Colour Textures Discrimination of Land Images by Fractal Techniques

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Abstract: - Many land images can be considered as textured ones. In this paper we will demonstrate that the fractal dimension can be considered an efficient feature in texture classification. Fractal dimension is evaluated by box counting algorithm from binary image type. In the grey level case, an average fractal dimension is proposed. The average is made on several fractal dimensions calculated for binary type images obtained from the original image for specified segmentation thresholds. Also, we introduced the notion of improved fractal dimension (IFD) which is more efficient for texture classification than fractal dimension (FD). IFD is calculated by elimination of a constant zone which appears in all textured images. In the colour texture case, we proposed the classification method based on minimum distance between the vectors of the improved fractal dimension of the fundamental colour components. The experimental results made on three land textured images (asphalt, stone, grass) validate that IFD offers a grater discriminated power than FD.

Key-Words: -Land image classification, Fractal dimension, Box-counting algorithm, Texture classification, Minimum distance criterion, Grey level images, and RGB components

1 Introduction

The texture can be considered as a structure of repeated primitives, named *texels or textons*, in some regular relationships. These components do not appear enumerable. Wilson [3] points out that textured regions are spatially extended patterns based on more or less accurate repetition of some unit cells; the origin of the term is related with the craft of weaving. Gonzalez [1] relates texture to other concepts like smoothness, fineness, coarseness, graininess and describes the three different approaches for texture analysis: statistical, structural and spectral. Texture segmentation and classification are two important sides of texture analysis. The process called texture classification involves deciding what texture class an observed image belongs to. Because texture has many different dimensions and characteristics there is no single mathematical method of texture representation and classification that is everywhere adequate. The methods include grey level histograms, co-occurrence matrices, spatial autocorrelation functions, fractals, Fourier transforms, convolution filters, etc. The most utilized statistical method to textured image analysis is based on features extracted from the grey-level co-occurrence matrix, proposed by Haralick in 1973 [8].

Like the grey-level co-occurrence matrices, the fractals are two spatial analytical techniques used to measure geometric complexity [6] and conveniently describe many irregular, fragmented patterns found in nature. Thus, the fractal based texture analysis is another approach that correlates texture coarseness and fractal dimension. A fractal is defined [5] as a set for which Hausdorff-Besicovich dimension is strictly greater than the topological dimension and lesser than geometrical dimension.

The focus of this paper is the analysis and classifications of textural color images based on fractal dimension with box-counting algorithm. To increase the discriminating power, we propose a fractal dimension evaluation that considers only the differentiating points in the box counting algorithm. We called this *improved fractal dimension* (D_{if}). We define D_{if} for the RGB components as features in the texture classification process.

The rest of the paper is organized as follow. Section 2 describes the modalities of the utilization of the fractal dimension estimators like features in the texture classification process. Section 3 presents the notion of improved fractal dimension (notion introduced by the authors) like texture feature. Section 4 discusses a case study on a road analysis application, which validates the theoretical contribution of the authors. Finally, a section of conclusion outlines the results of the research work, the advantages, limitations and possible applications.

2 Fractal Dimension as Texture Discriminator

There are a number of methods proposed for estimating the fractal dimension *D*. One method is box-counting algorithm that assumes determination of fractal dimension as function of the evolution of the object size in connection with the scale factor. For the box counting basic algorithm, the image must be binary type. The method consists in dividing the image, successively, in 4, 16, 64, etc. equivalent sub-images. If (1/*r*) is the order of the dividing process on x and y axes (lattice of grid size *r*) and *N(r)* is the number of squares covered by the object image (containing pixels with value 1) same size squares and computing every time, where r is the step size. The dividing process is limited by the image resolution. This procedure will provide a set of points in a graphical representation, defined by the logarithmic coordinates *(log(1/r), log(N(r)))*. A linear regression is performed using the logarithmic coordinates (1). The regression slope *a* is used to determine the box counting fractal dimension *FD* (2).

$$y = a\,x + b \qquad (1)$$

$$a = FD = \frac{n \sum_{i=1}^{n} x_i y_i - \left(\sum_{i=1}^{n} x_i\right)\left(\sum_{i=1}^{n} y_i\right)}{n \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \qquad (2)$$

The notation significances in equation (1) are the following: $x_i = \log_2 (1/r_i)$, $y_i = \log_2 (N(r_i))$, n – number of partitions, $i = 1,2,3,\ldots,n$ – the function points in the graphical representation.

A number of different fractal dimension estimations of textured images, based on box counting algorithm, are used.

Firstly, applying the box counting algorithm to the contour image extracted from binary image, the fractal dimension FD is evaluated.

Towards evaluating the fractal dimension of a grey level image, we applied the box-counting algorithm to contours extracted from the binary images which are obtained by different thresholds. Because the binary image (and also the fractal dimension) depends on the threshold, we used in our algorithm all the significant grey levels contained in the image. The fractal dimensions computed for every grey level can be represented into a graphic named fractal dimension spectrum. We can consider the average of the nonzero fractal dimensions, or the plateau region of the graphical representation like fractal dimension for grey level image. The proposed algorithm calculates the mean fractal dimension *MFD* (3):

$$MFD = \frac{1}{k}\sum_{j=1}^{k} FD_j \qquad (3)$$

The algorithm, which was implemented in MATLAB, consists of the following steps:

1) Reading and converting of the color image in 256 grey levels;
2) Converting of the 256 grey levels image to a binary level image using a fixed threshold T_j;
3) Extraction of the image contour using 3x3 neighborhoods;
4) Computing of the fractal dimension FD_j, from the contour image, applying the box-counting algorithm;
5) Iteration of the steps 1-4, for j = 1,…,*k*;
6) Determination of *MDF* from equation (2).

In the colour image case, we considered the natural decomposition by R, G, and B components. For each component we calculated the average fractal dimension by means of the preceding algorithm: MFD_R, MFD_G, and MFD_B. These features are utilized as features in the texture classification process.

3 Colour Texture Classification Based on Improved Fractal Dimension

In the colour image case, the fractal analysis is made on the fundamental components R, G, B. For each component, the grey level box counting algorithm is applied. In order to increase the discriminating power in texture classification applications, we introduce the notion of improved fractal dimension.

For every logarithmic graphical representation *(log(1/r), log(N(r)))* in the textured image cases, one can observe that there is a beginning zone of the curve which is identically with a line segment of slope 2 (namely, all dividing squares contain pixels with value 1). Therefore, we propose to renounce to this zone when it is calculate the fractal dimension by box counting algorithm. Thus, the result is a new estimated value for fractal dimension, which we called *Improved Fractal Dimension* (*IFD*). The *IFD* values are less than *FD* values, but the relative differences between two different textures are grater in the *IFD* case than in the *FD* case. For texture classification purpose, this aspect will conduct to a grater discriminating power of *IFD* than *FD*.

In order to exemplify the difference between *IFD* and *FD*, we can consider the log-log representation for R component of the I_1 image (Fig.1). Let *v* the division vector (values of 1/*r*) along the horizontal and the vertical coordinates, and *w* the corresponding vector of *N(r)* values:

v = [2 4 8 16 32 **64** **128** **256** **512**]

w =[4 16 64 256 1024 **4079** **13621** **30138** **51816**]

If:

$$x = \log_{10}v,\ y = \log_{10}w,$$

x = [0.301 0.602 0.903 1.202 1.505 **1.806 2.107 2.408 2.709**]

y = [0.602 1.202 1.806 2.408 3.010 **3.610 4.134 4.479 4.714**]

then, *FD* is calculated by equation (3), where *n* = 9, from *x* and *y* vectors, and the numerical result is:

$$FD = 1.781$$

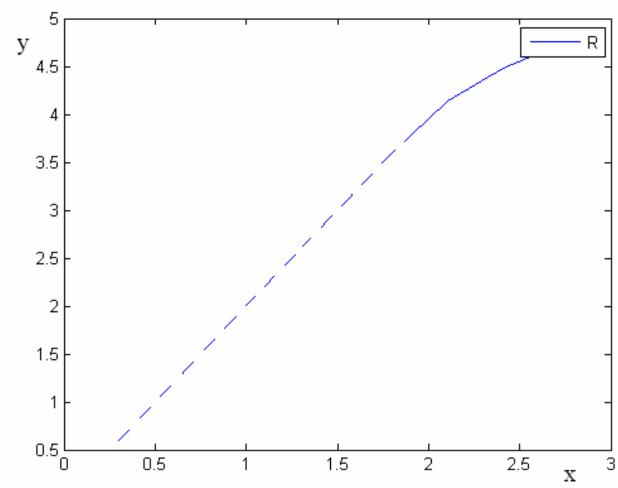


Fig.1. Log-log representation for R component of the I_1 image.

For *i* = 1,2,3,4,5, one can observe that *y(i)* = 2 *x(i)*, i.e. the slope is 2. If we disregard these points it is obtined two shorter set of points, x_1 and y_1, from which it is calculated IFD. The new log-log diagram is presented in Fig.2. For fractal dimension evaluation, the algorithm is the same, but n = 4.

x_1 = [1.81 2.11 2.41 2.71]

y_1 = [3.60 4.13 4.47 4.71]

The result, *IFD*, is less than *FD*:

$$IFD = 1.215$$

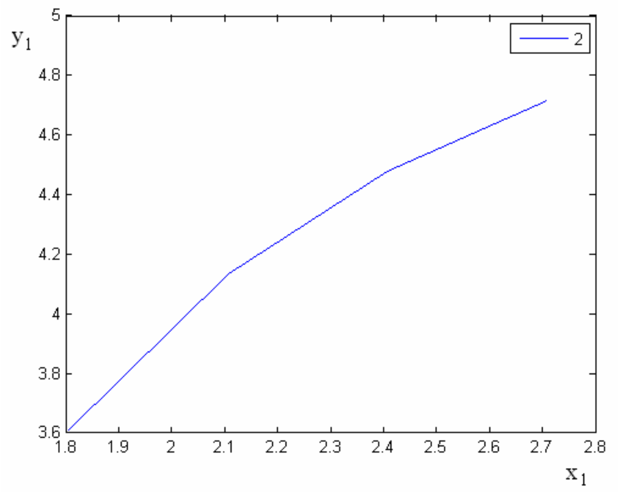


Fig.2. Log-log reduced representation for R component of the I_1 image.

In order to classify textures, based on fractal analysis, we considere the fractal dimension vectors of the colour components of the image (R, G, B):

$$IFD = [IFD_R, IFD_G, IFD_B,] = [F_R, F_G, F_B] \quad (4)$$

For two images (I_1, I_2), the euclidian distance between the feature vectors of fractal dimensions is represented by the following equation (5):

$$D_f(I_1, I_2) = \sqrt{(F_{R2}-F_{R1})^2 + (F_{G2}-F_{G1})^2 + (F_{B2}-F_{B1})^2} \quad (5)$$

Thus, the classification of the colour textures is made by minimum distance criterion.

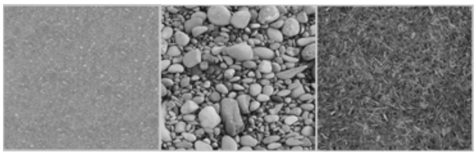
4 Experimental results

With the purpose of validating the efficiency of IFD in colour texture classification, we considered the images from Fig.3: I_1 - asphalt, I_2 - stone, I_3 – grass, and another asphalt image – I_4.

Each analized image is decomposed in its colour fundamental components: Red R, Green G, and Blue B (Fig.4). From these components we calculated the fractal dimension vectors FD (6) and IFD (4), where:

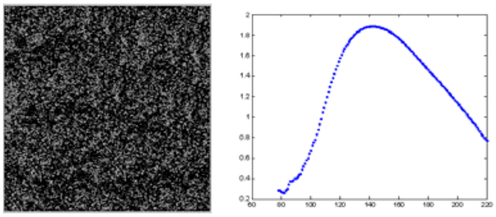
$$FD = [FD_R, FD_G, FD_B,] \quad (6)$$

For each component, the algorithm is like in the grey level case.

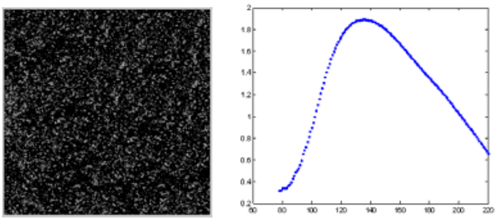


I_1 I_2 I_3

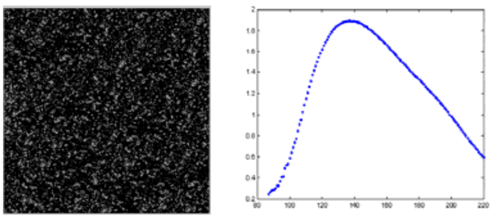
Fig.3. Textured images: I_1 - asphalt, I_2 - stone, I_3 - grass.



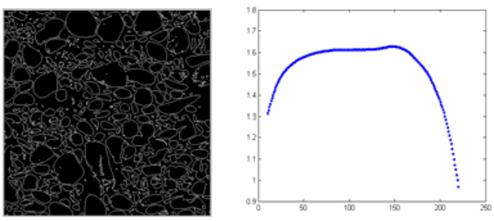
a. The red contour image from I_1; Spectrum of fractal dimension for red component of I_1



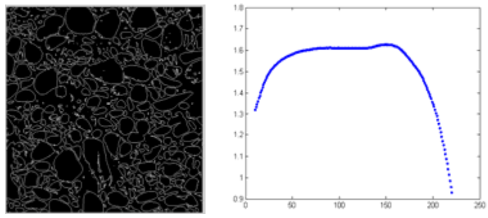
b. The green contour image from I_1; Spectrum of fractal dimension for green component of I_1



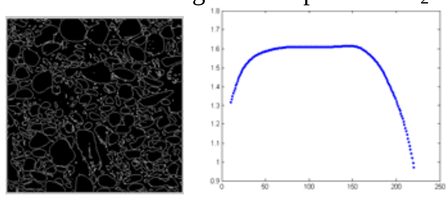
c. The blue contour image from I_1 ; Spectrum of fractal dimension for blue component of I_1



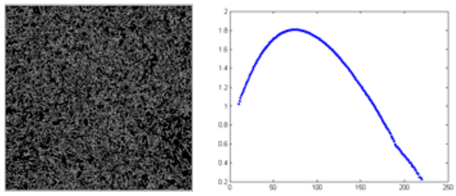
d. The red contour image from I_2; Spectrum of fractal dimension for red component of I_2



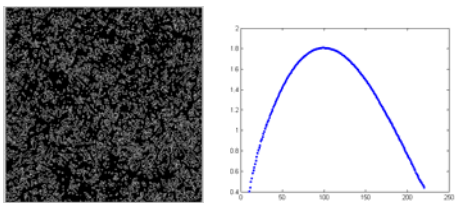
e. The green contour image from I_2 ; Spectrum of fractal dimension for green component of I_2



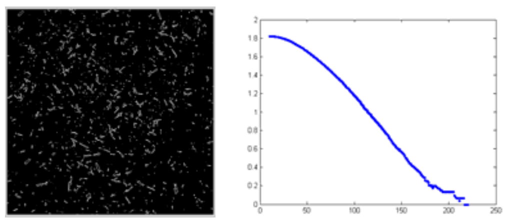
f. The blue contour image from I_2 ; Spectrum of fractal dimension for blue component of I_2



g. The red contour image from I_3; Spectrum of fractal dimension for red component of I_3



h. The green contour image from I_3; Spectrum of fractal dimension for green component of I_3



i. The blue contour image from I_3 ; Spectrum of fractal dimension for blue component of I_3

Fig.4. Decomposition of images in RGB components.

The experimental results are presented in Table 1.

Also, we calculated the euclidian distances like (5) between I_1 and I_2 (D_f (I_1 , I_2) – for FD, and

$D_{if}(I_1, I_2)$ for IFD), between I_1 and I_3 ($D_f(I_1, I_3)$ – for FD, and $D_{if}(I_1, I_3)$ for IFD), between I_1 and I_4 ($D_f(I_1, I_4)$ – for FD, and $D_{if}(I_1, I_4)$ for IFD). It can be observed that the distance between two images with different textures (I_1, I_2 or I_1, I_3) is grater than the distance between two images with similar textures (I_1, I_4), both in the FD case and IFD case. However, IFD offers a grater discriminating power than FD, because of the following reasons:

- IFD is less than the corresponding FD,
- The distances between two images with different textures are grater in the IFD case than in the FD case,
- The distance between two images with similar textures is less in the IFD case than in the FD case.

Table1. Fractal dimension and improved fractal dimension for color components of the images I_1, I_2, I_3

Image	Threshold (T)	Fractal dimension *FD*	Improved fractal dimension *IFD*
I_1 – R	160	1.781	1.215
I_1 – G	160	1.680	0.967
I_1 – B	160	1.674	0.956
I_2 – R	120	1.614	1.175
I_2 – G	120	1.610	1.169
I_2 – B	120	1.608	1.172
I_3 – R	80	1.804	1.295
I_3 – G	80	1.745	1.369
I_3 – B	80	1.403	1.010
I_4 – R	160	1.796	1.219
I_4 – G	160	1.668	0.958
I_4 – B	160	1.679	0.950

$$D_f(I_1, I_2) = 0{,}190, \quad D_{if}(I_1, I_2) = 0{,}295,$$

$$D_f(I_1, I_3) = 0{,}280, \quad D_{if}(I_1, I_3) = 0{,}414,$$

$$D_f(I_1, I_4) = 0{,}02, \quad D_{if}(I_1, I_4) = 0{,}011$$

5 Conclusion

Fractal dimension can be used occasionally to discriminate between textures in land image applications. The classification method based on box counting algorithm implies a less calculus amount than the method based on the co-occurrence matrices. Average of fractal dimensions for significant binary thresholds, both in the grey level case and also in the colour case, gives good results.

We can observe that the improved fractal dimension has a grater discriminated power in texture classification than current fractal dimension, and is easier to evaluate. Improved fractal dimensions for RGB components constitute significant features for land image classification and interpretation.

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