LoS/NLoS Identification Based on Double-Polarized Antenna and Convolutional Neural Networks

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Abstract

5G New Radio has a unique value in improving positioning capabilities, which can achieve centimeter-level indoor positioning. This not only brings convenience to our daily life, but also will play an important role in the industrial field. At present, the Industrial Internet of Things (IIoT) based on 5G private network has emerged. However, none-line-of-sight (NLoS) and line-of-sight (LoS) channel states have a great influence on the accuracy of indoor positioning. If the LoS/NLoS channel propagation states cannot be distinguished, the quality and efficiency of industrial production will be affected. In this paper, we innovatively use the characteristics of dual polarized antennas between the transmitter and receiver, and combine Convolutional Neural Networks (CNN) to propose a LoS / NLoS identification method. We use the Quadriga channel model which conforms to the channel standard of The 3rd Generation Partnership Project Technical Report 38.901 for simulation, and the simulation results show that the accuracy rate of selecting 3 base stations with LoS path can reach 98.5% and 99% respectively in the two IIoT baseline scenarios. Therefore, the proposed algorithm has good classification performance.

Keywords

LoS/NLoS, Double-polarized Antenna, CNN, 3GPP TR 38.901, IIoT, Quadriga

1. Introduction

In the field of indoor wireless positioning, many wireless positioning technologies are based on time of arrival (ToA), time difference of arrival (TDoA), direction of arrival (DoA), and received signal strength (RSS). The localization technology based on ToA and DoA parameters is very sensitive to the reliability of line-of-sight (LoS) propagation. When the LoS signal is unavailable, that is to say, the system is in none-line-of-sight (NLoS) state, the received signal will lead to a longer propagation distance. After one reflection, the wireless signal will not only introduce a large positive deviation to the target node's ranging, but also bring a wrong direction of arrival

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estimation to the target node, which will eventually lead to a large number of positioning errors in the whole system. For this kind of application in complex multipath propagation scenarios, a number of studies have been conducted to identify the state of channel propagation.

Generally speaking, the identification methods of channel propagation state can be divided into two categories. One is based on statistical information identification: this kind of method is mainly based on the change of statistical characteristics of signals caused by two different propagation states. For example, [1] found that ranging noise under LoS propagation condition can be regarded as Gaussian distribution with mean value of zero, while NLoS is Gaussian distribution with non-zero mean value, thus classification and identification can be realized based on this statistical characteristic. [2] used the statistic of skewness parameter to measure the distribution of receiving intensity in WiFi system, so as to realize classification. However, this kind of method has high requirements for threshold division, and the threshold is sensitive to the environment. In addition, this method still needs some time to obtain the statistical characteristics between samples. The other is based on channel impulse response or propagation path Loss. The idea of this method is to extract the channel characteristic parameters, and then realize the channel propagation state identification according to the distribution of channel characteristic parameters combined with hypothesis testing. For example, Rician factor is widely used to distinguish LoS from NLoS, [3] finally achieved 88% discrimination accuracy through selecting appropriate threshold. Parameters such as root mean square delay spread (RMSDS), kurtosis, skewness, departure/arrival angle spread are also used to identify the channel state with further research. Although this kind of method can classify almost in real time, this method still requires high threshold division and sufficient prior information is required to determine the appropriate threshold.

Machine learning (ML) method can extract features from various dimensions, which makes the machine learning method very suitable for solving classification problems. Therefore, applying the technology based on machine learning to the identification of LoS/NLoS conditions can provide more accurate results. Many literatures have improved the traditional methods of manually extracting features and then setting thresholds. [4] used support vector machine (SVM) to identify LoS/NLoS scenarios, in which rise time, kurtosis and delay diffusion were taken as input data. [5] also made use of typical channel features and combined with ANN. In recent years, the method of using Convolutional Neural Networks (CNN) [6] or combining CNN with long short-term memory (LSTM) [7] directly uses the time domain channel impulse response (CIR) of the signal to identify LoS/NLoS has appeared. In [8] and [9], the characteristics of multipath in the angle domain are considered, and LoS/NLoS is identified by power angle spectrum (PAS). In [10], CIR information in time domain is transformed into time-frequency domain by wavelet transform to identify LoS/NLoS. The method of ML can extract a variety of features and avoid the problem of inaccurate threshold determination. Merely a part of samples with known propagation status be used as the training set to obtain a model, and which can distinguish the propagation status of new samples in this scenario.

However, most of the above methods are based on Ultra Wide Band (UWB) system and WiFi system, and no research has been done on the channel conforming to the channel standard of The 3rd Generation Partnership Project Technical Report 38.901 (3GPP TR 38.901). 5G New Radio (NR) provides unique value in enhancing positioning capability, can achieve centimeter-level high-precision indoor positioning, and will play an important role in the industrial field.

At present, the Industrial Internet of Things (IIoT) based on 5G private network has emerged, which has effectively improved the quality and efficiency of industrial production. Therefore, it is meaningful to study the channel state discrimination in accordance with 3GPP TR 38.901 channel standard [11] . Under the TR 38.901 channel condition, [12] used the dual polarization characteristics of the transceiver antenna to distinguish LoS condition, which improved the performance of NR high-precision positioning, but it depends on the appropriate threshold. Based on the above reasons, this paper innovatively proposes a CNN-based method of LoS / NLoS identification , which uses the dual polarization characteristics of the transceiver antenna under the channel conditions conforming to the 3GPP TR 38.901 channel standard and avoid the problem of inaccurate threshold determination.we consider the polarization features extracted from CIR as the input of CNN, there is no published literature discussing this method at present. At the same time, the channel data generated by QuaDRiGa channel model [13] is simulated in two usage scenarios of IIoT: Indoor factory with dense clutter and high base station height (InF-DH) and Indoor factory with sparse clutter and high base station height (InF-SH).

The remaining of the paper is organized as: Section 2 describes the dual polarization characteristics of the antenna and introduces the details of the proposed CNN-based method. Section 3 describes the experimental settings and simulation results in detail. Section 4 is the conclusion.

2. Proposed LoS/NLoS identification method

2.1. Antenna polarization

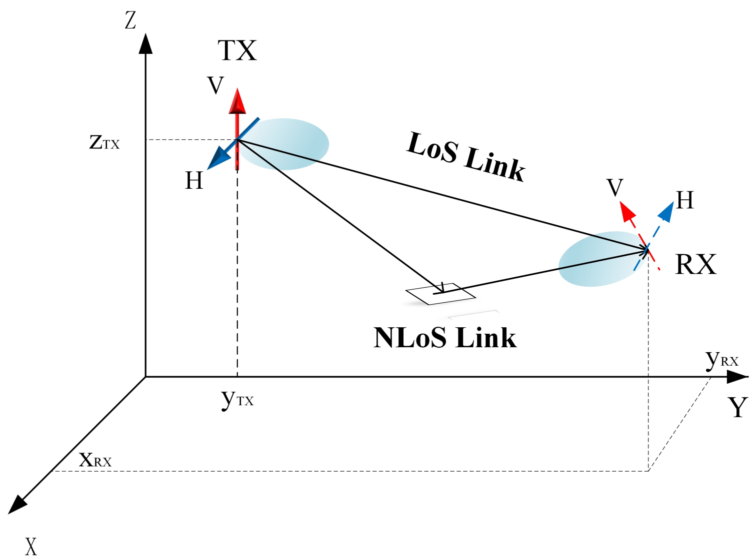

Figure 1: link between transmitter and receiver

In the Global Coordinate System (GCS), signal propagation in NLoS and LoS scenarios is shown in Fig.1. Under the LoS scenario, the wireless signal propagates in a straight line between the transceiver and the receiver without shielding. In the case of obstacles, the wireless signal can only reach the receiver by reflection, scattering and diffraction, which is called NLoS scenario.The amplitude of the received signal can be given by the channel impulse response CIR, which can be formulated as [12] :

$$|H_{u,s}| = \left| \left[\begin{array}{c} F_{rx,u,\theta}\left(\theta_{ZoA}, \varphi_{AoA}\right) \\ F_{rx,u,\varphi}\left(\theta_{ZoA}, \varphi_{AoA}\right) \end{array} \right]^T S \left[\begin{array}{c} F_{tx,s,\theta}\left(\theta_{ZoD}, \varphi_{AoD}\right) \\ F_{tx,s,\varphi}\left(\theta_{ZoD}, \varphi_{AoD}\right) \end{array} \right] \right| \tag{1}$$

where *u* represents the polarization direction of the transmitted signal and *s* represents the polarization direction of the received signal. There are two polarization directions *V* and *H*, which respectively represent vertical polarization and horizontal polarization. The signal transmitted in a specific polarization mode can be expressed as a two-dimensional field vector $F = [F_\theta(\theta, \phi), F_\phi(\theta, \phi)]$. *ZoA/D* and *AoA/D* are respectively represent zenith angles of arrival/departure and azimuth angles of arrival/departure. *S* is the scattering matrix, which simulates the reflection, scattering and attenuation in the path.

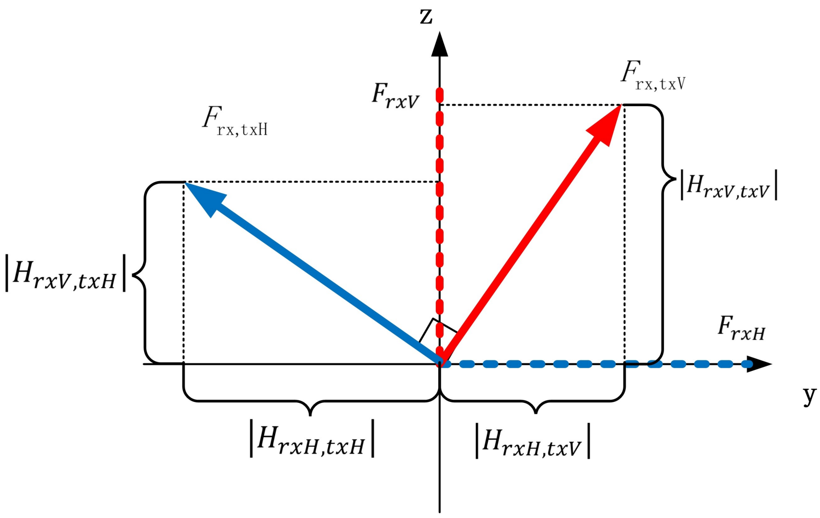

Figure 2: Received signals field projections on the UE Local Coordinate System.

As shown in Fig.2, transmitted signals are dual orthogonally polarized. User Equipment (UE) receiver is dual orthogonally polarized. LoS/NLoS identification can be performed by using the difference of polarization characteristics of received signals in multipath environment, where $F_{rx,txs}$ represents the polarization signal of received transmitted signals in UE local coordinate system, and F_{rxu} represents the polarization direction of receiving antenna in UE local coordinate system.

By the conclusion in [14], for the LoS path in theory , the attenuation of both polarization will be the same,that is say$|H_{u,v}|^2 + |H_{u,u}|^2 - |H_{v,u}|^2 + |H_{v,v}|^2 = 0$. While for the NLoS paths is not equal to zero, because its through reflection and scattering process. Therefore, for the detection of polarization power difference or power imbalance, the following power-based characteristic formula is used [4] :

$$d_{\text{power}} = \left| \frac{|H_{2,1}|^2 + |H_{2,2}|^2 - \left(|H_{1,2}|^2 + |H_{1,1}|^2\right)}{\max\left(|H_{2,1}|^2 + |H_{2,2}|^2, |H_{1,2}|^2 + |H_{1,1}|^2\right)} \right| \tag{2}$$

According to the Angle balance of the LoS path and the fact that the angle between the two polarizations at the transmitter remains orthogonal at the receiver. While the polarization angles of NLoS path do not keep orthogonal because of the reflection and scattering of electromagnetic waves. The following angle-based characteristic formula is obtained [14] :

$$d_{\text{angle}} = \left| \text{atan} \cdot \frac{|H_{1,1}|}{|H_{2,1}|} - \text{atan} \cdot \frac{|H_{2,2}|}{|H_{1,2}|} \right| \cdot \frac{2}{\pi} \tag{3}$$

where $|H_{rxV,txV}| = |H_{1,1}|$, $|H_{rxH,txV}| = |H_{2,1}|$, $|H_{rxV,txH}| = |H_{1,2}|$, $|H_{rxH,txH}| = |H_{2,2}|$. $|H_{rxV,txV}|$ represents the CIR generated by the array elements with vertical polarization at the originating end and vertical polarization at the receiving end. $|H_{rxH,txV}|$, $|H_{rxV,txH}|$, $|H_{rxH,txH}|$ in the same way.

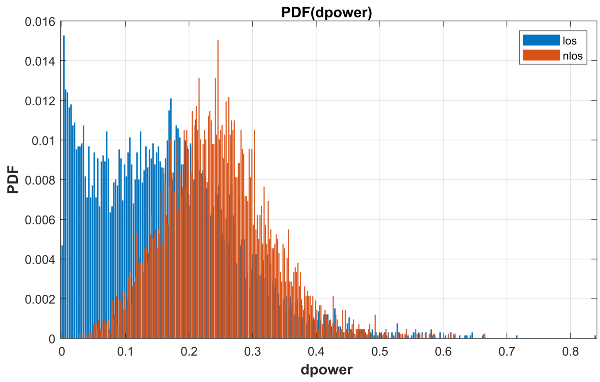

Figure 3: Probability distribution function of the d_{power} characteristic.

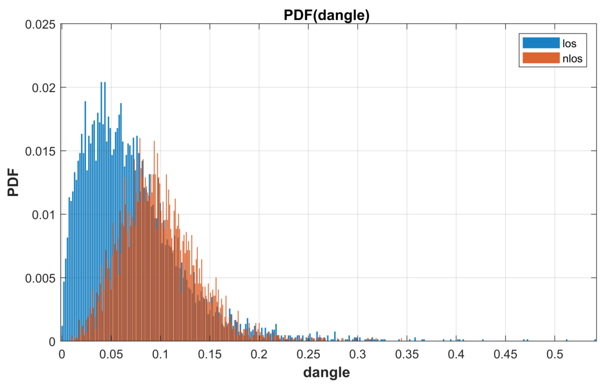

Figure 4: Probability distribution function of the d_{angle} characteristic.

It can be seen from Fig.3 and Fig.4, LoS and NLoS scenarios do show different probability distributions of these features. However, there are still many overlapping areas, which may lead to inaccurate identification of LoS/NLoS. Since the CNN-based algorithm can automatically extract features and classify them to a certain extent,we combine the dual-polarization characteristics of antenna with CNN's self-extracting features, and innovatively propose an LoS/NLoS identification algorithm based on dual-polarization antenna characteristics and CNN. we consider the four polarization features ($|H_{1,1}|, |H_{1,2}|, |H_{2,1}|, |H_{2,2}|$) extracted from CIR as the input of CNN.

In order to improve the accuracy of the algorithm, two additional statistical characteristics are added as the input of CNN, which are the mean value $\overline{|H_{u,v}|}$ and $\sigma_{|H_{u,v}|}$ The variance their formulas as follow:

$$\overline{|H_{u,v}|} = \frac{\sum_{l=1}^{L} |H_{u,v}|_l}{L} \tag{4}$$

$$\sigma_{|H_{u,v}|} = \sqrt{\frac{\sum_{l=1}^{L} \left(|H_{u,v}|_l - \overline{|H_{u,v}|} \right)^2}{L}} \tag{5}$$

where l represents the l_{th} path and L represents the total multipath number. u and v could be 1 or 2.

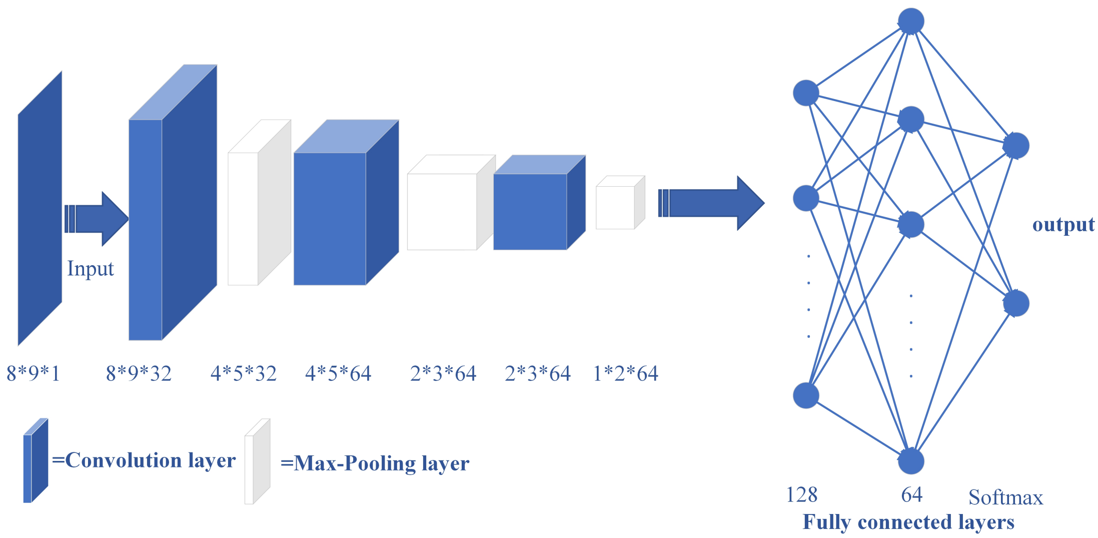

Figure 5: The CNN structure of the proposed method.

2.2. Convolutional Neural Network

CNN is a kind of feedforward neural network.CNN reduces the complexity of network model through three strategies: local receptive field, weight sharing and downsampling. At the same time, the network extracts more abstract features from the original data through simple nonlinear functions. CNN usually consist of three parts. The first part is the input layer. The second part is formed by stacking *n* convolution layers and pool layers. The third part is composed of a fully connected multi-layer perceptron classifier. Convolutional neural network takes into account that the spatial distribution of input data can learn more adjacent features than DNN, and can extract the potential nonlinear structure of input data. In addition, it has the characteristic of sharing weights, which makes CNN achieve a deeper network structure and better recognition effect. The CNN structure involved in this paper is shown in Fig.5.

In the forward propagation, the convolution kernel performs convolution operation with the input data, and extracts features to generate a feature map as the input of the next layer. It can be expressed by the formula:

$$x_j^l = f\left(\sum_{i\in M_j} x_i^{l-1} w_{ij}^l + b_j^l\right) \tag{6}$$

where M_j represents the input feature map, w is the convolution kernel connecting $(l-1)_{th}$ layer to the l_{th} layer, and b_j^l is the j_{th} of the l_{th} layer bias of neurons. f is the rectified linear unit (ReLU) activation function and the formula is:

$$f_{ReLU}(x) = \begin{cases} x & if\ x > 0 \\ 0 & otherwise \end{cases} \tag{7}$$

The convolution layer is usually followed by the pooling layer, which is used to reduce the dimension of the extracted features of the same type to reduce the amount of computation. At the same time, the use of pooling reduces over-fitting and noise propagation. After being processed by convolution layer and pooling layer, deeper features are extracted from the input data.

The last part of the fully connected layer uses a softmax activation function when outputting. The features extracted from the previous layers are combined and then classified. the output result can be interpreted as the probability of each class.Its function is:

$$P(s \mid X) = \frac{e^{\boldsymbol{X}^T \boldsymbol{w}_s}}{\sum_{r=1}^{R} e^{\boldsymbol{X}^T \boldsymbol{w}_r}} \tag{8}$$

where $\boldsymbol{X}$ is the output of the previous layer, *T* is transpose, $\boldsymbol{w}$ is the weight of neurons, $R = 2$ is the number of labels, $s = 1, 2$ is the subscript of the predicted class, and P is the probability of LoS/NLoS classification.

Then, the training loss is measured by cross entropy loss, and the weights are updated by back propagation.

In the CNN structure we designed, both convolution layer and pooling layer adopt the strategy of zero-filling, and Batch normalization is adopted as the input. Our CNN has a total of five layers, the first three layers adopt the structure of convolution layer superimposed on pooling layer, and the last two layers are fully connected. The convolution layer uses a convolution kernel with a step size of 3*3 and is activated by an activation function ReLU. Pooling layer uses the maximum value of 2*2 with step size of 2.

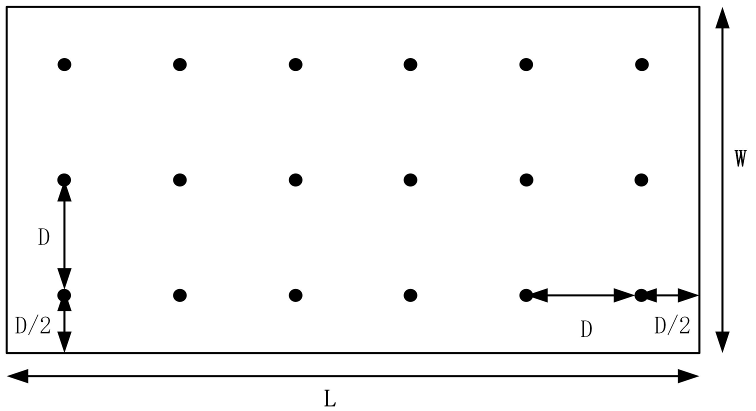

Figure 6: BS locations.

Table 1
Simulation Configuration

Parameters	Values
Hall size	InF-SH: 300x150 m,InF-DH: 120x60 m
BS locations	18 BSs on a square lattice with spacing D, located D/2 from the walls
BS antenna configuration	(M,N,P,Mg,Ng) =(4,4,2,1,1) dH=dV=0.5 +/-45°dual-polarization
UE antenna configuration	(M,N,P,Mg,Ng) =(2,2,2,1,1) dH=dV=0.5 H/V dual-polarization
UE drop procedure	100% indoor, uniformly distributed over the horizontal area
UE antenna height	1.5m
BS antenna height	8m
Centre frequency	3.5GHZ

3. Results and discussion

3.1. Simulation setting up and dataset description

The data set is generated from the channel data generated by the Quadriga channel model in MATLAB2020b, which compliance with 3GPP TR 38.901 channel standard. CNN is implemented under the framework of python 3.6 TensorFlow. The simulation conditions [15] for data generation are set as the TABLE I and Fig.6.

The transceiver antenna is modeled by a single antenna panel. On the antenna panel, antenna elements are placed vertically and horizontally, where N is the number of columns and M is the number of antenna elements with the same polarization mode in each column. The antenna elements are evenly distributed in both horizontal and vertical directions, with horizontal spacing d_H and vertical spacing d_V. As is shown in Fig.7, the polarization mode of antenna panel is dual polarization ($P = 2$). The specific receiving and transmitting antenna array configuration is as follows:The transmitting antenna configuration includes $M_t = 4$, $N_t = 4$ and $P_t = 2$, +/-45 dual polarization with a total of 32 array elements. The receiving antenna configuration:$M_r = 2$, $N_r = 2$, $P_r = 2$ H/V dual polarization with 8 elements. In addition, set the originating antenna panel to be placed in the *YoZ* plane of GCS coordinate system, the receiving antenna panel is placed parallel to the transmitting panel.

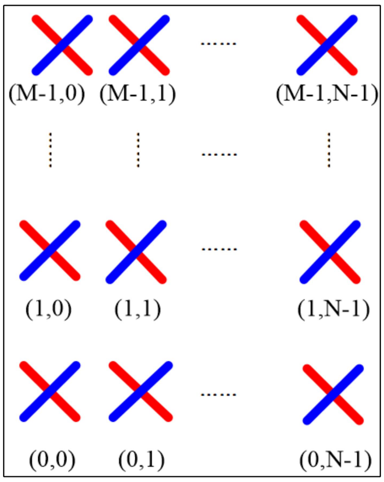

Figure 7: Antenna layout diagram.

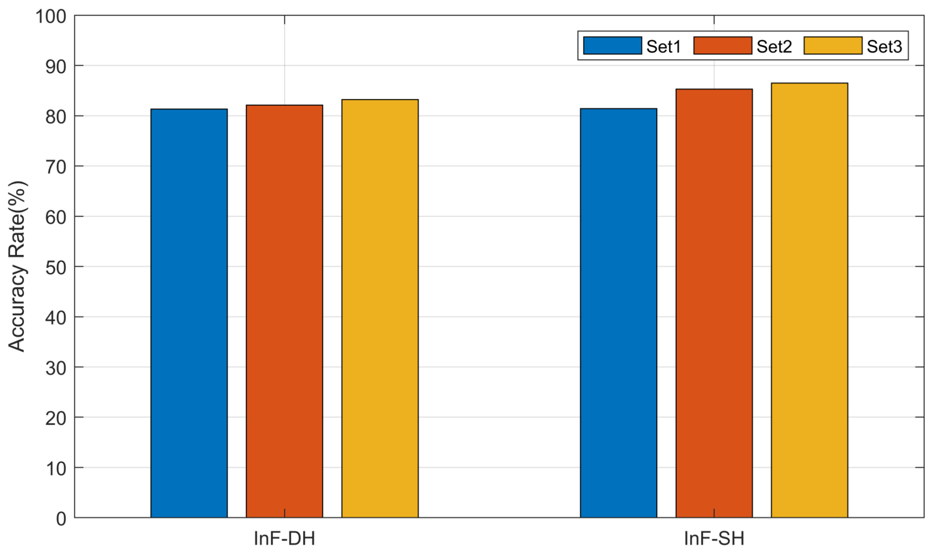

Figure 8: Accuracy of the different datasets.

3.2. Identification accuracy of CNN

In order to make the CNN algorithm for LoS/NLoS identification based on dual polarization characteristics of antenna achieve better identification performance. We used three different datasets for our tests.

- Set1 contains only CIR data of four polarization characteristics, and the input data size is 8*8.
- Set2 Bases on Set1, the average value of four polarization characteristics in multiple paths are added, and the input data size is 4*17.
- Bases on Set2, the variances of four polarization characteristics in multiple paths are added, and the input data are 8*9 dimensions.

In the InF-DH scenario, the identification accuracy rate of CNN training data Set1, 2, 3 were 81.3%, 82.1% and 83.2%, respectively. In the InF-SH scenario, the identification accuracy rate of CNN training data Set1, 2, 3 were 81.4%, 85.3% and 86.5% respectively. Fig.8 shows that statistical characteristics are helpful to improve the accuracy of LoS/NLoS recognition. This is because among the multiple paths with LoS paths, the polarization characteristics of LoS paths have a great influence on the statistical characteristics. CNN can extract the corresponding features and apply them to classification.

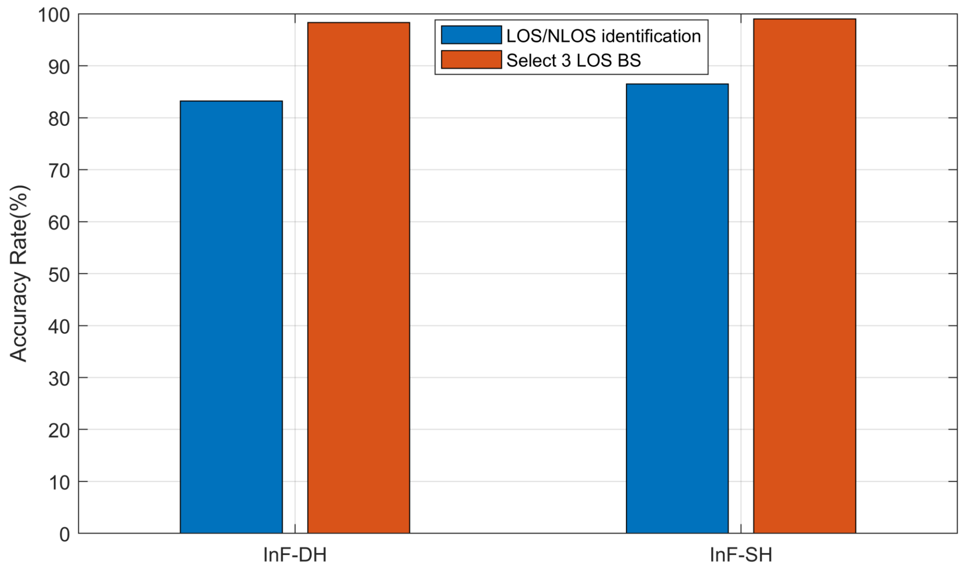

Figure 9: Accuracy of selecting 3 BSs with LoS path.

In a 5G NR cellular system with multiple cells, the distinction of LoS/NLoS channel states may not perform so well in actual scenes. For the existing 5G high-precision positioning algorithm, only a few BSs containing LoS path need to be selected to achieve high-precision positioning. Therefore, we select 10 BSs with the highest CIR power at the receiving end as LoS candidate cells among 18 BSs, and then select three cells with the highest LoS probability to be directly judged as LoS cells as the mitigation scheme of NLoS channel state. The accuracy of selecting 3

BSs with LoS path scheme is shown in Fig.9. We can see a significant improvement in accuracy. In the two scenarios, the accuracy of selecting 3 BSs with LoS path are 98.3% and 99% respectively. The improvement in accuracy is largely due to the high CIR power of BS containing LoS paths, and the advantage of multiple cells not only further improves the system's effectiveness, but also improves the system's robustness.

3.3. Classification accuracy comparison with traditional methods

In order to compare the performance of the proposed algorithm, we also verify and compare the threshold-based dual polarization method for LoS/NLoS scene identification.

From Fig.10 and Fig.11, we can see that CNN-based algorithm is higher in LoS/NLoS identification accuracy than the traditional threshold-based algorithm, and its identification performance is better than the traditional threshold-based algorithm. In the case of directly identifying the propagation state of LoS/NLoS, the identification accuracy of the proposed algorithm is at least 16.2% and 12.9% higher than that of the traditional threshold-based discrimination algorithm in IIoT two scenarios. Under the decision criterion of selecting the three LoS BSs with the highest LoS probability, the identification accuracy of the algorithm proposed in this paper has been further improved by at least 1.3% and 2.5% respectively on the basis of the high accuracy of the traditional threshold-based algorithm. what's more the algorithm proposed in this paper avoid the problem of accuracy reduction caused by improper threshold determination. On the one hand, this is because the algorithm based on CNN has a good effect in extracting the nonlinear characteristics between the data, and on the other hand, the error caused by the need to determine a threshold value for classification is avoided by using CNN classification.

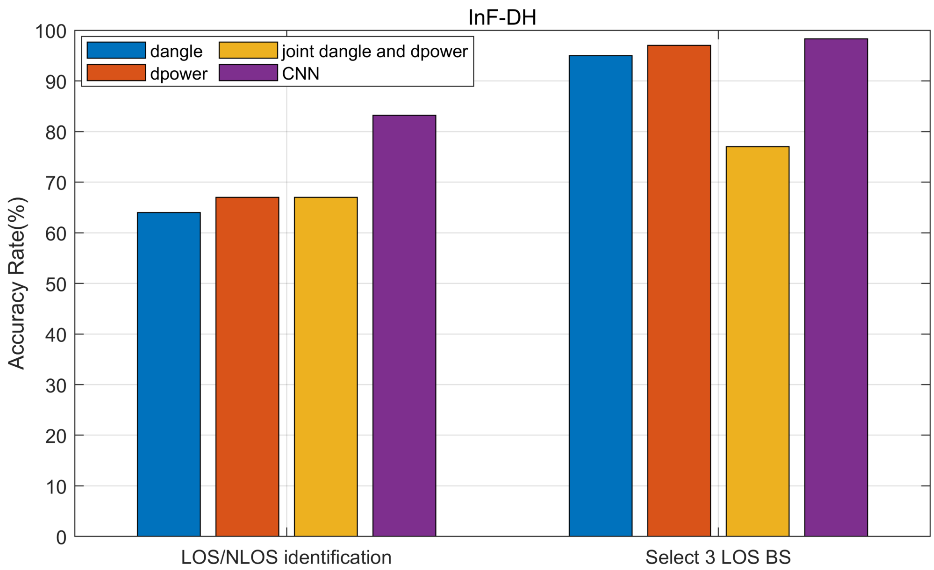

Figure 10: The accuracy rate of the two ways was compared under InF-DH scenario.

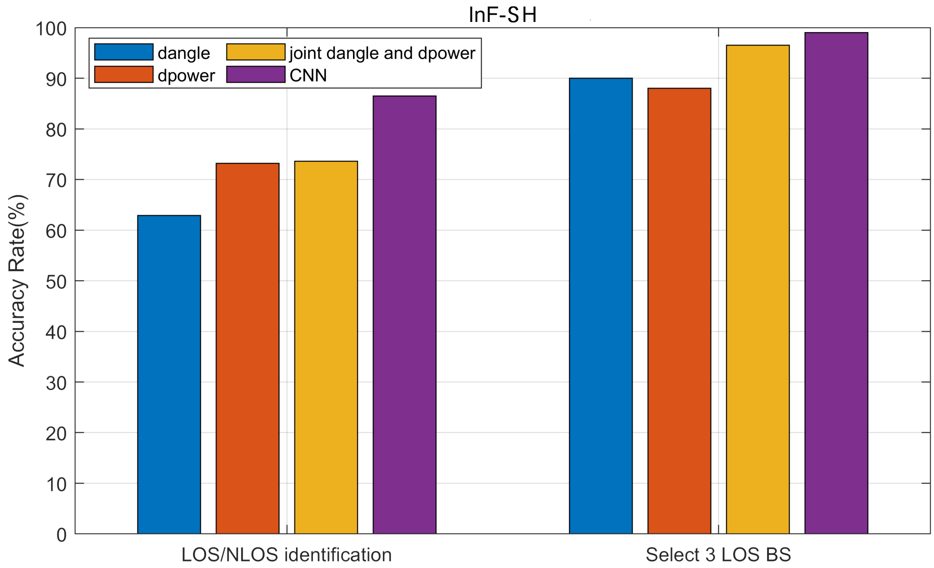

Figure 11: The accuracy rate of the two ways was compared under InF-SH scenario.

4. Conclusion

In this paper, a LoS/NLoS identification method based on the characteristics of double-polarized antenna and convolutional neural network is innovatively proposed. This method can accurately identify LoS/NLoS propagation state in the channel environment conforming to 3GPP TR 38.901 standard. The simulation results of the proposed algorithm show that the accuracy rate of LoS/NLoS identification is 86.5% (InF-SH scenario) and 83.2% (InF-DH scenario). Under the two baseline application scenarios of multi-base station IIoT, the accuracy rate of selecting 3 BSs with LoS path can reach 99% (INF-SH scenario) and 96% (InF-DH scenario). Therefore, the proposed algorithm has good classification performance, and can better provide services for 5G NR related applications.

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