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Human Crowds Estimation based on Mobile Sensing
モバイルセンシングによる人流推定

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Abstract

In this paper, we propose a client-server system that provides crowd detection and mobility capture. Crowd detection is to detect and calculate the density of crowds within a specified area. Mobility capture is to track the direction of the people. The mobility information of human crowds has been widely used from urban design and traffic management to disaster evacuation and mobility prediction.

Currently, several common methods of capturing crowd mobility information have different performances in terms of accuracy, cost and scope of application. One of the main reasons for the difference is that the technology or equipment used to detect crowd flows are different.

Compared to common methods, such as cameras, our proposed system has the advantages of low cost and location flexibility. Our system can detect almost any area without pre-deployed, as long as there is a sufficient number of users involved. In this paper, we conducted several experiments in real environments to determine the feasibility, accuracy and applicable environment of the system. The result shows that with sufficient users participation and the Bluetooth devices turned on, the system can effectively grasp the flow of people in the experimental area. At the same time, under the same environment, it can obtain almost the same mobility tracking information with less equipment than the GPS method.

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Chapter 1
Introduction

A crowd is a deformable group of people occupying a particular area. We can obtain crowd information within a specified area, such as the number of people, the trend or speed of the crowd. Crowd analysis has a massive impact on several applications including surveillance and security, situation awareness, crowd management, public space design, etc. For example, the government can decide how to widen existing roads to alleviate traffic congestion based on the location of high-density populations. Besides, merchants can decide how to put the advertising labels that can attract the most customers according to the walking track of the crowd on the commercial street. In the real-time environment, if an early warning mechanism is added to the crowd detection system, once a high-density crowd in a certain area are detected, staff can immediately start evacuation work to avoid injury caused by crowding.

To achieve the crowd information, specific equipment and techniques are needed to assist. The common methods are cameras, GPS, Wi-Fi and Bluetooth. Because the equipment and methods used to collect the raw data are different, the above approaches will have different performance in terms of cost, accuracy, and the scope of application. In this paper, we propose a crowd mobility capture system based on Bluetooth. It does not need to deploy devices such as cameras or Radio Frequency Identification (RFID) tag in advance and only needs enough users to carry smartphones with Internet access, which can obtain the crowd information in a certain area. We conducted several experiments in the actual environment to verify the feasibility and accuracy by our proposed method, and whether the possibility of walking the trajectory can still be obtained with a small number of users participating.

The rest of the paper is organized as follows. Chapter 2 introduces the background and application scopes of crowd detection. Chapter 3 describes the related works by other researchers. Chapter 4 proposes the motivation for developing the system and gives details of the system structure and design. Chapter 5 shows the experiments that we conducted and the evaluation of the results. Chapter 6 is the conclusions.

Chapter 2

Background

2.1 Definition of Crowd Detection

Crowds can be seen in various public places, such as stations, concerts and shopping streets. Normally, the formation of crowds and the orderly movement of people are caused by certain reasons. When the trains arrive, people who get off the train go to the station exit. A store on a busy commercial street offers a great discount and attracts many passersby. When the concert is about to begin, the audience enters in an orderly manner. These are the reasons for arising crowds under normal circumstances. But in some extreme situations, such as a disaster, panic will lead the crowd will flock disorderly to adjacent areas. Lack of evacuation instructions can arise a sharp increase in the number of people in these areas. This can easily cause congestion and stampede after the disaster. Therefore, it is necessary to control the crowds in a controllable range to prevent crowding or even stamping. This leads to the need for crowd detection.

Crowd detection has various forms. Let the staff holds a counter to count passers-by in a certain area, or count people entering the surveillance video, which may be the original crowd detection. These methods, which almost relies on manpower without the help of any tools, will inevitably cause negative results such as large errors and waste of manpower. Today's crowd detection is more than just counting people in the area. Trends in the number of people, the moving direction and speed are also the key information obtained by crowd detection. These kinds of information can be captured with the help of cameras, mobility sensors or social platform information.

2.2 Application of Crowd Detection

The application areas of current crowd detection will be introduced as followed. As to which technologies and equipment are currently used in crowd detection, they will be introduced in the next chapter.

We name the data obtained from the crowds, such as the number of people, direction of movement, speed, etc., as context information. Based on whether the application field has real-time requirements on context information, we divide the application fields of crowd detection into two types. The former is focused on real-time, similar to the application scope of real-time changes in the number of people such as regional congestion monitoring. The latter is focused on the relevance and directiveness of the data, such as urban design.

2.2.1 Real-time Data Analysis

Real-time monitoring of crowd should be direct application area for crowd detection. Under normal circumstances, crowds appear and move in an orderly manner for some reason. However, once the number is too dense, the mass scale unexpected huge human crowd is a serious threat to public safety. An impressive tragedy is the 2014 Shanghai Stampede, where 36 people were killed in celebration of the New Year's Eve on December 31th 2014 in the Shanghai Bund[1]. This is a typical stampede accident caused by excessive crowd density. The serious result reveals the importance of crowd detection to prevent serious consequences from overcrowding.

Figure 2- 1 2014.12.31 Shanghai Bund Stampede

Due to the randomness and independence[2], it is not easy to predict what kind of crowd will potentially lead to crowd disasters. Therefore, more attention is paid to real-time monitoring. The crowd detection needs to capture the context information of the current monitoring area in a timely and accurate manner. If the safety threshold is exceeded in the area, staffs can be notified immediately to execute traffic control around the area and prevent further people increases to cause serious accidents.

2.2.2 Design Planning

In the application of design planning, crowd detection is responsible for providing reference data for the design. Compared to real-time, this application area pays priority to the relevance or indicative of the data. These data may be collected over a month or even a year. With the help of smartphones and pervasive computing, Basic crowd context information can be added with attribute data such as the male-female ratio and age level. These data of multiple attribute combinations are great value for regional research or urban planning[3]. For example, the government designs bus schedules with reference to passenger context information to maximize the use of buses and reduce traffic congestion and vehicle exhaust pollution. The cosmetics company refers to the place with the highest female occurrence ratio in the crowd context information and sets it as the best position for cosmetics advertising[4][5][6].

In the past, the collection of these data will require a lot of manpower to conduct field investigations. With the help of various automated crowd detection technologies, not only does it save a lot of manpower, but it is also possible to add specific attribute tags when collecting data for subsequent research to improve the accuracy and effectiveness of the data.

2.3 Summary

This chapter introduces what is crowd detection and its main application areas. It can monitor the crowd in a certain area in real-time, or collect flow information for reference in future urban development and design.

The rest of this paper will focus on aspects of real-time monitoring of people flow.

Chapter 3
Related Work

According to the different equipment and technologies, we can divide the current common crowd detection methods into three types. 1. Infrastructure-based methods, using public infrastructure equipment to collect crowd context information. 2. Mobile-based methods, obtaining pedestrian flow information from mobile devices of passersby in the surveillance area. 3. Social media network-based methods, mining the text information of people's social platforms in turn to get the crowd information. These methods have different performances in terms of cost, accuracy, and real-time due to different equipment and technologies. Therefore, each method has its best-fit scenario.

3.1 Infrastructure-based Methods

Cameras are one of the main devices for obtaining the raw data in the image data method. These cameras are usually Closed Circuit Television (CCTV) cameras that monitor roads or building security. Image processing and computer vision techniques can contribute a great deal in extracting instantaneous pedestrian flow state through examining CCTV footage.

The methods adopt a detection-style framework that scans a detector over two consecutive frames of a video sequence to estimate the number of pedestrians, based on boosting appearance and motion features[7][8]. In detection based crowd counting methods, people typically assume a crowd is composed of individual entities which can be detected by some given detectors[9].

Figure 3- 1 A result of the image detection

The limitation of such methods is that occlusion among people in a clustered environment or in a very dense crowd significantly affects the performance of the detector and the final estimation accuracy. In other words, the angle of the camera and the density the crowd will cause the image overlap, resulting in inaccurate results.

Among the latest research contributions in related fields, Due to the capability of deep learning networks[10], the overlapping problem is well resolved[11][12][13]. It can be said that the method combines CCTV cameras and image processing algorithms to obtain the crowd information in the video is a method with high accuracy and speed. But at the same time, this method has some significant limitations[14]. First, its effectiveness depends to a large extent on the quality of the captured images and lots of calculations, and the cost of installation and video processing is very high. Second, for such a system to work properly, a great deal of effort must be spent during preparation to install the cameras. This makes the method inflexible and immovable, and cannot cover all aspects due to the expensive and limited detectable range of the camera. Third, because the camera can record the appearance and behavior of people. This creates privacy issues. Many people are still resistant to cameras in public places

3.2 Mobile-based Methods

Nowadays, many people carry one or more mobile devices with them, such as mobile phones, wireless headsets, smartwatches, etc. These products have multiple mobile sensors or wireless communication chips. Cellular network chips and gyroscopes on smartphones and Bluetooth chips on wireless headsets, etc. These bring convenience to our modern life, meanwhile, can also actively or passively obtain crowd context information around the devices. The biggest difference from the infrastructure-based method is that the mobile-based method gets rid of the complex process of image recognition to obtain the crowd information, reflecting the crowd information in the area by the information on the mobile devices. Based on different methods of obtaining information, we can subdivide mobile-based methods into three methods: GPS-based, WiFi-based, and Bluetooth-based.

3.2.1 GPS-based

Because of the spread of smartphones, with map service applications and GPS on smartphones, we can easily get our location or route navigation information. In the stage of generating the navigation route, the smartphone sends its GPS location information to the map server. Then the server provides the best route from the user's current location to the destination. After that, during the navigation phase, the smartphone will periodically send GPS location information to the server to ensure that the user is on the best route or correct the route in time for a better one. Not only smartphones, other smart wearable devices, or health-care equipment send GPS location information to the server to obtain related services.

The server can obtain the spatiotemporal trajectory data of each device by combining the series of location information uploaded by the devices with the upload timestamp. Combined with analysis[15], this method is very efficient for pedestrian detection which has been applied to many aspects such as commuting choice, transportation management, commercial recommendation, urban planning, tourism service, criminal investigation etc[16].

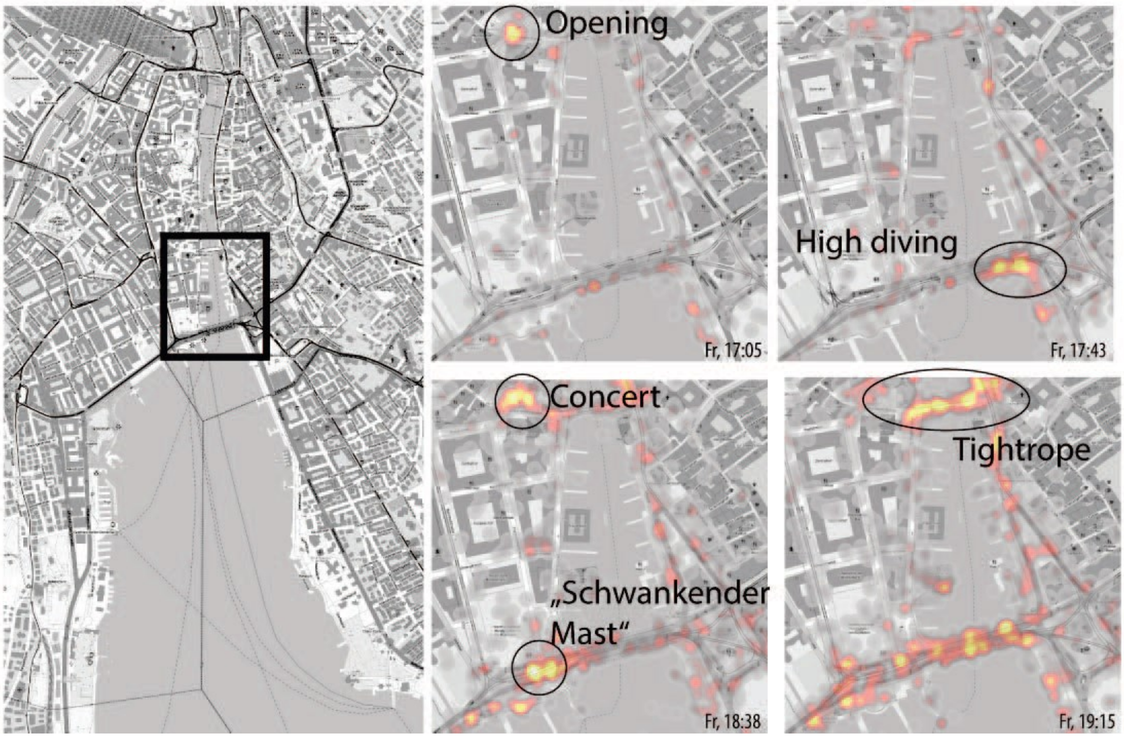

Figure 3- 2 Human density collected by GPS method

Compared with using fixed equipment to collect people flow data, the GPS method is more flexible. However, this method will be ineffective indoors, because the GPS signal will be blocked by the walls and roof of the buildings. At the same time, the long-term collection of personal device's location information will still cause privacy issues.

3.2.2 WiFi-based

WiFi-based methods usually refer to wireless access points (AP). It is a networking hardware device that allows other Wi-Fi devices to connect to a network.

The raw data for reflecting crowd situation is the information of each wireless device scanned by AP. Regardless of whether the wireless device is connected to ap, as long as a user turns on the WiFi function of the device, the device will periodically send data to its surrounding AP to confirm the WiFi state and other related information. If analyze the confirmation information collected by the AP, we can know the context information of the devices near that AP[17][18][19]. This is similar to the GPS-based method. However, WiFi-based method can be used indoors. The signal range of a commercial-grade AP is about 100 meters[20]. After deploying AP in the required area, it can collect context information of WiFi devices in that place.

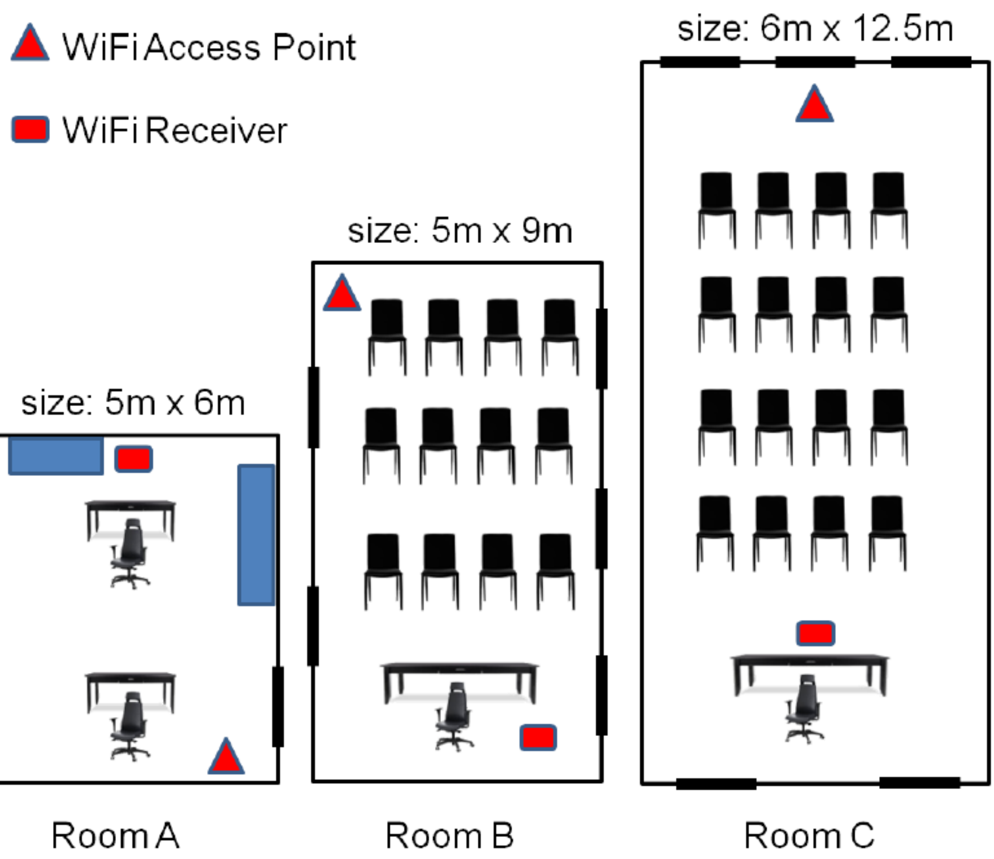

Figure 3- 3　WiFi method application environment case

AP does not have to be limited to fixed devices, but can also be smartphones[21]. However, WiFi scanning greatly reduces the battery life of smartphones, it cannot be truly mobile[22]. The WiFi method is still limited by the signal range of the AP device.

3.2.3 Bluetooth-based

Bluetooth is a wireless communication system designed for short-range communication[23]. The Bluetooth range of a smartphone is typically about ten to twenty meters. Almost a tenth of the WiFi signal transit distance. To create Bluetooth connections, an inquiry mode has been defined. Basically, a device which wants to initiate a Bluetooth connection with another device sends out an inquiry packet and other devices listening for them can answer. Most devices only react to such inquiry packets, when made visible by the user through a user interface dialog. The inquiry response frame contains the Bluetooth MAC identifier of the discovered device and can contain additional information including the local name of a device.

The inquiry mode of the Bluetooth device is switchable. This means that the Bluetooth method does not require an AP to do the data collection device like WiFi. After the mobile phone turns on the Bluetooth search mode, it can find the surrounding Bluetooth devices which are in inquiry mode. At the same time, it can also be discovered by other surrounding Bluetooth devices.

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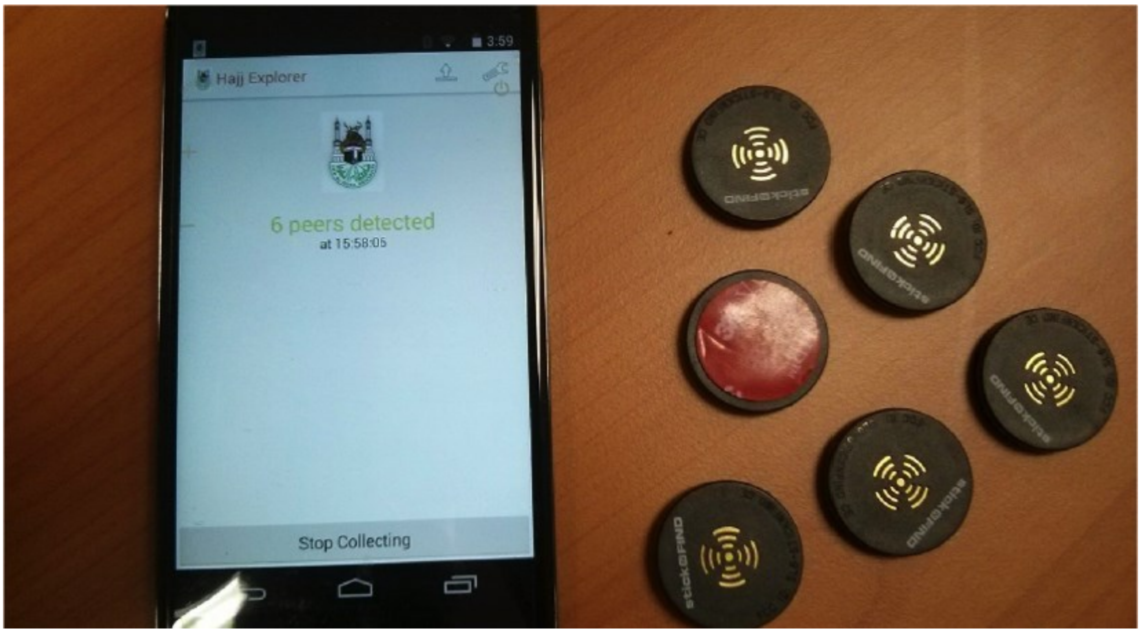


Figure 3- 4 Equipment required for Bluetooth-based methods

Bluetooth is very suitable for indoor localization instead of GPS[24][25][26]. Multiple Bluetooth beacons are placed in the wall to collect context information sent by Bluetooth devices. Although the Bluetooth signal range is very short, and its effectiveness is easily affected by the environment, due to its cheapness, multiple beacons can be placed redundantly in the environment, increasing accuracy[27][28]. Compared with WiFi methods, Bluetooth gives up certain accuracy to free from the restrict of APs, reducing costs and improving flexibility.

3.3 Social Media Network-based Methods

Social media such as Twitter and Facebook not only bring the convenience of information sharing in normal life but also play a very important role in disaster warning and post-disaster rescue.

On March 11th 2011, the north-east coast of Japan was struck by one of the strongest earthquakes in history. When the communication network was almost paralyzed after the disaster, social media provided a key communication platform for people in Japan send information including photos and live videos, rapidly spread across the world[29]. This valuable information not only helped the rescue teams to find the surviving victims on time but also provided valuable reference data for future reconstruction plans[30].

The difference between the social platform-based method and the previous methods is that the raw data comes from text or photos sending by people. The subjectivity of the user greatly affects the accuracy of the data[31]. When an emergency occurs, even if some users are in the event area, it is not guaranteed to share information on social media platforms at once. This is a challenge for the real-time respond of the method.

3.4 Comparison of related methods

We make a comparison of the crowd detection approaches mentioned above. This comparison is not to find out which method is the best but to understand the advantages and disadvantages of each method and the scope of application.

🟢 Good
🟡 Acceptable
🔴 Not Good

Table 3- 1 Comparison of data collection methods

Method	**Cost**	**Privacy**	**Extra Devices**	**Flexibility**	**Precision**
Video	🔴	🔴	Yes	🔴	🟢
GPS	🟡	🟡	No	🟡	🟢
WiFi	🟡	🟡	Yes	🔴	🟡
Bluetooth	🟢	🟡	No	🟢	🟡
Social Media Network	🟢	🔴	No	🟢	🔴

In addition to CCTV, image data methods include light detection and ranging (LiDAR), infrared imaging, etc. These methods are different in the equipment for collecting raw data, and the rest of the analysis process is similar. Finding the crowd area from the image data and converting it into crowd information is a feature of this method. Image recognition technology and equipment that can capture high-resolution images to make the method highly accurate. But this method relies on the image collecting equipment, so the method is costly. At the same time, the method will have occlusion, insufficient light, inflexibility, etc. So it is more suitable for the government to monitor traffic flow and safety, etc.

In the non-image data methods, the GPS-based method has been published by many map service companies. When using the map service applications, the user can get the crowd information from the server, at the same time, his phone as a participating sensor uploads information. This method does not require complicated image information conversion process. However, the GPS signal cannot reach indoors, therefore, it cannot be applied to every place.

By analyzing the change of the WiFi signal between multiple APs or analyzing the WiFi connection data collected by the AP, we can know the flow of people in that area. This method needs to deploy an AP which is suitable for indoor detection.

A Bluetooth method is similar to a device-based method of WiFi. There is no need for additional devices like APs, just make sure that the proportion of people carrying Bluetooth in the crowd is enough. Although the effective range of Bluetooth is very short, its low cost and wide usage make this method be applied to almost anywhere. But the premise is that there are enough people who are willing to turn on the Bluetooth.

Using text, photos, and other information from the social media platform to analyze and predict the crowd in a place is more cost-effective than a device-based approach. if the information is sufficient, any area can be monitored by this method. But because it is human input information. Credibility and real-time are greatly affected.

3.5 Summary

This chapter introduces several common methods of crowd detection. In addition, compare them in several factors such as cost, real-time, accuracy and flexibility that usually need to be considered.

Chapter 4

Proposal of the Human Crowds Information System

4.1 Motivation

For existing methods, there are several common problems.

1. Cost issue
2. Real-time problem
3. Limited application range

In this paper, we propose a client-server system that provides users with real-time crowd information such as population density and trajectory in an area.

Our system is designed based on the following three points.

1. No additional devices are other than users' smartphones and the server.
2. The users' devices are also sensors that provide surrounding crowd context information.

Our goal is to achieve a low-cost crowd detection system that is not limited by the location of the equipment installation, which means that the system can detect crowd information in almost any location without the need to install the detection equipment in advance.

4.2 Design of the System Structure

According to statistics, in 2018, Bluetooth device shipments have reached 3.9 billion, of which smartphones, tablets and other mobile devices have reached 2.05 billion[23]. This proves that Bluetooth is everywhere in people's lives. Bluetooth has two main communication protocol technologies, Basic Rate/Enhanced Data Rate (BR/EDR) and Bluetooth Low Energy (BLE). Due to the low power consumption of BLE and the official announcement that 97% of Bluetooth chips will contain BLE mode in 2022, we decided to use Bluetooth scan as the method of crowd detection, Because of the low cost, the number of users increases dramatically that almost everyone has a Bluetooth device, flexible and can be used almost anywhere.

We define the following roles to make our system easier to understand.

1. The user: After the users installed our application on their smartphones, they can check the crowd information in their area through the application. At the same time, their smartphones become crowd sensors, sending the crowd information surrounding them to our server through the network at regular intervals. The rest of this paper will use the user to refer to the people with smartphones installed our application.

2. The Bluetooth device: Bluetooth devices are the devices detected by the smartphones through Bluetooth scanning. It could be any Bluetooth device that can be discovered, such as mobile phones, watches, headphones, etc.

3. The server: The server is the computer we set to provide the crowd information for the smartphones. After processing the information sent by the smartphone, the server sends the result back the smartphone, such as people crowd's density, mobility and location.

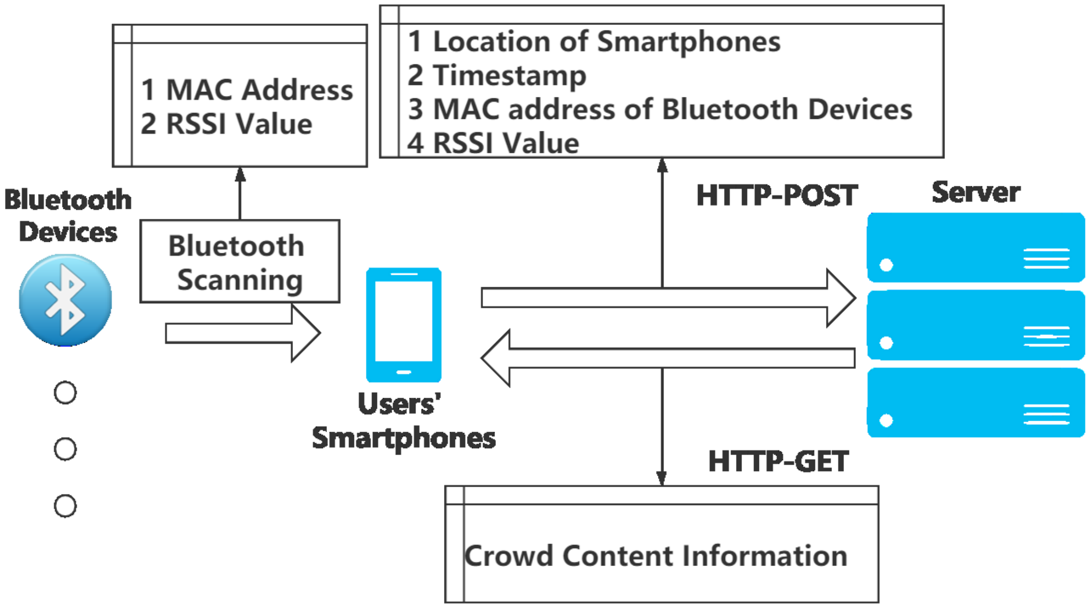


Figure 4- 1 Structure of the system

When the application of smartphone starts working, it will scan the surrounding Bluetooth devices in BLE mode, then users upload the device information to the server at regular intervals. The context information includes the timestamp, the location of the smartphone, and the Received Signal Strength Indicator (RSSI) value and the Media Access Control (MAC) Address of the scanned Bluetooth devices. The server stores the con context tent information collected from each smartphone in three tables: 'user', 'bluetooth_scanevent', and 'bluetooth_device'. After processing, the server sends the crowd information to each smartphone, and the application displays to the user in three graphical modes: real-time mode, heat map mode and direction mode.

RSSI value: It is a measurement of the power present in a received radio signal. In this paper, it stands for the strength of the Bluetooth devices' signal scanned by users' smartphones. RSSI can be used to approximate distance between the scanned Bluetooth device and the smartphone. If we have the location of users' smartphones and the RSSI value of the Bluetooth devices scanned by the users, we can get the approximate location of the Bluetooth devices[32].

MAC address: A MAC address of a device is a unique identifier assigned to a network interface controller (NIC). For communications within a network segment, it is used as a network address for most IEEE 802 network technologies, including Ethernet, WiFi, and Bluetooth. Like the license plate, in theory, every Bluetooth device has a unique MAC address. Therefore, we can use it to distinguish different Bluetooth devices. We can estimate the number of people in that area by the number of Bluetooth devices. Or we can predict the trend of the crowd through the change in the number of Bluetooth devices[33].

Location: Through measurement, we know that in an environment with a large population, the Bluetooth signal from a general mobile device can transmit no more than 20 meters. The main purpose of this paper is to grasp the general mobility information of the crowd, rather than precise positioning. This level of error is still acceptable. We will define the location of the Bluetooth device scanned by the smartphone as the location of the smartphone. In other words, we mainly use the location data of the smartphone to determine the location of the Bluetooth device. Use the GPS location information of the smartphone directly in the outdoor situation, and use the WiFi fingerprint positioning method in the indoor situation[34].

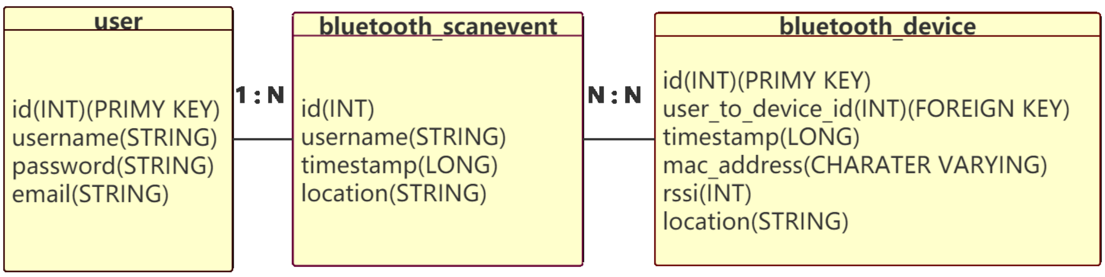


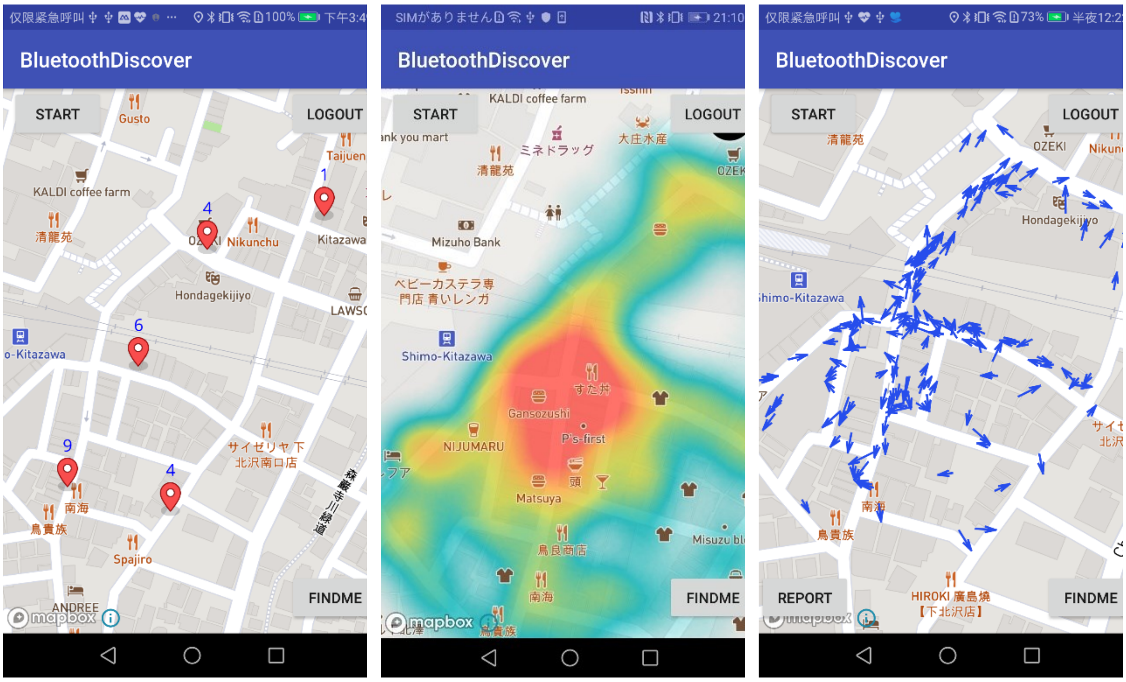
Figure 4- 2 Entity relationship diagram of the collected data

Table ‘user’: This table records user information. Each row includes the user's name, password and other common information during registration.

Table ‘bluetooth_scanevent’: This table records all events of Bluetooth scanning. Each row means a certain user (username) performed a Bluetooth scan and upload the context information at a certain time (timestamp) and a certain place (location).

Table ‘bluetooth_device’: This table corresponds to table ‘bluetooth_scanevent’, recording what data is obtained from each Bluetooth scanning. Each row means a certain user (username) finds a certain Bluetooth device (MAC address) in a certain Bluetooth scan event (user_to_device_id and timestamp) with detail information (RSSI value and location).

Each user is unique, but each user performs more than one Bluetooth scan. So table ‘user’ and table ‘bluetooth_scanevent’ have a one-to-many relationship. The same Bluetooth device may be discovered in multiple Bluetooth scan events, and one Bluetooth scan event may find multiple Bluetooth devices. table ‘bluetooth_scanevent’ and table ‘bluetooth_device’ have a many-to-many relationship.



(a) Real-time **(b)Heatmap** **(c) Direction**

Figure 4- 3 Three visualization modes

After collecting the crowd information from each user, we need to further analyze the data on the server to provide useful information for the users. Each piece of data is stored by the format including the timestamp, MAC address, geographic location and RSSI value. The specific meaning is that at a certain moment, a certain location, a Bluetooth device with a certain mac address is found. In order to make it the easiest and most intuitive way for users to get information about the crowd in the area, we decided to use counting number, the heat map and direction arrows to display the data analyzed by the server[35].

ALGORITHM: Real-time mode

Input: Query Range *QR*

Output: Array of location points *locationArray*

1: Search for Bluetooth devices *bd* in *QR* in the last 10 seconds

2: **For** each *bd* in *QR*:

Sort by *timestamp, RSSI* **desc**
Remove *bd* with duplicate MAC address
Put the location of all rest *bd* into *locationArray*
Return *locationArray*

Heat map: A heat map is a graphical representation of data where the individual values contained in a matrix are represented as colors. We define a ten meter long, ten-meter wide area as a grid point, and such multiple grid points form a grid map. By counting different MAC addresses in the same grid point at one time window, the number of the Bluetooth devices appearing in the grid point area can be obtained. Finally, using color gradients to represent the different densities of the number of people.

ALGORITHM: Heatmap mode

Input: Query Range *QR*
Output: Array of location rectangle *rectArray* with frequency value *fv*
Search for Bluetooth devices bd in *QR* in the last 10 minutes
Divide the last 10 minutes into each 1 minute
Divide *QR* into squares sq_n with 50 meters long and 50 meters wide
For each 1minute in 10 minutes:
    If *bd* appeared in one of sq_n
        $counter_{sqi}$++
Sum and **Average** 10 $counter_{sqi}$ for each sq_i, which is *fv*
Return Array of location squares sq_n with *fv*

Direction arrow: The direction arrow can intuitively display a certain mobile node's displacement information including the starting position, ending position and moving direction. The MAC address is used to distinguish between different Bluetooth devices. If one MAC address is captured at different time points, we can get the movement track of the device[36].

ALGORITHM: Direction mode

Input: Query Range *QR*

Output: Array containing the start and end of each arrow

Search for Bluetooth devices *bd* in *QR* in the last 10 minutes *T*

Divide *T* into 3 group // t_1: 0~2 min, t_2: 4~6 min, t_3: 8~10 min

For each Bluetooth devices *bd* in each t_n: // t_n includes t_1, t_2, t_3

    Use the earliest location as the starting point *sp*

    // sp_1 in t_1, sp_2 in t_2, sp_3 in t_3

    Use the latest location as the end point *ep*

    // ep_1 in t_1, ep_2 in t_2, ep_3 in t_3

Put each pair of *sp* and *ep* points into an array *arrowArray*

// Every *bd* has at least one set of points and at most three sets

Return *arrowArray*

4.3 Summary

This chapter proposes a method based on the Bluetooth scan of users' smartphones to realize the collection and sharing of crowd information, Aiming at the problems of common crowd detection methods, high cost, inflexibility, etc. The structure and data storage format of the client and server are introduced in detail. And showed the three interface modes on the smartphone application, including explaining the algorithms of the three modes.

Chapter 5

Experiment and Evaluation

5.1 Effective Range Experiment

The Bluetooth signal strength is reflected by the RSSI value, which is a negative number. The closer the value is to zero, the closer the distance to the Bluetooth device.

The RSSI value can be converted to the distance value by the following equation.

$$RSSI = -\ (10n\log_{10}d + A) \qquad (5\text{- }1)$$

A is the RSSI value when the equipment is 1 meter apart from the receiver.

n is the signal transmission constant, and it is relevant to signal transmission environment.

d is the distance we want to know.

5.1.1 Experiment Environment Setup

First, we need to confirm the actual sending range of Bluetooth devices which often be used in our daily lives. We conducted experiments both indoors and outdoors. We set a smartphone and a Bluetooth headset as the sender separately. We took every 5 meters from 0 m to 30 m as a test point. At each point, we measured the RSSI value.

5.1.2 Results and Analysis

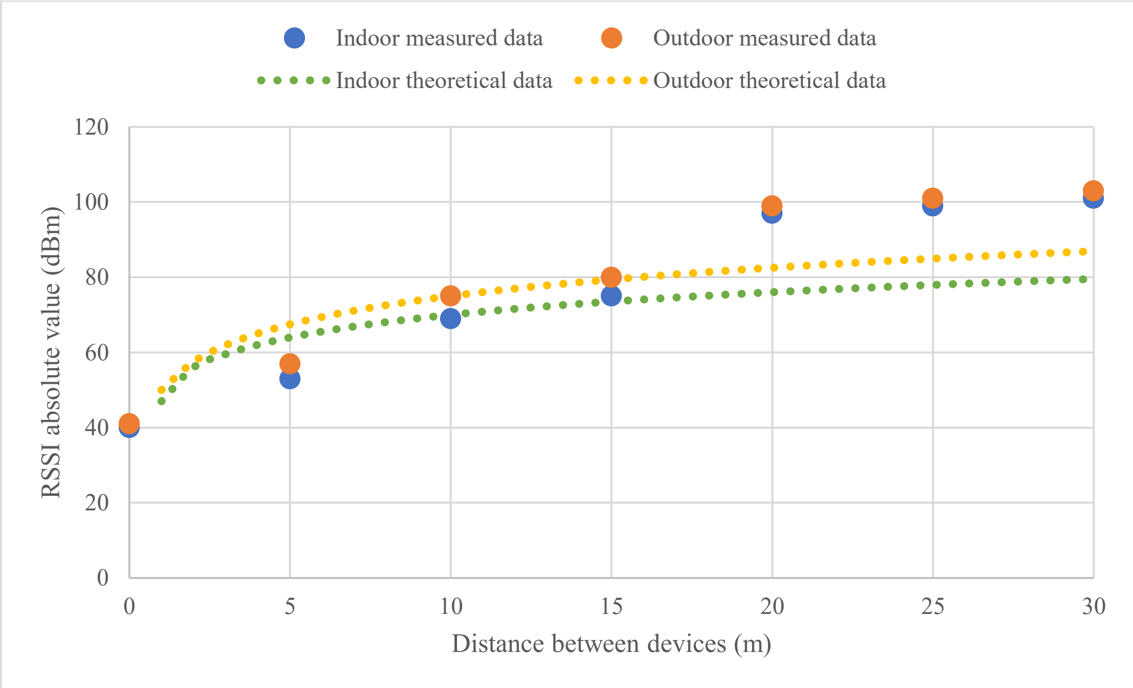


Figure 5- 1 Result of Range Test

Multiple RSSI data sets were collected at each test point and averaged. As shown in Figure 5- 1, the blue point set represents the RSSI value of indoor testing, and the orange point set represents the RSSI value of outdoor testing. The dashed green line is the results from (5- 1) with the parameters of the indoor, and the dashed yellow line is the results from (5- 1) with the parameters of the outdoor. According to the results, we can conclude that although the Bluetooth signal can still be detected at around 30 meters, it is difficult to distinguish the distance of Bluetooth devices through the RSSI value when it is more than 20 meters. And the measured RSSI value collected more than 20 meters away has already deviated greatly from (5- 1). Therefore, in the following experiments, we set the software acceptable threshold to -75 dBm in an indoor environment and -80 dBm in an outdoor environment. In other words, the farthest Bluetooth device that the mobile phone can detect is 15 meters.

5.2 Feasibility Experiment on Single Device

Many non-image analysis-based crowd detection methods reflect the flow information by detecting mobile devices. For example, the number of devices connected to the WiFi AP can reflect the density of people around that AP. In this paper, the detected Bluetooth device information is the raw data that reflects the crowd context information in the system proposed in this article.

5.2.1 Experiment Environment Setup

In order to verify the feasibility of Bluetooth detection, we conducted the experiments in 4 different scenarios.

1. The classroom (20 m × 10 m) where the professor had a lecture
2. The metro compartment (18 m × 3 m) with a random number of people getting on and off at each station
3. The street with the low pedestrian flow
4. The crowded crossroad during the rush hour

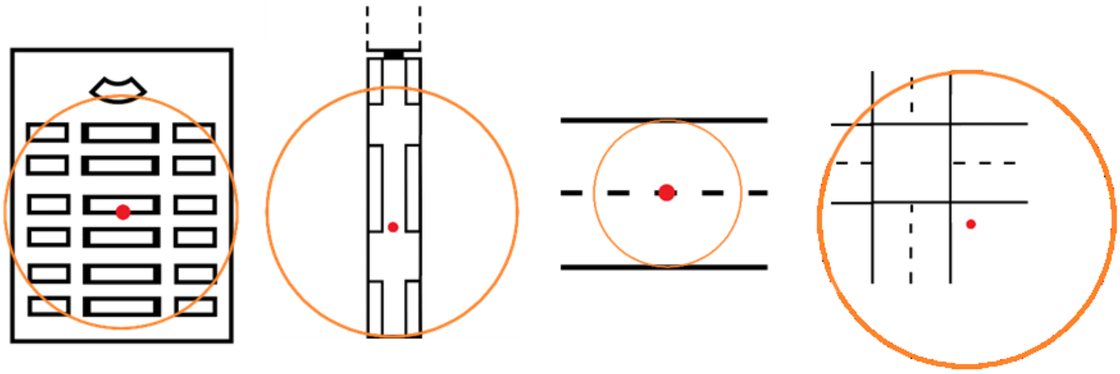


Figure 5- 2 Test configurations for different scenarios

As shown in Figure 5- 2, the red dot in each scenario is a smartphone placed as a Bluetooth scanning device. The orange circles represent effective range threshold, 15 meters. In each experiment, we conducted a 30-minute data collection and collected a set of data every minute. Every time we collect data, we scan the Bluetooth device within a radius of 15 meters with a smartphone installed our application. At the same time taking a 360-degree panoramic photo and manually calculate the number of people within 15 meters.

5.2.2 Results and Analysis

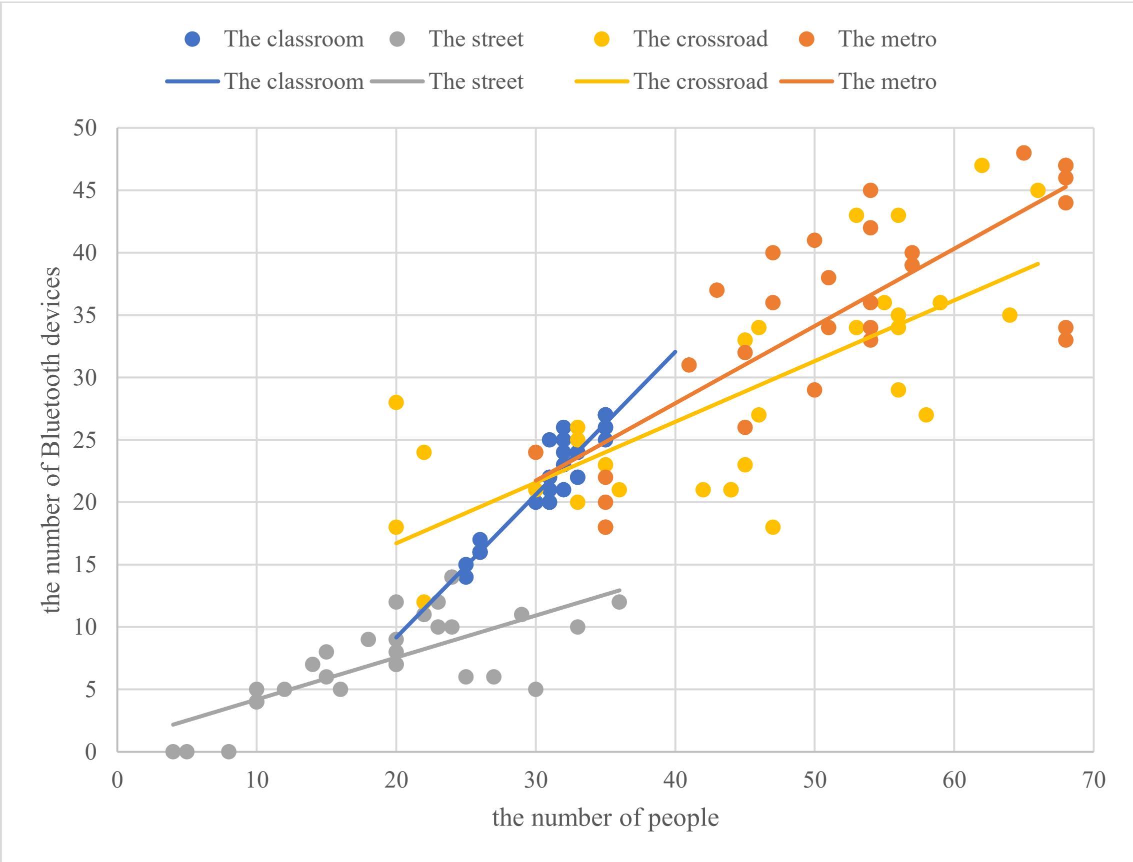


Figure 5- 3 Scanned numbers and manual counting

The results of Figure 5- 3 obtained by comparing the number of Bluetooth devices scanned by smartphone with manual counting number of people. Although the coefficients between the number of people and the number of devices in the four scenarios are different, each scenario maintains a fixed coefficient in a certain amount of continuous-time. In addition, in the event of a sudden change in the number of people in the test range, such as trains arriving, traffic signal changing, etc., it can be reflected in the change in the number of Bluetooth devices at the time. In other words, we can determine from the degree of change in the number of Bluetooth devices whether some events happen that changes crowd. The method of Bluetooth scanning has a large deviation in the coefficient between the devices and the people in the case of a small number of people or the low usage of Bluetooth devices. However, when the density of people is high or the number of people is unchanged or steadily changing, the results of Bluetooth scanning have high credibility. The research and application scope of this paper should also be in areas with high population density such as stations, concerts, and exhibitions, etc. For areas with very low numbers, other more suitable methods should be considered.

Table 5- 1 Correlation between Bluetooth devices and people

	Device/per person	Pearson correlation coefficient
The classroom	1.1442	0.9463
The metro	0.6182	0.8047
The street	0.3363	0.7483
The crossroad	0.4867	0.7416

The number of Bluetooth devices recorded by the smartphone may contain fixed devices, such as Bluetooth enabled printers, iBeacon, etc. As shown in Table 5- 1, the value, ‘Device/per person’ should be larger than the actual. The accuracy of directly converting the number of Bluetooth devices to the number of the crowd will be affected. Some researchers have proposed that after analyzing the MAC address, we can roughly get the brand name, product type, and even the model name of the devices[37]. But even if the device is known to be mobile, it could be a display product fixed in a store. In addition, the MAC address can also be tampered with, so the method of the MAC address cannot reach 100% accuracy. Combined with the Spatiotemporal information collected by the proposed system, the fixed equipment can also be deleted through a period trajectory analysis. But this will be another research topic and will not be discussed further in this paper.

Through the experiments, we know that the trend of the number of Bluetooth devices can reflect the trend of changes in the number of people. Although the relationship between the two is different depends on the regions, some researchers have proposed that the relationship value of each region is fixed or changes regularly[38][39][40]. Yamamoto, who has graduated from our laboratory with master's degree further proposed a model to explain that the correlation value between the number of Bluetooth devices and people in each area will be affected by the gender, age, and business of the area[41]. The rest of this paper will not study the correlation between people and devices but analyze how the system extracts the mobile devices' mobility information from the obtained context information.

5.3 Efficiency Experiment on Multiple Devices

After the feasibility test of Bluetooth scanning, we need to deploy the proposed system in a real situation. The previous experiments were all done by a single smartphone, verifying the feasibility of Bluetooth as an effective way to get information about people flows. In this experiment, we want to verify the feasibility of the entire system, including the case where multiple smartphones are used at the same time.

5.3.1 Experiment Environment Setup

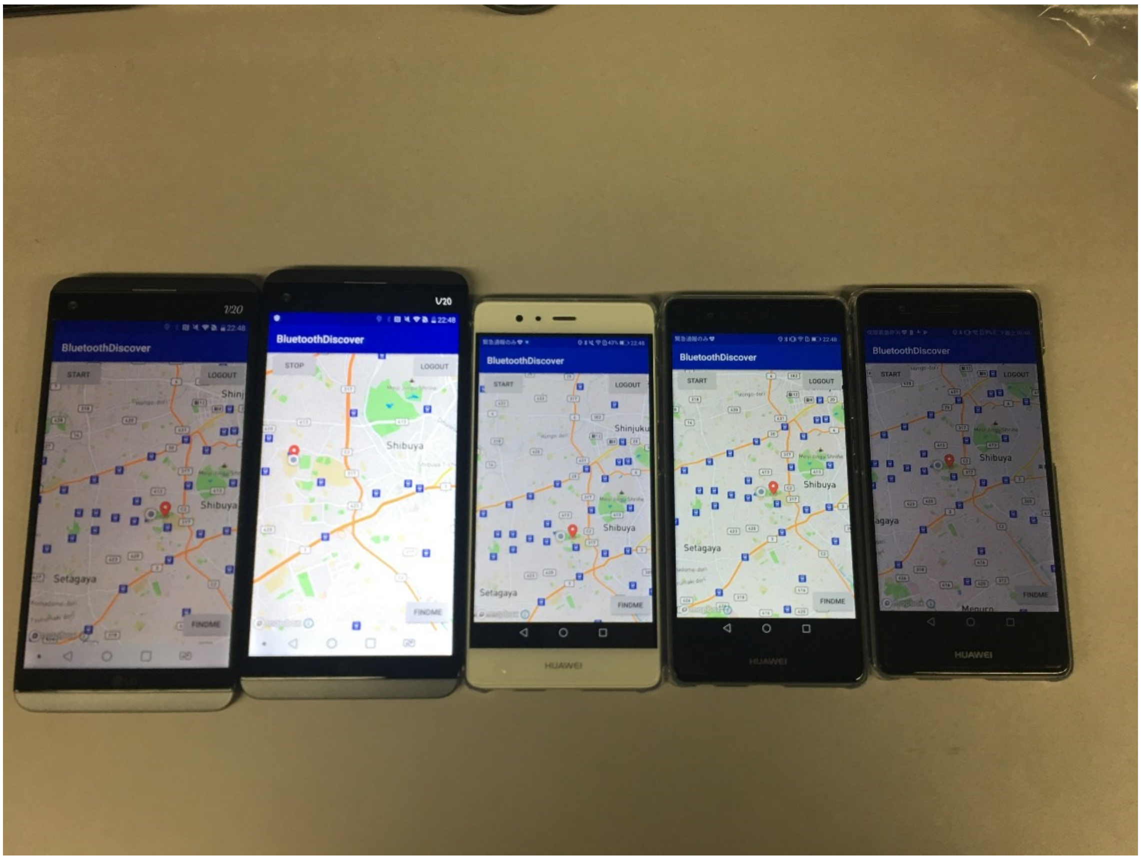
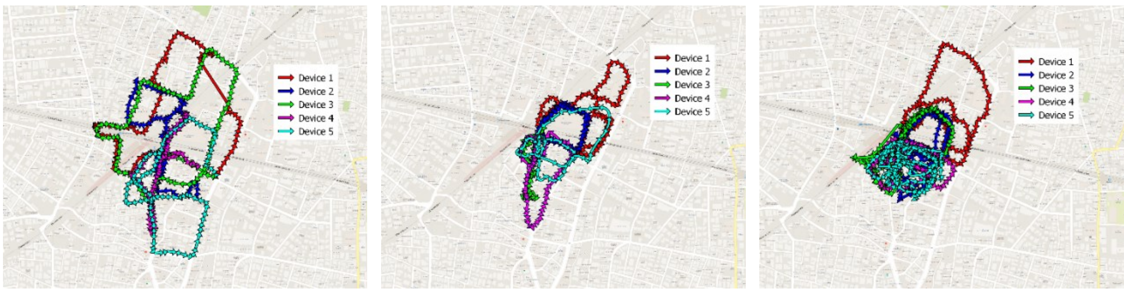


Figure 5- 4 The smartphones used in the experiment

We selected the test area near the train station in Shimokitazawa, Tokyo. We asked 5 participants to walk around the station, each holding a smartphone installed our application. The overlapping in Table 5- 2 refers to the percentage of route repetitions of the 5 people.



(a) Route 1 (b) Route 2 (c) Route 3

Figure 5- 5 Three routes of the efficiency experiment

For the location information of the smartphone, we use the GPS on the smartphone to obtain. The application on the smartphone will send the surrounding crowd context information to the server every 10 seconds and display the analyzed data sent from the server. That means the server will receive 6 records per minute from one smartphone. Because there are 5 smartphones, in the first two routes it records 450 times context information respectively, and the third route recorded 600 times. Every time a record has information of 0 to multiple Bluetooth devices.

Table 5- 2 Environmental parameters of the experiments

	Time (min)	Area (m²)	Length (km)	Overlapping
Route 1	15	95048.32	1.78	20%
Route 2	15	37726.35	1.12	54%
Route 3	20	36723.47	1.14	60%

We consider Bluetooth devices that have been detected more than 6 times by smartphones as an effective point information. Bluetooth devices that are only detected once are classified as a suspicious point. By the magnitude of the displacement of the same point between different times, we can determine if it is a fixed device. But we can't classify devices that are only detected once.

5.3.2 Results and Analysis

Table 5- 3 Mobile devices detection result

	Detected devices	Effective points	Suspicious points
Route 1	726	217(29.9%)	290(40.0%)
Route 2	549	357(65.0%)	126(23.0%)
Route 3	1122	639(57.0%)	381(34.0%)

Combine with Table 5- 2 and Table 5- 3 we can see that the route overlapping rate will affect the proportion of suspicious points and effective points.

A smartphone or several smartphones with a low overlapping rate can obtain device information only within its Bluetooth scan range (In this experiment, it is 15 meters.). The low overlapping rate also means that in most cases, multiple smartphones are in their own range, scanning and uploading crowd information, working as a single node. Once the Bluetooth device is out of the measurement range of the smartphone, the device can no longer be captured. However, if the overlapping rate rises, even if the Bluetooth device is outside the scanning range of one smartphone, it is possible to be captured again by other smartphones in the overlapping range, the detection of the device remains valid.

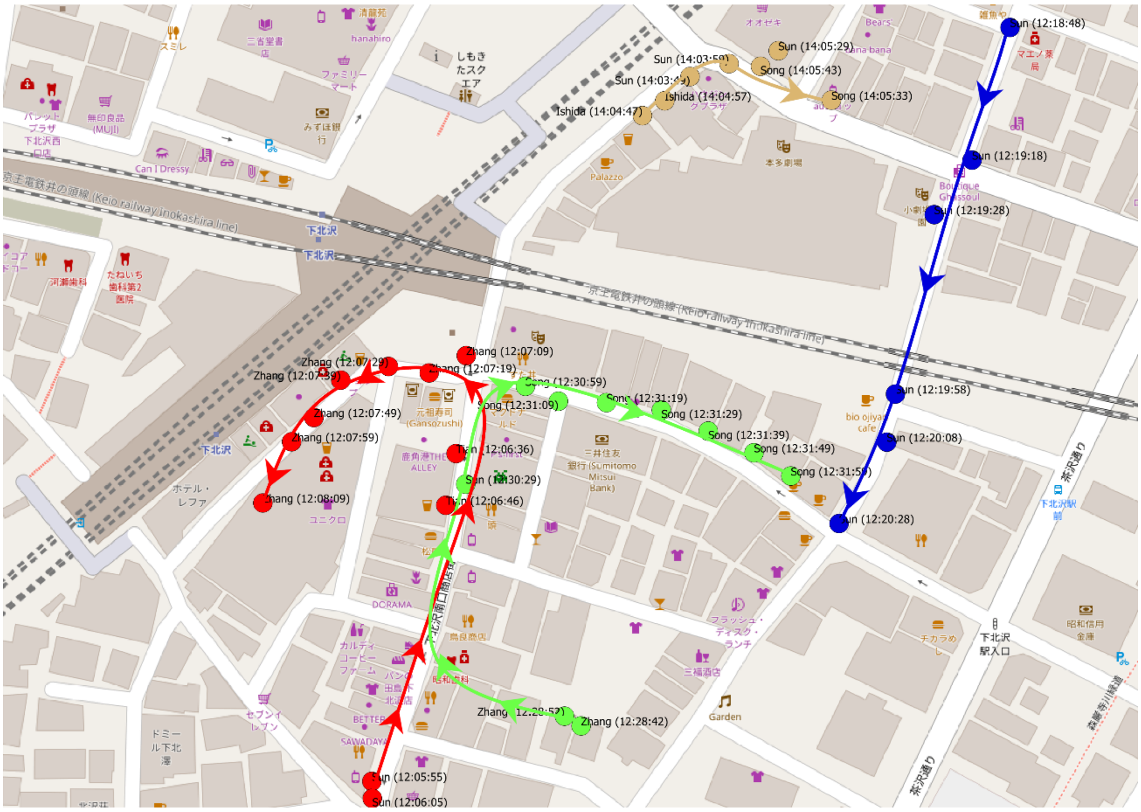


Figure 5- 6 Effective point movement sample

In addition to real-time detection of the density and approximate location of the crowd in an area, the proposed system can also capture the movement of people in a certain period time.

For the context information of all Bluetooth devices scanned within a certain time in a certain area, we first use MAC address to distinguish each Bluetooth device, combining the timestamp recorded by the smartphone when uploading the crowd information and the smartphone's location information, the system can show the movement of the device with this MAC address during this period. Although the location information is from testers' smartphone rather than a Bluetooth device, however, due to the short transmission distance of the Bluetooth signal, and the research focus of this article is to capture the movement of people, rather than precise positioning. Therefore, we treat location information as the location of the Bluetooth device and ignore errors in the location value.

As shown in Figure 5- 6, the dots in different colors represent captured Bluetooth devices with different MAC addresses. The set of dots with the same color represents the situation where devices with the same MAC address are detected at different time. Combining dots sets with timestamps, we can sketch out the movement information of detected devices. The movement information of these devices reflects the movement of the crowd in the area.

In addition, almost all device movement information collected by multiple mobile phones. This proves that the number of smartphones installed the proposed application and the scanning overlap rate of the smartphones will affect the accuracy of the system for mobile information.

5.4 Comparison Experiment to Existing Methods

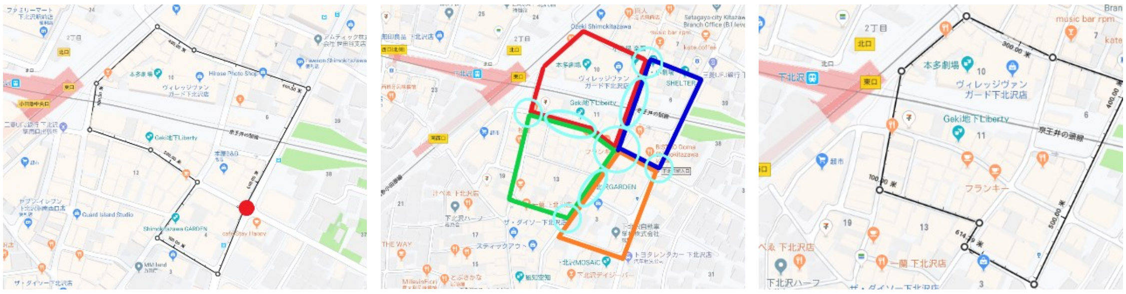
In this experiment, we will compare the proposed system with existing crowd detection methods in the same environment. Here we choose the GPS method for comparison. There are many similarities between the operation process of the GPS method and the proposed system. When using two methods, users' smartphones will become a detection point or part of the mobile information. And there are already some applications that provide GPS-based crowd supervise service. The GPS method has advantages in flexibility and mobility. But because the GPS method collects the user's location information, privacy issues are still controversial. It is also limited by GPS signals and cannot be used indoors. The number of people using the GPS method affects the accuracy of the method. If no one uploads information in an area, or if the proportion of people who upload information in the area is too low, it will affect the detection results of the GPS method for the crowd in the area.

Through this experiment, we want to verify whether the proposed system can still capture the same or close to mobile information as the GPS method when the number of users is far less than the number of users of the GPS method.

5.4.1 Experiment Environment Setup

In this experiment, each participant carries a smartphone. It will record its GPS location information at regular intervals as the raw data of the GPS method. At the same time, the context information of the Bluetooth devices around participants are also recorded by Bluetooth scanning as the raw data of the proposed system. Through the comparison of these two kinds of data, we want to verify whether data of one smartphone recorded by the GPS method can also be captured by other nearby smartphones through the proposed method. And further, verify whether the data obtained by the GPS method in one area can be obtained by a smaller number of devices through the proposed method.

The location of the experiment was the same as in 5.3. This time, a total of 10 people participated, each of whom carried a smartphone. We installed AWARE on each participant's phone. AWARE is the application dedicated to instrument, infer, log and share mobile context information by sensor instrumentation, for application developers, researchers and smartphone users[42]. This application allows users to obtain data from almost all sensors or components on smartphones. Changing the parameters through the interface to complete custom data collection. It saves time of reprogramming for the experiments. In the experiment, we walked three routes to simulate three scenarios.



(a) Route 1 (b) Route 2 (c) Route 3

Figure 5- 7 Route planning

Route 1: As Figure 5- 7 (a) shows, participants are divided into two groups, all starting from the red dots in the picture, walking clockwise and counterclockwise around the black line. The members of each group are close to each other during walking. The route simulates a scenario of people rushing to a safe area after the disaster.

Route 2: As Figure 5- 7 (b) shows, participants are divided into four groups. Each group walks along one color line. The directions for walking between groups are not necessarily the same, but the members in each group are walking in the same direction. The circles in the figure indicate the areas where the groups overlap. This route simulates, for example, the scenario where the audience evacuates from multiple exits after the concert.

Route 3: As Figure 5- 7 (c) shows, participants, walk randomly within the range of the black line to simulate the situation in the area with high population density.

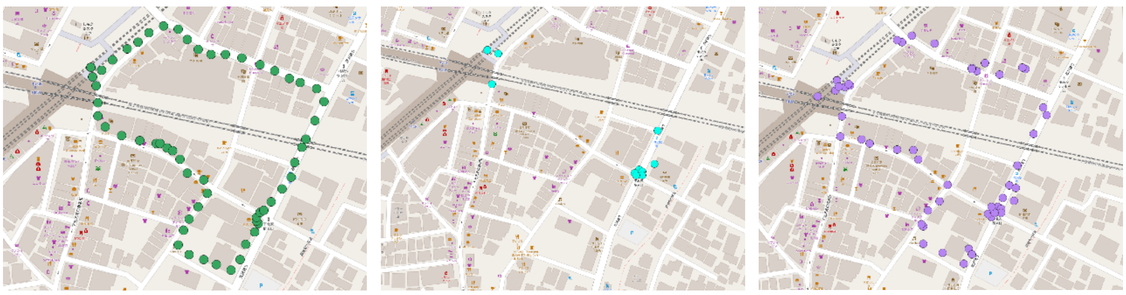
Participants in Route 1 were divided into two groups and walked counterclockwise and clockwise along the black line in one lap. In Route 2, we divided into 4 groups, each group walked along a color course for 20 minutes at the same time. In Route 3, the participants walked within the black line for 20 minutes at their own will.

5.4.2 Results and Analysis

We classified 10 smartphones into two categories, the standard and the explorer.

Standard: We read the GPS location information from the standard. This series of GPS location information is the path that this standard person walked in the experiment. This is also the data that common GPS methods need to collect. The set of data will be used as a reference for verifying the proposed method.

Explorer: Besides the standard, everyone else is an explorer. We read the Bluetooth context information from the explorers. This information is combined with the GPS location information of the explorer, which is the data set collected by our proposed method.

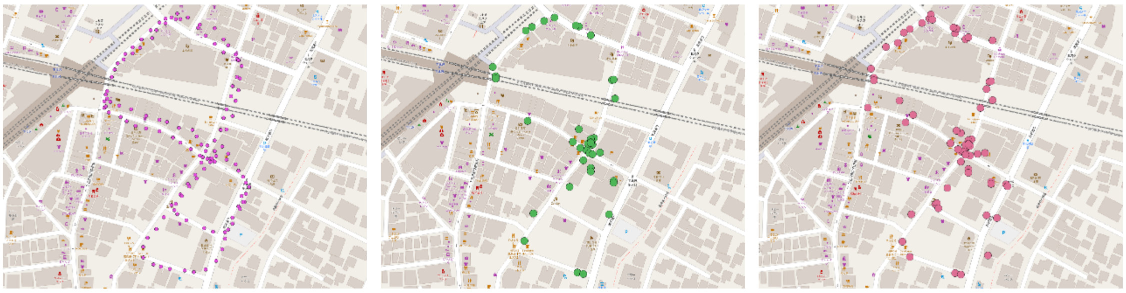


(a) Data from a standard himself (b) Data from the explorer from another group (c) Data from the explorer in the same group

Figure 5- 8 A sample from Route 1

(a) Data from a standard himself (b) Data from explorers from the other three groups (c) Data from all 9 explorers

Figure 5- 9 A sample from Route 2



(a) Data from a standard himself (b) Data from 4 explorers (c) Data from all 9 explorers

Figure 5- 10 A sample from Route 3

As shown in Figure 5- 8 (a), Figure 5- 9 (a) and Figure 5- 10 (a), we extract the GPS data of each smartphone and obtain all the walking trajectories of the participants in the three routes. Then we extract the Bluetooth context information of each smartphone, search for 9 other participants by MAC address to find out when and where this smartphone find the other 9 participants. Because the Bluetooth signal range is short, we consider the scanning location as the location of the participant being scanned. In this way, we use the scanning location to compare with the GPS location of all the 10 smartphones to verify whether the proposed method can obtain all or most of the GPS method information. Further, verify whether the Bluetooth context information provided by a small number of devices can obtain the same crowd information as the GPS method.

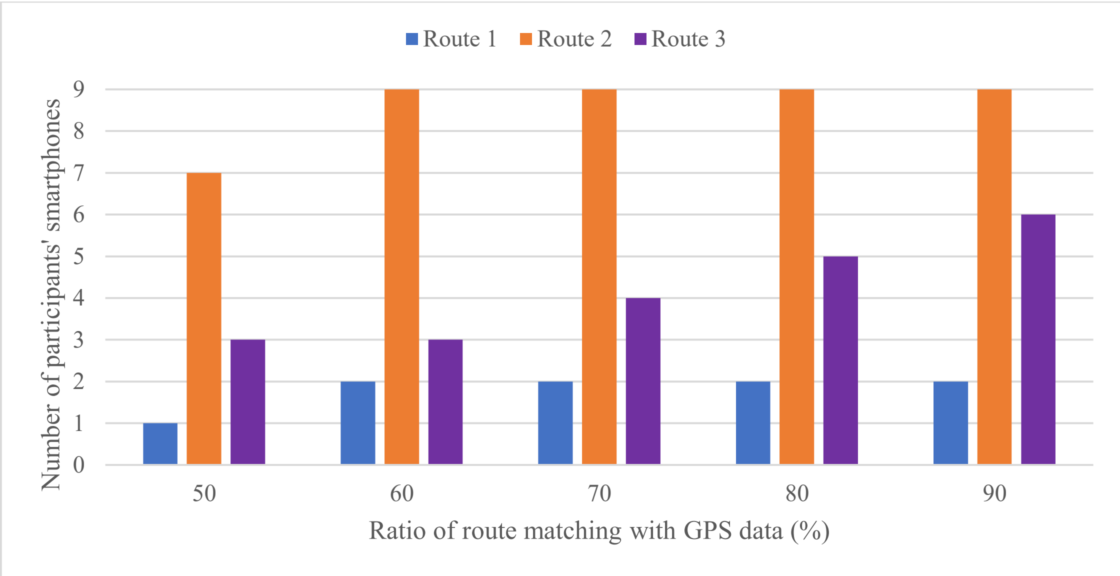


Figure 5- 11　Conformity and number of devices required

As shown in Figure 5- 11, it lists, in three routes separately, how many devices are needed on average to achieve 50% to 90% of the GPS route data using the proposed. In Route 1 and Route 3, it achieved that devices with less than half of the GPS method can obtain more than 80% of the route data of the GPS method. In Route 1, it only needs one smartphone in each group using the proposed method can obtain the walking trajectory data of all 10 people participating in the experiment. This is mainly because Route 1 simulates a scene where, for example, a high-density crowd moves to the same place when a disaster occurs. So participants were very close and walked in the same direction at the same speed. Route 3 simulates a high-density area. Participants did not walk in the same direction but were more random. Since the Bluetooth scanning range of multiple smartphones can cover this area, only half devices of the GPS method needed to obtain the trajectory information close to the GPS method.

In Route 2, almost the same number of devices as GPS method is required to display the trajectory of all participants. After analyzing the context information recorded by each device's Bluetooth scan, we find that it is rare for devices between different groups to find each other using Bluetooth scan. Even if they are in the same group, there are not many discoveries between group members. Based on the data set of timestamp and location, we find that in Route 2, the participants are scattered. The degree of overlap between groups becomes low due to grouping. And in the same group, although walking on the same line, they are not as close as Route 1. In this way, in Route 2, the participants become separated from each other, beyond Bluetooth scanning range of their smartphones.

Through this experiment, it can be concluded that in the same area, if the overlap rate between participants is enough high, the proposed method can use a small amount or even half of the GPS method equipment, and can collect the movement information of crowd similar which almost the same to the GPS method. In addition, since the GPS method is based on the location information of each device itself. So when users in one area are not enough to summarize the entire area, for example, only 10 people provided their respective location information in this experiment. In this way, the GPS method only obtains the location information of these few people, and there will be errors in generalizing the information to the crowd information in the area. But the method proposed in this paper not only provides the same information as the GPS method. At the same time, this method scans Bluetooth devices around the device. Besides the walking path information of the 10 people mentioned in this experiment. There is also context information collected by proposed method about Bluetooth devices around the device like in 5.3. Through the conversion of the Bluetooth device context information to the people crowd mobility information, the movement of the crowd in the area can also be obtained.

5.5 Summary

In this chapter, several experiments conducted to put forward the valid range of Bluetooth, the relationship between the context information of Bluetooth scanning with the crowd. Further, we operated the proposed system into the real environment and did the comparison with the GPS method in the same area. It proves that as long as there are enough people carrying Bluetooth device, even if the number of users in the area is not large, the proposed method can effectively capture the pedestrian flow information in the area.

Chapter 6
Conclusions

6.1 Contributions of the Thesis

Aiming at the problems existing in the common methods of pedestrian crowd detection, such as high equipment cost, insufficient flexibility, and limited application scope, this paper proposes a method of crowd detection based on Bluetooth scanning. When each user obtains the crowd information in the area from the server, user’s smartphone also becomes a detector, and uploads the surrounding context information by Bluetooth scan to the server.

Because the device used for detection is the user's smartphone. As long as users in a certain area use the proposed application, the proposed system can get the crowd information in that area. Therefore, high cost, inflexibility and small scope can be solved.

Through experiments, we verified that the effective signal range of Bluetooth devices for daily use is 15 meters. And through real-environment experiments, it is verified that multiple smartphones in a certain overlapping area can effectively detect the crowd. Finally, through comparative experiments, we verified that in areas with high crowd density, the method proposed in this paper can use fewer devices than GPS methods to obtain information about crowds in the area.

6.2 Future Work

Due to limited time and resources, the experimental sites and the number of participants in this paper are not enough. Further testing is needed to observe actual results for different locations and a larger number of users.

The method of using fixed Bluetooth beacons is also a general method with wide application scope and low cost similar to the proposed paper. However, some flexibility is reduced due to beacon fixation. Will the fixed beacon be more accurate than the method in this paper? In other words, it needs to prove if combining with fixed Bluetooth beacons with the proposed method can improve the accuracy. This will also another future work.

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