PSEUDO-UNKNOWN CLASS GUIDED-BASED OPEN-SET LEARNING NETWORK FOR SAR AUTOMATIC TARGET RECOGNITION

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ABSTRACT

Most synthetic aperture radar (SAR) automatic target recognition (ATR) methods are developed for the closed-set environment, so these ATR methods can only identify known classes in the target library. However, it is known that the real scenario is open, so it requires the ATR model should be capable of identifying unknown categories while classifying known categories. Therefore, this paper proposes a pseudo-unknown class guided-based open-set learning network for SAR ATR tasks. First, to enhance the separability between known categories, a separable feature embedding space based on von Mises-Fisher (vMF) distribution is established. Second, unknown class decision boundaries are constructed based on pseudo-unknown classes synthesized by known categories, and are expanded based on the idea of contrastive learning, which is very helpful in promoting the ability of the model to identify unknown categories. Experiments on moving and stationary target acquisition and recognition (MSTAR) dataset demonstrate the effectiveness of the proposed method.

Index Terms— Synthetic aperture radar, automatic target recognition, open-set learning, contrastive learning

1. INTRODUCTION

As an active microwave detection device, synthetic aperture radar (SAR) has been widely used in remote sensing, environment surveillance, and military applications because of its ability to all-weather and all-day imaging. Automatic target recognition (ATR) is one of the major means to obtain valuable information from SAR imagery, so ATR has always been a crucial topic in the field of SAR image interpretation.

With the rapid development of deep learning in an end-to-end learning manner, numerous deep learning-based SAR ATR methods have been proposed in recent years. For instance, Chen *et al.* [1] designed an all-convolutional classification network to achieve SAR ATR for the first time. Ren *et al.* [2] proposed a multi-scale convolutional capsule network to realize SAR target recognition under various complex scenarios. Zhou *et al.* [3] integrated attributed scattering center and deep convolutional neural networks to address the problem of the adversarial attack in SAR ATR tasks.

Currently, most existing deep learning-based SAR ATR systems are designed for the closed-set environment, which faces a significant challenge when encountering novel targets in real-world scenarios. To effectively identify unknown targets while classifying known targets, open-set recognition (OSR) [4] has received great attention over the past few years. In [5], the maximum logit score (MLS) is employed to design the open-set classifier. Ma *et al.* [6] developed a multitask learning network based on generative adversarial network (GAN) for open-set SAR target recognition. Giusti *et al.* [7] introduced the OpenMax classifier to achieve open-set SAR target recognition.

Although some preliminary achievements have been achieved in open-set SAR target recognition recently, there are still many issues to be addressed. In particular, the sensitivity characteristic of SAR images to radar view variation results in intra-class divergences being greater than inter-class divergences, which brings great challenges to unknown category identification and known category classification. In this paper, we propose a pseudo-unknown class guided-based open-set learning network for SAR ATR tasks. Specifically, to improve the separability between known categories, we construct a separable feature embedding space based on von Mises-Fisher (vMF) distribution. Moreover, inspired by the advantage of contrast learning, we establish and expand the unknown class decision boundaries by using pseudo-unknown classes synthesized by known classes, aiming to boost the ability of the ATR to identify unknown classes.

2. METHODOLOGY

In this section, the proposed open-set SAR ATR method is elaborated. The overall framework consists of two parts: separable feature embedding space modeling and open-set recognition, as shown in Fig. 1.

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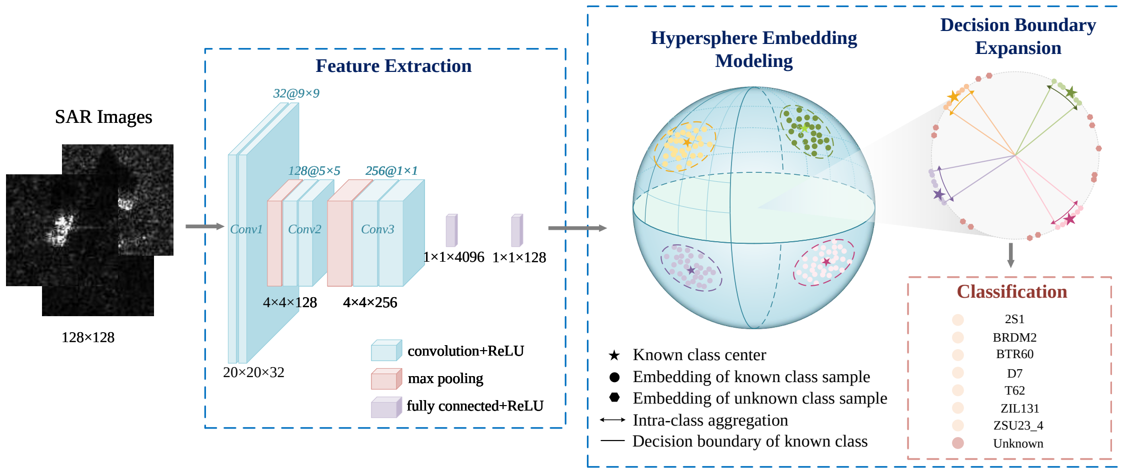


Fig. 1. Overall framework of the proposed method.

2.1. Separable feature embedding modeling

Since SAR images are sensitive to radar sensor view, the divergences within classes are greater than the divergences between classes. As a consequence, in order to extract separable and discriminative SAR features for robust open-set recognition, we model a separable feature embedding space based on von Mises-Fisher (vMF) distribution [8], which is defined on the unit sphere in n-dimension space. The probability density function of vMF distribution is written as follows:

$$p_d\left(\mathbf{z}; \boldsymbol{\mu}_c, \kappa\right) = Z_d(\kappa) \exp\left(\kappa \boldsymbol{\mu}_c^\top \mathbf{z}\right) \tag{1}$$

where $\mathbf{z}$ represents the normalized feature embedding after the feature extraction network, i.e., $\|\mathbf{z}\|^2 = 1$, $\boldsymbol{\mu}_c$ represents the prototype of c-th class, and $\kappa \geq 0$ describes the concentration of the distribution around the class prototype $\boldsymbol{\mu}_c$. $Z_d(\kappa)$ is the normalization factor, which is defined as:

$$Z_d(\kappa) = \frac{\kappa^{n/2-1}}{(2\pi)^{n/2} I_{n/2-1}(\kappa)} \tag{2}$$

where $I_v(\kappa)$ denotes the modified Bessel function of the first kind at order v.

According to [8], angular distance can better measure the similarity between high-dimensional features compared to Euclidean metric, thus enhancing the separability of known classes. To this end, we design a hypersphere classification loss based on cosine similarity to encourage the embedding to be tightly distributed around its class prototype, which is expressed as:

$$\mathcal{L}_{cls} = -\frac{1}{N} \sum_{i=1}^{N} y_i \log\left(\frac{e^{\kappa \mu_{y_i}^\top z_i}}{\sum_{k=1}^{K} e^{\kappa \mu_k^\top z_i}}\right) \tag{3}$$

where N denotes the size of the known samples.

2.2. Unknown decision boundary expansion

In order to effectively identify unknown classes, we first introduce the idea of manifold mixup to synthesize pseudo-unknown classes through known classes, and then expand the boundaries of unknown classes based on supervised contrastive learning. As one can see from Fig. 1, targets from existing known classes can be modeled to be several subspheres in the hypersphere space. Thus, we argue that each subsphere is compacted in separable feature embedding space, which is beneficial to identifying known classes and unknown classes.

In view of the fact that the similarity of SAR images from the different targets can be higher than that of SAR images from the same target. For this reason, we first introduce the idea of manifold mixup [9] to synthesize pseudo-unknown classes using known classes, and then compact the known classes based on contrastive learning, so as to expand the decision boundary of unknown class, as depicted in Fig. 2.

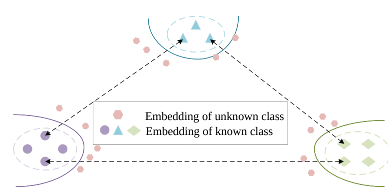


Fig. 2. Illustration of manifold mixup of pseudo-unknown embeddings.

Let $(\mathbf{z}_i, y_i)$ and $(\mathbf{z}_j, y_j)$ are two random embedding-target pairs from different classes $(y_i \neq y_j)$, the manifold mixup process of pseudo-unknown embedding $(\tilde{\mathbf{z}}, \tilde{y})$ is as follows:

$$\begin{aligned} \tilde{\mathbf{z}} &= \lambda \mathbf{z_i} + (1-\lambda)\mathbf{z}_j \\ \tilde{y} &= \lambda y_i + (1-\lambda) y_j \end{aligned} \tag{4}$$

where $\lambda \in [0, 1]$ represents the mixing factor sampled from $\text{Beta}(\alpha, \alpha)$ distribution.

Then, we leverage the idea of supervised contrastive learning [10] to obtain an embedding space with intra-class compactness. In simple terms, an intra-class aggregation loss is defined as follows:

$$\mathcal{L}_{itra} = -\sum_{i \in I} \frac{1}{|P(i)|} \sum_{p \in P(i)} \log \frac{\exp\left(\boldsymbol{z}_i \cdot \boldsymbol{z}_p / \tau\right)}{\sum_{a \in I \backslash \{i\}} \exp\left(\boldsymbol{z}_i \cdot \boldsymbol{z}_a / \tau\right)} \tag{5}$$

where I is the total number of the training samples, $P(i)$ is the set of positive samples sharing the same label as z_i, and τ is a scaling parameter.

The total loss of the proposed method is composed of hypersphere classification loss and intra-class aggregation loss, which can be written as:

$$L_{total} = L_{cls} + \gamma L_{itra} \tag{6}$$

where γ is the loss weight parameter to balance the two terms.

2.3. Target identity inference

In the reference stage, we determine the identity of a test sample $\mathbf{x}$ based on the similarity score, which is defined as the maximum cosine distance between the embedding and class prototypes of known classes:

$$sim = \max_{c \in (1,\ldots,K)} cosine\left(\mathbf{z}, \mu_c\right) \tag{7}$$

where $\mathbf{z}$ is the learned embedding of the test sample $\mathbf{x}$.

3. EXPERIMENTAL RESULTS

In this section, we present several experiments on the moving and stationary target acquisition and recognition (MSTAR) [11] dataset to validate the effectiveness of the proposed method. The MSTAR dataset is established by the U.S. Defense Advanced Research Projects Agency (DARPA), which contains 10 classes of military ground targets. Following previous studies [2, 6], images with 17° depression are selected for training, and those with 15° depression are used for testing. All SAR images are used with 128×128 pixels.

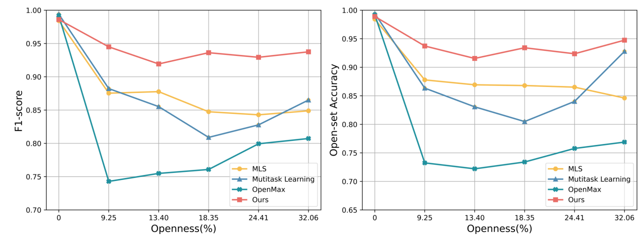
To evaluate the performance under the open-set environment, we select 7 types of SAR targets as known targets for training, including 2S1, BRDM2, BTR60, D7, T62, ZIL131, and ZSU23/4, and a total of 2425 images from all the 10 types of targets are used to test the ATR model. Stochastic gradient descent (SGD) optimizer is used to optimize the proposed method. The learning rate is set to 0.001, and γ is set to 0.5.

3.1. OSR performance evalution

To demonstrate the superiority of the proposed method, three advanced open-set SAR target recognition methods, including MLS[5], Mutitask Learning[6], and OpenMax[7] are employed as competitors in this paper.

Table 1. Recognition performance of each method.

Method	AUROC	F1	OA*	OA
MLS[5]	86.30	0.8754	86.29	87.51
Mutitask Learning[6]	92.97	0.8823	84.14	86.35
OpenMax[7]	86.80	0.7429	68.28	69.60
Ours	**96.35**	**0.9450**	**94.02**	**93.73**



(a) (b)

Fig. 3. Recognition performance with various openness. (a) F1-score, (b) Open-set Accuracy.

Four evaluation metrics, i.e., area under ROC curve (AUROC), F1-score (F1), closed-set accuracy (OA*), and open-set accuracy (OA), are leveraged to comprehensively evaluate the proposed method. Among them, AUROC, F1 and OA are widely employed for OSR algorithm assessment, and OA* can reflect the classification performance of known classes under open-world scenarios. From the experimental results in Table 1, one can see that our proposed method is superior to state-of-the-art open-set SAR ATR methods.

Moreover, a desirable open-set target recognition model should perform robustly regardless of the ratios of known and unknown classes. Thus, *openness* [4] is defined to describe how open the environment is:

$$openness = 1 - \sqrt{\frac{2 \times |C_{TR}|}{|C_{TR}| + |C_{TE}|}} \tag{8}$$

where C_{TR} and C_{TE} represent the number of training and testing classes, respectively.

In the following experiments, we compare the performance of different methods under various *openness*. Specifically, the number of known classes decreases from 7 to 3 with a step of 1, and the corresponding openness increases from 9.25% to 32.06% according to Eq. (8). Due to the space constraints, only F1-score and open-set accuracy are presented in Fig. 3. One can see that the OSR performance of the proposed method still outperforms all competitors under different open environments. These experimental results validate the robustness of our proposed method.

3.2. Ablation studies

To assess the effectiveness of key components of the proposed method, we conduct ablation studies on MSTAR dataset. For simplicity, the model with the separable feature embedding modeling, or an unknown decision boundary expansion are dubbed SFEM and UDBE, respectively. As shown in Table 2, each key component contributes to the known class classification and unknown class identification in the proposed method.

Table 2. Results of ablation experiments.

SFEM	UDBE	AUROC	F1	OA*	OA
✓	✗	94.76	0.9157	92.39	92.58
✗	✓	90.98	0.8967	89.30	87.71
✓	✓	**96.35**	**0.9450**	**94.02**	**93.73**

3.3. Visualization of hyperspherical embedding space

To intuitively observe the proposed separable feature embedding space, we use t-SNE to visualize the learned feature space. The experimental results are presented in Fig. 4. It can be observed that different known classes are well separated from each other as well as from the unknown class.

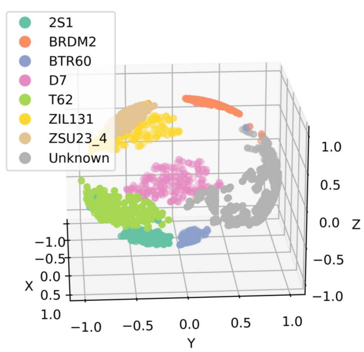


Fig. 4. Visualization of separable embedding space.

4. CONCLUSION

To achieve robust open-set SAR target recognition, this paper proposes a pseudo-unknown class guided-based open-set learning network. The contribution of this paper includes two aspects. On the one hand, a separable feature embedding space is modeled to enhance the discrimination between known and unknown classes. On the other hand, an unknown decision boundary expansion strategy is developed to improve the open-set recognition performance. Several experiments on MSTAR show that the proposed method outperforms some advanced open-set SAR ATR methods.

5. REFERENCES

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