Statistical Landscape Features for Texture Classification

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Abstract

This paper proposes the use of information derived from the graph of a texture image function for texture description. The graph of an image function is a rumpled surface in the three-dimensional space that appears like a landscape. Four novel texture feature curves are used to characterize the texture. This method is named Statistical Landscape Features (SLF). SLF achieves a very high correct classification rate of 94.53% on the entire Brodatz set. Besides the very good performance, another remarkable advantage of the proposed method is that it has no parameter to tune.

1. Introduction

Texture is an important characteristic for the analysis and understanding of images. It plays an important role in a wide range of applications such as remote sensing, quality control for industries, and medical diagnosis. Despite its importance in image analysis, a formal approach or precise definition of texture has yet to be worked out. Coggins [1] has compiled a catalogue of texture definitions in the computer vision literature. These different definitions demonstrate that the *definition* of texture is formulated by different people depending upon the particular application and that there is no definition that is generally agreed upon. Image texture can be qualitatively evaluated as having one or more of the properties of fineness, coarseness, smoothness, granulation, randomness, lineation, irregular, or hummocky [2], which give important clue to texture feature extraction. During the past decades, texture classification has received considerable attention and a large number of various approaches to texture feature extraction have been proposed [2, 3]. These methods can be loosely categorized into statistical, structural, model-based, and signal processing methods [3].

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Structural approaches [4] are based on the theory of formal languages: textures are made up of primitives, which appear in near regular repetitive spatial arrangements, using a set of placement rules. Haralick [2] discussed and generalized some structural approaches to texture in detail. These approaches work well on *deterministic* textures but most natural textures, unfortunately, are not of this type.

In contrast to structural methods, statistical approaches do not attempt to describe the exact structure of the texture. From a statistical point of view, texture images are complicated pictorial patterns, on which, sets of statistics can be obtained to characterize them. The autocorrelation (ACF) method [2], edge frequency (EF) method [2] and the well-known Spatial Grey Level Dependence Matrix (SGLDM) method [5] are classical statistical approaches to texture analysis.

Model based textural approaches such as Markov Random Field (MRF) [6] , fractal dimension [7] etc. attempt to interpret an image texture by use of, respectively, stochastic model and generative image model. Recently one-dimensional Boolean model [8] has also been used for texture classification when a grey image is split into a set of binary slices.

Signal processing techniques such as Gabor filters [9] and the Discrete Wavelet Transform (DWT) [10] have also been applied to texture classification. A common denominator for most signal processing approaches is that the textured image is submitted to a linear transform, filter, or filter bank, followed by some energy measure [11].

Geometrical information has been proved to be useful for texture description. Statistical Geometrical Features (SGF) [12] reflects the structural and geometrical information of texture in a statistical way. SGF has achieved a high performance for texture classification [12], however, it only uses two-dimensional information and does not characterize texture features integrally. We believe that describing texture features of an image from a three-dimensional view will be more effective.

This paper proposes a new method, Statistical Landscape Features (SLF), which uses three-dimensional information

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of a texture image function. It first defines a bijective mapping of the texture images into a series of three-dimensional landscapes. Accordingly, the problems of texture description and classification have been converted into the ones of analysis of three-dimensional landscapes. We then obtain four novel texture feature curves based on the statistics of geometrical and topological properties of the solids induced by the graph of a texture image and a horizontal plane to characterize the image texture.

The organization of this paper is as follows. Section 2 presents a description of Statistical Landscape Features. The results of comparison experiments are given in Section 3. Finally, Section 4 gives the conclusions of this paper.

2. Statistical Landscape Features

An $n_x \times n_y$ digital image with n_l gray levels can be modeled with a function $z = f(x,y)$, where $(x,y) \in \{0,1,\cdots,n_x-1\} \times \{0,1,\cdots,n_y-1\}$, and $z \in \{0,1,\cdots,n_l-1\}$. The graph of this function is bounded in the box $\Omega = \{(x,y,z) \in R^3 : 0 \le x \le n_x-1, 0 \le y \le n_y-1, 0 \le z \le n_l-1\}$ and divides the box Ω into a lower part $\Omega_L^f = \{(x,y,z) \in R^3 : 0 \le x \le n_x-1, 0 \le y \le n_y-1, 0 \le z \le f(x,y)\}$ and an upper part $\Omega_U^f = \{(x,y,z) \in R^3 : 0 \le x \le n_x-1, 0 \le y \le n_y-1, f(x,y) \le z \le n_l-1\}$ as illustrated in Figure 1(a). The intersection between the graph and the box Ω is denoted by $\Omega_{z=f(x,y)}$. This box Ω can also be cut by the plane $z=\alpha$, $\alpha \in \{0,1,\ldots,n_l-1\}$ into a lower part $\Omega_L^\alpha = \{(x,y,z) \in R^3 : 0 \le x \le n_x-1, 0 \le y \le n_y-1, 0 \le z \le \alpha\}$ and an upper part $\Omega_U^\alpha = \{(x,y,z) \in R^3 : 0 \le x \le n_x-1, 0 \le y \le n_y-1, \alpha \le z \le n_l-1\}$ as shown in Figure 1(b). The intersection of Ω with the plane $z=\alpha$ is denoted by $\Omega_{z=\alpha}$.

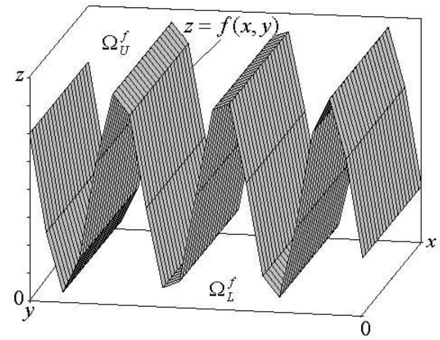
The proposed features are extracted from the two intersections $A^\alpha = \Omega_L^f \cap \Omega_U^\alpha$ and $B^\alpha = \Omega_U^f \cap \Omega_L^\alpha$ as illustrated in Figure 1(c). As illustrated in the figure, the former intersection is composed of hills above the plane $z=\alpha$ while the latter of inverted hills below the plane. The graph of the image function $z=f(x,y)$ is integrally contained by these two intersections; therefore, this method broadens the range of feature extraction from the image function $z=f(x,y)$ itself to these two intersections.

The set A^α consists of a number n_A^α of connected solids (the hills) A_i^α, $i = 0,1,\cdots,n_A^\alpha-1$. Similarly, B^α consists of n_B^α connected solids (the inverted hills) B_i^α, $i = 0,1,\cdots,n_B^\alpha-1$. The values n_A^α and n_B^α are two functions of α. From A_i^α, $i = 0,1,\cdots,n_A^\alpha-1$, and B_i^α, $i = 0,1,\cdots,n_B^\alpha-1$, two functions of α can be derived as follows:

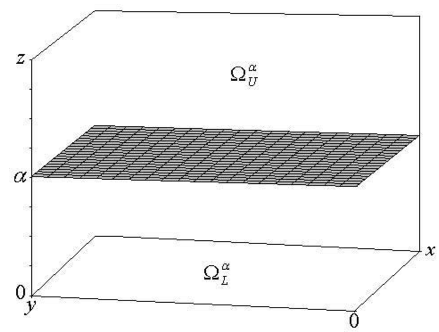
$$h_A^\alpha = \frac{1}{n_A^\alpha} \sum_{i=0}^{n_A^\alpha-1} \frac{|A_i^\alpha \setminus (A_i^\alpha \cap \Omega_{z=\alpha})|}{|A_i^\alpha \cap \Omega_{z=\alpha}|} \tag{1}$$

$$h_B^\alpha = \frac{1}{n_B^\alpha} \sum_{i=0}^{n_B^\alpha-1} \frac{|B_i^\alpha \setminus (B_i^\alpha \cap \Omega_{z=\alpha})|}{|B_i^\alpha \cap \Omega_{z=\alpha}|} \tag{2}$$

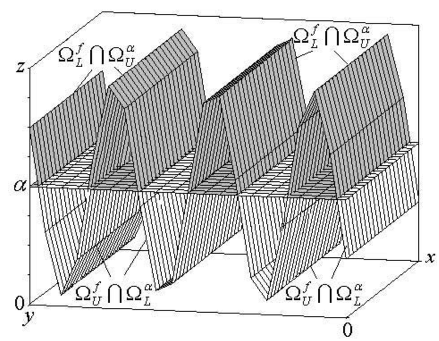
where $|A_i^\alpha \setminus (A_i^\alpha \cap \Omega_{z=\alpha})|$, $|A_i^\alpha \cap \Omega_{z=\alpha}|$, $|B_i^\alpha \setminus (B_i^\alpha \cap \Omega_{z=\alpha})|$ and $|B_i^\alpha \cap \Omega_{z=\alpha}|$ are the cardinalities (the number of elements) of the sets $A_i^\alpha \setminus (A_i^\alpha \cap \Omega_{z=\alpha})$, $A_i^\alpha \cap \Omega_{z=\alpha}$, $B_i^\alpha \setminus (B_i^\alpha \cap \Omega_{z=\alpha})$ and $B_i^\alpha \cap \Omega_{z=\alpha}$.



(a)



(b)



(c)

Figure 1: Partition of three-dimensional box in SLF. (a) $\mathbf{z = f(x,y)}$ divides Ω into $\Omega_\mathbf{L}^\mathbf{f}$ and $\Omega_\mathbf{U}^\mathbf{f}$. (b) $\mathbf{z} = \alpha$ cuts Ω into $\Omega_\mathbf{L}^\alpha$ and $\Omega_\mathbf{U}^\alpha$. (c) The proposed features are extracted from $\mathbf{A}^\alpha = \Omega_\mathbf{L}^\mathbf{f} \cap \Omega_\mathbf{U}^\alpha$ and $\mathbf{B}^\alpha = \Omega_\mathbf{U}^\mathbf{f} \cap \Omega_\mathbf{L}^\alpha$.

By now, for a given texture image, four functions of α, n_A^α, n_B^α, h_A^α and h_B^α are obtained, with each being one feature curve. We use these four feature curves to characterize the texture.

3. Experimental evalutation

3.1. The database

The set of all 112 pictures in the Brodatz's photographic atlas of texture images [13] was used in the experiments. Each image was of size 640 $\times$ 640 with 256 gray levels and was seamlessly subdivided into sixteen non-overlapping 160 $\times$ 160 sub-images. As noted by Randen and Husøy [11], many previous texture classification studies used overlapping training and test sets and selected only a subset of the entire Brodatz texture set for comparison, and this is likely to yield unreliable and over-optimistic performance results. To make the comparison fair and objective, we used completely non-overlapping sub-images for the training and test sets, and the entire Brodatz texture set for performance evaluation.

3.2. Five other techniques for comparison

The proposed Statistical Landscape Features (SLF) was compared on the same aforementioned database under the same conditions with the following five frequently used techniques:

(1) The autocorrelation (ACF) [2] function is a textural feature indicating the sizes of the tonal primitives. One hundred such features were used in the experiments.

(2) The edge frequency (EF) [2] measures local property of an image with gradient. Fifty such features were used in the experimental comparison.

(3) The Spatial Grey Level Dependence Matrix (SGLDM) [5] is widely used for extracting texture features. Five commonly used features as suggested by Conners and Harlow [14]: energy, entropy, correlation, inverse different moment and inertia were computed in the experiments. Four directions $(0°, 45°, 90°$ and $145°)$ were adopted. So for a given distance d , an adjusted parameter in the experiments, four matrixes were produced and twenty such statistical features were taken out.

(4) The Statistical Geometrical Features (SGF) [12] was also compared with. Sixteen statistical features were applied, four obtained from $NOC_1(\alpha)$, four from $NOC_0(\alpha)$, four from $\overline{IRGL_1}(\alpha)$, and another four from $\overline{IRGL_0}(\alpha)$. Sixty-three binary images (evenly spaced thresholds $\alpha = 4, 8, \cdots, 252$ as suggested by Chen etc. [12]) were used in the experiments.

(5)The use of the Discrete Wavelet Transform (DWT) [10] for texture characterization was also considered for comparison. Using the discrete wavelet transform (DWT), twenty-four wavelet statistical featues (WSFs) such as the mean and standard deviation of approxmiation and detail sub-bands of three level decomposed images (i.e., LLk, LHk, HLk and HHk; for $k = 1, 2, 3$) (as proposed by Arivazhagan and Ganesan [10]) were used. By using Daubechies-8 compact support 8-tap wavelet transform [15], we considered Daubechies-8 filter in the experiments.

For the proposed Statistical Landscape Features, there are 256 horizontal planes at most during the period of extracting the feature curves from a texture image with 256 gray levels. To reduce computational costs, 31 horizontal slicing planes with an evenly gray spaced interval, $z = \alpha$, $\alpha \in \{8, 16, \cdots, 248\}$ were used in the experiments.

3.3. Feature normalization

All the features were normalized by their sample means and standard deviations, which amounts to saying that every component was normalized using the following equation:

$$x' = \frac{x_i - \mu}{\delta}, \quad i = 0, 1, \cdots, n-1, \tag{3}$$

where

$$\mu = \frac{1}{n}\sum_{i=0}^{n-1} x_i \tag{4}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(x_i - \mu)} \tag{5}$$

and n is the number of samples.

The k-nearest neighbor rule using the Euclidean distance and "leave one out" estimate [16] were then adopted for feature evaluation($k = 3$). The k-nearest neighbor rule is widely used in cases where the underlying probability distribution is unknown, and the "leave one out" estimate is unbiased and is generally desirable when the number of available samples for each class is small. For each feature extraction method, sixteen trials were conducted. In each trial, one sub-image was taken from the sixteen sub-images of each Brodatz texture image for testing, and the other fifteen sub-images for training. In each trial, therefore, a different set of 1680 training sub-images and a different set of 112 sub-images were used. The recognition performance of each method is averaged across all sixteen trials.

Statistical Landscape Features used four feature curves for texture classification, the distance between each curve pair is computed using the following formula:

$$d(f, f') = \sum_{\alpha=0}^{n_l-1} |f(\alpha) - f'(\alpha)| \tag{6}$$

where f and f' correspond to one of the four feature curves: n_A^α, n_B^α, h_A^α and h_B^α , respectively. Suppose that d_i represents the distance between one of these four curve pairs,

$i = 1, 2, 3, 4$. The distance between texture D and D' is calculated as follows:

$$d(D, D') = \left| \sum_{i=1}^{4} d_i \right| \tag{7}$$

3.4. Experiment results

The results of the performance comparison of different texture classification methods on the entire Brodatz set are presented in Table 1. From this table, it can be seen that Statistical Landscape Features (SLF) has achieved the highest correct classification rate of 94.53%, which is considerably higher than the other five methods.

Table 1: Correct classification rates of various methods on the entire Brodatz set.

Texture methods	Correct Classification Rates (%)
ACF	58.82
EF	53.91
SGLDM	78.79
SGF	87.72
DWT	88.78
SLF	94.53

Besides achieving such high performance, Statistical Landscape Features has no parameter to tune. We performed with several evenly gray spaced intervals such as 1, 2, 4, 16, and 32 (corresponding to these planes $z = \alpha$, α values belong to $\alpha \in \{0, 1, \cdots, 255\}$, $\alpha \in \{2, 4, \cdots, 254\}$, $\alpha \in \{4, 8, \cdots, 252\}$, $\alpha \in \{16, 32, \cdots, 240\}$ and $\alpha \in \{32, 64, \cdots, 224\}$, respectively) between the neighboring slicing planes in the experiments. All of the cases gave similarly high correct classification rates.

4. Conclusions

This paper considers the graph of a texture image function as a surface in the three-dimensional space that appears like a landscape and proposes a novel texture description method - Statistical Landscape Features (SLF). Four texture feature curves, which are based on the statistics of geometrical and topological properties of the solids induced by the graph of the texture image function and a horizontal plane, have been developed and used to characterize image texture. Systematic comparison using the entire Brodatz set has been carried out, and the experiment results indicate that the SLF method offers a considerably higher classification performance than other methods including ACF, EF, SGLDM, SGF and DWT. Apart from the very good performance, another remarkable advantage of the proposed method is that it has no parameter to tune.

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References

[1] J. M. Coggins, A Framework for Texture Analysis Based on Spatial Filtering, *Ph.D. Thesis*, Computer Science Department, Michigan State University, East Lansing, Michigan, 1982.

[2] R. M. Haralick, Statistical and Structural Approaches to Texture, *Proc. IEEE*, 67(5), pp.786-804, 1979.

[3] M. Tuceryan and A.K. Jain, Texture Analysis, *Handbook Pattern Recognition and Computer Vision*, C.H. Chen, L.F. Pau, and P.S.P. Wang, eds., ch. 2, pp. 235-276. Singapore: World Scientific, 1993.

[4] Guillermo Ayala and Juan Domingo, Spatial Size Distributions: Applications to Shape and Texture Analysis, *IEEE Trans. Pattern Analysis and Machine Intelligence*, 23(12), pp. 1430-1442, 2001.

[5] R. M. Haralick, K. Shanmugam and I. Dinstein, Textural features for image classification, *IEEE Trans. Systems, Man and Cybernetics*, 3, pp. 610-621, 1973.

[6] S. Krishnamachari and R. Chellappa, Multiresolution Gauss-Markov Random Field Models for Texture Segmentation, *IEEE Trans. Image Processing*, 6(2), pp.251-267, 1997.

[7] B. Chaudhuri and N. Sarkar, Texture segmentation using fractal dimension, *IEEE Trans. Pattern Analysis and Machine Intelligence*, 17(1), pp. 72-77, 1995.

[8] P. Garcia, M. Petrou, S. Kamata, The use of Boolean model for texture analysis of grey images. *Computer Vision and Image Understanding*, 74(3), pp. 227-235, 1999.

[9] M. Idrissa, M. Acheroy. Texture classification using Gabor filters, *Pattern Recognition Letters* 23, pp. 1095-1102, 2002

[10] S. Arivazhagan, L. Ganesan. Texture classification using wavelet transform, *Pattern Recognition Letters*, 24, pp. 1513-1521, 2003.

[11] T. Randen and J.H. Husøy, Filtering for Texture Classification: A Comparative Study, *IEEE Trans. Pattern Analysis and Machine Intelligence*, 21(4), pp. 291-310, 1999.

[12] Y. Q. Chen, M. S. Nixon and D. W. Thomas. Statistical geometrical features for texture classification, *Pattern Recognition*, 28(4), pp. 537-552, 1995.

[13] P. Brodatz, *Textures: "A Photographic Album for Artists and Designers"*, Dover, Paris, 1966. http://www.ux.his.no/ tranden/brodatz.html.

[14] R. W. Conners and C. A. Harlow, A theoretical comparison of texture algorithms, IEEE Trans. Pattern Anal. Mach. Intell. (2) pp. 204-222, 1980.

[15] I. Daubechies, Ten Lectures on Wavelets, CBMS-NSF Lecture Notes nr. 61, *SIAM*, 1992.

[16] P. A. Devijver and J.Kittler, *Pattern Recognition: a Statistical Approach.* Prentice Hall International, Eagle Cliffs, New Jersey, 1982