Paper L 25

# AUTOMATIC INTERPRETATION OF ERTS DATA FOR FOREST MANAGEMENT

Leonard Kirvida and Greg R. Johnson, Systems & Research Division, Honeywell, Inc., and College of Forestry, University of Minnesota, St. Paul, Minnesota

## ABSTRACT

Automatic stratification of forested land from ERTS-A data provides a valuable tool for resource management. The results are useful for wood product yield estimates, recreation and wild life management, forest inventory and forest condition monitoring. Automatic procedures based on both multi-spectral and spatial features are evaluated. With five classes, training and testing on the same samples, classification accuracy of 74% was achieved using the MSS multi-spectral features. When adding texture computed from 8 x 8 arrays, classification accuracy of 99% was obtained.

#### INTRODUCTION

Managers of forest resources are faced with increasing demands for forest products as well as the needs of alternative uses for the land surface. Consideration must be given to the environmental problems associated with the removal of forest by harvesting, diseases or pests, and the effects of forest areas on the everincreasing needs for pure water.

ERTS-A data have opened up many possibilities for effective management. However, new processing and analysis techniques will be required to exploit these data. In particular, automatic data processing appears mandatory for many interpretation and inventory functions. For example, automatic stratification by type and density class provides a common basis for multiple uses. The data are formatted for convenient insertion into a computerized data bank. Processing of repetitive coverages increases the accuracy of the inventory data and detects changes and trends.

Our investigation is to determine both the feasibility of automatic interpretation from ERTS-A data and the insertion of the data into a computerized data bank. This is a cooperative effort with the

1075

Original photography may be purchased from: EROS Data Center 10th and Dakota Avenue Sioux Falls. SD 57198 University of Minnesota and the Minnesota State Planning Agency. Initial results on the automatic classification of areas by forest type are described herein.

## PROCEDURE

The automatic classification of forested areas to be discussed was performed for the Cloquet, Minnesota area, located 25 miles west of Duluth. An aerial photograph of the approximately 24,000 acres of forest and associated types that were stratified is shown in the left half of Figure 1. Ground truth information was obtained by using aerial photo interpreters from the University of Minnesota's Institute of Agriculture Remote Sensing Laboratory (IARSL) located in the College of Forestry. Since the College's Cloquet Forestry Center, an experimental forest, is in the midst of this area, much information was previously known about the forest types. Spring 1:90,000 panchromatic aerial photographs, numerous field checks, and previous ground experience in the study area were used by the interpreters in generating the ground truth map. The Cloquet area was delineated into five types: conifers, hardwoods, open, water, and city.



AERIAL

ERTS - Band 7

Figure 1. Aerial and ERTS Images of Cloquet Study Area

The features used for classification were derived from the four MSS bands of ERTS-A image 1075-16312, an October 6, 1972 cloud free coverage of the Cloquet study area. Data from the bulk, black and white 70 mm transparencies and 7 track 800 BPI computer compatible tapes (CCT) were used as the data base. The imagery

was used for orientation and registration, and the digital data was used to perform the automatic stratification and analysis.

The ERTS digital data of the study area was then reproduced on film by writing with a digital magnetic tape to film printer for purposes of registering with ground truth information. The film output for Band 7 is shown on the right half of Figure 1. It provides an image of the study area containing grid lines corresponding to record and word on the digital magnetic data tape. Registration of ground truth with ERTS-A data was accomplished by recognition of landmarks such as water bodies in the area. Registration with ground truth maps was required for both training and evaluating the automatic classification system and for producing the stratification output.

Once ground truth and ERTS-A data were registered, type boundaries were encoded in terms of record and word numbers. From within the type boundaries, 8 x 8 arrays were isolated to serve as training samples. During training two categories of features, multi-spectral and texture, were generated for a number of 8 x 8 array samples in each class as illustrated in Figure 2.

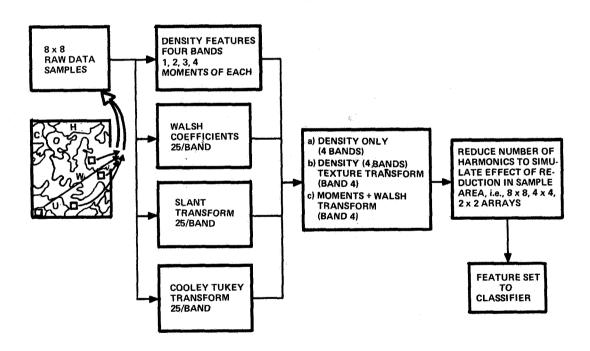


Figure 2. ERTS-A Feature Extraction Procedure

The first experiment was run using only spectral features. An illustration of the separability between the five classes is shown by the density histograms in Figure 3. The four sets of histograms were derived from each of the four MSS bands. Band 4 has a great deal of overlap between classes. Band 7 is excellent for separating water from land and was usually used for locating lakes for ground truth landmarks.

Two dimensional histograms for the five classes were also computed. These indicated high cross correlation between some pairs of bands for a few classes; however, no consistent conclusions could be drawn.

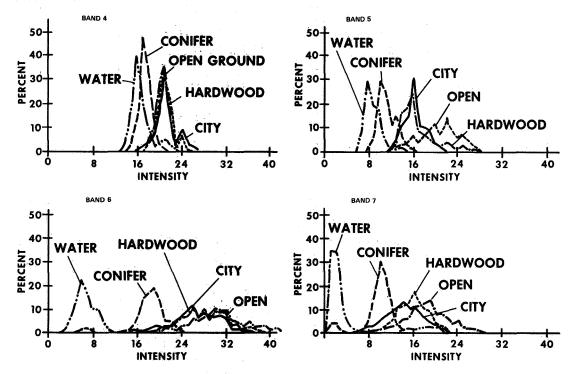


Figure 3. Histograms of Intensity Levels ERTS 1075-16312

For texture features, two dimensional Fast Walsh, Fast Fourier and Slant Transforms were utilized. Texture features were computed from an 8 x 8 array representing approximately 70 ground acres. Texture was also computed on a 4 x 4 array to determine the effect of array size on performance. Increasing the array size increases frequency resolution which increases the classification

accuracy. However, the larger array size increases the minimum area to be classified.

Having selected the features to be used and the training set, a linear discriminant classifier is trained. Briefly, the classifier algorithm groups each of the features of the training set around an orthogonal basis vector in a least mean square sense. The "weight" matrix required to do this is computed for subsequent application to the input data during testing and during the generation of overlay maps. The class to which the input data point belongs is determined by the distance from the various orthogonal vector points. A block diagram illustrating the procedures used for automatic interpretation is shown in Figure 4.

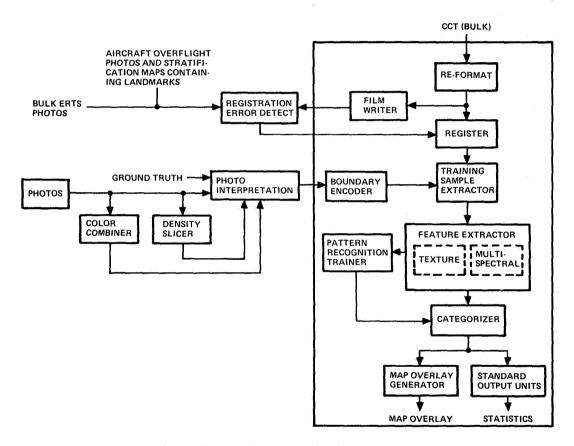
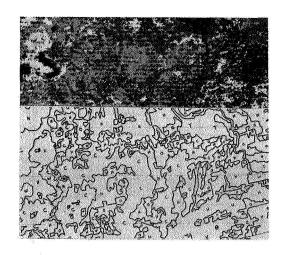


Figure 4. Data Analysis Procedures

## RESULTS

Using only multi-spectral features, the classifier was trained on data derived from the 8 x 8 sample arrays from each class. The total training area was 4687 acres proportioned into five classes. Each training sample consisted of one data point, approximately one acre. After training, a delineation map was generated for the 24,000 acres including the training area. The results of the automatic classification are shown in the top half of Figure 5. Decisions were made for each acre data sample. The five classes, hardwoods, conifers, open, water, and urban, are presented as density levels increasing in density in the order listed. The performance of the automatic classification procedure can be estimated by comparing its output on the top half of Figure 5 with the photo interpreter overlay on the bottom half of Figure 5. The distortion of the classification output photo is due to the unequal spacing between ERTS samples in the x and y directions.



# Key

H - Hardwood

C - Conifer

O - Open

W - Water

T - City

Figure 5. Automatic Classifier Results Based on Density and Ground Truth

When the classifier is trained and tested on the same data points, its performance is shown by the confusion matrix in Table I. Seventy-four percent of the data points are correctly classified. An indication of the types of mistakes made are shown in the confusion matrix. Notice that confusion is most common where city is called open, the next most common is open classed as hardwood and then open classed as city.

Table I. Automatic Classification Results Based on Density

| Туре   | Sample<br>Size | Automatic<br>Hardwood | Classification<br>Conifer | Assig<br>Open | nments<br>Water | in Percent<br>City |
|--------|----------------|-----------------------|---------------------------|---------------|-----------------|--------------------|
| Hardwo | od 896         | 80.7                  | 4.1                       | 4.9           | 1.8             | 8.5                |
| Conife | r 1152         | .5                    | 80.9                      | 2.3           | 13.9            | 2.4                |
| Open   | 960            | 20.4                  | 3.5                       | 61.6          | .6              | 13.9               |
| Water  | 640            | 10.2                  | .0                        | .3            | 88.6            | .9                 |
| City   | 640            | 8.1                   | 6.1                       | 24.1          | 6.4             | 55.3               |
| Total  | 4288           | Correct               | Classification            | Assign        | ments :         | = 3167             |

The performance using only multi-spectral data is shown also in Figure 6. When training and testing on individual data points, the performance is 74% using the 4 MSS density bands as features.

An indication of the effect of adding texture to multi-spectral features is shown by the curve in Figure 6. Texture was computed from Band 7 using the Slant Transform. The Slant Transform is an image transform with a basis vector matched to the gradual brightness changes along an image line which compacts the image energy to as few of the transform domain samples as possible. It can be computed using a fast computational algorithm. When computed on a  $4 \times 4$  array, the performance increases to 90% and if computed on an  $8 \times 8$  array, the performance increases to 99%.

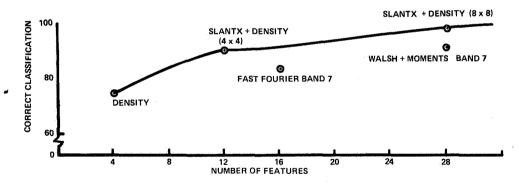


Figure 6. Performance Using Both Density and Texture

Texture was also computed using the Cooley-Tukey Fast Fourier and Walsh Transforms. The performance of these two transforms is generally very similar, the Walsh Transform utilizing a binary waveform for computational advantages. When an  $8\times8$  array from Band 7

was used for calculating the Walsh coefficients and the first through the fourth moments of density from Band 7 were used for density features, the performance classification accuracy was 91%. This is an indication of the performance achievable using only Band 7 for input data.

The final point on Figure 6 was computed using the Cooley-Tukey Fast Fourier Transform on an  $8\times8$  array from Band 7. Only the first four spectral components were used resulting in 16 features. The lowest frequency component contains the least amount of information and contributes 9 of the features. In the interest of minimizing features, it was deleted and a resulting performance of 89% was achieved.

#### DISCUSSION

Even though the results given in this paper are of a preliminary nature derived from a small test site, they indicate the feasibility of automatic stratification. In further study they will be extended in the following ways: (1) increased area of coverage to provide a larger statistical base, (2) inclusion of a finer classification by forest cover type, site, and stand density, (3) incorporation of data from multiple coverage, (4) comparison with other texture measurement techniques, and (5) application to a national forest already under an intensified management system.

The information content of the texture features may be improved by applying the Fast Fourier Transform to two MSS bands simultaneously with one band as the real input and the second as the imaginary input. The easily calculated Haar Transform may be adequate for texture, but its performance should be compared with the optimum performance achievable with the Karhunen-Lowe Transform. The latter transform is difficult to compute, but it provides the least mean square truncation error and the maximum entropy interpretation. In addition, performance of the linear classifier may be improved by cluster analysis whereby classes are generated on the basis of similarity of features.

Stratification information is useful to natural resource land managers. Our goal is to determine the capabilities of automatic classification from ERTS-A data, the maximum number of classes, and an acceptable operational data format. In addition, we seek to determine the best combination of automatic and human interpretation. We will compare automatic techniques to studies being done by IARSL on the Chippewa National Forest and the state of Minnesota Land Management Information System.