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Radio Frequency Fingerprint Identification Based on Deep Complex Residual Network

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ABSTRACT Radio frequency fingerprint identification is a non-password authentication method based on the physical layer hardware of the communication device. Deep learning methods provide new ideas and techniques for radio frequency fingerprint identification. As a bridge between electromagnetic signal recognition and deep learning, the electromagnetic signal recognition method based on statistical constellation still needs to go through data preprocessing and feature engineering, which is contrary to the end-to-end learning method emphasized by deep learning. Moreover, in the process of converting electromagnetic signal waveform data into images, there is inevitably information loss. Establishing a universal radio frequency fingerprint recognition model suitable for wireless communication scenarios is not only conducive to optimizing the communication system, but also can reduce the cost and time of model selection. Therefore, how to design a deep learning radio frequency fingerprint recognition model suitable for wireless communication is an important problem for researchers. Aiming at the problem that the existing radio frequency fingerprint extraction and identification methods have low recognition rate of communication radiation source individuals, a radio frequency fingerprint identification method based on deep complex residual network is proposed. Through the deep complex residual network, the radio frequency fingerprint feature extraction of the communication radiation source individual is integrated with the recognition process, and an end-to-end deep learning model suitable for wireless communication is established, which greatly improves the identification accuracy of the communication radiation source individuals compared with typical constellation based methods.

INDEX TERMS Wireless communication, radio frequency fingerprint, constellation, deep learning, end-to-end, deep complex residual network.

I. INTRODUCTION

Common wireless network signals include GSM, CDMA, WCDMA, LTE, WiFi, WiMax, RFID, Bluetooth, ZigBee, Z-Wave, etc. Information security issues brought about by wireless communication networks continue to appear, especially issues such as user identity impersonation, replay attacks, and device cloning [1]. How to accurately identify and authenticate the objects of the Internet of Things is the primary problem facing the Internet of Things, and it is also the basis of the application of the Internet of Things [2]. The traditional authentication mechanism is implemented at the application layer, using cryptographic algorithms to generate numerical results that are difficult for third parties to counterfeit, but this mechanism has the risk of protocol security loopholes and key leakage. Physical layer authentication is one of the core technologies to ensure the security of wireless communication [3]. The physical layer authentication technology provides a broad platform for dealing with wireless communication security issues. At present, the research on physical layer security authentication technology is still in its infancy, and its basic theory has not kept up with the development

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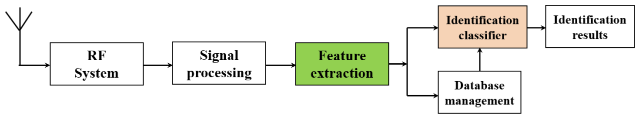


FIGURE 1. **A typical radio frequency fingerprint identification process.**

speed of other wireless communication technologies. At the same time, the abundant physical layer resources have not been fully utilized, and they have huge research space and application value. Radio frequency fingerprints generated by wireless devices due to device tolerances have physical characteristics that are difficult to clone. Using radio frequency fingerprints to distinguish illegal devices from legitimate devices is a new physical layer method to protect the security of communication systems. Just as everyone has their own unique biometric fingerprint characteristics, radio frequency fingerprints of different devices are also different, so radio frequency fingerprints can be used for physical identification and access authentication of wireless devices. A typical radio frequency fingerprint identification process is shown in fig.1.

Radio frequency fingerprint identification process extracts the characteristics of the individual information of a specific radiation source from the received signal time series for classification and recognition, which is essentially a pattern recognition problem. And the radio frequency fingerprint identification process includes the following steps: i. The segment of the RF signal used to extract the radio frequency fingerprint is intercepted and preprocessed. ii. After the signal to be identified is obtained, the RFF can be obtained by various transform domain methods such as frequency domain analysis, time-frequency analysis, fractal, high-order spectrum, etc., or RFF can also be extracted in the modulation domain. When the dimensionality of the radio frequency fingerprint features is too high, dimensionality reduction processing is needed, and finally the classifier is used for classification and recognition. Such methods require an understanding of signal types and features, which can be summarized as feature engineering methods. iii. The deep learning method can also be used to directly process the signal to be recognized. The advantage is that it does not require manual feature design, feature selection or feature dimensionality reduction, and feature extraction and classifier design are integrated.

Radio frequency fingerprint identification is a non-password authentication method based on the physical layer hardware of the communication device. It does not need to consume additional computing resources or embed additional hardware. And it is a very promising technology to build a low-cost, simpler and safer identification and authentication system. The radio frequency fingerprint recognition technology based on the waveform domain uses signal samples from the time domain as the basic processing block, which provides the greatest flexibility at the cost of complexity. The waveform domain method uses the time-domain waveform of the signal to be identified to extract features, and uses the fractal dimension of the waveform and the duration of the transient signal as fingerprint features directly. It can also perform various domain transformations on the signal to be identified before extracting the features, for example, Fourier transform, wavelet transform, Hilbert–Huang transform [4], bispectral transform, inherent time scale decomposition, synchrosqueezing wavelet transform [5], improved fractal box dimension [6], [7] and other methods. The transform domain method attempts to transform the time domain signal to other domains to maximize individual differences, but the features extracted by the transform domain method will vary with the changes in the transmitted data. In order to avoid the feature extraction method from being affected by the transmission data of the signal to be identified, radio frequency fingerprint extraction methods based on steady-state signals mostly use preamble sequences that appear repeatedly in the signal as the signal segment to be identified. Electromagnetic signals are affected by transmitter defects. These factors that cause damage to the signal include carrier frequency offset, power amplifier nonlinearity, quadrature modulator imbalance, and DC offset. The influence of the defects of the transmitter on the signal will also be manifested in the modulation domain of the signal, which makes it possible to construct the radio frequency fingerprint of the transmitter in the modulation domain [8]. The quadrature modulation method is widely used in current communication signals, and almost all digital communications will use it. The modulation domain features currently used include carrier frequency offset, modulation offset, I/Q offset, constellation trace figure [9], and differential constellation trace figure [10]. The modulation domain method uses I/Q signal samples as the basic processing unit, and uses the signal structure forced by the modulation scheme, which makes it easier to identify the specific attributes of the signal transmitter. In addition, some modulation schemes use this design to protect data from unfavorable factors such as channels. The symbols in the modulation domain are less affected by factors such as noise that distort the original waveform, and do not require receiver with an excessively high sampling rate. The requirements on the receiver are also lower, and feature extraction can be completed by using a low-cost receiver.

In the identification and authentication stage, according to the different classifiers, it can be divided into fingerprint identification technology based on traditional machine learning and fingerprint identification technology based on deep learning. Classifier design is one of the key processing modules after the use of feature engineering methods to extract radio frequency fingerprints. There are currently a large number of mature classifiers available, such as k nearest neighbor, support vector machine, neural network, gray relation algorithm [11], and extreme learning machine and so on. Related research has shown that it is best to combine feature selection, feature dimensionality reduction and classifiers together, so that correlation analysis can be performed better, and radio frequency fingerprint features that are more conducive to classification can be obtained. In addition, by combining multiple classifiers by strategy, better classification performance can be obtained than that of a single classifier. This is the idea of ensemble learning classifiers. Deep learning methods have been successfully applied in image recognition, speech recognition, autonomous driving and other fields. Scholars continue to try to introduce deep learning methods into the field of radio frequency fingerprint recognition to solve the difficulties of poor adaptive ability in radio frequency fingerprint recognition [12], [13]. Deep learning methods provide new ideas and technologies for radio frequency fingerprint recognition [14]. However, many deep learning models currently used in the communication field are designed based on general models. For example, convolutional neural networks are usually used for image classification problems, and recurrent neural networks usually used in the field of natural language processing (NLP). Although the current general models in the field of computer science can be applied to the communication field, in actual communication engineering projects, establishing a general model suitable for communication scenarios not only helps to optimize the communication system, but also reduces the cost and time of model selection. Therefore, in the communication framework based on deep learning, how to design a deep learning model suitable for wireless communication is also an important issue for researchers.

In this paper, a radio frequency fingerprint identification method based on deep complex residual network is proposed, which is an end-to-end deep learning model suitable for wireless communication. First, collect the radio frequency baseband signal of the individual communication radiation source through the receiver, which can be used as the radio frequency fingerprint of the transmitter, as the biggest advantage of the complex network over the real network is that it can fully extract the correlation information between the in-phase component and the Quadrature component of the radio frequency baseband signal. And after offline training, the deep complex residual network can identify the radio frequency fingerprint of the transmitter, which can greatly improve the identification accuracy of the communication radiation source individuals.

II. PROBLEM DESCRIPTION OF TYPICAL CONSTELLATION BASED METHODS

The constellation diagram is a vector diagram obtained by drawing the endpoints of the modulation signal under a specific base vector projection on the two-dimensional coordinates with I and Q as the horizontal and vertical axes. Each vector endpoint (also called a symbol point) can express two basic information of the amplitude and phase of the signal relative to the carrier at a certain moment, and its projection on the two coordinate axes is the two baseband signals at the current moment. The number of symbol points of the digital modulation signal is limited, and all symbol points are represented in the same vector diagram to form a constellation diagram [15], [16].

In 2018, S.Peng *et al.* first proposed a deep learning recognition method based on the statistical graph domain of modulated signals [17]. This method pointed out the statistical

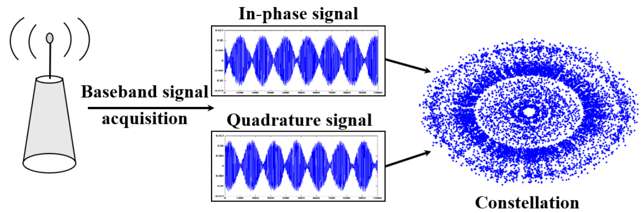


FIGURE 2. Typical constellation based radio frequency fingerprint identification method.

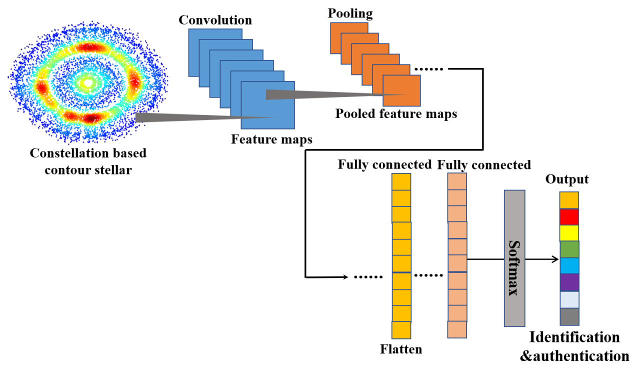


FIGURE 3. Contour stellar based radio frequency fingerprint identification method.

characteristics of electromagnetic signals, such as amplitude imbalance, quadrature error, correlation interference, phase and amplitude noise, phase error and so on, can be characterized by the constellation diagram, seen in fig.2.

However, because the constellation diagram is a binary diagram, the statistical features will be overwhelmed by noise under low signal-to-noise ratio. The contour stellar [18] can recover the lost statistical characteristics of the constellation diagram under a certain low signal-to-noise ratio through the point density feature, thereby improving the performance of the recognition algorithm, seen in fig.3.

As a bridge between electromagnetic signal recognition and deep learning, the electromagnetic signal recognition method based on statistical graph domain still needs to go through data preprocessing and feature engineering, which is contrary to the end-to-end learning method emphasized by deep learning. What's more, in the process of converting electromagnetic signal waveform data into images, there is inevitably information loss. Deep learning methods provide new ideas and technologies for radio frequency fingerprint recognition. However, many deep learning models currently used in the communication field are designed based on general models. For example, convolutional neural networks are usually used for image classification problems, and recurrent neural networks usually used in the field of natural language processing. Although the current general models in the field of computer science can be applied to the communication field, in actual communication engineering projects, establishing a general model suitable for communication scenarios not only helps to optimize the communication system, but also reduces the cost and time of model selection. Therefore, in the communication framework based on deep learning, how to design a deep learning model suitable for wireless communication is also an important issue for researchers.

III. THE PROPOSED METHOD

In view of the above problems, this paper will study the electromagnetic signal recognition method based on the complex waveform domain. In 2016, O'Shea *et al.* first proposed a two-channel real number network for the identification of electromagnetic signal waveforms in the complex number domain [19]. In their subsequent work in 2018, they pointed out that although the two -channel real number network solved the input problem of complex waveform signals, it was unable to dig deeper into the I/Q related information in the electromagnetic signal [20]. A. Hirosc *et al.* proved in [21] that the complex network can effectively extract the I/Q related information in the electromagnetic signal waveform through the I/Q fusion channel, thereby effectively improving the recognition accuracy of the electromagnetic signal. To this end, this paper will design a complex network recognition model to accurately identify electromagnetic signal categories.

Compared with real-valued neural networks, complex neural networks are easier to optimize and generalize, and have better learning potential. For complex convolution, consider a typical real-valued 2D convolution layer that has N feature maps such that N is divisible by 2; to represent these as complex numbers, we allocate the first $N/2$ feature maps to represent the real components and the remaining $N/2$ to represent the imaginary ones. Thus, for a four dimensional weight tensor W that links N_{in} input feature maps to N_{out} output feature maps and whose kernel size is $m \times m$, we would have a weight tensor of size $(N_{out} \times N_{in} \times m \times m)/2$ complex weights.

In order to perform the equivalent of a traditional real-valued 2D convolution in the complex domain, we convolve a complex filter matrix $W = A + iB$ by a complex vector $h = x + iy$ where A and B are real matrics and x and y are real vectors.

$$W * h = (A * x - B * y) + i\,(B * x + A * y) \tag{1}$$

If we use matrix notation to represent real and imaginary parts of the convolution operation, we have:

$$\begin{bmatrix} \Re\,(W * h) \\ \Im\,(W * h) \end{bmatrix} = \begin{bmatrix} A & -B \\ B & A \end{bmatrix} * \begin{bmatrix} x \\ y \end{bmatrix} \tag{2}$$

And an illustration of the complex convolution operator can be seen in fig.4.

The biggest advantage of the complex network over the real network is that it can fully extract the correlation information between the in-phase component and the quadrature component of the radio frequency baseband signal, which means it can fully extract the nonlinear characteristics of radio frequency fingerprints of the transmitter. In addition, this paper uses residual learning to solve the problem of difficult training of deep complex convolutional neural network models and a radio frequency fingerprint Identification method based on deep complex residual network is proposed, seen in fig.5.

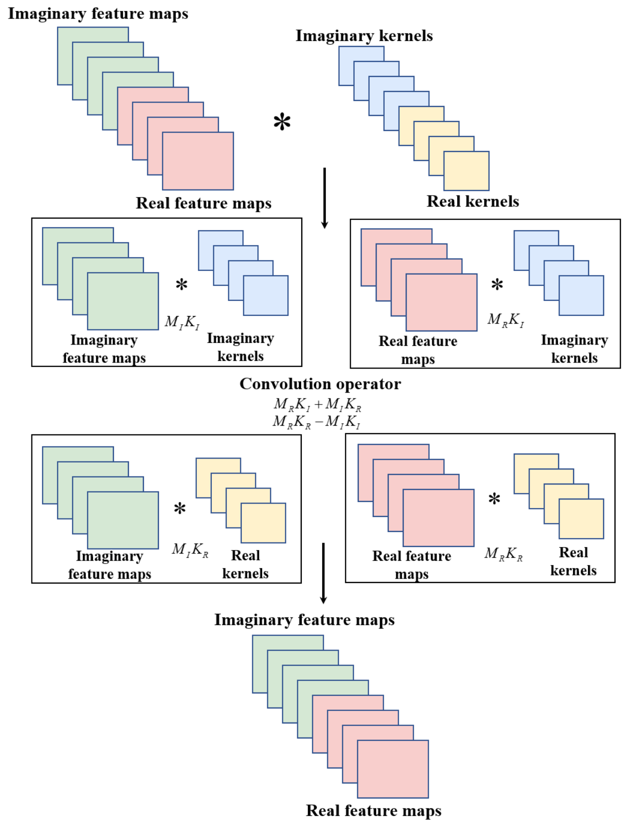


FIGURE 4. An illustration of the complex convolution operator.

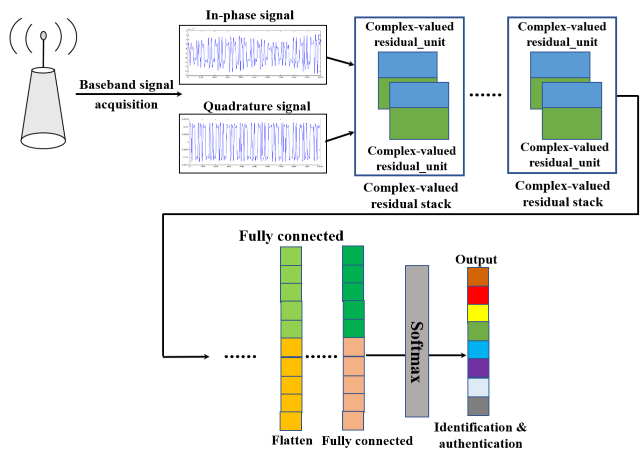


FIGURE 5. A radio frequency fingerprint identification method based on deep complex residual network.

The proposed radio frequency fingerprint identification method based on deep complex residual network is an end-to-end deep learning model suitable for wireless communication. First, collect the radio frequency baseband signal of the individual communication radiation source through the

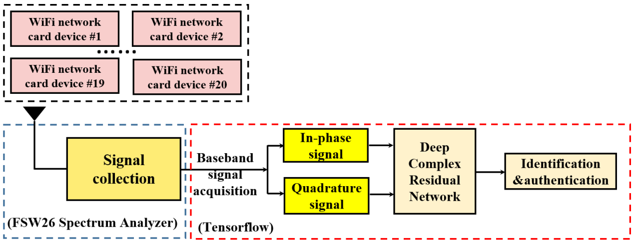
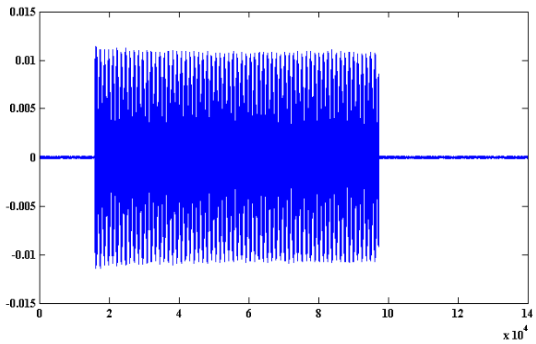
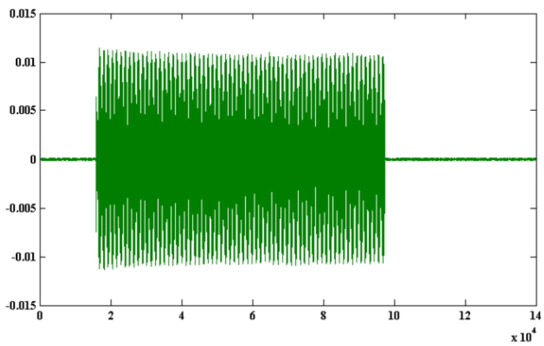


FIGURE 6. Experimental test scheme.

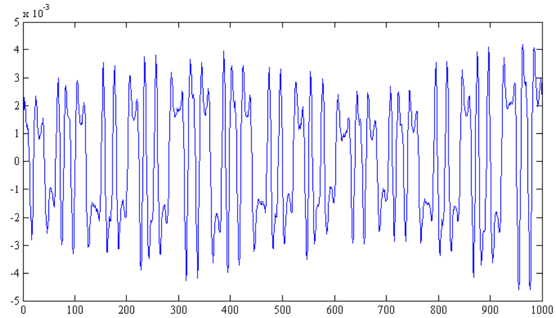


(*a*) In-phase signal

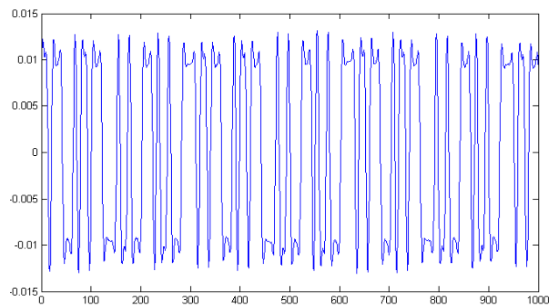


(*b*) Quadrature signal

FIGURE 7. One raw sample for one WiFi network card device.



(*a*) In-phase signal



(*b*) Quadrature signal

FIGURE 8. One new sample for one WiFi network card device.

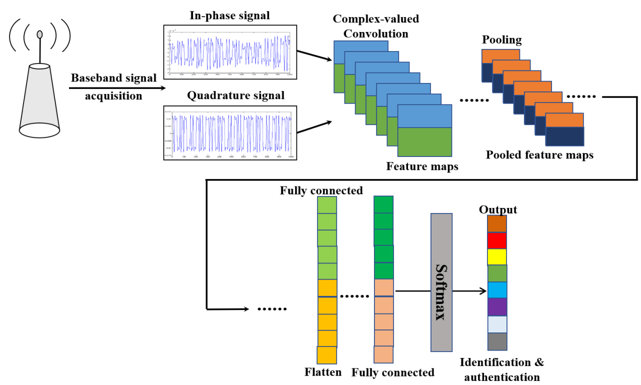


FIGURE 9. A radio frequency fingerprint identification method based on deep complex convolutional neural network.

receiver, which can be directly used as the radio frequency fingerprint of the transmitter. And after offline training, the deep complex residual network can be used to identify the radio frequency fingerprint of the transmitter.

IV. APPLICATION AND ANALYSIS

The specific implementation scheme takes as an example the identification of 20 WiFi network card devices of the same manufacturer, the same type, and the same batch, seen in fig.6.

Among them, the radio frequency baseband signal acquisition equipment adopts FSW26 spectrum analyzer. The collection environment is a laboratory line-of-sight (LOS) scene. Collect 50 samples per device; The signal acquisition bandwidth is 80MHz, and each acquisition is 1.75ms, that is, 140,000 points per sample (take a single channel as an example, seen in fig.7).

The effective data transmission section excluding the channel noise section is 80,000 points (all are steady-state signals). And then slice the effective data transmission section, and take 1000 points as a new sample, and there is a total of 80,000 samples for these 20 WiFi network card devices. After processing for each new sample, randomly selects 3200 samples for each device to be used for the training of the deep complex residual network, and the remaining 800 samples are tested for recognition. And one new sample for one WiFi network card device is seen in fig.8.

And the deep complex residual network structure is unified as shown in Table 1.

In order to illustrate the effectiveness of the method proposed in this paper, compare it with the radio frequency fingerprint identification method based on contour stellar (seen in fig.3), and the radio frequency fingerprint identification method based on deep complex convolutional neural network (seen in fig.9). And the deep complex convolutional neural network structure is unified as shown in Table 2 and the deep

TABLE 1. The deep complex residual network structure.

Layer	Output shape
Input	1000x2
Complex-valued Residual Stack	500x32
Complex-valued Residual Stack	250x32
Complex-valued Residual Stack	125x32
Complex-valued Residual Stack	62x32
Complex-valued Residual Stack	31x32
Complex-valued Residual Stack	15x32
Complex-valued Residual Stack	7x32
Complex-valued Residual Stack	3x32
Flatten	96
FC/Relu	128
FC/Relu	128
FC/Softmax	20

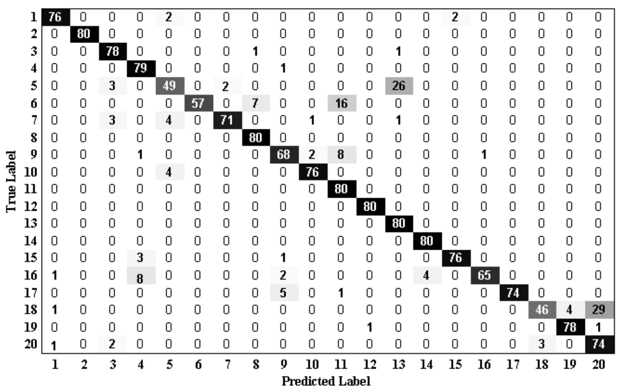


FIGURE 10. The recognition results of the individual communication radiation source based on the contour stellar.

convolutional neural network structure for contour stellar is shown in Table 3.

Finally, through the recognition and authentication, the recognition results of the individual communication radiation source by these three methods are obtained respectively, as shown in fig.10, fig.11 and fig.12.

Note: The effective data transmission section excluding the channel noise section is 80,000 points (all are steady-state signals). And then slice the effective data transmission section, and take 10,000 points as a new sample, and there are a total of 8,000 samples for these 20 WiFi network card devices. After generating a contour stellar for each new sample, randomly selects 320 samples for each device to be used for the training of the deep convolutional neural network, and the remaining 80 samples are tested for recognition.

TABLE 2. The deep complex convolutional neural network structure.

Layer	Output shape
Input	1000x2
Complex-valued Conv	500x32
AveragePooling	250x32
Complex-valued Conv	125x64
AveragePooling	62x64
Complex-valued Conv	62x128
AveragePooling	31x128
Complex-valued Conv	31x128
AveragePooling	15x128
Complex-valued Conv	15x256
Complex-valued Conv	15x256
AveragePooling	7x256
Flatten	1792
FC/Relu	2048
FC/Softmax	20

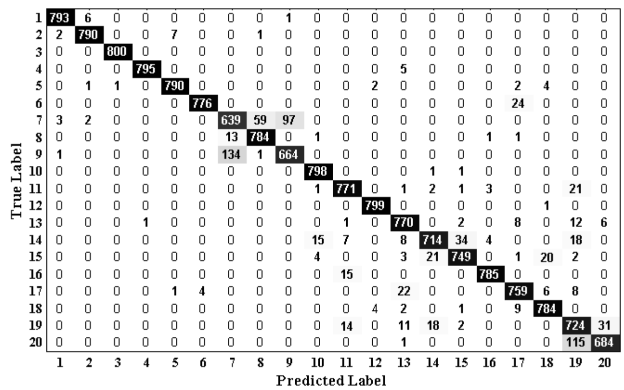


FIGURE 11. The recognition results of the individual communication radiation source based on deep complex convolutional neural network.

From fig.10, we can see, the overall recognition success rate of a total of 1600 test samples from 20 WiFi network card devices is 90.4%. And a total of 6 devices are fully recognized correctly. And there are 5 devices with a recognition rate of below 87.5%, which are device#5, device#6, device#9, device#16, and device#18, and the recognition rate of device#18 is the lowest, only 57.5%.

From fig.11, we can see, although only device#3 is fully recognized correctly, the overall recognition success rate of

TABLE 3. The deep convolutional neural network structure.

Layer	Output shape
Input	227x227x3
Conv	55x 55x96
MaxPooling	27x 27x96
BatchNormalization	27x 27x96
Conv	27x 27x256
MaxPooling	13x 13x256
BatchNormalization	13x 13x256
Conv	13x 13x384
Conv	13x 13x384
Conv	13x 13x256
MaxPooling	6x 6x256
BatchNormalization	6x 6x256
Flatten	9216
FC/Relu	4096
FC/Relu	4096
FC/Softmax	20

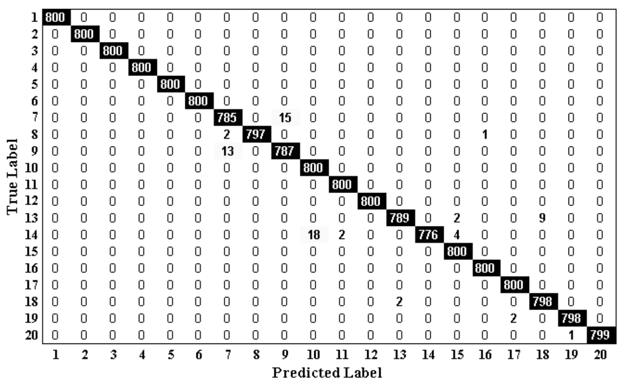


FIGURE 12. The recognition results of the individual communication radiation source based on the proposed method.

a total of 16000 test samples from 20 WiFi network card devices is 94.8%. And there are 3 devices with a recognition rate of below 87.5%, which are device#7, device#9 and device#20, and the recognition rate of device#7 is the lowest, only 79.9%.

From fig.12, we can see, the overall recognition success rate of a total of 16000 test samples from 20 WiFi network card devices can reach 99.56%. And a total of 12 devices are fully recognized correctly. The recognition rate of device#14 is the lowest, still as high as 97%, which shows the proposed method has the best recognition performance compared with other two typical methods.

And the comparison of the recognition performance of these three methods is shown in Table 4.

TABLE 4. Recognition performance comparison.

	Approach 1	Approach 2	Approach 3
Identification accuracy	90.4%	94.8%	99.56%
Time cost for each test sample	1.980s	0.89ms	13.6ms

Note: Approach 1 means radio frequency fingerprint identification based on the contour stellar; Approach 2 means radio frequency fingerprint identification based on the deep complex convolutional neural network; Approach 3 means radio frequency fingerprint identification based on the proposed method in this paper.

From figures 10 to 12, and Table 4, we can see that, because the constellation-based method needs to first convert a one-dimensional signal into a two-dimensional image, the required length of the collected data is longer. However, in the process of converting electromagnetic signal waveform data into images, there is unavoidable information loss. The complex network can effectively extract the I/Q related information in the electromagnetic signal waveform through the I/Q fusion channel, thereby effectively improving the identification accuracy of the electromagnetic signal with better real-time performance.

V. CONCLUSION

The radio frequency baseband signal (including the in-phase component and the Quadrature component of the radio frequency baseband signal) of the individual communication radiation source is mathematically complex signal in nature, that is, each signal point is a symbol on the complex plane that contains amplitude information and phase information. The complex convolutional neural network can effectively learn the RF fingerprint of each RF baseband signal that contains the essential characteristics of the physical layer of the transmitter (communication radiation source individual), so the identification of communication radiation source individual can be realized. On this basis, this paper further proposes an end-to-end deep complex residual network model suitable for wireless communication. In the case of using the same training sample and test sample, compared with the radio frequency fingerprint identification method based on contour stellar (with the overall recognition success rate of 90.4%), and the radio frequency fingerprint identification method based on deep complex convolutional neural network (with the overall recognition success rate of 94.8%), The method proposed in this paper can greatly improve the accuracy of radio frequency fingerprint recognition with the overall recognition success rate of 99.56%. Through the proposed method in this paper, even if the carrier frequency deviation and phase deviation of the receiver are not estimated and compensated, the shorter steady-state radio frequency baseband signal collected (compared to the typical constellation based methods) can be used to achieve high radio frequency fingerprint recognition accuracy rate.

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