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P. E. Anuta

C. Pomalaza

F. Davallou

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COMPARISON OF EDGE DETECTION METHODS FOR LANDSAT IMAGERY

P.E. ANUTA, C. POMALAZA, F. DAVALLOU

Purdue University/Laboratory for Applications of Remote Sensing West Lafayette, Indiana

I. INTRODUCTION

This poster paper describes the evaluation of four popular or new edge detection algorithms for Landsat imagery. These algorithms would, of course, be applicable to any similar type of imagery. The factors considered in selection of algorithms were:

- Numerical complexity.
- Nature of the particular analysis.
- Quality of the results obtained on test data on areas that contain typical field patterns.

Algorithms chosen for analysis were:

1. Sobel Gradient
2. Kirsch's Gradient
3. Frei and Chen Algorithm
4. Hueckel Algorithm

The algorithms and test data are first described and the experimental results are then briefly presented.

II. ALGORITHM DESCRIPTION AND TEST DATA

The gradient type algorithms tend to use a common neighborhood:

$b_1 \ b_2 \ b_3$   
 $b_4 \ b_5 \ b_6$   
 $b_7 \ b_8 \ b_9$

denote  $b$ , the image intensity vector, as  $b = (b_1 \dots b_9)$

The application of most algorithms involves the scalar product of  $b$  with particular weighting vectors.

Description of Algorithms

SOBEL GRADIENT[1]

$$\begin{aligned} dx &= b \cdot w_1 \\ dy &= b \cdot w_2 \end{aligned}$$

where  $w_1$  and  $w_2$  are defined as

$w_1$	$w_2$
1 0 -1	1 2 1
2 0 -2	0 0 0
1 0 -1	-1 -2 -1

KIRSCH'S GRADIENT [2]

Evaluate the "contrast" function,

$$\max (1, \max_{i=1}^8 |b \cdot w_i|)$$

where  $w_1 \dots w_8$  are

5 5 5	5 5 -3	5 -3 -3	-3 -3 -3
-3 0 -3	5 0 -3	5 0 -3	5 0 -3
-3 -3 -3	-3 -3 -3	5 -3 -3	5 5 -3
-3 -3 -3	-3 -3 -3	-3 -3 5	-3 5 5
-3 0 -3	-3 0 5	-3 0 5	-3 0 5
5 5 5	-3 5 5	-3 -3 5	-3 -3 -3

FREI and CHEN [3]

- Define an "edge" subspace by finding a set of orthogonal basis vectors. ( $w_1 \dots w_e$ ).

-- Complete the basis with 9-e "nonedge" basis vectors.

-- Project the image subarea intensity values b onto the edge subspace.

-- Evaluate the angle between b and its projection onto the edge subspace by

$$\theta = \arccos \left( \frac{\sum_{i=1}^e (b \cdot w_i)^2}{\sum_{j=1}^9 (b \cdot w_j)^2} \right)^{\frac{1}{2}}$$

-- The image subarea is considered as containing an edge element if  $\theta$  is small, i.e., thresholding the value of

$$\frac{\sum_{i=1}^e (b \cdot w_i)^2}{(b \cdot b)}$$

The nine orthogonal set of basis vectors for Frei & Chen method are:

-- Edge subspace

isotropic	1	$\sqrt{2}$	1	1	0	1
average	0	0	0	$\sqrt{2}$	0	$-\sqrt{2}$
gradient	-1	$-\sqrt{2}$	-1	1	0	-1
ripple	0	-1	$\sqrt{2}$	$\sqrt{2}$	-1	0
	1	0	-1	-1	0	1
	$-\sqrt{2}$	1	0	0	1	$-\sqrt{2}$

-- Line subspace

line	0	1	0	-1	0	1
	-1	0	-1	0	0	0
	0	1	0	1	0	-1
discrete	1	-2	1	-2	1	-2
laplacian	-2	4	-2	1	4	1
	1	-2	1	-2	1	-2

--Average

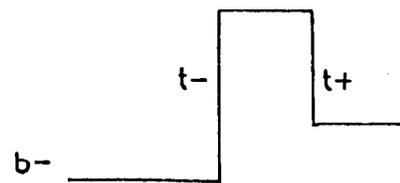
1	1	1
1	1	1
1	1	1

## HUECKEL ALGORITHM[4,5]

The key elements of the Hueckel algorithm are as follows:

-- Optimal values of an ideal edgeline to the image intensity values in a small circular neighborhood.

-- The ideal edge is determined by a 6-tuple of parameters: Three parameters determine the intensity levels (b-, t-, t+ as shown in figure below) and the other three parameters determine the position, orientation, and width of the line.



-- The fitting process consists of determining the value of the six parameters for a best fit with the image intensities, i.e., when,

$$N = || b - S(\text{tuple}) || \text{ is minimum}$$

S is an ideal edge image.

-- The minimization process is approximated by expansion of the input image disk and the edgeline in an orthogonal Fourier series. The minimization is then approximated by choosing a tuple such that,

$$N = \sum_{i=0}^8 (a_i - s_i)^2$$

where,

$a_i$  are the coefficients of expansion for the image and

$s_i$  are the coefficients for an ideal edgeline.

-- The reasons for using only the first nine terms of the expansion are:

(a) Higher order terms correspond to noise in the image and should be ignored.

(b) An analytical solution to the minimization problem is found using nine terms.

### III. ANALYSIS

The four algorithms were implemented and tested on Landsat MSS and RBV data from areas in Iowa. These selections were based on data availability and were tested as acquired. The RBV imagery exhibited a speckled noise much like that of radar imagery. These artifacts are thought to be due to analog telemetry and preprocessing problems. Since other data sets could not be acquired and inspected in the time frame of the study, the data on hand were used. In order to reduce the noise in the image, the following procedures were considered:

Linear Filtering. This is a common method to improve the S/N. However, due to the low-pass frequency characteristic of almost all common linear filters, the edges will be smoothed, making their detection more difficult when applying some of the algorithms discussed before.

Non-Linear Filtering. Some non-linear filters have the property of increasing the S/N, preserving at the same time the edges of the image. One of these filters is the median filter. To compare the effect of this filter, a 3-pixel by 3-pixel window linear box filter was applied to test data from Iowa along with the median filter, also using a 3x3 neighborhood. The doubly median filter results were judged best for use in edge detection. The linear filter result is still quite noisy and the fields show some blurring.

The various algorithms for edge detection were applied to the doubly median filtered RBV data. Results obtained by the Algorithms Kirsch and Frei & Chen are indistinguishable from those from the Sobel algorithm. Computation times are compared in Table 1. Taking into account that the computation of the Sobel gradient requires less CPU time than the other algorithms, it was concluded the Sobel gradient method is the most attractive of the gradient algorithms.

The application of Hueckel's algorithm seems more appropriate for a localized edge detection and/or location problem rather than an image preprocessing step to produce an enhanced image. The output of this algorithm is a sextuple of parameters that defines the intensity levels, position, location and width of the ideal edge that best fit the circular neighborhood where a successful edge de-

Table 1. Computation time for the four algorithms for an area of 300 by 300 pixels on an IBM 3031.

Algorithm	CPU Seconds
Sobel	30
Kirsch	60
Frei & Chen	40
Hueckel	50

tection has been made. By using these parameters, the resolution of the edge location is available at a subpixel level. Registration applications could take advantage of these results especially when registering images that have different resolutions. The need to incorporate a line-following algorithm in order to process a scene that has several edge-line patterns could make the application of this method more expensive in terms of computer time than the use of the previously mentioned algorithms, followed by some type of postprocessing graph interpolation procedure.

### IV. SUMMARY

Sobel, Kirsch, and Frei & Chen algorithms give basically the same type of image. A threshold operation to obtain a binary image provides a more interpretable edge image. The value of the threshold depends on the particular characteristics of the scene being analyzed. One method that could be used is the threshold selection procedure developed by C.M. Gurney[7]. Also some postprocessing algorithms to interpolate graphs and remove isolated noisy segments are necessary.

Hueckel's algorithm has the advantage of providing an equation for the edge-line pattern detected inside the area of analysis (disk of pixels). This equation can define the location of the edges and lines within a subpixel resolution which could be used for registration purposes. For the processing of a scene, a line-following algorithm has to be used in combination with the edge-line detection program in order to obtain a continuous type image.

## REFERENCES

1. Rosenfeld, A. and A. Kak, Digital Picture Processing, Academic Press, 1976.
2. Kirsch, R., "Computer Determination of the Constituent Structure of Biological Images," *Comput. Biomed. Res.* 4, 1971, pp. 315-328.
3. Frei, W. and C. Chen, "Fast Boundary Detection: A Generalization and a New Algorithm," *IEEE Trans. on Computers*, Oct. 1977, pp. 988-998.
4. Hueckel, M.H., "A Local Visual Edge Operator Which Recognizes Edges and Lines," *J. Assn. Comput. Mach.*, 20, 1973, pp. 634-647.
5. Hueckel, M.H., "An Operator Which Locates Edges on Digitized Pictures," *J. Assn. Comput. Mach.*, 18, pp. 113-125.
6. Frieden, B.R., "A New Restoring Algorithm for the Preferential Enhancement of Edge Gradients," *J. Opt. Soc. Amer.*, Vol. 66, pp. 280-282, 1976.
7. Gurney, M.G., "Threshold Selection for Line Detection Algorithms," *IEEE Trans. on Geosc. and Remote Sens.*, Vol. GE-18, pp. 204-211, Apr. 1980.

## AUTHOR BIOGRAPHICAL DATA

PAUL E. ANUTA is Associate Program Leader for Data Handling Research at the Laboratory for Applications of Remote Sensing (LARS) at Purdue University. He received a B.S., Electrical Engineering, Purdue University in 1957; M.S.E.E., University of Connecticut in 1962; and an M.S. in Computer Science, Purdue University in 1967.

Mr. Anuta joined the LARS staff in 1967 and has researched data handling systems for a multispectral aircraft scanner

system, interferometer spectrometer, and other sensors. He is responsible for research and evaluation of remote sensor data preprocessing techniques. Key data handling research areas are image registration, geometric correction, and resolution enhancement of satellite multispectral imagery.

His current interests are in the area of multitype data integration and preprocessing and analysis methods. He is a member of Tau Beta Pi, Eta Kappa Nu, The Institute of Electrical and Electronics Engineers, and the American Society of Photogrammetry.

CARLOS POMALAZA, a post-doctoral research associate and research assistant at LARS for several years, is now with the Department of Electronics at the National Institute of Higher Education at Limerick, Ireland. Dr. Pomalaza came to Purdue University from Peru where he had been research assistant in the remote sensing program at the Institute of Geophysics for Peru.

Dr. Pomalaza's most recent work at LARS involved the use of signal processing and information extraction disciplines and also research and development of advanced technology for processing remote sensing data obtained from satellite and aircraft systems.

He received both his M.S.E.E. (1977) and Ph.D. in E.E. (1980) from Purdue.

FARZIN DAVALLOU is graduate research assistant at LARS. His work has included programming and running research software for various research projects. More recently he has conducted research on image processing techniques associated with remote sensing.

A native of Tehran, Iran, Mr. Davallou came to Purdue in 1979 after graduation from Azar High School where he majored in math and physics. He received his B.S.E.E. from Purdue in May 1982 and is working toward his M.S.E.E. He is a member of Phi Eta Sigma and Eta Kappa Nu.