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Mobile health monitoring system based on activity recognition using accelerometer

Yu-Jin Hong, Ig-Jae Kim *, Sang Chul Ahn, Hyoung-Gon Kim

Imaging Media Research Center, Korea Institute of Science and Technology, 39-1 Hawolgok-Dong, Seongbuk-Gu, Seoul 136-791, Republic of Korea

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ABSTRACT

We propose a new method to recognize a user's activities of daily living with accelerometers and RFID sensor. Two wireless accelerometers are used for classification of five human body states using decision tree, and detection of RFID-tagged objects with hand movements provides additional instrumental activity information. Besides, we apply our activity recognition module to the health monitoring system. We derive linear regressions for each activity by finding the correlations between the attached accelerometers and the expended calories calculated from gas exchange analyzer under different activities. Finally, we can predict the expended calories more efficiently with only accelerometer sensor depend on the recognized activity. We implement our proposed health monitoring module on smart phones for better practical use.

1. Introduction

Activity of Daily Living (ADL) is a way to describe the functional status of a person [1]. Therefore the recognition of ADL is a significant problem in human caring system, especially in elder care. Due to the advance in sensor technology, people have an interest in the development of systems for monitoring human subjects over long period of time using wearable monitoring units. Recently, a number of researchers have investigated ADL inference with accelerometers.

Accelerometers can provide quantitative measurements and respond to both acceleration for gravity and acceleration for body movement [12,13]. This makes them suitable for measuring postural orientations as well as body movements. Using these accelerometers, many researchers have proposed different approaches to classification, including fixed-threshold classification [2], pattern matching based classification [3] and neural network based classification [4]. Kiani et al. [5] presented a more systematic approach to classification based on a Decision Tree classifier. Each node of the tree had multiple branches leading to all of the movements of interest at the next level of the hierarchy. The decision at each node was obtained by the measurement of parameters such as average, norm and standard deviation and then classification on the basis of these parameters. Bao and Intille [6] calculated mean, energy and frequency domain entropy of acceleration data and tested several classifiers, such as decision table, IBL, decision tree and naive Bayes, using these features. Among them, they showed Decision Tree classifiers had the best performance in recognizing activities of daily living. Although Decision Tree classifiers had been used, recognition accuracy on a variety of activities is around 80%, the accuracy is not satisfactory so that it must be increased for the general uses, especially under a natural and out-of-lab environment. Some researchers tried to infer the human activities by detecting human–object interactions [9]. To do this, they used RFID technology that facilitates applications that are triggered by handling tagged physical objects. This approach has the advantage of very high accuracy. There are little false negatives. However, these approaches have a weakness that false positive may occur when the object is detected without

* Corresponding author. Tel.: +82 2 958 5766; fax: +82 2 958 5769.
E-mail address: kij@imrc.kist.re.kr (I.-J. Kim).

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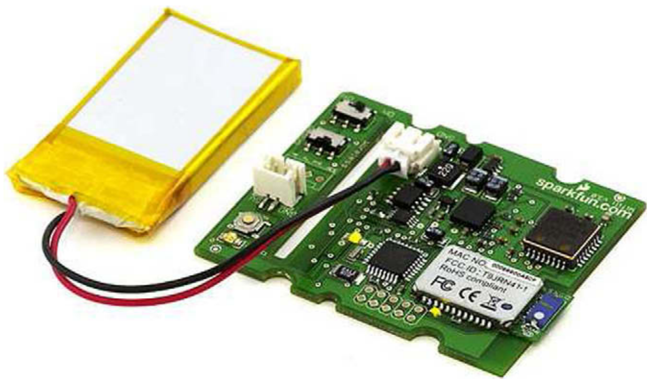

Fig. 1. Bluetooth based triaxial accelerometer.

being truly used. In this paper, a novel and robust recognition of ADL based on human motion and object identification has proposed. By combining the recognition of body states using low body motion sensors with the human–object interaction detected by the RFID-tagged object grasped, the recognition accuracy of ADL can be improved significantly in a real usage.

With the help of using sensors, we can recognize user's activities automatically. And besides, we expand our activity recognition module to health monitoring system by measuring the expended calories without additional devices.

One of the best way for estimating calorie consumption is to use a gas analyzer which measures calorie consumption from the exchange rates of VO_2 and carbon dioxide production, VCO_2 [13,14]. Although it is the most precise way to predict the energy expenditure, it is hard to be used as a daily health monitoring system due to its heavy intrusiveness of wearing mask. We therefore try to find correlation between the sensor data and the consumed energy by wearing both gas analyzer and accelerometer. After finding the linear regressions under different activities, we can measure the energy expenditure automatically with only small accelerometer attached to the body.

2. Motion analysis with accelerometers

To detect the physical activities of a user, three triaxial accelerometers were worn on thigh, waist and wrist. We used Freescale MMA7260Q with Bluetooth module so that we can get motion data with wireless connection. Fig. 1 shows our motion unit used in our experiment. The feature vectors of mean, energy, entropy and correlation in frequency domain are calculated from acceleration data with 256 sample window. The way of extracting each feature is as follows. To extract features, we apply FFT transform in advance. For the mean feature, we can get easily by extracting DC component of sample window. DC component means the average acceleration value for the duration of sample window. For the energy feature, we multiply every magnitude after FFT without DC component by itself and add it all together. Then, we normalize the value by dividing with the window length.

For the entropy, we calculate the normalized information entropy of every magnitude without DC component. The following equation is for getting information entropy.

$$\text{Info. Entropy} = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i) \tag{1}$$

We can get the probability $p(x)$ by counting the number of magnitude in a specific bin after dividing the range of magnitude into several bins. Because we use triaxial accelerometers to get motion information, we can get the correlations by calculating the normalized cross product between each axis value. Fig. 2 shows the overview of feature extraction process. Consecutive sample windows are overlapped with 128 samples and each sample window represents 4 s. Overlapped sampling window of 4 s is used to capture the cycles in activities such as walking, running, or brushing. Activity recognition based on these features is performed using a Decision Tree classifier [6]. Two triaxial accelerometers worn on thigh and waist are used to classify five states of current body states, such as standing, lying, sitting, walking and running. One accelerometer worn on wrist is used to decide hand motion with object ID. Even though Decision Tree method is slow to train, a pre-trained Decision Tree classifier enables the classification of user activities in real-time.

3. RFID module

RFID systems have been widely applied over recent years for the identification and tracking applications [8,9]. Passive RFID tags do not need battery and are small enough to be attached on small objects like screw driver and tooth brush. List of the RFID-tagged objects used for detecting the ADL is shown in orange, blue, green and purple box in Fig. 5.[1] Before the

[1] For interpretation of color in Fig. 5, the reader is referred to the web version of this article.

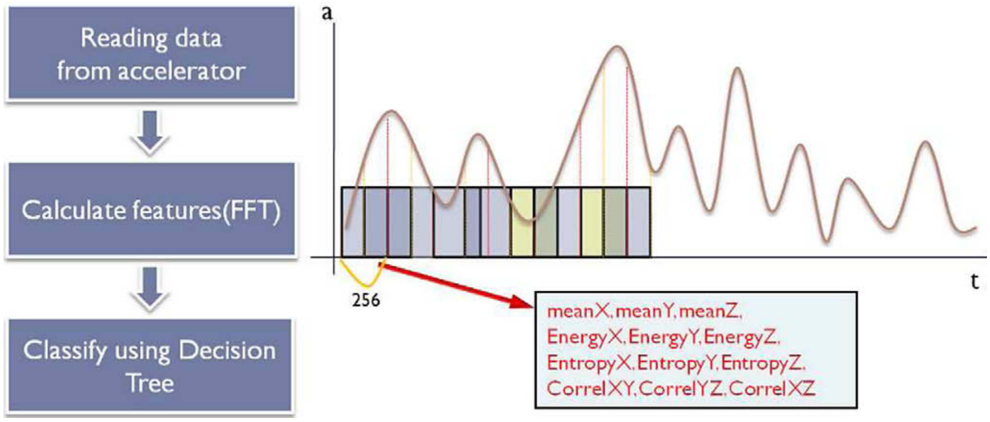

Fig. 2. Feature extraction process.

detection process, we assign ID of the object of interest to each tag. The RFID-tagged objects are detected by the glove which integrates the HF RFID reader of 13.56 MHz (Fig. 3). The reader is also small enough so that can be embedded in a wearable glove similar to that of Philipose et al. [9]. Unlike previous method of using UHF RFID, the designed glove can only read object ID within 50 mm range from the palm of the hand and only the object taken by the hand can be detected. It can help us to detect only the object being truly used. The reader samples three times per second.

4. Sensor fusion

Fig. 4 shows our sensor fusion architecture to classify the ADL. We observed that most people stay in one of the five body states of standing, lying, sitting, walking and running, and may act some kinds of hand activity with different object, called instrumental activity (I-ADL), under each body state. For example, people may brush his/her teeth in standing position, sitting position or walking position.

Previous works based on motion data only have less recognition accuracy under real environment because they did not differentiate these body states with hand activities. The proposed method classifies the current state of user's body using Decision Tree classifier over lower body motion information from waist and thigh. After classification of user's body state, the results are combined with instrumental activities. For instrumental activities, we examine the movement of hand and object ID to infer the more detailed intension of the user. For the hand movement analysis, we categorize the movement of hand as three categories, such as rotating, vertical movement and lateral movement. If the movement of hand is detected, then we try to detect the object ID taken by the hand using our RFID reader. If an object is detected, we can infer user's activity (I-ADL) from the detected object ID in a classified body state. In our experiment, I-ADL [7] is defined as the characteristic nature of the activities which are mostly done with tools, particularly in the home. To get rid of false positive cases of hand activity recognition, we use the categorized hand motion information (Fig. 5). For example, if we are to drink something, the hand movement will be vertical movement. In this case, we can classify the activity as drink activity if we detect cup by RFID reader and detect the movement as vertical movement. However, the classified hand movement is lateral motion or circular motion while the detected object is cup by RFID reader, we cannot call it drink activity.

Fig. 3. iGrabber and RFID-tagged object.

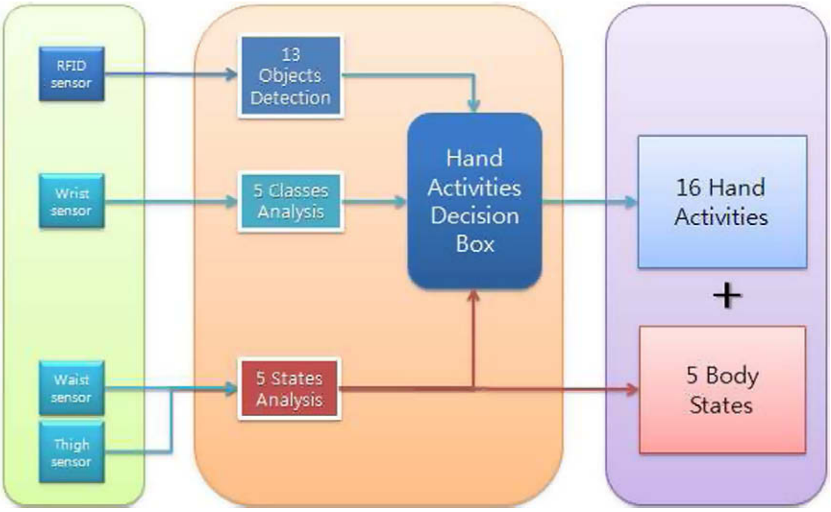

Fig. 4. Sensor fusion architecture.

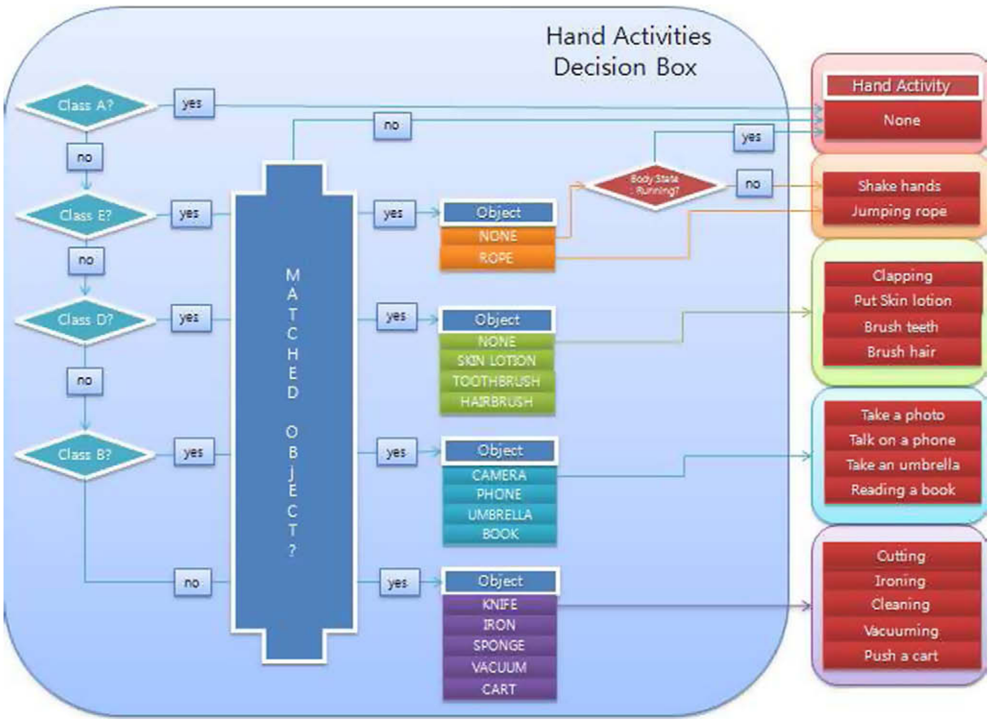

Fig. 5. Architecture for detecting the categorized hand motion.

5. Calculating energy expenditure

As mentioned in the section of introduction, it is the most precise way to predict the energy expenditure with gas exchange analyzer. Energy expenditure is related to volume of oxygen [10]. We can measure energy expenditure from the oxygen consumption during physical activities and the respiratory exchange ratio corresponding both oxygen and carbon dioxide in the lungs. For doing this, we used MetaMax (CORTEX Biophysik GmbH, Leipzig, Germany) – gas analyzer in Fig. 6. It transmits wirelessly the amount of inspired oxygen and expired carbon dioxide to the laptop per 1 s. However, it is hard to be used as a daily health monitoring system due to its heavy intrusiveness of wearing mask. We therefore try

Fig. 6. MetaMax: gas exchange analyzer.

to find correlation between sensor data and the consumed energy by wearing both gas analyzer and accelerometer. For this, we have collected integrated accelerometer signals of 15 subjects from accelerometer sensor attached to the waist of body and measured EE/day by wearing the gas exchange analyzer simultaneously. Each subject was asked to do the predefined activities repeatedly under the different body states for 3 min for recording training data set. (Table 1 shows the predefined activities). To capture the amount of force and magnitude of movement on each body state, we accumulated the magnitude of accelerometer data from each axis during time ∂. In our experiment, we set four for ∂.

$$AccumulatedMagnitude = \int_{t}^{t+\partial} |a_x(s)| + |a_y(s)| + |a_z(s)| ds \tag{2}$$

As the measurements of oxygen rate from MetaMax is sensitive to the ambient temperature, we conducted our experiment after enough calibration under the regular temperature. We let the subjects walk and run on a treadmill wearing accelerometers and gas exchange analyzer. Fig. 7 shows our experimental setup for capturing the training data.

6. Experimental results

We have collected acceleration data from 15 subjects using three triaxial accelerometers. The average age of subjects is 22.9. Each subject was asked to repeat the performance of predefined sequence of 18 activities (Table 2) for 45 s for each activity and repeated each activity twice to record the training data set. Acceleration data collected were marked with the start and stop times, and labeled with the name of each activity. Mean, energy, entropy and correlation features were extracted from acceleration data. As shown in Fig. 8, a user wears three accelerometers in wrist, waist and thigh. She also puts on the iGrabber.

As we divided ADL into 'Body State' and 'Hand Activities', two accelerometers attached to thigh and waist are used to detect the user's body state and the other in wrist is used to classify the hand movements. Hand movements are so diverse that it is difficult to discriminate every hand motion from learning. To make a robust recognition of hand movements, we classified hand motion into five categories in advance from learning dataset using Decision Tree method. The categorized movements are shown in Table 3.

For the generalization of the results, we tested only a subject left out of the training data set. This leave-one-subject-out validation process was repeated for all 15 subjects. We first evaluate how well we recognize the hand movements. Table 4 shows the confusion matrix for the result of hand movement recognition. We verify what class the detected hand motion is corresponded. After verifying the motion class, we check whether the object information from iGrabber is match up to the detected motion class or not. If it is, we can determine the I-ADL. The recognition results are shown in Table 5.

We evaluate how our proposed method has higher accuracy than the previous works. In Table 6 shows the comparison result between the representative previous work that use only motion sensor and our proposed method that use both motion sensor and RFID sensor. The results show that our proposed method is strongly confident especially for the object re-

Table 1
List of predefined activities.

Body states	Detail
Upright	Sitting and standing, doing nothing
Walking	Walk at 2 km/h and 4 km/h speed, respectively
Running	Run at 7 km/h and 9 km/h speed, respectively

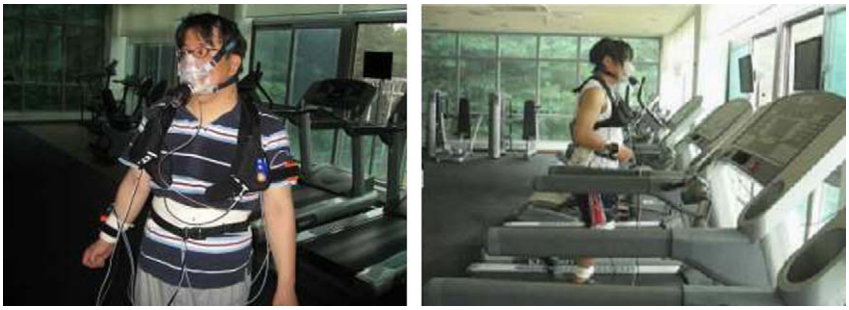

Fig. 7. Experimental setup for gathering training data.

Table 2
List of activities for our experiment.

Activity list	
Sitting	Brush hair + standing
Standing	Phone calling + sitting
Walking	Taking picture + standing
Lying	Reading + sitting
Running	Wiping with cloth + standing
Hand shaking	Running a vacuum cleaner
Rope jumping	Put on an umbrella + standing
Put on skin conditioner	Toothbrush + standing
Pushing a shopping cart	Cutting + standing

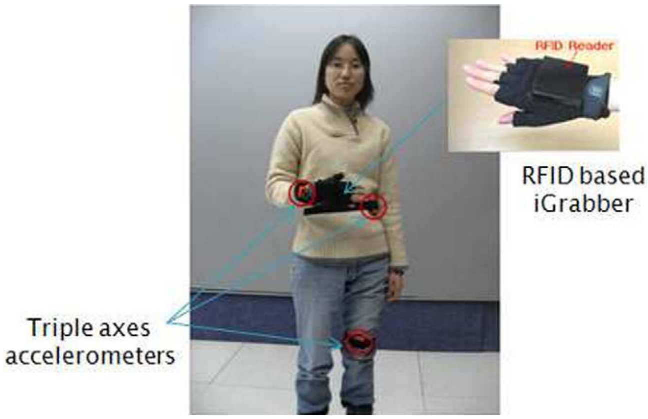

Fig. 8. User wearing three accelerometers and iGrabber.

Table 3
Five categories for hand movement.

Category	Activities
A	None
B	Take a photo, talk on a phone, take an umbrella, reading
C	Cutting, ironing, cleaning, walking, vacuuming, pushing a cart
D	Put skin lotion, clapping, brushing, teeth, brushing hair
E	Shaking hands, running, jumping a rope

lated hand activities compared other results [3,6]. Some I-ADL, such as put on an umbrella, ironing, running a vacuum cleaner and pushing a shopping cart, may constrain user's body so that the recognition results show high accuracy. Some activities which can be occurred as a different action from force of habit, such as tooth brushing and put on a skin conditioner, have less recognition accuracy compared to other activities. The results for body state recognition is shown in Table 7. In the recognition of body states, 'Walking' activity shows low accuracy, this is because people could walk faster or slower depend

Table 4
Confusion matrix for classification accuracy.

A	B	C	D	E	Total	Class	Accuracy (%)
894	82	20	8	1	1005	A	88.96
24	**1267**	0	65	0	1356	B	93.44
52	0	**1911**	1	46	2010	C	95.08
24	65	0	**1197**	32	1318	D	90.82
4	8	40	25	**929**	1006	E	92.35
998	1422	1971	1296	1008	**6695**	Total	**92.58**

Table 5
I-ADL recognition result.

Activities	Accuracy (%)
None	97.94638
Cutting	95.28024
Tooth brushing	90.79755
Taking a picture	93.69370
Shaking hands	89.31751
Wiping with cloth	92.54695
Put on an umbrella	99.69697
Jumping a rope	94.34542
Running a vacuum	100.0000
Pushing a shopping cart	100.0000
Put on a skin conditioner	87.98799
Overall	94.69206

Table 6
Comparing accuracy motion only and motion + rfid.

Activities	Motion only (%)	Motion + RFID (%)
Sitting + drinking	94.57	94.38
Standing + drinking	62.86	97.68
Walking + drinking	88.19	94.86
Ironing + standing	69.23	97.94
Cutting + standing	56.35	98.67
Brush hair + standing	84.16	98.34
Repairing + standing	55.02	94.98
Overall	82.26	97.16

Table 7
Body state recognition results.

Activities	Accuracy (%)
Sitting	100.0000
Standing	100.0000
Walking	84.3629
Lying	92.66409
Running	92.03036
Overall	93.78858

on their style. It may cause a wrong decision as 'Standing' or 'Running' depend on the style. Nevertheless, we can also get a high accuracy for the body state recognition. From these results, we can know what the user does in which body state he is. After prediction of user's activity using accelerometers, we can also measure the energy expenditure under the activity without additional devices. From the preprocessing with accelerometer data and the consumed energy data from gas analyzer, we could make a compact equation for calculating energy expenditure with only small accelerometer. We show how it is correlated between the energy expenditure and accumulated magnitude from accelerometers under the different activities in Fig. 9. We apply linear regression method for each activity.

Using calculated compact equations, we can calculate the energy expenditure automatically with only accelerometer sensor. To evaluate our proposed method for measuring energy expenditure, we compare our results with the data from American College of Sports Medicine (ACSM) formulas and the data measured by MetaMax. ACSM serves as a scientific information source for basic and applied exercise science. ACSM formulas are applied anyone with no difference of individuals

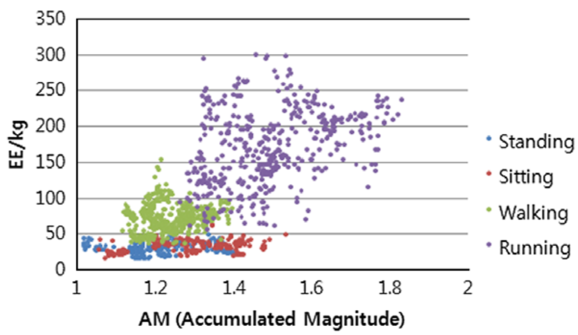

Fig. 9. Relation between the energy expenditure and accumulated magnitude under different activities.

Table 8
Energy expenditure (kcal) for 45 kg during 4 s.

Activities	MetaMax	Our result	ACSM
walking (3 km/h)	0.144 kcal	0.128 kcal	0.127 kcal
running (8 km/h)	0.422 kcal	0.479 kcal	0.451 kcal

because the energy needed to walking, running or cycling is not affected that much by age, gender, technique of exercise or other components [11]. The measured data by MetaMax can be the ground truth for comparison in our experiment. The compared results are shown in Table 8.

We also tested with more people of different weight and compared again our method with ACSM result. Table 9 shows the list of subjects who are not included in training set. Fig. 10 shows the comparison energy expenditure from the proposed

Table 9
Each subject's number and weight.

Subject (no. 1)	Weight (kg)
1	45
2	53
3	55
4	72
5	76
6	79

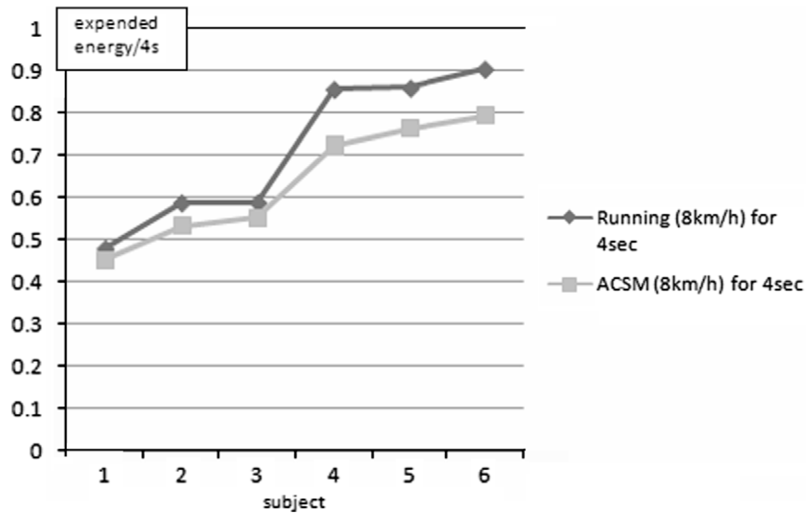

Fig. 10. Comparison the energy expenditure for 8 km/h between the proposed method and ACSM.

method and ACSM formula under the different weights. As we expected, the result shows that the weighty people consume more calorie and the increasing tendency is similar between two methods. To make good use of the proposed method, we implemented the proposed method on smart phone that has a triple axes accelerometer, GPS and 806 MHz CPU. Besides, as the mobile phone has display screen to visualize some information, it can be a good environment for mobile health

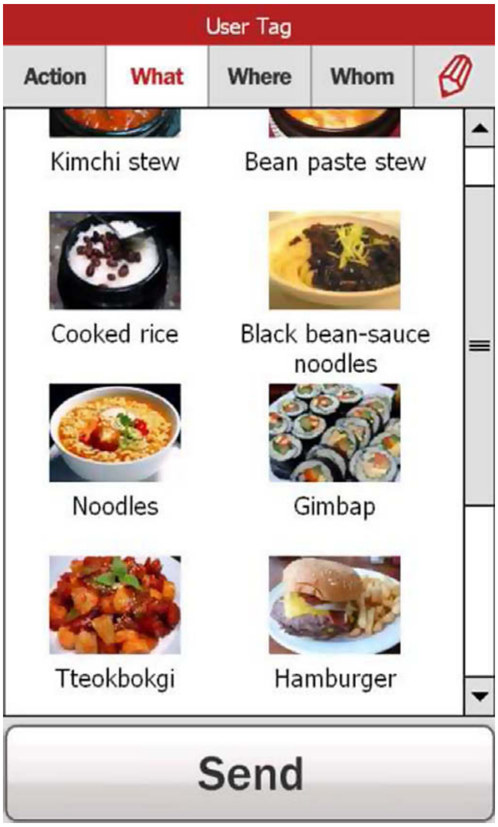

Fig. 11. Screenshot of logging tool for intake calorie.

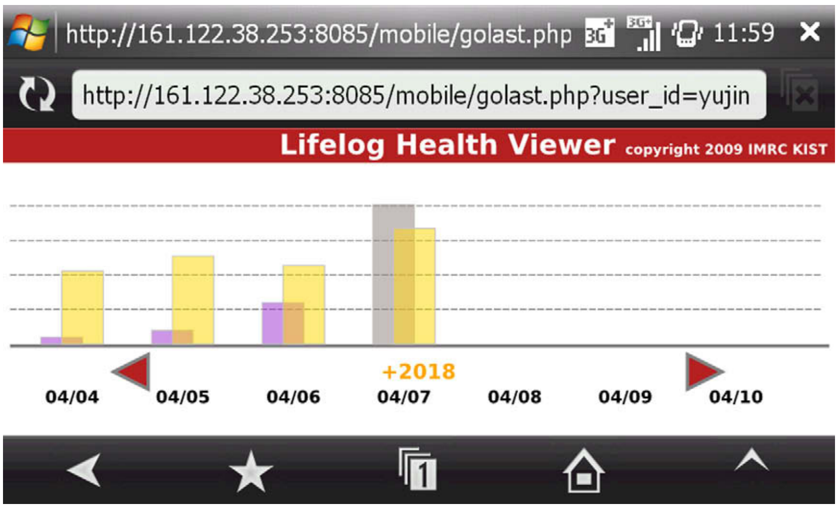

Fig. 12. Visualization tool for health monitoring on mobile phone.

monitoring to check his/her body state and calorie balance status. For more accurate health monitoring, we also have to check the intake calories so that we develop the web based tool for counting intake calories by manual tagging. Fig. 11 shows the snapshot of implemented tagging tool on mobile phone. Besides, we support the visualization tool for health monitoring in Fig. 12.

7. Conclusions

A novel and robust recognition method for ADL inference based on human motion and object identification has been proposed. The suggested system uses sensor fusion of 3 accelerometers and RFID reader. Two accelerometers are used for the classification of five human body states using decision tree, and detection of RFID-tagged objects with hand movement provide object related instrumental activities. This hierarchical approach of recognition of human activities provide robust and high accurate recognition results. The overall recognition rate of 18 ADL is about 95%, which can be applicable to a real environment with strong confidence. For practical utilization of the proposed method, we downsize our activity recognition algorithm and find the interrelation between captured sensor data and the consumed energy by wearing both gas analyzer and accelerometer. We then can make compact statistical models under the different activities so that we can measure the energy expenditure automatically with only small accelerometer attached to the body. Fortunately, current most smartphones have already accelerometer for user interaction so that we could implement our proposed method easily on smartphone without additional devices. As we already developed our tagging tool and visualization tool for health monitoring on smartphone, we hope that our system can be widely used for caring one's health.

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