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AN AGRICULTURAL REMOTE SENSING INFORMATION SYSTEM

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ABSTRACT: An information system capable of delivering timely knowledge of the state and trends of earth resources is described. The system is composed of data acquisition, data processing, and information extraction and interpretation phases. Data acquisition is accomplished by an optical-mechanical scanning spectrometer measuring spectral radiance from the earth scene in atmospheric windows from 0.35 to 15 micrometers wavelength. Radiance data from a flight swath in 10 to 20 spectral bands are recorded on analog tape. The data contain spatial information in radiance variations over the scene raster, spectral information in each recorded band, and temporal information in the time of year of the flight. Flight tape processing yields computer prints of the scene with better gray scale and worse spatial resolution than an aerial photo. Spectral information extraction is shown through crop and soil identification on a thresholded maximum-likelihood basis in a 12-dimensional radiance space. The outcome, a digital classification map of the agricultural scene, is shown and anomalies due to a variety of agricultural and instrument factors are illustrated. The interplay of physical phenomena, instrumentation choices, data format choices, and information extraction success is discussed, with examples from actual flight data.

INTRODUCTION

An information system capable of delivering timely knowledge of agricultural conditions of crop type and status, soil type and drainage, and hydrologic data is a powerful aid in a variety of decision tasks of governmental administrative services, agri-business managers, and local producers. A few of these tasks are crop yield estimation, pest and environmental damage survey for control and alternate planning, timely supply of seed, fertilizers and pesticides, appropriate transportation and leasing of farm machinery, grain drying and storage routing, intent-to-plant decisions, and regional land-use planning. Significant portions of such an information system are in operation today in this country; these portions are usually in the form of conventional communication by visit, telephone, mail, and news media. In most parts of this system the primary sensor is the human, usually the local producer who views his fields, makes known his needs, and answers questions from agri-business suppliers and county agents. In addition, the U.S.D.A. Agricultural Stabilization and Conservation Service does contract for aerial photo surveys of agricultural counties on a continuing basis, covering a given area once every five to ten years. A mosaic made of such aerial photos is shown in Figure 1 for Tippecanoe County, Indiana; this region is 21 miles east-west, 24 miles north-south, slightly over 500 square miles in area.

This photo-mosaic of Figure 1 is a valid conversation piece to begin the description of an automated agricultural resource survey system to augment the present-day information system. In addition to vocal or written information of agricultural importance, each spatial resolution element of the agricultural scene itself has spectral radiance through reflected or emitted electromagnetic energy; the arrangement of spatial elements of various scene object classes makes the image of Figure 1. The spectral information content of each resolution element in this mosaic is an integrated spectral radiance over the spectral bandpass of the film emulsion and optical system transfer function. Of course, similar spatial images may be made in narrow spectral bands with filters and emulsion or other photodetectors of a broad variety and wavelength range. The main point is that the scene gives forth, at any given time, both spatial and spectral data which may be expected to have a causal relation with agricultural conditions. If the information of the agricultural conditions can be extracted in a timely way, then the additional information contained in temporal change is available.

Current imaging remote sensing data acquisition systems other than conventional film-camera systems include a variety of vidicon, orthicon, and image dissector sensors operating in the UV, visible, and near IR portions of the spectrum.[1] Optical-mechanical scanner sensors can cover the full spectral window range of the atmosphere from 0.35 to 15 μm, though these units are commonly employed in thermal mapping beyond 3 μm. Much of the data acquired is analyzed spatially by human interpreters, with integrated or average spectral content necessary only to yield contrast. Meteorological satellites for the observation of cloud cover, and 8-14 μm or 3-5 μm military thermal mappers are cases in point; vortex patterns are sought in cloud cover, abnormal apparent temperature targets are enhanced from ambient backgrounds, and so on. Thus far, it has proven difficult to automate the recognition of significant spatial information. The human observer readily detects the winding ribbon of the Wabash River, the agricultural field shapes, the urban area of 60,000 population, and even road network structure in the mosaic of Figure 1; a

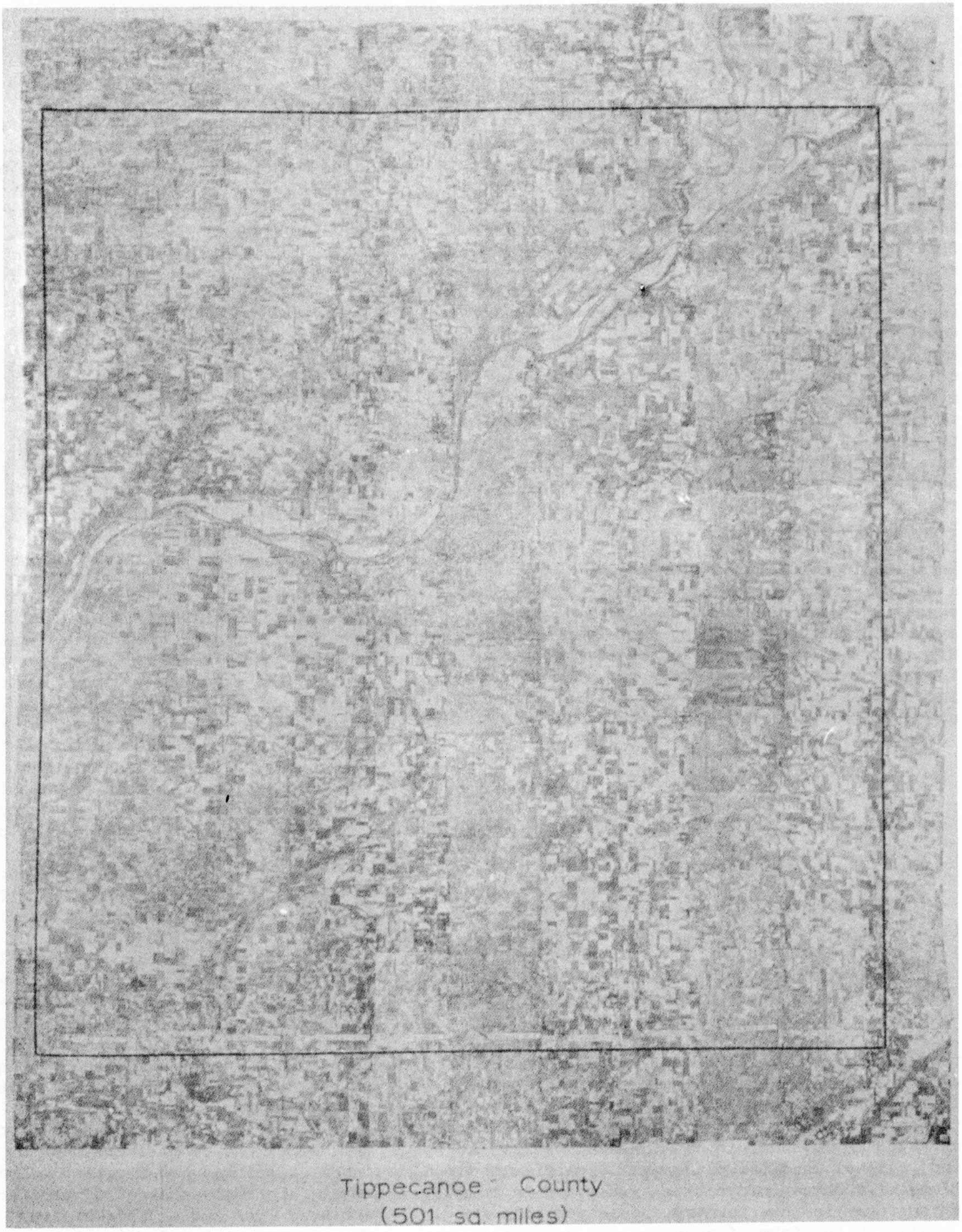

Figure 1. An aerial photo mosaic of a typical agricultural county in Indiana.

machine does not.

On the other hand, a human interpreter faced with images of the same scene in each of five or ten spectral bands is inefficient at keeping track of relative tones of the same portion of the scene, and comparing this tonal, or spectral, radiance pattern with that of another portion of the scene. In short, he is poor at spectral information extraction. A machine, however, can easily keep track of n ordered numbers representing the spectral radiance of a given scene point in n bands.

This paper describes a remote sensing system using automated spectral scene object recognition together with scene image presentation to achieve timely analysis of agricultural conditions in areas typified by Figure 1.

DATA ACQUISITION

The major data sources for the Laboratory for Agricultural Remote Sensing (LARS) at Purdue University are two modified optical-mechanical scanners instrumented, installed and flown by the University of Michigan since June, 1966. Figure 2 shows a sketch of one of these scanners.

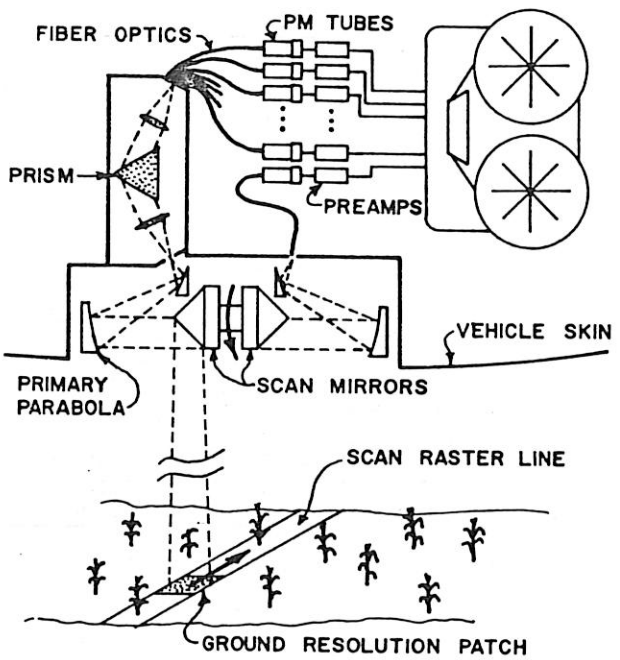

Figure 2. UV, visible, and near IR data acquisition by multispectral optical-mechanical scanners.

One-half of the unit is used for an ultraviolet channel from 0.32 to 0.38 μm. The other half consists of a prism monochromator beyond the field stop-entrance slit, dispersing radiant energy from the ground patch to a fiber optics array, which in turn leads to a bank of photomultiplier tubes. The 12 spectral bands of this monochromator portion cover 0.4 to 1.0 μm as follows:

0.40 - 0.44 μm	0.55 - 0.58
0.44 - 0.46	0.58 - 0.62
0.46 - 0.48	0.62 - 0.66
0.48 - 0.50	0.66 - 0.72
0.50 - 0.52	0.72 - 0.80
0.52 - 0.55	0.80 - 1.00 μm

The second scanner contains an 8-14 μm band in one half, and a four-element InSb detector with filter coatings for the following bands:

1.5 - 1.9 μm	3.0 - 4.1
2.0 - 2.6	4.5 - 5.5 μm

The UV channel and 12 visible and near IR channels are recorded on standard 14-track analog tape with a roll-correcting synchronization pulse track. The infrared channels beyond 1.5 μm are recorded on 7-track analog tape.

Spectral recognition work has been concentrated on the 0.4 to 1.0 μm channels because of difficulties in precise overlay of the infrared channels beyond 1.5 μm from a different scanner recorded on a different recorder. There is a definite need for a multispectral scanner with a single aperture covering the spectrum from 0.35 to 15 μm, in part to remove overlay problems, and this need will be met by plans under way in NASA.

The spectral radiance differences among scene objects may be striking, as in Figure 3. These

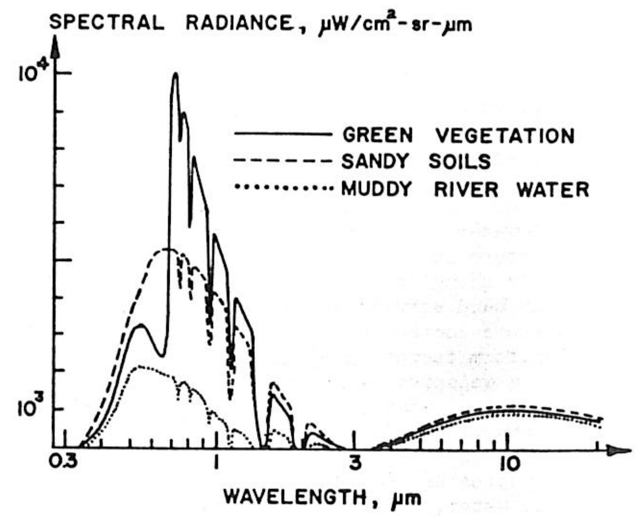

Figure 3. Agricultural scene spectral radiances for soil, vegetation, and water.

radiance graphs are made up from several radiance measurements in the agricultural scene over limited wavelengths, since a single field spectrometer is not available for the entire wavelength range shown. Figure 4 shows relative spectral radiance graphs for vegetation types illustrating that differences may also be more subtle, yet distinguishable. The strong absorption in the blue region from 0.45 μm to 0.4 μm and in the red centered about 0.66 μm are

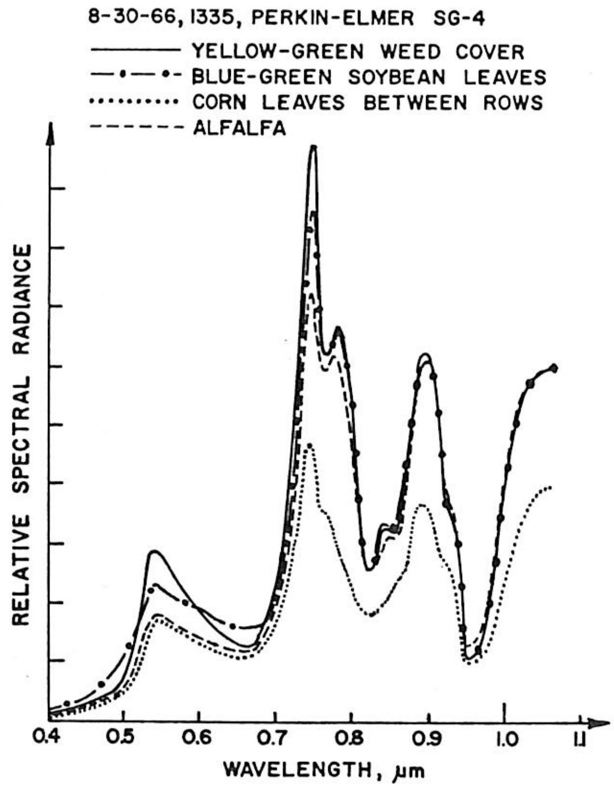

Figure 4. Relative spectral radiances of turgid vegetation types from 0.4 to 1.05 μm.

due to chlorophyll. Beyond this chlorophyll absorption band at 0.66 μm, there are no significant absorption processes in the leaf until some of the shorter wavelength H_2O molecular vibration modes at 1.14 and 1.38 μm. However, scattering by the leaf of incident radiation does occur at air-cell wall-water dielectric interfaces and at cellulose structure in the cell wall.[2] Soils usually show gently changing reflectance up to 3 μm, with some water band structure due to adsorbed water. Soil moisture content appears to lower reflectance by a uniform factor except in the absorption bands. In the emissive range from 4 μm to 15 μm green vegetation appears to be a gray body with little discernible emissivity structure, while soils usually show some optical phonon or restrahlen absorption between 8 and 10 μm. Figure 5 shows soil, water, and vegetation spectral radiance measurements taken from a cherry picker-mounted interferometer spectrometer.

In the research phase of seeking spectral information in natural scenes, it is appropriate to have a versatile optical-mechanical scanner system to cover the entire atmospheric window spectrum in fine bands. LARS has recommended band choices to NASA, and calculated the noise-equivalent changes in scene reflectance, emissivity, temperature to be expected from a 180 cm^2 aperture area, 1-milliradian resolution, f/3 scanner with a 4-sided mirror. An optical efficiency of 0.4 was assumed, and standard tables were used for atmospheric transmission, detectivities, and

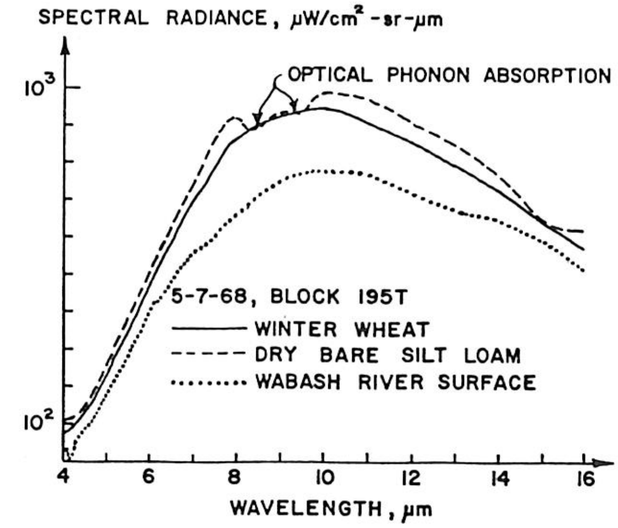

Figure 5. Spectral radiance of vegetation, soil, and water as measured with a Block interferometer spectrometer.

so on. The results are shown in Figure 6.

Wavelength Band	Detector	Noise-Equivalent Change Δρ	Δε	ΔT°K
0.40-0.44	Si(PV)	0.012		
0.46-0.50	↓	0.012		
0.53-0.57		0.0056		
0.57-0.63		0.0026		
0.64-0.68		0.0032		
0.71-0.75		0.0042		
0.76-0.80		0.0044		
0.80-0.90		0.0019		
0.96-1.06		0.0027		
1.18-1.30	InAs(PV)	0.0082		
1.55-1.75	↓	0.0083		
2.10-2.30		0.01		
3.5- 4.1	InSb(PV)	0.07	0.18	4.2
4.5- 5.0	↓		0.10	3.0
8.0-10.0	Ge:Hg(PC)		0.018	1.0
10.0-12.0	↓		0.012	0.83
12.0-13.5			0.035	2.8

Figure 6. Noise-equivalent changes in reflectance, Δρ, emissivity, Δε, and temperature, ΔT, for a 1-milliradian, 180 cm^2, f/3 scanner with a 4-sided mirror.

Approximately 400 kHz bandwidth is required per channel for such a scanner. If specific mission requirements can be relaxed to about 3-milliradian resolution for complete ground coverage, or only 10% ground coverage at 1-milliradian resolution, then only 40 kHz bandwidth is required per channel. While it is tempting to make hasty calculations on the vast quantity of data, it is foolish to do so without understanding the user's need for information and its bearing on the peak-to-average data rate ratio. The user of agricultural information recognized long ago that he was concerned with statistical estimation rather than total measurement.

DATA PROCESSING

The data on the analog flight tape of Figure 2 consists of amplified detector responses along several tracks, at present one track per spectral band. Figure 7 depicts the relation of spectral

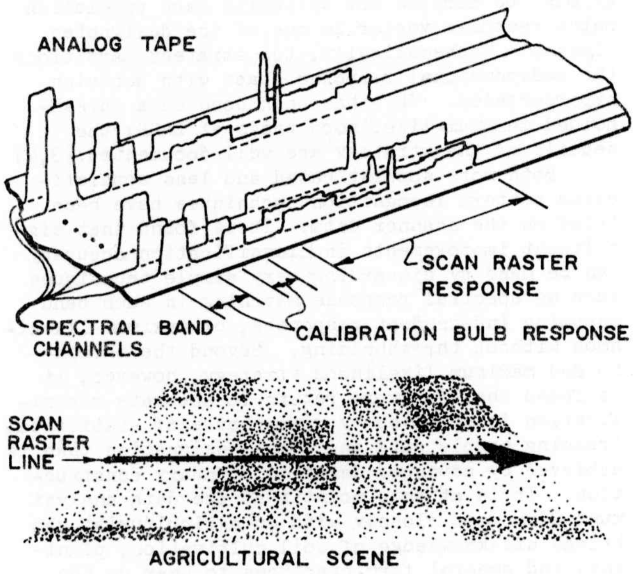

Figure 7. Spectral and spatial distribution of scan raster response on the analog flight tape.

and spatial information to the actual scan raster line across the scene. It is apparent that simultaneous sampling of the spectral band channels will give the response in each band from a single ground resolution patch; the spectral data are conveniently extracted from the tape. On the other hand, spatial data is chopped up and distributed along the tape in such a fashion that it is difficult on the analog tape to sample data from, say, a given field or the road up through the scene in Figure 7. Some kind of addressing scheme must be employed to extract data spatially oriented in the typical agricultural scene. A basic decision was made at LARS to do this in a digital system.

The data on the analog flight tape of Figure 7 is digitized in the LARS A/D Conversion System. The system consists of an Ampex 1800 tape recorder for playing analog tapes, fourteen signal amplification channels, a fourteen channel sample-hold network, two Raytheon Multiverters to share the sampling load, a buffer core memory, and a Control Data digital tape transport, all under the command of a control unit. The system packs a digital tape at the rate of 100,000 eight-bit words per second. This "raw" digital tape contains the spectral band responses and calibration bulb responses of the analog tape in digital form.

The raw digital tape must be reformated into a suitably addressed, registered, and calibrated data tape. Data from even and odd analog channels must be aligned, then each scan raster line addressed; each sample point or ground resolution patch within a scan line is addressable by counting from the raster line start. It is also necessary to make the calibration pulse height identical, line-to-line, along a flight run. This removes gain changes by the instrument operator. In effect, the instrument operator is a semi-automatic gain control to account for large dynamic range in scene brightness. The calibration pulse measures this human gain control system. Full automation is sought in future systems. It should be noted that the calibration pulses are not used at LARS as radiance calibrators, but simply as consistency monitors of the entire instrumentation transfer function. In the data reformating the centroids of both calibration bulb pulses are found, and the mean and variance of the two calibration pulses and the black level are determined. Correction can then be made to equalize the instrument transfer function along a flight run. This has been done primarily on the 0.4 to 1.0 μm channels, using two quartz-iodine lamps, one of high intensity for the blue end of the spectrum, one of lower intensity for the near IR end of the spectrum.

Once all this has been done, the data analyst can print out an image in any spectral band directly from the data tape. He selects a gray scale from response data, and implements this by using more or less inky characters such as M, $ or Z, -. This obviously allows considerable and convenient latitude in contrast selection, which has proven to be a pleasant asset of the digital system. An example of the gray-scale printouts is shown in Figure 8. The detail is too small to

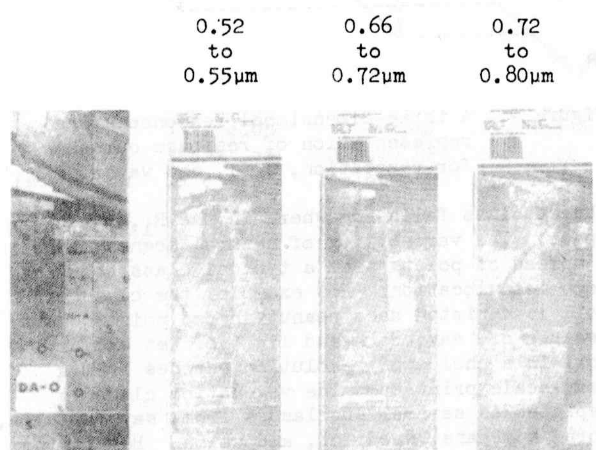

Figure 8. Gray-scale printouts of the photo scene in three wavelength bands.

show, but on the original printout each symbol has a row and column address. It is at this point that the data analyst can make contact with both spatial and spectral data in a most convenient form, for he can state row and column address boundaries or contours on punch card, and call for spectral band response histograms from a given class of scene objects. The data processing task begins to merge with the data analysis and information extraction task.

The n spectral band responses from a ground resolution patch constitutes the components of an n-dimensional vector. An illustration of this is given in Figure 9. Each sample point from an

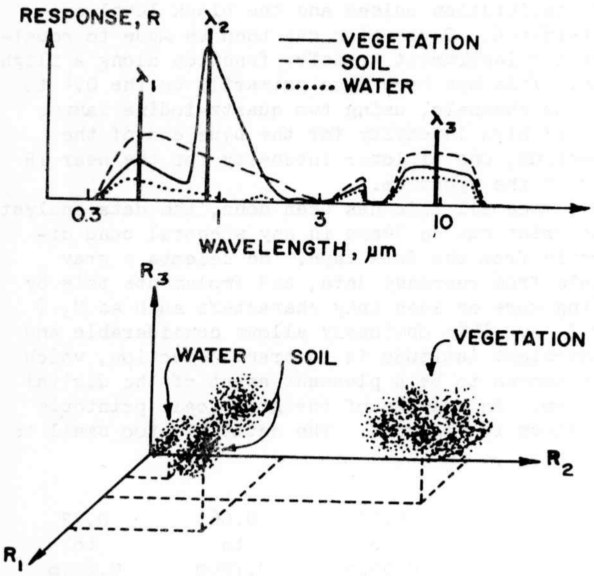

Figure 9. A three-dimensional response space representation of response curves for vegetation, soil, and water.

object class falls somewhere in the R_1, R_2, R_3 space. The variability of natural scenes causes a spread of points from a typical class about some mean location. For example, the class of soil is depicted as a peanut-shaped point density because of, say, dark and light or wet and dry soil in a choice of resolution patches from a gray-scale printout. The vegetation class is depicted as several subclasses from, say, alfalfa, corn, soybeans, wood lot, and so on. Before the data analyst can employ pattern recognition strategies on object classes, he must learn the statistics of the classes in such a response space by choosing samples from known areas in the flight scene, i.e., training samples. Though the example of Figure 9 uses only 3 bands for pictorial necessity, the analogous determination of statistics is actually done in a 12-space with the spectral bands from 0.4 to 1.0 μm.

INFORMATION EXTRACTION AND INTERPRETATION

Once the statistical point density picture of Figure 9 is available in actual histogram form for chosen object classes, it is desirable to fit a convenient functional form to the density. At LARS the multivariate Gaussian probability density has been the standard working choice, [3] though other methods are being investigated. Following the Gaussian density approximation to object classes (which may be as broad as vegetation, soil, and water, or as detailed as winter wheat, spring wheat, oats, corn, and soybeans), a strategy must be adopted for assigning each resolution patch response vector to one of the designated classes. Mathematically, the strategy partitions the n-dimensional response space with decision hypersurfaces. This has been done on a threshholded maximum-likelihood basis at LARS; the details of the strategy are well-documented.[3,4]

Both more sophisticated and less sophisticated pattern recognition techniques have been tried on the scanner data. It is found that significant improvements in classification accuracy can be made by discarding very simple techniques such as spectral response matching in each band assuming independent responses, or maximum likelihood without threshholding. Beyond the threshholded maximum likelihood strategy, however, it is found that far more return in accurate classification is achieved by wise choice of statistical training sample data and class designation than is achieved by advanced decision boundary construction. It is at this point that the data analyst must work most closely with an agriculturist who brings his knowledge of soil cultivation, planting, and general farm practices to bear on the object class choices.

The vegetation, soil, and water classification result of Figure 10 was made on flight

Figure 10. Vegetation, soil, and water classification on Indiana Highway 37.

data from a 70-mile strip of Indiana Highway 37. In the first printout the darkest regions are vegetation, the lightest regions are bare soil and stubble fields, and the intermediate broad ribbon is the White River. Blank regions, including the highway pavement, are threshholded out into an "everything else" class. Training samples were chosen from portions of this single 10-mile section, and the probabilities so found were employed in the classification of the remaining 60 miles with excellent success. The third printout is just the water classification, showing how one may enhance particular portions of a scene that may be of interest to a hydrologist during spring floods, for example.

Figure 11 shows a more subtle classification

Row Crops	Cereal Grains
Corn C	Wheat W
Soybeans S	Oats O

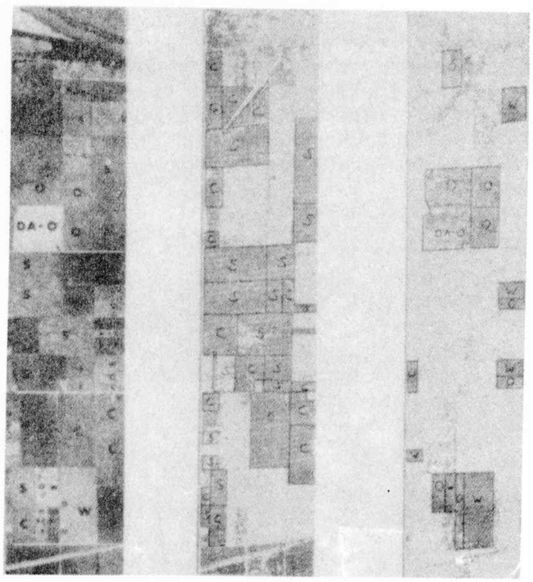

Figure 11. Row crop (corn and soybeans) and cereal grain (wheat and oats) classification.

of some row crops (corn and soybeans) and cereal grains (wheat and oats). At the time of year of this flight, late June, corn and soybeans are difficult to classify separately; the scène is about 70% soil and 30% green vegetation for these crops. Wheat and oats are easier to separate, but they have been lumped into one class in the second printout. On the row crop printout one field in hay and red clover was classified as corn or soybeans. All other fields classified as corn or soybeans were, in fact, one or the other.

A classification result on several crop types is shown in Figure 12, for corn (C), soybeans (S), wheat (W), alfalfa (A), oats (O), red clover (R), and rye (Y). Notice that the pasture of alfalfa and red clover denoted by P-A-R.C. on the photo classifies as a mixture of oats, alfalfa, and red clover. Some of the large soybean field in the

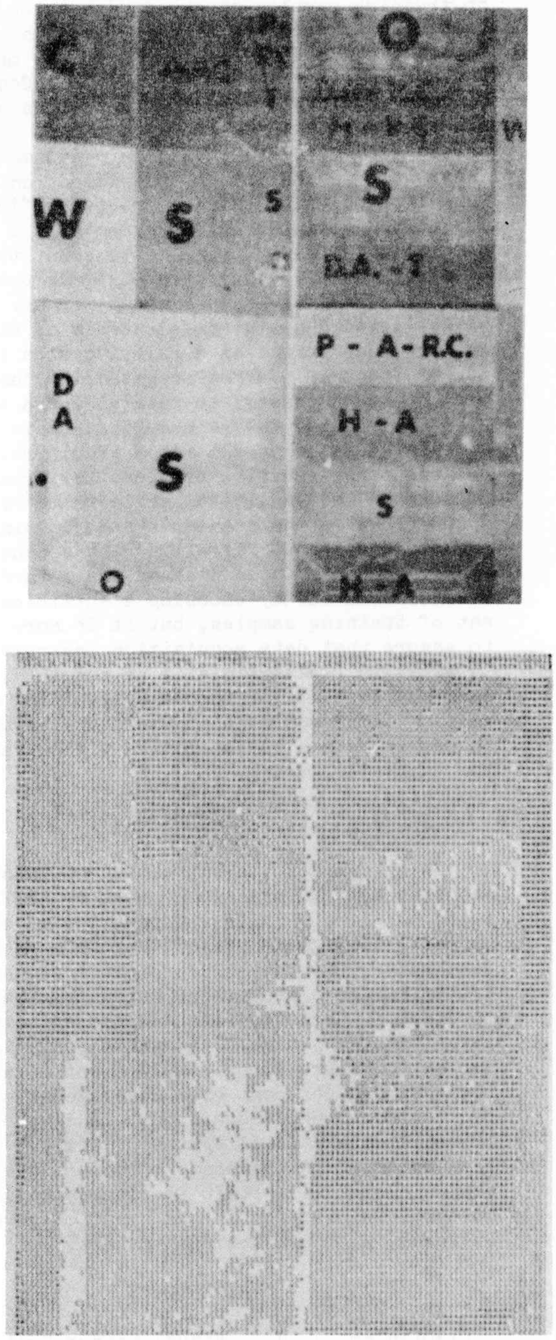

Figure 12. Seven-crop classification using four spectral bands between 0.4 and 1.0 μm.

lower left-hand quarter is threshholded out; too much soil shows to permit solid classification as soybeans. Note the field of alfalfa crop used for hay, denoted by H-A on the photo about a third of the way up on the right-hand side. The center is lighter than the perimeter and is classified as oats (O) while the perimeter is classified as alfalfa (A). The farmer actually filled his seeding drill with an alfalfa-grass mixture and planted from the perimeter towards the center. On the way to the center the alfalfa seed gave out, so the interior is actually planted in grass. Since no training samples on grass were taken, the resolution patches were categorized as something else, which happened to fall into the oats volume of response space. The Agricultural Conservation Program results in uncultivated fields with unplanned vegetative growth, denoted by D.A. (diverted acres) in the photo; this causes similar interesting anomalies in classification.

If resolution patches are identified as class objects and printed out as symbols on a line printer, it is certainly possible to count the number of each kind of symbol printed for a total flight area. Indeed, the symbol count for any one class may be divided by the total number of classifications made to attain a relative area cover measure. In some information gathering tasks, it will not be necessary to make an image at all; the user may require only a numerical ratio.

In addition to all the agricultural variability, classification problems may arise because of scanner look angle-sun angle geometry, optical aberrations in the scanner system causing radiometric throughput variation with scanner look angle, and so on. In a sense these variables may be accounted for by choosing a sufficiently broad set of training samples, but it is more desirable to assure that data acquisition instrumentation is as rigidly deterministic as possible. The same may be said for the data recording and processing instrumentation. There are enough problems in natural scene variabilities without adding to the analyst's burden.

CONCLUSION

A system for the extraction of information about an agricultural scene must be sufficiently rapid to yield results within a period of weeks, at most, to augment present-day information gathering. The research prototype of one such system has been described, using spectral data to classify scene objects and present either an identification image to a spatial data interpreter as in Figure 10 or simply a set of numbers representing per cent area coverage by selected crop types or soil conditions. A developmental or nearly operational system of similar type can be formulated on the basis of this experience; such a system will begin to place timely agricultural information in the hands of government, business, and farm decision-makers.

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