Indoor Localization Using Multi-Bluetooth Beacon Deployment in a Sparse Edge Computing Environment

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Abstract

Bluetooth Low Energy (BLE)-based indoor localization has been extensively researched due to its cost-effectiveness, low power consumption, and ubiquity. Despite these advantages, the variability of Received Signal Strength Indicator (RSSI) measurements, influenced by physical obstacles, human presence, and electronic interference, poses a significant challenge to accurate localization. In this work, we present an optimized method to enhance indoor localization accuracy by utilizing multiple BLE beacons in a Radio Frequency (RF)-dense, modern building environment. Through a proof-of-concept study, we demonstrate that using three BLE beacons reduces localization error from a worst-case distance of 9.09 meters to 2.94 meters, while additional beacons offer minimal incremental benefit in such settings. Furthermore, our framework for BLE-based localization, implemented on an edge network of Raspberry Pis, has been released under an open-source license, enabling broader application and further research.

1 Introduction

Indoor localization has recently gained significant attention due to its wide range of applications, especially in clinical settings [1, 2, 3]. For example, in patients with Mild Cognitive Impairment (MCI), there is a correlation between their movement patterns and behavior [4]. By tracking these patients, we can gain a better understanding of this relationship, which can help the safety of both the patients and their caregivers or families. To do this, there are different technologies like radio-frequency identification (RFID) [4], infrared (IR) [1], WiFi [2], and Bluetooth [3]. Among these various technologies, Bluetooth stands out for its popularity due to its low cost and long battery life, making it a practical choice with minimal maintenance requirements. There are many algorithms available to integrate data from technologies like Bluetooth for estimating an individual's location in indoor spaces. These algorithms can be broadly classified into two categories: fingerprinting [5, 6, 7, 8, 9, 10, 11] and trilateration [12, 13, 14, 15, 16]. One of the significant challenges in both fingerprinting and trilateration techniques is the instability of Received Signal Strength Indicator (RSSI) values, which poses difficulties in real-world conditions [17, 18]. This instability arises from the complexity of large indoor facilities, which often contain metallic structures such as steel beams, filing cabinets, or metal partitions, as well as the presence of furniture like desks, chairs, and shelving units. These elements can disrupt

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signal propagation, leading to fluctuations in RSSI readings and impacting the accuracy of localization methods. For example, a signal might be stronger in one area of the room but significantly weaker just a few meters away due to interference from nearby metal objects or the layout of the furniture [19, 20, 21].

There is a trade-off between the number of receivers and transmitters in large facility areas. Having too few can lead to poor localization accuracy due to insufficient data while having too many can negatively affect accuracy because of signal interference. Some studies have focused on determining the optimal number of receivers for indoor localization [22]. In this work, we will use a trilateration method that combines data from at least three receivers simultaneously, incorporating their corresponding RSSI values as weights in the localization algorithm. This approach, known as Received Hits Strength Index (RHSI)-Edge Trilateration, has demonstrated consistently stable accuracy in large facility areas [23]. By incorporating this algorithm we aim to tackle the ongoing challenge of improving system performance by increasing the number of BLE beacons, or transmitters, assigned to each individual. Our objective is to determine the optimal number of devices where adding more beacons no longer significantly enhances the accuracy of this algorithm. By identifying this threshold, we can achieve a balance between resource efficiency and system accuracy, ensuring that the addition of extra devices yields diminishing returns in terms of performance.

2 Data Collection

Data were collected in a large (1700m2) space with complex features that is designed for supporting lifestyle interventions for individuals with MCI. It incorporates diverse areas such as a gym, kitchen, library, dining area, open theater, maker lab, and other customized spaces (see Fig. 1). To monitor any type of movement within this environment, we require a transmitter to send signals and a receiver to capture this information. In this study, the transmitter used is a BLE beacon (Smart Beacon SB18-3 by Kontact.io) with a sampling frequency of $2Hz$, while the receivers consist of 39 edge computing Raspberry Pi 4 Model B devices (4GB of RAM) equipped with BLE 4 antennas, designed for installation on the ceiling (blue dots in Fig. 1).

During data collection, participants wore a belt equipped with up to seven BLE (Bluetooth Low Energy) beacons. The experiment aimed to evaluate the accuracy of a localization algorithm using RSSI (Received Signal Strength Indicator) data generated by these devices. Two distinct analytical approaches were employed, each with specific methods and objectives.

In the **first approach**, the performance of each BLE device was evaluated individually, and the devices were ranked from worst to best based on their localization accuracy. For example, if BLE-5 exhibited the lowest accuracy and BLE-3 performed slightly better, they were ranked accordingly. The analysis then incrementally combined data from the worst-performing device (e.g., BLE-5) with the next lowest-ranked device (e.g., BLE-3) to assess whether this improved the performance of the worst-ranked device. This process continued systematically by adding devices in order of performance until all seven devices were included. This approach provided a controlled framework to evaluate whether integrating data from less accurate devices with higher-performing ones enhanced the overall localization results. In the **second approach**, the focus was on incrementally incorporating devices during data collection. The process began with a single device (e.g., BLE-1), whose performance was recorded. In subsequent trials, additional devices were introduced one at a time (e.g., BLE-2), and the cumulative performance of the active devices was measured. This process continued until all seven devices were active simultaneously. While this method allowed for direct observation of how performance evolved as more devices were added, it was heavily influenced by the inherent variability among BLE devices. For instance, BLE-1 might perform well in one trial but yield inconsistent results in another due to environmental factors or device-specific variations. Such variability introduced noise into the data, complicating efforts to draw reliable conclusions.

The first approach proved to be more robust because it isolated the contribution of each device to the overall performance and systematically assessed whether the addition of poorly performing devices impacted accuracy. For instance, combining BLE-5 with BLE-3 clarified their interaction and determined whether their joint performance enhanced localization. In contrast, the second approach was more susceptible to inconsistencies, as variations in device performance and environmental conditions across trials could obscure the impact of adding specific devices. Overall, while both methods provided valuable insights, the first approach offered greater reliability for testing hypotheses and understanding the role of individual devices. By focusing on incremental combinations of ranked devices, it enabled a more effective evaluation of their collective impact on localization accuracy, making it the preferred method for this study.

The benchmark dataset was collected in the right corridor of the therapeutic space, which comprises several distinct

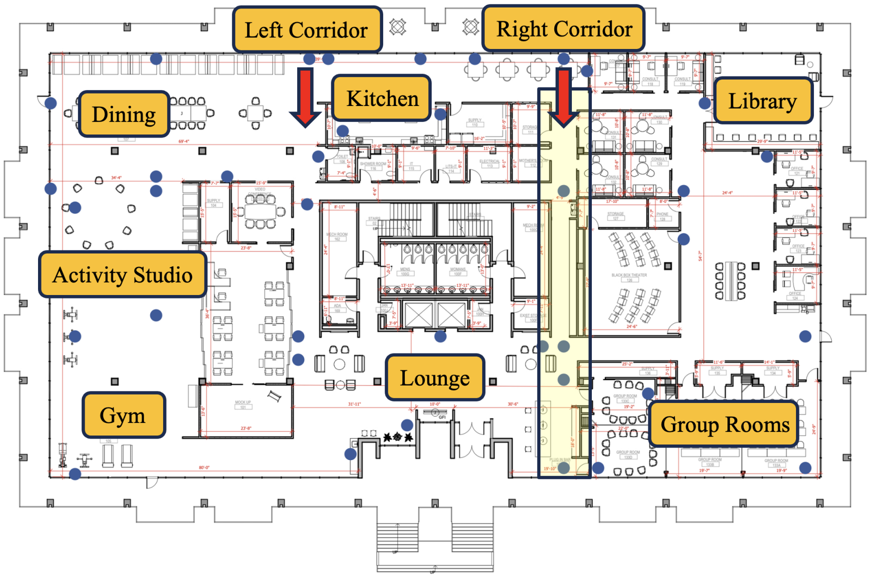

Figure 1: The therapeutic study site - data collection process. The study sites are designed to include a variety of utility spaces, such as a gym, kitchen, lounge, and other areas. A total of 39 edge computing devices (Raspberry Pi v4 Model B) are installed in the ceiling, represented by blue dots on the map.

regions. This corridor was chosen primarily due to its higher density of edge devices, with a ratio of 6 devices per 50 m². In contrast, the left corridor has 4 devices per 66 m², the kitchen has 5 devices per 70 m², the lounge has 3 devices per 176 m², and the activity area has 7 devices per 312 m². This selection will allow us to test our hypothesis with greater precision. We placed markers at two-meter intervals along the entire length of the right corridor, resulting in 15 distinct points from the bottom to the top (see red dots in Fig. 3-Panel (A) and (B)). The subject stepped on each marker for 10 seconds to replicate the typical spatial navigation scenarios encountered in a therapeutic facility.

3 Method

3.1 RHSI-Edge Trilateration Algorithm

In this study, we deployed the **RHSI-Edge Trilateration** technique introduced in the paper by Kiarashi et al. [23]. In this method, we first need to calculate the lateral distances, referred to as r_i, representing the distance from the individual to the edge computing device, denoted as p_i. Using the strength of the RSSI (dB), we can compute d_i, the hypotenuse of a right triangle formed by r_i, and the fixed height to the ceiling. This height, approximated at 2 meters, is measured from the waist of each individual to the ceiling and can be calculated using the following formula:

$$d = 10^{\frac{M_{RSSI} - I_{RSSI}}{10N}} \tag{1}$$

In this formula, M_{RSSI} represents the RSSI measured at a reference distance of 1 meter from the beacon, while I_{RSSI} denotes the instantaneous RSSI recorded by the receiver. In the denominator of the power in this equation, N accounts for the environmental factors affecting the receiver, which can be influenced by various metallic structures in the ceiling, such as air ducts, pipes, and other construction materials. The value of N is determined empirically to achieve optimal performance, typically ranging from 2 to 4. For our analysis, we have selected N to be 3.5. In this algorithm, we first compute the weighted d_i values by incorporating the ratio of the RHSI for different pairs of devices, which is calculated based on the number of RSSI hits (or detections made by edge computing devices), h_i. For example, the weight between two edge computing devices is determined using $W_{i,j} = \frac{h_i}{h_i + h_j}$, as shown in Fig. 2. With this information, we can compute the r_i values using the Pythagorean theorem, which allows us to estimate the location of the moving individual using the following formula:

$$m_{i,j} = (x_i + \frac{r_i}{r_i + r_j}(x_j - x_i), \quad y_i + \frac{r_i}{r_i + r_j}(y_j - y_i)) \tag{2}$$

In this formula, each (x_i, y_i) represents the 2D coordinates of the edge devices from a top-down view of the study site. Based on the estimated locations from each pair of edge devices, we can combine all this information to compute the final position of the individual wearing the BLE beacon. This is done by averaging all the m_{ij} values using the following formula[1]:

$$L_{RHSI-Edge} = \frac{1}{N(N-1)} \sum_{i \neq j} m_{i,j}.$$

3.2 Multi-Beacon Concept - Statistical Representation

The designed algorithm encounters a challenge when there are examples with no hits or at most one hit from the edge devices. In such cases, the algorithm lacks sufficient information and will estimate the location of the BLE beacons directly beneath the edge device if one is present. If no data is available, it will retain the previous location. If there is no information for the previous location, the algorithm will wait until it receives some data before updating the location accordingly. In general, if we denote the probability of receiving an RSSI value from a BLE beacon as p within a specific time frame, each beacon operates with an independent probability of transmitting this signal. This independence implies that the performance of one beacon does not influence the others. Consequently, the probability of not receiving any signal from a single beacon would be $1 - p$. Although this p may vary from one device to another, we can simplify our analysis by assuming that all devices from the same brand originate RSSI - X - comes from the same probability density function of RSSI ($X \sim f_X(x)$). While there may be slight variations among them, we can consider this p value as a fixed number for all devices.

Based on this assumption, the problem can be explored more precisely. Suppose the receiver (edge devices) is designed with a specific sensitivity threshold T, which defines the minimum signal strength required for successful reception. When the RSSI, exceeds this threshold T, the signal is considered strong enough to be received. We define the probability of successfully receiving a beacon as follows:

$$P(\text{successful reception}) = P(X \geq T) = \int_T^\infty f_X(x)\, dx \tag{3}$$

Let this probability be represented by p:

$$p = P(X \geq T)$$

The probability of failing to receive any beacon is expressed as:

$$P(\text{miss}) = 1 - p$$

For N independent transmissions of beacons, the likelihood that none of them are received is given by:

$$P(\text{all misses}) = (1 - p)^N$$

Therefore, the probability of receiving at least one beacon successfully can be formulated as:

$$P(\text{at least one reception}) = 1 - (1 - p)^N$$

As the number of transmissions N becomes very large, the probability of achieving at least one successful reception converges to:

$$\lim_{N \to \infty} P(\text{at least one reception}) = 1$$

Increasing the number of BLE beacons enables the reception of more signals from various edge devices, improving the algorithm's performance, particularly in scenarios where no signals are initially received. However, a common

[1]For more information about the RHSI-Edge algorithm please check out the Kiarashi et al. paper [23].

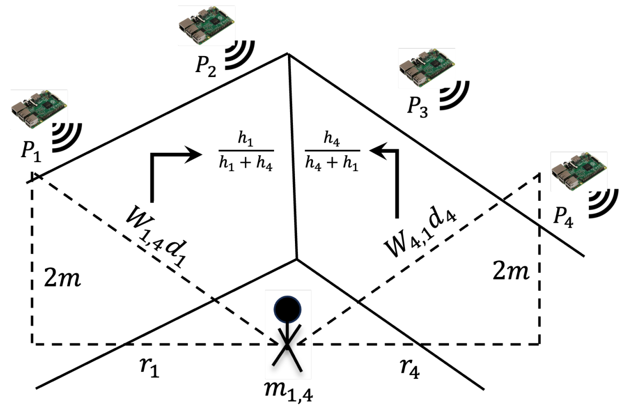

Figure 2: Visualization of RHSI-Edge Trilateration Method: The method estimates distances using RHSIs between the subject and two reference points (e.g., i = 1, j = 4). The subject's location is then determined by averaging all edge-based estimates.

challenge occurs when a device is closer to one edge device but receives signals from a more distant one instead. Such discrepancies can significantly affect the algorithm's accuracy. Nevertheless, even when the available information is inaccurate, averaging the data can help mitigate these effects and slightly enhance localization performance. This will be discussed further in the results section.

4 Results

As described in the data collection section, the experimental data was obtained from an individual wearing a belt fitted with up to seven different BLE beacons. The recorded RSSI data from each beacon was extracted individually by edge devices and fed into the algorithm. The algorithm's localization performance was ranked from worst to best accuracy based on the devices used. We then progressively combined the data from the next least accurate device with the previous ones to see if adding more information could improve the algorithm's performance. This process continued until data from all devices was included. Figure 3 compares the performance of using multiple BLE devices (i.e. using 7 devices at the same time) versus a single device. In this figure, red dots indicate the ground truth regions where the subject moved at each 10-second interval, while orange dots show the detected path produced by the algorithm. Panel A demonstrates a much more accurate capture of the path compared to Panel B, where every time the subject moved from the bottom to the top of the right corridor, a single location in the middle was consistently detected. This limitation results in a significant localization error in the algorithm due to the lack of sufficient positional data. Figure 4 shows the localization error plotted against the number of BLE beacons used. The plot indicates that as more BLE beacons are incorporated into the algorithm, the error (measured in meters) decreases. Notably, the error drops significantly after adding data from 3 beacons, but beyond that, adding more devices results in only marginal improvement, with the error stabilizing. A red dashed horizontal line marks where the error plateaus at around 4 meters, and a green vertical line highlights that this threshold is reached when data from 3 devices is used.

We conducted further analysis and found that, regardless of the combination of devices used, the localization accuracy consistently outperformed that of the least accurate individual device. Figure 5 - Panel A displays the localization accuracy of each BLE beacon used individually, ranked from the least accurate at the top to the most accurate at the bottom. In the two least accurate cases, the localization errors were 9.09 meters and 7.59 meters, respectively. However, when the data from these two beacons were combined, the error decreased to 5.14 meters. This trend is evident throughout Panel A, where combining the data from any two consecutive BLE beacons consistently reduces localization errors compared to the worst-performing individual beacon. For instance, the next two beacons showed localization errors of 7.59 meters and 5.71 meters, but when their data was combined, the error dropped to 4.46 meters.

In Panels B through F of the analysis, we observed that the strategy of combining three to seven consecutive BLE devices yielded a similar improvement in localization accuracy, as seen with the combination of the worst two devices in Panel A. Regardless of the specific combination employed, the overall trend indicated that the localization accuracy consistently exceeded that of the least accurate individual device. This pattern persists, demonstrating that even when combining multiple beacons—ranging from three to seven—the localization errors significantly decreased. The findings underscore the effectiveness of aggregating data from consecutive BLE devices to enhance localization precision, maintaining the trend of reduced errors observed in Panel A with the two least accurate devices.

(A) (B)

Figure 3: Comparison of performance between multiple BLE devices (panel A) and a single BLE device (panel B). Panel (A) demonstrates the lowest error rates, highlighting the improved accuracy with multiple devices, whereas panel (B) shows the highest error, indicating reduced precision when only one device is used.

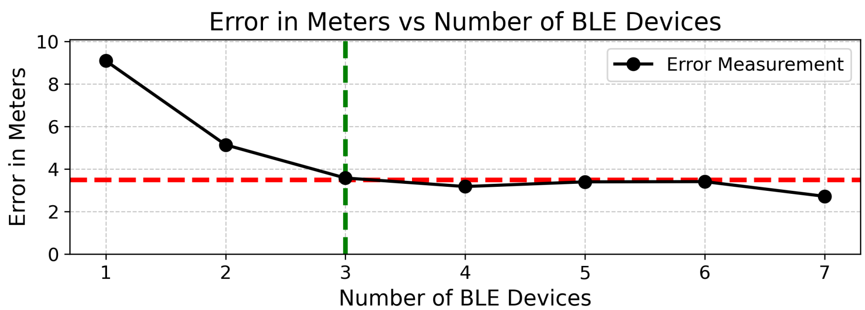

Figure 4: Localization error as the number of BLE beacons increases from 1 to 7 devices. The plot shows a decrease in error (measured in meters) as more beacons are added, with the error stabilizing after 3 beacons. A red dashed line indicates the 4-meter error threshold, while a green vertical line marks the point where the error reaches this threshold.

5 Discussion

Our analysis reveals that the localization accuracy of BLE devices significantly improves when data from multiple beacons are combined, highlighting the potential of this approach in enhancing positioning systems. According to Sec. 3.2, increasing the number of BLE beacons enhances the likelihood of receiving more hits from various edge devices. This is because a higher number of beacons increases the probability that at least one of the devices will surpass the RSSI threshold. However, this doesn't necessarily mean that simply increasing the number of BLE beacons will always improve accuracy. Generally, adding more BLE beacons raises the likelihood of receiving more RSSI readings from different edge devices, giving the algorithm more data to work with. On the other hand, due to significant variability between transmitters and receivers, there may be instances where a BLE device is closer to one edge device but fails to record any information, while a more distant edge device successfully captures the RSSI value. However, using multiple BLE devices can improve performance by averaging the data, which helps minimize the impact of inaccurate information. In general, it is recommended to undergo a calibration process in different environmental settings to determine the optimal number of BLE beacons before starting data collection. This approach ensures the best performance from the algorithm, ultimately helping to reduce localization errors.

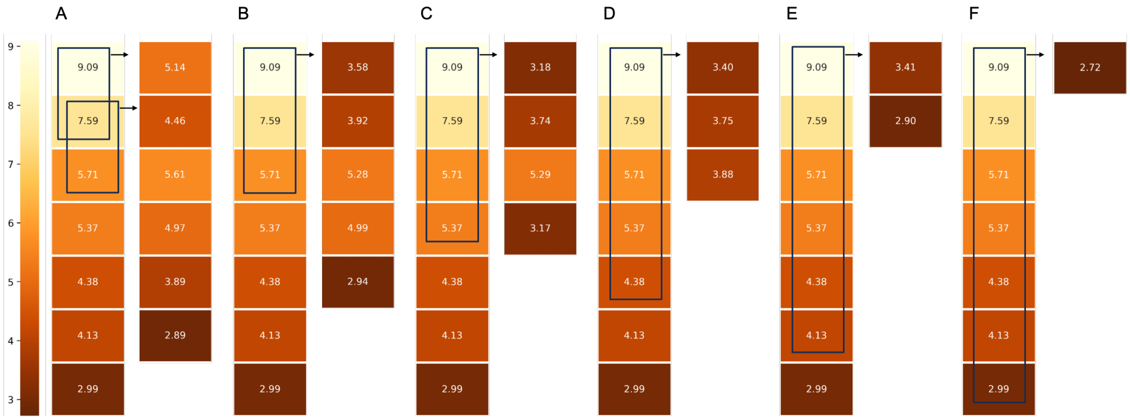

Figure 5: Localization error (in meters) using BLE beacon devices. Panel A shows the localization error when using individual beacons, with subsequent beacon pairs selected by shifting one device to the bottom. Panel B shows the error when combining three beacons, and this process continues through to Panel F, which illustrates the localization error when using all seven beacons together. The progression across the panels highlights the impact of increasing the number of beacons on localization accuracy.

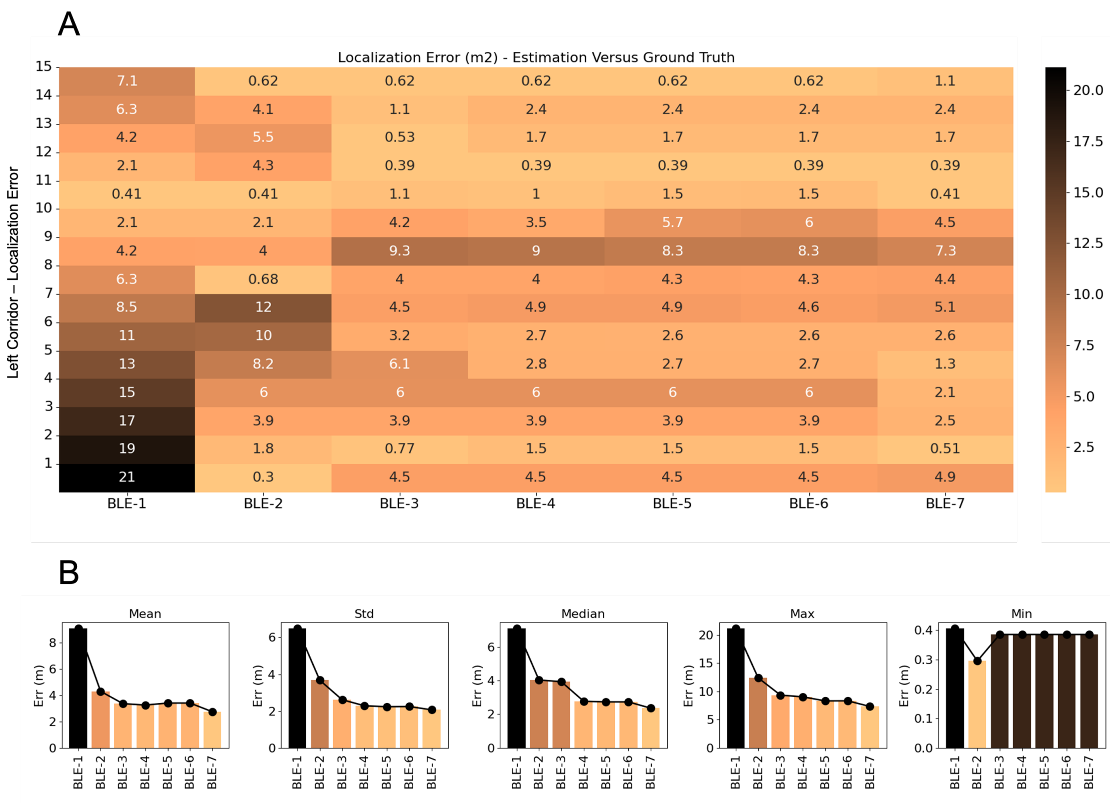

Figure 6: Effect of multi BLE beacons on localization error. Panel A shows the localization error across 15 locations along the right corridor (position 1 at the bottom and position 15 at the top) on the y-axis, with the x-axis displaying varying numbers of BLE devices used for the localization algorithm. Panel B summarizes key statistics of the localization error, including Mean, Standard Deviation (Std), Median, Minimum (Min), and Maximum (Max), as the number of BLE devices increases from 1 to 7.

The localization error from the experimental data, as described in Sec. 2, is illustrated in Fig. 6. In Panel A, the y-axis displays the estimated locations derived from the RHSI-Edge Trilateration Algorithm (refer to Sec. 3.1), alongside the ground truth region indicated by the red dots in the right corridor of Fig. 3. The x-axis represents performance as a function of the number of BLE devices. It is evident that the localization error decreases with an increasing number of BLE devices. Panel B presents statistics such as the mean, standard deviation, median, minimum, and maximum values from the data in Panel A. A clear trend emerges: increasing the number of BLE devices significantly reduces localization error across all statistical measures. The only exception is the minimum value, which remains relatively constant across all cases.

6 Conclusion

In summary, this study addresses the challenges of indoor localization by optimizing the number of Bluetooth beacons. Through a proof-of-concept study, we demonstrated that, despite the variability in RSSI caused by environmental factors, using three BLE beacons significantly improves localization accuracy, reducing the worst-case error from 9.09 meters to 2.94 meters, while additional beacons provide minimal incremental benefits in such scenarios.

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