SHIP DETECTION IN SAR IMAGERY: A COMPARISON STUDY

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ABSTRACT

This paper presents a ship-detection study with Synthetic Aperture Radar (SAR) images acquired at two different frequencies: X- and C-band. The detection procedure relies on a novel algorithm based on the likelihood functions of both canonical ship target and sea clutter. Spaceborne images were acquired over the same area in the Solent Channel in UK at approximately the same time on the 7th June 2016. Here, datasets are compared in terms of probability of detection (PD), probability of false alarm (PFA) and Target-to-Clutter Ratio (TCR). Detection maps are validated with Automatic Identification System (AIS) data when available and preliminary results show a higher TCR for the X-band SAR image.

Index Terms— Synthetic Aperture Radar (SAR), ship-detection, Constant False Alarm Rate (CFAR), Generalized Likelihood Ratio Test (GLRT).

1. INTRODUCTION

Maritime Surveillance has gained a lot of interest in the last few years and, consequently, the request for maritime security and safety application has greatly increased. It is clear that in such environment the authorities need to guarantee the safe navigation and the security of all marine activities by controlling the borders, fighting pirates and traffickers and monitoring ocean pollution [1].

In this scenario, one of the main applications of Maritime Surveillance is ship-detection. There are several ways to monitor and tracks ships even if there is no single mean which can be used in every situation. The most used technique is the Automatic Identification System (AIS); it is mainly a shipborne radio system by which ships inform the coastal receiver about position, course, speed and identification information [2]. It allows the tracking up to about 40 km off the shore (due to the Earth’s curvature), while a global coverage is provided by Satellite AIS (SatAIS). However, not all vessels are required by law to have such a system on board [2].

Synthetic Aperture Radar (SAR) sensors are considered a valid alternative to the coastal-based means and are particularly suitable for the detection of ships in open sea scenarios thanks to their capability to acquire images independently from daylight and weather conditions.

Traditionally, SAR ship-detection algorithms rely on Constant False Alarm Rate (CFAR) methods: the sea clutter background is modelled according to a suitable distribution and a threshold is set to achieve a given probability of false alarm [3]. All the clusters of pixels with intensity greater than the computed threshold are regarded as potential ships.

Other ship detection approaches, instead, rely on fully polarimetric data showing an improved performance in target detectability [3-4]. However, the availability of full polarimetric data is very limited and, consequently, the authors focus on the development of a ship detector based on a single polarimetric channel. In all the detectors already presented in literature, the ship model is never considered to reduce the complexity of the detector itself. However, to achieve better performance, the ship model has to be taken in account as already done in [5-6] where a likelihood function for a canonical ship target was derived and employed in a Generalized Likelihood Ratio Test (GLRT) algorithm. This paper is based on the same detector which is here used to test and compare two SAR images acquired over the same area by two different sensors operating at two different bands.

The paper is organised as follows: in section 2 the GLRT algorithm is introduced; in section 3 the case study is presented; in section 4 results are shown; finally in section 5 conclusions are drawn and future perspectives briefly commented.

2. GLRT DETECTOR

The ship detector employed to test the SAR images is based on the scattering models presented in [7] and on the
detection procedure introduced in [5-6]. Here, the model parameters are introduced and the block diagram to implement the GLRT is shown in fig. 1. The diagram is made up of two branches: one to estimate the clutter parameters $\alpha$ and the other to estimate the target parameters $\beta$. Firstly, a clutter Region of Interest (ROI) is isolated and analysed. In the Clutter estimation block, assuming a negative Exponential intensity distribution, the clutter parameter is estimated by computing the sample average of the ROI. The ratio between the standard deviation and the correlation length describing the sea clutter ($\sigma_{dc}/L$) is estimated in the Roughness estimation block by minimising the absolute error between the theoretical Radar Cross Section (RCS) within Geometric Optics (GO) approximation and the RCS directly measured on the SAR intensity image [7]. This roughness ratio represents an input along with the vector $a = (\vartheta, \lambda, \Delta \lambda)$ which includes the parameters retrievable from the ancillary data of the SAR sensors (radar look angle $\vartheta$, the radar wavelength $\lambda$ and the spatial resolution $\Delta \lambda$); the vector $b = (\varphi, h, \epsilon_{sw})$ which includes the parameters computed through suitable distribution functions (the orientation angle $\varphi$, the freeboard height $h$ and the dielectric constant of the hull $\epsilon_{sw}$) and the dielectric constant of the saline water ($\epsilon_{sw}$) to the Target histogram block. In this block, the histogram relevant to the double reflection contribution arising between the ship hull and the sea clutter is computed. It has been demonstrated in [7] that such a histogram can be modelled according to a Gamma distribution for the co-polarized channels (HH and VV). The target parameters ($\alpha$, $\beta$) of this Gamma distribution are then estimated in the Target estimation block by using numerical methods.

The GLRT, based on the likelihood functions of both sea clutter and ship target, is then performed according to a desired PFA, which is an input to the GLRT block. Finally, the pixels with an intensity greater than the set threshold are detected as potential ships.

Similarly to the CFAR, the estimation procedures can be done by using a moving window and computing the clutter and the target parameters along with the threshold at each iteration (Adaptive Threshold algorithm). Viceversa, the target and clutter parameters can be estimated for a single representative ROI leading to a fix threshold (Global Threshold algorithm).

3. CASE STUDY

The GLRT algorithm is tested on a couple of SAR images acquired over the Solent Channel in UK by the European Sentinel-1 (operating at C-band) and the German TerraSAR-X (operating at X-band) sensors. The two images were acquired on the same date (7th June 2016) a few minutes apart. In particular, the Sentinel-1 and the TerraSAR-X datasets were acquired at 6:23am and 6:26am, respectively. In addition, AIS data from ExactEarth were acquired on the same date and will be used as ground-truth information.

The original SAR images have been cropped to match the area where reference data (AIS) were available and a Region of Interest (ROI) of 3238x5344 pixels in range and azimuth respectively was selected on both datasets. The complete acquisition parameters are reported in Table 1. Both images were acquired with VV polarization and ScanSAR mode. However, it is well known from literature that the best polarization for ship-detection is HH while VV is preferable for oil-slick detection [3]. The reason why VV was chosen is due to the Sentinel-1 Interferometric Wide Swath routine acquisition mode, which implements a VV/VH dual polarization acquisition scheme [8]. Unfortunately, it was not possible to task the Sentinel-1 sensor and only VV datasets were available over the area of interest (the Solent) in the time window needed (June 2016) for this project. Both images have been firstly projected on the ground and then multilooked. In particular, a 2(azimuth) x 16(range) and a 2(azimuth) x 10(range) multilooking have been performed on the TerraSAR-X and Sentinel-1 dataset, respectively. Furthermore, the two SAR datasets have been radiometrically calibrated to Sigma nought, orthorectified to consider the slight differences in the incidence angle and coregistered to allow accurate comparison between them. Finally, the slave image (the TerraSAR-X dataset) has been resampled in order to get exactly the same resolution (20 m x 20 m) of the master image (the Sentinel-1 dataset).

A land mask is computed by using Shuttle Radar Topography Mission (SRTM) 1 arc-second data (approximately 30 m spatial resolution) and the SNAP software developed by the European Space Agency (ESA). The preprocessing results are shown in fig. 2(a)-(b) for the Sentinel-1 and the TerraSAR-X image. In fig.2, the white pixels represent the land (masked out from the following processing steps) and the black ones the sea areas. In the next section, preliminary detections results are shown and analysed.

4. RESULTS

First of all, the clutter and the target distribution parameters need to be estimated in order to apply the GLRT algorithm. A Global Threshold approach has been employed and a ROI of 200x200 pixels is selected to statistically analyse the sea clutter and to estimate the roughness parameters on both images. This ROI is highlighted with a red rectangle in fig.2 (a)-(b). A Gaussian model is here assumed for the sea clutter, while the target distribution is computed from the evaluation of the double-bounce contribution within the GO-GO approximation [7]. According to the model and the hypotheses introduced in [6], the Gamma distribution is the best distribution for the ship statistical model at C- and X-band for VV polarization.
Once the clutter and the target parameters have been estimated and the relative distribution function computed, the likelihood function can be evaluated for both datasets. Results are shown in fig. 3(a)-(b) for the Sentinel-1 and TerraSAR-X images, respectively. From a visual inspection, it results that the contrast between the clutter and the targets over the sea is enhanced for both images. In order to quantify the improvement in the Target-to-Clutter-Ratio (TCR) a ROI of 310x650 pixels in azimuth and ground range is isolated, respectively. The ROI is highlighted with a green rectangle in fig. 4 and include the signatures of 5 ships. In fig 5, the Normalised RCS (NRCS) profile is shown for the Sentinel-1 image before (top left) and after applying the GLRT (bottom left) and for the TerraSAR-X image before (top right) and after applying the GLRT (bottom right) in dB scale. From this ROI the TCR is computed and it has been evaluated that the TCR varies from 19.4 dB to 41.1 dB at C-band and from 22.1 dB to 49.4 dB at X-band before and after applying the likelihood ratio. X-band shows better results with a higher increment of the TCR than the C-band. As a consequence, the novel GLRT algorithm performs better than CFAR showing a higher detection and lower false alarm rate at X band.

5. CONCLUSIONS

The novel GLRT algorithm was tested on datasets acquired from TerraSAR-X (at X-band) and Sentinel-1 (at C-band) on the same area at the same time. Outcomes show that the GLRT presents a much higher TCR (21.7 dB in the worst case scenario) than the original SAR intensity and that X-band shows better results with a higher increment of the TCR than the C-band. In addition, the novel GLRT algorithm presents a higher detection rate (28 vs 25) and a lower false alarm rate (1 vs 21) compared with the classical CFAR at X band.

6. REFERENCES

Fig. 2: Preprocessing images from Sentinel-1 dataset (master) (a) and TerraSAR-X image (slave) (b) in range (y)/azimuth (x) plane.

Fig. 3: GLRT SAR images relative to the Sentinel-1 (a) and TerraSAR-X (b) datasets.

Fig. 4: NRCS profile relative to the Sentinel-1 dataset before (top left) and after applying the GLRT (bottom left) and to the TerraSAR-X dataset before (top right) and after applying the GLRT (bottom right).