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Analysis of Acceleration Value based on the Location of the Accelerometer

Shin-Hyeong Choi

***Abstract*—Physical activity is essential for human health maintenance. We investigate the effects of acceleration change amount to the location of the accelerometer on the estimation of energy expenditure. We analyze the user's walking motion, and classify them into three based on walking action in order to estimate the estimation of energy expenditure of smart phone users. In order to estimate activity energy expenditure, we use the method based on MET (Metabolic equivalents) values. All activities are assigned METs. MET is a value for expressing the intensity of physical activities. Through our experiment, it is clear that the acceleration data measured by holding smart phones in hand is more regularly than by wearing smart phones in the pocket, and also that the measurement method holding smart phones on hand is able to distinguish more easily activity type. In addition, we propose the activity classification algorithm to estimate the energy expenditure. This algorithm distinguishes between the three activities. And this algorithm is performed only for slow walking, fast walking and running. The reason is that three activities belong to different the motion of arms and the location of smart phones according to the activity type. In this paper, we confirm that the location of the smart phones varies with the three walking motion and are able to estimate more accurately energy expenditure.**

***Index Terms*—Physical Activity, Metabolic Equivalents, Accelerometer, Energy Expenditure, Location**

I. INTRODUCTION

With the rapid development of the latest IT technology, people are interested in IoT(Internet of Things). IoT is a technology that a built-in sensor and the communication function to various objects associated with the space of the Internet[1]. The object is embedded systems combined with software and hardware together such as electronics and mobile devices. In addition, this includes also a physical object such as a human, vehicle, various types of electronic equipment. This technology extends the concept of existing M2M(Machine to Machine) and then has evolved to the stage that people and objects exchange information and interact in the space of the Internet. A smart device such as smart phones has become central to these circumstances, and smart phones have become a necessity for most people. Our daily life even can be said to begin and end with smart phones.

On the one hand, physical activity is an integral part of our lives; people should exercise to stay healthy. Physical activity on a regular basis is very important to maintain a good physical and mental state of health. However, most people don't know their own physical activity. That is, it is difficult to estimate the amount of their own physical activity and do not achieve the recommended amount of physical activity[2-5]. This paper investigates the effects of acceleration change amount to the location of the accelerometer on the estimation of energy expenditure[6]. In this paper, we analyze the user's walking motion, and classify them into three based on walking action in order to estimate the estimation of energy expenditure of smart phone users. Through this analysis, we confirm that the location of the smart phones varies with the three walking motion and are able to estimate more accurately energy expenditure.

The remainder of this paper is organized as follows. Section 2 describes a brief-overview of physical activity and energy expenditure. Section 3 presents experimental environments. Section 4 analyzes the acceleration data collected and presents activity classification algorithm. Section 5 is conclusion.

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S.H. Choi is with Kangwon National University, Department of Control & Instrumentation Engineering, Samcheok-si, Gangwon-do, 25913, Republic of Korea (e-mail: cshinh@kangwon.ac.kr)

II. RELATED WORKS

Humans naturally spend a lot of time and make effort to walk. A long time ago, humans run to hunt or protect themselves from the beasts, while humans should exercise such as walking or running in order to live a healthy life in the modern society. Through physical activity, immunity of humans is increased, and then it is helpful in weight control by consuming the energy. In other words, physical activity is essential for human health maintenance and promotion and humans are devoting a lot of time and effort to their health. There are many ways to measure how much of that exercises; the energy expenditure is a representative measurement. The energy expenditure can be variously measured according to sex, age, type of physical activity and intensity; it is possible to track back to these. We can determine and monitor the health condition[7,8].

Method for measuring the energy expenditure can be generally divided into direct and indirect calorimetry. Direct calorimetry is a method for measuring how much the water is heated by the experimenter to leave and move a space isolated from the outside, indirect calorimetry is to measure the energy expenditure over the experimenter masks that can measure the lung capacity. However, both methods measure in a place of expensive measuring equipment and laboratory environment and so reliability of the measurements is high but is expensive.

With these earlier methods the experimenter must wear much equipment. For this reason, in recent years it has been used tools that can measure more easily and readily. Pedometer is considered as representative and people are able to see daily physical activity. Due to the recent development of MEMS, various applications based on the smart phones including a digital pedometer are being developed.

Smart phones are equipped with a sensor such as an accelerometers, magnetometers, gyroscopes and GPS, and powerful processors capable of executing complex work and a high-quality display[9,10]. In addition, through wireless communication including the Bluetooth it may be able to interact with the external data. Most of the appliances in accordance with the rapid development of hardware technology are compact in size, but to the contrary, smart phones are getting bigger rather for searching information and viewing video over the Internet connection. So, the most common form is not wearing in the pocket but carrying in a bag or on hand. Most people carry a smart phone on hand. Because recent smart phones grew more than four inches in screen size and people use SNS (Social Network Service) while moving. With the changed environment, the energy expenditure measurement utilizing the smart phones is more convenient rather than using the pedometer in many ways.

A. Energy Expenditure

In order to estimate activity energy expenditure, we use the method based on MET (Metabolic equivalents) values. All activities are assigned METs. MET is a value for expressing the intensity of physical activities[11]. When we use a calorie as an indicator, this is equal to 0.0175 kcal per kilogram of body weight per minute as show in following equation (1).

$$Energy\ expenditure\ \left(\frac{kcal}{min}\right) = 0.0175kcal \times kg^{-1} \times min^{-1} \times MET^{-1} \times METS \times Weight(kg) \qquad (1)$$

In this paper, we analyze walking motion of the smart phone users in order to estimate the energy expenditure, and then present an algorithm that walking motion can be divided into three types. In addition, the location of the smart phones of the person to move can vary, and the energy expenditure of each motion can be estimated.

III. EXPERIMENTAL DESIGN

In the experiment, we collect the acceleration data for analyzing walking motion at first. Experimental environments are as follows:

A. Subjects

The subjects were four healthy volunteers (two males and two females, height 155~175 cm, weight 55~70 kg, age 20~45 years).

B. Procedure

Each subject holds smart phones on hand. We use smart phones with acceleration sensor (Galaxy series, manufactured by Samsung). For each of the four healthy subjects tested so far with smart phones, acceleration data was collected from slow walking, fast walking and running on the treadmill (manufactured by CYBEX). Four subjects repeat three activities such as slow walking, fast walking and running for 2 minutes for a total of about 30 minutes.

IV. ANALYSIS AND RESULT

In this section, we analyze the acceleration data collected through the experiment in section 3.

Figure 1 shows the graph of x axis, y axis and z axis values of the acceleration measured when a subject walks slowly holding smart phones in hand. In figure 1, (a) is x axis values of slow walking; (b) is y axis values of slow walking; (c) is z axis values of slow walking.

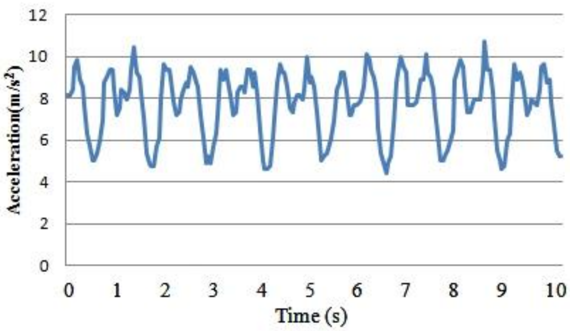
Figure 2 shows the graph of x axis, y axis and z axis values of the acceleration measured when a subject walks slowly wearing smart phones in the pocket. In figure 2, (a) is x axis values of slow walking; (b) is y axis values of slow walking; (c) is z axis values of slow walking.

Figure 3 shows the graph of x axis, y axis and z axis values of the acceleration measured when a subject walks fast holding smart phones in hand. In figure 3, (a) is x axis values of slow walking; (b) is y axis values of fast walking; (c) is z axis values of fast walking.

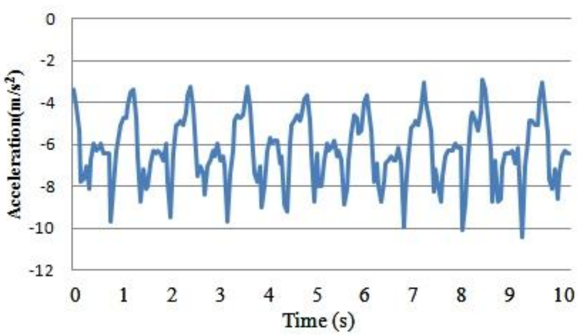
Figure 4 shows the graph of x axis, y axis and z axis values of the acceleration measured when a subject walks fast wearing smart phones in the pocket. In figure 4, (a) is x axis values of fast walking; (b) is y axis values of fast walking; (c) is z axis values of fast walking.

Figure 5 shows the graph of x axis, y axis and z axis values of the acceleration measured when a subject runs holding smart phones in hand. In figure 5, (a) is x axis values of running; (b) is y axis values of running; (c) is z axis values of running.

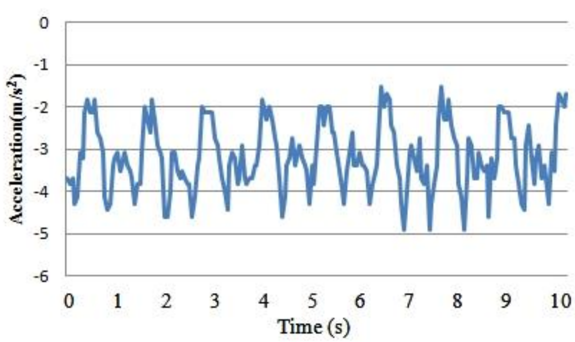
Figure 6 shows the graph of x axis, y axis and z axis values of the acceleration measured when a subject runs wearing smart phones in the pocket. In figure 6, (a) is x axis values of running; (b) is y axis values of running; (c) is z axis values of running.



(a) **Male with slow walking (x axis)**

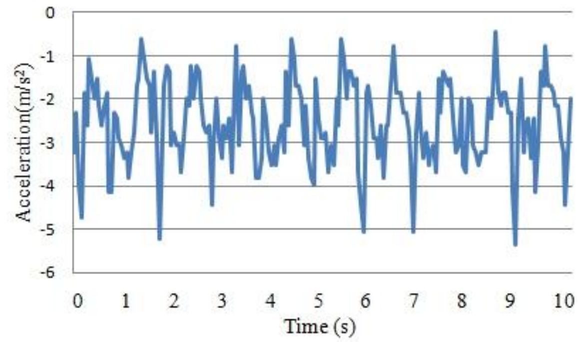


(b) Male with slow walking (y axis)

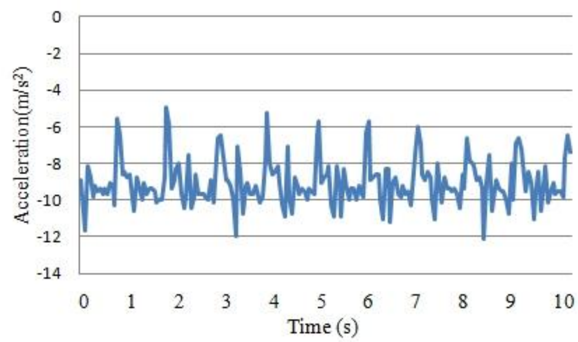


(c) Male with slow walking (z axis)

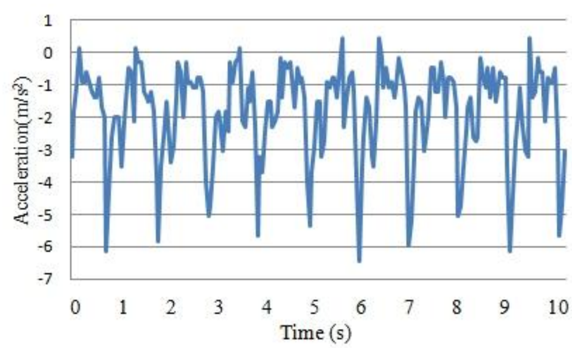
Fig. 1. Holding smart phones in hand



(a) Male with slow walking (x axis)

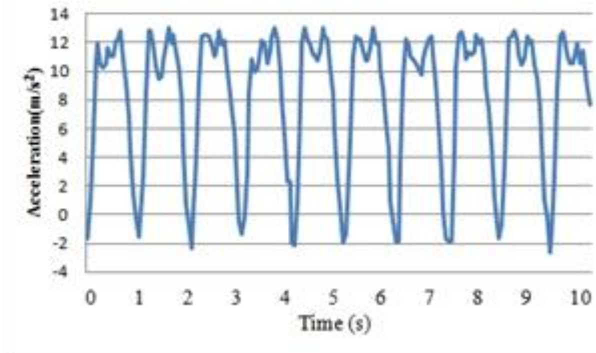


(b) Male with slow walking (y axis)

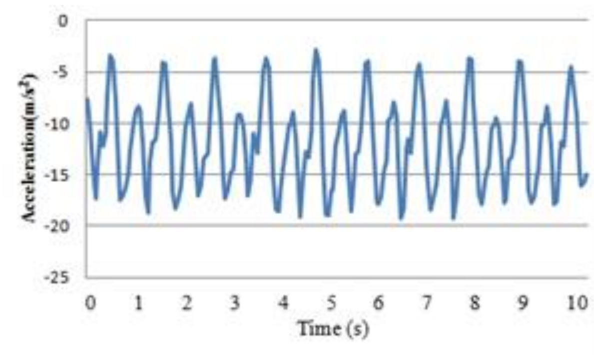


(c) Male with slow walking (z axis)

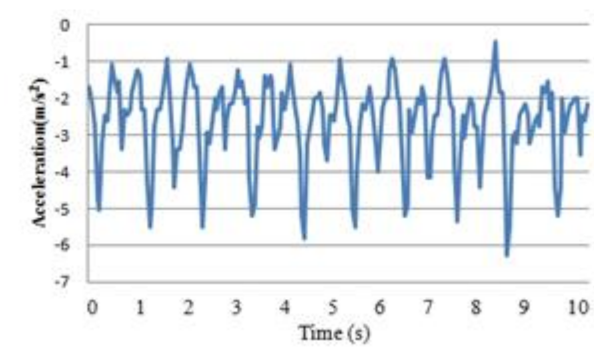
Fig. 2. Wearing smart phones in the pocket



(a) Male with fast walking (x axis)

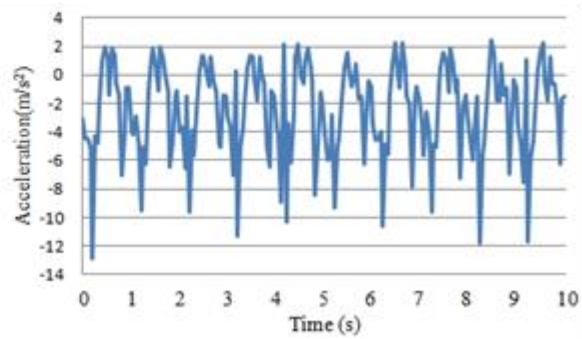


(b) Male with fast walking (y axis)

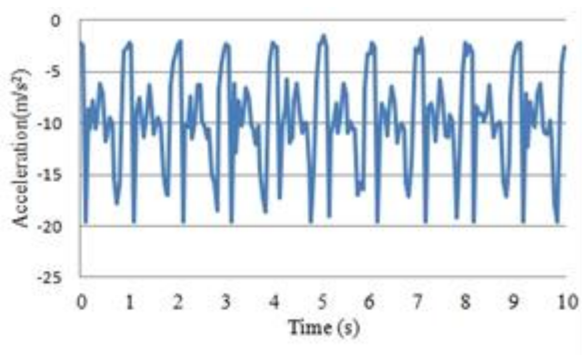


(c) Male with fast walking (z axis)

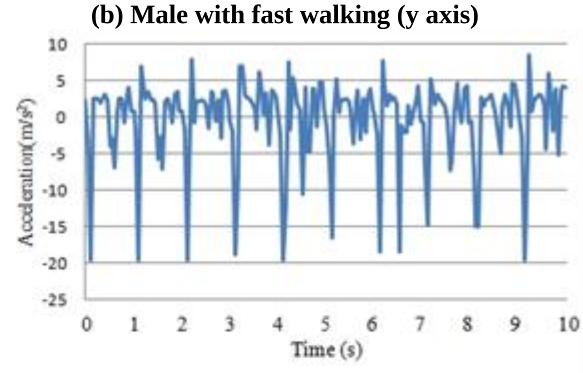
Fig. 3. Holding smart phones in hand



(a) Male with fast walking (x axis)

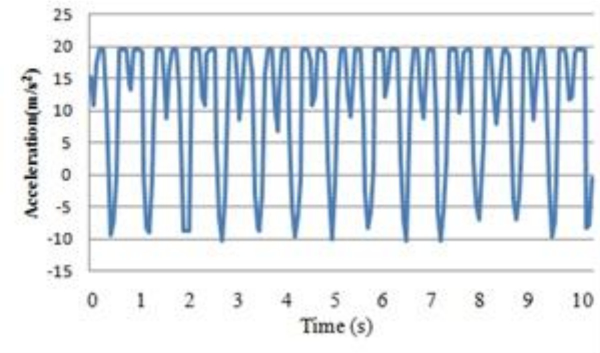


(b) Male with fast walking (y axis)

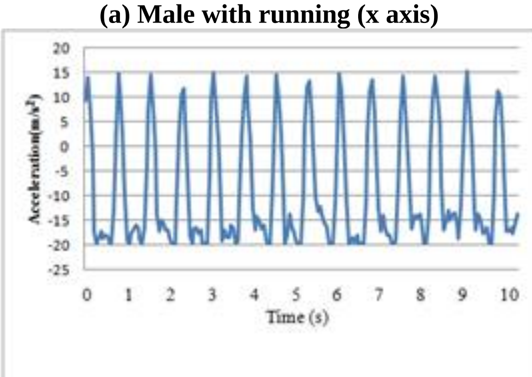


(c) Male with fast walking (z axis)

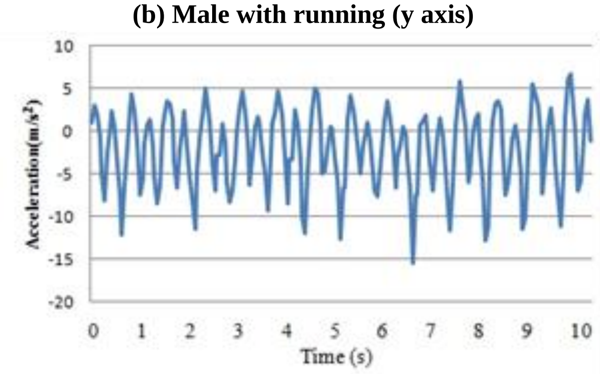
Fig. 4. Wearing smart phones in the pocket



(a) Male with running (x axis)

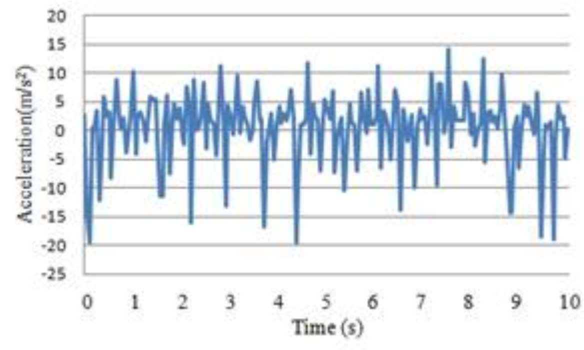


(b) Male with running (y axis)

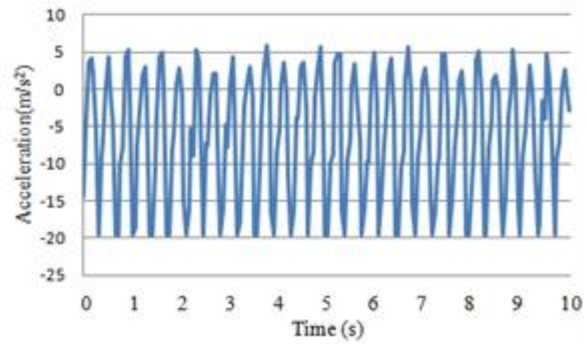


(c) Male with running (z axis)

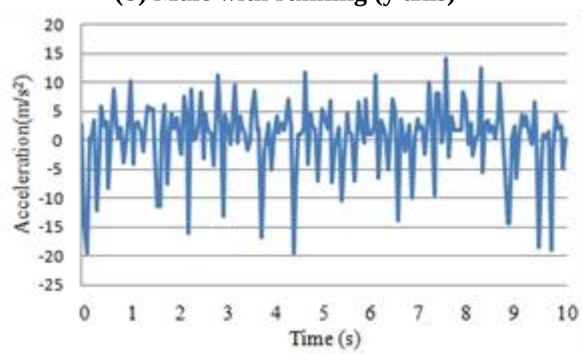
Fig. 5. Holding smart phones in hand



(a) Male with running (x axis)



(b) Male with running (y axis)



(c) Male with running (z axis)

Fig. 6. Wearing smart phones in the pocket

Through this result, it is clear that the acceleration data measured by holding smart phones in hand is more regularly than by wearing smart phones in the pocket, and also that the measurement method holding smart phones on hand is able to distinguish more easily activity type. In addition, we propose the activity classification algorithm to estimate the energy expenditure. Figure 7 shows the algorithm of activity classification distinguishes between the three activities. This algorithm is performed only for slow walking, fast walking and running. The reason is that three activities belong to different the motion of arms and the location of smart phones according to the activity type.

Step1:

Initialize x, y, z axis values of acceleration in the standing position.

X_i = initial x axis value

Y_i = initial y axis value

Z_i = initial z axis value

Step2:

Collect x, y, z axis values when moving

X_t = x axis value at *t*

Y_t = y axis value at *t*

Z_t = z axis value at *t*

Step3:

Calculate difference value from initial value each x, y, z

$X_d = | X_i - X_t |$

$Y_d = | Y_i - Y_t |$

$Z_d= |Z_i - Z_t |$

Step4:

Classify activity type

If $X_d<X_{th1}$ and $Y_d<Y_{th1}$ and $Z_d<Z_{th1}$ then

activity type is slow walking

else If $X_d<X_{th2}$ and $Y_d<Y_{th2}$ and $Z_d<Z_{th2}$ then

activity type is fast walking

else If $X_d<X_{th3}$ and $Y_d<Y_{th3}$ and $Z_d<Z_{th3}$ then

activity type is running

end if

Fig. 7. Activity classification algorithm

V. Conclusion

Physical activity is essential for human health maintenance. Energy expenditure due to physical activity is a parameter closely related to mobility. The use of accelerometers for the assessment of physical activity is based on demonstrated relationships between accelerometer output and energy expenditure. In this paper, we investigate the effects of acceleration change amount to the location of the accelerometer on the estimation of energy expenditure. We analyze the user's walking motion, and classify them into three based on walking action in order to estimate the estimation of energy expenditure of smart phone users. Through this analysis, we confirm that the location of the smart phones varies with the three walking motion and are able to estimate more accurately energy expenditure.

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