Mobile Healthcare

Miwako Doi and Kazushige Ouchi

Corporate Research & Development Center, Toshiba Corporation
1, Komukai Toshiba-cho, Saiwai-ku, Kawasaki 212-8582, Japan
{miwako.doi,kazushige.ouchi}@toshiba.co.jp

Abstract. It is important to easily and cheaply monitor elderly person's activities of daily living in order to allay the anxiety of their relatives and caregivers. We developed a smartphone-based monitoring system. 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. The evaluation experiment showed that the proposed system had practical recognition accuracy and satisfied the users' needs.

Keywords: Activity recognition, Smartphone, Accelerometer, Microphone.

1 Introduction

The developed countries face the aging problems. After 30 years, emerging countries also will face the aging problems. The monitoring of the 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 an indoor-outdoor activity recognition system on a smartphone which switches two engines based on GPS signal. The indoor engine recognizes various activities of daily living based on accelerometer data and environment sound. The outdoor engine recognizes the behavior based on accelerometer data and GPS data.

2 Related Works

Activity recognition researches are categorized into two types; embedded type and wearable type. Georgia Tech's Aware Home [4], Microsoft Research's EasyLiving

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Project [5], NiCT's UKARI Project[6] are works of the embedded types activity recognition. The embedded type activity recognition needs many sensors, to be installed in the environment in order to get the accurate activity recognition. In the result, the cost is high and the installation to the legacy home is difficult. Intelligent distribution panel is one of the embedded type commercialized examples. It realizes the power use visualization. Intelligent distribution panel only recognizes whether householders is or not at home and cannot recognize the daily activities because the sensor information is only poser usage.

The wearable type activity recognition uses wearable sensors such accelerometers, GPS, and other sensors. Early many researchers developed the special wearable devices. LifeMinder™[7] is an example of the wearable device. LifeMinder™ is able to collect two axis accelerometer, temperature, blood wave data and sends them to a cell phone in order to analyze and recognize behavior, such as walking, running, eating meals and so on. The prototyped healthcare application gives advices to the user; taking drug, exercising, and so on. LifeMinder™ was commercialized as a body motion sensor with sleep monitoring software [8] in 2004.

Nowadays, mobile phones equipped with a 3-axis accelerometer are becoming popular [9]. Studies on activity recognition using an accelerometer on mobile phones have also been reported. For example, [10] recognizes 5 migration activities—walking, fast walking, climbing up stairs, climbing down stairs, and running—with about 80% accuracy. In such studies, several migration activities are detectable by a mobile phone. It is difficult, however, to precisely recognize our target activities—in-home living activities, including not only migration but also housework and so on—by using an accelerometer and GPS.

A mobile phone naturally has a microphone for its primary function and it can also be used as an acoustic sensor. [11] recognized 19 sounds of 4 groups such as Kitchen, Office, Workshop and Outdoor, with more than 80% accuracy by using acoustic features. However, acoustic analysis needs higher sampling frequency than acceleration sensing and needs to compute a large amount of data. So, considering processing power and power consumption, it is undesirable to continuously execute acoustic analysis. Thus we propose a low-throughput in-home living activity recognition method combined with acceleration sensing and acoustic sensing that firstly estimates a user's movement condition roughly by acceleration sensing and then classifies the working condition in detail by acoustic sensing based on the estimated condition.

3 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 [12] as shown in Figure 1. 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.

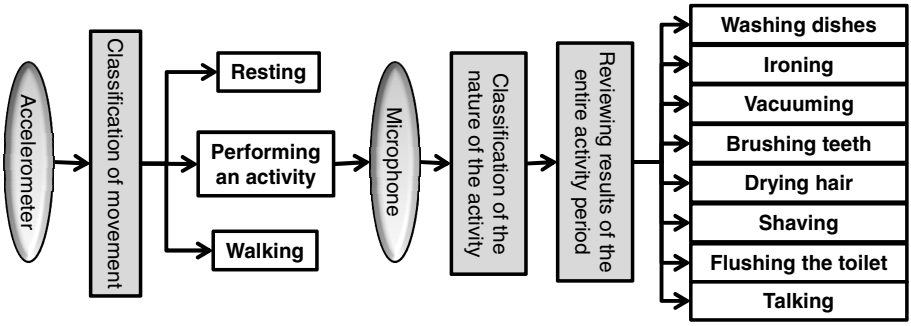

Fig. 1. Processing flow of indoor living-activity recognition

Outdoor Migration Activity Recognition

It works according to the following steps [13] as shown in Figure 2. 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.

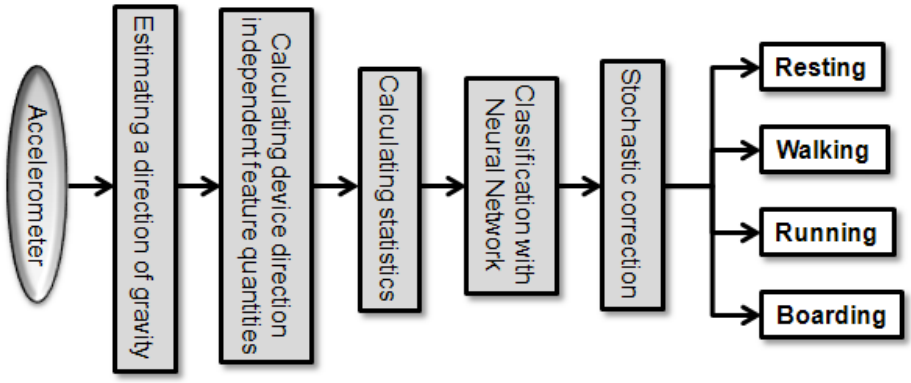

Fig. 2. Processing flow of outdoor migration activity recognition

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 generator. The activity log database stores the results of activity recognition from the smartphone in the elderly person's home. Figure 4 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

Fig. 3. An example of one-week activity log

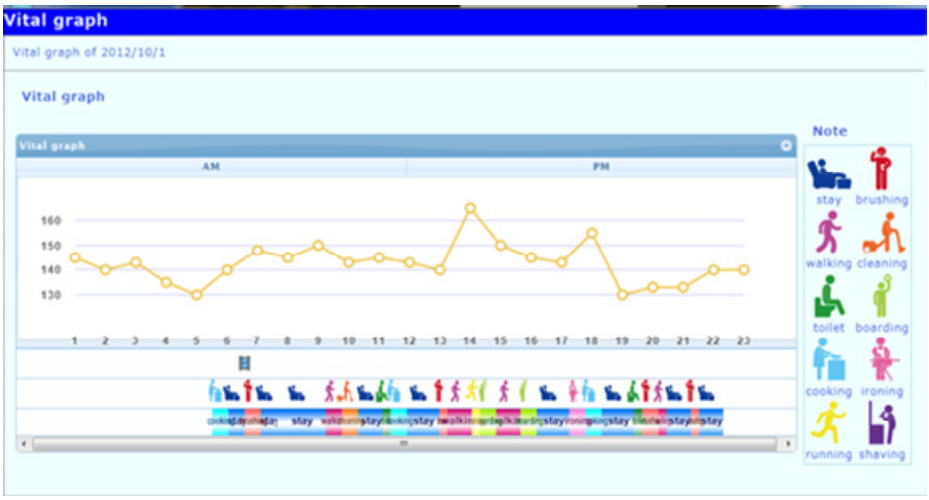

Fig. 4. An example of simultaneous monitoring of activity and biological information

cooperation with the smartphone [14]. Simultaneous monitoring of activity and biological information enables users to analyze their health condition in detail as shown in Figure 4. It is also equipped with an anomaly detector and an e-mail generator to notify them of anomalous conditions.

4 Evaluation Experiment

An evaluation experiment was held 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, (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 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 3 and Figure 4, 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.

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

(a) Breast pocket

Actual \ Classified as		Trained tasks								Untrained task	Recall (%)
		Washing dishes	Ironing	Vacuuming	Brushing teeth	Shaving	Drying hair	Flushing the toilet	Talking		
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								Untrained task	Recall (%)
		Washing dishes	Ironing	Vacuuming	Brushing teeth	Shaving	Drying hair	Flushing the toilet	Talking		
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								Untrained task	Recall (%)
		Washing dishes	Ironing	Vacuuming	Brushing teeth	Shaving	Drying hair	Flushing the toilet	Talking		
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 2. The result of the questionnaire survey on the necessity of each monitoring activity

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

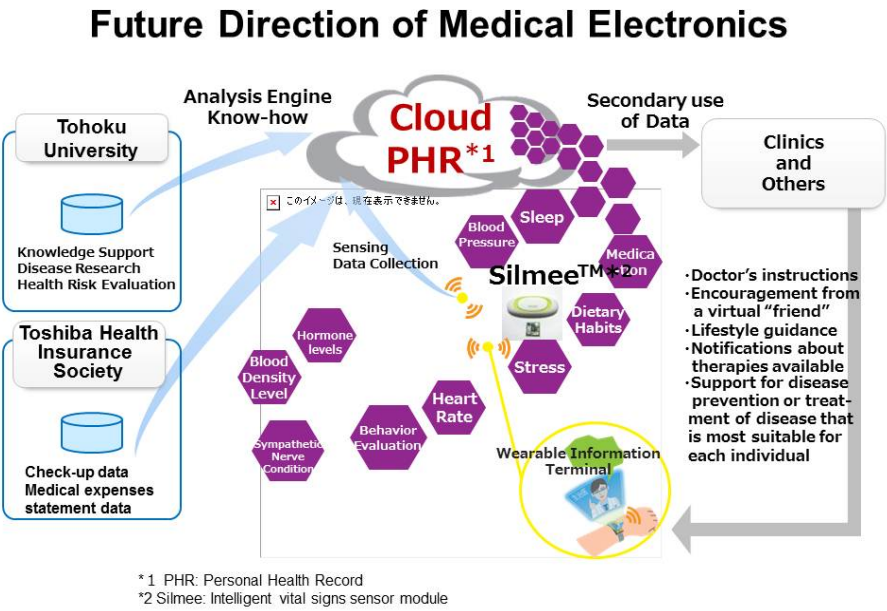

Fig. 5. Toshiba's direction of medical electronics

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.

Toshiba continues to focus on the scheme of easy access to electronic medical records and sensing data concerning individuals' health in order to improve overall healthcare shown in Figure 5.

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References

1. Bao, L., Intille, S.S.: Activity Recognition from User-Annotated Acceleration Data. In: Ferscha, A., Mattern, F. (eds.) PERVASIVE 2004. LNCS, vol. 3001, pp. 1–17. Springer, Heidelberg (2004)
2. Maekawa, T., Yanagisawa, Y., Kishino, Y., Ishiguro, K., Kamei, K., Sakurai, Y., Okadome, T.: Object-Based Activity Recognition with Heterogeneous Sensors on Wrist. In: Floréen, P., Krüger, A., Spasojevic, M. (eds.) Pervasive 2010. LNCS, vol. 6030, pp. 246–264. Springer, Heidelberg (2010)
3. Miluzzo, E., et al.: Sensing Meets Mobile Social Networks: The Design, Implementation and Evaluation of the CenceMe Application. In: Proc. SenSys 2008, pp. 337–350 (2008)
4. `http://www.cc.gatech.edu/fce/ahri/projects/`
5. `http://research.microsoft.com/apps/pubs/?id=68393`
6. Yamazaki, T., et al.: Real-life Supporting Services by Distributed and Cooperative Service Platform "UKARI-Core": Development and Implementation at NICT Ubiquitous Home, UBI, IPSJ, 2004-11-10, pp. 71–77 (2004)
7. Ouchi, K., Suzuki, T., Doi, M.: LifeMinder A Wearable Healthcare Support System Using User's context. In: Proc. ICDCS Workshop 2002, pp. 791–792 (2002)
8. Suzuki, T., Ouchi, K., Kameyama, K.-I., Takahashi, M.: Development of a Sleep Monitoring System with Wearable Vital Sensor for Home Use. In: Proc. BIODEVICES 2009, pp. 326–331 (2009)
9. iSuppli Press Release (July 9, 2009)
10. `http://www.isuppli.com/MEMS-and-Sensors/News/Pages/One-Third-of-Mobile-Phones-to-Use-Accelerometers-by-2010-Spurred-by-iPhone-and-Palm-Pre.aspx`
11. Iso, T., Yamazaki, K.: Gait Analyzer based on a Cell Phone with a Single Three-axis Accelerometer. In: Proc. MobileHCI 2006, pp. 141–144 (2006)
12. Peltonen, V., Tuomi, J., Klapuri, A., Huopaniemi, J., Sorsa, T.: Computational auditory scene recognition. In: Proc. ICASSP 2002, pp. 1941–1944 (2002)
13. Ouchi, K., Doi, M.: Living activity recognition using off-the-shelf sensors on mobile phones. Annals of Telecommunications 67(7-8), 387–395 (2012)
14. Cho, K., et al.: Human Activity Recognizer for Mobile Devices with Multiple Sensors. In: Proc. UIC-ATC 2009, pp. 114–119 (2009)
15. Suzuki, T., et al.: Wearable wireless vital monitoring technology for smart health care. In: Proc. ISMICT 2013, pp. 1–4 (2013)