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Examination of Ship Object Recognition in High-Determination Sar Metaphors Based on Information Theory and Harris Corner Detection Technique

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ABSTRACT

In demand to make up the defects of some prevailing ship object recognition systems for high-determination synthetic aperture radar (SAR) images, a ship object recognition system centered on information theory and Harris corner recognition for SAR images is anticipated in this paper. At the outset, the SAR appearance is pretreated, and later, it is alienated into super pixel squares by consuming the upgraded simple direct iterative bunching super pixel generation algorithm. Then, the self-statistics rate of the super pixel squares is deliberate, and the threshold T1 is fixed to hand-picked the aspirant super pixel squares. And formerly, the prolonged vicinity biased statistics entropy progression level threshold T2 is set to exclude the false alarm aspirant super pixel squares. As a final point, the Harris corner detection algorithm is used to route the recognition outcome and the quantity of the corner threshold T3 is set to riddle out the false alarm squares, and the ultimate SAR image object recognition outcome is attained. The efficiency and supremacy of the recommended algorithm are certified by equating the recommended method with the outcomes of constant false alarm rate (CFAR) recognition algorithm shared with morphological handling algorithm and further ship object recognition algorithms.

KEYWORDS: *SAR image, Ship recognition, CFAR, Superpixel, Information theory and Harris*

1. Introduction

Synthetic aperture radar imaging is inadequate by meteorological conditions, illumination, or further circumstances. To perform exploration on ship SAR object recognition is significant for marine observing management and appropriate military statistics acquisition [1].

There are several systems for ship object recognition, but the constant false alarm rate (CFAR) recognition system is most widely used [2]. Scholars have recommended some recognition systems based on dissimilar statistical distribution typical of sea clutter in SAR images, as well as the gamma distribution model, Weibull distribution model, therefore on[3–5]. Though, they are not autonomous on the clutter statistical model, and they are not vigorous. Furthermore, CFAR recognition systems are centered on pixel-level recognition, and they will cause some false alarm recognition objects. Subsequently the conception of superpixel is recommended, the target recognition in SAR images based on superpixel has established quickly [6]. It uses the superpixel as an alternative of the pixel as the handing out unit, and it can acquired improved recognition outcome [7].

In modern years, the awareness of visual consideration has been familiarized into SAR object recognition and it has attained some good enactment. Hou et al. [8] suggested a ship recognition system in SAR images centered on visual consideration model consistent with the erstwhile awareness that ships are in the water region instead of on the land, the ship recognition enactment is well, and the ship recognition enactment can be amended although there are still specific false alarm objects and specific lost ship objects in the recognition outcome.

Liu and Cao [9] have shared the pyramid model of visual consideration with singular value decomposition(VA-SVD) to discover the objects in SAR turning images; however, the reckoning speed of the processis very slow, and the recognition enactment is not very good when the SAR pictures have a huge and multifaceted scene. Wang et al. [10] recommended a visual consideration-based target recognition method for high-determination SAR images in multifaceted scenes; despite the fact the recognition rate in multifaceted is high, the unique morphology of the objects cannot be well-looked-after the ultimate recognition outcome.

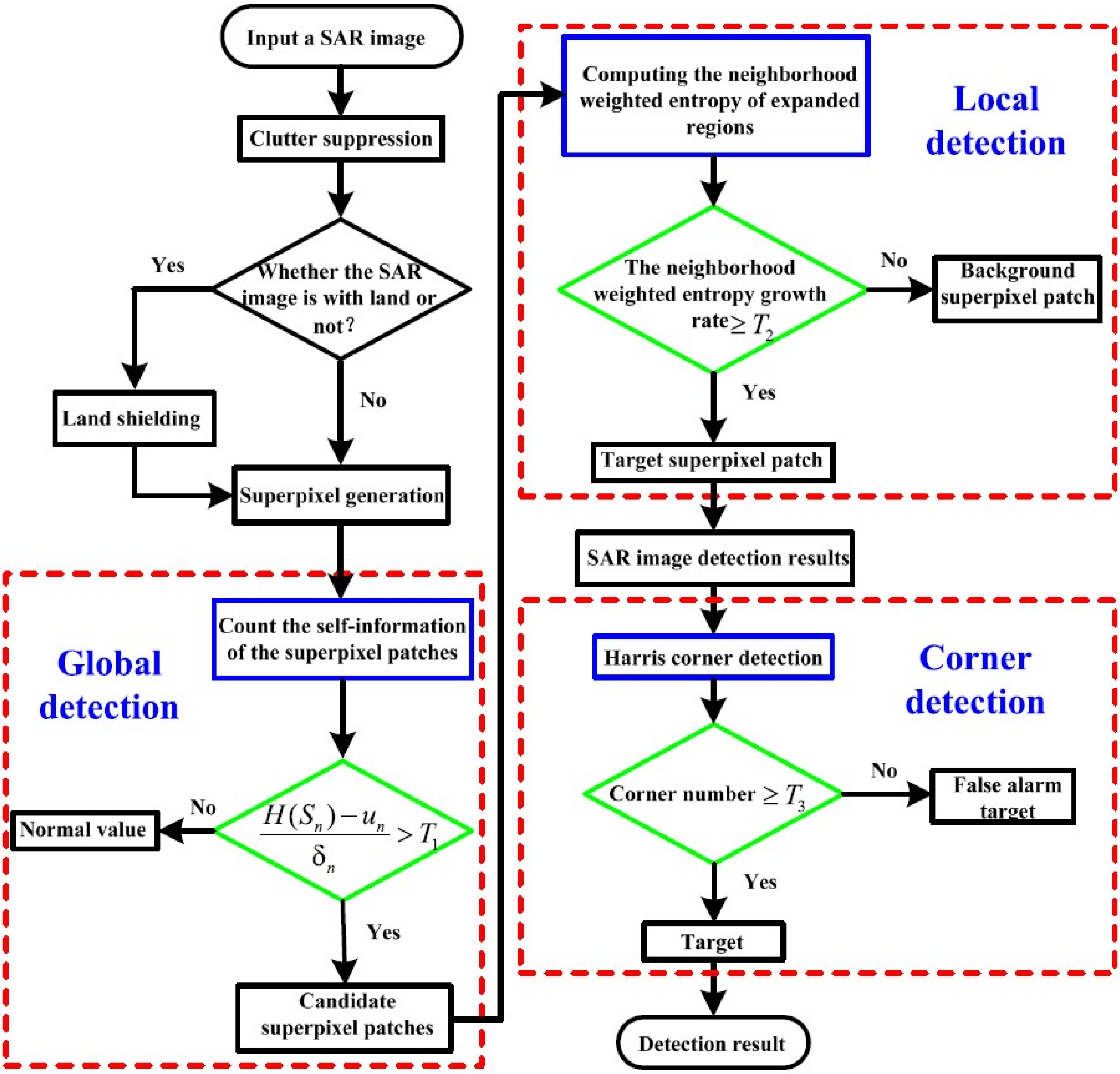


Fig. 1 Flowchart of the proposed ship object detection algorithm

For instance the recognition system based on statistics, Caoet al. [11] recommended a fast object recognition system for high-tenacity SAR images established on variance weighted information entropy (VWIE), and Wang and Chen [12]have secondhand the system based on multiscale variance weighted image entropy (MVWIE) system to identify the ship objects in the multifaceted related SAR images. They are verified to be operative to identify the true objects magnificently; conversely, the refinement of the object and the immediate cells is challenging, and there are habitually specific false alarm objects in the recognition outcome.

With the intention of expanding the recognition enactment of the prevailing ship object recognition method for high determination SAR images, a ship object recognition system centered on information theory and Harris corner detection for high-determination SAR images is suggested in this paper.

The residue of this paper is organized as surveys. Section 2 presents the recognition system based on information theory and Harris corner detection. Section 3shows the particulars of our experimentations and gives the outcome investigation based on the suggested method. As a final point, the decisions given in Section 4.

2. Methods

The suggested recognition method involves of three phases, comprising the global recognition, local recognition, and Harris corner detection, as demonstrated in Fig. 1.

2.1 Super pixel generation algorithm

Presently, the superpixel generation processes such as watershed algorithm, mean shift system, and K-means system are broadly used in the optical image processing. For ship object recognition in SAR images, the succeeding processing will be at ease if the brink of the superpixel squares can concur oralmost concur with the brink of the objects in the SAR image. The simple linear iterative clustering(SLIC) superpixel generation algorithm [13] which is centered on clustering can come across the requirement declared above. Yet, as the SLIC algorithm is used for optical image processing, without allowing for that the SAR image is the gray image, the color space of an optical image must be in tuned to the grayscale. The further steps are the alike as the SLIC algorithm.

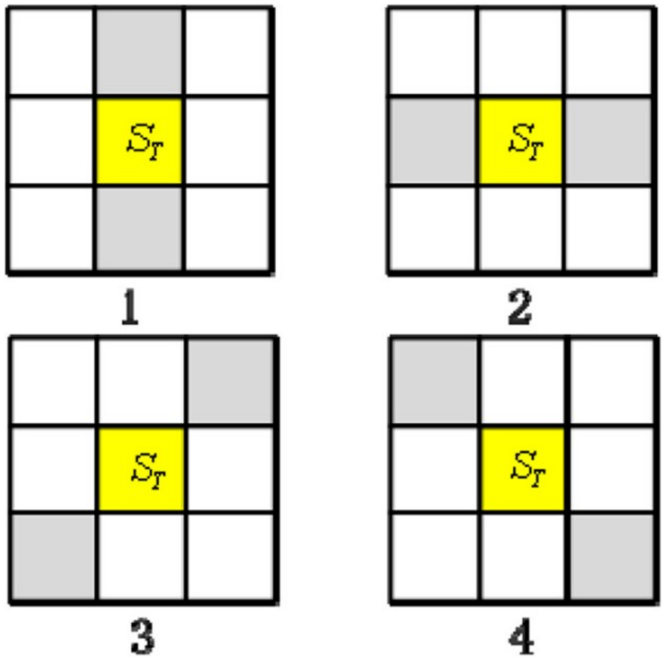


Fig.2 the four extended vicinity

2.2 Self-statistics of SAR image

In the information theory, the self-statistics of a random event ei is distinct as:

$$H(e_i) = -\log_m p(e_i) \tag{1}$$

Midst the expression, p(ei) is the occurrence probability of the random event ei, and the variable i epitomizes the ith conceivable event. If the base of the exceeding alogarithm is 2, the unit of H(ei) is bits.

For any superpixel squareSn in SAR representation I, pretentious that the superpixel square is self-possessed of a × a pixels,the intensity distribution model of Sn can be articulated by the following formula:

$$\begin{pmatrix} r \\ p(r) \end{pmatrix} = \begin{pmatrix} 0, & 1, & \ldots, & 255 \\ p(0), & p(1), & \ldots, & p(255) \end{pmatrix} \tag{2}$$

Amongst the expression, the variable p(r) symbolizes the probability of the pixel whose grayscale concentration value is r. The likelihood function is used to convey the probability of each superpixel square. Its provisional probability value is:

$$P(S_n|\mathrm{I}) = \prod_{k=1}^{a^2} P_I(S_n(k)) \tag{3}$$

Within the expression, PI(•) is the probability distribution of the SAR representation I, and Sn(k) is the analogous gray value of the kth pixel. As the order of pixels in superpixel squares is not painstaking, the upper expression can be symbolized by the probability distribution of superpixel square Sn.

$$P(S_n|\mathrm{I}) = \prod_{i=1}^{255}\left(P_I(i)^{P_{Sn}(r)\cdot a^2}\right) \tag{4}$$

b Superpixel fragmentation outcome Substituting Eq. (4) to (1), the consequent self-in sequence of the superpixel square Sn can be obtained,as demonstrated in the subsequent expression:

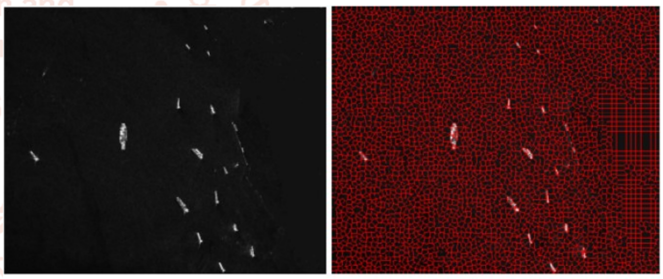
$$\begin{aligned} H(S_n|\mathrm{I}) &= -\log_m(P(S_n|\mathrm{I})) = -\log_m\left(\prod_{r=0}^{255}(P_I(r)^{P_{Sn}(r)\cdot a^2}\right) \\ &= -a^2\cdot\sum_{r=0}^{255}(P_{Sn}(r)\cdot\log_m(P_I(r))) \end{aligned} \tag{5}$$

A definition is prepared that if PSn(r) ≠ 0, PSn(r) = 1. Then,it can be acquireed that:

$$H(S_n|\mathrm{I}) = -a^2\cdot\sum_{r=0}^{255}\log_m(P_I(r)) \tag{6}$$

Fig. 3 Original SAR representation

In this approach, the self-in sequence of any superpixel square Sn can be estimated by using the probability distribution of the grayscale concentration value for the whole representation.



a **b**

Fig.4 The super pixel generation outcome of the original SAR representation. a The land shielding outcome.

2.3 Outlier recognition and false alarm filtering

2.3.1 Outlier recognition

Firstly, the self-information of all the superpixel squares is counted, and the consequent distribution histogram is recognized. The outlier recognition term for the self-information of the superpixel square is shown as follows:

$$\begin{cases} \dfrac{H(S_n)-u_n}{\delta_n} > T_1, & n\in(1,2,\cdots w), \; H(S_n) \text{ is outlier} \\ \dfrac{H(S_n)-u_n}{\delta_n} < T_1, & n\in(1,2,\cdots w), \; H(S_n) \text{ is normal} \end{cases} \tag{7}$$

In the term, H(Sn) is the self-information of the superpixel Sn and assume that the number of superpixel squares is w. The variables un and δn are correspondingly the mean and variance of the histogram allocation of the self-information consequent to the n superpixel squares, and the variable T1 is the recognition threshold.

Following the global recognition, there could be some background superpixel squares in the aspirant superpixel squares, and they can be filtered by means of the subsequent methods.

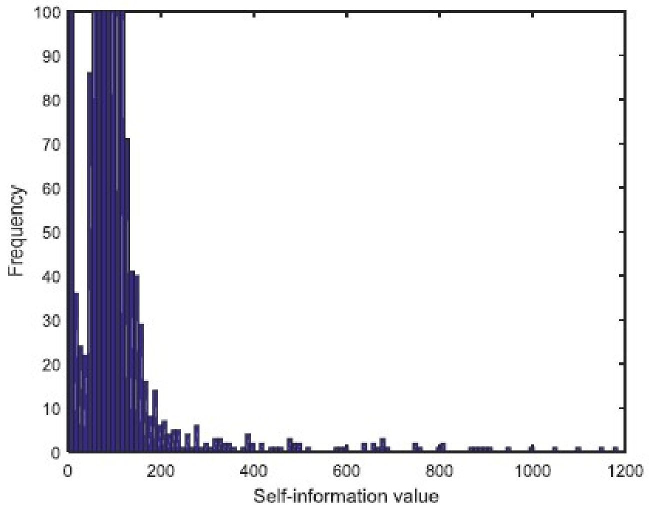


Fig.5 The self-information statistics graph of the superpixel squares

2.3.2 The false alarm filter method founded on weighted information entropy

By means of ST as the core, the four absolute 3 × 3 neighborhood ST(d) in the vertical path, horizontal path, right diagonal path, and left diagonal path can be obtained. The extensive neighborhood areas are exposed in Fig. 2.

The information entropy reflects the normal amount of information in the figure, and it can be uttered as:

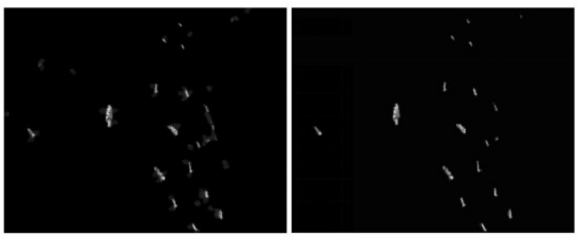
$$H = -\sum_{r=0}^{255} p(r)\ \log p(r) \qquad (8)$$

When p(r) = 0, assent to p(r) log p(r) = 0. along with the expression,p(r) represents the emergence probability of the pixels whose grayscale strength value is r. The weighted information entropy of the trying superpixel square STcan be articulated as follows:

$$E(S_T) = -\sum_{r=0}^{255} (r-\overline{r_V})^2 P_{S_T}(r)\ \log_2(P_{S_T}(r)) \qquad (9)$$

The variable rV is the mean grayscale strength value,and the weighted information entropy E(ST(d)) of the extensive neighborhood ST(d) in four guidelines can be articulated as follows:

$$E(S_T(d)) = -\sum_{r=0}^{255} \left(r-\overline{r_{ER}(d)}\right)^2 \cdot P_{S_T(d)}(r)\ \log_2\left(P_{S_T(d)}(r)\right) \qquad (10)$$



a b

Fig. 6 the recognition outcome based on information theory. A The aspirant superpixel squares. B The weighted entropy filtered outcome

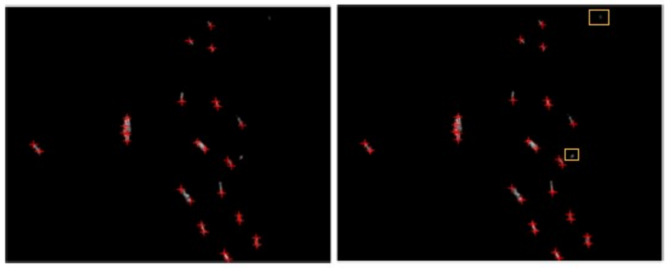
In the equation, rERðdÞ represents the mean grayscale strength value, and PST ðdÞðrÞ is the possibility of the pixel whose grayscale strength value is r. The weighted entropy variation between the aspirant superpixel square and the extensive neighborhood is:

$$V(S_T) = \ \arg\ \min(E(S_T(d)))-E(S_T) \qquad (11)$$

Next, the enlargement value of weighted entropy can be represent by VðST Þ

EðSTÞ . Evaluate it with the succeeding threshold T2 to establish whether the aspirant superpixel square belongs to the object area or the backdrop area, Therefore the false alarm superpixel squares can be detached,as demonstrated in the subsequent expression:

$$\begin{cases} \dfrac{V(S_T)}{E(S_T)} > T_2, S_T \text{ belongs to the target area} \\ \dfrac{V(S_T)}{E(S_T)} < T_2, S_T \text{ belongs to the background} \end{cases} \qquad (12)$$



a b

Fig.7 The Harris recognition outcome and false alarm object marking outcome. a Harris corner recognition outcome. b The false alarm objects marking outcome

2.3.3 The false alarm filtering method founded on Harris corner recognition

Harris corner recognition algorithm is frequently used in optical icon object exposure; however, it is rarely used for object recognition in SAR images [14]. The high-declaration marine ship objects regularly have some crooks, and they can be recognized. The Harris crook algorithm is used to recognize the corner of ship objects in high-declaration SAR metaphors. After that, the crook amount threshold T3 is lay down to advance filter out the false alarm squares, and the final object recognition result in SAR metaphors can be attained. If the crook number is additional than T3, the ship object can be obtained; if not, it will be filtered.

3. Experimental intend and outcome

3.1 Experiment on ship SAR representation with terrain

A high-declaration marine ship SAR image with terrain is selected, as revealed in Fig. 3. The declaration is 1.25 m×1.25 m, and its extent is 961 × 762 pixels; Besides, theSAR image contain 17 ships.

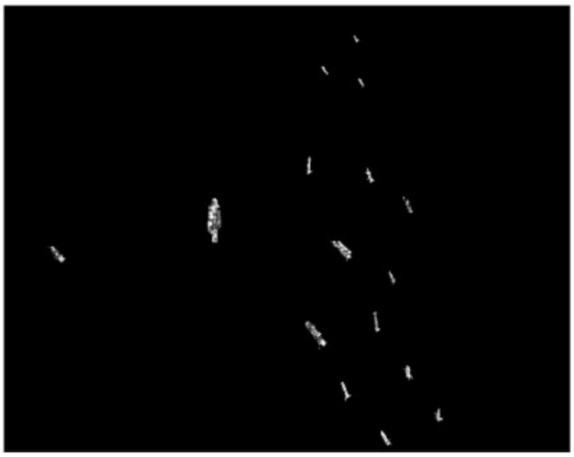


Fig. 8 The final recognition outcome

Initially, Otsu's system combining with the morphological handing out method is worn to guard the land area in the ship SAR representation [15], and the land protecting outcome is shown in Fig. 4a. Next, the enhanced SLIC superpixel fragmentation algorithm is second-hand to process it. The step size of the square area is lay down to 13 pixels, and the superpixel generation outcome is shown in Fig. 4b.

The self-information of the superpixel squares is evaluated, as shown in Fig. 5 underneath, and followed by set the outlier constraint T1 as 1.4, and the aspirant superpixel squares are revealed in Fig. 6a. There are several false alarm superpixel squares in the diagram. After that, set the expansion rate of the neighborhood weighted information entropy T2 as 20%, and the exposure outcome is shown in Fig. 6b.

Accomplish the Harris corner recognition on the filtering outcome of Fig. 6b, and the recognition outcome is shown inFig. 7a. Then, lay down the threshold T3 as 1, following filtering out the two false alarm objects distinct by yellow rectangle box as revealed in Fig. 7b, the final recognition result can be attained as shown in Fig. 8.

Measure up to the recognition performance of the anticipated algorithm with further two recognition algorithms, including the VWIE recognition algorithm and visual consideration with the VA-SVD recognition algorithm, and all experimentation are conducted in the similar Matlab R2016b environment and in the similar desktop PC with a processor of Intel Core i7-8700 K and a memory of 32.0 G. The recognition outcome based on the two recognition algorithms for contrast are shown in Fig. 9.

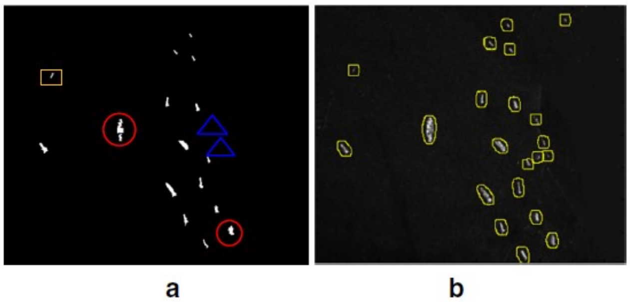


Fig.9 Recognition outcome for comparison. a Recognition outcome of the VWIE algorithm. b Recognition outcome of the VA-SVD algorithm

In Fig. 9, the false alarm objects are patent by the yellow rectangle box and the missing objects are patent by the blue triangles in their consequent position of the unique ship objects. The objects whose form is gravely vague are patent by the red circles. The figure of merit (FoM) is distinct as a superiority factor of the recognition concert, and FoM ¼ Ntt NgtþNfa In the equation, Ntt, Nfa, and Ngt symbolize the number of distinguished objects, the number of properly false alarm objects, and the number of actual objects, correspondingly.

The recently distinct recognition deformation rate is the ratio of the vague object number to the total number of ship objects, and Ndd represents the number of the vague objects. The concert of the three recognition algorithms is shown in Table 1.

Table 1 Similarity of recognition concert among the three recognition algorithms

Detection algorithm	N_{tt}	N_{fa}	Number of missing targets	N_{dd}	Detection distortion rate (%)	FOM	Time (s)
VWIE	15	1	2	2	11.76	0.833	31.6531
VA-SVD	17	4	0	0	0	0.810	56.3753
The proposed algorithm	16	0	1	0	0	0.941	29.0221

It can be seen that the recognition outcome of the anticipated algorithm has a elevated recognition rate and a lower misplaced recognition rate, and the false fright rate and recognition alteration rate are mutually lower. There are some false alarm objects in the recognition outcome of the VA-SVD algorithm although the ship objects are all suitably distinguished. Additionally, the anticipated recognition algorithm has a elevated function efficiency, and the unique shape of the ship objects can be entirely retained. Furthermore, the ship objects can be commonly positioned and can be revealed evidently in the SAR representation.

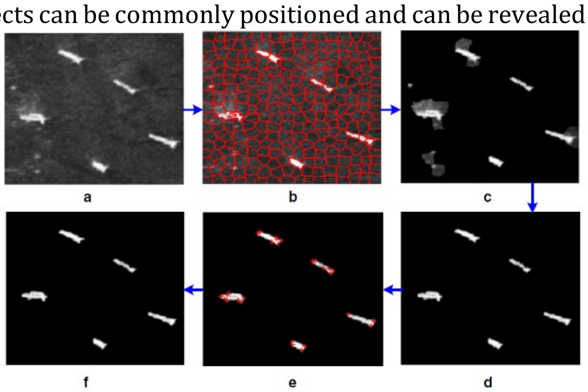


Fig.10 The recognition outcome of the SAR image without land area. a The unique SAR image. b Super pixel segmentation outcome. c The aspirant super pixel patches. d The weighted entropy filtering outcome. e Harris corner recognition outcome. f The final recognition outcome

3.2 Experimentation on ship SAR representation without land

Whilst there is no land area in the ship SAR representation, there is no necessitate to guard the land area. A high-declaration maritime ship SAR representation without land is preferred, as shown in Fig. 10a. The resolution is1.25 m× 1.25 m, and its dimension is 376 × 319. It can be seen that the SAR representation contains five ships. While there is no land area in the SAR representation, it is not required to guard the land area in the ship SAR representation. Subsequently, the enhanced SLIC superpixel division algorithm is used to progression the SAR representation. The stair size of the patch area is set to 13 pixels, and the superpixel production outcome is shown in Fig. 10b. Then, estimate the self-in sequence of the superpixel squares, and set the outlier constraint T1 as 1.4; the aspirant superpixel squares are exposed in Fig. 10c

It can be seen that there are some false alarm superpixel squares, and then deposit the enlargement pace of the neighborhood weighted information entropy T2 as 20%; the recognition outcome is shown in Fig. 10d. Clutch out the Harris corner recognition on the filtering outcome of Fig. 10d, the recognition outcome is exposed in Fig. 10e, then deposit the threshold T3 as 3, the ultimate recognition outcome can be obtain as revealed in Fig. 10f. Since the false alarm objects have previously been filtered out in the previous global recognition and local recognition steps, the Harris corner recognition can only be used to scratch the position of the ship objects.

Evaluate the recognition presentation of the anticipated algorithm with other three recognition algorithms, and all experimentation are carry outed in the similar Matlab R2016b environment. The recognition outcome based on the three recognition algorithms for assessment is revealed in Fig. 11.

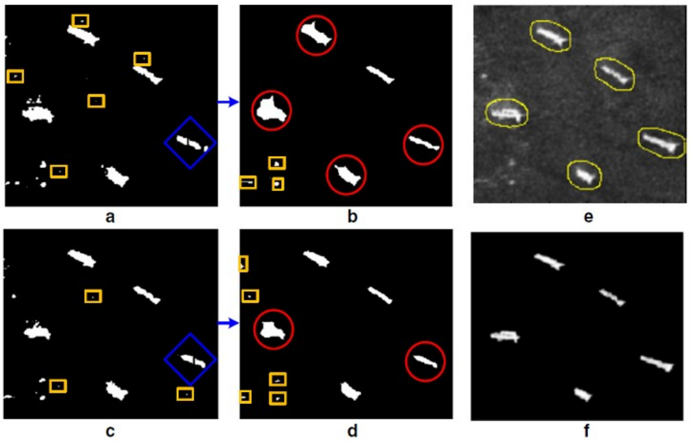


Fig. 11 the recognition outcome based on the three recognition algorithms for contrast. a CFAR recognition outcome based on gamma distribution. b. Morphological dispensation. c Recognition outcome based on two-parameter CFAR. d Morphological dispensation. e. VA-SVD recognition outcome. f The proposed recognition outcome algorithm

In Fig. 11, the false alarm objects are patent by yellow rectangle boxes, and the broken object is patent by blue rhombus. The objects whose structure is critically vague are patent by red circles. The presentation of the four recognition algorithms is shown in Table 2.In Fig. 11 and Table 2, we can see that even though some false alarm objects can be filtered

by using the morphological dispensation, the original outline of the ship objects cannot be well maintained.

Table 2 Evaluation of recognition performance among the four recognition algorithms

Detection algorithm	N_{tt}	N_{fa}	Number of missing targets	N_{dd}	Detection distortion rate (%)	FOM	Time (s)
Gamma CFAR	5	6	0	4	80	0.455	6.7276
Two parameter CFAR	5	5	0	2	40	0.500	7.5361
VA-SVD	5	0	0	0	0	1.000	3.1749
The proposed algorithm	5	0	0	0	0	1.000	2.2252

4. Summary and conclusion

A ship object recognition algorithm based on information theory and Harris corner recognition for SAR representations is anticipated in this paper. A self-in sequence-based global recognition and a weighed entropy-based local recognition can almost divide the ship objects from the background; moreover, the Harris corner recognition algorithm is used to auxiliary filter out the false alarm objects. The replication researchs authenticate the effectualness and superiority of the anticipated algorithm. Not only can a higher recognition rate of SAR ship objects and a lower missing recognition rate can be guaranteed, but also it can guarantee a inferior false alarm rate and a lower recognition alteration rate. In toting up the proposed recognition algorithm has a higher function efficiency, and the inventive shape of the ship objects can be completely preserved. In succeeding further research, we will mingle other features of the ship objects to progress the algorithm for ship object recognition in SAR metaphors with a larger scene and wealthier information. Likewise, adaptive superpixel fragmentation will be considered so that the algorithm can fragment the SAR representation adaptively according to the number and size of the ship objects in the SAR image.

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