INTELLIGENT INTERPRETATION OF SPOT DATA FOR EXTRACTION OF A FOREST ROAD NETWORK

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Abstract

This paper describes the development of a (semi)automated process for detection of a road network in a forest area near Perth, Western Australia using SPOT satellite images. Initially, the imagery was processed with specially designed local spatial operators, where the primal sketch was extracted. The data were then linked and vectorised, and C programs used to extract low-level image features from the spatial domain. The method also utilised morphological operators to give a geometric description of the linear features. Subsequently, a prototype expert system was implemented to improve the results. Knowledge was encoded in the form of rules, incorporated into a backward chaining expert system shell, VP-Expert. Based on the attributes of the low level image features, the knowledge base defines the road network by eliminating extraneous elements from the image. The system utilises only data derived from the image, without ancillary information from other sources, keeping the process *autonomous*. Results showed good correlation between the road network extracted from the SPOT data and the structure of the ground features. Application of the system to a second test area confirmed these results.

1 Introduction

In remote sensing the problem of identifying land-cover types from their spectral signatures is traditionally carried out by pattern recognition techniques based on an underlying statistical model [e.g. 1, 2, 3]. But these methods cannot cope with pattern structure, which must be provided by an expert, so that the system can look for a particular configuration of objects to identify specific patterns [4]. The gap left from the use of traditional general image analysis models can be bridged by specific domain systems, which require higher level techniques for intelligent interpretation.

Artificial Intelligence (AI) provides an alternative to human interpretation by incorporating a degree of intelligence into the image analysis system and mimicking the ways humans interpret an image. Among the AI techniques, expert systems offer the opportunity to capture the specialised knowledge and heuristics of experts, encode it into a knowledge base to provide a permanent record, and so make the knowledge available for public use.

Expert systems have been described as *computer systems that use knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution* [5]. Such systems, in contrast to conventional programming techniques, are designed to incorporate a large amount of fragmentary, judgmental, and heuristic knowledge. This knowledge helps people in decision making, even if human expertise is not available at that time, and accelerates the process of problem solving [6].

Regardless of which pattern recognition approach is adopted there are some fundamental elements which stand above these techniques. These are called primitives. Primitives represent raw intensity changes and local geometrical structure within an image [7, p. 366]. The most common primitives are edges and lines. They are the building elements of an image, so they are beyond the pattern recognition model and are extracted by lower level techniques. Attributes can be extracted from primitives, with the derived characteristics dependent upon the pattern recognition model utilised, e.g. topologic, geometric. It is important for descriptors to be insensitive to changes in size, translation and rotation, so that spatial and temporal consistency may be achieved [8, p. 391].

2 Intelligent Image Interpretation

2.1 Expert Systems in Remote Sensing

Although the use of expert systems covers a wide range of application areas, there has been limited research in using expert systems in remote sensing compared to the use of other techniques. This can be explained by two reasons [9]. The first is that the data in remote sensing are usually numerical, and of very low granularity. Expert systems prefer data and information at a symbolic level. The second is the persistence of the remote sensing community to concentrate on traditional classifiers and analysis methods.

One of the first attempts for expert system development for information extraction was undertaken in 1973, at the Canada Centre for Remote Sensing (CCRS). In 1982 CCRS started the development of the Landsat Digital Image Analysis System (LDIAS) in order to compare maps with images [10]. Since then the main application of expert systems in remote sensing has been on the guidance of the user through complex procedures of image processing, image interpretation and classification, and they have generally concentrated on simple classification tasks [9]. However, some research has also been carried out into the extraction of cartographic primitives. Examples include feature detection on maps [11], feature recognition for input into a GIS database [12] and drainage pattern identification [13].

A road network extraction system from SPOT imagery was presented by van Cleynenbreugel *et al* [14]. They extracted two types of primitives: crossroads and road segments. They used relations, such as proximity, collinearity and visibility, to decide about the actions the system should follow. Wang and Newkirk [15] discussed algorithms for developing a knowledge-based system for automated extraction of a highway network, locating highway intersections, and identifying different road patterns in rural areas. Domenikiotis *et al* [16] studied the feasibility of developing an expert system for edge linking, designed to work on binary images, which result from the use of edge detection algorithms.

2.2 Extraction of Linear Features

The study of linear elements is significant, whether they are viewed as primitives for the construction of a primal sketch, or extracted simply as representing specific natural or manmade features. Although the application areas of remote sensing are broad, no significant effort has been put into extracting roads from remotely sensed images. However there is an increased range of applications associated with the detection of linear features, e.g. in base mapping, in thematic mapping, in geological mapping and the updating of GIS.

The algorithms available in remote sensing for line detection can be classified as local operators, when the information for the detection of a feature is local (performed in parallel), and global operators when they use global information, such as line tracking or following, and hence are more sequential in nature [17]. Local operators can be divided into linear, semilinear and nonlinear. Other line detection techniques are the state-space search, dynamic programming, syntactic analysis, graph theory, and the road grower tracking technique [e.g. 18, 19, 20].

The extraction of linear elements from remotely sensed imagery is a complex process. The brightness and contrast surrounding the area will vary along the feature, and the spectral characteristics are sensitive to seasonal changes. That is, in rural areas it is very likely vegetation will grow along roads and tracks, which will dry out during the summer. Most of the above techniques are local-oriented, with fragmented and error-prone results. A solution to this problem is the use of global information *about lines and surrounding areas, such as the geometric shapes of roads, as well as land cover information to improve the output from the initial processing* [21].

3 Research Methodology

The objective of this research was to design and implement a prototype image analysis system for automated line detection. Since automated image interpretation encompasses algorithmic functions for pattern recognition, as well as symbolic functions for object identification and scene description, the system was implemented using both procedural modules and knowledge-based modules.

The study area is located in the rural/urban fringes of Perth, Western Australia, approximately 25 km northeast of the city. It includes the Gnangara pine plantation and comprises mainly open woodland, pine forest, cleared land and scattered semi-rural farmlets. The area is dissected by cleared swaths through the forest up to 50 m in width which contain roads 10 to 20 metres wide. In places, these swaths contain substantial amounts of natural vegetation. Between the major roads, numerous firebreaks and minor tracks, three to four metres wide, also occur.

Two sets of SPOT data were utilised. These comprised a winter data set acquired in August 1990 and a summer data set from January 1993. In the winter image the occurrence of annual grasses within the access roads results in their being represented by non-contiguous lines of pixels. The summer data set was obtained to examine the effects of sun elevation on the recognition of linear features. The aim was to reduce shadow effects caused by low sun elevation and tall pine trees, with the expectation that improved line detection would result. Additionally, the senescence of annual grasses also improved the definition of road segments. Ground truth was provided by base maps and aerial photographs, as well as through several site visits.

This research required the co-ordination and development of a diverse range of data sources and software. IDRISI raster-based image processing and GIS software were used for most of the image processing for this project. Additionally, it provided a data management framework for implementing new processing functions created during the research. Although IDRISI provides a wide range of raster operations, it is restricted to standard image processing modules. For specific needs, extraction programs were written in the C language and interfaced with the software. These programs carry out image processing, vector processing and attribute extraction operations.

ProVec vectorisation software was utilised to carry out two major functions: raster conversion and tracing. For this research the most important of the raster edit modules is thinning. When a thinning pass is applied, a single layer of pixels is removed from each side of the line. This process is repeated until only the centre line remains, which is a line one pixel wide. A condition of the thinning process, however, is that the original connectivity is maintained. The tracing option is designed to convert the edited raster image (skeleton) to an equivalent vector form.

VP-Expert is an expert system shell which has a built-in editor for developing the knowledge base, and interfaces with a number of databases and spreadsheets for reading and storing values. A trace facility shows the logic paths as a graphic tree or text file. It also gives the choice of displaying how a consultation is affected if a different answer to a question is chosen. VP-Expert contains a backward chaining inference engine (although forward chaining is also possible) and the rules are in the IF-THEN form. Each rule may be followed by text, which explains the purpose of the rule, and can be activated during the consultation. VP-Expert was selected as an entry-level expert system, because of its flexibility and interface capabilities, plus the ability to implement the system on a readily available MS-DOS platform.

4 Image Segmentation

4.1 Low-level Line Detection

A wide range of techniques was applied to the segmentation and extraction of edges and linear features in the study area. These techniques were applied to the SPOT multispectral and panchromatic images and included formation of colour composites, supervised/unsupervised classification, principal components analysis, RGB/HIS transformations, and edge detection using the Sobel filter. All these techniques were evaluated, but it became clear that the results were not appropriate for higher level analysis and symbolic description. The major deficiencies included an inability to separate the objects from their surroundings, and the high level of noise remaining in the data. This led to an alternative approach for extracting features by the implementation of line detection methods.

Line detection techniques may be used to identify the road network directly. Several different filters were designed, ranging from 3x3 to 11x11 in size. The filters contain a central column (or columns) of weights designed to identify linear features. The width of lines detected is determined by a combination of the width of the central band of pixels in the filter and the ground dimension of the pixel. Masks for four orientations can be applied to detect lines along different directions. In this study the central bands of pixels were one and three pixels wide, which optimally detect lines 10 and 30 metres wide for a 10 m ground resolution pixel.

The filters were applied to a series of images (i.e. panchromatic, colour composite, first principal component). The convolution of the filters with these images created new images which, following thresholding, enhanced the linear features. However considerable noise was still present. The images resulting from thresholding were left with gaps between the lines and additional noise. Noise needs to be removed but the lines retained. The use of a postclassification modal filter was deemed to be the most appropriate. However, a square mask (e.g. 3x3, 5x5) removed almost all linear features.

Accordingly, a series of specially designed elongated (1xn) filters was applied. These removed the noise without affecting the road network. Testing was carried out with 1x5, 1x7, 1x9, and 1x11 modal masks. The best results were obtained using the summer panchromatic image convolved with a 5x5 line detection filter, and then applying a 1x9 modal filter. Both filters were applied separately in the horizontal, vertical and diagonal directions, and combined to produce a composite image. As a result, the noise was significantly reduced, but at the same time the main roads were retained.

4.2 Thinning, Linking and Vectorisation

Thinning is the primary raster operation in the vectorisation process. Using ProVec software, this process can be applied repeatedly. In each stage a single pixel layer is removed from the image detail, until a single pixel-wide line remains and no other pixels can be removed. This produces a raster skeleton of the original image in which the connectivity is maintained. After the skeletons of the roads have been defined, the raster image is vectorised.

Overall, the final segmented image was acceptable as a first result. However, some noise is still present in the form of line segments which do not belong to the road network. As well there are still a small number of spikes and irregularities. Although human perception can assess discontinuous linear features, image processing algorithms have many difficulties in identifying them. As a result, many features appear as residual segments looking like noise, rather than linear sections which contain significant information.

4.3 Moment Invariants

In general, after the primitive image features have been identified, it is desirable to map them to a much smaller set of descriptors that can serve as data for subsequent semantic interpretation. The problem in image analysis is that there is no generally accepted set of visual symbols that are necessary and sufficient to describe an image. There are also the problems of determining which symbols should be formed from the image features for a particular analysis task and specifying the required accuracy of symbol formation [22, p. 514].

A property is defined as a function that translates qualitative descriptors (pictures) into quantitative parameters. Picture descriptors generally specify properties of parts of the picture and relationships among these parts [23, Vol. 2, p. 277]. One such template property is the moment. A proper combination of moments can provide translation-scale-rotation invariant quantities, the moment invariants. The moment invariants give a shape description of an object based on the joint moments of probability theory. The two-dimensional moment invariants were firstly proposed by Hu [24].

The 2D moment of p+q order is the continuous transform:

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q f(x,y)\, dxdy \qquad (1)$$

The central moment is given by:

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\overline{x})^p (y-\overline{y})^q f(x,y)\, dxdy \qquad (2)$$

$$where \quad \overline{x} = \frac{m_{10}}{m_{00}}, \quad \overline{y} = \frac{m_{01}}{m_{00}}$$

are the coordinates of the centroid making Equation (1) location invariant. The above equation can be simplified for a binary image, where f(x,y)=1, with one to represent the regions. The central moments in terms of simple moments up to the second order are as follows:

$$\begin{aligned} \mu_{00} &= m_{00}, & \mu_{10} &= 0 \\ \mu_{01} &= 0, & \mu_{11} &= m_{11} - \overline{y} m_{10} \\ \mu_{20} &= m_{20} - \overline{x} m_{10}, & \mu_{02} &= m_{02} - \overline{y} m_{01} \end{aligned} \qquad (3)$$

Their physical meaning is described by Schalkoff [25, p. 306]. The normalised central moment removes the scale factor and is given by:

$$n_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}, \quad where\ \gamma = \frac{p+q}{2} + 1 \qquad (4)$$

and μ_{00} is the area of the region. The invariant moments up to second order, properly transformed to incorporate the orthogonal transformation for rotation, are:

$$\phi_1 = n_{20} + n_{02} \qquad (5)$$

$$\phi_2 = (n_{20} - n_{02})^2 + 4n_{11}^2 \qquad (6)$$

It can be loosely interpreted that Equation (5) expresses the variance and Equation (6) elongation. The parameters are usually called *spread* and *slenderness* respectively. Normally, the moment invariants apply to areal features. However, in this research they were applied to line segments. Here, the spread refers to the two-dimensional distribution of the line and slenderness its shape.

The values ϕ_1 and ϕ_2 were calculated for each line segment using all the individual pixels. To uniquely identify an object, the shape values must have sufficient discrimination power, and the values defined by the object shapes must be independent of the location, rotation and size of the object in the images [26]. Moment invariants satisfy these criteria and can significantly support image classification.

Each region or linear feature can be regarded as an n-dimensional vector X with the pixel brightness values (specifically the averages) and the moment invariants the identifying features. This constitutes a pattern recognition problem, where similarity criteria can be applied for feature identification. In this way all the problems arising from this approach are confronted.

5 Knowledge-based Interpretation

An expert system was implemented to work on the vector files, resulting from the line detection, linking and vectorisation processes discussed previously. The aim of this system was to prune off all the unwanted line segments which are not part of the road network. In terms of knowledge acquisition, the elements considered crucial for deciding if a linear feature is a road or not need to be specified. For the implementation of this prototype three criteria were considered: brightness value, length and shape. Brightness value is necessary because roads have a particular signature over the three multispectral bands which can be roughly identified, length because very small segments are not likely to represent roads and, finally, shape because the roads, as artificial structures, should be expected to follow a *logical* pattern or, rather, they should not be expected to follow an *illogical* pattern.

The expert system was designed to analyse the line segments derived by the line detection operations. The characteristics of these segments are extracted by C programs and include average pixel brightness values. The range of values for the bands showed that the means and variances of lines classified as roads/non-roads generally overlap, making their distinction by applying statistical pattern recognition techniques almost impossible. This confusion can be resolved by incorporating knowledge about their spread and slenderness. Threshold values can be estimated for a variety of features. The size-shape-scale invariance allows a global application of these values, i.e. in a variety of circumstances.

Based on the criterion of the brightness value in three bands and moment invariants, the knowledge based system decides whether a line is to be kept. If the answer is *yes*, a C program is called, passing the identification of the line, reading the corresponding co-ordinate values from the IDRISI vector file, and appending it to the new vector file.

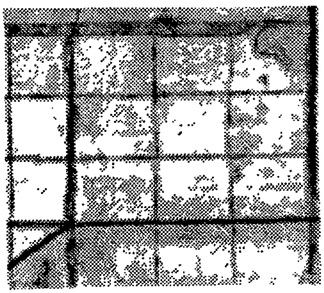

Figure 1: Study area (1.7x1.7 km)

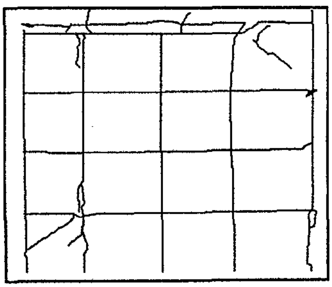

Figure 2: Extracted road network

The user has the choice of including smaller segments in the vector file. Sometimes small road segments are part of the road network, but because of the spread and slenderness they do not qualify as roads. The knowledge base has a rule which examines small segments, but is more restrictive regarding the pixel values (smaller acceptance) of the bands. That is to say, if there is a strong indication from the brightness point of view that a short line may be a road, then it is kept regardless of its small length.

At the end of this process a complete vector file is formed comprising the refined road network. The enhanced panchronatic band of the study area is shown in Figure 1 and the extracted road network in Figure 2. For this regular structure all roads have been successfully identified, and some diagonal and curved elements have also been correctly extracted.

6 Validation and Performance

6.1 Image Segmentation

In order to examine its validity and performance, the system was applied to an area with a higher degree of complexity. The test area is located at the centre of the Gnangara forest approximately two kilometres to the east of the original study area. This area is characterised by an irregular pattern of roads, with a regular road network only in the southeast part. The majority of the roads are formed by smooth curves with intersections formed at a range of angles (Figure 3).

The vegetation of the area consists predominantly of pine plantation with a cleared zone in the northern quadrant and at the centre of the image. Limestone-based tracks, which provide major access through the area, are 10 to 20 m in width. Secondary access tracks are five to eight metres in width and are generally located within pine plantation blocks. Minor tracks are totally within the plantation blocks and consist of a gravel base, and are approximately four to five metres wide.

The complete image segmentation process was carried out as discussed above. Visual comparison with an aerial photograph showed that major and secondary access roads have been detected, but there are many line segments which are not part of the road network. Numerous small segments are present in the centre of the image, where a large cleared area is located. Even after the application of vectorising parameters, these anomalies were not resolved. Another dominant problem is a long linear segment at the top right hand side of the image.

6.2 Expert System Implementation

In order to remove unwanted lines, the knowledge base described earlier was applied. The results were satisfactory, but not at the required level. This incorporates the brightness value in each of the three bands, and the first two moment invariants. Most of the line segments not part of the road network were removed, however some segments were not identified.

Careful examination of the attribute values extracted by the *moment* program, showed values of the moment invariants which were related to the shape of the roads. It was also seen that, conceptually, three major groups of segments were present which could be classified according to their length. New elements had to be added into the knowledge base to accommodate these characteristics. The knowledge base was therefore modified to deal with three types of line according to their length: short, medium and long. A further element added is the threshold value. This determines the level of confidence that the given line is actually a line.

Other operations were also included to invoke an appropriate combination of rules according to what the user specifies. The user interface collects the information through a menu, and compares the values to those in a stored set of rules. After a rule is activated, other rules are invoked to check for the validity of a road, using features coming from the database.

The knowledge base is organised in such a way that the user can specify which combination of lines to retain, e.g. the small only, the large only, or both medium and large. After the lines have been selected the expert system requests the user to define the confidence values (e.g. from 100 to 40 percent). In this way the user can select one type of linear feature, a combination, or all of them. For each feature the confidence may also be selected. For example, if the medium and large features are selected, *medium and large* is specified with a confidence of 40 percent for both.

6.3 Evaluation

Although the configuration of the rules within the knowledge base was altered and improved, the fundamentals remain the same. For example, the range of brightness values in the original and modified knowledge bases is almost identical. That is a first indication of the *globality* of the range of values adopted. Of course, more testing could confirm this result.

The enhanced panchromatic band of the test area is shown in Figure 3 and the extracted road network in Figure 4. This shows that all the main roads were identified, however in some places, links are still missing. On the other hand there are a few topological errors. Some line entities appear to have weird polygons at the centre and southeast part of the image. Further analysis can aim to examine line segments individually and try to remove them.

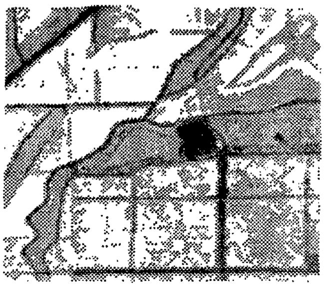

Figure 3: Test area (10x10 km)

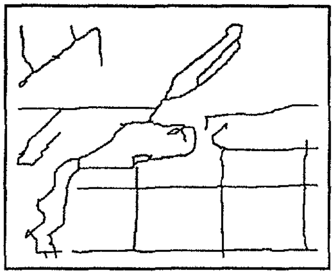

Figure 4: Extracted road network

7 Conclusions

The development of a front-to-end system for road network detection was examined. Segmentation begins with low-level line detection, followed by thinning, linking and vectorisation, resulting in a line map which, however, has many inaccuracies. An expert system was implemented to refine the image. This used brightness values and length and shape characteristics, defined using moment invariants. These were incorporated into a knowledge base and included confidence factors based on experience.

Testing was then carried out as an essential process for improving and expanding the expert system. Knowledge acquisition within an expert system is a discovery process and the knowledge must be collected and tested against a variety of situations. As a result of the testing process the knowledge base was reorganised, although the core rules remained the same. New elements were added to the system to facilitate the selection of the line segments.

Overall, the research shows that effective road reconstruction is possible, even when the initial results from the edge detection operation are poor. However, in order to refine the final structure, incorporation of domain knowledge concerning the nature of the road features and their specific characteristics is essential. As a future modification, additional attributes from different sources can be obtained to contribute further information to the database. Moreover the system can be expanded to incorporate feedback control, which will examine sequentially the attributes according to their significance.

8 References

[1] Batchelor, B.G., 1978. *Pattern Recognition: Ideas in Practice*, Plenum Press, New York, N.Y., 485 pp.

[2] Bezdek, J.C., 1981. *Pattern Recognition with Fuzzy Objective Function Algorithms*, Plenum Press, New York, N.Y., 256 pp.

[3] Fukunaga, K., 1990. *Introduction to Statistical Pattern Recognition* (Second Edition), Academic Press, Boston, Massachusetts, 591 pp.

[4] Argialas, D.P. and Harlow, C.A., 1990. Computational Image Interpretation Models: An Overview and a Perspective, *Photogrammetric Engineering and Remote Sensing*, Vol. 56, No. 6, pp. 871-886.

[5] Karimi, H.A. and Lodwick, G.D., 1987. A Simple Rule-Based System for Selection of Remote Sensing Imagery, *Proceedings of Eleventh Canadian Symposium on Remote Sensing*, Waterloo, Ontario, June 1987, Vol. II, pp. 591-598.

[6] Lodwick, G.D. and Stadelmann, M., 1988. Remote Sensing Data and GIS: Developing Intelligent Image Interpretation Systems, *Proceedings of International Symposium on Low Cost LIS - State of Art and Future Implications*, Gold Coast, Qld, September 1988, pp. XII.2.1 - XII.2.11.

[7] Marr, D., 1982. *Vision*, W.H. Freeman and Company, New York, N.Y., 397 pp.

[8] Gonzalez, R.C. and Wintz, P., 1987. *Digital Image Processing*, Addison-Wesley, Reading, Massachusetts, 503 pp.

[9] Tsatsoulis, C., 1993. Review Article: Expert Systems in Remote Sensing Applications, *IEEE Geoscience and Remote Sensing Society Newsletter*, No. 87, pp. 7-15.

[10] Goodenough, D.G., Goldberg, M., Plunkett, G. and Zelek, J., 1987. An Expert System for Remote Sensing, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-25, No. 3, pp. 349-359.

[11] Schenk, T. and Zilderstein, O., 1990. Experiments with a Rule-Based System for Interpreting Linear Map Features, *Photogrammetric Engineering and Remote Sensing*, Vol. 56, No. 6, pp. 911-917.

[12] Taib, A.K. and Trinder, J.C., 1992. An Object-Oriented Approach to the Design of Knowledge-Bases and Geographic Information Systems, *Proceedings of Twentieth Australasian Conference on Urban and Regional Information Systems*, Gold Coast, Qld, November 1992, pp. 149-156.

[13] Hadipriono, F.C., Lyon, J.G., Li, T.W.H. and Argialas, D.P., 1990. The Development of a Knowledge-Based Expert System for Analysis of Drainage Patterns, *Photogrammetric Engineering and Remote Sensing*, Vol. 56, No. 6, pp. 905-909.

[14] Van Cleynenbreugel, J., Fierens, F., Suetens, P. and Oosterlinck, A., 1988. Knowledge-Based Road Network Extraction on SPOT Satellite Images, Lecture Notes in Computer Science, J. Kittler (ed.), *Proceedings of Fourth International Conference on Pattern Recognition*, Cambridge, U.K., March 1988, pp. 352-359.

[15] Wang, J. and Newkirk, R., 1987. A Knowledge Based System for Highway Network Extraction, *Proceedings of IGARSS'87 Symposium*, Ann Arbor, Michigan, pp. 343-347.

[16] Domenikiotis, C., Lodwick, G.D., and Wright G.L., 1993. Automated Interpretation of Digital Remote Sensing Imagery, *Proceedings of Advanced Remote Sensing Conference*, University of New South Wales, Sydney, N.S.W., July 1993, 9 pp.

[17] VanderBrug, G.J., 1976. Line Detection in Satellite Imagery, *IEEE Transactions on Geoscience Electronics*, Vol. GE-14, No. 1, pp. 37-44.

[18] VanderBrug, G.J. and Rosenfeld, A., 1978. Line Feature Mapping, *IEEE Transactions on Systems, Man and Cybernetics*, Vol. SMC-8, No. 10, pp. 768-774.
[19] Bajcsy, R. and Tavakoli, M., 1976. Computer Recognition of Roads from Satellite Pictures, *IEEE Transactions on Systems, Man and Cybernetics*, Vol. SMC-6, No. 9, pp. 623-637.
[20] Gurney, C.M., 1980. Threshold Selection for Line Detection Algorithms, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. GE-18, No 2, pp. 204.211.
[21] Wang, J. and Liu, W., 1994. Road Detection from Multi-Spectral Satellite Imagery, *Canadian Journal of Remote Sensing*, Vol. 20, No. 2, pp. 180-191.
[22] Pratt, W.K., 1978. *Digital Image Processing*, John Wiley and Sons, New York, N.Y., 750 pp.
[23] Rosenfeld, A. and Kak, A., 1982. *Digital Picture Processing* (second Edition), Academic Press, New York, N.Y., Vol. 1, 435 pp., Vol. 2, 349 pp.
[24] Hu, M., 1962. Visual Pattern Recognition by Moment Invariants, *IRE Transactions on Information Theory*, Vol. IT-8, No.2, pp. 179-187.
[25] Schalkoff, R.G., 1989. *Digital Image Processing and Computer Vision*, John Wiley and Sons, New York, N.Y., 489 pp.
[26] Trisirisatayawong, I. and Shortis, M.R., 1993. Automatic Recognition of Cartographic Objects by the Moment Invariants, *Proceedings of Conference on Advances in Urban Spatial Information and Analysis (Second International Colloquium of LIESMARS)*, Wuhan, China, October 1993, pp. 180-189.