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INTERACTIVE CLUSTERING ON A HIGH-SPEED IMAGE DISPLAY SYSTEM

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I. ABSTRACT

An interactive implementation of cluster analysis for remote sensing image processing is described. The implementation utilizes the capabilities of a modern image display system, thereby facilitating analyst control of the processing and evaluation of the results.

II. INTRODUCTION

A. THE ROLE OF CLUSTERING

An essential aspect of any pattern-recognition-based approach to classification of multispectral remote sensing data, whether supervised or unsupervised¹, is the development of training statistics. These statistics characterize the training classes and enable the classifier to assign each point in the image data to one of the classes. Cluster analysis (or "clustering") provides an important method for determining the sets of multidimensional data vectors that can best represent each of the training classes; it isolates spectrally similar "clusters" of data vectors (i.e., clusters in the feature or measurement space) from which the training statistics for each class may then be computed. As part of a supervised training procedure for which collections of pixels of known classification are available, clustering is used to discern whether any ground cover class consists of spectrally dissimilar subclasses. For unsupervised training, clustering locates spectrally similar pixels which are subsequently associated with ground cover types based on "ground truth."

B. INTERACTIVE CLUSTERING IN CLASSIFIER TRAINING

A great variety of cluster algorithms has been developed for remote sensing data analysis and numerous other applications. One of the great frustrations for people working in this field, however, has been the elusiveness of a universal definition of "cluster." Basically, clustering is a measure of intraclass similarity versus interclass differentiability, and most clustering algorithms embody this notion in a more-or-less explicit way. Even so, when, as is often the case in practice, the clustering tendency in a data set is fairly subtle and may even vary from class to class, the skillful data analyst must step in and play a critical role in guiding the algorithm to the desired result. Typically, the analyst is expected to perform some or all of the following tasks:

- Specify the number of clusters into which the data shall be subdivided by the algorithm.
- Specify prototypes (typical pixels) to serve as initial estimates of the cluster means.
- Provide parameter values which control the algorithm's sense of similarity (split/combine thresholds).
- Define a stopping criterion for iterative processes and/or monitor the progress of the algorithm and stop it when the results are deemed satisfactory.
- Assign a label (class identifier) to the clusters distinguished by the algorithm.

Consequently, it is most advantageous for the clustering algorithm to be implemented in an interactive mode which includes a keyboard for input of processing parameters, an image display for viewing

the data and clustering results (preferably in color to increase detail), and screen cursor under control of a trackball, joystick or similar device. The speed of processing must be sufficient to support the interactive environment, and serious attention must be paid to making the implementation "user friendly." We describe below one such implementation based on the COMTAL Vision One/20. It was developed at Purdue University's Laboratory for Applications of Remote Sensing as one component of a georeferenced information processing system.

III. CLUSTERING ON THE COMTAL VISION ONE/20

A. THE CLUSTERING ALGORITHM

Figure 1 defines the clustering algorithm implemented, a basic ISODATA-type iterative algorithm² used in many remote sensing software systems¹. A set of initial cluster centers is defined (by the analyst, in this case) and each data point in the selected area is assigned to the cluster center to which it lies nearest in the feature space. All points assigned to a cluster center constitute a cluster, and the cluster means are computed. The cluster means become the new cluster centers and the data points are again assigned to the nearest cluster center; the new cluster means are again computed. This process is repeated until there is no change in the cluster assignments on two successive iterations. It can be shown that the process must terminate in a finite number of steps.

Experience has shown that when the clusters in the data are well defined, that is, are easily differentiated and the proper number of clusters is requested by the analyst, the algorithm will converge very rapidly to the final result independent of the specific initial cluster center selection. When the clusters are ill-defined, convergence is much slower and may depend heavily on the initial cluster center selection. Observing the latter behavior, the analyst may wish to terminate processing and try again.

B. THE IMPLEMENTATION

The COMTAL Vision One/20 is a modern image display system with features which make it exceptionally well-suited for interactive processing of multispectral remote sensing data.

Image Display Capabilities. The Vision One/20 has a random-access display refresh memory which can accommodate up to 16 512x512-pixel, 8-bits-per-pixel images. These images, which may be selected and displayed in black-and-white or color on a high-resolution video monitor, are loaded from an associated tape drive or video camera or a host computer. Graphic overlays facilitate annotation and labeling of images.

Image Processing Capabilities. Image processing electronics incorporated in the data path between the refresh memory and the display monitor implement a number of very-high-speed operations including gray-scale and color mapping, image-to-image arithmetic operations, convolution (filtering), and a simple form of classification. An on-board microprocessor (LSI-11) serves as a system control computer but is also available to implement user-defined processing operations. An integrated external-host interface facilitates division of labor between the interactive image display system and additional external computational facilities.

Interactive Capabilities. The Vision One/20 is well equipped to facilitate interaction between the analyst and the data. In addition to the usual alphanumeric keys, the display keyboard has 15 programmable "command keys," typically set to invoke frequently used processing operations. A target or cursor, controlled by trackball, data tablet, or software, may be used to pinpoint pixels, define image coordinates, and to "trace" linear features into the graphics or the image. Hardware zoom and roam under trackball/data tablet control further enhance the interactive process.

The iterative clustering algorithm described above has been implemented in code to run in the LSI-11 processor of the Vision One/20. On a four-image system, the area processed may consist of up to three channels of multispectral data, up to 512 x 512 pixels in size. The distance measure used to assign pixels to cluster centers is L1-distance (sum-of-componentwise-differences) because this is faster to calculate than other distance measures. The results are stored as a cluster map in an additional image plane which may be viewed in black-and-white or pseudocolor, permitting the analyst to make visual evaluation of the results. The cluster map may also be transferred back to the host computer for further processing such as the computation of training class statistics.

After loading the data to be processed into the display refresh memory, the analyst displays the image and outlines the area to be clustered. The analyst also specifies how many clusters are desired and the maximum number of iterations to be performed. Finally, the trackball and cursor are used to designate pixels to be used to define the initial cluster centers. The initial cluster centers should be representative of the spectral variation in the scene; such a selection is facilitated by color display of the multispectral data.

Once the clustering operation has commenced, the analyst can view its progress on the display screen and is also informed at the end of each iteration as to how many pixels have changed their cluster "allegiance." These forms of feedback both help the analyst decide whether to allow the process to continue and increase his/her tolerance with respect to the time required. The analyst may terminate clustering if it appears that the original parameters were inappropriate or when the results are satisfactory for the application at hand even though convergence has not yet been achieved. If the analyst does not intervene, the process will terminate itself when convergence is reached (no change on two successive iterations) or the analyst-specified maximum number of iterations is complete, whichever occurs first.

Figure 2 shows a portion of a Landsat scene and the results of the clustering. In the cluster map, different gray levels are used to represent different clusters.

Once the process has terminated, the analyst may view the results, applying various enhancements made available by the Vision One/20 (histogram equalization, pseudocolor display), to evaluate the results and to determine the ground cover types of the resulting cluster classes. The analyst may elect to repeat the clustering with different parameters or transmit the cluster map back to the host computer for use in further steps of the data analysis process.

C. EVALUATION

Interactive clustering on the image display system has numerous advantages over alternative implementations. Some advantages have been cited earlier, namely those associated with facilitating the steps requiring analyst judgment. On-line control of clustering and evaluation of the results aid considerably in speeding

and improving the results of the overall classifier training process.

The large display refresh memory enables relatively large areas to be clustered; at 512 x 512 pixels, more than 256,000 multispectral data vectors may be processed. Of course, this depends on the processor speed being adequate for interactive processing of such large numbers of pixels. The present implementation, based on an LSI-11/02 processor, requires 20 seconds per iteration to cluster 10,000 3-dimensional pixels into 10 clusters. Processing time per iteration increases linearly with the number of dimensions, the number of pixels, and the number of clusters. The number of iterations required to achieve convergence is highly data dependent, influenced by all of the factors that effect computation time per iteration plus the inherent clustering tendencies in the data and the locations of the initial cluster centers relative to their final positions in the feature space. Most users of noninteractive implementations of this same algorithm rarely allow it to run to convergence. It is common practice to halt processing when fewer than one percent (sometimes even ten percent) of the pixels change allegiance on successive passes. Here at least the analyst has the added advantage of being able to view the changes and estimate their import with respect to the analysis goals.

D. USER SUPPORT

In addition to the carefully designed analyst/machine interface, user-oriented documentation has been prepared to aid the data analyst³. A User's Guide describes the role of clustering in the remote sensing data analysis process as well as defining and giving examples of all program inputs and outputs. A tutorial "Hands-On Experience with Cluster on the COMTAL Vision One" speeds the process of familiarizing the analyst with this data analysis tool.

IV. CONCLUSION

Clustering is but one of many data analysis tools required for multispectral image analysis. It is one which can be most effectively used if implemented in an interactive mode. Our implementation on a COMTAL Vision One/20 image display system provides one demonstration of the feasibility of utilizing this mode by exploiting the facilities of a modern high-speed image display system. It should encourage the development of

comprehensive georeferenced information systems in which the user/data analyst can play an active role in effectively and efficiently extracting the information needed for monitoring and managing the earth's resources.

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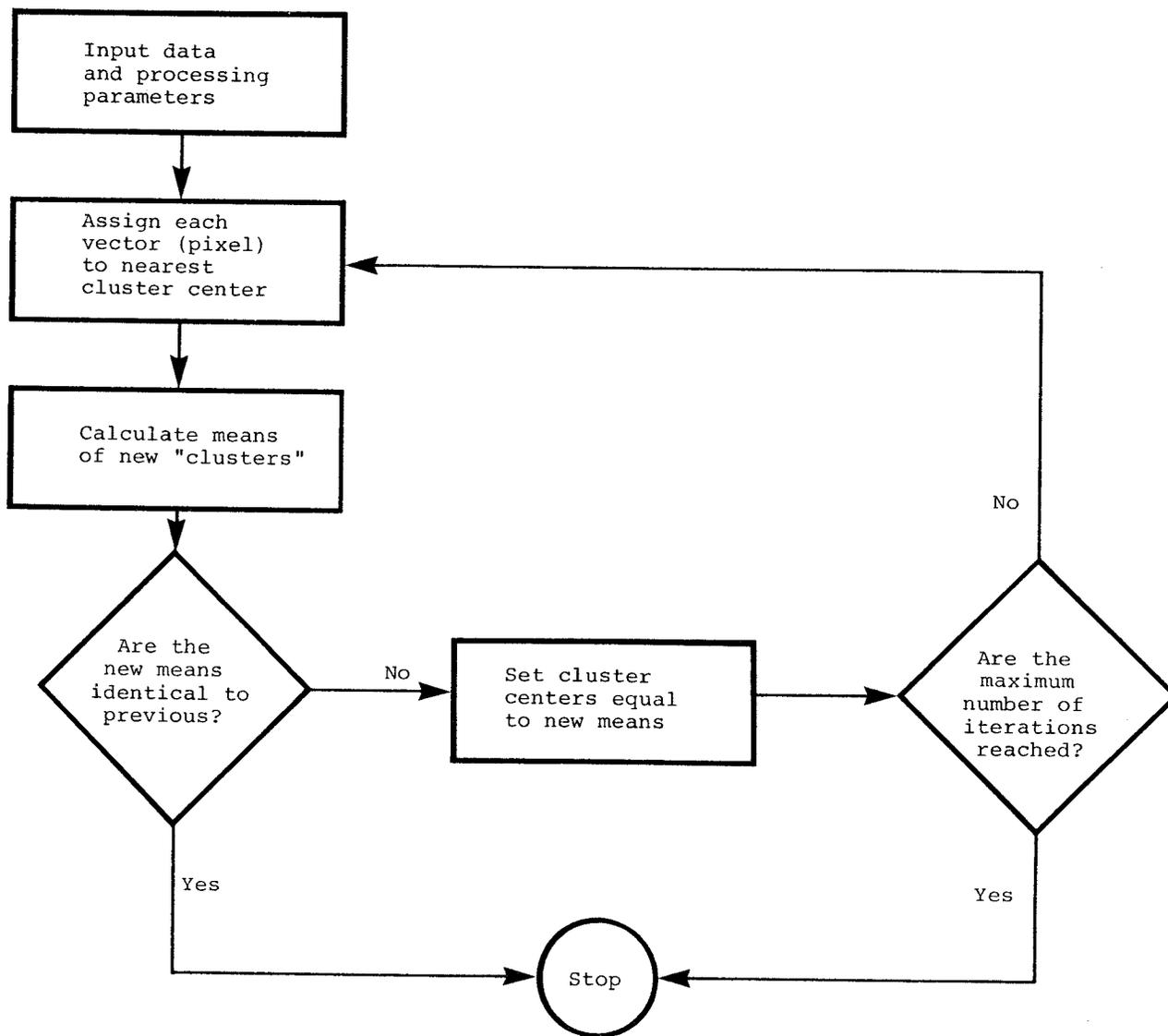


Figure 1. Basic flowchart of clustering algorithm.



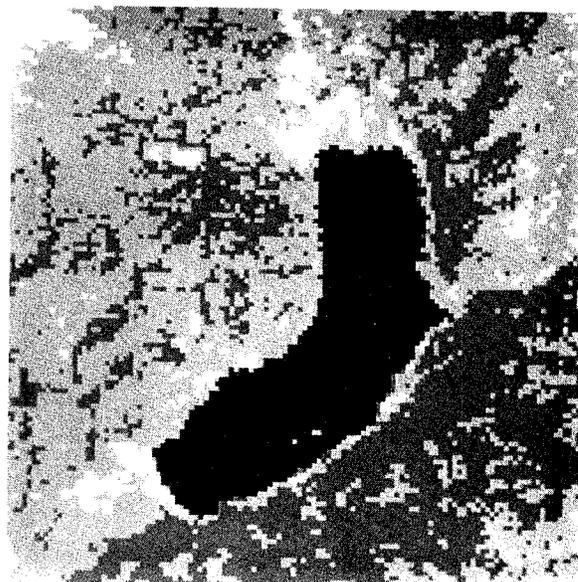
(a) Feature 1: Landsat data in .5-.6 μm band



(b) Feature 2: Landsat data in .6-.7 μm band



(c) Feature 3: Landsat data in .8-1.1 μm band



(d) Five-class results image from clustering

Figure 2. Display of Landsat data in three channels and a sample results image from clustering.

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Affiliated with LARS since its inception in 1966, Dr. Swain has developed methods and systems for the management and analysis of remote sensing data. He has been employed by the Philco-Ford Corporation and Burroughs Corporation and served as consultant to the National Aeronautics and Space Administration (NASA) and the Universities Space Research Association. His research interests include theoretical and applied pattern recognition, methods of artificial intelligence, and the application of advanced computer architectures to image processing. He is co-editor and contributing author of the textbook Remote Sensing: The Quantitative Approach (New York: McGraw-Hill, 1978).

Dr. Swain received the B.S. degree in electrical engineering from Lehigh University in 1963 and the M.S. and Ph.D. degrees from Purdue University in 1964 and 1970, respectively. He is a member of the Pattern Recognition Society, the IEEE Computer Society and the IEEE Geoscience and Remote Sensing Society.

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