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Abstract

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Experimental Results for Indoor Positioning Based on Wi-Fi FTM and RSSI

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***Abstract*—Indoor positioning methods using wireless signal propagation data have attracted significant interest for applications such as monitoring IoT devices and tracking human behavior. The IEEE 802.11 FTM (Fine Timing Measurement) protocol, used for Wi-Fi location, was introduced to the market in 2016. The FTM protocol can measure the distance between Wi-Fi access point (AP) and station (STA). By measuring the distances between multiple Wi-Fi APs and STAs, the indoor position of the STA can be estimated. In this paper, we collected FTM and RSSI measurements in an indoor environment using FTM-enabled Wi-Fi APs and STAs, and evaluated indoor positioning accuracy through geometric calculations based on FTM data as well as a machine learning approach using both FTM and RSSI data as inputs. Furthermore, for the machine learning approach, we also assessed the impact of varying the number of Wi-Fi AP data elements supplied to the model in increments of AP count. The results demonstrated that positioning accuracy achieved by the machine learning approach surpassed that of geometric calculations. Moreover, even when the number of input data elements to the machine learning model was limited, utilizing FTM data obtained from at least one AP mitigated the degradation in positioning accuracy within the machine learning framework.**

***Index Terms*—Indoor Localization Estimation, Fine Timing Measurement, IEEE 802.11-2016, Wi-Fi, Machine Learning.**

I. Introduction

High-precision indoor positioning estimation for indoor location management and people flow data analysis is attracting attention. Examples of such applications include flow line analysis in airports, warehouses, commercial facilities, and campuses, as well as location management in factories. Bluetooth, UWB, and Wi-Fi have been considered as indoor positioning methods. Bluetooth 6.0 extends to support channel sounding feature for ranging with RTT (Round Trip Time) and PBR (Phase-Based Ranging) in addition to AoD (Angle of Departure) defined in Bluetooth 5.1 [1]. Next generation UWB, discussed in IEEE 802.15.4ab [2], also updates PHY and MAC to enhance ranging capability. While these standards have the advantage of more accurate ranging, the installation of additional infrastructure equipment such as anchors is required. In particular, Wi-Fi is widely used as an indoor infrastructure, and products are being introduced to the market as Wi-Fi Location [3]. Wi-Fi Location Release 1 uses the FTM (Fine Time Measurement) protocol specified in IEEE 802.11-2016 [4], which allows Wi-Fi APs and STAs to communicate with each other to measure the distance by the arrival time of the radio waves in addition to conventional RSSI-based ranging.

Several existing indoor positioning methods using data have been investigated, but they all have their challenges. For example geometric methods for calculating the relative position from an Wi-Fi AP by converting RSSI attenuation to distance values or using FTM distance measurements have been widely studied. These method of indoor position methods are not suitable for real-world applications. The slightest disturbance, where by human traffic or the line of sight from access point may be obstructed, can cause a large deviation in distance values from the accurate distance values. For machine learning methods applying RSSI or FTM values, these methods can basically estimate indoor positions with high accuracy, but requiring detailed data collection for each location and large-scale measurements. For example, the third and fifth floors of a building will often have similar floor structures. The most of the walls and obstacles will be the same, and only the placement and propagation of the Wi-Fi APs will be different. Existing machine learning-based methods do not allow these two models to be used interchangeably, and data must be acquired for each floor.

The ultimate goal of this research is to develop an indoor positioning method that can be applied to different radio propagation environments from the time the dataset was created, eliminating the need for repeated large-scale data acquisition. As a first step towards achieving this goal, this paper presents the collection of detailed FTM and RSSI data and an analysis of the combination of frequency bands and methods. Data collection was conducted using densely placed Wi-Fi APs and a robot in an indoor environment. Using FTM distance measurement values, we evaluated position estimation through geometric methods and machine learning. Additionally, for machine learning-based position estimation, we investigated the number of Wi-Fi APs required for actual deployment.

The rest of this paper is organized as follows. Section II presents related work. Approach description including experimental set up for data collection is provided in Section III. Experimental and analysis results are described in Section IV. Finally, we conclude our paper in Section V.

II. Related Work

The specification for calculating the distance between a STA (Initiator) and an AP (Responder) is incorporated into the IEEE 802.11-2016. RTToF (Round Trip Time of Flight) method, which calculates a distance based on RTT and the speed of light between the Responder and the Initiator, is applied [4]. The sequence of FTM is shown in Figure 1. Initial FTM Request is transmitted from the Initiator. After an acknowledgment (ACK) is sent from the Responder, FTM frame is sent at time $t_{1,1}$, and the frame arrives at the Initiator at time $t_{2,1}$. Then, ACK sent at time $t_{3,1}$ from the Initiator reaches the Responder at time $t_{4,1}$. The Responder transmits time information ($t_{1,1}$ and $t_{4,1}$) in an FTM frame to the Initiator at time $t_{1,2}$. The FTM is terminated after 7 sets of the same sequence to calculate the average. The theoretical RTT can be calculated as

$$RTT = (t_{4,1} - t_{1,1}) - (t_{3,1} - t_{2,1}) \tag{1}$$

In practice, to improve the measurement accuracy, the RTT is averaged over n round trips as

$$RTT = 1/n(\sum_{k=1}^{n}(t_{4,k} - t_{1,k}) - \sum_{k=1}^{n}(t_{3,k} - t_{2,k})) \tag{2}$$

Then the distance d between the Initiator and the Responder can be computed using $d = (RTT/2) \times c$, where c is the speed of electromagnetic wave propagation.

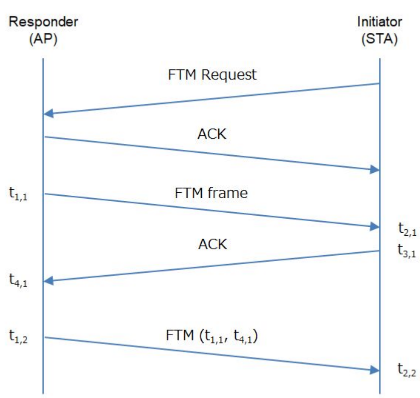

Fig. 1. FTM Sequence

Indoor positioning technologies are widely used in the market and have also led to extensive performance studies in research community.

A bunch of indoor positioning researches using RSSI (Received Signal Strength Indicator) have been conducted. H. Neyaz et al. compares the accuracy of indoor localization schemes by machine learning using Wi-Fi fingerprinting, in which the RSSI data of about 200 Wi-Fi Access Points are used [5] [6]. H. Rizk et al. propose transfer learning mechanism, named GlobLok, for Wi-Fi indoor positioning using RSSI data. This proposal tries to generalize models trained in one building to other buildings [7]. Y. Li et al. pays attention to the impact of mobile Wi-Fi APs like mobile phones operating as Wi-Fi mobile hotspots on indoor Wi-Fi localization error bound. Simulation results using RSS (Received Signal Strength) show that mobile Wi-Fi APs have non-ignorable impact on indoor Wi-Fi localization error bound [8].

For FTM-based localization, T. Kovácsházy et al. present baseline measurement performance of FTM using the Espressif System ESP32-S2 and ESP32-S3 Wi-Fi-enabled Wireless SoCs [9]. P.E.N et al. propose a dropout autoencoder fingerprint augmentation approach for the enhanced Wi-Fi FTM and RSS signals-based indoor localization with DNN (Deep Neural Network). The CDF of localization error are presented [10]. Authors of this paper also present the development of FTM automatic measurement robot for indoor localization estimation using Wi-Fi [11], in which the architecture of the automatic measurement system and test data with FTM-enabled Wi-Fi module is described.

However, although there have been studies on RSSI and FTM, there have been no comprehensive studies on the number of access points required for real-world deployment and the advantages of different frequencies. This paper presents a detailed dataset of FTM and RSSI data acquired at 1-meter intervals and analyzed results for the combination of frequency bands and positioning estimation methods on Section III Data acquisition was conducted using a dense arrangement of Wi-Fi APs, and the number of Wi-Fi APs required for real-world deployment was investigated on Section IV

III. Approach Description

This Section presents our measurement device and experiment approach.

A. Implementation of Measurement Device

To measure indoor ranging accuracy, measurements need to be taken at many points for ground truth and learning data. In this study, we implemented measurement device using line tracing and QR codes, which automatically collects sensing data including FTM, RSSI, and IMU(Inertial Measurement Unit). Our proposed measurement device consists of a JetSon Orin Nano, an Intel AX-210 NIC, and a rover equipped with a line tracer and QR code reader. Figure 2 shows the details of the measurement device and system. The AX-210 used as STA is FTM-enabled. Additionally, an FTM-enabled Aruba 535 is used for the Wi-Fi AP [12].

B. Measurement Condition

Figure 3 shows the measurement condition from the top view. Eight Wi-Fi APs, Aruba 535, were placed in classrooms on the school campus.To verify the impact of the AP selection method on the accuracy of position estimation, an excessive number of APs relative to the size of the room was used. These Wi-Fi APs are capable of making FTM measurements at both 2.4 GHz and 5 GHz. In this paper, measurements were conducted twice, using each frequency individually. Wi-Fi APs were placed at a height of 2 m, considering the actual installation environment. The Intel AX-210 was mounted on

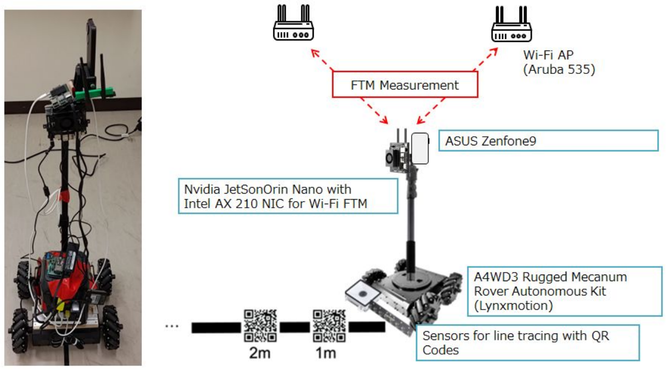

Fig. 2. Measurement Device

our measurement device for FTM measurements. The height of the Wi-Fi STA was set to 1 m above the ground surface. This measurement device automatically moves within the measurement environment by line tracing and stops for one minute each time it identifies a QR code laid at the measurement points indicated by the circles in Figure 3. While stopped, the Wi-Fi STA performs FTM measurements sequentially with each Wi-Fi AP.

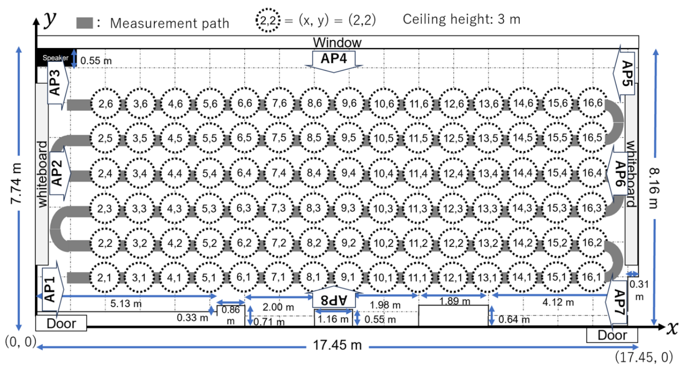

Fig. 3. Measurement Condition

IV. Experimental and Analysis Results

This paper presents the positioning results using FTM and RSSI data with the Intel AX-210. Two indoor positioning accuracy methodologies were evaluated. Section IV-A describes the indoor positioning accuracy based on geometric calculations using FTM distance data. Section IV-B presents the indoor positioning accuracy using machine learning with radio wave propagation data as input. 2.4 GHz and 5 GHz were evaluated separately.

A. Indoor Positioning Accuracy by Geometric Calculations

In each measurement, the distance d from the STA to multiple Wi-Fi APs can be obtained. Assuming the coordinates of the Wi-Fi APs are known, circles with radius d centered at the coordinates (x, y) of the Wi-Fi APs can be plotted on a map. For example, if distance data from four Wi-Fi APs are obtained, four equations of circles centered at the Wi-Fi APs can be established.

$$\begin{aligned}(x-x_1)^2+(y-y_1)^2 &= d_1^2\\(x-x_2)^2+(y-y_2)^2 &= d_2^2\\(x-x_3)^2+(y-y_3)^2 &= d_3^2\\(x-x_4)^2+(y-y_4)^2 &= d_2^2\end{aligned} \tag{3}$$

By subtracting the equation of Wi-Fi AP1 from the equations of AP2, AP3, and AP4, three linear equations can be derived.

$$\begin{aligned}2(x_2-x_1)x+2(y_2-y_1)y &= d_1^2-d_2^2-x_1^2-y_1^2+x_2^2+y_2^2\\2(x_3-x_1)x+2(y_3-y_1)y &= d_1^2-d_3^2-x_1^2-y_1^2+x_3^2+y_3^2\\2(x_4-x_1)x+2(y_4-y_1)y &= d_1^2-d_4^2-x_1^2-y_1^2+x_4^2+y_4^2\end{aligned} \tag{4}$$

The intersection points of these linear equations are calculated, and the centroid of the polygon they form is used to estimate the position of the Wi-Fi STA [13]. Measurements were conducted using data from eight Wi-Fi APs on both the 2.4 GHz and 5 GHz bands.

In this subsection, the following Wi-Fi APs were selected for the geometry-based positioning evaluation:

- **Reference value:** use the FTM values from AP 1, AP 3, AP 5, and AP 7, which are located at the four corners of the room.
- **All AP selected:** use the FTM values from all eight APs (AP 1–AP 8) placed in the room.
- **RSSI-based AP selection:** select the four APs with the highest RSSI values among AP 1–AP 8 and use their FTM values for positioning.

Figure 4 shows the CDF for each frequency configuration and Wi-Fi AP selection method, and Figures 5, 6, and 7 present heat maps of the positioning accuracy at each measurement point when using 5 GHz. In those heat maps, , the CDF is computed for each measurement location, and the CDF value at a 2 m error threshold is displayed. This 2 m threshold was chosen to match our previous study [12]. For both frequency bands, the “All AP selected” case yielded the worst accuracy. We believe this is because unconditionally using all available APs allows FTM values with large errors to enter the calculation. Moreover, the CDF curve for the RSSI-based AP selection method crosses below that of the Reference value method in the 3–5 m error range and remains lower thereafter. Since the high-accuracy regions in Figure 7 are clustered near the walls, accuracy in the room’s center is actually worse than with the Reference value method. Although RSSI does attenuate with distance to some extent, multipath interference and reflections dominate, so RSSI-based AP selection failed to perform well in most areas away from the room edges.

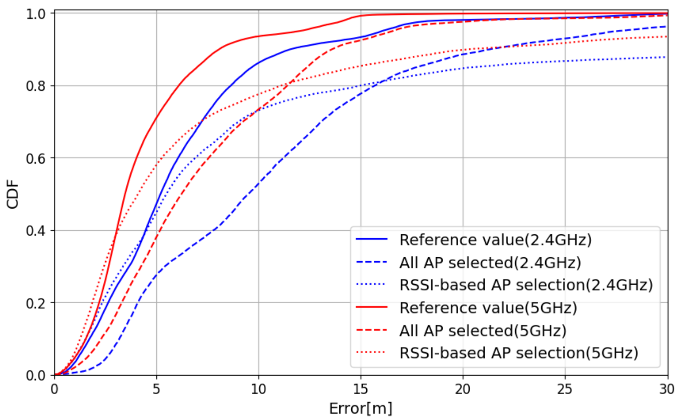

Fig. 4. CDF of position estimation by numerical calculation

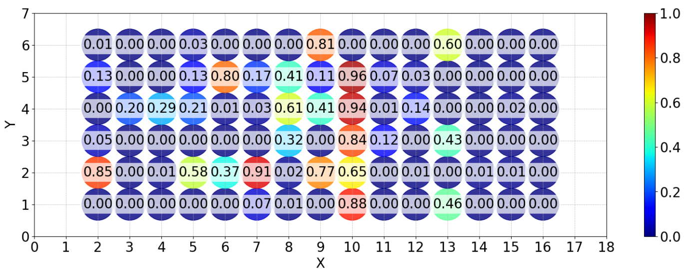

Fig. 5. Reference value (5 GHz, 2 meter error)

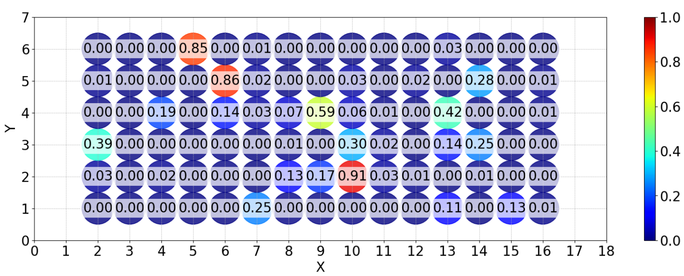

Fig. 6. All AP selected (5 GHz, 2 meter error)

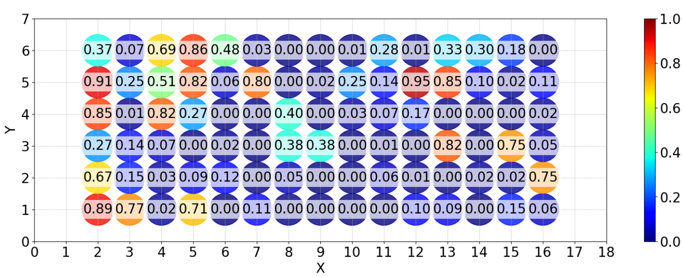

Fig. 7. RSSI-based AP selection (5 GHz, 2 meter error)

B. Indoor Positioning Accuracy Using Machine Learning

In each measurement, FTM and RSSI data from Wi-Fi APs placed in the environment are obtained. We conducted machine learning using these values as training data and evaluated its accuracy. The machine learning method used was random forest regression. This method was selected to perform evaluations as quickly as possible for prototyping, and we believe that similar results can be obtained with support vector machines or k-nearest neighbors. The source code used for training is publicly available and can be obtained from GitHub [14].

In this paper's measurements, eight Wi-Fi APs were installed in the environment, and data can be obtained from each of them. However, in this section, to match the conditions with the reference value in numerical calculations using machine learning, we used data from four APs: AP1, AP3, AP5, and AP7. The X and Y coordinates where the data were obtained were used as the correct labels, and the FTM and RSSI data obtained from each Wi-Fi AP were used as training data. Since the training data consists of FTM and RSSI data from four Wi-Fi APs, up to eight elements can be used.

Among these, we evaluated the impact of including FTM in the training data by excluding the four elements of FTM values from the machine learning input in the following three ways:

- **All FTM-enable:** Uses FTM data from all four Wi-Fi APs. The data consists of eight elements: FTM and RSSI from AP1, AP3, AP5, and AP7. (same with Section IV-A)
- **One FTM-enable:** Uses only the FTM data from AP1. RSSI data is valid for all Wi-Fi APs. The data consists of five elements: FTM from AP1 and RSSI from AP1, AP3, AP5, and AP7.
- **Zero FTM-enable:** Does not use any FTM data and learns only with RSSI. The data consists of four elements: RSSI from AP1, AP3, AP5, and AP7.

Similarly to Section IV-A, Figure 8 shows the CDF for each frequency setting and AP-selection method, and Figures 9,10 and 11 present heat maps of the positioning accuracy at each measurement point when using the 5 GHz band. In contrast to Chapter 1, the heat maps in Figures 9,10 and 11 display the CDF value at an error threshold of 0.5 m. Keeping the threshold at 2 m produced uniformly high values across all points, which obscured any differences between locations, so we adopted a stricter threshold. We chose 0.5 m because the measurement spacing between adjacent points was 1 m, making this threshold sufficient to fully distinguish each location. Across all AP-selection methods, the measured positioning accuracy is overall higher than in the numerical-simulation case. Moreover, Figure 8 shows that including FTM measurements in the learning process further improves localization accuracy. Although both FTM and RSSI vary with distance, relying on FTM yields higher precision than using RSSI alone, which is heavily affected by reflections and multipath.

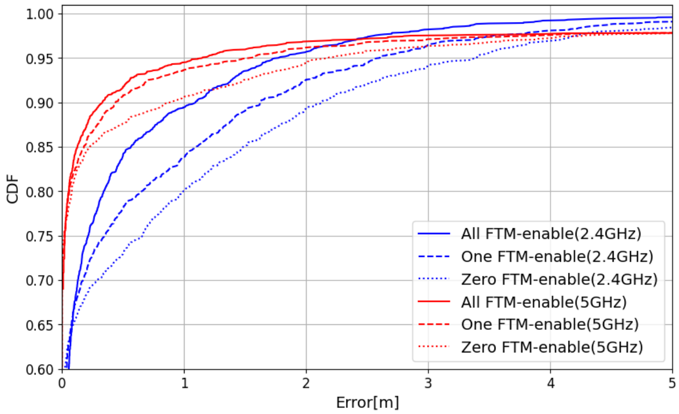

Fig. 8. CDF of position estimation by Machine Learning

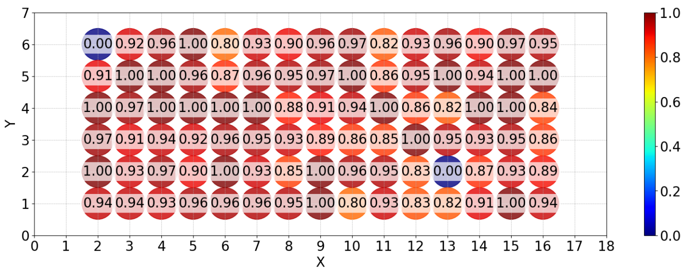

Fig. 9. All FTM-enable (5 GHz, 0.5 meter error)

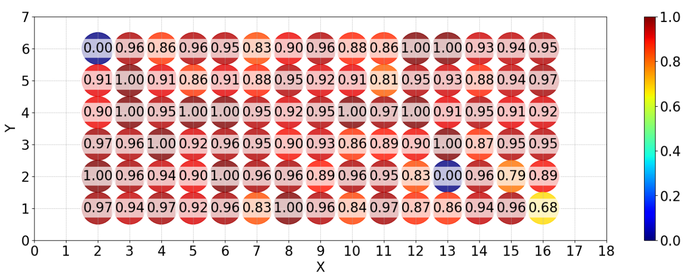

Fig. 10. One FTM-enable (5 GHz, 0.5 meter error)

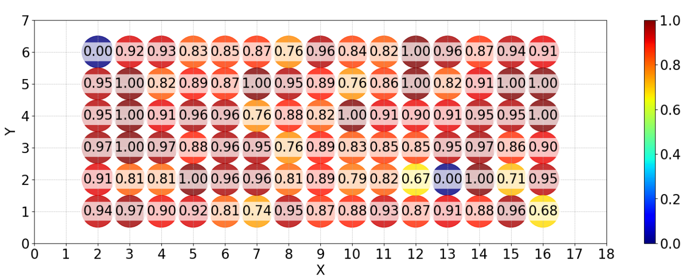

Fig. 11. Zero FTM-enable (5 GHz, 0.5 meter error)

Since it was confirmed that high-precision positioning could still be achieved when using data from only four Wi-Fi APs as input, we also examined how the number of AP data elements—and whether or not FTM measurements are included—affects accuracy. Machine-learning inputs were restricted according to the number of Wi-Fi APs and, in accordance with the All, One, and Zero FTM-enable schemes, by the presence or absence of FTM measurements. Consistent with the methodology applied in the heat maps, the CDF at a 0.5 m error threshold was employed as the metric for positioning accuracy. Figure 12 illustrates the positioning accuracy corresponding to each frequency band and data-element restriction. The x-axis denotes the number of Wi-Fi APs utilized as input. Overall, the 5 GHz band exhibited superior accuracy compared to the 2.4 GHz band. Incremental improvements in accuracy plateaued at approximately four to five APs, converging to values of approximately 0.85 for 2.4 GHz and 0.90 for 5 GHz. In the Zero FTM-enable case, accuracy dropped sharply once fewer than three to four APs were used—an effect especially pronounced at 5 GHz. We attribute this to a reduced AP count causing RSSI values that are too similar for the model to distinguish. The shorter propagation range of 5 GHz further amplifies this issue. This pronounced decline in accuracy is largely mitigated under both the All and One FTM-enable configurations. For practical deployments of machine-learning–based positioning systems, provisioning one FTM-capable AP per room—thereby enabling the acquisition of RSSI data from APs in adjacent rooms—is sufficient to maintain acceptable positioning accuracy.

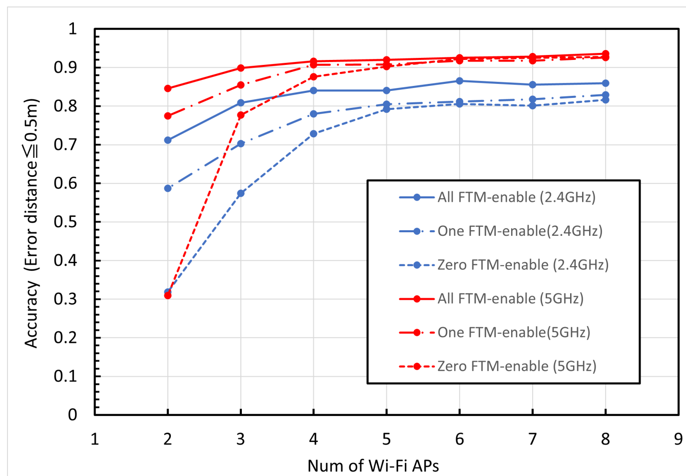

Fig. 12. Relationship between the number of Wi-Fi APs and accuracy (0.5 meter error)

V. Conclusion

In this paper, we collected FTM and RSSI measurements from eight Aruba 535 access points and an Intel AX-210 and evaluated positioning accuracy using both geometric computations and machine learning. Data collection and subsequent evaluations were conducted on the 2.4 GHz and 5 GHz frequency bands. In the geometry-based approach, three AP-selection schemes were compared:(1)Reference Value, which uses measurements from the four APs located at the room's corners; (2)All AP Selected, which utilises data from all available APs; (3)RSSI-Based AP Selection, which selects the four APs with the highest RSSI values; For both frequency bands, the All AP Selected scheme yielded the lowest accuracy, likely because unconditionally including all APs allowed large-error FTM measurements to influence the estimate. Furthermore, RSSI-Based AP Selection proved susceptible to multipath interference and did not produce uniform accuracy improvements across the monitored area. In the machine learning–based approach, we varied the number of APs contributing data to the training set to assess its impact on positioning performance. Training with data from more than four or five APs produced negligible accuracy gains. Conversely, when FTM values were entirely excluded and the training set was restricted to fewer than four APs, positioning accuracy deteriorated markedly. However, incorporating FTM data from at least one AP mitigated this degradation substantially. These experiments established a dataset framework characterised by diverse AP counts and measurement-point densities, providing a basis for the systematic comparison of various positioning methods. Within the scope of this study, machine learning leveraging FTM ranging data achieved high-precision positioning, and the inclusion of a single AP's FTM data markedly alleviated accuracy loss even when fewer APs were used. Future work will investigate AP deployment configurations in more complex environments and explore training methodologies toward the development of a generalized positioning model.

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