Crowd Density Mapping Based on Wi-Fi Measurements on Train Platforms

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***Abstract*—Crowd distribution is a challenging issue in the management and design levels. This paper provides a passive method to derive the crowd density distribution using Wi-Fi measurements on a real scenario. Six WiFi access points (AP) were deployed across two co-located platforms at a train station to monitor the platforms for a week. Based on the probability maps that are built using RSSI measurements and prior knowledge, the crowd distribution is calculated on the platform to increase the accuracy of the estimations in scenarios with sparse data collection. The estimated distribution results are compared with distributions acquired from CCTV images and final density heat maps correlate well with the acquired results from CCTV cameras.**

***Index Terms*—Crowd Estimation, WiFi, Crowd Density, Crowd distribution.**

I. Introduction

Understanding crowd behavior and its distribution plays an increasingly important role in planning, management and safety for architects and safety officials involved in the design and organisation of urban spaces, transport facilities and public events.. To this end, there is a need to detect people and map them into the area to be able to determine the density and its distribution. There are several methods to detect people such as CCTV camera images [9], [4], RFID tags [19], device probing using Wi-Fi [2], [8], [18], [15] or Bluetooth [1], [16]. Analyzing the images of CCTV cameras can provide an accurate estimation of the number of people in the area. However, the coverage of video cameras is limited and it's not possible to install them everywhere. Moreover, processing video streams from video cameras is computationally expensive. Tracking RFID tags, requires participation from people being measured as they need to carry the tags. Further RFID readers need to be deployed quite densely to be able to detect the RFID tags. More recently, mobile phones have become increasingly pervasive enabling alternative and more effective scanning methods for detecting people.

Using WiFi scanning raises two main challenges. First challenge is to provide an accurate estimation of the number of people within the scanning range, considering the probability of having unavailable or undiscovered WiFi nodes. To address this issue, we introduce a parameter called penetration rate which is defined as the ratio of available devices over the total number of people. Second challenge in using WiFi scans, is to locate the detected nodes and map it into the area to derive the density distribution map. Researchers have been focused in localizing the node using WiFi signals for the last decade. Most of the localization methods are based on the RSSI measurements and channel modeling to estimate the location [6], [20], [17], [12]. WiFi fingerprints used for localization, also relies upon RSSI sampling at different locations and comparing the fingerprints with measured values [15], [13], [5]. These measurements are usually done on the carrying device, such as mobile phones, to estimate the location of the user. This approach is not applicable in crowd density estimation, since the scanners (WiFi Access Points) should collect data and locate the nodes. However, due to the symmetry of the measurements, WiFi fingerprints on the AP side can be used to locate the nodes in the area.

An issue with using any of the methods described so far, is that they require a significant number of data samples to be able to locate a node effectively. Therefore, the accuracy of localization with a limited number of samples is limited. People getting off the train are usually walking fast to reach the gates as soon as possible. So, the measurements and RSSI values can change quickly during this period, resulting in sparse data samples.All these will result in having a sparse data samples.

This chapter presents a method to estimate crowd density and its spatial distribution based on RSSI measurements on Wi-Fi access points on a train platform at Redfern station, Sydney. Considering the limited number of measurement samples, a probabilistic method is introduced to create a probability map instead of an exact fingerprint map to help localize nodes derive the density distributions. The main contributions of this paper can be summarized as:

1) Localizing the nodes based on the received signal strength measurements on each AP using probability map which is constructed using fingerprint map.
2) Crowd Density Estimation using multiple using multiple scans from multiple WiFi APs.
3) Determining spatial distribution of the crowd.

To interpret the spatial distribution of a crowd, it is important to measure RSSI accurately and compensate for non-guassian noise from interference, reflection, and fading. The remainder of this paper is organized as follows. Section II defines the problem and challenges. Proposed solution is described in Section III. Section IV describes the experiments and discusses outcomes of the research. Section V, concludes.

II. Problem statement

Ubiquity of WiFi technology and representation of specific characteristics in different situations made it a practical solu-

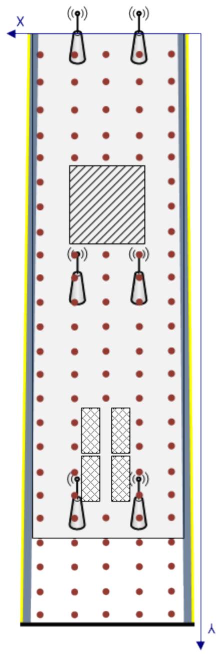

Figure 1. Test environment and problem statement.

tion in crowd estimation and device localization. Leveraging characteristics such as location-specific RSSI values enables one to determine the spatial distribution of available devices. Although WiFi probes are very useful in detecting available nodes, locating the nodes while they are not engaged is quite challenging. To define the problem, the scenario on the platform has been described and then the challenges are specified.

A. *Experiments and data collection*

The experiments and data collection, have been done on a train platform (Platform 2/3) in Redfern station, Sydney. Fig. 1 represents the test environment with a small cabin, available seats, and six APs installed on the platform for scanning purposes. Part of the platform that is covered with metallic shades are also indicated in Fig. 1. During the experiment, the whole platform is divided into $1m \times 1m$ grids; which the centers are indicated by dots. All APs scan the area continually and record timestamps and RSSI values for any detected device. To satisfy privacy preservation, any individual node indicated with a unique hash ID.

To determine crowd density, the easiest way is to count the number of available individual devices appear in each AP as scans its coverage environment. However, there is a high chance of missing a node due to packet collision, signal attenuation or blockage. Furthermore, a recent feature on phones which enable them to create dynamically changing MAC addresses can result in multiple detections of the same node over a specified period of time.

B. *Spatial-Temporal variation of signal*

Recorded RSSI values are the main characteristics to localize a node. However, the received value of signal strength can vary in time due to various reasons such as blockage, OS of the devices, and battery level of the device. While WiFi or Bluetooth sampling provides a potentially effective means of detecting devices, the use of WiFI security and power saving techniques implemented in the IEEE 802.11 standards can severely degrade this capability. The IEEE 802.11 standard defines how devices associate with a WiFi AP. A WiFi AP will transmit periodic beacon frames to advertise itself - typically every 100ms. Devices upon receiving beacon advertisements attempt to associate with the WiFi AP. If the device does not associate with the AP, then it will go to sleep for a random period of time. This process can cause issues in localizing devices due to the detection period.

III. Proposed approach

To estimate crowd distribution, two steps are required. First step is to have an understanding of the number of nodes on the platform. The second step, the location of each device is determined and mapped to the area (e.g. train platform).

A. *Localization*

As previously described, each AP listens to the probe requests of devices and records RSSI values of the receiving packets. To find the location of a node based on the RSSI packet measurements several methods have been introduced in the literature. Use of fingerprint map based on prior measurements is one of the more promising techniques [10], [7], [3], [11][14]. In this technique, WiFi signal are measured in the space time domain and then, new measurements will be compared to the recorded values to estimate the location of the node. In this section, we described the WiFi signal fingerprint map construction approach and its issues dealing with limited sample numbers of data. A new approach will be introduced to minimize the uncertainty of fingerprint map based localization in dealing with a sparse dataset.

Fingerprint and Probability map construction : The experiments in this project were based on passive scanning process [1] which results in a sparse set of data obtained during rush hours; while people are leaving or entering a train as quickly as possible. Considering the average speed of people during these hours and WiFi power save protocols the number of samples that can be recorded are limited. The limited number of data leads to a very challenging issue in terms of localization and node mapping.

Given a set of APs, $AP = \{AP_1, AP_2, AP_3, ..., AP_N\}$ where N is the number of APs in the test field $\mathcal{F} \subseteq \mathbb{R}^2$. The field, $\mathcal{F}$, is divided into $1m \times 1m$ grids and large number of received signal strength samples is recorded in each AP from a device on the cell, C_{ij}. Where i and j are indicators of row i and column j in the grid. So, the signal signature of any Wi-Fi device on each cell can be described as $Signature(C_{ij}) = \{S_{ij}^1, S_{ij}^2, ..., S_{ij}^N\}$. S_{ij}^N represents recorded signal strength on AP_N from a device at cell ij. Assuming the receiving signal from cell i and j in AP N as

$$x_{ij}^N = S_{ij}^N + n \tag{1}$$

Where S_{ij}^N is the actual value of the receiving signal and n is a spatially uncorrelated zero mean Gaussian noise. The probability of the location can be formulated as a Gaussian probability:

$$\Pr(L_{ij} \mid x_{ij}^N) = \frac{1}{\sigma\sqrt{2\pi}} \exp(\frac{1}{\sigma^2} \parallel x_{ij}^N - S_{ij}^N \parallel^2) \qquad (2)$$

During this project, we assume that the node k is on a 2D environment and its position at time t can be described as $X_t^k = \begin{bmatrix} x^k & y^k \end{bmatrix}^T$ which is mapped to the center of cell that it's associated. Assuming that the average value for signal strength can be measured from any AP within each cell. Then, we have a tensor describing WiFi RSSI measurements within each cell. To determine the position of each node, we define the probability function of the position as $f(X_t^k = x_t^k)$. Thus, considering the measurements of each AP and assuming that measurements are $i.i.d$, the probability of having the node in cell C_{ij} will be

$$f\left(X_t^k = C_{ij} \mid measurements\right) = \prod_{l=1}^{N} f\left(S_{ij}^l \mid x_{ij}\right) \qquad (3)$$

Having measurements for device k at time t as z_t^k, we aim to estimate node's position, $\hat{x_t^k}$, for the state x_t^k. Thus, assuming Markov properties for the system, we can model it as follows; using particle filters:

$$x_t^k = g\left(x_{t-1}^k, w_t^k\right)$$

$$z_t^k = h\left(x_t^k, v_t^k\right)$$

Where $g\left(\cdot\right)$ is the transition function from state x_{t-1}^k to x_t^k and $h\left(\cdot\right)$ is the measurement function. $w_t^k \sim N\left(0, Q\right)$ and $v_t^k \sim N\left(0, R\right)$ are noise with covariance matrices $Q = diag\left(\sigma_x^2, \sigma_y^2\right)$ and $R = diag\left(\sigma_1^2, ..., \sigma_N^2\right)$, respectively.

Deriving the fingerprint map based on the experiments helps to determine locations more accurately. However, localization with this method requires sufficient number of measurements due to temporal variation of the RSSI measurements. To overcome this issue, probability map is introduced. Using this method, a probability will be assigned for every measurement and the expected value for each cell will be calculated using assigned probabilities.

It is noteworthy to mention that in this map, the grids that are blocked with different obstacles will receive the value of zero as the probability of existence.

B. Leveraging prior knowledge

As mentioned above having limited number of samples of received signal strength poses tremendous challenges in finding the location of each node. Leveraging prior knowledge can help to compensate the lack of samples. To acquire this knowledge, the platform is monitored for a day. It is noted that people trying to avoid the middle of platform due to the obstacles such as pillars and seats. They also tend to stay on the side that train stops. However, some try the other side of platform to be able to walk faster and avoid other people. Considering all these observations, the distribution on the X-axes of the platform (as illustrated in Fig. 1), according to the trains' timetables, can be modeled using Gaussian mixture model with variable variance values as shown in Fig. 2.

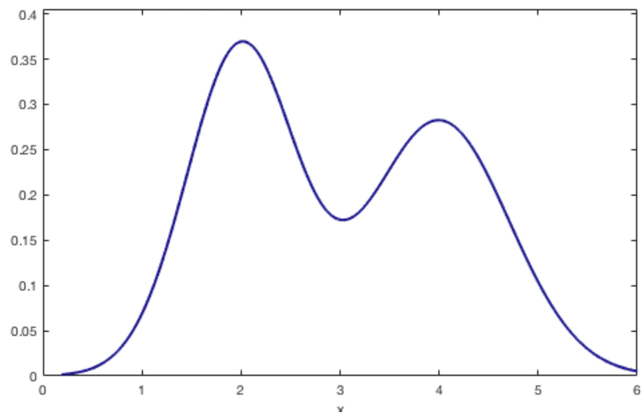

Figure 2. Distribution on the X axes of the platform.

$$f(x) = (1 - \alpha)g_1(x) + \alpha g_2(x) \qquad (4)$$

Where $g_i(x) = \phi_{\theta_j}(x),\ \theta_j = (\mu_j, \sigma_j^2)$.

On the other hand, people form a nearly uniform distribution as reaching the concourse as shown in Fig. 3. This phenomena can be modeled by defining variance of the Gaussian mixture model as a function of Y-axes (distance from concourse). So, a multi-dimentional model obtained which provides the distribution of the platform.

$$f(x) = \sum_{i=1}^{K} \alpha_i N(x \mid \mu_i, \Sigma_i) \qquad (5)$$

$$N(x \mid \mu_i, \Sigma_i) = \frac{1}{\sqrt{(2\pi)^k \mid \Sigma \mid}} \times \exp\left(-\frac{1}{2}\left(x - \mu_i\right)^T \Sigma_i^{-1}\left(x - \mu_i\right)\right) \qquad (6)$$

This probability function is used to adjust the final probability map of crowd distribution aiming for better accuracy.

C. Crowd estimation and crowd distribution

The most straightforward method to estimate the crowd around each AP is to run a scan for any nearby device and assuming that each discovered device is indicating a person within a given radius. However, even with this assumption, device detection is a function of random variables due to synchronization and signal propagation with distance and there is a possibility of miss-detection. Furthermore, considering real world situation, this method may not be accurate due to undiscoverable devices. To take undiscoverable devices into account, we define penetration rate (ρ) as the ratio of discoverable devices to the total number of people within radius R. This ratio would be obtained through field experiments.

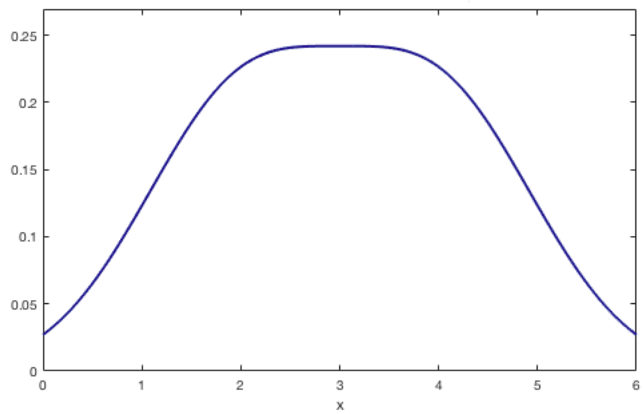

Figure 3. Distribution on the concourse entrance.

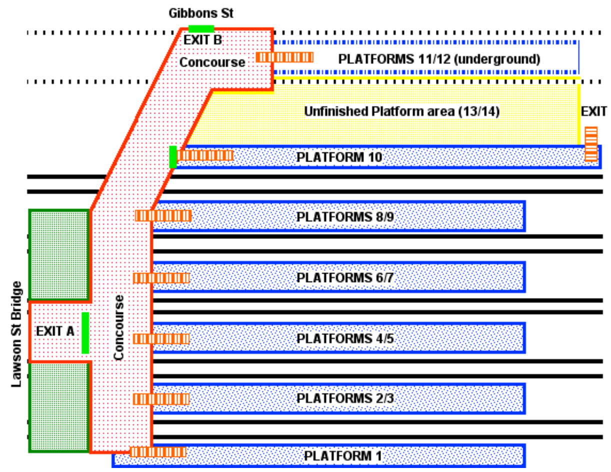

Figure 4. Map of Redfern train station. [https://www.triposo.com/poi/N__603520919]

$$\rho \triangleq \frac{Number\ of\ people\ with\ discoverable\ Bluetooth\ devices}{Total\ number\ of\ people} \tag{7}$$

Considering the probability of having a node in cell i and j, the expected value of the number of people in each cell is determined as

$$\mathbb{E}(\text{Number of people}) = \sum_{i}^{M} 1 \Pr(L_{ij}) \tag{8}$$

IV. Experiments

The experiments are done on platform 2/3 of Redfern station, Sydney. Fig. 4 provides layout of the platforms in the station. Sydney Trains provided facilities and managed data collection on the platform during the experiments. The experiments were divided into two sections. In the first section, we have recorded data to extract fingerprints and probability map of the platform. As it is clear, there is a small gap between platforms, around 13 meters. Therefore, adjacent platforms (1 and 4/5) also considered during the experiments and initial data collection. Then, CCTV images and WiFi data is collected for a week to provide and estimate the crowd density map. Final results are compared with the results of CCTV images to validate the approach.

A. Fingerprint map extraction

To drive the fingerprint map for the platform and considering our limited access to the data collection systems, we have to design series of experiments to derive the RSSI values at the center of the grids as described in Fig. 1. To collect RSSI values, three participants with six different mobile phones followed predefined paths with specific rules. Each person had a Nexus 6p and one other phone (Samsung, Apple, Sony). The platform divided into three section for the measurements and defined different paths for each person as shown in Fig. 5. Each person followed the defined paths while standing steady at the centre of each cell for a minute. This process enabled us to record enough data samples to extract the fingerprint map of the platform.

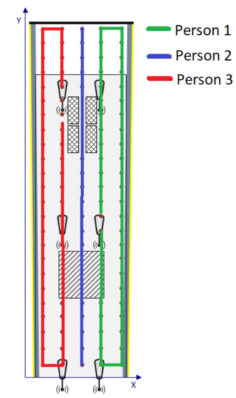

Figure 5. Grids and paths during the experiments for fingerprint map.

When we collected the data provided by Sydney Trains (according to the defined rules and recorded timestamps) we extracted the averaged RSSI values for each point aiming to build the fingerprint map. Fig. 6 shows the averaged values of measured RSSI for each person from all the six APs. As mentioned, each person follows a specific defined rules during this stage. So, the measurement can be verified based on the patterns of change and its values according to its distance from each AP. Then, considering AP positions and defined paths for each participant, the fingerprint map were created using the average values of measurements to build the fingerprint map for each AP through the platform.

Having new measurements, the probability map for each node is calculated regarding each AP. The probability map is created based on the probability of being in different cells according to the fingerprint map. Considering the fact that measurements from each AP are independent from each other, all the probability maps are combined and the expected number of people for each grid is described in Eq.(8). Finally, the density map is calculated according to the estimated numbers for each cell.

Figure 6. Averaged RSSI measurements for three different person in all the six APs. (a) First person. (b) Second person. (c) Third person.

B. Density map extraction

CCTV images and RSSI measurements data were collected for a week from the platform. The CCTV images are used to extract the penetration rate (ρ) and validate the calculated density map. Comparing both data, the penetration rate is calculated as one device per four person on the average $(\rho = 4)$.

To extract the density map, the probability map for every detected node is calculated regarding each AP and the final probability map is created for each node. Then, all the probability values formed the final density map for one minute set of measured data. Finally, using KNN (K-nearest neighbors) method the final heat map is generated for every minute. Fig. 7 shows samples results for the crowd distribution and density map on the platform at four different time stamps on 27 June 2017. According to the definition provided by Sydney Trains, more than five people in a square meter is considered dangerously crowded. So, the density heat map reflects these values by assigning blue color to zero (no one in a cell) and red color to six people in a cell.

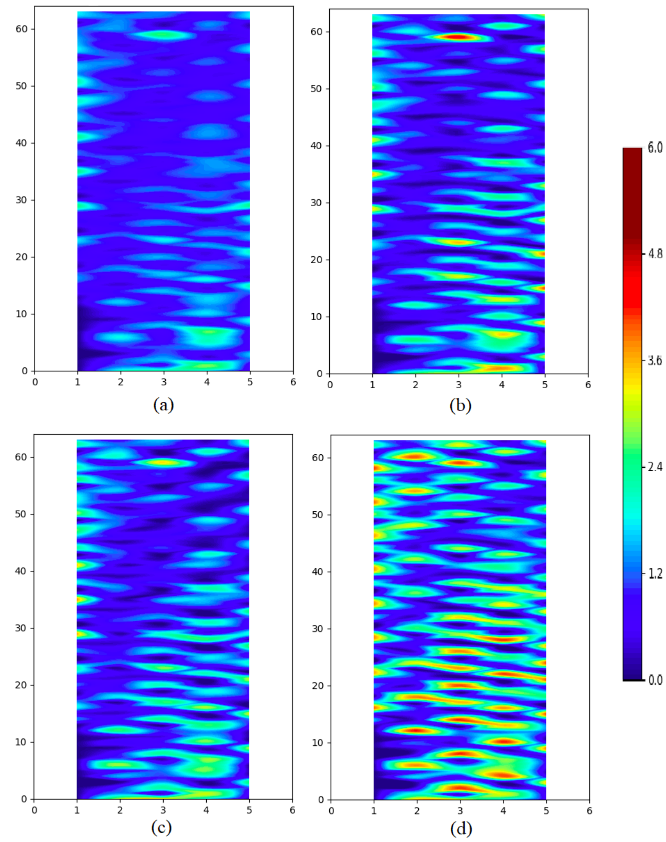

Figure 7. Crowd distribution on the platform 2/3 of Redfern station. (a) 27 June 2017 at 16:02 (b) 27 June 2017 at 16:03 (c) 27 June 2017 at 16:31 (d) 27 June 2017 at 17:00

Fig. 7(a), (b) and (c) shows three continuous intervals at 16:01, 16:02 and 16:03, respectively. The changes of the crowd distribution in the platform before, during and after train arrival can be seen. In Fig. 7(c) and (d) nearly uniform distribution of the crowd density also can be noted near the concourse. Another interesting point that can be seen in Fig. 7 is the fixed high density cells on the sides of the platform which are indicators of train doors.

The analysis results are compared with the results of analysis of CCTV images. Fig. 8 shows the crowd density analysis using CCTV images at 16:02, 16:03 and 16:31. Comparing Fig. 8(a) and (b) with Fig. 7(b) and (c) that show the results for 16:02 and 16:03, respectively, proves that both are following similar patterns in terms of density distribution. Fig. 8(c) represents the distribution for 16:31 to compare with Fig. 7(d), as well.

Considering the sparse measurements during the experiments, it can be noted that using the proposed method for calculating probability maps increases the accuracy of distribution estimation. Although the results are in good match with recorded images, it should be mentioned that there is a chance for discrepancy due to the resolution of data in both approaches. Wi-Fi detection is highly depended upon the number of available devices and the quality of images, while camera placement plays an important role in counting people and estimating their locations.

V. Conclusion

In this paper, an experimental evaluation of WiFi crowd estimation and a new approach in estimating its distribution over the platform 2/3 in Redfern train station, Sydney is presented. A probability map based on RSSI measurements and prior knowledge is constructed which is used to determine the location of new nodes and measurements. Final results are compared to the density maps extracted from CCTV images during same period and exhibits good accuracy. However, it is noteworthy to mention that both methods have their own shortcomings. Image based techniques rely on having high quality images and camera deployment in proper angle of view. WiFi measurement accuracy is also limited due to power save methods and security measures. To address these short comings an ideal solution would be to combine both techniques thereby providing more accurate density maps.

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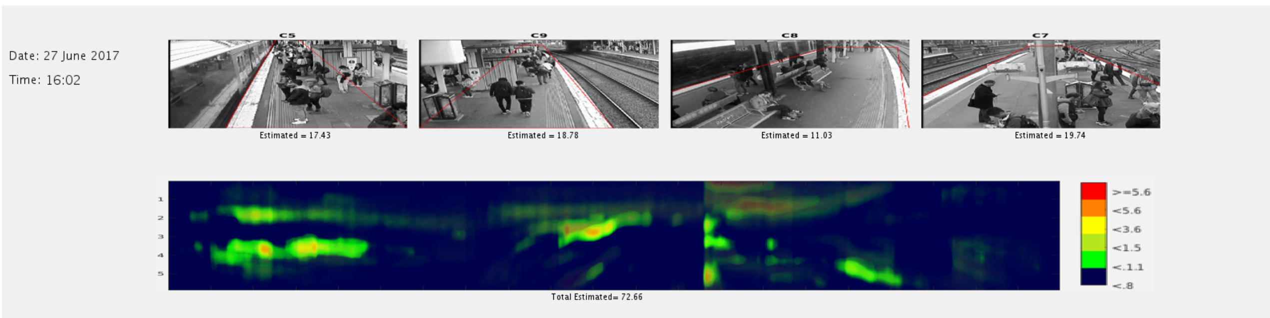
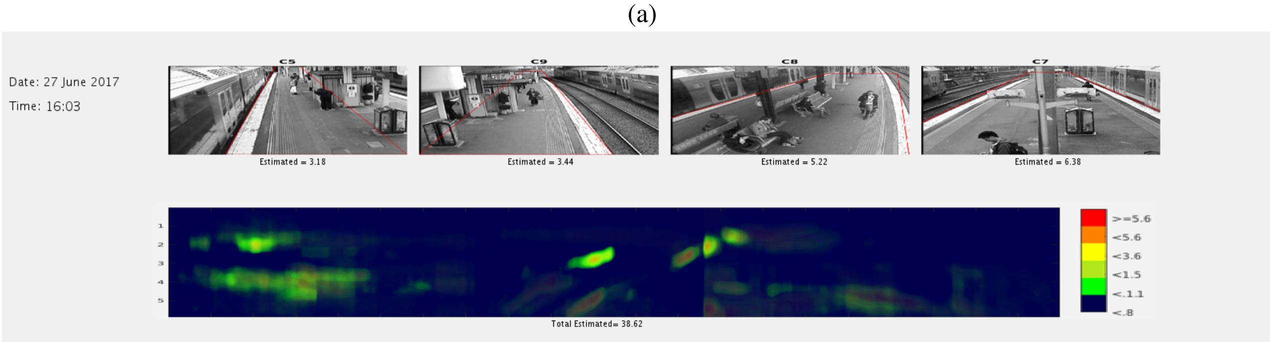


(a)



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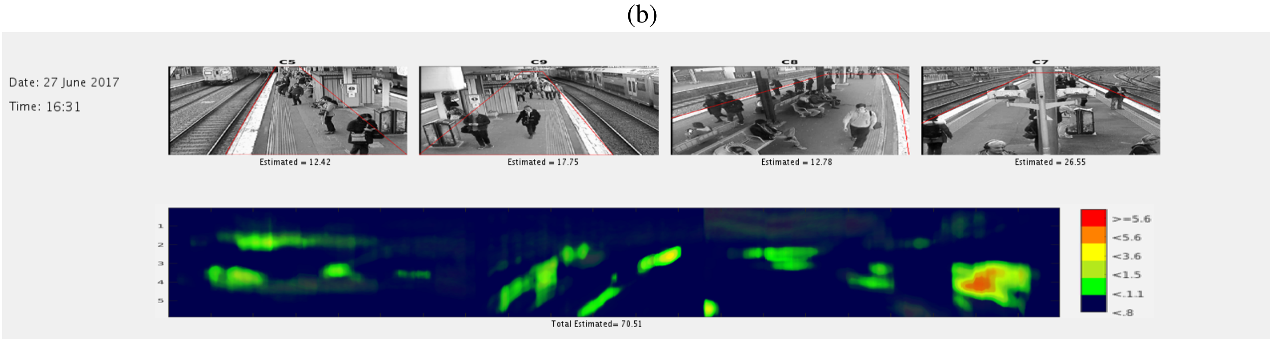

(c)

Figure 8. Crowd distribution based on CCTV images. (a) 27 June 2017 at 16:02 (b) 27 June 2017 at 16:03 (c) 27 June 2017 at 16:31