A Methodology for Predicting Paroxysmal Atrial Fibrillation Based on ECG Arrhythmia Feature Analysis

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Abstract

This article addresses the Computers in Cardiology Challenge 2001 for predicting the onset of paroxysmal atrial fibrillation (PAF) from the surface electrocardiogram (ECG). To predict PAF, we developed an algorithm based upon the number and timing of atrial premature complexes (APCs) in the ECG. The algorithm detects classical isolated APCs, then predicts PAF based on a measurement of APC rate that favors the most recent APCs. The challenge database consists of 100 pairs of 30-minute ECG segments that may or may not directly precede an episode of PAF. We used the learning set of the challenge database to optimize our algorithm. On the test set, it achieved scores of 40 out of 50 for PAF screening (event 1) and 44 out of 50 for PAF prediction (event 2).

1. Introduction

We address here the Computers in Cardiology Challenge 2001 [1] for predicting the onset of paroxysmal atrial fibrillation (PAF) from the surface electrocardiogram (ECG). The challenge is motivated by the possibility of therapeutic intervention to prevent the onset of atrial arrhythmias and their consequences such as thromboembolism and atrial remodeling, as well as to improve hemodynamic performance.

To develop an automated algorithm for PAF screening and prediction, we first visually examined all the ECG data segments in the learning set of the PAF Prediction Challenge Database (see Section 2), so as to understand better the ECG characteristics during episodes of PAF, prior to PAF, and distant from PAF. Next, we used a previously developed automated arrhythmia detection algorithm [2, 3] which identifies beat types (normal, atrial premature complex (APC), ventricular premature complex, unknown, etc.) as well as rhythm types (supraventricular tachycardia, ventricular tachycardia, etc.). After examining the detected arrhythmia patterns, we found that the number and timing of the detected APCs appeared to be of significant value in terms of predicting imminent PAF episodes. These preliminary findings are supported by both physiologic intuition and several previous studies (see, for example, [4]).

Based on these findings, we developed automated algorithms for PAF screening (identifying subjects at risk of PAF from a larger population) and for prediction of imminent PAF in at-risk subjects. Section 2 describes these algorithms in detail, and section 3 presents their performance on the test set of the challenge database.

2. Materials and methods

The PAF Prediction Challenge Database [1, 5] consists of 100 pairs of 30 minute segments of two channel ECG data. Each pair is obtained from a 24 hour ECG recording from a single subject. Subjects in group A experienced PAF. For these subjects, one ECG segment ends just prior to the onset of PAF, while the other ECG segment is distant in time to any PAF episode (no PAF 45 minutes before or after the segment). Subjects in group N do not have PAF. For these subjects, the pair of ECG segments was chosen at random times in the 24 hour recording period. The database is divided into a learning set and a test set of equal size, each containing approximately an equal number of subjects from group A and group N. The classifications of the recordings in the learning set are provided. (All of the recordings were digitized at a sampling frequency of 128 Hz, with 12-bit resolution over a 20-mV range.)

The challenge had two specific objectives: (1) to distinguish subjects in group A from those in group N (Event 1: PAF screening), and (2) to predict which ECG segments are immediately followed by PAF (Event 2: PAF prediction).

The algorithms we developed to address these two objectives include the following steps: (1) automatically

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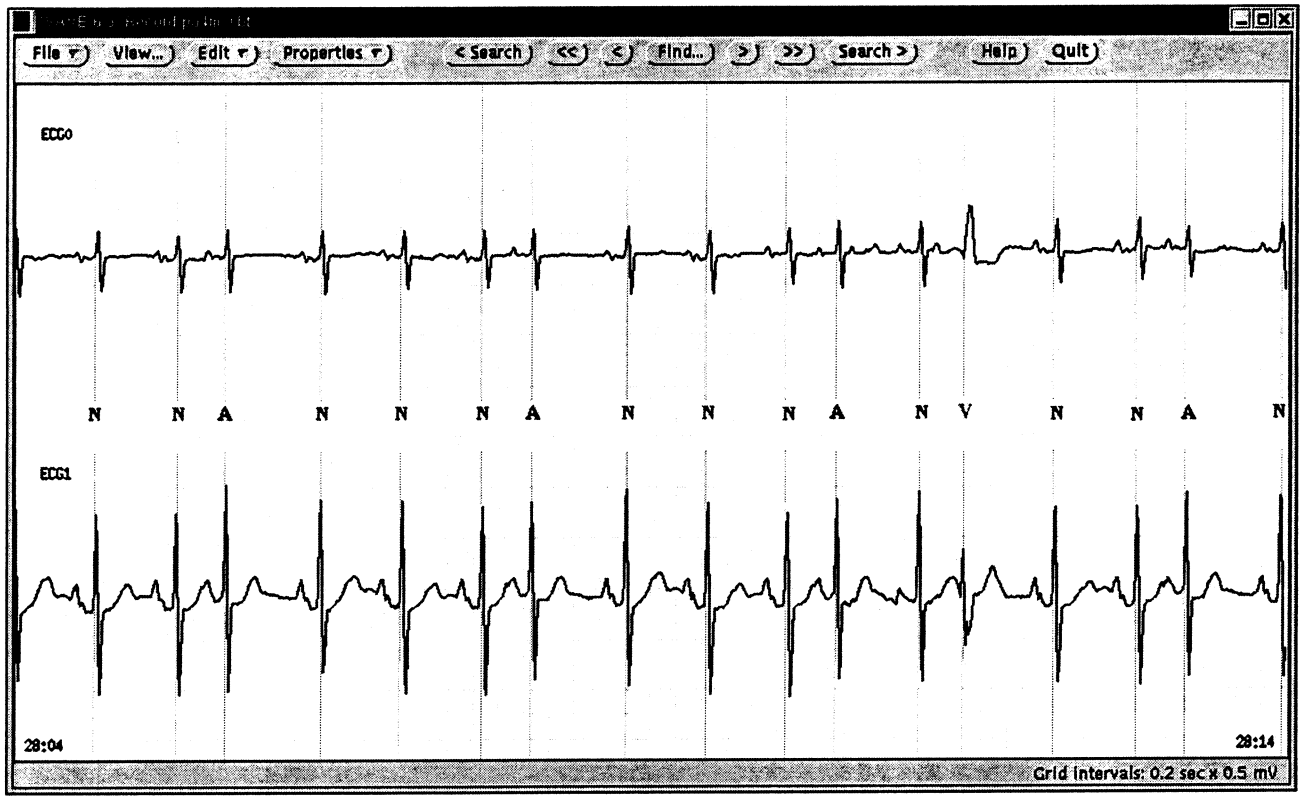

Figure 1. An example of APC detection performance. See text for details.

detecting APCs in each of the 30-minute ECG segments; (2) weighting the APCs so as to favor those APCs that occur towards the end of each ECG segment; (3) creating a decision rule that is optimized (in terms of, for example, the weighting function) with respect to the learning set; and (4) applying the optimized decision rules to each ECG segment of the test set to screen for and to predict PAF.

2.1. APC Detection

APCs were detected by our previously developed automated beat type and arrhythmia detector [2, 3]. The detector first locates the position of a QRS complex, then measures its width (duration), amplitude, and area. Any beat that is at least 15% premature and similar to the normal (dominant) beats is classified as an APC. More precisely, the RR interval preceding any beat classified as an APC must be at least 15% less than a weighted average of the most recent RR intervals, computed according to the following autoregressive, moving average difference equation:

$$RRa_n = 0.9RRa_{n-1} + 0.1RR_n \qquad (1)$$

where n is the beat number and RRa is the weighted average of the most recent RR intervals. Note that RR_0 is arbitrarily set to 800 ms.

The second criterion that must be met by any beat classified as an APC is that the QRS complex shape is similar to that of a normal beat, as determined by a fuzzy logic-based analysis of the beat's QRS width, amplitude, and area [3].

We previously evaluated the performance of the APC detector with the MIT-BIH Arrhythmia Database [6]. We found the detector's sensitivity to be 53.63% and its positive predictive accuracy to be 46.46% (both statistics are "average" measures, weighting each record in the database equally). Figure 1 illustrates how this APC detector performs on an excerpt near the end of record p34 of the challenge database learning set (shortly before the onset of PAF). The figure demonstrates that the detector is able to identify "classical" isolated APCs (beats labelled A) but not aberrantly conducted APCs (beat labelled V) or non-conducted APCs (run of unlabelled APCs preceding beat labelled V).

2.2. Weighting the APCs

Once an APC is identified by the automatic detector,

its time of occurrence in the ECG segment is annotated. Rather than simply counting the APCs, we compute a weighted sum in which the weighting favors those APCs that have occurred most recently. As discussed in Section 1, this unequal weighting is motivated by both intuition and empirical observations (see example in Figure 2).

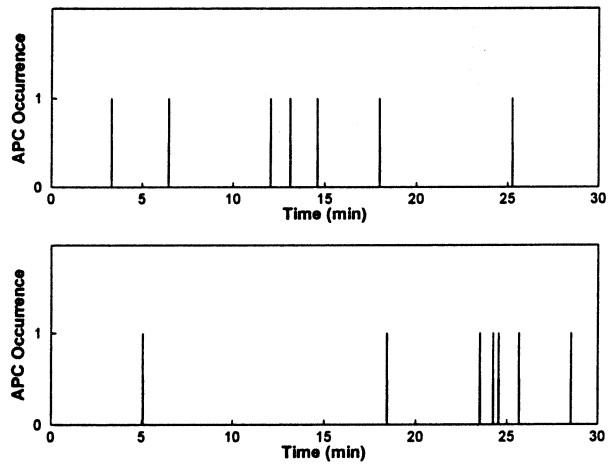

Figure 2: Impulses indicating the times of occurrence of APCs from two segments of ECG data obtained from a subject in group A. Although each segment has the same number of APCs, note the cluster of APCs near the end of the second segment, which immediately precedes an episode of PAF.

The weighted sum is computed as:

$$WSUM = \sum_i \exp\left(\frac{t_i}{\tau}\right) \cdot u_{-1}(t_i - T + w) \qquad (2)$$

where $u_{-1}(t)$ is the unit step function, t_i denotes the time of the i^{th} detected APC, T is the current time, and τ and w are free parameters which completely specify the weighting function. Figure 3 provides a pictorial representation of the weighting function. Since the challenge stipulates that PAF, if it occurs at all, begins immediately after the end of a 30-minute segment, we evaluated *WSUM* at $T = 30$ minutes for each of the two segments associated with each subject; these values are denoted by $WSUM_1$ and $WSUM_2$.

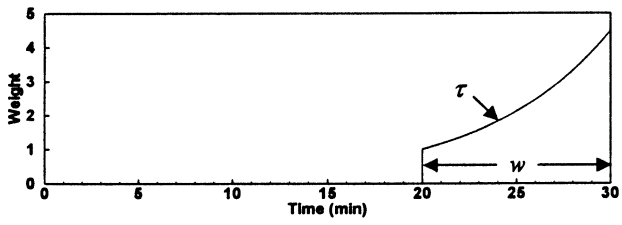

Figure 3. Pictorial representation of the weighting function (at $T = 30$ minutes).

2.3. Creating an Optimal Decision Rule

In order to map $WSUM_1$ and $WSUM_2$ into a single numerical quantity that characterizes each subject, we considered the following three scalar statistics:

$$Sum = WSUM_1 + WSUM_2$$
$$Diff = |\, WSUM_1 - WSUM_2 \,|$$
$$Max = max[WSUM_1, WSUM_2]$$

Any of these three types of scalar quantities could then be compared to a pre-defined threshold in order to establish a decision rule for Event 1. Note that the type of scalar statistic and threshold are also free parameters.

We determined optimal numerical values for the four free parameters (τ, w, scalar statistic type, and threshold) with respect to the learning set in two steps. First, we empirically established a range over which each parameter is to be considered (see Table 1). Then, we exhaustively searched over the entire four-dimensional range in order to find the parameter values that maximized the learning set score for Event 1.

Table 1. Free parameters and corresponding search range. See text for details.

Free Parameter	Search range
w	5, 10, 30 min
τ	2, 2.33, ...60 min
Scalar statistic type	Sum, Diff, Max
Threshold	1, 2, ... 99999

The resulting optimized decision rule for Event 1 is:

IF $max[WSUM_1(\tau=6.33, w=10), WSUM_2(\tau=6.33, w=10)] > 105$
THEN *PAF subject*
ELSE *Non-PAF subject*

It should be noted that the optimal threshold value ranges from 100 to 220 and is thus not unique. The threshold value above achieved our highest score on the test set.

For Event 2, we simply identified the ECG segment with the larger *WSUM* value as the segment that immediately precedes PAF. The decision rule for Event 2 is:

IF $WSUM_1(\tau=6.33, w=10) > WSUM_2(\tau=6.33, w=10)$
THEN *Segment 1 precedes PAF*
ELSE *Segment 2 precedes PAF*

Note that, for simplicity, we utilized the optimal τ and w values obtained for Event 1.

3. Results

These algorithms were used to prepare classifications of the learning and test sets of the PAF Prediction Challenge Database. For Event 1, we received a score of 38 out 50 for the learning set (sensitivity 92%, positive predictive accuracy 70%) and 40 out of 50 for the test set. For Event 2, we received a score of 47 out 50 for the learning set. We did not seek a score for the test set based on the decision rule for Event 2 given above, since we had previously achieved a score of 44 out 50 (which was the high score for the event) by simply comparing the number of detected APCs in each ECG segment. Note that this simpler decision rule achieved a score of 45 out of 50 on the learning set. Thus, it is quite possible that our score on the test set for Event 2 would be improved with the decision rule above, which achieved a higher score on the learning set.

4. Discussion

We conclude that APC number and timing is indeed of great value in screening and predicting PAF, at least for the database provided by the challenge. Interestingly, our study demonstrates that classical isolated APCs are of first-order importance in terms of PAF screening and prediction, while aberrantly conducted APCs, non-conducted APCs, and the numbers of APCs in runs of consecutive APCs may, at best, be of second-order importance. In addition to all types of APCs, it may also be possible to improve performance by incorporating P-wave shape and heart rate variability features into our methodology.

Our methodology resulted in a very high sensitivity and a reasonably high specificity with respect to the learning set provided by the challenge. These results should be considered with caution, however. Since the PAF Prediction Challenge Database does not reflect a typical clinical population in terms of the incidence of PAF, evaluation of the screening algorithm on data representative of the population in which it might be used is required.

A particularly interesting subject for further study is the question of how far in advance of an occurrence of PAF can the event be predicted with a given confidence. The answer to this question will have great importance with respect to the clinical utility of this or any other PAF prediction algorithm.

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