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A Novel Method to Estimate Heart Rate from ECG

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Abstract

Heart rate variability (HRV) in electrocardiogram (ECG) is an important index for understanding the health status of heart and the autonomic nervous system. Most HRV analysis approaches are based on the proper heart rate (HR) data. Estimation of heart rate is thus a key process in the HRV study. In this paper, we report an innovative method to estimate the heart rate. This method is mainly based on the concept of periodicity transform (PT) and instantaneous period (IP) estimate. The method presented is accordingly called the "PT-IP method." It does not require ECG R-wave detection and thus possesses robust noise-immune capability. While the noise contamination, ECG time-varying morphology, and subjects' physiological variations make the R-wave detection a difficult task, this method can help us effectively estimate HR for medical research and clinical diagnosis. The results of estimating HR from empirical ECG data verify the efficacy and reliability of the proposed method.

Key words : heart rate (HR), heart rate variability (HRV), instantaneous period, periodicity transform, PT-IP method, electrocardiogram (ECG)

I. INTRODUCTION

The electrocardiogram (ECG) has been extensively studied due to the low cost and easy implementation of ECG recording instrumentation. Most importantly, clinical and medical significance of ECG has been well explored during the past decades. Among various parameters derived from ECG, the heart rate variability (HRV) [1] measuring the fluctuation or deviation of heart rate (HR, the number of heart beats per unit time) has been drawing the attention of researchers and medical experts. HRV not only provides information concerning the health condition of heart [2] but also relates to the autonomic nervous system (ANS) [3]. ANS behavior directly causes physiological changes and thus closely affects our health [4]. For example, ANS plays an important role in various pathological settings such as diabetic neuropathy, myocardial infarction and congestive heart failure.

Spontaneous heart beat fluctuations are mainly due to interactions between cardiac pacemaker cells and the autonomic nervous system including sympathetic and parasympathetic nerves. The HRV results from the balance between both components [5]. Therefore, the HRV is considered as one of the most important techniques used to study ANS and relative diseases. As a practical example, clinical evidence of the depressed HRV caused by sympathetic overdrive and decrease in vagal activity provides a reliable predictor of mortality after myocardial infarction [6]. Due to its merits of quantitatively exploring the autonomic nervous activity, HRV study has emerged as a subject of great interest in physiology, clinical medicine and clinical pharmacology.

Methods for HRV analysis are mostly based on the proper HR data. Estimation of heart rate is thus an important and fundamental process in the HRV study. Traditionally, the estimation of HR is based on the ECG R-wave (QRS complex) detection [7~9]. The HR is inversely proportional to the time span between two consecutive R-waves. However, the noise contamination [10], ECG time-varying morphology [11], and subjects' physiological variations often make it difficult to accurately detect the R-wave. Some concepts or methods such as mathematical morphology [12], higher-order statistics [13], moving average-based computing [14], artificial neural network [15, 16], fuzzy inference system [17], dyadic wavelet transform [18], wavelet modulus maxima [19], delay-coordinate mapping [20], optimum linear and nonlinear filters [21], index function based on resonance theory [22], and so on, have been proposed to deal with these problems. Some researchers also suggested combining different R-wave detection algorithms for the

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better performance [23]. To avoid the problems of detecting R-wave, methods based on spectral analysis of ECG [24, 25] were presented. These methods calculate the heart rate value from the instantaneous frequency of ECG signal, and thus need not know the occurring point (time) of R-wave. However, computational methods involving transformation between different domains often cause extra erroneousness to the final estimate.

In this paper, we propose a novel method based on the concept of periodicity transform [26, 27] to extract HR data from ECG signal. The proposed method estimates the instantaneous heart rate from the instantaneous period of ECG, and does not require the use of R-wave detection nor spectral computing. The proposed method, PT-IP (abbreviation for "periodicity transform-instantaneous period") method, can correctly estimate the HR data from ECG, even of poor quality. Results of estimating HR data from empirical ECG signals demonstrate the reliability of proposed method. In the following sections, we will describe the proposed method and show its performance in estimating HR data.

II. MATERIALS AND METHOD

Periodicity transform (PT) can detect the periodicities, repetitions, and regularities in a data sequence and decompose the sequence into a set of periodic-basis elements [26]. Based on PT theory, this paper reports our development of HR estimation approach in the following two aspects:

A. The Process of Finding "*p*-periodic Element" in a Data Sequence

An infinite sequence of real numbers $x[n]$ is called p-periodic if there exists an integer p such that $x[n+p]=x[n]$, $\forall\, n\in I$ (integer). In practical situation, one may focus on evaluating the periodic behavior over a finite length of N points. Consider a data sequence $x[n]$, $0 \le n \le N-1$ (N is even). The p-periodic element $x_p[n]$, $2 \le p \le N/2$, of $x[n]$ can be derived by

$$x_P[n]=P(x[n],\triangle_P)=\sum_{i=0}^{p-1}\overline{x_p}[i]\cdot u_{p,i}[n], \quad 0 \le n \le N-1 \tag{1}$$

where $P(x[n],\ \triangle p)$ is the function to calculate the p-periodic element of $x[n]$. The p-periodic basis vectors, $u_{p,j}[n]$, $j=0,\ 1,\ \cdots,\ p-1$, are defined as

$$u_{p,j}[n]=\sum_{l=-\infty}^{\infty}\delta[n-(p\cdot l+j)] \tag{2}$$

where $\delta[\cdot]$ is the unit impulse sequence. The sequence $\overline{x_p}[i]$, $0 \le i \le p-1$ represents the average periodic pattern of all the periods in $x[n]$. The number of periods is computed by $N_p=\partial\{N/p\}$, that is, the round-off integer of N/p. Then, the average period is

$$\overline{x_p}[i]=\frac{1}{N_p}\sum_{m=0}^{N_p-1}x[i+mp] \tag{3}$$

B. The Criterion of Judging the "Degree of Significance" of *p*-periodicity in *x[n]*

The degree of significance (DOS) is estimated by computing the norm ratio of the p-periodic vector x_p: $(x_p[-k],\cdots,x_p[0],\cdots x_p[k])$ to that of the vector x : $(x[-k],\cdots,x[0],\cdots x[k])$. The norm is defined below:

$$\| x \| = \sqrt{\langle x, x\rangle} = \sqrt{\lim_{k\to\infty}\frac{1}{2k+1}\sum_{n=-k}^{k}(x[n]\cdot x[n])} \tag{4}$$

where $\langle a,\ b\rangle$ is the inner product of vectors a and b. In $x[n]$, DOS (denoted by ζ_p) of the p-periodic element $x_p[n]$ is thus evaluated by

$$\zeta_p=\frac{\| x_p \|}{\| x \|} \tag{5}$$

A larger value of ζ_p indicates a higher degree of significance of p-periodicity in $x[n]$.

Main scheme of the proposed method is illustrated in Figure 1. For an ECG sequence $s[n]$ (n is integer), the flow chart in Figure 1 explains how to find the estimated value of heart rate at sampling point n, that is, $HR(n)$. First, we derive $x[n]$ by filtering sequence $s[n]$ with a band-pass filter. The band-pass filter is designed with a pass-band of 0.45Hz-5Hz so that the sequence $x[n]$ can befree from most noises and disturbances (such as the base-line drift) but still preserve information of heart beat rhythms. Given a sampling point n, the main period of sequence $x[n]$ around n (centering on n) is considered as the "instantaneous period" of ECG at n. We then estimate the value of heart rate at n by the instantaneous period. To

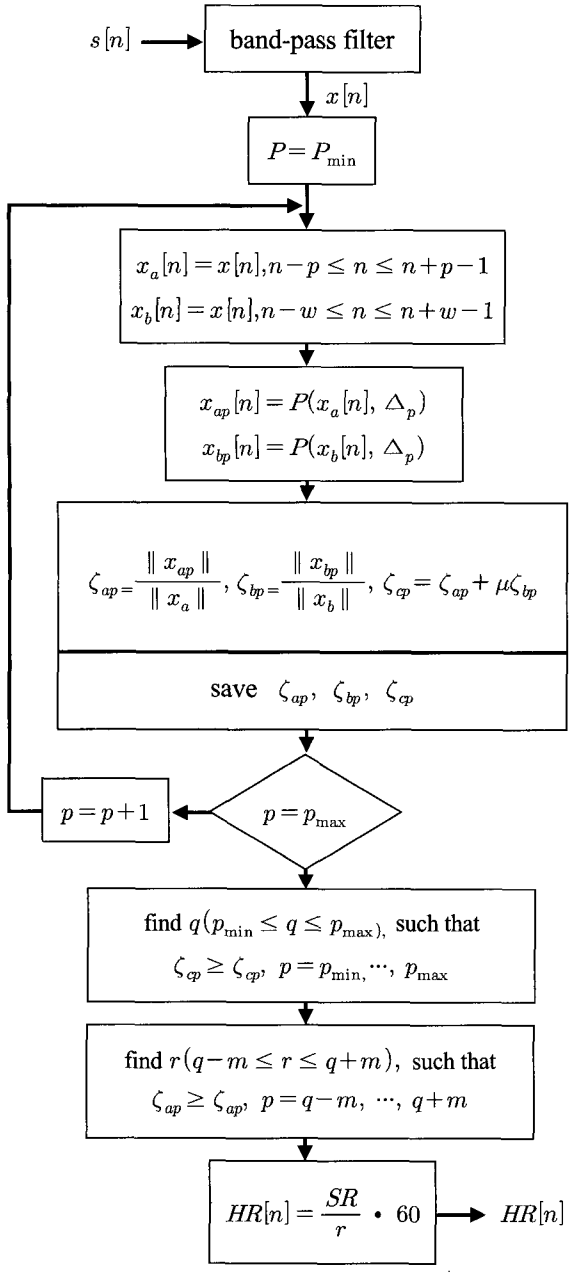

Fig. 1. Block diagram of PT-IP scheme.

find the instantaneous period, we first limit the value to the range of $p_{\min} \sim p_{\max}$ sample points per heart beat cycle. In our case of 250Hz sampling rate, our investigation resulted in a moderate choice of $p_{\min} = 50$ and $p_{\max} = 500$ samples, corresponding to the heart rates ranging from a maximum of 300 beats/min to a minimum of 30 beats/min. Conventional PT process tries to find all possible periodic elements in a finite data sequence, that is not necessary for our aim at HR estimation based on ECG rhythms. In addition, highly non-stationary behavior of ECG rhythm increases the difficulty in exhausted search for all periods [28]. The method developed in this study is described below.

For $p = p_{\min}, p_{\min}+1, \cdots p_{\max}$, let

$x_a[n] = x[n], n-p \le n \le n+p-1,$

$x_b[n] = x[n], n-w \le n \le n+w-1, w > p$

(we let $w = 2p$),

we then derive:

$x_{ap}[n] = P(x_a[n], \Delta_p)$, $x_{bp}[n] = P(x_b[n], \Delta_p)$,

and finally

$$\zeta_{ap} = \frac{\| x_{ap} \|}{\| x_a \|}, \zeta_{bp} = \frac{\| x_{bp} \|}{\| x_b \|} \quad (6)$$

According to PT theory, a larger value of ζ_{ap} (ζ_{bp}) indicates a higher degree of significance of p-periodicity in $x_a[n]$ ($x_b[n]$). Note that ζ_{bp} is the DOS of the p-periodic element in a length-$2w$ sequence $x_b[n]$, an extended version of $x_a[n]$. If the instantaneous period at sampling point n is p, we will obtain a larger ζ_{ap}. Therefore, by searchingthe local maximum of ζ_{ap}, we can find the instantaneous period at sampling point n and further estimate the heart rate at n. Notice that the length of $x_a[n]$ is $2p$. According to the limitation of PT theory, the sequence length must be at least $2p$ in order to find the p-periodic element in the sequence. However, sometimes value of ζ_{ap} may not correctly reflect the instantaneous period due to the similarity between two halves of $x_a[n]$ each. Evaluation of ζ_{bp} was mainly aimed to avoid this mistake. Although period (frequency) variation in ECG is a time-varying signal, it does not change very abruptly in a short interval [24]. If the instantaneous period at n is p, a relatively large value of ζ_{bp} will still appear. On the contrary, a relatively small value of ζ_{bp} will be observed while the instantaneous period is not p. However, due to the time-varying periodicity of ECG, too long the length of $x_b[n]$ will reduce the DOS of p-periodic element in $x_b[n]$. By trying out various lengths of $x_b[n]$, we found the $4p$ length of $x_b[n]$ is an ideal choice in practical ECG analysis. Next, we combine ζ_{bp} with ζ_{bp} to estimate the instantaneous period at sampling point n. Let

$$\zeta_{cp} = \zeta_{ap} + \mu\zeta_{bp}, \quad 0.5 \le \mu \le 1.5 \text{ (we let } \mu = 1) \quad (7)$$

and find $q(p_{\min} \le q \le p_{\max})$, such that

$\zeta_{cq} \ge \zeta_{cp}, p = p_{\min}, \cdots, p_{mix}$, where q is an approximate estimate of period. Next, the final estimate of instantaneous

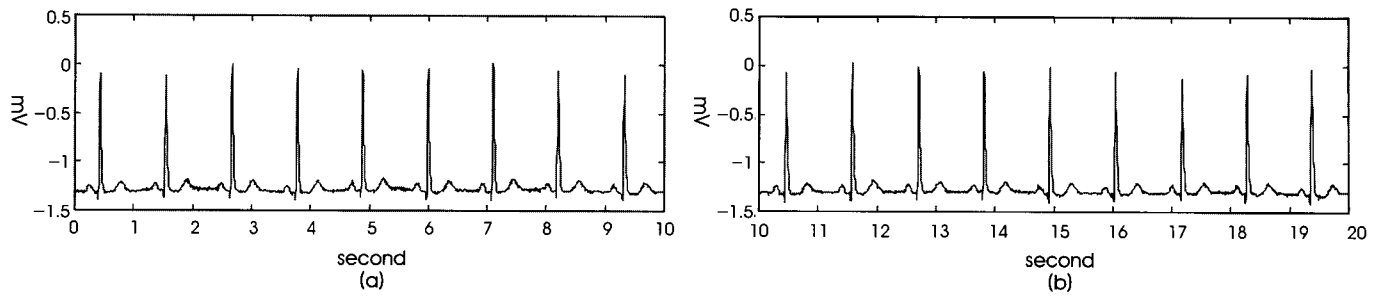

Fig. 2. A normal ECG signal.

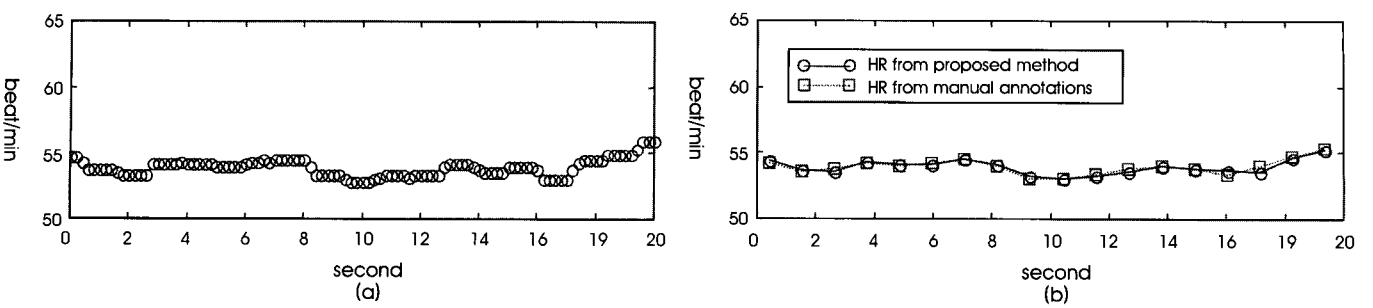

Fig. 3. (a) The HR sequence estimated by proposed method, and (b) the HR sequence (interpolated) from proposed method (circle), and the HR sequence from manual annotations (square), for the ECG signal in Figure 2.

period r is derived by examining $\zeta_{ar} \geq \zeta_{ap}, p = q-m, \cdots, q+m$ for the range $q-m \leq r \leq q+m$, where m is a proper integer. Finally, the heart rate at sampling point n is calculated by

$$HR[n] = \frac{SR}{r} \cdot 60 \tag{8}$$

where SR is the sampling rate. Although computational time required by our method is more than some conventional methods, we will demonstrate in the next section the robust noise-immune capability of the proposed method at the cost of more computational time.

In practical situation, there is no need to estimate the heart rate at every sampling point. In this paper, we evaluated the heart rate at an interval of 0.2 second, resulting an HR sequence with 5Hz sampling rate. Normally, 1Hz sampling rate is feasible for analyzing the spectrum of HR sequence. Similar to the voice pitch [29], heart rate does not change abruptly. Therefore, instantaneous period r will not largely change in a short interval. In normal or high estimation frequency, current value of r can be found by directly searching in the neighborhood of the previous one. Let $r(l)$ denote the l^{th} r to be determined by the PT approach. With the previous $(l-1)$ known values, $r(1), r(2), \cdots r(l-1)$,we suggest that the searching range be restricted to $0.55r(l-1) \leq p \leq 1.9r(l-1)$. The computational load can thus be largely reduced.

III. RESULTS

In this section we present the results of estimating the HR data based on the proposed PT-IP method. ECG signals analyzed here were acquired from MIT-BIH Database [30]. Each ECG record analyzed in this studycontains manual annotations for each QRS complex (heart beat), with its location (time of occurrence) and type (normal, ventricular ectopic, etc.) indicated. Therefore, we can compare the HR data estimated by our method with a priori HR data information and evaluate the performance of our method.

A. Noise-Immune Capability of Proposed PT-IP Method

Figure 2 displays a 20-second normal ECG sequence sampled at 250Hz. We first evaluated the heart rate by PT-IP method at a step of 0.2 second that resulted in an HR sequence at an equivalent sampling rate of 5Hz as shown in Figure 3(a). To evaluate the performance, we interpolated linearly the estimated HR values to the sampling frequency of ECG sequence (250Hz) so that the HR values of the novel method could be obtained at the same points at which the ECG R-waves occurred. The interpolated values of HR data from

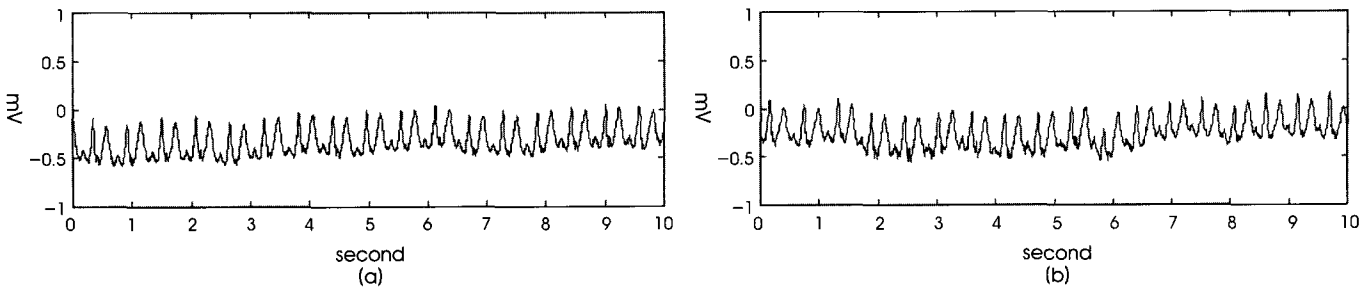

Fig. 4. An abnormal ECG recorded from a subject with severe congestive heart failure.

the novel method and the HR data calculated from manual annotations (phase corrected) are both plotted in Figure 3(b) (circle and square, respectively). According to eq. (9), deviation between the two HR sequences is 0.003.

$$\varepsilon = \sqrt{\frac{1}{M}\sum_{j=1}^{M}\left[\frac{HR_{new}[j] - HR_{old}[j]}{HR_{old}[j]}\right]^2} \qquad (9)$$

where HR_{new}represents the value of HR from the novel method, and HR_{old} the HR value from manual annotations.

To demonstrate the robust noise-immune capability of proposed method, we added noise component to the ECG in Figure 2 to simulate a noisy ECG signal. In this analysis, we first investigate three kinds of noise sequences: noise 1 is the EMG signal [31, 32], noise 2 is the random noise, and noise 3 is the power-line interference [33]. The novel method's errors caused by these noise signals with various signal-to-noise ratios (SNR) are listed in Table 1. The SNR is defined as

$$SNR = \frac{P_{signal}}{P_{noise}}, \qquad (10)$$

where P_{signal} represents the power of ECG signal (excluding base line drift), and P_{noise} the power of noise. In general, smaller SNR makes the R-wave detection more difficult. Since the PT-IP method does not require R-wave detection to estimate HR, it therefore works well in most cases of contaminated ECG signals. According to Table 1, even with a noise power ten times the ECG's (that is, SNR=0.1) the proposed method still performed well.

For comparison, we adopted a widely used R-wave detection method [7, 10] to analyze the same ECG data. Estimation errors based on the conventionalmethod are also listed in Table 1. We next inserted the interference of base-line drift resulted from respiration. This type of interference can be simulated by adding a low frequency (~0.33Hz) sinusoid to the noise-free ECG. The errors of PT-IP method and R-wave detection method are listed in Table 2. According to Tables 1 and 2, both methods successfully resisted low-frequency base-line drift, however, PT-IP method preformed more superior than R-wave detection method when ECG was contaminated by EMG (electromyograph), random noise, or power-line interference.

Table 1. Comparison of errors resulted from PT-IP method and R-wave detection method (Part 1).

SNR		16/5	8/5	4/5	2/5	1/5	1/10
Noise1	PT-IP	0.004	0.004	0.004	0.005	0.006	0.008
	R-wave	0.007	0.131	2.456	3.304	3.726	4.186
	PT-IP	0.005	0.005	0.006	0.007	0.010	0.013
Noise2	R-wave	0.005	0.007	0.008	0.008	1.182	3.037
	PT-IP	0.004	0.004	0.004	0.004	0.004	0.004
	R-wave	0.009	0.010	0.009	3.563	3.960	4.278

Table 2. Comparison of errors resulted from PT-IP method and R-wave detection method (Part 2).

Amplitude (peak to peak)	0.8mV	1.6mV	2.4mV	3.2mV	4.0mV
PT-IP	0.004	0.005	0.006	0.006	0.006
R-wave	0.005	0.005	0.005	0.006	0.006

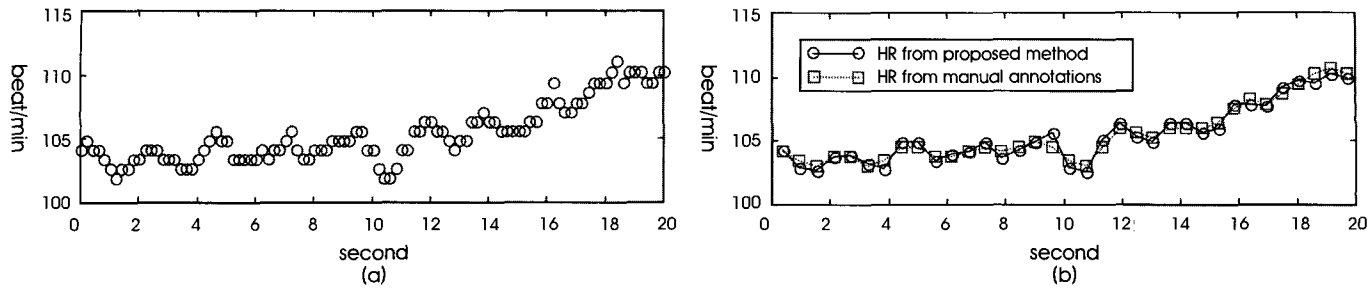

Fig. 5. (a) The HR sequence estimated by proposed method, and (b) the HR sequence (interpolated) from proposed method (circle), and the HR sequence from manual annotations (square), for the ECG signal in Figure 4.

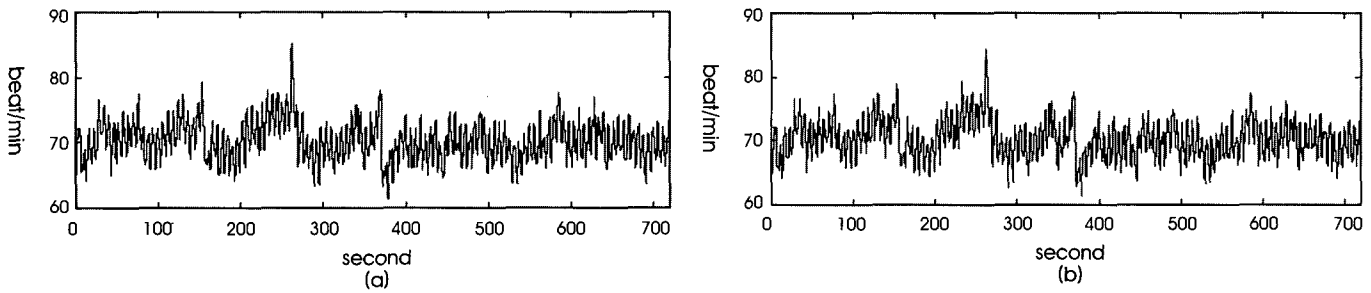

Fig. 6. HR sequences derived respectively (a) by PT-IP method and (b) by manual annotations.

B. HR Analysis for ECGs with Special QRS Complexes

Sometimes, difficulty of R-wave detection is not due to the noise interference but due to the R-wave itself. The ECG sequence shown in Figure 4 (sampling rate is 250Hz) was collectedfrom a male subject with severe congestive heart failure (NYHA class 3-4). In this case, the shapes of R-wave make R-wave detection nearly impossible. However, the proposed PT-IP method still allows us to obtain a satisfactory estimate of HR. We estimated heart rate at a step of 0.2 second and plotted the estimated HR sequence in Figure 5(a). Similarly, for evaluating the correctness of the novel method, we interpolated linearly the estimated HR values to the sampling frequency (250Hz) so that the HR values of the novel method could be obtained at the same points at which the ECG R-waves occurred. The interpolated values of HR from the proposed method (circle) and the HR data from manual annotations (square) are both plotted in Figure 5(b). According to eq (9), deviation between two HR sequences is minute (0.004).

C. Spectral Analysis for HR Sequence Derived by PT-IP Method

HRV evaluation mostly involves the spectral analysis of HR sequence [5, 34].We accordingly justify the feasibility of our method by examining the spectral characteristics. The ECG data was acquired from a male subject suffering from arrhythmia. We estimated heart rate at a step of 0.2 second, then interpolated linearly the estimated HRV values to the sampling frequency of ECG sequence (250Hz), and plotted the result in Figure 6(a). Note that the sampling rate of HR sequence from the proposed method in Figure 6(a) is 250Hz. On the other hand, we calculated HR values from manual annotations, then also interpolated linearly the HR sequence to 250Hz and plotted the result in Figure 6(b). The relative error between the two HR sequences in Figures 6(a) (from the proposed method) and 6(b) (from manual annotations) is 0.007. If we only consider these points at which the ECG R-waves occurred, the relative error is 0.005. To conduct spectral analysis in the frequency range of 0~0.5Hz, we

Table 3. Power percentages in the three regions.

Regions	VLF	LF	HF
PT-IP method	33.34%	29.91%	36.75%
Manual annotations	34.89%	30.92%	34.19%

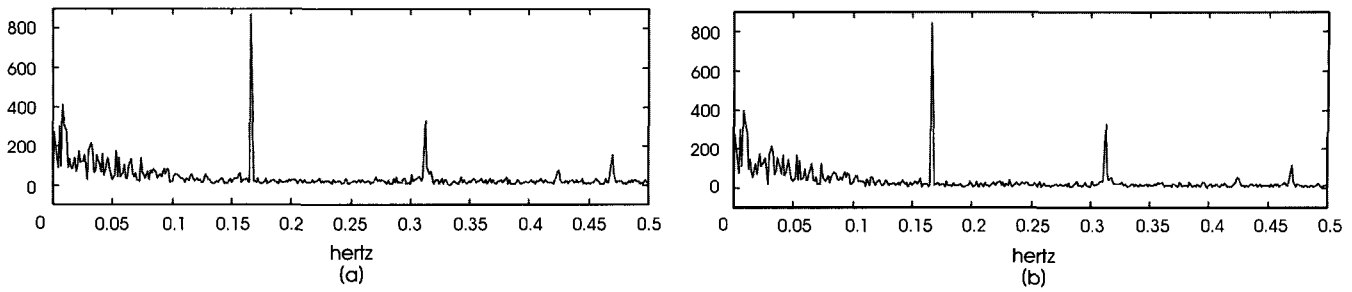

Fig. 7. The Fourier magnitude spectra of HR sequences derived respectively (a) by PT-IP method and (b) by manual annotations.

down-sampled the HR sequences in Figure 6 to 1Hz (originally, 250Hz). Power spectra of the re-sampled HR sequences are plotted in Figures 7(a) (PT-IP method) and 7(b) (manual annotations). Note that HR sequence spectrum includes three frequency bands of particular interest: very-low-frequency region (VLF, 0~0.04Hz), low-frequency- region (LF, 0.04~0.15Hz), and high-frequency region (HF, 0.15~0.40Hz). Both HR sequence spectra in Figure 7 well coincide in three regions. Additionally, the high frequency region is normally related to respiratory activity. In Figure 7, we find the HR sequence is obviously influenced by a stable respiratory activity (the patient was sleeping with a stable respiratory frequency about 0.167Hz). The proportions (in percentage) of spectra power in these three regions are tabulated in Table 3. Obviously, the spectrum of HR sequence estimated from novel method is proper and correct.

IV. DISCUSSION AND CONCLUSION

HRV is not only a useful index for understanding the status of ANS but also an important tool in the study of life system. For the study or analysis of HRV, the correct estimation of HR is very important to the researchers and physicians. In general, R-wave detection is a good way to estimate HR from ECG signal. However, many unexpected or unavoidable factors often make the correct detection of R-wave very difficult. The proposed method estimates HR by the instantaneous periods of ECG, therefore can avoid the problems of R-wave detection, and provide the proper and correct estimation of HR. However, the superior performance has been achieved at the expense of more computational time. Considering the estimate of one HR value for the ECG signal in Figure 2, elapsed time required by the proposed method (in standard process) was ~0.08 second, which was ~0.003 second if employing R-wave detection method [7] (Pentium 1.6GHz with 256-MByte RAM). Due to the characteristic of PT-IT method, the proposed method is also suitable to estimate HR from blood pressure data. However, we must note that sometimes the HR estimated from blood pressure data is different from the HR estimated from ECG. For example, some researchers have found that the spectra of the two HR signals are similar in low frequencies (below 0.15Hz) but different in high frequencies (above 0.15Hz) [35]. This also explains that the extracting HR from ECG is necessary and significant in HRV analysis. Finally, the results of estimating HR from various empirical ECG signals have shown that the novel method is very effective and reliable. In the correlative study domains of HR and HRV, the proposed PT-IP method is helpful and valuable to the medical research and clinical diagnosis.

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