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Next Generation Mobile E-commerce based on Opportunistic Context Sensing

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Abstract

Mobile e-commerce is becoming an important component of the second economic tide. With the popularity of various types of sensors on mobile terminals, mobile phones can provide a variety of services in e-commerce, such as shopping sites and product positioning, navigation, products information recommendation, etc. However, the current information infrastructure in the indoor environment has not become pervasive, and hence, phone service cannot guarantee the continuity of time and space. In this paper, based on the multi-mode signal inputs on mobile terminals, including GPS, WiFi module, Bluetooth module, GSM module, camera, accelerometer, gyroscope, and magnetometer memory, we propose a multi-level opportunistic sensing system, which can make maximum use of the information facilities and signals to provide navigation and recommendations with maximum space-time continuity. The experiment of a book perchasing process shows that the system is able to provide users with timely and personalized e-commerce services.

1. Introduction

Mobile e-commerce is the combination of the Internet, mobile communication technology, short-range communication technology, and other information processing technology, to provide users with various e-commerce activities at any time and place, such as online and offline trading, online payment, and other related services.

An important carrier of e-commerce is the smart phones. In recent year, smart phones have experienced rapid development. In china, the number of smart phones has reached 190 million, with the annual growth rate of 50%. The U.S. market research firm iSuppl expected that the smart phone shipments in 2015 can reach 1.03 billion, and surmount the feature phones. The smart phones integrate more and more sensors and functional modules, and its rapid development has brought new opportunities for mobile e-commerce activities. More than half smart phone users in China have been accustomed to do shopping and other business activities via mobile phones.

Also, due to the incompleteness of the information infrastructure (especially in indoor environment), mobile phone services are not consistent and continuous in time and space. For example, while moving from the outdoor to the indoor environment, GPS services are often interrupted. In indoor circumstances, the mobile terminals usually make use of WiFi, GSM or Bluetooth wireless signals for positioning, but these radio signals do not guarantee continuity at any time and space. For example, there are positioning blind spots in places such as corners, the basements, etc. What’s more, even when users reach the destination, it may require them to spend a considerable amount of time to filter the complex product information.

In this work, we propose an opportunity context-aware system, which can keep the continuity of mobile services in time and space. This system can seamlessly perceive the indoor and outdoor environment, based solely on users’ personal mobile terminals, to provide precise recommendation. For experiment, we choose the scenario of book purchasing. In the experiment, the system can provide seamless positioning and navigation, and based on the individual's social context and behavioral context, provide recommendations for books, food and beverage. The system senses the environment from three aspects: location context, social context and behavioral context. Location context allows the system to navigate. The information of user’s social context and behavior context allows the system to recommend more targeted products. For example, if the user is carrying children while shopping, the system will recommend books, toys or diet for children. The information of user’s behavior context can determine whether the user is currently in fast-paced activities, and in the recommendation of dining, the system can recommend nearby fast-food locations correspondingly.

The three layer of context-awareness are shown in Table 1:

Table 1.The layers and contents of context-awareness

Layer	Context	Service	Sensor
Layer 1	Location context	Positioning, navigation, reach destination	GPS, GSM, WiFi, accelerometer, gyroscope
Layer 2	Social context	Provide more targeted products	Bluetooth，camera
Layer 3	Behavior context	Provide more targeted products	Acceleration sensor, gyroscope

Next, we will first describe the context-aware techniques for the three layers of context-awareness. Then, we will discuss the benefits of this system through a specific user shopping process.

2. Seamless Indoor and Outdoor Positioning and Navigation in Business Activities

In general, personal mobile e-commerce activities relates to both indoor and outdoor scenarios. In recent years, the indoor and outdoor positioning and location-based services, which can provide personal information query and navigation, has become an important direction of the development of pervasive computing technology [1].

Kesh Bakhru et al. [2] proposed a positioning mechanism, which is based on GPS and Inertial Measurement Unit (IMU). In their system, micro-electromechanical machines can provide indoor positioning using IMU with weak indoor signals. Mike Emery et al. proposed in [3] an indoor and outdoor positioning mechanism in WLAN using the Received Signal Strength Indication (RSSI). Based on the signal propagation attenuation model, the system can establish a map of the location and signal strength. The system calculates the current location by contrasting the real-time signal strength with the stored map of location and signal strength, to achieve real-time positioning. K. Krishna Naik et al. [4] proposed positioning mechanisms in wireless LAN based on IEEE 802.11. They proposed four frameworks: the source - purpose framework, the client - server framework, the sniffing framework, and the access point framework. B.D.S.Lakmali et al [5] proposed a positioning mechanism based on GSM signal and fingerprint identification method, which obtained a 95% accuracy rate in the range of 276 m in urban outdoor environment, in the range of 626 m in suburban outdoor environment; in the range of 700 m in rural outdoor environment; and in the range of 17.3 m in indoor environment.

The above mentioned outdoor positioning methods, have the property of high-precision, high stability, high coverage range and mature applications. Positioning method based on Bluetooth has high accuracy in indoor environment. However, the effective distance of Bluetooth is generally around10m, which is too small. The positioning method based on ultrasonic RF requires a large number of hardware devices to be emplaced in the location area, which is too much overhead and is not suitable for large-scale applications. Relatively speaking, the positioning method based WiFi has longer effective distance and the wide deployment of WiFi can highly reduce hardware overhead. However, current WiFi based positioning method requires a lot of calibration work and cannot be widely applied.

In this paper, we propose to use GPS-based positioning method in the indoor environment, and apply adaptive method. During indoor and outdoor environment switching, we propose to use satellite signals for seamlessly and automatic switching.

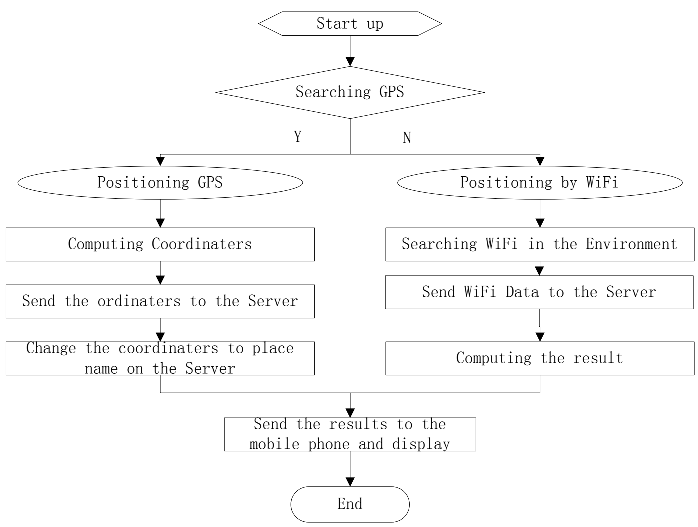

Figure 1. Flow diagram for indoor and outdoor seamless positioning

In outdoor environment, GPS positioning module can get the latitude and longitude information of the current location. In indoor environment, we adopt WiFi positioning method based on fingerprint information [6,7,8]. The positioning process consists of two phases: the offline phase and online phase. The calibration is done in offline phase, which calibrate the required region and establish the table of corresponding relation between location and signal strength. In online phase, the system search WiFi signals in the current environment, and contrast the signals with the table of location and signal strength mapping, to obtain the positioning result.

Meanwhile, the system also provides functions based on mobile communication base stations (GSM) positioning, accelerometer, gyro inertial navigation, in case the former described positioning method cannot provide timely navigation. Inertial navigation method is mainly based on the accelerometer and gyroscope, to distinguish between the different behavioral contexts of users [9], which are realized by particle filter method. Figure 2 below are the data collected by the accelerometers and gyroscopes in the process of climbing downstairs.

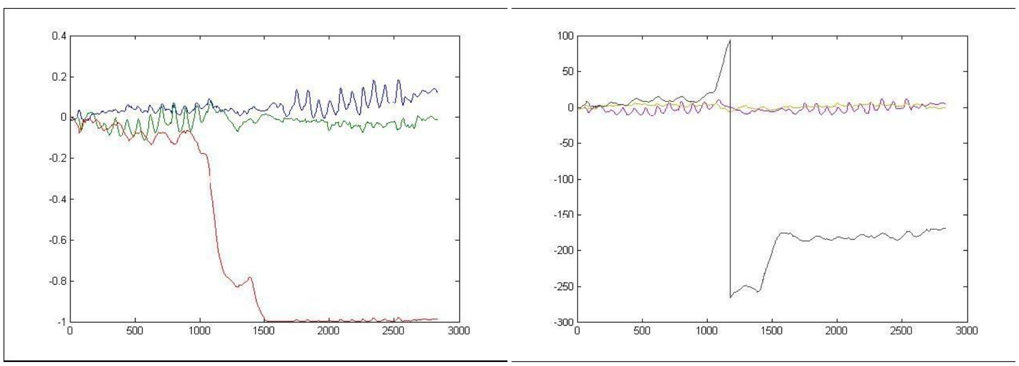

Figure 2. Data collected by the accelerometers (left) and gyroscopes (right) in the process of climbing downstairs.

Figure 3 is the travel path calculated using the particle filter method in the turning process. The finer polyline in the figure indicates the actual movement of the object process; the other polyline is the tracking results of the particle filter algorithm. It can be observed that the particle filter can effectively achieve the object tracking in stair area. The blue thick line in the bellowing figure shows that the particle filter can effectively control the accumulation of errors. The particle filtering algorithm can achieve an average error of less than 0.5m in behavior recognition.

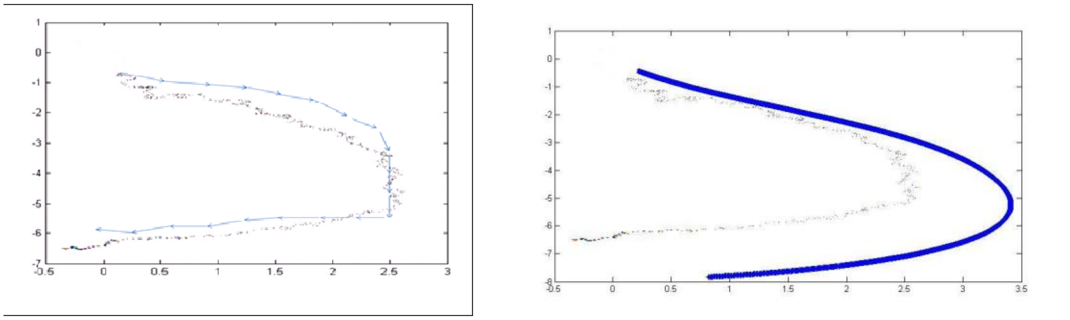

Figure 3. Particle filter tracking results, left arrow indicates the real trajectory. The blue thick line on the right indicates the direct result of acceleration and angle, and the other line is the calculation results of the particle filter algorithm

3. Social Context Sensing in Business Activities

Social context sensing is to judge whether the user is shopping alone or in group. If the user is shopping in group, then further judge the user is shopping with friends or family (including children). In this paper, we adopt the Bluetooth sensor in the mobile terminals for social context sensing.

The first key research in adopting Bluetooth on mobile platforms to infer social context is the MIT Reality Mining project [10]. This project demonstrated the effectiveness of using mobile phones with standard Bluetooth module, to obtain large context information and infer user's behavior patterns and life patterns. Some researchers study the life patterns based on the data collected by Reality Mining project [11]. These researches adopted Bluetooth as the proximity sensors to determine the number of people in the surroundings, and treated this as a property of life pattern.

Other works mainly focused on measuring the interactive relationships with other detected Bluetooth devices. Wireless Rope [12] made use of the information collected by Bluetooth module in mobile phones to analyze the familiarity between different users. They also showed that the high dynamic changes in states between acquaintance and strangers are closely related to the social activities.

In this work, we abstracted some new dynamic properties of Bluetooth. The definition of variables is given in Table 2:

Table 2. The definition of variables

N	The number of Bluetooth devices appeared in each sampling period
Ns	The fixed number of Bluetooth devices in each time slot
Nm	The number of mobile Bluetooth devices in each time slot
Nall	The number of different Bluetooth devices in each time slot Nall = Ns + Nm
Nnew	Compared to the last sampling period, the number of newly appeared Bluetooth devices

In this paper, each time slot is defined as t, which consists of w sampling periods. In each timeslot, the system will extract the value of different properties and classify the contexts. Each time slot t is the smallest processing unit, and each time slot corresponds to one context type. There are six Bluetooth properties, which are divided into the following four categories:

(1) The number of Bluetooth devices

In each time slot t, the number of Bluetooth devices (Nall) reflects the density of Bluetooth devices in the environment. In most cases, the device density has direct relationship with the density of people in the environment.

(2) The ratio of fixed devices

As mentioned before, we divide the Bluetooth devices into fixed devices (desktops, laptops, etc.) and mobile devices (mobile phone, PDA, tablet, and earphones, etc.) In each time slot t, the fixed device ratio Rs is defined as:

$$R_s = \frac{N_s}{N_{all}} \quad \textbf{(1)}$$

In door environment, there are often many fixed devices. Hence, the ratio of fixed device is very effective in differentiating the indoor scenario with other scenarios.

(3) The changing rate of Bluetooth devices

We define a the changing rate of devices C in the sampling period as Nnew/N. In time slot t, the mean value of changing rate (from the second sampling period forward) is defined as:

$$\overline{C} = \frac{1}{w-1}\sum_{i}^{w-1} C_i \quad \textbf{(2)}$$

The standard deviation is:

$$\sigma_c = \sqrt{\frac{1}{w-1}\sum_{i}^{w-1}(C_i - \overline{C})^2} \quad \textbf{(3)}$$

The changing rate of Bluetooth devices reflects the flow of Bluetooth devices.

(4) The continuity of Bluetooth devices

In each timeslot, the times of each device appeared in w sampling periods is defined as the continuous time D (0≤D≤w). The continuity threshold is Dmin (Dmin≤ w). For device j, if Dj≥Dmin, then j is defined as a continuous device. The number of continuous device is represented by Nd. In this paper, the continuity of Bluetooth devices is reflected by the mean and ratio of continuous devices. The mean is defined as the average of continuous time of all the devices in the time slot:

$$\overline{D} = \frac{1}{N_{all}}\sum_{j}^{N_{all}} D_j \quad \textbf{(4)}$$

The ratio of continuous devices:

$$R_d = \frac{N_d}{N_{all}} \quad \textbf{(5)}$$

The continuity of Bluetooth devices can reflect whether the user is in a static or dynamic state. The changing rate and continuity of Bluetooth devices together reflect the local dynamic information in this time slot.

The experiment results showed that the above mentioned properties and C4.5 decision tree model together can achieve a good classification of whether users are alone or in a group [13].

Table 3. Comparison of different methods in classifying user single/ group behavior

Context	Episode	Acc/WiFi/GPS	Bluetooth
Meeting	Meeting	√	√
	Talking	×	√
Walking	Alone	√	√
	Group	×	√
Dining	Alone	√	√
	Group	×	√
Taking Subway	Alone	√	√
	Group	×	√
Go Shopping	Alone	√	√
	Fri./sep.	×	√
Watching Movies	Alone	√	√
	Group	×	√

Besides, we also adopt multimode (camera, accelerometer and MIC, etc.) recognition model [14], to recognize the identities of other people in the group and determine their relationships with the user (friends or family).

4. The Behavior Context Sensing in Business Activities

The behavior context sensing focuses on the detection of users' current behavior patterns and properties through the sensors on the mobile terminals. Existing literatures have discussed about the behavior recognition based on accelerometer signals [15], which can record the acceleration values when users perform different actions. Also, it showed that among various classification method, decision tree performs best, achieving the accuracy rate of 84%. In [16], an algorithm irrelevant to the direction of accelerometer was proposed. By mapping the three axis signals to diagonal and horizontal direction, the users do not need to worry about the direction of mobile phones, which widely expands the application domain of behavior recognition algorithm.

The existing works mainly focused on how to find a universal recognition model. We propose a self-adaptive recognition method AdaMar (Adaptive Motion Activity Recognition) [17] based on model migration. This method first train a universal behavior recognition model based on the behavior data of a small number of people. When new users use this universal model, the proposed method will self-adapt the model based on new user data and the previous universal model, which can gradually form the personalized model with high recognition accuracy. We use mobile phone to collect the data of accelerometer. The testers perform the following actions in sequence: stand, sit, stand, walk, stand, jog, stand, climb upstairs, stand, climb downstairs, stand, in upgoing elevator, stand, in downgoing elevator, stand, etc. Each action continues at least 5 minutes. In the experiment, it has been observed that sit, stand, in upgoing elevator and in downgoing elevator do not have acceleration change, and hence different to classify. We classify all of them in the static category. In this way, the actions can be classified into static, climbing downstairs, walking, jogging and climbing upstairs.

The migration of universal model and its self-adaptation process are shown in Figure 4.

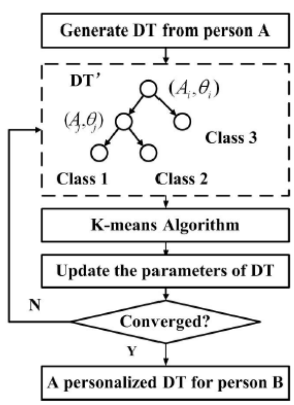

Figure 4. The migration of universal model and its self-adaptation process

The universal recognition model adopt C4.5 decision tree model. Starting from the center determined by the recognition model, continuously adapt till the square error reaches minimum value. The experiment showed that before adaption, the average recognition accuracy is 67.31% and after adaptation, the average recognition accuracy reaches 83.54%.

5. The Experiment

In this experiment, we take the example of Xiaohua perchasing a book and observe the benefits of using the proposed system.

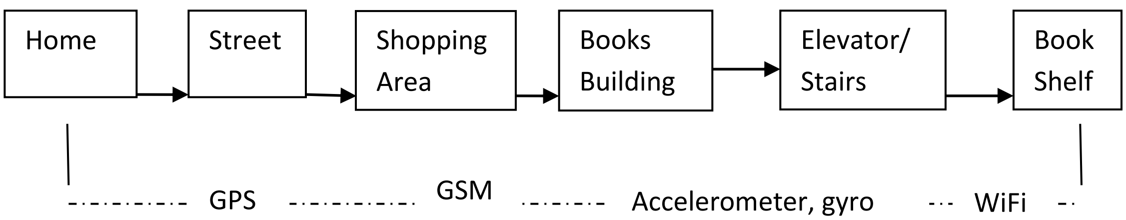

Figure 5.The process of buying book and the navigation service provided by the mobile

The whole process is shown in Figure 5.

Positioning and Navigation: first, from home to street to shopping area, Xiaohua can make use of traditional GPS navigation to the destination. However, in shopping area, the density of buildings is very high and GPS signal is weak. At this time, the system will automatically switch to GSM mobile base station positioning and navigation mode and direct Xiaohua to the Books building.

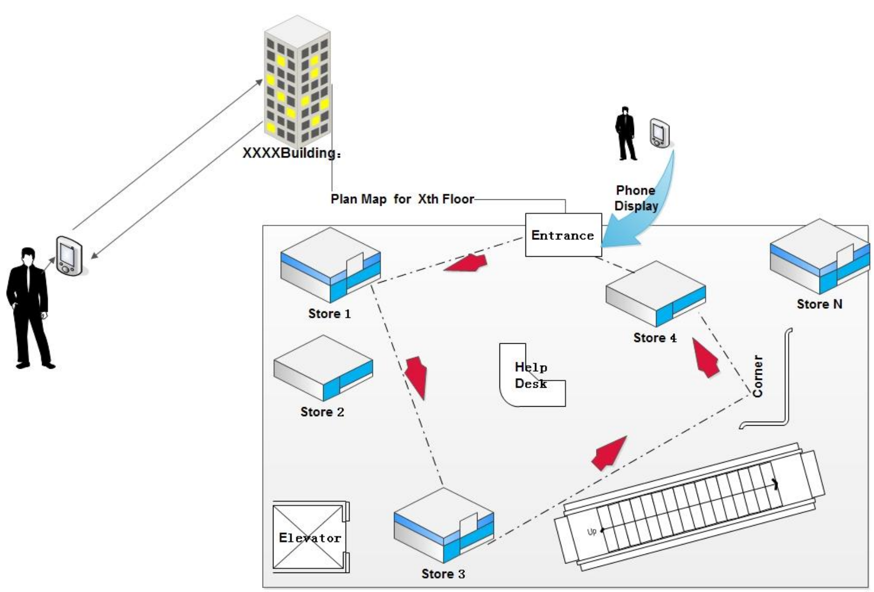

Figure 6. The positioning and navigation system based on the fusion of multiple sensors

Product recommendation based on social context sensing: for product recommendation, the system first judges the social context of the user. If the user is single, the system will automatically recommend books suitable for adults. If the user also takes children, then recommend books for children, as shown in Figure 7.

Figure 7(a) Interface for book list display Figure 7(b) Interface for book list selection

Store recommendation based on behavior context sensing: the user search restaurant in the noon. The system monitors user's previous behavior patterns. If the user is in a fast tempo, then recommend some fast food restaurant. Otherwise, if the user is in a slow tempo, recommend the food types which is favored by the users.

6. Conclusion

Mobile terminal devices have integrated various sensors. With the help of intelligent software techniques such as pattern recognition and data mining, it is possible to infer the user's context information in individual mobile business activities and provide users with continuous service in time and space. This paper took the process of buying books as example and discussed a system to provide users with seamless navigation service, recommend books based on whether user is single or taking children, and recommend different restaurant based on user's tempo. These functions can improve the effectiveness of users in mobile business activities.

7. References

[1]. Xiaolin Wang, Xiao Pang, Yingwei Luo. LBS-p: A LBS Platform SupportingOnline Map Services.Vehicular Technology Conference Fall (VTC 2010-Fall): 1~5, 2010

[2]. Kesh Bakhru.A Seamless Tracking Solution for Indoor and Outdoor Position Location.IEEE 16th International Symposium onPersonal, Indoor and Mobile Radio Communications (PIMRC 2005): 2029~2033,2005

[3]. Mike Emery, Mieso K. Denko.IEEE 802.11 WLAN based Real-time LocationTracking in Indoor and Outdoor Environments. Canadian Conference onElectrical and Computer Engineering (CCECE 2007): 1062~1065, 2007

[4]. K. KRISHNA NAIK, Dr. M.N. GIRI PRASAD.A System for Locating Users of WLAN using Statistical Mapping in Indoor and Outdoor Environment-LOIDS.Fourth International Conference onWireless Communication and Sensor Networks (WCSN 2008):111~115, 2008

[5]. B.D.S.Lakmali, Dileeka. Dias.Database Correlation for GSM Location in Outdoor & Indoor Environments.4th International Conference onInformation and Automation for Sustainability (ICIAFS 2008): 42~47, 2008

[6]. Hua Yang, Junfa Liu, Yiqiang Chen, Zhao Mi, 011 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 21-23 September 2011, Guimarães, Portugal.

[7]. Junfa Liu, Yiqiang Chen, Yadong Zhang, Transfer Regression Model for 3D location Estimation. MMM 2010, Chongqing, China, 2010.

[8]. Mi Zhao, Hua Yang, Junfa Liu, Yiqiang Chen, Jingye Zhou, Directional Wi-Fi Based Indoor Location System for emergency， IEEE UIC 2001, Xi An, China 2010-10-26.

[9]. O. Woodman. An introduction to inertial navigation. Technical Report 696, University of Cambridge, 2007.

[10]. Nathan Eagle, Alex Pentland. Reality mining: sensing complex social systems, Personal and Ubiquitous Computing, Springer-Verlag London, 10(4):255~268, 2006.

[11]. K. Farrahi and D. Gatica-Perez. “Learning and Predicting Multimodal Daily Life Patterns from Cell Phones,” In ICMI-MLMI ’09, pages 277–280. ACM, 2009.

[12]. E. Paulos and E. Goodman. The familiar stranger: Anxiety, comfort, and play in public places. In Proc. CHI’04, pages 223-230. ACM, 2004

[13]. Zhenyu chen, Yiqiang Chen, Junfa Liu: Surrounding Context and Episode Awareness using Dynamic Bluetooth Data , Ubicomp 2012, USA.

[14]. Qiong Ning, Yiqiang Chen, Junfa Liu, Huiguo Zhang, Heterogeneous multimodal sensors based activity recognition system. 2011 IEEE International Conference on Multimedia and Expo(ICME), July 11-15, 2011. Barcelona, Spain.

[15]. L.Bao and S.S Intille. Activity recognition from user annotated acceleration data. In Proceceedings of the 2nd International Conference on Pervasive Computing, pages 1-17,2004.

[16]. Jie Y, Xiaoyong Chai,and Qiang Y. High-level goal recognition in a wireless lan.p578-584. AAAI,2004.

[17]. Zhongtang Zhao, Yiqiang Chen, Junfa Liu, Zhiqi Shen, Mingjie Liu: Cross-People Mobile-Phone Based Activity Recognition. IJCAI 2011: 2545-2550.

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