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Texture Classification Based on Topographic Image Structure

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Abstract

In this paper, we present a structural and statistical approach for texture classification. It can achieve with a higher accuracy rate comparing to the Spatial Gray Level Dependence (SGLD) method and Laws' method. Our method uses the previously proposed operator, the Surface-Shape operator (SS-operator), for describing topographic structure of texture images. The SS-operator describes shape of each pixel comparing with its neighbourhood in terms of topographical shapes such as hill, dale, ridge, valley, etc. Then, we use co-occurrence matrices, a statistical measure, to summarize the spatial distributions of such topographical shapes over the considered image to form texture features. This method yields good classifications of MIT vision textures.

1 Introduction

Texture is one of the fundamental pattern elements which humans use in interpreting objects. Especially, it plays an important role for identifying an object which has no specific shape such as sand, water, etc. B. Julesz had found evidence that humans discriminate textures based on simple statistics of texture primitives called textons and found that difference in first-order statistics of texture primitives are sufficient to explain human performance [1]. Therefore, to develop a system for texture classification, descriptions of spatial distributions are needed and they should be matched to the texture primitives being used. R. M. Haralick et al. have suggested two-dimensional spatial dependence of gray tones in a co-occurrence matrix to measure textural features [2]. Generally, it is among the most successful ones. However, it has some drawbacks. For example, it needs a large number of computations. It does not capture the shape aspects of the tonal primitives which is not likely to work well for textures composed of large-area primitives [3]. B. P. Kjell and C. R. Dyer have proposed the method which use long single-orientation edge segments as texture primitives and uses a matrix giving the average distance separating edges of each orientation as a spatial description [4]. However, some natural textures have ambiguous or confused edge information which is too irregular to be analyzed in this way. Furthermore, edge has no invariant property under monotonic gray tone transformation, so the approach based on edge information does not have robustness with light intensity variations. In this paper, we propose a new method which can overcome these problems by characterizing texture patterns based on topographic shapes and using co-occurrence matrices for describing their spatial distributions.

2 Topographic Structure

We consider an image function as a surface. From a geometric view point, local shape of a surface can be determined by surface curvatures and it also can be determined by the eigenvalues of Hessian matrix (Eq. (1)). R. M. Haralick et al. have previously proposed the "Topographic Primal Sketch" [5] for describing image structure by utilizing signs of the eigenvalues. As an extension of this work, we have established an operator called the *Surface-Shape operator* or the *SS-operator*[6]. It can give descriptions of surface shapes in much more details. It is established by considering an angle θ on the eigenvalues $\lambda_1\lambda_2$-plane (see Figure 1) to be a shape index, which can be defined in an explicit form as shown in Eq.(2). We have derived that it has the invariant properties under linear and monotonic gray tone transformations, so it has robustness with lighting condition variations as desired.

Actually, the SS-operator (θ) gives values for describing surface shapes in the range of 0 to π and each value specifies a unique shape. It depends on applications how many categories of shape should be classified. Figure 1 shows an example of the to-

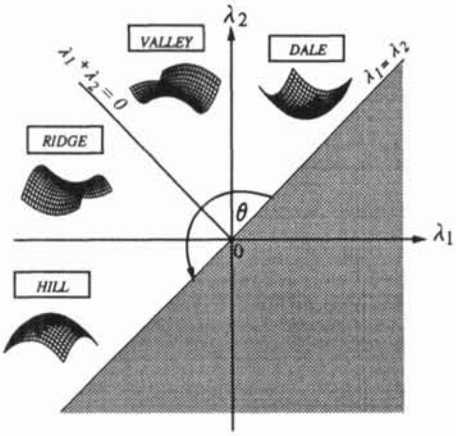


Figure 1: Surface shapes described by the Surface-Shape operator (θ)

pographical shapes classified to 4 categories: dale, valley, ridge, and hill.

$$H = \begin{bmatrix} f_{xx} & f_{xy} \\ f_{xy} & f_{yy} \end{bmatrix} \tag{1}$$

$$\theta(x,y) = \arctan\left(\frac{\sqrt{(f_{xx}-f_{yy})^2 + 4f_{xy}^2}}{f_{xx}+f_{yy}}\right) \tag{2}$$

where f_{xx}, f_{xy}, f_{yy} are the second-order partial derivatives of an image function $f(x,y)$.

3 Texture Features

Since topographical shapes can be considered as elements which contain information about structure of a texture image. And a co-occurrence matrix is a good tool for describing their arrangements. These concepts are used for analysing texture images in this paper.

We use the SS-operator (θ) for describing texture images with 8 categories of topographical shapes, i.e., representing with 8 discrete values {0,1,...,7} for $\theta \in [0,\pi]$. To calculate the partial derivatives needed for calculating θ (see Eq.(2)), we use kernels accomplished by fitting a two-variable cubic polynomial to a 5×5 neighbourhood of each pixel [7]. Then, use co-occurrence matrices for indicating the joint probability of occurrence of topographical shapes occuring over the considered image at a separating distance. We select the separation of 1 pixel in four directions (vertical, horizontal, left diagonal and right diagonal) yielding 4 co-occurrence matrices (size 8 by 8) defined as follows:

Vertical direction: $V = [v_{ij}]$

$$\begin{aligned} v_{ij} &= \text{Prob}(\theta(x,y)=i, \theta(x,y+1)=j \\ &\quad \text{or } \theta(x,y)=i, \theta(x,y-1)=j) \end{aligned}$$

Horizontal direction: $H = [h_{ij}]$

$$\begin{aligned} h_{ij} &= \text{Prob}(\theta(x,y)=i, \theta(x+1,y)=j \\ &\quad \text{or } \theta(x,y)=i, \theta(x-1,y)=j) \end{aligned}$$

Left diagonal direction: $L = [l_{ij}]$

$$\begin{aligned} l_{ij} &= \text{Prob}(\theta(x,y)=i, \theta(x+1,y+1)=j \\ &\quad \text{or } \theta(x,y)=i, \theta(x-1,y-1)=j) \end{aligned}$$

Right diagonal direction: $R = [r_{ij}]$

$$\begin{aligned} r_{ij} &= \text{Prob}(\theta(x,y)=i, \theta(x-1,y+1)=j \\ &\quad \text{or } \theta(x,y)=i, \theta(x+1,y-1)=j) \end{aligned}$$

where $i,j = 0,1,...,7$.

An element in the ith row jth column of each matrix is a measure of the co-occurrence of θ values i and j with separation of 1 pixel represented in terms of probability. To form texture features, primarily, we use three descriptors of each co-occurrence matrix: maximum probability, inverse moment order 2, and uniformity which are the useful features for describing texture patterns as stated in [8]. Let $C = [c_{ij}]$ be any co-occurrence matrix. The features are defined as follows:

- *maximum probability (M):*
  It indicates the strongest response of c_{ij}'s.
  $$\max_{i,j}(c_{ij})$$
- *inverse moment order 2 (I):*
  It gives a high value when high values of c_{ij}'s are near the main diagonal.
  $$\sum_i \sum_j c_{ij}/(i-j)^2, \qquad i \neq j$$
- *uniformity (U):*
  It gives the lowest value when c_{ij}'s are all equal. Conversely, a higher value indicates randomness.
  $$\sum_i \sum_j c_{ij}^2$$

From recent work concerning a new framework called aura matrix [9] (compatible to co-occurrence matrix), it induces us to establish a new feature from a co-occurrence matrix called *miscibility*. It is defined as follows:

- *miscibility (S):*

  It gives a high value when high values of c_{ij}'s are in the anti-diagonal.

$$\sum_i \sum_j c_{ij}, \qquad i+j=n$$

  where $i,j = 0,1,...,n$.

Since miscibility gives more intuitive meaning than maximum probability, we expect that it should give a better description for characterizing image textures. It is evaluated by experiments explained in the next section.

4 Experiments

In experiments, we use samples from MIT vision textures divided into 3 sets. Set I consists of 24 images (size 128 by 128) belonging to 6 categories, each 4 images. Set II consists of 72 images (size 64 by 64) belonging to 9 categories, each 8 images. Set III consists of 144 images (size 128 by 128) belonging to 9 categories, each 16 images. Examples of textures in each set are shown in Figure 2. The 72 samples of Set II are obtained by dividing the original images (size 128 by 128) into 4 windows. And the 144 samples of Set III are obtained by dividing the original images (size 512 by 512) into 16 windows.

The procedures of our method are as follows: Firstly, transforming intensity images to topographical structure representation by the SS-operator (θ) quantizing to 8 gray levels. Examples of the transformed images are shown in Figure 3. Secondly, measuring spatial distributions of topographical shapes in an image by using 4 co-occurrence matrices (V,H,L,R) as described in the previous section. Next, computing texture features of the 4 co-occurrence matrices. Finally, classifying texture images based on those features by a minimum distance classifier which a prototype set and a test set are identical. We do experiments with 2 sets of texture features (M,I,U) and (S,I,U).

The results are shown in Table 1 (col.2 and 3). We obtain the satisfactory high correct classification rates. And as expected, *miscibility (S)* can give a better description than *maximum probability (M)*. Actually, texture samples in each category used in our experiments rather have various shading patterns. Therefore, the high accuracy rates also show the good performance of the SS-operator for suppressing shading effects.

5 Comparison with other methods

It seems our method is the Spatial Gray Level Dependence (SGLD) method adding a step of using the SS-operator as a pre-precessing. However, the concepts are different; our method characterizes texture images based on topographic structure instead of gray tones as performed in the SGLD method.

For comparison purposes, we have performed classifications by the SGLD method based on the following features: maximum probability, inverse moment order 2, and uniformity. The results are shown in Table 1 (col. 4). The procedures are same as our method but ignore a step of using the SS-operator as pre-processing. In addition, we have compared our method with Laws' method, a bench-mark method. We use the standard deviations of nine 3×3 Laws' masks [10] responses to be texture features. The standard deviations are calculated in windows of 15×15 pixels moving over the image, then average of the standard deviations is used as a feature of each mask. The classification results by a minimum distance classifier are shown in Table 1 (col. 5).

By comparing means of correct classification rates as shown in Table 1, our method based on (S,I,U) features gives the highest rate.

6 Conclusions

In this paper, we propose a new method for texture classification. We use the SS-operator for describing topographic structure of texture images and form texture features from co-occurrence matrices. We can obtain higher correct classification rates comparing to the SGLD method and Laws' method. However, we need more investigations about misclassification and limitations of the proposed method.

References

[1] B. Julesz "A theory of preattentive texture discrimination based on first-order statistics of textons," Biological Cybernetics,41, pp.131-138,1981.

[2] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural Features for Image Classification," IEEE Trans. on systems, man and cybernetics, vol. SMC-3,6,pp.610-621,Nov,1973.

[3] R. M. Haralick, "Statistical and Structural Approaches to Texture," Proceeding of the IEEE, vol.67,no.5,pp.786-804,May 1973.

[4] B. P. Kjell, C. R. Dyer, "Edges separation and orientation texture measures," Proc. of CVPR'85, pp.306-311, 1985.

[5] R. M. Haralick, L. T. Watson, T. J. Laffey, "The Topographic Primal sketch, The International Journal of Robotics Research," vol.2, no.1,pp.195-217,1983.

[6] P. Sukanya, R. Takamatus, M. Sato, "New operator for determining surface shapes," Proceeding of SPIE, vol.2826, Aug 1996.

[7] R. M. Haralick, L. G. Shapiro, Computer and Robot Vision Vol.1,Addison Wesley,1992.

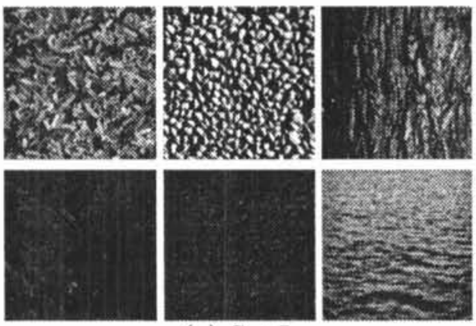
[8] R. C. Gonzalez, R. E. Woods, Digital Image Processing, Addison-Wesley, 1993.

[9] I. M. Elfadel, R. W. Picard, "Gibbs Random Fields, Cooccurrences, and Texture Modeling," IEEE trans. on PAMI,vol.16,no.1,pp.24-37,1994.

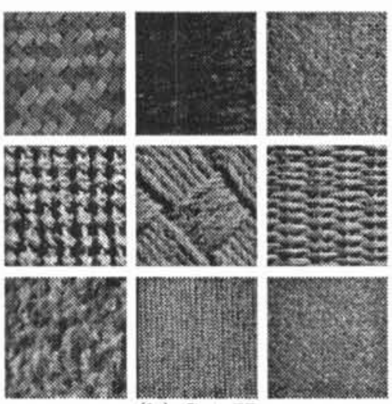
[10] W. K. Pratt, Digital Image Processing, John Wiley & Son Inc., 1991.

Table1: Comparison of correct classification rates

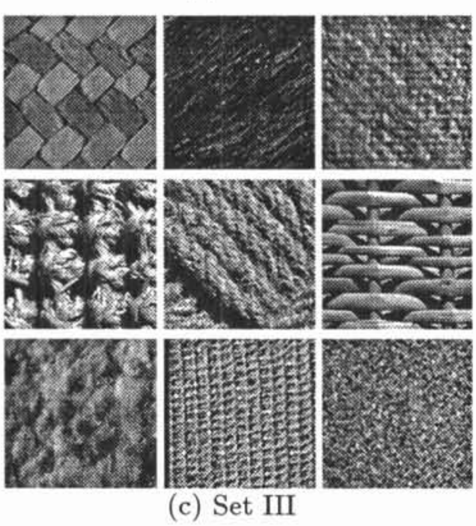
Texture samples	**Correct classification rates (%)**			
	Method 1 (M,I,U)	**Method 2 (S,I,U)**	**the SGLD method**	**Laws' method**
Set I (24 images)	91.7	95.8	75.0	79.2
Set II (72 images)	93.1	98.6	88.9	100.0
Set III (144 images)	93.1	95.1	90.3	94.4
Mean	92.6	96.5	84.7	91.2



(a) Set I

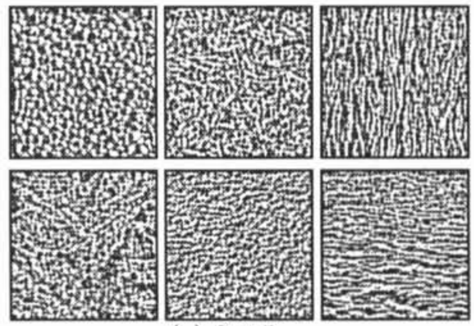


(b) Set II

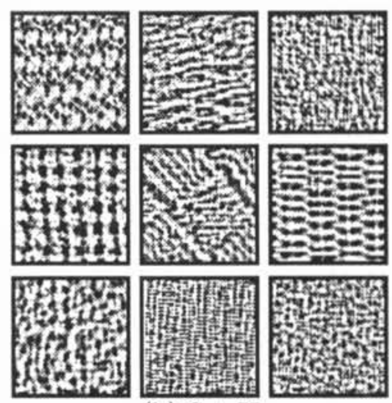


(c) Set III

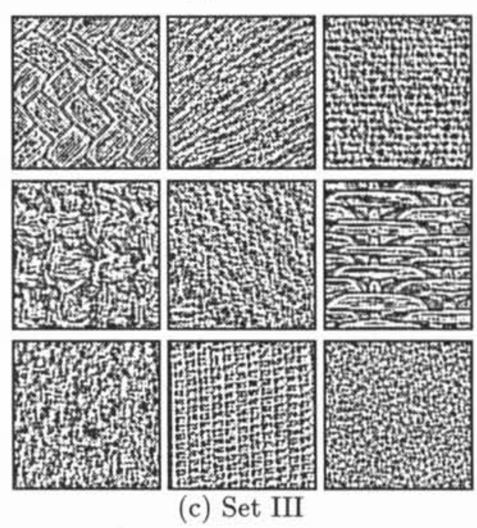
Figure2: Texture samples from MIT vision texture database.



(a) Set I



(b) Set II



(c) Set III

Figure 3: Transformed images by the SS-operator.