

DMET 901 – Computer Vision

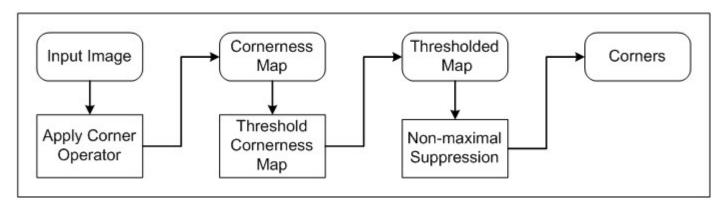
Local Feature Extraction (1)

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Corner Detectors

- It is always useful to find pairs of corresponding points in two similar images
- This could be used in the analysis of moving images
- This could be done by comparing all possible pairs of pixels in the two images. However, it is computationally intensive
- This process might be simplified by comparing interest points only such as corners
- A corner can be defined as a pixel in its small neighborhood where two dominant and different edges meet

General structure of corner detectors

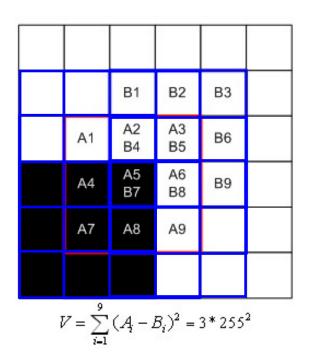


http://kiwi.cs.dal.ca/~dparks/CornerDetection/algorithms.htm

 Moravec operator estimates the cornerness of a point by computing a measure of intensity variation in a given neighborhood w with a shift of u and v

$$V(x,y)_{w(u,v)} = \sum_{i=-1}^{1} \sum_{j=-1}^{1} (f(x+i,y+j) - f(x+u+i,y+v+j))^{2}$$

• It measures the cornerness by shifting a window around the considered pixel by 1 pixel in each of the 8 principal directions and calculating the corresponding ${\it V}$



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$V = \begin{bmatrix} 3*255^{2} \\ 2*255^{2} \\ 3*255^{2} \\ 2*255^{2} \\ 5*255^{2} \\ 2*255^{2} \\ 2*255^{2} \\ 2*255^{2} \end{bmatrix}$

Window B Centered at

* 255² A3

* 255² A1

* 255² A4

* 255² A7

* 255² A8

* 255² A8

* 255² A9

* 255² A6

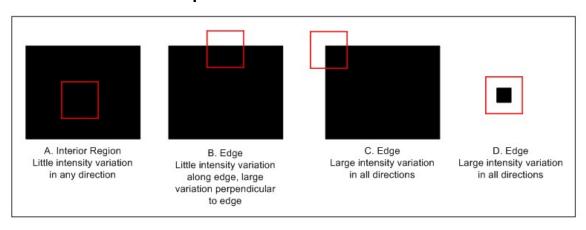
The cornerness at a pixel (x, y)

$$C(x,y) = \min_{u,v} V(x,y)_{w(u,v)}$$

Example (using a 3 x 3 window)

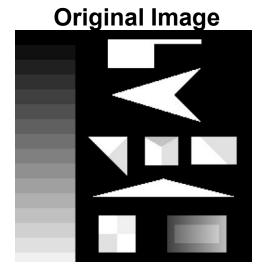
X	X	x	X	×	X	X	×	X	×	×	×	×	×	×	Х
Х	х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х	Х
Х	х	0	0	0	0	0	0	0	0	0	1	1	1	Х	Х
Х	х	0	0	0	0	0	1	1	0	0	1	2	1	Х	х
Χ	X	0	0	0	0	0	2	1	0	0	1	1	1	Х	Х
X	X	0	0	0	0	0	0	0	0	0	0	0	0	х	х
Χ	X	Χ	Χ	Χ	Χ	Χ	Χ	Х	Х	Х	Х	Х	Х	Х	Х
Χ	X	Χ	Χ	Χ	Χ	Χ	Χ	Χ	Х	Х	Х	Х	Х	Х	Х

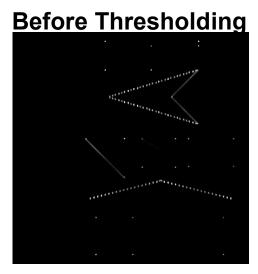
Why would Moravec operator work?

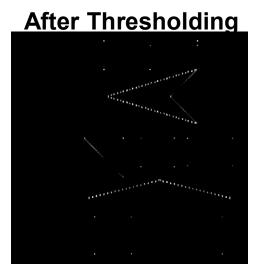


http://kiwi.cs.dal.ca/~dparks/CornerDetection/algorithms.htm

 By setting all points with cornerness below a threshold T to 0, corner points can be detected

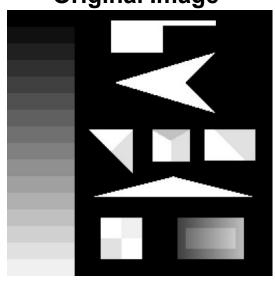




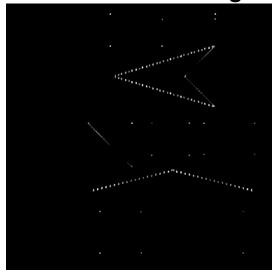


Finally, non-maximal suppression can be applied

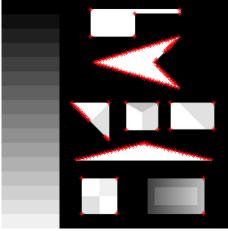
Original Image



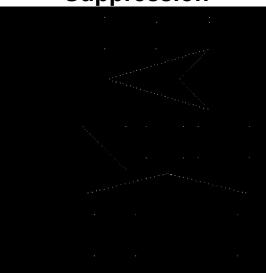
After Thresholding



Final Output



After Non-maximal Suppression



Cornerness of any pixel is set to 0 if it is not larger than the cornerness of all 8-neighbors

Improved upon Moravec operator

$$S_W(\Delta x, \Delta y) = \sum_{x_i \in W} \sum_{y_i \in W} \left(f(x_i, y_i) - f(x_i - \Delta x, y_i - \Delta y) \right)^2$$

- Similar to the goal of Moravec operator, we try to find the minimum value of $S_{\it W}$
- This could be found analytically if the shifted image patch is approximated by the first-order Taylor expansion

$$f(x_i - \Delta x, y_i - \Delta y) \approx f(x_i, y_i) + \left[\frac{\partial f(x_i, y_i)}{\partial x}, \frac{\partial f(x_i, y_i)}{\partial y}\right] \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

• Substituting in the expression for S_W

$$S_{W}(\Delta x, \Delta y) = \sum_{x_{i} \in W} \sum_{y_{i} \in W} \left(f(x_{i}, y_{i}) - f(x_{i}, y_{i}) - \left[\frac{\partial f(x_{i}, y_{i})}{\partial x}, \frac{\partial f(x_{i}, y_{i})}{\partial y} \right] \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \right)^{2}$$

$$\begin{split} S_{W}(\Delta x, \Delta y) &= \sum_{x_{i} \in W} \sum_{y_{i} \in W} \left(f(x_{i}, y_{i}) - f(x_{i}, y_{i}) - \left[\frac{\partial f(x_{i}, y_{i})}{\partial x}, \frac{\partial f(x_{i}, y_{i})}{\partial y} \right] \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \right)^{2} \\ &= \sum_{x_{i} \in W} \sum_{y_{i} \in W} \left(- \left[\frac{\partial f(x_{i}, y_{i})}{\partial x}, \frac{\partial f(x_{i}, y_{i})}{\partial y} \right] \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \right)^{2} \\ &= \sum_{x_{i} \in W} \sum_{y_{i} \in W} \left(- \left[\frac{\partial f(x_{i}, y_{i})}{\partial x}, \frac{\partial f(x_{i}, y_{i})}{\partial y} \right] \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \right)^{2} \\ &= \sum_{x_{i} \in W} \sum_{y_{i} \in W} \left[\Delta x, \Delta y \right] \left(\begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix} \right) \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \\ &= \left[\Delta x, \Delta y \right] \left(\sum_{x_{i} \in W} \sum_{y_{i} \in W} \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \end{bmatrix} \right) \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} \\ &= \left[\Delta x, \Delta y \right] A_{W}(x, y) \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}, \end{split}$$

The goal now is to minimize

$$S_W(\Delta x, \Delta y) = [\Delta x, \Delta y] A_W(x, y) \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

- This is equivalent to finding the eigenvector of A_w corresponding to the minimum eigenvalue
- What are the eigenvectors and eigenvalues?
 For any matrix L, the eigenvectors and eigenvalues are defined as

$$Lf = \lambda f \quad \Rightarrow \quad f^T L f = \lambda$$

f is an eigenvector of L

 λ is the eigenvalue corresponding to f

• For A_w , the eigenvector is $\begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$ and the eigenvalue is the corresponding S_w

• Therefore, finding the eigenvalues of A_w would be sufficient to solve the minimization problem where

$$A(x,y) = \begin{bmatrix} \sum\limits_{x_i \in W} \sum\limits_{y_i \in W} \frac{\partial^2 f(x_i, y_i)}{\partial x^2} & \sum\limits_{x_i \in W} \sum\limits_{y_i \in W} \frac{\partial f(x_i, y_i)}{\partial x} \frac{\partial f(x_i, y_i)}{\partial y} \\ \sum\limits_{x_i \in W} \sum\limits_{y_i \in W} \frac{\partial f(x_i, y_i)}{\partial x} \frac{\partial f(x_i, y_i)}{\partial y} & \sum\limits_{x_i \in W} \sum\limits_{y_i \in W} \frac{\partial^2 f(x_i, y_i)}{\partial y^2} \end{bmatrix}$$

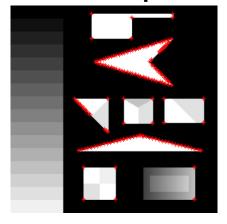
Instead of computing the eigenvalues, Harris suggested using the following approximation

$$R(A) = \det(A) - \kappa \operatorname{trace}^{2}(A)$$

where det(A) is the determinant of the local structure matrix A trace(A) is the trace of matrix A (sum of elements on the diagonal) κ is a tunable parameter

- Algorithm
 - 1. Filter the image with a Gaussian filter
 - 2. Estimate intensity gradient in 2 perpendicular directions for each pixel $\frac{\partial f(x,y)}{\partial x}$ and $\frac{\partial f(x,y)}{\partial y}$
 - 3. For each pixel and a given neighborhood window
 - Calculate the local structure matrix A
 - Evaluate the response function R(A)
 - 4. Set all pixels with response less than a threshold T to 0 and perform non-maximal suppression

Moravec Operator



Harris Detector

