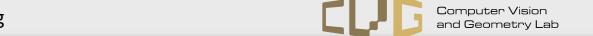


Computer Vision

Local Features





Assignment

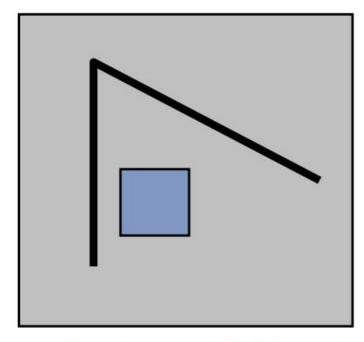
- Task 1: Harris corner detection
- Task 2: Description & matching



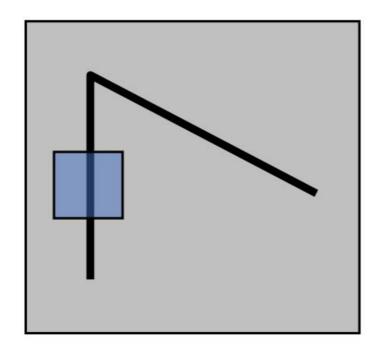
- Compute intensity gradients in x and y direction
- Blur Images to get rid of noise
- Compute Harris response
- Thresholding and non-maximum suppression



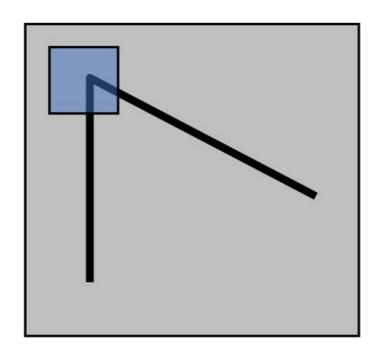
Corners: area of large intensity changes



flat area: no change in all directions



edge area: no change along edge direction



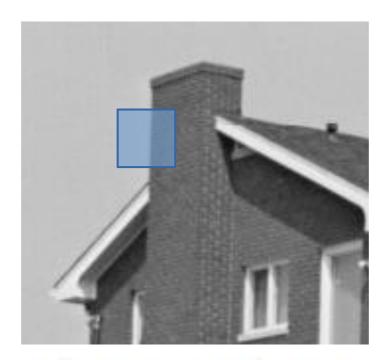
corner area: large change in all directions



Corners: area of large intensity changes



flat area: no change in all directions



edge area: no change along edge direction

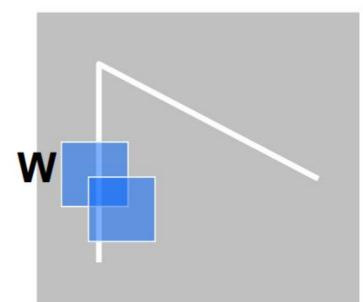


corner area: large change in all directions



Now Consider shifting the patch or `window' **W** by (u,v)

Consider shifting the patch or 'window' W by (u,v)



- how do the pixels in W change?
- compare each pixel before and after by summing up the squared differences (SSD)
- this defines an SSD "error" or E(u,v):

$$E(u,v) = \sum_{(x,y)\in W} [I(x+u,y+v) - I(x,y)]^2$$





$$E(\Delta x, \Delta y) = \sum_{(x,y)\in W} [I(x + \Delta x, y + \Delta y) - I(x,y)]^2$$
 (1)





$$E(\Delta x, \Delta y) = \sum_{(x,y)\in W} [I(x + \Delta x, y + \Delta y) - I(x,y)]^2$$
 (1)



Taylor polynomial

$$I(x + \Delta x, y + \Delta y) = I(x, y) + I_x(x, y)\Delta x + I_y(x, y)\Delta y + O(\Delta x^2, \Delta y^2)$$

$$E(\Delta x, \Delta y) = \sum_{(x,y)\in W} [I(x + \Delta x, y + \Delta y) - I(x,y)]^2$$
 (1)



Taylor polynomial

$$I(x + \Delta x, y + \Delta y) = I(x, y) + I_x(x, y)\Delta x + I_y(x, y)\Delta y + O(\Delta x^2, \Delta y^2)$$

Negligible for small Δx , Δy .





$$E(\Delta x, \Delta y) = \sum_{(x,y)\in W} [I(x + \Delta x, y + \Delta y) - I(x,y)]^2$$
 (1)



Taylor polynomial

$$I(x + \Delta x, y + \Delta y) = I(x, y) + I_x(x, y)\Delta x + I_y(x, y)\Delta y + O(\Delta x^2, \Delta y^2)$$

$$\approx I(x, y) + I_x(x, y)\Delta x + I_y(x, y)\Delta y$$



$$E(\Delta x, \Delta y) = \sum_{(x,y)\in W} [I(x + \Delta x, y + \Delta y) - I(x,y)]^2$$
 (1)



Taylor polynomial

$$I(x + \Delta x, y + \Delta y) = I(x, y) + I_x(x, y)\Delta x + I_y(x, y)\Delta y + O(\Delta x^2, \Delta y^2)$$

$$\approx I(x, y) + I_x(x, y)\Delta x + I_y(x, y)\Delta y$$

$$E(\Delta x, \Delta y) \approx \sum_{(x,y)\in W} [I_x(x,y)\Delta x + I_y(x,y)\Delta y]^2$$
$$= [\Delta x \ \Delta y] M \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

Where
$$M = \sum_{(x,y) \in W} \begin{bmatrix} I_x^2(x,y) & I_x(x,y)I_y(x,y) \\ I_x(x,y)I_y(x,y) & I_y^2(x,y) \end{bmatrix}$$

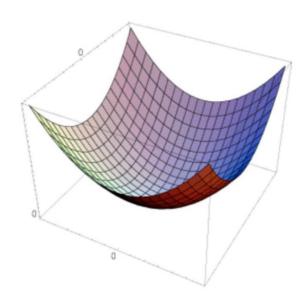




- Direction of largest changes in the intensity: eigen vector of λ_{max}
- Direction of smallest changes in the intensity: eigen vector of λ_{min}

$$E(\Delta x, \Delta y) \approx [\Delta x \ \Delta y] M \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

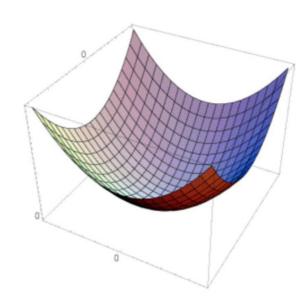
$$M = \sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$



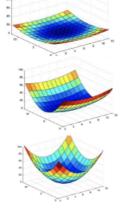
- Direction of largest changes in the intensity: eigen vector of λ_{max}
- Direction of smallest changes in the intensity: eigen vector of λ_{min}

$$E(\Delta x, \Delta y) \approx [\Delta x \ \Delta y] M \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

$$M = \sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$



- λ_1, λ_2 both small: flat areas
- $\lambda_1 >> \lambda_2$ or $\lambda_1 << \lambda_2$: edge
- λ_1, λ_2 both large: corner



- Compute intensity gradients in x and y direction
- Blur gradients to get rid of noise
- Compute Harris response
- Thresholding and non-maximum suppression



Step 1: compute image gradients

$$I_{x} = \frac{I(x+1,y) - I(x-1,y)}{2}$$

$$I_{y} = \frac{I(x,y+1) - I(x,y-1)}{2}$$

$$M = \sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

You may use scipy.signal.convolve2d

Step 2: blur the image

$$M = \sum_{(x,y)\in W} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Window function w: gaussian with standard deviation σ

You may use cv2.GaussianBlur

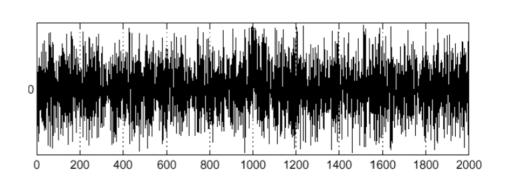


Why blur?

Intensity

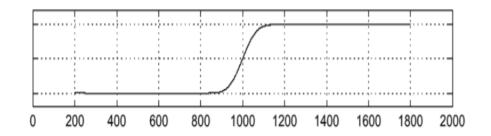
Without

Gradient

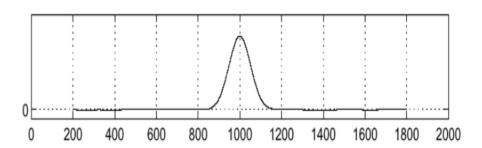


With blur

blur



1200



Images taken from DZO course by Václav Hlaváč @ CTU in Prague





Step 3: compute Harris response

 λ_1, λ_2 both large: corner

$$M = \sum_{(x,y)\in W} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

$$R = \det(M) - k \operatorname{trace}^{2}(M)$$
 $k=0.04\sim0.06$

- det(H) = product of eigenvalues
- trace(H) = sum eigenvalues
- related to eigenvalues but cheaper to compute

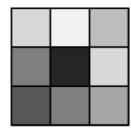


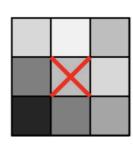


Step 4: non-maximum suppression

For every pixel above the threshold, check the surrounding pixels inside a window for the maximum response intensiy.

If the center pixel response is smaller than a pixel inside the window, remove the center pixel from the corner candidates.



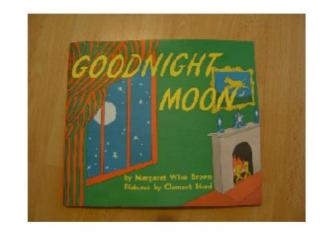


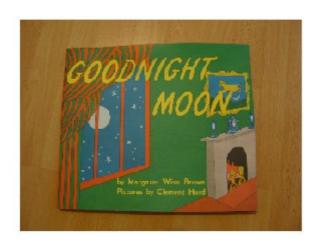
You may use scipy.ndimage.maximum_filter



Description & Matching

- Input: a pair of images
- Convert to gray image -> Harris corner detection
- Extract local patch descriptors
 - Filter out keypoints around the edges
 - Extract 9x9 patches around the detected keypoints as descriptor (this function is provided)









Description & Matching

Feature distances:

$$SSD(p,q) = \sum_{i} (p_i - q_i)^2$$

Make sure to avoid Python for-loop with vectorized computation.

Description & Matching

- One-way nearest neighbors matching
 - each feature from the img1 is matched to its closest feature from img2
- Mutual nearest neighbors matching
 - for each one-way match, check if it's also valid if switch img1 and img2
- Ratio test matching
 - in one-way match, if the ratio between the 1st and the 2nd nearest neighbor is lower than a threshold



