Estimating the number of people using existing WiFi access point in indoor environment

Takuya Yoshida
Kindai University
Faculty of Science and Engineering
3-4-1, Kowakae, Higashi-Osaka, Osaka
Japan
1210370068h@kindai.ac.jp

Yoshiaki Taniguchi
Kindai University
Faculty of Science and Engineering
3-4-1, Kowakae, Higashi-Osaka, Osaka
Japan
y-tanigu@info.kindai.ac.jp

Abstract: In various situations, there are demands for estimating the number of people in an area. On the other hand, the number of WiFi access points and WiFi client devices have been widely increasing in recent years. In this paper, we propose methods for estimating the number of people using information on the received signal strength in existing WiFi networks. To estimate the number of people, we apply linear regression-based approach and support vector regression-based approach in this paper. To evaluate our proposed methods, we construct an experimental environment in our laboratory with an existing WiFi access point. Through experimental evaluation, we show that the accuracy of support vector regression-based method is better than that of linear regression-based method. In addition, we show that the accuracy rate of support vector regression-based method for estimating the number of people is 0.772, that for estimating the degree of congestion is 0.946, and that for estimating the presence/absence of people is 0.982.

Key–Words: WiFi, IoT, RSSI, people detecting, people counting, indoor environment, machine learning

1 Introduction

In various situations, such as marketing in commercial area, facility management in public facility, there are demands for estimating the number of people or degree of congestion in an specific area. For example, in the leisure facilities such as amusement parks, by measuring the congestion degree for each attraction and optimizing operations, it is possible to enhance the convenience for visitors. Manual counting is the traditional way to count the number of people. However, it requires high labor costs and there is a problem that accuracy is decreased under a crowded environment. Therefore, there have proposed a various methods for counting people or estimating the degree of congestion automatically by using cameras [1–5], sensors [6–9], and devices attached on people such as RFID and smart phones [10, 11].

On the other hand, the number of WiFi access points and the number of WiFi client devices have been increasing in recent years. For example, the government of Japan has decided to construct 30,000 new public WiFi access points by 2020, the Tokyo Olympics year, to provide free Internet access services for visitors. In addition, a variety of Internet of Things (IoT) services have attracted attentions and some IoT services have been realizing in recent years. Therefore, it is expected that WiFi modules are attached at a variety of products in the future.

In general, the received signal strength at a receiver node is varied depending not only on the transmission power of sender node and distance between receiver and sender nodes but also on other factors such as obstacles around the area. Since the presence or behavior of people near the nodes also affects the received signal strength, wireless signals can be used for sensing human behavior. In particular, some researchers used WiFi radio signals for detection of intruders, detection of activity range of people, detection of pulse and breathing number of people, and so on [12–14]. In these studies, they used dedicated WiFi devices for measurement or they intended pedestrians moving in an open space.

In our research group, we have considered to use the information on received signal strength indication (RSSI) at existing WiFi devices from an existing WiFi access point for estimating the number of people in an area. Figure 1 shows the overview of our proposal. As existing WiFi devices, we consider computers, tablets, televisions, printers and so on. The information on RSSI at WiFi devices is collected to a people counting computer, and it estimates the number of people in the area. We assume that measurement and collection of the RSSI can be accomplished by installing new applications to the devices or updating firmware of the devices. In our research, we do not assume that people have special devices such as smart phones or RFID. In addition, we use existing WiFi networks for estimating the number of people. Therefore, low-cost people counting can be accomplished.

In this paper, as the first step of our research, we propose methods for estimating the number of people by utilizing RSSI of beacon signals from an existing WiFi access point installed in a room. To estimate the number of people, we apply liner regression-based approach and support vector regression-based approach in this paper. In addition, to investigate the relationship between RSSI and the number of people, we construct an experimental environment in our laboratory at the Kindai University, Japan. In the experimental environment, we use an existing in-use WiFi access point. As WiFi devices, we use multiple dedicated devices, i.e., Raspberry Pi [15], in this paper for fundamental evaluation of our proposed methods. We evaluate our proposed methods through experimental results obtained from the experimental environment.

The rest of this paper is organized as follows. In section 2, we explain related work. Next, in section 3, we propose the methods for estimating the number of people using RSSI from existing WiFi network. We then evaluate our proposed methods through experimental evaluations in section 4. Finally, we conclude this paper with an outlook on future work in section 5.

2 Related work

In the field of computer vision, there have been many researches for estimating the number of people or the degree of congestion from images obtained from one or more cameras [1–5]. In particular, there are a lot of studies for detecting region of human from an image as summarized in [1], and they can be used for estimating the number of people. In recent years, for estimating the number of people in crowded scenes, feature-based methods have attracted attentions [2–5]. However, in these camera-based methods, the estimation accuracy is affected by many factors such as the brightness of the surroundings. In addition, privacy issues may occur when a person can be identified from the obtained image.

There have been also researches for estimating the number of people using passive sensors such as laser range finders, infrared sensors, and so on [6–9]. However, these approaches require costs for sensors and its installation. In addition, there have been researches for estimating the number of people using active human-attached sensors such as RFID or special communication devices. In these approaches, accurate estimation can be accomplished in some specific situations, however, they can not be applied to public spaces such as shopping mall where many unspecified people move. In some researches, they consider to use WiFi devices or smart phone attached at human for estimating the number of people or flow of people [10, 11]. However, in these research, it is assumed that a person has a device whose WiFi function is enabled.

In recent years, there have been some researches for using WiFi as sensors [12–14]. For example, RSSI of WiFi is used for detection of intruders, detection of activity range of people, detecting health status of people such as pulse of breathing number [12], and estimation of the number of people [13, 14]. In the literature [13], the authors proposed a method for counting pedestrians in an specific area using a couple of dedicated WiFi transmitter and receiver. They evaluate their method through experiments in two environment: indoor corridor and outdoor open space. Unlike to these research, in this research, we assume to use the existing WiFi access point and WiFi devices for estimating the number of people whose mobility is low.

3 Methods for estimating the number of people

In this section, we propose methods for estimating the number of people using RSSI from existing WiFi network.

3.1 Overview

Figure 1 shows the overview of the environment intended in this paper. In this paper, we assume one WiFi access point (hereinafter, access point) and N WiFi devices (hereinafter, nodes) $\mathcal{N} = \{n_1, n_2, \cdots, n_N\}$ are placed in a room. Laptops, televisions, printers, tablets are the examples of nodes. Information on the RSSI measured at the node is collected to a people counting computer, and it estimates the number of people.

An access point generally broadcasts beacon frames at fixed intervals to notify its existence to nodes in its service area. The transmission interval of the beacon is set to around 100 milliseconds in many products. A node receives a beacon frame from the access point with a certain level of RSSI. Here, if there are people in the room, it affects the propagation of radio signals between access point and nodes, and the RSSI of node may be changed. In this paper, we use this feature for estimating the number of people in the room.

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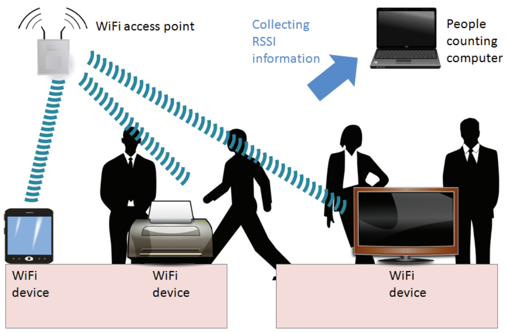

Figure 1: Overview of our proposed system

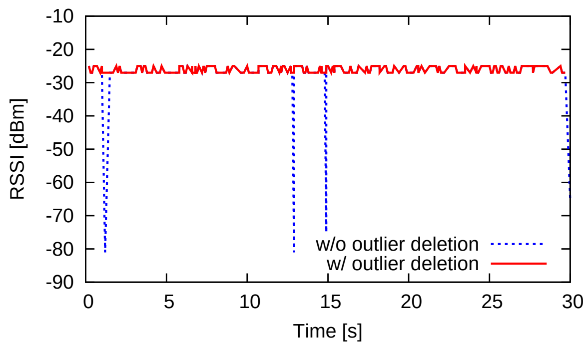

Figure 2: RSSI with/without outlier deletion

The overview of our proposed method is as follows. In our proposed method, a node first measures the RSSI of the bacon frame transmitted from the access point. Then, it transmits the measurement results to the people counting computer at the interval of T. We use 300 seconds as T in this paper. The people counting computer first removes outlier from the collected RSSI data. Then it estimates the number of people in the interval using two kind of regressions: linear regression and support vector regression. We assume coefficients of the regression formula are obtained by prior learning.

Here, we note that the number of people in an interval is estimated independently for the sake of simplicity in this paper. We plan to use the results obtained in previous interval for estimation in the current interval to improve the accuracy as future work. In the succeeding sections, we explain the details of the proposed methods.

3.2 Removal of outlier

The obtained data from a node includes outlier. In this paper, we remove ourliers as follows.

First, we denote the RSSI at node n_i from j-th beacon in interval t_k as $r_{k,i,j}$ [dBm]. In addition, we denote the set of RSSI at node n_i in interval t_k as $\mathcal{R}_{k,i} = \{r_{k,i,1}, r_{k,i,2}, \cdots\}$. Furthermore, we define the outlier degree of RSSI $r_{k,i,j}$ as follows:

$$d_{k,i,j} = \frac{r_{k,i,j} - r_{k,i}^{\text{mid}}}{\sigma_{k,i}}, \qquad (1)$$

where $r_{k,i}^{\text{mid}}$ is the median of the measured data $\mathcal{R}_{k,i}$ and $\sigma_{k,i}$ is the standard deviation of the measured data $\mathcal{R}_{k,i}$. When $d_{k,i,j}$ is less than the threshold D_{min} or it is higher than the threshold D_{max}, the RSSI data $r_{k,i,j}$ is removed from $\mathcal{R}_{k,i}$ as outlier.

Figure 2 shows the time-series RSSI data with or without outlier deletion. Here, we used $D_{\text{min}} = -2$, $D_{\text{max}} = 2$ as the thresholds. It should be noted that the median value of the data is -27 dBm and the standard deviation is 16.837 at this time. As shown in Fig 2, the outliers are removed by using the method in this section.

3.3 Estimation methods

From pre-processed data obtained by the processing of the previous section, we estimate the number of people in the room. In this paper, we consider two regression-based approaches for estimating the number of people.

3.3.1 Linear regression-based method

The first method is a linear regression (LR)-based method. LR is one of the simplest ways for estimation, and we use LR as reference approach to estimate the number of people in this paper. In this method, the estimated number of the people $\hat{m}_k$ in the measurement interval t_k is estimated by the following equation.

$$\hat{m}_k = a_0 + \sum_{n_i \in \mathcal{N}} a_i r_{k,i}^{\text{mid}}. \qquad (2)$$

Here, $a_0, a_1, a_2, \cdots, a_N$ are coefficients.

3.3.2 Support vector regression-based method

The second method is a support vector regression (SVR)-based method. SVR is a non-linear regression technique based on support vector machine (SVM) which is one of the most popular machine learning techniques. In this paper, we adopt the radial basis function kernel (RBF kernel, a.k.a. Gaussian kernel) as the kernel function so that non-linear regression model can be constructed. In the RBF kernel, there is parameter σ to determine decision boundary, and we use $\sigma = 0.08$ in this paper.

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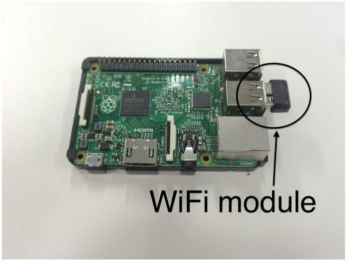
(a) Access point



(b) Node

Figure 3: Experimental equipment

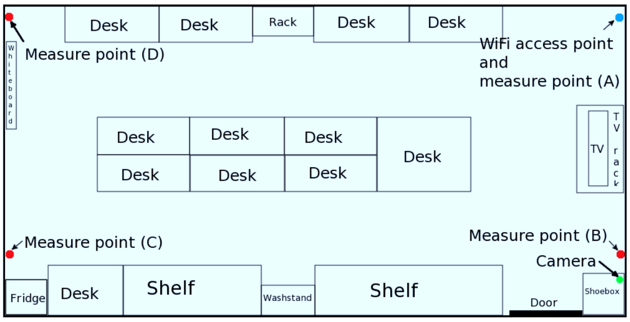
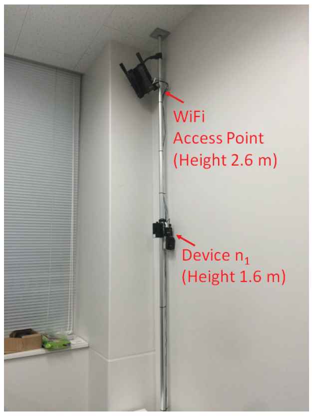
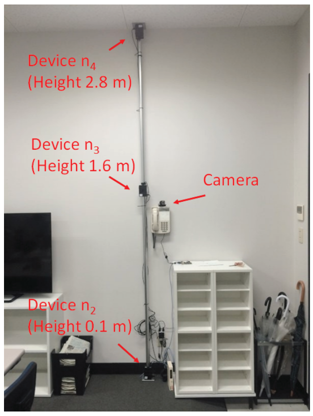


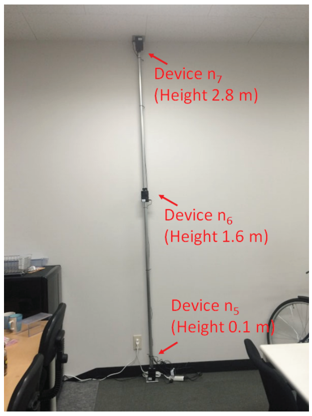
Figure 4: Layout of room



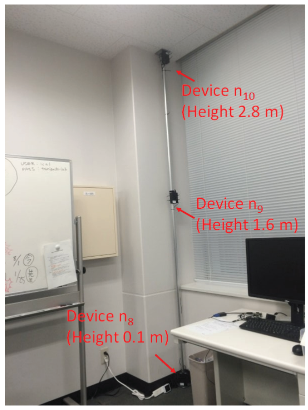
(a) Measurement point A



(b) Measurement point B



(c) Measurement point C



(d) Measurement point D

Figure 5: Photo of measurement points

4 Experimental evaluation

In this section, we confirm the effectiveness of the proposed method through experimental evaluations.

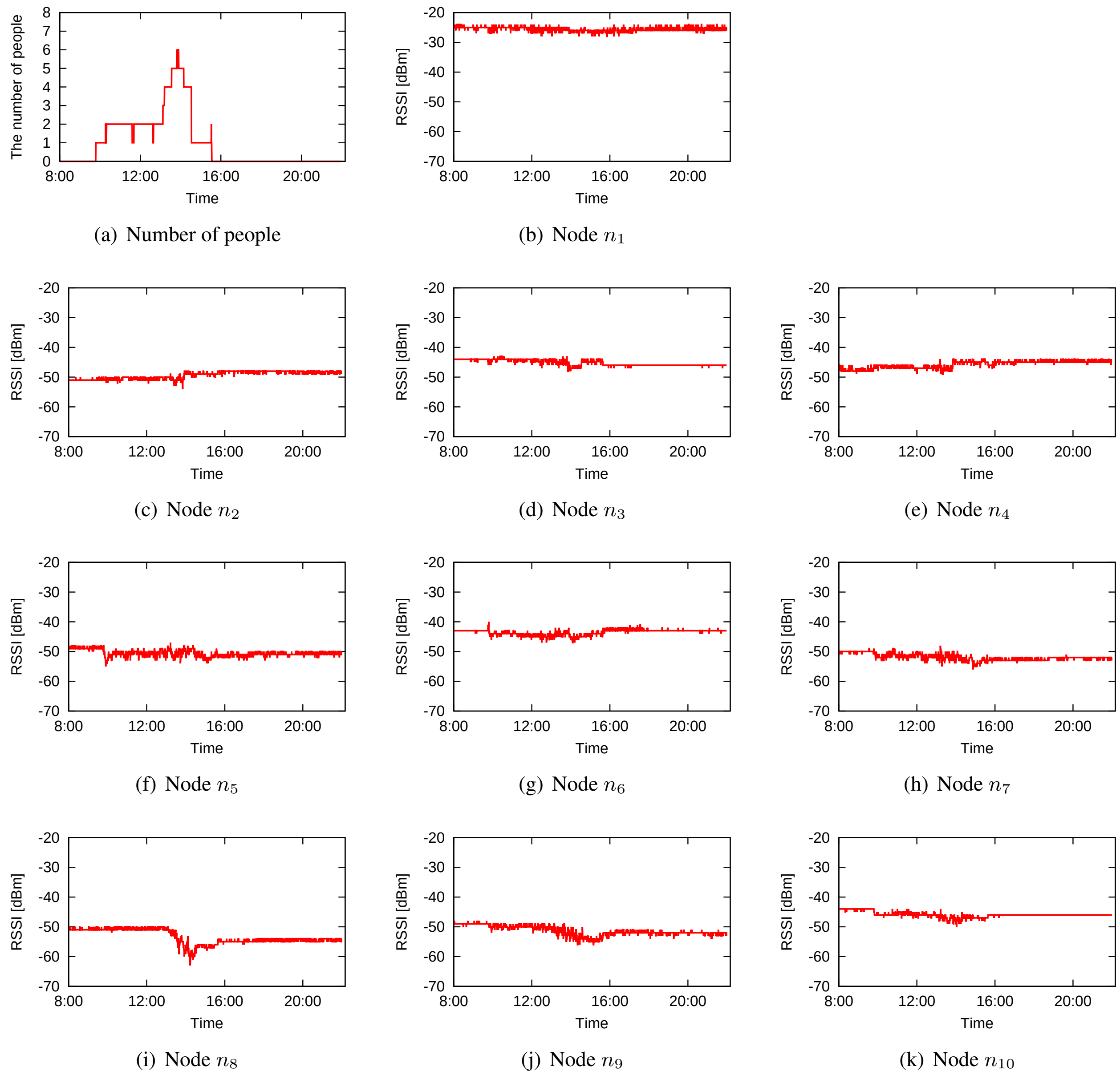
4.1 Experiment environment

In order to verify the proposed method, we constructed an experimental environment in our laboratory in Kindai University. In the experimental environment, we used an access point, Buffalo WZR-300HP [16], as shown in Fig. 3(a). This access point is used for providing network access in our laboratory, and is compliant with IEEE 802.11a/b/g. At the access point, the wireless channel is set to 6ch (2.437GHz) which is the lowest degree of congestion around the laboratory. The beacon interval is set to 100 milliseconds (the default value for the access point).

As nodes, we used Raspberry Pi 2 Model B [15] attached with a USB WiFi module, Buffalo WLI-UC-GNM2 [17], for fundamental evaluation as shown in Fig. 3(b). We installed debian linux-based operating system, Rasbian, to the Raspberry Pi nodes. WiFi network adapter is set to monitor mode to capture all WiFi frames, and tcpdump [18] is used to record the time of beacon frame reception and its RSSI. To synchronize time among nodes, each node synchronizes its timer with external NTP server once a day. Since there are no people in the room at night, the time duration for beacon frame capture is limited between 8:00 to 20:00.

Figure 4 shows the layout of room and the installation point of the access point and the nodes. In the experimental environment, a pole is set for each corner (measurement point A, B, C, and D) of the room. A node is attached using a pole as shown in Fig. 5. At the measurement point A, the access point is installed at the top (height 2.6 m), and a node is installed at the middle (height 1.6 m). At the measurement point B, C, and D, three nodes are installed at the top (height 2.8 m), middle (height 1.6 m), and bottom (height 0.1 m).

In order to obtain the actual number of people m_k in measurement interval t_k, we installed an additional Raspberry Pi node with camera module to monitor entrance and exit of a person near the door as shown in Fig. 5(b). At the node, a motion detection software motion [19] is installed and the node deposits a captured image of the door when it detects changes of scenery. By using the images, we obtain the actual number of people in the room manually.



(a) Number of people (b) Node n_1

(c) Node n_2 (d) Node n_3 (e) Node n_4

(f) Node n_5 (g) Node n_6 (h) Node n_7

(i) Node n_8 (j) Node n_9 (k) Node n_{10}

Figure 6: The number of people and RSSI of each node (June 11, 2015)

4.2 Evaluation of the variance of RSSI

First, we investigate the variance of RSSI. Figure 6 shows the number of people and RSSI $\bar{r}_{k,i}$ of each node n_i measured in June 11, 2015. As shown in the figure, the average RSSI of node n_1 is the highest since node n_1 is the closest node from the access point. Also, RSSI of node n_1 is hardly affected by the number of people compared to other nodes. On the other hand, for example, RSSI of nodes n_3, n_5, n_6, n_{10} are changed depending on the changes of the number of people. When one person enters to the room at 9:44, the variance of RSSI becomes higher. In addition, when the number of people increases gradually at 13:11, the variance of RSSI also increases gradually. When all people exit and the number of people becomes zero at 15:40, the variance of RSSI becomes smaller again. Therefore, there is a relationship between the number of people and RSSI.

4.3 Evaluation of the proposed methods

Next, we evaluate our two proposed methods proposed in section 3. We used measurement data of three days (June 2, June 11, June 16) that the number of people is relatively high among entire experimental period to obtain coefficients of regression equations. Then, we used measurement data of one day (June 18) for evaluation of the proposed methods.

In this paper, we evaluate our proposed methods

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in three estimation situations as follows.

- Estimation of presence/absence of people
  In this situation, presence or absence of people is the estimation results. We define two categories m_k^{pre} as follows.

$$m_k^{\text{pre}} = \begin{cases} 0 & (m_k = 0) \\ 1 & (m_k \neq 0) \end{cases}. \tag{3}$$

  The estimated presence of people $\hat{m}_k^{\text{pre}}$ is determined similar to Eq. (3). In this estimation, the estimated value $\hat{u}_k$ equals to $\hat{m}_k^{\text{pre}}$ and the correct value u_k equals to m_k^{pre}.

- Estimation of the degree of congestion
  In this situation, the degree of congestion is the estimation results. In this paper, we define three categories for the degree of congestion m_k^{deg} as follows.

$$m_k^{\text{deg}} = \begin{cases} 0 & (m_k = 0) \\ 1 & (1 \leq m_k \leq 3) \\ 2 & (3 < m_k) \end{cases}. \tag{4}$$

  The estimated degree of congestion $\hat{m}_k^{\text{deg}}$ is categorized to three similar to Eq. (4). In this estimation, the estimated value $\hat{u}_k$ equals to $\hat{m}_k^{\text{deg}}$ and the correct value u_k equals to m_k^{deg}.

- Estimation of the number of people
  In this situation, the number of people is the estimation results. In this estimation, the estimated value $\hat{u}_k$ equals to $\hat{m}_k$ and the correct value u_k equals to m_k.

In order to evaluate the accuracy of our proposed methods, we use three indexes, accuracy rate e_{ar} , mean absolute error (MAE) e_{MAE}, mean relative error (MRE) e_{MRE}, as follows.

$$e_{\text{ar}} = \frac{1}{K_{\max}} \sum_k match(\hat{u}_k, u_k). \tag{5}$$

$$e_{\text{MAE}} = \frac{1}{K_{\max}} \sum_k |\hat{u}_k - u_k|. \tag{6}$$

$$e_{\text{MRE}} = \frac{1}{K_{\max}} \sum_k \frac{|\hat{u}_k - u_k|}{u_k}. \tag{7}$$

Here, $K_{\max}$ is the total number of measurement periods in a day. Function $match(x, y)$ returns 1 when $x = y$, otherwise it returns 0.

Figures 7, 8 and 9 show actual number of people and estimated number of people by using the two estimation methods. Table 1 summarizes overall results

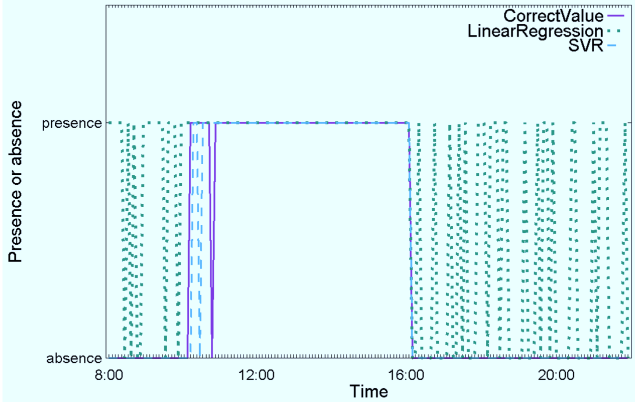

Figure 7: The estimation results of presence/absence of people

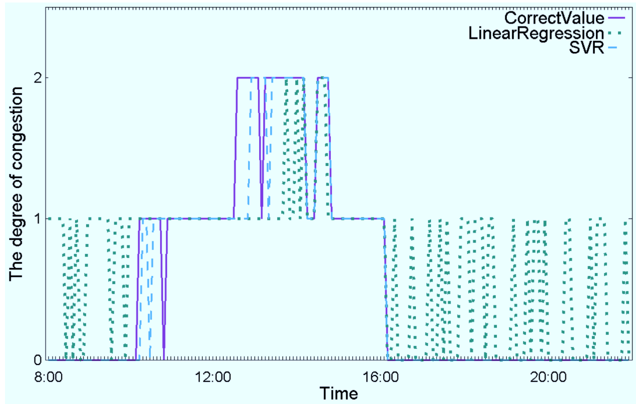

Figure 8: The estimation results of the degree of congestion

of our proposed methods. As shown in Table 1, the accuracy rate of SVR-based method is significantly higher than that of LR-based method in all estimation situations. This indicates that the relationship between RSSI and the number of people is not linear. For the estimation of presence/absence and for the estimation of degree of congestion, the accuracy rate of SVR-based method is high. Therefore, SVR-based method can be used for these situations achieving high accuracy. For the estimation of the number of people, the accuracy rate of SVR-based method is 0.772 which is much lower than that for estimation of presence/absence and that for estimation of degree of congestion, although it is significantly higher than that of LR-based method. Improvement of accuracy rate of our proposed method is one of our future work.

Figures 10 and 11 show the MAE and MRE for each number of people. As shown in Figs. 10 and 11, the error increases as the number of people increases in both methods. This reason is as follows. When the number of people is zero, there is no moving object in the room and RSSI of each node becomes rela-

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Table 1: The evaluation results

	Estimation of presence/absence	Estimation of degree of congestion	Estimation of the number of people		
	Accuracy rate	Accuracy rate	Accuracy rate	MAE	MRE
LR-based method	0.724	0.622	0.455	0.893	0.383
SVR-based method	0.982	0.946	0.772	0.471	0.298

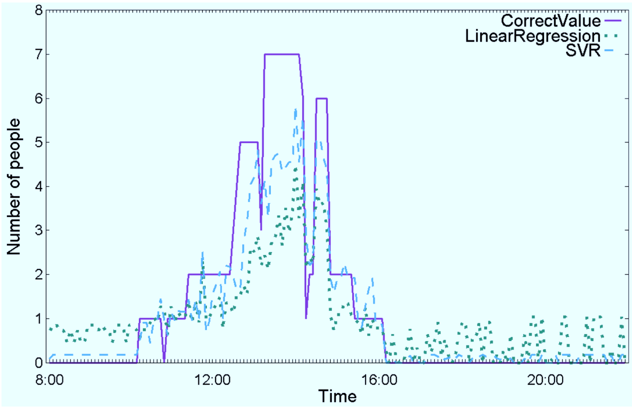

Figure 9: The estimation results of the number of people

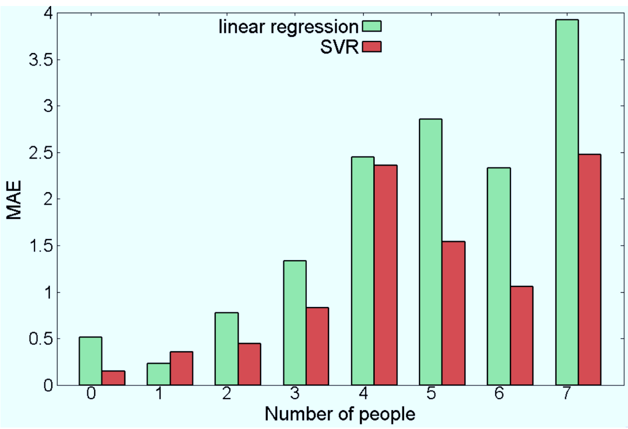

Figure 10: MAE for each number of people

tively stable. On the other hand, when the number of people increases, it affects to the radio wave propagation path and causes multi-path fading between access point and nodes. As a result, the variance of RSSI becomes higher and the estimation error also becomes higher. By removing highly-varied RSSI data, the effect of multi-path fading can be suppressed and we can obtain the effect of radio wave absorption by the human body from RSSI data. Detailed investigation and discussion is planned for future work.

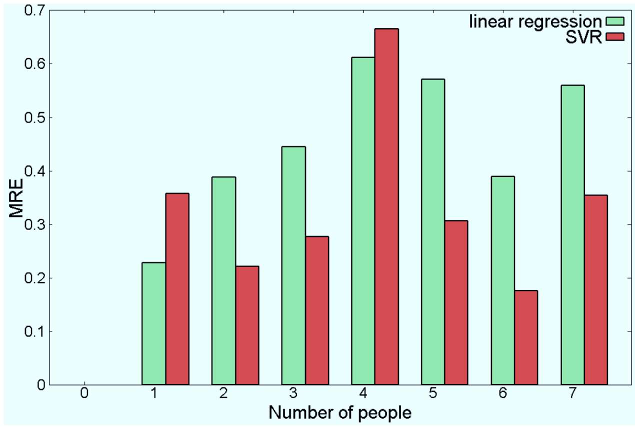

Figure 11: MRE for each number of people

5 Conclution

In this paper, we tried to estimate the number of people using only RSSI at the node from the existing WiFi access point. We proposed two methods for estimating the number of people: linear regression-based method and support vector regression-based method which is based on support vector machine algorithm. In order to verify the proposed methods, we constructed an experimental environment for collecting RSSI data using existing WiFi access point in our laboratory at Kindai University. Through experimental evaluations, it was shown that the accuracy of support vector regression-based method is better than that of linear regression-based method. In addition, we showed that the accuracy of support vector regression-based method for estimating the number of people is 0.772, that for estimating the degree of congestion is 0.946, and that for estimating the presence/absence of people is 0.982.

As future research, we should evaluate our methods in various environments such as lecture halls, outdoor environment, and so on. In addition, we plan to extend our proposed method to estimate the number of people by using multiple WiFi access points. Furthermore, we should implement our methods to existing WiFi devices, such as tablets, television, and evaluate our methods through experiments.

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