Smartphone-based Monitoring System for Activities of Daily Living for Elderly People and Their Relatives Etc.

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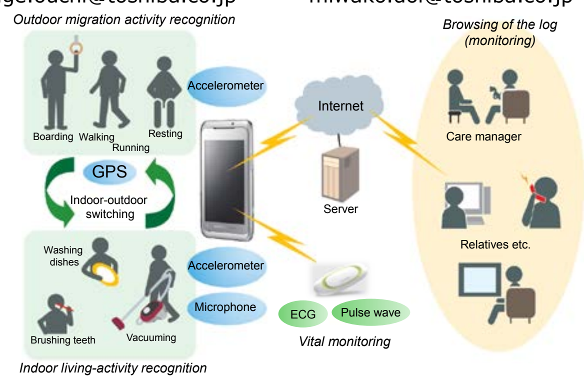

Figure 1. System overview.

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Abstract

We developed a smartphone-based monitoring system to allay the anxiety of elderly people and that of their relatives, friends and caregivers by unobtrusively monitoring an elderly person’s activities of daily living. A smartphone of the elderly person continuously recognizes indoor-outdoor activities by using only built-in sensors and uploads the activity log to a web server. By accessing the server, relatives etc. at remote locations can browse the log to make sure the elderly person is safe and sound. We conducted an evaluation experiment and confirmed that the proposed system had practical recognition accuracy and satisfied the users’ needs.

Author Keywords

Activity recognition; smartphone; accelerometer; microphone

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

Introduction

In view of population aging and the growing prevalence of nuclear families, the monitoring of the

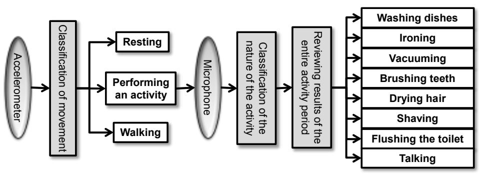

Figure 2. Processing flow of indoor living-activity recognition.

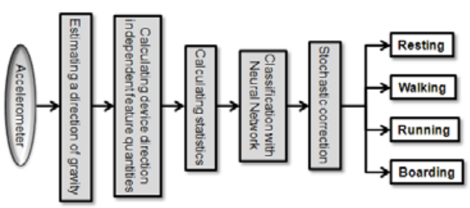

Figure 3. Processing flow of outdoor migration activity recognition.

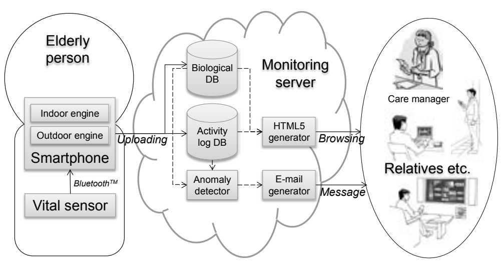

Figure 4. Overview of the monitoring server architecture.

activities of daily living of elderly people is increasingly important not only for the elderly people but also for their relatives, friends and caregivers. Various activities have become recognizable by wearing accelerometers on several parts of the body [1], or wearing a dedicated device on the wrist [2]. However, it is impractical for users to continuously wear many accelerometers in daily life or, from the viewpoint of the cost, to use a special device. On the other hand, outdoor activities such as migration have become recognizable by using built-in sensors on a mobile phone [3]. Although activity recognition by commonly used devices has an advantage over the solutions envisaged in the above-mentioned studies in terms of practicality, it is difficult to recognize various indoor activities.

We proposed indoor-outdoor activity recognition to recognize various activities of daily living by using a smartphone [4]. In the present work, we applied the technology to a smartphone-based monitoring system to allay the anxiety of elderly people and that of their relatives etc. by unobtrusively monitoring activities of daily living as shown in Figure 1. A smartphone of the elderly person continuously recognizes indoor-outdoor activities by using only built-in sensors and uploads the activity log to a server. By accessing the server, relatives etc. at remote locations can browse the log to make sure the elderly person is safe and sound.

System Overview

We developed an indoor living-activity recognition engine and an outdoor migration activity recognition engine, and combined them into an Android™ application. By switching between the two engines depending on the acquisition condition of GPS satellites, the system enables users to continuously monitor indoor-outdoor activities.

Indoor living-activity recognition

It consists of a two-step classification process [5] as shown in Figure 2. Firstly, it roughly classifies the user's movement into "Resting," "Walking," and "Performing an activity" by using variances of 1-sec data series from the 3-axis accelerometer. When it classifies "Performing an activity," it activates the microphone and calculates MFCC (Mel-Frequency Cepstral Coefficient), RMS (Root Mean Square) and ZCR (Zero-Crossing Rate) as acoustic features. Then it classifies the nature of the activity by SVM (Support Vector Machine) every 1 second. Then, it smoothes the classification results through an additional recognition scheme by majority voting for each task.

Outdoor migration activity recognition

It works according to the following steps [6] as shown in Figure 3. It calculates device direction-independent feature quantities, namely, "Length of the acceleration vector," "Inner product of the acceleration vector and the gravity vector," and "Their cross product." Then, it calculates statistics of the 3 quantities, namely, average, minimum, maximum and variance of these quantities in a certain time window. It classifies these quantities into 4 migration classes by a neural network using back-propagation learning. Finally, it smoothes the fluctuating result by using a stochastic model generated by several heuristics.

Monitoring server

The monitoring server is built on a web server. It is composed of an activity log database, an HTML5 generator, an anomaly detector and an e-mail

Figure 5. An example of one-week activity log.

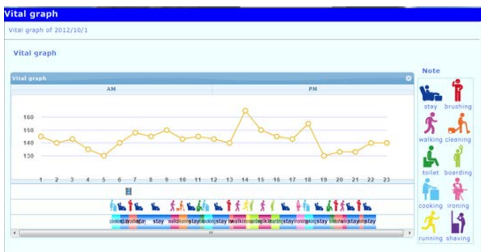

Figure 6. An example of simultaneous monitoring of activity and biological information.

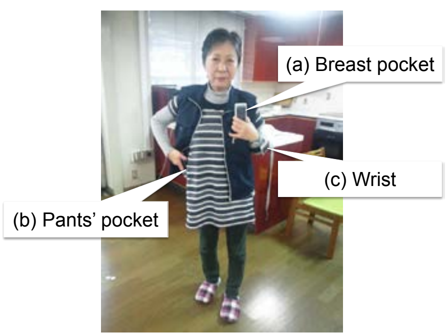

Figure 7. Comparison among three positions.

generator as shown in Figure 4. The activity log database stores the results of activity recognition from the smartphone in the elderly person's home. Figure 5 shows an example of a one-week activity log generated in HTML5 format by the HTML5 generator. It allows observers, such as care managers and relatives, at remote locations to browse the log data on most browsers of various information devices. Additionally, we also created a biological database to collect biological information such as ECG, pulse wave from a wearable vital sensor in cooperation with the smartphone [7]. Simultaneous monitoring of activity and biological information enables users to analyze their health condition in detail as shown in Figure 6. It is also equipped with an anomaly detector and an e-mail generator to notify them of anomalous conditions.

Evaluation experiment

We conducted an evaluation experiment with 22 subjects (6 men and 6 women in their 60s, and 5 men and 5 women in their 20s to 40s) at a mock living room to assess the accuracy of indoor activity recognition and the requirements for a monitoring service.

Assessment of the recognition accuracy

In order to contrast smartphone positions, the subjects were asked to carry smartphones in three different positions, as shown in Figure 7: (a) in the breast pocket, (b) in the pants' pocket and (c) on the wrist with a wrist band. The wrist position anticipated application of the proposed technology to wristwatch-shaped wearable devices. Target activities were "washing dishes," "ironing," "vacuuming," "brushing teeth," "drying hair," "shaving," "flushing the toilet," and "talking." First, in order to collect training data, we asked the subjects to perform each activity for 10

(a) Breast pocket

Actual \ Classified as	Trained tasks: Washing dishes	Ironing	Vacuuming	Brushing teeth	Shaving	Drying hair	Flushing the toilet	Talking	Untrained task	Recall (%)
Trained tasks: Washing dishes	20			1					1	90.9
Ironing		19						1	2	86.4
Vacuuming			22							100.0
Brushing teeth				19				1	2	86.4
Shaving					20				2	90.9
Drying hair			1			21				95.5
Flushing the toilet							21		1	95.5
Talking		1						18	3	81.8
Precision (%)	100.0	95.0	95.7	95.0	100.0	100.0	100.0	90.0	F-measure 93.8	

(b) Pants' pocket

Actual \ Classified as	Trained tasks: Washing dishes	Ironing	Vacuuming	Brushing teeth	Shaving	Drying hair	Flushing the toilet	Talking	Untrained task	Recall (%)
Trained tasks: Washing dishes	19			2					1	86.4
Ironing		19		1				1	1	86.4
Vacuuming			22							100.0
Brushing teeth	1			17				2	2	77.3
Shaving		1			18			1	2	81.8
Drying hair			1			21				95.5
Flushing the toilet							21		1	95.5
Talking		2		1				16	3	72.7
Precision (%)	95.0	86.4	95.7	81.0	100.0	100.0	100.0	80.0	F-measure 89.5	

(c) Wrist

Actual \ Classified as	Trained tasks: Washing dishes	Ironing	Vacuuming	Brushing teeth	Shaving	Drying hair	Flushing the toilet	Talking	Untrained task	Recall (%)
Trained tasks: Washing dishes	19			1				1	1	86.4
Ironing		18						2	2	81.8
Vacuuming			22							100.0
Brushing teeth	1			18				1	2	81.8
Shaving					18			1	3	81.8
Drying hair			1			21				95.5
Flushing the toilet							22		0	100.0
Talking		2						17	3	77.3
Precision (%)	95.0	90.0	95.7	94.7	100.0	100.0	100.0	77.3	F-measure 91.0	

Table 1. Confusion matrices of activity recognition results corresponding to the attached position.

Activity	Yes (%)	No (%)
Brushing teeth	100	0
Drying hair	82	18
Shaving	93	7
Toileting	100	0
Washing dishes	75	25
Vacuuming	89	11
Talking	100	0
Walking	95	5
Running	65	35
Going outside	100	0

Table 2. The result of the questionnaire survey on the necessity of each monitoring activity.

seconds. Then, we asked them to perform all target activities as usual. Confusion matrices of activity recognition are shown in Table 1 corresponding to the attached position. Averaged f-measures were 93.8% for the breast pocket, 89.5% for the pants' pocket, and 91.0% for the wrist. This shows that the breast pocket is the best position. However, the other positions are also available.

Assessment of needs for a monitoring service
We also conducted a questionnaire survey with the same subjects to assess the needs for a monitoring service. We prepared a list of specific questions on a monitoring service and some demonstrations on the assumed service that would allow relatives etc. at remote locations to monitor the activity log and the biological information of an elderly person, as shown in Figure 5 and Figure 6, via a general-purpose browser on a TV. All subjects answered 'Yes' to the first question, "Do you find this kind of monitoring service beneficial?" Then, we asked them about the necessity of each monitoring activity from the perspective of an observer. Table 2 shows the result. From the perspective of an observer, they want to monitor various activities of the elderly person. Conversely, from the perspective of the elderly person, there were great differences among individuals as to which activities are acceptable to monitor. It suggests that the activities to be monitored should be customizable. Although, for the proposed technology, it is necessary to train each target activity for 10 seconds beforehand, the technology is highly customizable.

Conclusion and future work
We developed a smartphone-based living-activity monitoring system to allay the anxiety of elderly people and that of their relatives, friends and caregivers by unobtrusively monitoring activities of daily living.

We continue to focus on the scheme of a monitoring service for elderly people and their relatives etc. and to evaluate the feasibility in an actual usage environment with many subjects of various ages.

Acknowledgements
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References
[1] L. Bao and S. Intille. Activity Recognition from User-Annotated Acceleration Data. In *Proc. PERVASIVE 2004*, LNCS 3001, (2004), pp.1-7.

[2] T. Maekawa, et al. Object-Based Activity Recognition with Heterogeneous Sensors on Wrist. In *Proc. PERVASIVE 2010*, LNCS 6030, (2010), pp.246-264.

[3] E. Miluzzo, et al. Sensing Meets Mobile Social Networks: The Design, Implementation and Evaluation of the CenceMe Application. In *Proc. SenSys 2008*, (2008), pp.337-350.

[4] K. Ouchi and M. Doi. Indoor-Outdoor Activity Recognition by a Smartphone, In *Adjunct Proc. UbiComp 2012*, (2012), pp.600-601.

[5] K. Ouchi and M. Doi. Living activity recognition using off-the-shelf sensors on mobile phones. *Annals of telecommunications*, Volume 67, Numbers 7-8, (2012), pp.387-395.

[6] K. Cho, et al. Human Activity Recognizer for Mobile Devices with Multiple Sensors. In *Proc. UIC-ATC '09*, (2009), pp.114-119.

[7] T. Suzuki, et al. Wearable wireless vital monitoring technology for smart health care, In *Proc. ISMICT 2013*, (2013), pp.1-4.