Condensed-Sphere Ship Detection on Space Borne Optical Image Using Machine Learning Approach

Pavithra S[1], Vartika Sharma [2], Syed Thouheed Ahmed[3]

[1]*MTech student, Computer Science & Engineering, GSSSIETW, Mysuru*
[2]*Assistant Professor, Department of Computer Science & Engineering, GSSSIETW, Mysuru*
[3]*HR & Sr. Research Engineer, Thinksoft, Bengaluru*

Corresponding Email: s.pavitra07@gmail.com,

ABSTRACT

Ship detection in space borne remote sensing images is of fundamental importance for maritime protection and other operation. This method is helpful for protection against illegal fisheries, oil discharge control, and sea pollution monitoring. Ship monitoring from satellite images provides a broad observable ground and covers large sea area and thus achieves a continuous monitoring of ship locations and movements. It is also known that optical space borne images have higher resolution and more visualized contents than other remote sensing images, which is more suitable for ship detection or recognition in the preceding applications. Machine learning technique can be trained hundred times faster than traditional neural network since its input weights and hidden node biases are randomly generated and the output weights are analytically computed. The advanced framework for ship detection is faster detection of ships than pixel domain, more reliable results to ensure accurate classification in large data volume and better utilization of information where the results are not affected by weather conditions like clouds, mist and ocean waves.

INTRODUCTION

Ship detection from satellite imagery is a valuable tool for the identification of illegal oil spills and monitoring maritime traffic in the fisheries, and the commercial transportation sector. Basically two remote sensing techniques have been employed for ship detection: synthetic aperture radar (SAR) with capacity to image day and night under most meteorological conditions became the state-of-the-art technique for ship detection (Crisp 2004). The second technique for ship detection lies on optical remote sensing, which has been explored since the launch of Landsat in the 1970s. McDonnel and Lewis demonstrated the possibility to detect ships of 100-m length using Landsat Multi-Spectral Scanners (MSS). Burgess (1993) applied Landsat Thematic Mapper (TM)and Satellite Pour l'Observation de la Terre (SPOT) data to identify smaller ships. In a recent work, Corbane *et al.* (2008) developed an approach based on genetic algorithms and neural networks for the detection and classification of small fishing boats on 5-m resolution SPOT 5 imagery. Increased false alarm rates (FARs) were obtained when using this approach on particular types of images with a high percentage of cloud cover and a cluttered sea background.

Related Work

(1). A complete processing chain for ship detection using optical satellite imagery[1]

Ship detection from remote sensing imagery is a crucial application for maritime security, which includes among others traffic surveillance.In the framework of a European integrated project Global Monitoring for Environment and Security (GMES) Security/Land and Sea Integrated Monitoring for European Security (LIMES), Developed an operational ship detection algorithm using high spatial resolution optical imagery to complement existing regulations, in particular the fishing control system. The automatic detection model is based on statistical methods, mathematical morphology and other signal-processing techniques such as the wavelet analysis and Radon transform. The prototype was tested on panchromatic Satellite Pour l'Observation de la Terre (SPOT) 5 imagery taking into account the environmental and fishing context in French Guiana. In terms of automatic detection of small ship targets, the proposed algorithm performs well. Its advantages are manifold: it is simple and robust, but most of all, it is efficient and fast, which is a crucial point in performance evaluation of advanced ship detection strategies.

(2). Automatic detection of ship tracks in ATSR-2 satellite imagery [3]

In this paper an algorithm has been developed to automate the detection of ship tracks in Along Track Scanning Radiometer 2 (ATSR-2) imagery. The scheme has been integrated into the Global Retrieval of ATSR Cloud Parameters and Evaluation (GRAPE) processing chain. The algorithm firstly identifies intensity ridge lets in clouds which have the potential to be part of a ship track. This identification is done by comparing each pixel with its surrounding ones. If the intensity of three adjacent pixels is greater than the intensity of their neighbors, then it is classified as a ridge let. These ridge lets are then connected together, according to a set of connectivity rules, to form tracks which are classed as ship tracks if they are long enough. The algorithm has been applied to two years of ATSR-2 data. Ship tracks are most frequently seen off the west coast of California, and the Atlantic coast of both West Africa and South-Western Europe. The global distribution of ship tracks shows strong seasonality, little inter-annual variability and a similar spatial pattern to the distribution of ship emissions.

(3). Towards Face Recognition in JPEG2000 Compressed Domain[4]

The main concept of this paper is to examine the feasibility of implementing face recognition algorithms directly into JPEG2000 compressed domain. By exploring some standard face recognition algorithms' behavior when fed with standard JPEG2000 DWT coefficients (CDF 9/7 wavelet), this will prove that recognition can be done directly in JPEG2000 compressed domain, avoiding inverse discrete wavelet transform (IDWT). Such an approach would consequently enable the use of compressed images in recognition purposes, thus reducing both computational time and storage requirements. Our experimental results indicate that face recognition performance in JPEG2000 compressed domain is comparable, or even better in some cases, than face recognition performance in pixel domain.

PROPOSED SYSTEM

The ship detection problem can be considered as a simple detection of bright point targets against a noisy background. However, the reality is more complicated because of possible confusions associated with small clouds and wave crests that could be falsely detected as ships. An optimum detector for this situation should maximize the probability of detection while minimizing the probability of false alarm. The basic structure of the detection preprocessing algorithm is summarized in figure 1.

Preprocessing

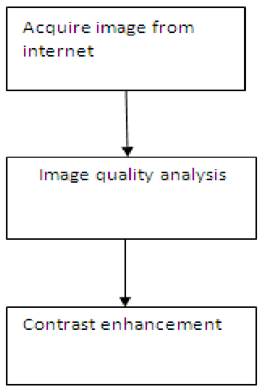

Figure 1. Flow chart of the pre processing algorithm for automatic ship detection

The aim of preprocessing is to facilitate the subsequent detection stages by first decomposing the image into rectangular segments or tiles, and then by using statistical characteristics of the data in these segments to extract localized information for the cloud-masking operation.

(a) ***Image acquisition***: Acquire images from the internet and suppose the average size of SPOT 5 (5-m resolution) image data is around 15,000_15,000 pixels. The original scene is divided into 25 tiles of 3000_3000 pixels. This operation results not only in a faster processing time but also in a more effective handling of local information especially in images with heterogeneous sea clutter background.

(b) ***Image quality analysis***: The intensity of SPOT 5 image data is coded in 8 bits (256 grey levels). The presence of brightly reflecting clouds over the sea surface can detract from the application of contrast enhancement techniques. Besides, clouds can contaminate the prescreening approach as small clouds can be easily mistaken for potential ship targets. The modal value of the grey-level histogram corresponds to sea background pixels. Cloud masking is then tackled using threshold information determined through histogram method. In order to remove uneven illumination, a morphological operator, i.e., top-hat transform (THT), is used for ship extraction and background suppression. As ships are usually brighter than their surroundings, the white THT is employed in the proposed work. The mathematical definition of white THT is as follows:

$$\mathrm{Tw}(f) = f - f \circ b$$

Where f is the input LL coefficients of the original image, $\circ$ denotes opening operation, and Tw is the enhanced image. In the simulations, b is set as a circular structuring element with a radius of 12. With this empirically derived value, the cloud masking performed well for bright and thick clouds or ships.

(c) ***Contrast enhancement:*** Contrast enhancement will be used to perform adjustment on darkness or lightness of the image. It mainly used to bring out the feature hide in an image or increase the contrast of low contrast image. A linear contrast stretching is applied on each image segment. However, instead of computing the lowest pixel intensity, the modal value of the Gaussian distribution is considered as the minimum value. Hence the highest ($x$max) and the modal intensity values ($x$min) are set to 255 ($y$max) and 0 ($y$min), respectively, and all other pixel intensities are scaled accordingly. This yields considerable improvement for subsequent ship target detection.

The Filtering Strategy

12μm brightness temperature images before applying the ship track detection algorithm. This is done by comparing the observed 12μm brightness temperature with the calculated clear sky 12μm brightness temperatures produced by the Radioactive Transfer for TOVS (RTTOV) algorithm (Saunders et al., 1999) applied to European Centre for Medium range Weather Forecasting (ECMWF) reanalysis data. Since the tracks only occur at low altitude the brightness temperature of tracks seen by the satellite will be close to that of the surface. The rate of change of temperature with height (the atmospheric lapse rate) close to the Earth's surface is about 6.5Kkm−1 (Stephens, 1994). Given that the tracks form in the boundary layer, mostly well below 1 km, and allowing for temperature variation and errors, suggested that there is potential for ship track formation only in clouds whose temperatures are within 10K of the surface temperature.

This criterion was used to eliminating those pixels containing higher cloud from analysis. In 1.6μm channel images, cloud-covered areas show up as areas of higher intensity compared to the ocean surface. It is therefore reasonable to set a lower limit on the intensity of pixels which are to be considered. In the algorithm this is done by setting a parameter for the lower limit, relative to the median pixel intensity for the orbit from which the image is taken. By using exactly the median value it can be said that half the pixels will be automatically discounted.

3.3 Track Classification

With rideglets defined from a filtered set of pixels the algorithm has a basis from which to find longer sections of ridge.

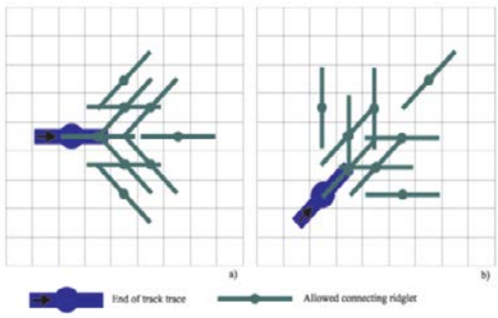

Figure. 2. The connectivity rules for progressing the trace of a track. (a) Shows this for a horizontal segment tracing from the left, (b) shows this for a diagonal segment coming up from the left.

The method used consists of a set of connectivity rules: from each ridgelet pixel the surrounding pixels are examined to determine whether or not any other ridgelet pixels are located such that they may reasonably form part of the same ridge. If an appropriate ridgelet exists the algorithm then traces along to it and searches for more ridgelets according to the same set of rules.Allowed continuation ridgelets for the tracing are shown in Fig. 2. With 4 (1×3 pixel) ridgelet types defined this leads to 8 different track end situations to be accounted for in the connectivity rules, i.e. each ridgelet could be followed by the code in both end tracks. The general rule applied was that part of a ridge could turn by up to 45 degrees in the image between ridgelets. It was also deemed acceptable that gaps could be jumped when tracing ridges, provided the ridge segment continued in a straight line along the image from the previous ridgelet.

Figure 2 shows this for a horizontal ridgelet and a diagonal one; rotations of these apply for the other six track directions. The algorithm traces a track until it reaches a dead end, this being where it cannot find another ridge let to which it can connect. Up to this point the path taken from the start pixel is recorded so that at the end of the trace it can be decided whether or not to retain the track. In theory the best criterion in deciding whether or not to retain a trace, and mark an area as ship track, is length. This could be done on pixel count, but to speed computation it was based on iterations through the connectivity rules. This gives a higher weighting for a continuing straight line segment than one with the same number of pixels which changes in direction. This is because when tracing along a straight line the jump between ridgelet centres for each iteration is only one pixel, hence increasing the number of pixels in the track by 1 for each iteration rather than 2 or 3, as can be seen in Fig. 2. However, since tracks are generally locally straight this was seen as no disadvantage.

Conclusion

In this paper, we have proposed a condensed-sphere ship detection framework using preprocessing, filtering strategy and track classification for optical space borne images. As for the possible shortcomings of the proposed work, the parameters in coarse ship locating should be more adaptive to the image content s. In addition, due to the availability of image data sets, the simulations in the proposed work are conducted using panchromatic images, and other remote sensing image could be further tested or verified in a future work. Moreover, in the experiments, the images of resolution of 5 m are used. In this case, the ships that we succeed to detect may be larger than 50 m (10 × 10 pixels). However, the limitation on the size of the detected ship is not induced by the proposed framework; it is mainly due to the resolution of the original images. In other words, when 5-m-resolution images are used for ship detection, it is not reasonable to detect smaller ships (for example, 20 m), as very limited object details/features can be extracted from such a small region (4 × 4 pixels).Thus, the proposed framework is expected to work well for multispectral or synthetic aperture radar images. Our future work may focus on the use of the proposed work for ship detection from multiple sensors.

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