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Correlates of the shift in heart rate variability with postures and walking by time–frequency analysis

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ABSTRACT

Heart rate (HR) variability derived from electrocardiogram (ECG) can be used to assess the function of the autonomic nervous system. HR exhibits various characteristics during different physical activities attributed to the altered autonomic mediation, where it is also beneficial to reveal the autonomic shift in response to physical-activity change. In this paper, the physical-activity-related HR behaviors were delineated using a portable ECG and body acceleration recorder based on a personal digital assistant and the smoothed pseudo Wigner–Ville distribution. The results based upon eighteen subjects performing four sequential 5-min physical activities (supine, sitting, standing and spontaneous walking) showed that the high-frequency heartbeat fluctuations during supine and sitting were significantly larger than during standing, and that the ratio of low- to high-frequency fluctuation during standing was significantly higher than during supine and sitting. This could be linked with the parasympathetic predominance during supine and sitting, and a shift to sympathetic dominance while standing. During spontaneous walking, the high-frequency fluctuation was significant lower than during supine. The low- to high-frequency ratio decreased significantly from standing to spontaneous walking, which may imply an increased vagal predominance (autonomic effect) or an increased respiratory activity (mechanical effect).

1. Introduction

The variation of heart period or heart rate, generally called heart rate (HR) variability can reflect the function of the autonomic nervous system by the spectral analysis of HR variability [1,2]. In general, the low-frequency (LF) heart rate fluctuation (about 0.1 Hz) is related to the vasomotor effect, mediated by the sympathetic nervous system. The high-frequency (HF) fluctuation is synchronized with respiration, mediated by the parasympathetic nervous system. The ratio of LF to HF fluctuation behaves a sympathovagus balance index: a high LF/HF ratio shows the predominance of sympathetic activities and a low ratio for parasympathetic (vagal) dominance. Owing to the autonomic-linked characteristics, the analyses of HR variability were widely used to investigate the autonomic behaviors in cardiovascular dysfunctions [3,4], diabetes [5], and so on.

HR exhibits various characteristics during different postures [6–9] or during daily physical activities [10,11] owing to the alteration of the autonomic mediation. The altered HR behavior in response to postural change was used as a sensitive measure of the shift in autonomic balance from parasympathetic predominance at rest to sympathetic control while standing [8]. Moreover, HR variability during dynamic physical activities was also employed to investigate autonomic shift or physiological response [12].

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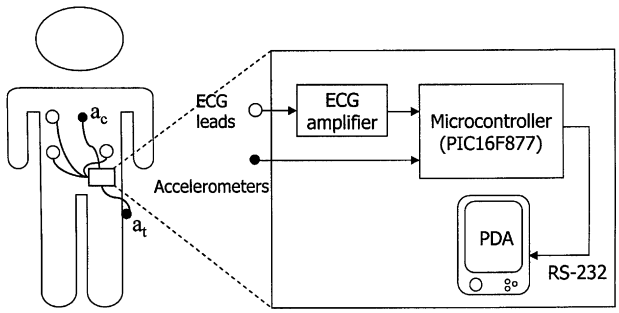

Fig. 1 – The block diagram of the ECG and body accelerations recorder.

Most researches dealing with HR variability during exercise asked subjects to walk on a treadmill [13,14] or to pedal on a cycle ergometer [15–17]. Nevertheless, HR behaviors during spontaneous dynamic physical-activity were less presented.

In the present study a portable recorder based on a personal digital assistant (PDA) that can parallel record electrocardiogram (ECG) and body accelerations was developed. The actual timing of physical-activity change can be captured upon the physical-activity classification based on body accelerations. The physical-activity-related HR characteristics can be well depicted by the smoothed pseudo Wigner–Ville distribution. These aspects make the proposed method be able to give detailed HR behaviors during different phases of physical-activity in an unrestricted space. Eighteen healthy subjects who performed four sequential physical activities (supine, sitting, standing and spontaneous walking) were included for system validation and for delineating HR characteristics during these physical activities.

2. Materials and methods

2.1. *System description and data recording*

The block diagram of the portable recorder based on a PDA (Casio Cassiopeia E-200 with Window CE 3.0 operating system, Japan) is shown in Fig. 1. Two IC accelerometers (ADXL105, Analog Device, USA) affixed on the chest and thigh were used to measure the body accelerations. A microcontroller (PIC16F877, Microchip, USA) was used to acquire one-channel ECG and two acceleration signals with a sampling rate of 125 Hz. The recorded data were stored in the PDA via RS-232 communication. A graphical user interface for data recording and transmission was developed using the eMbedded Visual C++.

Eighteen healthy male volunteers (age: 23.4 ± 1.6) were included for the present study. Each subject was at rest for at least 5 min before data collection, and then performed a series of physical activities: supine, sitting, standing and walking with 5-min recording for each physical-activity. There are no particular requirements for walking. The subject took a walk mildly and spontaneously. The data stored in the PDA was transmitted to personal computer for data analyses developed in the MATLAB 6.5 (The MathWorks, USA).

2.2. *Physical-activity classification*

The accelerometer can measure the orientation of the body segment in relation to the direction of gravitational acceleration, so the analyses of the accelerations measured in specific segments of the body can be used to distinguish different human postures [11,18,19]. In the present study each body acceleration was normalized to a value between −1 and 1 which maps to a gravitational acceleration from −1 to 1 g. The normalized acceleration was then filtered by a lowpass filter with a cutoff frequency of 2 Hz. The median (med) and root-mean-squared (RMS) values within every 1 s were calculated. Through the above preprocesing, four representative accelerations were generated: $a_{c(med)}$ and $a_{t(med)}$, respectively, stand for the static accelerations of the chest and thigh; $a_{c(RMS)}$ and $a_{t(RMS)}$, the dynamic accelerations. Fig. 2a shows the median accelerations obtained from one subject which performed a series of physical activities: supine, sitting, standing and spontaneous walking.

The data clustering was used to classify static physical activities consisting of lying, sitting and standing, based on the vector composed of static accelerations, $\mathbf{a} = [a_{c(med)} a_{t(med)}]$. The cluster centers (**cc**) for lying, sitting and standing clusters are initially set as [1 0], [0 0], and [0 1], respectively. For each acceleration vector $\mathbf{a}_i$, $i = 1, \ldots, N$, the distances with respect to all cluster centers are calculated; the cluster with minimun distance is assigned, and the center of the assigned cluster (**cc***) is then updated by:

$$\mathbf{cc}^* = \mathbf{cc}^* + \eta(\mathbf{a}_i - \mathbf{cc}^*), \quad i = 1, \ldots, N \tag{1}$$

where η is the adaption rate, set as 0.01 in the first iteration and 0.005 in the second iteration. The higher adaption rate adopted in the first interation is to provide a coarse eatimate of the cluster centers, and the adaption rate in the second interation is halved for fine adjustment.

The RMS accelerations at the chest and thigh are merged into a new RMS acceleration:

$$a_{RMS} = \sqrt{\frac{4a_{c(RMS)}^2 + a_{t(RMS)}^2}{5}} \tag{2}$$

The adoption of a smaller weight for $a_{t(RMS)}$ than $a_{c(RMS)}$ is due to that the thigh dynamic acceleration had a larger fluctuating range than the chest dynamic acceleration, in particular during spontaneous walking. The detection of dynamic activity is performed by comparing a_{RMS} with two thresholds. If the static acceleration is clustered as lying or sitting, its corresponding dynamic acceleration a_{RMS} is subsequently compared with a high threshold, $thres_{high}$. As shown in Fig. 2b, the high threshold, $thres_{high}$ set as 0.08 provides a strict threshold for identifying the dynamic activity. On the contrary, a low threshold, $thres_{low} = 0.02$ is used to detect the dynamic activity while standing is assigned. The use of two thresholds can classify the walking slowly as a dynamic activity and avoid recognizing the sitting with high-trembling as a dynamic activity [11].

In the present study, the dynamic activity detection is improved by incorporating hysteresis into the detection based on the low threshold, which can reduce the confounding effect in distinguishing walking from standing. If the previ-