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AN INTEGRATED METHOD OF SHIP DETECTION AND RECOGNITION IN SAR IMAGES BASED ON DEEP LEARNING

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ABSTRACT

Ship target interpretation in SAR images has become an important topic in research in recent years. With the improvement of SAR image resolution, the performance of traditional automatic target recognition (ATR) method decreases gradually. The emergence of deep network provides a new solution for SAR image ship interpretation. Ship target interpretation in SAR images based on deep learning is divided into detection and classification, but they haven't been integrated yet. Based on the process flow of traditional ATR system, an integration method of ship target detection and recognition based on deep network is proposed in this paper. And at the end of the network, the squeeze-and-excitation (SE) module is added to the classification subnetwork. The effectiveness of the proposed integration method is verified by experiments, and the classification accuracy of the ship increased by 3.7% after adding SE module.

***Index Terms*—** ship, SAR images, integration, automatic target recognition, deep learning

1. INTRODUCTION

Ship target interpretation is a significant part of modern intelligent maritime monitoring and control system. Synthetic Aperture Radar (SAR) is not constrained by time and space, so ship interpretation in SAR images is a research focus currently.

The traditional SAR images ATR system is divided into three steps: preprocessing, detection and recognition. The preprocessing refers to the sea-land segmentation and noise reduction. Detection methods mainly include CFAR[1] algorithm. However, the CFAR method has limitations in suppressing clutter and controlling near-shore false alarms. In recent years, there are some improved CFAR methods were proposed [2]. The recognition part includes feature extraction and classification. Common feature extraction methods cover principal component analysis(PCA), wavelet transform(WT) and independent component analysis(ICA) and so on. The classification methods have some classification models, such as support vector machine(SVM), decision tree algorithm and nearest neighbor classifier. Traditional SAR ATR methods rely heavily on hand-made features and have poor generalization performance. Small problems at all stages will have a great impact on the identification accuracy of the system. In addition, with the promotion of SAR imaging technology, the traditional ATR methods have shown limitations in detection and recognition stage.

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The emergence of deep network breaks the process flow of traditional ATR method, and deep network can realize automatic target recognition easily. The ATR technology in optical images grows quickly, which has been applied in various industries. Whereas, under same conditions, Ship target in SAR images have fewer features than in optical images, which makes SAR images ship ATR difficult. Ship detection based on deep network not only does not need land-sea division, but also has a high detection rate[3]. The classification accuracy of ship chips based on deep network is improving [4] [5]. However, the classification method based on chips is not ideal in real scene. Wei $et\ al.$[6] used deep network method in ship target detection and rough classification, and divided ships into large ships and small ships according to the size of ship. A framework of intelllgence SAR ship recognition was proposed [7], but it still cannot realize the integration of detection and recognition.

In this paper, the integration method of detection and recognition is achieved to identify ship target in SAR images, and the structure of classification subnetwork is also improved. The proposed method is introduced detailedly in section 2, experiments are used to verify the effectiveness of the proposed method in section 3.

2. METHODOLOGY

2.1. The improved classification subnetwork

RetinaNet [8] is used as the network framework for the proposed method. The classification subnet network of RetinaNet is a full convolutional layer network, and focal loss is used as the loss function. The focal loss is designed to address the one-stage object detection scenario in which there is an extreme imbalance between foreground and background classes during training. Some SAR images have complex

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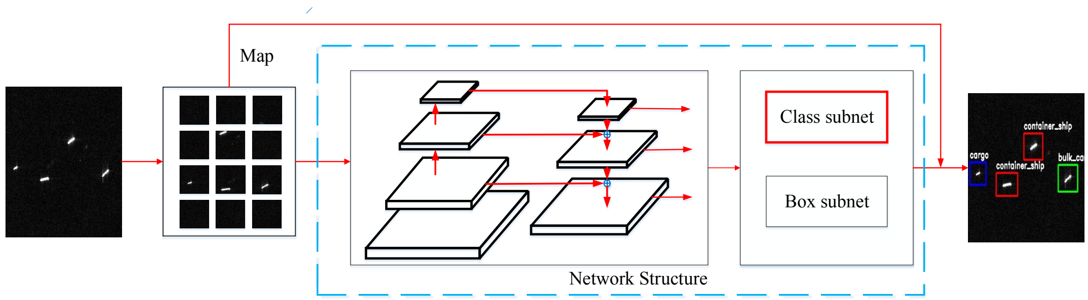

Fig. 1. The flowchart of the proposed method.

background characteristics, but the number of real objects is limited. Focal loss can reduce effectively the influence of sea clutter and land false alarm target in SAR images, therefore it is of great significance for target interpretation in SAR images. The focal loss formula is as follows:

$$FL(p_t) = -\alpha_t(1-p_t)^\gamma \log(p_t) \tag{1}$$

The optimal values of the parameters have been obtained through a large number of experiments in [8], $\gamma = 2$ and $\alpha = 0.25$. So the formula for focal loss in our network is as follows:

$$FL(p_t) = -\frac{1}{4}(1-p_t)^2 \log(p_t) \tag{2}$$

The false alarm in the background is effectively suppressed by focal loss, but the ship classification in SAR images also has the problem of the classification accuracy is very low.

The differences of diverse ship classes is not obvious, which brings great difficulties to solve the tasks of ship identification. Current classification tasks, such as classification of cats and dogs in optical images, the classification of roads and buildings in SAR images. Obviously, current classification networks can not meet requirements of our ship fine classification. There are two reasons for the low classification accuracy of ships in SAR images, which using the conventional classification network. Firstly, ship targets are too small to extract features easily. Secondly, the similarity of categories is very high, in other words, there are many similar features among ship categories but few distinguishing features. To solve the problem of too high similarity of categories, Amplifying difference features and narrowing or suppressing similar features is a good idea, so the squeeze and excitation (SE) [9] module is introduced.

SE module in Fig.2 mainly includes a pooling layer, two fully connected layers and an activation layer of sigmoid function. The SE module is added at the end of the second Convolution layer of the classification subnetwork in this paper. In the integrated ship detection and identification network, the SE module can obtains automatically the importance of each feature channel by learning, then it promotes useful features and inhibits features that are useless for

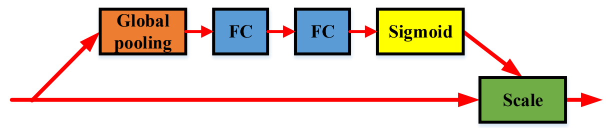

Fig. 2. SE modul.

the current tasks according to the importance. In addition, SE module has good portability. The current research is to add the SE module to the basic network. In this paper, the SE module is added to the classification subnetwork. Using SE module to reward and punish the features can effectively improve the ship classification accuracy. A large number of experiments have been used to prove that the improved classification subnetwork can improve the accuracy of ship target classification.

2.2. The integration method of detection and classification.

An integration method is proposed in this paper, as shown in the flowchart Fig.1, which mainly has three parts: image preprocessing, deep network module and result image combination.

Image preprocessing is the first step. Input image will be resampled when the size of input image is larger than the size of the network specified. So preprocessing is a necessary step to prevent ship feature information loss caused by resampling. The specific process is as follows: a large scene SAR images are grouped into subimages of network uniform size. Then these subimages are sent to the network for detection and recognition. After preprocessing, the image enters the deep network.

RetinaNet is used as the network framework for the proposed method, which includes backbone ResNet[10], feature pyramid networks (FPN) [11], classification and regression subnetworks. FPN utilizes both the high resolution of the low level features and the high semantic information of the high level features to achieve the predicted effect by combining the features of these different levels. Moreover, the prediction

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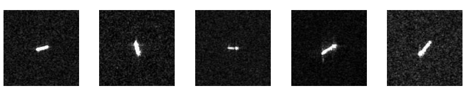
is carried out separately on the feature layer after each fusion, which is different from the conventional feature fusion. Therefore, feature extraction based on FPN has advantage in automatic recognition of ship targets. The end of RetinaNet network has two full convolutional subnetworks. They have same network structure but are independent without shared parameters, which are respectively used to complete the target box category classification and location regression tasks. RetinaNet's detection and classification subnetworks are designed independently of each other, which provides a basis for the integration of ship detection and recognition.

The last step is the subimages combination. According to the segmentation relation, subimages are merged into the final result images.

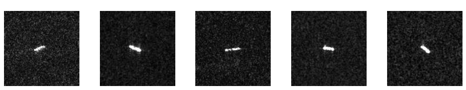
3. EXPERIMENTS

The hardware environment is the Intel Core i5-6500U CPU at 3.20 GHZ and 64-RAM, GPU at Nvidia-1070. The experiments dataset is real SAR images from OpenSARShip[5] and Sentinel-1[6].

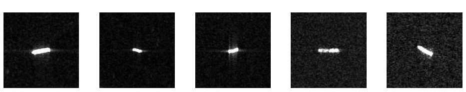
3.1. ship chips classification experiment



(a)



(b)



(c)

Fig. 3. Three types of ship SAR image chips. (a) bulk carrier. (b) cargo. (c) container ship

In experiment 1, three class ship chips in Fig.3 is used for classification. Table 1 shows the confusion matrix of the proposed method for the classification of ships. Table 2 is the comparison of experimental results, the traditional machine learning methods of SVM, deep network SSD and RetinaNet were used to compare with the proposed method. In tables, class1 is bulk barrier, calss2 is cargo, class3 is container ship.

As can be seen from table 1, the classification accuracy of the proposed method for the three types of ships is above 90%. Through the comparison experiment in table 2, three existing methods are used for comparison, the proposed method has the highest classification accuracy. Experimental results

Table 1. Confusion matrix of ship classification

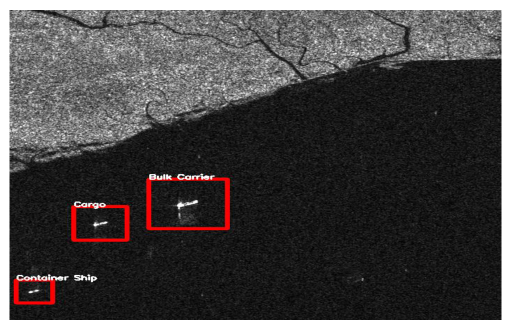
Category	Class1	Class2	Class3	Accuracy
Class1	187	9	4	93.5%
Class2	7	183	10	91.5%
Class3	6	9	185	92.5%

Table 2. Contrast experiment

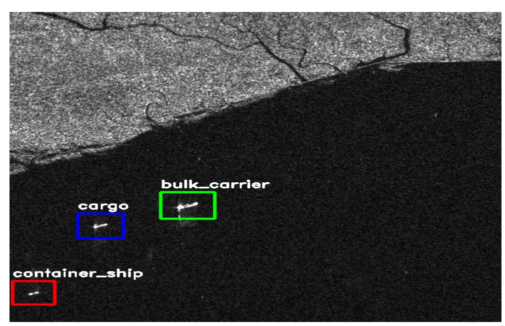
	Class1	Class2	Class3	Accuracy
SVM	82.5%	72.0%	76.5%	77.0%
SSD	88.5%	76.5%	83.0%	82.7%
RetinaNet	91.5%	90.0%	85.0%	88.8%
Our Method	93.5%	91.5 %	92.5%	92.5%

show that adding SE module to the classification subnetwork can effectively improve the classification accuracy.

3.2. The proposed integration method validation experiment



(a)



(b)

Fig. 4. Off-shore experiment. (a) an off-shore truth image; (b) the results image of the proposed method.

The experiment 2 based on truth scene, SAR images are used to verify the effectiveness of the proposed integrated method of ship detection and recognition. The size of Fig.4(a) is 700 by 700, Fig.5(a) is 920 by 600. From the experimen-

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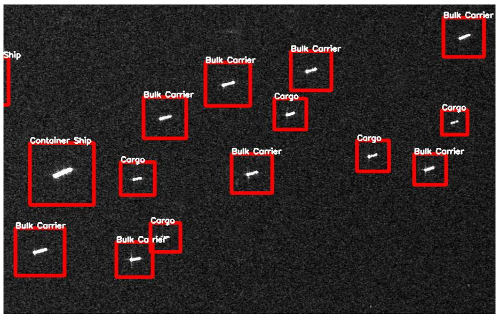
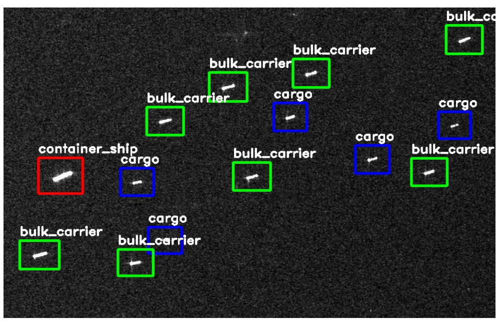
tal results in Fig.4(b), our method can not only detect and classify accurately ship targets, but also well suppress false alarms near the coast. The result of ocean Fig.5(b) show that the prroposed method detects all targets and correctly classifies ships.



(a)



(b)

Fig. 5. Large scene sea experiment. (a) an ocean scene truth image; (b) the results image of the proposed method.

Experimental results show that our method can not only suppress false alarm but also have high classification accuracy. It also verify the effectiveness of the proposed integration method, and adding SE module can effectively improve the classification accuracy of ships.

4. DISCUSSION

In this paper, an integrated method of ship target detection and recognition in SAR images based on deep network is proposed, which achieves target automatic recognition. In addition, SE modules are added into the classification subnetwork. The experimental results show that the proposed method is not only accurately classification of ship chips, but also can recognition ship targets automatically in real scene.

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