Atrial fibrillation detection based on heart rate and atrial activation analysis

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Although atrial fibrillation (AF) is not directly life threatening, this kind of arrhythmia significantly increases the risk of stroke, according to several papers since the 1980s based on the Framingham Study. Therefore the early diagnostics of AF is very important, which can be performed practically by ECG-based detection. During our work we developed a method which can efficiently distinguish AF from non-AF cases (including normal rhythm and other arrhythmias), considering heart rate and atrial activation. The AF-detection algorithm (which was preliminarily tested on reference ECG databases) has been integrated into the WIWE mobile ECG system produced by Sanatmetal Ltd. Until now, 27 AF (age: 69±12 y, female: 6) and 261 non-AF validated cases have been recorded and evaluated, mostly in cooperation with the Semmelweis University Heart and Vascular Center. The non-AF group can be further divided into 3 subgroups: 37 normal (age: 26±4 y, female: 21), 67 top athlete (age: 20±7 y, female: 40) and 157 pathological (age: 62±12 y, female: 41, typical diseases: coronary artery disease, heart failure and diabetes mellitus) subjects. No false decision has been occurred related to these cases, which demonstrates the efficiency of the AF-detection method.

Introduction

Atrial fibrillation (AF) is a supravenctricular arrhythmia which is characterized by a chaotic atrial activation. Therefore, the performance of the atrial function decreases drastically [1]. The disorder can produce several symptoms, e.g. palpitation, dizziness, weakness, chest pain. However, the arrhythmia is often asymptomatic [2]. AF does not belong to the group of malignant arrhythmias, since it is not directly life threatening. Despite of this, it should not be considered unimportant. Based on the Framingham Study, in the 1980s it was shown, that AF significantly increases the risk of stroke (approximately 5 times the normal) [3]. Furthermore, it can contribute to the development of other diseases, such as heart failure [4]. According to a recent report of the American Heart Association (AHA), 1% of AF patients are below the age of 60, and more than 1/3 of them are above 80 years. Consequently, the probability of AF occurrence increases exponentially in function of the age [5].

As mentioned before, AF is asymptomatic in many cases, therefore its early detection is particularly important in order to begin the necessary treatment as soon as possible. In the diagnosis various computerized AF detection methods can support medical doctors in decision making. These algorithms – that are usually based on ECG – try to identify the arrhythmia by investigating the heart rate and/or the atrial activation. This is because during AF the heart rate is completely irregular (randomly varying RR intervals) and P waves (which normally represent the coordinated atrial activation) are replaced by high frequency and low amplitude so-called fibrillatory waves [5].

During the past few decades, several methods have been published in the literature regarding computerized AF detection. For example, some of them apply Bayes classification [6], others investigate RR histograms [7], and there are some algorithms analyzing Poincaré plots of RR intervals [8-10]. In the case of AF detection methods, the efficiency is typically measured by the sensitivity (*Se*) and specificity (*Sp*). (The exact definition of *Se* and *Sp* can be seen in the Appendix.) The vast majority of methods from the literature produce significantly lower *Sp* than *Se* or vice versa. Therefore it is very difficult to find a method which is greater than 95% both in *Se* and *Sp*. This is confirmed by two recent studies which show that algorithms investigating only the RR intervals are generally more efficient than the ones that (also) take atrial activation into account [11,12].

The aim of our work in the Medical Informatics R&D Center of University of Pannonia was to develop a more accurate AF detection method compared to the ones found in the literature. We also tried to design the algorithm so that the implementation could be easily integrated into a mobile ECG system which is user-friendly, applicable in home monitoring and easily accessible for any kind of people. This idea seemed to be a good point of view according to a paper from 2014 which implies that the increasing computing capacity of smartphones combined with small and simple wireless measuring devices may open new perspectives in AF detection (among others) for the vast majority of people [13].

Analysis of the heart rate

Our AF detection method consists of two parts: heart rate and atrial activation analysis. This section describes the former one.

Based on the ECG signal, the easiest way to determine the heart rate is the calculation of the distances (RR intervals) between the consecutive steep ventricular depolarization waves (QRS complexes).

The analysis of the RR data can be performed by several ways, as mentioned in the previous section. Our method was developed based on the work of Park et al. who investigated Poincaré plots of RR intervals and tried to make decision about AF by the dispersion of points (along the diagonal) and the number of clusters [10]. Our method takes the dispersion and the possible groups of points into account as well, however in a different way. The dispersion can be calculated according to Equation (1).

$$d = \frac{\sqrt{\frac{1}{2(n-1)}\sum_{j=1}^{n-1}(I_j - I_{j+1})^2 - \left(\frac{1}{(n-1)\sqrt{2}}\sum_{j=1}^{n-1}|I_j - I_{j+1}|\right)^2}}{\frac{1}{2(n-1)}\left(-I_1 - I_n + 2\sum_{j=1}^{n-1}I_j\right)} \quad (1)$$

where $I_1, I_2, I_3, I_4, ..., I_{n-1}, I_n$ are the consecutive RR intervals (with n value overall), from which the coordinates of the Poincaré plot can be derived as $(I_1, I_2), (I_2, I_3), (I_3, I_4), ..., (I_{n-2}, I_{n-1}), (I_{n-1}, I_n)$ [10].

The first step of the algorithm is the evaluation of the dispersion. If it is low enough, then the heart rate is considered to be stable, therefore AF is not assumed. In the case of high dispersion, k-means clustering is performed in order to check whether well defined clusters can be found on the Poincaré plot. If this is true, just like in the previous case, AF is not detected: although some kind of arrhythmia is assumed, the fluctuation of RR intervals cannot be considered random. AF can be assumed only if the cluster analysis of the high dispersion Poincaré plot results in one cluster (i.e. no well-defined clusters were found).

The mentioned three cases are illustrated by Figure 1. The details of this method can be found in an earlier paper [14].

Analysis of the atrial activation

Although – according to our experience and the literature – AF can usually be identified merely based on the fluctuation of RR intervals, there are some exceptions which justify the investigation of the atrial activation as well. A good example is the sinus arrhythmia which is the fluctuation of heart rate depending on breathing. This phenomenon is the result of the coordination between the circulatory and respiratory systems, and it is commonly expressed in the case of young healthy people. Therefore, it is considered rather a sign of good health than

a disorder [15]. In some cases, the heart rate fluctuation produced by this arrhythmia can be so high, that the distribution of the related Poincaré plot becomes similar to the AF case (i.e. high dispersion without well-defined clusters). In order to avoid false positive detections due to sinus arrhythmia, we decided to take also the atrial activation into account during AF detection.
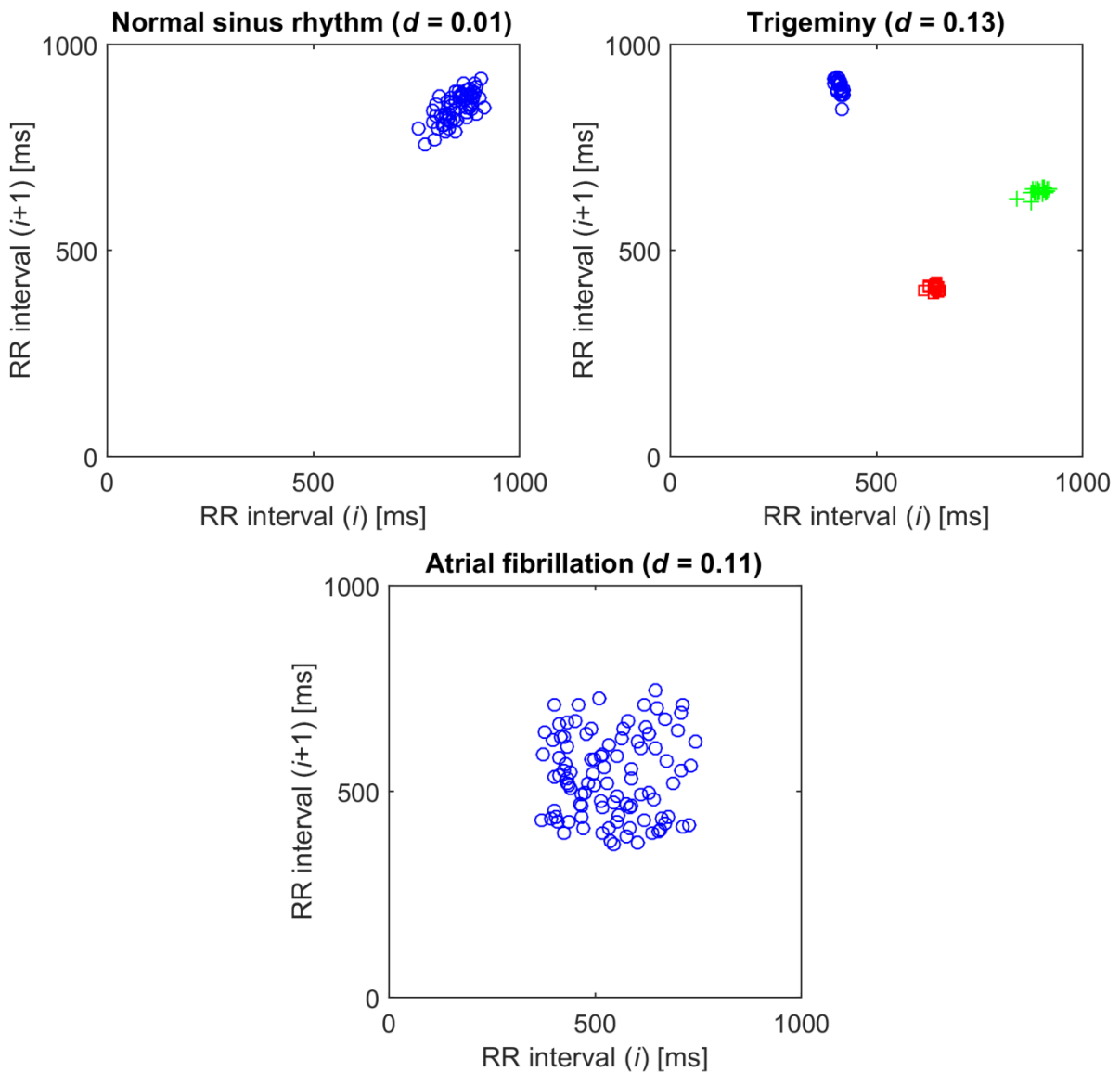

Figure 1. Poincaré plots representing normal, trigeminy (with 3 well-defined clusters) and AF rhythm. Each Poincaré plot belongs to a 1 minute long ECG record with approximately 70 points. The parameter of *d* is the dispersion along the diagonal.

Regarding the analysis of the atrial activation we used the relevant ECG marker of AF that was already mentioned in the Introduction section: during AF P waves cannot be seen on the

ECG signal, because they are replaced by fibrillatory waves. The latter ones show stochastic behavior, which is the result of the uncoordinated atrial activation sequence. This property can be advantageous when the average majority cycle is investigated right before the QRS complex (where the P wave is expected in the case of normal activation). This is because – during AF –averaging significantly decreases the amplitude of random fibrillatory waves which can be essentially removed from the signal. Therefore, if significant P wave cannot be identified on the average majority cycle, AF can be suspected.

In the first step of atrial activation analysis, the detected cardiac cycles are classified based on waveform (using Pearson's linear correlation coefficient) in order to exclude ventricular ectopic beats and artifacts. After that the averaging of the majority cycles is performed in a time window depending on the heart rate, by synchronizing each majority cycle to the steepest point of the QRS (fiducial point). Finally, wave limits are determined on the average cycle by a self-developed algorithm, regarding the P, QRS and T waves.

AF is detected if and only if P wave cannot be identified on the average majority cycle, and the previously introduced Poincaré analysis raises the suspicion of AF. Figure 2. shows the comparison of sinus arrhythmia and AF, in terms of Poincaré plot and average majority cycle.
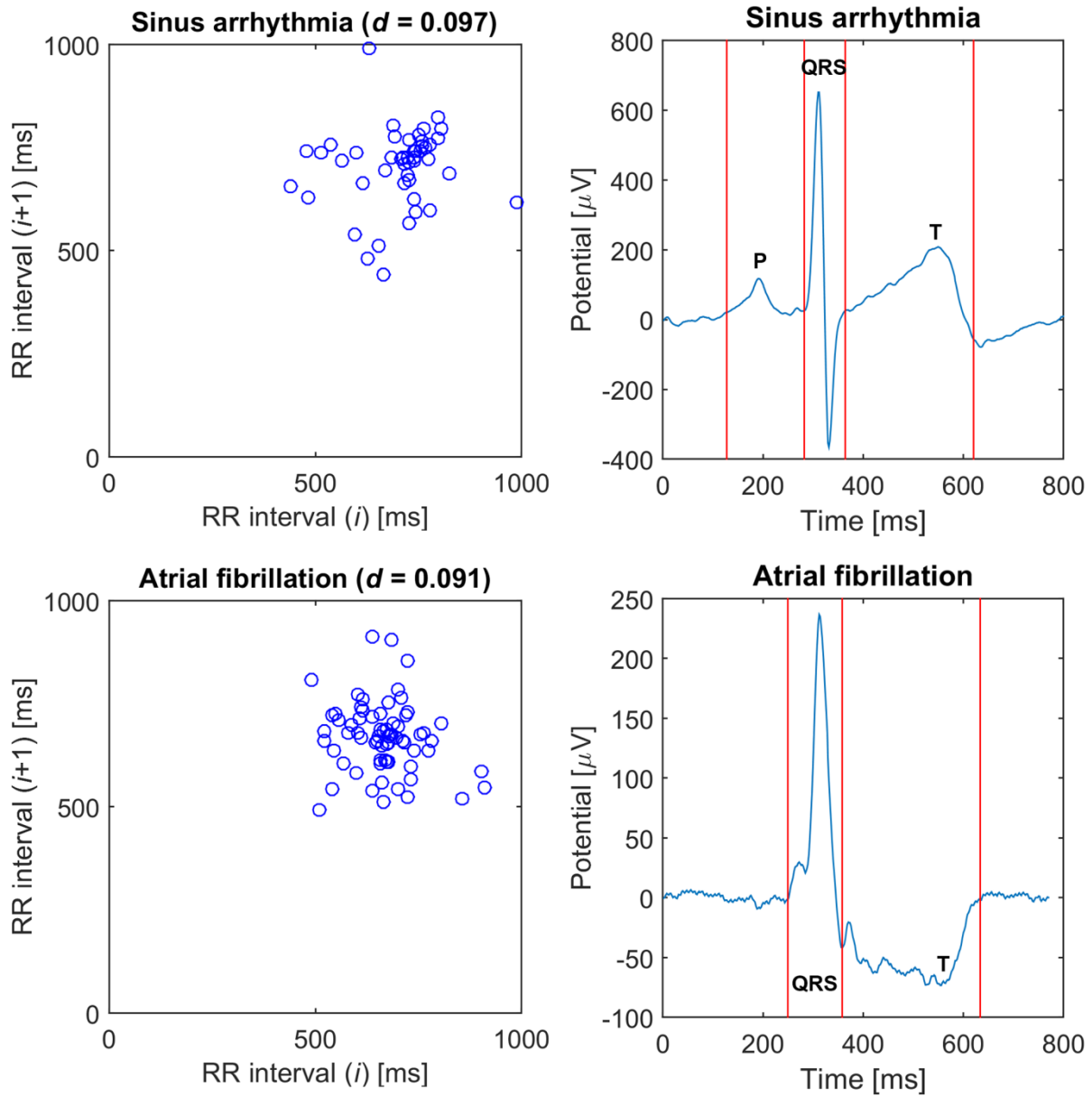
Figure 2. Poincaré plot (on the left) and the corresponding average majority cycle (on the right) with the identified ECG wave limits (vertical red lines) related to sinus arrhythmia and AF. In the case of AF, P wave cannot be seen on the average cycle.

Results and discussion

The Poincaré analysis of RR intervals has been tested on various datasets. First, 4 records of the PhysioNet MIT-BIH Arrhythmia Database were selected, containing both AF and non-AF episodes annotated by medical doctors. Approximately 200 Poincaré plots (100 AF and 100 non-AF) were analyzed per record. Later the algorithm was tested on 10-10 records belonging to the PhysioNet MIT-BIH Normal Sinus Rhythm Database and Long-Term AF Database, evaluating 500 Poincaré plots per record [16]. We also performed 20 clinically validated heart

rate measurements in cooperation with the Cardiac Rehabilitation Centre of the Hungarian Military Hospital. This time, approximately 10 Poincaré plots were analyzed per measurement. The tests mentioned above resulted in an average *Se* of 96% and an average *Sp* of 97%. The quantitative details of the results related to the Poincaré analysis are described in our earlier papers [14,17].

The Poincaré analysis extended with the investigation of the atrial activation was integrated into the WIWE mobile ECG system produced by Sanatmetal Ltd. This system consists of a small (size of a credit card) ECG measuring device and a smartphone application. The former one performs the 1 minute long ECG recording (limb lead I.), while the latter one evaluates the measurement, presents the results and stores the data which can be shared with other people [17].

By now, nearly 300 clinically validated cases have been measured with the WIWE system, mainly in cooperation with the Semmelweis University Heart and Vascular Center. This set of records contains 27 AF (age: 69±12 y, females: 6) and 261 non-AF cases. The non-AF group can be divided further as follows:

1. Normal: 37 (age: 26±4 y, female: 21)
2. Top athlete: 67 (age: 20±7 y, female: 40)
3. Pathological: 157 (age: 62±12 y, female: 41)

The pathological group consists of people with the following diseases: coronary artery disease (99), heart failure (83) and diabetes mellitus (41). High dispersion Poincaré plot occurred in 11 cases related to the non-AF group: 3 of them belong to top athletes with expressed sinus arrhythmia, the other 6 are related to pathological ones with frequent ectopic beats.

This far, the developed AF detection method (i.e. the combination of Poincaré plot evaluation and atrial activation analysis) has not made any wrong decision on the validated ECG data set. Although the number of AF cases is significantly lower than the amount of non-AF cases regarding the validated measurements of WIWE, our current results imply a very high level of accuracy. We hope that through the WIWE system, our AF detection algorithm will contribute greatly to the early detection of AF and therefore to the reduction of stroke risk.

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Appendix

$$Se = \frac{TruePos}{TruePos + FalseNeg} \cdot 100\%$$

$$Sp = \frac{TrueNeg}{TrueNeg + FalsePos} \cdot 100\%$$

TruePos: number of correctly detected positive cases (e.g. AF)

FalseNeg: number of positive cases that were detected as negative

TrueNeg: number of correctly detected negative cases (e.g. non-AF)

FalsePos: number of negative cases that were detected as positive