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SPECIAL SECTION ON INTELLIGENT AND COGNITIVE TECHNIQUES FOR INTERNET OF THINGS

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Specific Emitter Identification Techniques for the Internet of Things

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ABSTRACT Specific Emitter Identification (SEI) detects the individual emitter according its varied signal characteristics. The method operates in the physical layer of the internet and can effectively improve the security of the Internet of Things (IoT). Generally, SEI identifies the uniqueness of the transmitting platform by using the unintentional modulation information of the emitter such as radar, which has "fingerprint" characteristics. Existing SEI methods are based on hand-crafted features to distinguish different emitters. In this paper, traditional feature extraction methods are studied and a new recognition method is proposed. To determine the effectiveness of the method, the output signals of eight amplifiers are collected as the research object. The power spectrum characteristics and adjacent channel power ratio (ACPR) of the signal are then extracted and eight amplifiers are distinguished. Finally, the quadrature-phase signals are converted into pictures, and convolutional neural networks are used to automatically extract features for classification and recognition. The results show that the recognition rate of converting signals into pictures can reach 95%, when SNR is 20dB.

INDEX TERMS Specific emitter identification, IoT, power amplifier.

I. INTRODUCTION

Specific emitter identification(SEI) technology measures the characteristics of received electromagnetic signals to determine the individual emitter of the signal according to prior information. This information is then associated with the individual emitter and its platform and weapon system. The SEI designates the individual emitter by discriminating it from all other emitters [1]–[4]. uch features are extracted from the received signal and termed as radio frequency fingerprints. In the military, SEI is used for communications, radar systems, interference source determination, military spectrum management process [5], cognitive radio [6], self-organized networks [7], [8]. The specific emitter identification device used in military electronic reconnaissance is illustrated in Fig. 1.

In the civil field, due to the broadcast nature of radio propagation, the wireless air interface is open and accessible to both authorized and illegitimate users. Compared to wired communication, the open communication environment makes wireless transmissions more vulnerable to attacks including passive eavesdropping for data interception and active jamming for disrupting legitimate transmissions. With the rapid increase of wireless devices, SEI is of great significance for improving wireless network security, including for the (IoT).

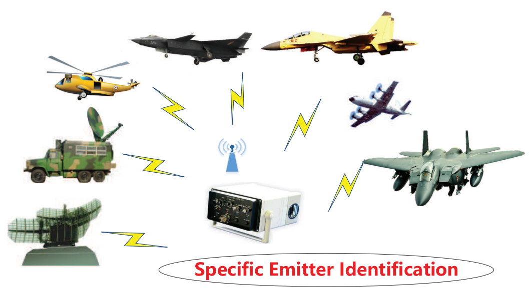

FIGURE 1. Specific emitter identification device for military applications.

The advance in communication technology has resulted in a gradual increase in communication frequency, which can also speed up communication. However, according to the characteristics of electromagnetic wave propagation, with

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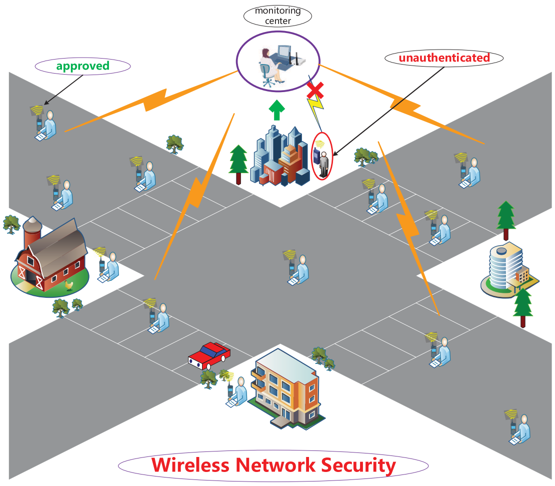

FIGURE 2. **The SEI technique is a way to improve the wireless network security of Internet of Things.**

higher frequency, the wavelength is shorter, and the closer the propagation path is to a straight line. This means that the diffraction ability of the electromagnetic wave is weakened. Due to this condition, the 5G network requires a larger number of base stations than 4G to cover the same area, dramatically increasing the number of wireless networks. It is estimated that approximately 20 billion devices will be connected to the IoT in 5G networks. Due to the openness of the transmission channel, the wireless network is more vulnerable to large-scale malicious attacks compared with the traditional wired network [9]. Traditional methods for securing wireless networks are often based on bit-level security protocols. However, vulnerabilities are often present in such methods [10]. Radio frequency fingerprinting (RFF) is an inherent feature of wireless devices which is difficult to tamper with, and has thus been studied extensively in recent years. The RF fingerprint refers to the difference of transmitters caused by production, processing, and debugging. The signal received from the transmitters can be used to extract this difference in order to individually identify wireless devices. The process of extracting the difference is called RF fingerprint extraction [11] or RFF [12]. In specific devices, the method is also called specific emitter identification (SEI), which aims at distinguishing the authorized transmitters of various users based on the unique features of radio frequency signals at the physical layer. Only authorized users are allowed to intervene in the network, which improves network security to a certain extent. The SEI technique has been used in numerous systems including intrusion detection, radar, satellite communication, IoT, and network security systems in 4G and 5G networks.

According to the signal type, the SEI technology is based on transient or steady state signal. It is difficult to collect the transient signal because the existence time is ephemeral and has high requirements for the receivers [13]–[15]. Therefore, SEI based on steady state signals is investigated in this paper. The steady state signal is easy to collect, however, the features of the transmitter are hidden in the sent data stream, which increases the difficulty of feature extraction [12], [16], [17]. Efficient methods are thus required to extract transmitter features from the transmitted data.

The concept of artificial intelligence (AI) was first introduced in 1956. With the continuous development of AI technology, machine learning and deep learning have been extended to occupy numerous aspects of people's lives. The development of AI in the field of communications has also been rapid, with numerous studies presented on the subject [18]. This paper explores the use of AI algorithms to solve specific radiation source identification problems. The SEI procedure generally includes four primary steps: signal acquisition and processing, extraction of features from the obtained signals, matching the features with reference fingerprint dataset, and assigning the best matching aggregate to these features. In the last step, if there is no suitable class, the signals under testing will be determined as malicious signals of unauthorized transmitters and forbidden from accessing the network.

In this paper, traditional signal processing algorithms are compared with image-based methods. The experiments are initially carried out using collected quadrature-phase (IQ) data from power amplifiers. Power spectral density and adjacent channel power ratio (ACPR) are utilized as fingerprint features, principal component analysis (PCA) is used to reduce the dimension of features, and finally, K-nearest neighbor (KNN) is employed to classify them. In addition, IQ signals are converted into pictures and then classified using neural networks.

In this paper, we studied the Specific Emitter Identification technology using the measured data. The main contribution are summarized as follows:

- We have established Specific Emitter Identification measured data sets.
- Exploring spectral features and ACPR feature for Specific Emitter Identification.
- Contour Stella Image is used to convert IQ signals into pictures. Compared with traditional feature extraction methods, Graph-based method has better performance.

II. RELATED WORK

Existing methods for radiation source identification include statistical feature extraction based on signal parameters, signal transform domain, nonlinear characteristics of the transmitter, or image processing methods. The identification method based on statistical features of the signal works by locating a linear or nonlinear transformation to reflect the intrinsic structure of the preprocessed signal. The original signal is then projected into the distinguishable feature space, which can reduce the dimension of the original signal as well as classify over-fitting problems. Common signal parameters include time domain, frequency domain, high-order moment, and high-order spectral parameters. In literature [19], [20], authors identified the amplitude of transient signals using Bluetooth and IEEE 802.11 transceiver devices. The average detection rate was found to reach 95%, but with relatively high time complexity. In literature [21], authors used the IQ imbalance of the modulation domain as an RF fingerprint. The method was based on the verification of the two parameter hypothesis test and likelihood ratio test, and simulations were used to illustrate its. In 2015, the author of literatur [22] extracted the phase information of the baseband signal by filtering the signal of the same model from the same manufacturer, and used it as the radio frequency fingerprint. The experimental results show that the phase information can be used to classify different devices, but the classification performance will change due to the channel distance difference. The average accuracy of classification in short range distance was 99.6%, but this decreased to 81.9% as the channel distance became longer. Entropy embodies the degree of internal chaos in a system. The more chaos, the higher the entropy. Entropy characteristics are commonly used as features in RF fingerprinting. For example, a new fingerprint recognition method based on multi-dimensional permutation entropy was proposed in [23] and demonstrated to be efficient. In the experiment, the distance of the transceiver was set to 10 m, so that the signal could propagate in the short-wave line of sight (LOS) channel.

For weak differences between similar devices, transmitter hardware nonlinearities and internal noise can produce spurious components at the receiving signal. Most of these signal components are non-stationary and non-Gaussian, so statistical analysis methods for time domain and frequency domain parameters may no longer be suitable. As a result, scholars have gradually begun to use signal processing methods to analyze signals, converting them to certain transform domains, then processing and analyzing the signals. Such methods include wavelet analysis, time frequency analysis, fractal features, empirical mode decomposition (EMD) transformations, and intrinsic time decomposition (ITD) transformations. In 1998, Huang *et al.* [24] proposed a data analysis method based on EMD which can generate a set of intrinsic mode functions (IMF). The Hilbert transform can then be used to derive local energy and instantaneous frequency from the IMF to obtain a complete energy-frequency-time distribution. However, in [25], the authors pointed out the shortcomings of the EMD method. For example, the process of obtaining an IMF in EMD is inefficient and serious boundary effects exist. More importantly, the EMD process produces new components that do not exist in the original signal. In 2012, Klein *et al.* [26] used a dual-tree complex wavelet transform (DT-CWT) feature extracted from a non-transient preamble response of an orthogonal frequency-division multiplexing (OFDM)-based 802.11a signal to identify four Cisco devices of the same model with different serial numbers. The classification accuracy was demonstrated to reach 80% when the signal-to-noise ratio (SNR) was lower than 20 dB.

Nonlinear characteristics of the transmitter consist of nonlinear model parameters and nonlinear systems. Methods based on nonlinear model parameters model the components of the transmitter. For example, Polak *et al.* [3] used the Brownian Bridge stochastic process to model a digital-to-analog converter (DAC) and perform nonlinear behavior on the transmitter DAC device. All nonlinear components of the transmitter can also be observed as a nonlinear system and the nonlinearity of the whole system is easy to evaluate. For example, in 2016, Huang *et al.* [27] extracted the normalized permutation entropy (NPE) of the transmitter system output signal, obtaining an individual recognition rate of different stations of over 95%.

Another method for radiation source identification besides signal processing is to convert the signal into images. The advantage of this method is that image processing methods can be used to extract features. A typical example is modulation constellation. In literature [28], a new radio frequency fingerprint identification method based on constellation error was proposed which analyzed the error between the received signal constellation and the ideal constellation.

III. METHOD OVERVIEW

A. POWER SPECTRUM ESTIMATION

The power spectral function represents the frequency function of the unit bandwidth power with the spectrum component of the finite average power signals. The important characteristics of the random signal are studied and analyzed. Power spectrum estimation is one of the main contents of signal processing. It mainly studies the characteristics of signal in frequency domain [29]. In this paper, the power spectrum estimation of the amplifier output signals based on Welch method is used.

Periodogram method assumes that $x_i(n)(i = 0, 1, \cdots K-1)$ is the uncorrelated implementation of stochastic process $x(n)$. The length of every $x_i(n)$ is M. The periodogram of $x_i(n)$ is:

$$P_{per}^{(i)}(e^{i\omega}) = \frac{1}{M}\left|\sum_{n=0}^{M-1} x_i(n)e^{-j\omega n}\right|^2 \quad i = 1, 2, \ldots K \tag{1}$$

Then, computing the average of these independent periodogram and the result is the estimation of power spectrum as shown below.

$$P_{per}^{(av)}(e^{j\omega}) = \frac{1}{K}P_{per}^{(i)}(e^{j\omega}) \tag{2}$$

In application, it is seldom to get repeatedly implementations of a random signal. Accordingly, Bartlett proposed dividing a random signal with length N into K segments on average. Further, define every sub signal as $x_i(n) = x(n + iM)(n = 0, 1, \cdots M-1; i = 0, 1, \cdots K-1)$ And, computing the periodogram of every sub signal and computing the average. Final,the expression of average periodogram is:

$$P_{per}^{(BT)}(e^{j\omega}) = \frac{1}{M}\sum_{i=0}^{K-1}\left|\sum_{n=0}^{M-1} x(n + iM)e^{-j\omega n}\right|^2 \tag{3}$$

Welch's method has two modifications to the average periodogram method.

- The Welch's method improves segmentation scheme of $x(n)$. The method allows a certain degree of overlap between the data of each segment and its adjacent data segment. For example, when the data of each segment coincides with half of the segment, the number of segment turn into $K = N - (M/2)/M/2$.
- Data windowing for each segment may not be a rectangular window. Such as Hanning window and Hamming window. This can improve the distortion caused by the larger side lobe of rectangular window.

The expression of power spectrum estimation based on Welch's method is:

$$P_w^{(i)}(e^{j\omega}) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_i(n)\omega(n)e^{-j\omega n}\right|^2 \tag{4}$$

where $\omega(n)$ is a window function, $x_i(n)$ represents the i-segment data sequence.

B. ACPR

For modern digital communication systems, the nonlinearity of power amplifiers results in a spread of the output signal power spectrum, which affects the signals of adjacent channels. In this case, the traditional multitone and single tone test cannot meet the requirements of system performance analysis. Therefore, the adjacent channel distortion caused by nonlinearity is often used to measure the nonlinearity of power amplifiers. The most commonly used indicator is the adjacent channel power ratio (ACPR), which refers to the ratio of the average power of adjacent channel signals to the average power of the main channel [30]. The characteristic curve is shown in Fig. 3.

Assuming a specified center frequency is f_c and its offset bandwidth is B_1. The offset bandwidth of adjacent frequency f_0 is B_0. The powers of the B_1 and B_0 are P_{B1} and P_{B0} respectively. The calculation of ACPR is as follows:

$$ACPR = \frac{P_{B1}}{P_{B2}} \tag{5}$$

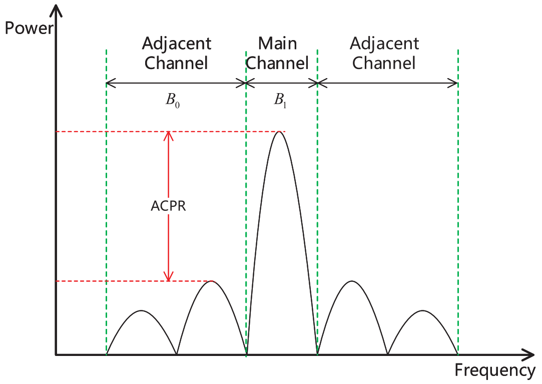

FIGURE 3. The characteristic curve of ACPR.

ACPR is mainly used to measure the nonlinearity of power amplifiers relative to the interference of adjacent channels. If the ACPR is large, it means that the power of the main power leakage to the adjacent channel's intermodulation component is large, which will cause interference to the communication system. In practical engineering applications, In general, the APCR of power amplifier can be improved by predistortion method.

C. CONTOUR STELLA IMAGE

In the field of digital communication, the digital signal is always shown in complex plane for the presentation signal. This image is called the constellation diagram. In the constellation diagram, although each sampling point is disturbed by noise, it will produce random disturbance [31]–[33]. However, if each signal sample is large, a large number of random samples will reflect the statistical characteristics of radio frequency signals on the constellation diagram. Therefore, constellation diagram is used to extract the fine features of the digital signal in this work, including characteristics of amplitude imbalance, orthogonal error, correlation interference, phase and amplitude noise, and phase error and modulation error caused by equipment difference. However, using a traditional constellation diagram for extracting fine features has drawbacks. For example, in the actual data acquisition process, internal device noise can seriously contaminate radio frequency signals and likely assign the constellations of different radio frequency signals with the same graphics.

A Contour Stella Image can be obtained based on constellation diagram by using density rectangular window function to calculate the point density in the constellation diagram. When the density window function slides on the image, it will count the number of points in different area windows and then divide it by the number of sampling points of the entire constellation to obtain the normalized point density value. The overall calculation process can be expressed by the following formula:

$$\rho(i,j) = \frac{\sum_{i=x_1}^{x_2}\sum_{j=y_1}^{y_2} dots(i,j)}{\sum_{x1=W_0}^{W_1}\sum_{y1=H_0}^{H_1}\sum_{i=x_1}^{x_2}\sum_{j=y_1}^{y_2} dots(i,j)} \tag{6}$$

where W_0 and H_0 are the top left corner coordinates of the constellation diagram, W_1 and H_1 are the lower right corner coordinates, x_1 and y_1 are the top left corner coordinates of the density window function, x_2 and y_2 are the lower right corner coordinates of the density window function. In this paper, different colors are used to mark different density areas. Yellow denotes the relatively high density area of sampling points, green denotes the relatively medium density area of sampling points, and blue denotes the low density area of sampling points. Figure 4 show the color of different point density.

Contour Stella Image works to convert the communication signal into a picture to assist in analysis. The problem of

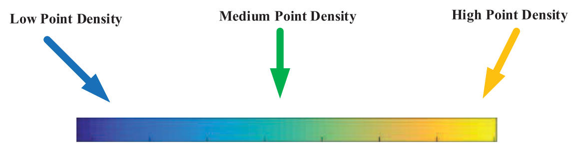

FIGURE 4. The color of different point density.

specific emitter identification can then be solved by methods of image classification in computer vision.

D. CONVOLUTIONAL NEURAL NETWORK

Convolutional neural networks have been used for a long time. In the 1990s, LeCun used convolutional neural networks for handwriting recognition in the MNIST [34] database and achieved 99% accuracy. The whole network was comprised of five layers consisting of two convolutional layers, two pooling layers, and one fully connected layer. The input of the network was a 28*28 digital image and the output was the recognition result of the handwritten digits by the neural network. In a later ImageNet competition, a sample of the image was expanded on a large scale, and the categories were added to thousands of other groupings in which countless people engaged in the image research.

1) AlexNet

The AlexNet network structure contains 60 million parameters and 65,000 neurons, five layers of convolution, three layers of fully connected networks, and the final output layer is 1000 channels of softmax. AlexNet uses two GPUs for calculations, which significantly improves the efficiency of the operation [35]. The network structure is illustrated in Fig. 5.

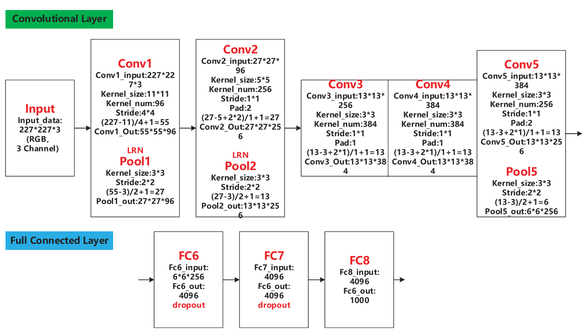

FIGURE 5. The network structure of AlexNet.

2) SQUEEZE-NET

In the field of deep learning, scholars generally focus on how to improve the accuracy of neural networks. Therefore, the neural network is increasingly deep, with a growing number of parameters. Neural networks require an increasing amount of hardware, however, this is difficult to fulfil in embedded hardware such as mobile phones and autonomous computing platforms. Thus, a focus on methods to streamline and optimize the network model so that it can run smoothly on embedded devices with limited hardware is important. In this work, SqueezeNet is utilized as a simplified and lightweight convolutional neural network structure [36].

The network model SqueezeNet was proposed by Landola to reduce model parameters rather than to improve classification accuracy. SqueezeNet is not only concerned with the accuracy of model classification, but also with the speed of calculation and the size of the model. In general, the deeper the number of layers of a convolutional neural network, the stronger its expression ability. Improved parameters and structures can always be obtained to solve problems such as image classification and target positioning. SqueezeNet can achieve the accuracy of the AlexNet network, but the parameter size is reduced by more than 50 times. Fire Module is the core component of SqueezeNet. As shown in Fig. 6, the concept is very simple, and works to respectively change the original simple layer of convolution into the squeeze layer and expand layer, with the activation layer of ReLU. In the squeeze layer, all convolution kernels of 1×1 are present and the number is denoted as S11. In the expand layer, kernel convolution of 1×1 and 3×3 exist, and the number is respectively denoted as E11 and E33. In this process, S11 must be greater than the input map number. After the expand layer, the convolving output feature maps of 1×1 and 3×3 are spliced together in channel dimension. As illustrated in Fig. 6, the Fire Module contains convolution kernels of 1×1 and 3×3, but their number is a super parameter which must be set. Fire Module is divided into two parts, squeeze and expand. The squeeze component is comprised of 1×1 convolution kernel, while expand is composed of the convolution kernel of 1×1 and 3×3. As we can see, the Fire Module has convolution kernels of 1×1 and 3×3, but the number of them is super parameter, which needs to be set. Fire Module is divided into two parts, squeeze and expand. The squeeze part is fully composed of 1×1 convolution kernel, which reflects the design idea (1) above. Expand is composed of the convolution kernel of 1×1 and 3×3.

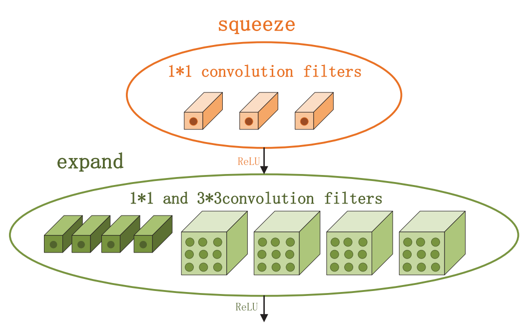

FIGURE 6. Organization of convolution filters in the fire model.

3) ResNet

The residual learning framework was proposed in 2016 by Kaiming. As it contains more layers in deep model but with lower complexity, it can simplify the training of networks. ResNet is a phase of the recent convolutional neural network, which learns the residual between the feature map and the true value [37]. Residual learning is much easier than the learning of overall features. In this way, the designer can extend the entire neural network, so that the convolutional neural network can be designed to thousands of layers. As the network deepens, the granularity of image feature extraction becomes more detailed, providing superior image processing effects.

Theoretically, with more layers of convolutional neural network, richer features can be extracted from the layers, and so the accuracy will be higher. However, under the premise that deeper networks start to converge, when more layers are added, accuracy is saturated and can degrade rapidly. The residual learning framework works to resolve this degradation problem by setting the added layers behind the deep network as identity mapping by learning the identify mapping function so that the framework is transformed into a shallow network. More layers will therefore not create more parameters and complexity, but improve the accuracy. The experimental result shows that residual networks are easier to optimize, and that accuracy can be easily improved by an increase of depth. The framework of ResNet network is as shown in Fig. 7. In this paper, ResNet18 was trained to identify the test set samples.

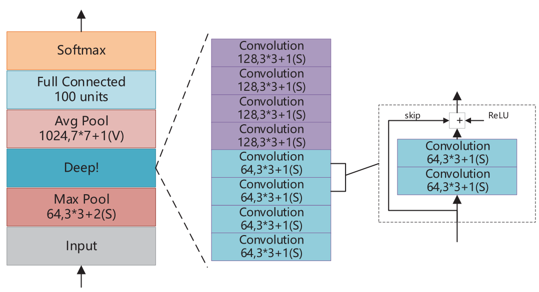

FIGURE 7. ResNet convolutional neural network model.

IV. EXPERIMENTAL ANALYSIS

A. EXPERIMENTAL SETUP AND SCENARIOS

The power amplifier is a vital component of a transmitter. Due to the inherent non-linear characteristics of the emitter power amplifier, fingerprints can provide distinguishable characteristics for emitter identification. Therefore, the power amplifier is extracted from the whole transmitter system in the proposed method. The overall setup for signal generation and reception is provided in Fig. 8 in which signals from a PC were generated by MATLAB and exported in fixed signal format to the signal generator as a baseband signal. The signal generator was then used to set up a carrier frequency conversion to transmit the signal and set the carrier frequency and input power of the input signal. MATLAB can produce a variety of modulation signal styles. The maximum power output from the signal generator to the power amplifier was 10 dBm in this experiment. During the acquisition process, the signal generator was used to change the input power, modulation mode, and center frequency of the input signal of the power amplifier. The signal generator was programmed to transmit random data on 433 MHz using 16 Quadrature Amplitude Modulation (QAM).

The modulated signal was transmitted through the radio frequency connection line to the power amplifier with an

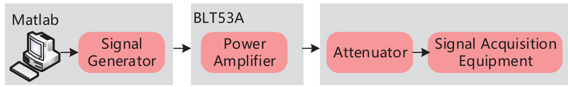

FIGURE 8. Signal generation and data collection setup.

input signal power of 0 dBm. In order to distinguish similar transmitters, eight BLT53A power amplifiers were used. The power amplifier was the principal research object in this study. The output signals were then collected, illustrating the individual differences produced by the inherent dynamic nonlinearity of the amplifier. Figure 9 shows the power amplifiers under test in this paper. For the receiver, signal acquisition equipment was used to collect the IQ signal data of the power amplifier with sample rate of 5 MHz and a sample point of 20,000. The bandwidth of the signal was 500 KHz, and 100 samples were obtained from each power amplifier.

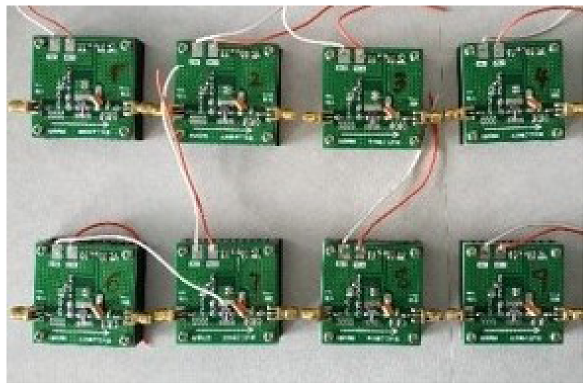

FIGURE 9. Power amplifiers.

B. RECOGNITION RESULT

1) RECOGNITION RESULT BASED ON POWER SPECTRUM

After the signal passes through the power amplifier, individual differences are produced due to the amplifier's non-linear distortion and spectrum regeneration. Using these characteristics, individual amplifiers can be distinguished. Figure 10 shows the power spectrum of signals passing through different amplifiers.

As illustrated in Fig. 10, the non-linear effect of the input signal is varied due to the individual conditions of the amplifier. The same type of amplifier of the same batch will have a different output when the same signal is input. This nonlinearity is directly reflected in the power spectrum of the output signal. By calculating the power spectrum of each amplifier's output signal as a feature, eight individuals can be distinguished.

The cable direct connection method was used to collect data in which the SNR was approximately 30 dB, which is a high ratio. However, it is difficult to obtain such a high recognition rate in practical application, thus the power spectrum of signals under different SNR were analyzed. The number of fast Fourier transform (FFT) points will affect the spectrum characteristics of the signal and Fig. 11 shows the recognition effect based on different FFT points.

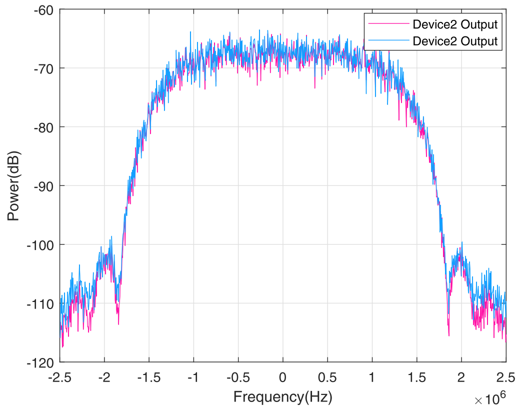

FIGURE 10. The power spectrum of signals passing through different amplifiers. The sample rate is 5MHz. The FFT point is 1024.

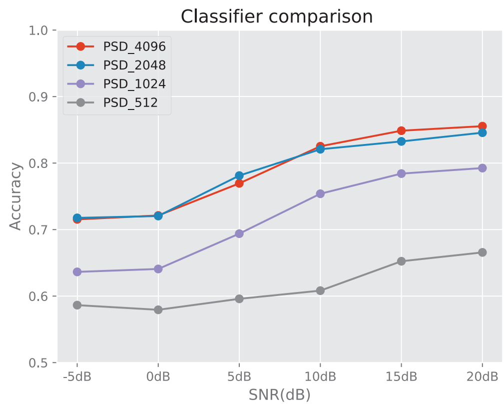

FIGURE 11. The recognition rate with different FFT point. The sample rate is 5MHz. The FFT point is 1024.

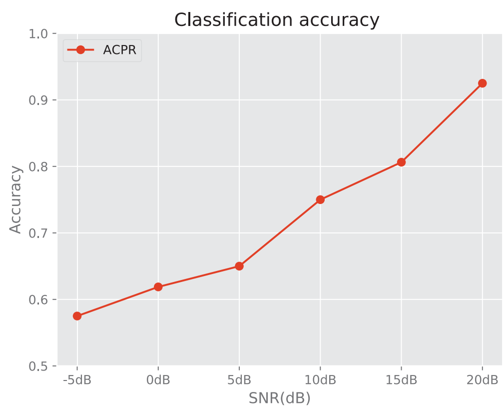

FIGURE 12. The recognition rate with ACPR.

2) RECOGNITION RESULT BASED ON ACPR

The index ACPR is commonly used for describing the nonlinearity of amplifiers as it can extract the nonlinearity of signals from the power spectrum of signals more thoroughly. The recognition result using ACPR is illustrated in Fig. 12. From figure 12 we can see that the recognition rate increases as the SNR increases, and it can achieve more than 90% when the SNR is higher than 20 dB. The result proves the effectiveness of the ACPR method.

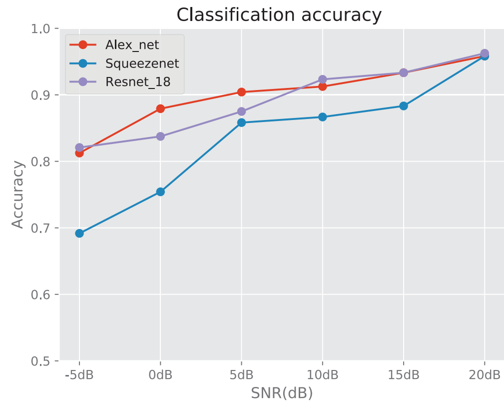

FIGURE 13. The recognition rate using CNN.

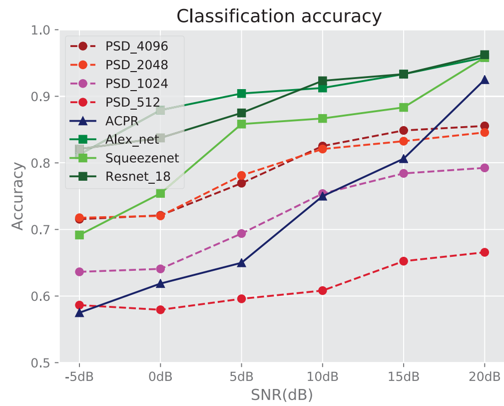

FIGURE 14. The comparative analysis results of the power spectrum-based feature extraction method and graph-based recognition method.

3) RECOGNITION RESULT BASED ON CNN

The recognition results using three convolutional neural networks (CNNs) in varied SNR are illustrated in Fig. 13. The methods are AlexNet, SqueezeNet, and ResNet-18. It can be observed that the identification rate increases with the rise in SNR for all methods, reaching over 90%. This identification rate is achieved when SNR is 5 dB for AlexNet and 10 dB for ResNet-18.

4) COMPARATIVE ANALYSIS OF RECOGNITION METHODS

Figure 14 depicts the comparative analysis results of the power spectrum-based feature extraction method and graph-based recognition method. As illustrated by the recognition rate curve with SNR ratio change, the graph based method is superior to the traditional feature extraction method.

The traditional method mainly diagnoses according to the information carried by the radio frequency signal such as working frequency, modulation mode, and pulse repetition frequency. However, it struggles to operate when the information carried by the radio frequency signal is the same. In this paper, a new radio frequency signal feature extraction method is adopted in which graph-based recognition is used to perform deep feature mining on the radio frequency signal and the mined features are classified and identified by convolutional neural network. This new method can provide superior recognition effect.

Convolutional neural networks have achieved significant results in picture recognition tasks. However, the amount of computation required by the neural network is over 100 million, meaning it cannot be widely used in practical tasks. Traditional feature extraction algorithms have less computational complexity.

V. CONCLUSION

Specific emitter identification based on power amplifiers was studied in this paper. Novel RF fingerprint features were integrated in the proposed method, and extensive experiments were carried out to evaluate performance. Firstly, a power amplifier with wide application was selected as the research object and measured data sets for individual identification studies were collected. The power spectrum and ACPR characteristics of the signal were then extracted. Finally, IQ signals were converted into pictures using Contour Stella Image, and then classified using convolutional neural networks. The results show that the proposed method obtains higher average recognition rate under different SNR and does not require manual feature extraction. Future work will be focused on increasing the network architecture robustness to allow an extension of the proposed approach to include data captured from a large set of devices.

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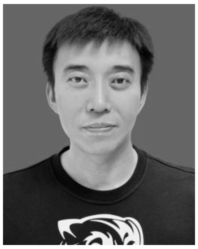

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