International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 11 Issue: 08 | Aug 2024 www.irjet.net p-ISSN: 2395-0072

Saliency segmentation and Structure LBP feature model for ship detection from satellite Images

Aziha M [1], Dr. Jasmine J.C Sheeja, M.E., Ph.D., [2]

[1]PG Student, Dept. of Electronics And Communication, Rohini College of Engineering and Technology, Kanniyakumari Tamil Nadu, India

[2]Professor, Dept. of Electronics And Communication, Rohini College of Engineering and Technology, Kanniyakumari, Tamil Nadu, India.

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Abstract — *The acquisition of satellite images with the highest resolutions is not possible because of the current optical satellites' technical limitations as well as their limited budgets. In existing framework, produce items with high ghastly (HS) and fleeting goals, presented a two-stream otherworldly worldly combination method in view of consideration component called STA-Net. Because of the intricate attention mechanisms that are used both spatially and temporally, STA-Nets frequently necessitate a significant amount of computational power. This project proposes a detection algorithm based on ship structure and the local binary pattern (LBP) descriptor to overcome the shortcomings. Due to cluttered scenes and varying ship sizes, ship detection from optical satellite imagery is difficult. Present a novel saliency segmentation framework that allows for the flexible integration of multiple visual cues to extract candidate regions from various sea surfaces. This is important for a variety of applications, including illegal smuggling, traffic surveillance, fishery management, and so on. Then, straightforward shape analysis is used to get rid of clearly false targets. Finally, true ship targets are distinguished using a structure-LBP feature that identifies ships' inherent topology structure. Multiple panchromatic satellite image results confirm that the proposed method outperforms other current methods in terms of detection time and accuracy.*

Key Words: Hyperspectral image, Local Binary Pattern (LBP), Saliency Segmentation, Shape Analysis.

1. INTRODUCTION

For a wide range of applications, such as traffic surveillance, fishery management, and illegal smuggling, remote sensing imagery's ability to identify ships is crucial. Because they are little affected by weather and time, synthetic aperture radar (SAR) images play an important role in detecting and tracing targets in previous research. However, high-level speckles are common in SAR images, they are insensitive to wood, and they are difficult for humans to interpret. Optical satellite images have a higher resolution and contain more detailed information than SAR and other types of remote sensing images; Consequently, they are better suited for target recognition or detection.

Yuan Yao An et al. [1] proposed In the field of remote sensing, ship target detection in optical images has received increasing attention. Optical remote sensing images' ship target detection technology is susceptible to numerous factors, whereas real data are difficult to contain. To get the different circumstances in the huge ocean scenes, we foster a reproduction framework for high-goal optical remote detecting picture of boat targets.

Xiaoyang Xie et al. [2] proposed Ship distribution probability analysis enables rapid ship detection from optical satellite images. It is still difficult to detect ships automatically using optical satellite images. By analyzing the ship distribution probability, this paper proposes a novel method for ship detection from optical satellites. The sea cluster histogram model is used to first construct an anomaly detection model; The ship candidates are then identified by examining the ship distribution in light of the ship safety navigational criterion, and the area properties of the ship candidates remove obvious non-ship objects; Lastly, a ship candidate's structural continuity descriptor is intended to eliminate false alarms.

Shuchen Wang et al. [3] proposed The Saliency Adjusted Deep Network for Optical Satellite Image Ship Detection. a Saliency Adjusted YOLO (SA-YOLO) for optical satellite image ship detection is developed. First, due to the fact that the ship in low resolution imagery can be regarded as a salient object, they designed a saliency guided dense sampling layer (SDSL) to improve the spatial sampling of small ship targets. Secondly, the saliency region-aware convolution (SAConv) strategy is designed to improve the representation capability of salient regions and increase the attention of network to these regions. Sergey Voinov et al.

[4] proposed Detection of Multiclass Vessels. With a spatial resolution of up to 0.3 meters per pixel, a growing constellation of very high resolution (VHR) optical satellite sensors can frequently cover large areas, allowing for the identification and differentiation of various vessel types. With the help of principle component analysis (PCA) and deep convolutional neural networks (DCNN), a novel approach to automatic multiclass vessel detection is presented in this paper.

Yin Zhuang et al. [5] proposed ship detection based on Multi-Orientation Sparse Representation. They proposed a multi-orientations sparse dictionaries (MOSDs) algorithm combining with comprehensive structure voting (CSV) to address existed problem and achieve refined docked ship contour region proposal (RP).

Guang Yang et al. [6] designed Ship Detection Using Sea Surface Analysis from Optical Satellite Images To address this issue, they propose a novel sea surface analysis-based detection technique. Using two brand-new features, the proposed method first determines whether or not the sea surface is homogeneous. After that, ship candidates are chosen using a novel linear function that combines pixel and region characteristics. To finally eliminate false alarms, compactness and length-to-width ratio are utilized.

Yiqun He et al. [7] designed Without Sea-Land Segmentation, Ship Detection In the context of applications in remote sensing, ship detection is a significant and challenging issue. Sea-land segmentation is typically required prior to ship detection, according to current literature. The methods' implementation becomes extremely difficult as a result of this. This paper therefore proposes a ship detection method for large-scale images based on Faster R-CNN that does not require sea-land segmentation as a preprocessing step and can detect ships directly from a complex background that includes both land and sea.

Yu-Hui Ma et al. [8] proposed Multi-Scale Salient-Region Detection for Optical Remote Sensing Images. In this method, they first use hypercomplex Fourier transform to get the amplitude matrix and phase matrix of the image and then use wavelet transform to calculate six saliency images of different scales in the frequency domain. And then use the evaluation function to select two best multi-scale saliency maps to generate the final saliency map by adaptive weight combination. Finally, the threshold is used to process the enhanced saliency map to locate the ship target.

Mesut Kartal et al. [9] proposed deep learning technique for ship detection. An open-source, fast-running ship detection system based on optical satellite images and the deep learning algorithm was proposed in this paper. The framework needn't bother with any thorough equipment, even can chip away at a typical PC. Tensorflow Article Identification Application Programming Connection point (API)is prepared by optical satellite pictures with ships and utilized as item recognition Programming interface.

Chunbo Zhu et al. [10] proposed Segmentation of Ship Instances Using Cross-Domain Transfer The sample transfer module and the knowledge transfer module of the proposed method simulate images from optics to SAR and use simulation images to pre-train the instance segmentation network's ship detection component. We also make a Res-Pyramid network to make sure that the deep network can still extract useful features from SAR images.

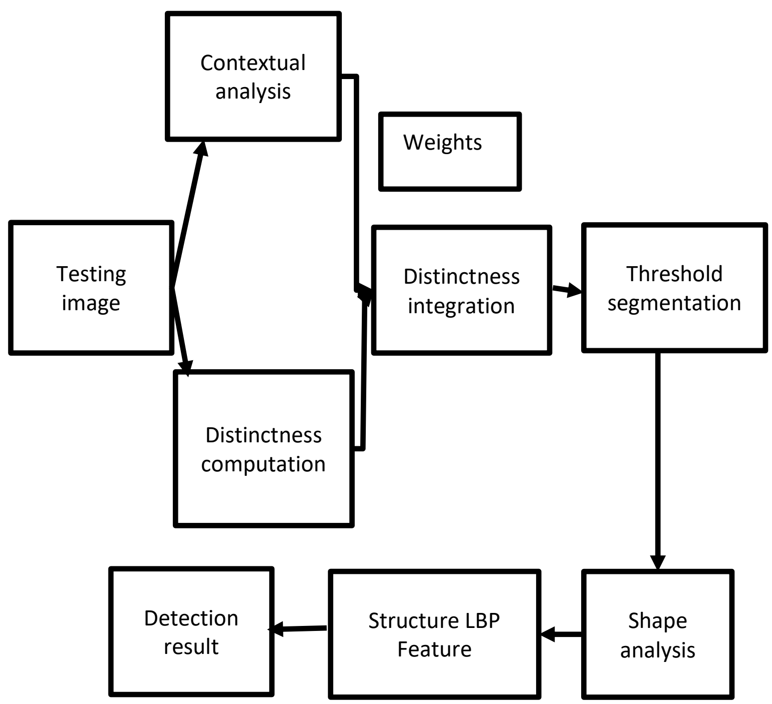

Fig-1 BLOCK DIAGRAM SHIP DETECTION

2. METHODOLOGIES

In order to find candidate regions for a subsequent classifier, this paper develops a novel saliency segmentation framework that allows for the flexible integration of multiple visual cues. Second, this letter is the first to, to our knowledge, incorporate intensity distinctness, pattern distinctness, and contextual analysis into the ship detection procedure from optical satellite images. Regardless of the detection scene's variations, the combination of these three image cues results in a high detection rate. Third, we propose a construction neighborhood parallel example (LBP). feature that applies ship bodies' inherent topology structure by combining spatial information with local features to produce a more discriminative ship description.

2.1. DATASET COLLECTION

Panchromatic satellite images from Google Earth with a 2-m spatial resolution were used in the experiments, which involved two data sets: a testing data set and a training data set for the patch. The classifier is trained with the help of the patch training data set. It contains training samples in total, each of which measures 40 x 40 pixels. Positive samples are divided into eight classes according to the various target orientations because the structure-LBP feature is sensitive to orientation. In order to find ships in various orientations, we made eight classifiers that corresponded to the eight classes.

DISTINCTNESS COMPUTATION

Ships have much lower intensity frequencies in panchromatic satellite images than the background of the sea because sea water makes up the majority of the sea surface. Additionally, ships' intensity distribution typically differs from the background of the sea surface. Consequently, we use the gray statistics of the input image to define the intensity distinctness values for image pixels using a histogram-based contrast method.Specifically, the intensity distinctness value of a pixel I_k in the input image I is defined as follows,

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

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

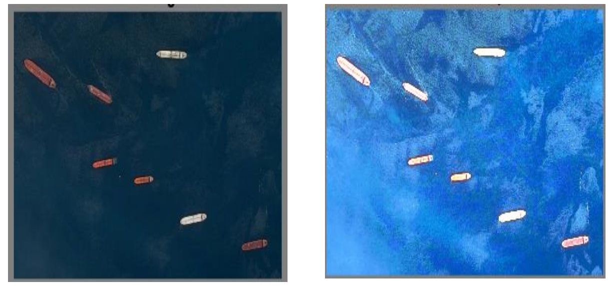

Fig-2 (a) Input image **(b)** Distinctness computation

2.2. PATTERN DISTINCTNESS

Influenced by the sensor attributes and enlightenment, transport powers are in some cases very like the forces of different sorts of messiness in pictures. As a result, in situations like these, the cue of intensity distinctness alone is insufficient to locate targets. We apply a pattern distinctness measure based on the phase spectrum of a Fourier transform to the distinct patterns of ships, also known as the boundary between an object and its background. This measure can be used to identify areas of the image that have a distinct appearance.

2.4 .CONTEXTUAL ANALYSIS

Although intensity and pattern distinctness have the potential to significantly aid in the identification of ship candidates in input images, their efficacy varies depending on the scene. 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:

$$r = \sum_{i=1}^{n} f_i^2 \qquad \text{----------------(2)}$$

where n is the number of different pixel intensities, and fi is the probability of pixel intensity gi . A larger r (r ∈ (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. As a result, the pattern distinctness cue has more discriminative power than the intensity distinctness cue and should be given more weight in the distinctness measure. A smaller r value, on the other hand, indicates that the intensity distinctness cue ought to be emphasized when selecting ship candidates.

2.5 DISTINCTNESS INTEGRATION

The force and example uniqueness calculations produce the saliency maps S and D, individually. Each map works well with 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:

$$C = (1 - r).S + r.D \qquad \text{-------------(3)}$$

The likelihood that a pixel in the input image is a component of an object is quantified by the object map C. Ship candidates are more likely to be found if their C values are higher. Then, the adaptive segmentation method is applied to locate ship candidates where the threshold is defined as follows:

$$T_c = m(C) + k.\sigma(C) \qquad \text{-----------------(4)}$$

where m and are the object map's mean and standard deviation, respectively. Here, k is a coefficient and observationally set to 4. As a result, all other pixels in the object map are set to 0 and any pixel that is larger than Tc is set to 1. Ship candidates can be easily extracted from their corresponding positions in the input image while this binarized object map is being generated.

2.6 SHAPE ANALYSIS

Effective features must be extracted in order to distinguish ships from false alarms after ship candidates have been identified. As a result, we use a two-step approach to distinguish ship targets. To begin, clearly false targets are eliminated through straightforward shape analysis. Second, a trainable classifier based on the structure-LBP descriptor is used to determine whether the ship candidate is a real ship.

1) Area: The number of pixels in the connected region corresponds to the area in this case. The range of ships is very limited; Consequently, this constraint allows for the elimination of land, clouds, and other obvious false targets that are either too large or too small.

2) Length–Width Ratio: It is defined as

$$R_{ls} = \frac{Long_m}{Width_m} \qquad \text{-------------(5)}$$

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:

$$Compactness = \frac{Perimeter^2}{Area} \qquad \text{-------------(6)}$$

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

2.7 STRUCTURE LBP FEATURE

Even after analyzing the shape, there are still some subtle false alarms that may have a shape that is similar to that of real ships. For the purpose of final ship identification, we must therefore conduct additional visual analysis of their features. During this stage, we encode the retained candidate patches with a brand-new structure-LBP feature descriptor. To encode these competitor fixes really, we resize each fix to a decent size (40 × 40 pixels in this letter) and afterward extricate its construction LBP descriptor of each resized fix. Based on the inherent topology structure of ship bodies, the resized patch is divided into four areas. The prow, left hull, right hull, and stern are the four regions. Because it is typically v-shaped, the prow is cropped as a single area. A ship's body is bilaterally divided into two symmetrical regions in the middle. The stern has been cropped as a separate area in order to account for wake interference. The LBP feature descriptors are then independently extracted from each region. At last, we link these nearby descriptors into a worldwide descriptor named structure-LBP include. The structure-LBP description separates out LBP features for different regions, which can make the process of training the next classifier easier.

Region-based features make it easy for the classifier to assign different weights to different regions based on their importance, as different regions are important to the recognition process in different ways. As a result, the proposed structure-LBP, which combines spatial information with local features, can produce a ship description that is more discriminative than the original LBP. After highlight extraction, we utilize the AdaBoost calculation to create the speculations for ships. By maintaining a set of weights over the training set, the AdaBoost algorithm aims to transform a weak learner into an arbitrarily accurate "strong" learning algorithm. Increasing iterations are used to update these weights on a regular basis. A weighted majority was reached after several iterations. 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.

RESULT AND DISCUSSION

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.

Fig -3 (a) Object map **(b)** Threshold image

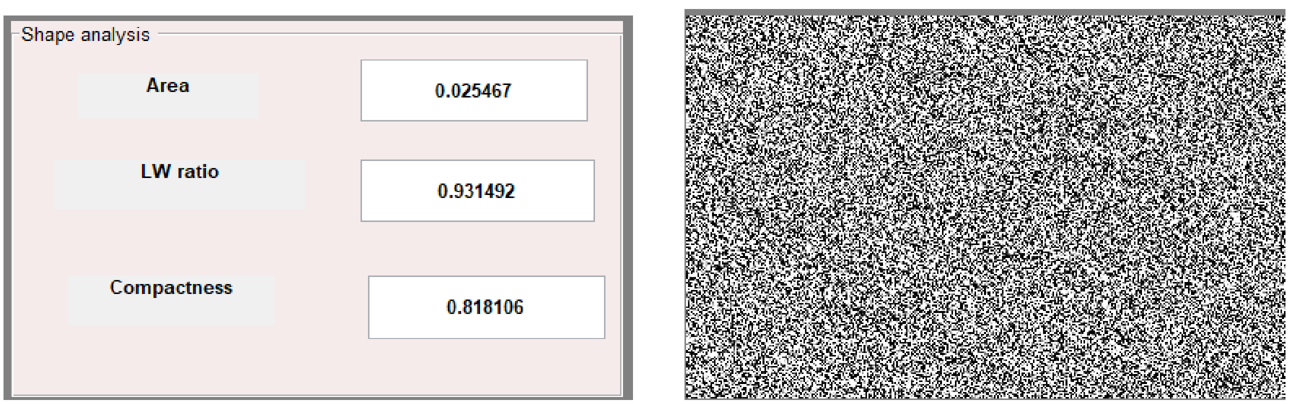

Fig-4 (a) Shape Analysis **(b)** LBP image

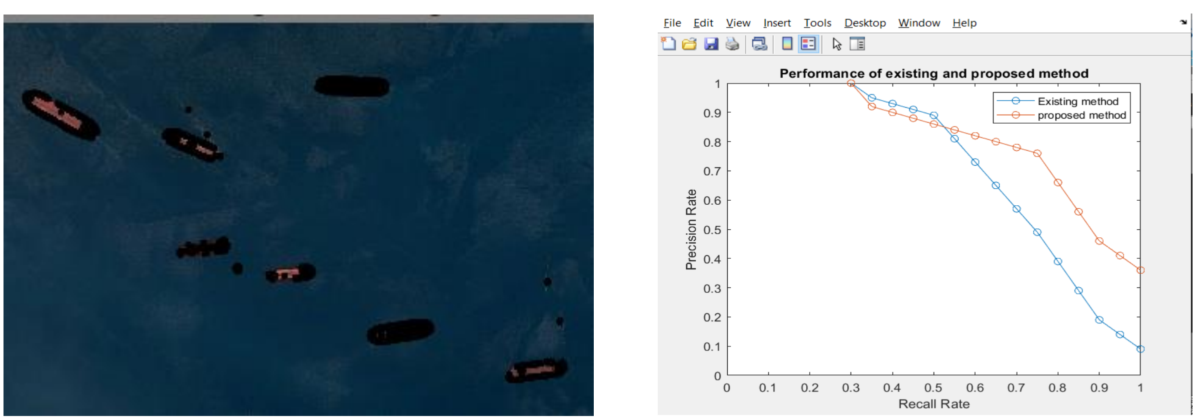

Fig-5 (a) Detection Result **(b)** Performance measure

Table-1 Comparison table.

	Precision	Recall	Accuracy
Existing system	87.1	92.1	93.7
Proposed method	89.8	94.4	95.2

CONCLUSION

A novel ship detection technique for optical satellite images was presented in this letter. To locate potential regions, this strategy incorporates contextual analysis, intensity distinctness, and pattern distinctness into a saliency segmentation framework. These three image cues make it simple to separate suspected targets from the background clutter. In addition, it is proposed to distinguish actual ships using a structure-LBP feature that identifies the inherent topology structure of ships.

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