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A Wearable System for Heart Rate Recovery Evaluation with Real-Time Classification on Exercise Condition

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Abstract— **Heart rate recovery (HRR) is a convenient index to assess a cardiovascular autonomic function response to physical exercise. HRR monitoring during daily exercise can be an effective way to verify cardiorespiratory performance. Because HRR varies depending on exercise intensity and resting condition, an exercise condition needs to be acquired for a reliable HRR analysis. This study presents a wearable system for HRR evaluation with automatic labeling of exercise conditions using real-time activity classification. We developed an activity classification algorithm using two features from accelerometer sensor: an acceleration peak and an angle tilt peak. The classification algorithm was applied to a chest-attached wearable device with an embedded electrocardiogram sensor and accelerometer sensors. We classified daily activities such as running, walking, and postural transitions performed under supervised conditions. The wearable device system accurately detected activities with a sensitivity of 99.2 % and posture transitions with a sensitivity of 92 % and specificity of 93.3 % for seven healthy subjects. The proposed wearable system can help monitor HRR during exercise training by labeling the exercise condition simultaneously.**

I. Introduction

Measuring heart rate recovery (HRR) is a convenient, inexpensive and non-invasive way to evaluate the autonomic function of a parasympathetic system [1]. HRR is used to monitor abnormal cardiac autonomic function, mortality, increased risk of various cardiovascular diseases [2-3] and known to be dependent on age and exercise capacity [4]. Because HRR can be improved by cardiac rehabilitation [5] and even weight loss [6], its long-term trend can be of interest when evaluating the effectiveness of physical training. Typically, it was evaluated through standardized tests requiring specific equipment and physician's supervision, which was difficult to perform outside certain facilities [7].

Running and walking in daily activities provide an effective opportunity to evaluate the exercise capacity by monitoring the change of HRR [8]. Several wearable devices with photoplethysmogram (PPG) or electrocardiogram (ECG) sensors monitored the heart rate and provided the HRR information [9]. However, those devices offer HRR without information on exercise and rest conditions. HRR data is not sufficient for monitoring of physiological status as it is strongly affected by exercise and rest [10]. For accurate HRR assessment, a quantitative measurement on training conditions should be supplemented.

This paper proposes a wearable system to evaluate HRR with automatic labeling of exercise intensity and recovery condition. We used a wearable device integrated with ECG and accelerometer sensors to classify the activity during training. A simple classification algorithm using acceleration and angle tilt peaks was developed in this study. We performed a test to distinguish three different states (running, walking, stationary) and transitions of sit-to-stand and stand-to-sit. Also, we demonstrated HRR evaluation using the wearable sensor system during daily training.

II. Device and Methods

A. Wearable Sensor Hardware Configuration

Our wearable device (Fig. 1a) consists of an analog front-end (ADS1292), an accelerometer (BMI270), and a microcontroller (NRF52832). An overall operation of wearable sensor system was illustrated in Fig. 1b. The analog front-end acquires ECG at a sampling rate of 200 Hz, and the accelerometer measures 3-axis acceleration at 100 Hz. The microcontroller sends ECG and 3-axis acceleration to a mobile device via Bluetooth-Low-Energy (BLE) communication in real-time. In a mobile device, such as a smartphone or laptop, heart rate is calculated by using a modified Pan-Tomkins algorithm, and the activity is analyzed simultaneously

B. Motion classification

The classification was performed using 3-axis acceleration data to distinguish three different activities (running, walking, and stationary) and two posture transitions (sit-to-stand transition and stand-to-sit transition). Fig. 2 illustrates a block diagram of signal processing. Acceleration and tilt peaks are the main features to classify the different motions. First, the mobile device computes the root-mean-square acceleration (a_{rms}) using 3-axis acceleration (a_x, a_y, a_z). and standard gravity as shown in the formula:

$$a_{rms} = \sqrt{(a_x^2 + a_y^2 + a_z^2)} - 9.81 \text{ ms}^{-2}. \qquad (1)$$

We used a moving average filter with a 15-samples window to suppress high-frequency noise. After the filtering, The moving average filtering the noise was significantly reduced and the acceleration peaks appear clear. After applying the moving average filter, a threshold was used for digitizing peaks. The values of thresholds were chosen empirically.

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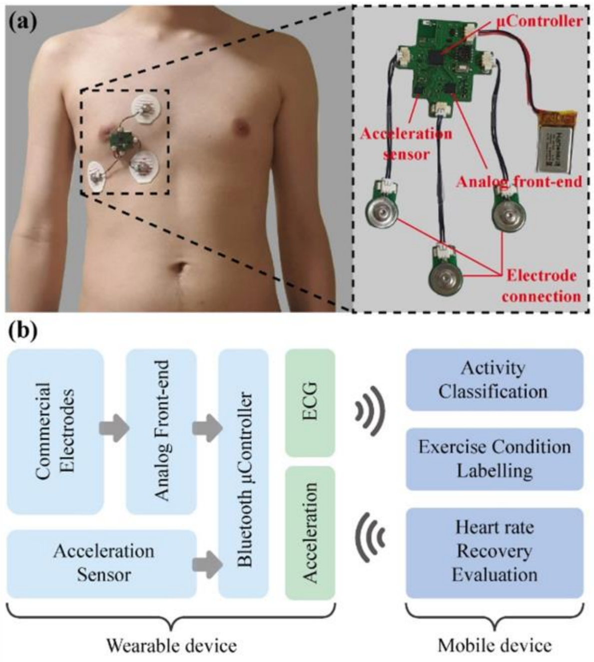

Fig.1 (a) Photograph of the wearable device and (b) Flow-chart illustration of the HRR evaluation system. The wearable device includes an analog front-end and acceleration sensor for monitoring ECG and motion simultaneously.

A trunk angle tilt was computed using a scalar-product method [11]. First, we measured a 3×1 matrix a, representing a mean value of 3-axis acceleration data during which a subject is standing. Then, the scalar product was performed between the matrix a and 3×N matrix b, representing the 3-axis acceleration output with data length N. Eq. (2) shows the scalar product of a and b. The angle tilt is an arccosine value of a scalar product a and b divided by the norm of each matrix. The 1 × N angle tilt matrix is shown in Eq. (3).

$$a \cdot b_N = \left[\sum_{l=1}^{3} a_l b_{ln} \cdots \sum_{l=1}^{3} a_l b_{lN}\right]_{n=1}^{N} \qquad (2)$$

$$\theta_N = \cos^{-1}\frac{(a \cdot b_N)}{|a| \cdot |b_N|} \qquad (3)$$

We applied a moving average filter with a 60-samples window.

The sit-to-stand and stand-to-sit can be detected using a product of acceleration and angle tilt peaks. An angle tilt during the transition was illustrated in Fig. 3a. When we sit down, the acceleration peak becomes negative and then changes to positive (Fig. 3b) because the vertical force is initially reduced and then increases in the opposite direction due to the reaction with a seat. When we stand up, the acceleration peak changes from positive to negative. The trunk angle tilt is positive during the transition because we stand up or sit down by tilting our trunk forward. A single positive peak followed by a negative peak, and the opposite case was deemed a sit-to-stand transition and a stand-to-sit transition.

The motion cycle of walking and running starts with pushing a foot and ends with the foot contact (Fig. 3c). The magnitude and direction of acceleration between steps are illustrated. When we push off a foot behind, the acceleration in vertical and horizontal directions increases. Until a foot contact, the horizontal acceleration decreases, and the vertical acceleration increases and then decreases. The RMS acceleration and angle tilt during walk and run are shown in Fig. 3d. In walking, the angle tilt is lower than the threshold because the average forward acceleration is too low. The average forward acceleration is high in the running state. Thus, a periodic change on the RMS acceleration peak with a continuous peak on the angle tilt was determined as running. Otherwise, a periodic change on the acceleration peak without angle tilt peak was determined as walking.

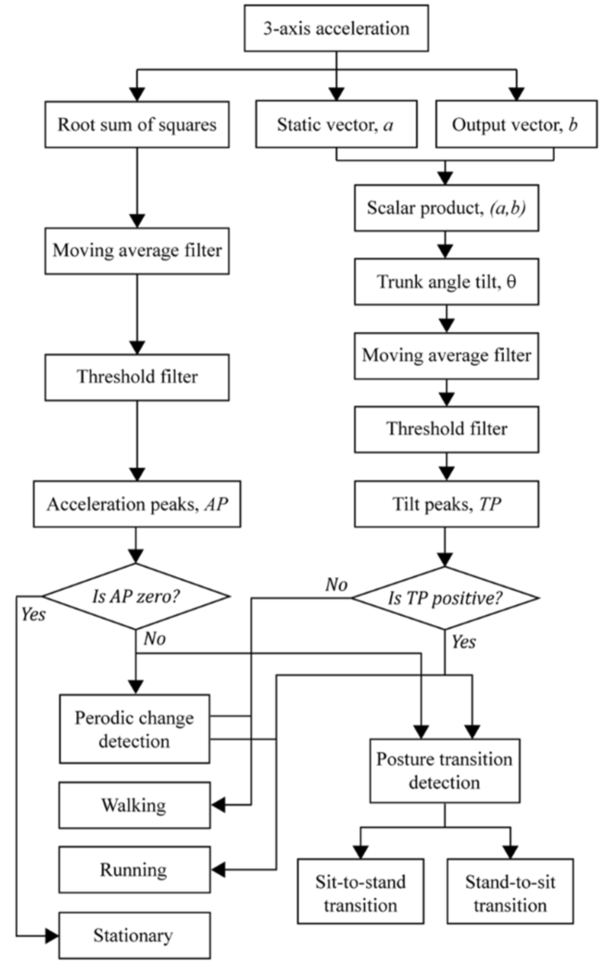

Fig.2 Functional block diagram of signal processing for motion classification.

C. *Experimental Protocol*

Two different cases were studied. The first set of experiments was performed in a laboratory, and the second was at an outdoor field. In both cases, subjects wore the aforementioned wearable device. This study was approved by the Institutional Review Board of Pohang University of Science and Technology (PIRB-2021-E013). Seven healthy volunteers participated in the study.

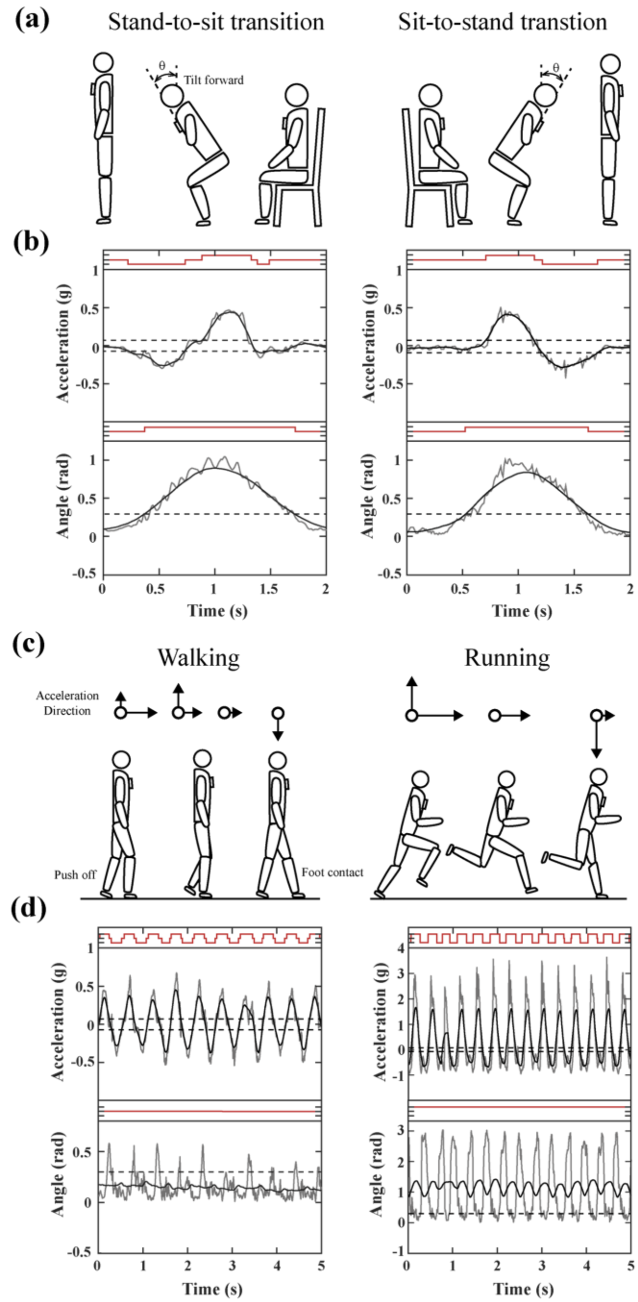

Fig.3 (a) Illustration of angle tilt during the posture transition and (b) corresponding RMS acceleration and angle tilt. (c) Magnitude and direction of the acceleration during walk and run, and (d) corresponding signals. Solid grey: acceleration signal before moving average filter; black: after moving average filter; dotted black: threshold; red: signal after threshold filter.

1) Validation of activity classification

Seven subjects (age: 26.3 ± 1.8) performed four different tests, including running, walking, sit-to-stand/stand-to-sit transitions. The number of dataset is shown in Table I. We recorded each test with a smartphone camera for a reference and labeled the activities manually. The sensitivity is defined as the "true positives" divided by the sum of "true positives" and "false negatives." The specificity is the "true negatives" divided by the sum of "true negatives" and "false positives."

TABLE I. SET OF TESTS AND NUMBER OF DATASET

Test Number	Type of Activity	Number of Dataset: Running	Walking	Stationary	Sit-to-stand	Stand-to-sit
1	Run + Walk + Stand	352	901	343	-	-
2	Sit-to-stand + Walk + Stand-to-sit	-	813	-	35	35
3	Sit-to-stand + Run + Stand-to-sit	401	-	-	35	35
4	Sit-to-stand + Stand-to-sit	-	-	254	139	138
Total		753	1714	397	209	208

2) Demonstration of HRR evaluation

The HRR evaluation with automatic labeling was assessed by work out for 40 mins at outdoor field. A subject (age: 25; height: 171 cm; weight: 65 kg) participated in the test. The wearable device measured heart rate and motions simultaneously during the test. The subject rested at least 3 mins between exercises. This process was recorded with a smartphone camera.

We evaluated the HRR with short time constant ($T30_{min}$) and absolute recovery (*ΔHRR*) [12]. The short time constant was calculated according to a previous report from Imai et al. [13]. After the onset of the recovery, heart rate data of the first 1 min was transformed as its natural logarithm (*ln HR*). We performed linear regression of ln HR within the first minute using a dataset of 30-secs durations. Negative reciprocal values of the rendered slope were calculated from the fitted functions. We chose the short time constant as the smallest value. The absolute recovery was determined to the difference of HR between recovery onset and after 3 mins.

III. RESULTS

A. Validation of Activity Classification

Table II shows the sensitivity and specificity for all 140 activities performed in this study. The sensitivity was 99.2% for running, 98.3% for walking, and 100% for stationary. Sensitivity and specificity were 91.9% and 95.4% for sit-to-stand transition and 92.1% and 91.3% for stand-to-sit transition. The average sensitivity and specificity of the classification on posture transition were 92% and 93.3%, respectively.

B. Demonstration of HRR Evaluation

Acceleration, angle tilt, and peak product obtained during the workout (Fig. 4a and b). Classified activities and posture transitions were marked. HRR indexes were calculated for every exercise-to-rest sequence (Fig. 4c). Different exercise and rest conditions resulted in different HRR values. During the walking after the first running, $T30_{min}$ was 526.3 secs, and ΔHRR was 35 bpm. When the subject sat down and rested after the same exercise, $T30_{min}$ was 201.6 secs, and ΔHRR was 61 bpm. In the case of standing, $T30_{min}$ was 340.1 secs, and ΔHRR was 40 bpm. Both ΔHRR measured during sitting down and standing up after walking were almost same (29 bpm vs. 30 bpm), but $T30_{min}$ were different (142.7 vs. 201.6).

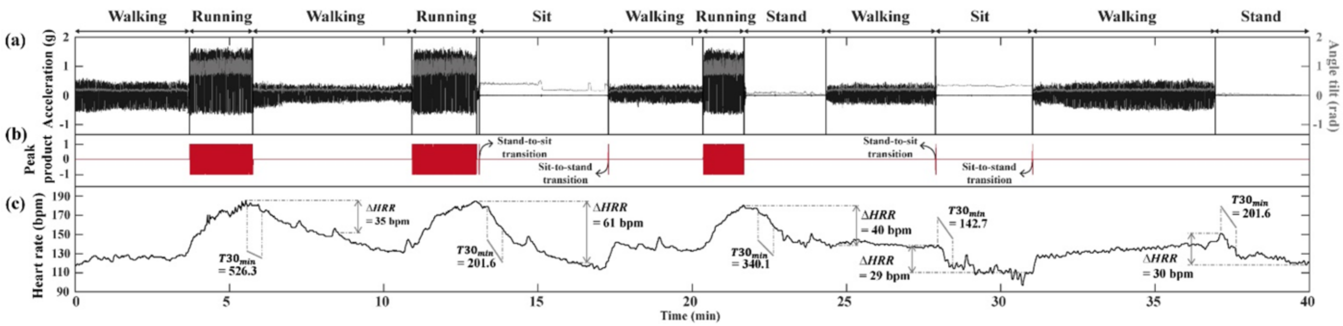

Fig. 4 (a) RMS acceleration and angle tilt, (b) product of the acceleration and angle tilt peak, (c) heart rate during the exercise at the outdoor field. The classified activity and transitions are indicated. The short time constant ($\boldsymbol{T30_{min}}$) and absolute recovery ($\Delta\boldsymbol{HRR}$) was calculated for every exercise-to-rest sequence.

TABLE II. OVERALL SENSITIVITY AND SPECIFICITY OF ACTIVITY DETECTION

Test number	Sensitivity (%)					Specificity (%)	
	Running	**Walking**	**Stationary**	**Sit-to-stand transition**	**Stand-to-Sit transition**	**Sit-to-stand transition**	**Stand-to-Sit transition**
1	99.6(±0.9)	96.9(±3.8)	100(±0)	-	-	-	-
2	-	99.6(±0.5)	-	93.9(±8.6)	93.9(±8.7)	91.9(±11.7)	84.4(±11.8)
3	98.8(±1.5)	-	-	89.1(±11.4)	87.2(±14.7)	97.2(±6.2)	94.4(±7.9)
4	-	-	100(±0)	92.8(±7.6)	95.3(±4.8)	97.2(±6.2)	95.2(±10.6)
Mean	**99.2(±1.3)**	**98.3(±3.0)**	**100(±0)**	**91.9(±9.6)**	**92.1(±10.8)**	**95.4(±8.8)**	**91.3(±11.4)**

IV. CONCLUSION

In this study, we present a wearable system for HRR evaluation with classification on exercise and rest conditions. We developed a wearable device with an embedded ECG sensor and accelerometer. The activity classification algorithm was developed based on the detection of acceleration and angle tilt peaks. Three different activities, running, walking, and stationary, and two different posture transitions were successfully detected with high accuracy. We evaluated HRR during a free exercise condition at outdoor field. Different exercise intensity and rest conditions showed different HRR indexes.

As HRR is strongly affected by exercise intensity and rest conditions, labeling the exercise and resting conditions is essential for assessing physiological conditions. The proposed wearable system offers a convenient method for detecting exercise intensity and classifying the rest condition.

ACKNOWLEDGMENT

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