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MA-129TA

FINAL REPORT

NASA CONTRACT NAS9-14016

JUNE 1, 1974 - MAY 31, 1975

D. A. LANDGREBE, PURDUE UNIVERSITY
PRINCIPAL INVESTIGATOR

A. E. POTTER, NASA/JSC
TECHNICAL MONITOR

SUBMITTED BY

The Laboratory for Applications of Remote Sensing

Purdue University, West Lafayette, Indiana

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FINAL REPORT

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Preface

This report provides a summary of results for the first year's effort under contract NAS9-14016. The contract called for work on a wide variety of separate and distinct but related tasks. Table 1. lists the tasks as contained in the original Work Statement indicating modifications made through the year.

As a result of this contract a large volume of results has been generated. Technical and research reports previously submitted or presently being published are listed in Table 2.

Because of the diversity present in the task list for the contract, each major subdivison of this report has been written to be relatively self-contained. We hope this will facilitate use of the report by readers with different interests.

The various tasks have been managed by various Purdue staff members during the year and a NASA-appointed task monitor was associated with each. It is appropriate that the contributions of these people be recognized.

Task	Purdue Task Manager	NASA Task Monitor
Spectral Class Definition	Dr. M. E. Bauer	Mr. J. Garcia
CITARS	Dr. M. E. Bauer	Mr. Robert Bizzell
Field Measurement Research	Dr. M. E. Bauer	Dr. Michael McEwen
Forestry Applications	Mr. R. P. Mroczynski	Mr. Linwood Smelser
Land Use Patterns	Dr. R. A. Weismiller	Mr. Gerald McKain
Remote Terminal and Technology Transfer	Mr. T. L. Phillips	
Multispectral Image Registration	Mr. P. A. Anuta	Mr. John Detrick
Data Dimensionality	Dr. P. H. Swain	
Preprocessing Algorithms	Mr. P. A. Anuta	Mr. Norm Hatcher
Spatial Information	Dr. P. H. Swain	
Soil Inventory	Dr. J. E. Cipra	
Soil Moisture Measurements	Dr. L. F. Silva	
EROS Data Center Tasks	Mr. T. L. Phillips	Dr. Gene Thorley
NASA/Langley Terminal	Mr. T. L. Phillips	Mrs. Ruth Whitman

The efforts of Dr. A. E. Potter, the contract Technical Monitor are especially to be noted and greatfully acknowledged.

Table I. Work Statement Task List and Revisions

Exhibit A	Revisions during the year
I. Acreage Estimation	
(1) Crop Identification	Deletion Requested 11/8/74
(2) Improved Definition of Spectral Classes	Revision Requested 11/8/74
(3) Crop Acreage Estimation	Deletion Requested 11/8/74
(4) CITARS	Task significantly increased
II. Yield Prediction and Estimation	Deletion Requested 11/8/74
(III.) Field Measurements Research Task	Task added 11/8/74
IV. Forestry Application Project	
V. Analysis of Land Use Patterns	
VI. Remote Terminal and Technology Transfer	Portions Deleted 1/30/75
VII. Multispectral Image Registration	
Registration Algorithms	
Data Base Interface	Deletion Requested 11/8/74
IX. Research Tasks	
1. Effective Utilization of Data Dimensionality	
2. Preprocessing Algorithms	
3. Extraction and Analysis of Spatial Information	
4. Soil Inventory Applications	Deleted 1/30/75
5. Electrical Measurements of Available Soil Moisture	Deleted 1/30/75

Exhibit B

EROS Data Center Tasks

Exhibit C

NASA/Langley Remote Terminal Support	Added 11/15/74

Table II. Technical and Research Reports

090174	Wu, Swain, and Landgrebe. Decision Tree Approach to Classification
090274	McGillem and Svedlow. Image Registration Error Variance As A Measure of Overlay Quality.
101574	Wilson. The Digital Display Photographic Operations Manual.
103874	Anuta. Spline Function Approximation Techniques for Imagery Geometric Distortion Representation.
110474	Lindenlaub and Russell. Introduction to Quantitative Remote Sensing.
111774	Follestad. Computer Analysis of ERTS-1 Imagery and Mapping of Surficial Deposits in a Test Area Within the Monticello North Quadrangle, Ind.
112174	Silva, Schultz, and Zulusky. Electrical Methods of Determining Soil Moisture Content.
112674	Montgomery and Baumgardner. The Effects of the Physical and Chemical Properties of Soils on the Spectral Reflectance of Soils.
120974	Wu, Landgrebe, and Swain. On Optimal Dimensionality for Classifying Normally Distributed Data.
121874	Moore, Whitsitt, and Landgrebe. Variance Comparison for Unbiased Estimation of Probabilities of Correct Classifications.
022175	McGillem. Interpolation of ERTS-1 MSS Data.
022575	Anuta and Mobasseri. ERTS Multispectral Image Transformation.
022675	Wilson. Digital Display User's Guide.
040375	Wu, Swain, and Landgrebe. Two Approaches to a Decision Tree Classification.
040775	Stockton. The Use of ERTS-1 Multispectral Imagery for Crop Identification in a Semi-Arid Climate.
050975	Kettig and Landgrebe. Computer Classification of Remotely Sensed Multispectral Image Data by Extraction and Classification of Homogeneous Objects.
051975	Lindenlaub, Davis, and Morrison. Bringing Remote Sensing Technology to the User Community.
052175	Svedlow. Experimental Examination of Sensitivity Measurements and Preprocessing Methods for Image Registration.
052275	Che, N. Y. Analysis of the Effect of LANDSAT data Enhancement on Classification and Area Measurement Accuracy.

OTHER REPORTS

Bauer, CITARS Volumes - 1975.
I. Task Design Plan
V. The First Earth Resources Technology Satellite (ERTS-1) Data Preparation
VI. Results of CITARS Experiments Performed by LARS
IX. Statistical Analysis
X. Interpretation of Results

Laboratory for Applications of Remote Sensing Staff. 1975.
A Data Processing system for Earth Resources with an Applications Example

Laboratory for Applications of Remote Sensing Staff. 1975.
Demonstrator's Guide for A Data processing System for Earth Resources with an Application Example.

T. L. Phillips, H. L. Grams, J. C. Lindenlaub, S. K. Schwingendorf, P. H. Swain, and W. R. Simmons 1975.
Remote Terminal Project Final Report: Purdue University

I. Spectral Class Definition

Spectral Strata Determination

INTRODUCTION

As the Large Area Crop Inventory Experiment (LACIE) developed in the past year it became increasingly clear that one of the major technical requirements of the experiment would be a capability to extend training statistics from one location/time to other locations/times. Without such a capability new training statistics would have to be developed for each segment to be classified, greatly reducing the cost-effectiveness of the technology.

Thus, work was begun at LARS in early 1975 on developing methods for accurately classifying as large an area (or as many segments) as possible before re-training the classifier. Our approach to the problem has been based on two premises: (1) the segments to be classified must be stratified, i.e., similar segments grouped together for classification, and (2) stratification should be performed on the LANDSAT data itself since the factors which will affect the extendability of training statistics will be manifested in the data. The term "spectral stratum" has been defined as an area in which the classes cover types present and their spectral responses are sufficiently similar that training statistics developed for one segment can be applied to other segments in the stratum without appreciable change in classification permance.

During the January-May, 1975 period work has been pursued in two areas: (1) classification and comparison of LANDSAT data from several areas (LACIE intensive test sites) in Kansas, and (2) definition of multivariate pattern recognition procedures which can be used to determine the delineate spectral strata in multispectral scanner data.

Analysis Results, 1973-74 Kansas LANDSAT Data

Fifteen frames of 1973-74 LANDSAT-I data containing the five LACIE intensive test sites in Kansas along with "ground truth" data were received from JSC/EOD. To date, two frames, 1583-1652- (acquired February 26, 1974 and containing Finney and Morton Co. Sites) and 1689-16382 (acquired June 12, 1974 and containing Ellis and Rice Co.) have been analyzed.

Our initial work consisted of preparation of imagery to determine if strata could easily be delineated on either three-band color composites or color-coded maps produced from non-supervised classifications. While differences could be seen across the scenes which may correspond to strata, it was concluded that this approach to determination of spectral strata was too qualititive and subjective to rely upon, at least without further investigation and verification.

We then turned to a more quantitative analysis of the intensive test sites. This analysis has consisted of: (1) classification of

Table 1. Classification accuracy of wheat and non-wheat test fields classified with "local" and "non-local" training statistics.

Source of Statistics	Area Classified	Classification Accuracy (% Correct) Wheat	Non-Wheat	Overall
Finney*	Finney	72.5	92.0	86.8
	Morton	61.6	87.7	76.9
Morton*	Morton	81.3	82.0	81.7
	Finney	83.6	62.6	73.1
Ellis+	Ellis	100.0	98.4	99.5
	Rice	69.9	82.3	73.6
Rice+	Rice	89.3	100.0	98.8
	Ellis	94.2	75.0	80.6

* LANDSAT Scene ID 1583-16525 (February 26, 1974)
\+ LANDSAT Scene ID 1689-16382 (June 12, 1974)

each site with training statistics from the other site within the frame, and (2) comparison of the means and variances of the spectral data from the pairs of sites within the same frame. These results, which are summarized in Table 1, have provided information on the spectral characteristics of wheat and some of the problems associated with extending training from one area to another.

The results shown in Table 1 indicate that accurate classifications (as measured by test fields) of wheat and non-wheat can be achieved when training statistics developed from the segment to be classified are used. There was, however, a definite reduction in classification accuracy when the statistics were applied to segments 65-100 km (40-60 miles) away.

The reason for the reduction in classification accuracy for the non-local classification is clear when the spectral responses of wheat and non-wheat classes are examined. While there are similarities in the relative response characteristics of the data from the two segments from each frame, there are also differences in the absolute mean responses of the various classes. Because, the classifier deals in "absolute" terms rather than relative differences between classes, there is some misclassification.

Our conclusions from these results are that Finney and Morton are in different spectral strata and Rice and Ellis are in different strata. In both cases, this should be qualified or limited to the dates considered. More dates as well as more areas must be analyzed before conclusions concerning the number, location, and consistency over time of strata can be drawn.

Although not all of the data received has been analyzed, we believe additional segments of LANDSAT and ground observation data will be required for a full evaluation of strata or procedures used to determine strata. With only five sites for an entire state, the likelihood of each site being in a different stratum is high. Statistical tests or comparisons required for evaluation are impractical in such a situation.

To evaluate the consistency over time or permanency of strata, a three date temporal overlay of the frames containing Finney Co. were prepared and will be analyzed in CY76.

Definition of Clustering Procedures for Determination of Spectral Strata

During the latter part of the contract year, several alternative approaches or procedures for determining spectral strata (or determining which segments are members of the same stratum or population) have been defined. All the procedures utilize clustering of the multispectral data as the basis for determination of strata. During CY76 the procedures will be implemented and tested on LACIE data from Kansas and North Dakota. The procedures will be briefly summarized here, although they are subject to modification as they are developed and tested.

Procedure I: Characterization of blocks of LANDSAT data by a mean vector and covariance matrix (parametric representation). The procedure would consist of (1) sampling the area of interest to obtain blocks of data, (2) determining the mean vector and covariance matrix of each block, (3) applying parameter space clustering to the statistics of the blocks to find groups of similar blocks, and (4) delineating the boundaries of strata using a boundary finding algorithm.

Procedure II: Characterization of blocks by histogram vectors (nonparametric representation). This procedure is similar to the first except each block would be represented by a histogram vector. The vector is obtained by dividing the range of possible response values of each channel into levels; the number of pixels of each level are tabulated for each block and become entries in the histogram vector. Then the histogram vectors are clustered to find groups of similar blocks.

Procedure III. Characterization of segments by mean vector and covariance matrices of clusters. Each segment would be clustered and parameter space clustering applied to the statistics of the cluster classes to find groups of similar segments.

Procedure IV. Characterization of training fields by mean vector and covariance matrices of clusters. This procedure differs from the other procedures in that it would make use of training fields. Known fields of wheat and non-wheat would be clustered separately for each segment, then parameter space clustering applied to the cluster statistics. This procedure may be most useful for evaluating results of the other procedures since it uses known fields, rather than as a procedure to be used for the "operational" LACIE.

Cluster Analysis

Rationale

This section of the report deals with work done on clustering itself. The problem of finding the number of spectrally distinct classes present in a data set is of special concern when very little is known about the types or number of different ground covers in the data set. Finding such a set of distinct classes is called "unsupervised classification" or "clustering." The approach which has been used at LARS in such cases is to choose a number approximately twice that of the number of different ground cover types estimated to be represented by the data and then cluster the data into that number (MAXCLAS) of clusters using the LARSYS CLUSTER processor. This processor contains iterative routine which calculates a set of initial cluster centers and then assigns each point to the nearest center and recomputes new centers, repeating these last two steps until a specific (user-defined) percentage of point assignments remains unchanged for two successive iterations. The output from this program includes, among other things, statistics (mean vector and covariance matrix) for each of the clusters found and tables indicating the "distinctness" of the clusters and recommendations on combining clusters in subsequent steps of the analysis.

Ideally, one would like an "automatic" method of determining the number of spectrally distinct clusters present in a data set when the analyst has little or no information upon which to base a decision as to the number of classes to request. Such an automatic procedure should reliably combine clusters which are not spectrally separable and split into parts those clusters which are large and possibly multimodal.

Background

Some work has been done on the development of automatic clustering procedures. The ISODATA (Iterative Self-Organizing Data Analysis Technique(A)) program was developed at Stanford Research Institute by Ball and Hall [1-3] and applied to grouping sociological and atmospheric data. This approach was adapted at LARS by Swain [8,9] and Wacker [10] for use with multispectral remote sensing data. A similar program was also used at the Johnson Space Center where extensive modifications were made to it by Kan and Holley of Lockheed Electronics Co.[4-6] resulting in the ISOCLS program. However, none of these efforts were completely satisfactory with respect to automatically determining the number of spectrally distinct clusters present in the given data set.

Objectives and Approach

It was desired to modify the LARSYS CLUSTER program to develop a means of determining in an "automatic" fashion the number of distinct spectral classes contained in a set of multispectral data. The output would be a statistics deck containing the mean and covariances for each cluster whihc could then be used by the LARSYS CLASSIFYPOINTS processor. Therefore, in the LARS approach, the basic structure of CLUSTER was retained and the split-combine approach was incorporated into the core of the CLUSTER processor.

Goals

The goal of this work is to implement a program which will determine the number of spectrally separable, unimodal clusters present in a data set. This implies that, for a specific data set, the program should find the same number of clusters regardless of the initial number (MAXCLAS) of clusters requested, provided that MAXCLAS is large enough (since the program can never have more than that number of clusters due to storage limitations). Also, these clusters hould have a Gaussian distribution, since this is the assumption used in the CLASSIFYPOINTS program which uses the cluster statistics for training. If these two goals were achieved, the user would be freed from making a decision on the number of clusters to choose and classification results would be improved since all clusters would indeed be Gaussian-distributed.

Accomplishments

A LARSYS-type program, VARCLU (Variable Number of Clusters), has been implemented, and limited results have been obtained. All of the user options in the LARSYS CLUSTER program are available in VARCLU. In addition, the user specifies a transformed divergence value (corresponding to DLIM in ISOCLS) which is used as a threshold for combining clusters.

The results obtained thus far indicate that the number of clusters obtained by the program is somewhat dependent upon the initial value assigned to MAXCLAS; a higher MAXCLAS value tends to result in more final clusters. However, for the data sets analyzed thus far where ground reference data is available, it appears that an initial value of MAXCLAS at least 20 gives a final number of clusters which corresponds very closely to the number of cover types actually present. These results are obtained using a transformed divergence threshold value of 1700.

The number of final clusters is, of course, dependent on the transformed divergence value chosen, a higher value resulting in fewer clusters. A higher transformed divergence value will also tend to produce more multimodal clusters, since more clusters will be combined.

Theoretical Background

The approach taken by the ISOCLS program is to begin with the entire data set as one cluster and split the clusters along the channel of maximum variance until a certain percentage of clusters are of nominal size. A series of split and combine iterations are performed on the data. Between each split and combine operation all points are reassigned to the nearest cluster center and new cluster centers are recomputed. If any cluster has less than a specified number of points at this stage, the cluster is deleted, eliminating those points assigned to that cluster.

The criterion used by ISOCLS for a split iteration is to split any cluster where the maximum standard deviation in any channel is greater than a specified number (STDMAX). The new cluster centers are set at $\mu_j \pm \sigma_j$ where μ_j is the old mean for channel j and σ_j is the standard deviation in channel j. Centers in all other channels remain the same. The combine criterion is to combine pairs of clusters if the distance between them is less than a specified threshold (DLIM), with the new centers being a weighted average of the means of the combined clusters. The distance measure is defined by

$$d_\omega^2\left(\mu^{(p)}, \mu^{(q)}\right) = \sum_{j=1}^{L} \frac{1}{\sigma_j^{(p)}\,\sigma_j^{(q)}} \left(\mu_j^{(p)} - \mu_j^{(q)}\right)^2$$

which is the distance squared between clusters p and q where $\mu^{(i)}$ is the mean vector for cluster 1, and $\sigma_j^{(i)}$ is the standard deviation in channel j for cluster 1.

There are four basic differences between the ISOCLS approach and that taken by LARS. First, the number of initial clusters in the LARS approach is user-defined and the centers are calculated by the CLUSTER program to lie along the axis of the principal eigenvector of the data, rather than finding the initial number and centers of clusters via a series of split iterations as is done in ISOCLS.

Second, in the LARS approach, after finding initial cluster centers and after each split or combine iteration, the reassignment of points to the nearest center is an iterative process, reassigning points and recalculating new centers, which ends when a certain (user-defined) percentage of points are unchanged between two iterations, rather than the one-step reassignment process used by ISOCLS.

Third, in the delete operation of the LARS approach, only centers which have no points assigned to them are deleted, and, therefore, no actual data points are deleted. Clusters which are too small (less than NCHAN+1, in general, where NCHAN is the number of channels) to calculate covariances are simply marked and not considered for future combines unless more points are assigned to that center in a subsequent reassignment of points and a valid covariance matrix is calculated.

The fourth difference is in the combine operation. The sequence of operations for the LARS approach is

I DCS DCS DCS DC C

where I is initialization of cluster centers, D is a delete operation, C is a combine operation, and S is a split operation. After each operation (I, D, C, or S), the reassignment process and recalculation of statistics is performed. The combine operation here is a grouping of all clusters for which the pairwise distance between every pair is less than the threshold value. The final statistics represent the clusters resulting from the reassignment process after the final combine.

In the ISOCLS program the sequence of operations is

SS...S CS CS ... CS Ch

where S is a split operation, C is a combine operation, and Ch is a chain operation. Here the delete operation is part of the reassignment of points and recalculation of statistics and is performed after the initial sequence of splits and after each subsequent iteration (S or C). The combine operation here combines only pairs of clusters, and the final chain operation combines groups of clusters for which any pairwise distance is less than the threshold. Note, however, that no reassignment of points occurs after the chain operation, and statistics are for the clusters present before the chaining. The results of the chaining are shown in the output map with a single symbol used for all clusters in a chained group.

To implement the VARCLU program, three new algorithms were developed. These were the delete, split, and combine algorithms.

The delete algorithm searches the array containing the number of points assigned to each cluster center. If any cluster center has no data points assigned to it, that center is removed from the list, leaving one less cluster.

The split algorithm uses two criteria to decide if a cluster should be divided into two parts. The first is that there be at least 2*(NCHAN+1) points in the cluster. This is the minimum number of points which could result in two clusters with valid covariance matrices, NCHAN being the number of channels being used. The second criterion (corresponding to STDMAX in ISOCLS) is that the maximum standard deviation in any channel must be greater than 3.0. This value is appropriate only for data values in the range 0-127 (e.g., LANDSAT data). In addition to meeting these two criteria, there must be space available in the arrays for storage of statistics for an additional cluster. The maximum storage available at any time is set during the initialization phase of the program to MAXCLAS number of clusters, therefore, that parameter must be chosen relatively large to allow for adequate space.

The combine criterion is based on transformed divergence which is a measure of the separability of clusters. The transformed divergence measure is based on divergence between two clusters i and j which is given by

$$D_{ij} = .5 \text{ tr } ((K_i - K_j)\ (K_j^{-1} - K_i^{-1}))$$
$$+ .5 \text{ tr } ((K_i^{-1} + K_j^{-1})\ (M_i - M_j)\ (M_i - M_j)')$$

where

K_i and K_j are the class covariance matrices
M_i and M_j are the class means vectors
tr(.) denotes the trace of a matrix
(the sum of the elements on the main diagonal)
(.)' denotes the transpose of a vector.

Transformed divergence, then, is given by

$$D_{ij}^{T} = 2000(1 - \exp(-D_{ij}/8))$$

It has been demonstrated that maximizing the average pairwise transformed divergence is a useful strategy for maximizing overall separability of classes and, hence, maximizing classification accuracy [7] .

The combine algorithm combines groups of clusters for which every pairwise distance is less than the user-defined threshold value. A threshold value of 1600-1800 is reasonable, where the maximum transformed divergence value is 2000. The new mean vector of a cluster comprised of old clusters i,j,..., ℓ is a weighted average of the old cluster means and is given by

$$\mu_{new} = (C_i/TC)\mu^{(i)} + (C_j/TC)\mu^{(j)} + \ldots + (C_\ell/TC)\mu^{(\ell)}$$

where C_i is the number of points in cluster i, TC is the sum of points in all clusters to be combined, and $\mu^{(i)}$ is the mean vector for cluster i.

In addition to the above three algorithms used in the split-combine process, a method of assigning initial cluster centers was used which differs from the present LARSYS method. The new method calculates the principal eigenvalue and eigenvector of the data and assigns the initial centers along the axis of the principal eigenvector. This approach substantially improves the probability that the initial centers will fall within the range of the data and minimizes the number of clusters which will be deleted in the first step due to lack of points.

Experimental Results

Three test sites were chosen from a region in the San Juan Mountains

TABLE 1
DATA SETS

TEST AREA	LARS RUN NO.	LINES	COLUMNS	TOTAL NO. OF POINTS
A	73057201	263-292	330-363	957
B	73057201	375-410	365-420	1925
C	73057201	343-374	426-448	682

TABLE 2
EXPERIMENTAL RESULTS

DATA SET	THRESH	MAXCLAS	FINAL NO. OF CLASSES	CPU TIME (SEC)	NO. COVER TYPES
A	1700	15	7	490.15	10-13
		20	12	718.36	
		25	14	624.01	
		30	15*	720.79	
B	1700	15	9	864.71	10-11
		20	10*	1317.29	
		25	16	1448.66	
		30	15	1356.68	
C	1700	15	6	95.13	6
		20	6*	147.85	
		25	6	197.74	
		30	7	226.79	

Judged to give the best results based on type maps of the area of Colorado. Clustering was performed using LANDSAT data from the three areas. These data sets are given in Table 1.

A series of runs were made for each data set using a transformed divergence threshold value of 1700. The MAXCLAS parameter (which determines the initial number of clusters) was varied. Runs were made for MAXCLAS values of 15, 20, 25 and 30. All runs were made using a convergence value of 100 percent and using all four channels of the LANDSAT data. The results of these runs are shown in Table 2 which gives the final number of clusters and CPU time used for each run.

Ground reference data for these sites are available in the form of type maps prepared by photointerpreters using color infrared photography. This information was obtained from INSTAAR at the University of Colorado. The number of different ground cover types identified by this technique for each site is shown in the last column of Table 2.

The evaluation of results utilized two-dimensional plots of the data from each site using different combinations of channels. The data from channels 2 and 3 for test site C is shown in Figure 1, with the location of the final cluster centers determined by the VARCLU program (using MAXCLAS=20) indicated by small circles. Also used for analysis was the map produced by VARCLU showing the area with different symbols representing each cluster. Figure 2 shows the map for test site C with the boundaries of the ground cover types identified by photointerpretation superimposed on the map. The numbers identifying each area represent the following ground cover types:

1 moderately dry tundra

2 turf

3 dry tundra

4 willow

4B willow and krummholtz

5 coniferous forest

6 meadow

*This data set was used because, unlike LACIE data at that time, a complete analysis and cluster set evaluation was already available for comparison.

Test site C proved to be interesting because results from three different runs (MAXCLAS - 15, 20, and 25) all found six separable classes, and one run (MAXCLAS-30) found seven classes. For two of these runs (MAXCLAS-20 and 25) the results were identical, and this result also was judged to be the best representation of the area based on the type map of the area. In general, however, as shown by the other two test areas, the number of final clusters was found to depend somewhat on the number of initial clusters.

For test site C (using MAXCLAS-20) the resulting six clusters include two clusters of data which do not represent any of the cover types but are, in fact, bad data values as seen in Figure 1. The remaining four clusters represent the six major cover types; meadow and moderately dry tundra were indistinguishable from the other types using the data available. This can be seen in Figure 1, also, where there are actually only four major clusters in the data (in the channels represented; channels 1 and 4 show even less variation and separation of clusters).

Overall, the results appear to be very promising. Intensive analysis on each of these sites has been performed by an independent researcher to find the optimum number of clusters by maximizing average transformed divergence for all clusters and minimizing total variance, as determined by separate runs of the regular LARSYS CLUSTER processor. The optimum number of clusters found by this method corresponds almost exactly to the number of final clusters using VARCLU in the run judged to be the best based on type maps of the areas (indicated by an asterisk in Table 2).

There still remains the question, however, of what value to choose for MAXCLAS yo obtain this "best" result when ground reference data is not available. Nevertheless, it is clear that this decision is much less critical using VARCLU than with the regular LARSYS cluster; and, in general, as the value for MAXCLAS becomes larger, the effect appears to become less severe. The results for MAXCLAS-15 in each of the three areas were less satisfactory than those with higher values. Currently, there is a maximum value of 30 for MAXCLAS due to storage limitations in the program.

<u>Status</u>

The VARCLU program is completely operational and is available to all LARSYS users on the experimental program library. The control cards are identical to those in the LARSYS CLUSTER program with the exception of the options card. The THRESH(xxxx.) option now refers to the transformed divergence threshold used for combine operations as well as the final grouping recommendation table based on transformed divergence. A new option, QUOT(x.xx), was added which is the threshold value used for the final grouping recommendation based on quotient value (same as the old THRESH option card).

RESULTS

The results obtained to this point are based on a very limited number of tests. Additional tests need to be made to determine the effect of varying the threshold value, and further observations need to be made on the effect of the value of MAXCLAS using a variety of data sets.

In addition, further consideration needs to be given to a different split criterion. The present one (that the maximum standard deviation in any channel be greater than 3.0) is rather arbitrary, and a criterion which is data-dependent may prove to give better results. Also, some rule or guideline needs to be found which will aid the user in determining the best value to choose for MAXCLAS under different conditions.

The approach implemented in VARCLU represents a step toward a tool better suited for non-supervised cluster analysis of multispectral data. Subsequent work will pursue its application in classification analysis, particularly for determining spectral homogeneity characteristics of large area agricultural data.

IELD CARDS
73057201 343 374 1 426 448 1

CHANNEL 2 IS WITH X-AXIS, RANGE FROM 0.0 TO 96.0
CHANNEL 3 IS WITH Y-AXIS, RANGE FROM 0.0 TO 96.0

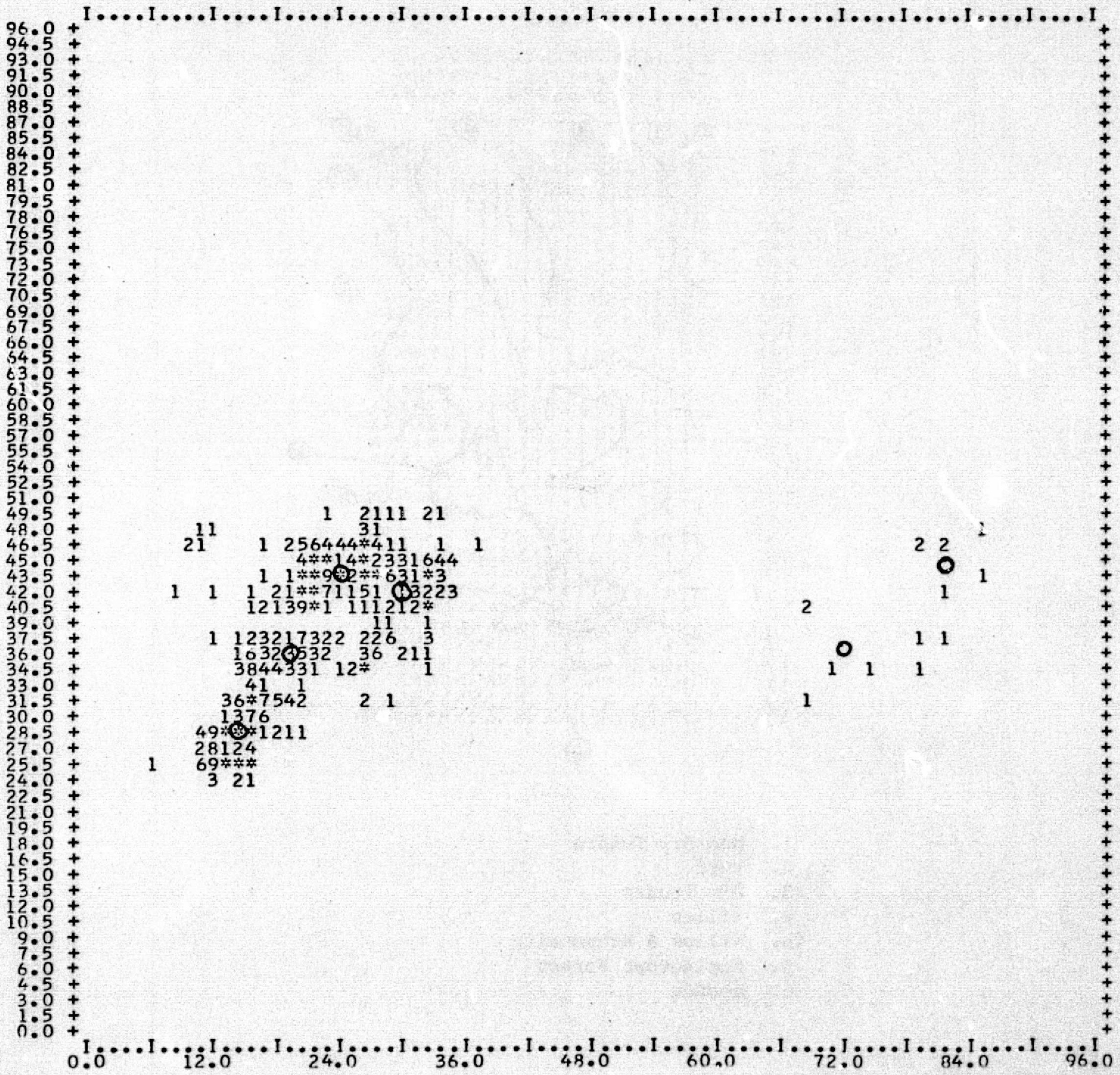
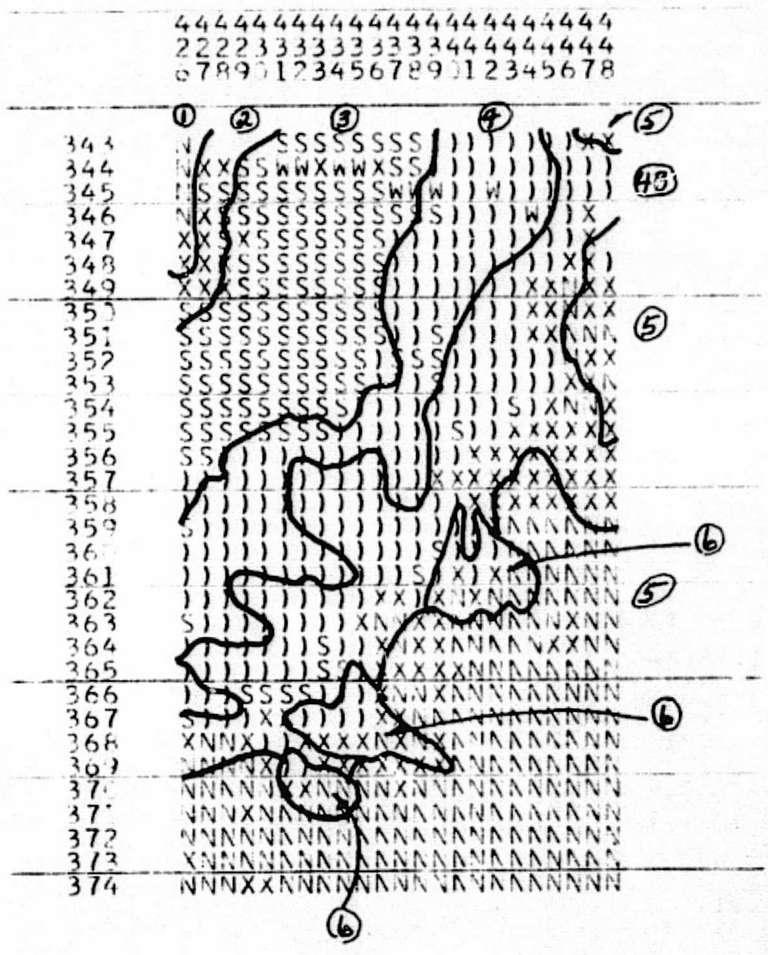


Figure 1.



1. Mod Dry Tundra
2. Turf
3. Dry Tundra
4. Willow
4b. Willow & Krummholtz
5. Coniferous Forest
6. Meadow

Figure 2.

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II. Crop Identification Technology Assessment for Remote Sensing (CITARS)

INTRODUCTION

During CY75* LARS has been involved in three major phases of the CITARS task: (1) Classification of the CITARS data sets, (2) statistical analysis and interpretation of the classification results, and (3) documentation of the experimental procedures and results. This report summarizes our participation in the CITARS project during the past year and the results obtained by LARS. More detailed and complete descriptions have been submitted in previously prepared reports (i.e., listed as follows:

CITARS Volumes

I. Task Design Plan
V. The First Earth Resources Technology Satellite (ERTS-1) Data Preparation
VI. Results of CITARS Experiments Performed by LARS
IX. Statistical Analysis of Results
X. Interpretation of Results

PROCEDURES

Classification of CITARS Data Sets

During the June - September, 1974 period training statistics for the 15 ERTS data sets were developed and the data classified. In addition the training statistics were used to classify 20 data sets from a different location or date than the training statistics (non-local classification). Two classification procedures differing in the use of class weights were used in each case. The results of the classifications were submitted to JSC in October, 1974.

During the October - December, 1974 several additional investigations were performed using the CITARS data sets to increase our understanding of the results. The results of these classifications are summarized later in the results section of this report and in Volume VI, Results of CITARS Experiments Performed by LARS, of the CITARS final report.

Statistical Analysis and Interpretation of Classification Results

Although it was not originally designated as a LARS task, at the

*CY75 refers to the 1975 Contract Year which extends from June 1, 1974 through May 31, 1975.

request of JSC/EOD, LARS accepted responsibility f r a major portion of the statistical analysis and interpretation of the classification results of EOD, ERIM, and LARS. This task performed during January to April included definition of the independent variables used to measure classification performance, analyses of variance, interpretation of the analyses of variance, and documentation of the procedures and results (i.e., Volume IX Statistical Analyses of Results, of the CITARS final report).

Documentation of Experimental Procedures and Results

During CY75 LARS prepared three volumes for the CITARS final report and coordinated the initial preparation of a fourth. The volumes are: (1) Volume V. -- ERTS-1 Data Preparation, (2) Volume VI. -- Results of CITARS Experiments Performed by LARS, (3) Volume IX. -- Statistical Analyses of Results, and (4) Volume X. -- Interpretation of Results.

RESULTS

CITARS Experiments Performed by LARS

One of the important results of CITARS at LARS has been the definition, implementation, and evaluation of an automatable and repeatable data analysis procedure. The newly defined procedure was first used for CITARS, but it performed very well relative to other procedures, both in terms of data analysis efficiency and classification performance. The efficiency of the procedure is indicated by the fact that the 15 local and 20 non-local classifications using two classification procedures were completed by two part-time analysts in three months. The procedure was also shown to yield nearly identical results when used by several analysts on the same data sets. Subsequent tests showed that the performances obtained using the procedure were similar to those obtained using analyst dependent procedures.

Statistical comparisons of the two LARS procedures showed no significant difference between them as measured by either classification accuracy or proportion estimation. The procedure identified as SP1 used equal prior probabilities, while SP2 used unequal prior probabilities based on 1972 county acreage estimates by the Statistical Reporting Service of the U.S. Department of Agriculture.

Three possible reasons account for why unequal prior probabilities did not produce significantly better results than equal prior probabilities: (1) the weights came from 1972, while data was from 1973, and the true proportions could have changes from one year to the next; (2) the weights pertain to counties but were applied to segments, which are fractions of counties and might therefore have different true proportions; (3) the analysis of variance was performed on results for sections and sections vary within segments.

Classification performances for CITARS were generally lower than originally anticipated. For this reason and also as a task not originally planned, several experiments were performed to investigate the effect of various factors, and the results were presented in Volume VI, Part 2 of the CITARS final report. Six factors which may have affected the performance were identified and investigated: (1) method of evaluation used, (2) data analysis and classification procedures used, (3) availability of training data, (4) registration accuracy, (5) spectral characteristics of the scene, and (6) characteristics of the ERTS data. The results of these investigations are summarized in the following paragraphs.

Evaluation of the classifications was based on crop identifications determined by photointerpretation. These identifications must be accurate if performance evaluation are to be reliable. Tests of photointerpretation accuracy indicated that the crops in 95-98 percent of the fields were correctly identified. It was, therefore, concluded that photointerpretation errors did not substantially influence classification performance.

To investigate the effects of the data analysis procedures used, an experiment was conducted using several alternative procedures. The alternative procedures did not result in improved classification performances, indicating that the generally low classification performances obtained in CITARS cannot be attributed to the data analysis procedures used.

Another experiment was conducted to determine the effects of training set size and selection. Results showed that significant differences in classification performance can be obtained with different training sets, and that training set size alone does not determine the representativeness of a training set.

Comparisons of classification performance for registered and non-registered data showed that there was no significant difference between the two forms of LANDSAT data.

Classification performance depends largely on the degree of spectral separability of the cover types of interest. An investigation of the data characteristics showed that there were some cases in which the cover types of interest were spectrally different enough to enable discrimination among them (provided adequate training data was available). However, in other instances the cover types of interest were so spectrally similar (as measured by the LANDSAT sensor) that they could not be discriminated regardless of the amount of training data used.

Since accurate identification of crops requires spectral separability, classification performance depends not only on the spectral characteristics of the cover types but also on the ability of the scanner to detect and measure spectral differences. To study the effect of the LANDSAT scanner on classification performance, a data set collected by an airborne multispectral scanner system having more wavelength bands over a wider region of the spectrum and greater sensitivity, and dynamic range was analyzed for comparison. Although there were substantial differences in performance for individual classes between the LANDSAT aircraft data analyses, overall performance for the two data sets was nearly identical.

III. Field Measurements Experiment

INTRODUCTION

During the first quarter of CY75 field measurements research was a part of the LACIP Crop Yield Prediction task. This task was subsequently replaced by the greatly expanded field measurements for remote sensing of wheat project. This report summarizes the work performed under both projects or tasks, although the major emphasis is on the wheat project.

LACIP CROP YIELD PREDICTION

Spectral reflectance factor data were collected during June-August for a study of the effect of percent ground cover, leaf area index, and maturity stage on the spectral reflectance of corn and soybeans. The study was performed on both dark and light colored soils. This was the third summer of data collection for corn and second for soybeans. Analysis of the data from the three years is described later in the final report.

A capability to measure the hemispheric reflection distribution function in 20 minutes in a field environment was developed and demonstrated. Measurements for mature and harvested wheat were obtained along with detailed data describing planting density, row width, plant height, stem diameter, etc. of the crop. Analysis of the data has not been performed, however, due to the time spent in planning and collecting data for the field measurements for remote sensing of wheat project.

Other projects during this period included the development of a technique to measure the optical depth of a corn canopy. After the method is evaluated it will, if successful, be applied to wheat canopies. In addition, a large collimated illuminator and detector for making laboratory measurements on microscale canopy models or other materials was completed.

Brackets and a mirror mounting device were designed for a new parabolic collimating mirror for the high intensity uniform source for the "indoor" Exotech model 20C. It is used in calibration of the the model 20C and was also used in measuring the spectra of a wide range of soil types having closely controlled moisture contents.

Other activities included preparation of two documents describing the field spectroradiometer system and its use. The first is a paper entitled "A Visible and Infrared Field Spectroradiometer for Remote Sensing Field Research." The second is an "Exotech User's Handbook."

Improvements in the Exotech data collection system included the construction of a device to simulate Exotech signals to enable evaluation of analog and digital data processing systems. Consideration of converting to digital data collection was begun.

In summary, these activities provided excellent preparation for the field measurements work on wheat which was defined and initiated in the second quarter.

FIELD MEASUREMENTS RESEARCH FOR REMOTE SENSING OF WHEAT

In August 1974, NASA/JSC/EOD recommended that a coordinated field measurements investigation be established. Its overall objective was to acquire, process, and analyze spectral, agronomic, and meteorological data from the various field sensor systems. Research results from the effort would support the Large Area Crop Inventory Experiment (LACIE) and provide a fully annotated, documented data set for other research, as well.

Previously, investigations had been conducted independently by various investigators, but were often limited by their ability to bring enough resources to bear on the problem. It was felt that by combining the resources of several agencies within a single project with common objectives that greater progress could be made. Thus, the field measurements project, as it is now known, was established in the fall of 1974. The participants include: NASA/JSC/EOD, NASA/ERL, USDA/ASCS, ERIM, Texas A & M University, Colorado State University, and Purdue University/LARS.

At that time the field measurements capability at LARS was redirected and expanded to support the new field measurements project for remote sensing of wheat. Because of their previous experience and capabilities already developed and tested for acquiring, processing, and analyzing data from field measurements systems, LARS was assigned responsibility to provide the technical leadership and coordination for the project, as well as major responsibilities in the acquisition, processing, dissemination, and analysis of data.

The remainder of this report describes the activities of LARS in support of the field measurements research project since analytical results have not yet been obtained. The major activities include: project planning, data acquisition at Garden City, Kansas and Williston, N. Dakota, instrumentation development, data processing and analysis of data previously acquired.

Project Planning

A major activity since September 1974 has been to design and plan the project. This activity has resulted in preparation of three iterations of the project plan which presents an overview of the project, objectives, experimental approach, test site description, description of experimental plot work, measurements and observations of crop parameters, reflectance and emittance measurements, atmospheric and meteorological measurements, data processing, data analysis, schedules, and organization and management. The latest version of the project plan with additions and revisions was submitted at the end of June, 1975.

A series of meetings among the project participants have been held. These have included meetings in October and March at LARS and a third at JSC in January with representatives of all participating institutions. In addition, LARS data processing and measurements personnel met with ERL and EOD personnel at ERL and JSC, respectively, in December to discuss the acquisition and processing of Exotech Model 20D and S-191 data. Trips to Garden City were made in March and May to assist in establishing and carrying out the work there. There have also been numerous phone calls and letters exchanged among the project participants, as well as frequent meetings of LARS staff to discuss and plan the project.

Data Acquisition

LARS acquired spectral data with their Exotech Model 20C field spectroradiometer system at the agriculture experiment station at Garden City, Kansas on October 18-19 and November 5 and 7, 1974, along with supporting agronomic observations and measurements. The data collection system, instrument van and aerial-boom truck, were driven to Williston, North Dakota just prior to the end of the contract year. The system will be used to collect data there throughout the June - August, 1975 period.

Instrumentation Development

The following items of equipment or instrumentation have been especially constructed for the field measurements project by LARS Measurement's Program Area personnel:

1. Three large 4' X 4' calibration panels coated with barium sulfate reflectance compound have been prepared and distributed to participating parties in the project. In addition, two small 2' X 2' barium sulfate calibration panels were prepared for the special use by participating experimenters at the Garden City, Kansas and Williston, North Dakota sites.

2. Two hemispherical transmittance attachments were designed and fabricated for use with the Exotech Model 100 radiometer. These attachments permit the measurement of leaf transmittance in the four LANDSAT spectral bands. One of the attachments is located at Garden City, whereas the other one is now at Williston, North Dakota. LARS loaned one of its Exotech Model 100 instruments to TAMU. The attachments permit the measurement of leaf transmittance over a wide variety of leaf types using solar input as the illuminating source.

3. A complete weather station was assembled and placed into service at Williston. Additional equipment was fabricated to permit rapid deployment and safe transportation of the weather station equipment. The station can monitor and record total solar input, barometric pressure, relative humidity, sensible temperature, wind direction, and wind velocity. All of the data are recorded for analysis at a later time so that continual attendance of the station is not required.

4. A multiplexor capable of recording all of the housekeeping data from the Exotech model 20-D spectroradiometer on the analog tape was designed and constructed. Ultimately the Exosys Software System will be able to automatically retrieve this data and process it properly into the computer compatible tapes produced by Exosys.

5. A complete system for monitoring the temperature profile in a wheat canopy has been designed and fabricated. This system consists of several stakes equipped with thermistors that may be positioned to measure leaf and/or air temperature at several heights through the canopy. The thermistors are adjustable so that the profile can be monitored at any stage of the canopy growth. The system consists of the appropriate interconnecting cables which bring the thermistor signals together through a switching system. The design for an automatic data recording module that can be battery operated in a field environment has been completed, but was not constructed due to late delivery of parts. The data produced by the system are used in conjunction with the thermal portion of the project.

6. Several pieces of auxillary apparatus to implement the calibration procedures and experimental procedures in the field have been designed and constructed for use at the Williston test site. These are small pieces of equipment that are designed to facilitate and expedite data acquisition and preliminary data reduction.

7. A radio-clock system was constructed that permits annotation of the data to a WWV time signal.

In addition to the above items of equipment, a staff member in the measurements program area, made arrangements for private aerial transportation to the Williston test site. The staff member is a commercial pilot and the use of a rented airplane has resulted in considerable travel savings.

Data Processing, Storage, and Retrieval

Data processing activities have centered around development of data processing requirements and software development. For the project specific tasks addressed include: plenary sessions with participating data collection and analysis groups to develop data processing requirements and procedures, definition of a centralized library data format and data formats for transmittal of data between participating groups, preparation of a data quality monitoring algorithm, data flow procedures, preparation for handling large volumes of data, software upgrades and new programs, and processing of Fall-1975, Kansas data.

1. Data Reformatting: The data library tape format developed for the project is a modified form of the format used for the LARS Exotech 20C data. This approach allows use of current software for data processing, analysis, and distribution. Modifications made in order to accommodate the field project include addition of run ID parameters: name of data collection facility, data quality values, scene type, illumination source, and certain comments. In addition, standard spectral ranges and sample intervals for the reflective and emissive regions of the spectrum for storage of data on central library tapes were specified.

Data quality values to be stored on data tapes were defined as the standard deviation of repeated target and reference samples (separately) at seven specific wavelength bands: 0.55, 0.65, 1.05, 1.65, 2.20, 4.50 and 10.00 micrometers.

S-191 helicopter data reformatting software has been developed. This software combines onto the central library tape: EOD S-191 digital data, EOD tape-to-film log information, ASCS inventory data and ASCS periodic observation data. At this writing, sample data from the S-191 system have been reviewed at LARS.

VISS data reformatting software have been written. This software will copy data received from the EOD VISS system into the central library. This data is written by EOD in the library format on 7-track tape in BCD form. The copy process at LARS is very straight forward, since the EOD system tapes include all ground truth and ancillary data in addition to the reflective values. A test data tape has been received and processed for the VISS system.

Exotech 20D data reformatting software have been written. This data will be sent to LARS on tape in ERL format. In addition, ERL will complete and send to LARS ground truth data sheets associated with the data. LARS reformatting software will combine the tape data and ground truth data to generate central library tapes. At this writing, test data have been received from ERL and the LARS software for handling the test data has been debugged.

Exotech 20C data reformatting systems for handling data collected by the LARS spectroradiometer have been upgraded for the field measurements project. Significant upgrades include: new software to display raw unprocessed data on a graphic terminal for screening and quality control, special forms to aid speedy and accurate data flow, provisions for batch mode computer processing, and a band conversion processor. The band conversion process rewrites the LARS 20C data into the standard wavelength range and sample interval form as specified by the central library tape format.

2. Analysis Software: Data analysis at LARS will be achieved through the use of software developed prior to the onset of this project. The analysis software has, however, been upgraded as required by the project, including: provisions for new run header information, new plotting formats, and printing of additional statistical results.

3. Data Processing: At this writing, 178 spectral runs collected at the Kansas test site in the Fall 1974, and calibration data collected in Spring-1975, by the LARS 20C system have been reformatted and written into the central library.

4. Data Library: A data bank or library system to receive, catalog, and disseminate data from the various acquisition systems has developed and is ready for operational use by the project.

Data Analysis

Data collected by LARS with the Exotech field spectroradiometer system was analyzed during CY75. Data from other sensor systems in the project were not available for analysis by the end of the contract year. Analysis work has included a preliminary analysis of the data collected in October and November, 1974 at the Garden City, Kansas Agriculture Experiment Station and a detailed analysis of data collected on the Purdue University Agronomy Farm during the summers of 1972 - 1974. The latter has provided experience in the analysis of field-acquired data, particularly in the use of analysis of variance and multiple regression which will be useful in analyzing the wheat data. Analysis of variance has been used to determine the significance of differences in spectral response among various treatment combinations, while multiple regression techniques have been used to determine the contribution of agronomic factors to the spectral response. Typical factors included have been:

percent ground cover, leaf area index, plant height, stand density, maturity, and soil color. Results of these analyses are currently being completed and will be published early in CY76.

Project Status and Outlook

As of June 30, 1975 the field measurements project is well underway. A substantial portion of the field measurements have been acquired and most systems to handle and process the data are in place. Analysis of the data should begin in September or October, 1975 and initial results should be available by the end of the calendar year.

Activities by LARS for the CY76 contract will include: continuing to provide technical leadership to the project, data acquisition at the North Dakota test site, reformatting and cataloging in the library of data from all data acquisition systems, analysis of data, and planning and initiating data acquisition for the 75-76 crop year.

It is recommended that serious consideration be given to continuing the project over a longer term than one year. The rationale for continuing the project is twofold: (1) from an agronomic and meteorological viewpoint, results and conclusions based on one year's data are "soft". Since no two years are ever identical, more confidence can be placed in results obtained over a two to four year period. (2) A considerable amount of capability and experience was obtained by all participants during the first year. This experience can be used to good advantage in improving our collective field measurements capability. Finally, in looking ahead, investigations with other crops besides wheat should begin now, prior to the larger scale experiments such as LACIE.

IV. Forestry Application Project

INTRODUCTION

Background

LARS involvement in the Forestry Applications Project has been to support development of computer-aided analysis techniques used to identify forest features. The major thrust during this first year has been in developing, evaluating and documenting analysis of aircraft-collected MSS data. Work with LANDSAT-I (ERTS) MSS data has also been pursued.

The primary test site has been the Sam Houston National Forest, an area typically representative of the Southern Coastal Plain Region. Additionally, some developmental work utilizing LANDSAT data was performed with data collected over the Hoosier National Forest in central Indiana. This site was selected because of its proximity to LARS, an item felt to be important to the evaluation of the data analysis results.

This report summarizes the significant findings to date. Preliminary results are, through necessity, presented for a few tasks. Completion and presentation of final results for those cases will be presented as soon as is feasible.

Objectives

Broadly stated in the contract, the objective of this research was to evaluate and document procedures utilizing computer-aided analysis of multispectral scanner data for forest resource inventories.

MATERIALS AND METHODS

LARSYS

To insure that the FAP could transfer LARS-developed technology in computer-aided analysis to the Southern Region U.S.F.S., any efforts to develop new computer programs were avoided. Standard LARSYS programs were utilized throughout this research.

Efforts of this research centered on defining procedures to follow when performing classification of forested areas. Methods used to achieve this end will be documented.

Data Availability

Data sets available for analysis consisted of:

1) LANDSAT-1 data, multiple dates for both the Sam Houston

National Forest and the Hoosier National Forest in central Indiana.

2) NC130 aircraft data, Bendix 24 channel scanner, collected as part of NASA Mission 230.

PROCEDURES

Channel Selection

A study was undertaken to determine which combination of channels of the Bendix 24 channel scanner data were best suited for separating the forest cover types in the Sam Houston National Forest test site. Because of the small resolution of the airborne scanner (approximately 8 meters) it was felt that larger data points might be better for classification purposes. Kan (JSC-09478) has shown that data sets of simulated larger resolution produced from existing scanner data could be classified with greater accuracy than data of the original resolution. Areas represented by a 15 x 15 array of scanner data points were selected from each of the appropriate cover types within the forest. From this 15 x 15 array of data points, subsets of sizes varying from 2 x 2 to 7 x 7 were randomly selected and statistics generated from each of the sub-fields. The means of all channels were used as a simulated data point of larger resolution. The variation of the means of sub-fields at each resolution within the 15 x 15 area was calculated. The results of this investigation were plotted for several channels. The plotted results indicated that the variability reduces dramatically from single point (8 meter resolution) to approximately 3 x 3 or about 24 meter resolution. As sub-field size increases the variability remains relatively constant up to a 7 x 7 subfield (56 meters).

The 7 x 7 sub-field size was used to generate a set of statistics, one class per field, from each of the selected cover types for processing with the separability processor. Although the constant variation at 4 x 4, and greater sizes indicated that statistics from fields of these sizes would be acceptable, the 7 x 7 size was used in order to include 9 channels and have enough data points for usable statistics. Several fields were selected from each cover type and all subclass combinations were weighed to zero. This causes the channel selections to be made on separations between the larger groups (types) and separation within groups is not considered in the calculations. Combinations of channels were found from 9 through the including 4. In addition, the subset which best approximates LANDSAT channels were also shown. This set was ranked 36th within the 4-channel sets.

Only 9 channels of the 12 available were used. Channels 1 (0.38-0.40 µm) and 2 (0.40-0.44 µm), which are in the extreme blue region were deleted since atmospheric scattering and absorption render them unsuitable for use with extremely high altitude scanners or with spacecraft scanner systems. Channel 6 (0.65-0.69 μm), which is the visible red channel, was deleted because of severe data quality problems caused by clipping of data values below a certain level. These data points were set to 0, thereby, causing extremely large values in the data variance of that channel. Unfortunately, one of the middle infrared channels (1.50-1.70 μm) was not available. For these reasons the channels selected may not constitute optimum channel sets which would be selected if the additional infrared and visible red channels were available. The resulting sets of statistics were used to classify several data sets including some beyond the training site.

Preliminary Results of Mixture Analysis

Since statistics were available for several sizes of sub-fields within a local area of 15 x 15 aircraft scanner data points, the sample classify processor of LARSYS was used to simulate the mixed target condition which exists in larger resolution sizes. The process was as follows: the small resolution sizes of 4 x 4, 5 x 5, 6 x 6, and 7 x 7 within the 15 x 15 overall data area were classified using the sample classifier. This area was then shifted from one type to another by increments of two lines or two columns. In each new position all subfields were again classified using the sample classifier and a map of the classification of all subfields was made. The areas studied were the transition zone of pine to hardwood type through a mixed pine-hardwood class and the change from pine to cleared area. The results of this preliminary study can give some insight to the behavior of these various forest types if they were being classified with scanner data of various resulution sizes. The effect of resolution size on definition of boundaries between cover types is evident in this example. A larger data set will be used in future work to examine the changes in areal estimations caused by varying resolution sizes.

Classification Technique Development: Modified Cluster

Production of training statistics is the single, most important phase in computer-aided analysis of MSS data. But the commonly used supervised and non-supervised techniques are not adequate for satellite MSS data with diverse spectral classes, especially if the ground scene is complex. LARS, therefore, devised a hybrid approach, modified cluster, which combines advantages of both supervised and non-supervised training approaches. Whereas supervised approach procedes from informational classes to spectral classes and the non-supervised approach procedes in reverse order, modified cluster interacts between spectral and informational classes.

The modified cluster technique consists of four main steps. First, one defines training areas (each of which includes three to five cover types) which are dispersed over the study site. Second, each training area is clustered separately, the cluster map is compared with support data, and the area is reclustered if necessary. Third, the analyst, using SEPARABILITY information combines the spectral classes of all areas into a single statistics deck. Fourth, all training areas are classified, the statistics deck is modified if necessary, and the entire study site is classified. This approach has been tested on LANDSAT data sets for all F&P test sites.

This new analysis technique is superior to the modified supervised and non-supervised classification approaches. When the training areas are clustered separately, boundaries between cover types are more clearly defined (therefore, more refined, meaningful spectral-informational classes) and less computer time is necessary to cluster the training fields. Higher classification accuracies are achieved in the modified cluster than with supervised and non-supervised classifications of the same data set.

Modified cluster is recommended for classification of satellite MSS data, particularly for a complex ground scene such as a forested area. By combining the advantages of supervised and non-supervised classification, this approach permits the analyst to compromise between desired informational classes and the reality of spectral class separabilities.

Statistical Evaluation of Classifications

In previous quantitative evaluations of classification results, analysts haven't taken full advantage of statistical theory. Numerical test-field results have been biased, particularly by the arbitrary location of irregularly-sized test fields. LARS developed and tested a more statistically sound procedure for classification evaluation.

Four statistical approaches to classification evaluation were tested. These differed primarily by how the test fields were located. Fields were either randomly or systematically located to prevent bias by the analyst. To enable analysis of variance and confidence interval calculations, equisized test fields were used. The 16-pixel test fields had 4 inner tally pixels and a 1-pixel buffer which decreased the misclassification error due to edge or boundary pixels.

The analyses of variance indicated that all four methods were statistically similar. Thus, all four approaches similarly estimated classification accuracy.

The systematic approach is recommended for future classification evaluations because it is easier to implement. Using this method, the analyst can easily correlate support data with the test-field locations, and he can manipulate the test fields and their X-Y coordinates more easily than with the random approach. The 16-pixel test fields are perhaps too large for complex ground scenes and for broad resolution scanners. Single-pixel fields should be considered in future evaluations of classification results, especially if detailed cover types are to be tested.

Image Interpretation Techniques Assessment

Principal components transformation of MSS data enables combination of spectral information from many wavelength bands (channels) into a fewer number of channels. In a sense, this is data reduction. This technique is useful for image enhancement, but the transformed data can also be analyzed by LARSYS classifications in addition to photo-interpretation. There may be a cost savings in computer classification of transformed data since fewer channels are necessary to classify the data.

The transformation of three LANDSAT-1 data sets (May 4, 1973, August 19, 1973, and February 15, 1974) has been completed. Using the digital display unit, false color composites were made of the first three components.

A major portion of the spectral-temporal information of the three dates is contained in the first several principal components. Nearly 80 percent of the data variance in the 12-dimensional multi-date LANDSAT data set is contained in the first three components which were combined to produce the color composites.

Color composites of the first three components reveal definite image enhancement of the test-site scene in Hoosier National Forest of central Indiana. In effect, the information of three dates has been combined into a single image. Computer printouts of the first component suggests that they will aid the analyst in test and training field selection since more than one spectral band is represented in a single printout (50.27% of the data variance is included in the first principal component for the Hoosier test site). Classification of the transformed data will be accomplished during the second year of this effort, and should reveal how feasible the principal components transformation is in terms of computer-analyst cost and classification accuracy.

RESULTS

Significant results obtained during the past year include:

1. Forty meter or greater resolution appears better suited to forestry type analysis than 8 meter resolution.

2. No significant increase in classification accuracy was achieved by using more than four data channels of aircraft MSS data.

3. Extension of aircraft MSS training data to other test sites did not prove feasible because of problems in the aircraft data collection system.

4. The capability exists to classify mixed forest stand conditions using aircraft MSS data. However, the problem of defining the components of the mixture class has not been solved.

5. Forest stand density appears to have a greater effect on spectral response than forest condition class or species composition when only similar species are present in southern pine.

6. In the Sam Houston test site high visual correlation to ground truth data was obtained with a single date LANDSAT-1 classification. Classes separated included: two separate pine density classes; hardwood class; mixed pine/hardwood; cutover class; a clear class (no major forest land use) and several classes of water.

7. Spectral channels (from the data channels available for this study) which appear most adaptable to forestry classifications include: one visible and three near-infrared channels.

8. The modified cluster technique is superior to either the supervised or non-supervised analysis technique.

9. A systematic approach to selecting fields for evaluation of classification accuracy is recommended.

10. Principal component analysis of temporally overlayed LANDSAT data suggests that this technique will be beneficial in selecting test and training fields.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

Although many of the results may appear to be of a preliminary nature, they are sufficiently detailed to allow the following conclusions.

- Low altitude, high-resolution aircraft MSS data is not suitable for forestry type classifications over extended areas.

- Development of new procedures to utilize existing data analysis programs appear beneficial from a time and monetary standpoint.

- Species identification within general groups and further classification within species to condition classes is extremely difficult with available data and the current test site.

- Statistical evaluation of classification results will be an important facet of the analysis package.

Recommendations

Further research on these problems will continue to build on the foundation developed during CY75. In order to attempt to answer some of the prob ems encountered, the following recommendations are suggested:

- Data should be collected over pure stands and plantations of southern pine. Furthermore, intensive ground-based information should be collected for these stands to allow corollaries to be developed between stand parameters and spectral response.
- Areas having a broader range of hardwood species should be selected. If the hardwood category is important, additional areas must be defined to evaluate the capability of existing techniques to differentiate between these stands.
- Access is needed to a data set containing a full range of spectral channels with sufficient data quality and improved resolution to be studied for spectral band and resolution selection.

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Computer Aided Analysis of LANDSAT -1 MSS Data: A Comparison of Three Approaches, Including a "Modified Clustering" Approach
(Presented at the LARS Symposium June 2-5, 1975) LARS Information Note in preparation.

V. Analysis of Land Use Patterns

INTRODUCTION

Inventorying and monitoring land resources is fundamental to the interests of national, state, and local government. In response to Federal legislation designed to give impetus to programs in land resource management at the state level, NASA/JSC conceived the Regional Applications Project (RAP). The primary RAP objective is:

> "To define, design and develop, and demonstrate a Regional Land Resources Inventory System(s), which utilizes in part information extracted from remotely sensed data for the inventory and monitoring of regional land resources in support of resource development and use management." [1]

In concert with other efforts to reach that objective, a Supporting Research and Technology (SR&T) program with the Laboratory for Applications of Remote Sensing (LARS) was initiated as part of RAP. Two technical objectives were proposed in the LARS/SR&T effort to initiate a remote sensing inventorying and monitoring capability in Texas. These were:

1) Determining the feasibility of replicating the Bureau of Economic Geology (BEG) environmental planning units using computer-aided classification of ERTS data, and
2) Development of a change detection procedure.

The first objective was addressed during CY75. The CY76 SR&T effort will be mainly concerned with the second objective. To achieve the first objective, LARS implemented the on-line LARSYS software system (2) and other available operational programs on the IBM 360/67 computer to analyze the ERTS data supplied by NASA/JSC. Data processing procedures derived from this activity will be documented and transferred, after NASA/JSC verification, to investigators in the State of Texas.

With the present State of Texas emphasis on the development of a coastal zone management program, an obvious and immediate requirement arises for coastal zone remote sensing applications. For this reason, and for technical reasons associated with the natural diversity of coastal environments and socioeconomic dynamics, the Texas Coastal Zone was the first problem area to be addressed in the RAP.

The test site selected by the RAP Project scientist encompasses the Matagorda Bay, Texas estuarine system. The site includes most of the categories in the BEG Environmental Geologic Atlas (3) classification, has sufficient ground truth in terms of aerial photographs, map coverage, and ground surveys to evaluate classification performance, and is one focus of interest for several agencies within the State of Texas.

Thirty-four natural environments in the Texas Coastal Zone are defined in several sources of Texas information. (4,5,6,7). In general, the thirty-four environments defined as planning units are useful for inventorying and monitoring purposes. It was assumed that recognition of these environments will be critical to state planning activities in the coastal zone, and further that automatic spectral discrimination of environments utilizing ERTS-1 type data may greatly aid inventorying procedures. Previous studies, (8) having demonstrated the broad variety of identifiable coastal zone environmental units in ERTS data, serve as the basis for assuming that at least the subaerial environments are spectrally discrete.

Description of Study Area*

Nine study areas in the Matagorda Bay were selected for investigation. These areas are encompassed by the following 7 1/2 minute USGS quadrangles: Pass Cavallo SW, Port O'Connor, Austwell, Seadrift NE, Seadrift, Tivoli SE, Port Lavaca E, Point Comfort, and Lolita. All nine study areas are characterized by diversity in geography, resources, climate, natural waterways and estuaries simiiar to the entire coastal zone of Texas. They are all subjected to a diversity of natural hazards: shoreline erosion, land-surface subsidence, flooding from streams and hurricane, tidal surges and active surface faulting. Land use within the site areas is divided principally among agriculture, rangeland, industry, urban, recreation, and broad marsh-covered tracts with abundant wildlife. The native vegetative stands represent a collection of vegetation of similar species dominated by a single characteristic species or a small number of co-dominant species. The lower part of the coastal areas and river valleys are covered with marshes and swamps (marsh-swamp system). When aquatics are kept wet by salt water, the marshes are salt-water marshes. Salt marshes include both low marsh and high marsh. The low salt water marsh is characterized by pure stands of cordgrass that grows in water a few inches deep. The high salt water marsh is inundated almost daily by normal tides and is characterized by numerous salt-tolerant succulent plants. Salinity of the water in which both the high and low salt-water marshes are situated varies from less than to greater than the normal marine salinity (35 ‰). Climatological conditions are key factors in controlling salinity fluctuations normally experienced by high salt-water marsh. Along the coastal lowlands are closed brackish-water marshes.

*Much of the material of this section is derived from reference 3. It is considered important enough to the understanding of the results reported to merit inclusion here.

Under normal climatic conditions, salinity of the ground water and overlying shallow water is intermediate between that of fresh water and sea water. During dry periods, salt-tolerant plant species associated with brackish and fresh to brackish marshes become the dominant elements of the closed brackish marsh. Fresh to brackish-water marshes are developed extensively along coastal lowlands at higher elevations than the closed brackish-water marshes. The fresh water is contributed by overbanking of the rivers during flood stage and by runoff from the adjacent uplands. Salt water is supplied mainly by storm surges. During prolonged dry periods, both surface and ground water have salinity in excess of 35‰, whereas during periods of excessive rainfall, surface water may be virtually fresh. Salinity of substrata water is the factor that has the greatest influence on the kind of vegetation which will develop in an area. Toward bays or areas of either salt-water or closed brackish-water marshes, salt-tolerant plants are increasingly dominant; toward the mainland and away from salt water influence, fresh water plants become dominant. Geographically, marsh wetlands are located on the lower portion of the Guadalupe and Lavaca Rivers, the bayside of Matagorda Islands (barrier islands), and topographically low sites found inland. Salinity and topography strongly influence the typical vegetal succession. Normally, high elevations are drier and less saline than lower elevations. In the deltaic environments of the Guadalupe and Lavaca Rivers vegetal groups include subaqueous and emergent hydrophytes, such as Roseau cane (Phragmites communis), alligator weed (Alternanthera piiloxeroides), etc. When salinities are higher Juncus spp. and Spartine spp. are common. Topographically low, frequently-inundated areas may or may not be occupied by vegetation. Vegetation is aquatic such as Salicornia spp. and a green algal mat incorporated within a two cm thick sand layer. From the green algal mat which with its filaments holds sand grains partially protected from wave action come the transitional zones with Salicornia spp. and Distichlis spicata to dry parts of the marsh with Spartina patens and Spartine spartinae. In addition, various shrubs and weeds, such as rattlebox, bluestem grass, mesquite, and some oaks may be found.

Each change in vegetal type indicates a change in edaphic conditions and also normally corresponds with changes in spectral responses. Within the wetland of the study area is the zone of the dunes behind the beach. When dunes are not covered by vegetation, they are unstabilized. Dunes become stabilized by plants such as beach morning glory and sea oats.

Physical use of wetlands in their natural states is limited by very low relief, very poor drainage, a susceptibility to flooding, and a permanently high water table. These lands are subject to inundation during very high tides or storms; accordingly, they range from fresh to intermittently brackish. The soils and substrates underlying these wetlands are highly organic. Although permeabilities are very low, they have little suitability for most direct physical use. For most of these uses reclamation or filling is necessary, but this activity destroys the marshland permanently.

The coastal uplands consist chiefly of clay and mud soils, material deposited from overbanking streams and sediments during the Pleistocene history of the area. Materials classes in this group have low permeability. Relief of the land in this group is low with slopes chiefly less than 1.4 percent. The soils are poorly drained and have very slow runoff and internal drainage due to a fine-grained texture and the high content of plastic, montmorillonitic clay. Areas situated almost entirely on the Pleistocene coastal uplands between the coastal wetlands and the inland woodland is used for production of rice or grain sorghum. Most of the cultivated lands were originally prairie grasslands. An extensive network of drainage canals, irrigation canals, and water reservoirs is utilized in agricultural production and crop cultivation.

Sands form a major part of the modern coastal strandplains and cheniers, including the beach, beach ridges, cheniers, and strandplain flats. Materials classes in this physical group have high to very high permeabilities. Sands have high to very high permeabilities, low water-holding capacity, and rapid internal drainage.

Fresh water marshes and swamplands are areas not subjected to salt water flooding except during very high hurricane-surge floods. Swamps differ from marshes in that they support tree rather than grass vegetation. Land classes in this group (fresh water marshes and swamps) have a permanently high water table that essentially intersects the ground surface, have depressed relief, and are subjected to fresh water flooding. Permeability is generally very low and internal drainage slow; water holding capacity is high.

Salt marshes are similar to fresh water marshes, except that salt marshlands are regularly inundated by salt water and are thus subjected to a greater impact by wave activity. Utilization of salt marshes requires land reclamation and filling, a practice that permanently destroys the marshlands.

Each of the environmental units defined and mapped by the Texas Bureau of Economic Geology (BEG) in the Environmental Geologic Atlas of the Texas Coastal Zone is an agglomeration of environmental subunits which correspond, in some degree, with a resource capability required to sustain a human activity. These units are listed in Table 1.

The hydrological, geological, chemical and biological properties which form the basis for the BEG definitions can be found in reference 3. Environmental descriptors of the eight primary divisions are essentially geomorphological. Lower level descriptors integrate static and dynamic geological, ecological, and hydrological characteristics which, in turn, may be related to human use. Although previous studies have shown that several elements of the taxonomy display a spectrally unique radiance, the taxonomic categories represented by Table 1 has not been tested.

Table 1. Coastal Environmental Units

Inner Continental Shelf

Coastal Barriers

- Beach and Shoreface
- Fore-Island Dunes and Vegetated Barrier Flats
- Active Dunes
- Washover Areas
- Swales
- Tidal Flats

Bays, Lagoons, and Estuaries

- Tidal Inlet and Tidal Delta
- Tidally Influenced Open Bay
- Enclosed Bay
- Mobile Bay-Margin Sands
- Reef and Reef Related Areas--Living
- Reef and Reef Related Areas--Dead
- Grassflats
- River Estuary
- Spoil Areas
- Wind-Tidal Flats

Coastal Wetlands

- Salt Marsh
- Freshwater Marsh
- Brackish Marsh
- Brackish Marsh (closed)
- Swamp

Made Land and Spoil

Coastal Plains

- Highly Permeable Recharge Sands
- Impermeable Muds
- Moderately Permeable Recharge Sands
- Broad Shallow Depressions
- Steep Lands
- Stabilized, Vegetated Dunes and Sand Flats
- Unstabilized, Unvegetated Dunes
- Freshwater Lakes, Ponds, Sloughs, Playas
- Mainland Beaches
- Areas of Active Faulting and Subsidence
- Highly Forested Upland Areas

Major Floodplain Systems

- Point Bar Sands
- Overband Muds and Silts
- Water

Air

Approach

In order to meet the stated objectives of this project, LANDSAT-1 data was used as the source of all computer analysis input requirements. The following data was furnished LARS by NASA/JSC:

Scene ID	Date of Collection
1127-16260	November 27, 1972
1146-16134	December 16, 1972
1289-16261	May 8, 1973
1505-16230	December 10, 1973

As received initially, most of the data was unusable due to noise and other related problems. After considerable effort usable data for scenes 1127-16260, 1289-16261 and 1505-16230 were obtained. These data were studied as individual data sets and as a three date temporally overlayed data set. Both supervised and non-supervised classification techniques were employed.

Several other types of data were required to support the analysis of the LANDSAT data. Color and color infrared photography, collected during 1970 and 1971 by the WB-57F and NC-130 aircraft, and the Geologic Atlases compiled by the Texas Bureau of Economic Geology were used for locating training and test fields, locating boundaries and evaluating the performance of classifications.

PROCEDURES

Preprocessing

The LANDSAT data was reformatted into a form compatible with the LARSYS system. After this bulk-to-LARSYS reformatting was completed, data from the three usable frames covering the Matagorda Bay area were spatially registered to produce a three date multitemporal data set. Multitemporal data sets were prepared for seven of the nine quadrangle areas. The Austwell and Tivoli SE quadrangles were only covered by the May 8, 1973 data set and thus were not be observed temporally. In order to be able to more easily compare the computer-aided classifications to the BEG maps, the overlayed data were corrected to:

1) Eliminate skew due to the earth's rotation,

2) rotate the data to a N-S orientation, and

3) rescale the data to be geometrically correct for digital display and line printer output (1:24,000).

Classification

Several approaches for analysis of LANDSAT data can be utilized depending upon the reference data available and the information desired.

The RAP classification effort was divided into three phases. Prior to the receipt of appropriate reference data, non-supervised single-date classifications were accomplished for the nine quadrangle areas. Later, as maps and ground truth information were received at LARS, the same areas were classified using a supervised technique to produce single-date classifications. Finally, three-date temporal classifications of seven of the nine quadrangles were completed. The procedures utilized in these classification tasks are discussed below.

Non-Supervised Technique

In order to obtain an overview of the area contained within the various quadrangles, false color images of each quadrangle from each of the dates were produced and observed. Some detailed information about the surface features of the coastal zone could also be obtained from these images.

After studying the false color images, the data for each quadrangle was displayed on the digital display unit and an area, approximately 100 lines by 100 columns, was selected for clustering. This area represented about one-fourth of the area of each quadrangle. The *CLUSTER algorithm was then used to divide the data of the selected training area into cluster groups of data points of similar spectral characteristics. The maximum number of classes was set at 15 and the processor was requested to punch field description cards. The minimum number of points required to describe a field was set at three. Once the training fields were selected, the field description cards were input as data into the *STATISTICS processor. The output from this processor was then input to the *CLASSIFYPOINTS processor and the selected quadrangle classified. The *PRINTRESULTS algorithm was then used to obtain a non-supervised classification printout. Each of the nine quadrangle areas was classified using the non-supervised method for each of the dates for which data had been collected.

Prior to the receipt of reference data, the resulting non-supervised classifications were difficult to interpret because the cluster classes could not be related to field classes. In an attempt to identify the cluster classes, a heuristic ratio technique was utilized. A ratio

$$A = \frac{V}{IR}$$

was computed, where V is the relative intensity of the visible wavelenths

[(0.5 to 0.6µm) + (0.6 to 0.7µm)] and IR is the relative intensity of the reflective infrared wavelengths [(0.7 to 0.8µm) + (0.8 to 1.1µm)].

By summing the relative intensity values of all four bands the magnitude of relative spectral responses can be obtained as shown in the following equation:[11]

Summed response = (0.50 to 0.60µm) + (0.60 to 0.70µm) + (0.70 to 0.80µm) + (0.80 to 1.10µm).

By observing the ratio A and the summed response, the analyst delineated major vegetation and land use categories within the coastal zone area.

As reference data became available, a first estimation of classification performance was obtained by visually comparing the classification results with known areas on photographs, or existing topographic, land use, geologic or other maps. Analysis of these results indicated that the non-supervised procedure did indeed approximate the field situation; however, it was hypothesized that a supervised classification approach, utilizing proper ground reference data, would produce a more accurate and usable classification.

Supervised Technique

Since the data had been preprocessed so that line printer output from the non-supervised classification printouts would be at a scale of 1:24,000, these classifications could be overlayed onto existing topographic maps and the Environmental Geologic Atlas maps which were converted to a scale of 1:24,000.

Using this overlay method, the cluster classes could be related to field classes. Different cluster classes which represent like field classes could be combined and vice versa. Thus, a spectral representation could be assigned to many of the existing field classes. Then training fields for the supervised approach could be defined by line and column coordinates. The coordinates from each of these fields were punched on cards and this data input into the *STATISTICS processor. These statistics were then input into the *CLASSIFYPOINTS algorithm and a supervised classification was generated for each quadrangle for each of the dates. A *PRINTRESULTS printout was obtained for each classification during which a threshold value of 0.5 was applied. Those data that were thresholded were then separately specified by line and column coordinates and input into the *STATISTICS processor as additional training fields. A reclassification was then accomplished using the additional statistics generated from the thresholded areas. This procedure appeared to increase the classification accuracy over the initial classification. However, a quantitative evaluation of the classification accuracy has yet to be performed.

Multitemporal Technique

After the single-date classifications had been completed, the quadrangles were classified using the three-date temporally overlayed data and a supervised approach. This data set did not include the Austwell or Tivoli SE quadrangles as previously discussed.

Since this data was an overlay of three dates, twelve channels of LANDSAT data were available for classification. The same training fields (field description cards) were input into the *STATISTICS processor as were utilized in the May single-date supervised classifications. The output statistics were then utilized in the *SEPARABILITY processor to determine the optimum set of four channels to use in classification of each of the quadrangles. Table 2 shows the channels selected for each quadrangle. The statistics were then input into the *CLASSIFYPOINTS processor and each quadrangle classified. Output at a scale of 1:24,000 was obtained using *PRINTRESULTS.

RESULTS

Table 3 lists the various classification tasks performed by quadrangle during the CY75 effort of the RAP. Both Level I and II type maps were generated for each classification task. These levels closely approximated the Level I and II categories listed in USGS Circular 671[12]. Table 4 indicates the classes in USGS Circular 671 which were classified within the Texas coastal zone study area. Table 5 lists these classification categories in a more descriptive format and by quadrangle.

Computer printouts (scale 1:24,000) for each of the non-supervised, supervised, and multitemporal classification tasks listed in Table 3 are being supplied to NASA/JSC for evaluation.

Discussion

A preliminary evaluation of the three classification techniques was conducted by comparing the computer printouts with the 1970 and 1971 aerial photography supplied by NASA/JSC. Only general comparisons could be made because of the large time gap which existed between the dates of collection of the aerial photography and the LANDSAT data. Indications are that the supervised classification of the temporal data sets yielded the best results with the single date supervised classifications being second. The single date non-supervised classification yielded the least accurate results. The May data set in the single date classifications appeared to give better results than either the November or December data sets. A more meaningful discussion of the results can be completed upon final evaluation of the classifications by NASA/JSC.

However, this study has shown that computer-aided classification

Table 2. Channel Selection for Temporally Overlayed Data

Quadrangle	Date of Data Collection											
	November 27, 1972				May 8, 1973				December 10, 1973			
	MSS Bands				MSS Bands				MSS Bands			
	4	5	6	7	4	5	6	7	4	5	6	7
Pass Cavallo SW	X					X	X	X				
Port O'Connor		X				X	X	X				
Austwell	----	----	----	----	----	----	----	----	----	----	----	----
Seadrift NE	X						X	X				X
Seadrift	X			X			X	X				
Tivoli SE	----	----	----	----	----	----	----	----	----	----	----	----
Port Lavaca E						X	X	X	X			
Point Comfort		X		X		X	X					
Lolita		X		X		X	X					

Table 3. Classification Tasks Accomplished by Quadrangle

Quadrangle	Date of Data	Non-Supervised Classification	Supervised Classification	Supervised Multitemporal Classification
Pass Cavallo SW	November May December	X X X	X X X	X
Port O'Connor	November May December	X X X	X X X	X
Austwell	November May December	X	X	
Sea-drift NE	November May December	X X X	X X X	X
Tivoli SE	November May December	X	X	
Port Lavaca E	November May December	X X X	X X X	X
Point Comfort	November May December	X X X	X X X	X
Seadrift	November May December	X X X	X X X	X
Lolita	November May December	X X X	X X X	X

of LANDSAT data can be used to characterize the coastal zone environment. A large number of Level I and II classes are identifiable and computer-aided analysis can rapidly inventory and represent the land cover and land use of this area.

It should be noted that the BEG environmental units were not precisely replicated. This may be due to the subresolution element size of some features and the subaqueous nature of others. However, the computer classifications generated appear to contain information useful to the State agencies concerned with the management of the Texas coastal zone. The success of this effort cannot be fully determined until the results are evaluated by NASA/JSC and cooperating State agencies.

Table 5. Categories Identified on Computer Classification Map

Categories	QUADRANGLES								
	Pass Cavallo SW	Port O'Connor	Aust-well	Seadrift NE	Seadrift	Tivoli SE	Port Lavaca E	Point Comfort	Lolita
Agricultural cultivated land			X	X		X	X	X	X
Range-pasture, uncultivated or permanently removed from crop use	X	X		X	X				
Vegetated flats, higher coastal marsh, cleared land on fluvial sands	X	X	X	X	X	X	X	X	
Woodland-timber, water tolerant on flood-plains, chiefly on Pleistocene fluvial sands		X	X	X	X	X	X	X	X
Trees mixed with shrubs - low density trees	X	X	X	X	X	X	X	X	X
Swamp Timber, wet floodplains and abandoned channels of modern fluvial systems			X				X	X	X
Saline marsh populated with Spartina alterniflora, Salicornia perenis, Borrichia frutescens and Suaeda spp.	X	X	X	X	X		X		
Brackish-water marsh vegetated with Spartina patens, Spartina cynosuroides, Dictichlis spicata and Juncus spp.	X		X				X		
Fresh-water marsh vegetated with Juncus spp. Scirpus spp., and Spartina pectinata			X					X	X
Residential-urban, commercial and residential		X					X	X	X
Industrial areas, refineries - chemical plants								X	X
Wildlife refuge, restricted areas						X			

Table 5. (Continued) Categories Identified on Computer Classification Map

Categories	QUADRANGLES								
	Pass Cavallo SW	Port O'Connor	Aust-well	Seadrift NE	Seadrift	Tivoli SE	Port Lavaca E	Point Comfort	Lolita
Government land, airbases	X								
Recreational land, sand beach between mean low tide and mean high tide	X	X		X	X		X		
Made land, filled, mud, sand and shell, locally some vegetation, reclaimed land	X	X		X	X		X	X	
Grasses in forest uplands with scattered trees						X		X	
Grass and locally covered ridges, sand and shell elongate topographic ridges	X					X		X	
Unvegetated coastal mud flats frequently flooded	X	X	X	X	X				
Vegetated strandplain flat, beach ridge and vegetated flat	X	X	X						
Moist to dry circular ponds	X	X		X	X				
Shrub or tree dominant environments - background of grasses occupy dry land. Shrubs or trees are mesquite, hackberry huisache, chaparral, cactus, and Bochurus		X	X						
Sewage disposal								X	
Oil fields								X	X
Pasture with basic grasses - Bermuda grass, Bahia grass, Johnson grass	X	X	X	X	X	X	X	X	X

Table 4. USGS Circular 671 Land Use Classes Identified in the Texas Coastal Zone

Level I	Level II
01. Urban and Built-up Land - X	01. Residential - X
	02. Commercial and Services
	03. Industrial - X
	04. Extractive
	05. Transportaion, Communications, and Utilities
	06. Institutional
	07. Strip and Clustered Settlement
	08. Mixed - X
	09. Open and Other
02. Agricultural Land - X	01. Cropland and Pasture - X
	02. Orchards, Groves, Bush Fruits, Vineyards, and Horticultural Areas
	03. Feeding Operations
	04. Other
03. Rangeland - X	01. Grass - X
	02. Savannas
	03. Chaparral - X
	04. Desert Shrub
04. Forest Land - X	01. Deciduous
	02. Evergreen (Coniferous and Other)
	03. Mixed - X
05. Water - X	01. Streams and Waterways - X
	02. Lakes - X
	03. Reservoirs - X
	04. Bays and Estuaries - X
	05. Other - X
06. Non-Forested Wetland - X	01. Vegetated - X
	02. Bare - X
07. Barren Land - X	01. Salt Flats - X
	02. Beaches - X
	03. Sand other than Beaches - X
	04. Bare Exposed Rock - X
	05. Other - X
08. Tundra	01. Tundra
09. Permanent Snow and Icefields	01. Permanent Snow and Icefields

X - indicates levels classified

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VI. Remote Terminal Project and Technology Transfer

INTRODUCTION

The remote terminal project and Technology Transfer activities include the evaluation of the remote terminal concept and further development of Technology Transfer concepts and materials. Purdue's participation in the remote terminal project is documented in the report entitled, "Remote Terminal Project Final Report: Purdue University", by T. L. Phillips, H. L. Grams, J. C. Lindenlaub, S. K. Schwingendorf, P. H. Swain, and W. R. Simmons. The Technology Transfer portion of these activities are reported in several Information Notes listed at the end of this section.

A draft of the remote terminal final report (Reference 1) has been sent to NASA for their approval. This report will be published when approval is given. A brief review of Purdue's participation in the remote terminal project and a summary of the significant accomplishments resulting from this participation are included in this report.

The Technology Transfer portion of this report summarizes the activities of the Technology Transfer Program Area supported by the SR&T contract during the 1975 fiscal year. Included in this portion of the report is a description of the Technology Transfer concept which has evolved over the past several years. The framework described provides the logical context in which to discuss specific accomplishments during this reporting period. These accomplishments include the generation of new titles in the FOCUS Series, experimentation with video tape as a media for remote sensing education, substantial revision of the LARSYS educational package, and the generation of the LANDSAT case study addendum to the LARSYS educational package.

Remote Terminal Project

About 10 years ago, the Laboratory for Applications of Remote Sensing at Purdue University began to pursue research to develop data processing techniques for remote sensing applications. The results of this research led to the development of an earth resources data processing system which is being used by both LARS personnel and remote terminal users to evaluate the value of the system for training, technology transfer*, and data processing. The major objective of this task during the 1975 fiscal year was the completion of the evaluation of the existing system, and to design and test a more cost effective terminal for future systems.

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*The term 'training' is used in this section of the report to refer to the conventional activity of transmitting knowledge to an individual, while the term 'technology transfer' is used to refer to the transfer of technological capability from one group to another. It includes, besides training of individuals in individual skills, the imparting of the interrelationship of those skills to one another, and to the hardware, software and user needs involved.

A number of significant accomplishments have resulted from Purdue's participation in this project. The facility has been used at seven separate sites in the Eastern, Midwestern and Southwestern U.S. and demonstrated to be a cost effective system for training personnel and technology transfer as well as a valid prototype for the operational availability of data processing, meeting many of the data processing needs at several sites. These accomplishments are summarized below and are organized so that they relate to the objectives of Purdue's participation in the project.

A remote terminal facility has been provided for a period of 2 1/2 years. By December 1974, seven separate sites were connected to the earth resources data processing system located at Purdue. Although most of these sites experienced the usual start-up difficulties, at only one site (Langley) were these severe enough to make the installation at that site be considered less than highly successful.

The basic approach to the development of a facility for training personnel in the use of advanced processing techniques for remote sensing is sound and has proven itself to be effective. The instructional materials designed for individual use with a minimum of instructor participation meet the needs of most remote terminal situations and may be adopted for group use by an imaginative instructor. Through the use of these materials and the remote terminal network, 600 personnel have been trained in the use of data processing techniques for remote sensing application.

The current configuration of remote terminals has been shown to be a cost effective facility for training of personnel, transferring technology, and meeting most of the current data processing requirements. Two cost effective measures have been applied. From the terminal point of view the system is cost effective in that the cost of less effective systems for similar needs has been shown to range between slightly less than the cost of a terminal to much greater than the cost of a terminal. From a system point of view, the cost of personnel to support a network has increased insignificantly with respect to services provided and number of sites served when compared to the cost of providing separate facilities at each location.

It has been demonstrated that the remote terminal approach is an effective way to make available the evolving remote sensing data processing technology to a wide community of users. As a result of the commonality of data processing environment to a broad community of users, the interchange of ideas and the experiences between sites has been facilitated. In some cases a reverse flow of technology has occurred in which new techniques and methodology developed at remote sites are transmitted to the central location to be made available across the network.

The remote terminal project has shown that the initial requirements for a processing site are necessary and sufficient to meet the training, technology transfer, and processing objectives of the site. These requirements briefly stated are: 1. A hardware link to these services, 2. A software system which provides a specialized analysis technology, 3. A personnel link between the remote site and the central site consisting of a systems specialist and a techniques specialist which provide reasonable responses to the user's needs, 4. A training concept including materials, documentation and instructor's available to the potential users, and 5. An available data library and access to data preprocessing services.

In addition to demonstrating both feasibility and practibility of the concept, the remote terminal project provided a basis for further development of requirements for more effective terminal systems. The following hardware requirements were realized and reconfirmed as a result of the experiment. These are in order of their priority: 1. A low cost interactive image display device supported by LARSYS, 2. A wide range or family of terminal configurations supported by the system, 3. A high quality hard copy display capability located at the central facility for operational use by the remote sites, and 4. A volume communication link between the central facility and the primary data dissemination facility to provide near immediate access to remote sensing data by users of the entire network.

The Matrix Concept for Education and Training Materials in Remote Sensing

Because of the newness of the field of remote sensing there exists only a limited amount of instructional materials available to the user community. (See Reference 2.) Furthermore the traditional university course format requiring upwards of 150 hours of student time to complete a course does not lend itself to the needs of the scientist preparing to work in the field of remote sensing or to the user community interested in applying remote sensing technology to their specific needs. What is needed is a flexible training environment to meet the varied needs of this community. A training concept which can achieve this revolves around a collection of learning units or modules from which specific training programs can be synthesized. The modules, each requiring from several minutes to tens of hours of student time cover a wide variety of topics, are as self-instructional as possible, and when possible are designed for use in the student's office or at his home. They also utilize the latest in instructional technology, i.e., video tapes, audio-tutorial lessons, slide/tape presentations, simulation exercises, case studies, films, hands-on experiences, programmed textbooks, and computer-assisted instruction. The instructional format is not arbitrarily chosen in advance, but is selected on the basis of the content, objectives, learner characteristics, ease of use, and educational effectiveness.

The point of development of this concept, achieved during the past year may be described in terms of a matrix of education and training materials (see Figure 1). Each column in the matrix represents a subject area in remote sensing and the rows in the matrix represent levels of instruction requiring increasingly intensive study.

Single concept overviews developed during the past year take the form of a two-page foldout consisting of a diagram or photograph and an extended caption. Materials of this type, known as the FOCUS series, developed during the past year are described in the next section. A student would typically spend 10 to 20 minutes on materials at this level. They are especially useful for general briefings and introductory treatment of remote sensing topics.

The second level modules in the matrix deal with fundamental principles of remote sensing. Formats used at the fundamental principles level include minicourses consisting of audio tapes, slides and printed study guides and video tapes with viewing notes. Units at the fundamental principles level are designed to take one to two hours of student time. Staff members of the LARS Technology Transfer program area are developing a series of minicourses on the fundamentals of remote sensing under the sponsorship of Purdue University's Continuing Education Administration and prototype video presentations and viewing guides have been produced as a result of LARS' 1974 Remote Sensing Short Course offerings also sponsored by the University's Continuing Education Administration. Thus while not specifically supporting the development of materials at this level in the matrix NASA has benefited both in terms of the contributions these efforts have made in the development of the instructional matrix concept and the availability of these materials to NASA and the public sector through Purdue's Continuing Education activities.

Simulation exercises, third level modules in the matrix, are designed to lead the student through the professional thought and decision-making processes typical of those required by remote sensing practioners. These units, requiring three to four hours to complete, illustrate and explain the rationale and decision processes of the professional remote sensing analyst.

Case studies require the student to make his own decisions, specify computer analysis requirements and interpret analysis results. Intermediate results are reviewed with a tutor located in the same facility. Case studies require on the order of 40-50 hours of student time. Upon completion of a case study, the student is equipped to undertake an individual research project which would be defined by the individual perhaps with the help of a colleague. Units VI and VII of the LARSYS Education Package are at the case study level.

Research projects are conducted in the scientist/engineer's working environment. He may be assigned to work with another scientist/engineer with similar background and research interests, but one who has had experience in the use of remote sensing techniques and machine-assisted data analysis. The student conducts his own research with the aid of a tutor when needed.

The matrix concept allows specific training programs to be synthesized by selecting units from the matrix of instructional modules. Typically a larger number of units would be selected from the top row (single concept overviews) with smaller numbers of units being selected as the student progresses down through the matrix (see Figure 2 for sample individualized training program).

During the 1975 fiscal year Technology Transfer staff members have developed materials in various portions of the matrix. The materials developed under the SR&T contract are discussed in the remaining sections of this summary report. In addition, work under other programs - the Purdue supported projects mentioned above, two Lockheed Electronics Corporation funded training courses for LACIE analysts, and the demonstration package developed in conjunction with the EROS Data Center remote terminal contract - have contributed to the matrix organizational concept for education and training materials in remote sensing.

Additions to FOCUS Series

The first horizontal row on the matrix of educational materials is represented by a series of short pamphlets describing or explaining concepts fundamental to remote sensing. These pamphlets, which make up the FOCUS series, typically contain one page of text and one page of supporting figures and take 10 to 15 minutes of reading time. So that they may be widely available, they are designed to be inexpensive to produce in quantity and yet are attractively prepared. Technical accuracy is insured by extensive in-house review. Eight additional titles were added to the series this past year.

The audience for these pamphlets has ranged widely from people who are relatively new to remote sensing to those who seek explanations of more complex topics. The FOCUS pamphlets on "Remote Sensing," "The Multispectral Scanner," and "LANDSAT" require no prior understanding of remote sensing, while the ones on "Pattern Recognition" and "Sample Classification" assume at least a minimal understanding of the objectives of remote sensing and the nature of the data available. Several other issues in the FOCUS series contain basic descriptions of remote sensing applications: "Cover Type Classification," "Mapping Soil Characteristics," and "Crop Species Identification." Because of the readers' varied backgrounds, the number of technical terms used in the descriptions is kept to a minimum. Each issue also contains a list of suggestions for further reading. In choosing these lists, authors give preference to titles which are easily available in the general literature.

The FOCUS titles available as of May 31, 1975 are:

- The Multispectral Scanner
- Cover Type Classification
- Pattern Recognition
- Mapping Soil Characteristics
- Sample Classification
- Remote Sensing
- Crop Species Identification
- Earth Resources Data Processing System
- LANDSAT
- What is LARSYS?
- Role of Images in Numerical Data Analysis

Purposely designed to be brief in nature, individual titles from the FOCUS series do not lend themselves to being submitted as technical reports and this has tended to limit knowledge of their existence. A collection of all titles currently in the series has been assembled and bound together as LARS Information Note 052975 (Reference 3).

Experimentation with Video Media

The loan of video tape equipment by NASA/JSC to Purdue/LARS has allowed us to experiment with closed circuit television as a medium for technology transfer. The equipment has been used in three modes: the recording of LARS technical seminars, viewing of prerecorded materials and prerecording demonstrations for viewing as part of a seminar presentation.

During the months of October, November and December, 1974 eight LARS seminars were video-taped and 66 viewing hours were logged by LARS staff watching these tapes. Using normal room lighting and one mike, the equipment proved sensitive enough to give adequate video reproduction, including shots of projected slides and overhead transparencies. The availability of the seminars on tape has been especially valuable for people forced to miss seminars because of conflicting commitments and trips out of town.

The equipment was also used to view tapes that were produced in Purdue's Telecommunications Center studio by LARS staff members. While the production of these tapes was not funded by NASA, the equipment on loan from JSC allowed us to evaluate these more formal presentations. It was quickly determined that because of the highly technical nature of the subject matter on these tapes that the video presentations themselves were not sufficient to effectively transfer these complex ideas to the viewer. For complex technical subjects it is recommended that video presentations be supplemented with written materials.

In one instance the equipment was used to prerecord a demonstration for presentation to a seminar audience. This roving-camera approach provides an excellent mechanism for presenting equipment demonstrations or field measurement techniques to a large audience.

The loan of JSC video equipment to LARS has provided the Technology Transfer staff with the opportunity to gain experience in the use of this medium and has served to establish guide lines upon which to judge the appropriateness of using television to meet remote sensing training objectives.

LARSYS Educations Package Revision

The LARSYS Educational Package is a set of instructional materials developed to train people to analyze remotely sensed multispectral data using LARSYS, a computer software system developed at LARS/Purdue. The Educational Package is one of the columns of the matrix shown in Figure 1. It corresponds to the column headed "Using LARSYS Computer System." The LARSYS Education Package has been in use at remote terminals since October, 1973 and student evaluations have been collected from a number of sites. With the technical content fairly well established the education package was examined from a pedagogical standpoint. As a result of this examination, student comments and the Technical changes required as a result of putting LARSYS Version 3.1 on line in January 1975 significant revisions of the education package were made this past year.

In the previous set of instructional materials there were six units (5 at the fundamental principles level and one case study). Presently there are seven units (5 on fundamental principles and two case studies). A flow chart of the materials, shown in Figure 3, briefly summarizes the purpose of each unit and gives a time estimate for completing each unit.

Students begin with a background manual entitled An Introduction to Quantitative Remote Sensing. (Reference 4.) This is an introduction to remote sensing stressing the role of pattern recognition in numerically-oriented remote sensing systems. Its specific purpose is to provide a common background and orientation for the LARSYS computer software system. For newcomers to remote sensing, this manual introduces concepts and terminology which are needed later on. Remote sensing veterans will be introduced in this material to numerically-oriented remote sensing data analysis. Unit I has been reduced from 83 pages to 63 pages with no significant changes in content. Diagnostic pretests and posttests have been added to allow the student to check his progress and mastery of the materials presented.

The second unit entitled LARSYS Software System - An Overview consists of an audio tape which accompanies a display book and student notes. It takes the viewer through a typical remote sensing data analysis sequence and illustrates the commonly used features of the LARSYS set of processing functions. Unit II has a new format. The earlier version was a set of slides or flip chart book and audio tape which the student or students viewed rather passively. The new version incorporates a set of student notes which contain activities to actively involve the students in learning. The slides have been replaced by a display book which makes the computer printouts much more readable. Three decks of computer cards allow the student to examine control card decks typical of those they will be generating later in the Educational Package.

Revisions in Units III, IV, and V include those needed for consistency with changes in LARSYS, some organizational improvements to increase ease of use by both students and instructors, and numerous smaller changes as suggested by students who had used earlier versions of the LARSYS Educational Package. Unit III Demonstration of LARSYS on a 2780 Remote Terminal provides the student with an introduction to the data processing hardware that he will be using and introduces him to some additional aspects of the LARSYS software system. He observes several LARSYS jobs run at the 2780 remote terminal. The demonstration requires an instructor to present the material and guide the student. Instructor's notes have been designed so that persons with only a modest amount of experience with the terminal can satisfactorily run the demonstration. Notable additions to the Demonstration (Unit III) include student follow-up activities, a conference with the instructor, and greater emphasis on the computer system environments and user aids.

Students are instructed in the use of the terminal by means of an audio-tutorial lesson The 2780 Remote Terminal: A Hands-On Experience.

The student is guided by an audio tape on how to use the terminal off-line as a card lister, login to the computer and initiate the LARSYS system, run sample LARSYS jobs and transmit data to and receive data from the main computer. The audio tape is accompanied by a set of student notes. In Unit IV, students now learn to use the system to communicate with the operator and with other users, and look closely at the details of the typewriter, lineprinter and punched output.

LARSYS Exercises, Unit V, are short problems which the student solves by using the computer terminal and LARSYS processing functions. The purpose of these problems is to increase the student's experience in the use of LARSYS for multispectral data analysis and to help him develop an appreciation for the capabilities and limitations of the LARSYS software system. An addition to the unit is experience using the batch processor.

At this point in learning to use LARSYS, the student has a choice between Unit VI, Guide to Multispectral Data Analysis Using LARSYS and Unit VII, A Case Study Using LARSYS for Analysis of LANDSAT Data. Both units provide a detailed breakdown of the philosophy of the analysis methods -- describing the steps in the analysis, why they are necessary and how they are carried out. A detailed example parallels the description, and the student has the opportunity to carry out an analysis of his own by means of a case study. Unit VI, Guide to Multispectral Data Analysis Using LARSYS, has undergone the least change. It is geared toward a supervised analysis approach and uses aircraft data. Basically only typographical errors were corrected, awkward sentence structures changed and the computer printouts updated to the format generated by LARSYS 3.1.

Unit VII, A Case Study Using LARSYS for Analysis of LANDSAT Data (Reference 5), is a totally new addition to the Educational Package. It has been designed to parallel the Guide (Unit VI) but uses data from LANDSAT for the analysis sequence. As in the Guide, the students actually complete a case study. Unit VII combines techniques from both supervised and non-supervised approaches and applies these techniques to data collected by the Earth Resources Technology Satellite, now known as LANDSAT. If the student has the time, and interest, a study of both units is recommended.

Each unit in the LARSYS Educational Package has been designed and modified to take a student from an initial point, defined by the prerequisites, to an end point, defined by its objectives. Each unit provides informational materials, an opportunity for the student to practice and study the skills or ideas presented, and a problem or test situation to help him determine whether he has met the objectives of that unit. A variety of media is used in the educational package, the selection dependent on the nature of the material and the defined objectives of each unit. Reinforcement of certain concepts, such as the multispectral concept and the multidimensional statistical approach, is interwoven throughout the package.

Instructor notes (Reference 6), designed to assist those serving as instructors, accompany each unit. The function of the instuctor is not to plan and preside over formal classroom sessions, but rather to serve as a tutor helping clarify troublesome points for each student. It is intended that student/instructor sessions be brief with the instructor providing the necessary corrective feedback or encouragement to enable the student to continue on his own.

The Educational Package has proven to be very successful in the training of data analysts using the LARSYS software system. The use of these materials will continue to be monitored and additional revisions made when necessary to increase student achievement and efficiency with LARSYS.

Listed below are a number of separate documents which serve as references to this summary report of SR&T Remote Terminal and Technology Transfer activities for the period June 1, 1974-May 31, 1975. These volumes have been submitted separately through regular reporting channels.

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INSTRUCTIONAL MATERIALS

Research Problems	Case Studies	Simulation Exercises	Fundamental Principles: information note	Fundamental Principles: video tape with notes	Fundamental Principles: minicourse	Single Concepts: focus	Single Concepts: poster	Single Concepts: overview	REPRESENTATIVE TOPICS
									Introduction to Remote Sensing
									Characteristics of the E-M Spectrum
									Image-Oriented Systems
									Numerically Oriented Systems
									Comparison of R S Systems
									Photographic R S Systems
									Color IR Film Interpretation
									Optical Mechanical Scanners
									Interpretation of MSS Data
									Side Looking Radar
									Satellite Systems
									Spectral Char. of Earth Surface Features
									Using LARSYS Computer System
									Pattern Recognition
									Applications of Remote Sensing to..: Forestry
									Applications of Remote Sensing to..: Geology
									Applications of Remote Sensing to..: Crop Inventory
									Applications of Remote Sensing to..: Urban Planning
									Applications of Remote Sensing to..: Water Quality Monitoring

FIGURE 1
Matrix of Instructional Modules

INSTRUCTIONAL MATERIALS

REPRESENTATIVE TOPICS	Research Problems	Case Studies	Simulation Exercises	Fundamental Principles: information note	Fundamental Principles: video tape with notes	Fundamental Principles: minicourse	Single Concepts: focus	Single Concepts: poster	Single Concepts: overview
Introduction to Remote Sensing						X	X		
Characteristics of the E-M Spectrum						X			
Image-Oriented Systems								X	
Numerically Oriented Systems						X			
Comparison of R S Systems				X			X		
Photographic R S Systems									X
Color IR Film Interpretation						X		X	
Optical Mechanical Scanners							X		
Interpretation of MSS Data					X				X
Side Looking Radar									
Satellite Systems				X			X		
Spectral Char. of Earth Surface Features						X			X
Using LARSYS Computer System						X		X	
Pattern Recognition					X				X
Applications of Remote Sensing to.. Forestry	X	X	X	X	X	X	X		
Applications of Remote Sensing to.. Geology									
Applications of Remote Sensing to.. Crop Inventory									
Applications of Remote Sensing to.. Urban Planning									
Applications of Remote Sensing to.. Water Quality Monitoring									

FIGURE 2
A Sample Individualized Training Program Using Materials in the Matrix

THE LARSYS EDUCATIONAL PACKAGE

UNIT I

Title: An Introduction to Quantitative Remote Sensing
Purpose: Orientation to remote sensing terminology, principles and pattern recognition.
Time estimate: 4 hours

UNIT II

Title: LARSYS Software System - An Overview
Purpose: Summary of LARSYS data analysis capabilities.
Time estimate: 1 hour

UNIT III

Title: Demonstration of LARSYS on the 2780 Remote Terminal
Purpose: Orientation to terminal hardware and terminal procedures.
Time estimate: 1.5 hours

UNIT IV

Title: The 2780 Remote Terminal: A "Hands-On" Experience
Purpose: Experience in transmitting cards, receiving punched and printer output, and running a LARSYS program when given the control card listings.
Time estimate: 4.5 hours

UNIT V

Title: LARSYS Exercises
Purpose: Practice in using the terminal, writing and executing simple LARSYS programs.
Time estimate: 5 hours

UNIT VI

Title: Guide to Multispectral Data Analysis Using LARSYS (with accompanying Example and Case Study)
Purpose: Analysis of a detailed example and a case study using aircraft data.
Time estimate: 40 hours

UNIT VII

Title: A Case Study Using LARSYS for Analysis of LANDSAT Data
Purpose: Analysis approach of a detailed example and a case study.
Time estimate: 45 hours

FIGURE 3
LARSYS Educational Package
Flow Chart

VII. Multispectral Image Registration

Correlation Algorithms for Temporal Data

INTRODUCTION

An important part of the LACIE project is the utilization of the temporal variations in the scene made possible by the repetitive coverage of LANDSAT. Temporal variations can be used to improve classification accuracy, augment training data for single time (purely spectral) classifications, image enhancement for improved visual interpretation and field location, and other benefits. In order that temporal effects be utilized for machine processing multiple frames over the same area must be digitally registered very accurately. Research and development activities at LARS have produced an image registration system which works well but has a rather high processing cost. Research conducted during this year was directed toward comparison of image correlation algorithms to define methods which would be more accurate and have lower cost. A detailed discussion of this work is presented in Reference 1 and a brief discussion of the main features of the study are presented below.

Similarity Measures

In order to find the correct registration position one must choose some sort of measure of the similarity of the two images to use. The registration position is then that location at which the two images are most similar. For this study three measures are compared: the correlation coefficient, the correlation function, and the sum of the absolute value of the difference.

The correlation coefficient measures the linear relationship of two images on an absolute scale ($|p| \leq 1$). A value for $|p|$ close to one indicates that the two images are highly similar. This is the measure presently used in the registration system at LARS.

The correlation function is the sum of the cross product of the corresponding points in both images. This is an unnormalized measure, so that it denotes the registration merely by a maximum or minimum, the actual value having no bearing on the similarity.

Ths sum of the absolute difference method is like the correlation function in that it is an unnormalized measure. This is the measure used for a class of similarity detection algorithms developed at IBM.[2]

Enhancement Algorithms

Location of the correct registration position may be facilitated by preprocessing the images prior to use of a similarity measure to do the actual registration. Such preprocessing, if shown to give an improvement, can be viewed as part of an optimum type processor for the registration. For example, the entire registration procedure may be more reliable with a preprocessed data set, or one may gain a substantial saving in the time and number of operations required.

For this study five types of preprocessing were chosen: magnitude of the gradient (thresholded and non-thresholded), CSC gradient* (thresholded and non-thresholded), and thresholding the image at its median.

Algorithm Evaluation

The first part of this study is concerned with the comparative performance between the similarity measures with the original data and preprocessing techniques. For all cases it was found that the correlation coefficient gave the best performance (ability to locate acceptable registration positions). However, the absolute value of the difference also performed quite well for the magnitude of the gradient, and gave almost the same results as the correlation coefficient for the thresholded magnitude of the gradient. In consideration of the number of operations and time required for locating the registration positions, it may be advantageous to use the absolute value of the difference instead of the correlation coefficient for these latter two preprocessing techniques, since the performance is about the same.

The relative reliability between the preprocessing methods for a given similarity measure is the object of the second part. The abilities to locate acceptable registration positions for the preprocessing techniques using the correlation coefficient as the similarity measure are compared. The results can be divided up into three sections: overall results; high correlation results ($|p| \geq 0.5$ for the original data); and low correlation results ($|p| < 0.5$ for the original data).

Overall the magnitude of the gradient performed the best (fewest number of false registration positions) while the thresholded gradient and thresholded CSC gradient also did quite well. In this case there did seem to be a slight improvement using the preprocessed data as opposed to the original data.

For the high correlation case all of the methods including the original data did exceeding well with the magnitude of the gradient again doing the best. One may infer from these results that any choice would give about the same performance.

The most striking results were obtained for the low correlation comparisons. For this case there was a substantial increase in performance over the original data for the magnitude of the gradient, thresholded magnitude of the gradient, and thresholded CSC gradient. The magnitude of the gradient again gave the superior performance.

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* "CSC gradient" refers to an algorithm developed by P. Beaudet at Computer Sciences Corporation.

Based on these three sets of results one may conclude that it may prove useful to use preprocessing prior to the image registration. Of the preprocessing techniques examined above, the best choice seems to be the magnitude of the gradient since it had fewer indicated false positions than any of the other methods. It also requires fewer number of operations for implementation than the other two methods that also did fairly well (thresholded gradient and thresholded CSC gradient).

Several other points of interest are also discussed in Reference 1. The results supported the concept that a correlation coefficient value close to plus or minus one should give virtually no false registration positions. And when the magnitude of the correlation coefficient surface has a peak at a false registration location, it is possible to have a smaller peak at the correct shift position. This implies that search for a secondary peak may be useful in the false peak cases.

One will notice when looking through the correlation coefficient results for the original data that both positive and negative values appear. This is acceptable since it is possible that a span of time will bring negative type changes in the imagery (e.g., planting and harvesting of crops). One circumvents the problem of searching simultaneously for a maximum and minimum of the correlation coefficient by looking only at its absolute value. However, for the correlation function and absolute difference function there is no such way of avoiding this double search, which can be ambiguous since these have no absolute scale. One might consider it desirable to use a data set that inherently bypasses this problem. This is achieved via the magnitude of the gradient and CSC gradient preprocessing techniques. For these data sets it is necessary to record only one value for any similarity measure used.

One of the most important points of this entire study is, what would be the recommended processor combination of similarity measure and preprocessing technique presented here. Basing the decision on the performance and number of operations involved, a good choice is the magnitude of the gradient with the sum of the absolute value of the difference. In all cases the magnitude of the gradient using the correlation coefficient performed better than all other methods. And in lieu of the number of operation involved, the reduction by use of the absolute difference measure should warrant its use since it still gave a high performance.

Registration Error Variance as a Measure of Overlay Quality

A theoretical investigation was carried out as part of the registration project to develop a model for estimating the ultimate registration accuracy that could be achieved under given assumptions. The difference in the two images obtained at different times over the same areas is assumed to be due to additive noise. The method of solution employed is an adaptation of that used for the determination of the error in the measured delay time in a radar system. Several analyses of the radar problem have been carried out based upon different premises. These approaches may be categorized as those which use the probability density function of the noise directly and those which do not. The first case utilizes maximum a posteriori, maximum likelihood, or minimum mean square error estimates. All three estimators are based upon knowledge of the noise probability density function. The second case is based only upon the output of a filter which gives a maximum output at the correct time delay when the input is noise free.

An analysis such as this should prove useful in several respects. The results should give an indication of the best possible registration of two images given the models of the data and noise. Once the models of the parameters involved have been found or assumed, an optimum receiver to implement the overlaying procedure may be developed. Comparison of existing registration systems with the results obtained herein may also be performed. However, it must be kept in mind that for different assumptions upon which the entire analysis is based different results may be obtained.

It was assumed in the investigation that the useful signal is present, reducing the problem to one of estimation only rather than detection as well as estimation. It is further assumed that the signal shape is known and nonrandom, although the parameter that is to be measured is a random variable. Since the original signal is known, it does not have a probability density function. However, the received signal does depend upon the noise and its distribution. The problem was approached with this in mind. A detailed discussion of the work is presented in Reference 3. An expression was developed which expresses the expected error in the registration as a function of the signal-to-noise ratios of the images.

Image Distortion Function Research

INTRODUCTION

The second task area in registration research was concerned with the utilization of the checkpoints or matching points for transforming or warping the image data to match a reference image. Work in this area explored several approaches to functional approximations of the geometric distortions present in the images to be corrected. This work is applicable to the image-to-image registration problem or to the image-to-reference coordinate system registration which is referred to as geometric correction.

The existing LARS image registration system uses a bi-quadratic image distortion function for representing the transformation necessary to achieve registration of one image with respect to another. This function has performed satisfactorily for most LANDSAT registration tasks, however, alternate functions have not been tested to determine the adequacy of the current approach. Two functions other that the bi-quadratic were tested on LANDSAT data to observe the performance of those simpler functions. Another activity in this task has developed a bi-cubic spline function approximation algorithm which is intended as a general purpose distortion function for handling all types of registration and geometric correction tasks. A single cubic function would be able to handle purely translational (zero order), linear, quadratic (one extremum) and cubic (two extrema) distortions. This is expected to be satisfactory for most cases; however, for aircraft scanner data and certain other troublesome cases the cubic spline algorithm will enable a set of cubic polynomials to be joined together with continuity in value and derivative so that any order of distortion can be represented. The functional approximation work is discussed briefly below and a larger report is included in Reference 4 for the bi-cubic spline research. No further report is intended for the comparison of the two simpler functions since the results indicated the bi-quadratic produced superior results.

Comparison of Basic Functions

Three functions were compared for accuracy of representation of checkpoints obtained from LANDSAT-1 data over Tippecanoe County in 1972. In this experiment, the reference image was an aerial photograph, and 104 checkpoints were obtained manually from the photo and LANDSAT image. The aerial photography was at a scale of approximately 1:24,000 and the LANDSAT data when reproduced on a line printer to simulate an image also has a scale of the vicinity of 1:24,000. The checkpoints were obtained by visually finding matching points in the two images and measuring the spatial coordinates.

The 104 points were used in two ways in a least squares solution for their mathematical models. The first is called the four parameter transformation and is of the form:

$$z = a_0 + a_1 x + a_2 y$$

$$w = b_0 - a_2 x + a_1 y$$

where x and y are the coordinates in one image and z and w are the transformed coordinates. In this transform there are four degrees of freedom which represent translation in two dimensions, rotation and change of scale. Two checkpoints are sufficient to specify the parameters here. The second transformation is called the projective and is of the form:

$$z = \frac{a_1x + a_2y + a_3}{c_1x + c_2y + 1}$$

$$w = \frac{b_1x + b_2y + b_3}{c_1x + c_2y + 1}$$

This transformation has eight degrees of freedom and can model a more complex geometric variations. For the case of four checkpoints the transform matches these points exactly. The third transform is the one currently used in the LARS registration system. It is termed bi-quadratic and is of the form:

$$z = a_0 + a_1x + a_2y + a_3x^2 + a_4y^2 + a_5xy$$

$$w = b_0 + b_1x + b_2y + b_3y^2 + b_4y^2 + b_5xy$$

Here there are twelve parameters and nonlinear distortions having no more than one extremum can be modeled.

The 104 checkpoints were used to compute the parameters for the three transformations in three experiments; one using all points, one of 52 points and one of 8 points.

The remaining points were used as test in the last two cases. The root mean square error in each case was computed for the three transforms. The results are presented in Table 1. In every case the bi-quadratic model gave lower error than the other two. This indicated that even over a small portion of a frame (approximately one quarter of a frame) the linear transforms were less accurate than the quadratic but the margin was small over the projective equations. The conclusion drawn was that the current quadratic is adequate for the area and data studied and it was recommended that the registration system continue using this function.

Bi-Cubic Spline Function Algorithm

A general solution to the image distortion approximation problem was pursued to develop an approach which would handle distortions in aircraft scanner, satellite scanner, photographic and other data without registration system modifications. A considerable research effort went into the study and the bi-cubic spline function approach emerged as particularly attractive. An algorithm is under development which will implement the cubic spline function and a general description of the techniques involved are included in Reference 4.

ITTING EQ.	RMS ERROR									
	ALL POINTS (104)		USING HALF THE POINTS				USING EIGHT POINTS			
			CONTROL (52)		CHECK (52)		CONTROL (8)		CHECK (96)	
	LINE	COL	LINE	COL	LINE	COL	LINE	COL	LINE	COL
4 PARAMETER	1.0390	1.6536	.9466	1.6267	1.1227	1.7031	------	------	-------	-------
BIQUADRATIC	.6675	1.2074	.6546	1.1807	..7168	1.2819	.1560	.3647	.8440	1.4180
PROJECTIVE EQNS.	.6714	1.5008	.6167	1.4682	.7432	1.5658	.1798	.4531	1.0006	2.1331

Table 1. Results of Approximation of 104 LANDSAT-1 checkpoints with three tranformation models for geometric correction and overlay.

The algorithm accepts randomly located checkpoints defining image distortion and generates a set of least squares two-dimensional cubic polynomial approximations which join with continuity in value, first and second derivative. For low distortion cases such as portions of a LANDSAT frame usually one polynomial is adequate. Should cases be encountered with distortion more severe such that a single cubic cannot accurately describe the variations, additional functions can be added and joined together so that an accurate approximation is obtained without increasing the order of the approximating polynomial. Completion of the algorithm is expected early in CY76 and a final report will be generated fully describing the work.

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VIII. Effective Utilization of Data Dimensionality

Layered Classification

INTRODUCTION

Rationale

Numerically-oriented remote sensing systems have attempted to provide fast and accurate information on the types of ground cover on the earth's surface beneath the sensor. Traditionally single multiclass decision logic has been utilized to achieve a point-by-point classification of the scene. The most commonly used decision rule has been the Gaussian maximum likelihood rule. This decision rule minimizes the probability of misclassification under the assumption that the data in the individual spectral classes are normally distributed. Such a scheme has the following inherent features:

a) The same feature set is used to classify all points in the scene;

b) for each point in the scene the likelihood function must be computed for all possible classes, thus requiring a large amount of computation; and

c) with a relatively small size training set the classification accuracy may actually decrease when the number of features is increased (the "dimensionality phenomenon").

Given these inherent features, use of a more complex decision logic called the Decision Tree Classifier (Layered Classifier), is being developed because it can provide improved classifier performance, both in terms of accuracy and computational efficiency.

Previous Work at LARS

The theoretical foundations for this classification approach and the design of decision trees have been discussed at length in Reference 1 and will not be treated again here. A draft package of FORTRAN programs including a decision tree classifier and software for the design of decision trees was developed in the course of this study.

Objectives and Goals

The goal of the most recent work has been to extensively test the performance of the layered classifier with regard to both accuracy and efficiency and to attempt to develop an effective procedure for optimal decision tree design. Furthermore we wished to establish a criterion for deciding whether a decision tree is both accurate and efficient without having to actually classify the data. Various applications have been investigated to determine if these applications are appropriate for the decision tree classifier.

Accomplishments

To achieve these goals, several data sets previously classified at LARS were reclassified using the layered classifier approach. We have been able to establish that in general the results obtained with the layered classifier are comparable in accuracy to those obtained with a conventional maximum likelihood classifier, but the layered classifiers are generally more efficient.

We have not yet been able to establish a stringent theoretically-founded criterion to decide whether or not a decision tree is good. However, we have succeeded in developing a procedure for optimal tree design which includes an a priori rule for determining the actual performance of a decision tree. We have also been able to show that the decision tree classifier has potential far beyond that of the conventional maximum likelihood classifier with regard to multitemporal data sets containing clouds.

DESCRIPTION OF RESEARCH

Theoretical Approach

The research described in this report is wholly based on the work presented in Reference 1, and the following paragraphs are intended to give a short summary of this work:

The decision tree classifier is essentially a maximum likelihood classifier using multistage decision logic. It is characterized by the fact that an unknown sample is classified into a class using one or several decision functions in a successive manner. The classification strategy can be most easily illustrated by a tree diagram.

Several procedures for the design of decision trees have been established[1], two of which will be described here:

The Manual Design Procedure

After a mean vector and covariance matrix for each class have been calculated, a graph of the means and variances of each class for each feature is obtained (i.e., a LARSYS coincident spectral plot). It is then possible to determine suitable decision boundaries from this plot, so that all classes can be separated in a finite number of decision stages. This is equivalent of determining at each stage mutually dissimilar groups of classes and an appropriate set or subset of features to perform the classification at that stage.

The Optimized Tree Design Procedure

In the manual design procedure mentioned above little concern is given to the cost of classification expressed in terms of the probability of misclassification and the classification time. One soon finds, on utilizing the above procedure, that a unique decision tree does not result; there are numerous possibilities. In order to determine the optimum tree under given constraints a heuristic search through the classes and feature subsets is used.

When the number of available features exceeds about 4, an exhaustive search of all feature subsets is not feasible and a smaller group of feature subsets must be selected to be used in the search.

For these selected feature subsets a measure of pairwise interclass separability is computed for all class pairs. This measure can either be the transformed divergence or a transformed Bhattacharyya distance which is closely related to the Bhattacharyya error bound. For each feature subset, a non-supervised clustering[1,2] is then performed on the class distance matrix in order to find mutually dissimilar and separable groups of classes. The cost (a combination of accuracy and efficiency) of the decision at each node of the tree is then evaluated and the feature subset with the minimum cost is chosen. In case the clustering procedure is not successful, the decision at a certain stage will be made using a conventional maximum likelihood classification with the feature subset having the largest average pairwise separability, thus minimizing the probability of error.

The cost function used to evaluate the feature subsets in the search is an additive measure of efficiency and accuracy. A thorough discussion of the nature of this function can be found in Reference 1.

The search is terminated when each class can be separated from the others and no more decisions need to be made.

The class statistics and the decision tree, with information about the feature subset and the classes used in each node, are used to classify an unknown sample by following a sequence of decisions through the tree until a final decision (terminal node) is reached.

RESULTS

The Manual Design Procedure

The manual design procedure has not been our main concern, because its usefulness is limited to relatively elementary problems. However, during the course of this study we have had opportunity to investigate a few of its properties. This procedure has been mainly used for the thermal mapping of water bodies, where the number of spectral classes is usually small. Also, water is very easily separated from other cover types using only one feature, usually in the near infrared. The performance of the different decision trees used in thermal mapping has varied; the experience of the analyst and his understanding of the problem are of major importance in the design of accurate and efficient trees. Efficiency comparisons with the LARS Maximum Likelihood Classifier are not easily made since the classifying subroutines in the two classifiers are written in different languages. The layered classifier, with a FORTRAN classifying subroutine, actually is less efficient than the LARSYS Classifypoints processor, which has an assembly language classifier.

Generally we do not recommend the Manual Design Procedure at this stage as it is subjective and depends greatly on the skill of the analyst.

The procedure, however, is advantageous in cases where one or more of the following circumstances pertain:

a) few classes

b) ill-conditioned statistics

c) the analyst is only interested in a subset of all classes in the data, which can be easily separated from the rest of the classes using a single feature.

A typical example of the applicability of this approach is given in Reference 3.

The Optimized Tree Design Procedure

A series of experiments has been performed designing a large number of trees for a 19 class, 4 feature classification. The data was taken by LANDSAT-I over Kenosha Pass, Colorado, on August 15, 1973. The training statistics were provided by Michael D. Fleming of LARS from work supported by USFS Contract #21-292. The area classified was part of LANDSAT Frame No. 1388-17134. Since the number of possible feature subsets was small (15), all subsets were considered in the search procedure. The two main input parameters to the design program--the threshold used in the clustering and tradeoff constant (a constant that determines the relative weight of accuracy and efficiency)--were systematically varied.

Performance and accuracy of the trees have been compared to classifications obtained by one-stage procedures using the layered classifier program and the LARSYS maximum likelihood classifier using 4, 3 and 2 features (Table 1). The feature subset used in a one-stage classification with 3 or 2 features was the feature subset having the maximum average pairwise divergence among the classes. For each set of parameters, two trees, one using transformed divergence and the other using the Bhattacharyya error bound, were constructed. The data set was classified for as many trees as seemed appropriate (a large number) and the training field performances and computation times were recorded. Generally, all trees were more efficient than the layered classifier using a one-stage procedure. The least efficient tree was 40% faster than the one-stage procedure and the most efficient tree was approximately 70% more efficient. This was true for all possible combinations of features. Many trees were more efficient than the LARSYS classifier despite the fact that the layered classifier is programmed in FORTRAN, whereas the LARSYS Program has been optimized in assembly language. This suggests that additional gains in computational efficiency will result when the layered classifier is reprogrammed in a more efficient code.

Comparing trees designed using transformed divergence to those designed using the Bhattacharyya bound we found that generally the latter were more efficient with an insignificant reduction in accuracy.

The results of the above study have led us to suggest the following procedure for using the heuristic search to design trees:

1. Train (determine class statistics) carefully and combine or delete those classes that have very low separability.

2. Use a feature selection algorithm to determine the feature subsets to be used in the search procedure. It is recommended that no more than 30-50 feature subsets should be used. The feature subsets chosen for the search procedure need not necessarily fulfill the criterion of maximum separability for all classes. Subsets that provide good separability for a small subset of the classes may be selected. The feature subsets should always be selected with regard to the particular problem the analyst is working with. In the case of LANDSAT data it is recommended that all 15 feature subsets be used in order to maintain acceptable accuracy.

3. Use the "distance program" (a FORTRAN program that computes either transformed divergence or the Bhattacharyya error bound for selected feature subsets) to obtain pairwise interclass separabilities for all feature subsets to be used in the search. This program is also very useful in the manual design procedure, as the separabilities can be computed for selected feature subsets.

4. Use the search program to design a tree, or design a tree manually with the help of the coincident spectral plot and the interclass separability information for the candidate feature.

5. Draw the tree.

A good tree should have the following properties:

It should have both breadth and depth. A tree that is only deep or only broad will either be less accurate or very inefficient, and sometimes both. The tree might not have any terminal nodes in the first layer and as few as possible in the second layer. The more terminal nodes in the first layer, the closer the tree approaches a conventional maximum likelihood classifier.

The rules outlined above are not theoretically founded but appear practicable. However, it is not always possible to obtain a tree both broad and deep. The tree structure is highly dependent on the inter-class separabilities and the distance measure used. One should therefore design several candidate trees by keeping the threshold for inter-class separability fixed and varying the tradeoff constant.

Classification under clouds using multitemporal data

Cloud cover in a scene has traditionally decreased the value of an image, as it has inhibited a point-by-point classification of the ground cover types. The decision tree classifier is a new tool which we can use in classifying a multitemporal scene which is partly obscured by clouds.

In a small experiment we have been able to successfully classify such a scene completely into cover types.

A sequential approach to classification is used in this application. The data is first classified into the classes existing at one date, including clouds and cloud shadow. Whenever a terminal decision cloud or cloud shadow is reached, the pixel is classified once more, in one or several steps, using another date with no clouds at this point in the scene. The scene we classified using this approach is Livingston County, Illinois, data originally acquired for the CITARS project. Data for Livingston County had been obtained for five dates in 1973: June 10, June 29, July 16, August 3, and August 21. These five dates were overlaid to produce a 20 feature data set.

The experiment was performed in two parts:

a) Training statistics were obtained from training fields of known cover type by clustering with the LARSYS CLUSTER processor. Eight features used for clustering: the four channels from June 29 and the four from July 16. Two trees were derived containing classes "clouds" and "cloud shadow," and another tree was derived for July 16 containing no cloud classes. The trees were interconnected so that the terminal nodes for the cloud classes served as the root node for the tree without clouds.

b) We trained the classifier separately for each of the two dates, using four features in the training phase. The same tree design procedure was used as in part a. Training field performance was approximately 70 percent and test field performance was 60 percent, results comparable to the CITARS analysis results.

We believe that the method outlined above can be successfully applied to multitemporal data sets with up to 30 percent cloud cover on a single date. LANDSAT collects data over a given region every 18 days and the probability of clouds over any point in the scene is on the order of 0.5 (averaged over the whole year for the central USA). Assuming less than 30 percent cloud cover in a scene we find that the probability of a given point on the ground being covered with clouds on both dates is less than 0.0225. Including data from a third pass in the third pass in the analysis reduces this probability even further.

RESULTS

Our investigation has shown that for any given problem a layered classifier can generally be designed which is comparable in accuracy to and more efficient than the conventional maximum likelihood classifier. The design of optimal decision trees, however, is not a simple matter and at this point must be considered an unsolved problem. For very simple applications involving a small number of easily separable classes, a manual design procedure is available by means of which suitable decision trees can be derived. For most practical applications, though, a computerized design procedure is required because of the vast number of possible decision trees which must be considered. One such procedure has been developed, based on a heuristic search method, and tested on multispectral LANDSAT data. Although the trees produced by this specific procedure have proven satisfactory, it is known that they cannot in general be expected to be optimal. Also, selection of the best tree from a number of candidates depends on the judgement of an experienced analyst.

The flexibility of the layered classifier approach makes it possible to apply effectively machine classification to a wide range of remote sensing problems which are at best awkwardly handled using conventional single-stage classifiers.[3,4] A number of examples are shown in Table 2. But the development of the layered classifier method is only in its infancy; extensive research and development of this machine processing approach may be anticipated to pay substantial dividends in the future. In particular, we recommend that further effort be expended on the following fronts.

1. Further study is required to better understand the characteristics of the tree design procedures developed under this study. A number of design parameters are involved as well as user judgment as to the best of the candidate trees produced. Objective criteria for setting these parameters and selecting the "best" decision tree are needed.

2. Efforts to date have produced research software which can only be effectively used by the programmer. Refinement of the software and improvement of its compatibility with LARSYS would improve its availability to user scientists at LARS and at NASA. By making available to the potential users the capability developed to date, we expect to accelerate the applicability of this new technology to practical remote sensing problems. Several applications of immediate concern are now awaiting progress on this front.

3. Further research is required into optimal decision tree design procedures. The decision trees produced by the currently available procedure, while generally superior to comparable single-stage classifiers, are generally not optimal. A wide range of mathematical programming techniques should be investigated as possible means for solving this problem.

Table 1: PERFORMANCE OF DECISION TREES

I. Tree Designation Code

II. Number of Feature Subsets Searched

III. Maximum Number of Features Used in a Node

IV. Number of Nodes in Tree

V. Threshold

VI. Tradeoff Constant

VII. Time Constant

VIII. Virtual CPU Time (sec.)

IX. Overall Performance (percent correct)

A) One-Stage Classifier

I	II	III	IV	V	VI	VII	VIII	IX
2/18	15	4	20	1600	20.0	15.15	1574.18	93.7
2/52	14	3	20	1800	100.0	10.21	1035.82	93.0
2/123	10	2	20	1850	90.0	6.03	652.79	90.2
LARSYS	--	4	--	----	----	-----	920	93.7
LARSYS	--	3	--	----	-----	-----	650	93.0
LARSYS	--	2	--	----	----	-----	360	90.2

B) Transformed Divergence used as selection Criterion

I	II	III	IV	V	VI	VII	VIII	IX
2/1	15	4	57	1950	20.0	5.09	756.40	93.7
2/2	15	4	62	1950	10.0	4.58	655.23	93.6
2/3	15	4	52	1950	30.0	4.49	672.40	93.7
2/4	15	4	47	1950	40.0	4.64	662.50	93.7
2/5	15	4	41	1950	50.0	5.53	721.59	93.7
2/6	15	4	30	1950	60.0	7.20	862.97	93.7
2/7	15	4	30	1950	70.0	7.20	862.91	93.7
2/8	15	4	30	1950	80.0	7.20	863.56	93.7
2/9	15	4	30	1950	90.0	7.20	864.35	93.7
2/10	15	4	30	1950	100.0	7.20	863.08	93.7

Table I: PERFORMANCE OF DECISION TREES (continued)

2/11	15	4	70	2000	20.0	5.25	735.47	93.7
2/13	15	4	44	1850	20.0	4.75	674.53	93.6
2/14	15	4	46	1800	20.0	4.92	702.03	92.6
2/15	15	4	43	1750	20.0	5.18	765.75	92.4
2/16	15	4	32	1700	20.0	5.40	773.85	93.5
2/17	15	4	33	1650	20.0	5.68	727.90	92.1
2/18	15	4	33	1600	20.0	5.68	727.34	92.1
2/19	14	3	54	1950	20.0	3.97	581.58	92.9
2/20	14	3	54	1950	10.0	3.97	581.43	92.9
2/21	14	3	59	1950	5.0	3.66	521.44	92.9
2/22	14	3	38	1950	30.0	4.16	547.01	92.9
2/23	14	3	38	1950	40.0	4.16	542.63	92.9
2/24	14	3	30	1950	50.0	5.16	747.98	51.3
2/25	14	3	30	1950	60.0	5.16	747.15	51.3
2/26	14	3	30	1950	70.0	5.16	746.36	51.3
2/27	14	3	30	1950	80.0	5.16	747.34	51.3
2/28	14	3	30	1950	90.0	5.16	745.37	51.3
2/29	14	3	30	1950	100.0	5.16	733.54	50.5
2/30	14	3	37	2000	100.0	4.38	585.60	77.3
2/31	14	3	37	2000	90.0	4.38	736.44	61.5
2/32	14	3	37	2000	80.0	4.38	734.40	61.5
2/33	14	3	37	2000	70.0	4.38	734.31	61.5
2/34	14	3	37	2000	60.0	4.38	735.61	61.5
2/35	14	3	37	2000	50.0	4.38	735.81	61.5
2/36	14	3	37	2000	40.0	4.38	737.50	61.5
2/37	14	3	37	2000	30.0	4.38	737.36	92.7

Table I: PERFORMANCE OF DECISION TREES (continued)

2/41	14	3	61	1900	5.0	3.56	525.76	90.9
2/42	14	3	54	1900	10.0	4.06	611.24	77.0
2/44	14	3	43	1900	30.0	4.57	612.87	79.3
2/56	14	3	37	1800	60.0	4.24	560.27	84.8
2/60	14	3	43	1800	20.0	3.81	529.33	91.9
2/61	14	3	48	1800	10.0	3.61	525.88	91.1
2/63	14	3	40	1700	5.0	3.45	498.38	92.4
2/65	14	3	32	1700	20.0	4.10	653.09	60.1
2/70	14	3	55	1850	5.0	3.20	470.03	91.7
2/71	14	3	55	1850	10.0	3.49	526.96	91.9
2/72	14	3	38	1850	20.0	3.80	625.18	52.5
2/81	10	2	47	1950	5.0	3.22	555.19	62.3
2/82	10	2	47	1950	10.0	3.22	555.19	62.3
2/85	10	2	30	1950	40.0	3.43	523.81	65.7
2/92	10	2	38	2000	5.0	3.12	538.82	61.0
2/103	10	2	37	1900	5.0	3.32	549.34	65.3
2/114	10	2	38	1850	5.0	3.14	435.94	92.2
2/118	10	2	35	1850	40.0	3.07	429.99	90.0
2/125	10	2	37	1800	5.0	3.02	396.38	89.9
2/133	10	2	34	1700	5.0	2.99	413.62	69.9

C) Bhattacharyya-bound USED as Selection Criterion

2/1	15	4	54	1950	20.0	3.99	544.97	93.5
2/2	15	4	54	1950	10.0	3.80	546.17	93.5
2/3	15	4	48	1950	30.0	4.39	565.53	93.5
2/4	15	4	43	1950	40.0	4.55	571.59	93.5
2/5	15	4	44	1950	50.0	6.12	857.23	93.6

Table I: PERFORMANCE OF DECISION TREES (continued)

2/6	15	4	44	1950	60.0	6.12	854.32	93.6
2/7	15	4	44	1950	70.0	6.12	853.50	93.6
2/8	15	4	50	1950	80.0	5.25	706.48	93.7
2/9	15	4	50	1950	90.0	5.25	706.16	93.7
2/10	15	4	50	1950	100.0	5.25	706.61	93.7
2/11	15	4	57	2000	20.0	7.87	1035.87	92.9
2/12	15	4	40	1900	20.0	5.04	668.58	93.7
2/13	15	4	51	1850	20.0	4.51	662.30	93.1
2/14	15	4	37	1800	20.0	5.01	681.87	93.5
2/15	15	4	36	1750	20.0	5.10	700.64	91.3
2/16	15	4	36	1700	20.0	4.71	654.75	91.1
2/17	15	4	35	1650	20.0	4.64	640.92	91.2
2/19	14	3	44	1950	20.0	3.45	453.59	92.9
2/20	14	3	50	1950	10.0	3.22	440.51	92.9
2/21	14	3	50	1950	5.0	3.22	440.03	92.9
2/22	14	3	39	1950	30.0	3.54	460.57	88.0
2/23	14	3	44	1950	40.0	4.52	811.49	54.5
2/24	14	3	44	1950	50.0	4.52	809.29	54.5
2/25	14	3	44	1950	60.0	4.52	804.25	54.5
2/26	14	3	44	1950	70.0	4.52	807.50	54.5
2/27	14	3	44	1950	80.0	4.52	805.29	54.5
2/28	14	3	38	1950	90.0	5.02	819.37	55.7
2/29	14	3	35	1950	100.0	5.22	773.67	56.7
2/30	14	3	46	2000	100.0	5.75	847.27	55.6
2/31	14	3	46	2000	90.0	5.75	844.97	55.6
2/32	14	3	46	2000	80.0	5.75	844.86	55.6

Table I: PERFORMANCE OF DECISION TREES

2/33	14	3	46	2000	70.0	5.75	844.05	55.6
2/34	14	3	46	2000	60.0	5.75	847.89	55.6
2/35	14	3	46	2000	50.0	5.75	848.57	55.6
2/36	14	3	46	2000	40.0	5.75	860.05	55.6
2/37	14	3	46	2000	30.0	5.75	860.12	55.6
2/41	14	3	61	1900	5.0	3.39	449.74	91.3
2/42	14	3	56	1900	10.0	3.61	480.89	92.1
2/43	14	3	35	1900	20.0	4.30	692.88	46.7
2/56	14	3	33	1800	60.0	4.16	655.33	57.6
2/61	14	3	41	1800	10.0	3.49	552.48	65.1
2/62	14	3	44	1800	5.0	3.38	627.22	45.4
2/63	14	3	35	1700	5.0	3.77	584.12	66.3
2/70	14	3	53	1850	5.0	3.24	442.70	87.0
2/71	14	3	48	1850	10.0	3.55	659.18	50.5
2/72	14	3	43	1850	20.0	3.71	633.59	41.1
2/81	10	2	44	1950	5.0	3.16	451.17	91.6
2/82	10	2	44	1950	10.0	3.16	471.67	91.6
2/83	10	2	38	1950	20.0	3.39	484.22	78.6
2/92	10	2	29	2000	5.0	4.74	666.97	70.9
2/103	10	2	39	1900	5.0	3.09	509.33	48.6
2/106	10	2	35	1900	30.0	3.04	517.49	67.0
2/114	10	2	43	1850	5.0	2.77	388.03	90.4
2/116	10	2	37	1850	20.0	3.04	405.74	83.4
2/125	10	2	34	1800	5.0	3.03	415.25	75.1
2/127	10	2	33	1800	20.0	2.96	414.39	91.0
2/133	10	2	35	1700	5.0	2.79	394.08	86.7

Table 2. SOME APPLICATIONS OF LAYERED CLASSIFIERS

General Application	Example
Change Detection	Snow pack variation Water level variaton (e.g., reservoirs) "Urban sprawl" Logging practices
Use of Mixed Feature Types	Texture Topography Geophysical data (e.g., aeromagnetic)
Class-specific Properties	Crop disease detection Forest type mapping Water quality mapping Water temperature mapping
Other	Avoidance of cloud effects Minimization of data dimensionality

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IX. Pre-Processing Algorithms Research

Scanner Instantaneous Field of View Compensation

An SR&T research project begun in CY74 was completed during CY75 and it produced an algorithm for compensating for the finite (i.e. non-infinitesimally small) instantaneous field of view of scanning sensors such as the LANDSAT MSS system. No image collecting or imaging system will produce a perfect replica of the original image; further processing can usually result in higher data quality. The area of image restoration deals primarily with the problem of processing the output of an imaging system in such a way that the significant spatial parameters or features of the original image are, in some sense, enhanced or restored. This processing may be linear or non-linear, shift-variant or shift-invariant depending upon the type of degradation produced by the imaging system.

The primary purpose of this research project was the development of a technique to reduce the effective aperture radius of the multispectral scanner system used for remote sensing of earth resources. Because of the finite point-spread function of the scanner and the response limitations of the image sensors and signal conditioning electronics, a slight two-dimensional spatial smearing or blurring of the original image is produced. This type of imaging degradation essentially maps many points from the original image into a single resolution element. In other words, a single resolution element of the imaging system output represents a two-dimensional weighted sum of many points adjacent to the correspondingly located sample of the original image. Thus, depending upon the density and shape of the effective aperture and the spatial and multispectral characteristics of the original image, this type of imaging degradation may not only introduce significant error in the visual presentation of this data, but also introduce serious errors when classification of this data is attempted.

An optimum shift-invariant restoration filter was formulated here based upon minimizing the radius of gyration of the overall or composite system point-spread function subject primarily to constraints on the radius of gyration of the restoration filter point-spread function and on the total noise in the restored image. In addition, an iterative technique was developed which suppresses secondary oscillations in the composite system point-spread function. For numerical solution convenience, the problem was transformed into the spatial frequency domain and a system of linear differential equations which specify the spectrum of the restoration filter was developed.

The application of well-known digital computer algorithms to the solution of the system of linear differential equations specifying the spectrum of the restoration filter was carried out. An investigation of the fundamental properties of the restoration filter was performed and a study of the filter performance as a function of its parameter variations was included. The restoration filter was applied to LANDSAT MSS data to begin evaluation of the benefits of this particular algorithm. Two significant problems were encountered that are inherent in the LANDSAT data collection system. The first problem is the poor signal-to-noise ratio of the LANDSAT data. This problem could be reduced by both reducing the quantization level increment size and by increasing the dynamic range of the data prior to quantization. The second problem, the need for relatively large interpolation ratios to match the effective blurring aperture of the LANDSAT data system to the available restoration functions, could be minimized by increasing the data sampling rate. Since less interpolation would be required, both greater interpolation accuracy and increased processing efficiency could be achieved. By addressing both of these problems, more powerful restoration functions may be applied to the data thus producing even greater resolution improvement.

The study has demonstrated that it is possible to design a restoration filter based upon minimizing the radius of gyration of the composite system point-spread function while constraining the radius of gyration of the point-spread function of the restoration filter and the noise power in the restored image. By assuming that the blurring aperture and composite system noise process are separable, a significant reduction in solution complexity was introduced. Transformation of the defining spatial equations into the frequency domain led to a further simplification in that a system of linear differential equations results for second-order spatial weighting functions in both the radii of gyration of the composite system and restoration filter point-spread function. Through application of well-known numerical solution techniques to this system of equations, a solution which satisfied the original constraints was obtained. Additional control over secondary oscillations in the composite system point-spread function was made possible by the introduction of an iterative technique. It was further shown that the resulting restoration filters satisfied the fundamental design criteria: reduction of the radius of gyration of the composite system point-spread function, and reduction of truncation error by constraining the radius of gyration of the restoration filter point-spread function.

One of the most significant results of this study was the successful application of this restoration technique to data which was blurred by an unknown function. By assuming a Gaussian model for the LANDSAT multispectral scanner aperture and employing an interpolation technique to match the effective scanner blurring aperture to the Gaussian aperture for which the most powerful restoration functions had been computed, a significant restoration of truncated LANDSAT data was obtained. In addition, because of the constraint on the radius of gyration of the restoration filter point-spread function, the truncation error was almost entirely limited to a small region near the edges of the image. Thus substantial restorations having a high signal-to-noise ratio and negligible truncation error were achieved.

The work performed during the study is described in detail in Reference 1. Full evaluation of the usefulness of this filter will require its application to several data sets followed by a detailed evaluation of the filtered and unfiltered data. Both image evaluation and evaluation of the classification results need to be done. Some evaluation of the effects on classification accuracy is reported, beginning on page IX-4 . Filtered data was provided to JSC as part of a LACIE image enhancement project and details of this activity are discussed in Section F.

Interpolation Techniques for Image Enhancement

A parallel study to the one discussed above was begun to explore the value of basic interpolation schemes for enhancement of LANDSAT and other remote sensor image data. Three basic interpolation techniques were chosen as being most likely to be of benefit in enhancing multispectral scanner imagery; 1) Polynomial Interpolation, 2) Trigonometric Polynomial Interpolation and 3) Sine x/x commonly called SINC function interpolation. These three functions were implemented and each was applied to a sample of LANDSAT data for comparison. The mathematical basis and the details of the research are discussed in Reference 2. Only a brief discussion of the work will be included here.

When continuous data is discretized through sampling there is inevitable distortion that occurs when the data is reproduced. Furthermore, there is no simple way to increase the scale of the sampled data set. A good example of a data set having this problem is the output of the LANDSAT Multispectral Scanner System. This data set is sampled at a discrete set of spatial coordinates and is quantized in amplitude. When the data is reproduced for visual observation, there is an intrinsic graininess in the picture due to the sampling. When an attempt is made to enlarge the picture, difficulty is encountered because data exists only at discrete spatial coordinates and there is no data between these points. One method of attacking this problem is to repeat each point a number of times thus generating a picture that is enlarged in proportion to the number of times thus generating a picture that is enlarged in proportion to the number of repetitions of the points. As can be imagined this type of enlargement does not lead to an improvement of the picture but rather serves to make some of the details more easily seen.

An alternative method of producing an enlarged picture is to compute new values between the original sample points by means of an appropriate kind of interpolation. There are various rationales for selecting interpolating functions. However, none has been found that indicates the appropriate function to use for interpolating the LANDSAT MSS data so as to minimize any errors between the interpolated image and the true original image. There are reasons to believe that such a rationale may exist and when it has been properly defined a new kind of interpolation may be appropriate. In the meantime the three more or less conventional procedures will be used. The first two methods involve passing an appropriate curve through the data points surrounding the range of coordinates where the interpolation is to be performed and then computing the interpolated values from the curve. The third method consists of taking a weighted sum of all data points in the set to compute the interpolated values. The weighting function is the SINC function and this type of interpolation is exact for samples taken from a continuous function having no spatial frequency components higher than one-half the sampling frequency.

The three functions were applied to MSS data from a portion of a frame covering the Washington, D.C. area and a frame over Gary, Indiana. The results using the polynomial method displayed smooth transition between points of greatly differing contrast with no ghosting evident. The results using the trigonometric polynomial were very similar to those for polynomial interpolation. The results using the SINC function interpolator were basically similar to the other two; however, the texture of the image appeared to have a mottled effect. This sort of effect is a known characteristic of the SINC function and can be due to several causes relating to the bandwidth of the function being interpolated. Also it is possible that the SINC function interpolator is providing a type of enhancement in which adjacent points are more completely separated than in the other forms of interpolation.

It can be concluded from examination of the above examples of interpolated imagery that the scene appears to be enlarged without introducing any major changes in its appearance. In many cases details of the scene are more easily discerned.

Lineament Enhancement in LANDSAT Data

A study was conducted as part of the image transformation task into the effectiveness of gradient and Laplacian transformations in enhancing lineaments in LANDSAT imagery. This was a small project but initial results suggested that these techniques would produce an enhancement of some value to geologists. The area studied was small, however, and only one band was studied in detail with limited development of parameters. A more extensive study is recommended to fully explore the enhancement capability of these and other methods of linear feature enhancement. The work done in CY75 is presented in Reference 3.

Evaluation of Enhancement on Classification Accuracy

As part of the evaluation activity for the image interpolation and

IFOV enhancement algorithms developed in CY75 under the preprocessing Algorithms Research Task, a classification study was conducted to determine the effects of these operations. A crop classification test was performed on a site in northern Illinois which had been studied as part of another project. A lake area estimation study was also conducted to determine what effects interpolation and enhancement had on the ability to determine the acreage of small lakes in LANDSAT data using LARSYS classification techniques. The results indicated that basic interpolation did not significantly effect results however the IFOV compensating enhancement greatly improved the lake area estimation accuracy. The details of this work are presented in Reference 4. Again the study was limited and only preliminary results were obtained. More evaluation should be carried out to determine the overall benefits of enhancement on all classification tasks of interest.

Image Enhancement

An image enhancement task was defined for the Preprocessing Algorithm Research Task in mid-CY75 which consisted of two additional objectives:

1. Apply the aperture (IFOV) compensation model for LANDSAT data to LACIE test site imagery and deliver the enhanced imagery and tapes to the LACIE project for evaluation.

2. Evaluate a supervised spectral enhancement technique based on the use of linear combinations of features which maximize the statistical distances between training classes.

These two objectives were pursued during the January-June 1975 period with two examples of enhanced imagery being produced for 1. above, and a research plan was formulated for 2. These achievements are discussed below.

Aperture Compensation Filtering

An image restoration filter has been developed at LARS and it is fully described in Reference 1. This filter was applied to LANDSAT imagery for a site in Finney County, Kansas and a site in northern Indiana. The filter algorithm both interpolates and enhances the data and in the present case it expands the number of lines by a factor of four. This both enlarges the images numerically and approximately corrects for the LANDSAT unequal sampling rates. The enhanced imagery was supplied on tape and in film form to JSC for evaluation. The Kansas imagery was processed for band 5 only and the Indiana imagery was processed for bands 4, 5, and 6.

It is unclear what the best reference imagery is against which to evaluate the enhancement. Two forms of reference were supplied to give JSC a choice (however other forms may be decided on). One was a direct reproduction of each LANDSAT pixel after correction for the higher across track sample rate by dropping each 4th column. This produces an image which has no new estimated pixels and has a nearly square aspect ratio. The images produced by this data must be photographically enlarged by a factor of four to match contact prints of the enhances data. The second method performs a 3x across track, 4x along track duplication of points to expand the data in the same way as the enhancement. This is in effect a zero order interpolation and it produces a blocking effect in the image but the result is at the same scale as the enhancement; thus no photographic enlargement is required. Both processes produce artifacts in the reference, one via distortions in the photographic process and the second in the blocking effect. The best reference depends on the point of view of the user and these decisions are best made by the LACIE program personnel.

Linear Combination Enhancement

The second objective of the Image Enhancement Task concerns linear combinations of bands to give maximum contrast with respect to the classes of interest. Feature extraction in pattern recognition has been an important problem. Tou and Heydorn[5] proposed a procedure for two pattern classes to find a dimension-reducing transformation matrix that maximizes the divergence in the reduced dimension. C. Babu[6] extended the idea to the multiclass problem. Since both approaches have shortcomings, J. A. Quirein of the University of Houston has proposed some comparatively simple methods for computing the transformation matrix for greater separability among reduced data.

In the current project the usefulness of a supervised spectral image enhancement technique based on the use of linear combinations of features which maximize the statistical distance among training classes is being evaluated.

Description of Research

After the number of classes to be classified has been determined, linear combinations of features which will reduce the dimension of the data vector and yet maximize the class separability are desired. The class separability depends not only on the class distributions but also on the classifier to be used. At LARS a Bayes classifier is implemented and so we wish to choose the optimum feature set with reference to the Bayes classifier, in order to minimize the probability of misclassification. There are three popular criterions used in attempting to maximize the class separability: the maximum divergence method, minimum Bhattacharyya bound method and minimum transformed divergence method. Given a feature space X of dimension n from the original data, we are seeking a transformation matrix B of dimension k by n such that $Y = BX$ where Y is a vector of dimension k.

For example, given two crop classes, each with a Gaussian distribution, finding a feature space transformation which satisfies the Bhattacharyya distance criterion means finding an mxn transformation matrix A for a given m to maximize

$$u(s) = \text{B-distance} = \tfrac{1}{2}s(1-s)\,[A(M_1 - M_2)]^t x \; [(1-s)A\Sigma_1A^t + sA\Sigma_2A^t]^{-1} \; x[M_1 - M_2)] + \tfrac{1}{2}\ln\left[\frac{|(1-s)A\Sigma_1A^t + sA\Sigma_2A^t|}{|A\Sigma_1A^t|^{1-s}\,|A\Sigma_2A^t|^{s}}\right]$$

where M_1, M_2, Σ_1, and Σ_2 are mean vectors and covariance matrix for both classes. Even though the explicit solution for maximizing u(s) with respect to A is not easy to obtain, one can find the optimum A numerically by a search technique.[8]

Since we are interested in using this technique to obtain an enhanced image, we wish to reduce the dimension of the image down to a single linear combination. Thus we are seeking a 1xn transformation matrix B such that the new transformed feature will show increased contrast between the classes of interest.

Experimental Procedures

Test data (mean and covariance matrix for classes from chosen training sites) will be supplied to a linear feature selection program. Using the criterion of transformed divergence to increase class separability, a feature space transformation matrix is obtained.[9] This matrix is used to transform the original data stored in the multispectral image storage tape into a new feature which is a linear combination of the original features. This new feature can then be displayed by either the LARSYS PICTUREPRINT processor or by the IMAGE DISPLAY processor. The improvement in contrast between classes will be evaluated by comparing the new image to previous classification results. Particular attention will be given to wheat and its confusion classes.

Further Areas to be Explored

In accordance with the objectives of LACIE, we want to determine whether a linear combination which has been determined from a particular test site can be applied to other test sites in the same spectral strata with the same improvement in contrast. If the same enhancement effect is observed, the images of all sites in a strata can be enhanced with the same linear combination of features.

The reduction of dimension achieved by the use of linear combinations of features can also aid the study of the tradeoff between the cost of classification (as measured by computer time) and the probability of misclassification of a function of the dimension of the new transformed subspace.

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X. Extraction and Analysis of Spatial Information

To date most of the machine analysis of remotely sensed earth resources data has emphasized the spectral information content. The multispectral domain has been made to yield a great deal of information about the ground scene. But it can be inferred from experience with photointerpretation of remote sensing data that there is a significant amount of useful information in the spatial relationships in the data. Efforts are therefore being pursued to characterize this information so that it can be effectively extracted by machine processing techniques and utilized effectively in conjunction with the multispectral information. We report here research into three approaches to accomplish this: the extraction and classification of homogeneous objects, the characterization of spatial features through Fourier transform methods, and the characterization and analysis of texture features.

A. THE EXTRACTION OF CLASSIFICATIONS OF HOMOGENEOUS OBJECTS (ECHO)

Rationale

A typical view of the earth's surface consists primarily of regular and/or irregular regions arranged in a patchwork manner, each containing one class of surface cover type. These homogeneous regions are the "objects" in the scene. Wheat fields and towns are examples of such objects. A basic processing goal is to locate the objects, identify (classify) them, and produce tabulated results and/or a "type-map" of the scene. The locations and spatial features (size, shape, orientation) of objects are revealed by changes in average spectral properties that occur at boundaries. Classification of an object is then based on its spectral features using statistical pattern recognition techniques.

Computer classification of multispectral scanner (MSS) data collected over a region is typically done by applying a "simple symmetric" decision rule to each resolution element (pixel) (e.g., the LARSYS CLASSIFYPOINTS algorithm). This means that each pixel is classified individually on the basis of its spectral measurements alone. A basic premise of this technique is that the objects of interest are large compared to the size of a pixel. Otherwise a large proportion of pixels would be composites of two or more classes, making statistical pattern classification unreliable; i.e., the prespecified categories would be inadequate to describe the actual states of nature. Since the sampling interval is usually comparable to the pixel size (to preserve system resolution), it follows that each object is represented by an array of pixels. This suggests a statistical dependence between consecutive states of nature, which the simple symmetric classifier fails to exploit. To reflect this property, we shall refer to simple symmetric classification as "no-memory" classification.

One method for dealing with dependent states is to apply the principles of compound decision theory or sequential compound decision theory. Abend[1] (1966) points out that a sequential procedure can be implemented fairly efficiently when the states form a low-order Markov chain. However, the prospect is considerably less attractive when they form a Markov mesh, which is a more suitable model for two-dimensional scenes. Furthermore, estimation of the state transition probabilities could be another significant obstacle to implementation of such a procedure.

The compound decision formulation is a powerful approach for handling very general types of dependence. This suggests that perhaps by tailoring an approach more directly to the problem at hand, one can obtain similar results with considerable simplification. A distinctive characteristic of the spatial dependence of MSS data is redundancy; i.e., the probability of transition from state i to state j is much greater if $j=i$ than if $j \neq i$, because the sampling interval is generally smaller than the size of an object. This suggests the use of an "image partitioning" transformation to delineate the arrays of statistically similar pixels before classifying them. Since each homogeneous array represents a statistical "sample" (a set of observations from a common population), a "sample classifier" could then be used to classify the objects. In this way, the classification of each pixel in the sample is a result of the spectral properties of its neighbors as well as its own. Thus its "context" in the scene is used to provide better classification. The acronym ECHO (Extraction and Classification of Homogeneous Objects) designates this general approach.

A characteristic of both no-memory and compound decision techniques is that the number of classifications which must be performed is much larger than the actual number of objects in the scene. When each classification requires a large amount of computation, even the no-memory classifier can be relatively slow. An ECHO technique would substantially reduce the number of classifications, resulting in a potential increase in speed (decrease in cost), provided the objects in the scene can be isolated efficiently.

Background

There are two opposite approaches to object seeking, which we shall call conjunctive and disjunctive. A conjunctive algorithm begins with a very fine partition and simplifies it by progressively merging adjacent elements together that are found to be similar according to certain statistical criteria. A disjunctive algorithm begins with a very simple partition and subdivides it until each element satisfies a criterion of homogeneity.

In an earlier investigation, we combined Rodd's conjunctive partitioning algorithm[2] with a minimum distance sample classifier and observed an improvement in classification accuracy over conventional no-memory classification, but processing time was increased.[3] Gupta and Wintz[4] added a test of second order statistics to Rodd's first order test, but obtained essentially the same results as the first order test at still greater cost in processing time. Robertson[5] implemented a disjunctive partitioning algorithm with the same minimum distance classifier. He obtained about the same classification accuracy as conventional no-memory classification with an order of magnitude increase in processing time.

Objectives and Approach

The objective of this research is to improve the classification accuracy of the ECHO technique by improving the estimate of the image partition and reducing the error rate of the sample classifier. It is also our goal to improve the efficiency of the process to make it more competitive with no-memory classification.

Our approach is based on refinement of the conjunctive partitioning scheme previously developed. New statistical criteria are investigated along with new partitioning logic. A much faster sample classifier is also studied.

Evaluation of the technique is accomplished by classifying several aircraft and LANDSAT-1 data sets for which substantial amounts of reference data (surface observations) are available from previous data analysis projects. The resultant test field accuracy provides an important quantitative measure of performance. Visual comparison of classification maps provides a qualitative assessment of the results.

Accomplishments

The new statistical criteria have resulted in a method of partitioning that is "supervised", as opposed to the original method which was non-supervised. Both methods can be described in terms of a generalized likelihood ratio test. The supervised mode was implemented along with multivariant and "multiple-univariant" versions of the non-supervised mode. The sample classifier was changed from a minimum Bhattacharyya distance strategy to a maximum likelihood strategy, based on a number of desirable properties that were recognized.

Experimental results were obtained for both the supervised and non-supervised modes as well as for the no-memory method. For additional comparison, a maximum likelihood version of the LARSYS SAMPLECLASSIFY processor was implemented and used to perform direct sample classification of the test areas. The minimum distance version was also used. The results indicate that the accuracy, stability, and efficiency of the ECHO technique have been significantly improved.

An additional accomplishment was the splitting of the ECHO processors into two "phases". Certain statistical quantities are computed in Phase One and saved on an intermediate data tape. This enables us to conveniently study the effect of varying the Phase Two input parameters without recomputing these statistics.

DESCRIPTION OF RESEARCH

Theoretical Aspects

The theory on which the ECHO processing is based is treated at length by Kettig[6] and will not be repeated here. An overview of the theory is also available, by Kettig and Landgrebe.[7]

An algorithm for two-level conjunctive partitioning, used in the experiments described hereafter, is shown in Figure 1.

Experimental Results

Two aircraft and two LANDSAT-1 sets, for which large amounts of training and test data are available, were classified by the following six methods:

1. Conventional ML* No-Memory Classification[8]
2. Supervised Cell Selection only (t=0); ML Sample Classification
3. Optimum MUV* non-supervised Partitioning; ML Sample Classification
4. Supervised Partitioning (t=4); ML Sample Classification
5. ML Sample Classification of Test Areas Only
6. MD* (Bhattacharyya) Sample Classification of Test Areas Only[8]

The cell size for #2-#4 was fixed at 2 x 2 pixels, which is the minimum allowed in the non-supervised mode.

A qualitative assessment of the results is provided by Figures 2 and 3. Figure 2 (left shows a section of aircraft data that has been

*The following abbreviations have been used here: ML = Maximul Likelihood
MUV = Multiple Univariant
MD = Minimum Distance

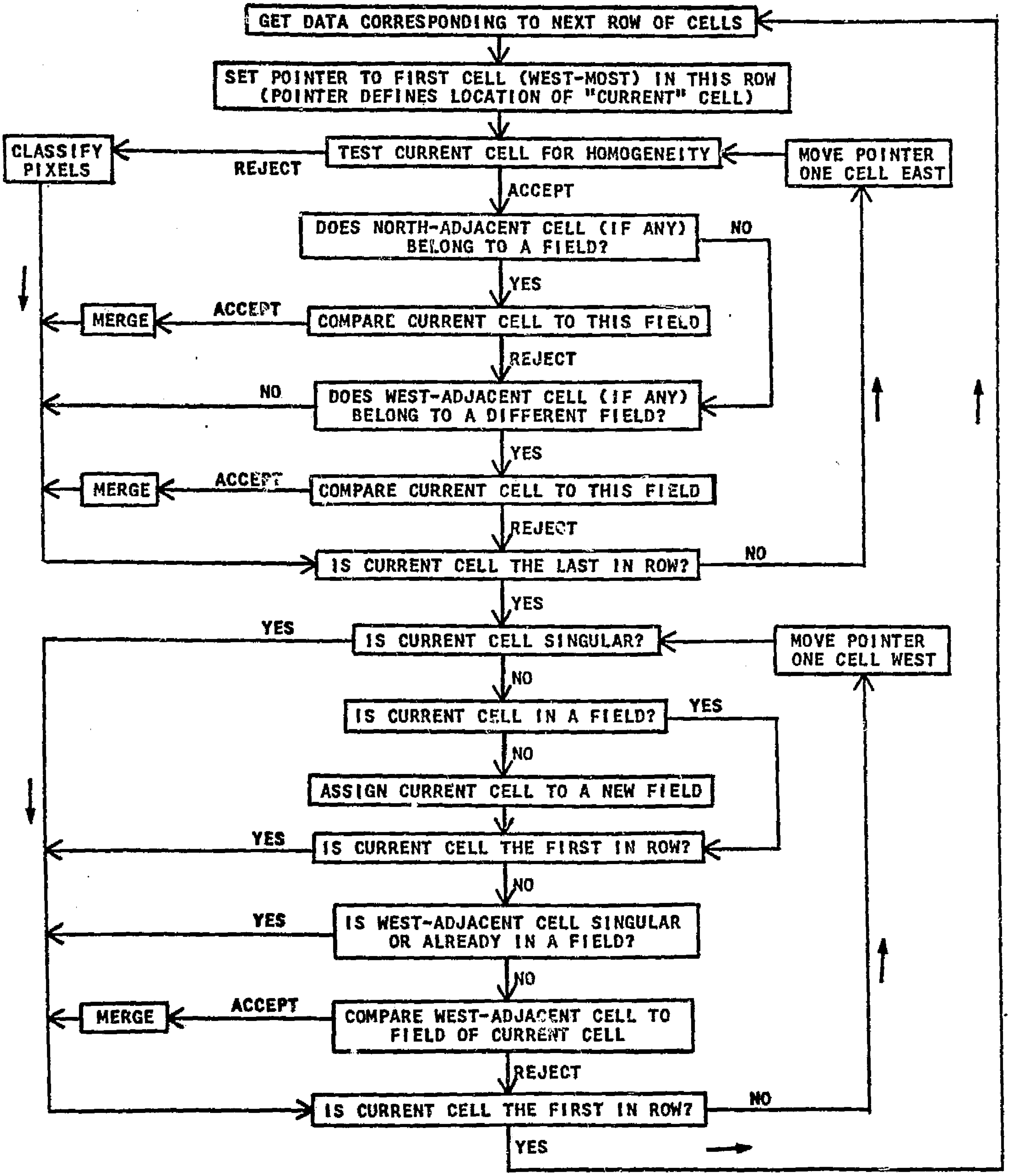


Figure 1 Basic Flow Chart for a Two-Level, Conjunctive, Partitioning Algorithm

classified by method #1. Each class has been assigned a gray level, and each pixel has been displayed as the gray level assigned to its classification. A great deal of "classification noise" is readily apparent. In contrast to this, Figure 2 (right) shows the same section as classified by method #4. The random errors have, for the most part, been eliminated. This map is much closer to the "type-map" form of output that is often desired.

Figure 3 shows the centers of these two maps in greater detail. Each class is represented by an assigned symbol and each symbol represents one pixel. The four rectangular areas are test areas designated as wooded pasture (displayed as a blank). The diversity of symbols in the test areas testifies to the inadequacy of the no-memory method for classifying this section, whereas most of the confusion is avoided by the ECHO technique.

The estimated probability of error for each method gives an important quantitative measure of performance. It is obtained as the ratio of the number of misclassified pixels in the test areas to the total number of pixels in the test areas. Figure 4 shows results obtained for each of the four data sets. Method #1 consistently has the highest error rate because of its lack of use of spatial dependence. Method #2 uses some spatial information and consistently does somewhat better than #1. Method #3 uses more spatial information, which accounts for its improvement over cell selection alone, and #4 does consistently better than #3 because it uses more of the available information in the partitioning phase.

Methods #5 and #6 usually provide the best performance, because they are given more a priori information to begin with. One reason for including them here is to determine if either provides a distinct advantage over the other. On 3 of the 4 data sets, maximum likelihood sample classification achieved lower error rates than the minimum Bhattacharyya distance strategy. The differences are small however. This justifies our use of the ML strategy in #2-#4. Another reason for including them is that the performance of #5 provides a "goal" (but not a bound) for the performance of #3 and #4; i.e. the nearness of the performance to this goal is an indication of the effectiveness of the partitioning process alone.

Although #3 appears to be fairly close to #4 in general, it must be pointed out that the "optimum" selection of the parameters s_1 and s_2 which achieves this performance is somewhat unpredictable at this time. All that we can say of a general nature is that s_1 tends to be effective at about .005 and s_2 at a smaller value such as .001 or 0. (See Reference 6.)

The results for the supervised mode, however, are much more stable. Figure 5 shows only the results for t=4, which are not always the optimum

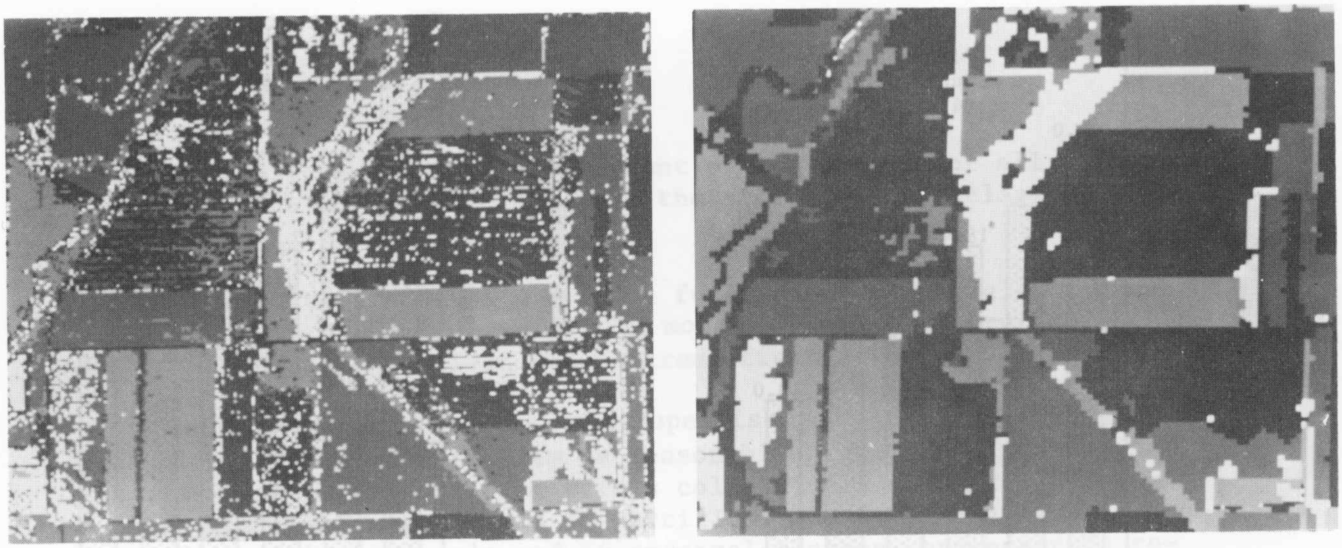
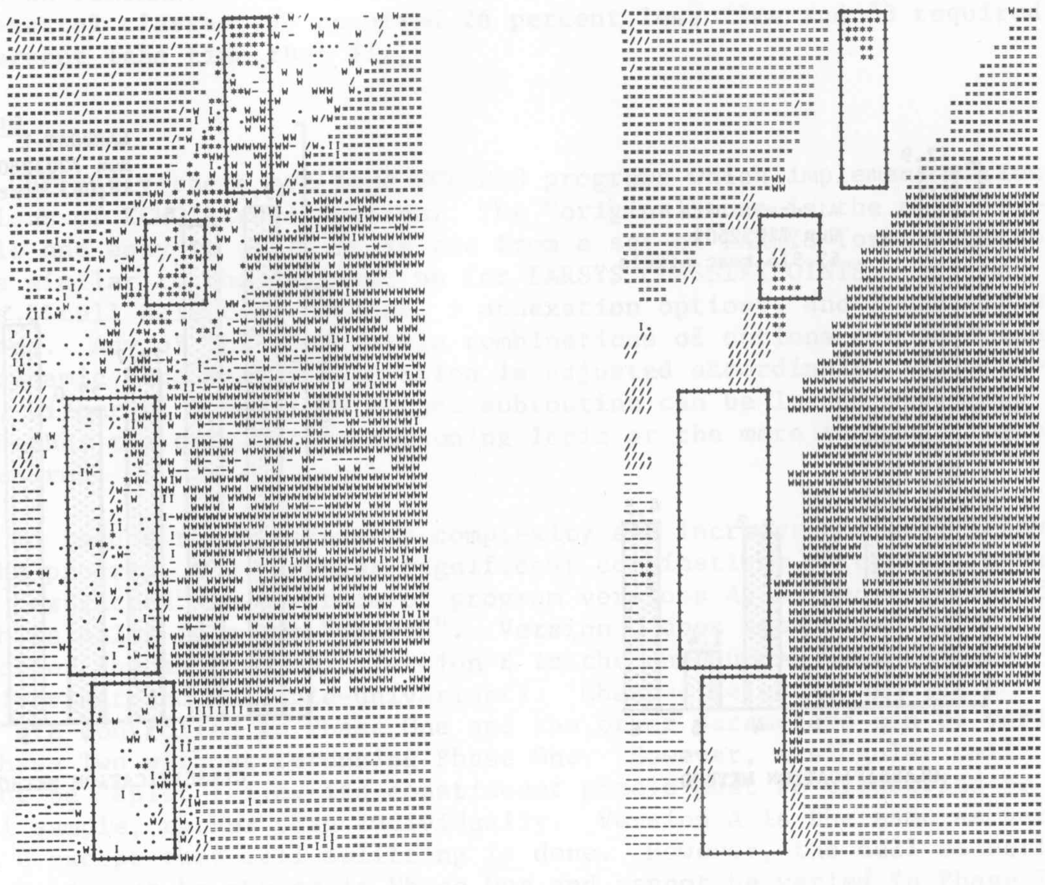


Figure 2 Gray-Scale-Coded Classification Maps Produced by No-Memory Classifier (left) and Sample Classifier (right)



Wheat (W); Corn,Soy,Rye,Hay (·); Lespedeza (=); Pasture (-); Idle (I); Forest (*); Wooded Pasture ( ); Non-Farm (/)

Figure 3 Logogrammatic Classification Maps Produced by No-Memory Classifier (left) and Sample Classifier (right)

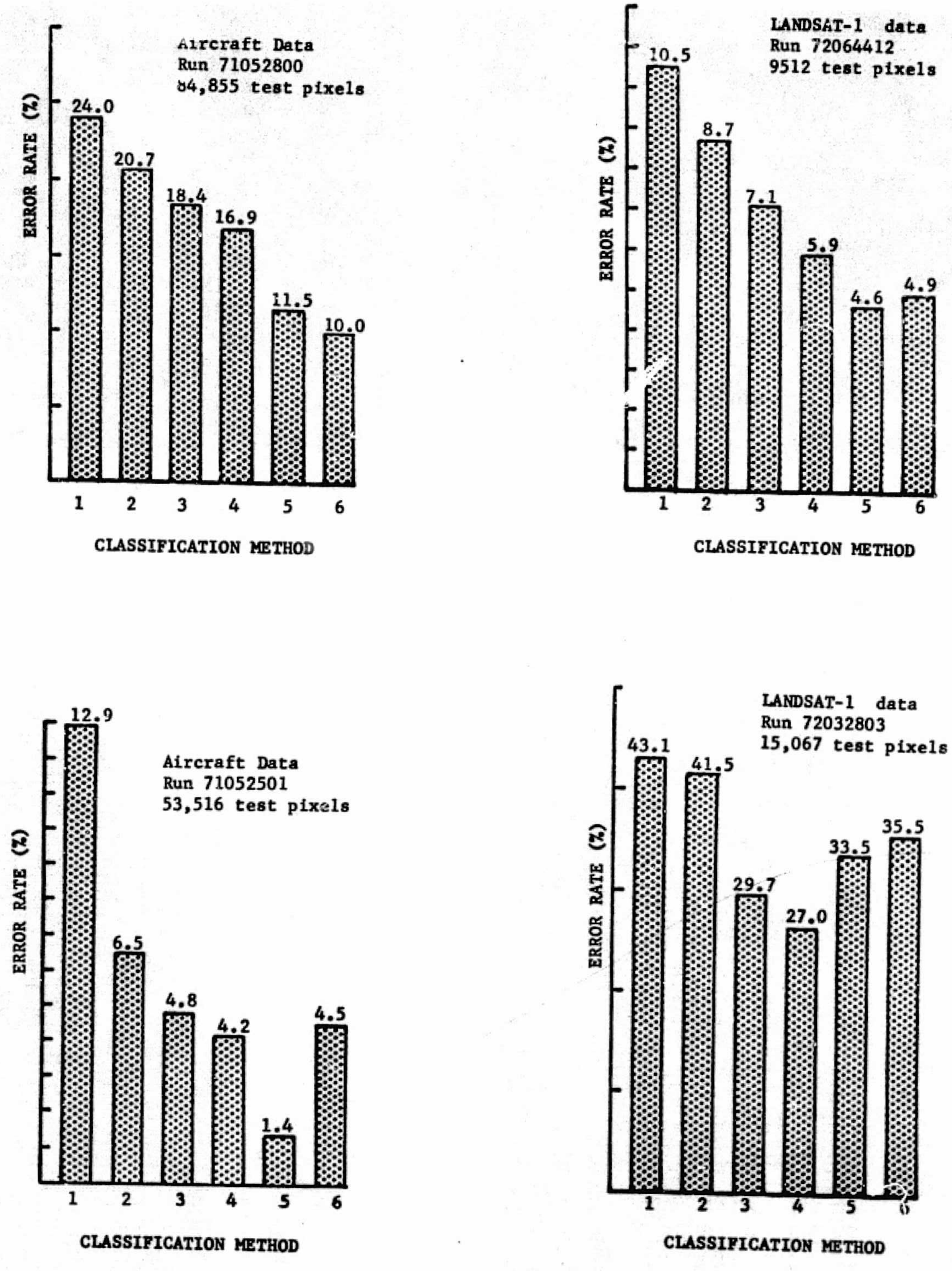


Figure 4 Classification Performance of Six Different Methods Applied to Four Different Data Sets

results, but they are within 1 percent of the optimum of all 4 cases. Figure 5 shows a typical example of the effect of t on classification error rate.

The results are not a sensitive function of the Level-1 threshold, c. The values c=.25 (non-supervised mode) and c=15q (supervised mode, $3 \leq q \leq 6$) usually provided the desired effect.

The main advantage of the non-supervised mode appears to be speed, when classification complexity is reasonably high. This is because the time saved by classifying pixels collectively can more than compensate for the time required to partition. For a LANDSAT-1 data set classified with 4 channels and 14 spectral classes, processor #3 required 22 percent less CPU time than #1, in spite of the fact that the classification subroutine in #1 has been coded in assembler language for peak efficiency. Methods #3 and #4 are developmental versions coded in FORTRAN. But for an aircraft data set with 6 channels and 17 spectral classes, #4 required 26 percent less time and #3 required 56 percent less time than #1.

Status

Currently there are four FORTRAN programs which implement various versions of ECHO classification. The "original" one is the most versatile and easy to use. It is run from a set of LARSYS-format control cards similar to the deck set up for LARSYS CLASSIFYPOINTS. It contains 5 cell selection options, 5 annexation options, and 2 classifier options. Any of the 50 possible combinations of options can be chosen, and dynamic core memory allocation is adjusted accordingly. In addition, either of 2 versions of one subroutine can be loaded depending on whether the original partitioning logic or the more thorough logic is desired.

To reduce the unnecessary complexity and increase the efficiency of the program, the two most significant combinations of options have been "extracted" in the form of program versions A, B, and C, each of which is split into two "phases". Version C does supervised cell selection and annexation. Version B is the non-supervised mode (both multivariant and multiple-univariant). Channel selection and cell size are controlled in Phase One and the other parameters can be varied in Phase Two without rerunning Phase One. However, a singular cell cannot be "split"; i.e. its constituent pixels must be classified as a small sample, rather than individually. Version A is the same as version C except that cell splitting is done. However, the cell selection threshold must be chosen in Phase One and cannot be varied in Phase Two.

Documentation of this work exists in the form of program listings, liberally commented (including control card listings), and a thesis.[6]

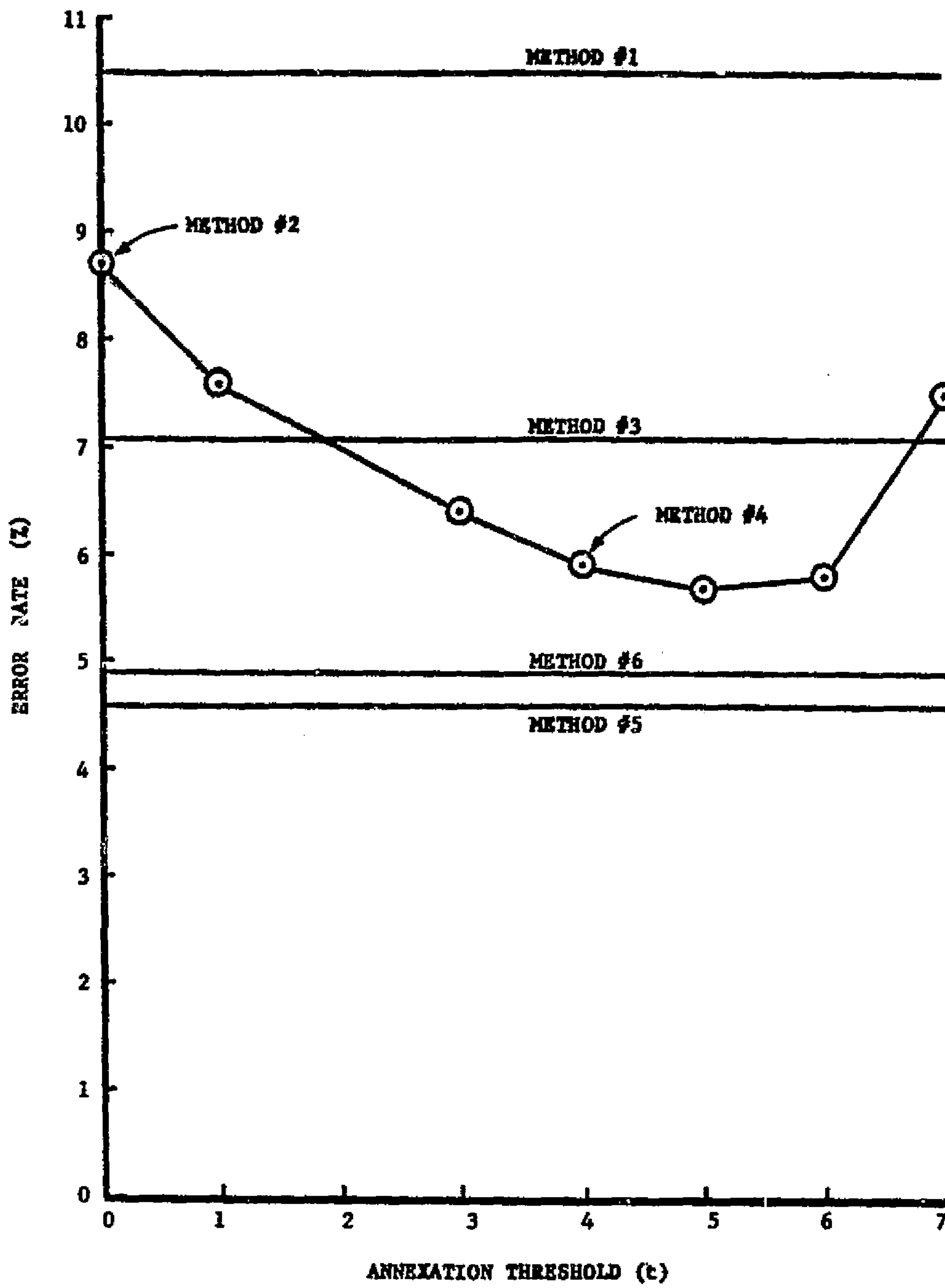


Figure 5 Effect of Annexation Threshold (t) on Classification Performance - Run 72064412

CONCLUSION

We have successfully exploited the redundancy of states characteristic of sampled imagery of ground scenes to achieve better accuracy and reduce the number of actual classifications required. The training used is the same as that required by a conventional maximum likelihood, no-memory classifier, i.e., estimates of the class-conditional, marginal densities for single pixels. Thus we have not relied on specific spatial features, textural information (class-conditional spatial correlation), or on the contextual information associated with spatial relationships of objects.

It is recommended that future research be directed toward the use of these potential sources of information. Use of texture seems particularly well-suited to the computerized approach. Other research areas include selection of input parameters (especially the non-supervised mode) and field-building logic. Of course the ultimate goal is to integrate the techniques that we develop for exploiting various spatial and spectral dependencies into a unified approach to computer recognition of surface cover types.

B. FOURIER TRANSFORM ANALYSIS

INTRODUCTION

Some previous work has been done in applying Fourier Analysis techniques to the spatial information contained in multispectral scanner data. Hornung and Smith[9] applied the two-dimensional discrete fast Fourier transform (2DDFFT) to aircraft multispectral scanner data.

The Hornung and Smith report divided the data into square blocks, took the 2DDFFT of each block, sampled the 2DDFFT, and then performed classifications using the spatial information. The effects of different sizes of data blocks, and of different sampling techniques were discussed.

At LARS, work is presently being done with the extraction of homogeneous objects and with texture. Both of these areas depend upon spatial information. Work may also be started with context, which also incorporates spatial information.

The basic approach at LARS to use Fourier analysis techniques to extract spatial information is similar to that employed by Hornung and Smith. A square block of data is taken from the upper left hand corner of the area being transformed, and the 2DDFFT is the found for this data block. Due to the large number of resulting spatial frequencies, the 2DDFFT is sampled in order to provide data compression. The resulting spatial frequency vector is then considered a characteristic of the data pixel in the middle of the original data block. Next, the data block is moved one pixel to the right. The above process is repeated until the entire area has been covered.

This project has attempted to determine to what extent spatial information extracted by Fourier analysis techniques can be employed in the classification of multispectral data.

The Fourier transform was chosen to study spatial information largely due to its wide applicability to many fields of science. Some areas of interest that should be investigated in order to apply Fourier analysis techniques are:

1) The optimum size of data blocks to be transformed;

2) effects of different sampling methods of the 2DDFFT;

3) which spatial frequencies yield the most useful additional information;

4) how fast the data block can be moved without loss of useful spatial information; and

5) whether spatial information can be useful with LANDSAT data, or it is only practical with aircraft data (as shown by Hornung & Smith).

The routines to perform the spatial analysis via the Fourier Transform have been written and debugged. The resulting spatial frequency vector of each data pixel is written on a multispectral data tape as additional channels. These additional spatial channels can be used by the existing LARSYS functions.

A land use analysis of Indianapolis has been performed using the spatial channels. The analysis used the same run as a previous land use analysis by Todd & Baumgardner[10]. The major problem that Todd & Baumgardner had experienced was the confusion between agriculture/grassy areas and older housing.

DESCRIPTION OF RESEARCH

Fourier transforms can provide a physical insight into the spatial frequency composition of multispectral data. For example, Fourier transforms can be used to characterize the spatial nature of objects. Any sort of rapid change in a picture will cause a very large response in the Fourier transforms (see Figures 7 and 8). If we sampled the Fourier transform and fed this sampled data into a digital computer, we could tell by the large data values that a rapid change of some sort existed in the picture.

A brief review of Fourier transforms is necessary to understand the approach taken here to obtain spatial information. The formula for the discrete Fourier transform is

$$x_{f(k)} = \frac{\Delta x}{\lambda} \sum_{i=0}^{N-1} y(i) \quad \exp\left[-2\pi j \; f_k \; i\Delta x\right]$$

where

Δx = interval between each sampling points

$\lambda = N \cdot \Delta x$

N = # of samples

$y(i)$ = the amplitude of the pixel i

f_k = the frequency at which the DFT is being calculated. Usually f_k is some multiple of $\frac{1}{\lambda}$. So $f_k = \frac{k}{\lambda}$

$k = 0, 1, 2, \ldots, [\frac{N}{2}]$.

The Discrete Fast Fourier Transform, while much faster than the Discrete Fourier Transform (DFT), has basically the same properties as the DFT. Some properties of interest in this application are:

1) The Fourier transform of a rectangular pulse is a SINC wave;
2) the transform of an impulse function is a constant valued frequency response; and
3) the transform of a Gaussian curve is a Gaussian curve.

These properties are illustrated in Figure 1.

When LANDSAT data is being transformed, only one channel is used, in order to save computer time in this preliminary study. Which channel is chosen will depend on the analyst's problem and the spatial features he wishes to emphasize. For example, channel 1 may be chosen because it tends to increase the prominence of roads and roads can provide a wealth of information in land use studies. A principal components transform of all four ERTS channels may be able to be used as a best channel.

When the two dimensional Fast Fourier Transform is desired, each row of the data block is transformed, and then each column of the resulting frequency response is transformed. This is shown in Figures 2 and 3 (The DFFT routine used in this procedure at LARS had already been written by R. L. Kettig).

After the 2DDFFT has been performed, the frequency response is as shown in Figure 4. It is seen that the (0,0) frequency point is in the upper left hand corner. Since most literature dealing with 2 dimensional Fourier Transforms has the (0,0) frequency in the middle of the frequency block, it is desirable to switch the necessary quadrants so as to put the (0,0) frequency point in the middle (Figure 5).

Next the 2DDFFT is sampled in order to provide data compression. Presently, the 2DDFFT is sampled by circular rings around the (0,0) frequency. A table of the possible number of circular rings is shown in Figure 6. (Other sampling techniques are possible but have not yet been tried).

The circular sampling technique measures the frequency response of LANDSAT data by simply measuring the magnitude of the response. Since all points on a ring are averaged, orientational differences are minimized.

The lowest frequency that the Fourier Transform can observe is

$$\nu_{min} = \frac{1}{N\Delta x}$$

while the highest observable frequency is

$$\nu_{max} = \frac{1}{2\Delta x}$$

If we are using a 16x16 square data block (sometimes referred to as a 16x16 square 'aperture'), with LANDSAT data, the lowest frequency we can hope to observe is

$$\nu_{min} = \frac{1}{(16)\ (79\ m)} = 0.00079 \text{ cycles/m}$$

while the highest frequency we could observe is

$$\nu_{max} = \frac{1}{2\ (79)} = 0.00632 \text{ cycles/m}$$

From Parseval's Theorem one can show that for any 2DDFFT the maximum amplitude that can occur is

$$A_{max} = (T\ N^2)^2$$

where T - 256 for the LARSYS system. This equation is an important consideration when programming the Fourier transforms.

Some pictures of 2DDFFT's are shown in Figures 7, 8 and 9. These pictures were taken on the digital display at LARS.

Several types of errors can effect Fourier Transformations.

1) Frequency Aliasing

Figure 1. SOME COMMON FOURIER TRANSFORMS

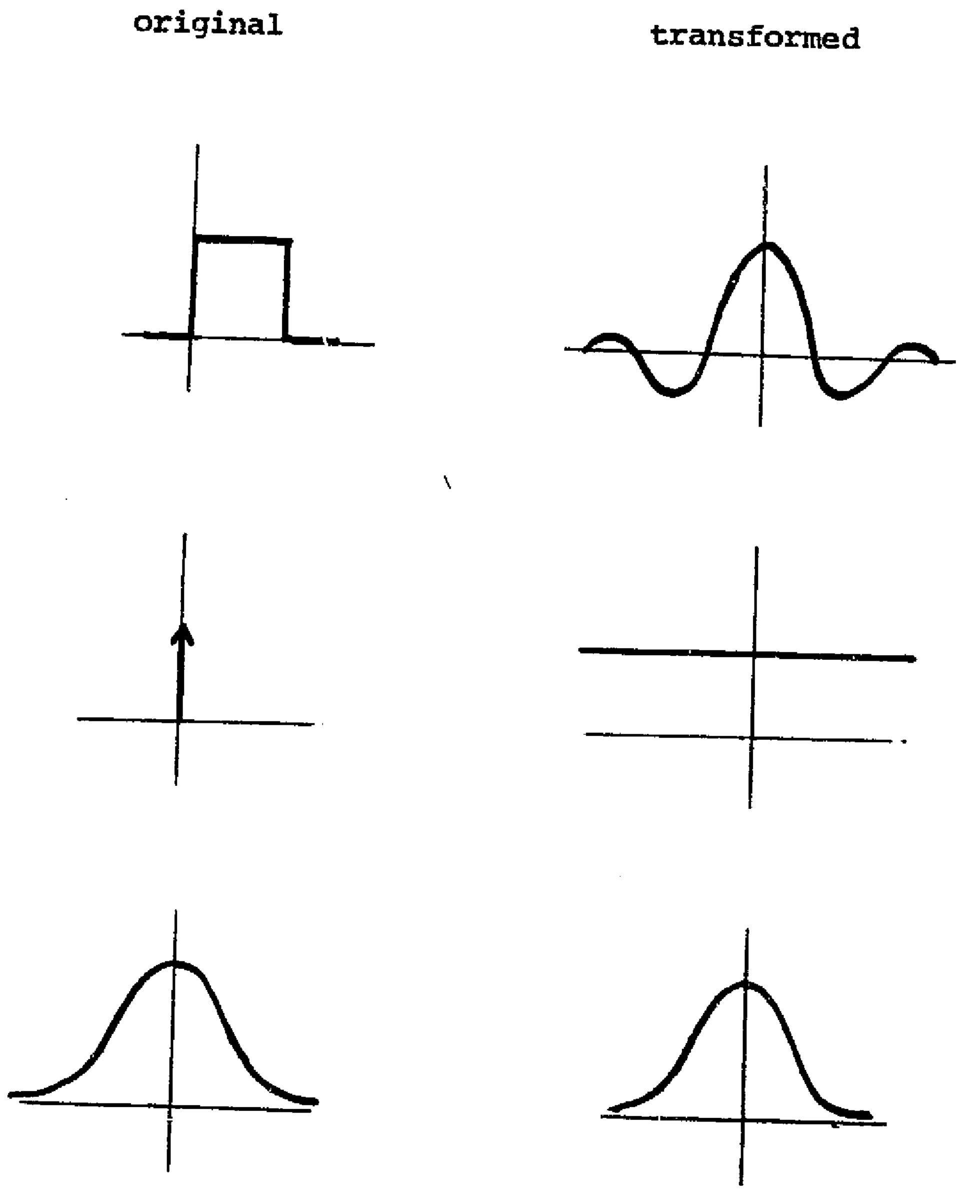
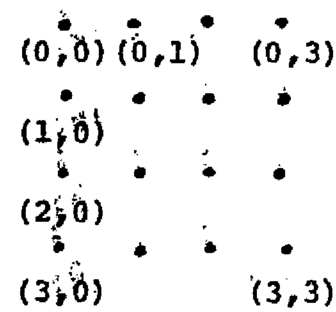
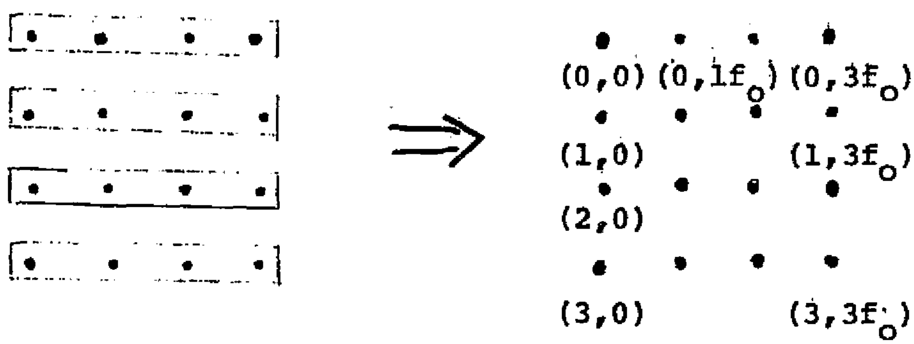


Figure 2. FINDING A 2DDFFT.

Given a block of data:



Transform each row:



Then transform each column:

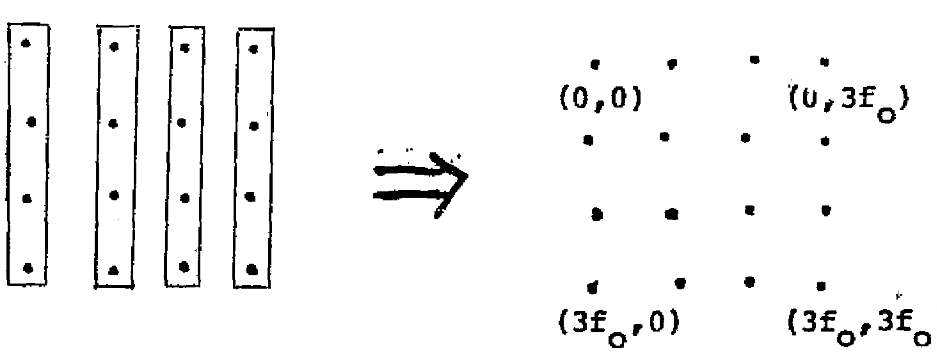
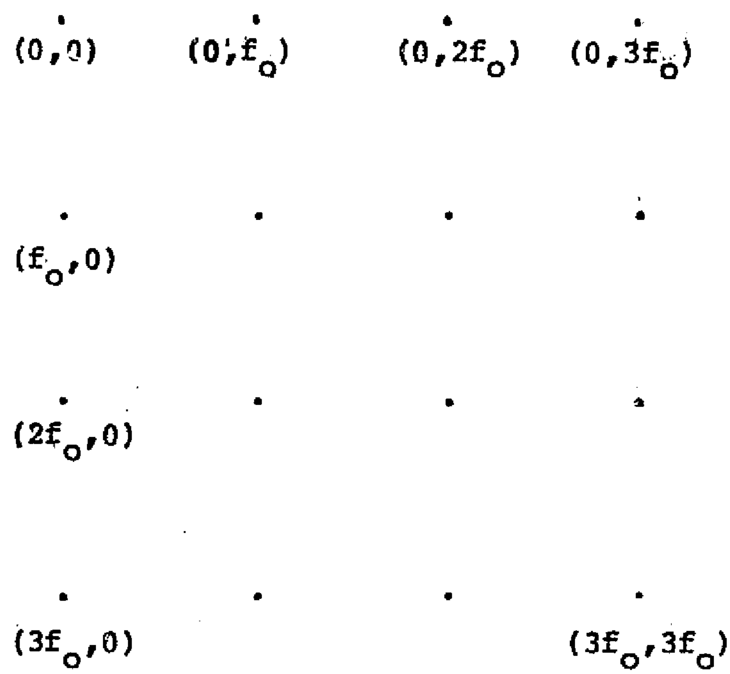


Figure 3. DATA BLOCK AFTER TAKING FFT OF EACH ROW.

$(0,0)$	$(0,f_o)$	$(0,2f_o)$	$(0,3f_o)$
$(1,0)$	$(1,f_o)$	$(1,2f_o)$	$(1,3f_o)$
$(2,0)$	$(2,f_o)$	$(2,2f_o)$	$(2,3f_o)$
$(3,0)$	$(3,f_o)$	$(3,2f_o)$	$(3,3f_o)$

(i,jf_o) refers to row i, frequency jf_o.

Figure 4. 2DDFFT BEFORE TRANSLATING QUADRANTS



f_o is the fundamental frequency

Figure 5. SWITCHING QUADRANTS TO CENTER THE (0,0) FREQUENCY

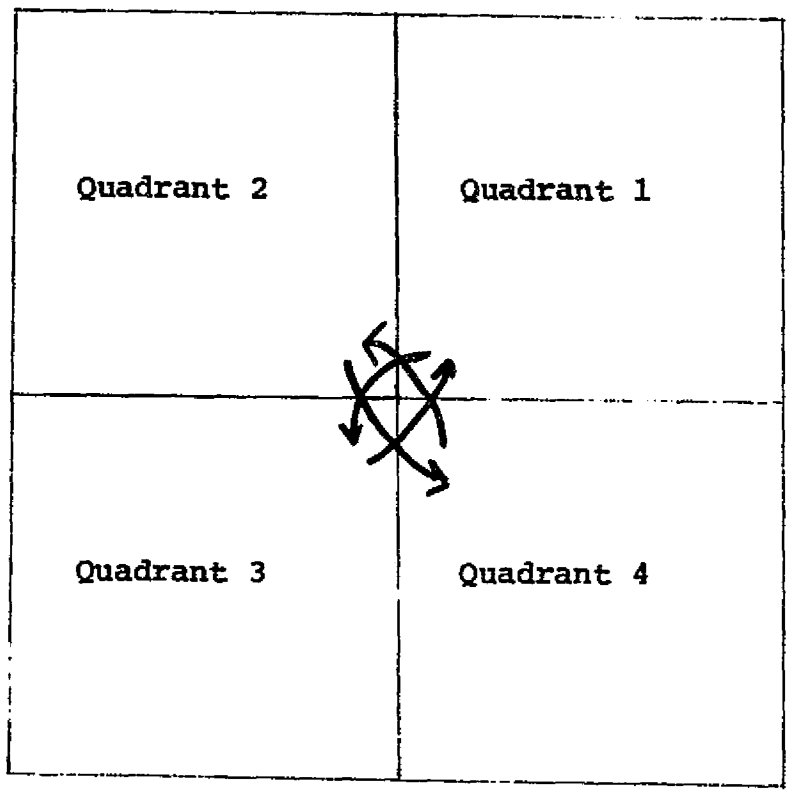
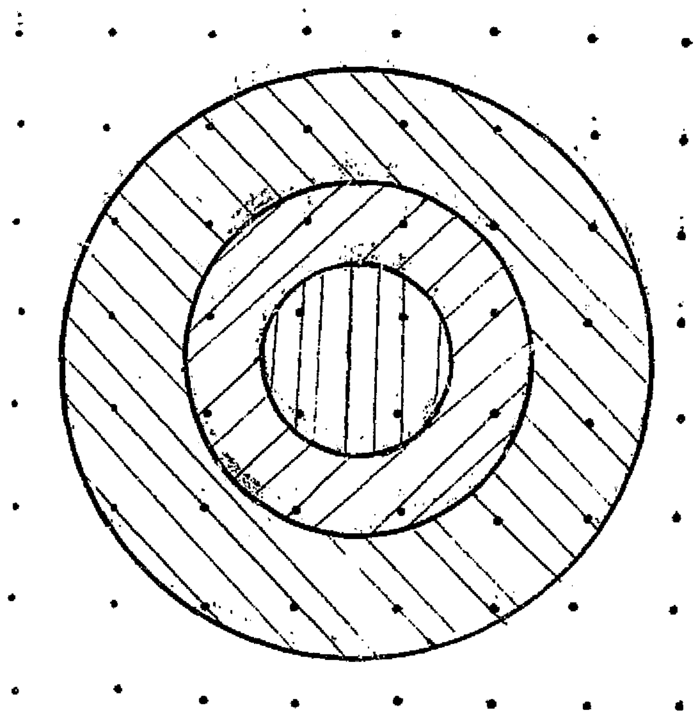


Figure 6. Determining the largest possible spatial vector size (the number of circular rings).



Aperture	Spatial Vector Size
4x4	1
8x8	3
16x16	7
32x32	15
64x64	25*
128x128	28*

*limited due to computer core limitations

The higher spatial frequencies will not be observable. An example is given in Figure 10.

2) Sampling 'jitter'.

Each pixel may not be equally spaced apart. This causes a phase shift in the spatial frequency response. Figure 11 gives an example of scanner 'jitter'.

3) Frequency 'artifacts'.

These are spurious responses characteristic of the 2DDFFT.

The software to perform spatial analysis now exists. Completion of the previously mentioned goals will be attempted next. Other areas that also need to be investigated are:

1) Do the frequency artifacts need to be removed by filtering?

2) Will a switch to Walsh functions make certain spatial information more apparent?

3) Possibly spatial information would be most useful with a layered classifier. Thus, in a land use study, the 2DDFFT need only be taken over grassy/agricultural and older housing areas.

The flowchart of the computer programs used for Fourier Transform analysis is shown in Figure 12. A description of each program follows:

CNTRL is the controlling FORTRAN program. CNTRL calls the other main FORTRAN subroutines. CNTRL mounts the various tapes, and then calls DATGET to obtain the required block of data. Next, TWODM is called to take the 2DDFFT of the data block. RESLTS is then called to sample the 2DDFFT thus providing data compression. After an entire line of data has been transformed, WRITE is called to put the results on tape.

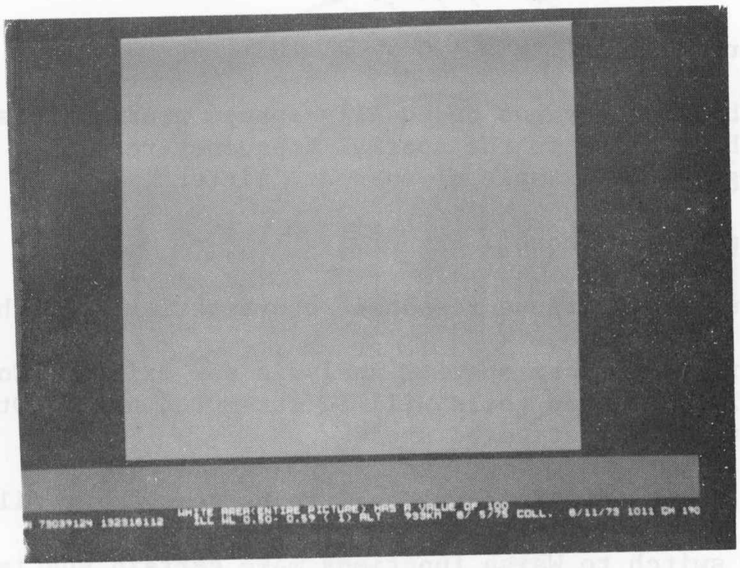
DATGET gets the block of spectral data to be transformed.

TWODM takes the 2DDFFT of the data block passed to it. First TWODM takes the data values and divides them by 100, so that the magnitude of the 2DDFFT is limited to values measurable in four byte owrds. Next, TWODM takes the 1DDFFT of each line of data, of each column. This results in the 2DDFFT of the original data block.

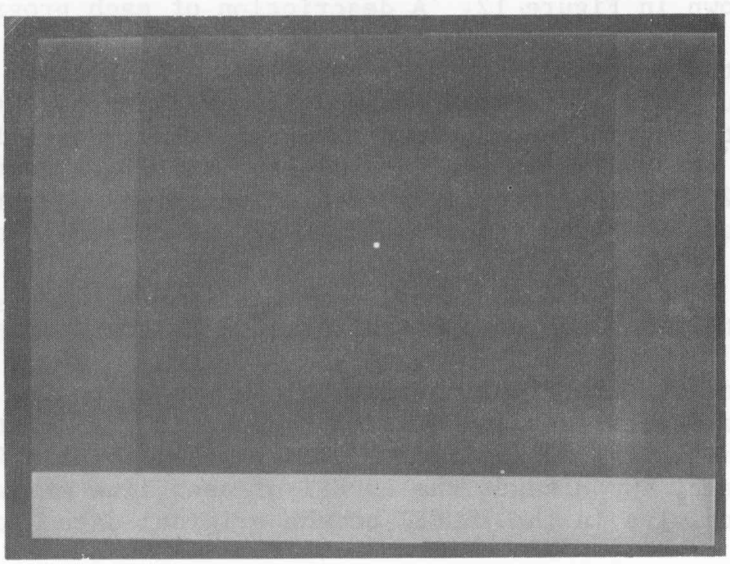
TWODM then calls transl.

TRANSL is used to shift the (0,0) frequency to the middle of the frequency block. TWODM then calls PICTRE if a picture of the 2DDFFT is desired.

Figure 7. TRANSFORM OF A CONSTANT VALUE

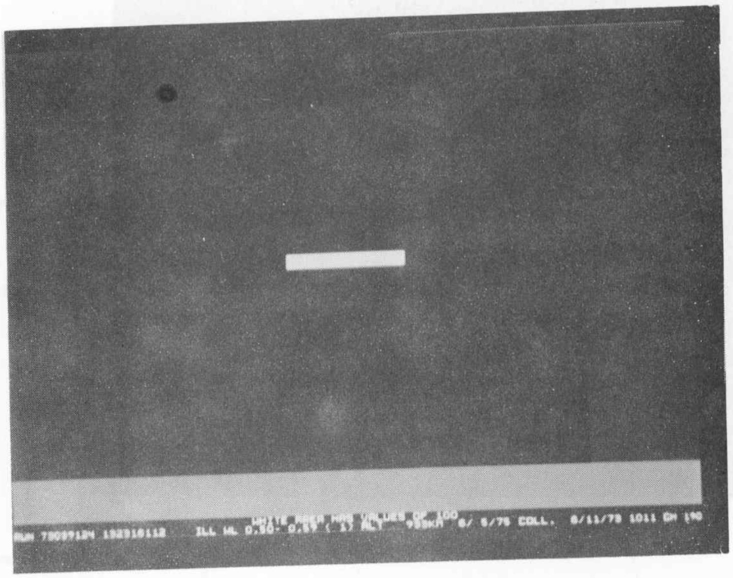


original

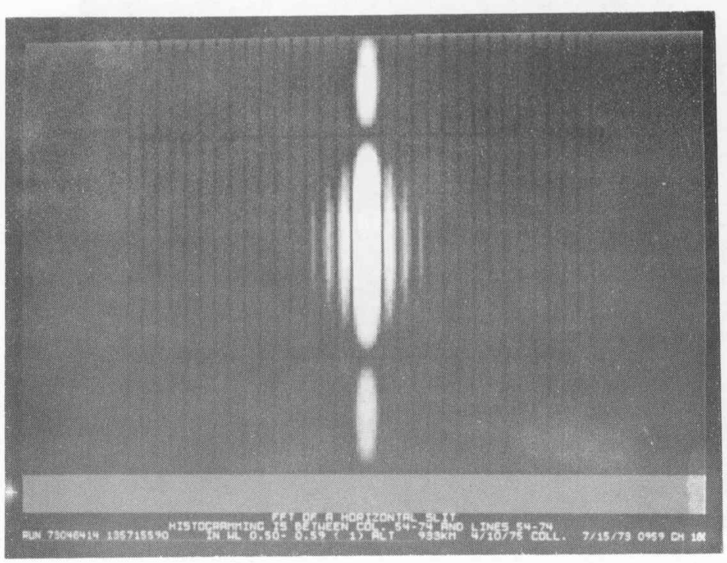


transformed

Figure 8. TRANSFORM OF A HORIZONTAL SLIT

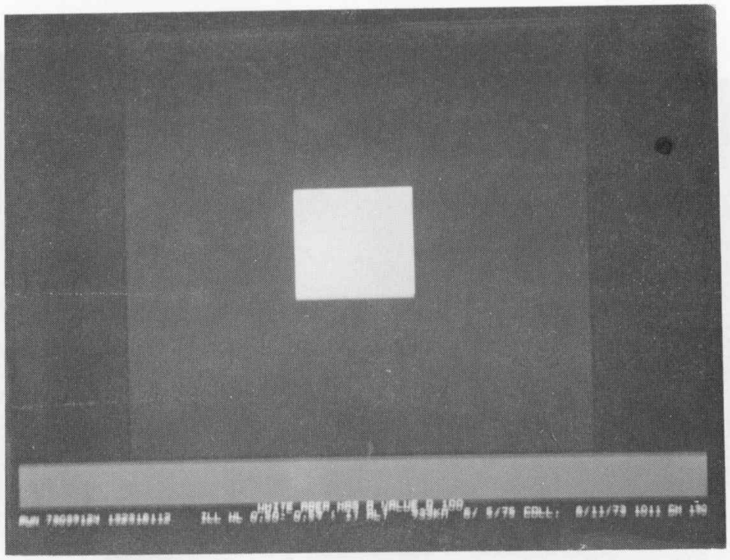


original

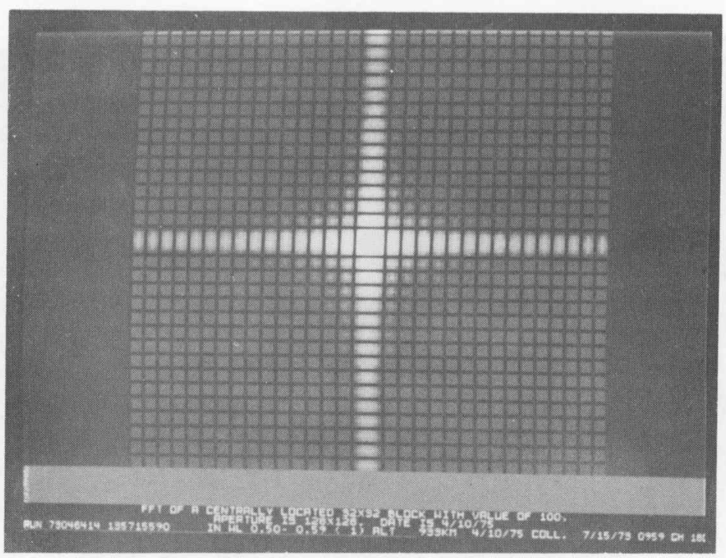


transformed

Figure 9. TRANSFORM OF A SQUARE BLOCK

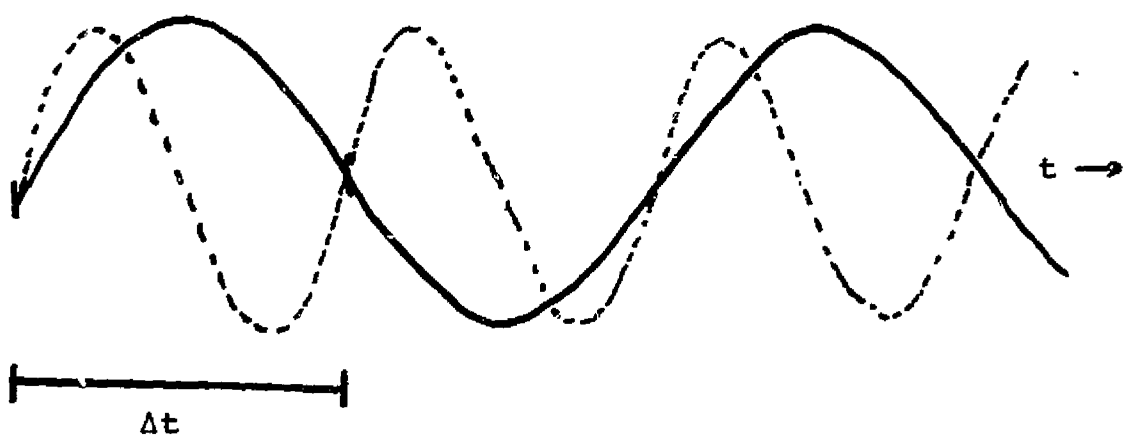


original



transformed

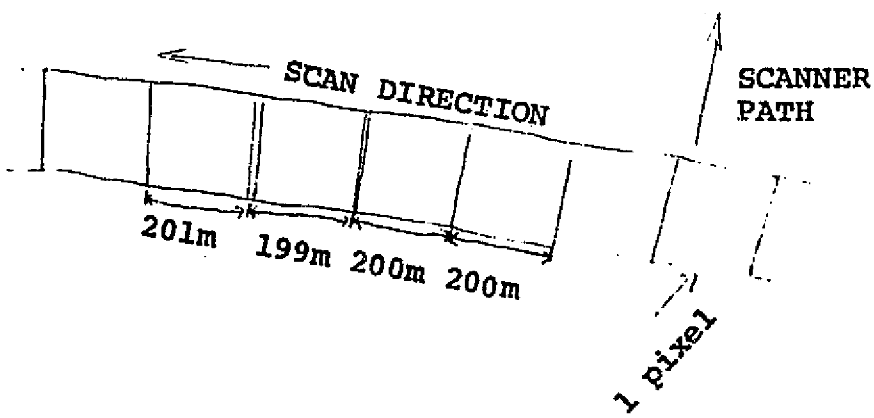
Figure 10. FREQUENCY ALIASING



Masking of the --- lines caused by the —— lines

Δt = sampling interval (in time)

Figure 11. AN EXAMPLE OF 'JITTER' OF A SCANNER



RESLTS takes care of the data compression. RESLTS does this by calling SAMPLE. Presently, the 2DDFFT is samples by circular rings around the (0,0) frequency. A table of the possible number of circular rings is shown in Figure 6. (It is expected that other sampling techniques will be tried as time permits).

WRITE is called when an entire line of data has been transformed.

WRITE first reads the original multispectral data from the multispectral tape. Then the original data and the new spatial data is packed into an I*1 format. Then the spectral data and spatial data are both written onto a data tape.

(Note that WRITE also creates a suitable ID record and writes the ID record before any other data is written).

C. TEXTURE ANALYSIS

INTRODUCTION

The texture in an image is one form of spatial information contained in the image. Several methods have been proposed to use spatial information or texture, including spatial frequencies (previous section) gradients or edge detection (Hayes, et.al.[11]), and textural features (Haralick, et.al.[12]). Since textural information contains information which is additional to the spectral information, it should be possible to improve classification accuracy by including texture as part of the input to the classifier.

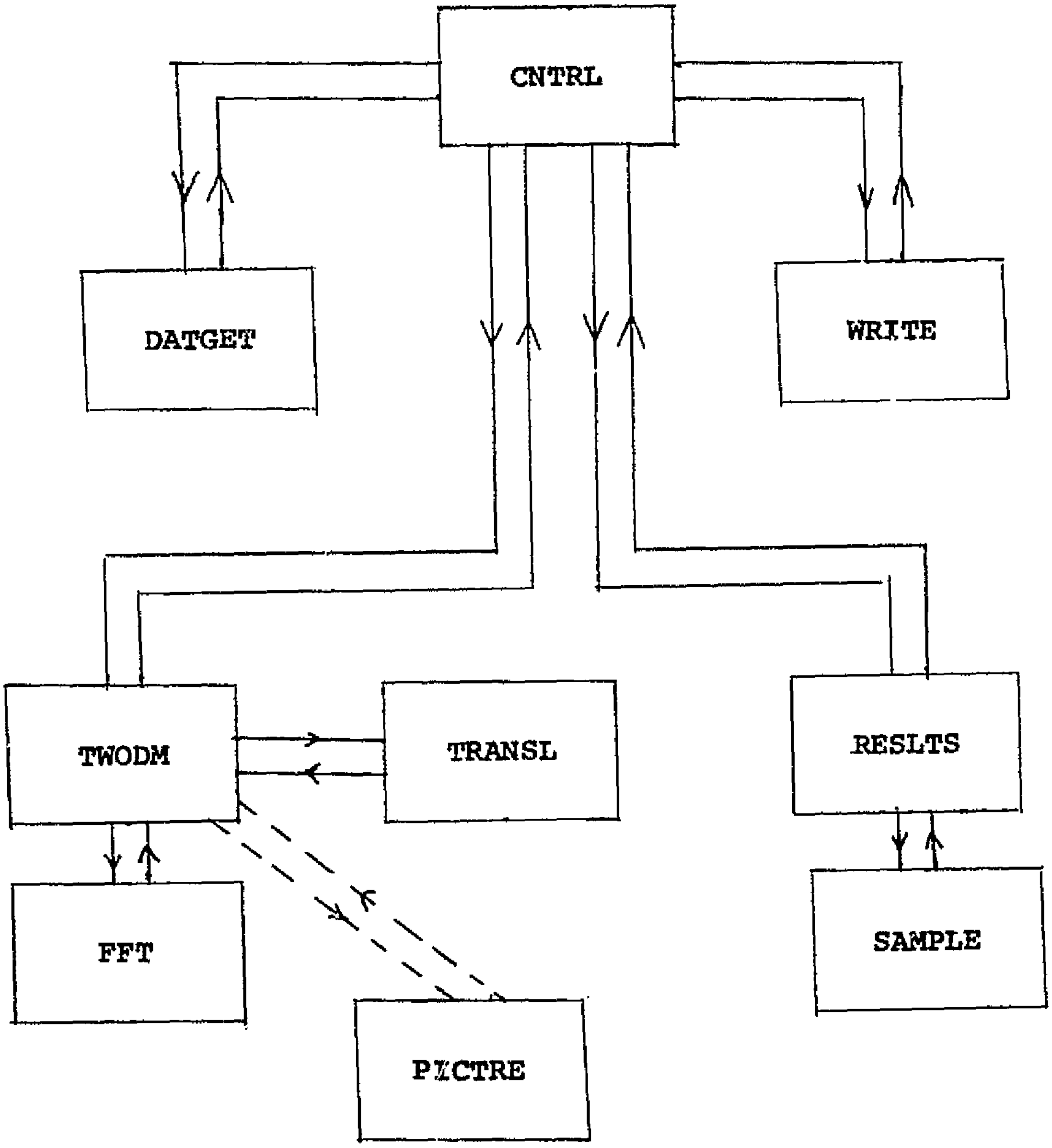
DESCRIPTION OF RESEARCH

The method of textural features has been chosen to be studied because textural features are relatively easy to implement and will give a good feel for the value of texture in remote sensing data analysis. Haralick used textural features to classify sandstone photographs, aerial photographs, and LANDSAT multispectral imagery. He achieved 83.5 percent classification accuracy using a combination of spectral and textural features as compared to 74 to 77 percent using only spectral features.

The approach we have taken is to calculate the textural features suggested by Haralick using data from the multispectral image storage tape, and to perform classification using the spectral channels already on the tape plus additional channels composed of the textural features. The primary goal is to use textural features in conjunction with spectral information to determine if classification can be improved over classification using spectral features only.

The major tasks which must be accomplished in data analysis using textural features are preprocessing, calculation of texture features, and classification. The principal preprocessing which must be done to the multispectral image data is to quantize it into from four to

Figure 12. FOURIER ANALYSIS SOFTWARE



FILE. . .   CNTRL   FORTRAN P1

```
      IMPLICIT INTEGER*4 (A-Z)
      INTEGER*4 ID(200),RSLTS(134,134),STO1(200)
      REAL*4 RID(200),STO2(200)
C
C
C      BOB IS THE MAIN CONTROL PROGRAM.  IT MOUNTS THE TAPES AND CALLS
C      THE OTHER SUBROUTINES.  DATGET GETS THE DATA FROM A STORAGE
C      TAPE.  TWODM TAKES THE TWO DIMENSIONAL FFT OF THE DATA
C      FROM DATGET.  RESLTS SAMPLES THE DATA AND PUTS IT INTO
C      THE ARRAY 'B'.  'WRITE' WRITES THE SAMPLED FFT
C      ALONG WITH THE ORIGINAL DATA ON A SPECIFIED TAPE.
C
C
      EQUIVALENCE(ID(1),RID(1)),(STO1(1),STO2(1))
      WRITE(6,777)
 777  FORMAT(2X,'HI'/)
      DO 11 NA=1,134
      DO 12 NB=1,134
      RSLTS(NA,NB)=0
 12   CONTINUE
 11   CONTINUE
      RUNSEL=72053612
      CHANSL=1
      FIRDTL=232
      LASDTL=400
      FIRDTC=242
      LASDTC=508
      INTVL=1
      N=16
      TAPE=175
      FILE=1
      NPLS6=N+6
      NORIGC=4
      STARTC=FIRDTC+N/2
      ENDCOL=LASDTC-N/2
      DO 15 I=1,200
      ID(I)=0
 15   CONTINUE
      DATUNT=12
      CALL GADRUN(RUNSEL,DATUNT,ID,ERROR)
C
C          HERE THE ID INFORMATION IS PRESERVED.
C
      DO 30 I=1,200
      STO1(I)=ID(I)
      STO2(I)=RID(I)
 30   CONTINUE
      DO 31 I=1,150
      J=I+50
      STO2(J)=0
   31 CONTINUE
      DSRN=11
      CALL MOUNT(TAPE,DSRN,'RI')
      IF(ERROR.GE.1)GO TO 20
      NUMSCL=LASDTC-(FIRDTC+(N-2))
      NUMSLN=LASDTL-(FIRDTL+(N-2))
      DO 40 I=1,NUMSLN,INTVL
      FIRSTL=FIRDTL+I-1
      LASTL=FIRSTL+N-1
      DO 50 J=1,NUMSCL,INTVL
      FIRSTC=FIRDTC+J-1
      LASTC=FIRSTC+N-1
      WRITE(6,988) FIRSTC,LASTC
 988  FORMAT(25X,2I4)
      WRITE(6,988) J,N
 17   CALL DATGET(FIRSTL,LASTL,FIRSTC,LASTC,N,INTVL,CHANSL,ID,RSLTS,
     1DATUNT,RID)
      CALL TWODM(RSLTS,N,STO1,STO2,TAPE)
      WRITE(6,988) N,INTVL
      CALL RESLTS(RSLTS,N,I,J,B,NN)
 50   CONTINUE
      IF(I.EQ.1)GO TO 61
 45   CALL WRITE(I,STARTC,ENDCOL,STO1,STO2,TAPE,FILE,
     1B,NORIGC,INTVL,NN,N,NUMSLN,NUMSCL,RUNSEL,ID,RID)
 40   CONTINUE
      CALL TOPEF(DSRN,ERROR)
      CALL TCLOSE(DSRN)
```

```
      CALL TCLOSE(DATUNT)
      WRITE (6,60)
 60   FORMAT(5X,'SPATIAL SAMPLING COMPLETED'/)
      STOP
 20   WRITE(6,25) ERROR
 25   FORMAT(10X,'PROGRAM STOPPED IN GADRUN DUE TO
     1ERROR TYPE',I2,'.  TOUGH LUCK BOB.'/)
      STOP
 61   MM=NN+NORIGC
      MMM=MM*5
      DO 65 II=1,MMM
      JJ=II+50
      STO2(JJ)=1
 65   CONTINUE
      GO TO 45
      END
```

FILE. . .   DATGET   FORTRAN   P1

```
      SUBROUTINE DATGET(FIRSTL,LASTL,FIRSTC,LASTC,N,INTVL,CHANSL,ID,
     1RSLTS,DATUNT,RID)
      IMPLICIT INTEGER*4 (A-Z)
C
C
C           DATGET GETS A DATA BLOCK FROM A DATA TAPE.
C           DATGET ASSUMES THAT THE TAPE IS ALREADY MOUNTED.
C
C           FIRSTL IS THE FIRSTL TO BE READ
C           LASTL IS THE LAST LINE TO BE READ.
C           FIRSTC IS THE FIRSTC TO BE READ.
C           LASTC IS THE LAST CLOUMN TO BE READ.
C           N IS THE SIZE OF THE DATA BLOCK TO BE READ ON A SIDE.
C           INTVL IS THE INTERVAL BETWEEN POINTS.
C           CHANSL IS THE DESIRED CHANNEL.
C           ID IS THE ID FROM THE DATA TAPE.
C           RSLTS IS THE ARRAY WHERE THE DATA BLOCK IS STORED.
C           DATUNT TELLS WHICH TAPE UNIT THE DATA TAPE IS MOUNTED.
C           RID IS THE REAL PART OF THE ID.
C
C
      INTEGER*2 BLOCK(4),CSEL(30)
      REAL*4 CSET(3,30),RDATA(4050),RID(200)
      DIMENSION BDATA(4050),RSLTS(134,134),ID(200)
C
C           THIS IS THE INITIALIZATION.
C
      ROLL=0
      DO 880 I=1,3
      DO 882 J=1,30
      CSET(I,J)=0.
  882 CONTINUE
  880 CONTINUE
      DO 15 I=1,3000
      BDATA(I)=0
      RDATA(I)=0.
   15 CONTINUE
      DO 20 I=1,134
      DO 25 J=1,134
      RSLTS(I,J)=0
   25 CONTINUE
   20 CONTINUE
      BLOCK(2)=FIRSTC
      BLOCK(3)=LASTC
      BLOCK(4)=INTVL
      DO 125 I=1,30
      CSEL(I)=0
  125 CONTINUE
      CSEL(CHANSL)=1
      NCD=30
      I=5*CHANSL+48
      J=I+1
      K=I+2
      CSET(1,CHANSL)=ID(I)
      CSET(2,CHANSL)=ID(J)
      CSET(3,CHANSL)=ID(K)
      NSD=N/INTVL+7
C
C           THIS DO LOOP GETS THE DATA FROM THE TAPE.
C
      DO 130 I=FIRSTL,LASTL,INTVL
      BLOCK(1)=I
      K=I-FIRSTL+1
      ERROR=0
      CALL GADLIN(BLOCK,CSEL,CSET,ID,DATUNT,NCD,NSD,BDATA,
     1RDATA,ROLL,ERROR)
      DO 140 J=1,N
      RSLTS(K,J)=RDATA(J)
      IF(ERROR.GT.0) GO TO 135
  140 CONTINUE
  130 CONTINUE
  433 FORMAT(20X,I4)
      RETURN
  135 WRITE(6,145) ERROR,I
  145 FORMAT(10X,'PROGRAM STOPPED IN DATGET DUE TO ERROR
     1TYPE',I3,1X,'IN ITERATION',I4/)
      RETURN
      END
```

```
      SUBROUTINE TWODM(RAWDAT,N,STO1,STO2,TAPE)
      IMPLICIT INTEGER*4 (A-Z)
C
C
C     THIS SUBROUTINE TAKES THE 2D FFT OF THE DATA BLOCK FROM DATGET.
C     FFT IS CALLED TO TRANSFORM EACH LINE.  THEN EACH CLOUMN IS
C     TRANSFORMED.  TRANSL IS CALLED TO PUT THE ZERO FREQUENCY IN
C     THE MIDDLE OF THE PICTURE.  PICTRE IS AND OPTION TO TAKE THE
C     PICTURE OF THE FFT OF A SINGLE DATA BLOCK.
C
C
C            RAWDAT IS THE DATA BLOCK TO BE TRANSFORMED.
C            N IS THE SIZE OF THE DATA BLOCK ON A SIDE.
C            STO1 IS THE INTEGER PART OF THE ID.
C            STO2 IS THE REAL PART OF THE ID.
C            TAPE IS THE TAPE TO BE WRITTEN ON.
C            BIGNBR PROVIDES THE LARGEST NUMBER IN THE 2DFFT BEFORE
C            SCALING.  NORM SCALES THE 2DFFT INTO THE PROPER RANGE.
C
C
      REAL*4 X(256),Y,NORM,STO2(200),BIGNBR
      REAL*8 HOLD1,HOLD2
      DIMENSION STO1(200),L(256),W(256),RAWDAT(134,134)
      N2N=2*N
      DO 63 II=1,256
      X(II)=0.
 63   CONTINUE
C
C            THE FIRST ROW OF DATA IA TRANSFORMED.  THE
C            FACTOR OF 100 CONTROLS THE EVENTUAL MAG ITUDE OF
C            THE 2DDFFT.
C
 65   DO 79 I=1,N
      X(I)=RAWDAT(1,I)
      X(I)=X(I)/(1.)
 79   CONTINUE
      CALL FFT(X,W,L,N,-1,0)
      DO 80 I=1,N
      J=I+N
      HOLD1=X(I)**2
      HOLD2=X(J)**2
      RAWDAT(1,I)=DSQRT(HOLD1+HOLD2)
 80   CONTINUE
      DO 66 II=1,N2N
      X(II)=0.
 66   CONTINUE
C
C            NOW THE OTHER ROWS ARE TRANSFORMED.
C
      NMIN1=N-1
      DO 104 I=2,N
      DO 105 MM=1,N
      X(MM)=RAWDAT(I,MM)
      X(MM)=X(MM)/(1.)
 105  CONTINUE
      CALL FFT(X,W,L,N,-1,2)
      DO 81 K=1,N
      MMM=K+N
      HOLD1=X(K)**2
      HOLD2=X(MMM)**2
      RAWDAT(I,K)=DSQRT(HOLD1+HOLD2)
 81   CONTINUE
      DO 67 II=1,N2N
      X(II)=0.
 67   CONTINUE
 104  CONTINUE
C
C            NOW THE COLUMNS ARE TRANSFORMED.
C
      DO 310 I=1,N
      DO 320 J=1,N
      X(J)=RAWDAT(J,I)
 320  CONTINUE
      CALL FFT(X,W,L,N,-1,2)
      DO 330 K=1,N
      KK=K+N
      HOLD1=X(K)**2
      HOLD2=X(KK)**2
```

```
      RAWDAT(K,I)=DSQRT(HOLD1+HOLD2)
  330 CONTINUE
      DO 340 K=1,N2N
      X(K)=0
  340 CONTINUE
  310 CONTINUE
  109 BIGNBR=RAWDAT(1,1)
C
C            THE LARGEST NUMBER IN THE 2DDFFT IS NOW FOUND
C            FOR SCALING PURPOSES.
C
      DO 121 I=1,N
      DO 123 J=1,N
      IF (BIGNBR.LT.RAWDAT(I,J)) BIGNBR=RAWDAT(I,J)
  123 CONTINUE
  121 CONTINUE
C
C            SCALING INTO THE 0-256 RANGE IS NOW PERFORMED.
C
      CALL TRANSL(RAWDAT,N)
      RIGNBR=BIGNBR
      NORM=255./(ALOG10(RIGNBR+2.))
      DO 203 I=1,N
      DO 205 J=1,N
      RIGNBR=RAWDAT(I,J)
      RAWDAT(I,J)=NORM*(ALOG10(RIGNBR+2.))
  205 CONTINUE
  203 CONTINUE
  206 DO 207 I=1,6
      DO 209 J=1,N
      B=I+N
      RAWDAT(J,B)=1
  209 CONTINUE
  207 CONTINUE
      IF(N.GT.1000) GO TO 855
      RETURN
  855 CALL PICTRE(RAWDAT,STO1,STO2,TAPE,N)
      RETURN
      END
```

FILE. . .   FFT   FORTRAN   PI

```
      SUBROUTINE FFT(X,W,L,N,ISIGN,NUSE)
      DIMENSION X(1),W(1),L(1)
C
C
C           FFT IS A ROUTINE WRITTEN BY BOB KETTIG TO TAKE THE
C           FAST FOURIER TRANSFORM OF DIGITAL DATA.
C
C           X IS THE ARRAY TO BE TRANSFORMED.
C           W IS A WORK SPACE AND SHOULD BE DIMENSIONED AS LARGE AS X
C           L SERVES THE SAME PURPOSE AS W.  I DIMENSION W&L TWICE AS
C           X.
C           N IS THE NUMBER OF POINTS TO BE TRANSFORMED AND MUST BE
C           A POWER OF 2.
C           ISIGN DETERMINES WHETHER THE TRANSFORM OR INVERSE TRANSFORM
C           WILL BE TAKEN.
C           NUSE TELLS WHETHER THSI ROUTINE HAS BEEN CALELED BEFORE FOR
C           THE GIVEN 'N'.  IF SO, THE ROUTINE WILL PERFORM FASTER.
C
C
      RECIP=1./N
      LIMHI=0
      INCR=N
      IF(ISIGN) 1000,1000,1005
 1005 DO 1010 I=1,N
      X(I)=RECIP*X(I)
      IN=I+N
 1010 X(IN)=-RECIP*X(IN)
 1000 IF(NUSE-1) 1060,1060,2000
 1060 N4=N/4
      L(1)=1
      N40=N4-1
      N341=3*N4+1
      W(1)=1.
      W(2*N4+1)=-1.
      W(N4+1)=0.
      W(N341)=0.
      PIN=6.2831853*RECIP
      DO 1020 I=1,N40
      INN=N4-I
      INP=N4+I
      W(INN+1)=COS(PIN*INN)
      W(INP+1)=-W(INN+1)
      K=N341+I
      W(K)=W(INN+1)
      K=N341-I
 1020 W(K)=-W(INN+1)
 2000 NR=N/INCR
      IDEL=INCR
      INCR=INCR/2
      IF (INCR-1) 4000,2025,2025
 2025 IF (NUSE-1) 2035,2035,2050
 2035 LIMLO=LIMHI+1
      LIMHI=2*LIMLO-1
      DO 2010 J=LIMLO,LIMHI
      K=J+1-LIMLO
 2010 L(J+1)=L(K)+INCR
 2050 LOC=1
      DO 2020 I=1,NR
      KLO=(I-1)*IDEL+1
      KHI=KLO+INCR-1
      LCOS=L(LOC)
      LSIN=LCOS+N4
      IF(LSIN-N) 2095,2095,2090
 2090 LSIN=LSIN-N
 2095 WR=W(LCOS)
      WI=W(LSIN)
      DO 2040 K=KLO,KHI
      KINC=K+INCR
      AR=X(K)
      M=K+N
      AI=X(M)
      BR=X(KINC)*WR
      BI=X(KINC)*WI
      MI=KINC+N
      CR=X(MI)*WI
      CI=X(MI)*WR
      X(K)=AR+BR-CR
      X(KINC)=AR-BR+CR
```

```
      X(MI)=AI-BI-CI                                                    FFT00790
      X(M)=AI+BI+CI                                                     FFT00800
 2040 CONTINUE                                                          FFT00810
 2020 LOC=LOC+2                                                         FFT00820
      GO TO 2000                                                        FFT00830
 4000 DO 4020 I=2,N                                                     FFT00840
      NEW=L(I)                                                          FFT00850
      IF(I-NEW) 4010,4020,4020                                          FFT00860
 4010 DR=X(I)                                                           FFT00870
      IN=I+N                                                            FFT00880
      DI=X(IN)                                                          FFT00890
      X(I)=X(NEW)                                                       FFT00900
      M=NEW+N                                                           FFT00910
      X(IN)=X(M)                                                        FFT00920
      X(NEW)=DR                                                         FFT00930
      X(M)=DI                                                           FFT00940
 4020 CONTINUE                                                          FFT00950
      IF (ISIGN) 7000,7000,5500                                         FFT00960
 5500 DO 5000 I=1,N                                                     FFT00970
      IN=I+N                                                            FFT00980
 5000 X(IN)=-X(IN)                                                      FFT00990
 7000 RETURN                                                            FFT01000
      END                                                               FFT01010
```

```
      SUBROUTINE TRANSL(DATAIN,N)
C
C
C     THIS ROUTINE SWITCHES THE FIRST AND THIRD QUADRANTS, AND
C     THE SECOND AND FOURTH QUADRANTS OF AN N BY N ARRAY 'DATAIN'.
C
C          DATAIN IS THE ARRAY TO BE TRANSFORMED.
C          N IS THE SIZE ON A SIDE OF DATAIN.
C          STORE IS A STORAGE ARRAY.
C
C
      IMPLICIT INTEGER*4(A-Z)
      DIMENSION DATAIN(134,134),STORE(64,64)
      NDIV2=N/2
      DO 110 I=1,NDIV2
      DO 109 J=1,NDIV2
      STORE(I,J)=0
  109 CONTINUE
  110 CONTINUE
      DO 10 I=1,NDIV2
      DO 11 J=1,NDIV2
      IPLSND=I+NDIV2
      JPLSND=J+NDIV2
      STORE(I,J)=DATAIN(IPLSND,JPLSND)
      DATAIN(IPLSND,JPLSND)=DATAIN(I,J)
      DATAIN(I,J)=STORE(I,J)
   11 CONTINUE
   10 CONTINUE
      DO 15 I=1,NDIV2
      DO 16 J=1,NDIV2
      IPLSND=I+NDIV2
      JPLSND=J+NDIV2
      STORE(I,J)=DATAIN(IPLSND,J)
      DATAIN(IPLSND,J)=DATAIN(I,JPLSND)
      DATAIN(I,JPLSND)=STORE(I,J)
   16 CONTINUE
   15 CONTINUE
   13 FORMAT(20X,I60/////)
      RETURN
      END
```

FILE. . .   RESLTS   FORTRAN   P1

```
      SUBROUTINE RESLTS(A,N,I,J,B,NN)
      IMPLICIT INTEGER*4 (A-Z)
C
C
C          RESLTS TAKES THE 2DFFT AND BY CALLING SAMPLE PERFORMS
C          DATA COMPRESSION.  THE MAIN PURPOSE OF RESLTS IS TO
C          KEEP TRACK OF THE DYNAMIC STORAGE FOR BLOCK SIZES
C           OF LESS THAN (LE) 8.
C
C          A IS THE 2DFFT
C          N IS THE SIZE OF THE ARRAY 'A' ON A SIDE.
C          J IS THE CURRENT COLUMN IN THE MAIN CALLING ROUTINE.
C          B IS THE ARRAY WHERE THE SAMPLED DATA IS STORED.
C          NN IS THE DIMENSION OF THE RESULTING FEATURE VECTOR.
C
C
      DIMENSION A(134,134),DATA(25),B(25,250)
      REAL*4 C(4)
      Y=0
      WRITE(6,925) N
  925 FORMAT(50X,I5)
      NN=0
      IF(N.GT.9) GO TO 40
      IF((J.EQ.1) .AND.(I.NE.1)) GO TO 25
      IF((J.EQ.1).AND.(I.EQ.1))GO TO 50
   15 CALL SAMPLE(A,N,DATA,NN)
   16 X=I/2*2
      IF(X.EQ.I) Y=1
      Z=Y*3
      DO 20 II=1,3
      ZZ=Z+II
      B(ZZ,J)=DATA(II)
   20 CONTINUE
      RETURN
   25 DO 30 II=1,249
      II1=II+1
      DO 35 JJ=1,3
      JJ1=JJ+3
      JJ2=JJ+6
      C(1)=B(JJ,II)
      C(2)=B(JJ,II1)
      C(3)=B(JJ1,II)
      C(4)=B(JJ1,II1)
      B(JJ2,II)=C(1)/4.+C(2)/4.+C(3)/4.+C(4)/4.
   35 CONTINUE
   30 CONTINUE
      GO TO 15
   40 CALL SAMPLE(A,N,DATA,NN)
      DO 45 II=1,25
      B(II,J)=DATA(II)
   45 CONTINUE
      WRITE(6,999) N
  999 FORMAT(2X,I2)
      RETURN
   50 CALL SAMPLE(A,N,DATA,NN)
      DO 55 II=1,NN
      II6=II+6
      DO 60 JJ=1,249
      B(II6,JJ)=DATA(II)
   60 CONTINUE
   55 CONTINUE
      GO TO 16
      END
```

FILE. . .   SAMPLE   FORTRAN   P1

```
      SUBROUTINE SAMPLE(A,N,DATA,NN)
      IMPLICIT INTEGER*4 (A-Z)
      REAL*4 R4,XARRAY,YARRAY,R1,R2,X,Y,DIV,HOLD(25),SAVE
      DIMENSION ARRAY(16,16,2),A(134,134),DATA(25)
  1   DO 11 MM=1,25
      HOLD(M)=0.
      DATA(MM)=0
 11   CONTINUE
      NN=7
      DIV=4.
      DO 12 M=1,7
      R1=M
      R2=M-1
      IF(M.EQ.2) DIV=8.
      IF(M.EQ.3) DIV=20.
      IF(M.EQ.4) DIV=20.
      IF(M.EQ.5) DIV=28.
      IF(M.EQ.6) DIV=32.
      IF(M.EQ.7) DIV=44.
      DO 10 I=1,16
      DO 15 J=1,16
      ARRAY(I,J,1)=I
      ARRAY(I,J,2)=J
 15   CONTINUE
 10   CONTINUE
      DO 20 I=1,16
      DO 25 J=1,16
      X=ARRAY(I,J,1)
      Y=ARRAY(I,J,2)
      XARRAY=ABS(8.5-X)
      YARRAY=ABS(8.5-Y)
      R4=SQRT(XARRAY**2+YARRAY**2)
      SAVE=A(I,J)
      IF((R4.LT.R1).AND.(R4.GT.R2)) HOLD(M)=HOLD(M)+SAVE/DIV
 25   CONTINUE
 20   CONTINUE
 12   CONTINUE
      DO 30 BBB=1,25
      DATA(BBB)=HOLD(BBB)
 30   CONTINUE
      WRITE(6,999) N
 999  FORMAT(2X,I2)
      RETURN
      DEBUG UNIT(6),INIT(N)
      AT 1
      DISPLAY N
      END
```

FILE. . .   WRITE   FORTRAN   P1

```
      SUBROUTINE WRITE(J,STARTC,ENDCOL,STO1,STO2,TAPE,FILE,
     1B,NORIGC,INTVL,NN,MN,NUMSLN,NUMSCL,RUNSEL,ID,RID)
      IMPLICIT INTEGER*4 (A-Z)
C
C
C            WRITE TAKES THE SAMPLED 2DFFT DATA AND WRITES
C            THE SAMPLED DATA ON A TAPE IN DATA TAPE
C            FORMAT.   'WRITE' ALSO WRITES THE ORIGINAL DATA
C            ON THE TAPE.
C
C            J IS THE LINE OF THE MAIN PROGRAM.
C            STARTC IS THE FIRST COLUMN TO BE WRITTEN.
C            ENDCOL IS THE LAST COLUMN TO BE WRITTEN.
C            STO1 IS THE INTEGER PART OF THE ORIGINAL TAPE ID.
C            STO2 IS THE REAL PART OF THE ORIGINAL TAPE ID.
C            TAPE IS THE TAPE TO BE WRITTEN ON.
C            FILE IF THE FILE OF 'TAPE' TO BE WRITTEN ON.
C            B IS THE ARRAY HOLDING THE FEATURE VECTORS TO BE WRITTEN.
C            NORIGC IS THE NOUMBER OF ORIGINAL COLUMNS READ.
C            INTVL IS THE INTERVAL BETWEEN POINTS TO BE READ.
C            NN IS THE DIMENSION OF THE FEATURE VECTOR.
C            MN IS THE  SIZE OF THE ORIGINAL DATA BLOCK IN THE CALLING
C               ROUTINE.
C            NUMSLN IS THE NUMBER OF LINES TO BE WRITTEN.
C            NUMSCL IS THE NUMBER OF COULUMNS TO BE WRITTEN.
C            RUNSEL IS THE RUN THE ORIGINAL DATA IS FROM.
C            ID IS THE ORIGINAL ID.
C            RID IS THE ORIGINAL REAL PART OF THE ID.
C
C
      INTEGER*2 BLOCK(4),CSEL(30),LINE,ROLL
      REAL*4 CSET(3,30),RDATA(360),STO2(200),RID(200)
      DIMENSION BDATA(3000),STO1(200),IDATA(7501),HOLD(7501),B(25,250)
      DIMENSION ID(200)
      LOGICAL*1 LDATA(30004),PNT4(4),PNT
      EQUIVALENCE (LDATA(1),LINE),(LDATA(3),ROLL)
      EQUIVALENCE (IDATA(1),LDATA(1)),(PNT,PNT4(4)),(ITEMP,PNT4(1))
C
C            THIS IS THE INITIALIZATION
C
      LINE=J
      DATUNT=11
      UNIT=12
      NPLS6=N+6
      TOTAL=(NN+NORIGC)*(N+6)
      TOTALC=NORIGC+NN
      N=ENDCOL-STARTC
      NSD=360
      NCD=1
      DO 25 I=1,30
      CSEL(I)=0
      DO 30 JJ=1,3
      CSET(JJ,I)=0.
   30 CONTINUE
   25 CONTINUE
      DO 35 I=1,360
      RDATA(I)=0.
   35 CONTINUE
      DO 36 I=1,3000
      BDATA(I)=0
   36 CONTINUE
      BLOCK(1)=LINE
      BLOCK(2)=STARTC
      BLOCK(3)=STARTC+NUMSCL-MN/2
      BLOCK(4)=INTVL
      OLDAT=NORIGC*(N+6)
      OLDAT1=OLDAT+NN*(N+6)
      DO 20 I=1,NORIGC
      KKK=(N+6)*(I-1)
      CSEL(I)=1
      CHANSL=I
      II=5*CHANSL+48
      JJ=II+1
      KK=JJ+1
      CSET(1,I)=RID(II)
      CSET(2,I)=RID(JJ)
      CSET(3,I)=RID(KK)
C
```

```
C          THE OLD DATA WILL BE RE-READ SO THAT IT CAN BE
C             WRITTEN ALONG WITH THE NEW DATA.
C
      CALL GADLIN(BLOCK,CSEL,CSET,ID,UNIT,NCD,
     1NSD,BDATA,RDATA,ROLL,ERROR)
      IF(ERROR.GT.0) WRITE(6,40) I,ERROR
 40   FORMAT(10X,'PROGRAM STOPPED IN GADLIN IN WRITE ON ITERATION',
     12X,I2,'  DUE TO ERROR TYPE',I8/)
      DO 50 K=1,N
      KJJ=KKK+K
      HOLD(KJJ)=RDATA(K)
 50   CONTINUE
      CSEL(I)=0
      DO 45 K=1,6
      DO 47 II=1,TOTALC
      STORE=(II-1)*(N+6)+N+K
      HOLD(STORE)=1
 47   CONTINUE
 45   CONTINUE
 20   CONTINUE
C
C          NOW THE TAPE TO BE WRITTEN ON WILL BE POSITIONED.
C
      WRITE(6,998)
 998  FORMAT(15X,'HELLO')
      IF(LINE.NE.1) GO TO 49
      FILPOS=FILE
 72   FILPOS=FILPOS-1
      IF(FILPOS.EQ.0)  GO TO 75
      CALL TOPFF(11)
      GO TO 72
 75   STO1(1)=TAPE
      STO1(2)=FILE
      STO1(3)=RUNSEL
      STO1(5)=NORIGC
      STO1(6)=NUMSCL+6-MN/2
      STO1(20)=NUMSLN
      COUNT=800
C
C          THIS WRITES THE NEW ID AND ALSO STORES THE
C             SPATIAL INFORMATION.
C
      CALL TOPWR(DATUNT,COUNT,ERROR,STO1)
 49   DO 57 JJ=1,NN
      JJ6=JJ
      IF(MN.LT.9) JJ6=JJ6+6
      DO 55 II=1,N
      NEWDAT=OLDAT+(JJ-1)*(N+6)+II
      HOLD(NEWDAT)=B(JJ6,II)
 55   CONTINUE
 57   CONTINUE
C
C          PACKING NOW TAKES PLACE
C
      WRITE(6,999) ROLL
 999  FORMAT(5X,I2)
      DO 60 K=1,OLDAT1
      ITEMP=0
      ITEMP=HOLD(K)
      LDATA(K+4)=PNT
 60   CONTINUE
      COUNT=TOTALC*(N+6)+4
      ROLL=1
C
C          HERE THE ENTIRE LINE IS WRITTEN
C
      CALL TOPWR(DATUNT,COUNT,ERROR,IDATA)
      IF(ERROR.GT.0) WRITE(6,65) ERROR
 65   FORMAT(10X,'ERROR IN TOPWR OF TYPE',2X,I2/)
      RETURN
      END
```

```
      SUBROUTINE PICTRE(A,STO1,STO2,TAPE,N)
      IMPLICIT INTEGER*4 (A-Z)
C
C
C          PICTRE WILL WRITE A 2DFFT ON A TAPE.  THIS IS USUALLY SO THAT
C          A PICTURE OF THE 2DFFT CAN BE TAKEN ON THE DIGITAL DISPLAY.
C
C          'A' IS THE ARRAY HOLDING THE 2DFFT.
C          STO1 IS THE INTEGER PART OF THE ID.
C          STO2 IS THE REAL PART OF THE ID.
C          TAPE IS THE TAPE TO BE WRITTEN ON.
C          N IS THE SIZE OF THE 2DFFT ON A SIDE, NOT COUNTING THE ADDED
C          CALIBRATION VALUES.
C
C
      DIMENSION A(134,134)
      REAL*4 STO2(200)
      INTEGER*2 LINE,ROLL
      INTEGER*4 IDATA(140),ITEMP,STO1(200)
      LOGICAL*1 LDATA(560),PNT4(4),PNT
      EQUIVALENCE  (LDATA(1),LINE),(ROLL,LDATA(3))
      EQUIVALENCE (IDATA(1),LDATA(1)),(ITEMP,PNT4(1)),(PNT,PNT4(4))
      STO1(1)=TAPE
      STO1(2)=1
      STO1(5)=1
      STO1(6)=N+6
      STO1(20)=N
      NPLS6=N+6
      DO 15 I=1,145
      J=I+55
      STO2(J)=0.
   15 CONTINUE
      DATUNT=11
      CALL TOPRW(DATUNT)
      COUNT=800
      CALL TOPWR(DATUNT,COUNT,ERROR,STO1)
      ROLL=1
      COUNT=N+10
      DATUNT=11
      DO 10 I=1,N
      DO 20 J=1,NPLS6
      ITEMP=0
      ITEMP=A(I,J)
      LDATA(J+4)=PNT
   20 CONTINUE
      LINE=I
      CALL TOPWR(DATUNT,COUNT,ERROR,IDATA)
   10 CONTINUE
      UNIT=11
      CALL TOPEF(UNIT,ERROR)
      RETURN
C     DEBUG UNIT(6),INIT(STO1,STO2),SUBCHK
      END
```

16 gray levels. This can be done by dividing the range of possible data values into the desired number of intervals and assigning a value to each data point based on the interval in which it lies. However, the texture measures which will be calculated later will show a variation due to a monotonic transformation of the image. One would like the texture features to have the same value regardless of whether the image is viewed on a sunny day or cloudy day. To maintain this invariance over monotonic transformations, it is necessary to equal-probability quantize the data. That is, each data point will be assigned to a gray level with equal probability.

The textural features are computed from angular measures of the spatial relationship that gray tones have to one another in an image. These measures are termed gray-tone spatial-dependence matrices. Each elements a_{ij} in the matrix corresponds to the frequency with which the i^{th} gray-tone is adjacent to the j^{th} gray-tone. To compute the gray-tone spatial dependence matrices that will be needed the image is divided into resolution cells such that the image is X cells wide by Y cells long, where each cell has a single gray-level assigned to it. Each cell has eight neighbors as shown in the figure below. Resolution cell 0 has cells 1 and 5 as horizontal neighbors, 3 and 7 as vertical neighbors, 6 and 2 as left diagonal neighbors, and 4 and 8 as

6	7	8
5	8	1
4	3	2

right diagonal neighbors. The horizontal gray-tone spatial-dependence matrix is calculated from the horizontal neighbors. Similarly the vertical, left diagonal, and right diagonal matrices are computed using the appropriate set of neighbors. It should be noted that the matrices are symmetric.

The elements of the gray-tone spatial-dependence matrices can be normalized by dividing each element by the number of resolution cell pairs. For horizontal and vertical matrices the number of pairs is equal to 2(Y) (X-1) and 2(X) (Y-1), respectively, while for the diagonal matrices the number of pairs is equal to 2(X-1) (Y-1).

The gray-tone spatial-dependence matrix represents a statistical measure of the textural information contained in the spatial relationship which the gray-tones in the image have to one another. From each of these matrices textures features can be calculated. Haralick lists fourteen possible texture features. Three of these features: angular second-moment, contrast and correlation, have been emphasized during the early stages of this work.

The angular second-moment feature is a measure of the homogeneity of the image,

$$ASM = \sum_i \sum_j [p(i,j)^2]$$

where p(i,j) is a normalized element of the gray-tone spatial--dependence matrix. The range of values for ASM is from one, when all the resolution cells in the image have the same gray-level value, to approaching zero, when the image is fairly inhomogeneous.

Contrast is a measure of the local variations in the image.

$$C = \sum_{n=0}^{N_g-1} n^2 \{ \sum_{|i-j|=n} p(i,j) \}$$

where p(i,j) is a normalized element of the gray-tone spatial-dependence matrix and N_g is the number of gray-levels. The range is from zero, where the image consists of cells having the same gray-level and hence, no local variation, to a number on the order of 10^1 for large local variations.

Correlation is a measure of the gray-tone linear dependencies in the image. It is similar to a normalized correlation coefficient.

$$p = \frac{\Sigma_i \Sigma_j \ (ij) \ p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

where μ_x, μ_y, σ_x, and σ_y are the means and standard deviations of the marginal probability matrix by summing the rows (for μ_x and σ_x) or the columns (for μ_y and σ_y) of p(i,j). The range of the correlation is from -1 to 1.

Computer programs have been written and tested to take quantized multispectral image storage tape data and obtain the three discussed texture features: angular second-moment, contrast, and correlation.

Subroutine GTSDM computes gray-tone spatial-dependence matrices from the quantized image data. Subroutine TEX3 calculates the three texture measures: angular second-moment, contrast, and correlation from the matrices computed by GTSDM.

Classification will be attempted using the classification algorithms in LARSYS. The spectral channels will be augmented by the texture features for classification. The average and range of the four values calculated for each texture feature will each constitute a new channel. Therefore, for each spatial point in the image there will be a set of spectral channels plus a set of textural channels.

Textural features have been calculated from synthesized 4-level images. The primary purposes for constructing these images was for program debugging and for getting a feel for the range and values of the texture features.

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XI. Soil Inventory Applications

INTRODUCTION

Only about half of the 1.2 billion hectares of land in the United States has been described by recent soil surveys. Mounting pressures from increased land use and the critical need for resource planning demands that the present rate of preparing soil surveys and land inventories be accelerated dramatically.

Preliminary studies have indicated that a LANDSAT-LARSYS data collection and computer-aided analysis system has several significant advantages over other methods of characterizing and mapping land resources. It is not being suggested at this stage that the LANDSAT-LARSYS system of classifying multispectral data replace the conventional soil mapping approach being used in the United States today. However, it is suggested that satellite images and multispectral data may be valuable to the soil surveyor for producing very rapidly soil association maps in counties where no maps are presently available and for planning field observations for detailed mapping.

To integrate effectively remote sensing technology and the present methods of soil survey, an evaluation of the present methods of soil survey must be made. The objective of this study was to assess the utility of the LANDSAT-LARSYS system as a tool in soil survey.

Test Site

White County, Indiana was selected as the target area for this study. The county is located in the Till Plain section of the Central Lowland province of the United States. The major soils in the area include Miami, Crosby, Odell, and Brookston series in the uplands and Chelsea, Brems, Granby, and Maumee series in the sandy areas.

Approach

LANDSAT-1 multispectral scanner data were collected over White County, Indiana on 9 June, 1973. The data, in computer compatible tape format, were geometrically corrected and rescaled by computer processing to a scale of 1:20,000 and 1:24,000 to facilitate comparisons between field sheets and other available data with line printer output. Additional processing of the data produced false color (simulated color infrared) images from the digital display. These images were evaluated at a scale of 1:160,000.

Simulated Color Infrared Imagery

The false color imagery was produced by displaying the data on the digital display unit and exposing 35mm color film to the blue, green and red regions of the spectrum (.50-.60 μm, .60-.70 μm and .80-1.1 μm, respectively). The synoptic view provided by LANDSAT ruled out the need for producing a mosaic of the county; thus all color tones in the imagery were comparable for the entire county. The false color (simulated color infrared) LANDSAT imagery proved to be a useful tool in comparing surface features for the entire county.

It was possible to make various interpretations by overlaying road maps, surficial geology maps, soil association maps, topographic maps and surface drainage maps. Comparison of existing soil association boundaries with the imagery showed that definite relationships do exist between the boundaries and various false color patterns. Many soil boundaries were visible on the imagery which were not delineated on any soil maps. It was noted that this imagery could have aided the soil mapper drawing boundaries for the general soils map. Also, the false color image, when overlayed with road maps, made field checking of complex soil patterns a very productive effort.

Line Printer Output

Spectral soils maps (cluster and non-supervised classification maps) produced as line printer output were utilized at scales of 1:24,000 and 1:20,000. The 1:20,000 line printer maps were used because they were the same scale as the field mapping sheets. The 1:24,000 maps were the same scale as USGS topographic 7½ minute quadrangle maps.

Both gray-level maps of individual LANDSAT spectral bands and spectral soil maps were used throughout the analysis to aid in locating features and for information extraction. The larger scale spectral soil maps were used in the field to determine if they would yield more information than the small scale false color images. However, it was soon realized that it was almost impossible to locate precisely a given pixel with its ground position.

Information Extraction

To be able to overlay informational boundaries (roads or soil boundaries) from maps to LANDSAT data, checkpoints (points of known location in both data sets) must first be located. To locate pixels in the LANDSAT data for use as checkpoints, the *TRANSFERDATA function was employed. Smal[illegible] areas in which a candidate checkpoint on a map had been located w[illegible] hosen for use in the *TRANSFERDATA. This met od was chosen because [illegible] large amount of data that would have been involved if large indiscriminant areas were used.

*TRANSFERDATA proved useful in locating checkpoints. Aerial photography at a scale of 1:20,000 was overlayed with 1:20,000 LANDSAT data with less than 1 percent error in location of pixels.

Very subtle changes in surface features could be detected in the LANDSAT data. However, these differences were subdued or lost entirely whenever the data were clustered to produce the spectral soil maps. LANDSAT can detect these small differences in responses, but with the present computer techniques it was difficult to delineate these more subtle features.

SUMMARY AND RECOMMENDATIONS

The LANDSAT-LARSYS system provides new, exciting possibilities for characterizing and inventorying land resources. Soil survey, according to conventional definition, is only one of many methods for describing and mapping land resources. Although the objective of this study was to evaluate the LANDSAT-LARSYS system as a tool for the soil surveyor, it must be noted that results suggest a broad array of applications in characterizing and inventorying the land areas of the world. In this study the synoptic view of the target area provided by false color images from LANDSAT data was of great benefit in obtaining a broad understanding of the soils, soil/land use relationships, and topographic features at a scale of 1:160,000. Surface features maps at scales of 1:20,000 and 1:24,000 obtained with the computer printouts provided the valuable opportunity to overlay and compare LANDSAT data with conventional soils and topographic maps.

The capability to digitize to a desired scale topographic maps, geology surveys, precipitation maps, and other data will greatly extend the use of the LANDSAT-LARSYS system. Such a capability will increase the utility of remote sensing for soil survey, soil productivity ratings, land use capability mapping, delineation of different land deterioration categories, and the inventory of lands with agricultural limitations. It is recommended that strong support be provided for research to develop the remote sensing methodology for application to these various measurements and classifications of land resources.

XII. Electrical Methods for Determining Soil Moisture Content

ABSTRACT

In this section of the report, electrical methods for determining soil moisture content, are explored. Since the magnetic permeability and electrical conductivity of soils are known to be unreliable indicators of soil moisture content, the study reported here focuses on the electrical permittivity of soils. The first part of the report gives an assessment of the permittivity as a indicator of soil moisture content based upon experimental studies performed at LARS. The conclusion is that the electrical permittivity of soils is a useful indicator of available soil moisture content.

In the second part of the report, a method for determining the permittivity profile of soils is examined in light of the findings in the first part of the report. A variation of a method of Slichter[1] is extended to the proposal of an instrument design that could measure available soil moisture profile (percent available soil moisture as a function of depth) from a surface measurement to an expected resolution of 10 centimeters to a depth of 1 meter. Extension of the results to an airborne remote sensing problem is considered.

PROJECT OBJECTIVES

One of the principle objectives of the project was to determine whether permittivity is a good indicator of soil moisture content. Certainly, moisture content influences soil permittivity. Basically it is possible to measure or determine soil moisture content to acceptable accuracy from the knowledge of the permittivity alone.

Some complicating factors which influence permittivity of soil are soil type, soil condition, ion concentration, time, temperature, and frequency of measurement. Experimental procedures were developed which took account of these factors in determining the relationahip between available soil moisture and electrical permittivity.

An appropriate literature review and background survey is not given in this summary report; the reader is referred to LARS Information Note 112174[2] for such detail.

INTRODUCTION

In the field of agronomy, many scientific investigations, as well as field applications, make us of soil moisture content data. Soil moisture is also an important variable in water resources management. Unfortunately, however, soil moisture content is not easy to measure in the field. The commonly used methods (gravimetric, conductivity, neutron thermalization, gamma ray attenuation) all have important disadvantages. Thus, there is a need for a better technique which can be used in remote sensing applications to field work. The method should have better accuracy than the conductivity technique, greater speed than the gravimetric method, and better portability and safety than the radiation techniques.

Ideally, the method should permit the determination of the available (for plant growth) soil moisture profile (i.e., percent available moisture as a function of depth). Electrical methods of measuring soil moisture appear to be able to satisfy these needs). Three properties of matter can be measured by electrical methods: magnetic permeability, conductivity, and electrical permittivity. Except under unusual circumstances, the permeability of soil is very close to its value in free space, μ_0(1). The conductivity of soil is not a reliable indicator of moisture content because of the large influence of ions in the soil. Measuring the conductivity of porous blocks buried in the soil overcomes this difficulty, but leads to inconvenience and inaccuracy. Only permittivity remains. It is plausible that permittivity could be a reliable indication of soil moisture, since the dielectric constant (relative permittivity) of soil is around five, while water has a relative permittivity of 80.

Furthermore, the electrical permittivity method of soil moisture measurement discussed herein has three important advantages. First, it is well suited to remote sensing, which is important from the standpoints of economy of time and financial resources required. Second, it <u>has the capability of measuring the moisture content as a function of depth below the surface of the earth, to a depth of the order of a meter</u>. Third, it is not affected by irregularities in the flatness of the soil, of the order of a few centimeters within a radius of a meter, or so.

It is possible, of course, to determine the amount of moisture at various depths in the soil (i.e., the moisture profile) by augering a hole and lowering some sort of probe into the soil. Another technique is to remove a core of the soil and to measure the soil moisture directly. Both of these methods are very time consuming. The proposed electrical permittivity method would not disturb the soil in any way since the electromagnetic waves to be used (at a frequency of about 300 megahertz (MHz) or a free-space wavelength of one meter) can penetrate most soils to a depth of about a meter and also determine the available soil moisture profile with a definition in soil depth of the order of ten centimeters, or so.

Active and passive radar methods are under consideration by other organizations. These normally involve airborne instruments operating at frequencies ranging from a few gigahertz (GHz) to perhaps 25 GHz. In general, these methods (operating at wavelengths from about 1 to 10 centimeters) are handicapped by the existence of earth surface roughnesses of the order of a few millimeters and by the fact that, at these high frequencies, the waves penetrate the earth no more than a few centimeters, at the most, depending upon the conditions (moisture content and free ion content) of the soil. Furthermore, they give a measure of the total moisture content of the soil, from the surface to their deepest point of penetration. This is a serious limitation for several of the more important applications of the measurements. The use of lower frequencies (longer wavelengths) is limited by the required increase in size of the antennas to be carried by the aircraft.

The research involved in this present project naturally divided itself into two parts. The first part was concerned with determining accurate quantitative relations between soil moisture and electrical permittivity for various common soils, and the second part dealt with methods for determining the permittivity profile. The first part of this research has been completed and the results are contained herein. The investigation of the second part seems to indicate that the most promising method for meeting the end requirements involves the development of an electrical instrument to be placed on the surface of the earth. The measurements made by this instrument on the soil moisture profile could then be telemetered to some central point, if desired. As mentioned previously, it is anticipated that the electrical measurements would be made at a frequency of about 300 MHz (a free-space wavelength of about one meter).

Experimental Procedures

The experimental procedure for measure of the electron electrical permittivity of soils was developed first with a laboratory prepared soil-moisture mixtures and later tested and evaluated on field samples of soil-moisture mixtures. A sample holder design was evolved over a considerable period of time and produced a sample holder that was resistant to the chemical action of both laboratory and field soil samples as well as being of suitable dimensions for the frequency range of measurement employed. The sample holder was fabricated from stainless steel and was designed in such a way that the effects of electrode polarization could be considered. The investigators noted that many previous researchers had neglected electrode polarization effects to the eventual detrimant of their results. Basically, the procedure consisted of measuring the capacitance of the sample holder with the soil sample installed compared to the capacitance of the sample holder with no soil sample installed. After appropriate correctional calculations are made, the permittivity can be determined from the capacitance measurements. The best results were obtained using a frequency in the 250-450 megahertz range. This frequency range was chosen because of several factors; the two principal ones are that water still had a significantly high permittivity in this frequency range and that the dimensions of the sample holder are reasonable in this frequency range.

The results of the measurements are summarized in Figure 1. Four different soil types are displayed in the figure; one should pay special attention to the break in the curve shown for the Crider Clay Soil. The knee of the curve breaks at about 17 percent moisture content, the so-called wilting point of the water/clay mixture. By locating this break in the permittivity-moisture content curve, one can determine the amount of available soil moisture as well as total moisture for any given soil. Notice that the other three soil types displayed do not show such a break in the curve since these soils do not exhibit a wilting point and all of their moisture is available to take-up by plants.

The data for the curves in Figure 1 were obtained at a frequency of 450 megahertz, but it was determined that the permittivity is relatively independent of frequency over the range of 250 to 450 megahertz. The permittivity being measured, of course, is complex and it is the real part of that permittivity which is being plotted in the figure. Results on a number of other soils are presented in the previously cited Information Note. It should be pointed out that the real part of the complex permittivity is relatively independent of the electrical conductivity of the soils. This fact was established by making the permittivity measurements over a wide range of salt concentrations in the soil water mixtures.

Measurement of Soil Moisture Profile

The ultimate goal of this investigation was to explore the feasibility of electrical methods for determining soil moisture profile, defined as the soil moisture content as a function of depth in the soil. As seen above, satisfactory relationships can be obtained between the available soil-moisture content and the electrical permittivity for several different soils. Thus, the problem reduces to determining the permittivity as a function of depth in the soil. The object is to develop a method for determining permittivity profile that does not involve disturbing the soil in any significant way. A procedure was developed which suggests an instrument that could be placed upon the surface of the soil. The data from this instrument could be reduced by a computer to yield the desired soil moisture profile to a depth of approximately 1 meter and to a resolution of approximately 10 centimeters. The proposed instrument requires that a circular symmetric magnetic dipole antenna be established upon the surface of the soil. The antenna would be excited with a frequency of the order of 300 megahertz. Then the magnitude and phase with respect to the source of the z-component of the magnetic field along any line extending radially away from the antenna would be measured. An analysis of Slichter's method, which is the theoretical basis of this experimental procedure,

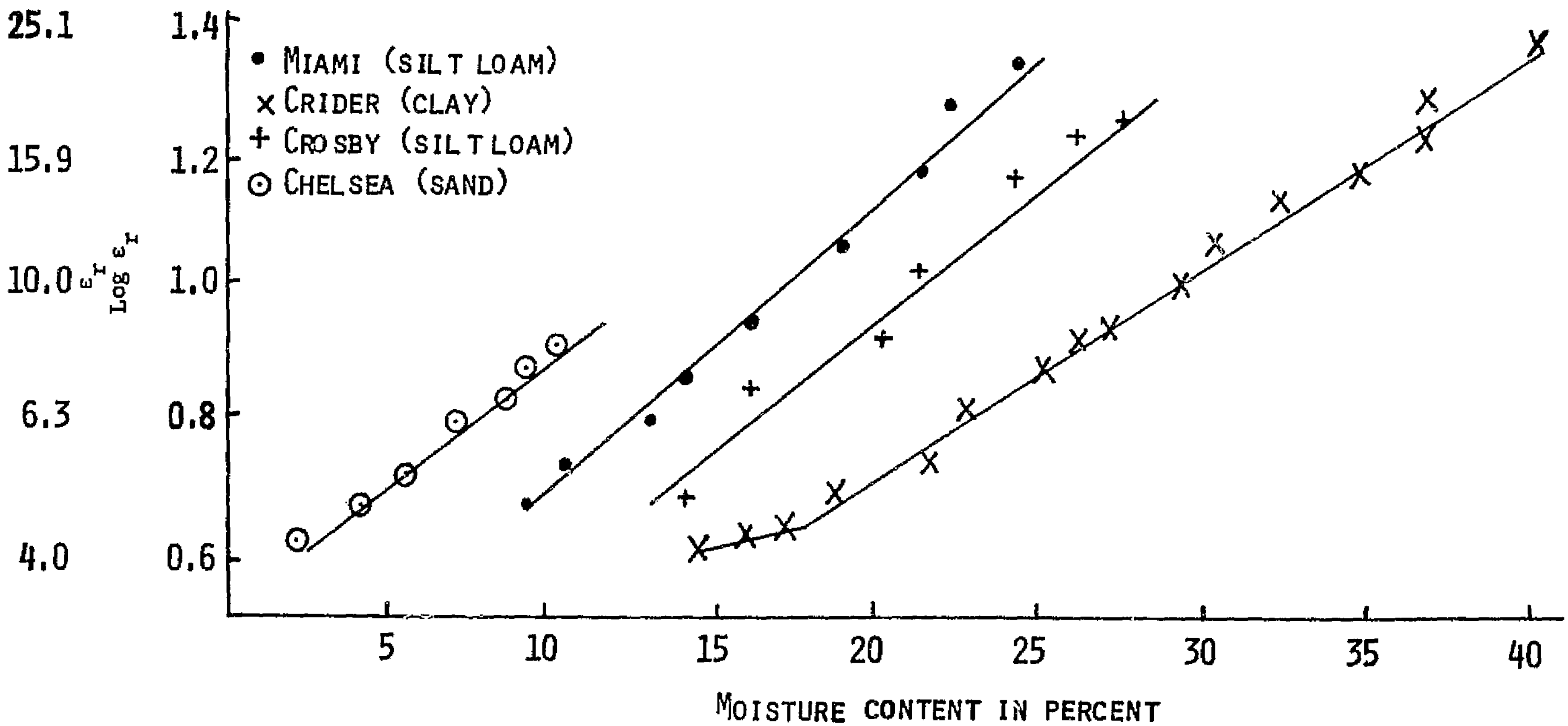

Figure 1. Permittivity of All Soils Measured Vs. Moisture Content at a Frequency of 450 MHz.

must be done out to a distance of approximately one wavelength (about 1 meter) from the center of the antenna.

Then a mathematical procedure is employed which allows an inversion of this magnetic field data into the desired permittivity as a function of depth. The details of this procedure are summarized in the following equations. First the kernel is calculated using:

$$K(\lambda) = \frac{a\mu_0 J_2(\lambda a)}{\lambda \int_0^{\rho_m} B_z(0,\rho) J_0(\lambda\rho)\rho d\rho} - \sqrt{\frac{\lambda^2 - k_0^2}{\lambda}}$$

Then the kernel is expanded as a power series:

$$K(\lambda) \cong \sum_{n=0}^{\infty} a_n \lambda^{-n}.$$

A coefficient, $\alpha(z)$, that is relatable to the complex permittivity is defined. When z-0 $\alpha(0)$ is related to the coefficients of the kernel power series by:

$$\alpha(0) = a_2$$
$$\dot{\alpha}(0) = 2a_3$$
$$\ddot{\alpha}(0) = 2a_4 = a_2^2$$
etc.

Using a MacLaurin series $\alpha(z)$ is calculated as:

$$\alpha(z) = \alpha(0) + \dot{\alpha}(0)z + \frac{\ddot{\alpha}(0)}{2} z^2 + --- .$$

Then the permittivity is calculated using:

$$\varepsilon = - \frac{2}{\omega^2 C^2} \mathrm{Re}[\alpha(z)]$$

Where ε = permittivity
ω = antenna driving frequency
c = velocity of light
k_0 = w/c
λ = separation constant
ρ = distance from center of antenna
a = radius of antenna
ρ_m = maximum radius of measurement

B_z = z - component of magnetic induction on surface

J_0&J_2 = zero and second order Bessel functions of first kind

μ_0 = permeability of free space

z = distance normal to earth's surface

More work is required to implement the method including a study of more easily realizable antenna structures than that used in the analysis. The inversion procedure also needs to be programmed for general cases. The equipment design and construction would be straight forward. Of course, an analysis of depth of measurement possible and resolution would follow construction of the instrument.

The basic technique used in the analysis can be extended to the case of a plane wave impenging on the earth's surface rather than an antenna lying on the surface. Such a study would give insight into the use of a VHF radar remote sensing syptem for moisture profile measurements.

This project was terminated during the 1975 fiscal year.

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Exhibit B

XIII. EROS Data Center Remote Terminal

INTRODUCTION

During the past year an addendum to the contract was completed to install and support a remote terminal at the EROS Data Center. As a part of this effort, Purdue was also expected to develop a demonstration package for the Data Center and aid personnel at the Data Center in converting LARSYS Version 3 to run on an EDC computer.

MATERIALS AND METHODS

Installation:

The installation of the remote terminal at the EROS Data Center was completed in early October. The hardware for this terminal consisted of an IBM 2741 and 2780 terminal, phone lines between Purdue and the Data Center, a Codex 7200 modem at EDC and Purdue, the necessary hardware and software required at Purdue to support the EDC terminal, 30 tapes, and 2 copies of the LARSYS Educational Package. In addition, the LARSYS Analysis for Instructor's course was given to Fred Waltz and David Greenlee, September 9 through 20, 1974.

Terminal Support:

After the installation of the terminal at the Data Center, Purdue provided the computer services required to support this terminal, a techniques specialist and a systems specialist, a three-day advanced analysis seminar, and other support as required. The remote terminal at the EROS Data Center continues to be a successful terminal in that each of the requirements set by the Data Center for the terminal have been successfully met.

Demonstration Package:

Purdue developed a "demonstration package" for use at the EROS Data Center. The materials were developed for use by EROS personnel so that they could demonstrate to visitors and visiting scientists the remote terminal concept and the potentials of numerical processing of remotely sensed data. The materials, when used in conjunction with the 2780 remote terminal, serve to demonstrate key analysis steps, intermediate results, and final output of a land use analysis of multitemporal LANDSAT data collected over Sioux Falls, South Dakota.

The "demonstration package" contains the following materials:

1) Fifteen copies of a demonstrator's guide containing flow charts for three demonstration plans, and lists of the visual aids and activities along with suggested commentary for each demonstration plan.

2) Five sets of control card decks.

3) Five posters illustrating concepts discussed in the demonstrations.

4) A supply of 150 "take away" handouts to be given to the demonstration audience.

5) Four copies of a flip chart showing a typical analysis sequence, accompanied by example printouts of each step.

6) Five sets of printouts annotated to show demonstrators the point to be discussed.

The three demonstration plans vary in length and in depth of discussion. Plan 1 takes approximately 20 minutes, and involves a discussion of concepts illustrated on the five posters: Earth Resources Data Processing Network, Land Use Mapping from LANDSAT, Multispectral-Multitemporal Data, Cover Type Mapping (Colorado), and Remote Sensing Applications. Plan 2 takes about 30 minutes. In addition to a discussion of the posters, this plan includes usage of the LARS terminal to run the PRINTRESULTS processing function, and discussion of the output. Plan 3 takes about an hour. In addition to the discussion of the posters, this plan includes an extended terminal session in which three LARSYS processing functions are run: PICTUREPRINT, CLUSTER, and PRINTRESULTS.

The demonstrator's guide begins with Notes to the Demonstrator, indicating what material is included and how it is to be used. Then a Master Flow Chart of the points to be discussed for all three plans is presented, followed by a separate flow chart for each individual plan. The remainder of the guide has three sections, one for each plan. The material is presented in the following format: There are three columns on each page, one lists visual aids being used, one names things the demonstrator is to do, and the third si suggested commentary.

Each set of control card decks contains a deck for running PICTUREPRINT (called deck A), a deck for running CLUSTER (deck B), and a deck for running PRINTRESULTS (deck C).

Posters were designed to illustrate the concepts of a remote terminal network, land use mapping from LANDSAT, multispectral-multitemporal data, cover type mapping, and applications of remote sensing in a variety of disciplines.

The handout[1] contains figures and text which compliment the demonstration. The material begins with a brief description of what remote sensing is, followed by material on the EROS Data Center, the remote terminal network, and orientation to numerical data analysis, an applications example, and other applications.

The flip chart, provided as part of the demonstration package is based on a flow chart showing a typical analysis sequence. Each step in the sequence is briefly described, and output from the LARSYS processing function used at that step is shown. The flip chart is intended to serve as an aid to the demonstrator in answering specific questions beyond the scope of the demonstration.

As a mechanism for familiarizing demonstrators with the output to be generated during the course of the demonstration, copies of all output are provided. A felt tip marker has been used to indicate on the output points which the demonstrator will discuss.

These materials were designed with the assistance of EROS Data Center personnel Fred Waltz and Bill Todd.

The materials illustrate the remote terminal concept and the potentials of numerical processing of remotely sensed data by using a 2780 remote terminal to carry out key analysis steps, and produce intermediate and final results of a land use analysis of multitemporal LANDSAT data.

LARSYS Conversion:

The LARSYS Version 3 conversion to the EDC Computer System portion of the Work Statement has been changed due to the changing needs of the data center. Purdue did provide one copy of complete documentation for LARSYS Version 3 and Version 3.1. Purdue did aid the EDC staff in the writing of functional specifications for the conversion of LARSYS Version 3 to the EDC computer. Purdue provided a two week training course for David Greenlee and Charlotte Muchow on LARSYS programming techniques between March 10 and March 21, 1975. Purdue did not provide the remaining two weeks of this type training, aid in the system design of the implementation of LARSYS Version 3, and provide up to 1.5 man months of application programmer time to assist in LARSYS Version 3 installation on the EDC Computer.

RESULTS

Purdue personnel did continue through the year working closely with EDC personnel on their LARSYS requirements. The first activity of the type was reported on October 10, 1974 by Susan Schwingendorf. This report on EDC benchmarks advised EDC personnel on different benchmarks run on various computers for the maximum likelihood classification, field retrieval, and geometric image transformation programs.

In December of 1974, LARS presented EDC personnel with a proposal of activities for LARSYS Version 3 conversion to EDC computer. This proposal was helpful in defining interaction between personnel of the two facilities.

In April of 1975, Dr. Philip Swain and Paul Spencer spent one week with the Image 100 located at EDC. A report of these activities entitled, "Integration of Image 100 and LARSYS at the EROS Data Center", by Philip H. Swain was prepared for EDC as a result of that activity.

As a result of the use of the remote terminal by EDC personnel and changes in the 4th portion of the Work Statement, some funds were remaining at the end of the contract period. These funds were estimated to be approximately $14,000 and a no-cost extension for support of the EDC terminal was requested and approved by the end of the contract year.

Exhibit C

XIV. NASA Langley Remote Terminal Support

During the past year an addendum to the contract was completed to continue to support a remote terminal at NASA/Langley. This support included leasing the 2741 and 2780 terminals, maintenance of the necessary hardware and software required at Purdue for the Langley/ODU terminal, provide computer and other data processing services, designate Purdue employees to serve as a techniques specialist and a systems specialist, provide a three-day seminar at NASA/Langley, and give a financial report on the services used by NASA/Langley. This system was maintained and reported during the year.

The Langley terminal was used primarily for the instruction of new analysts during the year. The primary activity of Purdue personnel was to provide consultation to these new trainees.

An advanced LARSYS analysis seminar/workshop was presented to nine analysts at NASA/Langley on March 12, 13, and 14, 1975 by Philip H. Swain and Forest E. Goodrick. Half-day seminar session topics included pattern recognition concepts, statistical characterization of pattern classes, clustering and non-supervised classification, discriminate functions separability and feature selection, and sample classification. Workshop sessions covered batch operation and access to the experimental program library, and a survey of lesser used features of LARSYS.

The Langley/ODU terminal has now been disconnected and negotiations have been conducted to re-establish it at ODU.