Combining Human and Computer Interpretation Capabilities to Analyze ERTS Imagery

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Conference on

Machine Processing of

Remotely Sensed Data

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The Laboratory for Applications of
Remote Sensing

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Indiana

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COMBINING HUMAN AND COMPUTER INTERPRETATION
CAPABILITIES TO ANALYZE ERTS IMAGERY

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I. ABSTRACT

The human has the ability to quickly delineate gross differences in land classes, such as wildland, urban and agriculture on appropriate ERTS images, and to further break these gross classes into meaningful subclasses. In agricultural areas, the subclasses can be delineated on the basis of general tone and texture differences that relate to crop type and field size. In the wildland areas, delineations can also be made, based on tone and texture, which represent general vegetation systems, such as grasslands, brush, trees, and barren areas. The computer, however, can more efficiently analyze point-by-point spectral information and localized textural information which can result in a much more detailed agricultural or wildland classification based on species composition and/or plant association.

These complementary capabilities are combined to provide the "minimum cost" processing of Remote Sensing data for resource inventory.

II. INTRODUCTION

When processing ERTS imagery, several factors affecting the cost and accuracy of land use classification become apparent. (1) There are numerous, irregularly shaped areas in the imagery which can be rapidly delineated into classes by the photo interpreter accurately enough to meet user requirements. (2) Some of these areas, because they are of little or no interest to the user, can be disregarded. (3) In localized areas, detailed automatic spectral pattern classification of plant species and plant communities can be done with a high degree of accuracy. (4) Computer classification costs increase rapidly with the number of classes being considered for each picture element. (5) There is a one-to-one relationship between the number of points being classified and the cost of computer classification.

With these factors in mind, a hardware-software system has been developed at the Center for Remote Sensing Research that integrates human and computer capabilities to increase classification accuracy and reduce processing costs.

III. PROCESSING

Human and automatic processing of the ERTS data goes on in parallel as shown in Figure 1 to the point where the information generated by both methods is merged and the final product is output in the form of a classified image and summary statistics.

Human processing starts using the appropriate ERTS image of the study area. The interpreter quickly delineates gross differences in land use classes, such as wildland, urban and agriculture. If possible, these classes are further divided into meaningful subclasses. In agricultural areas, they can be delineated on the basis of general tone and texture differences that relate to crop type and field size. In wildland areas, delineations which represent general vegetation
Figure 1. This flow chart represents the basic processing of an ERTS image that integrates the human and computer information extraction capabilities to optimize the cost effectiveness of the system.
systems such as grasslands, brush, trees, and barren areas, can also be made based on tone and texture. The boundaries of the strata are then digitized and recorded on magnetic tape, using either the comparator or coordinate digitizer, and a description of the individual stratum is entered on the tape. The image coordinates of control points are also recorded to be used to relate the image coordinate system to the ERTS tape coordinate system.

At this point in the processing, the tape coordinates of the control points obtained from the reformatted study area along with scale and skew data are input into a transform which then converts photo interpreter strata coordinates to tape data coordinates. This transformation is verified and then applied to the digitized coordinates of the strata boundaries. This produces a point-by-point overlay in which each boundary point corresponds to an ERTS picture element. Within these boundaries each point on the ERTS tape is then assigned to the corresponding photo interpreter strata. The training set for automatic classification is extracted by stratum from the ERTS image, statistics computed and test sets classified to ensure accurate classification within each stratum.

The next step is the detailed classification of each of the ERTS picture elements. A picture element and the corresponding stratification point are read. If the strata is one to be spectrally classified, the classification is done and the results put in the corresponding point of output image. If not, the photo interpreter stratum is put in the output image. This is continued point-by-point or by some sampling scheme until the processing is completed. The resultant image is a combination of photo interpretation and automatic classification with a statistical summary of the classification. As an alternative to photo interpreter delineation of strata, existing geological, geographical, or political maps can be used to stratify the ERTS data for classification or used to partition the statistical summary into meaningful reporting areas after classification.

Evaluation of Combined Analysis

To evaluate the utility of the combined human and computer discriminant analysis of ERTS-1 multispectral multidate imagery in estimating the area of agricultural crops, the information obtained from the discriminant analysis, ground data and high flight imagery of the intensive test site was used to determine the optimum size of the "Sampling Unit" (SU) and the number of sampling units required to obtain acceptable estimates of crop area for San Joaquin County.

The size of the sampling units required for agricultural estimate in San Joaquin County using ERTS-1 data in the first phase is 25 x 35 picture elements ("Pixels") 386 hectares, on the ground. This was chosen based on the estimate of the coefficient of variation as shown in Figure (2) and the plot of expected error in transferring the ERTS SUs to the corresponding low altitude photography for precise area measurement Figure (3).

Based on the error between the ground and discriminant analysis, estimates of the value of each sampling unit (SU), the number of ground samples (n) required to estimate the area of each of the major crops present in San Joaquin County using both a stratified and unstratified model was computed using a probability sampling scheme.

\[
\begin{align*}
n &= \frac{N t^2 (s_e)^2}{N(AE) + t^2 (s_e)^2} \\
N &= \text{total number of SU in population} \\
t &= t \text{ value from "students t" distribution for .95} \\
AE &= \text{Allowable error in acres} \\
s_e^2 &= \text{Variance between ERTS estimate and ground estimate.}
\end{align*}
\]

The \( s_e^2 \) was computed for single and multidate discriminant analysis estimates. For crop classes where harvesting had taken place prior to or shortly after the ERTS-1 launch on estimates of \( s_e^2 \) were based on previous results from multispectral photographs and multispectral scanner surveys.

The estimates of \( n \) were based on an allowable error of ±5% with a probability of .95.

An estimate of the cost of a survey (Table 1) was made, based on the estimated \( n \), the cost of the processing of the ERTS-1 data, and the subsequent costs of processing the selected SU. The costs used are estimates and used here to demonstrate the relative utility of each of the
Figure 2. This plot of the coefficient of variation of the crop value estimated by discriminant analysis of ERTS-1 data versus the size of the Sampling Units (SU) was used to determine the optimum SU size for random sampling.

Figure 3. This plot of the expected error in transferring the Sampling Unit (SU) to the aircraft photography for further field size measurements was used in determining the optimum SU size.
IV. CONCLUSIONS

The plot of the relative costs (Figure 4) of the various types of inventory procedures shows the combined human-computer processing using two dates of ERTS information provides the least cost method. This least cost point is caused by reductions in computer costs due to the human stratification, reduction in the number of ground samples required, and increased computer cost as the number of dates used increases. Computer costs are reduced significantly by reducing the number of classes to be considered during automatic point-by-point classification. If, for example, 40 classes exist over the entire study area but through stratification only 8 classes are considered for each point using ten strata, a 4 to 1 reduction in computer costs would be realized. A second source of saving is the elimination of areas from automatic classification by interpreter delineation when the human can adequately specify the land use or that the area is not of interest to the resource manager. This saving is nearly one to one for each point eliminated, but the saving is reduced by the computational overhead needed to determine the point-by-point strata assignment. The sample size is reduced because the classification accuracy is increased significantly by separating, through stratification, classes that have spectral signatures so similar that they cannot be separated by the discriminant analysis routine. The sample size (n) is further reduced by the additional information obtained from the multidate discriminant analysis. The cost reduction from the remote sensing information is counteracted by the increased processing cost of utilizing more dates of imagery.

Figure 4. This plot illustrates estimated relative costs of performing a crop inventory in the San Joaquin County test area using various information inputs, with an accuracy of ±5% at the 95% confidence level.
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**TABLE I.**