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SAR Ship Detection Based on Deep Domain Adaptation with Limited Samples

Shangyi Liu[a], Zhaocheng Wang[a]*, Ruonan Wang[a], Yu Chen[a], Xu Fan[b], Weijiao Li[c]

[a] *School of Electronics and Information Engineering, Hebei University of Technology, Tianjin 300401, China.*

[b] *School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China.*
[c] *Business School, Nankai University, Tianjin 300071, China.*

Abstract

Ship detection in synthetic aperture radar (SAR) images have important applications in military and civil fields. Nonetheless, SAR images usually suffer from the disadvantage of having limited labeled samples. This is undoubtedly a challenge for the deep learning based methods, which require a large number of samples for training. To solve this problem, many researchers have applied the domain adaptation (DA) methods for the SAR ship detection tasks, which use optical images as the source domain and transform optical images to SAR domain directly. However, there is large difference between SAR and optical images. Hence, the deep learning detector may not be able to learn the target features accurately when the transformed images are used for training. In order to solve above problem, a novel ship detection method with limited labeled samples is proposed, whose training and test process is mainly implemented in the optical domain. In the training stage, optical images are used to pre-train the model. Here, the transformed optical images from SAR images are used to further fine-tune the pre-trained model. Accordingly, in the test stage, SAR images are transformed to optical domain and input in the model to obtain the detection results. Experimental results based on the real dataset demonstrate the effectiveness of the proposed method for SAR ship detection.

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Keywords: Synthetic aperture radar (SAR); ship detection; domain adaptation (DA); deep learning

* Corresponding author. Tel.: +0086-18522798853; fax: +0086-022-60438263.
E-mail address: zcwang@hebut.edu.cn

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1. Introduction

Remote sensing system [1] has been widely used in various fields because of its advantages of being time-efficient, wide-range, and with few restrictions [2], [3]. Based on different types of imaging results, remote sensing images can be divided into optical remote sensing images and synthetic aperture radar (SAR) images. Optical images usually have rich colors information, high resolution, and can be easily recognized directly by the human eyes. Unlike the optical images, SAR images can be obtained with any condition of day and weather. However, the existence of speckle noise in SAR images leads to the blurry target edges. In addition, it is difficult to obtain the labels (targets information) of SAR images due to the unique geometric characteristics, such as inversion, shadow, perspective contraction, close-range compression, etc. Therefore, it is necessary to develop a new method for SAR ship detection with limited labeled samples.

The transfer learning is adopted for SAR ship detection to avoid the impact of insufficient labeled SAR samples. Some datasets containing similar targets (including datasets in the SAR and optical images fields) are used to assist training for SAR target detection. For example, in 2019, Wu et al. [4] proposed a small sample SAR ground object recognition and detection method which base on the transfer convolutional neural network (CNN). The CNN was pre-trained with rich labeled SAR images, and then fine-tuned with low quality and small sample SAR images. Similarly, a large-scale SAR dataset is used to pre-train SAR specific model for transfer learning in SAR recognition task in references [5]. Moreover, the knowledge of few-shot learning is also useful for limited samples. Wang et al. [6] proposed a few-shot SAR detection method in 2022, which train detection network first and then fine-tune by few-shot learning and transfer learning with optical images.

Recently, with the development of domain adaptation (DA), many labeled optical images have been used to transform into the SAR domain to augment the dataset. In 2021, Guo et al. [7] introduced a semi-supervised method for SAR target detection, in which a DA method used to lessen the domain difference between optical images and SAR images by the embedding matching. To further align the features of simulated SAR and real SAR images, multi-stage DA methods have been used in many researches to reduce the domain differences between optical and SAR images. In 2022, Wang et al. [8] proposed O2SNet based DA for SAR ship detection, which include two stages. Firstly, the GeminiGAN is proposed to transfer optical data to SAR-style samples. Then a prototype alignment is adopted to further align the simulated SAR and real SAR images. Shi et al. [9] transformed optical images into SAR domain for SAR ship detection at three levels: pixel, feature, and prediction level. Similarly, Zhang et al. [10] introduced a HSANet to achieve the SAR detection, in which structural alignment module works in image-level and prototype alignment module works in instance-level.

While DA combined with many labeled optical images has achieved satisfactory results in SAR ship target detection, most deep DA methods are used to transfer optical images to SAR images for training. Apart from the alignment of SAR and optical images at pixel level, many methods pursue it at feature level, which make the adopted model obtain relatively satisfactory performance. However, with the improvement of the performance of the DA model, its complexity and computational cost also increase correspondingly.

In order to further enhance the effectiveness of SAR ship detection method with limited samples, a new thought of DA is adopted, which employs the deep DA from SAR to optical images. Specifically, there are two stages in the detector training: pre-training, fine-tuning. In the pre-training stage, the pre-trained model is trained with optical images. In the fine-tuning stage, the transferred optical images are employed to fine-tune the model, which are transferred from SAR images by the CycleGAN [11]. In the test stage, SAR images are transferred to optical images as input to the model and the final results are obtained. In addition, the proposed method is not limited to ship detection in seas, but can also be used to detect other targets, such as aircraft and vehicles on the land.

The contributions of this paper can be summarized as follows:

(1) A novel SAR ship detection based on deep domain adaptation with limited samples is proposed in this paper. The detector is pre-trained with optical images with rich labeled and fine-tuned with limited pseudo-optical images transformed from SAR domain. It effectively improves the performance in the case of unsatisfactory results of the DA model.

(2) The use of abundant labeled optical images enables the model to achieve superior results in pre-training. It avoids the problem of inaccurate learned features due to domain differences when the model is trained directly using SAR images transferred from optical images. Furthermore, a better pre-trained model can achieve more satisfactory

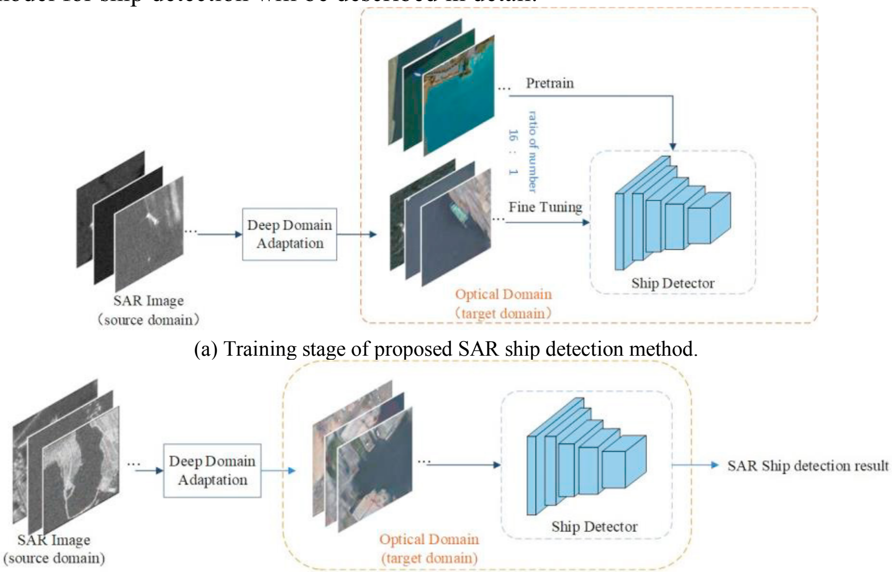
results with the small SAR datasets.

The remainder of this paper is organized as follows. Section 2 introduces the proposed SAR ship detection method based on deep domain adaptation in limited samples. Section 3 shows the results and analysis of proposed method based on specific datasets. Finally, Section 4 concludes this paper.

2. Proposed SAR ship detection method

2.1. Framework of the proposed method

The specific framework of the proposed ship detection method is shown in Fig.1. The proposed method of training stage shown in Fig. 1(a) includes the pre-training and fine-tuning. Firstly, a lot of labeled optical images are used to pre-train the ship detector. Subsequently, the labeled SAR images are transferred into the optical domain by deep DA to complete the pixel-level transformation. Then the transferred images are used to fine-tune the detector. Specifically, the proportion of images used in pre-training and fine-tuning training is about 16: 1. In the test stage, as shown in Fig. 1(b), since the detector is pre-trained and fine-tuned in the optical domain, the test images need to be transferred into the optical domain through deep DA. Then the detection results are obtained from the ship detector whose input is the transformed images. Subsequently, the deep DA method for transferring SAR images to optical images and the model for ship detection will be described in detail.



(a) Training stage of proposed SAR ship detection method.

(b) Test stage of proposed SAR ship detection method.

Fig. 1. The overall framework.

2.2. Deep domain adaptation method

Because of the significant domain discrepancy between optical and SAR images, the images obtained by deep DA method cannot achieve complete alignment with the target domain images. Therefore, a new DA thought is proposed in this paper. Here, the original optical images can be used for model training in the pre-training stage. And SAR images are transferred to optical domain in fine-tuning stage and testing stage. Specifically, the transferred pseudo-SAR images by the deep domain method are used to fine tune the detector. The adopted DA method is derived from CycleGAN and shown in Fig. 2, which uses a circular model structure to complete the interconversion between two domains. Here, the generator includes encoding, converting, and decoding. And the discriminator is not used in the test and mainly consists of several convolution layers. The optical image generated by CycleGAN is shown in Fig. 3. CycleGAN realizes the transformation from SAR images to optical images at pixel level. The transformed pseudo-optical images are basically similar to the original optical images.

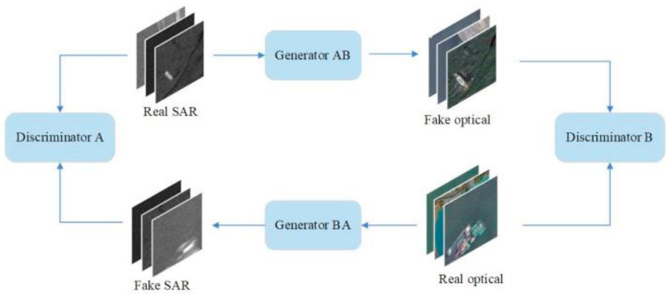


Fig. 2. Structure of CycleGAN.

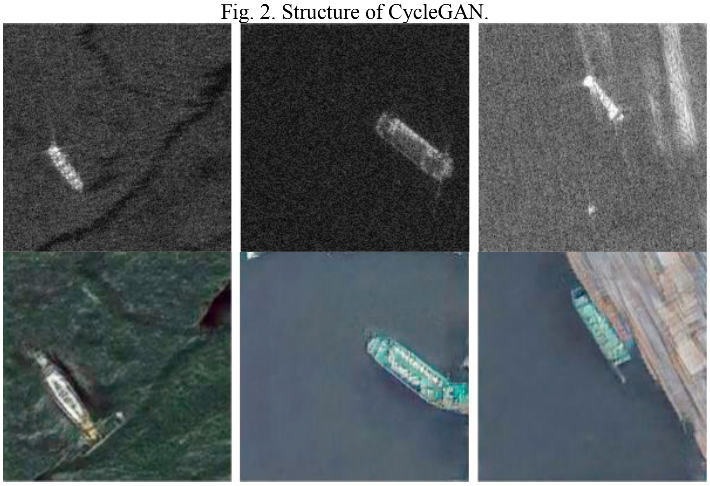


Fig. 3. Original SAR images (the first row) and transformed optical images (the second row).

2.3. Ship detection model

In this paper, the ship detector is SSD [12]. It is a classic one-stage multibox prediction architecture that delivers higher detection accuracy at a faster speed. Therefore, it is applied in a wide range of various target detection tasks and achieves excellent results in SAR ship detection. The SSD is selected as the detector of proposed method because of its excellent performance. It should be pointed out that the focus of our proposed detection method is the thought of DA. Theoretically any deep learning detector can be employed in the proposed method. Here, the SSD includes a VGG16-based feature extraction network, an additional feature extraction layer, and a detection network.

3. Experiment results

3.1. Introduction to data sets and configuration

The dataset of optical images[1] includes 720 images with the size of 1024×1024, and the labels are ships. In the training stage, owing to the large size of the optical images, the sub-images of optical images are obtained by the sliding-windows. In addition, to enrich the training data and alleviate the over-fitting of the network, data augmentation is adopted in this paper, which includes rotation, mirroring and so on the dataset of SAR images used in this paper is AIR-SARShip-1.0[13], which contains 31 large images with the size of 3000×3000 and come from Gaofen-3 satellite. Here, five images are selected for the test, and the rest are used for training. The SAR images used for training are also clipped to small images with the size of 256×256 by sliding window. It should be noted that the SAR images are not augmented.

For training detection model, the batch size is 8, and the iterations is 160,000.

[1] https://www.yuanwangfw.com/hjjtzs.

3.2. Quantitative evaluation criteria

For scientific evaluation of experimental results. Precision and Recall are introduced for evaluating the results of the SAR ship detection in this paper. Precision is the proportion of correctly predicted targets to all positive targets predicted. Recall is the proportion of correctly predicted positive samples to all true positive samples. They are defined as follows:

$$P(precision) = \frac{TP}{TP + FP} \tag{1}$$

$$R(recall) = \frac{TP}{TP + FN} \tag{2}$$

where TP, FN, FP are the number of detected targets, missed targets and false alarms respectively.

To synthetically measure the performance of the method, the F-measure is introduced. It comprehensively reflects the precision and recall, which is defined as:

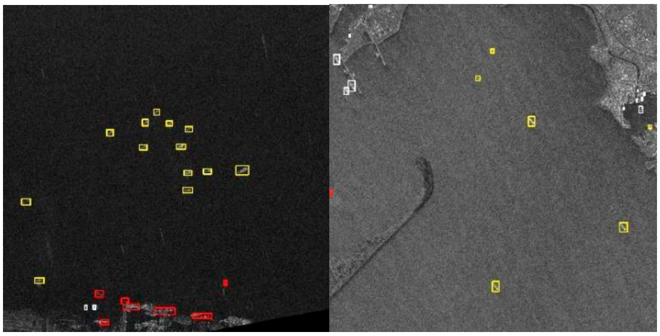
$$F - measure = (1+\beta)\frac{P(precision) \times R(recall)}{\beta^2 \times P(precision) + R(recall)} \tag{3}$$

In this paper β=1, at this time F1-measure is often referred as F1-score.

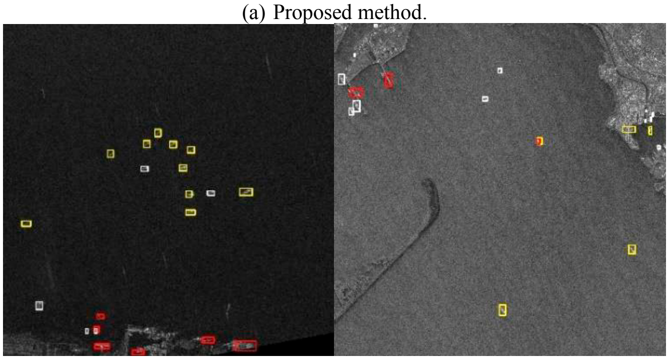
3.3. Detection results of the proposed method

In the test stage, the SAR images used for test are similarly cropped to the size of 256×256 and transferred to optical domain. Then, the transferred sub-images are input to the ship detector to obtain the detection results. The final detection result will be restored to the original size of 3000×3000.

Fig.4 shows the result of proposed method and traditional SSD method. It demonstrates that the proposed ship detection method has more satisfactory effectiveness. Even in the nearshore area it still has superior performance than the comparison method.



(a) Proposed method.



(b) Training with SAR images only.

Fig. 4. SAR detection results. The yellow, red and white boxes are the true ship targets, false alarms and missed targets.

To verify the performance of the proposed method, a method is selected as a comparison experiment, in which the SSD is trained with SAR images only. Fig.4(a) shows the result of the fine-trained model, which use all of the SAR train images. Fig.4(b) shows the detection results of the SSD network trained using SAR images only. As shown in Fig.4(b), the proposed method is obviously superior to the SSD detector trained by SAR images only. The model has learned many useful feature representation in the pre-training stage with proposed method. As a result, fine-tuning the detector based on the pre-trained model is more advantageous than training SSD directly with the same number of images.

In order to prove the universality of the proposed method with limited samples, 0%, 25%, 50%, and 100% of the SAR training dataset are used for the fine-tuning of the proposed method and SSD training. The specific results of the experiment are shown in Table 1. It is worth to note that the proposed method still achieves the F1-score of 0.36 without any SAR images for training. It demonstrates that the proposed method is still useful with limited labeled SAR images or even without labeled images. Compared with general deep learning methods, it includes two stages of pre-training and fine-tuning. The model can learn more knowledge depending on abundant labeled optical images in the pre-training stage.

Table 1. Comparison between SSD and proposed method.

Proportion of the number of SAR images	Precision（%）	Recall（%）	F1-score
0%(SSD)	0	0	0
0%(Ours)	37.25	36.65	0.3689
25%(SSD)	30.67	44.23	0.3622
25%(Ours)	45.29	46.15	0.4571
50%(SSD)	36.62	50.00	0.4228
50%(Ours)	48.28	53.85	0.5091
100%(SSD)	55.36	59.01	0.5741
100%(Ours)	60.38	61.54	0.6095

Fig. 5 shows the results of the proposed method and training SSD with SAR images only as line graph, in which F1-score changes depending on the number of SAR images. The proposed method based deep DA is clearly superior to training SSD with SAR images only, which has a significantly higher F1-score than the SSD at any proportion. In particular, the advantages of the proposed method are more obvious when fewer SAR images are used.

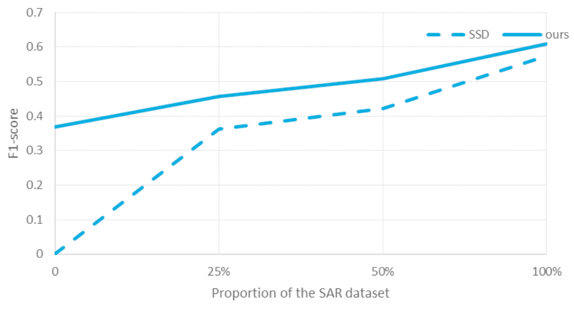


Fig.5. F1-score curve with the number of SAR images.

Table 2. Comparison between another domain transfer method and proposed method (0%,100%).

Method	Precision（%）	Recall（%）	F1-score
Method of Ref. [14]	17.65	17.31	0.1748
Ours (0%)	37.25	36.65	0.3689
Ours(100%)	60.38	61.54	0.6095

3.4. Comparison with other ship detection method

In recent researches, many DA method transfer optical images to SAR domain to obtain pseudo-SAR images [14]. The SAR images transferred from optical domain are subsequently used for training the detector together with the original SAR images. To further verify the effectiveness of the proposed method, the DA method of Ref. [14] is compared with the proposed method. Here, about 10,000 optical remote sensing images are selected and transferred by CycleGAN to obtain pseudo-SAR images. Then, these pseudo-SAR images are added to the SAR training set to train the detector.

The specific experimental results are shown in Table 2. The F1-score of comparative experiment is even lower than that obtained using the proposed method with 0% of SAR images fine-tuning. This may be caused by the following reason. The transferred images from optical domain are not satisfactory which have a large difference with original SAR images. Owing to the huge domain discrepancy between the two domains, it is difficult to learn features better by training directly with the generated new images, which lead to a worse performance of the deep learning detector. Here, the direct use of transformed pseudo-SAR images for training has higher requirements for the effectiveness of the DA method. By contrast, the performance of the detector in the proposed method can still be effectively improved even in the case of the unsatisfactory DA results.

4. Conclusion

Current researches on SAR ship detection based on domain adaptation methods mainly convert optical images into SAR images. The direct use of transformed pseudo-SAR images for training is likely to cause bias in network training due to feature misalignment. In this paper, a novel SAR ship detection method based on deep domain adaptation with limited samples is proposed, which improves the performance of SAR ship detection. Firstly, numerous labeled optical images are used to pre-train the detector which makes the detector obtain more accurate feature in the pre-training stage. Then, a small amount of pseudo-optical images are used to fine-tune the detector. Finally, the SAR images are transferred to optical domain and input to detector to obtain the detection result. Experimental results based on the real dataset demonstrate the effectiveness of the proposed method for SAR ship detection.

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