Position Estimation for People Waiting in Line Using Bluetooth Communication

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Abstract*—Unpredictable wait time at such places as bus stops, banks, and amusement parks is likely to create frustration to people in line. So far, efforts have been focused on estimating and displaying the wait time of users or customers in line. In most cases, the time has been estimated by counting the number of people waiting in line. It is not cost-efficient, however, as the method requires human resources or installation of expensive equipment. Moreover, the method can only provide the wait time for the last person in line, and cannot deal with such problems as fluctuations caused by wait time due to the latency of service. Therefore, it is desirable to extract the wait time corresponding to each person's position in line, without relying on human resources and equipment. This paper proposes a position estimation method based on the relative positions of users in line, using mobile terminals and a position management server. The devices held by the users are classified into groups depending upon their positions. Specifically, the device at the front of the line detects other devices using Bluetooth communication, and then places them into a second group. In the same way, devices in the second group detect the following devices and assign them to a third group. When this process has been repeated, the relative positions of terminals are identified. In addition, the Received Signal Strength Indicator (RSSI) values are also collected from Bluetooth communication to restrict the number of devices in each group. While generating smaller, subdivision groups, the nearby devices are picked out from the closest ones having strong RSSI values. As a result of experiments, the terminal's position has been estimated with an accuracy of 94.2% in a typical scenario.

Keywords–Relative Positioning; Mobile Phone; Bluetooth; Location; Waiting in Line.

I. INTRODUCTION

In a crowded urban city, there are many occasions when waiting in line might increase frustration of people in their everyday lives. Lines form constantly at entrance gates to amusement parks, security gates at the airport, department store doors during sales, or occasionally at train stations and bus stops. Companies and stores that provide products and services are also concerned about wait time, as it is one factor affecting customer satisfaction. Houston states that there is a strong negative correlation between waiting time and a customer's evaluation of the quality of a service [1]. Maister addresses the fact that customer waiting at the store is the most important factor affecting customer satisfaction, and states eight rules regarding waiting time [2]. He states that customers are likely to be stressed and feel that the wait time is longer than the actual time if the wait time is unpredictable.

Considering these circumstances, if the waiting time in line is provided to the customer, it might be possible to reduce stress and raise customer satisfaction. There are various approaches to extract the waiting time. For example, by considering the number of people in line or the time taken to provide the service. The number of people can be calculated by counting them while in line, or estimating the number of people from the length of the line. There are also methods to estimate the wait time employing special equipment. Queuing time estimation system [3], for example, calculates the wait time automatically by extracting the length and moving speed of the line from the images of surveillance cameras. It is not cost efficient, however, as it requires human resources to count the number of people and the installation of special equipment on site. Moreover, the wait time can change due to the latency of providing the service. Furthermore, it can only estimate the wait time of the last person in line, and cannot easily estimate the wait time for all customers in the line.

Two points must be considered in order to estimate wait time according to location in line: estimating the position of customer in line, and estimating the time for providing the service. Here we focus on estimating the position of each person in line. The location of each person in line can be estimated by generating groups of terminals according to the Received Signal Strength Indicator (RSSI). RSSI is extracted from wireless communication hardware of customers' mobile terminals, and groups are assigned sequentially. Bluetooth has been used as the wireless communication technology in our work; however, the authors believe that the proposed algorithm works with other communication technologies as well. Note that the geographical locations of people are not determined absolutely, but rather we determine their relative location within the line. An experiment has been conducted to verify the effectiveness of the proposed method.

This paper is organized as follows. Section 2 describes the estimation of wait time in line and relative location using Bluetooth communication. The method for estimating the location in line is presented in Section 3. Section 4 presents the evaluation results and discussion, and Section 5 concludes the paper and suggests future work.

II. RELATED WORKS

Related work concerns the estimation of wait time and user location for lines of people.

A. Wait Time Estimation in Line

Most existing work on estimating the wait time or monitoring the line are conducted by installation of fixed devices such as cameras [4], infrared sensors [5] and floor mats [6] on site. These systems focus on macroscopic movement of pedestrians in both single or multiple lines, and usually require preparation and installation of single or multiple special devices. Such systems can provide information such as the length of the entire line, the average wait time, and the fastest lane among multiple lines. This overall line information is only useful for passengers before deciding to wait in line. Those already waiting in line are more likely to appreciate information about their precise location in line and the time it will take until the service is provided.

Other research has focused on estimating the wait time from the user's mobile terminal instead of installing special devices or using human observers. LineKing [7] employs the users' carry-on devices and a data aggregation server, and estimates the wait time by measuring the number of people in line. The number of people is estimated by observing the terminals within a radius of 50m–100m of the line, and terminals that leave the area. To determine the terminal location either GPS, or the distance from a base station or access point, is used. However, errors of predicted wait time may occur as the estimated number of people differs from the actual number of people in line, because this method detects all terminals within a radius of 50m–100m. To reduce the rate of error, it is necessary to measure the wait time beforehand. The error can be reduced to between two and three minutes if the measured wait time and the detected data are used together, but it requires effort to measure the wait time before the system is launched. The order of people waiting in line cannot be extracted. Therefore, it is difficult to obtain the wait time for a specific location in line.

Wang [8] investigates smartphone WiFi signals to track people waiting in line by installing a fixed monitoring device near the service area. Some experimental scenarios and analyses show that monitoring WiFi signals from a fixed device enables estimating total wait time in a queue and distinguishing different phases such as waiting, service and leaving periods. If the line is not too long, WiFi communication distance may be wide enough to cover the entire line, however, this method cannot estimate the location and wait time for each individual in line.

B. Estimation of Relative Location

Some work has focused on the features of Bluetooth RSSI to estimate the relative location of users. Maekawa estimates a train user's car number and the congestion of the train by extracting the RSSI from the user's personal devices [9]. They look at the changes of RSSI due to train doors, distance, and intervening people in order to determine whether or not the user is in the same car as other users. Other work recognizes relative location by aggregating RSSI and user movement traces at gathering places such as special event sites [10]. Exploiting the fact that weak signals beyond 6km will not be detected, they classify nearby and distant devices with high accuracy. This work estimates relative location from the features of RSSI fluctuation caused by obstacles, but the situation of people waiting in line is not considered.

Luciani and Davis have performed experiments to find a correlation between RSSI values and distance in a grassy field, on a concrete surface, and in a hallway with various elevations [11]. There seems to be a tendency for RSSI value to decrease proportionally with increasing distance. However, the variance of the RSSI tends to increase considerably with an increase of distance. The RSSI value for 1m to 2m indicates a strong signal that settles in the range of −60dBm to −80dBm, while the RSSI values for distances over 2m are widely scattered in the range of −80dBm to −100dBm. Thus, it seems difficult to deal with the entirety of long lines since the RSSI value is not a reliable measure of large distances. However, it seems highly accurate to measure short distances

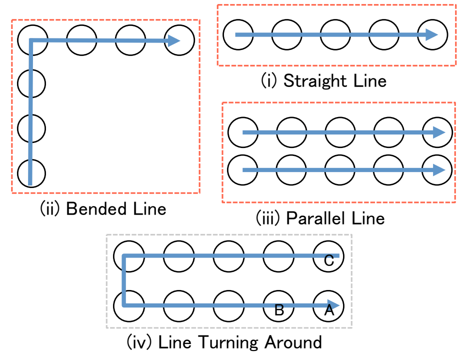

Figure 1. Types of Line Formation

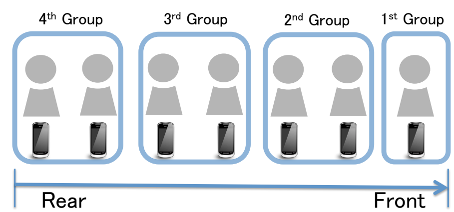

Figure 2. Groups Subdivision for Location Estimation in Line

up to approximately 2 meters, which is sufficient to detect the device of a person in front or behind.

In this paper, we explore a method to estimate location considering RSSI and the relative positions of people waiting in line. The proposed method is not intended to extract the geographic location of users, but rather deals with their relative locations.

III. Location Estimation in Line

This section describes our method to estimate location in line and its implementation.

A. Environment Settings

There are various types of line, as shown in Figure 1, such as: (i) a straight line, (ii) a curved or bent line, (iii) two parallel lines, and (iv) a line that turns back upon itself. In (iv), the RSSI of terminals B and C, as received by A, are almost the same when the distance to those terminals is the same. The proposed method generates groups using the RSSI between pairs of terminals, thus it is difficult to estimate locations for the line in (iv). We therefore focus on lines which do not turn around, such as in (i)–(iii).

The proposed method uses Bluetooth communication to detect devices in the line. Therefore, all of the Bluetooth devices in the line are assumed to be in Discoverable mode, which allows other devices to detect them.

B. Location Estimation Method

The location estimation is performed with user terminals and a location management server. The relative location is determined by dividing terminals into groups, from the front to the rear, as shown in Figure 2. The location estimation method to determine the relative location is shown in Figure 3. The first terminal in line determines the base of location estimation.

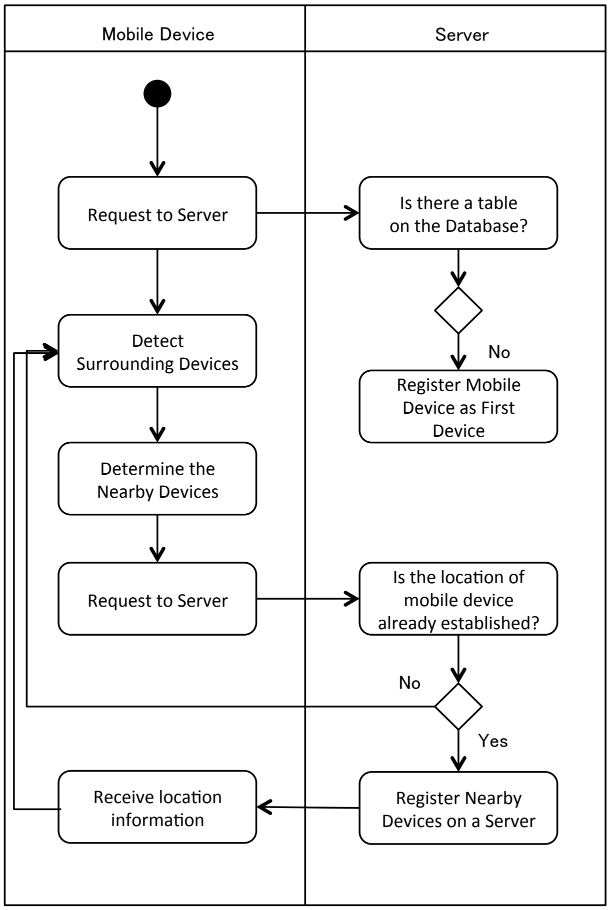

Figure 3. Location Estimation Method

It is assumed to be the first terminal to join a server in which no other terminals with location information are yet registered. Next, the first terminal detects nearby terminals, and registers them on the server as a second group. Then, the second terminal group performs the same process, and registers a third group. This process is performed repeatedly, until the relative locations of all terminals have been determined.

Bluetooth is used to detect nearby terminals. The maximum value for signal strength is determined by each device's Class, and the approximate range of communication is known for each Class, as shown in Table I. The approximate distance is calculated from signal strength. Mobile terminals usually fall into class Class 1 or Class 2. Devices within approximately 5m can be detected even though there are human obstacles. However, if all of the detectable terminals are registered as the next group, the group will have too many terminals and location accuracy might fall. Therefore, it is necessary to classify detected devices as 'nearby devices' and 'other devices', and register only the nearby devices as the next group.

C. Classification of Nearby Devices

The RSSI between pairs of terminals is used in order to distinguish nearby devices from other devices, and the nearby devices are added to the next group. RSSI has the following features.

TABLE I. REACHABLE DISTANCE OF BLUETOOTH COMMUNICATION

	Class 1	Class 2	Class 3
Reachable Distance	100m	10m	1m

RSSI value generally decreases proportionally to the square of distance, but human obstacles and the surrounding environment can greatly weaken the signal strength. In addition, the RSSI differs depending upon the types of user terminal (e.g., mobile phone brand). As the Bluetooth Class indicates the maximum RSSI value, the user terminal will be classified with an appropriate Class with according to the RSSI value irrespective of the type of terminal. Some terminals in the same Class have different RSSI values. Therefore, it is impossible to determine whether or not the terminal is within the designated distance shown in Table I or to assign the threshold of RSSI in such situations.

In this paper, we aim to identify the nearby devices from the RSSI. The signal of terminals in a line can be received several times, and the average RSSI calculated. The terminals with a relatively large RSSI are assigned as nearby devices. This process limits the number of terminals in each group, and enables accurate determination of location.

D. Experiment Settings

There are several steps in our method, namely, detecting the surrounding terminals, choosing the Nearby Devices among the detected terminals, and designating the terminal's location in line.

Detection of Surrounding Terminals

Bluetooth functionality is used to scan for the surrounding terminals. When a new terminal is detected, the Bluetooth MAC address, RSSI, detection time and detection count are registered in the database (SQLite) installed in users' terminals. If the detected terminal has already been registered, the RSSI and detection counts are updated.

Let $AvgRSSI$ be the average RSSI, $Count$ be the number of times a device has been detected, and $InRSSI$ be the incoming newly-received RSSI value, then the average RSSI is calculated by equation (1), and the database is updated.

$$AvgRSSI = \frac{(AvgRSSI \times Count) + InRSSI}{(Count + 1)} \quad (1)$$

After the detection of terminals in range, the next step separates nearby devices from other devices.

Determination of Nearby Devices

Nearby Devices are chosen among all of the detected devices one minute after the first detection. A one-minute interval is necessary because without the interval only a few values of RSSI may be sampled, which is not enough to decide whether or not it is a nearby device. The four devices having the highest average RSSI are assigned as Nearby Devices. In other words, the two terminals in front of and behind each terminal are assigned as Nearby Devices. The first terminal, however, has no terminal in front of it and therefore only the top two terminals are assigned as Nearby Devices. After

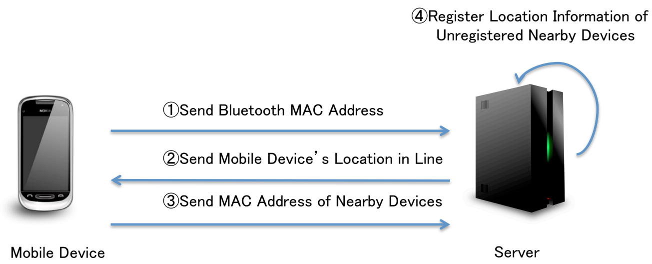

Figure 4. Process for Designating Location in Line

the assignment of Nearby Devices, the next step identifies locations.

Designation of Location in Line

The location management server stores the MAC address of terminals, and their locations once determined. The process for determining location is shown in Figure 4.

Terminals send their MAC addresses to the server. If the location of the terminal is known then the server responds with the terminal's location in line; otherwise the server registers the MAC address but does not yet respond. When a terminal receives its location information it responds to the server by sending the MAC addresses of its Nearby Devices, which allow the server to determine the location information of the following group. Any of these Nearby Devices that do not yet have a location must be behind the terminal in the line (those in front have already been assigned a location) and belong to the following group. The server therefore assigns that location to those terminals and informs them about their location. They in turn respond with their Nearby Devices, and the process repeats continuously to determine sequentially the location of all terminals in the line.

IV. Evaluation of our Proposed System

An experiment has been conducted in order to verify the accuracy of the location in line, by comparing the actual location and the location determined by the proposed method.

A. *Method of Experiment*

All of the terminals are assumed to be in Discoverable mode, as explained in Section III-A. Under such conditions, if there is an existing terminal running the system within the detectable range of Bluetooth, the location can be estimated even though not all of the terminals are running the system. However, this experiment has been conducted in a desirable situation in which all of the terminals are running the system, in order to verify the efficiency of the proposed method. As shown in Figure 5, the experiment has held in an outdoor environment, where six users holding an Android terminal stand in line at intervals of 0.5m. We cannot prepare the same model of Android terminal, so different terminals were used as listed in Table II. The first person in line runs the system and registers as the first terminal on the server, and then the other terminals run the system consecutively. The experiment concludes when all of the location information of the terminals has been registered by the server. The experiment was performed seven times.

Figure 5. Experimental Environment

TABLE II. TYPES OF TERMINALS USED FOR EXPERIMENT

Terminal Number	Terminal Model
1st terminal	Galaxy Nexus
2nd terminal	Nexus 5
3rd terminal	Xperia A
4th terminal	Nexus S
5th terminal	Galaxy Nexus
6th terminal	Galaxy Nexus

TABLE III. THE RESULT OF CHOSEN NEARBY DEVICES

Loss Count	False Detection Count	Number of Trials
4	10	35

TABLE IV. THE RESULT OF NEARBY DEVICES FOR EACH TERMINAL

	1st	2nd	3rd	4th	5th
Loss	0	0	1	3	0
False Detection	0	1	1	5	3

B. *Experiment Results*

It is important to choose the Nearby Devices correctly in order to estimate locations accurately. Thus, the results are analyzed in two ways: for correctness of choosing Nearby devices and for accurate estimation of location.

1) Correctness of Choosing Nearby Devices: The two devices in front and behind are examined to verify the correctness of choosing Nearby Devices. We examine the correspondence between the Nearby Device information aggregated on the server and the actual nearby terminals. The first five terminals chosen as Nearby Devices are analyzed in this experiment.

The correspondences are shown in Tables III and IV. Table III shows the overall result of terminal information aggregated on the server, and Table IV shows the result for each terminal individually. "Loss" refers to terminals which were supposed to be (but were not) identified as Nearby Devices, and "false detection" refers to incorrect detection of a remote terminal that was more than two terminals away.

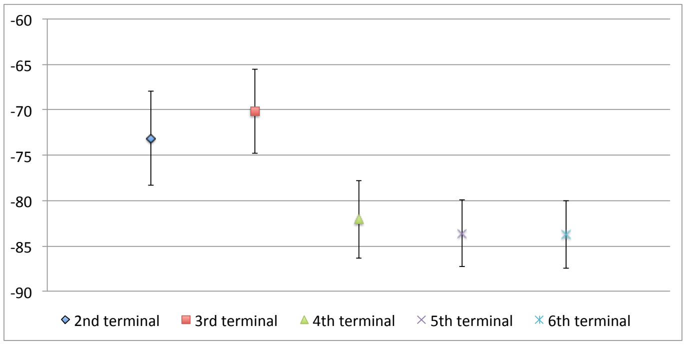

Figure 6. Average RSSI Received by the 1st Terminal

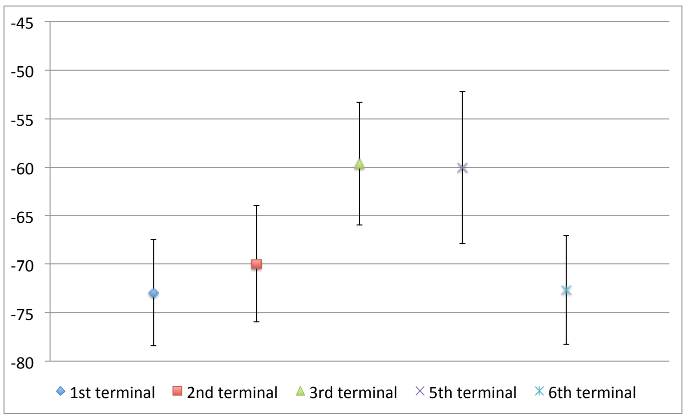

Figure 7. Average 4th Terminal RSSI Received by the Other Terminals

The RSSI values received from each terminal are also analyzed, as they are used to pick out the Nearby Devices. The average RSSI values that the first terminal received for the other five terminals in line are shown in Figure 6. The fourth terminal in the line was the one most often incorrectly detected as a Nearby Device by the other terminals; Figure 7 shows the RSSI of the fourth terminal as received by the other five terminals in the line.

2) Location Estimation Accuracy: When the proposed method is properly performed, the groups are classified as shown in Table V and the sequential order for each terminal can be assigned. The correct location (Table V) and the location determined by the server are compared in Table VI. The result for the first terminal is omitted as it is automatically registered by the server as the first group and the first terminal in line. The number of trials for the 2nd and 3rd Groups differs from that of the 4th Group because the number of terminals included in a Group varies.

The result shows that the 2nd and 3rd Groups are formed correctly. However, the 4th Group was incorrectly included in the 3rd Group twice, because a 2nd Group terminal determined the last (6th) terminal as a Nearby Device. The overall result shows that the proposed method determines location with an accuracy of 94.2%.

TABLE V. GROUPING OF PEOPLE IN LINE

Groups	Terminals
1st Group	1st Terminal
2nd Group	2nd and 3rd Terminal
3rd Group	4th and 5th Terminal
4th Group	6th Terminal

C. Discussion

The experiment has shown that the proposed method can estimate the relative location in the line with high accuracy, but false location estimation can occur when the Nearby Devices are incorrectly chosen.

Table IV shows that the 4th terminal had low accuracy when choosing Nearby Devices. The 4th was supposed to choose the 2nd, 3rd, 5th and 6th terminals. However, it sometimes choose the 1st terminal as a Nearby Device. This occurred probably because the average RSSI of the 1st terminal was approximately the same as that of the 6th terminal, even though the 1st terminal was located 0.5m farther away than the 6th terminal, and its signal attenuated by one additional intervening person. The incorrect choice of Nearby Device by the 4th terminal increased the number of terminals in another Group and adversely affected the accuracy.

D. Applicability to the Real Environment

Further issues relating to deployment in a real environment are discussed in this section.

Terminal Conditions in Line

In the proposed method, all terminals are assumed to be in Discoverable mode. In real situations, on the other hand, not many terminals are in Discoverable mode, because of security vulnerabilities and increased energy consumption. However, this situation may start to change as security and energy consumption are improve [12], and several services with low energy consumption have been developed. Thus, owing to these improvements, we believe that the number of users who would set their terminal to Discoverable mode will increase.

Signal Strength Depending Upon the Terminal's Brand

The signal strength and accessible range of Bluetooth may differ depending upon the types of user terminals. A distant terminal emitting a strong signal can be recognized as a Nearby Device and consequently affect the accuracy of location estimation. Such problems can be reduced if terminals and the server work cooperatively to determine the Nearby Devices. The server, which aggregates the RSSI received from multiple terminals, designates the strong signal terminal by comparing the values of RSSI and then determines the closest terminal as the Nearby Device. The location accuracy can be improved by excluding distant terminals with strong signals.

Distinguishing Other Devices from Those in Line

When people are waiting in line or moving forward, the signals of their terminals are detected in a consistent pattern. If some of them leave the line, the strength of their signals will be gradually weakened and may eventually disappear. By checking the detection count of terminals in the line, the signals of people leaving the line can be detected. For

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TABLE VI. LOCATION ESTIMATION RESULT

	Successful Counts	Num. Trials	Accuracy
2nd Group	14	14	100%
3rd Group	14	14	100%
4th Group	5	7	71.4%
Total	33	35	94.2%

people outside of or away from the line, the signals from their Bluetooth devices can also be falsely detected and chosen as Nearby Devices. Thus, it is necessary to distinguish these devices from those of people in the line. People who are standing still, or moving towards or away from the line, will have terminals transmitting in an inconsistent pattern different from those picked up from the line. The terminals distributing the consistent patterns are thus classified as Nearby Devices to perform location and wait time estimation in line.

Reduction of RSSI due to Obstacles

In our experiment, users held the terminals in their hands. However, terminals are more likely to be placed inside pockets or in bags, which may cause inaccurate selection of Nearby Devices. It is necessary to consider these points by investigating the RSSI values in order to enhance the method of choosing the Nearby Devices.

Number and Distance between People

The experiment was held with a limited number of people, but there are usually more people waiting in line. It is necessary to examine the applicability of our method in such situations. The location estimation accuracy may improve if the distance between the devices increases, as the difference of RSSI will be more pronounced.

V. Concluding Remarks

We have presented a method to estimate the location of terminals of users waiting in line. In the proposed method, employing the user's terminal and a server, the relative location between users has been assigned in order starting from an initial user (the first in line). Bluetooth RSSI from mobile terminals was used to determine the Nearby Devices to enable more detailed location estimation. An experiment was conducted to verify the effectiveness of the proposed method with the result that the user terminal location was estimated with high accuracy. However, false detection of Nearby Devices has caused the grouping process to overestimate the number of terminals, which reduced the accuracy of location estimation.

In the recent social trend, the use of Bluetooth technology has been declining due to the evolution of new radio technologies such as D2D, M2M, mmWave, and Massimo MIMO. However, iOS devices are installed with iBeacon which uses Bluetooth Low Energy (BLE). Furthermore, deployment of iBeacon technology to OS X, Android and Windows Phone devices implies that it is not the end of Bluetooth technology. Therefore, it is necessary to watch for the wave of future consumers. Whichever wireless communication technology is used, the necessity of the proposed algorithm will remain. Further planning is necessary to investigate the feasibility of the proposed algorithm to these other radio technologies.

WiFi technology is currently being used very often as it is widely deployed in everyday environments at home, school, company, office, and so on, since it is convenient to connect smartphones in such an environment. Recent work shows good detectability of WiFi packets emitted from smartphones in public transportation [13]. Our next target will be application to WiFi technology in conjunction with other new radio technologies.

Identifying terminals leaving the line, locating coordinates of user terminals, terminals emitting different signal strengths, and energy consumption issues other than the use of BLE are currently not considered. For future work, these issues and the characteristics of RSSI need to be examined in order to explore the application of our method in real environments.

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