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Detection of Atrial Fibrillation from Non- Episodic ECG Data: A Review of Methods

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Abstract— **Atrial fibrillation (A-fib) is the most common cardiac arrhythmia. To effectively treat or prevent A-fib, automatic A-fib detection based on Electrocardiograph (ECG) monitoring is highly desirable. This paper reviews recently developed techniques for A-fib detection based on non-episodic surface ECG monitoring data. A-fib detection methods in the literature can be mainly classified into three categories: (1) time domain methods; (2) frequency domain methods; and (3) non-linear methods. In general the performances of these methods were evaluated in terms of sensitivity, specificity and overall detection accuracy on the datasets from the Physionet repository. Based on our survey, we conclude that no promising A-fib detection method that performs consistently well across various scenarios has been proposed yet.**

I. INTRODUCTION

Atrial fibrillation (A-fib) is the most common cardiac arrhythmia. While it is not life threatening in itself, persistent cases of A-fib may cause palpitations, fainting, chest pain, or congestive heart failure and even stroke. To effectively treat or prevent A-fib, automatic A-fib detection based on Electrocardiograph (ECG) monitoring is highly desirable. However, accurate detection of A-fib episodes based ECG signals is technically challenging. A-fib can easily go unnoticed as it does not show any severe symptoms, particularly in paroxysmal cases. In such cases, no obvious signs can be visually observed from the ECG signal shortly after or before an episode of A-fib. In this paper, we review recent works which attempt to address this problem. Most of the works employ a two-steps procedure: first extract the features of interest from the ECG signal; then a classifier is built based on the extracted features. In literature, the performances of these methods have been evaluated on the datasets from Physionet [1], an online repository for cardiac arrhythmia data. In particular, three data sets are commonly used: The MIT-BIH Database (AFDB), The Physionet Normal Sinus Rhythm Database (NSRDB) and Atrial Fibrillation Prediction Database (AFPDB).

II. TIME DOMAIN FEATURES FROM ECG

In clinical practice, cardiology experts visually inspect ECG signals to detect any kind of arrhythmia in the heart. In an automated A-fib detection algorithm, this step is translated into feature extractions from the raw ECG signals. The commonly-used parameters extracted from the ECG signals numerically define the P-wave morphology, QRS morphology and RR dynamics.

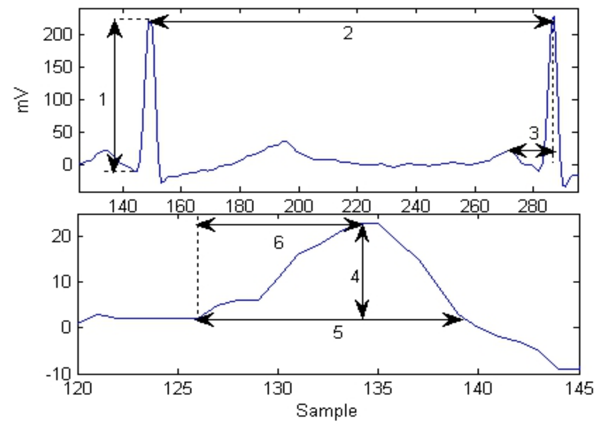

Fig. 1. Illustration of time domain parameters. The top figure shows (1) QR, (2) RR and (3) PR, while the bottom figure shows (4) P_amp, (5) P_wide and (6) P_ini from the zoomed part of the ECG containing P-wave.

A. P-wave morphology

Prolongation of the sinus node recovery time or the increase in the duration of P-wave has been used by physicians as a sign for abnormal atrial activities that could potentially lead to an A-fib episode. The RMS voltage of the filtered P-wave has also been reported as a good feature by many investigators [2]. Apart from these two, some other P-wave related parameters have been considered in the literature. The parameters associated with P-wave morphology are listed below (see Fig.1):

1) *P_amp* : Amplitude of the P-wave.
2) *P_int* : Area under the P-wave.
3) *P_wide* : Width of the P-wave measured for a particular heart pulse.
4) *P_ini* : Time distance of the beginning of the P-wave till its maximum.
5) *PR* : The distance from one P peak to the following R peak.

In order to get the these parameters, each beat in the ECG is identified by detecting the R peaks and a time window is defined where the P-wave can be localized. If multiple P-waves occur in the predefined time window, the average values are computed. In addition, some statistical measurements of these parameters have also been used. In [3], [4] minimum, maximum, mean and standard deviation

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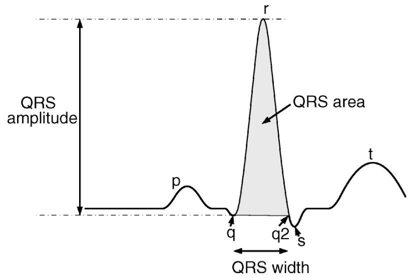

Fig. 2. Measurements for QRS morphology.

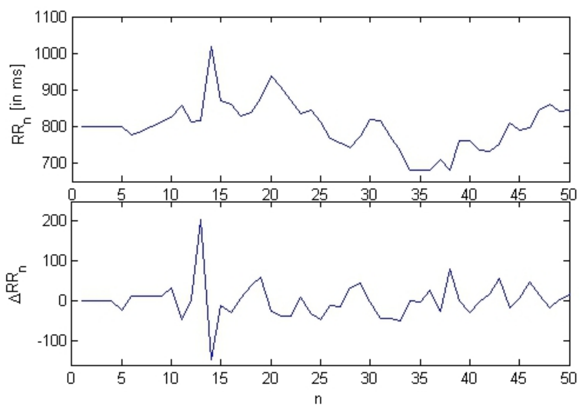

Fig. 3. Example of RR_n and ΔRR_n series

of P_amp, P_int, P_wide, P_ini and PR were taken as features for automated A-fib detection.

B. QRS morphology

In medical context, the occurrence of Atrial Premature Contraction (APC) is associated with A-fib. In the ECG signal, APC manifests as a beat with abnormal QRS morphology. The parameters used in the literature to study the QRS morphology are listed below, and shown in Fig.2.

1) *QR* : Amplitude of the R peak measure from the base of Q.
2) *QRS_int* : Area under the QRS complex.
3) *QRS_wide* : Total time duration for the QRS complex.

The QRS parameters for each pulse are extracted by detecting the R peaks. The minimum, maximum, mean and standard deviation of QRS_wide were employed in [4] as the feature for A-fib classification. In [5] QRS_int was used to to detect APC in a given ECG signal. QRS_int is calculated from QR and QRS_wide using trapezoidal method.

C. RR dynamics

R peak is the most visible point in an ECG signal and it is relatively easy to detect. It is considered as the center of a beat in the ECG, and thus the count of R peaks per minute is our heart beat rate. In recent years, researchers have studied its dynamics to identify any arrhythmia even prior to its onset. Some popular parameters associated with the RR dynamics are:

1) RR_n : Time interval between two consecutive heart beats.

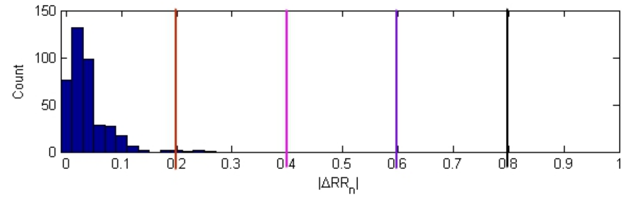

Fig. 4. Example of Histogram of ΔRR_n in seconds

2) ΔRR_n : Excess time taken by the present RR interval from the next RR interval. i.e.

$$\Delta RR_n = RR_n - RR_{n+1} \quad (1)$$

3) *HRV* : Heart rate variability (HRV) is an index that measures the variation of the RR interval over a time duration. HRV is quantitatively defined by many parameters, such as: mean heart rate (HR), standard deviation of NN interval (SDNN), coefficient of variation (CV), the percent of RR intervals above x milliseconds over a time duration (pNNx), etc. A detailed list of HRV-related parameters can be found in [6].
4) *SDSD* : Standard deviation of the time difference in consecutive RR interval. i.e.

$$SDSD = SD|_1^{n-1} \Delta RR_n \quad (2)$$

where SD stands for standard deviation.

RR interval can be generated from a manually-annotated ECG file or automatically through the use of a QRS detector. In [3], [4], [5] the minimum, maximum, mean and standard deviation of RR were considered as detection features. In [7], histogram is plotted for every 0.02 second increment in $|\Delta RR|$. The histogram was divided into four regions, where the mean $|\Delta RR|$ value was calculated for each region and used as features (see Fig.4). In [8], [9], RR time series were normalized to resulting a 15 second heart rate of 60 beats per minute (bpm), then SDSD was calculated as metric to judge the risk factor of occurrence of A-fib.

III. Frequency domain features from ECG

In some research works, authors have extracted frequency domain parameters from the raw ECG signals by transforming the time series data into the frequency domain. Sometimes signals look very similar in time domain, while they become differentiable in the frequency domain. Listed below are the commonly-used frequency domain parameters.

1) *PSD(ECG)* : The power spectral density (PSD) of the ECG time series. There are methods like Periodogram estimator, Auto-regression estimator and Lomb estimator to estimate PSD. Periodogram estimator is the simplest one to implement for uniformly sampled data. As shown in (3), $S(e^{j\omega})$ is the PSD of ECG signal x.

$$S(e^{j\omega}) = \frac{1}{n} |\sum_{l=1}^{n} x_l e^{-j\omega}|^2 \quad (3)$$

2) *PSD(RR_n)* : The PSD of the RR interval time series. An example is shown in Fig. 5.

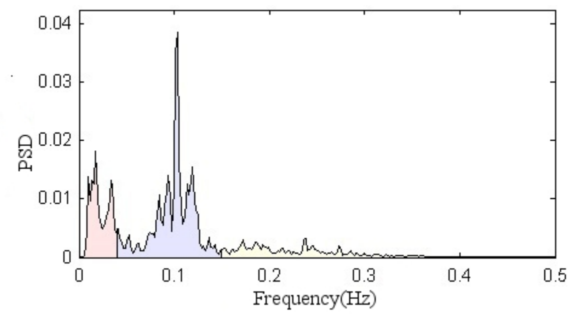

Fig. 5. Example of $PSD(\Delta RR_n)$ using periodogram method.

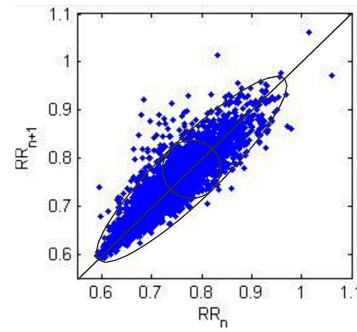

Fig. 6. Example of Poincare plot (RR_n vs. RR_{n+1})

3) *FFT(RR_n)* : Discrete Fourier transform of the RR interval time series using Fast Fourier Transform (FFT).
4) *FFT(HRV)* : The FFT of the heart rate series. Heart rate is the reciprocal of the RR interval.

In [4], the PSD of the ECG signal computed through Lomb and Periodogram methods were used as detection features. In [5], PSD was computed for the $RR(n)$ interval. The correlation between high frequency (HF) and low frequency (LF) was considered as a metric for the first stage of classification. Following this, a 64-point PSD was computed and used as input features in the last stage of classification. In [7], FFT of RR_n was computed and the summation of the absolute value of the coefficients over predefined frequency bands were taken as input features for the classifier, while in [9], the ratio of the integral over predefined frequency bands and the center frequency were taken as features. In [10], 30-min heart rate (HR) segment was interpolated to 2Hz and FFT coefficients were computed for the band 0.01 - 0.5Hz with a sampling interval of 0.01Hz, which results in a 49-points feature vector for A-fib detection.

IV. Nonlinear features extracted from ECG

Efforts have been made to separate the RR dynamics of A-fib and non-A-fib cases through the use of two nonlinear transforms: Poincare Plot [8] and Symbolic Dynamics [11].

1) *Poincare Plot* : It is a plot between RR_n vs. RR_{n+1}. This plot shows the relationship between two consecutive beats. It is intuitive to assume that the plot for a person with normal sinus rhythm will be close to a straight line with slope $45°$. Example of a Poincare plot is shown in Fig.6.
2) *Symbolic Dynamics of* ΔRR_n : The purpose of symbolic dynamics is to study the dynamic behavior in the time series by abstracting the measurement details. It transforms the discrete time series to series with fewer number of symbols. In [11], for example, only 3 symbols $A = \{1, 2, 3\}$ are used. The mapping function of the transform is:

$$Z_n(\Delta RR_n) = \begin{cases} a: & \Delta RR_n < 0 \\ b: & \Delta RR_n = 0 \\ c: & \Delta RR_n > 0 \end{cases} \quad (4)$$

An example of the transformation output is shown in Tab. I.

In [7], [8], [9], prior to the RR_n vs. RR_{n+1} plot, the RR time series are normalized (to get a 15 second heart rate of 60 beats per minute). Then the plotted image was rotated to $-45°$ to facilitate automatic analysis of the plot. Subsequently, analysis was performed by computing the density of the plot on a predefined region. In [11], approximate entropy (ApEn) was computed for each of the "words" obtained from the transformation. Classes were formed by grouping the words with equal approximate entropy, the average number of words per class was taken as the metric to identify A-fib.

V. Detection or Classification Methods

After extraction of the important quantitative features from the ECG signals a classifier was used to learn and automatically determine whether the features belonging to A-fib or non-A-fib cases. There exist many classifier in the literature. In this survey, researchers have employed different classifiers depending on the features extracted.

A. K-nearest neighbor(KNN)

KNN assigns a sample vector to a class which has the majority of vectors in the k nearest neighbors in terms of Euclidean distance. In this classification method, the value of k is optimized for classification accuracy [4]. In [3], KNN was implemented with feature reduction for optimal classification with varying neighborhood k.

B. Bayes Optimal Classifier

In the case of equal priory probability $P(H_i)$, the posterior probability $P(H_i|x)$ can be computed as the likelihood of x with respect to class H_i. So the decision rule takes the form of

$$x \in H_i \quad \text{if} \quad P(x|H_i) = \max_j P(x|H_j) \quad (5)$$

In [4] the aforementioned classifier was used in the specific feature space.

C. Artificial Neural Network(ANN)

In most cases, a neural network is structured with one hidden layer, while the number of hidden neurons and input parameters are optimized for accuracy. Full Error Back Propagation (FEBP) was commonly used to train the ANN (such as in [7], [10], [4]). While in [4] Partial Error Back Propagation (PEBP) and Conjugate Gradient (CG) algorithms were used to train the network.

TABLE I

EXAMPLE OF TIME SERIES TO SYMBOLIC SEQUENCE TRANSFORMATION

$\mathbf{RR_n}$[ms]	650	673	652	638	627	627	632	622	635	653	639	638	638
$\mathbf{\Delta RR_n}$	23	-21	-14	-11	0	5	-10	13	18	-14	-1	0	*
symbols	c	a	a	a	b	c	a	c	c	a	a	b	*
word-1	c	a	a	a	b	c	a						
word-2		a	a	a	b	c	a	c					
word-3			a	a	b	c	a	c	c				
word-4				a	b	c	a	c	c	a			
word-5					b	c	a	c	c	a	a		

D. Linear Discriminant Analysis (LDA)

LDA partitions the feature space into different classes using a set of hyperplanes. Unlike Bayesian classifier, LDA gives a probability estimation y_k of each class for any input feature vector x. Let μ_k be the mean of the feature vectors from class k of the given training samples and Σ is common covariance matrix for the whole training feature vectors. Thus

$$y_k = -\frac{1}{2}\mu_k^T\Sigma^{-1}\mu_k + \mu_k^T\Sigma^{-1}x + log(\pi_k) \tag{6}$$

where π_k is the prior probability of vector x being in class k. LDA was used for A-fib detection in [5], where 64-point PSD of RR were employed as the input feature.

E. Empirical Detector (ED)

Empirical detector involves the derivation of a single or multiple parameters to separate two classes via comparisons with some empirically-found values. This approach is very promising in terms of reducing computational complexity. However, it requires substantial prior knowledge about the classes of data and a selection of good metric for comparison. In [5], the correlation between HF and LF components of RR segment was considered as a metric for the first stage of classification. Subsequently, the area under QRS complex was employed to detect APC, and this information was used in the second stage of classification. The use of empirical detector has also been demonstrated in [8], [9], [11].

VI. DISCUSSION AND CONCLUSION

A. Discussion

The methods that we have surveyed in this paper come with merits and drawbacks. Some methods tend to employ too many ECG parameters to characterize A-fib, which resulted in increased computational complexity. In order to reduce the computational burden some methods have attempted using only several important parameters for the characterization, which resulted the trade-off in the classification performance. A rough comparison of the detection performances can be made from Tab. II, which gathers the published results across the methods (subjects under test are different in many cases). The results on selected patients or segments were published in some cases, which is mainly due to the difficulty in parameter extraction. In addition most of the works in literature have used the ECG segments only prior to A-fib episodes, while the segment preceding A-fib has not been taken into consideration.

TABLE II

COMPARISON OF PER SEGMENT DETECTION ACCURACY PUBLISHED

Ref	SE	SP	Comments
[3]	96.0	88.0	KNN on various time parameters
[4]	’70.0	’70.0	KNN on time/frequency parameters
[5]	46.5	98.6	ED/LDA on time/frequency
[6]	90.5	94.7	ED on HRV parameters only
[7]	84.6	96.5	ANN on time/frequency/nonlinear
[8]	82.9	96.9	ED on time/nonlinear
[9]	96.3	*	ED on frequency
[10]	94.5	96.5	ANN on HRV frequency analysis
[11]	n.a.	n.a.	ED on ApEn of symbolic dynamics

{’xx.x}=overall accuracy calculated combining NSR and A-fib data, {*}=result not published, {n.a.}= no result for non-episodic data.

B. Conclusion

This study has reviewed the techniques developed in recent years on the A-fib detection from non-episodic ECG monitoring data. Considerable progress has been made in A-fib detection throughout the years. However, no promising method has been proposed yet. This is mainly due to lack of precise characterization of ECG signal. Hence searching for better metrics to characterize the ECG signal for A-fib detection is a future direction of work.

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