VERY HIGH SPATIAL RESOLUTION IMAGE SEGMENTATION BASED ON THE MULTIFRACTAL ANALYSIS

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ABSTRACT:

The availability of very high spatial resolution images in remote sensing brings the texture segmentation of images to a higher level of complexity. Such images have so many details that the classical segmentation algorithms fail to achieve good results. In the case of IKONOS images of forest areas, a texture can be so different within a same class that it becomes very difficult even for a human to segment or interpret those images. The study of the high frequency content of the data seems to be a good way to study those images. We work on a new method which uses the singularity information to achieve the segmentation. It is based on the computation of the Hölder regularity exponent at each point in the image. From this parameter we can compute the local Legendre or the large deviation multifractal spectrum which gives information about the geometric distribution of the singularities in the image. So we use global and local descriptors of the regularity of the signal as input parameters to a k-means algorithm. The whole algorithm is described and applied to IKONOS images as well as to an image made of brodatz textures. The segmentation results are compared to those obtained from the laws filters and the co-occurrence parameters techniques. The proposed method gives better results and is even able to segment the image in tree density classes.

1. INTRODUCTION

Very high spatial resolution images provide a huge amount of details and information. Thus, it is possible to extract new thematic classes and to detect smaller objects. But all those advantages are strongly tied to a major drawback from an image processing point of view. The processing of such images becomes very tricky; the local variability of the grey level values and the large number of data is a limiting factor for most of the classical analysis tools. Even the visual interpretation is not obvious and needs experience to recognize each region. Therefore, new segmentation algorithms have to be created in order to achieve good classification results with high spatial resolution images. Classical segmentation tools fail to give homogeneous segments and usually give very sparse results where the classes are not compact. To overcome those issues, it seems appropriate to use a textural analysis approach. Thus, for each pixel, we study the neighbourhood and not only the grey level value.

Image segmentation based on texture is a complex problem. Many theories were developed but their all result in partial solution to the problem. None can fully characterize all the kind of textures. Even the definition of a texture is not clearly defined. Depending on the field of application and the nature of the image, the definition of a texture can be very different. Co-occurrence matrices (Haralick *et al*, 1973), Markov random fields (Chellappa and Chatterjee, 1985), Gabor filters (Turner, 1986), the fractal analysis (Kaplan, 1999), etc. are tools which are not able to analyze all the textures. In the particular case of very high spatial resolution images, the high variability of the grey level of each thematic objects prevent from using the previously quoted analysis methods. Furthermore, we do not have any *a priori* information about the nature of the grey level distribution of those objects. Pentland, (Pentland, 1984), showed that the fractal dimension is a good tool to study natural scenes, but this kind of analysis reach its limits when the image is strongly irregular. On the opposite, the multifractal analysis is the perfect tool to analyze signals having a highly varying regularity from point to point.

It is to circumvent all these problems and to bring a new approach to the segmentation of remote sensing images that we propose a method based on the analysis of the fractals components of the image. No *a priori* knowledge of the image is required and it enables to study simultaneously the local and global regularity of a signal by the means of the Hölder exponent and the multifractal spectrum. The singularities often carry most of the information contained in a signal. It is generally possible, for a human being, to determine the nature of an object only from its boundaries and its texture. Many works are dedicated to the analysis of the "high frequencies" components of an image. Edge density, Zero crossing analysis and every method based on the gradient of an image are not efficient to characterize textures sufficiently well to give satisfactory segmentation results for this type of image. They do not take into account the nature of the singularities of the signal nor even their spatial distribution, while the multifractal analysis does.

In a first section we will recall the basics of the multifractal analysis, then we will describe the proposed segmentation method and finally, before concluding, we will comment and expose some results which are compared to classical segmentation results.

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2. MULTIFRACTAL ANALYSIS BASICS

The multifractal formalism was created to describe the properties of very turbulent systems with change in scale. It is the case, in particular, in the study of fluids turbulences in physics, (Grassberger and Procaccia, 1983) or (Frisch and Parisi, 1985). It is used to describe the local behaviour and nature of the singularities of irregular functions in a geometrical or statistical way. A more complete theoretical description of the multifractal analysis can be found in (Abry *et al*, 2001; Lévy-Vehel *et al*, 2001).

2.1 Regularity and Hölder exponent

The concept of specific regularity, in a point x_0, was created to quantize, using a positive real number α, the "roughness" of the graph of a function in this point. The Hölder regularity is a generalization of the concepts of derivability and continuity of a function. It is defined as following:

Let α be a positive real number and $x_0 \in \Re$; a function $g : \Re \to \Re$ is said to be $C^{\alpha}(x_0)$ if it exists a polynomial P with maximum degree $[\alpha]$ such that:

$$\left| g(x) - P(x - x_0) \right| \le C \left| x - x_0 \right|^{\alpha} \tag{1}$$

where $[\alpha] = \alpha - 1$ if α is an integer.
Therefore, the regularity of a function g is computed using an estimation of the maximum difference of g with respect to a polynomial P of degree lesser or equal to $[\alpha]$.

From the definition of the regularity we can define the Hölder exponent α_g of a function g as:

$$\alpha_g(x_0) = \sup\left\{ \alpha : g \ is \ C^{\alpha}(x_0) \right\} \tag{2}$$

Thus, from its definition, it is obvious that the Hölder exponent can characterize the regularity of a function g in each point.

2.2 The singularity spectrum

The multifractal analysis is generally used to study signal without any *a priori* knowledge on its nature. It is a very useful tool to describe and analyze the variations of the local regularity of an unspecified signal. Most of the time it is used to characterize the regularity of highly irregular signals whose singularity spectrum is not a single point. The singularity spectrum of such signals is function of time, contrary to (mono)fractals signals which are entirely characterized by single exponent. These signals are called multifractal because they are characterized by infinity of fractal sets. Those sets have to be studied in order to deduce the signal singularity spectrum.

This spectrum is a global description of the singularities distribution. It exist various singularity spectrum types according to whether one uses a statistical or geometrical approach to estimate it. They all try, as well as possible, to approach the theoretical singularity spectrum by using different methods (Berroir, 1994). One of them is called the large deviation spectrum f_G and its definition is given below. The proposed algorithm is based on this spectrum.

To obtain the large deviation spectrum, we first have to compute the Hölder exponent for each point of the signal. From the image of Hölder exponents, we extract the fractal component sets F_α which are formed by the points having the same Hölder exponents: $F_\alpha = \left\{ \vec{x} : \alpha_g(\vec{x}) = \alpha \right\}$. In practice, this spectrum can be calculated by using the widened spectral components F_α^ε based on a quantization of α_g noted α_ε:

$$F_\alpha^\varepsilon = \left\{ \vec{x} : \alpha - \varepsilon \le \alpha_g(\vec{x}) < \alpha + \varepsilon \right\}, \tag{3}$$

because the number of different exponents can be large. The spectrum is then obtained by the following formula:

$$f_G(\alpha) := \lim_{\varepsilon \to 0} \limsup_{r \to 0} \frac{\log N_r(\alpha_\varepsilon)}{\log \frac{1}{r}} \tag{4}$$

where $N_r(\alpha_\varepsilon)$ is the number of balls C of size r which contain a Hölder exponent α_ε, so:

$$N_r(\alpha_\varepsilon) = \#\left\{ \vec{x} : \alpha \in \left[\alpha - \varepsilon, \alpha + \varepsilon \right] \right\}. \tag{5}$$

This is equivalent to the computation of fractal dimension of each fractal component F_α^ε. Thus, the large deviation spectrum can be approximated by using the box dimension of the fractal component sets, which is the slope of the points whose coordinates are $(\log r, -\log N_r(\alpha_\varepsilon))$.

The spectrum f_G is a statistical approach of the multifractal spectrum and can be interpreted as the probability of finding a Hölder exponent of order α in a ball of radius r centred in x_0. This is equivalent to:

$$P(\alpha_g(x_0) \sim \alpha) \sim r^{f_G(\alpha) - 1} \tag{6}$$

The aim of the multifractal formalism is to establish a strong relation between the different multifractal spectra. If one makes the assumption, not proved in our case, that the multifractal formalism holds, then $f = f_G$, but in a more general way: $f \le f_G$, where f is the theoretical spectrum.

2.3 The wavelet transform and the Hölder exponent

The Fourier transform is a powerful tool for studying the singularities of a signal, but it is only possible to perform a global analysis. Thus, it is not adapted to analyze the spatial distribution of discontinuities. However, the wavelet transform (Daubechies, 1992) enables to locally analyze a signal in time and frequency, and therefore to compute the local regularity of a signal.

In (Abry *et al*, 2001), it is shown that the continuous wavelet transform is an efficient tool for the computation of the Hölder exponent of a signal. For an accurate estimate of the Hölder exponent of a function, it is better to use only the maxima lines of the wavelet coefficients (the Wavelet Transform Modulus Maxima method) as introduced in (Mallat and Hwang, 1992; Muzy *et al*, 1993).
However, for the segmentation of an image, we need to estimate this exponent in each point of the image; therefore this method is not appropriate. Moreover, it is not the accuracy of the estimation which is important in our case, but rather the discriminating power of the resulting multifractal spectrum.

The choice of the wavelet basis is important. It should have a sufficiently large number of vanishing moments to eliminate the polynomial trends present in the signal. These polynomial trends are sometimes so important that it is impossible to study the local singularities of the signal. The more the wavelet basis has vanishing moments, the larger the degree of the polynomial we can get rid off. The wavelet basis must also have a relatively small support size, in order to preserve the local aspect of the analysis. It is desirable that the value of the wavelet transform of a function in a point depends only on the values of this function in its vicinity. A more complete study on the choice of the wavelet basis is made in (Turiel, 1998).

It was proved that for a multifractal signal g, its wavelet coefficients d_g are such that at the location $\vec{x}$ and for the scale r, we have:

$$E\left|d_g(\vec{x},r)\right|^2 \sim r^{2\alpha+1} \text{ when } r \to 0\,, \tag{7}$$

where $E\left|d_g(\vec{x},r)\right|^2$ is the mean of the squared wavelet coefficients.

Thus, the wavelet coefficients follow a power law and the Hölder exponent can be estimated as the slope of the regression line of the points $(\log r, \log(E\left|d_g(\vec{x},r)\right|^2))$. Therefore, according to the definition of the Hölder regularity, it is the decrease of the amplitude of the wavelet coefficients through the scales which characterizes the local regularity of a signal.

3. THE PROPOSED SEGMENTATION ALGORITHM

3.1 Principle

The proposed algorithm is based on the idea that an image can be divided into sets of points having a similar singularity spectrum. We make the assumption that a texture is a particular combination of Hölder exponents. In other words, a texture consists of singularities and the nature and the spatial distribution of these singularities are enough to entirely characterize this texture.

The proposed method is based on the estimation of the spectrum f_G in each point of the image. The formulas given in the previous sections are used. The spectrum is not computed on the whole image, but on a sliding window of fixed size. During the computation of the spectrum we also introduce a weighting filter. It represents the distance of the point studied compared to the nearest singularity. Its coefficients are computed as follows:

$$weight = \frac{1}{dist(\vec{x}_c, \vec{x}_s) + 1} \tag{8}$$

where $\vec{x}_c$ and $\vec{x}_s$ are the coordinate vectors of respectively, the pixel for which we compute the spectrum and the nearest singularity location. $dist(\vec{a},\vec{b})$ corresponds to the Euclidean distance between vectors $\vec{a}$ and $\vec{b}$.

This weighting filter was introduced in order to prevent all the points in the neighbourhood of a singularity to have the same spectrum. To some extent, this factor takes into account the neighbourhood of the singularity by affecting a decreasing weight according to the distance.

Obviously, the local analysis of a signal is very important, because an image is made of several thematic classes, each one having its own texture. If a particular discontinuity is rather rare in a class, it can be much more frequent in another. Locally, the histogram of the singularities of a texture can be very different according to the class that is studied. Therefore, to achieve a good segmentation result, it is necessary to take account of both, the strength and the spatial distribution of the singularities.

An interesting advantage of the multifractal analysis is that it is completely independent of the grey level values of the image. Therefore, it is not affected by the low frequency variations of the grey levels within a class. As this method is based on the local spectrum multifractal, we name it the LMS method in the remainder of this article. In (Arduini *et al*, 1991; Kam and Blanc-Talon, 1999), methods of image classification based on multifractal tools were proposed and give interesting results based on different ideas.

The method that we propose is unsupervised and is based on the k-means clustering algorithm, therefore only the number of classes in the image is required as input to the method.

3.2 The method parameters

The first step of this algorithm is the computation of the wavelet transform of the image. A two-dimensional "Mexican hat" wavelet is used, but other tests with the Morlet wavelet lead to similar results. We chose to use the continuous wavelet transform rather than the discrete one because it better fits the needs for the analysis, which are a high degree of accuracy and invariance under translation. The redundant information present in the continuous wavelet transform enables to compute more robust estimators, and thus to have a better stability of the estimate. Tests showed that 5 to 8 levels of decomposition were sufficient to obtain good segmentation results. The Hölder exponents were computed for each point of the image by linear regression on a neighbourhood of 16 by 16 pixels. The large deviation spectrum was computed for each point of the image by the box method over a 32 by 32 pixels window. The number of quantization values of the fractal components was fixed to a reasonable value to avoid a too long computing time. The singularity spectrum values in each point are the input to a k-means algorithm.

All the parameters of the LMS algorithm were fixed in an empirical way. The choice of the sizes of the neighbourhood and of the studying windows results from a compromise between the processing time and the quality of the results. However, the size of the neighbourhoods is strongly related to the characteristic dimension of the objects that have to be detected in the image. The automatic estimation of all these parameters will be the subject of future work, so that the segmentation algorithm will be completely automatic.

4. RESULTS AND COMMENTS

In order to appreciate the contribution of the LMS method, we compare the results with those obtained by the grey-level co-occurrence method (Haralick *et al*, 1973) and by the Laws filters method (Laws, 1980). We use only six of Haralick texture parameters: energy, entropy, dissimilarity, contrast, homogeneity and the correlation. The Laws filters of size 5 are used, then the energy measures used for the segmentation are computed by averaging the output of the filters on a square window of size 15. Then, for each method, the computed parameters are used as input to the k-means algorithm.

We initially carried out tests on images of the brodatz set of textural images, then on a very high spatial resolution image of a forestry scene. The results obtained for each image are then compared with those resulting from the analysis based on the grey-level co-occurrence matrices. The results are compared by means of percentage of good classification in the case of the brodatz image, and qualitatively in the case of the satellite image. A ground truth map of this region will be done in a future work. This will enable the computation of classification rates for the IKONOS image. This map will be realized by image-interpretation.

4.1 The brodatz image

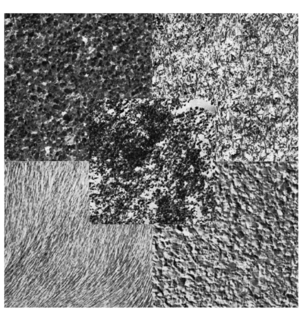

Figure 1. Image created from 5 brodatz texture images

The brodatz set of textural images provides many images of natural textures. Some of them are rather close to what can be seen in our IKONOS image. That is why we chose them to try out our algorithm. They are usually used in the field of the textural analysis, and thus it is easy to compare the results provided with those presented in other articles. We have created an image of 500×500 pixels with 5 different textures from the brodatz set of natural textures (D29, D93, D100, D9 and D4), see Figure 1.
The results given by the three methods are presented in Figure 2, Figure 3 and Figure 4.

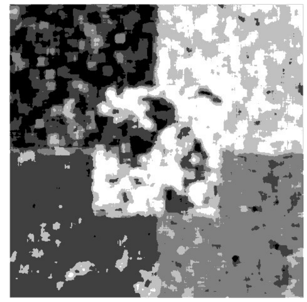

Figure 2. The grey-level co-occurrence matrices

Figure 3. The Laws Filters

Figure 4. The LMS method

We noticed that the LMS method gives more homogeneous and compact segments and that the rate of classification is much better. The Laws filters method is not efficient for the central texture because it is a very chaotic texture which can be easily confused with the others. The grey level co-occurrence method can not differentiate some of the classes and gives the worst results.

Method used	Classification results (in %)
LMS algorithm	81
Grey level co-occurrence	57
Laws filters	67

Table 1. Classification results on the brodatz image

4.2 The IKONOS image.

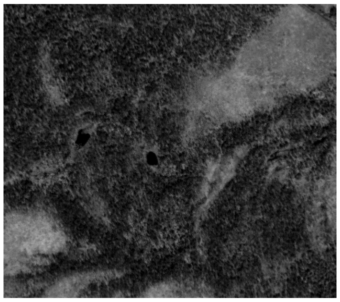

Figure 5. The IKONOS image of a forestry zone

The goal of this work is to perform an efficient classification of forestry scenes and more particularly to segment the forest in tree density classes. The classes of density of trees are visually very close from one to another; they differ only by their high frequency distribution.

A test was carried out on a IKONOS panchromatic image of 635×563 pixels which represents a forest scene of Labrador (Figure 4). On this image we can clearly distinguish different tree density classes, two lakes and non-stocked zones. We chose to fix the number of classes to 5: 3 different tree density classes (from dense to sparse), a class for the clear land and a class for the lakes. The results are given in the Figure 6, Figure 7 and Figure 8.

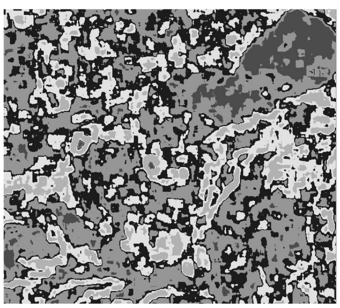

Figure 6. The Haralick parameters

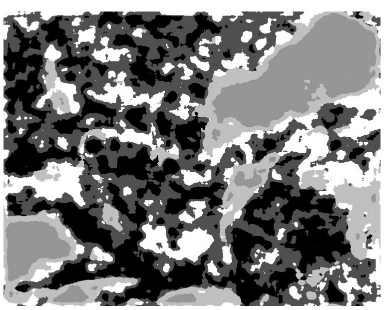

Figure 7. The Laws Filters

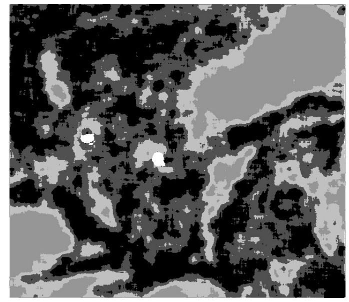

Figure 8. The LMS method

From these results, it clearly appears that the proposed algorithm gives more homogeneous segments and that the 3 tree density classes can easily be differentiated (Figure 8). Furthermore, the results given by the analysis based on the Haralick texture parameters are very heterogeneous. The lakes are not detected and the density classes as well as the "non-stocked" class are completely mixed (Figure 6). Generally, the obtained classes do not seem to correspond to those which one can visually detect in the IKONOS image. The Laws filter approach gives homogenous results but the lakes are missed and confusion exists between the tree density classes.

5. CONCLUSION

We have seen that the method based on the multifractal analysis, that we propose, gives good results in the case of IKONOS image, but also with brodatz textures. The tree density classes appear clearly and the non-wooded zones and the lakes are well detected. The LMS method uses only the high frequencies to classify the image. It would be interesting to integrate additional information, such as low frequencies, to the approach. This could help to identify regions with smooth textures, and to differentiate classes having very little local grey level variability but very different mean values. The multifractal analysis is an interesting tool for the texture analysis because it enables to characterize the singularities in a local and global way. However, the parameters required for the algorithm are not easy to compute automatically. A study on the automatic estimation of these parameters will be considered in a future work. It is also envisaged to use other classification methods than the K-means in order to see the possible profits in term of percentage of classification. Preliminary tests on the use of the Legendre spectrum are also in hand and give promising results.

A ground truth image is to be produced by a photo-interpreter so that it will be possible to quantitatively measure the effectiveness of the method on the IKONOS images at our disposal.

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