Performance Evaluation of Fingerprint-Based Indoor Positioning Using RSSI in 802.11ah

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***Abstract*—In incineration plants, indoor positioning systems are needed to prevent workers from approaching hazardous areas and to facilitate rescue operations in emergencies. Although many positioning systems using signal strength indicators such as Wi-Fi Received Signal Strength Indicator (RSSI) have been proposed, the vast interior of incineration plants increases the cost of constructing a communication infrastructure using 5GHz Wi-Fi. Therefore, by adopting Low Power Wide Area (LPWA), which allows for long-distance communication, the number of Access points (APs) that need to be installed in the environment can be reduced, thus lowering the cost of constructing the communication infrastructure. IEEE 802.11ah (11ah) is a new LPWA standard that uses the Sub-GHz band. In this study, we deployed new 11ah receivers in an incineration plant where IEEE 802.11ac (11ac) is already established and evaluated their coverage and area classification performance. The experiment demonstrated that the entire incineration plant can be covered with fewer units compared to 11ac. Additionally, when a small number of 11ah receivers were installed, the system identified individual rooms with higher accuracy than 11ac, suggesting that 11ah RSSI is a promising feature that can be obtained at low cost.**

***Index Terms*—Indoor localization, Wi-Fi HaLow, IEEE 802.11ah, Fingerprinting**

I. Introduction

In recent years, there has been a rapid increase in the number of services that utilize indoor location information to extend various applications. Indoor positioning technology plays a crucial role in providing the data needed for such services. In outdoor environments, the Global Navigation Satellite System (GNSS) effectively determines a person's position when a GNSS module is available. However, GNSS signals cannot reach indoor or underground structures, necessitating alternative methods to estimate a person's location indoors using sensor data.

A critical environment where indoor positioning is incineration plants that process municipal solid waste. In these plants, workers maintain and operate equipment. Indoor positioning is necessary for a plant manager to manage workers safely. For instance, if a worker approaches a restricted area, they can be warned, and if a worker becomes stuck due to heat stroke or a fall, the location information can be used for rescue operations. Given the structure of the building's interior, the goal is to achieve a positioning error of less than 10 meters, with smaller error ensuring greater safety.

Currently, the most common indoor positioning method uses Received Signal Strength Indicator (RSSI) of 2.4 GHz or 5 GHz from radio waves emitted by Wi-Fi. However, the main limitation of IEEE 802.11ac (11ac)-based positioning in incineration plants is its often inadequate coverage throughout large facilities. Establishing a comprehensive 11ac system would require significant investment, given the vast area to be covered.

As an alternative approach, the use of Low Power Wide Area (LPWA) communication standards, which support long-distance communication with a single base station and cover a wider area than 11ac, is considered. By introducing LPWA as a communication infrastructure within buildings, effective indoor positioning can be achieved with fewer base stations, thereby maintaining positioning performance and reducing costs, especially in cases where high bandwidth is not required. Although numerous studies on indoor positioning using LPWA have been reported, IEEE 802.11ah (11ah), called Wi-Fi HaLow, is a new LPWA standard, and studies using 11ah for indoor positioning have not yet been reported.

In addition, we are focusing on positioning methods using magnetic fields to achieve low-cost indoor positioning. Using magnetics as a feature has the advantage of not requiring additional infrastructure installation, allowing for the construction of a positioning system without needing extensive communication infrastructure. However, it is known that magnetic positioning accuracy decreases as the area to be positioned increases.

Therefore, we are considering adopting an area estimation method that can roughly identify areas within the building as a preliminary step to magnetic positioning, and then conducting positioning within the identified area using magnetics. In this positioning system, workers carry devices equipped with environmental sensors and 11ah modules necessary for positioning. The devices carried by the workers transmit collected environmental sensor data, 11ah RSSI, and other measurement data to a server via 11ah network. The environmental sensor data is assumed to include low-cost measurements such as magnetism and air pressure. The server uses a pre-trained model to estimate the area. Within the estimated area, positioning is performed using the environmental sensor data, and the positioning results are output. The administrator uses the outputted positioning results to monitor the workers' locations.

This paper focuses on evaluating the area estimation performance using only 11ah RSSI. The area estimation performance is evaluated using an actual dataset from the incineration plant. In this paper, we evaluate the feasibility of adopting 11ah for area estimation and communication equipment, and its practicality as an area estimation method.

The contributions of this study are as follows:

- By measuring the RSSI of 11ac and 11ah at the same locations in an incineration plant, we demonstrated that 11ah can cover the entire environment with fewer units than 11ac.
- We showed that 11ah, with fewer receivers, has higher performance in distinguishing between distant rooms compared to 11ac, indicating that 11ah can be expected to perform well as a feature for positioning.
- This study is the first to conduct a positioning experiment using 11ah, demonstrating its potential for indoor positioning.

II. Related Work

Current indoor positioning systems employ various methods to determine location by identifying the features of each point and calculating the coordinates of the current location. These features, referred to as fingerprints (FPs), are measured in advance for the entire building, and a database linking the coordinates of points with their corresponding FPs is created [1]–[4]. When a user performs positioning, the observed fingerprint (FP) at that point is matched against the database, and the coordinates of the most similar FP are used to determine the location. The features adopted as FPs should exhibit similar values when observed at the same precise location and should not change significantly over time. Additionally, it is desirable for these features to show different values depending on the location. RSSI of a wireless infrastructure meets these requirements as a feature.

Previous research on indoor positioning using LPWA technology has reported results using LoRa, one of the LPWA standards. Islam et al. [5] collected the RSSI of LoRa, 802.11ac, and Bluetooth Low Energy (BLE) under the same experimental conditions. They reported that with LoRa, communication occurred without packet loss through 13 walls, and only $6\,\%$ packet loss occurred even 7 floors away. Under the same conditions, Wi-Fi and BLE experienced $100\,\%$ packet loss. Zhu et al. [1] defined Extreme RSS (ERSS) to obtain stable FPs and proposed an FP-based method using ERSS. When FPs were measured at $3\,\mathrm{m}$ intervals using four gateways, they reported a mean distance error (MED) of $1.075\,\mathrm{m}$. Messaoud et al. [6] proposed a machine learning-based method using the Channel State Information (CSI) of LoRaWAN. Guo et al. [7] proposed a Time Difference of Arrival (TDoA)-based approach using accurate time synchronization with LoRa's Channel Activity Detection (CAD). They reported median positioning errors of $8.36\,\mathrm{m}$ in a $70 \times 32\mathrm{m}^2$ environment and $15.16\,\mathrm{m}$ in a $110 \times 70\mathrm{m}^2$ indoor plaza with many Non-Line Of Sight (NLOS) paths, both using six anchors. From these numerous studies on indoor positioning using LoRa, it is expected that 11ah, which uses a similar frequency band, will also achieve similar positioning performance.

Sébastien et al. [8] reported on the performance of 11ah in real environments. One of the features of 11ah compared to other LPWA standards is that, being part of the IEEE 802.11 family, it can utilize Internet Protcol (IP), which is expected to facilitate the proliferation of compatible devices. Additionally, 11ah offers higher bandwidth compared to LoRaWAN, making it more suitable for handling image and video data or scenarios requiring higher real-time performance. LoRaWAN provides a bandwidth of 300 Kbps to 500 Kbps, while 11ah offers a bandwidth ranging from 150 Kbps to 78 Mbps [9]. In the Sub-GHz band, the transmission time that a single device can transmit is regulated. With larger bandwidth, the time that beacon frames occupy the transmission time can be reduced, allowing other data to be transmitted more efficiently. Furthermore, 11ah can periodically transmit beacon frames from Access points (APs), making RSSI measurement straightforward. This study evaluates the characteristics of radio wave propagation and area identification performance using RSSI in real environments from the perspective of indoor positioning.

Magnetic positioning in an incineration plant was verified within a single floor by Okumura et al. [2]. When the entire building is targeted for positioning, an area estimation method is necessary. Lee et al. [10] proposed a positioning method combining magnetics and particle filtering. Focusing on area estimation, Suining et al. [11] proposed an area estimation method using Wi-Fi RSSI.

In our previous study [4], we evaluated an area estimation method using barometric pressure differences and LPWA RSSI for an incineration plant, demonstrating that these features could be used to divide the interior of the plant into multiple areas. This study differs from the previous study [4] in terms of the radio standard used and the building targeted for experiments. Additionally, we used a higher density dataset by changing the FP collection method. To focus on evaluating the performance of 11ah, we used only 11ah RSSI as the explanatory variable for area estimation, excluding barometric pressure differences.

TABLE I: Measured sensor data

Item name	Name of equipment
802.11ah RSSI	SILEX SX-NEWAH(JP)
802.11ac RSSI	IO-DATA WN-AC433UK
Coordinate	Apple iPhone 15 Pro Max / iPad Pro with RTAB-MAP [12]

III. Area Estimation Using 11ah

Area estimation is divided into two phases: an offline phase and an online phase. In the offline phase, environmental data and 11ah RSSI are collected to create a FP dataset, as described in previous research [3]. The detailed process of generating the FP dataset is explained in Secion IV. A machine learning model is trained using 11ah RSSI as the explanatory variable and the area name as the objective variable. A Random Forest algorithm is employed as the machine learning model. In the online phase, area names are inferred by inputting sensor data into the trained model.

The experiment took place at Otsu City North Clean Center located in Otsu City, Shiga, Japan. This building is six stories high, consisting of four above-ground floors and two basement floors. At the center of the building, there is a large space called the furnace room, which houses incineration equipment and spans all floors. The floor area of the furnace room is approximately $23\,\mathrm{m} \times 36\,\mathrm{m}$. Around the incineration equipment, there are grated walkways constructed for equipment inspection. There are separate rooms such as ventilation equipment rooms and storage rooms arranged around the furnace room. The incineration plant already has a sufficient number of 11ac APs installed, making it a suitable environment for evaluating the performance of 11ah.

To estimate the location in the incineration plant, it is first necessary to determine whether the location is inside the furnace room or in any of the other rooms. If it is determined to be outside the furnace room, area estimation is necessary among the other rooms. Therefore, the units of area division are "inside/outside the furnace room" and "room names (excluding the furnace room)". Since radio waves attenuate due to walls and ceilings, we expect significant signal strength attenuation across rooms, distinguishing the characteristics between rooms. For further detailed area division within the furnace room, previous research [4] suggests that using barometric pressure differences can provide finer floor-level identification. However, this study focuses on evaluating the performance of 11ah, and thus does not cover this aspect.

IV. Dataset

For the positioning experiments using the proposed method, a dataset was created using the building of the Otsu City North Clean Center.

The sensor data measurements were conducted from December 4 to December 6, 2023. The dataset consists of sensor data measured at each position within the experimental environment and the coordinates of each position.

The items collected and the devices used are shown in Table I. 11ah and 11ac RSSI were measured simultaneously on all channels using our proposed data collection method, as described in [3]. The measurer carried a measurement device equipped with multiple 11ac interfaces and one 11ah Access point (AP). The reason for having multiple 11ac interfaces was to capture one channel per interface. Conversely, for 11ah, the measurer carried an AP rather than a receiver to minimize the number of 11ah devices carried, as 11ah boards are larger than 11ac interfaces. The dataset was generated based on frames from 11ah at $923\,\mathrm{MHz}$ and from 11ac within the $5180\,\mathrm{MHz}$ to $5240\,\mathrm{MHz}$ range.

There are 29 11ac APs installed in the incineration plant. These 11ac APs were already in place for the plant's operational purposes. However, since some APs' locations could not be visually confirmed and some were located far from the experimental environment, only a subset of APs were used for the measurements. The 11ah receivers were placed near the already installed 11ac APs. The 11ac APs were installed at a height of about 2 meters overhead. Most 11ah receivers were placed on the floor directly below the 11ac APs or, where installation was difficult, within a few meters. 11ah RSSI was measured at each installed receiver, and the data was collected after the experiment.

To determine the position of the surveyor, an iPhone 15 Pro Max or iPad Pro was affixed to the measurement device, and the iOS implementation of the RTAB-MAP application [12] was utilized to acquire the surveyor's position. RTAB-MAP, a type of 3D Visual SLAM, has been reported to achieve a positioning error (Absolute Trajectory Error, ATE) of less than $12\,\mathrm{cm}$ in a small office setting, which is sufficiently accurate for the coordinate data of the FP dataset. In our previous research [3], we demonstrated that using RTAB-MAP facilitates the efficient creation of datasets in an incineration plant. In this study, AprilTags [13] were placed on the walls to ensure the same level of accuracy as in our previous research [3]. The measurements were conducted in multiple sessions. By setting the walking route in such a way that the same AprilTag could be detected in multiple measurement sessions, RTAB-MAP was able to merge these sessions into a single map using the AprilTags. This method enabled the acquisition of three-dimensional coordinates throughout the entire building. The surveyor carried the measurement device and walked through the target environment to collect the data. There were no restrictions on the surveyor's walking speed, and they walked at a natural pace.

The dataset includes the 3D coordinates of the self-positioning results, the RSSI of each 11ac AP, and the RSSI of each 11ah receiver, recorded at $10\,\mathrm{Hz}$. The rationale of this frequency is that the beacon frames transmitted from both the 11ac APs and the 11ah APs are sent at $100\,\mathrm{ms}$ intervals. To synchronize multiple RSSI readings from different devices, the actual reception times at each receiving device were truncated with 100 ms granularity, thereby including the RSSI from multiple 11ac APs and multiple 11ah receivers in a single sample. For APs that could not be received, a dummy value of -150 dBm, which is an undetectable signal strength for both 11ac and 11ah, was recorded.

The measurements were conducted by two surveyors. Each surveyor conducted measurements simultaneously but followed different walking routes. This dataset is referred to as the full dataset. The full dataset includes data measured in the furnace room and 17 other rooms.

To estimate areas and calculate Median Absolute Error (MedAE) while reducing computational load, a smaller dataset was created by setting the data interval to 1 second. Since Surveyor A collected more samples, the data measured by Surveyor A was used as the training data, and the data measured by Surveyor B was used as the test data. For area estimation and MedAE calculation, it is essential that both the training and test data include FP measurements taken at geographically close locations. Therefore, in the smaller dataset, the positioning space was divided into 1-meter squares on the floor, and only the spaces containing FPs from both surveyors were extracted. The smaller dataset includes data measured in the furnace room and 6 other rooms. This study evaluates the performance using both the full dataset and the smaller dataset. These datasets are available on GitHub[1].

V. Evaluation

This section demonstrates the feasibility of adopting 11ah for area estimation in incineration plants.

A. Path Loss

To compare the stability of signal strength relative to the distance between the AP and the receiver, the path loss of 11ac and 11ah was compared. The Euclidean distance from each 11ac AP/11ah receiver to the surveyor was calculated, and the Euclidean distance along with the number of RSSI samples obtained at each point are illustrated. Among these, the results for a specific 11ac AP/11ah receiver are presented. The 11ac RSSI is shown in Figure 1, and the 11ah RSSI is shown in Figure 2. This 11ac AP and 11ah receiver are located close to each other, as shown in Secion IV. Note that the number of measured samples is influenced by the walking route of the surveyor. Additionally, dummy data of -150 dBm inserted for out-of-range measurements are excluded from the plots.

When measured at the same point, 11ah shows greater variance in signal strength with respect to distance compared to 11ac. Moreover, for 11ah, there is a noticeable reduction in the number of samples around -55 dBm, -69 dBm, and -75 dBm, irrespective of distance.

B. Coverage Comparison Based on the Number of Installed APs/receivers

To compare the number of APs required for deploying a communication infrastructure for each standard, we show the coverage for each number of installations using the full dataset. In the case of 11ah, let N be the total number of receivers included in the dataset, and $n \in \{1, 2, ..., N\}$ be the number of selected receivers. For 11ac, N and n represent the number of APs. The target space is divided into 1-meter grid areas, with A representing the total number of areas and a representing the number of areas where at least one RSSI was observed. The coverage c is calculated as follows:

$$c = a/A. \tag{1}$$

The results are shown in Figure 3. For the combination $C(N, n)$ of selecting n receivers, the coverage c for all possible combinations is calculated, and the combination with the highest c is adopted. The intermediate data points in Figure 3 were not evaluated to reduce computation time. For the same reason, intermediate data points are not displayed in other figures as well.

As shown in Figure 3, 11ah achieved $100\,\%$ coverage with 5 receivers. 11ah can cover the target area with fewer installations compared to 11ac.

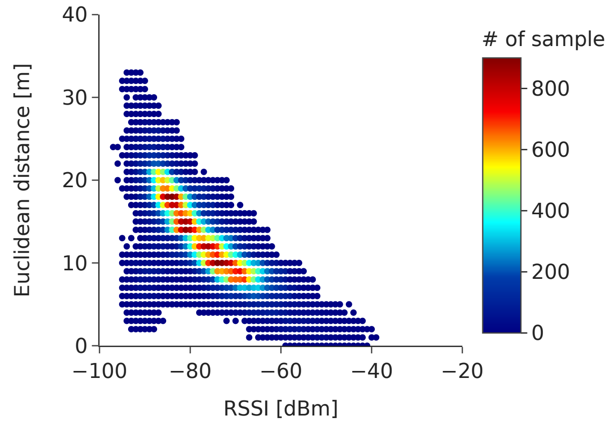

Fig. 1: Path Loss of 11ac AP

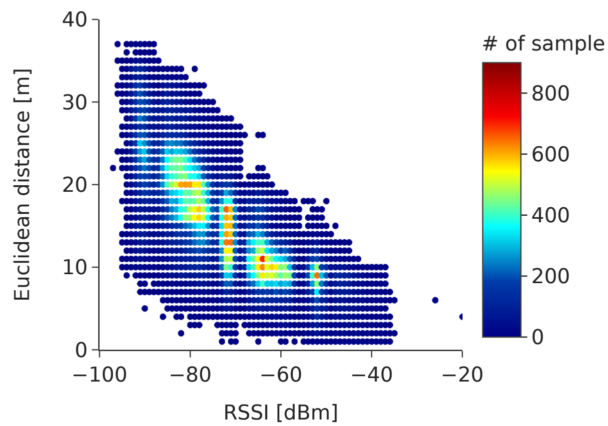

Fig. 2: Path Loss of 11ah Receiver

[1]https://github.com/inet-lab-naist/ipin2024-dataset

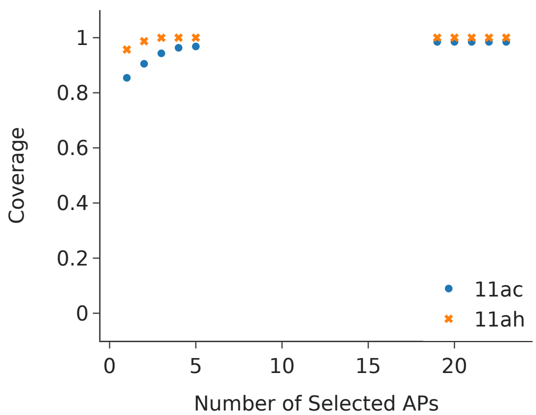

Fig. 3: Coverage for each number of installed APs

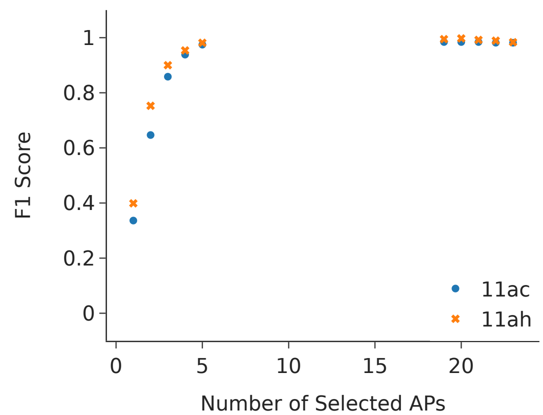

Fig. 5: Area classification performance for each number of installed APs (excluding the furnace room)

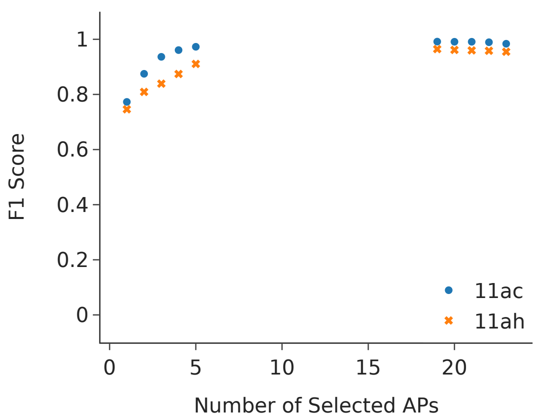

Fig. 4: Area classification performance for each number of installed APs (inside/outside the furnace room)

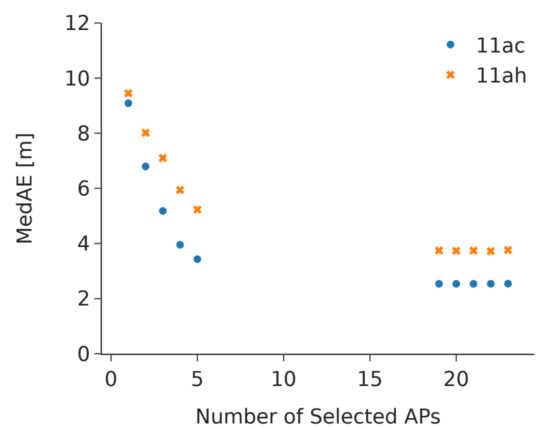

Fig. 6: MedAE for each number of installed APs

C. Area Estimation Performance Comparison Based on the Number of Installed APs

As shown in Secion V-B, 11ah can cover a broader space with fewer receivers/APs than 11ac. This increased coverage enhances the likelihood of receiving beacon frames, potentially improving area estimation performance with fewer receivers. To verify this, we present the maximum achievable area classification performance (F1 Score) for each number of receivers. For all combinations $C(N, n)$ of selecting n receivers, area estimation models were trained, and the F1 Score f was calculated. To reduce computational load, the smaller dataset was used. The combination of receivers that yielded the highest f was adopted. The results for area classification considering inside/outside the furnace room are shown in Figure 4, and the results for area classification by rooms (excluding the furnace room) are shown in Figure 5. From Figure 4, the highest F1 Score was achieved when 19 11ac APs were selected, with an F1 Score of 0.992. The lowest F1 Score was achieved when one 11ah receiver was selected, with an F1 Score of 0.746. It can be seen that the classification performance for distinguishing inside/outside the furnace room is lower with 11ah than with 11ac. From Figure 5, the highest F1 Score was achieved when 20 11ah receivers were selected, with an F1 Score of 0.997. The lowest F1 Score was achieved when one 11ac AP was selected, with an F1 Score of 0.336. It is evident that 11ah RSSI shows higher area classification performance when the number of receivers is small.

D. Comparison of Positioning Error Based on the Number of Installed APs

Similarly, using the smaller dataset, a Random Forest model was trained for each combination, with RSSI as the explanatory variable and 3D coordinates as the objective variable, and

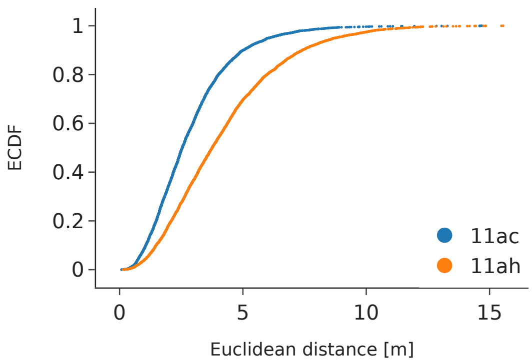

Fig. 7: ECDF of positioning error for maximum installations

MedAE was calculated using the test data. The MedAE was calculated using the following formula:

$$\mathrm{MedAE} = \mathrm{median}\left(\left\{\sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2 + (\hat{z}_i - z_i)^2} \;\middle|\; i = 1, 2, \ldots, M\right\}\right). \quad (2)$$

- M is the number of samples.
- $(\hat{x}_i, \hat{y}_i, \hat{z}_i)$ are the estimated coordinate of the ith sample.
- (x_i, y_i, z_i) are the true coordinate of the ith sample.

The results are shown in Figure 6. Among the combinations of selecting n receivers, the combination with the smallest MedAE was adopted. As shown in Figure 6, 11ah shows lower performance compared to 11ac. The smallest MedAE for each standard was achieved using 21 APs for 11ac, resulting in a MedAE of $2.537\,\mathrm{m}$, and using 22 receivers for 11ah, resulting in a MedAE of $3.722\,\mathrm{m}$.

Additionally, using the smaller dataset, the Empirical Cumulative Distribution Function (ECDF) of positioning error was calculated for the maximum number of installations for each standard. Let N_{ac} be the total number of 11ac APs in the dataset and N_{ah} be the total number of 11ah APs. In this dataset, since $N_{\mathrm{ac}} = N_{\mathrm{ah}} = 23$, we calculated the positioning accuracy ECDF using 11ac RSSI for $N_{\mathrm{ac}} = 23$ and 11ah RSSI for $N_{\mathrm{ah}} = 23$, and the results are shown in Figure 7. Even when the maximum number of APs/receivers are installed, 11ah shows larger positioning errors. The probability that the positioning error is less than 10 meters was $97.4\,\%$ for 11ah and $99.6\,\%$ for 11ac.

VI. Discussion

A. Path Loss

The difference in signal strength over distance in 11ah is primarily due to its use of a lower frequency band compared to 11ac, which affects the linearity of the signal. The missing signals at certain signal strengths of 11ah may be attributed to the characteristics of the antenna and its installation location, as similar phenomena were observed at other installation sites.

B. Coverage Comparison Based on the Number of Installed APs/receivers

The reason why 11ah demonstrates wider coverage is considered to be that 11ah uses a lower frequency band compared to 11ac, which allows for higher diffraction capability and the ability to reach around obstacles. Furthermore, it is evident that the number of already installed 11ac APs is more than the number required to achieve nearly $100\,\%$ coverage. When constructing a communication infrastructure using 11ac, it might be possible to provide stable IP communication with fewer APs.

C. Area Estimation Performance Comparison Based on the Number of Installed APs

When classifying the rooms excluding the furnace room, we believe that the high performance of 11ah is due to its wide coverage. We hypothesize that the rooms other than the furnace room were sufficiently distant from each other, resulting in a clear difference in radio wave strength. In contrast, the performance of 11ah was lower than that of 11ac in discriminating between the inside and outside of the furnace room. This may be due to the greater influence of the dispersion of radio wave strength with respect to distance, as discussed in Secion VI-A, rather than the advantage of wider coverage. We believe that the dispersion of radio wave strength had a greater impact than the difference in attenuation due to walls, leading to similar radio wave strengths inside and outside the furnace room.

D. Comparison of Positioning Error Based on the Number of Installed APs

Similar to Secion VI-C, 11ah exhibited a larger positioning error compared to 11ac. The decrease in positioning accuracy, as discussed in VI-C, is thought to be due to the greater impact of RSSI variability rather than the coverage area. Although adopting only 11ah RSSI as a feature for constructing a positioning system is not sufficient, the results indicate that it possesses a certain level of positioning performance. Incorporating 11ah RSSI into the explanatory variables is expected to enhance indoor positioning accuracy. In this study, we compared the positioning error of 11ah and 11ac to demonstrate the potential of 11ah. Although the positioning error observed in this study is not smaller compared to other previous studies, there is potential to achieve higher accuracy by improving the positioning algorithms.

VII. Conclusion

To reduce the cost of installing communication infrastructure, we evaluated the coverage and area estimation accuracy when using 11ah. With fewer receivers, 11ah demonstrated wider coverage compared to 11ac. The adoption of 11ah is expected to reduce the number of APs required, thereby lowering installation costs. Additionally, when there are few receivers and the rooms are sufficiently separated, 11ah showed high performance in identifying rooms.

For future work, we plan to construct a positioning system that combines 11ah RSSI and magnetic field, and compare the construction cost with the existing 11ac positioning system. Moreover, we will evaluate the coverage and positioning accuracy under scenarios assuming actual communication to achieve the required signal strength.

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