Reprinted from

Symposium on Machine Processing of Remotely Sensed Data

June 27 - 29, 1979

The Laboratory for Applications of
Remote Sensing

Purdue University
West Lafayette
Indiana 47907 USA

IEEE Catalog No.
79CH1430-8 MPRSD

CLASSIFICATION OF AREAS USING PIXEL-BY-PIXEL AND SAMPLE CLASSIFIERS

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ABSTRACT

The purpose of this study was to compare the area classification accuracy of each of the following options of image classification: 1. a pixel-by-pixel maximum likelihood gaussian classifier. 2. a sample classifier based on B-distance (derived from the Bhattacharyya distance). 3. a sample classifier based on the generalized maximum likelihood approach. 4. the pixel-by-pixel "single-cell signature acquisition" option of the Image-100 System. 5. same as option 1, but using the following simple decision rule for classification: if the percentage of pixels classified into the same class, within a given test field, exceeded a threshold value of 60%, they were all classified into the same class. 6. same as option 4, but using the decision rule given in option 5.

LANDSAT multispectral scanner data of the following three test sites of the state of São Paulo, Brazil, were classified using each of the above six options: 1. São José dos Campos 2. Cachoeira Paulista 3. Jardinópolis.

Considering both the errors of omission as well as commission, the sample classifier (option 2) yielded better classification accuracy, as compared to the maximum likelihood gaussian classifier (option 1) as well as single cell (option 4). Options 5 and 6 considerably improved the classification accuracy of options 1 and 4 respectively.

A part of the work on São José dos Campos reported here was presented at the International Conference on Machine-aided Image Analysis, 4-6 September, 1978, Oxford, England.

I. INTRODUCTION

The purpose of this study was to compare the results of area classification using pixel-by-pixel and sample classifiers applied to multispectral scanner (MSS) LANDSAT data. The following three test sites were selected for analysis in the state of São Paulo, Brazil: 1. São José dos Campos (23° 10'S, 45° 50'W). 2. Cachoeira Paulista (22° 40' S, 45°W). 3. Jardinópolis (21°S, 47° 50' W).

Cloud free multispectral scanner data from LANDSAT, of reasonable quality, over these three test sites were available. In addition, aerial photography and ground observations were available, to assist the data analysis. A short description of the above mentioned three test sites is given below: 1. São José dos Campos: São José dos Campos was selected because it is one of the fastest growing small-size towns of Brazil and the authors are well familiar with it. Many of the problems of this town are similar to the problems of much larger urban centers. 2. Jardinópolis: It is one of the most important agricultural areas of the state of São Paulo. The principal crops in this area are: corn, soybeans, cotton and sugar canes. The municipality of Jardinópolis has a population of about 17,000 and an area of 552 km^2. 3. Cachoeira Paulista: It is a small town situated approximately half way between two large cities, São Paulo and Rio de Janeiro. It has a population of 20 000 and an area of 279 km^2. A good part of this town is covered by pasture, while there is a small urban area including some of INPE's installations.

II. LITERATURE REVIEW

Many investigators have analysed the multispectral scanner (MSS) data of LANDSAT satellite for applications to land

CH1430-8/79/0000-0420$00.75

use classification. For example, Todd and Baumgardner[1] (1973) analysed LANDSAT MSS data obtained over Marion County (Indianapolis), Indiana, by computer-implemented techniques to evaluate the utility of satellite data for urban land use classification. Several land use classes, such as commerce/industry, single-family (newer) residential, trees, and water exhibited spectrally separable characteristics and were identified with greater than 90 percent accuracy. Ellefson et al.[2] (1973) did computer-aided analysis of LANDSAT MSS data of the San Francisco Bay area. Smith et al.[3] (1974) have given the application of spatial features to satellite land-use analysis. Ellefson et al.[4] (1974) have given new techniques in mapping urban land use and monitoring change for selected U.S. metropolitan areas. They analysed LANDSAT MSS data using automatic pattern recognition techniques for classification. Kumar and Silva[5] (1977) have analysed the statistical separability of agricultural cover types in much detail, data quantity and depth in the subsets of one to twelve spectral channels.

Cipra[7] (1974) compared multispectral imagery from LANDSAT to a soil association map of Tippecanoe County, Indiana, based on a conventional field survey. Hanuschak[6] (1976) gave a technique for estimating crop acreage, utilizing LANDSAT imagery that is not cloud free. Aaronson[8] (1977) described the LANDSAT Agricultural Monitoring Program (LAMP) to monitor Iowa's corn crop in near real-time. The program utilized LANDSAT data, in conjunction with collateral data sources, to monitor crop development and identify/assess anomalies and crop stresses.

Goldberg et al.[9] (1975) described methods and procedures which outside investigators may use, with the automated processing equipment of the Canada Centre for Remote Sensing (CCRS), for the purpose of natural resource exploration and mapping. They have compared the accuracies of unsupervised and supervised methods, on the basis of the confusion matrices generated by classifying exactly the same areas.

III. METHOD OF ANALYSIS

With the help of ground observations and aerial photography, a map of three test sites mentioned, showing the following classes, was obtained: 1. São José dos Campos: residential, multi-family residential, commercial, industrial, agricultural and unoccupied. 2. Jardinópolis: sugar canes, vegetation, pasture and bare soil. 3. Cachoeira Paulista: constructed areas, water, bare soil and agriculture.

LANDSAT multispectral scanner data, on computer compatible tapes, of these three test sites were analysed using Image-100*. With the aid of aerial photography and ground observations, rectangular areas of each of the above mentioned classes of each of three test sites were selected, avoiding the boundaries of the respective classes, on the Image-100 display. The areas of each of these classes were selected carefully, so that they could be considered to be representative of the respective classes.

Each of these classes was then divided into the following two independent groups: training and test areas. The purpose of this study was to compare the classification accuracy for the test areas of these test sites, using the training areas, for each of the following options of classification: 1. a pixel-by-pixel maximum likelihood Gaussian classifier. 2. a sample classifier based on B-distance (derived from the Bhattacharyya distance). 3. a sample classifier based on the generalized maximum likelihood approach (the probability distributions of the pixels within a sample were assumed to be independent). 4. the pixel-by-pixel "single-cell signature acquisition" option of the Image-100. 5. same as option 1, using the following simple decision rule for classification: if the percentage of pixels classified into the same class within a given test field exceeded a certain user selected threshold value, for example 60%, they were all classified into the same class. 6. same as option 4, using the decision rule given in option 5. A brief explanation of options 1 to 4 is given below.

Pixel-by-Pixel Maximum Likelihood Gaussian Classifier (MAXVER): This system[10], developed at INPE's Informatics Division, is available on-line-mode in the Image-100. In this system, the covariance matrix of each of the training classes is decomposed into an upper triangular and a lower triangular matrix. A maximum of 18 classes can be used.

Sample Classifier Based on B-Distance: Assuming that each of the classes has a multivariate gaussian

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* Image-100 is a data processing system marketed by General Electric Co. to extract thematic information and enhance multispectral imagery.

distribution, the B-distance between two classes is given by[11]

$$B = 2\ (1 - e^{-\alpha}), \tag{1}$$

where

$$\alpha = \frac{1}{8}(U_1-U_2)^T \Sigma^{-1} (U_1-U_2) + $$

$$+ \frac{1}{2} \log_e \left[\frac{\det \Sigma}{\sqrt{\det\Sigma_1 \cdot \det\Sigma_2}}\right] \tag{2}$$

where U_1 and U_2 are mean vectors of classes one and two respectively; whereas, Σ_1 and Σ_2 are the covariance matrices of the same two classes,

$$\Sigma = \frac{1}{2}\left[\Sigma_1 + \Sigma_2\right] \tag{3}$$

and T denotes transpose.

The average B-distance over all pairs of classes is given by

$$B_{AVE}(C_1,C_2,\ldots C_n) =$$

$$= \frac{2}{m(m-1)} \sum_{i=1}^{m-1} \sum_{j=i+1}^{m} B(i,j|C_1,C_2,\ldots C_n) \tag{4}$$

where

m = number of classes

$B(i,j|C_1,C_2,\ldots,C_n)$ = B-distance between classes i and j in the channels $C_1,C_2,\ldots,C_n$.

A sample classifier based on B-distance is available on-line-mode in the Image-100[12,13]. The B-distance is computed between a test field and each of the training classes and the test field is classified into the class for which the B-distance is minimum. Fields classified into the same class are stored in the same theme, to give them a distinct color.

Sample Classifier Based on the Generalized Maximum Likelihood Approach: This classifier is available on-line-mode[14] in the Image-100. The maximum likelihood decision is based on the joint probability distributions of the pixels within a sample, assuming independence of the probability distributions of pixels within a sample.

Pixel-by-Pixel Single Cell Signature Acquisition Option of the Image-100: This option creates a four-dimensional rectangular parallelepiped, each side of which corresponds to the signature limits of the training areas in each channel. For example, in the case of Jardinópolis, using the training areas of vegetation, the number of pixels classified as "vegetation" by the 'single-cell option" inside the test fields of each of these four classes -- sugar canes, vegetation, pasture and bare soil, was determined. An identical analysis was repeated for each of the other three classes -- sugar canes, pasture and bare soil. Thus, a confusion matrix showing the total number of pixels (picture elements) of each class classified correctly as well as classified incorrectly into each of the other classes was obtained. Similarly, a confusion matrix was obtained for São José dos Campos and for Cachoeira Paulista.

Unfortunately, due to lack of machine time, the following options of classification of these three test sites, out of the six options mentioned above, could not be carried out: (1) São José dos Campos: option no. 3; (2) Jardinópolis: option no. 6; (3) Cachoeira Paulista: option no. 1, 3, 5 and 6.

In addition to these six options of classification, the effect of the size of training samples on the percentage of correct classification was investigated. Using 20% of the total area of each class for training, the three test sites were classified using option 2 as well as option 4. An identical analysis was done using 10% as well as 5% of the total area of each class for training, but using the same test fields, to investigate the effect of size of the training samples on the percentage of correct classification. This analysis was done for each of the three test sites, with the exception of classifying São José dos Campos using option 2, due to lack of time available.

In the same case of São José dos Campos, B_{AVE} was computed for all possible subsets of one to four spectral channels, out of four available channels. For each value of B-distance, the probability of correct classification was reasonably estimated from the curve of Swain and King[11] (1973).

For São José dos Campos, in addition to the six options of classification mentioned earlier, the "multicell signature acquisition" as well as the "interactive acquisition" options of the Image-100 were used. In the multicell signature acquisition, the parallelepiped of spectral signature is subdivided into cells, each of unit volume, and the number of pixels in each of these unit cells is counted. These cell counts are, thus, measures of the probability distribution of the spectral cluster. By raising or lowering the threshold on the cell counts, one can vary the size of the four dimensional probability distribution of the spectral cluster by deleting or adding cells with counts greater than the variable threshold. In the interactive signature modification option, the user performs training on the misclassified area, adding the errors of omission and subtracting the errors of commission until satisfied with the results.

IV. RESULTS AND DISCUSSION

A. SÃO JOSÊ DOS CAMPOS

Table 1 gives the values of B_{AVE} in all possible combinations of one, two, three and four channels out of the four available channels. As one would expect, the values of B_{AVE} increase with an increase in the number of channels. In the subsets of one to three spectral channels, channel 4, channel 4 & 7 (one in the visible and one in the near infrared), and channels 4, 5 & 7 (two in the visible and one in the near infrared) are found to be the best choices. Table 1 shows that in the subset of two channels, channels 4 and 5 (visible wavelength region) give higher probability of correct classification than channels 6 & 7 (near infrared wavelength region). The authors believe that each wavelength region -- visible, near infrared, middle infrared and thermal infrared, has independent information content. Thus, in the subset of two spectral channels, one channel in the visible and one channel in the near infrared wavelength region are found to be the best choice. Kumar[15] (1978) has analysed aircraft-collected MSS data in much detail, data quantity and depth in the subsets of one to twelve spectral channels, to evaluate each spectral channel as well as possible combinations of wavelength regions for statistical separability of agricultural cover types.

The errors of omission (for example, while using training fields of residential areas, number of pixels of test fields known to be residential, not classified as residential constitute the errors of omission, etc.) and the errors of commission (while using training fields of residential areas, number of pixels of classes other than residential but which are classified by the Image-100 as residential) were calculated and are shown in Table 2. Similarly, the errors of omission and commission using the multi-cell signature acquisition (m=1, m=2 and m=3), for the same training and test fields of each class were calculated and are given in Table 2. The option m=1 means that all the unit cells in the four dimensional spectral space, which had less than one pixel, were deleted from the spectral signature of the training fields for doing classification. Similarly, the option m=2 means that all the unit cells in the four dimensional spectral space which had less than two pixels were deleted from the spectral signature of the training fields for doing classification, etc. Table 2 shows that for the single-cell (option 4), the errors of omission vary from 16.3% for the class commercial to 33.3% for the class multifamily residential. The errors of commission vary from 5.6% for the class commercial to 39.0% for the class industrial. This shows that the classification accuracy for all the classes is rather poor, except the class "commercial", where the percentage of errors are reasonably small (errors of omission = 16.3%, commission = 5.6%). This is because of the small values of standard deviation for this class (and hence, less overlap with other classes) in each of the spectral channels, especially in the channels one (0.5 to 0.6 μm) and four (0.8 to 1.1 μm).

In general, an increase in the standard deviations of a class in the spectral channels tends to reduce the errors of omission and increase the errors of commission. It was found that, taking into account both the errors of omission as well as those of commission, the classification accuracy generally decreases with an increase in the standard deviations, as expected.

Table 2 shows, as expected, that the multicell option increases the errors of omission and decreases the errors of commission. The multicell option for m=1 considerably decreases the percentage of correct classification for each of the classes. This is because the number of pixels used for training in each class were relatively small for statistical purpose. Thus, the unit cells in the four dimensional spectral space were sparsely populated. Thus, there may be many cells which are actually representative of the class, but do not have any pixels, because the total number of pixels for training for each of the classes was rather small. For the multicell option, the errors of omission increase and the errors of commission decrease as we go from m=1 to m=2 and m=3. Considering the errors of omission as well as the errors of commission, the percentage of correct classification decreases as we go from m=1 to m=2 and m=3.

Table 2 also shows that the

interactive signature acquisition option does not improve the classification accuracy, as compared to the "single cell" option, because of the overlap between the classes in the four-dimensional spectral space. It shows that considering both the errors of omission as well as commission, the sample classifier (option 2) gave better classification accuracy, as compared to the pixel-by-pixel classifier (option 1) as well as single cell (option 4). Options 5 and 6 considerably improve the classification accuracy of options 1 and 4 respectively. This is very encouraging, because using a simple decision rule in options 5 and 6 can considerably improve the classification accuracy. These results still need to be confirmed by a similar analysis of more test sites.

Table 2 also shows the effect of the size of training samples on the classification accuracy using the single cell (option 4). As one would expect, with the reduction in the size of training samples, the errors of omission increase, whereas the errors of commission decrease. Considering both errors of omission and commission, it seems that the percentage of correct classification decreases as the size of the training samples decreases. However, the cost of classifying the data increases with an increase in the size of the training samples. Future studies will include a cost-benefit analysis to find an optimum trade off between cost of classification and size of training samples.

B. CACHOEIRA PAULISTA

Table 3 shows results obtained on the site of Cachoeira Paulista. It shows that the sample classifier (option 2) gives much better classification accuracy, as compared to the single cell (option 4). In addition, it shows that, considering errors of omission as well as commission, the percentage of correct classification decreases as the size of the training samples decreases, for the single cell option as well as the sample classifier. It can be seen that bare soil has large errors of omission, whereas constructed area has large errors of commission. This is because the class "constructed area" had a large standard deviation and considerable part of the interval of spectral response of bare soil was within that of constructed area.

C. JARDINÓPOLIS

Table 4 shows the errors of omission and commission for the municipality of Jardinópolis. It shows that options 1, 2, 3 and 5 give considerably higher percentage of correct classification, as compared to option 4. In addition, it shows, as one would expect, that the errors of omission increase, whereas the errors of commission decrease with a decrease of size of the training samples. However, even when the training area constitutes 20% of the total (training + test) area, the errors of commission are much smaller than the respective errors of omission. Thus, the authors believe that, in this particular case, the sizes of the training samples constituting 5% or even 10% of the total area are not adequate for achieving a reasonable percentage of correct classification, using option 4.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the assistance of Dr. Celso de Renna e Souza, Head, Informatics Division, INPE, for his assistance with this work. In addition, we would like to thank Mrs. Maria Helena Lopes da Silva for typing this manuscript and Dr. Nelson de Jesus Parada, Director of INPE, for his permission to publish this paper.

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Table 1. Values of B_{AVE} in Subset of One to Four Channels.

Channel	P_c	Channels	P_c	Channels	P_c
4	84.3	4-5	85.0	4-5-6	86.6
5	84.0	4-6	85.0	4-5-7	88.5
6	74.5	4-7	86.1	4-6-7	86.7
7	74.4	5-6	85.1	5-6-7	84.6
		5-7	86.0	4-5-6-7	89.0
		6-7	79.8		

Note: P_c denotes probability of correct classification estimated from the values of B_{AVE} using the curve of Swain and King[11].

Test Site: São Josê dos Campos.

Table 2. Percentage Errors of Omission and Commission (São Josê dos Campos).

Class	Training Areas 20% Single Cell Option 4	Multi-Cell m=1	Multi-Cell m=2	Multi-Cell m=3	Interactive Signature Acquisition	Maximum Likelihood Option 1	Sample Classifier Option 2	Single Cell Option 6	Maximum Likelihood Option 5	Training Areas 10% Single Cell Option 4	Training Areas 5% Single Cell Option 4
(A) Percentage errors of omission (%)											
Res.	26.8	63.2	73.9	83.6	23.2	22.7	4.35	33.0	13.0	34.2	48.3
Com.	16.3	74.7	78.5	83.4	25.6	26.4	0	0.0	0	46.4	59.2
Agr.	19.4	73.5	80.3	86.7	21.1	22.6	26.8	6.0	10.0	35.2	60.3
Unoc.	16.9	77.5	82.3	88.4	34.2	46.0	32.5	0	16.0	32.8	37.9
M.Res.	33.3	80.2	88.5	94.3	37.5	64.0	44.0	44.0	80.0	53.1	67.3
Ind.	5.0	68.4	86.0	90.0	6.3	49.0	6.8	13.0	40.0	20.2	36.8
(B) Errors of commission (%)											
Res.	17.7	2.3	1.6	0.6	15.5	6.8	1.9	5.0	11.0	7.3	3.1
Com.	5.6	1.9	1.0	0.4	29.6	1.8	1.5	21.0	5.0	1.3	1.2
Agr.	30.0	4.9	2.7	2.1	24.9	8.0	12.4	0	5.0	18.3	6.9
Unoc.	33.2	7.0	5.3	4.7	38.6	19.8	11.0	4.0	6.0	20.4	6.3
M.Res.	35.6	0.9	0.3	0	34.2	0.4	5.0	0	3.0	18.1	5.1
Ind.	39.0	11.1	1.9	1.6	42.5	6.0	0	0	3.0	18.5	5.7

Note: An explanation of options of classification one to six is given in Section III.

Res. = Residential, Com. = Commercial, Agr. = Agricultural, Unoc. = Unoccupied, M.Res. = Multifamily Residential, Ind. = Industrial.

Table 3. Percentage Errors of Omission and Commission (Cachoeira Paulista).

(A) Percentage errors of omission (%)

Class	Single Cell (Option 4) Training Areas 20%	Sample Classifier (Option 2) Training Areas 20%	Single Cell (Option 4) Training Areas 10%	Sample Classifier (Option 2) Training Areas 10%	Single Cell (Option 4) Training Areas 5%	Sample Classifier (Option 2) Training Areas 5%
Constructed Area	16.4	5.1	27.9	5.1	31.2	5.1
Water	14.3	0	16.9	0	37.9	0
Bare Soil	35.5	35.7	65.5	44.7	65.5	58.7
Agriculture	20.0	0	22.0	0	22.4	0

(B) Percentage errors of commission (%)

Class	Single Cell (Option 4) Training Areas 20%	Sample Classifier (Option 2) Training Areas 20%	Single Cell (Option 4) Training Areas 10%	Sample Classifier (Option 2) Training Areas 10%	Single Cell (Option 4) Training Areas 5%	Sample Classifier (Option 2) Training Areas 5%
Constructed Area	21.4	3.3	6.4	5.5	5.0	6.9
Water	2.6	0	2.4	0	1.5	0
Bare Soil	5.4	1.4	4.8	1.4	4.8	1.4
Agriculture	8.4	0	7.3	1.0	7.3	1.9

Table 4. Percentage Errors of Omission and Commission (Jardinópolis).

(A) Percentage errors of omission (%)

Class	Single Cell (Option 4) Training Areas 20%	Single Cell (Option 4) Training Areas 10%	Single Cell (Option 4) Training Areas 5%
Sugar Canes	29.0	41.9	83.6
Vegetation	5.9	5.9	8.9
Pasture	14.8	32.4	32.4
Bare Soil	2.3	2.3	35.8

(B) Percentage errors of commission (%)

Class	Single Cell (Option 4) Training Areas 20%	Single Cell (Option 4) Training Areas 10%	Single Cell (Option 4) Training Areas 5%
Sugar Canes	1.6	0	0
Vegetation	0.3	0.3	0.2
Pasture	1.5	0.6	0.6
Bare Soil	0	0	0

Note: Options 1, 2, 3 and 5 gave 0% errors of omission and 0% errors of commission for each of the four classes for each of training areas of 20%, 10% and 5%. The option 6 was not used due to lack of time.

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