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An Effective Method for Small Targets Detection in Synthetic Aperture Radar Images Under Complex Background

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ABSTRACT Synthetic Aperture Radar (SAR) is a useful tool in marine surveillance. Small targets detection in SAR images especially in nearshore area is a difficult issue. Due to the complex background, there exist a lot of false targets. Therefore, we propose an effective method for small targets detection in SAR images under complex background, which combines the features of SAR images and those of SAR time series. A new neural network which integrates a neighborhood similarity module is constructed to enhance the features of small targets in SAR images. Then, a false alarm suppression method is put forward, which is based on empirical orthogonal functions to extract spatio-temporal features. Compared with other false alarm suppression methods, our proposed method is easily-implemented, highly efficient and in no need of a priori information. Simulation results on real datasets prove the efficiency and effectiveness of our proposed method.

INDEX TERMS SAR detection, complex background, false alarm suppression, neural network.

I. INTRODUCTION

Synthetic Aperture Radar (SAR) is a kind of high-resolution and all-time surveillance tool which is widely applied in marine surveillance [1]. Target detection and classification are the prominent fields in SAR applications and deep learning is proved to be the most effective method for target detection and classification in SAR images [2]. However, there still exist many problems to be solved in SAR target detection and classification, such as multiple scales of targets, discrimination of closely spaced targets, high intra-class diversity and large inter-class similarity due to irradiation conditions, and high false alarm rate brought about by complex background [3]. Real scenes of complex background are shown in Fig. 1.

There are two mainstream detection methods based on deep learning. The first category, called two-stage detectors, is based on region proposal, such as faster R-CNN. The first stage is to generate candidate object proposals using a regional generation algorithm. The second stage is to extract features from the candidate object proposals by applying convolutional neural networks (CNNs). The second category, called one-stage detector, is based on regression, such as SSD (single-shot detection) and YOLOV3 (“you only look once” version 3) [4]. Although one-stage detectors are faster and easily-optimized, their performace is inferior to two-stage detectors due to the region proposal generation and refinement paradigm [5].

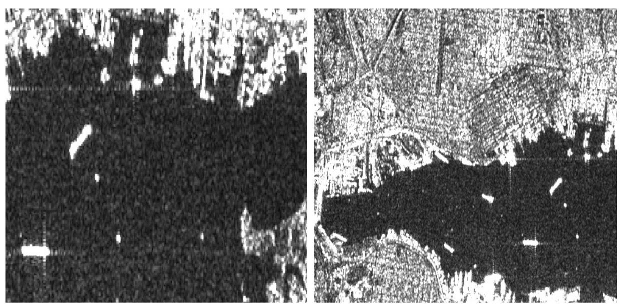
(a) (b)

FIGURE 1. Real scenes of complex background. (a) Scene 1. (b) Scene 2.

In this paper, we propose an effective method for small targets detection in complex background based on combination of SAR time series and SAR images. The principle of our method is shown in Fig. 2. A new neural network

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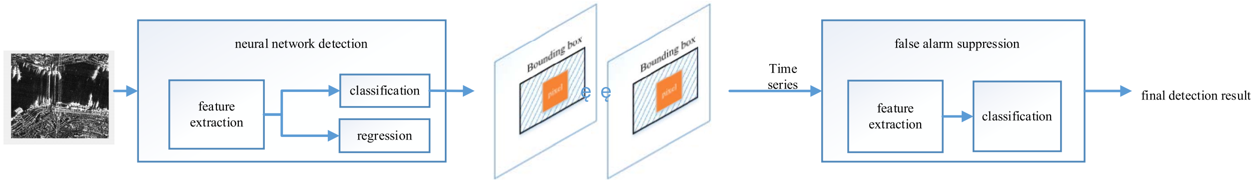

FIGURE 2. The principle of our method.

is designed to find the suspicious targets with a neighborhood similarity module integrated in this framework. This module aims to enhance the features of small targets, which can assist small target detection. Then, a false alarm suppression method is put forward. Recent studies show that empirical orthogonal functions have a good performance in extracting spatio-temporal features of time series [6]. This is because they are easily-implemented, highly efficient and in no need of a priori information. Through experiments with real dataset, the proposed detection method is proved to achieve better performance than other state-of-art methods.

The rest of this paper is organized as follows: Section 2 reviews the mainstream method for small targets detection in complex background. Section 3 describes the proposed detection method. Experimental results are also carried out to demonstrate the effectiveness of the proposed framework in Section 4. Section 5 concludes this paper.

II. RELATED WORK

In this section, we review the related work with respect to small targets detection in complex background based on SAR images.

For the problem of small target detection, researchers strive to solve it from different perspectives [7]. One strive is to increase the resolution of SAR images in order to improve the signal to noise ratio. However, SAR cannot reach the resolution that other sensors achieve. Another strive is to fuse SAR with other sensors. Some researchers engage in statistical analysis. Most prefer to use deep learning methods. Hong *et al* [4] used linear scaling based on the k-means++ algorithm to satisfy the difference of anchor boxes between different detection scales. Cui *et al* [8] adopted a pyramid structure with dense connnections in the top-down network to obtain more semantic information for small targets detection. Since features stemming from low-level layers indicate structure information whereas those stemming from high-level layers represent semantic information [9], [10]. Further, he also devised an anchor-free method called CenterNet which regarded keypoint of targets as the targets to detect ships in large scale SAR images [11]. Kang *et al* [12] combined CFAR and Faster R-CNN to detect small targets. Faster R-CNN generated classification score and CFAR was applied on the lower confidence proposals. Ju *et al* [13] proposed new detection frameworks for small targets detection which included three modules, namely, dilated module, feature fusion and passthrough module. Shadow-aided detection methods are also investigated to be used in detecting small targets, especially moving ones [14]. Also, methods utilizing target peripheral features can perform better in small targets detection [15]. But all methods above cannot avoid introducing false targets while detecting small targets.

In order to reduce false targets, many researchers resort to the attention mechanism and saliency information which are mainstream methods to suppress false alarms [11], [16], [17]. The essence of attention mechanism is to force the model to concentrate on key information and discard irrelevant information [18]. There are three types of attention models: spatial attention model, channel attention model and spatial and channel mixed attention model [11]. However, attention module will increase the cost of model and reduce the speed of detection. Furthermore, Lin *et al.* [19] Devised a new network based on faster R-CNN with squeeze and excitation mechanism to suppress false detections. Sun *et al.* [20] introduced a category position module into an anchor-free detection network to improve target positioning in complex scenes. Later, they also employed an angular classification structure to the head network in more complex scenes with arbitrary-oriented and densely arranged ships [21]. Fu *et al* [22] designed an anchor-free network called scattering keypoints guided network which incorporated a context-aware feature selection module. Yang *et al.* [23] devised a new loss function so as to reduce false targets in complex background, especially in nearshore area. Nieto-Hidalgo *et al.* [24] proposed a domain-tailored two-stage CNN for small target detection in specific backgrounds by introducing a postprocessing stage of morphological opening filter to eliminate false targets. Xiong *et al.* [25] combined the advantages of time-frequency analysis and fractal theory to improve the detection performance. Chen *et al.* [26] proposed a hybrid model combining classification, localization, and segmentation with a novel multi-task loss function to suppress false alarms. The methods above need more complex networks so more parameters should be trained, leading to large computational load.

III. PROPOSED METHOD

In this section, we give a description of our proposed method. First, we put forward a new neural network which is incorporated with a neighborhood similarity module. Then, we introduce a false alarm suppression method.

A. THE FRAMEWORK OF PROPOSED NEURAL NETWORK

The structure of our proposed neural network is shown in Fig. 3. CNN is helpful for improving the detection performance of small targets so our proposed neural network is based on CNN. For the problem of small target detection, the most common method is to combine features from different

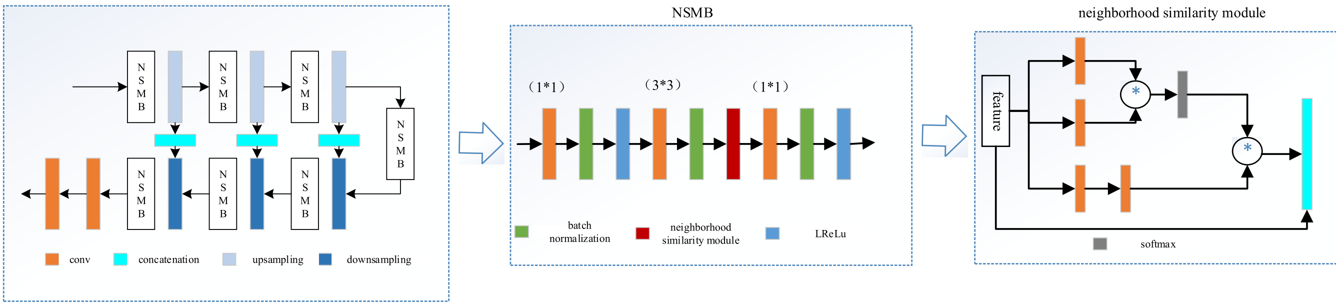

FIGURE 3. Detail structure of our proposed neural network.

TABLE 1. Details of our proposed neural network structure.

Type	Kernel size	Input size
NSMB	3×3	512×512×3
Downsampling	2×2	512×512×32
NSMB	3×3	256×256×32
Downsampling	2×2	256×256×64
NSMB	3×3	128×128×64
Downsampling	2×2	128×128×128
Dropout	0.2	64×64×128
NSMB	3×3	64×64×128
Upsampling	2×2	64×64×128
NSMB	3×3	128×128×128
Upsampling	2×2	128×128×128
NSMB	3×3	256×256×128
Upsampling	2×2	256×256×64
NSMB	3×3	512×512×64
Conv	3×3	512×512×32
Conv	1×1	512×512×3

CNN layers. In order to avoid losing useful pixels, we should reduce the layers of downsampling. So there are only three layers of downsampling included in our proposed neural network [27], whose structure and details are given in Table 1.

A new block integrated with neighborhood similarity module (NSMB) is incorporated in our proposed neural network. The structure of this new block is shown in Fig.3. It consists of three convolution layers, three batch normalization block, two leaky ReLU and a neighborhood similarity module.

The generic neighborhood similarity for neural networks is formulated as

$$\mathbf{y}_i = \frac{1}{C(x)} \sum\nolimits_{\forall j} f(\mathbf{x}_i, \mathbf{x}_j) g(\mathbf{x}_j), \tag{1}$$

where $\mathbf{x}_i$ is the input feature, $\mathbf{y}_i$ is the output response at pixel i, and j enumerates the neighborhood pixels of i. $C(x)$ is a normalization factor, $g(\cdot)$ represents an input function at pixel j and $f(\cdot)$ denotes the similarity between pixel i and j [28].

Instead of using the whole image to calculate output response, we prefer to use a small neighborhood surrounding pixel i. Then the neighborhood similarity module is revised as

$$\mathbf{y}_i = \frac{1}{C(x)} \sum\nolimits_{\forall j \in N_i} f(\mathbf{x}_i, \mathbf{x}_j) g(\mathbf{x}_j), \tag{2}$$

where N_i indicates the neighborhood of i.

The distance between pixel i and other pixels in its neighborhood is computed using embedded Gaussian,

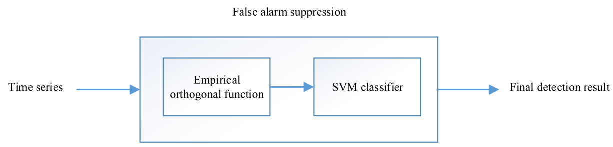

FIGURE 4. Principle of false alarm suppression.

so (2) becomes

$$\mathbf{y}_i = \frac{1}{C(x)} \sum\nolimits_{\forall j \in N_i} e^{\theta^T(\mathbf{x}_i)} e^{\varphi(\mathbf{x}_j)} g(\mathbf{x}_j), \tag{3}$$

where θ and φ are two imbedding functions.

As shown in Fig. 3, in order to implement this neighborhood similarity module, we employ softmax operation to represent normalization. Two embedding functions θ and φ are represented by single layer of convolutional block with (1×1) kernel. Function g is represented by 2 layer convolutional blocks with (3×3) kernel.

B. FALSE ALARM SUPPRESSION

The principle of false alarm suppression is shown in Fig. 4.

Suppose a time series extracted from a detected object is represented by a matrix $\mathbf{X}(s, t)$, in which s denotes space point and t denotes time point:

$$\mathbf{X}(s,t) = (\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_n) = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}, \tag{4}$$

where each column is an observation over m points at a given time t and each row is an observation over time t at a given point m [29].

In order to get the temporal covariance, we calculate the mean of each column to obtain spatial anomaly $\mathbf{X}'$:

$$\mathbf{X}' = \mathbf{X} - \mathbf{1}_n \overline{\mathbf{X}}, \tag{5}$$

where $\mathbf{1}_n$ is a unit vector of length n. $\overline{\mathbf{X}} = (\overline{\mathbf{x}}_1, \overline{\mathbf{x}}_2, \cdots, \overline{\mathbf{x}}_3)$ contains the mean of each column,

$$\overline{\mathbf{x}}_t = \frac{1}{m} \sum_{s=1}^{m} x_{st}. \tag{6}$$

Then the temporal covariance is formulated as

$$\mathbf{C} = \frac{1}{m-1}\mathbf{X}'^T\mathbf{X}'. \tag{7}$$

Eigenvectors can be obtained by solving the eigenvalue equation

$$\mathbf{CU} = \mathbf{U}\Lambda, \tag{8}$$

where $\mathbf{U}$ is an orthogonal matrix and $\Lambda = diag\,(\lambda_1, \lambda_2 \cdots, \lambda_n)$ contains eigenvalues of temporal covariance $\mathbf{C}$ in descending order.

It is proved that the first eigenvalues represent the main features of the signal, so we decide the number of eigenvalues by selecting the eigenvalues which can amount to 95% of the sum of all eigenvalues [29]. The eigenvalues of different objects is classified by a support vector machine (SVM) classifier so as to achieve false target suppression.

IV. IMPLEMENTATION AND EXPERIMENT

In this section, our new neural network is implemented on SAR images from SSDD dataset to obtain potential targets. It is compared with some state-of-art detection methods for weak targets. Then, our false alarm suppression method is applied to verify the effectiveness of our proposed method.

A. DATASET

To verify the performance of our proposed method, we use dataset called SAR ship detection dataset (SSDD), which can be obtained in [30]. SSDD is the first public dataset for ship target detection in SAR images, which has been widely used to compare the performance of different detectors. SAR images in this dataset comes from different sensors and scenes, such as Radarsat-2, Sentinel-1, and TerraSAR-X with the resolution ranging from 1 to 15 m, which contains multiscale ships labeled with BBox in various environments. The polarization modes of these samples include HH, HV, VV and VH. There are totally 1160 images in SSDD, which are randomly divided into training set and test set with the proportion of 8:2 for the training and testing of the proposed method.

B. EXPERIMENTAL SETUP

Simulations are conducted under TensorFlow framework. Weights of this new neural network are set under He initialization. In the training stage, initial learning rate is set as 0.005. Adam optimizer is adopted for training loss optimization. This network is trained with 500 epochs and the minibatch size is set as 8.

C. EVALUATION CRITERIA

In order to evaluate different models properly, we choose average precision (AP), false alarm rate (p_f) and missing rate (p_m) to quantify the performance of the models.

AP is defined for target detection algorithms, which is expressed as

$$AP = \int_0^1 P_d\,(R_d)\,dR_d \tag{9}$$

where d is the IoU threshold judging a detection result is true positive or a false positive. The value of AP ranges between 0 and 1. Regularly, d is set as 0.5.

The precision rate p_d is defined as

$$p_d = \frac{TP}{TP + FP} \tag{10}$$

where TP denotes true positive targets and FP denotes the false positive targets.

The recall rate R_d is defined as

$$R_d = \frac{TP}{TP + FN} \tag{11}$$

where FN denotes false negative targets.

The missing rate p_m is defined as

$$p_m = \frac{FN}{GT} \tag{12}$$

where GT denotes the actual number of ships.

The false alarm rate p_f is defined as

$$p_f = \frac{FP}{GT} \tag{13}$$

D. DETECTION RESULTS OF OUR PROPOSED NEURAL NETWORK

In order to prove the effectiveness of our proposed neural networks, we compare it with some state-of-the-art detection methods, such as YOLOv3, Retina-Net and Faster R-CNN [31]. To evaluate the performance of different detection methods, average precision (AP), false alarm rate (p_f) and missing rate (p_m) are introduced as indicators. The results of three complex backgrounds are shown in Fig. 5 and the overall comparison is shown in Table 2.

As shown in Fig. 5 and Table 2, the detection performance of our proposed neural netowrk is better than the other three. The detection performance of YOLOv3 is better than that of Retina-Net and of Faster R-CNN because Faster R-CNN is not suitable for small targets detection which has a high missing detection rate. Both of these four methods have unbearable false alarm rates. All targets are enlarged on the feature maps and their boundaries become blurred. This is because neighborhood similarity module not only enhances the features of targets but also enhances features surrounding the target edges, which causes the edges to be incorrectly determined as targets. This is why our proposed method has a high false alarm rate.

E. FALSE TARGET SUPPRESSION

The false alarm suppression method is implemented after applying detection based on neural network. It is based on the classification result of the proposed neural network.

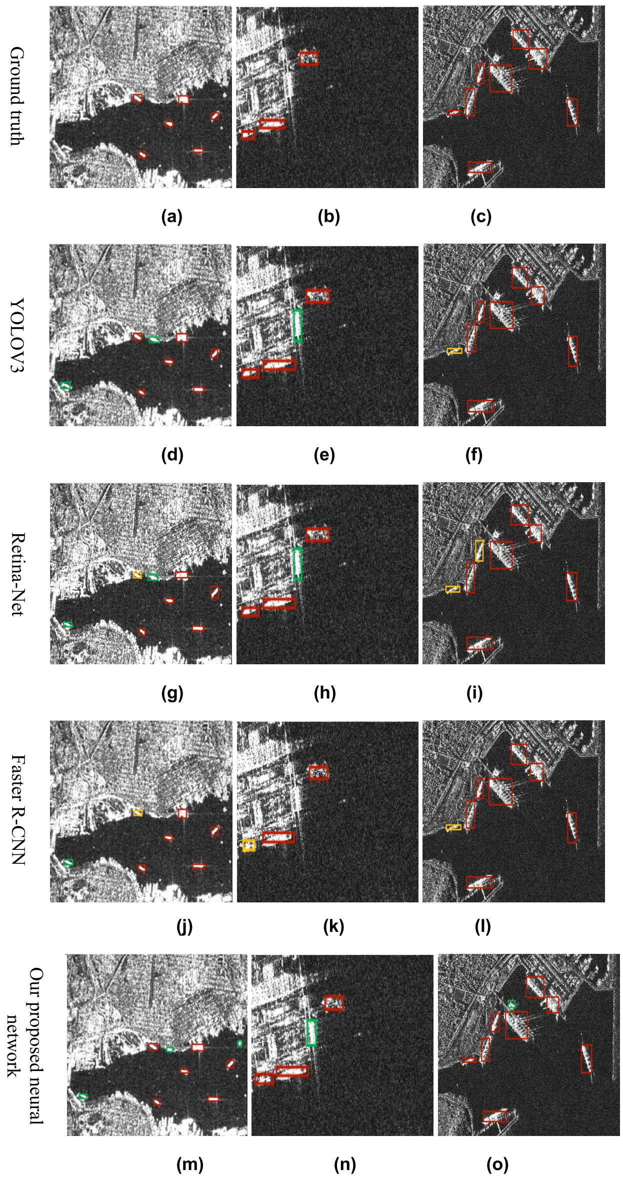

FIGURE 5. Comparison between different detection methods. (a) Ground truth of scene 1. (b) Ground truth of scene 2. (c) Grouth truth of scene 3. (d)YOLOv3 for scene 1. (e) YOLOv3 for scene 2. (f) YOLOv3 for scene 3. (g) Retina-Net for scene 1. (h) Retina-Net for scene 2. (i) Retina-Net for scene 3. (j) Faster R-CNN for scene 1. (k) Faster R-CNN for scene 2. (l) Faster R-CNN for scene 3. (m) Our proposed neural network for scene 1. (n) Our proposed neural network for scene 2. (o) Our proposed neural network for scene 3. (real targets are marked in red, false targets are marked in green and missing targets are marked in yellow.)

TABLE 2. The overall comparison between different detection methods.

Detection methods	AP	P_f	p_m
YOLOv3	0.780	0.194	0.144
Retina-Net	0.717	0.188	0.150
Faster R-CNN	0.733	0.181	0.187
Our proposed neural network	0.848	0.197	0.080

Since the false alarms are caused by inshore facilities in the scenario concerned, it is necessary for us to discriminate true targets from those inshore facilities. As stated in Section III, the number of eigenvalues is selected by the principle that all components can reach 95% of the signal. Therefore, the number of eigenvalues is set to be 5. The eigenvalues corresponding to true targets and false ones are shown in Table. 3. It is obvious that there is difference between the eigenvalues of true targets and those of false ones. So it is proved that empirical orthogonal function is a useful tool to suppress false targets.

After calculating eigenvalues, we perform an SVM classifier to discriminate true targets and false ones. The results of three complex backgrounds are shown in Fig. 6 and the comparison of p_f is shown in Table 4.

As shown in Fig. 6 and Table 4, there are only true targets left in the radar image after implementing our false target suppression method. p_f decreases dramatically, which proves the effectiveness of our method.

TABLE 3. The eigenvalues.

Radar series	Eigenvalue 1	Eigenvalue 2	Eigenvalue 3	Eigenvalue 4	Eigenvalue 5
True targets	1.91	1.53	0.73	0.15	0.06
	1.94	1.58	0.84	0.23	0.05
	1.91	1.54	0.82	0.17	0.07
False targets	1.85	1.28	0.45	0.04	0.02
	1.85	1.24	0.51	0.04	0.01
	1.87	1.27	0.42	0.05	0.01
	1.88	1.26	0.43	0.05	0.02
	1.87	1.27	0.45	0.04	0.01
	1.88	1.23	0.43	0.05	0.01
	1.82	1.25	0.42	0.04	0.02

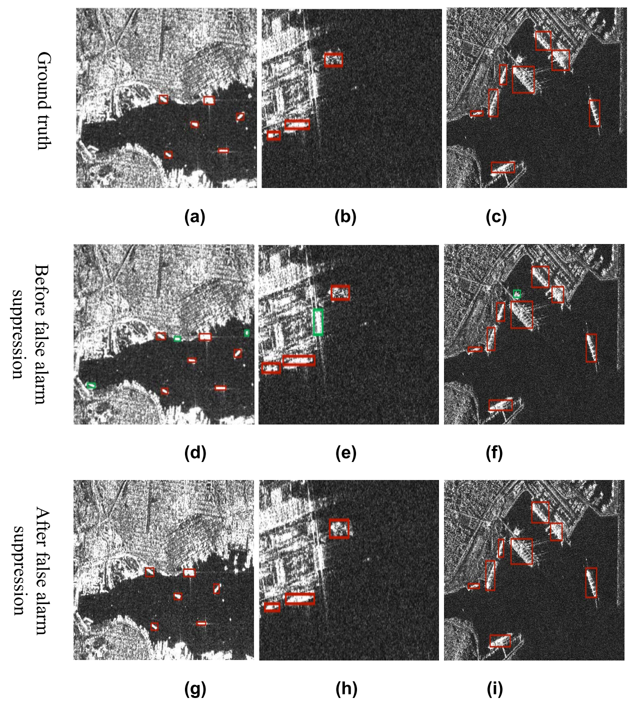

FIGURE 6. False alarm suppression. (a) Ground truth of scene 1. (b) Ground truth of scene 2. (c) Ground truth of scene 3. (d) Scene 1 before false alarm suppression. (e) Scene 2 before false alarm suppression. (f) Scene 3 before false alarm suppression. (g) Scene 1 after false alarm suppression. (h) Scene 2 after false alarm suppression. (i) Scene 3 after false alarm suppression. (real targets are marked in red, false targets are marked in green and missing targets are marked in yellow.)

TABLE 4. The comparison of probability of false alarms.

Detection methods	P_f
Before false alarm suppression	0.197
After false alarm suppression	0.084

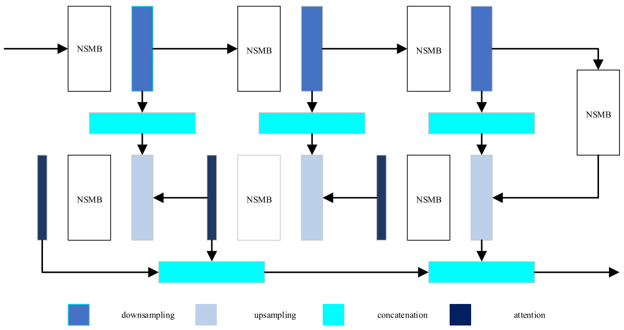

FIGURE 7. The structure of our detection neural network with attention module.

TABLE 5. The Comparison between our proposed method and our neural network with attention.

Methods	P_f	Time(ms)
Our proposed method	0.084	67.7
Our neural network with attention	0.093	83.4

Finally, we compare our detection neural network with the attention mechanism in terms of the performance of false alarm suppression. The attention module which is added into our detection neural network is the same as that in [18]. The structure of our detection neural network with attention module is shown in Fig. 7.

The comparison result is shown in Table. 5. It is obvious that our proposed method is better than our detection neural network with attention module in false alarm suppression and running time. This is because the latter utilises a complex neural network, introducing a large amount of training parameters.

V. CONCLUSION

In this paper, we propose an effective detection method for small targets based on combination of SAR time series and SAR images. Our method has two advantages: it incorporates a neighborhood similarity module to improve detection performance of small targets; and develop a computationally-efficient method to suppress false targets. Its performance is verified by real data recordings. Future work will extend real field processing to complex field processing by using Wasserstein–Fourier analysis to further reduce false alarm rate.

REFERENCES

[1] H. Bi, J. Deng, T. Yang, J. Wang, and L. Wang, "CNN-based target detection and classification when sparse SAR image dataset is available," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, pp. 6815–6826, 2021, doi: 10.1109/JSTARS.2021.3093645.

[2] Y. Zhao, L. Zhao, B. Xiong, and G. Kuang, "Attention receptive pyramid network for ship detection in SAR images," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 13, pp. 2738–2756, 2020, doi: 10.1109/JSTARS.2020.2997081.

[3] S. Wang, Y. Wang, H. Liu, and Y. Sun, "Attribute-guided multi-scale prototypical network for few-shot SAR target classification," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, pp. 12224–12245, 2021, doi: 10.1109/JSTARS.2021.3126688.

[4] Z. Hong, T. Yang, X. Tong, Y. Zhang, S. Jiang, R. Zhou, Y. Han, J. Wang, S. Yang, and S. Liu, "Multi-scale ship detection from SAR and optical imagery via a more accurate YOLOv3," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, pp. 6083–6101, 2021, doi: 10.1109/JSTARS.2021.3087555.

[5] D. Feng, C. Haase-Schutz, L. Rosenbaum, H. Hertlein, C. Glaser, F. Timm, W. Wiesbeck, and K. Dietmayer, "Deep multi-modal object detection and semantic segmentation for autonomous driving: Datasets, methods, and challenges," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 3, pp. 1341–1360, Mar. 2021, doi: 10.1109/TITS.2020.2972974.

[6] A. Hippert-Ferrer, Y. Yan, and P. Bolon, "EM-EOF: Gap-filling in incomplete SAR displacement time series," *IEEE Trans. Geosci. Remote Sens.*, vol. 59, no. 7, pp. 5794–5811, Jul. 2021, doi: 10.1109/tgrs.2020.3015087.

[7] G. Xiong, F. Wang, W. Yu, and T.-K. Truong, "Spatial singularity-exponent-domain multiresolution imaging-based SAR ship target detection method," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, pp. 1–12, 2022, doi: 10.1109/TGRS.2021.3113919.

[8] Z. Cui, Q. Li, Z. Cao, and N. Liu, "Dense attention pyramid networks for multi-scale ship detection in SAR images," *IEEE Trans. Geosci. Remote Sens.*, vol. 57, no. 11, pp. 8983–8997, Nov. 2019, doi: 10.1109/TGRS.2019.2923988.

[9] Q. Ming, L. Miao, Z. Zhou, and Y. Dong, "CFC-Net: A critical feature capturing network for arbitrary-oriented object detection in remote-sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, pp. 1–14, 2022, doi: 10.1109/tgrs.2021.3095186.

[10] F. Zhang, Y. Wang, J. Ni, Y. Zhou, and W. Hu, "SAR target small sample recognition based on CNN cascaded features and AdaBoost rotation forest," *IEEE Geosci. Remote Sens. Lett.*, vol. 17, no. 6, pp. 1008–1012, Jun. 2020, doi: 10.1109/lgrs.2019.2939156.

[11] Z. Cui, X. Wang, N. Liu, Z. Cao, and J. Yang, "Ship detection in large-scale SAR images via spatial shuffle-group enhance attention," *IEEE Trans. Geosci. Remote Sens.*, vol. 59, no. 1, pp. 379–391, Jan. 2021, doi: 10.1109/TGRS.2020.2997200.

[12] M. Kang, X. Leng, Z. Lin, and K. Ji, "A modified faster R-CNN based on CFAR algorithm for SAR ship detection," in *Proc. Int. Workshop Remote Sens. With Intell. Process. (RSIP)*, May 2017, pp. 1–4.

[13] M. Ju, J. Luo, P. Zhang, M. He, and H. Luo, "A simple and efficient network for small target detection," *IEEE Access*, vol. 7, pp. 85771–85781, 2019, doi: 10.1109/ACCESS.2019.2924960.

[14] L. Wen, J. Ding, and O. Loffeld, "Video SAR moving target detection using dual faster R-CNN," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, pp. 2984–2994, 2021, doi: 10.1109/jstars.2021.3062176.

[15] M. Kang, K. Ji, X. Leng, and Z. Lin, "Contextual region-based convolutional neural network with multilayer fusion for SAR ship detection," *Remote Sens.*, vol. 9, no. 8, pp. 860–873, Aug. 2017, doi: 10.3390/rs9080860.

[16] Y. Zhao, L. Zhao, C. Li, and G. Kuang, "Pyramid attention dilated network for aircraft detection in SAR images," *IEEE Geosci. Remote Sens. Lett.*, vol. 18, no. 4, pp. 662–666, Apr. 2021, doi: 10.1109/lgrs.2020.2981255.

[17] L. Du, L. Li, D. Wei, and J. Mao, "Saliency-guided single shot multibox detector for target detection in SAR images," *IEEE Trans. Geosci. Remote Sens.*, vol. 58, no. 5, pp. 3366–3376, May 2020, doi: 10.1109/tgrs.2019.2953936.

[18] C. Chen, C. Hu, C. He, H. Pei, Z. Pang, and T. Zhao, "SAR ship detection under complex background based on attention mechanism," in *Proc. Chin. Conf. Image Graph. Technol.*, 2019, pp. 565–578.

[19] Z. Lin, K. Ji, X. Leng, and G. Kuang, "Squeeze and excitation rank faster R-CNN for ship detection in SAR images," *IEEE Geosci. Remote Sens. Lett.*, vol. 16, no. 5, pp. 1–5, May 2019, doi: 10.1109/LGRS.2018.2882551.

[20] Z. Sun, M. Dai, X. Leng, Y. Lei, B. Xiong, K. Ji, and G. Kuang, "An anchor-free detection method for ship targets in high-resolution SAR images," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, pp. 7799–7816, 2021, doi: 10.1109/JSTARS.2021.3099483.

[21] Z. Sun, X. Leng, Y. Lei, B. Xiong, K. Ji, and G. Kuang, "BiFA-YOLO: A novel YOLO-based method for arbitrary-oriented ship detection in high-resolution SAR images," *Remote Sens.*, vol. 13, no. 4209, pp. 1–28, Oct. 2021, doi: 10.3390/rs13214209.

[22] K. Fu, J. Fu, Z. Wang, and X. Sun, "Scattering-keypoint-guided network for oriented ship detection in high-resolution and large-scale SAR images," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, pp. 11162–11178, 2021, doi: 10.1109/JSTARS.2021.3109469.

[23] R. Yang, G. Wang, Z. Pan, H. Lu, H. Zhang, and X. Jia, "A novel false alarm suppression method for CNN-based SAR ship detector," *IEEE Geosci. Remote Sens. Lett.*, vol. 18, no. 8, pp. 1401–1405, Aug. 2021, doi: 10.1109/LGRS.2020.2999506.

[24] M. Nieto-Hidalgo, A. J. Gallego, P. Gil, and A. Pertusa, "Two-stage convolutional neural network for ship and spill detection using SLAR images," *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 9, pp. 5217–5230, Sep. 2018, doi: 10.1109/TGRS.2018.2812619.

[25] G. Xiong, F. Wang, W. Yu, and T.-K. Truong, "Spatial singularity-exponent-domain multiresolution imaging-based SAR ship target detection method," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, pp. 1–12, 2022, doi: 10.1109/TGRS.2021.3113919.

[26] P. Chen, H. Zhou, Y. Li, B. Liu, and P. Liu, "Shape similarity intersection-over-union loss hybrid model for detection of synthetic aperture radar small ship objects in complex scenes," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, pp. 9518–9529, Sep. 2021, doi: 10.1109/JSTARS.2021.3112469.

[27] W. Jiang, M. Liu, Y. Peng, L. Wu, and Y. Wang, "HDCB-Net: A neural network with the hybrid dilated convolution for pixel-level crack detection on concrete bridges," *IEEE Trans. Ind. Informat.*, vol. 17, no. 8, pp. 5485–5494, Aug. 2021, doi: 10.1109/TII.2020.3033170.

[28] S. Bera and P. K. Biswas, "Noise conscious training of non local neural network powered by self attentive spectral normalized Markovian patch GAN for low dose CT denoising," *IEEE Trans. Med. Imag.*, vol. 40, no. 12, pp. 3663–3673, Dec. 2021, doi: 10.1109/TMI.2021.3094525.

[29] R. Prebet, Y. Yan, M. Jauvin, and E. Trouve, "A data-adaptive EOF-based method for displacement signal retrieval from InSAR displacement measurement time series for decorrelating targets," *IEEE Trans. Geosci. Remote Sens.*, vol. 57, no. 8, pp. 5829–5852, Aug. 2019, doi: 10.1109/TGRS.2019.2902719.

[30] J. Li, C. Qu, and J. Shao, "Ship detection in SAR images based on an improved faster R-CNN," in *Proc. SAR Big Data Era, Models, Methods Appl. (BIGSARDATA)*, Nov. 2017, pp. 1–6.

[31] T. Zhang, X. Zhang, J. Shi, S. Wei, J. Wang, J. Li, H. Su, and Y. Zhou, "Balance scene learning mechanism for offshore and inshore ship detection in SAR images," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, pp. 1–5, 2022, doi: 10.1109/lgrs.2020.3033988.

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