Specific emitter identification based on CNN

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Abstract. Specific emitter identification is one of the important technologies of electronic countermeasures. The convolutional neural network (CNN) has a strong ability to process image classification. To solve the problem that the bispectral feature of the radiation source does not perform well in the specific emitter identification, this paper proposes a method of combining the two-dimensional bispectrum of the radiation source and CNN. In order to test the performance of the method, this article designed a semi-physical system to collect the radiation source signal. It is verified by experiments that this method has a 92.4% correct rate for identifying different radiation source signals. Compared with other algorithms that combine bispectral features, the proposed method has advantages in accuracy and complexity.

1. Introduction

Specific emitter identification (SEI) is the method to identify the individual emitter based on the radio frequency (RF) fingerprint of signal. SEI is often used for the intrusion detection to improve the security of mobile very high frequency (VHF) radio networks, Wi-Fi networks, cognitive radios and cellular networks [1-5]. It is also used in the determination of the source of interference in military and civilian spectrum-management operations [1].

When an emitter is turned on, the signal goes through a transient state which is caused by a combination of effects, such as the acquisition characteristics of frequency synthesis subsystems, modulator subsystems and amplifiers [2]. The transient signals from different emitters usually have special RF fingerprints for SEI [1-5]. The fingerprint of the radiation source is an inherent feature of the hardware of the transmitting device, which is unforgeable, unchanged, and unavoidable. It is attached to the transmitting signal in the form of unintentional modulation.

Specific emitter identification technology is divided into three parts: preprocessing, feature extraction and classification recognition. Preprocessing is to eliminate uncertain factors that affect the signal. Feature extraction is divided into manual extraction and automatic extraction [6]. Manual extraction mainly studies transient features and steady-state features. The method of extracting the characteristics of transient signals is mainly based on the obvious change of the transition state level of the radiation source between the switch machine and the stable working state to carry out the feature extraction. Steady-state feature extraction refers to the extraction of features based on the influence of the signal’s noise characteristics, spurious characteristics, frequency stability and other characteristics on the radio frequency signal when the radiation source is in a stable working state [7]. Automatic extraction is combined with classification and recognition, and model self-learning is adopted to realize automatic feature extraction and radiation source classification.

In this paper, the high-order spectral features of the radiation source signal are combined with the convolutional neural network learning model. The results show that the method can realize the effective
identification of radiation source fingerprint features and improve the classification and recognition accuracy.

2. Signal bispectrum

For the radiation source signal, the high-order spectrum is an effective method for expressing subtle features. The high-order spectrum of the signal can map the signal to higher dimensions, so as to obtain richer information and reveal the differences between the signals. As the simplest high-order spectrum, bispectrum has a good suppression effect on Gaussian noise. Compared with other conventional signal processing methods, it is more suitable for the analysis and classification of subtle features [8].

Compared with the traditional low-order spectrum, the essence of bispectrum is to express one frequency factor by the other two frequency factors. Bispectrum estimation methods are divided into direct method and indirect method usually. In this paper, non-parametric direct bispectrum estimation is used. Its advantage is that the algorithm is simple and FFT is directly used. When the data sampling rate meets the requirements, not only the resolution requirement is met, but the bispectrum value method is also reduced [9-11].

Suppose $s(1), s(2), \cdots s(N_0)$ is a set of radiation source signal data, and $f_s$ is the sampling frequency of the signal, and $N_0$ is the number of sampling points of the signal. Then the process of obtaining the signal bispectrum by the direct method is as follows

Step1: Divide the signal data into K segments, each segment of signal data contains M signal sample data, then $N=K*M$.

Step2: Calculate the discrete Fourier transform DFT coefficients. Denote the $i$ segment of data as $\{y^{(i)}(n), n = 1, 2, \cdots, M-1\}$, and then,

$$\langle \lambda \rangle = \frac{1}{M} \sum_{n=0}^{M-1} y^{(i)}(n) \exp(-j2\pi\lambda/M)$$  
(1)

Where $\lambda = 0, 1, \cdots, M/2; i = 1, 2, \cdots K$.

Step3: Calculate the triple correlation of DFT coefficients,

$$\langle \lambda_1, \lambda_2 \rangle = \frac{1}{4\lambda} \sum_{k_1=-L_1}^{L_1} \sum_{k_2=-L_1}^{L_1} Y^{(i)}(\lambda_1 + k_1)Y^{(i)}(\lambda_2 + k_2)Y^{(i)}x$$  
(2)

Where $0 \leq \lambda_2 \leq \lambda_1, \lambda_1 + \lambda_2 \leq f_s/2, N_0$ and $L_1$ satisfy the value of $M = (2L_1 + 1)N_0$.

Step4: The bispectrum estimation value of the radiation source signal can be obtained by calculating the average value of the entire signal for the bispectrum estimation value of the K-segment radiation source signal. Then there is,

$$B(\omega_1, \omega_2) = \frac{1}{K} \sum_{i=1}^{K} \tilde{a}(\omega_1, \omega_2)$$  
(3)

Where $\omega_1 = \left(\frac{2\pi f_s}{N_0}\right)\lambda_1, \omega_2 = \left(\frac{2\pi f_s}{N_0}\right)\lambda_2$.

According to formula (3), the bispectrogram of the two radiation source signals is calculated as shown in Fig. 1, and the three-dimensional diagram is shown in Figure 2.

Figure 1 and 2 show that the models and batches of the two types of signals are the same, there are still obvious differences in the energy distribution of the bispectrum because they come from different individual radiation sources. In addition, the bispectral three-dimensional image contains more signal information than the two-dimensional bispectral image, but it is more complicated to process. Therefore, this paper focuses on the study of the distribution law of the signal bispectral energy on the two-dimensional image and seeks an efficient recognition algorithm.
3. Convolutional neural network

A typical neural network structure is composed of a series of processes, generally including input layer convolutional layer, pooling layer, fully connected layer, activation function, etc. The convolutional neural network learning model used in this article is shown in Fig.3.

This paper makes full use of the powerful feature extraction and classification recognition capabilities of the convolutional neural network to further extract the signal characteristics of the radio station, and complete the identification and classification of the individual radiation source. Convolutional neural networks include input layers and a total of eight layers of networks are: input layer (INPUT), convolutional layer (Convolutions, C1), pooling layer (Subsampling, S2), convolutional layer (C3), pooling layer(Subsampling), fully connected layer (S4), output layer (radial base layer), the size of the convolution kernel is 3*3, and the pooling layer kernel is divided into 2*2.
4. Experiment and analysis

4.1. Style and spacing
The radiation source signal is generated by the vector signal generator VSG60A as shown in Fig.6, and the real-time spectrum analyzer BB60C collects the signal and forms a data set through a 4-way wide channel. The radiation source signal is BPSK modulation style, the frequency is 600MHz, and the specific parameters are as shown in Fig.4.

The time domain and frequency domain signals collected by BB60C are as shown in Fig5 and Fig7, The time-domain signal of the collected signal extracts bispectral features once every 2048 points, and extracts 1000 bispectral feature data for each radiation source signal, and a total of 3000 bispectrum feature data for three radiation source signals. The 3000 signal features generated are randomly shuffled, and the training set and the test set are divided according to 7:3.

4.2. Identification process
In order to classify and identify the radiation source signal, preprocess the labeled ones and convert them into a two-dimensional bispectrum. Divide the bispectrum into a training set and a test set, and then use a convolutional neural network to train the training set and save the trained network parameters. The test set is used to verify the pros and cons of the network's recognition effect. The identification process is shown in Fig8.
4.3. Experimental result

The part of signal acquisition and preprocessing is implemented on the platform of Windows10 AMD Ryzen5 and MATLAB R2019a, and the network training and testing process is implemented based on the Tensorflow framework. The network optimization method is the Adam method, the initial learning rate is set to 0.0001, the batchsize is set to 128, and the epoch is set to 40 times. Under the setting of the optimal parameters, the relationship between the number of training times and the correct rate we get is shown in Figure 9.

![Recognition rate and loss value change curve.](image)

After training the network, we save the network model. Use untrained data to make a test machine, call the saved neural network model to test the test set, and the result is:

| Table 1. Identify experiment results |
|-------------------------------------|
| Train set Correct rate | Test set correct rate |
| 99.17% | 92.40% |

The experimental results show that the bispectral feature, combined with the convolutional neural network can better characterize the characteristics of the signal, and has a good performance in the fingerprint recognition of the radiation source.

5. Conclusions

Aiming at the problem of large dimensions of bispectral 3D data and difficulty in network training, this paper studies the classification and recognition effect of multiple regions based on bispectral feature data, and constructs a radiation source fingerprint recognition algorithm based on bispectral 2D image features. Based on the bispectral features, this method is combined with the LeNet-5 convolutional neural network learning model to classify individual radiation sources, with an average recognition rate of 92.4%. Compared with the direct use of bispectral features for radiation source recognition, the recognition rate of the algorithm in this paper has increased by 18.8%, and the comparison with the one-dimensional feature after bispectrum dimensionality reduction has also increased by 7.3%. However, the limitation of the algorithm in this paper is that the complexity of the algorithm has increased, which is not conducive to the realization of portable radiation source identification equipment.
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