Atrial Fibrillation Episode Patterns and Their Influence on Detection Performance

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Abstract

Existing studies offer little insight on how atrial fibrillation (AF) detection performance is influenced by the properties of AF episode patterns. The aim of this study is to investigate the influence of AF burden and median AF episode length on detection performance. For this purpose, three types of AF detectors, using either information on rhythm, rhythm and morphology, or ECG segments, were investigated on 1-h simulated ECGs. Comparing AF burdens of 20% and 80% for a median episode length of 167 beats, the sensitivity of the rhythm- and morphology-based detector increases only slightly whereas the specificity drops from 99.5% to 93.3%. The corresponding figures of specificity are 99.0% and 90.6% for the rhythm-based detector; 88.1% and 70.7% for the segment-based detector. The influence of AF burden on specificity becomes even more pronounced for AF patterns with brief episodes (median episode length set to 30 beats). Therefore, patterns with brief episodes and high AF burden imply higher demands on detection performance. Future research should focus on how well episode patterns are captured.

1. Introduction

Little is known about the role of temporal atrial fibrillation (AF) episode patterns in AF progression and development of complications. The need for AF episode pattern analysis, complementing the often used AF burden, is emphasized in recent clinical guidelines [1]. However, to take a further step in AF pattern characterization, it is essential to understand how well episode patterns can be captured when using different AF detectors.

A huge number of AF detectors have been published in recent years. However, the influence of various physiological and technical factors on detection performance is rarely investigated, despite that essential information on detector properties can be uncovered [2]. Strengths and weaknesses in detector design can be more efficiently addressed by providing information on what particular AF pattern properties cause frequent false alarms.

AF patterns can vary considerably with respect to episode duration and AF burden [3]. The interest in brief (<30 s) episodes and their association with future risk of stroke [4,5] motivates the analysis of episode patterns with varying length to enrich the understanding of detection performance. Also, it is unclear how detectors perform in patterns with different AF burden, i.e., whether detection performance is the same in a pattern with a few brief episodes and a pattern dominated by long episodes.

The present study aims to investigate how AF burden and median AF episode length influence detection performance. For this purpose, three types of AF detectors, using either information on rhythm, rhythm and morphology, or ECG segments, are investigated on a database of simulated ECGs.

2. Methods

Rhythm-based and rhythm- and morphology-based detection require prior QRS detection, here accomplished by the wavelet-based detector described in [6], whereas segment-based detection does not.

2.1. Rhythm-based detector

Rhythm-based detection makes use of that AF episodes are manifested by irregular RR intervals, often associated with increased heart rate. The detector, able to detect AF episodes as short as 8 beats, includes blocks for ectopic beat filtering, bigeminy suppression, characterization of RR interval irregularity, and signal fusion [7].

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2.2. Rhythm- and morphology-based detector

The rhythm- and morphology-based detector, capable of detecting AF episodes as short as 8 beats, is based on four parameters which characterize rhythm irregularity, P-wave absence, f-wave presence, and noise level [8]. The latter three parameters are determined from an f-wave signal, extracted using an echo state network [9]. The parameters are fed to a fuzzy logic classifier producing a fuzzy output, i.e., a value between 0 and 1, reflecting the likelihood of AF being present in the sliding detection window. AF is detected whenever the output exceeds a fixed threshold. The detector requires two ECG leads, one with negligible atrial activity used as reference (e.g., V_6) and another with atrial activity (e.g., V_1) [8].

2.3. Segment-based detector

The deep learning-based detector described in [2] uses a 1D convolutional neural network (CNN) to process 30-s non-overlapping ECG segments. The ECG signal is preprocessed using a band-pass filter (0.5–40 Hz) to remove baseline wander and high-frequency noise. The CNN is composed of two convolutional layers and one fully connected layer. Both convolutional layers rely on 128 kernels with a stride of one, followed by a 1×32 average-pooling layer with a stride of 32. The fully connected layer consists of 256 neurons with a rectified linear unit activation function and two output neurons with a softmax activation function. To mitigate the risk of overfitting, all layers are followed by dropout layers with probabilities of 0.5. The outputs of the convolutional layers are batch-normalized.

The detector was trained on two-thirds of MIT–BIH Atrial Fibrillation Database (AFDB) from Physionet [10] and validated on the remaining one-third. To equalize the signal amplitude across a recording, the modulus of each segment was taken and normalized to the interval $[0, 1]$.

3. Database

To investigate the influence of AF pattern properties on detection performance, simulated ECGs with paroxysmal AF episodes are used [11]. The model produces 12-lead ECGs composed of real signal components randomly selected from three datasets, each consisting of ventricular rhythm, atrial activity (f-waves or P-waves), and QRST complexes. Accounting for the switching between non-AF and AF, these components, together with noise, are summed to produce simulated ECGs.

Two datasets with median AF episode lengths of 30 and 167 beats were produced. The first dataset consists of AF patterns with brief episodes, while the second dataset consists of patterns similar to those in AFDB. Each dataset contains 100 1-h simulated ECGs with AF burden set to 20%, 50%, and 80%, resulting in a total of 300 ECGs. The histograms of episode duration are provided in Fig. 1.

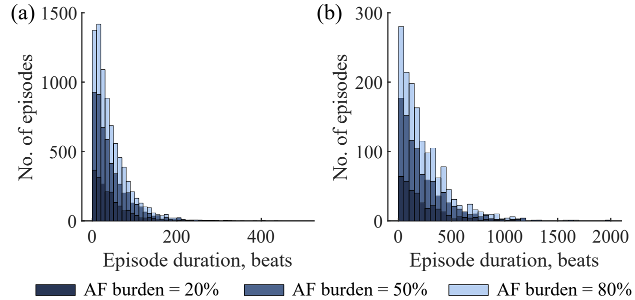

Figure 1. Histograms of AF episode duration in dataset with a median AF episode length of (a) 30 and (b) 167 beats.

4. Performance evaluation

Simulated ECGs were processed with each detector type to obtain detector-produced AF patterns. The reference AF patterns were compared to the detector-produced AF patterns using beat-to-beat comparison. For this purpose, the segment-to-segment output of the segment-based detector was converted to beat-to-beat output, i.e., all beats of a segment were assigned to AF or non-AF depending on whether the segment was detected as AF or non-AF.

Detection performance is evaluated using sensitivity, Se, specificity, Sp, and accuracy, Acc. All statistical results are based on 100 simulated ECGs and expressed as mean $\pm$ confidence interval (95%).

5. Results

For high AF burden (80%), the sensitivity increases only slightly independently to the detector used, however, the specificity is considerably influenced by AF burden (Fig. 2 a–b). That is, the specificity drops from 99.5% to 93.3% for high AF burden (80%) compared to low (20%) using the rhythm- and morphology-based detector, from 99.0% to 90.6% for the rhythm-based detector, and from 88.1% to 70.7% for the segment-based detector when the median AF episode length is set to 167 beats. The influence of AF burden on specificity becomes even more evident for AF patterns with brief episodes, i.e., the specificity drops from 98.0% to 70.0% using the rhythm- and morphology-based detector, from 97.2% to 61.7% for the rhythm-based detector, and from 82.7% to 31.7% for the segment-based detector.

The detection accuracy decreases only slightly for high AF burden compared to low AF burden using the rhythm- and morphology-based detector, while the accuracy of the

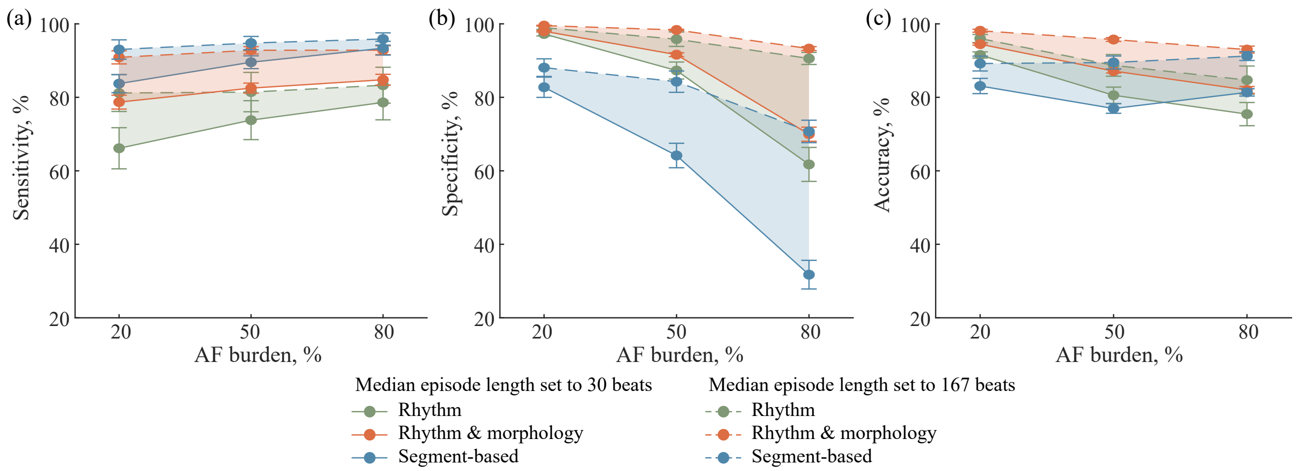

Figure 2. Detection performance as a function of AF burden for three types of AF detectors: (a) sensitivity, (b) specificity, and (c) accuracy. Shaded area shows detection performance depending on median AF episode length.

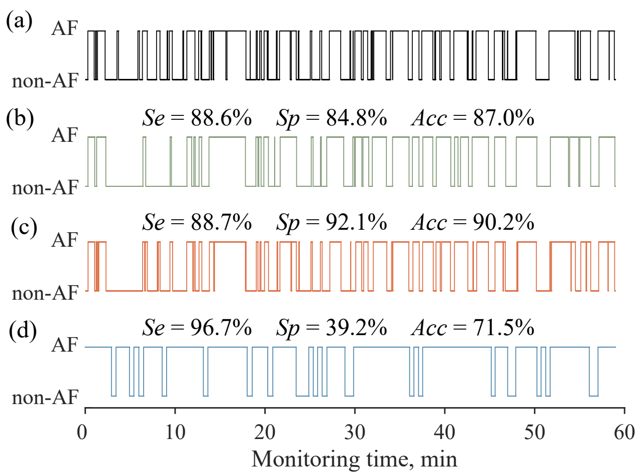

Figure 3. (a) Reference AF pattern with brief episodes and detector-produced pattern using (b) rhythm-based, (c) rhythm- and morphology-based, and (d) segment-based detector.

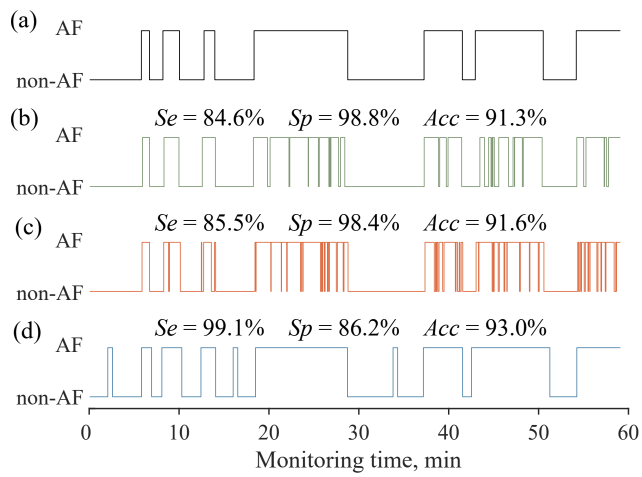

Figure 4. (a) Reference AF pattern and detector-produced pattern using (b) rhythm-based, (c) rhythm- and morphology-based, and (d) segment-based detector.

rhythm-based detector is more influenced by the change in AF burden (Fig. 2 c). On the contrary, the accuracy of the segment-based detector increases from 89.2% to 91.2% for high AF burden when the median AF episode length is set to 167 beats.

The performance of all detector types decreases when AF patterns with brief episodes are processed (Fig. 2). For low AF burden, detection specificity drops only slightly. However, sensitivity decreases from 90.9% to 78.7% for patterns with brief episodes using the rhythm- and morphology-based detector, from 81.2% to 66.1% for the rhythm-based detector, and from 93.0% to 83.7% for the segment-based detector. While for high AF burden, specificity is substantially influenced by the change in median episode length, i.e., the specificity decreases from 93.3% to 70.0% using the rhythm- and morphology-based detector, from 90.6% to 61.7% for the rhythm-based detector, and from 70.7% to 31.7% for the segment-based detector.

Figure 3 shows an AF pattern with brief AF episodes, best captured by the rhythm- and morphology-based detector. The segment-based detector has the largest sensitivity, however, the detector-produced pattern differs from the reference pattern since a few consecutive episodes are merged into a single episode. Therefore, the AF pattern can not be captured properly, i.e., AF burden for the reference pattern is 56%, while AF burden resulting from the segment-based detector is 81%. For comparison, AF burden resulting from the rhythm-based and the rhythm- and morphology-based detectors is 57% and 53%, respectively.

On the contrary, Fig. 4 illustrates a pattern with longer episodes. In this case, both the rhythm-based and the rhythm- and morphology-based detectors tend to split single AF episode into a cluster, while the segment-based detector does not since it processes ECG segments. This result also influences the AF pattern, i.e., AF burden for the reference AF pattern is 53%, while AF burden for the detector-produced patterns using rhythm-based, rhythm- and morphology-based, and segment-based detectors are 45%, 46%, and 59%, respectively.

6. Discussion

AF pattern properties, such as median AF episode length and AF burden, influence detection performance. This may be a challenge aiming at characterization of temporal AF patterns, e.g., analysis of episode clustering [12] or temporal distribution of AF episodes [13]. Therefore, further research should investigate the influence of missed and falsely detected AF episodes in terms of pattern characterizing parameters.

The sensitivity of the segment-based detector is less influenced by AF pattern properties than are the other detector types. However, the specificity of the segment-based detector decreases considerably when processing AF patterns with brief episodes. The reason behind is that the segment-based detector uses quite long 30-s segments, therefore, it is still going to detect AF if, e.g., only half of that segment contains AF. Another reason is the comparison of different AF detection approaches, where one is based on the analysis on ECG segments, while two others process ECG on a beat-to-beat basis. The selection of detector structure should be based on the purpose.

7. Conclusions

AF patterns with brief episodes and high AF burden imply higher demands on detection performance. Therefore, future research should focus on how well episode patterns are captured.

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