100, \] \hfill (14)  

Specificity ($\%$) = \[ \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100, \] \hfill (15)

### Table 1. Mean value and standard deviation of the features for episodes before PAF and episodes far from PAF.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Mean ± STD</th>
<th>Mean ± STD</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PAF episode</td>
<td>Non-PAF episode</td>
<td></td>
</tr>
<tr>
<td>Recurrence rate</td>
<td>0.301 ± 0.193</td>
<td>0.161 ± 0.136</td>
<td>0.000035</td>
</tr>
<tr>
<td>Determinism</td>
<td>0.935 ± 0.031</td>
<td>0.928 ± 0.036</td>
<td>0.277</td>
</tr>
<tr>
<td>$L_{\text{max}}$</td>
<td>0.282 ± 0.169</td>
<td>0.168 ± 0.141</td>
<td>0.0003</td>
</tr>
<tr>
<td>$L_{\text{mean}}$</td>
<td>0.474 ± 0.149</td>
<td>0.086 ± 0.129</td>
<td>0.000006</td>
</tr>
<tr>
<td>Entropy</td>
<td>0.738 ± 0.089</td>
<td>0.513 ± 0.096</td>
<td>0.000008</td>
</tr>
<tr>
<td>Laminarity</td>
<td>0.582 ± 0.244</td>
<td>0.558 ± 0.248</td>
<td>0.614</td>
</tr>
<tr>
<td>Trapping time</td>
<td>0.569 ± 0.144</td>
<td>0.389 ± 0.129</td>
<td>0.000009</td>
</tr>
</tbody>
</table>
Table 2. The results of classification of the test set.

<table>
<thead>
<tr>
<th></th>
<th>Segments before PAF</th>
<th>Segments distant from PAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Segments before PAF</td>
<td>TP = 28</td>
<td>FP = 0</td>
</tr>
<tr>
<td>Segments distant from PAF</td>
<td>FN = 1</td>
<td>TN = 27</td>
</tr>
</tbody>
</table>

TP = true positive, FP = false positive, FN = false negative, TN = true negative.

Positive predictivity (%) = \( \frac{TP}{TP + FP} \times 100 \), \( 16 \)

Negative predictivity (%) = \( \frac{TN}{TN + FN} \times 100 \), \( 17 \)

where TP, TN, FP, and FN stand for true positive, true negative, false positive, and false negative, respectively. If for example a PAF episode is classified as a PAF episode, then it is said that the episode is classified as TP. On the other hand, if a non-PAF episode is classified as a non-PAF episode, then it is said that the episode is classified as TN. Any non-PAF episode which is classified as a PAF episode by mistake will produce a FP, while any PAF episode which is classified as a non-PAF episode by mistake will produce a FN result. The results of classification of the test data for each class are summarized in table 2. The obtained sensitivity, specificity, positive predictivity, and negative predictivity of the proposed method were 97%, 100%, 100%, and 96%, respectively. The proposed methodology presents better results than the other existing approaches.

5. Discussion

This study shows that prediction of a PAF event based on RQA of an RR-interval signal works well. To our knowledge, this is the first paper to use the RP to analyze the RR-interval data for predicting the onset of PAF attacks. We have extracted five statistically significant features including the recurrence rate, \( L_{\text{max}} \), \( L_{\text{mean}} \), entropy, and trapping time from the RR-interval signal and the obtained results show that these features can be used as good markers for predicting the onset of PAF attack.

The recurrence rate, which quantifies the recurrence points, exhibits a higher value in episodes before PAF compared to distant ones. It can be related to the greater periodicity of the signal dynamics in the episodes before PAF events. The length of longest diagonal segment, \( L_{\text{max}} \), which inversely scales the largest positive Lyapunov exponent, also represents a higher value in episodes before PAF. It can be interpreted that the episodes before PAF are more stable (less chaotic) than non-PAF episodes. The average length of the diagonal lines, \( L_{\text{mean}} \), which reflects the average duration of a stable interaction in the signal, also exhibits a higher value in the episodes before PAF. The entropy of the length of diagonal segments exhibits a statistically significant increase in PAF episodes compared to non-PAF episodes. The increase in the value of entropy in PAF episodes is related to the greater complexity of the deterministic structure of the RP before PAF events. The trapping time, which measures the average length of vertical structures, has a higher value in PAF episodes compared to non-PAF ones. It means that the mean time that the system abides at a specific state in PAF episodes is statistically longer than that in non-PAF episodes.

We found that this RP-based feature set (five features) can be used as a good marker for predicting the onset of PAF attacks. Afterward, these features are used for training a SVM-based classifier to identify which episode precedes the PAF event. The results show
that combining these useful features and the SVM classifier yields an accurate predictor of PAF attacks. As shown in table 3, evaluation of the developed algorithm using the AFPDB exhibits high efficiency in terms of sensitivity, specificity, positive predictivity, and negative predictivity.

Several methods have been developed in the past for automatic prediction of PAF using the ECG signal. Different automatic PAF prediction methods together with their reported results in terms of the commonly used measures of sensitivity, specificity, positive predictivity, and negative predictivity are summarized in table 3. All of these methods used the AFPDB to evaluate their approaches. Zong et al (2001), Lynn and Chiang (2001), Hickey and Heneghan (2002), and Yang and Yin (2001) participated in Computers in Cardiology Challenge 2001 (PAF prediction challenge) and Zong et al (2001) could achieve the highest score. They used the number and timing of PACs as their main discriminator to predict PAF events and achieved a sensitivity of 79% for predicting the onset of PAF. Thong et al (2004) developed an algorithm based on the analysis of isolated PACs not followed by a regular RR-interval in 30 min ECG segments. They calculated the difference in the number of PACs between two records of a subject, and considered the record with the larger number of PACs as the one preceding PAF. They achieved a sensitivity of 89% and a specificity of 91% for predicting the onset of PAF. Chesnokov in 2008 used complexity and spectral analysis of HRV, but his method could not achieve good sensitivity for prediction of PAF events. Our proposed algorithm presents acceptable performances in terms of both sensitivity and specificity in identifying episodes preceding PAF. As seen in table 3, the obtained results are better than those of the other existing approaches. Moreover, as in our method there is no overlapping between the training and test datasets, it seems to be an efficient PAF predictor in real clinical applications. It must be noted that in our proposed method, the SVM classifier has been trained using the training dataset and then it is ready for classifying the new test dataset. In other words, there is no need for daily application of the training set for the SVM.
5.1. Limitations

This study presents a new perspective in predicting the onset of PAF from a nonlinear point of view. However, there are some limitations due to the nature of the database. The relatively low sampling frequency of 128 Hz at which the ECG signals of the database have been sampled may lead to inconsistent results in the context of nonlinear methods. Hence, the effect of low sampling rate on the efficacy of the proposed nonlinear method must be investigated. Also, the database analyzed in this study is not sufficiently large to draw any definite conclusions. Moreover, although we have calculated positive predictive values, we have not really tested our prediction algorithm against other rhythms than sinus rhythm. It seems that a larger database containing more types of arrhythmia will be very useful for validation and improvement of the algorithm’s performance.

6. Conclusions

In this paper, we have presented an effective RR-interval-based algorithm to predict the onset of PAF attacks. We have demonstrated that the structures of the RP contain useful information which can characterize distinct levels of chaoticity among episodes before PAF and episodes distant from PAF events. We have also shown that features based on the structure of RP including the recurrence rate, $L_{\text{max}}$, $L_{\text{mean}}$, entropy, and trapping time can be used as good markers for predicting the onset of PAF attack. These extracted features are fed to a SVM classifier to identify episodes preceding PAF events. To evaluate the proposed method for predicting PAF, we have used the AFPDB. The overall sensitivity, specificity, positive predictivity and negative predictivity of the proposed method in predicting the PAF events were 97%, 100%, 100%, and 96%, respectively. Comparing the performance of the proposed algorithm to those of the previously reported methods in the literature shows that the proposed algorithm is more effective than any of those methods.

Appendix

In this appendix, a didactic figure which represents the various patterns of the RP for different signals is presented. As shown in figure A1, the RP exhibits various patterns which are caused by the specific behavior of the system. For an uncorrelated or weakly correlated signal, stochastic or chaotic behavior (for example Gaussian noise), the RP consists of
many isolated points and none or very short diagonal structures (figure A1(a)), whereas periodic and deterministic processes cause longer diagonals and less single recurrence points (figure A1(b)). Features related to the diagonal structures, i.e., \( L_{\text{max}} \) and \( L_{\text{mean}} \), represent higher values in deterministic processes than stochastic signals. ENTR also exhibits a smaller value for uncorrelated noise, indicating its low complexity. For systems in which a state does not change or changes very slowly, we find vertical lines in their RPs and features such as TT and LAM can interpret this characteristic. Also, abrupt changes in the dynamics as well as extreme events (for example Brownian motion) cause white areas or bands in the RP (figure A1(c)).

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