PATTERN RECOGNITION IN SAR IMAGES USING FRACTIONAL RANDOM FIELDS AND ITS POSSIBLE APPLICATION TO THE PROBLEM OF THE DETECTION OF OIL SPILLS IN OPEN SEA

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Abstract: In this note we deal with the detection of oil spills in open sea via self similar, long range dependence random fields and wavelet filters. We show some preliminary experimental results of our technique with Sentinel 1 SAR images.

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1 INTRODUCTION

Assuming that an intensity SAR image is modeled by a self similar random process [1] we propose a possible rather simple analysis scheme for the detection of oils spills in open sea. Moreover as this is essentially a smoothness or complexity analysis technique of the image it can be potentially applied to the recognition and classification of other patterns. To explode notions related to self similarity and fractals related to SAR image processing (and optical images) is not completely new. In e.g. [4, 5] computing an approximate Box/Hausdorff fractal dimension of the neighborhood of each pixel some possible algorithms for oil spill detection are proposed. Indeed, since "fractal" is a more or less vague term, several underlying models with varying results and computational complexity can be proposed. As suggested in [4, 5] box counting techniques have a rather good performance in solving this detection problem. However this may be not the case from the the point of view of the required computational time to perform this task. In contrast, Fourier analysis methods or similar as wavelet analysis [1] are potentially much simpler and fast since there exist several optimal FFT algorithms. Here, among all possible models of self similar random fields to model the image we propose the class of the stationary (or locally stationary) $\frac{1}{f}$-processes [1]. These fields were introduced by A. Kolmogrov in a first statistical study of turbulent flows. An $X = \{X(p), p\}$ random field of these class, with p in $\mathbb{R}^2$, has an spectral density of the form (or asymptotically near the frequency $\omega = 0$) [7]

$$S_X(\omega) = \frac{C}{\|\omega\|^a}. \tag{1}$$

The exponent a gives a quantitative measure of the the correlation of the random field. For greater a, X is more correlated and in particular for appropriate values of a, X displays *Long Range Dependence*. In contrast, for $a \longrightarrow 0$, X is nearly white noise. The parameter a is linearly related to the so called Hurst parameter [1], which measures the self similarity of the random field. Finally, at least in the Gaussian case, a is also related to the Hausdorff dimension of the graph of X and the roughness of it.

2 Proposed Numerical Methods

In this context, we shall assume that the portion of image containing the oil spill fluid will be approximately behaving as a $\frac{1}{f}$-random field with a certain parameter a. Waves are supposed to be attenuated in contact in the presence of oil, which under suitable conditions, will traduce in a smoother and highly correlated surface in comparison to non contaminated open sea water. The proposed detection scheme is basically to test if the possible oil spill area follows model (1) for some a. To do this, given any finite energy filter $h_1(p)$ with a Fourier transform $H_1(\omega)$ we consider a scaled version of it $h_2(p) := h_1\left(\frac{p}{2}\right)$ and if X is our image/field we obtain two filtered (convoluted) versions of it, namely:

$$Y_1(p) = (h_1 * X)(p) \text{ and } Y_2(p) = (h_2 * X)(p).$$

The corresponding spectral densities then are given by :

$$S_{Y_1}(\omega) = |H_1(\omega)|^2 S_X(\omega)$$

and

$$S_{Y_2}(\omega) = 16|H_1(2\omega)|^2 S_X(\omega).$$

Assuming stationarity [7] and after some Fourier domain calculations, one gets that if X has indeed an spectral density as (1) then the variances σ_1 and σ_2 of Y_1 and Y_2 respectively, are related by:

$$\sigma_2^2 = 2^{a+2}\sigma_1^2. \tag{2}$$

Equation (2) is the key to obtain estimates for a. In particular, this scale relation makes the estimation procedure easy tom implement by wavelet filters [3, 6]. Furthermore, recalling that if R_X is the correlation function of X then S_X is related by its Fourier Transform with S_X, i.e. $\hat{R_X} = S_X$, we can prove a kind of reciprocal of this result:

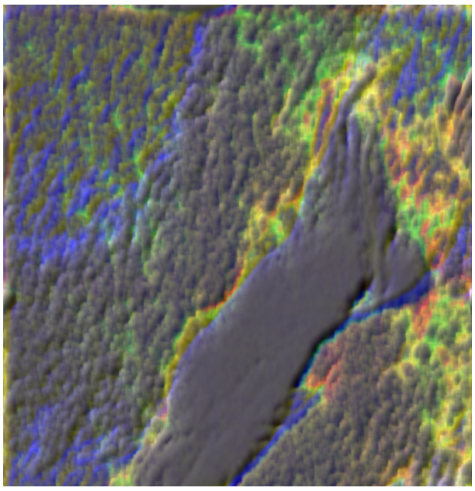
Theorem **2.1** *Let $R_X(p)$ be a radial function and decreasing in $\|p\|$. If for some $a > 0$ equation 2 holds for every $h_1 \in L^2(\mathbb{R}^2, S_X d\omega)$ then $\int_{\mathbb{R}^2} |R_X(p)|dp = \infty$.*

The divergence of the integral of the correlation function is one of the usual forms to describe random fields with long range dependence. Thus, if an equation like (2) holds for some fixed a and any finite energy filter then X displays long range dependence, and moreover, with additional conditions equation 1 holds. In practice, a is unknown and one can only test with a finite number of filters. However, based in these calculations, in this work we propose that for a finite suitable parametrized family of wavelet filters $h(s,p)$, $s = s_1, ..., s_n$ and corresponding estimates of $a(s)$ we can design a rather simple first warning detection scheme which in a first stage heavily relies only on linear, matrix and spectral numerical operations.

3 Conclusion and some experimental Results

Here we present some practical examples with real images (see Figure 1). We note that $a(s,p)$ defines in some way a transformation or map of the original X. To illustrate the idea, if for certain fixed values s_1, s_2, s_3 we generate an RGB auxiliary image assigning to each color component a value linearly related to the corresponding estimates of $a(s)$ for each filter. In the zones of the image where these values are, ideally, equal the related RGB intensities must be equal as well generating a nearly dark grey flat area where $a(s)$ equals a constant. Obviously if more filters ($n \geq 3$) are involved more accurate the following decision will become. The second stage (classification and decision) takes the transformed image $a(s,p)$ as an input into a combination of a neural network and a classical statistical hypothesis [2] testing previously trained with several images samples and its respective transforms $a(s,p)$. In this work we present some promising experimental results with this technique.

(a) Original image



(b) RGB map of estimated a

(c) Neural Network Output stage

(d) Hypotesis Test Classification Stage. White/Positive = Oil Spill

Figure 1: Image analysis with Gaussian wavelet filters for Sentinel 1 Caspian Sea Oil Spill

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