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Research on Communication Radiation Source Identification Based on Deep Neural Network

Jianing Guo, Yazhong Chen, Ziming Qiao

Department of Electrical Information, Shandong University of Science and Technology, Jinan, Shandong, 250031, China

Abstract

Aiming at the problem that it is difficult to characterize the subtle differences of individual radiation source signals based on traditional expert features that rely on manual extraction, this paper proposes an individual identification algorithm for communication radiation sources based on the combination of short-term Fourier transform and deep convolutional neural networks(DCCN), and uses the traditional identification algorithm and this algorithm to identify the measured radiation source data sets, and the experimental results show that the network model in this paper has better identification efficiency in the identification of individual communication radiation sources.

Keywords

Communication Radiation Source Identification, Deep Neural Network.

1. Introduction

Individual radiation source identification is a new technology in the field of wireless communication, which uses fingerprints contained in individual radiation sources to identify targets [1]. Fingerprint extraction mainly revolves around transient feature and steady-state feature extraction [2]. The method of extracting the characteristics of transient signals is mainly based on the obvious changes in the transition state level of the radiation source between the on-off and stable working state [3]. 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 [4]. Whether it is transient feature extraction or steady-state feature extraction, the premise of the research is to have a large number of labeled training sets from which comprehensive fingerprint information of each individual can be extracted. However, in actual scenarios, the acquisition of labels often requires a lot of manpower and material resources, which makes it difficult to obtain a sufficient number of labeled training samples.

As a new research method in the field of machine learning, deep learning has powerful advantages in efficiently extracting and distinguishing the powerful features of different radiation sources from the target signal [5-6]. Literature [7-8] introduced the deep learning method to the algorithm research of individual radiation source identification, and obtained a high recognition accuracy rate.

In the scenario where there is no obvious difference between radiation source individuals, the accuracy of the radiation source individual identification algorithm based on traditional machine learning is often not ideal, and its complexity is relatively high and the recognition time is long. In order to solve the above problems, this paper uses the radiation source recognition technology based on deep convolutional neural network to identify the individual signal, and uses the traditional identification algorithm and the proposed algorithm to identify

the measured radiation source data set, and the experimental results show that compared with the traditional machine learning method, the network model constructed in this paper has better recognition ability, and the accuracy rate is as high as 96.5%.

2. Feature extraction based on short-term Fourier transforms

When processing the signal, the short-term Fourier transform is based on the Fourier transform (STFT) to introduce the "window function" first use the window function to intercept a small piece of signal from the non-stationary signal, and then the intercepted signal Fourier transform to obtain the corresponding frequency domain information at that time, the "window" is moved on the timeline, you can obtain its two-dimensional time spectrum, the time spectrum reflects the signal changes over time spectral information. STFT splits the entire unstable time domain signal into multiple near-stationary time domain signals through windowed processing, and then analyzes the fourier changes of these smooth fragment time domain signals quickly. The size of the window function should be reasonably adjusted according to the actual radiation source sample, so as to obtain the spectral information of the time-varying signal.

Let the communication signals x(t), t∈(−∞, +∞), and the window function be w(t), then the short-term Fourier transform is equation (1).

$$STET(\mathrm{t},w)=\int_{-\infty}^{+\infty}[x(\tau)^{*}w^{*}(\tau-t)]e^{-jw\tau}d\tau \tag{1}$$

Assuming that the duration of the window function is Δt, STFT performs a fast Fourier change on a time domain signal with a length of [t−Δt/2, t+Δt/2] to obtain its frequency domain information. The length of the window in the short Fourier transform determines the time domain accuracy when performing signal processing. Assuming that the discrete radiation source signal is x(n) and the window function is γ(n), then the short-term Fourier spectrum is equation (2).

$$\begin{aligned} STFT(n,w)&=\sum_{m}x(m)\gamma(m-n)e^{-jnw}\\ &=\sum_{m}x(m)e^{-jnw}\gamma(m-n)e^{-j(m-n)w}\\ &=\sum_{m}x_{w}^{'}(m)\gamma_{w}^{'}(m-n) \end{aligned} \tag{2}$$

Also known as formula (3).

$$STFTw=x_{w}^{'}*\gamma_{w}^{'} \tag{3}$$

In the formula $x_{w}^{'}(m)=x(m)e^{-jnw},\gamma_{w}^{'}=\gamma(m)e^{-jmw}$, from the above equation, the short-term Fourier transform can be understood as first mapping the communication signal into $x_{w}^{'}(m)=x(m)e^{-jnw}$, and then convoluting the signal after the mapping with window $\gamma_{w}^{'}(m)$.

In this paper, the received radiation source signal is preprocessed for short-term Fourier change, which makes the data sample more easily recognized by the deep convolutional neural network, thereby improving the accuracy of radiation source identification. Subsequent experiments have shown that the sample data processed by STFT is easier to be recognized by the network than other feature extraction methods.

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3. Communication radiation source signal recognition based on deep convolutional neural network

The convolutional neural network-based radiation source identification constructed in this paper is shown in Figure 1. In the communication radiation source individual identification process, the original radiation source signal is first collected by the signal receiver, and then the radiation source signal is downsampled to eliminate redundant information in the original signal. When receiving the radiation source signal through the receiver, some time periods have not received a valid signal, so there is a blank information segment in the received signal, so it is necessary to intercept these blank information segments to extract the valid signal in the signal, and then process the signal by the short-term Fourier transform method, extract the spectral information of the radiation source individual, and then normalize the signal. The purpose of normalizing the data is mainly to mitigate the impact of different value ranges and different dimensions between signal data. The data normalization process is the standardization of the data, and the definition of standardization is to convert the data that obeys the normal distribution into Z-score standardization that obeys the standard normal distribution process, first obtain the mean $\bar{x}$ and standard deviation s of the signal data characteristics, and then convert them under the same dimension. The formula is shown in (4).

$$x' = \frac{x - \bar{x}}{s} \tag{4}$$

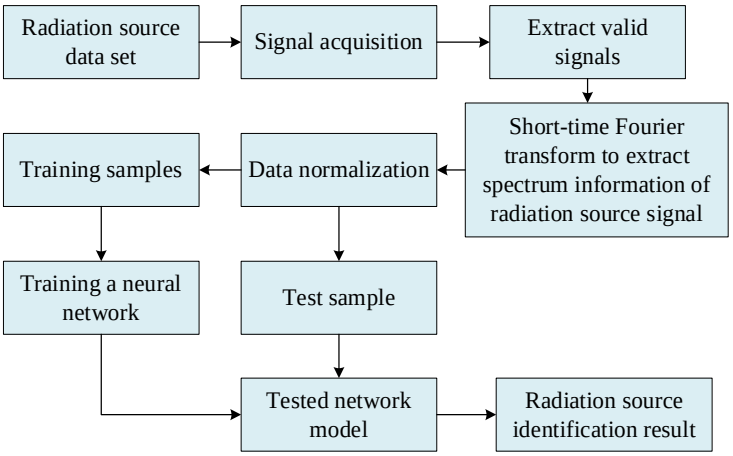

Figure 1. Flowchart of individual identification based on CNN radiation sources.

After the signal data is normalized, it can be used to train the DCNN network built in this paper. The result is a concrete network model. The test sample is then entered into the network model to obtain the radiation source identification result.

This paper not only refers to typical network models such as Lenet, Resnet, etc., but also considers the application scenarios of individual identification of radiation sources in this paper, as well as the characteristics of sample data after short-term Fourier transforms. The detailed network parameters are given in Table 1, and Figure 2 constructs the deep convolutional neural network model structure in this paper.

Table 1. Network parameters of convolutional neural networks

Network layer	Network layer parameters	Input/output feature map dimensions	Amount of weight parameter	Bias parameter amount

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Input layer	—	128*128	—	—
Convolutional layer one	3*3@2	128*128	576	32
Pooling layer	2*2	—	—	—
Convolutional layer two	3*3@32	64*64	9216	32
Convolutional layer three	3*3@32	64*64	9216	32
Convolutional layer four	3*3@32	64*64	9216	32
Convolutional layer five	3*3@32	64*64	9216	32
Convolutional layer six	3*3@32	64*64	9216	32
Convolutional layer seven	3*3@32	64*64	9216	32
Convolutional layer eight	3*3@32	64*64	9216	32
Convolutional layer nine	3*3@32	64*64	9216	32
Pooling layer	2*2	—	—	—
Convolutional layer tan	3*3@128	32*32	36864	128
Convolutional layer eleven	3*3@128	32*32	147456	128
Convolutional layer twelve	3*3@128	32*32	147456	128
Convolutional layer thirteen	3*3@128	32*32	147456	128
Pooling layer	2*2	—	—	—
Convolutional layer fourteen	3*3@256	16*16	294912	256
Convolutional layer fifteen	3*3@256	16*16	589824	256
Convolutional layer sixteen	3*3@256	16*16	589824	256
Convolutional layer seventeen	3*3@256	16*16	589824	256
Pooling layer	16*16	—	—	—
Fully connected layer	—	—	2048	8

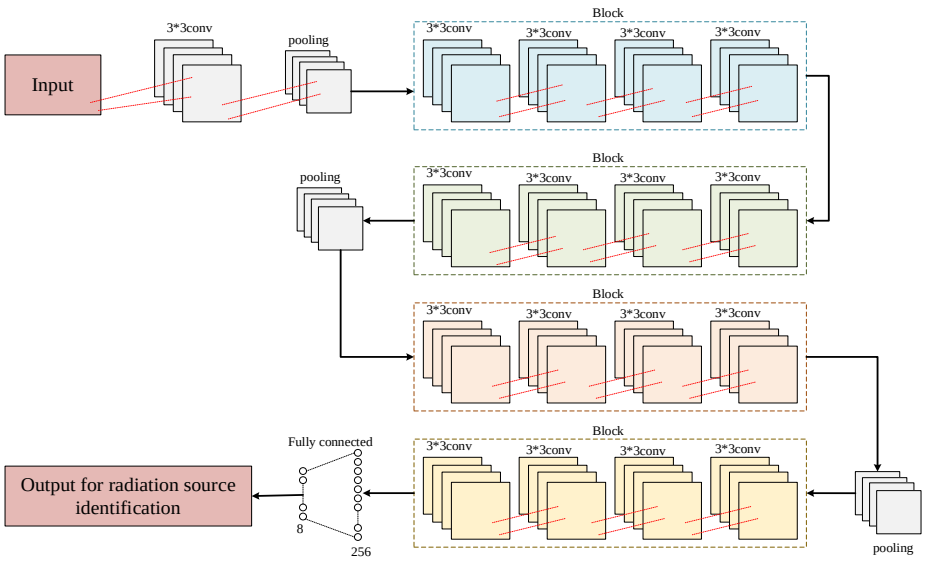

Figure 2. Deep convolutional neural network structure diagram.

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4. Communication radiation source signal recognition based on deep convolutional neural network

The measured radiation source dataset includes a total of 8 radiation source radio signals of two models, each of which contains a different modulation method, and each modulation method contains a different carrier frequency signal. First, the processed samples are labeled, and then 80% of the sample data is used as a training set to train the network network model, and then tested with the remaining 20% of the data. Assuming that the recognition accuracy is Accuracy, then Accuracy is shown in Equation (5).

$$Accuracy = \frac{number_1}{number_1 + number_2} \tag{5}$$

Number1 is the correct number of radiation source individuals, and number2 is the number of radiation source individual identification errors. The measured dataset has a total of five radiation source individuals, and each radiation source individual has differences in bandwidth, modulation mode, waveform ID, and radiation source individuals themselves. As shown in Figure 3, the individual confusion matrix of 8 radiation sources based on the network model of this paper has an accuracy of 96.5%.

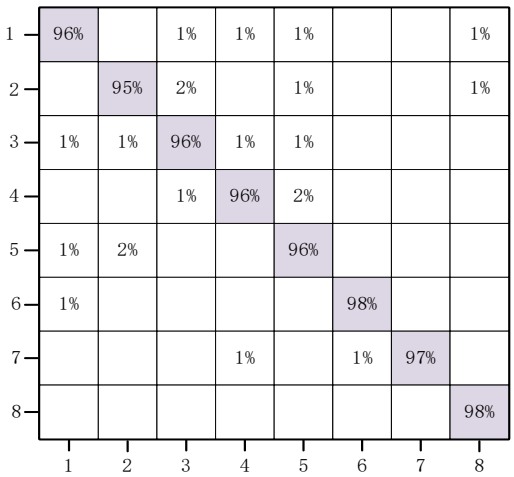

Figure 3. Confusion matrix for individual identification of radiation sources.

This paper uses different algorithms and the algorithms built in this paper for feature extraction, as well as traditional machine learning methods for classification. The methods of extracting individual radiation sources mainly include extracting the R value and J value of the signal. The main classifier algorithms used are KNN, SVM, etc. As can be seen from Table 2, compared with the second to fifth rows of the table, it can be seen that the short-term Fourier transform used in this article is more effective for feature extraction. Comparing the data from the first to third rows of the table, it can be concluded that the network model constructed in this paper has better recognition ability than the traditional machine learning method, and the accuracy rate is as high as 96.5%.

Table 2. Comparison of different radiation identification methods.

Numbering	Classifiers	Sample data	Radiation source identification accuracy
1	Network model in this paper	STFT time-frequency information	96.5%
2	KNN	STFT time-frequency information	72.1%

3	SUV	STFT time-frequency information	87.6%
4	KNN	R.J	61.2%
5	SUV	R.J	70.5%

In this paper, other deep learning models, such as Resnet18, VGG16 and Lenet, were used to identify radiation source individuals on the radiation source dataset. In Figure 4, the horizontal coordinate is the number of iterations of the network model and the vertical coordinate is the recognition accuracy of the network model. From the figure, we can learn that, compared with the common deep learning algorithm models, the convolutional neural network-based radiation source individual recognition algorithm constructed in this paper has a better performance, with stronger robustness as well as recognition efficiency.

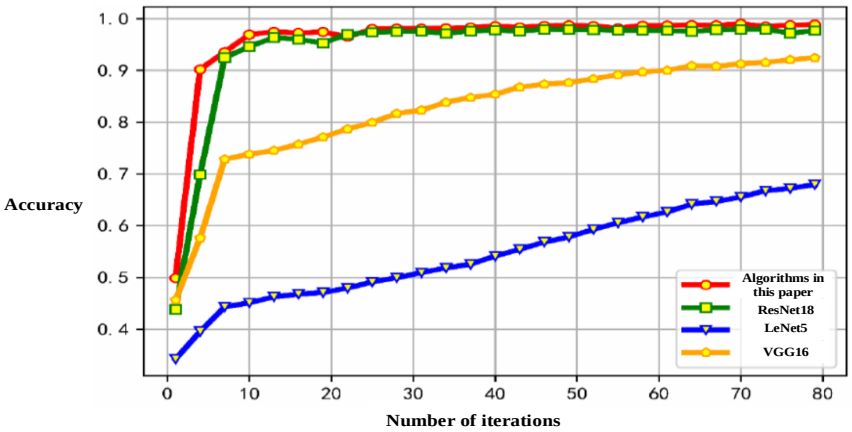

Figure 4. Recognition accuracy of different network models.

5. Conclusion

This paper focuses on the identification of individual radiation sources based on convolutional neural networks. Firstly, the signal envelope is extracted using the short-time Fourier transform, and then a network model based on deep convolutional neural network is constructed for the recognition of communication radiation source signals.The research on radiation source identification algorithms in this paper focuses on convolutional neural networks in deep learning, and less on recurrent neural networks and codec models, which are widely used in deep learning. The next step will be to further investigate the application of these algorithms to individual radiation source identification.

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