Fractal Models and Tools for Disaster Monitoring

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Abstract — **The fractal geometry is the most appropriate mathematical instrument to describe the irregularity of a natural scene, by means of few effective and reliable parameters. Therefore, fractal concepts can be used to model and to identify geometrical changes occurred in areas hit by disasters. An overall framework employing fractal based models, algorithms and tools to support identification of natural area changes due to natural or man-made disasters is considered and applied on simulated SAR imagery. Such a framework provides an innovative instrument for disaster monitoring applications and helps to improve the understanding of the mechanisms underlying SAR image formation. In the last section, a case study is discussed, showing the potentiality of our framework for flooding detection.**

Keywords – Synthetic Aperture Radar, Fractals

I. Introduction

Several approaches devoted to define instruments and tools for data interpretation were presented in literature [1]. Most of them are based on empirical analyses of remote sensing data, essentially driven by user needs. These analyses are generally supervised and, to be effective, it is often required that the supervisor holds a remarkable level of competence with reference both to the remote sensors (and data), and to the effects of different disasters on the environment.

When a disaster occurs, the scenario of the observed scene dramatically changes, and remote sensing instruments should be, at least in principle, able to detect the changes in the scenes. These natural disasters modify (according to different rules) the surface profile from scales smaller than the sensor coverage but comparable to the sensor resolution, up to scales comparable to the electromagnetic wavelength.

We focus our attention on SAR sensors. The microwave frequencies employed by radar instruments and the obtained geometric resolutions are better tailored to exploit the geometrical features of the area under survey: as already stated, these features exhibits the major changes whenever disasters take place. Anyway, the difficulty in interpretation of this kind of data often limits their use to expert observers. So the development of unsupervised or semi-unsupervised tools for the extraction of geometrical features from remotely sensed images is a fundamental issue. To develop these tools it is crucial to introduce appropriate models to understand and quantitatively describe the physical phenomena that govern the modification of the scenario textures.

In this paper, we suggest the combined use of a SAR raw signal simulator [3] and of appropriate direct and inverse models. As far as the models are under concern, the fractal geometry [2] has the required characteristics to manage the problem at hand, because it simply accounts for geometrical irregularity of the observed objects. On the other hand, a SAR data simulator is an important added-value tool to help scientists and non-expert users in better understanding the mechanisms underlying SAR image formation and in the interpretation of this kind of data and phenomena.

II. The Proposed Method

In this Section we present the direct and inverse models involved in the fractal framework and outline the rationale of the proposed method.

A. Direct models

1) The simulator

In past years, a SAR raw signal simulator was developed and tested [3], [4]. In this Section we describe briefly the key issues for SAR signal simulation.

Let x and r be the independent space variables, standing respectively for azimuth and range. By using primed coordinates for the independent variables of the SAR raw signal, $s(x',r')$, this can be expressed as [3]:

$$s(x',r') = \iint dx dr \gamma(x,r)\, g(x'-x, r'-r; r), \qquad (1)$$

where $\gamma(x,r)$ is the reflectivity pattern of the scene and $g(x'-x,r'-r;r)$ the unit impulse response of the SAR system [3], [4]. Evaluation of the reflectivity pattern requires a description of the observed surface as well as a model for their interaction with the electromagnetic fields radiated by the SAR antenna [3].

Note that the considered simulator requires as input a DEM relative to the scene of interest, sampled with a resolution coherent with the considered sensor parameters: in practice, we need to interpolate the available DEM [4].

2) Fractal surface model

Fractal models are widely considered the most appropriate to quantitatively describe natural surfaces [2]. Fractal geometry is able to simply account for the non-stationarity of natural surfaces, as well as for their self-affinity. The most used fractal model is the fractional Brownian motion (fBm) [5]. The fBm is defined in terms of the probability density function of its height increments: a stochastic process $z(x, y)$ is an fBm surface if, for every x, y, x', y', it satisfies the following relation:

$$\Pr\{z(x,y)-z(x',y')<\bar{\zeta}\}=\frac{1}{\sqrt{2\pi}s\tau^{H}}\int_{-\infty}^{\bar{\zeta}}\exp\left(-\frac{\zeta^{2}}{2s^{2}\tau^{2H}}\right)d\zeta \quad , \qquad (2)$$

where τ is the distance between the points (x,y) and (x',y'), and the two parameters that control the fBm behaviour are:

H : the *Hurst coefficient* ($0<H<1$), related to the fractal dimension D by means of the relation $D=3–H$.

s : the standard deviation, measured in [$\mathrm{m}^{(1-H)}$], of surface increments at unitary distance, a real parameter related to an fBm characteristic length, the topothesy T, by means of the relation $s=T^{(1\_H)}$.

It has been demonstrated [2] that the spectrum of an isotropic fBm process exhibits a power law behaviour.

We use the fBm to model the surface imaged by the SAR sensor. We utilize the fractal parameters, retrieved from the considered DEM (see Section II.B), to statistically interpolate the available DEM. In this way, the interpolated DEM inherits the fractal behaviour of the original surface [4].

3) *Fractal scattering model*

Theoretical [2] and experimental [7] studies suggest that use of fractal models improve the scattering method results. In this paper we used the fBm fractal model for describing the surface roughness and the small perturbation method (SPM) as scattering model for evaluating the reflectivity pattern [6].

Comparison between simulated and actual SAR data was presented in [4] with respect to image single point normalised moments and autocorrelation function, thus assessing the simulator reliability. In those comparisons the fractal parameters accounting for the microscopic description of the scene were assumed to be constant. In this case the extension we propose allows considering for the microscopic scale (up to the electromagnetic wavelength scale) the fractal parameters estimated from the available DEM so that in order to compute the reflectivity function we use fractal parameters varying all over the scene.

B. *Inverse models*

In the open literature, many methods for the extraction of information from SAR images relative to scenarios subject to changes are proposed. The majority of them are based on classical magnitude change detection techniques such as ratioing and differencing [8]. In this paper we suggest a novel approach based on change detection techniques applied to fractal parameters retrieved from pre- and post-crisis images. Discussion on the retrieving techniques of these parameters is now then in order.

For a given surface the structure function (variogram), $V(\tau)$, is defined as the mean square increment of elevation points placed at distance τ :

$$V(\tau)=\left\langle\left(z(x,y)-z(x',y')\right)^{2}\right\rangle \qquad (7)$$

The variogram of an fBm surface can be evaluated in terms of the parameters H and s and expressed in logarithmic form as:

$$\log V(\tau)=2\log s+2H\log\tau \qquad (9)$$

which defines in a log-log plane a linear behaviour with slope $2H$, and ordinate intercept $2\log s$. Such dependence leads to retrieve the fractal parameters with a linear regression over the log-log plots of measured values of $V(\tau)$ [6].

Note that the application of this technique to SAR images is someway critical, because it is necessary to take into account the non equal spacing of the data set. In this work we adapted it to deal with such a situation.

III. The Case Study

In the following, we present a case study, showing the potentiality of our framework applied to the monitoring of flooding.

The region of interest is the area of Maratea, Italy, a costal area surrounded by steep mountains. A digital elevation model (DEM) of a 20 x 20 Km^2 area was available for the considered area.

As first, we used our DEM as input for the simulator: the DEM was fractally interpolated and the fractal parameters retrieved from the available DEM were used in the simulation process to model the microscopic behaviour of the surface. Then, the SAR image was obtained from the simulated raw signal via standard processing and averaged with a 2 x 10 multi-look, to obtain an azimuth-ground range approximately square pixel (see Figure 1).

The second step was the modification of the original DEM to simulate a flooding: to obtain this, we created a river’s spate in a valley. In order to appropriately simulate the presence of water in the flooded region, we modified the microscopic roughness and the dielectric parameters as well. As far as the microscopic fractal parameters are concerned, in the areas affected by the flooding we set H to a typical value for the water surface (H=0.75), and we set s to one half of the value in the pre-crisis scenario. As for the dielectric characterization, the area affected by the flooding is assumed to have a dielectric constant of $20\varepsilon_0$, and a conductivity of 1 S/m, which are typical values for extremely wet terrain; the surrounding area is assumed to have a dielectric constant of $4\varepsilon_0$ and a conductivity of 10^{-3}S/m, typical of terrains with low water content [9].

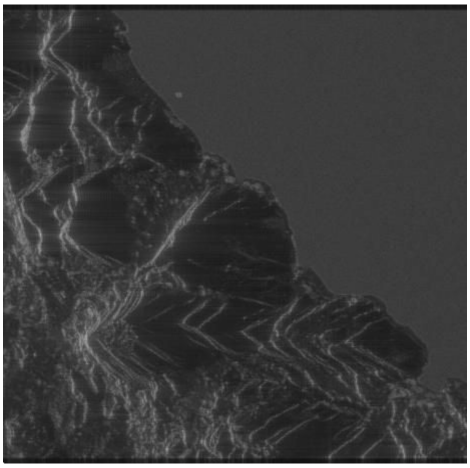

Figure 1. Simulated SAR image relative to the area of Maratea, Italy.

In order to define a reference map, we exploited the simulator facilities of simulating the SAR image in absence of speckle. Such an approach allows the definition of the "ground truth" in the SAR image by differencing pre- and post-crisis intensity images in absence of speckle, and the creation of the reference mask of Figure 2a, where flooded regions are identified by white pixels.

Then, we implemented a change detection technique, based on the fractal framework presented in the previous sections. In Figure 2c we show a classification map obtained by the difference between the fractal dimensions of pre- and post-crisis scenes. In Figure 2b the result obtained with a classical magnitude differencing technique is shown.

Observing Figures 2b and 2c, we note that the distribution of misclassified pixels is completely different, due to the different causes that generate it. In fact, the image intensity difference is very sensitive to the signal magnitude changes, therefore most of the misclassified pixels are grouped in the layover areas (it is consistent with the fact that SAR signal decorrelation increases in layover areas). Conversely, the fractal dimension is more sensitive to gradients of the signal, therefore most of the noise is gathered in correspondence of the grazing angle areas, where the differences between the side lobes of the layover areas create steep gradients. Above considerations suggest to combine the obtained results in order to get a significant improvement on the detection performances.

A simple multiplication of the obtained masks and a further low complexity processing consisting in a smoothing allows deleting most of the misclassified pixels, causing a strong reduction of the false alarm rate, corresponding to the classification mask presented in Figure 2d.

IV. Conclusions

In this paper was shown how fractal concepts can be used both for describing the formation of the SAR signal and for extracting information from it. An overall framework was presented, providing a procedure whose implementation can be tailored on several disaster monitoring cases.

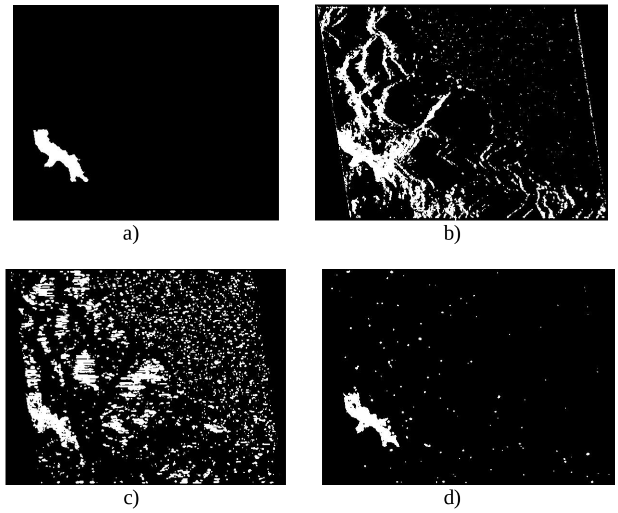

Figure 2. a) Reference map; b) Magnitude differencing (hit rate: 97.2%; false alarm rate: 11.2%); c) Fractal technique (hit rate: 83%; false alarm rate: 15.4%); d) Combined technique (hit rate: 90.2%; false alarm rate: 0.6%).

Finally, a change detection approach for the identification of a flooded area was presented, by combining the classical signal magnitude differencing technique and an innovative fractal technique, based on the differencing of the fractal parameters of the pre- and post-crisis area. The obtained result shows that the proposed combined technique leads to a significant performance improvement because it exploits the complementary information extracted by the two methods.

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