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An Open-Set Recognition Approach for SAR Targets Using Only Classification Scores

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Abstract

Focusing on the open set recognition problem of Synthetic aperture radar (SAR) targets, a simple and robust open-set recognition approach using only a simple convolutional neural classification network is proposed in this paper. The proposed approach constructs the D-SCORE feature and uses the statistical method to model the D-SCORE obtained in the training phase, so as to obtain the threshold for identifying the known and unknown classes, and ultimately realizes the open-set recognition of SAR targets. Experiments on the moving and stationary target acquisition and recognition (MSTAR) dataset show that the proposed approach achieves better open-set recognition performance.

1 Introduction

Synthetic aperture radar (SAR) is a remote sensing technology that offers several advantages and unique characteristics [1]. Firstly, SAR has the ability to operate day or night and can penetrate through clouds, fog, providing an all-weather imaging solution. Additionally, SAR systems have wide-area coverage capabilities, allowing for the acquisition of large amounts of data in a single pass. Hence, a large number of SAR image processing research has been undertaken.

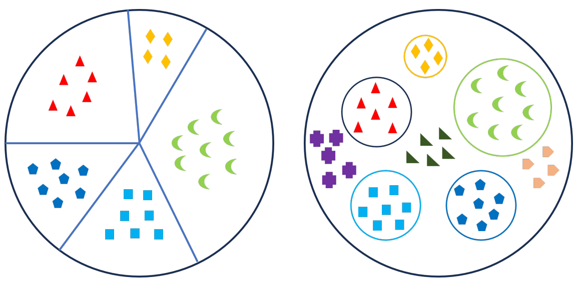

Figure 1. Schematic diagrams of closed-set and open-set. (a) Close-Set. (b) Open-Set.

In recent years, the application of deep learning techniques in SAR image processing has gained significant popularity [2, 3, 4]. Deep learning has demonstrated its powerful feature extraction ability, enabling the accurate processing of SAR images. However, as shown in Fig.1(a), it is important to note that deep learning algorithms typically operate under closed-set assumptions, i.e., training and testing on data with the same number of classes. In real-world scenarios, such as classification or recognition, it is usually an open-set problem. Open-set recognition involves classifying not only known classes but also identifying unknown classes that were not part of the training data, as shown in Fig.1(b). This introduces additional challenges as the system needs to differentiate between known and unknown classes.

Therefore, some scholars have paid attention to the open set recognition of SAR targets. For instance, Liao *et al.* [5] propose an encoder-decoder-Classifier network that introduces class information to learn the latent multivariate Gaussian distribution of each known class, and then discriminates the known classes from the unknown classes through the reconstruction loss difference. Ma *et al.* [6] propose a generative adversarial network (GAN), which uses a generator with category information to enhance the discriminator's ability to distinguish unknown classes in the training phase. Ma *et al.* [7] propose an open-set recognition method based on joint training of class-specific sub-dictionary learning. However, the above methods have complex network structures, including multiple sub-network structures, so that the loss between each sub-network is not well balanced in the training phase, resulting in difficulties in training, and ultimately making the methods not robust.

In this paper, we propose a simple and robust SAR target open-set recognition approach, the network structure of which contains only a convolutional neural network (CNN) classifier, and finally we essentially utilize the difference in class scores between the known and unknown classes for open-set recognition of SAR targets..

2 Proposed Approach

2.1 Network Structure

Fig.2 shows the network structure used in our proposed approach. The network structure is a CNN architecture used

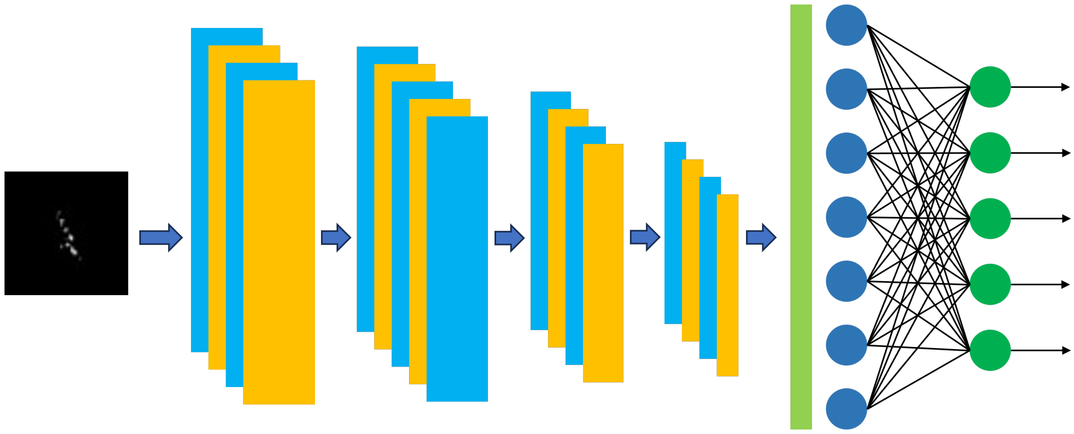

Figure 2. Schematic diagram of network structure in the proposed method.

for classification. Due to the excellent feature extraction ability of denseNet [8], we use it as the backbone of the network structure in this paper. And we use cross entropy as the classification loss in the training phase. The formula is as follows

$$L_c = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{K} I_{y_i}(j) log(\tilde{y}_i(j)) \quad (1)$$

where N is the number of training samples, K is the number of known classes, I_{y_i} is a one-hot vector for label y_i, and $\tilde{y}_i$ is the predicted class probability vector by the network.

In general, when the network performs classification, the class with the largest class score in the classifier is taken as the target class. However, we found that other classes of scores are also useful in SAR target open-set recognition. When the network classifies the target test samples of known classes, the maximum class score obtained by the classifier generally has a large gap with other class scores because the network has already recognized the traing samples of known classes in the training phase. As a comparison, the maximum class score obtained by the classifier for target samples of unknown classes is generally not significantly different from the scores of other classes due to lack of training phase. Therefore, we utilize this feature for SAR target open-set recognition.

2.2 Unknown Class Identification

In this paper, we use the difference between the maximum class score and the second largest class score as the feature for identifying unknown classes. And we abbreviated the difference as D-SCORE. As shown in Fig. 3, the D-SCORE of known and unknown classes is presented.

Using the relevant strategies of constant false alarm rate (CFAR) detection, we conduct statistical modeling on the known classes D-SCORE obtained in the training phase, and obtain the D-SCORE threshold for identifying the unknown classes. The formula for obtaining the D-SCORE

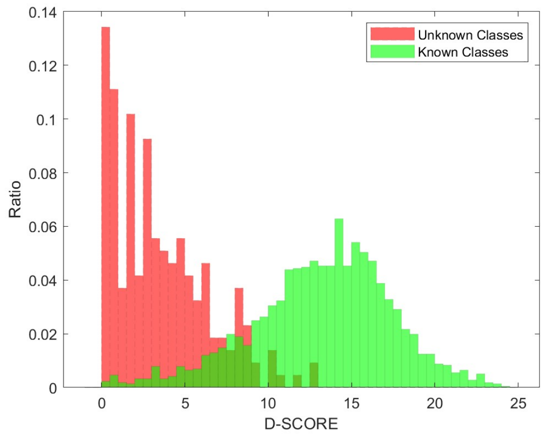

Figure 3. D-SCORE distributions for known and unknown classes.

threshold is as follows

$$1 - P_r = \int_0^T f(x)dx \quad (2)$$

where P_r is the recall rate of the known classes, T is the D-SCORE threshold. And $f(x)$ is the probability density function of the known classes D-SCORE, which is modeled as a normal distribution in this paper.

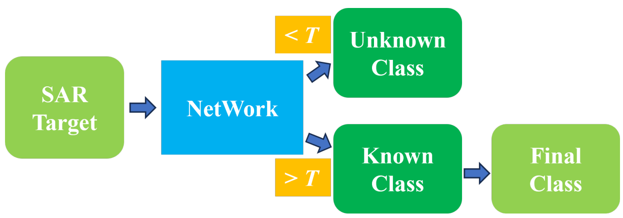

Figure 4. Schematic diagram of open-set recognition process.

The SAR target open-set recognition process is shown in Fig. 4. After network classification, the unknown and known classes are first identified. For those identified as the

Table 1. The Specific Number of Various Target Classes in MSTAR

Target Class	BMP2	BTR70	T72	BTR60	2S1	BRDM2	D7	T62	ZIL131	ZSU23/4
Number	820	429	814	451	573	572	573	572	573	573

known classes, the class with the highest score is selected as the final class.

3 Experiments and Results

To evaluate our proposed method, experiments are performed on the moving and stationary target acquisition and recognition (MSTAR) dataset. The MSTAR dataset contains 10 classes of SAR target images. And the size of the images is 128×128. The specific number of various target classes in MSTAR is shown in Table 1.

In the experiment, we train the network using SAR target images of 9, 8 and 7 classes in MSTAR dataset respectively. The tests are performed on all classes of SAR images. And we use $F1$ score to measure the performance [9]. The formula of $F1$ score is

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{3}$$

$$precision = \frac{tp}{tp + fp} \tag{4}$$

$$recall = \frac{tp}{tp + fn} \tag{5}$$

where tp is the number of true positives, fp is the number of false positives, and fn is the number of false negatives.

In Table 2, two methods are used to compare with the proposed approach. One of them is MLOSR [10], and the other is the classifier that removes the open-set recognition process in our approach. And it can be seen that our approach has achieved better performance in SAR target open-set recognition with different number of unknown classes. And P_r in our approach is set to 0.9995 at this moment.

Table 2. $F1$ with Different Unknown Classes of Different Methods

(Known, Unknown)	(9, 1)	(8, 2)	(7, 3)
MLOSR	0.9401	0.8680	0.8299
Classifier	0.9467	0.8925	0.8296
Our approach	**0.9631**	**0.9209**	**0.8863**

Under the condition that the number of known classes is 7 and the number of unknown classes is 3, we conduct experiments with different P_r. The experimental results are shown in Table 3. It can be seen that the best performance is achieved when P_r is 0.999.

Table 3. $F1$ with Different P_r

P_r	0.99999	0.9999	0.999	0.99
Our approach	0.8641	0.8782	**0.8826**	0.8566

4 Conclusion

In this paper, we propose an open-set recognition approach for SAR targets with simple network structure and using only classification scores. By utilizing the different features of the known classes and the unknown classes in D-SCORE, a threshold for identifying the known and unknown classes is obtained by modeling the D-SCORE obtained during the training phase. Ultimately a good SAR target open-set recognition performance is achieved. For future research, the work of this paper lays a foundation for further incremental SAR target recognition.

5 Acknowledgements

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References

[1] Q. Sun, M. Liu, S. Chen, F. Lu and M. Xing, "Ship Detection in SAR Images Based on Multilevel Superpixel Segmentation and Fuzzy Fusion," *IEEE Transactions on Geoscience and Remote Sensing*, **61**, 2023, pp. 1-15, doi: 10.1109/TGRS.2023.3266373.

[2] Y. Shang et al., "HDSS-Net: A Novel Hierarchically Designed Network With Spherical Space Classifier for Ship Recognition in SAR Images," *IEEE Transactions on Geoscience and Remote Sensing*, **61**, 2023, pp. 1-20, doi: 10.1109/TGRS.2023.3332137.

[3] Q. Guo, H. Xu and F. Xu, "Causal Adversarial Autoencoder for Disentangled SAR Image Representation and Few-Shot Target Recognition," *IEEE Transactions on Geoscience and Remote Sensing*, **61**, 2023, pp. 1-14, doi: 10.1109/TGRS.2023.3330478.

[4] W. Li, W. Yang, W. Zhang, T. Liu, Y. Liu and L. Liu, "Hierarchical Disentanglement-Alignment Network for Robust SAR Vehicle Recognition," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **16**, 2023, pp. 9661-9679, doi: 10.1109/JSTARS.2023.3324182.

[5] N. Liao, M. Datcu, Z. Zhang, W. Guo, J. Zhao and W. Yu, "Analyzing the Separability of SAR Classification Dataset in Open Set Conditions," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, **14**, 2021, pp. 7895-7910, doi: 10.1109/JSTARS.2021.3100342.

[6] X. Ma, K. Ji, L. Zhang, S. Feng, B. Xiong and G. Kuang, "An Open Set Recognition Method for SAR Targets Based on Multitask Learning," *IEEE Geoscience and Remote Sensing Letters*, **19**, 2022, pp. 1-5, doi: 10.1109/LGRS.2021.3079418.

[7] X. Ma, K. Ji, L. Zhang, S. Feng, B. Xiong and G. Kuang, "SAR Target Open-Set Recognition Based on Joint Training of Class-Specific Sub-Dictionary Learning," *IEEE Geoscience and Remote Sensing Letters*, **21**, 2024, pp. 1-5, doi: 10.1109/LGRS.2023.3342904.

[8] G. Huang, Z. Liu, L. Van Der Maaten and K. Q. Weinberger, "Densely Connected Convolutional Networks," *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, USA, 2017, pp. 2261-2269, doi: 10.1109/CVPR.2017.243.

[9] A. H. Oveis, E. Giusti, S. Ghio and M. Martorella, "Extended Openmax Approach for the Classification of Radar Images With a Rejection Option," *IEEE Transactions on Aerospace and Electronic Systems*, **59**, no. 1, Feb. 2023, pp. 196-208, doi: 10.1109/TAES.2022.3183953.

[10] Oza, Poojan, and Vishal M. Patel, "Deep cnn-based multi-task learning for open-set recognition." *arXiv preprint* 2019, arXiv:1903.03161.