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MULTISPECTRAL IMAGE CLASSIFICATION IN REMOTE SENSING: THE CLASS-BOUNDARIES APPROACH

ABSTRACT

A method using mathematical functions to represent the boundaries among ground cover classes has been found to be more efficient than the Maximum Likelihood Method for the classification of covers with poor within-the-class variances. Fictitious data as well as LANDSAT MSS data have been used to demonstrate the efficiency of this method.

INTRODUCTION

The Maximum Likelihood Method of multispectral image classification /6,12/ has been widely accepted as a very powerful tool. However, its precondition of normally distributed data has also been accepted as a major worry. A lot of work has therefore been going on for some years in the search, not necessarily for a replacement but at least for an alternative when the situation demands it /3,4/. This paper describes an alternative where image class discriminators are the mathematical boundaries among the several image classes.

This investigation was done in two stages: the fictitious data and the real (LANDSAT) data stages. The fictitious data stage was necessary for the development of adequate procedures and also for confirming these procedures as both mathematically correct and economically justifiable.

MATHEMATICS OF THE CLASS BOUNDARIES

Members of any class must exist within definite boundaries or hyperplanes. If the total number of classes is k, then the total number of hyperplanes is given by

$$l = \frac{k \cdot (k - 1)}{2}$$

A hyperplane may be a first order or a second order polynomial, and its coefficients are computed in an iterative procedure using the known samples of the two classes that it tries to separate /8/. The hyperplane actually runs down the middle of a "dead zone" whose width is chosen arbitrarily and which becomes unnecessary when the data have zero within-the-class variability.

Let,

Spectral values vector for an unknown sample	=	G
Coefficients of an hyperplane	=	C
No. of spectral bands	=	n
No. of classes	=	k

A discriminator for the unknown sample,

$$f_{i,j}\ (G) = C^{T}_{i,j}G + C_{(n+1)\ i,j}$$

where i,j are the classes on both sides of the hyperplane. And obviously 1 different values of $f_{ij}(G)$ may be computed.

The unknown sample is classified as member of class 1 if and only if

$$f_{1,2}\ (G),\ \ldots\ldots,\ f_{1,k}\ (G) \text{ are } \geq 0$$

It is however member of any other class q if and only if

$$f_{q,\ (q+1)}\ (G),\ \ldots\ldots,\ f_{q,k}\ (G) \text{ are } \geq 0$$

for $q < k$,

and also if

$$f_{1,q}\ (G),\ \ldots\ldots,\ f_{(q-1),q}\ (G) \text{ are } < 0$$

PREPROCESSING OF MSS DATA

The preprocessing of multispectral scanner digital data by eigen-vector transformation has become a very well known data compression procedure /1, 2, 5, 9, 10/. In the present investigation, however, no data compression is intended. The same transformation is used for higher image classification accuracy and, for the class-Boundaries method, also for higher savings in computer time resulting from the quicker convergence of the algorithm. The procedure is as follows:

a) division of every spectral value by the corresponding band standard deviation, and then,

b) transformation of the values for every picture element with the nxn matrix of eigen-vectors of the covariance matrix computed using all training samples.

INVESTICATION WITH FICTITIOUS DATA

A grid, 30 rows by 50 columns, was constructed and divided up into four zones to represent four image classes (Fig. A 1 in the Appendix). For the spectral data generation, starting values were taken from curves of actual measurements as reported by K. T. KRIEBEL /7/ for Savannah (class 1), Bog (class 2), Pasture (class 3) and Coniferous Forest (class 4), for the following illumination conditions:

Zenith angle of incidence = 0^{o}

zenith angle of reflection = 0^{o}

azimuth difference between the incident and the reflected rays = 0^{o}

Savannah was measured in Namibia in late winter; and Bog, Pasture and Coniferous Forest in the Federal Republic of Germany in late summer. Values extracted from the curves were those corresponding to the LANDSAT bands as follows:

MSS band 4: .5 - .6 μm

MSS band 5: .6 - .7 μm

MSS band 6: .7 - .8 μm

MSS band 7: .8 - 1.1 μm

Data actually stored on tape were these starting values which were then assumed to be 100 % pure spectral signatures, so that the amount of variance in the data could be varied at will, by changing the value of a constant, c, which represents the level of overall variance in the whole data (see Appendix A for the mathematical basis for the fictitious data generation).

CLASSIFICATION WITH THE FICTITIOUS DATA

Results of classifications at various values of c by the Maximum Likelihood method for both the preprocessed and the unpreprocessed data are represented by curves in Fig. I, and may be summarized as follows:

a) Classification by the Maximum Likelihood method is impossible at c = 0.

b) Classification accuracy increases generally with increasing c. There exists, however, for each curve, a zone of confusion, where accuracy may decrease with increasing c.

c) Data preprocessing generally raises classification accuracy. However, there may be an apparent lowering of accuracy within the zones of confusion.

With the preprocessed data, classifications were then carried out by both the Maximum Likelihood and the Class Boundaries methods for c = 0.3 which is too low for the Maximum Likelihood method and just outside the zone of confusion (Fig. 1). 40 training samples were used for each class. The results are shown in Tables 1 and 2. The elements in the first row (class 1) for example, tell how the algorithm sees the group of 340 pixels labelled class 1. Each class-accuracy (or "% GOOD") is calculated as

$$\frac{\text{diagonal element in perform. matrix}}{\text{number of the class test samples}} \times 100\ \%$$

The overall accuracy of classification is calculated as

$$\frac{\text{sum of diag. elements in perform. matrix}}{\text{total number of test samples}} \times 100\ \%$$

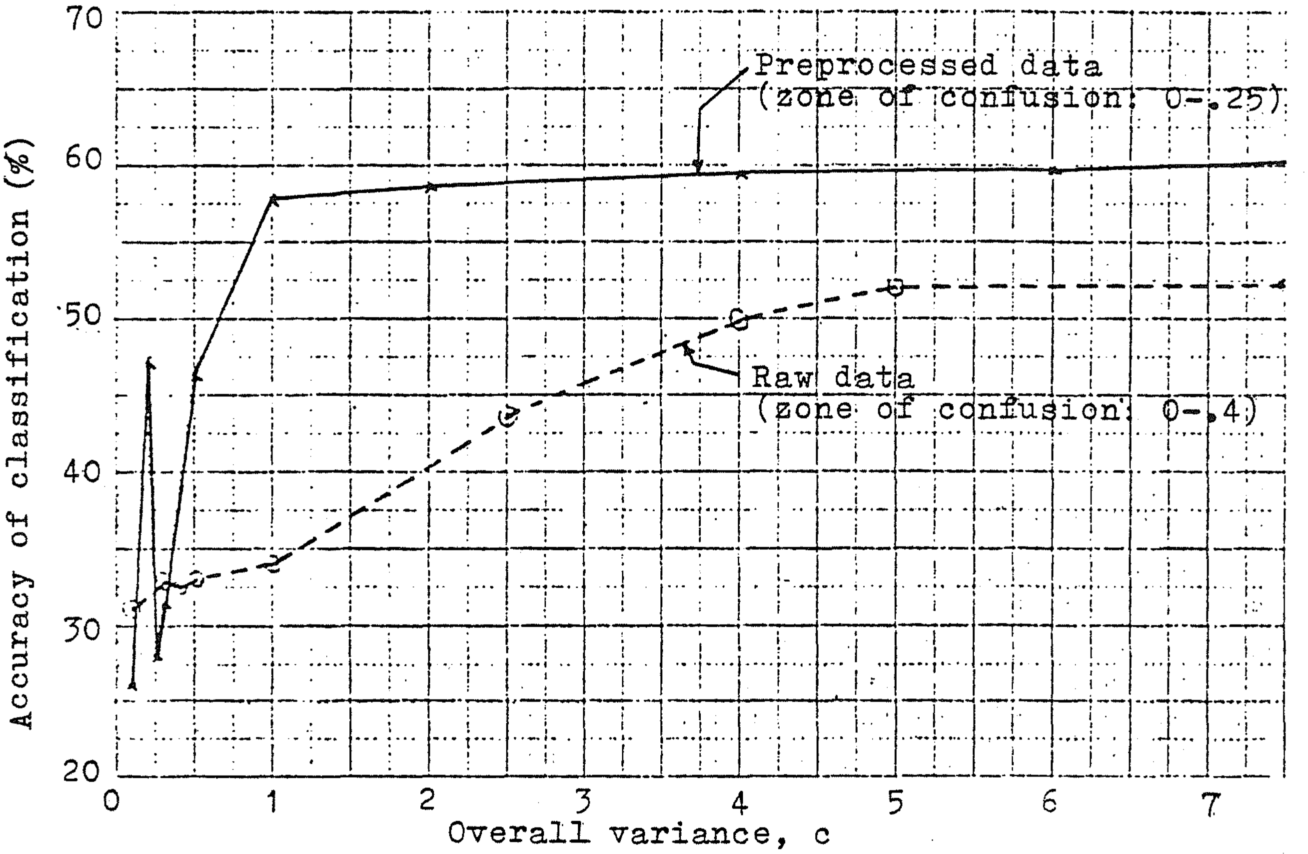

Fig. 1. Behaviour of accuracy of classification by the Maximum Likelihood Method.

These results show clearly the suitability of the Class Boundaries method for the classification of data with low overall variances, c. Infact, classification accuracy is 100 % for c = 0; and such data (see Table A 2 in the Appendix) may be classified with only one training sample per class.

Table 1. Fictitious Data Classification by the Maximum Likelihood Method.

THE PERFORMANCE MATRIX
(LAST 2 COLUMNS REPRESENT -TOTALS- AND -%GOOD- RESPECTIVELY)

	CL.1	CL.2	CL.3	CL.4		
CLASS 1	113	12	212	3	340	33
CLASS 2	128	97	11	61	297	33
CLASS 3	114	3	108	2	227	48
CLASS 4	85	119	1	27	232	12

ACCURACY OF CLASSIFICATION = 31.48%

THE MISCLASSIFIED TRAINING SAMPLES
25 FROM CLASS 1
22 FROM CLASS 2
18 FROM CLASS 3
36 FROM CLASS 4

Table 2. Fictitious Data Classification by the Class Boundaries Method:
(degree of polynomials=1, dead zone=0.5)

THE PERFORMANCE MATRIX
(LAST 3 COLUMNS REPRESENT -REJECTS-, -TOTALS- AND -%GOOD-

	CL.I	CL.2	CL.3	CL.4			
CLASS 1	320	4	14	0	2	340	94
CLASS 2	0	272	0	25	0	297	92
CLASS 3	10	2	215	0	0	227	95
CLASS 4	0	22	0	210	0	232	91

ACCURACY OF CLASSIFICATION = 92.79%

THE MISCLASSIFIED TRAINING SAMPLES
0 FROM CLASS 1
2 FROM CLASS 2
0 FROM CLASS 3
4 FROM CLASS 4

INVESTIGATION WITH LANDSAT DATA

Multispectral image classification of vegetative cover is now almost always successful by the Maximum Likelihood method. Most vegetative covers, therefore, have high levels of variance. It was then necessary for this investigation to find an area with little vegetation, but with as many as possible of other types of ground cover.

A 90 x 40 km terrain, involving 923,400 picture elements, in the plateau area of the Plateau State of Nigeria, with the State Capital city of Jos to the North, was found to be adequate. But for the Government Timber Plantations and Forest Reserves, vegetation is almost non-existent in this area during the dry season. Being a strip-mining region, large water bodies are every where all year round. The LANDSAT scene, ID No. E-2317, center 10 ^{o} 12' N, 8^{o} 35' E, was exposed on December 5, 1975 at 9 a. m. Eight ground cover classes were chosen as follows:

- Class 1: Sedimented waters.
- Class 2: Heavily sedimented waters.
- Class 3: Government Timber Plantations; the Melina is the specie that never completely sheds its leaves, but maintains the process of gradual replacement in winter.
- Class 4: Government animal and forest reserves. They contain scattered bushes.
- Class 5: Bare ground, sandy.
- Class 6: Asphalt (samples taken from the airport).
- Class 7: Towns and cities.
- Class 8: Irrigated vegetable farms.

Forty training samles were chosen for each class. It must be mentioned however that asphalt (class 6) samples were so few that the training samples were again included in the test samples. The training samples of sedimented waters (class 1) are presented in Table A 3. Both the unpreprocessed and the preprocessed data were classified by the Maximum Likelihood method. Only the preprocessed data was classified by the Class-Boundaries method.

Table 3. Landsat Data Classification by the Maximum Likelihood Method, without preprocessing.

THE PERFORMANCE MATRIX
(LAST 2 COLUMNS REPRESENT -TOTALS- AND -%GOOD- RESPECTIVELY)

	CL.1	CL.2	CL.3	CL.4	CL.5	CL.6	CL.7	CL.8		
CLASS 1	168	0	0	0	0	0	0	0	168	100
CLASS 2	12	143	0	0	0	0	0	0	155	92
CLASS 3	0	130	0	0	0	0	0	0	130	0
CLASS 4	4	116	0	0	0	0	0	0	120	0
CLASS 5	0	120	0	0	0	0	0	0	120	0
CLASS 6	0	44	0	0	0	0	0	0	44	0
CLASS 7	0	103	0	0	0	0	0	0	103	0
CLASS 8	0	154	0	0	0	0	0	0	154	0

ACCURACY OF CLASSIFICATION = 31.29%

THE MISCLASSIFIED TRAINING SAMPLES
0 FROM CLASS 1
5 FROM CLASS 2
40 FROM CLASS 3
40 FROM CLASS 4
40 FROM CLASS 5
40 FROM CLASS 6
40 FROM CLASS 7
40 FROM CLASS 8

Table 4. Landsat Data Classification by the Maximum Likelihood Method, with preprocessing.

THE PERFORMANCE MATRIX
(LAST 2 COLUMNS REPRESENT -TOTALS- AND -%GOOD- RESPECTIVELY)

	CL.1	CL.2	CL.3	CL.4	CL.5	CL.6	CL.7	CL.8		
CLASS 1	0	0	0	0	0	0	168	0	168	0
CLASS 2	0	0	118	0	0	33	4	0	155	0
CLASS 3	0	1	46	0	0	83	0	0	130	35
CLASS 4	2	19	8	29	3	7	46	6	120	24
CLASS 5	2	31	0	25	10	0	52	0	120	8
CLASS 6	1	3	7	2	13	6	5	7	44	14
CLASS 7	10	41	4	9	11	2	26	0	103	25
CLASS 8	0	5	76	0	0	62	11	0	154	0

ACCURACY OF CLASSIFICATION = 11.77%

THE MISCLASSIFIED TRAINING SAMPLES
40 FROM CLASS 1
40 FROM CLASS 2
25 FROM CLASS 3
35 FROM CLASS 4
29 FROM CLASS 5
34 FROM CLASS 6
29 FROM CLASS 7
40 FROM CLASS 8

DISCUSSION ON LANDSAT DATA CLASSIFICATIONS

Considering the lowering of the Maximum Likelihood classification accuracy through data preprocessing (Tables 3 and 4), it is clear that this combination of ground covers has an overall variance, c, that falls within the zone of confusion. Three more observations should be made:

a) Table 3 should not be taken seriously, and hence there exists no real lowering of accuracy as is apparent in Table 4. The fair chance given to each class through the preprocessing should be appreciated.

b) In spite of the poor condition of the leaves at that time of the year, the Plantations (class 3), still stand out as the best classified (Table 4).

c) The water bodies and the irrigated vegetable farms (classes 1, 2, 8) are not classified at all (Table 4).

Table 5 shows the result of the classification by the Class-Boundaries method which may be compared with that by the Maximum Likelihood method. Both the sedimented and the heavily sedimented waters (classes 1 and 2) were classified 100 % correct. One further comparison is in the computation times. While the Maximum Likelihood method used 2.9 minutes, the Class-Boundaries method used 2.4 minutes.

Table 5. Landsat Data Classification by the Class Boundaries Method:
(degree of polynomials=1, dead zone=0.5)

THE PERFORMANCE MATRIX
(LAST 3 COLUMNS REPRESENT -REJECTS-, -TOTALS- AND -%GOOD-, RESPECTIVELY)

	CL.1	CL.2	CL.3	CL.4	CL.5	CL.6	CL.7	CL.8			
CLASS 1	168	0	0	0	0	0	0	0	0	168	100
CLASS 2	0	155	0	0	0	0	0	0	0	155	100
CLASS 3	0	0	125	0	0	0	0	5	0	130	96
CLASS 4	0	0	0	104	0	8	0	8	0	120	87
CLASS 5	0	0	0	0	113	1	5	0	1	120	94
CLASS 6	0	0	0	0	2	38	4	0	0	44	86
CLASS 7	0	0	0	0	8	10	84	0	1	103	82
CLASS 8	0	0	4	7	0	18	0	122	3	154	79

ACCURACY OF CLASSIFICATION = 91.45%

THE MISCLASSIFIED TRAINING SAMPLES
0 FROM CLASS 1
0 FROM CLASS 2
0 FROM CLASS 3
4 FROM CLASS 4
1 FROM CLASS 5
4 FROM CLASS 6
8 FROM CLASS 7
1 FROM CLASS 8

CONCLUSION

Results have shown the effectiveness of Class Boundaries of first order polynomials for the classification of ground covers with low variances. Although investigations are not yet complete, tests with fictitious data confirm the goodnesss of the second order polynomials for higher levels of variances. Impressive is the fact that this method is more economical, at least at low variances, than the Maximum Likelihood method. The importance of preprocessing, as described here, to both the Maximum Likelihood and the Class Boundaries methods has also been demonstrated.

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APPENDIX:

THE MATHEMATICAL BASIS FOR THE FICTITIOUS DATA GENERATION

The measured spectral value of a picture element for a particular spectral band may be represented as

$$y = B + E$$

where,

B is a constant representing the characteristics of the object, and

E represents the random influence contributed by object impurities, illumination, detectors, digital recording, data transmission, reception and reduction systems /7, 11/.

In the data generation, while B is the same for all pixels of the same class for any particular band (Tables A 1 and A 2), E varies for every pixel. For any particular class for any particular band, the E's are random variables of mean B and standard deviation,

$$\sigma = c \times B$$

where c is a constant for all the classification data. By this arrangement, the belonging-to-the-same-family of all pixels in the same class is maintained.

Fig. A1. The 1,500 fictitious picture elements in their respective classes.

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Table A1. Spectral Reflectance Factors taken from Tables and assumed to be 100% pure.

Ground Cover	Wave Lengths (μm) .5-.6	.6-.7	.7-.8	.8-1.1
Savannah (class 1)	.0825	.1100	.1300	.1700
Bog (class 2)	.0255	.0425	.0850	.1350
Pasture (class 3)	.0415	.1000	.2450	.3900
Conif. Forest (class 4)	.0140	.0275	.0620	.1070

Table A2. Some Samples from Fictitious Data with c=0. (Row and Column numbers are indicated)

	14	31	.0825	.1100	.1300	.1700
	14	32	.0825	.1100	.1300	.1700
	15	25	.0825	.1100	.1300	.1700
	I5	26	.0825	.1100	.1300	.1700
	15	27	.0825	.1100	.1300	.1700
5 FROM	CLASS	1				
	10	49	.0255	.0425	.0850	.1350
	10	50	.0255	.0425	.0850	.1350
	I1	47	.0255	.0425	.0850	.1350
	11	48	.0255	.0425	.0850	.1350
	I1	43	.0255	.0425	.0850	.1350
5 FROM	CLASS	2				
	20	27	.0415	.1000	.2450	.3900
	20	28	.0415	.1000	.2450	.3900
	20	37	.0415	.1000	.2450	.3900
	20	38	.0415	.1000	.2450	.3900
	20	43	.0415	.1000	.2450	.3900
5 FROM	CLASS	3				
	24	24	.0140	.0275	.0620	.1070
	25	24	.0140	.0275	.0620	.1070
	25	24	.0140	.0275	.0620	.1070
	26	24	.0140	.0275	.0620	.1070
	29	24	.0140	.0275	.0620	.1070
5 FROM	CLASS	4				

Table A3. Landsat Data Training Samples for the Sedimented Waters (class 1).

509	641	25.0000	25.0000	13.0000	2.0000
510	641	26.0000	26.0000	13.0000	1.0000
510	640	26.0000	26.0000	13.0000	1.0000
510	639	26.0000	26.0000	13.0000	1.0000
510	638	26.0000	24.0000	12.0000	1.0000
511	641	25.0000	24.0000	13.0000	2.0000
511	640	24.0000	26.0000	12.0000	2.0000
511	639	25.0000	24.0000	13.0000	2.0000
511	638	25.0000	26.0000	11.0000	2.0000
512	641	24.0000	24.0000	15.0000	2.0000
512	640	26.0000	26.0000	15.0000	1.0000
512	639	26.0000	26.0000	13.0000	2.0000
512	638	26.0000	26.0000	15.0000	2.0000
1042	794	25.0000	20.0000	9.0000	1.0000
1042	793	28.0000	20.0000	9.0000	1.0000
1042	792	28.0000	21.0000	9.0000	1.0000
1042	791	28.0000	20.0000	9.0000	1.0000
1046	789	26.0000	21.0000	11.0000	1.0000
1046	788	26.0000	22.0000	11.0000	1.0000
1046	787	26.0000	21.0000	10.0000	1.0000
1046	786	26.0000	22.0000	10.0000	1.0000
1046	785	27.0000	21.0000	11.0000	1.0000
1048	785	25.0000	21.0000	10.0000	1.0000
1048	784	25.0000	21.0000	9.0000	1.0000
1051	773	27.0000	21.0000	9.0000	1.0000
1052	779	27.0000	21.0000	10.0000	1.0000
1052	778	26.0000	21.0000	11.0000	1.0000
1052	777	26.0000	22.0000	11.0000	1.0000
1052	776	26.0000	21.0000	10.0000	1.0000
1052	775	27.0000	21.0000	11.0000	1.0000
1052	774	26.0000	21.0000	10.0000	1.0000
1054	764	28.0000	20.0000	9.0000	1.0000
1055	764	25.0000	20.0000	9.0000	1.0000
1055	763	27.0000	20.0000	9.0000	1.0000
1055	762	27.0000	20.0000	10.0000	1.0000
1055	761	27.0000	20.0000	9.0000	1.0000
1055	760	27.0000	21.0000	9.0000	1.0000
1055	759	25.0000	20.0000	9.0000	1.0000
1055	758	27.0000	21.0000	9.0000	2.0000
1055	757	27.0000	20.0000	10.0000	1.0000