Modulation Recognition of 5G Signals Based on AlexNet Convolutional Neural Network

Qing Zhang1,2, Guobing Hu1, Pinjiao Zhao2, Li Yang2

1School of Electronic Information Engineering, Jinling Institute of Technology, Nanjing 211169, China
2School of Electronics and Optical Engineering, School of Microelectronics, Nanjing University of Posts and Telecommunications, Nanjing 210023, China;
Corresponding author: Guobing Hu(s0304152@jit.edu.cn)

Abstract: Aiming at the problem that signal modulation recognition under a non-cooperative condition requires substantial a priori information of the signal and a complex artificial selection of the features, this paper proposes a modulation recognition method for the 5th-generation (5G) signal modulation based on the AlexNet convolutional neural network. For the five commonly used 5G signals (3GPP R15 protocol recommendations) of $\pi/2$-BPSK, QPSK, 16QAM, 64QAM, and 256QAM, the constellation is selected as input feature of the AlexNet network to construct the recognition classification algorithm. The simulation results show that the average recognition accuracy of the five commonly used 5G signals is up to 90% under a 15 dB signal-to-noise ratio (SNR), an improved performance compared with that of the existing recognition algorithms based on signal scatter plots.

1. Introduction
In cognitive radio (CR) and communication reconnaissance, the task of modulation mode identification is to identify the modulation mode of the observed signal under the condition of a noisy interference environment and no prior information, for subsequent signal analysis. The information is provided in links with intelligence mining. This technology, which has a wide range of military and civilian applications such as signal detection, interference identification, spectrum supervision, cognitive radio, and software radio, is one of the classic topics in the related fields [1].

At present, modulation recognition algorithms mainly include two methods based on the likelihood ratio test and feature extraction [2]. The recognition algorithm based on the likelihood ratio test refers to using the likelihood function of the signal sample or its statistic to perform the likelihood ratio and determining the corresponding threshold according to the maximum likelihood criterion to complete the classification and identification of the modulated signal. Various reports [3–4] have studied the signal recognition method based on the likelihood ratio test under cooperative and non-cooperative conditions, but it requires a priori information of the signal and a large amount of calculation. The feature extraction rule refers to the extraction of features such as cyclic cumulant, high order cumulant, and constellation from the received signal. The signal modulation recognition is accomplished using pattern recognition methods such as clustering, neural networks, and support vector machines [5]. In [6], a signal intrapulse modulation recognition algorithm based on the energy focus efficiency test is proposed, which is modulated by extracting the energy focus efficiency characteristics of the signal hysteresis product spectrum under different nonlinear operation conditions. Mobasser [7] proposed to

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.
Published under licence by IOP Publishing Ltd
use the shape of the signal constellation to perform modulation mode identification and complete the recognition of signals such as MQAM. In [8], a constellation-based blind carrier synchronization algorithm is studied. The signal is modulated and identified by the constellation point density estimation of the signal. When the signal-to-noise ratio (SNR) is increased, the signal recognition accuracy is reduced. In [9], a constellation feature recognition algorithm based on subtractive clustering for MQAM signals is studied. The clustering radius of different signals and the difference of density values of the clustering points are used to complete the modulation recognition of signals, but the above signals are based on signals. The feature recognition algorithm requires manual design or definition of features to complete the automatic identification signal. In recent years, with the rapid development of artificial intelligence, the deep learning technology has made breakthroughs in the fields of speech, image, and natural language [10–12]. As one of the branches of deep learning, convolutional neural networks perform well in the field of image recognition, and their application in signal modulation recognition is increasing [13–14]. Previous reports [15] have proposed a modulation recognition algorithm based on scatter plot features and the AlexNet convolutional neural network, which can identify MPSK and MQAM signals, but the recognition of high-order QAM signals, such as 256QAM signals, is not effective. In recent years, the fifth generation of mobile communication systems (5G) has become a central topic in the communication industry and academia. Modulation recognition for 5G signals has become a key topic in the fields of cognitive radio and communication reconnaissance, but there are few related documents.

In this paper, a 5G signal modulation recognition algorithm based on the AlexNet convolutional neural network is proposed. The 5G signal modulation model and its constellation feature differences are analyzed, and the constellation diagram of the signal is generated to create the training and test sets. Based on this, the AlexNet volume is utilized. The neural network model is trained and tested to achieve automatic signal recognition. The simulation performance analysis of the algorithm is also carried out. The results show that the average recognition performance of the proposed algorithm is better than that reported in previous studies [15].

2. Signal Model And Characteristics

2.1. Signal Model. According to the recommendations in the 3GPP R15 protocol [16], five commonly used 5G modulated signal models are presented in Table 1.
Table 1. Common signal modulation methods in 5G

| SIGNAL  | MAPPING |
|---------|---------|
| π/2-BPSK | $x = \frac{e^{j\frac{\pi}{2}(i \mod 2)}}{\sqrt{2}} \left[ (1-2b(i)) + j(1-2b(i)) \right]$ |
| QBSK    | $x = \frac{1}{\sqrt{2}} \left[ (1-2b(i)) + j(1-2b(i+1)) \right]$ |
| 16QAM   | $x = \frac{1}{\sqrt{10}} \left[ j(1-2b(i)) \left[ 2 - (1-2b(i+1)) \right] \right]$ |
| 64QAM   | $x = \frac{1}{\sqrt{42}} \left[ j(1-2b(i)) \left[ 2 - (1-2b(i+1)) \right] \right]$ |
| 256QAM  | $x = \frac{1}{\sqrt{6}} \left[ j(1-2b(i)) \left[ 2 - (1-2b(i+1)) \right] \right]$ |

In the above table, $b(i)$ is an input signal and $x$ is a modulated signal that is mapped by different modulations, and its value is a complex number. The modulation order is as follows: π/2-BPSK is 1, QBSK is 2, 16QAM is 4, 64QAM is 6, and 256QAM is 8.

2.2. Constellation Characteristics. In general, the amplitude and phase digital modulation [13] transmitter signal can be expressed as

$$s(n) = \sum R_n g(t-nT_s) \exp\left[ j(2\pi f_c t + \theta_n + \varphi_c) \right]$$

where $T_s$ is the symbol period, $R_n$ and $\theta_n$ are the amplitude and phase of the n-th symbol, $f_c$ and $\varphi_c$ are the carrier frequency and initial phase, respectively, $g(t)$ is the baseband pulse, and $M$ is the phase order. $\theta_n \in \{2\pi i/M, i = 0,1,\ldots,M-1\}$.

After the modulated signal passes through the additive white Gaussian noise (AWGN) channel, the receiving end orthogonally samples the signal to obtain a sampled signal, and the received signal can be expressed as

$$r(k) = \sum R_n g(kT_s - nT_b - \varepsilon T_b) \exp\left[ j\left(2\pi (f_c + \Delta f_c) kT_s + \theta_n + \Delta \varphi_c\right)\right] + \omega(kT_s)$$

where $T_s$ is the sampling period, $\varepsilon T_b$ is the sampling timing error, $\Delta f_c$ and $\Delta \varphi_c$ are the carrier frequency offset and phase offset, respectively, and $\omega(kT_s)$ is the additive white Gaussian noise. $-0.5 \leq \varepsilon \leq 0.5$.

3. Modulation Recognition Algorithm Based On Alexnet Convolutional Neural Network

3.1. Algorithm Framework. This study will characterize the above constellation diagram and combine the AlexNet convolutional neural network to construct the recognition algorithm. The algorithm can be divided into six main steps, as follows:

**Step 1:** Perform time-frequency conversion on the received signal and estimate the carrier
frequency and bandwidth of the signal in the frequency domain.

Step 2: The signal is filtered based on the carrier frequency and bandwidth estimate of the received signal.

Step 3: The sampling rate of the signal is adjusted according to the symbol rate, the signal is resampled with the adjusted sampling rate, and the resampled signal is obtained.

Step 4: The sampled signal is sampled at a symbol rate to obtain a timing error estimate, and the sampling rate is readjusted to obtain an optimal sampled signal.

Step 5: Carrier frequency offset correction is performed to reduce the influence of carrier frequency offset on the constellation. The carrier signal frequency offset is debugged, and the carrier is output with an optimal sampling signal.

Step 6: The signal is visualized into a constellation, and the constellation of the signal is used as an input to the AlexNet network to classify and identify the modulated signal.

3.2. Construction Of Alexnet Convolutional Neural Network. The AlexNet convolutional neural network is a deep feedforward neural network, which is based on the LeNet neural network. Compared with the LeNet neural network, the AlexNet neural network has a deeper network layer and more convolution kernel parameters, in which the convolutional layer and the pooled layer are the core. It has the following layers:

1) Convolution layer: The convolution kernel is an n × n matrix that moves on the map in a set step size. Each time it moves in steps, a convolution operation is performed on the map at the corresponding position to finally generate a new map. This figure is a new feature of convolution kernel extraction, and n convolution kernels can generate n features. The calculation formula for the convolution layer is

\[ X_n = f \left( \sum W_m^n X^m + b_n \right) \]  

where \( X_n \) represents the n-th feature map, \( W_m^n \) represents the convolution kernel, \( m \) represents the number of pixel channels, and \( b_n \) represents the offset vector of the corresponding position map.

2) Pooling layer: The pooling layer is also called the downsampling layer. Its main function is to reduce the data scale. It is highly invariant to other forms such as translation and contraction and avoids over-fitting.

3) Flat layer: The function of the flat layer is to convert the data output in a matrix form after multiple convolutions and pooling operations into a one-dimensional vector output to provide calculations for the fully connected layer.

4) Fully connected layer: Each neuron of the fully connected layer is connected to each neuron of the upper layer, and the final calculation result is obtained by the selected activation function.

5) Output layer: The output layer acts as the last layer and is used to calculate the probability response.

This study chooses the AlexNet convolutional neural network as the core of the modulation recognition algorithm, and the main steps are as follows:

Step 1: Data set generation and processing: the experimental signal data set is generated by Matlab software simulation. The five different modulation pattern signals are π/2-BPSK, QPSK, 16QAM, 64QAM, and 256QAM, and simulation signals at 5, 10, 15, and 20 dB SNR are generated. The modulated signal generated by the simulation is first obtained by the digital modulation in Section II, and then the signal is preprocessed into a unified format of 227 × 227 × 1 (as shown in Figure 1) as the input data of the convolutional neural network model. The data set is divided into a training set and a test set, and the number of pictures of each type of modulation pattern signal for each type of SNR is 800 and 300, respectively in the training set and test set.
Figure 1. Constellation diagram of five types of modulated signals with different signal-to-noise ratios when the number of sampling points is N=4000

Step 2: Structure construction: set up AlexNet's convolutional neural network flow chart and change the last layer of Softmax to 5 neurons.

Step 3: Training: the training process mainly comprises training and testing. The training parameters of the training set are 15 training sessions, 10 iterations per round. Each iteration randomly samples 20 samples in the training set. The initial learning rate is set to 0.001. The drop optimization algorithm uses AdamOptimizer. The test process is the same as the training process, and signal samples are extracted from the test set for verification.

Step 4: Optimization: improve the model recognition performance and select optimization methods commonly used in Tensorflow such as data enhancement. The data enhancement method refers to generating a new image data by scaling, panning, rotating, etc., for augmenting the data set.

Step 5: Prediction: the test set data is tested using a trained network model.

4. Performance Simulation

4.1. Simulation Condition. In this study, a random binary sequence of length 4000 is generated by using Matlab, and each sequence occupies two symbol widths and is modulated by five digital methods, π/2-BPSK, QPSK, 16QAM, 64QAM, and 256QAM. The signal is superimposed with additive white Gaussian noise. The constellation of the corresponding signal is extracted by signal preprocessing, and the training set under each SNR has 3000 samples, whereas the test set has 1000 samples.

4.2. Performance Analysis. The AlexNet convolutional neural network training environment is run in the Python 3.6 environment. It is calculated using Google's Tensorflow framework. The experimental data is divided into 3000 training data, 1000 test data, 15 learning cycles, and 10 iterations per round. The number of pictures taken at a time is 20 sheets. Figure 2 (a) depicts a schematic diagram showing the relationship between the loss value and the number of iterations, wherein the training loss is the difference between the signal tag value and the signal identification value; Figure 2 (b) shows the relationship between the correct rate of signal recognition and the number of iterations under different SNRs; Figure 2 (c) exhibits the recognition accuracy of five different signals when iterating 14 times.
Figure 2. Signal performance simulation diagram. (a) Relationship between the loss function and the number of iterations under different SNRs. (b) Rate of change of recognition accuracy and iteration number under different SNRs. (c) Recognition accuracy of different modulated signals when iterating 14 times.

Figure 2 (a) reveals that the training loss value of the signal is stabilized as the training iteration reaches a certain number of times. The higher the SNR, the closer the loss value is to 0, and the closer the predicted value of the modulated signal is to the tag value of the original signal, the lower the signal recognition error rate. Figure 2 (b) shows that when the training is iterated to a certain number of times, the recognition accuracy of the signal tends to be stable and there is a small range of fluctuations. As the SNR increases, the average recognition accuracy of the signal increases. For example, when the SNR reaches 10 dB, the average recognition accuracy of the signal attains 80%. When the SNR reaches 15 dB, the average recognition accuracy of the signal attains 90%. As shown in Figure 2 (c), when the training is iterated 14 times and the SNR is 5 dB, the recognition accuracy of the MPSK signal is over 95%, and the recognition accuracy of the MQAM signal is lower when the SNR is less than 10 dB. As the ratio increases, the recognition rate of the MQAM signal increases significantly. At a SNR of 20 dB, the average recognition accuracy of the five signals is 99%.

4.3. Performance Comparison. Reference [15] uses the AlexNet network to identify the algorithm of the scatter plot generated by the signal. Re-adjust network training parameters, the initial learning rate is 0.005, the learning rate is reduced to 0.5 every two training periods, the iteration period is 15, and the number of pictures extracted per iteration is 64.

| Signal Type | 15 dB | 20 dB |
|-------------|-------|-------|
| π/2-BPSK    | 100%  | 100%  |
| QPSK        | 100%  | 100%  |
| 16QAM       | 100%  | 100%  |
| 64QAM       | 70%   | 50%   |
| 256QAM      | 70%   | 50%   |

From Table 2, it is found that when the SNR is 15 dB, in the algorithms of this paper and a reference [15], the recognition rate of the π/2-BPSK and QPSK signals is 100%; however, the accuracy of recognition of the 16QAM signals in the reference [15] algorithm is 80%, whereas in the algorithm of this study is 100%. The algorithm of this study has superior recognition of the 64QAM and 256QAM signals. When the SNR is 20 dB, the correct rate of recognition of the π/2-BPSK, QPSK, 16QAM, and 64QAM signals reaches 100% and that of the 256QAM signal can attain 97%. In [15], only the recognition rate of the π/2-BPSK and QPSK signals is 100%. In the reference [15], the correct rate of recognition of the 16QAM signals is 84% and that of the 64QAM and 256QAM signals is 55%. At the same SNR, the separability of the signal constellation is higher than the separability of the scatter plot. This is the main reason for the better performance of the algorithm in this study.
5. Conclusion
Aiming at the identification problem of five types of 5G modulated signals defined in the 3GPP R15 protocol, a signal modulation and recognition framework based on the AlexNet convolutional neural network is constructed with the constellation of signals as input. The simulation results show that, compared with the existing scatter map feature recognition algorithm, the algorithm in this study has higher recognition accuracy rate for high-order QAM signals. The algorithm has clear application value in cognitive radio and communication reconnaissance. Later, we will further use deeper convolutional neural networks such as VGGNet and ResNet to construct a modulation identification network and enhance the recognition of 5G signals.

Acknowledgments
This study is financially supported by Natural Science Foundation of the Jiangsu Province (Project No. BK20161104)

References
[1] Tie K, Zhou J, Liu X. (2019) Design and implementation of fsk modulation based on software radio[J]. Electronic Design Engineering, 27(10):45-49.
[2] Dobre O A, Abdi A, Bar-Ness Y, et al. (2007) Survey of automatic modulation classification techniques: classical approaches and new trends[J]. IET communications, 1(2):137-156.
[3] Su W, Xu J L, Zhou M. (2008) Real-time modulation classification based on maximum likelihood[J]. IEEE Communications Letters, 12(11):801-803.
[4] Xu J L, Su W, Zhou M. (2010) Likelihood-ratio approaches to automatic modulation classification[J]. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 41(4):455-469.
[5] Liu Y, Pi D, Cheng Q. (2016) Ensemble kernel method: SVM classification based on game theory[J]. Journal of Systems Engineering and Electronics, 27(1):251-259.
[6] Hu G, Xu L, Xu S, et al. (2013) Signal intrapulse modulation recognition based on energy focusing test[J]. Journal on Communications, 34(6):136-145.
[7] Mobasseri B G. (2000) Digital modulation classification using constellation shape[J]. Signal processing, 80(2):251-277.
[8] Qiu Y, Huang W, Ouyang X. (2016) Blind carrier synchronization algorithm based on constellation statistics[J]. Systems Engineering and Electronics, 38(12):2855-2862.
[9] Zhang H, Lou H. (2019) Automatic identification method of MQAM signal modulation method[J]. Journal on Communications, 40(8):200-211.
[10] Li H, Lin Z, Shen X, et al. (2015) A convolutional neural network cascade for face detection[C]//Proceedings of the IEEE conference on computer vision and pattern recognition.: 5325-5334.
[11] Zbontar J, LeCun Y. (2016) Stereo matching by training a convolutional neural network to compare image patches[J]. Journal of Machine Learning Research, 17(32): 2.
[12] Phaye S S R, Benetos E, Wang Y. (2019) SubSpectralNet--using sub-spectrogram based convolutional neural networks for acoustic scene classification[C]//ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE,: 825-829.
[13] Peng C, Yan W, Du Z. (2018) Digital modulation recognition based on deep convolution neural network[J]. Computer Measurement & Control, 26(8):222-226.
[14] Yang S, Peng H, Xu M, et al. Spectral recognition of ultrashort wave specific signals based on convolutional neural networks[J]. Systems Engineering and Electronics, 2019, 41(4):744-751.
[15] Yan H, Qu Y, Li J, et al. (2018) Modulation recognition of MPSK and MQAM class signals based on AlexNet network[J]. Journal of Laser Science, 39(10):75-78.
[16] Channels N R P. (2018) Modulation—Release 15, V15. 0.0[P].