



Open-Set Recognition Algorithm of Signal Modulation Based on Siamese Neural Network

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Abstract. To realize the open-set recognition of various signal modulations, we propose a three-stage recognition algorithm based on the siamese neural network. Firstly, the convolutional neural network (CNN) is employed to extract the features of the original signal to obtain the multi-dimensional feature vector, thereby constructing the feature data set. Then, a double-threshold method based on average values is designed to distinguish signals with known modulation types and unknown ones. Finally, unknown modulation types are recognized by the siamese neural network. We proposed an iterative algorithm based on the siamese neural network to obtain modulation types of the unknown signals. Experimental results show that the proposed algorithm model can be used for open-set recognition and is suitable for applications in complex wireless communication environments.

Keywords: CNN · Modulation recognition · Open-set recognition · Siamese network

1 Introduction

With the popularization of 5th Generation Mobile Communication Technology (5G) and the development of 6th Generation Mobile Communication Technology (6G), the electromagnetic spectrum has become more crowded. Complex signals have a wider frequency range and more diverse modulation types. The realization of the unknown signal detection and recognition system becomes a more challenging task. To solve this problem, one fundamental work is to apply automatic modulation classification (AMC) to identify the modulation of the signals. The classic AMC methods use likelihood methods [1–3] and traditional feature analysis [4, 5]. However, the calculation based on the likelihood method is complicated, and once it is simplified the classification performance will decrease.

Deep learning has achieved rapid development and great success in AMC. O'Shea et al. used GNU Radio to simulate 11 types of modulated signals in [6] and used CNN to explore the effect of hyperparameters on recognition. In [7], the authors combined the spectrum with CNN to improve the accuracy of AMC.

However, the above methods are all closed-set identification problems. In the actual non-cooperative communication environment, a variety of samples with unknown modulation types may be collected. If the closed-set recognition system is still used, the

system will mistakenly identify the test sample of the unknown class as belonging to one of the known closed set classes, and the accuracy rate will decrease. To solve this problem, open-set recognition is introduced. In [9], the authors proposed a method based on generative adversarial network and anomaly detection, which realized the open-set recognition by reconstructing and discriminating the network and achieved good results within additive white Gaussian noise (AWGN) channels. However, only digital modulation types are considered in [9] while the analog modulation is not taken into account. Moreover, only a few modulation types, including three closed set signals and three open-set signals, can be recognized. In practice, the multipath fading channel should also be considered because it has a great influence on the recognition results.

In this paper, we propose a three-stage recognition method for the open-set recognition of signal modulation. The output of the two convolutional layers and the two fully connected layers are used as the extracted features. Feature comparison analysis is performed to obtain the best features needed. We designed a double-threshold method for screening unknown signals. This method combined with appropriate feature processing methods can further improve the robustness and recognition effect of the proposed recognition algorithm. Then, the siamese neural network is applied to the open-set scene. The signal in the closed set can be recognized and then the open-set classification of the signal can be realized.

2 Signal Model and Open-Set Recognition System Model

2.1 Signal Model

The signal received on the receiver can be expressed as

$$x(t) = h(t) * s(t) + n(t) \quad (1)$$

Among them, $*$ is the convolution operation, $n(t)$ represents the AWGN, $h(t)$ represents the channel impulse response, $s(t)$ is the modulated signal, and $x(t)$ is the received signal which is usually represented by IQ formatted data. The purpose of modulation recognition is to give the class of $s(t)$. Therefore, this problem can be reduced to a classification problem. Since the interference introduced by $h(t)$ and $n(t)$, the change of $x(t)$ will be unpredictable. This also poses a huge challenge to the open-set recognition of modulation types.

2.2 Open-Set Recognition System Model

The closed-set recognition and open-set recognition tasks of signal modulation are illustrated in Fig. 1. As shown in Fig. 1(a), in the open scene, the traditional closed-set recognition may cause errors: different categories are classified into one category, such as category 1 and category 2, and the same category is classified into two categories, such as category 4.

The open-set recognition tasks of signal modulation can be defined as follows. Give a training signal set as

$$D = \{(x_i, \hat{y}_i)\}_{i=1}^q. \quad (2)$$

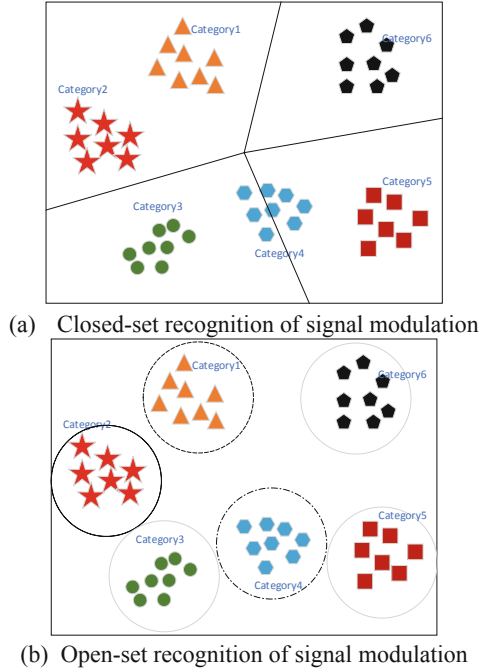


Fig. 1. Closed-set recognition and open-set recognition tasks of signal modulation.

In (2), x_i is a training signal sample. q represents the number of samples in the training set. $\hat{y}_i \in \mathbf{Y}_{\text{closed}}$ is the known modulation label corresponding to the training signal sample x_i . $\mathbf{Y}_{\text{closed}} = \{1, \dots, K\}$ is the modulation type category set.

In the open-set recognition problem, a signal sample is taken from the open space of an unknown modulation signal

$$D_0 = \{(x_i, \hat{y}_i)\}_{i=1}^{\infty} \tag{3}$$

where $\hat{y}_i \in \mathbf{Y}_{\text{open}}$ and $\mathbf{Y}_{\text{open}} = \{1, 2, \dots, K, K + 1, \dots, M\}$ is the label of the possible modulation types. $M > K$ means there exist some unknown modulation types in the considered signal samples. Our task is to realize the open-set recognition of all modulation types in \mathbf{Y}_{open} .

3 Three-Stage Open-Set Recognition Algorithm

In this section, the proposed open-set recognition algorithm of modulated signals based on siamese network will be introduced.

The first stage is feature extraction in part A. Then, the double-threshold method is designed to screen the signal in part B. At the third stage, the closed-set and open-set recognitions of the modulation types are realized in part C. The algorithm flow chart is shown in Fig. 2.

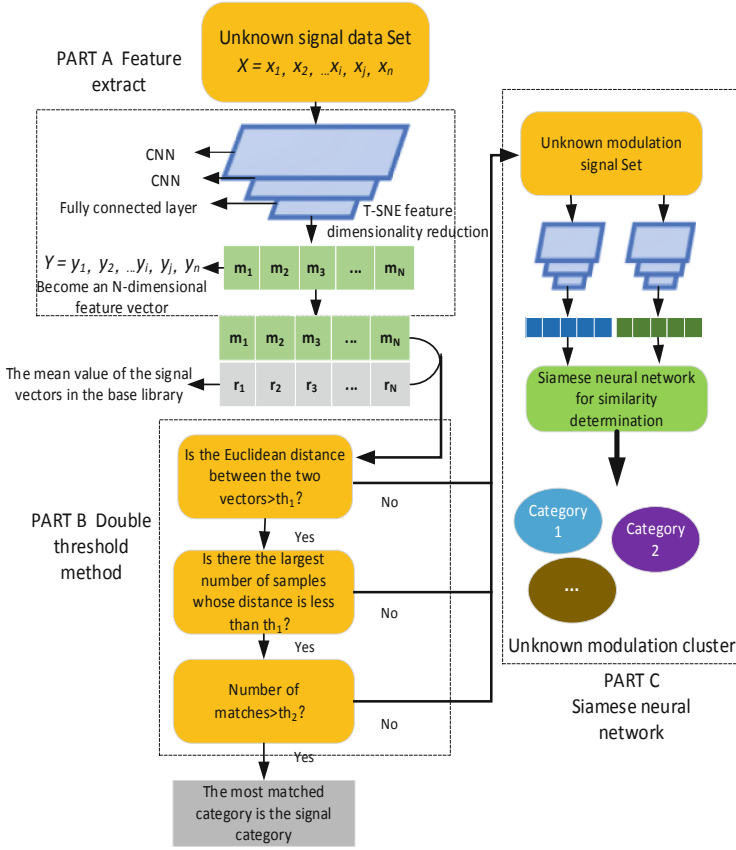


Fig. 2. The three-stage open-set recognition algorithm flow chart.

In part A, the signal is extracted with different layers of CNN, and then clustered after t-distributed stochastic neighbor embedding (T-SNE) dimensionality reduction processing. Take the neural network layer with the best clustering effect as the output layer of the feature extraction module. The feature extraction module converts the input IQ signal into a computable N -dimensional signal feature. Here, we use $[m_1, m_2, \dots, m_N]$ and $[r_1, r_2, \dots, r_N]$ to represent the feature vector. N can be set according to the size of the data set and the type of signal.

In part B, we use the double-threshold method based on the average values to screen the signal. The signal to be recognized is compared with a base library signal, and two different thresholds are used to classify this signal into a known modulation type and an unknown one. The source of the base library signal is composed of M samples selected under different signal-to-noise ratios (SNRs) for each type of signal in the data set. By adding samples with different SNRs to the base library, we solve the problem of sample bias caused by a single base library signal. Although this will bring a certain amount of calculation to the calculation of Euclidean distance, the effect is improved compared to a single base library.

We use the double-threshold based on the average values to screen the signal. Firstly, the model is used to extract the input sample x_i to obtain the output feature F_i .

$$F_i = v(x_i) \quad (4)$$

Then, F_i and the sample feature F_j from the base library are used to calculate the Euclidean distance. When the distance value is less than the first set threshold Th_1 , the sample is considered to match the base library samples and we set a counter, D_{ij} , as 1. otherwise, D_{ij} is set as 0, i.e.,

$$D_{ij} = \begin{cases} 0 & \text{if } \|F_i - F_j\|_2 > Th_1 \\ 1 & \text{if } \|F_i - F_j\|_2 < Th_1 \end{cases}. \quad (5)$$

Then, according to the category, calculate the number of matches between the input signal and the base library signal.

$$nums(i) = \sum D_{ij} \quad (6)$$

Compare $nums(i)$ and Th_2 , if it is greater than Th_2 , then the type with the most matching base library is the type of the signal, if it is less than Th_2 , it is considered as an unknown signal type.

$$g_i = \begin{cases} k & \text{if } nums(i) > Th_2 \\ n + 1 & \text{if } nums(i) < Th_2 \end{cases} \quad (7)$$

Regarding the choice of threshold Th_1 and Th_2 , according to the central limit theorem, the average value of the sum of multiple independent signal statistics conforms to the normal distribution. Therefore, when selecting these two thresholds, setting the threshold range based on the average value will make the screening of unknown modulation signals more accurate. It will be proved in the experiment of the double-threshold recognition method based on the average value.

At the beginning of the recognition task, only the existing training data is used as the base library. As the recognition task progresses, a certain number of unknown signals can gradually accumulate. However, it should be noted that at this time the type of unknown signals is still uncertain.

In part C, in order to solve the problem of being unable to distinguish different unknown signals, the siamese neural network is introduced to complete the recognition task. The distance between two different inputs is calculated by the siamese neural network. The output distance is finally obtained by the sigmoid function to obtain a value between (0, 1). The appropriate threshold is used to judge the two inputs are in the same category or not.

For each unknown signal confirmed by the double-threshold method, the siamese neural network will classify these signals based on similarity.

In summary, the following cyclic iterative algorithm process is used to complete the category classification of the input signals, as shown in Algorithm 1.

Algorithm 1

Algorithm : Signal modulation type recognition algorithm

Step 1:

Input: Unknown signal set $X = x_1, x_2 \dots x_i, x_j, x_n$ Output: Unknown modulation signal set output by double threshold method $K = \{x_1, x_2, x_3 \dots x_Q\}$, Q is the number of elements in the set of K.

1. Unknown signal set $X = x_1, x_2 \dots x_i, x_j, x_n$ goes through CNN and T-SNE feature dimensionality reduction, get the set $Y = y_1, y_2 \dots y_i, y_j, y_n$.
2. Comparing the set Y vector with the mean value of the signal feature vector in the base library, the Euclidean distance between the two vectors is greater than the threshold th_1 , then put it into K, otherwise, proceed to 3.
3. Whether the number of samples smaller than th_1 is the largest, if it is not the largest, put the signal into K, if it is the largest, proceed to step one 4.
4. Determine whether the number of signal matches is greater than th_2 . If yes, consider the modulation type of the most matched category, that is, the modulation type of the signal. If not, put the signal into K.

Step 2:

Input: The set of unknown modulation signals output by the double-threshold method based on the average value method $K = \{x_1, x_2, x_3 \dots x_Q\}$, Q is the number of elements in the set in K, and the threshold is L.Output: Final recognition and classification of different types of unknown modulation signal sets $W_1, W_2, W_3 \dots W_p$, p is the total number of position signal sets.

1. Create a new signal set W_1 ;
 2. $p = 1$;
 3. For $i = 1, 2 \dots Q$
 4. Take a signal X_i from the signal set K;
 5. For $j = 1, 2 \dots p$;
 6. Compare X_i with the set W_j
 7. similarity array $L_{W(j)}$
 7. End
 8. Calculate the maximum similarity L_{Wmax} in the array $L_{W(j)}$, and the corresponding array number is marked as m;
 9. If $L_{Wmax} > \text{Threshold L}$
 10. Put the signal sample X_i into the signal set W_m ;
 11. Else
 12. Create a new signal set W_{p+1} , and put X_i into W_{p+1}
 13. End
 14. End
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From the actual modulation signal analysis, it is found that there will be confusion between different QAM modulations. Therefore, in the open-set identification process, a separate identification module for QAM is introduced to classify different QAM signals. The specific analysis will be further detailed in Sect. 4.

4 Experimental Test and Result Analysis

In the experiment, we use a CNN with two convolutional layers and two fully connected layers to extract features from a part of the training set. Select the training set under the same SNR. This training set contains 11 types of samples, each type of sample has 100 signals. The output of different layers reduced by T-SNE is shown in Fig. 3, where the horizontal and vertical axis is the normalized distance.

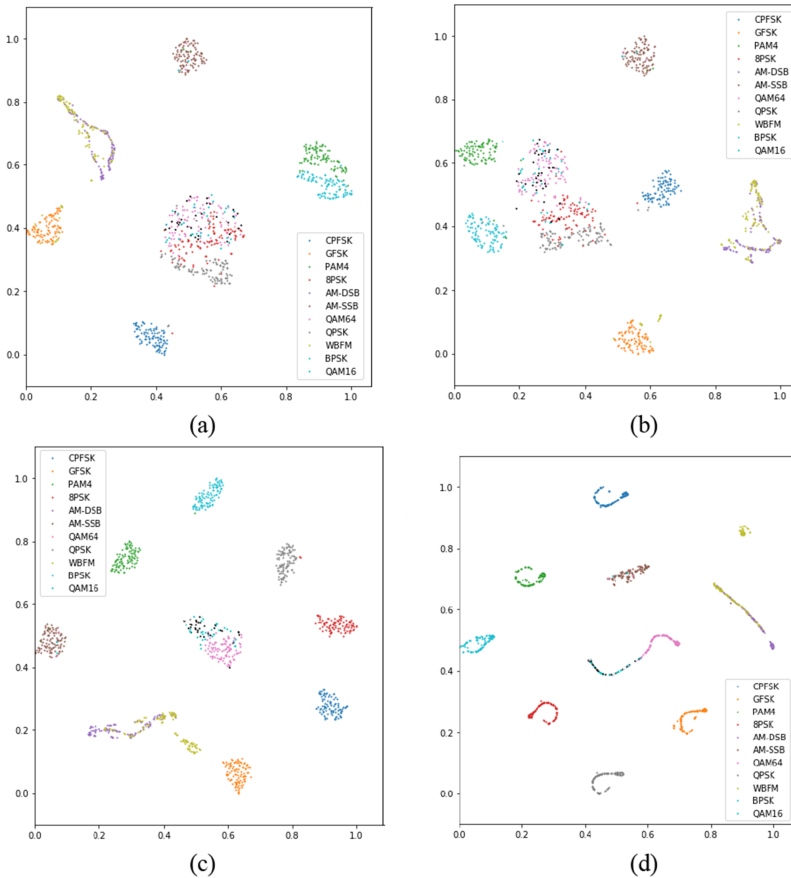


Fig. 3. Dimensionality reduction map of different layers of discriminative features.

Figure 3(a) is the output of the first convolutional layer. It can be seen from the dimensionality reduction graph that the features extracted by the model at this stage

can be used for preliminary classification, but there are still a variety of signal features, and the signals are clustered together. It is difficult to distinguish them; Fig. 3(b) is the output of the last convolutional layer. Compared with Fig. 3(a), the distance between some modulation types has become clearer and obvious. The features of PAM4 and BPSK are closely connected in Fig. 3(a). In Fig. 3(b), there is an obvious classification boundary, which shows that as the number of convolutional layers continues to deepen, the representativeness of the features becomes stronger and stronger. Figure 3(c) is the output of the penultimate fully connected layer, which is the best feature in the general sense. Compared with Fig. 3(b), its classification effect has changed significantly. QPSK and 8PSK signals have been completely separated. The distance between different modulation signals has been clearly distinguished; Fig. 3(d) is the output of the last fully connected layer, which is the vector before entering the softmax. Because it is directly supervised by the label during training, the classification boundary of this layer is the most obvious, but the data space is compressed too tightly, and using the output of this layer as a feature is more likely to cause overfitting. Therefore, this paper finally chooses the output of the penultimate fully connected layer as the extracted signal feature.

The experimental results are evaluated on the dataset RadioML.2016.10a [6], The number of samples in the data set is 22000, and each sample is a 2×128 vector. For channel simulation, the dynamic channel model hierarchical block uses frequency offset, sampling rate offset, AWGN, multipath, and fading. The data set is divided into 80% of the training set and 20% of the test set. Epochs = 1000 and batch size = 500. In the training phase, the validation set is used for parameter adjustment, such as batch size, optimizer, learning rate, etc.

Use the double-threshold method based on the average value proposed in this paper. When training the model, only 9 types of dataset at different SNRs are used, and the BPSK and BFSK data are removed from the training set to test the open-set recognition effect of the algorithm. The experiment not only needs to identify the existing 9 types of signal modulation types in the training set but also needs to verify the modulation of the two open-set types of signals. In the current stage of the experiment, both BPSK and BFSK signals are marked as unknown signals in the experiment. The experimental results are shown in Fig. 4.

The vertical axis is the accuracy rate, and the horizontal axis is the signal-to-noise ratio. In Fig. 4, the green curve named “max1thresh” is the experimental result of the threshold method based on the maximum value method in [10]. The pink curve named “max2thresh” is the experimental result obtained by improving the method in [10] using the double-threshold method. It is obvious that the use of the double-threshold method after the SNR reaches a certain level can significantly improve the accuracy of classification. The definition of accuracy here: the ratio of the number of unknown modulation type identified to the number of the actual unknown modulation types, the black curve named “average1thresh” uses the average threshold method but does not use the double threshold, which is a certain improvement compared to the maximum threshold method. However, the classification accuracy performance is worse than that of the double-threshold method based on the maximum threshold method. The blue curve named “average2thresh” is the double-threshold method based on the average method

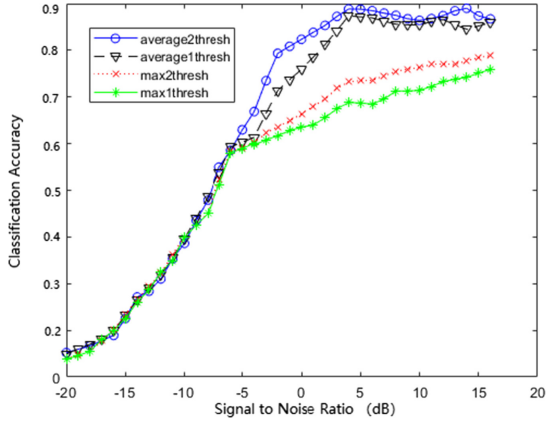


Fig. 4. Recognition results of different methods under open-set requirements (Color figure online)

proposed in this article. Its classification accuracy is higher than other methods, and the highest accuracy rate is 89.18% when the SNR is 14 dB.

Specific analysis of the recognition effect of each category plots all test data with a signal-to-noise ratio above 0 dB, and the confusion matrix is shown in Fig. 5.

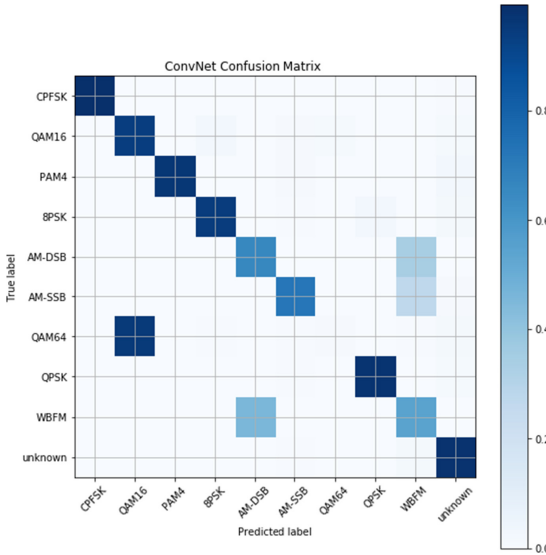


Fig. 5. Confusion matrix of the average value method and double threshold method classification results

In Fig. 5, the darker the color bar on the right represents the higher recognition accuracy, the ordinate represents the true category of the sample, and the abscissa represents the predicted category of the sample. The unknown categories are BPSK and BFSK. For

the 9 types of signals included in the training data set, the average accuracy rate can reach 86%. For a total of 11 types of signal input, the recognition accuracy rate is 77.14%. It can also be seen that the classification of QAM64 and QAM16 is the main factor that affects the classification results, and according to what we have learned, QAM64 and QAM16 signals can be distinguished by the zero center normalized instantaneous amplitude compactness (ZCNC).

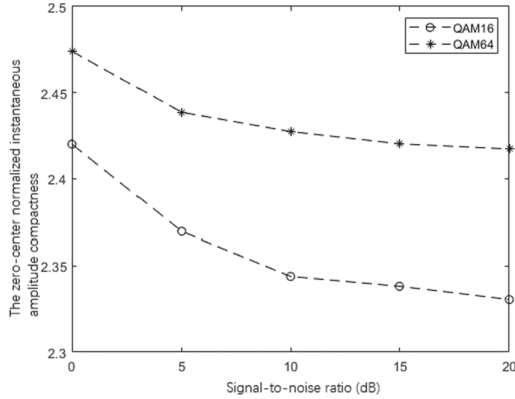


Fig. 6. The zero center normalized instantaneous amplitude compactness (ZCNC) of QAM64 and QAM16.

It can be seen from Fig. 6 that the ZCNC of QAM16 is smaller than that of 64QAM. Therefore, the two QAM signals can be distinguished by calculating this parameter threshold. Setting the threshold value to 2.42 can distinguish 85% of the two signals at different SNRs, and the effect is shown in Fig. 7.

Finally, the siamese neural network is used to reclassify the experimental results and analysis of the open-set category, and each signal is regarded as an unknown signal. The open-set recognition experiment of a single unknown signal with SNR higher than 0 dB is performed well. The experimental results are shown in Table 1.

It can be seen from Table 1 that for a single unknown modulation signal, the probability of identifying it as an unknown signal exceeds 85%. When the input is recognized as an unknown signal, it is clustered through the siamese network, and the main proportion of the set size is used to roughly determine the type of unknown signal. Then, take out BFSK and BPSK as unknown signals for testing. The experimental results of the average similarity calculated by the siamese neural network are shown in Table 2.

The number of final output sets is 4, of which the BPSK largest cluster set accounts for 72.5%, and the number of secondary cluster accounts for 27.5%. The recognition effect for BFSK is even better, with the largest cluster accounting for 93%, and the secondary cluster only accounting for 7%. The final output can also be filtered by adding a limit to the number of samples in each cluster to make it clear that the final unknown signal includes two types. Compared with [9], the types of digital modulation types and analog modulation types for recognition are increased, and multipath and fading factors are taken into account to realize open-set recognition in more complex environments.

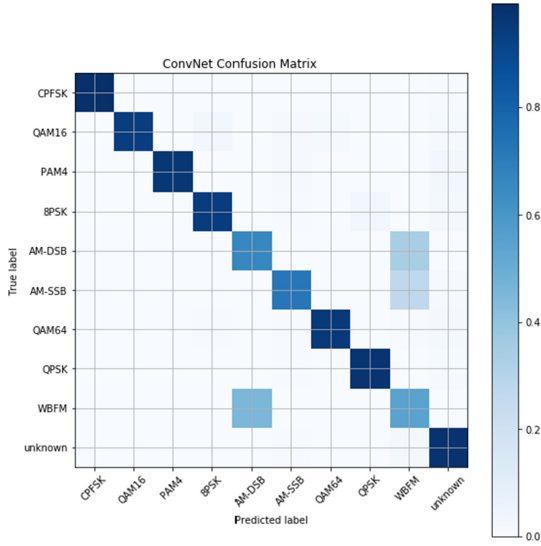


Fig. 7. Improved confusion matrix for QAM

Table 1. Signals of a signal unknown modulation type.

Actual modulation of signal	Probability of being recognized as an unknown signal	Percentage of main clusters	Percentage of secondary clusters
BPSK	87.31%	88.50%	11.50%
QPSK	85.14%	92.45%	7.55%
8PSK	86.67%	94.90%	5.10%
16QAM	87.84%	94.73%	5.27%
64QAM	86.49%	92.13%	7.87%
BFSK	85.50%	95.22%	4.78%
CPFSK	89.33%	96.47%	3.53%
PAM4	91.79%	92.79%	7.21%
WBFM	84.75%	90.90%	9.10%
AM-SSB	90.51%	97.15%	2.85%
AM-DSB	89.62%	93.21%	6.79%

Table 2. The similarity between unknown modulation signals.

Similarity	BPSK	BFSK
BPSK	0.5645	0.0010
BFSK	0.0010	0.7494

5 Conclusions

In this paper, we proposed a three-stage algorithm for open-set modulation recognition. First, we examined the selection of the appropriate network output as the discriminative feature. Then, a double-threshold method based on the average values was proposed. It can divide the input signals into known types and unknown ones, and complete the preliminary identification of unknown signals. Subsequently, the siamese neural network was employed to measure the similarity between two different signals, and the similarity threshold was used to finally complete the classification of the unknown modulation type. Experimental results showed that the proposed three-stage modulation recognition algorithm can maintain an 87% recognition rate for traditional closed-set recognition signals when the SNR was greater than 0 dB. It can also effectively identify 84% of signals with unknown modulation types.

Acknowledgement. This work was supported by the National Key R&D Program of China under Grant 2020YFB1804901, the National Natural Science Foundation of China under Grant 61871035, and the National Defense Science and Technology Innovation Zone.

References

1. Wang, F., Dobre, O.A., Chan, C., Zhang, J.: Fold-based Kolmogorov–Smirnov modulation classifier. *IEEE Signal Process. Lett.* **23**(7), 1003–1007 (2016)
2. Zhu, D., Mathews, V.J., Detienne, D.H.: A likelihood-based algorithm for blind identification of QAM and PSK signals. *IEEE Trans. Wirel. Commun.* **17**(5), 3417–3430 (2018)
3. Chen, W., Xie, Z., Ma, L., Liu, J., Liang, X.: A faster maximum likelihood modulation classification in flat fading non-Gaussian channels. *IEEE Commun. Lett.* **23**(3), 454–457 (2019)
4. Kharbech, S., Dayoub, I., Zwingelstein-Colin, M., Simon, E.P.: On classifiers for blind feature-based automatic modulation classification over multiple-input-multiple-output channels. *IET Commun.* **10**(7), 790–795 (2016)
5. Wang, Y., Yang, J., Liu, M., Gui, G.: LightAMC: lightweight automatic modulation classification via deep learning and compressive sensing. *IEEE Trans. Veh. Technol.* **69**(3), 3491–3495 (2020)
6. O’Shea, T.J., Corgan, J., Clancy, T.C.: Convolutional radio modulation recognition networks (2016). <https://arxiv.org/abs/1602.04105>
7. Zeng, Y., Zhang, M., Han, F., Gong, Y., Zhang, J.: Spectrum analysis and convolutional neural network for automatic modulation recognition. *IEEE Wirel. Commun. Lett.* **8**(3), 929–932 (2019)
8. Bu, K., He, Y., Jing, X., Han, J.: Adversarial transfer learning for deep learning-based automatic modulation classification. *IEEE Signal Process. Lett.* **27**, 880–884 (2020)
9. Hao, Y., Liu, Z., Guo, F., Zhang, M.: Open-set recognition of signal modulation based on generative adversarial networks. *Syst. Eng. Electron.* **41**(11), 2619–2624 (2019)
10. Guo, Y.: Automation modulation recognition of the communication signals based on deep learning. Master’s thesis, China Academy of Engineering Physics. <https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFD201901&filename=1019025043.nh>