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UNDERSTANDING FEATURES, OBJECTS, AND BACKGROUNDS
Project Status Report 1 August 1981 - 31 July 1982

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ABSTRACT

Current activities on the project are summarized under the following headings:

(a) Preprocessing and segmentation,
(b) Feature detection and texture analysis,
(c) Hierarchical representations,
(d) Matching and motion,

1. Introduction

This project is concerned with the study of advanced techniques for the analysis of reconnaissance imagery. It is being conducted under Contract DAAG-53-76-C-0138 (DARPA Order 3206), monitored by the U.S. Army Night Vision and Electro-Optics Laboratory (Dr. George Jones). The Westinghouse Systems Development Division, under a subcontract, is collaborating on implementation and application aspects.

Work on the current phase of the project was initiated in April 1980. Accomplishments and publications during the period 1 April 1980 - 31 July 1981 are summarized in two earlier status reports [1-2], the first of which also appeared in the Proceedings of the April 1981 Image Understanding Workshop [3]. The present report, covering the period 1 August 1981 - 31 July 1982, is being issued separately and will also appear in the Proceedings of the September 1982 Image Understanding Workshop. For convenience, publications since February 1981 are also cited here, since they were not cited in the April 1981 Workshop Proceedings.

The project is concerned with three principal areas: segmentation techniques; context-based target detection in FLIR imagery; and analysis of time-varying imagery. Work in the first area is summarized in Section 2 (Preprocessing and segmentation) and 3 (Feature detection and texture analysis), while Section 4 summarizes work on the use of hierarchical image representations ("pyramids") in both segmentation and feature detection. Three papers in these areas, dealing with a comparative study of segmentation techniques as applied to FLIR imagery [4], and with the use of pyramids for extracting compact objects from an image [5,6], also appear in the Workshop Proceedings. Work on context-based target detection is covered in a report that also appears in the Workshop Proceedings [7]; a second report on this topic is in preparation. Finally, Section 5 summarizes work on image matching and time-varying imagery analysis; one paper in this area also appears in the Workshop Proceedings [8].

2. Preprocessing and segmentation

2.1 Comparative segmentation study

A comparative study of FLIR image segmentation techniques was conducted, using a database of 51 images obtained from four different sources. The techniques compared included two- and three-class relaxation, "pyramid linking", and "superspike" (see below). The results are described in detail in [4] and in a paper appearing in the Workshop Proceedings.

2.2 Constraint-based region identification

A context-based approach to region identification on FLIR imagery was developed; it uses constraint filtering techniques to identify regions as (possibly) belonging to the classes sky, smoke, ground, tank, and tree. A detailed description of the approach and examples of its use can be found in [7], which also appears in the Workshop Proceedings.

2.3 Histogram-based image smoothing

A powerful method of edge-preserving image smoothing known as "superspike" has been developed. It is based on repeatedly averaging each pixel with a subset of its neighbors, where the neighbors used are chosen on the basis of their relationships with the given pixel on the image's histogram. Specifically, we use a neighbor if its value is more probable than the pixel's, and there is no concavity on the histogram between its value and the pixel's; these conditions imply that it belongs to the same histogram peak as the pixel, and is higher up on that peak. This method can also be applied to multi-spectral imagery, using the scattergram rather than the histogram [9]. Figure 1 shows an example of this type of smoothing applied to a color image of a house, using only two bands (red and blue). The result is

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quite cartoon-like, and the scattergram of the smoothed image is virtually reduced to a small set of spikes.

2.4 Segmentation by bimean clustering

The mean is the best-fitting constant, in the least squares sense, to a given set of data. We define the "bimean" of the data as the best-fitting pair of constants. If the data are image gray levels, the bimean defines a segmentation of the levels into two populations, each consisting of those levels that are closer to one of the constants than to the other. An algorithm for finding the bimean of a set of scalar data has been developed. It yields good segmentations in some cases which are not well segmented by the two-class ISODATA clustering algorithm. The details, and examples, can be found in [10].

3. Feature detection and texture analysis

3.1 Edge and corner detection

Hueckel-type edge detectors are based on finding a best-fitting step edge to a given image neighborhood. Some general properties of such detectors have been derived, and applied to defining Hueckel-type detectors for various simple types of neighborhoods. The details are presented in [11].

If an image contains an object on a contrasting background, corners on the object's contour give rise to slope changes in the x- and y-axis projections of the image. Thus detecting such changes indicates which rows and columns of the image are likely to contain corners. The details of the approach, as well as examples, were presented in [12] (also summarized in [2]).

3.2 Texture analysis

A comparative study of texture classification using various types of features was conducted. The best features were (simplified versions of) the "texture energy measures" developed by Laws at USC. The Laws features and texture samples used are shown in Figures 2 and 3, and the results are summarized in Table 1. The details can be found in [13].

Texture analysis methods can be applied to terrain classification using arrays of elevation data, rather than intensity data. Some simple examples and a brief discussion can be found in [14]. This approach will become of increasing interest as high-resolution digital terrain elevation data becomes available over the coming years.

4. Hierarchical methods

A class of methods for image segmentation and object detection has been developed that makes use of a "pyramid" of successively reduced-resolution versions of the image. One such method constructs subtrees of the pyramid representing homogeneous subpopulations of pixels, by creating links between nearby pairs of pixels on consecutive levels of the pyramid based on their similarity in value. This method has been generalized to multispectral imagery, where better results can be obtained using two bands than using one band at a time. The details were given in [15] (also briefly summsrized in [2]).

Pyramid linking methods can also be used to extract significant edges from an image, by creating links between nearby pairs of edge segments on consecutive levels based on similarity in slope. The details of this approach were given in [16] (also briefly summarized in [2]).

A more recent application of pyramid linking is to the detection and extraction of compact objects from an image using local "spoke filters" on each level of the pyramid. This method is described in detail in [5], which also appears in the Workshop Proceedings.

Pyramid linking is usually based on forced choices, where a pixel must link to one of the nearby pixels on the level above it. A "softer" approach is to use weighted links (the more similar, the stronger). This too gives rise to trees whose roots are pixels that have only negligibly weighted links to the level above them. Typically, the leaves of such a tree constitute a compact, homogeneous piece of the image. The approach is described in detail in [6], which also appears in the Workshop Proceedings.

5. Matching and motion

5.1 Corner-based image matching

Some experiments on relaxation image matching, based on "corner" features extracted from the images, were described in [17] (also briefly summarized in [2]). Further experiments, in which local gray level correlation was used to resolve ambiguous cases, are described in [18].

5.2 Corner-based motion computation

By computing (approximately) the spatial and temporal derivatives of the image gray level at a given pixel, the component of the velocity of that pixel in the gradient direction can be estimated. If the pixel is at a "corner" of an object, where edges having two different directions meet, its velocity is thus completely determined. When the velocities are due to observer motion ("optical flow"), knowing them at a few points suffices to determine the translation and rotational components of the flow [19]. When an object is moving, estimates of the velocities of its corners can be "propagated" along its contours to yield a consistent estimate of object motion [20,21]. Further details of this approach, together with examples, are presented in [8], which also appears in the Workshop Proceedings.

REFERENCES

1. Understanding Features, Objects and Backgrounds, Semi-Annual Report, 1 April 1980 - 31 January 1981, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, Md.

2. Understanding Features, Objects and Backgrounds, Semi-Annual Report, 1 February - 31 July 1981, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD.

3. Understanding Features, Objects, and Backgrounds, Project Status Report 1 April 1980 - 31 January 1981, Proceedings, DARPA Image Understanding Workshop, April 1981, 208-215.

4. R. L. Hartley, L. J. Kitchen, C. Y. Wang, and A. Rosenfeld, A comparative study of segmentation algorithms for FLIR images, TR-1104, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, September 1981 (an abridged version appears in the Workshop Proceedings).

5. T. H. Hong and M. Shneier, Extracting compact objects using linked pyramids, TR-1123, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, November 1981 (also in the Workshop Proceedings).

6. T. H. Hong and A. Rosenfeld, Unforced image partitioning by weighted pyramid linking, TR-1137, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, January 1982 (also in the Workshop Proceedings).

7. L. Kitchen, Scene analysis using region-based constraint filtering, TR-1150, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, February 1982 (also in the Workshop Proceedings).

8. L. S. Davis, Z. Q. Wu, and H. F. Sun, Contour-based motion estimation, TR-1179, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, June 1982 (also in the Workshop Proceedings).

9. C. Y. Wang and L. Kitchen, Improvements in multispectral image smoothing, TR-1152, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, March 1982.

10. S. Dunn, L. Janos, and A. Rosenfeld, Bimean clustering, TR-1106, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, September 1981.

11. R. B. Boppana and A. Rosenfeld, Some properties of Hueckel-type edge operators, TR-1178, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, June 1982.

12. Z. Q. Wu and A. Rosenfeld, Filtered projections as an aid in corner detection, TR-1078, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, July 1981.

13. M. Pietikäinen, A. Rosenfeld, and L. S. Davis, Texture classification using averages of local pattern matches, TR-1098, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, September 1981.

14. C. Y. Wang and A. Rosenfeld, Elevation texture, TR-1086, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, August 1981.

15. T. H. Hong and A. Rosenfeld, Multiband pyramid linking, TR-1025, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, March 1981.

16. T. H. Hong, M. Shneier, and A. Rosenfeld, Border extraction using linked edge pyramids, TR-1080, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, July 1981.

17. C. Y. Wang, H. F. Sun, S. Yada, and A. Rosenfeld, Some experiments in relaxation image matching using corner features, TR-1071, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, July 1981.

18. H. F. Sun, Image registration by combining feature matching and gray level correlation, TR-1091, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, August 1981.

19. K. Prazdny, Computing motions of (locally) planar surfaces from spatio-temporal changes in image brightness: a note, TR-1090, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, August 1981.

20. L. S. Davis, H. F. Sun, and Z. Q. Wu, Motion detection at corners, TR-1130, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, December 1981.

21. Z. Q. Wu, H. F. Sun, and L. S. Davis, Determining velocities by propagation, TR-1132, Computer Vision Laboratory, Computer Science Center, University of Maryland, College Park, MD, December 1981.

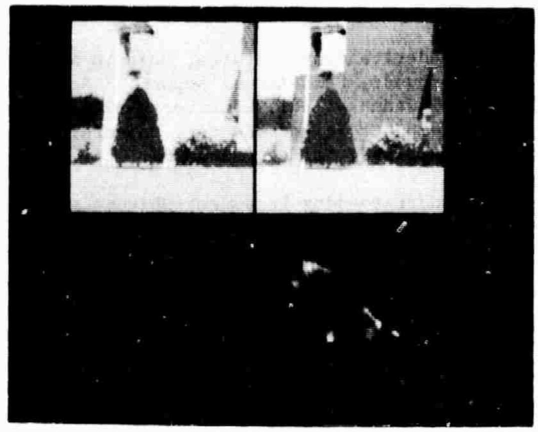
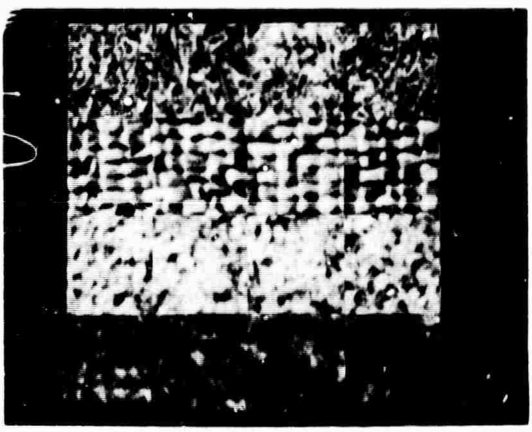


Figure 1. Multispectral "superspike". a) (Top) Red and green bands of a color image of a house. (Bottom) Scatter plot of (red, green) values, linearly (left) and logarithmically (right) scaled.

b) Results after application of "superspike"; the parts correspond to those in (a).



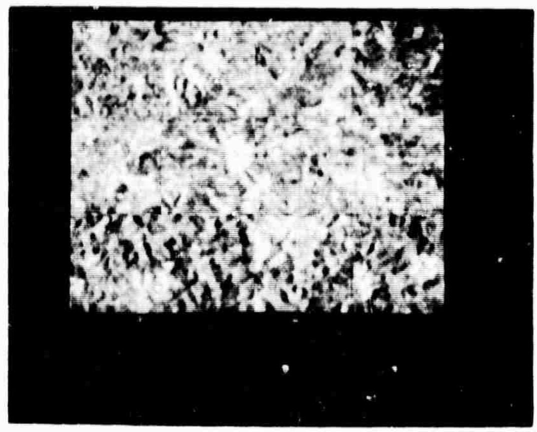


Figure 2. 28 texture samples. Left: grass, raffia, sand, wool. Right: three geological terrain types.

L5E5:

-1	-2	0	2	1
-4	-8	0	8	4
-6	-12	0	12	6
-4	-8	0	8	4
-1	-2	0	2	1

E5S5:

-1	0	2	0	-1
-2	0	4	0	-2
0	0	0	0	0
2	0	-4	0	2
1	0	-2	0	1

L5S5:

-1	0	2	0	-1
-4	0	8	0	-4
-6	0	12	0	-6
-4	0	8	0	-4
-1	0	2	0	-1

R5R5:

1	-4	6	-4	1
-4	16	-24	16	-4
6	-24	36	-24	6
-4	16	-24	16	-4
1	-4	6	-4	1

Figure 3. Four 5x5 Laws masks.

Feature:	L5E5	E5S5	L5S5	R5R5	CONX	CONY	E/A	WE/A
Score:	23	25	22	25	20	19	19	19

Table 1. Numbers of samples correctly classified using a single texture feature. CONX and CONY are Haralick's CON feature for displacements (1,0) and (0,1); (W)E/A is (magnitude-weighted) amount of edge per unit area.