Smartwatch/Smartphone Cooperative Indoor Lifelogging System

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Abstract

In this study, a lifelogging system is proposed for logging the daily activities of a user using a smartphone and a smartwatch cooperatively in indoor environments. The proposed system attempts to recognize a user's activities of daily living, including sleeping behavior and various physical activities, and to estimate the user's daily total energy expenditure (TEE) based on the recognized lifelogs. The TEE has the potential to be useful in personal healthcare management. The system includes both mobile and server systems. The mobile system consists of both a smartwatch and a smartphone used to classify ten activities, including sleeping activities, using sensors on both devices. The server system includes a database server and a set of programs to handle the collected lifelogs for users. An Android app is also developed to display the collected lifelogs and the estimated daily TEE on smartphones to assist in managing users' health. The experimental results show that the overall average recognition rate of seven activities is 97.5% with four subjects, and the total average error for the three states of sleeping behaviors is 6.64%.

Keywords: lifelogging system, smartphone, smartwatch, activity recognition

1. Introduction

Lifelogging is a collection of information about daily activities of a user. The stored information can include documents, photos, Web browser information, biometric sensors, etc. which can draw a picture about the activities of the user in a day [1]. The lifelogging systems have been developed for years ago. The initial system that inspired many lifelogging systems as well as lifelog tools is "Memex" vision (a sort of desk) which was introduced by Bush in 1945. This system can help manage the personal information of a user from the documents that he/she interacts with. After a long time of development and improvement, today's lifelogging systems extend their scale not only in a small area such as in a room or a building but also to the worldwide due to the development of the technology. However, there are challenges when designing and using personal information in lifelogging system. The main challenges include the policy to access to the information, the security of personal information, and the long-term preservation of the information [2-3].

There are different ways to classify the lifelogging systems. According to Sellen and Whittaker, the lifelogging systems are classified into two main classes [2]. The first one is total capture, which means the system will attempt to catch and collect the data related to the user as much as possible from different sources such as documents, images, videos, etc. The second class is situation-specific capture which limits the range of collected data due to different purposes. For example, during the medical treatment, the information from the biometric sensors is more useful than Web browser or email information. Another way to classify the systems is based on the way they are collected [1]. Active lifelogging is one uses

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sensors and capture tools to store the useful information about himself only. Meanwhile, passive lifelogging is one uses tools to track the information of another one. For example, the doctors use sensors attached to the patient's body to collect the movement of the patient in vestibular rehabilitation therapy.

The dramatic development of technology has given rise to a new trend in the mobile healthcare industry, which focuses on using mobile devices to assist in providing medical health service support. In recent years, the mobile healthcare has received increasing attention, because the biosensors that are used for healthcare purposes can be miniaturized and integrated with wearable wireless communication technology into smart devices such as smartphones or smartwatches [4]. In addition, the increasing affordability of wearable devices can be expected to increase their popularity and the roles they play in people's lives. Attention has been shifting from disease treatment to disease prevention, giving rise to many healthcare-related applications that can help people track their daily activities, energy intake and expenditure. Using these applications assists people in adapting their lives and habits to improve their health. Furthermore, in a day, a user might engage in various activities both indoors and outdoors. Since people who live in urban areas spend 90% of their time indoors [5], the ability to recognize their activities when they are indoors through the use of wearable devices such as smartphone/smartwatch is important.

This paper proposes an indoor lifelogging system for recognizing the activities of daily living (ADLs) of a user, using both a smartphone and a smartwatch cooperatively as a mobile system, together with a server system that collects, processes, and provides feedback for the user to assist in health management. The mobile system first attempts to recognize the user's ADLs, and then to send the recognized logs to a database server. The server system stores the log data in a database from multiple mobile systems via a network, and then estimates each user's TEE based on the classified activities of the user. The user can see his or her own lifelogs and the TEE of a given day conveniently on the smartphone.

The contributions of this paper are as follows:

- An indoor lifelogging system is designed to use a smartphone and a smartwatch to track the ADLs of a user for 24 hours.
- A method is proposed using a smartphone and smartwatch simultaneously and cooperatively to recognize seven ADLs that can be used to estimate energy expenditure.
- A method is proposed to classify the sleeping status of a user using two mobile devices.
- A method is proposed to estimate the TEE of each user based on the classified lifelogs with the basal metabolic rate (BMR). The estimate can be calculated and stored in the server system, and then visualized on the user's smartphone.
- An Android platform application is developed that can display the stored lifelogs and the daily TEE and provide login and preference setting services to the user.

2. Related Work

Due to a long history of development, there exist many lifelogging systems. Some famous efforts are listed in [1]. LifeLog was a project which attempted to capture the life-long information and supported by the American Defense and Advanced Research Projects Agency (DARPA). One of the most famous systems is MyLifeBits which was designed by Gordon Bell from Microsoft in 2001. This system focuses on capturing the activities of a user in his/her office. Another lifelogging project from Microsoft is SenseCam which used a wearable camera to capture the images. In the field of using wearable devices for collecting information, especially the mobile phones, many systems are investigated and developed [6-8]. Chennuru et al. [9] attached the smartphone on a helmet to get data from both the integrated camera and accelerometer sensor of that smartphone for their lifelogging system. UbiLog [6] was a lifelog framework which also uses the smartphone as the main tool to record the information. The authors attempted to build a flexible and extensible framework which aims to increase the connectivity between their system and other digital devices, therefore enriches the lifelog data.

For human activity recognition, many studies have been conducted to develop offline machine learning tools, such as the Waikato Environment for Knowledge Analysis (WEKA) [10-11]. However, increasing battery capacity has also led to the introduction of more online activity recognition applications. There are applications that can track users' activities for a mobile diary or a fitness tracker through real-time processing [12-15]. Moreover, there are several activity recognition systems that calculate the daily total energy expenditure (TEE) of a user and display the results on a mobile device to help the user learn about his or her conditions immediately. Liu et al. [16] used an accelerometer and magnetometer to classify activities and calculate the energy expenditure based on those activities. Jung et al. [17] proposed a method for computing energy expenditure based on Global Positioning System (GPS) analysis and an accelerometer installed on a smartphone. Chiang et al. [18] proposed a system to recognize the pattern of user's activity and to calculate the TEE based on data obtained from the smartphones. Chowdhury et al. [19] compared the accuracy of energy expenditure estimation of different commercial wearable devices which can be used to monitor the physical activity of a user. Recently, by using acceleration data from a smartphone and a smartwatch, Duclos et al. [20] introduced an intelligent system to discriminate human sedentary and active behaviors to precisely estimate the TEE of the user by applying their new energy expenditure function.

The accurate detection of sleep is not easy using only the sensor outputs of a smartphone and smartwatch, without monitoring such physiological indicators as the electroencephalographic (EEG), electrooculographic (EOG), and electromyographic (EMG) factors. However, the latest commercial activity trackers such as Jawbone [21], Fitbit [22] or Xiaomi [23] are used not only for tracking the strength of activities but also for recognizing the sleeping behavior of a user automatically by using an accelerometer and/or heart rate detector. Chen et al. [24] used a smartphone to detect the sleep duration and distinguish between the awake and sleep states of a user. With a smartphone/smartwatch combination, the method uses features calculated from both devices to detect the user's sleep. Gu et al. [25] utilized built-in sensors on the smartphones to sense four sleep-related events, then predict the dwelling time of each sleep state by a statistical model.

3. Proposed System

3.1. System overview

Fig. 1 shows a block diagram of the proposed system, including both its mobile and server systems.

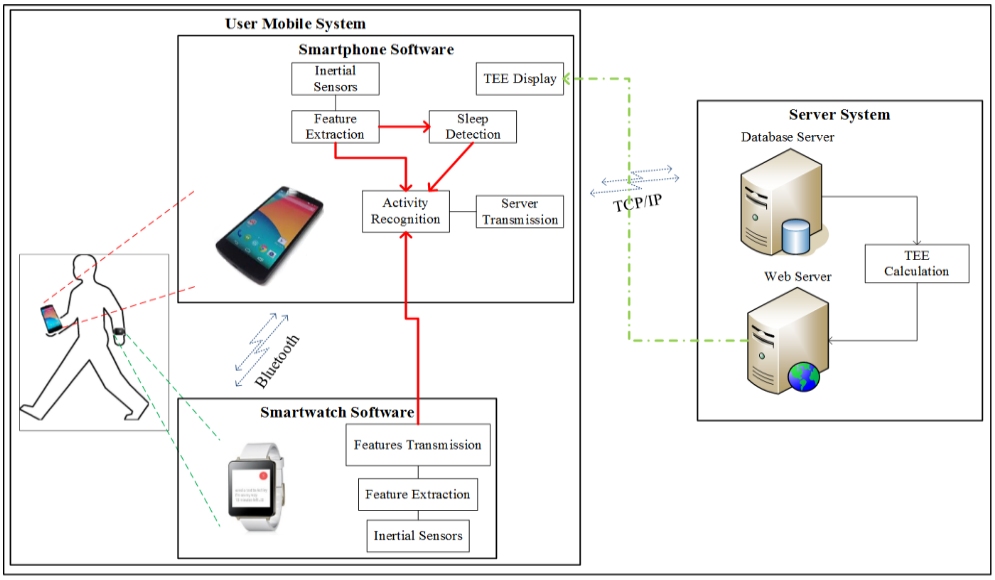


Fig. 1 Block diagram of the proposed system

The mobile system has both a smartphone and a smartwatch. First, the smartphone attempts to classify the user's activity through a set of features from both the smartphone and the smartwatch. The smartwatch sends feature values to the smartphone at predetermined intervals. Seven activities are defined as indoor activities: walking (WA), jogging (JO), running (RU), sitting (SI), standing (STA), rope jumping (RJ), and doing push-ups (PU). The developed classifier can also count the number of repeated activities for WA, JO, RU, RJ, and PU. In addition, the mobile system can track the sleeping behavior of the user. The system attempts to classify the sleeping status as awake, restless, or deep sleep. Finally, the mobile system can display the recognized and stored lifelogs and daily TEE data obtained from the server system in many forms.

The server system consists of a database server, a web server, and a set of server programs for handling the log data. The server system manages several users at the same time. The database receives the data from multiple mobile systems and stores their lifelogs. A server program calculates the TEE based on personal information, such as gender, age, height, weight, etc. The computed daily TEE values are stored in another database. In addition, every user is required to log in to the system in order for his or her personal information to be considered.

3.2 Mobile system

3.2.1. Activities recognition

A feature is introduced to divide all of the activities into two categories. For some activities, such as sitting or doing push-ups, the smartwatch/smartphone just moves in a comparably small space. In contrast, for walking or jogging, both devices move in a larger space (e.g., moving from room to room). Signals of the magnetometer and the linear acceleration of the smartphone were selected to compute this feature. At every sampling time (1/20 second), the system calculates these two features. The first is the standard deviation of the magnitudes of the magnetic sensor signals, $\sigma_{|\vec{m}|,12}, \vec{m} = (m_x, m_y, m_z)$ for the latest 12 samples. The second is the sum of the magnitudes of the linear acceleration vectors for the latest 12 samples, as described by the following equation:

$$S_{|la|}(t) = \sum_{k=1}^{12} k \left\| \vec{la}(t-k) \right\| \tag{1}$$

where k is a scaling factor and $\left\| \vec{la}(t) \right\|$ is the magnitude of the linear acceleration vector $\vec{la} = (la_x, la_y, la_z)$. To provide a better result, a new feature $f_{fw}(k)$ computed by fusing the two features described above, is introduced. The complementary filter technique is applied in accordance with the following equation:

$$f_{fw}(t) = \alpha\sigma_{|m|,12}(t) + (1-\alpha)\,\mathrm{S}_{|la|}(t) \tag{2}$$

At each sampling time, the feature $f_{fw}(k)$ is calculated and saved in a buffer. The scheme then computes the standard deviation $(\sigma_{f_{fw},12}(t))$ for the last 12 samples of the feature $f_{fw}(t)$ again. Finally, the average $\mu_{\sigma fw}(t)$ is calculated using the last four values of the standard deviation values, $\sigma_{f_{fw},12}(t-k), k = 0, ..., 3$. The feature $\mu_{\sigma fw}(t)$ is referred to as the moving feature.

A simple but effective recognition method is proposed for classifying indoor activities. At every sampling time, the activity estimator reads the signals, such as accelerations, angular velocities, and magnetic fields, from the hardware sensors of both devices, as well as signals such as the gravity and the linear accelerations from the software sensors. After every second, the smartwatch sends the features to the smartphone using the Google Data API protocol. The smartphone plays the role of the host processor to recognize the current activity of a user by analyzing the features of the smartphone itself with the features coming from the smartwatch. From the experiments, it is believed that 30 seconds is an adequate sampling time to maintain the user's daily lifelog. Therefore, the estimator recognizes an activity every second for a period of 30 seconds and then determines the most frequent activity among the collected activities as the final lifelog that is sent to the server system.

The smartwatch computes five features, the moving component $\mu^{w}_{\sigma fw}(t)$, the x-axis component of the acceleration vector, the mean of the x and y components of the acceleration vector, the maximum value of the magnitudes of the linear acceleration vectors for the last 12 samples, and the magnitude of the vectors of the gyroscope sensor signal. The moving feature is calculated in both the phone ($\mu^{p}_{\sigma fw}(t)$) and the watch ($\mu^{w}_{\sigma fw}(t)$). The superscripts "p" and "w" represent smartphone and smartwatch, respectively. Based on the values of the two moving features, the scheme attempts to classify activities into three categories, as shown in Table 1. The three categories represent different cases, depending on the degree of moving of both devices. For instance, in the case of rope jumping, this is represented by a big movement of the watch and a small movement (or no movement) of the phone.

First, the scheme determines the category using the two moving features. To distinguish (SI), (STA), and (PU) activities in category 1, a simple threshold-based method is proposed using four features, the x component of acceleration (denoted by a^{w}_{x}), the mean of the x and y components of the acceleration (μ^{w}_{a}=0.5(a^{w}_{x}+a^{w}_{y})), the magnitude ($\|\vec{\omega}^{w}\|$) of the angular velocity vector from a gyroscope, and the maximum value (denoted as $\max_{la,12}$) of the magnitude of the linear acceleration vectors, $\|\vec{la}\|$) among the last 12 samples. The rules are as follows: IF $\|\vec{\omega}^{w}\|$ < Th_3 AND $\max_{la,12}$ < Th_4, THEN the subgroup of (SI) and (STA) is categorized; OTHERWISE, IF $\|\vec{\omega}^{w}\|$ > Th_{10} AND Th_4 < $\max_{la,12}$ < Th_5, THEN (PU) is recognized. For (SI) and (STA), (STA) is recognized if a^{w}_{x} < Th_5, and if a^{w}_{x} > Th_5 and Th_6 < $\mu^{w}_{a_{xy}}$ < Th_7, then (SI) is recognized.

Table 1 Category of seven activities

Groups	Watch	Phone	Activities
1	$\leq Th_1$	$\leq Th_2$	(SI), (STA), (PU)
2	$> Th_1$	$\leq Th_2$	(RJ)
3	$> Th_1$	$> Th_2$	(WA), (JO), (RU)

The (RJ) activity is classified into category 2, indicating that the smartphone's movement is small and the watch's movement is big, especially that the movement of the watch is bigger than those of the activities in category 3. Therefore, the scheme checks that the values of the feature $\max_{la,12}$ are bigger than the threshold Th_8; if this is true, then the current activity is classified as (RJ).

Table 2 Features used to estimate seven activities

Activity	Features					
	$\mu^{p}_{\sigma fw}$(t)	$\mu^{w}_{\sigma fw}$(t)	a^{w}_{x}	$\mu^{w}_{a_{xy}}$	$\|\vec{\omega}^{w}\|$	$\max_{la,12}$
Sitting (SI)	●	●	●	●	●	●
Standing (STA)	●	●	●	●	●	●
Push-ups (PU)	●	●			●	●
Rope jumping (RJ)	●	●				●
Walking (WA)	●	●				●
Jogging (JO)	●	●			●	●
Running (RU)	●	●				●

For classifying three similar activities in category 3, the scheme just uses the feature $\max_{la,12}$. The value of $\max_{la,12}$ reflects the strength of the linear acceleration of the user movement, with the result that its value increases from (WA) to (RU). Three thresholds are used to discriminate three activities. Table 2 summarizes all of the features used to classify different activities.

As described previously, the mobile system can recognize some activities and also count the number of times repeated activities, such as doing push-ups, rope jumping, walking, jogging, and running, are performed. For the (WA, JO, RU) cases, the scheme counts the number of steps. For example, for the activities in category 3, the magnitude of the gyroscope vector

($\|\vec{\omega}^w\|$) exhibits better repeatability than the magnitude of the linear acceleration vector ($\|\vec{la}\|$). In contrast, for the activities (PU) and (RJ), it is easier to use the feature $\|\vec{la}\|$ to count the number of repeated motions.

To count the number of steps, the scheme attempts to find the two peaks in a gait cycle, the positive peak $p^{(+)}$ and the negative peak $p^{(-)}$, of $\|\vec{\omega}^w\|$ and the two moments, the $t_{p(+)}$ moment (when $p^{(+)}$occurs) and the $t_{p(-)}$ moment (when $p^{(-)}$ occurs). The system detects all of these features, and then checks two conditions: the magnitude of the difference between positive and negative peaks, e.g., ($p^{(+)}$-$p^{(-)}$) > Th_9, and the time interval between the two moments: $Th_{10} \leq (t_{p(+)}-t_{p(-)}) \leq Th_{11}$. IF these conditions are satisfied, THEN the number of steps is increased. The same idea is applied to count the number of times of performing the activities (PU) and (RJ) using the linear acceleration signals, but other threshold values are chosen for (PU) and (RJ).

3.2.2. Sleep detection

In order to log the sleeping behavior, the mobile system attempts to estimate the sleep status of a user among three states, deep sleep (DS), restless (RL), and awake (AW). The definitions of these states are similar to those of the Fitbit tracker [12]:

- Deep sleep: when the body is completely at rest and unmoving.
- Restless: when the body has transitioned from a very restful position with little movement to movement or when the surrounding conditions are not good for sleep (light on, loud noise). The purpose of the restless state is to show that the user is not currently getting the most restful sleep at that time.
- Awake: when the user keeps moving his or her body, preventing restful sleep while sleeping.

Compared to other activity trackers, this scheme uses different sensor signals from both watch and phone. A method is proposed using five features, the maximum magnitude of the linear acceleration vectors of the watch ($\max_{la,12}$) for the last 12 samples, the output of the light sensor (light), the sound value (sound), the moving feature of the phone ($\mu^{p}_{\sigma fw}$(t)), and the screen-touch count (count). The classification rules are as follows:

IF both the smartwatch and the smartphone are not moving (checking the values of the two features $\max_{la,12}$ and $\mu_{\sigma fw}$(t)) AND light < Th_{12} AND sound < Th_{13} AND count < Th_{14} THEN it is (DS).

IF the phone and watch move OR the phone moves, THEN it is (AW). OTHERWISE it is (RL).

At every second the scheme determines the sleeping state and stores it in a list. After 15 seconds, the system finds the most frequent state, which is determined to be the final state. Fifteen seconds is sufficiently long enough to catch small body movements while sleeping, therefore, many people experience involuntary periodic limb movements during sleep (PLMS) every 10 to 60 seconds[26-27].

3.3. Server system

3.3.1. Server components

The software specifications of the actual server system are as follows:

- The "active" table saves the lifelogs with six fields: user (username), no_act (code number of activity), name_act (activity name), cnt (number of repetitions of each activity), and st_et (start/stop time).
- The database table includes three tables: "active," "use," and "cal".
- The "user" table contains the user's private information, consisting of five fields: user, age, sex, height, and weight.
- The "cal" table contains three fields for storing the daily TEE of each user: user, cal (TEE), and date.

Table 3 Server system specifications

Server name	HallymHealthServer
Operating System	Windows Server 2008 R2 Enterprise
Web Server	Apache 2.2.14
Database management system	Mysql 5.1.41-community
Hypertext preprocessor	PHP 5.2.12

3.3.2. TEE estimation

The energy expenditure for each activity can be computed through various means, such as the BMR or the metabolic equivalent of task (MET). In this system, the BMR, which is the minimal rate of energy expenditure per unit time at rest [28], is used and is reported in energy units per unit time. Eq. (3a) and Eq. (3b) are revised Harris-Benedict equations [29], modified from the original equation using a new data set for more accurate results.

$$\text{For men, } P = \left(\frac{13.397\text{m}}{1kg} + \frac{4.799\text{h}}{1cm} - \frac{5.677a}{1year} + 88.362\right)\frac{\text{kcal}}{day} \tag{3a}$$

$$\text{For women, } P = \left(\frac{9.247\text{m}}{1kg} + \frac{3.098h}{1cm} - \frac{4.330a}{1year} + 447.593\right)\frac{\text{kcal}}{day} \tag{3b}$$

where P is total heat production at complete rest (kcal/day), m is mass (kg), h is height (cm), and a is age (years). For each recognized activity, the physical activity ratio (PAR) is used, as shown in Table 4. Then, the TEE of a user A in a day is calculated using Eq. (4):

$$TEE_A = P_A \sum_{i=0}^{N} PAR_i t_i \tag{4}$$

where P_A can be calculated from Eq. (3a) and Eq. (3b) depending on the user's gender, N is the number of activities, i is one specified activity, PAR_i can be found in Table 4, and t_i is the execution time of activity i (hours).

Table 4 Physical Activity Ratio (PAR) for seven activities and three sleep states

	SI	STA	WA	JO	RU	RJ	PU	DS	RL	AW
PAR	1.2	1.2	2.8	4.8	6.9	6.9	6.9	1.0	1.2	2.8

3.3.3. Communication

After each 30-second period, the mobile system sends the activity to the remote server if it is a new activity different from the previous one. Otherwise, the smartphone does not send it and waits until an activity is detected. The data include (1) ID of the user, (2) code number of the activity, (3) name of the activity, (4) count of repetitions for each activity (except (SI), (STA)), and (5) starting/ending time. Whenever one activity ends, at that moment, it is also the starting time of the next new activity. When a new activity is detected, all of the information listed above is sent to the server. The message is sent to the remote server via a TCP/IP connection. A buffer is used to save the logs when a connection is broken or unstable, and all of the data in the buffer are sent to the server whenever a connection recovers. This feature guarantees that the server does not miss any updated logs even if the network is unstable.

The received data are used to calculate the TEE on the server, and the results are visualized on the server as well as on the mobile devices.

4. Experimental Results

4.1. Performance of Activity Recognition

A set of experiments was conducted to evaluate the performance of the proposed classification method for the seven activities with four subjects (all male, average age of 24.75 years). Each subject was equipped with both a smartphone and a smartwatch, and the smartwatch was worn on the wrist of the subject's dominant hand. For each activity, the subjects executed the (Activity)-(Standing/Stop) cycle repeatedly five times. The subjects were asked to participate in an activity for over 30 seconds because that is the minimum time required for logging. The results are summarized in Table 5. Here, the UNK represents the unknown case. As shown in the table, perfect recognition performance for five activities is pointed out, with the worst result being the case of (JO). However, the jogging activity was misrecognized as walking and running, reducing its importance, especially with respect to calculating energy expenditure. The overall average recognition rate was 97.5% (with a standard deviation of 4.18).

Table 5 Confusion matrix for activity recognition

		UNK	WA	STA	SI	JO	RU	JU	PU
Recognized	UNK	0	0	0	0	0	0	0	0
	WA	0	20	0	0	1	0	0	0
	STA	0	0	19	0	0	0	0	0
	SI	0	0	0	20	0	0	0	0
	JO	0	0	0	0	18	0	0	0
	RU	0	0	0	0	1	20	0	0
	JU	0	0	0	0	0	0	20	0
	PU	0	0	1	0	0	0	0	20
Precision (%)			95.24	100	100	100	95.24	100	95.24
Recall (%)			100	95	100	90	100	100	100
F-score			0.98	0.97	1	0.95	0.98	1	0.98

4.2. Counting performance

To evaluate the counting performance, a set of experiments are conducted with the following scenarios for the same four subjects:

- Walking - Jogging - Running: 100 steps for each activity, 20 times.
- Doing push-ups: 20 push-up actions, 20 times.
- Rope jumping: 30 jumps, 10 times.

The scheme attempts to count the number of steps for the (WA), (JO), and (RU) activities. The error rate was calculated with the estimated count value and the true value. The average error rate is summarized in Table 6. (JO) had the lowest error rate of step detection with a value of 3.71%, and (RJ) had the highest error rate with 6.67%. The total average error rate for the five activities was 4.97%.

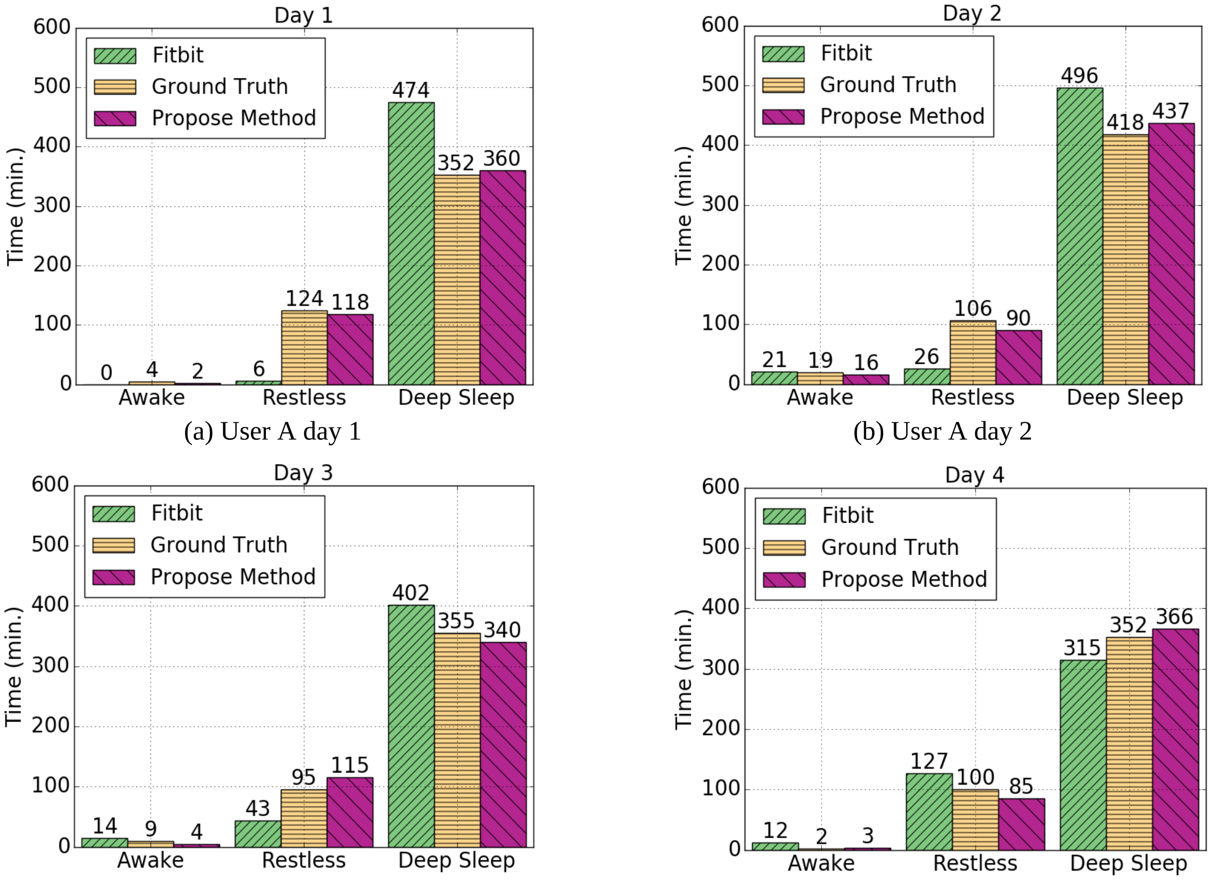
Table 6 Error rate for counting performance

	WA	JO	RU	RJ	PU
Error Rate (%)	4.50	3.71	5.43	6.67	4.53

4.3. Sleep state estimation performance

In this section, the sleeping status estimation performances of the suggested method and a commercial activity tracker (Flex by Fitbit) are compared. Two subjects were asked to wear the Fitbit Flex wristband and the smartwatch simultaneously while sleeping for two nights. Both devices started to track the sleeping state at 0:00 AM and ended at 8:00 AM. A video camera was installed to record the user’s behaviors while he or she slept. Analyzing the video established actual sleeping states as the ground truth with a unit time of one minute.

Fig. 2 shows the results of sleeping state estimation for two different nights for two users: the two former days for user A and the two latter days for user B. Each graph shows one night’s total duration in each of the three sleeping states: awake, restless, and deep sleep. Different colors are used to denote three results: red is the ground truth, green is the Fitbit record, and blue is the record of our scheme. Here, the error is defined as the difference between the duration of the truth and the estimate. As shown in Fig. 2(a), the error of the Fitbit results can reach as high as 124 minutes, as in day 1 of user A (Restless). In comparison, the maximum error of the scheme is only 19 minutes, as in day 2 of user A (Deep Sleep). The total average error for the three states was 31 minutes using the proposed method, compared to 145 minutes using Fitbit. Table 7 summarizes the error rate of sleeping behavior estimation that shows the lower error rate of the proposed method compared with Fitbit.



(a) User A day 1 (b) User A day 2

(c) User B day 3 (d) User B day 4

Fig. 2 Comparison of sleep state estimation

Table 7 Error rate for sleep estimation

	Day 1		Day 2		Day 3		Day 4	
	Fitbit	Proposed Method	Fitbit	Proposed Method	Fitbit	Proposed Method	Fitbit	Proposed Method
Ground Truth (minutes)	480	480	543	543	459	459	454	454
Error (minutes)	244	16	160	38	104	40	74	30
Error rate (%)	50.83	3.33	29.47	7.91	22.66	8.71	16.30	6.61

4.4 Lifelogging performance

In this section, the performance of the logging system was evaluated for indoor activities in a day of a user. For convenience in conducting experiments, one day, excluding eight hours for sleeping, was divided into four four-hour-long time durations as shown in Table 8. Four subjects with the mobile system were asked to perform their usual daily activities for each time duration. The users were also asked to wear their smartwatches and to hold their phones for the (WA), (JO), and (RU) activities. When the users performed other activities (SI), (JU), (PU), they put the phone down on a desk just as in a normal daily situation. The lifelogs recognized by the mobile system were sent to the server system. The true data were obtained from annotations written by the users themselves.

Table 8 Time durations for lifelogging activities

Label	Morning	Lab	Dinner	Night
Time Period	8:00am-12:00pm	12:00pm-4:00pm	4:00pm-8:00pm	8:00pm-12:00am

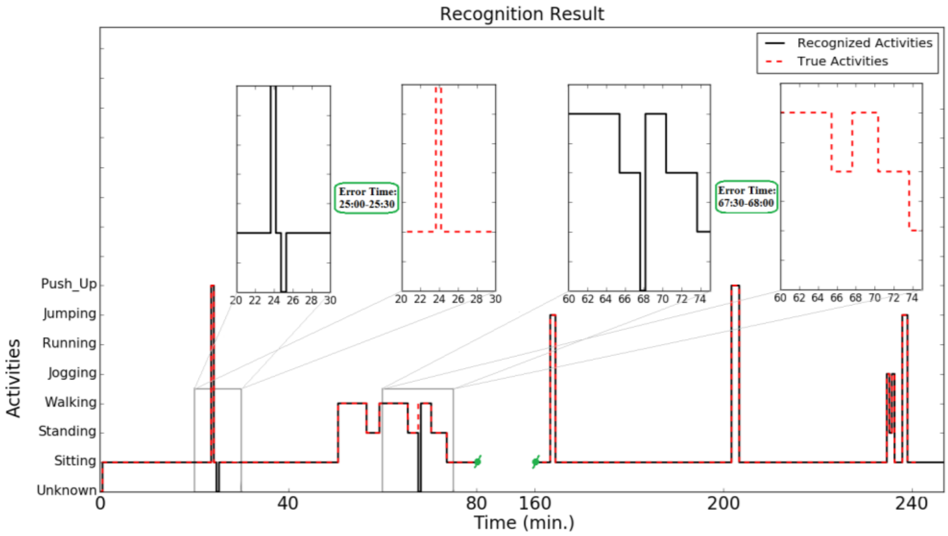


Fig. 3 Stored life-logs of user A for 'Morning' time duration

As an example, the stored life-logs of user A for a 4-hour time duration is shown in Fig. 3, respectively. The x-axis represents the time (in a minute) and the y-axis represents seven activities. The red dashed line on the graph is the actual activity while the black solid line represents the recognition result. Some short length errors can be noted. In Fig. 3, the activities of user A in the morning can be imagined as getting up, having breakfast, going to lab and sitting in front of a desk most of the time with some activities for relaxing such as jumping or doing push-ups. The activity from 80th to 160th minute was the same between true and estimated activity and the user did not change to other activities. Therefore, the plotting in this phase is skipped. As a performance measurement, the amount of time of misrecognized activities was chosen. The experimental results are shown in Table 9.

Table 9 Activity tracking for four users

User	Label	Total (mins)	Right (mins)	Wrong (mins)	Error (%)
A	Morning	241.38	240.28	1.1	0.016
	Lab	235.29	234.73	0.55	
	Night	132.02	123.76	8.24	
B	Lab	235.84	235.29	0.55	0.034
	Dinner	237.78	225.13	12.65	
	Night	207.16	197.26	9.9	
C	Morning	206.96	203.66	3.3	0.019
	Dinner	69.59	67.94	1.65	
	Night	175.34	171.84	3.5	
D	Morning	111.56	108.81	2.75	0.031
	Lab	60.37	60.37	0	
	Dinner	223.94	214.59	9.35	

As shown, each subject collects three kinds of time durations, although the length of each duration does not last a full four hours, ranging instead from one hour to four hours. The average error rates are very low, with the highest error rate of 0.034%. Such a high accuracy occurs, because all of the experimental subjects were graduate students, with quite simple daily activities, repeated in a specified amount of time. For example, after getting up and having breakfast in the morning, they would stay at their offices until late afternoon, and then have dinner and return home. Thus, they have uniform patterns of activities with the recognized activities.

4.5. App for displaying the stored logs

As the final step in developing a lifelogging system, an Android app was implemented that can provide a simple user interface (UI) to login to a personal account, to enter some physical information, and to display the stored logs and daily TEE. The graphical user interface (GUI) navigation flowchart of the application is shown in Fig. 4.

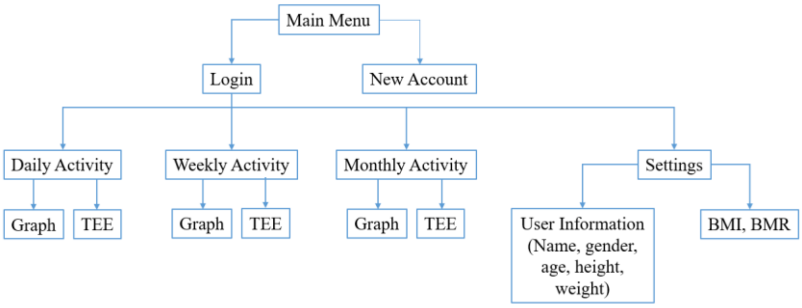
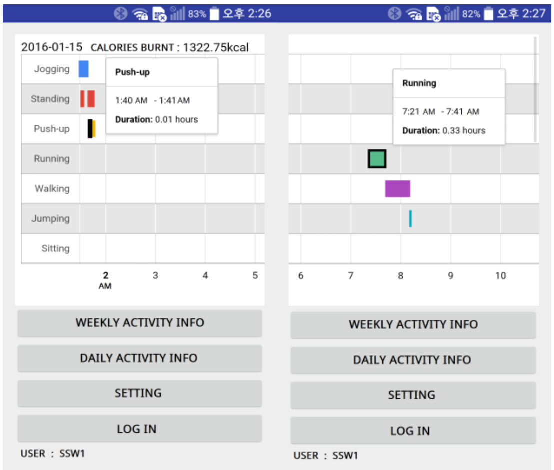
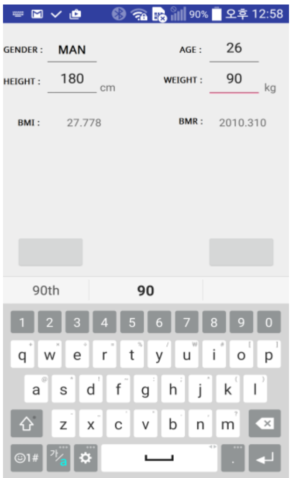


Fig. 4 GUI screens navigation flowchart



(a) Display the stored lifelogs



(b) Enter personal physical information

(c) Display TEE for a month

Fig. 5 Screen captures of the developed UI on smartphones

Fig. 5 shows the screen-captured images of this developed UI screen. When the user logs in to his or her account, the user can see the stored daily logs from 0:00 to the current time, as shown in Fig. 5(a). This screen shows that the user ran from 7:21 AM to 7:41 AM, and then walked for a while and performed some jumping actions. Fig. 5(b) shows the UI screen for entering physical information. Meanwhile, Fig. 5(c) also shows a bar graph in which each bar shows the daily TEE for a given month. If the user taps on a bar chart, the app displays a popup message with more detailed information, as shown in Fig. 5(c).

5. Conclusions

In this study, an indoor lifelogging system including both mobile and server systems was proposed to recognize many kinds of lifelogs for the daily life of a user. The mobile system contains a smartwatch and a smartphone. A method was proposed using both a phone and a watch simultaneously and cooperatively to recognize seven ADLs that could be useful for estimating energy expenditure. The proposed threshold-based method could provide an overall average recognition rate of more than 97%. Recognizing the importance of logging sleeping behavior, sleeping states were estimated using two mobile devices, and the results of the scheme were then compared to a well-known commercial product, Fitbit. The experimental results showed the superiority of the suggested scheme. A simple method was suggested to estimate the daily TEE based on the stored activities using the BMR and PAR of the activities. An app for Android devices was developed to display the stored lifelogs and the daily TEE to help users manage their health better.

For future work, a more energy-efficient method for activity recognition should be investigated. The current method requires that the watch device continuously processes the sensor data and regularly sends some features to the paired phone, resulting in the battery consumption to be a problem for the watch than for the phone. It is also possible to expand the number of target activities to record users' daily lives in more detail. Moreover, the protection of user personal information is a necessary point that we need to focus on. Finally, a simpler and more accurate method for estimating energy expenditure would be desirable.

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