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ABSTRACT

Oil spillage is one of the most common sources of environmental damage in places where coastal wild life is found in natural reservoirs. This is especially the case in the Patagonian coast, with a littoral more than 5000 km long and a surface above a million and half square km. In addition, furtive fishery activities in Argentine waters are depleting the food supplies of several species, altering the ecological equilibrium. For this reason, early oil spills and vessel detection is an imperative surveillance task for environmental and governmental authorities. However, given the huge geographical extension, human assisted monitoring is unfeasible, and therefore real time remote sensing technologies are the only operative and economically feasible solution. In this work we describe the theoretical foundations and implementation details of a system specifically designed to take advantage of the SAR imagery delivered by two satellite constellations (the SAOCOM mission, developed by the Argentine Space Agency, and the COSMO mission, developed by the Italian Space Agency), to provide real-time detection of vessels and oil spills. The core of the system is based on pattern recognition over a statistical characterization of the texture patterns arising in the positive and negative conditions (i.e., vessel, oil, or plain sea surfaces). Training patterns were collected from a large number of previously reported contacts tagged by experts in the National Commission on Space Activities (CONAE). The resulting system performs well above the sensitivity and specificity of other avalilable systems.

Keywords: Pixel prototypes, Vessel detection, Oil spill detection, SAR imagery, Image processing, Statistical inference

1. INTRODUCTION

The ocean plays an important role in regulating the Earth's environment and the global climate, and provides essential resources for mankind. Human activities on the sea are increasing and, as a consequence, altering the ocean equillibrum 1, of which oil spills constitute the major anthropogenic threat to marine ecosystems. Oil pollution can be produced by accidental or deliberate discharges. Recent investigations correlate oil spills with shipping routes 2. Deliberate oil spills are more frequent than those produced by the reported ship accidents. Furthermore, about half of the total oil spills in the marine environment come from operative discharges, which in most cases are illegal. These illegal discharges are not limited to oil tankers, as different vessel classes are suspect of being responsible [*].

Remote sensing imagery based on optic, microwave, infrared and ultraviolet sensors has proved to be useful for oil detection 3. Active microwave sensors using Synthetic Aperture Radar (SAR) technology, in particular, have the ability to detect features beyond other sensing technologies on the ocean surface. For this and other reasons, SAR imagery is widely used in satellite constellations, due its wide area of coverage, high resolution, all-weather and all-day capabilities. SAR sensors capture the backscatter of microwave pulses on the surface, a signal that is adequate for capturing specific features, in this case to infer properties arising in the sea surface.

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This can be used to distinguish apart normal sea background from anomalous objects, such as oil spills, algal formations, vessels, among many others 4.

Most space agencies operate satellite constellations that produce imagery at high revisiting rates like that required for real time oil spill monitoring and vessel detection. This increasing amount of available SAR imagery implies a growing load for the operators at analysis centers. An oil spill detection carried out by operators is subjective to the experience of the individual operator and the accuracy could be affected by errors due to distractions or fatigue 5, 6. The difficulty for the human eye to distinguish fuzzy boundaries between slick and background, overestimation of pixels delineating the oil spill edges, and long processing time is also a disadvantages of this manual process 7. Several efforts are described in the literature for developing supervised and semi-supervised algorithms and monitoring systems focused on vessel and oil spill detection through SAR images 5, 7–18. In particular, an oil spill is a complex task because of the existence of objects that resemble oil spills called "lookalikes" such as organic film, grease ice, wind front areas, areas sheltered by land, rain cells, among others 8.

An oil spill detection system usually consists on three stages. The first one is the dark spot segmentation, where each oil spill candidate is highlighted from the image background. The second stage is feature extraction, where the segmented spot is analyzed to produce feature vectors that can be analyzed in a feature space. The last stage is the dark spot spot classification, where each feature vector is labeled either as a look-alike or as an oil spill 7. In this paper we present an alternative strategy, based on a statistical inference performed over local windows. We regard the pixel backscatter information in a local window as a population that can be characterized by a statistical distribution. Instead of using feature vectors, the classification is carried out using parameter estimation and divergence measures with respect the tagged contacts. The resulting monitoring system is able to deliver real-time vessel and oil spill detection using the imagery available through the Argentine SAOCOM and Italian COSMO constellations. These results are incorporated in a software product that is being deployed at the National Aerospace Activities Council of Argentina (CONAE)[†].

2. METHODS

2.1 Vessel and dark spot segmentation

The core of the system was developed using a set of COSMO-SkyMed[‡] SAR satellite imagery (see Fig. 1a) provided by CONAE. In addition, we employed a dataset of geographic information of the continental shelf, maritime boundaries, lateral maritime boundaries and the coastline of the Argentinian Sea provided by the Argentinian Spatial Data Infrastructure (IDERA)[§] (see Fig. 1b). With this geographic information we generated a mask that contains the interest area where the detection of vessel and oil spills was carried out. In this example there is a large number of sample contacts with sea surface, vessels and dark spots in varying sea conditions. We selected local windows containing vessels (magenta), oil spots (red) and open sea (blue). The pixels were tagged manually by several experts Fig. 2. After applying radiometric correction, the Gamma distribution was used to model the distribution of pixel intensities in local windows around each of the tagged contacts. Then, each type of contact (open sea, dark spot, vessel) can be characterized by the shape μ and scale v distribution parameters in the local window that surrounds the pixel Fig. 2c. Typically we explored from 5×5 to 11×11 window sizes. Then, every pixel in the complete image can be tagged with respect to the prototype that is closest to the distribution parameter of the intensities in its associated window. In this case, given that the shape versus the scale parameters of the local Gamma distributions is not a metric space, we used the Kullback-Leibler divergence (KLD) 19 for establishing a distance notion between two distributions, given their parameters:

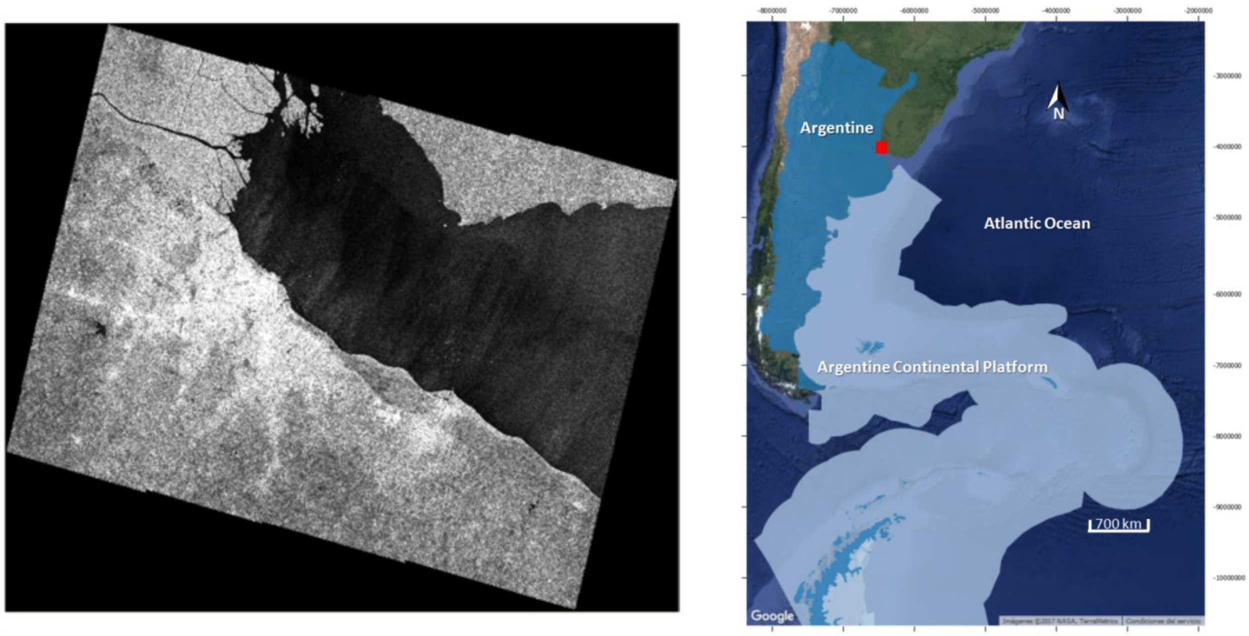
$$Kld(p,q) = (\mu_p - \mu_q)\Psi(\mu_p) - log(\Gamma(\mu_p)) + \mu_q(log(v_p - log(v_q)) + \mu_p(v_p - log(v_q))/v_p, \tag{1}$$

where $\Psi(.)$ is the digamma function, μ_p, v_p, μ_p and v_p represent the shape and scale parameters of the pixel window and prototypes respectively. The segmentation then classifies every pixel p on the image computing μ and v of the neighborhood around p, and associates that pixel with the class q for which the KLD is smaller.

[†] http://www.conae.gov.ar/index.php/espanol/

[‡] http://www.e-geos.it/cosmo-skymed.html

[§] http://www.idera.gob.ar/



(a) (b)

Figure 1. SAR imagery and geographic information of the continental Shelf. a) SAR image with vessels near the coastline in Buenos Aires, Argentina. b) Geographic Information of the continental shelf represented by a polygon in light blue, the polygon is used as a mask and further algorithms will only be applied on the pixels inside this region.

2.2 Dark spot feature extraction

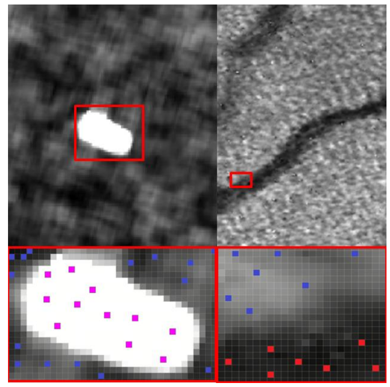
The classification performed above is a per-pixel segmentation procedure that assigns each pixel to the most statistically similar class. This produces some misclassified spots (i.e. isolated groups of pixels representing the same object), which can be attributed to several reasons, including the inherent speckle noise of SAR imagery, and the numerical limitations of the statistical inference procedure. As a simple procedure to produce cleaner segmentations, we computed the borders around each object in a class and only retained the outermost contour associated with an object.

After isolating dark spots in the segmentation, the next stage of the system involves the classification of each slick as an oil spill or a look-alike. Oil spill candidates are characterized by features that belong to many different categories, such as morphological, physical, contextual and textural 12. For this, a feature vector describing relevant characteristics of the spot was computed and stored in a database. This vector includes shape, texture and some additional features specially developed for oil detection.

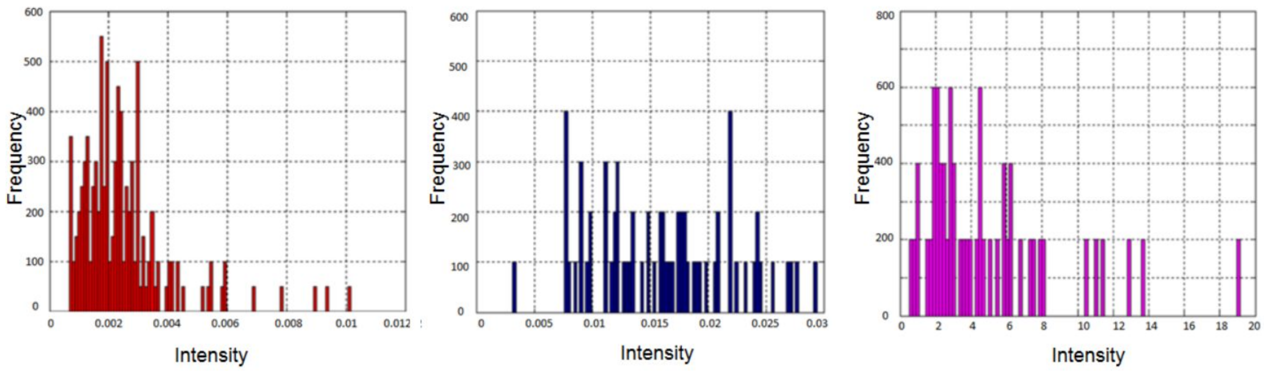
The shape features considered are: area (A), perimeter (P), length (L), breadth (B), aspect ratio (AR), elongation (E), curl (C), convexity (Co), solidity (S) and compactness (CC) 20. The texture features are based on Haralick's grey level co-occurrence matrix features, including homogeneity (GLCMH), contrast (GLCMC), dissimilarity (GLCMD), entropy (GLCME), mean (GLCMM), standard deviation (GLCMSD) and correlation (GLCMCO) 21. These GLCM texture descriptors were computed by selecting randomly inside and outside of the slick boundary. These descriptors could be used to train a Support Vector Machine(SVM) classifier with very high accuracy and precision, using these descriptors as feature vectors.

3. RESULTS

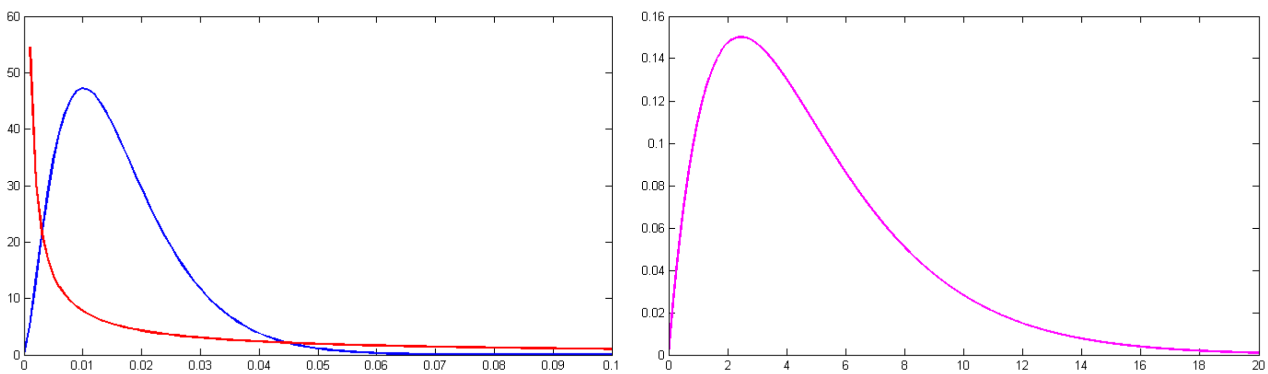
The workflow was implemented and tested on a set of different images. The software takes the SAR image and a shapefile as input parameters. The shapefile is used as a mask to only process the pixels inside the polygon represented by the file. When a new image is analyzed, the system search the prototype database and classifies



(a)



(b)



(c)

Figure 2. Contacts. a) Vessel (in magenta), dark spots (in red) and sea (in blue). The contacts were selected and tagged manually by experts. b) The corresponding intensity histograms. c) Resulting distribution computed using the pixels prototypes of sea, spot and vessel in blue, red and magenta respectively.

each pixel with the minimum KLD distance. Figure 3 summarizes the complete framework of the vessel and oil spill system.

The first processed information product of the software is the vessel detection. Figure 4b shows a zoom out of Figure 4a, where many factory ships are located near the coastline of Buenos Aires, Argentina. The system detected and represented the vessels on a map for further analysis by the trained operators Fig 4c. In every tested case, the main detection targets were found successfully, in several cases outperforming other commercial products used by the Agency.

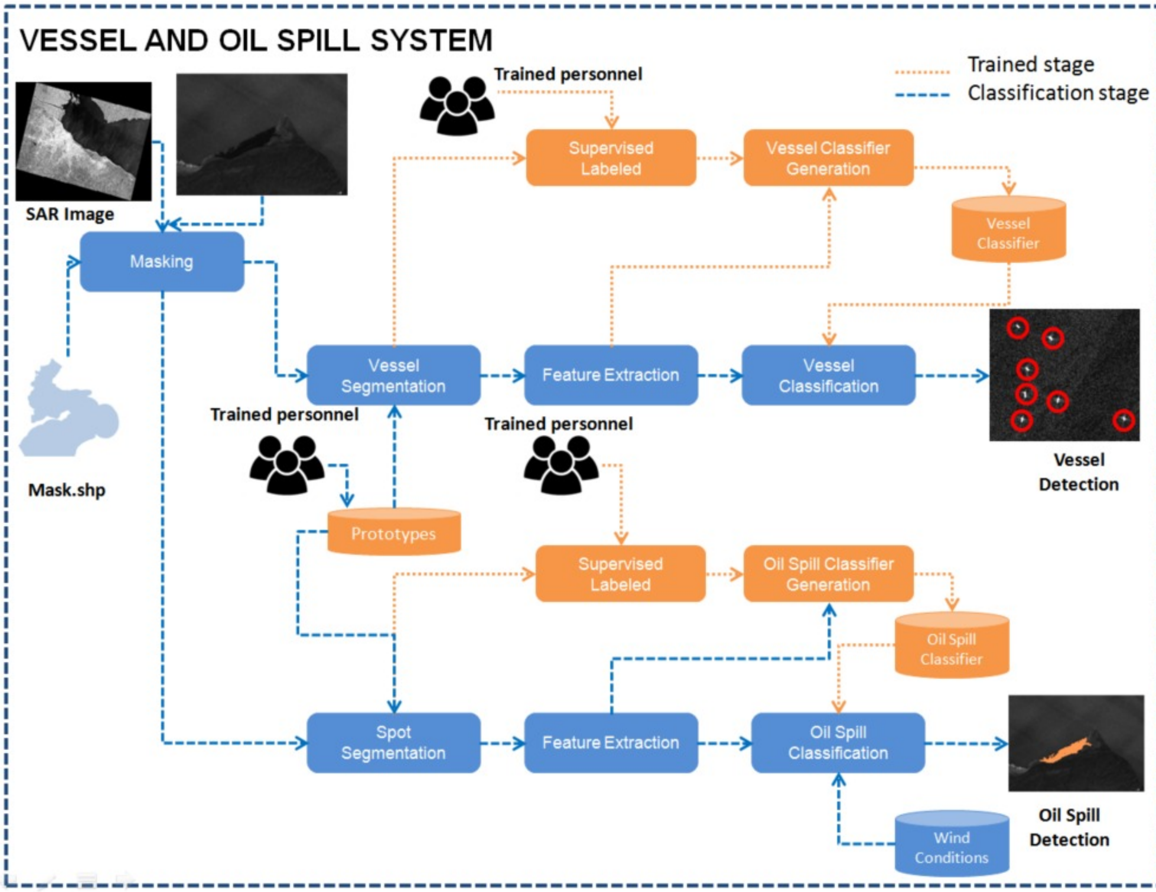


Figure 3. Trained and classification stages of the Vessel and Oil Spill System.

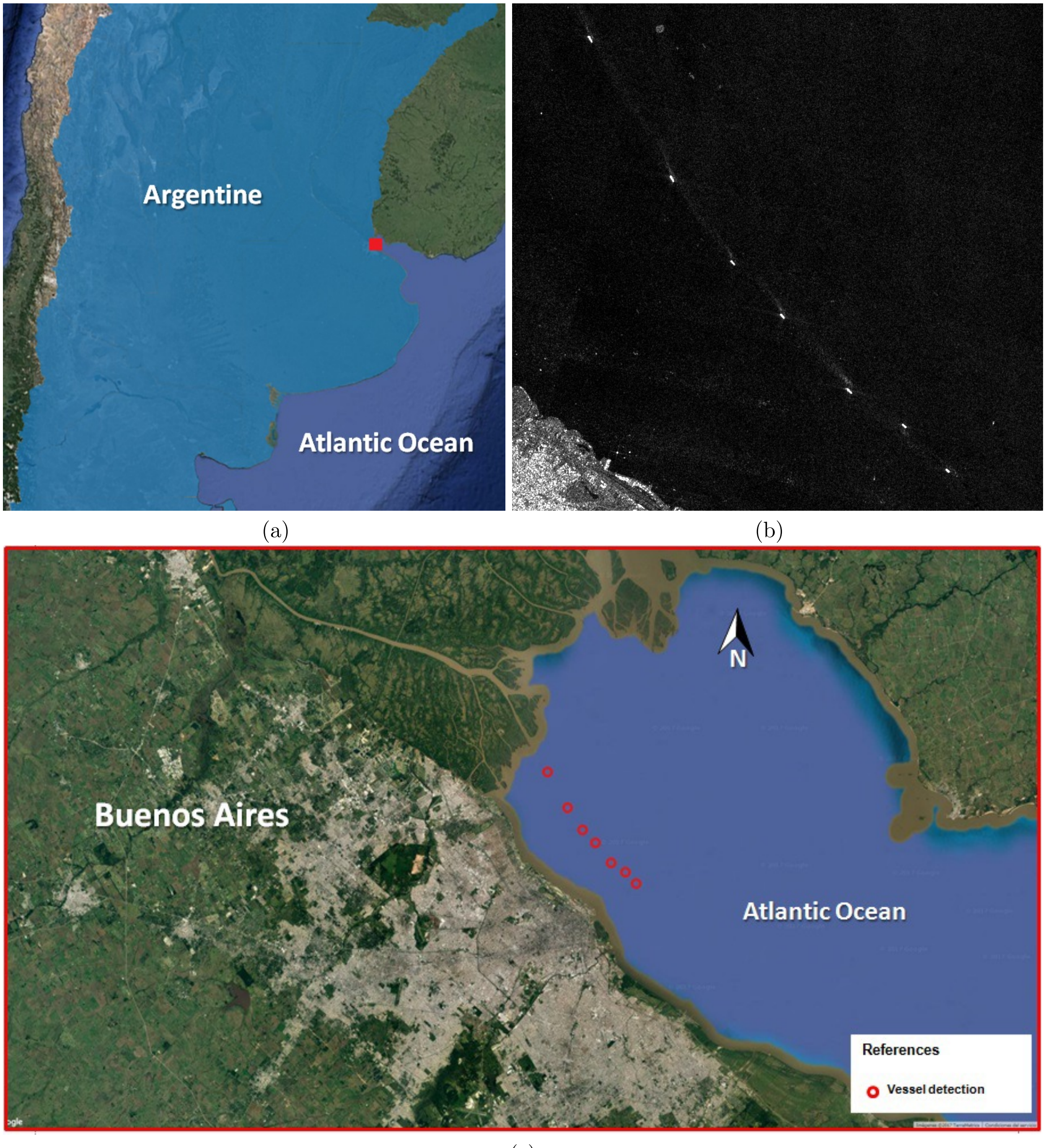
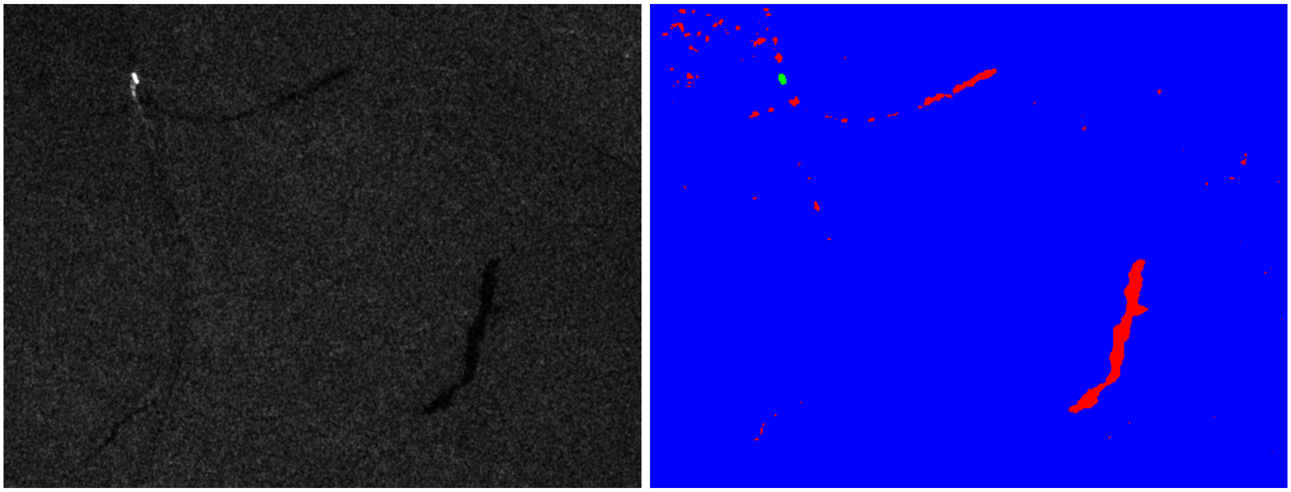


Figure 4. Vessel detection. a) Detection region in the Argentinian Sea. b) COSMO-Skymed SAR image with many ships along the coastline. c) Detected vessels on the Geographic Information System.

As a second product, the software detects the spot for further classification, as an oil spill or look-alike. In Figure 5c an example of a look-alike is shown, where the detection was also robust with respect to the sample cases. Information in vector format (point layer) of vessel and (polygon layer) of oil spills was generated, integrated and stored in a Geographic Information System (GIS).

The software features allow potential users to process the same region over different periods of time. For

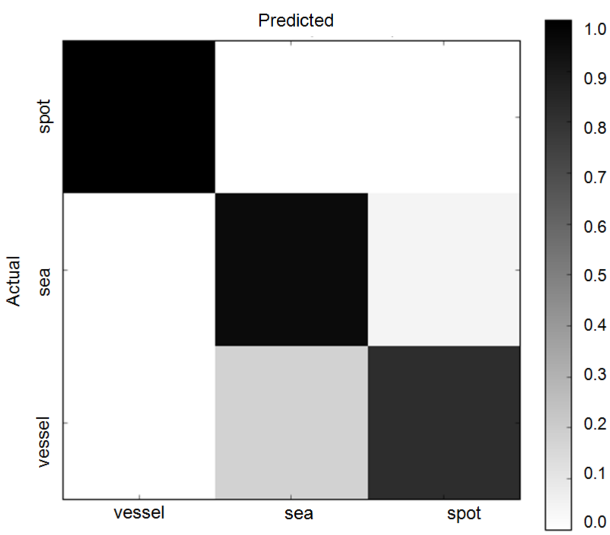


(a) (b)

Figure 5. Vessel and oil spill detection. a) Original Skymed-COSMO SAR image corresponding to March, 2016 in the Argentinian Sea. b) Classification of the image where vessel, oil spill and sea are in green, red and blue, respectively.

quantifying the results, a supervised training set of 500 vessel contacts were used.

To evaluate the segmentation performance, we calculated a confusion matrix to summarize the results of the automatic vessel, sea and spot detection that considered a sample of about 19800 pixels prototypes Fig. 6a. We also calculated statistic measures and summarized them in Figure 6b. Finally, the achieved accuracy was 94 % for the classifier.



Classes	Classification Metrics		
	precision	recall	F1-score
vessel	1.00	1.00	1.00
sea	0.96	0.95	0.96
Spot	0.78	0.82	0.80
Avg/total	0.94	0.94	0.94

(a) (b)

Figure 6. Classification Results. a) Confusion matrix. b) Classification metrics.

4. CONCLUSION AND FURTHER WORK

Image processing of artificial or natural phenomena posses a significant challenge and an opportunity in social, economical and environmental studies. In this paper we present a system that is able to detect vessels and oil spills using the Argentine SAOCOM and Italian Cosmo constellations. The results show a better detection performance than the software employed in the agency. The system is very simple, it requires a minimum investment and can be set up in a short time. It was developed integrally with open source programs which are readily accessible to any interested organization. Finally, all the gathered information is added to the GIS application.

The software is currently being deployed at the National Commission on Space Activities (CONAE). Several ideas are currently under exploration with the National Commission. We are working on identification and tracking of vessel routes with validation from the Argentinian Naval information. Furthermore, we are considering the generation of models based on sea currents and wind information for validating oil spill detections. On the operative side, a mobile-based system is currently being developed.

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