Specific Emitter Identification at Different Time Based on Multi-domain Migration

Jiaxu Liu, Jianqing Li, Jiao Wang and Hao Huang
University of Electronic Science and Technology of China, Chengdu, China
E-mail: liujiaxu97@foxmail.com Tel: +86-18113650812

***Abstract*— Specific emitter identification technology aims to identify the signal emitted by a specific emitter from multiple signals. Existing techniques for specific emitter identification are faced with the problem that the identification performance decreases with the passage of time. In this paper, we propose a method for specific emitter identification at different time. The method treats the signals of radiation sources at different time as signals of separate domains, and resolves the influence of time on specific emitter identification by eliminating the factor of different domains. The experimental results show that the method has better performance on both data corresponding to the time involved in training and data corresponding to the time not involved in training compared with both domain-free migration and ordinary domain migration methods. At the same time, the proposed tagging flexible loss function is more efficient in the face of new time tag free data.**

Index Terms: Specific emitter identification, Domain migration, Convolution Neural Network, Radiation fingerprint

I. INTRODUCTION

Specific emitter identification is the technology to match the electromagnetic characteristics of the radiation source with the individual radiation source. Due to the difference of hardware equipment technology and nonlinear components, the electromagnetic signals emitted by the same type of equipment produced by the same manufacturer are slightly different. Therefore, unknown radiation sources can be individually identified by the subtle characteristics of different radiation sources. The subtle characteristics of radiation source signal can be divided into transient fingerprint feature and steady fingerprint feature.

Traditional specific emitter identification mainly focuses on the extraction of transient features. Existing methods include transform domain processing of the original transient signal [1], and the instantaneous amplitude, phase angle, power, transform domain coefficient and other parameters of the transient signal are taken as fingerprint characteristics [2,3,4]. There are also single feature methods for single domain feature of signal or one-sided measurement of signal, including feature matching of pulse envelope front [5], high-order moment characteristics of pulse impulse envelope front [6], Empirical Mode Decomposition based on Empirical Mode Decomposition (EMD) method for extracting stray features [7], feature optimization based on fuzzy function [8] and based on time spectrum singular value and singular vector [9], etc. However, the features extracted by traditional radiation source specific recognition methods are relatively simple and one-sided, which makes it difficult to effectively and completely characterize the individual information of radiation sources and achieve the classification of radiation sources.

Deep learning can effectively extract steady-state fingerprint features of radiation sources because of its powerful feature extraction and nonlinear fitting capabilities. There are methods of sending three-dimensional images composed of traditional features into deep convolutional neural network (CNN) for classification [10], methods of directly using three-layer neural network to identify radar signals [11], and methods of radar radiation source recognition based on fuzzy ARTMAP neural network integrating two neural networks [12].

At present, the individual identification algorithm based on deep learning has high accuracy in the identification of radiation source signals which in the same time period. However, the subtle characteristics of the radiation source will vary over time, which leads to the poor performance of the existing algorithms in identifying the radiation source signal at different time from the training data. And the longer the time spins, the lower the recognition accuracy of existing algorithms.

To address the problems above, we proposed a cross-time specific emitter identification method based on multi-domain transfer learning, which can realize the specific emitter identification quickly and accurately, and can effectively address the problem that the radiation source identification accuracy decreases greatly with time. We apply the instance - based transfer learning algorithm in transferring learning to radiation source identification and improves it. Instance migration learning algorithm based on how the source domain and target domain confusion together, thus using the model obtained from the source domain training can also be used for the recognition of the target domain, generally move for only two areas namely source domain and target domain. Multi-domain transfer learning proposed by us takes the constant changes of the fingerprint of the radiation source into account, and regards every radiation source signal in each time period as a data domain. The ultimate goal is to ensure that the model performs well in each domain through comprehensive training in several existing fields.

Our contributions of the proposed method can be

978-616-590-477-3 ©2022 APSIPA

summarized in the following two folds:

1. We propose a cross-time specific emitter identification method based on multi-domain transfer learning (see Fig. 1),

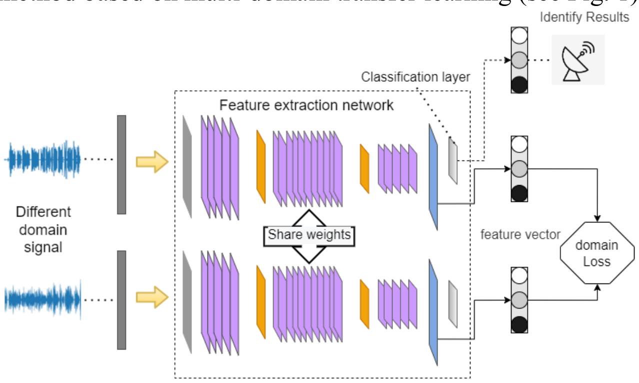

Fig. 1 Cross-time specific emitter identification framework.

which takes the radiation source signal in each time period as a data domain. By mixing different data fields, the influence of the characteristics of the radiation sources changing with time on specific emitter identification is eliminated.

2. we propose a label flexibility loss function and combine it with the maximum mean discrepancy (MMD) loss [13] to form a multi-domain combined loss function. Our experiments show that the proposed combining loss can better deal with the time-varying fingerprint of radiation sources in real data than the non-domain migration and traditional domain migration methods.

II. RELATED WORK

In this section, we will briefly introduce related technologies and methods in two aspects: deep learning methods for specific emitter identification and transfer learning.

A. *Deep learning methods for specific emitter identification*

Deep learning proposes a method for computer to automatically learn pattern features, and integrates feature learning into the process of model building, which can reduce the imperfection caused by artificial design features, skip the stage of manual design of fingerprint features, and save a lot of scientific research costs. In addition, the deep learning method characteristics of data compression in the form of greed dream step by step, can make the final extract fingerprint characteristics have lower dimensions, in low dimension characteristics of effective characterization of individual communication source at the same time also can dock with the traditional classifier and general, solves the problem that common classifier can't complete use of the fingerprint characteristic information.

Shamnaz Riyaz[14] used the deep convolutional network to realize the reliable specific emitter identification, and compared the performance of support vector machine and logistic regression method, proving the effectiveness of convolutional neural network in identifying individual radiation sources. Qingyang Wu[15] uses Long short-term Memory (LSTM) in Recurrent Neural Network (RNN) to effectively capture the long-term and short-term hardware characteristics of radiation sources. It is proved that LSTM architecture has high detection accuracy for individual identification of radiation source. Yiwei Pan[16] proposed an individual identification method of radiation sources based on Deep Residual Network, and demonstrated that compared with CNN Network, Deep Residual Network has lower computational complexity and better individual identification performance. Compared with traditional methods for individual identification of radiation sources, the method proposed in this paper can adapt to the changes of radiation source fingerprints over time, thus significantly improving the stability of individual identification of radiation sources.

B. *Transfer learning*

Traditional machine learning methods usually assume that training data and test data have the same distribution. However, in the practical application, the change of channel environment and various disturbances leads to frequent and unpredictable changes in data. The emergence of transfer learning breaks through the limitations of traditional machine learning. Despite the difference in data distribution between source domain and target domain, the knowledge of source domain can still be used to train the classification model of target domain [17]. Generally, existing knowledge is called source domain, and new knowledge to be learned is called target domain. The core idea of transfer learning is to realize the reuse and transfer of knowledge between related fields by virtue of experience and ability acquired in auxiliary domain [18].

Deep transfer learning methods can be described from three aspects: feature extraction, fine-tuning network and building a new learning framework. In 2014 PRICAL Conference, DaNN[19] proposed that the characteristic of this network is the MMD adaptation layer after the feature layer, which calculates the RKHS spatial distance between the source domain and the target domain and optimizes its loss. The main idea of DDC[20] method is to fix the first seven layers and add MMD metric in front of the classifier layer to realize the transfer learning of deep network. DAN network [21] adopted MK-MMD, combined with the idea of multi-core, which has stronger characterization ability and achieved better classification effect. In the 2017 ICML conference, JAN[22] proposed the method of extending the adaptive method of data to the adaptive method of categories, and proposed the JMMD (Joint MMD) metric. In addition, due to the development and superiority of generative adversarial network GAN[23], research on the transfer learning method based on generative adversarial network has also made some progress [24][25][26]. Compared with the common domain adaptation method, this paper treats the changes of radiation source fingerprints with time as different data domains and performs domain adaptation on an infinite data domain, which is more adaptable to the changes of domains.

III. PROPOSED METHOD

Most of the existing methods for specific emitter identification can only identify the signals of radiation sources at similar time, but the recognition accuracy of the signal with a long-time span is low or even cannot be recognized. Motivated by transfer learning methods like [22], we propose a time-independent method for specific emitter identification, in which the signals of radiation sources at different time are regarded as different signal domains, and the individual recognition system of radiation sources is not affected by time through domain adaptation method.

In addition, our system is equipped with a specially designed combined loss function, which has been experimentally proved to be more efficient in the identification of time-related radiation sources signals.

A. The Proposed System

In the specific emitter identification system of the proposed method , a time-independent radiation source fingerprint extraction network is used as feature extraction. The temporal IQ signal of the radiation source is processed by carrier frequency shifting, filtering and variable sampling rate. The processed signals are then input into the time-independent fingerprint extraction network to generate the 128-dimensional fingerprint feature vector of the radiation source. After that, the fingerprint feature vector of the radiation source is passed through the separation layer and then input into the individual classification layer of the radiation source to obtain the final identification result.

In the feature extraction, we used multiple residual modules in tandem [27] and reduced dimensions at the same time, and used the SwitchNormalization layer to ensure the stability of the feature extraction network (see Fig. 2). The feature extraction network is composed of two convolution layers and four residual modules, each of which contains three convolution layers and hops between input and output. The classification layer consists of a fully connected layer and equipped with Sigmoid activation, and each other layer of the model is equipped with P-Relu activation.

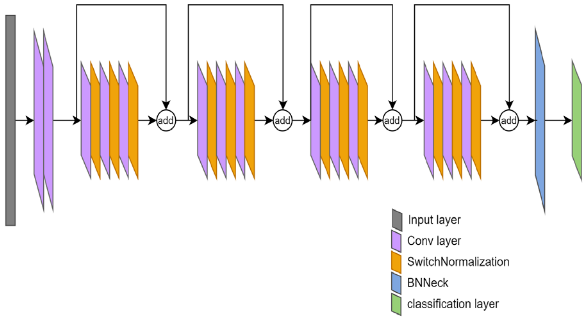

Fig. 2 Network structure diagram.

It's important to note that, in order to make the result not affected by the time domain, loss constraint should be added to the feature vector, but there is still inconsistency between feature loss and classification loss in training optimization. In terms of loss value, it is very likely that classified loss will always decrease while feature loss will increase first and then decrease. The optimization process of the two will affect each other, making the final result learned not optimal. Therefore, we proposed to add BNNECK layer between feature extraction network and classification layer, and its formula is:

$$x_l = \alpha \frac{x_l - E(x_l)}{Var(x_l)} + freeze(\beta), \qquad (1)$$

Where x_l represents the feature graph at layer l of the network, $E(x_l)$ and $Var(x_l)$ represents the mean and variance of the feature graph respectively, and α and β represent learnable parameters to adjust the distribution of features after BNNeck. Because BNNeck smoothed the optimized inconsistencies between the two losses, the learned embedding layer clustering characteristics are better, and thus has better performance in the process of test inference identification.

B. Combinative Loss Function

MSE is the commonly used loss function in specific emitter identification, and MMD is the commonly used loss function in transfer learning. Although simple combination of them can have some effects, they cannot deal with the lack of data's label in the new time period. Considering this inevitable situation, we proposed a multi-domain and flexible labels(MDFL) loss function for specific emitter identification. The loss function is composed of domain adaptation and individual prediction:

$$L_{MDFL} = \lambda_1 \cdot L_{FL-MSE} + \lambda_2 \cdot L_{FL-MMD}, \qquad (2)$$

λ_1 =0.2 and λ_2 =0.8 are the weights values of the two branches loss respectively. L_{FL-MSE} is the individual recognition loss function improved from MSE, and L_{FL-MMD} is the time domain adaptation loss function improved from MMD.

Data labels consist of two parts: individual labels and time labels. Time labels are easy to obtain at the time of collection, but individual labels are often difficult to obtain. For data that has only a time label but no individual label, its individual label is treated as None. Based on this, L_{FL-MSE} can be written as:

$$L_{FL-MSE} = \begin{cases} (y-\hat{y})^2, & \hat{y} \neq None \\ 0 \quad , & \hat{y} = None \end{cases}, \qquad (3)$$

When the individual label is None, it is ignored when calculating the classification Loss function.

L_{FL-MMD} is a parameter to examine the mixing degree of signals from different time periods, which requires the feature vectors of the two signals. During the signal combination of two different time periods, if both signals have individual labels, the two signals are required to be the same individual. If there are signals without individual labels in the two signals, the individual of the signal pair is not required. The expression is as follows:

$$L_{FL-MMD} = \begin{cases} \|F_{a1} - F_{a2}\|_H, & y_1 = y_2 = a \neq None \\ \|F_1 - F_2\|_H, & y_1 = None \text{ or } y_2 = None \end{cases}, \quad (4)$$

Where F_{a1} and F_{a2} represent the feature vectors of individual a, F_1 and F_2 represent the feature vectors of any individual, and $\| \|_H$ represents the distance between two vectors in Hilbert space.

In this way, the improved loss function can not only make full use of the signals with individual labels, but also make use of the signals without individual labels on the basis of ensuring the completion of individual identification and time domain adaptation.

IV. EXPERIMENT

A. Experimental setup

The AD signals collected by 16 different radio stations from April 25 to May 05, 2022 and May 24 to 27, 2022 were used as data sets. Specifically, the data collected on April 25, 26, and 27 in 2022 are used as the original data set, and the data collected on April 28, 29, and 30 in 2022 are used as the unlabeled data set. All radiation sources are FM radio stations, and multiple signal samples are generated in each time period of each radiation source (the received signals are all received under actual conditions, so the SNR of each signal sample is a random value under actual conditions), and 7,346,500 signal samples are finally obtained. The length of all samples was 8192 sampling points, which were divided according to 9:1 to obtain the data of training set and test set. During the training, only the original training data set and the unlabeled training data set were involved in the training, while the data at all times were involved in the test. To verify the model, we respectively set up not using the migration method of controlled trials (using the original training set for training only) and the use of a conventional migration method of controlled trials (the original training set as the source domain, no labels training set as the target domain to migrate training), so as to verify the model of the radio signal recognition effect after across time. Each method was trained with 100 epochs, and the initial learning rate was set to 1e-5.

B. Experimental results

We conducted comparative tests between the experimental group and the two control groups in all time data, and the results were shown in Figure 3.

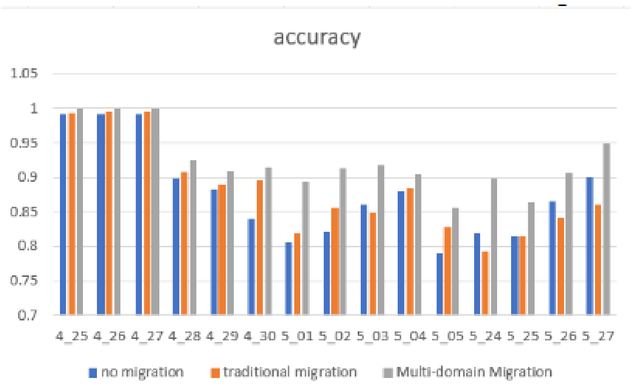

Fig. 3 Effect comparison of different methods at different times

The horizontal axis in Figure 3 represents the different times tested. On the same horizontal axis, the blue bar chart on the left corresponds to the control group without the migration plan, the orange bar chart in the middle corresponds to the control group using the traditional migration plan, and the gray bar chart on the right corresponds to the multi-domain migration method. The vertical axis represents the recognition accuracy of different training methods at different times.

It can be seen from Figure 3 that there is little difference in the accuracy of the three groups at the corresponding time of the original test set, because there is label training at these times. However, in the unlabeled test set and subsequent time, the recognition accuracy of the control group without transfer learning decreased significantly, while that of the multi-domain transfer method did not decrease significantly. At the same time, the experimental group of multi-domain migration method is obviously better than the control group of traditional migration scheme without label. The above test experiments show that the proposed multi-domain migration radiation source identification method can complete the identification task of different radiation sources. The longer the time span between the identified data and the training data, the better the performance of the proposed method compared with the traditional method. On data with partial dates, the non-domain adaptation method performs better than the traditional domain adaptation method. The reason for this may be that the traditional domain adaptation does not have enough precision when matching the unlabeled data to the labeled data for adaptation, thus having a negative optimization effect on the model.

When only the data of April 25 is used with labels, the corresponding feature map of the data of May 5 after training without the domain adaptation method is shown in Figure 4.

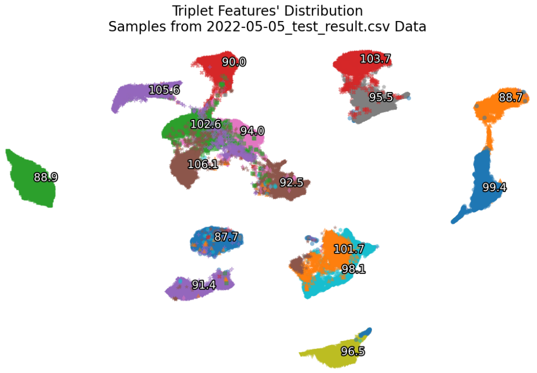

Fig. 4 Feature map of May 5 without domain adaptation training

When only the data of April 25 is used for labeling, the corresponding feature map for May 5 after training using multi-domain adaptation is shown in Figure 5.

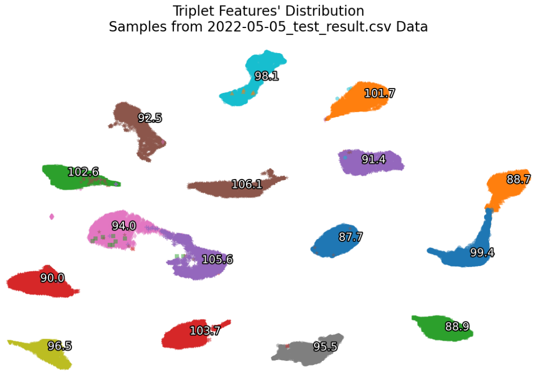

Fig. 5 Feature map of May 5 using multi-domain adaptation training

What can be clearly found is that the data of May 5, which is not involved in the training and has the largest time span with the training time, can be more clearly distinguished from the characteristics of the individual radiation sources after the multi-domain adaptation is applied.

V. CONCLUSIONS

We propose a method for specific emitter identification based on multi-domain transfer learning, which emphasizes the mixing of signals at different time of the radiation source with the multi-domain transfer learning method, so that the specific emitter identification will not be affected by its fingerprint changes with time. In addition. We design a combined loss function to give full play to its capability. A large number of experiments show that this method can achieve high recognition accuracy in radiation source identification, and solve the problem that the recognition accuracy of traditional individual radiation source identification method decreases greatly with time, and simplifies the complex data preprocessing of traditional method, and retains more original signal information.In the future, we will continue to explore and address other factors that affect the effectiveness of specific emitter identification to significantly improve the stability of specific emitter identification.

REFERENCES

[1] Choe, H. C. , et al. "Novel identification of intercepted signals from unknown radio transmitters." Proceedings of SPIE - The International Society for Optical Engineering 2491(1995):504-517.
[2] Hall, J. , M. Barbeau , and E. Kranakis . "Detection Of Transient In Radio Frequency Fingerprinting Using Signal Phase." (2003).
[3] Hall, J. , M. Barbeau , and E. Kranakis . "Detecting rogue devices in bluetooth networks using radio frequency fingerprinting." Iasted International Conference on Communications & Computer Networks DBLP, 2006.
[4] Hall, J. , M. Barbeau , and E. Kranakis . "Radio Frequency Fingerprinting for Intrusion Detection in Wireless Networks." (2005).
[5] Fu, Q. , et al. "Emitter signal sorting based on fractal dimensions of pulse envelope's front edge." International Conference on Military Communications & Information Systems IEEE, 2016.
[6] Signe, et al. "Gradient system characterization by impulse response measurements with a dynamic field camera." Magnetic Resonance in Medicine (2013).
[7] MET ★, et al. "A complete ensemble empirical mode decomposition with adaptive noise." IEEE International Conference on Acoustics IEEE, 2011..
[8] Chakraborty, B. . "Feature Subset Selection by Particle Swarm Optimization with Fuzzy Fitness Function." 0.
[9] Ding, G. , Z. Huang , and X. Wang . "Radio Frequency Fingerprint Extraction Based on Singular Values and Singular Vectors of Time-frequency Spectrum." 2018 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC) IEEE, 2018.
[10] Cain, L. , et al. "Convolutional Neural Networks for Radar Emitter Classification." IEEE CCWC 2018 IEEE, 2018.
[11] Matuszewski, J. . "Radar signal identification using a neural network and pattern recognition methods." 2018 14th International Conference on Advanced Trends in Radioelecrtronics, Telecommunications and Computer Engineering (TCSET) IEEE, 2018.
[12] Granger, E. , et al. "A What-and-Where fusion neural network for recognition and tracking of multiple radar emitters." Neural Netw 14.3(2001):325-344.
[13] Gretton, A. , et al. "A Kernel Two-Sample Test." Journal of Machine Learning Research 13(2012):723-773.
[14] Riyaz, S. , et al. "Deep Learning Convolutional Neural Networks for Radio Identification." IEEE Communications Magazine 56.9(2018):146-152.
[15] Wu, Q. , et al. "Deep Learning Based RF Fingerprinting for Device Identification and Wireless Security." Electronics Letters 54.24(2018):1405-1407.
[16] Pan, Y. , et al. "Specific Emitter Identification Based on Deep Residual Networks." IEEE Access 7(2019):54425-54434.
[17] Long, M. , et al. "Transfer Joint Matching for Unsupervised Domain Adaptation." IEEE Conference on Computer Vision & Pattern Recognition IEEE, 2014.
[18] Long, M. , et al. "Transfer Learning with Graph Co-Regularization." IEEE Transactions on Knowledge and Data Engineering 26.7(2014):1805-1818.
[19] Ghifary, Muhammad , W. B. Kleijn , and M. Zhang . "Domain Adaptive Neural Networks for Object Recognition."

Pacific Rim International Conference on Artificial Intelligence Springer International Publishing, 2014.
[20] Tzeng, E. , et al. "Deep Domain Confusion: Maximizing for Domain Invariance." Computer Science (2014).
[21] Long, M. , and J. Wang . "Learning Transferable Features with Deep Adaptation Networks." JMLR.org JMLR.org, 2015.
[22] Long, M. , et al. "Deep Transfer Learning with Joint Adaptation Networks." 2016.
[23] Goodfellow, Ian , et al. "Generative Adversarial Nets." Neural Information Processing Systems MIT Press, 2014.
[24] Zhang, W. , et al. "Collaborative and Adversarial Network for Unsupervised Domain Adaptation." 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) IEEE, 2018.
[25] Volpi, R. , et al. "Adversarial Feature Augmentation for Unsupervised Domain Adaptation." IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018 IEEE, 2017.
[26] Fang, X. , et al. "DART: Domain-Adversarial Residual-Transfer Networks for Unsupervised Cross-Domain Image Classification." (2018).
[27] He, K. , et al. "Deep Residual Learning for Image Recognition." 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) IEEE, 2016.