Paper A 2

USER ORIENTED ERTS-1 IMAGES

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ABSTRACT

Photographic reproductions of ERTS-1 images are capable of displaying only a portion of the total information available from the Multispectral Scanner. For these reasons, methods are being developed by the Applications Division of the Canada Centre for Remote Sensing, to generate ERTS-1 images oriented towards special users such as agriculturists, foresters, and hydrologists by applying image enhancement techniques and interactive statistical classification schemes.

Spatial boundaries and linear features can be emphasized and delineated using simple filters. Linear and nonlinear transformations can be applied to the spectral data to emphasize certain ground information.

An automatic classification scheme was developed to identify particular ground cover classes such as fallow, grain, rape seed or various vegetation covers. The scheme applies the maximum likelihood decision rule to the spectral information and classifies the ERTS-1 image on a pixel by pixel basis. The user must first furnish the classifier a set of training areas for the classes of interest so that the statistical information can be extracted. The classifier then gives the user an estimate of how well it can distinguish the classes on the basis of these data and attempts to classify a designated area. Preliminary results indicate that the classifier has limited success in distinguishing crops, but is well adapted for identifying different types of vegetation.

Illustrative examples are presented for areas in the ERTS-1 frame, 1007 - 16531, which covers the area around Winnipeg, Manitoba.

INTRODUCTION

Owing to the fact that photographs are only able to display a fraction of the total information available from ERTS imagery, digital methods that directly process the original data were investigated. The goal of this study was to develop techniques that automatically interpret the images or enhance different characteristics of the images. The investigation was carried out with the use of a Bendix "Multispectral Analyzer Display" which was interfaced to a time-sharing DEC PDP-10 computer system. All the methods described were applied to the ERTS-1 frame 1007 - 16531 which was imaged on July 30, 1972 and covered the area centered on Winnipeg, Manitoba (Figure 1).

The three methods described are presently at different stages of development. Most of the emphasis in this report will be given to supervised digital classification which was studied extensively. The two other image processing techniques applied by us are summarized briefly.

BOUNDARY ENHANCEMENT AND DETECTION

Linear features such as boundaries between agricultural fields, topographical features, and roads are important in the production of maps. If the spatial boundaries of different ground cover classes were known in advance then the data pixels enclosed by the boundaries could be classified more rapidly and accurately. A simple scheme involving minimum computation to enhance these features is a form of differentiation. The image is displaced one or two pixel units and a new image is determined from the absolute difference of the original and displaced image. High spatial frequency content such as texture and boundaries is amplified at the expense of the DC components. Thresholding techniques and logical manipulations as described by Holdemann and Kazmierczak (1971) are necessary to extract and follow the linear features. The method was very successful for very sharp boundaries such as water land interfaces seen in band 7 but only moderately successful for agricultural fields.

CANONICAL TRANSFORMATION OF SPECTRAL INTENSITIES

The chromaticity transformation conceived by Taylor (1973) and described in a separate paper at this conference was applied to agricultural and forested areas of the ERTS frame. The technique works basically as follows. By use of a canonical transformation (Kendall and Stuart, 1968) the spectral intensities are transformed to a set of uncorrelated variables, thus eliminating the redundant information. The new variables are then transformed to a set of chromaticity coordinates. In this presentation the intensity of the red and green guns of the "Multispectral Analyzer Display" were controlled by the eigenvector with highest eigenvalues, the ratio of red to green was controlled by the second highest eigenvector, and the blue gun was controlled by the third eigenvector. This transformation of eigenvectors to colour is far from optimum, but is one of several easy transformations tried.

Very impressive colour images were generated in this way. Small shades in intensities show up dramatically as different hues.

To get the optimum transformation, the statistical characteristics of the portion of the original image should be used.

AUTOMATED CLASSIFICATION OF GROUND COVER TYPES

Rapid and timely evaluation of Canada's agriculture, forest, and water resources has important economic benefits. For this reason a study to determine the feasibility of automatic classification using the maximum likelihood decision rule was made. The emphasis in this study was the determination of classes which are easily separable using ERTS data and the estimation of the misclassification error.

The maximum likelihood decision rule basically partitions the observation space, consisting here of the four spectral bands, into 4-dimensional regions associated with these classes. The underlying assumption to this statistical classification scheme is that the probability distributions associated with each of the ground cover classes are known exactly. Provided that this is true then it has been shown (Van Trees, 1968) that the scheme is optimum in sense of minimum misclassification error. Though this assumption is not strictly true for ERTS imagery, the maximum likelihood decision rule was still favoured since it is one of the most established statistical schemes and includes the minimum distance rule (Sebestyen, 1960) in special cases.

The maximum likelihood decision rule was applied as follows. Given the spectral intensities of a particular pixel the likelihoods of observing these intensities are computed for each of the possible classes in consideration. The class with the maximum likelihood is chosen. If the maximum likelihood is below a certain threshold then no decision is made. To reduce the problems inherent in the determination of the likelihoods it was assumed that the four MSS bands can be adequately approximated by a multivariate normal distribution. Crane, Malila and Richardson (1972) found that there is not serious loss in accuracy due to this assumption. Letting $\bar{m}_i^T = (m_4, m_5, m_6, m_7)$ and C_i be the mean vector and covariance matrix associated with class i, then the logarithm of the likelihood of observing sample $\bar{x} = (x_4, x_5, x_6, x_7)$ is given by equation (1).

$$l(x|i) = -2 \ln (2\pi|C_i|) - (\bar{x}-\bar{m}_i)^T C_i^{-1} (\bar{x}-\bar{m}_i) \qquad (1)$$

Where $|\cdot|$ denotes determinant, the superscript "T" denotes transpose and C_i^{-1} denotes the inverse matrix of C_i.

Two contrasting areas were studied in the determinations of the performance of the classification scheme. The first area located 40 miles SE of Winnipeg contained various types of vegetation. The second area in the Red River Basin was entirely agricultural. Ground truth was obtained from Thie (1973) and Woo (1973) for the two respective areas. Using this ground truth we determined the statistical parameters of a set of classes. They are listed in Tables 1 and 2.

Several independent methods were used to estimate the class separability and the misclassification error. In the first method the divergence measure (Kullback, 1959) was calculated for each pair of classes i and j using equation (2):

$$J(i,j) = \tfrac{1}{2}\mathrm{tr}\,(C_i-C_j)(C_j^{-1}-C_i^{-1}) + \tfrac{1}{2}\mathrm{tr}\,(C_i^{-1}+C_j^{-1})(\bar{m}_i-\bar{m}_j)(\bar{m}_i-\bar{m}_j)^T$$

Where C_i, C_j, $\bar{m}_i$, $\bar{m}_j$ are the covariance matrices and mean vectors of the two classes and "tr" denotes the sum of the diagonal elements of the following matrix the divergence measure is always positive, and is zero only when the two classes have identical distributions (Kullback, 1959; Wacker and Landgrebe, 1971; Fu and Min, 1968). There is no exact relation between the divergence and the misclassification error. However, some lower and upper bounds have been established by Ma.ill and Green (1963) and Kadota and Shepp (1967). For 95% classifications accuracy the divergence measure should be above 50. The divergence matrices are listed in Tables 3A and 4A.

In the second method, the original "training" data were run through the classifier and the maximum likelihood classifications obtained was compared with the true classification. The results of this analysis are listed in the confusion matrices in Tables 3B and 4B. In the third approach synthetic data having the class means and covariances were generated by Monte Carlo methods and run through the classificer. The results of this last approach are listed in Tables 3C and 4C.

The three different approaches give similar results. Except for Jack Pines, Black Spruce and Tamarack the different vegetation types were distinguishable with less than 3 per cent error. Black Spruce and Tamarack were most difficult to distinguish. A projection of the decision ellipses in observation space is given in Figure 2.

The agricultural aclasses were considerably more difficult to discriminate. Fallow and rape seed were the only classes that could be discriminated with certainty. The statistical distributions of the grain stubble, grain fields, corn, and sunflower had much overlap resulting in a high misclassification. Wheat was correctly identified more than 95% of the time but this result is probably optimistic since the ground truth was obtained from only two fields.

CONCLUSIONS

The main conclusions of this study are listed below.

1. The visual appeal of colour ERTS-1 images can be remarkably improved by transforming the spectral data from the 4 bands to a set of uncorrelated coordinates and displaying the transformed data in chromaticity coordinates to which the eye is most sensitive. Small changes in intensities stand up better in the new colour images.

2. The maximum likelihood decision rule can discriminate the vegetation classes Jack Pines, Black Spruce, Sedges, Trembling Aspen, Community Pasture, and Tamarack with more than 85 per cent accuracy. Errors were largely due to confusing Jack Pines, Black Spruce and Tamarack. The classifications of the different agricultural crops was found to be more difficult. The only agricultural classes that could be identified with certainty were fallow, rape seed, and possibly wheat.

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TABLE 1

VEGETATION COVER ERTS FRAME 1007-16531

Mean Intensities

Class / Band	4	5	6	7
Water	21.5	17.4	10.0	1.4
Jack Pines	14.5	12.6	22.3	13.1
Black Spruce	14.9	11.7	24.7	15.0
Sedges	17.3	17.8	25.5	16.8
Trembling Aspen	14.6	11.3	35.1	29.6
Community Pasture	21.9	21.6	39.0	30.2
Tamaracks	15.4	12.3	26.9	18.2

Covariance Matrix

Class / Bands	4,4	5,4	5,5	6,4	6,5	6,6	7,4	7,5	7,6	7,7
Water	0.5	0.1	0.7	0.0	0.1	0.9	0.0	0.0	0.1	0.3
Jack Pines	1.0	1.0	2.4	0.9	1.3	2.1	0.7	1.2	1.1	1.3
Black Spruce	0.5	0.0	0.7	0.3	0.3	1.8	0.3	0.4	1.3	1.8
Sedges	0.5	0.0	0.8	0.1	0.2	1.2	-0.1	0.0	0.2	0.4
Trembling Aspen	0.5	0.1	0.9	0.0	-0.2	2.3	-0.2	-0.4	1.2	2.0
Community Pasture	1.0	0.7	1.9	1.0	0.6	5.1	0.9	0.3	4.3	5.4
Tamarack	0.4	0.0	0.6	0.1	0.2	1.8	0.1	0.1	0.9	1.2

TABLE 2

AGRICULTURAL COVER ERTS FRAME 1007-16531

Mean Intensities

Band / Class	4	5	6	7
Fallow	18.0	17.4	18.4	7.6
Wheat	17.9	16.4	27.7	18.0
Grain Stubble	19.5	18.7	31.7	21.8
Corn	17.9	15.2	33.8	26.1
Rape	22.2	20.4	43.2	36.5
Sunflower	18.1	15.8	31.8	23.6
Grain Field	19.0	17.9	32.7	24.0

Covariance Matrix

Bands / Class	4,4	5,4	5,5	6,4	6,5	6,6	7,4	7,5	7,6	7,7
Fallow	0.8	0.6	1.7	0.7	1.4	2.2	0.4	0.7	0.9	0.9
Wheat	0.7	0.5	1.6	0.2	0.4	1.3	0.2	0.4	0.4	0.9
Grain Stubble	3.2	4.9	8.8	0.5	1.2	4.3	-1.3	-2.1	3.0	4.8
Corn	0.9	0.6	2.1	0.5	0.0	8.9	0.3	-0.9	10.6	14.9
Rape	0.9	0.6	2.0	-0.2	0.9	2.8	-0.3	0.9	3.4	6.5
Sunflower	0.6	0.7	3.0	0.0	-0.7	2.7	-0.2	-1.3	2.0	3.3
Grain Field	2.2	3.2	7.3	0.4	-0.2	8.5	-0.6	-1.9	8.1	11.1

VEGETATION COVER ERTS FRAME 1007-16531

DIVERGENCE MATRIX

TABLE 3A

Class	1	2	3	4	5	6	7
Class							
1	0.						
2	559.	0.					
3	645.	9.	0.				
4	761.	54.	75.	0.			
5	1702.	307.	141.	284.	0.		
6	1673.	186.	181.	291.	149.	0.	
7	836.	35.	7.	69.	98.	208.	0.

CONFUSION MATRIX - TRAINING AREAS

TABLE 3B

True Class	1	2	3	4	5	6	7
Chosen Class							
0	0	0	0	0	4	2	3
1	550	231	0	0	0	0	0
2	0	21	16	1	0	0	0
3	0	8	192	0	0	0	41
4	0	0	0	613	0	0	0
5	0	0	0	0	275	0	0
6	0	0	0	0	0	472	0
7	0	0	28	0	1	0	554

CONFUSION MATRIX - MONTE CARLO

TABLE 3C

True Class	1	2	3	4	5	6	7
Chosen Class							
0	0	0	0	0	0	0	0
1	100	0	0	0	0	0	0
2	0	91	10	1	0	0	0
3	0	8	77	0	0	0	10
4	0	0	0	99	0	0	0
5	0	0	0	0	100	0	0
6	0	0	0	0	0	100	0
7	0	1	13	0	0	0	90

Legend: (0) Neither (1) Water (2) Jack Pines (3) Black Spruce
(4) Sedges (5) Trembling Aspen (6) Community Pasture
(7) Tamarack

AGRICULTURAL COVER ERTS FRAME 1007-16531

DIVERGE MATRIX

TABLE 4A

Class	1	2	3	4	5	6	7
1	0.						
2	203.	0.					
3	213.	20.	0.				
4	383.	62.	8.	0.			
5	865.	309.	74.	49.	0.		
6	313.	31.	6.	4.	98.	0.	
7	270.	36.	2.	4.	50.	4.1	0.

CONFUSION MATRIX - TRAINING AREAS

TABLE 4B

Chosen Class \ True Class	1	2	3	4	5	6	7
0	0	0	2	0	0	0	1
1	171	0	0	0	0	0	0
2	0	169	1	3	0	1	4
3	0	1	34	3	0	3	22
4	0	0	0	53	0	10	17
5	0	0	0	0	49	0	1
6	0	0	39	22	0	43	44
7	0	1	4	8	0	0	54

CONFUSION MATRIX - MONTE CARLO

TABLE 4C

Chosen Class \ True Class	1	2	3	4	5	6	7
0	0	0	0	2	0	0	3
1	100	0	0	0	0	0	0
2	0	96	8	2	0	3	5
3	0	1	55	0	0	8	21
4	0	2	6	61	0	10	11
5	0	0	0	0	100	0	0
6	0	0	23	31	0	72	26
7	0	1	8	4	0	7	34

Legend: (0) Neither (1) Fallow (2) Wheat (3) Grain Stubble (4) Corn (5) Rapeseed (6) Sunflower (7) Grain Field

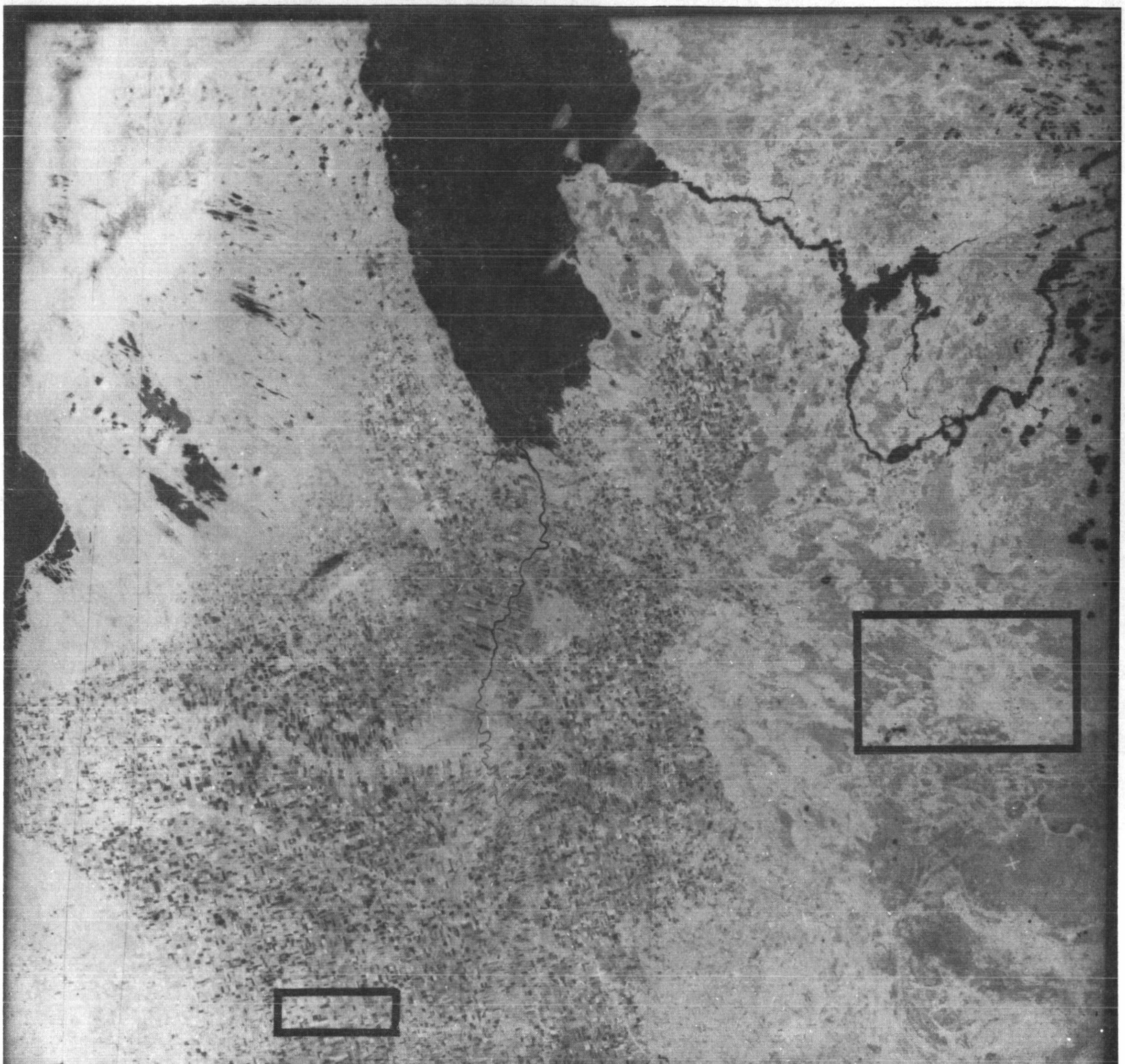

Fig 1: ERTS-1 frame 1007-16531 band 7 imaged July 30 1972. The agricultural area is indicated at the lower left. The vegetation area is indicated on the right and extends about 30 kilometers beyond the southern boundary.

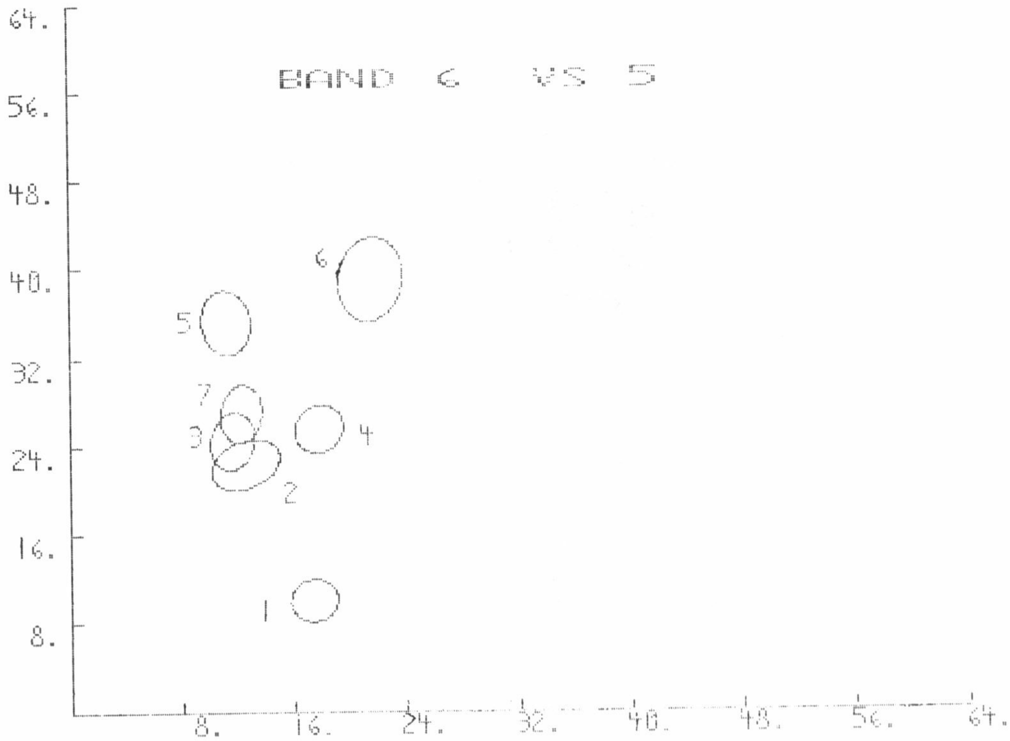

Figure 2: Projection of the vegetation decision regions in observation space. (1) Water (2) Jack Pines (3) Black Spruce (4) Sedges (5) Trembling Aspen (6) Community Pasture (7) Tamarack.

Figure 3: Boundary detection applied to agricultural area East of the Southern end of Lake Winnipeg.