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A Novel Saliency-Based Method for Ship Detection in SAR Image

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Abstract—This paper presents a hierarchical saliency detector for ship detection in synthetic aperture radar (SAR) imagery. First, the nonlinear anisotropic diffusive process has been adopted to eliminate clutter, while preserving the target edge feature in SAR image. Second, each pixel in the filtered image is assigned to its corresponding super-pixel region via an adaptation of optimization technique. Third, Gamma manifold for feature representation has been presented for the modeling of intensity of all super-pixels in SAR imagery. Finally, a threshold segmentation method is used to realize ship detection. Experimental results accomplished over real SAR images demonstrate that the proposed detection method can achieve a good performance.

1. INTRODUCTION

Synthetic aperture radar (SAR) is active microwave remote sensing imaging radar. It can acquire data in all weather conditions and has been playing an increasingly essential role in maritime traffic supervision and marine monitoring [1]. For the research of ship detection in SAR image, many algorithms have been put forward in the past few decades. In general, detection models for ship in SAR images can be divided into two major categories according to feature extraction and description: traditional statistical methods and deep learning methods. Each method has their advantages and disadvantages and their respective scope of application [2].

It is generally too difficult to model ship targets, owing to a lot of complicated factors, such as resolution, corner reflections, and multiple reflections from the ship and sea surface. Most traditional statistical detectors are based on modeling the clutter background statistically and finding bright pixels which are statistically unusual. Among these methods, adaptive threshold algorithms are the most common algorithms for ship detection in SAR images. For these algorithms, any pixel intensities which are above the estimated threshold are declared as targets of interest. However, complicated sea conditions cause the high non-stationary and non-homogeneity of sea clutter in SAR images, which directly influence the detection results [3].

Current state-of-the-art deep-learning methods for ship detection are usually based on convolutional neural network framework. It is, in essence, one of the data-driven machine learning frames [4]. The core idea is multilayered or deep models for representation of the ship targets in SAR images. A key aspect of these algorithms is the exploitation of the convolution operator, which considers all possible shifts of canonical bases or filters. In designing and implementing these algorithms, the important thing is to take care with the type of SAR imagery to which they are applied [5]. The critical factors which influence the performances of generalization ability include clutter distribution, resolution, computationally expensive, imaging conditions, environment, etc. Each detection method has its own advantages and disadvantages; generally, we use certain detection method according to the actual condition.

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In this work, we present a hierarchical saliency method for ship detection in SAR image. The proposed method consists of four processes, i.e., nonlinear diffusive filtering, super-pixel segmentation, saliency representation, and threshold segmentation. The nonlinear diffusive process has been adopted to improve the robustness of detection. Optimization-based super-pixel method is used to segment SAR image. It allows geometrical features to be applied to problems in locally homogeneous region in SAR images. And, information geometry method is used to implement local saliency representation of SAR image.

The main contributions in the proposed method are as follows: 1) a new Riemannian metric for Gamma statistical manifold is constructed to exploit the microstructure features of ship in SAR images based on information geometry; 2) super-pixel segmentation algorithm is adopted to improve the performance of ship detection.

2. PROPOSED METHODS

The framework of the proposed method is depicted in Fig. 1. The whole process consists of four parts: nonlinear filtering, super-pixel segmentation, saliency representation, and classification. In this section, we begin with a basic discussion of nonlinear diffusive filtering of SAR image, followed by an introduction to super-pixel segmentation. Then, we consider the salience representation of ship targets in segmented SAR image via statistical manifold feature. Finally, the automatic detection of the ships is realized by using threshold method.

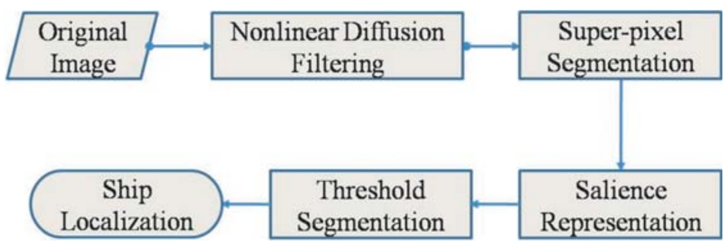


Figure 1. Processing strategy for ship detection in SAR images.

2.1. Nonlinear Diffusion Filtering

The nonlinear diffusive process has shown the good property of eliminating clutter while preserving the accuracy of edges and has advantages in SAR image processing. In this work, nonlinear diffusive filtering is used to filter out a certain amount of clutter information and to preserve the target information. In addition, the nonlinear diffusive process is suitable for distributed parallel computing.

Diffusivity is proportional to the gradient magnitude of the intensity, which is based on the well-known diffusion Equation [6], that is,

$$\frac{\partial}{\partial t} I^t(i,j) = D^t(i,j)\Delta I^t(i,j) + \nabla D^t(i,j)\nabla I^t(i,j) \tag{1}$$

with initial condition $I^0(i,j) = I(i,j)$. $I^t(i,j)$ denotes the grey value at position (i,j), and t denotes the iteration time. ∇ and Δ denote the gradient and Laplacian operators, respectively, and D^t is a symmetric positive definite tensor which depends on the local structure of I^t, that is

$$D^t(i,j) = \left(\left\|\nabla(G_\sigma * I^t)\right\|^2 + \eta^2\right)^{\frac{-\rho}{2}} \tag{2}$$

where $\rho \in (1,2)$, G_σ is a Gaussian filter, $*$ the convolution operator, and $\eta > 0$ the conductance parameter. We denote the filtered image as I_f, where the clutter filter not only is adaptive but also takes account of different image structures between targets and background.

2.2. Super-Pixel Segmentation

The super-pixel refers to image blocks made up of neighbor pixels with similar features. Super-pixel segmentation algorithms group pixels into perceptually meaningful atomic regions according to pixel location and the property of images. Following this idea, optimization algorithm is proposed to generate super-pixels for filtered SAR image by using the nonlinear diffusive filter. We consider the super-pixel segmentation as a maximization problem which is used to generate super-pixels [7].

For filtered images in the gray space, initial cluster centers $\theta_{(i,j)}$ are sampled on a regular grid spaced S pixels apart. Here, each element of $\theta_{(i,j)}$ represents pixel which belongs to super-pixel at position (i,j). In this case, let $\Theta = \{\theta_{(i,j)}\}_{(i,j)}$ be a set of super-pixels, which represents the whole partitioning of an image. Hence, the super-pixel segmentation can be transformed into an energy maximization problem.

$$\Theta^* = \arg\max E(\Theta) \tag{3}$$

where Θ^* is the optimized solution, and $E(\Theta)$ denotes the energy function of solution Θ. Following this scheme, we can compute the super-pixels using intrinsic manifold clustering [7] with random initialization.

2.3. Saliency Representation

Because of its highly flexible form and good fitting capability, Gamma distribution has been applied in many cases of practical applications. It is one of the most chosen models for sea-clutter modeling.

In this work, the family of Gamma probability distributions is considered. Without much loss of generality, we restrict ourselves to the two parameter Gamma distribution. A random variable x is said to be a Gamma distribution with scale parameter $\gamma > 0$ and shape parameter $\kappa > 0$, if its probability density function has the form

$$f(x|\gamma,\kappa) = \gamma^{-\kappa}[\Gamma(\kappa)]^{-1}x^{\kappa-1}\exp\left(-\gamma^{-1}x\right) \tag{4}$$

By using the method of maximum likelihood estimation, the scale parameter γ and shape parameter κ are obtained according to the simultaneous equations from the data sample x [8].

$$\gamma = m^{-1}k^{-1}\sum_{j=1}^{m} x_j \tag{5}$$

$$\log(\kappa) - \varphi(\kappa) = \log\left(m^{-1}\sum_{j=1}^{m} x_j\right) - m^{-1}\log\left(\prod_{j=1}^{m} x_j\right) \tag{6}$$

where $\varphi(\kappa)$ is the digamma function with argument κ. The mean and variance of the Gamma distribution with parameters γ and κ can be obtained by using explicit formulae,

$$\mu = \gamma\kappa \tag{7}$$

and

$$\sigma = \gamma^2\kappa \tag{8}$$

According to the theory of information geometry [9], we are given a Riemannian metric (a second-order symmetric covariant tensor field)

$$g_{11} = \sigma^4, \quad g_{12} = g_{21} = 2\mu\sigma^4, \quad g_{22} = 4\mu^3\sigma^4 + 2\mu\sigma^8 \tag{9}$$

Let $\nu = 1/\gamma$ and $\vartheta = \nu\partial_1 + \kappa\partial_2$. A direct computation gives

$$\|\vartheta\|^2 = g(\vartheta,\vartheta) = \nu^2\sigma^4 + 4\nu\kappa\mu\sigma^4 + 2\kappa^2\mu\sigma^4\left(2\mu^2 + \sigma^4\right) \tag{10}$$

2.4. Detection Algorithm for Ships

In this subsection, we advance the algorithm of saliency detection for ships in SAR image. Let I denote the SAR image and pixel values $I(i,j) \in [0,255]$. The SAR image I is used to obtain the final detection result I_d.

The main steps of the presented detection algorithm are as follows:

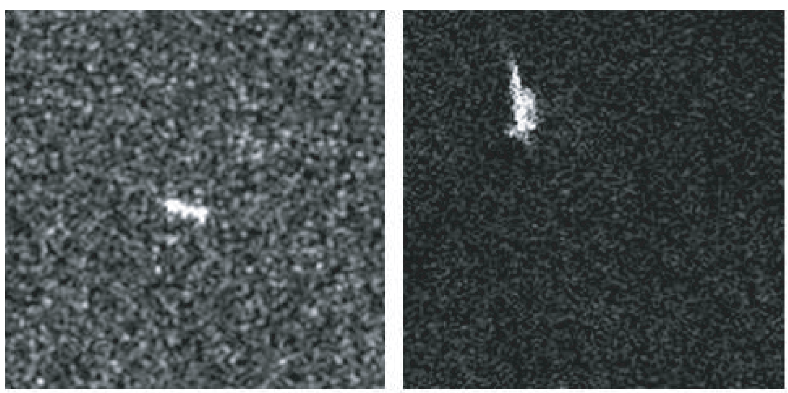
(1) SAR image I is filtered by using the nonlinear diffusion filter. The filtered image is denoted by I_f;
(2) Super-pixel algorithm is used to obtain super-pixels from the image I_f;
(3) For each super-pixel, Riemannian metric $[g_{ij}]$ is constructed;
(4) For each super-pixel, $\|\vartheta\|^2$ is calculated;
(5) Reshaping value $\|\vartheta\|^2$ of each super-pixel into matrix I_G;
(6) Super-pixels with large value in the saliency map are selected to the target set according to threshold

$$T_h = \left\{ C_{(i,j)} \left| \max\left(C_{(i,j)}\right) > \beta \max\left(S^*\right) \right. \right\} \tag{11}$$

where $\max(C_{(i,j)})$ represents the maximum value of the super-pixel $C_{(i,j)}$; $\max(S^*)$ represents the maximum saliency value of the super-pixel nodes in the saliency map S^*; $\beta = 0.3$.

3. EXPERIMENTAL RESULTS AND ANALYSIS

In this experiment, the effectiveness of the proposed algorithm is verified on real SAR images. The SAR images are shown in Fig. 2. Fig. 3 displays SAR images with 3D scenes.



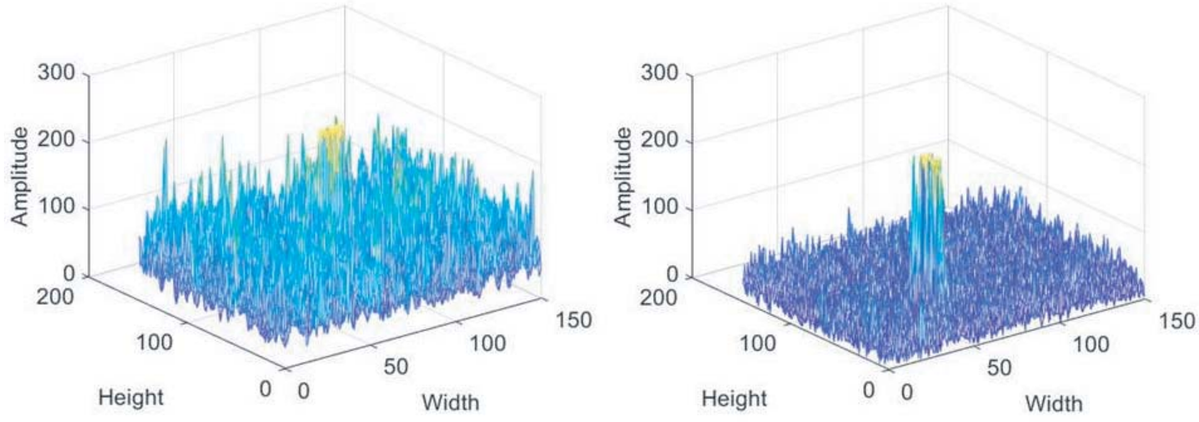
(a) (b)

Figure 2. Original SAR images.

The variations in ocean backscatter impact seriously on the effect and efficiency of ship detection in SAR image. Most detectors cannot assure accuracy and provide the reliable detected results, compatible with the limited statistics allowed by the non-homogeneous and non-stationary characteristics of the sea clutter.

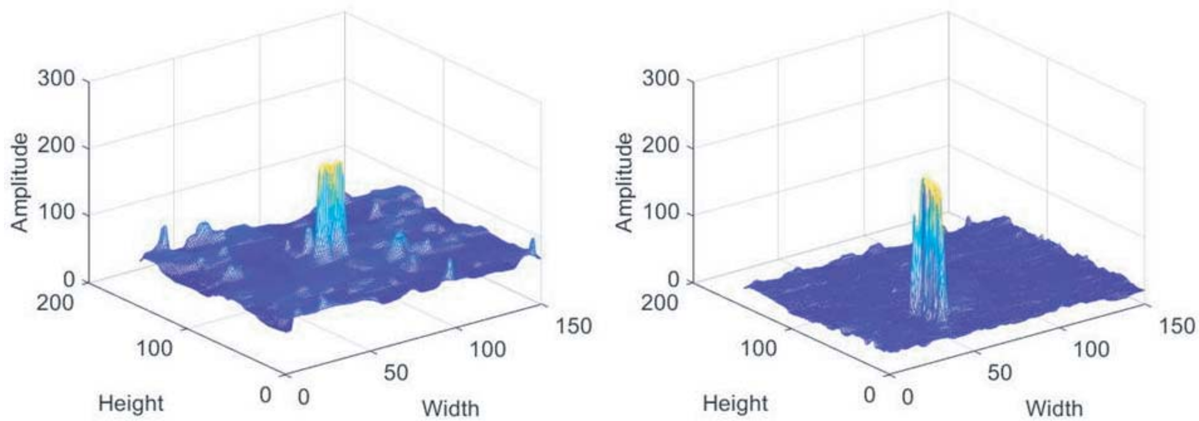
In this work, SAR images are filtered by using the nonlinear diffusion filter. The filtered images are shown in Fig. 4 (with 3D scenes). During the experiments, set the following parameters: time step size $t = 5$, $\eta = 10^{-13}$, $\rho = 1.4$, $\sigma = 1$, and the number of iterations $T = 25$. The main goal of nonlinear diffusion filtering is to filter out a certain amount of clutter information and to preserve the target information. As shown in Fig. 4(a), the difference of the geometrical feature between artificial target and natural background is not obvious in the whole region.

Figure 5 shows super-pixels from the filtered image I_f obtained by using the nonlinear diffusive filter. Super-pixel representation can act as meaningful priors for further processing tasks.



(a) (b)

Figure 3. Mesh plots for the SAR images. (a) Fig. 2(a). (b) Fig. 2(b).



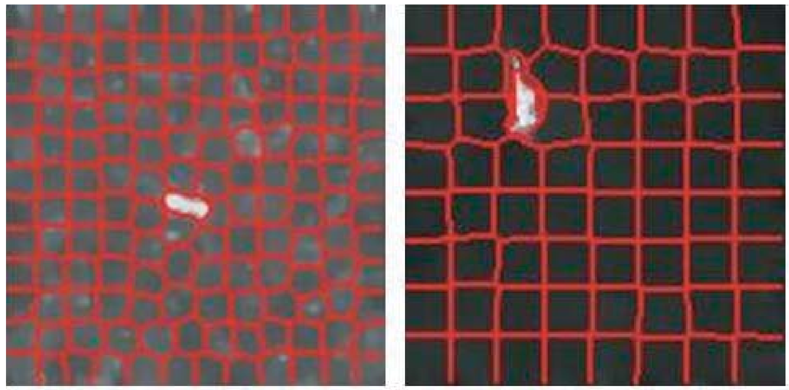
(a) (b)

Figure 4. Mesh plots for the filtered images by using nonlinear diffusive filtering. (a) Fig. 2(a). (b) Fig. 2(b).

By using the maximum likelihood estimation method, the local parameters in the Gamma distribution are solved. We compute the normalized Riemannian metric matrix I_G from the super-pixels. As shown in Fig. 6, the saliency representation of SAR images can achieve a higher contrast between targets and background because of the ship superstructure. The threshold method is implemented to locate regions of interest (ROIs). Fig. 7 shows the final detection results.

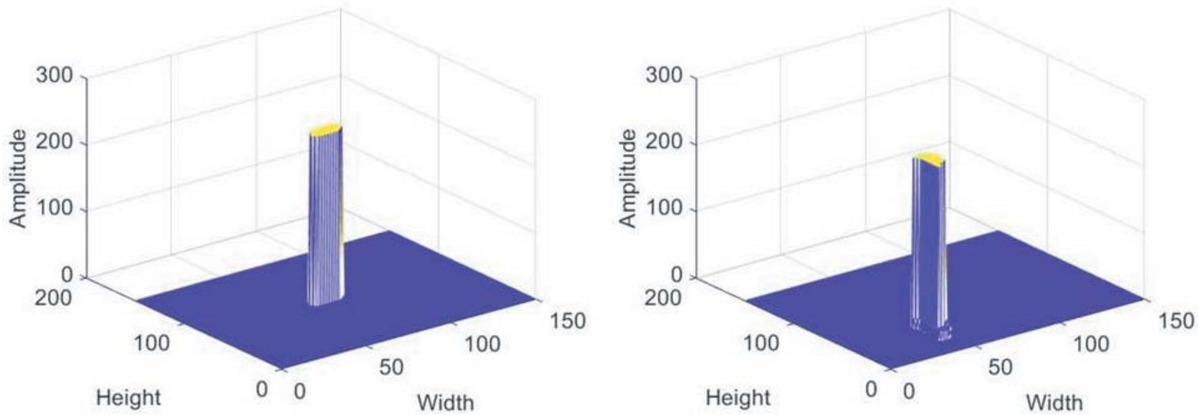
Figure 8 shows the detected results by using a constant false alarm rate (CFAR) detector based on Gamma distribution model [10]. As shown in Fig. 8(a), it tends to have a high rate of false alarm by choosing design parameters, the false alarm rate (FAR) 10^{-6} and window-size 25×25. As shown in Fig. 8(b), the detection result tends to have many undetected pixels which are unusually bright compared to those in the surrounding area by using the same experimental parameters. Fig. 9 shows the detection results by using superpixel-level CFAR detector, as proposed in [11]. Because of the nonhomogeneous and non-stationary characteristics of the sea clutter, the implementation of superpixel-level CFAR detector tends to have some false alarms (as shown in Fig. 9(a)). The comparison between the proposed method and CFAR detectors demonstrates that the proposed method performs much better when the SAR images are corrupted by clutter.

In summary, the proposed frame assures accuracy and provides reliable detection results, compatible with the limited statistics allowed by the non-homogeneous and non-stationary characteristics of the sea



(a) (b)

Figure 5. Super-pixels from the images I_f. (a) Fig. 2(a). (b) Fig. 2(b).



(a) (b)

Figure 6. Salience representation I_G of SAR images. (a) Fig. 2(a). (b) Fig. 2(b).

(a) (b)

Figure 7. Final detection results I_d by using the proposed method. (a) Fig. 2(a). (b) Fig. 2(b).

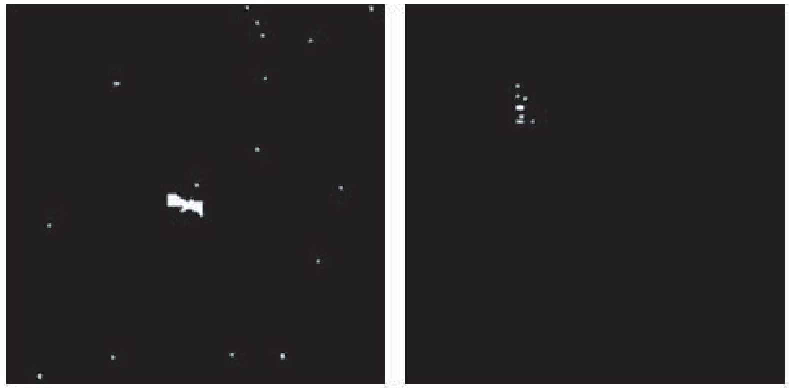


Figure 8. Detection results by using the Gamma-based CFAR detector [10]. (a) Fig. 2(a). (b) Fig. 2(b).

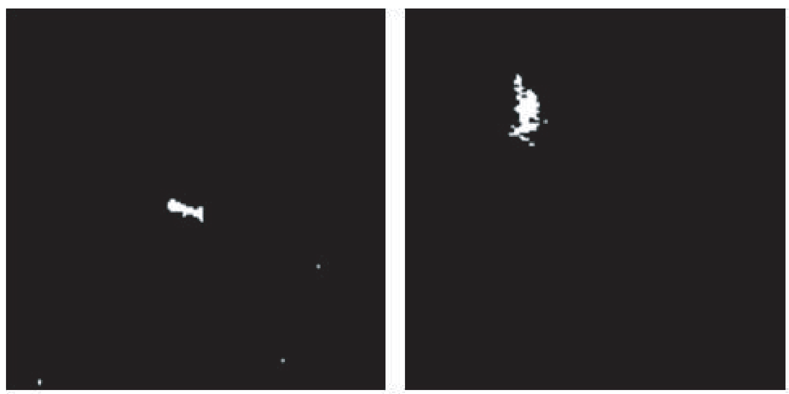


Figure 9. Detection results by superpixel-level CFAR detector [11]. (a) Fig. 2(a). (b) Fig. 2(b).

clutter. It can efficiently restrain the false alarm caused by incorrect mathematics model and inaccurate parameter estimates. Therefore, it has potential application prospect in ship detection of SAR images.

4. CONCLUSIONS

This paper presents a new algorithm for ship detection via a saliency detector. This approach reaches a robust detection, taking advantage of the difference of statistical behavior of the ships and sea clutter. More specifically, as a consequence of the super-pixel segmentation of the images obtained after the application of the nonlinear diffusive, background clutter is drastically reduced, whereas the presence of the ships, behaving as structured patterns, is greatly enhanced. The presented geometric model for the process of local saliency representation in SAR image achieves a higher contrast between targets and background because of the ship superstructure. Experiment results on real SAR images demonstrate the effectiveness of the proposed algorithm.

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