Detect the Daily Activities and In-house Locations Using Smartphone

Sittichai Sukreep, Pornchai Mongkolnam, and Chakarida Nukoolkit

School of Information Technology
King Mongkut's University of Technology Thonburi
Bangkok 10140, Thailand
{sittichai.s,pornchai,chakarida}@sit.kmutt.ac.th

Abstract. Falls are a key cause of significant health problems, especially for elderly people who live alone. Falls are a leading cause of accidental injury and death. To help assist the elderly, we propose a system to detect daily activities and in-house location of a user by means of a smartphone's sensor and Wi-Fi access points. We applied data mining techniques to classify activity detection (e.g., sitting, standing, lying down, walking, running, walking up/downstairs, and falling) and in-house location detection. Health risk level configurations (threshold model) are applied for unhealthy activity detection with an alarm sounding and also short messages sent to those who have responsibility such as a caregiver or a doctor. Moreover, we provide various forms of easy to understand visualization for monitoring and include health risk level summary, daily activity summary, and in-house location summary.

Keywords: Activity of Daily Living (ADL), Smartphone, Accelerometer, Access Point, Wireless Signal, In-house Location, Data Mining, Classification, Visualization.

1 Introduction

Fall accidents can cause severe health problems and can happen to anybody. The World Health Organization (WHO) reported in 2012 that falls were the second leading cause of accidental injuries and deaths worldwide; 424,000 individuals died from falls (1,160 persons/day), and over 80% of such deaths occurred in low and middle income countries [1-3].

Currently, the world is changing toward ageing societies. More elderly people live alone rather than with their families. When those people fall during their daily activities, they cannot help themselves. Without anybody taking notice and providing help, their injuries could be fatal. Therefore, timely assistance and care may reduce the severity of the injuries.

We aimed to improve the detection of Activities of Daily Living (ADL) and in-house location in real-time, using a smartphone's accelerometer sensor, three in-home's Wi-Fi access points (APs), and data mining classification methodology. We provided monitoring and warning of health risk levels. Moreover, we created various

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data visualization tools for generating frequently used in-house locations and providing summarized health risk level reports.

2 Related Work

There are several systems available which detect daily activities and indoor locations. However, those systems or methods require rather sophisticated hardware or infrastructure. This has motivated our work to overcome their shortcomings.

In 2013, Jian et al. [4] developed an automatic fall warning system. This system used an accelerometer and gyroscope sensors attached to a vest or other garment and collected the activities and fall data from elderly people. Daniel et al. [5] proposed a methodical algorithm which classified 11 activities and posture transitions (i.e., stand, sit, sit to stand, stand to sit, bend down, bend up, walking, lying, lying to sit, sit to lying, and bent) using an inertial tri-axial accelerometer located on the waist. The support vector machine (SVM) algorithm was used for classifications. Several researchers established elderly people received injuries or in some cases death from falling [6-16]. In addition, more recent research has focused on activity or movement detection by using smartphones or sensors such as accelerometer or gyroscope.

In 2014, Stephen et al. [16] developed a system for rehabilitation and diagnoses to understand the patients' activities (e.g., walk or sit) by carrying a phone in different positions, including belt, pocket, hand, and bag. The authors used a smartphone's accelerometer and SVM classifier to classify the activities. Guiry et al. [17] proposed a method to accurately detect human activities, including sitting, standing, lying, walking, running, and cycling using two accelerometers and to compare activity recognition classifiers using C4.5, CART, SVM, Multi-Layer Perceptrons and Naïve Bayes with accuracies as high as 98%. Quoc et al. [18] developed a wireless sensor system and algorithm to identify falls such as forward fall, backward fall, and sideway fall (left and right) by using ADXL345 (3-axis digital accelerometer sensor) and ITG3200 (3-axis digital gyroscope sensor), MCU LPC17680 (ARM 32-bit cortex M3), and Wi-Fi module RN13. Paliyawan et al. [19] developed a prolonged sitting detection system for office worker syndrome by using Kinect.

Liu et al. [20] developed a technique and system for surveying wireless indoor positioning. Premchaisawatt [21] proposed machine learning techniques for enhancing indoor position in an experiment area of 30x10 meter^2 with 77.32% accuracy. Zhongtang et al. [22] developed an in-house location detection system with an experiment area of 16x29 meter^2 and with 5 marked spots.

3 Methodology

3.1 System's Overview

We propose a system which classifies falls, basic daily movement activities, and in-house location detection, and provides health risk feedback with several easy to understand visualizations. The system obtains input data from a smartphone's accelerometer sensor and the Wi-Fi signal strength from 3 APs in real-time. Detection of the daily activities and in-house locations are done using data mining classification as shown in Fig. 1(a). Knowing the activities and locations, an alarm sounds and SMS is sent when a high risk situation or unhealthy condition is detected. The system can also provide summary reports on the safety level of the user's activities and in-house locations.

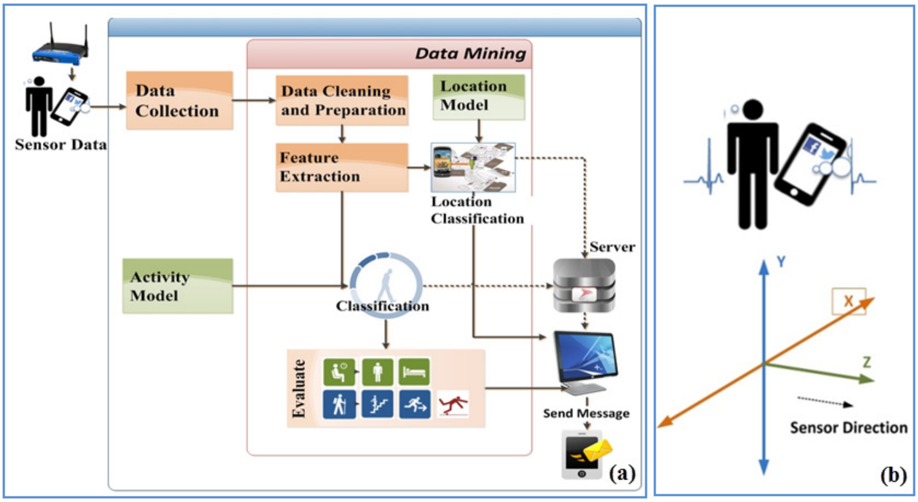

Fig. 1. (a) System's Architecture and (b) Accelerometer's Sensor Coordinates

3.2 Daily Activity Detection Algorithm

We develop an Android application for collecting acceleration data from a smartphone sensor and use a Windows application for processing the data. The smartphone sends the acceleration data of occurred movements to a server. The data are obtained by a tri-axial accelerometer as X, Y, and Z coordinates as shown in Fig. 1(b). The system supports 7 activities (sitting, standing, lying down, walking, running, walking up/downstairs, and falling) and 4 selectable positions for the smartphone (i.e., waist, leg, front trouser's pocket, and arm). It is necessary that the smartphone be attached to one of those positions.

The method we use is based on machine learning. We divide the activity detections into two parts. First, in an offline phase, we build a learning system by letting the users perform activities and collecting the data when they are performed. After that we clean and prepare the data, extract their features, compare the classifiers provided by WEKA [23], including decision tree (J48), naïve Bayes, support vector machine (SVM) and k-nearest neighbor (KNN), and select the optimal classifier. Second, in a real-time phase, we use the program developed for the Android smartphone to classify the 7 daily activities.

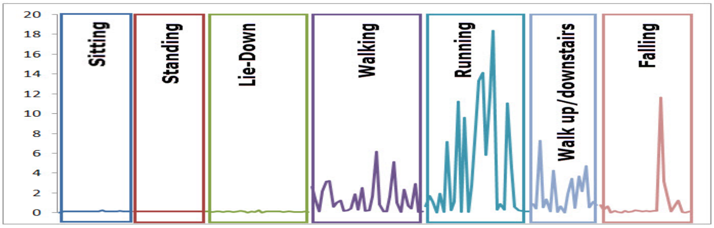

Fig. 2. Sensor's Velocity of Different Activities

3.2.1 Offline Training Model of Daily Activities

The velocity data from the accelerometer's sensor shows that different activities have different signal patterns. For example, the velocity of running is greater than sitting, standing, and lying down as shown in Fig. 2.

We collected the data from 25 human subjects in about 120,000 frames. We requested the subjects to perform 7 activities (i.e., sitting, standing, lying down, walking, running, walking up/downstairs, and falling) and repeat each activity three times. Each time took about 10 seconds, and all of them included four smartphone positions (i.e., waist, leg, front trouser's pocket, and arm). The Euclidian method was used to compute a rate of change of velocity. We used it to calculate the slope between two points of the accelerometer's sensor data. We collected the data, cleaned, prepared, and then extracted the features using the Euclidian method as shown in Equation (1).

$$Acc(i,j) = \sqrt{(Xi - \mathrm{Xj})^2 + (Yi - Yj)^2 + (\mathrm{Zi} - \mathrm{Zj})^2} \quad , \tag{1}$$

where Acc(i, j) represents the accelerometer from the i^{th} and j^{th} records, and X, Y, and Z represent the coordinates.

We trained the data using WEKA with various classifiers such as decision tree (J48), naïve Bayes, support vector machine (SVM), and k-nearest neighbor (KNN). Then we compared the results and chose the optimal classifier.

3.2.2 Real-Time Activity Classification

We applied our optimal classifier, the KNN model (using 3 nearest neighbors for classification), on our system for detecting various kinds of activities. The system collected the acceleration data (the X, Y and Z coordinates) from the smartphone in real-time every 0.2 second. The data were processed as the input of the KNN model, and then the system predicted the activities.

3.2.3 Noise Filtering

Acceleration of movement data from the accelerometer's sensor can be adversely affected by the abrupt transitions in activity detection and interference. We used the following method to prevent this problem. For example, when the user changed an activity immediately from one activity to another, such as from sitting to standing, the system would accept the state change from sitting to standing only when the activity transition state had been continuously changed for more than 5 frames (~1 second). Otherwise, the state change would be rejected and it remained as the previous activity.

3.3 In-house Location Detection Algorithm

Our in-house location detection algorithm used the Wi-Fi signal strength to position the user's whereabouts. We developed an Android's application for collecting the Wi-Fi signal strength levels from 3 APs. APs were set up on the same side of the house because we could reduce interferences and consider only one side of the Wi-Fi signal coverage as shown in Fig. 3(a).

The algorithm used for classifying the in-house locations was based on machine learning. We divided our in-house location detection into two phases. First, in offline phase, we collected the data in the two-story house (with 24 marked locations). We collected the signal strength 50 frames for each marked location and repeated 10 times around those spots. A data mining process was used to clean and prepare the data, and extract the features. We then compared four classifiers, including decision tree (J48), naive Bays, support vector machine (SVM) and k-nearest neighbor (KNN) and chose the optimal one. Second, in a real-time phase, we developed the system to detect in-house locations and evaluated the accuracy.

3.3.1 Offline Training Model for Location Detection

The Wi-Fi signal strength data from APs showed that different locations had different values. We used 3 APs for the in-house location detections, and we experimented with them in the two-story house. The house had an area of 3.5x10.5 meter^2 on both floors as shown in Fig. 3(b).

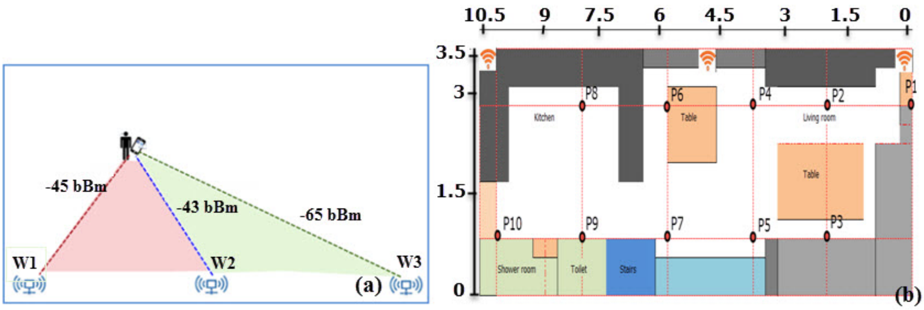

Fig. 3. (a) Signal Strength and Positions of Access Points and (b) Marked In-house Locations

We collected the data from 24 marked spots (11 spots on the first floor and 13 spots on the second floor) as shown in Fig. 3(b). The distance between each spot was about 2 meters, both vertically and horizontally. We used the smartphone to collect the Wi-Fi signal strength data also known as Received Signal Strength Indication (RSSI) from 3 APs. For each marked spot we collected the data 10 times, and each time we collected 50 frames/spot. So we had data equal to 50x10x24 = 12,000 frames in total. The data underwent a data mining process. They were cleaned and prepared, and the features were extracted by the Euclidian method. The Euclidian calculation involved two parts. First, we calculated signal strength from the first AP and the second AP as shown in Fig. 4(a) using Equation (2). Second, we calculated it from the second AP and the third AP as shown in Fig. 4(b) using Equation (3).

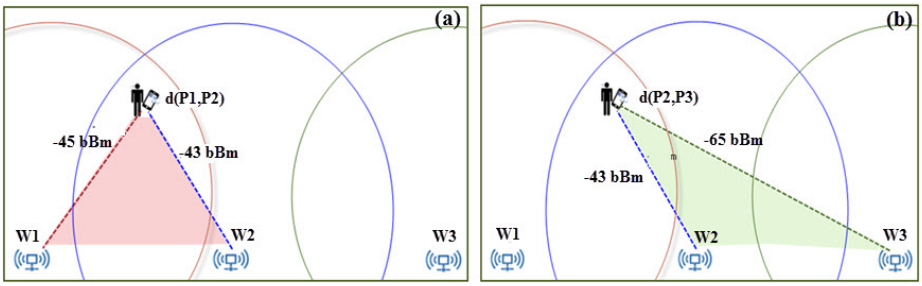

Fig. 4. Signal Strength from (a) First AP and Second AP and (b) second AP and third AP

$$Distance(W1, W2) = \sqrt{(W1 - P1)^2 + (W2 - P2)^2} \quad , \tag{2}$$

$$Distance(W2, W3) = \sqrt{(W2 - P2)^2 + (W3 - P3)^2} \quad , \tag{3}$$

where W1, W2, and W3 represent the mean value of signal strength from the 1^{st} , 6^{th} and 11^{th} marked spot, and P1, P2, and P3 represent the signal strength from APs.

We trained the data using WEKA with four classifiers, including decision tree (J48), naive Bays, support vector machine (SVM) and k-nearest neighbor (KNN). Then we compared the results of those classifiers and chose the optimal one.

3.3.2 Real-Time Testing Model

KNN was used as our optimal classifier for the in-house location detection. The signal strength data were collected in real-time every three seconds and were calculated by the Euclidian method. The data were processed as input data of the KNN model, and then the system predicted the in-house locations as shown in Fig. 5.

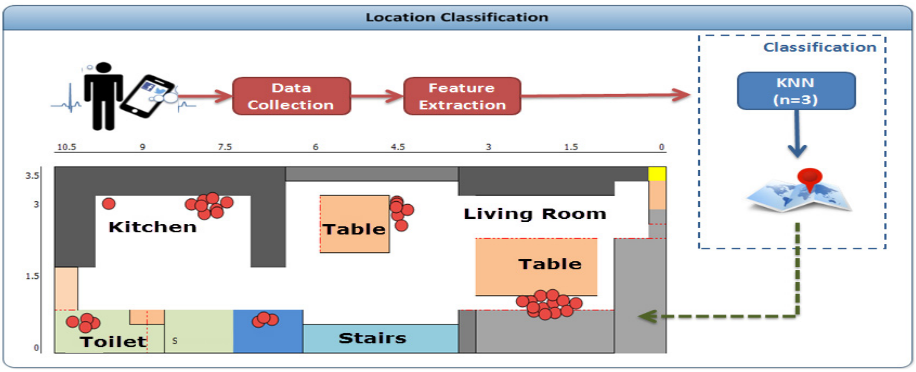

Fig. 5. In-house Location Detection

4 Experiment and Results

4.1 Experiment Setup

In our test, we set up the 3 APs in a two-story house. The house floor area was approximately 3.5x10.5 meter^2. There were 24 marked spots, with 11 marked points on the first floor and 13 marked points on the second floor. All 3 APs were on the first floor and on the same wall. All activities and in-house locations were covered. Ten volunteers were asked to perform various activities, using a Samsung Galaxy S5 phone equipped with the accelerometer and Wi-Fi signal receiver.

4.2 Data Collection

4.2.1 Activity Data Collection

We collected the accelerometer data for the 7 activities (sitting, standing, lying down, walking, running, walking up/downstairs, and falling). The activities were performed by 10 volunteers. We let the volunteers with the attached smartphones move freely from one position to another position. The smartphone was attached to four different positions, including the front trouser pocket, arm, leg, and waist.

The volunteers performed activities 10 seconds (~5 frames/second) for normal activities without fall and 3 times for falling. So there was a total of 12,580 frames for testing. All data were saved to a database server in real-time.

4.2.2 In-house Location Data Collection

We collected location data from the Wi-Fi signal strength of the smartphone. We requested the volunteers to stand at the marked spots for collecting the data. At each marked spot, 50 frames were collected and saved to the database. There were 24x50 = 1,200 frames per volunteer. So there was a total of 1,200x10 = 12,000 frames altogether.

4.2.3 Evaluation

4.2.3.1 Activity Detection Evaluation. The accelerometer data that we collected from the volunteers were feature-extracted and evaluated using the KNN (K=3) model and recorded an average accuracy of 97.48% of all activities combined. The accuracy of each activity is listed in Table 1.

Table 1. Accuracy of Activity Detection

No.	Gender	Age	Weight (kg.)	Height (cm.)	Sit	Stand	Lie-down	Walk	Run	Walk Up/Downstairs	Fall
1	Male	43	60	167	100.00	100.00	100.00	92.69	98.02	88.94	100.00
2	Female	24	54	152	100.00	100.00	100.00	95.79	99.50	89.24	100.00
3	Female	48	80	158	100.00	99.03	99.04	94.62	100.00	91.23	100.00
4	Male	63	45	165	100.00	99.01	100.00	93.84	100.00	88.33	100.00
5	Female	36	73	165	100.00	100.00	100.00	92.73	98.48	92.89	100.00
6	Female	60	69	155	98.57	100.00	99.50	92.56	98.50	88.09	100.00
7	Female	38	58	157	100.00	100.00	98.58	93.12	99.04	92.69	100.00
8	Female	45	65	167	98.04	99.02	98.05	95.85	100.00	93.75	100.00
9	Male	42	68	170	99.51	100.00	99.04	95.81	95.00	94.69	100.00
10	Male	50	60	172	100.00	100.00	99.03	91.96	98.53	91.11	100.00
Average (%)					**99.61**	**99.71**	**99.32**	**93.90**	**98.71**	**91.10**	**100.00**

4.2.3.2 Location Detection Evaluation. The in-house location data which we collected from the volunteers were feature-extracted and evaluated using the KNN (k = 3) model. We evaluated each marked spot (F01-F24) and recorded an average accuracy of about 94.11%. The accuracy table is shown in Table 2.

Table 2. Confusion Matrix Showing Accuracy of In-house Location Detections

Marked Spot	F01	F02	F03	F04	F05	F06	F07	F08	F09	F10	F11	F12	Accuracy
F01	98.80	0.00	0.80	0.00	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**98.80**
F02	0.00	96.02	0.20	2.19	1.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**96.02**
F03	2.65	1.43	92.87	0.20	2.85	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**92.87**
F04	0.00	1.06	0.00	92.39	0.42	5.50	0.63	0.00	0.00	0.00	0.00	0.00	**92.39**
F05	0.80	3.99	2.00	0.20	92.42	0.20	0.20	0.00	0.20	0.00	0.00	0.00	**92.42**
F06	0.18	0.73	0.91	2.73	0.73	94.36	0.36	0.00	0.00	0.00	0.00	0.00	**94.36**
F07	0.00	1.67	0.42	1.88	3.55	2.92	86.85	1.04	1.67	0.00	0.00	0.00	**86.85**
F08	0.00	0.00	0.00	0.00	0.00	0.00	2.88	88.89	3.29	0.62	4.12	0.00	**88.89**
F09	0.19	0.00	0.00	0.00	1.33	0.19	3.05	3.05	91.24	0.00	0.95	0.00	**91.24**
F10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.21	0.00	98.79	0.00	0.00	**98.79**
F11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.25	2.43	1.42	92.90	0.00	**92.90**
F12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	95.61	**95.61**
Marked Spot	**F13**	**F14**	**F15**	**F16**	**F17**	**F18**	**F19**	**F20**	**F21**	**F22**	**F23**	**F24**	**Accuracy**
F12	0.60	0.60	1.80	0.20	0.40	0.00	0.80	0.00	0.00	0.00	0.00	0.00	**95.61**
F13	96.79	0.20	1.80	0.00	0.20	0.00	0.20	0.00	0.00	0.00	0.00	0.00	**96.79**
F14	1.41	93.33	0.40	0.20	0.61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**93.33**
F15	3.59	0.80	91.43	0.00	1.59	0.00	1.59	0.00	0.00	0.00	0.00	0.00	**91.43**
F16	0.00	0.00	0.00	96.89	0.97	0.00	1.95	0.00	0.00	0.00	0.00	0.00	**96.89**
F17	2.43	1.77	4.86	2.65	86.31	0.00	1.10	0.00	0.00	0.00	0.00	0.00	**86.31**
F18	0.00	0.00	0.00	0.00	0.00	99.56	0.00	0.44	0.00	0.00	0.00	0.00	**99.56**
F19	0.89	0.89	3.12	0.67	4.45	0.00	89.31	0.00	0.00	0.00	0.00	0.00	**89.31**
F20	0.00	0.00	0.00	0.00	0.00	1.22	0.00	98.09	0.70	0.00	0.00	0.00	**98.09**
F21	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.05	97.26	1.05	0.42	0.21	**97.26**
F22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	3.21	95.99	0.00	0.00	**95.99**
F23	0.00	0.00	0.00	0.00	0.00	0.49	0.00	0.00	1.23	0.62	96.54	0.86	**96.54**
F24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	1.39	1.98	96.03	**96.03**
Average (%)													**94.11**

It could be seen that some locations were misclassified because the signal strength from APs were affected by the surrounding environment, such as door opening, door closing, or postures of the volunteers; therefore, data from the signal strength could change, resulting in misclassified locations.

5 Conclusions and Future Work

In this paper, we propose a practical and affordable system using a smartphone's accelerometer sensor and the Wi-Fi signal strength from APs to detect and visualize the in-house locations and daily activities such as sitting, standing, lying down, walking, running, walking upstairs and downstairs, and falling. We apply data mining techniques for those daily activities and in-house locations of the user. The changes of activities and in-house locations are detected by the threshold model. We provide an easy to use and understand user interface and visualization to monitor the activities and in-house location in real-time by displaying the related information on a separate monitoring computer screen. Moreover, our system can warn the user when his or her health risk level exceeds the preset level. The achieved accuracy of activity detections is 97.48%, and the accuracy of the in-house location detections is 94.11%. Moreover, our proposed system can detect the fall activity, the detection of which is crucial for one's well-being, with 100% accuracy. In addition, our proposed system is much easier to set up than previous systems.

We hope to use this system with elderly people in order to track their daily physical movement activities so that we can learn more about them, e.g., used at home, nursing homes, or hospitals; for example, some elderly may prefer sitting idly on the couch while watching television. Some might spend more time in the bedroom than in the kitchen. This information is very helpful to family members and healthcare providers, particularly in an ageing society.

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