Indoor activity monitoring system for elderly using RFID and Fitbit Flex wristband

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Indoor Activity Monitoring System for Elderly Using RFID and FitBit Flex Wristband

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***Abstract*— An indoor activity monitoring system for the elderly is proposed in this paper by using a Fitbit Flex wristband (FFW) and an active RFID. Two methods have been presented for identification of an activity place and a best accuracy of 98.89% has been achieved. The activity level of the elderly is evaluated via dissimilarity measurement by employing an activity density map. The presented system has the advantages of avoiding invasion of one's privacy and monitoring the daily activity unobtrusively. Experimental results show the potential of the proposed system for practical application.**

I. Introduction

The elderly population (age 65 or older) of developed countries drastically increases in the last few decades due to the advances in medicine. The World Health Organization (WHO) [1] defines that a society to be "ageing", "aged", or "super aged" as its elderly population reaches to 7%,14%, or 20% of the total population. Taiwan has become "aging" since 1993, and is expected to be "aged" and "super aged" in 2018 and 2025, respectively [2]. In addition, the WHO indicates that there will be 1.2 billion people aged 60 or above by 2025 and 2 billion by 2050 [3]. The increasing aging population will result in various problems and challenges for society, such as increase in diseases and health care burden, shortage of caregivers, and so on [4]. To overcome the problem of shortage of caregivers, and consequently reduces health care cost, various systems using information and communication technology (ICT) have been proposed for elderly care in the past decade [5].

While living in the beadhouses is an acceptable arrangement for more and more seniors, a survey conducted in the USA reports that 89% [6] of the older people prefer to stay at their own homes for comfort and easy reasons. With this trend, it is urgent to develop environment to keep older adults healthy and living independently in their own homes. One solution to this problem is to build Assisted Living Environment (ALE) using ICT for providing daily support unobtrusively and hence elderly people can age in place.

There are various types of elderly care systems have been proposed, which use different technologies such as image surveillance, infrared (IR) motion detection and wearable devices. For instance, Zhou *et al.* [7] use intelligent image processing to monitor and identify elderly people living alone. However, living under surveillance encroaches on one's privacy right. Shin *et al*. [8] presented an IR sensor-based system to detect the activity of the elderly people. However, the IR-based system is unable to identify specific individual and the place where activity is conducted. Furthermore, it cannot accurately measure energy expenditure of daily activity of the elderly people. Shiraishi *et al.* [9] use a passive UHF RFID technology to locate residents in a home. They installed RFID tags on a ceiling and each resident needs to carry an RFID reader for the localization. However, attaching the RFID reader causes much inconvenience for the elderly people. Zhang *et al.* [10] proposed to use a near field communication (NFC) supported smart phone together with wireless pulse oximeter and EKG sensors to monitor patient's health. Wireless sensors send the signal to a smartphone to store measured data and the smartphone automatically sends data to a server when patient comes in close proximity of the NFC. The major problem is that carrying multiple complicated devices for long term monitoring might not be acceptable for most of the elderly people. This motivates us to develop an indoor monitoring system which has the following features:

1. Avoiding from invasion of privacy;
2. Being able to identify people and activity place unobtrusively;
3. Providing the accurate energy expenditure of daily activity;
4. Being easy to be built with affordable cost, in which only a small and light device needs to be carried by an elderly.

In this paper, an indoor activity monitoring system for elderly (IAMSE) is developed by using RFID technology and Fitbit Flex Wristband (FFW) [11]. The proposed system is aimed for use in the family with elderly persons who need continuous monitoring. A moving average (MA) filtering and *k*-nearest neighbor algorithm (KNN) are employed to identify individuals and activity area. The FFW equipped with wireless 3 axis accelerometer is utilized to extract accurate energy expenditure of daily activity. An activity density map

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(ADM) based on the extracted energy expenditure and co-occurrence matrices (CM) computed by means of the ADM textural features are employed to calculate a dissimilarity measurement of the elderly people for tracking activity level and daily patterns during the observation period.

II. Proposed System

The proposed system consists of a local-side and a remote-side, as shown in Fig. 1. The local-side built in a resident house mainly comprises active RFID readers [12] and active RFID tags [13], the FFW, and a SQL server. In the local side, elderly person wears an active RFID tag and FFW for the activity monitoring. On the other hand, the remote-side consists of an e-health center and remote user(s). The main function of each component is explained as follows:

1. RFID readers and active tag identify the elderly and place where the elderly stays. The identified message is then sent to the SQL server.
2. The FFW measures the walking steps and energy expenditure of the elderly, which is then sent to the SQL server via Bluetooth.
3. The gateway extracts the activity data from the SQL server and then sends the data to the remote-side.
4. The e-Health center receives and stores data transmitted from the gateway through the Internet for computing the ADM and dissimilarity.
5. The authorized remote user(s) (i.e., family members /caregiver/doctor) can hold a mobile device, anytime and anywhere, to access the e-Health center server to check the status of the elderly people.

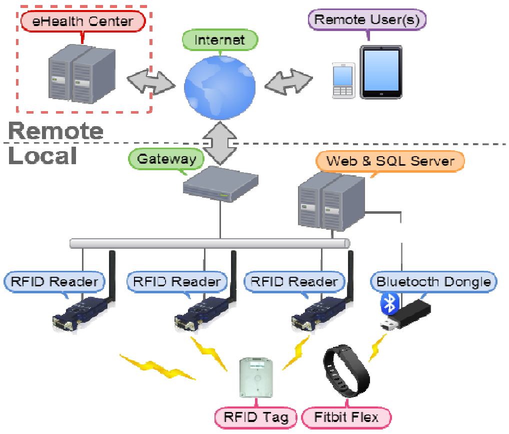

Figure 1. Diagram of the proposed system

The proposed system calculates the dissimilarity after obtaining the RFID and FFW data from the server. The system will send an alarm message to family members/caregiver/doctor if an abnormality is found. The abnormality may happen in various conditions, e.g., sudden over activities detected, or no activity in a long time period and so on. The user can access to the system via graphical user interface (GUI) to observe his/her expended calories, walking distance, the ADM, dissimilarity graphics, and sleep duration.

A. RFID Identification

Identification of the resident and the activity area are performed by two different methods, as shown in Fig. 2. In Fig. 2(a), the sampled RSSI current values (CV_{R1}, CV_{R2}, CV_{R3}) obtained from three readers are filtered by the MA algorithm and the one with maximum output value determines a room number (R#). Accuracy of the result depends on the number of samples used in the MA. In Fig. 2(b), the KNN algorithm finds *k* nearest vectors within reference vectors $\overrightarrow{\mathrm{RV}}$s for a current vector $\overrightarrow{\mathrm{CV}}$. Then, it counts vectors coming from each readers and the reader with the maximum number of vectors determines the R#. $\overrightarrow{\mathrm{RV}}$ and $\overrightarrow{\mathrm{CV}}$ are three dimensional vectors, i.e., $\overrightarrow{\mathrm{RV}} = \{\mathrm{RV}_{R1}, \mathrm{RV}_{R2}, \mathrm{RV}_{R3}\}$, $\overrightarrow{\mathrm{CV}} = \{\mathrm{CV}_{R1}, \mathrm{CV}_{R2}, \mathrm{CV}_{R3}\}$. To achieve a high accuracy, the number of $\overrightarrow{\mathrm{RV}}$s should be large enough and appropriate value of *k* needs to be found.

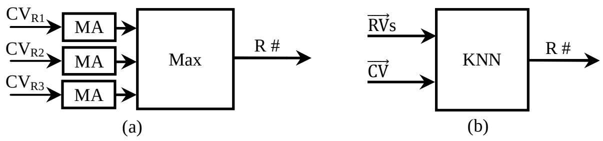

Figure 2. Identification methods: (a) Moving average; (b) k-nearest neighbor algorithm

III. Dissimilarity Measurement

Finding out dissimilarity of the physical activity pattern of the daily life is a crucial part for providing early detection of health change. First, the ADMs are built for the observation period. Then, textural features are extracted from the ADM using a gray-level co-occurrence matrix (GLCM) method [14]. Finally, textural features are used to find dissimilarity among the ADMs.

A. Activity Density Map

Two examples of the ADM are shown in Fig. 3. The X-axis represents days in a week and the Y-axis represents hours in a day. Each single cell represents the step counts that have taken in one hour. The lightest color refers to the lowest activity level (< 10 steps/hr) and the darkest refers to the highest activity level (> 3000 steps/hr). In this work, only step count is employed in the ADM. In the future, the other data including expended calories, walking distance, and time of stay in a room will also be considered. Observed from the left ADM in Fig. 3, this person went to bed regularly at around 2 a.m. and woke up at around 10 a.m. Thus, we can conclude that this person slept 8 hours in this day and he/she slept well, because there is no activity appeared during sleep. However, in the right ADM, some activities are found during sleep, which implies that the resident might have a problem of sleep disorder.

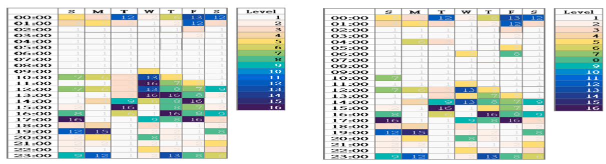

Figure 3. Examples of the activity density map

B. Co-occurrence Matrices

Let the ADM be a 2-dimentional matrix where each cell represents an activity level. Let $L_x = \{1, 2, \cdots, N_x\}$ and

$L_y = \{1, 2, \cdots, N_y\}$ are respectively X and Y spatial domains, and $G = \{1, 2, \cdots, N_g\}$ is a quantized gray tone value. Fig. 4(a) shows 3×3 resolution cells where x have eight adjacent or nearest neighbor resolution cells. In Fig. 4(a), resolution cells 1 and 5, 8 and 4, 7 and 3, and 6 and 2 are nearest neighbors to a resolution cell x in 0º, 45º, 90º, and 135º, respectively. Then, step counts I can be represented by a function $I : L_x \times L_y \rightarrow G$; which assigns G to each resolution cell as illustrated in Fig. 4(b).

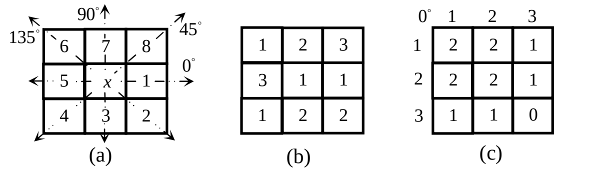

Figure 4. (a) 8 nearest neighbor resolution cells; (b) Activity density map with quantized activity levels; (c) Co-occurrence matrix result of $P(i,j,1,0º)$

The texture context information is specified by a matrix of relative frequencies $P(i, j, d, \Theta º)$ with which two neighboring resolution cells separated by a distance d occur on the image, one with level i and the other with level j computed as CMs. They are function of an angular relationship between the neighboring resolution cells as well as a function of the distance between them. The CMs are defined in (1) [15]. Fig. 4(c) demonstrates the result of $P(i, j, 1, 0º)$ derived from Fig. 4(b).

$$
\begin{aligned}
&P(i, j, d, 0º) = Cardinality\{((k, l),(m, n)) \in (L_y \times L_x) \times (L_y \times L_x) \\
&\quad where\ k-m = 0,\ |l-n| = d,\ I(k, l) = i,\ I(m, n) = j\ \} \\
&P(i, j, d, 45º) = Cardinality\{((k, l),(m, n)) \in (L_y \times L_x) \times (L_y \times L_x) \\
&\quad where\ k-m = \pm d,\ l-n = \pm d,\ I(k, l) = i,\ I(m, n) = j\ \} \qquad (1) \\
&P(i, j, d, 90º) = Cardinality\{((k, l),(m, n)) \in (L_y \times L_x) \times (L_y \times L_x) \\
&\quad where\ |k-m| = d,\ l-n = 0,\ I(k, l) = i,\ I(m, n) = j\ \} \\
&P(i, j, d, 135º) = Cardinality\{((k, l),(m, n)) \in (L_y \times L_x) \times (L_y \times L_x) \\
&\quad where\ k-m = \pm d,\ l-n = \pm d,\ I(k, l) = i,\ I(m, n) = j\ \} \\
&Q(i, j, d) = \textstyle\sum_a P(i, j, d, a)
\end{aligned}
$$

where Cardinality {S} is the number of elements in set S; a is a degree.

C. Textural features

Though, 14 different textural features are available, 4 [16] of them given below, are chosen to calculate the dissimilarty measurement:

$$x_1 = \sum_i \sum_j \{Q(i,j,d)\}^2 \qquad (2)$$

$$x_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{\substack{i=1 \\ |i-j|=n}}^{N_g} \sum_{j=1}^{N_g} Q(i,j,d) \right\} \qquad (3)$$

$$x_3 = \sum_i \sum_j \frac{1}{1+(i-j)^2} Q(i,j,d) \qquad (4)$$

$$x_4 = -\sum_i \sum_j Q(i,j,d) \log\left(Q(i,j,d)\right) \qquad (5)$$

Notably, (2) is the angular second moment feature (ASM), a measurement of homogeneity; (3) is the contrast feature; (4) is the inverse difference moment; and (5) is the entropy. We also used average activity density x_5 as an additional textural feature.

D. Euclidean Distance

After all features are properly calculated from ADMs, we can compare them with each other. We assume that each feature is represented as a row vector, $\{x_1, x_2, \ldots, x_m\}$. A weighted normalized Euclidean distance d_{rs} between two vectors is further defined as follows:

$$d_{rs} = \sqrt{\sum_{i=1}^{5} \omega_i [x_{rn}(i) - x_{sn}(i)]^2} \qquad (6)$$

where $x_{rn}(i) = \frac{x_r(i)}{\max[x_r(i), x_s(i)]}$, $x_{sn}(i) = \frac{x_s(i)}{\max[x_r(i), x_s(i)]}$ and, $\omega_i = 1/5$, $i = 1, \cdots, 5$. x_{rn} and x_{sn} are textural features of the reference and current ADM, respectively.

IV. Experimental Results and Discussions

One male volunteer is invited to perform the experiments. A house with a layout illustrated in Fig. 5 is adopted for the experiments, where three RFID readers are respectively installed in a bed room (Reader 01), a living room (Reader 02), and a rest room (Reader 03). The volunteer wore the FFW and one RFID tag for eight weeks (Oct. 07, 2013 - Dec. 02, 2013). A total of 7730 reference vectors were collected at spots 1-13. Identification accuracy for the activity obtained by using the MA and the KNN algorithms is presented in Table I.

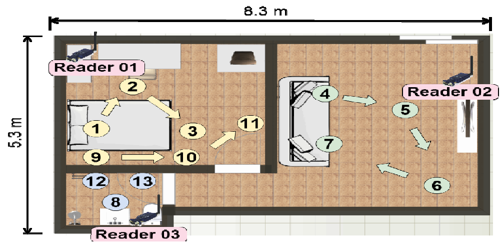

Figure 5. House layout

A. RFID Identification

Experimental results demonstrate that the MA achieves best performance of 98.89% when the sample number is 10. On the other hand, the KNN algorithm attains best performance of 96.84% as k=30. Furthermore, the KNN needs a training phase before identification can be performed. Therefore, the MA is a better choice for the identification.

TABLE I. Identification Accuracy for Activity Place Obtained by Using Moving Average and KNN Algorithms (%)

	MA (samples)			KNN (k)		
	2	4	10	1	10	30
Room 1	81.27	88.94	98.57	94.41	93.71	96.50
Room 2	100	100	100	89.81	100	100
Room 3	94.52	98.15	98.12	90.73	92.05	94.04
Total	91.93	95.69	98.89	91.64	95.25	96.84

B. *Dissimilarity Measurement*

Fig. 6 illustrates 8 weeks ADMs which are used for the dissimilarity measurement. ADM maps indicate an activity starting at around 8 a.m., indicating the volunteer woke up regularly early in the morning. Similarly, he went to bed around 11 p.m.−12 a.m. This reveals that he slept regularly 8−9 hours a day. He looks active regularly between 8 a.m. − 11 p.m., 1 p.m. − 3 p.m, and 6 p.m. − 9 p.m. during a day except for the 4^{th} week. In the 4^{th} week (Oct. 28, 2013 – Nov. 01, 2013), the map shows almost no activity starting since Tuesday due to he had a minor skin grafting surgery on his leg; hence, he had to stay immobilized for one week. In 3^{rd} and 4^{th} weeks, the average steps in a day were 4211, 1324, respectively. In the 5^{th} week (next week of the surgery), the map shows higher activity level as compared to the previous week; but is lower as compared to 3^{rd} week. This is because he was not completely recovered from the surgery. In the 6^{th} week, the map shows that he had returned to the normal daily life, and the average steps in a day increased to 4830.

Fig. 7 shows the dissimilarity measurement of the density maps by using Fig. 6, which compares each week to the 1^{st} week. Dissimilarities between 1^{st} and 2^{nd} weeks, and 1^{st} and 3^{rd} weeks are respectively 0.15, 0.04; the 2^{nd} and 3^{rd} weeks had similar daily life pattern compared to the 1^{st} week, where 2^{nd} week had higher average steps in a day (5199) than the 3^{rd} week (4211). However, the dissimilarity between 1^{st} and 4^{th} weeks being 0.33 exhibits a drastic change, due to the volunteer's leg surgery. In the 5^{th} week, his activity level increased as compared to the 4^{th} week, this explains the decreased dissimilarity of 0.24. In 7^{th} and 8^{th} weeks, he kept his daily life pattern as was before the surgery and his average steps in a day increased from 4830 to 5127.

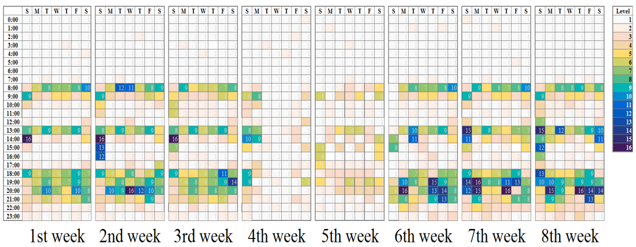

Figure 6. Eight weeks ADM for dissimilarity measurement

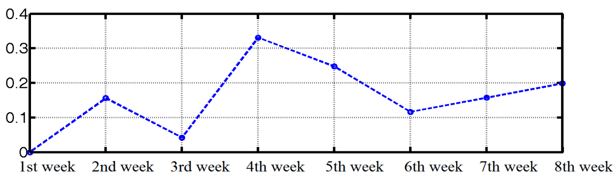

Figure 7. Dissimilarity measurement for the density maps shown in Fig. 6 with weekly baseline.

We also analyzed dissimilarity measurement for one day baseline. Moreover, dissimilarities of a half day, and a quarter day are analyzed. However, graphs and analysis are not included in this paper due to page limitation.

V. Conclusions

An indoor activity monitoring system for the elderly has been implemented in this study. Because the elderly person needs only to wear the Fitbit Flex Wristband (FFW) and RFID tag, the problem of invasion of privacy can thus be avoided and meanwhile the daily activity can be monitored unobtrusively. An accuracy of 98.89% for activity place identification was achieved by using the MA algorithm. The activity level of elderly is evaluated via dissimilarity measurement by employing the ADM. Experimental results indicate potential of the proposed system for practical application. Currently, we are cooperating with the elderly center of a hospital in Taiwan to conduct real-life experiments. In the future, we will consider more features for accurate activity level evaluation, which include time away from home, time stay in a room, other activity data of FFW, and the distribution of activity in different rooms.

Acknowledgment

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