Atrial Fibrillation Detection Based on Poincaré plot of RR Intervals

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Abstract. *Atrial fibrillation (AF) is one of the most common types of arrhythmia which significantly increases the risk factor of stroke – especially in elderly population. In this paper an algorithm is presented which is suitable for the effective detection of AF, by using merely heart rate data as input. The method is based on the processing of Poincaré plots constructed from the set of 30 RR intervals. During the analysis of Poincaré plots the dispersion of points around the diagonal line is calculated and the number of clusters is determined by a self-developed cluster analyzer. The decision criterion of AF relies on these two parameters. On the one hand, the algorithm was tested on 10 AF and 10 normal rhythm ECG signals of the PhysioNet Database, achieving the average sensitivity (Se) of 98.69% and the average specificity (Sp) of 99.59%. On the other hand, 10 AF and 10 normal clinically confirmed records of a heart rate meter were also processed, resulting the average Se and Sp of 96.89% and 99.00%, respectively.*

Keywords: Atrial Fibrillation Detection, RR intervals, Poincaré plot, Cluster Analysis

1. Introduction

Atrial fibrillation (AF) is a supraventricular arrhythmia characterized by irregular atrial activation. Consequently, the performance of atrial myocardium decreases drastically [1]. Although this kind of arrhythmia is not directly life-threatening, its importance cannot be underestimated. In the 1980s the Framingham Study revealed that AF is a major risk factor of stroke [2]. Later on it was found that ischemic stroke associated with AF is approximately twice as likely to be fatal than without AF. The severe consequences of stroke among survivors are also claimed to be more frequent with the presence of this arrhythmia [3]. For the earliest start of AF treatment, it is essential to develop efficient detection algorithms that can identify this cardiac disorder as soon as possible, and can be made available for the vast majority of people – e.g. as part of smartphone applications [4].

There are two main ECG markers of AF. The first one is the replacement of P waves by high frequency low amplitude fibrillatory waves and the another one is the irregular heart rhythm [1]. The absence of P waves can be very difficult to investigate in ECG signals with significant level of noise, e.g. in telemedical circumstances. Thus it is practical to develop AF detection methods relying merely on the heart rate, which can be determined more easily and accurately than the presence of P wave. In the spirit of this approach, several algorithms have been proposed in the last decade based on Poincaré plots consisting of RR intervals [5-7]. Inspired by the work of Park et al. [7] we tried to develop an AF detector which surpasses the previously developed methods in terms of sensitivity (*Se*) and specificity (*Sp*).

2. Subject and Methods

The processing of ECG signals was designed according to the following two steps: preprocessing and AF detection.

Preprocessing

The filtering of ECG signals is performed by applying two Butterworth filters: a 4th order highpass filter at 1 Hz to eliminate baseline wandering and a 8th order lowpass filter at 40 Hz to remove power line interference and higher frequency noise components. After filtering, the cardiac cycles are identified by an adaptive QRS detection algorithm elaborated by Christov [8]. Finally, the fiducial point is determined for each cardiac cycle as the steepest point of the QRS complex.

Atrial fibrillation detection

The series of RR interval values is divided into sections containing 30 consecutive RR values. For each section, a “yes or no” type decision is made regarding AF according to the Poincaré plot related to the corresponding 30 RR intervals.

The Poincaré plot can be defined as follows. Let $I_1, I_2, I_3, I_4, ..., I_{n\text{-}1}, I_n$ denote the consecutive RR interval values in milliseconds. Then the coordinates of points in the Poincaré plot are given by the pairs of $(I_1, I_2), (I_2, I_3), ..., (I_{n\text{-}2}, I_{n\text{-}1}), (I_{n\text{-}1}, I_n)$. The dispersion of points around the diagonal line – which is an important factor in AF detection – is calculated as

$$d = \frac{\sqrt{\frac{1}{2(n-1)}\sum_{i=1}^{n-1}\left(I_i - I_{i+1}\right)^2 - \left(\frac{1}{(n-1)\sqrt{2}}\sum_{i=1}^{n-1}\left|I_i - I_{i+1}\right|\right)^2}}{\frac{1}{2(n-1)}\left(-I_1 - I_n + 2\sum_{i=1}^{n-1} I_i\right)} \qquad (1)$$

where

I_i	i^{th} RR interval value [ms]
n	number of RR intervals (in our case: n = 30)
d	dispersion of points around the diagonal line [7].

If d is less than or equal to the empirical threshold of 0.06, then the algorithm does not detect significant level of heart rate irregularity, therefore it marks the section as non-AF. In the case of $d > 0.06$, an additional step is needed to check the distribution of points. If the high-dispersion set of points is systematically organized, the possibility of significant heart rate irregularity (therefore AF) can be ruled out. This can happen for example due to ectopic beats, that produce much more consequent rhythm changes than AF. However if d is high and no system can be found in the distribution of points, then a chaotic heart rhythm can be assumed. In this case, the algorithm marks the section as AF.

To decide whether the points in the high-dispersion Poincaré plot are systematically organized, we developed a clustering algorithm based on k-means [9], to determine the number of well-defined clusters. The principle of this method is to perform the k-means clustering with 9 different configurations: by setting the number of clusters from 2 to 10. After that the optimal clustering is chosen by the average silhouette values [9] corresponding to the results with different clustering configurations. If the maximum of the 9 average silhouette values ($s_{\max}$) is below 0.85 then no optimal clustering is found and the number of detected clusters (k) is set to 1. Otherwise, k becomes the number of clusters corresponding to $s_{\max}$.

Essentially, AF is detected if the high-dispersion ($d > 0.06$) Poincaré plot does not contain well-defined clusters (i.e. $k = 1$) or it has too many clusters (currently used threshold: $k = 10$). Four Poincaré plot examples can be seen in Fig. 1.

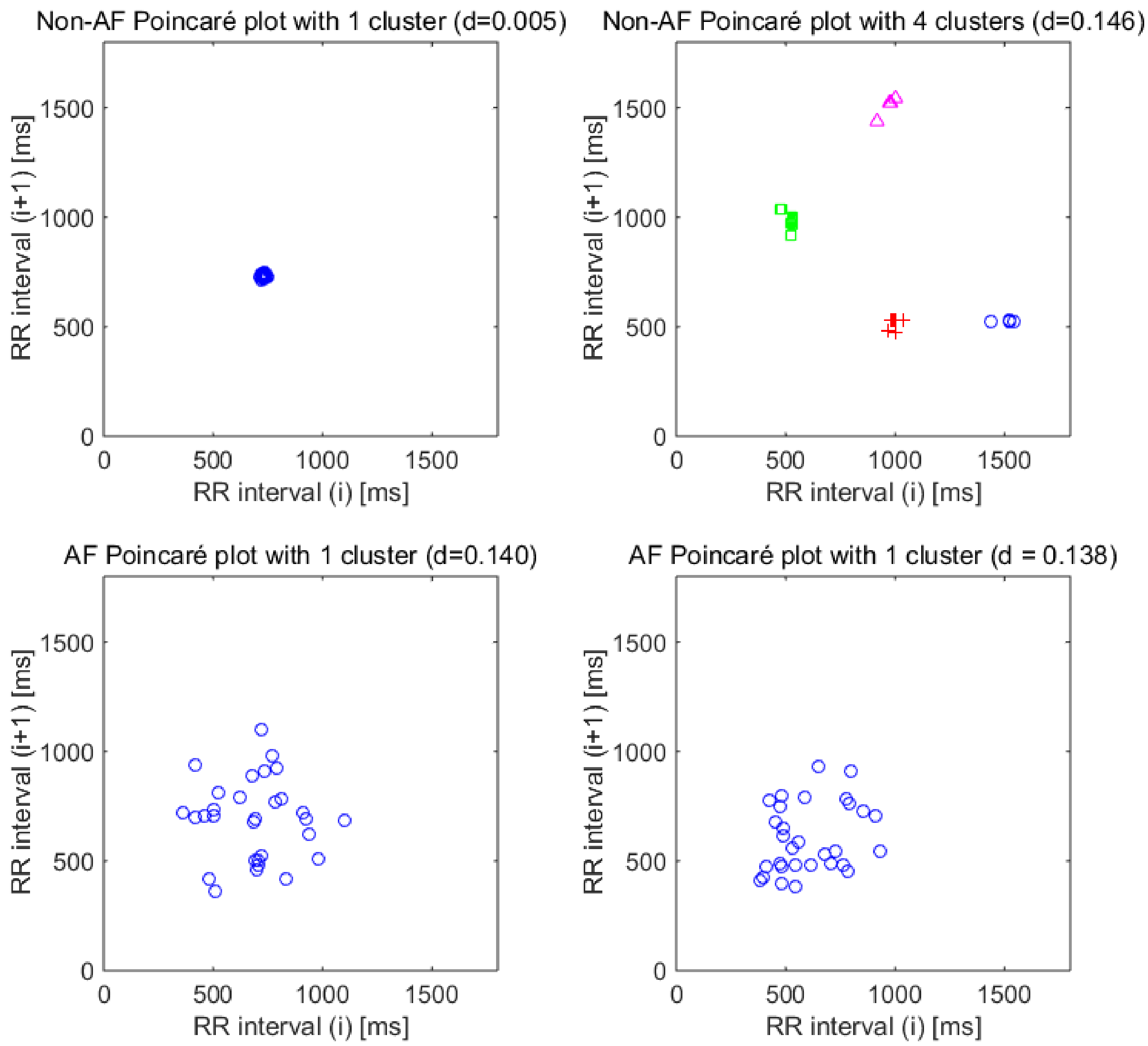

Fig. 1. Poincaré plots with the detected clusters. Upper left: non-AF case with 1 cluster and low dispersion. Upper right: non-AF case with 4 clusters and high dispersion. Lower left and right: AF cases with 1 cluster and high dispersion.

3. Results

The algorithm was tested on ECG signals of the PhysioNet Database. 10 AF records were selected from the Long-Term AF Database and 10 control signals were chosen from the MIT-BIH Normal Sinus Rhythm Database [10]. In each case, we processed around 500 consecutive RR sections (each section contained 30 RR intervals). In summary, 5263 AF and 5237 non-AF sections were analysed, resulting an average *Se* = 98.69% and an average *Sp* = 99.59%.

In addition, 10 AF and 10 normal clinically confirmed records of a heart rate meter (Cardiosport TP3, [11]) were also processed. These measurements were only few minutes long, producing 105 AF and 93 normal RR sections overall, resulting an average *Se* = 96.89% and an average *Sp* = 99.00%.

4. Discussion and Conclusions

Based on the results, the developed AF detection algorithm is very effective in terms of *Se* and *Sp*, considering both the ECG signals of PhysioNet and the records of a commercial heart rate meter. Since the similar previously published algorithms seem to be less efficient (e.g. *Se* = 91.4% and *Sp* = 92.9%, [7]), we claim that this is a significant progress in AF detection. By relying only on the heart rate, our method can be used in the processing of ECG signals even with relatively high level of noise, which makes it very suitable in telemedical or home care application.

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