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Squeeze and Excitation Rank Faster R-CNN for Ship Detection in SAR Images

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Abstract—

Synthetic aperture radar (SAR) deliver detection is an essential a part of marine monitoring. With the improvement in pc vision, deep gaining knowledge of has been used for deliver detection in SAR pics including the quicker area-primarily based totally convolutional neural community (R-CNN), single-shot multibox detector, and densely related community. In SAR deliver detection field, deep gaining knowledge of has plenty higher detection overall performance than conventional strategies on near shore areas. This is due to the fact conventional strategies want sea–land segmentation earlier than detection, and inaccurate sea–land masks decreases its detection overall performance. Though cutting-edge deep gaining knowledge of SAR deliver detection strategies nonetheless have many fake detections in land areas, and a few ships are missed in sea areas. In this letter, a brand new community structure primarily based totally at the quicker R-CNN is proposed to in addition enhance the detection overall performance with the aid of using the use of squeeze and excitation mechanism. In order to enhance overall performance, first, the function maps are extracted and concatenated to achieve multistage function maps with Image Net retrained VGG community. After area of interest pooling, an encoding scale vector which has values among zero and 1 is generated from sub feature maps.

I. INTRODUCTION

WITH the speedy improvement of space borne synthetic aperture radar (SAR) which includes Tarrasa-X, RADARSAT-2, and Sentinel-1 [1]–[3], SAR deliver detection has end up an critical a part of marine monitoring. Many investigations relate to deliver detection in SAR imagery has been carried out. Traditional strategies which includes constant fake alarm rate (CFAR) [4] and generalized probability ratio test [5] hit upon ships after sea–land segmentation and utilize homemade functions for discrimination, that have poor overall performance in near shore regions of high-decision SAR pictures due to the incorrect sea–land mask. Moreover, the speckle noises and movement blurring in SAR snap shots will additionally lower the overall performance of Conventional techniques. Due to a hit try in classification [6], the deep getting to know will become a brand new choice. Current modern-day deep getting to know item detection techniques are commonly primarily based totally on a two-degree mechanism and region-primarily based totally convolutional neural network (R-CNN) framework [7], [8]. After extracting shared characteristic maps with a CNN, the community generates candidate place proposals for ability objectives within side the first stage. In the second one stage, the community classifies those proposals and outputs corresponding categories. In faraway sensing field, deep getting to know has additionally been used for item detection tasks [9]. In previous studies, deep getting to know strategies which construct on quicker R-CNN framework [10]–[12] have proven that those strategies can get excessive detection accuracy in sea regions. Meanwhile, those strategies can locate ships in near shore regions with a few fake detections in land regions.

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To acquire higher detection results, CFAR set of rules is used to lessen the wide variety of fake detections in land areas [10], and multistage data is extracted to shape shared characteristic maps [11], [12]. In preceding studies, there are specifically 3 approaches to enhance the detection overall performance of the quicker R-CNN. First, extracting multistage data or the usage of new complex CNN structure to get shared characteristic maps for first-degree location thought network (RPN) and second-degree classification [13]–[15]. Second, the usage of changed RPN architectures to enhance the first-degree overall performance and generate more correct location proposals [16], [17] for the second-degree classification.

Third, rather than the usage of layers of completely related community for second-degree category, the usage of convolutional layers integrate with completely related layers to enhance second category overall performance of proposals [18]. In this letter, we awareness on the primary and the second one ways to enhance detection overall performance and layout our squeeze and excitation rank quicker R-CNN (SER quicker R-CNN). First, multistage facts are extracted primarily based totally on Image Net retrained VGG community [19] to reap shared function maps. The squeeze and excitation (SE) mechanism [20] is used to modify RPN structure and enhance community detection overall performance. An encoding excitation scale vector which has values between zero and 1 is generated from sub feature maps. Instead of direct recalibrating sub feature maps with the aid of using the excitation vector as [20], on this letter, the excitation vector is ranked and handiest pinnacle K values might be preserved. Other values might be set to zero. Then, the redundant sub feature maps are suppressed the usage of ranked excitation vector with the aid of using multiplying it with sub feature maps. This operation can in addition enhance detection overall performance. The experimental outcomes primarily based totally on Sentinel-1 photos display that the detection overall performance of the proposed SER quicker R-CNN is higher than that of the kingdom of the artwork and plenty quicker. The the rest of this letter is prepared as follows. Section II affords a quick assessment of the quicker R-CNN. Section III introduces our SER quicker R-CNN. Experimental outcomes primarily based totally on Sentinel-1 photos are proven in Section IV to confirm the effectiveness of the proposed methods. Finally, Section V concludes this letter.

II. FASTER R-CNN This segment makes a quick assessment of the quicker R-CNN. The quicker R-CNN is a two-level item detector, which generates a sparse set of candidate item places through an RPN based on shared characteristic maps after which classifies every candidate notion as one of the foreground instructions or background. After extracting shared characteristic maps with a CNN, the first stage RPN takes shared characteristic maps as enter and generates a set of square candidate item places named anchors, every with an objectless score [8]. The length of every anchor relies upon on hyperparameters named scales and issue ratios. A small community is slid over the shared characteristic maps and mapping every sliding window to decrease dimensional characteristic.

III. METHODOLOGY

In this section, the proposed SER quicker R-CNN is introduced. First, the SE mechanism and our rank modification are introduced. Then, we display the structure of SER quicker R-CNN. Finally, the education information is presented. A. Squeeze and Excitation Mechanism Current CNNs are primarily based totally on convolution options, which extract spatial and channel clever data from the local receptive region. To enhance the illustration energy of CNNs, the SE mechanism is proposed to encode feature maps and offer a weight for every channel of the feature maps [20]. Assume that enter function maps of the SE block X have form $W \times H \times C$, wherein W is the width, H is height, and C is the channels of function maps. The function maps are first pooled via way of means of a worldwide common pooling layer to form $1 \times 1 \times C$. Then, the pooled vector is encoded to form $1 \times 1 \times (C/r)$ and decoded lower back to $1 \times 1 \times C$ with absolutely related layers

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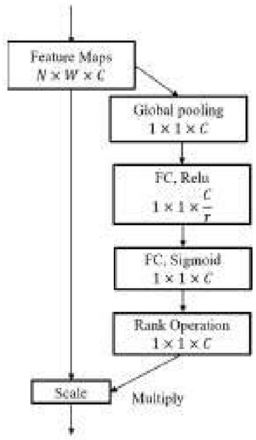

Fig. 1. Architecture of SER block. To get the excitation vector V. The output Y of SE block is defined as follows:

$$Y = \sum_{i} X_i * V_i. \quad (1)$$

In (1), every channel Xi in enters characteristic maps X is multiplied with a corresponding excitation weight VI within side the excitation vector V. The goal of SE block is to examine a weight for every characteristic maps after which suppress redundant characteristic maps. The quicker R-CNN primarily based totally in this mechanism is known as SE quicker R-CNN. B. Rank Modification When the use of SE block to enhance the overall performance of RPN, we examine that the fee of every VI is round 0.5. Although the overall performance has improved, the redundant characteristic maps aren't absolutely suppressed. Related experiments are proven in Section IV. In this letter, with a view to similarly enhance the overall performance, the rank operation is proposed. The values in excitation vector V are ranked and simplest pinnacle K values might be preserved. Other VI might be set to zero to bolster the suppress function. So, within side the output Y, the characteristic maps associated with VI = zero might be absolutely suppressed. In the experiments, this can assist similarly enhance the overall performance and we name this SER block. The structure of SER block is proven in Fig. 1.

C. Squeeze and Excitation Rank Faster R-CNN The structure of SER quicker R-CNN is proven in Fig. 2. First, the function maps from the closing convolutional layers of VGG community Conv1_x, Conv2_x, and Conv3_x are normalized with the aid of using l2 normalization and concatenated together. Then, the concatenated function maps are fed into RPN after reducing to 512 channels with the aid of using a 1 × 1 convolutional layer and generate area proposals.

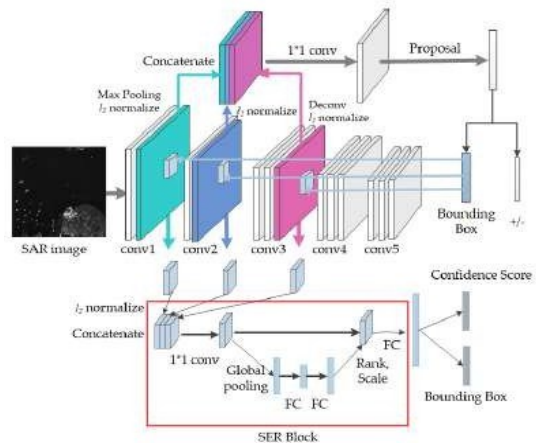

Fig. 2. Architecture of SER faster R-CNN. Preserved.

The excitation vector is used to recalibrate sub feature maps and output to the second classification stage. Finally, the bounding box and confidence score of each proposal are output.

D. Training Details

1) Concatenation of Multiple Layers: In current CNN architecture, the max-pooling layers are used to extract high-level feature representations. So, one pixel in feature maps corresponds to the information of an area in the input image. In order to obtain multistage information, the feature maps from last convolutional layers before max-pooling layers are concatenated. In this letter, we concatenate the last convolutional layer of VGG network Conv1_x, Conv2_x, and Conv3_x to obtain multistage feature representations. The layer from Conv1_x is up sampled by a deconvolution layer to the same size of the layer from Conv2_x. At the same time, the layer from Conv3_x is down sampled by a max-pooling layer to the same size of the layer from Conv2_x. Then, these layers are concatenated along the channel axis as [13] and [20].

By offering $l2$ normalization to each layer before concatenation, the training can be more stable and the performance can be improved. For a layer with N-dimensional input $X = (x1 \ldots an)$, the output of $l2$ normalization $\hat{X}$ can be denoted as follows:

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$$\|X\|_2 = \left(\sum_{i=1}^{N} |x_i\right)^{1/2} \quad (2)$$

$$\hat{X} = \frac{X}{\|X\|_2}. \quad (3)$$

In order to accelerate the training, a scaling parameter *if* is introduced for each channel, which scales the normalized
Value by *yes* = *if x*ˆ*i* [22]. In this letter, *γi* is set to 40. This parameter will not influence performance.
3) Hyperparameters Setting: The learning rate of network is set to 1 × 10−4 initially, and maximal iteration is 20 000.
The parameters of layers in SER block is initialized from the Gaussian distribution with zero mean and a standard deviation of 0.01. The first-stage feature stride is 2 when concatenating Conv1_x, Conv2_x, and Conv3_x as feature maps. The RPN anchor scales are 1, 2, 4, and 8 and aspect ratios are 0.125, 0.25, 0.5, and 1.

IV. EXPERIMENTAL RESULTS

In this section, first, the experimental records set and settings are introduced. Next, a test is designed to explore which layers have to be concatenated to get higher characteristic representations for the primary level and the second one level. Then, the overall performance of SE quicker R-CNN is proposed, and the values of excitation vector are investigated to reveal that the redundant characteristic maps aren't absolutely suppressed. Finally, the proposed SER quicker R-CNN is evaluated and compared with the SE quicker R-CNN and cutting-edge methods. In addition, the computational price of fashions is presented. A. Experimental Data Set and Settings The records set used on this letter is from Sentinel-1A, which turned into accumulated in interferometric extensive swath mode. The pixel spacing is 10 m. Twenty picas with 6484 ships are used for schooling, and greater picas which reinstated by professionals with 1348 ships are used for trying out. The schooling records aren't divided into greater validation records like different object detection literature in pc vision [8]. Some AIS records are used to assist manually annotation [23]. For schooling records set, the classified picas have been reducing into 512 × 512 sized patches without overlap. The patches with ships are fed into the community for schooling. The trying out pics is processed in the identical way. In order to assess the detection overall performance of the network, the goal detection opportunity, fake detection opportunity which refers back to the opportunity that one goal in detection effects to be a fake detection, and F1 score [12] are defined as

$$P_d = \frac{N_{td}}{N_{\text{ground\_truth}}} \quad (4)$$

$$P_f = \frac{N_{fd}}{N_{\text{total\_target}}} \quad (5)$$

$$F1 = 2 \times \frac{P_d \times (1 - P_f)}{P_d + (1 - P_f)} \quad (6)$$

Where Ntd is the number of true detections, Nground_truth is the total number of ground truth, $N f d$ is the number of false detections, and Ntotal_target is the number of total detections.

TABLE I
DETECTION PERFORMANCE OF DIFFERENT CONCATENATION STRATEGIES

Layers	P_d (%)	P_f (%)	$F1$
5	61.7	30	0.656
1+2+3	71	18.5	0.759
1+3+5	70.8	18.7	0.757
3+4+5	69	16.5	0.756
2+3+4	72	23.4	0.742

TABLE II
DETECTION PERFORMANCE OF A DIFFERENT FASTER R-CNN BEFORE AND AFTER USING THE SE BLOCK

Layers	P_d (%)	P_f (%)	$F1$	r
Faster R-CNN 1+2+3	71	18.5	0.759	-
SE faster R-CNN	72.5	24.7	0.739	1
SE faster R-CNN	76.5	16.5	0.799	2
SE faster R-CNN	78.7	17.8	0.804	4
SE faster R-CNN	77.8	18.1	0.798	8

Considering the tradeoff among Pd and Pf, F1 is used as metric for the community overall performance evaluation. B. Multilayer Concatenation Strategies Multistage records received via way of means of concatenating distinct function maps is powerful for vicinity suggestion era and detection, particularly due to its richness and suitable resolution. In this section, distinct fashions are educated and tested to reveal that concatenate Conv1_x, Conv2_x, and Conv3_x are the first-rate strategy. The fundamental version makes use of function maps from Conv_5 layer for the first-level RPN and the second-level classification

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the 2d version combines layers 1, 2, and three. The 1/3 version combines layers 1, 3, and 5, the fourth version combines layers 3, 4, and 5, and the very last version combines layers 2, 3, and 4. The outcomes are proven in Table I. As proven in Table I, the F1 overall performance of different concatenation techniques are near and all outperform basic version. However, the version which mixes layers 1, 2, and three outperforms different fashions on F1 overall performance under experimental situations on this letter. So, this method is used to extract shared characteristic maps for the first-degree RPN and the 2d-degree classification.

C. SER Faster R-CNN In this section, first, the overall performance of SE quicker R-CNN with a distinct hyperparameters r which determines the length of encoding vector is presented. The multistage function map concatenation approach combines layers 1, 2, and 3. The overall performance of SE quicker R-CNN fashions is in comparison with the version which simplest use multistage function map concatenation approach and is proven in Table II. As proven in Table II, maximum SE quicker R-CNN fashions could have higher F1 overall performance. The outcomes display that the SE blocks is effective. However, while gazing the values in excitation vector as proven in Fig. 3, maximum values are round 0.five and the redundant function maps aren't absolutely suppressed. In order to similarly enhance overall performance, the SER block is proposed to absolutely suppress redundant function maps. The overall performance of proposed SER quicker R-CNN with K = 256 and a distinct hyperparameters r is proven in Table III. At the equal time, the proposed technique is

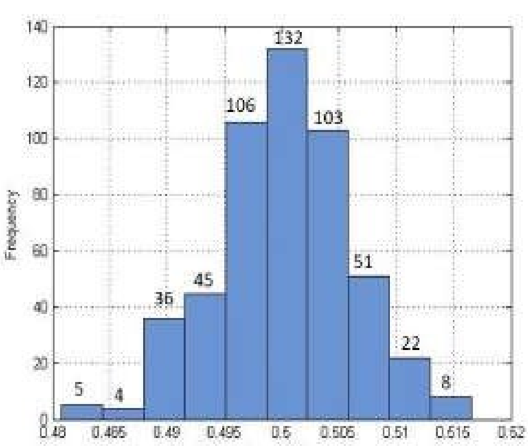

Fig. 3. Distribution of values in excitation vector.

TABLE III

COMPARISON OF DETECTION PERFORMANCE BETWEEN SER FASTER R-CNN AND THE STATE-OF-THE-ARTMETHODS

Layers	P_d (%)	P_f (%)	$F1$	r
SER faster R-CNN	**81.1**	**13.8**	**0.836**	1
SER faster R-CNN	80.5	24.4	0.779	2
SER faster R-CNN	76.6	19.1	0.787	4
SER faster R-CNN	79.5	17.3	0.811	8
Contextual faster R-CNN [12]	72.7	20	0.762	-

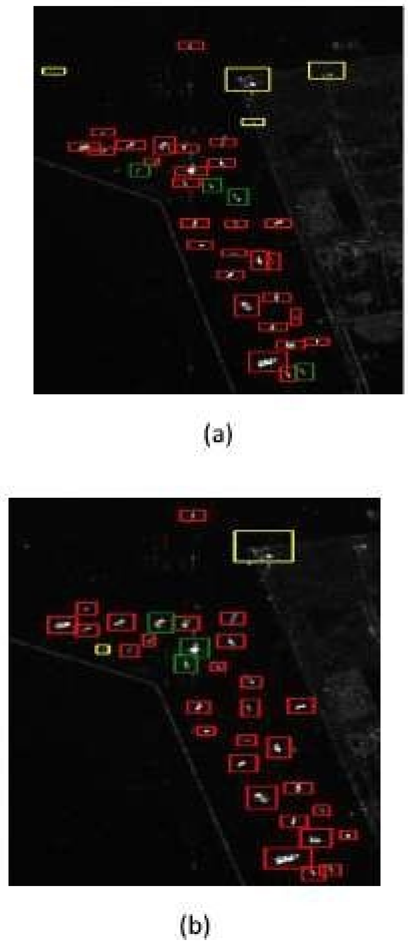

Fig. 4. Detection end result of contextual quicker R-CNN and SER quicker R-CNN on near shore region. (a) Contextual quicker R-CNN. (b) SER quicker R-CNN. The pink container denotes proper detections, yellow container denotes fake detections, and inexperienced container denotes lacking ships. The end result is a small a part of Sentinel-1 SAR photograph which taken in April 7, 2016, Tianjin, China, product identifier 00FFEA_ADBD. As compared with the preceding research. The overall performance of the proposed community is 9.7 better than that of the kingdom of the art [13]. Network receives nice overall performance while r = 1. This might also additionally due to the fact a huge encode

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layer enables community to higher discover ways to separate essential function maps, which will be preserved after SER block of community. An instance of detection end result on near shore region is proven in Fig. 4. As proven in Fig. 4, the proposed SER quicker R-CNN can successfully locate near shore ships which tough to be detected through traditional methods. D. Rank Threshold of SER Block in SER block, most effective pinnacle K values of the excitation vector V is preserved. The proposed SER quicker R-CNN with a different hyperparameters K is provided in Fig. 5. As proven in Fig. 5, the community receives the nice overall performance while K = 256. This fits with the phenomenon that approximately 1/2 of values of

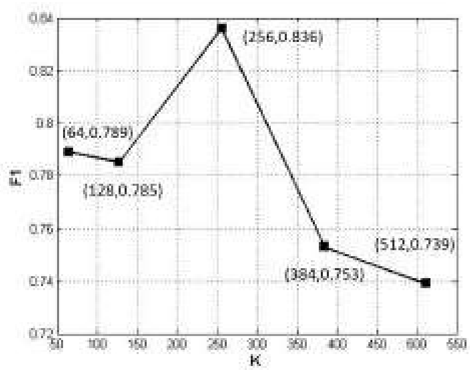

Fig. 5. $F1$ performance of SER faster R-CNN with hyperparameters $r = 1$ and a different K.

TABLE IV
RUNNING TIME OF DIFFERENT NETWORKS

Network	r	K	Time (s)	Normalized time
SER faster R-CNN	1	256	0.25	3.42
SE faster R-CNN	1	512	0.244	3.34
Faster R-CNN 1+2+3	-	-	0.243	3.32
Faster R-CNN 5	-	-	0.073	1
Contextual faster R-CNN [12]	-	-	0.285	3.90

Excitation vector much less than 0.5, because of this that that approximately half function maps need to be suppressed. E. Running Time of Models In this section, the jogging time and normalized jogging time of various networks referred to on this letter are presented. As proven in Table IV, the jogging time of the proposed SER quicker R-CNN is 14 than that of the state of the art [12]. The time value of SER quicker R-CNN with r = 1 and K = 256 is nearer with that of the SE quicker R-CNN with r = 1 and K = 512. This suggests that our change on SE mechanism does now no longer carry an excessive amount of extra computational value.

V. CONCLUSION

In this letter, a unique item detector for ships in SAR images referred to as SER quicker R-CNN is proposed. The multistage function map concatenation approach is used to enhance the high-satisfactory of shared function maps extracted through a CNN. The SER mechanism is used to enhance the first-level RPN overall performance of quicker R-CNN. The experimental consequences gift how we layout such high-overall performance item detector. The consequences display that our SER quicker R-CNN outperforms the modern day method and plenty quicker. In destiny works, we can look into the 1/3 manner which improves community overall performance through designing appropriate structure for the second-level classification.

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