FEKNN: A Wi-Fi Indoor Localization Method Based on Feature Enhancement and KNN

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Abstract. Utilizing Wi-Fi signals for indoor localization significantly improves location-based services in indoor environments, though challenges arise due to unpredictable Wi-Fi signal propagation. We propose an innovative Feature Enhancement and K-Nearest Neighbor (FEKNN) approach, which refines RSSI data distribution for a more accurate feature database and employs a refined Weighted K-Nearest Neighbor (W-KNN) algorithm to calculate locations by Euclidean distances between enhanced features. Extensive experiments validate that our FEKNN has remarkable accuracy for indoor localization applications, achieving state-of-the-art performance with an impressive average localization error of 1.86 meters on the public UjiIndoorLoc training dataset, and an average error of 0.68 meters on our custom-built dataset.

Keywords: Wi-Fi Indoor Localization · Received Signal Strength Indicator · Indoor Positioning · Indoor Navigation · Location-Based Services

1 Introduction

Wi-Fi-based indoor localization is a burgeoning field within wireless communication, navigation, and security research, with a wide array of applications such as indoor navigation [1][2][3], security monitoring [4][5], and home automation[6]. In recent years, there has been a surge in interest towards integrating machine learning techniques [7] [8] to establish a robust link between location fingerprints and their corresponding physical coordinates.

The primary challenge in Wi-Fi signal-based localization lies in the vulnerability of RSSI signals to environmental interference, which can cause considerable signal variance. The variability in signal fingerprints, induced by environmental changes, complicates the deployment of indoor localization systems, increasing both the workload and associated costs. Consequently, developing adaptable fingerprint databases and structured fingerprint localization algorithms capable of adjusting to varying environmental conditions has emerged as a critical area of research.

Moreover, understanding the distributional characteristics of Wi-Fi signal strength values is crucial. Features that encapsulate information invariant to scale provide a significant advantage over raw numerical data, enabling models to detect complex patterns across diverse scales. This is especially relevant in addressing the challenges posed by device variability in indoor localization, necessitating the enhancement of raw data with informative features prior to further analysis.

In addressing the challenges, our research pivots towards enhancing both data processing and model innovation. Traditional machine learning methods typically necessitate manual feature selection, a need that has been diminished by the advent of deep learning. AutoEncoders [9] [10], for instance, enable autonomous feature extraction through advanced techniques like gradient descent optimization. Building on the straightforward, intuitive, and highly effective K-Nearest Neighbor methodology, we propose the Feature Enhancement and K-Nearest Neighbor (FEKNN) approach. This approach synergizes RSS data refinement with a weighted KNN algorithm for precise location prediction using Euclidean distance metrics. Our contributions are delineated as follows:

- We propose the Feature Enhancement and K-Nearest Neighbor (FEKNN) method for Wi-Fi indoor localization. It combines feature enhancement and K-Nearest Neighbor to improve accuracy in indoor localization, potentially addressing the challenges posed by complex indoor environments.
- We design a feature enhancer, which plays a pivotal role in refining the distribution of Received Signal Strength Indicator (RSSI) data to build a more robust feature library. This enhances the quality of data used in the localization process.
- We conduct extensive experiments on both public dataset and our custom dataset to rigorously evaluate the efficacy of our FEKNN approach, validating that our FEKNN achieves state-of-the-art performance in Wi-Fi indoor localization.

2 Related Work

2.1 Machine Learning Method

The utilization of machine learning methodologies in indoor localization[7] [8] has markedly surged in recent years, propelled by the ambition to forge a dependable correlation between Received Signal Strength (RSS) measurements and precise locations. Prominent among the array of algorithms deployed are K-Nearest Neighbor (KNN) [11] and Support Vector Machine (SVM) [12], each distinguished by its application and efficacy. KNN operates by pinpointing the nearest reference points in a database, matching the RSS patterns of a target location and employing these points' coordinates for location estimation. In contrast, SVM leverages a kernel function to elevate lower-dimensional data into a higher-dimensional space, facilitating the more nuanced classification of fingerprint data for location prediction.

The adeptness of machine learning in associating signal intensity data with physical coordinates renders it exceptionally suitable for managing fingerprint databases. However, the effectiveness of these techniques is inherently linked to the statistical models they rely on, which may not universally exhibit robust performance across varied indoor settings. The continuous exploration and research into enhancing the resilience of machine learning applications in diverse environments are therefore imperative.

2.2 Deep Learning Method

Parallelly, the adoption of deep learning for indoor localization[13] [14] has captivated considerable interest, chiefly attributed to its proficiency in feature extraction from signal fingerprints through stacked self-encoders. This approach significantly diminishes neural network complexity while concurrently augmenting localization precision. Convolutional Neural Networks (CNNs) [15] are particularly adept at distilling discriminative features from fingerprint data, setting the stage for accurate location determination.

Deep learning models excel in identifying intricate patterns within datasets, leveraging these meticulously extracted features, thereby showcasing enhanced generalization capabilities. Nonetheless, it's critical to acknowledge that deep learning may occasionally neglect statistical subtleties, which could be detrimental for smaller datasets and potentially culminate in suboptimal performance outcomes. Thus, a meticulous balance between deep learning methodologies and the dataset's size and attributes is vital for attaining the pinnacle of success in indoor localization endeavors.

3 Method

In this section, we delineate the architecture and operational mechanism of our Feature Enhancement and K-Nearest Neighbor (FEKNN) methodology. We commence with a succinct overview of the FEKNN model, followed by a comprehensive exposition of its three constituent modules. Concluding this section, the implementation nuances are meticulously discussed.

3.1 Overview

The architecture of the FEKNN framework encompasses three core components: the Feature Enhancement Block, the Feature Database, and the Weighted K-Nearest Neighbor (W-KNN) Function, as illustrated in Figure1. The Feature Enhancement Block is tasked with refining the Received Signal Strength (RSS) values through an encoder-decoder mechanism, imbuing the process with domain-specific insights to augment task performance. Subsequently, the refined data is archived in the Feature Database, setting the stage for juxtaposition with new

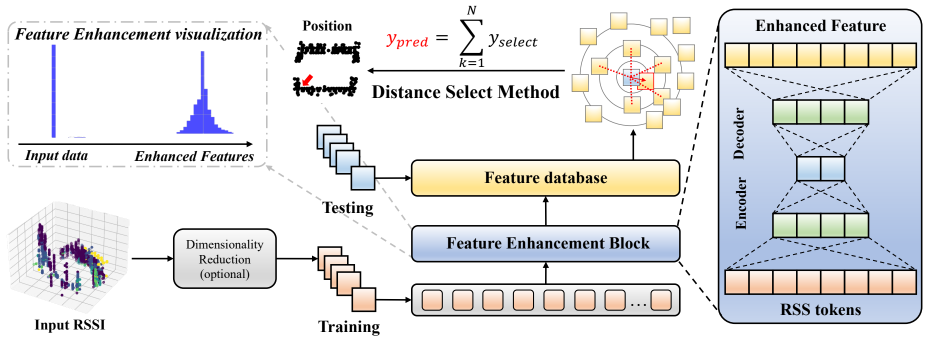

Fig. 1. The architecture of our FEKNN model. During the training phase, the input RSS data can be dimensionally reduced (optional) and then flattened into a 1D vector, serving as the input to the Feature Enhancement Block. In the testing phase, the input RSS data is flattened and directly matched with the data in the Feature database for feature matching. Finally, the closest approximate RSS feature is determined through distance selection and used to predict the real-world location of the test data.

test data. The W-KNN Function is designed to harness these enhanced features in conjunction with test data to culminate in predictive outcomes.

3.2 Feature Enhancement Block

The Feature Enhancement Block (FE Block) is engineered to receive RSS data, initiating an automated procedure of feature extraction and representation learning. This intrinsic functionality enables the identification and encapsulation of complex patterns within the dataset. Characterized by its distinctive encoder-decoder architecture, the FE Block is instrumental in isolating critical features and facilitating their reconstruction.

Encoder. The encoder component is pivotal, transmuting the initial high-dimensional input into a condensed, lower-dimensional latent representation. This act of dimensionality reduction concentrates the neural network's focus on assimilating the most salient features present in the data, encapsulating the quintessential aspects of the input for efficient pattern and characteristic learning.

$$h = g_{\theta 1}(x) = \sigma(W_1 x + b_1) \tag{1}$$

where σ is the activation function applied to the linear transformation W_1x+b_1. Here W_1 is the weight matrix associated with the first layer, x represents the input to the encoder, while b_1 is the bias vector for the first layer.

Decoder. Inversely, the decoder reconstructs the latent variables from the hidden layer back to their original high-dimensional state. Its primary objective is to replicate the original input data with fidelity, ensuring the preservation of initially encoded information through accurate reconstruction. This step is crucial for the authentic restoration of input data.

$$x = g_{\theta 2}(x) = \sigma(W_2 x + b_2) \tag{2}$$

where σ is the activation function applied to the linear transformation W_2x+b_2. Here W_2 is the weight matrix associated with the decode layer, x represents the input to the decoder, while b_2 is the bias vector for the decoder layer.

3.3 Feature DataBase

Post-processing by the Feature Enhancement Block, the augmented features are aggregated into a repository, constituting enhanced RSS feature representations alongside their corresponding real-world coordinate positions. The dimensionality of these augmented RSS features is determined by the decoder within the Block, with label features in the database aligning with dataset labeling conventions, such as real-world coordinates (longitude and latitude in meters, using UTM from WGS84) and building floor information (vector from 521 to 523 in UjiIndoorLoc [16]). This repository is thus primed for feature comparison and selection.

3.4 Weight KNN Function

Upon receipt of feature tokens as input, the Weight KNN function employs an instance-based learning paradigm for prediction formulation. This strategy is contingent upon evaluating the similarity between the input tokens and the dataset. For any given datum denoted as x, its prediction is derived by calculating the mean response from its K-Nearest Neighbors (KNN). Specifically, when the model processes input t_i, the K-Nearest Neighbor algorithm discerns K data points most closely mirroring the features of the input within the token repository, previously refined by the FE Block. The average of these neighbors' responses is then utilized to generate the regression prediction outcome. This process can be succinctly formulated as:

$$K(t_i) = \frac{1}{\sum_{j=1}^{k} w_j} \sum_{i=1}^{K} w_i argmin \sqrt{\sum_{u=1}^{n} |x_i - x_j|^2} \tag{3}$$

where $K(t_i)$ represents the predicted value for input sample t_i, $\sum_{j=1}^{k} w_j$ denotes the sum of weights of the K nearest neighbor samples, w_j stands for the weight of the j-th nearest neighbor sample, while x_i and x_j are feature vectors of sample t_i and the j-th nearest neighbor respectively.

3.5 Implementation Details

Pre-processing. The preparatory phase entails a standardization process across varied data types, encompassing Wi-Fi signal strength, latitude, and longitude metrics. The objective of this standardization is to normalize the data range, rendering it amenable to subsequent analytic modeling.

Training. The training regimen for our FEKNN model is executed on an Intel Core i5-9400F CPU, with a batch size of 64. This process is extended over 85 epochs, permitting iterative enhancement of the model's predictive accuracy. The learning rate is initially established at 0.001 to commence the training phase.

4 Experiments

In this section, we present an extensive evaluation of our FEKNN across two datasets, along with a detailed exposition of the experimental outcomes. We further engage in a comparative analysis against existing methodologies, supplemented by an ablation study and insights into model visualization.

4.1 Datasets

UjiIndoorLoc. The UJIIndoorLoc dataset [16], a comprehensive multi-building and multi-floor database, was curated at the University of Jaén, Spain, to benchmark indoor localization algorithms. It comprises 19,937 data points, each linked to 520 Access Points (APs).

Our Dataset. OurDataset encapsulates data from a single building, structured across three floors to test model robustness. It includes 1,110 data instances and 378 APs, aimed at validating the effectiveness of our approach under varied spatial distributions, as depicted in Figure 2. The RSSI level distribution in OurDataset mirrors the methodology of UjiIndoorLoc, with RSSI ranges of [-100, -95] and [-45, 0] constituting 0.756% and 0.684% of the data, respectively, as illustrated in Figure 2(b).

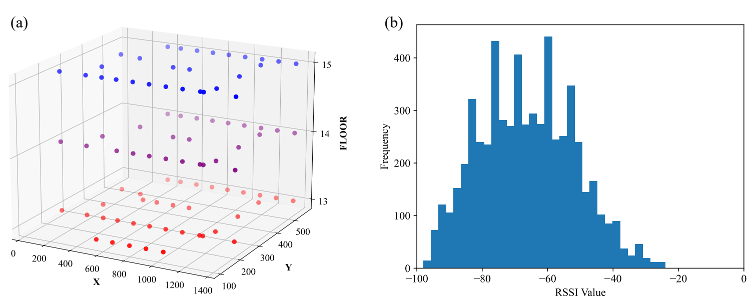

Fig. 2. (a)A three-dimensional visualization showcasing a subset of data from our dataset. (b) The frequency distribution of the number of times that RSSI values appears in the Ourdataset.

4.2 Comparison with the State-of-the-art methods

Our FEKNN method demonstrates superior performance over state-of-the-art approaches, including K-Nearest Neighbor (KNN) [17], Deep Neural Network

(DNN)) [18], Extreme Gradient Boosting (XGB) [19], as well as deep learning approaches like Convolutional Neural Network (CNN)[15], CNN [20] combined with KNN [21], and Transformer [22], across metrics like $RMSE$, MAE, R^2 and Error in Meters. Notably, our model exhibits rapid convergence and enhanced generalization, establishing it as a viable solution for Wi-Fi indoor localization.

Method	Extra Annotation	RMSE (↓)	MAE (↓)	R^2-Score (↑)	Error in Train (m)	Error in Val (m)
KNN [17]	✗	2.56	1.45	**0.99**	3.33	10.12
DNN [18]	✗	2.73	4.03	0.98	9.47	16.79
XGB [19]	✗	2.48	2.48	**0.99**	5.82	16.29
CNN [15]	✗	2.79	4.37	**0.99**	10.24	18.81
CNN [20]+KNN [21]	✗	2.52	1.44	0.98	3.23	10.33
Transformer [22]	✗	3.41	6.72	0.97	15.80	18.54
FEKNN(Ours)	✗	**2.34**	**0.81**	**0.99**	**1.86**	**8.20**
UJIIndoorLoc BASELINE [16]	✓	-	-	-	-	7.9
FEKNN(Ours)	✓	-	-	-	-	**6.5**

Table 1. The Mean Square Error, Mean Absolute Errors, R^2-Score and Error in Meters on the UjiIndoorLoc dataset. The first seven methods take an RSS values as the input and can be trained free from Extra Annotations, such as Correct range selection. The last two have Extra Annotations (Correct Building and Floor).

Experiment 1. Evaluation on the UjiindoorLoc dataset revealed that FEKNN significantly outperforms contemporary models, as summarized in Table 1, reducing Mean Absolute Error (MAE) by 0.64 and localization error by 1.44 meters, substantiating its efficacy over DNN [18], CNN [20], and Transformer [22] methods. Our method's localization error of 6.5 meters, compared to the UjiIndoorLoc BASELINE of 7.9 meters, further underscores its robustness and accuracy.

Method	RMSE(↓)	MAE(↓)	R^2-Score(↑)	Error in val (m)
KNN [17]	7.529	33.061	0.980	1.116
DNN [18]	10.555	74.712	0.917	2.443
CNN [15]	9.802	61.662	0.939	2.007
CNN [20]+KNN [21]	8.315	42.489	0.962	1.624
FEKNN(Ours)	**6.394**	**24.11**	**0.989**	**0.684**

Table 2. The Mean Square Error, Mean Absolute Errors, R^2-Score and Error in Meters on Ourdataset. All methods are trained on the Ourdataset.

Experiment 2. The robustness and scalability of FEKNN were rigorously tested on OurDataset, demonstrating its adaptability and performance in diverse environmental conditions. The results, summarized in Table 2, underscoring the model's reliability, highlight its potential for real-world indoor localization applications.

4.3 Ablation Study

Feature Enhancement Block. Integrating the Feature Enhancement Block (FE Block) for raw data processing markedly improves FEKNN's performance, enhancing feature distinctiveness and model interpretability. Specifically, the block contributed to a reduction in errors by 23% in training and 13% in validation phases, as shown in Table 3.

FE Block	Error in Train(m)	Error in Validation(m)
✗	2.39	9.91
✓	**1.86**	**8.20**

Table 3. The effect of Feature Enhancement Block (FE Block). The k is set to 1.

Input Dimensional	Encoder Layer 1	Encoder Layer 2	Error in meters (m)
520	64	32	2.96
520	64	16	3.57
520	128	32	2.33
520	128	64	2.22
520	256	128	2.01
520	512	128	2.04
520	512	256	**1.86**

Table 4. The encoding dimensional of Feature Enhancement Block.

The encoding dimensional of Feature Enhancement Block. Our experimentation with different encoding dimensions highlighted the pivotal balance between achieving feature diversity and maintaining computational efficiency, as shown in Table 4. By carefully selecting an optimal encoder configuration of 512 units for the first layer and 256 units for the second, we significantly enhanced our model's performance. This strategic choice not only improved the quality of feature representation but also judiciously managed the computational resources, demonstrating that a 512-256 dimensionality configuration optimally boosts the model's efficacy while keeping computational overhead in check.

Distance Metric. In our detailed examination of Manhattan and Euclidean distance metrics for Wi-Fi-based indoor localization, we explored their unique effects on model performance through an extensive analysis. This study, covering a range of $K = 1$ to $K = 20$, enabled us to observe and document the error rates associated with each distance measurement approach. Our results, depicted in Figure 3, reveal distinct patterns of error fluctuations across various K values, providing valuable insights. Notably, we observed that the Manhattan distance metric demonstrated a pattern of narrowing and widening in Maximum Errors in Test (MET) and Maximum Errors in Validation (MEV), in contrast to the more consistent variations seen with the Euclidean distance. This difference highlights the subtle yet significant impact of distance metrics on the accuracy of indoor localization, enhancing our understanding of the localization process.

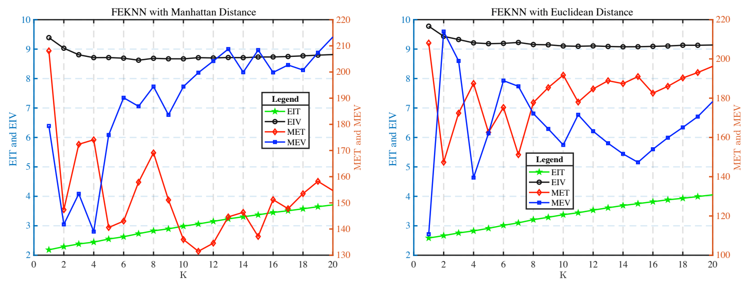

Fig. 3. The visualization of the performance of Manhattan Distance and Euclidean Distance. EIT and EIV represent Error Meters in Test and Error Meters in Validation respectively; MET and MEV denote the Maximum Errors in Test and Maximum Errors in Validation respectively.

4.4 Visualization

To provide a visual representation of our FEKNN estimation outcomes, we have generated informative visualizations using data from the UjiIndoorLoc dataset as illustrated in Figure 4.

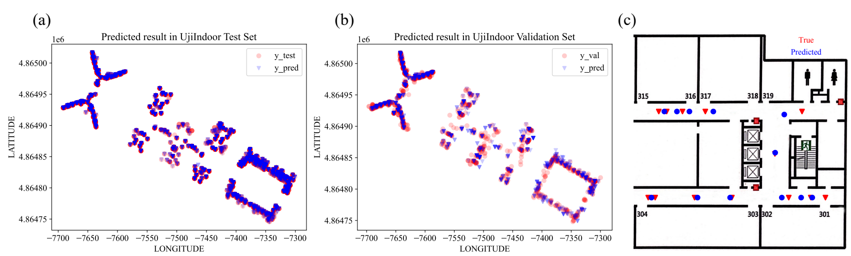

Fig. 4. The visualization of the performance of FEKNN in the UjiIndoorLoc test(a) and validation sets(b). The blue triangle represents the ground truth, while the red circle illustrates the localization result. The visualization of the performance of our FEKNN in the Ourdataset(c). The red triangle represents the ground truth position, while the blue circle denotes the localization result.

Furthermore, on the UjiIndoorLoc validation set, our FEKNN has consistently performed within an acceptable margin of error. It's worth noting that this margin of error is typically smaller than the inaccuracies commonly associated with mobile phone GPS positioning. Besides, Figure 4 illustrates the prediction results of our FEKNN for 13 randomly selected points in our dataset. The average error is approximately 0.68 meters, with a maximum error of about 1.62 meters, which is highly satisfactory.

5 Discussion

During our experimental investigation, we identified two primary areas of concern in our FEKNN approach: device variability and inherent limitations, which suggest directions for future research and methodological refinement.

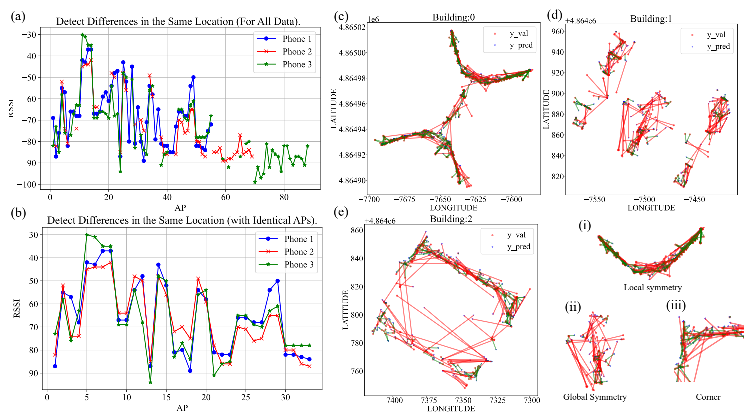

Fig. 5. (a): Three devices display varying results detected at the same location.(b): Three devices demonstrate differences in signal strength detected for the same access point at the same location. The limitation of our FEKNN. (c), (d), and (e) represent the connect results of our FEKNN on the UjiIndoorLoc validation set. Additionally, (i), (ii), and (iii) illustrate three typical symmetry issues.

Device Variability. In the process of constructing our custom dataset, we encountered variations in localization accuracy attributable to the differing capabilities of mobile devices in detecting Wi-Fi signal strength, as depicted in Figure 5. Notably, Phone3 exhibited superior detection capabilities compared to Phone2. To mitigate this discrepancy, we propose enhancing the dataset's diversity by incorporating data from a variety of devices to compile a more representative database. Nonetheless, this strategy may not fully account for all device-related variances. Our method focuses on normalizing detected signal strengths to identify more consistent patterns across devices, thereby prioritizing Wi-Fi signal characteristics over device-specific detection capabilities.

Limitation. However, our FEKNN method encounters challenges with symmetrically sampled data, which can degrade performance. Empirical analysis, illustrated in Figure 5, highlights errors exceeding a 10-meter threshold in red and those below in green, revealing significant predictive inaccuracies. We identified three symmetry patterns affecting predictions: **local symmetry**, characterized by mirror-like predictions along a single axis; **global symmetry**, indicating double-axis symmetry; and **corner symmetry**, specific to floor corners with unique geometries. The presence of architectural irregularities in datasets like

UjiIndoorLoc complicates the model's ability to handle symmetry, emphasizing the need for further research to enhance FEKNN's adaptability and accuracy.

6 Conclusion and Future work

In this work, we propose the FEKNN model to enhance Wi-Fi indoor localization accuracy. Our analysis reveals the significant impact of undetected RSS values and dataset biases, leading to the development of a Feature Enhancement Block. This block refines RSS features into context-rich, low-dimensional representations, enabling improved optimization.

We discussed device variability's effect on accuracy by proposing a normalization strategy for signal strengths, thus prioritizing signal characteristics over device differences. However, the FEKNN model encounters challenges with symmetric data, affecting accuracy due to inherent building symmetries.

Future work will focus on investigating symmetry issues, exploring advanced data handling techniques, and analyzing device variability further. Expanding the dataset and broadening the range of indoor environments for data collection will enhance model robustness. Additionally, integrating emerging technologies and real-time environmental data holds potential for advancing Wi-Fi localization accuracy.

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