Individual identification of communication radiation sources based on Inception and LSTM network

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Abstract. The difference in fingerprint characteristics of communication radiation sources is small, and it is difficult to extract characteristics for recognition using traditional machine learning algorithms, so deep learning methods are considered. LSTM is an improved recurrent neural network that is good at processing long-term sequence data. The Inception module can obtain features of different scales on the same layer. This article combines the inception structure and the LSTM network to identify 5 USRPs. The data set used in the experiment was collected by USRP and LabVIEW. Two sets of data were collected based on the obstacles between the sending end and the receiving end, which are closer to the real environment than the data set that only uses software simulation. Compared with other network structures, this method has a higher recognition rate.

1. Introduction

In the battlefield environment, different individual radio radiation sources need to exchange information. Individual identification of communication radiation sources is the prerequisite for intelligence reconnaissance and electronic support, and is the basis for tracking the target source location and obtaining the enemy's communication network. The identification of different types of communication radiation sources is relatively simple, because the characteristics of the transmitted signals are quite different. However, there are only subtle differences between similar communication radiation sources, which are difficult to distinguish. Due to the increasingly complex electromagnetic environment, individual identification of communication radiation sources poses a great challenge, which has become a hot and difficult point of research.

In recent years, the following methods have been mainly used to study the identification of individual radiation sources. Literature [1] uses bispectrum as the basic feature vector for individual identification, and integrates radiation source feature parameters that have significant contributions to classification, and uses a radial basis neural network classifier to achieve individual classification and identification of communication radiation source signals. Literature [2] uses the characteristic that the high-order moment characteristics of the pulse envelope front waveforms is less affected by Gaussian noise, and improves the effectiveness of individual characteristic parameters of the radiation source. Literature [3] proposed an individual identification method based on ambiguity function subspace feature optimization. While significantly improving the individual identification performance of the radiation source, it further eliminated the redundancy of ambiguity function features. Literature [4]
proposed a method for individual identification of communication radiation sources based on empirical mode decomposition, which uses the EMD method to separate the main signal components of the steady-state signal from the spurious components, and then extracts the frequency domain characteristics of the spurious components as For the subtle characteristics of the signal, the support vector machine (SVM) classifier is used to classify and identify multiple communication radiation sources. Literature [5] uses technologies such as broadband digital reception, signal sorting and tracking, and digital quadrature mixing to instantly extract the rising edge waveform of the envelope, and calculate the Hausdorff distance from the "fingerprint" template to achieve the recognition and matching of the radar radiation source purpose. Literature [6] proposed a novel method based on time-frequency singular values and singular vectors, which introduces a spectrum that requires little prior information into a more suitable classifier, which can capture signals from three radios of the same type. The system is designed to evaluate this method. Other documents also select different characteristics, and have achieved certain results in the study of individual recognition.

However, with the continuous development of deep learning, neural networks are very effective in the research of individual radiation source identification. This article mainly discusses the task of individual identification of communication emitters based on the Inception-LSTM network, which extracts multi-scale features through different convolutional layers, and increases the convergence speed while ensuring the recognition rate by jumping connections. By comparing with other networks, we got a higher recognition effect.

2. Relation Work

Traditional machine learning algorithms can complete the learning of features, but they do not have the ability to extract features. Deep learning methods have good feature extraction capabilities, and the extracted features can more accurately describe the data. Powerful deep learning models can deeply show the rich information contained in big data and can make more accurate predictions for the future. In the process of studying individual identification of communication radiation sources, deep learning technology has slowly entered the field of vision and has become a method of competition.

The Inception module in GoogLeNet [7] is a successful way to increase the depth of the network. Connect from the input layer to convolutional layers of different scales, then combine the output connections of each convolutional layer, and then connect to the softmax classifier. This structure can increase the depth and width of the network while reducing parameters, effectively preventing the occurrence of gradient disappearance. The Inception module used in the thesis has three branches: (1) 1×1 kernel (2) 3×3 kernel (3) two 3×3 kernels. Two 3×3 kernels can replace 5×5 kernels, which reduces the amount of parameters and calculation cost with similar effects. If \( y^k \) it is used to represent the k-th feature map, then \( y_{1x1}^k \), \( y_{3x3}^k \), \( y_{5x5}^k \) represents the output after different convolutions. \( w_{1x1} \), \( w_{3x3} \) is the weight, * is the convolution operation, and \( b^k \) is the bias. The multi-kernel convolution operation can be expressed as:

\[
y_{1x1}^k = \text{relu}(w_{1x1} * x + b_{1x1}^k) \\
y_{3x3}^k = \text{relu}(w_{3x3} * x + b_{3x3}^k) \\
y_{5x5}^k = \text{relu}(w_{3x3} * (\text{relu}(w_{3x3} * x + b_{3x3}^k)) + b_{3x3}^k)
\]

\( y_{1x1}^k \), \( y_{3x3}^k \), \( y_{5x5}^k \) are used as input to the next layer.

ResNet [8] was proposed by He Kaiming and others in 2015. By introducing the concept of residual learning, it solved the problem of the disappearance of gradients in deep convolutional network models. The representation of residuals makes it easier to approximate multi-layer networks. The idea of ResNet is to prevent gradient degradation, allowing information to flow through shortcut connections to the shallow layer. The residual structure is shown in figure 1.
CLDNN [9] is mainly composed of a convolutional neural network and a longshort-term memory neural network, and was initially used for speech processing. CNN can reduce frequency changes, LSTM is good at capturing time series information, and DNN non-linearly maps features to the space where the signal can be separated.

3. Methods
In order to study the identification of individual communication radiation sources, we used 6 USRP-N210 as the radiation source for signal collection, and fixed one as the receiver. The sending and receiving end programs are set up using LabVIEW software, and the USRP is connected to the computer through a network cable. To explore the recognition effect in different environments, we set up two environments. One is an environment that is close and un covered, and the other is an environment that is far away and blocked by obstacles. The frequency bandwidth set when collecting data is 1GHz, and the sampling frequency is 1MHz. The collected data is an IQ signal, and the two carriers are orthogonal to each other.

3.1. Datapreprocessing
The IQ signals of 5 individual radiation sources have been collected through USRP. The signal content is a sine wave, and the storage format is a TXT file. Each file has millions of sample points. The file content is two columns of data, namely I and Qroad. During the collection process, it is found that the starting point data of each frame is abnormal, and these points should be removed. The amplitude or power of the signal emitted by each radiation source may be different, which may make it easy to identify each individual. In order to prevent this situation, we have carried out a normalization operation. $I_{\text{new}}$ and $Q_{\text{new}}$ are formed by expanding the data of channel I and channel Q in equal proportions, as shown in equation (4) and (5), and are standardized in the interval $[0, 1]$. Before entering the network, the sample points are divided into groups and labeled. The label uses one-hot encoding.

$$I_{\text{new}} = I_{\text{old}} / \sqrt{I_{\text{old}}^2 + Q_{\text{old}}^2} \quad (4)$$
$$Q_{\text{new}} = Q_{\text{old}} / \sqrt{I_{\text{old}}^2 + Q_{\text{old}}^2} \quad (5)$$

3.2. Neural network structure
Using deep learning methods to identify individual communication radiation sources, the choice of neural network is very important. We draw lessons from the idea of Inception structure multi-scale convolution, and designed a network combining Inception and LSTM, as shown in figure 2. Compared
with ordinary CNN, CLDNN, Inception networks, it is found that better results are obtained. Among them, CLDNN is a framework composed of CNN, LSTM, and DNN. Our work is to extract features in parallel with convolution kernels of different sizes in the convolution stage, and add residual connections on this basis.

![Inception-LSTM network structure](image)

**Fig.2 Inception-LSTM network structure**

4. Result

The data collection is divided into the laboratory environment and the actual environment. A total of 5 USRP emission sources are collected. In the process of collecting signals, try to keep the environmental conditions and collection methods unchanged, so that the radiation source is only identified by physical differences between individuals. The deep learning network structure used is divided into CNN, CLDNN, Inception and Inception-LSTM. The sample length is set to 128, the loss function uses categorical_crossentropy, the optimizer is adam, and the regularization uses dropout with a parameter of 0.5 and batch normalization layer [10]. When the number of network layers and the amount of parameters are roughly the same, we get the result as shown in the figure 3. In the laboratory environment, due to the small influence of noise and the high accuracy of individual recognition, the advantages of the Inception-LSTM method have not been reflected. In the actual environment, due to obstacles at the sending and receiving ends and the distance between them, the signal is significantly weakened and the recognition rate is reduced. The Inception-LSTM method performs better than other methods under the same conditions. The specific recognition effect in different environments is shown in figure 4.
5. Conclusion

The radiation source data collected by USRP and LabVIEW is more authentic than the data simulated by software alone, and is more convincing in the field of individual identification. In this paper, we use the combination of Inception and LSTM networks through laboratory environment and actual environment data, and compare them with other networks of comparable complexity, and find that the combined effect is higher. The reason is that the Inception structure can extract multi-scale features with different sizes of convolution kernels, and the chain structure of LSTM is more conducive to processing the timing signals from the radiation source. We have also studied the robustness of this method by artificially adding noise, and found that the effect will not weaken quickly in the case of low signal-to-noise ratio, and it is obviously due to other networks proposed in this paper.

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