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Indoor Crowd Density Estimation Through Mobile Smartphone Wi-Fi Probes

Xiaoyong Tang, Bin Xiao, *Senior Member, IEEE*, and Kenli Li

***Abstract*—Crowd density estimation is one of the critical issues in social activities. The traditional solution to this problem is to leverage video surveillance to monitor a crowd. However, this is not accurate for crowd density estimation because it is still hard to identify people from background. In the past few years, more and more people use Wi-Fi enabled smartphones. Smartphones can send Wi-Fi request packets periodically, even when they are not connected to access points. This gives another promising solution to the crowd density estimation even for the public environment. In this paper, we first develop a Wi-Fi monitor detection that can capture smartphone passive Wi-Fi signal information including MAC address and received signal strength indicator. Then, we propose a positioning algorithm based on smartphone passive Wi-Fi probe and a dynamic fingerprint management strategy. In real-world public social activities, a person may have zero, one, two, or multiple smartphones with variant Wi-Fi signals. Therefore, we design a method of computing the probability of a user generating one Wi-Fi signal to identify people population. Finally, we propose a crowd density estimation solution based on Wi-Fi probe packets positioning algorithm. Experiments were conducted in an indoor laboratory class and three public social activities, clearly demonstrated that the proposed solution can effectively and accurately estimate crowd density.**

***Index Terms*—Crowd density, indoor positioning algorithm, received signal strength indicator (RSSI), smartphones, Wi-Fi probe.**

I. Introduction

CROWD density estimation is a key work for management to avoid any potential hazard in public social activity. Public activities include conference meetings, transportation in busy bus stations, holiday celebrations, open concerts and lectures, sports, and other big events that a huge number of people would gather together to a certain place in a certain period of time. The organizers should guide and control the attendees, and also monitor the crowd density for predicting the people movement and avoiding any potential accident. Otherwise, the social activities cannot continue smoothly, or even cause crowd disasters because of the lost of control. For example, three people trampled to death in Madrid Halloween Party for an "avalanche" of people rushed for the stadium's exits on Nov. 01, 2012 [1]. Therefore, it is necessary to adopt some new techniques to prevent such disaster to happen again.

The most common solution to crowd density estimation is to leverage video (or image)-based automatic surveillance system, which recognizes persons by detecting image features of crowd behavior from multiple frames [2]–[6]. However, the video-based solution is negatively affected by environmental factors, such as small line-of sight areas (obstructions) and light conditions (dark, direct sunlight, smoke etc.) [7]. Second, surveillance systems' accuracy is severely limited by computer vision and pattern recognition techniques [3], [4]. Third, its complexity, high equipment, and installation cost are still a heat debate.

In recent years, more and more people carry their own smartphones with Wi-Fi connections [8], [9]. The smartphone periodically transmits automatic connectivity request packets (known as *Probe Requests*), even when they are not connected to access points (APs). The transmission interval of Wi-Fi probe request frames ranges from 30 s to 60 s (depending on the power state of the device). In every interval, an AP can detect about ten frames. Every frame contains network configuration parameters, such as, service set identifier (SSID), frame control, destination MAC address, source MAC address, duration, BSSID, and sequence control [31]. The MAC address shows a unique device identifier, which can be used to identify the carried smartphone and is easier to recognize individual person than the image-based approach.

By capturing and analyzing these packets, we can also get received signal strength indicator (RSSI) from the smartphone's probe request frame. The RSSI can be used to estimate the distance from the smartphone to a receiver [10], [11]. Thus, we can locate the position of a smartphone (and its user) in specific areas, which provides a preferable choice to crowd density estimation in comparison to video-based solutions.

Crowd density estimation based on indoor Wi-Fi positioning is a common solution when GPS signals are not

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available [16], [17], [25], [35]. However, most indoor positioning systems are based on active Wi-Fi signal uploading from smartphones [17]–[19], [27], [29], [33]. Smartphones need to be connected and cooperatively upload their wireless signal information periodically. In fact, for public social activities, the dynamic changing crowd active use their smartphone to send Wi-Fi signal information is a very difficult social problem. Therefore, in an indoor environment, a better solution is to obtain passive Wi-Fi signal information [12]–[14], [22], [36]. In the passive Wi-Fi signal collection, the social activity organizers can easily get Wi-Fi signals and its MAC address, RSSI, SSID, BSSID from smartphone probe requests, which are the key value of smartphone positioning and crowd density estimating. The most advantage of this solution is that it does not need the highly dynamic changing crowd of public social activities active send its smartphone Wi-Fi signal. Thus, the passive Wi-Fi positioning crowd density estimation solution can easily to widely and quickly deploy.

In this paper, we focus on the crowd density estimation by proposing an indoor positioning algorithm that is based on passive wireless Wi-Fi packets (*Probe Requests*). We make the following *contributions*. First, we propose a new indoor positioning algorithm based on passive Wi-Fi probe request packet. Different from active positioning solutions, this algorithm does not need the collaboration from users and can be widely applied in various public social activities. Second, we incorporate a dynamic fingerprint management strategy into the positioning algorithm to minimize the inaccuracy of RSSI. Third, in real-world public social activities, a person may generate zero, one, two, or multiple Wi-Fi signals based on how many smartphones in hands. We design a method of computing the probability of a person generating one Wi-Fi signal by a multiple linear regression model. Finally, we give a crowd density estimation solution based on Wi-Fi enabled smartphones. This solution is easily deployed and has good accuracy that is confirmed by performance evaluation. The experimental results also demonstrated that it is better than an existing Wi-Fi hybrid-based method.

The rest of this paper is organized as follows. The related work is summarized in Section II. We describe the crowd density estimation system architecture in Section III. In Section IV, we provide a crowd density estimation solution based on wireless Wi-Fi probe packets positioning algorithm for public social activities. In Section V, we verify the performance of the proposed technique in an indoor laboratory classroom and some public places. Finally, we summarize the contributions and propose directions for further research in Section VI.

II. Related Work

Crowd density is one of important local characteristics of mass social activities. It has been found to be convenient to assess the criticality of a crowd situation by estimating the crowd density [3], [23]. In this manner, proper crowd control and management can be effected as a key task in large-scale public social activities.

The most common automated crowd density estimation and counting technique is by use of video surveillance systems, which can detect individual's movements once they appear in the field of view of the cameras. Individual identification of people from these videos can be accomplished by the key methods of computer vision and pattern recognition [3]. Abundant research has been conducted to address the issues related to these technologies over the past several years. For example, Lin *et al.* [4] proposed the use of Markov random fields (MRF)-based approach to model changes in pixel value, and they minimized the MRF-based objective function to obtain optimum foreground images. Wang and Xu [5] introduced a spatio-temporal texture-based crowd modeling technique, which can extract and integrate crowd textures from live or recorded videos to match personal features. Hussain *et al.* [6] used a combination of image processing and artificial intelligence technologies to develop an automatic crowd density estimation system (CDES). In crowd feature extraction, the background removal and edge detection were applied to the image, after which the authors scaled the extracted crowd foreground blob pixels accordingly using to appropriate perspective distortion. Finally, a back propagation neural network was adopted to estimate the number of people within the blob. A review of reports [23] introduced two main approaches, for estimating crowd density, the direct approach (i.e., object-based target detection) and the indirect approach (e.g., pixel-based, texture-based, and corner points-based analysis).

These video-based technologies offer a respectable good solution to solving the crowd density estimation problem. However, until now, computer vision and pattern recognition-based techniques still remain many challenges for identifying individual persons from massive images and videos. On the other hand, the automatic video surveillance system is severely restricted by environmental factors [7]. Use of alternative techniques for estimating crowd density has recently become of interest to the research community. One feasible solution is smartphone wireless signal positioning technology.

There have been a number of reports use wireless technologies including, Wi-Fi, Bluetooth, GPS, and various approaches to deal with indoor positioning problem. The most commonly used techniques are Wi-Fi or a combination of Wi-Fi and Bluetooth. Bose and Heng [16] classified Wi-Fi-based indoor positioning methods into time difference of arrival, angle of arrival, cell identity, time of arrival, and RSSI categories. The RSSI-based fingerprint method is a popular solution and has attracted much research interest. The Microsoft Radar system is probably one of the pioneering works employing integrating the RSSI-based fingerprinting measurements with radiomap [17], which used the k-nearest neighbor approach as a proximity matching algorithm and achieved a localization accuracy of up to 5 m. Several studies focused on the improving the accuracy of the RADAR's fingerprint matching algorithm have been suggested by Liang *et al.* [18]. However, RSSI-based fingerprinting method involves the laborious task of collecting a radiomap and dynamical RSSI fingerprints. To overcome this problem, Laoudias *et al.* [19] proposed a novel device with a self-calibration method that uses histograms

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of the RSSI values. However, the fingerprint accuracy and collection workload of this approach is also very complicated. The RSSI-based fingerprinting technique has also been applied to heterogeneous wireless networks for indoor positioning [20]. Gu *et al.* [34] proposed a collaborative indoor localization system that comprehensively use Wi-Fi, magnetic fingerprints, image-matching, and people co-occurrence to improve localization accuracy.

Many research work have used smartphone wireless Wi-Fi signals to estimate crowd. Higuchi *et al.* [24] proposed a positioning system that provides a *local map of surrounding persons* based on sensing data gathered from smartphones in the crowd without relying on any infrastructure or exhaustive fingerprinting. Li *et al.* [30] proposed a smartphone-based people counting system: Wi-Counter, which can estimate the number of people based on the resulting model. Wirz *et al.* [26] considered the use of location-aware smartphones for monitoring crowds during mass gatherings, where the wireless Wi-Fi signals were shared by volunteers. However, these methods are constrained by the active Wi-Fi signals of smartphones, which require user smartphones have connected to monitor and active send its Wi-Fi signal information. In fact, this kind of situation is very difficult to achieve in public social activities.

In recently years, increasing research has considered smartphone passive Wi-Fi signals, which does not require smartphone active sending its Wi-Fi signal information. Musa and Eriksson [12] described a system for passively tracking unmodified smartphones, and proposed a trajectory estimation method based on Viterbi's algorithm to track a moving device. Luo *et al.* [15] proposed a self-bootstrapping system for fine-grained passive indoor localization using non-intrusive Wi-Fi monitors, which enables training data to be crowdsourced without explicit effort of site surveyors. Barbera *et al.* [13] passively collected smartphone Wi-Fi automatic connectivity requests (known as *Probe Requests*) and used the SSID to analyze a social-network graph of the smartphone users. Wang *et al.* [14] used a single monitor to detect the smartphones' Wi-Fi received signal strength (RSS), and extracted the feature of RSS to determine the critical time points of human queues. A similar scheme applied to social robot, which uses Wi-Fi signal strength varies to identify person in a crowd of pedestrians [32]. Fukuzaki *et al.* [28] developed a system, which can analyze the rough tendency of pedestrian flow using Wi-Fi packet sensors. Schauer *et al.* [22] deployed two passive Wi-Fi and Bluetooth probe request captured Monitor on both sides of pedestrian flow and tried to estimate crowd densities. However, these approaches are limited that people must walk from one end to the other. Such situation is rare in most real-world public social activities. These reports also illustrate that using passive smartphones' Wi-Fi *Probe Requests* packets is an effective method for tackling the location problem of indoor individual and for estimating crowd density.

III. System Architecture

This section describes a crowd density estimation system architecture based on Wi-Fi enabled smartphones, which is composed of Wi-Fi Monitor Detection, Data Processing, and a Cloud Server, as depicted in Fig. 1.

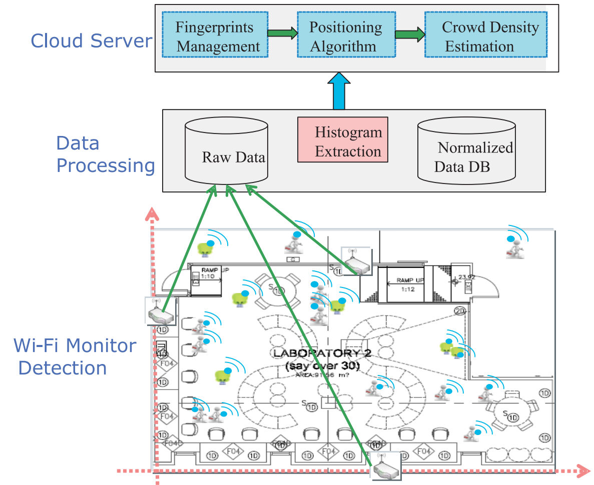

Fig. 1. Crowd density estimation system architecture.

TABLE I
IEEE 802.11 Management Frame Structure

Domain:	Frame Control	Duration	DA	SA	BSS ID	Seq ctrl	Frame body	FCS
Bytes:	2	2	6	6	6	2	0-2312	4

A. Wi-Fi Monitor Detection

Wi-Fi enabled smartphones periodically broadcast a wireless signal *Probe Request* frame to any network. The AP belonging to a network within range will reply a *Probe Response*, which allows smartphone to initiate a connection. The *Probe Request* and *Probe Response* are management frames that follow the wireless local area network IEEE 802.11 standard [31]. The structure of management frame is provided in Table I, and the type, subtype of the frame control domain are the key values for the *Probe Request* frame. These values are easy to intercept (sniffer) from *Probe Request* packets. To obtain *Probe Request* information, the wireless signal monitor detection (such as the internal wireless card of a notebook, wireless router) should turn on monitor mode.

In this paper, a smartphone detection program was developed that was written in QT and run on Ubuntu operating system. This program employs an open source software Libcap to capture wireless packets [21]. The data structure such as ieee80211_radiotap, ieee8011_frame_header are used to analyze the wireless signal data frame. Therefore, the *Probe Request* frame can be acquired as the type and subtype of the frame control domain $b_7b_6b_5b_4b_3b_2 = 010000$. This smartphone detection monitor can be deployed in an indoor environment, such as a classroom, a busy station, a footbridge, stadium's exits, offices, restaurants, retailers, etc.

B. Data Processing

As smartphones' MAC address and the RSSI are the key values used to identify and position a person in an indoor

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TABLE II
RAW WIRELESS SIGNAL DATA STRUCTURE

Smartphone	Type	RSSI	Time	Monitor
18:34:51: DC:DE:FC	Wi-Fi	-83	3-2 11:21:35	8C:70:5A: BD:61:9C
98:0D:2E: 31:2C:52	Wi-Fi	-52	3-2 11:21:35	60:6C:66: B2:52:CD
98:0D:2E: 31:2C:52	Wi-Fi	-45	3-2 11:21:35	60:6C:66: B2:52:CD
98:0D:2E: 31:2C:52	Wi-Fi	-52	3-2 11:21:35	60:6C:66: B2:52:CD
98:0D:2E: 31:2C:52	Wi-Fi	-52	3-2 11:21:35	60:6C:66: B2:52:CD
98:0D:2E: 31:2C:52	Wi-Fi	-45	3-2 11:21:35	60:6C:66: B2:52:CD
98:0D:2E: 31:2C:52	Wi-Fi	-68	3-2 11:21:35	60:6C:66: B2:52:CD

environment. This information can be captured from each smartphones' *Probe Request* packets using monitor detection. Therefore, this wireless Wi-Fi signal information raw data structure can be constructed as to Smartphone, Type, RSSI, Time, and Monitor. Table II shows an example of the raw data structure, where the smartphones and monitors are expressed by their MAC address, and the monitor is a device that can capture smartphones' wireless *Probe Request* packets. The RSSI is the strength of the received wireless signal and can estimate the distance between smartphone and monitor. The smartphone detection program is in control of acquiring this information and transmitting it to the data processing module as fast as possible.

In fact, a monitor can probe hundreds of *Probe Request* packets in one second. The total quantity of raw wireless signal packets for available monitors can be well over 100 million per day, which is big burden for data storage and analysis. On the other hand, a monitor usually sniffs several, or even dozens of wireless *Probe Request* packets in one second from a smartphone and their RSSI values are then distributed. That is to say, the RSSI values obtained from a smartphone are not all same in one second. Therefore, the raw wireless Wi-Fi signal information data are not directly suitable for positioning and estimating crowd density.

To obtain an effective solution, the Histogram Extraction technique was used to process the raw wireless Wi-Fi signal information data. An example of this Histogram Extraction technique is shown in Fig. 2. We collected 500 000 groups of Wi-Fi wireless signals and found that the 3 highest probability RSSI values in each group are stable over time and can be used to denote Wi-Fi signal characteristic. In fact, most RSSI values are occupied by 3 highest probability RSSI values in each group and other low probability RSSI values are frequent fluctuate. Therefore, our Histogram Extraction technique acquired the 3 highest probability RSSI values. In the next experiments,

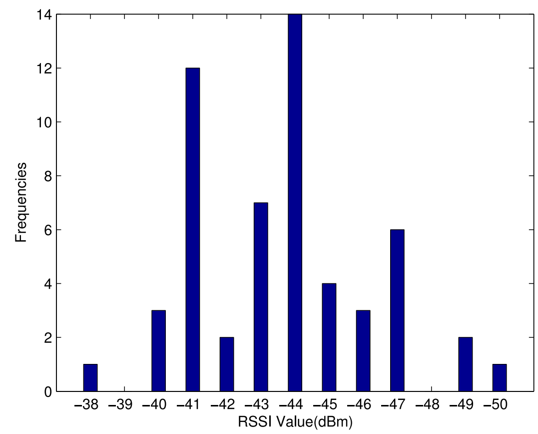

Fig. 2. Histogram extraction technique.

the results also show that this technique is high-efficient and practical in our indoor positioning algorithm. As a result, it is found that the effective RSSI values of Fig. 2 are −44, −41, −43. Moreover, this raw wireless Wi-Fi signal information was compressed into normalized data as a data structure shown in Table III. This stores three highest probability RSSI values which differ from raw data structure of Table II. This raw data processing technique also greatly reduces the overall quantity of data.

C. Cloud Server

This portion of the system controls the hosting applications/techniques responsible for: 1) fingerprints management; 2) positioning algorithm; 3) crowd density estimation; and 4) user with one Wi-Fi signal probability analysis, which are discussed in the next section.

IV. CROWD DENSITY ESTIMATION

A. RSSI Fingerprints Management

RSSI fingerprint-based positioning solutions have been widely studied as reported in the literature and adopted in real-world systems [17]–[20]. This technology consists primarily of two phases, the training and the positioning phases. In the proposed solution, the Wi-Fi fingerprints FP_i at each physical coordinates (x_i, y_i) were modeled as a finite observation space $\phi = \; < i, (x_i, y_i), \mathrm{FP}_i >$ and stored in the Wi-Fi fingerprint database D. Where the vectors FP_i consisted of n-dimensional RSSIs and monitors, such as $\mathrm{FP}_i = (< M_1, RSSI_{i,1,1}, RSSI_{i,1,2}, RSSI_{i,1,3} >, \ldots, < M_n, RSSI_{i,n,1}, RSSI_{i,n,2}, RSSI_{i,n,3} >)$. In this expression, M_n denotes the nth smartphone Wi-Fi signal detection monitor and expresses it as the MAC address, $RSSI_{i,n}$, which presents the three highest probability RSSI fingerprint values that can be captured by M_n. The RSSI fingerprints were processed by the Histogram Extraction technique (see Section III-B). The example of the fingerprinting data structure with two monitors is shown as Table IV.

The effectiveness of the RSSI fingerprints radiomap are affected by the wireless signal instability, Wi-Fi AP dynamicity and a variety of environments. Therefore, we propose

TABLE III
NORMALIZED WIRELESS SIGNAL DATA STRUCTURE

Smartphone	Type	$RSSI_1$	$RSSI_2$	$RSSI_3$	Time	Monitor
18:34:51:DC:DE:FC	Wi-Fi	-44	-41	-43	3-2 11:21:35	8C:70:5A:BD:61:9C
98:0D:2E:31:2C:52	Wi-Fi	-47	-52	-46	3-2 11:21:35	60:6C:66:B2:52:CD

TABLE IV
EXAMPLE OF FINGERPRINTING DATA STRUCTURE WITH TWO MONITORS

i	x_i	y_i	M_1	$RSSI_{i,1,1}$	$RSSI_{i,1,2}$	$RSSI_{i,1,3}$	M_2	$RSSI_{i,2,1}$	$RSSI_{i,2,2}$	$RSSI_{i,2,3}$
1	1.43	2.56	8C:70:5A:BD:61:9C	-78	-81	-79	60:6C:66:B2:52:CD	-45	-42	-46
2	7.2	8.9	8C:70:5A:BD:61:9C	-54	-53	-56	60:6C:66:B2:52:CD	-38	-39	-40

TABLE V
ADJUSTED FINGERPRINTING RADIOMAP

i	x_i	y_i	M_1	$RSSI_{i,1,1}$	$RSSI_{i,1,2}$	$RSSI_{i,1,3}$	M_2	$RSSI_{i,2,1}$	$RSSI_{i,2,2}$	$RSSI_{i,2,3}$
1	1.43	2.56	8C:70:5A:BD:61:9C	-78	-80	-81	60:6C:66:B2:52:CD	-45	-46	-47
2	7.2	8.9	8C:70:5A:BD:61:9C	-54	-53	-56	60:6C:66:B2:52:CD	-38	-39	-40

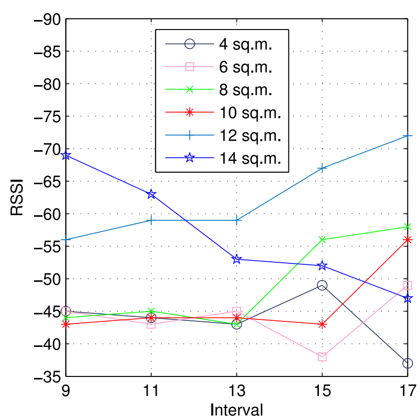

Fig. 3. Experimental results of fingerprints adjusting.

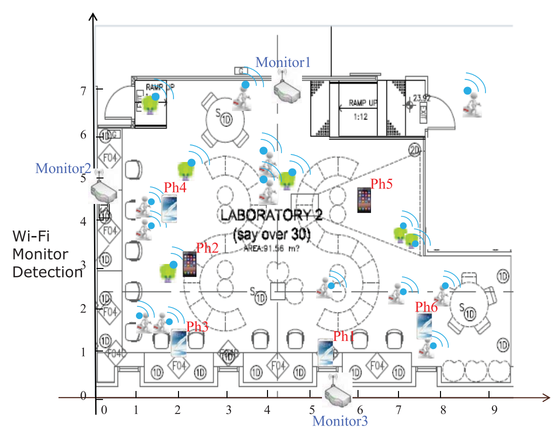

Fig. 4. Fingerprints periodical adjusting solution.

a fingerprints dynamic adjusting solution which uses some fixed positional smartphones to be connected and actively send Wi-Fi signal information. The fingerprints management have these smartphones' position, MAC address, Wi-Fi signal RSSI to adjust Wi-Fi fingerprint database D. In our solution, we set the adjusting interval as 15 min and the number of fixed smartphones as 1 per 10 square meters. This is due to that the wireless change become a little obvious in 10 square meters to every 15 min in our previous experiments, where the main experimental results are shown in Fig. 3.

Fig. 4 shows an example of laboratory with six fixed smartphones ($Ph1$, $Ph2$, $Ph3$, $Ph4$, $Ph5$, $Ph6$) are deployed to manage Wi-Fi signal fingerprints. The size of laboratory is 7.3×9.5 and about 62.5 square meters. The fixed smartphones deployment location follows the following three rules: All devices are almost distributed evenly across the entire test region, most devices cannot be blocked by objects such as walls, a device must be deployed to special place. In Fig. 4, a fingerprint $-78, -80, -81$ is shown for Monitor1 "8C:70:5A:BD:61:9C," while $-45, -46, -47$ is shown for Monitor2 "60:6C:66:B2:52:CD" at time "3-19 19:21:45" and the source smartphone is at position $x = 1.43$, $y = 2.56$. As a result, the fingerprint radiomap of position $x = 1.43$, $y = 2.56$ can be adjusted as depicted in Table V.

On the other hand, the task of collecting RSSI fingerprints radiomap involves difficult, laborious work. The best solution is to collect these fingerprints automatically. Therefore, the fingerprinting periodical adjusting technique is proposed together with the fingerprints management solution. It is known that the log-distance radio propagation model [19], [33] is

$$RSSI[dBm] = A - 10\gamma \log_{10} d + X. \tag{1}$$

In this model, d denotes the distance between the transmitter (e.g., smartphone) and the receiver (e.g., Monitor), while the intercept term A provides the RSSI value when $d = 1$ m. The path loss exponent parameter γ depends on the propagation environment, $X \sim N(0, \sigma^2)$ is the noise and follows normal distribution.

Regular adjustment of the parameters of (1) according to the RSSI obtained by fixed positional smartphone Wi-Fi signals and its aforehand position. In this way, we can use (1) to automatically collect the fingerprints information. First, parameter A can be obtained using smartphone $Ph1$ and Monitor, whose distance is only $d = 1$ m. Furthermore, the least squares data fit approach can be used to obtain path loss exponent parameter γ, which its accuracy has directly affected on the log-distance radio propagation model. To do this, the six fixed positional smarpthones $Ph1, Ph2, Ph3, Ph4, Ph5, Ph6$ are chosen and checked their wireless Wi-Fi signal strength RSSI values, corresponding to distance defines as $[(RSSI_1, d_1), (RSSI_2, d_2), \ldots, (RSSI_6, d_6)]$. Then, the least squares approach is used to construct a fitting function $Q(\gamma)$ as

$$\begin{aligned} Q(\gamma) = &\left[RSSI_1 - \left(A - 10\gamma \log_{10} d_1 + X\right)\right]^2 \\ &+ \left[RSSI_2 - \left(A - 10\gamma \log_{10} d_2 + X\right)\right]^2 \\ &+ \cdots + \left[RSSI_6 - \left(A - 10\gamma \log_{10} d_6 + X\right)\right]^2. \end{aligned}$$

For least squares approach, we try to get minimum fitting function $Q(\gamma)$ value. Therefore, the goal of this approach is

$$\text{minimum } Q(\gamma).$$

To find the minimum of function $Q(\gamma)$, the partial derivatives of $Q(\gamma)$ with respect to γ is calculated and setting it to zero. Thus,

$$\begin{aligned} \frac{\partial Q}{\partial \gamma} = 0 = 20\big\{&\log_{10} d_1\left[RSSI_1 - \left(A - 10\gamma \log_{10} d_1 + X\right)\right] \\ &+ \log_{10} d_2\left[RSSI_2 - \left(A - 10\gamma \log_{10} d_2 + X\right)\right] \\ &+ \cdots + \log_{10} d_6\left[RSSI_6 - \left(A - 10\gamma \log_{10} d_6 + X\right)\right]\big\}. \end{aligned}$$

The previous equations can then be solved to obtain the value of path loss exponent parameter γ. Thus, we can obtain a new and accurate expression of (1) as time varies. In our solution, we propose a new fingerprint computing method and defined as

$$RSSI = \zeta \times RSSI_p + (1 - \zeta) \times RSSI_n \tag{2}$$

where $RSSI_p$ is the old fingerprint RSSI value for a coordinate (x_i, y_i), and $RSSI_n$ is an RSSI value that computed by the adjusted (1) at the same coordinate. Here, $RSSI_n$ is a new value because of the (1) path loss exponent parameter γ is adjusted and computed by the above least squares approach. Therefore, we can get new fingerprint RSSI value according to the new parameter γ of (1). Parameter ζ indicates the importance of previous fingerprint RSSI value, which can be determined by some simple experiments in real-world environment. In the following evaluation, the example of Hunan Changsha Railway Station Ticket Office with crowd density as 5.3, the relationship between our proposed crowd density estimation and parameter ζ is shown in Fig. 5. From Fig. 5, we can conclude that the optimal ζ value is 0.34. Here, the

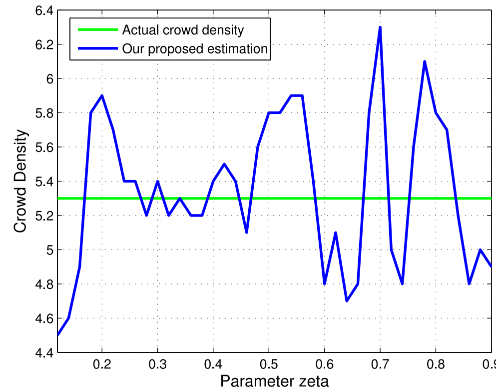

Fig. 5. Relationship between our proposed estimation and parameter ζ.

parameter ζ is affected by environments and may change with the environmental changing. Finally, the database D fingerprint row FP_i is updated by this $RSSI$.

B. Wi-Fi Probe Signal Positioning Algorithm

In this section, a positioning algorithm based on the smartphone's *Probe Request* packets is proposed. The pseudo code of the Wi-Fi probe signal positioning algorithm (WPPA) is shown in Algorithm 1. The positioning algorithm attempts to find the best match between the current Wi-Fi probe signal vector P and the reference fingerprints ϕ in the RSSI fingerprint radiomap. Here, the Wi-Fi probe signal vector P is defined as $p_j = < M_j, RSSI_{j,1}, RSSI_{j,2}, RSSI_{j,3} >$. In the proposed solution, the closest physical coordinate (x_i, y_i) is obtained by minimizing the Euclidean distance between signal vector P and fingerprints ϕ. Here, we define the Euclidean distance d_k between probe signal p_j and one of the ith fingerprint monitor M_l as (3), where the MAC address of monitor M_j is as the same as fingerprint monitor M_l MAC address

$$d_k = \text{Min}\begin{cases} \Big[\left(RSSI_{j,1} - RSSI_{i,l,1}\right)^2 + \left(RSSI_{j,2} - RSSI_{i,l,2}\right)^2 \\ \quad + \left(RSSI_{j,3} - RSSI_{i,l,3}\right)^2\Big]^{\frac{1}{2}} \\ \Big[\left(RSSI_{j,1} - RSSI_{i,l,1}\right)^2 + \left(RSSI_{j,2} - RSSI_{i,l,3}\right)^2 \\ \quad + \left(RSSI_{j,3} - RSSI_{i,l,2}\right)^2\Big]^{\frac{1}{2}} \\ \Big[\left(RSSI_{j,1} - RSSI_{i,l,2}\right)^2 + \left(RSSI_{j,2} - RSSI_{i,l,3}\right)^2 \\ \quad + \left(RSSI_{j,3} - RSSI_{i,l,1}\right)^2\Big]^{\frac{1}{2}} \\ \Big[\left(RSSI_{j,1} - RSSI_{i,l,2}\right)^2 + \left(RSSI_{j,2} - RSSI_{i,l,1}\right)^2 \\ \quad + \left(RSSI_{j,3} - RSSI_{i,l,3}\right)^2\Big]^{\frac{1}{2}} \\ \Big[\left(RSSI_{j,1} - RSSI_{i,l,3}\right)^2 + \left(RSSI_{j,2} - RSSI_{i,l,1}\right)^2 \\ \quad + \left(RSSI_{j,3} - RSSI_{i,l,2}\right)^2\Big]^{\frac{1}{2}} \\ \Big[\left(RSSI_{j,1} - RSSI_{i,l,3}\right)^2 + \left(RSSI_{j,2} - RSSI_{i,l,2}\right)^2 \\ \quad + \left(RSSI_{j,3} - RSSI_{i,l,1}\right)^2\Big]^{\frac{1}{2}}. \end{cases} \tag{3}$$

The WPPA initially reads all the smartphones' MAC addresses over a given time interval. Here, each MAC address

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Algorithm 1: Pseudo Code for WPPA

```
Input: The smartphones' Wi-Fi probe signal data and
       time interval
Output: The position information of smartphones
Read smartphones' MAC address at given time interval
for each MAC address do
    Read its Wi-Fi probe signal values into P vector at
    given time interval
    minEucDistance ← Maxvalue
    for each fingerprint in φ do
        Euclidean distance d ← 0 and num ← 0
        for each monitor M_l of fingerprint do
            for each probe signal p_j of vector P do
                if M_j == M_l then
                    Compute Euclidean distance d_k use
                    Eq. (3)
                    d ← d + d_k and num ← num + 1
                end
            end
        end
        if minEucDistance > d/num then
            minEucDistance ← d/num
            Take the fingerprint coordinate (x_i, y_i) as
            current position
        end
    end
    if minEucDistance < θ then
        Output the position as smartphone's optimal
        position
    end
end
```

represents a person or user. Then, for each MAC address, the WPPA attempts to find an optimum physical coordinate using the fingerprinting technique. Moreover, WPPA searches the same monitor M_l of the fingerprint and M_j of the probe signal p_j pair for each fingerprint and computes the average Euclidean distance. The physical coordinate (x_i, y_i) with a minimum average Euclidean distance is accepted as the candidate. Finally, if the minimum Euclidean distance is less than the threshold θ, the candidate coordinate will be considered as the actual physical coordinate for this MAC address (smartphone) or person.

C. Crowd Density Estimation

Crowd density is the number of people per square meter for a standing crowd and a moving crowd, and the crowd density estimation is important to understand the safety of crowd. In this paper, we adopt WPPA algorithm based on smartphone probes to calculate the number of people in a specified area S. We assume that $\xi(t)$ denotes the number of persons as time t varies. We use WPPA algorithm to compute persons' coordinate (x_i, y_i) at time t and judge the coordinate (x_i, y_i) is belonging to the area S. If coordinate (x_i, y_i) in area S, we accept this person and increase crowd number $\xi(t)$. Therefore,

TABLE VI
PEOPLE WITH ONE WI-FI SIGNAL FOR DIFFERENT AGE STAGES

Age	Number	None	More	$\psi(S, T, A)$	$\psi(S, T, A, w)$	$\psi(S, T, A, m)$
≤ 18	33	27	1	21.2%	81.8%	3%
$[18, 22]$	128	22	33	108.6%	17.2%	25.8%
$[22, 30]$	219	31	78	121.5%	14.2%	35.6%
$[30, 45]$	102	45	34	89.2%	44.1%	33.3%
$[45, 60]$	76	32	7	67.1%	42.1%	9.2%
≥ 60	42	23	3	52.4%	54.8%	7.1%

the crowd density $\rho(S, t)$ can be defined as

$$\rho(S, t) = \frac{\xi(t)}{\psi(S, T) \times s} \tag{4}$$

where s is the square of area S and $t \in T$. For a time interval T, such as [11:00, 12:00], $\psi(S, T)$ is a parameter that denotes the average probability of person with one Wi-Fi signal. In this case, one person may have some smarthphones and only has one Wi-Fi turned on.

For a given area S, standing crowd or moving crowd are also dynamic certainty. That is to say, these people always have some characteristics in a certain period of time. For example, between 8:00 P.M. and 9:00 P.M. of Hong Kong Hung Hom footbridge, most people are belong to office workers, young students. All of them have intelligent mobile phone with Wi-Fi turned on. For the time from 10:00 to 11:00, there are more tourists, old person. Some have two or more smartphones, some use smartphones without Wi-Fi. Therefore, we compute the parameter $\psi(S, T)$ according to different interval T.

For crowd of area S, some may not have Wi-Fi signal for no smartphone or smartphone's Wi-Fi turned off, some may have one, two, and more Wi-Fi signals. Here, the probability of person with one Wi-Fi signal $\psi(S, T)$ can be defined as

$$\psi(S, T) = 1 - \psi(S, T, w) + \psi(S, T, m) \tag{5}$$

where $\psi(S, T, w)$ denote the average probability of people without wireless Wi-Fi signal. In this case, they do not have smartphones, ipads, notebooks, and so on, or these devices' Wi-Fi turned off. $\psi(S, T, m)$ is the average probability of people has two or more Wi-Fi signals.

On the other hand, people at different age stages use smartphones' Wi-Fi with different habits. For example, primary school students do not have smartphones, most of young people have one smartphone with Wi-Fi turned on, and successful middle-aged people have many devices, which will generates multiple Wi-Fi signals. Therefore, we divide the crowd into different age stages, such as, ≤ 18, [18, 22], [22, 30], [30, 45], [45, 60], ≥ 60, and so on. Accordingly, (5) can be expressed as

$$\psi(S, T, A) = 1 - \psi(S, T, A, w) + \psi(S, T, A, m). \tag{6}$$

In this solution, $A \in \{\leq 18, [18, 22], [22, 30], [30, 45], [45, 60], \geq 60\}$. Table VI illustrates an investigation for people with one Wi-Fi signal according to different age stages.

TABLE VII
INVESTIGATION RESULTS OF HUNG HOM FOOTBRIDGE AT TIME FROM 9:00 TO 10:00

$\psi(S,T)$	$\psi(S,T,\leq 18)$	$\psi(S,T,[18,22])$	$\psi(S,T,[22,30])$	$\psi(S,T,[30,45])$	$\psi(S,T,[45,60])$	$\psi(S,T,\geq 60)$
y	x_1	x_2	x_3	x_4	x_5	x_6
96%	21.2%	108.6%	121.5%	89.2%	67.1%	52.4%
99.3%	18.2%	106.1%	120.8%	105.7%	68.4%	57.1%
88.3%	33.3%	96%	91.3%	104.6%	52.6%	63.6%
102.6%	36.8%	105%	121.4%	80.8%	87.5%	48.5%
97.2%	57.1%	114.5%	100.8%	120.7%	77.8%	63.1%
86.8%	42.6%	66.2%	118.1%	87.8%	95.5%	35.4%
88.2%	50%	80.9%	102.2%	114.5%	79.5%	25%
82.1%	33.9%	76.4%	112.7%	86.3%	78.3%	18.8%

Here, we randomly interviewed 600 people in Hong Kong Hung Hom footbridge at time from 9:00 to 10:00. From Table VI, we summarize that 180 persons do not have Wi-Fi signal, 156 persons have two Wi-Fi signals, and the average probability of person with one Wi-Fi signal $\psi(S,T) = 96\%$ according to (5).

D. User With One Wi-Fi Signal Probability Analysis

In reality, the average probability of a person with one Wi-Fi signal is $\psi(S,T)$ which is the dynamic stability for a given area at a regular time. Therefore, as time varies, only its partial characteristics need to be changed, such as, $\psi(S,T,A)$ for $A \in [18, 22]$, to obtain an accurately value of $\psi(S,T)$. So, in this section, the relationship between $\psi(S,T)$ and $\psi(S,T,A)$ is deduced for $A \in \{\leq 18, [18, 22], [22, 30], [30, 45], [45, 60], \geq 60\}$.

Here it is assumed that the multiple linear regression model for this problem is

$$\begin{aligned}\psi(S,T) = \alpha &+ \beta_1\psi(S,T,\leq 18) + \beta_2\psi(S,T,[18,22]) \\ &+ \beta_3\psi(S,T,[22,30]) + \beta_4\psi(S,T,[30,45]) \\ &+ \beta_5\psi(S,T,[45,60]) + \beta_6\psi(S,T,\geq 60) + \varepsilon \quad (7)\end{aligned}$$

where α is regression constant, $\beta_i, i \in [1, 6]$ are regression coefficients, and the notation for the model deviations is ε. The least squares approach is used to fit the regression equation

$$\hat{y} = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_5x_5 + b_6x_6 \quad (8)$$

where y denotes $\psi(S,T)$ and x_i represents $\psi(S,T,A)$. Thus, the fitting function $Q(x)$ can be defined as

$$Q(x) = \sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2 = \sum_{j=1}^{n}\left(y_j - b_0 - \sum_{i=1}^{6} b_i x_{j,i}\right)^2. \quad (9)$$

To find the minimum of function $Q(x)$, the partial derivatives of $Q(x)$ are computed with respect to $b_i, i \in [0, 6]$, and setting them to zero. The equation can be easily solved and to obtain the value of the regression coefficients. For example, the average probability of person with one Wi-Fi signal $\psi(S,T)$ and $\psi(S,T,A)$ is considered on the Hong Kong Hung Hom footbridge at a time from 9:00 to 10:00, as shown in Table VII. The solution of these equations is $b_0 = 0.948$, $b_1 = -0.967$, $b_2 = 0.633$, $b_3 = -0.987$, $b_4 = 0.025$, $b_5 = 1.155$, and $b_6 = -0.131$. Thus, the average probability of person with one Wi-Fi signal $\psi(S,T)$ can be expressed as

$$\begin{aligned}\psi(S,T) = 0.948 &- 0.967\psi(S,T,\leq 18) \\ &+ 0.633\psi(S,T,[18,22]) - 0.987\psi(S,T,[22,30]) \\ &+ 0.025\psi(S,T,[30,45]) + 1.155\psi(S,T,[45,60]) \\ &- 0.131\psi(S,T,\geq 60). \quad (10)\end{aligned}$$

V. PERFORMANCE EVALUATION

In this section, two set of experiments were conducted to evaluate the proposed solution. One is in a laboratory classroom, the other are three real-world public social activities, such as Hong Kong Hung Hom Footbridge, Hunan Changsha Railway Station Ticket Office, Changsha Furong Road Subway. The smartphone detection monitor is running on Linux and the mode of the wireless card must be set as monitor, this can be achieved by Linux command "sudo ifconfig wlan0 down," "sudo iwconfig wlan0 mode monitor," and "sudo ifconfig wlan0 up." We compare our proposed solution with ground truth and a Wi-Fi hybrid-based method proposed by Schauer *et al.* [22]. The evaluation was intended not only to present experimental results, but also to qualitatively analyze the results for a better insight in the overall model.

A. Evaluation in the Laboratory

The experiments were conducted in classroom p507 of our laboratory as shown in Fig. 6, where the students, teachers usually study and discuss. In this experiment, eight persons stayed in the room, and they all had one smartphone with Wi-Fi turned on. Locating eight MAC address of wireless Wi-Fi signals in the classroom using the WPPA algorithm, it can be concluded that there are eight persons in this classroom.

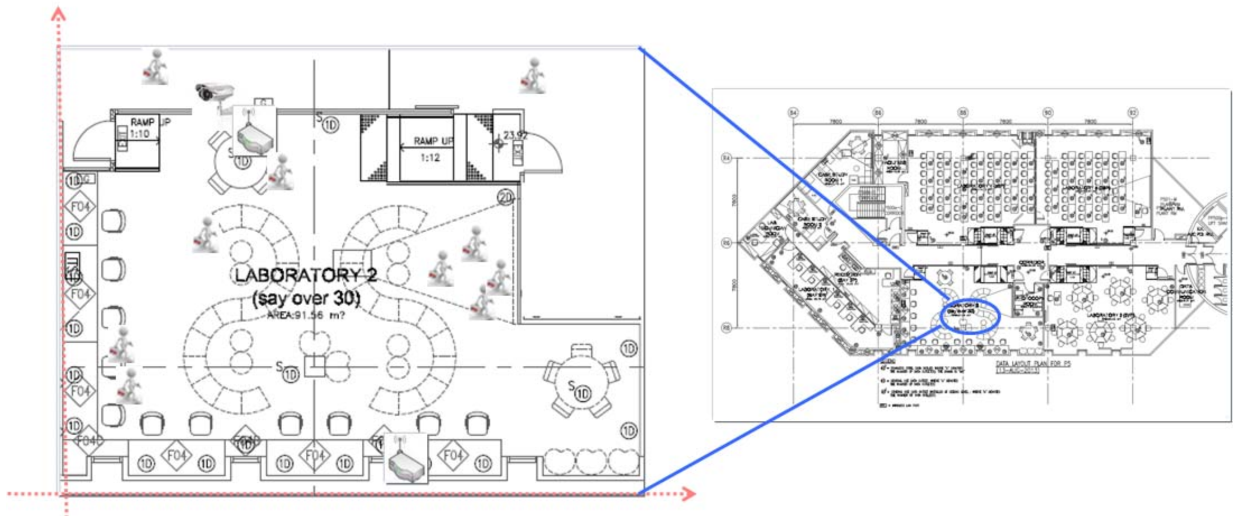

Fig. 6. Room structure and the persons.

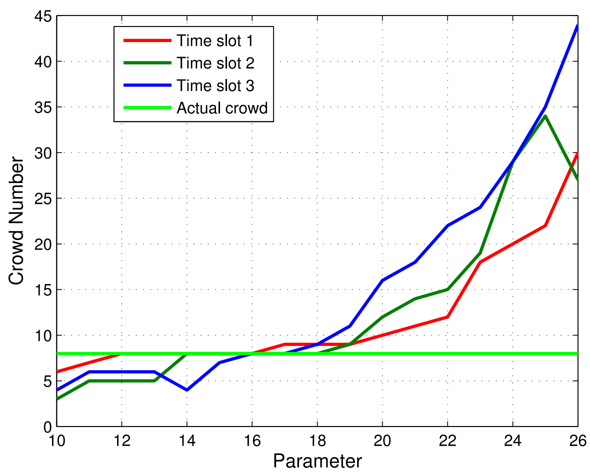

Fig. 7. Experimental results when varying parameter θ.

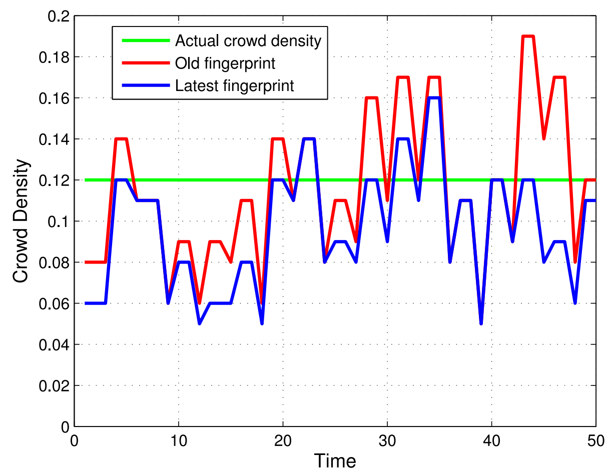

Fig. 8. Crowd density experiments in a laboratory class.

1) Various Parameter θ of WPPA Algorithm: The proposed solution of estimating crowd density is based on the WPPA positioning algorithm. However, the accuracy of the WPPA algorithm depends partially on parameter θ. Therefore, the parameter θ was varied from 10 to 26 to assess WPPA algorithm performance. The experimental results are shown in Fig. 7. The actual crowd line shows the residing eight persons, and this line is drawn to purposefully distinguish the experimental results. The other three lines of Fig. 7 were randomly picked from the time slots.

From Fig. 7, it can be concluded that the crowd number increased as the parameter θ increased. This phenomenon is reasonable, in fact, the larger parameter θ results in a greater Euclidean distance in detecting RSSI values and fingerprints. Therefore, there are more wireless Wi-Fi signal MAC addresses determined in specified area resulting in a greater number of sampled. Fig. 7 also shows that when the parameter θ is valued at 15 to 18, the experimental results were very close to the actual number of eight persons, and the optimum θ was 16. Consequently in the following experiments, the parameter θ was set at 16.

2) Crowd Density Experiments: In this experiments, two fingerprints set were used, first set is collected five days ago and second set is adjusted lately according to our RSSI fingerprints management strategy (see Section IV-A). As a result, the first set is old fingerprints and the second set is the newest. Since the eight subjects are all have one smartphone with Wi-Fi activated, the probability of person with one Wi-Fi signal $\psi(S, [11{:}13, 11{:}30])$ is 0 (see Section IV-C). The computation was run at an interval 20 s. Fig. 8 shows the crowd density experimental results for two sets of fingerprints from 11:13 to 11:30.

It can be seen from Fig. 8 that the crowd density calculated by the latest fingerprint is closer to actual crowd density than old fingerprint. In fact, the latest fingerprint has ten time slots, which is the same as the actual crowd density and the old fingerprint only has four time slots. These experimental results demonstrate that the proposed fingerprint periodical adjusting management techniques are effective in stabilizing the wireless Wi-Fi signal. In addition, these results also show that the proposed solution can approximately estimate the actual crowd density.

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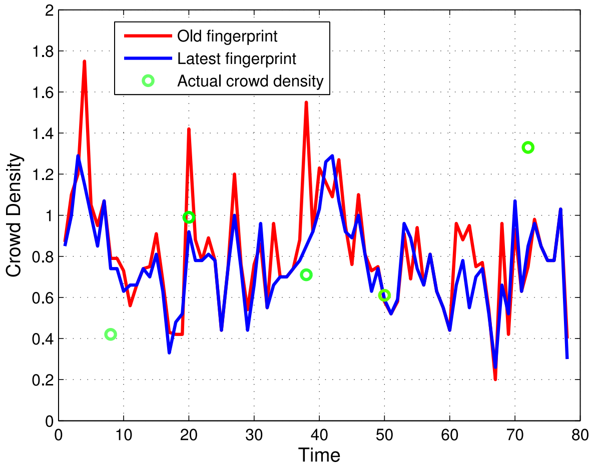

Fig. 9. Crowd density experimental results of Hung Hom footbridge.

B. Evaluation in Real-World Public Environment

1) Hong Kong Hung Hom Footbridge: The first real-world public social activities experiment was conducted using the proposed system at the Hong Kong Hung Hom Footbridge from 12:35 to 13:00. There are many persons walking across the footbridge, some are walking quickly, others slowly. We deployed two Wi-Fi Monitor Detections and a camera in footbridge. In this experiment, Wi-Fi Monitor Detections were used to collect smartphones' wireless signal and camera was responsible for recording the real scene of footbridge. The probability of person with one Wi-Fi signal $\psi(S, [12{:}30, 13{:}30])$ was 92.4% according to (10). The fingerprints used in this experiments were of two sets, one was collected a day before, the other was adjusted 15 min ago. The experimental results are shown in Fig. 9, where the old fingerprint curve line denotes the results for fingerprints collected a day before and the latest fingerprint curve line is for 15 min ago. The recording video was used to count the number of people at randomly time slots of 8, 20, 38, 50, and 72. Therefore, we can obtain these time slots' actual crowd density $\rho(S, t)$ according to (4). In Fig. 9, the actual crowd density is shown as green small circles.

From Fig. 9, it can be concluded that at time slots of 20, 38, 50, the proposed solution applied to the newest fingerprint data, shown as a blue line is very close to the actual crowd density. For all the 5 time slots, the rate of deviation for latest fingerprint line to ground truth is 25.1%, and for the old fingerprint line is 40.3%. Therefore, the newest fingerprint appears to be better than the old one. The experimental results also show that the estimation value of our proposed solution has a gap with the actual crowd density on the whole. One of the main reason is that many people walked too fast and they took less than 30 s in the experimental area. Therefore, our Wi-Fi Monitor Detection cannot collect their signals and make some errors.

2) Hunan Changsha Railway Station Ticket Office: The second real-world experiment was conducted at Hunan Changsha Railway Station Ticket Office from 15:10 to 17:40. Different from Hung Hom Footbridge, the people here to buy ticket and will spend a long time in the lobby. We deployed five

Fig. 10. Ticket Office at Hunan Changsha railway station.

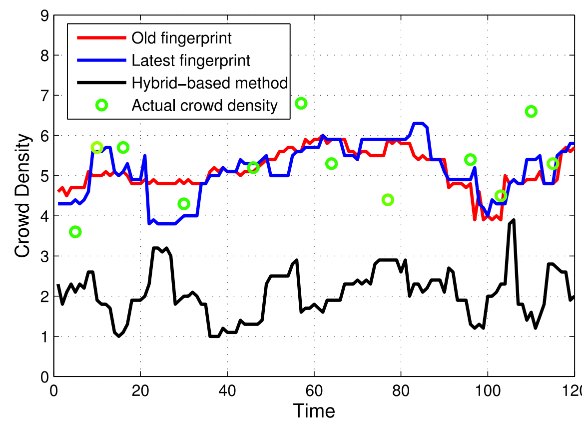

Fig. 11. Experimental results of railway station Ticket Office.

Monitor Detections($MD1, MD2, MD3, MD4, MD5$) to collect smartphones' wireless Wi-Fi signal, two cameras to record the real scene of ticket office. The Ticket Office real-world layout is shown as Fig. 10, where the probability of person with one Wi-Fi signal $\psi(S, [15{:}10, 16{:}40])$ was 96.3%, monitor detection $MD1, MD2$ are near Ticket Office two entrances. The fingerprints were of two sets, the old fingerprints were collected five hours before, the latest fingerprints were adjusted 10 min ago. The actual ticket office situation was randomly sampled at time slots of 5, 10, 16, 46, 30, 57, 64, 77, 96, 103, 110, and 115.

The experimental results are shown in Fig. 11, in which Hybrid-based method curve line are the data calculated by Wi-Fi hybrid-based method [22] using two entrance Monitor Detections $MD1, MD2$. For all the 12 time slots, the rate of deviation for latest fingerprint line to ground truth is 10.83%, and the old fingerprint line is 14.6%, which are much better than the experiments conducted at Hung Hom Footbridge. This is mainly due to the fact that the crowd in Ticket Office are relatively more stability and all smartphones' Wi-Fi *Probe Request* frames are captured by Monitor Detection.

On the other hand, the rate of deviation for hybrid-based method line to ground truth is 57.1%, which is much inferior to our proposed solution. It is reasonable that Wi-Fi hybrid-based method focuses on persons walk from entrance $MD1$ to entrance $MD2$, and the crowd in Ticket Office are not always obey this rule. Thus, the number of person computed by Wi-Fi

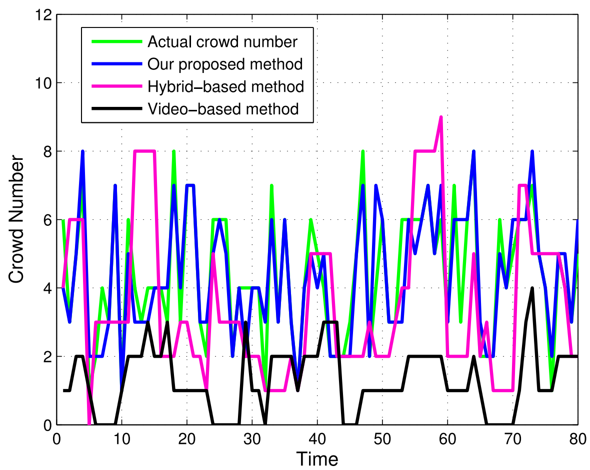

Fig. 12. Experimental results of Furong road subway.

hybrid-based method is much lower than the ground truth. Our proposed solution uses Wi-Fi probe positioning algorithm (WPPA) to locate persons' position and more accurate than Wi-Fi hybrid-based method. These experimental results also illustrate that the proposed solution can be used to estimate the approximate crowd density in real-world public social activities.

3) Changsha Furong Road Subway: The third real-world experiment was conducted at a Changsha Furong Road Subway from 21:30 to 21:50. In this experiment, we deployed a video-based surveillance system with computer vision libraries, which can automatically identify the crowd. Then, we only turned a faint light on, and it was difficult for video-based method to identify crowd. In such circumstances, there were not many people passing through subway and we could accurately count the number of persons in each time slot. The experimental results are shown in Fig. 12. From Fig. 12, we can conclude that the video-based method crowd recognition rate is very low, and our proposed method is closer to actual crowd number than Hybrid-based method and video-based method. This is due to the fact that video-based surveillance system can not effectively identify person in dim environments and the location accuracy of Hybrid-based method is inferior to our proposed method.

VI. Conclusion

In this paper, we build a crowd density estimation solution that is based on a wireless Wi-Fi signal indoor positioning algorithm. The system is composed of Wi-Fi Monitor Detection program, Data Processing component, and a Cloud Server. The Monitor Detection program uses Libcap to capture smartphones' MAC address and obtain the RSSI. We then develop a Wi-Fi probe positioning algorithm (WPPA) using dynamically fingerprints management strategy. Third, we propose a method of computing the probability of a person generating one Wi-Fi signal in public places. The performance of crowd density estimation solution was evaluated in a laboratory environment and three public social activities. The experimental results clearly confirmed that the proposed solution is better than an existing Wi-Fi hybrid-based method and can be used to approximately estimate crowd density in social activity.

This paper is one of the first attempts to estimate crowd density via passive smartphones' wireless Wi-Fi signal. Future studies in this domain are twofold. First, it will be interesting to improve the position accuracy of indoor positioning algorithm. Second, considering smartphones, ipads, notebooks with random MAC address to determine person is also a good direction in further studies.

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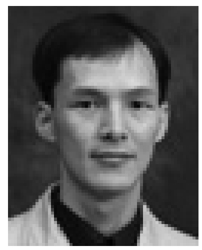

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