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Spatial feature extraction from radar imagery

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ABSTRACT: It is accepted that the major role of remote sensing as an information source will be in its contribution to geographical information systems. With the advances in remote sensing, images are being created at an increasing rate. The extraction of information from such data is traditionally done manually and is thus costly in both time and money. Therefore techniques need to be developed which automatically extract information from remotely sensed images.

This paper considers the extraction of thin line features such as forest rides, dykes and streams from active microwave imagery. Because radar images are coherently created speckle is produced which renders traditional feature extraction methods virtually useless. It is assumed that global techniques such as generalised hough transforms or intelligent graph searching will be more successful than simple local methods.

1 INTRODUCTION

This paper considers the extraction of thin line features such as forest rides, dykes and streams from remotely sensed active microwave imagery. In the context of this paper remote sensing is the aquisition of digital images of the Earth from either airborne or satellite sensor systems. Although digital remote sensing started as late as 1972 many satellite systems have been successfully initiated with a rapidly increasing variety of sensor types and specifications.

Several problems arise from this rapid advance in remote sensing technology. The efficient use of image data obtained from satellites or aircraft relies on the availability of human expertise and sophisticated computer systems. In particular radar imagery with its virtual continous monitoring capability and high resolution has shown itself to be superior to more conventional imagery for a variety of applications. But to fully utilise the potential information in this form of data, processing techniques which overcome the inherent speckle noise need to be developed.

In general, the problem is one of storage and processing of the data, which is not currently met by computers or human effort. Hardy(1985) states that the population of Earth resource satellites will generate something approaching 10^{16} bits in 1986. Assuming an average scene size of 4000x4000 pixels and 8 bits/pixel radiometric resolution, a simple calculation shows this data rate to be equivalent to about 200,000 single channel images/day. On common Computer Compatible Tapes (CCT's) which can store approximately 33 million bytes (MB), this data would require about 10^5 CCT's/day. This rate signifies an increase of the data volume/sensor/unit land area of more than an order of magnitude over the last ten years and results in large quantities of unused data. To alleviate this waste of data there is a need for the automatic interpretation of remotely sensed images by computer.

It is accepted that the major role of remote sensing as an information source will be in its contribution to geographical information systems. This role requires the extraction of semantic information from remotely sensed images and therefore automatic interpretation.

The two arguments concerning data rates and GIS bring us to the conclusion that automatic interpretation is needed to fully realise the potential of remote sensing.

The automatic interpretation process entails several other processes. One of the first steps is segmentation which aims to partition the image into separate distinct regions. Feature extraction techniques are also used to enable the segmentation. The segmented scene can then undergo a pattern recognition process using world knowledge giving an interpreted scene. Knowledge may also be used at different stages in the interpretive process. For example to assist or iteratively refine feature extraction. (see fig. 1).

Real world images can be considered as comprising of three major high level spatial feature types.

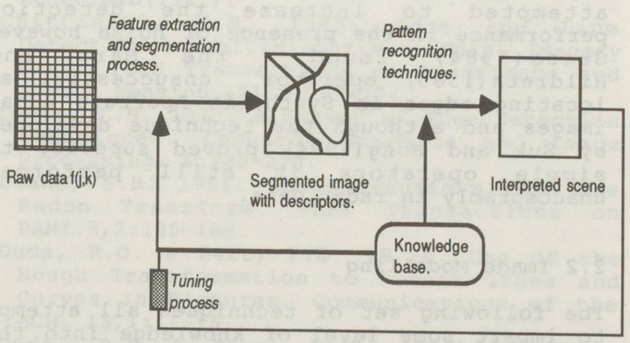

fig. 1 different schemes for the automatic interpretation process.

1) Areas e.g fields, lakes.
These are homogeneous features extending over several or more pixels.
2) Boundaries e.g field boundaries.
These consist of low-level edge elements where these are defined to be local discontinuities in image features. (Pratt(1978)).
3) Thin lines e.g rivers, forest rides, roads, hedges.
A line segment is defined by the u-shaped cross section of image features.

These three types reflect the different approaches to image segmentation. The so called region growing strategy starts by growing an object in an area until a significant change in the measured features is noted. Another segmentation strategy aims to locate object boundaries thereby isolating the objects.

The overall feature extraction process may consist of one or more of the following classes of operations.

1) Preprocessing: This is primarily to remove the effect of image noise on the following stages.
2) Feature Extraction: The actual process of transforming the image to a specific feature domain.
3) Post Processing: The process by which detected features are cleaned i.e filtered of invalid or unwanted results.

Knowledge of the features to be extracted can be used at any of the three stages. For example knowledge of the noise statistics (embodied into a noise model) may be used to optimally reduce noise in stage 1. In stage 2 a knowledge of the feature type may be used to reduce the computational cost. World knowledge can also be used in stage 3 to test the validity of detected features.

2 EDGE AND LINE FEATURE EXTRACTION

Extensive surveys of the following classes of techniques can be found in Ballard(1982), Pratt(1978), Davis(1975), Carlotto(1984), Duda & Hart(1972b).

2.1 Local Operators

Local operators use data from the neighbourhood of the edge candidate pixel. There are a wide variety of such local operators details of which can be found in Duda & Hart(1972b) and Pratt(1978). These simple operators often form the basis of commercial edge detection systems because of their computational simplicity and their potential parallel implementation. More sophisticated statistical operators have attempted to increase the detection performance in the presence of noise however Geiss(1984) found the Marr and Hildreth(1980) operator unsuccessful at locating edges in Synthetic Aperture Radar images and although the technique developed by Suk and Hong(1984) proved superior to simple operators it still performed unacceptably in radar data.

2.2 Image Modelling

The following set of techniques all attempt to impart some level of knowledge into the feature extraction process.

2.2.1 Parametric Modelling

The basis of parametric modelling is to fit some parametric surface representing an ideal edge model to a local region of pixels from which the edge characteristics can then be derived. Again many researchers have proposed operators in this category which can be found in Rosenfeld and Kak(1982), Haralick(1980) and Chittineni(1983).

2.2.2 Statistical Modelling

Statistical modelling forms the basis of a variety of methods which rely on statistical theory for edge detection and involves the combination of a noise and image model allowing calculation of probabilities of edge existence. Then statistical methods such as maximum likelihood estimation can be used to locate probable edges. Chen and Pavlidis(1980). Rosenfeld(1981).

2.2.3 Template Matching

In this method explicit knowledge of the desired feature shape is used to produce a template which is then matched to regions of the image. The feature will probably exist where the correlation between template and image data is greater than a set threshold. The method is successful for detecting very specific objects such as tanks and aircraft in military images where the template may be a section of an image containing the desired object.

Simple template operators such as the Kirsch operator in Pratt(1978) attempt to generalise the process by detecting line and edge elements with variously orientated templates.

Another method related to template matching by Stockman and Agrawala(1977) is the Hough Transform technique (Hough(1962)) later improved by Duda & Hart(1972a). For grey level images the transform produces peaks and troughs in Hough Space corresponding to light and dark straight lines in image space. These peaks or troughs can then be detected and the line parameters extracted, using traditional operators. In general the transform can be used to extract any feature shape which has a known parametric form such as the conic sections (Sloan & Ballard(1980)) and has been widely used because of its effectiveness in both clean and noisy images (see Shapiro(1978)). For radar images the technique performs successfully at detecting straight lines that are long relative to the scene size (Skingley & Rye(1985)). More recently a modified hough transform, the MUFF transform (Wallace(1985)) has been developed which uses a different parametric form for lines to enable the detection of short lines.

The radon transform shown to be equivalent to the hough method by Deans(1981) is an invertible transform and so has been used for linear feature enhancement as shown by Murthy(1985) for radar images and for detection of straight lines in simulated noisy imagery as illustrated by Nasrabadi(1984).

2.3 Transform Domain Processing

This class of processing technique comprises a global two dimensional weighted transform followed by a spatial frequency filter in the transform domain. The most common transform is the Fourier which when combined with a high pass filter and thresholding process produces an edge map equivalent to that produced by local operators. Various transforms and filtering strategies exist. Unfortunately even the most sophisticated processes fail at detecting thin line structures in noisy environments.

2.4 Graph Search Methods

A graph is a mathematical object that consists of a set of nodes $\{n_i\}$ and arcs between nodes $<n_i,n_j>$. Associated with each arc is a cost. The edge or line search is then seen as a search for the minimum-cost path between two nodes of a suitably weighted graph. If some measure of a best line is known then the search may be optimal and the solution found by dynamic programming as demonstrated by Montanari(1971) otherwise the solution may only be satisficing (Palay(1985)). Martelli(1972) demonstrated the usefullness of this class of technique for noisy images by using heuristics to guide the search.

3 DISCUSSION

Local operators as a method of edge detection are typically deterministic and aim to calculate the local gradient image. This approach involves difference operations and is thus susceptible to high spatial frequency noise. Other operators aim to reduce this susceptibility by combining noise suppression with edge detection but with derogatory effects on thin lines and the most sophisticated techniques prove unsuccessful in low signal to noise environments. Image modelling techniques offer some improvement but parametric modelling exhibits many of the disadvantages of local operators. Statistical modelling methods can be global but need accurate image and noise models. Consequently they work well for synthesised images with known noise distributions. Template matching algorithms are excellent for extracting specific feature shapes but still suffer from being local in nature. Hough transforms embody more global concepts but cannot be fully generalised. Spatial frequency techniques are insensitive to fine structures and do not distinguish between signal and noise. Graph search strategies can have both global or local predicates built into an evaluation function and so may be made robust to noise. They are flexible and can provide optimal or good satisficing solutions. Usually they embody both serial and parallel processes and thus may incorporate any level of knowledge. Their disadvantage is the extensive computation involved which may grow exponentially with scene size so that practical applications usually require an initial boundary estimate to be manually provided. However Bertolazzi and Pirozzi (1984) has developed a parallel algorithm for this class of problem offering much improved efficiency.

We may now think of the ideal technique for thin line feature extraction and its characteristics. For this one looks to the human visual system to suggest the following criteria.

1) Global predicates must be used.
2) The probability of an edge or line existing at a certain pixel location is dependent on other possible edges in the scene.
3) Noise models should not be needed.
4) Only simple models of features should be used.
5) The technique should allow for generalisation.
6) Computational effort involved should be related to the signal to noise level.

The published research indicates that the graph searching approach to thin line detection is the most appropiate for noisy scenes. The important problem that remains however is how to devise a suitable evaluation function which will encompass the criteria listed above. Various evaluation functions are currently being devised and studied. This is an important continuing part of the research.

The sophistication of this type of approach implies that very intensive computation is required but it is felt that recent advances in computer technology such as parallel processors & transputers render such concerns irrelevant. It is more important that the problems of feature extraction be tackled, rather than the specific dificulties of implementation on current computers.

4 CONCLUDING REMARKS

The major classes of thin line feature extraction techniques have been reviewed with emphasis placed on their suitability for line extraction in the presence of image noise. The decision has been taken to pursue the graph search strategy and to develop and test a generalised algorithm. Finally a successful line feature algorithm may be synergistically combined with an area based segmentation technique to produce the mythical perfect image segmentation. Such a technique may then be easily integrated into an automatic interpretation schema.

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