DR-FSL : Distribution Relation Based Few-Shot Learning for Indoor Localization With CSI

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Abstract

In this paper, we propose a few-shot indoor fingerprint localization model based on distribution relationship to solve the problem that it consumes a lot of labor and time costs again to collect and label fingerprint data in the scene after replacement. The model uses only a small amount of fingerprint data from the new scene and reuses the large amount of fingerprint data already collected in other scenes, which improves the scalability of fingerprint location and enables it to be quickly applied to new scenes. In DR-FSL, Fingerprint Graph and Distribution Graph are constructed with fingerprint and fingerprint similarity distribution as nodes respectively, and fingerprint features and similarity distribution features are aggregated through the graph network to classify fingerprints by comparing fingerprint similarity and combining the distribution similarity, so that the model can distinguish unlabeled fingerprint using a small amount of labeled fingerprint. CSI data were collected in a complex lab and an integrated office, and the two scenes were set up alternately as a training scene where a large amount of data had been collected and a test scene to be localized for experiments. The experiments validate the superior performance of DR-FSL in terms of localization accuracy and stability for cross-scene few-shot localization. The results show that the amount of fingerprint data required in the new scenes is significantly reduced in the case that the localization performance of DR-FSL is comparable to that of the CNN-based model.

Keywords

Indoor Localization, Fingerprint Localization, Few-Shot Learning, WiFi Channel State Information

1. Introduction

With the widespread deployment of wireless sensor devices in indoor environments, wireless sensor networks (WSN) make up for the difficulty of global navigation and positioning systems to achieve high-precision localization indoors, providing a strong prerequisite for indoor location services[1]. As common sensors and signal sources in WSN, Wi-Fi, Bluetooth, RFID, and Ultra-wideband (UWB) are widely used in indoor wireless localization[2]. Among them, Wi-Fi-based localization methods are favored by researchers because of their high localization accuracy and low equipment cost[3]. Channel state information (CSI) from the wireless signal of a Wi-Fi device contains multi-channel subcarrier phase and amplitude data, which provides detailed information about the indoor environment and has become the most common wireless

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signal feature for fingerprint construction[4].

The Wi-Fi-based fingerprint localization method includes an offline phase and an online phase[5]. The offline phase collects Wi-Fi signals at multiple reference points (RPS) to build a fingerprint database and train a localization model; the online phase collects real-time collected Wi-Fi signals as fingerprints to compare with the fingerprint database to obtain predicted location results for localization.The performance of Wi-Fi-based fingerprint localization mainly depends on the degree of matching between real-time Wi-Fi signals and fingerprints in the database, and the amount of fingerprint data collected in the offline phase will significantly affect the localization accuracy of the fingerprint localization system[6].

A key challenge of Wi-Fi-based fingerprint localization methods is data collection and labeling. When the location scene is replaced with a new scene, the space size, obstacle type, Wi-Fi device location and fingerprint point distribution are completely changed, so the old and new scenes are not correlated and heterogeneous with each other. Due to the environment dependence of Wi-Fi signal[7], the fingerprint database in the old scene is no longer available in the new scene, so to deploy a highly accurate and robust indoor fingerprint location system based on Wi-Fi in multiple scenes requires a lot of labor and time cost to repeatedly collect a large amount of Wi-Fi data in different scenes to construct a fingerprint database, which prolongs the deployment cycle of fingerprint location system and seriously hinders the widespread deployment of fingerprint location system in indoor scenes[8].

Some researchers have tried to apply transfer learning to solve this problem. The idea is to use the parameters of the localization model trained in other environments where a large amount of data has been collected to help train the localization model for the target environment, and in this way to accelerate and optimize the learning efficiency of the fingerprint localization model in the new localization scene, so that the fingerprint localization system can be deployed again in the new localization scene without using the same large amount of fingerprint data to support the first deployment. [9] used the idea of transfer learning to train a convolutional neural network localization model after combining the Wi-Fi fingerprint data collected in 15 scenes, and then fine-tunes it for specific scenarios to apply to each single localization scene. For fingerprint-based localization, [10] proposed a transfer learning-based framework to reshape the data distribution in the target domain based on the knowledge learned in the source domain, reduce the offline training overhead, and improve the system scalability of fingerprint-based indoor localization. [11] used a transfer learning approach to train the recognition neural network by densely deploying a grid to collect fingerprints in an existing localization scenario, and when redeployed to a new localization scenario, updating the localization network using 7% of the fingerprint samples can maintain high localization accuracy. To address the problem of dynamic changes in the localization scene, [12] proposed a CSI-based inter-temporal indoor localization method, which uses domain adaptive methods in transfer learning to shorten the distribution distance between CSI fingerprint data after dynamic changes in the localization scene and improve the ability of the localization system to cope with environmental changes. In these works, fingerprint data of target localization scenes are still needed as a priori knowledge to jointly participate in training localization models, and the obtained localization systems are only migrated for specific target localization scenes, which still cannot be rapidly deployed in different localization scenes and lack cross-scene robustness.

In order to further improve the cross-scene robustness of fingerprint localization system

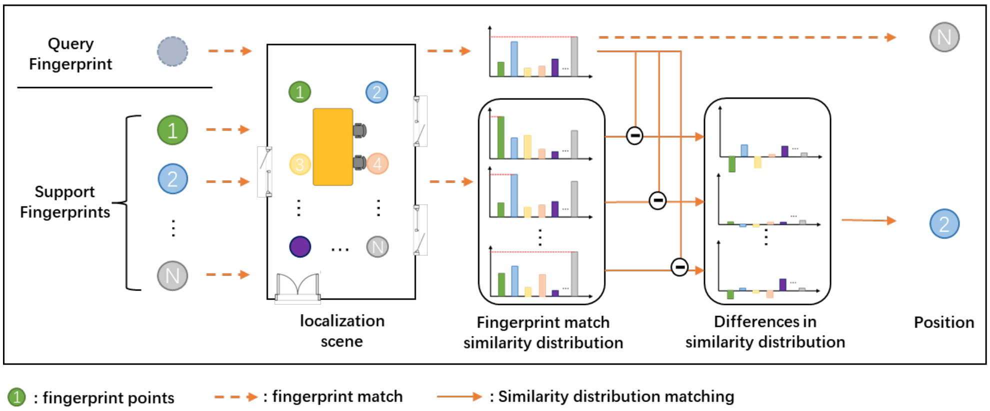

Figure 1: Schematic diagram of DR-FSL

and increase the feasibility of rapid deployment in multiple scenes, this paper introduces the idea of few-shot learning into the Wi-Fi-based fingerprint localization method[13]. Few-shot learning aims to train a generic model that is rapidly applicable to a variety of tasks[14][15], in the case of Wi-Fi-based fingerprint localization studies, the task is localization in multi-localization scenes.Unlike the transfer learning-based approach, our approach does not require fingerprint data from the target localization scene to participate in the training phase of the localization model, and the resulting generic localization model only needs a small amount of data in the target environment to achieve the localization effect through fingerprint recognition, which is robust across scenarios and can be rapidly deployed in different heterogeneous scenes.

Due to the influence of multipath propagation, Wi-Fi signals have the problems of low feature resolution and fingerprint blurring in complex indoor environments, which will lead to the similarity of the fingerprint data of wireless signals collected at different location points in a uniform localization scene, thus making the fingerprint matching-based localization method less accurate[16]. In order to ensure that when the wireless signal propagation in the localization scene is seriously affected by multipath effect and the fingerprint data collected from different fingerprint points are similar, the few-shot fingerprint localization method still has the ability to discriminate between fingerprints at different locations and maintain a high accuracy localization effect across scenes. As shown in Figure 1, inspired by [17], our method classifies fingerprint by comparing the similarity of fingerprints while considering the similarity distribution relationship between each fingerprint sample.

The main contributions of this paper are:

- We propose a fingerprint localization method that reduces the labor and time costs required to collect and label fingerprint data in new scenes. The method enables fingerprint localization in new scenes with only a small amount of fingerprint data by using fingerprint data already collected and labeled in other environments to train the model and apply it to new scenes.
- The method designs a few-shot learning model based on the distribution relationship to classify and localize fingerprints by combining the similarity distribution relationship

between each fingerprint sample while comparing the similarity of fingerprints. The model only needs to collect and label 1, 5 and 10 fingerprint samples at each RP in the new scene. The performance of the model using only 10 samples per RP in the new scene is comparable to that of the CNN-based fingerprint localization model using 400 fingerprint samples per RP in the new scene as the training set, and the number of fingerprint samples required is reduced by a factor of 40.

- In addition, we collected and labeled CSI data as fingerprint samples in two heterogeneous scenes, a complex laboratory and an integrated office, and set both of them alternately as a training scene with a large amount of data collected and a test scene to be localized for experiments, respectively, to verify the superior performance of the proposed method in terms of localization accuracy and stability for cross-scene few-shot fingerprint localization.

The rest of the paper is structured as follows. Section II introduces the preliminary knowledge and defines the few-shot localization problem. Section III describes the proposed method in detail. section IV shows the experimental setup and performance comparison, and concludes the paper with an outlook in section V.

2. Preliminary

Problem Definition: Few-shot learning trains a network model in the training phase to enable it to achieve task effects well with only a small number of labeled samples for the target task. As shown in Figure 2, we study indoor fingerprint localization in multiple heterogeneous scenes based on few-shot learning. The localization task is modeled as a classification problem to determine the fingerprint points belonging to the RP to be localized.Each localization task in a heterogeneous scene contains a support set S and a query set Q. The training phase collects the training dataset D_{train} in a certain scenario, and uses episodic training method to sample the support set S and query set Q from them in batches to simulate the few-shot learning setting (i.e., the N-way K-shot setting) of the test task to train the model for the localization task in an N-way K-shot few-shot learning localization task, the goal is to classify query fingerprints into N classes with only K support examples per class. Thus the support set S contains N classes, each with K samples, and can be denoted as $S = \{(x_1, y_1), (x_2, y_2), \ldots, (x_{N\times K}, y_{N\times K})\}$,The query set Q contains $\overline{T}$ fingerprint samples to be located, which can be expressed as $Q = \left\{(x_{N\times K+1}, y_{N\times K+1}), \ldots, \left(x_{N\times K+\bar{D}}, y_{N\times K+\overline{T}}\right)\right\}$. In the training phase, samples from both the support set S and the query set Q contain location labels and are used to optimize the network model. A test dataset D_{test} is collected in a localization scenario that is heterogeneous from the training data collection scene, and the unlabeled fingerprint samples in the query set $Q \subset D_{\text{test}}$ are located by the trained localization model based on a small number of labeled fingerprint samples in the support set $\mathcal{S} \subset D_{\text{test}}$.

CSI in few-shot learning: CSI represents the link characteristics of the wireless signal propagating between the transmitting and receiving devices. It reflects the attenuation of the wireless signal during propagation and the multipath effects caused by scattering, refraction, etc. Due to the multipath effect, multiple subcarriers will propagate along different paths, and the channel state information of each subcarrier has different amplitudes and phases, reflecting the

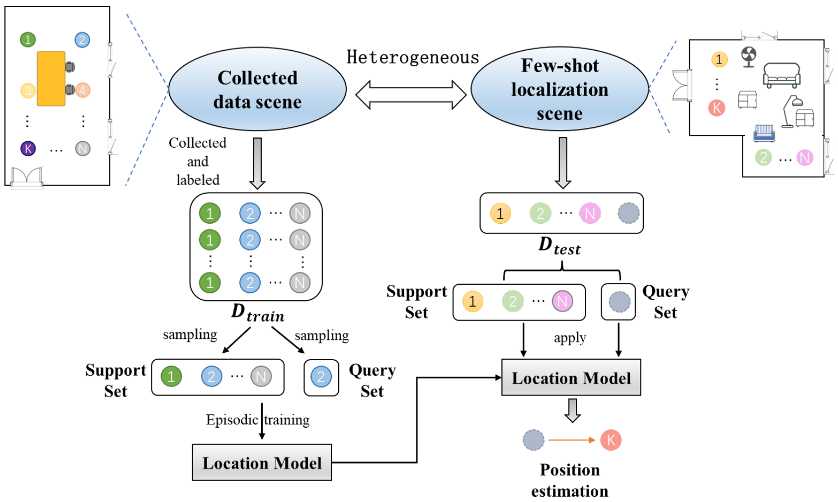

Figure 2: Schematic diagram of DR-FSL

channel variations and signal distortion caused by scattering, fading and power distance fading. CSI collected at different locations in indoor scenes is unique and can be used as "fingerprints" to provide effective location information, which provides a good data base for few-shot fingerprint localization based on CSI. When the localization scene is replaced, the old and new localization scenes are heterogeneous with each other, the wireless signal propagation path is changed, the CSI collected in the new scene reflects the new channel characteristics, and the CSI sample distribution in the new scene differs from that in the old scene, and the location labels are mutually exclusive, i.e., $D_{\text{train}} \cap D_{\text{test}} = \varnothing$, which is consistent with the actual situation of rapid deployment of fingerprint localization system across scenes.

3. Method

In this section, we present the proposed few-shot indoor fingerprint localization scheme in detail. Its core is to obtain the fingerprint similarity distribution relationship by propagating and aggregating different CSI fingerprint feature information through a few-shot learning graph neural network based on the distribution relationship to achieve fingerprint matching localization.

3.1. System Overview

The proposed DR-FSL framework is shown in Figure 3, and the overall framework of the scheme is an N-way K-shot few-shot learning model. First, the fingerprint samples from both the support set and the query set are fed into the feature extraction network, and the feature embeddings of all fingerprint samples are extracted as the features of the nodes through the convolutional backbone. The Fingerprint Graph(FG) is constructed based on all nodes and the inter-node similarity is calculated as a feature of the edges.

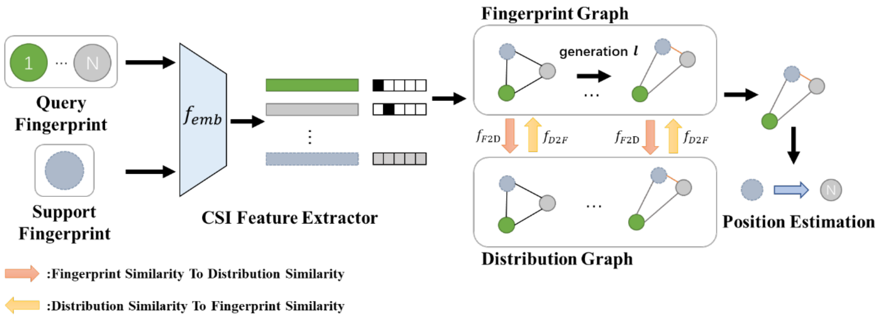

Figure 3: The overall framework of DR-FSL

Then we calculate the fingerprint sample similarity distribution features by Fingerprint Similarity To Distribution Similarity using node features and edge features, construct a fully connected graph Distribution Graph(DG) of distribution similarity as node features, and calculate the similarity between DG nodes as edge features to represent the similarity distribution relationship between fingerprint samples. Finally, the obtained edge features are passed through Distribution Similarity To Fingerprint Similarity algorithm to update the node features characterizing fingerprint information in FP. The above process is shown as arrows (f_{F2D}, f_{D2F}) in Figure 3. After repeating the process for iteration, propagating and aggregating the fingerprint sample features, the features of the nodes corresponding to the query set samples are input into the Position Estimation network to achieve fingerprint matching and localization. The specific algorithm and model information will be described in detail in the subsequent subsections.

3.2. CSI Feature Extractor

For a learning task T of N-way K-shot learning, the total number of CSI fingerprint samples is KN+1 in both the training and testing phases. The CSI fingerprint samples in the support set and query set are denoted by x_i,i=1,2,...,KN+1, and the true label of sample x_i is denoted by one-hot encoded vector y_i.If x_i belongs to the query set, then $y_i = \left[\frac{1}{N}, \frac{1}{N}, \cdots, \frac{1}{N}\right]^T$, to represent the uniform distribution of this sample in the label space. The CSI fingerprint sample consists of each subcarrier amplitude information, $x_i \in \mathbb{R}^{W \times H \times M}$, where W is the number of subcarriers contained in the CSI, H is the number of CSI packets composing the CSI fingerprint sample, and M is the number of wireless signal propagation links. The convolutional neural network f_{emb} is designed for CSI fingerprint samples to extract their features, and the network structure is shown in Figure 4.

Through the above network, we get$f_{emb}(x_i) \in \mathbb{R}^{d \times 1}$,spliced with y_i to get the initial features $v_{0,i}^F = \left[f_{emb}(x_i)^T, y_i^T\right]^T \in \mathbb{R}^{d_0 \times 1}$ of FG nodes, where $d_0 = d + N$.

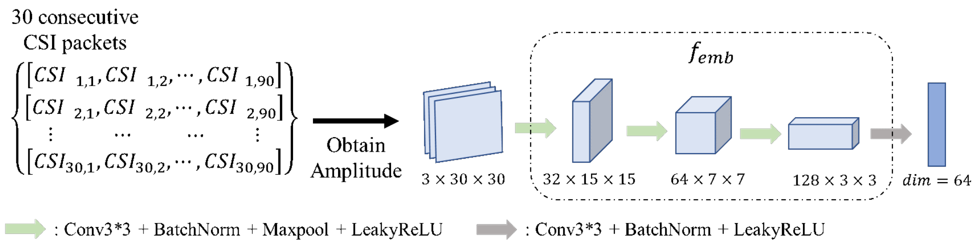

Figure 4: CSI feature extraction network, consisting of CSI feature map construction and CNN structure, with the output being a feature vector containing location information.

3.3. Fingerprint Similarity To Distribution Similarity

The features recorded at each edge in the FG represent the similarity of the fingerprint samples represented by the two nodes connected, and the initial stage is calculated as follows:

$$e_{0,ij}^{F} = f_{e^F}\left(\left|v_{0,i}^{F} - v_{0,j}^{F}\right|\right)$$

where $e_{0,ij}^{F} \in \mathbb{R}$,$|\cdot|$ denotes the absolute value and f_{e^F}:$\mathbb{R}^{d_0\times 1} \rightarrow \mathbb{R}$ is the encoding network that transforms the fingerprint sample similarity into certain dimensional features. f_{e^F} includes multiple fully connected layers as well as parameter settings θ_{e^F} and a sigmoid layer.

When the number of network iterations l>0, the existing node features $v_{l-1,i}^{F}$, $v_{l-1,j}^{F}$ and edge features $e_{l-1,ij}^{F}$ can be updated as follows:

$$e_{l,ij}^{F} = f_{e^F}\left(\left|v_{l-1,i}^{F} - v_{l-1,j}^{F}\right|\right) \cdot e_{l-1,ij}^{F}$$

In order to integrate the edge features in the FG graph from a global perspective, A normalization operation is conducted on all e_{ij}^{F} in E^F after computing the global fingerprint sample similarity in each iteration.

When the initialization or iterative update of the features of nodes and edges in FG is completed, the Distribution Graph (DG) $G^D = \left(V^D, E^D\right)$ is constructed using the similarity between the fingerprint sample features characterized by nodes and fingerprint samples characterized by edges. Where $V^D := \left\{v_i^D\right\}_{i=1,\cdots,K+N}$, $E^D := \left\{e_{ij}^D\right\}_{i,j=1,\cdots,K+N}$ denote the set of nodes and the set of edges of the FG, respectively. G^D integrates fingerprint samples' similarity to each other from G^F and transforms them into feature embeddings of fingerprint sample similarity distribution relationships as node information, aiming to increase sample feature differentiation by processing fingerprint sample similarity distribution level relationships to improve model localization capability. Each node $v_{l,i}^{D}$ in G^D is an N∗K dimensional feature vector representing the similarity distribution relationship of fingerprint samples (N∗K represents the number of support set samples in one learning task for few-shot learning), and the jth term of the vector represents the similarity between samples x_i and x_j, initialized as follows:

$$v_{0,i}^{D} = \begin{cases} \|_{j=1}^{NK}\alpha(i,j) & \text{if } x_i \text{ in } \mathcal{S} \\ \left[\frac{1}{NK}, \frac{1}{NK}, \ldots, \frac{1}{NK}\right] & \text{if } x_i \text{ in } Q \end{cases}$$

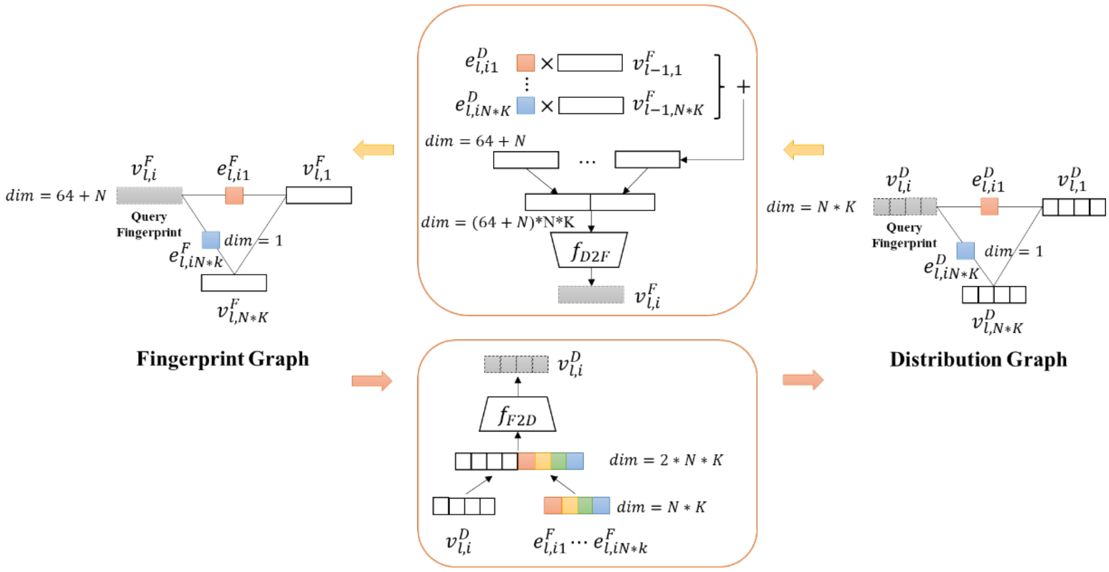

Figure 5: Details about Algorithm Fingerprint Similarity To Distribution Similarity and Algorithm Distribution Similarity To Fingerprint Similarity in DR-FSL.

where $v_{0,i}^{D} \in \mathbb{R}^{NK\times 1}$,$\|$ is the join operator that joins the results of multiple $\alpha(i,j)$ to form an N∗K array, $\mathcal{S}$ is the support set, and $\mathcal{Q}$ is the query set. $\alpha(i,j)$ is defined as follows:

$$\alpha(i,j) = \begin{cases} 1, & \text{if } y_i = y_j \\ 0, & \text{if } y_i \neq y_j \end{cases} \quad i,j = 1,\ldots,NK$$

where y_i , y_j are the location labels of fingerprint samples x_i , x_j .

For generations l>0 , the node feature $v_{l,i}^{D}$ in DG can be updated as:

$$v_{l,i}^{D} = f_{F2D}\left(\|_{j=1}^{NK} e_{l,ij}^{F}, v_{l-1,i}^{D}\right)$$

First, the fingerprint sample similarity information is integrated by connecting the features of N∗K edges associated with node $v_{l,i}^{F}$ in the FG graph, and then connecting them with the node features $v_{l-1,i}^{D}$ in the DG graph obtained from the previous iteration to form the cascade features. Finally, the feature transformation is realized by the aggregation network $f_{F2D} : \mathbb{R}^{2NK} \to \mathbb{R}^{NK}$ of fingerprint sample similarity distribution relationship, as shown in the F2D algorithm module in Figure 5. Where f_{F2D} consists of multiple fully connected layers and an activation function RELU with parameters set to θ_{F2D}.

3.4. Distribution Similarity To Fingerprint Similarity

The features recorded in each edge in DG represent the similarity relationship of the fingerprint sample similarity distribution represented by the two nodes connected, and the initial stage is calculated as follows:

$$e_{0,ij}^{D} = f_{e^D}\left(\left|v_{0,i}^{D} - v_{0,j}^{D}\right|\right)$$

where $e^{D}_{0,ij} \in \mathbb{R}$ and the fingerprint sample similarity distribution relationship encoding network f_{e^D}:$\mathbb{R}^{NK\times 1} \rightarrow \mathbb{R}$ consists of multiple fully connected layers and a sigmoid layer with parameters set to θ_{e^D}.When generations l>0, $e^{D}_{l-1,ij}$ can be updated as follows:

$$e^{D}_{l,ij} = f_{e^F}\left(\left|v^{D}_{l-1,i} - v^{D}_{l-1,j}\right|\right) \cdot e^{D}_{l-1,ij}$$

Similarly, in order to integrate the edge features in the DG graph from a global perspective, a regularization operation is also performed on all e^{D}_{ij} in E^{D} after each iteration.

Whenever the edge features $e^{D}_{l,ij}$ in the DG are updated iteratively, the fingerprint sample features are updated by aggregating $e^{D}_{l,ij}$ and all node features $v^{F}_{l,i}$ in the FG, and the similarity distribution relationship between each fingerprint sample flows back into the FG. As shown in the D2F algorithm module in Figure 5, it is calculated as shown below:

$$v^{F}_{l,i} = f_{D2F}\left(\sum_{j=1}^{NK+1}\left(e^{D}_{l,ij} \cdot v^{F}_{l-1,i}\right), v^{F}_{l-1,i}\right)$$

where $v^{F}_{l,i} \in \mathbb{R}^{d_0\times 1}$,$f_{D2F} : \mathbb{R}^{2d_0\times 1} \rightarrow \mathbb{R}^{d_0\times 1}$ is the fingerprint sample feature aggregation network of FG, which consists of multiple fully connected layers with parameters set to θ_{D2F}.

By aggregating the edge information in the DG and the node information in the FG, the distribution-level features of fingerprint sample similarity are integrated into the fingerprint sample FEASURE embeddings to improve the fingerprint sample feature differentiation and prepare for the next iteration to calculate the fingerprint sample similarity to each other.

3.5. Position Estimation

In this paper, the indoor localization task is defined as a multi-classification problem for fingerprint RPs, where the fingerprint samples in the query set are classified according to the edge features in the FG after the last round of iterations. Specifically, all the edge features $e^{F}_{l,ij}$ associated with the fingerprint samples x_i of the query set in the FG after the last iteration combined with the fingerprint sample category information are input into the softmax function, and the prediction of fingerprint reference points attributed to the fingerprint samples to be located is calculated by the following equation:

$$P\left(\hat{y}_i \mid x_i\right) = \operatorname{Softmax}\left(\sum_{j=1}^{NK} e^{F}_{l,ij} \cdot y_j\right)$$

where $P\left(\hat{y}_i \mid x_i\right)$denotes the probability distribution that the fingerprint sample with localization x_i is predicted to belong to the fingerprint reference point y_i, and y_j is the one-hot representation of the true label of the fingerprint reference point to which the jth fingerprint sample in the support set belongs. The position prediction of the fingerprint samples with localization is performed by the similarity between fingerprint samples stored by edge features.

In order to train the network model end-to-end in the offline phase, the fingerprint sample classification loss function and the fingerprint sample similarity distribution loss function are designed separately and weighted and summed as the total target loss function $\mathcal{L}_{\text{total}}$.

The fingerprint sample classification loss function uses cross-entropy and is expressed as:

$$\mathcal{L}_F = -\sum_i y_i \log\left(\hat{y}_i\right)$$

where y_i and $\hat{y}_i$ are the true labels and predictions of the query set samples x_i, respectively.

In order is to enhance the ability of the model to learn to distinguish the relationship between fingerprint sample similarity distributions, the fingerprint sample similarity distribution loss function is expressed as:

$$\mathcal{L}_D = -\sum_i y_i \log\left(\operatorname{Softmax}\left(\sum_{j=1}^{NK} e_{l,ij}^D \cdot y_j\right)\right)$$

where $e_{l,ij}^D$ is the edge feature in DG after the lth iteration, which represents the fingerprint sample similarity distribution relationship.

Ultimately, the total objective loss function is expressed as:

$$\mathcal{L}_{\text{total}} = \sum_{l=1}^{\bar{l}} \left(\gamma \mathcal{L}_F + \lambda \mathcal{L}_D\right)$$

where$\bar{l}$ denotes the total number of iterations in a training, γ and λ are the weights of the loss function to balance the importance of both, which are set to 0.9 and 0.1, respectively.

In the online phase, both the support set fingerprint samples and the query set fingerprint samples to be located are input, and the model will output the probability values of the query set fingerprint samples attributed to each RPs. To further obtain the accurate location estimation of the fingerprint samples, the RP locations with predicted probability top3 are selected and the final location prediction is obtained by the weighted mass center method as follows:

$$L = \frac{\sum_{i=1}^{3} P_i L_i}{\sum_{i=1}^{3} P_i}$$

where L is the final prediction coordinate, L_i and P_i correspond to the three maximum probability RP coordinates predicted by the model and the corresponding probability values, respectively.

4. Experiments

To verify the performance of our proposed DR-FSL, we collect CSI data in two heterogeneous real scenes at Beijing University of Posts and Telecommunications and design experiments to evaluate the cross-scene few-shot localization performance of the proposed scheme.

4.1. Experimental Environment and Datasets

We collect data in a complex lab and in an integrated office, respectively. These two scenarios are completely heterogeneous, and the experiments based on them can fully evaluate

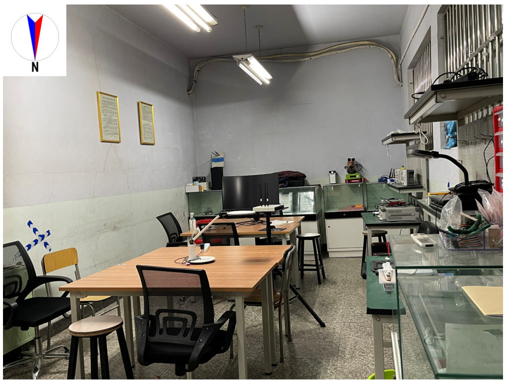

Figure 6: The real scene of the complex lab scene

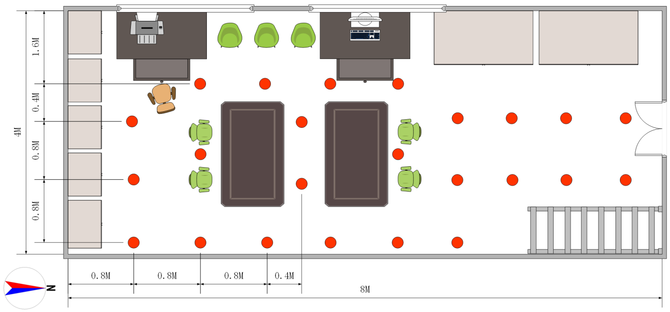

Figure 7: Layout of RPS in the complex lab scene

the cross-scene few-shot localization performance of the localization system. We collect CSI of Wi-Fi signals using a data acquisition device consisting of a transmitter and a receiver, both of which are industrial computers with built-in Intel 5300 wireless network cards. The transmitter uses one antenna and is deployed as a mobile terminal at different fingerprint points to continuously send packets at 20Mh bandwidth; the receiver uses three antennas and is deployed at a fixed location in a real scene to receive and store the corresponding packets.

The complex lab scene is located on the fifth floor of the main building of Beijing University of Posts and Telecommunications 523. the indoor environment consists of tables, chairs, display cabinets, computers and other experimental equipment, we deploy the receiver above the display cabinet about 1.5m high, near the wall in the corner of the scene; the transmitter is placed on a mobile platform about 1m high, as shown in Figure 6. The laboratory area is about 4m*8m, in which 24 fingerprint reference points are set, distributed as shown in Figure 7.

The integrated office scene is located at 906, the ninth floor of the research building of Beijing University of Posts and Telecommunications. the indoor environment consists of desks, chairs, lockers and other office equipment, we deploy the receiver on the wall at the corner of the scene, with a height of about 2m; the transmitter is placed on a platform about 1m high, as shown in Figure 8. The comprehensive office area is about 4.2m*13.2m, in which 24 fingerprint reference points are set, distributed as shown in Figure 9.

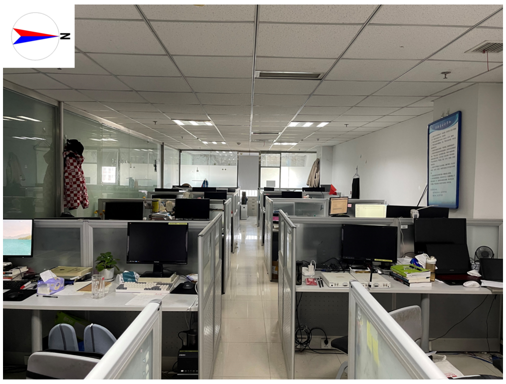

Figure 8: The real scene of the integrated office scene scene

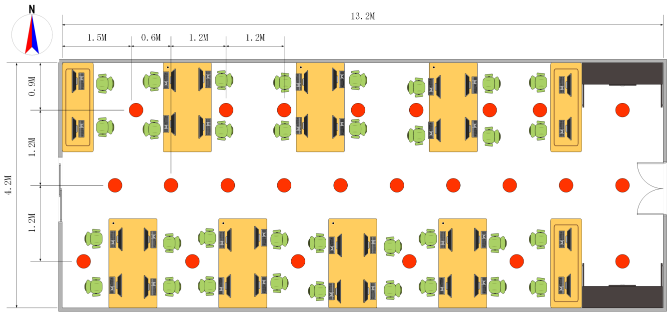

Figure 9: Layout of RPS in the integrated office scene

We collected data in the above complex lab scene and integrated office scene, respectively. 600 CSI samples are collected at each fingerprint reference point in both scenarios, and 9600 CSI samples are collected as fingerprint data in each scenario, each consisting of 30 consecutive CSI data packets. The laboratory scene and the office scene have completely different layouts, sizes, and fingerprint point distributions, which are heterogeneous scenes. The two CSI fingerprint data sets collected are completely mutually exclusive, which meets the a priori requirements for few-shot learning and is suitable for verifying the cross-scene few-shot localization performance of the proposed scheme.

4.2. Evaluation Metrics

In order to comprehensively analyze the cross-scene few-shot localization performance of the proposed scheme, we considered the following evaluation metrics in the evaluation process: fingerprint point classification accuracy, average localization error, standard deviation, and K-shot number setting. The fingerprint point classification accuracy reflects the accuracy of the proposed scheme in heterogeneous scenes using only a small number of samples, while the average localization error and standard deviation reflect the localization accuracy and stability of the fingerprint localization model, respectively.

For the fingerprint sample to be located i, the localization error is the distance between the predicted and actual coordinates and is calculated as shown below:

$$pos\_error_i = \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}$$

where (x_i, y_i) are the actual coordinates of the fingerprint sample i and $(\hat{x}_i, \hat{y}_i)$ are the predicted coordinates obtained from the localization model prediction. The average localization error and standard deviation of the model can be further obtained by calculating the localization error of all tested samples from the following equation:

$$mean = \frac{\sum_{i=1}^{N} pos\_error_i}{N}$$

$$std = \sqrt{\frac{\sum_{i=1}^{N} (pos\_error_i - mean)^2}{N}}$$

where N is the total number of test fingerprint samples.

4.3. Experimental Results and Analysis

To validate the cross-scene few-shot localization performance of DR-FSL, we designed two cases.

case 1: The integrated office scene is used as the training scenario for the DR-FSL model, and The complex lab scene is used as the test scenario for the model.

case 2: The complex lab scene is used as the training scene of the DR-FSL model, and the integrated office scene is used as the testing scene of the model.

For each case, all CSI data collected from each fingerprint reference point in the training scenario are used as the training dataset; CSI data collected from each fingerprint reference point in the test scenario are sampled according to the few-shot learning N-way K-shot setting and then used as the test dataset.

We compare the performance of CNN, GNN-based methods and the proposed model in the 24-way 1-shot, 24-way 5-shot, and 24-way 10-shot frameworks in two cases with setting few-shot support sets K = 1, 5, and 10.

Table 1 shows the localization performance of each scheme in case 1 when the fingerprint classification accuracy is used as the measure. The CNN scheme is a combination of the fingerprint feature extractor and output classification layer of size N described in 3.2, where we use N-way K-shot to refer to the scheme that uses only N∗K samples to train the CNN-based localization model. Table 2 shows the localization performance of each scheme in case 2 when the fingerprint classification accuracy is used as the measure.

As can be seen from Tables 1 and 2, first, the performance of the model based on the few-shot learning framework is significantly better than that of CNN. This illustrates the effectiveness of using fingerprint samples from different heterogeneous scenes for few-shot localization model training. The few-shot localization model can follow the N-way K-shot framework to sample the fingerprint samples from the training scenes several times, so that the model can learn abstraction from them and apply them to the few-shot localization task in the test scenes.Second, DR-FSL outperforms the GNN-based few-shot localization model, especially

Table 1
Localization performance (classification accuracy) under case 1

	24-way 1-shot	24-way 5-shot	24-way 10-shot
CNN	28.35%	56.25%	68.75%
Based_GNN	42.65%	66.50%	86.25%
DR-FSL（ours）	**48.45%**	**73.15%**	**91.35%**

Table 2
Localization performance (classification accuracy) under case 2

	24-way 1-shot	24-way 5-shot	24-way 10-shot
CNN	26.15%	53.50%	67.35%
Based_GNN	40.25%	61.15%	83.65%
DR-FSL（ours）	**48.50%**	**72.75%**	**90.45%**

Table 3
Localization performance in two cases (Mean and Std)

Case	Case 1		Case 2	
Model	Mean(m)	Std(m)	Mean(m)	Std(m)
CNN	1.67	1.57	2.13	2.42
Based_GNN	0.73	1.22	1.35	2.18
DR-FSL（ours）	**0.51**	**0.98**	**1.09**	**1.21**

in case 2 with higher performance improvement than case 1, especially in the case of very few shots.This is because in the integrated office scene, there are many obstacles, the wireless signal propagation between transmitter and receiver is severely affected by multipath effect, the CSI data samples have blurred characteristics, and the CSI of neighboring fingerprint reference points are easily confused. The GNN-based few-shot model only considers the similarity between fingerprint samples for localization, and the localization results are affected, while DR-FSL adds a fingerprint similarity distribution judgment layer while comparing the similarity between fingerprint samples, which mitigates the impact of CSI data samples of different fingerprint reference points being similar to each other on the model localization performance.

To further understand the localization accuracy and stability of the model, we counted the average localization error and standard deviation of the individual models in cases 1 and 2 under the 24-way 10-shot setting, respectively, as shown in Table 3. It can be seen that the localization accuracy and stability of DR-FSL are better than those of CNN and GNN-based few-shot localization models under the same N-way K-shot setting.

Figures 10 show the cumulative error distribution of each model in the 24-way 10-shot setting for the two cases 1 and 2, respectively, while we trained independent CNN localization models for the two cases that use a large amount of data (400 fingerprint samples per location).

As can be seen from the figure, the overall localization effect of DR-FSL model is better than

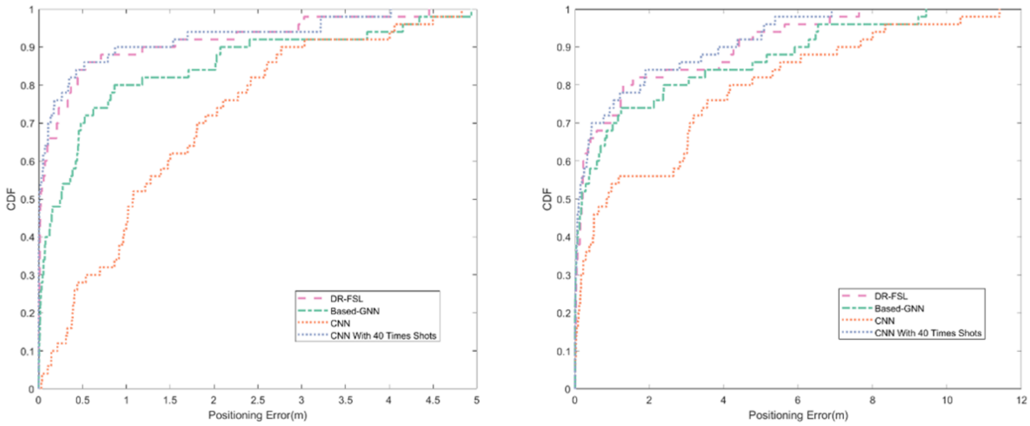

Figure 10: left: Comparison of CDFs with other models in case 1; right: Comparison of CDFs with other models in case 2

other few-shot localization models, with better stability and localization accuracy. In addition, DR-FSL achieves a performance close to that of CNN in cases 1 and 2 using a sample size of very few shots (40 times less). This confirms the superiority of the proposed method for cross-scene small-sample localization, which utilizes data collected in other heterogeneous scenes and applies the models learned in them to new scenes, thus simplifying the data collection and labeling effort required for fingerprint localization in new scenes.

5. Conclusion

To reduce the labor and time cost required to collect and label fingerprint data in new scenes, this paper proposes a few-shot indoor fingerprint localization model based on the distribution relationship, which learns abstraction from fingerprint data already collected and labeled in other heterogeneous environments and applies it to new scenes to achieve fingerprint localization. The location estimation is achieved by considering both the similarity of fingerprint samples and the similarity distribution relationship to distinguish the fingerprints to be located. As we have demonstrated in two heterogeneous scenes, the model has superior cross-scene small-sample localization capability. The average localization error is 0.51 m when the complex lab scene is used as the new scene, and 1.09 m when the integrated office scene is used as the new scene, and the localization performance of DR-FSL is comparable to that of the CNN-based fingerprint localization model when the amount of fingerprint data in the new scene is reduced by a factor of 40.

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