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DERIVING SPECTRAL AND SPATIAL FEATURES
TO ESTABLISH A HIERARCHICAL CLASSIFICATION SYSTEM

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ABSTRACT

Automatic processing of remotely sensed data has to date been constrained to using training sets to classify a small number of categories within the context of a limited geographical area.

In order to promote a more flexible user-oriented data processing system, a hierarchical taxonomic structure is proposed. This structure incorporates data inputs from several different sensors together with a priori information on the characteristics of different materials of interest to facilitate efficient design of feature sets to classify those materials. A Boolean approach may be used to assign these feature sets including both spectral and spatial criteria to different hierarchical levels.

The availability of sensors to sample portions of the electromagnetic spectrum (EM) has been increasing with the advent of advanced sensing systems. Each system that has been developed (i. e., radar, microwave, filtered photos, linescan systems) is designed to take advantage of some particular characteristics of materials or classes of objects of interest to investigators. This multitude of data sets from which features can be extracted has been used to discriminate among particular subsets of a scene (i. e., agriculture, soils, water, etc.). These data sets combined with a variety of user requirements to classify such data can and should be incorporated into a taxonomic scheme which will accept data from a multitude of sources. Such a scheme will provide a means of logically clustering like objects on the basis of similar subsets, or conversely, separating objects on the basis of differences among these subsets.

The concept discussed in this paper is an approach which would take advantage of both the similarities and differences among specific classes within the context of a taxonomic structure which can exploit the different combinations of features collected by different sensors. Such a system will necessarily demand a better understanding of the type of data to be collected for a particular need. Likewise, it will require further definition of the relationship between the reflected or emitted energy characteristics of different materials and the sensors employed to detect these different characteristics.

The development of such a taxonomic system would require (1) the specification of a common set of criteria or features to be evaluated at each stage of processing; (2) a clustering of general subclasses based on a feature or number of features as defined under (1); and (3) a method of specifying or directing a particular sequence for specific user requirements.

Any classification scheme operates on the premise that definitions for class descriptors, a vector discriminant or feature, depend on some commonality of all subsets within that class. For example, there exist some common denominators which permit one to categorize all types of vegetation in a single class, or all types of vehicular traffic, etc. To do so, one must be careful to choose those combinations of general characters which are constant for every unit assigned to a class. These common denominators permit the taxonomist to cluster data arbitrarily to best suit the objectives of his classification.

Similarly, as associations exist among objects within a class, within the context of a single

reference system there exist associations between different classes. These associations exist at different degrees of prevalence among the assigned classes in a population. In a sense then, any image scene can be broken up into a number of different classes, but these classes exist along some continuum or more likely within a matrix with some classes more closely aligned in terms of common characteristics than are others.

Before the associations among different classes can be defined, the boundaries for each class must be precisely delineated first. This is a task to be performed by the taxonomist before any classification of data begins. Once the major units are properly defined, they can be arranged in a hierarchical structure which shows the relationship among all the units. Each class is assigned to a level according to how general or specific the feature sets are which define that class.

So as to use a computer in constructing a taxonomic system, Sokal and Sneath (1963) used a numerical taxonomy wherein each unit character was described as a feature that represented an alternative which could be answered "Yes" or "No", "Possessed" or "Not Possessed". Such binary information could easily be transferred into bytes directing the processing operation through successive dichotomies until a satisfactory separation occurred between those divisions to be referred to as separate classes or subsets. Rogers et al (1967) refer to denominators for a class as characters or rules which define non-overlapping descriptions called character states. Such characters do not necessarily exist in any recognizable form in the real world. They may instead result from a linguistic or logical definition of a class rather than being derived from a natural class.

More recently, Sammon (1970) has described features as being generally selected on the criterion that they possess only essential information describing elements of a class while simultaneously distinguishing those elements from elements of other classes. The selection of features for classifying imagery, however, is determined in part by the hardware characteristics of the sensor and/or as often is the case, the type of sensor available to collect the data. The types of sensor input mostly determine the type of and number of features available to describe a class or subset. For example, narrowband multispectral scanners have at a minimum a set of features related to reflectance values for each channel. These feature sets can be selectively permuted to increase the number of alternatives for class separation. Likewise, sensor systems which selectively sample different parts of the electromagnetic spectrum produce information which yields independent feature sets for any given type of material. For instance, side-looking radar produces spatial information based on the angularity and roughness of terrain features. Different terrains exhibit characteristically different surface textural properties as a result of the type of radar return recorded. Emissivity properties of different materials, recorded in the thermal infrared bands, also exhibit independent features. Likewise, polarized light receptors and laser line scan systems provide information which may be used to select independent sets of features. Independent features describe the different phenomena exhibited by the way different substances or objects reflect or transmit energy in different parts of the electromagnetic spectrum. In addition, intrinsic surface textural properties may also serve as independent features (Dinstein, et al, 1972). In some cases, the feature set criteria may be similar or identical for different parts of the electromagnetic spectrum, thereby permitting similar parametric measures. For example, given similar resolution for a thermal scanner and a laser scanner, the vector for spatial characteristics of an object would be similar.

Figure I illustrates the use of these different features to establish a hierarchical taxonomic scheme. For each branching level there is a set of feature vectors which separate the subsets for that class or level. In this case, features are defined by either spectral or spatial characters ascribed to each class or subset. Assuming a normalized data source from a narrow band multi-spectral scanner including bands in the visible, near and far infrared, data separation is between dimensional and non-dimensional scenes within a selected grouping of defined data points. A dimensional scene may be identified by sharp contrasts, linear and curvilinear features. Hadamard or Fourier transforms may be applied to separate those areas of an image having a high probability of dimensionality from those areas which are generally non-dimensional. By comparing amplitude ratios of reflectance values in selected bandwidths in both the visible and near infrared, one can separate those spectral combinations more likely to exist in natural settings as opposed to what would be likely reflectance from cities or non-associated phenomena. On the basis of dimensionality and spectral reflectance values, it is possible to draw a logical assessment separating man-associated phenomena from what is generally referred to as a natural scene. This results in a separation of the data input into categories.

This subdivision of the data inputs continues systematically down to the level of classification desired. As illustrated in Figure I, different criteria are employed for each level of separation and in this case both spatial and spectral inputs are used to construct the features. At each hierarchical level an alpha-numeric code is attached to provide a library reference. Such a code becomes cumulative down to the final level of classification and is fixed to the position

coordinates for points or homogeneous areal measures.

To facilitate feature set design, one can make some a priori assumptions based on accumulated knowledge of specific spectral or spatial properties of different materials. Considerable effort has been expended in numerous laboratory and field studies to determine the spectral and spatial properties of a large number of materials, both natural and manmade. As has been shown in many of these studies, most laboratory and field measurements cannot be directly extrapolated to data collected from aircraft or satellites. This is primarily due to difficulty in simulating the large number of changing variables that occur under natural conditions during data collection flights. However, inferences can be made as to the spectral and spatial coefficients of different materials relative to one another. Such inference can aid in determining the feature sets, as well as in organizing a taxonomic structure. The difficulty is in determining the ordinal ranking for these coefficients so as to assign them common occurrence for a whole general class, or some secondary level of separation. Large volumes of this data could be fed into the computer to determine these coefficients, but such procedure may or may not be an effective use of computer time. To carry out such an operation to its conclusion would result in some artificial training set which may not be relevant to any data collected in aerial coverage. Therefore, it may be more useful to use such a priori data to set threshold limits in the design of feature sets. A Boolean approach to incorporate this a priori data on different materials into a classification system seems appropriate. It is particularly useful in determining what parts of the electromagnetic spectrum may be used to construct feature vectors to separate different materials. For instance, by establishing what the spectral and spatial properties are for a class or a material of interest, one can easily relate these properties to the characteristics of different types of sensor systems or to the latitude of variables within a single system. In this way different classes are defined precisely in terms most useful to the user, while also taking full advantage of the characteristics of the different sensors which might be used. What must remain of primary concern is that the combination of feature sets so derived for each series of class breakdown must uniquely define the material or object in question.

To recapitulate, a hierarchical approach offers several advantages: (1) An investigator can stop at any level of classification desired depending on the requirements for data dictated by the problem being examined. If the investigator is only interested in breaking out manmade objects from a vegetative background, the analysis could stop at the second or third level of classification. Similarly, any other intermediate level or subset could be selected as an output. (2) Each level of classification (branching) has its own identifier code permitting quick access to computer files and quick feedback as to the power of the feature vectors in separating categories or subsets within a class. Furthermore, assuming the data is normalized to reduce variance due to atmosphere, etc., checks can be built into each branch to spot false alarms or poor feature sets. In other words, where the selected feature vectors fail to define the data into one of the preselected subsets, an error message might indicate a change in anticipated conditions for that decision level, possibly resulting in an undefined data set. In this case, ground truth or refined features could affect the formation of a new subset or a broader definition of a particular subset. (3) Feature sets should be defined so as to allow for some variability in the data inputs taken from different aerial locations. Variance in the data inputs over a successive series of collection missions is a serious problem. Feature sets for each dichotomous level should ideally account for several variables. Decision logic comparing the data to the feature set will require some probability factor (e. g., $P=95\%$) that the data conforms to the feature set. Where minimum acceptance criteria are met, the decision logic immediately reverts to a binary "yes" or "no" status. The encoded data is again processed and subdivided through iterations in successive decision levels. At no time do any lines of decision logic cross over from one branched routine to another even though for different applications feature sets might be interchangeable. (4) As feature sets are refined and prove effective, they can be incorporated into feature vector libraries. Such libraries provide the flexibility for a user to build classification schemes suited to his specific application. These schemes would likely be constructed using both a priori and a posteriori reasoning on the associations as well as how they relate to the intrinsic properties of the classes under study.

To implement such a scheme on a computer, a flexible, interactive computer system must be used. The general pattern recognition problem can be divided into two main areas of consideration: (1) feature extraction, and (2) classification. The latter has been formalized by years of pattern analysis research resulting in the development of new computer software technology. Part of this technology has evolved into a set of library routines called OLPARS (On Line Pattern Analysis and Recognition System) developed at Rome Air Development Center. This system, together with other software and hardware, is described in detail by Hoffmann and Turinetti (1973) in another presentation at these proceedings.

OLPARS is a powerful interactive pattern analysis and recognition design tool which has been described by Sammon (1970). The system uses an interactive console to permit users to evaluate the structure or statistical variations of his data sets as well as to determine the discriminatory

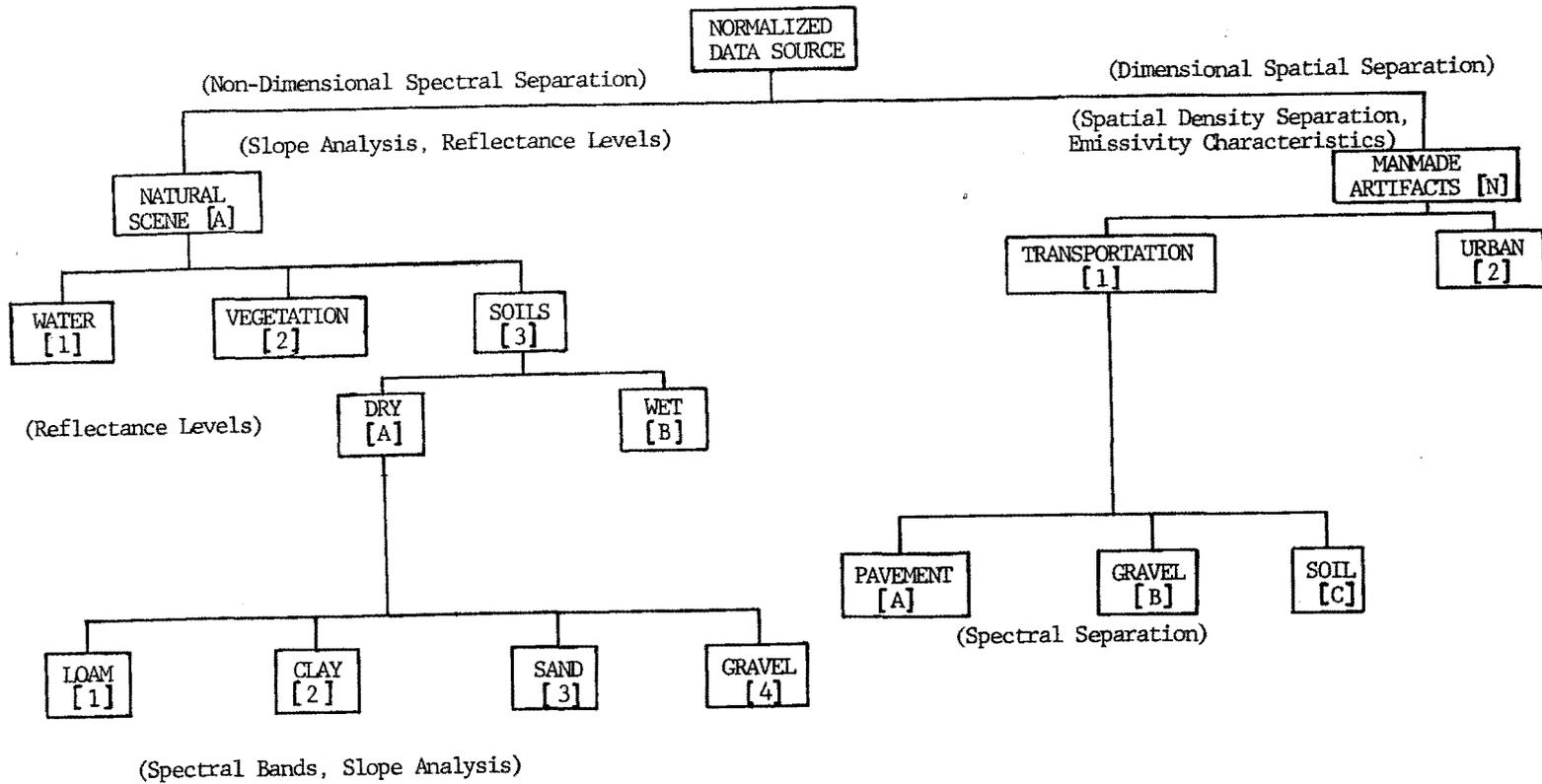
power of his features. In addition, it provides numerous transformation and display options that enhance the user's knowledge of his data and features. Finally it provides for the interactive design of sophisticated decision logic, using such decision criteria as Euclidian distances, or pairwise discriminant logic to divide the map input data points to defined regions in feature space so as to permit association and classification with specified classes. The final decision logic after testing and evaluation can then be implemented easily on the feature extractor and subsequently used for both classification and continued development.

As should be noted during both the feature extraction and OLPARS discussion, a heavy emphasis is being placed on interactive design wherein different library routines can be called upon to perform various options on imaged data. All this is under the complete, direct control and visual inspection of a user.

Moreover, the compilation of these feature sets into taxonomic associations will establish the beginnings of feature vector libraries. As numbers of feature sets including those from different parts of the EM spectrum are added to the library, the possibility of new taxonomic associations based on remotely sensed data emerges. In this manner, the power and flexibility of the system increases by providing more alternatives for the user to sort out and classify the data he has collected. Ultimately, these feature vector libraries may lessen the requirements for extensive field checks. In addition, they should provide flexibility in classification schema not now enjoyed by those which rely extensively on training sets for a limited number of classes in an image scene.

LITERATURE CITED

- Dinstein, I, R. M. Haralick, S. K. Shanmugam, and D. Goel, 1972. Texture Tone Study Classification Experiments - Fourth Interim Technical Report. University of Kansas. United States Army Topographic Laboratories ETL-CR-72-16. 195 pages.
- Gausman, H. W., W. A. Allen, C. L. Wiegand, D. E. Escobar, R. R. Rodriguez, and A. J. Richardson. 1971. The Leaf Mesophylls of Twenty Crops, Their Light Spectra, and Optical and Geometrical Parameters. Soil and Water Conservation Res Report 423, USAF, Weslaco, Texas. 88 pages.
- Hoffmann, R. J. and J. Turinetti. 1973. Pattern Analysis and Recognition Techniques Applied to the Identification of Ecological Anomalies. Conference on Machine Processing of Remotely Sensed Data, Purdue University (in press).
- Laboratory for Agricultural Remote Sensing (LARS). 1970. Res Bulletin 873. Volume 4. Purdue University. 112 pages.
- Rogers, D. J., H. S. Fleming, and G. Estabrook. 1967. Use of Computers in Studies of Taxonomy and Evolution. pages 169-196. In Evolutionary Biology. Volume I. T. Dobzhansky, M. K. Hecht, and W. C. Steere, editors. Appleton Century Croft, New York. 444 pages.
- Sammon, J. 1970. Interactive Pattern Analysis and Classification IEEE Trans on Computers. Volume C-19 #7: 495-616.
- Sokal, R. R. and P. H. A. Sneath. 1963. Principles of Numerical Taxonomy. W. H. Freeman and Company, San Francisco. 359 pages.



Dry Clay Identifier Code A3A2

- - Classes or Subsets
- () - Possible Types of Feature Vectors
- [] - Alphanumeric Filing/Classifying Code

Figure 1. A Hierarchical Tree Depicting Associations Among Hypothetical Classes Differentiated by Means of Feature Vectors