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FallAlarm: Smart Phone Based Fall Detecting and Positioning System

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Abstract

This paper presents a system called FallAlarm, which is utilized for fall detecting and positioning using a smart phone. A tri-axial accelerometer sensor and a Wi-Fi module embeded in the phone are employed to provide needed information. Data from the accelerometer is evaluated with a decision tree model to determine a fall. If a fall is suspected, a notification is raised to require the user's response. If the user is injured hardly and cannot respond in time, the system immediately begin to position the occurence of the fall event by detected surrounding Wi-Fi signals, then automatically send a alarm message to his pre-specified guardian with a message via SMS(Short Message System). Consequently, the victim of fall can be monitored and cared in real time. Tested on a real-world data set, the FallAlarm system can achieve an acceptable accuracy for practical application.

Keywords:
Location Based Services;Activity Recognition;Fall Detection;Machine Learning;Pervasive Computing

1. Introduction

If the occurence of a fall event can be observed, the person in most involved falls may be helped by others. On the contrary, his first aid will be hopeless if not any useful help, which may lead that he will suffer great pains and even pass away. Thus the worry about falls restricts people's area of movement and increases their dependence on others. To improve the quality of the elderly's life, it is necessary to develop a system which can detect the occurrence of a fall in real-time. However, the existing devices for monitoring the elderly are expensive, inaccurate, and impractical to use. Therefore, it is required to develop a system that can be used without sophisticated operations by an elderly person and is able to predict falls accurately in real-time, also the commercial price is acceptable for common people. In addition, when the fall occurs, it should have the function of informing the guardians or the health care institution.

There are some existing fall detecting systems in the literatures. Prado [1, 2] used a four-axis accelerometer located at the height of the sacrum to detect falls. Mathie[3] used a single, waist-mounted,

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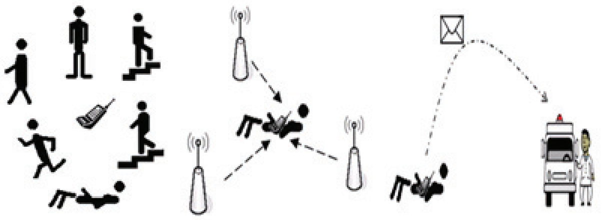

Fig. 1. The Sketch Map of FallAlarm System.(a)The smart phone can distinguish the activities of daily living.(b)When the elderly falls, the system starts to estimate the location.(c) The system sends a message including the location to the healthcare institute.

tri-axial accelerometer to detect falls. Lindemann [4] integrated a tri-axial accelerometer into a hearing aid housing, and used thresholds for acceleration and velocity to decide whether the falls happen. Under some constrained conditions, all these systems can detect falls accurately. But they do not pay attention to the occurence location problem. Not knowing about the location where fall occurs may lead to missing the best time to the first aid help.

In this paper, the smart phone based FallAlarm system is presented, which can detect falls, estimate the occurence location and send a message to the guardian, as shown in Figure 1.

Our contributions are as following:

(1)We build the FallAlarm system on the smart phone and the user doesn't need to buy any other device. The Fall state is recognized by analyzing the data of accelerometer embedded in the phone and the location is located by using the Wi-Fi signal in the environment.

(2)The FallAlarm system can both detect and position the fall. Discovering the Fall immediately is important in helping the people in fall as positioning him accurately. Therefore, a practical FallAlarm system should consider the two aspects simultaneously.

(3)The FallAlarm system is power efficient. To reduce the Wi-Fi module's power consuming, the fall state triggered RSSI positioning method is introduced.

2. Related Work

2.1. Fall Detection System

Some works have investigated the fall with image processing techniques. Nait-Charif [5] and Rougier [6] tracked the head movements and detected the fall with particles filters algorithms. Mihailidis [7] placed a video camera on the ceiling and developed scene algorithms to detect a fall. These video or image based systems usually require the monitoring cameras to be fixed on the ceiling, which are used in the indoor environment.

Other works have employed accelerometer based equipments. Prado[1, 2], Mathie[3] and Lindemann[4] respectively developed their devices using accelerometers. These devices are portable and the user can go anywhere with them. But they did not consider the location problem.

2.2. Positioning Method

For outdoor positioning, the Global Positioning System (GPS) is a common choice [8]. However, its performance degrades greatly in the indoors and high-rise urban areas. Furthermore, it has a relatively long start-up time and expensive cost. For indoor areas, different localization systems prefer different mediums, like infrared rays [9], RF signals[10], ultrasound [11] and so on.

Wi-Fi is nowadays widely deployed in shopping halls, hotels, airports, and many cities even launch ”Wireless City” program to realize entire wireless coverage over the whole city. Meanwhile, more and more mobile devices are equipped with wireless cards that can receive Wi-Fi signal easily, using the Wi-Fi wireless network infrastructure to locate users becomes practical. It costs little due to no need of additional hardware and can work both indoors and outdoors, which can provide a convenient and seamless experience for mobile users.

Ekahau[1] Real Time Location System (RTLS) is a Wi-Fi based asset management and people tracking solution for hospitals and other enterprises. AeroScout[2] Real Time Visibility Solutions for healthcare utilize standard Wi-Fi networks as a single unified wireless architecture for visibility. Ekahau and AeroScout are controller-centralized methods. The clients need to send information to the controller periodically. Our FallAlarm system considers the smartphone based power efficient problem, thus the fall state triggered RSSI positioning method is proposed.

3. System Design and Implementation

The main goal of the FallAlarm system is to empower the guardians or the health care institute to find and help the elderly immediately when the fall occurs. Hence the timely aid and help can lower the harm risk in the victims of falls. To accomplish this objective, the following requirements are defined:

(1)The system needs to distinguish fall from other activities of daily living.

(2)The system needs to estimate the location where the fall occurs.

(3)The system needs to have the module to send message to the guardians of the elderly.

The FallAlarm can be installed on a smart phone embedded with tri-axis accelerometer sensor and Wi-Fi module. When the elderly wants to go outside, he can run the system and hold the phone in his hand, put it in the bag, wear it on the waist via the belt. The FallAlarm always runs and collects the accelerometer data continuously. When the data in the interval of some seconds are ready, its' features are extracted to form a sample. With the sample as input information, the activity classifier can distinguish its' type. If current activity is a normal activity (stationary, walking, slowly running etc.), the FallAlarm discards it and monitors the next one. Otherwise, if it is a fall, the system collects the RSSIs (Received Signal Strength Indiction) from APs (Access Points) around the elderly and gets the current location by the positioning module. After the positioning phase, the system sends a short message including the location where the elderly falls to his guardians whose phone numbers have been stored in the system. When the corresponding persons receive the message, they can take measures to help the elderly at once, according to the occurence location in the message.

From the above description, it can be seen that the main research points are fall detection algorithm and positioning algorithm. In the following sections, they will be discussed in detail.

3.1. Fall Detection Algorithm

In this section, we explain our methods for detecting falls. Our methods are based on machine learning. As we know, machine learning algorithm is a method of two phases, offline training and online testing. In offline training phase, we collect data, extract features and train a classifier. In online testing phase, we design a program, install it on the cell phone and predict the fall occurence.

Hence, we design our fall detection algorithm in two steps: firstly, in offline phase, we train a activity recognition model. The model can distinguish and recognize various acivities of stationary, walking, running, fall. Secondly, in online phase, the model classifies the user's daily activities and distinguishes the fall event.

3.1.1. Offline Training Model Phase

From Figure 2, it can be seen that different activities have different patterns. For example, the standard deviation of the amplitude of the running is larger than that of the walking. The frequency of the walking is larger than that of the running. Three features in time domain are extracted: Mean, Standard Deviation and Slope. Another two features are from frequency domain:Energy, Correlation.

[1]Wi-Fi Tracking Systems, RTLS and WLAN Site Survey:www.ekahau.com

[2]RTLS | Wi-Fi Location | Wi-Fi RTLS | Wi-Fi Based RTLS:www.ekahau.com

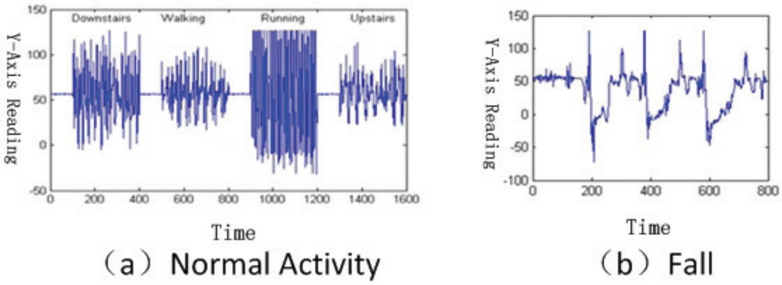

Fig. 2. Y-Axis Readings for Different Activities

The sampling frequency of our device is about 32 Hz. We collect 128 data for a sample. The sample covers 4 seconds which can sufficiently capture cycles in activity [12]. Features are extracted from the raw accelerometer data using a window size of 128 with 64 samples overlapping between consecutive windows. Feature extraction on windows with 50% overlap has demonstrated the feasibility in previous work [13]. Furthermore, a window size of 128 samples enabled fast computation of FFTs used for one of the features.

Let $RawData = \{(x_1, y_1, z_1), (x_2, y_2, z_2), \cdots, (x_n, y_n, z_n)\}$ denote the accelerometer data in a window. And Let $FrqData = \{(Fx_1, Fy_1, Fz_1), (Fx_2, Fy_2, Fz_2), \cdots, (Fx_n, Fy_n, Fz_n)\}$ denote the FFT of RawData. Then, the energy of X-axis can be calculated as following:

$Energy_x = \frac{\sum_{n=1}^{n} |Fx_i|^2}{n}$

The correlation between X-axis and Y-axis can be listed as following:

$Corr(x, y) = \frac{Cov(x,y)}{\sigma_x \sigma_y}$

Slope is used to calculate the largest distance between peaks in a window and can be defined as:

$slope = \sqrt{(x\_max - x\_min)^2 + (y\_max - y\_min)^2 + (z\_max - z\_min)^2}$

Where $x\_max = max(x_1, x_2, \cdots, x_n)$, $x\_min = min(x_1, x_2, \cdots, x_n)$. And y_max, y_min, z_max, z_min can be computed as x_max, x_min.

With these features, we collect a lot of samples for activities such as stationary, walking, running and fall. Based on information theory, we train a decision tree model which we call DTree model, as shown in Figure 3.

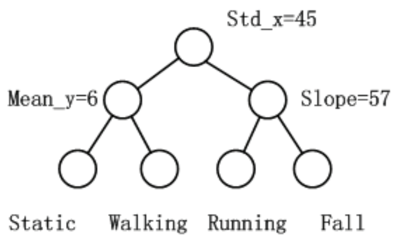

Fig. 3. The Fall Detecting Model

3.1.2. Online Activity Recognition Phase

When applying DTree model on the smart phone to recognize various kinds of activities, the system collects 128 data and features are extracted from them. All features are organized to be a sample. The sample is processed as the input data of DTree model. The output data is the activity type. If the activity is stationary, walking or running, the system will ignore it and collect the next 128 data. If the activity is a fall, the system will start a timer. At the same time, a confirmation dialog will be displayed. If the user does not hurt hardly, he can cancel the dialog. If he hurts too heavily to move a little, after ten seconds, the system will regard the current activity as a true-fall. Then the system will go to the positioning module.

3.2. Positioning Module

FallAlarm adopts the prevalent fingerprint method to estimate location. It contains two phases: an offline training phase and an online localization phase. In offline training phase, the system tabulates the signal strength received from access points at selected locations, to form a so-called radio map. In online localization phase, the location server uses the signal strength signature reported by the mobile device to estimate the user's location through matching the pattern within the radio map.

3.2.1. the Positioning System Based on Wi-Fi Signals

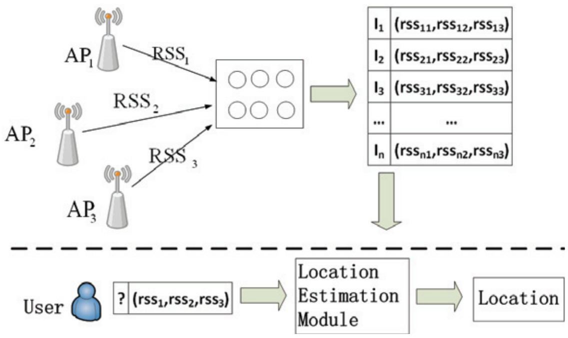

Fig. 4. The Positioning System Based on Wi-Fi Signals

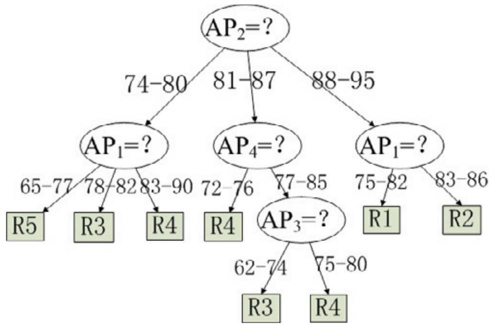

Fig. 5. The Decision Tree Based Positioning Algorithm

As shown in Figure 4, our FallAlarm system can only be used in a Wi-Fi signal coverage environment. In offline phase, on the marked spots whose location are known, we use the smart phone to collect RSSIs(RSSI, Received Signal Strength Indiction) from the surrounding APs(AP, Access Point). Then all the RSSIs are organized in a radio map. According to the radio map, we can train a decision tree model to predict the location. In online phase, FallAlarm can collect the RSSIs from APs, processes them with the position estimation model and returns the location.

3.2.2. The Decision Tree Based Positioning Algorithm

In offline phase, on each marked spot, we may collect RSSIs from surrounding APs. On every two spots, the APs set they collect may be different. In other words, each AP has different affect on different spots. The information entropy theory [14] is used to select APs which can distinguish spots maximally. Then the signals from all the spots are organized to the same format, $\{location, < AP_1, RSSI_1 >, < AP_2, RSSI_2 >, \cdots, < AP_n, RSSI_n >\}$. If the AP can not be detected on one spot, then corresponding RSSI is set to -100 which means that the signal is too weak to detect.

On the formatted radio map, we trained a decision tree model as shown in Figure 5. $AP_1 \sim AP_4$ are the selected APs. $R_1 \sim R_5$ are the marked Rooms. Now, a user collects the following signal, $\{< AP_1, 85 >, < AP_2, 83 >, < AP_3, 75 >, < AP_4, 80 >\}$. After the top-down process on the decision tree, we can predict that the user is near the R_4 room.

3.3. Sending Message Module

While the location is predicted, FallAlarm sends a short message including the user's name, time, location, to the user's guardians whose phone number has been stored in the system.

4. Experiment

4.1. Experiment Setup

Our experimental test-bed is deployed in the third floor of a 6-storey academic building. The dimension of this experiment site is approximately 16m by 29m, covering a hallway and five rooms. Figure 6 gives a whole layout of the test-bed. We deploy 7 APs among this area to build up an IEEE 802.11b wireless network infrastructure. These APs are denoted by red triangles in Fig 6. We have 10 participants and use Nokia N95 mobile phone to collect accelerometer and Wi-Fi signal.

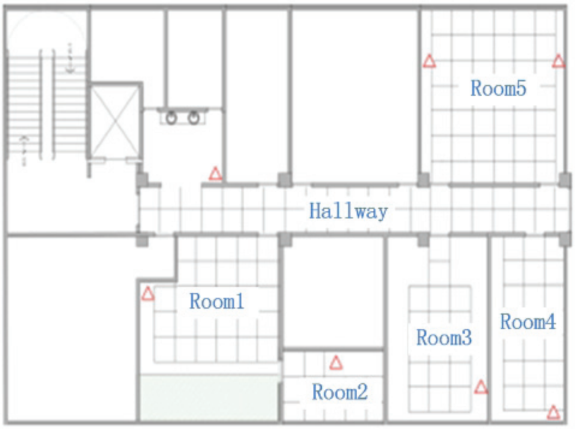

Fig. 6. The Layout of Experiment Test-bed

4.2. Data Collection

4.2.1. Collecting Activity Data alone

We have collected accelerometer data for normal activities and falls. Normal activities include stationary, walking, running. The activities were performed by ten participants. An efficient data collection application running on Nokia N95 was used.

These ten participants were divided into five groups and there are two participants in one group, without loss of generality, we call the two participants as A and B. Participant A worn the N95 on the waist with the z-axis facing the waist and performed activities to collect accelerometer data. He performed every activity for at least 5 minutes and performed forward falls, backward falls, left falls, right falls each for 10 times. Participant B recorded the start and end time of every activity. All the collected data were saved on the N95 and were uploaded to the server when all the data were completely collected. Then on the server, after feature extracting, we got our samples and they are listed in Table 1.

Table 1. Activity Samples Information

Activity	Labels	Number of Samples
Stationary	1	5200
Walking	2	3270
Running	3	2450
Falls	4	400

4.2.2. Collecting RSSIs Data alone

In order to build the radio map used in location estimation algorithms, we marked the middle of the room as one location. We develop data collection software running on smart phone to collect signal data for offline training stage. When collecting training data, participant A stood in the middle of each room, run the software. Participant B recorded the room number, the start time and the end time. On each location, 100 samples were collected. Later all these information are uploaded to the server. There are total 500 samples to construct the radio map and each sample has the same format which is:$\{room\_no, < AP_1, RSSI_1 >, < AP_2, RSSI_2 >, \cdots, < AP_n, RSSI_n >\}$.

4.3. Performance

4.3.1. Activity Recognition Performance

We compared several classifiers, namely C4.5 Decision Trees(DT), Naive Bayes(NB) and the Support Vector Machine(SVM). For each testing, we randomly divided the dataset into two parts. One 50% for training set, the other 50% for testing set. The average accuracy of each classifier is listed in Table 2.

Table 2. Fall Recognition Performance

	Precision	Recall
DT	100%	75.8%
SVM	99.81%	75.43%
NB	98.67%	73.20%

Precision and recall are then defined as:

$$Precision = \frac{Predicted\_True\_Falls}{All\_True\_Falls}$$

$$Recall = \frac{Predicted\_True\_Falls}{Predicted\_True\_Falls + Missclassified\_Falls}$$

As we can see from Table 2, DT is found to achieve high detection accuracy .

To analyse the reason why some samples are misclassified, we list a confusion matrix of the result in Table 3.

Table 3. Activity Confusion Matrix

	Stationary	Walking	Running	Fall
Stationary	2600	0	0	0
Walking	0	1635	0	0
Running	0	0	1161	64
Fall	0	0	0	200

As can be seen from Table 3, the falls are all recognized. But some samples of running are misclassified as fall. It can be seen from Figure 3 that running and fall are distinguished by attribute ‘Slope’. When the running activity is a little violent, it can show the features of fall.

4.3.2. Positioning Performance

To evaluate the performance of the location estimation algorithms, we randomly choose 50 samples each locations as the training data and the rest of them as the testing data. We repeat this process 10 times and get an average result, 98.4%. The average confusion matrix is list as Table 4.

Table 4. Positioning Confusion Matrix

	Room1	Room2	Room3	Room4	Room5
Room1	50	0	0	0	0
Room2	0	50	0	0	0
Room3	0	0	50	0	0
Room4	0	0	0	50	0
Room5	0	0	4	0	46

It can be seen that room5 are misclassified to room3. As illustrated in Figure 5 and Figure 6, their doors are face to face and they are distinguished by attribute ‘AP1’. Affected by the action of opening or closing the door, the signal can be changed and some samples can be misclassified.

5. Conclusion and Future Work

In this paper, we propose a novel location-based application, location-based fall detection service, which has great potential in health care field. We present a prototype system to provide a guideline to design real application system. A practical system called FallAlarm is also designed and implemented in the Wi-Fi environment. We describe the system architecture and state how its different components work together. FallAlarm achieves 98.4% recognition accuracy.

In the future, we are interested in the following topics:

(1)To improve the activity recognition accuracy, we will research on the information fusion of various sensors, such as accelerometer, gyroscope, vibration, voice, barometer, temperature and infrared lights etc.

(2)If the elderly people might fall in a new location, how to quickly find them? When the new APs are not in the radio map, we will employ the GSM signal to induce a coarse-grained location, such as the locations of the base stations around the falling location.

6. Acknowledgment

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