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Deep Learning-Based Signal Modulation Identification in OFDM Systems

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ABSTRACT Signal modulation identification (SMI) plays a very important role in orthogonal frequency-division multiplexing (OFDM) systems. Currently, SMI methods are often implemented via feature extraction based on machine learning. However, the traditional methods encounter a bottleneck where the probability of correct classification (PCC) is very limited and hence it is hard to implement in practical OFDM systems due to the fact that traditional methods are difficult to extract feature of the OFDM signals. In order solve these problems, we propose a deep learning (DL) based SMI method for identifying OFDM signals. Specifically, convolutional neural network (CNN) is adopted to train in-phase and quadrature (IQ) samples for OFDM signals. Then we choose dropout layer to prevent overfitting and improve its identification accuracy. In addition, datasets with different modulation modes are adopted to verify our trained CNN. Experiments are conducted to show that our proposed method achieves higher accuracy and better consistency than traditional methods. Moreover, extensive results confirm that the proposed method performs robustly in different datasets.

INDEX TERMS Orthogonal frequency-division multiplexing (OFDM), deep learning (DL), signal modulation identification (SMI), convolutional neural network (CNN).

I. INTRODUCTION

Orthogonal frequency-division multiplexing (OFDM) is one of most important techniques in designing advanced wireless communications systems [1], [2] since it can achieve high spectral efficiency while mitigate fading/interference [3], [4]. Conventional wireless communications focuses on cooperative relationship since they share underlying protocol for all of users [5]. As the fast development of wireless communications, non-cooperative communications are becoming ubiquitous in both civilian and military areas. In the non-cooperative scenarios, signal modulation identify-cation (SMI) techniques are required to recognize different modulations of all of the received signals [6], [7]. For example, it can identify various eavesdropping risks in wireless links and ensure security and integrity of the communication systems [8]. It is also important in many civilian areas such as radio spectrum monitoring, interference source control and cognitive radio [9]. Among these applications, the design of SMI method poses a big technical challenge to identify signal types in non-cooperative OFDM systems [10], [11]. Hence, it is necessary to develop accurate SMI technique for identify OFDM signals [12], [13]. In electronic countermeasures, by intercepting the electromagnetic waves in the wireless channel, types of the signal modulation are first required to demodulate and estimate [14], [15]. Then the intercepted signal can be further decrypted. Hence, SMI is considered one of the most important techniques in designing non-cooperative communications systems.

Most of existing techniques on modulation identification are based on feature extraction and machine learning classification algorithms [16], [17]. Traditional feature extraction methods are available, such as higher order cumulants (HOC) [18], discrete wavelet transform [19], adaptive wavelet transform [20], and mixed parameters [21], [22]. Machine learning based classifiers are designed with

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k-nearest neighbor (KNN) [23], support vector machine (SVM) [24], decision tree (DT) [25], naive Bayesian (NB), *et al.* Many SMI methods can be developed via combining different feature extraction strategies with different classifiers [26]. However, these methods are hard to extract the inherent signal features of different modulation modes because traditional feature extraction methods are based on statistics [27]. Hence, the classification results are vulnerable to confuse.

However, machine learning based SMI methods still encounter performance bottlenecks when meeting big data problems. In other words, the probability of correct classification (PCC) is not high and it is hard to implement in practical OFDM systems. In order to surmount the bottleneck, deep learning (DL) [28], [29] is considered as one of effective methods for implementing SMI [30]. Xie *et al.* propose an improved identification method with deep neural network (DNN) [31]. Ramjee *et al.* use a long short-term memory (LSTM) neural network and a deep residual networks (ResNet) to identify the modulation modes of the signal and significantly reduced training time [32]. Aslam *et al.* combine genetic programming (GP) and KNN to accurately identify four modulation modes, i.e., binary phase shift keying (BPSK), quadrature phase shift keying (QPSK), 16 quadrature amplitude modulation (16QAM) and quadrature amplitude modulation (64QAM) [33].

Unlike the aforementioned methods, we propose a DL-SMI method using convolutional neural network (CNN) to identify OFDM signals. It is worth noting that the proposed CNN method which consists of two convolutional layers and three fully connected layers. Furthermore, the addition of dropout layer helps to reduce the interaction between neurons in the same layer and prevents overfitting during network training. Different datasets are adopted to test the generalization of the proposed network and it can perform better with higher signal-sampling rate. At last, experiment results are given to verify the proposed DL-SMI method.

The reminder of the rest paper is organized as follows. The system model and the deep learning model are introduced in Section II. We propose DL-based SMI method in Section III. Section IV gives experimental results to verify the proposed method via giving the comparison between different methods and the performance analysis. Section V concludes our work.

II. SYSTEM MODEL AND DL MODEL

A. SYSTEM ARCHITECTURE

Fig. 1 demonstrates the system architecture of the proposed DL-SMI methods for identifying signal modulations in non-cooperative OFDM systems. Transmit symbols are converted into OFDM signals by OFDM modulation and Rician fading channel. It is assumed that each sub-carrier uses the same modulation mode. IQ samples are generated via simulation data to train CNN. Then our proposed DL-SMI can recognize modulation of the OFDM signals. In initial work, the trained CNN can accurately identify five mixed unknown modulated signals, i.e., BPSK, QPSK, 8 phase shift keying (8PSK), 16QAM and 64QAM.

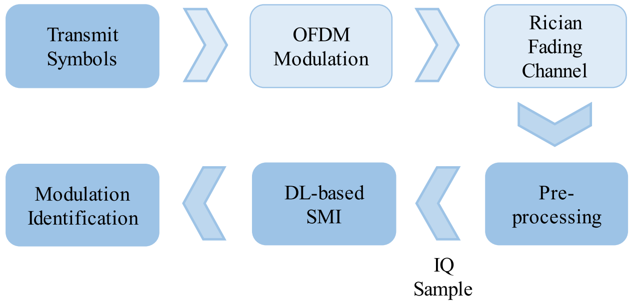

FIGURE 1. Architecture of the proposed DL-SMI method for identifying OFDM signals.

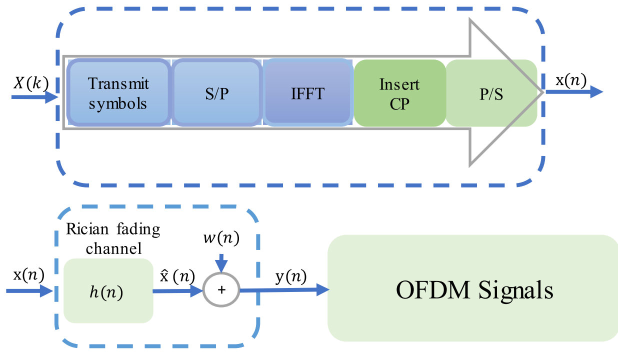

FIGURE 2. Production process of OFDM signals.

B. GENERATION OF OFDM SIGNALS

The generations of OFDM signal is shown in Fig. 2. The multiplexing of the data stream is achieved from transmit symbols by serial-to-parallel (S/P) conversion. The corresponding modulation is performed by using inverse fast Fourier transform (IFFT) to convert the frequency domain signals into time domain signals. After that, the cyclic prefix (CP) of the entire system signal is added to reduce the inter symbol interference (ISI) between the sub-channels. Then, the S/P sub-stream is converted into a serial data stream by parallel-to-serial (P/S) conversion and sent to the Rician fading channel. Additive Gaussian white noise (AWGN) is added to obtain the OFDM signals.

We consider that the signal passes through the Rician fading channel and the received signal can be expressed as

$$y(n) = x(n) \otimes h(n) + w(n) \tag{1}$$

where $\otimes$ is represented as the circular convolution, while $x(n)$ and $w(n)$ are represented as the modulated transmitted signal and AWGN, respectively. Here, we assumed that only a line of sight (LOS) between mobile terminal and base station over Rician fading channel, where it has a main path and other paths. The PCC of the Rician distribution can be expressed as

$$f(z) = \frac{z}{\sigma^2} \exp\left(-\frac{z^2 + A^2}{2\sigma^2}\right) \cdot I_0\left(\frac{zA}{\sigma^2}\right) \tag{2}$$

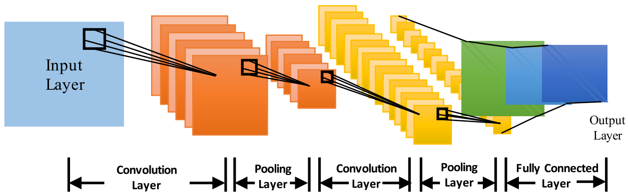

FIGURE 3. Basic structure of CNN.

where A is the peak of the amplitude of the main signal, σ^2 is the power of the multipath signal component, and $I_0(\cdot)$ is the modified Bessel function of the first kind of 0-th order. The Rician fading channel can be modeled as

$$h(n) = \sqrt{\frac{\kappa}{\kappa+1}}\sigma e^{j\theta} + \sqrt{\frac{1}{\kappa+1}}\mathbb{N}\left(0, \sigma^2\right) \tag{3}$$

where the first term corresponds to a mirror path that arrives at a uniform phase θ, and the second term corresponds to a large number of reflection paths and scattering paths that are independent of θ. The parameter κ commonly referred to the Rician factor is used to determine the Rician distribution, which is defined as the ratio of the power of the main signal to the power of the multipath component. When the factor κ gradually approaches 0, the Rician distribution is converted to Rayleigh distribution,

$$\kappa = \frac{A^2}{2\sigma^2} \tag{4}$$

As shown in Fig. 2, the generated OFDM signal will be converted to IQ samples, which are utilized to train the CNN.

III. OUR PROPOSED DL-SMI METHOD

A. CNN FOR DL-SMI

Neural network is a hot research topic in artificial intelligence. CNN is a commonly used network model, which has a unique effect on the processing of graphic images. Fig. 3 depicts the basic structure of CNN which mainly consists of input layer, convolution layer, pooling layer, fully connected layer and output layer.

The three characteristics of CNN are introduced as follows:

- Local connection: Each neuron is no longer connected to all neurons in the upper layer, but only to a small number of neurons. This reduces a lot of parameters.
- Weight sharing: A set of connections can share the same weight, rather than having a different weight for each connection. This reduces many parameters too.
- Down sampling: Pooling layer is used to reduce the number of samples per layer, further reducing the number of parameters, while also improving the robustness of the model.

The most important part of the CNN in Fig. 3 is the convolution layer, in which the convolution operation can be compared to the convolution in calculus. For example, to calculate the convolution $s(t)$ of two time-domain signals $x(t)$ and $w(t)$. Then $s(t)$ can be expressed as

$$s(t) = \int x(t-a)w(a)\,da \tag{5}$$

In the discrete case, it can also be denoted as

$$s(n) = \sum_a x(n-a)\,w(a) \tag{6}$$

The above formula can be obtained by using a matrix representation.

$$s(n) = (X \otimes W)(n) \tag{7}$$

If it is a two-dimensional convolution, it can be obtained according to recursion as follows:

$$s(i,j) = \sum_m \sum_n x(i-m, j-n)\,w(m,n) \tag{8}$$

In CNN, although we also say convolution, our convolution formula is slightly different from the definition in strictly mathematical. For example, for two-dimensional convolution, it is defined as:

$$s(i,j) = \sum_m \sum_n x(i+m, j+n)\,w(m,n) \tag{9}$$

CNN is the deep learning network that has been developed in recent years and is widely used by academics and in enterprises. Representative CNNs include LeNet-5, VGG, AlexNet, *et al.*

B. DL-SMI METHODS

The proposed DL-SMI method is mainly implemented by CNN, which consists of two convolutional layers and three fully connected layers. There are 128 convolution kernels in the first convolutional layer, where the dimension of each convolution kernel matrix is 1×16. The second convolu-tional layer has 64 convolution kernels with each size of 2×8. The number of neurons in the three fully connected layers is 256, 128 and m, which represents the number of modulation modes. The parametric rectified linear unit (PReLU) is selected as the activation function for all available layers except the last fully connected layer, where Softmax is applied to obtain the probability distribution matrix of the last layer. Compared to the earliest proposed nonlinear activation functions Tanh and Sigmoid, the use of PReLU can be much less computation in the entire process when calculating the error gradient. For deep networks. It can also reduce the appearance of gradient disappearance during backpropagation, thus effectively completing the training of deep networks. The basic structure of CNN is shown in the Fig. 4.

In the network structure we proposed, the first four layers are added with the dropout layer, which can significantly reduce over-fitting. Dropout is one of the most efficient and commonly used regularization methods for neural networks. In a cycle, we randomly select some neurons in the neural

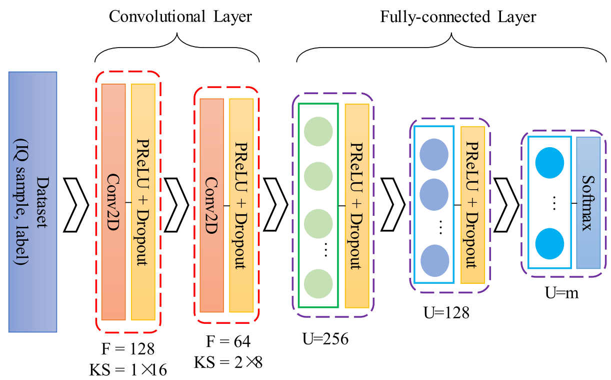

FIGURE 4. Structure of CNN for SMI.

layer and temporarily hide them. Then we carry out the training and optimization process of the neural network. In the next loop, we will hide some other neurons, until the end of the training. This approach can reduce the interaction between neurons in the same layer and make the model more generalizable.

C. DATASET

For the SMI task, we create two datasets with different modulation modes. Dataset Θ_1 includes modulation of BPSK, QPSK, 8PSK and 16QAM, while dataset Θ_2 consists of BPSK, QPSK, 8PSK, 16QAM and 64QAM. The above two datasets are used to verify the robustness of the proposed method. The signal-to-noise ratios (SNRs) range from 0 to 30 dB with the interval of 5 dB, and there are 20,000 data samples for each modulation for training and testing. So taking dataset Θ_1 as an example, under a specific SNR, there are 80,000 data input into the neural network, which are divided into training samples and test samples by 7:3.

1) IQ SAMPLES

Through OFDM modulation and the influence of the wireless channel, the ith sampling data we obtained can be represented by a complex vector as follows

$$S_i = [s_1, s_2, s_3, \cdots, s_n] \tag{10}$$

where n represents the number of sampling points. s_n denotes the value of the nth sampling point, which is a complex number. So s_n can be expressed as

$$s_n = \mathrm{Re}_n + j\mathrm{Im}_n \tag{11}$$

where Re_n represents the real part of the nth sampling point, while Im_n denotes the imaginary part of it. They are in-phase and quadrature components of signals respectively.

2) AP SAMPLES

On the basis of IQ Samples, the module A and the phase angle θ of s_n can be expressed as

$$A = \sqrt{\mathrm{Re}_n^2 + \mathrm{Im}_n^2} \tag{12}$$

$$\theta = \arctan \frac{\mathrm{Im}_n}{\mathrm{Re}_n} \tag{13}$$

where A and θ are the amplitude and phase components of signals respectively.

3) MANMADE FEATURES

By calculating the higher-order cumulants, the HOC features set can be obtained. Combining the extracted instantaneous features of the signal constitutes manmade features.

D. IMPLEMENTATION PLATFORM

The architecture of CNN is based on keras, which is a high-level neural network API. The above work is implemented with python. Matlab is used to generate the datasets for training and testing. GPU with four NVIDA GeForce GTX1080Ti are adopted for network training and testing to improve computational efficiency.

IV. EXPERIMENT RESULTS

We conduct several experiments to demonstrate the performance of DL-based SMI method in non-cooperative OFDM system. The CNN model is trained on the simulation datasets, and the identification accuracy at different SNRs is compared with conventional methods and machine learning methods. In the following experiments, the comparison of kappa coefficient and identification accuracy under different datasets proves that DL based method performs well than traditional methods. In our experiments, a non-cooperative OFDM system with 16 sub-carriers, 6 symbols of each sub-carrier, CP of length 2 and 256-point FFT is considered. The wireless channel follows Rician fading channel, where Sampling frequency is 10kHz, frequency shift of Doppler is 500Hz, and Rician factor is 20. Each sub-carrier uses the same modulation method.

A. PCC ANALYSIS

In the experiment, we compare three common classification methods based on machine learning with three neural network based methods, which are CNN trained on IQ samples, CNN trained on AP samples, Deep Neural Network (DNN) trained on manmade features, manmade features extraction followed by random forest (RF), support vector machine (SVM) and logistic regressive (Logistic). This part of the experiment is performed on dataset Θ_1.

As the SNR increases, the correct classification probability of proposed method is constantly improving, while the others remain basically the same. The performance curve is shown in Fig. 5. IQ samples are easier to identify than AP samples. When the SNR is greater than 20dB, the performance of our proposed method performs well with the accuracy of nearly 100%. On the other hand, the effect of CNN-based signal modulation identification is significantly better than others. CNN can automatically extract the features of data by using convolution kernel. Through the continuous training of the model, the accurate identification of the signal modulation can be realized.

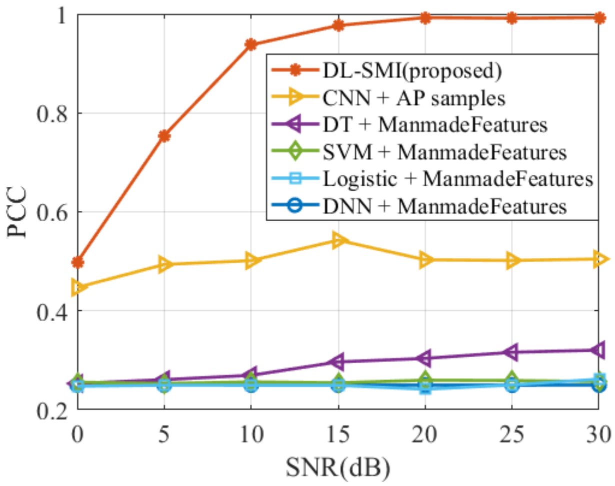

FIGURE 5. **PCC of the proposed method v.s. traditional methods in various SNRs(dataset Θ_1).**

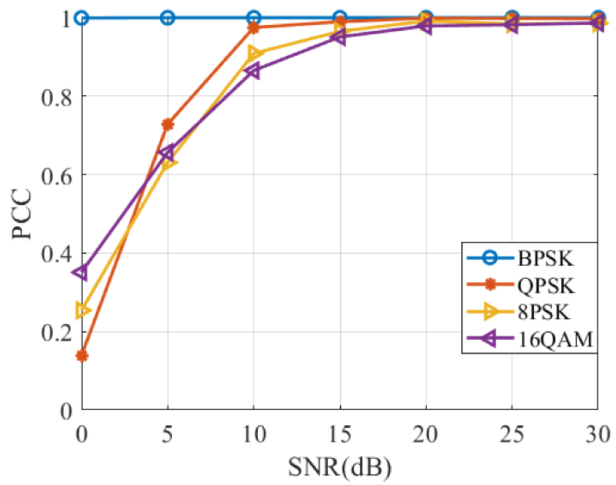

FIGURE 6. **PCC of different modulation modes (dataset Θ_1).**

The correct classification probability of different modulations in CNN trained on IQ samples is depicted in Fig. 6. BPSK can always be correctly identified in both low SNR and high SNR, while a considerable increase occurs from 0dB to 15dB of others. In the case of higher SNR, the rate of rise slows down and gradually stabilizes. The experimental results show that the proposed method has high accuracy in signal modulation identification.

B. CONSISTENCY ANALYSIS

The Kappa (κ) coefficient is used for consistency testing and is also an indicator for measuring classification accuracy. It can be expressed as

$$Kappa = \frac{p_0 - p_e}{1 - p_e} \tag{14}$$

where p_0 is the proportion of correctly classified samples to the total number of samples, that is the overall classification accuracy. Consider that the number of real samples

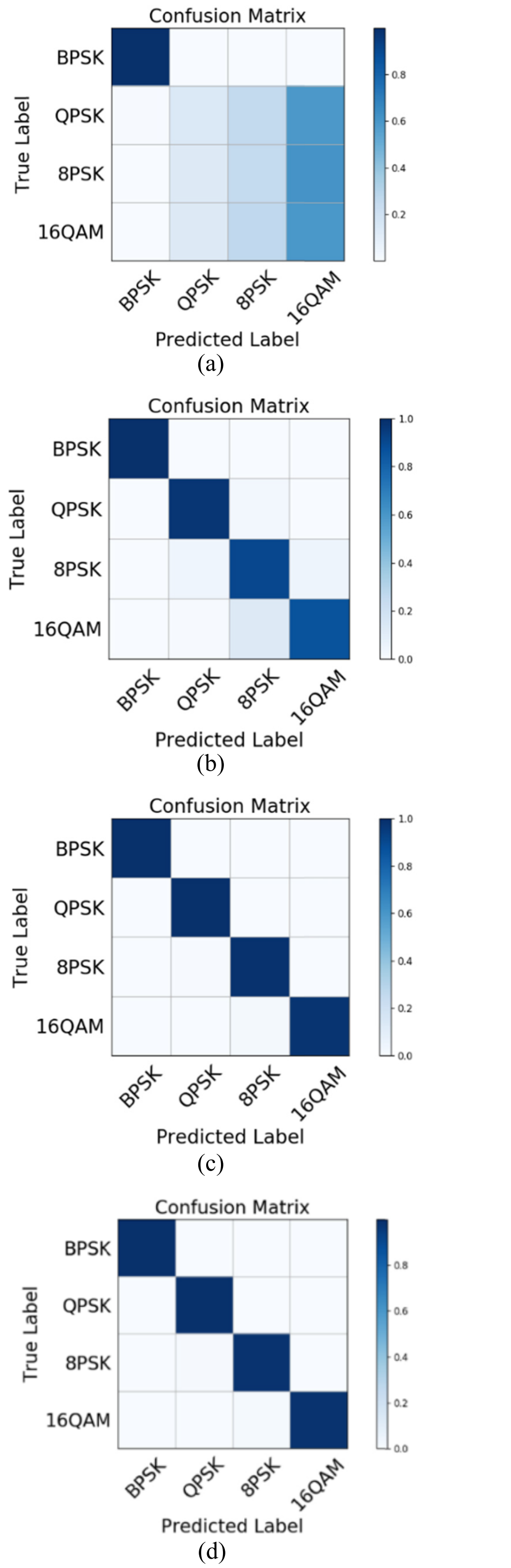

FIGURE 7. **Confusion matrices of proposed method in various SNRs: (a) SNR = 0dB, (b) SNR = 10dB, (c) SNR = 20dB, (d) SNR = 30dB.**

for each category is $[a_1, a_2, a_3, \cdots, a_i]$, the number of predicted samples is $[b_1, b_2, b_3, \cdots, b_i]$, and the total number of

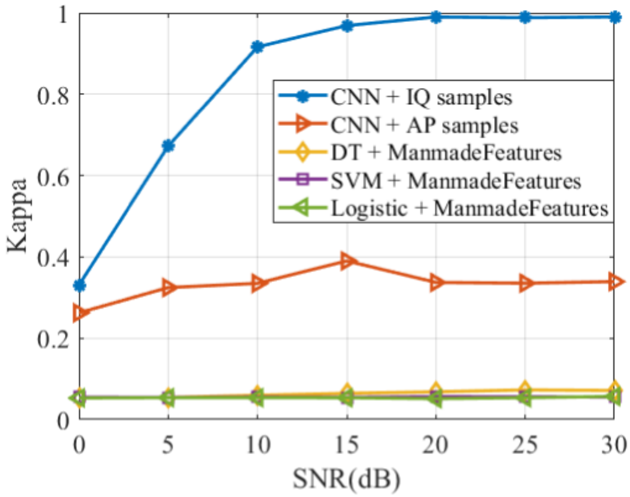

FIGURE 8. Kappa coefficients (κ) of different methods (dataset Θ_1).

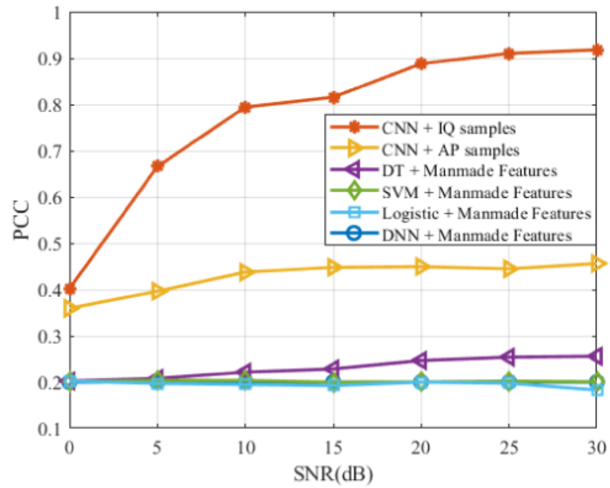

FIGURE 9. Comparisons of different methods via PCC in various SNRs (dataset Θ_2).

samples is N. So p_e is denoted as

$$p_e = \frac{\sum_i a_i b_i}{N^2} \tag{15}$$

From four confusion matrices in Fig. 7, it can be found that 16QAM has a great influence on the identification of the remaining modulation when the SNR is 0dB. This also explains the reason why the remaining identification results are poor except for BPSK at low SNR. In the case of 10dB, 8PSK and 16QAM are confused. Explain that it is easy to misjudge when the SNR is not very high. As the SNR increases, the influence of 16QAM gradually decreases. Finally, all modulation modes can be accurately identified.

Usually kappa falls between 0∼1 and can be divided into five groups to indicate the consistency of different levels: slight consistency (0.0∼0.20), fair consistency (0.21∼0.40), moderate consistency (0.41∼0.60), substantial consistency (0.61∼0.80) and 0.81∼1 are almost perfect. Fig. 8 shows the general trend in Kappa coefficient. Experiments show that the proposed method has high consistency in classification when the SNR is greater than 10dB.

C. ROBUSTNESS ANALYSIS

In the above experiments, we use dataset Θ_1 to verify that our proposed DL-based SMI has high identification accuracy and consistency. However, in the actual application, the introduction of new modulation modes may affect the original performance. Therefore, the method we propose must be relatively robust to this dataset mismatch. This part of the experiment is performed on dataset Θ_2 (increased 64QAM modulation) to verify the robustness of our proposed method.

In terms of curves trend, there is not a great deal of difference between Fig. 5 (based on dataset Θ_1) and Fig. 9 (based on dataset Θ_2). The identification accuracy of the proposed method is always remained steady above 90% with increasing SNR. It can be seen from the figure that the change of the dataset does not have damage on the performance of signal modulation identification.

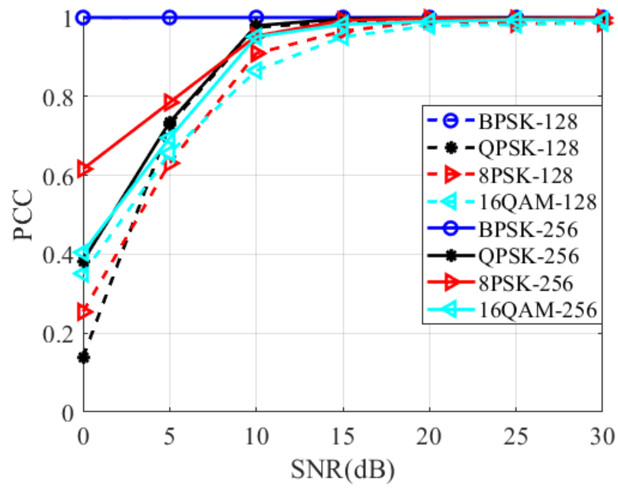

FIGURE 10. PCC of proposed method with different signal-sampling point (Dataset Θ_1).

D. IMPACT OF SIGNAL LENGTH

In this experiment, we increased signal-sampling points. It can be seen from Fig. 10 that under the same SNR, the CNN trained on the samples obtained with 256 sampling points have higher identification accuracy for different modulation modes than 128 sampling points. Especially at low SNR, performance is more obvious. The signal is described in more detail due to the increase in sampling points. The use of CNN can extract more features of signals in different modulation modes, thus effectively improving the identification accuracy.

V. CONCLUSION

In this paper, we propose an effective DL-SMI for identifying OFDM signals in non-cooperative systems. The proposed

DL-SMI method achieves high identification accuracy, high consistency and robustness. Simulation results show that CNN trained on IQ samples performs better than traditional machine learning based methods, since CNN can effectively extract the features of OFDM signals. Considering the practical applications, the proposed DL-SMI method has a good generalization ability via training different datasets.

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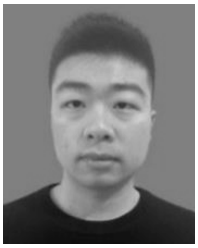

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