Automatic detection of oil spills in Envisat, Radarsat and ERS SAR images

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***Abstract*— We present a framework for automatic detection of oil spills in SAR images. Multi incident angle and multi polarization SAR data are ingested into the framework in order to optimize revisit times and thereby the temporal and spatial coverage. Dark spots in the images are primarily detected by adaptive thresholding. For each of them a number of features are computed in order to classify the slick as either an oil slick or a `lookalike' (other oceanographic phenomena which resemble oil slicks). A classification scheme is utilized based on statistical modeling. A data set of about 100 images from each of the sensors ERS, Radarsat and ENVISAT is or will soon be available to train and test the algorithm. In this paper, only results from ERS and Radarsat are reported because the delivery of ENVISAT images has been delayed.**

I. Introduction

Automatic identification of oil spills in SAR images is complex because of features that resemble oil spills ("lookalikes"), particularly in low wind conditions. The SAR signature of an oil spill and its surroundings depends on a number of parameters like wind speed, wave height, and the amount and type of oil released. The shape of the spill will depend on whether the oil was released from a stationary object or from a moving ship, the amount of oil involved, and the wind and current history between the release and the image acquisition. A trained human operator is mostly able to discriminate between oil slicks and lookalikes based on experience, extracted information like location and weather conditions, and by considering shape and contrast between the feature and the surroundings sea [1]. Such considerations have to be incorporated into an automatic classification system as well.

Our goal has been to develop a system in which probable oil slicks are automatically identified and presented for manual inspection. The advantage of using an automatic algorithm and not merely manual inspection of all possible SAR images is due to the number of images to be analyzed and their complexity. The amount of data for manual inspection can thus be greatly reduced.

II. THE OIL SPILL DETECTION ALGORITHM

The algorithm includes preprocessing, masking, detection of dark spots, spot feature extraction and dark spot classification (see Figure 1). The first step converts the original SAR data to a common format and geographical projection. A land water mask is applied in order to mask away all land areas, including small islets, and their innermost water areas where wind-dampening shadows often appear. ScanSAR images are divided into strip lines in the range direction in order to optimize processing time. This also prohibits large variations in backscatter across the relatively large incidence range. The remaining steps are mostly based on a combination of prior knowledge, Gaussian densities and rule-based density corrections in a statistical modeling scheme, which is described in [2]. The scheme aims to resemble the way a trained human operator views a possible slick in relation to the whole image and his knowledge about the weather conditions, location and oil spill patterns. The algorithm developed for ERS images has been modified to handle Radarsat and ENVISAT images by including sensor-specific modules.

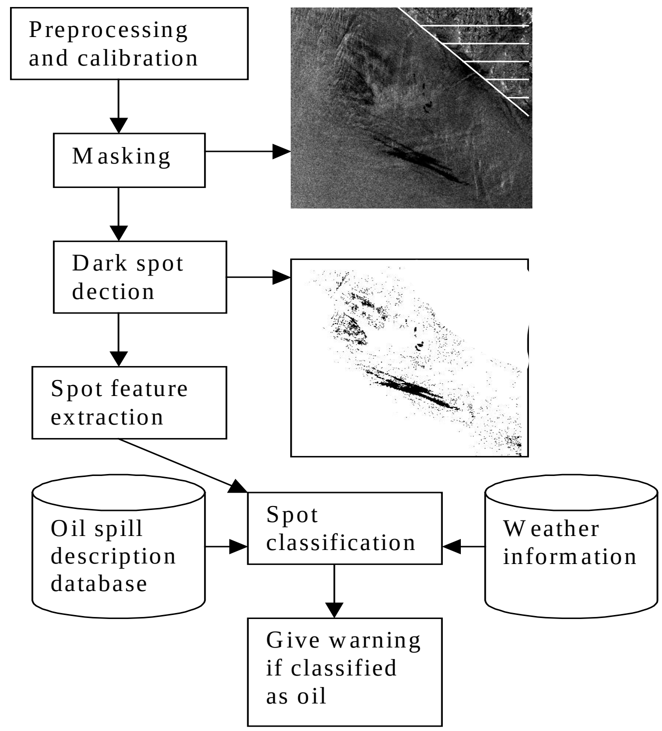

Figure 1. Overview of the oil spill detection algorithm

A. *DARK SPOT DETECTION*

The algorithm for detection of dark spots is based on adaptive thresholding. This thresholding is based on an estimate of the typical backscatter level in a large window. The adaptive threshold is set to k dB below the estimated local mean backscatter level. Wind data (the wind level) is used to determine *k*. Currently this is done manually, but automatic wind estimation is in progress.

After the initial thresholding, a clustering step is performed to check the border between the oil slick and the surrounding sea. Each spot is clustered into two clusters, if they are sufficiently apart and the darkest cluster is sufficiently large compared to the brightest, the darkest cluster is used as the spot otherwise the original spot is kept.

For Radarsat ScanSAR images, an improved spot detection algorithm was needed because of the different pixel resolution and radiometric resolution. A multiscale approach has been developed in a pyramid-like approach. An image pyramid where a pixel on level N consists of the mean of M pixels at level N-1 is constructed. Each level in the pyramid is thresholded yielding a binary pyramid. The final spot image is constructed by combing the different binary images in the pyramid. This is illustrated in Figure 2.

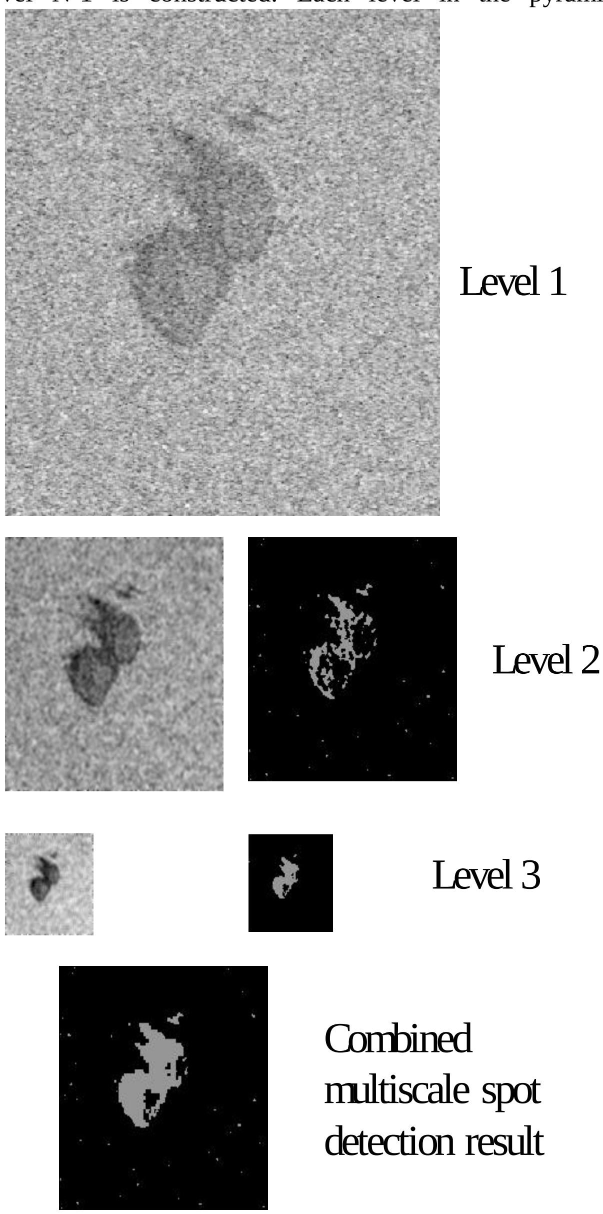

Figure 2. Multiscale spot detection for Radarsat images © ESA/KSAT/NR.

B. SPOT FEATURE EXTRACTION

For each region corresponding to a detected spot of certain minimum size, a set of features is computed. The features are a mix of standard region descriptors from image analysis, and features tailored to oil spill detection. The list of features is:

1. Slick complexity
2. Slick power-to-mean ratio
3. Slick local contrast
4. Slick width
5. Slick local neighbors
6. Slick global neighbors
7. Border gradient
8. Slick area
9. Distance to detected ship
10. Slick planar moment
11. Number of regions in the image
12. Slick smoothness contrast

C. SPOT CLASSIFICATION

After spot detection and feature extraction, we have a set of M dark spots that we want to classify as either oil slicks or look-alikes. This is not an easy task, because slick contrast depends on weather conditions, and the probability of observing look-alikes depends on wind level and other external conditions. For this task, we have developed a special algorithm, which is described in [2]. This algorithm is a combination of a statistical model for oil spills of different shapes and seen under different wind conditions, a prior model for the probability of observing oil and look-alikes, and a rule-based approach which can take care of certain expert knowledge related to oil spill detection.

III. DATA SET

The data set used to test the performance of the algorithm was selected to contain as many oil spills as possible, but also to include lookalikes. An operator has classified a number of oil spills or lookalikes in each image into low, medium or high oil probability. This manual inspection is considered as ground-truth observations although we have no guarantee that the manual classification is correct. Approximately 100 images from each of the sensors Envisat, Radarsat and ERS are included in the test, and they are mainly located in the Baltic, North Sea and outside the Atlantic coast of Spain.

IV. Experimental results

The system will be trained on approximately 100 images from each sensor. Then, the performance will be tested on approximately 30 additional images from each sensor. A high number of training images are used to cover oil spills belonging to different subclasses based on shape and wind level.

The system was previously trained on approximately 80 ERS images. 94% of the oil slicks and 99% of the lookalikes were correctly classified.

Currently, we have about 100 Radarsat ScanSAR images on disk, and we are now building the database for feature vectors computed from Radarsat images. We cannot classify a Radarsat image using the ERS slick database, because features like slick gradient and contrast is very different in the available calibrated ScanSAR images compared to the ERS LRI images.

Here, we present the results from the Radarsat spot detection module. Out of a preliminary test set containing 20 Radarsat images with more than 20 oil slicks, the spot detection module detects all oil spills with good precision and contour. Note that all the detected spots will be input to the spot classification module, which classifies each spot as either lookalike or oil based on the computed features and the prior information.

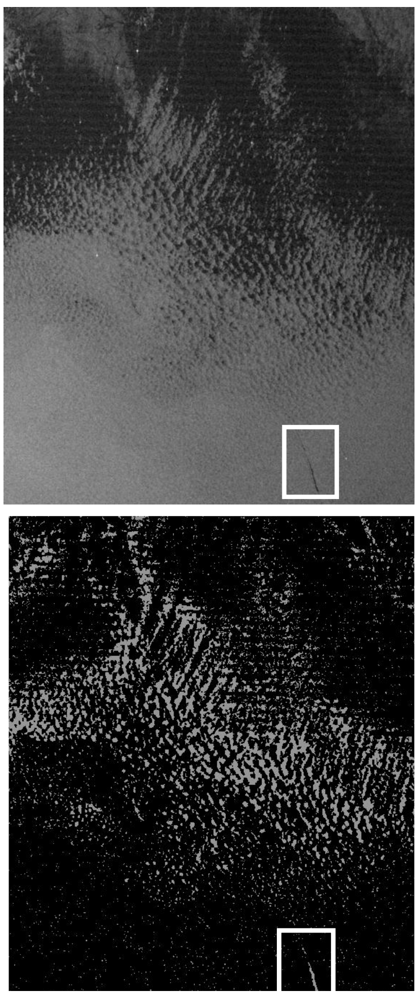

Figure 3. Original ScanSAR image (above) and all detected dark spots (below) (spots are in grey). Note that the highlighted oil slick is nicely detected © ESA/KSAT/NR.

Because of the delay of ENVISAT ASAR data delivery, results from ENVISAT images are not yet available.

V. Future improvements

Some major improvements are identified as necessary for further enhancement of the system. Firstly, the system will be fully trained on Radarsat and ENVISAT images. Secondly, ground truth observations using real-time airborne sensor observations are necessary to reveal deficiencies between real ground-truth observations and expected ground-truth information (i.e. manual SAR classification operators). The latter is planned for the summers 2003 and 2004 to coincidence with another 30 Radarsat and 30 Envisat images. Moreover, automatic wind retrievals in VV and HH polarized SAR images have shown differences in accuracy and needs to be improved. The system will also be tested using alternative polarization modes. We are also considering ingesting the detected oil spills into a numerical oceanographic oil-pollution-drift model in the near future.

VI. Main conclusion

The classification accuracy of the oil spill algorithm shows that the system is valuable in order to reduce the amount of images for manual inspection in an operational oil spill detection service. As the system is based on statistical training, the quality of the detection increases with increasing amount of ingested data. A unique data set consisting of 300-400 SAR images containing oil spills and look-alikes will be used for further evaluation of the algorithms soon.

Acknowledgment

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References

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