CORNER DETECTION USING THE FACET MODEL

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Abstract

We describe several techniques to detect corners in digital images which operate directly on the gray tone image. These gray tone corner detectors are based on the facet model which considers the pixels values in a given neighborhood to be discrete quantized noisy samples from an underlying continuous gray tone intensity surface. Under this model any property of the neighborhood is computed from that continuous surface.

Among the various facet model corner detectors proposed we find that the one that performs best is the one which considers a corner point as an edge point where incremental change in gradient direction along a contour line exceeds a given threshold and which uses the nearest facet neighborhood to each of the points tested on the contour line. The next best is the simplest one, which measures the incremental change along a tangent line and uses only the central facet neighborhood for all the points tested on the tangent line.

We show experimental results indicating that our corner detector performs better than the Kitchen-Rosenfeld corner detector and the Dreschler-Nagel corner detector using the criterion of probability of correct assignment.

I Introduction

The detection of corners in images has been shown to be extremely useful for computer vision tasks. Huertas (1981) uses corners to detect buildings in aerial images. Nagel and Enkelmann (1982) use corner points to determine displacement vectors from a pair of consecutive images taken in time sequence. Much of the past research in corner detection has relied on prior segmentation of the image and subsequent analysis of region boundaries. Rutkowski and Rosenfeld (1978) provide a comparison of several corner detection techniques along those lines.

More recent research has focused on developing ''gray tone corner detectors'' which detect corners by operating directly on the gray tone image. As Kitchen and Rosenfeld (1980) point out the main advantage of such corner detectors is that their performance is not dependent on the success or failure of a prior segmentation step. Among the earliest such corner detectors is Beaudet's DET operator (1978) which responds significantly near corner and saddle points. Kitchen and Rosenfeld report results using several operators which measure cornerness by the product of gradient magnitude and rate of change of gradient direction. Dreschler and Nagel (1981) investigate points lying between extrema of Gaussian curvature as suitable candidates for corner points.

Our approach to corner detection is based on the facet model for digital images (Haralick (1980), Haralick and Watson (1981)). The basic philosophy of this model derives from recognizing that the discrete set of values which form the digital image are the result of sampling and quantizing a real-valued function f defined on the domain of the image which is a bounded and connected subset of the real plane. Thus, any property associated with a pixel or a neighborhood of pixel values should be evaluated by relating it to the property of the corresponding gray tone surface f which underlies the neighborhood. This involves estimating the surface function f locally, from the neighborhood samples available to us. The most natural way of accomplishing this is by assumming a parametric form for f and then estimating its associated parameters. In this paper we have chosen to represent the gray tone surface f by a cubic polynomial in the row and column coordinates of the neighborhood array. More precisely for each neighborhood f is of the form:

$$f(r,c) = k_1 + k_2 r + k_3 c + k_4 r^2 + k_5 rc + k_6 c^2 + k_7 r^3 + k_8 r^2 c + k_9 rc^2 + k_{10} c^3 \quad (1)$$

In this paper we investigate that property of a pixel which we will call ''cornerness''. Suppose for instance that we are shown an aerial photograph of a city and are asked to identify corners in it. Our attention would be likely drawn first to objects such as buildings where the concept of corners expresses itself very clearly in a natural way. Two walls of a building meet usually at 90 degrees and we would declare the intersection point to be a corner. But there are other places where we would see corners as well, where the shadows due to two adjacent walls meet, where two roads intersect, in a patch of field of a certain shape, etc. In general what we are usually inclined to call a corner occurs where two edge boundaries meet at a certain angle or where the direction of an edge boundary is changing very rapidly. We associate corners therefore with two things: the occurence of an edge and significant changes in edge direction.

These two concepts have a very straight-forward and clear meaning under the facet model. Edges under this model have been investigated by Haralick (1980). In particular a step edge operator based on zero-crossing of second directional derivatives has been developed by Haralick (1982) with very encouraging results even in such difficult imagery as aerial scenes. Edge direction is most naturally expressed as a direction orthogonal to the gradient direction at the point of occurrence of an edge.

Section II describes the essentials of Haralick's zero-crossing of second directional derivative step edge detector which we will use as part of the corner detection process. In section III we describe several corner detectors based on the facet model and in section IV we present our experimental results and comparison against the Kitchen-Rosenfeld and Dreschler-Nagel corner detectors.

II Zero-Crossing of Second Directional Derivative Edge Detection

Under the facet model step edges occur at relative extrema in first directional derivative of the continuous gray tone function f underlying a given neighborhood of pixel values. Relative extrema in first directional derivative can reveal themselves as zero-crossings of the second directional derivative. More precisely, a pixel is marked as an edge pixel if in the pixel's immediate area there is a zero crossing of the second directional derivative taken in the direction of the gradient (Haralick (1982)). It has been shown that this kind of edge detector can respond to weak but spatially peaked gradients.

Given a surface function f defined in the row and column coordinate system of a given pixel neighborhood, the gradient vector function ∇f is given by

$$\nabla f = \left(\frac{\partial f}{\partial r}, \frac{\partial f}{\partial c}\right) \qquad (2)$$

For a given direction vector $(\sin\theta, \cos\theta)$, it is well known that the directional derivative $f'_\theta(r,c)$ of f in the direction θ can be evaluated as the component of the gradient ∇_f along the direction vector, that is

$$f'_\theta(r,c) = \frac{\partial f}{\partial r}\sin\theta + \frac{\partial f}{\partial c}\cos\theta \qquad (3)$$

Using (2) on $f'_\theta(r,c)$ the second directional derivative $f''_\theta(r,c)$ of f in the direction θ can be readily evaluated as:

$$f''_\theta(r,c) = \frac{\partial^2 f}{\partial r^2}\sin^2\theta + \frac{2\partial^2 f}{\partial r \partial c}\sin_\theta\cos\theta + \frac{\partial^2 f}{\partial c^2}\cos^2\theta \qquad (4)$$

Let us consider points (r,c) on a line passing through the point $(r_0 c_0)$ in the direction θ. Then:

$$r = r_0 + \rho\sin\theta,\ c = c_0 + \rho\cos\theta \qquad (5)$$

We take θ to be the gradient angle at $(r_0 c_0)$. Hence

$$\theta = \tan^{-1}\frac{\partial f/\partial r\ (r_0,c_0)}{\partial f/\partial c\ (r_0 c_0)} \qquad (6)$$

Using the cubic polynomial approximation of f given by (1) gradient angle θ becomes:

$$\theta = \tan^{-1}\frac{k_2+2k_4r_0+k_5c_0+3k_7r_0^2+2k_8r_0c_0+k_9c_0^2}{k_3+k_5r_0+2k_6c_0+k_8r_0^2+2k_9r_0c_0+3k_{10}c_0} \qquad (7)$$

and

$$\begin{aligned} f''_\theta(r,c) &= f''_\theta(r_0c_0;\rho) \\ &= 2(3k_7\sin^2\theta + 2k_8\sin\theta\cos\theta + k_9\cos^2\theta)r_0 \\ &+ 2\ (k_8\sin^2\theta + 2k_9\sin\theta\cos\theta + 3k_{10}\cos^2\theta)c_0 \\ &+ 2\ (k_4\sin^2\theta + k_5\sin\theta\cos\theta + k_6\cos^2\theta) \\ &+ 6\ (k_7\sin^3\theta + k_8\sin^2\theta\cos\theta + k_9\sin\theta\cos^2\theta \\ &+ k_{10}\cos^3\theta)\rho \end{aligned} \qquad (8)$$

Hence, we declare the point (r_0, c_0) to be an edge point if for some ρ, $|\rho| < p_0$ where p_0 is slightly smaller than the length of the side of a pixel, $f''_\theta(r_0, c_0; \rho) = 0$ and $f'_\theta(r_0, c_0; \rho) \neq 0$.

III Corner Detectors

As previously discussed, under the facet model corners occur at edge points where a significant change in gradient direction takes place. Now, this change in gradient direction should ideally be measured as an incremental change along the edge boundary. We do not desire, however, to perform boundary following since that would require a prior segmentation step. There are several ways in which we have tried to circumvent this problem based on the realization that according to our model the direction of an edge point, that is the tangent to the edge boundary at that point, is orthogonal to the gradient vector at that same point. The simplest approach is to compute the incremental change in gradient direction along the tangent line to the edge at the point which is a corner candidate. The second approach is to evaluate the incremental change along the contour line which passes through the corner candidate. Finally we can compute the instantaneous rate of change in gradient direction in the direction of the tangent line. In what follows we investigate each of these approaches. In all of them the analysis is based on a continuous surface f obtained by least squares fitting an NxN square neighborhood centered around the corner candidate pixel to the cubic polynomial described in (1).

The properties of those points away from the neighborhood center and possibly outside the pixel itself have been computed by two different methods: a) using the surface fit from the central neighborhood b) using the surface fit from the neighborhood centered around the pixel closest to the tested point.

Although the first method is computationally less expensive than the second one the possibility of better accuracy exists in the second one.

III.1 Incremental Change Along Tangent Line

Consider a row-column coordinate system centered at the corner candidate point. Let $\theta(r,c)$ be the gradient at coordinate (r,c) and let $\theta_0 = \theta(0,0)$. Then $(\sin\theta_0, \cos\theta_0)$ is a unit vector in the direction of the gradient at the origin. If the origin is an edge point, the tangent line to the edge boundary which passes through it has direction given by $(-\cos\theta_0, \sin\theta_0)$ and an arbitrary point lying on that line is $\rho(-\cos\theta_0, \sin\theta_0)$.

Consider two points $P_1 = (r_1, c_1)$ $P_2 = (r_2, c_2)$ equidistant to the origin and lying on the tangent line. (See fig. 1).

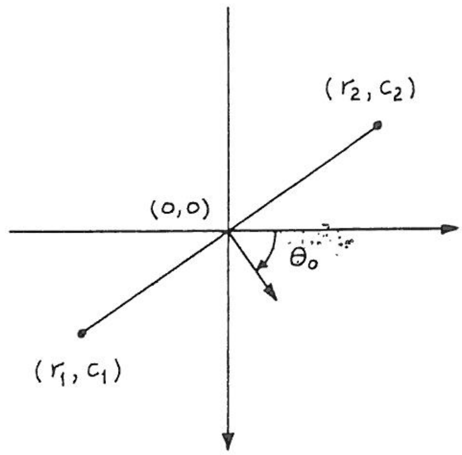

Fig. 1

P_1 and P_2 are given by $-R(\cos\theta_0, \sin\theta_0)$ and $R(-\cos\theta_0, \sin\theta_0)$ respectively where R is the distance from each point to the origin. If R is not too large we can expect the true boundary to lie not too far away from either P_1 or P_2. In this case a suitable test to decide whether the origin (0,0) is a corner point would involve meeting the following two conditions:

(1) $(0,0)$, (r_1, c_1), (r_2, c_2) are edge points
(2) For a given threshold Ω
$$|\theta(r_1, c_1) - \theta(r_2, c_2)| > \Omega$$

III. 2 Incremental Change Along Contour Line

It is reasonable to assume that points on the edge boundary to each side of the corner point and close to it are likely to have similar gray tone intensities. This motivates us to approximate the edge boundary by the contour line $f(r,c)=f(0,0)$ which passes through the corner candidate point at the origin of the coordinate system.

We consider two points $P_1 = (r_1, c_1)$ and $P_2 = (r_2, c_2)$ equidistant to the origin and lying on the contour line instead of the tangent line as in III.1. (See fig. 2). Let $\theta(r,c)$ be the gradient direction at coordinates (r,c).

The test to decide whether the origin (0,0) is a corner point is similar to the one used in the previous approach. That is, (0,0) is declared to be a corner point if the following two conditions are satisfied:

(1) $(0,0)$, (r_1, c_1), (r_2, c_2) are edge points
(2) For a given threshold Ω
$$|\theta(r_1, c_1) - \theta(r_2, c_2)| > \Omega$$

This approach is computationally more expensive than the previous one due to the need of

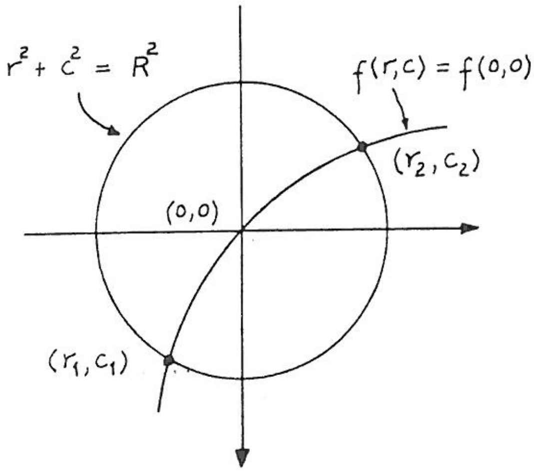

Fig. 2

intersecting the cubic curve $f(r,c) = f(0,0)$ (the contour line) with the quadratic curve $r^2+c^2 = R^2$ in order to determine the points P_1 and P_2 a distance R from the origin.

III. 3 Instantaneous Rate of Change

Let $\theta(r,c)$ be the gradient direction at coordinates (r,c) and let $\theta'_\alpha(r,c)$ be the first directional derivative of $\theta(r,c)$ in the direction α. We can compute $\theta'_\alpha(r,c)$ as follows.

Let $f(r,c)$ be the surface function underlying the neighborhood of pixel values centered at the corner candidate pixel. Let $f_r(r,c)$ and $f_c(r,c)$ denote the row and column partial derivatives of f. Consider the line passing through the origin in the direction α. An arbitrary point in this line is given by $\rho(\sin\alpha,\cos\alpha)$ and the gradient direction at that point is given by

$$\theta(\rho\sin\alpha,\ \rho\cos\alpha) = \frac{f_r(\rho\sin\alpha,\ \rho\cos\alpha)}{f_c(\rho\sin\alpha,\ \rho\cos\alpha)} \tag{9}$$

which can be written as:

$$\theta(\rho) = f_r(\rho)/f_c(\rho) \tag{10}$$

Differentiating with respect to the parameter ρ results in

$$\theta'(\rho) = \frac{f_c(\rho)f'(\rho) - f_r(\rho)f'c(\rho)}{(f_r(\rho))^2 + (f_c(\rho))^2} \tag{11}$$

Using the cubic polynomial approximation for f given in (1) we have:

$$f_r(\rho) = k_2 + (2k_4\sin\alpha + k_5\cos\rho)\rho + (3k_7\sin^2\alpha + 2k_8\sin\alpha\cos\alpha + k_9\cos^2\alpha)\rho^2$$

$$f_c(\rho) = k_3 + (k_5\sin\alpha + 2k_6\cos\alpha)\rho + (k_8\sin^2\alpha + 2k_9\sin\alpha\cos\alpha + 3k_{10}\cos\alpha)\rho^2$$

$$f'_r(\rho) = (2k_4\sin\alpha + k_5\cos\alpha) + 2\,(3k_7\sin^2\alpha + 2k_8\sin\alpha\cos\alpha + k_9\cos^2\alpha)\rho$$

$$f'_c(\rho) = (k_5\sin\alpha + 2k_6\cos\alpha) + 2(k_8\sin^2\alpha + 2k_9\sin\alpha\cos\alpha + 3k_{10}\cos\alpha)\rho$$

the rate of change of gradient direction

in the direction α evaluated at the origin (ρ=0) is then:

$$\theta'_\alpha(0) = \frac{k_3(2k_4\sin\alpha+k_5\cos\alpha) + k_2(k_5\sin\alpha + 2k_6\cos\alpha)}{k_2^{\,2} + k_3^{\,2}} \tag{12}$$

We are interested in the value of $\theta'_\alpha(0)$ when the direction α is orthogonal to the gradient direction at the origin (the edge direction). Since (k_2,k_3) is the gradient vector at the origin, $(-k_3,k_2)$ is a vector orthogonal to it, and

$$\alpha = \tan^{-2} -k_3/k_2 \tag{13}$$

Finally using (13) in (12) we obtain

$$\theta'_\alpha(0) = \frac{-2(k_2^{\,2}k_6 - k_2k_3k_5 + k_3^{\,2}k_4)}{(k_2^{\,2} + k_3^{\,2})^{3/2}} \tag{14}$$

The test to decide whether the origin (0,0) is a corner point is as follows. We declare (0,0) to be a corner point if the following two conditions are satisfied:

(1) (0,0) is an edge point

(2) For a given threshold Ω

$$|\theta'(0)_\alpha| > \Omega.$$

IV Experimental Results

We evaluate the performance of the various facet model based gray tone corner detectors by applying them to two digital images. The first one represents a set of artificially generated rectangular shapes at various orientations. The second one is a real aerial image of an urban scene. The first image is 90x90 pixels and contains rectangular shapes of 20x20 pixels with orientations ranging from 0 to 90 degrees in 10 degrees increments. The rectangles have gray tone intensity 175 and the background has gray tone intensity 75. Independent Gaussian noise with zero mean and standard deviation 10 has been added to this image. Defining the signal to noise ratio as 10 times the logarithm of the range of signal divided by the standard duration of the noise, the artifically generated image has a 10DB signal to noise ratio. The perfect and noisy versions are shown in figure 3.

Section IV.1 illustrates the performance of the various facet model based gray tone corner detectors. Section IV.2 compares the performance of the best facet model based gray tone corner detector against the performance of the best Kitchen-Rosenfeld gray tone corner detector and the Dreschler-Nagel corner detector. It is shown that the facet model based gray tone corner detector performs best on the basis of probability of correct assignment.

IV.1 Facet Model Based Corner Detectors

Figure 4 (a), (b), and (c) illustrates the results of applying each of the corner detector techniques discussed in section III to the artificially generated noisy image. In all cases the neighborhood size is 7x7 pixels. The gradient threshold for edge detection is 20. If the gradient exceeds the threshold value and a zero-crossing occurs in a direction of $\pm$ 14.9 degrees of the gradient direction within a circle of radius one pixel length centered at the point of test then this point is declared to be an edge point.

Also shown are the incremental change in gradient angle threshold for each of the cases. Two types of angle threshold have been used. The first type maximizes the conditional probability of assigning a corner given that there is a corner. The second type of threshold was chosen to equalize as best as possible the conditional probability of assigning a corner given that there is a corner and the conditional probability of these being a true corner when a corner is assigned.

A true corner is defined as the interior pixel in the rectangular shape where two adjacent sides meet. Table 1 shows the probability of correct corner assignment for each case, as well as the angle thresholds. This table shows that the method which performs best is the one which measures changes in gradient direction as incremental changes along a contour line and which computes properties of points away from the neighborhood center using the surface fit from the neighborhood centered around the pixel closest to the tested point. Surprisingly the simplest facet method which uses incremental changes along the tangent line and properties from the centered neighborhood performed next best. We also notice from table 1 in order to detect most of the true corners a significant rate of misassignment occurred. For most methods illustrated in table 1 only one out of every five pixels assigned a corner is a true corner assignment. Fortunately all misassigned points occur in connected clusters one or two pixels away from the true corner points, and the true corner points belong to the cluster. This leaves open the possibility of eliminating the misassigned points by further processing.

IV.2 Comparison With Other Gray Tone Corner Detectors

The performance of the best facet model based corner detector according to Table 1 has been compared against the performance of two recently developed gray tone corner detectors: the Kitchen-Rosenfeld corner detector (1980) and the Dreschler-Nagel corner detector (1982).

Kitchen and Rosenfeld investigated several techniques for gray tone corner detection. Each one computed for every pixel in the image a measure of cornerness and then corners were obtained by thresholding. Their best results are obtained by measuring cornerness by the product of gradient magnitude and instantaneous rate of change in gradient direction evaluated from a quadratic polynomial gray tone surface fit.

Dreschler and Nagel detect corners by the following procedure: For each pixel in the image compute its Gaussian curvature. This is done by doing a local quadratic polynomial fit for each pixel and computing the Hessian matrix. The Gaussian curvature is the product of the main curvatures (eigenvalues of the Hessian matrix). Next, locations of maximum and minimum Gaussian curvatures are found. A pixel is declared to be a corner if the following conditions are satisfied:

(1) It has the steepest slope along the line which connects the location of the maximum with the location of the minimum of Gaussian curvature. (This is done only for extrema lying within a given radius from the corner candidate pixel.)

(2) The gray tone intensity at the location of maximum Gaussian curvature is larger than the gray tone intensity at the location of minimum Gaussian curvature.

(3) The orientation of the main curvature which changes sign between the two extrema, points into the direction of the associated extremum.

Figure 5 (a) and (b) illustrates the results of applying the facet model based, Kitchen-Rosenfeld, and Dreschler-Nagel gray tone corner detectors to the artificially generated noisy image. In all cases we use a cubic polynomial fitting on a 7x7 pixels neighborhood. A slight modification of Kitchen-Rosenfeld corner detector is also reported which allows to consider only points whose gradient exceeds a given threshold. This results in a substantial improvement of the original Kitchen-Rosenfeld method. The Dreschler-Nagel corner detector showed to be the most sensitive to noise and also a gradient threshold had to be used to improve its performance. Since all three methods being compared use the same cubic polynomial surface fit and the same 7 x 7 pixels neighborhood size, the same gradient threshold of 20 was used in each of them to minimize the effects of the noise. The search for Gaussian curvature extrema was done in a 5x5 neighborhood. Table 2 shows the probability of correct corner assignment for each case. The best results according to this table are obtained by using the facet model based corner detector, next comes the Kitchen-Rosenfeld corner detector. The Dreschler-Nagel corner detector performs the worst.

Finally figure 6 illustrates the results obtained by applying each of these corner detectors to the aerial image. In all cases we use a cubic polynomial fitting on a 7 x 7 pixels neighborhood. Gradient thresholds are equal to 16.

V Conclusions

We have investigated various approaches for gray tone corner detection which are based on the facet model. We have compared their performance with Kitchen-Rosenfeld and Dreschler-Nagel gray tone corner detectors. We found that for both the artificially generated and the real image the facet model based gray tone corner detector had superior performance.

Further work needs to be done. We need to explore the relationship of basic function kind (polynomial, trigonometric polynomial, etc.), order of fit, and neighborhood size to the goodness of fit. An statistical analysis of each of the techniques described needs to be developed.

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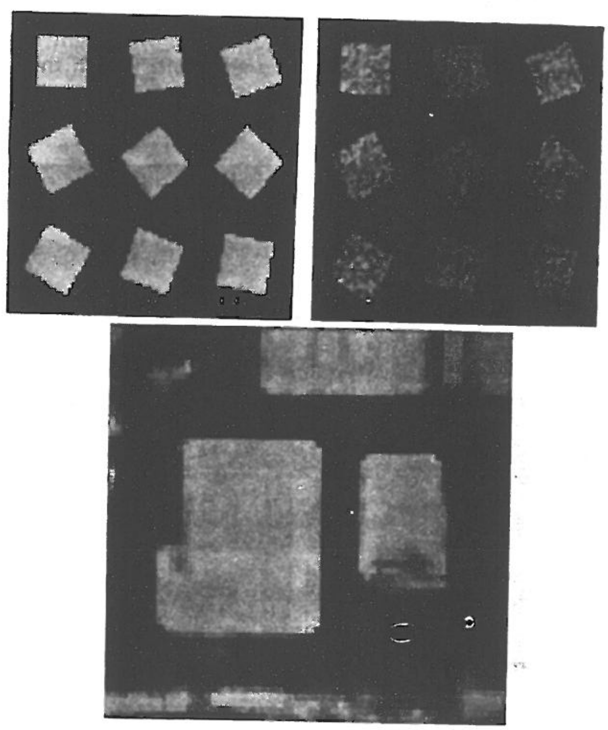

Fig. 3 shows the perfect and noisy artificially generated image and the aerial scene.

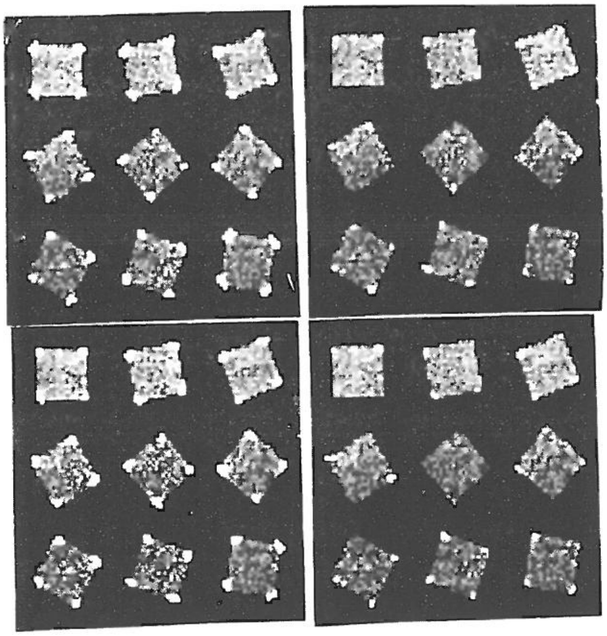

Fig. 4(a) shows the corner assignments for the facet method which uses incremental angle change along a tangent line. The ones on top use the same central neighborhood for all tested points. The ones on the bottom use the neighborhood centered around the pixel closest to the tested point. Two types of angle threshold are illustrated, the ones on the left maximize the conditional probability of assigning a corner given that there is a corner, the ones on the right equalize as best as possible this probability with the conditional probability of there being a true corner when a corner is assigned. Parameters are in Table 1.

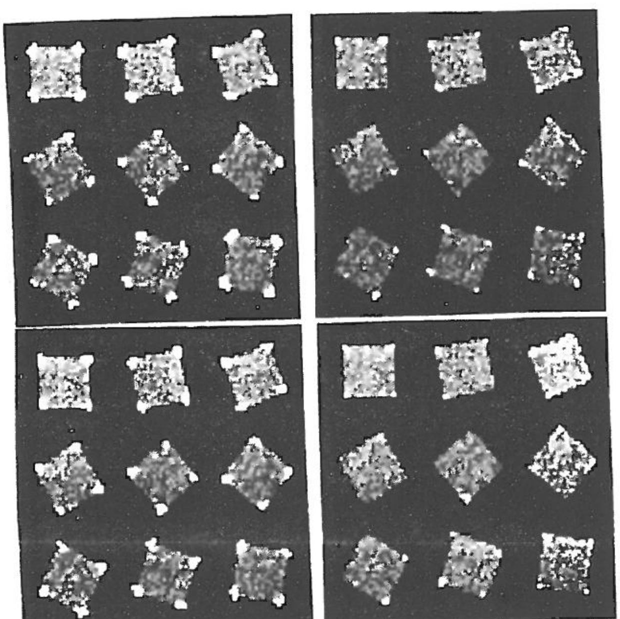

Fig. 4(b) Same as in fig. 4(a) but using incremental angle change along a contour line.

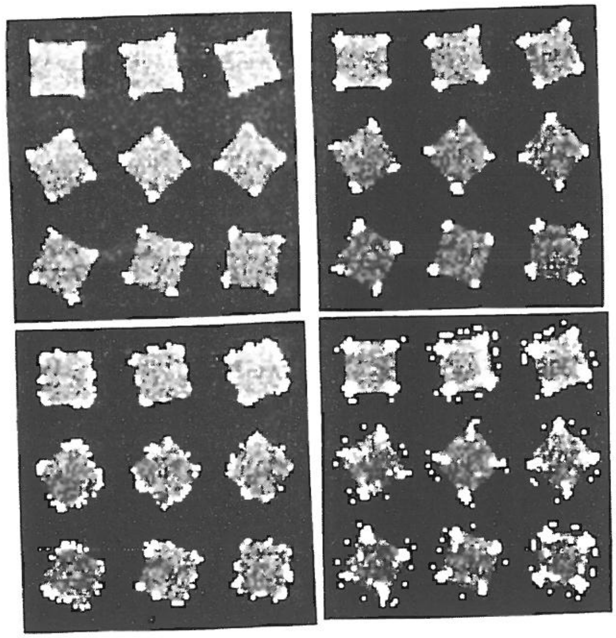

Fig. 5(a) shows in clockwise order from top-left the corner assignments for the best facet model, the Kitchen-Rosenfeld (with and without gradient threshold) and the Dreschler-Nagel corner detectors. Parameters are in Table 2. The thresholds used in each case maximize the conditional probability of assigning a corner given that there is a corner.

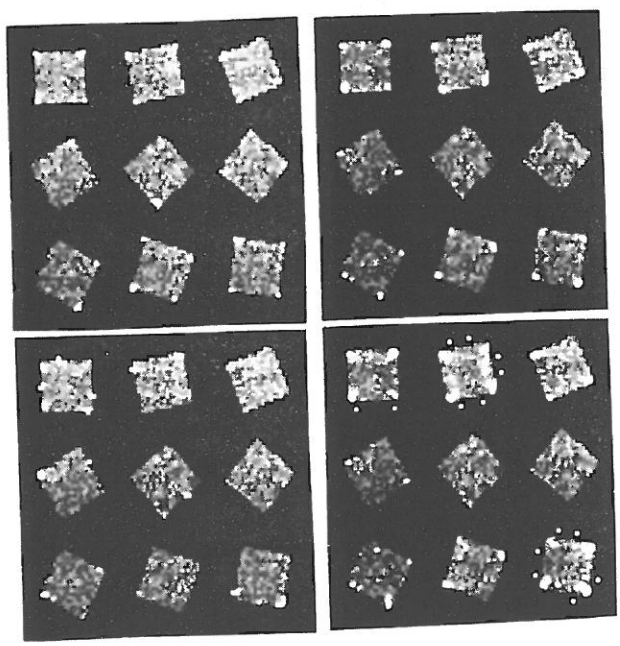

Fig. 5(b) Same as in fig. 5(a) but thresholds used equalize as best as possible the conditional probability of there being a true corner when a corner is assigned.

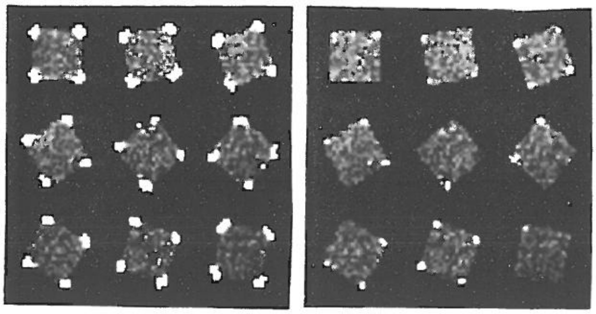

Fig. 4(c) shows the corner assignments for the facet method which uses instantaneous rate of change of gradient direction in a direction orthogonal to the gradient direction. Two types of rate of angle change threshold are illustrated, the ones on the left maximize the conditional probability of assigning a corner given that there is a corner, the ones on the right equalize as best as possible this probability with the conditional probability of there being a true corner when a corner is assigned. Parameters are in Table 1.

Gradient threshold = 20	Max P(ac/tc)			P(ac/tc) = P(tc/ac)		
	P(ac/tc)	P(tc/ac)	Angle thresh	P(ac/tc)	P(tc/ac)	Angle thesh
Incremental change along tangent line, central neighborh., increment=3.5pixels	0.972	0.210	40°	0.278	0.250	55°
Incremental change along tangent line, nearest neighborh., increment=3.5pixels	0.917	0.192	50°	0.111	0.108	80°
Incremental change along contour line, central neighborh., increment=3.5pixels	0.972	0.199	45°	0.278	0.294	63°
Incremental change along contour line, nearest neighborh., increment=4pixels	1.000	0.207	65°	0.361	0.361	94°
Instantaneous rate of change	0.972	0.139	9°/ pixel	0.083	0.075	16°/ pixel

Table 1 compares the performance of the facet model based corner detectors. P(ac/tc) is the conditional probability of assigning a corner given that there is a corner. P(tc/ac) is the conditional probability of there being a true corner when a corner is assigned.

	Max P(ac/tc)		P(ac/tc) = P(tc/ac)	
	P(ac/tc)	P(tc/ac)	P(ac/tc)	P(tc/ac)
Best facet model corner detector	1.000	0.207	0.361	0.361
Kitchen-Rosenfeld, no gradient threshold	0.972	0.071	0.055	0.021
Kitchen-Rosenfeld, gradient threshold = 20	0.972	0.146	0.055	0.050
Dreschler-Nagel, gradient threshold = 20	0.222	0.028	0.055	0.059

Table 2 compares the performance of the best facet model corner detector with the Kitchen-Rosenfeld and the Dreschler-Nagel corner detectors.

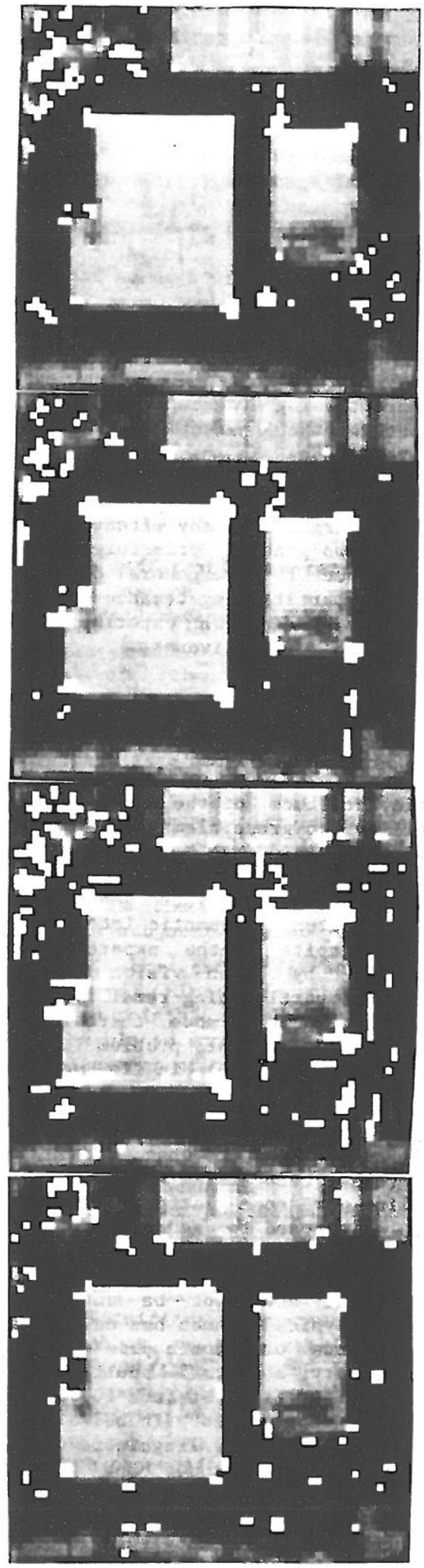

Fig. 6 compares the corner assignments in the aerial scene for the best facet model, the Kitchen-Rosenfeld (with and without gradient threshold) and the Dreschler-Nagel corner detectors.