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High-Dimensional Statistical Feature-Enhanced BLE Fingerprinting Indoor Localization

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Abstract

Indoor localization based on Bluetooth Low Energy (BLE) fingerprinting often suffers from accuracy degradation due to fluctuations in the Received Signal Strength Indicator (RSSI) and environmental dependencies. To mitigate these effects, this study proposes an advanced indoor localization framework that leverages high-dimensional statistical features of RSSI. Departing from traditional methods centered on mean RSSI values, our approach integrates five distinct metrics—mean, variance, maximum, minimum, and interquartile range (IQR)—to capture the complex temporal fluctuations and spatial signatures of RSSI at each reference point. Furthermore, a Back-Propagation Neural Network (BPNN) correction model is developed to learn the relationship between these observed statistical features and the ideal RSSI values derived from the Log-Normal Shadowing Model (LNSM). Experimental results obtained in a real-world indoor environment demonstrate that the proposed method significantly reduces localization errors, particularly in challenging areas such as near walls and corners. The evaluation confirms that the proposed approach improves localization accuracy across multiple algorithms, including k-Nearest Neighbor (k-NN), Weighted k-NN (WKNN), and Support Vector Regression (SVR). Notably, the proposed method achieves a mean localization error of 1.391 m and reduces the 95th percentile error by approximately 41.5% compared with conventional methods without correction.

Keywords

BLE Fingerprinting, Indoor Localization, RSSI Statistical Features, BPNN

1. Introduction

In recent years, there has been a growing interest in technologies for tracking the locations of people and objects in indoor environments. While the Global Positioning System (GPS) is commonly used for obtaining location information, it is difficult to achieve sufficient precision in indoor settings due to the attenuation and shielding of positioning signals by building structures [1]. Consequently, the importance of indoor localization technology using wireless communication, which can maintain high localization accuracy in indoor environments, has been increasing [2]. Among various wireless-based indoor localization methods, Bluetooth Low Energy (BLE)-based systems are becoming widely adopted because they can be implemented at a low cost and with low power consumption.

The fundamental approach for BLE-based localization relies on the Received Signal Strength Indicator (RSSI) [3]. Although Channel State Information (CSI) has been reported to provide higher localization accuracy by capturing fine-grained subcarrier information, its implementation requires specialized hardware and complex signal processing. In contrast, RSSI is readily available on almost all standard BLE devices without additional hardware costs. Therefore, this study focuses on RSSI-based localization to maintain the low-cost and low-power consumption advantages inherent to BLE systems. Under this premise, in an ideal environment, RSSI is assumed to follow the Log-Normal Shadowing Model (LNSM), which defines the relationship between signal strength and the distance between the transmitter and receiver [4]. However, in real-world indoor environments, RSSI is heavily influenced by factors such as signal shielding by walls and obstacles, reflections, and electromagnetic interference. These environmental factors induce significant stochastic fluctuations in RSSI, rendering simplistic distance-based estimation models vulnerable to significant inaccuracies. To address this issue, BLE fingerprinting has been widely used as a robust method for real-world environments [5]. This approach involves constructing a database—or "fingerprints"—from RSSI data collected at various locations in advance and estimating the position by comparing real-time measurements with the database. **Figure 1** illustrates the conceptual process of BLE fingerprinting-based localization, consisting of the offline and online stages. To determine the estimated position based on the similarity of RSSI patterns, various localization algorithms are typically employed, such as k-Nearest Neighbor (k-NN) [6], Weighted k-NN (WKNN) [7], and Support Vector Regression (SVR) [8].

Nevertheless, BLE fingerprinting still faces challenges; regardless of the localization algorithm used, the accuracy is highly dependent on the stability of the input RSSI data. RSSI measurements at the same location exhibit significant variability, particularly near walls, corners, or areas crowded with obstacles. Such fluctuations lead to increased localization errors and practical issues, such as the misjudgment of adjacent shelves or aisles in asset management applications. However, this RSSI variability may contain unique characteristics dependent on the measurement point and the surrounding environment. If these characteristics can be captured as statistical features, further improvements in the accuracy of BLE fingerprinting can be expected. Based on this observation, this paper proposes an indoor localization method that utilizes statistical features of RSSI fluctuations to construct an RSSI correction model. The objective of this study is to improve the accuracy of indoor localization by reducing errors caused by the temporal fluctuations and environmental dependencies of RSSI in BLE fingerprinting. In particular, the proposed method focuses on enhancing the localization precision in areas such as near walls and corners, where conventional methods often exhibit significant errors. The proposed approach quantifies the RSSI data collected over a certain period at each location into multiple statistical features, such as mean and variance. Furthermore, we evaluate the effectiveness and versatility of the proposed method by performing localization with the corrected fingerprint data across multiple algorithms. The performance is compared against conventional methods, specifically those with no correction and those using only the mean value for correction.

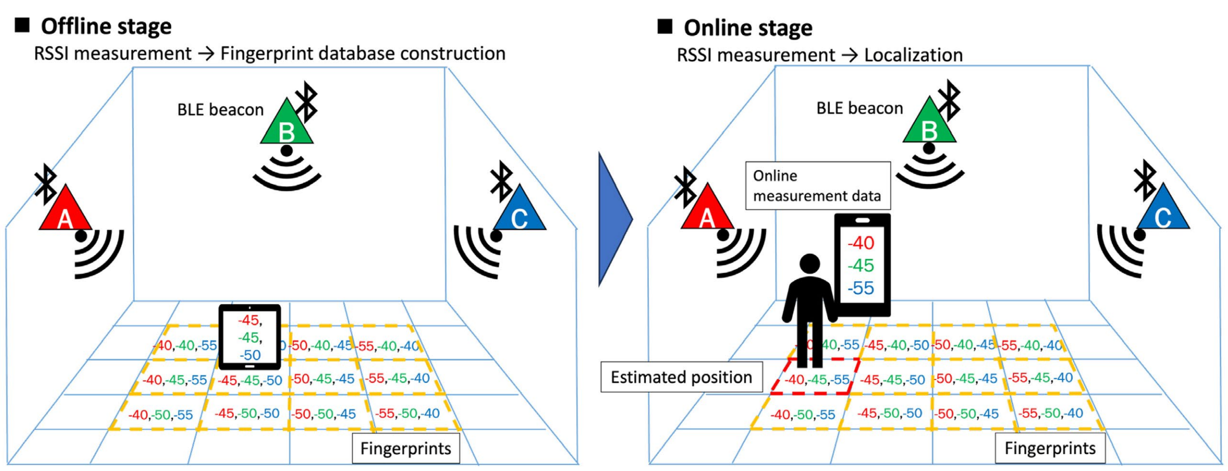

Figure 1. Concept and process of BLE fingerprinting-based indoor localization.

2. Related Work

Back-Propagation Neural Networks (BPNNs) were introduced by Rumelhart *et al.* [9]. Qian *et al.* proposed BPNN-based RSSI correction for RSSI fluctuations and environmental effects that degrade indoor localization accuracy [10]. In this approach, the BPNN learns the relationship between RSSI observed in real environments and the ideal RSSI derived from the LNSM, enabling the estimation of corrected RSSI values.

During the offline stage, the representative RSSI values (means) collected over a certain period at each measurement point are used as inputs, while the ideal RSSI values calculated from the LNSM are used as training labels for the BPNN. Figure 2 illustrates the architecture of this conventional RSSI correction model, which relies solely on mean RSSI values as input features. The trained correction model is then applied to measurement data in the online stage, and the corrected RSSI values are used as inputs for existing localization algorithms.

Experimental results demonstrated that this method could reduce the mean localization error by more than 10% compared with methods without correction.

However, because the correction model relies only on the mean RSSI value, it fails to capture the inherent signal dynamics, such as temporal variance and the underlying distribution profile of RSSI. Consequently, large localization errors may still occur in areas with high RSSI instability, such as near walls and corners, where reflection and shielding effects are significant. Existing methods, such as the one proposed by Qian *et al.*, primarily rely on the mean RSSI value as a representative metric. However, a single mean value fails to encapsulate the complex signal dynamics and distribution profiles encountered in multipath-rich environments. The novelty of this study lies in the integration of five-dimensional statistical features—mean, variance, maximum, minimum, and interquartile range (IQR)—which explicitly capture the unique spatial "signatures" and temporal instabilities of each measurement point. This multi-dimensional representation allows the correction model to distinguish between locations with similar mean values, significantly reducing errors in challenging areas such as near walls and corners.

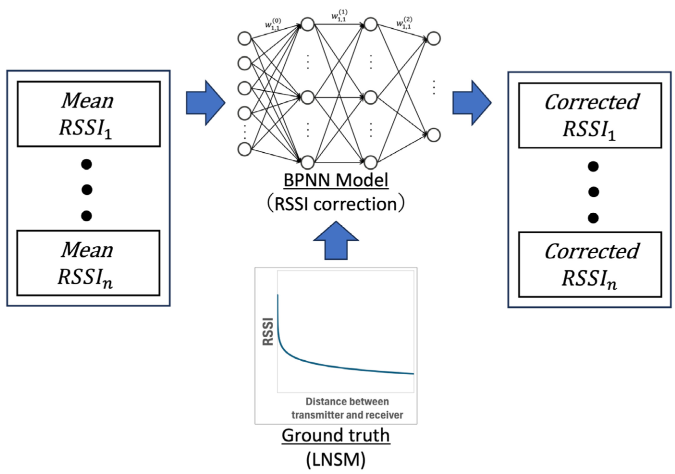

Figure 2. Conventional BPNN-based RSSI correction model using mean RSSI values.

3. Proposed Method

3.1. Overview and Process Flow

The proposed method improves localization accuracy by focusing on the temporal fluctuations and environmental dependencies of RSSI in BLE fingerprinting, utilizing multiple statistical features for RSSI correction. Figure 3 illustrates the overall architecture of the proposed system, which consists of two main stages: the offline stage for constructing a fingerprint database and the online stage for real-time position estimation.

In the offline stage, RSSI data are collected at each measurement point for a fixed duration, and multiple statistical features are extracted. These features serve as inputs for training a BPNN-based correction model, with ideal RSSI values derived from the LNSM used as the ground truth (labels). This process establishes a non-linear mapping from complex, stochastic RSSI observations to the idealized signal propagation defined by the LNSM. By using the trained model to associate corrected RSSI values with their respective coordinates, a refined fingerprint database is constructed, minimizing the impact of environmental fluctuations.

In the online stage, RSSI data are collected at the target location, and the same statistical features are extracted. The pre-trained BPNN model is then applied to these features to estimate corrected RSSI values, effectively suppressing environment-specific instabilities. Finally, these corrected values are compared with the fingerprint database, and a localization algorithm is applied to determine the final estimated position.

A key characteristic of the proposed method is that it functions as an independent correction process prior to position estimation. Consequently, the method is independent of specific localization algorithms and can be flexibly integrated with various approaches, such as k-NN, WKNN, and SVR.

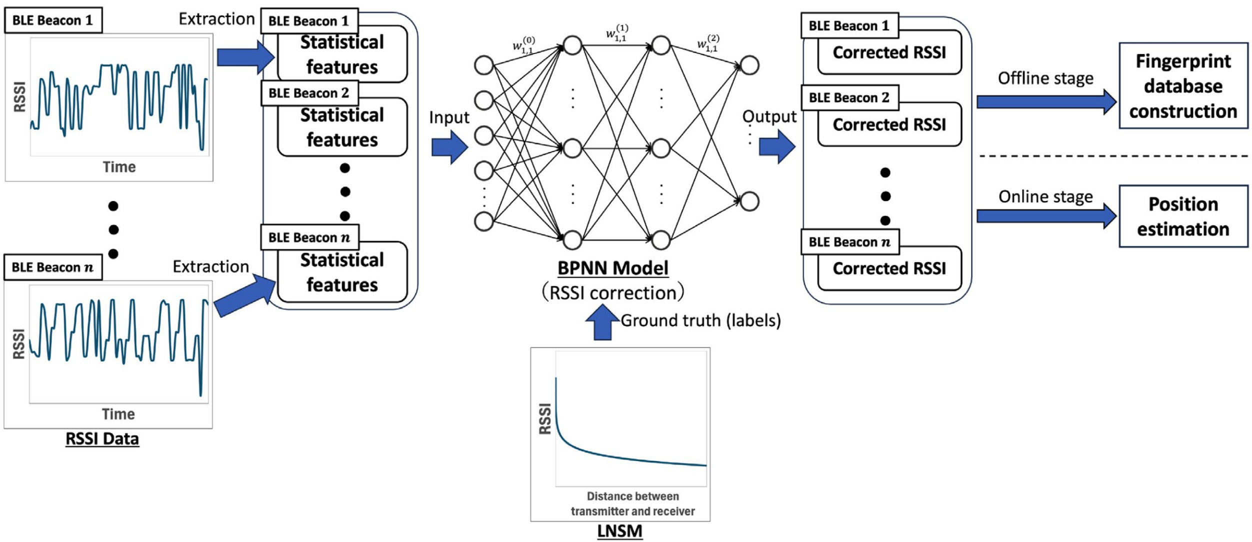

Figure 3. Proposed statistical feature-based RSSI correction model.

3.2. Extraction of RSSI Statistical Features

Rather than directly using raw RSSI sequences, this study summarizes the RSSI measurements using five statistical features that characterize the central tendency, variability, and distribution range of the signal. This representation enables the correction model to explicitly incorporate temporal fluctuations and distributional characteristics of RSSI while remaining independent of the downstream localization algorithm. The resulting statistical features are used as inputs to the BPNN correction model and can be combined with different localization algorithms such as k-NN, WKNN, and SVR.

To characterize the site-specific propagation environment, the proposed method transforms raw RSSI data into a multi-dimensional feature vector rather than utilizing raw signal values directly. While conventional methods rely solely on the mean value, which only represents the central tendency of the distribution, the proposed approach employs five distinct statistical features to characterize the underlying distribution and temporal instability of RSSI signals. These features are extracted from the RSSI data collected over a fixed period at each location and serve as the input vector for the BPNN correction model.

In this study, the five statistical features are defined to represent different aspects of the signal characteristics. The mean indicates the typical signal strength at the measurement point, while the variance quantifies the magnitude of temporal fluctuations, reflecting the instability of the reception environment caused by multi-path fading or shielding. To define the boundaries of RSSI fluctuations, the maximum and minimum values are utilized, which capture extreme variations resulting from temporary fading or signal blockage. Additionally, the interquartile range (IQR) is employed to quantify the spread of the RSSI distribution while effectively suppressing the influence of outliers.

By combining these statistics, it becomes possible to retain information about the instability and distribution patterns of the signal as location-specific features. This multi-dimensional representation is particularly crucial for constructing a high-precision correction model that accounts for environmental dependencies. As illustrated in **Figure 4**, these five statistical features collectively characterize the unique RSSI variability at each location, enabling the model to distinguish between different measurement points even when they exhibit similar mean RSSI values. This approach allows for more robust correction in challenging areas, such as near walls and corners, where RSSI instability is most significant.

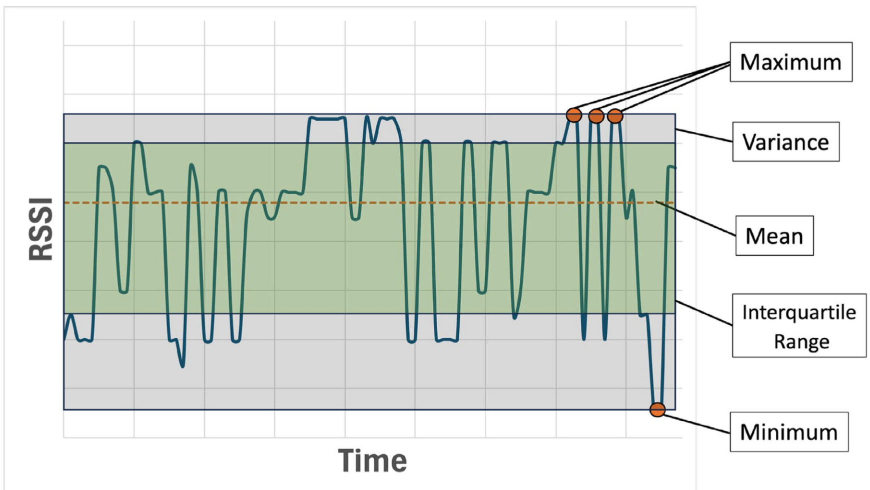

Figure 4. Visualization of the five statistical features extracted from an observed RSSI waveform.

3.3. BPNN-Based RSSI Correction Model

In this study, a BPNN is adopted as a regression model to estimate ideal signal strengths from the extracted statistical features. The BPNN is implemented as a multilayer perceptron consisting of a 20-dimensional input layer, two hidden layers with 20 and 15 neurons, respectively, and a four-dimensional output layer. The 20 input features correspond to five RSSI statistics—mean, variance, maximum, minimum, and interquartile range (IQR)—obtained from each of the four BLE beacons. The four output units provide the corrected RSSI values corresponding to the respective beacons. The hyperbolic tangent sigmoid transfer function (tansig) is used for the first hidden layer, whereas a linear transfer function (purelin) is used for the second hidden layer and the output layer. By simultaneously processing the statistical features obtained from multiple beacons, the model can learn the relationships among the RSSI distributions of the beacons and reflect the spatial characteristics of each measurement point. **Figure 5** illustrates the architecture of the correction model used in this study.

During the training process, sets of statistical features of RSSI observed in real environments are used as inputs, while the theoretical RSSI values calculated based on the LNSM are utilized as the ground truth (labels). The LNSM, which represents the ideal relationship between signal strength and distance, is defined as follows:

$$P(d) = P(d_0) - 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \tag{1}$$

where $P(d)$ is the received signal power at distance d, $P(d_0)$ is the signal power at the reference distance d_0, n is the path loss exponent, and X_σ represents a zero-mean Gaussian random variable with standard deviation σ, accounting for shadowing effects. While the LNSM is a simplified representation of radio propagation, it serves as a "stable reference point" for our correction process. The objective is not to physically simulate every multipath effect, but to map stochastic and fluctuating real-world observations to a consistent, idealized signal trend. Regarding the shadowing term X_σ, it is standardly modeled as a zero-mean Gaussian random variable in the logarithmic scale to represent large-scale fading effects. By training the BPNN to align fluctuating data with this deterministic model, we effectively suppress environment-dependent noise before the localization phase. Since the LNSM represents ideal signal propagation without reflections or interference, the model learns to map stochastic RSSI observations to the stable signal strengths defined by (1). This facilitates the construction of a model that estimates stable signal strengths while suppressing environment-dependent noise.

Before training, each input feature and target RSSI value was standardized independently using z-score normalization based on the mean and standard deviation of the offline data. No custom modifications were made to the default preprocessing settings of MATLAB's feedforward network. The network was trained using Bayesian regularization backpropagation (trainbr), which applies Levenberg-Marquardt optimization to minimize a Bayesian-regularized combination of squared errors and network weights and biases. The maximum number of training epochs was set to 4000. The offline samples were randomly divided into training, validation, and test subsets at ratios of 70%, 15%, and 15%, respectively. Except for the maximum number of epochs, the default stopping parameters of trainbr were retained: the performance goal was 0, the minimum performance gradient was 1×10^{-7}, and the maximum Marquardt adjustment parameter was 1×10^{10}. Accordingly, training terminated when the maximum number of epochs was reached, the performance goal was achieved, the performance gradient fell below the minimum threshold, or the Marquardt adjustment parameter exceeded its maximum value. Validation-based early stopping was not used because the default maximum number of validation failures for trainbr was zero.

Because BPNN training is affected by the random initialization of network weights, the correction model was trained 10 times using different random seeds (1 - 10). For each training run, the mean squared error (MSE) between the BPNN outputs and the LNSM-based target RSSI values was calculated. In the experiments reported in this study, the model with the lowest MSE among the 10 training runs was selected and used to construct the fingerprint database and perform the subsequent online evaluation. Once the model was selected in the offline stage, no additional training or model updating was performed during the online stage; only statistical feature extraction and inference using the pretrained BPNN were conducted.

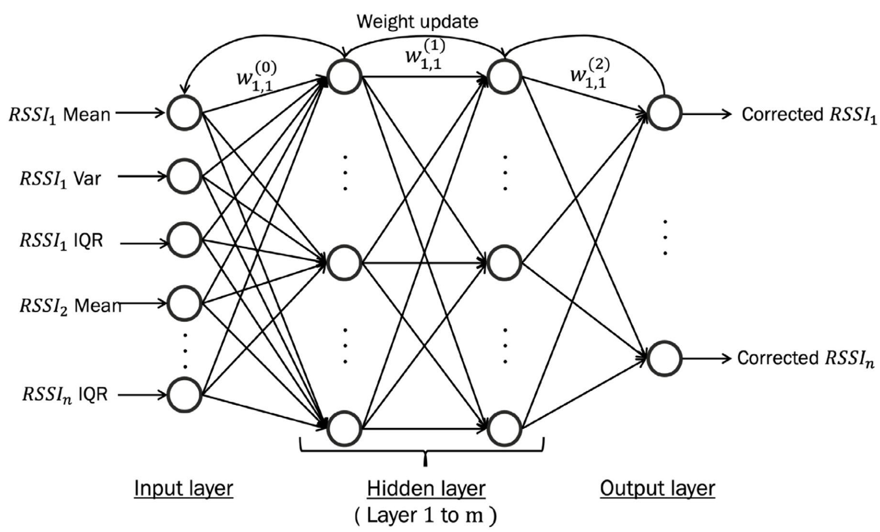

Figure 5. Architecture of the BPNN-based RSSI correction model with multiple statistical features as inputs.

4. Evaluation

4.1. Experimental Setup

In this study, indoor localization experiments based on real-world measurements were conducted to verify the effectiveness of the proposed method. The experiments were performed in Room 115, Keikikan, Doshisha University.

The indoor environment contains various obstacles, such as walls, desks, shelves, and monitors; therefore, the RSSI is significantly affected by shadowing and reflections. The dimensions of the evaluation space were 7.2 m × 9.6 m, and the layout of the measurement points and BLE beacons is shown in **Figure 6**. Four MM-BLEBC4 BLE beacons (SANWA Supply Inc.) were installed on the walls at a height of 2.0 m above the floor to cover the target area. The advertising interval of each beacon was set to 0.1 s, corresponding to a nominal advertising rate of 10 Hz. Thus, approximately 400 advertisement packets were transmitted by each beacon during each 40-s measurement period, although the actual number of received RSSI samples could be smaller because of packet loss during wireless reception. A MacBook Air equipped with an Apple M3 processor and a BCM-4388 Bluetooth controller compliant with Bluetooth Low Energy 5.3 was used as the RSSI receiver. Thirty-three measurement points were established at intervals of 1.2 m, excluding areas occupied by obstacles, and the receiver was placed at a height of 0.8 m during measurement.

The offline and online RSSI data were collected in separate measurement sessions. At each of the 33 measurement points, RSSI was collected for 40 s for the offline stage and for another 40 s in a separate online measurement session. One online measurement run was conducted at each point. Only the offline measurements were used to train and select the BPNN correction model and construct the fingerprint database, whereas the online measurements were used exclusively for localization evaluation. Therefore, no RSSI samples used for correction-model training overlapped with the localization test data. The collected RSSI data were processed, and the localization algorithms were implemented using MATLAB.

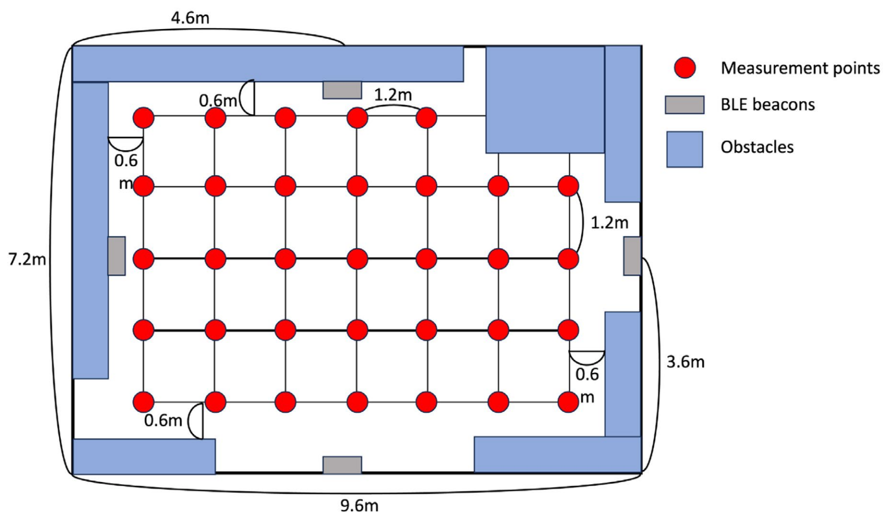

Figure 6. Layout of measurement points and BLE beacons in the experimental environment.

4.2. Evaluation Methodology

To verify the effectiveness and versatility of the proposed method, comparative experiments are conducted by combining different correction approaches and localization algorithms. First, to evaluate the impact of utilizing multiple statistical features, the performance of four methods is compared using the k-NN algorithm: No correction, Mean-based correction, Mean-variance correction, and Proposed method using five statistical features. Furthermore, to confirm that the proposed method is independent of specific localization algorithms, its performance is also evaluated using WKNN and SVR by comparing the no correction, mean-based correction, and proposed method.

The localization performance is quantitatively evaluated using the localization error, defined as the Euclidean distance between the estimated and ground truth coordinates. The evaluation metrics include the mean error, which indicates the overall accuracy trend. Additionally, the 95th percentile error is employed to assess the stability of the system. This percentile-based metric is particularly useful for evaluating the suppression of significant localization outliers typically encountered in multipath-prone areas, such as near walls and corners.

4.3. Results and Analysis

4.3.1. Effectiveness of RSSI Correction

Figure 7(a) compares the mean error and the 95th percentile error for each method. The proposed method achieved a mean error of 1.391 m, representing an accuracy improvement of 24% compared to the no-correction method and 15% compared to the conventional mean-based correction. More specifically, the 95th percentile error, which serves as an indicator of stability, was reduced from 4.348 m (no correction) to 2.542 m.

The cumulative distribution function (CDF) of the localization error is shown in Figure 7(b). While no significant differences in cumulative probability were observed among the methods for errors below 1.5 m, the curve for the proposed method was positioned furthest to the top-left for errors exceeding 1.5 m, confirming a higher cumulative probability compared to the other methods. Furthermore, the proposed method kept all localization errors within 3.0 m, eliminating the large errors that occurred in the mean-based and mean/variance-based corrections.

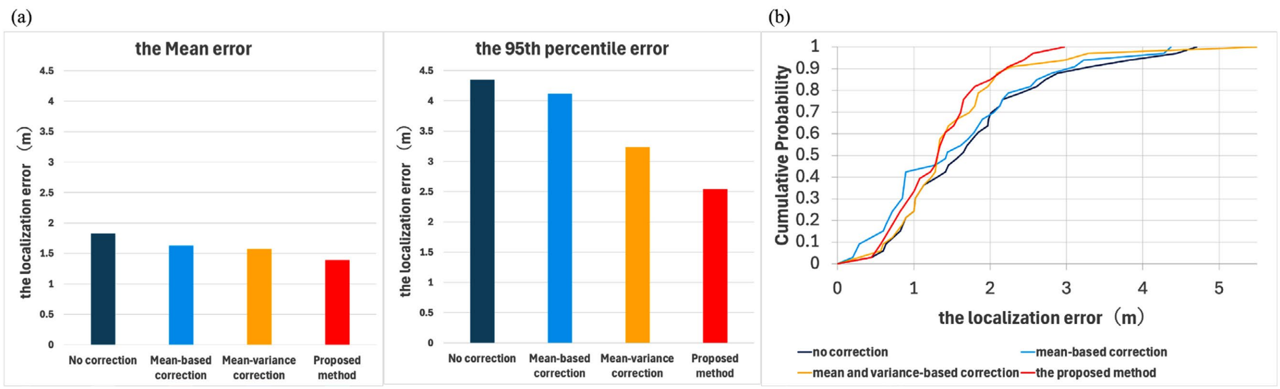

Figure 7. Localization performance of k-NN: (a) Mean and 95th percentile errors; (b) CDF.

To evaluate the spatial distribution of the errors, heatmaps for the no-correction and proposed methods are shown in Figure 8. In the no correction method (Figure 8(a)), large errors exceeding 3.0 m, indicated by warm colors, were widely distributed near walls and corners, which are susceptible to multi-path fading and shadowing. In contrast, these errors were improved in the proposed method (Figure 8(b)), enabling uniform and high-precision estimation across the entire evaluation area.

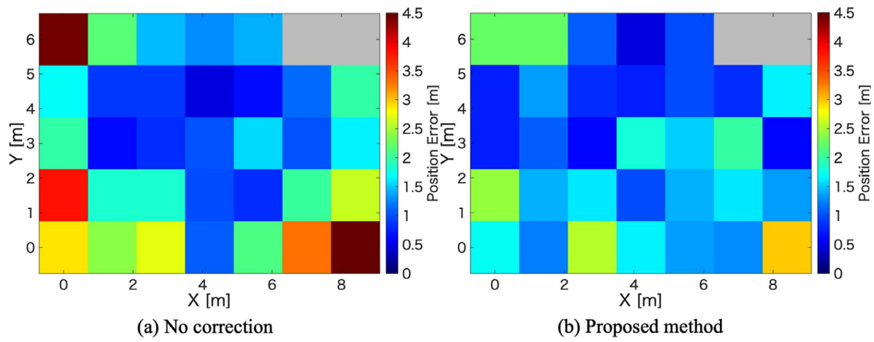

Figure 8. Spatial distribution of localization errors for k-NN: (a) No correction; (b) Proposed method.

4.3.2. Versatility across Different Localization Algorithms

The evaluation results using WKNN are shown in Figure 9. From Figure 9(a), the proposed method recorded a mean error of 1.373 m and a 95th percentile error of 2.602 m, demonstrating the highest accuracy among the three compared methods. Notably, for the 95th percentile error, a significant improvement of approximately 34% was confirmed compared to the no-correction method (3.930 m). The CDF in Figure 9(b) shows that the proposed method has the highest cumulative probability in the region where the localization error exceeds 1.8 m. This indicates that large errors are effectively suppressed, like the results obtained with k-NN.

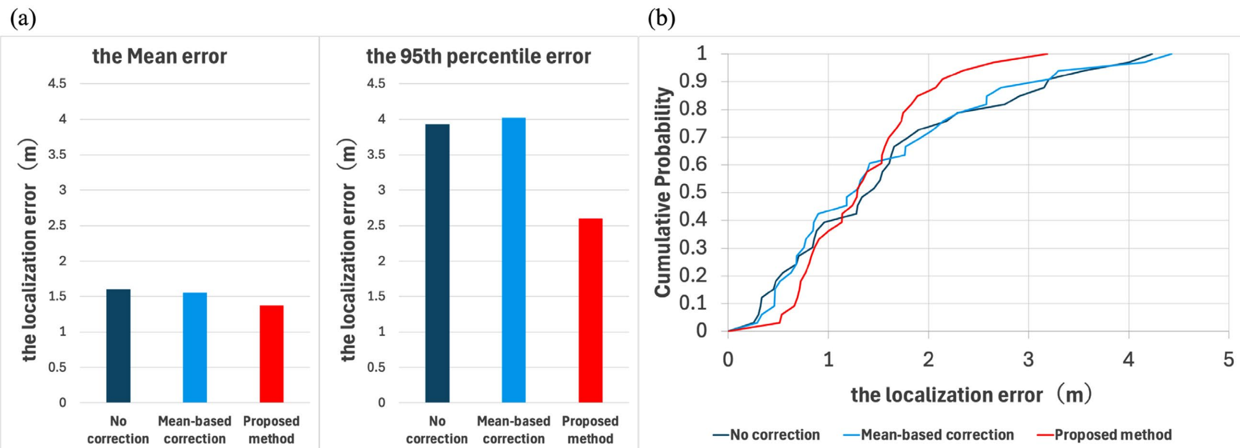

Figure 9. Localization performance of WKNN: (a) Mean and 95th percentile errors; (b) CDF.

Next, the evaluation results using SVR are shown in Figure 10. From Figure 10(a), the proposed method recorded the highest accuracy across all metrics, with a mean error of 1.578 m (an approximately 10% improvement over no correction) and a 95th percentile error of 3.226 m. While the accuracy improvement of the mean-based correction was unstable, tending to underperform compared to no correction in some metrics, the proposed method consistently improved performance. In the CDF shown in Figure 10(b), the curve for the proposed method is positioned furthest to the top-left for errors exceeding 2.5 m, confirming that the proposed approach is effective even when using a regression-based model.

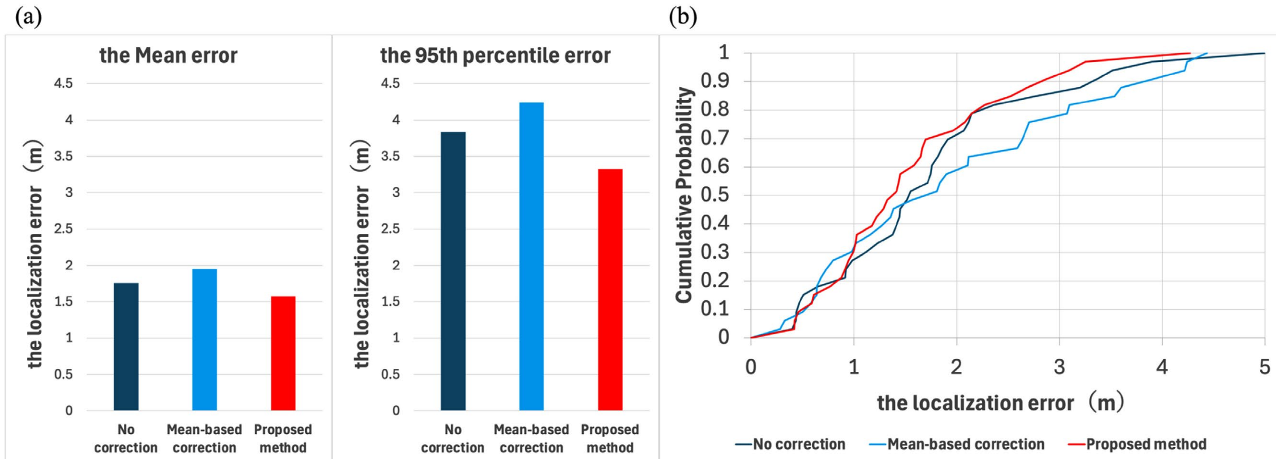

Figure 10. Localization performance of SVR: (a) Mean and 95th percentile errors; (b) CDF.

5. Discussion

5.1. Analysis of Localization Accuracy and RSSI Characteristics

The primary factor contributing to the improved localization accuracy is that the proposed method treats RSSI variability not as mere noise to be removed, but as a location-specific feature. In conventional BLE fingerprinting, RSSI fluctuations are often smoothed by simple averaging, which discards the environmental information embedded in the signal variance. However, as shown in Figure 11, the distribution shapes (variance and IQR) at Point A and Point B differ significantly, even when their mean values are similar. In areas near walls or corners, signal propagation is highly complex due to multipath fading and shadowing caused by building structures. By incorporating five RSSI statistics—mean, variance, maximum, minimum, and IQR—the proposed BPNN model effectively captures the "distortion" of the signal distribution at each point. This allows the model to distinguish between locations that would otherwise be indistinguishable using only mean values, leading to a more refined and stable fingerprint database.

5.2. Effectiveness and Robustness across Algorithms

The experimental results in Section 4 demonstrate that the proposed method consistently improves accuracy across different localization algorithms, including k-NN, WKNN, and SVR. This success stems from the fact that the method enhances the "input data quality" before the localization phase rather than modifying the localization algorithms themselves. For instance, in WKNN, where weights are determined by the similarity of RSSI patterns, the correction of unstable RSSI values directly leads to more reliable weight calculations and prevents the estimation from being skewed by temporal outliers. In the case of SVR, the regression function can become unstable when trained on data with high variance or significant outliers. The proposed statistical feature-based correction suppresses these instabilities by mapping the raw, fluctuating RSSI to ideal values based on the LNSM. This results in a more robust mapping between the signal space and the physical space, demonstrating that the proposed correction approach can improve localization performance across the different algorithms evaluated in this study.

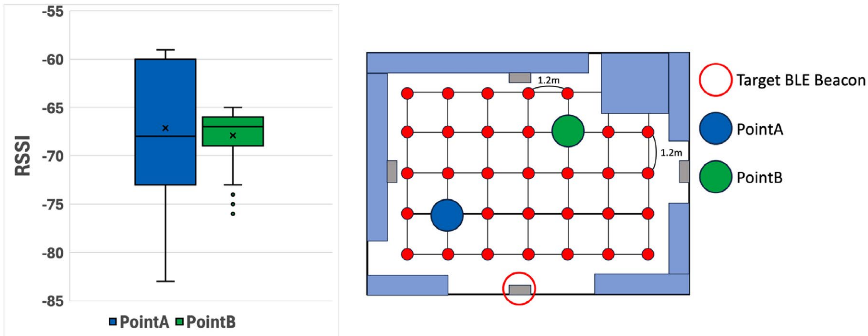

Figure 11. Comparison of RSSI distributions at different measurement points.

5.3. Limitations

This study was evaluated in a single static indoor environment with a fixed layout, using four BLE beacons and 33 measurement points. Therefore, the generalizability of the proposed method to different room layouts, beacon configurations, and dynamic environments involving moving people or obstacles has not yet been verified. In addition, the computational cost of statistical feature extraction and BPNN inference, including processing latency and memory usage on resource-constrained edge devices, was not quantitatively evaluated. Future work will investigate the robustness and practical applicability of the proposed method under these different conditions.

6. Conclusions

BLE fingerprinting, which is widely used for indoor localization, has faced the challenge of unstable estimation accuracy due to temporal RSSI fluctuations and environmental dependencies, particularly near walls and corners. To address this issue, this study proposed an RSSI correction method using a BPNN model that takes five statistical features—mean, variance, maximum, minimum, and IQR—as inputs to correct RSSI data prior to the localization phase.

Experimental results showed that the proposed method consistently achieved higher accuracy compared to the no correction method and the mean-based correction across multiple localization algorithms with different characteristics, such as k-NN, WKNN, and SVR. By reducing the 95th percentile error, which serves as an indicator of stability, this study demonstrated that the proposed method effectively suppresses large localization errors that frequently occur near walls and corners. The proposed approach is algorithm-agnostic, allowing for seamless integration with various localization frameworks and contributes to improving localization accuracy in practical indoor environments.

While this study primarily evaluates the system in a static indoor environment, the proposed statistical features are inherently designed to capture temporal fluctuations. Metrics like variance and IQR provide the model with information about the stability of the reception environment. However, in highly dynamic environments involving moving obstacles or human traffic, the signal profile becomes non-stationary. Future work will investigate the robustness of these high-dimensional features under such dynamic conditions to further extend the applicability of the proposed framework.

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Author Contributions

Conceptualization, Sano S., Umeda H. and Sato K.; methodology, Sato S. and Umeda H.; software, Sano S.; validation, Sano S. and Alparslan O.; investigation, Alparslan O. and Sato K.; supervision, Sato K..; funding acquisition, Sato K.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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