CSC 422/522
Computer Vision and Pattern Recognition

Feature Detection (Edges and Lines)

2026 Spring

South Dakota State University

Today

- Features vs. Pixels
- How to detect edges?
- How to detect lines?
- How to detect other simple shapes?

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Why Features Matter in Computer Vision?

Image source: https://docs.opencv.org/4.x/da/df5/tutorial_py_sift_intro.html

Let's Play a Game: Jigsaw Puzzle!

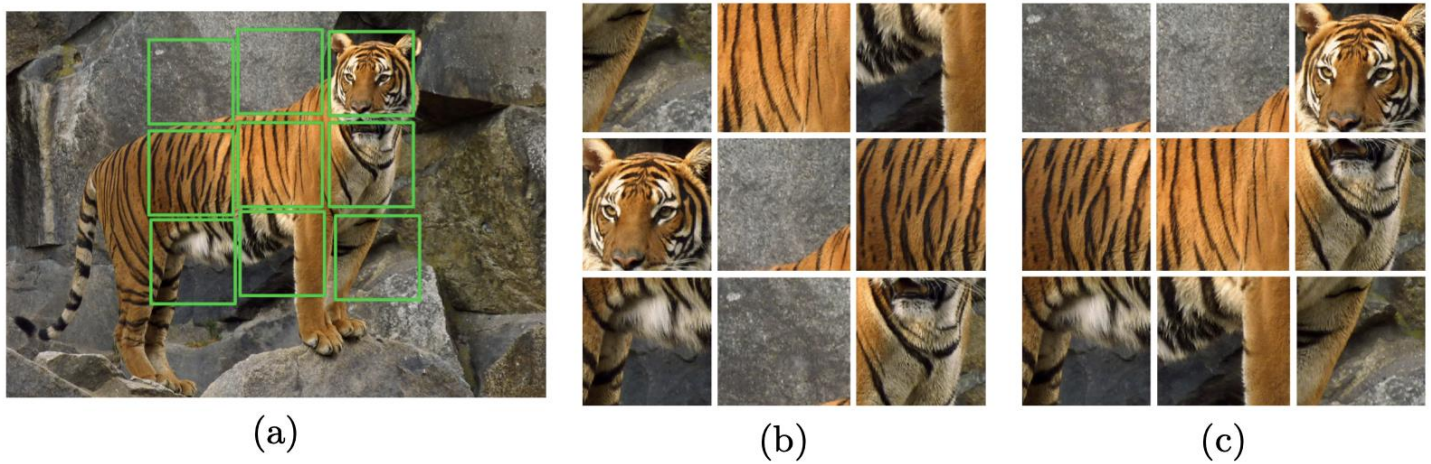
- Link: https://onlinejigsawpuzzles.net/puzzle.php?image=images/puzzle/Spring-in-farmland-Sweden-old-bar--in-rural-surroundings.jpg#
- Note: you can change the number of pieces
- Think: How do you solve the puzzle? What visual cues help you place pieces?

Jigsaw Puzzles in Computer Vision Research

- In a jigsaw puzzle, we reconstruct a global image from local pieces.
- During the process, we may consider edge continuity, texture similarity, color consistency, etc.
- Computer vision aims to automate the same reasoning process.
- Example research papers: Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles (ECCV 2016, paper link: https://arxiv.org/abs/1603.09246)

Screenshot for https://onlinejigsawpuzzles.net/puzzle.php?image=images/puzzle/Spring-in-farmland-Sweden-old-bar--in-rural-surroundings.jpg#

Jigsaw Puzzles in Computer Vision Research



(a) (b) (c)

Fig. 1: Learning image representations by solving Jigsaw puzzles. (a) The image from which the tiles (marked with green lines) are extracted. (b) A puzzle obtained by shuffling the tiles. Some tiles might be directly identifiable as object parts, but others are ambiguous (*e.g.*, have similar patterns) and their identification is much more reliable when all tiles are jointly evaluated. In contrast, with reference to (c), determining the relative position between the central tile and the top two tiles from the left can be very challenging [10].

Example research papers: Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles (ECCV 2016, paper link: https://arxiv.org/abs/1603.09246)

What is a Feature in Computer Vision?

- A feature in computer vision is an identifiable part of an image or video that conveys meaningful information for tasks like object detection, tracking, or classification.
- Features are often distinct patterns, such as edges, corners, textures, or specific shapes, that algorithms use to understand and analyze visual data.

Texts adapted from https://milvus.io/ai-quick-reference/what-is-a-feature-in-computer-vision

Screenshot for https://onlinejigsawpuzzles.net/puzzle.php?image=images/puzzle/Spring-in-farmland-Sweden-old-bar--in-rural-surroundings.jpg#

Why Not Just Use Pixels?

- Pixels are sensitive to noise, lighting variations, viewpoint changes, etc.
- Therefore, pixels are not stable representations for robust computer vision tasks.

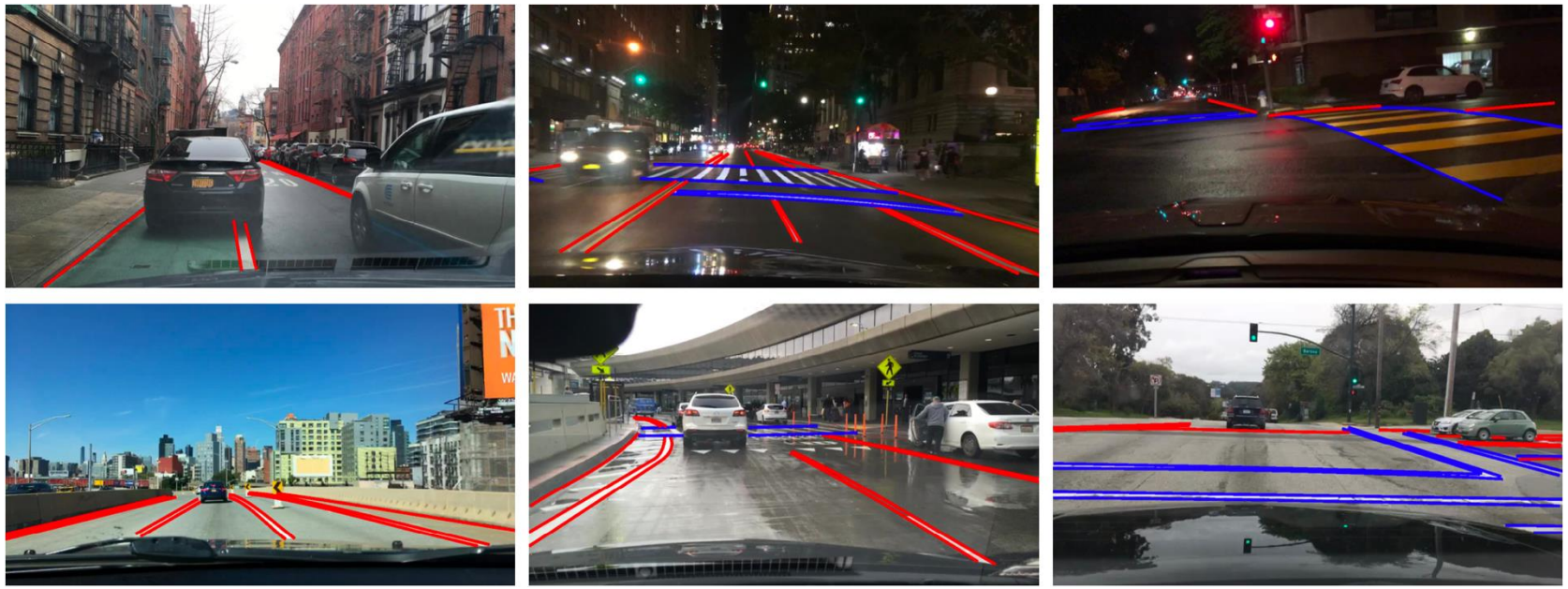
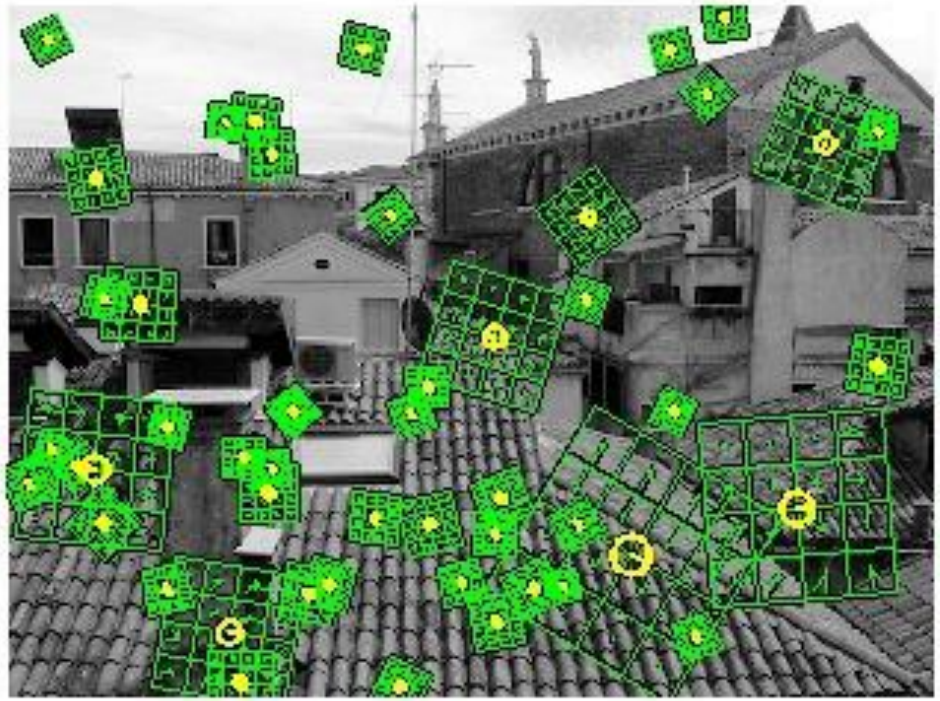


Image source: BDD100K: A Large-scale Diverse Driving Video Database
https://bair.berkeley.edu/blog/2018/05/30/bdd/

Classical (Hand-Crafted) Features

- Traditional feature extraction methods rely on mathematical techniques to identify and describe these key points.
- Algorithms like SIFT (Scale-Invariant Feature Transform) detect stable features by analyzing gradients, corners, or blobs in an image.



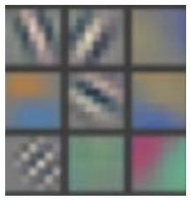
Texts adapted from https://milvus.io/ai-quick-reference/what-is-a-feature-in-computer-vision

Image found at https://ics.uci.edu/~majumder/VC/211HW3/vlfeat/doc/overview/sift.html

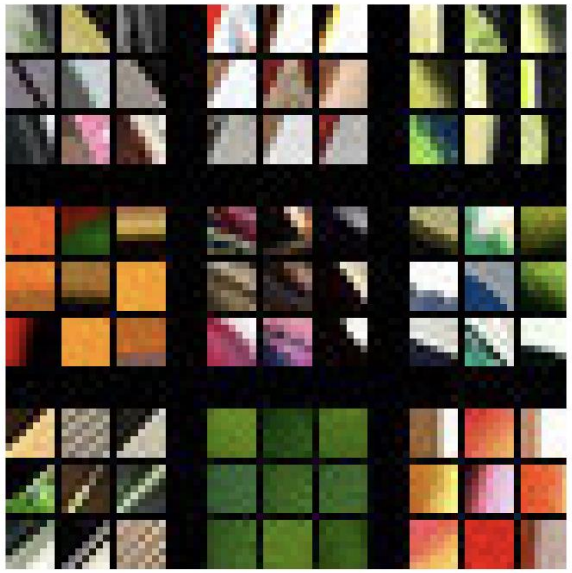
Learned Features

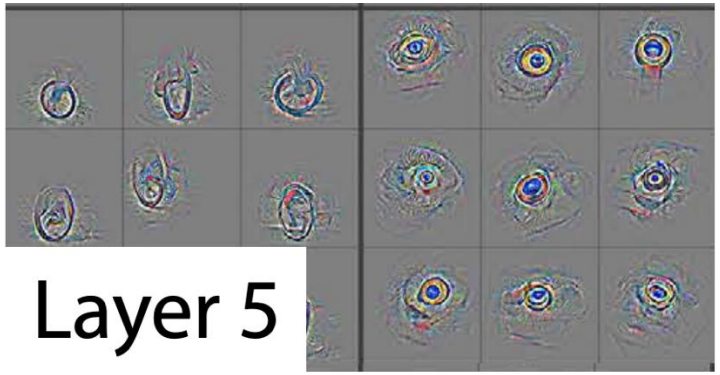
- Modern approaches, particularly deep learning, automate feature extraction using convolutional neural networks (CNNs).
- In CNNs, layers learn hierarchical features directly from data.
- Early layers detect simple patterns like edges or color gradients, while deeper layers combine these to recognize complex shapes or objects.

“Visualizing and Understanding Convolutional Networks” (ECCV 2014)



Layer 1





Layer 5

Check full Figure 2 in the original paper.
You can read the paper in this link:
https://arxiv.org/pdf/1311.2901

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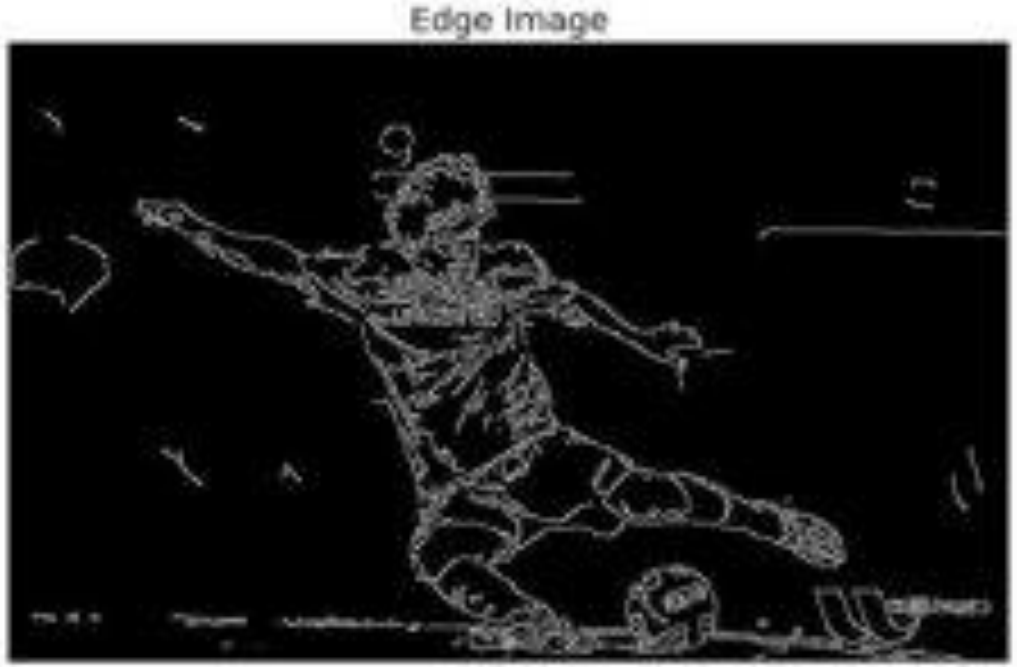
Edge Detection

Credit: slides of this section are adapted from CSC 492/592, Spring 2024

Image source: https://docs.opencv.org/4.x/da/d22/tutorial_py_canny.html



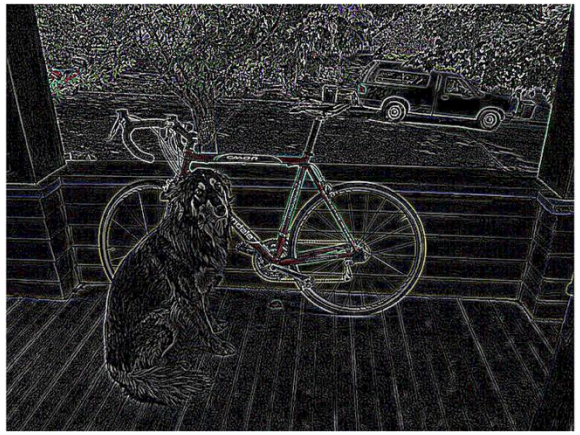
Recap: Edge Detection

	Prewitt			Sobel		
$\frac{\partial I}{\partial x}$	−1	1	1	−1	0	1
	−1	0	1	−2	0	2
	−1	1	1	−1	0	1
$\frac{\partial I}{\partial y}$	1	1	1	1	2	1
	0	0	0	0	0	0
	−1	−1	−1	−1	−2	−1

Laplacian of Gaussian

$$\nabla^2 \approx \frac{1}{6\varepsilon^2}$$

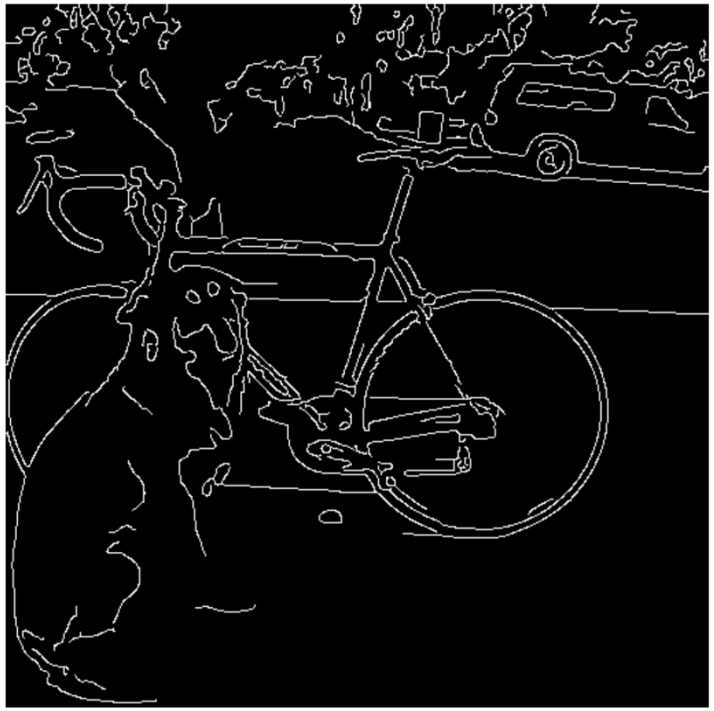
1	4	1
4	−20	4
1	1	1



Gradient	Laplacian
Provides **location**, **magnitude**, and **direction** of the edge	Provides only **location** of the edge
Detection using Maxima **Thresholding**	Detection based on Zero-crossing
- **Non-linear** operation - Requires two convolutions	- **Linear** operation - Requires only one convolution

Canny Edge Detection

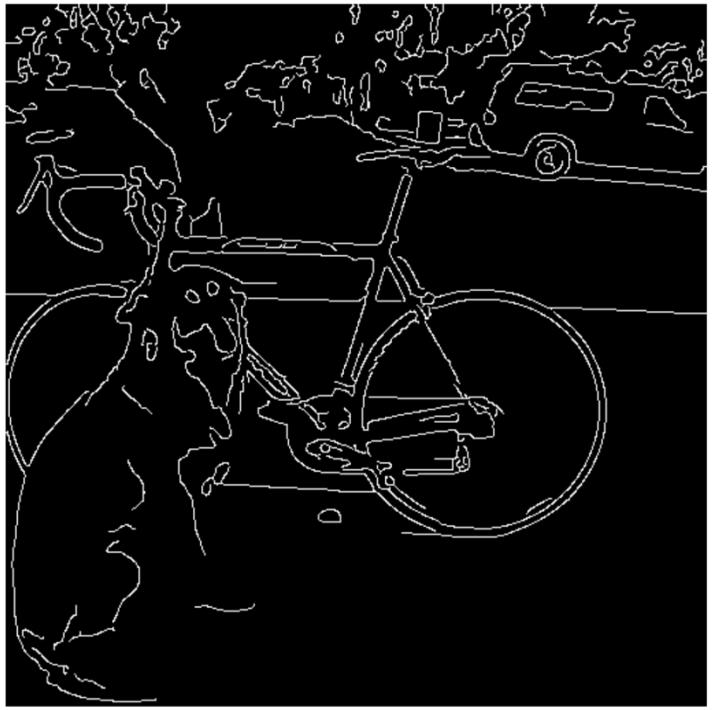
- The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images.
- It was developed by John F. Canny in 1986.
- Among the edge detection methods developed so far, Canny's algorithm is one of the most strictly defined methods that provides good and reliable detection.



Reference: https://en.wikipedia.org/wiki/Canny_edge_detector

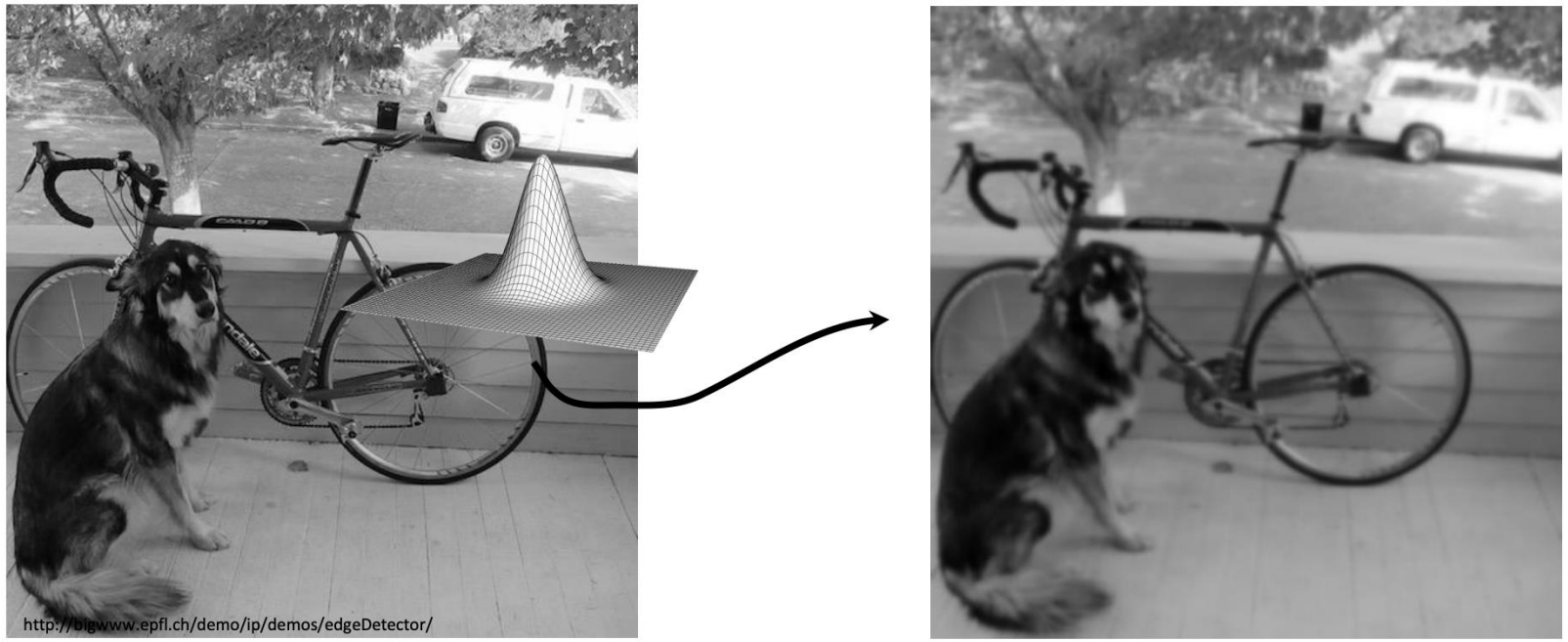
Canny Edge Detection: Algorithm

1. Smooth image
2. Calculate gradient direction and magnitude
3. Perform non-maximum suppression
4. Threshold the edges
5. Link the edges



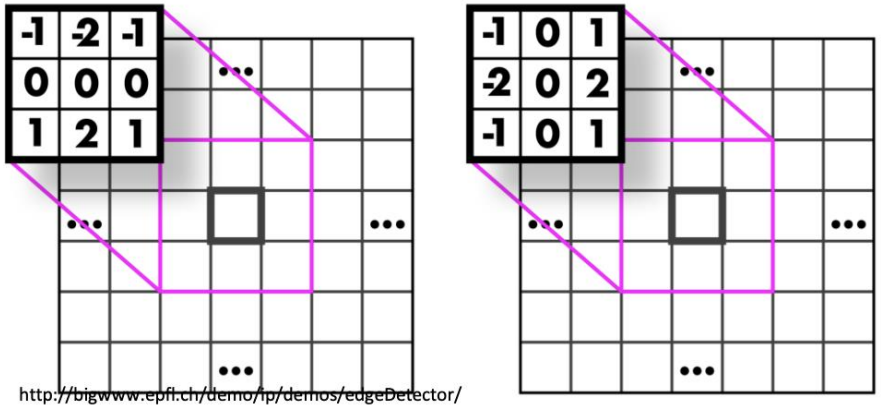
Step 1: Smooth image

Apply Gaussian filter to smooth the image to remove the noise.



Step 2: Calculate gradient direction and magnitude

	Prewitt	Sobel
$\frac{\partial I}{\partial x}$	$\begin{bmatrix} -1 & 1 & 1 \\ -1 & 0 & 1 \\ -1 & 1 & 1 \end{bmatrix}$	$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$
$\frac{\partial I}{\partial y}$	$\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$	$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$

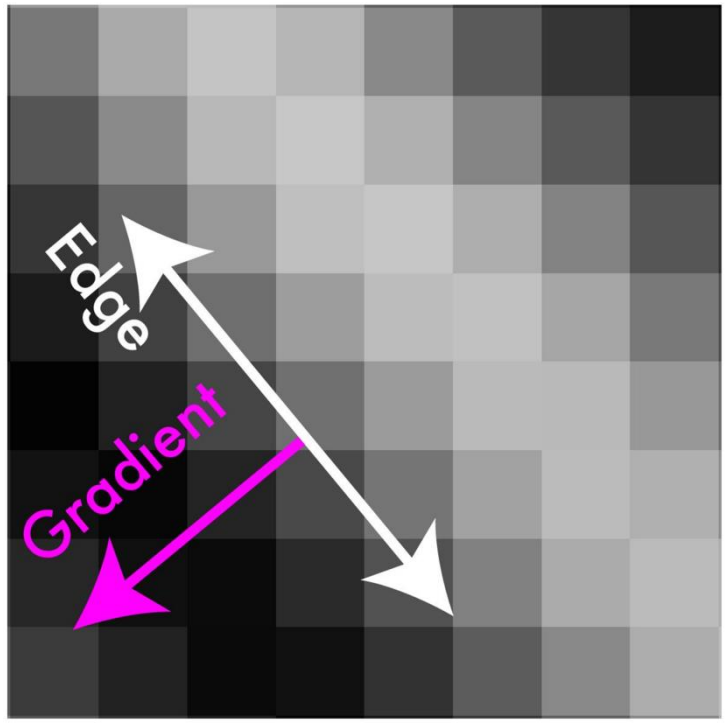


http://bigwww.epfl.ch/demo/ip/demos/edgeDetector/

Step 3: Perform non-maximum suppression

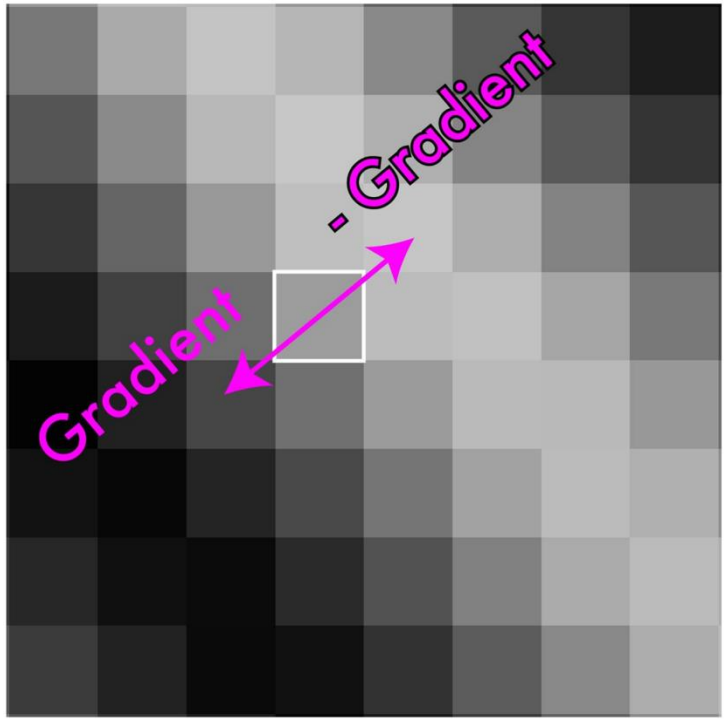
- ***Why?*** Want single pixel edges, not thick blurry lines
- ***Idea.*** Check nearby pixels and keep the high response
- ***How?*** Go through all the points on the gradient intensity matrix and finds the pixels with the maximum value in the edge directions

Step 3: Perform non-maximum suppression



Go through all the points on the gradient intensity matrix and finds the pixels with the maximum value in the edge directions.

Step 3: Perform non-maximum suppression

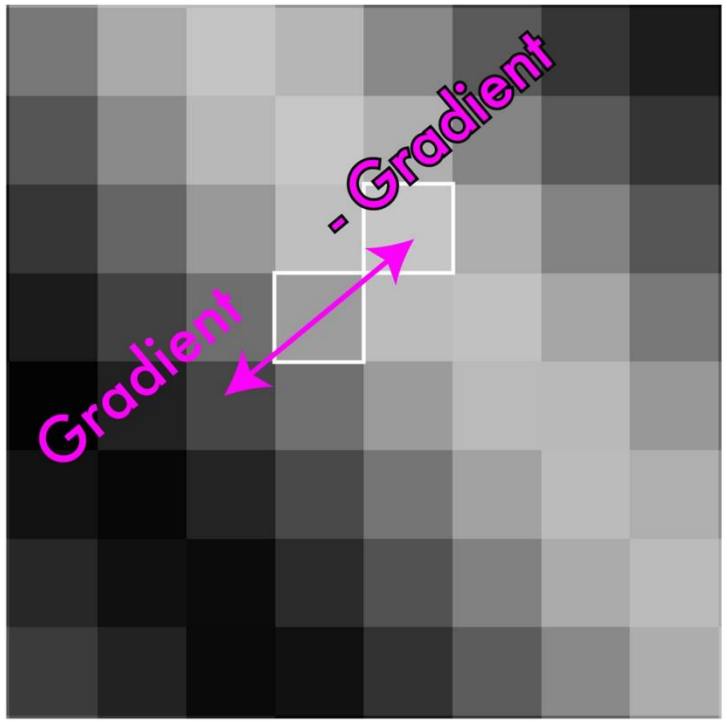


Example pixel 1:

(highlighted in white box)

compare its gradient magnitude with the magnitudes of its neighboring pixels along the gradient direction

Step 3: Perform non-maximum suppression



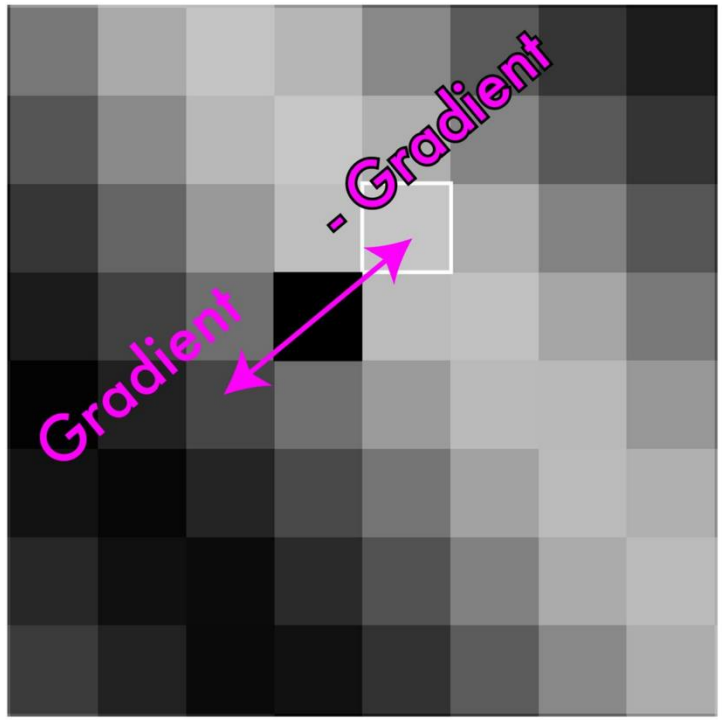
Example pixel 1:

(highlighted in left-bottom white box)

compare its gradient magnitude with the magnitudes of its neighboring pixels along the gradient direction

→ We find a neighboring pixel with larger gradient magnitude

Step 3: Perform non-maximum suppression



Example pixel 1:

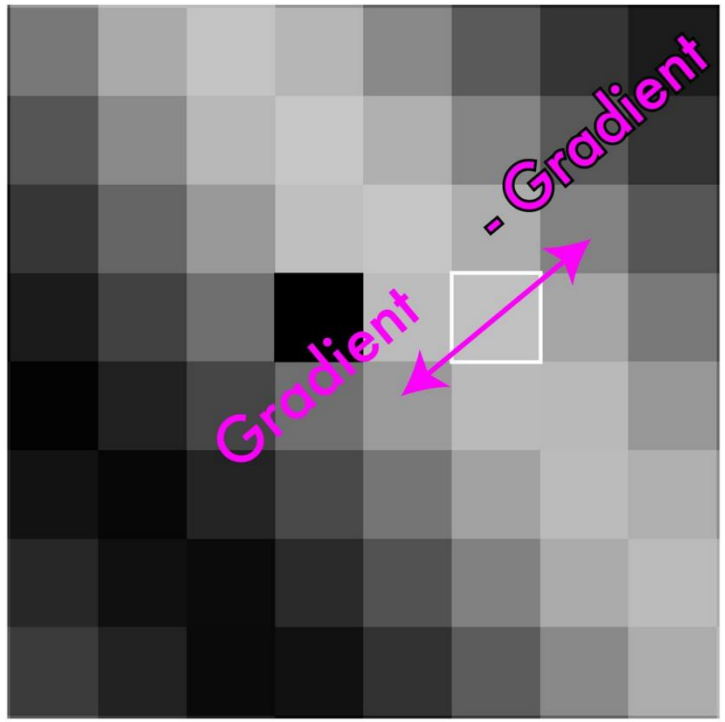
(highlighted in left-bottom white box)

compare its gradient magnitude with the magnitudes of its neighboring pixels along the gradient direction

→ We find a neighboring pixel with larger gradient magnitude

→ It is suppressed ☹

Step 3: Perform non-maximum suppression

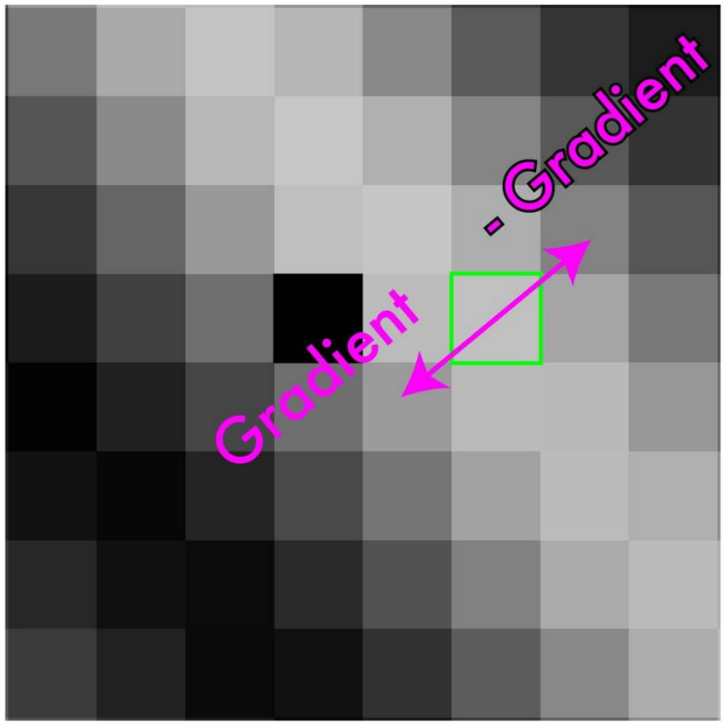


Example pixel 2:

(highlighted in white box)

compare its gradient magnitude with the magnitudes of its neighboring pixels along the gradient direction

Step 3: Perform non-maximum suppression



Example pixel 2:

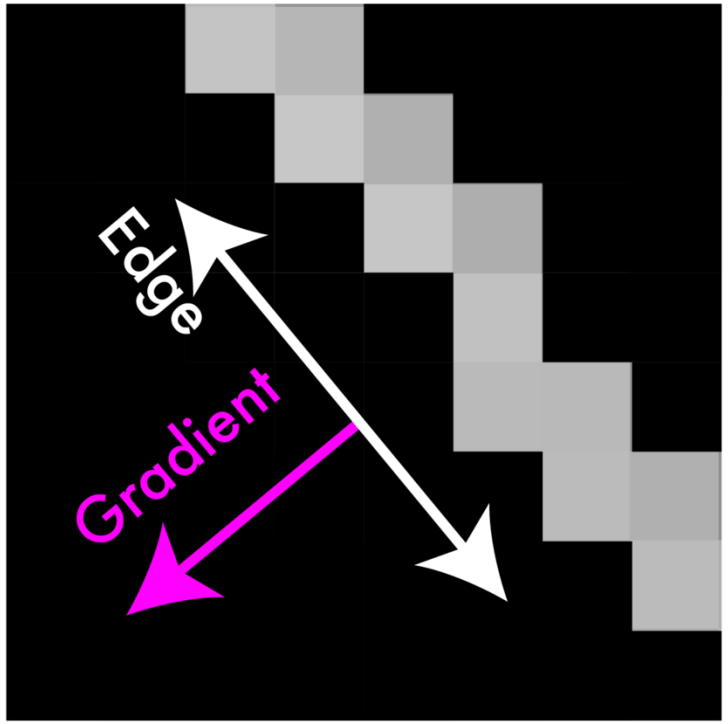
(highlighted in green box now)

compare its gradient magnitude with the magnitudes of its neighboring pixels along the gradient direction

→ Greater than that of both of its neighboring pixels

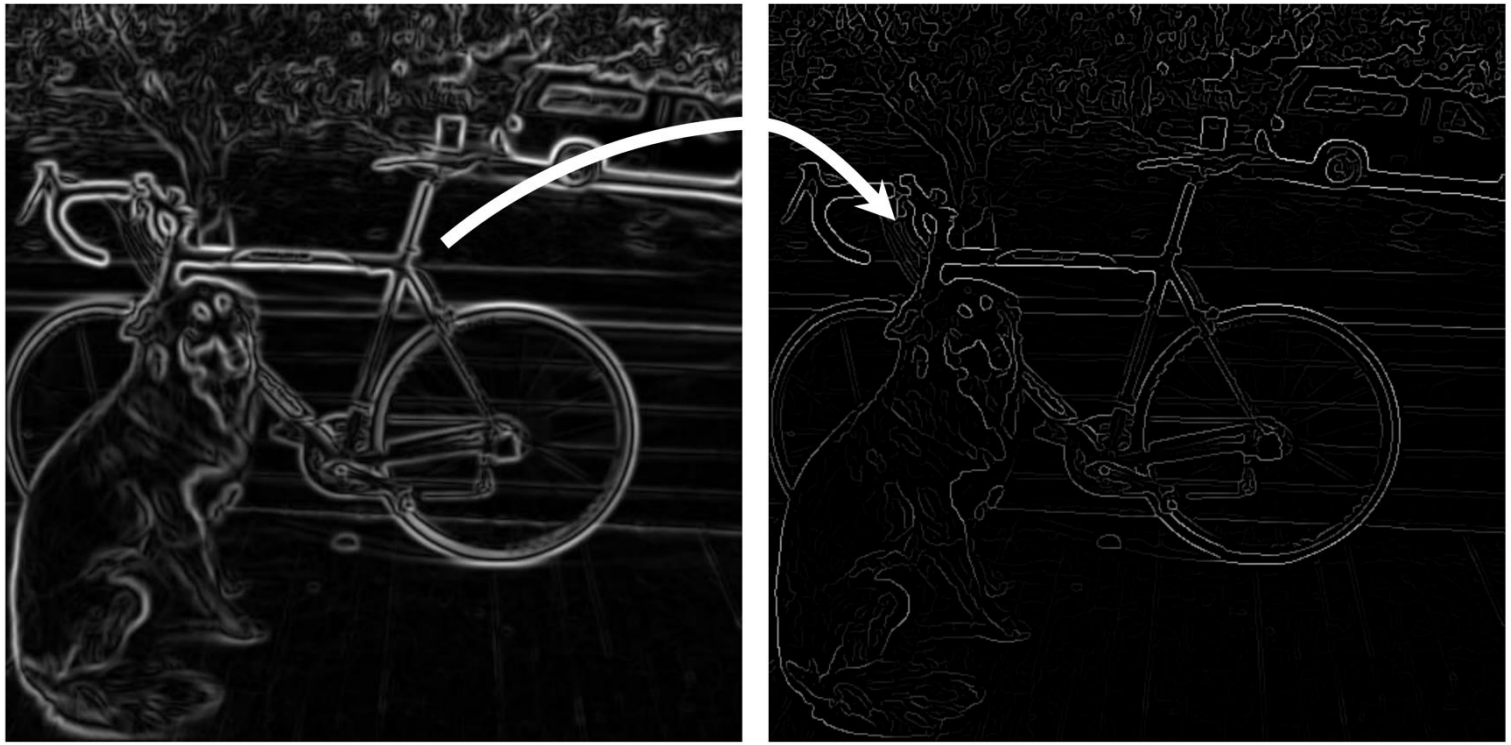
→ It is kept ☺

Step 3: Perform non-maximum suppression



This process is performed for all pixels in the image, resulting in a thinned set of edge pixels where only local maxima **along the edges** remain.

Step 3: Perform non-maximum suppression

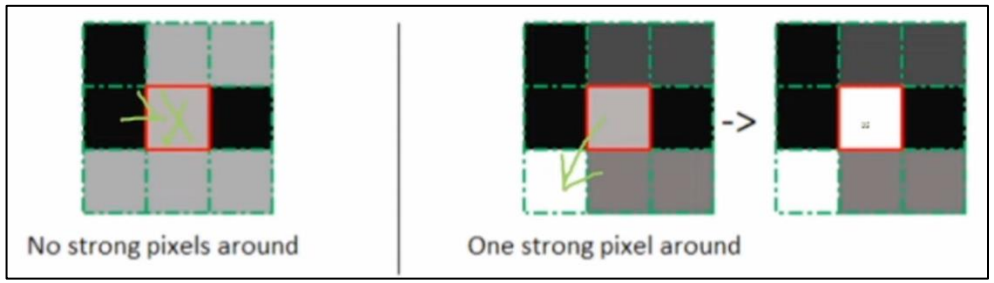


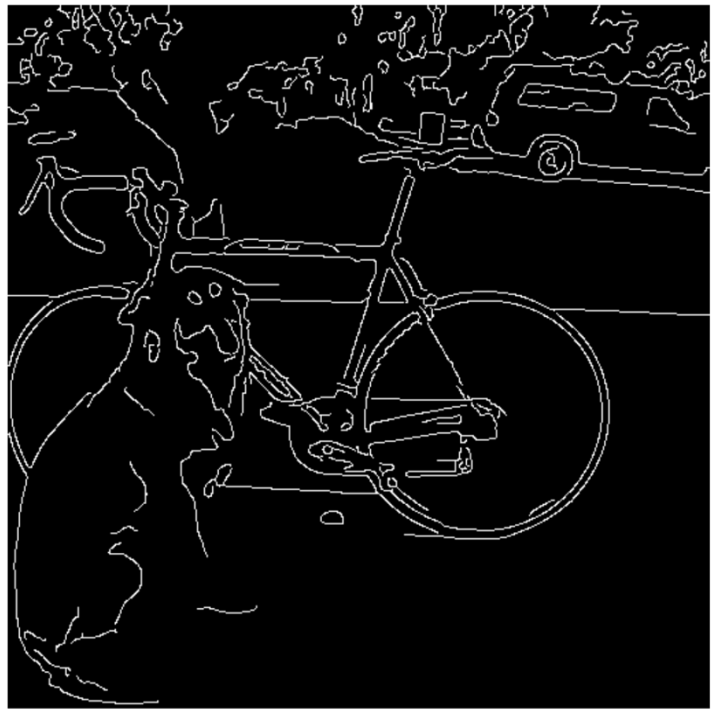
Step 4: Threshold the edges

- ***Why?*** Still some noise
- ***Idea.*** Thresholding edges
- ***How?***
  - Categorize edges into strong, weak, non-relevant
  - 2 thresholds T and t, 3 cases:
    - T < : strong edge
    - t < and < T : weak edge
    - < t : non-relevant

Step 5: Link the edges

- ***Idea.***
  - Strong edges are edges!
  - Weak edges are edges if and only if they are connected to strong edges
- ***How?***
  - Look in some neighborhood (usually 8 closet)



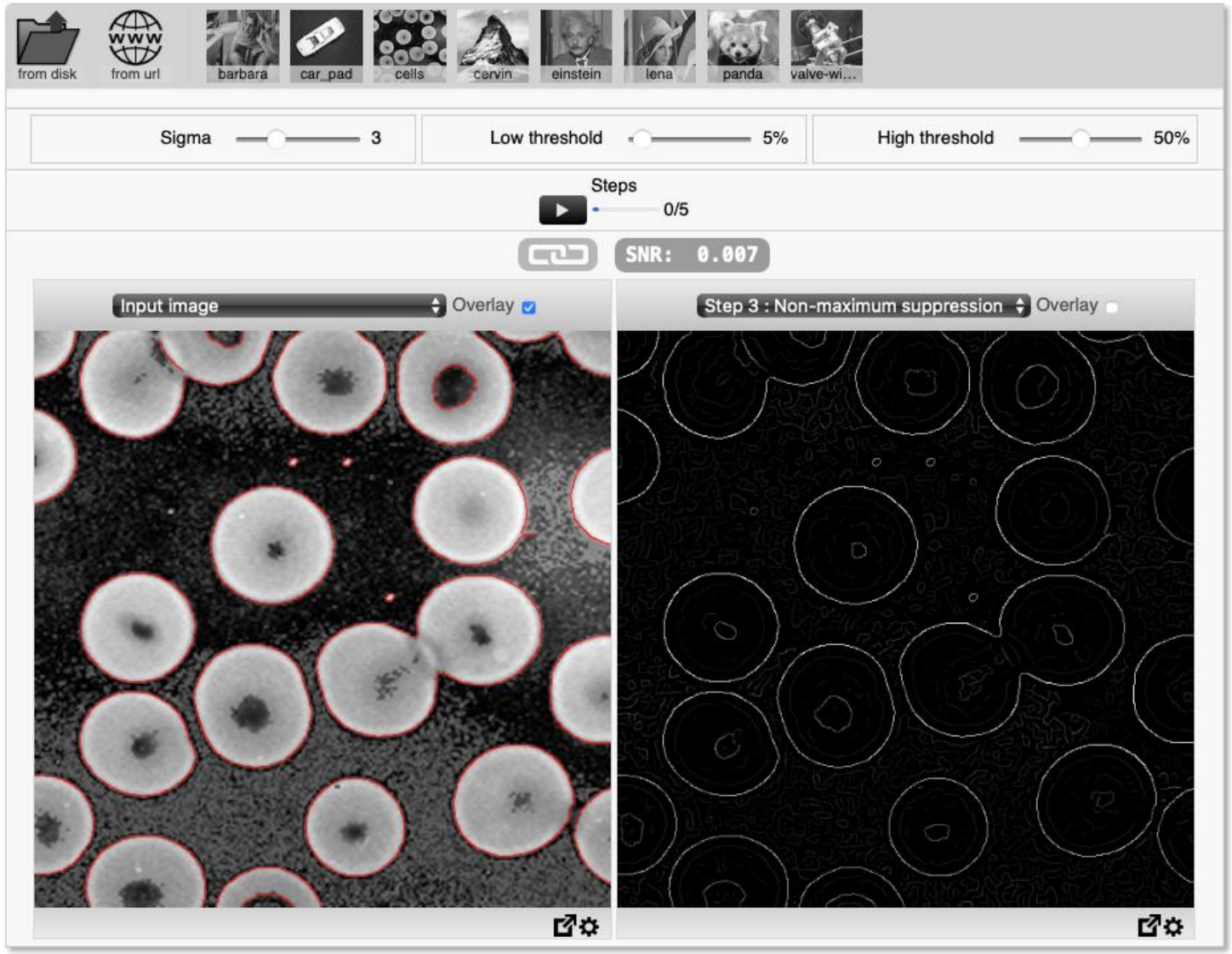


Demo

Let's try: https://bigwww.epfl.ch/demo/ip/demos/edgeDetector/

Think: how the hyperparameters affect the results?

In OpenCV: simply call "cv2.Canny" function (reference: https://docs.opencv.org/4.x/da/d22/tutorial_py_canny.html)



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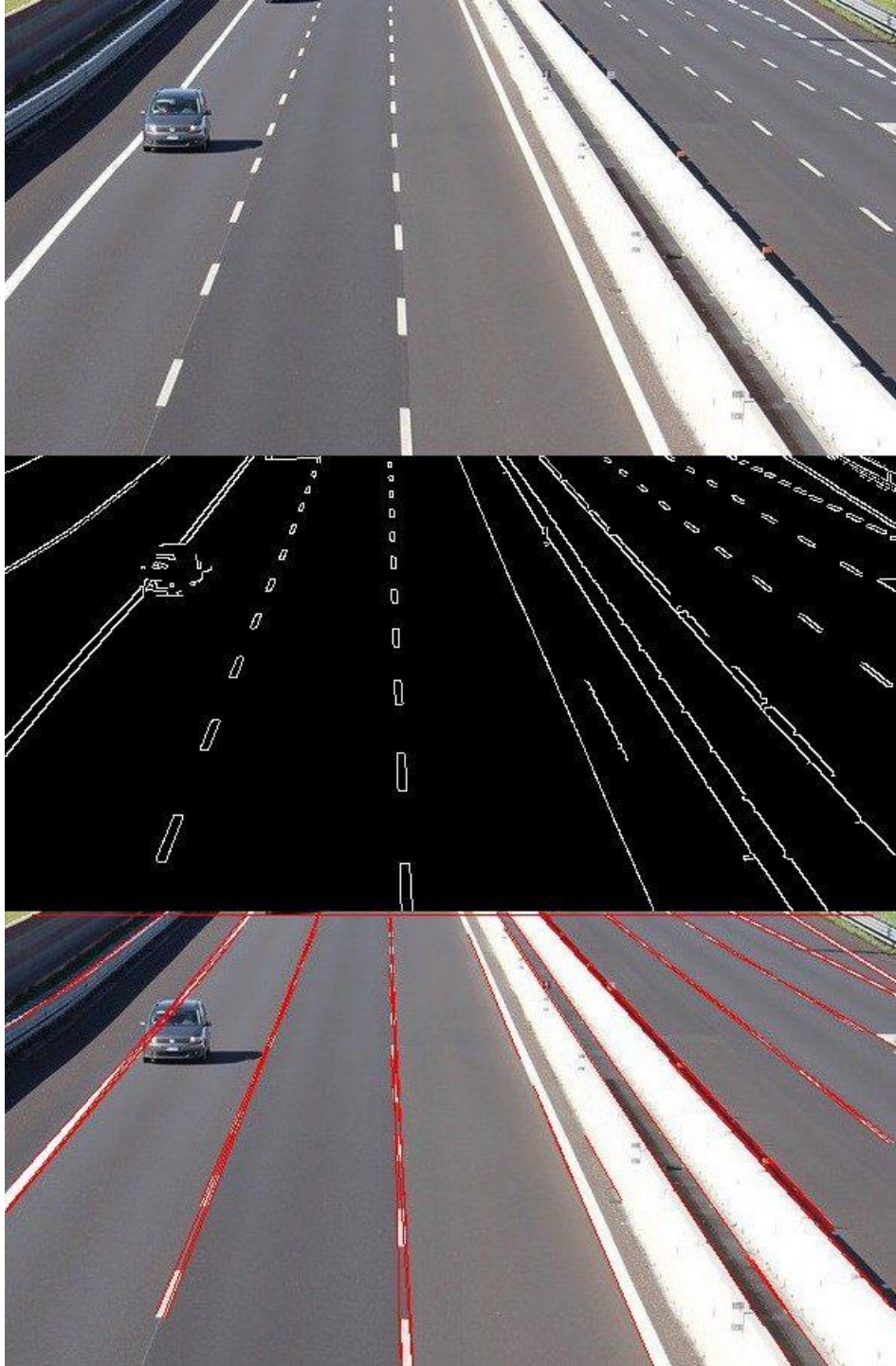
Finding Lines via Hough Transform

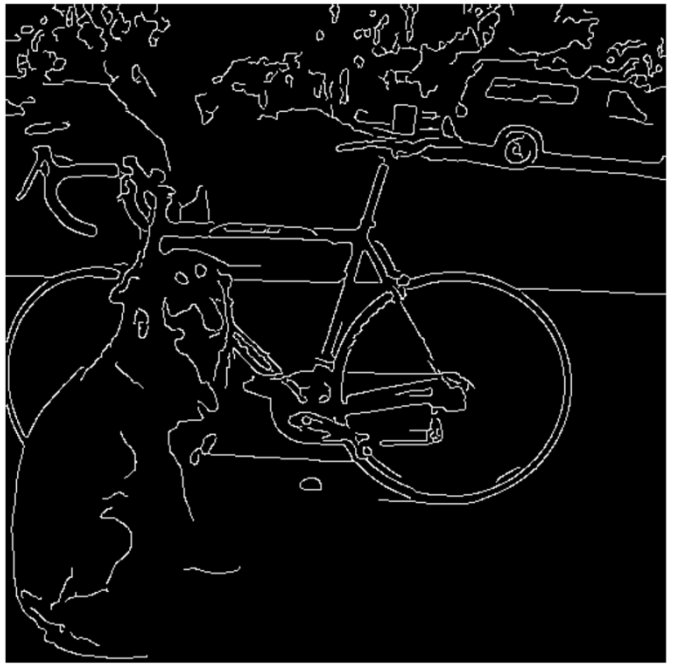
Credit: slides of this section are adapted from CSC 492/592, Spring 2024

Image source: https://learnopencv.com/hough-transform-with-opencv-c-python/



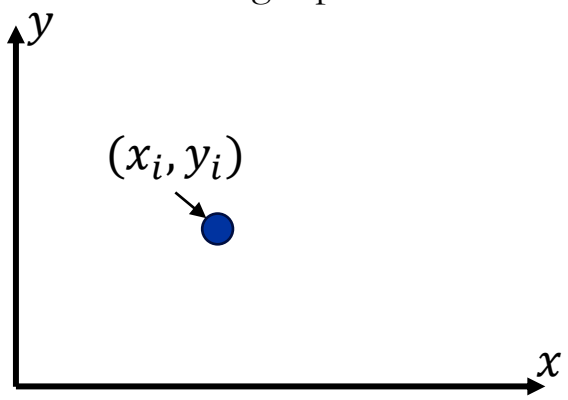
Finding lines: Hough Transform

- ***Problems.***
  - →Extraneous Data: Which points to fit to
  - →Incomplete Data: Only part of the model is visible
  - →Noise
- ***Solution.*** Hough Transform

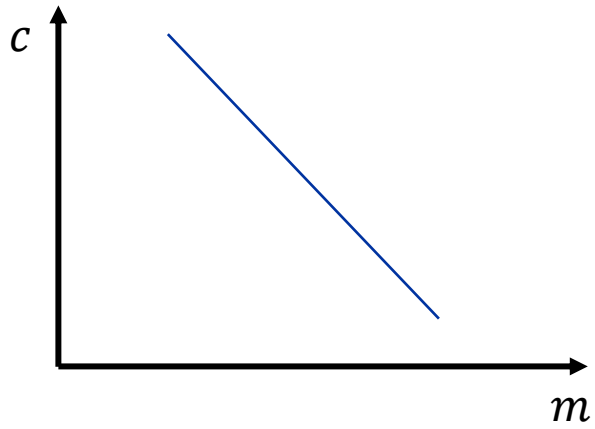


Example (Part 1)

Image space



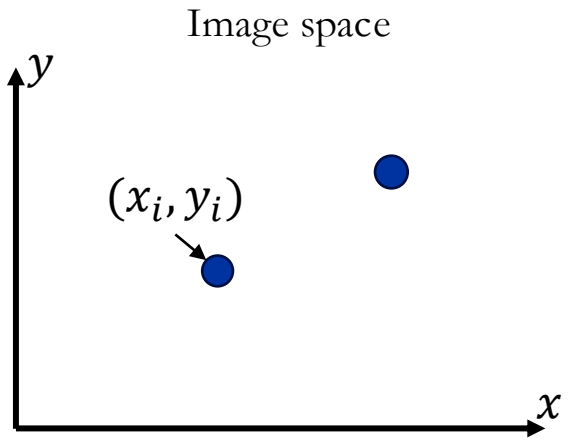
Parameter space

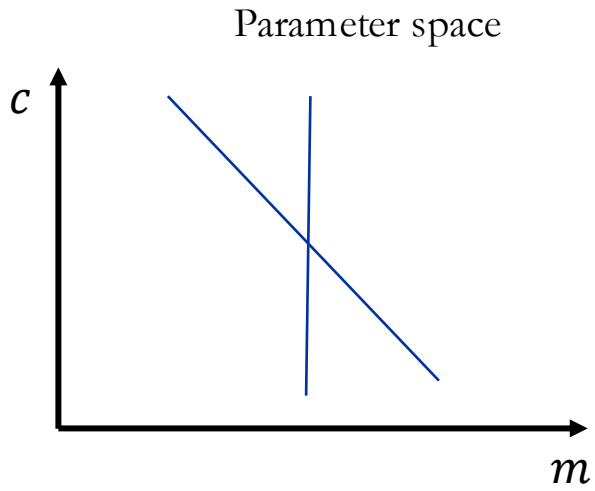


$y_i = mx_i + c$

$c = -mx_i + y_i$

Example (Part 2)

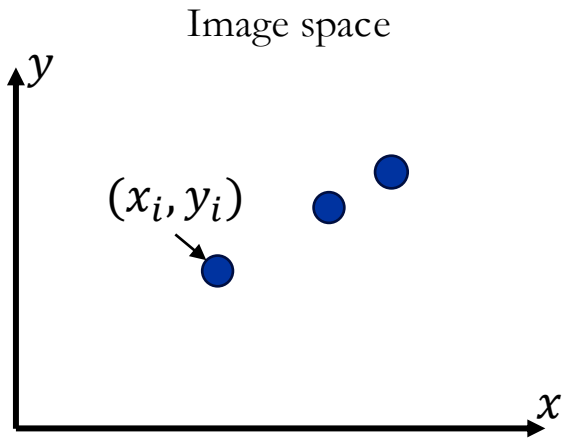


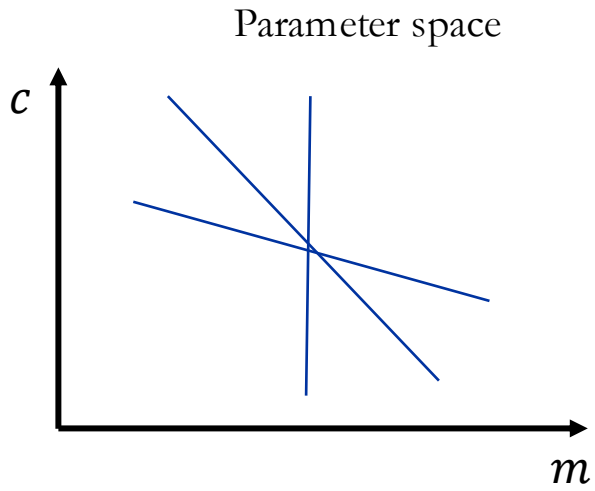


$y_i = mx_i + c$

$c = -mx_i + y_i$

Example (Part 3)

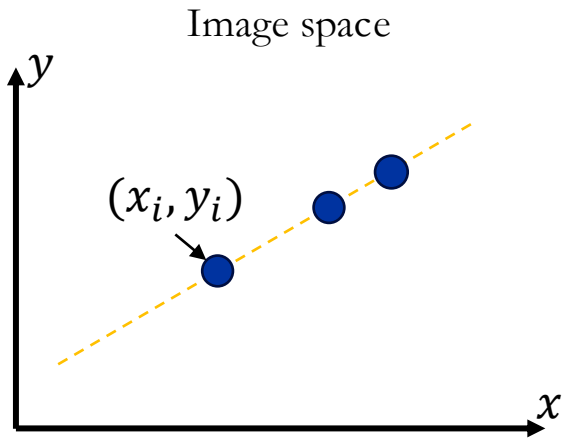


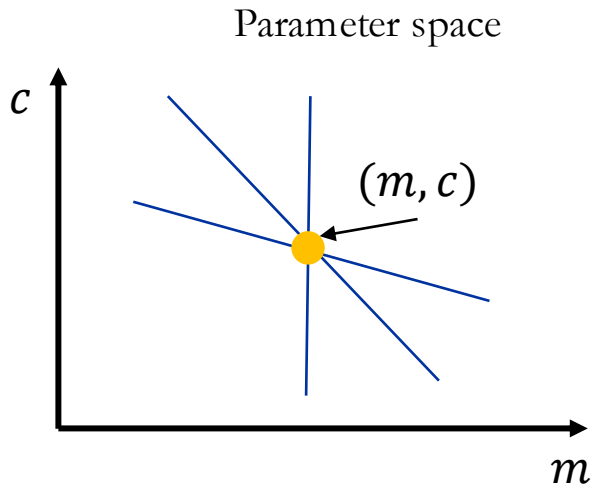


$y_i = mx_i + c$

$c = -mx_i + y_i$

Example (Part 4)

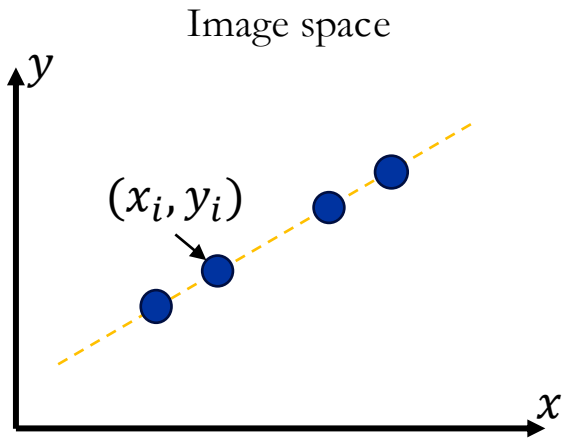


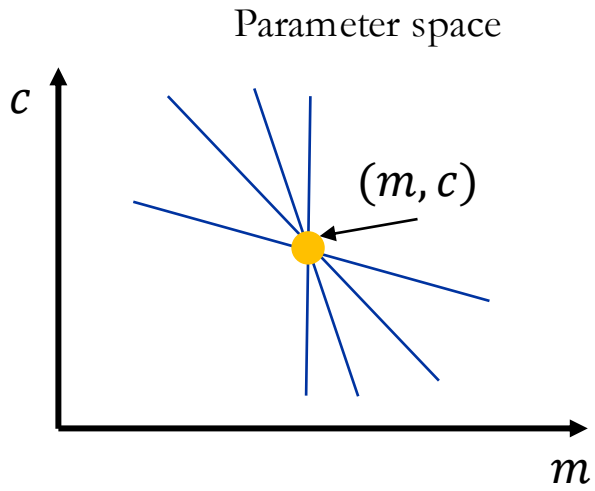


$y_i = mx_i + c$

$c = -mx_i + y_i$

Example (Part 5)

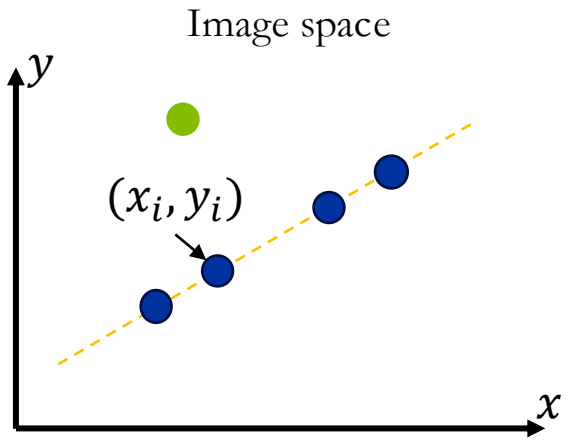


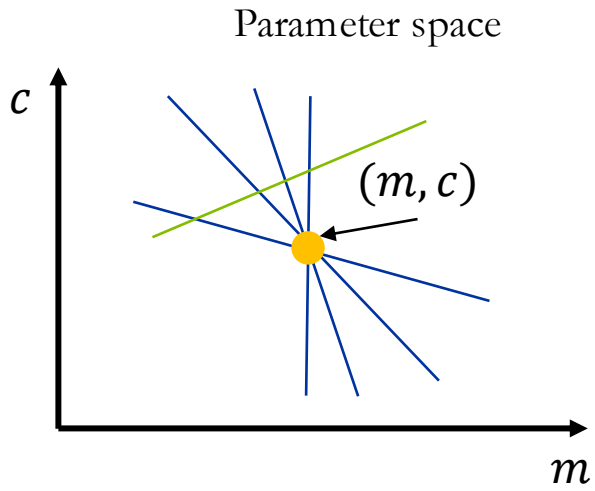


$$y_i = mx_i + c$$

$$c = -mx_i + y_i$$

Example (Part 6)

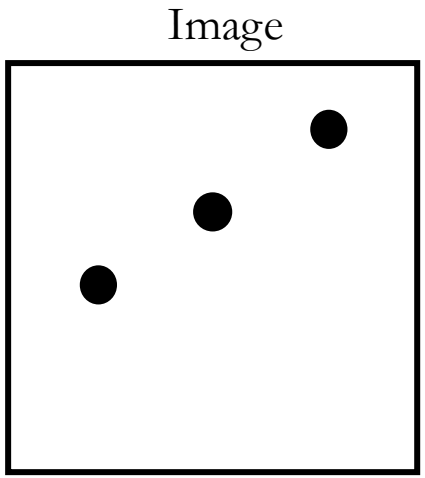




$y_i = mx_i + c$

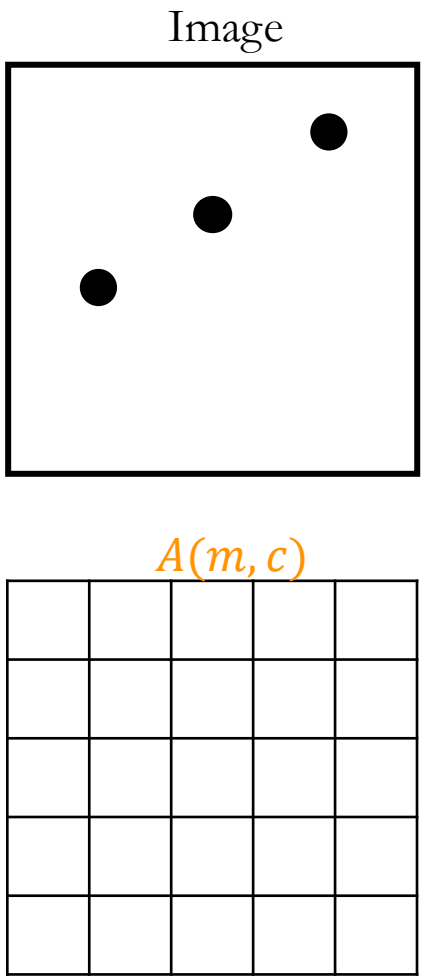
$c = -mx_i + y_i$

Now summarize the line detection algorithm!



Line Detection Algorithm

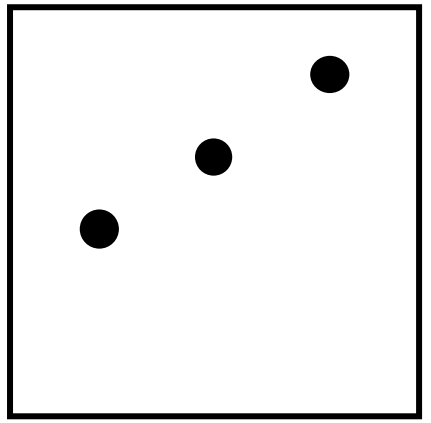
- Step 1. Quantize parameter space (m, c)
- Step 2. Create accumulator array $A(m, c)$



Line Detection Algorithm

- Step 1. Quantize parameter space (m, c)
- Step 2. Create accumulator array $A(m, c)$
- Step 3. Set $A(m, c) = 0$ for all (m, c)

Image



$A(m, c)$

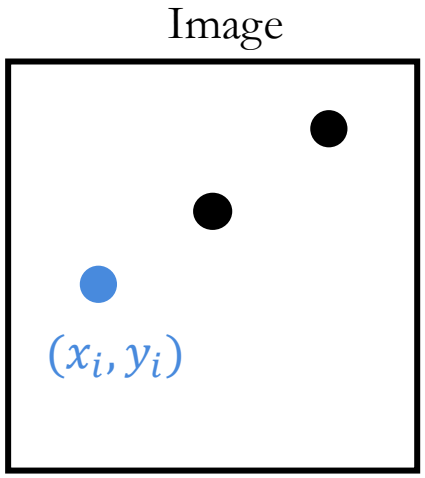
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0
0	0	0	0	0

Line Detection Algorithm

- Step 1. Quantize parameter space (m, c)
- Step 2. Create accumulator array $A(m, c)$
- Step 3. Set $A(m, c) = 0$ for all (m, c)
- Step 4. For each edge point (x_i, y_i),

$$A(m, c) = A(m, c) + 1$$

if (m, c) lies on the line: $c = -mx_i + y_i$



$A(m, c)$

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

Line Detection Algorithm

- Step 1. Quantize parameter space (m, c)
- Step 2. Create accumulator array $A(m, c)$
- Step 3. Set $A(m, c) = 0$ for all (m, c)
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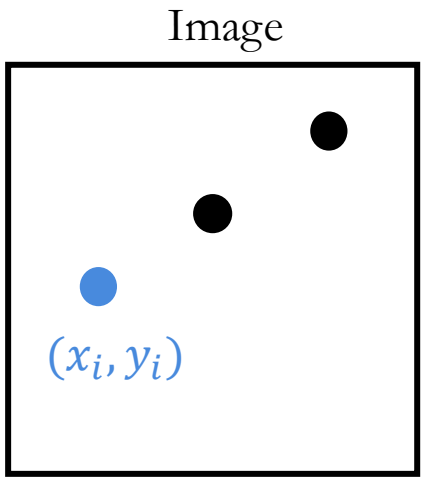


$A(m, c)$

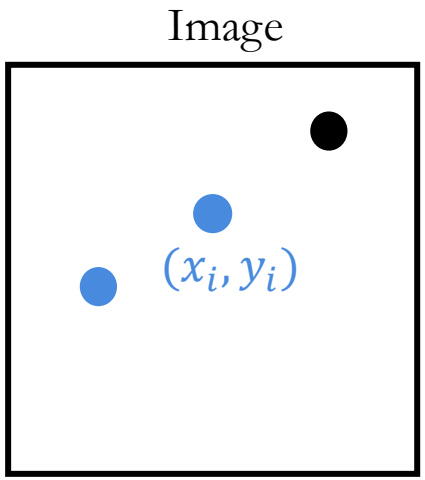
1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1

Line Detection Algorithm

- Step 1. Quantize parameter space (m, c)
- Step 2. Create accumulator array $A(m, c)$
- Step 3. Set $A(m, c) = 0$ for all (m, c)
- Step 4. For each edge point (x_i, y_i),

$$A(m, c) = A(m, c) + 1$$

if (m, c) lies on the line: $c = -mx_i + y_i$



$A(m, c)$

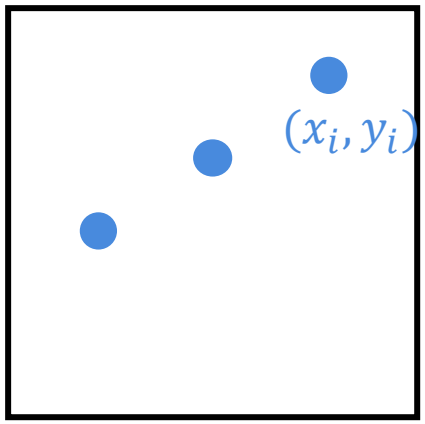
1	0	0	0	1
0	1	0	1	0
0	0	2	0	0
0	1	0	1	0
1	0	0	0	1

Line Detection Algorithm

- Step 1. Quantize parameter space (m, c)
- Step 2. Create accumulator array $A(m, c)$
- Step 3. Set $A(m, c) = 0$ for all (m, c)
- Step 4. For each edge point (x_i, y_i),

$$A(m, c) = A(m, c) + 1$$

if (m, c) lies on the line: $c = -mx_i + y_i$



$A(m, c)$

1	0	0	0	1
0	1	0	1	0
1	1	3	1	1
0	1	0	1	0
1	0	0	0	1

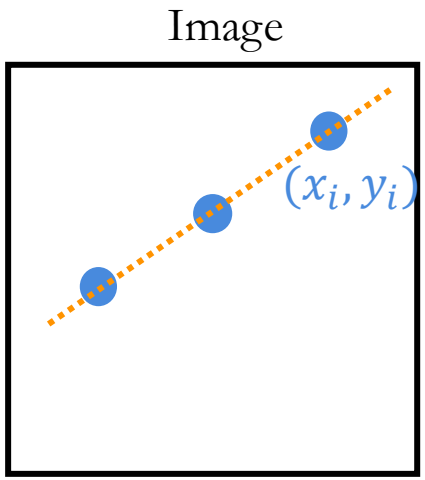
Line Detection Algorithm

- Step 1. Quantize parameter space (m, c)
- Step 2. Create accumulator array $A(m, c)$
- Step 3. Set $A(m, c) = 0$ for all (m, c)
- Step 4. For each edge point (x_i, y_i),

$$A(m, c) = A(m, c) + 1$$

if (m, c) lies on the line: $c = -mx_i + y_i$

- Step 5. Find local maxima in $A(m, c)$



$A(m, c)$

1	0	0	0	1
0	1	0	1	0
1	1	3	1	1
0	1	0	1	0
1	0	0	0	1

Multiple Lines?

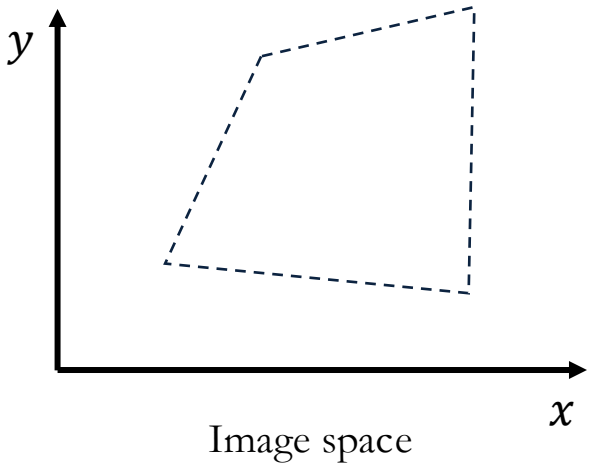
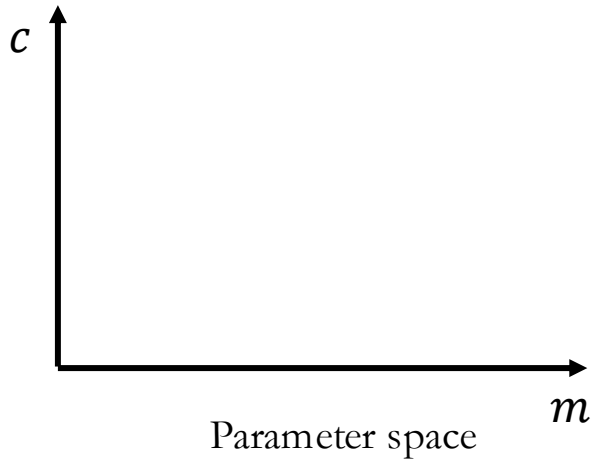


Image space



Parameter space

Multiple Lines?

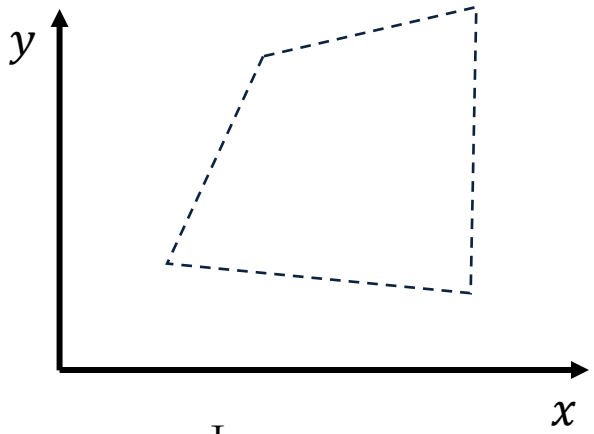
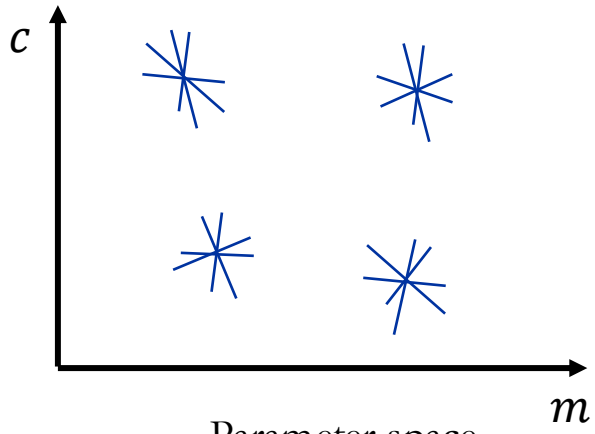


Image space



Parameter space

Multiple Lines?

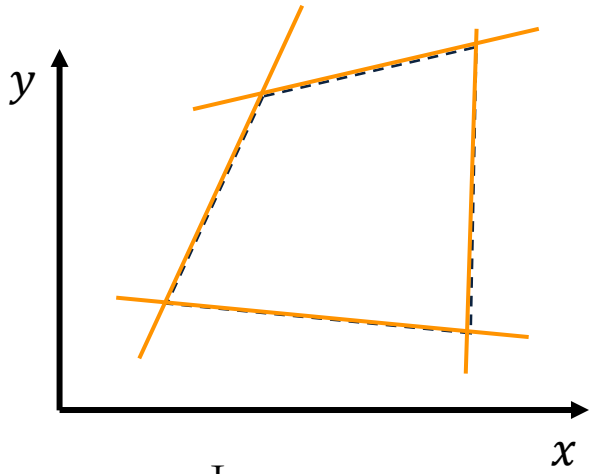
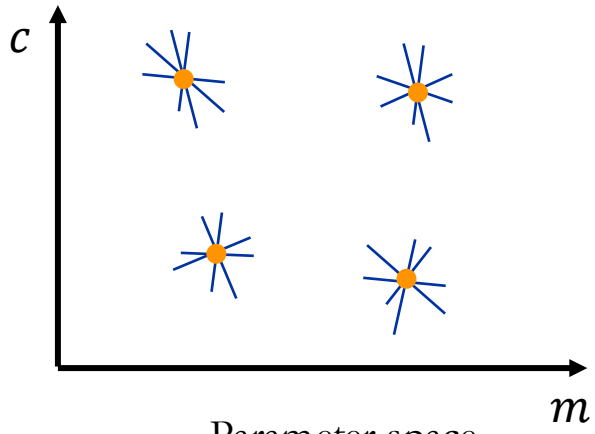


Image space



Parameter space

Better Parameterization?

- ***Issue:*** slope of the line $-\infty \leq m \leq \infty$
  - Large accumulator
  - More memory and computation

- ***Solution:*** use $xsin\theta - ycos\theta + \rho = 0$
  - Orientation θ is finite: $0 \leq \theta < \pi$
  - Distance ρ is finite

Better Parameterization?

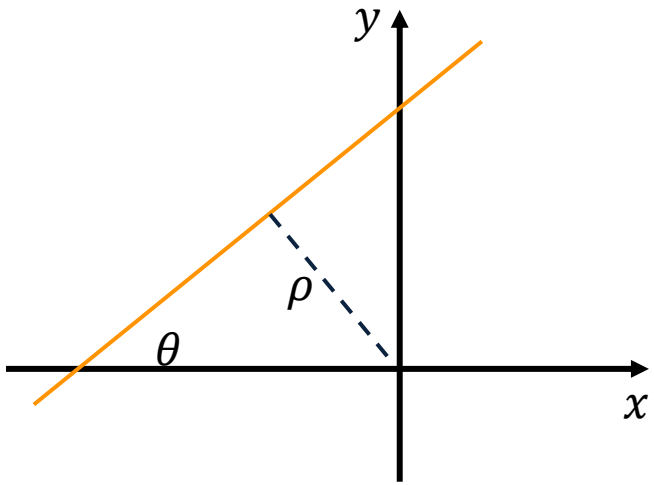
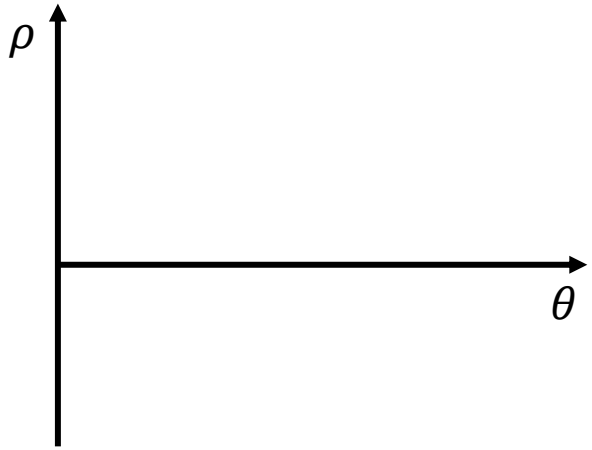


Image space

$$x\sin\theta - y\cos\theta + \rho = 0$$



Parameter space

$$x\sin\theta - y\cos\theta + \rho = 0$$

Better Parameterization?

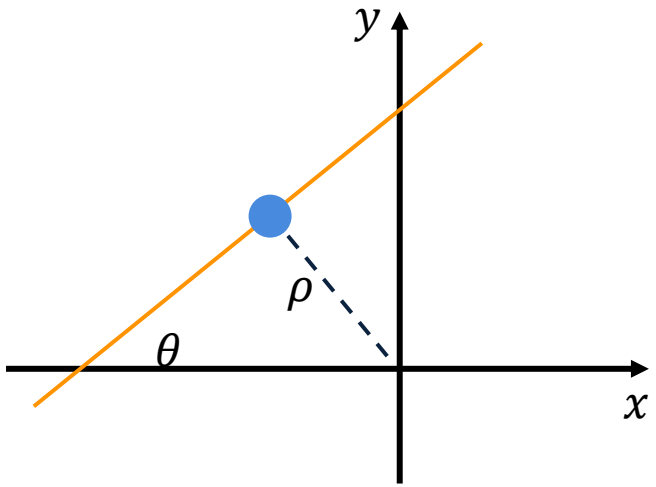
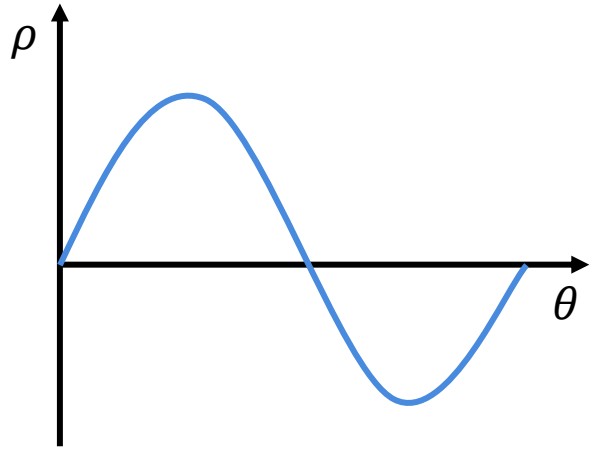


Image space



Parameter space

$$x\sin\theta - y\cos\theta + \rho = 0$$

$$x\sin\theta - y\cos\theta + \rho = 0$$

Better Parameterization?

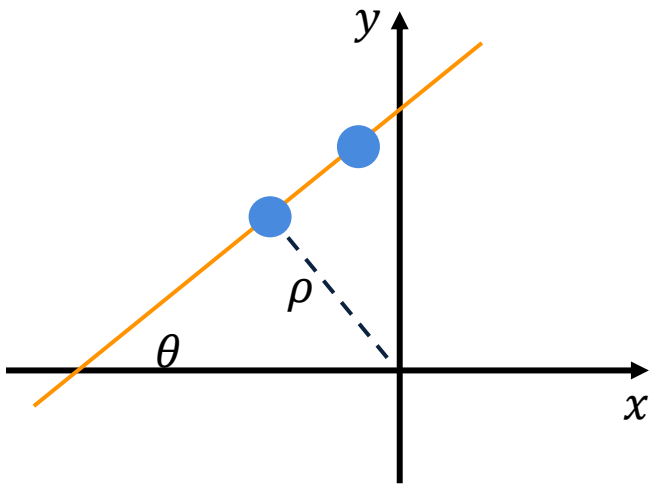
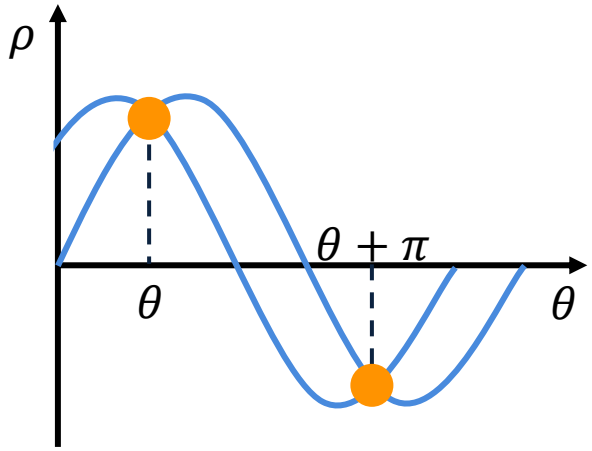


Image space

$$x\sin\theta - y\cos\theta + \rho = 0$$



Parameter space

$$x\sin\theta - y\cos\theta + \rho = 0$$

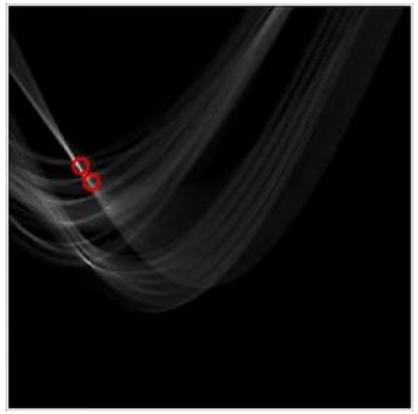
Detection Results

Original

Gradient

Edge

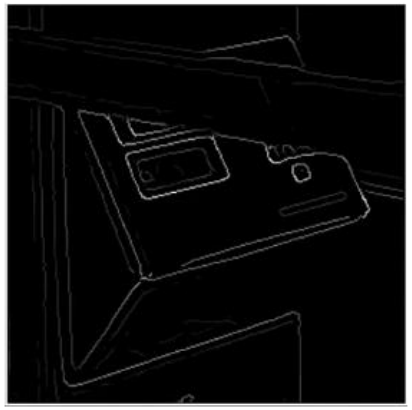
Hough Transform $A(\rho, \theta)$



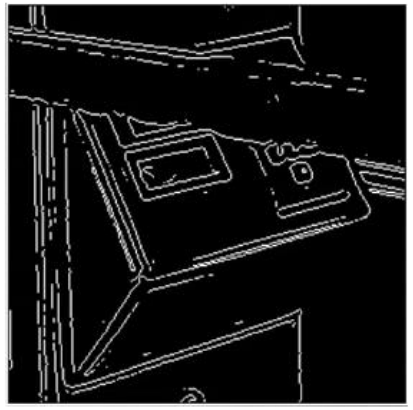
Detected Lines

Detection Results

Original

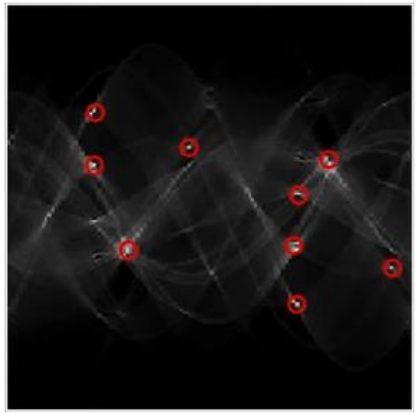


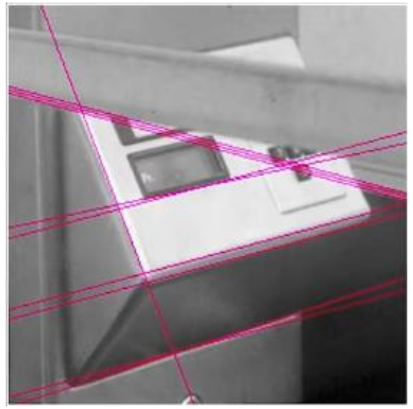
Gradient



Edge

Hough Transform $A(\rho, \theta)$





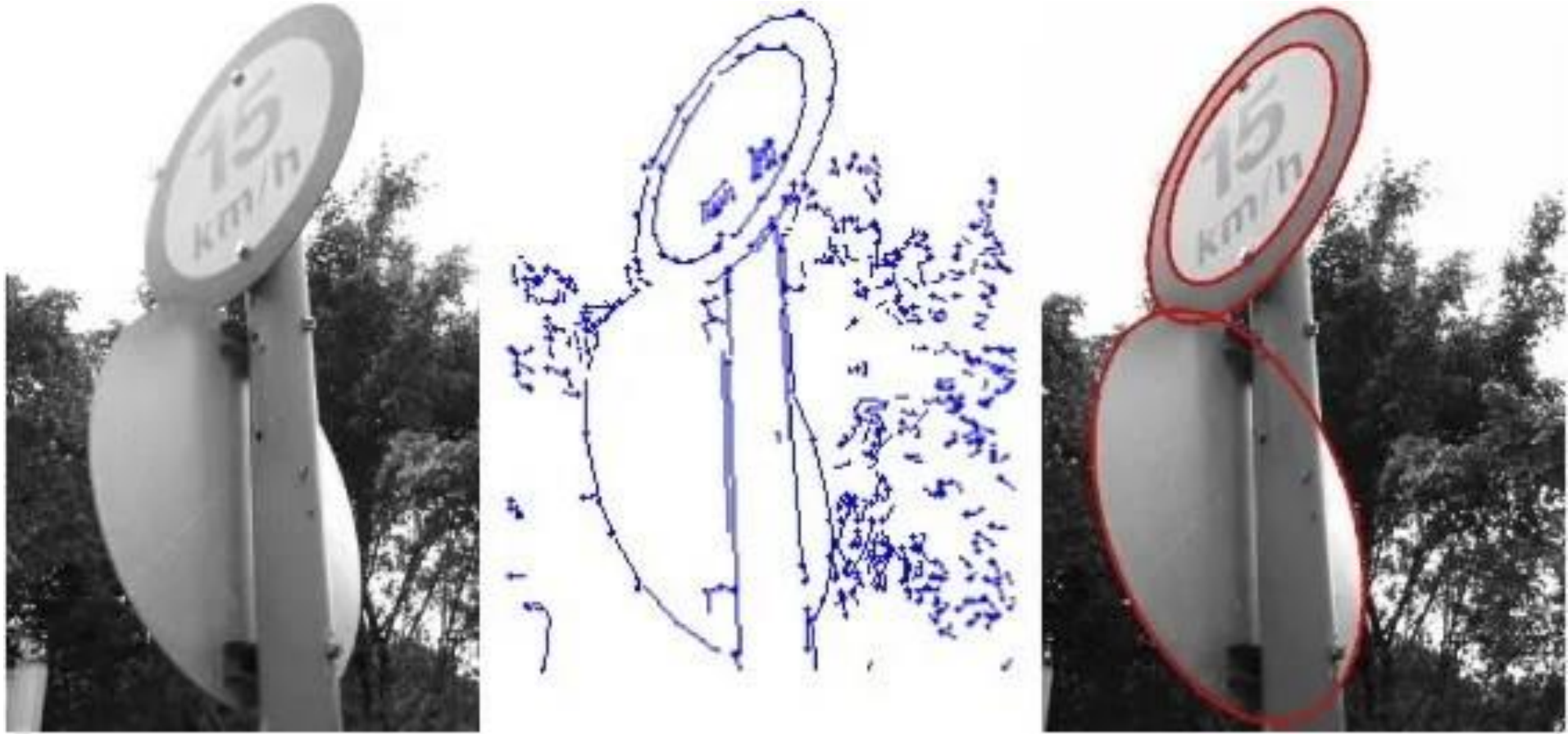
Detected Lines

SOUTH DAKOTA STATE UNIVERSITY

Hough Transform: Beyond Line Detection

Credit: slides of this section are adapted from CSC 492/592, Spring 2024

Image source: https://laid.delanover.com/hough-transform-ellipse-detection-and-space-reduction/



Hough Transform

- The Hough Transform is a feature extraction technique.
- Purpose: to find **imperfect** instances of objects within a certain class of shapes by a **voting scheme**.
- This voting procedure is carried out in a **parameter space**, from which object candidates are obtained as **local maxima** in a so-called accumulator space that is explicitly constructed by the algorithm for computing the Hough transform.

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

One Example: Finding Circle

- If radius r is known: Accumulator Array: $A(a, b)$

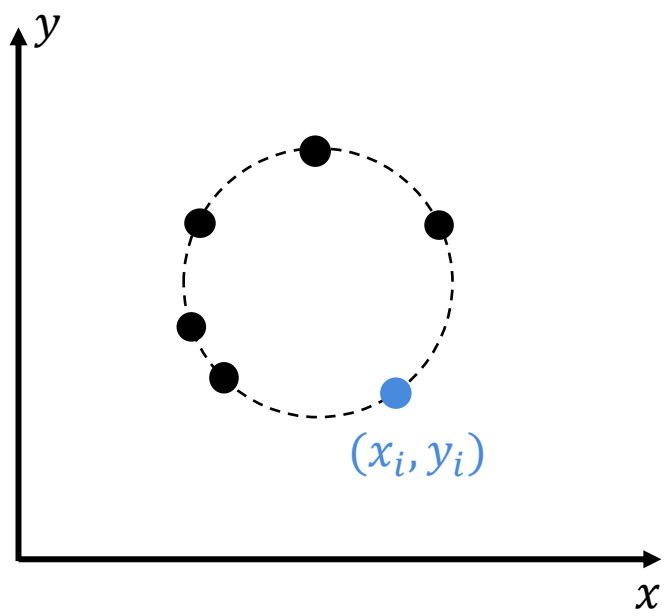
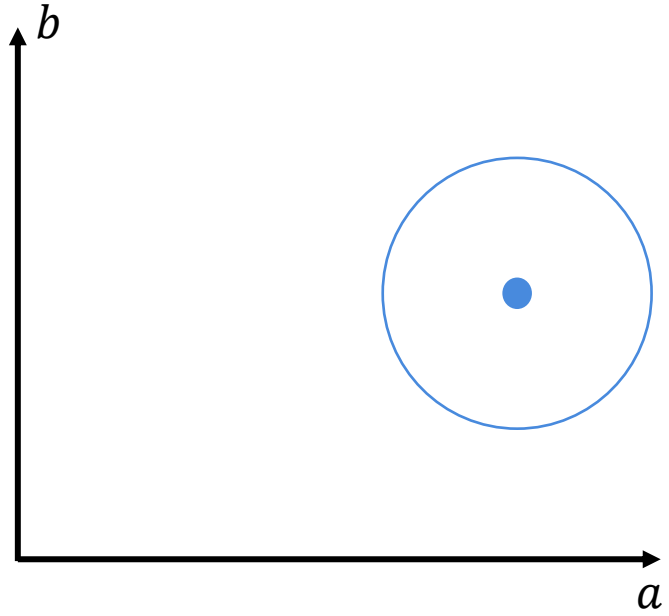


Image space

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$



Parameter space

$$(a - x_i)^2 + (b - y_i)^2 = r^2$$

Finding Circle

- If radius r is known: Accumulator Array: $A(a, b)$

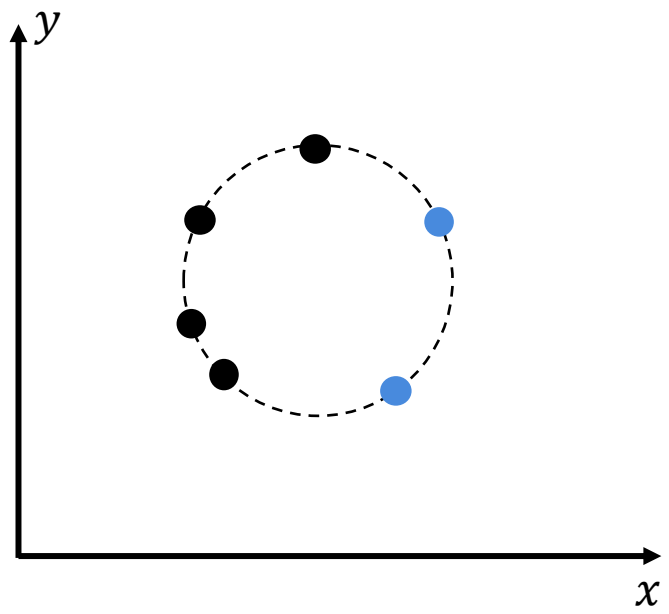
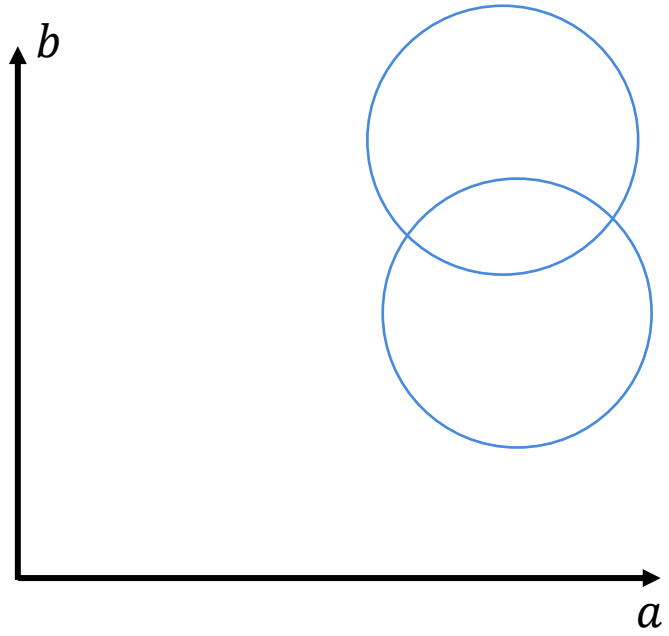


Image space

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$



Parameter space

$$(a - x_i)^2 + (b - y_i)^2 = r^2$$

Finding Circle

- If radius r is known: Accumulator Array: $A(a, b)$

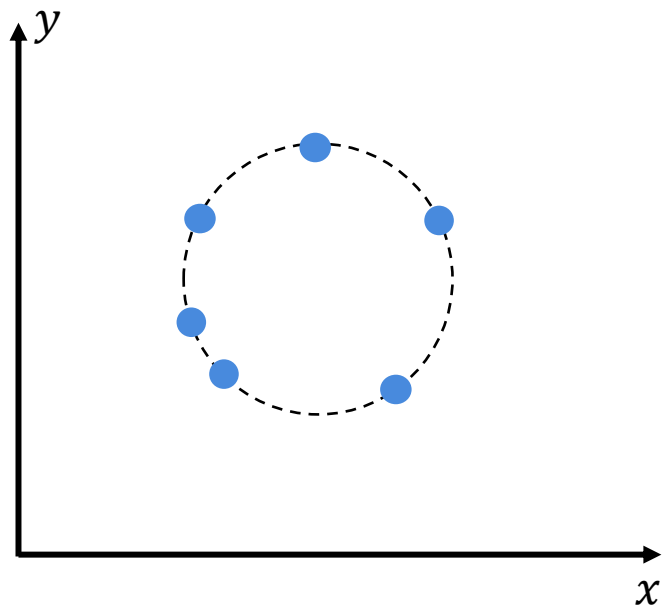
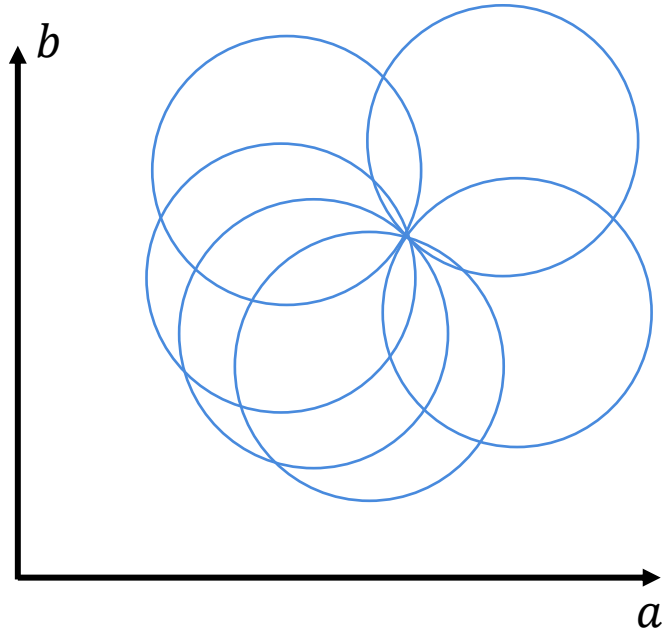


Image space

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$



Parameter space

$$(a - x_i)^2 + (b - y_i)^2 = r^2$$

Finding Circle

- If radius r is known: Accumulator Array: $A(a, b)$

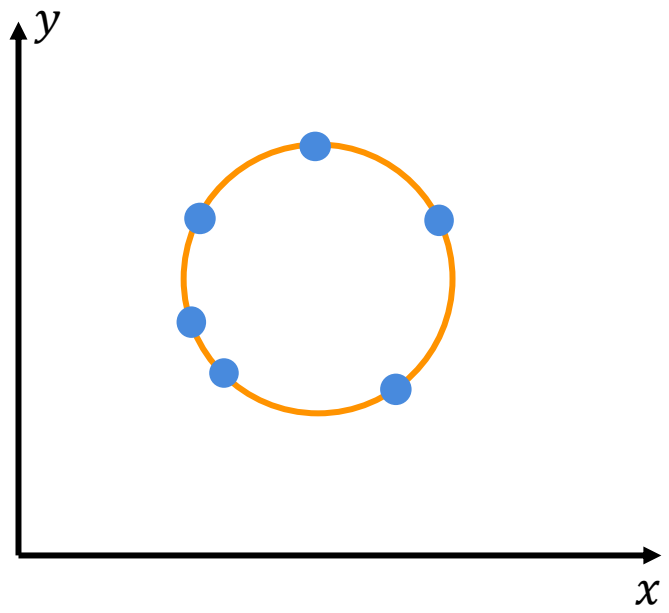
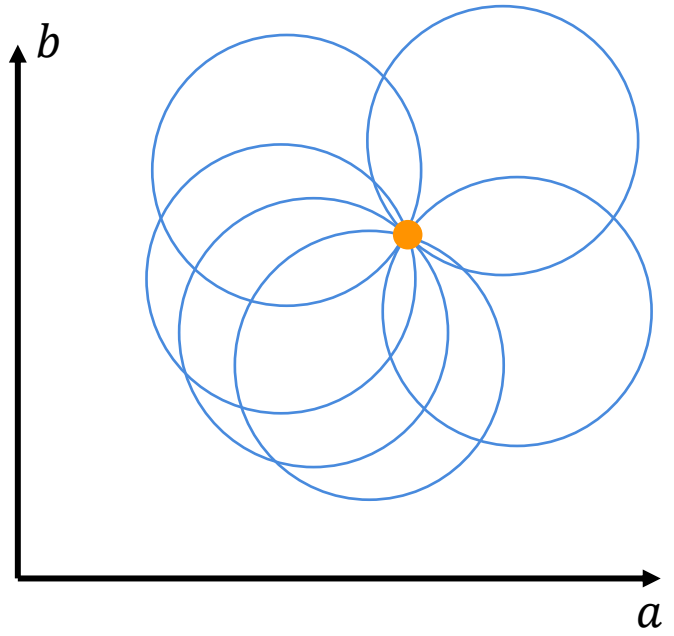


Image space

$$(x_i - a)^2 + (y_i - b)^2 = r^2$$



Parameter space

$$(a - x_i)^2 + (b - y_i)^2 = r^2$$

Circle Detection Results

Original

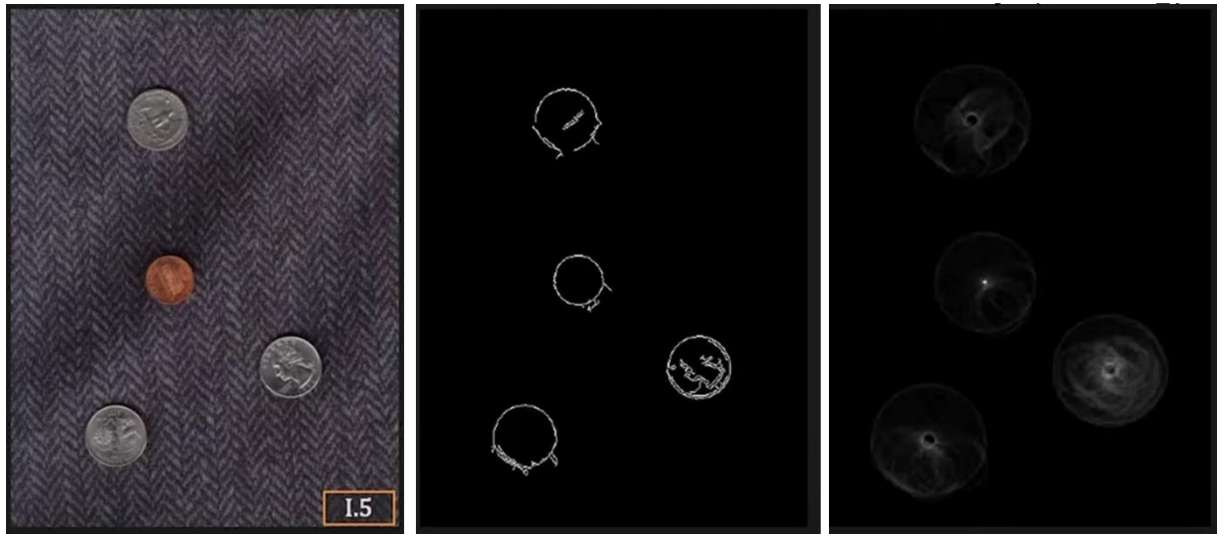
Circle Detection Results

Original

Edge

Circle Detection Results

Penny ($r = r_1$)



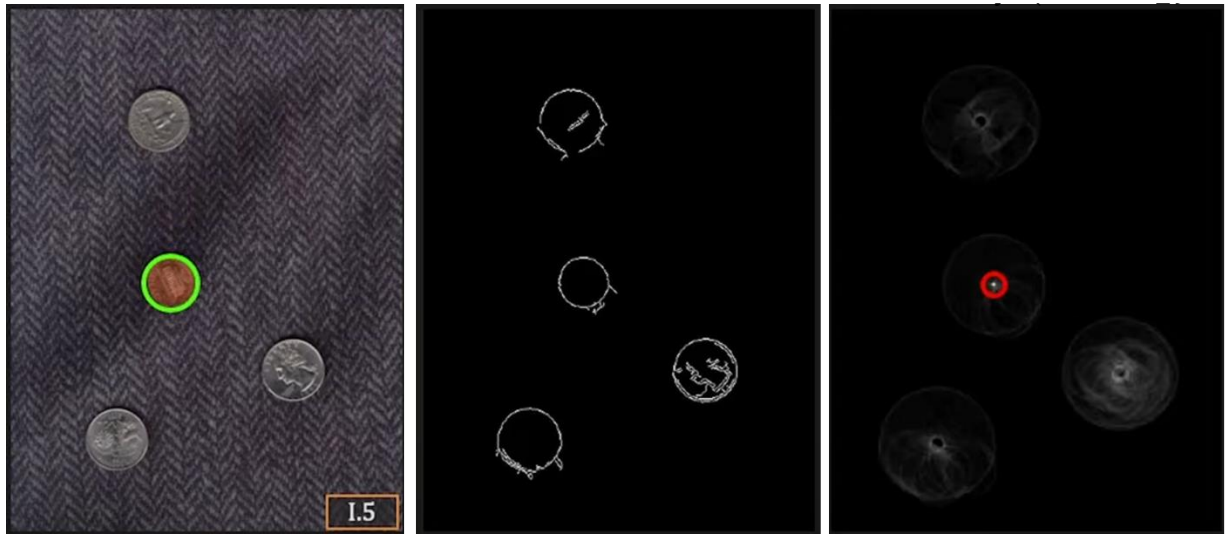
Original

Edge

Hough Transform
$A_1(a, b)$

Circle Detection Results

Penny ($r = r_1$)

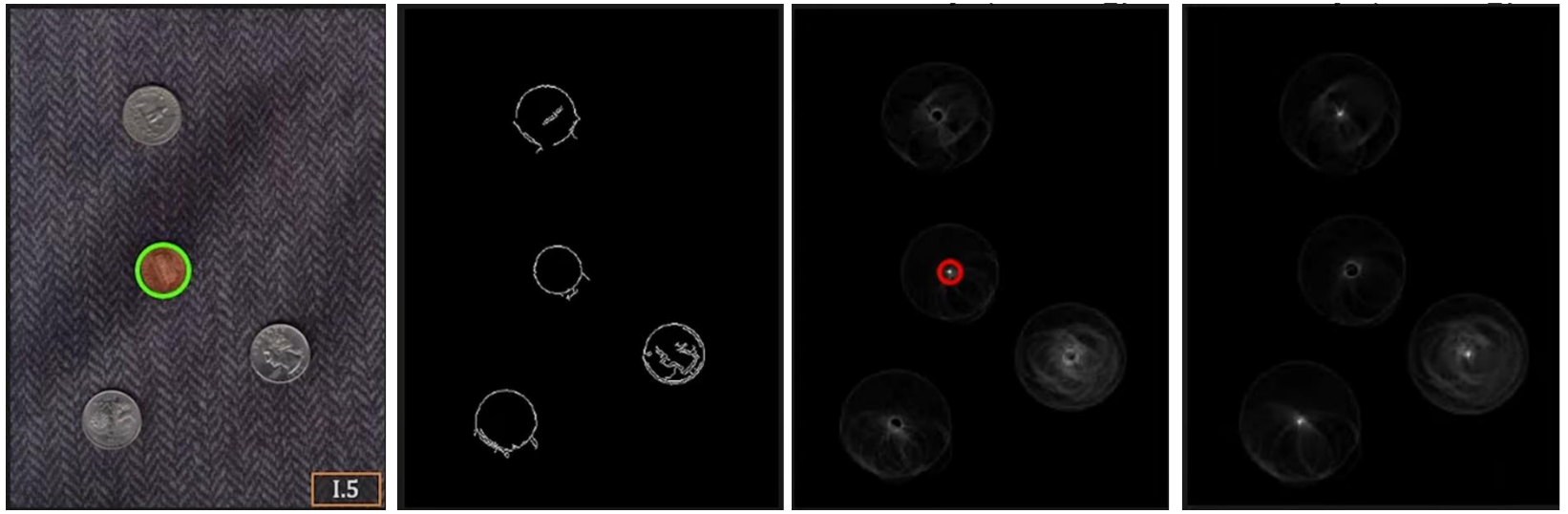


Original

Edge

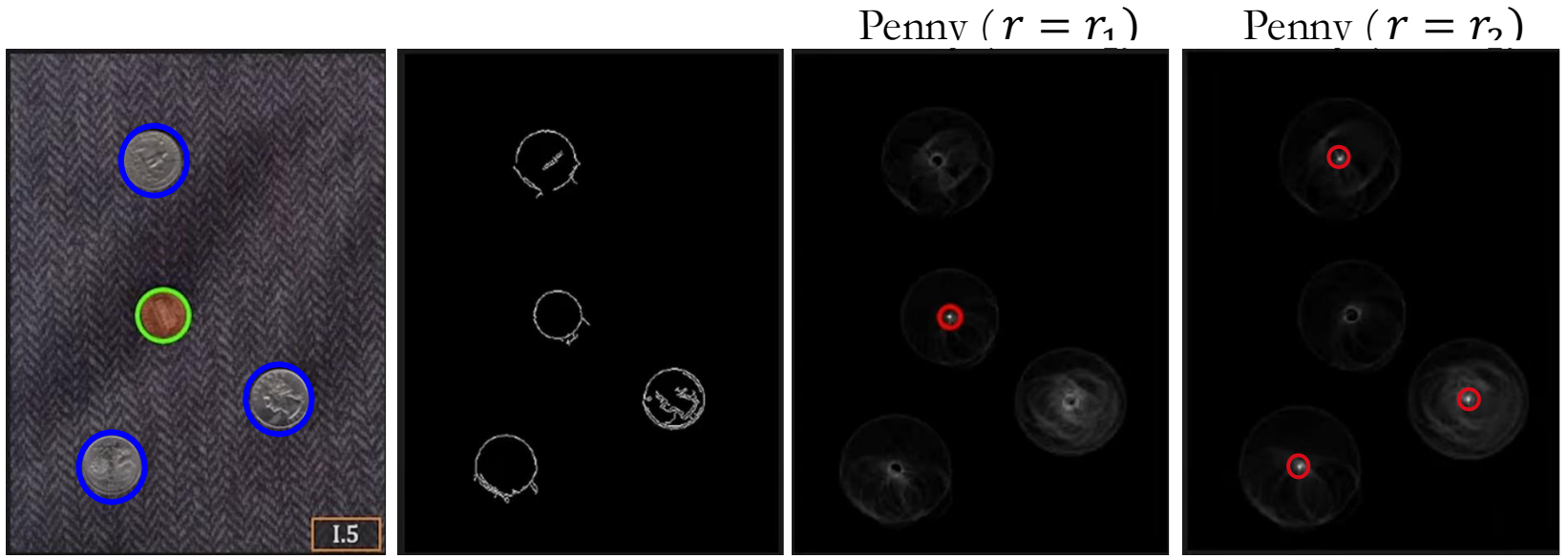
Hough Transform
$A_1(a, b)$

Circle Detection Results



Original | Edge | Hough Transform $A_1(a, b)$ | Hough Transform $A_2(a, b)$

Circle Detection Results



Original | Edge | Hough Transform $A_1(a, b)$ | Hough Transform $A_2(a, b)$

Takeaway

- Why Features matter in computer vision?
- Different ways to detect edges
  - Prewitt & Sobel
  - Laplacian of Gaussian
  - Canny Edge Detector
- Hough Transform
  - The voting scheme
  - How to detect lines
  - How to detect circles