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DETECTION OF RIVERS IN LOW-RESOLUTION AERIAL IMAGERY

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ABSTRACT

This paper describes an operator for detecting rivers in low-resolution aerial imagery. The operator provides results that would allow graph-traversing routines to delineate these structures. The approach is to look for the typical river profile involving not only the water component of the river, but its surrounding vegetation as well.

I INTRODUCTION

The detection of roads in low-resolution aerial imagery has previously been reported.* That work produced an effective technique for tracking roads in clear images of rural scenes at low resolution (roads with an image width of three or fewer pixels). This paper describes an effort to extend that technique to other linear structures, in particular to the tracking of rivers.

The approach employed in road tracking consists of three steps:

(1) The use of image operators to produce a score matrix showing the likelihood that the image point lies on a road. For road detection this step involves a number of operators; the score matrix constitutes a composite likelihood score.

(2) The clustering of high-likelihood image points into sets, provided they lie within some maximum distance of their nearest (high-likelihood) neighbor. For each cluster a minimal-spanning tree is found, the major branches of which are used as approximate road tracks.

(3) The application of a graph-traversing algorithm to the part of the score matrix surrounding an approximate road track discovered in Step 2.

The graph produced delineates the actual road detected and is used as an overlay to the image. The graph-traversing algorithm will detect "different" road tracks, depending on the manner in which the point scores are used to calculate the total road score. This allows a priori knowledge, such as road shape, to be added to the detection process.

Here we report the details of an operator that has been used for river detection with the approach outlined above. While this paper does not discuss the second and third steps, our continuing work indicates that the scores produced by this operator do allow an approach similar to that used in those steps. In this manner we would produce an image overlay that delineated river courses.

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* M. A. Fischler, J. M. Tenenbaum, and H. C. Wolf, "Detection of Roads and Linear Structures in Low-Resolution Aerial Imagery Using A Multi-Source Knowledge Integration Technique," A.I. Technical Note 200, SRI International, Menlo Park, California (December 1979).

II LOW-RESOLUTION RIVER DETECTION

A large stream of water flowing over the land may be an adequate definition of a river for literary purposes, but is unsuitable as a definition of its image manifestation. A human easily classifies an image feature as a river when the water component is both barely resolvable and significantly lacking in continuity. An image feature is classified as a river even when manifested as little more than a string of water holes. However, drainage patterns that are active only at times of heavy run-off are not detected as rivers, but as part of the more general topography. In this paper we consider the problem of detecting watercourses that are classified as "rivers" by human observers. We restrict our attention to aerial images of rural districts.

In low-resolution aerial images, human delineation of rivers seems to be at least a two-phase process. There is the detection of river segments, at first glance, "followed by a reasoning phase," that, in effect, postulates a certain course the detected river must take if its segments are to join in a manner known to be applicable to such a feature. Our aim in designing a river operator is to detect the first-glance river segments and then use steps like those in the road tracker--i.e., of finding the minimal-spanning tree and performing graph traversal to fill in the deduced river segments. One might see this as a partitioning of the detection process into those steps that can be performed adequately on the basis of local image operators and those that use image information that is more global, as well as a priori information about river properties. We expect a river operator to work well in those regions of first-glance recognition, but to be less useful in regions where more global knowledge is required for detection of river structure.

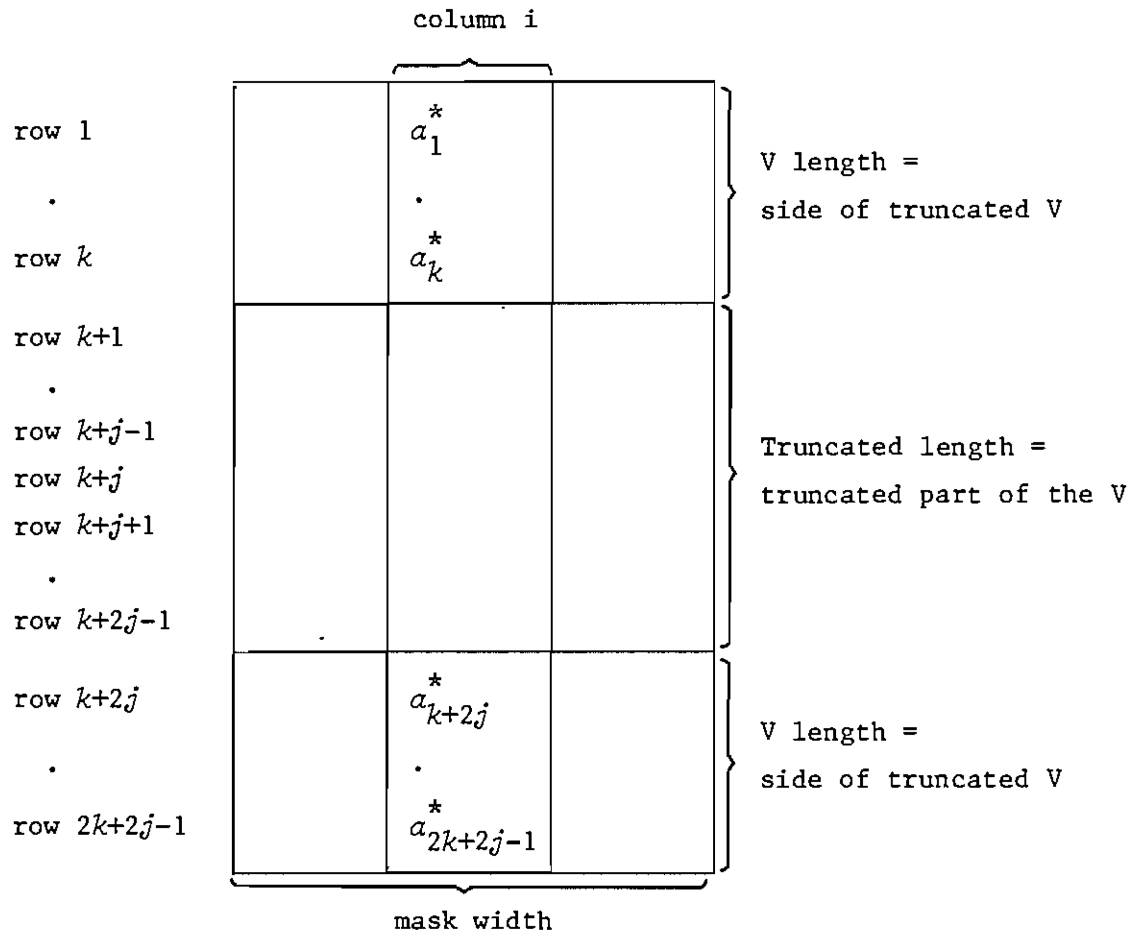
III THE RIVER OPERATOR

At low-resolution, in which the river's water component may only be a few pixels wide--possibly even less than one pixel in width--the image characteristics of a water feature are not predominant in detection of the river. While water bodies usually appear dark in nearly vertical aerial images (in the visible spectrum), the number of dark pixels is insufficient to allow a technique such as thresholding to be a river operator. The watercourses of rivers in rural scenes are characterized as much by their vegetation cover as by their water component. The denser vegetation present along the watercourse, the common farm practice of leaving natural vegetation about the river banks as an aid in consolidating the latter, and the unsuitablity of river bank topography for mechanized agricultural use are crucial factors that typically cause the cross-river intensity profile to display a characteristic shape that is much larger than the actual width of the water component.

Examination of river profiles suggests that the river is located at the locally darkest pixel in the profile when the intensity profile shape is a type of truncated V, as shown below:

The river operator presented here is built upon these two concomitant characteristics. It attempts to fit straight-line segments to the sides of the mask's intensity profile. The parameters of these fitted lines are used to calculate a score indicating the likelihood that the image point at the mask's center is part of a river. One mask is used to detect predominantly horizontal river segments, while the other is used to detect those that are predominantly vertical.

The mask to detect a predominantly horizontal river segment centered at $(k+j,\ i)$ is



a_l^* for $l=1, \ldots, k, k+2j, \ldots, 2k+2j-1$ is the average grey level of the lth row of the mask.

To the values $a_1^*, \ldots, a_k^*$ (and separately to the values $a_{k+2j}^*, \ldots, a_{2k+2j-1}^*$) a straight line is fitted by using the least-squares method.

The 'fitted' value of a_l^* is a_l^1, where

$$a_l^1 = A_1\ (k+j-l) + B_1 \qquad l = 1, \ldots, k$$

$$a_l^1 = A_2\ (l-k-j) + B_2 \qquad l = k+2j, \ldots, 2k+2j-1$$

A_1, A_2, B_1 and B_2 are calculated by the least-squares method.

A score for the cell $(k+j,\ i)$, the center of the mask, is calculated so as to indicate the likelihood that this cell is a river point. The higher the score, the greater the likelihood.

$$\text{Raw score} = \omega_1\ (A_1 + A_2) + \omega_2\ \left(\frac{1}{|B_1| + |B_2|}\right) \quad \text{if sum of square in fitting is less than a constant M}$$

$$= 0 \quad \text{otherwise}$$

ω_1 and ω_2 are weights.

A modified score is calculated for the cell $(k+j,\ i)$ by considering the maximum score of cells $(k+j-1,\ i-1)$, $(k+j,\ i-1)$, $(k+j+1,\ i-1)$ if the mask is applied left to right across the image. This adjacent score is used to modify the raw score of cell $(k+j,\ i)$. If we view the mask as one that finds horizontal river segments, then we modify the raw score by using the score of an approximately horizontal adjacent cell. We want to increase the raw score significantly if the adjacent cell has a high likelihood of being part of a river segment.

$$\text{Modified Score} = \omega_A\ \text{Raw Score} + \omega_B \cdot \ (\text{Max. score of cells } (k+j-1,\ i-1),\ (k+j,\ i-1),\ (k+j+1,\ i-1))$$

ω_A and ω_B are weights.

IV RESULTS AND DISCUSSION

Figure 1 shows the result of applying the river operator to four rural scenes. The digital images (a) have an approximate pixel size of 3 metres x 3 metres on the ground. The modified scores of the river operator are given in (b) and these scores are thresholded in (c) to show the high-scoring pixels. The parameters used here are

Mask width = 3 pixels
V length = 4 pixels
Truncated length = 3 pixels
$\omega_1 = 1.0$
$\omega_2 = 400.0$
$\omega_A = 1.0$
$\omega_B = 0.5$
M (maximum sum of squares) = 100.0

In open country, as seen in the first three examples in Figure 1, the operator produces scores that are relatively high in the "river" and comparatively low elsewhere. We see in the third and fourth examples that trees also score highly. This is particularly the case when the foliage is not dense enough to conceal the ground underneath. In Example 3, where the "sparse" tree cover does not adjoin the river, the linear structure of the latter is still present; in Example 4, on the other hand, the river is "lost" in the trees. However, we are not unhopeful that a graph-traversing algorithm using the modified scores would still detect the river (given the end points), but a minimal-spanning tree over pixel clusers appears unsuitable for finding the approximate track of the river. An approach using global knowledge appears preferable.

The above parameters were determined to be the best for the examples in Figure 1. However, the results obtained were not very sensitive to the values of the weights; small changes (< 20%) apparently did not alter the qualitative results. The mask size had to be matched to the resolution of the image, but, here too, the results were not very sensitive.

Several other forms of the scoring function were tried, as were such other processing procedures as thresholding out "white" areas of the image before applying the operator--but none were as useful as the operator and procedure described herein.

The operator is implemented in MAINSAIL and runs on the SRI VAX as part of an image-processing package.

V CONCLUSION

The operator described in this paper generates high-likelihood scores for image pixels that are a part of river structures in low-resolution aerial images. In a general rural context this enables a river to be isolated, provided it does not pass through a low-density tree-covered area in which individual trees are seen against a background of ground surface reflection. The operator appears to provide a score matrix that would allow techniques like graph traversal to delineate the river track.