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Design and Implementation of a Zone-Based BLE Indoor Localization System Using ESP32

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Abstract. Indoor localization is now an important part of intelligent environments, including smart buildings, retail spaces, hospitals, and industrial spaces. Bluetooth Low Energy (BLE) has become a potential technology in indoor positioning with low power consumption and ubiquitous nature. Nevertheless, traditional RSSI-based BLE localization schemes, such as fingerprinting and trilateration, usually experience multipath fading, environmental non-uniformity, calibration cost, and complexity of computation. The current paper describes the experimental validation of the design of a zone-based, calibration-free BLE indoor localization system with complete implementation on a low-power ESP32. Rather than calculating exact coordinates, the proposed method does the similar task of classifying zones proximity-wise by the use of lightweight sliding-window RSSI filtering and hysteresis-based zone stabilization. Signal processing and localization decisions are run directly on the embedded device without cloud dependency. Experimental analysis in a real indoor setting illustrates that the accuracy of zone detection of RSSI filtering increases on average, between 74% unfiltered and 91% filtered, at low computational complexity and infrastructure. The proposed architecture offers a scalable and efficient resource-based solution that can be used in real-life usage of proximity-sensitive types of applications.

Keywords: Indoor localization, Bluetooth Low Energy (BLE), Zone-based localization, ESP32, RSSI filtering, Edge computing, Low-power embedded systems.

1 Introduction

Indoor localization has emerged as the basic functionality of smart buildings, hospitals, shopping malls, warehouses, and industrial facilities. In contrast to outdoor positioning systems, indoor environments are very challenging due to multipath propagation, shadowing, signal attenuation, non-linear sight (NLOS) propagation, which deteriorates radio signal stability and localization in an indoor-like setting [13, 21]. Therefore, a lot of research has been done on the development of indoor positioning systems (IPS) that are precise, energy-efficient, scalable, and applicable in practice.

Wi-Fi, ultra-wideband (UWB), radio-frequency identification (RFID), and Bluetooth Low Energy (BLE) are some of the wireless technologies that have been considered in the context of indoor localization. Wi-Fi-based enjoy the advantage of using the available infrastructure and tend to be characterized by high power consumption and susceptible to environmental dynamics [20]. UWB systems offer high range precision; However, these systems are expensive to deploy and need specific hardware and are not easy to install on devices, unlike others [17]. In contrast, BLE has become a promising choice as it has low power usage and low hardware prices and is supported natively in the consumer market and embedded systems by default [3, 7]. The above features make BLE especially suitable for resource-constrained indoor applications.

The majority BLE-based localization systems are based on the Received Signal Strength Indicator (RSSI) between stationary beacons and a mobile receiver. There are two leading localization strategies, fingerprinting and trilateration. Fingerprinting techniques are capable of obtaining high coordinate accuracy in more controlled situations where there is a calibration state, yet they require dense reference mapping, large offline training, and periodic recalibration of performance maintenance [5, 15]. Trilateration based methods calculate the distance using path loss models and determine coordinates in real time; although they are very sensitive to the instability of RSSI due to multipath fading and changes in the environment conditions [14, 18]. Such variations in RSSI in practice offer a very low degree of localization in real-world indoor applications.

In order to cope with the instability in RSSI, recent research has argued for light weight filtering and signal conditioning methods to improve both the stability of measurements and robust positioning of measurements [1, 9, 11]. Moreover, more and more attention is paid to edge-based architectures, in which localization processing is performed at the embedded-level to minimize latency and communication overhead [2, 8]. Although such improvements have been made, many modern systems still focus on coordinate-level precision, which adds computational complexity, calibration effort, and density of beacon deployment.

However, in a large number of real-life indoor situations, there is no absolute need to have a good estimate of coordinates. This is because apps such as aisle-level navigation, section identification, asset proximity tracking, and context-aware services are mainly required by zone-level classification as opposed to centimeter-level positioning precision. Zone-based localization can also be seen that can offer a more powerful and computationally effective alternative, especially in resource-constrained settings.

This paper was inspired by these observations to design and develop a calibration free, all-encompassing embedded zone-based BLE indoor localization system on a low-power ESP32 platform. The proposed system uses sliding-window RSSI filtering, threshold-based zone mapping, and hysteresis-based zone stabilization to classify proximity stability, as opposed to the estimation of accurate spatial coordinates. The ESP32 does all signal processing and decision-making procedures on-the-fly, which means that it is not cloud-dependent, and it also minimizes the overhead of communication. Its goal is to obtain a localization of the zone level that is very reliable with low infrastructure requirements, low power usage, and less complex to compute than traditional coordinate-estimation methods.

2 Related Works

The area of indoor localization has been actively studied throughout the last decade, and researchers have devoted their research to enchancing the accuracy, robustness, and scalability of deployment. Current solutions may be broadly classified according to wireless technology and localization methodology.

Indoor positioning systems based on Wi-Fi are popular because the infrastructure is available. Some techniques have been found to provide moderate to high coordinate accuracy under controlled conditions, such as RSSI-based fingerprinting and Channel State Information (CSI) analysis [9, 10]. However, Wi-Fi systems have higher power consumption and are vulnerable to environmental changes; they should be regularly calibrated and maintained, as this incurs high costs to the organization due to their sensitivity to changes in the environment[20]. Nevertheless, Wi-Fi systems are sensitive to changes in the environment and tend to be high in power consumption, which means that they require frequent calibration and maintenance, which are expensive to the organization in the long run. Such constraints make them less appropriate in low-power embedded apps.

The UWB systems offer time of flight measurement with high ranging accuracy and wideband signal properties of the systems on time of flight measurements of circuits and systems of a wideband nature [17]. Although UWB has a higher precision than other RSSI-based systems, it requires specialized hardware and is more expensive to deploy, so it is only practical in large-scale or resource-constrained indoor settings. The use of RFID-based localization is also being researched, but there are still serious problems with dense reader deployment and limitations in scalability.

One of the alternatives that has been shown to be promising is Bluetooth Low Energy (BLE), because of its low power consumption, low hardware cost, and ability to fit within embedded platform compatibility. The majority BLE-based indoor positioning systems are based on RSSI measurements to determine the user's position. Fingerprinting and trilateration are the two main methods.

BLE systems with finger printing can run at high localization accuracy; however, this must be backed up by massive offline data collection, dense reference mapping, and in-frequent recalibration to meet environmental variations [5, 15]. Such requirements make the deployment more complex and costly to maintain. The trilateration-based methods determine the distance by path loss model and calculate the approaches based on the real-time spatial coordinate-based approaches to distance estimation [10, 14]. Nevertheless, trilateration techniques are extremely susceptible to RSSI variations due to multipath fading, shadowing, and changes in indoor environments based on dynamism [6, 9].

In order to overcome the problem of RSSI instability, various researchers have proposed lightweight filters such as moving average filters and adaptive filters to enhance the signal stability and localization strength of the signal strength. This type of measurement may increase consistency, although most of them are based on centralized processing environments or cloud-based computing. Thus, recent studies have focused on edge-based indoor localization architectures, in which signal processing and localization decisions are implemented in embedded devices to minimize latency and communication overhead [2, 8].

Nevertheless, many of the present studies on BLE localization remain preoccupied with coordinate-level localization. This can tend to add more complexity to the computation, calibration, and density of beacons. In contrast, zone-based localization methods based on zones focus more on proximity classification than on accurate coordinate estimation. These strategies have the potential to improve greater resilience to RSSI fluctuations, as well as lessen infrastructure and computation demands, especially in constrained resources.

The presented system is based on recent developments in lightweight RSSI filtering and embedded edge-based processing, but the emphasis is on the area of classification without calibrations on a zone level that runs fully on the ESP32 platform.

3 Proposed System Architecture

The suggested system introduces a zone-based indoor localization system that is intended to be used for resource-restricted and low-power applications based on the ESP32 platform. The primary project scope of the system is to achieve reliable indoor zone recognition with Bluetooth. Low Energy This technology has Low Energy (BLE) beacons with low computational complexity, low power large scale consumption, and low infrastructure needs.

The general processing of the proposed architecture is shown in Fig. 1. In this system, the BLE beacon nodes will be used as fixed stations and in the indoor environment and periodically broadcast BLE advertising packets with identifying data. A device of ESP32 in continuous scanning these advertising packets is received by mode and it serves as the central processing unit of the localization system.

The ESP32 on reception of BLE advertisements will read Received Signal Strength. RSSI is very sensitive to noise generated by multipath fading, shadowing, human mobility, and environmental interference. Rather, there is a lightweight pre-processing stage of RSSI using a sliding window. Averaging to even irregularities in short-term signals and at the same time suitable in real time implementation on embedded computers.

This is followed by the RSSI being filtered and subsequently sent as filtered values to a zone decision module where the RSSI has predefined values thresholds serving to define discrete zones of the proximity of the user instead of calculating the accurate coordinates. To enhance stability and eliminate frequent zones, a zone locking mechanism using hysteresis is used as a switching near the threshold boundary. This keeps the classification of zones steady even when there are slight changes in RSSI. According to the stabilized zone decision, there is a range of distance that is assumed, making it possible to obtain geometric intuition of space without achieving distance, which is computationally expensive or coordination estimation models. The system output, which is the identified zone, is included in the final system output associated distance range and contextual data, e.g product or floor position, equipping the system with applications such as indoor navigation, asset localization, and context-aware services.

The whole signal processing, decision making, and localization is done locally on the ESP32 device. This fully embedded design reduces communication overhead, latency, and scales better, so that the proposed structure is very suitable for large-scale indoor applications in resource-constrained environments.

4 Localization Methodology

This part explains that the suggested zone-based indoor localization methodology runs fully on an ESP32 platform that is resource constrained. The objective of the approach is to perform a stable and reliable localization of the zones using. Bluetooth Low Energy (BLE) consumes low energy, and such signals are complicated, with low memory, usage, and power consumption. Instead of estimating accurate spatial coordinates, the system is concerned with tough zone classification, which is more appropriate to practical use in-doors. The localization process is a pipeline sequence as shown in Fig. 1, of the appendix is composed of RSSI acquisition, RSSI smoothing , zone decision logic, distance range mapping and hysteresis based stabilization.

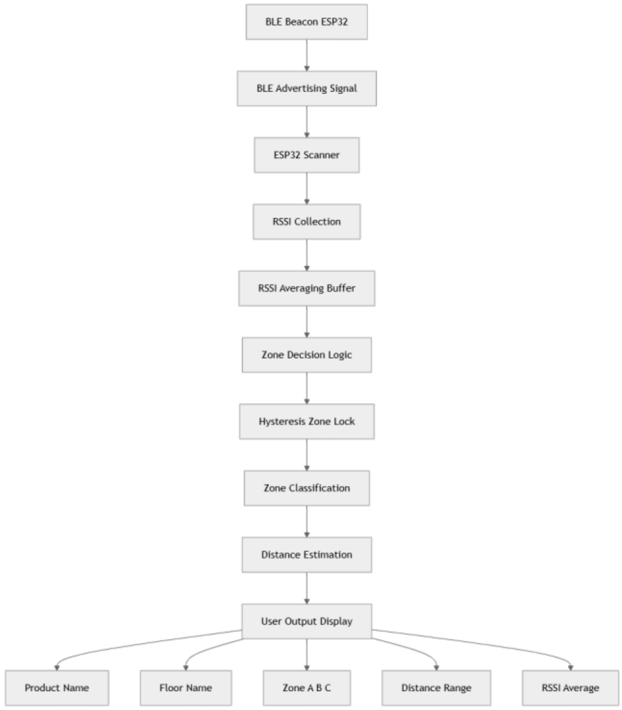

Figure 1. Block diagram of the proposed zone-based BLE indoor localization system using ESP32

4.1 RSSI Acquisition

The BLE beacon nodes are located at predetermined and fixed points in the indoor environment and periodically send unique identifier advertisement packets. The ESP32 works in continuous scanning with BLE and is a receiver of these packets in real time. The received packets are matched with the Received Signal Strength Indicator value is ripped off together with the beacon identifier.

Multipath is very sensitive in RSSI measurements in indoor settings propagation, shadowing, motion of human beings, and environmental interference. As a result, instantaneous RSSI values have strong time variations and are not usable to do reliable localization subsection Sliding Window RSSI Averaging.

4.2 Sliding Window RSSI Averaging

A sliding window averaging method is used to suppress the short-term variations of the applied RSSI. These samples measured during a fixed window of the recent measurements are buffered, and the mean of all the RSSI values is calculated as follows:

$$\bar{P} = \frac{1}{N} \sum_{k=1}^{N} P(k) \tag{1}$$

In which $P(k)$ is the current RSSI and N is the window size. This is a fast noise reduction averaging method with a great deal of reduction that is computationally efficient and able to run in real-time on the ESP32.

4.3 Zone Decision Thresholds

The average of RSSI is measured against set levels of RSSI divide the proximity of the user into discrete areas. Each zone represents a varying spatial area as opposed to a precise place. For a single-floor deployment, there are identified three zones:

- **Near Zone (A)**: Strong RSSI values indicating close proximity
- **Mid Zone (B)**: Moderate RSSI values
- **Far Zone (C)**: Weak RSSI values indicating larger separation

The threshold decision eliminates the instability and calibration overhead associated with accurate distance estimation models.

4.4 Hysteresis-Based Zone Locking

To avoid changing the zone often when the RSSI values vary around the decision, a zone locking mechanism is used in the form of a hysteresis-based boundary. A zone change is accepted when the newly found zone is constantly observed through several sequential localization cycles. This time validation is a great improvement to system stability, especially when the user is moving or is positioned close to zone edges.

4.5 Embedded Implementation Considerations

Each step of the pipeline localization process, such as RSSI acquisition, averaging, zone decision, hysteresis locking, and output generation-are locally executed on the ESP32, and without the use of external servers and cloud infrastructure. The methodology is simple in memory and processing, which allows low latency and power consumption operation in real-time. This fully embedded design provides scalability and enables the system to be used with large indoor deployments in resource-constrained environments.

4.6 Distance Range Mapping and Output

After a zone is locked, the estimate of the distance range that matches that zone is assigned (e.g., < 0.5 m, 0.5–1.5 m, > 1.5 m). The final output of the system consists of a set of identified zones, distance range, and context, such as the location of the floor and the name of the product. This product is presented to the user directly and allows uses like indoor navigation, aisle level product context-aware services, localization, and context-aware services.

5 Experimental Setup

It tells about the hardware platform, beacon deployment strategy, experimental environment, and measurement procedure to test the proposed zone-based BLE indoor localization system in the real world indoor environment.

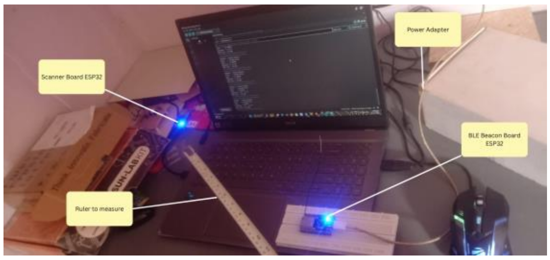

Figure 2. A Hardware prototype of the proposed indoor localization system based on zone, which comprises of ESP32-S3 receiver, BLE beacon module as well as regulated power supply.

5.1 Hardware Configuration

The localization receiver is an ESP32-S3 development board with the default setup of the localization receiver, and the advertisement-based BLE node. ESP32 spins around and captures the received signal strength indicators (RSSI) of live transmissions with BLE advertisements.

Signal processing functions, such as RSSI and distance filtering, zone classification, and hysteresis-based stabilization, are run on ESP32 without the need to use external servers or cloud computing. This is fully implemented with low power consumption and minimal latency and is appropriate for a resource constrained indoor environment.

The experimental test was carried out in a domestic setting of approximately 100 sq.ft (≈9.29 m^2). The further separation tested between the BLE beacon and the ESP32 receiver was 3.25 m. A sample size of 90 RSSI was gathered comprising 30 samples in each zone. The size of the RSSI smoothing window was set to a constant of 8 samples, with the scan duration of the BLE set to 2 seconds in each cycle.

Fig. 2 it depicts the Hardware prototype of the experiment established to measure all the measurements reported in this paper.

5.2 Beacon Deployment and Zone Layout

To measure the performance of localization at the zone level, the indoor test environment was divided into some proximity zones. A BLE beacon was deposited at a constant and known position in order to offer uniform signal coverage over the field of the experiment.

The environment was categorized into three regions according to the relative proximity to the beacon, the mid, near, and Far zones. The ESP32 receiver was placed at various fixed points in different orders with respect to these zones to test the consistency of the localization and transition of the zones.

Each zone is specified in relative proximity to signs instead of precise geometric positioning, as shown in Fig. 3, so one can perform localization effectively in the presence of fluctuating RSSI.

5.3 Data Acquisition and RSSI Sampling

RSSI samples were recorded at every predetermined test point during a set period of time when the receiver was

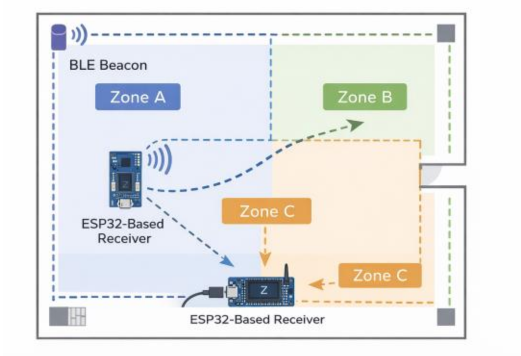

Figure 3. Experimental setup and zone plan of the BLE based indoor localization system with fixed beacon location and predetermined proximity regions.

not in motion to reduce signal variations due to motion. ESP32 continued to receive and capture the received BLE advertisement RSSI values.

Multipath fading and environmental interference on short term RSSI were reduced by sliding window moving average filter applied directly on ESP32. The smoothed value of RSSI is calculated as follows:

$$P(k) = \frac{1}{N}\sum_{i=0}^{N-1} P(k-i) \quad (2)$$

where $P(k)$ is the RSSI value of the sample number k, N is the window size, and $\bar{P}(k)$ is the filtered RSSI and used to localize.

5.4 Distance Estimation for Zone Assignment

RSSI filtered values were converted to rough distance measurements through a log-distance path loss model to facilitate zone-level localization. The calculation of the estimated distance is:

$$d = d_0 \times 10^{\frac{P_0-\bar{P}}{10n}} \quad (3)$$

In, which d is the estimated separation between the beacon and receiver, d_0 is the reference separation, P_0 is the RSSI in d_0, $\bar{P}$ is the filtered RSSI and n is the indoor path loss index.

These distance estimates are not applied to calculate the accurate spatial coordinates, but to find the most likely zone based on the relative proximity.

A portion of the measurement and ground truth procedure is described in the following subsection.

5.5 Measurement Procedure and Ground Truth

The real time ESP32 readings of both the raw and filtered RSSI values were recorded at each test location. The labels in the ground truth zone were recorded manually by taking measurements of the physical distance in terms of a measuring tape.

The data obtained were used to access the performance in zone classification, RSSI stability, and zone transition behavior, as reflected in the experimental results section.

Table 1. Zone distance ranges and averages of RSSI are determined

Floor	Zone	RSSI Range (dBm)	Distance Range (m)
Ground Floor	Zone A (Near)	-26 to -39	< 0.5
Ground Floor	Zone B (Mid)	-48 to -55	0.5 – 1.5
Ground Floor	Zone C (Far)	-56 to -62	1.5 – 3.25

Table 2. Zone detection accuracy comparison

Zone	Samples	Accuracy (Unfiltered)	Accuracy (Filtered)
Zone A (Near)	30	78%	93%
Zone B (Mid)	30	74%	91%
Zone C (Far)	30	71%	89%

6 Results and Discussion

The results of the experiment based on the proposed are presented in this section BLE indoor localization system using zone based implementation under the ESP32 platform. The proposed method concentrates on unlike localization system based on coordinates strong zone detection based on distance ranges based on RSSI. The evaluation focuses on RSSI stability, zone detection accuracy, and mapping of the distance consistency range under real indoor conditions. All results are derived from experiments, which are real-time experiments, as is described in Section V.

6.1 Zone-wise RSSI and Distance Range Mapping

The suggested system categorizes the location of the user into predetermined areas depending on the value of the filtered RSSI and the range of distances associated with it. Table 1 tabulates the averages of the RSSI experimentally measured and the mapped distance areas of the different zones of the ground floor.

6.2 Zone Detection Accuracy

Since the major objective of the proposed system will be the localization on a zone-level, the zone is the major performance measure, the detection accuracy. Table 2 compares the performance obtained in zone classification with the use of raw RSSI values filtered RSSI values.

The total accuracy of the proposed system to classify filters given by 90 samples of the experiment was 91%.

6.3 RSSI Stability Analysis

Raw and filtered RSSI values were monitored in order to measure signal stability esp32 continuous able to scan raw RSSI values had a significant variance short-term variations because of multi-path fading, shadowing and environmental interference. The sliding-window averaging and hysteresis-based zone locking is applied, and the resultant values are shown below filtered RSSI data values demonstrated significantly lower variance. This stabilization eliminated common zone oscillations of zone boundaries and led to a uniform zone classification, especially in the case when a receiver sat still or walked slowly along the adjoining areas.

Table 3. Outputs of the representative systems in real-time experimentation

Product	Floor	Zone	Distance Range (m)	RSSI Avg (dBm)
Dairy Product	Ground Floor	Zone C (Far)	> 1.5	-62
Dairy Product	Ground Floor	Zone B (Mid)	0.5 – 1.5	-48
Dairy Product	Ground Floor	Zone A (Near)	< 0.5	-38

6.4 Output Consistency Validation

The second test is the output consistency validation, which verifies that the software functions correctly and produces the intended output. The opinion of the system encompasses the product name, floor name, area name, RSSI average, and distance range. Representative aspects of the system output are given in Table 1 data collected in real time experiments.

6.5 Discussion

The experimental analysis indicates that the proposed zone-based BLE indoor localization system is capable of stable and reliable proximity classification with a total detectability of the filtered zone of 91%. Unlike traditional coordinate-based localization algorithms of BLE in dynamic indoor settings, where multipath fading and RSSI variation reduce the accuracy of reporting its location, the proposed zone-based approach makes it less sensitive to instantaneous changes in signals because it does not require accurate location determination, but instead its emphasis is on a classification of proximity.

Recent literature on fingerprint-based BLE systems tends to be higher coordinate accuracy when operating in a controlled calibration environment, but needs extensive off-line training, dense reference mapping, and regular recalibration. Unlike this, the suggested system will not require the building of fingerprint databases and recalibration, which will greatly simplify the complexity required to deploy it and the level of maintenance burden.

In the same way, RSSI systems based on trilateration are very sensitive to environmental variations and rely heavily on the proper modeling of path losses. In real-world indoor experience, distance estimation error is cumulative and has a direct effect on the accuracy of the coordinates. The suggested scale will guaranty slight swings about the boundary zones and produce stability in categorizing by applying fixed RSSI values and zone locking using a hysteresis element.

In addition, most of the recent BLE indoor positioning architectures are based on cloud computing or central computing. The integrated implementation of the ESP32 platform allows edge-based decision making along with low-latency decision making, lower communication overhead, and reduced energy consumption. This makes this system very much applicable to resource limited deployments like retail navigation, asset tracking, and contextual proximity services.

Although the presented approach lacks centimeter level positioning accuracy, the experimental results testify that zone level classification suffices for most practical real-world indoor tasks, yet the computational complexity and infrastructure cost are very low.

Table 4. Comparison with Existing BLE Localization Approaches

Method	Calibration	Processing Type	Beacon Density	RSSI Robustness
Fingerprinting	Required	Centralized/Cloud	High	Moderate
Trilateration	Required	Edge/Cloud	Medium	Low
Cloud-Based BLE	Partial	Cloud	Medium	Moderate
Proposed Zone-Based	**Not Required**	**Edge (ESP32)**	**Low**	**High**

6.6 Comparative Analysis with Existing Approaches

To additionally assess the usefulness of the suggested approach, a qualitative comparison of the proposed approach with the typically used BLE indoor localization protocols is provided in Table 4. The comparison is performed in terms of computational complexity, calibration requirement, infrastructure density, and RSSI fluctuations robustness.

Both the proposed zone-based approach and the existing approach, as demonstrated in Table 4, alleviate the complexity of deployments because the former does not require the construction of fingerprint databases and the latter does not require large beacon density requirements. The lightweight RSSI filtering and hysteresis-based stabilization are used to improve the robustness to the fluctuations introduced by multipaths and have low computational overhead. Determining the level of coordinate precision is not the goal, but the system provides better scalability and feasibility to real-world indoor applications.

7 Conclusion

The following paper discussed the design and implementation of an indoor zone-based BLE localization system with a full embedded platform, ESP32. Unlike traditional coordinate-based indoor positioning schemes, the suggested scheme concerns consistent proximity classification based on sparse RSSI filtering and zone stabilization using hysteresis.

The use of an 8-sample sliding window averaging technique was experimentally proven to enhance RSSI stability and improve the overall zone detection accuracy to an average of 91% (filtered RSSI) compared to the case of an average of 74% (unfiltered RSSI) in a real indoor setting. The findings show that zone-level classification is effective in reducing signal fluctuations caused by multipaths with low computations.

The proposed architecture also eliminates the need to perform calibration, decreases the required density of beacons, and uses an entirely edge-based device independent of the cloud, as compared to fingerprinting and trilateration-based systems based on BLE. This makes the system quite appropriate in resource-constrained indoor environments, such as retail navigation, asset localization, and context-sensitive proximity services.

The zone-based method is light weight and can be used with low-power embedded systems than traditional BLE localization methods such as fingerprinting and trilateration, has low computational and calibration costs, and is more resistant to variations in RSSI in dynamic indoor settings. Although fingerprinting offers greater accuracy in coordinate precision, trilateration is more dependent on the proper modeling of path-loss, the proposed method is more focused on stable proximity classification, and minimal infrastructure and edge processing are fully embedded, so that the method should be more applicable to the real-life resource-constrained deployment.

The next step of work is the multi-beacon deployment on multi-floor, adaptive threshold optimization, path-loss parameter estimation, and large-scale performance assessment in complicated indoor conditions.

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