Ship Detection From Optical Satellite Images Based on Saliency Segmentation and Structure-LBP Feature

Feng Yang, Qizhi Xu, and Bo Li

***Abstract*— Automatic ship detection from optical satellite imagery is a challenging task due to cluttered scenes and variability in ship sizes. This letter proposes a detection algorithm based on saliency segmentation and the local binary pattern (LBP) descriptor combined with ship structure. First, we present a novel saliency segmentation framework with flexible integration of multiple visual cues to extract candidate regions from different sea surfaces. Then, simple shape analysis is adopted to eliminate obviously false targets. Finally, a structure-LBP feature that characterizes the inherent topology structure of ships is applied to discriminate true ship targets. Experimental results on numerous panchromatic satellite images validate that our proposed scheme outperforms other state-of-the-art methods in terms of both detection time and detection accuracy.**

***Index Terms*— Context analysis, saliency segmentation, ship detection, structure-local binary pattern (LBP) feature.**

I. Introduction

DETECTING ships from remote sensing imagery is vitally important for a wide range of applications that include illegal smuggling, traffic surveillance, fishery management, and so on [1]. In existing works, synthetic aperture radar (SAR) images play important roles in detecting and tracing targets, because they are little affected by weather and time [2]. However, SAR images usually include high-level speckles, are insensitive to wooden materials, and are difficult for humans to interpret. Compared with SAR images and other types of remote sensing images, optical satellite images have higher resolution and contain more detailed information; thus, they are more suitable for target detection or recognition [3]. Therefore, in recent years, many ship detection algorithms intended for use with optical satellite images have been proposed even though optical satellite images usually suffer from interference by weather conditions, such as clouds or mist, or from ocean waves.

Most existing methods adopt the "coarse-to-fine" strategy, which includes two stages: ship candidate extraction and false alarm elimination. In the first stage, these methods extract ship candidates based on the distinctness between potential targets and the background. The difference between the various algorithms lies primarily in the way they compute distinctness. Some algorithms look for regions of distinct intensity [4]–[6], while others detect distinct patterns, favoring regions with a unique appearance within the entire image [1], [7]–[9]. Although both types of methods achieve impressive performance in ship detection on simple scenes, they perform poorly for complicated scenes, particularly those containing clouds, mist, or ocean waves, usually leading to recognition failures and false alarms. Besides intensity and pattern distinctness, context can be a rich source of information about an object's location, which enables humans to quickly guide their attention to regions of interest in natural scenes. Therefore, the use of contextual information can improve the performance of ship detection [3]. However, the current ship candidate selection methods seldom integrate contextual information with other cues for ship detection. Hence, their performances are easily affected by the variation of illumination and sea surface conditions.

In the second stage, most of the state-of-the-art algorithms utilize powerful ship features with candidate classifiers to discriminate ship objects from false alarms [2]–[5], [7]–[9]. In this stage, one key issue is finding efficient descriptors to characterize the ship targets. In addition to the shape and appearance of ships, the spatial relations of ship regions namely topology structure characterize the symmetry of the sides of ships and provide complementary information for ship identification. However, the issue of how to formalize topology structure of ship bodies is still largely open.

In contrast to the traditional methods, the novel ship detection approach we propose aims to solve all the issues discussed previously. Note that the proposed method focuses on detecting ships at sea in which the land regions have been removed using prior geographic knowledge. This letter includes three main contributions. First, motivated by the strong ability of humans to perceive objects before identifying them [10], we design a novel saliency segmentation framework with flexible integration of multiple visual cues to extract candidate regions for subsequent classifier. Second, to the best of our knowledge, this letter is the first to integrate intensity distinctness, pattern distinctness, and contextual analysis into the process of ship detection from optical satellite images. The combination of these three image cues results in a high detection rate regardless of variations in the detection scene. Third, we propose a structure-local binary pattern (LBP)

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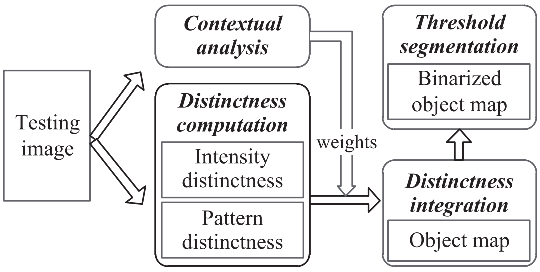


Fig. 1. Outline of saliency segmentation. We first compute intensity and pattern distinctness, respectively, and assign different weights to these two cues based on homogeneous degree of the scene. Then, all cues are combined to produce an integrated cue named object map. In the end, we locate ship candidates by using threshold segmentation of object map.

feature that applies the inherent topology structure of ship bodies, combining local features with spatial information to achieve a more discriminative ship description.

The remainder of this letter is organized as follows. Section II describes the saliency segmentation process for locating candidate regions. Section III introduces target discrimination for suspected ships with the structure-LBP feature. Section IV describes extensive experiments performed on panchromatic satellite images, and Section V presents conclusions.

II. Saliency Segmentation

In optical satellite images, ships are characterized by a different intensity distribution from their surroundings and unique patterns within the entire image. Therefore, integrating intensity and pattern distinctness in the proposed method is essential when handling complicated scenes. Moreover, incorporating contextual information can further enhance the detection accuracy of our method. Fig. 1 shows an overview of saliency segmentation.

A. Intensity Distinctness

In panchromatic satellite images, ships have much lower intensity frequencies than the sea surface background, because the main component of the sea surface is sea water. In addition, the intensity distribution of ships tends to be different from that of the sea surface background. Therefore, we apply a histogram-based contrast method to define the intensity distinctness values for image pixels using gray statistics of the input image [10]. Specifically, the intensity distinctness value of a pixel I_k in the input image I is defined as follows:

$$S(I_k) = \sum_{j=1}^{n} f_j D(g_k, g_j) \tag{1}$$

where g_k is the intensity value of pixel I_k, n is the number of different pixel intensities, f_j is the probability of pixel intensity g_j in image I, and $D(g_k, g_j)$ is the Euclidean distance between g_k and g_j. After calculating intensity distinctness value of every pixel in image I, regions of distinct intensity are highlighted in the output image S, as shown in Fig. 2(b).

B. Pattern Distinctness

Influenced by the sensor characteristics and illumination, ship intensities are sometimes extremely similar to the intensities of other types of clutter in images. Therefore, the cue of intensity distinctness alone is insufficient to locate targets in such cases. Considering the distinct patterns of ships (i.e., the boundary between an object and its background), we apply a pattern distinctness measure based on the phase spectrum of a Fourier transform [11], which can identify regions that have a unique appearance within the entire image

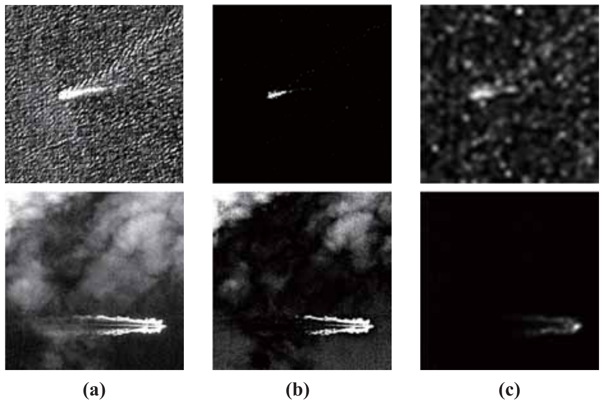


Fig. 2. Distinctness computation. (a) Input image. (b) Saliency map for intensity distinctness. (c) Saliency map for pattern distinctness.

$$\Theta = \phi(F[I]) \tag{2}$$

$$D = g * \| F^{-1}[e^{i \cdot \Theta}] \|^2 \tag{3}$$

where I is the input image, $F[\cdot]$ and $F^{-1}[\cdot]$ denote the Fourier transform and the inverse Fourier transform, respectively, $\phi[\cdot]$ represents the phase spectrum calculation. g is a 2-D Gaussian filter with a standard deviation defined as 0.9% of the shortest boundary of the image [8], and the output image D, shown in Fig. 2(c), is defined as a measure of pattern distinctness.

C. Contextual Analysis

Although intensity distinctness and pattern distinctness can contribute significantly in discriminating ship candidates in input images, their effectiveness varies on different scenes. To measure the effectiveness of these two cues on different scenes, we analyze context and define an important index, called the "surface regular index," which is calculated as follows:

$$r = \sum_{i=1}^{n} f_i^2 \tag{4}$$

where n is the number of different pixel intensities, and f_i is the probability of pixel intensity g_i.

A larger $r (r \in (0, 1))$ implies that the scene is more homogeneous; in other words, the target intensities are relatively similar to the background. Increased homogeneity weakens the effectiveness of the intensity distinctness cue for ship candidate selection. Therefore, compared with the intensity distinctness cue, the pattern distinctness cue has more discriminatory power and should be emphasized by increasing its weight in the distinctness measure. In contrast, a smaller r value implies that the intensity distinctness cue should be emphasized during ship candidate selection.

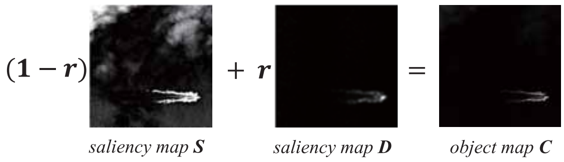


Fig. 3. Depiction of object map computation.

D. Cues Integration

The intensity and pattern distinctness computations produce the saliency maps S and D, respectively. Each map is complementary to the other. To extract regions, which are distinct in both intensity and pattern, we normalize both maps to the range [0, 1] and combine the two maps as follows to compute an object map:

$$C = (1 - r) \cdot S + r \cdot D. \tag{5}$$

The computation process of object map is shown in Fig. 3. The object map C quantifies the likelihood that a pixel of the input image is part of an object. Higher C values indicate higher possibilities of ship candidates. Then, the adaptive segmentation method is applied to locate ship candidates where the threshold is defined as follows:

$$T_c = m(C) + k \cdot \sigma(C) \tag{6}$$

where m and σ are, respectively, the mean and standard deviation of the object map. Here, k is a coefficient and empirically set to 4. Therefore, any pixel of the object map larger than T_c is set to 1, and all other pixels are set to 0. While this binarized object map is generated, ship candidates can be easily extracted from their corresponding positions in the input image.

III. Ship Target Discrimination

After locating ship candidates, effective features must be extracted to distinguish ships from false alarms. Therefore, we adopt a two-step solution to discriminate ship targets. First, simple shape analysis is used to eliminate obviously false targets. Second, a structure-LBP descriptor is calculated and a trainable classifier based on this feature descriptor is applied to determine whether the ship candidate is a real ship.

A. Shape Analysis

In the previous stage, several connected regions are extracted from the binarized object map by labeling the four connected neighbors of each pixel. Some obviously false alarms can be eliminated based on the geometric properties of the connected regions. Because of its low computing complexity and strong discriminative powers, area, compactness, and length–width ratio are selected to eliminate these obvious false alarms [12], [13].

1) Area: Here, the area equals the number of pixels in the corresponding connected region. Ships have a limited area range; consequently land, clouds, and other obviously too large or too small false targets can be eliminated based on this constraint.

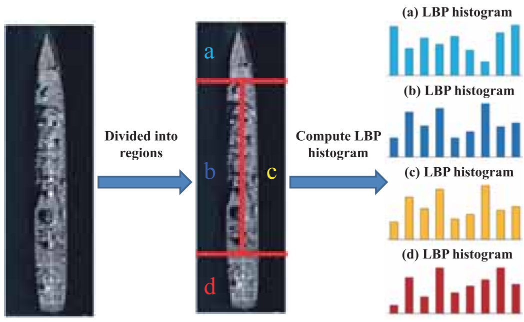


Fig. 4. Depiction of structure-LBP feature computation.

2) Length–Width Ratio: It is defined as

$$R_{ls} = \frac{\text{Long}_m}{\text{Width}_m} \tag{7}$$

where $Long_m$ and $Width_m$ are the length of the long and short axes of the bounding rectangle, respectively. Most ships are long and thin; therefore, this simple method can eliminate false alarms that have very low ratios.

3) Compactness: Compactness measures the degree of circular similarity, and is defined as follows:

$$\text{Compactness} = \frac{\text{Perimeter}^2}{\text{Area}} \tag{8}$$

where $Perimeter$ and $Area$ are the perimeter and area of the corresponding connected region, respectively.

B. Structure-LBP Feature

After shape analysis, there still exist some subtle false alarms that may have similar shape with real ships. Therefore, we need to further analyze their appearance features for final ship identification. In this stage, we use a new structure-LBP feature descriptor to encode the retained candidate patches. In order to encode these candidate patches effectively, we resize each patch to a fixed size (40 $\times$ 40 pixels in this letter) and then extract its structure-LBP descriptor of each resized patch.

As shown in Fig. 4, the resized patch is divided into four regions based on the inherent topology structure of ship bodies. These four regions correspond to the prow, left hull, right hull, and stern. The prow is generally v-shaped, so it is cropped as a single region. The middle of a ship's body is bilaterally divided into two symmetrical regions. Considering wake interference, the stern is cropped as a separate region. Then, the LBP feature descriptors [14] are extracted from each region independently. Finally, we concatenate these local descriptors into a global descriptor named structure-LBP feature.

The structure-LBP description separately extracts LBP features on different regions, which can facilitate the following classifier training process. Since different regions have different importance for the recognition process, region-based features provide the classifier a convenience to assign different weights to different regions according to their importance. Therefore, the proposed structure-LBP combining local features with spatial information can achieve a more discriminative ship description than the original LBP.

After feature extraction, we use the AdaBoost algorithm [15] to generate the hypotheses for ships. The AdaBoost algorithm is aimed at boosting a weak learner into an arbitrarily accurate "strong" learning algorithm by maintaining a set of weights over the training set [7]. These weights are updated repeatedly with boosting iterations. After several iterations, a weighted majority vote of the weak hypotheses is generated, making the final hypothesis. What should be emphasized here is that hypothesis generation is performed completely on the training data set.

IV. Experiments

In this section, we describe the extensive experiments that were conducted to evaluate our method's performance.

A. Data Set Description

Our experiments were performed using panchromatic satellite images from Google Earth with 2-m spatial resolution and involved two data sets: a patch training data set and a testing data set.

The patch training data set is used to train the classifier. In total, it contains 8000 training samples, each of which has a size of 40×40 pixels. As the structure-LBP feature is sensitive to orientation, the positive samples are divided into eight classes based on different target orientations. Thus, we generated eight classifiers corresponding to the eight classes, respectively, to detect ships in different orientations.

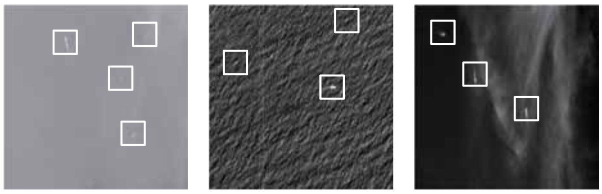
The testing data set is used to comprehensively evaluate our approach. It consisted of 200 images captured from various sea surfaces under different weather conditions. These testing images are approximately $10\,000 \times 10\,000$ pixels in size and subdivided into 6000 subimages with 512×512 pixels in size. All these subimages were classified into three groups: quiet sea, textured sea, and clutter sea.

B. Parameter Selection for Our Method

In this section, the parameters used in our method are presented.

1) Shape Criteria: With the goal of achieving a low missing alarm rate, the thresholds of the shape criteria were set to relatively low values. Considering the resolution of the experimental images and our detection task, the ranges of area, compactness, and length-width ratio were empirically set to $100 \sim 10\,000$, $30 \sim 200$, and $3 \sim 16$, respectively.

2) Detecting Window: In order to improve the detecting efficiency, our method uses a fixed-size detection window with the same size as the training samples. So each candidate patch will be resized to have the same size with detection window before target discrimination. If the size of detection window is too small, the information of the resized patch will be insufficient, which leads to poor classification performance. In contrast, if the size of detection window is too large, the computational cost of feature extraction and target classification will be too high for application in real-time systems. For a good compromise between recognition accuracy and efficiency, the sizes of the training samples and the detection window were set to 40×40 pixels.



(a) (b) (c)

Fig. 5. Detected results of our method on different sea surfaces. (a) Quiet sea with low contrast. (b) Textured sea. (c) Clutter sea.

C. Effectiveness of Our Method

In this section, we conducted several experiments to validate the effectiveness of our method. All the experiments were coded using MATLAB R2014 and Microsoft Visual Studio 2010, in a hardware environment consisting of a computer with an Intel 2.4-GHz CPU and 8 GB of DDR3 RAM. $Recall$ and $Precision$ are employed as performance metrics, defined as follows:

$$\text{Recall} = \frac{\text{Number of detected real ship targets}}{\text{Total number of ship targets of images}} \tag{9}$$

$$\text{Precision} = \frac{\text{Number of detected real ship targets}}{\text{Number of detected targets}}. \tag{10}$$

1) Performance on Different Sea Surfaces: In this group of experiments, we tested our approach on different sea surfaces in the three subimage groups. Fig. 5 shows some examples of the detection results. Even though some false alarms are generated due to interference by all kinds of clutter, our method achieves impressive performance on different sea surfaces. Our method efficiently detects ships on backgrounds with low contrast, strong waves, or cloud coverage. Table I shows a comprehensive perspective of the proposed method's detection performance on different sea surfaces. Although both the recall and precision of the proposed method decrease in cluttered sea conditions compared with quiet sea conditions, it achieves a good score and is quite robust even in complex scenes.

2) Comparison With LBP Feature: This part presents a performance comparison between LBP and structure-LBP features. In these experiments, we first used the patch training data set to train classifiers based on these two features. The trained classifiers were then applied to the testing data set to detect ships. For fair comparison, the coarse ship locating described in Section II was applied with LBP and structure-LBP features. Table I shows the results of these two features. For the LBP feature, only one classifier was produced that can detect ships in different orientations. For the structure-LBP feature, we trained eight classifiers to detect ships in different orientations. Consequently, as shown in Table I, the structure-LBP feature consumed more computational time than did the LBP feature. However, the structure-LBP feature outperformed LBP feature in both precision and recall, because it encoded not only the appearance but also the spatial relations of ship regions in characterizing ships.

3) Comparison of Overall Detection Performances: Finally, we compared our approach (SS) with three state-of-the-art methods (RB [1], ST [4], and SH [8]) on recall, precision,

TABLE I

DETECTION RESULTS

	Total number of real ships	Number of real detected ships	Number of falsely detected ships	*Recall*	*Precision*	Runing Time (min/per image)
Performance of our method on different sea surfaces						
Quiet Sea	139	137	11	98.6%	92.6%	
Textured Sea	139	133	14	95.7%	90.5%	
Clutter Sea	138	128	20	92.7%	86.5%	
Comparisons with LBP feature						
LBP based method	416	386	57	92.7%	87.1%	1.4
Our method (SS)	416	398	45	95.7%	89.8%	1.9
Comparisons with three state-of-the-art methods						
RB [1]	416	392	79	94.2%	83.2%	2.0
ST [4]	416	356	73	85.6%	82.9%	4.2
SH [8]	416	370	60	88.9%	86.0%	3.4

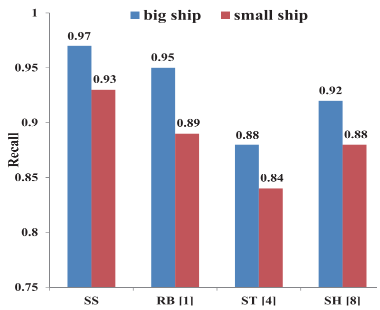


Fig. 6. Performance comparison of different state-of-the-art methods for different target types.

and running time. The results are shown in Table I. Because it integrates various cues into the structure-LBP descriptor, our approach is more effective at ship detection than the other three methods. Moreover, on average, our approach consumes less time to process an image. To conduct in-depth comparisons, we divided the ships into two categories in our experiments: big ships whose length exceeded 80 pixels and small ships whose length ranged from 20 to 80 pixels. In addition, we evaluated the detection accuracy of the various methods on ships with different sizes. As Fig. 6 shows, our proposed method performs the best among the tested methods on different target types.

V. CONCLUSION AND FUTURE WORKS

This letter presented a novel ship detection method for optical satellite images. In this method, intensity distinctness, pattern distinctness, and contextual analysis are integrated into a saliency segmentation framework to locate candidate regions. The combination of these three image cues enables suspected targets to be extracted easily from background clutter. Moreover, a structure-LBP feature that characterizes the inherent topology structure of ships is proposed to discriminate real ships. The experiments on real panchromatic satellite images demonstrate that our method is not only more computational efficient but also robust to various sea backgrounds and targets with different sizes compared with the state-of-the-art methods. Our future work will focus on the two aspects: to construct more effective features to improve the detection performance in extreme environments and to integrate the information from multispectral remote sensing images to extract ships near land.

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