DeFe: indoor localization based on channel state information feature using deep learning

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Abstract. With the development of mobile devices, more and more location-based services (LBS) on the devices are needed and fingerprint indoor localization has become one most important technique because of its low cost and high accuracy. In this paper, we use the fingerprinting method which based on Channel State Information (CSI) for indoor localization. Furthermore, we extract the raw phase information from the multiple antennas and multiple sub-carriers through the IEEE 802.11n network interface card (NIC 5300) on several special models. Then we extract the required phase information and introduce two methods of mathematical statistics to analyse the feature of CSI signals. We replace the processed phase information with the signal features obtained from the analysis. For the offline stage, we employ a deep network with three hidden layers to train the signal features data, and use weights to represent fingerprints. Introducing a greedy learning algorithm to train the weights layer-by-layer to reduce the computational complexity, and the sub-network between two continuous layers forms a restricted Boltzmann machine (RBM). For the online location estimation, we use a probabilistic method based on the radial basis function (RBF). The neural network method we used this time is tested under two different scenarios, and different data are compared. The final conclusion is that the new method we combined is superior to the previous.

1. Introduction
In recent years, with the continuous development and popularization of wireless communication technology and network technology, positioning service has become a new service industry, which has also become an important part of IT business. With the rapid development of positioning services’ market, people’s demand for positioning services reflects the trend of rapid development, and positioning services are also applied in many fields. At present, the positioning technology is mainly divided into two types, indoor positioning and outdoor positioning, according to the different environments and scenes used. Currently, a variety of wireless technologies are available for indoor positioning, including indoor GPS, ZigBee, radio frequency label RFID, Bluetooth, ultra-wide band radio(UWB), magnetic field and even lighting. However, the emerging indoor positioning technologies still have their own limitations. The main reason is that their exclusive positioning network systems must be specially deployed, which will cost a lot of construction costs. In recent years, a WiFi-based indoor positioning technology has come to our attention. At present, Wi-Fi technology has been widely used in modern life. People can connect with the wireless networks of major operators, such as CMCC, anytime and anywhere. Wireless channel is very complex, its characteristics are closely related to specific places, and will change significantly according to topographic features, working frequency, moving speed, interference sources and other uncertain
factors. In this paper, we focus on the problem of improving indoor localization accuracy. Many people have made remarkable contributions to improving accuracy.

First off, the introduction of CSI is to compare the effect of RSSI (Received Signal Strength Indication) in indoor positioning. Wu K et al. [1] built a model by using the relationship between CSI and distance, and measured CSI to predict distance for triangular positioning and it really does work better than RSSI. Then some people used the angle and the feature of CSI measurement to make linear array and circular array, analyzing the incident angle of the signal, and calculating the Angle of Arrive (AOA) for location. Alibi D et al [2] used the most classical MUSIC (Multiple Signal classification) algorithm in multi-signals transmission to obtain AOA through matrix transformation based on the phase ratio relation between antennas. Xiang Li et al [3] applied the communication discipline theory to the fine-gain measurement field, used the array antenna to receive the CSI signal, and placed it in a real experimental environment with a computable AOA at the time of signal reception, which provided convenience for CSI Angle localization. In view of the feature of multiple CSI sub-channels, it introduced classic MUSIC multi-path signal processing algorithm, which introduced a scientific interpretation concept to the CSI signal. At present, fingerprint location method is the most widely used. As a popular indoor positioning scheme, the fingerprint-based method establishes a database and makes a comprehensive measurement of it, and then, through comparison with the database data, determines the real-time location [4-9]. Some early papers show the accuracy of most indoor fingerprint positioning technology is around 1.5m [10-11]. Wang X [12] et al. combined the neural network with the CSI data, conducted phase correction for the CSI data, and set the threshold to screen the original phase data, so the data tended to be stable. Here, the processed data are used to present the fingerprint. The processed phase data enters the neural network as input data. At this point, the CSI indoor positioning technology has begun to take shape.

By installing Intel WiFi Link 5300 NIC, we can obtain channel status information. CSI includes 30 sub-carrier-level channel measurement, which brings a lot of research space for indoor fingerprint localization. For example, DeepFi [11] learned a lot of CSI data through three antennas for indoor localization based on deep network. CSI- MIMO [13] contains the magnitude and phase of each sub-carrier used for fingerprint identification, but the phase information cannot be calibrated. However, some of these schemes only consider the amplitude of CSI and ignore the phase information of CSI, which is largely due to the randomness and unavailability of the original phase information, and some do not calibrate the phase information. Articles in the field of Line-Of-Sight(LOS) and Non-Line-Of-Sight(NLOS) recognition have been successful [14-16], among what the use of phase features has inspired us. The paper used LDA classification algorithm to handle the wi-fi signal, and it is given a z-value for the data set. In indoor environment, a higher positioning accuracy is obtained. In the part of system testing, 10k cross-validation method is adopted in this paper, so that all data contained in the data set can be used for testing [17].

In this paper, we present an indoor fingerprinting system based on the feature of CSI. In our method, first we extract the raw phase information from the CSI values which is from the 30 sub-carriers of each of the three antennas of the Intel WiFi Link 5300 NIC (sub-carriers are 90 in total). Two kinds of CSI signal features are obtained as initial data through processing in time domain and frequency domain. In our research, it will be justified. For the offline stage, we used a deep network with three hidden layers to train the calibrated phase data, and saved weights as the fingerprints. We take a greedy learning algorithm to reduce the complexity and Restricted Boltzmann Machine (RBM) is used between the two connection networks. In the localization phase, we use a probabilistic method based on the radial basis function to calculate the position. Experimental results show the method we take can effectively reduce location error compared with three existing methods in the indoor scenes.

In summary, the main contributions in this paper can be included as follows:

1) We used skewness and kurtosis to extract CSI features for indoor fingerprint localization. We theoretically proved that the extracted effective information is CSI, and further filtered the noise caused by various external causes. As far as we know, this is the first time we've done this kind of combination.
2) On the basis of the deep network indoor positioning method, which is the work done by Wang et al., we bring our initial data. In our experimental environment, we improved the accuracy of the original content positioning.

The chapters are as follows. Two methods of data feature extraction are introduced in Section II. Demonstrating the process of the entire method in Section III and showing our results in Section IV. Section V concludes this paper.

2. Extraction method based on skewness and kurtosis
There are a variety of interference factors in the space of WiFi signal transmission, such as the reflection of walls, diffraction formed by signal transmission obstacles and the weakness of its own energy in the process of signal transmission. In traditional CSI fingerprint localization, if the CSI denoising method we used is not accurate enough and the noise is too much, it will seriously affect our final localization results. We also understand that it's impossible to eliminate noise 100%. In other words, we can guarantee that the environment will remain unchanged and no excessive noise will be generated. The change of signal itself will also cause the change of our final result. In order to solve this problem and improve the accuracy of CSI indoor fingerprint localization, we proposed a method to extract the features of LOS, and extract the feature values that can represent a certain point of CSI signal, so as to replace the changeable CSI signal and apply it to the CSI indoor fingerprint localization.

2.1. Skewness of dominant path power
This method is used if the receiver has a small amount of displacement, which is a mobile environment. This is to keep the propagation model and environmental factors as unchanged as possible. This variable is the phase and amplitude change of the data itself, so as to find the lightweight and independent features. Under the condition of mobility, the envelope lines received under the condition of LOS are almost symmetrically distributed, while under the condition of NLOS, the envelope lines show obvious skew. Therefore, we use skewness to quantify the tilt characteristics [14].

The slope of the two sub-carriers is calculated for each packet and the maximum value is taken. The latter data is regarded as the dominant path. If this sub-carrier is not in the first 10, the packet is removed.

In an indoor environment, the maximum latency is about 500ns. In processing the data, we end up taking only the first 10 sub-carriers of each packet.

\[ s = \frac{E[(x-\mu)^3]}{\sigma^3} \]  

Where \( E \) for computing expectation, \( x, \mu, \sigma \) represent the measured values, the mean and standard deviation.

2.2. Kurtosis of frequency diversity variation
The kurtosis corresponds to Rayleigh fading. Rayleigh fading assumes that there are a large number of multi-path components with roughly equal power and uniform azimuth distribution, which conforms to the spatial distribution relationship of CSI signals [14].

In the LOS environment, the attenuation of the channel is relatively smooth. Each sub-carrier in the packet has a similar frequency. The processing here is to standardize the amplitude data of CSI according to the central frequency:

\[ H_{\text{norm}}(f_k) = \frac{f_k}{f_0} \cdot H(f_k) \]  

The amplitude data of \( H_{\text{norm}}(f_k) \) and \( H(f_k) \) are normalized and the original \( k \)th sub-carrier respectively. \( f_k \) is the frequency of \( k \)th sub-carrier. \( f_0 \) is center frequency.

Kurtosis is defined as

\[ k = \frac{E[(x-\mu)^4]}{\sigma^4} \]
Where \( E \) for computing expectation, \( x, \mu, \sigma \) represent the measured values, the mean and standard deviation.

3. The position algorithm based deep learning

3.1. The system structure
Section II shows the extraction method. Our position system needs one access point and one mobile device equipped with an Intel WiFi link 5300 NIC. At the mobile device, raw CSI values can be read from the modified chipset firmware for packets received from the AP. The Intel WiFi link 5300 NIC has three antennas, each of which can collect 30 different sub-carriers. We can obtain 90 raw CSI values for one packet reception. Unlike FIFS, which reduces the received noise by averaging across multiple antennas, our system utilizes all CSI values of the three antennas of the interior fingerprint to exploit the diversity of MIMO channels. Since it is difficult to use the phase of CSI value to locate, the feature value of each point is used to replace the CSI signal. On the other hand, in order to learn more effectively, we limited the input value to the range of \((0,1)\). We normalized 90 CSI feature values of each different location, which can be used in the offline training stage and online positioning stage.

In the offline training stage, feature-based fingerprints can be generated, which is quite different from the traditional clustering method. Feature-based fingerprints represent different positions using a large number of weights derived from deep learning. Feature-based fingerprint servers can store ownership weights for different training locations. In the online positioning stage, the mobile device can estimate its location based on data fusion, and use the weight of different locations to normalize the size of the CSI feature value to get its estimated location.

![Deep learning structure](image)

**Figure 1.** Deep learning structure.

3.2. Offline training
In this part, we use the Constrained Boltzmann Machine (RBM). Boltzmann Machines (BMs) is a special form of log-linear Markov Random Field, where the free parameters of energy function are
linear. Make them powerful enough to represent complex distributions (that is, from finite parameter sets to non-parametric sets), and we assume that some variables will never be observed (they are called hidden variables). By adding hidden variables (also known as hidden units), the modeling ability of Boltzmann Machine (BM) can be improved. Restricted Boltzmann Machines further restrict BMs to those without visible-visible and hidden-hidden connections.

Figure 1 shows the overall network structure of deep learning. The whole deep learning system is divided into three steps: pre-training, expansion and fine-tuning. In the pre-training phase, it is a deep network with three hidden layers, each with a different number of neurons. To reduce the dimensions of CSI data, we assume that the number of neurons in the higher hidden layer is greater than that in the lower hidden layer. Suppose $K_1$, $K_2$ and $K_3$ represent the number of neurons in the first, second and third hidden layers respectively. Based on the above assumptions, we have $K_1 > K_2 > K_3$. We can set up different numbers of neurons in different indoor environments.

In addition, we propose a new method to represent fingerprint by the weight between two connection layers. $W_1$, $W_2$ and $W_3$ are respectively defined as the weight between the normalized modulus of CSI value and the first hidden layer, the first and second hidden layer, and the second and third hidden layers. The key idea is that by training ownership weights in deep nets, we can store them as fingerprints to help locate in the online testing phase. In addition, we defined $h_i$ as the hidden variable of layer $i$, where $i = 1, 2, 3$, and let $v$ represent the input data, that is, the standardized magnitude of CSI feature values.

We can use probability generating models to represent the deep network, and it has three hidden layers that can be written as

$$Pr(h^0, h^1, h^2, h^3) = Pr(h^0|h^1) Pr(h^1|h^2) Pr(h^2|h^3)$$  \hspace{1cm} (4)

Because the nodes in the deep network is mutually independent, $Pr(h^0|h^1)$, $Pr(h^1|h^2)$, and $Pr(h^2|h^3)$ can be represented by

$$Pr(h^{i-1}|h^i) = \prod_{j=1}^{K_i} Pr(h_j^{i-1}|h^i)$$

$$Pr(h^i|h^{i-1}) = \prod_{j=1}^{K_i} Pr(h_j|h^{i-1})$$  \hspace{1cm} (5)

It's hard to calculate the $Pr(h^{i-1}|h^i)$, generally this is a CD-1 algorithm to calculate its value, the product of the distribution of the edges of each node. The calculation formula of each node is:

$$Pr(h_j^{i-1}|h^i) = [1 + \exp(-b_j^{i-1} - \sum_{l=1}^{K_i} w_{j,l}^i h_l^{i-1})]^{-1}$$

$$Pr(h_j^i|h^{i-1}) = [1 + \exp(-b_j^i - \sum_{l=1}^{K_i} w_{j,l}^i h_l^{i-1})]^{-1}$$  \hspace{1cm} (6)

where $b_j^i$ are the biases for unit $j$ of layer $i$.

Finally, the marginal distribution of input data for the deep belief network is written by

$$\max_{(w_0,w_1,w_2)} \sum_{h^0} \sum_{h^1} \sum_{h^2} \sum_{h^3} Pr(h^0, h^1, h^2, h^3)$$  \hspace{1cm} (7)

We use the greedy algorithm to estimate the parameters of all weights for a stack of RBMs. Firstly, given the calibrated phase data, the parameters $\{b^0, b^1, W_1\}$ of the first layer RBM are estimated by using CD-1 method. Then we freeze the parameters $\{b^0, W_1\}$ of the first layer, and sample from the conditional probability $Pr(h^1|h^0)$ to train the parameters $\{b^1, b^2, W_1\}$ of the second layer RBM. Next, the parameters $\{b^0, b^1, W_1, W_2\}$ of the first and second layers are frozen, and then we sample from the conditional probability $Pr(h^2|h^1)$ to train the parameters $\{b^2, b^3, W_3\}$ of the third layer RBM.

The updated formula is

$$\Delta w_l = e(h^{i-1} h^i - \hat{h}^{i-1} \hat{h}^i)$$

$$\Delta b^i = e(h^{i-1} - \hat{h}^i)$$

$$\Delta b^{i-1} = e(h^{i-1} - \hat{h}^{i-1})$$  \hspace{1cm} (8)

Where $\epsilon$ is the step size, it is usually set to 0.001.

After the pre-training stage is completed, we get the optimal weight of the depth network. Then, in the expansion stage, the deep network is spread forward to obtain reconstructed calibrated CSI feature data. Finally, the back propagation algorithm is used to train the ownership value in deep network by calculating the error between the input calibration CSI feature data and the reconstruction calibration.
This phase is called fine-tuning. After minimizing the error, the optimal weight is stored in the fingerprint database.

3.3. Localization algorithm

In the online testing phase, based on the fingerprint database and the new CSI feature data, a method of mobile device location estimation based on probability is proposed. We calculate the posterior probability \( Pr(l_i|h^0) \) based on Bayes’ law, which is given by

\[
Pr(l_i|h^0) = \frac{Pr(l_i)Pr(h^0|l_i)}{\sum_{i=1}^{N} Pr(l_i)Pr(h^0|l_i)}
\]

where \( N \) is the number of reference positions, \( l_i \) is the reference position \( i \) in the fingerprint library, and \( Pr(l_i) \) is the prior probability to determine the positioning of mobile devices at the reference position \( l_i \). \( Pr(l_i) \) are assumed to be evenly distributed, the a posteriori probability \( Pr(l_i|h^0) \) can be simplified as

\[
Pr(l_i|h^0) = \frac{Pr(h^0|l_i)}{\sum_{i=1}^{N} Pr(h^0|l_i)}
\]

based on the deep web model, we consider the \( Pr(h^0|l_i) \) as a RBF in the form of Gaussian function to measure similarity between \( \hat{h}^0 \) and realign the phase data input calibration data \( h^0 \) phase, is given

\[
Pr(h^0|l_i) = \exp\left(-\frac{1}{2\sigma^2}||h^0 - \hat{h}^0||\right)
\]  

(9)

Where \( \sigma \) is the parameter of variance and variance \( \lambda \) input calibration phase data. Finally, the position shift device can be calculated as a weighted average reference position for all devices, such as

\[
\hat{l} = \sum_{i=1}^{N} Pr(l_i|h^0)l_i
\]  

(10)

4. Experimental Evaluation

4.1. Experiment Methodology

Our experiment is carried out in two environments. In our experiment, a TP Link router served as an AP, and a Lenovo laptop equipped with an Intel WiFi Link 5300 NIC served as a mobile terminal. On the mobile device, we receive the AP signal on the ubuntu system at a rate of 100 packets per second. We collect training data and test data respectively.

Laboratory: In Figure 2 we perform experiments in a 14.5×8.5 m² laboratory where there are many obstacles around the laboratory such as the student, many desks and PCs. We fix the receiving end to the table, about 1.5m above the ground, while the moving end remains at the same height to ensure there are LOS receptions between the two. We set 14 points as training points(in red) and 8 points as test points(in green). In addition, we collect CSI data for 240 packet receptions for each training point, and 30 packet receptions for each test point.
The Meeting Room: In Figure 3 we chose the conference room at 5.4×7.2 m² as the second scene. There are not many obstacles here, which can guarantee more LOS contacts. We totally collect 53 points, among which 40 are used as training points (in red) and 13 are used as test points (in green). In addition, we collect CSI data for 480 packet receptions for each training point, and 90 packet receptions for each test point.

We collect the CSI data of each point and extract their skewness and kurtosis as initial data and brought into the neural network for weight training. There are three hidden layers in the neural network, and the nodes of each layer are 150, 100 and 50 respectively.

4.2. Localization Performance

Table 1 presents the mean location errors, the average execution times of the meeting room and the laboratory experiments, respectively. In the meeting room, in case of kurtosis, we can see our method achieve a mean location error of 0.9597 m and the average training times of 334.824 s. In case of skewness, the result is 0.9457 m and 330.431 s. In the laboratory, in case of kurtosis, we can see our method achieve a mean location error of 0.9874 m and the average training times of 341.744 s. In case of skewness, the result is 0.9972 m and 336.542 s. We also carried out LAD localization experiment, extracted the RSSI of per CSI package, and substituted it into LAD clustering method. The experimental results are better than DeepFi and ML, but there is an average error of 0.15m compared with our method.

| Scenario       | My-kurtosis | My-skewness | DeepFi | ML  | LAD   | My-kurtosis | My-skewness | DeepFi | ML  | LAD   |
|----------------|-------------|-------------|--------|-----|-------|-------------|-------------|--------|-----|-------|
| Meeting room   | 0.9597      | 0.9458      | 1.2375 | 1.4536 | 1.1254 | 334.824     | 330.431     | 380.532 | 150.245 | 135.675 |
| Laboratory     | 0.9874      | 0.9972      | 1.3573 | 1.6435 | 1.3076 | 341.744     | 336.542     | 376.693 | 176.353 | 144.345 |

Table 1. Mean errors for the meeting room and laboratory experiments.
Figure 4. The mean errors of the meeting room and laboratory.

Figure 4 shows the mean errors of the meeting room and laboratory. Our system is 0.4m less than the previous DeepFi average positioning error and is about 0.65m more accurate than the most traditional fingerprint positioning method (ML). The positioning accuracy can reach within 1m in both environments with large noise and small noise, which indicates that our method is highly robust and can adapt to multiple environments.

5. Conclusions

In this paper, we combined CSI indoor localization algorithm based on neural network. In our algorithm, we firstly extract the skewness and kurtosis of CSI signal, and take the feature value as the initial input data. In the offline stage, we used the algorithm of neural network to train the extracted feature values by using a three-layer neural network. In order to reduce the complexity of the whole system, we also used a greedy learning algorithm to form RBM structure between hidden layers. In the online localization phase, the Bayesian algorithm based on RBF is used to estimate the position.

In the future, our next work is to extract real and effective CSI signals and apply them to experiments. This part involves the distinction between LOS and NLOS, which will greatly improve the positioning accuracy.

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