Detection of Oil Slick Signatures in SAR Images by Fusion of Hysteresis Thresholding Responses

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***Abstract*— A new method is proposed in this paper to detect oil slick signatures in oceanographic SAR images. This method is based on directional behavioural oil slick in the sea surface. Therefore, directional hysteresis thresholding responses are first computed in order to bring to the fore dark spots, and increase pixels connexity in each Freeman direction. Those responses are then merged with the help of a Context Independent Constant Behaviour (CICB) operator. The proposed method is tested on ERS SAR amplitude images of Mediterranean and Atlantic seas. The obtained results are promising and show a good qualitative detection.**

I. INTRODUCTION

The marine oil spills pollution of the world seas based on Synthetic Aperture Radar (SAR) images has been really studied since the ERS orbital focusing on 1991. Several approaches has been developed to explain and monitor the phenomena. The first studies (first generation) has allowed to validate SAR images [1]-[6]. They has based on experiments, physical and statistical analysis to identify the acquisition and sea surface conditions that are favourable to the goal. The second generation approaches has permitted to bring to the fore dark spots [7]-[10]. However, Oil Spill Detection and Monitoring Systems are disturbed by several other atmospheric and oceanic natural phenomena [11] called look-alikes (natural films, grease ice, threshold wind speed areas, wind sheltering by land, rain cells, internal waves, shear zones, upwelling and natural oil seepage), which can lead to false alarms detection, due to similar signatures to those of oil spill, in oceanographic SAR images. So that the last generation of methods [9] [12]-[16] has dealed with discrimination between oil and look-alikes, includes direct and contextual analysis [11]. For these raisons, the Oil Spill Detection and Monitoring Systems operate in three steps [7] [9] [17] : detection of dark spots, feature extraction, and slick classification.

In general, numerous approaches to the goal can be classified according to two criteria. Its depended on the type of data (amplitude, polarimetric, multifrequency, or multipolarization images) , and it processing goal (oil slick signatures detection or oil slick signatures classification). Concerning the first aim who is our development interest, several methods have been developed before, include the adaptative thresholding [7] [9], the fuzzy c-mean algorithm [8], and the polarimetrics likelihood discriminators [10].

The development of robust detection methods is then necessary to more improve performance of these systems, considering the importance of each step, and in particular the oil slick signatures detection. So that, the direct and contextual analysis are essential to perform the slick classification, and the feature extraction depend on the spot detection accuracy. The first step is therefore vital to perform a direct analysis, then very essential to the Oil Spill Detection and Monitoring Systems.

The exact definition of the contour of oil slicks in SAR images of sea is of mayor importance to predict their future evolution and prevent possible damages to the marine and coastal environment [10]. On the other hand, oil slick signatures have tendency to take a certain direction imposed by the wind and the modulation of the sea surface roughness due to gravity waves which spreads ocean pollution. To take these characteristics into account, a new method namely designed to detect the possible presence of an oil slick in a homogeneous environment is proposed. It goes further into the adaptative thresholding, one of the several image processing community numerous approaches. The paper is then organised as follows:

In section 2, we continue with the presentation of the detection method model. In this section, we explain the general synoptic and the different steps of the method, describe the Directional Hysteresis Thresholding (DHT) as a direc-

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tional decomposition of the model, and present the strategy for merging DHT responses to achieve the process. The section 3 illustrates the method efficiency with experimental results over several areas of Mediterranean and Atlantic seas. Finally some suggestions for future research and the conclusions are drawn in section 4.

II. DETECTION METHOD

A. Synoptic

The detection method proposed in this paper is based on the hysteresis thresholding. This transformation has been used first by Canny to detect edges of a Gaussian-smoothed image [18]. Because it accentuates linear feature, we need to identify oil slick candidates at the most on each direction imposed by the wind and the modulation of the sea surface roughness due to gravity waves which spreads ocean pollution. So the method [Fig.1] is applyed to cover all the angular space, hence the DHT. The given SAR image has to be decomposed using this to increase pixels connexity and bring to the fore dark spots, then theses binary responses are merged by an adaptative operator to detect oil slick signatures .

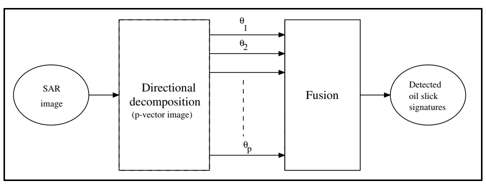

Fig. 1. Synoptic of the detection method

B. Direction Hysteresis Thresholding

The literal description of the hysteresis thresholding is developped in [18], and we need to explain it once here by introducing and varying the direction of the operation. Let then consider an image represented by a set of cells $\mathcal{S}$ so that $\mathcal{S} = \{s_i, i \in [1, N]\}$, the processing is done pixel by pixel by increasing i over each neighborhood to define the direction $\vec{d}$ of the transformation [Fig.2]. The hysteresis direction is given by:

$$\vec{d} = \frac{\overrightarrow{s_{i-1}s_i}}{||\overrightarrow{s_{i-1}s_i}||} = \vec{x}\cos\theta + \vec{y}\sin\theta \qquad (1)$$

where θ is the hysteresis angle ($0 \leq \theta \leq 2\pi$). In accordance with the direction $\vec{d}$, DHT is define as a function that depend on four parameters:

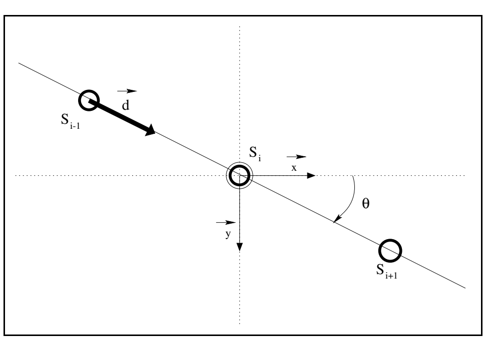

Fig. 2. DHT direction illustration

$$DHT_\theta(s_i) = \chi(t_h, t_l, p(s_i), DHT_\theta(s_{i-1})) \qquad (2)$$

$0 \leq \theta \leq 2\pi$, $0 \leq i \leq N$, where $p(s_i)$ is the present cell measure (local or global, gray scales or other measure),$DHT_\theta(s_{i-1})$ the DHT result of the precedent cell according to θ , t_h the high threshold, and t_l the low threshold. In the practice, the θ space must be discredited. This has been done by Freeman to code edges over an 8-connexity neighbourhood [19]. The method is then computed in the eight Freeman set directions $\mathcal{F}_{\vec{d}} = \left\{\vec{0}, \vec{1}, \vec{2}, \vec{3}, \vec{4}, \vec{5}, \vec{6}, \vec{7}\right\}$ to extract the information at the most.

C. Fusion of the DHT responses

The fusion problem is formulated as a clustering problem of the 8 dimensional image vector derived from the DHTs. The redundancy and the complementarity are characteristics of the information in these images. The best compromise numeric fusion operator ζ which is adapted to this problem is the probabilistic and Bayesian model, in particular the Context Independent Constant Behaviour (CICB) [20], define here as the maximum, located between means and T-conorms operators as follow:

$$\zeta(DHT_{\theta_l}(s_i), DHT_{\theta_h}(s_i)) = max(DHT_{\theta_l}(s_i), DHT_{\theta_h}(s_i)) \qquad (3)$$

$l \neq h$, $0 \leq i \leq N$, where θ_l and θ_h correspond to two Freeman directions of $\mathcal{F}_{\vec{d}}$.

III. EXPERIMENTAL RESULTS

Two ERS-2 SAR amplitude images [Fig.3] are available for the processing described in this paper. The first one [Fig.3a] coded in one byte is 270x270 pixels (range and flight directions) from the Atlantic sea in front of the Cameroonian and Guinean coast, acquired on 2000. It is a tropical rain forest region image. We can remark by photo-interpretation that it is characterized by good acquisition conditions. The second [Fig.3b] coded in two bytes is 656x656 pixels from the Mediterranean sea acquired on 1999. Here, It presented a different configuration, in particular a lot of small and linear darks due to difficult conditions with strong winds.

Each Freeman direction applied on original images is then explored to extract the linear feature corresponding. The oil slick signatures detected by the CICB operator are presented in [Fig.)]. In case of homogeneous context of the darks, the experimental results [Fig.4a] have proof his overall accuracy in accordance with previously works [7] [8] [9]. In another hand, spots are scattered around the sea. The simulation results [Fig.4b] show the robustness of this method because of his simplicity, with respect to keep on detecting linear feature taking by oil slick in accordance with directions imposed by strong winds.

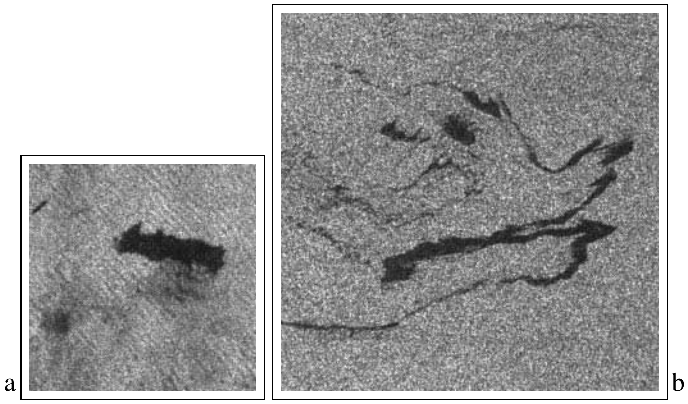

Fig. 3. Original SAR images

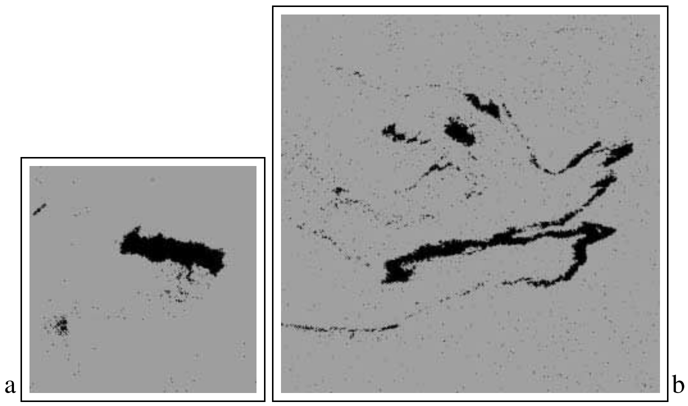

Fig. 4. Detected oil slick signatures

IV. CONCLUSION AND FUTURE RESEARCH

The proposed oil slick signatures detection method based on the DHT has given qualitative satisfactory and promising results. It has been tested on SAR amplitude images from satellites ERS of Atlantic sea in the Golf of Guinea regions in front of Cameroon, and of Mediterranean sea. We have noted that it accentuates linear feature in the corresponding Freeman direction. In any case, it explain the oil slick behaviour due to the directions imposed by the wind and the modulation of the sea surface roughness, submissive to gravity waves which spreads ocean pollution. But the method need to be quantitively evaluate on real truth data before any final conclusions can be drawn. The next step will then be the classification of these oil slick signatures to two classes, *oil slicks and look-alikes*, to complete the numerous processing on oil spill detection and monitoring system.

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