A method to detect oil spill based on SAR images.

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Abstract

Oil spills reduce water surface roughness and can be detected by the Normalized Radar Cross-Section (NRCS) on SAR (Synthetic Aperture Radar) images where they appear as dark areas. With the purpose to detect oil slicks, in the last years a probabilistic method to distinguish oil spills from other similar oceanic features in marine (SAR) images has been developed and tested. The method uses statistical information obtained from previous measurements of physical and geometrical characteristics for both oil spill and natural features. A sample image is evaluated using a procedure to determine the probability that it is an oil spill. The classification-algorithm performance was evaluated using a test dataset of SAR images containing hundreds of examples of oil spills and of features exhibiting characteristics similar to oil spills (look-alike): more than 80\% of the samples were classified correctly. The reliability of the method was then determined using a new dataset and similar results were obtained. The developed methodology and its capability in recognizing oil spills among look-alike are illustrated.

1 Introduction

A great aid in the effort of monitoring oil spill events comes from remote sensing techniques.
Oil and other surfactants are responsible for sea wave damping and reflectivity modulation over a broad range of frequencies from the visible to the microwave regions of the spectrum. Organic surface films form large damped sea areas (slicks) that are manifested in remotely sensed imagery. One of most visible film-induced effect is the attenuation of short gravity waves that alters the electromagnetic reflectance and makes the slicks detectable by both optical and microwave remote sensing systems, providing information useful to determine physical properties, origin, total volume discharged and trajectory of the pollution.

Among all the monitoring ways, the Synthetic Aperture Radar (SAR) is a powerful tool for the detection and characterization of substances forming sea surface films. In fact, during the last years, airborne and space-borne SAR availability has allowed to make several SAR application studies on artificial or natural slicks, confirming the ability of the multi-frequency SAR to be an ideal instrument to monitor sea surface slicks. Results of experiments performed in the Mediterranean Sea prove that it is possible to implement an automatic overseeing system able to give important information about the nature of the surface slick. A probabilistic approach has been developed and tested to distinguish oil spills from other similar oceanic features in marine SAR images. The method, using statistical information obtained from previous measurements of physical and geometrical characteristics for both oil spill and natural features, is able to discriminate between oil spills and other natural phenomena that cause backscattering attenuation and represents an useful step to an automatic monitoring system.

2 Sea surface slicks measured by SAR

The use of multi-frequency SAR for the detection and characterization of substances forming sea surface films was suggested more than fifteen years ago [1]. Today airborne and spaceborne SAR availability has allowed significant experimentations on slicks [2,3,4]. The basic mechanism involved is the normalized radar cross-section which, for large incidence angles, is proportional to the spectral energy density of the Bragg sea. The sea waves that are Bragg resonant with microwaves employed by the SAR systems fall in the short gravity wave region. In this same region, the theory of rheology of air-water interface predicts [5] a maximum in the frequency response of the ratio between the damping coefficients of waves for water covered by a surface film and pure water. Spectral measurements carried out both in tanks and in many oceanic sites [6,7,8] on slicked waters clearly show this damping effect. The ratios between spectra measured in pure water and in water covered by film have a maximum in the 3-10 Hz region [9,10]. Hence the multi-frequency SAR seems to be the ideal instrument to monitor sea surface substances, since SAR data contain information about the spectral components affected by damping. To prove SAR capability in monitoring sea surface films, a first experiment, with an artificial spreading slick of oleyl alcohol took place in October 1990 in the
northern Adriatic Sea, offshore the Venice coast in the area around the oceanographic platform "Acqua Alta" of the Italian National Research Council (CNR) [11]. In June 1991 in the Gulf of Genoa analogous experiment was performed observing slicked area after oil-tanker accident [12].

3 Oil spill automatic detection

Hydrocarbon compounds produce huge areas of surface film that reduce water surface roughness and therefore they can be detected by the Normalized Radar Cross-Section (NRCS) on SAR images where they appear as dark areas. With the purpose to distinguish oil spill from other similar oceanic features, in the last years we developed a method based on SAR images processing [13,14]. The method is based on a simpler classifying algorithm that represent the last step of research program in developing a completely automatic detection system, able to discriminate oil spill among all dark areas containing look-alike surface phenomena. The related operational activities are carried out at the Matera Geodesy Centre where the Italian Space Agency Processing and Archiving Facility (PAF) for the European Remote Sensing (ERS) satellite sensor data and the Telespazio mobile acquisition facility are located.

Hundreds of suspected spots detected by SAR have been screened, applying our methodology that turned out to be able to recognize oil spills among look-alike ones.

4 Acquisition and processing chain description

Since the November 1999 it is operative a satellite ground station in Matera (Italy) able to acquire data transmitted down by the European satellites ERS 1 and 2. The facility is composed of an 8 meter main dish, a down converter chain, a direct ingestion sub system. The acquisition area spans from the North Sea to Red Sea including the entire Mediterranean basin.

From the operational point of view there are in average two acquisitions in the morning and two in the evening. As soon as the data are recorded on the direct ingestion sub system, the coping activities and media start, then data are screened for the evaluation of quality parameters, the generation of the browse image and the updating of the archive catalogue. All these activities last on the average two hours. After that, the browse image is inspected by an operator to select any potential area interested by oil spill. The next step foresees the production of the full resolution image. At this point the data is fed into a system that provide the probability the suspected area is affected by oil spill. An automatic procedure first masks the land areas, then selects the dark regions with a NRCS lower than one half of the average NRCS for the sea area in the image, rejecting the selected areas that are too small or too large. The small regions are rejected because these slicks are not significant from the cost guard point of view and the large ones because these are probably areas with no wind.

At the end of the process a detection report is generated which shows the
acquisition region of the sensor, superimposes the shapes of the detected dark area and includes its perimeter, its area, the latitude and longitude of its center, and the probability that it is an oil spill.

5 Algorithm for the oil spill identification

There are a certain number of characteristics that are considered an oil spill signature; we have implemented measurements for some of these, selecting those that seem more useful in discriminating between an oil spill and other phenomena that cause backscattering attenuation, like natural films or areas with locally low wind intensity. For each selected dark area, first its border is identified, and then the following quantities are evaluated:

- Perimeter (P);
- Area (A);
- Average NRCS inside the dark area (SIGMAI);
- Average NRCS in a limited area outside the dark area (SIGMAO);
- NRCS Dark Area Standard Deviation (DASD);
- NRCS Outside dark area Standard Deviation (OSD);
- Gradient (GRD) of the NRCS across the dark area perimeter;
- Form Factor (FRM): the dispersion of dark area pixels from its longitudinal axis. And derived from these:
  - Perimeter to Area ratio (P/A);
  - Intensity Ratio (IRT) between average NRCS inside and outside the dark area;
  - NRCS Standard Deviations Ratio (SDR) inside and outside the dark area;
  - Ratio between NRCS Intensity and its Standard Deviation Inside the dark area (RISDI);
  - Ratio between NRCS Intensity and its Standard Deviation Outside the dark area (RISDO);
  - RISDI to RISDO Ratio (IOR).

We considered two sets of dark areas extracted from SAR images, one from confirmed oil spills and another caused by natural phenomena but looking like slicks. Figures 1 and 2 are examples. We performed the previously described measurements on these two sets, then we tested the hypothesis that there might be no difference between the two samples. As example, Table 1 provides the results of the analysis of the variance of data recently measured [14], in which the critical value of variance test $F$ is 3.95.

Figure 1: An example of oil spill in SAR image.
Table 1. The evaluated features on the oil and non oil datasets. F is the variance test value.

<table>
<thead>
<tr>
<th>Feature</th>
<th>F</th>
<th>AVERAGE</th>
<th>STANDARD DEVIATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIGMAI</td>
<td>20.4</td>
<td>194</td>
<td>127</td>
</tr>
<tr>
<td>SIGMAO</td>
<td>27.6</td>
<td>289</td>
<td>248</td>
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<tr>
<td>DASD</td>
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<td>145</td>
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<td>OSD</td>
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<td>GRD</td>
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<td>46</td>
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<tr>
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<td>5.9</td>
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<tr>
<td>IRT</td>
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<td>1.6</td>
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<tr>
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<tr>
<td>IOR</td>
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<td>1.26</td>
<td>1.27</td>
</tr>
</tbody>
</table>

6 Classification procedures

We adopted a multi regression new approach (or Fisher discriminating analysis) to set up a relation between the predictor variables and the dependent or criterion variable on a new dataset containing 153 verified oil spill and 237 look-alike. We have considered an equation as the following:

\[ Y = a + b_1X_1 + \ldots + b_nX_n \]  

where Y is criterion variable: it is assumed to be 0 for oil spill and 1 for look-alike. We have used the independent variables \( X_i \) in their canonical form, i.e. \( \ldots \)
\( \bar{X}_i \) is the average value of \( X_i \), while \( \sigma_i \) is its the standard deviation. Using a least square method the coefficients \( a \) and \( b_i \) are estimated. The regression coefficients represent the independent contributions of each independent variable to the prediction of the dependent variable, moreover higher coefficients also means the corresponding variable contribute more in discriminate the two groups. The figures 3 and 4 are showed the distributions of \( Y \) for the group oil spill and for the group of look-alike. These values are used to estimate the best normal distribution fitting the two histograms. Their expressions are:

\[
\begin{align*}
    p_o &= \frac{1}{\sigma_o \sqrt{2\pi}} \exp \left[ -\frac{(x - \bar{x}_o)^2}{2\sigma_o^2} \right] \\
    p_i &= \frac{1}{\sigma_i \sqrt{2\pi}} \exp \left[ -\frac{(x - \bar{x}_i)^2}{2\sigma_i^2} \right]
\end{align*}
\]  

(2)

Figure 3: Oil fit distribution
For a new case Y value is calculated and from it the probability it is an oil spill is obtained applying the following equation:

$$p(\text{oil}) = \frac{p_o}{p_o + p_l}$$  \hspace{1cm} (3)

The Table 2 reports on the raw the cases classified by the interpreter while on the column those classified by the algorithm.

We conclude that the proposed algorithm is able to effectively classify oil spills and look-alike phenomena. The methodology is easy to apply and able to determine the identification probability in an automated way.
Acknowledgments

This work has been done in the framework of European Space Agency (ESA) ERS A.O.3. All the data used are ERS data on which there is an ESA copyright. The data processing has been carried out at Italian PAF.

References


