IDENTIFICATION OF OIL SLICKS IN SAR IMAGES VIA MULTIFRACTAL TECHNIQUE

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ABSTRACT

In this paper we present a technique for the analysis of low intensity patches on SAR oceanic amplitude images, in particular oil slicks generated by moving ships. Oil presence on the ocean surface causes a damping effect of the ocean spectrum determining dark spots on observed SAR images accordingly to the Bragg theory. Nevertheless, the use of SAR data is still limited because similar dark areas in the images, said look-alikes, can be due to several other phenomena: lack of wind, natural oil, plankton and so on. So far, this ambiguity limited the development of automatic oil detection procedures. Developed algorithm is based on multifractal analysis of the edges of dark areas (here called *Regions Of Interest*, ROIs) and can be used to identify and to distinguish oil slicks from look-alikes. The core idea is that different physical-chemical interactions of oil slicks and look-alikes with the sea surface imply different fractal features for the edges of the ROIs on the acquired images. Accordingly, proposed approach is based on multifractal analysis of ROIs' edges, which consists in the estimation of their multifractal spectra and the "dispersion area" of these spectra. Proposed procedure is tested on simulated SAR images; methods and results are extensively discussed, with a focus on parameters and methods to be used for a proper box counting algorithm. First results seem to indicate that the observation of multifractal spectra is useful in order to distinguish between oil slicks generated by moving ships from look alikes, even when these phenomena have the same degree of irregularity thus an estimation of the classical fractal dimension is not suitable for discrimination purposes.

Keywords: SAR, oil slicks, multifractal analysis

1. INTRODUCTION

Synthetic Aperture Radar (SAR) systems offer incredible capability for earth observation; in particular for sea monitoring it can fill the lack of in-situ pollution surveys of seas and coasts, offering the ability to monitor oil slicks occurrences. In ocean environment SAR signal intensity is proportional to the ocean spectrum at spatial frequencies according to the Bragg theory; oil presence causes a damping effect of the ocean spectrum determining dark spots on observed SAR images. Nevertheless, the use of SAR data is still limited because similar dark areas in the images, said look-alikes, can be due to several other phenomena, as lack of wind, natural oil, plankton and so on. So far, this ambiguity limited the development of automatic oil detection procedures.

In this framework, the fractal geometry is widely recognized as the most appropriate instrument for the description of natural shapes. In this paper we deal with multifractals, a generalization of fractals which present different fractal behaviour at different observation scales [1]. Hence, while fractal processes can be described by a single number, the fractal dimension, multifractals present a continuous distribution of fractal dimensions and are described more effectively through some functions like multifractal spectrum [2]. The introduction of multifractals is convenient for the analysis of oil slicks on the sea surface: in fact, different physical-chemical interactions of oil slicks and look-alikes with the sea surface imply different multifractal features of the edges of the dark spots on the acquired images (in the following called *Regions Of Interest*, ROIs). In particular, the shape of the oil slicks due to illegal tank-cleaning from moving ships (at least those whose generation is close to the time of observation) present features determined by concurrent turbulent phenomena acting at different scales of magnitude, i.e. ship movement (that determines typical elongated shape of related oil slick), sea turbulence due to ship's engines and natural sea turbulence, thus implying a multifractal feature of ROIs' edges. Conversely, look-alikes due to lack of wind present a shape that is related to the wind turbulent behavior, implying a monofractal feature of ROIs' edges. Moreover, oil slicks not generated by moving ships or slicks staying on the sea surface for a long time, present a shape dictated essentially by sea turbulence only, implying a monofractal feature of ROIs' edges, as well.

In this work is proposed the use of multifractal analysis of oil slicks edges in order to identify oil slicks due to illegal tank-cleaning and to distinguish them from look-alikes. Proposed procedure is based on the estimation of the multifractal spectra and the definition of the "dispersion area" parameter. The procedure was tested on simulated SAR images, obtained by a SAR Signal Simulator using a combination of deterministic and stochastic models (the latter based on fractional Brownian motion, fBm) in order to describe the contour of oil slicks and look-alikes accounting the ocean description.[3].

Results and an extensive discussion on the methods used for the elaboration process is given. In particular, the box-counting method is adopted for the evaluation of multifractal parameters and a study on the choice of boxes dimension range is also performed, emphasizing the critical role of this processing step.

2. GEOMETRICAL AND PHYSICAL MODELS

Fractal geometry is widely recognized as the most appropriate instrument to model and analyse natural shapes. Fractals allow the description of complex natural objects, both in the one-dimensional and multi-dimensional cases (e.g., path of a river, contour of islands or lakes, natural surfaces) using a minimum number of independent parameters.

In order to generate slicks with fractal shapes on simulated SAR data, the most appropriate function is the fractional Brownian motion (fBm), a stochastic process described in terms of the pdf of its increments [1].

We synthesized fBm processes by means of the two-dimensional Weierstrass-Mandelbrot (WM) function, which is a superposition of sinusoidal tones with random amplitude, direction and phase, scaled through the Hurst coefficient $0 < H < 1$ related to the fractal dimension D_{WM} through $D_{WM} = 3 - H$; a cut of the WM function at fixed level provides a curve with fractal dimension equal to $D_{frac} = D_{WM} - 1$. By this way we effectively obtainded dark spots with fixed fractal dimension used to model the behavior of some look alikes or man-made slicks (whose acquisition is perfomed a long time after their generation). Conversely, to model the typical elongated shape of the slicks due to illegal tank-cleaning, we superimposed a bidimensional Gaussian function to the WM function with a ratio between the standard deviations in the two orthogonal directions of one order of magnitude. In this case extracted curves present different fractal behaviors at different spatial scales and a multifractal description is necessary in order to adequately describe this type of shapes.

An estimation of the fractal dimension of the ROIs was computed using a box counting technique (as detailed in [1]) performed by covering fractal set with non-overlapping boxes such that

$$N_b(\delta) \sim \delta^{-D_{BC}} \tag{2.1}$$

where $N_b(\delta)$ is the number of non-empty boxes of size δ and D_{BC} is the box counting dimension obtained by a linear regression.

Counting the number of ROI's pixel belonging to each box allowed us to compute the **moments of order q**

$$\chi(q, \delta) = \sum_{i=1}^{N_b(\delta)} \mu_i(\delta)^q \tag{2.2}$$

where $\mu_i(\delta)$ is the percentage of pixels belonging to the fractal edge, q is the order of the moment. **Generalized fractal dimension** is defined as follow

$$D(q) = \frac{1}{q-1} \lim_{\delta \to 0} \frac{\log[\chi(q, \delta)]}{\log(\delta)} \tag{2.3}$$

and it's a monotonic decreasing function of q, presenting an horizontal asymptote for $q \to \infty$ while for monofractal sets it's constant with q. The box counting dimension is a particular case of $D(q)$: $D(0) = D_{BC}$.

Now let's define the **local Holder exponent**

$$\alpha(q) = \tfrac{d}{dq}(q-1) \lim_{\delta \to 0} \frac{\log[\chi(q, \delta)]}{\log(\delta)} \tag{2.4}$$

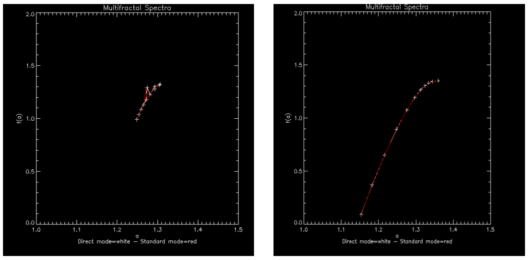
It can be shown that for a simple monofractal it holds $\mu_i(\delta) \sim \delta^{\alpha}$ hence α equals the standard fractal dimension. For a multifractal, indeed, α may vary from point to point and is a local quantity. It's possible to determine the number $N_\alpha(\delta)$ of boxes having similar local scaling behaviour characterized by the same index α; assuming self-similar scaling, the expression

$$N_\alpha(\delta) \propto \delta^{-f(\alpha)} \tag{2.5}$$

defines **multifractal singularity spectrum** $f(\alpha)$, as the fractal dimension of the set of index α.

In other words a multifractal set can be divided into subsets of index α, whose fractal dimension is equal to $f(\alpha)$. For a multifractal set the graph of $f(\alpha)$ is convex, with a maximum for $q = 0$ where it assumes a value equal to D_{BC}. For monofractal sets the multifractal spectrum degenerates into a point due to the fact that α assumes a unique value. Thus analysing multifractal spectra of ROIs' edges we can distinguish oil slicks due to illegal tank-cleaning from look-alikes.

3. RESULTS



(a) (b)

Fig. 3.1: Multifractal spectra: (a) look-alike monofractal contour, (b) oil slick multifractal contour

	Multifractal	Monofractal
Order of moment	$q \in [0, 10] \subset \mathbb{N}$	
D_{frac}	1.3	1.3
D_{BC}	1.22	1.30
A_d	$41.70 \cdot 10^{-3}$	$1.65 \cdot 10^{-3}$

Table 1: Multifractal analisys

In figure (3.1) is shown one of the outputs of our analysis; it shows multifractal spectra of simulated look-alike and oil slick. It's clear that in the monofractal case the multifractal spectrum is concentrated around a point: in fact, as mentioned above, it should ideally be a single point with a value equal to the box counting dimension. In the multifractal case the spectrum is much more dispersed. In order to measure this dispertion, was defined *dispersion area* A_d as the product of the standard deviations of the functions $f(\cdot)$ and $\alpha(\cdot)$:

$$A_d = \sigma_f \cdot \sigma_\alpha \tag{3.1}$$

As shown in table (1) computed values of A_d in the two cases present a ratio greater than one order of magnitude. This parameter should be used for automatic classification purposes. Both simulated images have fractal dimension D_{frac} set to 1.3, hence a proper classification is possible even when they have contours with the same fractal dimension.

Boxes dimensions δ used for the implementation of the partition function 2.2 play a central role in the calculus; we observed a great dependence of outputs from box dimensions range used. This range must obviously be limited and in order to achieve best results we realized that minimum and maximum box dimension must be properly set: the former must be almost one order of magnitude greater than the minimum dimension of the profile under test (which is the pixel, at least when no interpolation or re-sampling has been performed on the ROI); the latter must be one order of magnitude smaller than ROI's diameter. Whenever box dimensioning is done according to these simple rules, the number of boxes used for the analysis doesn't represent a key parameter.

Due to great dependence from the number of computed box $N_b(\delta)$, that could vary due to different reasons, box counting technique could fail, resulting in an incorrect fractal dimension estimation even when computed over different multifractal contours obtained from the same fractal surface. Otherwise, partition funtion, and hence multifractal spectra, is less dependent from this problem since they are *global indexes* of the pixel distribution over the set. In fact $\chi(q, \delta)$ was obtained from (2.2) by setting

$$\mu_i(\delta) = \frac{m_i(\delta)}{N_c} \tag{3.2}$$

where m_i is the number of contour pixels belonging to the i-th δ-box and N_c is the total number of contour pixels. So the standard box counting estimation is not an appropriate technique for classification purposes while multifractal analasys is stable even when the simple box counting estimation fail.

Another key parameter of the multifractal analysis is the order of moments q: in the proposed case study was set $q \in [0, 10]$ and only integer values were considered. We observed a significant dispersion of the multifractal spectra for $q > 5$; otherwise, when the upper limit for q is lower than 5 the dispersion area of the multifractal spectrum (relevant to the multifractal ROIs' edge) significantly decreases, thus implying an increased probability of missing oil slicks identification. Multifractal spectrum shown in fig 3.1a haven't its typical convex shape becouse it was computed using only positive values for q; results obtained for $q < 0$, in fact, were not trustworthy due to a well-known problem of this type of analysis [4].

4. CONCLUSIONS

In this paper we described the rationale of multifractal analysis applied to the analysis of dark spots contour on SAR images relevant to oceanic scenes in order to distinguish oil slicks due to illegal tank cleaning from look-alikes. The potentiality of the multifractal spectrum as a slick classifier were highlighted and tested on simulated images. Was defined the dispersion area parameter to be used as a compact segmentation index in an automatic classification system. Finally, the role of the multifractal analysis parameters and the criteria for their optimum choice were investigated.

5. REFERENCES

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