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RECENT ADVANCEMENTS IN INFORMATION EXTRACTION METHODOLOGY AND HARDWARE FOR EARTH RESOURCES SURVEY SYSTEMS

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ABSTRACT

Earth Resources Survey Systems are used to gather information to help government, private or foreign users with statutory or other requirements to solve problems or manage resources. These systems consist of remote sensors in aircraft or spacecraft, data formatting and telemetry links, preprocessors, extractive processors, and user applications models. Remote sensors register attributes of the terrain being covered. The sensor data may be relayed to ground facilities through telemetry links. At the facilities, preprocessing and extractive processing are performed, to extract information from data. Finally, user applications models are used to relate information outputs from the extractive processing, and ancillary data, to the user in terms most meaningful to him.

With the launch of the ERTS-1 satellite in July 1972, the ability of remote sensors to collect periodic multispectral data was significantly increased over the previous and continuing airborne sensor capability. The potential of coverage of a given site on the earth every 18 days facilitates change detection and opens up possibilities of analysis techniques using the time signature of remote sensible terrain attributes. Finally, the ability of the ERTS system to synoptically view 100 n.mi^2 "frames" (with 7.2×10^6 samples per frame) facilitates surveys of large areas, and because of this capability, more users of Earth Resources System data are actively interested.

At the same time however, considerable strain is being put on the existing preprocessing and extractive processing hardware and methodology because of the potential of ERTS for spectral-spatial-temporal analyses, because of the high data rates involved, because of the need to correlate data with existing airborne sensors for the high spatial resolution view often required, and because of user-imposed timeliness requirements. Additionally, considerable development of the user applications model area is required if the full potential of Earth Resources Systems to deliver cost-beneficial results is to be achieved.

At ERIM, we have been exploring for ten years the utility of remote sensing data to various natural resources problems, to developing the system methodology and hardware necessary to rapidly provide accurate information to users at low cost, and developing user applications models to enhance the value of Earth Resources System data. Some recent developments in extractive processing methodology and hardware and in user applications model development are the subject of this paper.

Techniques for spectral-temporal-spatial processing were developed to permit more reliable recognition of classes of vegetation and other terrain categories with distinctive time-varying spectral-spatial signatures. Examples of wetlands mapping and land resource inventory will be presented and discussed.

To perform extractive processing rapidly to meet user timeliness requirements, a high speed parallel digital special purpose processor MIDAS (Multivariate Interactive Digital Analysis System) is being developed at ERIM under NASA funding. This prototype processor will implement maximum likelihood classification, with versatile data processing, at rates comparable to the data collection rate of ERTS. The design philosophy of this processor will be discussed in this paper.

Last, an example of a user model developed to predict the yearly production of mallard ducks, an important migratory waterfowl, from remote sensing and ancillary data, will be described.

INTRODUCTION

With the launch of the Earth Resources Technology Satellite (ERTS-1) in late July 1972, the attention of over 300 NASA-funded scientists focused on the application of data from the return beam vidicon (RBV) and multispectral scanner (MSS) to earth resources problems in the United States and throughout the world. For those of us involved in the design of prototype earth resources systems to assist in resource management, ERTS provided a synoptic, hopefully periodic, broad scale look at the earth's resources attainable only with great difficulty from previously available aircraft sensors.

While data from aircraft sensors will still be sought and used by resource managers because of its relatively high spatial resolution, ERTS-like data from satellites is definitely here to stay. ERTS, because of its wide area coverage, has renewed the interest of resource managers in operational earth resource systems which can supply them data on a routine basis. For systems designers, this is a challenge for three reasons: 1) The data rate from earth resources sensor systems increased by over an order of magnitude with the launch of ERTS-1, creating problems of data acquisition and processing; 2) the demands for timely information from an earth resources system call for throughput requirements at least four orders of magnitude greater than can be obtained with currently implemented algorithms on general-purpose digital computers; 3) what is easily extracted from the data by current processors is often not digestible to users. An enzymatic user model must be developed to make the system complete.

To discuss these points in more detail, first refer to Figure 1, which is a familiar block diagram of a typical earth resources survey system. The system begins with a sensor viewing phenomena of the terrain or ocean. If the sensor is a multispectral scanner, the observed phenomena are the reflected or emitted spectral radiance of the scene. Sensor data is collected from remote platforms (hence the name remote sensing), so some method of data storage and telemetry are required. The next step in the system is geometric and radiometric preprocessing to permit production of a map-like rendition of the true radiance of the terrain. The goal is to reduce the distortions of geometry and of radiometric fidelity to negligible levels for further processing and analysis. This step in the procedure may require ancillary information (e.g., knowledge of spacecraft

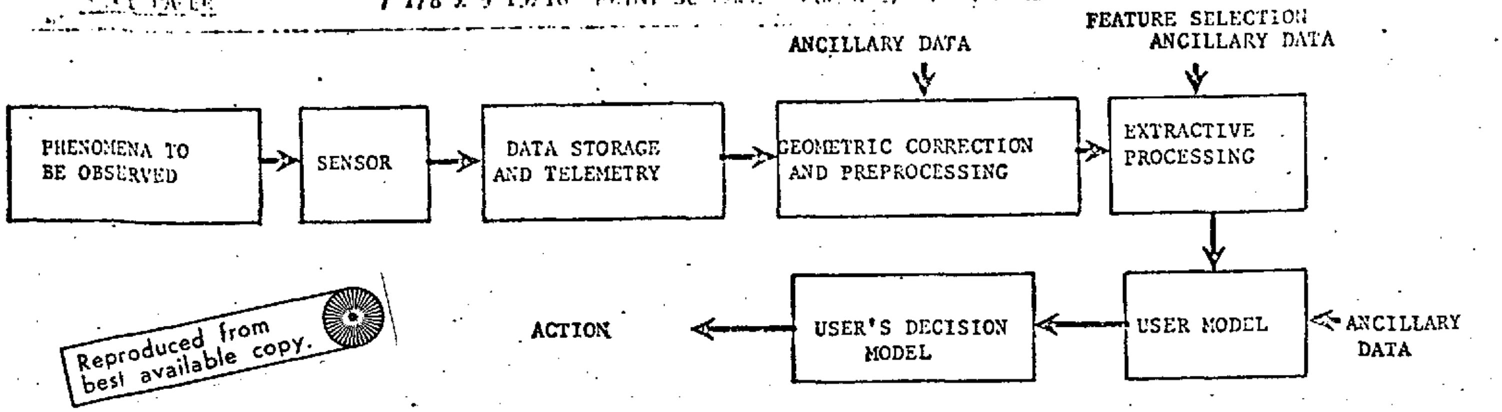

FIGURE 1. TYPICAL EARTH RESOURCES SYSTEM

attitude and ground "control points" for performing geometric connections and knowledge of atmospheric properties for connection of radiometric errors): The accuracy and scanner sensitivity to which these corrections must be performed are dependent on the application being addressed, and may vary widely.

The next step in the system is extractive processing, designed to extract information pertinent to the user from the data. For example the user may wish to know how many lakes there are in Minnesota (claims of 10,000 not withstanding), and extractive processing could be used to map all water bodies and count them.

The next step in the system is the user model. It is a crucial step because it translates the information extracted from the remote sensing data, adds ancillary information that a user may have at his disposal, and creates a product which can help a user make a decision. For example, suppose the previously mentioned user wanted to estimate the migratory waterfowl produced in Minnesota. Because these birds nest in or near water, the amount of water present is an important but not the only variable. The number of waterfowl present to breed is important, as are the food supply and predator information. These ancillary variables are required to calculate the number of migratory waterfowl.

Carrying this example a bit further, the user may want to know the number of waterfowl to be able to set hunting limits in the fall. He will need to consider other ancillary information, such as what neighboring states are doing, before making a decision. This is the user's decision model.

We do not want to convey the impression that user and decision models are necessarily formal, mathematical models implemented on computers. Rather these models are more nearly well defined procedures that managers follow to arrive at conclusions or to convert earth resources processed data to a form they can use. The trend is to increasing formalism and mathematics in user models where inputs and outputs are usually quantifiable. Decision models, with their typical socio-economic ancillary inputs, probably will seldom be formalized to the stage where computer implementation is feasible.

With this perspective on an earth resources system, it is perhaps pertinent to point out that with increasing development of high data rate sensors (by NASA) and of user interest in outputs from the system in more timely fashion (to have maximum impact on decisions, information must be timely), the squeeze is on the middle of the system (preprocessing, extractive processing, and user model areas.) In the remainder of the paper we consider some recent advancements in extractive processing and preprocessing and in user model development which we feel begin to close the gap between the sensor's abilities to collect data and the user's desires to digest it, and the ability of extractive processing systems to keep up with the data.

DEVELOPMENTS IN PREPROCESSING AND EXTRACTIVE PROCESSING

Detection and discrimination of an object by multispectral sensing requires differences in the radiation received from the object and its surroundings. This radiation "contrast" is due to differences in reflectance, emittance, or temperature between the object and its surroundings.

Discrimination means devising a decision rule, based on measurements from a sample from each of two or more given classes, which will enable us to assign new samples to the correct classes when we do not know to which they belong. Classification means to assign samples into groups which shall be as distinct as possible. In discrimination the existance of the classes is given; in classification it is a matter to be determined. Supervised learning or discrimination should achieve greater efficiency because it takes advantage of available human knowledge and intelligence. In some cases, such human assistance is not possible, and an unsupervised learning approach may be required. The user defines which process is employed. Having made the distinction we use the terms interchangeably. The terms identification and recognition will also be employed for convenience.

Basic to this process of discrimination is the concept of a signature. In general, a signature is any collection of observable features of a material or its condition that can be used for precise classification. The features that make up a signature may all be observed simultaneously or in a sequence of observations spread over a considerable time period.

A basic element of spectral information extraction is the realization that spectral signatures cannot be completely deterministic. That is spectral reflectivity and emissivity measurements of natural objects exhibit some dispersion around a mean value (i.e., spectral signatures are statistical in character). Thus, as we will use the term, a spectral signature is a probability density function (or set of such functions) which characterize the statistical attributes of a finite set of observations of a material and can be used to classify the material or its condition to some degree of fineness.

At the basis of discrimination theory is the necessity to realize that optimum discrimination techniques require not only that the procedures be tailored to recognize the item or material of interest, but also simultaneously, that they be tailored to reject other items or materials that lie in the vicinity of the desired materials but that are not of interest, i.e., the backgrounds in which the items of interest are embedded. Two types of error are possible: failure to classify all of the desired class actually present as that class and misclassification of other classes as that class. Photo interpreters commonly call these errors of omission and commission, respectively.

Examination of measurements of the spectral reflectivity and emissivity of materials can aid in the development of effective discrimination procedures by providing insight into the basic optical properties of the materials of interst and their natural variability.

The key to multispectral recognition is invariance. For example, it is desirable that the classification assigned to an object or pattern of interest be independent of the position of that object in the field of view, the aspect at which it is viewed, the background against which it is seen, partial obscuration of the object, minor changes within a class, and changes in illumination or atmospheric condition. It is not too difficult to provide any one of these invariances. To provide all of the desired invariances with a practical amount of hardware, however, requires that the preprocessing and feature extraction mechanism extract the essence of the classes to be identified.

In a multispectral recognition system, five major functional divisions must be considered. The input picture element or pixel is a vector quantity made up of many components hence the dimensionality of the input space may be large.

The purpose of signal conditioning, or "preprocessing" is to provide data preparation and handling, to provide geometric and radiometric correction, to provide a convenient input format, to provide invariance, to provide in many cases a reduction in the dimensionality of the input data, and most importantly, to emphasize or enhance aspects of the input signal which are deemed important.

An almost universal approach to recognition is to extract properties or features from the original signal, and to perform the recognition on the feature profile of the input signal. This serves several functions. First, by reducing the input pattern to its essential features, the memory required for storing the signatures is reduced. Secondly, by reducing the input pattern to independent features, a considerable amount of invariance to exact form is obtained. Finally, a degree of invariance to noise and background may be achieved.

Most decision mechanisms are based on multivariate discriminate analysis that partitions measurement space on the basis of the training set signatures which then allows a decision to be made for an appropriate classification for each input pixel.

The function of display is attendant with each and every one of the other functions of a multispectral processing system as one facet of the man-machine interaction. Interactive controls and commands allow the intervention of the operator to direct that certain things be done which would not otherwise be done automatically.

The Multivariate Interactive Digital Analysis System (MIDAS) system is an attempt to solve the problem of real time multispectral data processing in an operational system. We have been aware of this problem since the initial design and operation of the M-7 scanner and processing equipment at ERIM over ten years ago. A real-time processor (SPARC - SPectral Analysis and Recognition Computer) was completed in 1967, allowing parallel decision operations using a multivariate maximum likelihood algorithm thus making possible for the first time, rapid processing of 12-band data (Ref. 1). It was evident that a considerable amount of assistance and time was needed by the user in setting up such a machine and controlling its operation. This led to the evaluation of a hybrid system employing a general-purpose digital computer for control by the user of the system (Ref. 2). Processing of remotely sensed data is an interactive process in which the man and machine must, in fact, be considered as the real processing system.

This is not apparent in general purpose computer processing systems using software classifiers since the machine is so slow by comparison to parallel digital approaches that an operator is easily able to keep pace with the task (hours or days is the normal time interval). In this MIDAS system, where the parallel-pipeline processor is substantially faster, the time required by an operator is three or four times longer than that used in processing. Increases in processor speed will then provide little improvement in throughput. It becomes evident that well designed, interactive display and control subsystems will, in reality, offer the greatest gains in throughput.

From another point of view, the objective of providing greater speed also provides much lower cost. This is true directly for the operational situation but also for research and development. It has been estimated that processing costs in an operational system can be reduced by about a factor of twenty or more from some present day feasibility processing costs.

The overall system hardware is shown in Figure 2. The MIDAS system (ref. 3) consists of several principal subsystems: the general purpose computer (DEC-PDP-11/45), used for analysis and control but not preprocessing or classification, the classifier, the preprocessor, the input subsystem, the control subsystem, and the output displays. Of these, the PDP-11/45 computer, the classifier, the control system, and part of the input system have been designed and tested in the first year of the NASA AAFE supported program. The remaining units to be added are indicated as cross hatched blocks in Figure 2.

The input subsystem inputs data stored on 1) High Density Digital Tape (HDDT), 2) Computer Compatible Tape (CCT), and 3) Analog Tape. The HDDT input is the principal input medium because of its high data rate and digital format. Data stored on HDDT's at 20,000 bits per inch and played back at 120 inches per second gives a data rate of 2.4 megabits per second channel. For ten channel data this is a bit rate of 24 megabits per second. Another advantage of HDDT is the efficient storage of data and a NASA standard format for Earth Resources Surveys has been recommended. The data contained on an HDDT may be as much as on fifty CCT's.

The second input medium is a 7 or 9 track multi-density CCT. The availability of data from many sensors on a common format is desirable, however, the time to produce such tapes from the original data has been quite long and may make the data out of date.

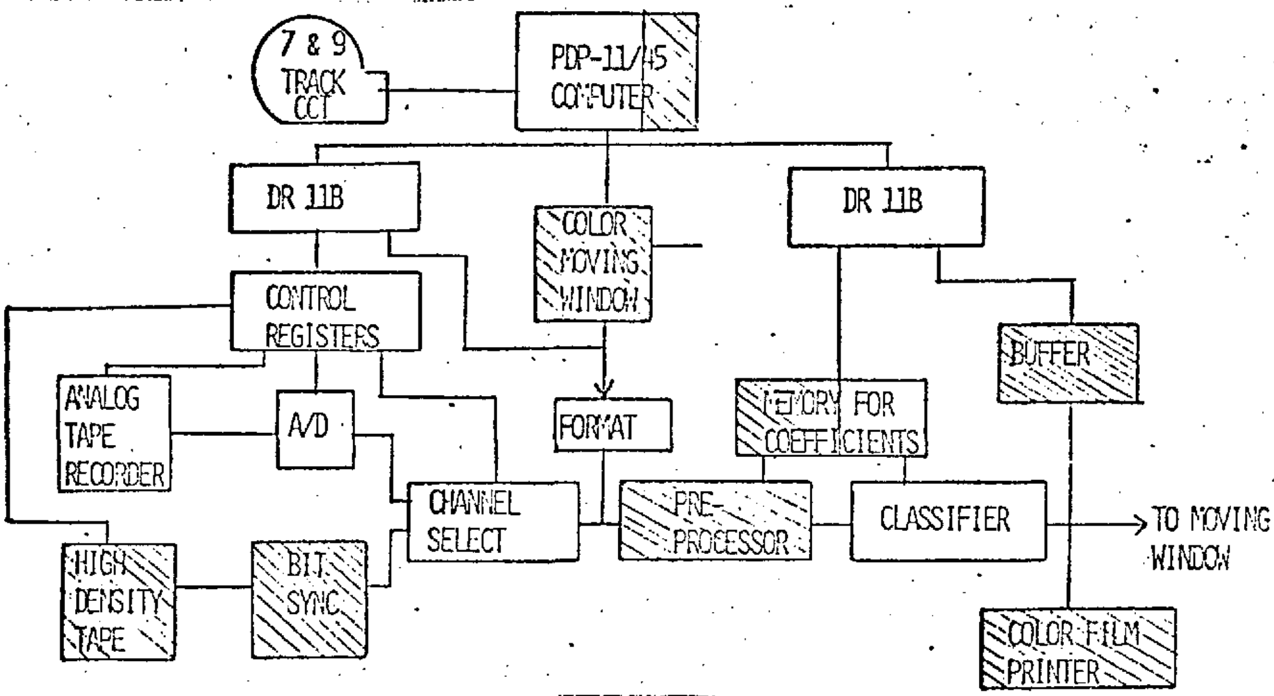

FIGURE 2

TO BE ADDED IN PHASE II

OVERALL SYSTEM BLOCK DIAGRAM

The data rate from CCT is at least an order of magnitude below the system capacity. A 58 megabyte disk is provided on the PDP-11/45 for data storage and storage of classification results.

The third medium of data input is from analog tape through the use of multiple A/D converters. Although this is an efficient data storage medium capable of maximum data rate for the MIDAS system, it appears as the third choice because few MSS systems record data in this form.

The preprocessor performs signature extension preprocessing calculations as needed. These are: 1) calculation of scan angle correction functions, both additive and multiplicative; 2) selecting and calculating channel ratio transforms, and 3) calculating a linear dimension reduction transform.

The calculation of scan-angle correction functions is a step normally required (ref. 4) to remove path radiance or other atmospheric and angle dependent variations.

Ratio transforms (ref. 5) may be used in preprocessing to provide data which is relatively insensitive to illumination and transmission variations, where transference of signatures from one frame to another is desired, or where spectral features can be enhanced. There is no clear-cut means of examining a data set to decide, in a priori manner, which of several possible transforms is needed for a particular scene. The method used would normally be one in which each of several transforms are performed on the training sets and the resulting data is tested for the optimal probability of correct classification using the training set and test set data to choose the transform to be employed.

The purpose of the linear transform (ref. 6) is to provide a new set of data in which the spectral data is combined in such a manner that the dimension-reduced, transformed data has essentially the same discriminability for the classes of interest to the user. This has the desirable effect that the classifier can perform a classification operation in which the accuracy of classification using the smaller number of dimensions is equivalent to that obtained with a larger number of untransformed dimensions.

The classifier performs a maximum-likelihood decision, assuming a multi-model Gaussian multivariate distribution. This assumption has been well justified at this time by over 100 experiments using multispectral data at ERIM (ref. 2) and, as time goes on, by more and more experience at NASA and other centers. Although simpler algorithms can perform well for some data sets, a significant percentage of applications demand this powerful decision rule. No penalty in speed and only a small additional cost occurs for using this algorithm.

The actual computations are performed by sets of time-shared arithmetic units arranged in parallel pipelines. Each stage supplies its results to a subsequent stage for further processing. Precision varies between 8 and 16 bits as the data progresses through the pipeline and acquires greater significance.

It will accept 8 input signals and can classify the results into one of 9 classes (including the null class) at its output on one mode of operation. In another mode of operation it can accept four input signals and classify the results into one of 17 classes at its output. The decision rate is 200 x 10^3/second allowing classification of an entire ERTS frame in less than one minute.

A three color video display using high resolution a shadow-mask CRT and a MOS storage for display refresh offers an interactive capability. The unit chosen at this time is the RAMTEK GX-100/200 series configured to hold a 5 bit color vector with 512 x 512 elements on the display.

The display offers image display, alphanumerics, vector generation, 2 movable cursors, digital zoom and move or moving window display and table look-up of predetermined colors. This color display provides the major interface for a fast man-machine interface. A scene or portions of a scene can be displayed almost immediately from disc as the user requests it. By having the ability to change colors quickly on the CRT through use of the table look-up, enhanced pictures can be viewed which help locate training sets of arbitrary shape. These enhanced pictures may also be put in hard copy form.

A second interactive CRT is part of the system for alphanumeric information display.

An extremely important device for the MIDAS system is a fast color printer. There have been a number of methods proposed for this function including CRT-color filter camera devices, multi-laser film devices, LED color array systems for printing on film and colored-ink printers. Of these, the most attractive method is the ink-jet printer since it produces a usable output immediately with no delay for color processing. This appears capable of producing a picture of about 10^7 elements in 10 minutes or less. An alternative possibility is a multi-LED scanning film printer using a Polaroid or Eastman fast color development method.

Having this fast turnaround for intermediate or final recognition results will permit the user to be much more efficient. This is especially true when enhanced false color maps of training areas can be made quickly. Present ERTS data sets can take up to 40 man hours or analysis to locate training sets because of low contrast on single channel black and white hardcopy, and because of the poor quality of available hardcopy.

In developing a complex system of digital hardware such as MIDAS, it is necessary to provide a method or set of methods which provide a quantitative report on the performance of the hardware for fast, low cost maintenance. This set of methods comes under the general category of machine diagnostics.

A substantial number of diagnostic programs have been developed which make use of the diagnostic bus designed into the system. The set of these diagnostics can be broken down into the following four types: 1) an automatic in-place fault isolation diagnostic, 2) classifier sub-assembly diagnostics, 3) off-line individual card diagnostics, and 4) a classification accuracy analysis package.

RECENT DEVELOPMENTS IN PROCESSING METHODOLOGY

The launch and subsequent long operation of the ERTS-1 multispectral scanner have allowed users to observe areas of interest repeatedly at 80 meter resolution. Because the ERTS MSS has four rather broad spectral bands, extractive processing using only spectral information frequently yields imperfect separation of classes of materials of interest. Partially to overcome the degraded performance of ERTS spectral channels relative to those available form typical aircraft scanners, users have exploited the spatial information inherent in the ERTS data along with the spectral data. Further, using the repetitive coverage capability of ERTS, some users have used the temporal variation of spectral data as inputs to the pattern recognition processors.

Spectral-Spatial Processing

ERIM has explored both applications of information from ERTS, with promising results. In one of the approaches we have tried spatial spectral processing, the key step is the formation of spatial "features" or quantified attributes of the scene. Following the suggestions of R. Haralick of the University of Kansas, spatial features were formed from ERTS data over Michigan as shown in Table 1. (Ref. 7). These spatial features were formed by measuring variations in ERTS band MSS-7 signal level in a 9 x 9 array with the pixel of interest at the center. Then both spectral and spatial sigantures were extracted for terrain categories in the Ann Arbor-Brighton, Michigan area.

We next ran an optimum feature selection program based on an algorithm which selects the channel which, along with the channels already selected, minimizes the average pairwise probability of misclassification between pairs of signatures. The results of the optimum channel ordering are presented in Table 2. Note that 2 of the first 4 features are spatial features.

TABLE 1. SPATIAL FEATURES DERIVED

1-4	mean signal level in each ERTS channel over 9 x 9 array ($\mu_4 - \mu_7$)
5-8	standard deviation over 9 x 9 array in each ERTS channel ($\sigma_4 - \sigma_7$)
9-14	normalized indicator of inter-channel covariance between ERTS channels over 9 x 9 array (R_{45}-R_{67})
15-22	average power in 4 spatial frequency bands (from 1/2 pixel to 1/5 pixel) for bands MSS-5 and MSS-7 (Q_{25}-Q_{55}, and Q_{27} - Q_{57})

TABLE 2. ORDERING OF SPATIAL-SPECTRAL FEATURES FOR TERRAIN CLASSIFICATION USING JUNE MICHIGAN ERTS DATA

No. of Channels	Feature No*	Prob. of Misclass.
1	1	77
2	11	41
3	20	24
4	4	18
5	8	14
6	2	13
7	22	12
8	10	11
9	5	10
10	6	8
11	3	8
12	9	8

*See Table 1 for identify of features.

Table 3 summarizes the performance of the pattern recognition classifier using the twenty-two features of Table 1. From the number of spatial features used in the classification, their position in the list of optimum channels, and the performance of the classifier using the spatial features, one may obtain some intuition of the utility of spatial features, when used with spectral features in pattern recognition.

While it would be premature to suggest that this type of spatial-spectral processing we have performed using ERTS data will be ultimately useful in all discipline areas particularly due to its coarsening of the resolution, we still conclude that the combined use of spatial and spectral features in conventional

TABLE 3. PERFORMANCE OF CLASSIFIER USING SPECTRAL/ SPATIAL FEATURES

ASSIGNED CATEGORY	TRUE CATEGORY: WATER	SOIL	URBAN	FOREST	AG
WATER	19	1	0	0	0
SOIL	0	0	0	2	4
URBAN	0	0	21	0	0
FOREST	0	1	1	18	9
AG	0	1	1	3	35
UNCLASS	2	2	1	1	1
AVERAGE PER CLASS	90%	17%	87%	75%	71%

OVERALL AVERAGE CORRECT CLASSIFICATION 76%

pattern recognition algorithms has definite promise and should be explored further. The work described here was performed for the U. S. Army-MERDC, under subcontract to ERIM from Batelle Memorial Labs.

Spectral-Temporal Processing

Because of the periodic coverage of ERTS, the temporal variation of spectral signatures can be utilized to help discriminate objects. This capability is enhanced with ERTS data over the previously available aircraft data because the periodic coverage is obtained from a sun-synchronous orbit. Further, the data are obtained from a relatively stable platform and at small scan angles from the nadir (typically $\pm$ 5.5°). Both facts greatly ease the data registration problem -- that of merging data collected at two different times so that pixels are precisely overlaid.

To illustrate the advantage of multitemporal spectral processing, consider the following example of mapping of natural vegetation in northern Michigan. (The work being discussed here was performed for NASA under grant NGR23-005-552).

Table 4 shows the signatures of a mixture of hardwoods, conifers, and grass and shrub swamp on two different dates -- June and March. Shown are the mean values of the signatures, with the standard deviations in parenthesis. Notice that in June, the two classes signatures overlap appreciably in each ERTS channel -- the mean difference between classes is less than the standard deviation in each channel. A pattern recognition device hopelessly confuses these two classes in June.

But in March, the two classes are more separable, as shown in the second half of Table 4. This separation of some classes at one time of year and not at others can be exploited to improve maps of natural vegetation areas. Now the challenge is to understand how vegetation signatures change with time, so that we may specify exactly when data are to be collected.

A second advantage of the periodic coverage is the ability to monitor the development of agricultural crops. While cloud coverage over agricultural areas significantly influences the amount of periodic coverage available, the coverage can still be used. The potential exists for crop yield estimation and prediction, by comparing the crop development, as sensed from ERTS, with a crop calendar of normal development. MIDAS can accept either spectral-spatial or spectral-temporal data as easily as spectral alone.

TABLE 4. SIGNATURES OF TWO VEGETATION CLASSES ON TWO DAYS.

June	MSS-5	MSS-5	MSS-6	MSS-7
Hdw/Conif/Grass	27.32 (0.91)	17.82 (1.45)	49.62 (5.52)	27.53 (3.88)
Shrub/Swamp	27.69 (1.20)	17.25 (1.53)	47.06 (5.69)	25.75 (3.94)
March				
Hdw/Conif/Grass	29.96 (3.75)	28.07 (3.11)	29.93 (2.96)	15.82 (1.28)
Shrub/Swamp	23.69 (1.74)	20.25 (4.04)	22.19 (3.60)	11.38 (2.60)

Mean signature values are shown, with standard deviations in parenthesis.

USER MODEL DEVELOPMENT

One critical portion of the Earth Resources Survey System is the User Model, which relates the output of the extractive processors and ancillary data to generate information which a user can employ directly. User models may be very simple -- if the user wants a map of vegetation types, the output of the extractive processing may directly serve him directly, and the user model is absent. But if a Department of Agriculture official wants to know what is the projected wheat production in Kansas, the user model may combine the total productive acreage of wheat (obtained) from a remote sensing system), with some farmers's estimates of the yield of particular fields, and some estimates from the weather service of future weather trends, to calculate the total production of wheat in Kansas.

As an example of a user model, consider Figure 3. This model predicts the population of migratory waterfowl, given the water supply conditions, the food supply conditions, and ancillary variables such as number of nesting pairs, predation, and mortality. Also shown in Figure 3 on the right are elements of the decision model used by the USDI Bureau of Sports Fisheries and Wildlife. The model shown is, at present, conceptual and represents the work of BSFW personnel. ERIM and BSFW are working jointly (under NASA funding from ERTS and Skylab programs) to develop remote sensing inputs to this model.

Figure 3 shows at the left, inputs to the user model. Asterisks indicate those types of information obtained from low altitude aircraft-borne observers (supplemented by ground observations), and data potentially derivable from remote sensing techniques. The goal of the user model is to estimate the fall population of mature and immature birds. Old birds are estimated by low altitude aerial survey and ground counts of nesting pairs on a sampled basis. Estimates of summer mortality are also made from ground observations and past experience. The number of breeding pairs, coupled with the May and July pond numbers are used to estimate the number of new ducks. This information is augmented by the number of broods obtained on a sampled basis from ground survey.

Hunting regulations are defined based on the population size, the estimate of harvesting of ducks in Canada, and the carrying capacity of the habitat. Remote sensing has an impact in assessing capacity of habitat, especially in the assessment of quantities and distribution of natural vegetation.

As an example of the annual production equation, Figure 4 shows a linear equation in several variables which BSFW personnel have derived to predict new production of mallard ducks. The coefficients of the model are derived on the basis of historical experience. If similar models can be constructed for other species, then the general user-decision model of Figure 4 can become more operational.

ACKNOWLEDGEMENTS

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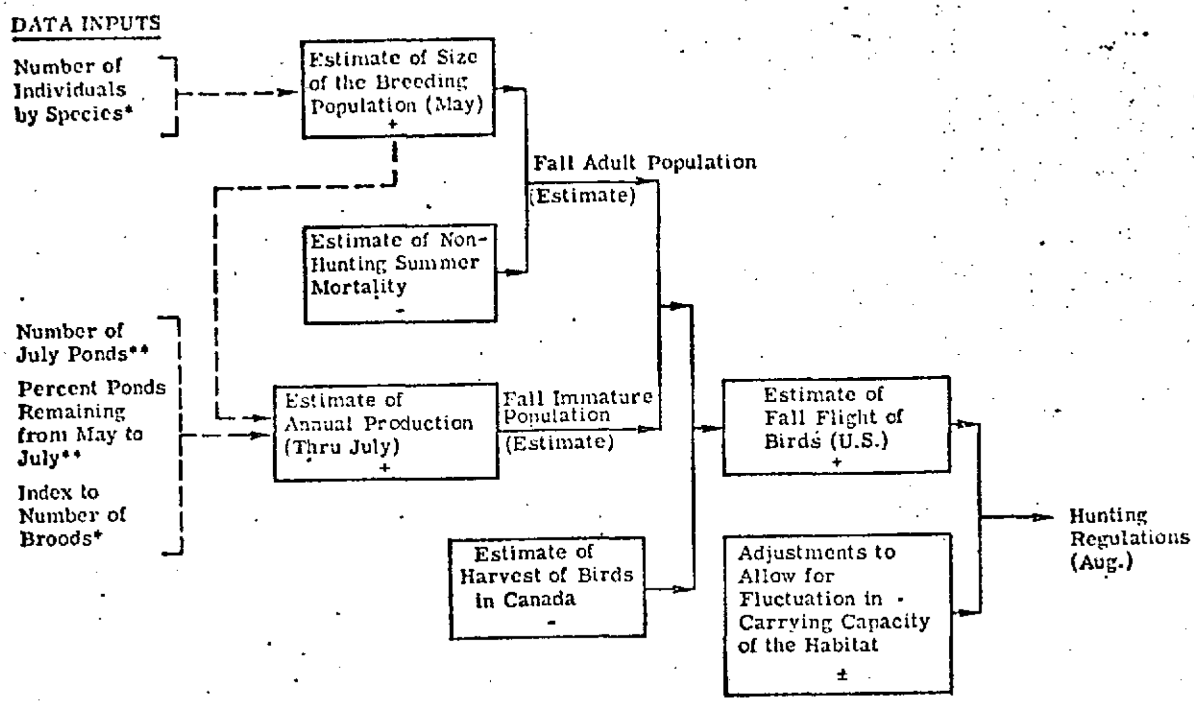

FIGURE 3

DETERMINING HUNTING REGULATIONS BASED UPON THE ESTIMATED MAGNITUDE OF THE FALL FLIGHT OF MIGRATORY WATERFOWL

*Obtained from aerial observations and adjusted based on selected ground counts
**Obtained from aerial observations—data potentially derived using remote sensing techniques

$$\hat{Y} = 7.926 + 1.468\,X_1 - 0.624X_2 - 0.028X_3 + 0.016\,X_4$$

where $\hat{Y}$ = Predicted number of mallard young (millions)

X_1 = July ponds (millions)

X_2 = continental mallard breeding population (millions)

X_3 = percent of ponds remaining from May to July

X_4 = index to number of broods (thousands) unadjusted

EXAMPLE OF A MODEL FOR PREDICTING ANNUAL PRODUCTION OF YOUNG MALLARDS*

*After Geis, A. D., R. K. Martinson, and D. R. Anderson (1969)

FIGURE 4