Angus Academic Press CCAM 2025
ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P196

One-dimensional Range Profile Target Recognition Based on Few-shot Learning

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Abstract. Using one-dimensional range profile(ORP) for radar target recognition has an important research value because of its easy acquisition, easy processing and fast calculation. Currently, the ORP recognition method represented by deep learning has been developed rapidly, while deep learning often relies on large, high-quality data sets. However, due to the particularity of requirements, it is difficult to obtain a large number of target data for model learning. When the amount of data is insufficient, the model is prone to overfitting. To solve this problem, this paper proposes a method for ORP target recognition based on few-shot learning. By using metric learning, a cascaded metric loss function is established to make the features of same class more clustered in the model, at the same time, increase the differentiation between different classes of features, so as to complete the task of target recognition under the condition of small samples. The simulation data of five aerial targets are used in the experiment, and the results show that this method can effectively realize the target recognition.

Keywords: ORP; Radar Target Recognition; Few-shot Learning.

1. Introduction

Radar target recognition technology uses algorithm analysis on target echoes acquired by radar to identify target attributes, categories or models. It is an emerging interdiscipline integrating sensor, target electromagnetic scattering characteristics, environment and signal processing methods, which can provide important technical support and services in civil fields such as meteorological observation, resource exploration, environmental monitoring, etc. So, it is of great value to study radar target identification. The one-dimensional range profile (ORP) of radar can contain rich physical structure information such as the size of target, echo amplitude, scattering point distribution, etc., which can realize precise target type recognition. In addition, ORP is easy to process and obtain. Therefore, the radar target recognition based on ORP plays an important role in actual application.

In recent years, artificial intelligence technology represented by deep learning has developed rapidly, and has obtained far more effects than traditional methods in various fields. The popularity and practicality of deep learning has also been greatly developed. Therefore, using deep learning to realize ORP-based radar target recognition technology has important research value, and the deep learning method is introduced into the field of radar high resolution range profile (HRRP) target recognition. The biggest difference between deep learning and traditional methods is that the extraction network and classifier network are jointly designed and optimized end-to-end, such as encoder-decoder [1], convolutional neural network (CNN) [2][3] and recurrent neural network (RNN) [4].

However, for ORP-based radar target recognition tasks, it is difficult for researchers to obtain a large number of accurate training data for target model learning. In order to obtain better algorithm performance, deep learning often relies on high-quality large data sets, which becomes a serious data-dependent and data-consuming algorithm. In practice, it is difficult to continuously detect and track non-cooperative targets due to their high mobility, long distance, complex environment and other factors. Therefore, it is difficult to obtain a large number of samples of the target under the

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P196

global attitude angle. When the data is insufficient, the classification decision boundary trained by small samples does not have the generalization classification ability, and the model is prone to overfitting problems. The lack of data has become a key problem that restricts radar target recognition.

Therefore, Few-shot Learning has become an important technique in the field of machine learning, the goal of which is to design machine learning models that can learn efficiently and make accurate predictions using only a small number of samples. At present, there are three mainstream methods of few-shot learning, which are based on data enhancement, based on meta learning and based on metric learning. The approach based on data enhancement uses generative networks, such as Generative Adversarial Networks (GANs) [3], to synthesize additional labeled samples to achieve samples expansion. The approach based on meta learning is trained to obtain a cross-task meta learner, which guides the model to generalize to new tasks quickly by accumulating general optimization methods, such as parameter initialization and parameter update rules. The approach based on metric learning aims to obtain an embedded space where the representations of the same class are close to each other and the representations of different classes are separated from each other. Metric learning consists of an embedded module for obtaining representations and a metric module for measuring the distance between representations. This method is simple and effective, so it has been widely applied in few-shot learning. The representation methods include Matching Network [6], Prototypical Network[7], Principal Characteristic Network[8], Relation Network[9], Transductive Propagation Network[10], Feature Map Reconstruction Networks [11].

In conclusion, considering the advantage of metric learning, a radar target recognition method based on few-shot metric learning is proposed in this paper. In this method, the spatial loss function is established, the cosine classifier is constructed, and the similarity between the features of the unknown class samples and a few labeled samples is calculated to achieve the radar target recognition ultimately.

2. Few-Shot Learning-Based One-Dimensional Range Profile Recognition

2.1 Few-Shot Learning

At present, small sample problems are usually trained and tested using a meta-learning cross-task mechanism. Each task is called meta task and is a standard N-way K-shot paradigm. Where, N means categories, K means only K samples in each category are labeled. In other words, the model only learns by training K samples in each category in a meta task. After the training, the remaining data in N categories can be classified and recognized.

For small sample target recognition task, a meta task T is an N-way K-shot task scene, which is sampled from specific data set D, and the data set of a meta task consists of a Support Set (S) and a Query Set (Q). The definition is shown as

$$S = \{(x_i, y_i)\}_{i=1}^{N\times K} \tag{1}$$

$$Q = \{(x_i, y_i)\}_{i=1}^{N\times q} \tag{2}$$

$$T = \{(S_i, Q_i)\}_{i=1}^{m} \in D \tag{3}$$

Where, x_i represents target, y_i indicates its corresponding label, N represents the number of target categories, K represents the number of targets for each category in the supported set, q represents the number of targets for each category in the query set, m represents the number of meta-learning tasks. The whole sampling process is to randomly sample N categories of data from data set D at first, then randomly select K samples from each category as the support set, and finally randomly select q samples from the remaining samples of each category as the query set.

Metric Learning aims to define a certain rule of distance between the elements of the set, and use it to complete the clustering task, which can be treated as a convex optimization problem. At present, most of the small sample classification and recognition framework still adopts the idea of

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P196
metric learning, which is to learn the similarity between sample information. The network structure of this kind of method is relatively simple and can achieve good classification effect.

In small sample tasks, It is often necessary to map the input sample information to feature vectors, and determine the category similarity by comparing the distance between vectors. Samples of the same category are closer, so classification can be completed according to the distance between them. Therefore, choosing a better distance measurement can improve the performance of the classifier in the network. The common distance functions are Euclidean Distance, Manhattan Distance, Cosine similarity function.

2.2 Few-Shot Learning Based on Metric Learning

In this paper, a cascaded metric loss function is constructed to increase the differentiation of different class features for metric learning, the similarity between the features of unknown target samples and a few labeled samples is calculated to complete the prediction of unknown radar target samples and realize the task of target recognition.

Firstly, the cross-entropy loss function L_{CE} is constructed in this paper to evaluate the similarity between the predicted value p and the real value q of the model. The smaller the loss function L_{CE}, the better the robustness of the model, which is defined as:

$$L_{CE} = -\frac{1}{N}\sum_{i=1}^{N}\left(q_i \log\left(p_i\right) + \left(1-q_i\right)\log\left(1-p_i\right)\right) \tag{4}$$

Where, N indicates the number of samples.

Secondly, the central loss function L_C is constructed. L_C learn the feature center of each class simultaneously, and punish the distance between the feature and its corresponding class center, which is defined as

$$L_c = \frac{1}{2}\sum_{i=1}^{B}\left\|x_i - z_{y_i}\right\|_2^2 \tag{5}$$

Where, y_i represents the class of the *i*-th target, and x_i represents the features of the *i*-th target extracted by the network, z_{y_i} represents the central feature of the *y*-class target, and B represents the number of samples.

Thirdly, the discriminant loss function L_d is constructed, which is used to increase the separability of features of different classes and maximize the difference between classes of the model, which is defined as

$$L_d = -\log\left(\frac{\exp\left(-ED\left(o_k, \mathrm{z}_k\right)\right)}{\sum_{k' \in N}\exp\left(-ED\left(o_{k'}, \mathrm{z}_{k'}\right)\right)}\right) \tag{6}$$

$ED(\cdot\,,\cdot)$ is the standardized Euclidean distance, and o_k represents the average feature of the k-class target in the sample B, which is defined as

$$o_k = \frac{1}{B}\sum_{x_k^i \in D_{train}} \boldsymbol{F}_{x_k^i} \tag{7}$$

The final metric loss function of the model is defined as

$$L_{loss} = \xi L_{CE} + L_c + L_d \tag{8}$$

Where $\xi \in [0,1]$ represents the equilibrium hyperparameter. After building the metric function, use the dot product operator to calculate the scores for each class of target.

To solve the problem that it is difficult to find the appropriate new class weights with only a few samples and optimization steps, this paper uses cosine similarity function classifier to distinguish the new class, which is defined as

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$$ConsineSimilarity\left(x_s, x_q\right) = \frac{\langle x_s \cdot x_q \rangle}{\|x_s\|_2 \cdot \|x_q\|_2} \tag{9}$$

Where, $\langle\cdot\rangle$ represents the dot product operation, $\|\cdot\|_2$ indicates $L2$ normalization, x_s and x_q represent support set eigenvectors and query set eigenvectors, respectively. By calculating the similarity between these two feature vectors, the prediction class of the query sample is obtained finally.

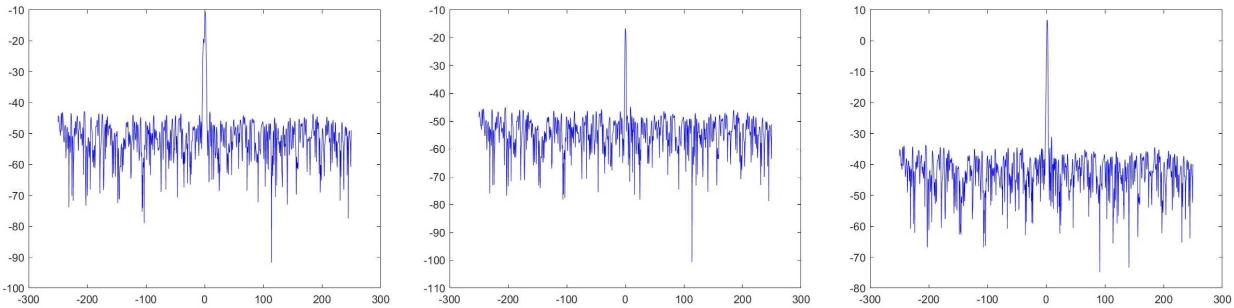
3. Experiment and Discussion

The experimental data used in this paper are aerial targets models of five types from the internet. The RCS data is obtained by electromagnetic simulation of the models, and the ORP of five types of radar targets is obtained by RCS. The simulation parameters are shown in Table 1.

Table 1. The Simulation Parameters of Aerial Targets RCS Data

Observation Distance	Azimuth	Elevation Angle	Step	Bandwidth	Center Frequency
10km	0° ~360°	-30° -30°	10°	150M	16GHz

Some ORP results obtained by simulation are shown in Fig. 1. Without loss of generality, this paper also adds noise in the simulation process, in which SNR is 10dB, 15dB and 20dB, respectively. Under different angles, the ORPs of same aerial target are different, resulting in a large intra-class gap of the aerial target. At the same time, due to the relationship between target size and radar bandwidth, the ORP between the aerial targets is relatively similar, which also creates difficulties for recognition.



(a) Target 1 (b) Target 2 (c) Target 3

Fig. 1 ORP simulation results of different satellites with elevation angle 120° and azimuth 10°

The ORP data is preprocessed first in this paper, a common preprocessing method is adopted to slice a whole strip of ORP data, so that one ORP can be divided into multiple ORP sequences. In this preprocessing method, multiple ORP sequences generated by one ORP have a certain correlation. In this paper, the sliding window length is 32 and the step length is 4. The prototype network used in this paper is the attention-based LSTM [12], which has the ability that combine the current and past moment information. 252 targets of each class were simulated. In order to verify the effectiveness of the few-shot learning method, 10 data for each class are taken as the support set and 242 samples for each class are taken as the query set. The target recognition results are shown in the Table 2.

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P196

Table 2. Recognition Accuracy with Different SNR

Target / SNR	Target 1	Target 2	Target 3	Target 4	Target 5	Accuracy
No Noise	80.53%	91.58%	97.89%	95.79%	90.00%	91.16%
10dB	83.16%	69.47%	96.32%	97.89%	87.37%	86.84%
15dB	83.68%	82.63%	95.79%	95.79%	82.63%	88.10%
2dB	80.53%	78.42%	97.37%	97.37%	90.00%	99.74%

It can be seen from the above table that with different SNR, the recognition accuracy of targets can all reach more than 85%, which illustrates that the proposed few-shot learning method has a good recognition capability under the condition of small samples. Without noise, the recognition accuracy is the highest, reaching 91.6%. After adding noise, the recognition accuracy decreases slightly. The lower the SNR, the lower the accuracy. When the SNR is 10dB, the accuracy decreases the most, which is reduced 4.32%. The experiment shows that noise affects the recognition of radar target signal, the higher the noise, the lower the recognition accuracy of target.

4. Summary

In this paper, a radar target recognition method based on metric learning is proposed to solve the few-shot samples problem of radar targets. By analyzing the distribution of features in the network model, the proposed method establishes a cascade metric loss function to increase the differentiation of different class features, and use cosine classifier to calculate the similarity between the features of unknown target samples and a few labeled samples. The experiment used five type of aerial targets simulation data and the experiment results demonstrated the proposed method can effectively realize the target recognition under the condition of small samples.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (42301467).

References

[1] Pan M, Liu A, Yu Y, et al. Radar HRRP Target Recognition Model Based on a Stacked CNN-Bi-RNN With Attention Mechanism[J]. IEEE Transactions on Geoscience and Remote Sensing, 2021, 60:1-14.

[2] Guo C, He Y, Wang H, et al. Radar HRRP Target Recognition Based on Deep One-Dimensional Residual Inception Network[J]. IEEE Access, 2019, 7:9191-9204.

[3] Wan J, Chen B, Xu B, et al. Convolutional neural networks for radar HRRP target recognition and rejection[J]. EURASIP Journal on Advances in Signal Processing, 2019, 21 (10):1725-1727.

[4] Chen W, Chen B, Peng X, et al. Tensor RNN with Bayesian Nonparametric Mixture for Radar HRRP Modeling and Target Recognition[J]. IEEE Transactions on Signal Processing, 2021, 69:1995-2009.

[5] Goodfellow I J, Pouget-Abadie J, Mirza M, et al. Generative adversarial nets[A]. Advances in Neural Information Processing Systems[C]. 2014, 3(January): 2672–2680.

[6] Vinyals O, Blundell C, Lillicrap T, et al. Matching network for one-shot learning[C]. Proceedings of the Conference on Neural Information Processing Systems, Barcelona, Spain, 2016: 3630-3638.

[7] Snell J, Swersky K, Zemel R. Prototypical networks for few-shot learning[C]. Proceedings of the Conference on Neural Information Processing Systems, Long Beach, USA, 2017: 4077- 4087.

[8] Zheng Y, Wang R, Yang J, et al. Principal characteristic networks for few-shot learning[J]. Journal of Visual Communication and Image Representation. 2019, 59: 563-573.

[9] Sung F, Yang Y, Zhang L, et al. Learning to compare: relation network for few-shot learning[C]. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Salt Lake City, USA, 2018: 1199-1208.

ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P196
[10] Liu Y, Lee J, Park M, et al. Learning to propagate labels: transductive propagation network for few-shot learning[C]. Proceedings of the International Conference on Learning Representations, New Orleans, USA, 2019: 1-14.

[11] Wertheimer D, Tang L, Hariharan B. Few-shot classification with feature map reconstruction networks[C]. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Electr Network, USA, 2021: 8008-8017.

[12] Graves A, Schmidhuber J. Framewise phoneme classification with bidirectional LSTM and other neural network architectures[J]. Neural Networks, 2005, 18(5-6): 602 -610.