

CS-570 Computer Vision

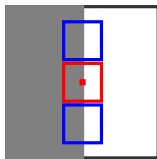
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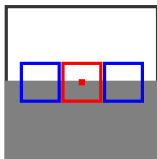
7. Corner Detection

Corners

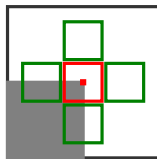
- ▶ Just like edges, corners are perceptually important.
- ▶ More compact summary of an image since corners are fewer than edge pixels.
- ▶ A patch around a corner pixel is different from all other surrounding patches.



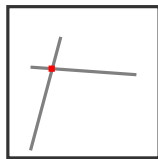
Vertical edge



Horizontal edge



Corner



Corner

Figure: A patch containing a corner is different from all surrounding patches. Blue squares represent patches similar to the red patch. Green squares represent patches different from the red patch. Author: N. Khan (2021)

Corner Detection via Structure Tensor

- ▶ What do the eigenvalues of the structure tensor reveal about the local structure around a pixel?

$$\lambda_{\text{large}} \approx \lambda_{\text{small}} \approx 0 \implies \text{flat region}$$

$$\lambda_{\text{large}} \gg \lambda_{\text{small}} \approx 0 \implies \text{edge}$$

$$\lambda_{\text{large}} > \lambda_{\text{small}} \gg 0 \implies \text{corner}$$

- ▶ So a simple corner detection criterion could be $\lambda_{\text{small}} > \tau$.

Corner Detection via Structure Tensor

- ▶ But eigenvalue computation is a little expensive.

- ▶ Using the facts that

1. $\det(A) = A_{11}A_{22} - A_{12}^2 = \lambda_{\text{large}}\lambda_{\text{small}}$, and

2. $\text{trace}(A) = A_{11} + A_{22} = \lambda_{\text{large}} + \lambda_{\text{small}}$

popular corner detectors avoid eigenvalue computations.

- ▶ Popular corner detectors use a cornerness measure and then a detection criterion.

Method	Cornerness Measure	Detector
Harris	$\frac{\det(A)}{\text{trace}(A)}$	$\text{trace}(A) > \tau$
Rohr	$\det(A)$	$\det(A) > \tau$

- ▶ To avoid multiple detections, non-maxima suppression must be performed on the cornerness values in 8-neighbourhoods or larger.

Corner Detection

Algorithm

Input: Image I .

Parameters:

- 1) Noise smoothing scale σ ,
- 2) Gradient smoothing scale ρ (should be greater than σ),
- 3) Threshold τ .

1. Compute Gaussian derivatives at noise smoothing scale σ

$$I_x = \frac{\partial G_\sigma}{\partial x} * I \quad \text{and} \quad I_y = \frac{\partial G_\sigma}{\partial y} * I$$

2. Compute the products

$$I_x^2, \quad I_y^2 \quad \text{and} \quad I_x I_y$$

3. Smooth the products at gradient smoothing scale ρ

$$G_\rho * I_x^2, \quad G_\rho * I_y^2 \quad \text{and} \quad G_\rho * I_x I_y$$

and construct structure tensor A at every pixel.

Corner Detection

Algorithm

4. Compute cornerness $C(i, j)$ at every pixel as

Harris	Rohr
$C_{ij} = \frac{A_{11}A_{22} - A_{12}^2}{A_{11} + A_{22}}$	$C_{ij} = A_{11}A_{22} - A_{12}^2$

5. Perform non-maxima suppression in 8-neighbourhood on cornerness image C .
6. Find corner pixels by thresholding remaining local maxima via

Harris	Rohr
$trace(A) = A_{11} + A_{22} > \tau$	$det(A) = A_{11}A_{22} - A_{12}^2 > \tau$

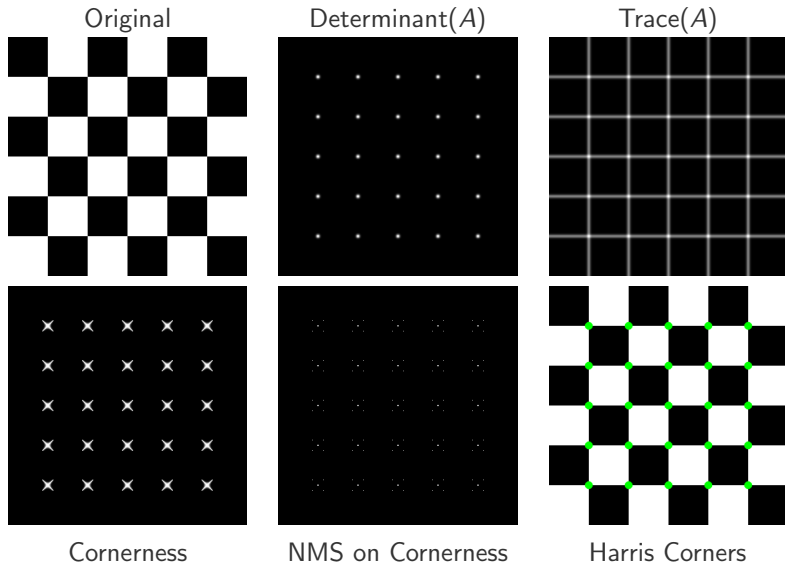


Figure: Harris corners detected with $\sigma = 0.2$, $\rho = 2$ and $\tau = 90$ th percentile of trace values. Author: N. Khan (2018)

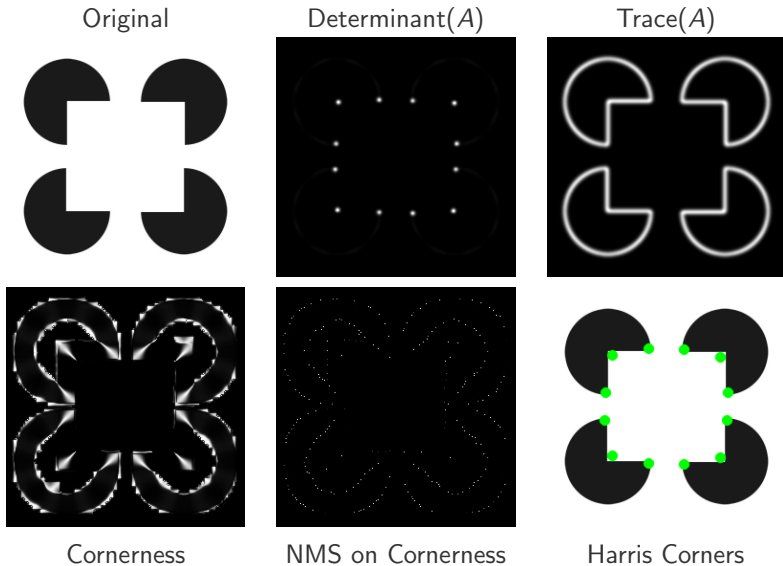


Figure: Harris corners detected with $\sigma = 0.5$, $\rho = 2$ and $\tau = 80$ th percentile of trace values. Author: N. Khan (2018)

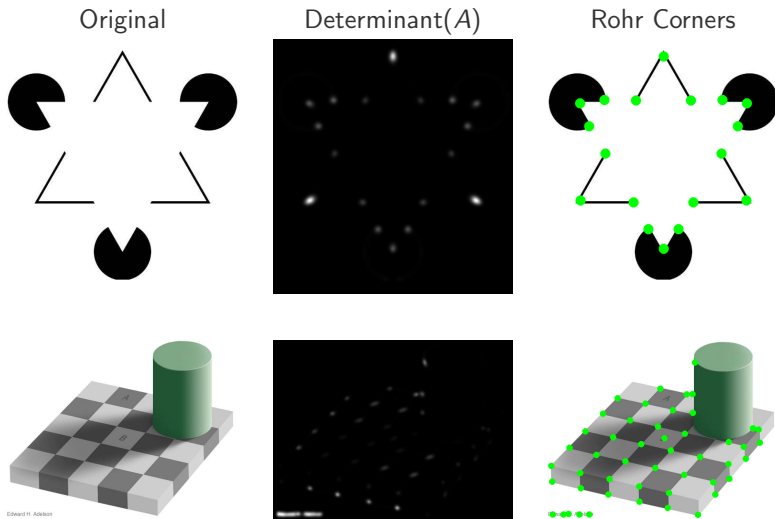
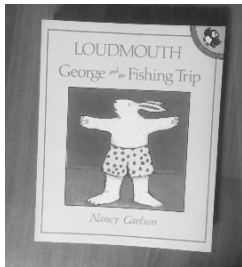
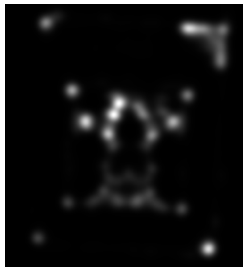


Figure: Corners detected by Rohr's method with $\sigma = 1$, $\rho = 6$ and $\tau = 98$ th percentile of determinant values for **top row** and 95th for **bottom row**. Author: N. Khan (2018)

Original



Determinant(A)



Rohr Corners

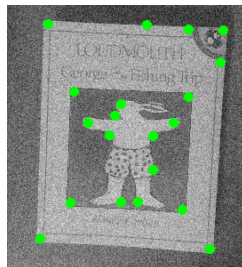
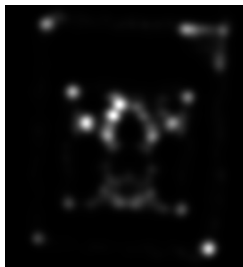
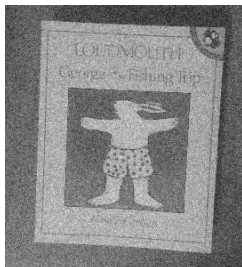
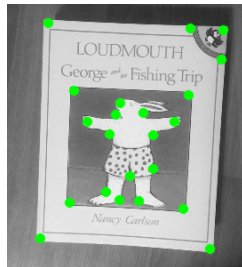
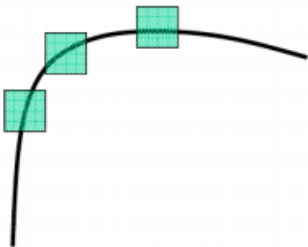


Figure: Corners detected by Rohr's method with $\rho = 6$ and $\tau = 95$ th percentile of determinant values. Noise smoothness scale was $\sigma = 3$ for **top row** and $\sigma = 4$ for **bottom row**. Author: N. Khan (2018)

Corners depend on scale



All points will be classified as **edges**

Corner !

- ▶ Structure tensors and therefore corner detection are not scale invariant.
- ▶ Therefore, corner detection should take place at multiple scales.
- ▶ This leads to the concept of a *scale space*.

Scale Space via Gaussian Pyramids



Figure: A Gaussian pyramid with 3 levels and 5 smoothing scales. **Top to bottom:** Subsampling in both dimensions by factor 2^i for $i = 0, \dots, 2$. **Left to right:** Gaussian blurring with $\sigma = \sqrt{2^j} \sigma_0$ for $j = 0, \dots, 4$ and $\sigma_0 = \sqrt{2}$. Author: N. Khan (2018)

Scale Space via Gaussian Pyramids

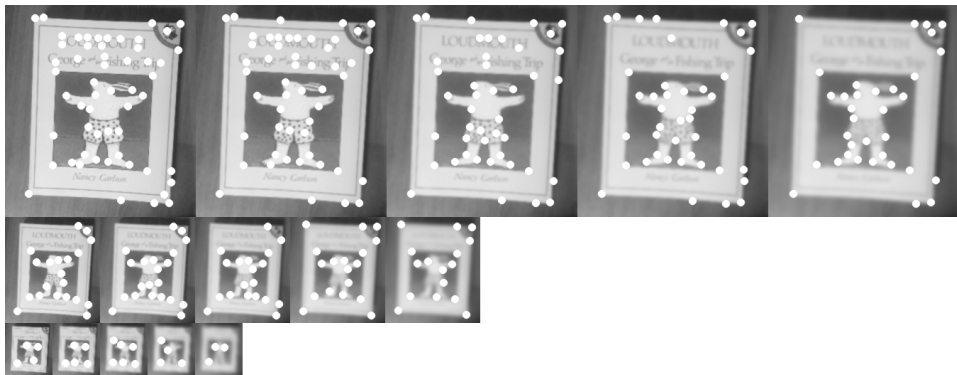


Figure: Corner detection in scale space obtained via Gaussian pyramids. Some corners are detected only at certain resolutions and certain smoothness scales. Corners that *persist across resolutions and smoothness scales* are called strong or stable corners. Author: N. Khan (2018)

Scale Space via Gaussian Pyramids

```
function makeGaussianPyramid(I,num_levels,num_scales,k, $\sigma_0$ )  
for  $i = 0$  to num_levels-1  
     $J = \text{subsample}(I, \frac{1}{2^i})$   
    for  $s = 0$  to num_scales-1  
         $\sigma = k^s \sigma_0$   
         $GP[i, s] = J * G_\sigma$ 
```