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Nonsupervised Crop Classification through Airborne Multispectral Observations

Abstract: Current methods of terrain classification by means of airborne multispectral observations are reviewed with emphasis on the selection of training sets for determination of the categorizer parameters. A method of selecting sample regions for assigning identities to the spectral signatures on the basis of statistically determined similarities, rather than on *a priori* considerations, is suggested. This method has been tested on data collected on two flights with the University of Michigan scanner over an agricultural region in California. We have found that a simple clustering algorithm, modified to take into account specific features of the crop-census problem, can be used to obtain the desired homogeneous regions with relatively little computation and that very sparse sampling of these regions is sufficient to assign the appropriate category to each cluster. Viewed as a two-stage sampling procedure, clustering improves the second stage classification on 15 crops from 20 to 50 percent over a random selection of the primary sampling units. The accuracy increases to 73 percent when only five classes are considered, with further improvement to 88 percent when a majority decision based on known field boundaries is used.

Introduction

The only currently operational satellite survey system in the United States is the weather satellite program of the National Oceanographic and Atmospheric Administration[1]. This program has already paid large dividends in better forecasts, including tornado warnings, resulting from routine cloud analysis over vast areas. The quality of the imagery remains, however, insufficient for most other prospective applications.

The first of the two unmanned Earth Resources Technology Satellites, ERTS-A, is scheduled to be launched in 1972[2,3]. This satellite, in a 500-mile near-polar orbit, is to be equipped with three boresighted high-resolution return-beam vidicon cameras sensitive to the red, green, and infrared regions of the electromagnetic spectrum and a four-channel electromechanical scanner with a transverse sweep. The field of view of both types of sensors will correspond to an area 100 miles square on the earth and will have a resolution of approximately 200 feet per picture element.

The manned satellite project (SKYLAB) is due for completion in 1973[4]. In addition to a ten-channel multispectral scanner, SKYLAB will be equipped with several aerial cameras, permitting high resolution multispectral film coverage of selected targets.

Examples of proposed applications are crop inventory and forecasting, including blight detection, in agriculture[5]; pasture management in animal husbandry[6]; species identification and inventory in forestry[7]; watershed management and snow coverage measurement in hydrology[8]; ice floe detection and tracking in oceanography[9]; demarcation of lineaments and other geomorphological features in geology[10]; and cartography[11]. In many of these applications the possibility of detecting changes in the natural vegetation, soil moisture content, cultivation, environmental pollution, etc. through synoptic, repetitive satellite surveillance appears to be as important to potential users as the generation of reliable land-usage maps[3,12].

It is too early to predict which of the proposed applications will prove workable. Certainly few applications have emerged to date in which satellite surveillance has been conclusively demonstrated to have an economic edge over alternative methods; it is only through the benefits accruing from many projects that this undertaking may eventually be justified.

In the United States much of the work in automatic multispectral classification has been concentrated in agriculture, where it has been shown that certain groups of crops may be identified by means of distinctive, remotely observed spectral characteristics, or signatures. The object of this paper is to review some of the current methods for signature analysis and to present a class of alternative techniques that offer some advantages. Since satellite multispectral scanner data are not yet available, only a small-scale experimental verification of the proposed methodology, based on low-altitude airborne multispectral scanner data, has been possible. Some of the problems experienced in the application of nonsupervised classification to ERTS and SKYLAB data are briefly considered, but the larger issues involved in the integration of satellite information-gathering platforms into an economically viable earth resources management system cannot be adequately dealt with here.

Current approach

The typical multispectral classification experiment is conducted as follows[13–22]. The data, collected in a single region under favorable conditions by airborne or spaceborne sensors, are examined in their entirety by the experimenter, who decides which areas are most representative of the region as a whole. The samples from these areas are assembled to form a training set, which is characterized by ground-truth information delineating the terrain types of interest. A statistical categorizer, or decision box, is constructed on the basis of the statistical parameters extracted from the training set. The classification performance is then evaluated on another portion of the data (the test set) for which the location and extent of the different types of ground cover are also known to the experimenter.

The details of the various experiments differ with respect to the sources of data, the methods of labeling the training and test sets, the terrain types to be identified, the number of spectral bands, the degree of statistical sophistication of the categorizer, and the methods of evaluating the results, but the general scheme of classifying samples of the test set according to their similarity to a preselected training set is the same.

Extrapolation of the performance levels evaluated in this manner to an operational satellite data gathering system is suspect on two counts. First, in most experiments both the training sets and the test sets are selected on the basis of visual inspection of the available data. Terrain classes without large uniform representation are frequently deleted from consideration, as are regions of abnormally high variability. The data are divided into training and test sets in such a way as to enhance the probability of successful classification. Even in as well conceived an experiment to extend the spatial recognition range as that described by Hoffer[18], an intruding cloud required complete reassignment of the intended training region! In view of the amount of information to be collected by the satellite systems, of the order of 10^{12} bits per year, it seems unlikely that a considerable fraction of this data can be visually screened in time to allow modification of the required decision parameters. If, on the other hand, interactive systems are developed to a sufficient degree to allow human analysis of much of the imagery, then the whole concept of automatic terrain classification becomes superfluous.

Second, the extrapolotion of performance levels is also suspect because the very idea of "representative" samples becomes meaningless in relation to the immense variability that will be encountered in satellite multispectral data. Major components of this variability are expected to be 1) occurrence of cloud shadows and unmonitored changes in the moisture content and other constituents of the atmosphere, which affect its scattering and transmission properties; 2) drift and noise in the sensor system, recording devices, analog-to-digital conversion equipment, and communication links; and 3) variations inherent in the appearance of the ground cover itself, due to the different types of vegetation, the changes in season and crop maturity, soil characteristics, ground water content, crop row spacing, wind direction and velocity, etc. A catalogue encompassing a majority of the spectral signatures of eventual interest would have to contain statistical characterizations corresponding to every possible combination of these conditions.

Proposed approach

The point of departure from standard statistical classification techniques advocated in this paper lies in the application of an unsupervised learning approach, by means of clustering algorithms[23], to circumvent the difficulties of collecting representative training sets. Applications of clustering techniques to other aspects of remote sensing, such as data compaction, mode determination in supervised classification, and edge detection, have been reported by Haralick[24–26], Anuta[19,22,27], and Fu[17,28], but to our knowledge this is the first attempt to simulate the acquisition of ground-truth information on the basis of unsupervised classification of the data.

In our procedure the clustering algorithm is used to divide the data into groups of sample points of similar (according to some well-defined criterion) spectral characteristics. The region on the ground corresponding to each cluster may then be examined by a ground crew (or maps and aerial photographs of the area can be consulted) to determine the correct label or category to be associated with each cluster.

The classifier is allowed, in effect, to designate the appropriate areas for the collection of identifying information on the basis of the actual data, rather than on *a priori* considerations. The necessary ground-truth information is collected after the analysis rather than before, thus reducing the risk that the areas sampled may not be typical of significant fractions of the data. Since this procedure is equivalent to a two-stage statistical sampling design[29], one possible criterion of evaluation is to compare the effectiveness of the primary sampling units selected automatically on the basis of spectral information with that of an equal number of randomly chosen units.

The successful United States weather satellite program already operates in a somewhat similar manner, the information derived from the satellite imagery being used mainly to guide meteorologists in the detailed evaluation of other atmospheric measurements[1]. Ground-sampling on the basis of satellite observations has also been applied to the timber census[30], and a successful "manual" clustering method for terrain mapping is described by Smedes[31]. In none of these projects, however, are the regions to be sampled determined automatically.

Perhaps closest in spirit to our work is a clustering experiment by Steiner[32] on 59 densitometric samples of aerial photographs, where the similarity of ground-truth collection on the basis of clustering results to conventional photointerpretation techniques is explicitly mentioned. The clustering algorithm in this experiment performed a within-group distance minimization on an iteratively calculated similarity matrix, a procedure which may be too time consuming for use with larger data sets. Another small clustering experiment of this type (2500 digitized samples of aerial photography) is described in Ref. 21, but since the study is oriented toward other objectives, the clustering results are not evaluated in detail.

In addition to facilitating the collection of ground-truth information, unsupervised classification offers the possibility of objective change detection through comparison of the boundaries of automatically generated homogeneous regions. The procedure would be unaffected, in principle, by seasonal changes, variations in illumination, or atmospheric effects as long as the categories of interest remain distinguishable from one another. Experimental examination of this aspect of the problem has been deferred, however, because of a lack of multitemporal coverage in our data set.

In general, unsupervised classification techniques tend to be more time consuming than supervised techniques of equivalent statistical sophistication, but two special features of the crop-census problem can be exploited to reduce the required amount of computation.

First, examination of digitized multiband satellite photography[19,22] indicates that, variegated as the satellite multispectral scanner data are likely to prove, they will probably include extensive segments of sample points of uniform, though *a priori* unknown, characteristics. Such segments may include widely cultivated crops in regions with uniform weather and soil conditions, forests, large bodies of water, desert areas, etc., all surveyed at satellite speed in time periods relatively short in comparison to atmospheric changes and drifts in the data collection equipment. The procedure described below exploits this feature by assembling adjacent sample points into homogeneous segments and performing the classification only once for each segment rather than once for each sample point.

Second, in any given region a small number of types of ground cover is likely to predominate. Thus, it is advantageous to examine first the resemblance of a given segment to clusters that contain many other points. If a match is found, the search may be terminated; if otherwise, nothing is lost. Such a scheme has already proved its worth in supervised classification[33].

An advantage of unsupervised methods is that small clusters of anomalous points, due to isolated spots with abnormal reflection characteristics, are assigned a low priority in the search scheme. In supervised schemes the inadvertent inclusion of such points in the training set for some category may cause a classification problem far out of proportion to their frequency of occurrence.

Once each sample in the data has been assigned to a cluster, it is necessary to determine which points should be inspected in order to label the cluster with the correct category information. The required sample size could be minimized by sequential sampling procedures[34], but we have implemented instead a simpler second-stage procedure. This procedure consists of the selection of an equal fraction of randomly located sample points from each cluster.

In practice, the selection of test sites for ground observation or low-altitude overflights necessarily includes additional programmed constraints pertaining to economic (or political) considerations, accessibility, and prevailing weather. In the experiments to be described, however, ground-truth information laboriously collected within a week of the overflight was available for the whole region. Hence the sampling scheme could be simulated on a digital computer in lieu of having to send a ground-crew into the field once the boundaries of the test site were known.

Direct comparison of unsupervised and supervised techniques is not feasible, since with a supervised technique it is always possible to reach arbitrarily high recognition rates through the simple expedient of iteratively including some of the misclassified areas in the training set[20,22,35]. Experienced investigators can, in fact, usually make an excellent initial choice. For instance, in Ref. 15 the training sets are the central portions of selected fields, whereas the test sets are the surrounding regions of the same fields. The extrapolation of the classification to more distant regions is, however, a hazardous matter, as reported in Refs. 17, 18, and 19, with success dependent on the degree of cooperation provided by nature in, for example, the constancy of atmospheric and illumination conditions.

Clustering algorithm

The clustering algorithm used to sort the observations into relatively homogeneous groups is a variant of Bonner's "chain" procedure[36], in which the samples are examined one at a time and either attached to already existing clusters or used to initiate new clusters. The particular version adopted for the multispectral vectors can be described as follows.

Each sample or observation is considered to be a point in the ten-dimensional feature space defined by the spectral components (Table 1). A distance measure is defined on this space to allow measurement of the similarity between any two points or groups of points. An observation is assigned to a cluster only if its distance to the cluster center is less than a preset (positive) constant θ_c, the cluster threshold. If there are several cluster centers within a distance θ_c, the observation is assigned to the cluster with the closest center. If there are none, a new cluster is started.

The distance measure used is either the sum of the component-by-component separations of the two points being compared or the Euclidean distance measure. The latter takes longer to compute and gives only slightly improved results.

The cluster center is the centroid, or average value, of all the observations assigned to that cluster. Whenever an observation is assigned to a cluster, the centroid is updated by adding the new vector to the vector sum of all the previous vectors. The distance computation actually uses this sum rather than the true average.

Aside from the specification of the distance measure, the only prior information used is the value of θ_c. This reflects a hypothesis on the expected differences in the spectral representation among the various crop categories of interest. The number of clusters created turns out to be a sensitive function of the cluster threshold, but the recognition accuracy remains stable within wide limits on θ_c.

This process may also be viewed as a method of estimating the modes of a multimodal probability distribution function[37]. The cluster threshold defines a window about the current value of the estimate for each mode. Whenever a sample falls within this window, the estimate is updated to take into account the new information. Only one pass is made through the data since a relatively coarse level of classification suffices for guiding the collection of ground-truth information. The additional computational cost of iteration with some of the identification information already in hand would probably yield a higher return in crop classification, but this interesting aspect of the problem is beyond the scope of our study.

• *Sequential search*

The expected distance between cluster centers is at least θ_c because a new cluster can be initiated only if the observation under consideration is at least a distance θ_c away from all of the existing cluster centers. Hence, if an observation falls within $\frac{1}{2}\theta_c$ of some cluster center, it may be assigned to the corresponding cluster with reasonable certainty that no subsequently examined centroid will be closer. This assumption may be used to decrease significantly the number of distance computations required.

Accordingly, the procedure was modified to test against $\frac{1}{2}\theta_c$ the distance of every new sample from each of the existing cluster centers. If a smaller distance is found, the search is halted and the observation is assigned to the tested cluster. If no value smaller than this modified threshold is found by the time all of the distances have been calculated, the smallest distance found is compared to θ_c. If this test is satisfied, the observation is assigned to the closest cluster. If, however, no distance smaller than θ_c is found, a new cluster is started.

The clusters are tested in decreasing order of population to take advantage of the varying *a priori* probability of occurrence of the different categories. The assignment of observations satisfying the various tests is shown for

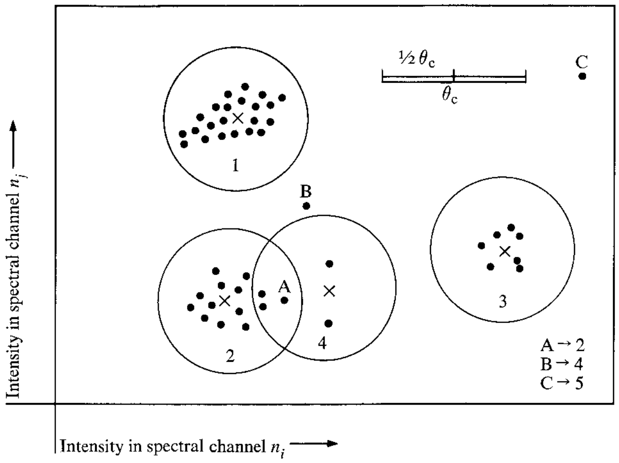


Figure 1 Example of a sequential search in assigning data samples to clusters.

Table 1 Multispectral scanner channels.

Channel number	*Zero-zero response band* (μm)
1	0.40–0.44
2	0.46–0.49
3	0.49–0.54
4	0.51–0.56
5	0.54–0.60
6	0.56–0.64
7	0.60–0.69
8	0.64–0.76
9	0.69–0.84
10	0.76–1.06

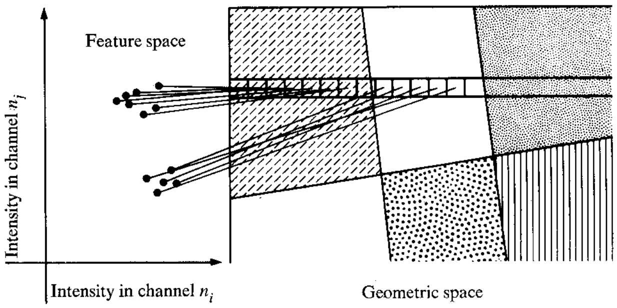


Figure 2 Strip formation; correspondence between feature space and geometric space.

a two-dimensional example in Fig. 1. The clusters are numbered in order of decreasing population; × denotes the cluster centroid. Samples A, B, and C are to be classified. Since A is not within distance $\frac{1}{2}\theta_c$ from C1, it would be assigned to C2; B is not within distance $\frac{1}{2}\theta_c$ from any of the four clusters but it is within distance θ_c from three of them (an unusual situation), and would be assigned to the closest, C4; C is not within distance θ_c of any of the existing clusters and would become the first point and current cluster center of a new cluster, C5.

Since in a vast region the overall distribution of classes may not be relevant to local conditions, we have also experimented, with comparable results, with the rate of increase in cluster population to guide the order of search. On a larger sample this would be equivalent to forgetting a no-longer-adequate signature in a changing environment.

• *Strip formation*

Another possibility for decreasing the amount of computation is provided by the likelihood of similarity between geometrically contiguous observations. Rather than assign the observations to a cluster one at a time, which typically requires dozens of distance computations per point even with the sequential scheme described, we assemble the observations into strips which, as entities, are assigned to clusters (Fig. 2).

The ten-dimensional vectors in each scan line are examined in the order they were recorded. In this example the first seven points of the scan line are close together in feature space and are assigned to the same strip, which is then assigned in a single operation to the appropriate cluster. The strips are allowed to grow until the addition of another point would raise the internal scatter of the strip above a designated strip threshold θ_s (comparable to θ_c). This test requires one computation for each vector. Thus the next five points in the example are also tested as a group, but in this case they are assigned to a different cluster. This correlation of spectral similarity and spatial proximity is used only along the scan lines rather than in two dimensions, to avoid keeping track of numerous small regions of arbitrary shape and size.

• *Debris collection*

The presence of many anomalous observations in the data creates an unmanageable number of small clusters. Since it would be wasteful to send a ground party to identify such ground-cover irregularities, a threshold value θ_g is specified to lump together all the insignificant clusters. Since the clusters are already ranked in order of population, the least populated ones, comprising less than θ_g percent of the samples, can be readily eliminated.

In our experiments, eliminating five percent of the samples typically reduced the number of clusters by 75 to 85 percent. This reduction has relatively little effect on the computing time since, in the sequential scheme, these smaller clusters are seldom consulted in any case. As implemented, debris collection was executed only at the end of each run, but on larger quantities of data it should be done periodically to delete inactive cluster centers.

• *Cluster identification*

Once all of the sample points have been assigned to clusters, the appropriate crop category for each cluster must be determined. It is acceptable to assign several clusters to one crop category, but only one crop may be assigned to each cluster. The object is to produce a land-usage map where the configuration of the various regions is based on the established cluster structure and the labels are determined by judicious sampling of the available ground-truth information.

The rule for assigning a cluster to a crop category is to count the number of observations representing each crop within the sample selected from the cluster and choose the crop with the largest representation. Suppose, for instance, that cluster 1 contains 1253 points. With one-percent sampling we would select at random 13 picture elements among the 1253 and determine their identities by reference to the ground-truth map. If six of these elements occur in beet fields, four in barley, and three are bare soil, we would assign the label "beets" to all of the 1253 points in C1. Performing the same operation in turn on each of the clusters, we develop a land-usage map within the computer.

To evaluate the efficacy of the combined clustering and sampling process, we compare the land-usage map to the map produced from the ground-truth information and determine the number of points of disagreement. It is also possible to prepare a confusion table (see section on experiments) that shows which types of ground cover are most likely to be mistaken for one another by this procedure.

The important parameters of the overall classification process are the cost of computation, the ground-truth information required, and the error rate. The experimentally determined relations among these parameters can be described in terms of the average number of distance computations per point, the number of significant clusters generated, the fraction of observations included in the ground sample, and the number of observations misclassified according to several different criteria obtained by merging some of the given crop categories (see section on ground-truth information).

Data collection

The University of Michigan AN/AAS-5(xe-2) multispectral scanner used for data collection is an electro-optical device for imaging radiation in a fixed set of spectral windows from an array of radiating or reflecting elements on the ground (Fig. 3). The instrument is operated in an unpressurized C-47 airplane flying as straight and level a course as possible.

The transverse component of the scan pattern is generated by a rotating axe-blade-mirror assembly with a field of view limited to 40° on either side of nadir. The longitudinal component is obtained directly from the forward motion of the aircraft. During the period that the axe-blade mirror is not collecting light from the ground, it views calibration sources that are used to normalize the data after the flight.

The detector assembly consists of a photomultiplier spectrometer with ten channels between 0.4 and 1.0 μm. The wavelength distribution of the spectral windows is listed in Table 1. The response of the photomultipliers is recorded on 14-track, one-inch tape at 60 inches per second.

Three calibration sources are viewed by the spectrometer during the 280° dead period of the scan. 1) The spectral calibration is provided by a quartz-iodine lamp filtered to match the solar spectrum as closely as possible. 2) The skylight reference is an opal-glass plate at the top of the aircraft, which integrates the diffused light. 3) The black reference is the dark interior of the scanner. These calibration signals are recorded on FM tape with time marks and synchronization signals generated by a gyro-stabilized roll indicator.

After a flight the analog signal containing the ten-channel measurements is corrected for roll angle, digitized, unskewed, and normalized with respect to the calibration signals. The final output is stored on seven-track, 200 bpi magnetic tape with eight bits for each spectral component.

In addition to the channels in the visible and near-infrared regions of the spectrum, the aircraft is equipped with a number of sensors designed to monitor ultraviolet and thermal infrared radiation. Nine aerial cameras can

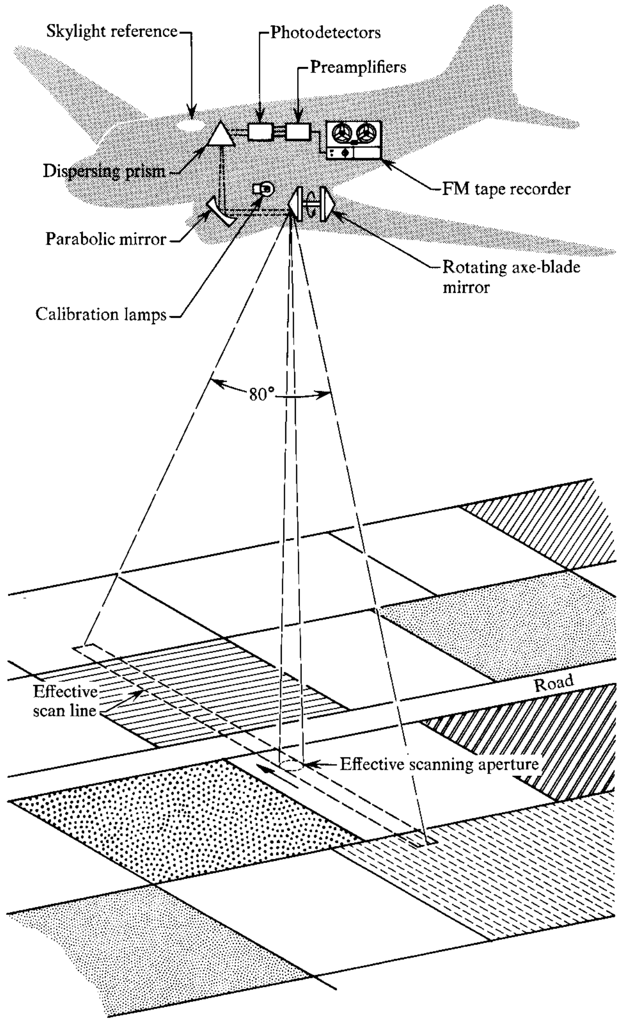


Figure 3 Multispectral data collection.

also be mounted to chart the exact course of the aircraft and to gather imagery to serve as the basis for collecting ground-truth information. The instrumentation and data processing facilities are described in a report by Nalepka[38], which also contains references to numerous other investigations in this area; current operations are described in Ref. 39. Some of the difficulties encountered in attempting to register multispectral data with respect either to a standard cartographic frame of reference or to data obtained at other times are discussed in Ref. 27.

- *McCabe Road flights*

Data provided by the Infrared and Optics Laboratory of the Institute of Science and Technology of the University of Michigan were collected under NASA auspices[40] in conjunction with the flight of Apollo 9 over the Imperial Valley agricultural test site in California on

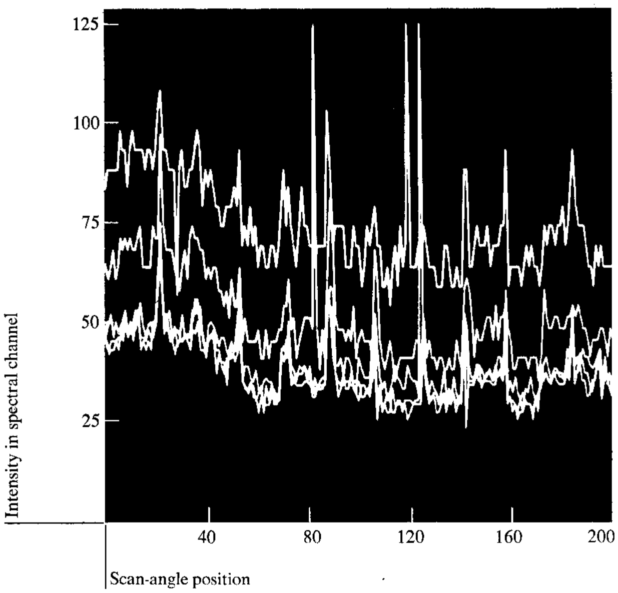


Figure 4 Oscilloscope traces of multispectral channel measurements.

March 12, 1969. The two flight lines selected for the experiments were over McCabe Road, near the town of El Centro, California, at altitudes of 5000 and 10,000 feet. The area covered by the 5000-ft flight is approximately 4000 acres and by the 10,000-ft flight, 10,000 acres. After deleting some of the scan lines in order to retain an aspect ratio of 1:1, the lower altitude flight data included 345 scan lines and the higher, 200 scan lines, each scan line having 200 pixels (picture elements). Since each pixel is a ten-dimensional vector and eight bits are necessary for each component, about 10^7 bits were retained for processing. A single scan, showing the variations encountered both within crop fields and across crop fields, is shown in Fig. 4. The five traces represent the first five spectral components of the scan. The three large spikes are due to defects in the analog-to-digital conversion equipment; the smaller spikes usually occur at field boundaries. The dependence of the average signal strength on the scan angle is quite evident.

For an indication of the statistical characteristics of the imagery, we computed several simple parameters of the distributions of the component values. The mean values of the ten spectral components ranged from 34 to 79 (units of relative intensity) when averaged over the entire data set, but the scan-angle averages were subject to an approximately 25 percent variation due to the non-lambertian response of the ground cover to oblique illumination. The standard deviations of the spectral components ranged from 9 for channel 5 to 22 for channel 1 (10,000-ft data). The pairwise deviations between the vector components of adjacent pixels on a scan line show that only about ten percent of the overall statistical variance can be explained by the different reflectances of the various crops, and the remainder must be attributed to fluctations due to other sources[41].

The correlation between adjacent pixels is about 20 percent greater within a given scan line than between successive scan lines, an effect which is probably due to the large effective field-of-view of the scanner. A further breakdown of the pairwise variances according to scan line and scan angle shows, as expected, greater reliability for small scan angles (the region directly below the plane) and little change along the flight line.

The most noticeable feature, about which we had been duly forewarned by the Infrared and Optics Laboratory, was the presence of noise spikes resulting from some quirk of the analog-to-digital conversion equipment. To keep within the eight-bit range of the clustering program, isolated spikes having peak values above 255 were truncated to 255. Visual inspection also revealed the existence of numerous smaller uncorrected abnormal values, including zeros, in the data.

• *Ground-truth information*

The ground-truth data were gathered during the week following the overflight and made available to us as a list (Table 2; the field code is given in Table 3) of fields, crops, fractional ground cover, and crop height keyed to a print of the analog signal[38]. One hundred seventy-two fields, comprising 15 types of ground cover, were included in the survey. The distribution was quite skewed, with some categories appearing in only two or three fields. The ground-cover descriptions in Table 2 show that one could hardly expect 100 percent correct classification, especially, for example, on fields 19, 22, and 23.

We used a graphic tablet connected to an IBM 1800 processor to enter this information into the computer. The coordinates of the corners of each field were entered by pointing a stylus to the appropriate location on a picture superimposed on the tablet. The field numbers, through which the complete description, including crop type, was keyed to each field, were also entered through the tablet by means of a small keyboard. The program permitted entry of an arbitrary number of vertices for each field, making it possible to approximate any desired shape by a polygon.

The geometry of an unrectified multispectral array differs considerably from that of an aerial photograph of the corresponding area, because of unmonitored changes in the speed, course, and attitude of the aircraft (mainly crabbing) and the cosine distortion introduced by the rotating mirror. Consequently, instead of an aerial photograph we used a scaled-down version of a computer

Table 2 Ground-truth information collected for evaluation of the classification of the McCabe Road overflight data.

Field number	*Field[a] code*	*Row direction*	*Estimated average crop height (in.)*	*Estimated average ground cover (percent)*	*Comment*
1	A+R	N-S	3–4	90	Recently cut
2	B	N-S	30–36	60	Large patches of bare soil in eastern portion of field
3	R	N-S	3–8	70	
4	R	N-S	3–8	80	
5	A+B	E-W	4–6	70	
6	A	N-S	6–12	60	30 percent weed cover
7	A+B	E-W	6–8	90	Recently pastured
8	A+B	N-S	10–34	80	Pastured
9	A+B	N-S	2–6	90	Pastured
10	A	N-S	2–4	100	Recently cut
11	CR	N-S	6–12	60	10 percent weed cover; field partially cut
12	A	N-S	8–10	90	
13	L	N-S	4–6	80	
14	A	N-S	2–6	90	
15	B	N-S	24–30	90	
16	B	N-S	2–6	90	Recently cut
17	A	N-S	12–16	100	
18	B	N-S	20–30	100	Heading stage
19	B	N-S	12–20	80	20 percent weed cover; pastured; large portions of bare soil in southern portion of field
20	R	N-S	10–16	80	
21	R	N-S	2–6	90	
22	R	E-W	2–4	90	Pastured; patches of bare soil with white salt deposits
23	R	N-S	4–8	80	Scattered areas of salt deposits and weeds at eastern end
24	A	N-S	2–8	70	10 percent weed cover; pastured

[a]See Table 3

printout on which the field boundaries were clearly visible.

The field descriptions were subsequently keypunched and stored on disk in the form of an annotated map of the area[Fig. 5(a)]. The boundaries of the 172 fields were entered via the tablet in less than 30 minutes, even though each vertex was entered several times, depending on the number of fields to which it belonged. An addition to the program allowed the combination of specified classes to form new classes without keypunching again all of the field labels. If, for instance, the feed crops barley, oats, and rye were to be considered a single class, one additional card would cause the program to make the three labels equivalent in computing the various performance statistics.

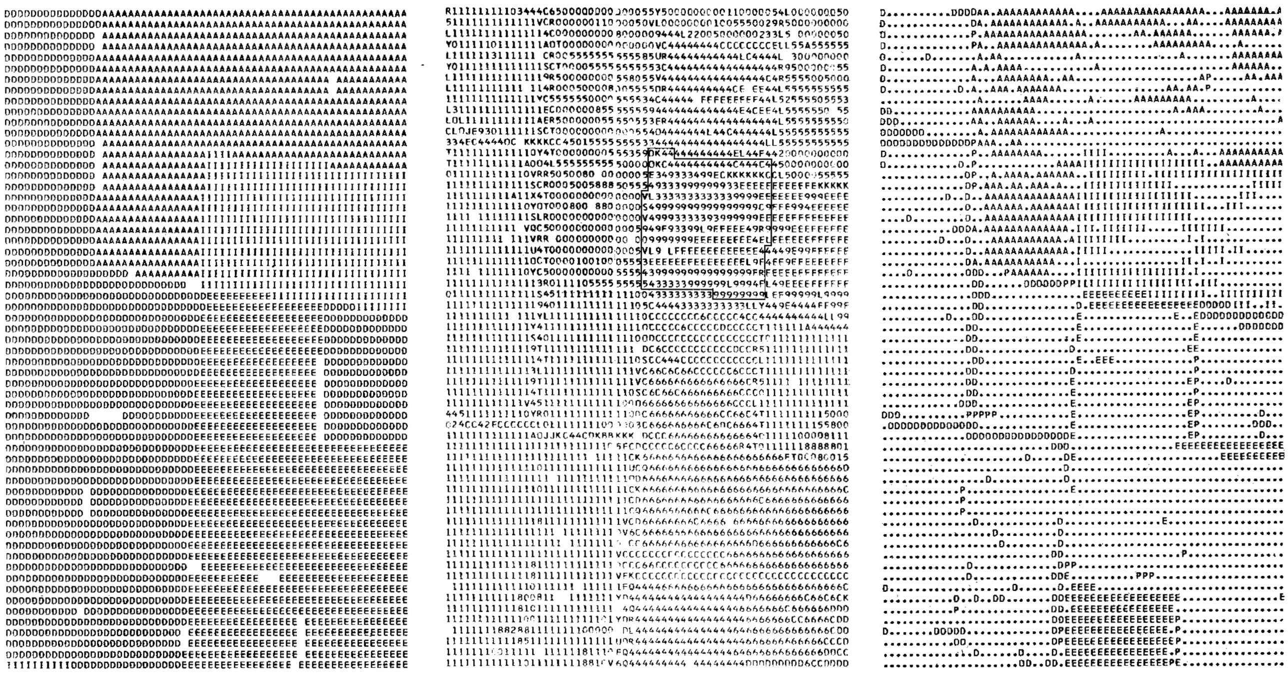
Table 3 Field key.

Field code	*Ground cover*
A	Alfalfa
A+B	Alfalfa and barley
A+R	Alfalfa and rye
B	Barley
BS	Bare soil
CR	Carrots
I	Idle
L	Lettuce
ON	Onions
PS	Pasture
R	Rye
SB	Sugar beets
SF	Safflower
SFT	Salt flat
R+U	Roads and unclassified patches

Experiments and results

The experimental programs designed to test the classification method were run in two steps to avoid repeating the time-consuming clustering process for different evaluation procedures:

1. The cluster *generation* routines divided the sample points into groups of homogeneous (though generally not contiguous) regions and constructed a cluster map [Fig. 5(b)] on disk. In this example most of the fields were assigned rather uniformly to a single cluster. An exception is field 50 (outlined), seen from the ground truth map to contain lettuce with 40 percent weed cover, which is partitioned in about equal proportions between clusters 3, 9, and E. All but 28 of



(a) (b) (c)

Field number	Field code[a]	Row direction	Crop height (in.)	Ground cover (percent)	Comment
28	A	E-W	8-16	90	Irregular cover
34	D	E-W	18-24	90	
35	A	N-S	16-18	90	Pastured
36	A	E-W	2-4	80	Recently cut; yellow-green stubble
49	I	N-S	6-8	60	Yellow mottling
50	I	N-S	6-8	40	40 percent weed cover
51	A	N-S	18-24	90	
52	D	E-W	24-30	100	
60	D	N-S	24-36	100	
61	E				
62	D	N-S	20-24	90	
76	E				
77	E				
78	E				Bedded for cotton
79	D	N-S	24-30	100	
80	D	N-S	24-30	100	

Legend Fig. 5(a)

[a]See figure caption.

Figure 5 Symbolic maps corresponding to an area about one mile square, including 16 fields. (a) Ground-truth map. Each type of ground cover is represented by a letter: A, alfalfa; D, barley; E, bare soil; I, lettuce; and P, roads. (b) Cluster map. Each symbol corresponds to a different cluster, not all of which are different ground-cover types. (c) Error map, legend as in (a). The dots represent correctly assigned points and the letters, the *true* categories of crops that had been incorrectly classified.

the clusters were eliminated by the significance threshold.

2. The cluster *evaluation* routines assigned each cluster to a crop by sampling the cluster points and prepared an error map [Fig. 5(c)] by comparing the resulting classification to the previously entered ground-truth map. For example, the large A region at the top of Fig. 5(c) is alfalfa, which had been assigned to a cluster dominated by barley, and the E region at the bottom is barley ("bedded for cotton"), which had been assigned to a bare-soil cluster.

The programs were run on both the 5000-ft and the 10,000-ft flight altitude data. Some of the earlier results, including a comparison of the two flights, some attempts at component selection, and an investigation of the effect of different distance measures, have been reported in Ref. 26 and are not repeated here. In all cases only very small fluctuations in the recognition performance were observed.

Most of the programs were written in FORTRAN and PL/I and executed on an IBM 360/91 under MVT-OS/360. A flowchart of the program logic for assigning multispectral samples to clusters and creating a cluster map is shown in Fig. 6.

• *Speed of operation*

The effect of the speed-up techniques of strip formation and sequential search on the number of distance compu-

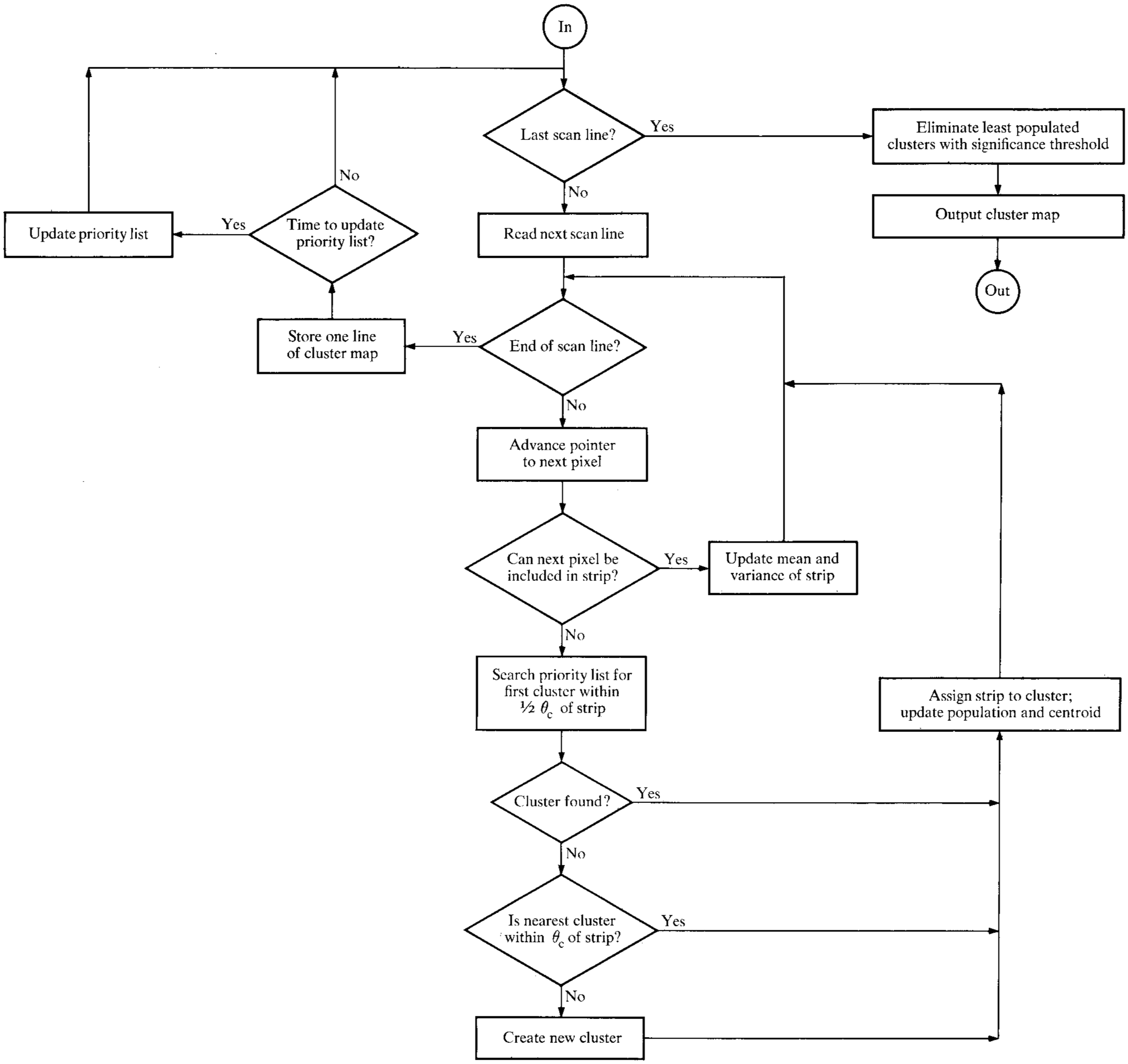


Figure 6 Partial flowchart of the program logic.

tations required to partition the data into a given number of clusters is shown in Table 4. The thresholds were set to produce about 100 significant clusters in each case. Strip formation and sequential search are about equally effective and in combination provide a roughly fivefold reduction in computation without significant deterioration in the final cluster configuration. Strip formation also seems to improve the recognition performance slightly.

The time required for each distance computation depends on both the distance measure used and the number of spectral components. Although most of our calculations were made with the Euclidean norm and all ten

Table 4 Effect of speed-up techniques on amount of computation.

Algorithm	*Relative number of distance computations per point*	*Recognition accuracy (percent)*
Unmodified chain	1.00	52
Chain with sequential search	0.60	51
Chain with strip formation	0.30	56
Chain with sequential search and strip formation	0.19	54

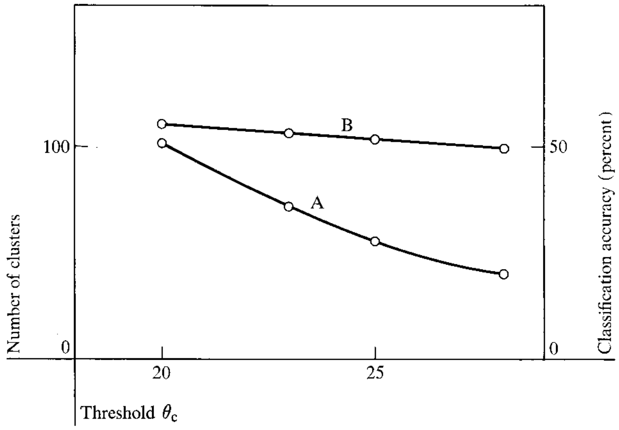


Figure 7 Effect of threshold value on number and classification of clusters.

spectral components, we determined for comparison that using the absolute distance measure and only six components could save about two thirds of the computation time without noticeable loss in performance. Under these latter circumstances the computation required 3 ms per sample point on a 360/91 computer; with optimized machine language code and a minimum of diagnostic output, we estimate this could be reduced to about 100 μs. In comparison, Eppler's optimized supervised classification program requires about 300 μs per six-dimensional sample on a 360/44 computer[33]. More complicated decision rules, such as the maximum likelihood ratio[17], would reduce the number of clusters required to represent the data, and might result in further improved speed of operation.

• *Cluster formation*

The dependence of the number of clusters on the cluster threshold is shown as curve A in Fig. 7. The number of clusters decreases rapidly with increasing threshold, but the classification accuracy (curve B) is a much less sensitive function of the threshold. Hence the selection of an appropriate threshold is not a problem.

The rate of formation of clusters decreased to virtually zero after the first 100,000 sample points had been assigned. It will be important to investigate the rate of cluster formation over much longer flights to confirm that the number of ground samples required increases only slowly with the size of the area surveyed.

• *Cost matrix and confusion table*

The performance of the clustering algorithm may be gauged from inspection of the three maps of Fig. 5, but a much better understanding of the contributions of the individual clusters to the recognition of each crop may be obtained from the "cost" matrix of Table 5. The entries in the cost matrix are the numbers of samples (picture elements) in each cluster assigned to the various ground-cover categories. The row and column totals are indicative of the area covered by each cluster and by each crop (one picture element corresponds to about 0.02 acres). The last two rows of the table refer to the number of correctly assigned samples.

With 100 percent sampling, the crop selected for each cluster is determined by the maximum value in each line, which is repeated in the second-last column of the table. The ratio of this number to the total number of points in the cluster is a measure of the usefulness of that cluster, and the sum of the areas shared by each crop and all the clusters assigned to it, shown in the second-last line, is a measure of how well that crop is recognized. The portion of the pixels correctly classified in this experiment was 52 percent.

The confusion among the various categories is shown in Table 6. The entries along the main diagonal are the numbers of sample points shared by each crop category and the clusters assigned to it. The off-diagonal entries are the numbers of misassigned points. The upper portion of the table is computed on per-point assignment, the bottom portion is based on the per-field rule (see section on per-field classification). As expected, the feed crops are not fully distinguishable from one another whereas bare soil does stand out, as indicated by the relative ratios of diagonal to off-diagonal elements in the table.

• *Merged crops*

To compare our recognition results with those obtained elsewhere, we have to reduce the number of crop categories to the usual five or six. For instance, by preassigning all of the data to only five classes, it is possible to raise the recognition rate to 73 percent. In this mode all of the available data points are still classified, but misassignments occurring between equivalent classes are no longer counted as errors.

• *Per-field classification*

A further improvement in accuracy (to 88 percent correct recognition) can be achieved by assigning each field to a crop category on the basis of a majority decision of all the elements in the field. This result is indicative of the performance to be expected if reliable automatic methods for detecting closed field boundaries can be developed.

It should be noted that in our experiments every point in the data was assigned to some crop category. Superior recognition results could be demonstrated in all cases if only the central regions of the fields (the easily recognized portions) were included in the evaluation.

Other gains may be expected from improved signal normalization and noise elimination. Since one of the

Table 5 Cost-matrix presentation of the classification results.

	Field code[a]																	
Cluster	A	A+B	A+R	B	BS	CR	I	L	ON	PS	R	SB	SF	SFT	R+U	*Total*	*Maximum*	*Percent*
1	761	48	0	4111	5	0	0	0	0	0	45	845	0	3	310	6128	4111	67
2	2201	535	10	1427	0	0	1	0	0	11	317	276	0	7	26	4811	2201	45
3	963	0	0	1368	37	13	0	0	0	7	51	1322	9	1	63	3834	1368	35
4	0	0	0	26	688	0	0	517	0	0	2	0	0	0	2	1235	688	55
5	922	0	18	671	1	0	1	20	0	9	1753	2	3	21	32	3453	1753	50
6	77	1	0	75	2233	1	0	20	0	5	73	11	2	28	38	2564	2233	87
7	49	0	3	32	1	2	20	1	0	2	2071	4	11	0	26	2222	2071	93
8	329	325	8	196	1	0	1	16	0	3	227	2	14	7	100	1229	329	26
9	807	244	150	296	27	14	16	4	0	50	794	146	189	2	78	2817	807	28
10	39	49	1	36	2117	1	1	14	0	0	65	6	3	5	221	2558	2117	82
11	872	171	19	142	24	0	7	209	1	128	632	13	107	18	253	2596	872	33
12	244	0	2	31	6	2	33	797	10	10	227	16	38	2	13	1431	797	55
13	16	20	0	26	744	0	0	58	0	0	89	0	0	1	80	1034	744	71
14	436	804	8	137	82	0	0	9	0	0	141	1	0	4	107	1729	804	46
15	2	0	0	1730	4	2	0	0	0	0	1	282	0	0	6	2027	1730	85
16	1537	0	0	480	0	0	0	0	0	0	72	17	0	0	27	2133	1537	72
17	202	315	0	39	5	1	28	478	40	1	209	7	33	9	41	1408	478	33
18	3	0	1	0	0	4	545	0	1	0	1	13	1667	0	0	2235	1667	74
19	509	1	7	96	5	5	721	1	0	36	516	39	21	6	19	1982	721	36
20	844	128	1	181	23	0	3	54	0	8	184	8	27	40	75	1576	844	53
21	145	115	9	99	218	3	36	8	0	6	72	11	84	39	287	1132	287	25
22	0	0	0	1	31	0	0	0	0	0	0	0	0	0	10	42	31	73
23	421	196	2	36	9	1	7	49	16	13	527	11	12	6	25	1331	527	39
24	27	9	2	24	230	1	5	0	0	0	12	10	1	7	81	409	230	56
25	460	0	74	175	4	0	0	4	0	2	179	11	13	2	24	948	460	48
26	54	0	0	173	14	144	1	0	2	0	2	550	11	0	5	956	550	57
27	267	91	0	13	0	10	155	52	4	53	206	10	59	4	13	937	267	28
28	185	61	6	29	9	3	5	5	0	17	529	23	82	2	44	1000	529	52
29	115	274	0	53	10	3	28	21	0	0	69	16	15	16	157	777	274	35
30	55	500	0	75	12	0	23	0	0	3	44	11	16	21	33	793	500	63
31	66	42	1	54	354	2	0	2	0	0	127	5	3	3	47	706	354	50
32	32	26	3	68	298	1	16	0	1	2	11	1	15	82	127	683	298	43
33	73	76	0	74	97	0	12	10	1	0	66	24	5	27	60	525	97	18
34	0	0	0	699	0	0	0	0	0	0	1	0	0	0	16	716	699	97
35	14	7	1	10	39	0	1	0	0	0	21	2	17	7	226	345	226	65
36	76	43	1	47	28	0	16	12	0	7	123	13	33	4	37	440	123	27
37	65	47	6	82	11	0	12	5	0	10	122	7	13	2	57	439	122	27
38	0	0	0	15	379	5	3	0	2	0	0	5	3	19	3	434	379	87
39	0	0	0	9	104	0	0	0	1	0	6	0	1	244	118	483	244	50
40	123	37	0	182	0	0	0	0	0	1	46	30	1	3	25	448	182	40
41	9	1	1	48	106	1	12	4	1	3	2	13	33	88	33	355	106	29
42	16	11	0	5	12	0	12	0	0	0	23	1	4	1	212	297	212	71
43	56	126	0	16	11	5	5	15	14	0	64	5	8	11	17	353	126	35
44	34	33	2	24	35	2	16	2	0	0	78	18	10	17	33	304	78	25
45	6	1	0	17	150	0	3	0	0	0	3	1	1	140	5	327	150	45
46	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	100
47	16	2	0	13	15	0	7	2	0	0	18	10	13	8	70	174	70	40
48	4	0	0	0	0	0	4	0	0	0	0	0	0	0	0	8	4	50
49	7	202	0	12	0	0	1	0	0	0	6	7	6	15	2	258	202	78
50	30	7	0	17	22	0	5	2	0	2	33	7	15	10	46	196	46	23
51	21	5	0	5	11	1	8	3	0	0	13	4	2	3	36	112	36	32
52	17	11	0	13	3	0	5	1	0	0	40	26	14	7	50	187	50	26
53	12	0	1	19	6	0	9	1	0	0	15	6	5	2	84	160	84	52
54	532	75	8	820	197	24	45	41	25	14	411	332	130	54	670	3378	820	24
Total	13751	4643	345	14027	8418	251	1829	2437	119	403	10339	4180	2749	998	4170	68659	36239	52
Correct	7317	1910	0	8910	7427	0	725	1275	0	0	5203	550	1667	244	1011	36239		
Percent	53	41	0	63	88	0	39	52	0	0	50	13	60	24	24	52		

[a]Use Table 3 to identify the ground cover.

Table 6 Confusion matrices for the classification results in Table 5.

Field code[a]	A	A+B	A+R	B	BS	CR	I	L	ON	PS	R	SB	SF	SFT	R+U
	Field code														
A	7317	669	0	2381	345	0	513	446	0	0	1752	54	3	0	271
A+B	1494	1910	0	160	225	0	1	315	0	0	380	0	0	0	158
A+R	262	8	0	8	8	0	7	2	0	0	38	0	1	0	11
B	2910	293	0	8910	464	0	96	70	0	0	921	173	0	9	181
BS	79	115	0	243	7427	0	5	11	0	0	94	14	0	104	326
CR	24	8	0	39	12	0	5	3	0	0	8	144	4	0	4
I	183	57	0	45	52	0	725	61	0	0	77	1	545	0	83
L	339	45	0	41	625	0	1	1275	0	0	94	0	0	0	17
ON	5	14	0	25	5	0	0	50	0	0	16	2	1	1	0
PS	255	3	0	22	10	0	36	11	0	0	58	0	0	0	8
R	2611	324	0	555	450	0	516	436	0	0	5203	2	1	6	235
SB	483	40	0	2811	76	0	39	23	0	0	78	550	13	0	67
SF	409	45	0	140	66	0	21	71	0	0	164	11	1667	1	154
SFT	80	67	0	61	400	0	6	11	0	0	52	0	0	244	77
R+U	596	316	0	1090	707	0	19	54	0	0	254	5	0	118	1011
A	10192	0	0	850	0	0	0	0	0	0	2709	0	0	0	0
A+B	1073	3566	0	0	0	0	0	0	0	0	0	0	0	0	0
A+R	0	0	0	0	0	0	0	0	0	0	345	0	0	0	0
B	2594	0	0	10759	0	0	0	0	0	0	674	0	0	0	0
BS	0	0	0	0	8418	0	0	0	0	0	0	0	0	0	0
CR	0	0	0	0	0	0	0	0	0	0	0	251	0	0	0
I	0	0	0	0	0	0	0	0	0	0	978	0	851	0	0
L	0	0	0	0	635	0	0	1802	0	0	0	0	0	0	0
ON	0	119	0	0	0	0	0	0	0	0	0	0	0	0	0
PS	403	0	0	0	0	0	0	0	0	0	0	0	0	0	0
R	864	0	0	0	0	0	0	0	0	0	9475	0	0	0	0
SB	1830	0	0	1720	0	0	0	0	0	0	0	630	0	0	0
SF	0	0	0	0	0	0	0	0	0	0	567	0	2182	0	0
SFT	376	0	0	0	0	0	0	0	0	0	0	0	0	622	0
R+U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4170

[a]Use Table 3 to identify the ground cover.

Table 7 Dependence of classification accuracy on fraction of data sampled using the clustering algorithm.

Percentage of points sampled in each cluster	*Percentage of pixels correctly assigned*			
	5000-ft flight		*10,000-ft flight*	
	38 clusters	*109 clusters*	*29 clusters*	*125 clusters*
100	49	53	44	50
5	49	52	44	
1			40	

Table 8 Dependence of classification accuracy on fraction of data sampled randomly.

Percentage of points sampled in each cluster	*Percentage of pixels correctly assigned*			
	5000-ft flight		*10,000-ft flight*	
	38 clusters	*150 clusters*	*30 clusters*	*150 clusters*
100	20	21	21	22
5	19	18	20	17
1	17			

objects of this study was to demonstrate that the method advocated is relatively insensitive both to irregularities in the signal and to lack of uniformity in the reflected spectra of the different types of ground cover, there was no need to attempt to experiment with the preprocessing techniques described in the literature[42–44].

• *Sampling*

The percentage of correctly assigned picture elements is given in Table 7 as a function of the percentage of points sampled in each cluster. There is no deterioration in performance down to five percent, and only a slight decrease at one percent. In other words, a handful of picture elements suffices most of the time to determine the dominant crop identity in each cluster.

• *Comparison sampling*

One way to evaluate objectively the performance of the clustering algorithm in producing homogeneous collections of points is to compare the classification results produced by sampling the clusters with those obtained in an identical manner from randomly generated clusters.

Such a comparison is shown in Table 8, for both a large number and a small number of clusters. Comparison of this table with the Table 7 shows that the performance with random clusters is far below that achieved by the clustering algorithm. The margin of superiority of the distance-based algorithm for defining primary sampling units over random assignment increases slightly, as expected, at low sampling percentages.

If, instead of random clusters, the whole area covered by the observations is divided into as many equal-sized rectangular regions as there are fields, with edges parallel to the field boundaries, the classification results are comparable to those achieved by the clustering algorithm, which also seeks to establish a field structure.

Summary

The principal object of this paper is to demonstrate an improved method of selecting ground samples for terrain classification on the basis of airborne multispectral observations. Although an attempt has been made to evaluate the method in as objective a manner as possible, the generalizability of the results is limited by the specific size and nature of the particular test area.

It has been shown that the inherently fast processing capability of the single-pass chain algorithm could be further augmented by taking into account the expected similarity of adjacent sample points and the distribution of terrain types in the area under consideration. With these speed-up techniques, a processing rate of 3 ms per sample point has been achieved; we estimate that in an operational system on a general purpose computer of the same capacity, this time could be reduced to 100 μs.

The classification performance we obtained is clearly too low for practical applications. Improvements in recognition accuracy can be obtained by preconditioning the data to take into account the relation between sun angle and observation angle[42–44], additional normalization based on back-scattering measurements[45], elimination of egregious instrument noise (spikes)[44], more sophisticated distance measures based on the statistical correlation among the spectral channels[17], and per-field classification[19,22] with, eventually, automatically extracted boundaries. Each of these items is subject to extensive research elsewhere and was not considered germane to the major issue in this paper.

The appropriateness of the method of evaluation depends on the importance attached to the efficient collection of ground-truth information. That our classification method is efficient in this sense is shown by the fact that a surprisingly sparse amount of ground sampling, of the order of one percent of the overflight area, proved sufficient to indicate the dominant identity of each cluster.

The scheme used for sampling the ground cover is not realistic in the sense that it would require the ground crew to check the identity of isolated points. In particular, a considerable amount of work is necessary to incorporate suitable constraints in the selection of the appropriate patches to be tested in each cluster. We learned, however, that the number of clusters developed at a given threshold levels off with the amount of data generated during a few miles of flight, in the absence of sharp regional disparities.

Since discrimination among crop types is based at least as much on the relative amount of ground-cover as on the other factors mentioned previously, any agricultural census will have to be based on repeated observations throughout the growing season. The scant amount of detail discernible with the proposed satellite instrumentation will require intermediate-level observations with both high-altitude and low-altitude aircraft before final reference to ground observations or to existing records can be made[30,46]. It is, in fact, not unlikely that such airborne observations will constitute the bulk of the data collection effort for some time to come. The concepts we have described may serve to reduce the amount of data that must be collected at these intermediate levels.

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