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Study of Corner Detection Algorithms and Evaluation Methods

S.Y.Pattar

Associate Professor, Department of Medical Electronics, BMS College of Engineering, Bangalore, India

ABSTRACT:Interest points are widely used in computer vision applications such as camera calibration, robot localization and object tracking that require fast and efficient feature matching. A large number of techniques have been proposed in the literature. Such comparative study is crucial for specific applications. It is always necessary to understand the advantages and disadvantages of the existing techniques so that best possible ones can be selected.
In this paper a study of Harris, Moravec and SUSAN Corner detection Algorithms has been done for obtaining features required to track and recognize objects in an image. Corner detection of noisy images is a challenging task in image processing. Natural images often get corrupted by noise during acquisition and transmission. As Corner detection of these noisy images does not provide desired results, hence de noising is required.

KEYWORDS: Corner detection, Interestpoints, Noisy images, Feature matching

I. INTRODUCTION

A corner is a point for which there are two dominant and different edge directions in the vicinity of the point. A corner can be defined as the intersection of two edges, where an edge is a sharp change in image brightness. Generally termed as interest point detection, corner detection is a methodology used within computer vision systems to obtain certain kinds of features from a given image. The Moravec operator is considered to be a corner detector because it defines interest points as points where there are large intensity variations in all directions.

For a human, it is easier to identify a "corner" but a mathematical detection is required in case of algorithms. Chris Harris and Mike Stephens in 1988 improved upon Moravec's corner detector by taking into account the differential of the corner score with respect to direction directly, instead of using shifted patches. Moravec only considered shifts in discrete 45 degree angles whereas Harris considered all directions. Harris detector has proved to be more accurate in distinguishing between edges and corners. In this method a circular Gaussian window is used to reduce noise.

II. HARRIS CORNER DETECTION

In this section the derivation of the Harris corner detector is presented .The Harris corner detector is a popular interest point detector due to its strong invariance to rotation, scale, illumination variation and image noise. The Harris corner detector is based on the local auto-correlation function of a signal where the local auto-correlation function measures the local changes of the signal with patches shifted by a small amount in different directions Given a shift (Δx, Δy) and a point (x, y), the auto-correlation function is defined as,

$$C(x, y) = \sum_{w}[I(x_i, y_i) - I(x_i + \Delta x, y_i + \Delta y)]^2 \quad (1)$$

where I(·, ·) denotes the image function and (xi, yi) are the points in the window W (Gaussian) centered on (x, y).The shifted image is approximated by a Taylor expansion truncated to the first order terms

$$I(x_i + \Delta x, y_i + \Delta y) = I(x_i, y_i) + \left[I_x(x_i\ , y_i)\ \ I_y(x_i\ , y_i)\right] \begin{bmatrix}\Delta x\\ \Delta y\end{bmatrix} (2)$$

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where Ix and Iy denote the partial derivatives in x and y, respectively .Substituting Eq. (2) into Eq. (1) yields,

$$C(x, y) = \sum_w [I(x_i, y_i) - I(x_i + \Delta x, y_i + \Delta y)]^2 \quad (3)$$

$$= \sum_w \left(I(x_i, y_i) - I(x_i, y_i) - [I_x(x_i, y_i)\ \ I_y(x_i, y_i)] \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} \right)^2 \quad (4)$$

$$= \sum_w \left(-[I_x(x_i, y_i)\ \ I_y(x_i, y_i)] \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} \right)^2 \quad (5)$$

$$= \sum_w \left([I_x(x_i, y_i)\ \ I_y(x_i, y_i)] \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} \right)^2 \quad (6)$$

$$= [\Delta x\ \ \Delta y] \begin{bmatrix} \sum_w (I_x(x_i, y_i))^2 & \sum_w I_x(x_i, y_i) I_y(x_i, y_i) \\ \sum_w I_x(x_i, y_i) I_y(x_i, y_i) & \sum_w (I_y(x_i, y_i))^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \quad (7)$$

$$= [\Delta x \Delta y]\, C(x, y) \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \quad (8)$$

where matrix C(x, y) captures the intensity structure of the local neighborhood. Let λ_1, $\lambda_2$be the eigenvalues of matrix C(x, y). The eigenvalues form a rotationally invariant description. There are three cases to be considered

a) If both λ_1, $\lambda_2$are small, so that the local auto-correlation function is flat (i.e. little change in C(x, y) in any direction) the windowed image region is of approximately constant intensity.

b) If one eigenvalue is high and the other low, the local auto-correlation function is ridge shaped, then only local shifts in one direction (along the ridge) cause little change in C(x, y) and significant change in the orthogonal direction, this indicates an edge.

c) If both eigenvalues are high, the local auto-correlation function is sharply peaked, then shifts in any direction will result in a significant increase, this indicates a corner.

Results for Harris corner detector

Fig.1 Original image used as inputFig.2 Output after passing through Gaussian filter with sigma=1 and Threshold=100 for Harris corner detector

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Fig.3 Output after passing through Gaussian filter with sigma=5 and Threshold=100 for Harris corner detectorFig.4 Output after passing through Gaussian filter with sigma=5 and Threshold=300 for Harris corner detector

III.SUSAN CORNER DETECTION

SUSAN (Smallest Univalue Segment Assimilating Nucleus) corner detector is realized by a circular mask . If the brightness of each pixel within a mask is compared with the brightness of that mask's nucleus then an area of the mask can be defined which has the same (or similar) brightness as the nucleus. This area of the mask shall be known as the "USAN", an acronym standing for "Univalue Segment AssimilatingNucleus". Consider Fig. 1, showing a dark rectangle on a white background, five circular masks are shown at different positions on the simple image. Corners can be detected according to the area of USAN. Nucleus is on the corner when the area of USAN is up to the smallest, such as position "a". In order to detect corners, the similar comparison function between each pixel within the mask and mask's nucleus is given by (9)

$$c(r, r_o) = \begin{cases} 1, & |I(r) - I(r_o)| \leq t; \\ 0, & otherwise \end{cases} \quad (9)$$

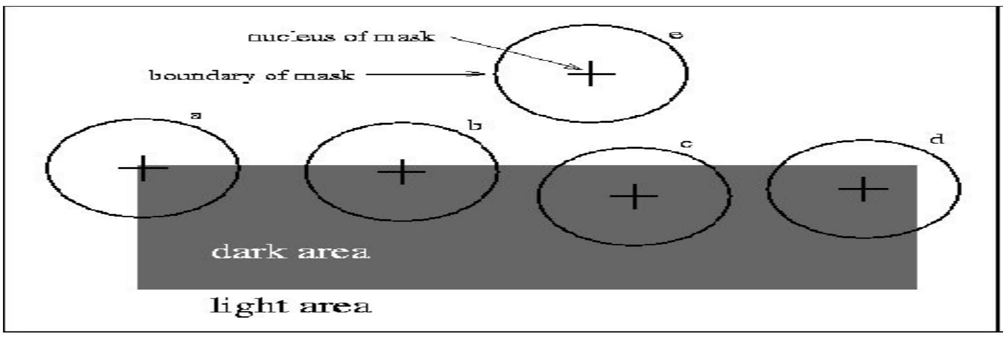

Fig.5 Four circular masks at different places on a simple image

Where $r_0$is nucleus's coordinates and ris the coordinates of other points within the mask. $c(r, r_0)$is the comparison result. $I(r)$is the point's gray value, t is gray difference threshold which determines the anti-noise ability and the smallest contrast that can be detected by SUSAN detector. In fact, (9) is not stable in practice, and an improved comparison function (10) is more often used because of its efficiency.

$$c(r, r_o) = e^{\left\{-\left[\frac{I(r)-I(r_o)}{t}\right]^6\right\}} \quad (10)$$

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The size of USAN region is given by

$n(r_o) = \sum_{r\in c(r_o)} c(r, r_o)$ (11)

And the initial response to corners is got from (12), which is in accord with the principle of SUSAN, that is, the smaller USAN region, the greater initial response to corners.

$$R(r_o) = \begin{cases} g - n(r_o), & n(r) < g \\ 0, & n(r) \geq g \end{cases} \quad (12)$$

In (12), g is geometric threshold which determines the acute level of a corner, the smaller the acuter. It enhances the corner information of an image. At last, corners can be found by non-maximum inhibition.

Results for Susan corner detector

Fig.6 Original image

Fig.7 Original image

Fig.8 Corner detection using susan corner detector

Fig.9Cornerdetection using susan corner detector

IV. MORAVEC CORNER DETECTION

Moravec's corner detector functions by considering a local window in the image, and determining the average changes of image intensity that result from shifting the window by a small amount in various directions. Three cases need to be considered:

a) If the windowed image patch is flat (ie. Approximately constant in intensity), then all shifts will result in only a small change.
b) If the window straddles an edge, then a shift along the edge will result in a small change, but a shift perpendicular to the edge will result in a large change.

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c) If the windowed patch is a corner or isolated point, then all shifts will result in a large change. A corner can thus be detected by finding when the minimum change produced by any of the shifts is large.We now give a mathematical specification of the above. Denoting the image intensities by I, the change E produced by a shift (x,y) is given by:

$$E_{x,y} = \sum_{u,v} \omega_{u,v}\left[I_{x+u,y+v} - I_{u,v}\right]^2$$

where w specifies the image window, it is unity within a specified rectangular region, and zero elsewhere. The shifts,(x,y), that are considered comprise {(1,0), (1,1), (0,1), (-1,1)}. Thus Moravec's corner detector is simply this: look for local maxima in min{E} above some threshold value.

The Moravec operator suffers from a number of problems listed below, together with appropriate corrective measures:

a)The response is anisotropic because only a discrete set of shifts at every 45 degrees is considered- all possible small shifts can be covered by performing an analytic expansion about the shift origin.

b)The response is noisy because the window is binary and rectangular - use a smooth circular window, for example a Gaussian because only the minimum of E is taken into account- reformulate the corner measure to make use of the variation of E with the direction of shift. The change E, for the small shift (x,y) can be concisely written as

$E(x,y) = (x,y)M(x,y)^T$ where M is a 2x2 symmetric matrix

$$M = \begin{pmatrix} A & C \\ C & B \end{pmatrix}$$

Note that E is closely related to the local autocorrelation function, with M describing its shape at the origin (explicitly, the quadratic terms in the Taylor expansion).Let α, β, be the eigenvalues of M. $\alpha$and β will be proportional to the principal curvatures of the local auto-correlation function, and form a rotationally invariant description of M. As before, there are three cases to be considered:

a) If both curvatures are small, so that the local autocorrelation function is flat, then the windowed image region is of approximately constant intensity (ie.arbitrary shifts of the image patch cause little change in E);

b) If one curvature is high and the other low, so that the local auto-correlation function is ridge shaped, then only shifts along the ridge (ie. along the edge) cause little change in E, this indicates an edge

c) If both curvatures are high so that the local autocorrelation function is sharply peaked, then shifts in any direction will increase E, this indicates a corner.

CORNER/EDGE RESPONSE FUNCTION

Not only do we need corner and edge classification regions, but also a measure of corner and edge quality or response. The size of the response will be used to select isolated corner pixels and to thin the edge pixels.

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$\mathrm{Tr}(M) = \alpha + \beta = A+B$

$\mathrm{Det}(M) = \alpha\beta = AB - C^2$

Consider the following formulation for the corner response

$R = \mathrm{Det} - k\,\mathrm{Tr}^2$

A corner region pixel (ie. one with a positive response) is selected as a nominated corner pixel if its response is an 8-way local maximum. Similarly, edge region pixels are deemed to be edgels if their responses are both negative and local minima in either the x or y directions, according to whether the magnitude of the first gradient in the x or y direction respectively is the larger. This results in thin edges.

Results for Moravec corner detector


Fig.10 Original Lena image.Fig.11 Output after passing through Gaussian filter

withsigma=1 and Threshold=100 using Moravec interest
point detector


Fig.13 Output after passing through Gaussian filter
Fig.12 Output after passing through Gaussian filter with
with sigma=5 and Threshold=300 using Moravec
sigma=5 and Threshold=100 usinginterest point detector
Moravec interest point detector

V. EVALUATION OF CORNER DETECTION ALGORITHMS

Here three quantitative evaluation methods of corner detection algorithm have been proposed which can reflect an algorithm's performance objectively.

A. Stability Criterion
Assume that the camera is fixed, grab two frames in an image sequence and use the given algorithm to detect

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corners in these two frames. If the detected positions of corners are unchanged, the algorithm is "absolute" stability. In fact, even in the image sequence, the gray value of each pixel will be changed because of many factors impacting imaging. So applying the same algorithm to them cannot ensure that the number and the positions of detected corners are exactly the same. Absolute stability is almost non-existent. The stability factor η to measure the stability of an algorithm is defined as:

$$\eta = \frac{A_1 \cap A_2}{min(|A_1|,|A_2|)} X100\%$$

Where $A_1$and A_2 are the corner sets of the first frame and the second respectively, $|A_i|$ represents the number of elements in A_i set, the numerator means the number of the same corners in two frames. From above equation, it can be concluded that the greater η is, the stable the corner detection algorithm is.

B. Anti-noise Criterion
Noise immunity is measured by anti-noise factor ρ which is defined as follows

$$\rho = \frac{B_1 \cap B_2}{min(|B_1|,|B_2|)} X100\%$$

Where B_1 is the corner set of the original image and B_2 is the corner set of the image adding noise. The greater ρ *is*, the stronger the anti-noise ability of the algorithm is.

C. Complexity Criterion
The speed and complexity of an algorithm must meet the demand of real-time task, that is, the algorithm should be fast enough to be usable in the final image processing system. The runtime of an algorithm can describe its complexity.

VI. CONCLUSION AND DISCUSSION

For a human, it is easier to identify a “corner”, but a mathematical detection is required in case of algorithms. Chris Harris and Mike Stephens in 1988 improved upon Moravec's corner detector by taking into account the differential of the corner score with respect to direction directly instead of using shifted patches. Moravec only considered shifts in discrete 45 degree angles whereas Harris considered all directions.

Harris detector has proved to be more accurate in distinguishing between edges and corners. In this a circular Gaussian window is used to reduce noise. Still in cases of noisy images it is difficult to find out the exact number of corners. In the presence of additive noise the resultant image through linear filters gets blurred and smoothed with poor feature localization and incomplete noise suppression. Image is passed through different gaussian filter with varying sigma values. As sigma value increases the blur in the image increases. Also with threshold the number of interest pointsdecrease.Harris algorithm is superior to SUSAN algorithm on the whole. The main disadvantages of SUSAN algorithm are:
(a) A fixed global threshold is not suitable for general situation. The corner detector needs an improved adaptive threshold and the shape of mask can be improved, too.

(b) The anti-noise ability is weak and the robustness of the algorithm should be strengthened. Similarly, there is still much space for Harris algorithm to be improved, such as how to choose difference operators and Gaussian smoothing filter operators better .

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