

Automatic Modulation Recognition algorithm based on phase transformation and ResCNN-BiLSTM

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Abstract. Aiming at the problem that the recognition rate of existing Automatic Modulation Recognition (AMR) models needs to be improved under high signal-to-noise ratio conditions, a model consisting of phase transformation, residual Convolutional Neural Network (CNN) network and bidirectional Long Short-Term Memory (LSTM) network is proposed. First, the DeepSig RadioML 2018.01A dataset is normalized as the model input; the phase parameter is extracted through the phase recognition module, and then the phase is corrected according to the phase parameter; then the spatial features are extracted through the residual CNN network to avoid gradient vanishing and explosion; then the data is passed to the bidirectional LSTM network to extract the bidirectional time series features of the data; finally, the deep neural network is used for classification and recognition. Experimental results show that under high signal-to-noise ratio conditions, the model improves the recognition rate of modulation modes such as 16PSK, and the highest recognition rate and average recognition rate reach 96.79% and 62.13% respectively. Compared with other existing models, the overall optimization of recognition rate and model efficiency is achieved.

Keywords: Automatic Modulation Recognition, bidirectional Long Short-Term Memory network, phase transformation, residual Convolutional Neural Network

1. Introduction

In wireless communications, in order to ensure the accuracy and speed of information transmission and relieve the pressure on communication spectrum resources, the low-frequency signal to be sent is generally modulated onto a high-frequency carrier signal and then transmitted. If the receiver wants to obtain the information, it must know the modulation mode of the baseband signal in order to demodulate it. With the continuous increase in the amount of communication information, people's demand for communication services has gradually increased, spectrum resources have become increasingly scarce, and the channel environment has become increasingly complex [1]. As a result, there are more and more modulation modes, and it has become increasingly difficult to accurately identify the modulation mode. Automatic Modulation Recognition (AMR) is an important application of modulation mode recognition technology in the field of signal processing. The goal of AMR is to identify the modulation mode used by the signal by analyzing the signal data without the need for a prior modulation mode of the signal.

Automatic modulation recognition can be divided into three categories: Likelihood-Based (LB), Feature-Based (FB) and Deep Learning (DL) research methods. Compared with the other two methods, the advantage of deep learning-based AMR is that it does not require any prior modulation information and does not rely on artificial feature extraction, which greatly reduces the complexity of extraction.

In recent years, research on AMR algorithms based on deep learning has made significant progress. O'Shea et al. used the original In-phase Quadrature (IQ) signal as a data set and input it into a Convolutional Neural Network (CNN). This structure has a more accurate recognition rate than most traditional recognition methods [2]. Liu et al. connected a Long and Short Term Memory Network (LSTM) to a multi-layer CNN. The new network is called a Convolutional Long and Short-Term Deep Neural Network (CLDNN), which achieves high-precision modulation recognition [3].

The method of directly inputting the original signal into the model for modulation recognition has limitations. Many scholars have begun to pay attention to the method of preprocessing the data before inputting it into the model. Wang et al. converted the IQ signal into a constellation diagram and used the image recognition model for modulation recognition. They effectively identified 16QAM and 64QAM under low Signal-to-Noise Ratio (SNR) conditions [4]. Li et al. took the logarithm of the data and performed a Fourier transform, and input it into the CNN training. The accuracy rate exceeded 90% when the SNR was 4dB [5].

With the rapid development of deep learning-based AMR, many studies have attempted to use different data sets, different data preprocessing methods, and different model structures. However, due to the combination of multiple factors, the performance of the model has not achieved a high recognition accuracy. At present, the main research directions of AMR are data preprocessing methods and neural network structures. In response to some current problems, this paper proposes an automatic modulation recognition algorithm based on phase transformation and Residual Convolutional Neural Network-Bidirectional Long and Short Term Memory Network (ResCNN-BiLSTM). This study uses the DeepSig RadioML 2018.01A dataset as a benchmark, extracts the phase parameter from the normalized IQ data, and uses the rotation matrix to correct the phase offset. The preprocessed data is passed to ResCNN-BiLSTM, the residual link alleviates the gradient vanishing problem, CNN deeply extracts spatial features, and the bidirectional LSTM captures bidirectional timing information. The recognition efficiency of 8PSK, 16PSK, and 32PSK is optimized under high signal-to-noise ratio conditions, and the overall optimization of modulation recognition accuracy and model efficiency is achieved compared to ResNet, CLDNN, DenseNet, and CGDNet models.

2. System model and phase transformation algorithm

2.1. Signal model and phase transformation

IQ signal, I is In-Phase (in-phase component), Q is quadrature (orthogonal component), they are two mutually orthogonal signals, that is, the data is divided into two channels for carrier modulation, and the two carriers are orthogonal to each other. IQ signal has high requirements for demodulation, and Q must be strictly different from I by an integer multiple of $\frac{\pi}{2}$, otherwise the IQ signals will be coupled with each other.

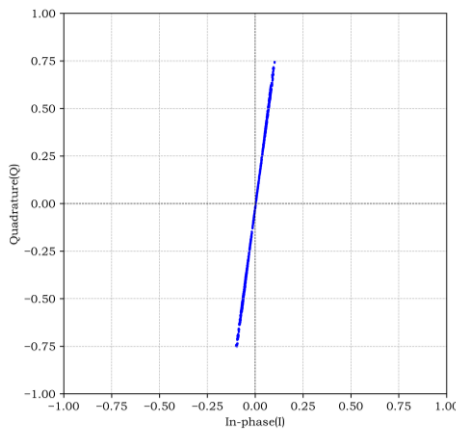
For deep learning training models, discrete input signals are more consistent with computer operation logic. The received signal $y(t)$ is sampled at an appropriate sampling frequency to ensure that the discrete signal is close to the continuous signal and represented in matrix form:

$$Y = [y_1, y_2, y_3, \dots, y_n] \quad (1)$$

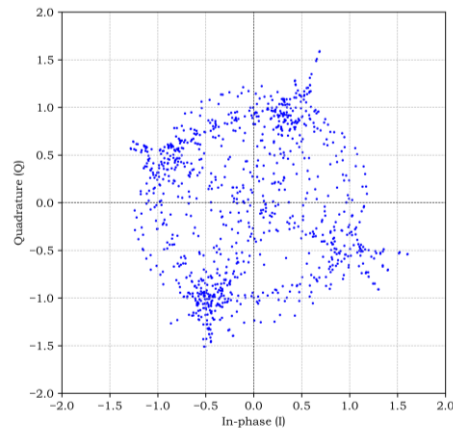
Among them, y_n is the n th sampling point, and the data of each sampling point is in complex form. The IQ format is to represent the real and imaginary parts of the data with I components and Q components respectively, and I and Q are both real numbers. In this way, the shape of the sampling matrix Y is $[2, \text{number of samples}]$, “2” is the number of channels, that is, I and Q channels, and the number of samples is the time series obtained by sampling the received signal according to the sampling frequency. This paper uses the DeepSig RadioML 2018.01A dataset as the original input data for deep learning. The shape of each sampling matrix is $[2, 1024]$, that is, each data has 1024 IQ components.

During the transmission of information, the multipath effect of the channel will cause the wireless signal to superimpose multiple paths at the receiving end, which may cause the points on the constellation diagram to stretch in a specific direction; the phase noise of the channel will cause the phase delay of the signal, causing the points on the constellation diagram to rotate.

In order to observe the presentation of IQ signals in the DeepSig RadioML 2018.01A dataset, data from several modulation methods are randomly selected to draw their constellation diagrams. When the SNR is 30 dB, Figure 1(a) is BPSK modulation, and Figure 1(b) is QPSK modulation. The horizontal axis is the I component, and the vertical axis is the Q component.



(a) BPSK



(b) QPSK

Figure 1. IQ signal constellation diagram of different modulation modes when SNR=30dB

Observe the constellation diagram. The standard BPSK constellation diagram should be two points ($\pm 1, 0$). The standard QPSK constellation diagram should be four points at 0° , 90° , 180° , and 270° phases, that is, at the positive and negative half axes of I and Q. However, the QPSK constellation diagram in the DeepSig RadioML 2018.01A dataset is obviously rotated and stretched. This is the result of considering the actual channel conditions during the generation of the dataset. The IQ two-way data originally has a 90° phase difference, but after the phase shift during the propagation process, the phase difference between the IQ two-way data is no longer maintained, and the two-way data is coupled.

In order to solve the problem of phase delay in the original signal, the original signal is preprocessed by the idea of reference coordinate system rotation transformation, and the phase difference of the IQ signal is converted to 90° , so as to more effectively identify the modulation mode. The phase transformation module in this paper is divided into two parts. The first part is the phase extraction module, and the second part is the phase rotation module. The structure of the entire phase transformation module is shown in Figure 2.

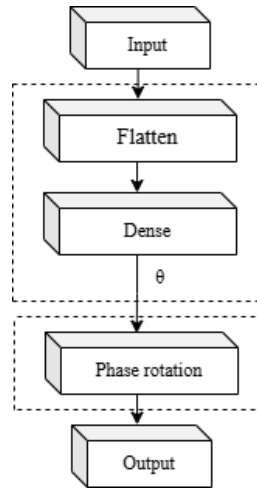


Figure 2. Schematic diagram of the phase transformation module structure

The phase extraction part consists of a flattening layer and a fully connected layer. First, the two-dimensional input data is passed to the flattening layer to be converted into a one-dimensional vector, and then the phase information is extracted through the fully connected layer to obtain a phase parameter θ . This network is constructed using a basic neural network structure, and can be trained together with subsequent models to produce a phase extraction network suitable for each piece of data.

The IQ signal phase offset in the constellation diagram is a rotation about the origin, so the rotated point can be corrected by the coordinate rotation matrix. Assuming the coordinates before rotation are (x, y) , the angle of the signal rotation clockwise is θ , and the coordinates after rotation are (x', y') , the coordinate rotation formula is:

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x' \\ y' \end{bmatrix} \quad (2)$$

The phase rotation module substitutes the phase parameter θ obtained by the phase extraction module into the rotation matrix, obtains the input IQ signal and multiplies the rotation matrix on the left to obtain the phase-corrected IQ signal.

2.2. Residual Convolutional Neural Network (ResCNN)

During deep learning training, as the number of neural network layers increases, the gradient will gradually decrease (gradient vanishing) or increase (gradient exploding), which greatly limits the performance of the traditional CNN structure. The residual convolutional neural network is an improved deep convolutional neural network architecture proposed by He et al., which introduces residual blocks into the traditional CNN structure. The skip link structure allows the gradient to be directly transferred from the previous layer to the next layer, effectively solving the problem of gradient vanishing and exploding when the network is deepened [6].

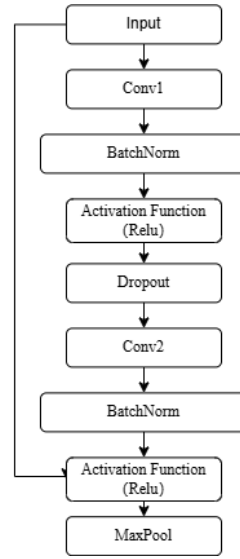


Figure 3. Schematic diagram of the residual convolutional neural network structure

The structure of the basic module of ResCNN used in this paper is shown in Figure 3. First, a copy of the input data is retained, and then a one-dimensional convolution operation is performed on the input data to extract spatial features. By sliding different convolution kernels on the signal sequence, various characteristic patterns in the signal are extracted. Then the output of the convolution layer is normalized, the mean of the data is adjusted to 0, and the variance is adjusted to 1, which accelerates the convergence speed of the model and improves stability. After that, Relu (Rectified Linear Unit) is used as the activation function to introduce nonlinear factors. The Dropout layer randomly discards neurons to provide regularization to prevent the model from overfitting. After that, it passes through the convolution layer and batch normalization layer, and the obtained data is added to the retained data copy and activated with Relu to realize the skip link of the residual block. Finally, it is passed to the maximum pooling layer to reduce the length of the sequence, improve computational efficiency, and prevent overfitting.

2.3. Bidirectional Long Short Term Memory network (BiLSTM)

The Long Short Term Memory Network belongs to the Recurrent Neural Network (RNN), which is mainly used to process time series features. It consists of an input gate i_t , forget gate f_t , output gate o_t and memory state C_t . The structure is shown in Figure 4. At time t , given the input x_t and the hidden state h_{t-1} of the previous moment, the forget gate decides which information to discard from the memory state. The calculation formula is $f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$, where W_f is the weight matrix of the forget gate, b_f is the bias, and σ is the sigmoid function. The input gate controls the extent to which new information enters the memory cell $i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$, and calculates the new candidate memory cell state $\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$. The memory cell is updated to $C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$, and the output gate determines the output information, $o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$, and the final output and hidden state $h_t = o_t * \tanh(C_t)$.

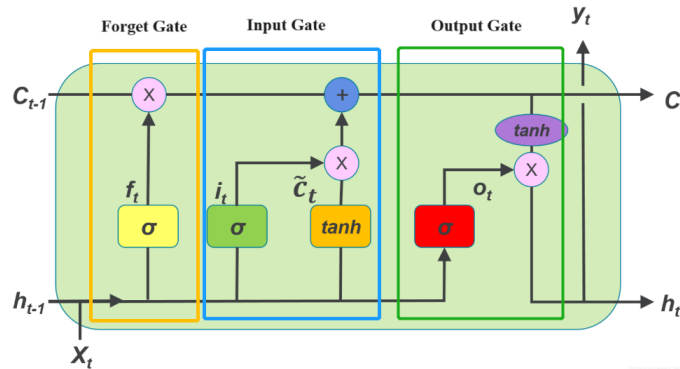


Figure 4. LSTM network schematic

Bidirectional LSTM builds two information flows in opposite directions based on LSTM, constructs reverse hidden states in the opposite direction of the input sequence, and also outputs a result sequence and concatenates it with the forward output sequence.

3. Model and dataset

3.1. Model structure

The model structure used in this paper is shown in Figure 5.

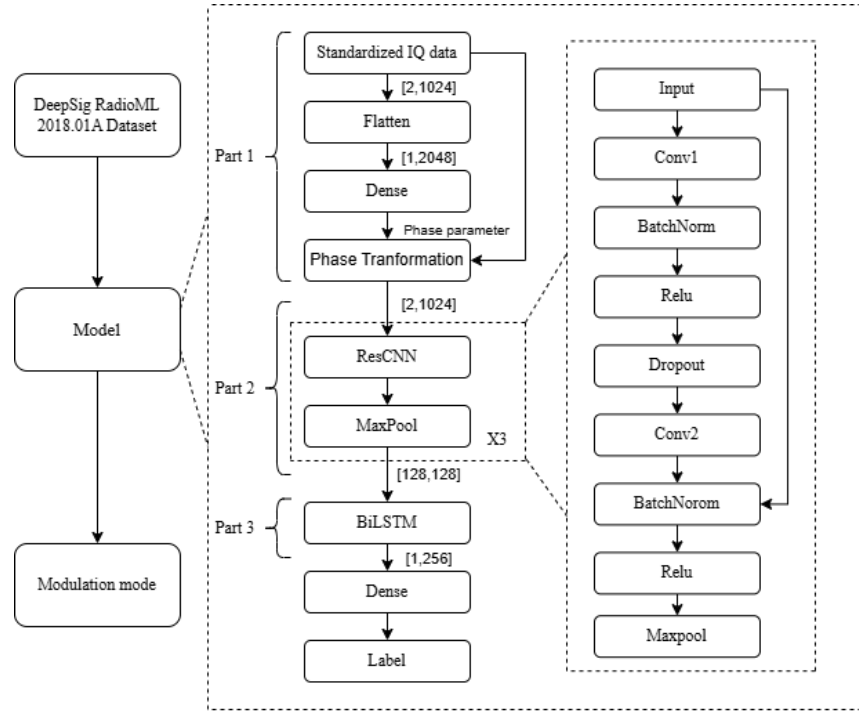


Figure 5. Schematic diagram of the model based on phase transformation and ResCNN-BiLSTM

The whole network consists of a phase transformation module, a ResCNN network, a BiLSTM network, and a final fully connected layer. Firstly, the initial IQ signal is normalized, the mean of the data is adjusted to 0, and the variance is adjusted to 1. Then, it is passed into the phase transformation module to obtain the signal sample matrix after phase correction, and then it is input into the ResCNN-BiLSTM network. The first part is a three-layer ResCNN network to extract signal spatial features. The second part is a BiLSTM network to extract bidirectional temporal features. The gate structure of BiLSTM effectively avoids the gradient explosion and gradient disappearance problems. Finally, the LSTM output data is passed through a fully connected layer to obtain the recognition result vector.

For the convenience of discussion, the ResCNN-BiLSTM network based on phase transformation designed in this paper will be denoted as the P-RCB network in the following, and the ResCNN-BiLSTM network without the phase transformation module will be denoted as the RCB network.

3.2. Model parameters

The number of input and output channels of the three-layer ResCNN network in the second part are (2, 32), (32, 64), and (64, 128), respectively. The structure of each layer of ResCNN is the same as the basic module introduced in Section 2, with a convolution kernel size of 1x5 for the convolution layer, a drop factor of 0.2 for the Dropout layer, and a pooling window of 2 for the Max pooling layer. The number of input features and sequence length of the one-layer BiLSTM network in the third part are both 128, and the global average of the sequences is taken as the BiLSTM output. The number of input and output channels of the final fully connected layer is (256, 24).

In the training process, the ReLU function is used as the activation function, CrossEntropyLoss is used as the loss function, weight decay regularization adaptive moment estimation AdamW is used as the optimizer, and ReduceLROnPlateau is used as the learning rate scheduler. The batch size is set to 32, the number of epochs is set to 100 and the learning rate is 0.001 by default.

All experiments use the PyTorch deep learning framework to build and train neural networks. The computer was configured with 12th Gen Intel (R) Core (TM) i7-12700H and NVIDIA GeForce RTX 3060 Laptop GPU.

3.3. DeepSig RadioML 2018.01A dataset

In terms of the dataset, this paper uses the more challenging modulation recognition dataset DeepSig RadioML 2018.01A. The dataset covers a large number of modulation modes, including a total of 24 analog and digital modulations, covering a wide range of single-carrier modulation schemes. The data set contains 24 different modulation modes, each modulation mode contains 26 SNR (-20 ~ 30dB), each modulation has 4096 data per SNR, each data is IQ data in format [2, 1024], and the data set contains 2555904 data in total. This data set also considers multiple influencing factors such as symbol rate offset, thermal noise, and multipath fading. Compared with other datasets such as RadioML 2016.10a, this dataset contains a wider range of modulation modes, a wider range of signal-to-noise ratios, more sampling points, and a significant increase in the total signal sample size. The specific parameters of this dataset are shown in Table 1 below.

Table 1. Dataset specific parameters

Modulation mode	'OOK', '4ASK', '8ASK', 'BPSK', 'QPSK', '8PSK', '16PSK', '32PSK', '16APSK', '32APSK', '64APSK', '128APSK', '16QAM', '32QAM', '64QAM', '128QAM', '256QAM', 'AM-SSB-WC', 'AM-SSB-SC', 'AM-DSB-WC', 'AM-DSB-SC', 'FM', 'GMSK', 'OQPSK'
Number of modes	24
SNR rang (dB)	-20:2:30
Total samples	$24 \text{ (modulation mode)} \times 26 \text{ (SNR)} \times 4,096 \text{ (sampling points)} = 2,555,904$
Sample Shape	IQ data [2, 1024]
Influencing factors	CFO, Symbol rate offset, Thermal noise, Multipath fading

3.4. Dataset segmentation and preprocessing

The DeepSig RadioML 2018.01A dataset contains 26 kinds of SNR and 24 kinds of modulation modes. The neural network in this paper needs to use a channel condition for training, that is, the model is trained at a certain SNR and tested and verified at this SNR. Therefore, in this paper, the whole data set is cut into 26 data sets according to each SNR, and random 80% data of each data set is used as the training set, and the remaining 20% data is used as the test set [7]. Each data set was then normalized to have a mean of 0 and a variance of 1. In the experiments, the model is trained at each SNR, the learning rate is adjusted according to the loss and accuracy of the validation set, and the recognition accuracy is tested on the test set.

4. Simulation experiment and result analysis

4.1. Model ablation experiment

Aiming at whether each module in the P-RCB model can effectively improve the accuracy of the model, this paper designs four ablation experiments. Compared with P-RCB, the four comparison models remove phase transformation module, residual module, LSTM module and CNN module respectively, and the specific parameters of the model are shown in Table 2. All experiments were carried out according to the conditions explained in Section 3 and only a certain module of P-RCB was changed.

Table 2. Comparison of models in ablation experiments

Comparison models	Network configuration
P-RCB	Phase Transformation + ResCNN+BiLSTM
RCB	ResCNN + BiLSTM
P-CB	Phase Transformation + CNN+BiLSTM
P-B	Phase Transformation + BiLSTM (add convolutional layers)
P-RC	Phase Transformation + ResCNN

The experimental results are shown in Figure 6, where the high SNR data is magnified for more intuitive comparison of the performance of the five models under all SNR conditions on the DeepSig RadioML 2018.01A dataset. The Maximum Accuracy

(MAcc) and Average Accuracy (AAcc) are calculated according to the accuracy performance of each model, and the comparison bar chart of MAcc and AAcc is shown in Figure 7.

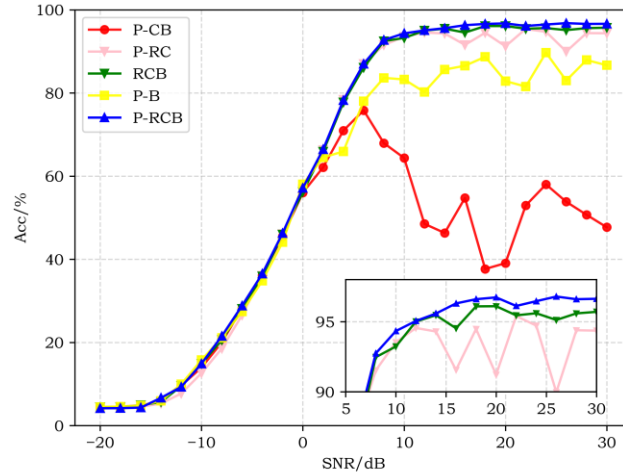


Figure 6. Recognition accuracy plots at each SNR for ablation experiments

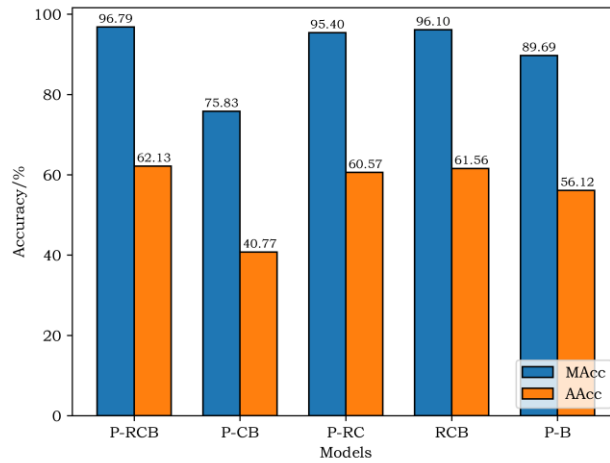


Figure 7. Plots of the highest and average accuracy for ablation experiments.

Figures 6 and 7 show that the accuracy performance of the P-CB model with the residual module removed is extremely unstable on this data set. Due to the gradient explosion and disappearance, the training process and recognition accuracy still have a wide range of fluctuations even under high SNR conditions. Comparing the model without CNN with the full model, due to the lack of spatial feature extraction module, the recognition accuracy is greatly reduced and fluctuates greatly, and the performance of the model is reduced. For the RCB model without the phase transformation module, although the highest accuracy is only reduced by 0.69% and the average accuracy is reduced by 0.57%, the recognition accuracy of some modulation modes is significantly improved. Figure 8(a) below shows the confusion matrix of the P-RCB model when SNR=22dB, and Figure 8(b) shows the confusion matrix of the RCB model when SNR=22dB. It can be observed that the recognition accuracy of the RCB model for 8PSK and 16PSK modulations is 77% and 34%, respectively, and after adding the phase transformation module, the recognition accuracy of the P-RCB model for 8PSK and 16PSK modulations is increased to 100%, respectively. This shows that under the condition of a high signal-to-noise ratio, the phase characteristics of the signal constellation are more obvious, and the phase transformation module can effectively extract the phase information from the signal constellation, which improves the recognition accuracy and stability of the model for 8PSK, 16PSK and 32PSK modulation. In summary, each part of the P-RCB model is complementary to each other, and its combination improves the performance of the model, so the P-RCB network structure is finally selected.

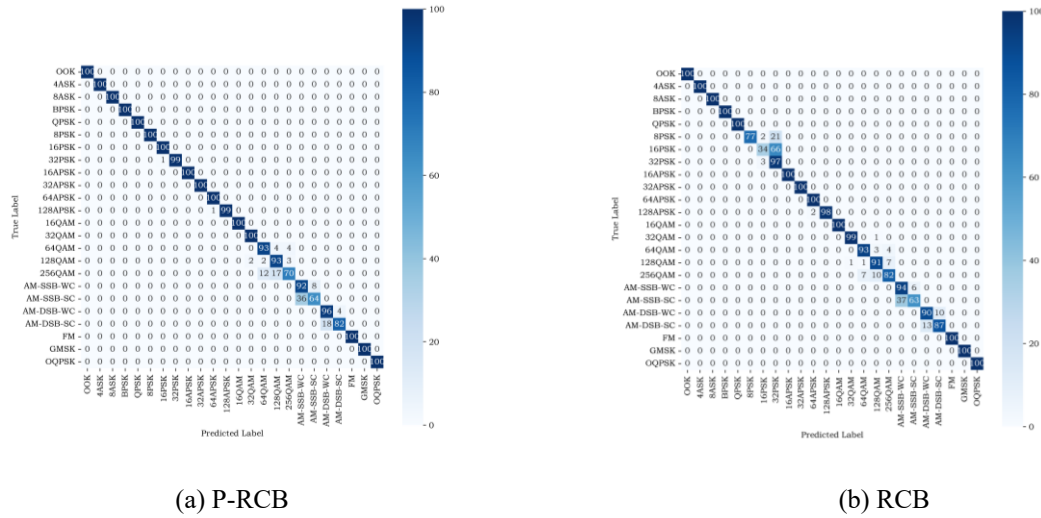


Figure 8. Model confusion matrix for SNR=22dB

4.2. Visual analysis of confusion in recognition

The original signals under different SNR in the DeepSig RadioML 2018.01A dataset are plotted into constellation diagrams, and a visual comparison is carried out to explore the confusion of recognition methods. Figure 9 below shows the comparison of the signal constellation diagram of different modulation modes when SNR is 20dB, 10dB, 0dB, and -10dB, respectively. Observing Figure 9(a) and 9(b), under the condition of high signal-to-noise ratio, BPSK, QPSK and other modulation modes have obvious differences, which are easy to distinguish through observation, and the accuracy is naturally high. For the three modulation modes of 16QAM, 32QAM and 64QAM, the constellation diagram is still very similar and cannot be distinguished, so their recognition accuracy is still not high under the condition of high SNR. Figure 9(c) and 9(d) show that under the condition of low SNR, almost all modulation modes lose obvious features and cannot be distinguished by the naked eye, which can explain the phenomenon that the recognition accuracy of the deep learning model will greatly decrease under the condition of low SNR.

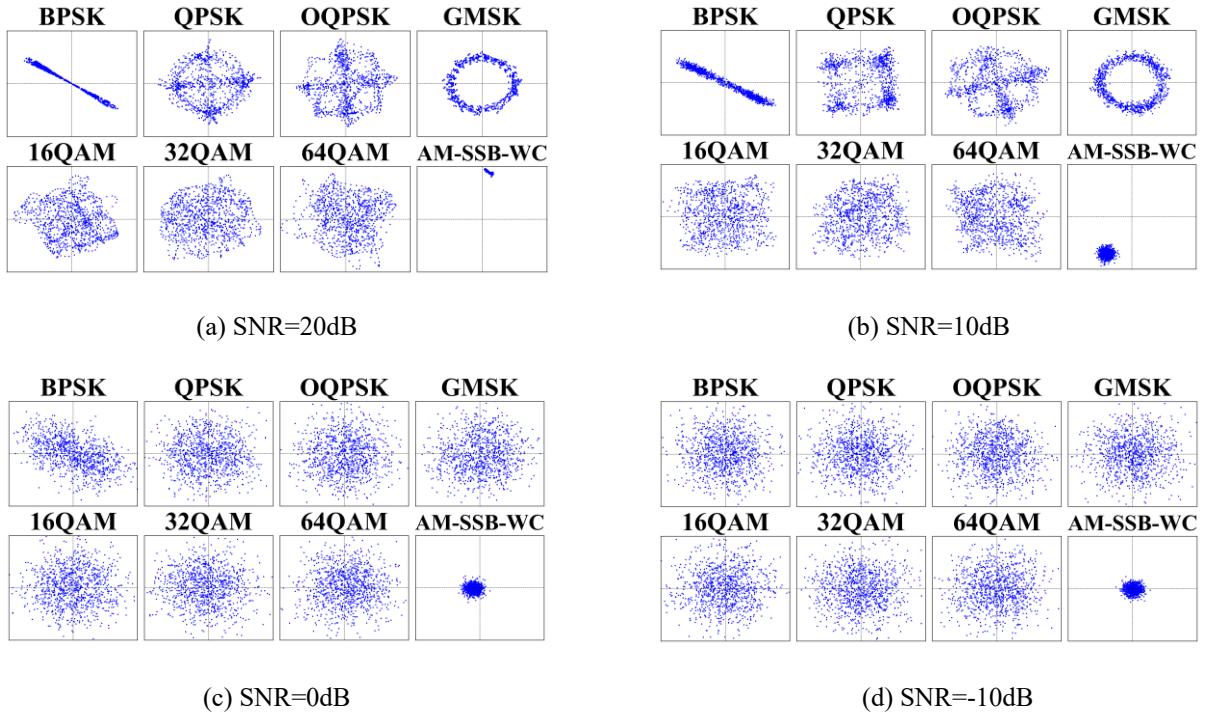


Figure 9. Constellation diagram of the signal

4.3. Comparison experiment of P-RCB model

In this section, the optimal network model P-RCB determined in the previous section is trained and compared with ResNet, CLDNN, DenseNet and CGDNet on the DeepSig RadioML 2018.01A dataset [8]. All experiments are carried out according to the conditions described in Section 3. Due to different loss functions, hyperparameters, etc., the recognition results may be different from the original text [8-10]. The results of this experiment are shown in Figure 10 and 11, where high SNR data are magnified for representation.

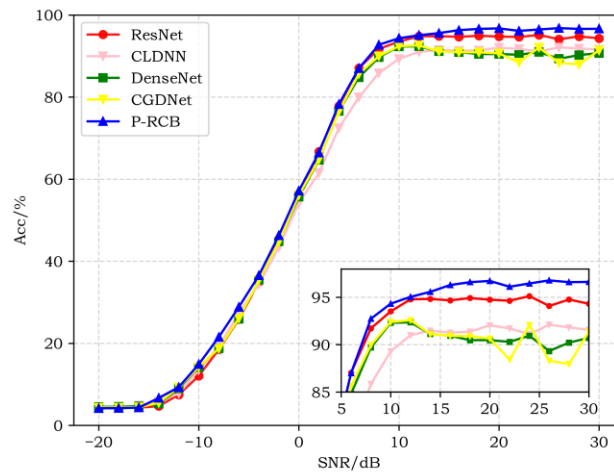


Figure 10. Recognition accuracy plots for each SNR of different models

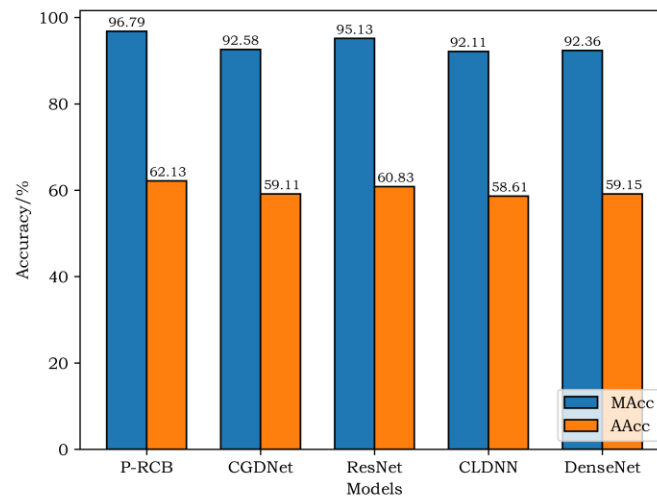


Figure 11. Highest accuracy and average accuracy of different models

As can be seen from Figure 10, under the condition of low SNR, due to excessive noise interference, the recognition accuracy of each model is not much different and is very low, and the P-RCB model has a higher recognition rate than other models. Under the condition of high SNR, the performance of each model gradually widened the gap, and the recognition rate tended to be stable. DenseNet uses dense links to achieve feature reuse, and the highest recognition rate reaches 95.13%, and the average recognition rate is 60.83%. CLDNN network integrates three network structures to extract spatial and temporal features, but its recognition rate is the lowest; the highest recognition rate is only 92.11%, and the average recognition rate is only 58.61%. ResNet network introduces residual connection, so that information is directly transmitted to the following neurons. Similar to the residual module of the network proposed in this paper, the highest accuracy is 95.13%, and the average recognition rate is 60.83%. Under the same

hyperparameters and training conditions, the P-RCB network proposed in this paper firstly performs phase transformation on the normalized data, then transmits information and extracts spatial features through residual CNN, and finally extracts bidirectional timing features through BiLSTM. The highest recognition accuracy reaches 96.79%, and the average accuracy reaches 62.13%. The performance of the model is better than other experimental models.

Table 3 shows the total number of parameters, each round of training time and the recognition rate of each comparison model based on DeepSig RadioML 2018.01A dataset. As can be seen from Table 3, for DenseNet, CGDNet and CLDNN models, the P-RCB model proposed in this paper increases the highest recognition rate and the average recognition rate by about 4% and 3% respectively under the condition that the total number of parameters is slightly increased or even unchanged. For the ResNet model, the P-RCB model still improves the highest recognition rate and the average recognition rate by about 2% when the total number of parameters and training time are greatly reduced.

Table 3. Model performance comparison

Model	Total number of parameters	Training time (seconds/epoch)	Max accuracy	Average accuracy
P-RCB	442,873	17	96.79%	62.13%
DenseNet	211,256	10	92.36%	59.15%
CGDNet	223,544	11	92.58%	59.11%
ResNet	1,758,424	36	95.13%	60.83%
CLDNN	461,208	13	92.11%	58.61%

5. Conclusion

Aiming at the problem that the recognition effect of the existing automatic modulation recognition model needs to be improved under high signal-to-noise ratio conditions, this paper proposes an automatic modulation recognition model P-RCB based on phase transformation and ResCNN-BiLSTM. Firstly, the phase parameter was extracted from the normalized data, and the phase was corrected according to the phase parameter. Then, the spatial information was extracted through the residual CNN network, and the bidirectional timing features were extracted through the bidirectional LSTM network. The experimental results based on DeepSig RadioML 2018.01A dataset show that the P-RCB model improves the recognition accuracy and stability of 8PSK, 16PSK and 32PSK modulation methods under high signal-to-noise ratio conditions, the highest recognition rate reaches 96.79%, and the average recognition rate reaches 62.13%. The recognition rate and model efficiency are improved compared with other models. In the future, we plan to fine-tune the model parameters and optimize the phase transformation module on the basis of the existing model, so as to further improve the accuracy of modulation recognition under high signal-to-noise ratio conditions.

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