Detection Ventricular Tachycardia and Fibrillation using the Lempel-Ziv complexity and Wavelet transform

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Abstract: - Detection of ventricular tachycardia (VT) and ventricular fibrillation (VF) is crucial for the success of saving the patient's life. The complexity of the heart signals has changed significantly when the heart state switches. In this study we proposed a novel method for detection of ventricular fibrillation (VF) and ventricular tachycardia (VT), based upon the Lempel-Ziv complexity and Wavelet transform. With Mallat's pyramidal algorithms, first decomposed electrocardiogram (ECG) signals and reconstructed it into approximate and detail coefficients. Then the complexity of each scale was used as a feature to be sent to SVM classifiers. Furthermore, other classification VT and VF methods were used. The experimental results showed the proposed method could successfully distinguish VF from VT with the highest accuracy up to 99.50%.

Key-words: Ventricular Fibrillation, Ventricular Tachycardia, the Lempel–Ziv Complexity, Mallat's Pyramidal Algorithms.

1 Introduction

In recent years, sudden cardiac death (SCD) is the most serious symptom of arrhythmia and performance, if treatments are not taken timely, SCD means the end of life; because of that, many national medical departments of health and biomedical research center are conducting the research. The research and experiment show the vast majority of cases of SCD are due largely to ventricular fibrillation (VF) and ventricular tachycardia (VT). Therefore, it is very pressing for the researchers to put forward a kind of efficient automatic detection of VT and VF algorithm.

Various VF and VT detection methods have been proposed for Electrocardiogram (ECG) arrhythmia recognition in the literature, such as time domain, frequency domain, time-frequency domain, the combination of ECG parameters in different domains and nonlinear analysis method. Time-domain methods, include autocorrelation analysis [1], a regression test on the autocorrelation function [2], a sequential hypothesis testing algorithm [3, 15, 17] and others, are used to analyze the morphology of the ECG. Frequency–domain measurements motivated by experimental studies supporting that VF is a certain degree of spatio-temporal organization exists. Time-frequency domain methods [7-8] mainly include the short-time Fourier transform, Wigner distribution, Choi-Williams's distribution, the wavelet transforms and etc. In the method of combination of ECG parameters in different domains, a set of temporal and spectral features that selected

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by the statistical learning algorithms such as clustering method, support vector machines and others [4,5,6,13,14,16]was used as input variables of a neural network. Nonlinear analysis methods haven put the nonlinear of VT and VF into consideration. A lots of nonlinear analysis methods for classification of VT and VF haven been proposed in recently decade, such as Lyapunov exponent method [26], correlation dimension method [27], approximate entropy and modified approximate entropy method [23,30], sample entropy and modified sample entropy method [24], empirical mode decomposition method [29] and the Lempel-Ziv complexity algorithm [9,10,11,12,18,19].

In 1976, Lempel and Ziv [18] suggested the Lempel-Ziv complexity algorithm for sequences of finite length. Zhang et al. [20] was first used a complexity-based method for VF and VT detection in 1999. The detection of Sinus rhythm (SR)、VT and VF achieved 100% for the 7s data length. In recently year, the Lempel-Ziv complexity algorithm has been widely applied to the biomedical signals including schizophrenia [9], mechanomyography [12], study brain function [21], EEG complexity in patients with Alzheimer's disease [10,11] and epileptic seizures [22],. However, this method is not suited for the short data lengths and noisy recordings in physiological signals.

The origin of Wavelet happened in the late 70's created by J.Morlet, which enabling analysis signals at different scales of time and frequency. The wavelet transform (WT) decomposes a time series into components in various frequency subbands or scales with various resolutions. It is a time-scale representative for the analysis of non-stationary signals particularly that has been applied to a variety of fields including detection of the onset of epileptic seizure [25, 29, 31], analysis of VT and VF [28].

Support vector machines (SVM), has been suggested as a useful approach to improve the detection efficiency. SVM is based on structural risk minimization principle and can construct an Optimal Separating Hyperplane (OSH) in the feature space. With the minimum risk of misclassification, the OSH can classify both the training samples and the unseen samples in the test set [4].

The paper is organized as follows. Section 2 introduces the methods, including data collection and preprocessing, ECG signals decomposition, the calculation of the complexity and classification. Section 3 first makes a widely comparison of the LZ complexity and our proposed method, and then report results of applying SVM classifiers to discriminate VF and VT. In the last, the sample entropy (SampEn) method is used to compare with our proposed method. Finally, Section 4 includes the conclusions.

2 Methods

Our proposed method first using the wavelet transform decomposes ECG time series into five scales. The sum of all these scales is equal to the original time series. The components are further subjected to calculate the LZ complexity. After that the got results are as the feature to be sent to SVM classifiers. The above description may be expressed as follows.

2.1 Data collection and preprocessing

ECG signals from MIT-BIH Malignant Ventricular Ectopy Database (MIT-BIH Database) and Creighton University Ventricular Tachyarrhythmia Database (CU Database) were considered. No preselection of ECG episodes was made. A total of 35 single-channel records are contained in CU Database, each containing an average of 8 min; while in the MIT-BIH Database, it contains 23 records and each record is about 35 minutes. From this record, 200 samples and 250 Hz sampling frequency were used. 100 VF episodes and 100 VT episodes are respectively extracted from CU Database and MIT-BIH Database. The data length is four-second times. A general signal preprocessing that called normalized was done. Each sample was normalized to center it at zero mean and scale it to unit standard deviation.

2.2 ECG signal decomposition

To obtain the most essential information regarding the evolution behaviors of the dynamic system: heart, decompose the ECG series into a set of components is particularly useful. The wavelet transform decomposes a time series into components in various frequency subbands or scales with various resolutions. It provides a framework for studying how frequency content changes with time. In this paper, we used the reconstruction formula of Mallat's algorithm to get five scales that decreased the frequency of ECG [31].

For a closed space $\{V_j\}_{j\in Z}$, $\forall f(t)$, $f(t)\in V_0$, we can decompose it into detail part W_1 and large-scale approximation part V_1, after that V_1 is deeply decomposed. Repeat this progress and we can get any scale of detail part and approximation part.

For space V_{j+1}、W_{j+1}, supposing $\phi(t)$ is the scale function and $\psi(t)$ is the wavelet function

$$c_{j+1,k} = \sum_m h_0(m-2k)c_{j,m} \quad k \in z \tag{1}$$

$$d_{j+1,k} = \sum_m h_1(m-2k)c_{j,m} \quad k \in z \tag{2}$$

While $h_0(n)$ and $h_1(n)$ are defined by Eq.(3) and Eq.(4)

$$h_0(n) = \langle \phi, \phi_{-1,n} \rangle \tag{3}$$

$$h_1(n) = \langle \psi, \phi_{-1,n} \rangle \tag{4}$$

$c_{j,k}$ is the scale coefficient and $d_{j,k}$ is the wavelet coefficient.

Similarly, the reconstruction formula can be defined according to the decomposition of coefficients for the same function f(t) .

$$c_{j-1,m} = \sum_k c_{j,k}h_0(m-2k) + \sum_k d_{j,k}h_1(m-2k)$$
(5)

2.3 Calculate the complexity

Because when the heart state switches from normal sinus rhythm to VT or VF, the complexity of the heart signals has changed significantly. After we got the scales of ECG signals, calculated the complexity of them and got the accuracy for detection. Repeat this until other scales were calculated.

The Lempel-Ziv (LZ) complexity algorithm was a measure that with the increase of the length of the sequence, the new model was also increases. This algorithm showed the approximate of the finite sequence and the random sequence. The greater of the LZ complexity degrees of the sequence, the sequence is more tend to be random. The LZ complexity of the ECG signals reflects the size of the cardiac information and then reveals the relevant rule of the heart.

The LZ complexity analysis, which based on a coarse-graining of the measurements, so a discrete-time signal *X* of *N* samples (*X* $= X_1, X_2 ... X_N$) must be converted into a sequence of symbols $S(s_1, s_2 \cdots, s_N)$, in which each s_i is a character of a finite alphabet A=0,1. $c(n)$ (n is the length of the sequence) is the LZ complexity of the sequence S. Then the number of distinct patterns P contained in S is determined.

The specific algorithm is expressed in [10].

2.4 Classification

In order to improve the detection precision, we used SVM classifier to discriminate VF and VT. To evaluate the generalization capability of the SVM and RVM models, data consisted of training and testing. In recent years, SVM algorithms have been successfully used in a wide number of practical classification problems, due to their good generalization capability derived from the Structural Risk Minimization principle [4,32].

Suppose the linear separable sample set is (x_i, y_i), $i = 1,2,\ldots n$, $x \in R_d$, and $y \in 1,-1$ denotes the class label. The idea of SVM algorithm is to locate Optimal Separating Hyperplane (OSH) , while OSH can separate the samples without error and maximize the distance from either class to the separating hyperplane. The OSH must satisfy the following condition if its can classify all the samples correctly [4]:

$$y_i[(wx_i + b) - 1] + \xi_i \geq 0,\ i = 1,2,\ldots,n \tag{6}$$

where ξi is slack variables.

Under the constraints of Eq. (6), the optimal discriminate function is

$$f(x) = \operatorname{sgn}\{\sum_{i=1}^{n} a_i^* y_i K(x_i, x) + b^*\} \tag{7}$$

where K(x,x') is a kernel function.

By minimizing following formula under the constraints of Eq. (6), the generalized OSH is determined

$$\phi(w) = \frac{1}{2}(ww) + C(\sum_{i=1}^{n} \xi_i) \tag{8}$$

3 Results

A sample of ECG epochs from MIT-BIH Database and CU Database are plotted in Fig.1. From the first five wavelet coefficients showed in Fig.3. We can find the waveform of the first IMF of VT and VF is not uniform. This is exactly consistent with the theoretical. According to the reconstruction formula (5), the first five scale1-scale5 of VT and VF is showed in Fig.4. From Fig.4, the first scale1showing the fast change frequency. With the increase of scale, frequency is gradually reduced. This indicates the different frequency band distributions of each scale. These results demonstrate that the wavelet transform can reliably extract various sub-band components from the original serious.

Fig.2. illustrates the LZ complexity analysis that performed the VT and VF samples. Based on the assessment formula, we can draw that the classification results for 63.10% of accuracy. As we know, the clinical signals are very complex, so the results are not good.

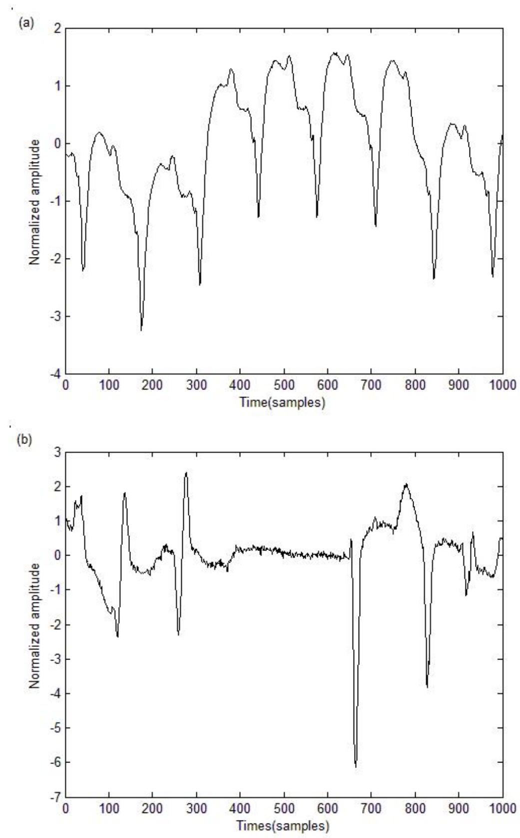


Fig. 1 Examples of ECG signal epochs: (a) VF time domain signal and (b) VT time domain signal

According to Mallat's pyramidal algorithms, Electrocardiogram (ECG) signals were decomposed and reconstructed into approximate and detail coefficients and the complexity of each scale is computed. The effect of the wavelet and scale coefficients is shown in Fig.3 and Fig.4. From the result, for example, when the features of Scale1 are used, the sensitivity and specificity are 86.08% and 100%, respectively. The effect of the scales1-3 detection is shown in Fig.5. The performances on classification of VF and VT patterns are shown in Tables 1. When using the LZ complexity-Mallat algorithm methods, the sensitivity and specificity can reaches 99.00% and 100%, respectively.

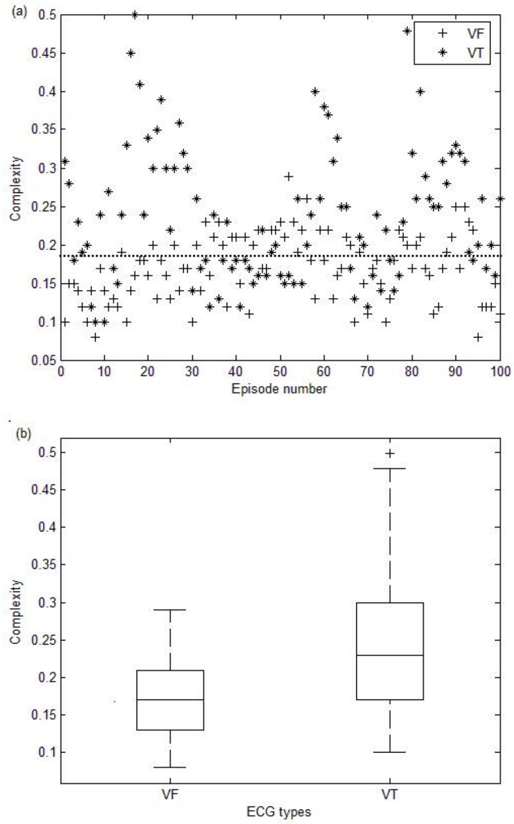


Fig. 2 （a）The complexity is calculated for different VT and VF episodes. The dotted horizontal line is the threshold. (b) The box-plot of the complexity of VT and VF from ECG data

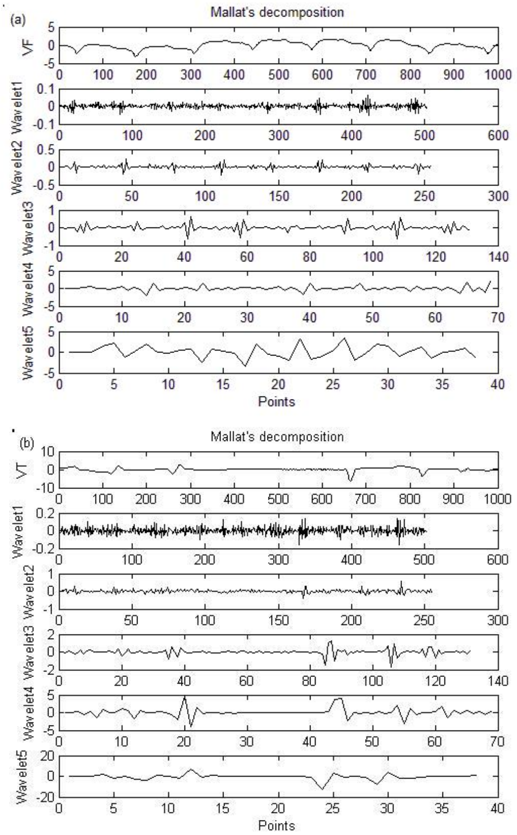


Fig.3 Examples of a segment of ECG signals: (a) represent the first five wavelet coefficients of VF (b) represents the first five wavelet coefficients of VT

From Tables 1, scale1-2 shows the sum of scale1 and scale2, until the scale1-4 which shows the sum of all scales (scale1 to scale4). We also observe that the accuracy of the first scale1-4 is not higher than that of the first scale1-3. This implies that redundant scales do not contribute to the accuracy of the reconstructed signals due to the noise component they represent. It can be found the accuracy of each scale for distinguish of VT from VF is higher than only using the LZ complexity. According to the relevant literature, the frequency of VF and VT is not the same. The frequency of VT is 150-200bmp (beats per minute), while the frequency of VF is the 200-500bmp. After wavelet transform, ECG signal is decomposed into five frequency scale. VT and VF are mostly located in the middle and high frequency band. The same scale of VT and VF are used as a feature in order to discriminate between VF and VT. The main features of the ECG are closely related to the first five Scales and each scale contains the important information of sub-band. So the results are better than only using the LZ complexity. Furthermore, the results of the first three scales are better; this is fit with the theory that the frequency of VT and VF are in the middle and high frequency band. From the scale2-3、scale2-4 and scale 3-4, we can conclude that using the middle frequency of VT and VF to detect VF and VT can also get a good results. The proposed method has greatly improved the effect of the classification. In the clinic application, we can use the middle and high frequency of VT and VF to distinguish VF from VT, particularly the first three scales.

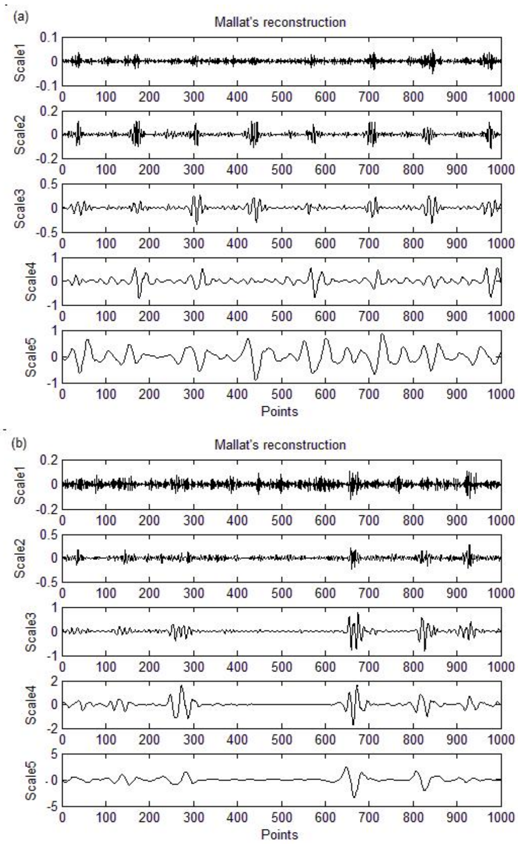
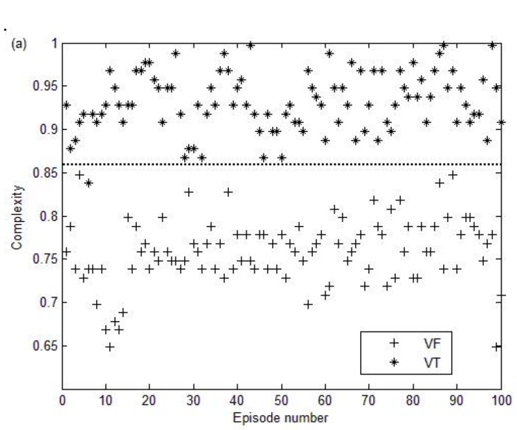


Fig.4 Examples of a segment of ECG signals: (a) represents the first five Scales of VF (b) represents the first five Scales of VT



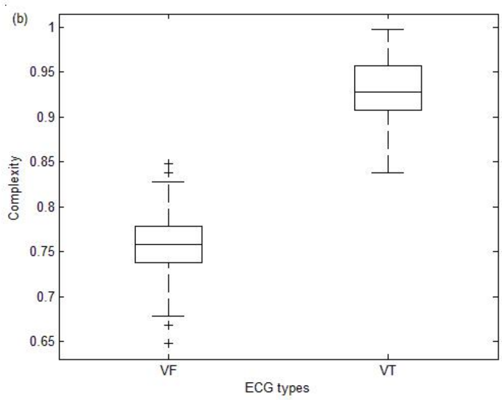


Fig.5 （a） The complexity of Scale1-3 is calculated after Mallat's reconstruction for different VT and VF episodes. The dotted horizontal line is the threshold (b) the box-plot of the complexity of VT and VF after Mallat's reconstruction

In addition, the sample entropy (SampEn) method is used. SampEn has been utilized for the discrimination of VT and VF patterns after it was developed. The results demonstrated SampEn potentially has a clinical value in predicting the onset of spontaneous VF or VT. In these methods, all conditions are the same. For the sample entropy, the value of the tolerance r is 0.1-0.3std, where std is the standard deviation of the sample X_M . The results can be finding in the table 2. From the table 2, the results to detection of VT and VF are the best using the Lempel-Ziv complexity and wavelet transform method. This is also full instructions that the proposed method has greatly improved the effect of the classification.

Table 1 The Lempel-Ziv complexity and the proposed method for CU and MIT-BIH data

Method	Component	VF sensitivity	specificity	VT sensitivity	specificity	ACC
Complexity		62.09	64.11	64.11	62.09	63.10
The Lempel-Ziv complexity and Wavelet transform	Scale1	86.08	100.00	100.00	86.08	**93.04**
	Scale2	73.23	89.14	89.14	73.23	81.19
	Scale3	83.17	96.08	96.08	83.17	89.63
	Scale4	63.12	64.07	64.07	63.12	63.60
	Scale5	69.25	84.23	84.23	69.25	76.74
	Scale1-2	92.87	97.65	97.65	92.87	**95.26**
	Scale1-3	100.00	99.00	99.00	100.00	**99.50**
	Scale1-4	98.55	96.00	96.00	98.55	**97.28**
	Scale2-3	90.13	96.21	96.21	90.13	93.17
	Scale2-4	93.15	90.21	90.21	93.15	91.68
	Scale3-4	90.16	92.18	92.18	90.16	91.17

Table 2 The comparison of different methods for CU and MIT-BIH data

Method	TH	VF		VT		ACC (%)
		Sensitivity (%)	Specificity (%)	Sensitivity (%)	Specificity (%)	
Complexity	0.1823	62.09	64.11	64.11	62.09	63.10
Sample entropy	0.1823	91.00	90.00	90.00	91.00	90.50
The Lempel-Ziv complexity and Wavelet transform	0.8685	100.00	99.00	99.00	100.00	**99.50**

In order to improve the detection precision, we used SVM classifier to discriminate VF and VT. To evaluate the generalization capability of the SVM models, data consisted of training and testing. The result is shown in Table 3.

Table 3 SVM classifier performance for VF and VT detection using the proposed method

4 Conclusions

We have presented a new method for VF and VT detection based on the LZ complexity and wavelet transform. The selection of the length of VT and VF is four seconds (1000 points). Compared

Method	Component	VF sensitivity	VF specificity	VT sensitivity	VT specificity	ACC
Complexity		63.93	91.92	91.92	63.93	77.93
The Lempel-Ziv complexity and Wavelet transform	Scale1	99.92	95.92	95.92	99.92	**97.92**
	Scale2	87.92	77.93	77.93	87.92	82.93
	Scale3	95.92	83.93	83.93	95.92	89.92
	Scale4	71.93	59.94	59.94	71.93	65.93
	Scale5	75.93	83.93	83.93	75.93	79.93
	Scale1-2	95.92	99.92	99.92	95.92	**97.92**
	Scale1-3	99.92	99.92	99.92	99.92	**99.92**
	Scale1-4	99.92	99.92	99.92	99.92	**99.92**
	Scale2-3	95.92	91.92	91.92	95.92	93.92
	Scale2-4	99.92	91.92	91.92	99.92	95.92
	Scale3-4	95.92	91.92	91.92	95.92	93.92

with the LZ complexity method, it was found that the method proposed here showed higher accuracy. The method presented in this paper also provided a new approach foe analyzing other noisy physiological signals. Efforts into investigating the applicability of the proposed method for studying other problems are currently underway.

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