

# Fundamentals of Image Processing

## Harris corner detector - Detailed solution



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Year 2020-2021

1. Gaussian window  $w(x, y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2+y^2}{2\sigma^2}}$ , used as a weighting function in the mean squared intensity variation:

$$E_{u,v}^1(x_1, y_1) = \sum_{x,y} w(x - x_1, y - y_1) \times [I(x + u, y + v) - I(x, y)]^2$$

*Note that in practice the sum is taken only over a limited domain (usually of size  $3\sigma$ ).*

2. The Taylor series expansion of  $I(x + u, y + v)$  at order 1 is:

$$I(x + u, y + v) = I(x, y) + u \cdot \frac{\partial I}{\partial x} + v \cdot \frac{\partial I}{\partial y} + \mathcal{O}(u^2, v^2) \approx I(x, y) + u \cdot I_x(x, y) + v \cdot I_y(x, y) \quad (1)$$

*Note that this holds for small displacements  $u, v$ .*

In the following derivations, we will write in short  $I_x$  for  $I_x(x, y)$ , and similarly for the other derivatives.

3. Matricial expression of  $E_{u,v}^1(x_1, y_1)$ :

Using the first order approximation, we get:

$$\begin{aligned} E_{u,v}^1(x_1, y_1) &\approx \sum_{x,y} w(x - x_1, y - y_1) \times [u \cdot I_x + v \cdot I_y]^2 = \sum_{x,y} w(x - x_1, y - y_1) [u^2 I_x^2 + 2uv I_x I_y + v^2 I_y^2] \\ &= u^2 \sum_{x,y} w(x - x_1, y - y_1) I_x^2 + v^2 \sum_{x,y} w(x - x_1, y - y_1) I_y^2 + 2uv \sum_{x,y} w(x - x_1, y - y_1) I_x I_y \\ &= (u, v) \times \begin{bmatrix} \sum_{x,y} w(x - x_1, y - y_1) \cdot I_x^2 & \sum_{x,y} w(x - x_1, y - y_1) \cdot I_x I_y \\ \sum_{x,y} w(x - x_1, y - y_1) \cdot I_x I_y & \sum_{x,y} w(x - x_1, y - y_1) \cdot I_y^2 \end{bmatrix} \times \begin{pmatrix} u \\ v \end{pmatrix} \\ &= (u, v) \times M(x_1, y_1) \times \begin{pmatrix} u \\ v \end{pmatrix} \end{aligned}$$

with

$$\begin{aligned} M(x_1, y_1) &= \begin{bmatrix} \sum_{x,y} w(x - x_1, y - y_1) \cdot I_x^2 & \sum_{x,y} w(x - x_1, y - y_1) \cdot I_x I_y \\ \sum_{x,y} w(x - x_1, y - y_1) \cdot I_x I_y & \sum_{x,y} w(x - x_1, y - y_1) \cdot I_y^2 \end{bmatrix} \\ &= \begin{bmatrix} \sum_{x,y} w(x_1 - x, y_1 - y) \cdot I_x^2 & \sum_{x,y} w(x_1 - x, y_1 - y) \cdot I_x I_y \\ \sum_{x,y} w(x_1 - x, y_1 - y) \cdot I_x I_y & \sum_{x,y} w(x_1 - x, y_1 - y) \cdot I_y^2 \end{bmatrix} = \begin{bmatrix} w \star I_x^2 & w \star I_x I_y \\ w \star I_x I_y & w \star I_y^2 \end{bmatrix} = \begin{bmatrix} A & C \\ C & B \end{bmatrix} \end{aligned}$$

*Note that the coefficients of the matrix  $M$ , denoted by  $A, B, C$  for short, are values, that depend on each pixel position  $(x_1, y_1)$ .*

The matrix  $M$ , called auto-correlation matrix, represents the local structure of function  $E^1(x_1, y_1)$  in a neighborhood of pixel  $(x_1, y_1)$ .

## 4. Reminder on linear algebra:

A real symmetric matrix  $M = \begin{bmatrix} A & C \\ C & B \end{bmatrix}$  has positive eigenvalues. An eigenvector  $(u, v)$  associated with an eigenvalue  $\lambda$  is defined as:

$$\begin{bmatrix} A & C \\ C & B \end{bmatrix} \begin{pmatrix} u \\ v \end{pmatrix} = \lambda \begin{pmatrix} u \\ v \end{pmatrix}$$

Solving for non zero vectors leads to

$$\lambda^2 - (A + B)\lambda + AB - C^2 = 0$$

$A + B = \text{Tr}(M)$  is the trace of the matrix, and  $AB - C^2 = \text{Det}(M)$  is its determinant.

The solutions in  $\lambda$  of the this second degree equation are the eigenvalues:

$$\lambda_1 = \frac{\text{Tr}(M) + \sqrt{\text{Tr}(M)^2 - 4\text{Det}(M)}}{2}$$

$$\lambda_2 = \frac{\text{Tr}(M) - \sqrt{\text{Tr}(M)^2 - 4\text{Det}(M)}}{2}$$

Hence the sum and product of eigenvalues are then:

$$\lambda_1 + \lambda_2 = \text{Tr}(M)$$

$$\lambda_1 \lambda_2 = \text{Det}(M)$$

5. Harris & Stephens proposed to compute the eigenvalues  $\lambda_1$  and  $\lambda_2$  of  $E^1$  to identify different types of local behavior of the intensity function (Figure 1(a)). To reduce the computational complexity, these authors proposed the following criterion  $R(x, y)$  (Figure 1(b)):

$$R(x, y) = \text{Det}(M) - k \cdot [\text{Tr}(M)]^2 \quad (2)$$

where  $k$  is a small positive value.

Let us show the equivalence between Figures 1(a) and 1(b):

- (a) If  $\lambda_1$  and  $\lambda_2$  are approximately equal, we note  $\lambda_1 \sim \lambda_2 = \lambda$ , and get

$$R(x, y) \sim \lambda^2 - k(4\lambda^2) = \lambda^2(1 - 4k)$$

Since in practice  $k$  is chosen as a small value, i.e.  $k \ll 1$ , we get  $R(x, y) \sim \lambda^2$ . Then:

- i. If  $\lambda \rightarrow 0$ , this means that the derivative of  $I$  are close to 0, i.e. the region is flat (homogenous gray levels), and  $R \rightarrow 0$ .
- ii. If  $\lambda > 0$  then  $R > 0$ , and we have locally a corner.

- (b) If  $\lambda_1 \gg \lambda_2$  (or the reverse) then

$$R(x, y) \sim \lambda_1 \lambda_2 - k\lambda_1^2 = \lambda_1^2 \left( \frac{\lambda_2}{\lambda_1} - k \right) \sim -k\lambda_1^2$$

If the pixel is an edge, it means that the variations of  $I$  are in one direction only, i.e.  $\lambda_1 \gg \lambda_2$ , and we get  $R < 0$ .

6. The Harris detector is invariant by rotation: Indeed the trace and determinant are intrinsic properties, that do not depend of the coordinate frame. To prove this, let us write the rotation in a matricial way as  $P \begin{pmatrix} u \\ v \end{pmatrix}$  where  $P$  is a rotation matrix. The the previous computations leads to

$$(u, v) \times P^t \times M(x_1, y_1) \times P \times \begin{pmatrix} u \\ v \end{pmatrix}$$

i.e.  $M$  is replaced by  $P^t M P$ . The determinant is equal to the product of the determinants of each matrix, and  $\text{Det}(P) = 1$  is  $P$  is a rotation matrix. Hence  $\text{Det}(P^t M P) = \text{Det}(M)$ .

A straightforward calculation with  $P = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$ , where  $\theta$  is the rotation angle, leads to  $\text{Tr}(P^t M P) = A + B = \text{Tr}(M)$ .

7. The local maxima of  $R(x, y)$  are invariant with respect to affine intensity variations, i.e. that can be written as  $I'(x, y) = a \cdot I(x, y) + b$ : Indeed each derivative writes  $I'_x = a I_x$ , etc. This means that every coefficient in  $M$  is multiplied by the constant  $a^2$ , and the new matrix writes  $M' = a^2 M$ . Then we get  $R' = \text{Det}(M') - k \text{Tr}(M')^2 = a^4 \text{Det}(M) - k(a^2 \text{Tr}(M))^2 = a^4 R$ . Then  $R'$  is locally maximal at the same points as  $R$ .
8. The detector is not scale invariant since it depends on  $w$ .
9. A simple method to detect corners at different scales, based on the Harris detector, would consist in choosing different sizes of  $w$  (i.e. different values of  $\sigma$ ).

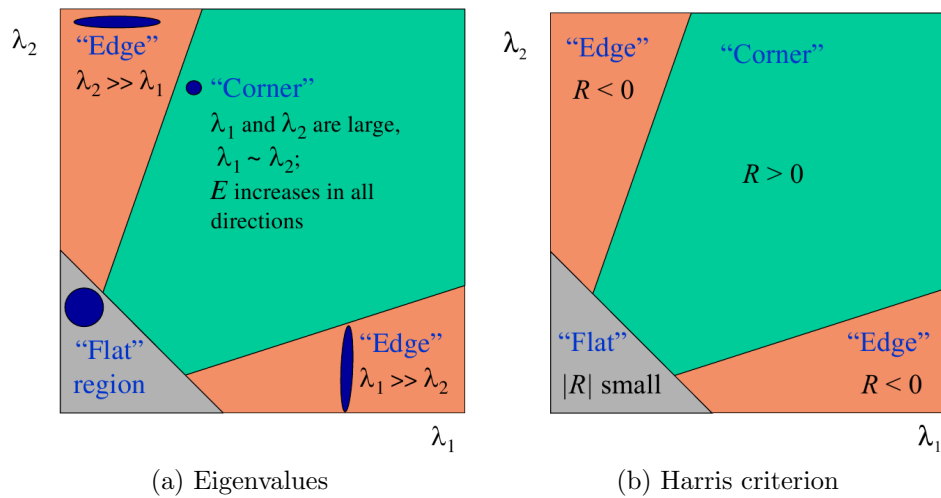


Figure 1: Harris detector.