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Incident Detection Based on Mobile Crowd Sensing for Smart City

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Abstract. In recent years, mobile devices have taken a significant role in improving the quality of people's life. In order to enhance the usability of those devices, more and more sensors have been built in. Furthermore, the data storage and data processing capacity are becoming larger and larger. To capture more information about the city conditions and make full use of the computing resource, mobile crowd sensing has been proposed. Incident detection is an important component of the safety monitoring system, however, existing incident detection methods are mostly based on computer vision which is vulnerability to environmental impacts. This paper proposes an automatic incident detection model based on Mobile Crowd Sensing to deal with the problem above. The incident detection algorithm in the model is based on the human activity recognition and the crowd density. The simulation results show that this model is feasible and effective.

Keywords: human activity recognition, incident detection, mobile crowd sensing, smart city

1 Introduction

With the development of sensor technology and Internet, together with the increasing data storage and data processing capacity, a mass of data about individuals and environment can be captured, transmitted, stored and processed to extract potential information. According to the statistical data from International Data Corporation (IDC) in 2011, the total data all over the world surpassed 1ZB in 2010 and will reach 35ZB by 2020 [1]. Study on rational utilization of those data without disclosing the private secret information provide a way to automatic resources management and harmonious lives especially in cities. It has been confirmed that more than half population in the world lives in cities which is still increasing [2]. Cities are more prosperous with some difficulties caused by the growing population, such as traffic

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congestions, public resources acquisition, precision navigation and timely detection of incident, Smart City [3] emerge as the times require. Smart city is more likely a result of fully utilizing the existing infrastructures and sensors together with the data captured in and around the city, in which urban residents know more about the real state of the city and are much easier to attain the expected purpose legitimately.

Although massive sensors include optical sensors and acoustic sensors have been installed around cities, it will no longer satisfy urban residents' precision requirements in the future. The number of new sensors required for urban expansion is the square of the city radius. Furthermore, most of sensors are fixed in traditional sensor networks and such factors as weather, light intensity and environmental noise directly affect the accuracy of the data. As the major components and the main service subjects in urban, acquiring data from residents separately is a possible solution.

Mobile crowd sensing (MCS) is based on the portable electronic products which is extremely popular, such as smartphones and wearable devices [4]. Utilizing the built-in sensors on those devices, both environment and personal information can be acquired. For instance, integrated temperature and humidity sensor can monitor the air conditions while the accelerometer and gyroscope monitoring the human activities. Due to the human involvement model, there are great differences between MCS and traditional sensor networks. MCS has two sensing paradigms, one is that the participants decide the way and content called participatory sensing, the other is that data are acquired in the background called opportunistic sensing [5]. Since data are acquired from urban residents that can move around the city, privacy preserving and participants' movement should be taken into account in practical application.

This paper focuses on opportunistic sensing to detect the incidents in the public activity spaces. In the study of human activity recognition context, high-precision activity recognition has been implemented utilizing data acquired by sensors built-in smartphone. In this paper, an automatic incident detection model has been proposed based on human activity recognition and crowd density. The result shows that the model is feasible and effective.

The rest of the paper is organized as follows. In Section 2 we present the related work in mobile crowd sensing and incident detection; Section 3 provides the incident detection model; Section 4 concerns the experiments to evaluate the reliability and validity of the model in this paper; finally, Section 5 discusses the future work and draws some conclusion.

2 Related Work

A decade ago, researchers started to utilize the cellphones and the other portable devices carried by people to capture data, called people-centric sensing [6]. Some applications have been built on this sensing model, such as the CenceMe [7] that users share their personal data (e.g., activity, disposition, habits) with friends via the CenceMe Web portal, the Global Sharing in Virtual Worlds [8] that users bring their real-world sensing presence to active subjects in the virtual world, the BikeNet [9] that merge multiple users' individual data to find the safest and healthiest ways to get around town. With the development of relevant technology, new human involvement sensing models that have stronger real-time processing capacity (e.g., MCS) have been proposed. Several privacy preserving techniques have been developed in the sensing models, for instance, adding data perturbation before data upload [10], utilizing data clustering to hide personal information [11], and building new architecture for stream privacy [12]. User's quality of information has been taken into account to design incentive mechanisms that achieves close-to-optimal social welfare in [13]. Furthermore, some MCS applications have been designed to build smart city, such as City Discovery and Mapping [14] and Bus Arrival Time Predicting [15].

With the increasing of the data that need to be transmitted, the network will become more and more congested. In order to eliminate the superfluous information and the unnecessary energy consumption caused by the network congestion, different models have been proposed. Zhang et al. [16] presented a mechanism based on information fusion, which consist of different fusion algorithms that can be used to reduce redundant information in multi-levels. The mechanism is a trade-off between information fidelity and energy consumption based on users' requirements. In view of the condition that the participants are moving around the city, the fusion centers that are located around the city working together can reduce the waste of resource. As proposed in [17], a hierarchical resource management method based on cooperative fog computing provides low-delay coordination services for Internet of Vehicles applications with lower energy consumption and packet dropping rate.

In wearable sensors human activity recognition studies, the majority of data processing is focused on feature extraction. Different strategies and algorithms have been proposed to extract appropriate features with which high recognition accuracy can be observed. He and Jin [18] presented a autoregressive model with SVM classifier that the average recognition results is 92.25%; Khan et al. [19] proposed a hierarchical scheme used linear discriminant analysis and ANNs to recognize human activity that the average recognition results is 97.9%; Tao et al. [20] classified 10 different activities with an ensemble manifold rank preserving algorithm that the average recognition results is around 80%; Ronao and Cho [21] used deep learning neural networks to recognize human activity, achieving an average recognition results around 95%. Other researches have proved that the recognition results of ambulation activities did not have significant gain when the accelerometer sampling rate exceeded 20Hz [22].

Incident detection has become a task of high interest in the last four decades [23], especially for traffic and medical. Many algorithms have been proposed to classify the abnormal events with the normalcy based on computer vision [24] or data processing [25]. The algorithms based on computer vision is vulnerability to environmental impacts while the existing algorithms based on data processing directing at individuals. In this paper, we aim to give an adaptive model based on the human activity recognition results and to detect incident happened in the public activity spaces.

3 Automatic Incident Detection Model

In this section, the proposed model is illustrated. Firstly, several basic hypotheses are given to help understanding the model. Secondly, the essential incident detection model is introduced. At last, the main processing to detect the incident events has been presented.

3.1 Basic Hypotheses

Hypothesis 1. The incident events that we take into account are divided into two classes. One is that something interesting has happened (e.g., street performance), therefore the participants huddled; the other is that something terrible has happened (e.g., traffic accident), the participants scattered.

Hypothesis 2. Participants' activities that we take into account in this paper are divided into three classes, walking, running and standing. Participants usually walk in the public activity spaces, but will change into other activities with a preset probability that concluded from the statistic data.

Hypothesis 3. Incident events happened in the public activity spaces that has enough participants. Participants are randomly distributed in the spaces and are able to move freely.

3.2 Essential Incident Detection Model

As shown in Fig. 1, the essential incident detection model contains 4 major components.

Mobile sensing. This module consists of many sensors built-in smartphones and wearable devices. Various data about environment and individuals such as picture, sound, temperature and acceleration, location, even the social network data are captured and waiting for selective uploading. Parts of data can be set in opportunistic sensing paradigm to be collected opportunistically without the involvement of participants.

Local data processing. In order to meet the real-time requirements of the task, we add a local data processing center for each public activity space. Furthermore, it can be a valuator to evaluate the selective uploaded data. Moreover, necessary preprocesses should be done locally to protect privacy information and reduce transmission costs. The cooperation of local data processing centers can also provide better services with less waste of resources.

Data storage and transmission. Requisite data can be stored in local data processing center and the data fusion center, for instance, the personal reliability information can be utilized to evaluate the quality of the selective uploaded data. Useful data may be stored in the fusion center for other researches after the anonymous processing. Data are collected from personal Internet communicators to the corresponding local data processing center and from local data processing centers to the data fusion center.

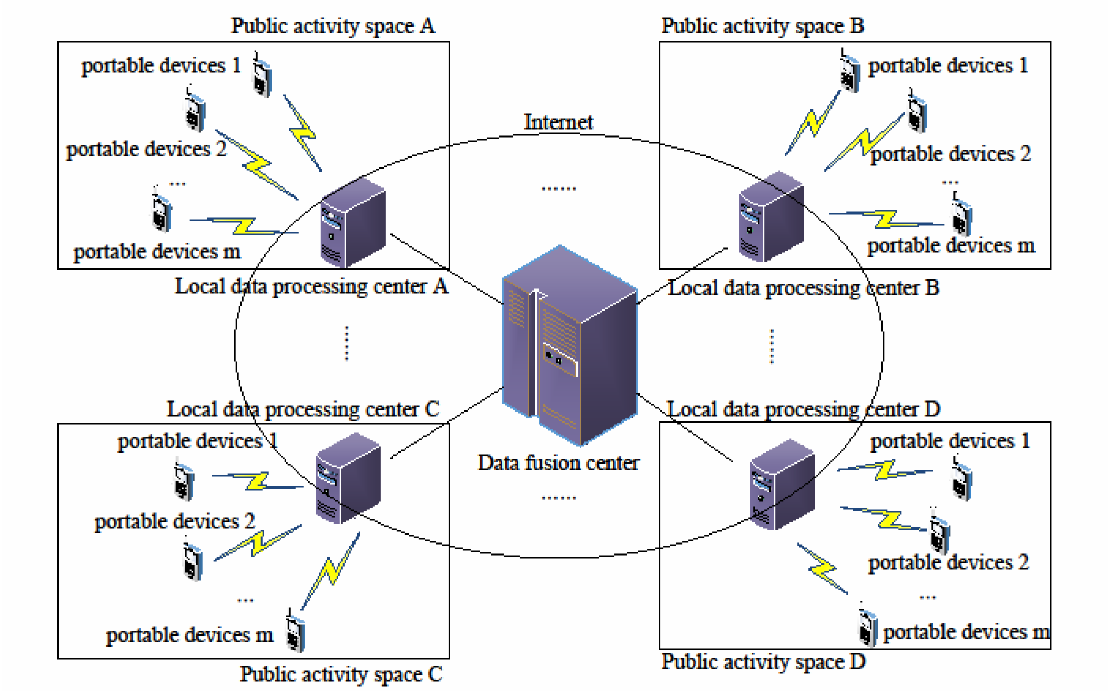

Fig. 1. The essential incident detection model

Data fusion and publishing. Data fusion center collect data from all the city and draw some conclusions about the real-time statuses of the city, for example, the traffic condition and the noise distribution. The conclusions and parts of statistical data will be published online after the anonymous processing.

This model is a universal model based on Fog Computing. It can be used to provide multiple services at the same time. The data captured by mobile sensing devices can be utilized in more than one tasks. Data transmission between portable devices and local data processing center is wireless while data transmitted through lineate network between local data processing center and data fusion center.

3.3 Main Process of Incident Detection

The most important feature of this model is that the participants is moving in the city. Participants can change their motion states such as the direction and the velocity as they want. As a result, the crowd density is always changed over time. In this paper, we propose an incident detection algorithm based on the change of participants' activities and the crowd density.

As mentioned in the related work, walking, running and standing can be distinguished by the existing human activity recognition methods with a high accuracy (nearly 100%). Utilizing the result of human activity recognition methods can diminish the influence of the phenomenon that people have their own comfortable speeds.

In this paper, we preset the threshold of the running or standing proportion X to detect the incident events and the threshold of crowd density variation to verify the incident events. The main process is described below.

Main Process

Incident detection algorithm
Input: The activities recognition results of all participants;
The total number of participants N;
The location data of all participants;
The threshold of the running or standing proportion X;
The threshold of crowd density variation Y.
Output: The incident detection results.
1. Count up the number of running or standing participants S;
2. Compare S/N with the proportion X, if S/N isn't small than X, go to 3; else go to 1.
3. Find out all the running or standing participants in the map, set an aggregation to envelop almost all the selected participants, the outliers are Discarded.
4. Compare the relative change of crowd density with the Y, if it isn't small than Y, go to 5; else go to 1.
5. The incident event happened around the center of the aggregation.

The data fusion center will calculate the thresholds based on the statistical data and the thresholds are changing over time. Then the thresholds are sent to the local data processing centers. Once the local data processing centers detected that the proportion of running or standing participants is larger than the corresponding threshold, the incident may happened. To further confirm the results, the relative change ratio of crowd density should be calculated. In order to reduce the calculation and improve the efficiency, the location data of running or standing participants are utilized to narrow the scope of the incident event. Since the incident event is the origin of the regular change, the place where the event happens is in the smallest region contains the most running or standing participants.

3.4 Crowd Density Variation Detection

The ultimate goal of incident detection is to find the precise location of the events. Before we seek the accurate location, it will be helpful to find out the approximate range. There are two different situations caused by the position of the events. One is that the location data of the running or standing participants can aggregate into an enclosed area, the accurate location of the events is in the enclosed area; the other is that the location data of the running or standing participants can only aggregate into an semi-enclosed area because of that the accurate location is extremely closed to the edge, the semi-enclosed area can be transformed into an enclosed area with the help of the edge, the accurate location of the events is in the convex enclosed area.

Then we can utilize the crowd density variation to detect the precise location of the events. Although the precise location of the events can be easy to find with the crowd density at last, the relative change of crowd density is a more effective method to find the location earlier than the crowd density.

In this paper, we divide the enclosed area into several square patches. As shown in Fig. 2, the width of the patch is d, the number of participants in patch i is N_i^t, t represents the time when the number is collected. The crowd density of each patch D_i^t can be written as

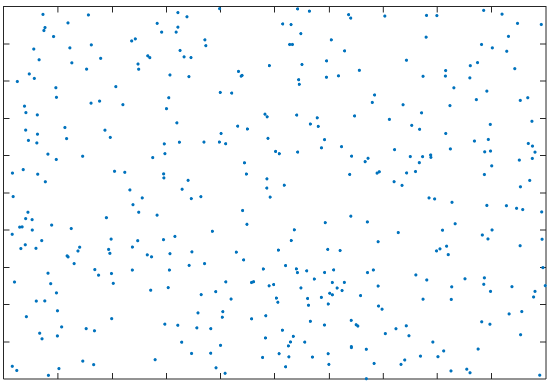

Fig. 2. Dividing the enclosed area into patches

$$D_i^t = \frac{N_i^t}{d^2}. \quad (1)$$

The value of crowd density depends on the size of each square patch, if the parameter d is too large, the crowd density is difficult to represent the movement of people; else if the parameter d is too small, the crowd density is sensitive and will bring in unnecessary noise. The relative change of crowd density R_i^t can be written as

$$R_i^t = \frac{D_i^{t+1} - D_i^t}{D_i^t} = \frac{N_i^{t+1} - N_i^t}{N_i^t}. \quad (2)$$

Based on all the values of R_i^t, we can calculate the gradient of the relative change of crowd density. Since the influence of the events is mainly related with the distance, the gradient direction of the relative change of crowd density points towards the location of the events. As mentioned before, the structure of R_i^t is very close to the digital images. Taking into account the effect of the distance between nearby R_i^t, we use the sobel operator to calculate the gradient G_i^t can be written as

$$G_i^t = \sqrt{(G_{i\,x}^t)^2 + (G_{i\,y}^t)^2}, \qquad \alpha = \arctan\left(\frac{G_{i\,y}^t}{G_{i\,x}^t}\right), \tag{3}$$

where $G_{i\,x}^t$ is the component on x-axis and $G_{i\,y}^t$ is the component on y-axis. A is the matrix of R_i^t. They can be written as

$$G_{i\,x}^t = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * A, \qquad G_{i\,y}^t = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} * A. \tag{4}$$

The two 3x3 matrixes in equation 4 are the corresponding component of sobel operator on x-axis and y-axis.

4 Experiment and Simulation

In this paper, we used an Intel Core *RR* I5-7300HQ 2.5GHz CPU, 8GB RAM, Win 7 *RR* professional operating system and Mathworks Matlab R2016a *RR* to perform the simulations. We assume that 400 participants evenly distribute in 200x200 m^2. The two types of incident events are tested 100 times to evaluate the reliability of the model.

4.1 Crowd Incidents

Crowd incidents happened when the participants huddled. In the area affected by the crowd incident events, the participants that is close to the location of the events will change their activities from walking to standing while the participants that is far away from the location of the events changing their activities from walking to running. We assume that the participants far away from the location of the events partial attracted by the events. The probability that the participants attracted by the events is set to 70%. The dynamic change of the participants affected by the event is shown in Fig. 3 and the figure of crowd incidents detection is shown in Fig. 4.

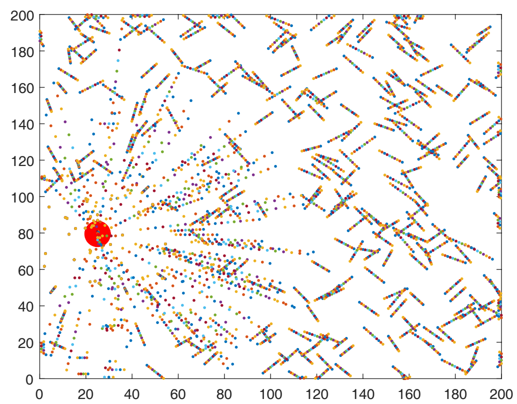

Fig. 3. Dynamic changes affected by crowd incident

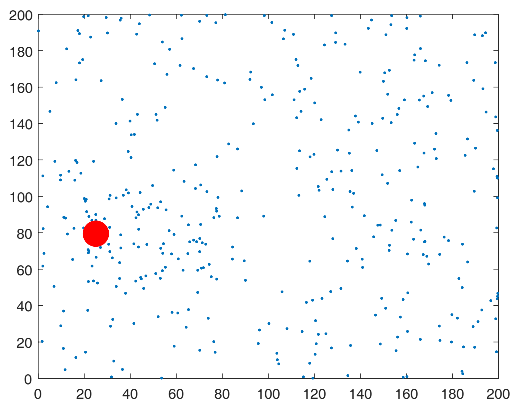

Fig. 4. Crowd incidents detection

As shown in Fig. 3 and Fig. 4, the size of the simulation area is (200 length units) x (200 length units), there are 400 points in the area that represent the 400 participants. Those points under different colors in Fig. 3 represent the actual locations of participants at different times, each color corresponds to a moment. It reveals the dynamic changes of participants' locations affected by crowd incident in 10 time units. Most of points closed to the location of the incident are being attracted by the event while most of points far away from the location are moving in a random way. The other figure reveals the location of participants at the last moment in Fig. 3. The red point is the position detected by the method proposed above. It is closed to the precise location of the events in Fig. 3 that demonstrates the effectiveness of our algorithm to detect the crowd incident.

4.2 Scattered Incidents

Scattered incidents happened when the participants scattered. In the area affected by the scattered incident events, the participants that is close to the location of the events will change their activities from walking to running while the participants that is far away from the location of the events increasing their walking speeds. We assume that the scattered incidents is dangerous so all of the participants in the area affected by the events tend to stay away from the location of the events. The dynamic change of the participants affected by the event is shown in Fig. 5 and the figure of scattered incidents detection is shown in Fig. 6.

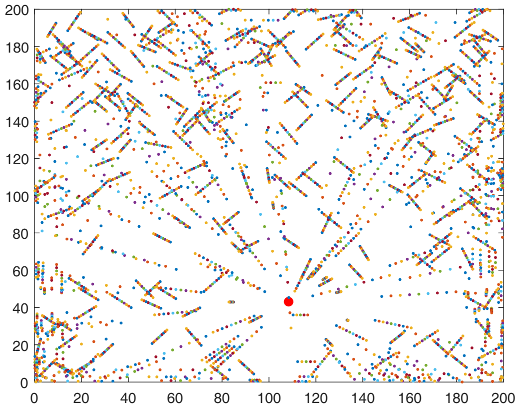

Fig. 5. Dynamic changes affected by scattered incident

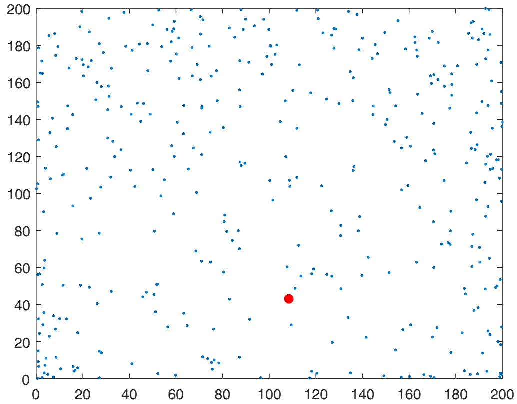

Fig. 6. Scattered incident detection

As shown in Fig. 5 and Fig. 6, the size of the simulation area is the same with the size in the crowd incidents detection, there are 400 points in the area that represent the 400 participants. Those points under different colors in Fig. 5 represent the actual locations of participants at different times, each color corresponds to a moment. It reveals the dynamic changes of participants' locations affected by scattered incident in 10 time units. Most of points closed to the location of the incident are getting away from the event while most of points far away from the location are moving in a random way. The other figure reveals the location of participants at the last moment in Fig. 5. The red point is the position detected by the method proposed above. It is closed to the precise location of the events in Fig. 5 that demonstrates the effectiveness of our algorithm to detect the scattered incident.

5 Conclusions

In this paper, we propose an incident detection model to supervise the condition of the public activity spaces based on Mobile Crowd Sensing and Fog Computing. In consideration of the human activities and the crowd density, an automatic incident detection algorithm is designed. The incident detection algorithm has been proved effectively to detect the two types of events. Future work includes the following: (1) finding the method to detected and distinguished events that have varying levels of influence; (2) improving the algorithm to detect many events that happen at the same time.

Acknowledgements

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