

MTRN4110 Robot Design

Week 8 – Vision II

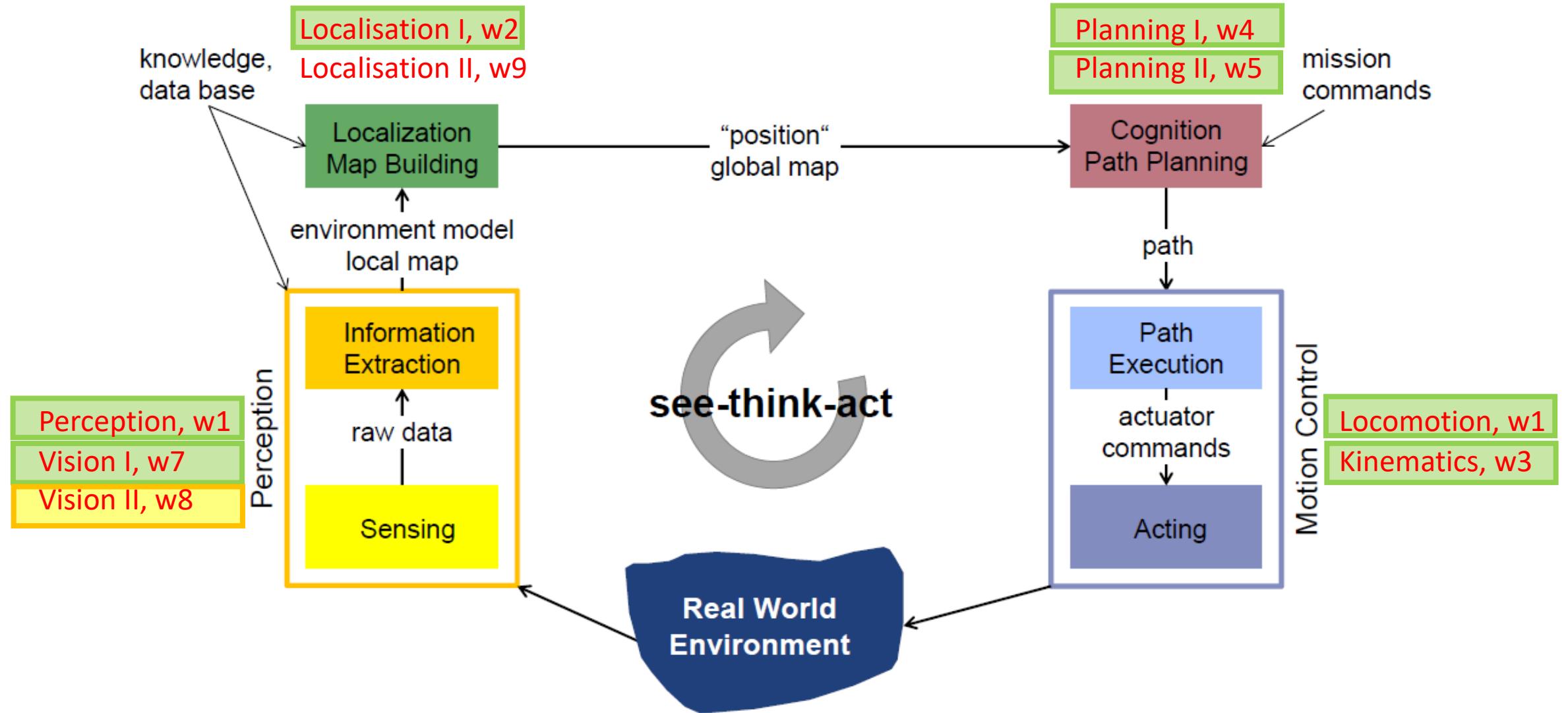
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The See-Think-Act cycle



Today's Agenda

- Feature detection
 - Edge detection
 - Hough transform
 - Contour detection
 - Corner detection
 - SIFT, SURF, and ORB
 - Marker detection
 - Face detection
- Object tracking
 - 8 object tracking algorithms

Feature Detection

Feature detection

- What?
 - Computing **abstractions** of image information
 - Making **local** decisions on whether there is a feature of a given type
- Why?
 - Make some “**high-level sense**” out of a given image (compared with pixel-level)
 - An important step towards **understanding** the image
 - from **image processing** to **computer vision**
- How?
 - **Edge** detector
 - **Contour** detector
 - **Corner** detector
 - **SIFT**
 - **SURF**
 - **ORB**
 - ...



Edge Detection

What is an Edge?

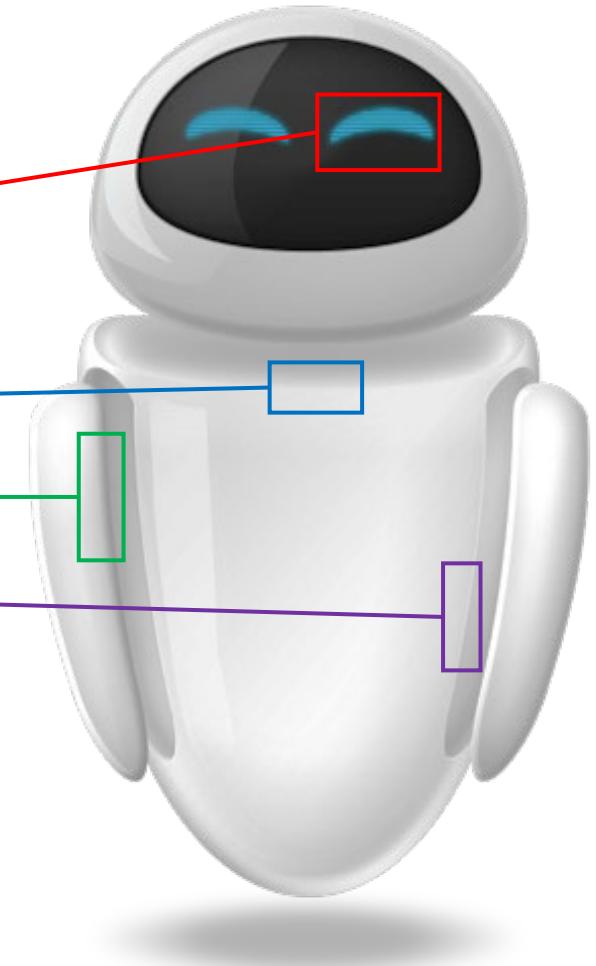
- Edge: Sharp change in brightness (**discontinuities**)

- Origin?

- Surface colour discontinuity
- Surface normal discontinuity
- Depth discontinuity
- Illumination discontinuity

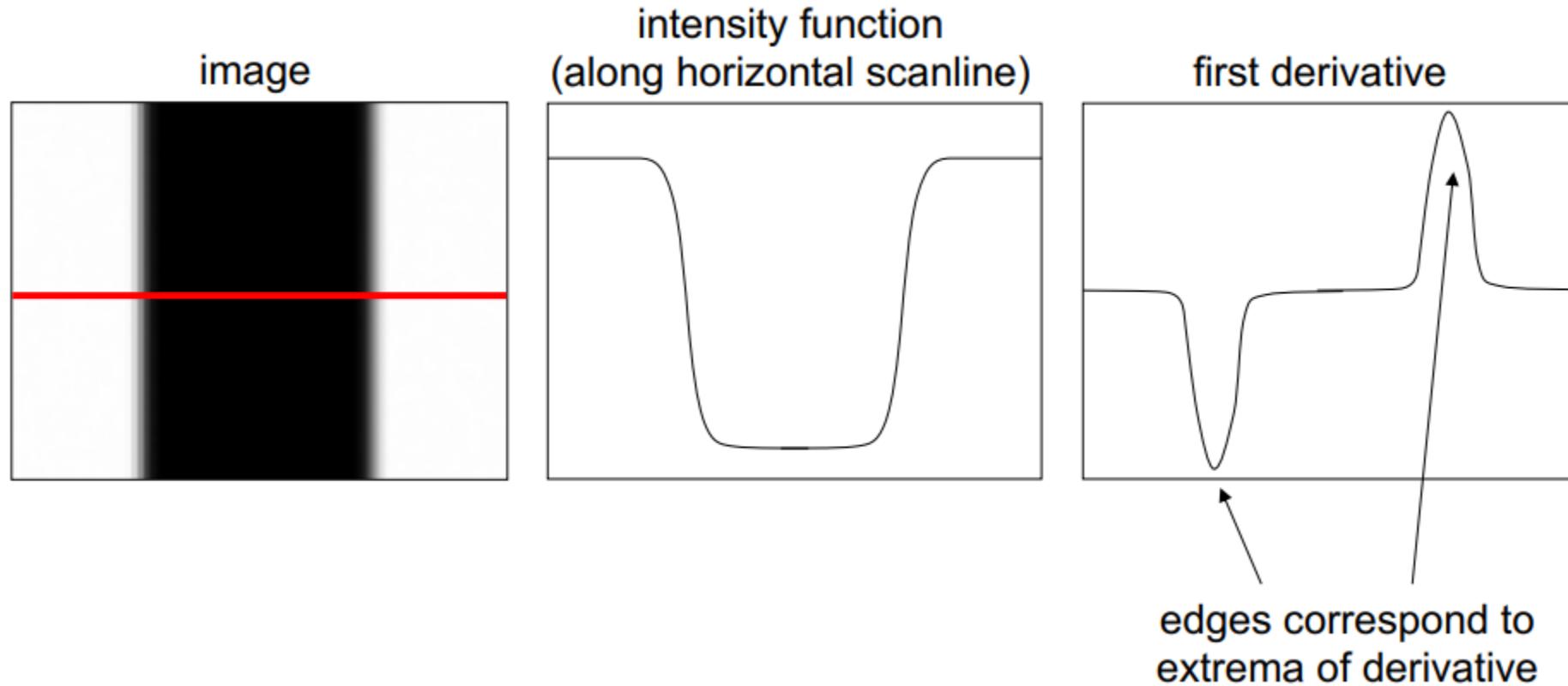
- Edge detection

- Image processing that finds **edges (discontinuities)** in images



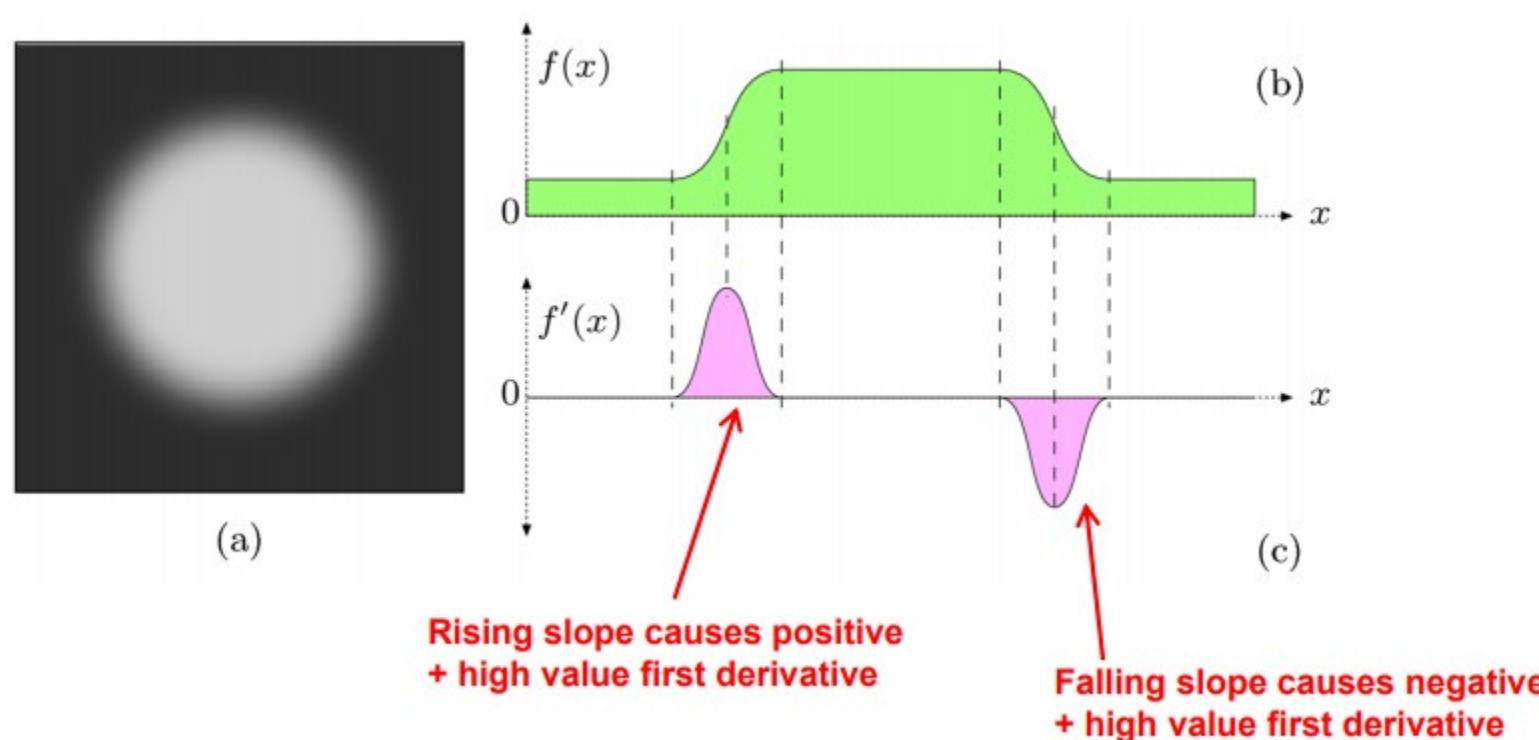
Characteristics of edges

- An edge is a place of **rapid change** in the image intensity function
- Positive or negative **high value** first derivative



Characteristics of edges

- An edge is a place of **rapid change** in the image intensity function
- Positive or negative **high value first derivative**



A simple edge detector – Image Gradient

- Image Gradient

- Image derivatives in **horizontal** and **vertical** directions

$$\frac{\partial I}{\partial u}(u, v) \quad \text{and} \quad \frac{\partial I}{\partial v}(u, v)$$

- Image **gradient** at location (u, v)

$$\nabla I(u, v) = \begin{bmatrix} \frac{\partial I}{\partial u}(u, v) \\ \frac{\partial I}{\partial v}(u, v) \end{bmatrix}$$

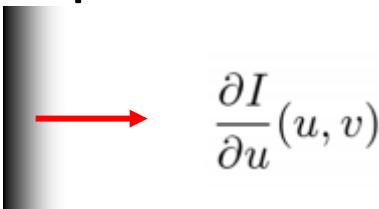
- Gradient **magnitude**

$$|\nabla I|(u, v) = \sqrt{\left(\frac{\partial I}{\partial u}(u, v)\right)^2 + \left(\frac{\partial I}{\partial v}(u, v)\right)^2}$$

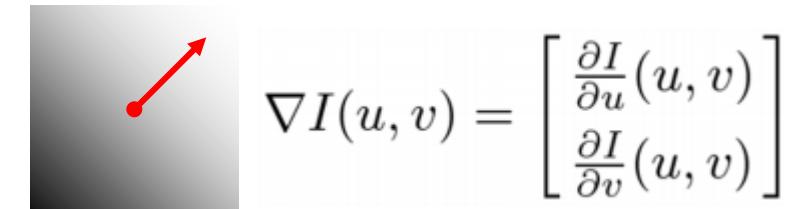
- Gradient **direction**

$$\theta = \tan^{-1} \left(\frac{\frac{\partial I}{\partial v}(u, v)}{\frac{\partial I}{\partial u}(u, v)} \right)$$

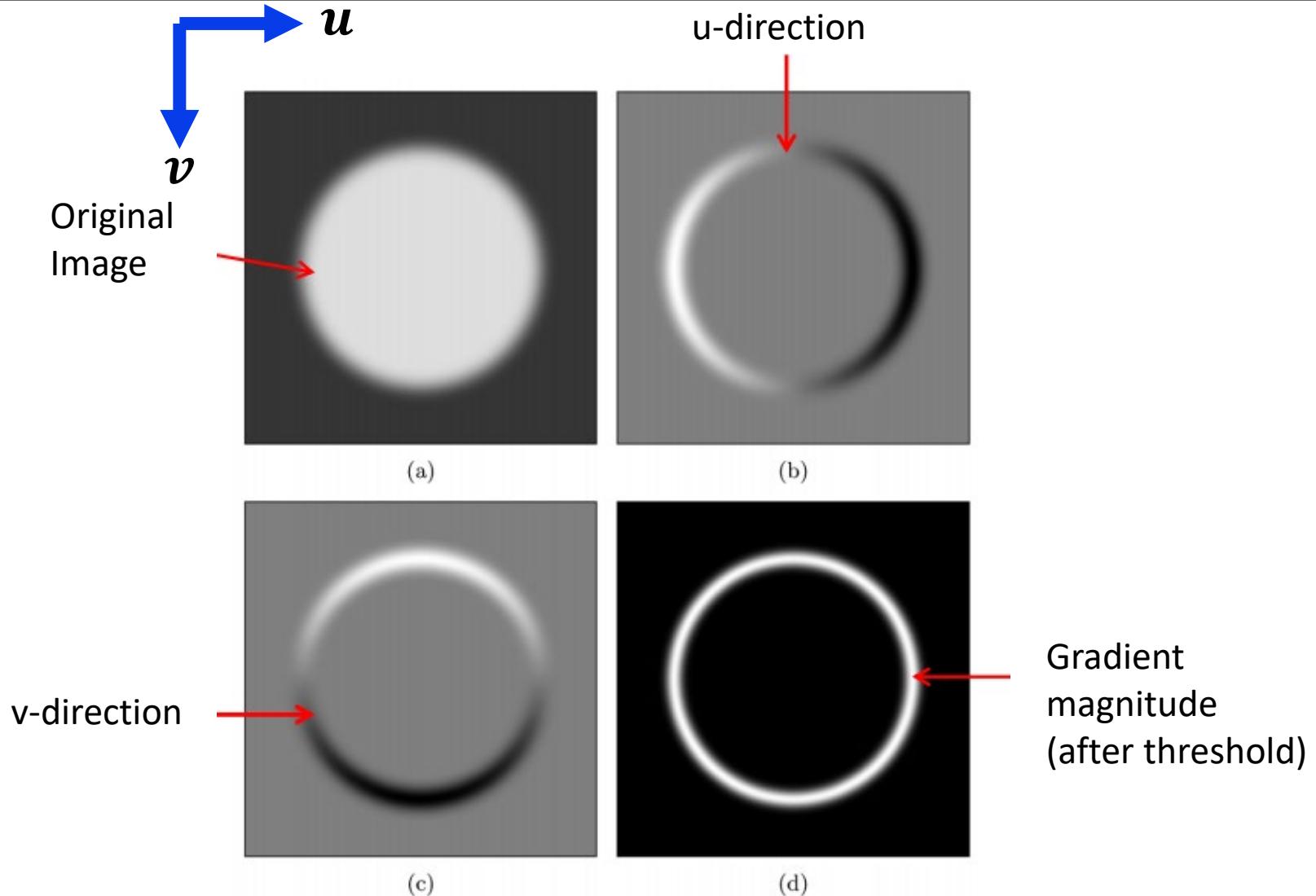
- Compute the Image Gradient


$$\frac{\partial I}{\partial u}(u, v)$$


$$\frac{\partial I}{\partial v}(u, v)$$

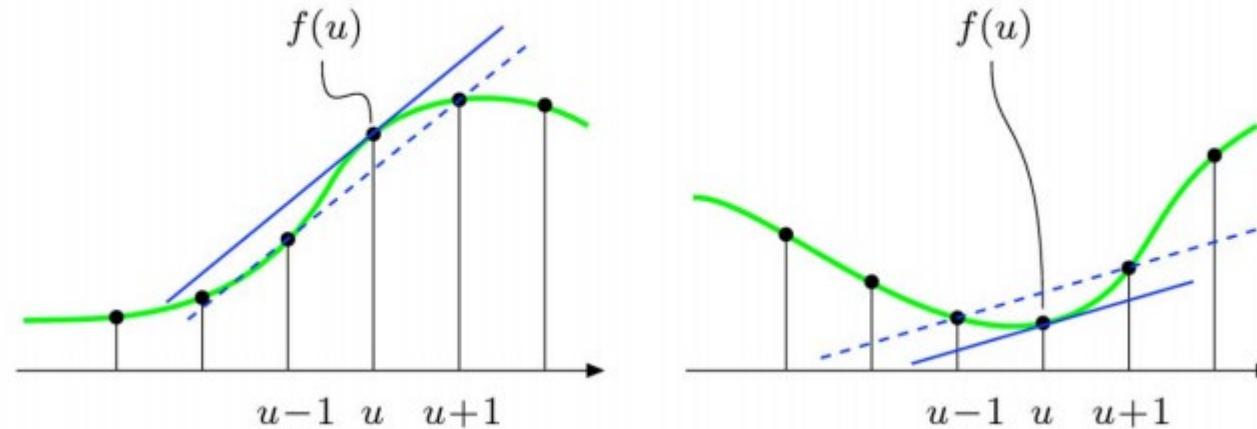

$$\nabla I(u, v) = \begin{bmatrix} \frac{\partial I}{\partial u}(u, v) \\ \frac{\partial I}{\partial v}(u, v) \end{bmatrix}$$

A simple edge detector - Image Gradient



How to compute the image gradient **efficiently**?

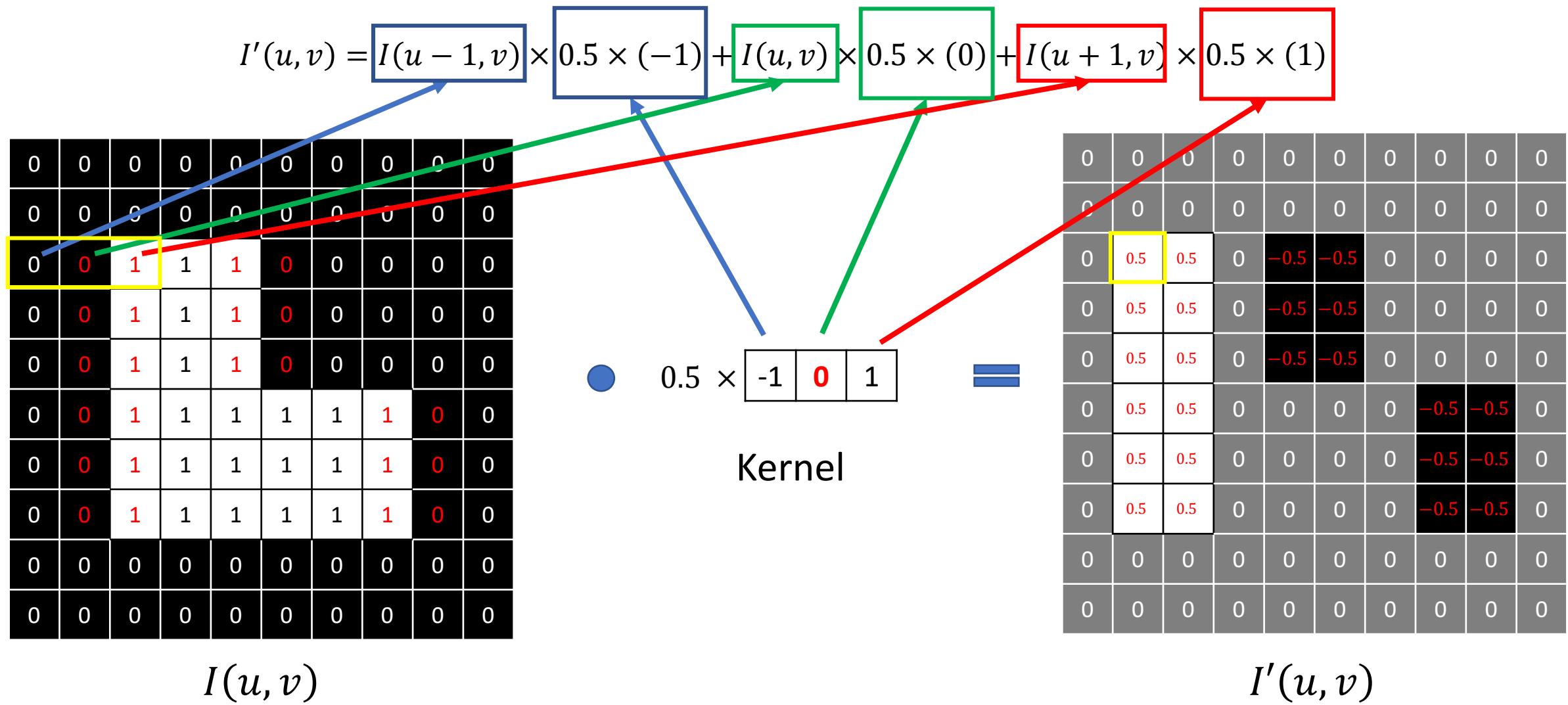
- Recall that we can compute **derivative of discrete function** as



$$\frac{df}{du}(u) \approx \frac{f(u+1) - f(u-1)}{2} = 0.5 \cdot (f(u+1) - f(u-1))$$

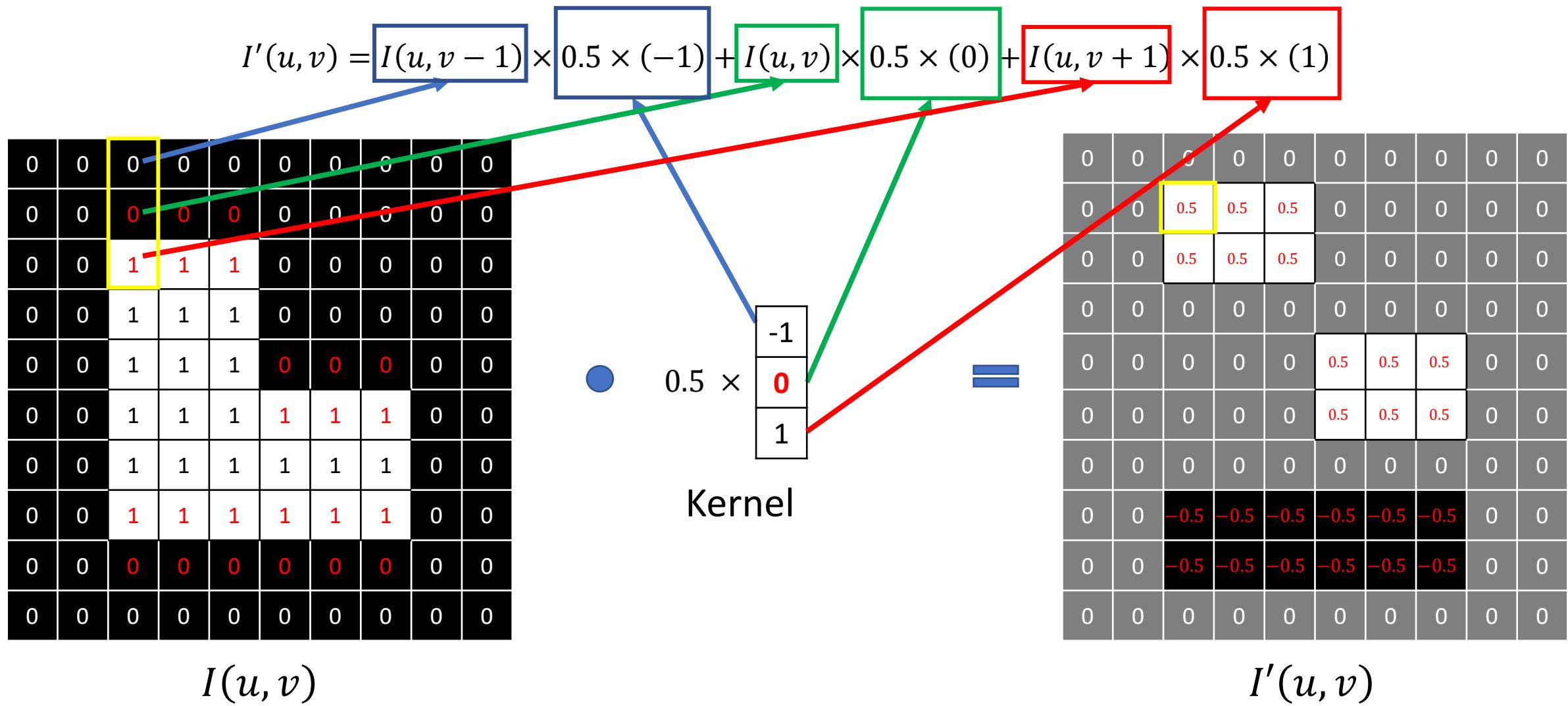
How to compute the image gradient **efficiently**?

$$\frac{df}{du}(u) \approx \frac{f(u+1) - f(u-1)}{2} = 0.5 \cdot (f(u+1) - f(u-1))$$

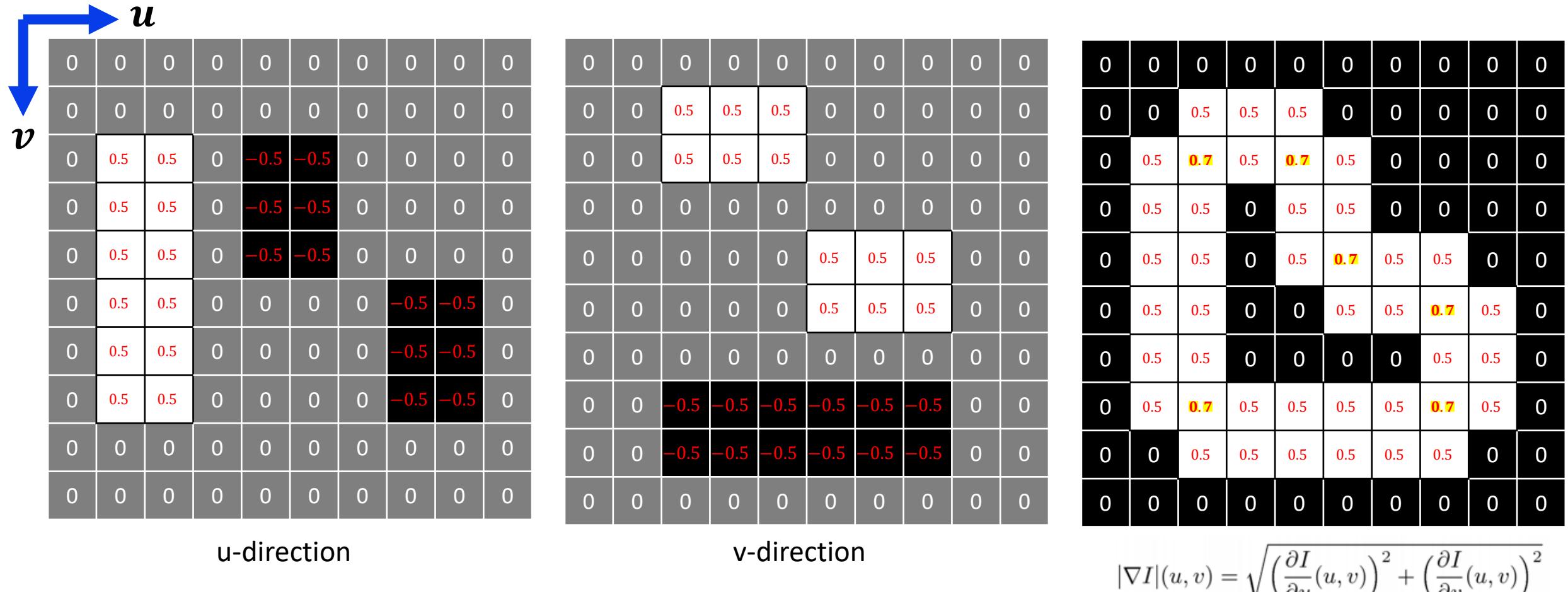


How to compute the image gradient **efficiently**?

$$\frac{df}{du}(u) \approx \frac{f(u+1) - f(u-1)}{2} = 0.5 \cdot (f(u+1) - f(u-1))$$



How to compute the image gradient **efficiently**?



u-direction

v-direction

$$|\nabla I|(u, v) = \sqrt{\left(\frac{\partial I}{\partial u}(u, v)\right)^2 + \left(\frac{\partial I}{\partial v}(u, v)\right)^2}$$

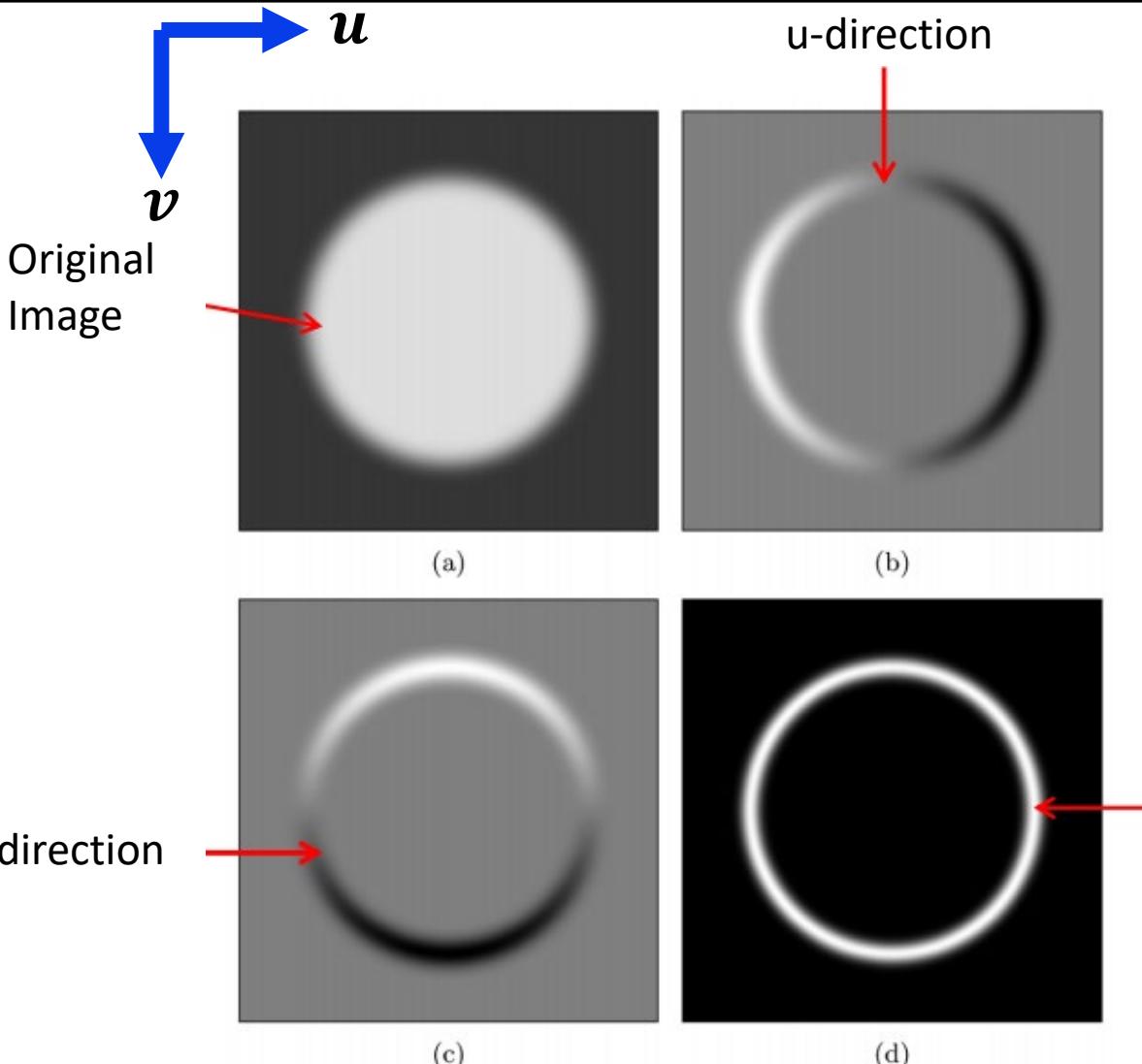
A simple edge detector – Finite differentiation filter

0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0

Kernel = $0.5 \times$

-1
0
1

0	0	0	0	0	0	0	0	0	0	0
0	0	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	0	0	0	0	0	0
0	0	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	0	0	0
0	0	0	0	0	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	$-\frac{1}{2}$	$-\frac{1}{2}$	$-\frac{1}{2}$	$-\frac{1}{2}$	$-\frac{1}{2}$	$-\frac{1}{2}$	0	0	0
0	0	$-\frac{1}{2}$	$-\frac{1}{2}$	$-\frac{1}{2}$	$-\frac{1}{2}$	$-\frac{1}{2}$	$-\frac{1}{2}$	0	0	0
0	0	0	0	0	0	0	0	0	0	0



Kernel = $0.5 \times$

-1
0
1

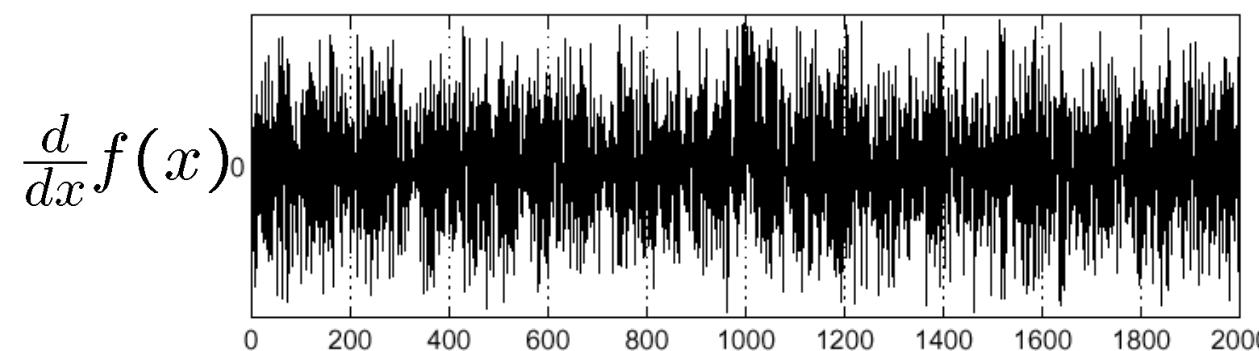
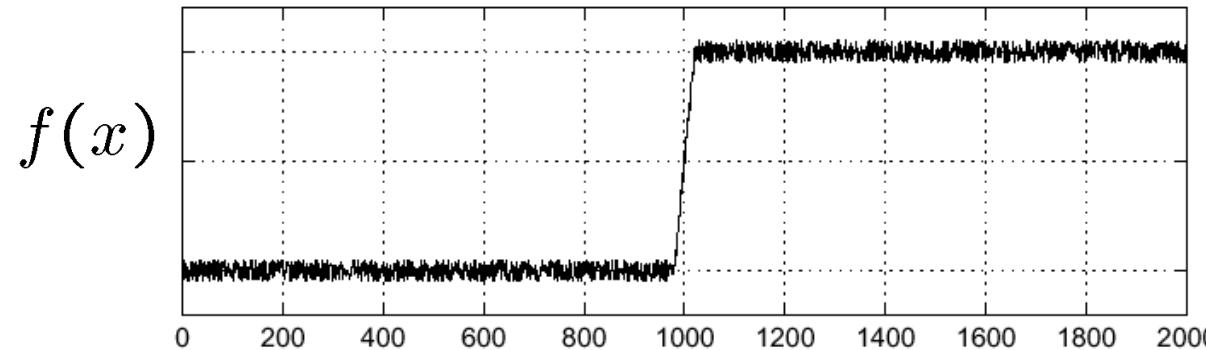
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	$\frac{1}{2}$	$\frac{1}{2}$	0	$-\frac{1}{2}$	$-\frac{1}{2}$	0	0	0	0	0
0	$\frac{1}{2}$	$\frac{1}{2}$	0	$-\frac{1}{2}$	$-\frac{1}{2}$	0	0	0	0	0
0	$\frac{1}{2}$	$\frac{1}{2}$	0	$-\frac{1}{2}$	$-\frac{1}{2}$	0	0	0	0	0
0	$\frac{1}{2}$	$\frac{1}{2}$	0	$-\frac{1}{2}$	$-\frac{1}{2}$	0	0	0	0	0
0	$\frac{1}{2}$	$\frac{1}{2}$	0	$-\frac{1}{2}$	$-\frac{1}{2}$	0	0	0	0	0
0	$\frac{1}{2}$	$\frac{1}{2}$	0	$-\frac{1}{2}$	$-\frac{1}{2}$	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0

$$|\nabla I|(u, v) = \sqrt{\left(\frac{\partial I}{\partial u}(u, v)\right)^2 + \left(\frac{\partial I}{\partial v}(u, v)\right)^2}$$

Gradient
magnitude
(after threshold)

Problem - Derivative usually suffers from noise

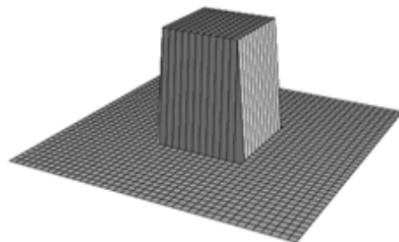
- Consider a single row or column of the image



Where is the edge?

Smoothing

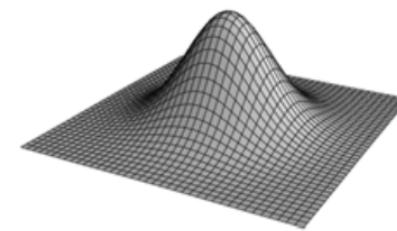
- Finite differentiation filters respond **strongly** to noise
 - Image noise results in pixels that look very different from their neighbours
 - Generally, the larger the noise, the stronger the response
- Smoothing the image to **reduce** noise **before** computing the derivative
 - Smoothing is a filter operation that averages a pixel using its surrounding pixels
 - Can be performed by using a **kernel filter** similarly as introduced previously



$$\frac{1}{3} \times [1 \quad 1 \quad 1]$$

Mean Smoothing

$$\frac{1}{3} \times \begin{array}{|c|} \hline 1 \\ \hline 1 \\ \hline 1 \\ \hline \end{array}$$



$$\frac{1}{4} \times [1 \quad 2 \quad 1]$$

Gaussian Smoothing

$$\frac{1}{4} \times \begin{array}{|c|} \hline 1 \\ \hline 2 \\ \hline 1 \\ \hline \end{array}$$

Smoothing with different filters

$$\frac{1}{9} \times \begin{array}{|c|c|c|} \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline 1 & 1 & 1 \\ \hline \end{array}$$

3x3

Mean



$$\frac{1}{25} \times \begin{array}{|c|c|c|c|c|} \hline 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 \\ \hline \end{array}$$

5x5

Gaussian



1/16

$$\begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline 2 & 4 & 2 \\ \hline 1 & 2 & 1 \\ \hline \end{array}$$

$$\frac{1}{49} \times \begin{array}{|c|c|c|c|c|c|c|c|} \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ \hline \end{array}$$

7x7



1/273

$$\begin{array}{|c|c|c|c|c|} \hline 1 & 4 & 7 & 4 & 1 \\ \hline 4 & 16 & 26 & 16 & 4 \\ \hline 7 & 26 & 41 & 26 & 7 \\ \hline 4 & 16 & 26 & 16 & 4 \\ \hline 1 & 4 & 7 & 4 & 1 \\ \hline \end{array}$$

1/1003

$$\begin{array}{|c|c|c|c|c|c|c|} \hline 0 & 0 & 1 & 2 & 1 & 0 & 0 \\ \hline 0 & 3 & 13 & 22 & 13 & 3 & 0 \\ \hline 1 & 13 & 59 & 97 & 59 & 13 & 1 \\ \hline 2 & 22 & 97 & 159 & 97 & 22 & 2 \\ \hline 1 & 13 & 59 & 97 & 59 & 13 & 1 \\ \hline 0 & 3 & 13 & 22 & 13 & 3 & 0 \\ \hline 0 & 0 & 1 & 2 & 1 & 0 & 0 \\ \hline \end{array}$$

Sobel filter

- Presented by Irwin Sobel and Gary Feldman in 1968.
- Uses two 3 x 3 kernels
- One for horizontal changes, and one for vertical

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \quad \mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

- Magnitude

$$\mathbf{G} = \sqrt{\mathbf{G}_x^2 + \mathbf{G}_y^2}$$

Sobel filter

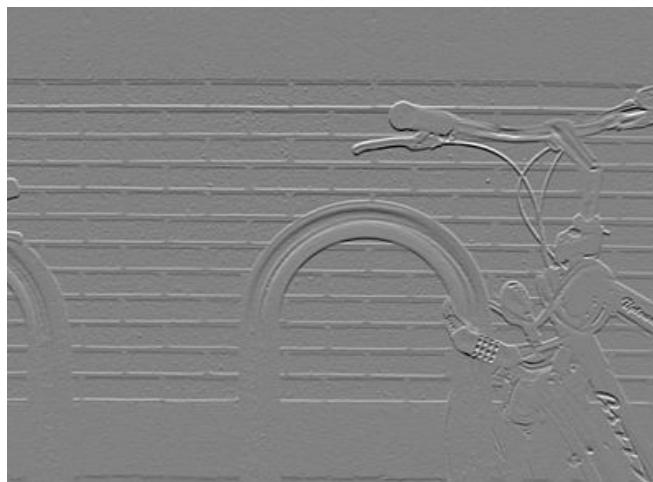
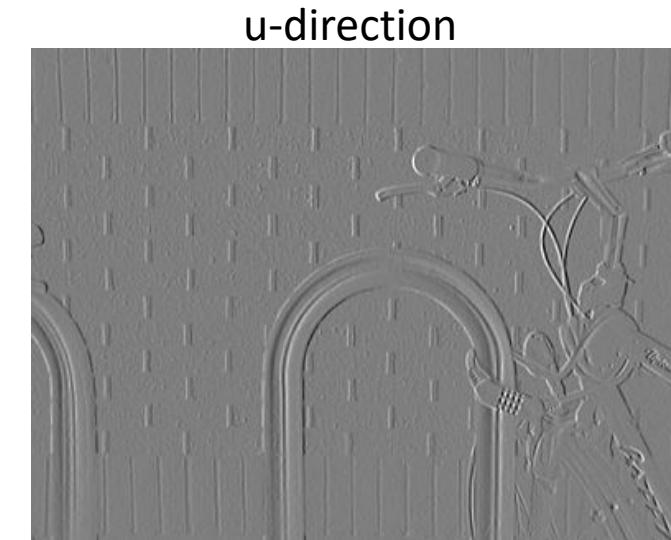
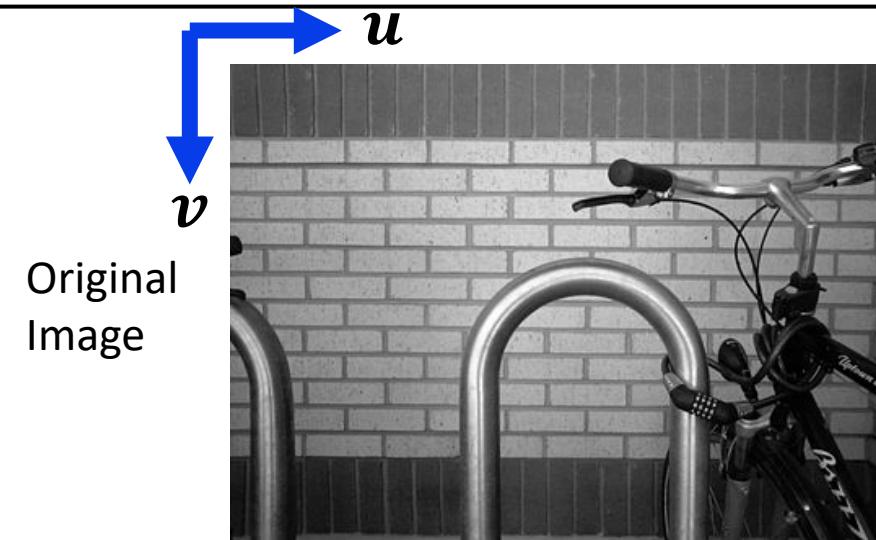
- Combination of Gaussian Smoothing and Finite Differentiation

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} [+1 \quad 0 \quad -1]$$

Gaussian smoothing Finite differentiation

The diagram illustrates the decomposition of the Sobel filter \mathbf{G}_x into Gaussian smoothing and finite differentiation components. It shows the original filter matrix \mathbf{G}_x on the left, followed by an equals sign, then a Gaussian smoothing kernel (a column vector) in the middle, and finally a finite differentiation kernel (a row vector) on the right. Two blue arrows point from the text labels "Gaussian smoothing" and "Finite differentiation" to the corresponding middle and right components respectively.

Sobel filter



Sobel filter – Example in x direction

0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0

1	0	-1
2	0	-2
1	0	-1

• $\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} =$

0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0

Sobel filter – Example in x direction

1	0	-1	0	0	0	0	0	0	0
0	0	-2	0	0	0	0	0	0	0
1	0	-1	1	1	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0
0	0	1	1	1	1	1	1	0	0
0	0	1	1	1	1	1	1	0	0
0	0	1	1	1	1	1	1	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

• $\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} =$

0	0	0	0	0	0	0	0	0	0
0	-1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

Sobel filter – Example in x direction

What should the value be for the yellow cell on the right?

0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0

1	0	-1
2	0	-2
1	0	-1

$$\bullet \quad \mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} =$$

0	0	0	0	0	0	0	0	0	0	0
0	-1									0
0	?									0
0										0
0										0
0										0
0										0
0										0
0										0
0	0	0	0	0	0	0	0	0	0	0

What should the value be for the yellow cell on the right?

- ⓘ Start presenting to display the poll results on this slide.

Sobel filter – Example in x direction

What should the value be for the yellow cell on the right?

0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	1	1	1	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0

1	0	-1
2	0	-2
1	0	-1

$$\bullet \quad \mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} =$$

0	0	0	0	0	0	0	0	0	0	0
0	-1									0
0	?									0
0										0
0										0
0										0
0										0
0										0
0										0
0	0	0	0	0	0	0	0	0	0	0

Sobel filter – Example in x direction

0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0	0
0	0	1	1	1	0	0	0	0	0	0	0
0	0	1	1	1	1	1	1	0	0	0	0
0	0	1	1	1	1	1	1	0	0	0	0
0	0	1	1	1	1	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0

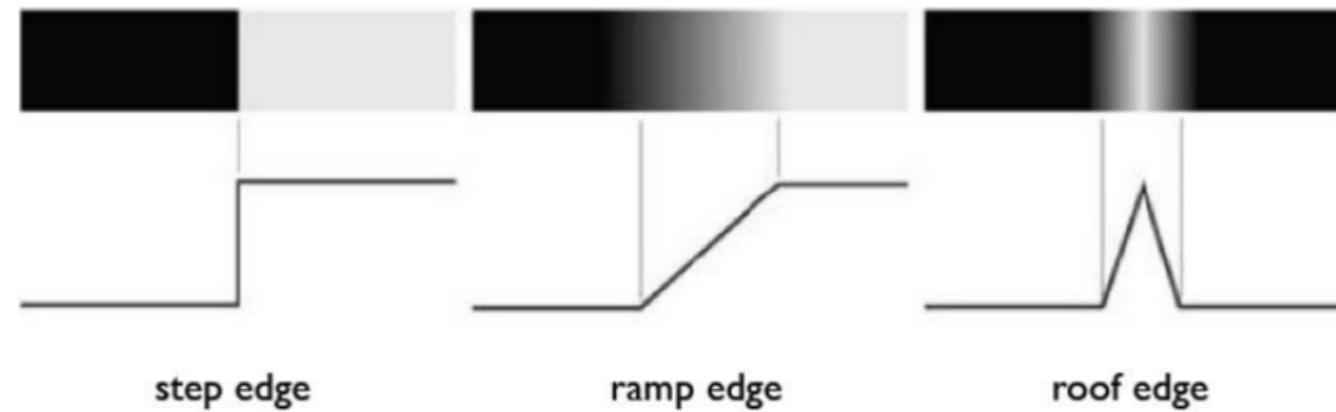
1	0	-1
2	0	-2
1	0	-1

$$\bullet \quad \mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} =$$

0	0	0	0	0	0	0	0	0	0	0	0
0	-1	-1	0	1	1	0	0	0	0	0	0
0	-3	-3	0	3	3	0	0	0	0	0	0
0	-4	-4	0	4	4	0	0	0	0	0	0
0	-4	-4	0	3	3	0	1	1	0	0	0
0	-4	-4	0	1	1	0	3	3	0	0	0
0	-4	-4	0	0	0	0	4	4	0	0	0
0	-3	-3	0	0	0	0	0	3	3	0	0
0	-1	-1	0	0	0	0	0	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0

Sobel filter problems

- Poor localisation
 - Trigger response in multiple adjacent pixels (Consider grayscale image instead of binary image)



- Thresholding value **favours** certain directions **over** others
 - Can **miss** oblique edges more than horizontal or vertical edges

$$\mathbf{G}_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \quad \mathbf{G}_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

Canny edge detector

- Developed by John F. Canny in 1986.
- Probably the most widely used edge detector in computer vision
- A multi-stage algorithm operating at different scales:
 1. Filter image with a Gaussian filter
 2. Find the intensity gradient of the image using Sobel filters
 3. Non-maximum suppression:
 - Thin multi-pixel wide “ridges” down to single pixel width
 4. Thresholding and linking (hysteresis):
 - Define two thresholds: low and high
 - Use the high threshold to start edge curves and the low threshold to continue them

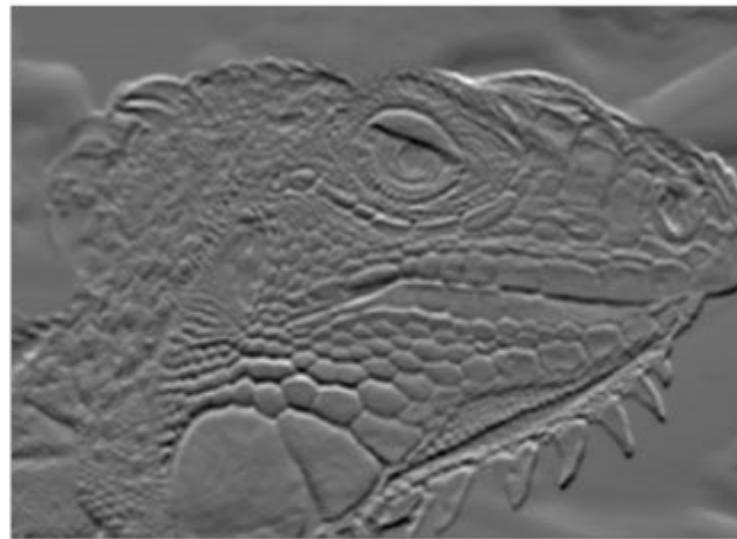
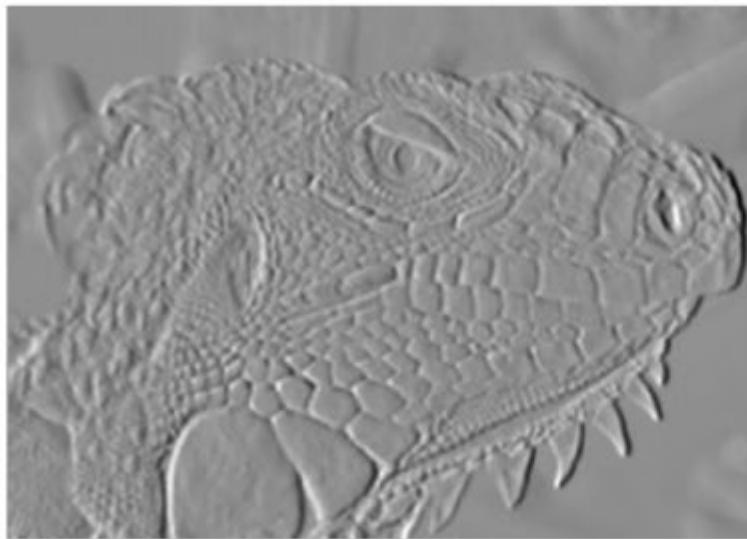
Canny edge detector

- Original image



Canny edge detector

1. Filter image with a **Gaussian filter**
2. Find the intensity gradient of the image using **Sobel filters**



X-Derivative of Gaussian

Y-Derivative of Gaussian

Gradient Magnitude

Canny edge detector

3. Non-maximum suppression:

- Thin multi-pixel wide “ridges” down to **single** pixel width



Before



After

Canny edge detector

4. Thresholding and linking (hysteresis):

- Define two thresholds: **low** and **high**
 - If less than Low, **not** an edge
 - If greater than High, **strong** edge
 - If between Low and High, **weak** edge

Thresholding (high)



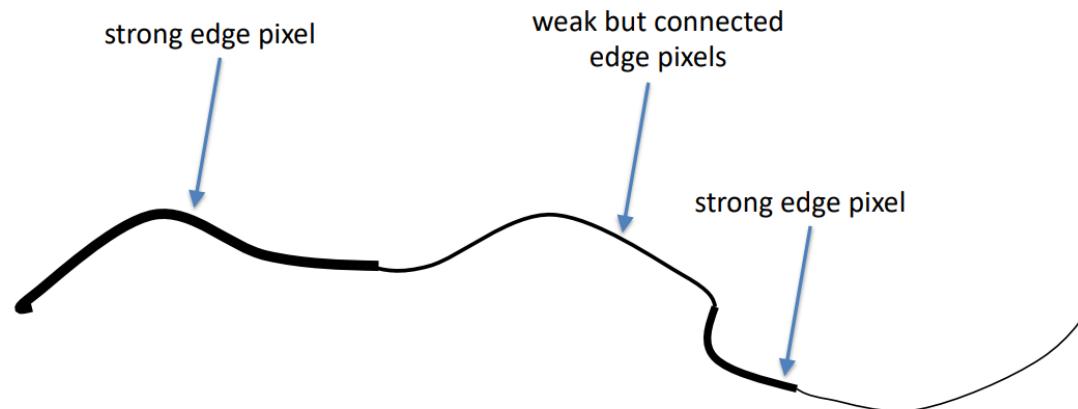
Thresholding (low)



Canny edge detector

4. Thresholding and linking (hysteresis):

- Define two thresholds: **low** and **high**
 - If less than Low, **not** an edge
 - If greater than High, **strong** edge
 - If between Low and High, **weak** edge
- Use the **high threshold** to start edge curves and the **low threshold** to continue them
 - For weak edges:
 - Consider its neighbours iteratively then declare it an “edge pixel” if it is connected to an ‘strong edge pixel’ directly or via pixels between Low and High



Canny edge detector

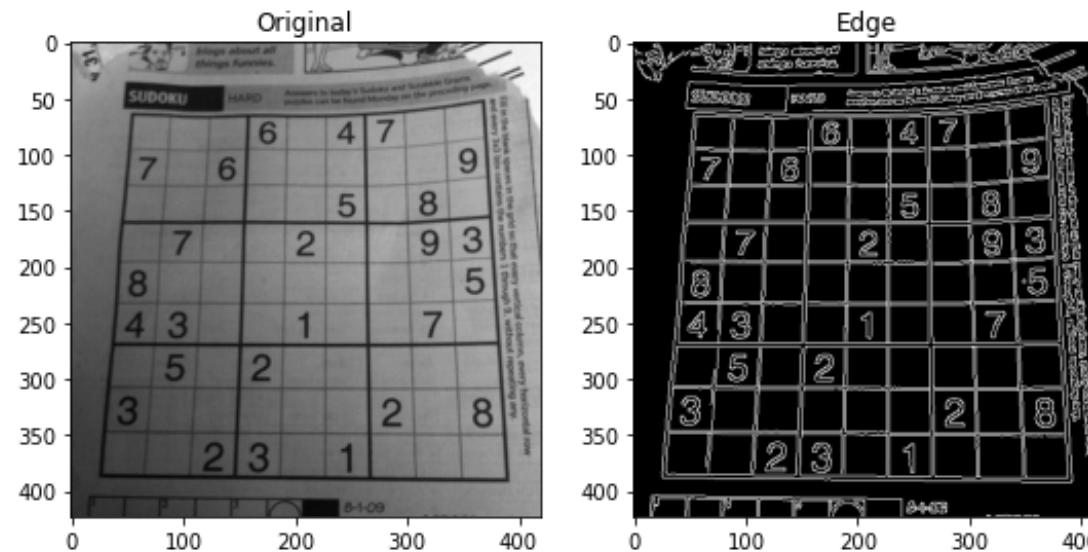
Final edges:



OpenCV examples – Edge detection

```
1 #import required Libraries
2 import cv2 # OpenCV Library
3 import numpy as np # Numpy Library for scientific computing
4 import matplotlib.pyplot as plt # Matplotlib Library for plotting
5
6 #canny edge detection
7 img = cv2.imread('sudoku.jpg',cv2.IMREAD_GRAYSCALE)
8 edges = cv2.Canny(img,50,100)
9
10 #plot the image
11 fig, (ax1, ax2) = plt.subplots(figsize = (9, 5), ncols = 2)
12 ax1.imshow(img, cmap='gray'), ax1.set_title("Original")
13 ax2.imshow(edges, cmap='gray'), ax2.set_title("Edge")
```

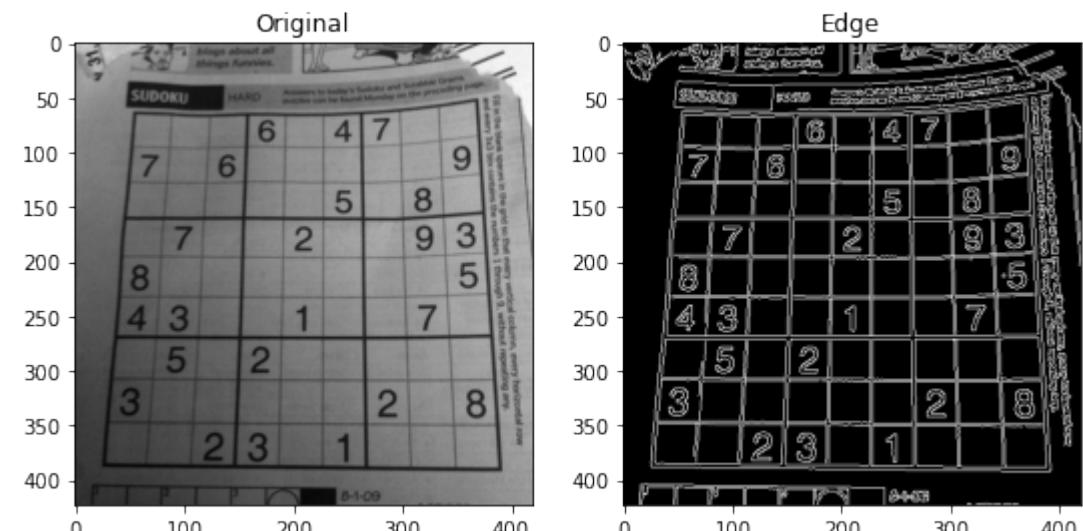
(<matplotlib.image.AxesImage at 0x1b383c02b88>, Text(0.5, 1.0, 'Edge'))



Hough Transform

Now we have the edges, can we extract **lines** out of the edge map?

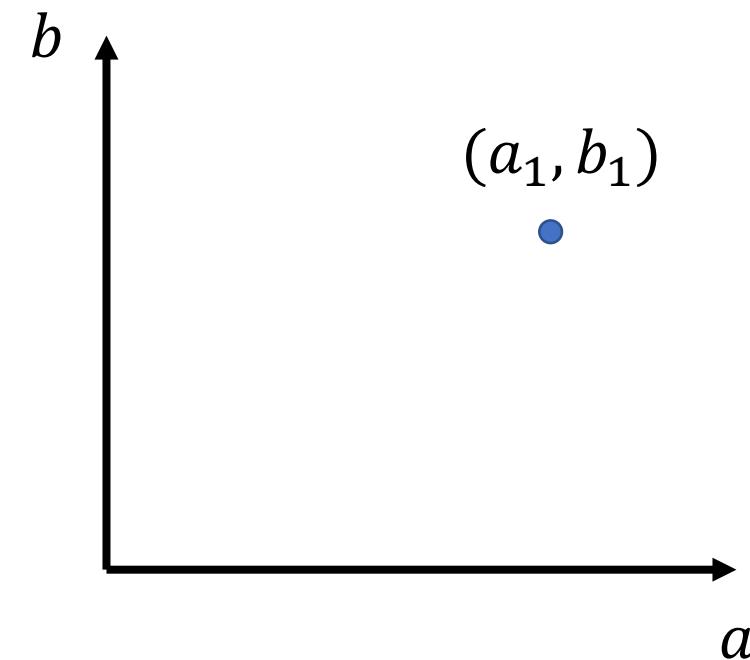
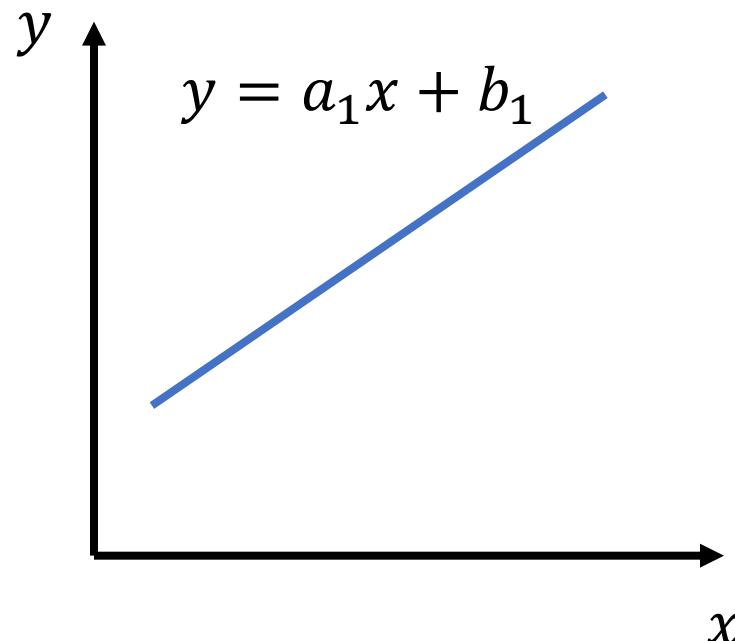
- Hough Transform (HT) can help with this.
- Introduced in 1962 by **Paul Hough**
- We will introduce **line detection** using Hough transform, however, note that it can be used for **other feature** detections such as **circle** or **ellipses** detection.



https://en.wikipedia.org/wiki/Hough_transform

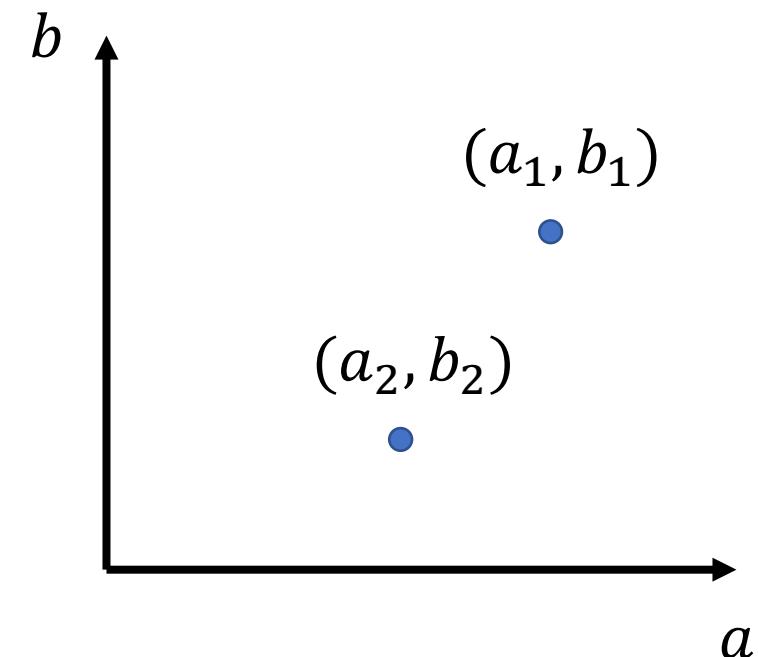
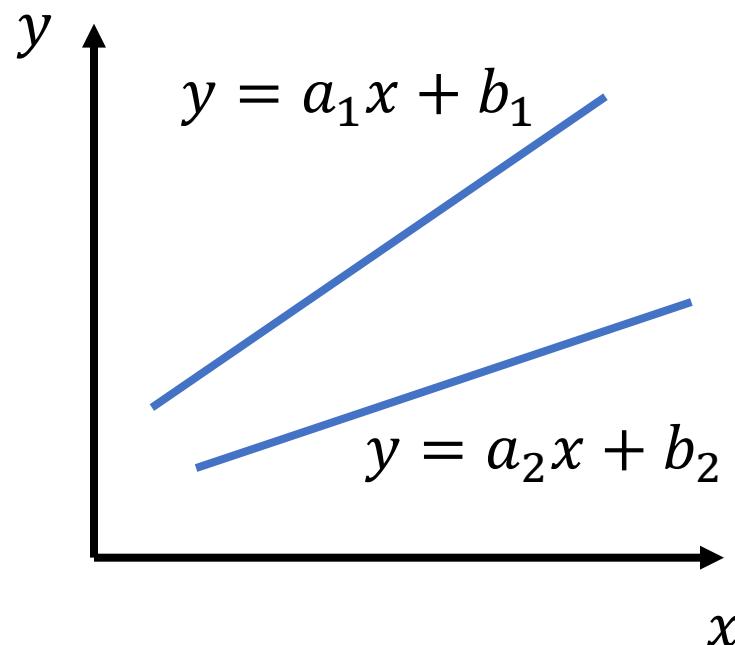
Parameter space

- A line can be represented by an infinite set of points (x_i, y_i)
 - A line can **also** be represented by a pair of parameters (a_i, b_i)
- A **line** in the “x-y” space gives a **point** in the “a-b” space;



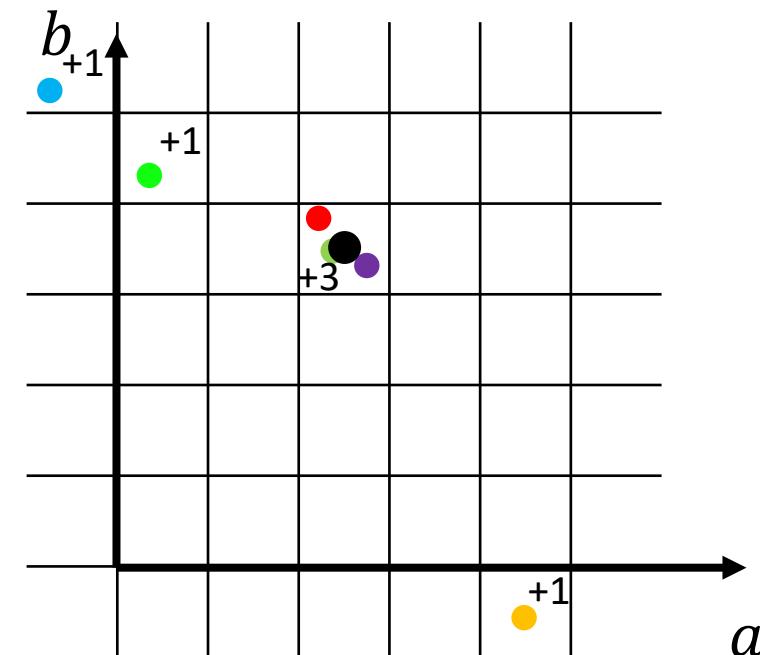
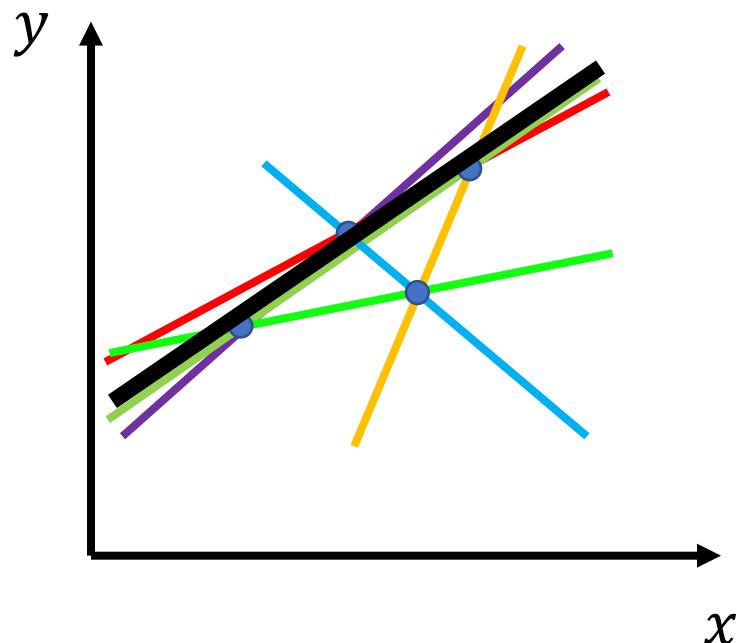
Parameter space

- A line can be represented by an infinite set of points (x_i, y_i)
 - A line can **also** be represented by a pair of parameters (a_i, b_i)
- A **line** in the “x-y” space gives a **point** in the “a-b” space;



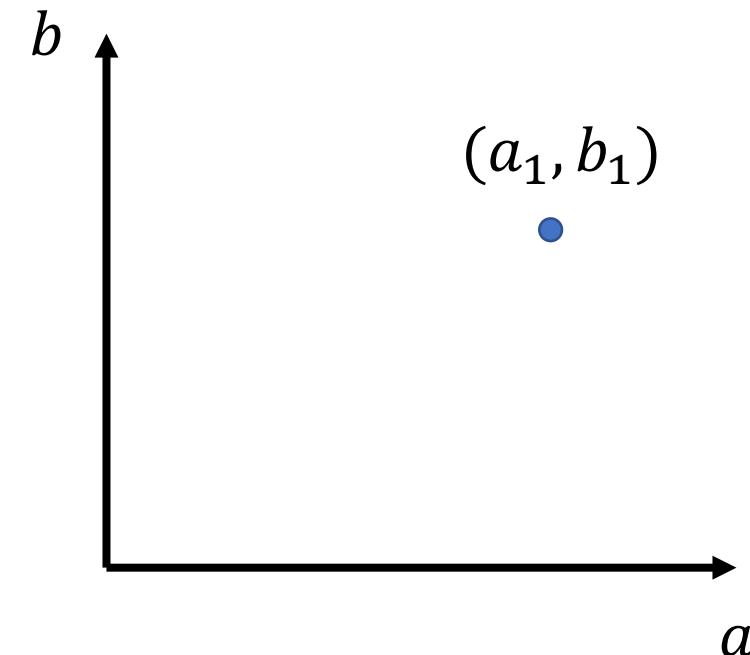
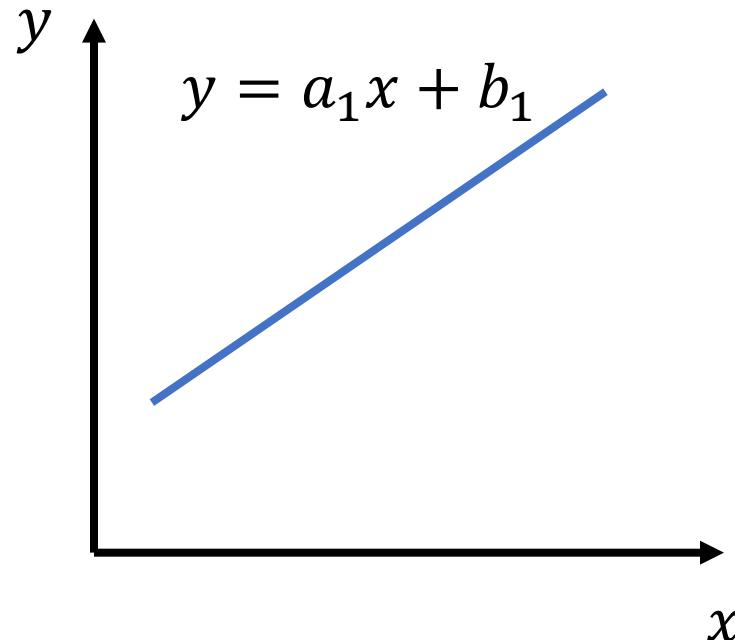
Hough line detection – Version 1

- 1. Quantize the parameter space “a-b” by dividing it into cells
- 2. For each pair of points (x_1, y_1) and (x_2, y_2) detected as an edge, find the point (a, b) in the “a-b” space
- 3. Increase the value of a cell if a point (a, b) belongs to this cell
- 4. Cells receiving more than a certain number of votes are assumed to correspond to lines in the “x-y” space



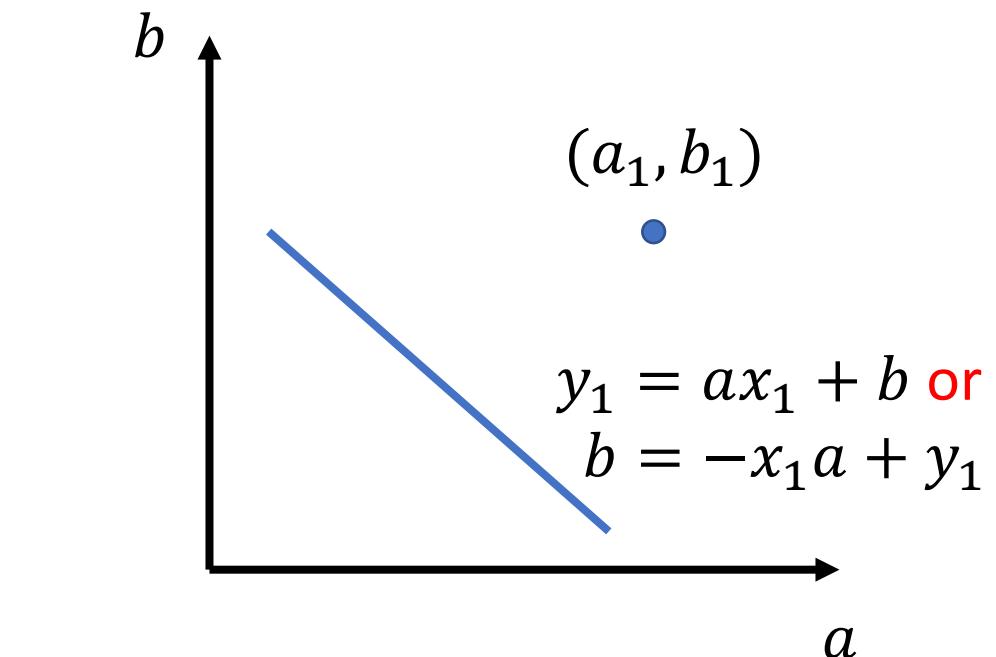
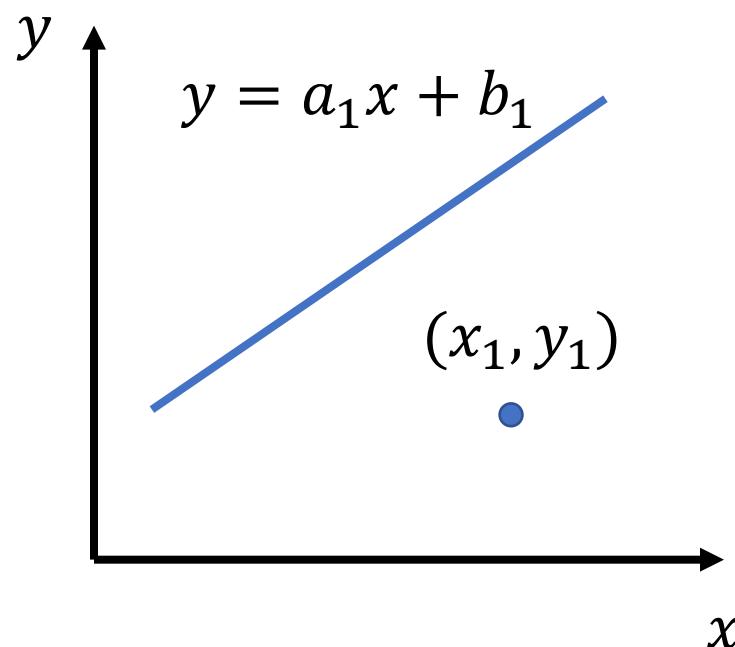
Parameter space

- A line can be represented by an infinite set of points (x_i, y_i)
 - A line can **also** be represented by a pair of parameters (a_i, b_i)
- A **line** in the “x-y” space gives a **point** in the “a-b” space;



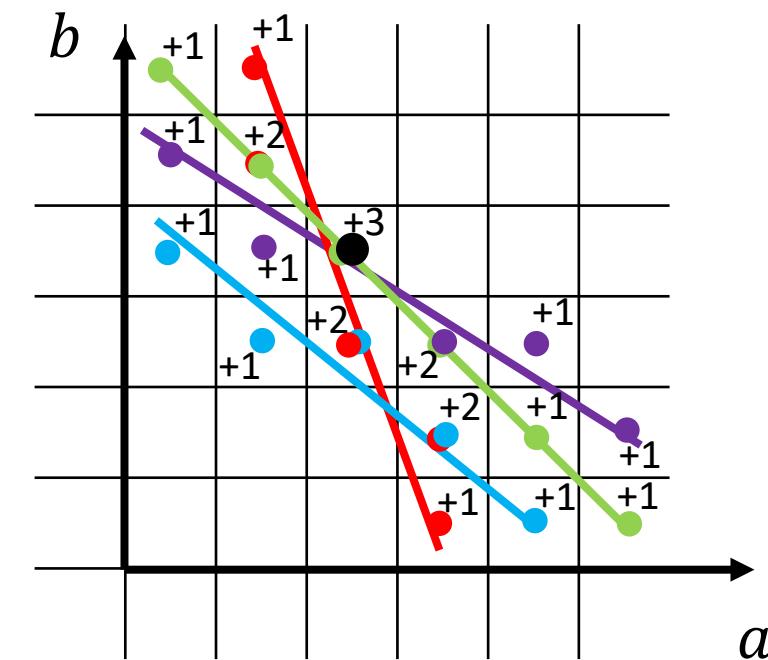
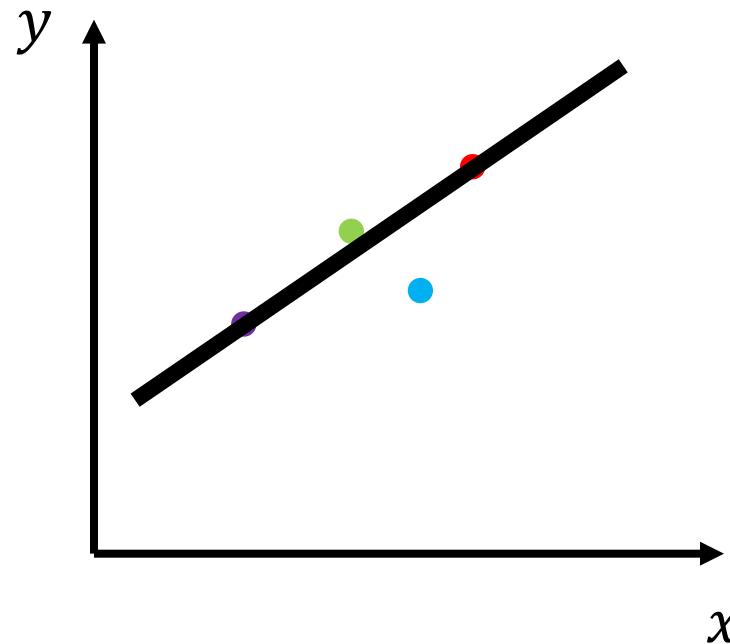
Parameter space

- A line can be represented by an infinite set of points (x_i, y_i)
 - A **line** in the “x-y” space gives a **point** in the “a-b” space;
 - A **point** in the “x-y” space also corresponds to a **line** in the “a-b” space.
- A line can **also** be represented by a pair of parameters (a_i, b_i)



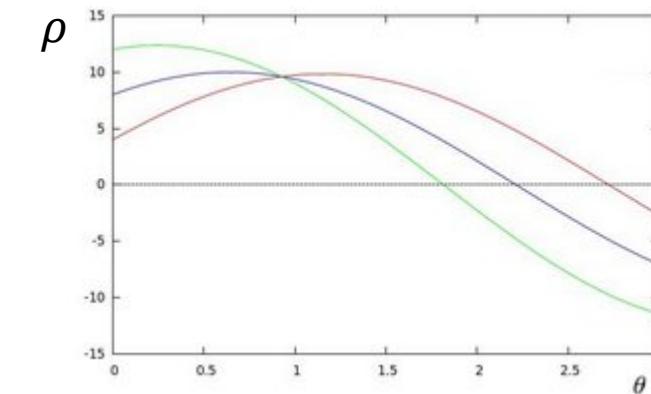
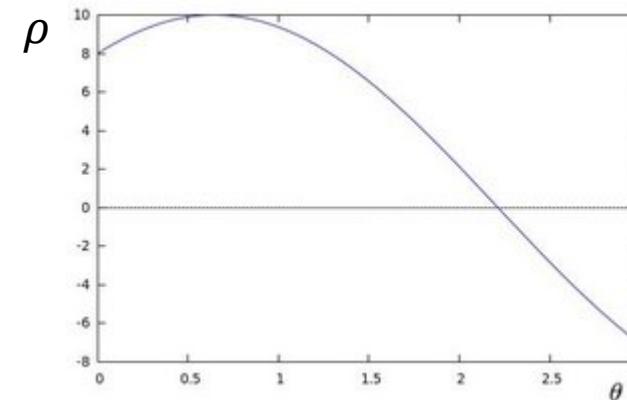
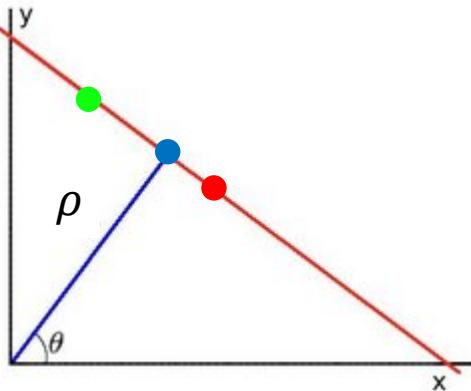
Hough line detection – Version 2

- 1. Quantize the parameter space “ $a-b$ ” by dividing it into cells
- 2. **For each point (x_1, y_1) on the detected edge in the “ $x-y$ ” space, draw a line in the “ $a-b$ ” space**
- 3. Increase the value of a cell if a point (a, b) belongs to this cell
- 4. Cells receiving more than a certain number of votes are assumed to correspond to lines in the “ $x-y$ ” space



Hough line transform using Polar Coordinates

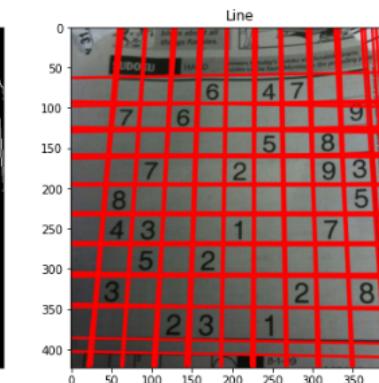
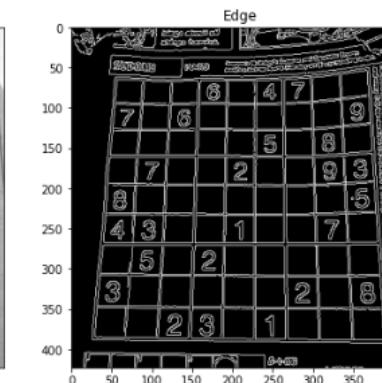
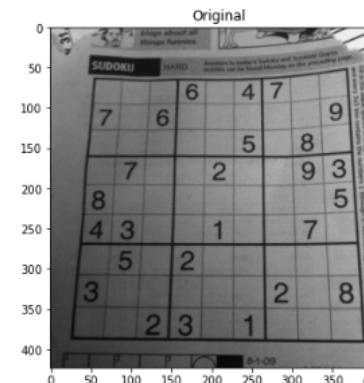
- It is better to use Polar Coordinate System than Cartesian Coordinate System to **avoid singularity of vertical lines**
- Parameters: (ρ_i, θ_i) $\rho = x_i \cos(\theta) + y_i \sin(\theta)$
- A **point** in the “x-y” space corresponds to a **curve** in the “ ρ - θ ” space
- An **intersection** of many curves in the “ ρ - θ ” space will define a line in the “x-y” space



OpenCV examples – Hough line transform

```
1 #import required libraries
2 import cv2 # OpenCV Library
3 import numpy as np # Numpy Library for scientific computing
4 import matplotlib.pyplot as plt # Matplotlib Library for plotting
5
6 #canny edge detection
7 img = cv2.imread('sudoku.jpg',cv2.IMREAD_GRAYSCALE)
8 img_bgr = cv2.imread('sudoku.jpg')
9 edges = cv2.Canny(img, threshold1 = 50, threshold2 = 100, apertureSize = 3)
10
11 #hough transformation
12 lines = cv2.HoughLines(edges, rho = 1, theta = np.pi/180, threshold = 160)
13
14 #draw lines
15 l,_ = lines.shape
16 for i in range(l):
17     rho = lines[i][0][0]
18     theta = lines[i][0][1]
19     a = np.cos(theta)
20     b = np.sin(theta)
21     x0 = a*rho
22     y0 = b*rho
23     x1 = int(x0 + 1000*(-b))
24     y1 = int(y0 + 1000*(a))
25     x2 = int(x0 - 1000*(-b))
26     y2 = int(y0 - 1000*(a))
27     cv2.line(img_bgr, (x1,y1), (x2,y2), (0,0,255), 2, cv2.LINE_AA)
28 img_rgb = cv2.cvtColor(img_bgr, cv2.COLOR_BGR2RGB)
29
30 #plot the image
31 fig, (ax1, ax2, ax3) = plt.subplots(figsize = (18, 10), ncols = 3)
32 ax1.imshow(img, cmap='gray'), ax1.set_title("Original")
33 ax2.imshow(edges, cmap='gray'), ax2.set_title("Edge")
34 ax3.imshow(img_rgb, cmap='gray'), ax3.set_title("Line")
```

(<matplotlib.image.AxesImage at 0x1b396854d08>, Text(0.5, 1.0, 'Line'))



Hough line detection - Summary

Advantages

- Conceptually **simple**
- **Easy** implementation
- Handles **missing** and **occluded** data very gracefully
- Can be adapted to **many** types of forms, not just lines

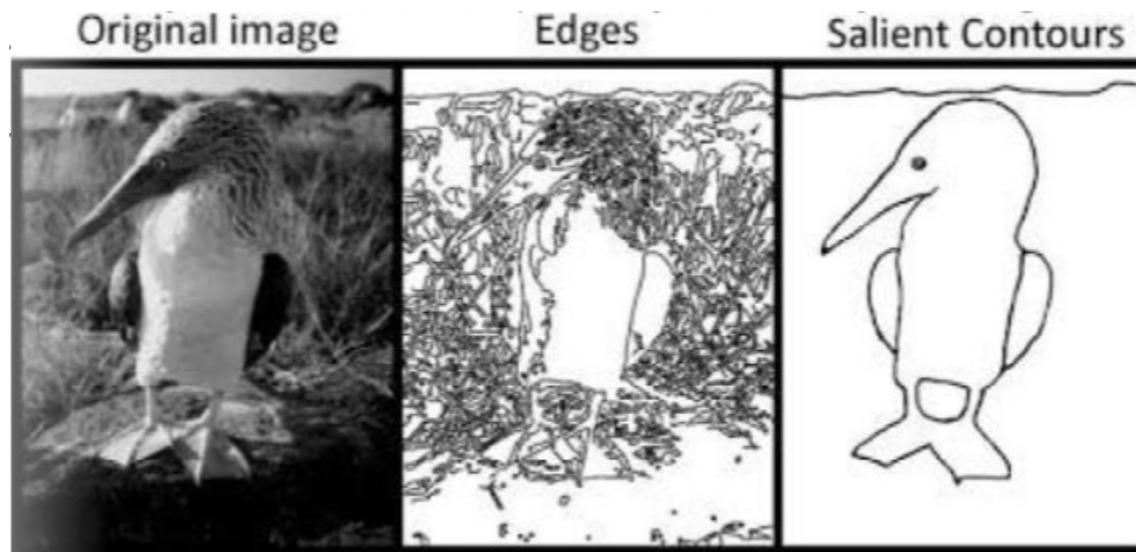
Disadvantages

- Computationally **complex** for objects with many parameters
- Looks for only **one single** type of object
- The length and the position of a **line segment cannot** be determined
- **Co-linear** line segments **cannot** be separated

Contour Detection

Contour detection

- Contour:
 - A curve joining all the continuous points (along the boundary), having same color or intensity.
 - Useful for **shape analysis** and **object detection and recognition**.
 - For better accuracy, use binary images. So before finding contours, apply threshold or canny edge detection.



<https://medium.com/swlh/contours-in-images-a58b4c12cff>

OpenCV implementation

- Following a method proposed by **Suzuki** and **Abe** in 1985
- Key idea: trace borders by **connectivity** and determine topological hierarchy

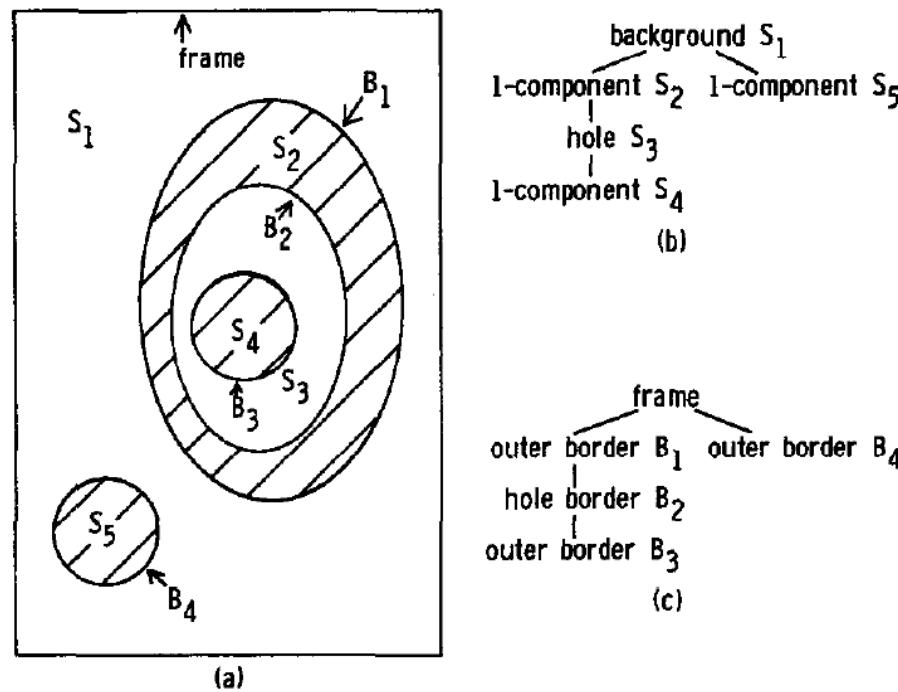


FIG. 1. Surroundness among connected components (b) and among borders (c).

Contour characteristics

- **Moment** (similar to moment of mass in physics)

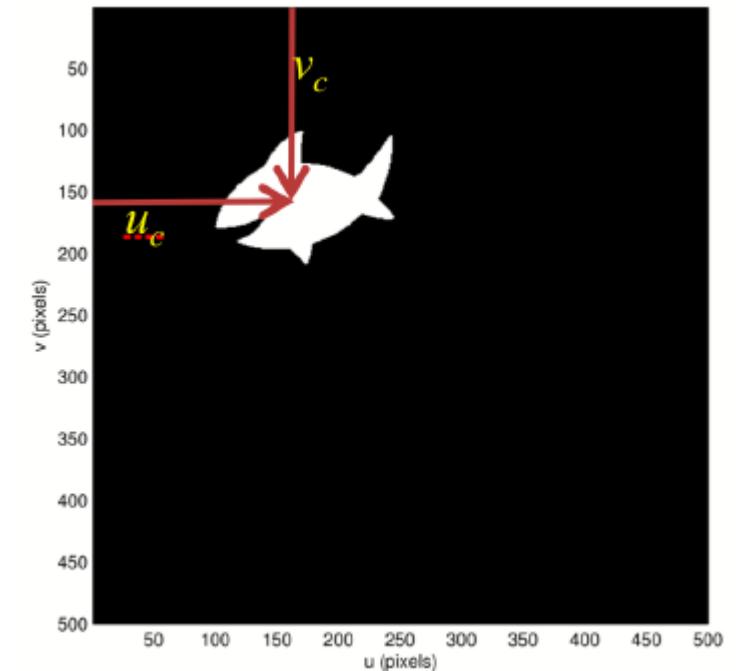
$$m_{pq} = \sum_{(u,v) \in \mathbf{I}} u^p v^q \mathbf{I}[u, v]$$

- **Area** (m_{00} for binary image)

$$m_{00} = \sum_{(u,v) \in \mathbf{I}} \mathbf{I}[u, v]$$

- **Centroid**

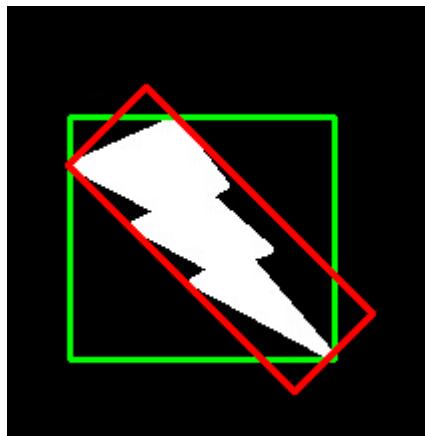
$$u_c = \frac{m_{10}}{m_{00}}, \quad v_c = \frac{m_{01}}{m_{00}}$$



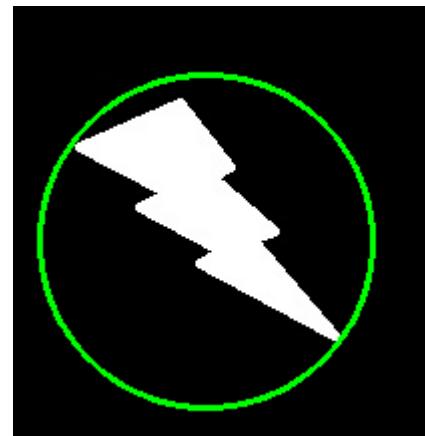
Contour characteristics

- Some other characteristics

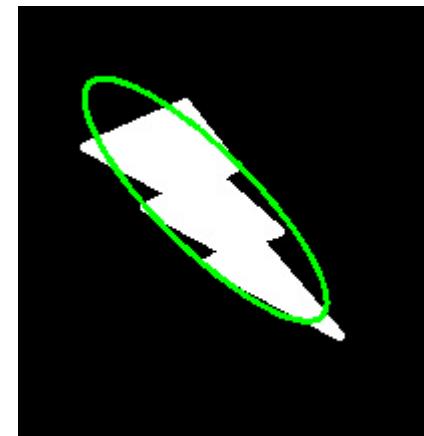
Bounding rectangle



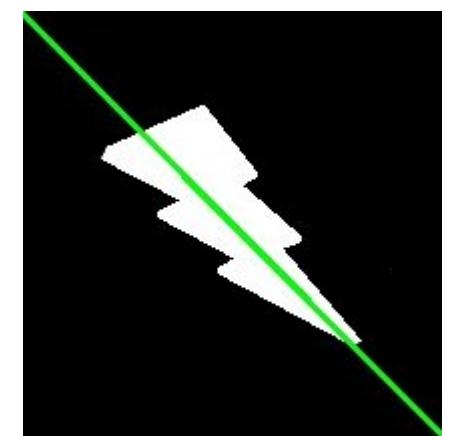
Minimum enclosing circle



Fitting an ellipse



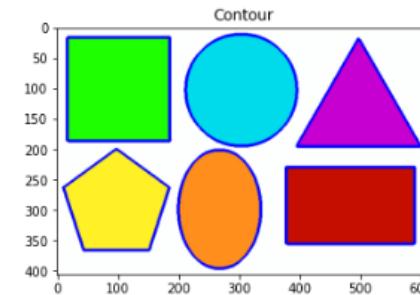
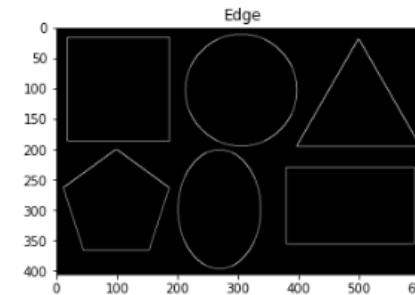
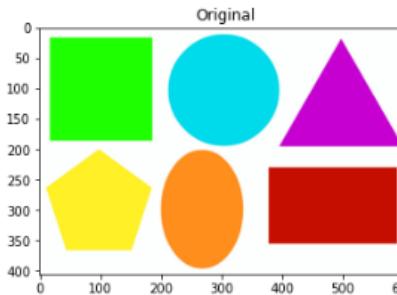
Fitting a line



OpenCV examples – Contour detection

```
1 #import required libraries
2 import cv2 # OpenCV library
3 import numpy as np # Numpy Library for scientific computing
4 import matplotlib.pyplot as plt # Matplotlib library for plotting
5 # show plots in notebook
6 %matplotlib inline
7
8 #canny edge detection
9 img_bgr = cv2.imread('shapes.png')
10 img_gray = cv2.imread('shapes.png',cv2.IMREAD_GRAYSCALE)
11 img_rgb_origin = cv2.cvtColor(img_bgr, cv2.COLOR_BGR2RGB)
12 edges = cv2.Canny(img_gray, threshold1 = 50, threshold2 = 100, apertureSize = 3)
13
14 #contour detection
15 img2, contours, hierarchy = cv2.findContours(edges, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
16 cv2.drawContours(img_bgr, contours, -1, (255, 0, 0), 3)
17 img_rgb = cv2.cvtColor(img_bgr, cv2.COLOR_BGR2RGB)
18
19 #plot the image
20 fig, (ax1, ax2, ax3) = plt.subplots(figsize = (18, 10), ncols = 3)
21 ax1.imshow(img_rgb_origin), ax1.set_title("Original")
22 ax2.imshow(edges, cmap='gray'), ax2.set_title("Edge")
23 ax3.imshow(img_rgb), ax3.set_title("Contour")
24
25 #calculate moments and areas
26 for i, cnt in enumerate(contours):
27     m = cv2.moments(cnt)
28     area = cv2.contourArea(cnt)
29     print("shape", i, ":", m['m00'], "-", area)
```

```
shape 0 : m00 - 26709.0 area - 26709.0
shape 1 : m00 - 20900.5 area - 20900.5
shape 2 : m00 - 20065.0 area - 20065.0
shape 3 : m00 - 18234.5 area - 18234.5
shape 4 : m00 - 28729.0 area - 28729.0
shape 5 : m00 - 26514.0 area - 26514.0
```



Corner Detection

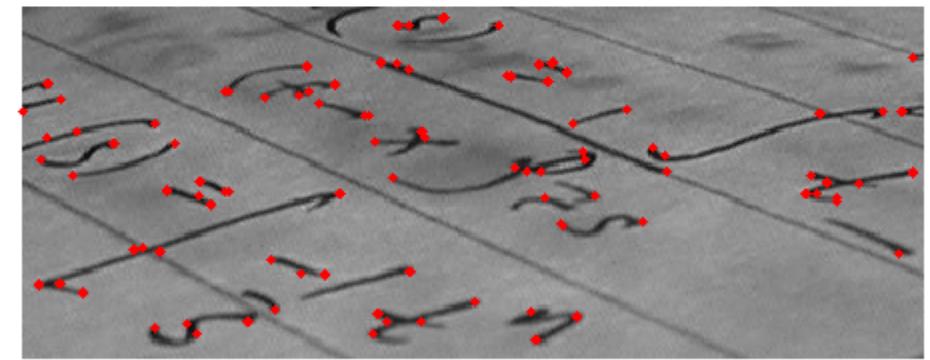
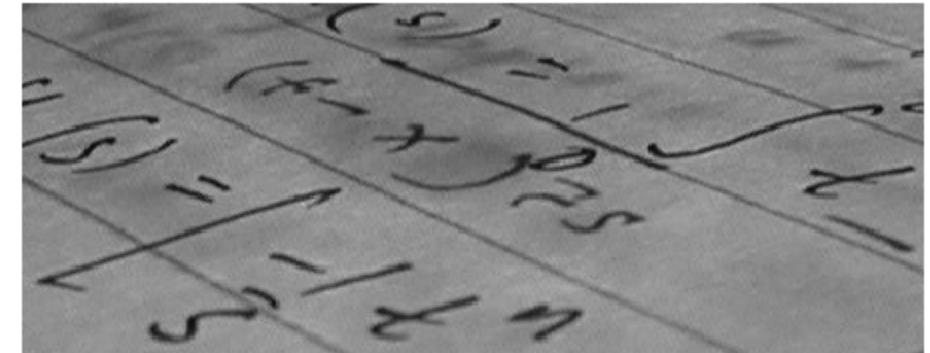
Why corner detection?

- Motivating problem:
 - Can you find the patches below in the right image?

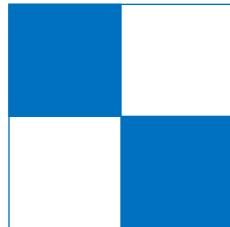


Corner detection

- Corners are usually more **unique** and **robust** features
- Corner detection is an approach to **extract** certain kinds of features and **infer** the contents of an image
- Frequently used in **motion detection**, **image registration**, **video tracking**, **image mosaicking**, **panorama stitching**, **3D reconstruction** and **object recognition**



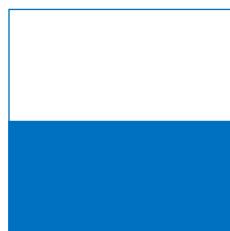
Corners vs edges



Intensity change in x → Large

Intensity change in y → Large

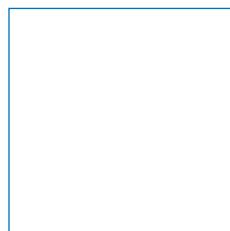
Corner



Intensity change in x → Small

Intensity change in y → Large

Edge



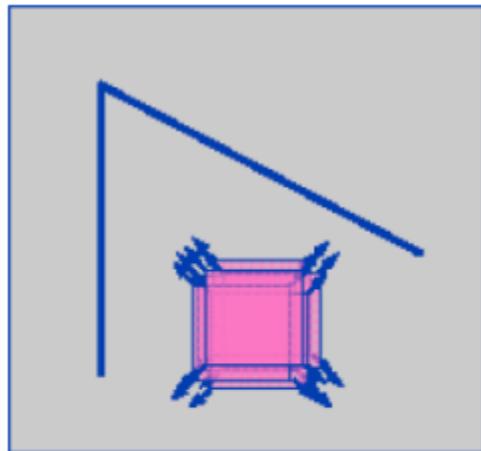
Intensity change in x → Small

Intensity change in y → Small

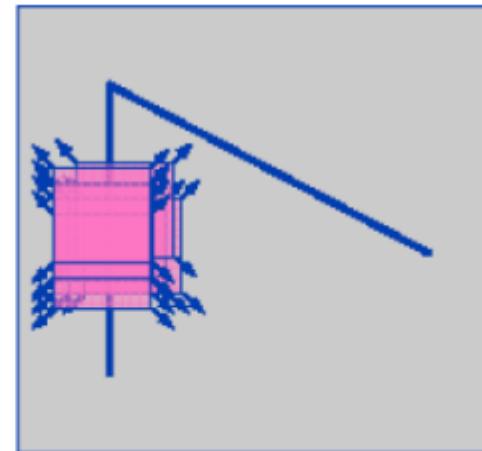
Nothing

Harris corner detector

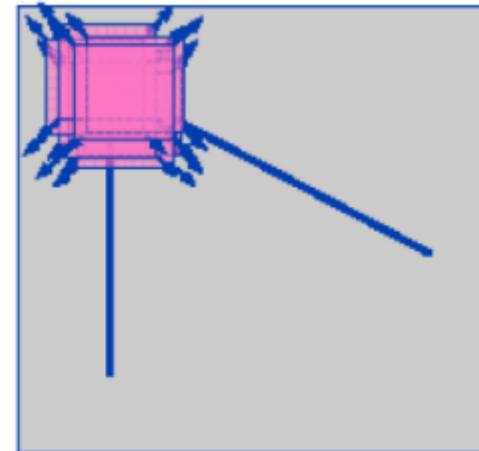
- Proposed by **Chris Harris** and **Mike Stephens** in 1988
- Shift patch by $[u,v]$ and compute change in intensity



Flat region: no intensity change in all directions



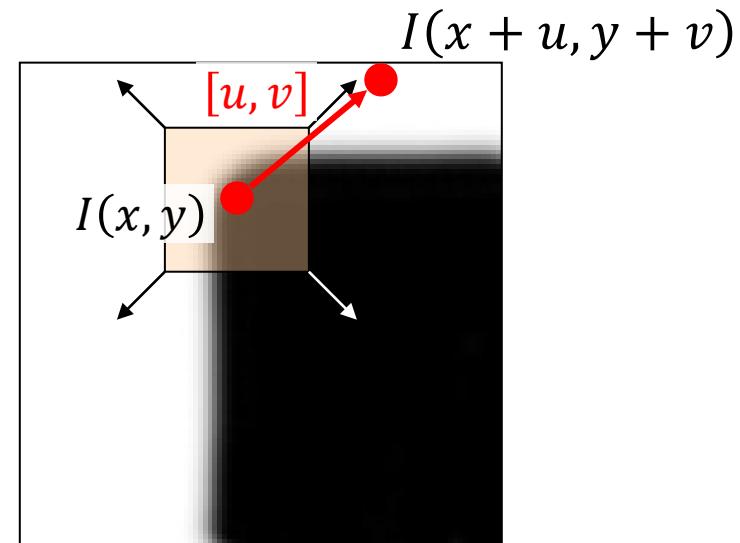
Edge: no change along edge directions



Corner: significant intensity change in many directions

Measure change as intensity difference:

$$I(x + u, y + v) - I(x, y)$$

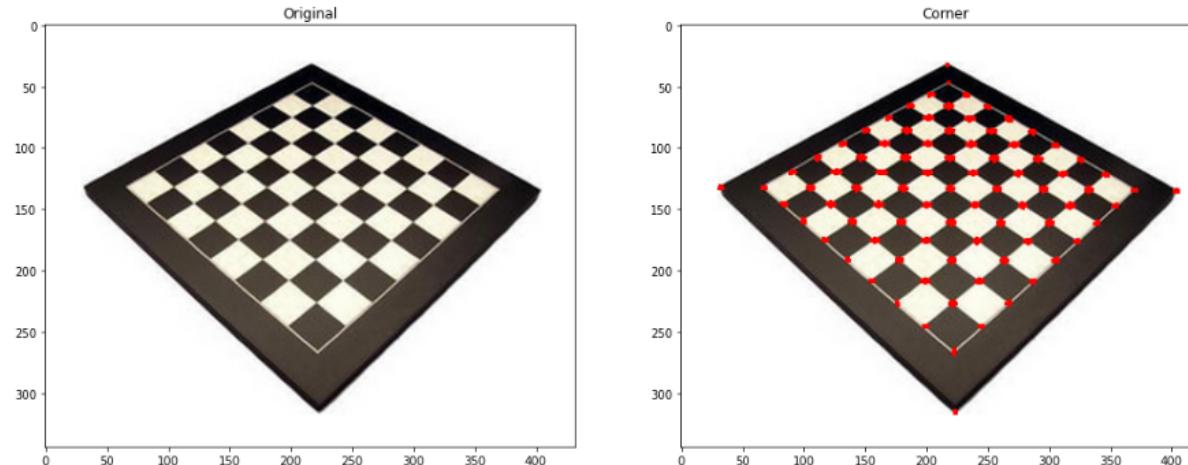


“corner”:
significant change
in all directions

OpenCV examples – Corner detection

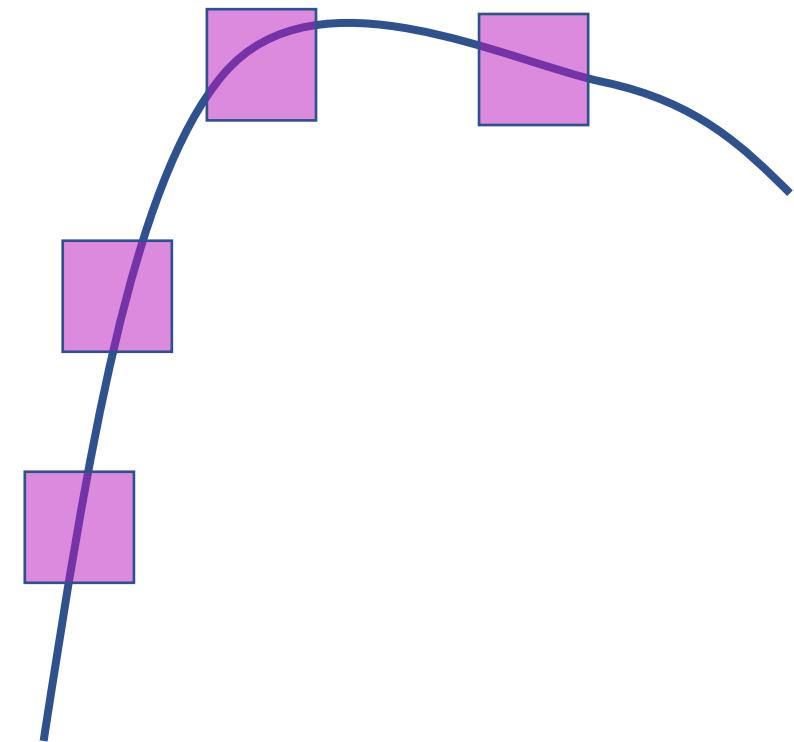
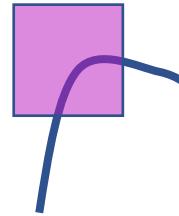
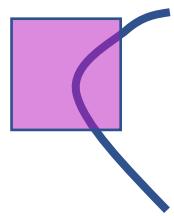
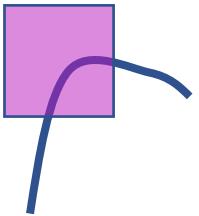
```
1 #import required libraries
2 import cv2 # OpenCV Library
3 import numpy as np # Numpy Library for scientific computing
4 import matplotlib.pyplot as plt # Matplotlib Library for plotting
5 # show plots in notebook
6 %matplotlib inline
7
8 # image is loaded with imread command
9 img_bgr = cv2.imread('chessboard.jpg')
10 img_rgb_origin = cv2.cvtColor(img_bgr, cv2.COLOR_BGR2RGB)
11 img_gray = cv2.cvtColor(img_bgr, cv2.COLOR_BGR2GRAY)
12
13 # modify the data type, setting to 32-bit floating point
14 img_gray = np.float32(img_gray)
15
16 # apply the cv2.cornerHarris method to detect the corners with appropriate values as input parameters
17 corners = cv2.cornerHarris(img_gray, blockSize = 2, ksize = 3, k = 0.03)
18
19 # Results are marked through the dilated corners
20 corners = cv2.dilate(corners, None)
21
22 # Reverting back to the original image, with optimal threshold value
23 img_bgr[corners > 0.01 * corners.max()] = [0, 0, 255]
24 img_rgb = cv2.cvtColor(img_bgr, cv2.COLOR_BGR2RGB)
25
26 #plot the image
27 fig, (ax1, ax2) = plt.subplots(figsize = (18, 10), ncols = 2)
28 ax1.imshow(img_rgb_origin), ax1.set_title("Original")
29 ax2.imshow(img_rgb), ax2.set_title("Corner")
```

(<matplotlib.image.AxesImage at 0x1b39c1f73c8>, Text(0.5, 1.0, 'Corner'))



Problems with Harris corner detector

- It is **rotation invariant**



- But what about **scale**?

SIFT, SURF, and ORB

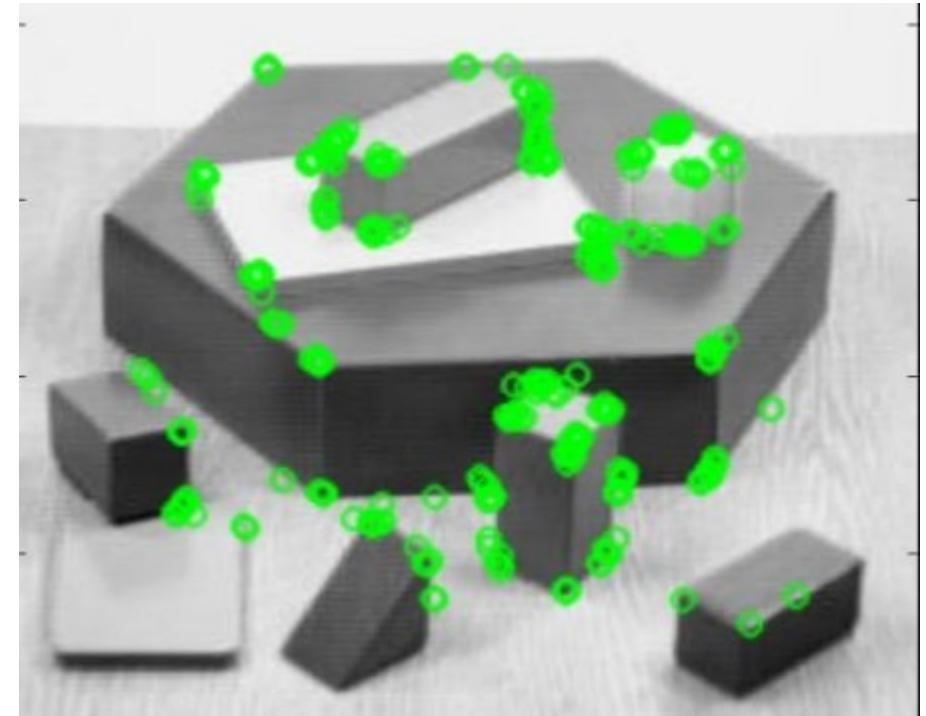
- Scale-Invariant Feature Transform
- Developed by D. Lowe in 2004
- Four main steps
 - 1. Scale-space Extrema Detection
 - 2. Keypoint Localization
 - 3. Orientation Assignment
 - 4. Keypoint Descriptor



- Speeded-Up Robust Features
- Developed by H. Bay, T. Tuytelaars, and L. Van Gool in 2006.
- A **speeded-up** version of SIFT

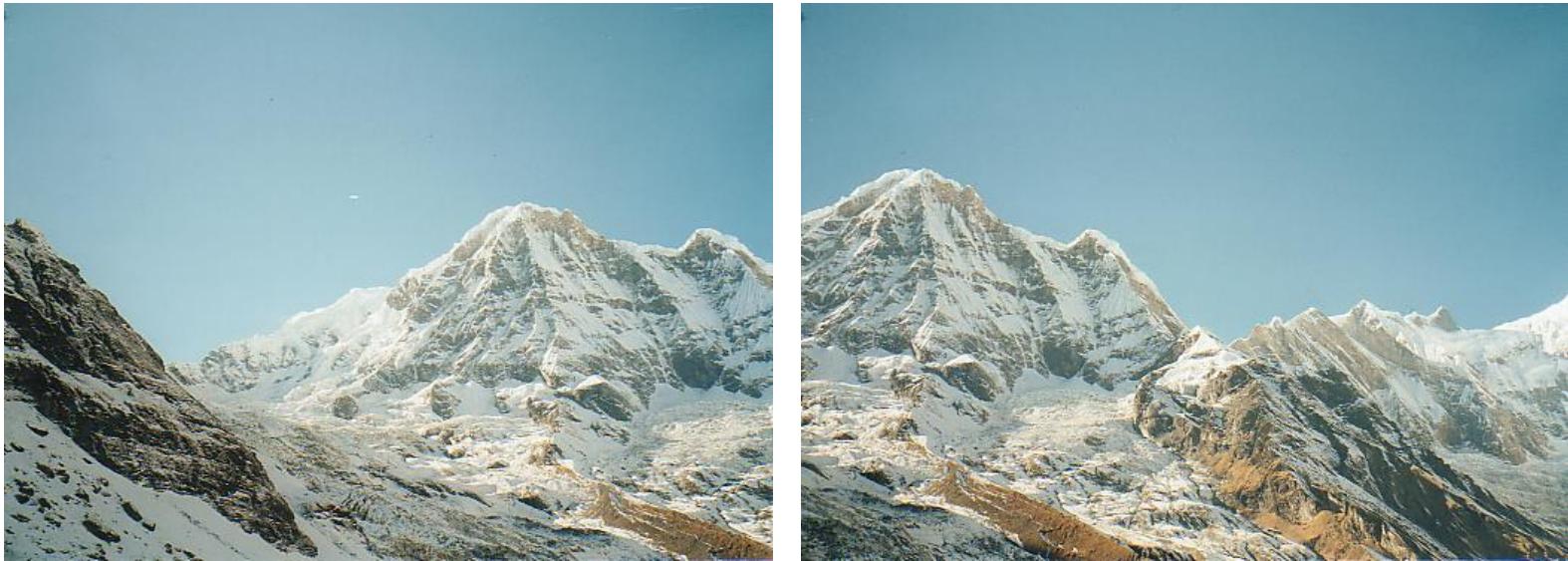


- Oriented FAST and Rotated BRIEF
- Developed by Ethan Rublee et al. in 2011.
- Aims to provide a fast and efficient alternative to SIFT



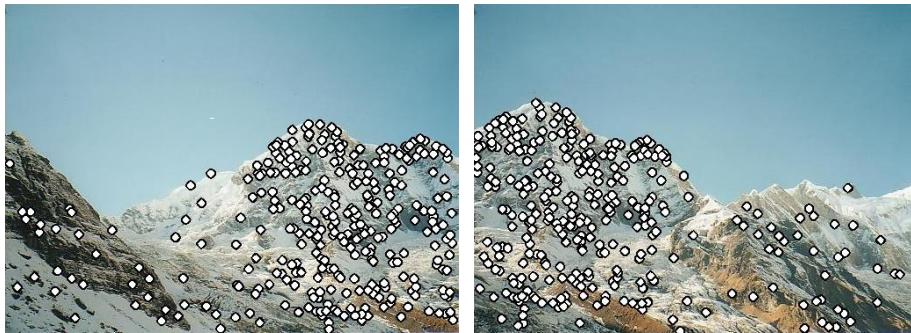
https://en.wikipedia.org/wiki/Oriented_FAST_and_rotated_BRIEF

Example application: Image stitching

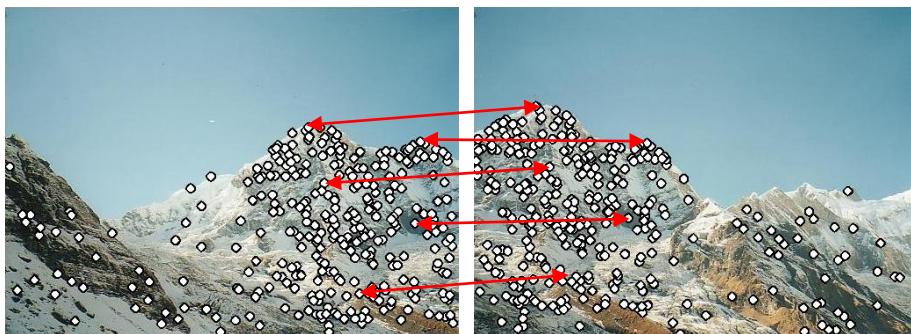


Example application: Image stitching

- Feature detection



- Matching



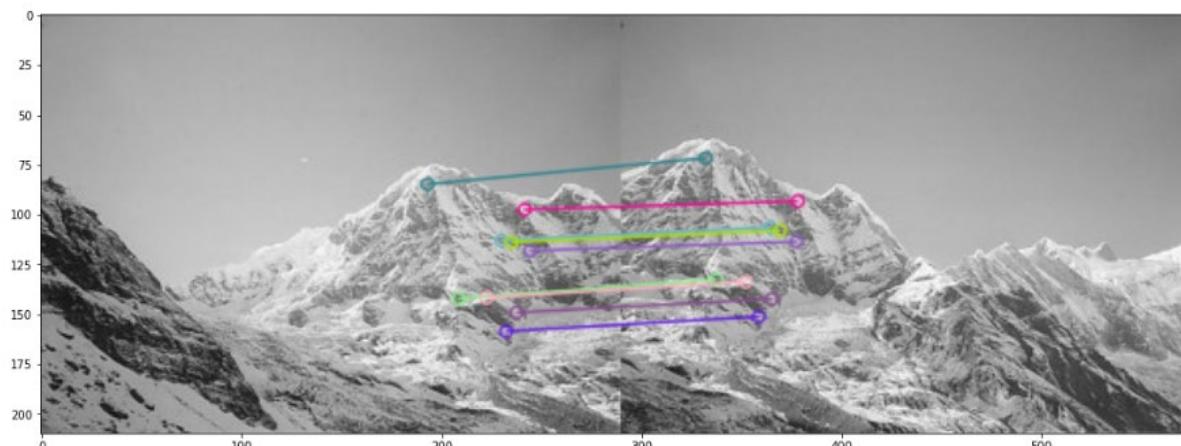
- Stitching



OpenCV examples - SIFT

```
1 #import required libraries
2 import cv2 # OpenCV Library
3 import numpy as np # Numpy library for scientific computing
4 import matplotlib.pyplot as plt # Matplotlib library for plotting
5 # show plots in notebook
6 %matplotlib inline
7
8 img1 = cv2.imread('mountain1.jpg',cv2.IMREAD_GRAYSCALE)           # queryImage
9 img2 = cv2.imread('mountain2.jpg',cv2.IMREAD_GRAYSCALE)           # trainImage
10
11 # Initiate SIFT detector
12 sift = cv2.xfeatures2d.SIFT_create()
13
14 # find the keypoints and descriptors with SIFT
15 kp1, des1 = sift.detectAndCompute(img1, None)
16 kp2, des2 = sift.detectAndCompute(img2, None)
17
18 # create BFMatcher object
19 bf = cv2.BFMatcher(cv2.NORM_L1, crossCheck=True)
20
21 # Match descriptors.
22 matches = bf.match(des1,des2)
23
24 # Sort them in the order of their distance.
25 matches = sorted(matches, key = lambda x:x.distance)
26
27 # Draw first 10 matches.
28 img3 = cv2.drawMatches(img1, kp1, img2, kp2, matches[:10], None, flags=2)
29
30 plt.figure(figsize = (18, 10))
31 plt.imshow(img3)
```

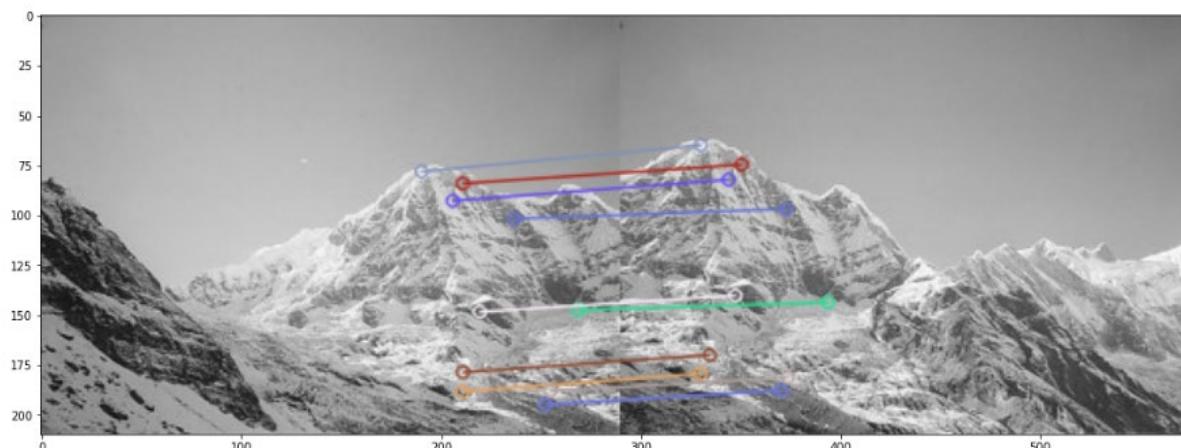
<matplotlib.image.AxesImage at 0x1b38d5c5348>



OpenCV examples - SURF

```
1 #import required libraries
2 import cv2 # OpenCV Library
3 import numpy as np # Numpy library for scientific computing
4 import matplotlib.pyplot as plt # Matplotlib library for plotting
5 # show plots in notebook
6 %matplotlib inline
7
8 img1 = cv2.imread('mountain1.jpg',cv2.IMREAD_GRAYSCALE)           # queryImage
9 img2 = cv2.imread('mountain2.jpg',cv2.IMREAD_GRAYSCALE)           # trainImage
10
11 # Initiate SURF detector
12 surf = cv2.xfeatures2d.SURF_create()
13
14 # find the keypoints and descriptors with SURF
15 kp1, des1 = surf.detectAndCompute(img1, None)
16 kp2, des2 = surf.detectAndCompute(img2, None)
17
18 # create BFMatcher object
19 bf = cv2.BFMatcher(cv2.NORM_L1, crossCheck=True)
20
21 # Match descriptors.
22 matches = bf.match(des1,des2)
23
24 # Sort them in the order of their distance.
25 matches = sorted(matches, key = lambda x:x.distance)
26
27 # Draw first 10 matches.
28 img3 = cv2.drawMatches(img1, kp1, img2, kp2, matches[:10], None, flags=2)
29
30 plt.figure(figsize = (18, 10))
31 plt.imshow(img3)
```

<matplotlib.image.AxesImage at 0x1b38d62e908>



OpenCV examples - ORB

```
#import required libraries
import cv2 # OpenCV Library
import numpy as np # Numpy Library for scientific computing
import matplotlib.pyplot as plt # Matplotlib library for plotting

img1 = cv2.imread('../mountain1.jpg',cv2.IMREAD_GRAYSCALE)           # queryImage
img2 = cv2.imread('../mountain2.jpg',cv2.IMREAD_GRAYSCALE)           # trainImage

# Initiate ORB detector
orb = cv2.ORB_create()

# find the keypoints and descriptors with ORB
kp1, des1 = orb.detectAndCompute(img1, None)
kp2, des2 = orb.detectAndCompute(img2, None)

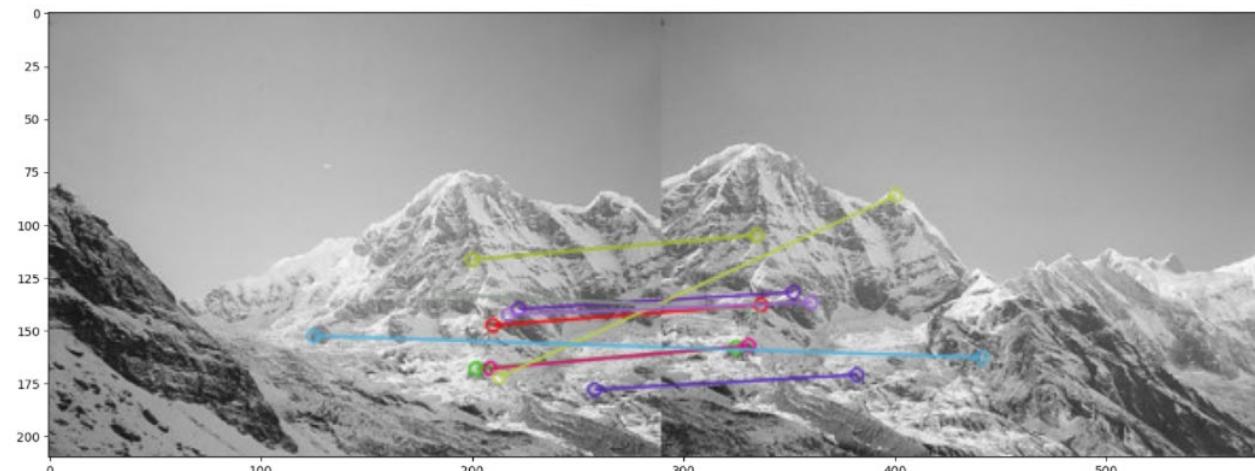
# create BFMatcher object
bf = cv2.BFMatcher(cv2.NORM_L1, crossCheck=True)

# Match descriptors.
matches = bf.match(des1,des2)

# Sort them in the order of their distance.
matches = sorted(matches, key = lambda x:x.distance)

# Draw first 10 matches.
img3 = cv2.drawMatches(img1, kp1, img2, kp2, matches[:10], None, flags=2)

plt.figure(figsize = (18, 10))
plt.imshow(img3)
plt.show()
```



Marker Detection

What if an image does **not** have unique corners?

- **Fiducial markers** can be used for object detection
- A popular one is the **ArUco** (Augmented Reality University of Cordoba) marker proposed by **S. Garrido-Jurado et al.** in 2014
- Popular in **AR, robotics, etc.**

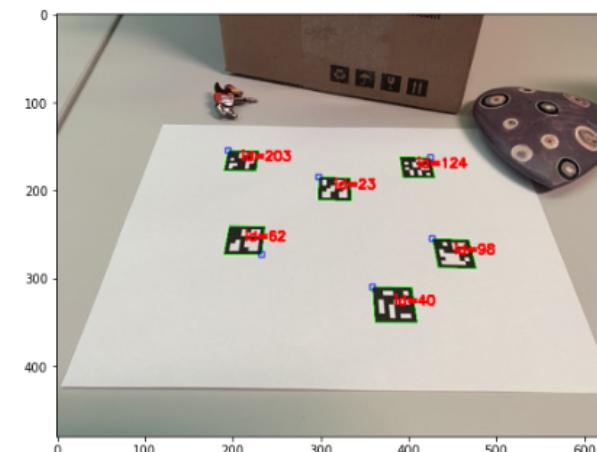
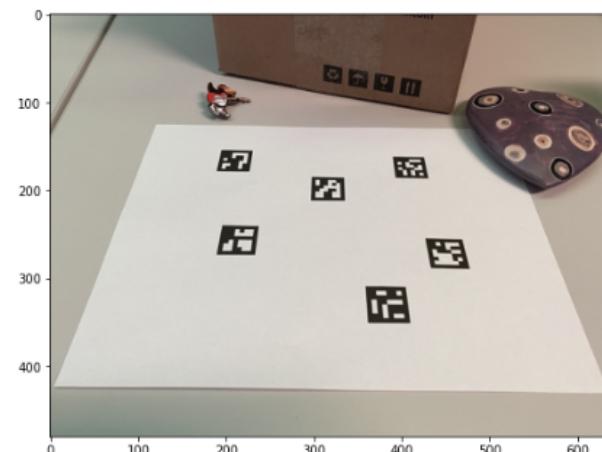


S. Garrido-Jurado, R. Muñoz-Salinas, F. J. Madrid-Cuevas, and M. J. Marín-Jiménez. 2014. "Automatic generation and detection of highly reliable fiducial markers under occlusion". Pattern Recogn. 47, 6 (June 2014), 2280-2292. DOI=10.1016/j.patcog.2014.01.005
<https://youtu.be/nsu9tNIJ6F0>

OpenCV examples – ArUco marker detection

```
1 #import required libraries
2 import cv2 # OpenCV library
3 import numpy as np # Numpy Library for scientific computing
4 import matplotlib.pyplot as plt # Matplotlib library for plotting
5 # show plots in notebook
6 %matplotlib inline
7
8 # Detect ArUco markers
9 # Image is loaded with imread command
10 img_bgr = cv2.imread('aruco.jpg')
11 img_rgb_origin = cv2.cvtColor(img_bgr, cv2.COLOR_BGR2RGB)
12 img_rgb = cv2.cvtColor(img_bgr, cv2.COLOR_BGR2RGB)
13
14 # Load the predefined dictionary
15 dictionary = cv2.aruco.Dictionary_get(cv2.aruco.DICT_6X6_250)
16
17 # Initialize the detector parameters using default values
18 parameters = cv2.aruco.DetectorParameters_create()
19
20 # Detect the markers in the image
21 markerCorners, markerIds, rejectedCandidates = cv2.aruco.detectMarkers(img_rgb, dictionary, parameters=parameters)
22
23 cv2.aruco.drawDetectedMarkers(img_rgb, markerCorners, markerIds)
24
25 #plot the image
26 fig, (ax1, ax2) = plt.subplots(figsize = (18, 10), ncols = 2)
27 ax1.imshow(img_rgb_origin)
28 ax2.imshow(img_rgb)
```

<matplotlib.image.AxesImage at 0x1b38ec34dc8>



Face Detection

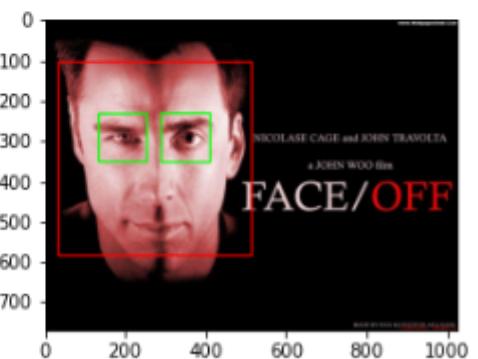
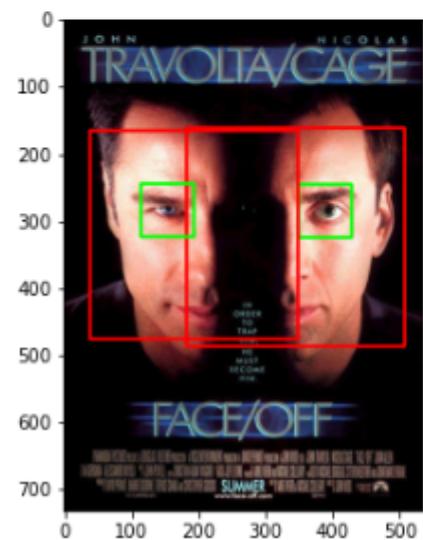
Face detection

- The methods introduced above are all based on **geometry**
- There are also methods using **machine learning**
- One example is face detection using **Haar Cascades**
 - A cascade function is trained from a lot of positive and negative images
- OpenCV comes with a **trainer** as well as a **detector**
- Pre-trained classifiers are available for **direct use**

OpenCV examples – Face detection

```
1 #import required libraries
2 import cv2 # OpenCV library
3 import numpy as np # Numpy Library for scientific computing
4 import matplotlib.pyplot as plt # Matplotlib library for plotting
5 # show plots in notebook
6 %matplotlib inline
7
8 #load the classifiers downloaded
9 face_cascade = cv2.CascadeClassifier('haarcascade_frontalface_default.xml')
10 eye_cascade = cv2.CascadeClassifier('haarcascade_eye.xml')
11
12 #read the image and convert to grayscale format
13 img = cv2.imread('face_off_1.jpg')
14 gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
15
16 #calculate coordinates
17 faces = face_cascade.detectMultiScale(gray, 1.1, 4)
18 for (x,y,w,h) in faces:
19     cv2.rectangle(img,(x,y),(x+w,y+h),(0,0,255),3)
20     roi_gray = gray[y:y+h, x:x+w]
21     roi_color = img[y:y+h, x:x+w]
22     eyes = eye_cascade.detectMultiScale(roi_gray)
23     #draw bounding boxes around detected features
24     for (ex,ey,ew,eh) in eyes:
25         cv2.rectangle(roi_color,(ex,ey),(ex+ew,ey+eh),(0,255,0),3)
26 face_1 = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
27
28 #read the image and convert to grayscale format
29 img = cv2.imread('face_off_2.jpg')
30 gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
31
32 #calculate coordinates
33 faces = face_cascade.detectMultiScale(gray, 1.1, 4)
34 for (x,y,w,h) in faces:
35     cv2.rectangle(img,(x,y),(x+w,y+h),(0,0,255),3)
36     roi_gray = gray[y:y+h, x:x+w]
37     roi_color = img[y:y+h, x:x+w]
38     eyes = eye_cascade.detectMultiScale(roi_gray)
39     #draw bounding boxes around detected features
40     for (ex,ey,ew,eh) in eyes:
41         cv2.rectangle(roi_color,(ex,ey),(ex+ew,ey+eh),(0,255,0),3)
42 face_2 = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
43
44 #plot the image
45 fig, (ax1, ax2) = plt.subplots(figsize = (9, 5), ncols = 2)
46 ax1.imshow(face_1)
47 ax2.imshow(face_2)
```

<matplotlib.image.AxesImage at 0x1b39c13d048>



Object Tracking

Object tracking vs object detection

- Option 1
 - Detect objects on **each** frame of the input video
- Option 2
 - Detect objects **once** and have the objects **tracked** every **subsequent** frame
 - **Faster** and more **efficient**



https://www.youtube.com/watch?v=JFVAy_uC0V4

OpenCV provides 8 object tracking methods

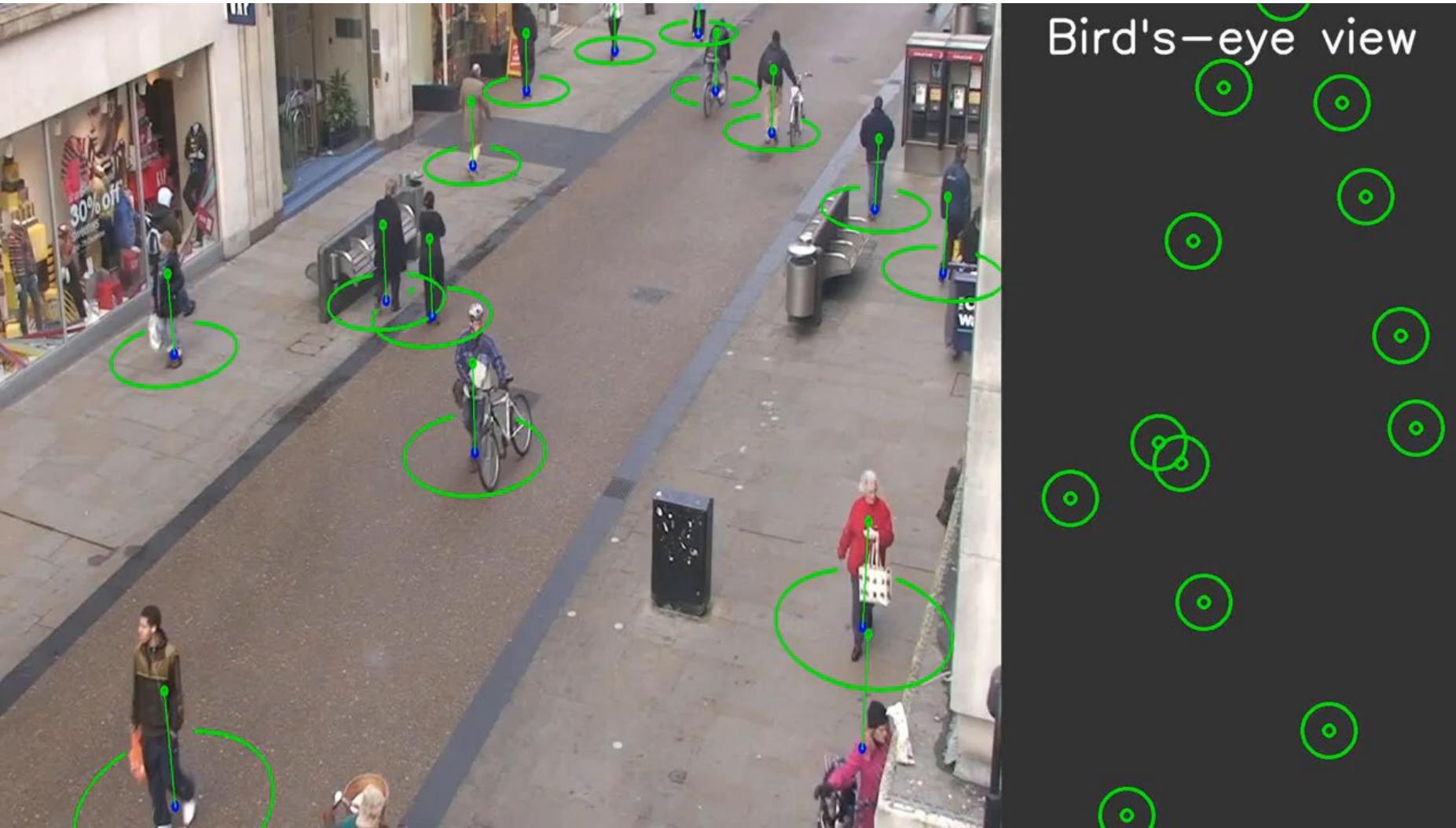
- 1 **BOOSTING Tracker:** Based on the same algorithm used to power the machine learning behind Haar cascades (AdaBoost), but like Haar cascades, is over a decade old. This tracker is slow and doesn't work very well. Interesting only for legacy reasons and comparing other algorithms. (*minimum OpenCV 3.0.0*)
- 2 **MIL Tracker:** Better accuracy than BOOSTING tracker but does a poor job of reporting failure. (*minimum OpenCV 3.0.0*)
- 3 **KCF Tracker:** Kernelized Correlation Filters. Faster than BOOSTING and MIL. Similar to MIL and KCF, does not handle full occlusion well. (*minimum OpenCV 3.1.0*)
- 4 **CSRT Tracker:** Discriminative Correlation Filter (with Channel and Spatial Reliability). Tends to be more accurate than KCF but slightly slower. (*minimum OpenCV 3.4.2*)
- 5 **MedianFlow Tracker:** Does a nice job reporting failures; however, if there is too large of a jump in motion, such as fast moving objects, or objects that change quickly in their appearance, the model will fail. (*minimum OpenCV 3.0.0*)
- 6 **TLD Tracker:** I'm not sure if there is a problem with the OpenCV implementation of the TLD tracker or the actual algorithm itself, but the TLD tracker was incredibly prone to false-positives. I do not recommend using this OpenCV object tracker. (*minimum OpenCV 3.0.0*)
- 7 **MOSSE Tracker:** Very, very fast. Not as accurate as CSRT or KCF but a good choice if you need pure speed. (*minimum OpenCV 3.4.1*)
- 8 **GOTURN Tracker:** The only deep learning-based object detector included in OpenCV. It requires additional model files to run (will not be covered in this post). My initial experiments showed it was a bit of a pain to use even though it reportedly handles viewing changes well (my initial experiments didn't confirm this though). I'll try to cover it in a future post, but in the meantime, take a look at [Satya's writeup](#). (*minimum OpenCV 3.2.0*)

OpenCV examples – Object tracking

```
1 import cv2
2 import sys
3
4 (major_ver, minor_ver, subminor_ver) = (cv2.__version__).split('.')
5
6 if __name__ == '__main__':
7
8     # Set up tracker.
9     # Instead of MIL, you can also use
10
11    tracker_types = ['BOOSTING', 'MIL','KCF', 'TLD', 'MEDIANFLOW', 'GOTURN', 'MOSSE', 'CSRT']
12    tracker_type = tracker_types[2]
13
14    if int(minor_ver) < 3:
15        tracker = cv2.Tracker_create(tracker_type)
16    else:
17        if tracker_type == 'BOOSTING':
18            tracker = cv2.TrackerBoosting_create()
19        if tracker_type == 'MIL':
20            tracker = cv2.TrackerMIL_create()
21        if tracker_type == 'KCF':
22            tracker = cv2.TrackerKCF_create()
23        if tracker_type == 'TLD':
24            tracker = cv2.TrackerTLD_create()
25        if tracker_type == 'MEDIANFLOW':
26            tracker = cv2.TrackerMedianFlow_create()
27        if tracker_type == 'GOTURN':
28            tracker = cv2.TrackerGOTURN_create()
29        if tracker_type == 'MOSSE':
30            tracker = cv2.TrackerMOSSE_create()
31        if tracker_type == "CSRT":
32            tracker = cv2.TrackerCSRT_create()
33
34    # Read video
35    video = cv2.VideoCapture("chaplin.mp4")
36
37    # Exit if video not opened.
38    if not video.isOpened():
39        print("Could not open video")
40        sys.exit()
41
42    # Read first frame.
43    ok, frame = video.read()
44    if not ok:
45        print('Cannot read video file')
46        sys.exit()
47
48    # Define an initial bounding box
49    bbox = (287, 23, 86, 320)
50
51    # Uncomment the line below to select a different bounding box
52    #bbox = cv2.selectROI(frame, False)
53
54    # Initialize tracker with first frame and bounding box
55    ok = tracker.init(frame, bbox)
56
57    while True:
58        # Read a new frame
59        ok, frame = video.read()
60        if not ok:
61            break
62
63        # Start timer
64        timer = cv2.getTickCount()
65
66        # Update tracker
67        ok, bbox = tracker.update(frame)
68
69        # Calculate Frames per second (FPS)
70        fps = cv2.getTickFrequency() / (cv2.getTickCount() - timer);
71
72        # Draw bounding box
73        if ok:
74            # Tracking success
75            p1 = (int(bbox[0]), int(bbox[1]))
76            p2 = (int(bbox[0] + bbox[2]), int(bbox[1] + bbox[3]))
77            cv2.rectangle(frame, p1, p2, (255,0,0), 2, 1)
78        else :
79            # Tracking failure
80            cv2.putText(frame, "Tracking failure detected", (100,80), cv2.FONT_HERSHEY_SIMPLEX, 0.75,(0,0,255),2)
81
82        # Display tracker type on frame
83        cv2.putText(frame, tracker_type + " Tracker", (100,20), cv2.FONT_HERSHEY_SIMPLEX, 0.75, (50,170,50),2);
84
85        # Display FPS on frame
86        cv2.putText(frame, "FPS : " + str(int(fps)), (100,50), cv2.FONT_HERSHEY_SIMPLEX, 0.75, (50,170,50), 2);
87
88        # Display result
89        cv2.imshow("Tracking", frame)
90
91        # Exit if ESC pressed
92        k = cv2.waitKey(10) & 0xff
93        if k == 27 : break
94
95    cv2.destroyAllWindows()
```



Object detection and tracking to monitor social distancing



<https://youtu.be/nDkVyAL6MdY>

What we have learnt in these two weeks

- Introduction to computer vision
 - Connection with image processing and machine learning
 - Tools available
- Image processing
 - Pixels
 - Perspective transforms
 - Colour spaces
 - Thresholding
 - Morphological operations
- Feature detection
 - Edge detection
 - Hough transform
 - Contour detection
 - Corner detection
 - SIFT, SURF, and ORB
 - Marker detection
 - Face detection
- Object tracking
 - 8 object tracking algorithms

Beyond what we have learnt

• Challenges of computer vision

“The goal of computer vision is to extract useful information from images. This has proved a surprisingly challenging task; it has occupied thousands of intelligent and creative minds over the last four decades, and despite this we are still far from being able to build a general-purpose “seeing machine.”

— Page 16, Computer Vision: Models, Learning, and Inference, 2012.

“Making a computer see was something that leading experts in the field of Artificial Intelligence thought to be at the level of difficulty of a summer student’s project back in the sixties. Forty years later the task is still unsolved and seems formidable.

— Page xi, Multiple View Geometry in Computer Vision, 2004.

“Perceptual psychologists have spent decades trying to understand how the visual system works and, even though they can devise optical illusions to tease apart some of its principles, a complete solution to this puzzle remains elusive”

— Page 3, Computer Vision: Algorithms and Applications, 2010.



Acknowledgment

- Many slides are adapted from Prof Emmanuel Agu
 - <https://web.cs.wpi.edu/~emmanuel/courses/cs545/S14/>
- And Juan Carlos Niebles and Ranjay Krishna
 - http://vision.stanford.edu/teaching/cs131_fall1920/slides/

Next week: Localisation II

