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Multiscale entropy based study of the pathological time series*

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This paper studies the multiscale entropy (MSE) of electrocardiogram's ST segment and compares the MSE results of ST segment with that of electrocardiogram in the first time. Electrocardiogram complexity changing characteristics has important clinical significance for early diagnosis. Study shows that the average MSE values and the varying scope fluctuation could be more effective to reveal the heart health status. Particularly the multiscale values varying scope fluctuation is a more sensitive parameter for early heart disease detection and has a clinical diagnostic significance.

Keywords: electrocardiogram, ST segment, multiscale entropy, coronary heart disease
PACC: 0545, 0547,9260X

1. Introduction

Heart disease is a major disease threatening human health and life. How effectively detecting and evaluating cardiac function and accurately forecasting and diagnosing heart disease, are important research topics on cardiac diseases treatment.[1] Detecting and analysing heart electrical activity by electrocardiogram (ECG) (Fig.1.) has always been the most important ways and means of cardiac function detection and diagnosis in clinical practice of medicine. ST segment elevation of ECG has important significance for the diagnosis of acute myocardial infarction (MI).[1]

The complexity quantification of healthy and unhealthy people's physiological signals has been a universal concern. The complexity reduction is a universal feature of the pathological dynamics.[2−8]

Many researchers used different methods to quantify the complexity problem. Pincus[2,9] proposed approximate entropy theory. Richman *et al*[6] put forward sample entropy (SE) method. Ning *et al*[10] brought forward model entropy method. Costa *et al*[9] proposed multiscale entropy (MSE) concept for heart rate variability study. We use the MSE algorithm proposed by Costa *et al*[11] to study the ST segments of ECG features. This paper attempts to measure the complexity of the ECG in the multi-scale in order to look for useful clinical diagnosis indication

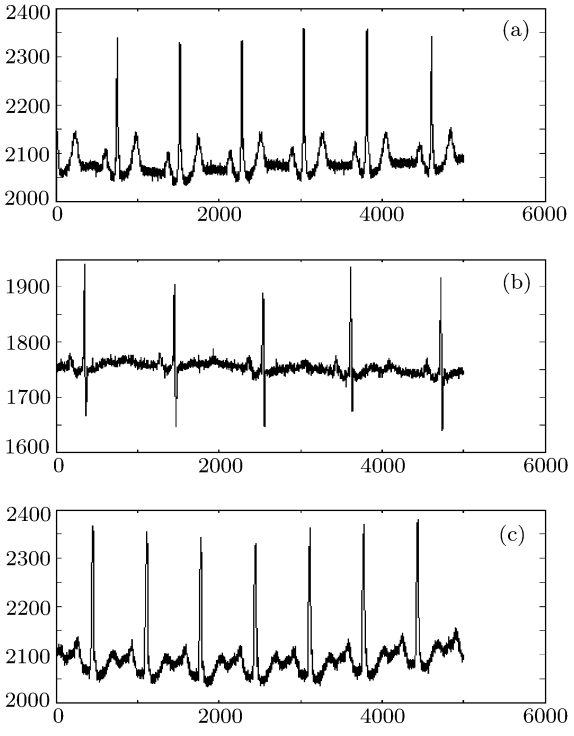


Fig.1. Three separate states of ECG: (a) the healthy; (b) coronary heart disease; (c) myocardial infarction.

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parameters. Study shows that average MSE values of ECG and the varying scope fluctuations can be more effective to reveal the heart health status. Especially MSE values varying scope fluctuations could characterize the dynamic process of heart disease evolution. It was a more sensitive parameter for early heart disease detection and had important clinical significance.

2. ST segment extraction algorithm of ECG

According to Fig.2, it can be shown in the following steps how to extract ST segment of ECG.

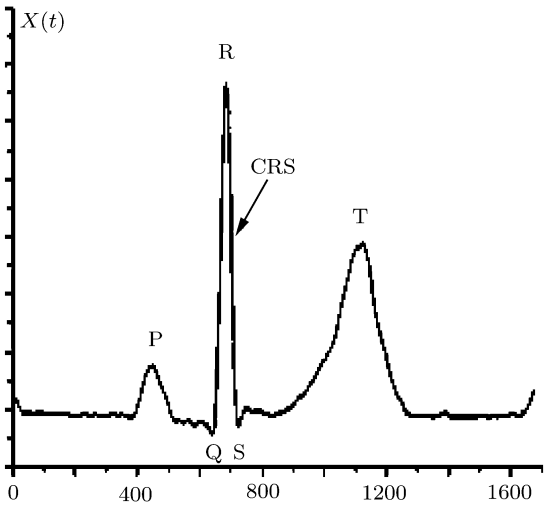


Fig.2. A typical normal electrocardiogram.

(1) Finding R-wave peak

Starting from one point of ECG data, one draws out consecutive 800 points to calculate the slope between points. The point of the largest slope is the R-wave peak.[12]

(2) Identifying S-wave peak

Determining the 100^{th} point after the R-wave peak, one draws a straight line between the R-wave peak and the 100^{th} point for calculating the distance between the line and the ECG data under the conditions of the same abscissa. The point of the largest distance is the S-wave peak.

(3) Determining J point

Determining the 100^{th} point after S-wave peak, one draws a straight line between the S-wave peak and the 100^{th} point for calculating the distance between the line and the ECG data under the conditions of the same abscissa. The point of the largest distance is J point[12].

(4) Extracting the ST segment

Consecutive 80 points extracted after J points is the ST segment of this heartbeat data.

(5) Repeating from step (1) to step (4), one can extract all the ST segments of overall ECG data.

3. MSE algorithm

Sample Entropy was named due to considering the application of sampling time series from a continuous process.[6]

The SE measure is calculated:[6,11]

For a N-points time series $\{u(j) : 1 \le j \le N\}$, construct $N-m+1$ vectors $X_m(i)\{i|1 \le i \le N-m+1\}$, among which $X_m(i) = \{u(i+k) : 0 \le k \le m-1\}$ is the m-points vector from $u(i)$ to $u(i+m-1)$.

The distance between two vectors is defined as

$$d[u(i), u(j)] = \max\{|x(i+k) - u(j+k)|\} \quad 0 \le k \le m-1, \tag{1}$$

i.e. the largest variance of their corresponding scalar components.

$B_i$is the quantity of vectors $X_m(j)$ whose distances from vector $X_m(i)$ are r, A_i is the quantity of vectors $X_{m+1}(j)$ whose distances from vector $X_{m+1}(i)$ are r. Thus sample entropy is defined as

$$SE = -\log(A/B), \tag{2}$$

where r is the standard deviation of the time sequence multiplied by 0.15, namely

$$r = 0.15 \times \mathrm{STD}(u(j)). \tag{3}$$

Costa *et al*[11] proposed MSE method for dealing with complex physiological time series.

The algorithm is as follows:[9]

Given a one-dimensional discrete-time sequence, $\{x_1, ..., x_i, ..., x_N\}$, we construct the coarse consecutive time series, $\{y^{(\tau)}\}$ which is decided by the scale factor τ. The equation is

$$y_j^{(\tau)} = 1/\tau \sum\nolimits_{i=(j-1)\tau+1}^{j\tau} x_i, \quad 1 \le j \le N/\tau. \tag{4}$$

For scale factor $\tau = 1$, the time sequence $\{y^{(1)}\}$ is simplified as original time series. The length of each one of coarse-grained time series is equal to the original time series length divided by the scale factor τ.

Here we consider the 40,320 points time sequences and coarsen them up to scale factor 10. So the shortest time series has 4,032 points.

Then, for each one of the coarse-grained time series we calculate the SE measure which is a function of the scale factor τ, and draw the corresponding function figures.

4. Data analysis

We adopted 12-lead ECG data from 23 healthy people, 24 coronary heart disease (CHD) patients and 8 myocardial infarction patients. ECG data sampling frequency is 1 kHz per second.

Firstly, data are wavelet filtered (using the bior 6.8 wavelet function), breathing wave (less than 0.5 Hz) and 50 Hz noise are filtered. The process is that: 1) after 10 layer decomposition, wavelet coefficients were extracted for each layer and then removed the layers where respiratory wave (less than 0.5 Hz) and 50 Hz noise located, 2) it is going on wavelet reconstructed and the data filtered breathing wave (less than 0.5 Hz) and 50 Hz noise is gained.

Then we extracted ST segments from ECG data.

As ECG data sampling frequency is 1 kHz per second and sampling time is a minute long, so each lead ECG data probably include about 60,000 discrete points. We extracted the ST segment data and linearly interpolated 9 points between every two adjacent points to meet the analytical needs.

We used 40,320 points in each data. And these points were firstly coarsened by scale factor τ ($\tau = 1 \rightarrow 10$). Then SampEn calculation of these coarse-grained time sequences was done and it was drawn (Fig.2.). The purpose of adopting 40,320-point data is that it can be divisible from 1 to 10.

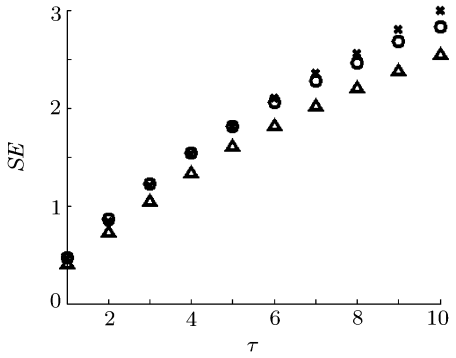


Fig.3. Source ECG data's direct sample entropy operational results ('◯' on behalf of healthy people, '×' on behalf of coronary heart disease patients, '△' represents myocardial infarction patients).

Figure 3 shows that sample entropy of healthy subjects and coronary heart disease patients could not be distinguished well. But it can make a good distinction between them with that of myocardial infarction patients and they were higher than that of MI patients. It could be concluded that the complexity of health subjects' and CHD patients' ECG were close. The complexity of MI patients' ECG declined markedly.

Furthermore, we analysed the linearly interposed ST segments extracted from source ECG. We also used 40,320 points in each ST segment data. And these points were firstly coarsened by scale factor $\tau(\tau = 1 \rightarrow 10)$. Then SampEn calculation of these coarse-grained time sequences was done and it was drawn (Fig.3.).

Figure 4 shows that the characteristics of not well distinguishing sample entropy of health subjects and CHD patients' ECG (Fig.3.), was not existed after analysing extracted ST segment of ECG. This further indicated the importance of studying the complexity of ST segments of ECG for its beneficial early clinical detection. In Fig.4, the sample entropy value of healthy subjects' ST segment of ECG was relatively low and that of CHD patients was the highest. The sample entropy of MI patients was lower than that of CHD patients but that was still higher than those in healthy people.

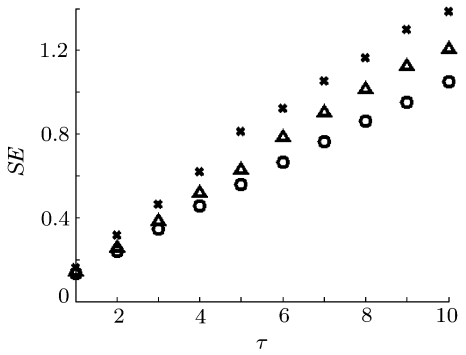


Fig.4. Operational results of sample entropy of ST segments extracted ECG data ('◯' on behalf of healthy people, '×' on behalf of coronary heart disease patients, '△' represents myocardial infarction patients).

In Fig.5, it could be concluded that the MSE varying scope fluctuations of ECG were in a relatively stable scope for healthy subjects, and were of relatively larger scope for the CHD patients, and were in relatively lower scope for MI patients. When studying the ST segments' MSE varying scope fluctuations, such varying law still existed. But the absolute MSE varying scope fluctuations were decreasing.

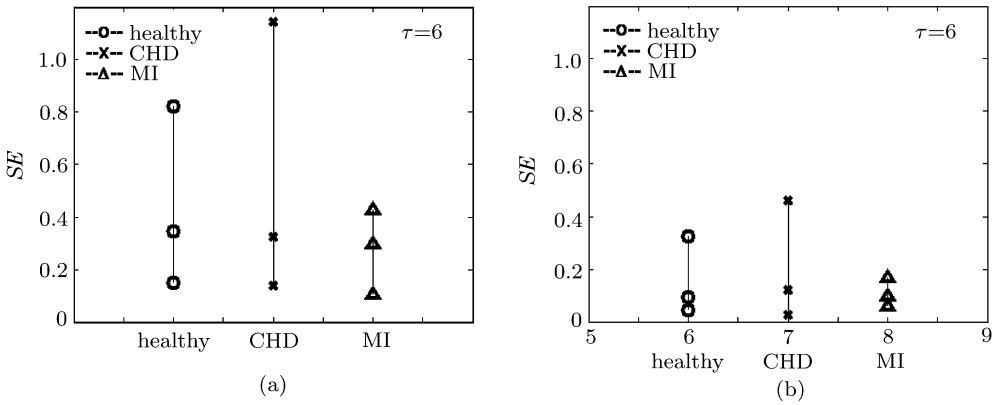


Fig.5. Comparison of MSE varying scope fluctuations of ST segment and that of ECG taken from healthy people, patients with coronary heart disease and patients with myocardial infarction at a single scale. In the circumstances of τ=6, (a) ECG data, (b) ST segment data.

5. Conclusions

This work found that SE of healthy subjects' and CHD patients' ECG were higher than that of MI patients. The complexity of MI patients' ECG was minimum and it could well illustrate MI attack. But it was far less than people's early expectations for the prevention of heart disease.

By further analysing SE of ST segments of ECG, we found that the SE value of ST segments of healthy subjects' ECG was minimum, that of CHD patients was highest, that of MI patients was in the middle which was below that of CHD patients but higher than that of healthy people. It disclosed that when SE of ST segments increases, it indicates the risk of CHD has come, which helps early clinical diagnosis and people's early prevention. Therefore, the study of the complexity changes of ST-segment curve was a strong clinical significance.

The MSE varying scope fluctuations of ST segment and that of ECG exist the law such as: in a relatively stable scope for healthy subjects, relatively larger scope for the CHD patients, and relatively lower scope for MI patients. And the absolute scope fluctuations of ST segment decrease.

Study shows that the average MSE values and the varying scope fluctuation could be more effective to reveal the heart health status. Particularly the multiscale values varying scope fluctuation is a more sensitive parameter for early heart disease detection and has a clinical diagnostic significance.

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