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In Perspective: Meeting the Image Processing Challenge for Remote Sensing

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INTRODUCTION

Although man has been observing the condition of his environment from aerial vantage points for many decades,[1] developments of the 1950s and 1960s could be pointed to as the origins of modern remote sensing technology.[2] The last twenty to thirty years have seen dramatic advancements in the design of sensor systems, particularly in the measurement of infrared energy, the advent of the digital computer, and progress in modeling some of the processes associated with human intelligence, notably pattern recognition. Within this decade we have developed the capability to marry these advancements with spaceborne systems which can provide us image data of the earth—and other planets as well—of unparalleled scope, scale, resolution and timeliness. The "dimensions" of the data, however, overwhelm our human capabilities to assess and assimilate it. The human visual system cannot deal effectively with the four or thirteen or more than twenty concurrent images of the same scene produced by modern multispectral imaging systems. Nor can we begin to cope with the volume of image data that has suddenly become available through the orbiting of such systems.

And thus the challenge: to develop effective computerized image processing techniques, either to reduce the flood of data to proportions we can handle in a useful way or to amplify our powers to manipulate the data and discern the useful information contained in it. How are we meeting this challenge? First, let us look a bit more closely at what is involved.

UNIQUE ASPECTS OF THE PROBLEM

In remote sensing, information about the earth and its atmosphere is conveyed to the sensor system through the spatial, spectral and temporal variations of the electromagnetic energy emanating from the scene.[2] Typically we organize the spatial variations into an image which can then provide a two-dimensional characterization of "things" in the scene in terms of their shape, size, orientation, and context.

To a limited extent, the spectral or wavelength-dependent variations in the scene can also be incorporated into an image through the dimension of color. However, these variations can be quantified to only a limited extent in this way because discernible "color" is a net effect which is uniquely definable by at most three fundamental components. Thus since our modern sensor systems can precisely measure more than three distinct spectral components we are bound to suffer loss of data (and usually, but not always, of information) if we attempt to represent these components in terms of color. An alternative is to represent the various spectral components as multiple images rendered in gray tones. Unfortunately such a representation is not only awkward but fails to display explicitly the subtle relationships between spectral components which may be essential for characterizing different ground covers.

Attempting visual display of temporal variations simply makes matters worse. Assuming that images of a given scene collected at different times can be precisely registered (the technology for accomplishing this has in fact been developed[3]), color renditions and multiple gray-tone images can again be used to convey temporal variations in the scene. But taking these variations together with the key spectral variations leads to a level of complexity guaranteed to overburden the human sensory system.

Thus, a characterizing feature of remote sensing data is its multi-image nature. Roughly speaking, a computer is as capable of dealing with four or thirteen or twenty dimensional data as it is with three dimensional data.[4] So it is natural to turn to the computer for assistance in making use of remote sensing data.

We have already mentioned the volume of remote sensing data that is available. Even early airborne systems (circa 1960s) typically produced "scenes" consisting of 10^6 multispectral pixels ("picture elements"). Today we often wish to process ten times that many pixels as a single unit. By the early 1980s, improvements in sensor resolution will increase the figure by another order of magnitude.[5]

Data volume is therefore another characterizing aspect of remote sensing imagery. We need computers to catalog as well as to analyze very rapidly the massive quantities of available data. But even with computers serving in these capacities, the situation is characteristically more demanding in the case of remote sensing than in any other application of image processing which comes to mind.

Remote sensing is very much an applied technology. Historically its development has been and continues to be most rapid when a potential application provides a focus. As a result, image processing for remote sensing has characteristically been a multidisciplinary effort, resulting in a need to make scientists who may not be computer-oriented feel "at home" with the image processing machinery. This has been accomplished by paying serious attention to the man/machine and man/data interfaces, developing, for example, English-like command languages to be used for directing the image processing operations.[6,7]

Having sketched some characteristic aspects of image processing for remote sensing, we shall now turn to an overview of some of the efforts which have been directed toward meeting the challenge, what is happening today, and some apparent needs for the future. In doing so, it is helpful to think in terms of fairly distinct image processing activities: enhancement, preceding either visual or machine-implemented analysis; analysis, typically but not exclusively classification; and product formating, storage and retrieval.

WHERE HAVE WE BEEN?

Attention began to focus on the computer analysis of multispectral remote sensing data in the mid-1960s.[8] To limit the task to one of manageable proportions, it was decided to concentrate in the main on the spectral variations in the data, practically ignoring, for the time being, the spatial and temporal variations. This choice was largely motivated by the wealth of information that the spectral domain was assumed to contain and optimism with respect to how much effort would be required to extract a significant proportion of that information.

Much of the earliest multispectral image data was recorded in analog form, either photographically on film or electronically on magnetic tape. Once it had been decided to use digital computers to analyze the data, techniques and hardware were needed to convert this data from analog to digital form and store it on computer-compatible tape. But of course the data analyst then needed a facility for displaying the digital data and referencing specific locations in it. These combined needs gave great impetus to the development of image digitizing and digital display devices. In essence, the skills and theories which had been developed for the photographic darkroom had to be translated into a new digital technology.

Statistical pattern recognition was quickly adopted as a promising approach for analyzing the multivariate data associated with each pixel in the multispectral image.[9] One of the earliest applications was crop species mapping. Commensurate with the relative complexity of this task (some of the spectral differences among crops in the field are fairly subtle), maximum likelihood classification assuming multivariate Gaussian data distributions was often used to accomplish the analysis.[4] Interestingly, although many alternative classification methods have been investigated since those early days, the Gaussian maximum likelihood classifier has remained the most widely used. Some reasons which account for this include its ease of implementation, its moderate level of computational complexity and memory requirements, and its ability to represent moderately complex decision surfaces in the feature space through use of second order statistics (class covariance matrices as well as means).

The products of the data analysis were largely in two forms: classification "maps" in raster format analogous to the data input, usually printed on conventional computer lineprinters using distinct characters to represent the ground cover classes; and tabular summaries listing total area coverage by class and, for selected areas for which adequate ancillary data were available, an estimate of classification accuracy. These products were fine for illustrating the kinds of information which could be extracted from remote sensing data, but they would eventually be found to fall far short of the needs of the potential users. The map makers needed photo-quality images with tightly controlled geometric characteristics and somewhat less detail than the computer analyses generally produced; and in color. The policy makers needed results reported according to specialized categories not always identifiable by their spectral properties alone; and on the basis of oddly shaped political or jurisdictional regions. Once the need for these types of products was realized, vigorous work toward their generation met with success.[10]

Most of the remote sensing data processing capabilities were initially implemented on general purpose computers. Although ideal for research and development purposes, these implementations were clearly inadequate for the high-volume processing which would be called for when satellite-borne remote sensor systems were orbited in the early 1970s. A few research organizations and commercial establishments attempted to predict the image processing capabilities which would be needed and to construct special purpose systems to meet the anticipated need. Although they succeeded in demonstrating that special purpose systems could achieve dramatically improved throughput performance compared to general purpose versions they also proved that the remote sensing image processing technology was advancing at a great rate: their systems were obsolescent even before producing their first results.

WHERE ARE WE TODAY?

Present-day image processing technology has gone beyond the spectral domain alone, making significant strides into the spatial domain and some tentative steps into the temporal domain.[8]

A number of cosmetic enhancements are routinely applied to the digital multispectral data.[11–16] These include a wide range of false color display techniques, geometric adjustments to match existing map products, edge enhancement, resolution enhancement (reduction of blurring due to various sensor system characteristics), and other filtering operations.[17] Methods have been developed for precisely registering multiple images of the same scene to a common template scene.[3,18,19] All of these advances have improved the interpretability of remote sensing image data and increased the potential utility of the final product to the user.

Methods for extracting information from remote sensing image data have developed to the point where they are testing the boundaries of what can be accomplished based on the spectral domain alone. With respect to some potential applications, the results achieved with data available from current sensor systems, of relatively limited spectral coverage and course spectral resolution, have fallen short of the results anticipated. This has had the unfortunate effect of discouraging segments of the potential user community and causing them and many interested layman to prematurely judge the limitations of the technology.

Texture and spatial contiguity are two geometric characteristics of the image data which have been demonstrated to be useful in the analysis process. Texture characterizes some ground covers of interest; the challenge has been to find effective measures of observable texture.[20–22] Detection of spatial contiguity permits scene segmentation and the delineation and classification of "objects" in the data.[23] When a large number of "objects" consist of many pixels, this leads to greater classification efficiency and accuracy. Statistical "sample classifiers" have been developed for this purpose.[23]

The products of the image processing operations today are a far cry from those available even a few years ago. Computer-driven precision film writers, ink-jet and electrostatic printers have made possible excellent quality map-like products at increasingly palatable prices. Capabilities for digitizing arbitrarily shaped polygonal boundaries have made it possible to report quantitative areal tabulations on a very flexible basis.[10] For applications where areal estimates are more feasible than "wall-to-wall" inventories, sophisticated statistical design and evaluation methods have been developed.[24,25]

Although they are exceedingly expensive, a few relatively powerful image processing systems are available for remote sensing data processing.[26] In the development of these systems, great attention has been paid to facilitating the role of the system operator who, in fact, is assumed to be a very capable data analyst. Thus an important element of the system is an interactive high-resolution digital display with a color CRT. A programmable array processor rather than a hard-wired special purpose processor may be used to implement the compute-bound steps in the processing. The processes for determining the appropriate parameters for various stages of the processing still involve the data analyst and often require considerable trial-and-error, however. As a result, the throughput of these specialized systems remains rather limited.

THE NEEDS OF THE FUTURE

We know from the performance of skilled image interpreters faced with visual analysis of available remote sensing data that there remains a wealth of information in the spatial and temporal domains as yet untapped by computer-implemented algorithms. Effectively characterizing and extracting this information constitute the challenge for the future.

A number of image enhancements appear feasible but have yet to be developed sufficiently for routine application. Examples include haze removal, scene-to-scene tonal normalization, and boundary detection and enhancement. The utility of the data and the task of the data analyst would both be improved by development of effective methods for coordinating ancillary data with the associated image data. This is not a trivial matter when one considers the spectrum of data types and formats that can be involved. It is not at all clear how to most effectively coordinate point, polygon, and line data with image data.

With precisely registered multitemporal remote sensing data promising to become more readily available, what means can be developed to effectively display the data and to enhance features of interest (often changes) to the image interpreter or the data analyst? What new problems will we have to deal with due simply to the gigantic proportions of the data sets? (Current Landsat scan lines consist of just over 3200 pixels, each of which is 4-dimensional. Projected systems will yield over 6000 6-dimensional pixels per scan line[5]).

Judging from the evolving image processing research, quite a range of new approaches for characterizing and extracting spatial information will be tested on remote sensing data and appropriately adapted. Texture, a complex visual phenomenon, is one of the features which seems quite obviously useful to human photointerpreters. Many very different approaches to the quantitative characterization of texture have been attempted and, in some instances involving remote sensing data, have been moderately successful. More progress in this area is needed.[21]

Where texture is a rather local spatial phenomenon, context might be thought of as a property bridging the local on one hand and the global on the other. Context is another phenomenon used effectively in manual photo-interpretation, since it can be quite helpful in characterizing a pixel or an object to take into consideration the nature of its neighbors. It has been demonstrated that the capacity to do this can be incorporated in pattern recognition algorithms for remote sensing, although the computational cost is substantial.[27]

Global relationships in images can be characterized using syntactic pattern recognition techniques.[28,29] This approach to remote sensing image analysis is very important because there are many instances in which rather general spatial relationships are key identifying characteristics. Rivers can be discriminated from lakes because they are "string-like" rather than "blob-like"; clouds can be discriminated from snow because clouds cast shadows. To use this approach, however, requires the abilities to infer the characterizing relationships from typical imagery and to capture them effectively in "pattern grammars". These are very difficult problems of image analysis in general and much remains to be done before practical applications of syntactic pattern recognition will be seen in remote sensing.

The decision processes needed for remote sensing data analysis can often be cast rather effectively as hierarchical and/or sequential processes.[30] One can envision, for example, classifying a pixel into successively more specific categories by selectively using additional spectral bands or other features. The features to be used could be adaptively determined by the decisions made at each stage. This sort of hierarchical process can lead to both faster and more accurate classification. Still another classifier model can be used to efficiently process multitemporal image data from successive passes of the sensor over the scene.[31] In this case, likelihood computations are "cascaded" and the results of each stage of computation are made available to the next stage when later data is obtained.

Early in the history of the development of image processing for remote sensing, the goal of total automation of the process was established. It was assumed that only through total automation could the throughput of the processing system be made adequate to the data volume and demand for processing. Now, more than a decade later, that goal still remains the ideal, but it is widely recognized that it may be some time before we learn how to make computers perform certain complex tasks that humans perform rather well. Experience has demonstrated that, at least for the present, we cannot devise streamlined automated analysis algorithms employing available technology which can serve as a reasonable replacement for the data analyst who has training related to the application of interest and the computerized analysis tools as well. For the foreseeable future, then, we can expect to see continued research to improve the effectiveness of the human data analyst as part of the total image processing system. We have already noted the need to better coordinate the various forms of data the analyst must use (point, line and polygon data as well as the image data). More effective means of interacting with the total data bank are needed, utilizing, in all likelihood, interactive display facilities with graphics, image overlay, and color image capabilities. Similar remarks apply to interaction with intermediate and final processing results so that the analyst can function in a feedback loop to iteratively improve the results obtained.

Most beneficial use will be made of both the sensor data and the image processing facilities when a common set of these resources can be made available to a wide range of potential users. One way to accomplish this is to store fairly detailed analysis results in a flexible "earth resources information system" capable of being interrogated and providing a wide range of graphical and statistical information. This can be thought of as the "users' data base", containing more "refined" information developed by applying image processing to the "remote sensing data base". Some efforts have already been made along these lines,[32,33] but the needs of the user community are not yet being widely met.

Finally, the still rapidly evolving computer technology—microprocessors and parallel and pipeline computation—have important implications for the future of remote sensing image processing. The sheer volume of the data to be processed has already provided motivation for implementing relatively conventional analysis methods (multispectral clustering and maximum likelihood classification) on the ILLIAC IV parallel processor. Demonstration runs have resulted in computational speed-up factors of two to three orders of magnitude (between 10^2 and 10^3).[34] Yet this represents a rather "general purpose" implementation using obsolescent technology. The near future will see availability of very high speed microprogrammable processors which can be dynamically organized into parallel/pipeline configurations potentially capable of performing staggering numbers of computations per second.[35] It will be no small challenge to utilize such computational power effectively. Significantly, the prospect of having such power available is allowing us to think about image processing in new ways, to consider developing computational methods which were infeasible for practical applications when conventional serial implementations had to be assumed. The programability of these advanced systems will at once ensure their general applicability and make them available for further evolving the remote sensing image processing technology.

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