LC-DNN: Local Connection Based Deep Neural Network for Indoor Localization With CSI

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ABSTRACT With the increasing demand of location-based services, channel state information (CSI) has attracted great interest because of the fine-grained information it provides. In this paper, we propose an original network structure, which exploits both the local information and global information in CSI amplitude for fingerprint localization. First, we validate the correlation between adjacent subcarriers and introduce the position-dependent local feature (PDL-feature). Next, local connection based deep neural network (LC-DNN) is designed to improve positioning performance by extracting and exploiting the correlation between adjacent subcarriers for indoor localization. LC-DNN consists of locally-connected layer and fully-connected layer. In the locally-connected layer, the variation of CSI amplitude in local frequency range is extracted and spliced for rich information. The frequency range and the times of extraction are determined by receptive field length and step size respectively. In the fully-connected layer, not only global features of CSI amplitude are further extracted, but also the function between features and position coordinates is obtained. Experiments are conducted to validate the effectiveness of LC-DNN and investigate the influence of hyper parameters on localization. Moreover, the positioning performance of LC-DNN is compared with four methods based on deep neural networks (DNNs). Results show that LC-DNN performs well in positioning accuracy and stability, with the mean error of 0.78m.

INDEX TERMS Indoor localization, deep neural network (DNN), position-dependent local feature (PDL-feature), local connection, channel state information (CSI).

I. INTRODUCTION

With the proliferation of mobile devices, location-based services (LBS) have become an important part of people’s lives. Global navigation satellite systems (GNSS) provide good quality for outdoor positioning. Indoor localization is still a challenge because of the complex indoor environment, including shadow fading, multipath effect and delay distortion [1], [2]. Various methods have been applied to achieve high-precision indoor positioning [3], [4]. For example, Team YAI uses the GPS data to determine the correct building, the Wi-Fi data to determine the floor differences and data from Wi-Fi, Accelerometer and Magnetometer to determine the coordinates in a shopping mall [3]. The HFTS team combines PDR/Wi-Fi algorithms and employs GNSS, Wi-Fi, accelerometer, compass, and gyroscope data for indoor positioning [3]. Team mCLIPS adopts an empirical approach, only based on Wi-Fi, for indoor positioning [4]. Among various methods, Wi-Fi fingerprinting is widely used in indoor localization due to the widespread deployment of Wi-Fi infrastructures. It usually consists of two basic phases: the offline phase and the online phase [5], [6]. In the offline phase, a database is constructed with the raw or pre-processed Wi-Fi data which are collected from different access points (APs) at many reference points (RPs). In the online phase, the position of a target device is estimated by matching the newly received Wi-Fi data with the database.

The received signal strength (RSS) was widely used as fingerprints due to its simplicity and low hardware requirements [6]–[8]. For example, the Radar system estimates the location by measuring the similarity between RSS of the target device and the RPs using Euclidean distance [6]. However, RSS based fingerprinting has two drawbacks. First, RSS values have a high variability at a fixed position in a period of time due to the complex indoor propagation environment. Second, RSS values provide coarse information,
which is limited in characterizing multi-path channels from different antennas and different subcarriers. Therefore, the accuracy of RSS-based localization is usually 1-3m, which is difficult to be improved further [9]. Channel state information (CSI) represents fine-grained channel information, including subcarrier-level channel measurements in orthogonal frequency division multiplexing (OFDM) systems. Besides, CSI is more stable than RSS for a given location, which provides more accuracy information. Nowadays, CSI is available from some Wi-Fi network interface cards (NICs) and is used as the fingerprint to improve the localization performances [10], [11].

Machine learning (ML) is an effective technique for feature extraction and fingerprint matching [12]–[26]. In CSI-based fingerprinting, it could improve the positioning accuracy, enhance the robustness and reduce the computation complexity. ML methods are further classified into traditional ML and deep learning [11]. Traditional ML algorithms, such as K Nearest Neighbor (KNN), Support Vector Machines (SVM), Random Forests (RF), Naïve Bayse (NB), are widely applied in CSI positioning systems and perform well [12]–[18]. For example, Z. Wu et al. develop a NB classifier enhanced with confidence level information for CSI-based passive indoor localization [17]. Fang S H et al. propose to reconstruct CSI through inverse MDWT with HEQ-normalized wavelet coefficients and the extracted features are adopted for the probability method [18]. However, these machine learning algorithms have two shortcomings. First, they need to be combined with complex feature engineering, which requires professional knowledge. Second, as the amount of data increases continuously, the performance will not be significantly improved. Deep learning solves these two problems with multi-layer neural network (NN) effectively, which extracts low-level features in shallow layers and learns high-level feature in deep layers [27].

**The feature extraction method in NN depends on the network structure.** In deep learning, the extraction and utilization of features are done in network without special feature engineering, and the performance could be improved dramatically with the rich information in large data sets. So deep learning has become a better choice for enormous amount of CSI and complex calculations.

Many deep learning-based CSI positioning systems have been proposed recently [19]–[26]. In DeepFi [9], deep learning is utilized to train all the weights of a deep network as fingerprints and a probabilistic method based on the radial basis function is utilized to obtain the estimated location. In experiments, the mean errors in the open environment and complex environment are 0.94m and 1.80m, respectively. In CiFi [19], the estimated angle of arrival (AOA) images are created based on CSI phase difference and then the images are used as input to train the deep convolutional neural network (DCNN). The location is predicted based on the trained DCNN and new CSI AOA images. In experiments, 40% of the test points have the errors less than 1m in a complex environment. In ConFi [20], CSI is organized into a time-frequency matrix that resembles image and utilized as the feature to train the convolutional neural network (CNN). In experiments, the mean error of ConFi is about 1.36m. In [22], autoencoder and back propagation network are utilized owing to their advantage of processing mass CSI data. In experiment, this plan achieves 2-dim localizing with an accuracy of 50 cm. In [23], the authors develop four deep neural networks (DNNs) implemented with multi-layer perceptron (MLP) and one-dimensional convolutional neural network (1D-CNN) using RSS and CSI. They investigate on the parameters of MLP-RSS, MLP-CSI, CNN-RSS, CNN-CSI and then compare the four methods through experiments. Results indicate that the 1D-CNN using CSI achieves excellent localization performance with much lower network complexity. The mentioned CSI positioning systems are based on some traditional NNs. However, structures of these NNs are mainly applied in computer vision, speech recognition, natural language processing [28]–[32]. Due to the difference in data, there are some restrictions on the feature extraction of CSI data with the existing NNs. To the best of our knowledge, there is no network structure which is designed for CSI amplitude-based fingerprint positioning.

In this paper, we propose a network structure, which exploits both the local feature based on the correlation of adjacent subcarriers and global feature in CSI amplitude for indoor localization. CSI records the propagation of multiple subcarriers in channel [33], [34]. Through our research in Section III, we infer the correlation of adjacent subcarriers in CSI amplitude from the frequency selective fading phenomenon and prove it in theory. The smaller the subcarrier frequency difference, the stronger the correlation. This correlation manifests as local features in CSI amplitude sequence. Besides, according to the fading phenomenon at different positions, we infer that this local feature is affected by the receiving position, and then prove it in theory. The local feature in CSI amplitude is called position dependent local feature (PDL-feature) in this paper. In essence, PDL-feature is the feature in local CSI amplitude data, which contains certain position information due to multi-path environment. To fully exploit the PDL-feature in localization, we propose local connection-based deep neural network (LC-DNN). It enhances the distinguish of each position by exploiting the correlation between adjacent subcarriers and further improves the positioning performances. LC-DNN has both local and full connections. Through local connection, variations of CSI amplitude on local scale are characterized with different convolution kernels and PDL-features during multipath propagation are effectively extracted. Through full connection, global information in CSI amplitude is integrated based on the extracted PDL-features and the function between features and coordinates is fitted. The main contributions of this paper are as follows:

1) PDL-feature is proposed based on the correlation between adjacent subcarriers in CSI amplitude. Through theoretical derivation and simulation experiment, we not only prove the local correlation in CSI amplitude but also verify
the relation between local feature and position. PDL-feature is introduced to describe this characteristic of CSI amplitude and it could provide rich information for localization.

2) LC-DNN is proposed to improve the positioning performance by exploiting the correlation between adjacent subcarriers in CSI amplitude. For LC-DNN, raw CSI amplitudes are set as the input and position coordinates are set as labels. LC-DNN adopts local connection with separate convolution kernels to extract PDL-feature and adopts the full connection to extract the global feature effectively. Therefore, the better localization performance can be achieved with richer position information in LC-DNN.

3) The influences of receptive field length and step size on localization are investigated. With appropriate parameter, we demonstrate the superior performance of LC-DNN over existing methods based on DNNs.

The remainder of the paper is organized as follows. In Section II, the preliminaries of CSI are given. In Section III, we theoretically and experimentally validate PDL-feature of CSI amplitude. And in Section IV, the proposed LC-DNN is expressed in detail, including the local connection strategy and training method. The experiments of parameter setting and performances comparison are conducted in Section V, and the paper is concluded in Section VI.

II. PRELIMINARIES OF CSI

CSI is the sampling of frequency response in OFDM system. It can be obtained by inserting reference signals at the transmitter and estimating the channel at the receiver. The process of transmission in frequency domain is:

\[ Y = HX + N \]  

(1)

where \( N \) is random noise, \( H \) is frequency response, \( X \) and \( Y \) represent the transmitted and received signal in frequency domain respectively. \( H \) can be estimated by the value of \( X \) and \( Y \).

Channel response can be described in two means, channel frequency response (CFR) and channel impulse response (CIR). Under the assumption of linear time-invariant, CIR in time domain can be expressed as follows:

\[ h(\tau) = \sum_{i=1}^{M} a_i e^{-j\theta_i} \delta(\tau - \tau_i) \]  

(2)

where \( M \) is the number of multi-path, \( a_i \) and \( \theta_i \) are the amplitude attenuation and the phase shift of the \( i \)-th path, \( \tau_i \) is the time delay of the \( i \)-th path. After the Fourier Transformation for Eq.(2), CFR in frequency domain can be obtained:

\[ H_i = |H_i| \exp \{ \sin (\varangle H_i) \} \]  

(3)

where \( |H_i| \) and \( \varangle H_i \) are the amplitude response and the phase response of the \( i \)-th subcarrier. CSI obtained by existing Wi-Fi devices is the sampling of CFR. The multipath effect leads to delay spread in time domain and frequency selective fading in frequency domain.

Both amplitude and phase of CSI can be utilized for localization. Since the phase of CSI is greatly affected by the indoor environment and could only be utilized after calibration, most positioning systems choose amplitude as the fingerprint. There are some advantages in CSI amplitude fingerprint. First, CSI amplitude is stable at fixed position for a period of time and shows great difference among the RPs. It provides effective information of position due to the stability over time and specificity over positions. Second, different antennas have different CSI features [35], [36]. Fig.1 shows CSI amplitudes on three antennas from 500 received packets at a single position, 30 subcarriers for each antenna. It can be seen that the shapes of three antennas are obviously different, which indicate subcarriers on each antenna provide specific information related to position. Therefore, more information could be exploited with multi-antenna system.

In this paper, CSI amplitudes on \( p \) antennas, \( q \) subcarriers for each antenna, are extracted for positioning. The total number of subcarriers is \( M = p \times q \), and CSI in each package can be expressed as:

\[ H = [H_1, H_2, H_3, \cdots, H_q, H_{q+1}, \cdots, H_M] \]  

(4)

With the rich information provided by CSI amplitude in multi-antenna and multi-carrier system, we could achieve better performances in localization.

III. PDL-FEATURE OF CSI AMPLITUDE

In OFDM system, CSI records the propagation of different subcarriers in wireless channel and describes the influence of multi-path and shadow fading. From the continuity of amplitude response in frequency selective fading, the correlation between adjacent subcarriers can be deduced. Besides, the fading of amplitudes at different positions has different shapes due to the multipath environment. Thus, the relation between local features and positions can be deduced. Based on this, we present the hypothesis about CSI amplitudes, which is validated through theoretical derivation and simulation.

**Hypothesis:** In multi-carrier system, there is a certain correlation between adjacent subcarriers in CSI amplitude, and the local correlation is related to the position.
Supposing that the transmitting signal is \( e(t) \), the received signal in multi-path (including one direct path and one path with time delay) can be represented as:

\[
r(t) = e(t) + \beta e(t - \Delta t)
\]

(5)

where \( \beta \) is the multipath fading factor determined by the indoor environment, and \( \Delta t \) is the time delay in multi-path. The expressions of \( e(t) \), \( r(t) \) in frequency domain can be obtained by Fourier Transformation:

\[
E(w) = F[e(t)],
\]

\[
R(w) = F[r(t)] = E(w) + \beta E(w)e^{-j\omega \Delta t}
\]

(6)

(7)

Thus, the function of frequency response is

\[
|H(w)| = \left| 1 + \beta e^{-j\omega \Delta t} \right|
\]

\[
= \left| e^{j\beta \Delta t} + \beta e^{-j\beta \Delta t} \right|
\]

\[
= \left| (1 + \beta) \cos \frac{w\Delta t}{2} + j(1 - \beta) \sin \frac{w\Delta t}{2} \right|
\]

\[
= \sqrt{1 + \beta^2 + 2\beta \cos w\Delta t}
\]

(8)

\( |H(w)| \) represents the effect of OFDM channel on amplitude of different frequency subcarriers.

At fixed position \( p \), the attenuation factor \( \beta \) and time delay \( \Delta t \) are constant, and cosine is a continuous function. From the expression, the correlation between adjacent subcarriers in CSI amplitude is validated. As the frequency difference increases, the correlation decreases. In CSI amplitude sequence, the correlation related to frequency difference is presented as local feature. At different locations, the relative attenuation factors \( \beta \) and time delay \( \Delta t \) are different due to the surrounding environment. Taking the simple environment of two multipaths as an example, Fig.2 shows the paths of the received signals at two different locations. The red solid line and red dotted line show the direct channel and reflection channel at position 1, respectively. The blue solid line and blue dotted line show the direct channel and reflection channel at position 2, respectively. The position determines the multi-paths of received signal, i.e. the attenuation factor \( \beta \) and time delay \( \Delta t \). Considering \( \beta \) and \( \Delta t \) in multi-path as the functions of the position \( p \), it can be obtained that

\[
\beta = \sigma_1(p), \Delta t = \sigma_2(p)
\]

(9)

\[
|H(w)| = \sqrt{1 + \sigma_1(p)^2 + 2\sigma_1(p)\cos[w\sigma_2(p)]}
\]

(10)

From the expression, we prove that the local feature is related to the position. The position-dependent local feature is called PDL-feature.

In order to verify the rationality of the formula derivation, we perform extensive simulations to compare the amplitude response in practice with the specific case in the derivation. Fig.3 shows the comparison of amplitudes on 30 subcarriers in practice and in simulation. We simulate subcarriers at the transmitter with 30 cosine signals at equal frequency intervals and then calculate amplitudes response in multi-path. The green curves represent amplitudes in 500 packets received at fixed position and the red curve represents the simulated amplitudes. In both curves, there are depressions in amplitude responses, which indicates a certain fading at certain frequency. And the response curves are continuous and smooth, which validate the correlation between adjacent subcarriers in CSI amplitude. Fig.4 shows the simulated amplitude response at different positions (i.e. different multipath attenuations and time delays). It can be seen that both the local feature and global feature varies with positions. The comparison validates that the derivation is consistent with actual propagation, and CSI amplitude sequence has PDL-feature in practice.

PDL-feature refers to the spliced position information from different local groups of CSI amplitude sequence. The clear mathematical expression is given as follows to describe it more specifically.

\[
PDL\text{-feature} = [f_1(g_1), f_2(g_2), \ldots f_i(g_i), \ldots, f_k(g_k)]
\]

(11)

where \( g_i \) denotes the \( i \)-th group of CSI amplitudes, \( f_i \) denotes the specific function to extract position-related information.
in group $i$, and $K$ denotes the total number of groups that CSI amplitudes are divided into. The exploitation of PDL features effectively extracts the detailed information, enhances the distinguishes of data.

IV. LC-DNN STRUCTURE

PDL-feature describes the correlation between adjacent subcarriers in CSI amplitude and provides position-related information. To the best of our knowledge, there has been no specific method for extracting and exploiting PDL feature. The methods based on fully connected NN, such as DeepFi, extract the frequency selective fading feature in global amplitude sequence, but fail to exploit the position information in local data [9]. The other methods based on locally connected NNs, such as ConFi, effectively extract various specific local features form low-level to high-level [20]. However, they are limited in the joint expression of multiple features in different local data and the application of rich information in local CSI amplitude. Thus, a great deal of work can be done to extract and utilize effective local information (PDL-feature) in CSI amplitude for indoor localization.

This paper innovatively proposes LC-DNN to fully exploit the correlation in CSI amplitudes. It considers localization as regression of position coordinates.

Fig.5 shows the structure of LC-DNN, which consists of one locally connected layer and four fully connected layers. The input $x$ denotes CSI amplitudes of subcarriers with different frequencies sequentially. The number of input nodes $M$ equals to the number of subcarriers and the number of neurons at the output layer $D_S$ equals to the dimension of coordinates. $x$ is first processed by locally connected layer to extract PDL-feature, and $D_1$-dimensional data $h^{(1)}$ can be obtained ($D_1 > M$). And then, fully connected layers are adopted to establish the function between CSI and coordinates. We define $h^{(j)} (j \in 1, 2, \cdots, 4)$ as the outputs of the $j$-th hidden layer, $\hat{y}$ as the final output data and $D_j (j \in 1, 2, \cdots, 5)$ as the number of neurons in each layer (except for the input layer).

LC-DNN could make full use of PDL-feature, which is a local and position-dependent feature in CSI amplitude, to improve the positioning performance. The local connection utilizes the correlation between adjacent subcarriers and increase the distinguish between positions. The full connection describes the function between the position information and the coordinates.

A. LOCAL CONNECTION STRATEGY

In general, the connections in NN are divided into full connection and local connection. Between them, local connection is especially effective in local feature extraction. It is an important strategy in PDL-feature extraction. In local connection, each neuron is only connected with local area of the input and the local area is called receptive field, denoted as $g$. The receptive field length refers to the number of neurons in each piece of receptive field, denoted as $G$. The connected weight matrix for local feature extraction is called the convolution kernel, denoted as $W^{(1)}$. The distance between two convolution kernels is called step size, denoted as $S$ [37].

$G$ and $S$ are two important parameters in local connection, which have great influence on the extraction of PDL-feature and the positioning performance. $G$ determines the frequency range of subcarriers in PDL-feature extraction. In different scenarios, the influence of multi-path on subcarriers in propagation is different, which leads to the difference in suitable frequency range for feature extraction. Therefore, the effects of feature extraction and location estimation depend on $G$. Besides, the step size of the convolution kernel also affects the local connection. $S$ controls the frequency of PDL-feature extraction in CSI. With small $S$, the extraction is intensive to get abundant information, but more network parameters and larger storage are needed. With large $S$, the sparse extraction may lose some information and lead to insufficient discrimination, but the parameters and storage are reduced. $G$ and $S$ are two adjustable parameters in local connection.

Fig.6 shows the local connection strategy in LC-DNN. The input data can be expressed as $x = [x_1, x_2, \cdots, x_M]^T$. 

FIGURE 4. Comparison of simulated CSI amplitudes on 30 subcarriers at different positions.

FIGURE 5. Structure of LC-DNN.
Basing on $G$ and $S \left( \frac{M-G}{S} \in \mathbb{Z}_+ \right)$, we divide $x$ into several local areas, which means considering the global data with length $M$ as $K$ groups of local data with length $G \left( K = \frac{M-G}{S}+1 \right)$. Each group is denoted as $g_i = [x_i, x_{i+1}, \ldots, x_{i+G}]$ ($i \in 1, 2, \ldots, K$). The locally connected layer processes $g_i$ with convolution kernel $W^{(1)}_i$ and activation function $\Phi$, extracting the local feature $h^{(1)}_i$ with length $D$. By splicing the local feature $h^{(1)}_i$ sequentially, the output $h^{(1)}$ with length $D_1$ can be obtained ($D_1 = K \times D$). The formulas are as follows:

\[
\begin{align*}
    h^{(1)}_i &= \Phi \left[ W^{(1)}_i g_i + b^{(1)}_i \right] \\
    h^{(1)} &= \left[ h^{(1)}_1; h^{(1)}_2; \ldots; h^{(1)}_K \right]
\end{align*}
\]

where $W^{(1)}_i$ is a convolution kernel in $D \times G$ size for the $i$-th receptive field, $b^{(1)}_i$ is a threshold in $D \times 1$ size for the $i$-th receptive field, $\Phi$ is an activation function, and $h^{(1)}_i$ is the feature extracted from the $i$-th receptive field.

Activation function is the key to realize nonlinear transformation. Popular activation functions include Sigmoid, tanh, Rectified Linear Units (ReLU) [27]. In LC-DNN, we choose ReLU as the activation function. ReLU is faster, more biological inspired and could reduce likelihood of vanishing gradient. In practice, networks with ReLU tend to show better convergence performance than others. The expression is as follows:

\[
ReLU \left( x \right) = \max(0, x)
\]

LC-DNN is inspired by CNN, but the design of local connection and network structure are greatly different in the two networks. First, the setting of convolution kernels is different. In CNN, the shared convolution kernel is always adopted in local connection, which means the same convolution kernel is used in each local part to extract specific features. Shared convolution kernel greatly reduces the number of parameters, but it is limited in the extraction and joint expression of different local features. In LC-DNN, separate convolution kernel is trained for each receptive field in CSI amplitudes. Therefore, the convolution kernels and activation functions extract the different position-related features in each local data for rich position information. The main disadvantage is that the number of parameters will be larger for more convolution kernels. Since only one local connection layer is set for PDL-feature extraction, the number of parameters is still acceptable. In fact, the storage of the network model is about 6MB, and the time for real prediction is about 0.1ms. Therefore, different convolution kernels are set instead of the shared one in LC-DNN to extract position information for localization. Second, LC-DNN does not use the pooling layer. In CNN, the pooling layer is usually connected to the convolution layer. The main advantages are reducing network complexity, extracting key features of data, and reducing dimensions. However, it also leads to the loss of information and the decrease of data resolution [27]. In LC-DNN, the effective position information from various receptive filed is obtained after local connection. In order to retain the resolution and distinguish of data, we do not apply pooling layer, and directly use the full connection to extract the global features.

For CSI amplitude, LC-DNN integrates the feature extraction into the neural network, extracts the local feature in each receptive filed with different convolution kernels and realize the joint expression of PDL-feature. In addition, the network adapts to various scenarios by adjusting parameters such as receptive field length $G$ and step size $S$. Considering the characteristics of CSI, LC-DNN can achieve better positioning performances.

## B. TRAINING AND LOCALIZATION

LC-DNN consist of training phase and localization phase. In the training phase, a large number of labels and data are used to train the weight of LC-DNN with back propagation (BP) algorithms. We set the real coordinates of RPs as labels and set CSI amplitudes collected at corresponding RPs as training data. In localization phase, CSI amplitudes at the measured points are fed into LC-DNN and the model outputs represent the estimated coordinates directly.

The cost function is an index to update the weights and thresholds in BP training. It measures the error between the output data and true position label. In LC-DNN, mean square error (MSE) is adopted as the loss function for single sample and the cost function can be expressed as:

\[
\text{Cost}_{\text{regression}} = \frac{1}{2N} \sum_{j=1}^{N} \sum_{i=1}^{D_3} (y_{i,j} - \hat{y}_{i,j})^2
\]

where $\hat{y}_{i,j}$ and $y_{i,j}$ are the predicted coordinate and the real coordinate of the $j$-th sample in the $i$-th dimension respectively, $D_3$ is the dimension of coordinate, $N$ is the total number of samples. The coefficient $1/2$ is set to simplify the process of the derivation. Besides, we employ dropout between two layers to avoid overfitting.
Adaptive moment estimation (adam), a modified gradient descent method, is employed in BP training to update the parameter set of LC-DNN iteratively [38]. The update is implemented by:

$$
\theta_t = \theta_{t-1} - \alpha \frac{\bar{m}_t}{\sqrt{\bar{v}_t} + \epsilon}
$$

where \( \alpha \) is the learning rate which controls the update rating, \( \epsilon \) is a very small constant to avoid zero denominator, \( \bar{m}_t \) and \( \bar{v}_t \) are the bias-corrected first moment estimate and the biased-corrected second moment estimate. The formulas of \( \bar{m}_t \) and \( \bar{v}_t \) are as follows.

$$
\bar{m}_t = \frac{m_t}{1 - \beta_1}, \quad \bar{v}_t = \frac{v_t}{1 - \beta_2}
$$

$$
\hat{m}_t = \beta_1 m_{t-1} + (1 - \beta_1)g_t
$$

$$
\hat{v}_t = \beta_2 v_{t-1} + (1 - \beta_2)g_t^2
$$

where \( \beta_1, \beta_2 \) are the attenuation rates of the first-order moment estimator and the second-order moment estimator respectively, \( g_t \) is the gradient of lost function at time \( t \).

As a neural network for positioning using CSI amplitude, LC-DNN utilizes locally connected layer with different convolution kernels to extract PDL-feature and fully connected layer to extract the global feature. LC-DNN is trained with collected CSI at various RPs using adam algorithm and could output the predicted coordinates using the received CSI amplitudes.

V. EXPERIMENTS
A. SETTINGS
In this section, various experiments have been conducted in garage to analyze the positioning performance of LC-DNN. We select a fixed area of 19.5m\(^2\)x4.5m in the garage as the test area. CSIs are influenced by the multi-path because of the obstacles between APs and mobile devices. During the testing, the movement of operators and cars also has a certain impact on the stability of CSI data. Fig.7 (a) shows the real garage environment. There are 56 RPs in test area. The distances between adjacent points are 1.5m. The test points are selected randomly within 56 RPs. Fig.7 (b) shows the distribution of the RPs (marked as red dots). There are three transmitters and one receiver, one antenna installed at each transmitter and three antennas installed at the receiver. The three APs are set as transmitters and send CSI packets at the intervals of 5ms. The mobile device equipped with Intel 5300 NIC is the receiver, which could also analyze the received packets for CSI data.

During the measurement, we place the mobile device on a tripod with height of 1m and the two-dimensional coordinates are recorded as the label \((D_5 = 2)\). For training and testing, we collect CSI data twice for all RPs. According to our previous research, the time stability of CSI data is affected by the restart of transmitter and the change of environment [35]. Thus, in this paper, both of the measurements are conducted without restart of transmitters to keep the stable environment.

At the first time, 500 packets are collected in 0.25s for each RP and the amplitudes are stored in fingerprinting database for training. At the second time, 200 packets are collected in 0.1s for each RP, and the amplitudes are used for testing. The variation between two measurements mainly comes from slight changes in the garage environment, such as the movement of people. The small variation could also avoid overfitting.

To evaluate the performances of network, we choose mean error, standard deviation and cumulative distribution function (CDF) as the metrics. The mean error and standard deviation refer to the average value and standard deviation value of distances between the predicted coordinate points and the real coordinate points respectively. These two metrics evaluate the positioning network from accuracy and stability. CDF curves of localization errors show the positioning performances intuitively.

Experiments consist of three parts: the analysis of receptive field length, the analysis of step size and the comparison with other DNNs.

B. ANALYSIS OF RECEPTIVE FIELD LENGTH
To investigate the influence of receptive field length on localization, we adjust \( G \) while keep \( S \) constant. Considering that each antenna provides 30 subcarriers in positioning, the maximum value of \( G \) is 30. In experiments,
TABLE 1. Parameters of LC-DNNs with different receptive field lengths.

| G   | Number of nodes | $D_1$ | $D_2$ | $D_3$ | $D_4$ | $D_5$ |
|-----|-----------------|-------|-------|-------|-------|-------|
| Full Connection | 60 | 50 | 40 | 30 | 20 | 10 |
| 3   | 88 | 60 | 50 | 30 | 20 | 10 |
| 5   | 258 | 200 | 100 | 50 | 20 | 10 |
| 10  | 405 | 300 | 200 | 100 | 50 | 20 |
| 20  | 710 | 500 | 300 | 100 | 50 | 20 |
| 30  | 915 | 800 | 500 | 300 | 100 | 50 |

TABLE 2. Localization effect of LC-DNNs with different receptive field lengths.

| $G$ | Mean(m) | std(m) |
|-----|---------|--------|
| Full Connection | 1.19 | 2.39 |
| 3   | 0.93 | 1.89 |
| 5   | 0.88 | 1.81 |
| 10  | 0.79 | 1.99 |
| 20  | 0.78 | 1.96 |
| 30  | 1.07 | 1.68 |

FIGURE 8. CDFs in LC-DNN with different receptive field lengths.

convolution kernels with sizes of $1 \times 3$, $3 \times 5$, $5 \times 10$, $10 \times 20, 15 \times 30$ are employed, i.e. receptive field lengths of LC-DNNs are set to 3, 5, 10, 20 and 30 respectively. The number of nodes in each receptive field is halved in feature extraction. At the same time, the step size $S$ is fixed as 1. The number of nodes in each layer is set as Table 1.

Comparing different networks, we can analyze the influence of $G$ on localization. The performances are shown in Table 2 and Fig.8.

As can be seen, both of the accuracy and stability are improved. The mean and standard deviation of the location errors in LC-DNN with different $G$ are presented in Table 2. For full connect network, the mean error is 1.19 m and the standard deviation is 2.39 m. After adding local connection strategy to NN, the mean error is effectively reduced due to the extraction of PDL-feature. The performances are different when $G$ changes. When $G$ is 20, the mean error and the standard deviation are 0.78 m and 1.96 m respectively. The result indicates that LC-DNN reaches a 34.4% improvement in accuracy and a 17.9% improvement in stability.

CDF curve presents the localization performance intuitively. In order to compare the curves within the error range of interest, logarithmic coordinates are used in the $X$ axis and common coordinates are used in the $Y$ axis. Fig.8 shows the CDF curves of localization errors in LC-DNNs with different receptive field lengths. For full connection network, the probability of location errors within 1 m is about 75%. For LC-DNN, the probability can be more than 80% when $G$ is 3, 5, 10, 20. And the curve with local connection is closer to the upper left corner, which is a more superior performance in statistics. Furthermore, we found that errors are concentrated in different data areas under different parameters. With $G$ taking 10 and 20, the errors center on the range of 0.01 m to 0.1 m. In the cases that $G$ takes 3, 5, 30 or full connection, errors center on the range of 0.1 m to 1 m. So local connection improves the accuracy and stability by increasing the probability of accurate localization with small error. LC-DNN achieves the best performances when $G$ takes 20. For the larger value 30, the accuracy is reduced because of the too large frequency range of feature extraction.

The experiments show that LC-DNN outperforms full connection network in positioning accuracy and validate the effectiveness of local connection in extracting PDL-feature. Besides, the comparison also reveals the influence of $G$ on localization. The receptive field length reflects the frequency range in PDL-feature extraction. For specific CSI data, different $G$ will lead to different effect in localization. Too large or too small receptive field length is not advisable in feature extraction.

C. ANALYSIS OF STEP SIZE

To explore the influence of step size on positioning, we fix $G$ as 20. Under the constraint $\frac{M - G}{S} \in Z^+$, we select $S$ as 1, 2, 5 and 10 in experiments. The number of nodes in each layer is set as Table 3.

Comparing different networks, we can analyze the influence of $S$ on localization and PDL-feature extraction. The performances are shown in Table 4 and Fig.9.

Table 4 presents the mean and standard deviation of the location errors in LC-DNN with different $S$. The location effect achieves best when $S$ takes 1. With the increase of $S$, the feature extraction is sparser and the effect of PDL-feature in localization is weakened. When $S$ takes 10, the mean error is 0.92 m which is 17.9% lower than the case and...
of $S$ taking 1. Fig. 9 shows the CDF curves of localization errors in LC-DNNs with different $S$. LC-DNNs with different step sizes could all locate the object within 1 m of the actual position with a probability of more than 80%. Moreover, we can see that the errors center on different data range when $S$ changes. In the case where $S$ is 1, errors are concentrated in the small value range of 0.01 m to 0.1 m. In the case where full connection is adopted or $S$ is 2,5,10, the errors of test points center on the range of 0.1 m to 1 m.

Step size affects the positioning performances. LC-DNN achieves the best performance when $S$ takes 1. With small step size, the network will extract PDL-features more frequently, which means more abundant information of each location and higher discrimination between location points. With large step size, the extraction is sparser which leads to a poor performance.

D. COMPARISON WITH OTHER DNNs

To validate the effectiveness of LC-DNN, the experiment compares LC-DNN with four state-of-the-art DNNs which have been verified to perform well in CSI localization according to the existing literature. The four DNNs are MLP [23], 1D-CNN [23], 2D-CNN [20], Autoencoder [22]. MLP uses 5 fully-connected layers and 1D-CNN uses the convolution blocks to extract hierarchical features from low level to high level. Both of the methods are explained in [23]. In ConFi, 2D-CNN is exploited to classify images which are constructed with CSI amplitudes at different locations [20]. Besides, autoencoder is used to extract feature in CSI amplitude and estimate the position in [22]. In this experiment, Table 5 and Fig. 10 present the mean errors, standard deviations and CDF curves of localization errors in different DNNs.

In Table 5, the mean error of LC-DNN is smallest, which is 0.78 m at $G = 20, S = 1$. From CDF in Fig. 10, the curve for LC-DNN achieves the best performance within the distance of 3 m. Compared with MLP, LC-DNN achieves a 34.4% improvement in mean error and a 17.9% improvement in standard deviation due to the exploitation of local information in CSI amplitude. LC-DNN also outperforms 1D-CNN in mean error by 39.1%. However, from the perspective of standard deviation, 1D-CNN is more stable and the distribution of location errors is more centralized. This is also why the curves of LC-DNN and 1D-CNN intersects. We found that the location error at the intersection point is about 3 m, which means 1D-CNN performs better than LC-DNN when the positioning errors are more than 3 m. For the error of 3 m is larger than the distance between grid points, it is beyond the scope of this article. For the 2D-CNN in ConFi, the mean error is 1.41 m and the standard deviation is 2.70 m. The reason for this instability may be the influence of time in the construction of two-dimensional images, which is not suitable for the environment with slight changes in this paper. Autoencoder performs worst due to the loss of valid information in the dimension reduction process.

The experiments verify that LC-DNN outperforms other DNNs in high precision positioning. It is efficient in fully exploiting CSI amplitude and extracting the PDL-feature to improve the localization performances.

VI. CONCLUSION

In this paper, we propose LC-DNN, which extracts both the local feature and the global feature of CSI amplitude for indoor positioning. First, the certain correlation between
adjacent subcarriers in multipath channel is validated through theoretical derivation and simulation experiment. The correlation manifests as local feature related to position, what we call PDL-feature in CSI amplitude sequence. Next, this paper proposes LC-DNN based on the PDL-feature. LC-DNN combines local connection and full connection for CSI-based indoor localization. The combination integrates the extraction and utilization of PDL-features into the network, enhances the distinguish between points and improves the positioning accuracy. Through extensive experiments, we select the appropriate receptive field length and step size for LC-DNN, investigate the influence of the two parameters, and compare the performance of LC-DNN with four state-of-the-art DNNs for localization. Results show that LC-DNN achieves prominent performance in positioning. Under the parameter setting of $G = 20$ and $S = 1$, the mean error is 0.78m. LC-DNN effectively exploits the correlation between adjacent subcarriers in CSI amplitude and improves the localization accuracy. It has instructive significance for the design of other neural network in positioning field.

However, only the characteristic of CSI amplitude is considered in this work, the information of amplitude and phase can be further combined to improve the localization performance in the future.

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