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Wi-Fi Fingerprint Based Indoor Localization Using Few Shot Regression

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Wi-Fi fingerprint based indoor localization using few shot regression

Xuechen Chen Jiaxuan Yi Aixiang Wang Xiaoheng Deng*

Abstract—**Deep learning techniques, particularly those based on Wi-Fi fingerprinting, have become increasingly prevalent in the field of indoor positioning. These methods typically require specialized training for specific environments and often lack adaptability to changes in indoor settings. In contrast, this study introduces an indoor positioning approach based on few-shot regression. The aim is to enable the model to rapidly adapt to new indoor environments using a limited number of labeled Wi-Fi Received Signal Strength Indicator (RSSI) samples. This research treats indoor location prediction as a regression problem, initially pre-training the model on a Wi-Fi dataset from a source domain and establishing a general mapping relationship between Wi-Fi signals and locations using the concept of basis functions. Subsequently, the model is fine-tuned with a small set of Wi-Fi samples from the target domain to learn specific weights. This process of transferring the model from the source to the target domain aids in achieving accurate positioning in new and constantly changing environments. Experimental results demonstrate the method's superior performance in positioning accuracy, showing a 57.9% improvement over few-shot classification and a 13% improvement over KNN.**

Index Terms—**Wi-Fi, few shot regression, adaptive localization.**

I. INTRODUCTION

The widespread use of smartphones and the rapid development of the Internet of Things (IoT) have significantly enhanced the reliability of indoor positioning services, on which many indoor applications heavily rely [1]. Although the Global Positioning System (GPS) performs exceptionally well outdoors, its effectiveness indoors is considerably diminished due to limitations in satellite signal reception. Consequently, the challenge of indoor positioning has garnered considerable attention from researchers.

Wi-Fi signals, readily available in indoor environments, enable smartphones to perform indoor positioning without the need for additional equipment installation or wiring. Due to its low cost, high accuracy, and user-friendliness, Wi-Fi technology has emerged as a predominant method for indoor positioning [2]–[5]. However, the aforementioned Wi-Fi-based indoor positioning methods are trained specifically for particular environments. When changes occur in the indoor environment, these previously trained models become unsuitable for the current context. Consequently, these models require retraining, which involves collecting new Wi-Fi data in the altered indoor settings. Yet, these methods lack the capability to automatically adapt to such changes. Moreover, collecting Wi-Fi data is a complex and time-consuming task, demanding significant human and material resources. Therefore, developing adaptive indoor positioning methods with limited Wi-Fi samples has become an urgent research topic.

It is well-known that solving problems using deep learning typically requires a large amount of labeled data. However, in real-world scenarios, such data is often scarce. This limitation has prompted researchers to explore solutions under data-constrained conditions, leading to the emergence of Few-Shot Learning (FSL) [6]. FSL aims to acquire the ability to recognize new, unseen data from a limited set of labeled data. It has achieved significant success in multiple fields, including Computer Vision (CV) [7]–[9] and Natural Language Processing (NLP) [10]. Currently, researchers are applying FSL to the field of indoor positioning. Chen et al. [11] conducted indoor positioning using Wi-Fi Channel State Information (CSI) data based on few-shot learning. They considered one room as the source domain and another as the target domain, collecting data in these areas to train their model. These trained models were able to accurately classify the location of CSI samples in the target domain. Zhang et al. [12] also proposed few-shot classification for adaptive indoor positioning. They used CSI samples from both the target and source domains to train their model, enabling it to analyze the similarity between samples across the two domains. Based on these similarities in the target domain, they estimated the sample's location coordinates using a weighted sum approach to determine the position. Both methods treat indoor positioning as a classification task. While effective, they fall short in accurately estimating precise locations. In classification problems, the primary goal is to assign samples to predefined categories. When the training data represents fewer categories, the model faces greater difficulty in accurately classifying new, unseen samples. In contrast, regression problems focus on establishing a mapping relationship between input and output variables. When well-trained, a model has the potential to produce more precise estimates compared to classification.

In summary, the contributions of this paper can be summarized as follows:

(1) We have redefined the indoor positioning problem as

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a regression task, where each unique indoor environment represents a different task. By training the model with Wi-Fi Received Signal Strength Indication (RSSI) data collected from various indoor environments, we enable the model to recognize the correlations between these different tasks, share foundational features, and then focus on the unique characteristics of each specific task. By leveraging parameter sharing, we effectively reduce the number of parameters that need to be learned for new tasks. This streamlined approach allows the model to quickly adapt to new positioning challenges, ultimately achieving the goal of adaptive indoor positioning.

(2)We propose an indoor positioning method centered around few-shot regression, aimed at minimizing positioning errors. This method utilizes a limited set of Wi-Fi RSSI values as a dataset and applies the concept of basis functions to address the regression problem. Similar to few-shot classification methods, this approach also simplifies the task of collecting Wi-Fi RSSI data. Experimental results validate that our method significantly enhances positioning accuracy in new environments.

The structure of this paper is as follows: In Section 2, we introduce the fundamental principles and provide the necessary background knowledge. The proposed method is elaborated in detail in Section 3. Section 4 presents the experimental results and analysis. Finally, the conclusions are summarized in Section 5.

II. PRELIMINARIES

In this section, we will detail the fundamental concepts and principles of few-shot regression. Our approach begins with the premise of a source domain A and a target domain B. Few-shot learning involves the process of acquiring knowledge from a limited set of labeled samples in source domain A, with the primary objective of rapidly adapting to tasks within target domain B to enhance model performance. When addressing indoor positioning challenges, we treat it as a regression problem. Specifically, we introduce the regression function $y = F(x)$ as the objective of learning.

It is widely acknowledged that attempting to accurately fit the regression function $F(x)$ with only a small number of samples is an impractical task, due to the inherent complexity that F(x) might possess. To address this challenge, literature [13] proposed a method for solving few-shot regression. Given a limited sample set, denoted as $D_{pretrain} = \{(x_j, y_j)|j = 1, 2, ..., k\}$, their method involves using this small dataset to enable the model to acquire sparse representation capabilities specific to a particular task. Thus, even with a minimal number of samples, there is sufficient information to estimate $F(x)$. This sparse representation of the regression function is versatile, as it can also adapt to other tasks. In this context, they assume that all different tasks follow the same but unknown task distribution, denoted as $p(\tau)$.

To elaborate further, the sparse representation of the function involves a set of basis functions$\{\phi_i(x)\}$, which means that the function can be represented through these basis functions. This can be expressed as follows:

$$F(x) = \sum_i \omega_i \phi_i(x), \tag{1}$$

For instance, if the goal is to predict a sine function, different sine curves all conform to the same sine distribution. They define $F(x)$ = sin(x), and sin(x) can be represented using a set of basis functions, as shown in Equation (2):

$$sin(x) \approx \omega_1^1 x + \omega_2^1 x^3 + \omega_3^1 x^5 + ... + \omega_M^1 x^M, \tag{2}$$

The representation of "sin(2x)" can be formulated as follows:

$$sin(2x) \approx \omega_1^2 x + \omega_2^2 x^3 + \omega_3^2 x^5 + ... + \omega_M^2 x^M. \tag{3}$$

Two different sine curves represent two independent regression tasks. Notably, both of these distinct sine curves can be represented using the same set of basis functions $\{x, x^3, x^5, ...x^M\}$, with their differences lying in the weights of each basis function. Essentially, our primary goal is to find a suitable set of basis functions and then use Equation (1) to model the regression function $F(x)$. This approach significantly reduces the degrees of freedom in $F(x)$. Therefore, it is possible to accurately estimate the regression function $F(x)$ with just k samples. In summary, our method involves selecting specific tasks for training and learning from the task distribution $p(\tau)$. This determines a suitable set of basis functions that can represent various specific tasks, provided that all these different tasks conform to the same task distribution $p(\tau)$. Thus, when faced with a new task, the model is fine-tuned using a small dataset from the new task to determine the appropriate weights, thereby enabling the modeling of the regression function for the new task.

III. LOCALIZATION METHOD BASED ON FEW SHOT REGRESSION

In this section, we introduce the model structure and methodology. The positioning model consists of two key components: a feature extractor and a weight generator. The parameters of the feature extractor are denoted by ξ, while those of the weight generator are denoted by θ. The primary objective of this model is to establish a mapping relationship between Wi-Fi RSSI and location coordinates, ultimately finding a regression function. Our method is based on the assumption that indoor positioning tasks conducted in different environments all follow the same task distribution. During the pre-training phase, the model is trained using Wi-Fi RSSI data collected in indoor environments, represented as $D_{tra} = \{(x_t, y_t)|t = 1, 2, ..., s\}$. The goal is to predict locations in this indoor environment, a task denoted as Task C, with this dataset acting as the source domain. Next, the entire dataset is input into the feature extractor. The dimension of the feature extractor, denoted as f_d, corresponds to the number of encoded basis functions. Thus, the feature extractor generates features of dimension s*f_d. These extracted features are then concatenated with their corresponding sample labels y_t and input into the weight generator. The dimension of the weight

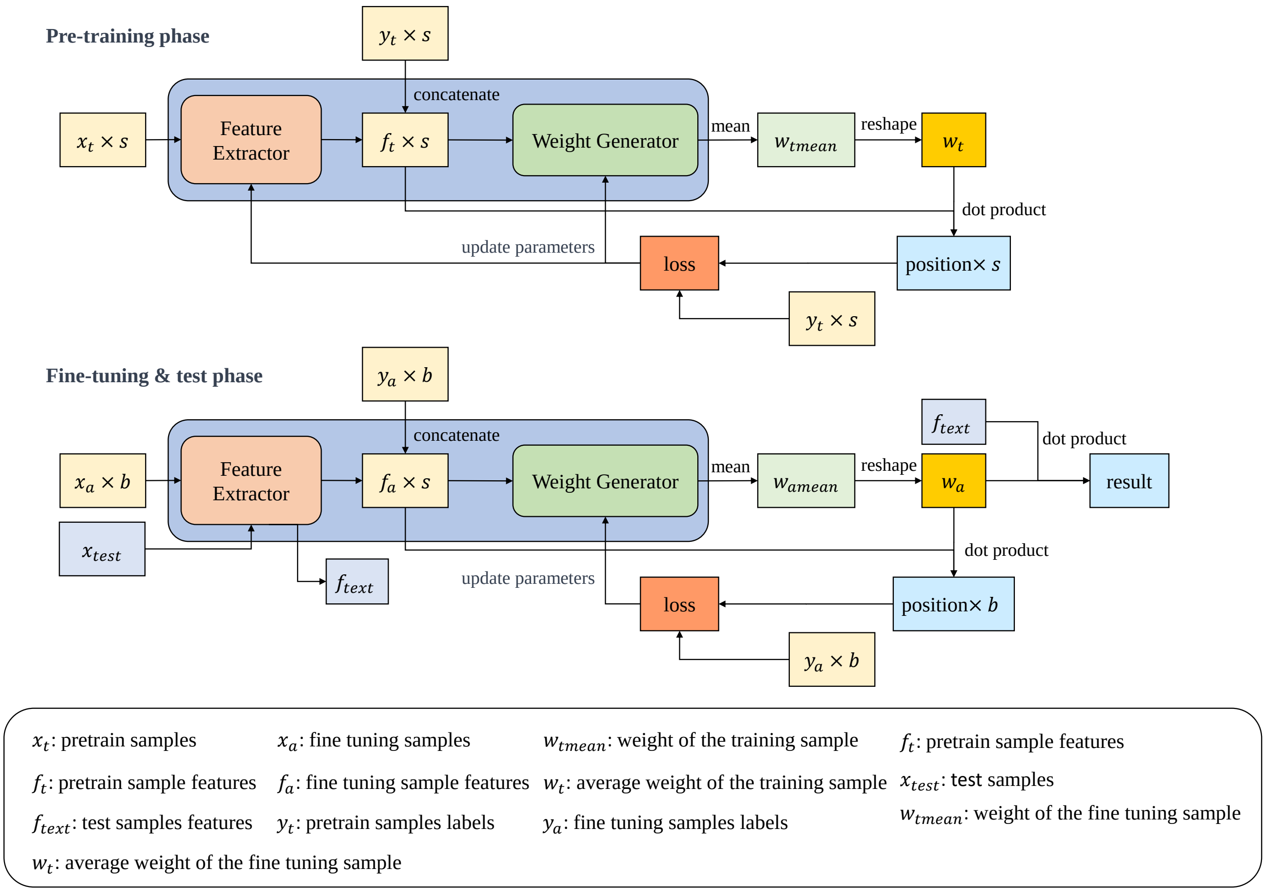


Fig. 1: Architecture diagram of indoor localization algorithm based on few shot regression

generator is denoted as w_d. The output weights are averaged and reshaped into dimensions of $2{*}w_d/2$, as the predicted location is two-dimensional, and it is essential to ensure that $w_d/2$ matches f_d. The weight generator itself consists of a series of self-attention blocks using scaled dot-product attention, a concept originally proposed by Vaswani et al. in [14]. Each self-attention module enables the weight generator to examine the embeddings of its inputs, selectively emphasizing the most relevant parts of the embeddings when generating optimal weights for each training sample. Subsequently, a dot product operation is performed between the average weights and the transpose of the features f_d to derive the estimated locations for the s samples. Finally, the loss function measures the total sum of squared differences between the estimated locations and the actual labeled positions, which can be represented in the following form:

$$Loss = \sum_{t=1}^{s} (y_t' - y_t)^2. \tag{4}$$

The process then enters the fine-tuning phase, assuming the need for indoor positioning in a new environment. We collect Wi-Fi RSSI data from this new environment, including b samples with location labels, denoted as $D_{fin} = \{(x_a, y_a)|a = 1, 2, ..., b\}$. Different indoor environments represent different positioning tasks, each requiring a unique regression function. However, these tasks conform to the same task distribution and can be represented using the same set of basis functions for different regression functions. Therefore, in the fine-tuning phase, the parameters of the feature extractor remain unchanged to achieve parameter sharing and reduce the number of parameters the model needs to train. The b samples are input into the feature extractor, yielding b features, each with a dimension of f_d. These features are then concatenated with their corresponding b labels and input into the weight generator. Subsequently, the average of the output weights is calculated. Similarly, the weights are reshaped to dimensions of $2{*}w_d/2$, and a dot product operation is performed between the average weights and the transpose of the b features to derive the estimated locations for the b samples. The loss function is consistent with the previously mentioned Equation (4).

Finally, in the testing phase, Wi-Fi RSSI samples collected from the new environment are input into the feature extractor, thereby obtaining features for the test samples, denoted as f_{test}. Subsequently, after inputting the b fine-tuned samples into the positioning model and calculating the average of the output weights, the weights are reshaped to dimensions of $2{*}w_d/2$. Then, by performing a dot product operation between the average weights and the transpose of f_{test}, the estimated locations of the test samples are obtained. Fig. 1 illustrates a flowchart of the indoor positioning method based on few-shot regression. Below is the pseudocode for our proposed indoor positioning algorithm based on few-shot regression.

Algorithm 1 Indoor Localization Algorithm in train phase

Initialize feature extractor parameters ξ , weighted generator parameters θ.
In pretrain phase.
for each episode **do**
    Input data D_{tra} into the feature extractor.
    Concatenate features and labels and input them into the weight generator.
    Average the weights.
    Perform dot product operations on weights and features.
    Calculate the loss value according to formula (4) and update the parameters ξ and θ.
end for
In fine tuning phase.
for each episode **do**
    Input data D_{fin} into the feature extractor.
    Concatenate features and labels and input them into the weight generator.
    Average the weights.
    Perform dot product operations on weights and features.
    Calculate the loss value according to formula (4) and update the parameters θ.
end for

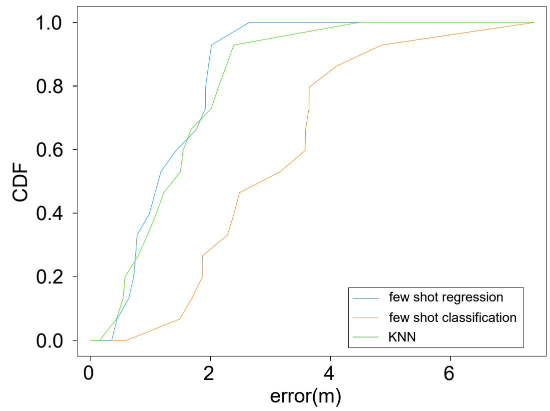


Fig. 2: Error CDF in scene 3

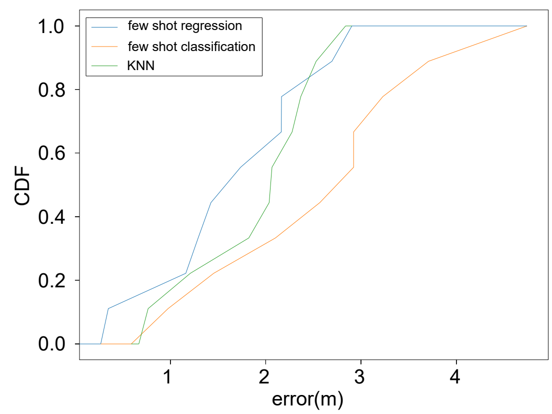


Fig. 3: Error CDF in scene 1

IV. Experimental Results and Analysis

A. Experimental Setup

We conducted experiments using a dataset from paper [15]. The first scenario was designated as the source domain, where they collected one Wi-Fi RSSI sample every 0.5 meters, totaling 49 samples. Subsequently, the third scenario was chosen as the target domain, with the dataset for this domain including 40 fine-tuning samples and 16 test samples. The model's feature extractor consists of two fully connected layers, while the weight generator comprises two fully connected layers and two self-attention blocks. Each self-attention block has the same structure, utilizing ELU and ReLU as activation functions. The learning rate was set to 0.0001.

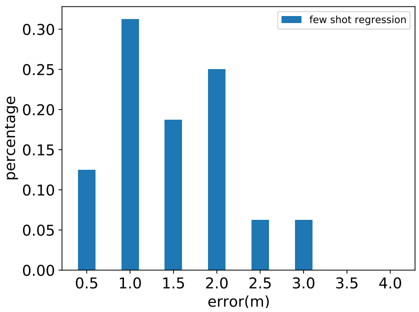
B. Experimental Results

We conducted comparative experiments with the few-shot classification method [12] and KNN. To evaluate the effectiveness of our proposed method, the average localization error was used as the assessment metric. The formula for calculating the average localization error is as follows:

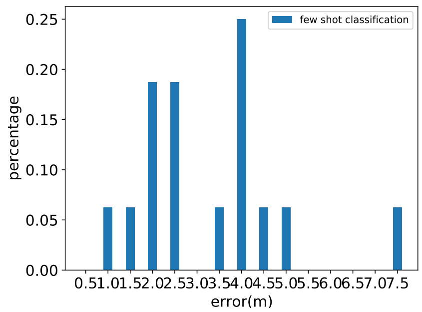
$$average \quad error = \frac{1}{N}\sum_{l=1}^{N}\sqrt{(x_l' - x_l)^2 + (y_l' - y_l)^2}. \quad (5)$$

Where N represents the number of test samples. x_l' and y_l' respectively denote the estimated horizontal and vertical coordinates of the location, while x_l and y_l represent the actual horizontal and vertical coordinates of the true location.

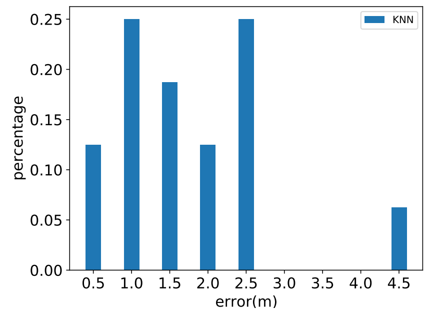
Initially, a localization experiment was conducted, designating Scene 1 as the source domain and Scene 3 as the target domain. In this experiment, our proposed few-shot regression method achieved an average localization error of 1.27 meters, compared to the few-shot classification method's average error of 3.02 meters and KNN's average error of 1.46 meters. Relative to the few-shot classification method, our approach improved localization accuracy by 57.9%, and by 13% compared to KNN. To depict the distribution of localization errors, Cumulative Distribution Function (CDF) curves were used. As observed in Fig. 2, the CDF curve of our few-shot regression method consistently remained above those of the few-shot classification method and KNN, indicating a clear advantage of our method over these approaches. For a clearer presentation of the error distribution, histograms were also utilized to visualize the experimental results. As shown in Fig. 4, approximately 13% of the locations had a localization error within 0.5 meters, 31% had errors between 0.5 and 1 meter, while errors between 1 and 1.5 meters and 1.5 to 2 meters accounted for about 19% and 25%, respectively. In contrast, the few-shot classification method had about 6% of errors in the 0.5 to 1 meter range and about 18% in the 1.5 to



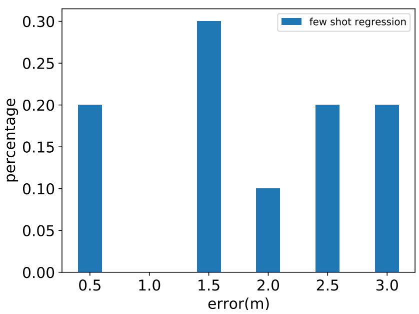
(a) The error distribution of few shot regression in scene 3



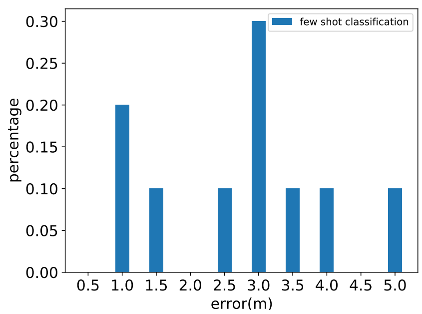
(b) The error distribution of few shot classification in scene 3



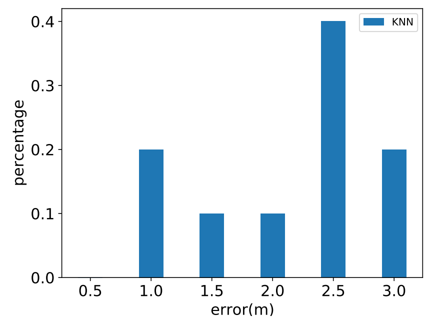
(c) The error distribution of KNN in scene 3



(d) The error distribution of few shot regression in scene 1



(e) The error distribution of few shot classification in scene 1



(f) The error distribution of KNN in scene 1

Fig. 4: Localization error bar chart

2 meter range, with some errors distributed between 3 and 7.5 meters. The KNN method had about 25% of errors in the 0.5 to 1 meter range and about 13% in the 1.5 to 2 meter range, with some errors around 4 to 4.5 meters.

Another localization experiment was conducted, with Scene 3 as the source domain and Scene 1 as the target domain. In this experiment, our proposed method achieved an average localization error of 1.61 meters, compared to the few-shot classification method's average error of 2.52 meters and KNN's average error of 1.85 meters. Our method significantly enhanced localization accuracy, improving by 36.1% over the few-shot classification method and by 12.9% over KNN. As illustrated in Fig. 3, it is evident that the CDF curve of our proposed method consistently outperformed the other methods, demonstrating its superior localization effectiveness. Fig. 4 displays the distribution of localization errors for the various methods. Our method had approximately 20% of locations with an error between 0 and 0.5 meters, about 30% with errors between 1 and 1.5 meters, and roughly 20% with errors between 2 and 2.5 meters. In contrast, the few-shot classification method had about 10% of errors in the 1 to 1.5 meter range and about 10% in the 2 to 2.5 meter range, with some errors distributed between 3 and 5 meters. The KNN method had about 10% of errors in the 1 to 1.5 meter range and about 40% in the 2 to 2.5 meter range. Our analysis suggests that the few-shot classification method, which labels Wi-Fi samples of the same class as 1 and different classes as 0 during training, may lead to overfitting. With a limited number of samples, this approach could result in inaccurate similarity judgments for new Wi-Fi samples, thus limiting the precision of estimated locations. In contrast, the few-shot regression method utilizes a feature extractor to learn commonalities between different tasks, identifying a set of universal basis functions. Then, using a weight generator, it learns weights specific to a particular task, establishing a mapping relationship from Wi-Fi to location, thereby achieving improved localization accuracy.

V. Conclusion

We have developed an indoor localization method based on few-shot regression, utilizing a pre-trained model with Wi-Fi RSSI data from the source domain. This approach enables the model to learn common features for localization across various environments. By fine-tuning the model, it can quickly adapt to new target environments, thereby reducing the complexity of model training and achieving parameter sharing. Furthermore, our method was compared and analyzed against few-shot classification methods and the KNN method. Experimental results demonstrate that our approach achieves higher localization accuracy in adaptive indoor positioning.

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