35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Exercise Amount Calculation Using a Wearable Half-Cell Potential Sensor for Mobile Aerobic Exercise Management

Changmok Choi, Byung-hoon Ko, Takhyung Lee, Gunguk Park, and Kunsoo Shin

Abstract—**The obesity has grown to concerning proportions in recent years, and it causes heart disease, type 2 diabetes, breast cancer, and colon cancer. To get healthy weight, commercial wearable devices with a accelerometer have been released to help users to quantitatively manage calories. However, an accelerometer has disadvantages: large power consumption and expensive price. We suggested a new method to measure the exercise amount using a HCP sensor. We performed an experiment to compare accuracies of exercise amount estimation using a HCP sensor with using an accelerometer with five subjects, and the accuracy of the HCP sensor was comparable to it of the accelerometer. Since a HCP sensor has lower power consumption and cheaper price than an accelerometer, wearable sensor can be smaller and cheaper than current commercial devices.**

I. Introduction

The leading causes of death in the United States in 2000 were tobacco (435,000 deaths; 18.1% of total U.S. deaths), poor diet and physical inactivity (400,000 deaths; 16.6%), and alcohol consumption (85,000 deaths; 3.5%) [1]. Recently, U.S. government has made an effort to reduce smoking population by banning smoking in public venues and increasing tobacco excise taxes, so that the prevalence of cigarette smoking among U.S. adults declined substantially, from 42.4% in 1965 to 20.8% in 2006 [2]. However, the prevalence of obese in U.S. has been gradually increased from 13.4% in 1960 to 36.1% in 2010 [3], mainly due to poor diet and physical inactivity as the 2nd leading cause of death resulting four major diseases (heart disease, type 2 diabetes, breast cancer, and colon cancer).

To get healthy weight, the calories taken (from foods) must be balanced by the calories used (in normal body functions, daily activities, and exercise). Recently, new wearable activity trackers have been released from Nike, Motolora, Bodymedia, Fitbit, and these trackers quantitatively how much a user moves throughout the day. Basically, the trackers includes an accelerometer that can calculate step counts and convert calories used based on a user's physical conditions such as height and weight. These devices help a user improve motivation and awareness to be physically active.

*This Research was supported by Samsung Electronics Co., Ltd.

C. Choi is with the Future IT Research Center, Samsung Advanced Institute of Technology (SAIT), Samsung Electronics Co., Ltd., Yongin, the Republic of Korea (phone: +82-31-280-9528; fax: +82-31-280-9560; e-mail: cm7.choi@samsung.com).

B. Ko, T. Lee, G. Park and K. Shin are with the Future IT Research Center, Samsung Advanced Institute of Technology (SAIT), Samsung Electronics Co., Ltd., Yongin, the Republic of Korea (e-mail: yh92.kim; byunghoon.ko; takhyung.lee; ggpark; bosco.shin@samsung.com).

In addition, several heart rate (HR) monitors has been released from Polar, Addidas, and Motolora for effective aerobic exercise management. These monitoring devices are based on physiological knowledge that the body fat is effectively oxidized at specific aerobic exercise intensities between 47% and 52% of maximum oxygen consumption [4]. It has been well known that HR is highly correlated with the amount of oxygen consumption during exercise [5], so that HR sensors can help a user to keep an optimal HR zone to effectively reduce the body fat.

Electrocardiography (ECG) needs to be measured during exercise to calculate HR, but motion artifacts impedes its accurate measurement. These authors presented a motion artifact rejection method using an adaptive digital filter based on a half-cell potential (HCP) sensor in 2012 Annual International Conference of the IEEE EMBC [6]. HCP is a major factor of motion artifacts and can be mathematically described as a Gouy-Chapman-Stern model. This model explains the electrical potential change depending on the metal electrode's area of the electrolyte, and we applied this knowledge to reduce motion artifacts produced by attached area change between an ECG sensor and skin surface [7].

We presents that an HCP sensor can be used not only for accurate HR calculation (by reducing motion artifacts) but also for exercise amount calculation such as step counts and the amount of energy expenditure. Most of wearable exercise management devices measure the exercise amount using an accelerometer. Considering mobile usage, an HCP sensor is more advantageous than an accelerometer to measure the exercise amount. HCP is measured by an instrumental amplifier, and its chip (e.g. AD627) has lower power consumption and less expensive than an accelerometer chip (e.g. ADXL103).

The purpose of this study was performance comparison of exercise amount calculation between an accelerometer and a HCP sensor. We measured walking/running steps on a treadmill using a manual hand counter, and obtained HCP and acceleration data from the attached sensors on the chest of the subjects. Step counts were extracted from the obtained data using Fourier transform analysis, and compared the each performance.

II. Materials and Methods

A. System Overview

A self-developed wearable ECG/HCP sensor including an analog-front-end chip (low-pass/high-pass filters, instrumental amplifiers, and analog-to-digital converters), a communication chip with the carrier frequency of 2.4 GHz (nRF24L01P, Nordic Inc.), and five electrodes (two are for ECG, another two are for HCP, and the other one is for the reference voltage) as shown in Fig. 1.

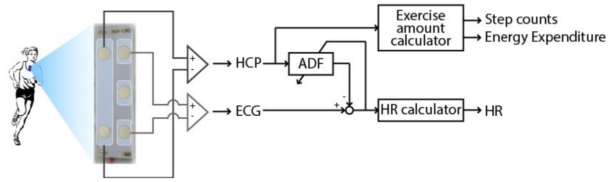

Figure 1. System overview of the mobile aerobic exercise management.

B. Experimental Protocol

Five subjects (Subject A–E; 32.6 ± 4.0 years old; height: 175.2 ± 2.6 cm; weight: 68.6 ± 75 kg) were participated for this experiment, and they wore the developed ECG/HCP sensor and a commercial accelerometer sensor (Cardio Development Kit, Shimmer Research). They were instructed to walk or run on a treadmill (7025T, STEX, Republic of Korea). An experiment consisted of four sessions including different walking or running speeds at 4, 6, 8, and 10 km/h. Each session continued for one minute, and a 5 minutes break was given to the subjects between all sessions. A manual hand counter was used to count steps of the subjects on a treadmill.

C. Step Count Calculation

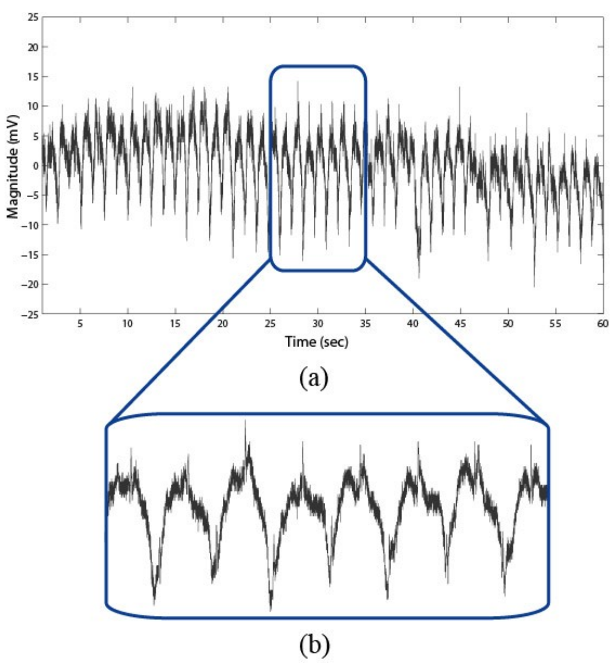

Figure 2. (a) Raw HCP data of Subject A during walking on a treadmill at 4 km/h, and (b) its partially magnified image.

The sampling frequencies of ECG and HCP data were 250 Hz. Fig. 2 (a) shows raw HCP data of Subject A during walking on a treadmill at 4 km/h. Subject A walked 101 steps at 4km/h for 1 min. Fig. 2 (b) shows the partially magnified image of the data shown in Fig. 2 (a). These figures shows that HCP periodically produced strong peaks downwards due to the steps. We found that a periodic data was produced by two steps (left and right steps). The number of the strong peaks in Fig. 2 (a) was almost 48, and this number was almost half of the actual steps of Subject A on a treadmill.

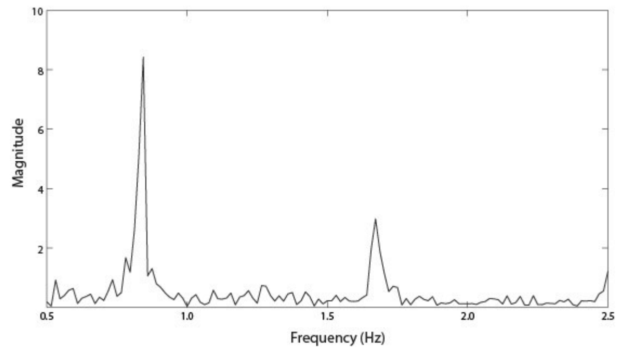

Figure 3. The freqency spectrum of the HCP data of Subject A shown in Fig. 2 during walking on a treadmill at 4 km/h.

Since HCP data was periodic due to the steps, fast Fourier transform was applied to get the data frequency spectrum of the raw HCP data to find step count information. Fig. 3 shows the frequency spectrum of the HCP data of Subject A shown in Fig. 2 (a) during walking on a treadmill at 4 km/h. It was easy to find the largest peak in the figure, and it appeared 0.8438 Hz. Since the frequency f where the largest peak appeared represented the periodic data by the steps, the number of the steps N could be calculated as follows:

$$N = f \times 2\ steps \times 60\ sec/min. \quad (1)$$

1 Hz of the HCP frequency spectrum represented 2 steps during 1 min. Therefore, 0.8438 Hz can be converted to 101.256 steps which is very close to the actual steps Subject A walked.

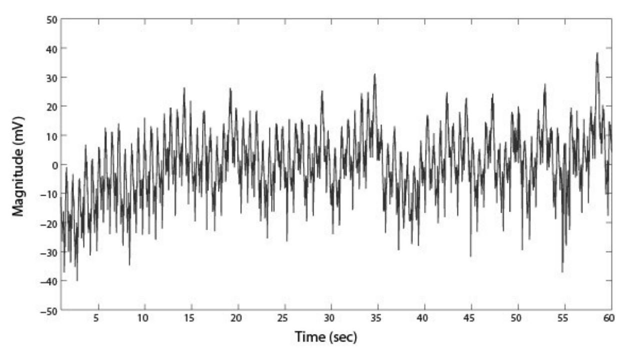

Figure 4. Raw HCP data of Subject A during running on a treadmill at 10 km/h.

Fig. 4 shows raw HCP data of Subject A during running on a treadmill at 10 km/h, and Fig. 5 shows its frequency spectrum. The largest peak appeared in the figure at 1.453 Hz, and the frequency could be converted to 174.36 steps by Eq. (1). The running steps of Subject A at 10 km/h was 176 which was similar to the estimated step counts.

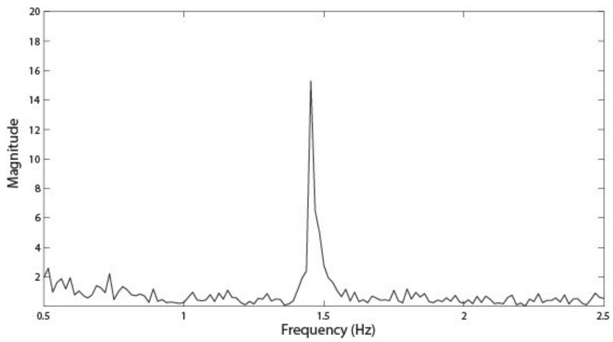

Figure 5. The freqency spectrum of the HCP data of Subject A shown in Fig. 4 during running on a treadmill at 10 km/h.

D. Energy Expenditure Calculation

Energy expenditure was calculated for each subject defined by the American College of Sports Medicine [8] as follows:

$$\textit{Energy Expenditure [kcal]} = 1.05 \times \textit{METS} \times \textit{Duration (hour)} \times \textit{Weight (kg)}. \quad (2)$$

METS represents metabolic equivalents, a physiological measure expressing the energy cost of physical activities. 1 *MET* equals to 1 *kcal/kg·h*, and is defined as the ratio of the work metabolic rate to the resting metabolic rate. *METS* are defied for aerobic exercise for walking and running, respectively, as follows [9]:

for walking,

$$\textit{METS} = 0.0272 \times \textit{speed (m/min)} + 1.2,$$

for running,

$$\textit{METS} = 0.093 \times \textit{speed (m/min)} - 4.7. \quad (3)$$

The *speed* can be estimated by the number of steps and stride length.

$$\textit{Speed} = \textit{Stride length/Time} \times \textit{Steps}. \quad (4)$$

The Stride length can be estimated by the average ratio between stride and height: 42.36% for male and 43.56% for female [10].

III. Results

Five subjects walked or ran depending on different treadmill speeds 4/6/8/10 km/h for 1 min, and an experimenter counted their walking or running steps using a manual hand counter. The average steps of the subjects were described in TABLE I.

For the performance comparison, acceleration data were also measured, and step counts were estimated from the data using the same method described in II. C. Fig. 6 shows raw acceleration data of Subject A during walking on a treadmill at 4 km/h, and Fig. 7 shows its frequency spectrum. The frequency spectrum of the acceleration data during walking was highly similar to it of HCP data. The largest peak appeared in the figure at 0.8438 Hz, and the frequency could be converted to 101.256 steps by Eq. (1). This number of the step counts was also close to the actual steps of Subject A.

TABLE I. Average Actual Steps of the Five Subjects During the Experiment.

Speeds (*km/h*)	**Walking or Running Steps**
4	106.6 ± 5.7
6	123.6 ± 9.1
8	158.4 ± 5.5
10	162.4 ± 10.6

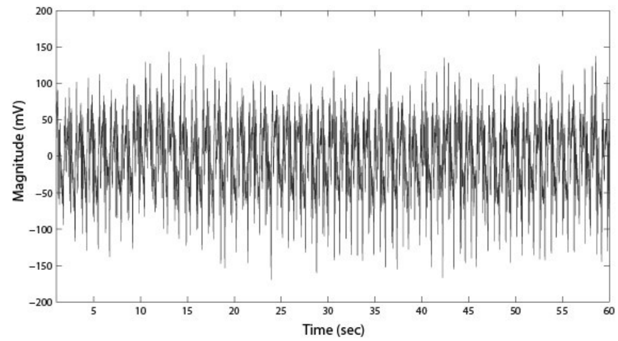

Figure 6. Raw acceleration data of Subject A during walking on a treadmill at 4 km/h.

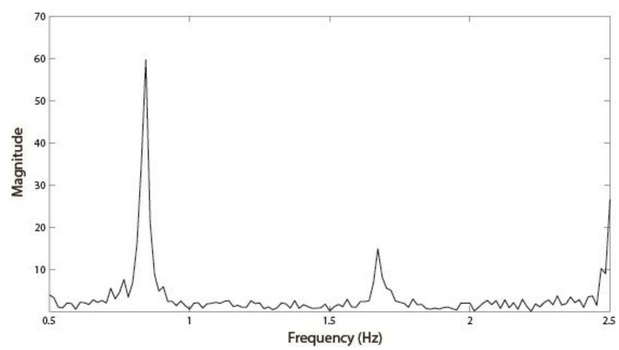

Figure 7. The freqency spectrum of the acceleration data of Subject A shown in Fig. 6 during walking on a treadmill at 4 km/h.

TABLE II summarizes the average estimated steps from the experiment using an HCP sensor and an accelerometer respectively. All estimated number of steps were comparable to the actual measured steps described in TABLE I. TABLE III summarizes the accuracy of the estimated steps using the HCP sensor and the accelerometer.

TABLE II. Average Estimated Steps of the Five Subjects from an HCP Sensor and an Accelerometer.

Speeds (*km/h*)	**Estimated Number of Steps**	
	HCP	**Accelerometer**
4	106.9 ± 5.8	107.8 ± 5.0
6	124.5 ± 8.1	124.0 ± 8.7
8	159.7 ± 6.4	159.0 ± 7.1
10	163.1 ± 9.8	163.5 ± 9.9

TABLE III. ACCRACY OF THE STEP COUNT ESTIMATION FROM THE HCP SENSOR AND THE ACCELEROMETER FOR THE FIVE SUBJECTS.

Speeds (*km/h*)	Accuracy (%)	
	HCP	**Accelerometer**
4	99.7 ± 0.2	98.8 ± 1.6
6	99.0 ± 0.7	99.0 ± 0.6
8	99.1 ± 0.7	99.1 ± 0.7
10	99.2 ± 1.1	98.9 ± 1.0
Average	**99.2 ± 0.7**	**99.0 ± 1.0**

A two-way Student's t test was performed to determine any performance differences among actual steps, estimated steps from the HCP sensors and the accelerometer. There were no statistically significant differences among any methods as described in TABLE IV. Therefore, we concluded that the performance of the step number using an HCP sensor was comparable to it using the accelerometer and a manual hand counter.

TABLE IV. AVERAGE ACTUAL STEPS OF THE FIVE SUBJECTS DURING THE EXPERIMENT. REFERENCE INDICATES THE ACTUAL STEP NUMBERS COUNTED USING A MANUAL HAND COUNTER.

Speeds (*km/h*)	***P* value**		
	Reference vs HCP	Reference vs Accelerometer	HCP vs Accelerometer
4	0.94	0.81	0.87
6	0.87	0.93	0.95
8	0.73	0.87	0.89
10	0.94	0.95	0.89

TABLE V summarizes the amount of energy expenditure for walking and running during the experiment. These values were estimated by eq (2).

TABLE V. ENERGY EXPENDITURE FOR WALKING AND RUNNING.

Speeds / Subject	Energy Expenditure (*kcal*)			
	4 *km/h*	6 *km/h*	8 *km/h*	10 *km/h*
A	3.3	3.6	4.6	4.8
B	3.5	3.9	4.5	4.6
C	3.5	3.8	4.5	4.5
D	3.3	3.5	4.3	4.5
E	3.3	3.8	4.3	4.2

IV. CONCLUSION

We suggested a new method to measure exercise amount calculation using an HCP sensor. This sensor was not only helpful for accurate HR calculation (by reducing motion artifacts) but also for exercise amount calculation such as step counts and the amount of energy expenditure. There have been many wearable commercial devices to measure such exercise amounts using an accelerometer. Disadvantages of the accelerometer are large power consumption and expensive price. A HCP sensor can be built in a wearable exercise management sensor with lower power consumption and cheaper price than an accelerometer. The low power consumption implies that the wearable sensor can be designed as a small and light form-factor by reducing the battery size which is highly desirable for wearable application. The cheap price would be beneficial for consumers to purchase the sensor.

REFERENCES

[1] A. H. Mokdad, J. S. Marks, D. F. Stroup, J. L. Gerberding, "Actual causes of death in the United States, 2000," *JAMA*, vol. 291, no. 10, pp. 1238–1245, Mar. 2004.

[2] G. A. Giovino, "The tobacco epidemic in the United States," *American Journal of Preventive Medicine*, vol. 33, no.6, pp. S318–S326, Dec. 2007.

[3] D. F. Cheryl, D. C. Margaret, L. O. Cynthia, "Prevalence of overweight, obesity, and extreme obesity among adults: United States, trends 1960–1962 through 2009–2010," Centers for Disease Control and Prevention Website (http://www.cdc.gov/nchs/), 2012.

[4] J. Achten & A. E. Jeukendrup, "Optimizing fat oxidation through exercise and diet," *Nutrition*, vol. 20, no. 7–8, pp. 716–727, Jul. –Aug. 2004

[5] J. H. Wilmore, D. L. Costill, and W. L. Kenney, "*Physiology of sport and exercise*," Champaign, IL: Human Kinetics Publishers, 2008.

[6] B. Ko, T. Lee, C. Choi, Y. Kim, G. Park, K. Kang, S. K. Bae, and K. Shin, "Motion artifact reduction in electrocardiogram using adaptive filtering based on half cell potential monitoring," in *Proc. Ann. Int. Conf. IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 1590–1593. 2012.

[7] A. B. Simakov and J. G. Webster, "Motion Artifact from Electrodes and Cables," *IRANIAN J. Elect. Comp. Eng.*, vol. 9, no. 2, pp. 139–143, 2010.

[8] American College of Sports Medicine (ACSM), "*ACSM's Guidelines for Exercise Testing and Prescription*," Baltimore: Lippincott Williams & Wilkins, 2009.

[9] N. Ryu, Y. Kawahara, T. Asami, "A calorie count application for a mobile phone based on METS value," in *Proceedings of 5th annual IEEE communications society conference on sensor*, pp. 583–584, 2008.

[10] B. J. Sung, J. W. Yoon, "Analysis of stride length and the ratio between height and stride length in 10–60 aged men and women," *Korean J Walk Sci*, vol. 8, no. 63–70, 2008.