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COMPUTERIZED INTERPRETATION OF ERTS DATA FOR FOREST MANAGEMENT

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ABSTRACT

Multispectral and spatial features are evaluated for automatic delineation of forest and associated land types. The principal components algorithm was used for determining the efficacy of multispectral bands in making class separations. Four spatial algorithms were evaluated for texture measurements. A thematic map was generated using four multispectral bands as features. Clusters were also used for generating a thematic map.

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 removal on the ever-increasing needs for pure water.

ERTS-A data have opened up many possibilities for effective management. However, new processing and analysis techniques are required to exploit these data. This paper will discuss the use of multispectral and spatial characteristics for automatic classification. 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 can be formated for convenient insertion into a computerized data bank. This allows processing of repetitive coverages to increase the accuracy of the inventory data and detect changes and trends.

One of the areas used for determining the feasibility of automatic classification of forested areas was the Cloquet, Minnesota area, located 25 miles west of Duluth. Approximately 24,000 acres of forest and associated land use types were stratified. Ground truth information was supplied by Gregg Johnson from the University of Minnesota's Institute of Agriculture Remote Sensing Laboratory (LARSL), 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 in generating the ground truth map. The Cloquet area was delineated into five classes: conifers, hardwoods, open, water and urban.

The features used for automatic classification were derived from the four MSS bands of ERTS-A image 1075-16312, an October 6, 1972 coverage of the Cloquet study area. Data was extracted from the 7-track 800 BPI computer compatible tapes (CCT).

Multispectral and spatial features were used for automatic classification. The multispectral data consisted of the output of the four MSS sensors which are sensitive to .5-.6, .6-.7, .7-.8, and .8 to 1.1 microns. The most effective bands for separating the five classes listed above were determined by using the principal components algorithm. MSS band 3 had the greatest effectiveness followed by MSS-4. To increase the amount of information contained in the feature set and improve classification accuracy, spatial features were added. An evaluation of four spatial frequency algorithms was made on the Cloquet test set. These algorithms were the Fourier, Karhunen Loev, Walsh and Slant transforms.

The spatial features were added in order to include pattern information. Edges in a picture introduce spatial frequencies along a line in the complex frequency plane orthogonal to the edge. High spatial frequencies correspond to sharp edges and low spatial frequencies correspond to regions of approximately uniform grey band. Spatial filtering in an image to detect texture is a natural extension to two dimensions of the traditional one-dimensional or temporal filtering process in communication networks. The Fourier transform, which has been a commonly accepted tool for computing the frequency components of a temporal waveform, utilizes sinusoidal orthogonal basis functions. Digital implementation of the Fourier transform became feasible for two dimensions with the development by Cooley and Tukey of the Fast Fourier transform (FFT). The FFT was our first algorithm used to generate spatial features. Although it is inferior to the Karhunen Loev transform in a mean square error sense, the FFT can be computed far more efficiently with $N^2 \log_2 N$ computer operations where N is the dimensionality of the pattern space.

The third algorithm used to measure spatial frequency was the Walsh Hadamard transform. This transformation has a number of advantages; it can be derived with $N^2 \log_2 N$ additions or subtractions and is binary so that it is amenable to digital computation. Sequency is proportional to the number of zero crossings of the Walsh wave; the analog with the sinusoidal frequency descriptor is obvious.

The fourth algorithm used for spatial features is the Slant transform. Pratt, et al., from the University of Southern California developed a computationally fast Slant algorithm. One of the advantages of the Slant transform is the compaction of the image energy into a minimum number of basis vectors which resemble typical horizontal or vertical lines of an image. Generally lines in an image will have a constant grey level, over considerable length or linearly vary in brightness over the length. The orthogonal set of basis functions in the Slant transform tend to accommodate this type of data. It also has a sequency property descriptive of frequency content. In fact, some of the basis vectors of the Slant transform are identical to the Walsh basis vectors. Pratt has shown that the mean square error between an image and the Slant transform is almost as small as that of the Karhunen Loev transform.

Once the feature vector was selected, the training and testing samples for an automatic classifier were extracted from the digital tape as follows: The ERTS computer compatible tapes were reproduced on film by writing with a digital magnetic tape to film printer for purposes of registering with ground truth information. The output film 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 from band 7 was accomplished by recognition of landmarks such as the numerous water bodies in the area. 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, data arrays were isolated to serve as training samples. Three array sizes were used, 8 x 8, 4 x 4 and a single element. This represents 70, 17.5 and 1.09 acres. As the array size increases, ground resolution is decreased however the feature set is better able to describe the original image and therefore the classification accuracy increases. This can be seen in Figure 1 which shows a curve of classification accuracy versus number of features. An accuracy of 74% was achieved using the four multispectral bands from the October 7, 1972 coverage of Cloquet. By adding texture computed with the Slant Transform on MSS-4 data, the performance increases to 90 or 99% depending on the array size. This performance was obtained by testing on the training set. The training arrays totaled 5000 acres. The training arrays were selected so as to avoid the transitional areas between the various classes.

Having selected the features to be used and the training set, a linear discriminant classifier was trained. Briefly, the classifier algorithm, which we call K-class, groups each of the features of the training set around an orthogonal basis vector in a least mean square sense. The matrix required to do this is computed for subsequent application to the input data during testing and during the generation of thematic maps. In the generation of a thematic map, each input data point is assigned to a class on the basis of its distance from the various orthogonal vector points. Figure 2 illustrates the thematic map for 24,000 acres in the Cloquet area. This thematic map was obtained using multispectral values only for features from the October 6, 1972 coverage 1075-16312. The density levels in the photo are assigned to the five classes in the following manner: hardwood, conifer, urban, open, water (going from light to dark). The accuracy of classification determined by cross correlation with the ground truth is approximately 70%.

Because the mapping errors and the distributions of the various classes are different, it would be a coincidence that the linear boundaries between classes determined by the K-class algorithm would be optimum when all the classes are weighted alike. Thus, we find it advantageous to adjust the weights of each class to minimize the total mapping error. This adjustment does not actually minimize the mapping error, but does minimize the number of mistakes in the training set of samples, which is surely directly proportional to the mapping error. In addition, a cost parameter is included which will "guard" one class over another.

Initially, all weights are set equal and the coefficient matrix is computed and used to test the training set of samples. Based on the testing results, the class weights are adjusted and the new coefficient matrix is tested. This is continued while the step size is varied until the step size is 0. Any time the testing results are worse than a previous best, the step size is reduced by a factor δ.

A by-product of the K-class algorithm is a distance formula which measures the statistical distance between classes. This formula is much like the Divergence measure. The only difference between the two is that the Divergence measure is based on the likelihood ratio algorithm, while the K-class distance is based on the K-class algorithm. The two measures can be derived using the same logical steps. The K-class program prints out the distance between classes and the component of that distance attributed to feature k. Thus features are ranked according to efficacy for separating classes and the least effective features can be deleted.

In comparing the texture algorithms, it was found that the Karhunen Loev transform provides the highest classification accuracy. For 8 x 8 arrays, the Slant transform outperforms both the Walsh and Fast Fourier as shown in Figure 3. As the dimensionality is increased, the Fourier transform performance is better than either the Walsh or Slant transforms since the Fourier transform is asymptotically equivalent to the Karhunen Loev transform.

An alternative technique has been used to group unknown data on the basis of natural clusters. The clustering technique is very useful for checking ground truth to be used for training a classifier. Errors in the training set are very serious. These become obvious because they do not fall into natural clusters. Clusters can also be used to make delineations which can then be assigned to the various ground truth classes. This is useful when class designations are still being invented. The Cloquet data from MSS bands 3 and 4 was clustered into eight clusters. The data from water forms an easily distinguished cluster. The open areas tended to form two clusters as did hardwoods and conifers. The eighth cluster occurred at the transition between conifer and hardwood. A thematic map is shown in Figure 4 where the water cluster is black, the two open clusters are grey and all forested regions are white.

This can be compared with the ground truth map shaded in a similar manner on Figure 5. This ground truth map can also be used to evaluate the K-class thematic map shown in Figure 2. The ground truth class assignments are as follows: C - conifer, H - hardwood, T - Urban, O - open and water is opague.

Having determined that land use classes can be delineated with reasonable accuracy on the Cloquet test site, i.e., that forested areas can be isolated from other land uses, the Chippewa National Forest was selected as a second test site for determining the feasibility of delineating forest types. The Chippewa National Forest contains 1.3 million acres with a broad spectrum of tree species. It contains approximately equal amounts of hardwoods and conifers and is a management unit to which automatic classification results may be applied. The Chippewa National Forest was covered by a NASA RB-57 overflight providing additional ground truth information at 1:60,000. Approximately 200,000 acres have been delineated by a trained photointerpreter familiar with the area. Twelve forest types were delineated, namely: hardwood, conifer, and mixed (containing more than 25% of both varieties); these three types are further delineated into upland or lowland and finally into high and low crown density (above or below 50%). The species included in the broad cover types are listed below:

	Upland	Transition	Lowland
Conifer	Jack pine Red pine White spruce White pine	Balsam fir	Black spruce Tamarack Northern white cedar
Hardwood	Trembling aspen Paper birch American basswood Sugar maple Big tooth aspen Red oak	Green ash American elm Yellow birch	Black ash Balsam poplar Silver maple

Features for automatic classification of the Chippewa Forest were derived from two cloud-free coverages on October 7, 1972 and January 5, 1973. The ERTS-1 frames are 1076-16370 and 116-16373 respectively. We are now in the process of developing thematic maps using features from these two dates.

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.

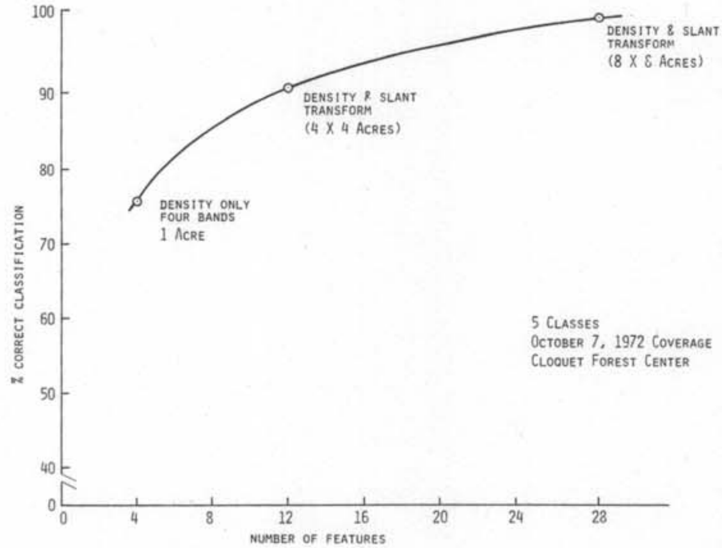

Figure 1. Automatic Classifier Performance Using Texture and Density

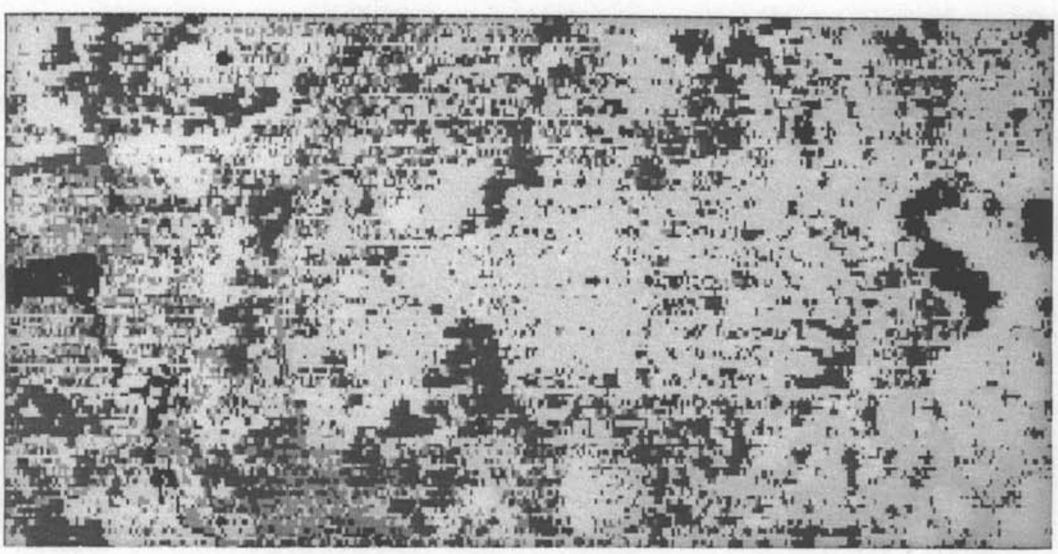

Figure 2. K-Class Output Thematic Map of Cloquet Forest Center Area

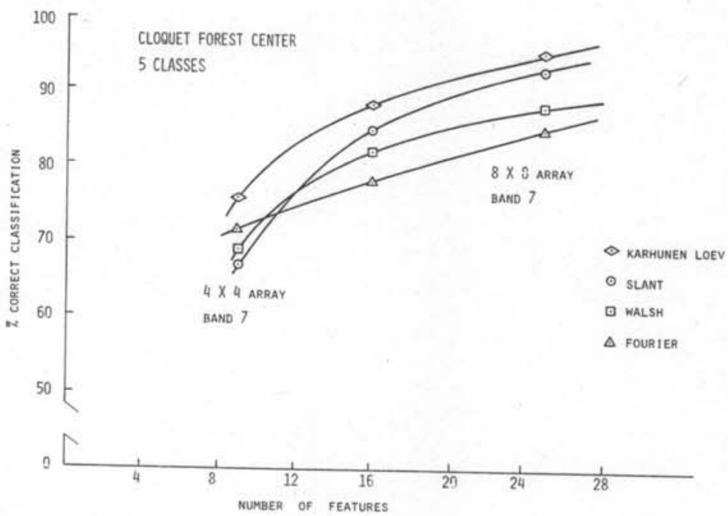

Figure 3. Performance Comparison of Texture Algorithms

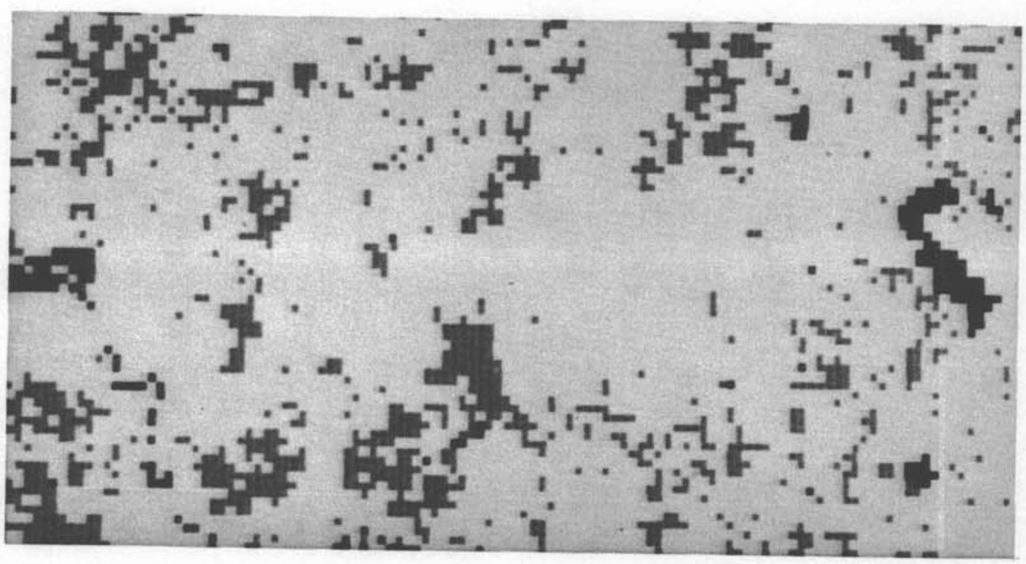

Figure 4. Thematic Map Generated by Assigning
Clusters to Forest, Open and Water

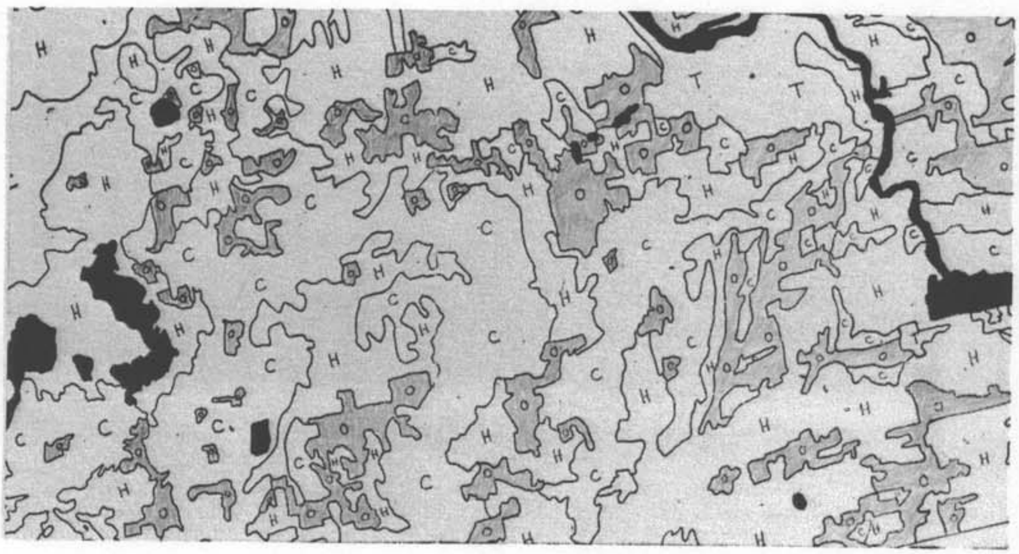

Figure 5. Ground Truth Map for the Cloquet Area