Segmentation of Heart Rate Variability in Different Physical Activities

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Abstract

Heart rate variability is due to the interaction of sympathetic and parasympathetic nervous system. The spectral analysis of HRV provides a noninvasive probe to assess the function of the autonomic nervous system. The recording of physiological signals on free-moving subjects provides a useful tool to evaluate the autonomic states in the daily activities, but the information of activities is lack in the conventional ECG Holter, so it is difficult to estimate HRV in different activities. In this paper, we developed a microcontroller-based system for ECG and physical-activity recording system. The acceleration signals located at chest and thigh is used to classify the basic activities, including lying (supine, left lateral, right lateral, and prone), sitting, standing, and dynamic activity. Time-frequency analysis is used to compute the time-varying spectra of heart rate variability. In the 24-hour recording, the high-frequency fluctuations are the largest and the second in the sitting, which means major dominance of parasympathetic tone. As the posture is changing form sitting to standing and dynamic activity, the low-frequency power to high-frequency power ratio increases which demonstrates the increase of sympathetic tone and decrease of parasympathetic tone.

1. Introduction

The period of heartbeat is not constant and changes over the time. The variation of heart period or heart rate, generally called heart rate variability (HRV) can reflect the function of the autonomic nervous system by spectral analysis of HRV [1,2]. In general, low frequency heart rate fluctuation (about 0.1 Hz) is related to vasomotor effect, mediated by the sympathetic nervous system. High frequency fluctuation is synchronized with respiration, mediated by the parasympathetic nervous system. As for lower frequency fluctuation, its mechanism is not very clear but the renin-angiotensin system was regarded as its possible mechanism [1]. The spectral analysis of HRV has been widely used to investigate the autonomic behavior in neurological dysfunction, cardiovascular dysfunction, diabetes, etc. [3,4,5,6].

Not only the autonomic nervous system, the external factors, like body posture will also change the spectral characteristics of HRV [7]. In the supine, the parasympathetic modulation is dominant, and causes stronger high-frequency heartbeat fluctuations. In contrast, decreased parasympathetic function occurs in the stand position. The 24-hour electrocardiogram (ECG) Holter recordings give lots of HRV data, so it can be used in the evaluating the autonomic function of patients. Owing to the lack of activity data, the researchers only can retrieve HRV characteristics over 24 hours or in the specific time. In fact, most of subjects are free-moving during 24-hour recording. We regards that the HRV characteristic changes in different activities, so it is necessary to link HRV with the physical activity.

In this paper, a portable ECG and physical activity data recorder is developed to investigate the association of HRV and physical activity in 6 healthy subjects. The Konhen self-learning neural network is used to detect the physical activity. Time-frequency HRV spectra are segmented an averaged based on the classified physical activity.

2. Methods

2.1. Data recording

Six healthy and active men (means ± SE: age 24 ± 2.1 yr, height 170.2 ± 2.1 cm, weight 50 ± 2.1 kg) were included in this study. The subjects were free-lived as usual. Mild activities like walking, etc. were allowed.

As shown in Fig.1, a microcontroller-based (MSP430F149, Texas Instrument, USA) data recorder is developed. One channel ECG with 0.05-Hz highpass filtering, 50-Hz lowpass filtering, and 60-Hz notch filtering is recorded. One accelerometer with downward sensing direction (a_t) fixed at the thigh, one x-y direction accelerometer (a_x and a_y) on the chest and one z-direction accelerometer (a_z) inside the recorder are used to record the acceleration signals of the body. All accelerators are built with biaxial accelerometers (ADXL202, Analog Device, USA). ECG and the acceleration signals are sampled at 200 and 20 Hz, respectively, and are stored in the 128-MB compact-flash memory card (Sandisk, USA). After the recording is completed, the data stored in the compact-flash memory card is retrieved via compact-flash card reader.

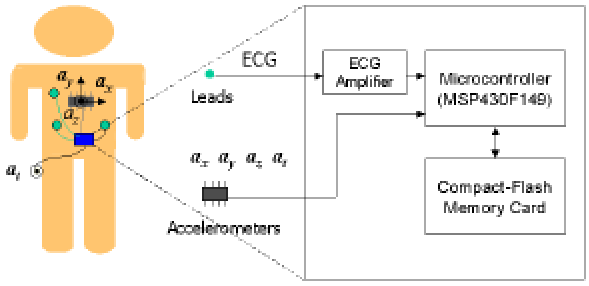

Figure 1 ECG and physical activity recording System

2.2. Classification of physical activities

The output signals of the accelerometers depend on the the angle of the gravity and the sensing direction. Most papers use fixed thresholds for activity detection [8]. However, it is difficult to use fixed thresholds for activity classfication because of the location of accelerometer and personal habitual postures. Thus, the Konhen self-learning neural network is used to classify the physical activity. The 1-s median value of the accelerations, $a_{x(med)}$, $a_{y(med)}$, $a_{z(med)}$, and $a_{t(med)}$ are the inputs to the network written in vector form as

$$\boldsymbol{a} = [a_{x(med)} \quad a_{y(med)} \quad a_{z(med)} \quad a_{t(med)}]$$

The weight vector assocaited with the ith activity is given by

$$\boldsymbol{w_i} = [w_{ix} \quad w_{iy} \quad w_{iz} \quad w_{it}] \qquad i=1, 2, ..., 6$$

There are 6 weight vectors representing left lateral, right lateral, supine, prone, sitting, and standing. The initial weight vectors are given by the standard value of each physical activity. The best match of activity weight vector $\boldsymbol{w_i}$ and acceleration vector $\boldsymbol{a}$ is determined from

$$m(a) = \min_{\forall i} \| a - w_i \|^2 \qquad i = 1,2,\cdots,6$$

where $m(a)$ is the index into output neuron that specifies the winning neuron (physical activity). The weight vector of the winning neuron $\boldsymbol{w}^*$ is updated as

$$\boldsymbol{w}^*(n+1) = \boldsymbol{w}^*(n) + u\,[\boldsymbol{a}(k) - \boldsymbol{w}^*(k)]$$

where u is the learning rate set as 0.01.

The dynamic activities are identified based on 1-s root-mean-squared value of all acceleration signals given by

$$a_{rms} = \sqrt{[a^2_{x(rms)} + a^2_{y(rms)} + a^2_{z(rms)} + a^2_{t(rms)}]/4}$$

2.3. Segmentation of HRV spectra

Fig.2 illustrated the analysis procedure. QRS is detected and verified. RR interval is calculated from the adjacent QRS. Since the location of QRS is not evenly spaced, so an equal-sampling heart period signal with 4 Hz is obtained by the cubic-spline interpolation. The heart rate signal is divided into consequent 128-sec data segment with 16-sec moving step. In each 128-sec data segment, the mean is subtracted, the Hanning window is multiplied, fast Fourier transform is used to estimate the time-related spectra of HRV.

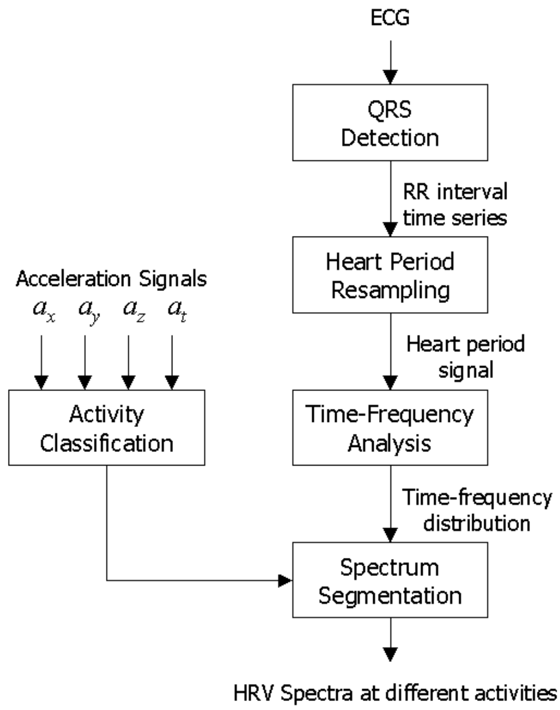

Figure 2 Segmentation of HRV spectra

Since there might be several kinds of activity in the 128-sec data segment, the activities within 64-sec around the center of data segment are included to calculate the representative activity. The reason for considering only the half of activity information is because the Hanning window will enhance the signal in the central portion of data segment. The likely activity state (LAS), defined as the activity with maximum occurrence in 64 sec, is retrieved as the representative activity-indicator.

Based on LAS activity, the HRV spectra with the same LAS activity are averaged. To quantify the modulation of the autonomic nervous system, four parameters are calculated from the HRV spectrum: (1) very-low-frequency (VLF) power, 0.0078 ~ 0.04 Hz; (2) low-frequency (LF) power, 0.04 ~ 0.15 Hz; (3) high-frequency (HF) power, 0.15 ~ 0.4 Hz; (4) LF/HF ratio. The LF and HF power are used to represent the nerve activity of sympathetic and parasympathetic nervous system. The LF/HF ratio behaves an autonomic-balance index. A low LF/HF ratio shows a dominant modulation of parasympathetic nervous system, and a high ratio for sympathetic dominance. A paired-t test is used to find difference of HRV parameters among different activity. $p<0.05$ is considered as significant.

3. Results

Fig.3 illustrates the classified activity and time-frequency HRV spectra in one subject. The spectra with the same classified activity are averaged (Fig.4). There are apparent high-frequency spectral peaks during the lying (supine, left lateral, right lateral, and prone) corresponding sleep stage. The averaged spectra of the lying also shows apparent high-frequency peak. It is associated with regular respiration and high parasympathetic modulation.

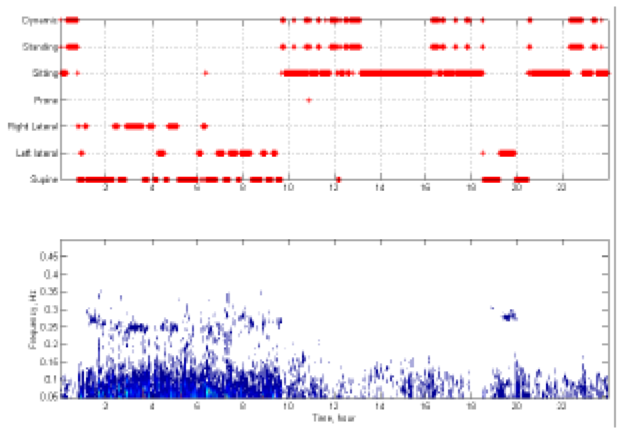

Figure 3 The classified activity and time-frequency distribution of HRV.

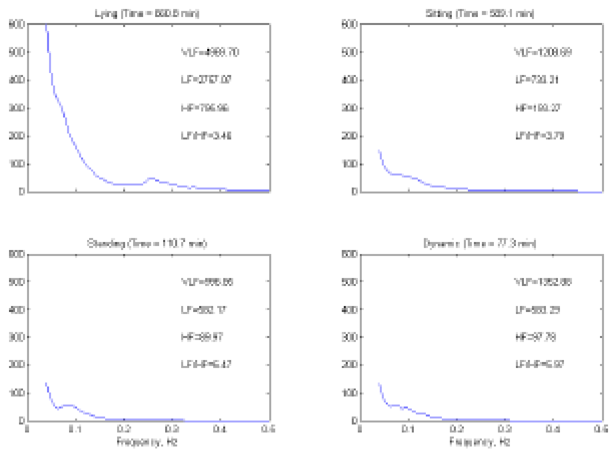

Figure 4 HRV spectra in different activities.

Table I shows the statistical results of frequency parameters of different activities in six healthy subjects. The high-frequency (HF) power is the largest in the lying, the second in the sitting, and decreases in the standing and dynamic activity. This reflects the changes of the parasympathetic modulation. The low-frequency (LF) power to high-frequency power ratios (LF/HF) are larger in the standing and dynamic activity than those in the lying and the sitting, which implies the increase of sympathetic dominance in the standing and dynamic activity. There are no significant difference between the standing and dynamic activity in frequency power parameters. It is due to the occurrence the dynamic activity is usually accompanied with the standing.

Table I. Frequency parameters in different activities

	Lying	Sitting	Standing	Dynamic
VLF	8.52 ± 0.33	7.71 ± 0.49*	7.68 ± 0.75*	7.90 ± 0.63*
LF	7.60 ± 0.44	6.95 ± 0.32*	7.00 ± 0.44	6.91 ± 0.43
HF	6.54 ± 0.42	5.72 ± 0.51*	5.33 ± 0.62*#	5.10 ± 0.56*#
LF/HF	3.00 ± 0.81	3.57 ± 1.03	5.46 ± 1.42*#	6.25 ± 1.60*#

Note: All data except LF/HF are in logarithmic values. *:$p<0.05$ v.s. Lying , #:$p<0.05$ v.s. Sitting

4. Discussion and Conclusion

Although there are several physical activities in the daily life, we used lying, sitting, standing and dynamic activity as activity-indicators for HRV. It is because that HRV has specific autonomic implications in these activities. By separating the HRV of different activities can help understanding the role of physical activity in mechanisms of HRV and avoid ambiguous activity interfering in interpreting the associated autonomic mechanisms.

In this paper, the spectral characteristics of HRV in different physical activities are concordant with the associated with autonomic modulation in these activities. In the future more clinical investigation is needed to study the role of physical activity in heart rate modulation.

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