

DESCRIPTION OF TEXTURES BY A STRUCTURAL ANALYSIS

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We introduce a method of a structural analysis for description of textures in natural scenes. The proposed texture analysis system automatically extracts the elements in a texture image, measures their picture properties, classifies them into some discriminable classes (one "ground" and some "figures"), and produces the description of elements in each class and also of their placement rules. This description can be used for learning and recognition of texture images. We also present a new idea for evaluating texture analyzers. In order to directly see what essential features or structures of the given textures each analyzer extracts, we propose an analysis-by-synthesis method. That is, the synthesis program in our system reconstructs the texture image on the basis of its description. Comparing the reconstructed image with the original one, we can evaluate what information is preserved and what is lost in the description and can improve our algorithms.

1. INTRODUCTION

When we observe objects in a scene, we use the textural information as follows.

- (1) identification of objects by the categories of textures,
- (2) discrimination of objects by the differences of textures, and
- (3) perception of a depth, a curved surface, or a inclination of a surface by the changes of textures.

Endowing machines with these recognition capabilities is not only an interesting problem in computer science but also practically important for automatic analysis of aerial photographs or medical images. Texture has been studied on at least two levels: statistical and structural [1]. On the statistical level, we regard a texture as defined by a set of statistics extracted from a large ensemble of local picture properties. On the structural level, a texture is considered to be defined by elements which occur repeatedly according to placement rules.

We have developed a structural analysis method first to segment an image into differently textured regions [2] and secondly to classify texture samples into several categories [3]. In this paper, we show what kinds of description can be given by the structural analysis and also present a new idea for

evaluating texture analyzers. A conventional method for testing performance of analyzers is to evaluate their classification abilities for some texture samples whose categories are specified by a user; a better analyzer is that which gets a higher score of classification [4]. The classification ability, however, is highly dependent on both the texture samples and the categories. Since categories of natural textures are not so definite as artificially made characters, the evaluation of texture classification algorithms is dependent on their application fields. Then, in order to directly see what essential features or structures of the given textures each analyzer extracts, we propose an analysis-by-synthesis method. That is, our system first analyzes texture samples and gives their descriptions. Next, the synthesis program reconstructs the texture image on the basis of its description. Comparing the reconstructed image with the original one, we can evaluate what information is preserved and what is lost in the course of the analysis and can improve our algorithms.

2. STRUCTURAL ANALYSIS

A texture is defined as a repetitive pattern in which "elements" are arranged according to "placement rules". The proposed texture analysis system automatically extracts the elements in a texture image and measures their picture properties and their placement rules.

2.1 Preprocessing

An input image is digitized into 64x64 pixels and is quantized into 64 gray levels. Fig. 1 shows digital images of three kinds of textures. Since input conditions may change the first order statistics of brightness distributions, the input image is normalized with respect to gray scale changes so that the mean of the brightness distribution is 32 and the standard deviation is 8. Next, the normalized image is deblurred by an edge preserving averaging method to extract texture elements easily.

2.2 Extraction of Elements

A texture element is defined as a connected area with almost same gray levels. To extract such elements, pixels which are adjacent and whose gray levels are almost same are merged into regions. The merging process used here is as follows.

First, any pixels which are adjacent and whose gray level differences are less than the threshold $d(=1)$ are merged into regions and their gray levels are averaged. Here, the total brightness change caused by averaging is examined. The total change is defined as

$$N(d) = \sum_{(x,y)} |\delta_d(x,y)|$$

where $\delta_d(x,y)$ is the gray level change at a point (x,y) . Next, d is increased by one ($d=d+1$) and the merging process is repeated until one of the following conditions is satisfied ($d>4$).

(1) the total change is very large, which implies that d has become large enough to merge different elements, or

(2) the total change is very small, which implies that there may be a brightness gap between different kinds of elements.

When the process stops at a threshold d^* on the condition (1), the regions obtained by merging at d^*-1 are used for the texture elements. When the process stops on the condition (2), the segmented region by thresholding the brightness histogram are used for the texture elements. For example, Fig. 2 shows the thus obtained elements of the images in Fig. 1.

2.3 Properties of Element

The following five kinds of properties are measured for each extracted element. They are used for global discrimination of elements.

- (1) brightness
- (2) area

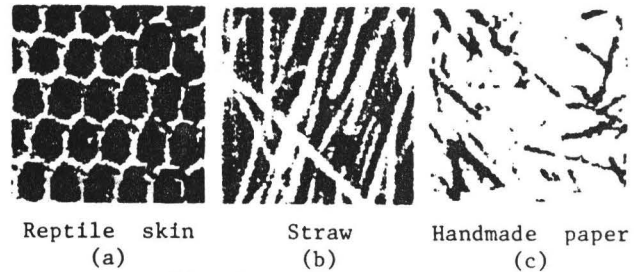


Fig. 1 Texture images

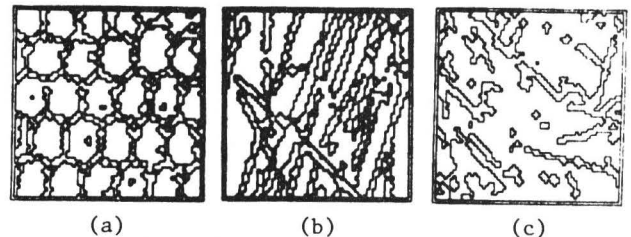


Fig. 2 Extracted elements

(3) size

The size of an element is defined as $2 \times \text{area/perimeter}$. For example, when an element is a circle of radius r , the size is r . The value of this size descriptor is not affected greatly by overlap of individuals which may be extracted as one element on the image level.

(4) directionality (direction and magnitude)

The directionality of an element is measured by the principal component analysis. The direction of the element is defined by the slope of the major axis. The magnitude D of the directionality is defined by the eigenvalues λ_1 and λ_2 ($\lambda_1 \geq \lambda_2$) of the covariance matrix for the distribution of (x,y) coordinates of points in the element, as

$$D = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2}$$

When an element is a circle, $D=0$. When an element is a straight line, $D=1$.

(5) curvatures along the contour

In the distribution of curvatures along the contour of an element is meaningful information about the complexity of the shape. We measure the k -curvature ($k=5$) [5] at each contour point. Next, a measured curvature ρ is classified into six zones:

- i) high concave curve: $-75^\circ \leq \rho \leq -45^\circ$
- ii) low concave curve: $-45^\circ \leq \rho \leq -15^\circ$
- iii) straight line: $-15^\circ \leq \rho \leq 15^\circ$
- iv) low convex curve: $15^\circ \leq \rho \leq 45^\circ$
- v) high convex curve: $45^\circ \leq \rho \leq 75^\circ$
- vi) zig-zag line: the other

and the occurrence probabilities of curvatures in the first five zones are calculated for the element properties.

2.4 Classification of Elements

On the basis of the distributions of these properties, elements are classified into some discriminable classes. In our system, elements are classified by thresholding the histogram of each property. In computing the histogram of a property, we use the weighted value as its frequency to give large weight to dominant elements. The weighting values are shown in Table 1. For example, the frequency of brightness b is defined as the total area (not number) of elements whose brightness are b . Therefore, the system can stably analyze a texture image in which there are comparatively small number of elements. Since each property has a different domain and range, the histogram is normalized and the thresholds are set automatically at the bottoms of deep valleys between the prominent peaks, if any [3].

2.5 Description of Texture

Statistical Features

Now, the system calculates the following statistical features about elements in each class.

- (1) the number of classes: N_c
 (2) the mean and the deviation of each property p of elements in each class i : (μ_{ip}, σ_{ip})
 ($i=1 \dots N_c$ and $p=1 \dots N_p$, where N_p is the number of properties). The weighted values in Table 1 are also used for calculating these

Table 1 Weightings in histogram computation

PROPERTY	WEIGHTING
BRIGHTNESS	AREA
SIZE	PERIMETER
AREA	AREA
DIRECTIONALITY	
.DIRECTION	AREA x MAGNITUDE
.MAGNITUDE	AREA
CURVATURES	PERIMETER

distributions.

Furthermore, the following features concerning to placements of elements are easily measured.

(3) the density of elements in each class i : A_i ($i=1-N_c$), which is the ratio of the total area of elements in class i to the image area.

(4) the adjacency probability between class i and class k : P_{ik} ($i, k=1 \dots N_c$), which is defined as the probability that a boundary point of an element in class i is adjacent to that in class k . When $i=k$, it is especially called 'auto-adjacency probability'.

Table 2 shows the values of these textural features of the images in Fig. 1.

Figure and Ground

If there is more than one class of elements, one of them can be regarded as the "ground" of the image. The "ground" class is defined as

Table 2 Statistical features of elements and placements

TEXTURE	(a)				(b)				(c)			
No. of class	1		2		1		2		1		2	
properties	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.	MEAN	S.D.
brightness	19.2	5.2	36.1	1.4	18.5	3.8	35.0	2.4	27.0	0.2	45.4	2.9
size	2.9	0.6	8.2	2.1	3.6	0.9	6.9	3.1	8.9	0.8	3.4	0.9
area	12.9	11.7	73.3	70.0	32.6	36.2	67.4	175.2	2664.5	438.3	144.1	105.2
directionality												
magnitude (%)	56.6	26.5	34.3	24.4	78.8	28.0	71.4	22.7	7.0	6.9	28.7	29.0
direction	16.4	4.2	17.7	2.0	17.7	2.7	17.3	1.2	17.9	0.8	23.0	3.8
curvatures												
[-75°, -45°] (%)	4.4	6.1	5.3	4.5	1.9	3.5	4.4	3.2	9.6	2.1	8.6	5.9
[-45°, -15°] (%)	21.0	15.2	17.9	7.7	20.8	9.8	19.8	9.9	24.7	5.1	24.3	12.8
[-15°, 15°] (%)	13.9	13.4	16.0	8.3	32.6	17.5	32.1	16.1	28.8	5.6	22.8	13.7
[15°, 45°] (%)	24.4	22.1	36.2	13.3	31.4	17.5	24.5	12.8	23.7	8.5	19.6	10.8
[45°, 75°] (%)	9.1	10.5	18.9	8.5	6.1	8.6	7.0	8.0	9.2	3.1	8.3	9.9
density (%)	30		70		29		71		73		27	
adjacency-probabilities (%)												
	1	2	1	2	1	2	1	2	1	2	1	2
	22	78	22	78	10	90	10	90	0	100	0	100
	93	7	93	7	60	40	60	40	97	3	97	3

(1) a class whose average area of elements is very large (for example, class 1 of (c) in Table 2), otherwise,

(2) a class whose ratio of the deviation to the mean of areas of elements is very large (for example, class 2 of (b) in Table 2), otherwise,

(3) a class which has the largest auto-adjacency probability (for example, class 1 of (a) in Table 2).

The other classes are in turn regarded as the "figures" of the image. If the image has only one class of elements, it is regarded as both the "figure" and the "ground". For example, the "grounds" of the images in Fig. 1 are smeared with black as shown in Fig. 3.

Typical Element

The system selects one typical element from each "figure" class to give a detailed shape description of the elements in that class. The typical element in each "figure" class is the one whose shape properties are the closest to the means of those of that class. The function that evaluates the closeness of an element j in class i is defined as

$$E_{ij} = \frac{\sum_{p=1}^{N_p} \exp\left[-\frac{(x_{jp} - \mu_{ip})^2}{2\sigma_{ip}^2}\right]}{N_p}$$

where x_{jp} is the value of a property p of an element j and the shape properties used are area, size, directionality and curvatures. For example, the dotted areas in Fig. 3 are the typical elements of the image in Fig. 1.

It is an important problem how a typical element is to be described for a detailed comparison needed in recognition phase of the system. There are many algorithms for shape analysis [6] and we should select a information preserving technique. In this paper, however, only the points in a typical element are memorized in terms of the relative coordinates from the centroid of the element for simplicity.

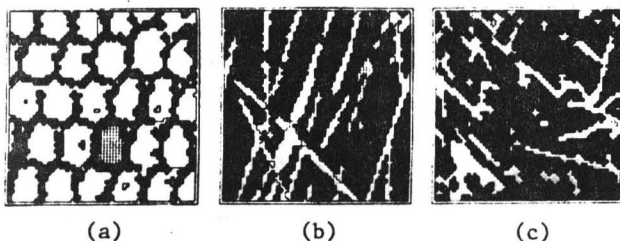


Fig. 3 "Grounds" of images (■) and typical elements (□) in "figure" classes (□)

Relative Position Vectors

To give a detailed description also of placements of elements, the system measures relative positions among elements in "figure" classes. A relative position between two elements is defined as the relative coordinate between their centroids. The two dimensional histogram H_{ik} of the relative positions of every pair of elements, one in class i and the other in class k (including $i=k$), are computed. Here, in computing the histogram we use the weighted value as its frequency as follows. Let E_{ij} be the closeness of an element j in class i and E_{kl} be that of an element l in class k . Then the weighted value is defined as $\min(E_{ij}, E_{kl})$. If the placement is regular, there are significant clusters periodically in the histogram. In such a case, the mean and deviation of each independent cluster which is nearest to the origin is measured as the placement rule R_{ik} . They are denoted as

$$R_{ik} = \{[\mu_x^n(i,k), \mu_y^n(i,k)], [\sigma_x^n(i,k), \sigma_y^n(i,k)]\} \quad (n=1 \sim N_{ik})$$

where N_{ik} is the number of independent clusters. If there is no significant cluster, the placement rule R_{ik} is regarded as random.

For example, Fig. 4 shows the distributions H_{22} of relative positions of elements in the "figure" class 2 of the image in Fig. 1(a). In this case, the placement is regarded as regular and two independent clusters (whose means are (13,-6) and (0,11)) are measured. On the other hand, those of the other images in Fig. 1 are regarded as random.

Now, the description of texture is completed. This description can be used for learning and

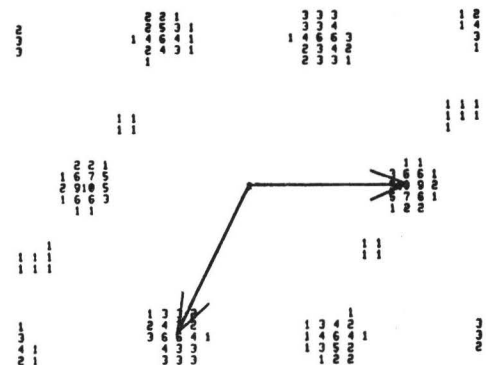


Fig. 4 2-D histogram of relative positions among elements in "figure" class

recognition (classification) of texture images. Classification experiments using only the statistical features are reported in [3].

3. RECONSTRUCTION OF TEXTURES

The synthesis program in the system generates a texture image on the basis of the description of the original texture. It reconstructs a texture image so that the statistical features may be the same as those of the original one.

3.1 Modification of Typical Element

To reconstruct the texture elements, the system uses the typical element in each "figure" class and modifies it according to the distributions of the properties of elements in its class. The properties used for modification are brightness (for light and darkness), size (for magnification and reduction), direction (for rotation), and the magnitude of directionality (for compression).

For example, let (μ_{ip}, σ_{ip}) be the mean and deviation of the property p of elements in class i . The typical element is modified so that the distribution of a property p is $N[\mu_{ip}, \sigma_{ip}]$ using a normal random number generator.

Modified elements in such a way are then arranged according to the placement rules as mentioned in the next section.

3.2 Placement of Modified Elements

The system determines the positions at which modified typical elements are placed as follows. If there are more than one "figure" class, one dominant "figure" class is selected. That is, the positions of elements of the dominant "figure" class (let it be now i) are at first determined according to the placement rule R_{ii} and those of other class k are determined later according to R_{ik} or R_{kk} . Our system defines a class i as the dominant one whose average deviation in the placement rule R_{ii} is the smallest. The positions of elements in the dominant class are determined as follows.

When the placement rule R_{ii} is regular, the distributions of relative positions in R_{ii} is used. First, the preliminary positions are determined using the means in R_{ii}

$$\{\mu_{x,i}, \mu_{y,i}\} \quad (n=1 \sim N_{ii})$$

as shown by white points in Fig. 5 (in this case, $N_{ii}=2$). Next, these preliminary

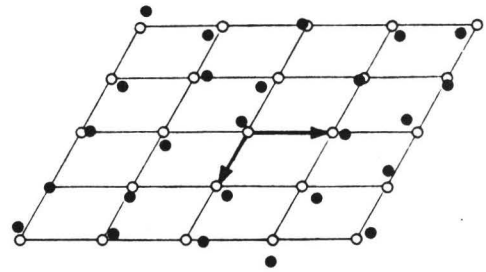


Fig. 5 Position determination in regular placement case (+: mean vector)

positions are fluctuated according to the normal distribution

$$N[(0,0), (\sigma_x/2, \sigma_y/2)]$$

as shown by black points in Fig. 5 using a normal random generator, where σ_x and σ_y are the average deviations in R_{ii} . These black points are the final positions at which modified elements are placed.

When the placement rule R_{ii} is random, the system uses the density A_i of elements to determine the positions. Since the number of arranged elements is expected as

$$N_i = \frac{\text{total area of elements in class } i}{\text{average area of elements in class } i}$$

the system arranges such number of positions randomly over the image using a uniform random number generator.

Next, the position of elements in other class k ($k \neq i$) are determined in almost the same way according to the placement rule R_{ik} or R_{kk} .

Referring to thus determined positions, modified elements in each "figure" class are placed. After all the "figure" elements are placed, there remains blank space which corresponds to the "ground" of the image. It is filled up with gray values on the basis of the statistical features of the "ground" class by a region growing method.

Now, the reconstruction of texture is completed. Fig. 6 shows examples of the reconstructed images from the original ones in Fig. 1.

4. DISCUSSIONS

For our experiments, we used the same texture samples from Brodatz's photographic album [7] as used in classification [3]. The structural analysis produces anthropomorphic descriptions and therefore they are easily understandable

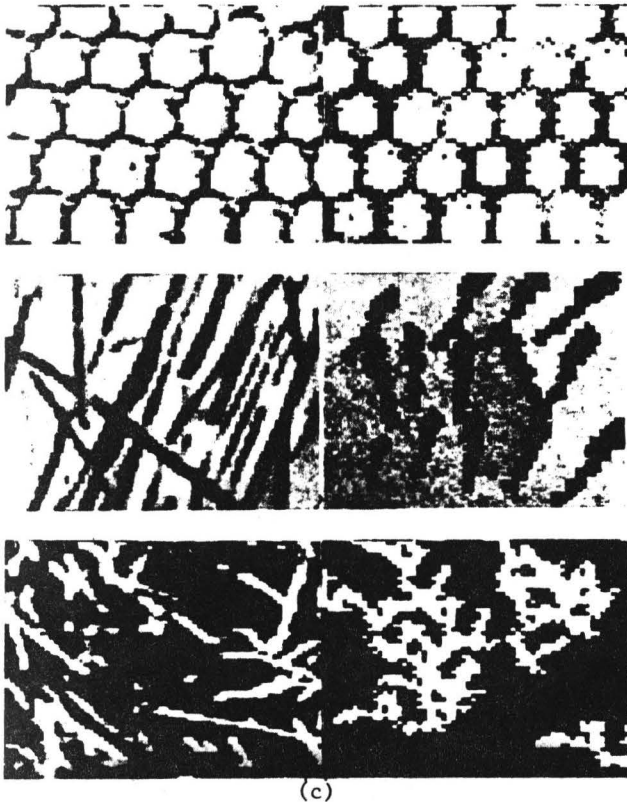


Fig. 6 Original images (left) and reconstructed images (right)

and useful. However, we found some important problems by reconstructing those texture images.

Since we only use brightness information to extract texture elements, they do not always correspond to real individuals or what human beings perceive. For example, overlapped individuals with same brightness are extracted as one element on the image level.

Also the "grounds" which the system selects do not always correspond to those which human beings select. This problem relates to the definition of elements.

The placement rules used (relative positions) is the second order statistics and may be still too simple. For example, though the position of an element is considered independently of its properties and those of surrounding elements, there are often correlations among them.

In this paper, we hardly deal with hierarchical textures. A hierarchical texture is such that

a set of several elements can be regarded as a unit and many such units are arranged according to their own placement rules. Such hierarchical textures, however, are more often found in artificial textures. If we add aggregation programs [8] to our system, we would be able to describe them in the same way.

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