Systolic and Diastolic Time Interval Variability Analysis and Their Relations with Heart Rate Variability

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***Abstract*—Heart rate variability (HRV) has been proved an efficient measure for evaluating the function of cardiovascular system under the autonomic nerve control. In fact, HRV includes two types of variability: systolic time interval variability (STIV) and diastolic time interval variability (DTIV). Towards a better understanding of STIV and DTIV, this study uses the methods of spectrum analysis with autoregressive (AR) model and sample entropy (SampEn) analysis to compare the differences of STIV, DTIV and HRV under three physiological states: rest, deep breathing, and immediately after exercise. The experiment results show that: 1) As the existence of HRV, systolic time interval (STI) and diastolic time interval (DTI) sequences still have the variability (i.e., STIV and DTIV); 2) DTIV is more obvious than STIV and it has a better ability to follow the change of HRV; 3) from the state of rest to deep breathing, LF powers in the power spectrum density (PSD) of HRV and DTIV are enhanced obviously, while both LF and HF powers in the PSD of STIV are enhanced; 4) after exercise, the SampEn of STIV, DTIV, and HRV all increase obviously because the exercise evokes the change of cardiovascular nonlinear dynamics.**

Keywords-heart rate variability (HRV); systolic time interval variability (STIV); diastolic time interval variability (DTIV); autoregressive (AR) model; sample entropy (SampEn)

I. INTRODUCTION

Heart rate variability (HRV) denotes the slight fluctuation of RR intervals. The quantitative analysis and assessment of HRV provides an estimate of autonomic nerve control of the heart and has become an important index for evaluating the function of cardiovascular system (for a review, see [1], [2]). With the development of signal processing technology, the methods of HRV analysis include the time domain, frequency domain, time-frequency analysis, as well as nonlinear analysis [2]. In these methods, spectrum analysis and entropy analysis are two important methods. Previous work has demonstrated that there are two major frequency components of heart rate: high-frequency (HF) component (its peak in about 0.25Hz) and low-frequency (LF) component (its peak in about 0.10Hz) [3]-[5]. Burr *et al*. applied the autoregressive (AR) model to deal with the power spectrum of heart rate, and the results showed the good performance of this method in distinguishing the spectrum peak [6]. Approximate entropy (ApEn) and sample entropy (SampEn) were introduced as entropy methods to assess HRV and they could be used to calculate the complexity of time series. SampEn improves on the limitation in the self-matching of ApEn and it has a better performance in prediction the complexity of the physiological systems [7]-[9].

RR interval consists of systolic time interval (STI) and diastolic time interval (DTI). As the existence of heart rate variability, STI and DTI sequences also have the variability. Although the physiological mechanisms underlying systolic time interval variability (STIV) and diastolic time interval variability (DTIV) would be important for clinical applications, they have not been systematically studied yet. In this paper, we use the methods of spectrum analysis with the AR model and SampEn analysis to compare the differences of STIV, DTIV, and HRV. The purpose of this paper is to discover the relations between STIV and HRV, DTIV and HRV, and analyze their physiological mechanisms. The analysis is based on the experimental data collected from fifteen healthy subjects under three physiological states.

II. METHODS

A. Data Acquisition

Fifteen healthy volunteers (six females and nine males; median age, 24.6 years; range, 22-30 years) were participated in this study. All subjects were selected to ensure that they were in good health and without known cardiovascular abnormalities. They did not take medications or smoke cigarettes. Each subject gave an informed consent before conducting the experiment. ECG and Phonocardiogram (PCG) signals were collected under three physiological states: rest, deep breathing, and immediately after exercise (within 3 minutes after exercise). Above signals were sampled at 1 kHz. The course of the experiment was arranged as follows: At the beginning, the subject was asked to lie on the bed and relax for a period of time. Subsequently, ECG and PCG signals were synchronously collected under the state of rest for 5 minutes. Then the subject continuously made the deep breathing and two signals were synchronously collected for 5 minutes again. One minute after above signals collection, the subject was asked to go up and down the stairs for 5 minutes. Immediately after the movement, the third 5-minute signals were collected. The whole course of experiment was summarized by Table 1.

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TABLE I. THE WHOLE COURSE OF EXPERIMENT

Course	*1*	*2*	*3*
Physiological state	rest	deep breathing	immediately after exercise
Recording length	5 minutes	5 minutes	5 minutes

B. Parameter Extraction

ECG and PCG signals were first processed by a band pass filter and the passband frequency of ECG is 0.1-100 Hz, and PCG is 50-200 Hz. Then R-wave peaks of ECG signal were extracted by the algorithm based on wavelet transform modulus maximum. Consecutive R-R intervals made up of the RR sequence. Using the position function of R-R intervals, we extracted the first heart sound (named S1) and the second heart sound (named S2) of PCG signal. STI was defined as the time between S1 and S2 in the same cardiac cycle and DTI was defined as the time between S2 and S1 of next cardiac cycle. The construction course of RR, STI, and DTI sequences were shown in Fig. 1. HRV, STIV, and DTIV were respectively represented by the variability of these three sequences.

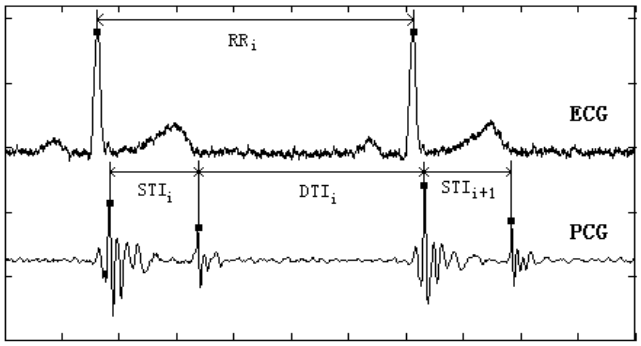

Figure 1. The method of constructing RR, STI, DTI sequences from ECG and PCG signals

C. Autoregressive (AR) Model

The AR model is essentially an all-pole infinite impulse response filter, in which the current output of the sequence can be estimated by a linear weighted sum of previous outputs in the sequence. The definition that will be used here is as follows:

$$x(n) = -\sum_{k=1}^{p} a_k x(n-k) + u(n) \qquad (1)$$

where $a_k\,(k = 1, 2, \cdots, p)$ denotes the AR model coefficient, $x(n)$ is the current output, and p is the order of the filter which is generally very much less than the length of the sequence. The noise sequence $u(n)$, of which the variance is σ^2, is always assumed to be Gaussian white noise.

Then the power spectrum can be defined as:

$$P_x(e^{j\omega}) = \sigma^2 \Big/ \left| 1 + \sum_{k=1}^{p} a_k e^{-j\omega k} \right|^2 \qquad (2)$$

The problem in AR model analysis is to derive the "best" values for $a_k(k = 1, 2, \cdots, p)$ given a sequence $x(n)$. Several methods and algorithms exist for calculating the coefficients of AR model. In this paper, we choose the Burg method to analyze the power spectrums of RR, STI, and DTI sequences.

D. Sample Entropy (SampEn)

The calculating process of SampEn is as follows [8]:

1) The original sequence: The sequence consists of N points: $u(1), u(2), \cdots, u(N)$.

2) Construct m-dimensional vectors: According to the sequence order, it forms the $N-m$ vectors $Xm(i)(1 \le i \le N-m)$, where $Xm(i) = [u(i+k)]$ $(0 \le k \le m-1)$ is the vector of m data points from $u(i)$ to $u(i+m-1)$.

3) Define the distance $d[Xm(i), Xm(j)]$ *between* $Xm(i)$ *and* $Xm(j)$*:* $d[Xm(i), Xm(j)] = \max(|u(i+k) - u(j+k)|)$, where $k = 0 \sim m-1,\ i, j = 1 \sim N-m,\ i \ne j$.

4) Calculate the $B^m(r)$*:* Let $N^m(i)$ be the number of $d[Xm(i), Xm(j)]$ less than threshold r. Define the function $B_r^m(r) = N^m(i) \big/ (N-m-1)$. Then calculate the mean of all i using the function given as:

$$B^m(r) = \sum_{i=1}^{N-m} B_r^m(i) \Big/ (N-m) \qquad (3)$$

5) Add the dimension from m *to* $m+1$*:* $Xm+1(i)(1 \le i \le N-m)$, and repeat above operation to calculate the $B^{m+1}(r)$.

The SampEn of the sequence theoretically is:

$$SampEn(m, r) = \lim_{N \to \infty} \ln\left[B^m(r) / B^{m+1}(r) \right] \qquad (4)$$

It is restricted by $N \to \infty$, the formula (4) is not suited to analyze the finite sequences derived from the experiment. So the SampEn is usually estimated by the formula:

$$SampEn(m, r, N) = \ln\left[B^m(r) / B^{m+1}(r) \right] \qquad (5)$$

The formula (5) calculates $SampEn(m, r, N)$ of sequence for fixed parameters *m*, *r*, and *N* as measure of complexity.

III. EXPERIMENT RESULTS

In order to discover the relations between STIV and HRV, DTIV and HRV, we first compare the differences of RR, STI, and DTI sequence curves. Then we use AR model to analyze the power spectrums of HRV, STIV, and DTIV under three physiological states. At last, the SampEn values of HRV, STIV, and DTIV are calculated to show the variability of physiological systems.

A. RR, STI, DTI sequence curves

Fig. 2 gives the typical change trend of RR, STI, and DTI sequences. It is very clear that DTI sequence is very similar to RR sequence in each physiological state, but STI sequence keeps fixedness basically. From the state of rest to deep breathing, RR and DTI sequences have an obvious fluctuation and their rhythms enhance. At the same time, STI sequence has a small fluctuation. Considering the heart rate could increase significantly after exercise, the relative decrease in RR, STI, and DTI intervals could be detected from the state of rest to immediately after exercise. However, there is no obvious fluctuation and rhythms enhance after exercise.

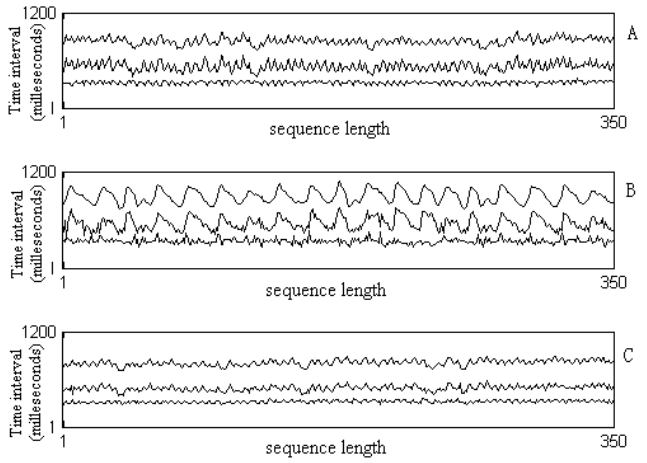

Figure 2. Examples of RR, STI, DTI sequence curves under three physiological states. The panel (A), (B), and (C) respectively denotes the state of rest, deep breathing, and immediately after exercise. In each panel, RR, DTI, and STI sequence curves are respectively arranged from top to bottom.

Fig. 3 gives the standard deviation (SD) of RR, STI, and DTI sequences, which correspond to the curves shown in Fig. 2. SD is defined as

$$SD = \sqrt{\frac{\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2}{N}} \qquad (6)$$

Where x_i denotes an element of the sequence, $\bar{x}$ denotes the mean value of the sequence.

It is clear that RR and DTI sequences have a larger SD, especially under the state of deep breathing, and STI sequence has a smaller SD, especially under the state of rest. The quantitative analysis for SD is summarized in Table 2.

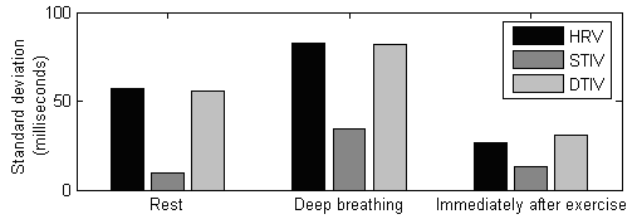

Figure 3. Standard deviation of RR, STI, and DTI sequences under three physiological states (i.e., rest, deep breathing, and immediately after exercise).

B. Spectrum Analysis with AR Model

The HF and LF components of HRV are usually used to evaluate autonomic regulations. This study also focuses on the comparison among HRV, STIV, and DTIV spectrums at these two frequency bands. It is generally believed that the HF band is defined as 0.15Hz-0.4Hz, and the LF band is defined as 0.04Hz-0.15Hz. Fig. 4 shows the power spectrum density of HRV, STIV, and DTIV from one typical subject under three physiological states. In this individual case, it shows that LF powers in the PSD of HRV and DTIV are enhanced from the state of rest to deep breathing, while, both LF and HF powers in the PSD of STIV are enhanced at the same time. After exercise, the glossy PSD curves become irregular in some sort. It indicates that the complexity of cardiovascular increase. The quantitative analysis for PSD is summarized in Table 2.

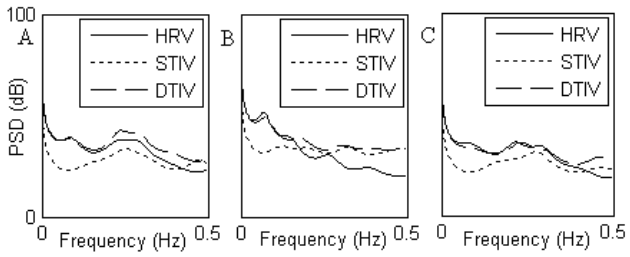

Figure 4. Power spectrum density (PSD) of HRV, STIV, and DTIV under three physiological states. The panel (A), (B), and (C) respectively denotes the state of rest, deep breathing, and immediately after exercise.

C. SampEn analysis

SampEn analysis technique is one of nonlinear analysis methods for HRV and it has been used to better discriminate adult HR data among normal, atria fibrillation, and congestive heart failure patients [10]. Fig. 5 shows the SampEn values of HRV, STIV, and DTIV from one typical subject under three physiological states. In this individual case, it shows that the SampEn value of HRV is almost the same as DTIV and their values are larger than STIV. Among the three physiological states, immediately after exercise reveals the maximum values, deep breathing reveals the minimum values, and rest reveals intermediate values. The quantitative analysis for SampEn is summarized in Table 2.

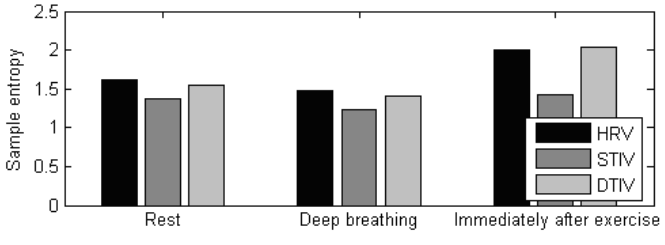

Figure 5. Sample entropy of HRV, STIV, and DTIV under three physiological states (i.e., rest, deep breathing, and immediately after exercise).

TABLE II. ANALYSIS RESULTS OF FIFTEEN SUBJECTS

state		*SD*	*LF*	*HF*	*LF/HF*	*SampEn*
Rest	HRV	57.2 ± 28.5	911 ± 285	1074 ± 359	0.82 ± 0.23	1.61 ± 0.31
	STIV	11.8 ±5.6	31 ± 15	172 ± 133	0.28 ± 0.14	1.38 ± 0.23
	DTIV	55.7 ± 30.6	905 ± 306	1447 ± 410	0.64 ± 0.26	1.55 ± 0.32
Deep breathing	HRV	82.4 ± 46.4	6510 ± 2864	1190 ± 299	5.8 ± 2.1	1.47 ± 0.25
	STIV	33.2 ± 17.5	163 ± 107	480 ± 214	0.43 ± 0.26	1.24 ± 0.23
	DTIV	81.2 ± 39.2	4947 ± 2392	1478 ± 375	4.3 ± 2.3	1.40 ± 0.19
Immediately after exercise	HRV	26.5 ± 17.5	301 ± 175	390 ± 205	0.76 ± 0.19	2.00 ± 0.31
	STIV	13.4 ± 5.9	27 ± 14	110 ± 69	0.22 ± 0.13	1.42 ± 0.29
	DTIV	34.7 ± 25.1	294 ± 181	354 ± 229	0.69 ± 0.22	2.04 ± 0.41

IV. DISCUSSIONS AND CONLUSIONS

Short-term HRV (about 5 minutes) under the state of rest may be considered as an index of cardiovascular regulation, which is rich of nonlinear mechanisms (e.g., saturation of receptors, nonlinear interactions between sympathetic and parasympathetic nervous system at sinus node level, nonlinear interferences among vasomotor, and respiratory oscillators at brain stem level, etc.) [11], [12]. However, when the physiological state has changed, the balances of these control mechanisms will be accordingly changed. From the state of rest to deep breathing, it is clear that breathing frequency becomes more rhythmed. On the one hand, it gives cause for the PSD increase of HRV at LF power as shown in Fig. 4. On the other hand, it gives cause for the SampEn of HRV decrease as shown in Fig. 5 because the nonlinear complexity of cardiovascular system reduces. After exercise, the SampEn of HRV increases obviously because the exercise evokes the change of cardiovascular nonlinear dynamics.

STIV and DTIV also have the above phenomenon reflected by HRV, which can be observed in Fig. 4 and Fig. 5. It is valuable to note that the change of STIV is inconspicuous, oppositely, the change of DTIV is obvious (i.e., the change range of STIV is much smaller than DTIV). Previous studies prove that the fluctuation of RR interval is mainly caused by DTI, while, STI makes a small fluctuation. It is useful to keep the normal heart function for pumping blood. The experiment results prove the above fact.

This study forms a conclusion that STI and DTI sequences still have the variability (i.e., STIV and DTIV) and DTIV is more obvious than STIV. DTIV has a better ability to follow the change of HRV, but STIV keeps a higher stability. Furthermore, STIV, DTIV, and HRV vary with the different physiological state. This is a reflection that the interaction of the sympathetic and parasympathetic nervous systems and the regulative mechanism in cardiovascular system. Further work will focus on the study of the physiological mechanisms of STIV, DTIV, and HRV and their potential use in the clinical estimation for cardiovascular disease.

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