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Support Vector Machine Algorithm for Real-Time Detection of VF Signals

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Abstract

An algorithm for detecting ventricular fibrillation (VF) by the method of support vector machine is presented. The algorithm first extracts the feature of electrocardiogram in every 4s sliding window by the improved time delay method and the parameter d is obtained as feature; the support vector machine method is used to realize the discrimination of VF and non-VF signals. For evaluating the new algorithm, the complete BIH-MIT arrhythmia database and the CU database were used to simulate without any pre-selection. The sensitivity, specificity, positive predictability and accuracy were calculated and compared these values with results from an earlier investigation of several different ventricular fibrillation detection algorithms. It shows that the new algorithm has good performance and has greater advantages in real-time execution.

Keywords: ventricular fibrillation (VF); electrocardiogram (ECG); Time-Delay algorithm; Support vector machine (SVM)

1. Introduction

Sudden cardiac arrest is a major public health problem and one of the leading causes of mortality in western world. In most cases, the mechanism of onset is a ventricular tachycardia that rapidly progresses to ventricular fibrillation [1]. Therefore, it is very important to build reliable and portable ECG monitoring equipment for prediction and prevention of ventricular fibrillation.

In this paper, we proposed a new algorithm, which was based on support vector machine and time delay method. The SVM method is based on statistical learning algorithm for finite samples. It has

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specific advantages in solving small samples, nonlinear and high dimensional pattern recognition problems [2]. The improved time delay method was utilized to extract features of ECG signals. Then the support vector machine method was used to discriminate VF and non-VF signals based the extracted feature.

To gain insight into the quality of an algorithm for ECG analysis, it is essential to test the algorithms with a large amount of data under equal conditions, which have already been annotated by qualified cardiologists [3]. Commonly used annotated databases are Boston's Beth Israel Hospital and MIT arrhythmia database (BIH-MIT)[4], the Creighton University ventricular tachyarrhythmia database (CU)[5], and the American Heart Association database (AHA)[6]. In this paper, the method was applied on the complete BIH-MIT database and CU database in [7], and there were about 277163 results in all. We also calculated sensitivity, specificity, positive predictability accuracy, and compared the parameters with other conventional algorithms.

2. Material and Method

2.1. Support Vector Machine (SVM)

The technique of SVM [8], which was developed by Vapnik, is a new machine learning technique developed on statistical learning theory. It is proposed essentially for classification problems of two classes, including linearly separable case and non-linearly separable case. It has great advantages in processing problems, such as classification and pattern recognition. The algorithm is as following:

Consider a dichotomy defined by a set of N independent observations with distribution of the sample: $\{(x_1, y_1)\ (x_2, y_2) \ldots (x_l, y_l)\} \subset R^N \times \{\pm 1\}$, where the data point x has to be classified positive if y=+1 or negative if y=-1.

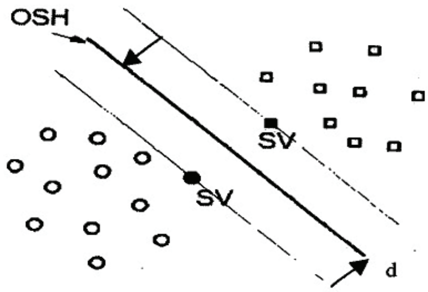

Fig.1 Illustration of the Optimal Separating Hyperplane

For linearly separable cases, it is the basic ideal of finding the optimal separating hyperplane (OSH) (Fig. 1). The hyperplane is defined by the equation:

$$(w_0 \bullet x) + b = 0 \qquad (1)$$

Where $\|w_0\|=1/d$, and d is the distance of the support vectors (SVs) from the hyperplane; b is the offset and x is a vector or input signal [9].

The OSH is obtained from support vectors (SVs). The SVs are individuals from each class that are chosen as representative of their classes. They are also chosen to minimize their distance to the hyperplane.

In Fig. 1, two different classes and the optimal separating hyperplane (OSH) are shown. We can see that the distance from the SVs to the hyperplane is the shortest.

To obtain the OSH, it is necessary to maximize the margin d, thus it can minimize the norm w_0. Lagrange multipliers α_i are used. An α_i is assigned to each vector of the training set, with α_i being non-zero for the SVs only. Hence, once α_i are obtained, the OSH unknown parameters are calculated as

$$w_0^* = \sum_{i=1}^{l} \alpha_i^* \bullet y_i \bullet x_i \tag{2}$$

And

$$b^* = \frac{1}{2} \cdot [(w_0^* \bullet x^*(1)) + (w_0^* \bullet x^*(-1))] \tag{3}$$

Where $x^*(1)$ and $x^*(-1)$ are SVs from classes $+1$ and -1 respectively. The values y_i are the class labels corresponding to each SV and b is the offset value of the OSH [9].

Having defined the OSH, the identification of the class of a new input test signal, x_{test} is reduced to

$$f(x) = sign\{ \sum_{vectores-soporte} \alpha_i^* \bullet y_i \bullet (x_i \bullet x) + b^* \} \tag{4}$$

If the sign is positive, the vector or test signal x_{test} will belong to the class defined with the label +1, and if it is negative, to the class -1.

For non-linearly separable cases, kernel functions are used to construct the OSH, so classification function changes to

$$f(x) = sign\{ \sum_{vectores-soporte} \alpha_i^* \bullet y_i \bullet K(x_i \bullet x) + b^* \} \tag{5}$$

To the kernel functions, mapping functions and feature spaces are corresponded. Once kernel function K(x, y) is defined, it means that the mapping function and feature space F are defined. Thus the selection of kernel function determines the performance of SVM.

2.2. Time Delay Method

The time delay method [3], which is also called phase space reconstruction (PSR), identifies a dynamic law or random behavior of ECG signals by reconstructing the so called phase space.

The method was implemented by plotting the original signal $x(t)$ on the x-axis and $x(t+\tau)$ on the y-axis. Based on the phase space plots ($x(t), x(t+\tau)$), the VF and non-VF can be differentiated by calculating the area of the plot filled by the curve. This is achieved by applying a 40×40 squares grid to the phase space diagram and counting the number of boxes filled by the curve. Then, the parameter d was calculated by the following formula:

$$\mathrm{d} = \frac{\text{number of visited boxes}}{\text{number of all boxes}} \tag{6}$$

VF episode is only recognized if d is higher than d_0. Here, the d_0 is a certain threshold.

Given the time delay method was used to extract ECG feature in this paper, some improvements of the time delay method were made as following:

- To simplify the computation, a 20×20 grid is produced and the grid stretches from the minimum to the maximum of the investigated raw ECG signal. The number of boxes is 400 after improvements [10].

- In the new algorithm, the sliding window length was set as 4s instead of 8s. The 4-s-length can not only extract the feature value we need, but also guarantee the real-time property of the signal.
- For the new algorithm, we only calculate a measure d, and make it as an input vector for SVM algorithm. So, it is not necessary to choose the threshold d_0 .

2.3. Implementation of New Algorithm

The flow of the new algorithm is as following (Fig. 2):

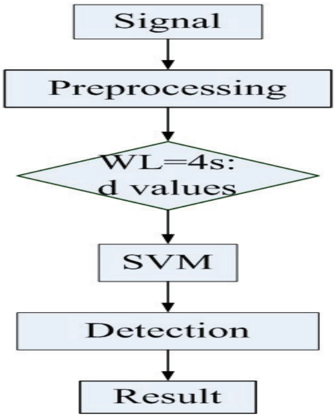

Fig.2 The flow chart of new algorithm

- Preprocess the ECG signal $x(t)$;
- In every 4s sliding window, Distribute $x(t)$ and $x(t+\tau)$ signal in the 20×20 grid and reconstruct phase space, in which extract feature value d. Here, $\tau = 0.5s$.
- Input the feature d into the binary support vector machine. If output is 1, it is non-VF signal, 0 for VF signal.

The new algorithm was carried out in matlab routine. During the simulation, the SVM package of Lu Zhenbo (SVM_luzhenbo, The package can be download on the website [11]) was utilized.

In order to obtain a prediction model, the data under study are divided into two sets. A training set, which is used to estimate the model, and a test set, independent of the training set, which is to determine the model's discrimination ability. In this paper, 10s episode from VF and non-VF signals are respectively chosen as the training set. Process these signals as above, thus we can obtain the optimal hyperplane and get the classification model. The rest of data is treated with the same processing as the test set. They are used to determine the model's discrimination ability.

The kernel function used in this paper was Polynomial kernel function. The formula is

$$K(x, x_i) = [(x \bullet x_i) + 1]^q \tag{7}$$

Polynomial kernel has strongest generalization ability than other kernel functions, and the ability decrease with the increase of order q. So the order q should not be too large. The parameters were chosen by trial and error method (method of exhaustion) [12]. In final, the parameters of the package were set as q=2, C=150.

3. Evaluation and Result

The data sets were taken from BIH-MIT database and CU database. Because the sampling frequency of application test equipments was 200HZ, the chosen signals, which recorded at a sampling of 250HZ or 360HZ, were resample to 200HZ. For the new algorithm tested in this paper, we used the same prefiltering process as in [13].

The filtering algorithm works in four successive steps: Firstly, the mean value of the signal is subtracted from the signal; Secondly, a moving averaging filter is applied in order to remove high-frequency noise; thirdly, a drift suppression is carried out. This removes slow signal changes, which originate from external sources and are not produced by the heart; lastly, a Butterworth filter with a cutoff frequency of 30 Hz eliminates frequencies higher than 30 Hz, which seems to be of no relevance in our simulations.

The data sets were taken from the BIH-MIT database (48 files, 2 channels per file, each channel 1805s long), the CU database (35 files, 1 channel per file, each channel 508s long). Thus, the total number of decisions per algorithm (window length = 4 s) is 48• 3• (1805 - 3) + 35• (508 - 3) = 277163. The quality parameters are presented in the following table.

Table 1 shows the values for the Sensitivity, the Specificity and the corresponding values for other algorithms investigated in [13]. They are threshold crossing intervals algorithm (TCI), VF filter algorithm (VF), spectral algorithm (SPEC), complexity measure algorithm (CPLX), and PSR algorithm.

Table 2 shows the values for the Positive Predictability, the Accuracy of the new algorithm.

Table 3 shows the overall results of the new algorithm to the complete MIT and CU database. They are directly calculated from all 277163 decisions.

Table 1 Quality of ventricular fibrillation detection algorithms: sensitivity, specificity in percent.

DB		**MIT DB**		**CU DB**	
parameter	***wl***	***Se***	***Sp***	***Se***	***Sp***
TCI	8s	74.9	83.9	71.0	70.5
VF	8s	29.4	100	30.8	99.5
SPEC	8s	23.1	100	29.0	99.3
CPLX	8s	6.3	92.4	56.4	86.6
PSR	8s	74.8	99.2	70.2	89.3
SVM(TD)	4s	70.7	85.3	68.6	85.1

Table 2 Positive predictability (Pp), accuracy (Ac) in percent of the real time of the data.

DB		**MIT DB**		**CU DB**	
parameter	***wl***	***Pp***	***Ac***	***Pp***	***Ac***
TCI	8s	0.8	83.9	38.9	70.6
VF	8s	82.4	99.1	94.5	85.2
SPEC	8s	60.6	99.8	92.0	84.6
CPLX	8s	0.1	92.3	52.7	80.3

DB		**MIT DB**		**CU DB**	
parameter	***wl***	***Pp***	***Ac***	***Pp***	***Ac***
PSR	8s	13.4	99.2	65.0	85.1
SVM(TD)	4s	1	85.3	54.4	80.0

Table 3 Overall quality in percent of CU&MIT database using the new algorithm

DB	**CU & MIT DB——overall result**			
parameter	***Se***	***Sp***	***Pp***	***Ac***
SVM(TD)	68.7	85.1	9.7	84.8

4. Discussion and Conclusion

In real application of AEDs, the specificity is more important than the sensitivity. That is because no patient should be defibrillated due to an analysis error which might cause cardiac arrests [3]. Therefore, a low number of false positive decisions should be achieved, even if it can increase the number of false negative decisions.

As shown in Table 1, the new algorithm's Specificity is better than Sensitivity. What's more, our new algorithm has good performance with short window length compared with other algorithms.

The length of the sliding window was set as 4s, which can not only extract the feature value we need, but also guarantee the real-time property of the signal. It made the ECG signal easy to process and achieved the real-time requirement of portable ECG monitor. The presented algorithm for feature selection, time delay method, played a key role in this algorithm.

After do this algorithm some improvements, the algorithm can be embedded into the remote heart monitor device to achieve real-time monitoring of ventricular fibrillation. When the VF is detected, the system alarms through the wireless communication equipment and then the patient can obtain timely and effective rescue.

Acknowledgements

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