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A Modulation Recognition Algorithm via Hybrid Feature Analysis in Aeronautical Wireless Channel

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ABSTRACT When communicating in aeronautical wireless channels, the difficulty of radio modulation recognition increases due to the loss of information caused by noise; particularly in circumstances with low signal-to-noise ratios (SNRs), it is difficult to achieve recognition rates exceeding 90.0%. To improve the radio modulation recognition performances of networks at low SNRs in complex electromagnetic environments, a modulation recognition method based on multidimensional feature analysis is proposed in this paper. It is realized through a cascaded structure including a Deep Cross Network (DCN) and an improved Visual Geometry Group Network 16 (VGG16). Our network framework is divided into two modules. In the one-dimensional data analysis module, we take the high-order cumulant of a transmitted signal as the one-dimensional feature input of the DCN. In the two-dimensional data analysis module, the color constellation density of the signal is extracted as the feature map input of the improved VGG16. Finally, we build a cascaded neural network with hybrid feature inputs for modulation recognition. Experimental results show that the recognition rate of our method is higher than 90.0% at an SNR of −4 dB. Compared with other methods, the proposed method has better recognition performance at low SNRs in aeronautical wireless channels.

INDEX TERMS Modulation recognition, cascade network, aeronautical channel, mixed data.

I. INTRODUCTION

The precise identification of modulation modes is the basis for analyzing intercepted signals under non-cooperative wireless communications. However, the complexity of aeronautical wireless channels and the diversity of modulation modes make it difficult to recognize modulation signals correctly. As a consequence, the conventional approaches have difficulty meeting the needs of communication countermeasures, especially at low SNRs. Therefore, the correct recognition of modulation modes has much research significance in the fields of signal processing and wireless communication.

Current modulation recognition methods based on feature extraction can be divided into signal processing-based methods and pattern recognition-based methods. The former mainly realizes recognition by manually calculating the time-frequency domain characteristics and transform domain characteristics of the signal. Reference [1] combined cumulants of different orders to form feature parameters, which have a strong ability to recognize ASK and FSK modulation modes. Nonetheless, the reference method cannot be used when dealing with 8PSK and MFSK modes because they have the same cumulative value. In addition, when the SNR is lower than 4 dB, the recognition rate is lower than 75%. Reference [2] comprehensively analyzed the instantaneous features and cumulant features of a signal and used stacked sparse autoencoders to achieve signal classification. This method only works well when the FSK modulation method is not considered; when the SNR is lower than 0 dB, the recognition rate of this method drops rapidly to 80%. Reference [3] extracted the instantaneous amplitude, phase and frequency parameters of a signal to realize automatic modulation recognition. Like the above methods, that of reference [3] only achieves a good recognition effect when the SNR is higher than 10 dB. In addition, the spectrum correlation function [4] and cyclic cumulant [5] have also been used to

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realize modulation recognition. The latter mainly uses pattern recognition to achieve signal recognition by converting the recognition issues from one-dimensional signal processing problems into image pattern matching problems.

Reference [6] realized signal modulation recognition through the superposition of two convolutional neural networks (CNNs), making use of the constellation map of a transmitted signal to perform shape matching and subdivide the modulation mode, thereby improving the recognition rate of the method at low SNRs; however, this approach ignores the influences of multipath fading and the Doppler frequency. Reference [7] reduced signal noise with a Gaussian filter and used a time-frequency map as the image input for network training. When the SNR is lower than 4 dB, the recognition rate is lower than 85%. In addition, two-dimensional signal image features, such as eye patterns and constellation maps, can also be used as feature inputs.

On the basis of existing studies, we find that high-order cumulants can weaken the influence of channel fading while suppressing Gaussian noise [8]. However, the modulation modes that can be identified are limited through high-order cumulant-based methods. In contrast, a constellation map can better reflect the mapping relationships of a modulation signal when noise interference is low. It can be seen that a one-dimensional feature and a two-dimensional feature have their own unique advantages in the field of modulation recognition. We jointly extract two kinds of features and propose a modulation recognition method based on hybrid feature analysis.

For the purpose of improving the modulation recognition performance of our approach at low SNRs, we select the high-order cumulant and the color constellation density of the signal as the one-dimensional feature and the two-dimensional feature, respectively. In addition, we build a DCN and an improved VGG 16 cascaded network framework to perform feature extraction, effectively combining the advantages of both types of features and realizing the accurate recognition of the modulation modes of the signal. DCN can effectively capture the effective feature crossover on the bounded degrees without artificial feature engineering, and it has low computational cost which is suitable for exploring the relationship between one-dimensional eigenvalue and modulation mode. VGG16 explores the relationship between the depth and performance of CNN, which is suitable for explore the relationship between image features and modulation mode.

The innovations of this paper are as follows:

1. A method of applying the one-dimensional and two-dimensional features of aeronautical signals to the task of modulation recognition is proposed, thereby maximizing the complementary advantages of features with different dimensions; this not only improves the ability of the method to resist noise but also enhances its adaptability to different modulation modes.

2. We improve the modulation recognition rate of the method for aeronautical wireless signals at low SNRs. When the SNR is higher than −4 dB, the recognition rate still exceeds 90% despite suffering from Doppler effects in the aeronautical fading channel.

3. We construct a cascaded network capable of processing multidimensional features. We explore the mapping relationships between the features of different dimensions and various recognition methods through the DCN and the VGG16 cascaded network by extracting the high-order features of signals. In addition, we introduce the idea of migration learning for training purposes, thereby simplifying the computational complexity of the proposed method.

FIGURE 1. Model of model aeronautical wireless model.

The subsequent sections of this paper are organized as follows. In the second section, channel modeling and two-dimensional features are introduced. In the third section, the network training framework and its advantages are introduced. In the fourth section, the experimental results are analyzed to verify the performance of the proposed algorithm. Finally, we summarize the defects of our method and suggest a direction for future research in the fifth section.

II. AERONAUTICAL CHANNEL AND MIXED FEATURE

To begin with, we built the complex channel model that aeronautical communication faces, mainly considering influencing factors including multipath fading, Doppler fading, Gaussian white noise interference, etc. Then the high-order cumulants and constellation graph features were analyzed from the formation mechanism. Finally, we constructed the data set according to the channel model and signal features, which consisted of the high-order cumulants and constellation graph.

A. AERONAUTICAL WIRELESS CHANNEL

In a complex electromagnetic environment, a signal is prone to decay due to factors such as the channel characteristics and noise. An aeronautical multipath fast fading channel model in cruise scenarios is shown in Fig. 1. As we can see, the transmitted signal suffers from Doppler deviation and dispersion [9], which are caused by the relative movement of the receiver B and the transmitter A in direction path or the receiver B and the reflection point in reflection path. In addition, the transmission path is blocked by obstacles, which cause multiple scattering paths to appear; this in turn leads to multipath fading and time delays [10]. In addition, the influence of noise, which exists in all flight scenarios, on the transmitted signal cannot be ignored. The purpose of our method is to improve the modulation recognition rate of the channel at low SNRs, so we fix the number of transmission paths and the maximum Doppler frequency when modeling the aeronautical wireless channel. The traditional received radio $r_t(t)$ is as follows:

$$r_t(t) = s(t) * a(t) * h(t) + \eta(t) * h(t) \tag{1}$$

where $r_t(t)$ represents the received signal, $s(t)$ represents the pure transmitted signal, $h(t)$ represents the impulse response of the receiver filter, $\alpha(t)$ represents the impulse response, and $\eta(t)$ represents the noise. When we consider the influence of doppler effects and multipath effects in aeronautical wireless channels, final transmitted signal is expressed as follows according to reference [11]:

$$\boldsymbol{r}(t) = \sum_{n=0}^{L} a_n(t)\boldsymbol{s}(t - nT)e^{j[2\pi\Delta f_{dn}(t-nT)+\varphi_n]} + \boldsymbol{\eta}(t) \tag{2}$$

where $\alpha_n(t)$ represents the impulse response of the n^{th} path, which demonstrates the impact of the multipath effect on $r(t)$. T represents the symbol period. $\Delta f_{dn}(t)$ represents the maximum Doppler frequency, which demonstrates the impact of the Doppler effect on the signal, φ_n represents the phase change of electromagnetic waves caused by scattering and reflection, randomly distributed between $-\pi$ and π, and $\eta(t)$ represents the constructed channel model, which comprehensively considers multiple interference factors and simulates the complexity of the aeronautical communication. On the basis of this channel, we can reasonably select signal features and design a network structure for realizing recognition at low SNRs.

B. FEATURE ANALYSIS

1) HIGH-ORDER CUMULANT FEATURE

The k^{th} order cumulant $C_{kx}(t)$ and the p^{th} order mixing moment of a stationary complex random process $\{X(t)\}$ and their mean value are expressed as follows:

$$\begin{aligned} C_{kx}(t) &= (f_1, f_2, \ldots, f_k) \\ &= Cum(x(t), x(t+f_1), \ldots, x(t+f_k)) \end{aligned} \tag{3}$$

$$M_{pq} = E\left[X(k)^p X^*(k)^{p-q}\right] \tag{4}$$

where $X^*(k)$ and $X(k)$ are mutually conjugated, so cumulants of $x(t)$ of different orders are:

$$C_{20} = Cum(X, X) = M_{20} \tag{5}$$
$$C_{21} = Cum(X, X^*) = M_{21} \tag{6}$$
$$C_{40} = Cum(X, X, X, X) = M_{40} - 3M_{20}^2 \tag{7}$$
$$C_{41} = Cum(X, X, X, X^*) = M_{40} - 3M_{21}M_{20} \tag{8}$$
$$C_{42} = Cum(X, X, X^*, X^*) = M_{42} - M_{20}^2 - 2M_{21}^2 \tag{9}$$
$$\begin{aligned} C_{60} &= Cum(X, X, X, X, X, X) \\ &= M_{60} - 15M_{20}M_{40} + 30M_{20}^3 \end{aligned} \tag{10}$$
$$\begin{aligned} C_{60} &= Cum(X, X, X, X^*, X^*, X^*) \\ &= M_{63} - 6M_{41}M_{20} - 9M_{21}M_{42} \\ &\quad + 18M_{21}M_{20}^2 + 12M_{21}^3 \end{aligned} \tag{11}$$

All of the above values cumulants are input to the neural network in the form of vectors. Since the 4^{th} and 6^{th} order cumulants of Gaussian white noise are 0, the high-order cumulants can be used for recognition at low SNRs. Moreover, the different cumulants of the signal, such as the absolute values of C_{20}^2/C_{42} and C_{40}/C_{42}, C_{63}^2/C_{42}^3 and others, which are used to distinguish between different types of modulation modes, can weaken the channel interference effect on the signal according to a theory in the literature [12]. However, modulation modes such as MFSK cannot be distinguished through high-order cumulants because those modes have the same cumulative value; when applying existing methods to high-order modulation recognition, the recognition performances are unsatisfactory. Based on the above analysis, simply making use of the cumulative values is insufficient for meeting diverse recognition requirements. Therefore, we select the absolute values of C_{20}, C_{21}, C_{40}, C_{41}, C_{42}, C_{60}, C_{63} and their corresponding combinations, C_{40}/C_{42}, C_{20}^2/C_{42}, C_{63}^2/C_{42}^3, C_{63}/C_{21}^3, and C_{42}/C_{21}^2, as 12 eigenvalues to form eigenvectors, and we combine these with signal constellation features for modulation recognition purposes. It should be noted that the second order cumulant cannot be used on its own as a decision threshold for distinguishing between modulation modes.

2) COLOR DENSITY CONSTELLATION MAP

A constellation map is a representation of the digital signal on the complex plane, and it reflects the amplitude and phase information of the signal [13]–[15]. Different from the process of feature extraction for a signal, it is essentially a method of shape matching. To improve the classification performance of the constellation map, we choose the improved color constellation density map as the feature map for recognition purposes. The color constellation density map refers to the color labeling of different density regions of the original constellation map, and the obtained multichannel image features can effectively characterize the mapping relationships between the constellation points and modulation signals. Fig. 2 shows the constellation maps of four modulation signals, QPSK, BPSK, 8PAM and 16QAM, at an SNR of 4 dB.

The different columns in Fig. 2 represent the clean constellation map that is not subject to multipath fading, the constellation map faded through the aeronautical channel, and the faded color constellation map, respectively. The abscissa represents the in-phase component, and the ordinate represents the quadrature component. Therefore, we can conclude that signal fading seriously distorts the constellation map. Considering that the color constellation map can add additional features while retaining the mapping relationships of the original constellation map, we use this improved map to replace the original image during signal classification.

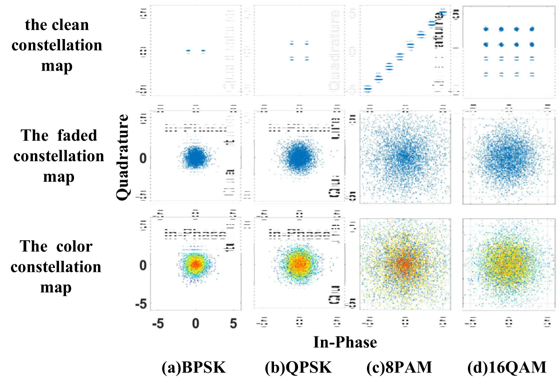

FIGURE 2. Constellation map comparison(BPSK, QPSK, 8PAM, 16QAM).

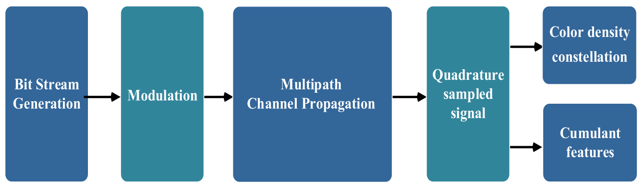

FIGURE 3. The flow of data set generation.

C. DATA SET GENERATION

The flow of the dataset generation process is shown in Fig. 3. A quadrature sampling signal with a sampling point of 1024 is generated by MATLAB2019b first, and then we select signal samples according to 9 modulation modes, including BPSK, QPSK, 8PSK, 8PAM, 16QAM, 32QAM, 64QAM, MSK and 2ASK. Each type of modulation mode generates 2000 samples. Afterwards, we calculate the fading signal output with a maximum frequency deviation of 200 Hz under the three-path channel according to (2), while simultaneously selecting different SNRs for noise superposition. In the end, we obtain the corresponding one-dimensional cumulant feature dataset and two-dimensional constellation dataset.

III. DCN AND VGG16 BI-LSTM CASCADE NETWORK

We design the hybrid data input network for processing multidimensional features by building the cascaded deep cross network and the VGG16 Bi-LSTM network for dealing with different features; the latter extracts signal features of different dimensions for training.

1) HIGH-ORDER CUMULANT FEATURE

In traditional recognition methods, cumulants of different orders and their combined forms are typically used as the thresholds of decision trees for recognizing modulation modes, but the thresholds must be set manually. To better explore the mapping relationships between high-order cumulants and modulation modes, we design a DCN with layers as in Fig. 4, where each layer includes a cross network and a deep network that can realize the cross features of all combined cumulants without being dependent upon manual feature extraction. The interlayer relationship of the cross network is expressed as:

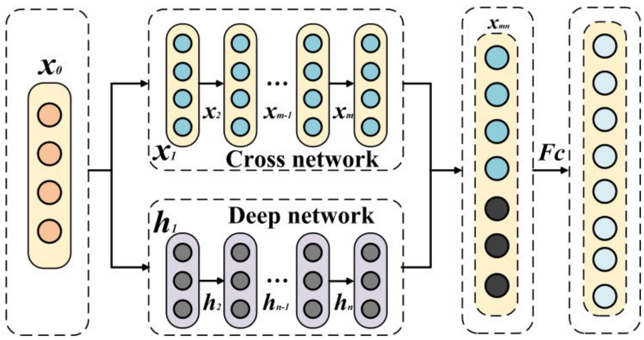

FIGURE 4. The frame of deep cross network.

$$x_m = x_0 x_{m-1}^T W_{m-1} + b_{m-1} + x_{m-1} \tag{12}$$

where x_0 represents the input feature vector, x_m represents the output of the m^{th} layer, and W_m and b_m represent the corresponding weight and bias terms, respectively. By setting x_0 to $[c_1 c_2]^T$ and W_0 to $[w_{0,1} w_{0,2}]^T$, if we ignore the influence of the bias term, we can obtain:

$$\begin{aligned} x_1 &= x_0 x_0^T W_0 + x_0 \\ &= \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} [c_1 c_2] \begin{bmatrix} w_{0,1} \\ w_{0,2} \end{bmatrix} + \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} \\ &= \begin{bmatrix} w_{0,1} c_1^2 + w_{0,2} c_1 c_2 + c_1 \\ w_{0,2} c_2^2 + w_{0,1} c_2 c_1 + c_2 \end{bmatrix} \end{aligned} \tag{13}$$

It can be seen that the input of each layer of the cross network is a cross-combination of all elements from the previous layer. As the number of network layers increases, the order of the characterization of the element combination also increases. Additionally, the highest cross-order of the m^{th} layer reaches m + 1. Moreover, a deep neural network is set up in parallel to improve the ability of the proposed network to learn high-level features, and the interlayer relationship is:

$$h_n = f(W_{n-1} h_{n-1} + b_{n-1}) \tag{14}$$

where $f(\cdot)$ represents the linear activation function [16] and h_n represents the output of the n^{th} layer. After combining the deep network and cross network layers, we obtain the network output x_mn as:

$$x_{mn} = f(\left[x_m^T, h_n^T\right] W_{\log its}) \tag{15}$$

2) VGG16 BI-LSTM NETWORK

We select VGG16 to extract features from the constellation map and add the Bi-LSTM layer for deep feature extraction. The network model, which is shown in Fig. 5, consisting of five convolutional layers, four pooling layers, one Bi-LSTM layer and two fully connected layers.

To improve the calculation speed of the network, the idea of migration learning is adopted by the training process, and some pre-trained model weights are fine-tuned and migrated to the VGG16 Bi-LSTM structure to optimize the results and reduce the total training cost.

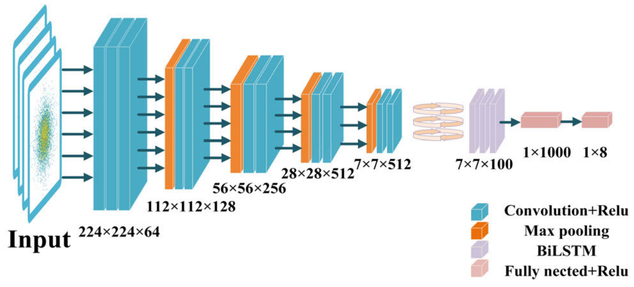

FIGURE 5. The framework of the VGG16 Bi-LSTM network.

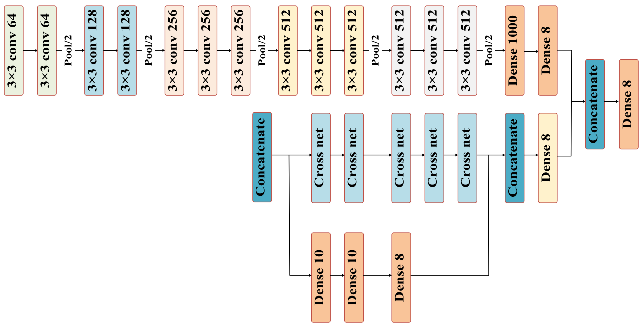

FIGURE 6. The framework of the cascade network.

3) DCN AND VGG16 CASCADE NETWORK

The design of the joint network model used for modulation recognition is shown in Fig. 6. The inputs consist of one-dimensional numerical features and two-dimensional image features. We combine the noise immunity of the cumulant with the modulation adaptability of the constellation map. Next, we construct a network framework for processing mixed data inputs, through which the modulation recognition performance of the proposed method under low SNRs is improved effectively. When training the model, we migrate some pre-trained and fine-tuned model weights to the network structure so that the calculation parameters of the network are reduced and the method becomes suitable for real-time signal analysis.

After combining the features of different dimensions, modulation mode classification is performed through the fully connected layer and the softmax activation [17] function. Our model uses the Adam optimizer [18] to determine the optimal solution of the network parameters and the cross-entropy classification error is selected as the loss function. This function is expressed as:

$$\ell(w, b; x_1, x_2, y) = -\sum_{i}^{N} (y_i)^T \log(f_1(x_{1,i}, x_{2,i}; w, b)) + \lambda_1 \sum \|w\|^2 \quad (16)$$

where $f(\cdot)$ is used to adjust the joint output value of the given feature and $\lambda_1 \sum \|w\|^2$ represents a regular term used to prevent overfitting and improve the feature generalization ability of our method.

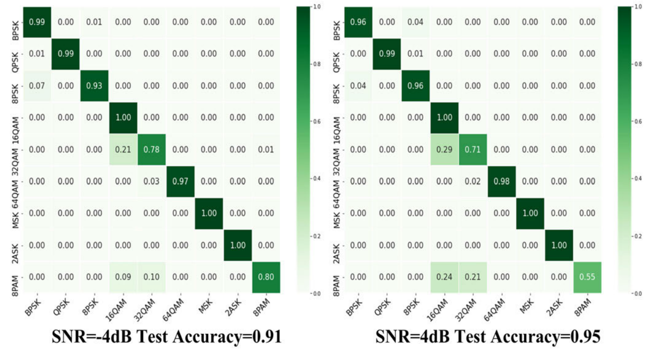

FIGURE 7. Confusion matrix at SNRs of −4 dB and 4 dB.

IV. ANALYSIS OF EXPERIMENTAL RESULTS

Aiming at verifying the effectiveness of the method proposed in this paper, we analyze the performance of the proposed network at different SNRs first, and then we compare our model with traditional methods and other network models used for analyzing the advantages of multidimensional feature inputs. Finally, we discuss the influence of the chosen network parameters on the recognition performance of our method. The comparison is based on the aeronautical multipath fast fading channel model in cruise scenarios.

4) COMPARISON OF RECOGNITION RATES

As shown in Fig. 7, we select the modulation recognition confusion matrix at SNRs of −4 dB and 4 dB for analysis. According to our experimental simulation results, it can be seen that when the SNR is below −4 dB, the overall recognition rate of this algorithm is higher than 90%. When the SNR is higher than 4 dB, the recognition rate reaches 95%. The confusion matrix shows that our method has a higher recognition rate than other methods for low-order modulation modes, but it is easily confused when trying to recognize 16QAM, 32QAM, and 8PAM, and this indicates that the cumulant is not suitable for high-order modulation recognition. Moreover, the shape of the constellation changes in aeronautical fading channel, and it is difficult to recognize modulation modes when their fading constellation shapes are close to each other.

The recognition rates of our method at different SNRs are shown in Fig. 8. When the SNR is lower than −10 dB, the recognition rate drops rapidly. The reason for this is that the shape features of the constellation are severely deformed, so they cannot be used for matching recognition. In this case, the main function of the cascade network is to extract the cumulant feature, but the modulation modes that the cumulant feature can recognize are limited, so when the SNR is less than −10 dB, the overall recognition rate decreases greatly.

5) COMPARISON OF DIFFERENT STRUCTURES

For the purpose of verifying the effectiveness of the cascaded network proposed in this paper, we conduct experimental comparisons from two perspectives: the feature input and the

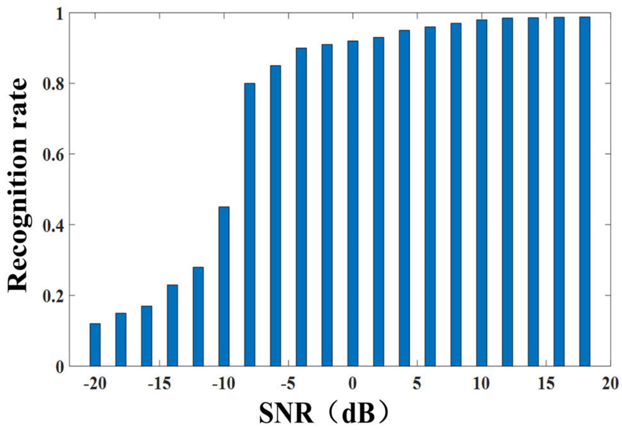

FIGURE 8. Recognition results at different SNRs.

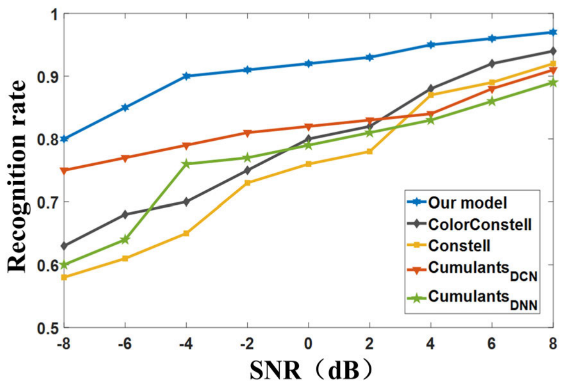

FIGURE 9. Comparison of feature inputs.

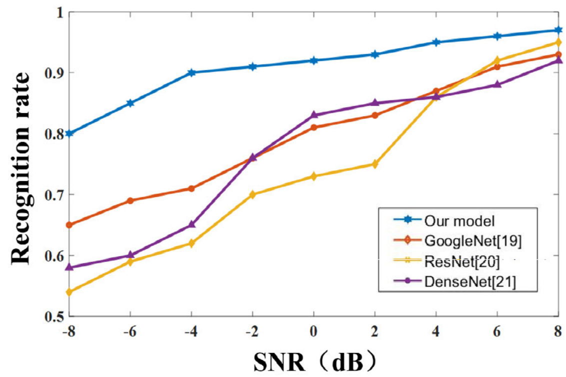

FIGURE 10. Comparison of network structure.

TABLE 1. Comparison between different numbers of cross network layers.

Number of layers	1	3	5	7	9
Recognition rate	80.3%	90.1%	93.1%	92.9%	93.1%

network model. Fig. 9 shows the comparison between the cascaded network in this paper and other methods that extract constellation features and cumulant features separately when the SNR is set to (−8, 8).

It can be seen that when the SNR is higher than 4 dB, the recognition rate achieved when inputting only the constellation map is significantly higher than that achieved when only inputting the cumulant, and the performance obtained using the color constellation map is higher than that obtained using the original constellation map. However, when the SNR is lower than 4 dB, the performance of the algorithm when using the constellation map as the input decreases rapidly. In contrast, the cumulant extraction-based method has a higher recognition rate than those of the compared methods. In addition, the recognition rate achieved when using only the DCN model is significantly higher than that achieved when using only the DNN model, and this proves the rationality of using cross features to achieve cumulant combination. The method in this paper combines the advantages of the two abovementioned types of features, and through cascade network training, the resulting recognition rate is higher than those of the methods based on single feature inputs.

Additionally, we compare the proposed network with other network structures. The comparison results are shown in Fig. 10, where the competing methods include GoogleNet [19], ResNet [20] and DenseNet [21]. It can be seen that our network framework has its best recognition effect when the SNR is higher than 2 dB, but when the SNR is lower than 2 dB, the recognition rate drops significantly. The model in this paper has a recognition rate of 90% or above when the SNR is higher than −4 dB, and its anti-interference performance is strong.

6) COMPARISON BETWEEN DIFFERENT NUMBERS OF CROSS NETWORK LAYERS

When setting the SNR to 2 dB, the relationship between the number of cross network layers [22] and the recognition rate is shown in Table 1. When the number of layers increases, the recognition rate gradually improves as well. However, when the number of network layers is more than five, the recognition rate does not improve further. The comparison shows that the ability of the high-order cumulant to distinguish between different modulation modes is related to the order of the cross feature. This ability is not improved further when we set five DCN layers. In other word, a seven-order crossover feature cannot be used to distinguish between modulation modes.

V. CONCLUSION

To improve the ability of networks to recognize modulation signals at low SNRs in aeronautical wireless channels, we analyze signal characteristics of different dimensions. In addition, cumulant features and constellation features are selected as the input for the hybrid feature model. The selection of hybrid features can not only suppress noise but can also efficiently identify high-order modulation modes. At the same time, we design a cascaded network framework for extracting mixed data features. We simplify the training process through transfer learning. Experimental results show that the recognition rate of our method is over 90% when the SNR is higher than −4 dB. It is proven that our method can be used for modulation recognition in complex electromagnetic environments. Next, we will continue to analyze the signal features, turn the research of modulation recognition to radio frequency fingerprint identification.

REFERENCES

[1] Y. Zhao, Y. T. Xu, H. Jiang, Y. J. Luo, and Z. W. Wang, "Recognition of digital modulation signals based on high-order cumulants," in *Proc. Int. Conf. Wireless Commun. Signal Process. (WCSP)*, Oct. 2006, pp. 1–5.

[2] M. Bouchou, H. Wang, and M. El Hadi Lakhdari, "Automatic digital modulation recognition based on stacked sparse autoencoder," in *Proc. IEEE 17th Int. Conf. Commun. Technol. (ICCT)*, Oct. 2017, pp. 28–32.

[3] A. K. Nandi and E. E. Azzouz, "Modulation recognition using artificial neural networks," *Signal Process.*, vol. 56, no. 2, pp. 165–175, Jan. 1997.

[4] X. Rao, X. Zhao, and L. Zhang, "MIMO radar signals modulation recognition based on partial instantaneous autocorrelation spectrum," *J. Eng.*, vol. 2019, no. 19, pp. 5855–5859, Oct. 2019.

[5] G. Qingyang and Z. Yue, "Cyclic cumulant based on communication signal multilayer neural network modulation pattern recognition," in *Proc. IEEE 3rd Int. Conf. Cloud Comput. Internet Things (CCIOT)*, Oct. 2018, Art. no. 042113.

[6] Y. Wang, M. Liu, J. Yang, and G. Gui, "Data-driven deep learning for automatic modulation recognition in cognitive radios," *IEEE Trans. Veh. Technol.*, vol. 68, no. 4, pp. 4074–4077, Apr. 2019.

[7] Y. Zeng, M. Zhang, F. Han, Y. Gong, and J. Zhang, "Spectrum analysis and convolutional neural network for automatic modulation recognition," *IEEE Wireless Commun. Lett.*, vol. 8, no. 3, pp. 929–932, Jun. 2019.

[8] C. Fricke, F. Hohls, N. Sethubalasubramanian, L. Fricke, and R. J. Haug, "High-order cumulants in the counting statistics of asymmetric quantum dots," *Appl. Phys. Lett.*, vol. 96, no. 20, May 2010, Art. no. 202103.

[9] R. G. Strauch, "A modulation waveform for short-dwell-time meteorological Doppler radars," *J. Atmos. Ocean. Technol.*, vol. 5, no. 4, pp. 512–520, Aug. 1988.

[10] V. S. Amin, Y. D. Zhang, and B. Himed, "Group sparsity-based local multipath Doppler difference estimation in over-the-horizon radar," in *Proc. IEEE Int. Radar Conf. (RADAR)*, Apr. 2020, pp. 436–441.

[11] K. C. Yi and Y. J. Sun, *Digital Communication Theory and System*. Beijing, China: Publishing House of Electronics Industry, 2013.

[12] J. Yang, *Communication Signal Modulation Recognition: Principle and Algorithm*. Beijing, China: People's Posts and Telecommunications Press, 2014.

[13] A. Eliaz, "Constellation map optimization for highly spectrally efficient communications," U.S. Patent 8 675 769 B1, 2015.

[14] V.-S. Doan, T. Huynh-The, C.-H. Hua, Q.-V. Pham, and D.-S. Kim, "Learning constellation map with deep CNN for accurate modulation recognition," in *Proc. GLOBECOM IEEE Global Commun. Conf.*, Dec. 2020, pp. 1–6.

[15] M. Karabacak, H. A. Cirpan, and H. Arslan, "An efficient modulation identification algorithm without constellation map knowledge," in *Proc. IEEE Radio Wireless Symp.*, Jan. 2011, pp. 146–149.

[16] Q. Liu and J. Wang, "A one-layer recurrent neural network with a discontinuous activation function for linear programming," *Neural Comput.*, vol. 20, no. 5, pp. 1366–1383, May 2008.

[17] J. Lücke and M. Sahani, "Generalized softmax networks for non-linear component extraction," in *Proc. Int. Conf. Artif. Neural Netw.*, Porto, Portugal, Sep. 2007, pp. 657–667.

[18] Z. Zhang, "Improved adam optimizer for deep neural networks," in *Proc. IEEE/ACM 26th Int. Symp. Qual. Service (IWQoS)*, Jun. 2018, pp. 1–2.

[19] N. A. Muhammad, A. A. Nasir, Z. Ibrahim, and N. Sabri, "Evaluation of CNN, AlexNet and GoogleNet for fruit recognition," *Indonesian J. Elect. Eng. Comput. Sci.*, vol. 12, no. 2, pp. 468–475, 2018.

[20] C. Szegedy, "Inception-v4, Inception-ResNet and the impact of residual connections on learning," in *Proc. AAAI Conf. Artif. Intell.*, Feb. 2016, pp. 1–52.

[21] D. Xu and Y. Wu, "Improved YOLO-V3 with DenseNet for multi-scale remote sensing target detection," *Sensors*, vol. 20, no. 15, p. 4276, Jul. 2020.

[22] R. Wang, B. Fu, G. Fu, and M. Wang, "Deep & cross network for ad click predictions," in *Proc. ADKDD*, Aug. 2017, pp. 1–7.

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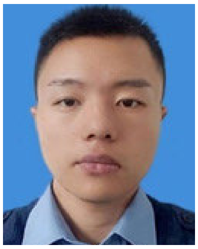

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