Feature Extraction Method of Radiation Source in Deep Learning Based on Square Integral Bispectrum

Yanyan Yao*, a, Lu Yu and Yiming Chen
Institute of Communication Engineering, Army Engineering University of PLA, Nanjing, Jiangsu, 210007, China
*triyyao@njust.edu.cn
triyyao@126.com

Abstract. The feature extraction method of radiation source based on deep learning is a hotspot of specific emitter identification research. In the selection of the initial radiation source data for feature extraction, there are mainly two kinds of time series IQ data and frequency domain bispectral data. Both the IQ signal and the signal bispectrum contain the information that can characterize the fingerprint of the radiation source, and the deep learning methods mostly use different deep network structures to obtain better classification performance. This paper proposes a feature extraction method of radiation source based on bispectral data, and designs a deep network structure combining convolution and long short memory network, which has a better classification and recognition rate than a single convolution network and a single LSTM network.

1. Introduction
The internal characteristics of the pulse signal emitted by the radio radiation source are relative to the basic characteristics. The unintentional modulation characteristics attached to the radio signal, also called the "fingerprint" of the radio station[1], are added because the radio radiation source uses a specific modulator In a certain characteristic of the transmitted signal, the characteristic does not change due to the change of the form of the transmitted signal, and at the same time it remains relatively stable. The article studies the feature extraction of the radiation source, deeply analyzes the internal subtle characteristics of the individual radiation source, and finds the stable hardware feature information of the communication radiation source carried on the communication signal through the communication signal processing technology. Communication Transmitter Fingerprint (CTF) feature[2] refers to the subtle features that additional modulation does not affect information transmission on the transmitted signal, and can be detected and reproduced. In military applications, the CTF can be used to identify the enemy's communication radiation source, and on this basis, the importance of the enemy's launch equipment can be judged, which provides an important guarantee for precision strikes. In the civilian field, CTF features can be used to accurately determine the use of electromagnetic spectrum by communication stations, and to discover illegal stations in time. In the modern communications and military fields, specific emitter identification (SEI) plays an important role in identifying illegal equipment, improving system security, analyzing opponents’ target individuals in non-cooperative communications, analyzing the electromagnetic situation of the battlefield, and obtaining value. There are very effective applications in intelligence and other aspects. The radiation source fingerprint recognition technology accurately distinguishes many electronic devices with
exactly the same manufacturer, model, and parameters, so that more valuable information can be obtained.

Considering that time-domain features of different radiation sources are easily affected by noise and interference, and the accuracy and continuity of measurement data will cause large differences in time-domain parameters, so the essential characterization of the radiation source and the differences between the modes will cause crossover and overlap, which is not conducive to correct identification judgment. Therefore, the current research focuses more on finding features that can be distinguished significantly in the transform domain. The effective practice of using the signal integral bispectrum as the individual characteristics of the radiation source or combining with other characteristics for classification [3-5] also pointed out the direction for the research of the radiation source feature extraction algorithm.

In recent years, Deep Learning (DL) [6-9] has been widely used in computer vision, speech recognition, and hyperspectral data classification due to its excellent performance. It extracts abstract and invariant high-level attribute features from low-level features, implements complex nonlinear function approximation, and can portray richer essential information of data. Generally, after extracting the abstract features, you need to add the output layer (that is, output classification results). This article uses the more popular softmax classifier. Deep learning methods have achieved very significant results in the field of image detection and recognition, and are widely used. In the SEI field, due to the different input data and signal generation mechanisms, it is effective. There is not much practice [10-15], and the theoretical foundation that can be supported is not perfect. The use of deep learning methods based on raw data to extract more signal features is the key to solving big data processing and eliminating redundancy in the future, and has great potential value.

In this paper, deep learning is applied to the research of feature extraction of communication radiation sources, so that SEI can obtain better performance.

2. Related Works
The deep learning neural network structure mainly includes: input layer, hidden layer, and output layer, as shown in Figure 1 below:

![Figure 1. Basic structure of neural network](image)

The number of hidden layers is determined according to needs, and there is no clear theoretical derivation to explain how many layers are appropriate.

2.1. Convolutional Neural Network
Convolutional neural network (CNN) has a more effective feature learning part than the original multi-layer neural network. In front of the original fully connected layer, a partially connected convolutional layer and a pooling layer are added. The emergence of convolutional neural networks has deepened the number of neural network layers and deep learning can be realized. The characteristic of the convolutional neural network is that the hidden layer is divided into a convolutional layer, a pooling layer (also called a downsampling layer) and an activation layer. The role of each layer: (1)
Convolutional layer: extract features by translating on the original inputs; (2) Activation layer: increase nonlinear segmentation capabilities; (3) Pooling layer: compress the amount of data and parameters, reduce over-fitting, reduce network complexity, (maximum pooling and average pooling). In order to achieve the classification effect, there will be a fully connected layer (FC), which is the final output layer, to calculate the loss for classification (or regression). The purpose of the convolution operation is to extract different features of the input. More layers of networks can iteratively extract more complex features from low-level features characteristics. The main function of the pooling layer is to compress the amount of data and parameters (maintain the most significant features), and further reduce the number of parameters by removing unimportant samples in the feature map. There are many methods of pooling, and maximum pooling is usually used.

2.2. Long Short-Term Memory Network

Long Short-Term Memory (LSTM) network is a special kind of RNNs, which can solve the long-term dependency problem well. It was first proposed by Hochreiter & Schmidhuber in 1997. Like most RNNs, an LSTM network is universal in the sense that given enough network units it can compute anything a conventional computer can compute, provided it has the proper weight matrix, which may be viewed as its program. Unlike traditional RNNs, an LSTM network is well-suited to learn from experience to classify, process and predict time series when there are very long time lags of unknown size between important events. This is one of the main reasons why LSTM outperforms alternative RNNs and Hidden Markov Models and other sequence learning methods in numerous applications. The original intention of the design was to solve the long-term dependency problem in neural networks, and make remembering long-term information the default behavior of neural networks, rather than requiring a lot of effort to learn. The hidden layer of the original RNN has only one state, namely h, which is very sensitive to short-term input. Add another state, c, and let it save the long-term state, called the cell state.

LSTM has the ability to delete or add information in the state of neurons. This mechanism is carefully managed by a structure called threshold. Thresholds are a way to allow information to pass through selectively. They are made of sigmoid neural network layers and pointwise multipliers.

The sigmoid layer outputs a number between 0 and 1, which describes how much information a neuron should pass through. The output "0" means "all can't pass", and the output "1" means "let all pass". An
LSTM has three such thresholds (input gate, forget gate, output gate) to protect and control the neuron state. It can control the degree of memory and forgetting of previous and current information, so that the RNN network has a long-term memory function, which has a huge effect on the practical application of RNN.

LSTM is an excellent variant model of RNN, inheriting most of the characteristics of RNN models, and at the same time solving the vanishing gradient problem caused by the gradual reduction of the gradient back propagation process. In terms of language processing tasks, LSTM is very suitable for dealing with problems that are highly related to time series, such as machine translation, dialogue generation, encoding/decoding. Although in the classification problem, the feed forward network represented by CNN still has performance advantages, but the potential of LSTM in the long-term and more complex tasks is unmatched by CNN. It more truly represents or simulates the cognitive processes of human behavior, logical development and neural organization. Especially since 2014, LSTM has become a very hot research model in RNN and even deep learning frameworks, and has received a lot of attention and research.

3. Proposed algorithm
This paper proposes a deep learning-based feature extraction method for temporal radiation sources. All use square integral bispectrum transform method for signal data preprocessing. Input the preprocessed SIB signal into the neural network, and adjust the parameters of the network through a lot of training. Including adjusting the network weight parameters of each hidden layer in CNN through unsupervised learning, and using the adjusted hidden layer state as the input of the next layer; adjusting the entire network parameters through the supervised back propagation algorithm. And then LSTM is input for high-level feature extraction, and then a fully connected layer is used for data fusion to enhance information expression, and finally input to the dense layer and use softmax to achieve the final classification goal.

When deep learning is applied to the fingerprint feature extraction of communication radiation sources, the unsupervised learning strategy allows it to directly extract fingerprint features from the input data, surpassing the stage of artificially designing fingerprint features, and can save a lot of scientific research costs; in a layer-by-layer greedy manner compression of data features can make the final extracted fingerprint features have a lower dimensionality. While CNN layer effectively representing the individual communication radiation source with lower dimensional features, it can be used in conjunction with the LSTM neural unit to extract coarse-grained data between longer distances. Then, through the fully connected layer, the previous local features are assembled into a complete graph through the weight matrix. The output value of the last fully connected layer is passed to an output, which can be classified by softmax regression, this layer can also be called a softmax layer.

4. Experiment result and analysis
In order to evaluate the feasibility and effectiveness of the bispectrum-based deep learning fingerprint feature extraction algorithm for radiation sources, this paper conducted a large number of experiments on the USRP N210 communication device data set. For the purpose of better analysing the experimental results, the proposed algorithm (SIB-CNN-LSTM) and the feature extraction method...
based on convolutional neural network (SIB-CNN) and the feature extraction method based on LSTM neural network (SIB-LSTM) conducted an experimental comparison.

The experiment mainly set up two groups. The first group is a classification and identification comparison experiment based on different radiation source feature extraction methods under the I/Q data set, mainly to verify the radiation source feature extraction algorithm based on the deep learning method. The fingerprint characteristics of the radiation source extracted by the individual communication radiation sources of different models and working conditions can reflect the feasibility of individual differences; the second group is the individual identification experiment of the radiation source based on the bispectral data set of the radiation source signal, and the Gaussian white is artificially added. The effectiveness of the algorithm is verified under the conditions of different signal-to-noise ratios of noise.

The USRP N210 communication equipment data set used in the experiment is five USRP N210 communication equipment of the same manufacturer, same model and working state collected in a laboratory environment. The sampling data is a zero intermediate frequency I/Q quadrature signal. The sampling duration of the samples is 10s. So as to better compare the performance of each feature extraction method in the experimental group, the same softmax classifier as the CNN-LSTM model is used. Each group of experiments is repeated 20 times, and the average recognition rate is taken as the final recognition result. All experiments were run on a laptop with the CPU of Intel Core i7-7700HQ 2.8 GHz.

| Different algorithms | Average accuracy |
|----------------------|-----------------|
| Only CNN             | 72.9%           |
| Only LSTM            | 60.7%           |
| CNN-LSTM             | 82.3%           |

It can be seen from Table 1 that the algorithm proposed in this paper has significant advantages in the feature extraction performance of the radiation source. Taking into account the advantages of signal high-order spectral information in noise reduction, the article adopts the bispectrum-based deep learning radiation source feature extraction method, and conducts comparative experiments under different SNR conditions. According to Figure 7, the algorithm proposed in this paper has obvious advantages. Compared with the original I/Q data set alone, it has a higher classification and recognition accuracy and is less sensitive to the signal-to-noise ratio.
5. Conclusion
The deep learning radiation source feature extraction method based on square integral bispectrum used in this paper can perform well in the identification and classification of individual radiation sources, and has no significant relationship with time and external environment changes, and has good stability. Besides, the neural network is relatively simple in structure, small in computation, and high in recognition probability. It solves the specific problem of identifying different individuals of similar communication radiation sources, and lays a certain theoretical and technical foundation for the study of individual identification of communication radiation sources in complex electromagnetic environments.

References
[1] Zhang Min, Zhong Zifa, Wang Ruobing. Research on Individual Identification Technology of Communication Radio. Chinese Journal of Electronics, 2009, 37(10): 2125-2129.
[2] BOASHASH B, COHEN L, CHEN V, et al. Time-frequency Approach to Radar Detection, Imaging, and Classification. IET Signal Processing, 2010, 4(4):325—328.
[3] Cai Zhongwei, Li Jiandong. Individual Identification of Communication Radiation Sources Based on Bispectrum[J]. Journal of Communications, 2007, 28(2): 75-79.
[4] Shouyun Deng, Zhtao Huang and Xiang Wang. A Novel Specific Emitter Identification Method Based on Radio frequency Fingerprints. IEEE ICCIA, 2017, 368-371.
[5] Ding Gangsong, Z. Huang, and X. Wang. Radio Frequency Fingerprint Extraction Based on Singular Values and Singular Vectors of Time-frequency Spectrum. (ICSPCC) IEEE, 2018.
[6] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Image-net Classification with Deep Convolutional Neural Networks. Proc.25th Int’l. Conf. Neural Info. Processing Systems, 2012, 1097-1105; http://dl.acm.org/citation.cfm?id=2999134.2999257.
[7] WOJEK C, SCHIELE B.A Performance Evaluation of Single and Multi-feature People Detection[C] //Joint Pattern Recognition Symposium. Berlin, Heidelberg: Springer, 2008:82-91.
[8] Sercan O Arik, Mike Chrzanowski, Adam Coates, Gregory Diamos, Andrew Gibiansky, Yongguo Kang, Xian Li, John Miller, Andrew Ng, Jonathan Raiman, et al. Deep voice: Real-time neural text-to-speech. arXiv: 1702.07825, 2017.
[9] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam. MobileNets: Efficient convolutional neural networks for mobile vision applications. arXiv: 1704.04861, 2017.
[10] Huang Jianhang, Lei Yingke. Individual Identification of Communication Stations Based on Semi-supervised Rectangular Network. Chinese Journal of Electronics, 2019, 47(1): 1-8.
[11] Shamnazz Riaz, Kunal Sankhe, Stratis Ioannidis, and Kaushik Chowdhury. Deep Learning Convolutional Neural Networks for Radio Identification. IEEE Communications Magazine • September 2018, 146-152.
[12] Nguyen, N.T., Zheng, G., Han, Z., et al. Device Fingerprinting to Enhance Wireless Security using Nonparametric Bayesian Method. 2011 Proceedings IEEE INFOCOM, Shanghai, China, April 2011, 1404-1412.
[13] Ke Li, Jinyi Zhang Yingke Leiband Cyn Ra. A Novel Fingerprint Feature Extraction Method for Communication Radiation Source. Journal of Intelligent & Fuzzy Systems, 2019, 37 :351–359.
[14] Qingyang Wu, Carlos Feres, Daniel Kuzmenk, Ding Zhi, Zhou Yu, Xin Liu and Xiaoguang ‘Leo’ Liu. Deep learning based RF fingerprinting for device identification and wireless security. ELECTRONICS LETTERS, 2018.
[15] Hossein Jafari, Oluwaseyi Omotere, Damilola Adesina, Hsiang-Huang Wu and Lijun Qian. IoT Devices Fingerprinting using Deep Learning. Milcom 2018 Track 5, Big Data and Machine Learning, 901-906.