

PAPER

Modulation Recognition of Communication Signals Based on Cascade Network

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SUMMARY To improve the recognition rate of the end-to-end modulation recognition method based on deep learning, a modulation recognition method of communication signals based on a cascade network is proposed, which is composed of two networks: Stacked Denoising Auto Encoder (SDAE) network and DCELDNN (Dilated Convolution, ECA Mechanism, Long Short-Term Memory, Deep Neural Networks) network. SDAE network is used to denoise the data, reconstruct the input data through encoding and decoding, and extract deep information from the data. DCELDNN network is constructed based on the CLDNN (Convolutional, Long Short-Term Memory, Fully Connected Deep Neural Networks) network. In the DCELDNN network, dilated convolution is used instead of normal convolution to enlarge the receptive field and extract signal features, the Efficient Channel Attention (ECA) mechanism is introduced to enhance the expression ability of the features, the feature vector information is integrated by a Global Average Pooling (GAP) layer, and signal features are extracted by the DCELDNN network efficiently. Finally, end-to-end classification recognition of communication signals is realized. The test results on the RadioML2018.01a dataset show that the average recognition accuracy of the proposed method reaches 63.1% at SNR of -10 to 15 dB, compared with CNN, LSTM, and CLDNN models, the recognition accuracy is improved by 25.8%, 12.3%, and 4.8% respectively at 10 dB SNR.

key words: *deep learning, modulation recognition, stacked denoising auto encoder, CLDNN, dilated convolution, ECA mechanism*

1. Introduction

Automatic Modulation Recognition (AMR) is a technology that automatically recognizes the modulation type of unknown signals in non-cooperative communication [1]. AMR is widely used in military and civilian fields, such as information interception, interference recognition, electronic countermeasures, and spectrum management [2]. Therefore, AMR technology has been widely researched by domestic and foreign scholars [3]. AMR methods can be divided into two types: likelihood estimation-based methods [4] and feature extraction-based methods [5]. In likelihood estimation-based methods, the modulation recognition problem is represented as a multiple hypothesis testing problem. By processing the signal through maximum likelihood estimation, the likelihood ratio of each signal is compared with a threshold to achieve signal modulation classification. Its recognition rate is limited mainly because of the high computational complexity. The modulation recognition method based on feature extraction extracts typical features of dif-

ferent signals from time and frequency domains, and its recognition rate depends mainly on the extracted feature parameters. Traditional classifiers require human intervention in feature extraction and have a weak feature learning ability, resulting in a generally low recognition rate. To solve the problem, in recent years, the academic community has used deep learning technology to classify signal modulations [6].

O'SHEA et al. applied deep learning to the modulation recognition field firstly, used IQ signals to train a lot of neural networks, and selected appropriate neural networks for modulation recognition, achieved higher recognition accuracy than traditional methods [7]–[10]. M. Zhang et al. combined the original IQ data with the calculated higher-order cumulants to represent signals, used three convolutional layers and one Long Short Term Memory (LSTM) for training and classification, but all signals' higher-order cumulants need to be pre-calculated [11]. Y. Guo et al. used signal cyclic spectra and deep autoencoders to complete the recognition of FSK, PSK, ASK, MSK, and QAM signals, but required pre-processing to obtain each signal's cyclic spectrum information [12]. D. Wang et al. used eye diagrams and a Convolutional Neural Network (CNN) to recognize 4PAM signals [13]. S. Peng et al. converted the signal constellation to an RGB image and used CNN to recognize ASK PSK and QAM signals, but all signals need to be pre-processed into images [14]. Y. Wu et al. The LSTM network is used to identify 11 IQ signals directly, loses part sequence information after passing through the convolutional layer, its recognition accuracy is limited at low SNR [15]. T. Sainath et al. proposed the CLDNN, which integrates CNN, LSTM, and Deep Neural Networks (DNN) into one network and has been widely used in solving speech recognition problems [16]. Experiments have proved that the network can achieve better results than single CNN, LSTM, and DNN networks. The noise of an electromagnetic environment limits recognition accuracy. Therefore, to further improve the accuracy of signal modulation recognition, it is necessary to study the method of adaptive noise reduction preprocessing of signals.

Therefore, this paper proposes a communication signal modulation recognition method based on a cascade network. Firstly, SDAE is used to denoise the data, and reconstruct the input data through encoding and decoding, the network weights and biases are adjusted constantly through the gradient descent algorithm to minimize the reconstruction error. Secondly, the DCELDNN network is proposed based on the CLDNN to extract signal features. Dilated convolution is used to increase the receptive field and extract deep features

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Fig. 1 Cascaded network.

of signals. The ECA module is introduced to enhance the expression ability of channel features. LSTM provides long-term memory to model the time domain information and DNN transforms the two dimension feature maps into one dimension vectors to mitigate the impact of feature position on classification results. Finally, the GAP layer is used to replace the Flatten layer for feature classification, the number of parameters is reduced, and overfitting is prevented. The Softmax layer outputs the classification results. Compared to the current advanced AMR methods, simulation results show that the proposed method can improve the recognition rate of the communication signals.

2. Proposed Method

2.1 Cascaded Network

In this paper, To improve the recognition rate of methods based on deep learning, a modulation recognition method based on a cascade network is proposed, as shown in Fig. 1. The model includes a denoising network SDAE and a feature extraction network DCELDNN. Firstly, the number of samples of the input IQ signals is 1024. Referring to the idea of image classification, corresponding to the width \times height \times channel in the image, IQ signals can be represented as $1024 \times 2 \times 1$. Secondly, IQ signals are inputted into the SDAE network for noise reduction. Then the data after noise reduction is transmitted to the DCELDNN network to complete feature extraction. Finally, the Softmax layer realizes classification, and the modulation mode of communication signals is obtained.

2.2 Denoising Network Based on SDAE

To reduce the noise in the input data, SDAE [17] is used as a denoising network and consists of two stacked Denoising Auto Encoders (DAE) [18] together, as shown in Fig. 2. Compared with the traditional Auto Encoder (AE) [19], the DAE can improve the noise-polluted input data and increase the robustness of the network. Each DAE consists of three layers: an input layer, a hidden layer, and an output layer. The input data with noise is transformed into a latent representation in the hidden layer through encoding and then transformed into output through decoding. The purpose is to reconstruct the input data and extract the deep information.

An example of DAE_1 assumes that the true signal X is composed of N data samples and each sample consists of x_1, x_2, \dots, x_n . X' represents noisy input data. The hidden layer feature vector set H composing of N feature vectors, and each feature vector consisting of h_1, h_2, \dots, h_n , where n is

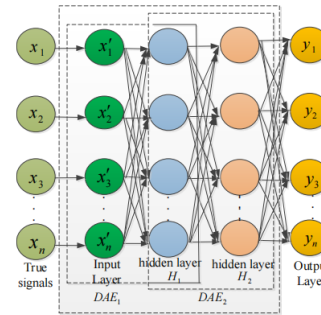


Fig. 2 The structure of SDAE.

the number of components in each feature vector. Therefore, the encoding relationship between X' and H is as follows:

$$H(X') = s_f [W(X') + B] \tag{1}$$

Where W and B are the weight matrix and bias matrix respectively between the input layer and hidden layer. s_f is the activation function of the encoder.

The decoding operation is the inverse process of the encoding operation. The original input is reconstructed using the hidden layer's feature vector as the input vector. Let y be the output data. The decoding relationship between H and y is as follows:

$$y(X') = s_g [W'[H(X')] + B'] \tag{2}$$

Where W' and B' are the weight matrix and bias matrix respectively between the hidden layer and output layer. s_g is the activation function of the decoder.

DAE_1 achieves feature learning by minimizing the reconstruction error between the true signals X and the reconstructed output data $y(X')$, continuously adjusting the network weights and biases using the gradient descent algorithm to reduce the reconstruction error. Reconstruction error L is as follows:

$$L[X, y(X')] = \frac{1}{n} \|X - y(X')\|^2 \tag{3}$$

After DAE_1 is trained, the output data of the hidden layer of DAE_1 is used as the input data of DAE_2 . In this way, SDAE trains the data through an unsupervised greedy layer-by-layer approach [20], which can extract deep features of the data.

2.3 Feature Extraction Network Based on DCELDNN

2.3.1 DCELDNN Network

DCELDNN network is proposed on the basis of CLDNN

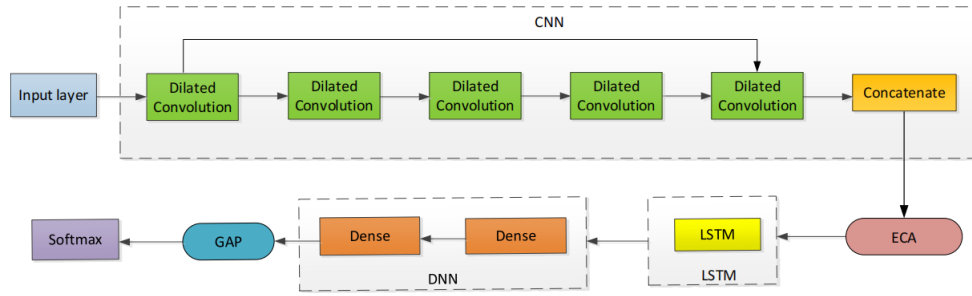


Fig. 3 DCELDNN network.

network [21], as shown in Fig. 3. The input layer of the network is the data after noise reduction through SDAE. Then the data is input into a five-layer CNN network, where the convolutional layer adopts dilated convolution to increase the receptive field of the feature map, and the deep information can be extracted. After concatenating the first layer and the fifth layer of convolution, ECA mechanism is introduced to extract locally the dependency between channels without dimensionality reduction, one dimension convolution is used interactively across channels to enhance the expression ability of data signals. Transmit to a one-layer LSTM with size 50, extract the time characteristics of the signal. The output of the LSTM layer is connected to a two-layer DNN for dimensionality reduction, the size of the first layer is set to 256, the size of the second layer is set to 24, which corresponds to the number of modulation styles to be identified in this paper. Adding a GAP layer after the second layer of DNN can improve the running speed and reduce overfitting. The Softmax layer is used as a classifier, the output is a 24 dimension probability vector. The index with the largest probability value is selected as the classification result.

2.3.2 Dilated Convolution

To improve the feature extraction capability of the network, dilated convolution [22] is used to increase the receptive field of the feature map and utilize the global information of the signals. Dilated convolution achieves different scale Max Pooling by setting the dilation rate. The comparison of dilated convolution with normal convolution is shown in Fig. 4. Figure 4(a) represents normal convolution and Fig. 4(b) represents dilated convolution with a dilated rate of 2. It can be seen from Fig. 4 that the receptive field of Dilated convolution is larger, resulting in more extracted information from the feature map.

The size l' of the dilated convolution kernel after dilation is given by:

$$l' = l + (l - 1)(d - 1) \quad (4)$$

Where l is the size of the original convolution kernel, and d is the dilation rate.

2.3.3 ECA Mechanism

According to research, adding attention modules to neu-

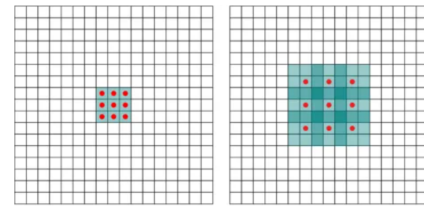


Fig. 4 (a) Normal convolution. (b) Dilated convolution with a dilated rate of 2.

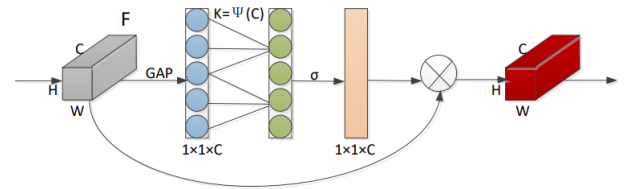


Fig. 5 The ECA channel attention module.

ral networks can significantly improve performance [23]–[27]. The ECA [25] module is an improved version of the Squeeze-and-Excitation (SE) module, a local cross-channel interaction strategy with non-dimensionality reduction and an adaptive selection method of one dimension convolution kernel size is proposed to optimize the performance. The ECA channel attention module is shown in Fig. 5.

Firstly, the input feature map F is averaged globally, and then a one dimension convolutional kernel with a size of k is used to achieve information interaction between channels. The weight ω of each channel can be expressed as:

$$\omega = \sigma [C1D_k(F)] \quad (5)$$

Where $C1D$ represents one dimension convolution, σ is the sigmoid function and k represents the coverage range of local cross-channel interaction and is a non-negative integer. To avoid manual adjustment of the value of k , an adaptive method is developed to determine the kernel size, and the adaptive size k of the kernel is expressed as:

$$k = \Psi(C) \quad (6)$$

Where the kernel size k is proportional to the channel dimension C [28]. Finally, the refined feature map F' is obtained by multiplying the weight ω with the corresponding element of the input feature map F .

Table 1 Ablation experiment.

network model	parameters	training loss	average accuracy(%)	FLOPs(G)
CLDNN	25718064	1.10	58.3	0.006
DCELDNN	25718068	1.05	59.5	0.002
CLDNN+SDAE	25746065	1.03	61.9	9.276
DCELDNN+SDAE	25746069	1.02	63.1	9.272

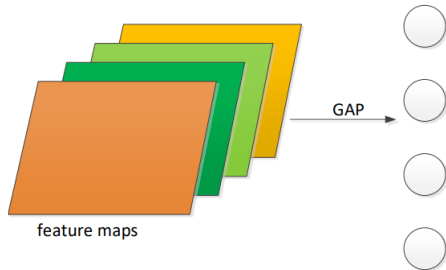


Fig. 6 Principle diagram of GAP.

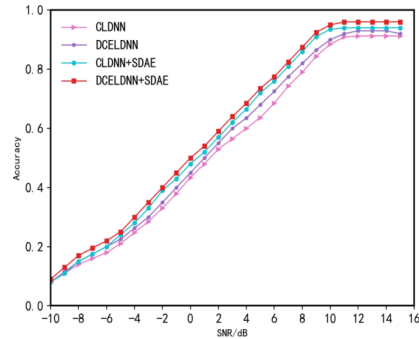


Fig. 7 The recognition rate of the ablation experiment.

2.3.4 GAP Feature Classification

In the design of neural networks, the output data of the feature extraction module can not directly connect to the Softmax layer due to dimension restrictions. Therefore, a Flatten layer is often used in the classification module to flatten the data before performing classification in the Softmax layer. However, the number of parameters in the Flatten layer is too large, which reduces the running speed and is prone to overfitting. Therefore, the GAP layer is used instead of the Flatten layer. The principle diagram of GAP is shown in Fig. 6.

The feature maps represent the input feature vectors, and the GAP operation calculates the average value of these feature vectors:

$$G_c = \frac{1}{N} \sum_{i=1}^N I_{c_i} \tag{7}$$

Where G_c is the average pooling output of the c -th channel, N is the length of the vector, and I_{c_i} is the i -th element of the vector in the c -th channel. GAP optimizes the neural network model by reducing dimensionality through the pooling layer, which not only preserves the spatial information extracted by the previous convolutional layer but also reduces the number of parameters. The objective of this paper is to identify 24 types of signals. In the last convolution layer of the feature extraction module, 24 feature maps are generated, and 24 1×1 feature maps can be obtained by GAP operation.

3. Results

3.1 Dataset and Experimental Environment

The experiment uses the RadioML2018.01a open-source dataset, which contains 24 signal modulation types, including 19 digital modulation methods: OOK, 4ASK,

8ASK, 16APSK, 32APSK, 64APSK, 128APSK, BPSK, QPSK, OQPSK, 8PSK, 16PSK, 32PSK, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, GMSK; 5 analog modulation methods: FM, AM-SSB-SC, AM-DSB-SC, AM-SSB-WC, AM-DSB-WC, using in-band SNR ranging from -10 to 15 dB, spaced by 2 dB. Each signal contains IQ data, with a sample point of 1024×2 , a sampling rate of 200 kHz, a symbol rate of 40 kSps for digital signals, and approximately 4096 samples per modulation type at each SNR, with a total of 1376256 samples. The signals are divided into a training set and a testing set with a ratio of 7:3.

The cascaded network is built using the Keras deep learning library, with TensorFlow as the backend. The training environment is Windows 10 operating system, AMD EPYC 7601 CPU, and NVIDIA GeForce RTX 3090 GPU. The parameters of the cascaded network are set as follows: select Adam as the optimizer, with a learning rate of 1×10^{-4} . During training, the batch size is 1000, the iteration times are set to 100.

3.2 Recognition Performance Analysis of Cascaded Network

An ablation experiment is designed to verify the effect of SDAE, and DCELDNN network parameters on the performance of the cascaded network. Four models are used on the RadioML2018.01a dataset at SNR of -10 to 15 dB. Evaluation criteria include the number of parameters, training loss, average recognition rate at SNR of -10 to 15 dB, and computational complexity measured in floating-point operations (FLOPs) in units of billions (G). Table 1 shows the experimental results. Figure 7 shows the recognition rate of the four network models at different SNRs.

According to Table 1, the designed CLDNN is used as the basic network. Constructing DCELDNN based on CLDNN, using dilated convolution with dilated rate of 2 and

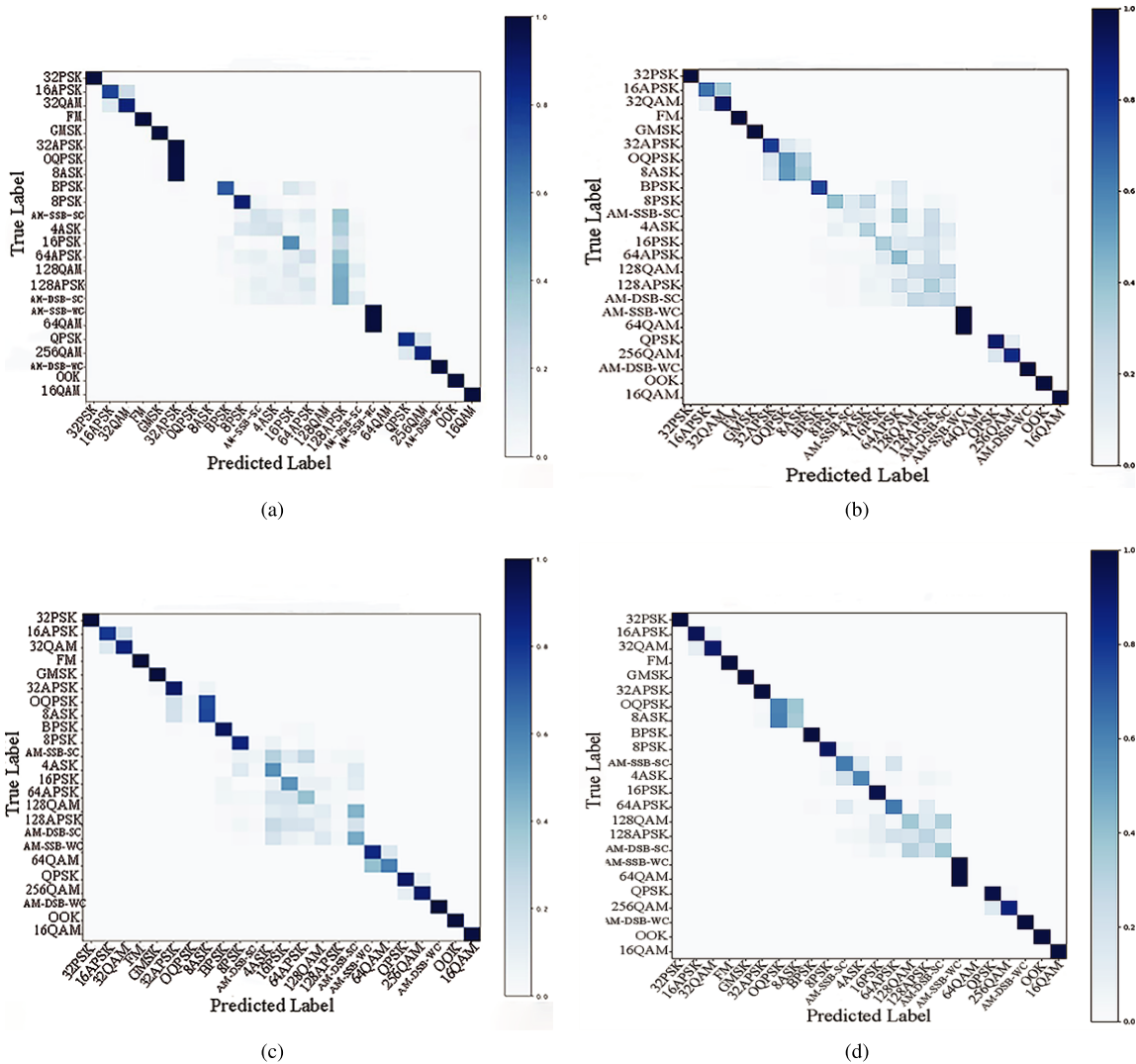


Fig. 8 Confusion matrix at 4 dB: (a): on CNN, (b): on LSTM, (c): on CLDNN, (d): on cascaded network.

adding a GAP layer, the computational complexity of the model is greatly reduced by 0.004G compared with CLDNN. The added ECA mechanism enhances the signals' feature characterization ability. The average accuracy of signal recognition is 1.2% higher than that of CLDNN. Therefore, DCELDNN not only has higher model accuracy but also has lower computational complexity. By adding SDAE to CLDNN, the signals are denoised and the training time and parameters are increased. Because both forward and backward propagation of SDAE needs to calculate neuron output values and gradient values layer by layer, including a large number of matrix multiplication and nonlinear function calculations, the computational complexity is relatively large. However, after signal noise reduction processing, the average signal recognition accuracy is 1.4% higher than CLDNN, and the training loss is reduced by 0.07. By adding SDAE to DCELDNN, the average recognition rate is 3.6% higher than DCELDNN, 2.2% higher than CLDNN+SDAE, the average recognition rate reaches 63.1%, and the training loss is 1.02. Figure 7 shows that the DCELDNN+SDAE model,

namely the proposed cascaded network, has the best modulation recognition performance among the four models.

3.3 Comparison Experiments

Four network models, including CNN [29], LSTM [30], CLDNN [21], and the proposed Cascaded Network, are selected to conduct simulation experiments on RadioML2018.01a. At 4 dB SNR, the confusion matrix of the four methods is shown in Fig. 8. The vertical and horizontal coordinates of the confusion matrix correspond to the true label and the predicted label respectively. Darker color represents higher recognition accuracy. From Fig. 8, we can see that the confusion matrix of the Cascaded Network has deeper colors on the diagonal than the other three networks, indicating that the recognition ability of the Cascaded Network is highest. Although there is confusion between low-order signals like 16APSK and 8ASK, the cascaded network algorithm can accurately recognize most low-order signals. For high-order complex signals, such as 64APSK, 128QAM,

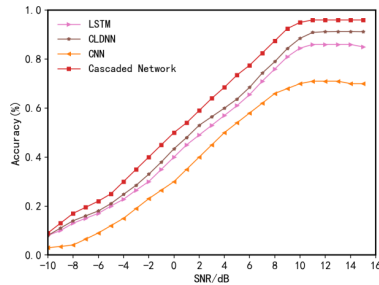


Fig. 9 Recognition performance.

and 128APSK, the cascaded network algorithm has deeper colors on the diagonal than the other three algorithms, and the confusion outside the diagonal is significantly reduced.

The performance of the four models on RadioML 2018.01a is shown in Fig. 9. Figure 9 shows that at SNR of -10 to 15 dB, the Cascaded Network has a higher recognition accuracy compared with the CNN, LSTM, and CLDNN networks. When the SNR is 10 dB, the proposed Cascaded Network has improved the modulation recognition accuracy by 25.8% , 12.3% , and 4.8% compared with the CNN, LSTM, and CLDNN networks, respectively.

4. Conclusions

To improve the accuracy of modulation recognition, a cascade network composed of SDAE and DCELDNN is proposed, it has two stages. In the noise reduction stage, SDAE reconstructed the input data by unsupervised greedy layer-by-layer superposition through DAEs. In the feature extraction stage, DCELDNN is constructed based on the CLDNN network, and dilated convolution with a dilation rate of 2 is used to replace the normal convolution, which can effectively integrate the feature information while increasing the receptive field. An ECA mechanism module is introduced to enhance the feature representation ability of the signals reduce training error and improve convergence speed. The GAP layer is used to integrate feature vector information, and finally, feature classification is performed in the Softmax layer. The simulation results show that this method has higher recognition accuracy than CLDNN at SNR of -10 to 15 dB, and the average recognition accuracy is 63.1% . When the SNR is 10 dB, the recognition accuracy of this method is improved by 25.8% , 12.3% , and 4.8% compared with the CNN, LSTM, and CLDNN networks respectively. The proposed method provides a new solution for the modulation recognition of communication signals.

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