A Noise-Adaptive Method for Detection of Brief Episodes of Paroxysmal Atrial Fibrillation

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Abstract

The aim of this work is to develop a method for detection of brief episode paroxysmal atrial fibrillation (PAF). The proposed method utilizes four different features: RR interval irregularity, absence of P waves, presence of f-waves and noise level. The obtained features are applied to the Mamdani-type fuzzy inference method for decision-making. The performance was evaluated on one hundred 90 s long surrogate ECG signals with brief PAF episodes (5–30 beats). The robustness to noise in ECGs where noise level in each set is incremented in steps of 0.01 mV from 0 to 0.2 mV was examined as well. When compared to the coefficient of sample entropy, our method showed considerably better performance for low and moderate noise levels (< 0.06 mV) with an area under the receiver operating characteristic curve of 0.9 and 0.94, respectively. Similar performance is expected for higher noise levels as atrial activity is less used in the detection process. Finally, the results suggest that our method is more robust to false alarms due to ectopic beats or other irregular rhythms than the method under comparison.

1. Introduction

The detection of brief episode paroxysmal atrial fibrillation (PAF) is an important problem to solve since atrial fibrillation (AF) is a progressive disorder. If not treated, PAF usually becomes more frequent and longer until it becomes permanent [1]. Recently, it was observed that brief episodes of AF, lasting from 5 to 30 s, occurred in 10% of patients who had cryptogenic ischemic stroke [2]. The authors hypothesized that another stroke may be prevented if patients were monitored during their first month after the first incidence of stroke.

Automatic AF detection can be done in different ways—one is based on identification of P-wave absence and another on the analysis of RR interval irregularity. Since P-waves are not apparent during AF such knowledge can be combined with RR irregularity information in order to improve the performance of AF detection [3]. Detection based on P-wave analysis only is impractical since smaller P-waves are susceptible to noise. On the other hand, despite the result that methods based on RR intervals suggest high sensitivity and specificity, PAF detection is precluded since a window of 30 s or longer is typically needed [4].

Recently, there has been a growing interest in developing algorithms for detection of brief AF episodes. A sample entropy based method was proposed that is capable of detecting AF using only 12 consecutive RR intervals [5]. The results show that AF episodes as short as 5 s can be detected with this method. However, reduced performance is expected in the presence of atrial ectopic beats.

A novel detector architecture was recently proposed, where information on P wave presence/absence, heart rate irregularity, and atrial activity analysis was combined, using an artificial neural network as classifier [6]. However, the results showed that AF detection performance was not better than that of the RR-interval based detector, suggesting that the information carried by atrial activity has not been optimally exploited.

In this study, the proposed method is based on atrial activity extraction using an echo state network (ESN) recently introduced as a unified solution to the problem of QRST cancellation in the presence of substantial variation in beat morphology and/or occasional ectopic beats [7]. The extracted atrial activity signal is used for characterization of the atrial activity as well as for assessment of noise level in ECG. The obtained variables are combined using a fuzzy inference system.

2. Methods

The main processing steps of the proposed AF detector are illustrated in Fig. 1. The detector requires two ECG leads as input, of which one needs to be positioned far away from the atria, e.g., the precordial lead V_6. A sliding window approach of M consecutive beats is taken to detection where P-wave absence, f-wave presence and noise level are computed from atrial signal $\hat{s}(n)$ produced by ESN. The ESN may be viewed as a classical adaptive

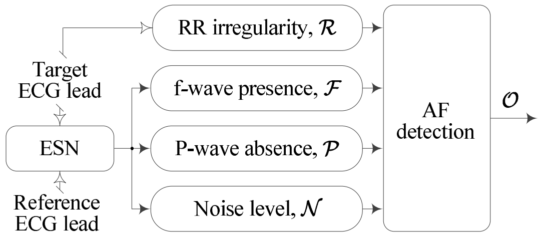

Figure 1. A block diagram of PAF detection method.

filter, where the atrial signal is extracted from a mixture of signals using a reference signal that is modified by a filter with time-variable transfer function—the ESN—and an adaptation algorithm. ESN is well-suited not only for cancellation of QRST complexes, but also for cancellation of P-waves, therefore the output signal during sinus rhythm (SR) contains only PQRST residuals and noise.

P-wave absence ($\mathcal{P}$) is quantified by first computing the error between two different PR intervals,

$$e_{ij} = \sum_{n=n_P}^{n_R} \big(\hat{s}(n_i - n) - \hat{s}(n_j - n)\big)^2, \tag{1}$$

where n_P and n_R denote the onset and end of the PR interval, respectively, both being fixed distances from n_i—the fiducial point of the i:th beat. Then, the squared error is averaged for all pairwise combinations of the M beats in the detection window,

$$\mathcal{P} = \sum_{i=1}^{M-1} \frac{1}{M-i} \sum_{j=i+1}^{M} e_{ij}. \tag{2}$$

The parameter $\mathcal{P}$ is close to zero in rhythms with stable P-wave patterns, whereas the presence of f-waves causes $\mathcal{P}$ to increase. The PR interval was set to $(n_R, n_P) = (50, 250)$ ms.

f-wave presence ($\mathcal{F}$) is quantified by a parameter reflecting the spectral concentration around the dominant spectral peak in the interval $[3, 10]$ Hz, defined by [8]

$$\mathcal{F} = \frac{1}{E_{\hat{s}}} \int_{\Omega_p} P_{\hat{s}}(\omega)\, d\omega. \tag{3}$$

where $E_{\hat{s}}$ is total energy contained in a windowed waveform. The power spectrum $P_{\hat{s}}(\omega)$ of $\hat{s}(n)$ in the detection window is obtained by Welch's method with a 1-s tapered cosine window and 50% segment overlap. The integration interval Ω_p is centered around the dominant peak of $P_{\hat{s}}(\omega)$. When f-waves are present, $P_{\hat{s}}(\omega)$ is concentrated around a dominant peak, corresponding to the AF frequency, and thus $\mathcal{F}$ is close to 1. For sinus rhythm, $\mathcal{F}$ is much smaller than 1. The parameter $\mathcal{F}$ was computed using the values given in [8].

RR interval irregularity ($\mathcal{R}$) is quantified by the coefficient of sample entropy, defined by [5]

$$\mathcal{R} = -\ln\left(\frac{A}{B}\right) + \ln(2r) - \ln(\bar{m}_r), \tag{4}$$

where A and B denote the total number of RR interval patterns of length $m+1$ and m, respectively, that match within a certain tolerance r; for details, see [5]. The mean length of the RR intervals contained in the detection window is denoted $\bar{m}_r$. The parameter $\mathcal{R}$ was computed using the values given in [5].

Noise is characterized by the RMS value of $\hat{s}(n)$ in the detection window, denoted $R_{\hat{s}}$, weighted with a spectral entropy ratio computed in intervals containing either atrial activity or noise:

$$\mathcal{N} = R_{\hat{s}} \cdot \frac{\displaystyle\int_{\omega_{n,0}}^{\omega_{n,1}} P_{\hat{s}}(\omega) \cdot \log_2 P_{\hat{s}}(\omega)\, d\omega}{\displaystyle\int_{\omega_{a,0}}^{\omega_{a,1}} P_{\hat{s}}(\omega) \cdot \log_2 P_{\hat{s}}(\omega)\, d\omega}. \tag{5}$$

The parameter $\mathcal{N}$ is small when $P_{\hat{s}}(\omega)$ reflects AF, whereas it is large when motion artifacts or electromyographic (EMG) noise is present. The parameter $\mathcal{N}$ was computed using the integration intervals $[\omega_{a,0}, \omega_{a,1}]$ and $[\omega_{n,0}, \omega_{n,1}]$ corresponding to $[3, 10]$ Hz and $[10, 125]$ Hz, respectively.

A Mamdani-type fuzzy inference method is employed for AF detection. The present fuzzy logic scheme has four inputs, i.e., $\mathcal{P}$, $\mathcal{F}$, $\mathcal{R}$, $\mathcal{N}$, sixteen rules, and one output denoted ($\mathcal{O}$). The crisp input values are converted via membership functions to fuzzy sets which serve as input to the inference mechanism. Spline-based s-shaped and z-shaped input membership functions are used to describe AF and SR, respectively. The input membership functions are defined by the parameters a and b which determine the extreme values of the functions. The following values were used: $(a, b) = (-3, 0.2)$ for $\mathcal{R}$, $(a, b) = (0, 0.6)$ for $\mathcal{S}$, $(a, b) = (0, 0.015)$ for $\mathcal{P}$, and $(a, b) = (0, 2)$ for $\mathcal{N}$.

Once the crisp inputs have been fuzzified, a set of "*if–then*" rules are activated. Each rule is composed of four members which are combined with the AND operator. The complete set of fuzzy rules is presented in Table 1. Furthermore, each rule has its own linguistic output, denoted AF_1 to AF_8, which is defined by the Gaussian membership function. Equidistant locations were assigned to the Gaussian output membership functions, defined by $c_i = c_0 + i\Delta c$, $c_0 = 0$ and $\Delta c = 0.143$. The width σ was set to 0.061. For each rule, the degree of activated output is determined by the *minimum* value of each member. The inference of a fuzzy block is based on all rules, and therefore the outputs of individual rules are combined using the *maximum* method for the accumulation in order to obtain overall fuzzy output. The crisp output $\mathcal{O}$ is obtained using

Table 1. Fuzzy rule base. Here $\mathcal{N}_L$ and $\mathcal{N}_H$ denote low and high noise, respectively.

			Decision	
$\mathcal{R}$	$\mathcal{F}$	$\mathcal{P}$	$\mathcal{N}_L$	$\mathcal{N}_H$
SR	SR	SR	AF_1	AF_1
SR	SR	AF	AF_2	AF_2
SR	AF	SR	AF_3	AF_3
AF	SR	SR	AF_4	AF_5
SR	AF	AF	AF_6	AF_4
AF	SR	AF	AF_7	AF_5
AF	AF	SR	AF_8	AF_6
AF	AF	AF	AF_8	AF_7

the centroid defuzzification method. The output is a value between 0 and 1 which reflects the likelihood that the current detection window contains AF.

The length of the sliding window is set to $M = 5$ consecutive beats. Since a small detection window will cause more false detections, median filtering (length 5) is applied to the output $\mathcal{O}$ to suppress outliers prior to threshold detection. Paroxysmal AF is detected whenever the output of the median filter exceeds a fixed threshold equal to η = 0.5.

3. Signals

Due to the lack of annotated databases with brief PAF, an ECG simulator was developed for evaluation of detection performance. During AF, the simulated signal is composed of ventricular activity, extracted from real ECGs, and f-waves produced by an extended sawtooth model [7]. During SR, the simulated signal is composed of ventricular activity, also extracted from real ECGs, and P-waves produced by an Hermite basis function model. A sinus rhythm model is used to generate the RR intervals [9] and an atrioventricular node model is used to generate RR intervals during AF [10]. T-waves are first resampled to have fixed duration, but later adjusted to match the prevailing heart rate. The noise, taken from the MIT–BIH Noise Stress Test Database [11], is normalized prior to the computation of a specific value of the noise parameter $\mathcal{N}$. In each alternating episode of SR or AF, the number of beats is uniformly distributed in the interval [5, 30]. It should be noted that the presented detector is unrelated to the simulator.

The proposed detector was developed using the AF database described in [12], without using of any simulated signals. The performance evaluation was based on simulated signals, where the ventricular activity was extracted from ECGs obtained from 100 subject signals contained in the PTB Diagnostic ECG Database [11]. The ECGs were decimated to 250 Hz to reduce the computational demands of the ESN [7]. Leads V_1 and V_6 were used as the target and reference signals, respectively.

4. Results

The area under receiver operating characteristic curve (P_A) is the measure for evaluating AF detection performance on beat-by-beat scale. The statistical results are expressed as mean±two-sided confidence interval (95%).

Figure 2 illustrates the performance of each separate part of the detector when brief AF episodes occur. Episodes were correctly detected even when corrupted with EMG noise that drowns the f-waves.

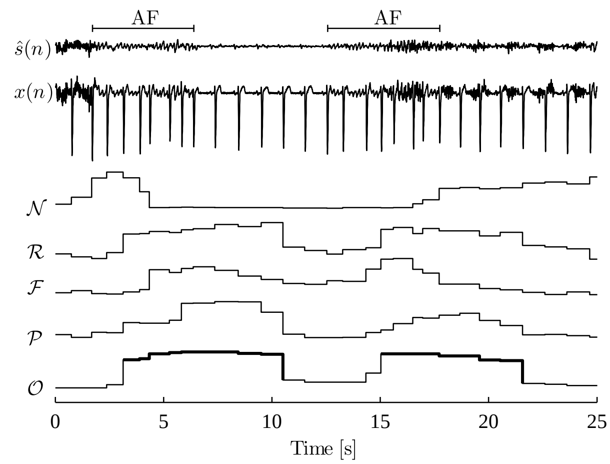

Figure 2. The performance of the proposed detector. Here $x(n)$ denotes the simulated ECG signal; thick line denotes the output signal after threshold.

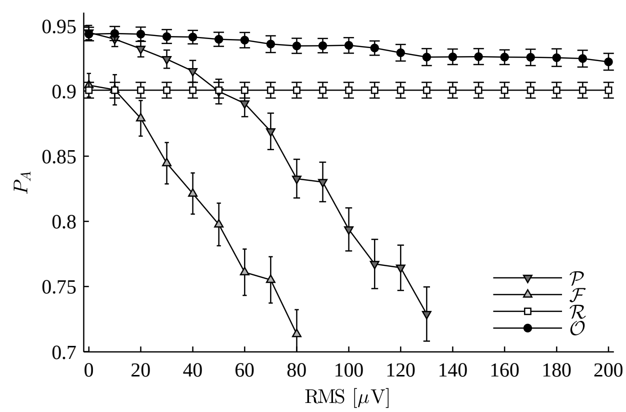

Figure 3. AF detection performance as a function of noise level.

Figure 3 compares performance of individual parameters used in the proposed AF detector to the synergistically combined, fuzzy logic based parameter. The results show that atrial activity describing features $\mathcal{P}$ and $\mathcal{F}$ are more reliable than RR irregularity index $\mathcal{R}$ when the noise component is less than 50 μV for $\mathcal{P}$ and less than 10 μV for

$\mathcal{F}$. The overall performance of the method starts deteriorating when the noise level is higher than 120 μV, although it remains much better than for $\mathcal{R}$ alone.

In order to support the results obtained on simulated data, some examples are taken from patients with brief episode PAF and ectopic beats, see Fig. 4. The proposed detector was compared to a detector based on sample entropy [5], denoted by $\mathcal{O}_{LM}$. The results suggest that the proposed method has shorter AF detection delay than $\mathcal{O}_{LM}$ and is more robust to the false alarms when ectopic beats occur.

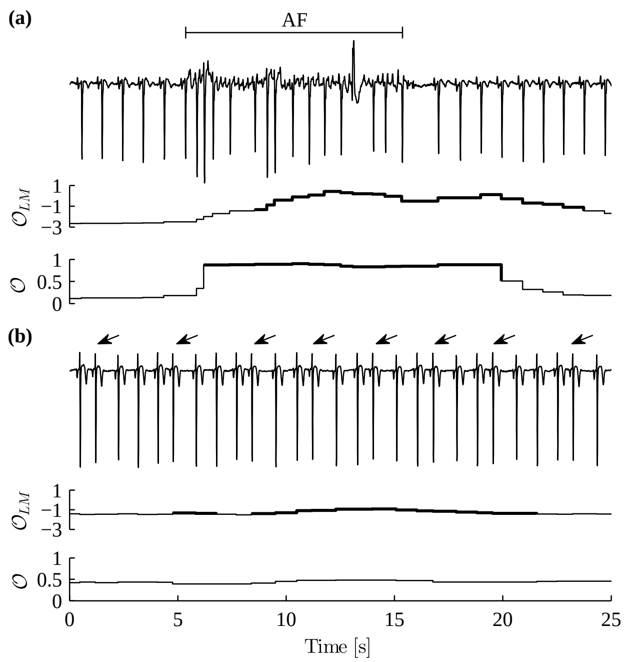

Figure 4. Detection performance on real ECGs with (a) a brief AF episode, (b) several ectopic beats. Thick line marks segments detected as AF.

5. Conclusions

This study shows that combination of parameters characterizing both atrial and ventricular activities and taking into account noise level can provide a solution to reliable detection of very brief episodes of atrial fibrillation in ECG signals.

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