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Automatic oil slick detection from SAR images: Results and improvements in the framework of the PRIMI pilot project

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ABSTRACT

An automatic system capable of discriminating oil spills from other similar sea surface features in Synthetic Aperture Radar images has been developed and tested. This system, called Oil Spill Automatic Detector (OSAD), was originally conceived for C-band SAR images (mostly ERS PRI) and afterward adapted to ENVISAT data. In the framework of the Progetto pilota Rilevamento Inquinamento Marino da Idrocarburi (PRIMI) national project sponsored by the Italian Space Agency, the OSAD system has been greatly improved and is now able to process L- and X-band images from various satellites as well. OSAD performance, confirmed using a different dataset of verified slicks, shows an a priori overall correct classification of 80%. Moreover, new features have been added, such as an enhanced land masking algorithm, a built-in wind and wave extraction module, and oil spill characterization. OSAD has been integrated into a complex hardware and software architecture for operational sea monitoring, alarm generation, and oil slick drift forecasting. The system's detection capabilities have been validated during a measurement campaign in the Mediterranean Sea. The new improved system is described herein, with special attention to latest enhancements.

1. Introduction

Oil spills are recognized as a threat to the marine environment.

Among all monitoring techniques, satellite remote sensing represents a valuable aid for sea surface monitoring and pollution prevention. Synthetic Aperture Radar (SAR), which provides radar images day and night and under all weather conditions, is extensively used to monitor the sea surface; in particular, SAR is able to detect sea surface slicks, achieving results similar to those obtained by in-situ measurements made with a wave meter (Trivero et al., 2001).

To identify oil slicks, several semi-automatic and fully automatic methodologies have been proposed in the literature. The basic approach consists of the following three steps (Solberg et al., 1999; Calabresi et al., 1999; Del Frate et al., 2000; Fiscella et al., 2000):

1. *Dark spot detection*. This is the initial processing step performed to identify candidate slicks. This identification is achieved by adopting thresholding and segmentation procedures. The thresholding step can be achieved by using a double threshold value valid for the whole image (Fiscella et al., 2000) or an adapted threshold value valid for the actual area (Solberg et al., 1999; Karathanassi et al., 2006; Mera et al., 2012; Ganta et al., 2012). More sophisticated approaches include region-growing techniques (Calabresi et al., 1999; Del Frate et al., 2000) and the application of a partial differential equation-based level set technique (Huang et al., 2005). Multiscale, multi-resolution approaches have also been proposed by employing both wavelet decomposition (Wu and Liu, 2003) and texture analysis with fractal dimension estimation (Benelli and Garzelli, 1999). Finally, texture analysis (Marghany, 2001), neural network capabilities and constraints (Topouzelis et al., 2008), fuzzy clustering (Barni et al., 1995), statistical region-based algorithms (Zhao et al., 2013) and spatial density thresholding (Shu et al., 2010) methods have been employed.
2. *Dark spot feature extraction*. This step consists in the extraction of geometrical (e.g., area, perimeter and shapes), radiometric (e.g., mean backscatter value) and contextual (e.g., distance to ships) features for each candidate slick. Many types of different

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features setting have been used (Topouzelis, 2008), and different numbers and typologies of features have been selected. For example, in the studies by Stathakis et al. (2006), Topouzelis et al. (2009), and Topouzelis and Psyllos (2012), genetic, neural networks and Decision Tree Forest algorithms were used, respectively, to select the most striking features for oil slick detection.

3. *Classification of dark formations as oil spills (OS) or look-alikes (LA)*. Several classifiers have been conceived, most of which assume a statistical approach for final classification decision. Solberg et al. (1999) proposed a Bayesian classification scheme by combining prior knowledge, Gaussian densities and rule-based density corrections. The method correctly classified 94% of OS and 99% of LA for ERS images using a leave-one-out approach. In the study by Solberg et al. (2007), an updated version of the method was presented, obtaining an accuracy of 78% in OS classification and of 99% in LA classification for Radarsat and Envisat images. A similar statistical classification methodology was used by Fiscella et al. (2000); in their study, a linear discrimination analysis approach based on the Mahalanobis distance was employed. The Mahalanobis classifier corresponded correctly in 71% of the test cases, and a compound probability classifier corresponded correctly in 76% of the cases. Nirchio et al. (2005) presented a statistical approach based on multiple regression analysis and reported an OS detection accuracy of 74%.

A different classification methodology was presented by Calabresi et al. (1999) and Del Frate et al. (2000), which exploited neural networks to classify the dark formations. Using the leave-one-out approach, the method correctly classified 82% of OS and 90% of LA. Neural networks were also used as classifiers for OS detection by Topouzelis et al. (2007), with a genetic algorithm applied to properly select topology and input features of the network. The OS detection accuracy reported for the test data was 91%, and the LA detection accuracy was 87%.

Another classification methodology, based on fuzzy logic, was implemented by Keramitsoglou et al. (2006), obtaining an overall detection performance of 88%, and by Karathanassi et al. (2006). The latter proposed an object-oriented image classification technique in which homogeneous image objects are first extracted in any chosen resolution and then classified by means of fuzzy logic. The application of this method yielded an overall performance of 99%.

The Support Vector Machine (SVM) was employed by Brekke and Solberg (2008), but poor results were reported relative to those of statistical classifiers for both OS and LA classes.

Finally, in the study by Singha et al. (2013), a classification algorithm based on a two-stage process that combines classification tree analysis developed for ENVISAT and RADARSAT data and a fuzzy logic approach was proposed. The algorithm achieved overall accuracies of 85% and 93%, respectively.

It should be noted that a homogeneous comparison of performances among different classifiers is very difficult to achieve. As indicated by Topouzelis (2008), this difficulty arises because of the different datasets, dark patch detection techniques and features used.

Another important issue to be considered for classifier evaluation is computational time. Indeed, the literature does not provide sufficient data with which to compare methodologies in terms of necessary time elapsed from image acquisition to final classification output (Topouzelis, 2008). It would be worthwhile to use a consistent dataset to benchmark both time frame and method accuracy. An example of a comparison made among different classification techniques using the same dataset was reported by Xu et al. (2014), in which (a) penalized linear discriminant analysis; (b) the generalized additive model; (c) tree-based ensemble methods (bagging, bundling, and boosting); (d) SVM; and (e) neural networks were selected for analysis. Results showed that the tree-based techniques of bagging and bundling yielded the most reliable and accurate results in OS classification.

Our approach is based on a previously implemented statistical methodology (Fiscella et al., 2000; Nirchio et al., 2005). The Italian Space Agency (ASI), in cooperation with private companies and public research bodies within the framework of the pilot project Progetto pilota Rilevamento Inquinamento Marino da Idrocarburi (PRIMI), established an operational system for OS monitoring and forecasting (Nirchio et al., 2009, 2010; Santoleri et al., 2011). Among all components, a software program called Oil Spill Automatic Detector (OSAD) was developed for OS detection using SAR images.

The aim of this paper is to demonstrate how OSAD has been improved from a previous version (Nirchio et al., 2005) in which only the C-band was exploited by implementing new features as well as by improving existing capabilities with results from research activities. The achievements can be summarized as follows:

- support for detection in the L- and X-bands has been added;
- an improved land masking algorithm has been implemented, with the aim of more precise detection in coastal areas;
- ancillary data (wind and wave fields) are now directly managed by OSAD; these fields can be imported from external sources or computed with state-of-the-art algorithms; wind and wave fields are important for OS detection and characterization and could lead to a better management of interventions and reclamation activities; and
- a prototypal characterization algorithm has been developed and calibrated to evaluate age, volume and type of OS.

The main improvement is the extension to the L- and X-bands. The literature shows that OS detection can be considered a mature technology in the C-band because of the extensive availability of data in the past 25 years. OSAD is able to detect OS in the L-, C-, and X-bands. By using all operating SARs, the system allows for higher temporal revisiting. In addition, the SAR detection system is coupled to an optical detection system and a drift model (Santoleri et al., 2011).

This paper describes the structure and the rationale of the OSAD system. The detection procedure is performed in the following steps: image pre-processing (calibration, compensation and land masking), automatic selection of dark spots on sea surface, discrimination of OS from LA, wind and wave field extraction, and OS characterization. The algorithms, established with suitable training datasets, have been validated by in situ measurements, and results are presented.

1.1. The background physics of the SAR oil slick detection

Oil slicks, released accidentally or deliberately by platforms or ships, appear as dark spots in SAR images because short sea waves, responsible for radar backscattering, are damped in the presence of surface slicks. However, other phenomena, such as low wind areas or organic films, are also imaged as dark areas. To distinguish OS from LA, further parameters other than the pixel intensity should be considered, e.g., geometric shape and contrast with surrounding areas (Xu et al., 2015).

Oil on rough sea, provided the sea contains surface-active material, acts indirectly by increasing the damping of short waves and leaves long gravity waves unaffected. The theory of rheology of air-water interfaces (Cini and Lombardini, 1978; Lucassen, 1982; Fiscella et al., 1985; Hünerfuss, 1986) predicts a maximum for the ratio between the damping coefficients of waves