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Automatic Synthetic Aperture Radar based oil spill detection and performance estimation via a semi-automatic operational service benchmark

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ABSTRACT

Today the health of ocean is in danger as it was never before mainly due to man-made pollutions. Operational activities show regular occurrence of accidental and deliberate oil spill in European waters. Since the areas covered by oil spills are usually large, satellite remote sensing particularly Synthetic Aperture Radar represents an effective option for operational oil spill detection. This paper describes the development of a fully automated approach for oil spill detection from SAR. Total of 41 feature parameters extracted from each segmented dark spot for oil spill and 'look-alike' classification and ranked according to their importance. The classification algorithm is based on a two-stage processing that combines classification tree analysis and fuzzy logic. An initial evaluation of this methodology on a large dataset has been carried out and degree of agreement between results from proposed algorithm and human analyst was estimated between 85% and 93% respectively for ENVISAT and RADARSAT.

1. Introduction

Oil spills resulting from intentional or unintentional releases into oceanic or coastal waters represent a major threat to marine ecosystems and the adverse effect of oil spills on these ecosystems is the subject of considerable political, environmental and scientific concern. The oil spill in the Gulf of Mexico, resulting from an explosion on the British Petroleum Deepwater Horizon rig was widely reported, with an estimated five million barrels of crude oil relished into the Gulf's ecosystem (BBC, 2010). It was found the that large quantities of oil spilled during the earlier 1989 Exxon Valdez disaster can still be found beneath gravel beaches in Alaska (Li and Boufadel, 2010). However, about half of the total oil spills in the marine environment come from operative discharges by shipping and in most of these cases the discharges are illegal. These illegal discharges are not limited to oil tankers, and many classes of ship are suspected of being responsible (GESAMP, 2007). During the last few decades, maritime transportation has grown steadily and the quantity of illegal oil discharges has grown with the volume of traffic. Europe provides the world's largest market for crude oil imports, representing about one third of the world's total. 90% of oil and refined products are transported to and from the continent by sea; unfortunately, some of this oil makes its final way into the sea. European Maritime Safety Agency's (EMSA) state of the art oil spill monitoring and vessel detection service, 'CleanSeaNet' has been continuously monitoring the EU waters since 2007 and decline in number of oil spills in EU waters has been observed through CleanSeaNet service from 10.77 possible spills identified per million km^2 in 2008 to 5.68 per million km^2 in 2010. (Trieschmann and Reichenbach, 2012).

CleanSeaNet is a pan-European satellite based surveillance program for the detection of possible discharges of oil resulting from marine transportation and offshore installations. The CleanSeaNet program is supported by the European Commission. 'CleanSeaNet' service use Synthetic Aperture Radar (SAR) images from multiple missions, based on coastal states definition of their service coverage requirements. In cooperation with the users EMSA plans and orders satellite images to meet these requirements. Accordingly satellite data are acquired via a network of receiving stations distributed over Europe in order to cover pan European waters in Near Real Time (NRT). Operators assess the images, together with supporting meteorological, oceanographic and ship reporting information (e.g. Automatic Identification System AIS) where available, to identify possible pollutions on sea, to determine the likelihood of being oil and to assist in identifying the source of the pollution. If a potential spill is detected, it is of utmost importance that coastal State administrations are immediately alerted by phone and

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email with the aim of increasing the likelihood of catching a polluter red-handed.

Moreover CleanSeaNet is providing a NRT service allowing the shortest possible delay between image acquisition, detection and alert. Detection results are reported to the affected countries in less than 30 min after satellite image acquisition.

The construction of a cost effective oil spill detection system has been the subject of research for approximately two decades (Ferraro et al., 2010; Karantzalos and Argialas, 2008; Bern et al., 1992; Skøelv and Wahl, 1993; Wahl et al., 1994). Satellite remote sensing techniques offer the advantage of being able to observe events in remote and inaccessible areas and thus represent an attractive source of information for detecting the location and extent of oil spills. Moreover, the rate and direction of movement of oil may be obtained through multi-temporal imagery thereby assisting in drift prediction modeling that may be used to facilitate clean-up operations and warning systems (Vespe et al., 2011). Methods for automatic detection and tracking of oil spills and illegal oil discharges are of fundamental importance to improving compliance with marine legislation and for the efficient surveillance and protection of coastal environments.

Early uses of remote sensing for oil spill detection only used data from visible and infrared sensors from aircraft. However, these sensors suffer a number of disadvantages in this context, including the absence of any clear discriminating feature between oil spills and the surrounding sea surface and the unavailability of data during the night or in bad weather conditions (Solberg et al., 2003; Fingas and Brown, 1997). These disadvantages do not apply to Synthetic Aperture Radar (SAR) sensors, which are capable of providing data at night and under adverse weather conditions, enabling satellite remote sensing to form the basis of an extremely viable and useful tool for detecting oil spills, particularly in a marine environment.

The backscatter energy from a spill free area is governed mainly by constructive and destructive interference. Oil films decrease the "capillary waves" on the sea surface and thus the backscatter, causing spills to appear as dark spots in SAR images while the surrounding spill-free sea remains relatively bright. The contrast between the spill and its surroundings depends on many parameters, such as wind speed, wave height, and the amount and type of oil released, along with some sensor-specific parameters like wavelength and polarization. In the band C frequency range, a minimum wind speed of 2–3 m/s creates sufficient backscatter from the oil free surface, in order to contrast between spill and spill free area and thus to make an oil film visible (Solberg et al., 2007; Mera et al., 2012). However, if the wind speed is too high (>10–12 m/s) it causes the spill pattern to disappear as short waves receive enough energy to counterbalance the damping effect of the oil film on the ocean surface. It was observed that the wind direction relative to the plane of the incident radar wave also affects the backscatter level in a scene (Alpers and Huhnerfuss, 1988). A crosswind (wind blowing perpendicular to the range direction) produces lower backscattering than an upwind or downwind (wind blowing along the range direction). Unfortunately, dark spots may occur in SAR images also due to other meteorological or oceanographic effects, and a major challenge in the implementation of SAR oil spill detection approaches is to discriminate between these look-alike spots and real oil spill (Brekke, 2007).

A typical SAR-based oil-spill detection process consists of four stages: image pre-processing, image segmentation, feature extraction and classification (Vespe et al., 2010, 2011). The segmentation stage identifies the candidate features within the imagery though a binary classification of image pixels. A feature dataset is then formed by extracting contiguous features from the segmented image and deriving a quantitative description (feature vector) of the shape and form of each feature. The final classification stage uses the feature vector information to segregate oil spills from lookalikes.

Segmentation techniques range from the relatively simple and straightforward, such as adaptive thresholding (Solberg et al., 1999; Brekke and Solberg, 2005a) and spatial density thresholding (Shu et al., 2010) to more complex fuzzy and neural network based methods (Fiscella et al., 2000; Del Frate et al., 2000; Topouzelis et al., 2007; Singha et al., 2012). The feature extraction stage is critical to obtaining an accurate classification. To this end, a considerable range of feature descriptors (usually referred to as "features") have been proposed (Brekke and Solberg, 2005b; Topouzelis et al., 2003, 2008). These may be broadly grouped into the following categories:

(i) Features based on the geometry and shape of the segmented region.
(ii) Features based on the backscatter values of the spot and its surroundings.
(iii) Contextual features.
(iv) Textural features.

The perimeter and the area of the object are usually considered as the most common geometrical and shape features. If the oil slick is a fresh oil spill released from a moving ship (a tanker cleaning its tank), *elongatedness* appears to be appropriate feature. It is expressed as a ratio between the width and length of the slick.

Several researchers have shown that some statistical parameters such as mean and standard deviation related the backscatter values of pixels may also be considered as feature datasets. It has been observed that the features related to the gradient of the backscattering value from background to slick provided valuable information to distinguish between an oil spill and look alike (Solberg et al., 1999). The background standard deviation was also proven to be a key discriminating parameter. The texture provides information about spatial correlation among the neighboring pixels. Power-to-mean ratio of the oil spill spot and surroundings was used as a feature in (Brekke and Solberg, 2005b) as a measure of homogeneity. A recent study by Topouzelis and Psyllos, 2012 shows that there might be several combination of feature which can produce similar classification accuracy.

For the final processing stage, a range of classification methods have been employed, including statistical classifiers (e.g., Mahalanobis and a compound probability classifier by Fiscella et al., 2000) neural networks (Calabressi et al., 1999; Del Frate et al., 2000; Topouzelis et al., 2007; Singha et al., 2012, in press) and artificial intelligence fuzzy modeling systems by Keramitsoglou et al., 2006. Recent study by Vespe and Greidanus (2012) shows that different aspects SAR image quality and its significant impact on the effectiveness of feature classification.

This paper introduces a rule based SAR oil spill detection system that employs set of predefined rules for classification. A range of features are employed in the classification stage, in order to discriminate between oil spill and lookalike.

2. Methodology

2.1. Training dataset

A total of 38 images were used to train the automatic oil spill detection system, and include ASAR Wide Swath mode and RADARSAT-2 HH polarized, ScanSAR Narrow mode. For each image, EMSA information on oil spill detections formed the training set, providing a total of 237 dark patches labeled as oil spills. Some of these patches are fragments of the same spilled area, and therefore belong to the same event. The dataset is significantly