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A METHOD OF SHIP DETECTION FROM SPACEBORNE OPTICAL IMAGE

M. S. Satyanarayana[1] and G. Aparna[2]

[1]Dept of CSE, Azad College of Engineering, Hyderabad, A.P, India
[2]Dept of CSE, Pragati Engineering College, Surampalem, A.P, India

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ABSTRACT

Operational SDSOI and Novel hierarchical complete approach based on shape and texture properties, which is considered a sequential coarse-to-fine deleting process of fake alarms. Simple shape analysis is adopted to delete evident fake candidates generated by image segmentation with world and local information and to extract ship candidates with missing alarms as low as possible and a novel semi supervised hierarchical classification approach based on different features is presented to distinguish between ships and non ships Besides a complete and operational SDSOI approach, the other contributions of our approach include the following three aspects: 1) it Identify ship candidates by using their class probability distributions rather than the extracted features; 2) the related classes are automatically built by the samples' appearances and their feature attribute in a semi supervised mode; and 3) besides commonly used shape and texture features, a new texture operator, i.e., local multiple patterns, is introduced to enhance the representation ability of the feature set in feature extraction. Experimental results of SDSOI on a big image set captured by optical sensors from multiple satellites show that our approach is effective in distinguishing between ships and non ships, and obtains a well ship detection performance.

INTRODUCTION

Ship detection from wireless sensing imagery is very important and has a large array of applications such as fishery management, vessel traffic services, and naval warfare. In particular, in recent years, because of the decrease in fishery resources in the world, ship detection has become much more important for effective and efficient ship monitoring to prohibit illegal fishing activities in time.

However, ship detection based on SAR has limitations. First, with a limited number of SAR satellites, the revisit cycle is relatively long and, then, cannot meet the needs of the application of real-time ship monitoring. Second, the resolution of most satellite SAR images is often not high enough to extract detailed ship information.

Ship detection based on satellite optical images can partly overcome the aforementioned shortcomings of ship detection based on SAR and is complementary to SAR-based ship detection. Thus, it is advantageous to investigate SDSOI to better satisfy the requirements of ship monitoring Nevertheless, for some negative influence from clouds and at night, currently, only a few publications on ship detection from space borne optical images (SDSOI) exist, except for publications on detection of long ship tracks in

Advanced Very High Resolution Radiometer (AVHRR) imagery and ship detection, or recognition from airborne infrared images with sky–sea backgrounds. Only Burgess, Wua et al, and Corbane et al, are found to have performed research on SDSOI from satellite images, and useful results have been obtained, including ship detection in satellite multispectral imagery, , ship classification in SPOT-5 HRG 5-m images using neural networks evolved by genetic algorithms, and the elimination of false candidates by using morphological filtering followed by wavelet analysis and radon transform. However, many open issues such as very high false-alarm rate due to cloud and sea clutter still remain for us to study and resolve. SDSOI is a challenging problem. We want to further investigate how we can resolve issues in SDSOI. SDSOI includes two stages: 1) sea detection and 2) ship detection in sea. This paper mainly focuses on how we can detect a ship in sea, assuming that sea regions have been detected by prior geographic information or algorithms. In addition, in this paper, we are only interested in ship detection on a panchromatic band or on a band of a multispectral image and not on multispectral images. In SDSOI, several factors such as clouds, ocean waves, and small islands are often detected as false ship candidates due to similar characteristics, which affect the performance of ship detection. cloud is the most difficult factor due to its random variation without a fixed shape and without a fixed gray distribution. Although some research on cloud detection has been conducted ,most of these studies are mainly based on multispectral information and thus are not helpful for SDSOI in the absence of multispectral information condition. In this paper, a novel hierarchical complete and operational SDSOI approach with multiple features is proposed, as illustrated. The proposed approach is considered as a cascade elimination process of false alarms. It includes the following coarse-to-fine two stages. Stage 1–Extraction of Ship Candidates: This stage includes image segmentation and simple shape analysis. On the one hand, image segmentation with global and local information, including the characteristics of gray and edge features, is applied to obtain possible ship candidate regions. On the other hand, because ships are generally thin and long, simple shape features are extracted to eliminate obvious false candidates. In this stage, the main aim is to extract ship candidates with missing alarms as low as possible, and false alarms that are due to objects such as small clouds and islands may be extracted as ship candidates. Stage 2–Classification of Ship Candidates: In this stage, a novel semi supervised hierarchical classification of ship candidates based on shape and texture features is further conducted to remove most false alarms and obtain the results of ship detection. Some differences between the feature distributions of ships and non ships can be noticed; therefore, we can remove non ship candidates and detect ships by pattern classification. Furthermore, a significant difference usually exists between the feature distributions of different samples within one class, which often has a negative influence on the classification performance. Thus, all candidates are divided into several subclasses according to their appearances, and the subclasses are divided into mini classes by feature clustering (so-called semi supervised) to improve the performance. In addition, a hierarchical ensemble classification approach based on the mini class distributions, rather than on the directed extracted features, is presented for candidate recognition. Moreover, in feature extraction, besides commonly used shape and gray distribution features, a new texture operator, local multiple patterns (LMP), for enhancing the representation ability of the feature set is first introduced. The basic idea of LMP is that it extends binary patterns to multiple patterns. In addition, the LMP preserves more structural information and is more suitable for image analysis than local binary patterns (LBP).

The rest of this paper is organized as follows. Section II describes the extraction of ship candidates, including image segmentation and simple shape analysis. Section III depicts shape and texture feature extraction of ship candidates. Section IV discusses the classification of ship candidates, including three classification strategies. Section V presents the experimental results of ship detection from a large image set captured by multiple optical sensors. Finally, Section VI provides a discussion and conclusion of this paper.

CLASSIFICATION OF SHIP CANDIDATES

The main aim of classification is to recognize true ships from the candidates. A hierarchical ship classification approach based on the Entailed pattern analysis of ships and non ships is proposed in this section. In addition, two other simple classification approaches, based on two classes and several sub classes, are presented for analysis and comparison. Furthermore, the support vector machine (SVM is adopted as the basic classifier in our classification approach due to its capability of providing classification probabilities aside from categories and its high performance in many applications.

A. Supervised Binary Classification: METHOD1

This method is a direct classification strategy that considers the classification as a two-class recognition problem. The approach is to find a single boundary between the ship and non ship classes in the feature space. In this classification approach, all samples are classified into two classes: 1) ship and 2) non ship.

B. Supervised Several Subclasses Classification: METHOD2

This method considers the classification as a multiple-subclass recognition problem. The non ship class includes many subclasses such as clouds, ocean waves, and islands. There are two classification hierarchies 1. subclass classification is conducted based on the SVM classifier with the simple combination of features. 2. class identification is performed based on whether the result of subclass classification is a ship or a subclass of a ship.

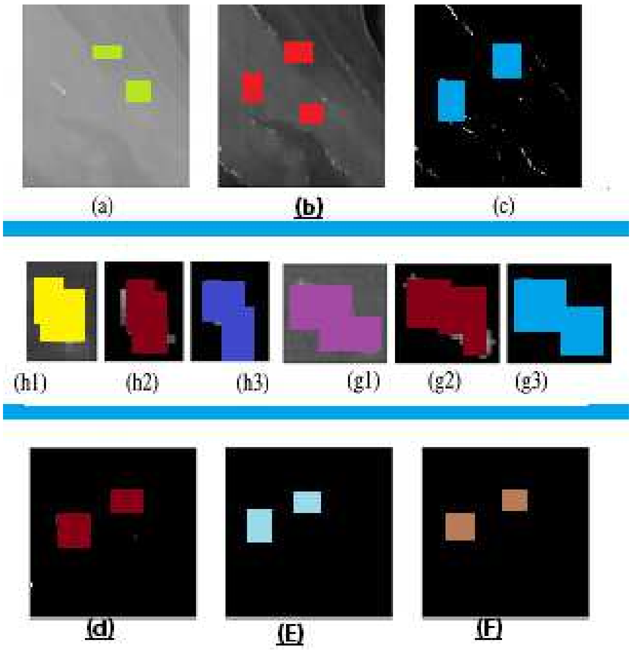

Fig. 1. Intermediate results of one typical image sample. (a) Original image.(b) New mixed image. (c) Segmentation result with an adaptive threshold. (d) Regions after morphologic operation. (e) Regions after simple shape analysis. (f) Refined segmentation with level set. To display clearly, the two ship candidates are shown in detailed forms. (g1) and (h1) Original images of the two ship candidates. (g2) and (h2) Segmentation results with an adaptive threshold of the two ship candidates. (g3) and (h3) Refined segmentation results with level set of (g1) and (h1).

C. Semi supervised Hierarchical Multiple Mini class Classification: METHOD3

In METHOD2, although all samples are artificially divided into several typical subclasses according to their appearances, the diversities of feature distributions within the subclass are not considered. Therefore, we present METHOD3 with the following hierarchical classification strategy. Foundation of Mini classes by Clustering: At first, for simplicity, we take clouds as an example to show the diversities of feature distributions within a subclass. The distributions of the first two principle components of shape, LTP, and MGDF of the cloud samples are shown in Fig. 5. After a close look at all samples and their feature distributions, we find that there sometimes exist large differences between the samples within the same subclass. Therefore, some subclasses can be divided into multiple mini classes based on their feature distributions to improve the performance as follows. First, the feature distributions of the training samples in every subclass are computed. Second, the mini classes are generated using a feature-clustering algorithm (therefore, the approach is called semi supervised). In our approach, the fuzzy c-mean algorithm that considers the distance between the centers of different clusters [46] is adopted for feature clustering. The number of mini classes is determined as follows. The minimum between-mini class distances in different numbers of mini classes are first computed. Then, the corresponding number with the largest minimum between-mini class distance is adopted as the optimal number of mini classes. The results of feature clustering are shown in Fig. 5. Note that, if there are very few samples in a cluster, the cluster is merged into the neighboring cluster, as shown in Fig. 5(d) and (f). Classification Based on the Ensemble Method: Ensembles have been shown to have better accuracy than a single classifier if the component classifiers in the ensemble are accurate and diverse [47]. Ensemble methods are learning algorithms that improve performance by combining the outputs of multiple component classifiers. Meta learning techniques employ a meta classifier that generalizes over the space of outputs from base level classifiers. Each component classifier outputs a posterior distribution of mini class labels rather than a single label. Distributions from the component classifiers are concatenated and used as input to the meta classifier.

EXPERIMENTS

A. Image Data Setup

Our experiments were conducted using a PC with a Pentium 4 CPU 1.8 G with 1-GB memory, and they involve the following two image data sets. Data Set 1: This data set consists of space borne optical images of CBERS and SPOT, about 2000 ∗ 2000 pixels in size, with a total of 232 images and a resolution of 5–20 m, as shown in Table II. Typical samples are shown in Fig. 1 and Section V-C. It was used to test our proposed approach of ship detection. For simplicity, all of the images were scaled to the spatial resolution of 10 m to train only one classifier in our experiments. Data Set 2: This data set includes more than 1600 typical ship candidate sub images obtained by our ship candidate extraction from the space borne optical images in Data set 1, The aim is to test the performance of the presented hierarchical classification approach, which is a very important section of our ship detection approach.

B. Feature Analysis and Classification Experiment Based on Ship Candidates

The experiment in this section was done based on Data set 2. All samples were intuitively divided into five typical subclasses: 1) ship; 2) clouds; 3) ocean waves; 4) islands; and 5) coastlines. For simplicity, in our experiments, ships were not divided into multiple subclasses, because there were no enough corresponding samples for the training of some subclasses In the following experiments in this section, the images of every class, subclass, or mini class in Data set 2 were divided into four even portions. One portion was randomly selected to build the training set, whereas the other three portions constituted the testing set. Experiment Based on Different Feature Sets: In this experiment, the classification of five subclasses based on SVM with every single feature set was directly adopted to analyze the feature performance. 1) Experiment of comparing LTP with both LBP and gray level co-occurrence matrix (CM) [48]. In our experiments, N was set to 3, s(x) defined as (7) was adopted, and then, the LTPriu2 P,R codes were defined. To be competent for multiple different spatial resolutions and different angular resolutions, we have utilized the combination of LTPriu2 8,1 , LTPriu2 16,2 , and LTPriu2 24,3 in our experiments. In addition, the combination of LBPriu2 8,1 , LBPriu216,2 , and LBPriu2 24,3 was implemented for the performance comparison. Moreover, the gray-level

CM [48], which is a typical classical method of texture feature extraction, was implemented for the performance comparison. In the CM method, the isotropic feature based on the combination of distances 1 and 2, which had the best performance in its experiment, was adopted. To illustrate the performance of LTP, LTPs with different thresholds were compared with both LBP and CM in the experiment. clearly shows that the ship detection performances of LTPs with different thresholds are all better than those of both LBP and CM. The average accuracy of the LTPs is 92.27%, which is about 4.86% higher than that of LBP. This result is because LTP preserves more information than LBP. On the other hand, the average accuracy of the LTPs is about 8.10% higher than that of CM, which further shows the advantage of LTP. Therefore, only LTP with a threshold of 7, instead of LBP and CM, was adopted in the following experiment. 2) Experiment based on every single feature set. The aim of this experiment was to compare the classification performances based on every single feature set. clearly shows that the classification accuracy of MGDF differential features is the lowest, and those of LTP and WBF are relatively high. MGDF's worse performance may be due to the instability of the high-frequency component.

CONCLUSION

In this paper, The segmentation results using level sets are near to the true edge of an object due to the usage of local gray characteristics and optimization. Second, a semi supervised hierarchical classification with various shape and texture features was adopted to remove most fake alarms. In feature extraction, besides commonly used shape and gray distribution features, a new texture operator, LMP, has been introduced to enhance the representation ability of the feature set. The discrete occurrence histogram of the uniform patterns over an image or a region of an image has been proven to be a powerful different texture feature [40]. Experimental results in this paper further show that the ship classification performance of LMP is better than that of LBP. In addition, experimental results show that the ship classification accuracies based on combined feature sets are higher than those based on every single feature set. Therefore, the combined features are helpful for ship classification. In classification, the analysis and comparison of three classification strategies and experimental results show that subclass division and hierarchical classification strategies are usefull for achieving a classification performance. In the experiment of ship detection from a large image set captured by multiple satellite optical sensors, it was easily demonstrated that simple shape analysis can remove some obvious large clouds, large islands, and small clutter regions, and our hierarchical classification approach can eliminate most of the non ship candidates while retaining the true ships. Our further work will focus on better image preprocessing, more effective feature extraction and detailed feature selection, hierarchical classification, the use of multispectral features, and a test of the proposed approach on a larger set of space borne optical images over a wide resolution range. Ships of more than four pixels long are considered, and thus, the detection of smaller ships requires that the images have a higher resolution, which, on the other hand, may introduce new false candidates. Although our approach has shown promising results overall, several issues that necessitate our further improvement or refinement to enhance the performance of SDSOI still remain. First, missing detection exists when a part of a ship is covered by a large cloud, when a ship adjoins a large island, or when the gray of a ship is very close to that of its neighbor. Local segmentation and matching may be a solution. Second, false candidates, which mainly comprise clouds and sea clutter, also exist. More effective features are needed to distinguish between them. For example, the information with regard to the context of an image should be helpful.

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