



Video Processing

Lab 1: Harris Corner Detector + VP
Intro



Administration - General Information

- Contact:
 - vptau2022@gmail.com
 - Course Forum
- Office Hours (by appointment): Sunday 11:00.
- 4-5 labs = 1 for every exercise + 1-2 for the project.
- 3 HW Exercises:
 - Harris Corner Detector + VP Basic Ops
 - Video Stabilization
 - Tracking
- 1 Project:
 - Input: Unstable video of a person walking.
 - Output: Stabilized Video with a different background + Tracking the person with a rectangle.

Administration - Homework Guidelines

```
def create_grad_x_and_grad_y(input_image):  
    """Calculate the gradients across the x and y-axes.  
  
    Args:  
        input_image: np.ndarray. Image array.  
    Returns:  
        tuple (Ix, Iy): The first is the gradient across the x-axis and the  
            second is the gradient across the y-axis.  
  
    Recipe:  
    If the image is an RGB image, convert it to grayscale using OpenCV's  
    cvtColor. Otherwise, the input image is already in grayscale.  
    Then, create a one pixel shift (to the right) image and fill the first  
    column with zeros.  
    Ix will be the difference between the grayscale image and the shifted  
    image.  
    Iy will be obtained in a similar manner, this time you're requested to  
    shift the image from top to bottom by 1 row. Fill the first row with zeros.  
    Finally, in order to ignore edge pixels, remove the first column from Ix  
    and the first row from Iy.  
    Return (Ix, Iy).  
    """
```

3 exercises + 1 project

Python3.9, conda, linux

Insert your code here

Report: PDF only. First line= your IDs.

Some items have changed from
previous years. Do not copy.

Administration - How do we run your code?

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    Return (Ix, Iy).  
    """
```

We install the conda virtual environment with the environment.yml which we supply.

We run the file or files containing:

```
if __name__ == "__main__":  
    from the command line.
```



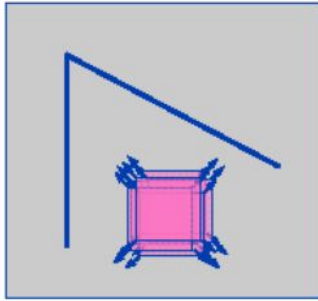
Administration - any other questions?



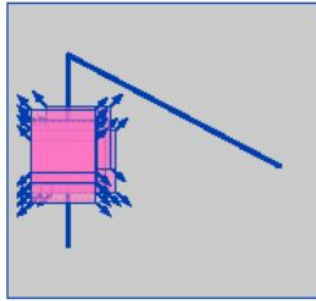
Harris Corner Detector

Why Corners?

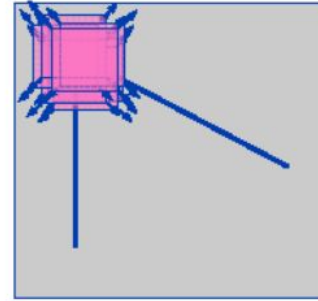
They're very different than their neighbourhood - that's why they're distinctive.



“flat” region:
no change in
all directions



“edge”:
no change along
the edge direction



“corner”:
significant change
in all directions

Harris corner detector gives a mathematical approach for determining which case holds.

How Do We Compute Corners?

For each window in the image, we compute:

$$\sum [I(x+u, y+v) - I(x, y)]^2$$

$$\approx \sum [I(x, y) + uI_x + vI_y - I(x, y)]^2 \quad \text{First order approx}$$

$$= \sum u^2 I_x^2 + 2uv I_x I_y + v^2 I_y^2$$

$$= \sum \begin{bmatrix} u & v \end{bmatrix} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} \quad \text{Rewrite as matrix equation}$$

$$= \begin{bmatrix} u & v \end{bmatrix} \left(\sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix}$$

How Do We Compute Corners?

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$$= \begin{bmatrix} u & v \end{bmatrix} \left(\sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \right) \begin{bmatrix} u \\ v \end{bmatrix}$$

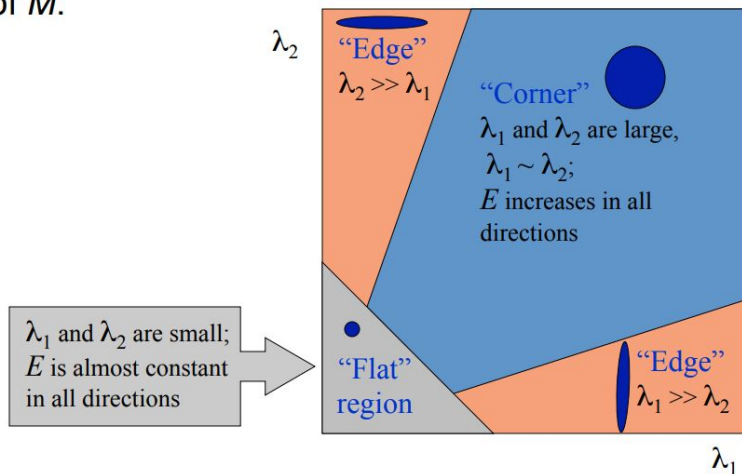
M

How Do We Compute Corners?

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

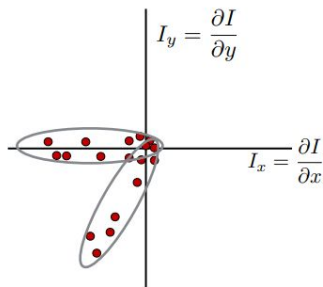
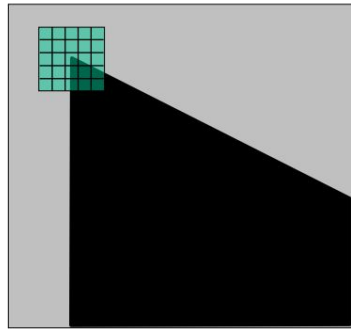
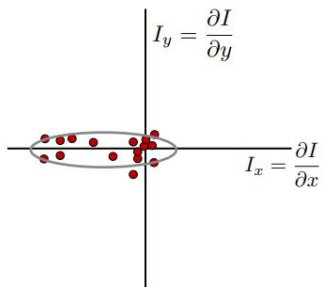
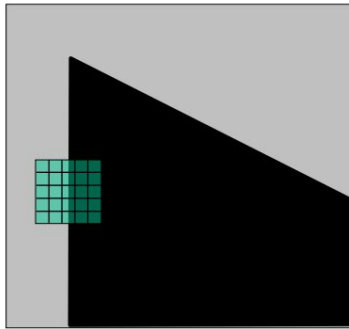
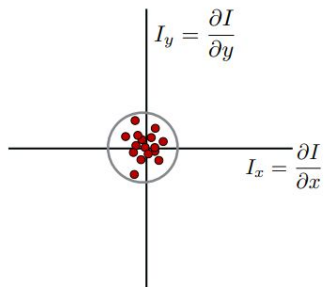
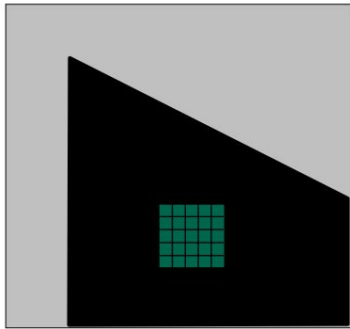
Interpreting the eigenvalues

Classification of image points using eigenvalues of M :



$$M = \sum_{x,y} \begin{bmatrix} I_x^2 & I_x * I_y \\ I_x * I_y & I_y^2 \end{bmatrix} = A^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} A$$

Intuition



Invariance

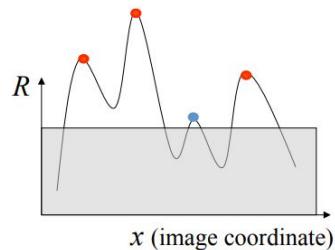
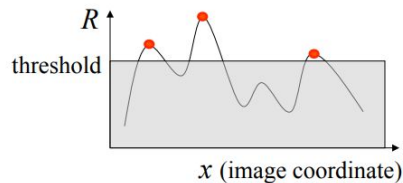
Affine intensity change



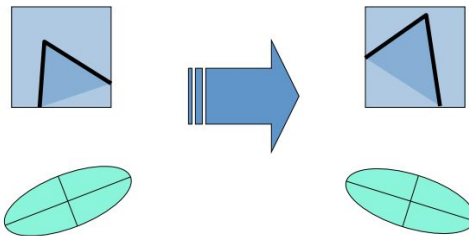
$$I \rightarrow aI + b$$

Only derivatives \Rightarrow invariance to intensity shift $I \rightarrow I + b$

Intensity scaling: $I \rightarrow aI$

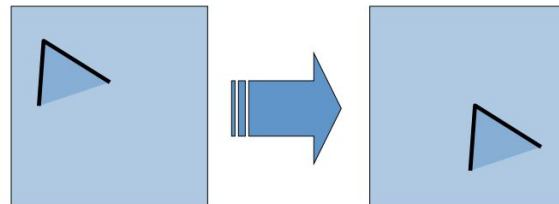


Harris: image rotation



Second moment ellipse rotates but its shape (i.e. eigenvalues) remains the same

Harris: image translation



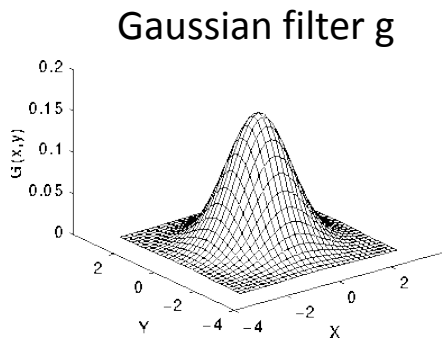
Harris Corner Detector - Algorithm

Input: Image I .

Output: Image with the same size indicating where corners are.

Alg:

- $[I_x, I_y] = \text{gradient}(I)$
 - I_x^2 - pixel-wise multiplication of I_x
- Define filter g – usually box filter (5X5 ones), or gaussian.
- $S_{xx} = \text{conv}(I_x^2, g)$, $S_{yy} = \text{conv}(I_y^2, g)$, $S_{xy} = \text{conv}(I_x \cdot I_y, g)$



$$\begin{aligned} \text{Det}(M) &= \lambda_- \cdot \lambda_+ \\ \text{Trace}(M) &= \lambda_- + \lambda_+ \\ 0.04 &< k < 0.06 \end{aligned}$$

Harris Corner Detector - Algorithm

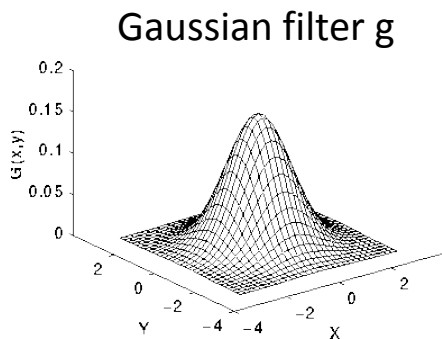
Input: Image I .

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- $[I_x, I_y] = \text{gradient}(I)$
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Window Sum Trick



$$\begin{aligned} \text{Det}(M) &= \lambda_- \cdot \lambda_+ \\ \text{Trace}(M) &= \lambda_- + \lambda_+ \\ 0.04 &< k < 0.06 \end{aligned}$$

Harris Corner Detector - Algorithm

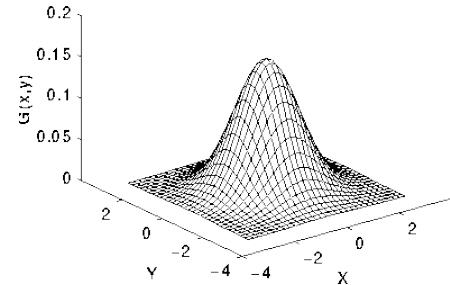
Input: Image I.

Output: Image with the same size indicating where corners are.

Alg:

- $[I_x, I_y] = \text{gradient}(I)$
 - I_x^2 - pixel-wise multiplication of I_x
- Define filter g – usually box filter (5X5 ones), or gaussian.
- $S_{xx} = \text{conv}(I_x^2, g)$, $S_{yy} = \text{conv}(I_y^2, g)$, $S_{xy} = \text{conv}(I_x \cdot I_y, g)$
- $R = \frac{\lambda_- \cdot \lambda_+}{\lambda_- + \lambda_+} \approx \det(M) - k \cdot [\text{trace}(M)]^2 = S_{xx} \cdot S_{yy} - S_{xy}^2 - k(S_{xx} + S_{yy})^2$
- $R(R < \theta) = 0$, where θ is a user defined threshold, R – Response image
- Optional: Non-maximum suppression of R in each tile

Gaussian filter g



$$\begin{aligned} \det(M) &= \lambda_- \cdot \lambda_+ \\ \text{Trace}(M) &= \lambda_- + \lambda_+ \\ 0.04 &< k < 0.06 \end{aligned}$$

Is this result good for us?

