AF-DCGAN: Amplitude Feature Deep Convolutional GAN for Fingerprint Construction in Indoor Localization System

Qiyue LI, *Member, IEEE,* Heng QU, Zhi LIU, *Member, IEEE,* Nana ZHOU, Wei SUN, and Jie LI

Abstract—Wi-Fi positioning is currently the mainstream indoor positioning method, and the construction of fingerprint database is crucial to Wi-Fi based localization system. However, the accuracy requirement needs to sample enough data at many reference points, which consumes significant manpower and time. In this paper, we convert the CSI data collected at reference points into amplitude feature maps and then extend the fingerprint database using the proposed Amplitude Feature Deep Convolutional Generative Adversarial Network (AF-DCGAN) model. Using this model, the convergence process in the training phase can be accelerated, and the diversity of the CSI amplitude feature maps can be increased significantly. Based on the extended fingerprint database, the accuracy of indoor localization system can be improved with reduced human effort.

Index Terms—Wi-Fi positioning, Fingerprint database, Channel state information, Generative adversarial network, Amplitude feature.

✦

1 INTRODUCTION

W ITH the increasing demand for location services, indoor localization technology based on fingerprint recognition has become the prevailing positioning technology due to its high precision and minimal hardware requirements. Most of the indoor positioning systems are based on wireless local area networks (WLANS), which are available in public places [1], [2]. In addition to the high accuracy requirement, an indoor positioning system should also have low complexity and short additional processing time for mobile devices. Fingerprint-based indoor localization is an effective method to satisfy these requirements, where the received signal strength (RSS) or channel status information (CSI) from surrounding access points must be measured at each reference location to build a fingerprint database [3].

Fingerprinting-based localization consists of two basic phases: 1) the offline phase, which is also called the training phase, and 2) the online phase, which is also called the test phase [4]. The training phase is for database construction when survey data related to the reference points are collected and pre-processed. In the online phase, a mobile device records real-time data and tests it using the fingerprint database. The test output is then used to estimate the position of the mobile device by searching each training point to find the most closely matched spot as the target location.

Many existing indoor localization systems use RSS as fingerprints due to its simplicity and low hardware require-

ments. For example, the Horus system uses a probabilistic method for location estimation with RSS data [5]. However, RSS data has a high variability over time for a fixed location due to the multipath effects in indoor environments [6]. Such high variability can introduce significant localization error. Additionally, RSS values are coarse information, which does not exploit the many subcarriers in an orthogonal frequency-division multiplexing (OFDM) system for richer multipath information. In the widely used OFDM systems, CSI can provide more multipath information than RSS, with different signal strength and phases in different subcarriers. Some IEEE 802.11n standard commercial off the shelf network interface cards provide detailed sub-carrier amplitude and phase information in the form of CSI. Thus, the CSI based fingerprint localization methods and systems are now widely used to provide positioning services with high accuracy.

However, during the offline phase in a localization method, it is difficult to determine how much data is needed to obtain the desired accuracy. In the following section, it can be seen that the more fingerprint data sampled, the better the results. Thus, building a large enough fingerprint database is an important, but time-consuming task [3]. In our experiments, it takes more than half an hour to collect the fingerprint data at one reference point and it is very labor-intensive. This affects the popularity and application of fingerprinting-based localization algorithm.

To reduce the time cost, several methods have been proposed [3], [7], [8]. For example, the authors in [3] proposed a method based on compressive sensing for recovering absent fingerprints. It showed the hidden structure and redundancy characteristics of fingerprints in a merging matrix. In [7], the authors presented a semi-supervised manifold learning technique for building fingerprint database from partially labeled data, where only a small part of the signal strength measurements must be marked with the corre-

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sponding coordinates. However, these methods only reduce the number of reference points or try to recover fingerprints. At each reference point, these methods fail to increase the number of samples and still require a significant amount of time to collect data.

To expand the fingerprint database with reduced human effort, we present a method to increase the number of training data at each point based on Generative Adversarial Network (GAN). First, we transform CSI data collected at each reference point into amplitude feature maps. Then, through resolution transformation, each amplitude feature map is transformed into an image of the same pixel to construct the initial fingerprint database. Since the initial database is constructed by mapping the amplitude feature maps of the reference points, it contains the location information of all reference points. Then, we propose an Amplitude Feature Deep Convolutional Generative Adversarial Network (AF-DCGAN) model as well as the corresponding training algorithm to generate images similar to the original amplitude feature maps. Finally, the generated amplitude feature maps are merged into the initial fingerprint database to obtain an expanded one.

As listed in the following section, the localization accuracy will be improved as the number of samples in the fingerprint database increases. We also evaluated the proposed fingerprint construction method with extensive experiments in a typical indoor classroom environment. Experimental results show that with the increase of the number of amplitude feature maps generated by AF-DCGAN, the fingerprint database used has higher localization accuracy. The accuracy of the initial database reaches 1.34m, and the accuracy of expanded one reaches 1.18m. This shows that our method is effective.

The main contributions of the paper are enumerated herein.

1. We build a fingerprint database by converting processed CSI data into amplitude feature maps. This visualizes the position of the sampling points. It also allows us to visually determine the location of the testing points.

2. According to the nature of the amplitude feature maps, an AF-DCGAN model is proposed, which converges quickly and generates samples with improved diversity.

3. We use the AF-DCGAN model to generate more amplitude feature maps of the sampling point position. It saves a great deal of time collecting each single sample point as well as human cost.

The remainder of this paper is organized as follows. Section 2 reviews the related work. Section 3 briefly describes the basic idea of this paper. Section 4 introduces the CSI and amplitude feature maps conversion technique. Section 5 presents the method for increasing the amplitude feature maps based on AF-DCGAN, including the training algorithm and generating steps. Simulation and experiment results are shown in Section 6. Finally, Section 7 concludes the paper.

2　RELATED WORK

Wi-Fi positioning technology can be divided into two categories: positioning based on propagation models and positioning based on fingerprint database. Although the propagation model-based methods do not require any pre-processing, fingerprinting based positioning has higher accuracy [9], [10], [11], [12], [13], [14]. Therefore, the method of Wi-Fi indoor positioning based on fingerprint database is becoming more and more popular.

Although the method of building a fingerprint database for localization is very efficient, the construction of fingerprint database usually requires significant manpower and time to collect data. Many researchers have put forward solutions to this problem. In [3] and [15], a novel approach based on compressive sensing was presented for recovering absent fingerprints. It showed that with incomplete fingerprints, it could recover all of the fingerprint information with little error. Jun used a scan from any reference location as an input to adjust a large portion of the fingerprint maps to achieve extremely low overhead in fingerprint map construction and maintenance [16]. The method in [17] leveraged a more stable RSS gradient to build a gradient-based fingerprint map (Gmap) by comparing absolute RSS values at a nearby position. A novel technique for collecting fingerprints was proposed in [18], which detected Wi-Fi APs to form Wi-Fi fingerprints from the signals collected by Zig-Bee interfaces. In [19], ACMI was presented to construct the fingerprint database based on the pure estimation of indoor RSS distribution. These published work try to recover the fingerprints with the existing partial ones, which would decrease the localization accuracy while saving human effort.

The authors of [20] presented a system that automatically constructs accurate radio maps for device-free WLAN localization systems. The system generated deterministic and probabilistic radio maps for the positioning systems. Milioris [21] used the Matrix Completion framework to build complete training maps from part of the reference fingerprints by learning the relevant structure of the fingerprints. In [22], the authors proposed a new method to effectively establish and maintain a fingerprint database. This method only required that a person carried a specific device consisting of a radio frequency identification (RFID) reader and a Wi-Fi scanner to record the coordinates and Wi-Fi signal strength. Fingerprinting databases can be generated automatically as investigators are moving in designated areas for purposes other than fingerprinting. The authors of [23] proposed the Enriched Training Database (ETD). It is a web-service that enables the management and storage of training fingerprints, and it also has an additional enriching functionality. The user can automatically generate virtual fingerprints based on propagation modeling in the virtual training points by using the enriching functionality. They also proposed a new method of training fingerprinting locations that eliminates the burden of manually defining training points and covers areas that do not have enough density to train fingerprints. In [24], the authors proposed a novel method to construct a fingerprint database with full fingerprints by using the radio propagation model. For limitations of the indoor dynamic measurement, the authors in [25] proposed a GPR-based radio map construction. It uses realistic and virtual indoor dynamic measurement data.

However, most of these methods use modeling to reduce the number of reference points. The accuracy of localization system decreases dramatically when many reference points are omitted, if manpower consumption is saved. In this

paper, we try to sample data at all the reference points, and then generate more data with an amplitude feature DCGAN model, with which can effectively expand the number of fingerprint database. Thus, we obtain better positioning performance with the expanded fingerprint database, while manpower consumption is also saved.

3 BASIC IDEA

In a fingerprint-based indoor localization system, the more data contained in the fingerprint database, the higher its positioning accuracy and efficiency. First, we conduct experiments to show this property. We use different methods in a classroom for fingerprint database construction and localization experiments. The environment and floor plan are illustrated in Fig. 1. We deploy a TL-WR742N wireless router as the transmitter (which is named AP in the figure), equipped with one transmitting antenna, and a ThinkPad laptop with Inter Wireless Link 5300 NICs (IWL5300) as receivers (which is named MP in the figure), with three receiving antennas. We divide the classroom into 49 (7×7) sections and set the center of each section as the corresponding reference point.

At each reference point, we collect 800 samples and test several fingerprint database construction methods, proposed in [5], [26], [27] and [28], including the Horus method, Gaussian process regression (GPR) method, Low-Rank matrix fill (LR-M) method, and thin spline interpolation method (SPL-M) respectively. The Horus system requires all the reference points data, uses location-clustering techniques and reduces the computational requirements of the algorithm. The GPR method uses one-half of the reference points and infers the posterior received RSS mean and variance at other points to build a whole fingerprint database. The LR-M represents the distribution of RSS as a low-rank matrix and constructs the dense radio map from relative sparse measurements using a revised low-rank matrix completion method. The SPL-M explores the use of different interpolation functions to complete the fingerprint mapping required to achieve the sought accuracy. During the experiments, we use 200, 400 and 800 samples at each reference point to build three different sizes of fingerprint database. Then, we use a k-means clustering algorithm to perform positioning, and the results are shown in Fig. 2. The ordinate indicates the mean error of localization. Experiments show that, as the fingerprint database in each location of the sample data increases, the localization accuracy gradually increases. Larger training datasets achieve more satisfactory results than smaller ones.

Increasing the amount of sampled data for each reference point improves the localization accuracy. However, it requires tremendous manpower to sample a large amount of wireless fingerprint data. Inspired by unsupervised learning, we use generative adversarial network to generate more sample data for each reference point, to expand the fingerprint database and improve the accuracy of the localization system. In the following section, we convert the CSI data into amplitude feature maps and then extend the fingerprint database by the proposed AF-DCGAN model. With this model, the convergence process in the training phase accelerates, and the diversity of the generated CSI
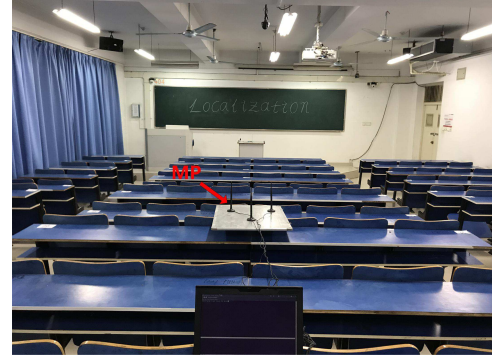
(a) The receiving antennas are placed behind the measurement area to cover all the experiment area.

(b) The router is placed in front of the measurement area.
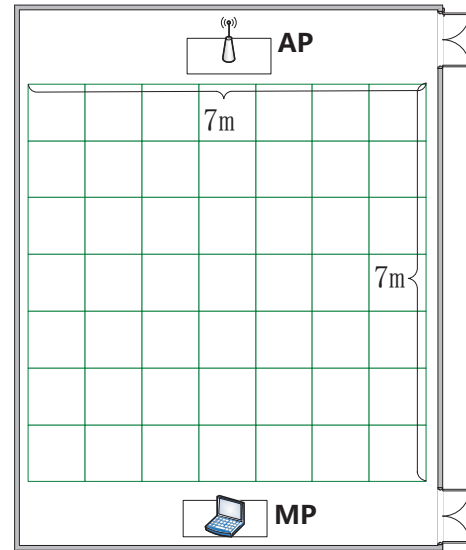
(c) Floorplan of the experiment area.

Fig. 1. The classroom experiment environment.

amplitude feature maps increases dramatically. Based on the extended fingerprint database, the accuracy of the indoor localization system can be improved with reduced human effort.

4 CSI COLLECTION AND FEATURE MAPS CONVERSION

CSI: In the field of wireless communication, CSI is the channel attribute of the communication link. It describes the
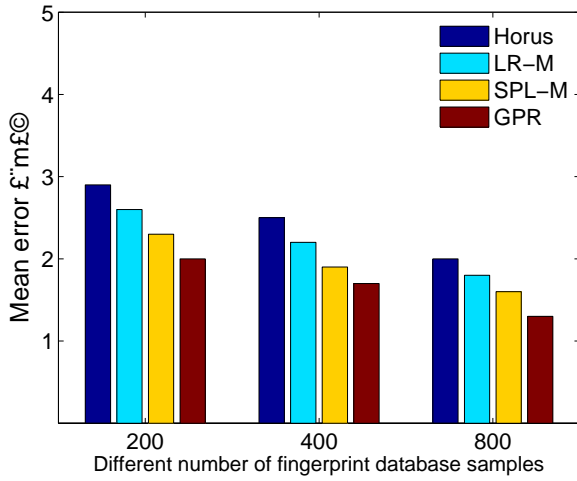
Fig. 2. Localization accuracy of different fingerprint database sizes. Through different localization methods, experiment results show that as the number of samples increases, the localization error gradually decreases.

signals attenuation factor on each transmission path. That is, the value of each element in the channel gain matrix H, such as signal scattering, multipath fading, shadowing fading, power decay of distance and other information. CSI allows the communication system to adapt to the current channel conditions. It provides high-reliability and high-speed communications in the multi-antenna system.

In the widely used OFDM system, CSI provides more multipath information than RSS, with different signal strength and phase in different subcarriers. Recently, some IEEE 802.11n standard commercial off the shelf network interface cards can provide detailed sub-carrier amplitude and phase information in the form of CSI. Specifically, with a ready-made Intel 5300 NIC and fine-tuned drivers, a sample version of CFR over Wi-Fi bandwidth can be obtained as CSI information which contains the number of transmitting antennas N_t, the number of receiving antennas N_r, the number of subcarriers N_S, packet transmission frequency f, and CSI matrix H [29], which is a imaginary number matrix as follows.

$$H = (H_{uv})_{N_t \times N_r} \qquad (1)$$

Each pair of transmitting-receiving antennas (a TX-RX pair) is a link, and H_{uv} is the CSI data of the link formed by TX u and RX v, containing information of N_S subcarriers.

$$H_{uv} = (h_1, h_2, \ldots, h_k, \ldots, h_{N_s})^T, \\ u \in [1, N_t], v \in [1, N_r], k \in [1, N_S] \qquad (2)$$

Each h_k characterizes the amplitude and phase of the corresponding subcarrier which can be expressed as $h_k = |h_k| e^{j \angle h_k}$, where $|h_k|$ denotes the amplitude response and $e^{j \angle h_k}$ denotes the phase response of subcarrier k. Because of unsynchronization and frequency shift between clock oscillators of the transmitter and receivers, it is hard to use the phases of CSI for localization. We only considered the amplitude responses for fingerprinting in this paper.

In a defined interior space as shown in Fig. 1, there is a clear difference in CSI data when people stand in different places. Fig. 3 shows the amplitude ($|h_k|$) of all

subcarriers in one link over time/packets when a person stands in two different positions in a classroom that are one meter apart. As seen in the figure, the amplitude of CSI varies significantly. Thus, we can use the characteristics of CSI amplitude changes to build a fingerprint database to perform indoor localization.
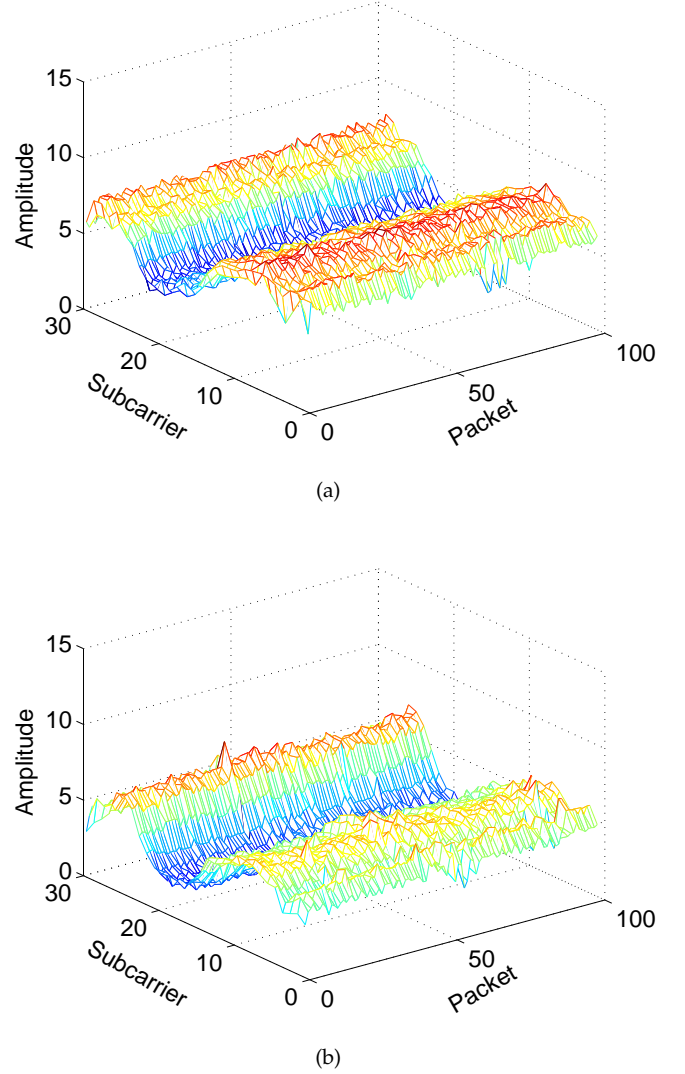

(a)

(b)

Fig. 3. There is a large change in CSI when people are in different places. (a) and (b) are two three-dimensional patterns of amplitude, subcarriers, and packets when the positions are separated by 1m.

4.1 CSI collection

First, we evenly divide the designated indoor space into M sampling spaces, and the center of the sampling space is used as a reference point to form an RP set as follows.

$$RP = [RP_1, RP_2, \cdots, RP_i, \cdots, RP_M] \qquad (3)$$

where RP_i denotes the reference point in the i-th ($i = 1, 2, \cdots, M$) square grid.

Assume N_{ap} wireless access points (wireless routers in IEEE 802.11) are deployed in the indoor space, with N_t antennas in each router. Then, each CSI sample has $N_{ap} \times N_t \times N_R \times N_S$ dimensions. During the collection stage,

N_X samples of CSI data are obtained with a fixed rate when people standing in the different reference points to form a time series set of the i-th reference point as follows.

$$CSI_i = \{csi^i_{1,N_X}, csi^i_{2,N_X}, \cdots, csi^i_{k,N_x}, \cdots, csi^i_{N_t \times N_r, N_X}\} \tag{4}$$

where csi^i_{k,N_x} denotes the N_X Wi-Fi signals of the k-th ($k = 1, 2, \cdots, N_t \times N_r$) link received by the k-th reference point. csi^i_{k,N_x} is a $N_X \times N_S$ two-dimensional imaginary number matrix.

4.2 Convert CSI to amplitude feature maps

The amplitude of CSI varies significantly in different positions which can be used to perform indoor localization. To obtain a fingerprint corresponding to a specific location, we represent the characteristics of a particular location by plotting the amplitude of the CSI as a feature map.

We randomly select 100 rows from N_X rows of the two-dimensional imaginary number matrix csi^i_{k,N_x} for n times to form n two-dimensional imaginary number matrices of $100 \times N_S$, to reconstruct the position information set at the i-th reference point CSI'_i as follows.

$$CSI'_i = \{csi'^{,i}_{1,n}, csi'^{,i}_{2,n}, \cdots, csi'^{,i}_{k,n}, \cdots, csi'^{,i}_{N_t \times N_r, n}\} \tag{5}$$

where $csi'^{,i}_{k,n}$ denotes n imaginary number matrices of $100 \times N_S$ of the k-th link at the i-th reference point RP_i.

The real parts and the imaginary parts of the imaginary number matrices in the reconstructed position information set CSI'_i are selected to make amplitude feature maps to obtain the amplitude feature maps set AFM_i of $N_t \times N_r$ links at RP_i. Further, a set of AFM of amplitude feature maps at M reference points can be obtained.

$$AFM_i = \{afm^i_{1,n} \cap afm^i_{2,n} \cap \cdots \cap afm^i_{k,n} \cap \cdots \cap afm^i_{N_t \times N_r, n}\} \tag{6}$$

$$AFM = \{AFM_1, AFM_2, \cdots, AFM_i, \cdots, AFM_M\} \tag{7}$$

where $afm^i_{k,n}$ denotes n amplitude feature maps of the k-th link at RP_i, and AFM_i denotes n amplitude feature maps of $N_t \times N_r$ links at RP_i. As shown in Fig. 4, amplitude feature maps of two positions in M reference points obtained through data processing are performed, so that the position information indicated by the CSI data could be visualized.

We transform the pictures in the AFM_i of RP_i into a picture with a resolution of 256×256. A training set of the i-th reference point can be obtained as follows. Then, we can get the initial fingerprint database AFM'.

$$AFM'_i = \{afm'^i_{1,n} \cap afm'^i_{2,n} \cap \cdots \cap afm'^i_{k,n} \cap \cdots \cap afm'^i_{N_t \times N_r, n}\} \tag{8}$$

$$AFM' = \{AFM'_1, AFM'_2, \cdots, AFM'_i, \cdots, AFM'_M\} \tag{9}$$

where $afm'^i_{k,n}$ denotes n amplitude feature maps of the k-th link at RP_i after the resolution transform, and AFM'_i denotes n amplitude feature maps of $N_t \times N_r$ links at RP_i.
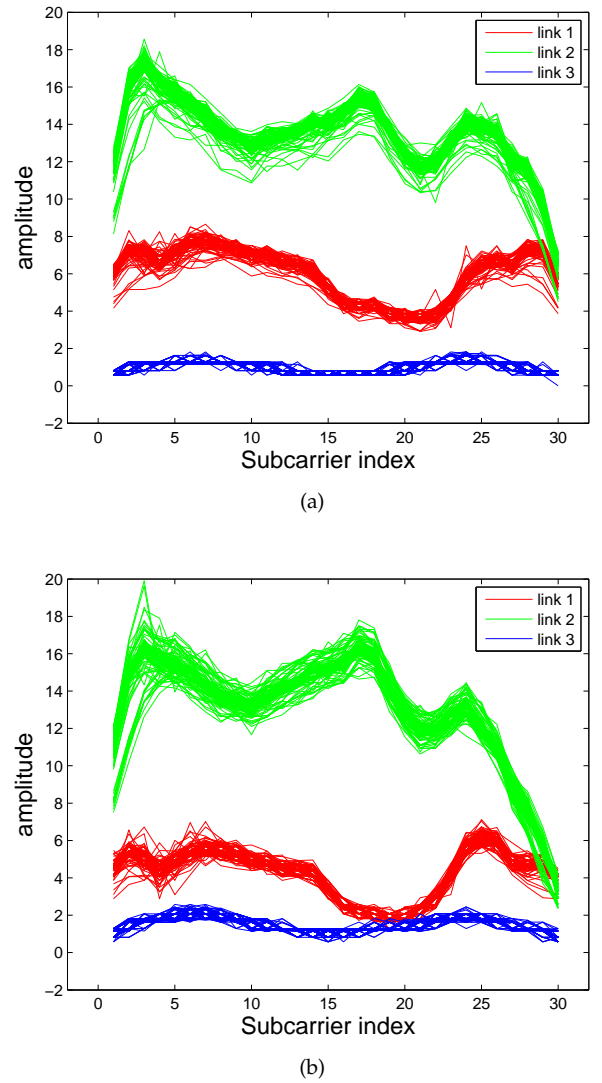

Fig. 4. Amplitude feature map samples. (a) and (b) are feature maps of two sampling points in M sampling points.

5 AF-DCGAN MODEL AND TRAINING METHOD

A more accurate localization result can be obtained with a larger fingerprint database as proven in Section 3. However, sampling CSI data at all reference points requires a significant time to measure. To reduce the sampling time and human effort, we use GAN to generate more amplitude feature maps for each reference point to expand the initial fingerprint database. In this way, we obtain more samples similar to the initial fingerprint database with reduced manpower, to expand the fingerprint database and improve localization accuracy.

5.1 AF-DCGAN model

GAN is inspired by the theory of a two-player game. The two players in the GAN model are the generative model (G) and discriminative model (D) [30]. G captures the distribution of sample data to generate a sample similar to the true training data with a noise obeying a certain distribution (uniform distribution, Gaussian distribution, etc.), and the best effect is as good as the real sample. D is a two kinds

classifier, which estimates the probability that one sample comes from the training data. If the sample comes from the real training data, D outputs a high probability. Otherwise, D outputs a small probability.

In the course of training, one side is fixed, and the network weights of the other side are updated and alternately iterated. During the training process, both sides attempt to optimize their network to form a rivalry until the two parties reach a dynamic balance (Nash Equilibrium). G restores the distribution of the training data, and creates the same sample as the real data. D cannot discriminate the result, with an accuracy of 50%, and it allows the discriminator and generator to reach Nash equilibrium. D and G play the following two-player minimax game with value function $V(D, G)$ as follows.

$$
\begin{aligned}
\min_G \max_D V(D, G) = & E_{x \sim P_{data}(x)}\{logD(x)\} + \\
& E_{z \sim P_z(z)}\{log(1 - D(G(z)))\}
\end{aligned}
$$
(10)

where $P_{data}(x)$ denotes the real sample set. z denotes the signal which has a uniform distribution. $P_z(z)$ denotes the fake sample set. $G(z)$ is the output of the generator, and $D(x)$ is the output of the discriminator.

Convolutional neural network performes well in all tasks of supervised learning but are rare in unsupervised learning. DCGAN [31] combines CNN in supervised learning with GAN in unsupervised learning. In this paper, we extend the fingerprint database by using DCGAN to generate more amplitude feature maps. DCGAN is a well-established GAN model, but in our application, it converges slowly when generating amplitude feature maps and the model falles into collapse mode during the training process. To resolve these problems, the AF-DCGAN model is proposed in the following section. With that model, the convergence process in the training phase is accelerated, and the diversity of generated CSI amplitude feature maps increase dramatically.

The model of AF-DCGAN is shown in Fig. 5a and Fig. 5b.

5.2 Training process

From WGAN [32], we know that GAN has some problems such as difficult training, loss of generators and discriminators, lack of diversity of training samples and generation of training samples. Therefore, generating a large number of CSI amplitude feature maps by GAN is not easy. We test the performance of WGAN and DCGAN, and the results are shown in Fig. 6.

When the traditional DCGAN is applied to expand the CSI fingerprint database, the diversity of the generated amplitude feature maps is poor and cannot yield any performance gain for the indoor localization system. Although WGAN reduces the difficulty of GAN training, it is difficult to converge in some settings, and the generated pictures are worse than DCGAN. When WGAN is used for our amplitude feature maps, the model collapses quickly during the training process, and the generated data seems to be random, which can be seen in Fig. 6b.

To solve these problems, we imitate part of WGAN to improve the diversity of the generated samples. We remove the sigmoid function from the last layer of the discriminator and return the fully connected layer directly. Next, we change the adaptive optimization algorithm from Adam to RMSProp to make our model stable for amplitude feature maps. The training process is shown in Algo. 1.

Algorithm 1 Training of AF-DCGAN Model

Require: AFM_i' from initial fingerprint database AFM'
Ensure: The amplitude feature maps set $GOAFM_i$ of the $N_t \times N_r$ links generated by the generator corresponding to RP_i;

1: Set the model training total batches s, the current batch t, the maximum number of iterations f, the current number of iterations z, the learning rate of change g. The i-th reference point is divided AFM_i' into s batches which are denoted as $DAFM$, and each batch has l amplitude feature maps;

2: Set $t = 1$, $z = 1$;

3: Taking the t-th batch of $DAFM_t$ containing l amplitude feature maps as real samples and l images generated by u-dimensional random vector z^t uniformly distributed as fake samples, they are respectively input to the discriminator D_1. Then, output an l-dimensional vector $D\_1\_logits_t$ and a l-dimensional vector $D\_1\_logits_{t\_}$, where $D\_1\_logits_t$ denotes the probability that the input sample comes from a real sample and $D\_1\_logits_{t\_}$ denotes the probability that the input sample comes from a fake sample.

4: Calculate averages for $D\_1\_logits_t$ and $D\_1\_logits_{t\_}$ respectively. Then, they are added to obtain the output error d_loss_t of the discriminator D_1;

5: The adaptive optimization algorithm $RMSProp$ is used to minimize the output error with the rate of change of the learning rate g, to update the parameters of the discriminator D_1;

6: Set $flag = 0$;

7: In the generator G, enter l uniformly distributed u-dimensional random vector z; then, output l feature maps with 256×256 resolution constitute a set of $GAFM_t$;

8: $GAFM_t$ is input to the discriminator D_2 to output a l-dimensional vector $D_2\_logits_t$;

9: Calculate the average for $D_2\_logits_t$ to obtain the g_loss_t of the discriminator D_2;

10: The adaptive optimization algorithm $RMSProp$ is used to minimize the output error with the rate of change of the learning rate g, to update the parameters of the generator G;

11: Let $flag = flag + 1$, if the $flag == 2$, go to 12; otherwise, go to 7;

12: Let $t = t + 1$, $z = z + 1$, if $(t == s)\&\&(z < f)$, go to 3, otherwise go to 13;

13: **Return** $GAFM$ as $GOAFM_i$

Enter AMF_i' sequentially into AF-DCGAN model to generate amplitude feature maps for all reference points, we can obtain the set of generated amplitude feature maps as follows.

$$
GOAMF = \{GOAMF_1, \cdots, GOAMF_i, \cdots, GOAMF_M\}
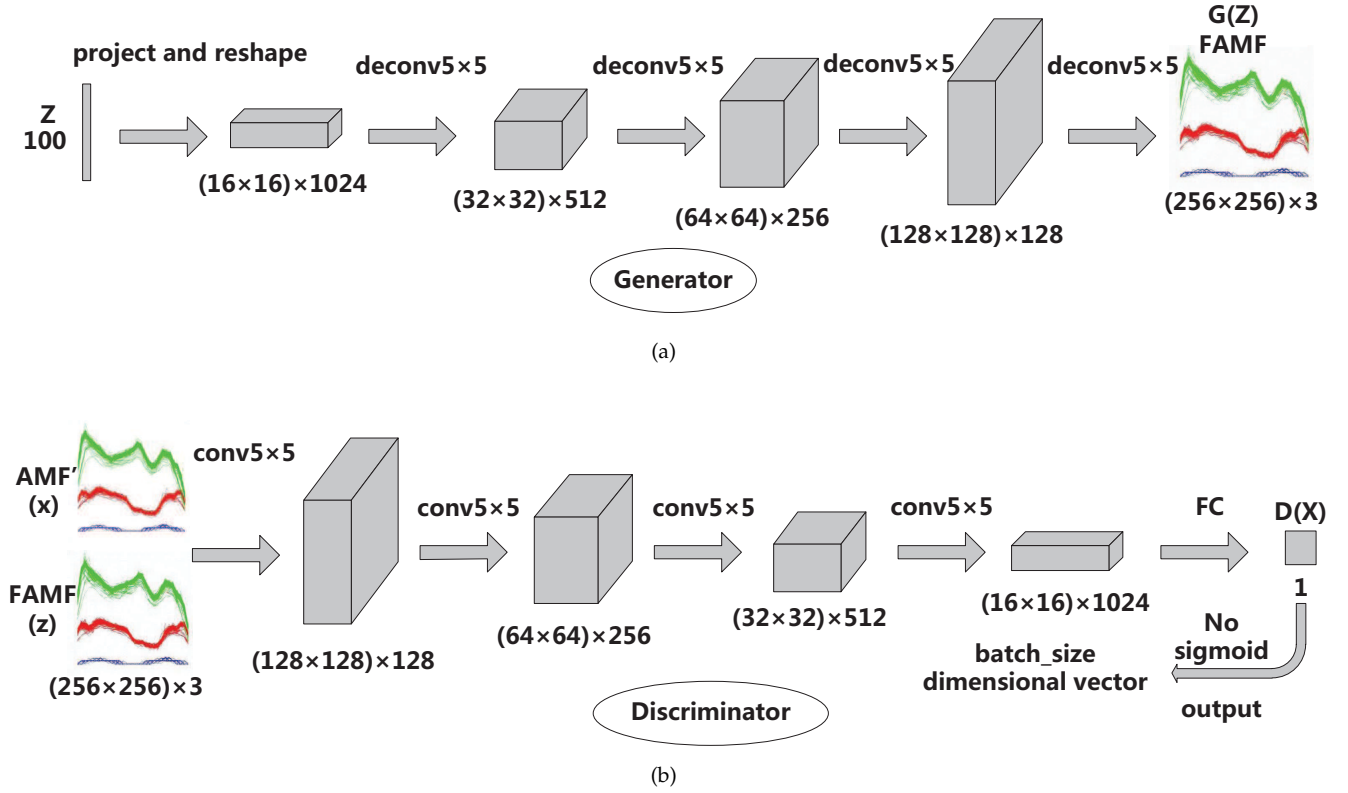$$
(11)

Fig. 5. Network structure of the AF-DCGAN model. (a) G, the generative model, implemented by a deconvolutional network; Z is the signal which observe uniform distribution; deconv represents the deconvolution layer in the CNN model; $FAMF$, feature maps generated by the deconvolutional layers in the generator. (b) Discriminative model, implemented by a convolutional network. AMF', feature maps from the training set; $FAMF$, the generated sample; $conv$ represents the convolution layer in the CNN model; $D(x)$ indicates the probability that the input sample was from the training set corresponding to x or $G(z)$ as the input; FC denotes the fully connected layers in the CNN models.

where $GOAMF_i$ denotes the amplitude feature maps of $N_t \times N_r$ links generated by AF-DCGAN model corresponding to RP_i. Some amplitude feature maps generated by a well-trained model is shown in Fig. 7.

So far, we use the AF-DCGAN to generate more amplitude feature maps, extending the initial fingerprint database and greatly reducing manual labor. And we can get an expanded fingerprint database $EAFM = \{AFM', GOAFM\}$.

6 EXPERIMENT VALIDATION

Experiments are conducted to evaluate the performance of the proposed fingerprint database extension method.
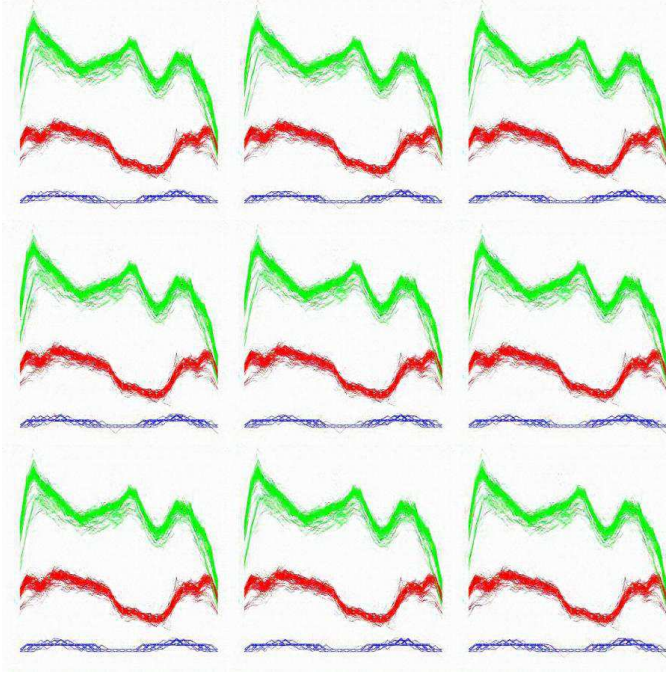
6.1 Experiment Methodology

The experiments are also conducted in the classroom, same as the environment listed in Fig. 1. The circumscribed rectangle of the classroom is taken as the indoor positioning $(7m \times 7m)$, which is evenly divided into 49 square grids. The center point of each square grid is used as a reference point to form a set of reference points. The distance between each reference point is one meter. The reason for choosing this distance is as follows. First, if the distance is too close, the receiving paths of the adjacent locations are very similar, and the features of the amplitude feature maps will resemble too, which will affect the localization accuracy. Second, if
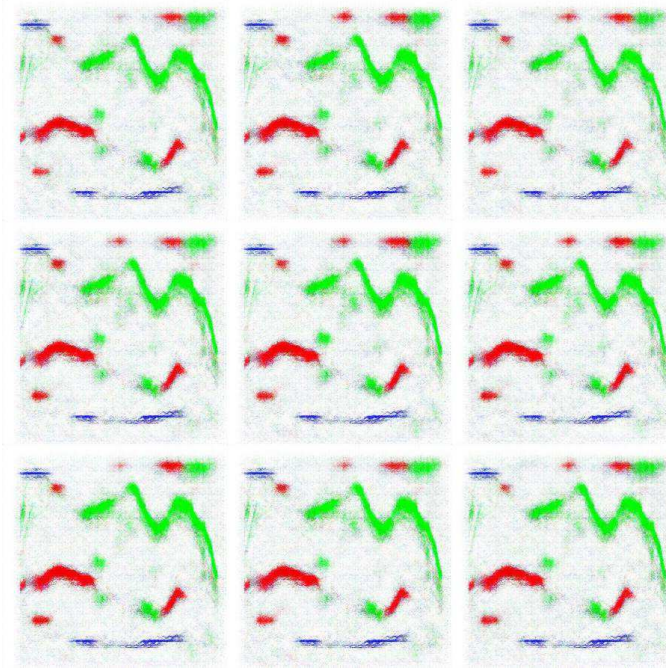
the distance is too far apart, the feature differences of the amplitude feature maps of adjacent locations will become larger, making certain features difficult to match, resulting in reduced localization accuracy.

In the classroom, we deploy a TL-WR742N wireless router as the transmitter, operating in IEEE 802.11n AP mode, equipped with one transmitting antenna, and a ThinkPad x201 laptop with Inter Wireless Link 5300 NICs (IWL5300) as receivers, with three receiving antennas. The Laptops operating system is Ubuntu 11.04, installed on a custom system kernel and modified network driver. The firmware and driver of IWL5300 are modified to export the CSI of each packet predictable IEEE 802.11 packet delivery from wireless channel measurements Linux 802.11n CSI Tool [33], containing information of all subcarriers. The router is placed in front of the measurement area. The receiving antennas are placed behind the measurement area to cover all the area. To collect CSI data, *Ping* commands are executed on the laptop every 0.4s to generate network traffic. The AF-DCGAN model is implemented on TensorFlow and accelerated by a GPU (GeForce GTX 1060).

During the experiments, we collect CSI data first, and after processing it into amplitude feature maps, we use AF-DCGAN to generate more fingerprint data. When transmitting CSI data between the transmitting antenna and the receiving antennas, the volunteers stand in turn at the reference point as shown in Fig. 8 as the green circles. At each

(a)

(b)

Fig. 6. CSI amplitude feature maps generated by GAN model. (a) Maps from DCGAN in the 100th epoch. (b) Maps from WGAN in the 10th epoch.
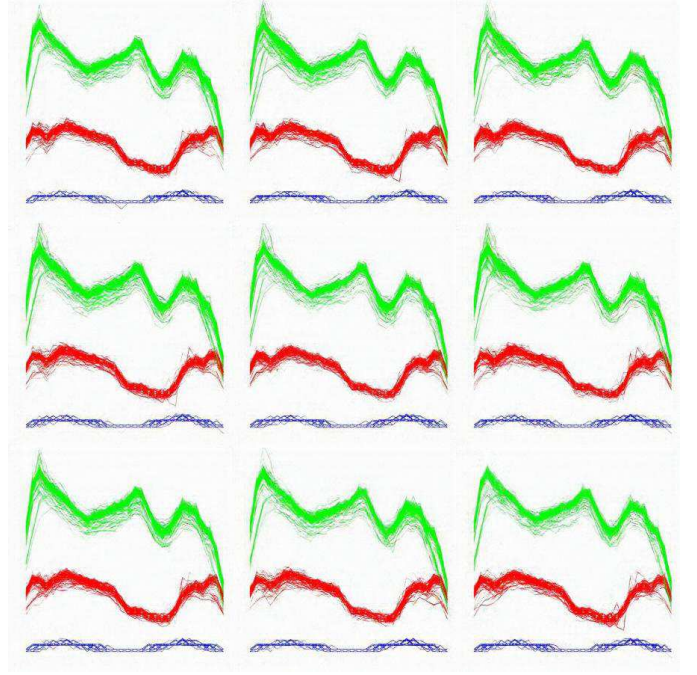

Fig. 7. CSI amplitude feature maps generated by the AF-DCGAN model. Maps from AF-DCGAN in the 60th epoch.

the initial database.

Then, we use SVM for localization experiment, which is a commonly used method in clustering and classification, and indoor localization systems. Compared to CNN, SVM is significantly easier to implement, train and its running time was shorter. We use SVM as a multi-class classification model, to determine to which reference points the test location should belong. During the experiments, we select 20 points in the experimental area as test points, which are different from the reference points, as the red stars show in Fig. 8. The data sampled in test point is processed in the same manner. Then, we put amplitude feature maps into the well-trained classification model for testing. Then we calculate the geometric center of the first four highest matching points as the localization results.

Finally, we verify the superiority of the extension fingerprint database by comparing the localization result of the initial fingerprint database and the fingerprint database expanded by AF-DCGAN. Additionally, our method is compared with existing database constructing methods, and we also compare our method with existing localization FIFS [34] and DeepFi [35] to prove that the method we proposed is competitive.

6.2 Localization performance

(1) Performance on different localization methods: We use SVM to estimate the position of test points. Fig. 9a shows the cumulative distribution function (CDF) of the localization error for the initial fingerprint database and the extended fingerprint database by AF-DCGAN. The red line represents the CDF curve that locates the test points using the initial fingerprint database, with an average error of 1.34m. For this original fingerprint database, the minimum error distance is 0.12m, and the maximum error distance is 2.68m.
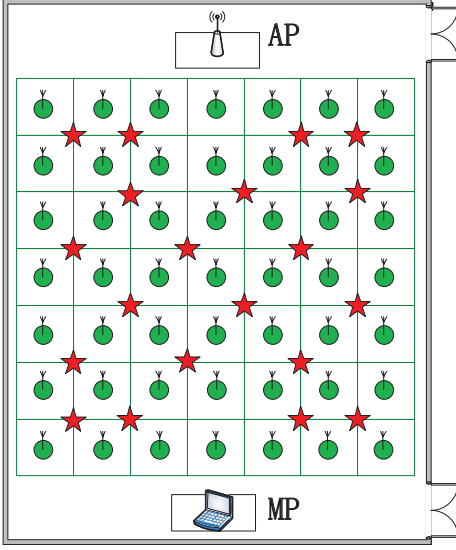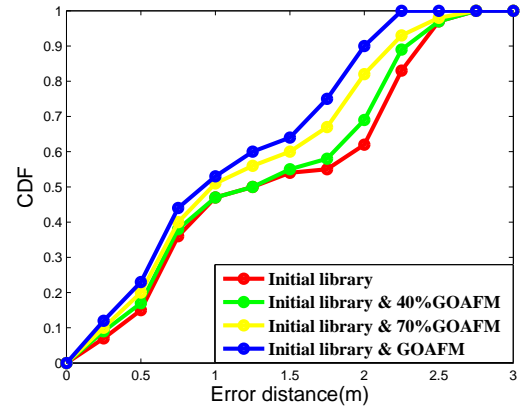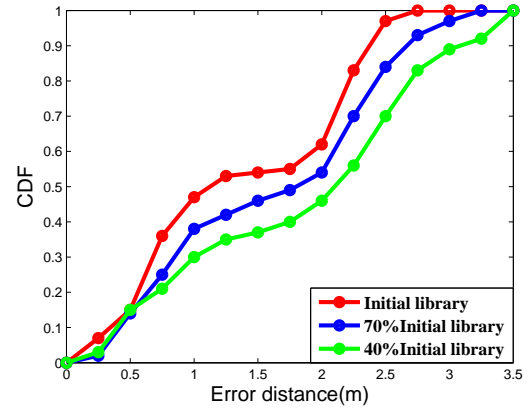
reference point, we collect 500 samples of CSI packets. There are three links and each link contains 30 subcarriers. Thus, each CSI sample had $1 \times 3 \times 30$ dimensions. For each sample point, we randomly selected 100 samples from 500 samples for 1000 times to draw the amplitude feature maps. After resolution transformation, the amplitude feature maps of the three links can be obtained to build the initial fingerprint database. Then, we use AF-DCGAN model to generate 1000 amplitude feature maps for each reference point to extend

Fig. 8. Layout of the classroom for training/test positions.

(a) Initial database.

(b) GOAFM.

(c) Initial database and GOAFM.

Fig. 9. As the number of samples increases, the localization accuracy of the fingerprints database increases.

The probability of error distance within 1m is 47%, within 2m 62%, within 3m 100%. The green line represents the CDF curve with 40% generated fingerprints of amplitude feature maps added in the initial database, and its average error is 1.31m. In this condition, the minimum error distance is 0.07m, and the maximum error distance is 2.63m. The probability of error distance within 1m is 48%, within 2m 70%, within 3m 100%. The yellow line represents the CDF curve that locates the test points using the fingerprint database which add 70% generated fingerprints for each reference point, with an average error of 1.23m. For this fingerprint database, the minimum error distance is 0.09m, and the maximum error distance is 2.61m. The probability of error distance within 1m is 51%, within 2m 82%, within 3m 100%. The blue line represents the CDF curve with 100% generated fingerprints of amplitude feature maps added in the initial database, and its average error is 1.18m. In this condition, the minimum error distance is 0.04m, and the maximum error distance is 2.23m. The probability of error distance within 1m is 53%, within 2m 90%, within 3m 100%. The localization results are shown in Table 1 and 2. Accuracy represents the mean error distance. Shown in Fig. 9b, compared with the initial fingerprint database, the extended database can provide higher positioning accuracy. After adding the generated amplitude feature maps to the initial database, the accuracy of localization improves as shown in Fig. 9a. After adding 40% GOAFM in the initial database, the accuracy was 1.31m, which improved by 2.23%. Adding 70% GOAFM in the initial database, the accuracy is 1.2m, which improves by 8.21%, and after all GOAFM are added, the accuracy is 1.18m, which improves by 11.94%. It illustrates the validity of the database we generate over AF-DCGAN model. We can use AF-DCGAN to augment the database without human labor while improving localization accuracy.
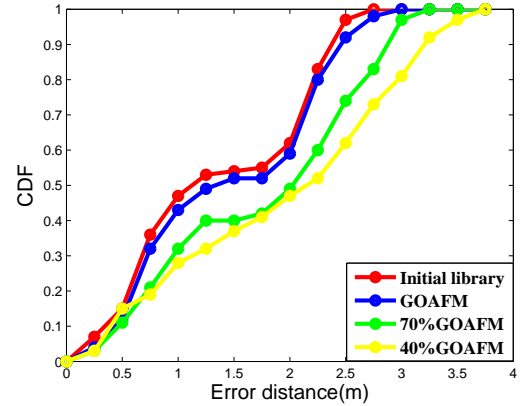
We also evaluate the localization performance based on our fingerprint database, by comparing it with existing methods of localization, FIFS and DeepFi. We conduct these three experiments in the classroom environment as illus-trated in Fig. 1. The results show that our method is superior to FIFS and DeepFi as shown in Fig. 10a and Fig. 10b, TABLE 1 and 2. It can be seen that the localization accuracy slightly improves by 3.6% when we use the initial database for positioning, as the database construction method are almost the same in FIFS and DeepFi. When we add GOAFM to the initial database, the localization accuracy improves by 12.95%, which means localization accuracy significantly improves while no additional manpower consumed to collect

more CSI data.

(a) Initial database with FIFS and DeepFi.

(b) Initial database and GOAFM with FIFS and DeepFi.

Fig. 10. Comparison with the other localization methods.
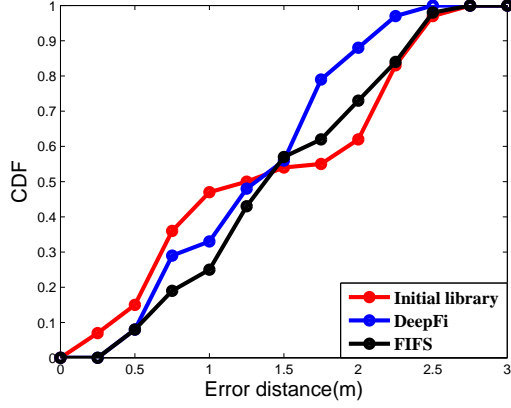

(a) Initial database.

(b) GOAFM.
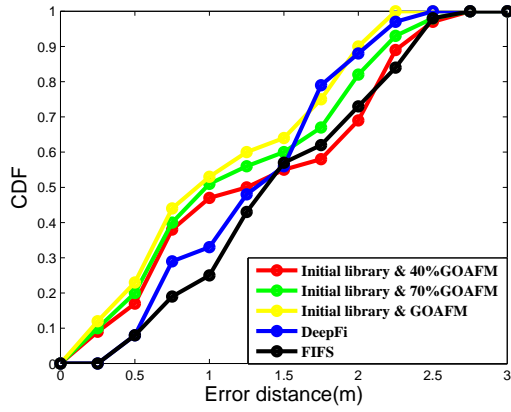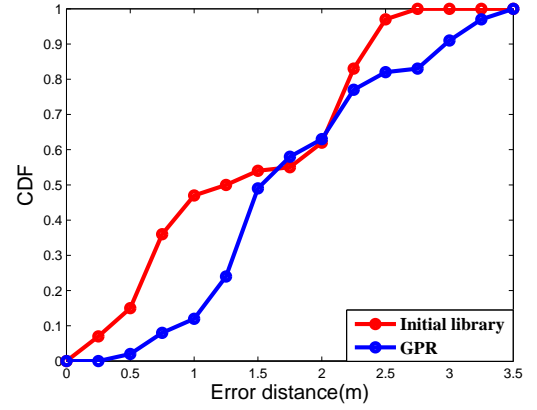
Fig. 11. As the number of samples increases, the localization accuracy of the fingerprints database increases.

TABLE 1
Localization Accuracy of Different Localization Methods

Method	Min.	Max.	Mean
Initial library	0.12m	2.68m	1.34m
Initial library and 40% GOAFM	0.07m	2.63m	1.31m
Initial library and 70% GOAFM	0.09m	2.61m	1.23m
Initial library and GOAFM	0.04m	2.23m	1.18m
FIFS	0.27m	2.71m	1.39m
DeepFI	0.29m	2.47m	1.22m

TABLE 2
Localization Range Probability of Different Localization Methods

Method	1m	2m	3m
Initial library	47%	62%	100%
Initial library and 40% GOAFM	48%	70%	100%
Initial library and 70% GOAFM	51%	82%	100%
Initial library and GOAFM	53%	90%	100%
FIFS	23%	73%	100%
DeepFI	33%	88%	100%

(2) Performance on different database construction methods: In this subsection, we evaluate the performance of our fingerprint database based on AF-DCGAN, by comparing it with existing GPR method for building fingerprint database. We conduct two experiments in the classroom using the

same dataset. With GPR construction method, we select four of the 30 carriers that were more accurate. Then, we determined the geometric center of these four models positioning results as the final positioning results. The results showed that our method of building a fingerprint database is superior to GPR as shown in Fig. 11a, Fig. 11b, TABLE 3 and 4. It can be seen that localization accuracy was improved by 23.42%. When we added all of the GOAMF to the initial database, the localization accuracy improved by 32.57%. Localization accuracy significantly improved without more manpower to collect CSI data.

TABLE 3
Localization Accuracy of Different Database Construction Methods

Method	Min.	Max.	Mean
Initial library and 40% GOAFM	0.07m	2.63m	1.31m
Initial library and 70% GOAFM	0.09m	2.61m	1.23m
Initial library and GOAFM	0.04m	2.23m	1.18m
GPR	0.34m	3.34m	1.75m

7 CONCLUSION

In this paper, a novel approach is proposed to construct the Wi-Fi fingerprints database with high efficiency and reduced human effort. The CSI data collected at reference

TABLE 4
Localization Range Probability of Different Database Construction Methods

Method	1m	2m	3m
Initial library and 40% GOAFM	48%	70%	100%
Initial library and 70% GOAFM	51%	82%	100%
Initial library and GOAFM	53%	90%	100%
GPR	24%	63%	83%

points is converted into amplitude feature maps and then used to extend the fingerprint database using the proposed AF-DCGAN, a improved generative adversarial network model which converges quickly and generated CSI data with more diversity. By using the AF-DCGAN model, more amplitude feature maps that are similar to the reference database are generated, which effectively increase the number of samples in the training set. We conduct exhaustive experiments to demonstrate the performance of the proposed method, and the results show the superiority of AF-DCGAN over the existing methods of building fingerprint database and localization methods.

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REFERENCES

[1] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1067–1080, Nov 2007.

[2] J. K. Y. Ng, K. Y. Lam, Q. Cheng, and K. C. Y. Shum, "An effective signal strength-based wireless location estimation system for tracking indoor mobile users," *Journal of Computer and System Sciences*, vol. 79, p. 10051016, 11 2013.

[3] Z. Gu, Z. Chen, Y. Zhang, Y. Zhu, M. L, and A. Chen, "Reducing fingerprint collection for indoor localization," *Computer Communications*, vol. 83, 09 2015.

[4] Q. Li, B. Chu, Z. Wu, W. Sun, L. Chen, J. Li, and Z. Liu, "Rmds: Ranging and multidimensional scalingbased anchor-free localization in large-scale wireless sensor networks with coverage holes," *International Journal of Distributed Sensor Networks*, vol. 13, p. 155014771772465, 08 2017.

[5] M. Youssef and A. Agrawala, "The horus wlan location determination system," in *Proceedings of the 3rd International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '05. New York, NY, USA: ACM, 2005, pp. 205–218.

[6] W. Sun, X. Yuan, J. Wang, Q. Li, L. Chen, and D. Mu, "End-to-end data delivery reliability model for estimating and optimizing the link quality of industrial wsns," *IEEE Transactions on Automation Science and Engineering*, vol. PP, no. 99, pp. 1–11, 2017.

[7] T. Pulkkinen, T. Roos, and P. Myllymäki, "Semi-supervised learning for wlan positioning," in *Proceedings of the 21th International Conference on Artificial Neural Networks - Volume Part I*, ser. ICANN'11. Berlin, Heidelberg: Springer-Verlag, 2011, pp. 355–362.

[8] S. Liu, H. Luo, and S. Zou, "A low-cost and accurate indoor localization algorithm using label propagation based semi-supervised learning," in *2009 Fifth International Conference on Mobile Ad-hoc and Sensor Networks*, Dec 2009, pp. 108–111.

[9] S. He, S. H. G. Chan, L. Yu, and N. Liu, "Fusing noisy fingerprints with distance bounds for indoor localization," in *2015 IEEE Conference on Computer Communications (INFOCOM)*, April 2015, pp. 2506–2514.

[10] Y. Chen, J. Liu, D. Lymberopoulos, and B. Priyantha, "Fm-based indoor localization." ACM International Conference in Mobile Systems, Applications, and Services (MobiSys), June 2012.

[11] Z. Xiao, H. Wen, A. Markham, and N. Trigoni, "Lightweight map matching for indoor localisation using conditional random fields," in *Proceedings of the 13th International Symposium on Information Processing in Sensor Networks*, ser. IPSN '14. Piscataway, NJ, USA: IEEE Press, 2014, pp. 131–142.

[12] P. Zhang, Q. Zhao, Y. Li, X. Niu, Y. Zhuang, and J. Liu, "Collaborative wifi fingerprinting using sensor-based navigation on smartphones," *Sensors*, vol. 2015, pp. 17 534–17 557, 07 2015.

[13] Q. Li, H. Fan, W. Sun, J. Li, L. Chen, and Z. Liu, "Fingerprints in the air: Unique identification of wireless devices using rf rss fingerprints," *IEEE Sensors Journal*, vol. 17, no. 11, pp. 3568–3579, June 2017.

[14] Q. Li, W. Li, W. Sun, J. Li, and Z. Liu, "Fingerprint and assistant nodes based wi-fi localization in complex indoor environment," *IEEE Access*, vol. 4, pp. 2993–3004, 2016.

[15] Y. Zhang, Y. Zhu, M. Lu, and A. Chen, "Using compressive sensing to reduce fingerprint collection for indoor localization," in *2013 IEEE Wireless Communications and Networking Conference (WCNC)*, April 2013, pp. 4540–4545.

[16] J. Jun, L. He, Y. Gu, W. Jiang, G. Kushwaha, V. A, L. Cheng, C. Liu, and T. Zhu, "Low-overhead wifi fingerprinting," *IEEE Transactions on Mobile Computing*, vol. PP, no. 99, pp. 1–1, 2017.

[17] Y. Shu, Y. Huang, J. Zhang, P. Cou, P. Cheng, J. Chen, and K. G. Shin, "Gradient-based fingerprinting for indoor localization and tracking," *IEEE Transactions on Industrial Electronics*, vol. 63, no. 4, pp. 2424–2433, April 2016.

[18] J. Niu, B. Wang, L. Shu, T. Q. Duong, and Y. Chen, "Zil: An energy-efficient indoor localization system using zigbee radio to detect wifi fingerprints," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 7, pp. 1431–1442, July 2015.

[19] S. Yoon, K. Lee, Y. Yun, and I. Rhee, "Acmi: Fm-based indoor localization via autonomous fingerprinting," *IEEE Transactions on Mobile Computing*, vol. 15, no. 6, pp. 1318–1332, June 2016.

[20] A. Eleryan, M. Elsabagh, and M. Youssef, "Synthetic generation of radio maps for device-free passive localization," in *2011 IEEE Global Telecommunications Conference - GLOBECOM 2011*, Dec 2011, pp. 1–5.

[21] D. Milioris, M. Bradonji, and P. Mhlethaler, "Building complete training maps for indoor location estimation," in *2015 IEEE Conference on Computer Communications Workshops (INFOCOM WK-SHPS)*, April 2015, pp. 75–76.

[22] M. Gunawan, B. Li, T. Gallagher, A. G. Dempster, and G. Retscher, "A new method to generate and maintain a wifi fingerprinting database automatically by using rfid," in *2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, Nov 2012, pp. 1–6.

[23] F. Lemic, V. Handziski, G. Caso, L. D. Nardis, and A. Wolisz, "Enriched training database for improving the wifi rssi-based indoor fingerprinting performance," in *2016 13th IEEE Annual Consumer Communications Networking Conference (CCNC)*, Jan 2016, pp. 875–881.

[24] C. He, S. Guo, Y. Wu, and Y. Yang, "A novel radio map construction method to reduce collection effort for indoor localization," *Measurement*, vol. 94, 08 2016.

[25] Y. Cho, J. Kim, M. Ji, Y. Lee, and S. Park, "Gpr based wi-fi radio map construction from real/virtual indoor dynamic surveying data," in *2013 13th International Conference on Control, Automation and Systems (ICCAS 2013)*, Oct 2013, pp. 712–714.

[26] S. Kumar, R. M. Hegde, and N. Trigoni, "Gaussian process regression for fingerprinting based localization," *Ad Hoc Networks*, vol. 51, pp. 1 – 10, 2016.

[27] H. Hu, W. Zhou, Z. Wen, Y. Sun, and B. Yin, "Efficient radio map construction based on low-rank approximation for indoor positioning," *Mathematical Problems in Engineering*, vol. 2013, no. 1, pp. 1–9, 2013.

[28] S. Ezpeleta, J. M. Claver, J. J. Perez-Solano, and J. V. Mart, "Rf-based location using interpolation functions to reduce fingerprint mapping," vol. 15, p. 27322, 10 2015.

[29] R. Zhou, X. Lu, P. Zhao, and J. Chen, "Device-free presence detection and localization with svm and csi fingerprinting," *IEEE Sensors Journal*, vol. 17, no. 23, pp. 7990–7999, Dec 2017.

[30] l. Goodfellow, J. Pouget-Abadie, M. Mirza, B. B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence,

and K. Q. Weinberger, Eds. Curran Associates, Inc., 2014, pp. 2672–2680.

[31] A. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," 11 2015.

[32] M. Arjovsky, S. Chintala, and L. Bottou, "Wasserstein GAN," *CoRR*, vol. abs/1701.07875, 2017. [Online]. Available: http://arxiv.org/abs/1701.07875

[33] D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Tool release: Gathering 802.11n traces with channel state information," *ACM SIGCOMM CCR*, vol. 41, no. 1, p. 53, Jan. 2011.

[34] J. Xiao, K. Wu, Y. Yi, and L. M. Ni, "Fifs: Fine-grained indoor fingerprinting system," in *2012 21st International Conference on Computer Communications and Networks (ICCCN)*, July 2012, pp. 1–7.

[35] X. Wang, L. Gao, S. Mao, and S. Pandey, "Deepfi: Deep learning for indoor fingerprinting using channel state information," in *2015 IEEE Wireless Communications and Networking Conference (WCNC)*, March 2015, pp. 1666–1671.