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Texture analysis by multi-resolution fractal descriptors

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ABSTRACT

This work proposes a novel texture descriptor based on fractal theory. The method is based on the Bouligand–Minkowski descriptors. We decompose the original image recursively into four equal parts. In each recursion step, we estimate the average and the deviation of the Bouligand–Minkowski descriptors computed over each part. Thus, we extract entropy features from both average and deviation. The proposed descriptors are provided by concatenating such measures. The method is tested in a classification experiment under well known datasets, that is, Brodatz and Vistex. The results demonstrate that the novel technique achieves better results than classical and state-of-the-art texture descriptors, such as Local Binary Patterns, Gabor-wavelets and co-occurrence matrix.

1. Introduction

Fractal theory plays a fundamental role as an auxiliary tool in the solution of problems in areas as different as Medicine (Lopes et al., 2010; Lorthois & Cassot, 2010; Tian-Gang, Wang, & Zhao, 2007), Physics (Chen, Chang, Weng, & Hung, 2010; Han, Wang, & Zhou, 2008; Scarlat, Mihailescu, & Sobetkii, 2010), Engineering (Chappard et al., 2003; Das, Agrawal, Gupta, Gupta, & Rastogi, 2009; Wool, 2008), among many others. Particularly, in tasks involving texture analysis, fractal geometry is a powerful modeling tool, achieving interesting results in the description and discrimination of such textures.

In the last two decades, some different fractal approaches to deal with texture analysis have arisen, for instance, multifractals (Harte, 2001; Lashermes, Roux, Abry, & Jaffard, 2008; Lovejoy, Garrido, & Schertzer, 2000), the multiscale fractal dimension (Costa et al., 2000; Manoel, da Fontoura Costa, Streicher, & Müller, 2002), the fractal descriptors (Backes, Casanova, & Bruno, 2009; Bruno, de Oliveira Plotze, Falvo, & de Castro, 2008; Florindo, De Castro, & Bruno, 2010; Plotze et al., 2005), among others. Here, we are interested in the fractal descriptors approach.

The main idea of fractal descriptors is to extract a set of features from the estimation of fractal dimension under different scales. Generally, the fractal dimension is based on a power-law relation which expresses the fractality of a structure as a function of measure scale. Unlike the fractal dimension which is a single value, the fractal descriptors are computed over the whole power-law curve.

An example that illustrates the power of fractal descriptors is showed in Backes et al. (2009). In that solution, the values in the power-law of Bouligand–Minkowski fractal dimension are used to compose a feature vector to discriminate among plant leaf textures. Actually, this method demonstrates to be successful in the discrimination of natural textures. Such kind of texture present an intrinsic self-similarity property which is notedly well represented by fractal modeling.

Despite their good results, conventional Bouligand–Minkowski fractal descriptors present still a limitation in the representation of textures, mainly when these textures present a higher degree of complexity. This limitation is due mainly to the fact that the descriptors are obtained from the global image, without a more specific treatment of local characteristics present in any real image. Thus, we can obtain more information by estimating those descriptors in different scales over the image.

Considering this assumption, the present work proposes a novel solution to extract fractal descriptors from a texture based on Bouligand–Minkowski method. Here, we propose the estimation of Bouligand–Minkowski descriptors at different scales (decomposition levels) of the image. The idea is to decompose recursively the image into 4 equal parts and, in each recursion step, we calculate an average and a deviation of the Bouligand–Minkowski descriptors. Thus, from both average and deviation descriptors, we extract entropy measures and compose the feature vector for the texture image.

The method is tested over well-known benchmark texture datasets in a classification task and the results are compared to classical and state-of-the-art texture features methods in the literature, like Gabor wavelets (Manjunath & Ma, 1996), Local Binary Patterns (LBP) (Pietikäinen, Hadid, Zhao, & Ahonen, 2011), Laws energy (Laws, 1984), Gray Level Difference Matrix (Weszka, Dyer, & Rosenfeld, 1976), etc. The results confirmed the better accuracy of the proposed technique and pointed to the possibility of using the proposed method in a large number of problems involving the description and/or discrimination of textures.

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This work divided into seven sections, including this introduction. The following provides mathematical background of fractal theory. The third section shows the original Bouligand–Minkowski fractal descriptors. The fourth presents the proposed method. The following explains the experiments. The sixth shows the results of experiments and the final section does the conclusions.

2. Fractal descriptors

Fractal geometry has been applied to a large extent of problems in several areas (Chappard et al., 2003; Scarlat et al., 2010; Tian-Gang et al., 2007). Actually, this geometry is more flexible than Euclidian classical approach to describe and identify a natural and complex object.

The most used fractal measure in the literature is the fractal dimension. This value captures the complexity of a fractal object or, still, its spatial occupation. Furthermore, these properties are also related to the visual aspect of a texture image. Thus, fractal geometry enables a link between the mathematical relations inside a pixel structure and the subjective concept of visual distinction. This link turns fractals into a particularly interesting tool to represent and describe textures.

The fractal dimension is estimated for real-world objects through the following expression:

$$D(X) = \lim_{\epsilon \to 0} \frac{\log(N(\epsilon))}{\log\left(\frac{1}{\epsilon}\right)}, \quad (1)$$

where N is some kind of complexity measure and ϵ is the scale over which the measure is taken.

Here, we use a particular method called Bouligand–Minkowski, in which the texture image is mapped onto a surface, being the (x,y) coordinates the image dimension and the height z the intensity of the pixel at that point in the image. Therefore, this surface is dilated by a sphere with a variable radius ϵ and, for each radius, the dilation volume $N(\epsilon)$ is computed. In this way, the fractal dimension is estimated by applying Eq. (1). Fig. 1 illustrates the process.

Although fractal dimension analysis has achieved great results, it is a unique value to describe all the richness of a complex image. Moreover, fractal dimension is scale-dependent. This aspect compromises its robustness to describe a global aspect of the object. In this context, the literature has presented other fractal approaches to describe texture images. Among such approaches, an efficient method are the fractal descriptors. This solution employs the whole $\log(\epsilon) \to \log(N(\epsilon))$ curve to compose the feature vectors of the image. These values may be used directly or after some kind of specific transform (Bruno et al., 2008; Florindo & Bruno, 2011; Florindo, Backes, de Castro, & Bruno, 2012).

Here, we used the fractal descriptors based on the Bouligand–Minkowski dimension, which obtained excellent results in texture analysis, as described in Backes et al. (2009).

3. Proposed method

Here, we propose the decomposition of the original texture image into decreasing cell sizes, followed by the calculation of Bouligand–Minkowski descriptors in each cell. The idea is in some way similar to that found in some classical multiscale approaches, like discrete wavelet transform or Gaussian pyramid.

The essential idea is to divide recursively the image into four equal parts. Each step in this process constitutes a decomposition level. At each decomposition level, we take the average and the standard deviation of descriptors in each cell. Thus, we construct a feature vector from the entropy measure of such descriptors. Finally, we apply a simple attribute selection approach to the feature vector to compose the final descriptors.

We start with a digital image $I : [N \times N] \to \Re$. This image is decomposed into levels $l | 1 \leqslant l \leqslant l_{max}$, where l_{max} is the maximum possible level in the image, given by $l_{max} = \text{ceil}(\log_2(N))$. In each decomposition level, the image is partitioned into equal regions R_{ljk}:

$$R_{ljk} = \{x, y | (j-1) * 2^l \leqslant x \leqslant (j) * 2^l,\ (k-1) * 2^l \leqslant x \leqslant (k) * 2^l\}.$$

In each region R, we apply the procedure described in the above section and obtain the Bouligand–Minkowski descriptors D_{ljk}. For each level l, we obtain the average descriptors D_l^M and deviation descriptors D_l^σ:

$$D_l^M = \frac{\sum_{jk} D_{ljk}}{2^l},$$
$$D_l^\sigma = \sum (D_{ljk} - D_M(l))^2.$$

In the following, we extract entropy features from both average and deviation descriptors in each level. Initially, for each component (index) i of Bouligand–Minkowski average descriptors at all levels, we construct another vector $\varphi(\vec{i})$, that is:

$$\varphi(\vec{i}) = \left[D_1^M(i) D_2^M(i) D_3^M(i) \cdots D_{l_{max}}^M(i)\right].$$

In the same fashion, we construct the vectors $\psi(\vec{i})$, from deviation descriptors:

$$\psi(\vec{i}) = \left[D_1^\sigma(i) D_2^\sigma(i) D_3^\sigma(i) \cdots D_{l_{max}}^\sigma(i)\right].$$

Then, we compute one Shannon entropy value for each vector. In order to simplify the notation, we call u a generic vector. The entropy is estimated through:

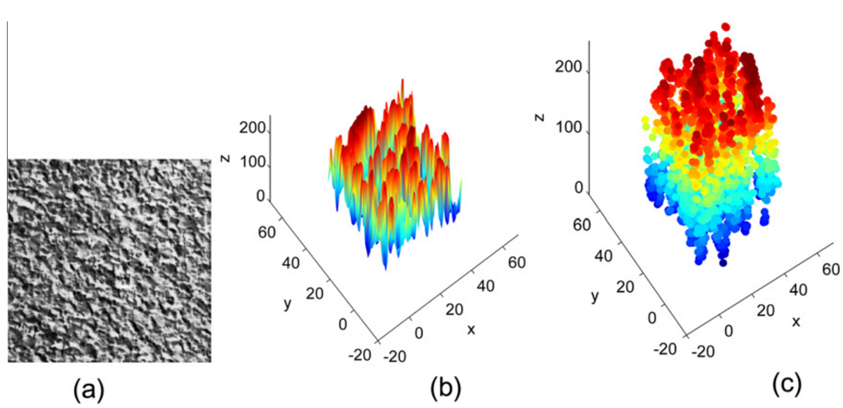

Fig. 1. Bouligand–Minkowski fractal dimension estimation. (a) Original texture. (b) The gray-level image is mapped onto a surface in $x-y-z$ coordinates. (c) Each point in the surface is dilated through a sphere with radius r.