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I hereby declare and confirm with my signature that the thesis is exclusively the result of my own autonomous work based on my research and literature published, which is seen in the notes and bibliography used. I also declare that no part of the thesis submitted has been made in an inappropriate way, whether by plagiarizing or infringing on any third person's copyright. Finally, I declare that no part of the thesis submitted has been used for any other paper in another higher education institution, research institution or educational institution.

Hanoi, 28/10/2016

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ABSTRACT

Recent years have witness the new trend of developing satellite-based ships detection and management method. In this thesis, we introduce the potential ship detection and management method, which to the best of our knowledge, is the first one made for Vietnamese coastal region using high resolution pan images from VNREDSat-1. Operational experiments in two coastal regions including Saigon River and South China Sea with different conditions show that the performance of proposed ship detection is promising with average accuracies and recall of 92.4% and 93.2%, respectively. Furthermore, the ship detection method is robustness to different sea-surface and cloud cover conditions thus can be applied to new satellite image domain and new region.

Chapter 1 INTRODUCTION

1.1 Motivation

Marine ship monitoring in coastal region is an increasingly important task for the safety and security of maritime traffic. Large ships are usually equipped with the Automatic Identification System (AIS), which transmit the local location of the ship to the ground center. However, the AIS might be purposely switched off, defected or simply not equipped by a small ship [15].

Synthetic Aperture Radar (SAR) and high resolution optical images are widely used operationally. SAR images are less affected by weather conditions [11-13] and can be utilized to estimate velocity of ship target [12]. However, they are usually with high level speckles and difficult for human interpretation [4, 14].

Ship detection on optical satellite images can extend the SAR based systems. The main advantage of optical satellite images is that they can have very high spatial resolution, thus enabling the detection of small ships and enhancing further ship type recognition. The main motivation of this thesis is to tackle two typical challenges. First, it is difficult to extract ships from complex backgrounds. In natural images, the loss and false alarms in ship detection can be affected by the complex sea surface, the appearance of other objects (e.g. cloud, waves, shore, port) which is very similar to the ship, and the variant in both ship shape and size itself. Second, due to the big size of optical satellite images (e.g. a VNREDSat-1 image has the size of ~9000×9000 pixels), an effective and fast method is much in demand when big data meet a platform with limited computation.

1.2 Proposed approach summary

The goal of this thesis is to robustly detect ships in various backgrounds conditions in VNREDSat-1 Panchromatic (PAN) satellite images. The framework is demonstrated in Figure 2.1.

The ship detection system consists of two main processing stages. The first stage is candidates scoring and selection which aims at detecting potential ship candidates.

In the second stage, three widely-used classifier including Support Vector Machine (SVM), Neural Network (NN) and CART decision tree (CART) is used for the false alarm elimination of potential candidates.

Experiments are carried out to compare the performances of the proposed method with other state-of-the-art methods.

1.3 Thesis structure

The rest of the thesis is organized as follows.. Chapter 2 presents the proposed ship detection approach. Experiments on real VNREDSat-1 panchromatic satellite images are studied in Chapter 3 and the conclusion is drawn in Chapter 4.

Chapter 2 SHIP DETECTION FROM VNREDSat-1

Figure 2.1 shows the processing flow of the proposed ship detection system. The system consists of 3 processing stages. The first stage is segmentation which aims at detecting potential ship targets.

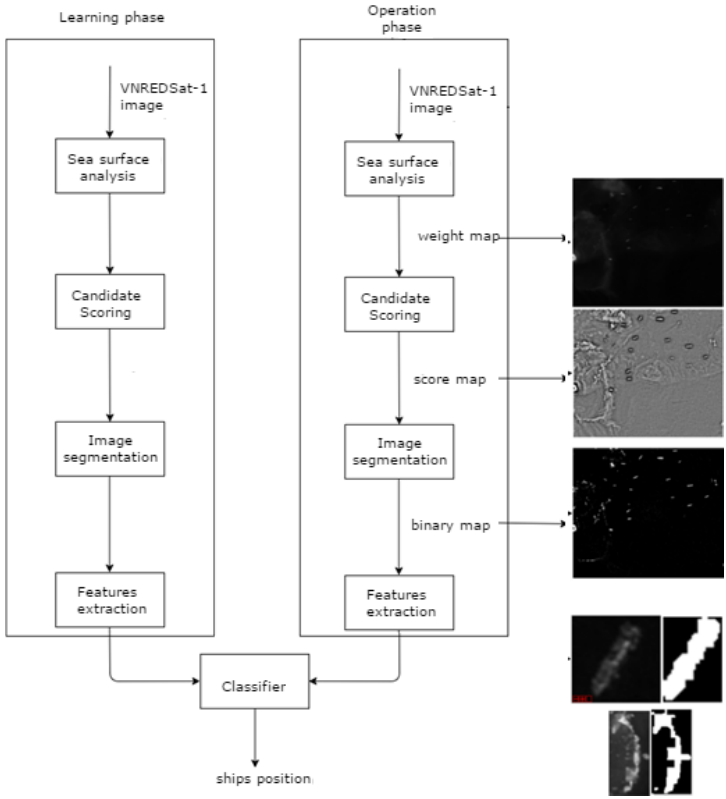

Figure 2.1 The processing flow of the proposed ship detection approach

Image objects are then characterized by spectral, shape and textural features during. The features extraction step is concerned with finding transformations to map features to a lower dimensional space for enhanced class separability and optimized performance [1].

In the last stage, three widely used classifiers including Support Vector Machine (SVM), Artificial Neural Network (ANN) and Decision Tree are used for the classification of image objects. Experiences over study area not only indicate a case study of ship classification but also present performance of those classifiers.

2.1 Ship candidate selection

The detector is applied for every location in the input image to find ships regardless its position. As a result, the computational complexity increases drastically. In this stage, we propose the methods which reduce the number of potential-appear ship position.

2.1.1 Sea surface analysis

Sea surfaces show local intensity similarity and local texture similarity in optical images. Ships can be viewed as abnormalities in open oceans and can be detected by analyzing the normal components of sea surfaces. Most of intensities of abnormal regions are different from the intensities of sea water, and the intensity frequencies of abnormal regions are much less than that of sea water.

Since the major region of the image is homogeneous sea water or large cloud coverage, the intensity frequencies of the majority pixels will be on the top of the descending array of the image histogram. Two features namely Majority Intensity Number and Effective Intensity Number proposed by Guang et. al. [4] are used to describe the image intensity distribution on the majority and the effective pixels, respectively as follow:

$$C_m = Min\left\{\arg\left(\sum_{i=1}^{2^b} X(I)\right) > P_1 N_I\right\} \tag{1}$$

$$C_e = Min\left\{\arg\left(\sum_{i=1}^{2^b} X(I)\right) > (1 - P_2)\, N_I\right\} \tag{2}$$

where X is the descending array of the image intensity histogram, 2^b is the number of possible intensity values, P_1 is the percentage which describes the proportion of majority pixels in the image, P_2 is the proportion of random noises in the image and N_I is the number of whole image pixels

To measure the effectiveness of intensity discrimination on different sea surfaces, another important feature, namely Intensity Discrimination Degree (IDD) is defined as follows:

$$C_d = \frac{C_m}{C_e} \tag{3}$$

The values of C_d is vary from 0 to 1 which larger indicate more homogenous background sea surface.

2.1.2 Candidate scoring function

Pre-screening of potential ship target is based on the contrast between sea (noise-like background) and target (a cluster of bright/dark pixels) [1]. The intensity abnormality and the texture abnormality suggested in [4] are two key features used for ship segmentation. The 256 x 256 pixels moving window is applied to the image pixel value to evaluate the abnormality of pixel brightness.

$$I(x,y) = (1 - C_d)\frac{1}{f(x_{i,j})} + C_d\frac{\sigma}{\mu} \tag{4}$$

where $f(x_{i,j})$ is intensity frequency of pixel $x_{i,j}$. Since the size of the ship is usually small in compare to moving window, the $f(x_{i,j})$ is considered low. Thus, $1/f(x_{i,j})$ is used to emphasize the abnormality of the ship intensity.

As for the texture abnormality, the standard deviation σ is employed to measure the texture roughness of sea surface due to its simplicity and statistical significance. σ is calculated on a region R centered at the pixel (x,y). The region has the size of 5 × 5 pixels and is normalized by the mean intensity frequency μ. As σ/μ for the edges of the ship is usually high due to the difference of intensities between ships and waters, it was to emphasize the texture abnormality at the edges of the ship.

As mentioned in Section 2.1.1, higher weights should be set to intensity abnormality on sea surfaces with smaller C_d values, where the intensity abnormality is more effective for ship iden tification. Similarly, the texture abnormality should be higher weighted on sea surfaces with larger C_d values. Therefore, $(1 - C_{d)}$ and C_d are set as the weight to the intensity and the texture abnormality, respectively.

The pixels above T_0 are considered as ship candidate pixels. T_0 will be properly set according to the training data

2.2 Features extraction

The classifiers base their predictions on a set of features extracted from image object segmented from segmentation stage. Based on a known knowledge of ships' characteristics, spectral, shape and textural features are screen out the ones that most probably signify ship from other objects, bearing in mind that rotation-position invariance is required.

28 features including shape, texture and spectral based on the ones proposed by [1] are investigated in this thesis (Table 2.1).

Table 2.1. List of features

Spectral	Number of pixels
	Mean
	Standard Deviation
	Min
	Max
	Asymmetry coefficient
Shape	Kurtosis
	Perimeter
	Area

	Compactness
	Major axe
	Minor axe
	Ratio Major axe/ Minor axe
Texture	GLCM mean
	GLCM variance
	GLCM uniformity
	GLCM correlation
	GLCM homogeneity

PCA is used reduce input dimensionality to obtain a classifier that performs well in term of both training and test accuracies.

2.3 False alarm elimination

Three widely used classifiers including SVM, NN and Decision Tree are tested in our experiment to find out the best one.

Chapter 3 EXPERIMENT RESULTS

3.1 Datasets

The full dataset of 9 scenes includes 119 ship objects and 512 non-ship objects. The images represent various sea surface states with small percentage of cloud and land cover.

3.2 Ship detection performance

Threshold optimization for ship candidate extraction is done using full dataset of 9 images with ship targets carefully located. The threshold is optimized in order to maximize the recall of ship targets while minimizing the number of false targets. The threshold is set for $T_0 = 0.18$.

Since well chosen parameters can strongly impact the performance of classifier, parameters that are not directly learnt within estimators can be set by searching a parameter space for the best cross validation score.

Table 3.1 shows the average results of 10-folds cross validation for each classifier. Analysis of the results shows that SVM and Neural Network outperform the Decision Tree method. Meanwhile, the F-score for SVM and NN respectively 46.15 and 45.86 show insignificance difference of performance. However, SVM is chosen since its precision is much higher than NN (93.2% in compare to 90.2% of NN). Based on experiment results, ship detection classification using SVM seem good enough for near real time application.

Table 3.1. Performance of different classifiers

	Precision (%)	Recall (%)	F-score
SVM	93.2	92.4	46.15

Neural Network	90.2	93.3	45.86
Decision Tree	85.4	68.9	38.13

Performance of ship detection procedure is strongly impacted by several extreme sea surface conditions. Hence, we evaluate the detection on extreme case to demonstrate its robustness.

Table 3.2. Performance on different sea surface conditions

Test Image Date	Training set	Testing set	Precision	Recall
2015/01/17	558	73	91.7	84.6
2015/02/02	540	91	100	100
2015/03/03	567	64	86.7	100
2015/04/17	543	88	100	95.2

2015/05/08	583	48	90.5	90.5
2015/06/09	524	107	100	92.3
2015/07/26	570	61	90	100
2015/09/04	599	32	100	100

Table 3.2 shows the ship detection performance of the proposed approach on different image with various types of sea surface conditions. We can see that, the precision and recall overally over 90% which shows good performance in various scenes.

Chapter 4 CONCLUSION

Chapter 5 This thesis analyzes the potential ability of VNREDSat-1 imagery to extract ships on coastal region and proposes an operational ship detection procedure using high-resolution data. What have been done so far in this thesis can be concluded as followed.

Chapter 6 First, state-of-the-art report and literature review on ship detection methods using optical satellite image. All methods have been analyzed to point out their advantages and disadvantages and how they can be applied to VNREDSat-1 data.

Chapter 7 Second, a complete processing chain for operational ship detection in VNREDSat-1 data is proposed. The sea surface analysis was employed to robustly select the ship candidate objects from image. A semi-automatic threshold is selected to produce a binary image by comparing the abnormality score of foreground objects (ship, wake) with sea as the background. The process can not only inherit the advantages of original method but also make an improvement in term of detection results. Experiment show that the most of the ships are identified correctly regardless of their size, which proves that detecting ships on coastal region using VNREDSat-1 imagery is feasible.

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