PRESEGMENTATION OF HIGH-RESOLUTION SATELLITE IMAGES WITH A MULTIFRACTAL RECONSTRUCTION SCHEME BASED ON AN ENTROPY CRITERIUM

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ABSTRACT

The last generation of satellites leads to the very high-resolution images which offer a high quality of detailed information about the Earth's surface. However, the exploitation of such images becomes more complicated and less efficient as a consequence of the great heterogeneity of the objects displayed. In this paper, we address the problem of edge-preserving smoothing of high-resolution satellite images. We introduce a novel approach as a preprocessing step for feature extraction and/or image segmentation. The method we propose is related with the idea of resolution reduction and is derived from the multifractal formalism used for image compression. First, a multifractal decomposition scheme allows to extract the most singular transitions of the image. Then, an entropy-based criterium enables to consider a particular manifold composed with the most, simultaneously, relevant and singular pixels. Finally, a reconstruction scheme performed over this manifold provides an approximation of the original image. Such an approach is ideal, as it assumes that objects can be reconstructed from their boundary information, and it provides presegmented images where the main structures are preserved.

1. INTRODUCTION

In the last decade, the improvement of the technology for observing the Earth from space has led to a new class of images with very high spatial resolution (*e.g.* $2.5\,m$ for Spot images or even $1\,m$ for Ikonos images) [1]. High resolution (HR) imagery offers a new quality of detailed information about the properties of the Earth's surface; they are mainly concerned with the land-surface observation. As smaller and smaller objects are now available, as well as precise contours of larger objects, automatic methods for extracting these objects are of great interest. Consequently, this has

given rise to a growing interest on image processing tools and their application to this kind of images [2]. However, due to the fact that HR images show great heterogeneity, standard techniques for analyzing, segmenting and classifying the data are faced with increasingly difficult hurdles. When the resolution increases, the spectral variability also increases, which can affect the accuracy of further classification or segmentation schemes. Classical approaches cannot produce satisfactory results because they may induce simultaneously under and over-segmentation within a single scene that confuse the global information and prevent further analysis. Generally several preprocessing steps may be required before such methods can be applied.

This paper introduces a new approach for segmenting HR images as a preprocessing step for feature extraction and/or image classification. The problem can be related with the idea of resolution reduction [3]: the retained technique should enable to preserve the main features of the original image corresponding to the boundaries of the objects while homogeneizing the other parts. The need for a multiscale approach is well recognized [4]: even on a single scene, different scales of analysis are needed, depending on the homogeneity of the objects under consideration and on the desired final application. Thus, for both reasons, we address this problem with a multifractal approach derived from data compression [5]. Like many image processing techniques, it makes use of the image edge information: it assumes that objects can be reconstructed from their boundary information [6]. The segmentation process consists in three main steps. First, meaningful subsets of the original HR image are extracted using a multifractal decomposition scheme. Then, an entropy-based criterium enables to select only the most relevant pixels in those subsets. The measure we propose enables to take into account spatial locations and scales of objects. Finally, a propagation kernel is used to partially reconstruct typical object shapes from the values of the signal over the selected manifold.

The paper is organized as follows. In section 2, we review the multifractal approach for extracting the meaningful entities and we introduce the method for reconstructing

the image. In section 3, we define the measure for selecting the reconstructing manifold and, finally, we present the presegmention algorithm. Some results are displayed and discussed for Ikonos HR acquisitions.

2. THE MULTIFRACTAL MODEL

Natural images can be characterized by their singularities, *i.e.* the set of pixels over which the most drastic changes in graylevel value occur [7]. In [5], the authors introduced a technique based on the multifractal formalism to analyze these singularities. For this purpose, a *multifractal measure* μ is defined through its density $d\mu(\mathbf{x}) = d\mathbf{x} |\nabla I|(\mathbf{x})$, where $|\nabla I|$ denotes the modulus of the spatial gradient $\vec{\nabla} I$ of the image I. This measure gives an idea of the local variability of the graylevel values around the point $\mathbf{x}$. It was observed that for a large class of natural images, the measure μ is multifractal [5], *i.e.* behaves like:

$$\mu(B_r(\mathbf{x})) \sim r^{2+h(\mathbf{x})} \quad (r \to 0), \tag{1}$$

with $B_r(\mathbf{x})$ the ball of radius r centered around $\mathbf{x}$. All the scale dependance in eq. (1) is provided by the term $r^{2+h(\mathbf{x})}$ where the exponent $h(\mathbf{x})$ depends on the particular point considered. This exponent is called *singularity exponent* and quantifies the multifractal behaviour of the mesure μ. Its estimation is done through a wavelet projection of the measure μ [8]. The reader is refered to [5] for a full discussion. This way, by assigning to each pixel the local measure of the degree of regularity of the signal, the image can be hierarchically decomposed. Namely, the subsets gathering pixels with similar exponent are fractal subsets and exhibit the same geometrical structure at different scales. Besides, this approach allows isolating a particular fractal component, the so-called MSM (*Most Singular Component*, denoted F_∞) associated with the strongest singularity (*i.e.* the most negative exponent, denoted h_∞) [5].

From multifractal theory, the MSM can be regarded as a *reconstructing manifold*. In [6], it has been shown that using only the information contained by this set and conveyed by the spatial gradient, it is possible to predict the value of the intensity field at every point. This result is in concordance with Marr's conjecture, who intuited that the image could be retrieved from its multiscale edges [7]. The algorithm canvas proposed in [6] produces a perfect reconstruction, the so-called FRI (*Fully Reconstructed Image*), from the MSM. It is performed by the use of a rather simple vectorial kernel $\vec{g}$ capable to reconstruct the signal I from the value of its spatial gradient $\vec{\nabla} I$ over the MSM. Namely, if we define the density function δ_∞ of F_∞ (which equals 1 over F_∞ and 0 elsewhere) and the gradient $\vec{v}_\infty \equiv \vec{\nabla} I \, \delta_\infty$ restricted to the same set (which equals $\vec{\nabla} I$ over F_∞ and 0 elsewhere), the reconstruction formula can then be expressed as:

$$I(\mathbf{x}) = \vec{g} \star \vec{v}_\infty(\mathbf{x}) \tag{2}$$
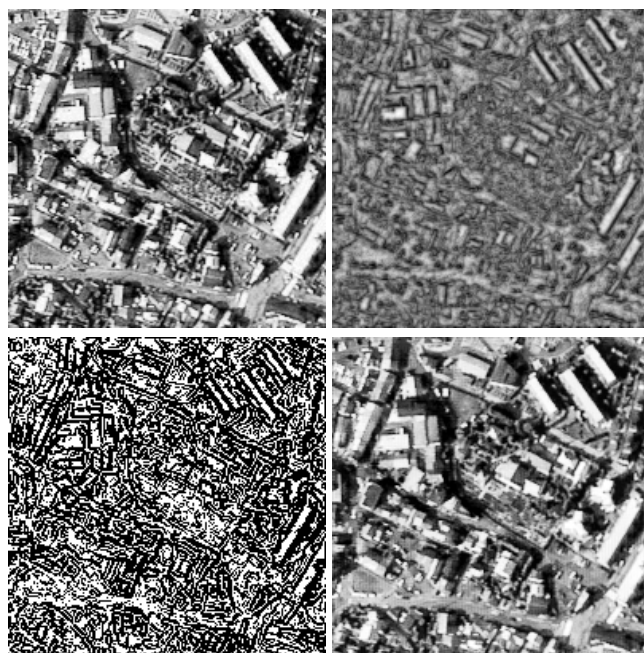

Fig. 1. **Top**: excerpt of a HR image acquired by the satellite Ikonos (left, $1\,m \times 1\,m$ per pixel) and graylevel representation of its singularity exponents (right). The brighter the pixel, the greater the singularity at this point; most singular pixels are mainly observed near the contours. **Bottom**: MSM (left, in black) extracted at $h_\infty = -0.12 \pm 0.28$ and FRI (right) reconstructed with eq. (2). The MSM gathers $65\,\%$ of the pixels of the image, which is a rather coarse estimation; the $PSNR$ for the FRI is $30.26\,dB$.

where $\star$ denotes the convolution. The universal reconstruction kernel $\vec{g}$ is easily represented in Fourier space by $\hat{\vec{g}}(\mathbf{f}) = i\,\mathbf{f} / |\mathbf{f}|^2$, where $\hat{}$ stands for the Fourier transform, $\mathbf{f}$ denotes the frequency and i the imaginary unit ($i^2 = -1$). The principle is that of a propagation of the values of the signal over the MSM to the whole image.

Practically, the extraction of the MSM depends on some parameter Δh that determines the range of values retained as the most singular. Namely, a pixel $\mathbf{x}$ is assigned to the set F_∞ if it verifies a relation of the form $h_\infty - \Delta h \leq h(\mathbf{x}) \leq h_\infty + \Delta h$. Besides, the rule for deciding which pixels will be incorporated into the MSM is rather empirical and we are not ensured that the FRI is the better reconstruction we could obtain. We would like to introduce some criterium for deciding which pixels should be considered into the reconstructing manifold so that the FRI is a good approximation of the original image.

3. ENTROPY BASED SELECTION

For extracting meaningful subsets in the image, it is rather natural to propose a measure that quantifies the information content. Namely, information theoretic concepts sur-
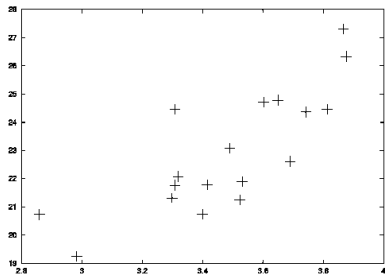
Fig. 2. Graph of the $PSNR$ values (y-axis) of the FRI *vs.* the average MLE (x-axis) over the MSM. The FRI's were reconstructed from 18 MSM's with equal density. The best $PSNR$'s were registered for the MSM's with the highest average MLE's.

vey for quantities that enable to estimate the relevance of patterns [9]. A key quantity is provided by the Shannon's definition of entropy: the greater the entropy, the greater is the number of required bits to encode the signal. In the domain of image processing, much work has been carried out on the applications of entropy, not only image coding but also image analysis, data filtering [10]... However, the concept of entropy following Shannon's definition is a global quantity. Moreover, it doesn't take into account the spatial relationship between pixels and it is not matched to quantify the distribution of the information at different scales of resolution. Thus, it is needed to define a local measure of the information content and it is necessary to introduce a multiscale processing in the estimation of entropy [11].

Following [12], we perform a multiscale generalization of the local entropy, for what we need to define the local multiscale distributions of graylevels. Namely for each pixel $\mathbf{x}$ in the image, all points in its neigbourhood are assigned a relative weight that decays with the distance to $\mathbf{x}$ as a power law. The local histogram $p_i(\mathbf{x})$ of graylevels in a window $\mathcal{W}$ around $\mathbf{x}$ is expressed by:

$$p_i(\mathbf{x}) \approx \sum_{\mathbf{y} \in \mathcal{W}:I(\mathbf{y})=i} |\mathbf{x} - \mathbf{y}|^{-2}. \quad (3)$$

For numerical reasons, we limit the computation to a window $\mathcal{W}$ of size 21×21 and the bit depth to 8 bits (256 graylevels). As desired, this model does not fix any scale of observation: it is scale invariant. The *Multiscale Local Entropy* (MLE) is then defined as the quantity: $s(\mathbf{x}) = -\sum_i p_i(\mathbf{x}) \log_2 p_i(\mathbf{x})$. It is then possible to observe spatial variations of this quantity (see Fig 3). This definition measures how relevant the value of the pixel $\mathbf{x}$ is for the knowledge of the graylevels distribution in its neighbourhood.

The selection scheme will depend on some threshold on the MLE. Singular pixels are gradually incorporated in the MSM according to their MLE value. It means that a pixel $\mathbf{x}$ will be incorporated into the reconstructing manifold if it
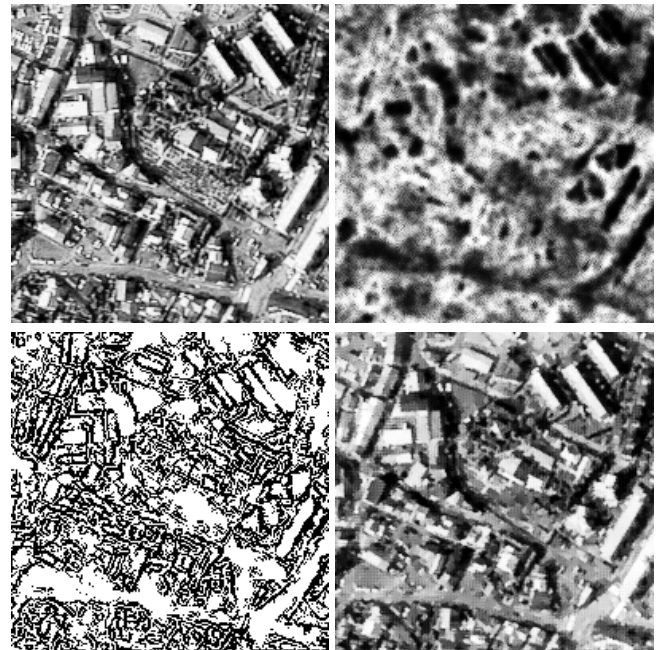

Fig. 3. Entropy-based segmentation. **From top to bottom, from left to right**: Ikonos excerpt, **MLE** over the excerpt (the brighter the pixel, the stronger the entropy at this point), filtered **MSM** according to local content of information and reconstruction using the filtered **MSM**. The PSNR is $27.75\,dB$.

satisfies a relation of the form:

$$h_\infty - \Delta h \leq h(\mathbf{x}) \leq h_\infty + \Delta h \quad \& \quad s(\mathbf{x}) \geq s_{thres} \quad (4)$$

where s_{thres} is some threshold value below what we consider that pixels don't carry relevant information. Following this criterium, we can show that for different MSM's extracted from the same image and gathering the same quantity of pixels, the best FRI's are obtained for the MSM's with the largest average MLE's (see Fig. 2). At this point, one may discuss the fact that high MLE values are correlated with strong singularities. However, from information theory, the MSM can also be interpreted as the most relevant set in the image [6]. In [12], it has been evidencied that this subset is related with the maxima of the MLE: the decomposition in fractal subsets is related with the hierarchy imposed by the MLE. It ensures that candidate pixels in the MSM will have rather high MLE values and it implies that our selection criterium won't suppress meaningful structures.

4. DISCUSSION

In Fig. 3, we show the results of the segmentation of some Ikonos image thanks to our approach, where the parameters Δh and s_{thres} were chosen empirically. It shows interesting

features, as we see that: there is a high degree of smoothing in rather homogeneous areas; the main edges are preserved, even those being represented by small gray value changes. The FRI provides an interesting segmentation of the original image: it cleans up noise in the homogeneous areas but preserves important structures and also preserves the graylevel distribution. Besides, the quality of the approximation is good, which is an essential requirement for further processing like feature extraction. Close inspection of the image also shows that the method is able to enhance subtle texture regions, like roads. Namely, it is good at enhancing textures, as it smoothens the image, and, thus, suppresses small elements corresponding to the unrelevant features.

One of the major advantages of the method is that it is parameterizable. We should notice that the reconstruction algorithm for computing the FRI defined by the eq. (2) is linear [6]. Thus, the more singular pixels the reconstructing manifold gathers, the closer to the original image the FRI is. So, we can theoretically approximate the original image as close as desired, just by adjusting the threshold parameter s_{thres}. This way, the degree of smoothing of objects in the image can be controlled. The main limitation lies in the fact that we need to define empirically some parameter, like the threshold parameter s_{thres}, if not theoretically.

5. CONCLUSION

In this paper, we have proposed to perform a presegmentation of HR images prior to any processing. For this purpose, we adopt an approach related with data compression and based on the multifractal analysis of images. The main idea is that of a partial reconstruction of the images from the extraction of their most important features.

The multifractal algorithm is performed in two steps, which consist in: first, extracting the most singular transitions of the signal, the MSM, that mainly consists in objects boundaries, and, then, propagating the graylevel values of the spatial gradient from the MSM to the other parts of the image. The multiscale approach allows to retain the relevant edges without significant artifacts, no matter at which scale they happen. The quality of the reconstruction depends on the set of pixels retained in the reconstructing manifold. Thus, the full reconstruction strategy implies an intermediate processing step, for automatically selecting those pixels. Namely, we propose a selection criterium for which we compute a multiscale local entropy-like variable, the MLE; we finally include in the reconstructing manifold the pixels retained as the most informative among those that were already detected by the multifractal analysis.

This approach results in very nicely smoothed homogeneous areas while it preserves the main information contained in the boundaries of objects. The image structures are not geometrically damaged, what might be fatal for fur-

ther processings like classification or segmentation. Indeed, it creates homogeneous regions instead of points or pixels as carriers of features which should be introduced in further processing stages. Moreover, the reconstruction is parameterizable. The fidelity to the original image can be adjusted, by gradually incorporating, according to the MLE values, as many details of the original image as desired so that the degree of smoothing can be controlled. It should be also noticed that this method can easily be extended to multispectral images, by processing each band separately. An improvment regards the automatic determination of, the threshold parameter used in this approach.

As a continuation, applications to noisy satellite images restoration should be considered.

6. REFERENCES

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