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CURVILINEAR NETWORK EXTRACTION FROM REMOTELY SENSED IMAGES

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ABSTRACT

We describe a new approach to the extraction of networks of narrow curvilinear features such as road and river networks from remotely sensed images. The approach begins with the identification of points in the image with a high probability of being on the network. In the second stage the broad topology of the feature is extracted using a minimum spanning tree and in the final stage a novel cost minimisation approach is used to refine the linear sections of the network so that they follow the underlying structure more closely.

INTRODUCTION

Curvilinear features are one of the most common feature types found in digital images, e.g. arteries in medical images, road and river paths in satellite images and characters and other line work in engineering drawings. Even if curvilinear features are not present in the raw image, they are often generated by gradient operators as an early stage in image analysis and their subsequent extraction is an essential task in many image interpretation procedures.

Networks of connected curvilinear features also occur widely in many images. In this project we have developed a new technique for the automatic extraction of explicit (vector) representations of road and river networks from remotely sensed images. These are of particular interest to a range of users, typically for subsequent manipulation in geographic information systems. In many instances, the lack of reliable software tools has necessitated the labour intensive process of manual digitisation. Although there have been several approaches to curvilinear network extraction[1, 2, 3], methods which seek to minimise human interaction are still of wide interest, not only in the analysis of remotely sensed images.

MINIMUM COST PATHS

In a recent paper[4] we describe an approach to the problem of curvilinear feature extraction which uses a combination of selective windowing and minimum cost path techniques to delineate a minimum cost path between specified points on a required feature. The cost function may be based on image properties and path curvature in a manner similar to that used by Kass et al[5] in their active contour model formulation, often referred to as a snake. However, our approach finds a global rather than a local solution to the path cost minimisation, constrained only by a search window specified around the feature of interest. It uses a minimum cost path algorithm based on an extension to D'Esopo's method[6].

The method is optimal and an important distinction may be drawn between optimal search algorithms which find the global minimum cost path and search algorithms which use heuristics to reduce the search space. For example, Montanari [7] introduced dynamic programming for optimal curve detection with respect to a particular figure of merit and Martelli [8] introduced heuristic search to detect edges and contours. Since these early papers, many authors have applied heuristic search techniques to the problem of boundary and line detection. Optimal search times have been significantly less attractive than search times when powerful heuristics are available, and their computationally intensive nature has reduced their popularity.

Although our optimal approach overcame some of these difficulties, it had the disadvantage that it only extracted a single path, specified by its end points or by end points and intermediate points indicating the path roughly, in order to accelerate the search. If a network of roads or rivers was required it was necessary to undertake the extraction as a series of discrete stages, each arc in the network being handled individually.

In the new approach described below, all systems of narrow curvilinear features in a given image which satisfy the chosen criteria are extracted as a single network or several separate (disconnected) networks of vectors representing the paths of roads or rivers, without the need for an operator to specify individual points on the features explicitly.

NETWORK ALGORITHM

For the purposes of description it is useful to view the algorithm as three separate stages. In the first stage, points are identified which have a high probability of being on the network to be extracted. In some cases, where the features are sufficiently distinct, this may be achieved simply by thresholding, but more typically it may be achieved by the application of line, edge or road detection operators to transform the image so that low pixel values indicate high confidence that the point is on the feature and high pixel values indicate low confidence. The algorithm has been implemented in an integrated, window-based toolkit for image analysis which makes the application of the preprocessing procedures quick and easy to apply. An example of part of the graphical user interface(GUI) is shown in figure 1.

A set of high confidence points is selected for further consideration by thresholding the confidence image interactively. Options also allow elimination of isolated points and broad feature responses may be thinned to a single pixel in width.

In the second stage of the algorithm, the aim is to extract a network representation of the broad topology of the underlying feature. The assumption, at this stage, is that there is a sufficiently high density of selected points in the confidence image, covering the feature, to obtain the correct topology for the network by finding the minimum spanning tree(MST) through the selected point set. (The idea of using a minimum spanning tree for network extraction was first proposed by Fischler et al[3]).

The minimum spanning tree algorithm treats the points as nodes in a graph and finds the graph which minimises the total cost of the arcs whilst simultaneously passing through each of the selected points. In our current implementation, the costs used to construct the arcs are directly related to the distance between the points considered. Only if distances are the same are the confidence values of the points taken into account. The operator may also specify a maximum cost between nodes and if it is not possible to link all selected points, without arcs exceeding the maximum cost, a second network and if necessary further networks are initiated until all selected high confidence points have been spanned.

The MST imposes straight line connections between the selected feature points, which is quite acceptable for closely spaced selected points. However, as the points become more widely separated it leads to increasingly inaccurate representations of the underlying features. To overcome this problem, we have introduced an optional third stage to our algorithm. In order to ensure that the extracted network is close to the underlying curvilinear feature in the original image, we have combined the minimum cost path approach of our earlier paper[4] with the minimum spanning tree method. Whenever the distance between two adjacent points in the network, extracted by the minimum spanning tree, is above a low threshold, a suitable search window is automatically placed around the region containing the two points on the original image (or an appropriate derived image) and a path between the pair of points is found which minimises a cost function appropriate to the problem domain and specified initially by the operator. The minimum cost path(MCP) algorithm used is the extension to the D'Esopo algorithm described in our earlier paper[4].

This procedure aims to ensure that the extracted network follows closely the underlying curvilinear features in the image and produces a curvilinear rather than a linearly connected network. Tools for editing, saving and reloading networks are also available in the toolkit.

Figure 2 shows part of a Landsat image of a river system and in figure 3 the extracted network is shown superimposed in black. No

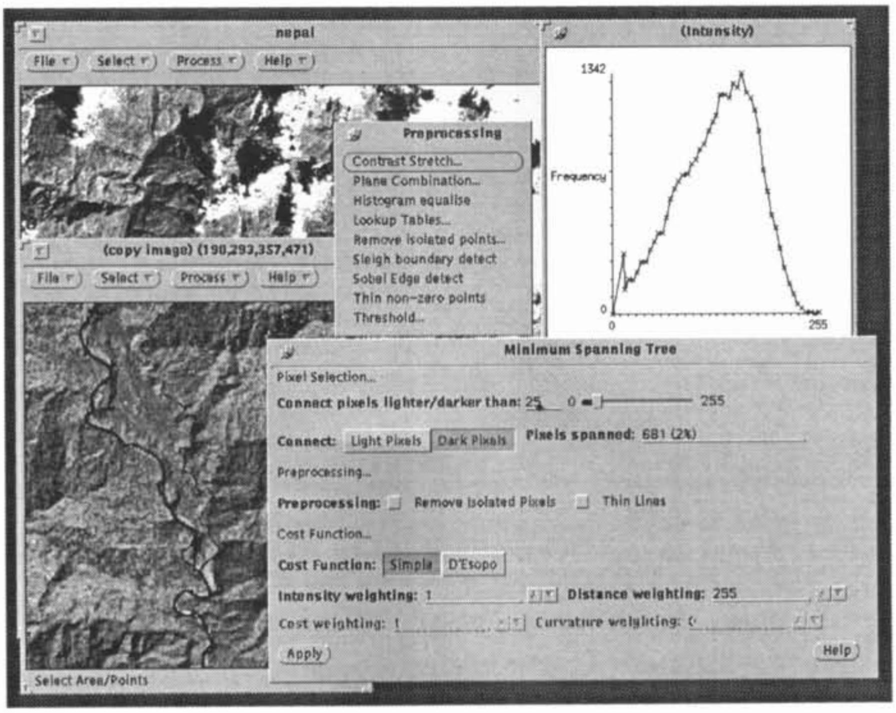

Figure 1: The GUI in action

manual selection of individual feature points was required and the resulting network may be saved as a vector representation for use independently of the original image. In this particular case, preprocessing involved thresholding, noise reduction and thinning before the second and third stages of the algorithm. It can be seen that not only has the broad river path been extracted, but also the main tributary together with other river features which, using the earlier approach, would have necessitated several user controlled extractions.

FURTHER REFINEMENT

In a proposed development, the MST approach and the MCP approach will be integrated more closely. Rather than simply using the MCP to refine the path between nodes of the MST after it has been constructed, it would be better if the cost associated with linking a point to a node in the MST as it is built, could be the cost of the MCP between the point and the node. However, this would be computationally very expensive as MCPs would have to be calculated between all combinations of selected high confidence points. The following modification to the MST algorithm takes us either part way or all the way to this ideal.

If, using distance alone as the cost, the next point to be added to the MST would be a distance, d, from the node to which it would be connected, calculate the costs of the MCPs to all points within some distance, $constant * d$, of the node and choose the one with the lowest cost. If the constant is one, the algorithm is as described earlier. As the constant becomes large we will move nearer to the position in which the point with the overall lowest cost MCP is linked in.

CONCLUSIONS

Although extracted networks are not always perfect, they provide a useful starting point for the operator and give a significant reduction in the need for manual digitisation. A valuable feature is the ease of use of the GUI allowing rapid experimentation to find the high confidence set. In the future, the development of more reliable procedures for the accumulation of high confidence feature points and the proposed improvements to the MST algorithm, described above, should lead to more robust automatic extraction of network topologies.

Figure 2: Raw Satellite Image

Figure 3: Extracted River Network

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