A Robust Detection Method of Atrial Fibrillation

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Abstract

Atrial fibrillation (AF) is a common atrial arrhythmia occurring in clinical practice and can be diagnosed using electrocardiogram (ECG) signal. A novel method is proposed to detect normal, AF, non-AF related other abnormal heart rhythms and noisy recordings based on the combination of deep features and handcraft features. We used Computing in Cardiology Challenge 2017 database as training set and MIT-BIH atrial fibrillation database (AFDB) as test set. The proposed algorithm was achieved an accuracy of 96.3%, F1 of 95.5%, sensitivity of 88.7% and specificity of 99.6% in MIT-BIH AFDB, better than the method which only adopted deep features or handcraft features. Experimental results show that our method would be a good choice for the detection of the AF.

1. Introduction

Atrial fibrillation (AF) is one of the most common age-related heart disease, accompanied by life-threatening complications such as myocardial infarction and ischemic stroke[1]. It affects 2.2 million people in the United States and 4.5 million in the European Union[2]. The AF can cause uncompleted blood transfer from atria to ventricle and decrease the efficiency of heart functioning. Therefore, early detection of AF and real-time warning of AF crucial for effective treatment, improving the clinical outcomes, and decreasing the costs, which have important clinical and practical significance[3].

The detection of atrial fibrillation is an essential function in the automatic electrocardiogram (ECG) algorithm, and various types of features based on the clinic symptoms such as irregular RR interval and absence of P-wave have been developed [4-5]. However, the prior art methods have certain limitations regarding the clinical deployments. 1) the irregular RR interval is also the characteristic of other kinds of arrhythmia, such as the bundle-branch block [6], and the P-waves are too weak to be correctly detected [7]. 2) Algorithms are mostly applied on carefully selected clean data. However, in practical scenario, ECG signals are often noisy in nature. 3) Most prior arts perform binary classification between AF and normal recordings only. 4) Most of the algorithm are validated on clinically accepted 12 lead ECG signals, recorded for a relatively longer duration.

This paper proposes a method to detect normal, AF, other abnormal rhythms and noisy recording by combining deep features and several kinds of handcraft features. Experiment on MIT-BIH atrial fibrillation database reports 0.96 F1 score, which is better than any of the single types of features.

2. Methods

The fig.1 shows the framework of the proposed method. After filtering the signal, we first extract the handcraft features. Then, we build deep neural networks (DNNs) to automatically extract deep features. We pre-train DNNs on the training data, feed the testing data and extract the last hidden layer as deep features. Finally, we combine handcraft features and deep features together, train several random forest classifiers, and the selected features are classified by these ensemble classifiers together.

2.1. Preprocessing

To eliminate baseline noise, a zero phase Butterworth high pass filter (cut-off frequency 0.5Hz) is applied to each ECG records. Then the Pan-Tompkins algorithm [8] is adopted to detect the QRS complex and the method [9] is used to extract the fiducial points of P, Q, R, S and T waves. Then, the records are split into 10s short records using slide window.

2.2. Feature Extraction

In this section, we will introduce seven kinds of feature extractors in detail: morphological features, prior art AF features, HRV features, phase space features, frequency

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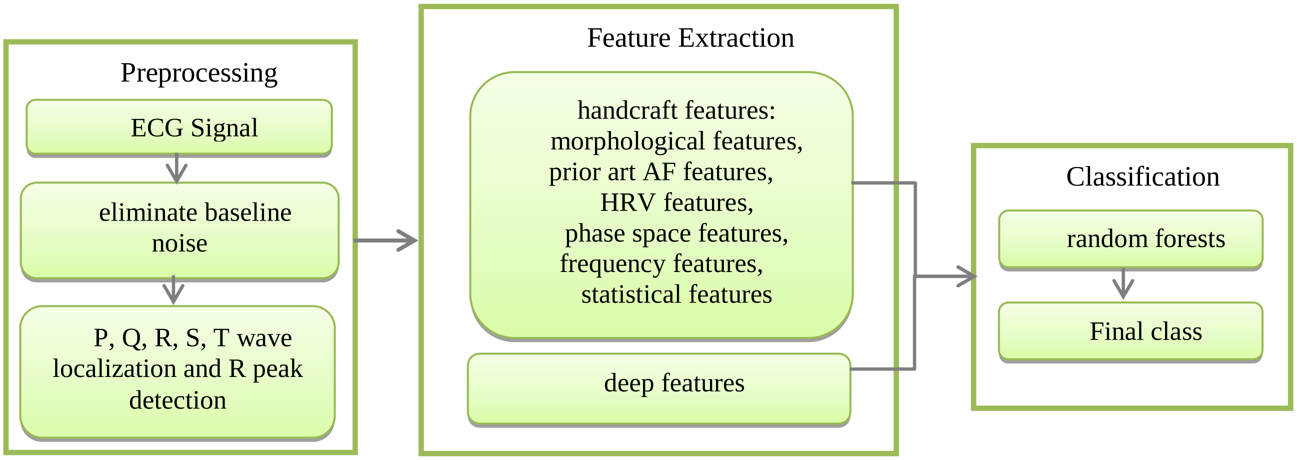

Figure 1. Classification algorithm

features, statistical features and deep features.

2.2.1 Morphological ECG features

ECG morphological features include PR interval, P amplitude, the ratio of P wave number to R wave number, QRS duration, the interval and slope of QR, QT, QS and ST, the distance between the ST segment and other S points, the amplitude of Q, R, S and T waves, and the difference of the amplitude of TR.

The actual signal inevitably contains various noises, so noise is an important indicator to interfere with the AF detection, and it is particularly important to extract noise-related features. The slope and statistical characteristics related to slope of the 10s slice in the frequency domain of the ECG signal are calculated.

2.2.2 Prior art AF features

Considering that RR interval irregularity is an important indicator of AF detection[10], we developed three types of AF prior features related to RR interval and deviation of RR interval (dRR), including: 1) sample entropy, coefficient and density histogram of sample entropy, and threshold of median absolute deviation of RR interval; 2) standard deviation, ratio of standard deviation to mean, density, approximate entropy, sample entropy and coefficient of sample entropy of dRR; 3) interval, duration, amplitude, position, slope and area of the 10s slice, the average RR interval within the 10s slice, the number of samples with a difference in the slice exceeding 0.1mV within the 10s slice, and the normalized power spectral density of the 10s slice; 4) normalized power spectrum at intervals of 0-0.05 Hz, 0.05-0.15 Hz, and 0.15-0.5 Hz of RR .

2.2.3 HRV features

We extract six types of HRV features, including SDNN (standard deviation of all normal heartbeat spacing), normalized RMSSD, NN50count (all pairs of adjacent normal heartbeat intervals in the ECG, the number of gaps over 50ms), pNN50 (NN50 divided by the total number of all normal heartbeat intervals in the ECG), NN20count (all pairs of adjacent normal heartbeat intervals in the ECG, the difference is more than 20ms) and pNN20 (NN20 divided by the total number of normal heartbeat intervals in the ECG)[11].

2.2.4 Phase space features

We calculated phase space feature, based on the probability density function of the the RR intervals' phase space. Let $x(n)$, $n=1,...m$ be the RR intervals, $y(n)$ be the RR intervals' phase space, $y(n)=(x(n),x(n+1),...,x(n+(m-1)t))$, $n=1,2,...,m$. The calculation of RR intervals variability ($RRIV$) was shown in Eq. 1.

$$RRIV = \sum_{i=1}^{N-1}\sum_{j=i+1}^{N} h(r\|y_i(t)-y_j(t)\|) \Big/ C_N^2 \qquad (1)$$

the $\|.\|$ indicates Euclidean distance, h is a step function, m is the embedding dimension and t is the delay time, C is the combination operation, r is the parameter(r>0).

2.2.5 Frequency features

The frequency features of ECG include power and band power of P, Q, R, S, T waves, Shannon entropy, Tsallis entropy, Renyi entropy, and signal to noise ratio of RR interval .

We also developed the entropy based features for the RR intervals, dRR and histogram of dRR through dividing the sample entropy by the threshold of entropy, as shown in Eq. 2.

$$dSaEn(A) = {SaEn(A,d,l\_A)} \big/ {d} \qquad (2)$$

where the *SaEn* be the operators of sample entropy, and *d* be the threshold of entropy, *A* is the input vectors, which is the RR intervals, dRR or histogram of dRR, *l_A* be the length of input vector.

2.2.6 Statistical features

The statistical features of ECG include the number, mean, maximum, minimum, range, variance, skewness, kurtosis, percentage, the linear prediction coefficient (LPC) of P, Q, R, S and T waves.

2.2.7 Deep features

Table 1. The architecture of deep feature extractor

Layer	Output size	Layer size
Conv1	64	16×2
ReLU1	64	
Residual_bottleneck1.x	64	$[16\times 2]\times 2$
Residual_bottleneck2.x	128	$[16\times 2]\times 2$
Residual_bottleneck3.x	256	$[16\times 2]\times 2$
Residual_bottleneck4.x	512	$[16\times 2]\times 2$
ReLU2	512	
LSTM1	256	256×2
Dropout1		
Fc1	4	4
Softmax1	4	

Deep feature extraction was performed based on the deep residual convolution networks (resNet)[12]. The network structure is shown in Table 1. The input is a single heart beat. The output is the class of the rhythm: normal sinus rhythm (N), atrial fibrillation (A), other abnormal rhythm except AF (O) and noise (P).

After training to get the best network structure, we feed the testing data and extract the last hidden layer as deep features, together with the handcraft features, as the input features of the four rhythm recognition classifiers of ECG by classification.

2.3. Classification

We choose random forest (RF) as the classifier. Random forest is one of the most widely used classification models, with high interpretability and good efficiency.

Research shows that the classification accuracy of ensemble classifiers is higher than that of single classifier[13]. We concentrate the above seven kinds of feature vectors into a vector, train several RF classifiers and ensemble them by the average prediction probabilities.

In the experiment, each RF has 1000 trees, and the depth of the trees was optimized adjusting from 2 to 7.

3. Experimental result

We use the dataset provided by Physionet/Computing in Cardiology Challenge 2017 (CINC AFDB) [10] and MIT-BIH atrial fibrillation database (MIT-BIH AFDB) for the training and test respectively. The detail of the two dataset can be found in [15].

In the training set, the records are labeled with 4 classes: N, A, O and P. The CINC AFDB was randomly divided into training set (70%) and validation set (30%).

In the test set, the records are labeled with 2 classes: normal sinus rhythm (N) and atrial fibrillation (A).

The 10-fold cross validation was used to optimize the parameters of RF and phase space features. The sensitivity (Se), specificity (Sp) and accuracy (Acc) are calculated to measure the performance of the proposed method, which are defined as:

$$Se = TP / (TP + FN) \tag{3}$$

$$Sp = TN / (TN + FP) \tag{4}$$

$$Accuracy = (TP + TN) / (TP + TN + FN + FP) \tag{5}$$

Three state-of-the-art methods [11-15] were used to compared with our method. The McNemar’s test was used to estimate the significant difference between the methods.

The experimental results are summarized in Table 2. The proposed method was achieved an accuracy of 96.3%, F1 of 95.5%, sensitivity of 88.7% and specificity of 99.6% in MIT-BIH AFDB, significantly better than results reported by baseline methods in MIT-BIH AFDB.

Table 2. Detector performance compared on CINC AFDB and MIT-BIH AFDB

Method	CINC AFDB		MIT-BIH AFDB				
	validation	train	Acc	F1	AF Se	AF Sp	P Value
Ours	0.965	0.971	0.963	0.955	0.887	0.996	-
Datta et al [10]	0.970	0.990	0.96	0.951	0.886	0.991	0.001
Hong et al [11]	0.968	0.990	0.954	0.942	0.859	0.992	0.001
Bin et al [12]	0.875	0.870	0.931	0.914	0.809	0.983	<0.001

4. Discussion

Table 3. Results of different feature extraction methods

Method	$F1_N$	$F1_A$	$F1_O$	$F1_P$	$F1_{NAO}$
Deep feature	0.918	0.952	0.902	0.888	0.924
Handcraft feature	0.978	0.939	0.798	0.668	0.905
Combination	0.982	0.979	0.928	0.892	0.963

Table 3 compares the performance of three different types of feature on the test set of MIT-BIH AFDB. The results show that the combination of the depth feature and the handcraft feature is the best. In generally, the deep feature can extract the local information of the ECG signal, and the handcraft feature can represent the global and local information, so the combination of both two types of feature can achieve a better result than the individual technique. For the classification of normal and other kinds of records, the global and local information would be considered, so the handcraft feature is better than the deep feature. For the other rhythms, the deep feature have more power represent ability than the handcraft feature.

5. Conclusion

This paper proposes a method of atrial fibrillation detection combining deep features and handcraft features. we first extract extract handcraft features. Then, we build DNNs to automatically extract deep features. Finally, we combine handcraft features and deep features together, and the selected features are classified by RF classifiers. Experiment on MIT-BIH atrial fibrillation database reports 0.96 F1 score. Our method would be a good choice for the detection of the AF.

In the future, we will be pay more attention to the following issues: 1) reduce noise interference in the collected ECG signals; 2) simply the deep feature extractor and decrease computational time. 3) improve the robustness of the proposed AF detection algorithm.

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