PATREC 4882
31 May 2010
ARTICLE IN PRESS
No. of Pages 8, Model 5G

Pattern Recognition Letters xxx (2010) xxx–xxx

Contents lists available at ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Texture analysis based on maximum contrast walker

André Ricardo Backes [a], Alexandre Souto Martinez [b], Odemir Martinez Bruno [c,*]

[a] Instituto de Ciências Matemáticas e de Computação (ICMC–USP), Universidade de São Paulo, Av. Trabalhador São Carlense, 400 13560-970, São Carlos, SP, Brazil
[b] Faculdade de Filosofia, Ciências e Letras de Ribeirão Preto (FFCLRP–USP), Universidade de São Paulo, Avenida Bandeirantes, 3900 14040-901, Ribeirão Preto, SP, Brazil
[c] Instituto de Física de São Carlos (IFSC–USP), Universidade de São Paulo, Av. Trabalhador São Carlense, 400 13560-970, São Carlos, SP, Brazil

A R T I C L E I N F O

Article history:
Received 13 May 2009
Available online xxxx
Communicated by Y.J. Zhang

Keywords:
Texture analysis
Image analysis
Deterministic walk
Agents
Tourist walk

A B S T R A C T

Recently, the deterministic tourist walk has emerged as a novel approach for texture analysis. This method employs a traveler visiting image pixels using a deterministic walk rule. Resulting trajectories provide clues about pixel interaction in the image that can be used for image classification and identification tasks. This paper proposes a new walk rule for the tourist which is based on contrast direction of a neighborhood. The yielded results using this approach are comparable with those from traditional texture analysis methods in the classification of a set of Brodatz textures and their rotated versions, thus confirming the potential of the method as a feasible texture analysis methodology.

1. Introduction

Texture is an important visual attribute which is presented in the most real world images. Although this attribute is naturally processed by natural vision and easily comprehended by humans, there is no formal definition for it. Indeed, textures are complex visual patterns formed by arrangements of pixels, regions or even set of patterns formed by other visual attributes, such as shape or color. These patterns can be composed by completely distinct factors, such as pixel organization or even its disorganization. In fact, depending of the context, the noise can be considered as a sort of texture. These characteristics of the texture attribute make it special and hard to be well defined. A detailed description of the texture perception and its applications to machine vision can be found in (Tuceryan and Jain, 1993).

There are many approaches for texture analysis and segmentation. Some consider different aspects of the visual attribute as also use different mathematics to handle it. Most popular approaches are based on spectral analysis of the image pixels (e.g., Fourier descriptors (Azencott et al., 1997), Wavelets and Gabor filters (Jain and Farrokhnia, 1991)), statistical analysis of the pixels (e.g., co-occurrence matrices (Haralick, 1979), local binary pattern, feature-based interaction map (Chetverikov, 1999) and complexity analysis by fractal dimension (Chaudhuri and Sarkar, 1995; Emerson et al., 1999; Kasparis et al., 2001).

Recently, we have proposed a novel approach to texture analysis based on deterministic walks (Campiteli et al., 2006; Backes et al., 2006), which overcomes the most popular and state of art texture analysis methods, specially for uniform biological textures (Backes et al., 2010). Although it is not so thoroughly investigated as random walks on regular latices and random media (Fisher, 1984; Metzler and Klafter, 2000; Derrida, 1997), deterministic walks in regular (Freund and Grassberger, 1992; Bunimovich and Troubetzkoy, 1992; Gale et al., 1995) and disordered media (Bunimovich, 2004) have also presented very interesting results. While the deterministic walk appears in computer science literature as intelligent agents, our approach explores trajectories inside the image using a statistical strategy. Thus, it brings a novel approach to explore walkers in pattern recognition and image analysis.

The deterministic tourist walks (DTW) was introduced in Lima et al. (2001) to study the models of deterministic walks. On images, the DTW is adapted to consider each pixel as a city with 8-connected neighbours. The distance between the cities is determined by the difference in pixel intensity. In this approach, there are some situations where some neighbours may present the same pixel intensity and a rule must be incorporated to choose just one of them. Special situations arise from this choice, and it can compromise with the accuracy of the DTW texture analysis. To correct this, we propose a different approach to model images for the DTW. In the new DTW image analysis, the connection between the pixels is established by vectors and a deterministic rule is determined by the vector arithmetic. It guarantees that there is just one direction for the walker to choose, even when some cities present the same distance. This new model is simple, efficient, and it improves considerably the DTW. These paper details the method

* Corresponding author. Tel.: +55 16 3373 8728; fax: +55 16 3373 9879.
E-mail addresses: backes@icmc.usp.br (A.R. Backes), asmartinez@ffclrp.usp.br (A.S. Martinez), bruno@ifsc.usp.br (O.M. Bruno).

0167-8655/$ - see front matter © 2010 Published by Elsevier B.V.
doi:10.1016/j.patrec.2010.05.022

and presents comparative experiments that demonstrate the advantages of this approach to the usual DTW and the performance of the method.

This paper starts by presenting an overview of the deterministic tourist walk in Section 2. In Section 3, the method is detailed for image applications as well as the problem of detecting an attractor during a walk. A new walk rule is proposed to improve the algorithm efficiency. In Section 4, a study of the dynamics of the tourist walk on texture images is presented. We also show how to build texture signatures vectors from the transient time and cycle period joint probability distributions. Experiments using synthetic and natural texture images are proposed in Section 5. The obtained results are presented in Section 6. Finally, in Section 7, conclusions and improvements of the method are discussed.

2. Deterministic tourist walk (DTW)

The deterministic tourist walk algorithm can be understood as a traveler wishing to visit N cities distributed on a map of d dimensions. Starting from a given city, the tourist moves according to the following rule: *go to the nearest city, which was not visited in the last μ steps* (Lima et al., 2001; Stanley and Buldyrev, 2001; Kinouchi et al., 2002; Tertariol and Martinez, 2005; Tercariol et al., 2007). This partially self-avoiding walk consists of a transient part of length t (where new cities can be visited) and a final cycle of period $p \geqslant \mu + 1$, called attractor, and where new cities are not visited any longer (Fig. 1). The tourist's movements are entirely performed based on its neighbourhood and its trajectory depends on the starting point and memory μ. Trajectories which start at different points can end in the same attractor of period p.

For image applications ($d = 2$), the tourist walk algorithm considers each pixel as a city in a two-dimensional map. Each pixel interacts only with its 8 nearest neighbor pixels. The tourist moves according to the deterministic rule of going to the pixel which presents the nearest intensity in comparison with the current pixel intensity. Also, this pixel must have not been visited in the preceding μ steps. For a given memory μ, the transient time and cycle

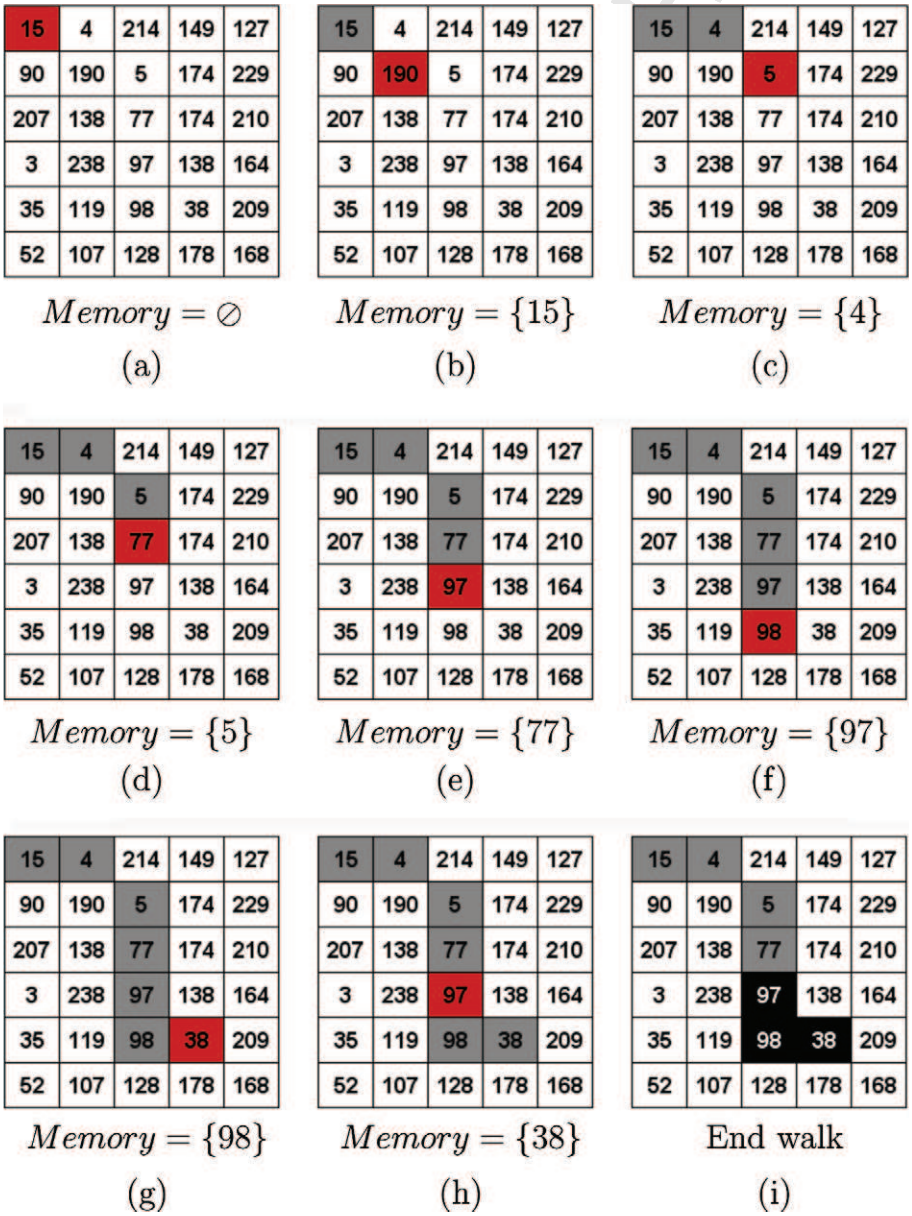

Fig. 1. Example of a tourist walk over an image using $\mu = 1$. (a)–(h) Tourist's current position in red, previous steps in gray; (i) The transient part, $t = 4$, is in gray, while the attractor part, $p = 3$, is in black. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Please cite this article in press as: Backes, A.R., et al. Texture analysis based on maximum contrast walker. Pattern Recognition Lett. (2010), doi:10.1016/j.patrec.2010.05.022

period are computed for all starting points of the image, thus resulting in the joint distribution of transient and attractor of the image $S_{2,\mu}^{(N)}(t,p)$, where $S_{2,\mu}^{(N)}(t,p)$ is a bi-dimensional histogram which represents the number of times that a walk presents transient size t and attractor size p when walking on a image containing N pixels. An example is depicted in Fig. 2.

The joint distribution can efficiently be used as features for image analysis and texture characterization purposes (Backes et al., 2006, 2010). This is due to the fact that the joint distribution behavior is a result of the different changes in the tourist trajectory during its walk. These changes in trajectory depend on the image context of the image, and therefore, it takes into account local and global information of the image. As a result, the texture information is stored in the joint probability distribution, which can be used for texture characterization and classification.

The drawback of the DTW on image is the presence of two or more directions complying with the tourist walking rule. To solve this problem, we propose the following strategy presented in the next section: the *maximum contrast direction*.

3. Maximum contrast direction

Consider a vector in the Cartesian space $\vec{V} = \{v_x, v_y\}$, where v_x and v_y represent its components along the x and y axis, respectively. Given an image pixel g_0, which here we consider as the pixel where the tourist is current placed, each one of its neighboring pixels g_i,i = 1,. . .,8, has its gray level intensity mapped into a vector $\vec{V_i}$ according to its relative position to pixel g_0. From this mapping, three types of vectors arise:

- Horizontal vectors: $\vec{V_3} = \{g_3, 0\}$ and $\vec{V_7} = \{-g_7, 0\}$.
- Vertical vectors: $\vec{V_1} = \{0, -g_1\}$ and $\vec{V_5} = \{0, g_5\}$.
- Diagonal vectors: $\vec{V_2} = \frac{\sqrt{2}g_2}{2}\{1, -1\}, \vec{V_4} = \frac{\sqrt{2}g_4}{2}\{1, 1\}, \vec{V_6} = \frac{\sqrt{2}g_6}{2}\{-1, 1\}, \vec{V_8} = \frac{\sqrt{2}g_8}{2}\{-1, -1\}$.

From the sum of the vectors achieved, it is possible to compute the maximum contrast direction relative to pixel g_0:

$$\vec{V_r} = \{r_x, r_y\} = \sum_{i=1}^{8} \vec{V_i}. \tag{1}$$

By normalizing the components of vector $\vec{V_r}$, we are able to determine the maximum contrast direction in the discreet space, which is the case of image pixels. This normalization is performed by dividing each component of vector $\vec{V_r}$ by its absolute value, thus resulting in:

$$\vec{V_d} = \{d_x, d_y\} = \left\{\frac{r_x}{|r_x|}, \frac{r_y}{|r_y|}\right\}, \tag{2}$$

where $|r_x|$ and $|r_y| \neq 0$. The components d_x,$d_y \in \{-1, 0, +1\}$ of the vector $\vec{V_d}$ represent the coordinates of the image pixel where the tourist must move into, relative to the pixel g_0, and which coincides with the maximum contrast direction at pixel g_0 (see Fig. 3).

The maximum contrast direction $\vec{V_d}$ is computed at each step of the tourist walk, and this rule is applied until the tourist finds an attractor and ends it walk. However, when the transient time reaches the number of cities/pixels of the image (which means that the tourist already visited all the cities on the map without finding a cycle) or when $\vec{V_d} = \{0,0\}$ (the tourist found a homogeneous region in the image where there is no contrast direction), the tourist is not able to find an attractor, and so it stops its walk.

4. Texture signature with DTW

As the tourist walks on an image, its trajectory changes according to the image context. These changes during the trajectory reflect on the behavior of the transient time and attractor period computed for each tourist walk throughout the joint distribution probability. Thus, measurements computed from the joint distribution probabilities can efficiently be used as features for texture analysis and characterization (Backes et al., 2006).

Let us consider the transient time $[ht_\mu(n)]$, attractor period $[hp_\mu(n)]$ and walking $[hw_\mu(n)]$ histograms as feasible texture signatures. These histograms are computed from the joint distribution as follows:

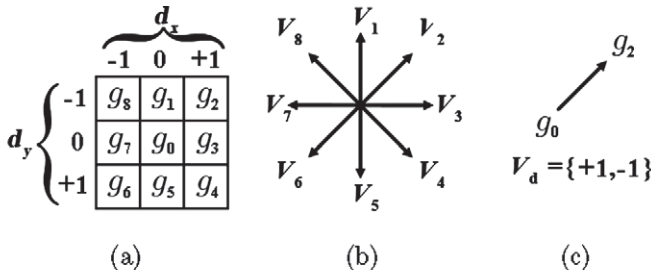

Fig. 3. Calculus of the direction where the tourist must move into during its walk from a pixel g_0: (a) Neighbor pixels and relative positions (d_x, d_y); (b) vectors computed considering the gray level intensity and the relative position to pixel g_0; maximum contrast direction $\vec{V_d}$ computed. In this case, tourist must move from g_0 to g_2.

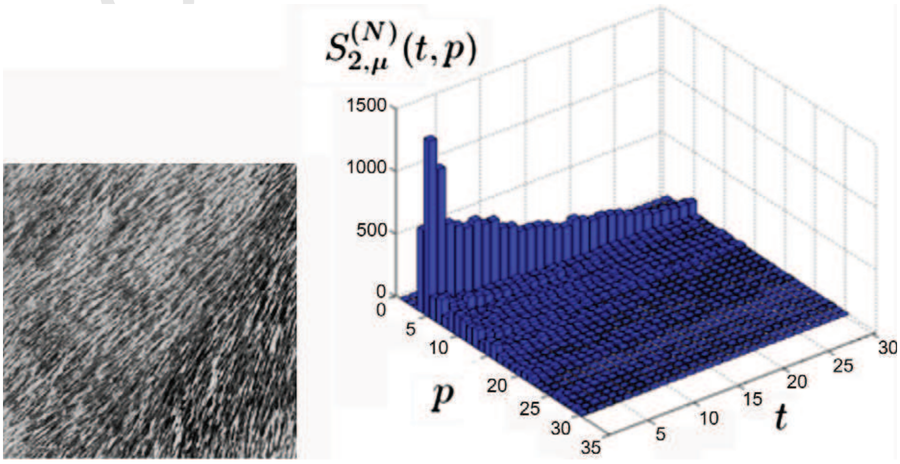

Fig. 2. Example of texture image and the tourist walk transient time t and cycle period p joint distribution, for μ = 1.

Please cite this article in press as: Backes, A.R., et al. Texture analysis based on maximum contrast walker. Pattern Recognition Lett. (2010), doi:10.1016/j.patrec.2010.05.022

$$ht_\mu(n) = \sum_p S^{(N)}_{2,\mu}(n,p), \tag{3}$$

$$hp_\mu(n) = \sum_t S^{(N)}_{2,\mu}(t,n), \tag{4}$$

$$hw_\mu(n) = \sum_{n=t+p} S^{(N)}_{2,\mu}(t,p), \tag{5}$$

where n represents, respectively, the distribution of transient time, attractor period and walk length on the image.

As the texture pattern and the memory μ employed changes, new joint distributions are achieved. Each joint distribution has a particular behavior which reflects in the histograms computed. It makes these histograms useful tools for texture analysis (see Fig. 4).

It is important to note that the attractors have period $p \geqslant \mu + 1$, unlike the transient time, which starts in $t = 0$. Thus, the first descriptor selected for the attractor and walking histograms necessarily has a size $\mu + 1$. The feature vector is built by concatenating the n first descriptors selected from one histogram for a given specific memory:

$$\vec{\psi}^{ht}_\mu(n) = [ht_\mu(0), ht_\mu(1), \ldots, ht_\mu(n-1)], \tag{6}$$

$$\vec{\psi}^{hp}_\mu(n) = [hp_\mu(\mu+1), hp_\mu(\mu+2), \ldots, hp_\mu(\mu+n)], \tag{7}$$

$$\vec{\psi}^{hw}_\mu(n) = [hw_\mu(\mu+1), hw_\mu(\mu+2), \ldots, hw_\mu(\mu+n)]. \tag{8}$$

As the transient time and cycle period joint distribution depends on μ value, a feature vector which considers different μ values is also evaluated:

$$\varphi^h_{\mu_1,\ldots,\mu_M}(n) = \left[\psi^h_{\mu_1}(n), \psi^h_{\mu_2}(n), \ldots, \psi^h_{\mu_M}(n)\right], \tag{9}$$

where h is the histogram adopted (ht, hp or hw).

This φ^h feature vector enables us to characterize a texture pattern considering different scales, where each scale is represented by a different μ value.

5. Experiments

Our proposed approach was evaluated using transient, attractor and walking histograms for different μ values in a texture analysis and classification context. A database containing 111 textures obtained from Brodatz texture album (Brodatz, 1966) was used. Brodatz textures are broadly used in computer vision and image processing literature as benchmark for texture analysis. A total of 10 samples of 200 × 200 size and 256 grey levels were considered for each texture class, which makes a total of 1110 texture images in the database. Fig. 5 shows an example of each texture class considered while Fig. 6 shows examples of texture variability inside a class.

Statistical analysis was performed by applying linear discriminant analysis (LDA) in a cross-validation scheme over the signatures computed for each texture sample considered. LDA enables us to estimate a linear subspace with good discriminative properties, i.e., a linear subspace where the variance between classes is larger than the variance within classes. As LDA is a supervised method, the class definition is necessary during its estimation process (Everitt and Dunn, 2001; Fukunaga, 1990).

To perform a better evaluation of the method, a comparison with traditional texture analysis methods was also performed. Thus, Fourier descriptors (Azencott et al., 1997), co-occurrence matrices (Haralick, 1979) and Gabor filters (Jain and Farrokhnia, 1991; Daugman and Downing, 1995; Idrissa and Acheroy, 2002) were tested with the proposed database. A brief description of each method is presented as follows:

Fourier descriptors: the Fourier Transform is applied over the image and, after a *shifting* operation, a feature vector is built containing the sum of the spectrum absolute values at a specific radius distance, thus resulting in a total of 99 descriptors.

Co-occurrence matrices: basically, the co-occurrence matrices are the joint probability distributions between pairs of pixels at a pre-specific distance and direction. During the experiments, distances of 1 and 2 pixels with angles of −45°, 0°, 45°, 90° were used. Descriptors of energy and entropy were computed from resulting matrices, thus resulting in a feature vector containing 16 descriptors. A non-symmetric version has been adopted in experiments.

Gabor filters: an input image is convolved by a family of Gabor filters. Each Gabor filter is a bi-dimensional gaussian function moduled with an oriented sinusoid in a determined frequency and direction. During the experiments, the best results were yielded by using a family of 16 filters (4 rotation and 4 scale filters), with lower and upper frequency equal to 0.01 and 0.3, respectively. Descriptors of energy were computed for each computed filter. Definition of the individual parameters of each filter follows mathematical model presented in Manjunath and Ma (1996).

To evaluate the rotation invariance of the method, an additional database containing 10 different orientations for each texture class was considered. It is important to emphasize that some Brodatz patterns cannot be freely rotated during the extraction of a

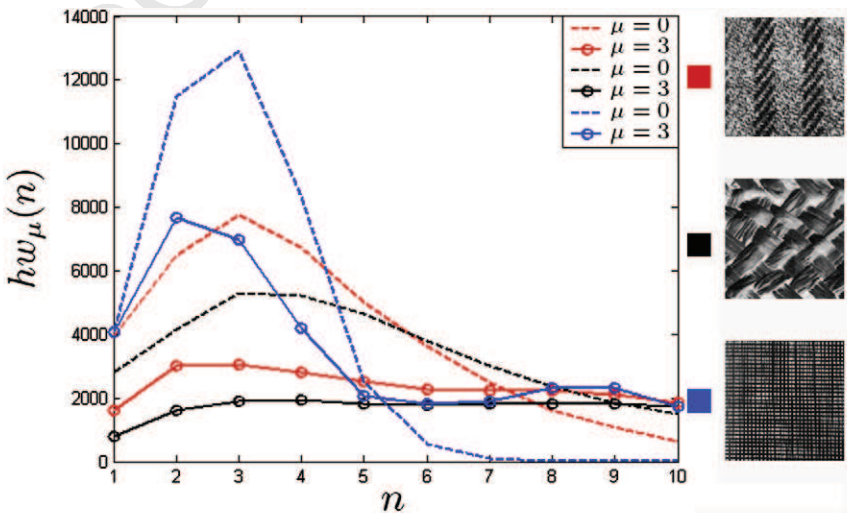

Fig. 4. Examples of the walking histogram for different texture patterns and μ values.

Please cite this article in press as: Backes, A.R., et al. Texture analysis based on maximum contrast walker. Pattern Recognition Lett. (2010), doi:10.1016/j.patrec.2010.05.022

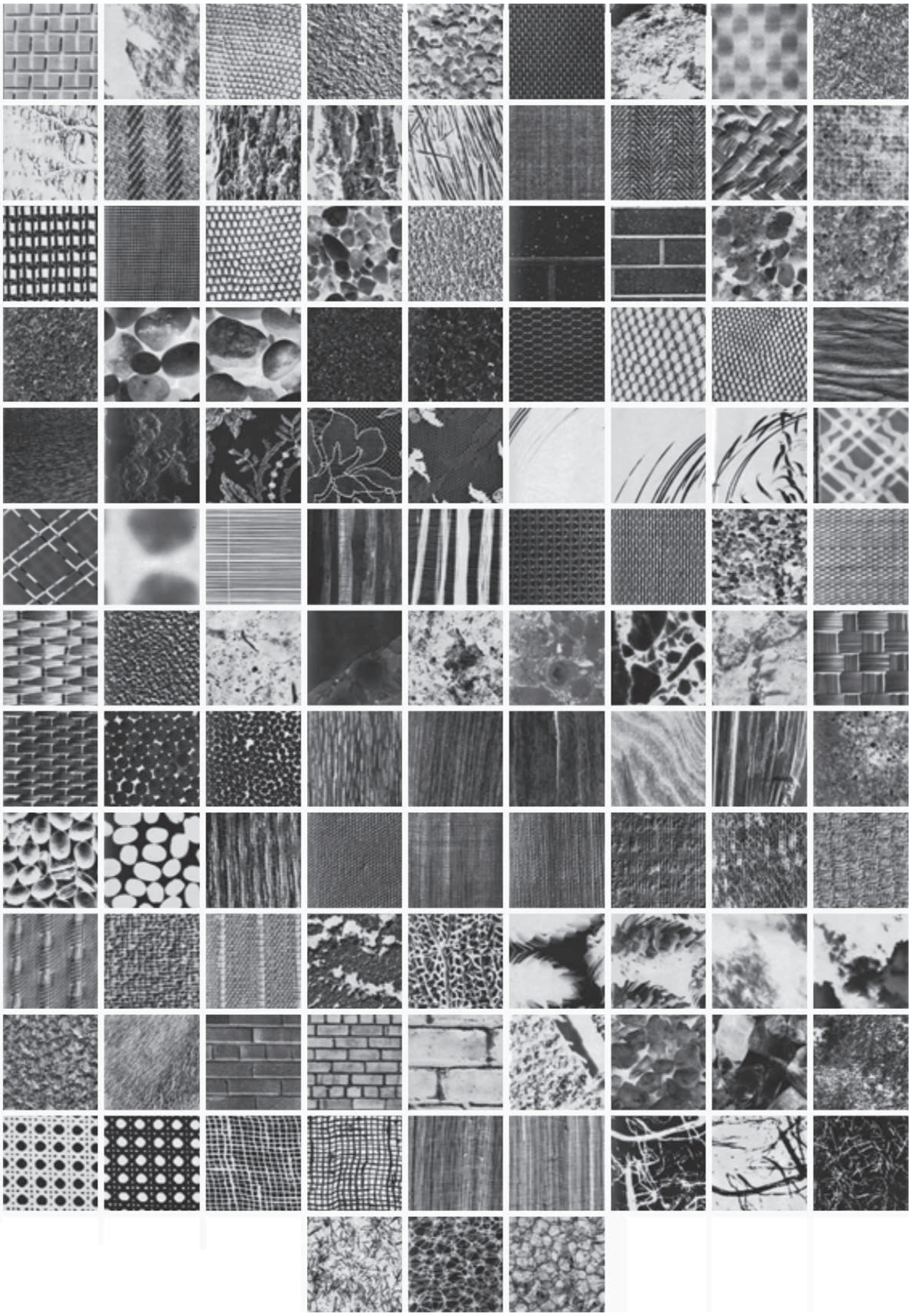

Fig. 5. One example of each of the 111 Brodatz's classes considered. Each image has 200×200 pixels and 256 grey levels.

200×200 size sample (e.g., Brodatz patterns D42, D43 e D44). These patterns, when rotated, may produce a constant pattern which does not correspond to the original Brodatz texture depending on the region where the samples are extracted from. Thus, in order to avoid this problem, a single region containing a well-defined pattern was considered during the extraction of the rotated samples. Fig. 7 shows examples of a given texture under different orientations.

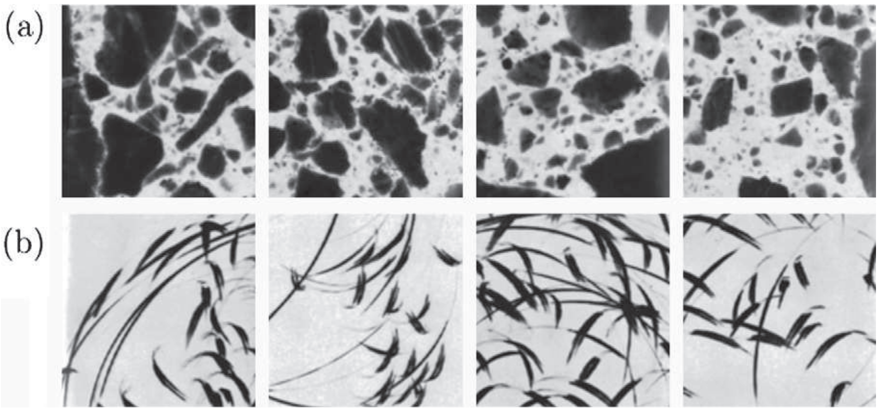

Fig. 6. Examples of variability in texture of two Brodatz classes.

6. Results

6.1. Comparison with other methods

Table 1 shows the yielded results of each method compared. For this comparison, we employed the parameters of the tourist walk which leads to the best result. Thus, the tourist signature here employed is the concatenation of the feature vectors $\varphi^{ha}_{0,1,2,3,4,5}(3)$, $\varphi^{ht}_{0,1,2,3,4,5}(5)$ and $\varphi^{hw}_{0,1,2,3,4,5}(8)$, totalizing 96 descriptors.

Although results yielded for proposed method show a superior performance over Fourier descriptors and co-occurrence matrices, Gabor filters presented a similar result for the considered database (89.37%). This result confirms that the combination of different features extracted from joint distribution, as also the use of different memory values, produces a texture signature with great discrimination power, which is also capable of dealing with a large number of texture patterns. Notice, however, that Gabor filters use only 16 descriptors while the tourist signatures need 96 descriptors to obtain the same result.

6.2. Rotation tolerance

An interesting and desirable characteristic in texture recognition applications is the ability of the method to recognize a texture pattern independent of its orientation.

In the proposed approach, the tourist walks on a texture image according to the maximum contrast direction from the current step. Rotation transform does not affect pixel intensities, and it does not change the neighborhood of a pixel, both items considered when computing the subsequent tourist step. Nevertheless, images are discreet structures, and they cannot be freely rotated. A small variation in the computed direction may occur for a given texture sample depending on the chosen rotation angle. However, for 90°-rotated versions of an image, the maximum contrast direction is maintained perfectly unaltered. This indicates that the proposed texture features are insensitive for rotation multiples of 90° (Fig. 8).

Table 2 shows the results yielded when the method is applied over rotated textures. Results show a superiority of the proposed approach over Gabor filter when dealing with different rotated versions of a texture pattern. As in the previous experiment, the tourist walk also presented a performance similar other methods (in this case, with the Fourier descriptors). It indicates that the proposed approach presents a performance similar to Gabor filter and Fourier descriptors for image analysis and rotation tolerance, respectively.

6.3. Computational complexity

To understand the computational complexity of the tourist walk, we must consider that the method considers each image pixel as a starting point. Thus, for an image of $N \times N$ size, this leads to N^2 walks. Each resulting walk consists of a transient part, of size t, and, an attractor of size $p \geqslant \mu + 1$, which may not be present. In

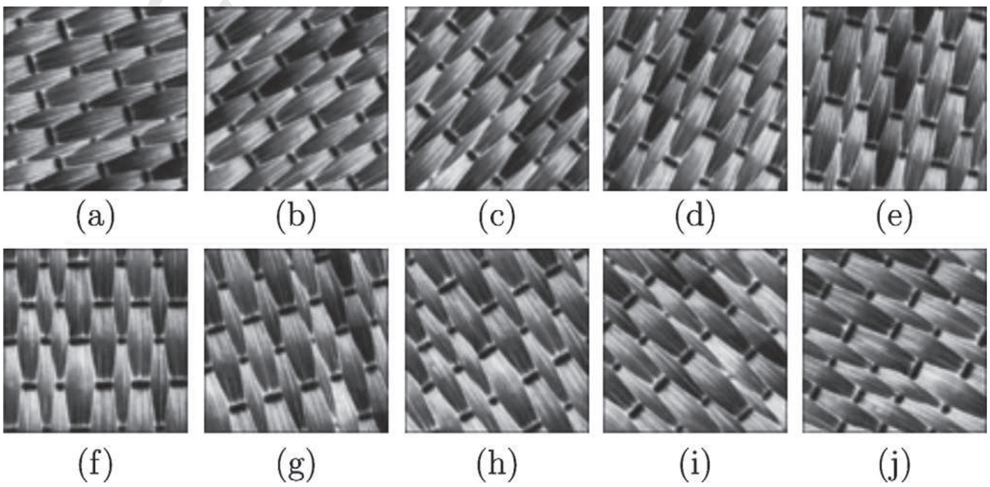

Fig. 7. Examples of Brodatz rotated samples: (a) 15°; (b) 30°; (c) 45°; (d) 60°; (e) 75°; (f) 90°; (g) 105°; (h) 120°; (i) 135°; (j) 150°.

Please cite this article in press as: Backes, A.R., et al. Texture analysis based on maximum contrast walker. Pattern Recognition Lett. (2010), doi:10.1016/j.patrec.2010.05.022

Table 1
Comparison with traditional texture analysis methods.

Method	No. of descriptors	Images correctly classified	Success rate (%)
Gabor filters	16	992	89.37
Fourier descriptors	99	888	80.00
Co-occurrence matrices	16	665	59.91
Tourist walk	96	992	89.37

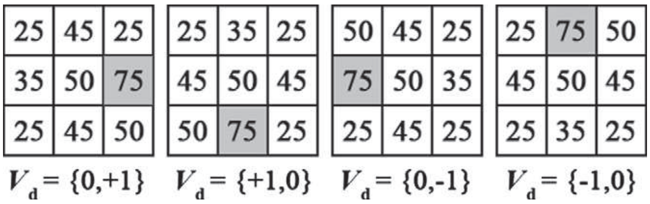

Fig. 8. For 90°-based rotation the maximum contrast direction is constant.

Table 2
Comparison with traditional texture analysis methods using rotated textures.

Method	No. of descriptors	Images correctly classified	Success rate (%)
Gabor filters	16	885	79.73
Fourier descriptors	99	966	87.02
Co-occurrence matrices	16	105	9.46
Tourist walk	96	966	87.02

this case, the transient part is considered as having its size equal to the number of image pixels, i.e., $t = N \times N$ and $p = 0$. All this considered, the computational complexity of the tourist walk is stated as $O(N^2(t+p))$, where $(t+p)$ is the size of a tourist walk.

Both best and worst case of the method are achieved only in special cases of image context or memory. The best case occurs when all walks already start on an attractor ($t = 0$) and only if the attractor presents the minimum size possible. The attractor's minimum size depends on the memory μ and it is achieved for $\mu = 0$, which minimizes the attractor size to $p = 1$. Therefore, in this case, the computational complexity of the method is $O(N^2)$. The worst case occurs when the attractor is never found during the walk. Thus, independent of the memory size μ, the tourist walk presents size $t + p = N^2$, which leads to complexity $O(N^4)$. However, it is important to emphasize that both cases, specially the worst case, are very rare cases. On one hand, the best case is easily found for some walks in a common image. On the other hand, the worst case requires a very specific configuration of pixels in the image, so that, even a random generated image does not produce this special case of walk.

7. Conclusion

In this paper, we proposed a different approach to compute the direction during the deterministic tourist walk in order to explorer an image in a given scale (memory). Instead of using a simple difference of intensities between pixels, we proposed to use the intensities and relative positions of the neighbor pixels to compute the maximum contrast direction of a pixel. This direction points to the neighbor pixel that a traveler must go in the next step of the Tourist Walk to find an attractor.

Signatures computed from joint distribution computed using this walk were tested in image classification experiments. Linear discriminant analysis was employed to classify a set of Brodatz textures and their rotated versions. Comparison with other methods shows a great potential of the method as a feasible texture analysis methodology.

Acknowledgments

A.R.B. acknowledges support from FAPESP (2006/54367-9). O.M.B. acknowledges support from CNPq (303746/2004-1 and 484474/2007-3) and FAPESP (2006/54367-9). A.S.M. acknowledges support from CNPq (303990/2007-4 and 476862/2007-8).

References

Azencott, R., Wang, J.-P., Younes, L., 1997. Texture classification using windowed Fourier filters. IEEE Trans. Pattern Anal. Machine Intell. 19 (2), 148–153.
Backes, A.R., Bruno, O.M., Campiteli, M.G., Martinez, A.S., 2006. Deterministic tourist walks as an image analysis methodology based. In: CIAPR. Lecture Notes in Computer Science, vol. 4225. Springer, pp. 784–793.
Backes, A.R., Gontalves, W.N., Martinez, A.S., Bruno, O.M., 2010. Texture analysis and classification using deterministic tourist walk. Pattern Recognition 43 (3), 685–694.
Brodatz, P., 1966. Textures: A Photographic Album for Artists and Designers. Dover Publications, New York.
Bunimovich, L.A., 2004. Deterministic walks in random environments. Phys. D 187, 20–29.
Bunimovich, L.A., Troubetzkoy, S.E., 1992. Recurrence properties of Lorentz lattice gas cellular automata. J. Stat. Phys. 67, 289–302.
Campiteli, M.G., Martinez, A.S., Bruno, O.M., 2006. An image analysis methodology based on deterministic tourist walks. In: IBERAMIA-SBIA. Lecture Notes in Computer Science, vol. 4140. Springer, pp. 159–167.
Chaudhuri, B.B., Sarkar, N., 1995. Texture segmentation using fractal dimension. IEEE Trans. Pattern Anal. Machine Intell. 17 (1).
Chetverikov, D., 1999. Texture analysis using feature-based pairwise interaction maps. Pattern Recognition 32 (3), 487–502.
Daugman, J., Downing, C., 1995. Gabor wavelets for statistical pattern recognition. In: Arbib, M.A. (Ed.), The Handbook of Brain Theory and Neural Networks. MIT Press, Cambridge, MA, pp. 414–419.
Derrida, B., 1997. From random walks to spin glasses. Phys. D 107 (2–4), 186–198.
Emerson, C.W., Lam, N.N., Quattrochi, D.A., 1999. Multi-scale fractal analysis of image texture and patterns. Photogrammet. Eng. Remote Sensing 65 (1), 51–62.
Everitt, B.S., Dunn, G., 2001. Applied Multivariate Analysis, 2nd ed. Arnold.
Fisher, D.S., 1984. Random walks in random environments. Phys. Rev. A 30 (2), 960–964.
Freund, H., Grassberger, P., 1992. The Red Queens walk. Phys. A 190 (3–4), 218–237.
Fukunaga, K., 1990. Introduction to Statistical Pattern Recognition, 2nd ed. Academic Press.
Gale, D., Propp, J., Sutherland, S., Troubetzkoy, S., 1995. Further travels with my ant. Math. Intell. 17, 48–56.
Haralick, R.M., 1979. Statistical and structural approaches to texture. Proc. IEEE 67 (5), 768–804.
Idrissa, M., Acheroy, M., 2002. Texture classification using Gabor filters. Pattern Recognition Lett. 23 (9), 1095–1102.
Jain, A.K., Farrokhnia, F., 1991. Unsupervised texture segmentation using Gabor filters. Pattern Recognition 24 (12), 1167–1186.
Kasparis, T., Charalampidis, D., Georgiopoulos, M., Rolland, J.P., 2001. Segmentation of textured images based on fractals and image filtering. Pattern Recognition 34 (10).
Kinouchi, O., Martinez, A.S., Lima, G.F., Lourento, G.M., Risau-Gusman, S., 2002. Deterministic walks in random networks: An application to thesaurus graphs. Phys. A 315 (3/4), 665–676.
Lima, G.F., Martinez, A.S., Kinouchi, O., 2001. Deterministic walks in random media. Phys. Rev. Lett. 87 (1), 010603.
Manjunath, B.S., Ma, W.-Y., 1996. Texture features for browsing and retrieval of image data. IEEE Trans. Pattern Anal. Machine Intell. 18 (8), 837–842.
Metzler, R., Klafter, J., 2000. The random walk's guide to anomalous diffusion: A fractional dynamics approach. Phys. Rep. 339 (1), 1–77. URL http://dx.doi.org/10.1016/S0370-1573(00)00070-3.
Stanley, H.E., Buldyrev, S.V., 2001. Statistical physics – the salesman and the tourist. Nature (London) 413 (6854), 373–374.
Tertariol, C.A., Martinez, A.S., 2005. Analytical results for the statistical distribution related to a memoryless deterministic walk: Dimensionality effect and mean-field models. Phys. Rev. E, 72.
Tercariol, C.A.S., González, R.S., Martinez, A.S., 2007. Exact analytical calculation for the percolation crossover in deterministic partially self-avoiding walks in one-dimensional random media. Phys. Rev. E 75, 061117.
Tuceryan, M., Jain, A.K., 1993. Texture analysis. Handbook of Pattern Recognition and Computer Vision, 235–276.