Analysis of Wi-Fi-based and Perceptual Congestion

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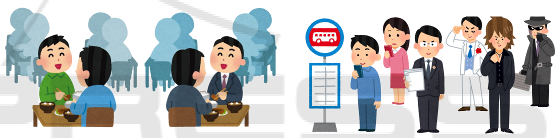
Abstract: Conventional works for congestion estimates focus on estimating quantitative congestion (e.g., actual number of people, mobile devices, and crowd density). Meanwhile, we focus on perceptual congestion rather than quantitative congestion toward providing perceptual congestion information. We analyze the relationship between quantitative and perceptual congestion. For this analysis, we construct a system for estimating and visualizing congestion and collecting user reports about congestion. We use the number of mobile devices as quantitative congestion measurements obtained from Wi-Fi packet sensors, and user-report-based congestion as a perceptual congestion measurement collected via our Web service. Base on the obtained quantitative and perceptual congestion, we investigate the relationship between these values.

1 INTRODUCTION

Congestion measurements and estimates are useful and important for various applications. Congestion information can assist congestion avoidance and mitigation. It is also important that we grasp the number of visitors to retail stores for customer analysis and marketing strategies. Additionally, evacuation planning for disasters requires congestion information (Choi et al., 2011).

The extent of congestion is measured or estimated manually or using sensors such as cameras and Wi-Fi packet sensors. Vision-based congestion estimates using cameras have recently been developed, and the accuracy of these methods improves with each year. Cameras must be carefully installed in the target area considering occlusion and blind areas, and the initial costs tend to be high. Wi-Fi packet sensors estimate the number of mobile devices (e.g., smartphones and laptop computers). The number of mobile devices tends to be proportional to the number of people, so we can use them to roughly estimate congestion. Wi-Fi packet sensors cover distances between dozens to a hundred meters. A Wi-Fi radio wave has a higher transmittance than visible light, therefore we can install packet sensors in typical situations without considering blind areas.

The above-mentioned techniques are aimed at estimating quantitative congestion measurements such as people count, crowd density, and the number of mobile devices. For customer analysis, the actual people count and density are useful and important factors.



(a) Dining hall (b) Bus stop

Figure 1: Two spots with similar crowd density.

Meanwhile, in terms of providing congestion information to people, qualitative congestion measurements such as a person's perception are also important. Figure 1 shows two spots with almost the same crowd density. There are few vacant seats in the dining hall, so we would feel that the dining hall is crowded. The crowd density at the bus stop is similar as the dining hall, but the bus stop cannot be considered crowded. Human perception about congestion depends on the people count and density and also the locations characteristics, such as area and seating capacity.

In this paper, we focus on the relationship between quantitative and perceptual congestion toward providing perceptual congestion information. We use the number of mobile devices as quantitative congestion measurements obtained from Wi-Fi packet sensors, and user-report-based congestion as a perceptual congestion measurement collected via our Web service. We investigate the relationship between these values.

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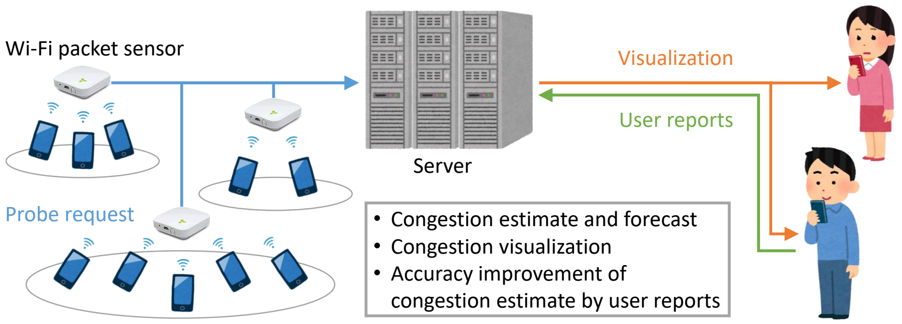

Figure 2: Overview of our system.

2 RELATED WORK

2.1 Preliminaries

2.1.1 Probe Request and Counting Mobile Devices

Probe request is a packet (or more precisely, a frame) defined in IEEE 802.11, which is broadcast by a mobile device with a Wi-Fi function when the device searches for access points before establishing a connection. The transmitting interval is between several to several hundred seconds and depends on the device. The probe request frame includes a MAC address for the sender, so the receiver can identify the sender and count the peripheral mobile devices. Additionally, the receiver can obtain a received signal strength (RSS) value. The RSS value is lower for larger distances between the sender and receiver. Therefore, the receiver can roughly estimate the distance to the sender using the RSS value.

2.1.2 Wi-Fi Packet Sensor

A Wi-Fi packet sensor is a sensor for collecting probe request frames. We can make a prototype Wi-Fi packet sensor using a single-board computer such as a Raspberry Pi[1]. Commercial Wi-Fi packet sensor products have recently become available[2]. A Wi-Fi packet can be sent from over one hundred meters away, so they can cost effectively cover a large area.

2.2 Estimation and Analysis of Crowd Density and Pedestrian Flow

Fukuzaki et al. analyzed pedestrian flow using Wi-Fi packet sensors (Fukuzaki et al., 2014). Yaik et al. compared the number of Wi-Fi frames and crowd counting manually (Yaik et al., 2016). They evaluate the correlation between manual and Wi-Fi frames counting. Above-mentioned methods used Wi-Fi probe requests. Xi et al. use Channel State Information (CSI) of Wi-Fi for counting crowd (Xi et al., 2014). Their method outperforms the state-of-the-art approaches in terms of accuracy and scalability.

Weppner et al. estimated crowd density by Bluetooth scan data (Weppner and Lukowicz, 2013). Schauer et al. proposed a hybrid method for estimating crowd density and pedestrian flow using Wi-Fi and Bluetooth (Schauer et al., 2014). They estimated the crowd density (defined as the number of people per unit area) for each spot using Wi-Fi and Bluetooth, and compared the estimated number of people with the ground truth.

These works considered the number of people or the number of devices, but not the peoples perception of the congestion.

[1] https://www.raspberrypi.org/
[2] http://aibeacon.jp/

3 SYSTEM FOR CONGESTION ESTIMATE AND COLLECTING USER REPORTS

In this section, we describe our system for estimating and visualizing the congestion, and collecting user reports.

3.1 System Overview

Figure 2 gives an overview of this system. We capture probe request frames and store tuples of the received time, location ID, and MAC address to the database. Then, we calculate the extent of the congestion using the data stored in the database. Our Web service plots a time series of the congestion for each location. This service has a function for receiving user reports

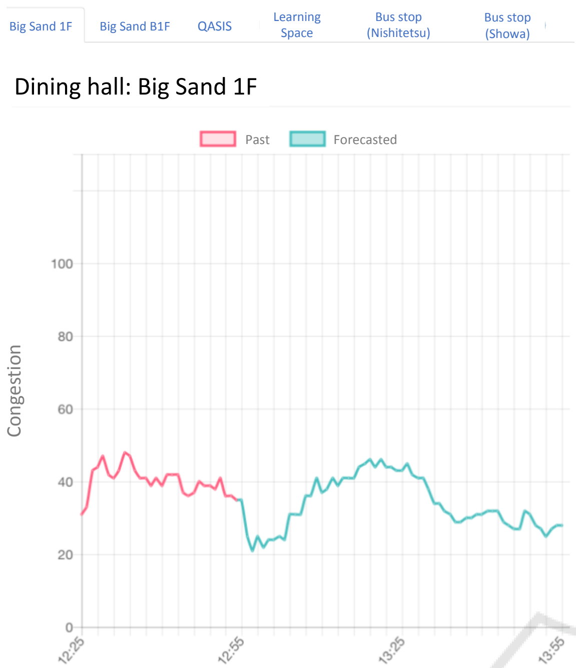

Figure 3: Web service for visualizing congestion.

about the congestion. The details of the system are described in following subsection.

3.2 Probe Request Capturing and Filtering

We used Wi-Fi packet sensors located in various locations to capture probe request frames. Wi-Fi packets can be received when the receiver is several hundred meters away from the sender. In this study, we estimated the congestion at dining halls and bus stops in a university campus. We filtered out packets with weak signal strengths (under -80dB) so that we only collected data from close devices. The received time t of the packet, place ID (sensor ID) p, and MAC address m are stored to the database D[3].

$$D \leftarrow D \cup \{(t, p, m)\} \tag{1}$$

3.3 Congestion Degree based on Probe Requests

We define the congestion degree $c(t, p)$ for each time and place using probe request data without prior

[3] Actually, we store hash values to the database instead of MAC addresses because of privacy issues.

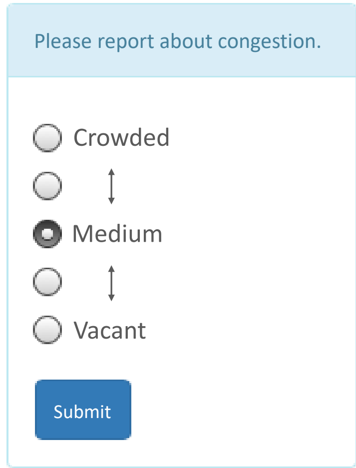

Figure 4: User report form.

knowledge of the location as

$$c'(t,p) = \\ |\{m \mid (t', m, p') \in D, t - 180 \leq t' \leq t, p' = p\}| \tag{2}$$

$$c(t,p) = \frac{c'(t,p)}{\alpha \max_t (c'(t,p))}, \tag{3}$$

where $c'(t, p)$ is the number of unique MAC address observed during the three minutes. We obtain $c(t, p)$ by normalizing $c'(t, p)$. The value α is determined empirically (in this paper, $\alpha = 0.75$).

3.4 Visualizing Congestion

We developed a Web service to visualize the extent of the congestion. Figure 3 plots the congestion degree calculated using Eq. 3. The red line represents the congestion during the last 30 minutes and the green line represents the forecasted congestion. Readers can browse other locations using the upper tabs.

3.5 User Report

We collected user reports as perceptual congestion measurements. Figure 4 shows the form for reporting the congestion degree on our website. There are five radio (option) buttons. Users can only select one radio button. After a user pushes the submit button in the form, the selected item, time, and location are submitted to the server.

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Table 1: Location of Wi-Fi packet sensors.

ID	Location	Floor	Type	Purpose
1	Dining hall A	GF	Indoor	Breakfast, lunch and dinner
2	Dining hall B	GF	Indoor	Breakfast, lunch and dinner
3	Learning space	3F	Indoor	Learning
4	Dining hall C	B1	Indoor	Lunch
17	Bus stop A	N/A	Outdoor	Returning home
18	Bus stop B	N/A	Outdoor	Returning home

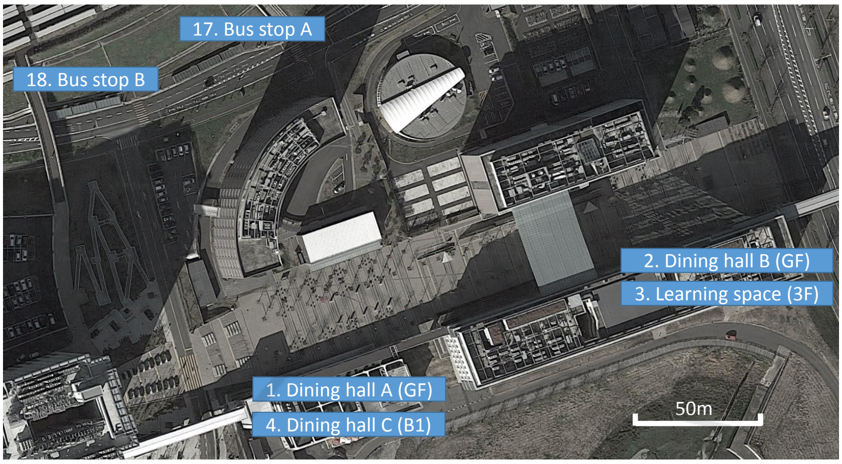


Figure 6: Wi-Fi packet sensors on a campus.

4 ANALYSIS OF CONGESTION AND USER REPORTS

In this section, we analyze the congestion and user reports obtained using our system.

4.1 Operation of Our System

We installed six Wi-Fi packet sensors on an university campus (Figures 5 and 6). Table 1 shows the installed spot, whether or not the spot is located indoors. We have been operating these packet sensors since January 2016.


Figure 5: Wi-Fi packet sensor.

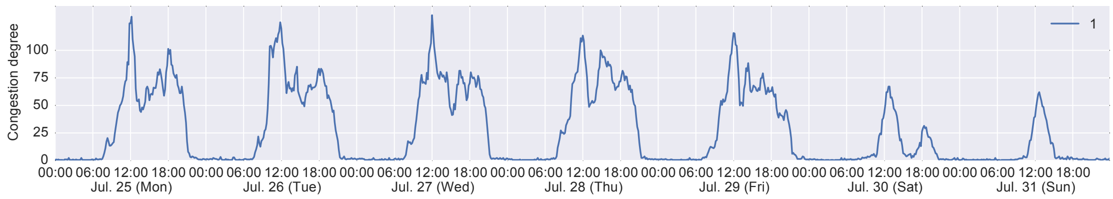
We have been operating our Web service for visualizing congestion and recording user reports since July 2016. We received over three hundred user reports about congestion via our Web service during the first four weeks.

4.2 Time Series of Congestion

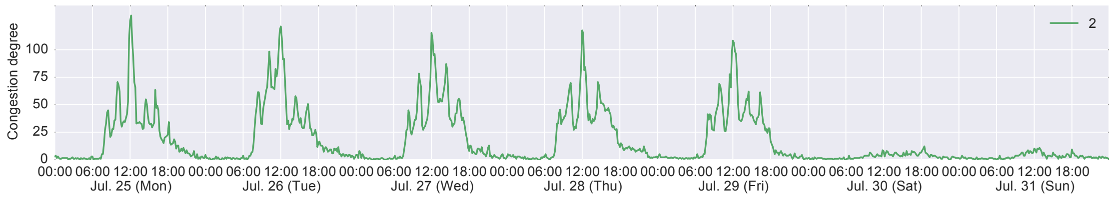
Figure 7 shows the congestion calculated using Eq. 3 for a typical week. We can see that the dining halls (IDs 1, 2, and 4) have a steep peak around 12:00 because of lunchtime. The congestion at the bus stops (IDs 17 and 18) tends to fluctuate intensely. This is because busses arrive every 5 to 15 minutes to collect passengers. Both bus stops are mainly used to go home, so peak congestion occurs around the evening.

4.3 Correlation Analysis of User Reports

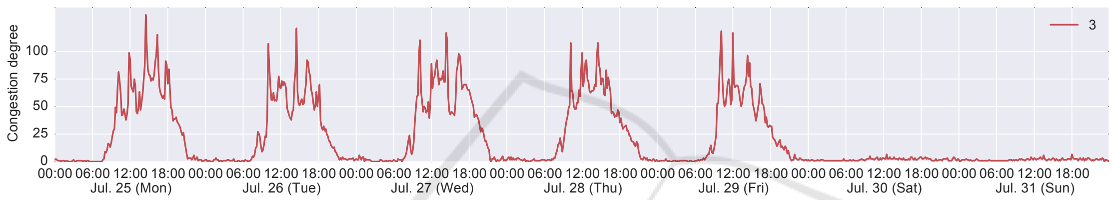
We analyzed the correlation between user reports and the congestion recorded using Wi-Fi packet sensors. Figure 8 shows the scatter diagrams and correlation coefficients for the user reports and Wi-Fi-based congestion for each location. The correlation coefficients for locations 1, 3, and 4 are over 0.6, so we can say that the quantitative and perceptual congestion of those spots have moderate correlations. Meanwhile, the correlation coefficient for location 2 is less than



(a) Location 1



(b) Location 2



(c) Location 3

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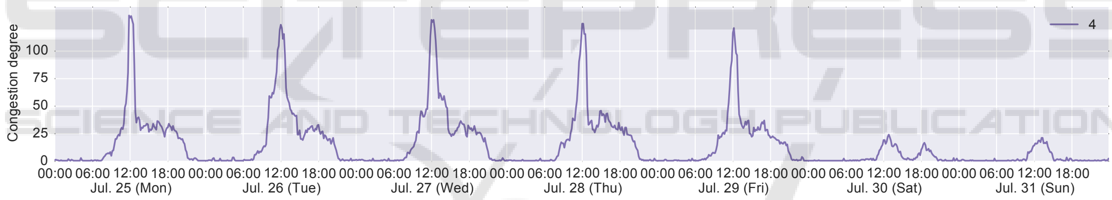
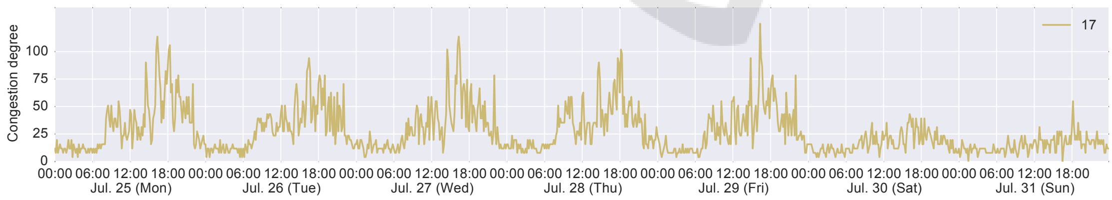
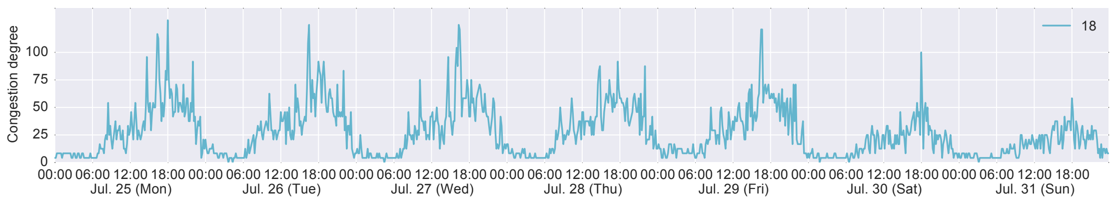


(d) Location 4

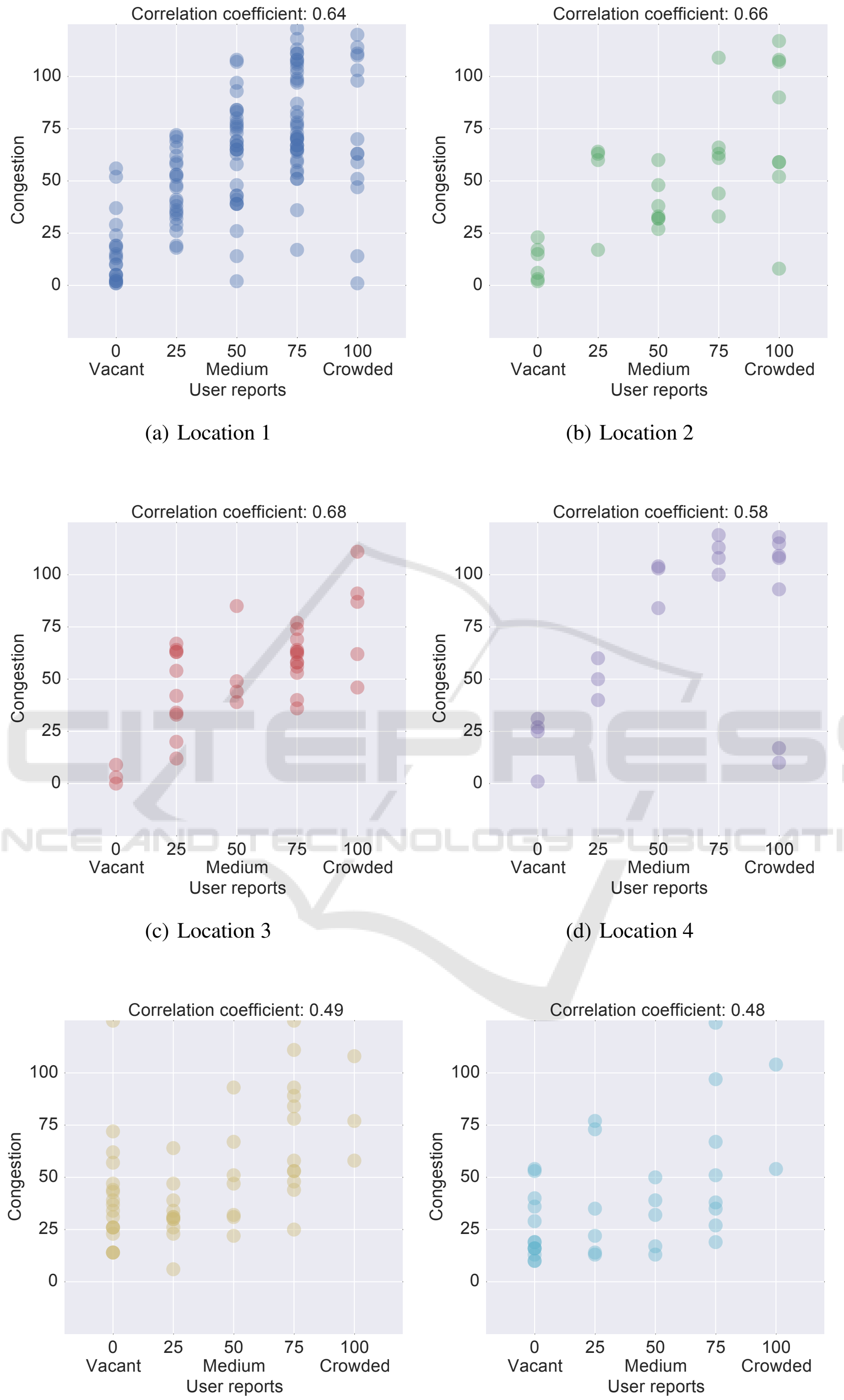


(e) Location 17



(f) Location 18

Figure 7: Congestion for a typical week.



(a) Location 1

(b) Location 2

(c) Location 3

(d) Location 4

(e) Location 17

(f) Location 18

Figure 8: Correlations between the congestion and user reports.

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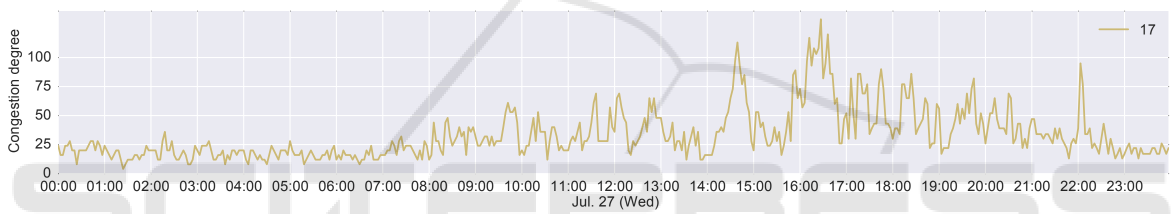
Table 2: Time table of bus stop (Location 17).

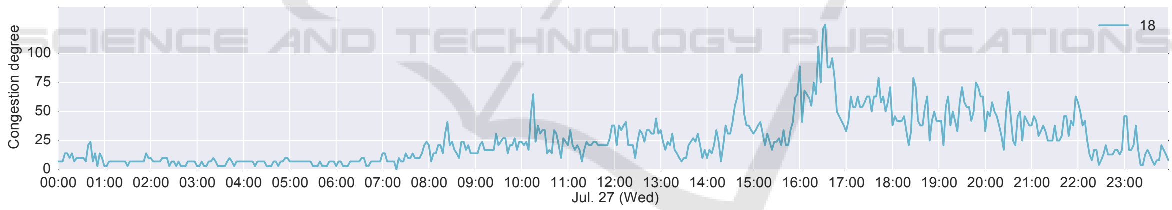
8:11	8:25	8:41	9:11	9:41	10:21	10:41	11:16	11:41	12:11	12:46	13:01
13:22	13:47	14:17	14:37	14:47	14:57	15:12	15:42	16:12	16:27	16:32	16:46
16:50	16:57	17:17	17:42	18:17	18:22	18:42	18:57	19:27	19:42	20:02	20:31
21:01	21:31	22:01									

Table 3: Time table of bus stop (Location 18).

6:57	6:59	7:11	7:21	7:37	7:39	7:46	7:56	8:13	8:21	8:34	8:39
8:44	8:49	8:54	8:59	9:04	9:14	9:30	9:36	9:46	9:57	10:12	10:17
10:26	10:36	10:44	10:57	11:01	11:12	11:27	11:41	11:51	11:56	12:04	12:11
12:16	12:21	12:26	12:41	12:57	13:06	13:12	13:26	13:36	13:46	13:57	14:11
14:21	14:26	14:37	14:41	14:44	14:47	14:51	14:54	14:58	15:01	15:04	15:11
15:16	15:21	15:26	15:37	15:41	15:46	15:56	16:01	16:04	16:09	16:14	16:19
16:24	16:27	16:31	16:34	16:38	16:43	16:46	16:51	16:56	17:04	17:06	17:12
17:14	17:19	17:22	17:24	17:26	17:29	17:35	17:39	17:42	17:44	17:48	17:52
17:55	18:01	18:04	18:06	18:11	18:17	18:21	18:26	18:31	18:37	18:41	18:44
18:53	18:56	18:59	19:06	19:11	19:14	19:17	19:26	19:31	19:36	19:46	19:51
19:54	19:57	20:06	20:11	20:14	20:26	20:29	20:41	20:49	21:01	21:06	21:09
21:14	21:24	21:26	21:41	21:59	22:01	22:06	22:21	22:48	22:53	22:59	23:13



(a) Location 17



(b) Location 18

Figure 9: Congestion of bus stops for a typical day.

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0.5 even though it is from the same category (dining hall) as locations 1 and 4. After analyzing user reports in more detail, we found this low correlation was caused by a lot of submissions of 'Crowded' in a short time. During this period, the Wi-Fi packet sensors did not estimate that the location was crowded. Therefore, we believe that these submissions were malicious. We will deal with such malicious submissions in the future.

The correlation coefficients of two bus stops (locations 17 and 18) are not large (around 0.5). This is because of the intense fluctuations in the congestion calculated using Wi-Fi sensors. Figure 9 shows the congestion of two bus stops. Tables 2 and 3 show the timetables of two bus stops. Because busses run frequently, congestion curve fluctuates intensely. Consequently, the correlation coefficients of the bus stops are not high, and forecasting congestion is not easy.

5 CONCLUSION AND FUTURE WORK

In this paper, we described a system for estimating and visualizing congestion using Wi-Fi packet sensors. We also collected user reports about congestion via our system. We analyzed the relationship between quantitative congestion measurements using Wi-Fi packet sensors and perceptual congestion measurements based on user reports. Based on our analysis, we found correlations between the quantitative and perceptual congestion measurements for each location.

We plan to install Wi-Fi packet sensors at more locations (e.g., lecture rooms, laboratories, and conference rooms) and then analyze the congestion in more detail. Based on the relationship between quantitative and perceptual congestion, we will improve the accuracy of congestion estimates and provide congestion information via our system.

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