

Wavelet permutation entropy analysis of Ventricular Fibrillation and Sudden Cardiac Death ECG signals

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Abstract. In this paper, we applied wavelet permutation entropy to analyze the Ventricular Fibrillation (VF) signals and Sudden Cardiac Death (SCD) signals for making an effective distinction from normal sinus rhythm (NSR) signals. Firstly, three different ECG signals are decomposed by wavelet and reconstructed in each single layer. Then highly discriminated frequency band will be chosen as our target band. Furthermore, under the circumstances of different series length, embedding dimension and delay time, the main work is to distinguish the three ECG signals in different frequency bands based on the permutation entropy (PE). The results show that permutation entropy method can make a distinction between normal and abnormal ECG signals which aren't decomposed, but the effect of decomposing with wavelets is better more. And the highest discriminated frequency band is from 15.625 Hz to 31.25 Hz. From the point of different data length, embedding dimension and delay time, it was found that permutation entropy method have different effects and the findings may assist cardiac clinical diagnosis.

Introduction

Ventricular fibrillation (VF) is one of the factors of sudden cardiac arrest death, which is the most severe symptoms and manifestations for arrhythmias. Numerous studies and experiments show that a significant proportion of sudden cardiac death due to ventricular fibrillation deterioration. So it is necessary to effectively differentiate ventricular fibrillation and sudden cardiac arrest death in order to provide a basis for clinical diagnosis in medicine.

ECG is a typical non-linear signal, and has a high degree of non-stationary and complex characteristics. And many nonlinear dynamics also be applied to the ECG signal, such as the correlation dimension [1], multifractality [2,3], approximate entropy [4], Kolmogorov entropy [5], etc. These methods largely promoted the study of ECG. The permutation entropy proposed by Bandt et al. [6] is widely used in many fields because of the simple, easy to calculate and strong robustness characteristics.

Compared with Fourier analysis, wavelet transform has the characteristics of multi-resolution analysis [7], which is a localized analysis method in time-frequency. This method can automatically adapt to the requirements of time-frequency signal analysis as well as can be focused to any signal details. Therefore, the wavelet transform is particularly suitable for analysis of nonlinear signals.

Firstly, we use bior4.4 to decompose the ECG into 4 layers, and then we would reconstruct in each single layer. Secondly, because each layer of discrimination are not the same, we could choose highly discriminated frequency band as our target band. Finally, we use permutation entropy (PE) to deal with the target frequency band. Results show that the PE of target band which is processed with wavelets does have better effects.

Permutation entropy

For a given time series $\{x(i), i = 1, 2, \dots, n\}$, we can reconstruct the times series with the theorem of

TAKENS[8] and get the reconstruction vector $X(i)$:

$$X(i)=\{x(i),x(i+\tau),\dots,x(i+(m-1)\tau)\}, \quad (1)$$

Where τ is the delay time, m is the embedding dimension. Then we arrange $X(i)$ in increasing order:

$$\{x+(j_1-I)t\} \leq \{x+(j_2-I)t\} \leq \dots \leq \{x+(j_k-I)t\}, \quad (2)$$

If there is equal component in $X(i)$ like $x(i+(j_{k1}-I)t)=x(i+(j_{k2}-I)t)$, we should arrange it according to the index j . That is, when $j_{k1} < j_{k2}$, the order is:

$$x(i+(j_{k1}-I)t) \leq x(i+(j_{k2}-I)t) \quad (3)$$

So we can get a symbol series $S(l)$ for each $X(i)$:

$$S(l)=(j_1, j_2, \dots, j_m), \quad (4)$$

where $l=1, 2, \dots, k$ and $k \leq m!$, and there are $m!$ different permutations for m different symbols or $m!$ different symbol sequences. The probability of each symbol sequence P_1, P_2, \dots, P_k can be calculated, and we can define permutation entropy of k different sequences of symbols for $X(i)$:

$$H_p(m) = -\sum_{j=1}^k P_j \ln P_j. \quad (5)$$

When $P_j = 1/m!$, $H_p(m)$ has reached the maximum and is usually normalized as:

$$0 \leq H_p = H_p / \ln(m!) \leq 1. \quad (6)$$

The value of H_p reflects the degree of randomness of time sequence $x(i)$. The less value of H_p , the more regular of time sequence $x(i)$, otherwise, the series is more random. The value of H_p is also amplified the slight changes of time series $x(i)$. Owing to not directly using the actual data values of the time series $x(t)$, the paper [9] argue the anti-noise robustness of permutation entropy is better than the traditional time series analysis. Furthermore, because DC and extremely low frequency interference will not change the size relationship of the data, it is not necessary to pretreat signals.

The study of SCD and VF signals with wavelet permutation entropy

We respectively extract the data from the MIT-BIH Malignant Ventricular Entropy Database (VFDB) including 22 records which sample with 250Hz, the MIT-BIH Arrhythmia Database (NSRDB) including 18 records which sample with 125Hz and the Sudden Cardiac Death Holter Database (SDDB) including 23 records which sample with 250Hz. For all of signals the data was extracted from the point of 10800, and we extracted 1000 points for each signal. First of all we need to convert the frequency of VF and SCD from 250Hz to 125Hz, which could facilitate analyzing and processing the three ECG signals with wavelet.

First of all we use bior4.4 to decompose the ECG of VF, NSR and SCD into 4 layers respectively. Then we can get 5 different frequency bands after reconstructing each layer. The 5 different frequent bands can be analyzed with permutation entropy (PE) and the results can be shown. We use one-way analysis of variance (ANOVA) to analyze the results with SPSS18.8 and then we can get the most distinguishable frequency band, which can be analyzed PE in various delay time L , length of time series N and embedding dimensions m .

We found that the p value of original signals without the wavelet processing is 0.001. And the minimum p value of the signals after the wavelet processing in different scales is in $D2$ layer, which is far less than the p value of original signals. Thus the frequency band of $D2$ (15.625~31.25Hz) will be studied. When the length of time series is 100, we get the highest discrimination, which means we get the best results.

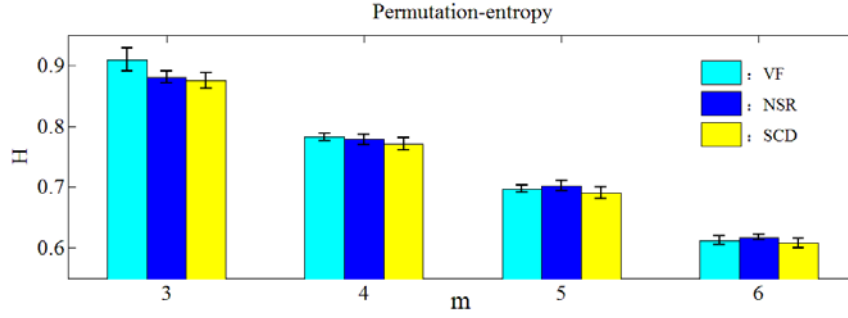


Fig.1 Results of PE analysis with different embedding dimensions m . Here length of time series $N=100$, delay time $L=1$.

We can conclude that the value of p after ANOVA in different embedding dimensions m is far less than 0.05, which illustrate that the three sets of ECG data generally exists significant difference. When the embedding dimension is 3, we get the minimum value of p which means the highest discrimination. And the Fig.1 shows that with the increasing of embedding dimension m , the value of H is declining.

In the condition of different delay time L , we firstly use the PE to deal with the data of $D2$ layer and then use ANOVN to analyze the outcome result from PE.

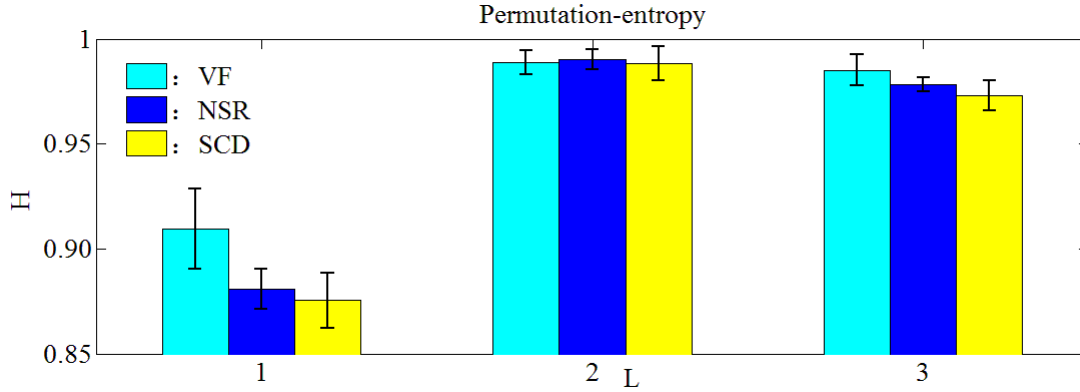


Fig.2 Results of PE analysis with different delay time L . Here length of time series $N=100$, embedding dimensions $m=3$.

We know that when the delay time L is 1 we can get the minimum value of p , which means the highest discrimination. And the Fig.2 shows that the value of H in the delay time of 2 and 3 is far more 1.

Discussion

Based on PE, we decompose ECG signals in 4 layers with bior4.4 wavelet and then reconstruct them respectively. In the process, highly discriminated frequency band is to be chosen as the target band. Next, we apply PE to analysis of the target band, and find that high frequency part of $D2$ layer (15.625~31.25Hz) has the most obvious distinction. Naturally, we take $D2$ layer as our target frequency band.

The experimental results show that PE can distinguish the three original ECG signals without the wavelet processing, but the effect is not ideal. However, the effects using PE decomposed and reconstructed by wavelet first is better more. Final result shows that PE with the wavelet processing can greatly improve the distinction between normal and abnormal ECG signals and has a better performance in describing the complexity of arrhythmia signals.

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References

- [1] Small M, Yu DJ, Simonotto J, Harrison RG 2000 Computers in Cardiology 27 147-150
- [2] Cunningham H, Maynard D, Bontcheva K, Tablan V 2002 40th Anniversary Meeting of the Association for Computational Linguistics, Univ Penn. Philadelphia, JUL 07-12, 2002
- [3] Bontcheva K, Cunningham H, Maynard D, Tablan V, Saggion H 2002 13th International Workshop on Database and Expert Systems Applications Aix Provence, France , SEP 02-06, 2002, 223-227
- [4] Chon K, Scully CG, Lu S 2009 IEEE Eng Med Biol Mag.28 18-23
- [5] Grassberger P, Procaccia I 1983 Phys Rev A 28 2591-2593
- [6] Bandt C, Pompe B 2002 Phys Rev Lett 88 174102
- [7] MALLAT S 1999 A Wavelet Tour of Signal Processing 2nd Edition Academic Press .
- [8] Takens F. 1981 Lecture Notes in Mathematics 898 361-381.
- [9] Li XL, Ouyang GX, Richards DA 2007 EPILEPSY RESEARCH 77 70-74