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Some nonlinear parameters of PP intervals of pulse main peaks*

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Abstract: The PP intervals of pulse main peaks from healthy and unhealthy people (arrhythmia) have different nonlinear characteristics. In this paper, the extraction of PP intervals of pulse main peaks is achieved by picking up P peaks of pulse wave with wavelet transform. Furthermore, several nonlinear parameters (correlative dimensions, maximum Lyapunov exponents, complexity and approximate entropy) of the PP intervals of pulse main peaks extracted from normal and unhealthy pulse signals are calculated, with the results showing that these nonlinear parameters calculated from the main wave interval signals are helpful for analyzing human's health state and diagnosing heart diseases.

Key words: PP intervals of pulse main peaks, Phase space reconstruction, Correlative dimension, Lyapunov exponent, Complexity, Approximate entropy

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INTRODUCTION

PP intervals of pulse main peaks are obtained from the measurement of the PP intervals by transforming the pulse waves into an event series, with the events being the PP intervals reference moments, which are obtained with the help of a PP detector (Chiu *et al*., 2000). It is known that PP intervals of pulse main peaks are mainly caused by cardiovascular neuro-autonomic control (Drinnan *et al*., 2001). PP intervals of pulse main peaks include so much information about the heart blood vessel neural system and body fluid regulation that it can be used to diagnose, treat and predict heart and blood concerned diseases.

Nowadays, some linear analyses, including statistical, spectral and transfer function methods are used to obtain PP intervals of pulse main peaks (Chiu *et al*., 2004). Meanwhile, some nonlinear analyses, such as Poincare mapping, fractal dimension and complexity, are adopted to analyze different disease subjects with PP intervals of pulse main peaks.

However, most of these methods cannot give a quantitative description of PP intervals of pulse main peaks, especially when their nonlinearity is considered. In fact, it was suggested that complex fluctuations in PP intervals of pulse main peaks may reflect deterministic chaos. Recent research showed that a perturbation of heart activity may lead to complexity loss of the PP intervals of pulse main peaks dynamics, which implied that the nonlinearity of pulse main peaks PP intervals could be used to detect abnormal pulse wave states.

In this paper, some nonlinear characteristic parameters of PP intervals of pulse main peaks in two typical states, healthy and unhealthy (arrhythmia) adults, are calculated comparatively. In Section 2, an extracting algorithm of PP intervals of pulse main peaks is discussed. In some other research work, bandpass filtering is adopted to get P wave, where the baseline excursion and de-noising must be enforced exactly (Sita and Ramakrishnan, 2000). The wavelet transform technique is adopted here to ascertain P peaks of pulse wave. A cubic spline function is used to interpolate the obtained PP intervals of pulse main peaks event series, with PP intervals of pulse main peaks time series being obtained via re-sampling at a

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proper frequency. In Section 3, the nonlinear theory is applied to calculate some nonlinear parameters of PP intervals of pulse main peaks time series data responding to normal and unhealthy states. The nonlinear parameters dealt with in this paper are the correlative dimensions of reconstructed phase space, the largest Lyapunov exponents, approximate entropy, and complexity. These calculated nonlinear parameters of PP intervals of pulse main peaks are significant for understanding the nonlinear characteristics of pulse waves and could be the essential quantitative indicators for diagnosing some diseases.

MATERIALS AND METHODS

Extraction of PP intervals of pulse main peaks time series

The average voltage range of pulse wave is 0.05~5 mV, and about 0.05~100 Hz (3 dB) in frequency domain. Pulse wave is often contaminated by muscle electricity pulse and other noises. A denoising algorithm for removing baseline drift, power-line interference and electromyographical interference in human pulse signals is proposed based on wavelet transform theory. Pulse wave with denoised treatment and depressed data of baseline drift was shown in Fig.1.

In order to detect P peaks accurately, a proper mother wavelet function is chosen, which should be symmetric. A symmetrical wavelet converts the signal peaks into maximum values, whereas a nonsymmetrical one will convert signal peaks into zeros. A mother wavelet of square spline is adopted here and a three-level wavelet transform is introduced as shown in Fig.2.

The P peaks are then extracted by using a proper threshold, since a too big threshold would cause peak lose and a too small one would get false peaks. In this paper, the average value of high frequency signal was considered as threshold 1 and its half value as threshold 2. When scanning high frequency signal, signal values exceeding threshold 1 are marked as position 1 and those less than threshold 2 marked as position 2. There will exist a P peak between positions 1 and 2.

Due to the uneven sampling frequency of the P peak series, it cannot be analyzed as PP intervals of pulse main peaks. So the P peak series should be interpolated and re-sampled. The interpolation is carried out with cubic spline interpolation, but not a linear one with two data point, both over the whole P peak series. Based on the interpolated signal, re-sampling under a proper sampling frequency is applied. Measured pulse wave and positions of P peaks are shown in Fig.3.

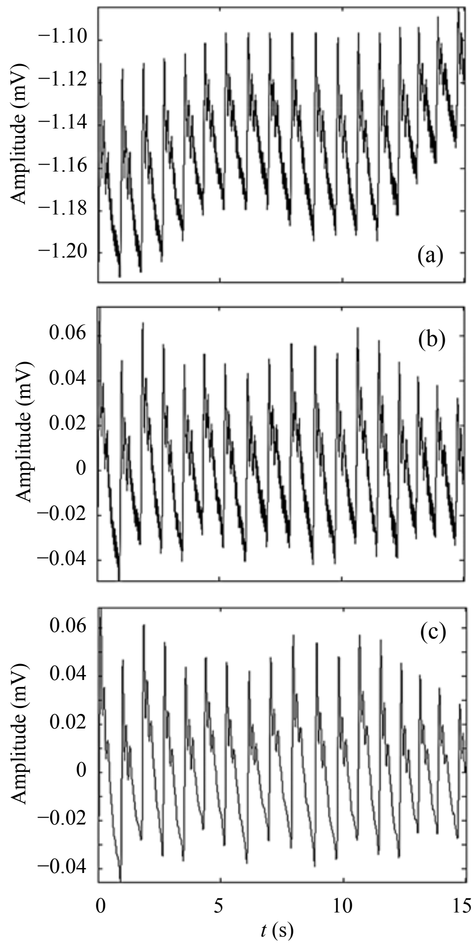

Fig.1 Test data of human pulse and denoised signals. (a) Test data of human pulse; (b) Depressed data of baseline drift; (c) Pulse wave with denoised treatment

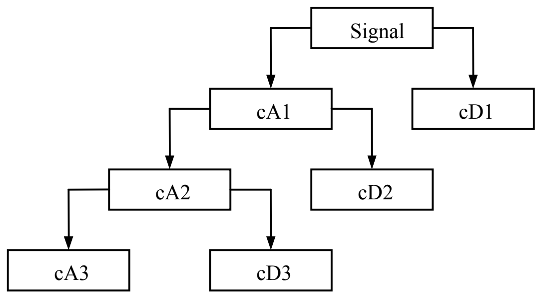

Fig.2 Three-level wavelet decomposition

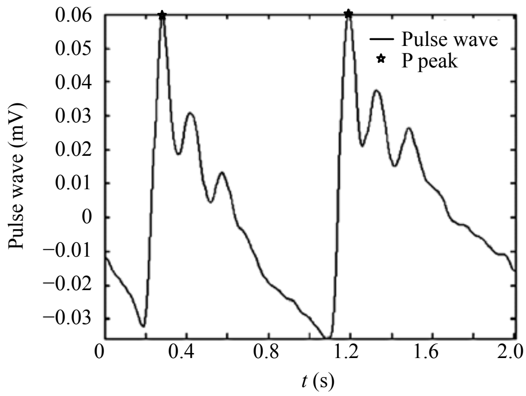

Fig.3 Extraction of five feature points of human pulse

Nonlinear parameters of PP intervals of pulse main peaks

1. Correlative dimensions

The fractal characteristics of PP intervals of pulse main peaks could be quantitatively described by correlative dimension (Ferri and Pettinato, 1999). Firstly, perform the time series in a phase space using a state vector with embedding coordinates. An optimum delay is selected via calculating the first minimum of the auto mutual information to ensure that the reconstructed phase space can represent the natural characteristics of the original time series. The optimum minimal embedding dimension is ascertained according to (Cao, 1997). Correlative dimension of reconstructed PP intervals of pulse main peaks data is calculated based on the optimum delay and minimal embedding dimension.

For an observed time series $x(n)$ of PP intervals of pulse main peaks, the reconstructed phase space and its vectors are

$$X=\{\boldsymbol{X}_i\},\ \boldsymbol{X}_i=[x_i, x_{i+\tau}, \ldots, x_{i+(m-1)\tau}],\ i=1, 2, \ldots, N_m, \quad (1)$$

where $\tau=k\Delta t$ is the delay time with k being positive integer and Δt the sampling interval of time series. $N_m=N-(m-1)\tau$, m is the embedding dimension.

τ is estimated via calculating the first minimum of the auto mutual information function, which is an index of the general stochastic correlation of two variables. The auto mutual information function is defined as

$$I(\tau)=\sum_{i,j} P_i(\tau)\cdot\ln\frac{P_{ij}(\tau)}{P_i P_j}, \quad (2)$$

where P is the probability distribution of time series $x(n)$ at each point, P_i is the probability in domain i, and $P_{ij}(\tau)$ the probability of the state that x_n is in domain i and $x_{n+\tau}$ is in domain j. When $I(\tau)$ reaches its first minimum, the corresponding τ is the rational delay time.

Considering a limited time series, correlative integration is

$$C_m(r)=\frac{2}{N_m(N_m-1)}\sum_{i=1}^{N_m}\sum_{j=1}^{N_m} H(r-\|\boldsymbol{x}_i-\boldsymbol{x}_j\|), \quad (3)$$

where H is Heaviside function: if $x>0$, $H(x)=1$; if $x\le 0$, $H(x)=1$. The correlative integration can be rewritten in exponential form

$$C_m(r)\propto r^{D^2}. \quad (4)$$

Assume

$$d_2(r,N_m)=\frac{\partial \ln C_m(r,N_m)}{\partial \ln r}, \quad (5)$$

the correlative dimension is defined as

$$D_2=\lim_{r\to 0}\lim_{N_m\to\infty} d_2(r,N_m). \quad (6)$$

The slope in the middle straight segment of the curve $\ln C_m(r)$ to $\ln r$ is correlative dimension D_2.

2. Largest Lyapunov exponents

The average radiation velocity of the adjacent orbits in phase space could be quantitatively described by the largest Lyapunov exponent, which is also one of the most important indexes to estimate whether the system is in chaos or not. There are many methods for calculating the largest Lyapunov exponents from a nonlinear time series (Kim and Jeong, 2000). In this paper, phase space reconstruction of PP intervals of pulse main peaks is first achieved, and then the largest Lyapunov exponents are calculated. The result indicates that the largest Lyapunov exponents of PP intervals of pulse main peaks in both healthy and unhealthy states are all positive, but the value of the latter is comparatively small.

Consider two trajectories in space X, L_1 and L_2, with initial points being x_0 and $x_0+\Delta x_0$, respectively. The former is taken as the standard trajectory and the latter as the adjacent one. At time t, distance of the two points on the two different trajectories is $\boldsymbol{w}(x_0, t)$=

$\boldsymbol{x}(x_0+\Delta x_0, t)-\boldsymbol{x}(x_0, t)$. When $\|\boldsymbol{w}\|$ is small, the exponential departure of the two trajectories is

$$\lambda(x_0, \boldsymbol{w}) = \lim_{\substack{t\to\infty \\ \boldsymbol{w}_0\to\boldsymbol{0}}} \frac{1}{t} \ln \frac{\|\boldsymbol{w}\|}{\|\boldsymbol{w}_0\|}, \tag{7}$$

where $\boldsymbol{w}_0=\boldsymbol{w}(x_0, 0)$. In phase space with m dimensions, all the vectors $\boldsymbol{w}$ form an m-dimensional moving tangent space along with the phase trajectory. Choosing a set of coordinate units of the space and rearranging them into a sequence numerically, the Lyapunov exponents of the time series are in the following sequence:

$$\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n. \tag{8}$$

On condition that the adjacent trajectory radiates apart from the standard exponentially, the length of $\boldsymbol{w}$ will increase immensely with time. Assume two adjacent trajectories, L_1 and L_2, with originations being x_0 and z_0 respectively, distance between the two originations is $d_0=|z_0-x_0|$. Then x_0 and z_0 move along each trajectory and arrive at x_1 and y_1 respectively after time Δt. The new distance is $d_1=|y_1-x_1|$. A new point z_1 is picked between x_1 and y_1, and set $d_0=|z_1-x_1|$. Points x_1 and z_1 locate on trajectories L_1 and L_3, respectively. After Δt, the new trajectories L_1 and L_3, with the original points of x_1 and z_1, will reach their new positions of x_2 and y_2, respectively. After p repetitions, d_i could be obtained as $d_i=|y_i-x_i|$ (i=1, 2, ..., p). The largest Lyapunov exponents are obtained as

$$\lambda_i = \lim_{p\to\infty} \frac{1}{p\Delta t} \sum_{i=1}^{m} \ln \frac{d_i}{d_0}. \tag{9}$$

Consider that the largest Lyapunov exponents obtained here are only statistical averages of the exponential radiation of each point on its trajectory, as p is a large finite integer.

Approximate entropy

Approximate entropy is an important quantitative index to describe chaos in phase space, and it reflects the apparent possibility of a new model when dimension of phase space increases (Pincus, 1991; 1995). The edge probability distribution is used to distinguish different processes, including regular movement, chaos, and random movement. Moreover, approximate entropy can also be used to measure the loss rate of data information. Positive and limitary entropy indicates that the time series and its inherent dynamics are chaotic.

Approximate entropy is deduced based on the concept of correlative integration of a time series. For a time series $x(n)$, n=1, 2, …, N, its correlative integration is defined as Eq.(3). Take the logarithm form of correlative integration $C_m(r)$ and note that as approaches $\Phi_m(r)$, the dimension of reconstructed phase space increases from m to m+1, and then the logarithm correlative integration is calculated again to obtain $\Phi_{m+1}(r)$. When the length of time series is a finite number N, the approximate entropy is estimated as

$$E_A(m, r, N)=\Phi_m(r)-\Phi_{m+1}(r). \tag{10}$$

Obviously, the value of E_A is related to those of m and r. The initial values of m and r could be taken as 2 and 0.1σ~0.2σ, respectively, with σ being the standard deviation of the original data.

Complexity

Complexity reflects the appearing speed of a new model with its length in 1D time series. The complexity of PP intervals of pulse main peaks time series is proposed to describe its nonlinearity, which is calculated based on L-Z algorithm (Klonowski, 2000). The value of the complex degree of regular movement (stable and periodic) is 0, while that of random movement (white noise) is 1, and that of regular movement with noise, color noise or chaos is often between 0 and 1.

Here the complexity for a character string is taken to demonstrate the L-Z algorithm. Assume that S consists of sub-strings, $S=S_1S_2...S_r$, and Q is a new string which is just added to S. SQ represents the new string formed by S and Q. $SQ\pi$ represents the string SQ with the last character omitted, and $V(SQ\pi)$ represents the set of all the sub-strings of $SQ\pi$. If Q is contained within S (i.e., Q is equal to S_i, a sub-string of S), it is called a "copy" of S, and the value of complexity remains unchanged. In contrast, if Q is not contained in S, it is called an "insert", and the value of complexity will increase by 1 (once an insert occurs).

The whole complexity, $C(N)$, is obtained after all operations stated above along the total string. Then a normalized complexity can be defined as

$$C_{LZ}(N)=C(N)/B(N), \tag{11}$$

where $B(N)=N/\log_2 N$, N is the length of the whole string.

RESULTS

The two sets of typical PP intervals of pulse main peaks time series were analyzed. The phase space reconstruction is conducted with time-delay coordinate method at the first step. The best time delay is determined with auto mutual information method. Here, the two values of delay time for healthy and unhealthy PP intervals of pulse main peaks are 8 and 6, respectively. Then, the minimum embedding dimensions of the two time series are, as curve kinks, both 3 (Fig.4), just according to the calculating method in (Cao, 1997).

The curve slopes in Fig.5 are estimated with the least square method, based on the linear segments of $\ln C_m(r)$ to $\ln r$, which are the logarithms of correlative integration and measuring scale. The slope values, i.e., correlative dimensions of the two sets of PP intervals of pulse main peaks, are 2.7743 and 1.6193, respectively. These correlative dimensions demonstrate that PP intervals of pulse main peaks are fractal in geometry.

The estimated values of the largest Lyapunov exponents of two sets of PP intervals of pulse main peaks, corresponding to the healthy and unhealthy states, are 1.8905 and 2.8393, respectively. Both of them are positive. The two positive values of the largest Lyapunov exponents imply that these two PP intervals of pulse main peaks time series are both chaotic.

Numerically, the largest Lyapunov exponent in unhealthy state is smaller than that in healthy state, i.e., the chaos in unhealthy state (arrhythmia) is weaker than that in healthy state (normal heart rhythm).

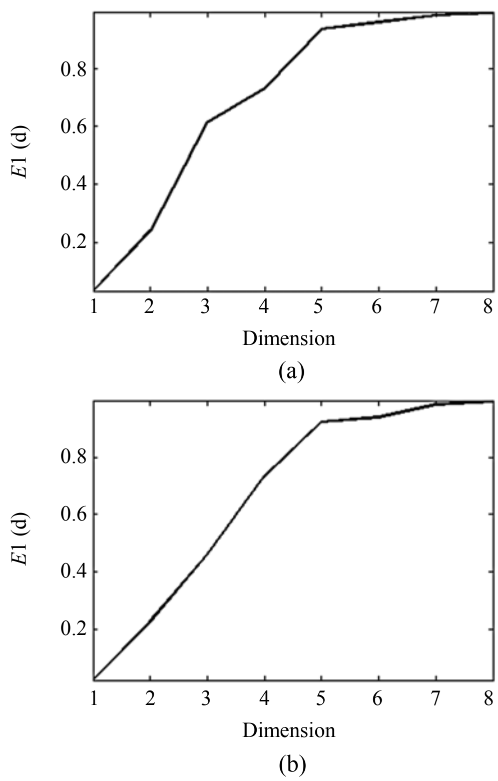

Fig.4 Determination of minimum embedded dimensions using Cao's method. (a) Healthy state; (b) Unhealthy state

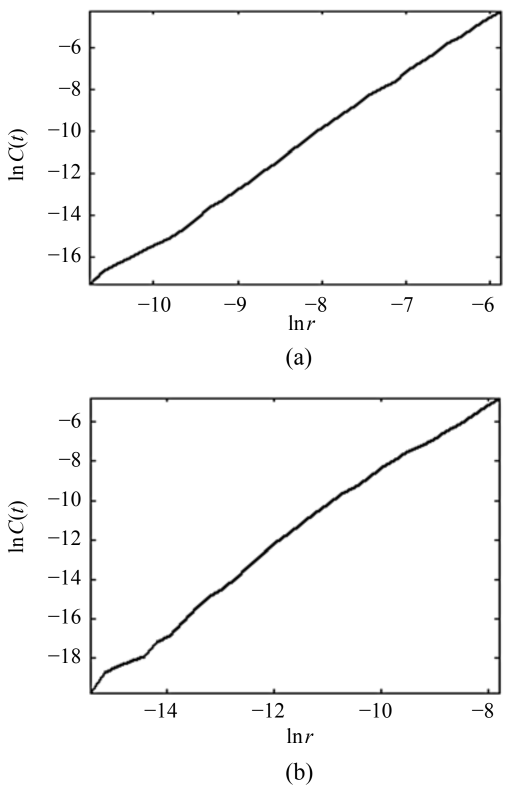

Fig.5 Logarithm diagram of correlative integration to measuring scale. (a) Healthy state; (b) Unhealthy state

Approximate entropy values of PP intervals of pulse main peaks time series in the two different healthy states are calculated; the results are both limitary, showing apparent difference. The calculated approximate entropies are shown in Fig.6.

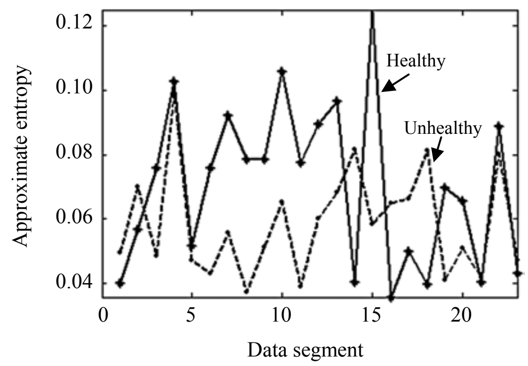

Fig.6 Approximate entropies of PP intervals of pulse main peaks for healthy and unhealthy states

As shown in Fig.7, the complexities of the two sets of PP intervals of pulse main peaks in both healthy and unhealthy states are illustrated, and the former turns to be greater than the latter. The calculated results showed that the complexity degree of PP intervals of pulse main peaks in healthy state is obviously higher than that in unhealthy state.

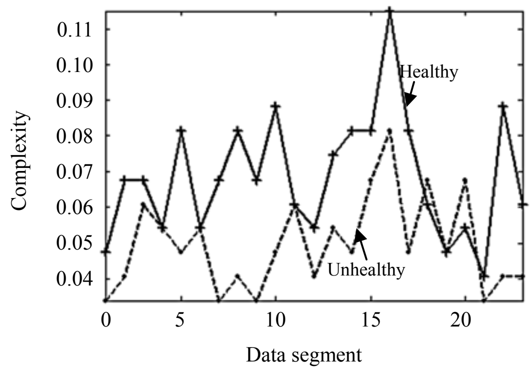

Fig.7 Complexity of PP intervals of pulse main peaks for the healthy and unhealthy states

Comparatively, fractal dimension, Lyapunov exponents, and approximate entropy could describe the system nonlinearity in certain ways. Fractal dimension only describes the static portrait of system in phase space without regarding dynamic characteristics; on the contrary is the Lyapunov exponent. Approximate entropy fails to work for signals contaminated with loud noise. The calculated approximate entropies appear to be much similar to complexity results.

DISCUSSION

PP intervals of pulse main peaks are known to directly reflect human-body health condition and mental state, and features apparent nonlinear characteristics. In the paper, several nonlinear characteristic parameters of PP intervals of pulse main peaks time series are calculated and discussed in order to identify the health condition from the differences of the nonlinear paparameters. P peaks are extracted from the original pulse waves with wavelet transform, and the PP intervals of pulse main peaks time series are obtained via re-sampling on PP intervals. Based on the optimized delay time and the minimal embedded dimension for phase space reconstruction, the correlative dimension is calculated and the largest Lyapunov exponents are estimated. The obtained results showed that, the largest Lyapunov exponents of PP intervals of pulse main peaks in healthy state (normal heart rhythm) and unhealthy state (arrhythmia) are both positive, but that the former is larger than the latter. The results of approximate entropy and complexity appear to be similar, with both the approximate entropy and the complexity in healthy state being much higher than their counterparts in unhealthy state.

The analysis of PP intervals of pulse main peaks time series approached in this paper could help further understanding of the nonlinear characteristics in pulse waves and also shows the potential for quantitative diagnosis of some heart diseases.

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