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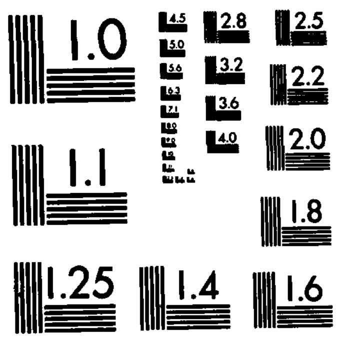

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ETL-0305

Feature component reduction through divergence analysis

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OCTOBER 1982

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An approach to developing a reduced set of texture-like descriptors is presented. Results of several experiments using multi-component vectors are presented including experiments with relaxation techniques to cleanse the test images. In view of these results, the particality of using more complex feature vectors is questioned.

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PREFACE

This study was conducted under DA Project 4A762707A855, Task B, Work Unit 00026, "Topographic Mapping Techniques."

The study was done during 1981 under the supervision of Mr. Dale E. Howell, Chief, Information Sciences Division; and Mr. Lawrence A. Gambino, Director, Computer Sciences Laboratory.

COL Edward K. Wintz, CE was Commander and Director and Mr. Robert P. Macchia was Technical Director during the report preparation.

CONTENTS

ILLUSTRATIONS

TABLES

TABLES (con't)

FEATURE COMPONENT REDUCTION THROUGH DIVERGENCE ANALYSIS

INTRODUCTION

It is becoming apparent that a large number of texture feature components do not segment an image significantly better than a smaller number of descriptors. Not only are large component signatures expensive to extract and process but, the well known texture measures are not even measuring image texture. Some investigators define very large numbers of texture primitives (20 or more in some cases), and then contradict their basic definitions by using techniques, such as principal components, to greatly reduce the dimensionality of the feature vectors.

Future image segmenting processes at ETL will use as few texture components as possible. Classification results will be coordinated with other image features in cooperative algorithms, wherein the several processes will be controlled by rules that relate the various data sets and will be bounded by existing data base entities. The purpose of this Research Note is to describe an approach to developing a reduced set of texture-like descriptors and to provide results of several experiments using a two-component feature vector.

NUMERICAL EXPERIMENT

Divergence, a statistical measure of information, is used to evaluate the effectiveness of various sets of texture components. Several measures are evaluated and pictorial results of the reduced set are compared to results derived from a full set.

Divergence. An overview of divergence is presented in an ETL Research Note[1] and a complete description can be found in Kullback's book.[2] Essentially, the divergence, J(I, J), is used here as a measure of the difficulty of discriminating between class I and class J. Large values of J(I,J) are indicative of strong discrimination power; whereas, small values of J(I,J) indicate poor discriminatory power. Note that $J(I,J) \geq 0$. The formula for divergence is

$$J(I,J) = \int [P(\bar{X}|C_I) - P(\bar{X}\ C_J)] \text{Log} \frac{P(\bar{X}|C_I)}{P(\bar{X}|C_J)} d\bar{X}$$

The probability $P(\bar{X} \mid C)$ is the conditional probability of the vector $\bar{X}$ given that C has occurred. The vector $\bar{X}$ is, for example, a signature of texture components from an unknown class. It has been assumed in this experiment that $\bar{X}$ is characterized by the multivariate normal distribution. Sample values of the mean vectors and covariance matrices were estimated from training sets in order to compute the required divergence value estimates.

Texture Measures. Three sets of texture measures were compared in this experiment, namely:

1. Max-Min
2. Edge
3. Ad Hoc

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[1] Michael A. Crombie, Robert S. Rand, and Nancy J. Friend, An Analysis of the Max-Min Texture Measure, US Army Engineer Topographic Laboratories, Fort Belvoir, VA, January 1982, ETL-0280.

[2] Solomon Kullbuck, Information Theory and Statistics, Dover Publications, Inc., New York, 1968.

An overview of the Max-Min texture is presented in an ETL Research Note[3] and a complete description can be found in Mitchell's paper[4]. A 14 component texture signature was extracted from the test regions for the analysis.

Edge statistics were calculated by convolving M over a variety of subwindows of gray shades extracted from the test regions:

$$M = \begin{matrix} 0 & -1 & -0 \\ -1 & 4 & -1 \\ 0 & -1 & -0 \end{matrix}$$

The mask M is an estimate of the LaPlacian and is a fairly good and inexpensive tool for detecting image gradients in a digital picture. The resultant gradient image was processed to determine sign changes that indicate locations of image edges. The final output was a measure of the steepness of the gradient function at sign change locations. The absolute change in the gradient at each of the sign change locations (along rows and along columns) was quantized into six intervals and an edge count was produced as a measure of image roughness.

A three-component ad hoc texture vector was defined to be the average gray shade over a window, the standard deviation over the window of gray shades, and finally the range (the largest gray shade minus the smallest gray shade). These descriptions were chosen for convenience and for ease of computation. The first component can be computed by convolution, and the other two can be computed by moving window methods. It was recognized that range and standard deviation are both estimates of flux and that it is next to impossible to reconcile the idea of texture with average gray shade. The objective of the tests was to compare the performance of the more sophisticated texture measures with the performance of the simplified signature in order to determine whether the more sophisticated measures were worthwhile over the test regions.

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[3]Michael A. Crombie, Robert S. Rand and Nancy J. Friend, Analysis of the Max-Min Texture Measure, US Army Engineer Topographic Laboratories, Fort Belvoir, VA, January 1982, ETL-0280.

[4]Owen R. Mitchell, Charles R. Myers and William Boyne, "A Max-Min Measure for Image Texture Analysis, "IEEE Trans Comput., Vol. C-25, April 1977.

Test Regions. Most of the tests were performed on scenes A and B, shown in figures 1 and 2. Six classes were defined and are designated by rectangles overlayed on the scenes. A corresponding infrared scene exists for both images and was used in many of the tests. The digital scenes are 1024^2 x 8 bits, and the resolution (line and pixel spacing) is approximately 1 meter. Generally, the tests were conducted in three phases. The first test was made to determine a reasonably small window size for the remaining tests. The second test was designed to compare the edge texture measures to the <u>ad hoc</u> texture measures. The third test was designed to compare the <u>ad hoc</u> texture measures to the 14 component Max-Min texture measures.

The comparison tests were performed by determining which of the components (9 in the second test and 17 in the third) produced the largest divergence value over the $C_{6,2}$ = 15 possible class comparisons. Then the "best" component was coupled with the remaining components (8 in the second test and 16 in the third) to determine which pair produced the largest divergence value over the $C_{6,2}$ possible class comparisons. This process was continued until there was an insignificant increase in divergence. Note that divergence is a monotonic increasing function and if a set of components has a definite advantage over the $C_{6,2}$ possible class comparisons then, under the guide lines of the tests, that set will be designated the "best" measure for discrimination. This experiment is not the same as the divergence tests described in a previous Research Note wherein it was determined that classification performance.[5] In that experiment, an attempt was made to develop a functional relationship between classification error and divergence.

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[5]Michael A. Crombie, Robert S. Rand and Nancy J. Friend, <u>An Analysis of the Max-Min Texture Measure</u>, US Army Engineer Topographic Laboratories, Fort Belvoir, VA, January 1982, ETL-0280.

Class	Type
1	Building and Road
2	Gray Field
3	Rough Field
4	Heavy Forest
5	Light Field
6	Light Forest

Figure 1. Scene A

Class	Type
1	Heavy Forest
2	Scrub
3	Building and Road
4	Dark Field
5	Light Field
6	Light Forest

Figure 2. Scene B

Numerical Results. The initial series of tests were designed to determine a consistent window size for sampling over the test regions. A subjective review of preliminary results showed that a window size of W = 15 x 15 produced consistent results. The following definitions were used in the tests:

B	:	Average gray shade over W
SD	:	Standard deviation of gray shades over W
R	:	Gray shade range over W
$E_{I;I=1,6}$	:	Edge texture values
$M_{I:I=1,14}$	:	Max-Min texture values

Results from the tests are presented in tables 1 through 4. In the second set of tests, where the ad hoc measure (B, SD and R) were grouped with the six edge texture values, B turned out to have the largest divergence value of all nine measures. In fact, B produced the largest divergence for almost all class pairs over both scenes for both IR and panchromatic. The second ad hoc measure, SD, when coupled with B, produced the next largest divergence value and again this result was typical for all tests. The divergence results for the second set of tests are tabulated in tables 1 and 2. In the third set of tests, the ad hoc measures were grouped with the 14-component max-min texture values. Again B and SD produced the largest divergence values. The results are tabulated in tables 3 and 4. Note that the IR scenes were not included in these tests.

Table 1. Comparison of Ad Hoc and Edge Texture Measures on Scene A

Scene A Pan Divergence

Class Pairs

Measure	1-2	1-3	1-4	1-5	1-6	2-3	2-4	2-5	2-6	3-4	3-5	3-6	4-5	4-6	5-6
B	2.4	16	24	198	31	19	18	227	16	5.9	78	20	177	3.0	285
SD	27	68	239	281	141	34	49	419	33	24	121	31	329	4.2	419
R	33	70	292	290	170	35	51	429	34	25	125	31	336	4.4	428
E_1	33	80	300	298	197	35	53	437	36	27	127	31	352	5.0	437
E_5	35	80	318	298	225	36	57	438	39	32	127	32	383	5.7	438

Scene A IR Divergence

Class Pairs

Measure	1-2	1-3	1-4	1-5	1-6	2-3	2-4	2-5	2-6	3-4	3-5	3-6	4-5	4-6	5-6
B	16	34	8.2	19	15	16	26	21	54	77	1.5	121	73	4.2	112
SD	75	74	73	28	180	19	30	28	62	81	13	130	100	4.7	160
R	86	81	88	30	207	19	32	30	64	81	14	127	102	4.9	160
E_1	89	83	89	32	211	20	32	31	69	83	14	139	104	5.2	178
E_6	89	83	96	33	216	20	33	31	71	84	15	146	106	5.9	188

Table 2. Comparison of Ad Hoc and Edge Texture Measures on Scene B

Scene B Pan Divergence

Class Pairs

	1-2	1-3	1-4	1-5	1-6	2-3	2-4	2-5	2-6	3-4	3-5	3-6	4-5	4-6	5-6
	2.3	14	3.7	13	2.7	3.4	6.8	3.0	.21	26	.78	3.9	17	4.4	2.6
SD	3.8	20	78	37	4.6	4.9	130	32	1.4	82	13	6.4	19	78	20
R	4.2	22	81	40	5.5	5.1	135	33	1.9	86	15	7.0	19	82	22
E_1	4.3	25	83	42	5.7	6.4	140	36	2.0	91	16	8.3	19	85	23
E_4	4.5	25	87	44	5.9	7.0	145	37	2.1	94	16	8.8	19	89	24

Scene B IR Divergence

Class Pairs

	1-2	1-3	1-4	1-5	1-6	2-3	2-4	2-5	2-6	3-4	3-5	3-6	4-5	4-6	5-6
B	12	16	59	69	.95	3.8	214	20	13	280	12	27	581	89	92
SD	15	19	330	94	1.2	5.0	700	52	15	620	31	28	600	360	110
R	16	20	367	96	1.7	6.1	791	60	16	696	39	29	615	406	112
E_1	16	22	372	110	2.0	8.4	800	64	17	706	43	40	652	411	140
E_6	17	25	391	119	2.4	9.8	825	78	18	728	45	41	671	427	152

Table 3. Comparison of Ad Hoc and Max-Min Texture Measures on Scene A

Class Pairs

Measure	1-2	1-3	1-4	1-5	1-6	2-3	2-4	2-5	2-6	3-4	3-5	3-6	4-5	4-6	5-6
B	2.4	16	24	198	31	19	18	227	16	5.9	78	20	177	3.0	285
SD	27	68	239	281	141	34	49	419	33	24	121	31	329	4.2	419
R	33	70	292	290	170	35	51	429	34	25	125	31	336	4.4	428
M_7	33	71	324	322	170	35	54	458	34	27	134	31	358	4.8	449

Table 4. Comparison of Ad Hoc and Max-Min Texture Measures on Scene B

Class Pairs

Measure	1-2	1-3	1-4	1-5	1-6	2-3	2-4	2-5	2-6	3-4	3-5	3-6	4-5	4-6	5-6
B	2.3	14	3.7	13	2.7	3.4	6.8	3.0	.21	26	.78	3.9	17	4.4	2.6
SD	3.8	20	78	37	4.7	4.9	130	32	1.4	82	13	6.4	19	78	20
M_{11}	4.7	26	85	46	5.5	5.9	135	35	1.6	85	13	7.0	19	81	22
M_9	5.1	27	92	49	5.7	7.4	149	37	2.0	93	13	8.1	20	89	23

Discussion of Divergence Study. The divergence tests clearly demonstrate that the measures B and SD can segment the pictures used in these experiments as well as the more complex edge and Max-Min measures. By definition, a significant increase in divergence as more components are added to the signatures indicates a significant increase in discriminatory power among classes. The increase in divergence appears to drop off considerably as the third or fourth components are added to B and SD. Consider tables 5 and 6 wherein the ad hoc measures are compared to the edge values. In those tables, $\overline{\Delta J}$ is the averaged fractional increase in divergence for the designated new component. The increase is [J (new)/J (old)-1]. The entries labeled $\sigma_{\Delta J}$ are standard deviations of the $\overline{\Delta J}$ over the class pairs. Similar results are shown in table 7 wherein the ad hoc measures are compared to the Max-Min measures for the panchromatic images.

Table 5. Fractional Increase in Divergence on Panchromatic Scenes (Edge)

Scene A Measure	$\overline{\Delta J}$	$\sigma\Delta J$	Scene B Measure	$\overline{\Delta J}$	$\sigma\Delta J$
B	-	-	B	-	-
B + SD	2.45	3.11	B + SD	6.64	7.44
B + SD + R	0.07	0.08	B + SD + R	0.09	0.09
B + SD + R + E_1	0.05	0.05	B + SD + R + E_1	0.07	0.07
B + SD + R + E_1 + E_5	0.06	0.06	B + SD + R + E_1 + E_5	0.04	0.03

Table 6. Fractional Increase in Divergence on IR Scenes (Edge)

Scene A Measure	$\overline{\Delta J}$	$\sigma\Delta J$	Scene B Measure	$\overline{\Delta J}$	$\sigma\Delta J$
B	-	-	B	-	
B + SD	2.26	3.63	B + SD	1.10	1.36
B + SD + R	0.07	0.06	B + SD + R	0.11	0.10
B + SD + R + E_1	0.04	0.03	B + SD + R + E_1	0.12	0.13
B + SD + R + E_1+ E_6	0.04	0.04	B + SD + R + E_1+ E_6	0.08	0.06

Table 7. Fractional Increase in Divergence on Panchromatic Scenes (Max-Min)

Scene A Measure	ΔJ	$\sigma\Delta J$	Scene B Measure	$\overline{\Delta J}$	$\sigma\Delta J$
B	-	-	B	-	-
B + SD	6.64	7.44	B + SD	2.45	3.11
B + SD + M_{11}	0.12	0.19	B + SD + R	0.07	0.08
B + SD + M_{11} + M_9	0.09	0.07	B + SD + R + M_7	0.05	0.04

CLASSIFICATION EXPERIMENT

The analysis performed in the divergence experiment suggests that there is little advantage to using many feature components as data for input into segmentation algorithms. Confidence in the conclusions of the experiment can be increased by studying the effects of the feature components as data in an actual segmenting algorithm.

Classification of Test Regions. The Maximum Likelihood Algorithm was used to classify test regions on the panchromatic scenes A and B. Results from the divergence study directed the selection of feature components as input data to this algorithm. The accuracy in classifiying the test regions was measured as the number of components was increased. Beginning with the average gray shade and the standard deviation of gray shades as initial components, the range was added followed by individual Max-Min texture components; a window size of 15 x 15 was used. Numerical results are presented in tables 8A, 9A, and 10A. In addition to this test, the effect of window size on classification accuracy was studied. Two components, average gray shade and standard deviation of gray shades, were extracted using window sizes 5 x 5, 9 x 9, 11 x 11, and 15 x 5. Results are shown in tables 8B, 9B, and 10B. Note that the forest and field type classifications have been combined for Scene B in tables 10A and 10B.

Table 8A. Classification Accuracy During Feature Component Reduction-Scene A Window Size = 15 X 15

Component	Bldg & Rds	Gray Field	Rough Field	Heavy Forest	Light Field	Light Forest
14	67.9	84.7	94.2	100.0	85.7	95.4
13	67.9	84.7	94.2	100.0	81.0	95.4
12	65.4	83.3	91.3	100.0	85.7	95.4
11	64.4	80.6	91.3	100.0	82.5	95.4
10	65.4	83.3	90.4	100.0	85.7	94.4
9	64.2	81.9	89.4	100.0	81.0	96.3
8	64.2	79.2	89.4	100.0	79.0	95.4
7	61.7	81.9	91.3	100.0	82.5	95.4
6	61.7	80.6	92.3	98.8	84.1	95.4
5	61.7	80.6	89.4	98.8	84.1	93.5
4	-	-	-	-	-	-
3	60.5	79.2	87.5	98.8	77.8	88.9
2	63.5	80.6	90.4	98.8	77.8	88.9

Table 8B. Classification Accuracy During Window Reduction - Scene A number of components = 2

Component	Bldg & Rds	Gray Field	Rough Field	Heavy Forest	Light Field	Light Forest
15 x 15	63.5	80.6	90.4	98.8	77.8	89.8
11 X 11	54.3	70.8	89.4	98.8	77.8	86.1
9 X 9	46.9	70.8	85.6	98.8	76.2	80.6
5 X 5	35.8	63.9	85.6	100.0	68.3	64.8

Table 9A. Classification Accuracy During Feature Component Reduction-Table B

Component	Bldg & Rds	Gray Field	Rough Field	Heavy Forest	Light Field	Light Forest
14	91.7	66.7	60.5	98.7	89.7	65.4
13	88.4	63.6	59.3	98.7	93.2	66.7
12	89.3	63.6	55.6	96.1	92.3	71.6
11	89.3	56.6	54.3	94.8	94.0	75.3
10	83.5	54.5	56.8	94.8	94.0	71.6
9	81.8	52.5	50.6	96.1	91.5	70.4
8	80.2	55.6	49.4	94.8	90.6	67.9
7	76.9	47.5	45.7	93.5	88.9	69.1
6	77.7	46.5	43.2	93.5	90.6	70.4
5	78.5	40.4	43.2	96.1	88.9	70.4
4	76.0	35.4	42.0	93.5	88.0	65.4
3	78.5	37.4	39.5	93.5	85.5	65.4
2	77.7	34.3	42.0	96.1	86.3	58.0

Table 9B. Classification Accuracy During Window Reduction-Scene B
Number of Components = 2

Window Size	Heavy Forest	Scrub	Bldg & Roads	Dark Field	Light Field	Light Forest
5 X 15	77.7	34.3	42.0	96.1	86.3	58.0
11 X 11	72.7	32.3	34.6	94.8	85.5	45.7
9 X 9	70.2	27.3	34.6	94.8	87.2	40.7
5 X 5	61.2	19.2	34.6	88.3	86.3	29.6

Table 10A. Classification Accuracy During Feature Component Reduction Combined Classes Scene B Window Size = 15 X 15

Component	Bldg & Rds	Forest	Field
14	60.5	98.0	93.3
13	59.3	94.3	95.4
12	55.6	94.4	93.8
11	54.3	93.1	94.3
10	56.8	92.6	94.3
9	50.6	92.3	93.3
8	49.4	92.7	92.3
7	45.7	92.7	90.7
6	43.2	91.4	91.8
5	43.2	92.4	91.8
4	42.0	91.0	90.2
3	39.5	91.0	88.7
2	42.0	90.5	90.2

Table 10 B. Classification Accuracy During Window Reduction-Scene B Combined Classes Number of Components = 2

Window Size	Bldg & Rds	Forest	Field
15 X 15	42.0	90.5	90.2
11 X 11	34.6	88.3	89.0
9 X 9	34.6	85.1	90.2
5 X 8	34.6	71.9	87.1

Classification of Images. The final test of a descriptor's effectiveness is its success with a segmentor processing an entire image. Using the test regions as a training model, a segmentor can be applied to feature data extracted from an image and the resulting classification can be compared to available ground truth information or the image itself. The comparison, along with considerations of cost, will measure the utility of applying a particular set of descriptors to real image processing situations.

Many classification runs were made using the Maximum Likelihood Algorithm as a segmentor. Scenes A and B, panchromatic, were used as source images and data was extracted from every point. Runs were made for window sizes 3 x 3, 5 x 5, 9 x 9, and 15 x 5, with each run processing 1000 x 1000 image points. Because of the tremendous amount of data processing involved, the results of the divergence study and considerations of cost could only justify classification using one component (average gray shade) and two components (average gray shade and standard deviation of gray shades). Six classes were chosen to correspond to test regions of the divergence experiment and previous ETL experiments[6]. However, in addition to these, runs were made using four classes that were thought, in retrospect, to be more appropriate for the images. These four were selections and combinations of data from the original test regions. The classification results were color coded for easy viewing on a soft copy display. Photographs of the results were taken, and some of these are shown in figures 3 thru 6.

Relaxation Experiment. Probabilistic relaxation[7] was applied to the classification results obtained from Scene A, Pan, using a 5 x 5 window and a two-component feature vector (see figure 3B), in order to remove noise and ambiguities. Because of the considerable expense involved in relaxing the data, only three iterations of Scene A, Pan were computed. The third iteration of relaxation of this image is shown in figure 7.

Future work will include interactive raster processing to refine classification results. At that time, a study will be made to determine

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[6]Michael A Crombie, Robert S. Rand, and Nancy J. Friend, An Analysis of the Max-Min Texture Measure, US Army Engineer Topographic Laboratories, Fort Belvoir, VA January 1982, ETL-0280.

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[7]Azriel Rosenfeld, Robert A. Hummel, and Steven W. Zucker, "Scene Labeling by Relaxation Operations, "IEEE Transactions on Systems, Man and Cybernetics, Vol. SMC-6, June 1976.

whether raster processing should be used in combination with relaxation techniques to remove noise or whether raster processing is sufficient in itself to remove noise from classification images. It is suspected that one or two iterations of relaxation may be instrumental in indicating trends in classification prior to raster processing.

Discussion of the Classification Study.

Classification of the test regions supports the divergence study in demonstrating little advantage to adding components to the average gray shade and standard deviation measures. Larger window sizes produce better results in general; however, the advantage seems to diminish when combining similar classes such as forest types or field types. The combined class results in tables 10A and 10B show that there was little loss in using smaller windows and fewer components when the discriminating requirements were reduced.

The photos in figures 3 thru 6 show many errors in classification. There is a definite resolution problem using large windows and a "speckle" problem using small windows. The boundaries between adjacent classifications are often confused with the "building and roads" class. The field in the center of Scene A is usually mislabeled as a forest (see figures 3A, 3B, and 5B), and a large section of the field in Scene B is mislabeled as "building and roads". Figures 5 and 6 demonstrate that there are trade-offs in reducing signatures to one component. In both Scene A and B, eliminating the standard deviation component increases the misclassification between a forest and field type; however, it helps to reduce the boundary problem. A correct labeling of the central field in scene A occurs with two components and a 3 x 3 window, but the lower forest area is mislabeled; eliminating the standard deviation component corrects the mislabeling of the forest at the expense of mislabeling the field.

The source of many of the misclassification errors cannot be determined without additional study. It is probably true that much of the problem is due to the lack of an effective descriptor; however, the possibility cannot be ruled out that poorly defined training models are at fault. This certainly is the reason for confusion between the "building and roads" class and "fields" class in Scene B.

The confusion between similiar classes, such as forest types, is probably due to the existence of too many similar training models. Much of this problem can be resolved by eliminating or combining training fields. This was the reason for reclassifying some of the runs using four classes. The problem can also be resolved by equating class labels after segmentation. This can be effected for example, by equating the colors green, yellow, and black in the labeling of Scene A. The latter procedure may actualy be preferred in many cases, since more information is lost when using too few classes than when using too many.

There may actually be an advantage to using smaller windows if post-processing is considered. It is much easier to remove mislabeled "specks" than it is to remove the mislabeled blobs that appear when using large windows.

Comparing figures 3 and 4 with results from a previous report[8] shows that the classification results using simple descriptors are not significantly worse than using the more complicated and expensive Max-Min texture. In fact, for some classes the results are much better. An example is the sharp delineation of buildings and roads in scene A, especially with small windows, which was not possible using Max-Min texture.

Considering the complexity, expense, and lack of significant improvement in classification, further investigation of the Max-Min texture measure can hardly be justified. Since the Edge texture measures performed no better than the Max-Min in the divergence study, it also seems unnecessary to investigate them further.

[8]Michael A. Crombie, Robert S. Rand, and Nancy J. Friend, An Analysis of the Max-Min Texture Measure, US Army Engineer Topographic Laboratories, Fort Belvoir, VA, January 1982, ETL-0280.

Figure 3A. Two Component Classification of Scene A (window size = 15 x 15, 6 classes).

Figure 3B. Two Component Classification of Scene A (window size = 5 x 5, 6 classes).

Color Assignments for Figures 3A, & 3B

Class	Type	Color
1	Bldg & Rds	Red
2	Gray Field	Yellow
3	Rough Field	Black
4	Heavy Forest	Blue
5	Light Field	Green
6	Light Forest	White

Figure 4A. Two Component Classification of Scene B (window size = 15 x 15, 6 classes).

Figure 4B. Two Components Classification of Scene B (window size = 5 x5, 6 classes).

Color Assignments for Figures 4A & 4B

Class	Type	Color
1	Heavy Forest	Red
2	Scrub	Green
3	Bldg & Rds	Blue
4	Dark Field	White
5	Light Field	Black
6	Light Forest	Yellow

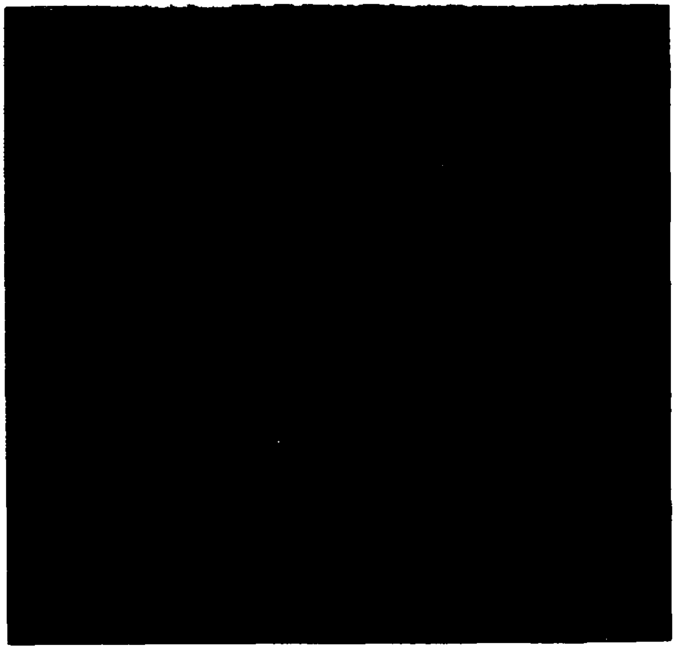

Figure 5A. Two Component Classification of Scene A (window size = 3 x 3, 4 classes).

Figure 5B. One Component Classification of Scene A (window size = 3 x 3, 4 classes).

Training Model and Color Assignments for Figures 5A & 5B

Class	Type	Color	Test Regions Used In Training
1	Bldg & Rds	Red	1
2	Heavy Forest	Dk Blue	4
3	Lt. Forest	Lt. Blue	6
4	Field	Green	2,3,5

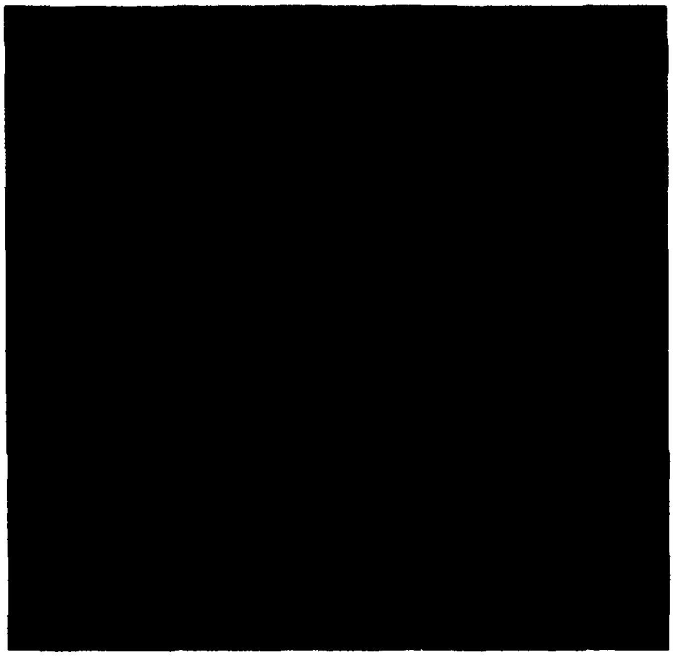

Figure 6A. Two Component Classification of Scene B (window size = 5 x 5, 4 classes).

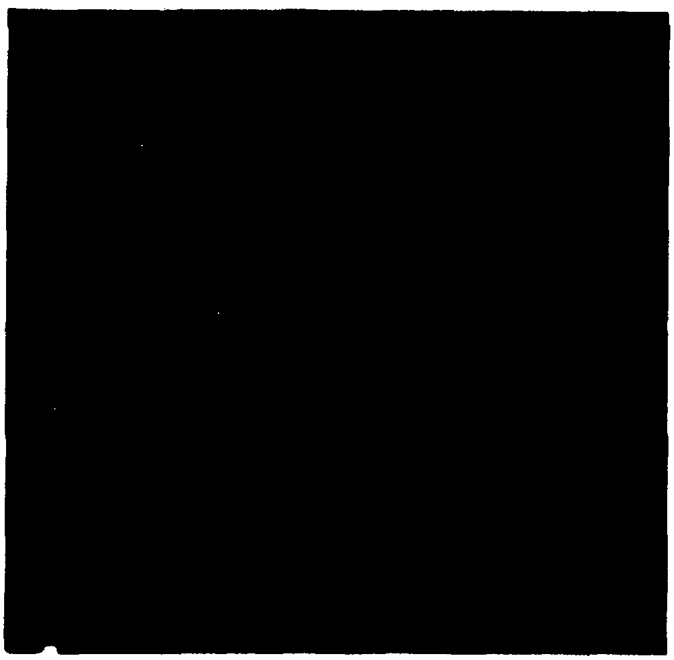

Figure 6B. One Component Classification of Scene B (window size = 5 x 5, 4 classes).

Training Model and Color Assignments for Figures 6A & 6B

Class	Type	Color
1	Bldg & Rds	Red
2	Heavy Forest	Dk Blue
3	Dark Field	Lt. Blue
4	Lt. Field	Green

Test Regions Used In Training

3
1
4
6

Figure 7. Relaxation of Two Component Classification of Scene A Color Assignments listed on p. 22. (window size = 5 x 5, 6 classes).

Conclusions

1. Divergence was shown to be an effective measure for selecting worthwhile signature components in image segmentation.

2. The average gray shade and standard deviation of gray shades over small windows provide reasonable image segmentation capability and should be investigated further.

3. Max-Min texture and the defined Edge texture descriptors do not provide an image segmentation capability that warrants their use.

4. Relaxation is a useful, but costly, tool for eliminating noise from classification results. More work is needed to determine whether raster processing, in combination with relaxation will provide an efficient means of "cleaning" an image.

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