Threshold-free Open-set Learning Network for SAR Automatic Target Recognition

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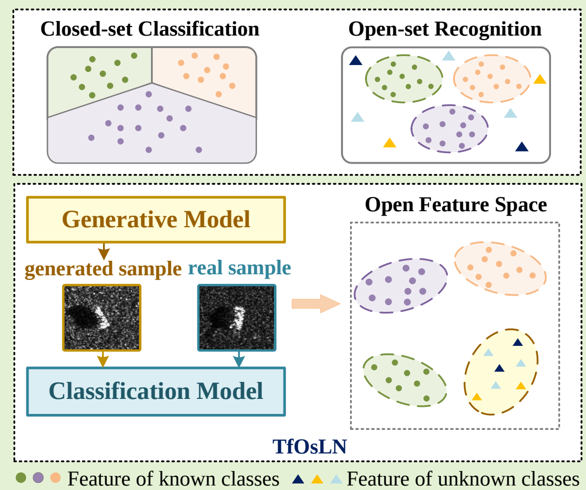
***Abstract*—Many advanced automatic target recognition (ATR) methods for synthetic aperture radar (SAR) encounter limitations as they heavily rely on the assumption of a closed-set environment. Consequently, these methods face challenges in effectively identifying and classifying targets from novel categories. Therefore, this paper puts forward an ATR method called threshold-free open-set learning network (TfOsLN) for unknown category detection and known category recognition of SAR targets in an open world. On the basis of generative adversarial network (GAN), the proposed TfOsLN abandons the threshold-based decision-making mechanism, and formulates the open-set problem as a K+1 classification problem. First, to avoid model collapse of the generator, we leverage Kullback–Leibler (KL) divergence to maximize the difference between images synthesized by two random noise inputs with the same label. Then, a dynamic-aware discriminator is proposed to dynamically learn discriminative features according to the target category, thereby enhancing the discrimination between known and unknown categories. Moreover, a multi-task loss is devised to optimize the proposed method, which aims to perform well on unknown categories detection and known categories recognition. Experiments on the moving and stationary target acquisition (MSTAR) and synthetic and measured paired and labeled experiment (SAMPLE) datasets illustrate that the proposed method is superior to some state-of-the-arts for open-set SAR target recognition tasks.**



***Index Terms*—Synthetic aperture radar (SAR), automatic target recognition (ATR), generative adversarial network (GAN), open set recognition (OSR).**

I. Introduction

SYNTHETIC aperture radar plays a major role in the fields of remote sensing, surveillance, and guidance due to its high resolution in all-day and all-weather conditions. Nevertheless, the inherent complexity of SAR imagery, such as speckle noise and electromagnetic scattering effect, poses a significant challenge for human interpreters as the number of collected SAR images continues to increase. Therefore, the development of SAR image interpretation techniques remains an important and urgent task.

Automatic target recognition (ATR) is an essential application of SAR image interpretation, and it appears to be one of the most challenging tasks in the SAR community. Over the past years, target recognition in SAR images has continued to make great advancements. Currently, SAR ATR methods can be roughly divided into two paradigms, i.e., tradition-based and learning-based. Among them, tradition-based method is dedicated to characterizing and distinguishing targets by their geometric and physical characteristics in the image domain [1]. In contrast, learning-based method first focuses on extracting handcrafted features in the transform domain, and then reasoning the identity of target based on a predefined classification criterion [2]. Nevertheless, these methods rely heavily on hand-crafted features, which struggle to achieve robust target recognition in complex SAR scenarios.

With the vigorous development of deep learning (DL) technology, it provides an alternative idea for achieving SAR ATR. After years of continuous efforts, a great number of deep learning-based SAR ATR methods have been proposed. For instance, Chen *et al.* [3] presented an all-convolutional neural network to achieve SAR target recognition for the first time. Pei *et al.* developed a parallel convolutional neural network to solve the problem of multi-view SAR target recognition [4]. Ren *et al.* [5] devised a convolutional capsule network to extract multi-scale equivariant features for SAR ATR tasks. Li and Du combined the attribute scattering center model and dis-

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criminative dictionary learning to extract global features that are more representative for SAR classification [6]. However, these methods are constrained by the closed-set environment assumption, i.e., the types of targets encountered during testing must align with those in the training set. Consequently, in real-world scenarios, traditional SAR ATR methods will inevitably misclassify unknown targets into one of known categories.

In order to endow the model with the ability to classify known categories and detect unknown categories, a novel learning paradigm called open-set recognition (OSR) [7] has been introduced. In recent years, many scholars have carried out research on this problem. Existing methods can be divided into two main categories: 1) traditional machine learning-based methods and 2) deep learning-based methods. Some traditional machine learning algorithms, such as support vector machine (SVM) [8], Gaussian mixture model [9] and nearest neighbor classifier [10], [11], have been extended to tackle open-set recognition tasks. Nevertheless, these methods tend to rely on hand-crafted feature extraction and parameter selection, resulting in unstable open-set recognition performance.

Currently, numerous deep learning-based open-set recognition approaches continue to emerge. Vaze *et al.* [12] proposed to exploit the maximum logit score (MLS) as the open-set indicator. Chen *et al.* [13] proposed an adversarial reciprocal point learning (ARPL) framework to achieve open-set recognition. Huang *et al.* [14] presented a novel OSR method based on class-specific semantic reconstruction (CSSR), which integrates the merits of auto-encoder and prototype learning. Recently, scholars have pursued preliminary explorations for open-set SAR target recognition. Zeng *et al.* proposed a new method based on feature extraction network, KL divergence, and relative position angle, called Fea-DA, to achieve open-set SAR target recognition [15]. Ma *et al.* presented a multi-task learning framework for open-set SAR target recognition [16]. Giusti *et al.* [17] examined the openmax (OpenMax) classifier to detect unknown categories and classify known categories in SAR images. In [18], a sub-dictionary joint learning method is proposed for open-set SAR classification. Safaei *et al.* [19] proposed a novel module, namely category-aware binary classifier (CBC), to realize open-set SAR target recognition. Ma *et al.* developed an open-set SAR target recognition method in the incremental learning framework by utilizing identified unknown targets [20]. However, existing methods are based on a fixed threshold for open-set SAR target recognition, whereas the threshold setting is still derived from empirical knowledge.

To promote the performance of unknown class detection and known class recognition, this paper proposes a novel method called threshold-free open-set learning network (TfOsLN) for open-set SAR target recognition. The main contributions are summarized as follows.

1) We formulate the open-set SAR target recognition problem as a K+1 classification problem with a diverse unknown sample generation strategy.
2) We develop a dynamic-aware discriminator that can enhance the discrimination between features of known classes and unknown classes, thus facilitating the detection of unknown targets.
3) A multi-task loss is proposed to optimize the model, which can achieve outstanding performance in both unknown class detection and known class recognition.

II. Related Work

A. Open-set Recognition

The traditional multi-classification problem has undergone thorough investigation and demonstrated satisfactory performance across diverse fields [6], [21], [22]. However, these methods are constrained by the closed-set assumption, which assumes an ideal match between the categories in the training set and those in the testing set. In real-world scenarios, novel categories that have not been seen during the training stage can inevitably appear. The closed-set classifier tends to incorrectly classify these samples as one of the known categories. Different from the conventional closed-set classification problem, open-set recognition is more challenging and realistic as it takes both known category classification and unknown category detection into account.

Over the past few decades, researchers have extensively investigated OSR methods in open-world environments. Early studies relied largely on traditional machine learning algorithms. For instance, POS-SVM [8] and 1-vs-set machine [23] are representative SVM-based approaches employed for OSR tasks. Mendes *et al.* [10] proposed a nearest neighbors distance ratio open-set classifier based on the similarity between a sample and its nearest known neighbors. Zhang *et al.* presented a sparse representation-based classification (SRC) framework to achieve open-set recognition [24].

With the advancement of deep learning techniques, many OSR methods based on deep neural networks have been proposed recently. According to [25], these methods can be categorized into two main groups: discriminative models and generative models. Among them, discriminative models, such as MLS [12], CSSR [14] and OpenMax [26], focus on learning a decision boundary to separate known classes from unknown classes. On the other hand, generative models learn the distribution of known classes and generate data to provide the OSR model with prior knowledge about unknown classes. GAN [16], [27], auto-encoder(AE) [28] are widely used to generate unknown data for open-set recognition tasks.

Currently, scholars have significantly contributed to the preliminary explorations of open-set SAR target recognition [15], [16], [17], [29], [19]. However, existing methods relied heavily on a predefined threshold to achieve SAR open-set recognition. Therefore, we propose a threshold-free open-set recognition network to tackle this problem.

B. Generative Adversarial Network

Generative adversarial network [30] is an impressive learning framework designed to generate new samples that resemble real data, which involves two neural networks, i.e., the generator and the discriminator. By engaging in an adversarial minimax game between these two networks, GAN is able to produce highly realistic data. Thus, GAN has been widely used in data augmentation, image-to-image translation, high-resolution image generation, and more.

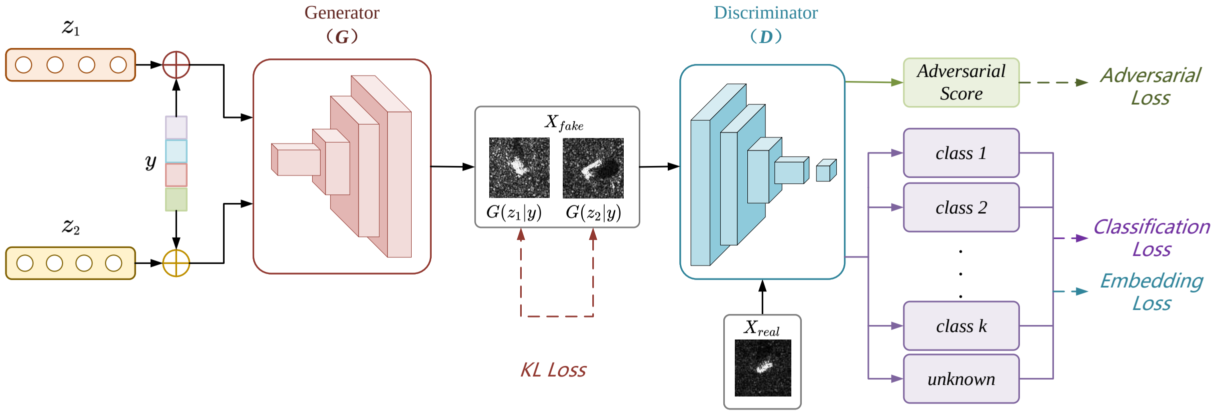


Fig. 1. Overall framework of the proposed method.

To adapt to real-world scenarios, many OSR methods based on generative models [16], [27] have leveraged the powerful generation ability of GAN to synthesize samples from novel categories. An example of such advancement is conditional generative adversarial network (CGAN), which can generate samples based on specific class labels, enhancing the quality of data generation. These generated samples can provide valuable prior knowledge about unknown data for the model.

However, the instability of GAN's training continues to pose a significant challenge for existing methods as it is difficult to reach a balance between the generator and the discriminator. Specifically, model collapse often leads to failure of training, that is, the generator fails to capture the entire distribution of the input data and only outputs a limited set of samples. Therefore, this paper designs a diverse generation strategy to mitigate this phenomenon.

III. Methodology

The proposed method consists of two components, i.e., the generative model G and the classification model D, as depicted in Fig. 1. Among them, the function of the generative model G is to generate unknown diverse samples outside the distribution of known categories targets, which is used to assist the classification model D in acquiring the ability to detect unknown categories. Unlike existing threshold-based open-set SAR target recognition methods, the classification model in the proposed TfOsLN formulates the open-set problem as a K+1 class classification problem. In what follows, we elaborate on each component of the proposed method.

A. Unknown Sample Generation

Compared with closed-set SAR target recognition, open-set SAR target recognition is challenging due to the lack of prior knowledge about unknown categories. Drawing on the merits of generative adversarial network (GAN), a generative model is developed to generate diverse unknown samples deviating from known category distribution, which is intended to assist the recognition model with the ability to detect unknown categories. Therefore, the effectiveness of our method is closely related to the quality of the generated SAR images produced by the generator. If the generated samples lack realism or diversity, the generative model cannot provide the classification network with rich information about unknown class. However, the model collapse problem, i.e., the generator fails to capture the entire distribution of the input and ends up replicating resemble samples. To mitigate this effect, we first propose to establish a dual-input generation model, and then leverage KL divergence to maximize the difference between images synthesized by two noise inputs with the same label to generate diverse samples of unknown categories. This strategy effectively forces a more varied distribution. of generated SAR images.

Let z_1 and z_2 be two random noise vectors with the same label, KL divergence is leveraged to maximize the difference between the distributions of images synthesized by the generator. Mathematically, it is expressed as follows:

$$\max\ KL\left[G(z_1|y)\,||\,G(z_2|y)\right] \tag{1}$$

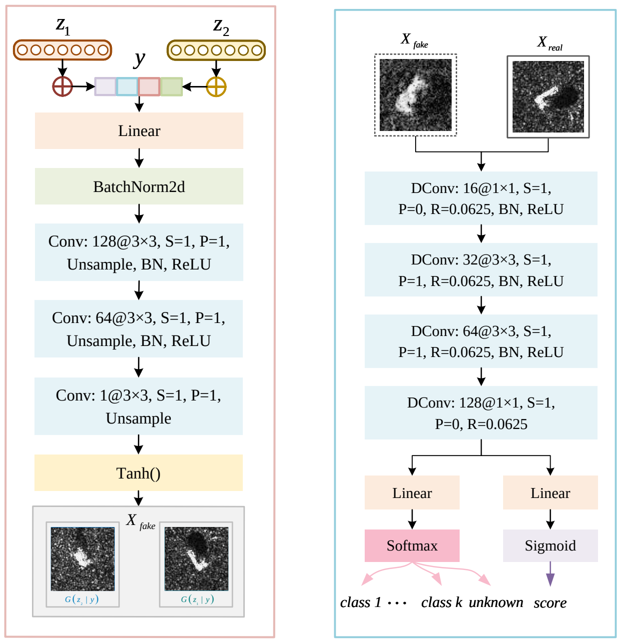
where $G(z_1|y)$ and $G(z_2|y)$ represent generated images by the noise vectors z_1 and z_2 given the class label y, respectively.

B. Threshold-free Open-set Recognition

In order to achieve open-set SAR target recognition, a threshold-free open-set recognition model is developed under the framework of GAN, as shown in Fig. 2.

The output of the threshold-free open-set recognition model consists of two items, i.e., the classification score and the adversarial score. Among them, the classification score is used to realize target classification. The adversarial score is exploited to assist the generative model in generating diverse unknown samples that deviate from the known categories distribution in an adversarial learning manner. The adversarial score ranges from [0,1]. If the adversarial score is close to 1, it indicates that the input is a real image; otherwise, it is a generated image.

The recognition model should be highly sensitive to samples of unknown categories in an open-world environment, it is desirable that the extracted features of unknown categories be as discriminative as possible. To this end, inspired by dynamic convolution [31], we develop a dynamic-aware discriminator to extract discriminative features according to input samples.



(a) (b)

Fig. 2. Network structure of (a) Generative model. (b) Classification model. DConv denotes the dynamic convolution operation layer. $\boldsymbol{c}$@$\boldsymbol{k} \times \boldsymbol{k}$, $\boldsymbol{S} = \boldsymbol{s}$, $\boldsymbol{P} = \boldsymbol{p}$, $\boldsymbol{R} = \boldsymbol{r}$ indicates the this layer contains $\boldsymbol{c}$ output channels and the kernel size of $\boldsymbol{k} \times \boldsymbol{k}$ convolution with stride $= \boldsymbol{s}$, padding $= \boldsymbol{p}$ and reduction ratio $= \boldsymbol{r}$.

The dynamic-aware convolutional layer is the core of the proposed dynamic-aware discriminator, which is depicted in Fig. 3. Different from conventional CNN, the dynamic convolution layer can update the convolution kernel with the help of an attention mechanism, so as to dynamically extract more representative features from different categories of images. The operation of the dynamic convolutional layer is as follows:

$$\begin{aligned}\mathbf{y} = (&\alpha_{w1} \odot \alpha_{f1} \odot \alpha_{c1} \odot \alpha_{s1} \odot W_1 + \ldots \\ &+\alpha_{wn} \odot \alpha_{fn} \odot \alpha_{cn} \odot \alpha_{sn} \odot W_n) * \mathbf{x}\end{aligned} \tag{2}$$

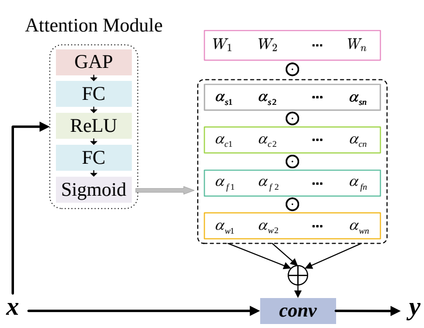


Fig. 3. Architecture of dynamic-aware convolution layer.

C. Multi-task Loss Optimization

It is well known that the optimization process of GAN is considered as a minimax game between the generator G and the discriminator D. The adversarial loss is defined as:

$$L_{G_{adv}} = -E\left[logP\left(S = fake \mid X_{fake}\right)\right] \tag{3}$$

$$L_{D_{adv}} = E\left[logP\left(S = real \mid X_{real}\right)\right] \tag{4}$$

where X_{real} and X_{fake} represent real SAR images and generated ones, respectively. And $P(S|X) = D(X)$ denotes the probability of a given SAR image being real or fake.

Meanwhile, the model needs to judge the generated unknown and known category samples in the adversarial game. Namely, the classification loss for the generated images and the real SAR images are defined as follows:

$$L_{G_{cls}} = E\left[logP(C = c \mid X_{fake})\right] \tag{5}$$

$$\begin{aligned}L_{D_{cls}} = &E[\log D(C = c \mid X_{real})] \\ &+ E[\log D(C = unknown \mid X_{fake})]\end{aligned} \tag{6}$$

where c is the label of one of the K known categories.

In order to enhance the generalization ability of the proposed method, we propose to use the soft label instead of the one-hot label during model training. Thus, $L_{D_{cls}}$ is the label smoothing cross-entropy loss function. The soft label of a sample is defined as:

$$y = (1 - \alpha)y_{hot} + \alpha/K \tag{7}$$

where y_{hot} is the one-hot label of a sample, and α is the smoothing parameter.

As mentioned above, KL divergence is leveraged to avoid model collapse of the generative model in the proposed method, which is defined as:

$$L_{G_{div}} = -KL\left[G(z_1|y) \,||\, G(z_2|y)\right] \tag{8}$$

In an open-set recognition task, it is more desirable to obtain a discriminative embedding space with intra-class compactness and inter-class divergence, which is not only beneficial for known categories classification but also very meaningful for enhancing unknown categories detection. Following this idea, we introduce a novel embedding loss, i.e., single-center loss [32], to learn a discriminative embedding space with intra-class compactness and inter-class separability. The embedding loss is defined as:

$$L_{D_{emb}} = M_{real} - M_{fake} + m\sqrt{N} \tag{9}$$

where M_{real} represents the average Euclidean distance between all real image representations and the prototype of known categories targets c, and M_{fake} represents the average Euclidean distance between all generated image representations and the prototype of known categories targets c. The role of the margin $m\sqrt{N}$ is to ensure that the distance measure-based embedding loss $L_{D_{emb}}$ is always positive.

M_{real} and M_{fake} are defined respectively as follows:

$$M_{real} = \frac{1}{|\Omega_{real}|} \sum_{i \in \Omega_{real}} \|f_i - c\|_2 \tag{10}$$

$$M_{fake} = \frac{1}{|\Omega_{fake}|} \sum_{i \in \Omega_{fake}} \|f_i - c\|_2 \tag{11}$$

where Ω_{real} and Ω_{fake} are the representation sets of real SAR images and generated ones, respectively.

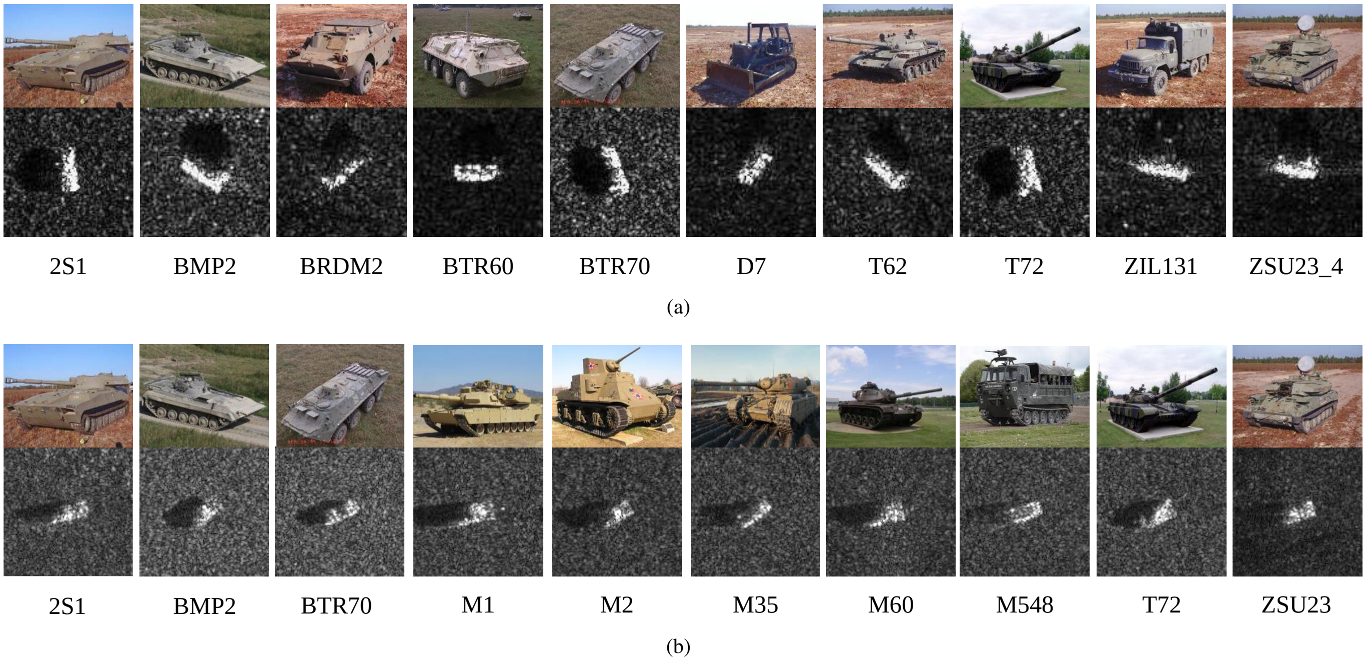


Fig. 4. Each type of ground target of two datasets. (a) MSTAR dataset. (b) SAMPLE dataset.

Therefore, the proposed multi-task loss is composed of three items, i.e., adversarial loss, classification loss, and embedding loss. The total loss for the generative model and the classification model are respectively summarized as:

$$L_G = L_{G_{adv}} + L_{G_{cls}} + \lambda_G \cdot L_{G_{div}} \tag{12}$$

$$L_D = L_{D_{adv}} + L_{D_{cls}} + \lambda_D \cdot L_{D_{emb}} \tag{13}$$

where λ_G and λ_D are two hyperparameters selected through the experiments in Section IV-F.

IV. EXPERIMENTAL RESULTS

A. Dataset Description

To demonstrate the effectiveness of our proposed method, this section conducts experiments on two public SAR datasets. One dataset is the moving and stationary target acquisition and recognition (MSTAR) [33] with 10 categories of military targets, which has been widely used for ATR algorithm evaluation. The other dataset is the synthetic and measured paired and labeled experiment (SAMPLE) [34] with 10 types of ground targets, which is composed of measured images and simulated images from computer aided design (CAD) models. The optical and SAR images of ten ground target classes for two datasets are shown in Fig. 4(a) and Fig. 4(b), respectively. It is worth mentioning that several categories of targets are the same in both datasets. As a matter of routine [4], [5], [16], SAR images with 17° depression are used for training, 15° are selected as testing data in MSTAR dataset. In SAMPLE dataset, only measured SAR images with depressions from 14° to 16° are utilized for training, and images with 17° depression are used for evaluation. Detailed data information for the two datasets are listed in Table I. To reduce the redundant background, all images in both datasets are cropped to 64×64 pixels regions of interest.

TABLE I
DETAILED DATA INFORMATION OF TWO PUBLIC DATASETS

MSTAR			SAMPLE		
Target	Training data	Testing data	Target	Training data	Tesingt data
2S1	299	274	2S1	116	58
BMP2	233	195	BMP2	55	52
BRDM2	298	274	BTR70	43	49
BTR60	256	195	M1	78	51
BTR70	233	196	M2	75	53
D7	299	274	M35	76	53
T62	299	273	M60	116	60
T72	232	196	M548	75	53
ZIL131	299	274	T72	56	52
ZSU23/4	299	274	ZSU23	116	58
Total	2747	2425	**Total**	806	539

B. Experimental Setup

Adam optimizer is used for optimizing the proposed model. The learning rate of both the generative model and the classification model is set to 0.00005, the number of training epochs is 100, and the batch size is set as 32. In order to mitigate the effect of class imbalance during model training, we randomly sample $32/K$ generated images in each batch as unknown SAR training samples to effectively train the recognition network. For the four hyperparameters, we empirically set $\alpha = 0.1$, $m = 0.3$, $\lambda_G = 0.5$ and $\lambda_D = 0.1$ in the following experiments. The proposed TfOsLN is implemented with PyTorch framework in Python programming language. All experiments are conducted on a personal laptop with an AMD Ryzen 7 5800H CPU, an NVIDIA GeForce RTX3060 GPU, and 16 GB memory.

TABLE II
FOUR EVALUATION METRICS OF EACH METHOD ON THE MSTAR AND SAMPLE DATASETS

Dataset	MSTAR				SAMPLE			
Method	Precision	Recall	F1 score	Accuracy	Precision	Recall	F1 score	Accuracy
MLS [12]	86.30	88.83	0.8754	87.51	89.31	92.78	0.9094	89.80
ARPL [13]	83.89	87.90	0.8595	85.81	88.44	90.81	0.8916	87.38
CSSR [14]	90.87	89.64	0.8972	89.44	91.70	88.65	0.8868	89.24
Fea-DA [15]	92.51	90.55	0.9122	90.77	95.14	91.09	0.9282	91.47
Mutitask Learning [16]	92.97	84.94	0.8823	86.35	90.47	92.65	0.9101	90.20
OpenMax [17]	86.80	69.71	0.7429	69.60	87.40	83.21	0.8440	80.80
CBC [19]	91.69	86.72	0.8827	86.31	93.37	93.40	0.9316	91.28
Ours	**95.15**	**94.60**	**0.9481**	**95.09**	**97.61**	**99.14**	**0.9801**	**97.59**

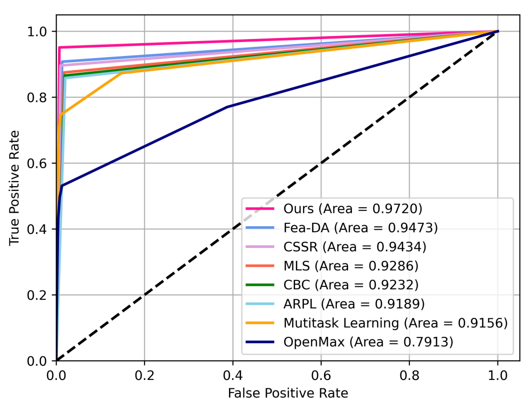


Fig. 5. Comparisons of AUROC on the MSTAR dataset.

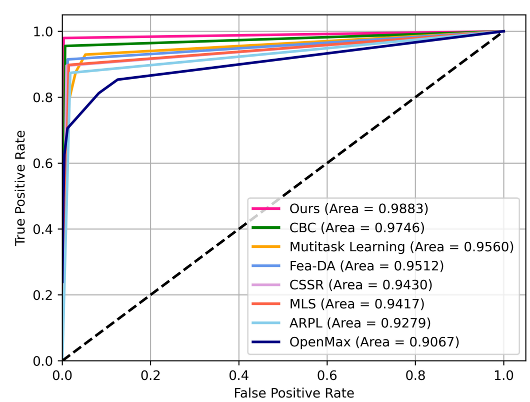


Fig. 6. Comparisons of AUROC on the SAMPLE dataset.

C. OSR Performance Evalution

Following previous studies [15], [19], seven categories of targets are selected as known, namely, 2S1, BRDM2, BTR60, D7, T62, ZIL131, ZSU23/4 for MSTAR dataset, and 2S1, BMP2, BTR70, M1, M35, M548, ZSU23 for SAMPLE dataset, while the other three categories of targets in two datasets are selected as unknown targets respectively. To illustrate the superiority of our proposed method, seven state-of-the-art methods, including MLS [12], ARPL [13], CSSR [14], Fea-DA [15], Mutitask Learning [16], OpenMax [17], and CBC [19] are employed as competitors in this paper.

Four evaluation metrics, i.e., precision, recall, F1-score, and accuracy, are adopted to comprehensively evaluate the proposed method. These metrics are defined as follows:

$$precision_i = \frac{TP_i}{TP_i + FP_i}, precision = \frac{\sum_{i=1}^{K} precision_i}{K} \tag{14}$$

$$recall_i = \frac{TP_i}{TP_i + FN_i}, recall = \frac{\sum_{i=1}^{K} recall_i}{K} \tag{15}$$

$$F1_i = \frac{2 \times precision_i \times recall_i}{precision_i + recall_i}, F1 = \frac{\sum_{i=1}^{K} F1_i}{K} \tag{16}$$

The experimental results of each method are presented in Table II. Among them, accuracy measures the overall performance of known class classification and unknown target detection, and F1-score which balances precision and recall, is used to comprehensively evaluate the performance of the open-set recognition model. One can see from Table II that four evaluation metrics of the proposed method are higher than those of all competitors on two datasets.

Moreover, we employ another indicator to evaluate the recognition performance in this experiment, i.e., area under receiver operating characteristic curve (AUROC). AUROC is a threshold-independent metric widely used to measure the unknown class detection ability of OSR methods. To compute the AUROC curve, we consider known classes as 'positive' while considering unknown classes as 'negative', and then plot the true positive rate against the false positive rate at all possible thresholds. Thus, AUROC effectively measures how well an OSR model can distinguish between known classes and unknown classes. The AUROC curves of each method on the two datasets are depicted in Fig. 5 and Fig. 6, respectively. Apparently, the AUROC indicator of the proposed method is always better than that of competitors.

It is noteworthy that both our proposed method and nearly all competitors demonstrate superior recognition performance on SAMPLE dataset in comparison to MSTAR dataset. This discrepancy primarily comes from the fact that the training set of SAMPLE dataset covers a broader range of depression angles, which makes it easier for recognition models to capture richer feature representations.

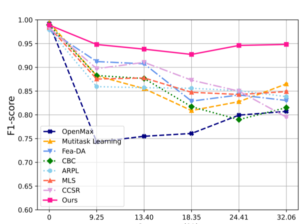
D. Impact of openness on OSR

In order to analyze the robustness of the proposed method under different proportions of known and unknown categories, the *openness* [7] is defined as follows:

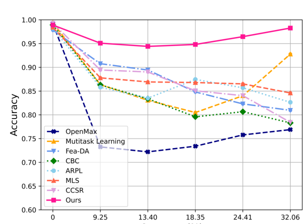
$$openness = 1 - \sqrt{\frac{2 \times |C_{TR}|}{|C_{TR}| + |C_{TE}|}} \tag{17}$$

where C_{TR} is the number of training categories, and C_{TE} is the number of test categories. The closer $openness$ is to 1, the more open the environment is, while $openness$ = 0 represents that the problem is equivalent to the closed-set classification.

In this experiment, we reduce the known classes from 7 to 3, and the $openness$ can be calculated with (17). Specifically, we construct the set of known class targets by removing one target class in each experiment following the right-to-left order: 2S1, BRDM2, BTR60, D7, T62, ZIL131, ZSU23/4 for MSTAR dataset, and 2S1, BMP2, M1, ZSU23, BTR70, M35, M548 for SAMPLE dataset. The remaining types of targets are selected as unknown targets, respectively. Under different open scenarios, the experimental results of each method on two datasets are shown in Fig. 7 and Fig. 8, respectively, in which only F1 score and accuracy are presented due to space constraints. As illustrated in Fig. 7 and Fig. 8, F1 score and accuracy of the proposed method fluctuate gently with the change of the $openness$, while the two indicators of all competitors change sharply. This is because a larger openness means more open scenarios. As openness increases, the model faces the challenge of identifying more unknown targets with less information about known classes. Thus, it becomes increasingly difficult for OSR models to maintain high accuracy and F1 score. In this context, the proposed method shows greater robustness compared to all competitors in the open world. This can be attributed to the fact that TfOsLN does not rely on a single rejection threshold, but adaptively achieves open-set SAR recognition by learning potential distribution of unknown classes.

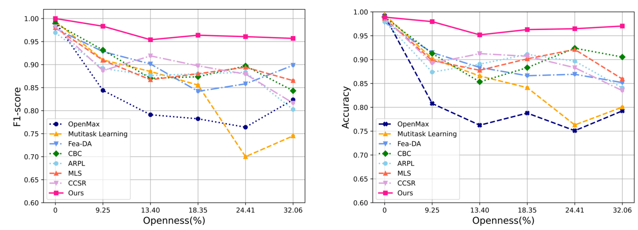


(a)



(b)

Fig. 7. Results with various openness on the MSTAR dataset. (a) F1-score, (b) Accuracy.



(a) (b)

Fig. 8. Results with various openness on the SAMPLE dataset. (a) F1-score, (b) Accuracy.

E. Visualization Results of Image Generation

In order to intuitively understand the diverse generation strategy of unknown SAR images, this section comprehensively analyzes the generation results from the perspective of visualization. Seven classes of SAR images from MSTAR dataset are used to train the proposed TfOsLN in the following experiments. Fig. 9 compares real SAR images with generated images during the training process. Each column of images represents one of the known classes, and seven instances are saved for each class. From a visual perspective, it is clear that our proposed method captures the characteristics of SAR ground targets, such as shape and shadow, enabling the generation of highly realistic images.

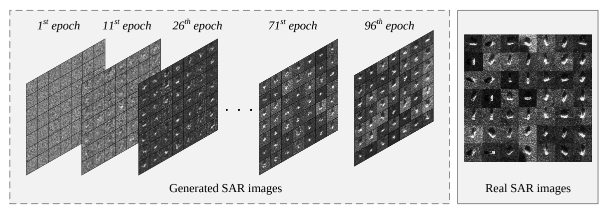


Fig. 9. Comparison between generated SAR images and real images.

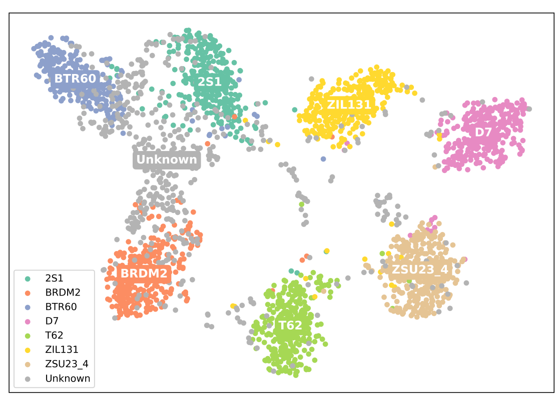
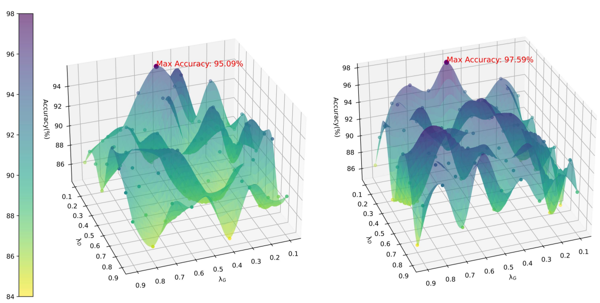


Fig. 10. Visualization of open-set feature space.

Furthermore, we aim to generate unknown samples that are highly close to real images but do not belong to any known classes for open-set SAR target recognition tasks. We illustrate the results of sample generation from the perspective of feature distribution. Fig. 10 shows the feature space after training via t-distribution stochastic neighbor embedding (t-SNE) visualization tool. One can see from Fig. 10 that the features of each known class are surrounded by generated unknown features. This observation validates the generation ability of the proposed TfOsLN. Therefore, our proposed method equips the classification model with effective prior information about unknown classes, enhancing its overall performance.

F. Impact of the multi-task loss weights

To determine the optimal values of the two weight hyperparameters λ_G and λ_D, for (12) and (13), we investigate the impact of these two hyperparameters of the proposed multi-task loss on the open-set recognition accuracy. The experimental results on two datasets are shown in Fig. 11. We set λ_G and λ_D of the multi-task loss from 0.1 to 0.9. One can see that the recognition accuracy of our proposed method generally remains above 91% and 93% with various weights on MSTAR dataset and SAMPLE dataset. The results obtained from the enumeration experiments demonstrate that our method achieves highest recognition accuracy with λ_G and λ_D at 0.5 and 0.1, respectively.



(a) (b)

Fig. 11. Impact of loss weights on OSR performance. (a) MSTAR dataset, (b) SAMPLE dataset.

G. Ablation Studies

In this section, we conduct a series of ablation experiments on the MSTAR dataset to verify the effectiveness of key components of the proposed TfOsLN. The experimental setup is the same as that of Section IV-C. For simplicity, on the basis of GAN, the model includes a generator with dual inputs, or a discriminator with dynamic-aware operation, or muti-task loss are dubbed DI, DAO and MTL, respectively.

TABLE III
RESULTS OF ABLATION EXPERIMENT ON THE MSTAR DATASET

DI	DAO	MTL	F1 score	Accuracy
✓	✓	✗	0.9158	92.45
✓	✗	✓	0.9032	90.85
✗	✓	✓	0.9345	93.81
✓	✓	✓	**0.9481**	**95.09**

The results of the ablation experiment are presented in Table III, where only F1 score and accuracy are listed due to space constraints. As can be observed from Table III, each key component contributes to boosting F1 score and accuracy of the proposed TfOsLN in the open world.

V. CONCLUSION

In this paper, we propose a threshold-free open-set learning network to achieve open-set SAR target recognition. Different from the existing methods, we formulate the open-set SAR target recognition problem as a K+1 classification problem with the help of GAN framework, in which the discriminator can directly work as an open-set classifier. The proposed generator with dual inputs can generate diverse unknown samples deviating from the distribution of known classes by maximizing the KL divergence. The proposed dynamic-aware discriminator can dynamically extract discriminative features according to the input samples, which is helpful for both the classification of known categories and the detection of unknown categories. The proposed multi-task loss optimizes the whole model in an adversarial manner, thereby improving its K+1 classification performance. Experiments on two public datasets illustrate that the proposed TfOsLN is competitive with seven advanced open-set recognition methods. Meanwhile, we realize the limitation of our proposed method, that is, the requirement of a sufficient number of known samples to enable high-quality unknown sample generation. We will further investigate how to achieve open-set SAR target recognition with limited known samples. Moreover, we intend to extend the K+1 recognition task into a K+N recognition task to enhance its applicability.

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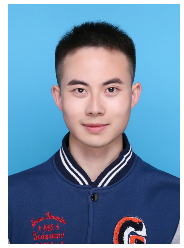

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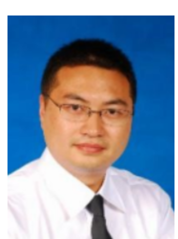

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