A Large-Scale Evaluation of Features for Automatic Detection of Oil Spills in ERS SAR Images

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Abstract We study the performance of automatic methods for oil spill detection in ERS SAR images. The presented algorithm has three main parts: (i) detection of dark spots; (ii) feature extraction; and (iii) dark spot classification. The dark spot detection locates all spots which can possibly be oil slicks in the image. For each slick, a set of backscatter, textural, and geometrical features are extracted. The dark spots are then classified into possible oil slicks and look-alikes based on the extracted features. Based on the current study, we believe that a semi-automatic oil slick identification system which can discriminate between oil slicks and look-alikes can be developed. To achieve this, some new features describing the surroundings of a slick and the slick itself must be defined and tested.

INTRODUCTION

Synthetic aperture radar (SAR) images from the ERS satellites have since the summer of 1994 been used in a pre-operational service for manual identification of oil spills at Tromsø Satellite Station in Norway. In this pre-operational service, SAR images of ocean areas are manually inspected to identify possible oil spills. During this pre-operational phase, a large data set of SAR images containing verified oil slicks and oil slick "look-alikes" has been collected.

In this paper, we study the performance of automatic methods for oil spill detection. A large data set consisting of verified oil slicks and oil slick look-alikes is used. The goal is to develop a semi-automatic system for oil spill detection, in which dark spots with a high probability of being an oil slick are automatically identified. These possible oil slicks are then presented to an operator. Presently, we do not believe that a fully automatic oil spill detection algorithm will be able to correctly discriminate between the most difficult oil slicks and their look-alikes. However, a semi-automatic procedure will greatly reduce the number of SAR images which need to be manually inspected compared to a fully manual detection prodedure.

An algorithm for semi-automatic detection of oil spills is presented. The algorithm has three main parts: (i) detection of dark spots; (ii) feature extraction; and (iii) dark spot classification. The dark spot detection locates all spots which can possibly be oil slicks in the image. For each slick, a set of backscatter, textural, and geometrical features are extracted. The dark spots are then classified into possible oil slicks and "look-alikes" based on the extracted features.

OIL SLICKS IN SAR IMAGERY

Oil slicks are visible in SAR imagery because they have a dampening effect on the Bragg waves in the sea (see, e.g., [6]). They will thus appear as dark spots in the SAR images, compared to the surrounding sea. Under strong wind conditions, the oil will be quickly resolved and will not be visible in the image. Under low to moderate wind conditions, dark spots caused by natural phenomena will also be seen in the image. The natural dark spots are termed oil slick look-alikes.

TEST DATA

A data set consisting of 59 ERS-1 SAR low resolution images (LRI) from Tromsø Satellite Station is used to test the performance of the automatic oil spill detection algorithm. These images have been manually inspected for oil slicks by TSS, as part of their manual pre-operational oil spill identification service.

Of the 59 images in the test data set, 29 images contain oil slicks. These 29 images contain a total of 42 oil slicks. These oil slicks can be divided into tree main categories:

- *Thin, linear slicks.* 16 slicks belong to this category. For some of the slicks, a bright object (possibly a ship or an oil platform) can be seen nearby. This type of slick might be caused by a moving ship or a stationary object releasing a small amount of oil under certain wind and current conditions.

- *Thin, piecewise linear slicks.* 15 slicks belong to this category. For some of the slicks, a bright object can be seen nearby. These slicks might be caused by a moving ship changing directions, or by changes in

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current or wind directions affecting oil released from a stationary object.

- *Thick/wide slicks.* 11 slicks of this category are found. They can be caused by a stationary object releasing a larger amount of oil. If the oil was released a short time before the image was acquired, the slick will have a regular shape. For an older slick, the wind and current will make the shape of the slick more irregular.

The remaining 30 images in the test data set contain a very large number of dark spots which are not oil slicks. Such dark spots frequently occur in SAR images under low-wind conditions. In many ways, these spots resemble oil spills.

SPOT DETECTION

The developed 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 mean backscatter level in the region. The window is moved across the image in small steps to threshold all pixels in the scene.

SLICK FEATURE EXTRACTION

For each dark spot, a set of features is computed. The features constitute general, standard descriptors often applied for regions, and additional features particularly suited for oil slick detection.

- *Slick complexity:* This feature will in general take a small numerical value for regions with simple geometry, and larger values for geometrical complex regions.
- *Grey level mean*
- *Grey level standard deviation*
- *Mean local area contrast ratio:* a measure describing the contrast between the slick and its surrounding.
- *Sobel mean border gradient [2]*
- *Smoothness contrast locally:* measures the smoothnes of the slick compared to the surroundings.
- *Mean border width:* the average length of the border ramp between the slick and the surroundings.
- *First invariant planar moments [3].*
- *Distance to bright object:* If a bright object (a ship or an oil platform) is detected in the image, the distance from dark spots in the local area to the bright object is used as a feature.

SLICK CLASSIFICATION

Due to the small number of oil slicks available for training, a classifier which utilizes second-order statistics of the data (e.g., a Gaussian classifier) should not be used because the oil class will result in a singular covariance matrix when several features are used simultaneously in a multivariate feature vector. A *K-Nearest-Neighbor* classifier [1] will neither be suited because the number of look-alikes is several orders of magnitude larger than the number of oil slicks. We have chosen to use a hierarchical classifier, a *classification tree*. A classification tree is a nested sequence of partitions of the feature space (see, e.g., [4, 5]). The features are considered one at a time, and each level in the sequence yields a further partition of the feature space.

Training a tree classifier consists of identifying the set of partitions based on a set of n training objects. In constructing the tree, a one-step look-ahead method is used. That is, the next split is selected in an optimal way, without attempting to optimize the performance of the whole tree.

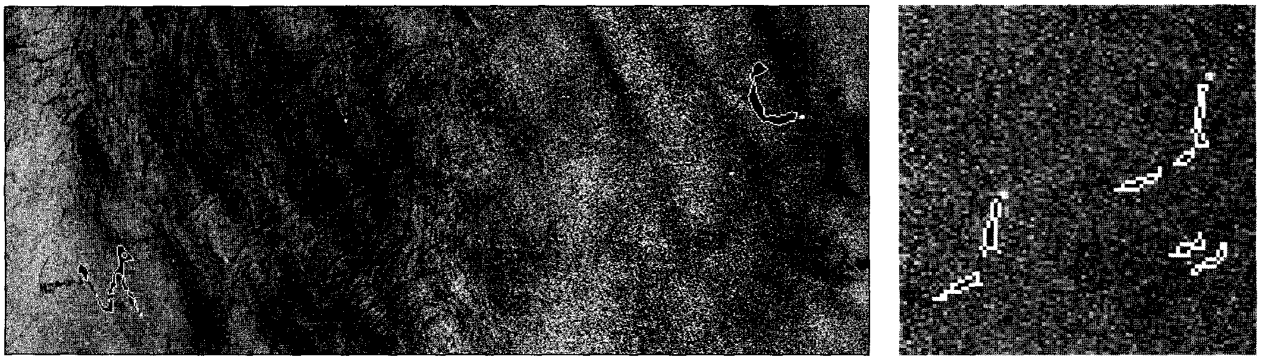
We have used the *S-Plus* implementation of classification trees. A detailed description of the methodology can be found in [5].

CLASSIFICATION PERFORMANCE

Because some of the features describe the shape of the dark spots, we will use several classes of oil slicks during the classification. The following classes are used:

- Class 1: Thin, linear oil slicks
- Class 2: Thick/wide oil slicks with a regular shape
- Class 3: Thick/wide oil slicks with a more complex shape
- Class 4: Thin, piecewise linear oil slicks
- Class 5: Look-alikes.

The classification tree utilized uses the fraction of the classes in the training set to estimate the prior probability of oil slicks vs. look-alikes. When a classification tree is trained on the set of 42 oil slicks and 2471 look-alikes, the resulting performance reflects the effect of using the fraction of the classes in the training set to estimate the prior probability of the classes (indicating a prior probability of look-alikes of 0.98). The implementation of the classification tree does not allow the user to specify proper prior probabilities or alternative loss functions. To overcome this problem, we use a resampling procedure to create a new training data set with a more equal number of oil slicks and look-alikes: from the oil slick classes, $n = 100$ objects are sampled from each class (with replacement), whereas $n = 100$ objects from the look-alike class are sampled at



(a) (b)

Figure 1: (a) Correctly classified oil slicks. (b) Very low-contrast oil slicks which are misclassified due to fragmentation during spot detection. The borders of the oil slicks are marked in white.

random, creating at new data set with equal prior probabilities.

With this more balanced data set, all oil slicks in the training set were correctly classified, but 3% (87/2516) of the look-alikes were classified as oil slicks.

To evaluate the performance of the classifier on an independent test data set, we use the leave-one-out method for error estimation [1]. In a data set with n oil slicks, $n-1$ objects are used for training, and the remaining for testing. This procedure is repeated n times. With this procedure, 14% (6/44) of the oil slicks were wrongly classified as look-alikes. 4% of the look-alikes were classified as oil slicks.

If we study the oil slicks which are misclassified, they fall into three main categories: (i) thin, piecewise-linear slicks; (ii) low-contrast slicks in homogeneous sea; and (iii) slicks on a very heterogeneous background where the dark spot detection algorithm fails to define a clear border between the slick and the surroundings. Fig. 1 (a) shows two oil slicks which were correctly classified. The borders of the detected slicks are indicated on the figure. In Fig. 1 (b) two small, low-contrast oil slicks are shown. These two slicks were fragmented during dark spot detection and are misclassified due to this.

Future research will include identification of new features designed particularly for these oil-slick categories. Further prior knowledge of the conditions will also be modelled.

CONCLUSIONS

Based on the current study, we believe that a semi-automatic oil slick identification system can accurately discriminate between oil slicks and look-alikes. To achieve this, some new features must be defined and tested. A classifier which can be guided by a manual operator and learn from experience must be implemented. Refinements of the spot detection algorithm are also desirable.

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