

Adaptive ship detection in SAR images using variance WIE-based method

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Abstract Automatic detection of ship targets from synthetic aperture radar (SAR) images is an important and challenging problem. Given the different nature of target returns in homogeneous and heterogeneous regions in SAR imagery, conventional detection algorithms fail to yield automatic and robust results. In support of automatic vessel monitoring, an adaptive detection framework designed for detecting ships from SAR imagery is proposed in this paper, and the variance weighted information entropy is introduced into the framework construction. Experimental results indicate that the proposed method can effectively detect the ship targets from various circumstances without any prior knowledge.

Keywords Variance weighted information entropy · Ship detection · Synthetic aperture radar

1 Introduction

Maritime surveillance is an important application of synthetic aperture radar (SAR) systems, and ship detection plays a central role in the maritime scenario observation [1]. With the increasing volume of image data that are collected from air- and spaceborne SAR systems, it is becoming increas-

ingly desirable for computer-aided or automated exploitation of SAR imagery, especially for automatic target recognition (ATR) systems. As the first stage of ATR systems for ship targets, ship detection provides a basis for the validity of subsequent recognition.

Many methods have been developed for detecting ship targets from SAR images during the last two decades, including direct ones and indirect ones. The direct methods detect ships directly. Of those methods, adaptive threshold way [2], probability neural network (PNN) model method [3] and distributed constant false alarm rate (CFAR) methods [4–6] are the generally used methods. The indirect methods firstly detect ship wakes and then seek ships around wakes, which mainly include Radon transform, mathematical morphology and wavelet analysis [7]. Among these methods, the distributed CFAR framework is the most widely accepted conceptual model. However, CFAR-like detectors involve parameter estimations of ships and sea/background clutters, and the threshold setting is essential so that a constant false alarm probability is guaranteed for all values of unknown clutter parameters. The strong dependence of the CFAR schemes on prior knowledge about ships and background observation limits their application. The variance weighted information entropy (WIE), recently being applied to the extraction of regions of interest (ROIs) from infrared and SAR images, has been proved to be a simple and effective quantitative description index for the complex degree of image background [8,9]. The variance WIE is particularly suitable for gray imagery to measure its non-uniformity. However, the existing researches mainly focus its applications on the rough extraction of ROIs. By relying on a simple central spot quarter scheme to subdivide image constantly, target is often segmented into different sub-blocks in searching for ROIs. Also, the involved image pretreatment (for expanding the image boundary into $2M \times 2N$) and the thresh-

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old parameters selection (for judging the potential ROIs) increase its manual intervention.

It has become an urgent problem to improve the detection automation on the condition of high detection rate. Aiming to develop an effective and adaptive ship detection method, the variance WIE was introduced into the ship detection of SAR images. Based on this, an adaptive ship detection framework has been established. Compared with the methods mentioned above, the proposed method is independent of any prior knowledge about ships and background observation, and the ship detection is simple and adaptive, which is more suitable for applying in the automatic detection tasks. Performance of the proposed method has been tested on various background SAR images. Experiments demonstrate that the proposed method has an adequate level of immunity to interference, and it works well in various circumstances with high detection rate.

2 Algorithms and methods

2.1 Variance WIE

Information entropy is a statistical form of characteristics, which reflects the average information of an image. For a digital image with a gray level s ($0 \leq s \leq 255$), suppose that p_s represents the probability of gray level s in the image, the information entropy of the image can be expressed as

$$H = \sum_{s=0}^{255} p_s \log(p_s) \quad (1)$$

when $p_s = 0$, let $p_s \log(p_s) = 0$.

Information entropy can reflect the degree of difference in the gray values of pixels, which can describe the accumulation characteristics of gray-level distribution in an image. With a smaller value of information entropy, the spatial distribution of energy within a certain region is more uniform and the difference in the gray values of pixels is weaker. On the contrary, when the entropy value is greater, the difference in the gray values of pixels within this region is big due to the existence of some targets, including the targets of interest in the detection tasks.

The classic information entropy cannot veritably reflect the complex degree of image background, since it ignores the importance of gray information. To measure the complex degree of different images, the weighted information entropy is developed [10]. Subsequently, the variance WIE concept is proposed and firstly applied to the ROIs extraction of infrared images. Due to the fact that objects with different radiation or reflection usually appear to have distinct gray value in real images, the variance WIE is proved to be an effective way

to evaluate the complex degree of intensity distribution upon an image robustly [9, 11]. For a 256 gray levels image, the variance WIE of the image is defined as follows:

$$H(s) = - \sum_{s=0}^{255} (s - \bar{s})^2 p_s \log(p_s) \quad (2)$$

when $p_s = 0$, let $p_s \log(p_s) = 0$. Where \bar{s} is the mean intensity of the image.

2.2 Variance WIE-based detection framework

As can be seen from Eq. (2), for pixels with gray level s , the impact on the weighted entropy can be reflected by a certain weight. Pixels that are significantly different from the local average can be given a big influence on the entropy, and then the variance WIE value H is high when its calculated region is limited into a local area where target locates. Taking this regional H as an information expression of the central cell, target contained in the local area should be detected by an appropriate threshold H_{th} when the corresponding H of each cell is calculated (Fig. 1). Unfortunately, it is difficult for the variance WIE thresholding to produce a satisfying target boundary, since the variance WIE values of some regions which contain parts of target are also high. As a result, target boundaries are broadened (Fig. 1b). To modify the target boundaries, auxiliary boundary cells discrimination is necessary in establishing our framework.

Considered that SAR images are non-uniformed, global detection cannot produce a satisfying result. Regional detection using a sliding window across the whole image is adopted in this paper. The block diagram of the proposed detection framework is shown in Fig. 2. A square sliding window of $(2n + 1) \times (2n + 1)$ pixels centered at the test cell is designed. For an SAR image I with size $M \times N$, the detection process can be briefly described as three steps:

Step 1: Variance WIE map calculation. For inputted SAR image, calculation of the regional variance WIE for each

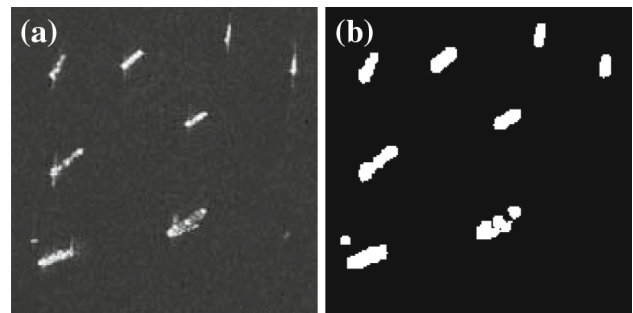


Fig. 1 Characteristics of the variance WIE thresholded binary map. **a** Original SAR image; **b** variance WIE thresholded binary map

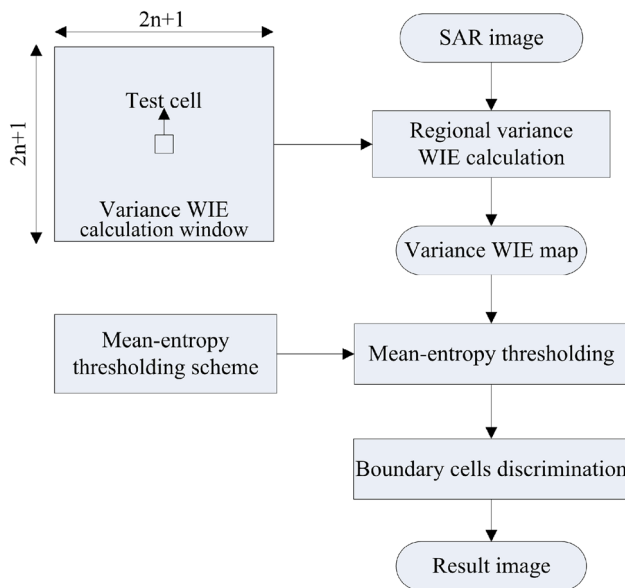


Fig. 2 Block diagram of the variance WIE-based ship detection method

local area is executed by sliding the window. When the window moves across the whole image, the regional variance WIE calculation is achieved and a variance WIE map is obtained.

Step 2: Mean-entropy thresholding. For the calculated variance WIE map, subsequent thresholding is assigned and a binary map containing the potential targets is presented. Since any fixed threshold cannot be satisfied for various situations, an adaptive-like variance WIE threshold H_{th} is set for ship targets:

$$H_{ships} > H_{th} \text{ with } H_{th} = k \times meanEntropy \quad (3)$$

where $meanEntropy$ is the mean of the variance WIE value of the whole image and k is an adaptive-like parameter.

Step 3: Boundary cells discrimination. For each potential target cell, an auxiliary gray-level discrimination based on its image intensity is made, and then, target boundary cells are differentiated from false alarms and boundaries are defined.

In above framework, the settings of the sliding window size $(2n + 1)$ and the parameter k can influence the detection results. The window size affects the calculated variance WIE map. Too large size is disadvantageous to calculation efficiency, while too small size is not enough to calculation stability. In order to obtain appropriate size to serve automatic detection, we have investigated the relationship between the optimal variance WIE map and the corresponding window size by statistical analysis method. Various marine SAR images with different background complexity (reflected in different $meanEntropy$) have been used for this analysis. As a result, an adaptive-like rule for the window size based on the $meanEntropy$ of the inputted image is assigned as:

$$2n + 1 = \begin{cases} 5, & meanEntropy < 5000 \\ 9, & 5000 \leq meanEntropy \leq 10,000 \\ 13, & meanEntropy > 10,000 \end{cases} \quad (4)$$

The value of k affects the number of the detected targets. More false alarms are detected due to a too small k , and less or even no real targets are detected because of a too big k . Similarly, an experimental analysis of the optimal detection result with the corresponding k is carried out, and then a fitted relational expression of adaptive k with the $meanEntropy$ is obtained:

$$k = 3000 / meanEntropy + 1.05 \quad (5)$$

where 3000 and 1.05 are fitted constants which have been tested to be suitable for most of marine SAR images.

The variance WIE-based detection framework uses a novel regional variance WIE concept to characterize the spatial intensity distribution of SAR imagery and then an adaptive complementary detection scheme to detect ship targets. The ship detection scheme not only highlights the advantages of the variance WIE algorithm, but also conduces to the regional detection. The framework is sensitive to the intensity difference and is also fast enough in calculation. Independent of any prior knowledge about ships and background observation, it is easy to implement and particularly well suited for automatic detection of SAR images.

3 Experiments and results

The proposed method has been tested over a series of SAR images, including homogenous background, heterogeneous background and strong noise background situations. Due to the lack of ground truth data, a precise cross-check could not be performed. The validation of the detection results was based on the visual inspection. For comparison, the widely used two-parameter CFAR method [7] is used, and the corresponding results at a false alarm rate of 0.05 % are presented.

3.1 Experiments under different backgrounds

The detection performance of the proposed method, in the case of homogenous situation, is shown in Fig. 3. Figure 3a shows a typical Radarsat C-band SAR image (631×619 pixels, 12.5 m pixel size) of Laizhou Bay in southern arm of Bohai Sea. The corresponding detection results by the CFAR method and our variance WIE-based method are shown in Fig. 3b, c. Due to the uniform sea clutters and the higher signal-to-clutter ratio, both methods produce similar results, which highlight all the ships without causing any false alarms. Despite some small ships and faint scattering ships

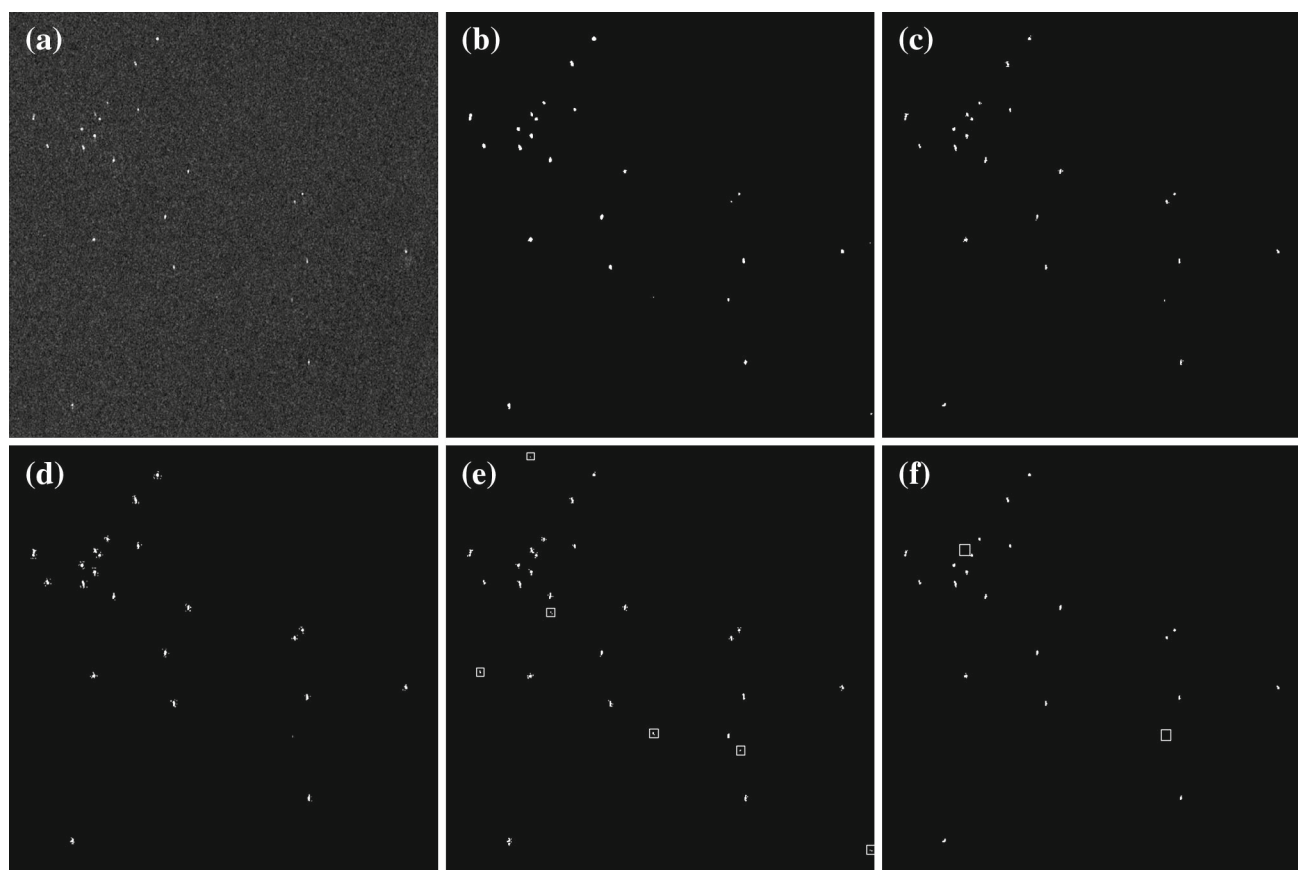


Fig. 3 Ship detection for homogenous background situation. **a** Original SAR image; **b** CFAR result; **c** variance WIE-based result (adaptive window size: 5×5 pixels; adaptive $k = 4.72$); **d** variance WIE-based

result (window size: 9×9 pixels; $k = 4.72$); **e** variance WIE-based result (window size: 5×5 pixels; $k = 2.5$); **f** variance WIE-based result (window size: 5×5 pixels; $k = 8.0$)

hiding in the sea clutter background, the proposed method performs a very promising detection.

To verify the validity of the adaptive parameters, different window sizes and k values are used to test our method. Figure 3d–f shows the representative results. As can be seen, the variance WIE-based method with a larger window of 9×9 pixels obtains the almost same result (Fig. 3d) as that with the adaptive window of 5×5 pixels (Fig. 3c), but it is more time-consuming. However, things are different for the parameter k . The variance WIE-based method with a larger and a smaller k value gives different detection results. Compared with the adaptive k value ($k = 4.72$), six false alarms as encircled by white boxes in Fig. 3e are detected due to a too small k , while two real targets as lost in white boxes in Fig. 3f are missed because of a too big k , as has been mentioned in Sect. 2.2.

Performance under heterogeneous background situation is a very important evaluation criterion to any target detectors. Generally, ships are brighter than background clutters in marine SAR images, since the scattering of ship targets can last longer than sea clutters in azimuth [12]. This is helpful to detect ship targets. But when the clutter background is heterogeneous and the scattering of a ship is faint, it is rather difficult

to separate the ship target from the non-homogeneous background clutters. Figure 4a gives a typical ERS C-band SAR image (500×500 pixels, 12.5 m pixel size) near the coast of Singapore containing five ships in heterogeneous regions, and Fig. 4b, c presents the detection results by the CFAR method and the variance WIE-based method, respectively. As can be seen, the CFAR method causes more false alarms than the proposed method. Although there are some sea clutters within the heavily heterogeneous regions mistaken to be ships (as encircled by white boxes in Fig. 4c), the detection result by our variance WIE-based method, compared with that of the CFAR method, is acceptable, which means that the proposed method has an adequate level of immunity to interference.

The strong noise background situation is always a challenge for most detectors, since ships will be mixed with the ocean clutters due to strong backscattering echo of them. To test this situation, an ALOS HH polarized L-band SAR image (284×238 pixels, 10 m pixel size) containing two ships hiding in sea clutters, as shown in Fig. 5a, is adopted in our experiment. The corresponding detection results by the CFAR method and the variance WIE-based method are

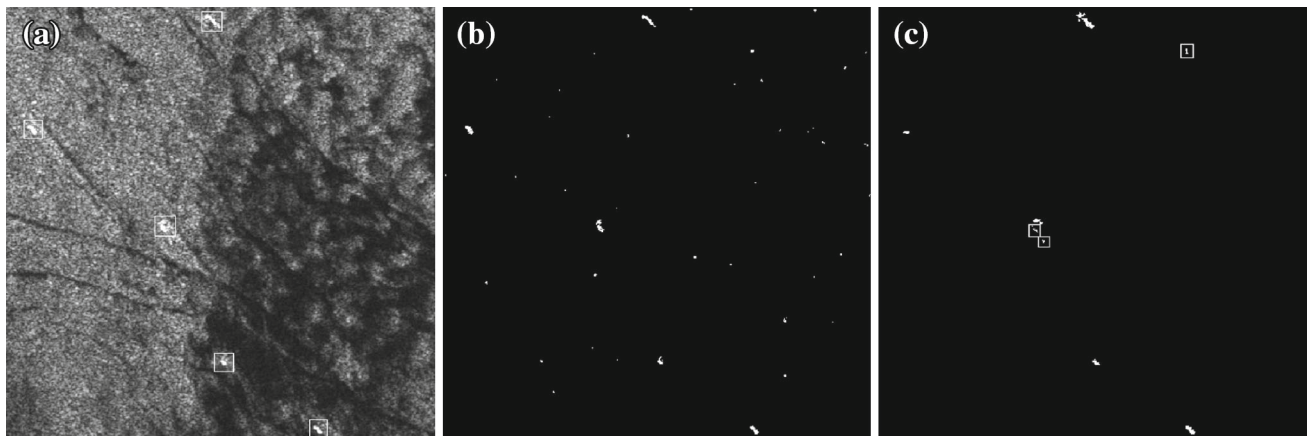


Fig. 4 Ship detection for heterogeneous background situation. **a** Original SAR image; **b** CFAR result; **c** variance WIE-based result



Fig. 5 Ship detection for strong noise background situation. **a** Original SAR image; **b** CFAR result; **c** variance WIE-based result

shown in Fig. 5b, c. It can be seen that the hidden ships can be detected perfectly by both of the CFAR method and our variance WIE-based method. However, the conventional CFAR method would cause some false alarms even though it works at a very low false alarm rate. **In contrast, the proposed method works well without producing any false alarm.**

3.2 Comparison and evaluation

The figure of merit (FoM) in [6] is used as the evaluation index to assess the detection results. The higher values of FoM mean higher detection rate and lower false alarm rate. FoM can be defined as follows:

$$F_{oM} = N_{tt} / (N_{fa} + N_{gt}) \quad (6)$$

where N_{tt} counts the accurate detected ship number, N_{fa} counts the false alarm number and N_{gt} counts the real ship target number.

Table 1 presents the evaluation indexes of the two methods. It is clear that the proposed method has much better adaptability than the traditional two-parameter CFAR

Table 1 Evaluation indexes of the two methods

	N_{tt}	N_{fa}	N_{gt}	FoM
Homogenous background (Fig. 3)				
Two-parameter CFAR	23	0	23	1
The proposed method	23	0	23	1
Heterogeneous background (Fig. 4)				
Two-parameter CFAR	5	33	5	0.132
The proposed method	5	3	5	0.625
Strong noise background (Fig. 5)				
Two-parameter CFAR	2	4	2	0.333
The proposed method	2	0	2	1

method for the heterogeneous background situation. It can extract single and multiple targets accurately, even under the conditions of low contrast and severe clutters.

4 Conclusions

A variance WIE-based detection method for ship targets in SAR images has been presented in this paper. The proposed

method is automatic, simple and robust against the speckles and heterogeneous regions in SAR images. Compared with the CFAR-like methods, the most merit of the proposed method is its adaptive ability. The method does not require any prior knowledge, and ship targets in SAR images can be detected robustly from their backgrounds. Since the sliding window size and the threshold level for ship discrimination is fully automatic adjustment, it is easy to implement and particularly well suited for an automatic detection application.

Due to the ability to measure the complex degree of images, the variance WIE-based detection method has an adequate level of immunity to interference and hence works well in various circumstances with high detection rate, especially for the heterogeneous and strong noise background situations. However, it is different for its target boundary discrimination ability. As shown in the experimental section, the sensitivity of the variance WIE algorithm to image intensity affects its discrimination ability. Thus, the detection framework still needs a further improvement in the discrimination of the target and the surrounding cells for its wide applications.

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