The Estimation Method of Physical Activity Energy Expenditure considering Heart Rate Variability

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Abstract

The purpose of this research was to effectively estimate the physical activity energy expenditure considering acceleration and ECG using the developed holter that is contained a tri-axial accelerometer.

For this research, we developed the specific device *that can measure three channels' ECG and three axes'* accelerations simultaneously. The every experiment was processed by the designed protocol in laboratory environment, and each subject performed the protocol wearing our device and portable gas analyzer together.

Three signals of acceleration were processed using the integration method, and the meaningful parameter was extracted through the frequency analysis of heart rate. Before the regression analysis, significant parameters were selected by correlation analysis, and then the estimating equation of physical activity energy expenditure was found out through the linear multiple regression analysis.

1. Introduction

Since the interest is increased about individual's health status, many studies have processed actively for ambulatory health monitoring in free life. The various vital signs can be measured through the health monitoring, but physical activity information is the one of most useful parameter for assessment both physical and mental health[1]. For this reason, many studies have verified on the relationship between disease and activity. The measurement of physical activity has been performed by several techniques such as direct observations, subjective reports, metabolic measurements and portable physical activity monitors. Even though each type of technique has certain strengths and weaknesses, the portable physical activity monitoring technique that uses accelerometer is suitable for long-term health monitoring in free life, and currently accelerometers have been shown to be an objective and reliable tool for the assessment of physical activity [2].

However, the estimating method of physical activity energy expenditure that uses accelerometer also has some problems. The one of these was that one regressive equation could not cover all types of activities [3]. This means that just information of acceleration is not enough for correct estimation of various types of physical activity's energy expenditure. Therefore, we proposed the different estimating method that was included the information of ECG.

The purpose of this study is effective estimation of physical activity energy expenditure through combination both conventional method using acceleration signal and additional parameters that are acquired from heart rate.

2. Methods

2.1. Data acquisition

Ten healthy males of twenties (26±1.9 years) attended to this experiment, and all of measurement had been processed by designed protocol in laboratory environment. Before performed the experiment, we had developed the device for data acquisition. As the device is added a tri-axial accelerometer (Freescale, MMA7260Q, USA) to the conventional holter, Figure 1 shows the instrument for measurement. It could measure three channels' ECG and three axes' accelerations simultaneously.

Figure 1. Instrument for data acquisition – 3 Ch ECG and 3 Axes' Accelerations

The sampling rate of ECG and acceleration are 250 and 50 samples per second respectively, and all of data were saved to the SD card (2 giga bytes, SanDisk). The standard measurement of energy consumption used the portable gas analyzer (Cosmed, K4b², Italy) as a indirect calorimetric method, and these values were used for comparing with measured data through our device.

Table 1 shows the designed protocol. This was organized for covering various types of activity from static to dynamic. The subjects performed the protocol on a treadmill wearing our device and Cosmed K4b² together. Each activity was maintained during 4 minutes and 1 minute transition period was existed, but the transition period was subtracted for reducing the transition effect when data processing.

2.2. Feature extraction

All of data that was saved to SD card was post-processed after experiment. Figure 3 shows detected R-peaks from acquired ECG by the conventional method [4]. The heart rate and its result of frequency analysis were calculated using detected R-peak. The frequency analysis of heart rate was tried different analysis method with conventional HRV analysis method [5].

Table 1. Experimental protocol

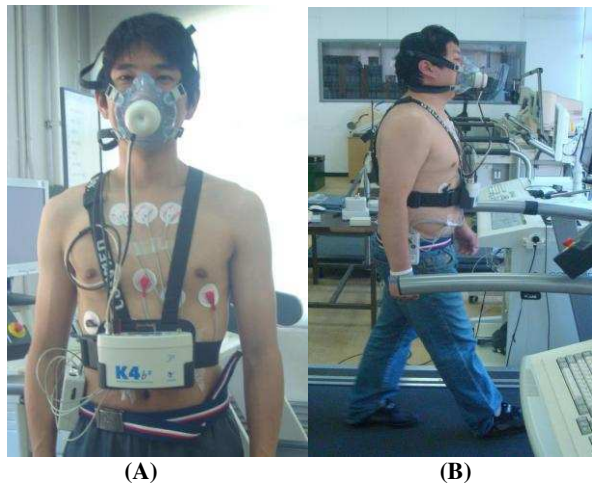|	Activity	Period(min.)
Static	Lying	4
	Sitting	4
	Standing	4
Dynamic	Slow Walking (3.0km/h)	4
	Fast Walking (4.5km/h)	4
	Slow Running (6.5km/h)	4
	Fast Running (8.0km/h)	4

(A) **(B)**

Figure 2. (A) Wearing the our device and Cosmed K4b², (B) Performing the protocol on a treadmill in laboratory environment

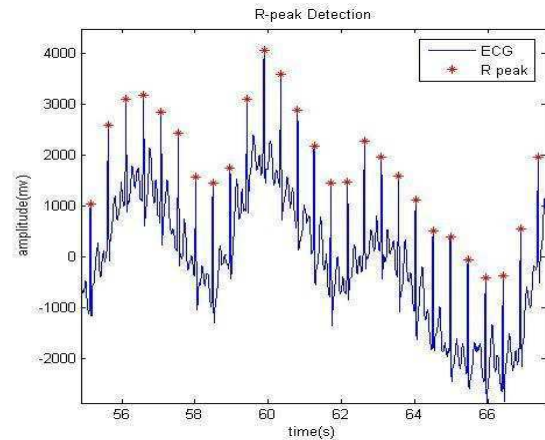Figure 3. R-peak detection using conventional method

Table 2. Specific wavelet band components

	Frequency Range(Hz)
Very Low Frequency	< 0.075
Low Frequency	0.075 ~ 0.15
High Frequency_1	0.15 ~ 0.3
High Frequency_2	0.3 ~ 0.6

As using wavelet analysis, acquired RR-interval was re-sampled to 2.4 Hz at first, and then a 4 levels discrete wavelet transform with the Daubechies-20 wavelet was applied to decompose a heart period signal. Table 2 shows the specific wavelet band components.

After the separating frequency of heartbeat fluctuations to LF and HF bands, each component was quantified by calculating the average power, and the LF/HF ratio was calculated. The advantage of discrete wavelet transform is that it has good time resolution to catch the instantaneous heartbeat fluctuations to link with the classified physical activities.

The accelerometer signals were normalized by the gain in mV by its sensitivity of the sensor, and then the activity signal at each axis, $x(t)$, was determined by integrating the acceleration signal, a_x, i.e.,

$$x(t) = \int_{t}^{t+\tau} |a_x(s)| ds$$ where τ was set to 15 s.

Total activity level is the vector magnitude (VM) of the activity signals that can be defined by $VM = x(t) + y(t) + z(t)$ [6]. Figure 4 was presented both the integrated value of accelerations and calorie consumption that was measured by Cosmed K4b². We can be aware of the relationship between acceleration and energy consumption through figure 4. This acceleration signal was to be integrated as a vector magnitude, and we can confirm to be also increased the PAEE as the acceleration signal is increased.
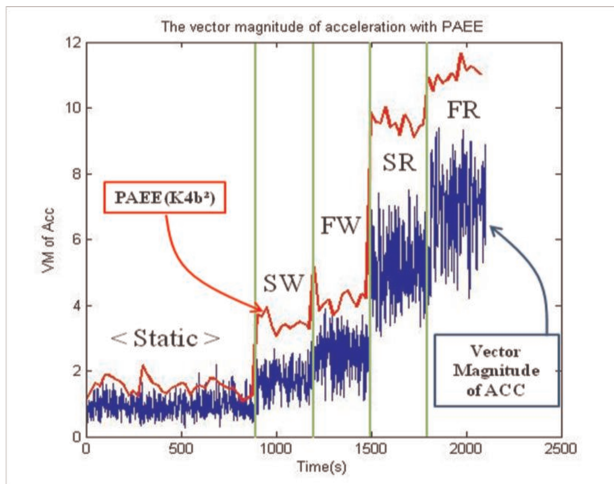
Figure 4. The integrated accelerometer output(VM) and measured physical activity energy expend using K4b²
(Static – lying, sitting, and standing, SW – slow walking, FW – fast walking, SR – slow running, FR – fast running)

2.3. Data Analysis

In this study, we performed multiple linear regression analysis for estimating physical activity energy expenditure. The SPSS 17.0 (SPSS Inc., USA) was used to derive the multiple linear regression models. Before the multiple linear regression analysis, correlation analysis was performed among variables to determine which independent variable is appropriate as predictor, and t and F value of each biometric parameter were analyzed to test the significance of the regression model coefficients [7,8]. Then, we performed multiple linear regression analysis using selected variables.

3. Results

Table 3 shows the results of the Pearson correlation analysis. In this table, we could find high correlation values such as Heart Rate, Integration of accelerations (VM), LF/HF ratio, and BMI among Age, Height, Weight, BMI, Heart Rate, Frequency components (LF, HF, and LF/HF Ratio), and VM.

Table 4 shows the t value and F value of each biometric parameter. The t and F value are used to test the significance of the regression model coefficients. Since $t^2 = F$, if the F of a parameter has been higher than 1, the parameter is significant [7,8]. As a result, every variable that we picked was statistically significant in this table, but we selected only Heart Rate, VM, LF/HF ratio, and BMI considering correlation coefficient and tolerance. Therefore, the multiple linear regression analysis was performed with Heart Rate, VM, LF/HF ratio, and BMI again. The multiple linear regression analysis was performed again using significant parameters for estimating any subject's physical activity. Consequently, multiple linear regression equation is

$$PAEE = -7.886 + 0.025 * HR[bpm] + 0.002 * VM$$
$$-0.027 * (LF / HF) + 28.233 * BMI[kg / m^2]$$

The regression was performed with 95% of confidence level, and the coefficient of determination (R^2) was presented to 0.953. This regression equation was confirmed to have the high fidelity through the above results.

4. Discussion and conclusions

Continuously monitoring of physical activity is very important for prediction and diagnosis of cardiovascular disease in free life. However, it is difficult to classify each activity and to estimate correct physical activity energy expenditure using only accelerometers.

This study verified that the combination of accelerometer's output and parameters from ECG had better performance than only using acceleration output.

Table 3. The correlation analysis of each biometric parameter (*: High correlation value)

		PAEE(k4b²)
	PAEE(k4b²)	1.000
	Heart Rate	0.929*
	VM of Acc	0.950*
	Low Freq.	0.130
Pearson Correlation Analysis	High Freq.	-0.179
	LF/HF Ratio	0.448*
	Age	0.199
	Height	0.038
	Weight	0.239
	BMI	0.247*

Table 4. The t and F value of each biometric parameter

	t	F(t²)
Heart Rate	6.683	44.662
VM of Acc	25.823	666.827
Low Freq.	1.937	3.752
High Freq.	2.479	6.154
LF/HF Ratio	-8.184	66.978
Age	5.810	33.756
Height	4.614	21.289
Weight	5.810	33.756
BMI	11.870	140.897

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In this study, we didn't focus on activity classification using frequency analysis of heart rate, but we confirmed that the information of frequency component was more meaningful parameter for static activity classification than others through other pre-test. Even though the information of frequency component didn't have an effect on estimating PAEE within static activity, if the performance of effectively classifying each posture is enhanced, it is possible to be a meaningful parameter for better estimating PAEE.

Because this research was processed by controlled protocol within limitable environment, it still leaves something to be desired. Therefore, this research will have to be applied to various subjects and activities for developing our algorithm.

Acknowledgements

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