Texture Classification Using Fractal Dimension Improved by Local Binary Patterns

André R. Backes
Faculdade de Computação
Universidade Federal de Uberlândia
Uberlândia, MG, Brazil
Email: arbackes@yahoo.com.br

Jarbas Joaci de Mesquita Sá Junior
Curso de Engenharia de Computação
Campus de Sobral - Universidade Federal do Ceará
Sobral, Ceará, Brazil
Email: jarbas_joaci@yahoo.com.br

***Abstract*—This paper presents a texture analysis method that combines Bouligand-Minkowski fractal dimension and local binary patterns (LBP) method. The LBP approach is used to obtain "pattern images" from an original input image in order to provide new information sources to be exploited by the Bouligand-Minkowski fractal dimension. Two hybrid approaches were proposed and their results are: "FD(Original image + LBP maps)" (97.12% and 63.80%) and "FD(Original image + LBP maps + STD)" (98.20% and 70.80%) for Brodatz and UIUC image databases, respectively. These results demonstrate that the proposed hybrid method provides a high discriminative feature vector for texture classification.**

I. Introduction

Since the birth of computer vision field, texture analysis has been one of its most important subjects. Texture has a great variety of definitions, once it is not possible to comprehend all the texture aspects with a single concept. For instance, [1] interpret a texture as sub-patterns repeated in its precise form or with small variations along the image. Obviously, such concept is very restrict and fits better into the artificial texture category (for instance, the image of a wall built with rectangular bricks). On the other hand, there exist a vast range of natural textures (images of smoke, bark, leaf surface etc.) that cannot be explained in this way. [2], for instance, defines them as persistent stochastic patterns with a cloud-like appearance.

Throughout the years many methods have been proposed to extract signatures from textures and it is common the literature classify them into four categories: statistical, which includes the classical co-occurrence matrices; frequency-domain (for instance, methods based on Fourier transform and wavelets); geometrical, which interprets the texture as composed of primitives; and model-based, which is based on fractal and stochastic models [3]. However, it seems that such categorization must be expanded in order to comprehend the methods proposed in recent years. For instance, we can cite approaches based on: tourist walk [4]; micro-structures [5]; complex networks [6], gravitational models [7] and so on.

In order to provide a high discriminative texture analysis method to the texture analysis field, this work proposes a hybrid approach based on local binary patterns (LBP) and fractal dimension, where LBP method is used to obtain "pattern images" from an original input image and the Bouligand-Minkowski fractal dimension is used to extract signatures from these pattern images. To explain our proposed approach, this paper is organized as follows: Sections II and III describe the LBP method and the Bouligand-Minkowski fractal dimension, respectively. Section IV shows how to combine LBP and fractal dimension in order to obtain a signature. Section V describes the texture benchmarks used in the experiments, the classification procedure, as well as the other methods used for comparison. Section VI presents the obtained results and a discussion on them, and, finally, Section VII shows some remarks about this paper.

II. Local binary patterns - LBP

First introduced by [8], local binary patterns are a highly discriminative source of texture information and have been extended to many and different approaches [9], [10]. The method examines the neighborhood of a pixel to compute the pattern code that must be associated to that pixel. Given a central pixel with gray value g_c in the image, we obtain its LBP pattern code as

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \quad (1)$$

with

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (2)$$

where g_p, $p = 1, \ldots, P$, is the gray value of its P neighbors and R is the radius of the neighborhood. As one can see, each neighboring pixel is compared to the central pixel in clockwise direction. We assign value 1 to this neighboring pixel if its intensity is greater than the central pixel; Otherwise, we assign value 0. This results in a binary sequence which is converted into a decimal value representing the LBP code of the pixel. Figure 1 shows an example of the LBP code obtained for a pixel using the traditional 3×3 rectangular neighborhood. This process is replicated to each pixel, so that the method is able to construct a histogram of code patterns that represents the texture under analysis.

ISBN 978-90-827970-1-5

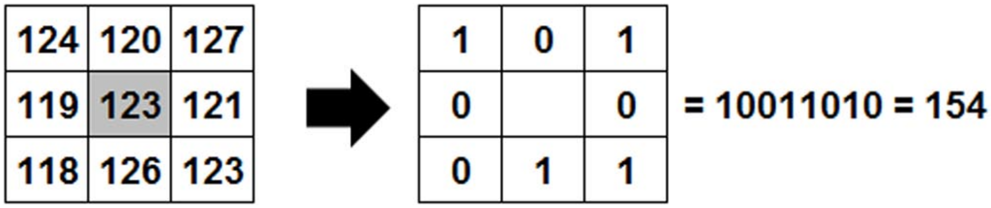

Fig. 1. Example of the LBP code obtained for a pixel using the traditional 3×3 rectangular neighborhood.

III. Fractal analysis

The literature presents different approaches to compute fractal descriptors (FD) from a texture image, as seen in [11], [1], [12]. A commonly used approach is the Bouligand-Minkowski, which is one of the most accurate methods to estimate the fractal dimension of a object [13], [11], [14]. Fractal dimension, as first introduced by Benoit Mandelbrot in 1970s, is a measure of the self-similarity of the object through the scales. This measure is also related to complexity and space occupation of the object [15], [16], [14].

For texture images, Bouligand-Minkowski method computes fractal descriptors by studying the influence volume of the pattern present in the image, which is very sensitive to structural changes in the pattern. First, the method maps a gray-level image I to a three-dimensional cloud of points C. Each point in the cloud is determined by a set of three coordinates (x, y, z) where

$$C = \{(x, y, z) | I(x, y) = z\} . \tag{3}$$

Next, each point c in the cloud point C, $c \in C$, is dilated by a sphere of radius r. This process occurs simultaneously for each point, thus resulting in the influence volume $V(r)$ of the texture pattern, where this volume is defined as

$$V(r) = \left\{c' \in R^3 | \exists c \in C : |c - c'| \leq r\right\} , \tag{4}$$

i.e., the influence volume is the sum of the points in the space whose distance from the cloud is not larger than r. As the radius r increases, spheres produced by different points start to interfere with each other, modifying the resulting influence volume. This interference depends on the value of the radius used, as well as the texture pattern under analysis. By using different radius values, we can obtain fractal descriptors directly from the influence volume $V(r)$ [14], [11] or by computing the images' fractal dimension D as

$$D = 3 - \lim_{r \to 0} \frac{\log V(r)}{\log (r)}. \tag{5}$$

IV. Combining LBP mask with fractal analysis

Traditionally, LBP method is applied over each pixel of a texture image, thus resulting in a map of LBP codes for that pattern. From this map, the method extracts a histogram of code patterns, which is used for texture classification purposes. However, histograms do not hold any spacial information about the image pixels, only the frequency that each pattern occurs. Moreover, the conversion from binary sequence to decimal code depends on the initial point used to travel the neighboring pixels in clockwise direction. The fact is that each pixel neighboring the central pixel can be used as initial point, thus resulting in 8 different LBP masks used to create the LBP map, as shown in Figure 2.

Figure 3 shows that by computing the 8 possible LBP maps from a texture pattern one can see that they hold not only spatial information, but that they are significantly different from each other. These differences are due to the emphasis that each LBP mask gives to the pattern present in the image in terms of orientation. Such information is not considered when a histogram is used to represent the LPB map.

To take advantage of the spatial information present in the LBP map, we propose to extract fractal descriptors (FD) from each map. Fractal analysis, as described in Section III, enables us to measure how regular/irregular an image pattern is, i.e., how homogeneous (or heterogeneous) the distribution of pixel is. To accomplish that, we propose to estimate the fractal dimension as the descriptors of the image. On one hand, we must emphasize that fractal dimension is a property of fractal objects and it is related to the concept of self-similarity at infinite scales. On the other hand, images have limited resolution and finite size, like any real object. As a consequence, the fractal dimension of an image is a multi-scaled measure, i.e., it depends on the dilation radius r used. Thus, we propose to compute this descriptor for different radius values, thus resulting in the following feature vector

$$\vec{\psi}(r_{min}, r_{max}) = [D(r_{min}), \ldots, D(r_{max})] , \tag{6}$$

where $D(r)$ is the Bouligand-Minkowski fractal dimension estimated using dilation radius $r = \{r_{min}, r_{min} + 1, \ldots, r_{max}\}$. This feature vector can be used to describe any image pattern, i.e., both original texture image or LBP maps. This enables us to combine, through concatenation, the descriptors obtained from different patterns into a single feature vector $\vec{\varphi}$ as follows

$$\vec{\varphi}_{p_1,\ldots,p_N}(r_{min}, r_{max}) = \begin{bmatrix} \vec{\psi}_{p_1}(r_{min}, r_{max}), \\ \ldots, \\ \vec{\psi}_{p_N}(r_{min}, r_{max}) \end{bmatrix}^T , \tag{7}$$

1	2	4
128	0	8
64	32	16

(a)

2	4	8
1	0	16
128	64	32

(b)

4	8	16
2	0	32
1	128	64

(c)

8	16	32
4	0	64
2	1	128

(d)

16	32	64
8	0	128
4	2	1

(e)

32	64	128
16	0	1
8	4	2

(f)

64	128	1
32	0	2
16	8	4

(g)

128	1	2
64	0	4
32	16	8

(h)

Fig. 2. 8 LBP masks used to create pattern images.

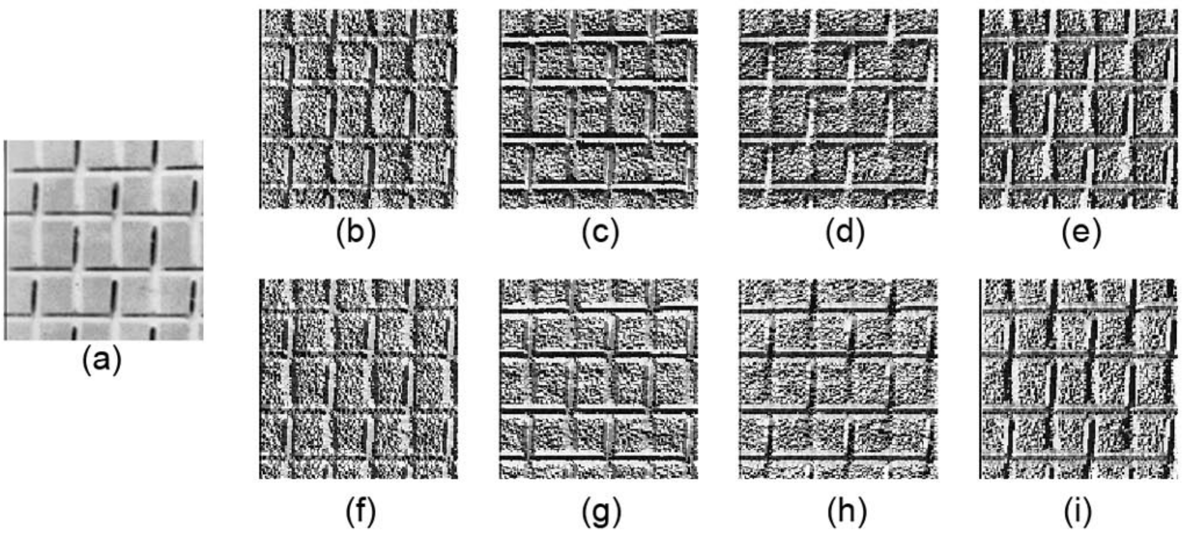

Fig. 3. Example of LBP maps obtained from an original input image.

where $p_1, p_2 \ldots, p_N$ are N different image patterns used to compute the feature vector.

V. Experiments

For the evaluation of our proposed approach, we used two grayscale image databases to perform the experiments. They are:

- Brodatz [17]: we used a dataset composed of 40 classes from the original Brodatz album, each class containing 10 images. Each image is 200×200 pixels size with intensity resolution of 256 graylevels.
- UIUC [18]: the original database is composed of 25 classes with 40 images 640×480 pixels size per class. These images are more difficult to classify because they were obtained from different viewpoints, with non-rigid transformations and different perspectives. In order to maintain coherence with the Brodatz experiment, we cropped a window 200×200 from the upper-left side of each image, thus creating a database of 1.000 images of 200×200 pixels size with intensity resolution of 256 graylevels.

For classification, we used Linear Discriminant Analysis (LDA) [19], a statistical method that considers that all the classes have the same covariance matrix (obtained from the whole database). To validate the experiments, we used the *leave-one-out cross-validation* scheme, which splits the database into one sample for testing and the remainder for training. This process is repeated N times, where N is the number of samples, each time with a different sample for testing. The performance measure is the mean accuracy of

ISBN 978-90-827970-1-5 © EURASIP 2018

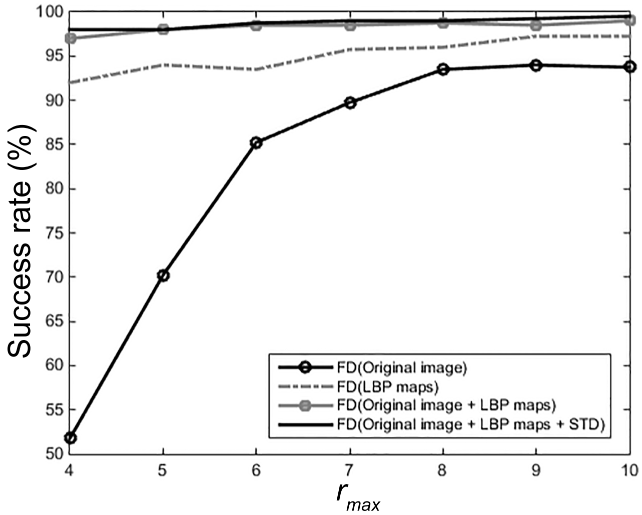

Fig. 4. Success rate in Brodatz dataset for different number of fractal descriptors and combinations of patterns.

the N classifications.

To improve the evaluation of our method, we compared it with other texture analysis methods found in the literature. They are: Gabor filters [20], Wavelet descriptors [21], Co-occurrence matrices [22], Tourist walk [4].

VI. Results and discussion

For this approach, we considered two feature vectors to characterize a texture sample: $\vec{\psi}(r_{min}, r_{max})$ and $\vec{\varphi}_{p_1,\ldots,p_N}(r_{min}, r_{max})$. The first feature vector, $\vec{\psi}(r_{min}, r_{max})$, depends on the choice of parameters for its computation: the initial and final radius value, r_{min} and r_{max}, respectively. These two values define the range of dilation radii used to compute the fractal dimension. For the initial radius we used $r_{min} = 3$ as the influence volume obtained for smaller dilation radii is not able to capture significant information about the texture pattern. In this way, we only evaluated the variations in the final radius value, r_{max}, as shown in Figure 4.

To use the second feature vector, $\vec{\varphi}_{p_1,\ldots,p_N}(r_{min}, r_{max})$, it is necessary to define the set of image patterns $p_1, \ldots, p_N$ from which the fractal descriptors (FD) will be extracted. Figure 4 shows the results achieved for four different sets of patterns in the Brodatz dataset:

- FD(Original image): $N = 1$ pattern
- FD(LBP maps): $N = 8$ patterns
- FD(Original image + LBP maps): $N = 9$ patterns
- FD(Original image + LBP maps + LBP's standard deviation (STD)): $N = 10$ patterns

These sets of patterns were carefully chosen to show that the fractal descriptors are very meaningful to describe a texture sample, i.e., the original image. However, the use of LBP maps as input patterns highly increases the success rate and diminishes the importance of larger radii during the analysis. By combining different sources of patterns into the feature vector we remove the necessity of using more fractal descriptors to discriminate each pattern.

As the LBP maps constitute different sources of patterns from the original image, one must understand them as a complementary information. Therefore, it would be interesting to evaluate their combination into a single feature vector. Moreover, since LBP maps are obtained using different orientations, the standard deviation present along the maps may also be an important source of information for the texture pattern. We notice that combining fractal descriptors from both original image and LBP maps increases even more the success rate of the method. Descriptors from LBP's standard deviation do not seem to play an important role in this classification. However, this is due to the success rate has already achieved a high value, leaving small space for improvement.

TABLE I
Comparison results for different texture methods.

Method	Success rate (%) Brodatz	Success rate (%) UIUC
Gabor filters	97.00	56.50
Wavelet descriptors	87.50	41.00
Co-occurrence matrices	93.75	41.10
Tourist walk	95.50	48.10
FD(Original image)	93.75	48.70
FD(Original image + LBP maps)	97.12	63.80
FD(Original image + LBP maps + STD)	98.20	70.80

Table I shows the results of the proposed approach and the compared methods. For this comparison, we used $r_{min} = 3$ and $r_{max} = 10$. As a result, the approach "FD(Original image + LBP maps)" has 72 descriptors while "FD(Original image + LBP maps + STD)" has 80 descriptors. "FD(Original image)" refers to the set of fractal descriptors computed exclusively from the original image, i.e., without combining with any other source of pattern. The first conclusion that can be deduced from these results is that the LBP masks really improve the "FD(Original image)" performance, since the "FD(Original image + LBP maps)" surpassed it in 3.37% and 15.10% for Brodatz and UIUC databases, respectively. When we consider the "FD(Original image + LBP maps + STD)", the improvement becomes even clearer because this method surpasses "FD(Original image)" in 4.45% and 22.10% for these two image databases.

Also, both "FD(Original image + LBP maps)" and "FD(Original image + LBP maps + STD)" obtained results higher than the accuracy of the other compared methods. Among these methods, we can stress the results of: Gabor filters (0.12% and 7.30% less images correctly classified for Brodatz and UIUC datasets, respectively, when compared to "FD(Original image + LBP maps)"); and Tourist walk (1.62% and 15.70% less images correctly classified for Brodatz and UIUC datasets, respectively, when compared to "FD(Original image + LBP maps)"). These differences become more relevant when we take into account the "FD(Original image + LBP maps + STD)" method and the other compared approaches. Thus, the presented results demonstrate that the combination of fractal dimension and LBP approach provides a high discriminative feature vector for texture analysis.

VII. Conclusion

This work presented a high discriminative texture analysis method that combines the Bouligand-Minkowski fractal dimension and LBP maps. The results demonstrated that this proposed innovative approach surpassed classical and recent texture analysis methods in two well-known benchmark datasets, thus proving to be an effective tool for image analysis. Moreover, such hybrid strategy opens a promising line of research to be explored in computer vision field.

Acknowledgments

André R. Backes gratefully acknowledges the financial support of CNPq (National Council for Scientific and Technological Development, Brazil) (Grant #302416/2015-3), FAPEMIG (Foundation to the Support of Research in Minas Gerais) (Grant #APQ-03437-15) and PROPP-UFU. Jarbas Joaci de Mesquita Sá Junior thanks CNPq (Grant: 302183/2017-5) for the financial support of this work.

References

[1] A. R. Backes, D. Casanova, and O. M. Bruno, "Plant leaf identification based on volumetric fractal dimension," *IJPRAI*, vol. 23, no. 6, pp. 1145–1160, 2009.

[2] L. M. Kaplan, "Extended fractal analysis for texture classification and segmentation," *IEEE Transactions on Image Processing*, vol. 8, no. 11, pp. 1572–1585, 1999.

[3] M. Tuceryan and A. K. Jain, "Texture analysis," in *Handbook of Pattern Recognition and Computer Vision*, C. H. Chen, L. F. Pau, and P. S. P. Wang, Eds. World Scientific, 1993, pp. 235–276.

[4] A. R. Backes, W. N. Gonçalves, A. S. Martinez, and O. M. Bruno, "Texture analysis and classification using deterministic tourist walk," *Pattern Recognition*, vol. 43, no. 3, pp. 685–694, 2010.

[5] G.-H. Liu, Z.-Y. Li, L. Zhang, and Y. Xu, "Image retrieval based on micro-structure descriptor," *Pattern Recognition*, vol. 44, no. 9, pp. 2123 – 2133, 2011.

[6] A. R. Backes, D. Casanova, and O. M. Bruno, "Texture analysis and classification: A complex network-based approach," *Information Sciences*, vol. 219, pp. 168 – 180, 2013.

[7] J. J. M. Sá Junior and A. R. Backes, "A simplified gravitational model to analyze texture roughness," *Pattern Recognition*, vol. 45, no. 2, pp. 732–741, 2012.

[8] T. Ojala, M. Pietikäinen, and T. Mäenpää, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *IEEE Trans. Pattern Anal. Mach. Intell*, vol. 24, no. 7, pp. 971–987, 2002.

[9] Z. Guo, L. Z. 0006, and D. Zhang, "A completed modeling of local binary pattern operator for texture classification," *IEEE Transactions on Image Processing*, vol. 19, no. 6, pp. 1657–1663, 2010.

[10] J. B. Florindo and O. M. Bruno, "Local fractal dimension and binary patterns in texture recognition," *Pattern Recognition Letters*, vol. 78, pp. 22 – 27, 2016.

[11] J. B. Florindo, L. Assirati, and O. M. Bruno, "Locally enhancing fractal descriptors by using the non-additive entropy," *Pattern Recognition Letters*, vol. 70, pp. 32 – 37, 2016.

[12] J. B. Florindo and O. M. Bruno, "Texture analysis by multi-resolution fractal descriptors," *Expert Systems with Applications*, vol. 40, no. 10, pp. 4022 – 4028, 2013.

[13] C. Tricot, *Curves and Fractal Dimension*. Springer-Verlag, 1995.

[14] J. Florindo, A. Backes, M. de Castro, and O. Bruno, "A comparative study on multiscale fractal dimension descriptors," *Pattern Recognition Letters*, vol. 33, no. 6, pp. 798 – 806, 2012.

[15] G. Neil and K. M. Curtis, "Shape recognition using fractal geometry," *Pattern Recognition*, vol. 30, no. 12, pp. 1957–1969, 1997.

[16] B. Mandelbrot, *The fractal geometry of nature*. Freeman & Co., 2000.

[17] P. Brodatz, *Textures: A photographic album for artists and designers*. New York: Dover Publications, 1966.

[18] S. Lazebnik, C. Schmid, and J. Ponce, "A sparse texture representation using local affine regions," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 8, pp. 1265–1278, 2005.

[19] K. Fukunaga, *Introduction to Statistical Pattern Recognition*, 2nd ed. Academic Press, 1990.

[20] B. S. Manjunath and W.-Y. Ma, "Texture features for browsing and retrieval of image data," *IEEE Trans. Pattern Anal. Mach. Intell*, vol. 18, no. 8, pp. 837–842, 1996.

[21] A. Laine and J. Fan, "Texture classification by wavelet packet signatures," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 15, no. 11, pp. 1186–1190, 1993.

[22] R. M. Haralick, "Statistical and structural approaches to texture," *Proc. IEEE*, vol. 67, no. 5, pp. 786–804, 1979.