Image-based map updating system

K.S. Savage, M.J. Carlotto, and D. Izraelevitz

TASC
55 Walkers Brook Dr.
Reading, MA 01867

ABSTRACT

We describe an integrated system developed to update maps by extracting and identifying roads and other linear features in imagery. Our approach involves registering the map to be updated to the image on a local basis using an affine transformation to eliminate costly preprocessing. Image features are converted to the map coordinate system by inverse transformation. Three strategies for linear structure identification and a method for classifying new roads are discussed.

1. INTRODUCTION

With the conversion of paper maps to digital map databases, the ability to update digital maps from imagery is becoming increasingly important. Traditional approaches which are based on registering new imagery to the existing map base are not often practical operationally. Operational systems must be able to deal with problems such as geometric distortions in imagery due to off-nadir viewing and relief, the detection of features near the resolution limit of the sensor, and obscuration (e.g., roads obscured by trees). We describe a prototype system implemented to extract and identify roads and other linear features in imagery. Our approach involves registering the map to be updated to the image on a local basis, extracting and identifying new features in the image coordinate system, and transferring these features into the map coordinate system. Local registration computes an affine transformation between the portion of the map being updated and the image. Image features are converted to the map coordinate system by inverse transformation. This approach eliminates costly preprocessing (stereo processing or registration to an existing elevation model and ortho-rectification) and supports interactive registration. Manual, interactive (road tracking) and automatic (line finders) feature extraction tools optimized for a variety of image conditions are discussed. Methods for classifying new roads using contextual information provided by the existing roads are also described. Preliminary results over upstate New York obtained using SPOT imagery are presented.

2. BACKGROUND

Most efforts in automatic road and linear structure extraction have concentrated on high-resolution imagery.[1,2,3] These approaches make full use of information known about the width of roads, markings, etc., to aid in detection and tracking. Automatic linear structure extraction from low resolution imagery is a much more difficult problem since these cues are not available. Moreover, the problem of occlusion is much more severe in the low-resolution case. Several approaches have been considered for this problem.[4,5,6]

In automated linear structure extraction, there are two basic steps: linear feature extraction, and linear feature interpolation and aggregation. In *linear feature extraction*, local intensity variations are analyzed to identify line-like features. Since this is strictly a local image-based analysis, the output of this process is typically fragmented. *Linear feature interpolation* addresses the problem of combining or joining fragmented linear structure fragments into continuous linear structures.

Crucial to the extraction of linear structures from imagery is the development of an effective image processing algorithm which will detect or enhance those areas of the imagery which are good candidates for the existence of linear structures. Previous approaches have centered on linear algorithms and simple nonlinear extensions.[5,7] These approaches suffer from the property that they are directionally sensitive, because they look for linear structures in cardinal directions (multiples of 45 degrees) only.

The linking of *edge* segments is a common problem in computer vision.[7] Several approaches have been suggested, such as those based on dynamic programming, and more general formal or heuristic search.[8] Many of these methods are in fact tracking strategies, since at least one initial point on the edge is required.

3. LINEAR FEATURE EXTRACTION AND INTERPOLATION

Our approach to linear feature detection is based on a local quadratic model for the image, and estimation of the curvature properties of the image intensities near the pixel of interest. It has many similarities to the analysis performed by Canny[9] for

 0-8194-1020-9/93/$4.00

edge detection. The curvature should be large and negative at a linear structure pixel and the intensity value should be a local maximum in the direction of this maximal curvature, i.e., normal to the direction of the linear structure. This leads to a directionally-isotropic approach which is sensitive to high contrast ridges in the intensity map at all directions as shown in Figure 1.

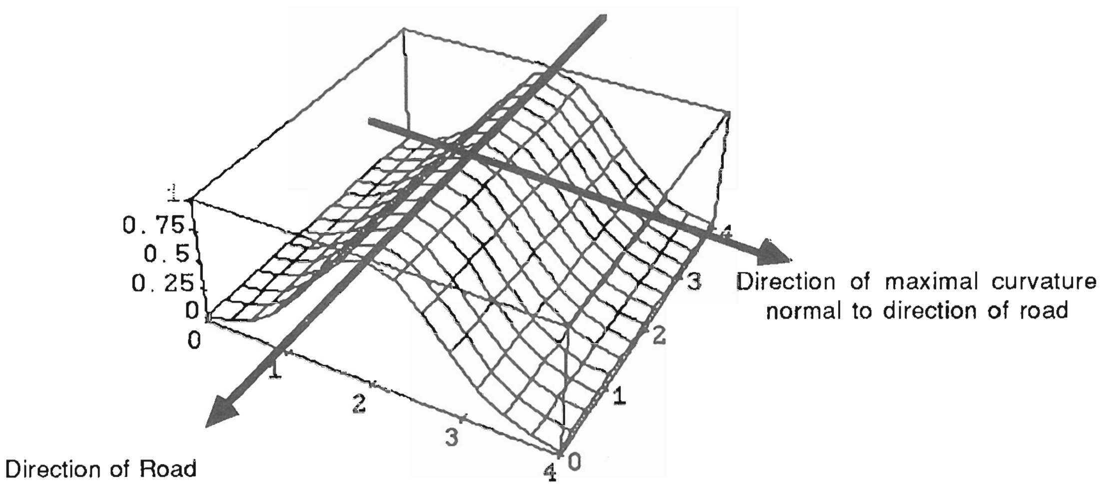

Fig. 1 Intensity map showing a typical linear structure signature. Maximal curvature should be large and negative and normal to direction of linear structure.

The approach uses a quadratic model for the image intensities about a given pixel location, which for the sake of argument is assumed to be (0,0). Consider the following equation which describes a quadratic model for the image intensities *F(x,y)* about the pixel location (0,0).

$$F(x,y) \approx \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} b_1 & b_2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + F(0,0)$$

After image smoothing, we estimate the values of the first and second order derivatives using standard finite-difference approximations.[10] These estimates lead directly to estimates of the $\{a_{ij}\}$ and $\{b_j\}$ coefficients. The direction and value of the maximum and minimum directional second order derivatives can be computed from the eigenvalues and eigenvectors of the matrix of second order derivatives.

From Figure 1, we see that the direction along which the second order derivative is *largest* is likely to be the direction normal to the linear structure direction. Conversely, the direction along which the second order derivative is smallest is likely to be the linear structure's direction itself. In order to have a linear feature at location (0,0) we expect that one of the eigenvalues will have a large absolute value and be negative (assuming that the linear structure is brighter than the background). The second eigenvalue should have a small absolute value. Moreover, we expect the ratio of maximum to minimum curvature to be large, indicative of a local "crest", (substantial curvature in one direction, but negligible along the perpendicular direction).

As a second constraint, we expect that the intensity map will be maximum at the center of analysis, when considering a cut across the image along the direction perpendicular to the estimated linear structure direction. To see if the image is a local maximum along this direction, we use an approach called non-maximum suppression[9], which is a robust test. Consider Figure 2, where we depict a pixel under study and its immediate neighborhood. We compute the values of a and b by linearly interpolating the values of the two nearest pixel values. Then we admit the center pixel as a possible linear structure element only if the value of the image at the center is larger than both a and b.

A simple approach to linear feature interpolation is to link the endpoints of segments identified by thresholding and thinning the output of the linear feature extraction algorithm described previously. The distance between endpoints and the length of the segment determines whether to link two segments together. Although this method works well for rural scenes where the complexity of linear structure networks is small and there are few intersections, it is necessary to consider more sophisticated approaches for complicated networks such as in densely populated areas.

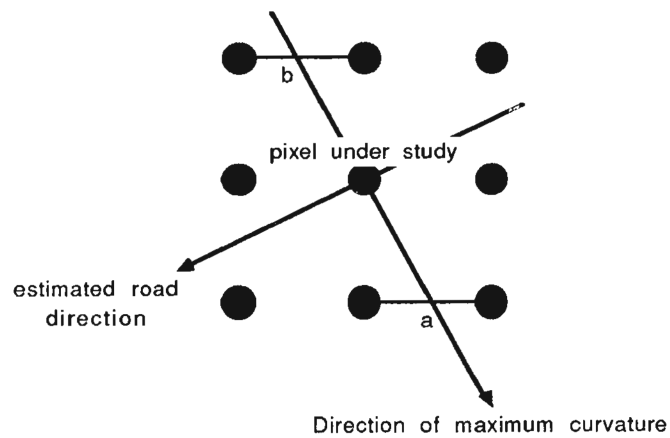

Fig. 2 Testing whether center pixel is local maximum in direction of maximum curvature.

4. LINEAR FEATURE TRACKING

As noted previously, there are many circumstances when one can reasonably expect that fully automatic linear structure extraction will miss linear structures due to occlusion, mixed pixel effects, or low contrast. Instead of forcing the analyst to "draw" such linear structures on the screen manually, an alternative is to provide a tool that requires the minimum operator interaction to delineate linear structures accurately. For this purpose, we have implemented and generalized the use of a linear structure tracking technique first developed by Fischler et al.[5] This approach has been very successful in allowing an analyst to accurately specify the location of low contrast linear structures even in very cluttered environments.

Consider the output of a linear structure feature extraction algorithm such as the one described previously. A mapping is performed such that likely linear structure pixels are mapped to a low cost value, while pixels which are deemed unlikely linear structure pixels are mapped to a high cost. There is a small residual cost assigned to every pixel, even if it is highly likely to be a linear structure pixel. This is done to prevent infinite length paths from being generated. Eight-connected paths which have a low *cumulative cost*, can be used as estimates of likely linear structure locations. The F* algorithm[5], is used to efficiently find the least cost path joining any two specified points. We use this algorithm to find the shortest path between two pixels A and B, which are interactively specified by an analyst. The computer then generates the path and displays it on the screen for acceptance by the user. We have modified the F* algorithm to apply a weighting factor that differentiates between horizontal/vertical transitions and diagonal transitions. This weighting provides more isotropic behavior of the tracking algorithm with respect to direction.

5. LINEAR STRUCTURE CLASSIFICATION VIA IMAGE AND CONTEXT DRIVEN INFORMATION

Once a linear structure track has been identified it is still necessary to classify the linear structure into a specific type, such as forest trail, paved road or river. There are several cues which can be used to aid in this classification,

- spectral cues, which indicate the composition of the linear structure. Because of the mixed-pixel problem, it is difficult to reliably identify the composition of the linear structure strictly from spectral information.
- spatial cues, e.g., the length/width and shape of the linear structure. Width computations can be expected to be unreliable given the relatively low resolution of the data being studied.

- contextual cues, e.g., how the linear structure is located in relation to a network of linear structures. For example, it is very unlikely that a major highway would join two forest trails, and vice versa. Road networks are typically structured so that lower-grade roads, such as forest trails, are joined to higher grade, secondary roads, and so on.

We developed an algorithm to estimate the linear structure class of a linear segment from a statistical analysis of the surrounding linear structure network. By histogram analysis, a class co-occurrence table is computed over all existing roads in an image. The co-occurence table gives the likelihood for each road class of being connected at either end by all possible road classes. Suppose that a road α has been detected, but its class is unknown. Let the class of the road adjacent at one end of α be ω_1, while the class for the road adjacent to α at the other end be ω_2. The co-occurrence table provides, $p(\omega_\alpha,\omega_1,\omega_2)$, the likelihood that a road of class ω_α is connected at either end by a road of classes ω_1 and ω_2. The most likely class can either be automatically assigned, or during an interactive session, the possible road classes are presented in order of likelihood to the analyst for verification.

We have performed an experiment to check the accuracy of this classification algorithm. Two regions in the Glens Falls, NY area were identified which consisted of a variety of roads such as forest trails, primary and secondary roads. Using either area, we developed the co-occurrence matrix $p(\omega_\alpha,\omega_1,\omega_2)$ and applied it to itself and the other region. Table 1 presents the correct classification rates.

Table 1 Correct classification rates for linear structure class prediction using contextual information.

		Testing Area	
		Area 1	Area2
Training Area	Area 1	.97	.97
	Area 2	.87	.92

A valuable contribution to the linear structure classification problem would be to extend our results in context-based linear structure classification to integrate spectral and spatial information. Thus, for example, the existence of a small linear structure joining two forest trails would be most likely classified as another forest trail, especially if further supported by spectral signature analysis.

6. INTEGRATED LINEAR STRUCTURE EXTRACTION CAPABILITY

Even under highly automated conditions, it will still be necessary for an analyst to review the results of the extraction process in order to prune false alarms and to add low-contrast linear structures which were missed by an automated procedure. Therefore, it is necessary to have an environment where automatic techniques are augmented by semi-automatic (i.e., techniques with some operator guidance), and manual techniques. Table 2 defines three complementary strategies to linear structure extraction from imagery.

The development of a linear structure extraction capability requires the integration of all three approaches to linear structure identification. We have developed a prototype system for extracting roads from imagery known as the image-based map updating system(IMUS) which integrates all three extraction strategies. Figures 3 and 4 show some of the capabilities of the system as applied to updating a road database over Glens Falls, NY using SPOT panchromatic imagery.

The system is initialized with a vector database which is typically obtained from the digitization of a paper map. The analyst is first asked to select the database to be edited/augmented. Once the database is loaded, the analyst is presented with an overview of the database, on which an area of interest can be specified . The user is then given a list of all images which have geographic overlap with the area-of-interest specified. Using database and image header information, a rough registration is performed in which the *database is warped to the imagery* rather than warping the imagery, directly. The advantage of this approach is that the imagery is not degraded by interpolation and also offers computational advantages since remapping a set of graphical objects (the linear structures) is much faster than remapping of the imagery.

Once rough registration has been performed, the user is presented with the opportunity to perform fine-grain, local registration by picking corresponding landmarks (control points) in the imagery and the database. An editor allows the user to add or delete control point pairs, and perform incremental registration, where control points can be picked iteratively with registration to increase accuracy.

Fig 3. Poly-line capability of image-based map updating system.

Fig 4. Road tracking capability of image-based map updating system.

Table 2 Strategies for linear structure extraction from imagery.

Method	Processing Steps	Characteristics
Manual Extraction	• Identify critical points on a linear structure via cursor • Interpolate between critical points without using imagery information	• Accuracy and performance are operator-dependent • Only recourse for ambiguous or poor contrast linear structure • Slow production rate
Semi-automated Extraction	• Identify critical points on a linear structure via cursor • Interpolate between critical points by using imagery information	• Operator can apply contextual information to linear structure extraction • Better opportunity for resolving ambiguous linear structures • Good tolerance for partially obscured linear structure or tunnel detection
Automated Extraction	• No selection of critical points prior to processing • Automatically identify linear structure segments • Final user review of extracted results	• Highest throughput, although efficient operator "final check" needed for false alarm reduction • Relatively high-contrast linear structures only can be extracted • Little or no contextual information used

Three road extraction/interpolation editing modes are allowed: segment selection, poly-line generation, and semi-automated extraction (called road tracking in this system). Segment selection allows the user to select road segments for deletion or reclassification. The deletion capability is used to delete road candidates which are false alarms from an automated extraction procedure, or are roads which no longer exist; e.g., removed to make way for a residential development. The reclassification capability allows the user to manually select a road class for the segment. Poly-line generation consists of the manual delineation of piece-wise road segments which are of too low contrast to have been extracted automatically (Figure 3). Finally, we have integrated our road tracking capability in an implementation of the operator-guided semi-automated road extraction (Figure 4).

To allow efficient and accurate placement of road additions, a local "magnifying glass" has been implemented which becomes activated whenever the user needs to specify a pixel location on the image. We have found this capability to be particularly useful during poly-line generation, as well as road tracking.

7. CONCLUSION

We have integrated three approaches to linear structure identification: automated generation of candidate linear structure locations, operator-guided linear structure delineation, and manual extraction, within a system to extract and identify roads and other linear features in imagery. Our approach involves registering the map to be updated to the image on a local basis, extracting and identifying new features in the image coordinate system, and transferring these features into the map coordinate system. For the automated generation of candidate road locations we have developed an approach based on a local quadratic model for the image and estimation of the curvature properties of the image intensities near the pixel of interest. We have implemented and generalized the use of a linear structure tracking technique for operator-guided road delineation. Finally, a method for classifying new roads using contextual information provided by the existing roads has been developed.

8. REFERENCES

1. L. J. Quam, “Road Tracking and Anomaly Detection in Aerial Imagery,” Proc. Image Understanding Workshop, 1978.
2. R. Nevatia, and K. E. Price, "Location Structures in Aerial Images," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. PAMI-4, 1982, pp. 476-484.
3. D. M. McKeown Jr., and J. L. Denlinger, “Cooperative Methods for Road Tracking in Aerial Imagery”, in Proc. IEEE Conf. on Computer Vision and Pattern Recognition, June, 1988.
4. R. Bajczy and M. Tavakoli, "Computer Recognition of Roads from Satellite Pictures," IEEE Trans. on Systems, Man, and Cybernetics, Vol. SMC-6, 1976, pp. 623-637.
5. M. A. Fischler, J. M. Tenenbaum, and H. C. Wolf, “Detection of Roads and Linear Structures in Low Resolution Aerial Imagery Using a Multisource Knowledge Integration Technique”, Computer Graphics and Image Processing, Vol. 15, 1981, pp.201-223.

6. D. Izraelevitz and M. J. Carlotto, "Extracting Road Networks from Low Resolution Aerial Imagery", Proc. SPIE Conf. on Visual Communications and Image Processing, 1988.
7. A. Rosenfeld and A. Kak, Digital Picture Processing, Academic Press, Orlando, 1982.
8. D. H. Ballard, and C. M. Brown, Computer Vision, Prentice-Hall, New Jersey, 1982.
9. J. Canny, "A Computational Approach to Edge Detection", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. PAMI-8, November 1986, pp. 679-698.
10. M. Abramowitz and I. A. Stegun, Handbook of Mathematical Functions, National Bureau of Standards, 1970.