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Automatic Atrial Fibrillation Detection Using Autoregressive Modeling

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Abstract. In this paper we have investigated the use of autoregressive modeling for atrial fibrillation episode detection. We considered AR coefficients of each 15 second segment of ECG as our features and compared the performance of three different statistical classifiers: SVM, LDA, and nearest neighbor classifier. The performance of the algorithm was evaluated on signals from MIT-BIH Atrial Fibrillation Database. The best obtained sensitivity, specificity, and positive predictivity were 96.14%, 93.20%, and 90.09%, respectively. Then, we examined the effect of signal length and model order on the classification results.

Keywords: Atrial Fibrillation (AF), Autoregressive (AR) model, Statistical classifiers

1. Introduction

Atrial fibrillation is one of the most common cardiac arrhythmia in old people all over the world. During AF, the heart's atria quiver instead of beating regularly. As the blood isn't pumped completely out of them, there might be blood clot formation in atria. So, it might increase the risk of stroke [1], [2].

Electrocardiogram (ECG) is one of the most valuable non-invasive tools for AF detection. The heart's status in AF is reflected in the ECG by three main distinguishing features:

- Absence of P waves,
- Fluctuating waveforms (called f-waves) instead of P waves,
- Irregular heart rate.

For each feature, there are several methods to detect AF [1]. RR interval based methods are proposed in [2-4], and methods based on P wave are presented in [5], [6]. There are some limitations in RR and P wave based methods [1]. When AF occurs with regular ventricular rates, or when the ECG changes rapidly between rhythms, RR interval based methods fail in accurate detection [7]. Due to small amplitude of P waves, determining the absence or presence of P waves is not easy [2]. So frequency domain techniques have been proposed to investigate the atrial activity during AF [8-12]. But as the fibrillatory waveform power is much smaller than ventricular waveform, QRST cancellation is usually needed to cancel the ventricular activity before FFT is applied. This cancellation process may be difficult in presence of noise [1] and usually involves high computation.

AR coefficients have been used for beat classification in [13]. In this paper, we will investigate the use of autoregressive modeling for discriminating between AF and non-AF episodes. We evaluated the proposed algorithm on segments selected from MIT-BIH Atrial Fibrillation Database [14]. In section 2, the proposed algorithm is presented, and the results are given in section 3. Conclusion is stated in section 4.

2. Method

2.1. Preprocessing

The first step in our algorithm is dividing the signal into desired length. After segmentation, we considered each segment as a column of a matrix for compact notation and used median filtering [15] to remove the baseline wander present in the signal.

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2.2. Feature Extraction

In AR modeling, each segment is considered to be the output of a linear system whose input is assumed to be white noise of zero mean and unknown variance as:

$$\sum_{k=0}^{M} a_k u(n-k) = v(n)$$

where M is the model order, u(n) is the ECG segment, v(n) is the white noise, and a_k's are the AR coefficients [13].
We computed AR model parameters using Burg method and the model order was selected experimentally.

2.3. Classification

Then we used the obtained AR coefficients as the input for our classifier. We examined the performance of three different classifiers: SVM, LDA and k-NN.

2.3.1. Support Vector Machines (SVM)

SVM finds the plane with maximum margins by focusing on the training cases placed at the edges of the class descriptors. Given a training set $\{(x_i,d_i)\}$, the SVM algorithm is summarized as :

$$\min: \tfrac{1}{2} W^T W \text{ (quadratic problem)}$$
$$\text{subject to: } d_i (W^T x_i + b) \geq 1$$

By using Lagrange multipliers $\alpha_i \geq 0$, the original problem is transformed into the dual problem. From the Kuhan-Tuker theory we have

$$\alpha_i [d_i (W^T x_i + b) - 1] = 0$$

which means only the points with functional margin unity, which are called the support vectors, contributes to the output function [16] . In our experiment, we just used linear SVM for classification.

2.3.2.Linear Discriminate Analysis (LDA)

A linear discriminate function can be written as

$$g(x) = w^T x + w_0,$$

where w is the weight vector and w_0 is the bias or threshold weight. A two-category classifier for AF episode detection is implemented using the following decision rule:
If $g(x) > 0$, then x belongs to AF category and if $g(x) < 0$, x belongs to non-AF category. If $g(x) = 0$, x can be assigned to either classes or can be left undefined. The equation $g(x) = 0$, defines the decision surface that separates points assigned to category one from points assigned to category two [17].

2.3.3.K-nearest neighbor (K-NN)

In the K-nearest neighbors rule, a new vector x (belonging to an unknown class) is classified on the basis of the nearest mean vector. The distance between vector x and the centroid of the jth cluster z^j is computed as the Euclidean distance:

$$d_j = \sqrt{\sum_{i=1}^{n} (x_i - z_i^j)^2}$$

where j is the cluster index, i the parameter index, and n is the number of the parameters used. Vector x is classified to class j at which d_j is minimum [18]. We selected the value of k as 1.

3. Results

In order to evaluate the performance of our algorithm, we used the MIT-BIH Atrial Fibrillation Database [12], which consists of 23 ten hours signals. We determined the start and end points of AF episodes according to the cardiologist's annotations and then divided each signal to AF and non-AF signals with regard to these points. As it was suggested in [1], we divided each signal into 15-second segments. We randomly selected 1250 AF segments and 1250 normal segments from our created segment database. After calculating the features, we removed the outliers from our database prior to classification process.

Three measures were used to compare the proposed method with other methods. They are:

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Positive\ Predictivity = \frac{TP}{TP + FP}$$

If an AF beat is classified as AF, it is said that the beat is classified as TP, and if it is classified as normal, it is called FN. If a normal beat is classified as normal, the beat is classified as TN, and if it is classified as AF, it is called FP.

The results of our method are shown in Table 1. As it can be seen from Table 1, linear classifier achieves the best results among the three classifiers.

Table 1: Classification results of our algorithm

Classifier	*Sensitivity (%)*	*Specificity (%)*	*Positive Predictivity (%)*
Linear	96.14	93.20	90.09
Linear SVM	95.71	92.92	89.69
NN	93.57	92.19	88.51

Next, we would investigate the effect of segment length on classification results. For this purpose, we divided the signals into 5, 30 and 60 second segments. The total number of segments used for examination before outlier removal for 5, 30 and 60 second segments were 3800, 640 and 320, respectively. The classification results with linear classifier for different model orders and different lengths are shown in Tables 2-5.

Table 2: Classification results for 5-second segments

Model order	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
Sensitivity(%)	78.38	83.72	88.13	90.49	89.47	89.88	89.17	90.72	88.72	91.76
Specificity(%)	87.88	86.71	87.59	88.09	87.16	87.76	88.60	87.34	90.08	87.73
P.Predictivity(%)	83.58	83.54	84.70	85.86	84.81	85.46	86.08	84.74	87.48	85.34

Table 3: Classification results for 15-second segments

Model order	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
Sensitivity(%)	85.28	86.96	91.86	94.76	95.29	95.67	96.14	95.29	96.29	94.01
Specificity(%)	88.34	91.51	91.51	91.39	90.07	91.78	93.20	91.77	89.47	93.13
P.Predictivity(%)	82.34	86.84	87.17	87.62	85.94	88.28	90.09	87.91	85.15	89.46

Table 4: Classification results for 30-second segments

Model order	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
Sensitivity(%)	84.21	88.33	92.06	96.21	96.18	94.38	94.08	94.64	93.37	92.90
Specificity(%)	91.17	92.08	90.18	91.30	91.58	93.26	95.81	92.60	93.80	93.47
P.Predictivity(%)	89.15	90.86	88.92	90.66	91.09	92.46	95.21	91.64	92.81	92.63

Table 5: Classification results for 60-second segments

Model order	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
Sensitivity(%)	91.16	90.66	93.06	93.75	95.38	95.98	94.80	94.77	95.38	95.35
Specificity(%)	91.96	91.96	89.23	88.83	90.00	88.54	95.29	92.78	92.75	92.59
P.Predictivity(%)	90.16	91.16	88.46	88.24	89.67	88.36	94.80	92.09	92.18	92.13

4. Conclusion

In this paper we have investigated the use of autoregressive modeling for atrial fibrillation episode detection. We compared the performance of SVM, LDA, and NN classifier on signals from MIT-BIH Atrial Fibrillation Database. LDA achieved the best results among the three classifiers. Then, we examined the effect of signal length and model order on the classification results. The minimum misclassified segments were achieved in 60-second segment, but selecting the desired length and order depends on the required precision and computational resources. The advantages of our algorithm are its real-time capability of AF detection, not needing processes such as QRST cancellation and R peak detection which might be hard in presence of noise.

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