A study of individual identification of radiation source based on feature extraction and deep learning

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Abstract. Emitter identification technology can distinguish the types of radiation sources and identify the identity of emitter. It has broad application prospects in both military and civilian fields. The article mainly reviews the radiation source feature extraction methods for individual identification in recent years, and discusses the advantages and disadvantages of manually extracted features and the feature extraction based on deep learning. The technical difficulties of radiation source feature extraction methods are summarized with respect to the environment, the number of radiation sources, and the performance of algorithms, etc. Finally, the article points out the possible future development directions of individual radiation source identification.

1. Introduction

Radiation source individual identification technology, also known as radiation source “fingerprint” identification or specific emitter identification (SEI), refers to measure the received electromagnetic signal characteristics, and according to the existed priori information to determine the individual radiation source that generated the signal, and associating it with the individual radiation source and the platform and weapon system to which it belongs, has a very important strategic and tactical significance [1]. The technology has a very broad application prospect in many fields such as military, wireless network security, equipment fault diagnosis and communication band management, etc., and is receiving more and more attention from international research institutions.

The U.S. military first led the research on SEI technology, along with the participation of a number of U.S. companies, including Raytheon, Nog, Loma, General Dynamics Mission Systems, Harris, Rockwell Collins, and so on. At this point, the radiation source identification technology had entered its infancy.

With the increasing popularity of mobile communication devices and the booming development of Internet of things technology, wireless communication played an irreplaceable role in both military and civilian applications and had become an indispensable part of modern society [2]. And because of its openness, the method of extracting individual information of radiation sources through electro-magnetic signals in the air had received a lot of attention at home and abroad. In 1995, the literature [3] and [4] proposed the method of device identification through communication signals, where the literature [4] also proposed that radiation source identification can actively send signals to the target equipment or passively receive electromagnetic signals from the target device, thus broadening the research direction of radiation source identification. So far, radiation source identification had stepped into the preliminary development stage.

In 2003, Hall introduced the concept of “RF fingerprinting” for the first time in the literature [5]. He pointed out that Radio Frequency Fingerprinting (RFF) was a technology used for wireless device
identification. It mainly included transient signal detection and fingerprint extraction.” He also explained that the most challenging part of RFF at this stage is the detection phase, and proposed a new algorithm for detection using phase characteristics that achieved 85%-90% accuracy in the detection of Bluetooth signals. And then, in order to solve the dynamic radiation source identification problem, the literature [6] proposed an identification method with the fusion of several classical parameters, which mainly referred to frequency, amplitude, pulse width and pulse repetition rate. So far, in the following years, people began to carry out research around the transient signal, and the radiation source identification stepped into the full development stage.

With the proposal of deep neural networks (DNN) [7], machine learning has rapidly become a current research hotspot and had already made impressive achievements in image analysis [8], speech recognition [9], natural language processing [10], video classification, etc. [11]. Methods based on manual feature extraction were characterized by excessive subjectivity and poor robustness, while methods based on deep learning precisely solved this problem and provided full vitality to the development of radiation source recognition.

This paper firstly analyzes the current individual radiation source identification methods based on transient and steady-state signals from the principle of radiation source identification with artificially extracted features; secondly, outlines the radiation source identification methods based on convolutional neural networks and recurrent neural networks for deep learning-based radiation source identification methods; finally, points out the current problems and development directions of radiation source individual identification research.

2. Research problems and solutions
This paper firstly elaborates the principle of radiation source identification based on manual extraction of features, then introduces the principle of radiation source identification based on deep learning.

2.1. Principles of radiation source identification based on manual extraction of features
The U.S. Army first began to study the research of radiation source individual identification technology, the radiation source identification technology based on manual extracted features had come into view. The main research objects included the features of transient signals and the features of steady-state signals in two categories.

2.1.1. Identification method based on transient signal feature extraction. The accuracy of individual identification of radiation sources based on transient signals was hugely dependent on the consistency and integrity of the transient signals. This required signal detection capability and feature extraction capability, so the research direction of radiation source identification was mainly included in two aspects: signal detection and feature extraction.

A transient signal detection method based on wavelet transform was proposed in the literature [12] It identified transmitters using the polar magnitudes and relative positions of multiple wavelet scales. Even with a reduced signal-to-noise ratio, a high identification accuracy of pseudo-noise was obtained. Of course, for the detection of transient signals, in addition to the above methods of threshold detection by transformation or model, there were Bayesian detection methods. When the radio transmitter was activated, it went through a relatively short transient phase, during which the signal generated by the device had unique characteristics, and Bayesian detection was more effective in the detection of the turn-on transient. The literature [13] also detected the turn-on transients by a Bayesian approach. The probabilistic automatic segmentation algorithm could effectively detect the noise at the moment of power-on, thus completing the detection of transient signals. Since then, the Bayesian approach had become a research hotspot. The literature [14] used Bayesian change detector to detect WI-FI turn-on transients, and the proposed technique was verified by transient data collected from several WI-FI radios, showing that the ramp detector outperforms the mutation detector in detecting transient switching of WI-FI transmitters, and the comparison with another method for amplitude phase characteristic detection, which was the third method to be presented in this paper. The literature [15] solved the
problem of detecting transients of unknown waveforms and arrival times embedded in white Gaussian noise by using the fourth-order correlated cepstrum coefficients of transient signals. Of course the above requirements were all high signal-to-noise ratio, i.e., strong signals were needed, and for weak signals, the detection of non-periodic weakly discharged signals could be transformed into the estimation of the period delay parameters and simultaneously reduce the noise, and then the detection algorithm into a generalized mutual correlation and chaotic sequence prediction was used for the detection of transient signals [16].

Once the transient signal was detected, it was time to perform the feature extraction of the transient signal. The generalized dimensional representation of transient signals was proposed in the literature [17], where the authors obtained fractals, information and associated dimensional trajectories by applying sliding windows to transient signals and used the dimensional values to construct feature vectors to complete feature extraction. The wavelet transform was also used in feature extraction, and the literature [18] filtered the optimal wavelet bases by calculating the interclass separation to extract features, and the wavelet coefficient complexity under a specific wavelet basis was selected according to the feature distribution as the signal-to-noise ratio reference value to assist in the individual identification of radiation sources, which could achieve 90% identification accuracy at signal-to-noise ratios greater than 6 dB. And by this year, Choe et al. proposed an automatic fast signal classification and recognition method based on the theoretical aspect of feature extraction combined with artificial neural networks, where multi-resolution features were first extracted manually by wavelet decomposition and then neural networks were trained on known signals and selected wavelets for classification and recognition [3]. In contrast, the literature [19] designed a system for individual identification of radiation sources based on automatic dependent surveillance broadcasting from a practical point of view. This system extracted a total of six parameters as individual features and could achieve an average radiation source individual identification accuracy of 88.3%. The literature [20] considered radiation source identification techniques in the case of low signal ratios and proposed a method based on scale-invariant feature transformation position and scale features to suppress the extracted noise feature points. The literature [21] extracted the features of transient signals through a time reversal technique based on the frequency domain approach of the standard genetic algorithm. Since the manually extracted features were usually subjective and speculative, the literature [22] investigated the method of radiation source signal feature selection based on rough set theory, which laid the foundation for using rough set theory for radiation source signal feature selection.

It could be seen that the transient signal of the radiation source were in the emission of the transition phase”, which was rich in a large number of non-linear characteristics, to the radiation source individual identification provides sufficient “fingerprint characteristics”. However, the signal “fingerprint characteristics” did not only exist in the transient process, the steady-state process of the device internal noise or device nonlinear effects of unintentional modulation could also be distinguished from the different radiation sources of individual.

2.1.2. Identification method based on steady-state signal feature extraction. For most of the radiation sources, it was difficult to do the transient characteristics of non-cooperative radiation sources due to a series of reasons such as unknown on-time, and for this reason the identification method for steady-state feature extraction of radiation sources was gradually on the agenda. Irwin O. Kennedy et al. clearly proposed the fingerprinting technique of radiation sources based on steady-state signals [23]. Since then, the research on steady-state signals had gradually heated up. In general, the feature extraction of steady-state signals relied on the following components: frequency stability [23], modulation parameters [24], signal envelope [25], and the most studied spurious output [26], which would be briefly described in the following. When the signal operated in steady state, the frequency could not be ideally fixed due to internal noise coupled with the inherent unintentional jitter of the crystal, so the individual identification for frequency stability had a good identification effect. The literature [23] moved the signal from the time domain to the frequency domain by FFT and could achieve 66% recognition accuracy at 0 dB signal-to-noise ratio; while the literature [27] analyzed and recognizes 2FSK signals by wavelet
transform; the literature[28] sampled the extraction method to transform the frequency fluctuation information into the pseudo-modulated envelope waveform and fitted between the extreme value points with three spline interpolation to accurately. The envelope features were extracted, and then the box dimension and information dimension features of the envelope signal fractal were calculated, and finally the nearest neighbor classification method was used to achieve the individual identification of communication radio stations, and the accuracy of the identification of the simulated signal reached more than 90%. Of course, for signals, frequency was not the only feature, and modulation was also a very critical part. The identification of the modulation of the signal by second-order statistics, using the cyclic smoothness of the oversampled communication signal, could also be obtained with better results [24]. And the literature [29] proposed the identification based on the type of signal modulation, according to the different types of modulation resulting in different ratios of envelope variance and mean square thus to classify the signal accurately. For the more important radar signals in radiation sources, pulses and envelopes made the focus of attention. Literature [25] extracted the envelope of radar signal by wavelet transform to classify the signal with 96.1% accuracy compared to STFT, WVD, DWT methods. Literature [30] proposed a method to identify radar based on multiple pulses as well as single pulses by using the rising edge of envelope.

For steady-state signals, the easiest method to extract and better results was the classification based on spurious output, and therefore had received more attention from scholars. A variable-parameter identification method based on higher-order spectra was proposed in [26], using the invariant parameters of a bispectral array to classify one-dimensional shapes, and good results were obtained even at low signal-to-noise ratios. The literature [31] proposed a moving invariant feature based on the distance like bispectral integration in the circular direction in the dual frequency plane thus identifying the high resolution radar. The literature [32] used radially integrated bispectrum (RIB), axially integrated bispectrum (AIB) and circularly integrated bispectrum (CIB) as the feature vectors of the signal to classify the signal by support vector machine. The literature [33] developed a time-varying real-beat AR model for non-smooth multicomponent signals and used time-varying power spectrum for signal separation. Xu Shuhua et al. used rectangular integral bispectrum to extract the main feature parameters, then used principal element analysis method to select low-dimensional and low-complexity feature vectors from a large set of training sample feature parameters, and fused the radiation source modulation feature parameters with significant contribution to classification in the identification feature vectors, and finally used kernel function-based support vector machine to perform individual radiation source identification, achieving 90% accuracy [34]. The literature [35] proposed a cross-receiver specific emitter identification method based on carrier leakage estimation. The joint estimation of carrier leakage and filter aberrations was integrated to eliminate the influence of the receiver, thus effectively reducing the feature shift caused by receiver aberrations and bringing a large accuracy improvement. In the literature [36], the identification and classification of radiation sources were performed by extracting the rectangular bispectral features of the signal and using the reduced-dimensional bispectral features of the signal.

The method based on manual extraction of features in a specific environment, for a specific radiation source individuals could generally have a better recognition accuracy. However, it required people with certain expertise to find the eligible features among many signal features, which possessed certain difficulties, and could not accurately achieve the local optimum or even the global optimum, and when the external environment changes, the recognition accuracy might deteriorate sharply and the model robustness is poor. Therefore, in order to solve a series of problems brought by manual extraction of features, some scholars proposed the principle of individual identification of radiation sources based on deep learning.

2.2. Principle of emitter recognition based on deep learning
Artificially extracted features to radiation source identification method had a strong interpretability, could reflect the more specific properties of the signal. However, for the radiation source with many data-rich features, the artificial features reflecting a specific attribute alone had limited ability to
characterize the RF signal, and often could only express the low-level features, mid-level features and deep abstract semantic features of the signal, which lacked strong feature description ability. In addition, the manual feature extraction process was based on various complex mathematical calculations and theoretical derivations, which required a large amount of manual participation to complete the feature extraction task. Considering the above-mentioned problems of manual feature extraction, it was quite important to explore more efficient, reliable and comprehensive feature extraction techniques for the practical application of individual identification of radiation sources.

The term “neural network” originated from scholars’ search for a mathematical representation of information processing in biological systems [37], and in fact, this model had been used in a wireless environment and covers a considerable number of different kinds of models, especially in the field of image processing and other high-dimensional, artificially difficult to extract features had made a major breakthrough. And among them, for the field of radiation source individual identification, the total neural network methods could be broadly divided into two categories, the radiation source identification methods based on the convolutional neural network (CNN) and the recurrent neural network (RNN).

2.2.1 The recognition method based on convolutional neural network. Convolutional neural network is a class of feedforward neural network that contains convolutional computation and has a deep structure, mainly including convolutional, pooling and fully connected layers, and is one of the representative algorithms of depth(figure 1). And it had been repeatedly used in recent years for individual identification of more real radiation sources. The literature [38] investigated the ability of convolutional neural networks to recognize the signal domain of complex-valued time-domain radiation sources and compared it with an expert feature-based approach, finding significant performance improvements. Especially in the case of low signal-to-noise ratios, the decrease in accuracy was not very significant. The literature [39] used the envelope frontier of the radar signal as the input of the network to automatically extract the individual features of the radiation source envelope and fit the Q-value of the current state action pair, and discussed the effectiveness of the deep Q-network model, the deep dual Q-network model, and the Dueling Network model in radiation source identification. Of course, radiation source identification mainly relied on its “fingerprint features”, and the literature [40] identified mobile communication signals by convolutional neural networks with an accuracy of 86.7%. The literature[41] combined SDR sensing capabilities with machine learning, using I/Q sequence examples for output and supported vector machines and logistic regression for classification, with an accuracy of over 90%.

Since the residual network was proposed in 2015, which to some extent solved the problem of feature loss as well as overfitting and degradation caused by too deep layers of convolutional networks, and shone in the publicly available Imaget dataset, the residual network had since then received a lot of affection from scholars. The design of the residual network can be summarized as:
\[ H(x) = F(x) + x \]  \hspace{1cm} (1)

As long as \( F(x) = 0 \) constitutes the identical mapping \( H(x) = x \). Here \( F(x) \) is the residual.

The literature [42] performed Hilbert-Yellow transform on the received signal, converted the obtained Hilbert spectrum into grayscale images as the input to the network and introduced a residual module for the identification of individual radiation sources with better results than previous research methods. The literature [43] let the neural network use multiple downsampling transforms to achieve automatic extraction and classification of multi-scale features, and experiments showed that the change method was robust over a wide range of signal-to-noise ratios in both LOS scenes and NLOS scenes. The literature [44] first used a combination of Hilbert-Yellow transform spectrum and bispectrum to form an image of the signal, and then used the resulting image as the input to the network, with a large improvement in accuracy of 99% over the direct input signal method without preprocessing. The literature [45] built an end-to-end deep learning model suitable for wireless communication based on deep residual networks.

The signal had been automatically feature extracted by neural network, which reduced many complicated formula derivation and the effect could reach more than 90%, but it also led to the lack of interpretability. For this reason, the radiation source identification method based on convolutional neural networks might make more breakthroughs for physical interpretability in the future.

2.2.2. The recognition method based on recurrent neural network. The radiation source signal was a continuous and highly correlated electromagnetic wave with coherent before and after information, which could be called a time series signal. Compared with the convolutional neural network, the recurrent neural network took into account the relationship information between the front and back inputs, and could better exploit the signal characteristics of continuous electromagnetic waves, which had been better applied in the individual identification of radiation sources. At present, the popular recurrent neural network models were Bi-RNN and LSTM.

In the literature [46], for distorted receivers, the signals were first preprocessed with empirical modal decomposition, intrinsic scale decomposition, and variational mode decomposition, and then the recognition performance under Gaussian and fading channels was improved by long short-term memory (LSTM) networks, coupled with multiple distorted receivers for diversity reception. And then, through research, recurrent neural networks were gradually fused with convolutional networks to form a common network model, typically: literature [47] combined deep bidirectional short-term memory and one-dimensional residual convolutional networks to extract temporal structure features directly from baseband homogeneous and orthogonal (I/Q) samples, solving the problem of deep learning in individual recognition prone to selecting invalid features. The literature [48] first extracted the squared integral bispectrum of the signal as the input of the network, combined LSTM with CNN, and the experimental results showed better classification recognition rate than a single convolutional network and a single LSTM network. The literature [49] extracted features at different scales on the same layer through the Inception module and identifies the communication radiation source signals through an LSTM network.

Deep learning-based radiation source individual identification method model framework was generally off-the-shelf popular network framework, easier to implement, extract features did not require expert knowledge, recognition accuracy was also more ideal. However, he also had the general problem of machine learning, which required a large amount of training data and is difficult to achieve effective migration among multiple radiation sources.

3. Problems and development direction

Compared to problems such as image processing with a large number of publicly available data sets, data on radiation sources are generally difficult to extract and confidential, making it difficult to form a convincing identification model. After thorough literature reading and data analysis, it is felt that radiation source identification still has the following deficiencies.
3.1. Small sample size problem
The more popular radiation source identification methods are all statistical methods based on deep learning, which require a large amount of training data. In practical terms, the general radiation source identification problem does not have a lot of corresponding training data. Especially nowadays, technology is developing rapidly and radiation sources are updated frequently, so how to accurately identify individual radiation sources with a small number of training samples has become a difficult problem in front of scholars, which is now commonly known as the small sample problem.

3.2. Problem of low accuracy of transfer learning
Through the study, it is easy to find that the radiation source identification is mainly through the individual “fingerprint characteristics” to extract to use and identify, and fingerprint characteristics for the same radiation source individual is not unchanging, it is like a person's palm of all the fingerprints, you may extract the thumb fingerprint, but it may be the emission of the fingerprints of the index finger, although they refer to the same person, but the difference is very large. In particular, the “fingerprint features” tend to change due to the change of frequency or bandwidth, so it is difficult to model them accordingly. For this reason, if the parameters of the test data and the training data are not the same, the recognition effect will be drastically reduced by the deep learning method of individual recognition of radiation source.

3.3. No labeling issues
The radiation source signal is different from the photo, the manual labeling workload is large, and the error rate is extremely high, and the general method based on deep learning requires high label accuracy of the training data, and at this stage it is not possible to self-judge the accuracy of the label, plus the high cost of labeling, so the future research direction of individual identification of radiation sources may shift from supervised learning to unsupervised learning or semi-supervised learning, from a large amount of labeled training data to small samples or even unlabeled data learning.

4. Conclusion
This paper reviews manual feature extraction-based and deep learning-based methods from the perspective of individual radiation source identification, and finally describes the current problems and development directions of individual radiation source identification. This research is in demand in both military and civilian applications, especially in the military, where the complex battlefield situation and cross-mixing of electromagnetic signals are increasing the requirements for individual radiation source identification. However, small samples, low accuracy of migration learning and no label are still unsolved problems at this stage. It is suggested that the next research direction can further go to the generation of RF fingerprint features of radiation sources and establish effective mathematical models. Or draw on the integrated learning idea to get strong classification results with multiple weak classifiers. It is also possible to move from supervised learning to a hybrid approach combining unsupervised and supervised learning, allowing the number of required labeled samples to be reduced. It is believed that in the near future, the individual radiation source identification technology will be able to shine.

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