IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 24 March 2025, accepted 1 April 2025, date of publication 8 April 2025, date of current version 24 April 2025.
Digital Object Identifier 10.1109/ACCESS.2025.3558988

RESEARCH ARTICLE

Using BLE Signals to Estimate Objective and Subjective Crowdedness Levels on Fixed-Route Buses

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This work was supported in part by Japan Agency for Science and Technology under PRESTO under Grant JPMJPR2039 and Grant JPMJPR2465, and in part by COI-NEXT under Grant JPMJPF2115.

This work involved human subjects or animals in its research. The authors confirm that all human/animal subject research procedures and protocols are exempt from review board approval.

ABSTRACT Accurately estimating the crowdedness inside a fixed-route bus is essential for improving transportation system efficiency and enhancing passenger comfort. While methods using cameras or sensors installed at bus entrances to count passengers have been proposed, these methods present challenges in terms of passenger privacy, installation costs, and placement. These approaches typically use the number of passengers as an objective indicator to evaluate crowdedness. However, even with the same number of passengers, the subjective crowdedness level experienced by each passenger can vary. Thus, it is important to estimate the objective crowdedness and the subjective crowdedness level perceived by bus passengers. In this study, we developed a method for estimating objective and subjective crowdedness levels using only Bluetooth Low Energy (BLE) information collected by the existing bus location tracking system installed in fixed-route buses to reduce privacy and installation costs. Specifically, Bluetooth device (BD) addresses obtained from BLE scans are filtered based on occurrence frequency and average RSSI to distinguish between passenger and surrounding BD addresses. The number of passenger BD addresses, along with their differences and rates of change, are used as features to estimate the number of passengers and the subjective crowdedness level using machine learning models. An experiment to evaluate the BLE method produced an accuracy of 0.653 for the objective crowdedness level (number of passengers) and 0.513 for the subjective crowdedness level, indicating that BLE signal information can capture the general trend of objective and subjective crowdedness.

INDEX TERMS Bluetooth low energy, machine learning, congestion estimation, objective crowdedness level, subjective crowdedness level.

I. INTRODUCTION

Accurately estimating bus crowdedness is essential for improving the efficiency of transportation systems and enhancing passenger comfort. Research has shown that bus passengers are concerned about the crowdedness inside buses [1], [2]. One of these studies demonstrated that passengers may choose to wait for the next bus if they perceive that the current bus's crowdedness level is high [1]. Furthermore, information about bus crowdedness (e.g., "crowded" or "uncrowded") has been found to influence passengers' travel choices [2]. While crowdedness is a key factor in passenger comfort, it is not the only determinant. Previous research has shown that factors such as driving

The associate editor coordinating the review of this manuscript and approving it for publication was Siddhartha Bhattacharyya.

style and vehicle movement also significantly impact passenger comfort, particularly for standing passengers [3]. Additionally, environmental conditions inside the bus, such as noise and cleanliness, influence the overall experience [4]. However, among these factors, crowdedness remains one of the most critical elements affecting passengers' travel decisions and overall satisfaction. In other words, by knowing the crowdedness of the bus in advance, passengers can avoid congestion, potentially improving their transportation experience. The benefits extend not only to passengers but also to bus operators, who can use information on the number of passengers to adjust the number of buses, change operational times, and optimize routes, thereby enhancing service quality and reliability and attracting more passengers to public transportation. In this way, a system that estimates bus crowdedness offers advantages to both bus users and operators. It is necessary to understand bus crowdedness in advance to provide such information. Because manually recording the number of passengers on all currently operating buses is not a practical method, an automated system for estimating and acquiring crowdedness is required.

To estimate bus crowdedness, an automated fare collection (AFC) system using smart card tap-in/tap-out data has been proposed [5], [6], [7]. While AFC systems can easily capture bus passenger numbers, they are often not installed in suburban or sparsely populated areas and do not account for passengers using transit passes or cash payments. Additionally, AFC systems tend to underestimate passenger numbers as they cannot capture fare evaders or passengers without a valid ticket [8], [9], [10]. Consequently, ticket-dependent AFC methods are not always accurate for ridership data planning or operational purposes. Additionally, methods have been proposed using image processing and deep learning on video data obtained from cameras to count passengers, as well as approaches that detect boarding and alighting using infrared sensors installed at bus entrances. Although these methods enable relatively accurate estimation of the number of passengers, they involve high installation costs if deployed on all buses, have restrictions on installation locations, and are less effective in highly crowded situations due to overlapping passenger images. Additionally, camera-based methods may pose privacy concerns for passengers. A method using Bluetooth Low Energy (BLE) for crowdedness estimation was proposed to address these issues. The Bluetooth device (BD) addresses obtained from BLE signals change every 10 to 20 minutes for security reasons, thereby minimizing privacy concerns. Moreover, because BLE signals can be received by a single, inexpensive, lightweight single-board computer such as a Raspberry Pi, and because it is a wireless communication technology, there are no constraints on installation locations. Thus, crowdedness estimation using BLE enables data collection that considers privacy and reduces installation costs. However, conventional approaches use the number of passengers as an objective indicator for evaluating bus crowdedness. Even when the number of passengers is the same, the subjective crowdedness experienced by different groups of passengers varies [11], [12]. Figure 7 is based on data obtained from the data collection experiment described later, where the number of passengers on the bus that the experiment participants boarded is plotted on the x-axis, and the subjective crowdedness level they perceived at that time is plotted on the y-axis. Figure 7 indicates a variation in the relationship between the number of passengers and the subjective crowdedness level. In other words, even with the same number of passengers, the perceived level of crowdedness varies among individuals, making it important to estimate the passengers' subjective crowdedness level.

In this study, a method was developed to estimate both objective and subjective crowdedness levels using only BLE information obtained from BLE sensing devices by transforming the existing bus location tracking system installed in buses into a sensing device. Specifically, BD addresses and received signal strength indication (RSSI) obtained from BLE scans are filtered based on the occurrence frequency and average RSSI to distinguish between passenger and surrounding BD addresses. The number of passenger BD addresses, along with their differences and rates of change, are used as features for a machine learning model to estimate the number of passengers and the subjective crowdedness level. To demonstrate the validity of this method, we conducted a data collection experiment on buses operating on the Nara City Loop Line with the cooperation of Nara Kotsu Co., Ltd..[1] The results of training and estimation from the collected data yielded accuracy rates of 0.653 (number of passengers) and 0.513 (subjective crowdedness level). The results indicate that the accuracy of estimating the number of passengers has improved compared to previous studies and that the general trend of the subjective crowdedness level can be estimated using only BLE signal information.

The contributions of this article include the following:

- We developed a BLE-based congestion estimation system that protects passengers' privacy while reducing installation costs.
- By introducing BLE sensing devices into the bus location tracking system of route buses, we achieved data collection compatible with practical bus operation.
- In addition to estimating the number of passengers, we verified whether subjective crowdedness level could be estimated. The results showed that it is possible to capture the tendency of passengers to perceive crowdedness.

The structure of this research is as follows: In Section II, we describe related work. Section III explains the BLE crowd estimation system. Section IV details the data collection experiment. In Section V, we present the evaluation and

[1] https://www.narakotsu.co.jp/

results. Section VI discusses the findings. Finally, Section VII concludes the research and summarizes future challenges.

II. RELATED WORK

There are many studies on detecting people and estimating human congestion using cameras, Wi-Fi, BLE, and participatory sensing for crowd counting and congestion estimation [13], [14], [15], [16], [17], [18].

In this section, we describe methods for estimating the number of bus passengers, estimating congestion using BLE signals, and evaluating subjective crowdedness, which are particularly relevant to our research.

A. ESTIMATING BUS CROWDEDNESS

There have been many studies on estimating bus crowdedness, methods using the AFC system count or smart card touch records [5], [6], [7], [19], [20]. This method allows for a relatively easy estimation of bus congestion by utilizing AFC systems installed on many buses in recent years. However, it has limitations in accurately counting passengers in buses where smart cards are only tapped upon boarding, as well as those using transit passes or cash payments. Additionally, AFC systems tend to underestimate the number of passengers because they cannot account for fare evaders or those without valid tickets [8], [9], [10]. Therefore, methods based on AFC systems are not always accurate for ridership data planning or operational management purposes. Wood et al. used real-time data, including operational conditions and weather information, to predict bus occupancy rates using linear regression and machine learning models [21].

Pinna et al. proposed an automatic passenger counting (APC) system with sensors at bus entrances to count passengers [22]. Although it can accurately detect boarding and alighting, this system poses high installation costs, entrance design inconsistencies, and space constraints. Therefore, Roncoli et al. combined real-time vehicle location data from an automatic vehicle location system with APC data to estimate in-bus crowdedness using a Kalman filter [23]. This method collects data from vehicles equipped with APC systems to estimate the crowdedness of those without such systems, reducing installation costs. However, extensive data from APC-equipped buses is required for accuracy, and there are struggles when the number of passengers suddenly increases.

Methods using cameras to estimate crowdedness at bus entrances have also been proposed [24], [25], [26], [27], [28]. Hsu et al. suggested a system that filters out all non-passenger objects in video data from cameras installed inside buses, using a convolutional autoencoder to count passengers [26]. Ghaziamin et al. proposed a system using fisheye cameras placed at a high position to avoid capturing passengers' faces, thus preserving privacy while performing real-time crowd estimation [28]. While camera-based systems enable accurate passenger counting, they involve high installation and operation costs, require a specific placement to minimize passenger overlap, and, despite efforts to avoid capturing faces, still pose potential privacy concerns. For these reasons, implementing camera-based crowd estimation systems on route buses is impractical.

To address the issues of privacy protection and cost, research has also been conducted on estimating bus congestion using Wi-Fi, a wireless communication technology [29], [30], [31]. Febre et al.. proposed a method that uses Wi-Fi sensors to automatically identify signals emitted by passengers by employing K-means clustering to distinguish passenger signals from surrounding noise [31]. While Wi-Fi can detect signals over long distances, resulting in a large amount of collected data, it also poses the challenge of increased noise. In fact, according to a study by Lesani and Miranda-Moreno, a comparison between Wi-Fi and BLE showed that BLE, which has less noise, is more suitable for monitoring specific areas [32].

B. ESTIMATING CROWDEDNESS USING BLE

With the widespread use of smartphones, crowd estimation methods that combine participatory sensing and BLE have been developed. Weppner and Lukowicz proposed a method to estimate crowd density by aggregating the number of nearby BLE devices detected by users' mobile devices as they move within a monitored environment [33], [34]. This method mitigates cost-related issues because it does not require the installation of new sensors. However, its estimation accuracy depends on the number of participating users, requiring mechanisms to encourage user involvement.

There have been several studies on congestion sensing using inexpensive single-board computers with BLE and Wi-Fi. Longo et al. proposed a method to estimate the occupancy of various spaces within a university, such as laboratories and large lecture halls, using both Wi-Fi and BLE with a Raspberry Pi computer [35]. Matsuda et al. proposed a method to estimate the congestion levels in restaurants and public facilities using BLE [36]. Additionally, some studies estimate the congestion levels in public transportation using BLE. Kanamitsu et al. worked on buses, and Taya et al. on trains, creating features from BLE signals emitted by passengers' mobile devices and proposing congestion estimation systems using machine learning models [37], [38]. However, their methods face accuracy challenges compared to APC or camera systems and focus solely on objective congestion without addressing passengers' subjective perception of crowdedness.

C. SUBJECTIVE CROWDEDNESS

Several studies have emphasized the importance of considering subjective crowdedness. Matsuda et al. surveyed the relationship between the objective crowdedness level (i.e., number of people) and subjective crowdedness level for 2,200 people via crowdsourcing [39]. Li and Hensher focused on the difference between objective crowdedness and passengers' Subjective Crowdedness in public transportation, highlighting the need to link objective indicators with passengers' experiences [11]. Mahudin et al. developed a scale to measure passenger crowdedness, evaluating its psychological elements [12]. The new scale includes three components: psychosocial aspects, evaluation of the surrounding environment, and emotional responses. These components suggest its usefulness for companies to understand passenger experiences comprehensively by considering subjective crowdedness in addition to traditional objective crowdedness.

D. POSITION OF THIS STUDY

While numerous studies exist on estimating bus crowdedness, most focus on estimating the number of passengers inside, with few addressing the estimation of passengers' subjective sense of crowdedness. Previous research has estimated the number of passengers in a vehicle [37], [38], but as shown in Figure 7, there is variability in the relationship between the number of people and subjective crowdedness. Therefore, this study developed a bus passenger subjective crowdedness estimation system using BLE signals, which preserves privacy and is practical for use in transportation systems. By sensing BLE signals emitted from passengers' mobile devices using BLE devices installed in bus on-board equipment, we aim to estimate the number of passengers and their subjective crowdedness, thereby providing more comprehensive crowdedness information to bus users.

III. BLE CROWD ESTIMATION SYSTEM

In this section, we summarize the system requirements and then describe a BLE-based system that satisfies the requirements.

A. SYSTEM REQUIREMENTS

The requirements of the system to be implemented on an actual bus route are as follows:

- Reduction of the installation cost of sensing devices.
- Flexible placement of sensing devices, and
- Collection of data that do not include private passenger information.

The above three factors present significant barriers to implementing congestion estimation systems in buses currently in operation. In installing an APC or camera system on buses, the cost is not limited to the sensors themselves; additional expenses include securing installation positions and routing the wiring needed to operate the sensors. Furthermore, because sensors need to be installed at bus entrances, their placement is restricted to the vicinity of these entrances. Therefore, it is necessary to devise solutions that minimize installation costs and avoid limitations on device placement. Research and public discourse also emphasize public resistance to surveillance technologies, including cameras. As a result, accuracy in estimation and the protection of passenger privacy is essential [40]. Therefore, the system design must account for the installation costs, spatial limitations, and passenger privacy protection.

B. SYSTEM DESIGN

We developed a bus congestion estimation system using BLE based on the system requirements described in Section III-A.Figure 1 shows an overview of the proposed system. The system consists of (1) the sensing mechanism and (2) the estimation mechanism. In Figure 1, (1) the sensing mechanism collects BLE signals from the surrounding environment using a BLE sensing device installed inside the bus. In Figure 1, (2) the estimation mechanism processes the collected BLE signals, including both passenger and ambient noise signals. To enhance the accuracy of congestion estimation, the system applies occurrence frequency filtering and average RSSI filtering to distinguish passenger signals from external noise. The extracted features are then input into a machine learning model to estimate the number of passengers and the subjective crowdedness level.

C. SENSING MECHANISM

The sensing mechanism uses BLE signals emitted from the passengers' mobile terminals as sensing data. BLE is a power-saving communication standard among the short-range wireless communication standards called Bluetooth. To connect with other BLE devices, a BLE device continuously broadcasts a communication signal, a one-way data transmission to an unspecified number of parties. The transmitted data include the BD address to identify the device and an RSSI to indicate the signal strength. The sensing mechanism obtains the BD address and RSSI from the data in the BLE signal emitted from the passengers' mobile devices. Because the BD address is randomly changed at certain time intervals for privacy reasons, there is little risk of violating the passengers' privacy. Therefore, it is difficult to identify individuals from BD addresses immediately, and thus, in Japan, this sensing method is recognized as a privacy-conscious approach.

Figure 2 shows the BLE scanner used in this study. This BLE scanner has been modified into a sensing device by rewriting the firmware of the bus location system, which is already installed beside the driver's seat (Figure 3). Ideally, the BLE scanner should be placed in the center of the vehicle or another optimal location; however, doing so would incur additional costs for the device and wiring and securing an installation position. To address this issue, converting the existing bus location system into a BLE scanner through firmware modification eliminates the need for additional devices and wiring, thereby resolving both installation cost and placement challenges.

The sensing mechanism scans the surrounding BLE devices every 15 seconds (Figure 4). The number of scans between each bus stop is denoted as N_{scan}. During these N_{scan} scans, the system records the BD addresses and RSSIs of the detected BLE devices, the latitude and longitude of the bus at the time of scanning, and the ID of the most recent bus stop. These data are then uploaded to the cloud as needed.

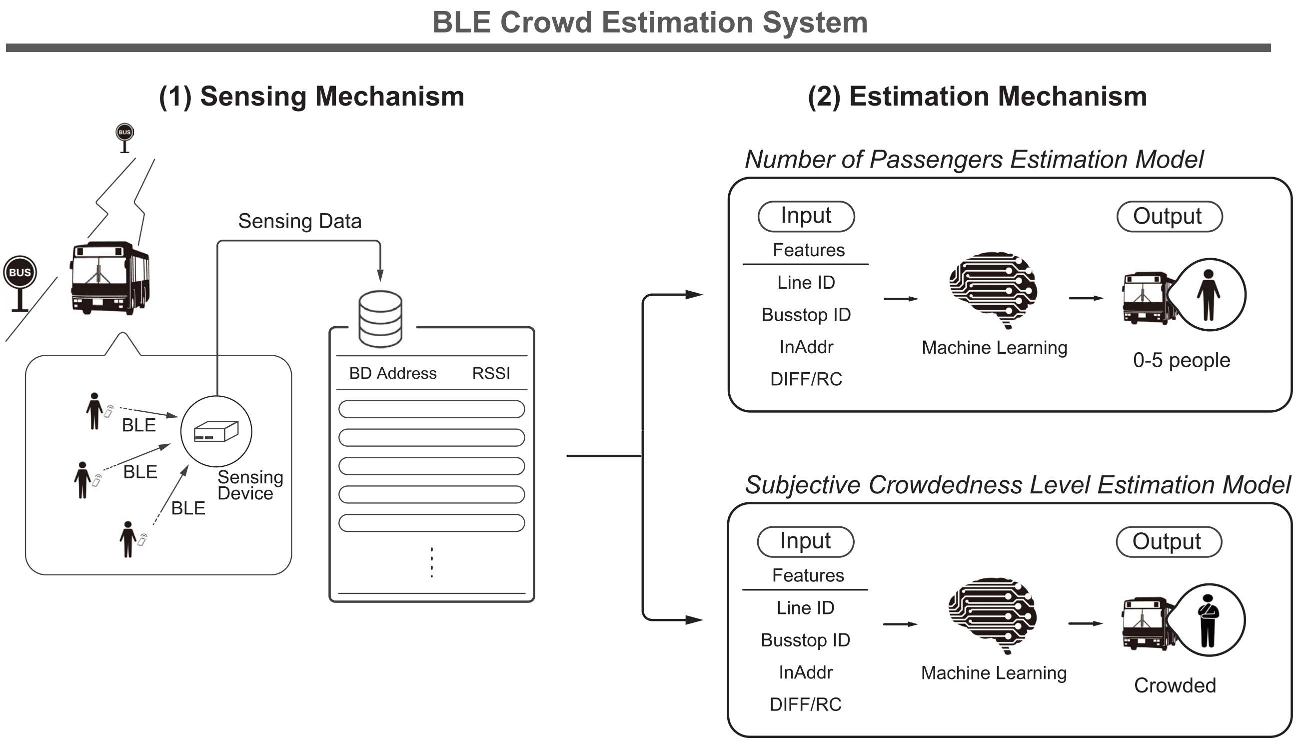


FIGURE 1. Overview of the BLE-based bus congestion estimation system. The system consists of (1) a sensing mechanism that collects BLE signals from passengers' mobile devices and (2) an estimation mechanism that processes the data to estimate both the number of passengers and the subjective crowdedness level.

D. ESTIMATION MECHANISM

The sensing mechanism scans the surrounding BLE devices every 15 seconds (Figure 4). The number of scans between each bus stop is denoted as N_{scan}. During these N_{scan} scans, the system records the BD addresses and RSSIs of the detected BLE devices, the latitude and longitude of the bus at the time of scanning, and the ID of the most recent bus stop. These data are then uploaded to the cloud as needed.

1) APPEARANCE FREQUENCY

BLE data frequently includes signals from outside the bus. Therefore, by calculating the appearance frequency of each BD address and filtering the data based on this frequency, we can distinguish between addresses inside and outside the bus. The frequency F at which a single BD address appears between each bus stop is calculated as follows:

$$F = \frac{N_{detected}}{N_{scan}} \tag{1}$$

where $N_{detected}$ represents the number of times the same BD address is detected between stops. In this method, a threshold is set for the appearance frequency, and counting the number of BD addresses that exceed this threshold is used as a feature.

FIGURE 2. BLE scanner for route buses integrated into the bus location system.

2) AVERAGE RSSI

When the distance between bus stops is short and the number of scans between stops is only one, using the appearance frequency may result in all detected BD addresses being identified as inside the bus. To address this, we calculate the

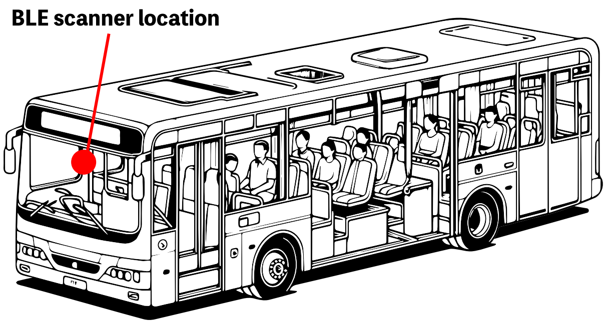


FIGURE 3. **Installation position of the BLE scanner (beside the driver's seat).**

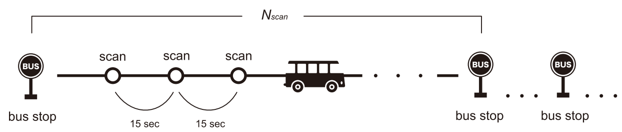


FIGURE 4. **Sensing process.**

average RSSI for each BD address and set a threshold for RSSI values to filter out signals from outside the bus. The average RSSI between each bus stop is calculated as follows:

$$RSSI\_mean = \frac{1}{N_{detected}} \sum_{i=1}^{N_{detected}} S(i) \tag{2}$$

where $S(i)$ represents the RSSI value at each scan. Similar to the appearance frequency, a threshold is set for the average RSSI, and BD addresses with an average RSSI above this threshold are counted and used as features.

3) DIFFERENCES AND RATE OF CHANGE

In the previous subsection, we created features representing the number of BLE devices inside the bus by calculating the appearance frequency and average RSSI and counting them using thresholds. We can create effective features at bus stops where boarding and alighting occur by calculating the difference in the number of BLE devices inside the bus between stops. Moreover, by calculating the relative rate of change between stops, not just taking the difference, we can generate features that effectively estimate subjective crowdedness. The perceived crowdedness may differ when the number of passengers increases from 0 to 10 compared to an increase from 30 to 40, even though the change is by an identical number of people. The difference *DIFF* and relative change rate *RC* between stops are calculated as follows:

$$DIFF = InAddr_{current} - InAddr_{previous} \tag{3}$$

$$RC = \frac{InAddr_{current} - InAddr_{previous}}{InAddr_{previous} + 1} \tag{4}$$

where $InAddr_{current}$ represents the number of BLE devices inside the bus at the current stop and $InAddr_{previous}$ represents the number at the previous stop, calculated from the features representing the number of BLE devices inside the bus introduced in the previous section. One is added to the denominator in *RC* to prevent division by zero.

4) ROUTE INFORMATION

Not everyone carries a BLE device; some individuals may possess multiple BLE devices. As a result, BLE-based estimations are susceptible to both underestimation and overestimation. Previous studies have demonstrated that simply counting the number of BD addresses after applying occurrence frequency and RSSI filtering is insufficient [37]. This study estimates congestion levels using machine learning with the number of passenger BD addresses as a feature to address this issue. Additionally, we incorporate route information—such as bus stop names, route names, and time—as features to improve estimation accuracy. This approach enables the model to capture contextual factors, such as the tendency for the number of detected BD addresses to be lower than the actual number of passengers during weekday midday hours due to a higher proportion of elderly passengers and those with children. In contrast, in the morning and evening, the number of detected BD addresses may exceed the actual number of passengers due to the prevalence of commuters carrying multiple BLE devices.

DEVELOPMENT OF THE CONGESTION ESTIMATION MODEL

In this study, we develop a congestion estimation model based on the features introduced in the previous section. Specifically, the model takes as input the number of passenger BLE signals obtained through appearance frequency and average RSSI filtering, along with the difference and rate of change in these values and route information, to estimate congestion levels. The threshold for appearance frequency was set at intervals of 0.1, ranging from 0.5 to 1.0. The threshold for average RSSI was set using values from -60 dB to -80 dB in 5 dB increments.

For the machine learning model, we employ LightGBM [41]. LightGBM is a high-performance framework based on the gradient boosting algorithm, known for its fast training and inference speed, making it suitable for real-time estimation tasks. It is also robust against data imbalance and missing values, making it highly effective for congestion estimation tasks using BLE signal data. The congestion estimation model using LightGBM consists of two separate models: one for estimating the number of passengers and another for estimating the subjective crowdedness level.

IV. DATA COLLECTION EXPERIMENT

To verify the effectiveness of our BLE system, a data collection experiment was conducted on actual route buses with the cooperation of Nara Kotsu Bus Lines Co., Ltd., over four days from March 24 to 27, 2023. The experiment was carried out on the Nara City Loop Line (Figure 5), a city loop bus that connects various landmarks and tourist sites in Nara City. The Nara City Loop Line consists of two routes:

the outer and inner loops, with the outer loop having 19 bus stops and the inner loop having 17 stops. These stops vary in nature, including those frequently used by tourists, such as Kintetsu Nara Station and Todai-ji Temple, and those located in residential areas with fewer tourist passengers. Details of the bus stops can be found on the official website of Nara Kotsu Bus Lines Co., Ltd.[2]

For data collection, 10 buses equipped with the BLE scanner shown in Figure 5 were used to scan nearby BLE devices. Additionally, 48 members of the public participated in the experiment to provide bus passenger counts and to report their perceived subjective crowdedness at each bus stop. Participants in the experiment were asked to respond to a Google Form we provided each time the bus reached a stop and the boarding and alighting process was completed. Figure 6 shows a screenshot of the actual Google Form used in the experiment. Participants were asked to input their pre-assigned participant ID, the bus stop, the number of passengers, and the perceived Subjective Crowdedness Level. For passenger count annotations, they selected one of the following categories: "0-5 people," "6-10 people," "11-20 people," "21-30 people," or "31 or more people," resulting in a total of 4,000 annotations. For subjective crowdedness annotations, they selected from six levels: "Very Uncrowded," "Uncrowded," "Slightly Uncrowded," "Slightly Crowded," "Crowded," and "Very Crowded," yielding a total of 6,597 annotations. This study was approved by the Ethical Review Committee for Research Involving Human Subjects at Nara Institute of Science and Technology (Approval No.: 2020-I16). Figure 7 shows a plot with the number of passengers on the bus on the x-axis and the subjective crowdedness level perceived by the passengers on the y-axis. Table 1 shows the breakdown of passenger count annotations, basic statistics of BD addresses, and basic RSSI statistics. Table 2 presents the breakdown of subjective crowdedness annotations, basic statistics of BD addresses, and basic RSSI statistics. Here, "basic statistics of BD addresses" refers to the basic statistics of BD addresses detected per scan, and "basic RSSI statistics" refers to the basic statistics of the RSSI values of BD addresses detected by the BLE scan.

V. EVALUATION AND RESULTS

A. DATA PROCESSING AND EVALUATION

The collected data from the sensing mechanism may contain outliers or missing values; therefore, the following preprocessing steps were applied.

First, if there was a significant discrepancy between the estimated bus position based on the stop ID stored in the internal bus system and the actual bus position obtained from the bus location tracking system, the data was considered an outlier and removed.

Additionally, when computing *DIFF* and *RC*, information from the previous stop is required. However, if the bus is at the first stop or if data from the previous stop is missing for any reason, it becomes impossible to compute *DIFF* and *RC*. To handle such cases, missing values in *DIFF* and *RC* were addressed by imputing them with the mean value.

[2]https://www.narakotsu.co.jp/language/en/local/nara_city.html

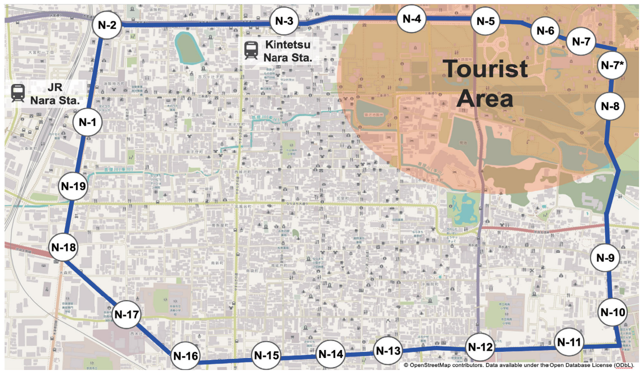


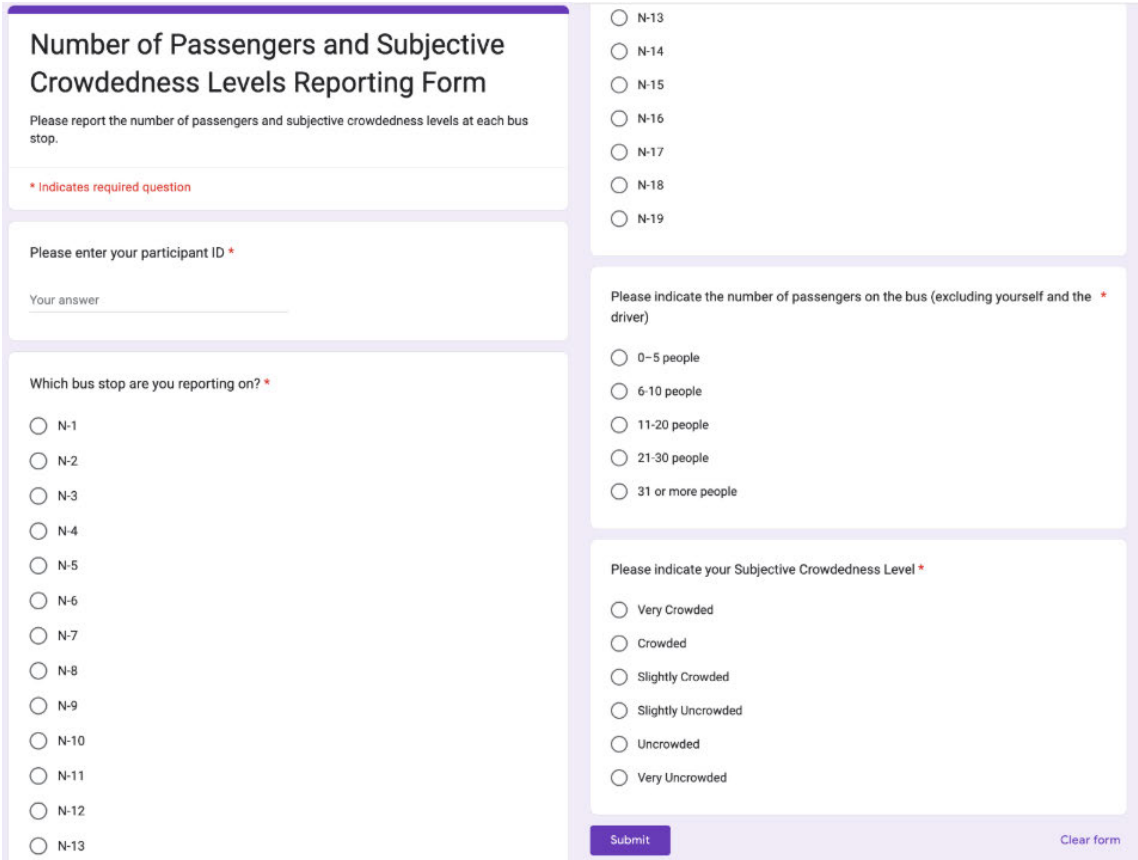
FIGURE 5. Nara City Loop Line. N-7 indicates the inner loop stop, and N-7* indicates the outer loop stop.

For the experiments, three types of features were used to build and evaluate models for estimating the number of passengers on the bus and the subjective crowdedness level: features from prior research by Kanamitsu et al. [37], features from our proposed method excluding differences and rates of change (our method without difference/rate of change), and features from our proposed method including all features (our method all). To verify the effectiveness of LightGBM for the congestion estimation task in this study, we employed not only LightGBM but also support vector machine (SVM) and random forest (RF) for training and evaluation of each model. The evaluation was conducted using 10-fold cross-validation, and the hyperparameters for each model were optimized using Optuna [42]. The evaluation metrics used were accuracy and F-score.

B. RESULTS

The estimation results for the number of passengers are shown in Table 3, and those for subjective crowdedness in Table 4. These tables show that the features of our BLE method are more effective than those of Kanamitsu et al., and LightGBM demonstrates high accuracy across all metrics and classification tasks. A comparison of the results of our method (without difference/rate of change) and our method (all) shows that the features of differences and rate of change are effective for both passenger count and subjective crowdedness estimation.

The confusion matrix for passenger estimation using LightGBM is shown in Figure 8, and that for subjective crowdedness is shown in Figure 9. Figure 8 indicates that passenger numbers are estimated with relatively high accuracy, though the estimation accuracy for "6-10 people" and "21-30 people" is lower. Additionally, Figure 9 shows that subjective crowdedness trends can be roughly captured using only BLE signal information. However, while the


Number of Passengers and Subjective Crowdedness Levels Reporting Form

Please report the number of passengers and subjective crowdedness levels at each bus stop.

* Indicates required question

Please enter your participant ID *

Your answer

Which bus stop are you reporting on? *

N-1
N-2
N-3
N-4
N-5
N-6
N-7
N-8
N-9
N-10
N-11
N-12
N-13
N-14
N-15
N-16
N-17
N-18
N-19

Please indicate the number of passengers on the bus (excluding yourself and the driver) *

0–5 people
6-10 people
11-20 people
21-30 people
31 or more people

Please indicate your Subjective Crowdedness Level *

Very Crowded
Crowded
Slightly Crowded
Slightly Uncrowded
Uncrowded
Very Uncrowded

Submit
Clear form

FIGURE 6. Screenshot of the Google Form used in the data collection experiment. (Originally created in Japanese and translated into English.)

TABLE 1. Number of passengers distribution and basic statistics of BLE data.

Number of Passengers		Basic Statistics of BD Addresses		Basic RSSI Sstatistics	
Number	Occurrence	Item	Value	Item	Value
0-5	1,930	Mean	28.9	Mean	-74.0 dB
6-10	934	Std	23.0	Std	6.2 dB
11-20	795	Min	1.0	Min	-79.0 dB
21-30	195	25%	12.0	25%	-79.0 dB
31+	146	50%	22.0	50%	-77.0 dB
		75%	39.0	75%	-71.0 dB
		Max	177.0	Max	-36.0 dB

TABLE 2. Subjective crowdedness distribution and basic statistics of BLE data.

Subjective Crowdedness		Basic Statistics of BD Addresses		Basic RSSI Statistics	
Crowdedness	Occurrence	Item	Value	Item	Value
Very uncrowded	2,809	Mean	28.4	Mean	-74.0 dB
Uncrowded	1,405	Std	22.4	Std	6.2 dB
Slightly uncrowded	1,148	Min	1.0	Min	-79.0 dB
Slightly crowded	748	25%	12.0	25%	-79.0 dB
Crowded	277	50%	22.0	50%	-77.0 dB
Very crowded	211	75%	38.0	75%	-71.0 dB
		Max	212.0	Max	-36.0 dB

general trends are captured, the estimation accuracy for categories other than "very uncrowded" and "very crowded" tends to vary.

VI. DISCUSSION

The estimation results presented in the previous section demonstrated that the number of passengers could be

TABLE 3. Estimation results for the number of passengers.

	Existing Method (Kanamitsu *et al.* [37])		Our Method (Without Difference/Rate of Change)		Our Method (All)	
Model	Accuracy	F-Score	Accuracy	F-Score	Accuracy	F-Score
SVM	0.572	0.388	0.588	0.395	**0.642**	**0.492**
RF	0.595	0.425	0.638	0.499	**0.649**	**0.516**
LightGBM	0.599	0.454	0.640	0.528	**0.653**	**0.530**

TABLE 4. Estimation results for subjective crowdedness.

	Existing Method (Kanamitsu *et al.* [37])		Our Method (Without Difference/Rate of Change)		Our Method (All)	
Model	Accuracy	F-Score	Accuracy	F-Score	Accuracy	F-Score
SVM	0.470	0.258	0.476	0.276	**0.501**	**0.322**
RF	0.487	0.316	0.508	0.355	**0.512**	**0.361**
LightGBM	0.492	0.331	0.506	0.367	**0.513**	**0.374**

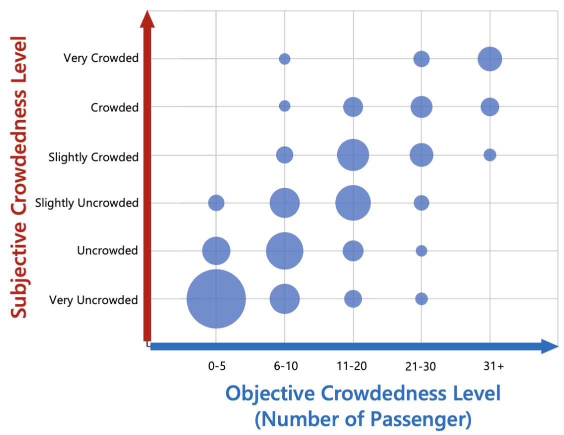


FIGURE 7. Relationship between the Objective Crowdedness Level (Number of Passengers) and Subjective Crowdedness Level. This figure plots the number of passengers on the bus that the experiment participants boarded on the x-axis and the subjective crowdedness level they perceived at that time on the y-axis.

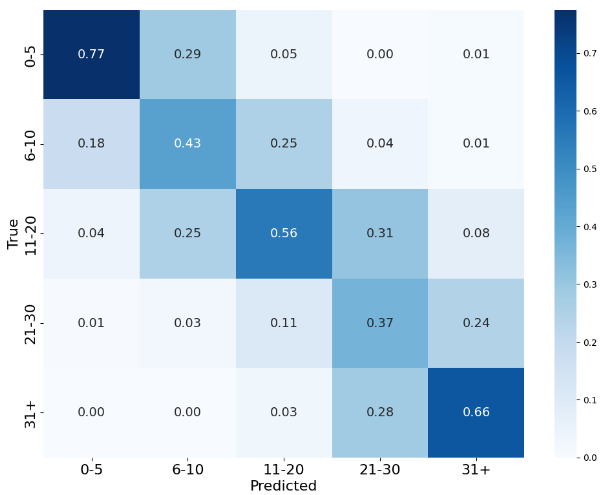


FIGURE 8. Confusion matrix for estimation of objective crowdedness level (number of passengers).

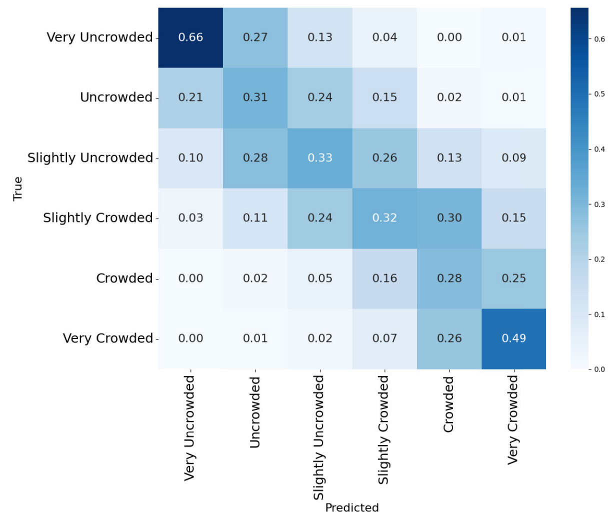


FIGURE 9. Confusion matrix of subjective crowdedness level estimation.

estimated with relatively high accuracy, although some variability in precision was observed. Similarly, while estimating subjective crowdedness captured general trends, it also exhibited fluctuations.

One common factor contributing to this variability is the number of BLE scans. Figure 10 presents a distribution plot of the number of BLE scans conducted between bus stops linked to the annotation data. The bus line used for data collection in Nara City has short distances between bus stops and a BLE scan interval of 15 seconds, resulting in fewer scans between stops. Since the accuracy of our method depends on the information obtained from BLE scans, a higher number of scans would likely provide more data and improve estimation accuracy. However, if passenger boarding and alighting take longer due to crowding, the number of scans could become excessive, making it more challenging to determine which addresses correspond to passengers inside the bus accurately. Therefore, treating the BLE scan interval as a hyperparameter and optimizing it based on specific routes and stops could enhance accuracy.

Another factor affecting estimation accuracy is BLE signal attenuation. BLE signals operate at a transmission frequency of 2.4 GHz, where the human body has a high absorption coefficient. In crowded environments, signal attenuation caused by passengers can make it difficult to detect signals from certain devices. In this experiment, the sensing device

TABLE 5. Ablation study on the effectiveness of route information.

	Number of Passengers		Subjective Crowdedness	
Feature Set	Accuracy	F-Score	Accuracy	F-Score
Without Route Information	0.638	0.519	0.498	0.360
With Route Information	**0.653**	**0.530**	**0.513**	**0.374**

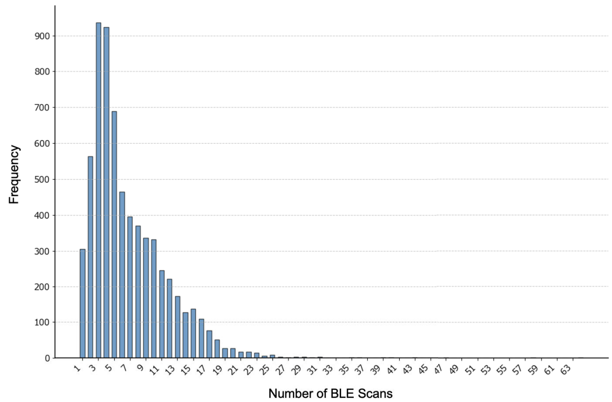


FIGURE 10. Distribution of the number of BLE scans between bus stops. The figure shows the number of scans conducted between bus stops, with the vertical axis representing their frequency.

was positioned at the front of the bus, which likely contributed to difficulties in detecting signals from passengers' devices located toward the rear of the bus.

To further validate the effectiveness of the route information feature , we conducted an ablation study by performing estimation using LightGBM with and without route information. The results are presented in Table 5. From Table 5, it can be confirmed that incorporating route information improves the estimation accuracy for both the number of passengers and subjective crowdedness.

In this study, we estimate the number of passengers using a machine learning model based on features extracted from BLE data, which are filtered by occurrence frequency and average RSSI, and combined with route information. This approach enables handling cases where passengers either do not carry BLE devices or possess multiple BLE devices, which cannot be addressed by simply counting BD addresses. However, distinguishing between passengers who do not carry BLE devices and those who possess multiple devices could further improve estimation accuracy. Furthermore, incorporating a clustering method to identify passengers carrying multiple BLE devices could enable more precise passenger estimation. Additionally, developing a complementary model to estimate the proportion of passengers without BLE devices could help mitigate errors caused by the absence or multiple possession of BLE devices, thereby achieving congestion estimation that better reflects passengers' actual BLE device ownership status.

In the results of the estimation of perceived crowding, the estimation accuracy for responses other than "very uncrowded" and "slightly crowded" is somewhat scattered. This is because, as shown in Figure 6, some people feel that it is "somewhat crowded" while others feel that it is "crowded," even when the number of people in the bus is the same. The constructed model produces the trend shown in Figure 6, and we believe that we have been able to construct a sufficiently effective model as a general-purpose model for estimating perceived crowding. On the other hand, the constructed model does not fully take into account the impact of situational variations (e.g., time of day and traffic conditions) on the perception of crowding. Considering factors such as temperature and humidity inside the bus, CO2 concentration, surrounding environmental conditions, and road conditions could further improve estimation accuracy. Therefore, it is necessary to explore the required sensors and passenger data to achieve this improvement.

The constructed general-purpose model captures the tendency of subjective crowdedness categories. However, it is challenging to clearly distinguish moderate levels of subjective crowdedness categories, which poses a challenge for practical use. Possible ways of using the constructed general-purpose model include reinterpreting the results to suit each individual's perception and fine-tuning the model to construct a customized model for each individual. For example, if a person constantly feels that the bus is more crowded than other passengers, he or she can match his or her feelings by interpreting that more people are on the bus than the estimated result. Alternatively, it is possible to fine-tune the general-purpose model by having the user report the degree of crowding several times.

In addition, it is thought that the perceived congestion level will vary depending on the person, location, and time. For example, if there are 20 people on a bus during the morning commute on a weekday and during midday on a weekday, the latter instance would probably be perceived as more crowded. The constructed model should be able to express this difference. To achieve this, validation is required not only on the Nara City Loop Line but also on multiple bus routes. Currently, we are deploying sensing devices on several routes other than the Nara City Loop Line and collecting data.

VII. CONCLUSION

We developed and evaluated a system that utilizes BLE signal information from passengers' mobile devices to estimate the number of passengers and their subjective perception of crowdedness. Conventional bus congestion estimation methods rely solely on the number of passengers, which does not fully account for the fact that individuals perceive congestion differently, even when the passenger count is the same. By incorporating subjective crowdedness estimation, our approach aims to provide passengers with a more intuitive and satisfactory representation of congestion levels. Furthermore, adopting BLE technology significantly mitigates installation location and cost challenges, which have been major drawbacks of traditional methods such as camera-based and APC-based congestion estimation. Specifically, our approach enables BLE sensing by simply modifying the firmware of the existing bus location tracking system, eliminating the need for additional hardware installation or dedicated space for sensors, thus making data collection more feasible and cost-effective.

To validate the effectiveness of our approach, we conducted data collection on the Nara City Loop Line and classified the collected data using machine learning models. The results demonstrated that our system can estimate the number of passengers with relatively high accuracy and capture general trends in subjective crowdedness. However, issues such as the need for optimal scan intervals at each bus stop and signal attenuation of BLE devices at the rear of the bus were identified. To estimate subjective crowdedness more precisely, fine-tuning the general model to individual perceptions is suggested. Future work aims to improve feature creation and sensing processes and explore additional data (e.g., passenger origin and personality) and sensors (e.g., light, temperature, and humidity) to develop more accurate models.

ACKNOWLEDGMENT

The authors would like to express their deep gratitude to everyone at Nara Kotsu Company Ltd., for their significant support in conducting this research.

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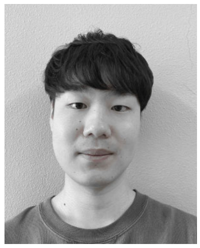

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