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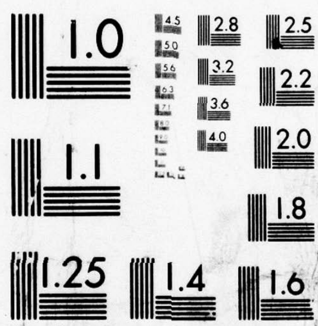

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A COMPARISON OF SOME SIMPLE METHODS FOR EXTRACTING TEXTURE PRIMITIVES AND THEIR EFFECTIVENESS IN TEXTURE DISCRIMINATION

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ABSTRACT

Three simple methods of extracting texture primitives are compared. It appears that the simplest of these, thresholding at a fixed percentile, yields primitives that are quite effective in texture discrimination.

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1. Introduction

One can view textures as composed of "primitives" (connected regions satisfying certain properties) placed in a certain spatial arrangement. In this view, to describe a texture one needs to describe both the primitives and the placement rules. For the primitives we can construct a property list, while for the placement rules we can select a set of spatial relations and list which pairs (triples, quadruples,...) of primitives satisfy these relations. This model has been used by many researchers initially to synthesize textures [1],[2] and, more recently, in texture discrimination [3],[4],[5].

In Tsuju and Tomita [3], the problem was to segment a picture consisting of regions of different textures. The primitives ("atomic regions") of which the textures were composed were defined to be connected sets of points with almost the same gray level. Once the atomic regions were extracted, for each one a set of properties was measured (shape, size, position, color, and average gray level). Histograms of the property values were constructed and the textures were identified as peaks in these histograms. Having identified the textures, the picture was segmented by labeling the primitives with the names of the textures they belonged to.

The pictures to which Tsuji and Tomita applied their methods consisted of artificially constructed objects covered by almost regular subpatterns. An extension of the method to more realistic scenes was proposed by Zucker et al. [4]. For "real-world" pictures it was argued that the notion of "atomic region" was not well defined, or better, that its definition did not lead easily to its extraction. Therefore, instead of segmenting the picture to extract the primitives, local property values were directly obtained through a set of "spot detectors" having a range of sizes. What was measured was the output intensity of the spot detector of a given size at all points in the picture. To prevent "spurious" spot detections, a spot value was ignored if a larger spot value occurred in its receptive field. In this way one can construct a histogram of the outputs of the spot detector. As in [3], the textures were identified as peaks in this histogram. Assuming that we have two textures in the picture, they can be retrieved by thresholding the histogram, e.g. at the lowest point between the two peaks. The spot size was selected as the one that gave the most strongly bimodal histogram. Although the method based on spot detection gives less detailed information about the primitives than the one proposed in [3], it is sufficient for discriminating some real-world textures.

In both papers ([3] and [4]) no attempt is made to use the spatial arrangement of the primitives to discriminate the textures (it was not necessary). In the work of Maleson et al. [5], however, both sources of information are suggested for texture discrimination. To simplify the description of the primitives, they are restricted to be clusters of pixels having "simple" shapes. As primitive properties, it is suggested that average intensity (gray level), eccentricity, axial orientation, and size constitute a sufficient set for most textures. The placement of primitives is described by a restricted set of spatial relations (such as collinearity) between primitives in the same class (i.e., having the same property values for a subset of the properties).

In our work we propose three related methods for extracting texture primitives. These methods are compared in connection with the discrimination of a few texture samples, including four Brodatz [6] textures and three LANDSAT geological terrain textures. In the methods proposed the primitives are not forced to conform to pre-specified shapes (as they were in [5]). This makes possible the use of shape attributes not present in [5] that may be useful in texture discrimination. Also we have not used spatial relationships between the primitives to characterize the textures.

2. <u>Three ways of extracting texture primitives</u>

The basic idea of all the methods is to segment the texture into primitives and background by thresholding of the gray level. We will define the primitives as being regions formed by connected sets of pixels whose gray level values are above (or below) the threshold.

Of course, by thresholding we should not expect, in general, to obtain exactly the perceptual texture primitives. But it is hoped that the regions obtained are sufficiently related to the "actual" texture primitives that the properties measured for these regions reflect property values of the "actual" primitives.

We can predict that this method will be computationally efficient, since connected components of the binary image produced by thresholding can be identified *in a single pass* through the picture. Also in the same pass much information about the primitives can be gathered (area, perimeter, moments...).

The main problem is how to select an adequate threshold. If the histogram of the gray level values is bi-modal, a natural candidate for a good threshold is the valley between the two peaks. To make easier the computation of the primitive properties we would like the primitives to be isolated regions. If the threshold that separates the two peaks is near the 50th percentile, most likely we will not get isolated regions. Also if the histogram is not bi-modal, the approach is not applicable. Therefore, instead of making the threshold depend on the histogram, in the first method we chose the threshold such that we have a fixed percentage of the pixels with above threshold gray level. The percentage must be low enough so we can expect to get a set of isolated primitives, but sufficiently high to make the primitive properties meaningful. We have chosen 25%, but other values near 25% would be good as well.

For each texture we have two possible thresholds depending on whether we choose to consider dark or bright primitives. Actually we may use both types of primitives for texture discrimination. The thresholding of the texture can be preceded by some pre-processing operations, such as noise cleaning or even blurring. Gray level transformations, however, such as histogram flattening, do not significantly alter the final output.

The second method of extracting texture primitives is based on the histogram peak sharpening algorithm of Peleg [7]. This algorithm, which can be thought of as a one-dimensional clustering algorithm, iteratively alters the histogram until it consists of a few spikes. The picture is segmented into the few gray levels corresponding to the spikes. The number of spikes (clusters) of the modified histogram is a function of the number of iterations and the "neighborhood" size used in the clustering process. These properties were used to produce a set of spikes that sums up as nearly as possible to 25% of the picture points. In this way we take into account characteristics of the histogram, which was not done in simple thresholding.

The third and last method ("Superslice") was developed by Milgram [8]. In it, the image is not segmented by using a single threshold; rather, a collection of thresholds is used to extract regions which are compared to a thinned edge map of the picture. The regions are accepted or rejected based on the coincidence of the boundary points of the regions with edge points. Surviving competing regions are compared and only the best match (with the edge map) is retained. This method not only uses histogram information but also complements it with local information derived from the picture. In our case we used thresholds at the percentiles 15%, 25%, and 35%.

For each method the output is a binary picture. The fixed threshold method is the computationally cheapest, while Superslice is the most demanding. The last two algorithms (iterative histogram modification and Superslice) are described briefly in Appendix A.

In order to get meaningful primitive statistics, we use 128x128 pictures. The textures shown in Figures 1a, 2a, 3a, and 4a were taken from Brodat [6] and show respectively wool, raffia, sand, and grass. The results of applying thresholding to the noise cleaned pictures are shown in Figures 1c to 12c. Figures 16a, 17a, and 18a show three different terrain types: Mississipian limestone and shale, Pennsylvanian sandstone and shale, and

Lower Pennsylvanian shale. These pictures were noise cleaned and then subjected to thresholding (bright 25% and dark 25%) and to Superslice. The results of these operations are shown in Pictures 13b, 14b, 15b (bright 25%), 16b, 17b, 18b (dark 25%), 19c, 20c, and 21c (Superslice).

3. Primitive properties

Once we have extracted the texture primitives, the next step is to measure properties that may characterize them. We have chosen a set of shape attributes (area, perimeter, compactness, eccentricity, direction) together with average gray level.

The area is defined simply as the number of pixels in the primitive, while the perimeter is its number of boundary pixels. Compactness is the ratio of the square of the perimeter to the area. Eccentricity is defined as the ratio of the major to the minor axis of inertia (the detailed formulas are given in Appendix B). Finally, direction is the angle that the major axis makes with a fixed orientation (vertical in the picture).

The property values of a given region serve to describe that particular region. The distribution of the values for all regions serves to characterize the texture; it can be thought of as a statistical description of the texture. The property value distribution is given by the property value histogram. In computing this histogram we do not take into account border regions, i.e., regions that are adjacent to a border of the picture, becuase such regions would falsify the property value distribution.

To discriminate the textures, we use features derived from the histogram. We could, for instance, take as features the values of the histogram for each interval. This would completely describe the histogram but would give too large a number of

4. Experiments

The features described in Section 3 were extracted for samples chosen from two sets of textures. The first consisted of four Brodatz textures [6]: wool, raffia, sand, and grass; the second consisted of three different geological terrains from a LANDSAT image. In each set there were four samples of each texture.

A feature is said to "separate" two given textures if the ranges of feature values for the two textures are non-overlapping intervals. The "separability" of two textures was measured in terms of the number of features that separated the two textures.

For the Brodatz textures all three methods described in Section 2 were used, while for the terrain textures only (dark and bright) 25% thresholding and Superslice were used. Figures 21, 22, 23 display the feature values obtained for the Brodatz texture samples (A, B, C, D are wool; E, F, G, H are raffia; I, J, K, L are sand; M, N, O, P are grass). (The textures depicted in Figures 1a, 2a, 3a, 4a are A, E, I, and M, respectively.) Tables 1, 2, and 3 summarize the effectiveness of the features for separating the textures. From these tables we see that no feauture alone separates all texture pairs. However, two features used independently are sufficient to separate all pairs of textures.

A comparison of the methods can be made if we look at the features that are common to every method. This information is features. We decided, instead, to use the mean and standard deviation as descriptors for the distribution of the property values. In the computation of the mean and standard deviation very small regions and very large ones were not considered. For very small regions most of the properties are not interesting; therefore every region having less than 10 pixels was ignored. For large regions we used a more complex rule (it is described in Appendix C). They were ruled out on the basis that they were "atypical" regions.

The effect of "erasing" these regions from the binary picture is shown in Figures 1d, 2d, 3d, 4d, 5d, 6d, 7d, 8d, 9d, 10d, 11d, 12d, 13c, 14c, 15c, 16c, 17c, 18c, 19d, 20d, 21d. (Actually the regions were not erased but just ignored.)

The only feature derived from direction was standard deviation. The mean was not used because it would vary if we rotated the texture. Also used as features were the number of small regions deleted and the number of regions used in the computation of the mean and standard deviation. Thus we obtained 13 features; certainly not all of them are independent of the others.

For the Superslice method, only ten features can be obtained. Since Figures 18a, 19a, 20a, 21a are pseudo-images, we lose three features: the number of small regions deleted, the mean gray level, and the standard deviation of gray level.

contained in the upper half of Table 7. From there it seems they are roughly equivalent with a slight advantage to simple thresholding.

For the geological terrain textures only thresholding and Superslice were used. In the case of thresholding, both the bright 25% and the dark 25% were used. The feature values are displayed in Figures 24, 25, and 26 (A,B,C,D are Mississipian; E, F, G, H are Pennsylvanian; I, J, K, L are Lower Pennsylvanian). The textures depicted in Figures 12a, 13a, and 14a are samples A, E, and I. The effectiveness of the features is summarized in Tables 4, 5, and 6 (for Figures 24, 25, and 26).

In this set of textures too the results are better for simple thresholding. The results differ from those obtained for the Brodatz textures, in that the best features were not the same ones. This should case no surprise, as the two sets of textures are quite different. Also we see that just one feature (mean gray level) is sufficient to separate all textures (Table 4).

5. Discussion

From the results obtained, it seems that the methods suggested for primitive extraction may be succesfully employed for texture classification. It was surprising (but pleasing) that the simplest method performed better for both sets of textures.

Although all texture pairs could be separated with two features used independently (Brodatz) or one feature (terrain), this does not mean that for larger sample sizes we would have the same results. However, it gives us an indication of the usefulness of the method. Note that we did not need to use pairs or triples of features concurrently.

Thresholding and iterative histogram modification are similar in that they *do not* use local information from the texture. Superslice does use such information in the form of an edge map. The binary pictures obtained using Superslice look (subjectively) more closely related to the original textures than those obtained using the thresholding and histogram modification techniques. In spite of this, Superslice did not perform as well as regards texture classification. This may be because the sample size was too small, or because of the dependence of the features (a method performing well with one feature will also perform well with a correlated one). Further studies are necessary to clarify this matter.

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Appendix A

Algorithms for Iterative Histogram Modification and Superslice

Algorithm A.1

Iterative Histogram Modification [7]

Input: Histogram.

Let B_i be the number of pixels having gray level i. For each histogram in i, the neighboring 2r (an input parameter) bins $i \pm j$ on each side of i (j=1,2,...r) are examined. If B_i is greater than the average A of $B_{i+1}, \ldots, B_{i+r}$ (and similarly on the other side of i), we compute the ratio $X = (B_i - A)/B_i$, which specifies the fraction of pixels whose gray levels will be shifted towards i. Then the following gray-level changes are executed:

$B_{i+r} \cdot X$ from i+r to i+r-1;

$B_{i+r-1} \cdot X$ from i+r-1 to i+r-2;...

$B_{i+1} \cdot X$ from i+1 to i.

The entire process is iterated.

Algorithm A.2

Superslice [8]:

Input: Gray level range for thresholding, thinned edge picture.

1. For each gray level in the range:

   a) threshold the image;

   b) label all connected regions of above-threshold points;

c) for each connected region:

   i. compute the percentage of border points which coincide with significant thinned edge points;

   ii. compute the contrast of the region with the background;

   iii. classify the region as object/non-object based on the size, edge match and contrast.

2. Construct the canonical tree for the set of object regions based on containment.
3. Prune the containment tree by eliminating adjacent nodes which are too similar.

Appendix B

Computation of Eccentricity and Direction

Eccentricity and direction can be computed from the second order moments of inertia I_{xx}, I_{yy} and I_{xy}. Given a set of points $\{(x_1,y_1),(x_2,y_2)....\}$ forming a region, the moments are defined to be:

$$I_{xx} = \Sigma m_i y_i'^2$$

$$I_{yy} = \Sigma m_i x_i'^2$$

$$I_{xy} = \Sigma m_i x_i' y_i'$$

where x_i' and y_i' are the coordinates of the point (x_i,y_i) relative to the center of mass of the region.

The angle φ which the larger axis makes with a horizontal line is given by

$$\varphi = \frac{1}{2} \tan^{-1}\left(\frac{2I_{xy}}{I_{yy}-I_{xx}}\right) .$$

The eccentricity is given by

$$\left(\frac{I_{xx}\cos^2\varphi + I_{yy}\sin^2\varphi - I_{xy}\sin 2\varphi}{I_{xx}\sin^2\varphi + I_{yy}\cos^2\varphi + I_{xy}\sin 2\varphi}\right)^{1/2}$$

Appendix C

Rule for Deleting Large Primitives

The area range of the region for a given texture sample is divided into 10 intervals; each interval corresponds to an entry in the histogram. (In this histogram, the very small primitives and the primitives touching the border are not included.) The upper half of the histogram (from the sixth to the tenth interval) is investigated for possible deletions. If we have more than three regions in this half, no deletion is performed. If we have three, every region (in this half) larger than 400 pixels is deleted; in case of two or one, the threshold is 300 pixels.

These thresholds (400,300) should not be thought of as absolute numbers but as percentages of the total window area of the sample. Considering that each window has 128x128 pixels, 400 and 300 are approximately 2.5% and 1.9% of the total window size.

TEXTURE PAIRS / FEATURES	WOOL X RAFFIA	WOOL X SAND	WOOL X GRASS	RAFFIA X SAND	RAFFIA X GRASS	SAND X GRASS	# OF PAIRS WITH "Y"
# OF SMALL PRIMITIVES	Y	N	Y	Y	Y	Y	5
# OF PRIMITIVES	Y	Y	Y	N	N	N	3
AREA MEAN	N	N	N	N	N	N	0
AREA ST. DEV.	N	N	N	N	N	Y	1
PERIMETER MEAN	N	N	N	N	N	Y	1
PERIMETER ST. DEV.	N	N	N	N	N	Y	1
COMPACTNESS MEAN	N	N	Y	N	Y	Y	3
COMPACTNESS ST. DEV.	N	Y	N	N	N	Y	2
ECCENTRICITY MEAN	Y	N	Y	Y	N	Y	4
ECCENTRICITY ST. DEV.	Y	N	Y	Y	N	N	3
DIRECTION ST. DEV.	N	N	Y	N	N	N	1
GRAY LEVEL MEAN	Y	Y	Y	Y	Y	N	5
GRAY LEVEL ST. DEV.	Y	N	Y	Y	N	Y	4
# OF FEATURES WITH "Y"	6	3	8	5	3	8	33

Table 1. Effectiveness of the features for the Brodatz textures, when the primitives are extracted by thresholding (25%). A "Y" entry means that the ranges of the feature values (corresponding to the two textures) do not overlap.

FEATURES \ TEXTURE PAIRS	WOOL X RAFFIA	WOOL X SAND	WOOL X GRASS	RAFFIA X SAND	RAFFIA X GRASS	SAND X GRASS	# OF PAIRS WITH "Y"
# OF PRIMITIVES	Y	Y	N	N	N	N	2
AREA MEAN	N	N	N	N	Y	N	1
AREA ST. DEV.	N	N	N	N	Y	N	1
PERIMETER MEAN	N	N	N	N	Y	N	1
PERIMETER ST. DEV.	Y	N	N	Y	Y	N	3
COMPACTNESS MEAN	N	N	Y	N	Y	Y	3
COMPACTNESS ST. DEV.	N	N	N	N	Y	N	1
ECCENTRICITY MEAN	Y	N	Y	N	Y	N	3
ECCENTRICITY ST. DEV.	N	N	Y	N	N	N	1
DIRECTION ST. DEV.	N	N	N	N	N	N	0
# OF FEATURES WITH "Y"	3	1	3	1	7	1	16

Table 3. Analogous to Table 1 for Superslice.

TEXTURE PAIRS / FEATURES	WOOL X RAFFIA	WOOL X SAND	WOOL X GRASS	RAFFIA X SAND	RAFFIA X GRASS	SAND X GRASS	# OF PAIRS WITH "Y"
# OF SMALL PRIMITIVES	N	N	Y	Y	Y	N	3
# OF PRIMITIVES	Y	Y	N	Y	Y	N	4
AREA MEAN	N	N	N	N	N	N	0
AREA ST. DEV.	N	N	N	N	N	N	0
PERIMETER MEAN	N	N	N	N	N	N	0
PERIMETER ST. DEV.	N	N	N	N	N	N	0
COMPACTNESS MEAN	N	N	Y	N	Y	N	2
COMPACTNESS ST. DEV.	N	N	N	N	N	N	0
ECCENTRICITY MEAN	Y	N	Y	Y	N	N	3
ECCENTRICITY ST. DEV.	Y	N	Y	Y	N	Y	4
DIRECTION ST. DEV.	N	N	N	N	N	N	0
GRAY LEVEL MEAN	Y	Y	Y	Y	Y	N	5
GRAY LEVEL ST. DEV.	Y	N	Y	N	N	Y	3
# OF FEATURES WITH "Y"	5	2	6	5	4	2	24

Table 2. Analogous to Table 1 for the spike program.

TEXTURE PAIRS / FEATURES	MISS. X PEN.	MISS. X L. PEN.	PEN. X L. PEN.	# OF PAIRS WITH "Y"
# OF SMALL PRIMITIVES	N	Y	Y	2
# OF PRIMITIVES	N	N	N	0
AREA MEAN	N	N	N	0
AREA ST. DEV.	N	N	N	0
PERIMETER MEAN	N	N	N	0
PERIMETER ST. DEV.	N	N	Y	1
COMPACTNESS MEAN	Y	N	Y	2
COMPACTNESS ST. DEV.	Y	Y	Y	3
ECCENTRICITY MEAN	N	N	N	0
ECCENTRICITY ST. DEV.	N	N	N	0
DIRECTION ST. DEV.	Y	N	Y	2
GRAY LEVEL MEAN	Y	Y	Y	3
GRAY LEVEL ST. DEV.	N	N	N	0
# OF FEATURES WITH "Y"	4	3	6	13

Table 5. Analogous to Table 4 but using the dark 25%.

TEXTURE PAIRS / FEATURES	MISS. X PEN.	MISS. X L. PEN.	PEN. X L. PEN.	# OF PAIRS WITH "Y"
# OF SMALL PRIMITIVES	Y	N	N	1
# OF PRIMITIVES	N	N	N	0
AREA MEAN	N	N	N	0
AREA ST. DEV.	N	N	N	0
PERIMETER MEAN	N	N	N	0
PERIMETER ST. DEV.	N	N	N	0
COMPACTNESS MEAN	N	N	N	0
COMPACTNESS ST. DEV.	Y	N	Y	2
ECCENTRICITY MEAN	N	N	N	0
ECCENTRICITY ST. DEV.	N	N	N	0
DIRECTION ST. DEV.	Y	Y	Y	3
GRAY LEVEL MEAN	Y	Y	N	2
GRAY LEVEL ST. DEV.	Y	N	Y	2
# OF FEATURES WITH "Y"	5	2	3	10

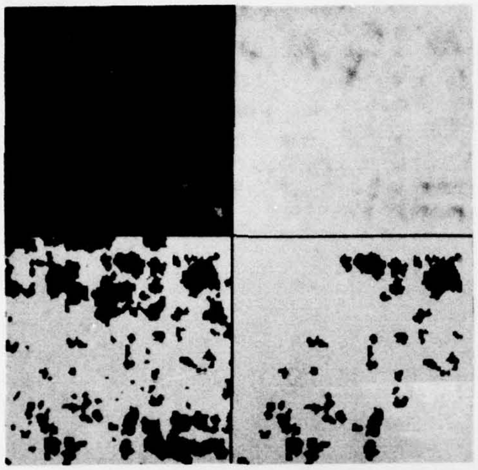
Table 4. Effectiveness of the features in discriminating pairs of terrain textures. A "Y" entry means that we have non-overlapping ranges of feature values. The primitives were extracted by thresholding (bright 25%).

		# OF SMALL REGIONS	# OF REGIONS	AREA MEAN	AREA ST. DEV.	PERIMETER MEAN	PERIMETER ST. DEV.	COMPACTNESS MEAN	COMPACTNESS ST. DEV.	ECCENTRICITY MEAN	ECCENTRICITY ST. DEV.	DIRECTION ST. DEV.	GRAY LEVEL MEAN	GRAY LEVEL ST. DEV.
BRODATZ TEXTURES	25%	5	3	-	1	1	1	3	2	4	3	1	5	4
	Spike	3	4	-	-	-	-	2	-	3	4	-	5	3
	Superslice		2	1	1	1	3	3	1	3	1	-		
TERRAIN TEXTURES	25% bright	1	-	-	-	-	-	-	2	-	-	3	2	2
	25% dark	2	-	-	-	-	1	2	3	-	-	2	3	-
	Superslice		-	-	-	-	-	-	-	1	-	1		

Table 7. Effectiveness of the features in discrimination of pairs of textures. The entries in the table show how many times a feature can be used to discriminate between two entries.

FEATURES \ TEXTURE PAIRS	MISS. X PEN.	MISS. X L. PEN.	PEN. X L. PEN.	# OF PAIRS WITH "Y"
# OF PRIMITIVES	N	N	N	0
AREA MEAN	N	N	N	0
AREA ST. DEV.	N	N	N	0
PERIMETER MEAN	N	N	N	0
PERIMETER ST. DEV.	N	N	N	0
COMPACTNESS MEAN	N	N	N	0
COMPACTNESS ST. DEV.	N	N	N	0
ECCENTRICITY MEAN	N	Y	N	1
ECCENTRICITY ST. DEV.	N	N	N	0
DIRECTION ST. DEV.	Y	N	N	1
# OF FEATURES WITH "Y"	1	1	0	2

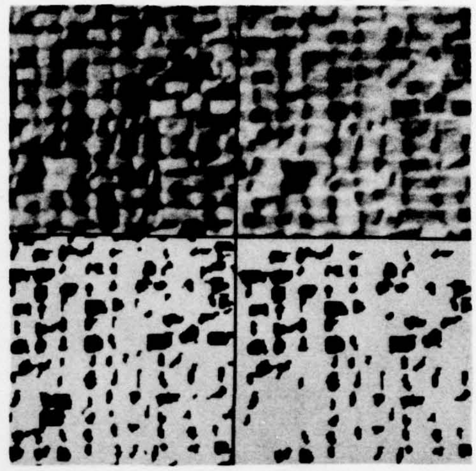
Table 6. Analogous to Table 4 but extracting the primitives using Superslice.



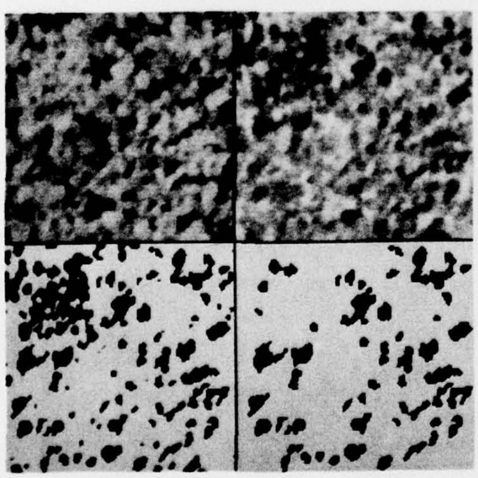
1. (a) Wool; (b) complemented wool; (c) thresholded (25%); (d) after the deletion of small, large, and boundary elements

a b

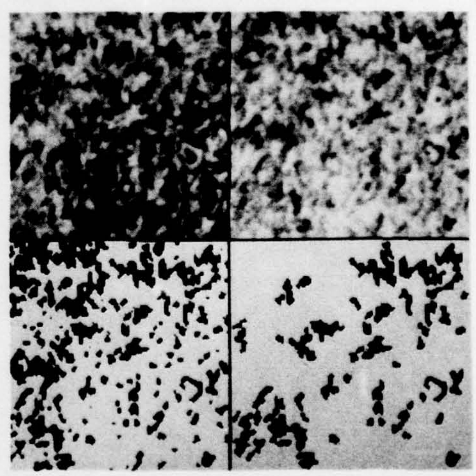
c d



2. Analogous to Figure 1, for raffia



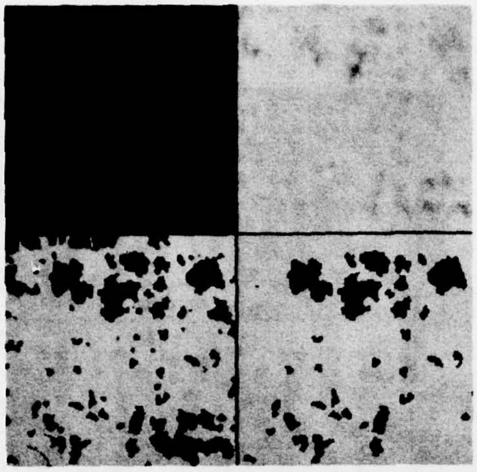
3. Analogous to Figure 1, for sand



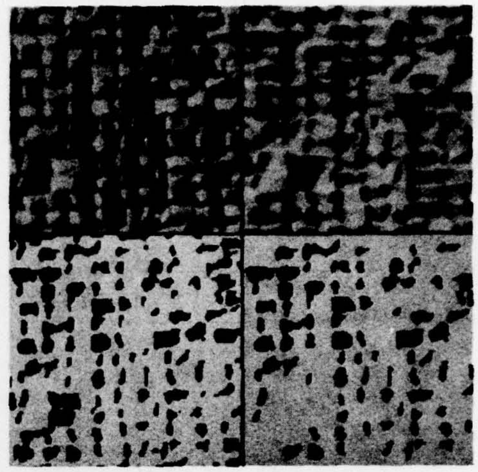
4. Analogous to Figure 1, for grass

a b

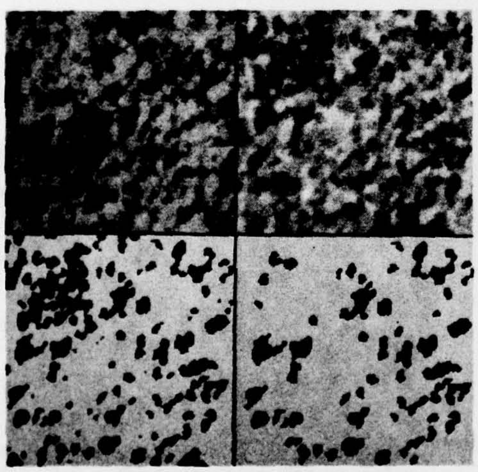
c d



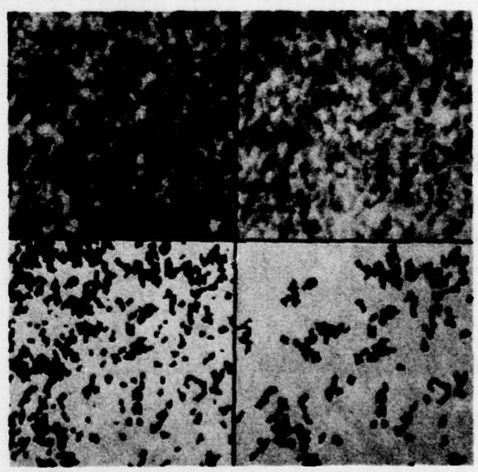
5. (a) Wool; (b) complemented wool; (c) result of spike program; (d) after the deletion of small, large, and boundary elements



6. Analogous to Figure 5, for raffia



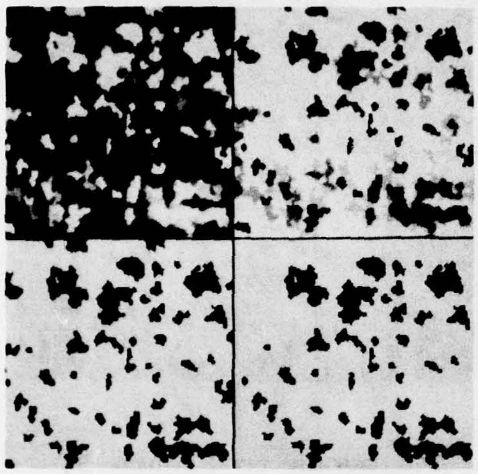
7. Analogous to Figure 5, for sand



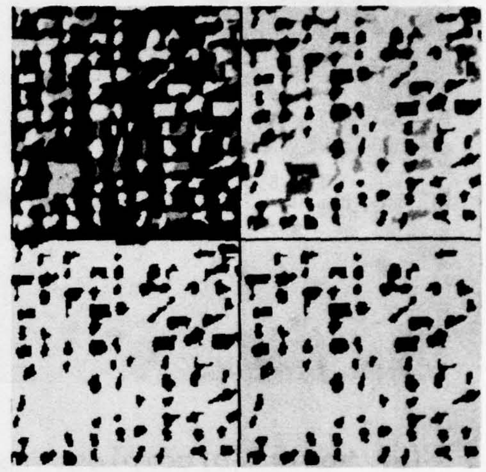
8. Analogous to Figure 5, for grass

a b

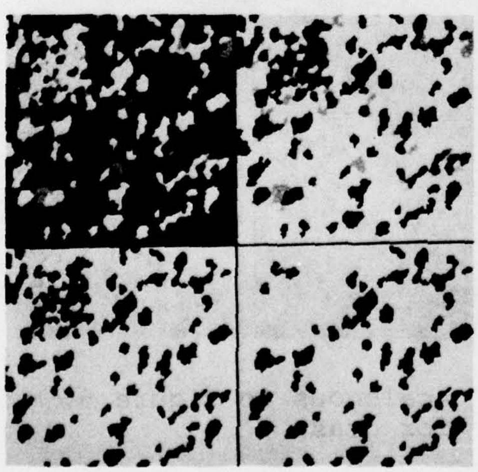
c d



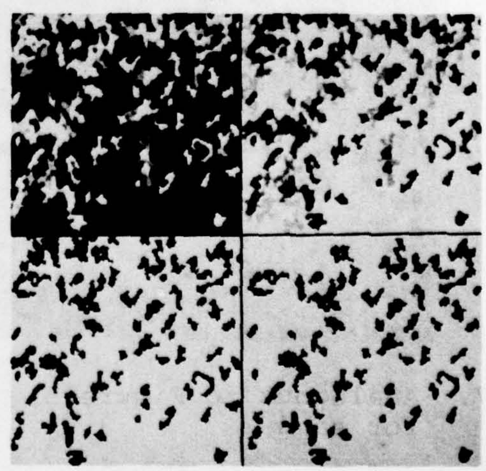
9. (a) Wool after applying Superslice: the lighter regions represent the best matches; (b) same as (a) but complemented; (c) after retaining the best matches; (d) after deleting small, large, and boundary regions



10. Analogous to Figure 9, for raffia



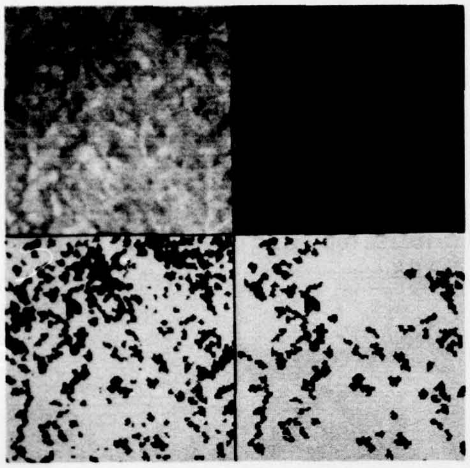
11. Analogous to Figure 9, for sand



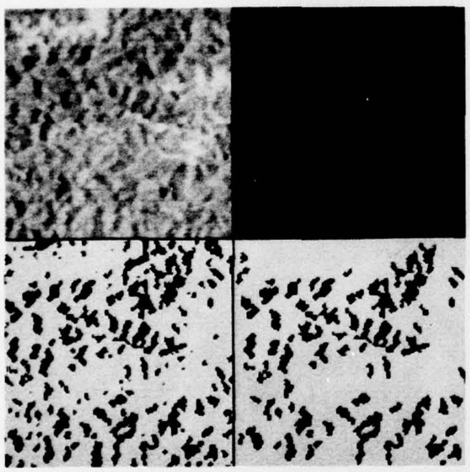
12. Analogous to Figure 9, for grass

a

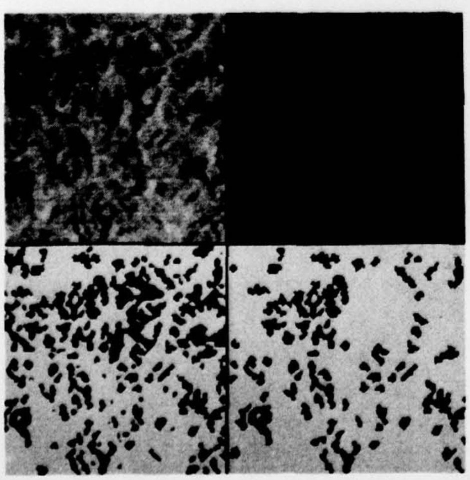
b c



13. (a) Complemented Mississipian limestone and shale
    (b) Thresholded (25% BRIGHT)
    (c) After deletion of small, large, and boundary regions



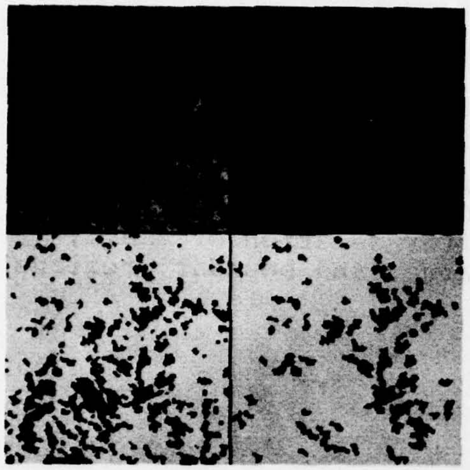
14. Analogous to Figure 13, for Pennsylvanian sandstone and shale



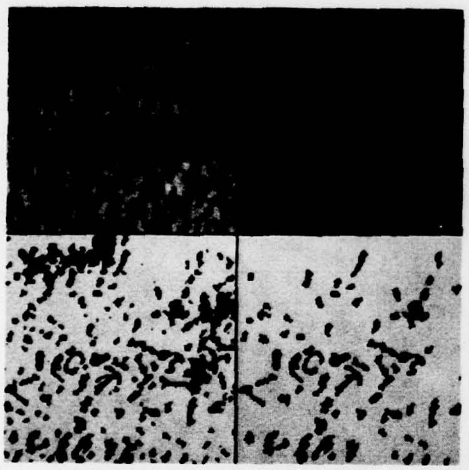
15. Analogous to Figure 13, for Lower Pennsylvanian shale

a

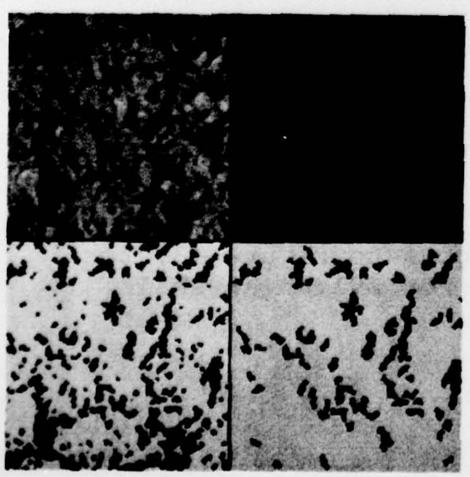
b c



16. Analogous to Figure 13, using 25% DARK



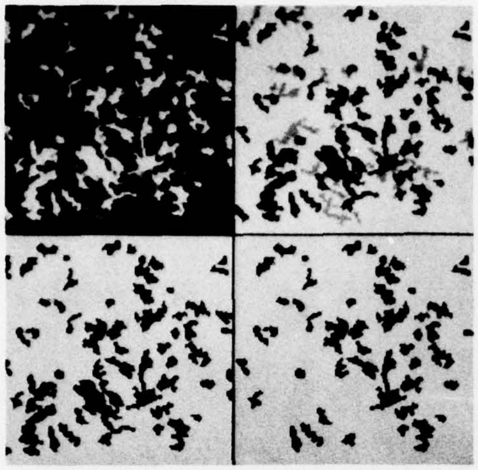
17. Analogous to Figure 14, using 25% DARK



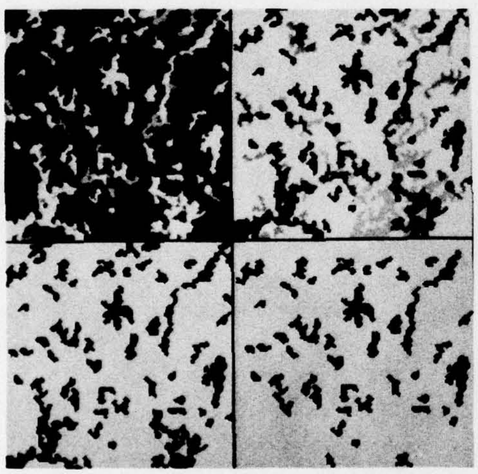
18. Analogous to Figure 15, using 25% DARK

a b

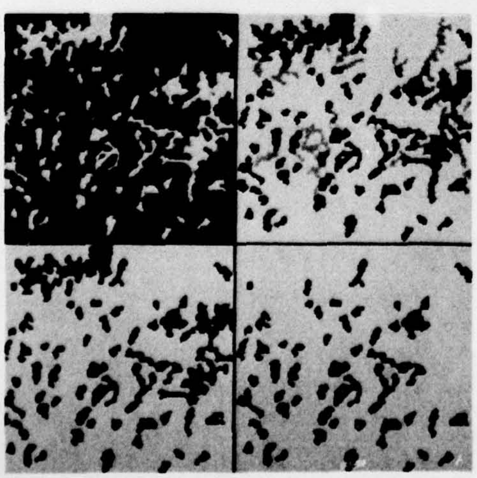
c d



19. (a) Mississipian limestone and shale after applying Superslice: the lighter regions correspond to the best matches
(b) Same as (a) but complemented
(c) After retaining the best matches
(d) After deletion of small, large and boundary regions



20. Analogous to Figure 19, for Pennsylvanian sandstone and shale



21. Analogous to Figure 19, for Lower Pennsylvanian shale