Professional Articles

Trends in Quantitative Remote Sensing¹

by

Robert J. Woodham²

Introduction

This paper describes present and future trends in quantitative remote sensing and provides a selected reference list for further reading. The trends identified are general in scope. Nevertheless, it is hoped that readers can draw their own conclusions related to forestry from the material presented. The references given have been chosen, so far as is possible, to be accessible to the non-specialist. They provide additional pointers to the scientific literature.

Seven trends are identified. The first six are technical in nature while the seventh is essentially political. The seven trends are listed below and elaborated upon in the sections that follow:

- Quantitative remote sensing means computer-based remote sensing.
- Satellite imagery can be geocoded on an operational basis.
- Satellite imagery is being integrated with other geocoded information sources.
- Quantitative methods depend increasingly on physical models of image formation.
- There is a current fascination with the technology of artificial intelligence expert systems.
- Expert systems for remote sensing must identify the levels of representation required and must specify the constraints that operate both within and between levels.
- Funding for research and development of remote sensing and geographic information systems is changing.

Quantitative Remote Sensing

In remote sensing, digital image analysis gained prominence with the first Landsat satellite launched in 1972. The Landsat multispectral scanner (MSS) is a digital sensor. That is, measurements of scene radiance are quantified and converted into numbers onboard the satellite. Images are transmitted to ground receiving stations as a stream of numbers. Some form of digital image processing is therefore required, if only to write the digital data on film for subsequent human interpretation (Moik 1980).

Clearly, an opportunity was created for automatic digital image analysis. The view that persisted, however, was that while it can be appropriate to use digital image analysis on images that are digital to begin with, manual photo-interpretation is preferable for imagery obtained by traditional aerial photography.

This view is changing. One reason is that it is now routinely possible to convert any product to a digital image without loss of information. For example, the Optronics film scanner of the UBC Laboratory for Computational Vision can scan film at a grid spacing of 12.5 μm per digital picture element. This is equivalent to 40 lines/mm, a resolving power comparable to that of many aerial photographs. Thus, digital image analysis is not inherently working with an inferior product.

Of course, demonstrating that there is no loss of information between film and digital image does not imply that there exist computer systems that can interpret all of this information. Results of quantitative image analysis based on spectral classification are still rather crude compared with the skilled photo-interpreter (Swain and Davis 1978). Nevertheless, it is clear that quantitative studies demand a precision and speed attainable only with computer-based systems. A variety of research is underway to provide computer-based systems with the additional knowledge representations and contextual rules required to correctly interpret digital data at the level of a skilled photo-interpreter.

As a practical matter, Canada's resource-based economy and vast, often inaccessible, land and water bodies make automatic remote sensing the only viable technology for resource management. In remote sensing, quantitative analysis means computer-based analysis.

Geocoded Image Data

Satellite images, like aerial photographs, cannot be overlaid directly onto a map. Digital processing can be used to rectify a satellite image. That is, the image can be geometrically warped into a standard coordinate frame, such as the Universal Transverse Mercator (UTM) projection used in Canadian National Topographic System (NTS) maps. Once an image has been rectified to a standard coordinate frame, it is said to be geocoded.

¹Paper presented at 9th BC Soil Science Workshop, UBC, February 21-22, 1985
²Departments of Forest Resources Management and Computer Science, University of British Columbia, Vancouver, BC. Fellow of the Canadian Institute for Advanced Research

Until recently, rectification was a rather tedious operation requiring manual attention and a large amount of computer time. Now, the process is sufficiently automated and supported by special purpose hardware that geocoded satellite imagery is available on an operational basis. In Canada, geocoded Landsat MSS imagery is produced using the Digital Image Correction System (DICS) at the Canada Centre for Remote Sensing (CCRS). Landsat Thematic Mapper (TM) imagery, as well as imagery from the forthcoming French SPOT satellite, will be geocoded using the Multi-Observational Satellite Image Correction system (MOSAICS) under development for CCRS by MacDonald, Dettwiler and Associates, Ltd. (MDA).

Geocoded images have several advantages. Images from different dates can be directly combined as a means of change detection. Images from different sensors also can be combined to produce novel image products. As one example, Landsat/Seasat composite images have been generated (Wong 1984). The composite combines radar measurements from Seasat that are sensitive to surface roughness with multispectral measurements from Landsat that are sensitive to ground cover. Finally and most importantly, geocoded images also can be combined with other geocoded information such as topographic maps, forest cover maps and soil maps to form an integrated resource management system.

Integrating Geocoded Data Sources

Two disciplines, remote sensing and geographic information systems, are both mature fields that have developed more or less independently. The challenge now is to integrate image analysis with other geographic information to form an effective resource management system. Geocoding to a common coordinate frame is a start but much work needs to be done.

Digital image analysis deals with image data represented on a regular grid, called a raster. Computerised mapping systems typically deal with line data represented as vectors or polygons. Some problems of conversion between representations are straightforward. For example, one can convert a topographic map, represented by contour lines, to a gridded array of elevations, called a digital terrain model (DTM). DTM's have been integrated into remote sensing image analysis for both the geometric rectification and radiometric correction of satellite imagery. Other problems of conversion can be more difficult because local topological relationships must be preserved. For example, conversion of vectors for a road and a river running side-by-side to raster form would lose connectivity and adjacency information if the result were an intermingling of isolated "road" and "river" raster elements.

In an integrated system, image data is used to verify and to update map information. At the same time, map information is useful in image analysis because it identifies spatial relationships and provides appropriate local context for interpretation. Some examples from research suggest what is possible although these ideas have yet to be incorporated into operational systems (Starr and Mackworth 1978, Tenenbaum *et al.* 1978, Tenenbaum *et al.* 1979, and Havens and Mackworth 1983).

A map contains a lot of information. Some information is explicit and can be accessed directly. Other information is implicit and must be inferred from what is represented explicitly. Automatic map interpretation is a problem in its own right that has received some attention (Havens and Mackworth 1983).

The major thrust of current research is to integrate remote sensing and geographic information systems. For example, the Canada Centre for Remote Sensing and the BC Ministry of Forests are collaborating to combine CCRS's image analysis system with the Ministry's Interactive Graphics Design System (IGDS) for forest cover mapping and inventory.

Physical Models of Image Formation

Computational vision is the study of computational systems that interpret images; that is, they produce descriptions of a world from images of that world (Barrow and Tenenbaum 1981 and Brody 1982). The central concern is the design and implementation of effective algorithms that represent and exploit knowledge of the world and knowledge of how images are formed. This knowledge includes properties of sensors, laws of physical optics and information about possible configurations in the world.

The brightness at each point in a remotely sensed image is determined by scene properties at the corresponding ground point. These properties include: sun and sky illumination, reflectance characteristics of the surface material and the slope and aspect of the ground point relative to the sensor, and the direction of illumination. Brightness is also influenced by transmission characteristics of the atmosphere. Atmospheric transmission, in turn, depends upon elevation and other factors. Thus, brightness encodes much information about the scene. Decoding brightness measurements requires a physical model of how the world determines what we see. Progress has been made to develop models that relate topography, ground cover, atmosphere, illumination and viewer position (Teillet *et al.* 1982, Woodham and Lee 1984). With these models, DTM's are used to account for the effects of topography to better delineate ground cover.

Even under the most favourable circumstances, image interpretation can be locally ambiguous. In such situations, information about possible configurations in the world can resolve a local ambiguity by appealing to a more global context (Starr and Mackworth 1978).

Artificial Intelligence and Expert Systems

Artificial intelligence (AI), once the avant-garde of computer science, has suddenly become a mainstream activity (Winston and Prendergast 1984). This is in part due to the emergence of commercially successful "expert systems" and in part due to major investments being made in Japan (Feigenbaum and McCorduck 1983), and elsewhere to develop "knowledge-based systems". Recent articles in *Business Week*³ and *Fortune*⁴ examine this AI technology from a business point of view.

There is a fascination with AI expert systems. Current expert systems are simple rule-based systems (Hayes-Roth *et al.* 1983). That is, knowledge in a certain domain is expressed as a set of rules. Given a particular set of initial facts, the system invokes whatever rules apply to deduce new facts or to take required actions. This process iterates until a desired goal has been achieved. For example, a remote sensing system might have the rule of the form, "If there is a river from point A to point B and if point A is higher in elevation than

³"Artificial intelligence is here", *Business Week*, July 9, 1984.

⁴"Thinking machines", (a three part series), *Fortune*, May 17, 31 and June 14, 1984.

point B then the river flows from A to B." This rule encodes the knowledge that water flows downhill. It might be useful in a remote sensing system whose goal was to identify distinct watershed areas.

One analogy is to image a senior university professor nearing retirement age. One way a professor passes on expertise is by direct contact with students and colleagues. This is a form of apprenticeship. To reach a wider audience, the professor can consider writing the definitive textbook in the field. Textbook knowledge, however, suffers from not being readily applicable. A more dynamic form of knowledge transfer would be ideal. One can think of AI expert systems as providing just such a new tool for knowledge transfer. An expert, or collection of experts, provide the rules in a given formalism. Computer systems apply the rules directly to actual situations so that the consequences are made immediately clear. The experts can add new rules to cover unanticipated situations. Similarly, existing rules can be altered, if needed, to restrict their domain of applicability.

Expert systems do not create sense out of nonsense. Rather, they provide a sometimes useful way to encode existing knowledge into computer systems. Expert systems for image analysis remain elusive, not because it is difficult to write down rules but because it is first necessary to determine representations in which the rules can be applied.

Expert Systems for Remote Sensing

The long-term goal of remote sensing research is to produce expert systems for image analysis and natural resources management. Two ideas from AI are of central concern. First, one must define the different levels of representation to be used at different stages of a computation. Second, the constraints (rules) that apply both within each level and when moving from one level to another must be identified.

These ideas can be illustrated by a sample problem I often pose to students, "What would it take to write a computer program that, given an aerial photograph of Vancouver, could locate all the golf courses?" The problem is difficult. One cannot go directly from raster elements in a digital image to golf courses. Multiple levels of representation are required. Fairways appear as elongated blobs, usually in groups of nine. There is a parking lot and a club house nearby. Usually, there are sand traps and water hazards. There must be a way to walk from each green to the next tee. Usually, pathways are provided for electric golf carts. The course must be accessible by road from the rest of the city. Certainly, some golf courses may violate one or more of these rules but that is not the point. The point is that to apply these rules descriptions must be computed that identify regions including properties of colour, shape and size. Descriptions also must be computed that identify relationships between regions.

The task of computational vision is to define the levels of representation required and to identify the constraints that operate both on and between the descriptions that can be computed at each level. Expert systems will not function simply as a post-processor to be applied once existing image analysis techniques have completed their work.

Funding Remote Sensing and Geographic Information Systems

In both Canada and the U.S., funding for satellite-based remote sensing has been included as part of each nation's

space program. It is evident from the trends identified above that new initiatives in remote sensing and geographic information systems relate more to ground-based systems than to space technology. Indications are that major funding for these initiatives will not be justifiable as part of a space budget.

At the same time, Canada is formulating a national plan to respond to "fifth generation" projects underway in Japan and elsewhere. This plan must take into account application areas of importance to Canada. It seems likely that natural resources management will be one area of application specifically targeted in any national plan. The Canadian Advisory Committee on Remote Sensing (CACRS) has established an Image Analysis Systems and Artificial Intelligence Working Group to make recommendations concerning the implications of artificial intelligence to remote sensing and geographic information systems. The working group is chaired by David Goodenough, Canada Centre for Remote Sensing. BC representatives are: Frank Hegyi, Ministry of Forests; John MacDonald, MacDonald Dettwiler and Associates, Ltd; and Bob Woodham, University of British Columbia. Forestry is also represented in the working group by Peter Kourtz of the Petawawa National Forestry Institute. In addition, Peter Kourtz chairs the CACRS Working Group for Users of Image Analysis Systems.

As one member of the Working Group, I encourage all interested parties to make their needs and views known. To those of us concerned with natural resource management, it is self-evident that this is an area of utmost importance to Canada. Nevertheless, much work will be required to achieve a level of funding commensurate with that importance.

References

- Barrow, H.G. and J.M. Tenenbaum. 1981.** Computational vision. *Proc. IEEE* 69: 572-595.
- Brady, M. 1982.** Computational approaches to image understanding. *ACM Computing Surveys* 14: 3-72.
- Felgenbaum, E.A. and P. McCorduck. 1983.** *The Fifth Generation.* Addison-Wesley.
- Havens, W.S. and A.K. Mackworth. 1983.** Representing knowledge of the visual world. *IEEE Computer* 16: 90-96.
- Hayes-Roth, F., D. Waterman and D. Lenat. 1983.** *Building Expert Systems.* Addison-Wesley.
- Molk, J.G. 1980.** *Digital Processing of Remotely Sensed Images.* NASA SP-431, US Government Printing Office.
- Starr, D.W. and A.K. Mackworth. 1978.** Exploiting spectral, spatial and semantic constraints in the segmentation of Landsat images. *Can. J. Remote Sensing* 4: 101-107.
- Swain, P.H. and S.M. Davis. 1978.** *Remote Sensing: The Quantitative Approach.* McGraw-Hill.
- Teillet, P.M., B. Guindon and D.G. Goodenough. 1982.** On the slope-aspect correction of multispectral scanner data. *Can. J. Remote Sensing* 8: 84-106.
- Tenenbaum, J.M., M.A. Fischler and H.C. Wolf. 1978.** A scene-analysis approach to remote sensing. TN-173, Artificial Intelligence Center, Stanford Research Institute, Menlo Park, CA.
- H.G. Barrow, R.C. Bolles, M.A. Fischler and H.C. Wolf. 1979.** Man-guided interpretation of remotely-sensed imagery. *Proc. IEEE Computer Soc. Conf. on Pattern Recognition and Image Processing:* p. 610-617.
- Winston, P.H. and K.A. Prendergast. 1984.** *The AI Business: The Commercial Uses of Artificial Intelligence.* MIT Press.
- Wong, F. 1984.** A unified approach to the geometric rectification of remotely sensed imagery. TR-84-6, UBC Dept. Computer Science, Vancouver, B.C.
- Woodham, R. and T.R. Lee. 1984.** Photometric method for radiometric correction of multispectral scanner data. TR-84-14, UBC Dept. Computer Science, Vancouver, B.C.