OIL SPILLS DETECTION IN SAR IMAGES USING MATHEMATICAL MORPHOLOGY

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ABSTRACT

A new method for marine oil spills detection is presented in this paper. It is shown that morphological images analysis techniques are powerful tools to extract accurately dark spots in SAR images, which are candidates to be oil spills. The main goal is that this segmentation can be carried out with no prior knowledge about ocean conditions during the image acquisition process. Moreover, these techniques can also be useful to extract some features used in the decision process of the candidates. Due to the homogeneity of the proposed algorithm it is suitable to be implemented in a quite efficient way. This work is focused to detect oil spills produced for cleaning the tanks of the oil tankers. Nevertheless, the main idea of the proposed algorithm is that it can be used with no restrictions.

1 INTRODUCTION

An important and worrying cause of marine pollution is oil spills. Everybody has seen images of ecological disasters due to accidents of big oil tankers. However this is not the main cause of marine oil pollution. Oil spills are almost constantly present in the main ship traffic routes, close to oil platforms or in estuaries of rivers [1]. Such events, of course, cannot be put down to accidents. Towards their control, several administrations are supporting projects for monitoring marine oil pollution by means of remote sensing.

SAR images are being widely used for monitoring such a kind of pollution. Their main advantages are independence of the sun light, no clouds occlusion and enough resolution. However, they present some drawbacks which make difficult to develop a fully automatic oil spills detection system.

Marine oil pollution dampens capillary waves. This means that a polluted area will appear in the SAR image as a zone darker than its surrounding. Therefore, we have to process the image to detect and segment dark spots. However, this procedure will only be possible if there is enough contrast between the dark spots and their background. With no wind, there is no capillary waves. In terms of SAR images, that means that is impossible to observe any water pollution on it, since the whole image has the same grey level. So, prior to the segmentation, one has to determinate whether the detection process is feasible (enough backscattering).

Besides the speckle noise, which always corrupts SAR images, there are some factors which complicate SAR image processing. Oceanographic and weather phenomena, such as internal waves, organic films, wind sheltering by land or rain cells, produce in the image the same signature as oil slicks [2]. These so-called “look-alikes” (see fig. 1b) depend as well on the wind. As a consequence, the number of false alarms due to look-alikes typically increases when the wind level is low.

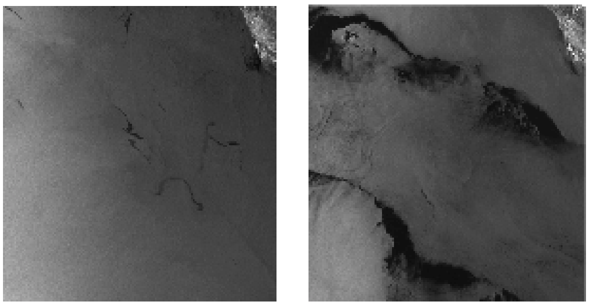
Taking into account the previous framework, the proposed detection method has a classical structure. First, accurate image segmentation is implemented to extract the candidates to be oil slicks. This paper is mainly oriented to this process that is detailed in section 2. Second, it is decided which features should be considered for separating real and false oil spills (classification), and they are extracted. This step is briefly presented in section 3.

In this work we have used ERS-2 SAR data. In general, low-resolution images are processed; that is, “quick-look” images having a 100x100 m. per pixel resolution. The use of such images largely reduces the computational load while preserving the image information and smoothing the noise. High-resolution images can be only used in some special cases and just to zoom in small windows.

2 SEGMENTATION

As mentioned above, the sought objects (oil spills) are mainly characterized by their dark level with respect to the background (see figure 1). That feature suggests the use of a threshold based segmentation approach. In such a case, the threshold level has to be estimated.

The dampen effect of the oil slicks has been widely studied [2-6] and modelled [2,7]. The mean backscattering level is estimated from the image; and using a model, the threshold is set to k dB below this mean level. The value of k depends on the wind. That means that either it is prior known or it is calculated from the level of the image [8].



a) b)

Figure 1. Low-resolution SAR images showing oil spills and look-alikes in front of Barcelona (in the top-right of the images).

However, a constant threshold value for the whole image is not recommended. The mean level of the background varies even in a homogeneous sea, due to the image acquisition system. An example can be seen in figure 1, where the right side is darker than the left side. Therefore, the most common approach is to use an adaptive threshold [9]. For this, the local mean level value is computed in a window which moves across the image.

This method has some drawbacks. The threshold extraction can be seen as the output of a mean filter. So, it behaves well removing noise and tracking low frequencies (the case of background without spots). However, dark spots will not be completely removed but they will became smaller than the local threshold, making difficult their segmentation by thresholding. Moreover, mean filters smooth the edges of the spots, specially when using large windows such as those needed to minimize the first commented drawback. Then, dark spots will not be accurately segmented. Finally, the computation of the value of k is usually not very precise.

2.1 Basic technique

We propose a new approach trying to overcome all the previous drawbacks. Non-linear filters are more adequate for obtaining a correct estimation of the background. They can track the slow variations of the background while preserving the contours of the dark spots. The "top-hat" filter [10] has been developed to solve this kind of problem. Since we want to set the threshold below the noisy background, we can used a modified version of it [11]. So, the adaptive threshold is calculated by

$$\sigma_{th}(x,y)= \phi_B\{\gamma_B[f(x,y)]\} \qquad (1)$$

which is the closing of the opening of the original image f(x,y), being B a flat structuring element (SE) typically of size (11x11). Figure 2 shows a result of this filtering process.

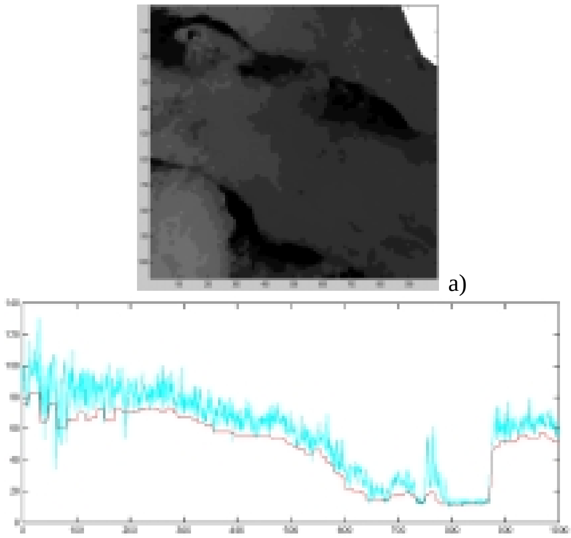


Figure 2. a) Background estimation ($\sigma_{th}(x,y)$) of the image of fig.1b). b) Profile of line 425: the original line is shown in light and the result in dark.

Instead of segmenting the original image, it is better to segment a less noisy version, trying to preserve the contours as well as the level of every dark spot. For speckle reduction, morphological tools perform even better than classical filters as the Lee filter. A close-open filter similar to that of equation (1) can be used, but with a smaller (3x3) SE, since peaks to be removed are narrow. Moreover, in this case we use an opening by reconstruction in order not to bias the edge position of the preserved components. In turn, the minimum of all directional closing is applied. Therefore, the output is

$$f_s(x,y)=\bigwedge\{\phi_{d1}[\gamma_R^{(B)}[f(x,y)]], \dots , \phi_{dn}[\gamma_R^{(B)}[f(x,y)]]\} \qquad (2)$$

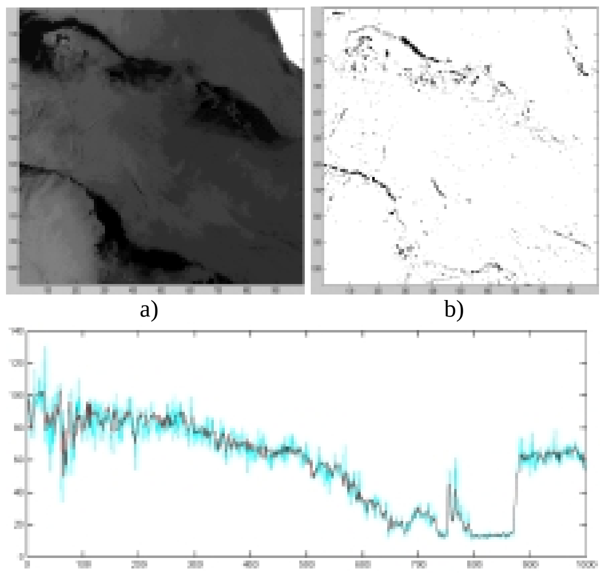


Figure 3. a) Example of fig.1b) after noise reduction. b) Result of the binarization of a) using fig. 2a) as threshold. c) Profile of a) compared with the original.

The idea is that when a pixel belongs to a dark spot there should be a directional SE totally included in it. Then, the output of this directional closing will keep the level of the dark spot. An example is shown in figure 3 a) and c).

Therefore, the segmentation is carried out by means of (1) and (2):

$m(x,y)=0$ if $f_s(x,y) < \sigma_{th}(x,y))$, $m(x,y)=1$ otherwise (3)

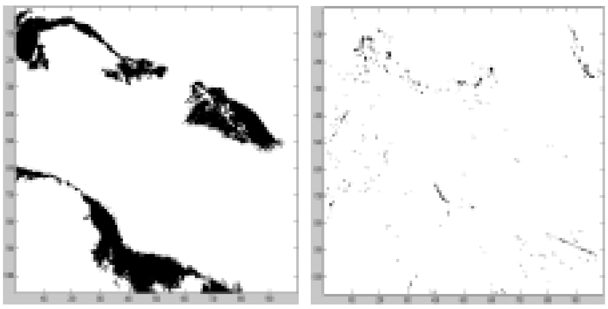
This binarization creates a mask with candidates to be oil slicks. An example of this procedure is shown in figure 3 b). Notice that in (3) the convention has been to set to 0 pixels of the desired objects just to maintain the original image order of levels.

2.2 Improving the shape accuracy

Results obtained applying (3) can be further refined. First, although large spots are correctly considered as background, some of them may have thin connected components. If such components are smaller than the SE, they will be detected as candidates (see figure 3 b)). Furthermore, it has to be noticed (see profiles in fig. 2 and 3) that in dark background areas f_s and σ_{th} take almost the same value. Thus, any small displacement of the edges can generate a candidate which will have similar characteristics to oil spills.

To solve these problems, an accurate mask of large spots is created, $m_{ls}(x,y)$. Towards this goal, a modified "top-hat" is applied, now with a large SE, in order to extract all dark spots. The original image is binarized by the new $\sigma_{th}(x,y)$ given by equation (1). Since we are now interested only in large components, small objects are removed. To obtain an accurate mask of the large spots, preserved large components are used as markers for a reconstruction process taking the original image as reference. This reconstructed image is now filtered using a modified "top-hat" with the same large SE as before, where an opening and a closing by reconstruction replace the previous morphological open and close, respectively.

From that, all the pixels of the first mask ($m(x,y)$) which are connected with pixels in the second mask ($m_{ls}(x,y)$) will be removed, given $m_1(x,y)$. See figure 4 b).



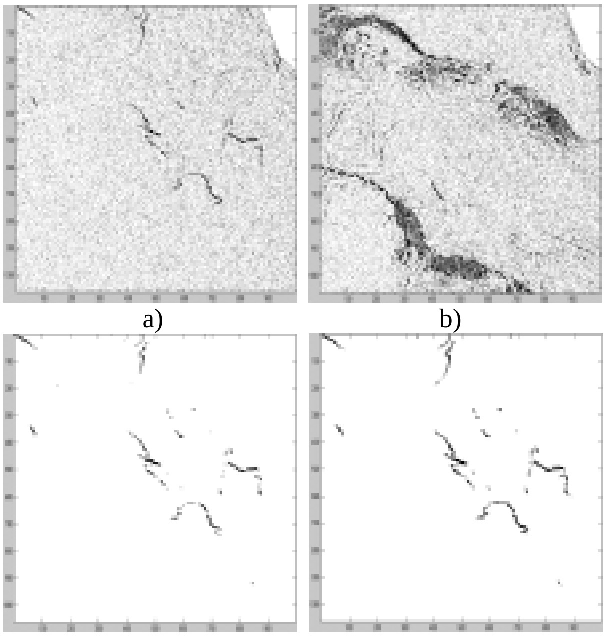
a) b)

Figure 4. a) Mask of large spots (m_{sl}) of the image in fig. 1 b). b) Result (m_1) of joining the information of a) and the mask in figure 3 b).

2.3 Filling gaps between unconnected components

Depending on the type of oil, the age of the oil spill and the ocean conditions, the dampen effect of the slick can be different across it. If any part of the slick is diffused, several connected components may appear broken (sometimes the oil spill is really broken). Thus, a further improvement tries, when possible, to fill these gaps.

The original image is binarized using a higher threshold than in the generation of the initial mask $m(x,y)$. Expression (3) is computed now using directly $f(x,y)$ and calculating $\sigma_{th}(x,y))$ with a small SE (7x7). The result is a detailed mask, $m_d(x,y)$, as can be seen in figures 5 a) and 5 b), where less dampen points appear. This image, although being noisy, contains points of the dark spots which were lost in the first segmentation



a) b) c) d)

Figure 5. a)-b) Noisy masks obtained with higher thresholds than those of the first segmentation. c) Mask containing candidates which may be broken. d) Result after filling the gaps.

This detailed mask is used as a reference in the process of binary reconstruction (by erosion), being $m_1(x,y)$ the marker. So, the result mask will hold all the connected points in $m_d(x,y)$ that belong to an object of $m_1(x,y)$.

The new mask is completed setting to 0 (marking as candidates) those pixels that are 0 in $m_1(x,y)$. This has to be done because some large spot pixels in the detailed mask are missing, as can be observed in figure 5 b). This happens because in this case no noise reduction has been done before binarization. Then, some local maxima in dark regions are above the threshold.

Finally, some false candidates may still appear in the mask. Such small spots are due to the remaining noise or the commented problem of similarity between f_s and σ_{th}. They are removed using an area filter.

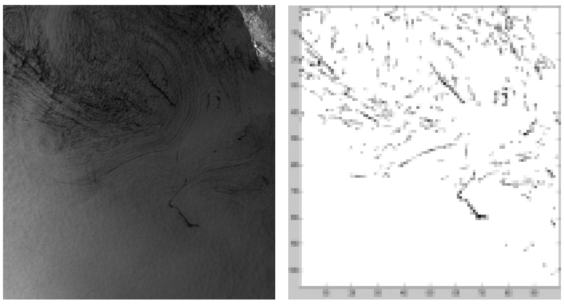
3 FEATURE EXTRACTION

The proposed method decreases the number of false slicks detected. However, some segmented regions contained in the final mask are look-alikes. Up to now, only level and size information has been used for discrimination purposes. Other features have to be taken into account in order to refine the detection.

As we are mainly interested in monitoring oil spills produced for cleaning tanks while oil tankers are sailing, an important feature for classification is how elongate the candidate is. It can be expressed as a ratio between its length and width. These parameters are estimated using the morphological skeleton of the objects in the final mask. The propagation function [12] is used to computed the longest path of the skeleton. Based on this path, the mean width of the object is obtained.

Since objects have been accurately segmented, the mean levels of the possible slicks and of the surrounding background can be precisely estimated. These values allow computing the dampen of the candidates.

Only using these parameters, a simple classification of the dark spots has been implemented which shows a good behaviour. Obviously, in more complex scenarios many more features are needed [9], even the fractal dimension is proposed [13] for some difficult frameworks (see figure 6).



a) b)

Figure 6. a) Complicate scenario with a whirlpool. b) Mask of candidates of a).

4 CONCLUSIONS

A new method for oil spill detection in SAR images has been presented which is based on morphological tools. An accurate extraction of possible oil slicks is performed. Although the algorithm requires more steps than classical approaches, the computational load is low. This is due to several aspects: (i) the algorithm can be applied to low resolution images, (ii) the various steps have a common algorithmical basis which allows fast implementations and (iii) the segmentation leads to less candidates which reduces the classification load.

In any case, it is difficult to get an error free detection and, therefore, automatic detection can be used to assist monitoring tasks.

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