



# Computer Vision

(Course Code: 4047)

## Module-2:Lecture-3: Hough Transform

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# Hough Transform

Challenge: One of the problem with boundary detection of an object in an image is knowing which edges in the image that are corresponding to the boundary we are looking for.

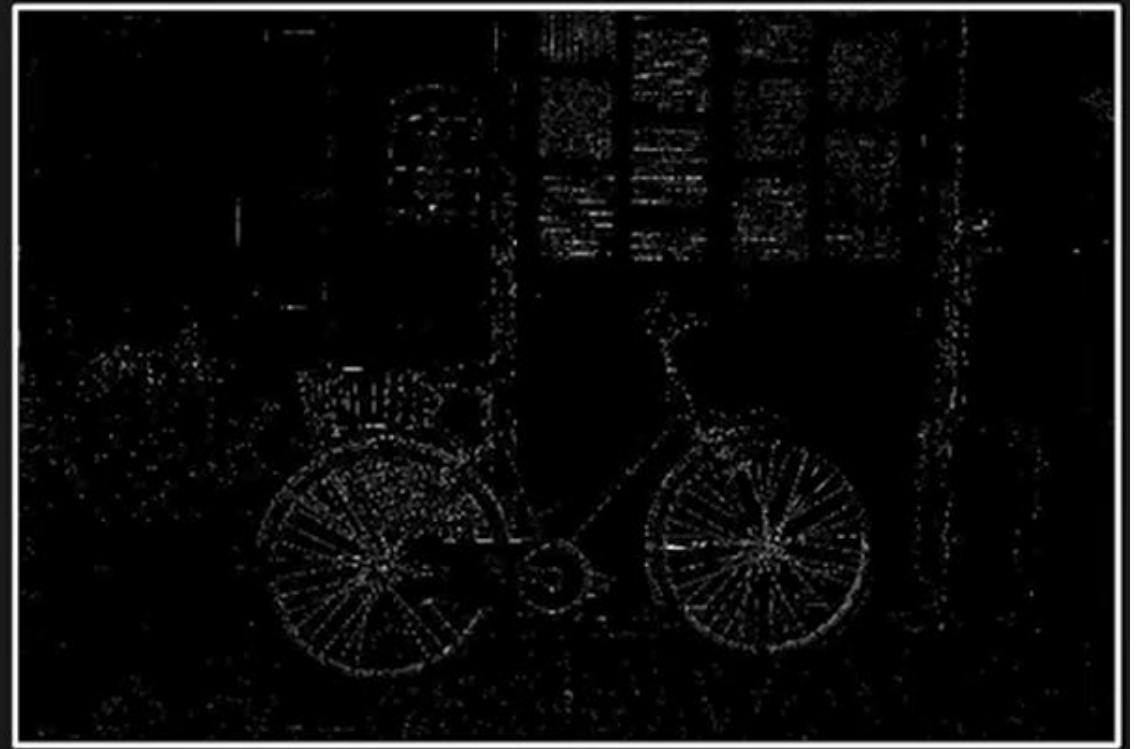
- ❖ Hough Transform provides an elegant solution to the problem when the boundary can be described by a small number of parameters.
- ❖ The Hough Transform is an algorithm patented by Paul V. C. Hough and was originally invented to recognize complex lines in photographs (Hough, 1962).
- ❖ The algorithm has been modified and enhanced to be able to recognize other shapes such as circles and quadrilaterals of specific types.
- ❖ Perform edge detection first on the Input image (using edge detection algorithms: Canny, Sobel, Laplacian etc.) to produce an edge image which will then be used as input into the Hough Transform algorithm.

# Difficulties for the Fitting Approach

Input Image



Edge Map



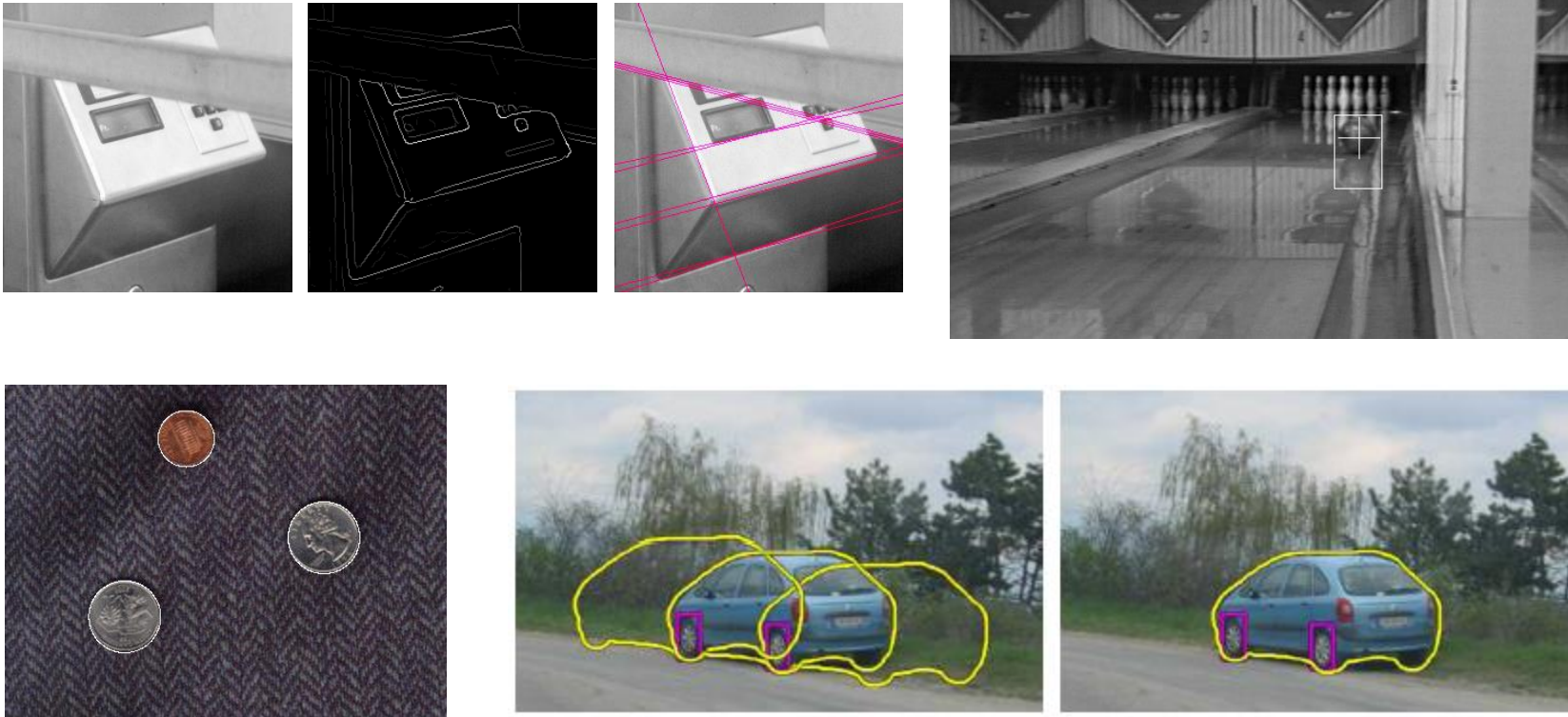
Task: Find the two wheels of the bicycle

- ❖ Extraneous Data: Which points to fit to? (e.g., to the bicycle circles, )
- ❖ Incomplete Data: Only part of the model is visible (e.g., Occlusion, Part of the wheel is incomplete.)
- ❖ Noise (e.g., edges close to the wheels which don't correspond to real edges)

**Solution: Hough Transform (1962)**

# Fit / Associate a model with observed features

❖ Want to associate a model with observed features



[Fig from Marszalek & Schmid, 2007]

For example, the model could be a line, a circle, or an arbitrary shape.

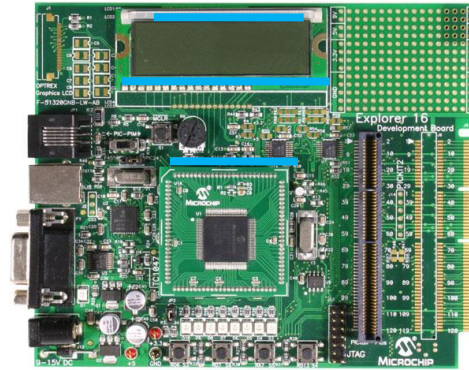
# Fitting: Main idea

- Choose a parametric model to represent a set of features
- Membership criterion is not local
  - Can't tell whether a point belongs to a given model just by looking at that point
- Three main questions:
  - What model represents this set of features best?
  - Which of several model instances gets which feature?
  - How many model instances are there?
- Computational complexity is important
  - It is infeasible to examine every possible set of parameters and every possible combination of features



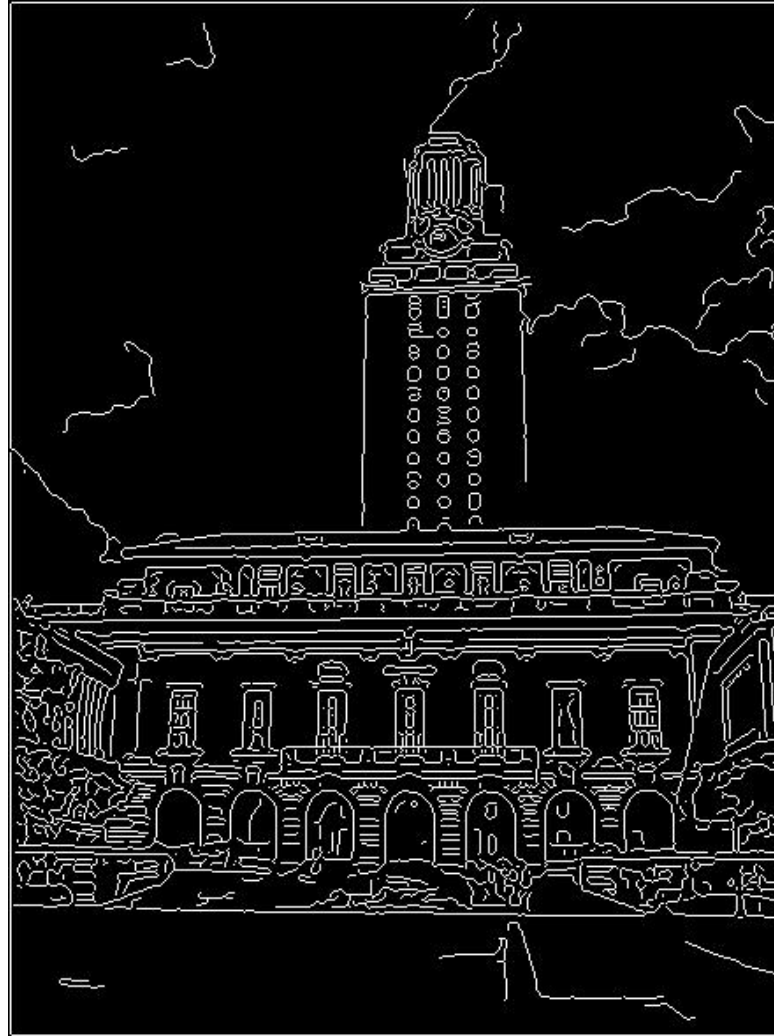
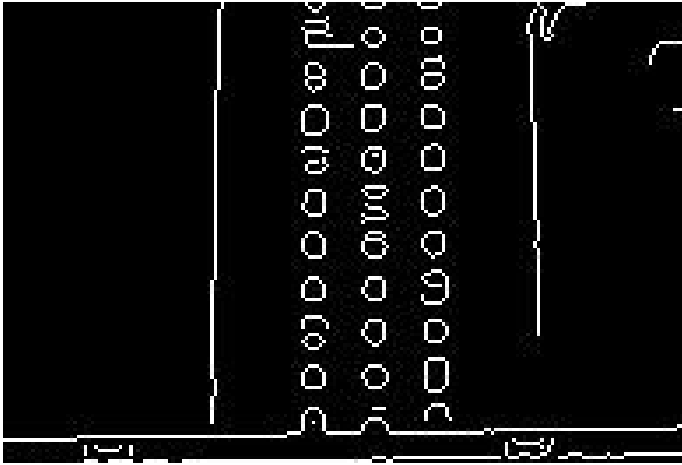
# Case study: Line fitting

- ❖ Why fit lines?  
Many objects characterized by presence of straight lines

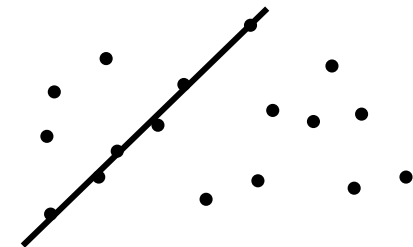


- Wait, why aren't we done just by running edge detection?

# Difficulty of Line Fitting



- ❖ **Extra edge points (clutter), multiple models:**
  - which points go with which line, if any?
- ❖ Only some parts of each line detected, and some parts are **missing**:
  - how to find a line that bridges missing evidence?
- ❖ **Noise** in measured edge points, orientations:
  - how to detect true underlying parameters?



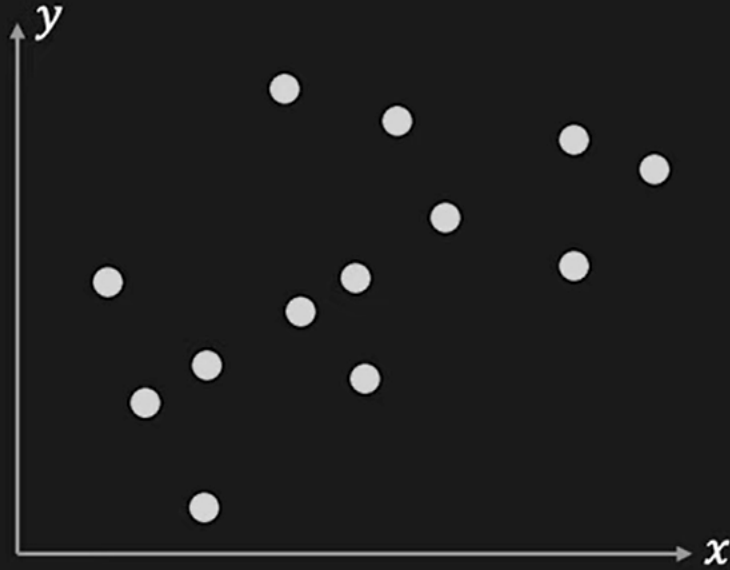
# Voting

- ❖ It's not feasible to check all combinations of features by fitting a model to each possible subset.
- ❖ **Voting** is a general technique where we let the features *vote for all models that are compatible with it*.
  - Cycle through features, cast votes for model parameters.
  - Look for model parameters that receive a lot of votes.
- ❖ Noise & clutter features will cast votes too, *but* typically their votes should be inconsistent with the majority of “good” features.



# Hough Transform: Line Detection

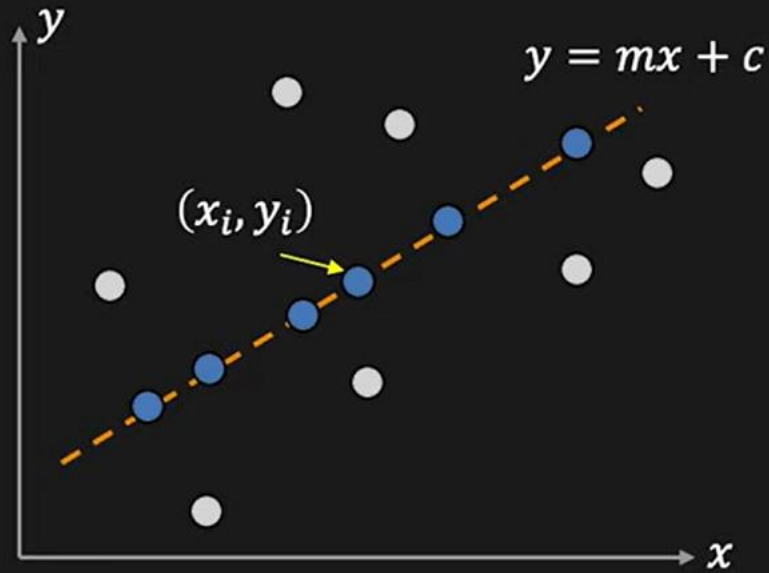
**Given:** Edge Points  $(x_i, y_i)$



# Hough Transform: Line Detection

**Given:** Edge Points  $(x_i, y_i)$

**Task:** Detect line  
 $y = mx + c$



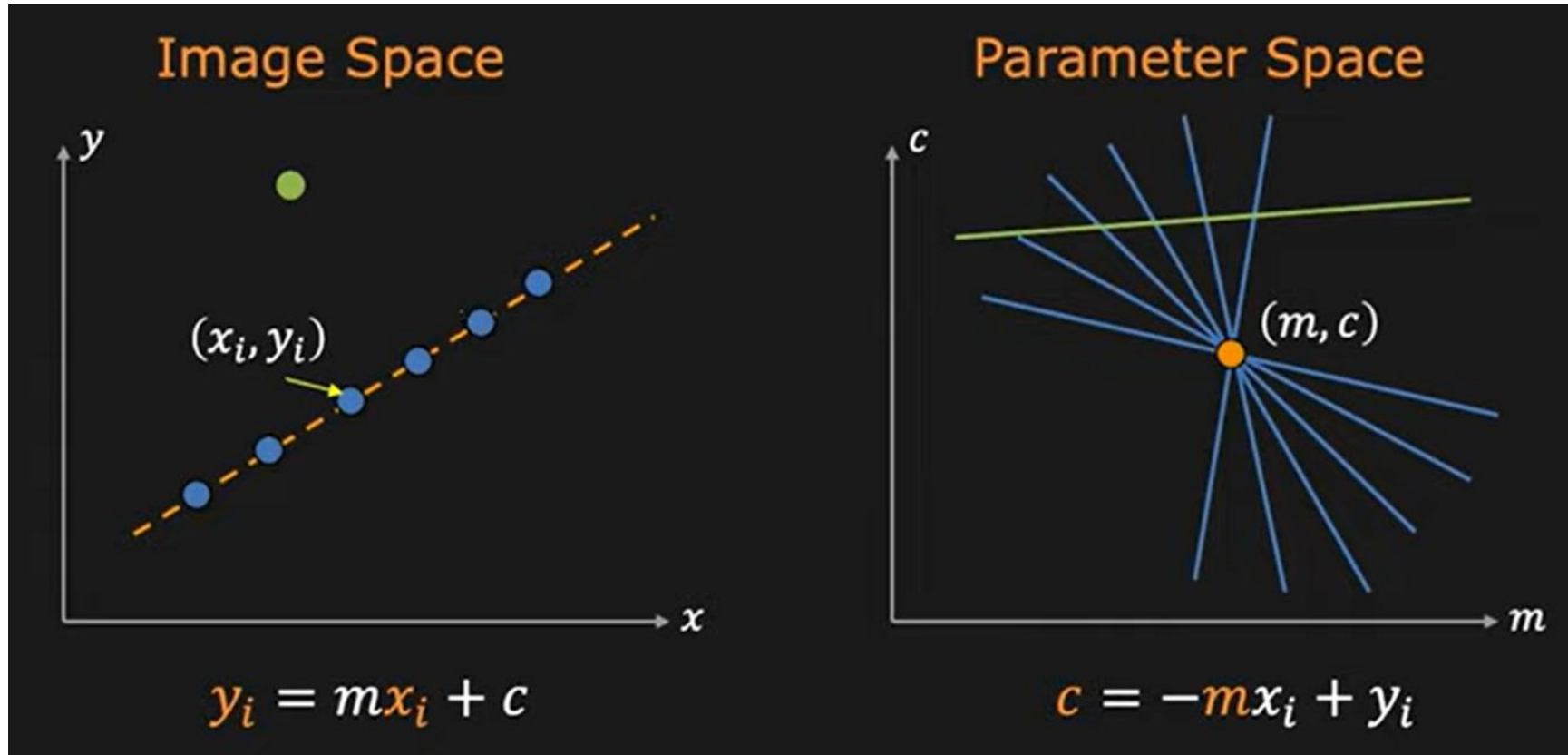
Consider point  $(x_i, y_i)$

$$y_i = mx_i + c \quad \Longleftrightarrow \quad c = -mx_i + y_i$$

Note: Straight line equation for m and c

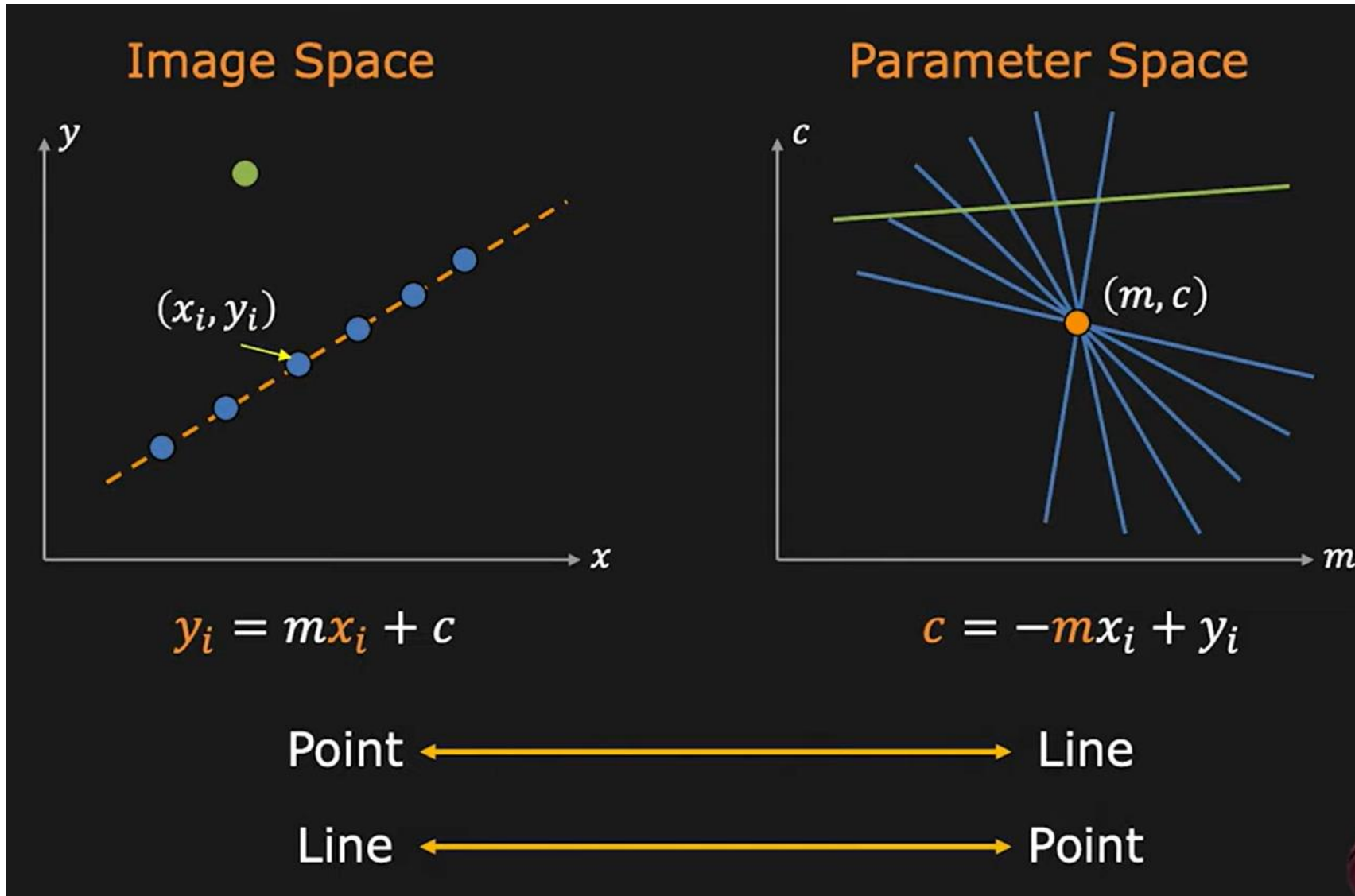
# Hough Transform: Line Detection (Hough Parameter Space)

Transform all the image points from Image Space to Hough Parameter Space



# Hough Transform: Concept

Transform all the image points from Image Space to Hough Parameter Space



# Hough Transform: Line Detection Algorithm (with a Voting scheme)

Step 1. Quantize parameter space  $(m, c)$

Step 2. Create **accumulator array**  $A(m, c)$

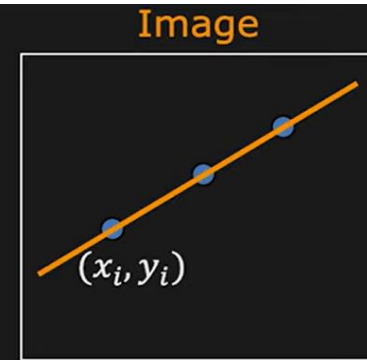
Step 3. Set  $A(m, c) = 0$  for all  $(m, c)$

Step 4. For each edge point  $(x_i, y_i)$ ,

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

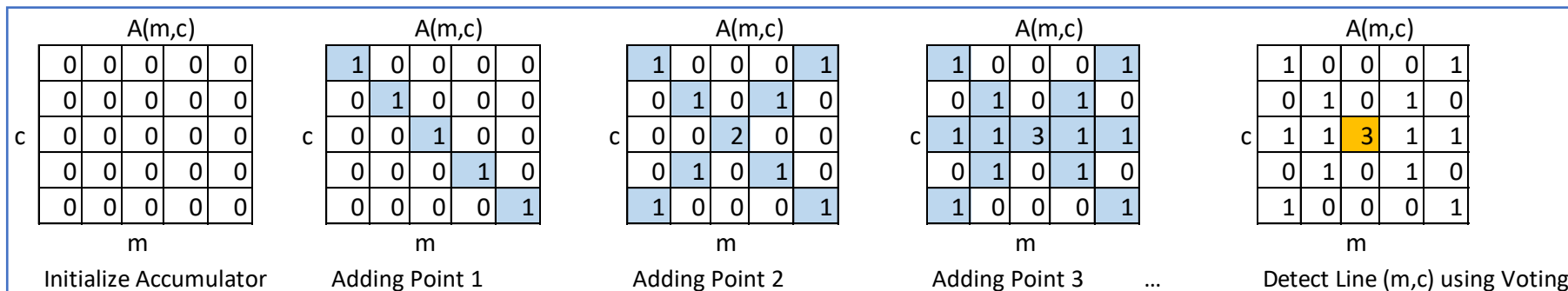
if  $(m, c)$  lies on the line:  $c = -mx_i + y_i$

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



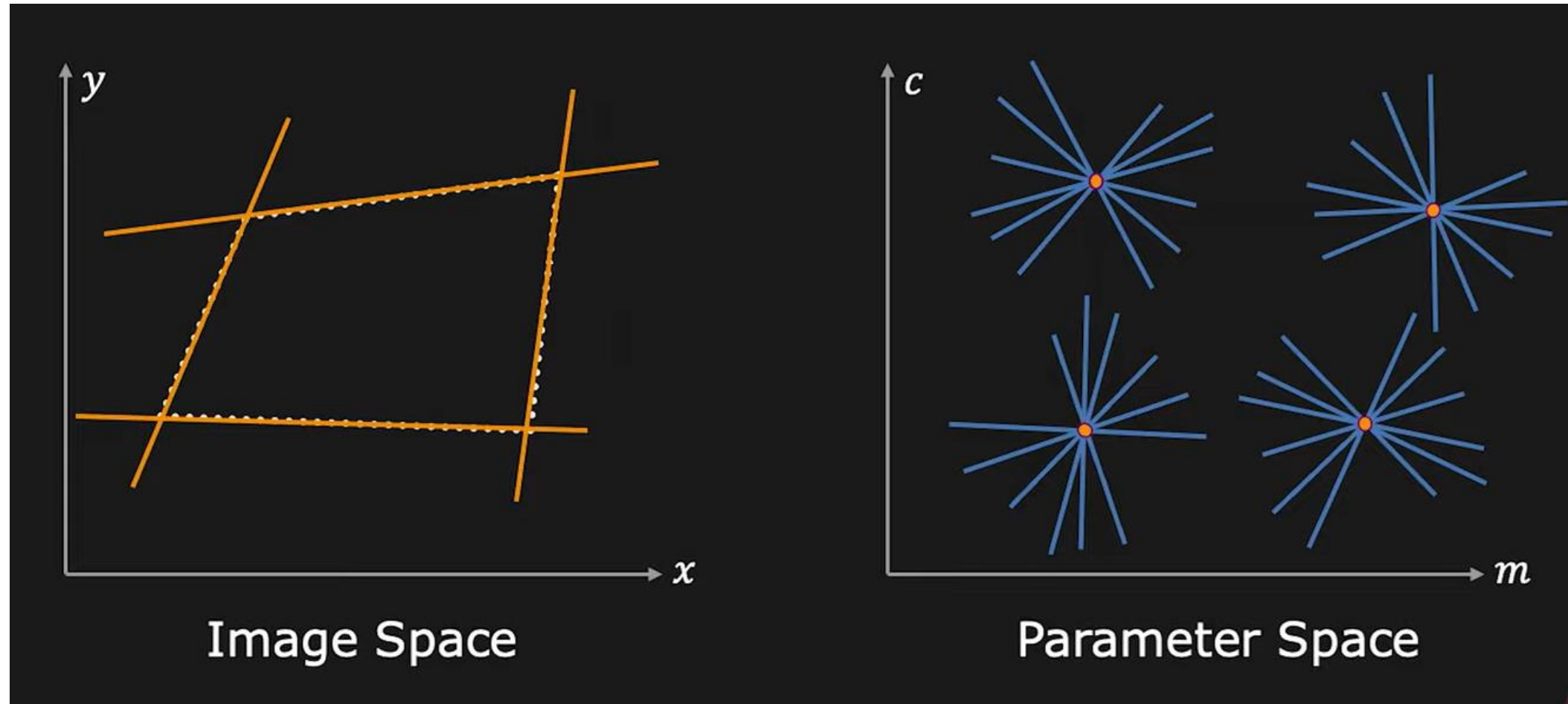
$A(m, c)$

$c$	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
	$m$				





# Multiple Lines Detection



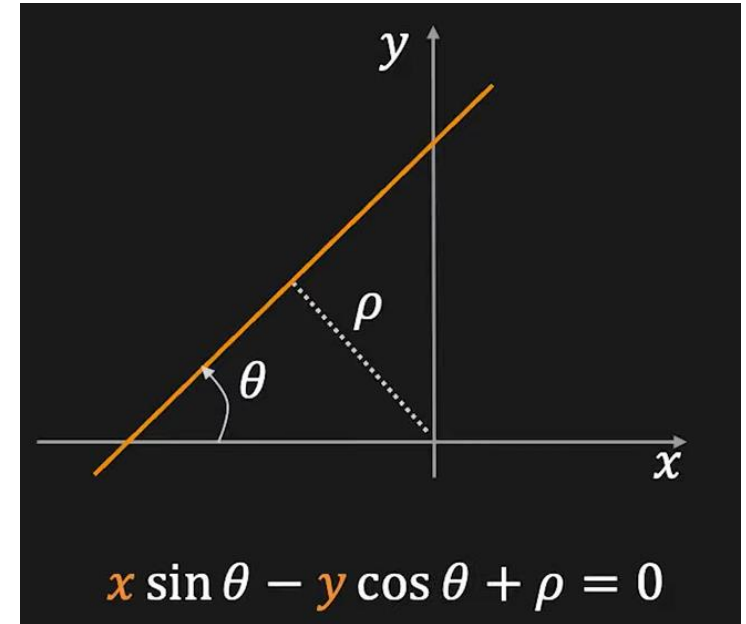
# Better Parameterization

**Issue:** Slope of the line  $-\infty \leq m \leq \infty$

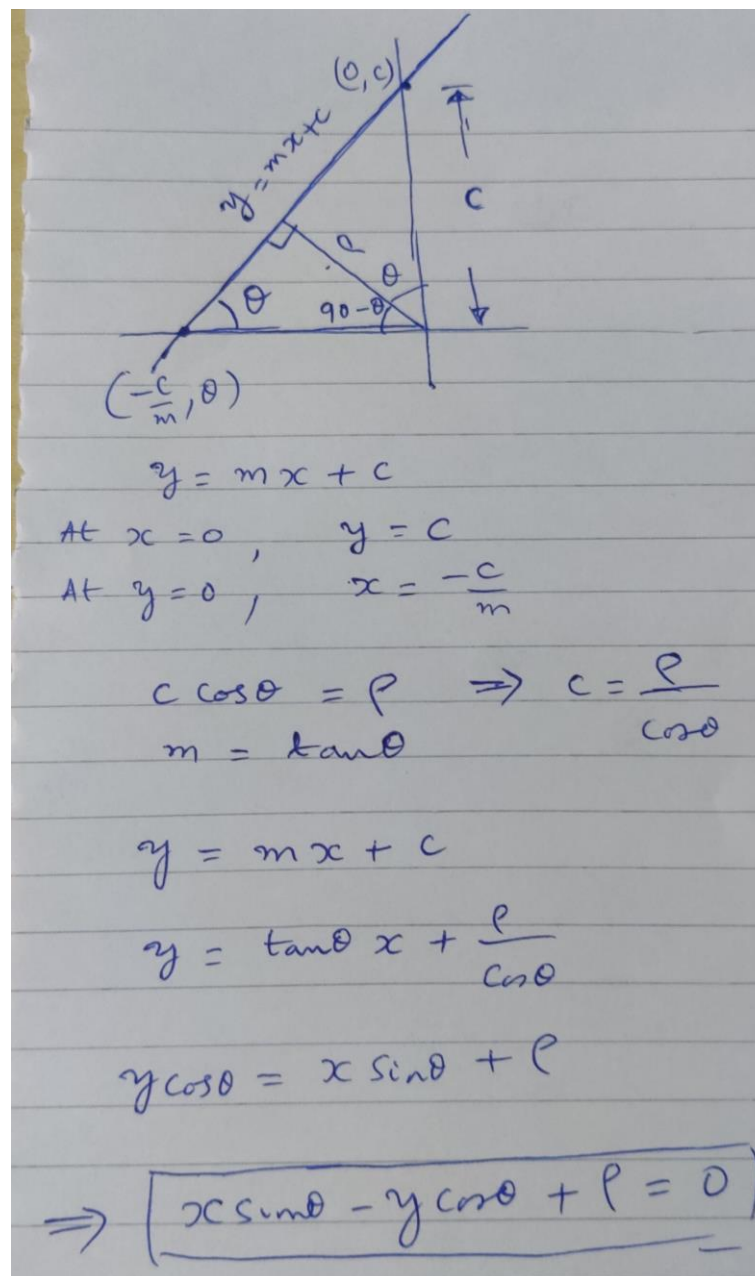
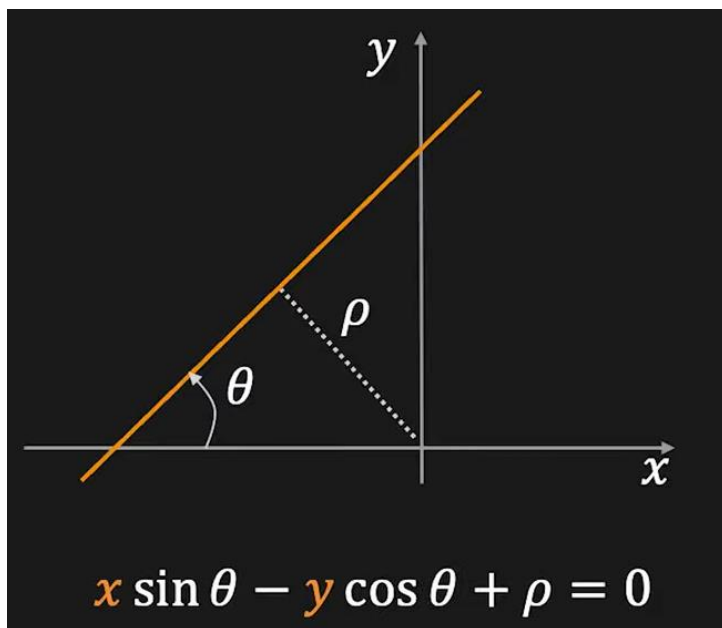
- Large Accumulator
- More Memory and Computation

**Solution:** Use  $x \sin \theta - y \cos \theta + \rho = 0$

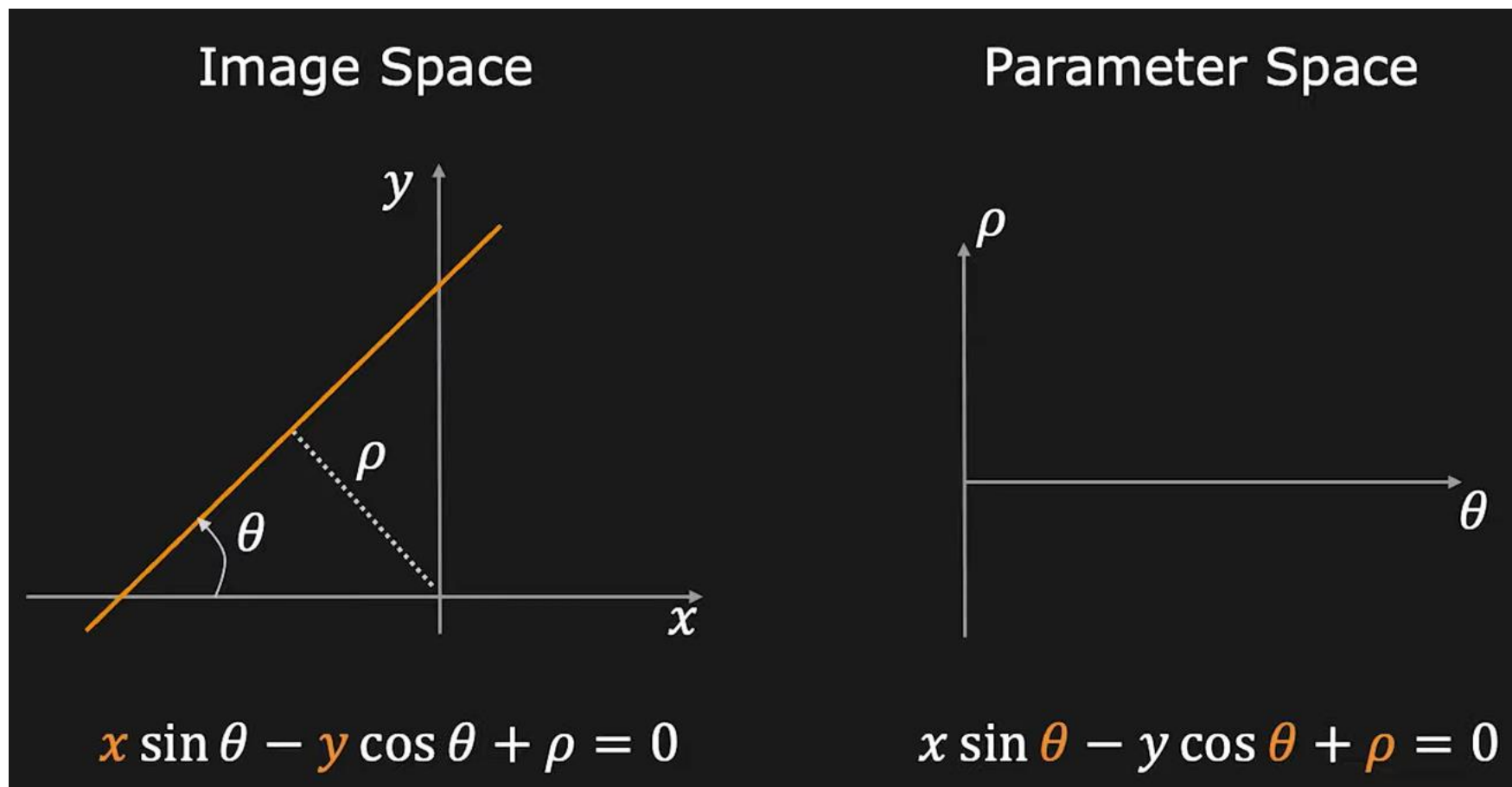
- Orientation  $\theta$  is finite:  $0 \leq \theta < \pi$
- Distance  $\rho$  is finite



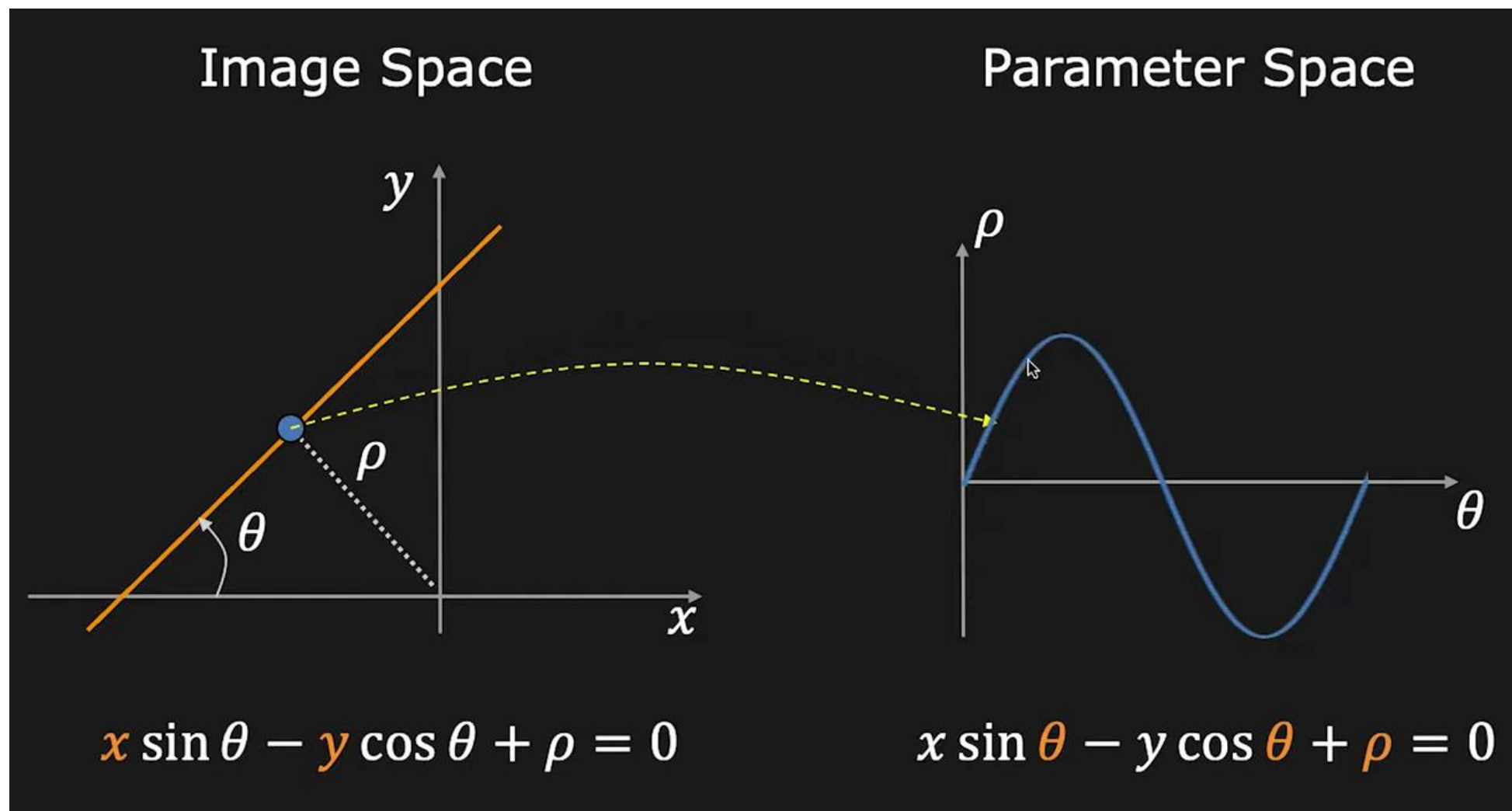
# Two Line Equations



# Better Parameterization

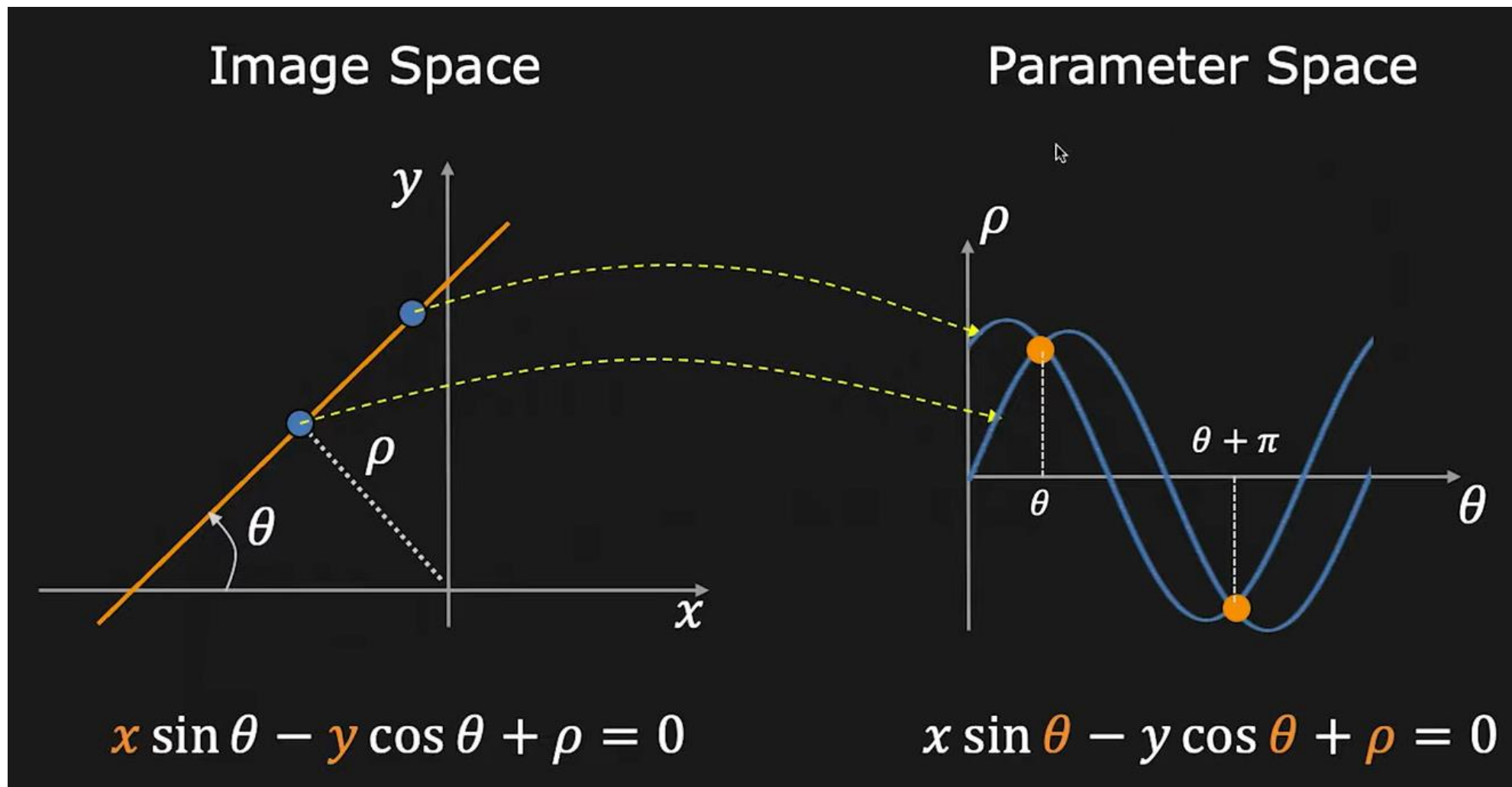


# Better Parameterization





# Better Parameterization



# Hough Transform Mechanics

## ❖ How big should the accumulator cells be?

- Too big: Different lines may be merged.
- Too small: Noise causes lines to be missed. Miss lines because some points that are not exactly collinear cast votes for different buckets

## ❖ How many lines

- Count the peaks in the accumulator array

## ❖ Try to get rid of irrelevant features

- Take only edge points with significant gradient magnitude

## ❖ Handling inaccurate edge locations:

- Increment patch in accumulator rather than single point

## ❖ Strong Edges

- Give more votes for stronger edges.
- Examine the surrounding pixels in the chosen cell
- Edge thinning can be beneficial

## ❖ Change the sampling of $(\rho, \theta)$ to give more/less resolution

## ❖ Increment neighboring bins (smoothing in accumulator array)

# Hough Transform Advantages and Disadvantages

## ❖ Advantages

- Can deal with non-locality and occlusion
- Can detect multiple instances of a model (e.g., line, circle, ...) in a single pass
- Some robustness to noise: noise points unlikely to contribute consistently to any single bin

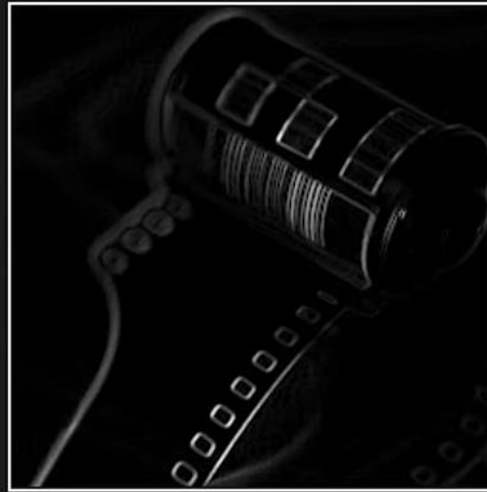
## ❖ Disadvantages

- Complexity of search time increases exponentially with the number of model parameters
- Non-target shapes can produce spurious peaks in parameter space
- It's hard to pick a good Accumulator (grid) size

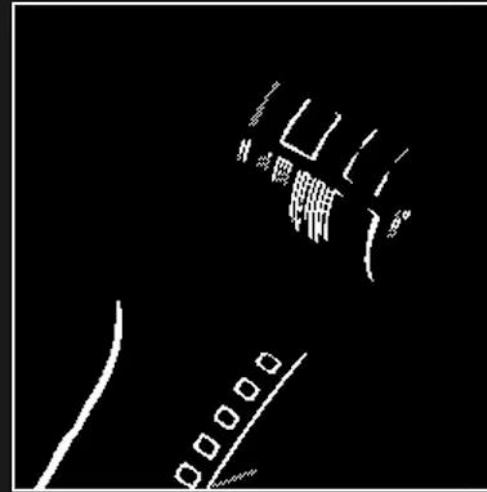
# Line Detection Results



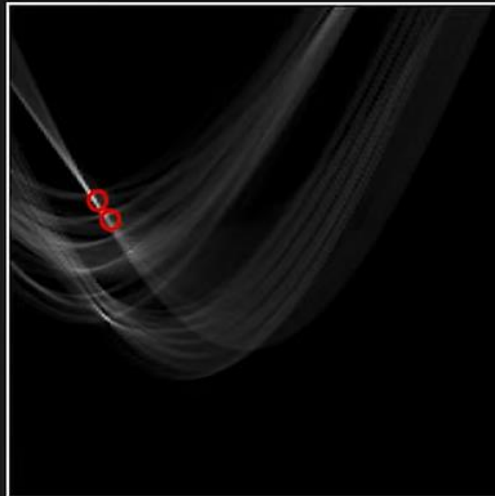
Original Image



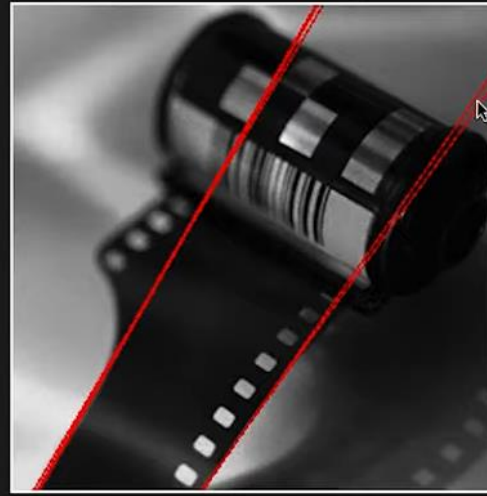
Gradient



Edge (Threshold)



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

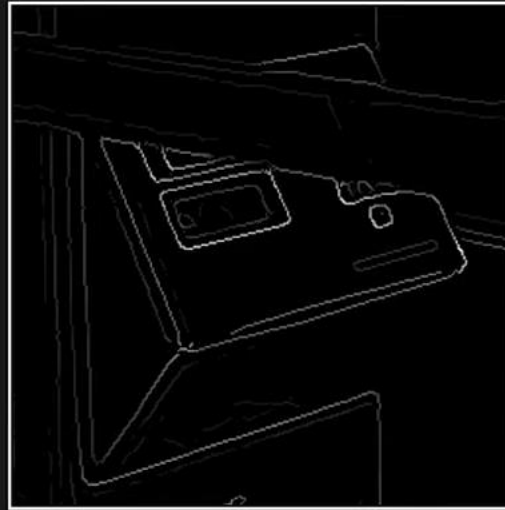


Detected Lines

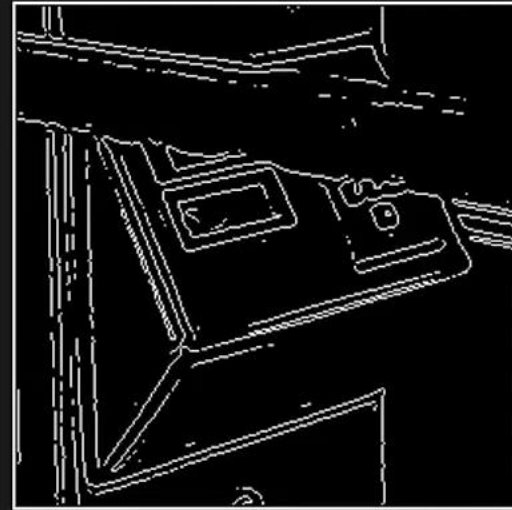
# Line Detection Results



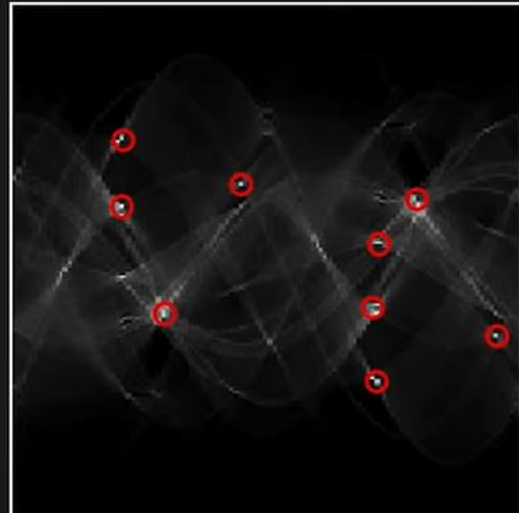
Original Image



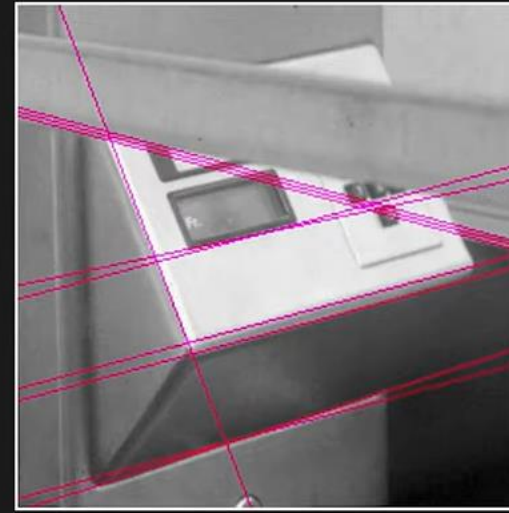
Gradient



Edge (Threshold)



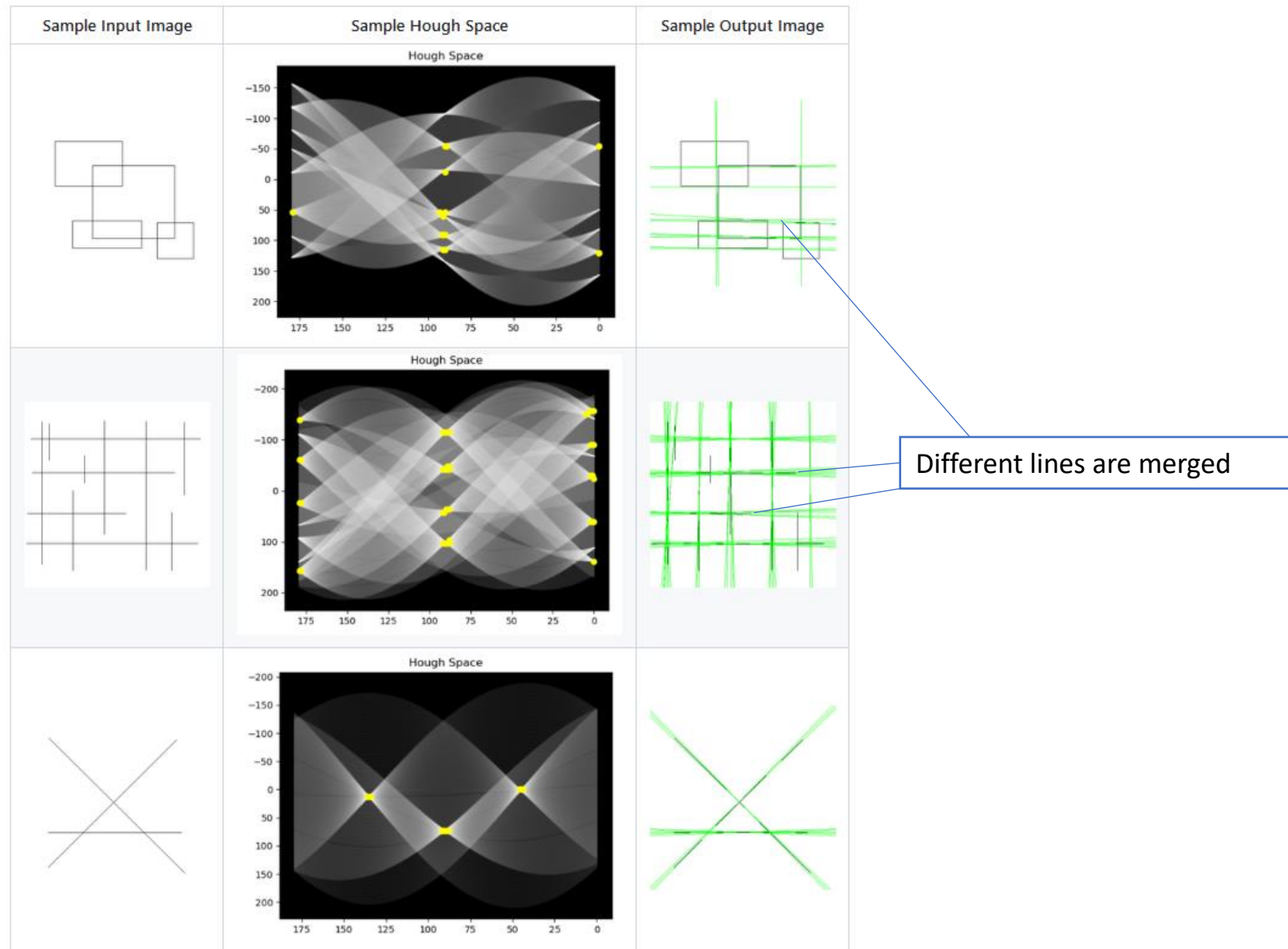
Hough Transform  $A(\rho, \theta)$



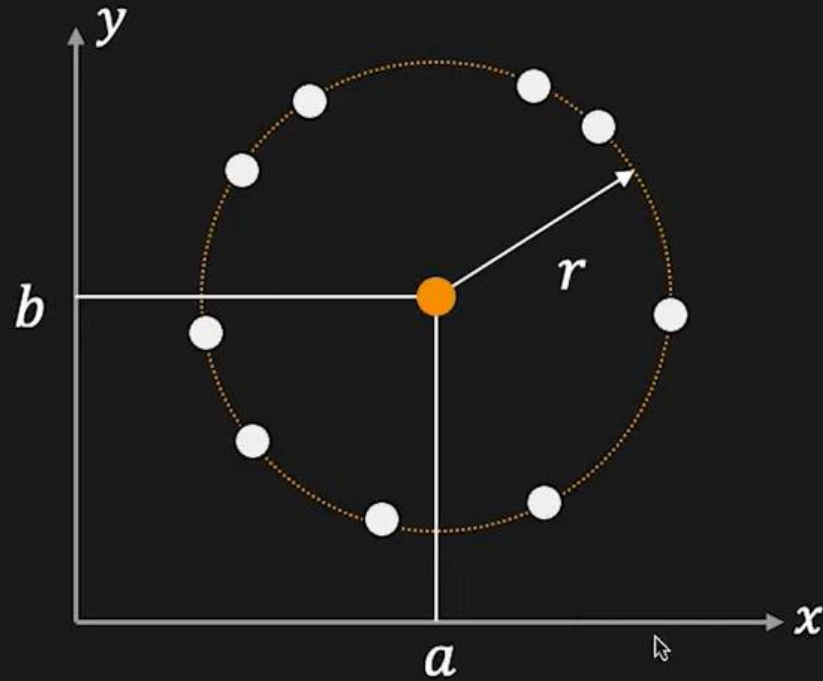
Detected Lines



# Line Detection Results



# Hugh Transform: Circle Detection

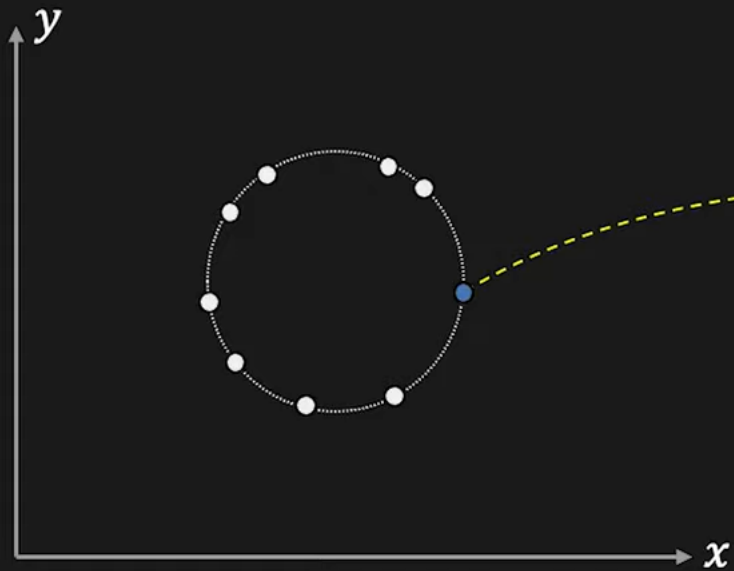


Equation of Circle:  $(x_i - a)^2 + (y_i - b)^2 = r^2$

# Hough Transform: Circle Detection

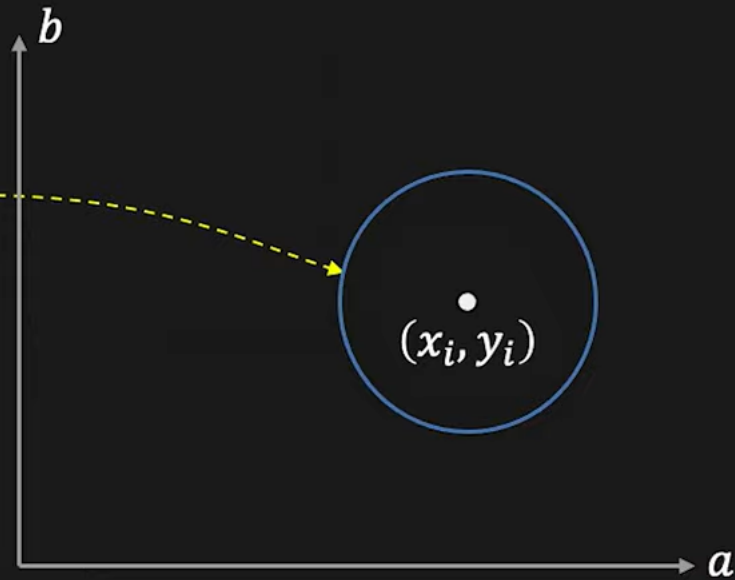
If radius  $r$  is known: Accumulator Array:  $A(a, b)$

Image Space



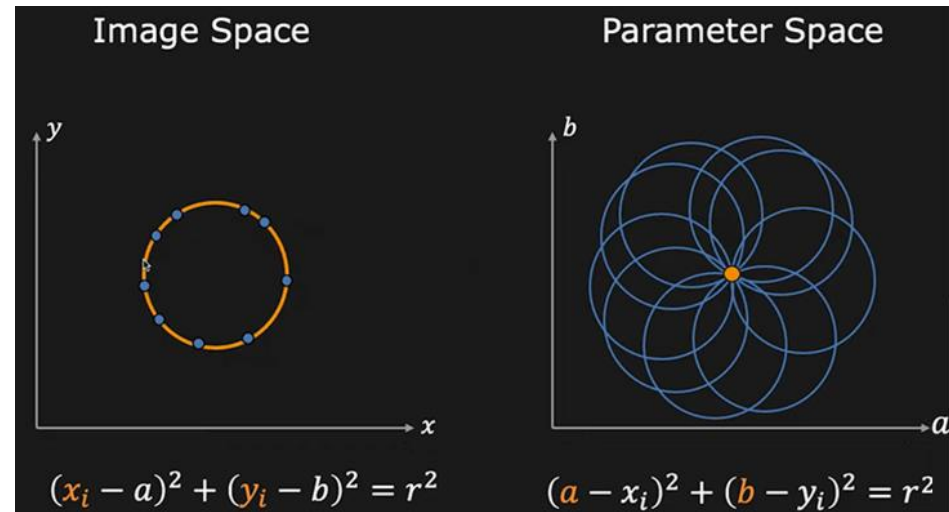
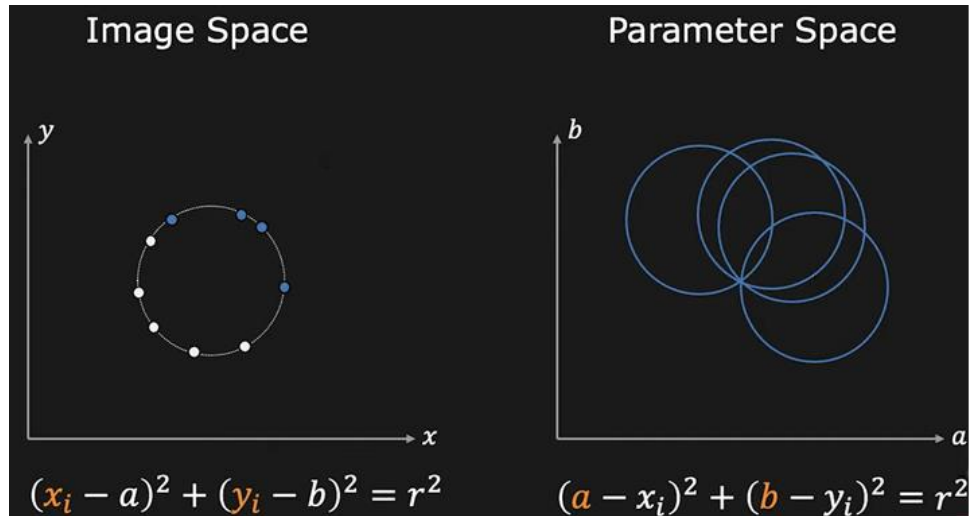
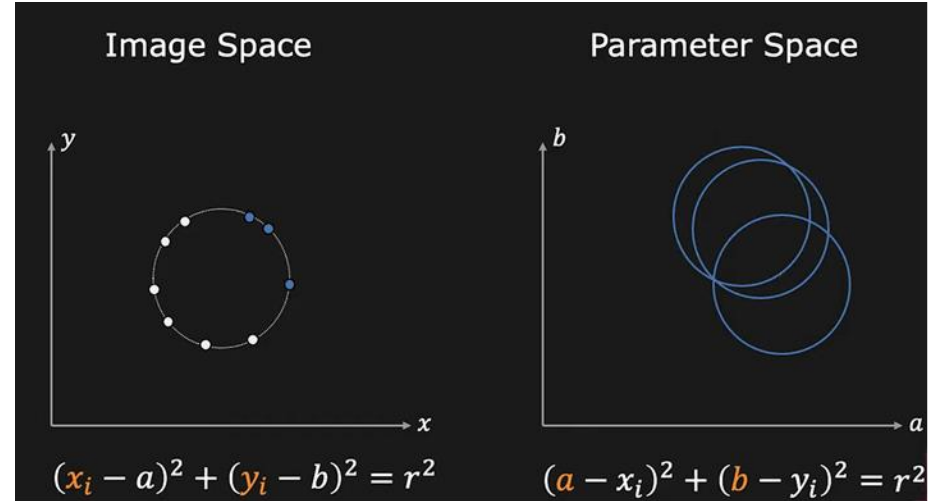
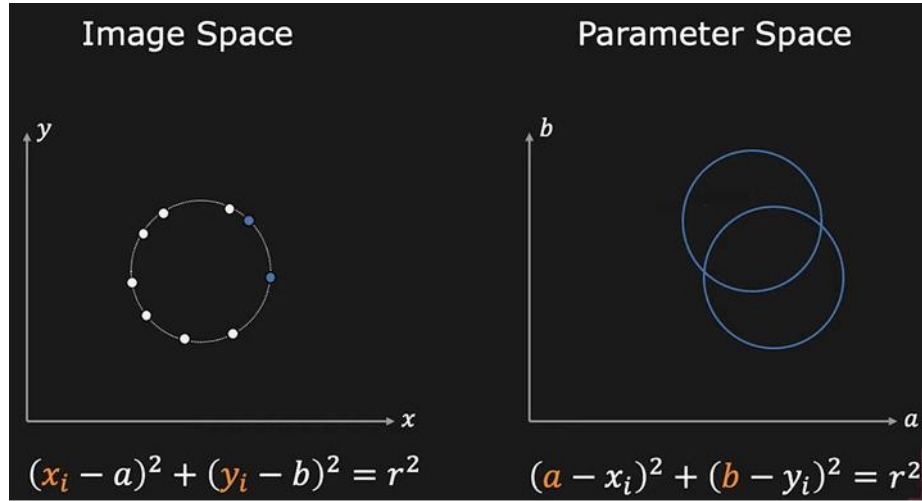
$$(x_i - a)^2 + (y_i - b)^2 = r^2$$

Parameter Space

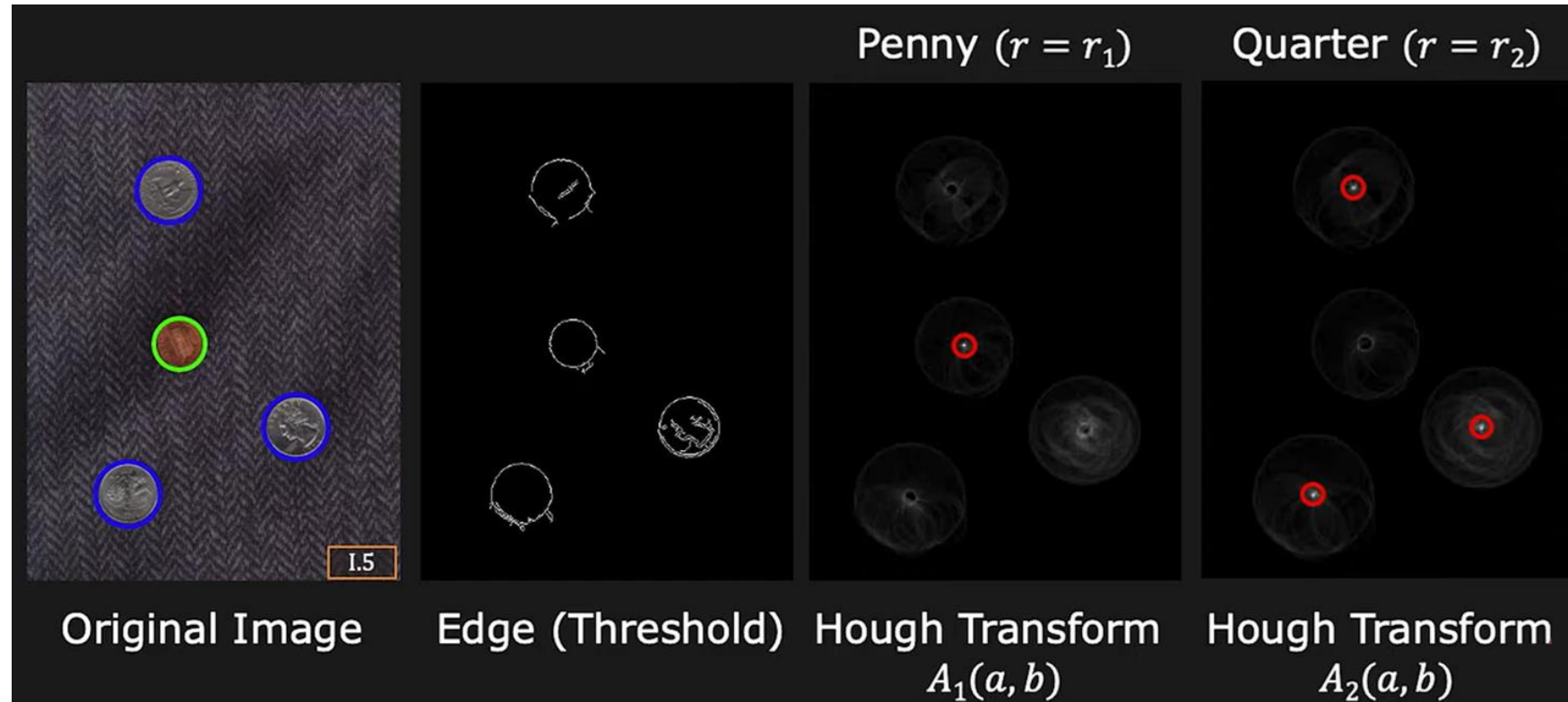


$$(a - x_i)^2 + (b - y_i)^2 = r^2$$

# Hugh Transform: Circle Detection



# Circle Detection Results

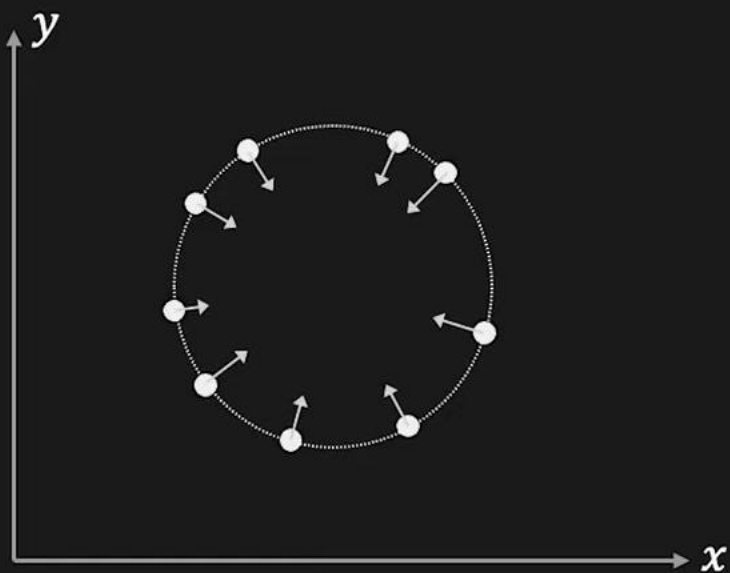




# Using Gradient Information

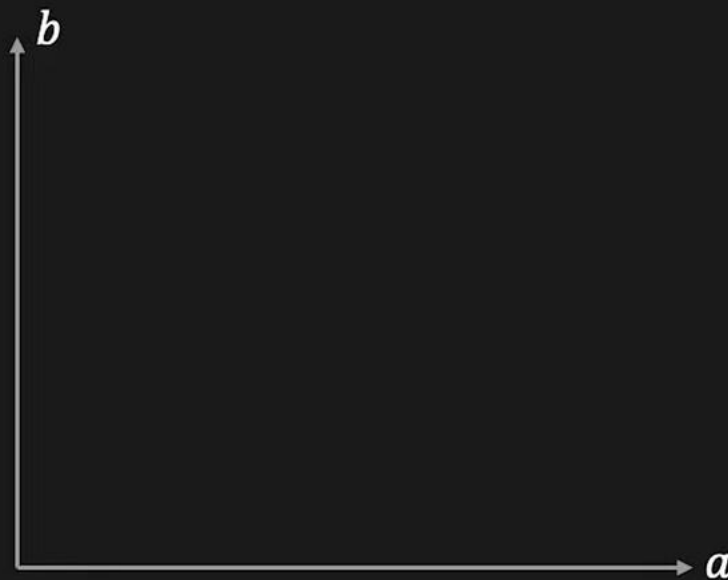
Given: Edge Location  $(x_i, y_i)$ , **Edge Direction**  $\varphi_i$  and Radius  $r$

Image Space



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

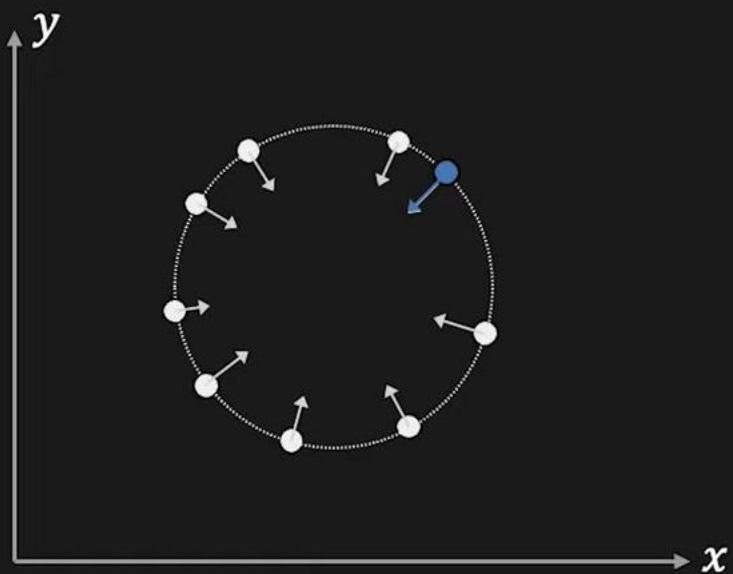
Parameter Space



# Using Gradient Information

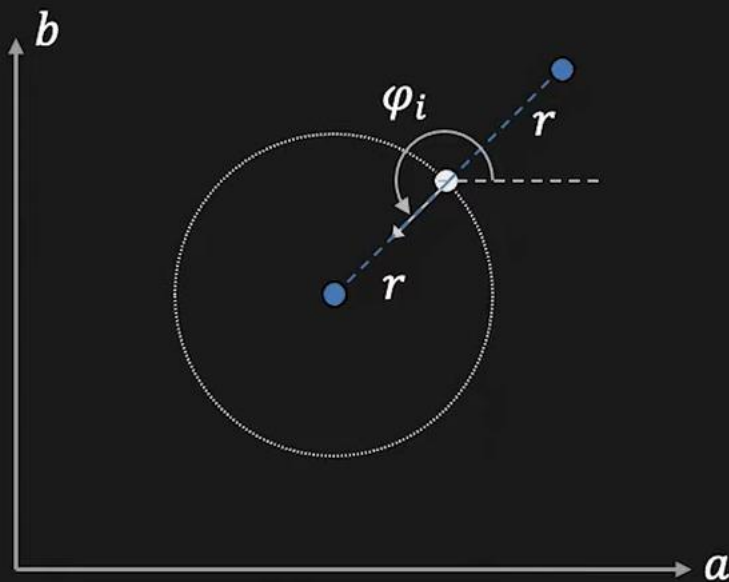
Given: Edge Location  $(x_i, y_i)$ , **Edge Direction**  $\varphi_i$  and Radius  $r$

Image Space



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

Parameter Space



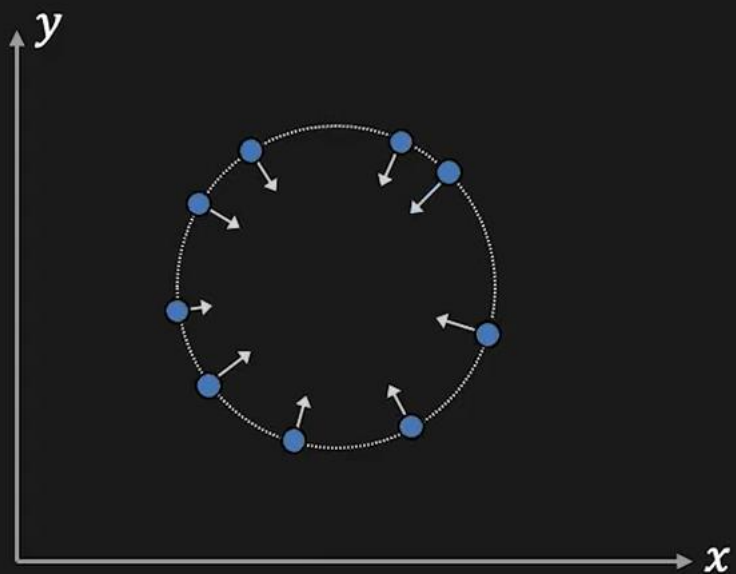
$$a = x_i \pm r \cos \varphi_i$$

$$b = y_i \pm r \sin \varphi_i$$

# Using Gradient Information

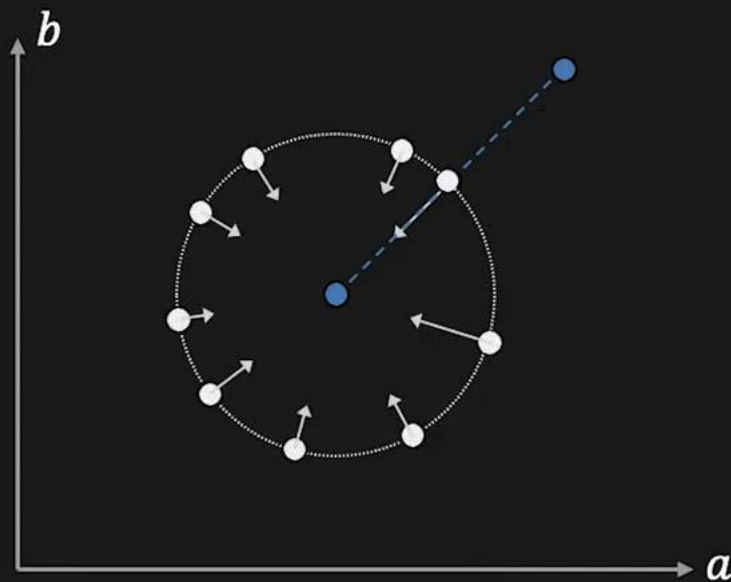
Given: Edge Location  $(x_i, y_i)$ , **Edge Direction**  $\varphi_i$  and Radius  $r$

Image Space



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

Parameter Space



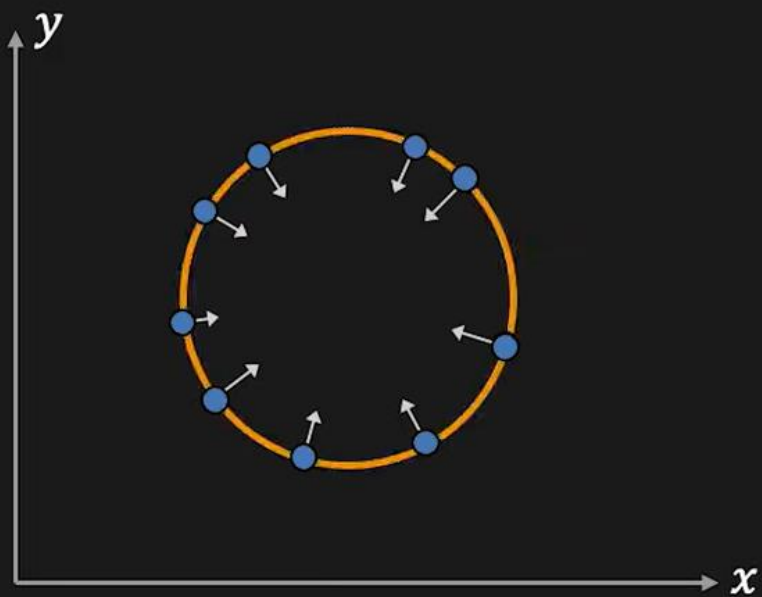
$$a = x_i \pm r \cos \varphi_i$$

$$b = y_i \pm r \sin \varphi_i$$

# Using Gradient Information

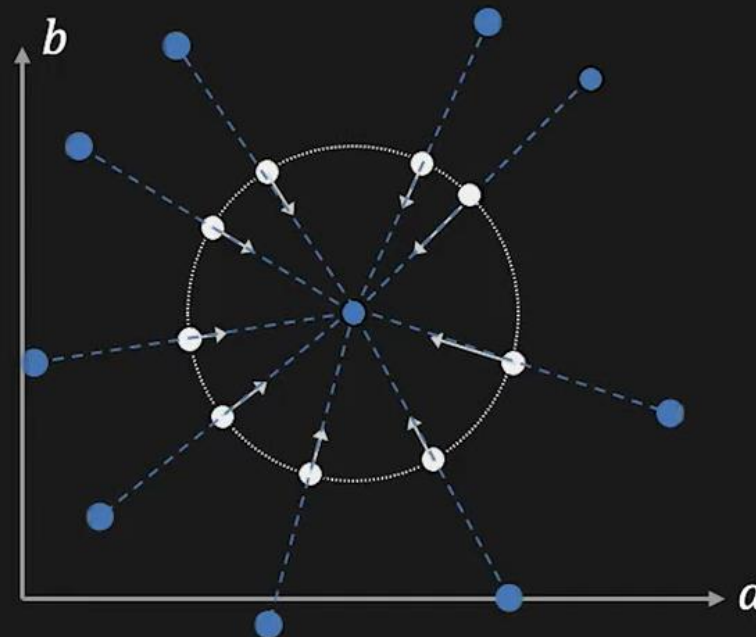
Given: Edge Location  $(x_i, y_i)$ , **Edge Direction**  $\varphi_i$  and Radius  $r$

Image Space



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

Parameter Space



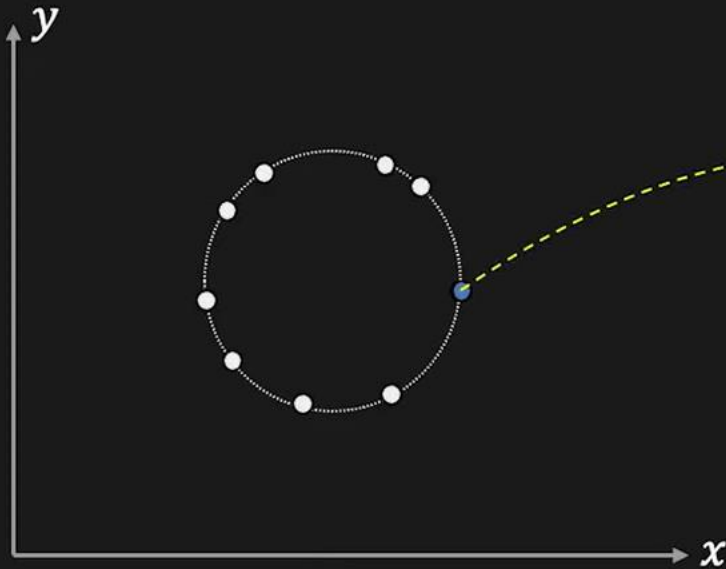
$$a = x_i \pm r \cos \varphi_i$$

$$b = y_i \pm r \sin \varphi_i$$

# Hough Transform: Circle Detection

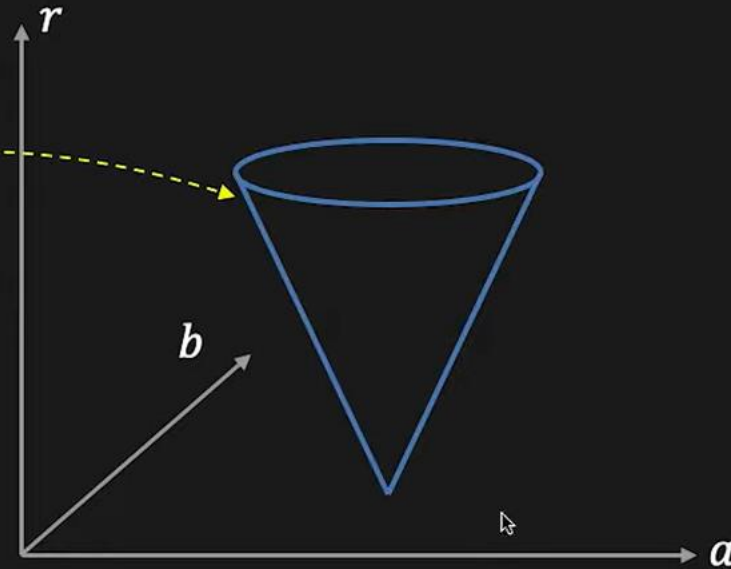
If radius  $r$  is NOT known: Accumulator Array:  $A(a, b, r)$

Image Space



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

Parameter Space

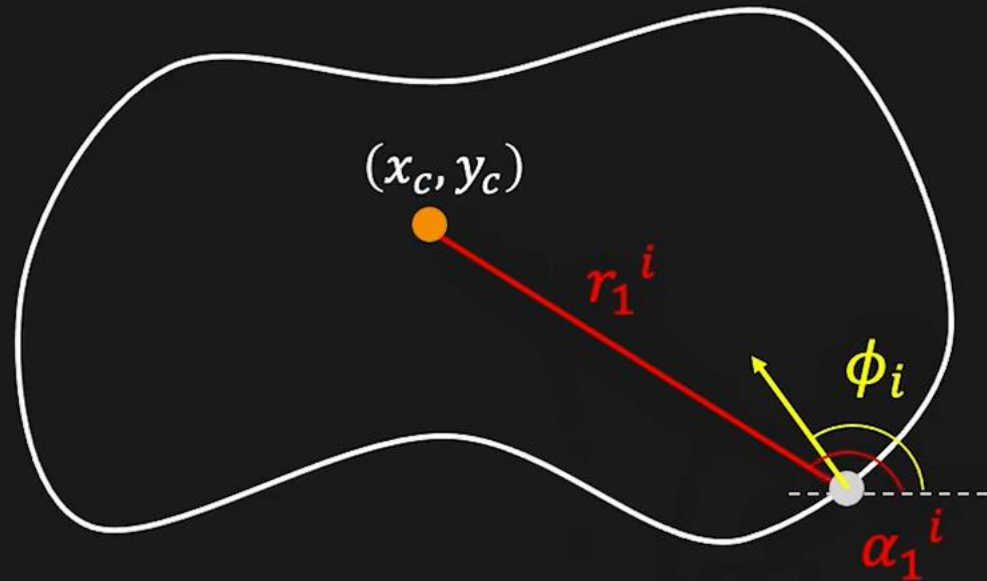


$$(a - x_i)^2 + (b - y_i)^2 = r^2$$

Note: Complexity of search time increases exponentially with the number of model parameters

# Generalized Hough Transform

Find shapes that cannot be described by equations



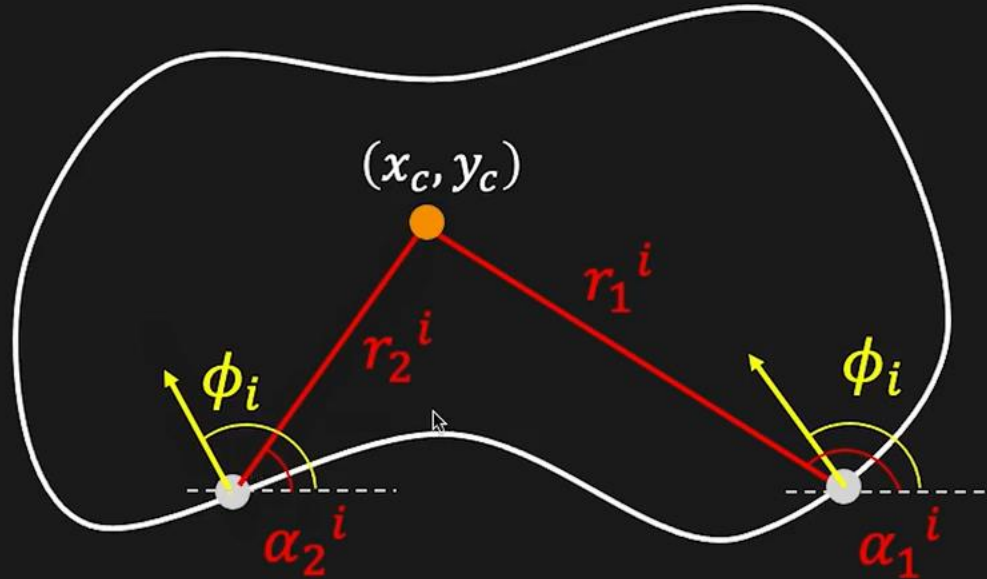
Reference point:  $(x_c, y_c)$

Edge direction:  $\phi_i$   $0 \leq \phi_i < 2\pi$

Edge location:  $\vec{r}_k^i = (r_k^i, \alpha_k^i)$

# Generalized Hough Transform

Find shapes that cannot be described by equations



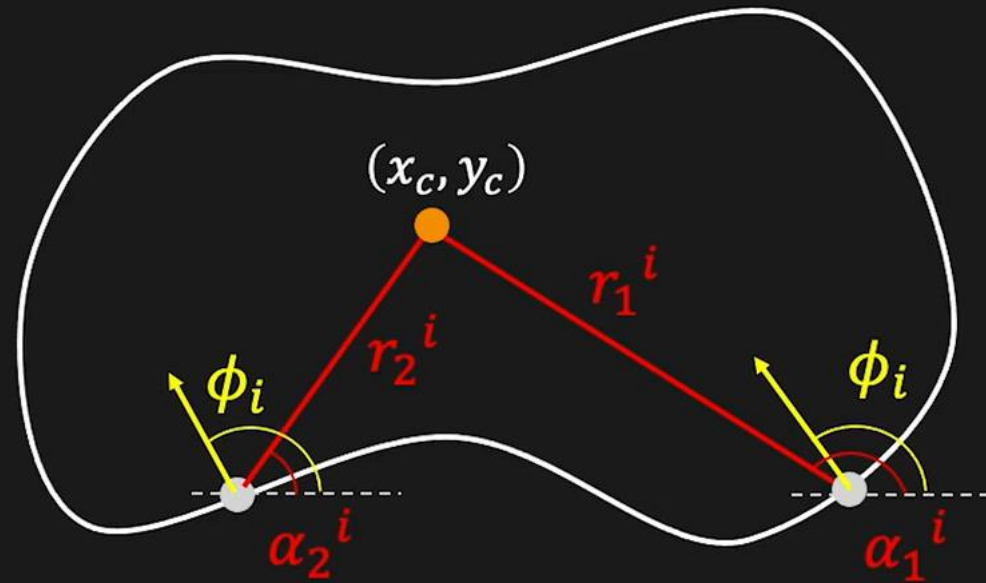
Reference point:  $(x_c, y_c)$

Edge direction:  $\phi_i \quad 0 \leq \phi_i < 2\pi$

Edge location:  $\vec{r}_k^i = (r_k^i, \alpha_k^i)$



# Hough Model



$\phi$ -Table:

Edge Direction	$\vec{r} = (r, \alpha)$
$\phi_1$	$\vec{r}_1^1, \vec{r}_2^1, \vec{r}_3^1$
$\phi_2$	$\vec{r}_1^2, \vec{r}_2^2$
$\vdots$	$\vdots$
$\phi_n$	$\vec{r}_1^n, \vec{r}_2^n, \vec{r}_3^n, \vec{r}_4^n$

# Generalized Hough Transform

- Create **accumulator array**  $A(x_c, y_c)$
- Set  $A(x_c, y_c) = 0$  for all  $(x_c, y_c)$
- For each edge point  $(x_i, y_i, \phi_i)$ ,  
For each entry  $\phi_i \rightarrow \vec{r}_k^i$  in  $\phi$  - table,

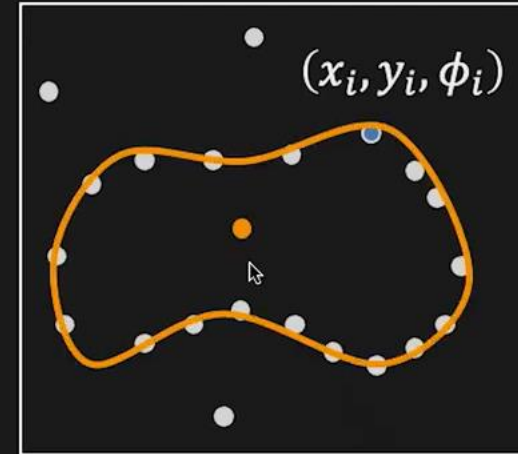
$$x_c = x_i \pm r_k^i \cos(\alpha_k^i)$$

$$y_c = y_i \pm r_k^i \sin(\alpha_k^i)$$

$$A(x_c, y_c) = A(x_c, y_c) + 1$$

- Find local maxima in  $A(x_c, y_c)$

Image

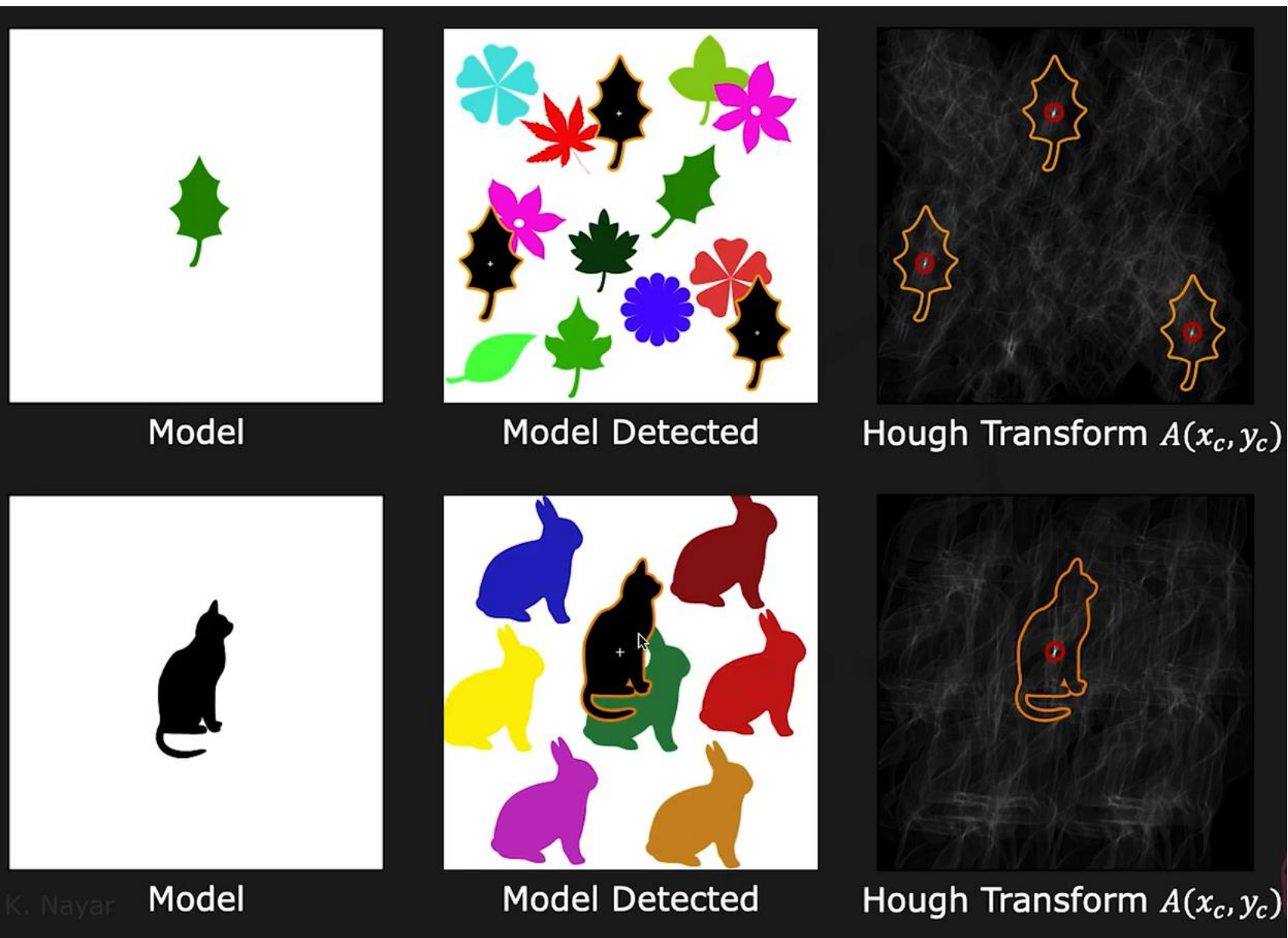


$A(x_c, y_c)$

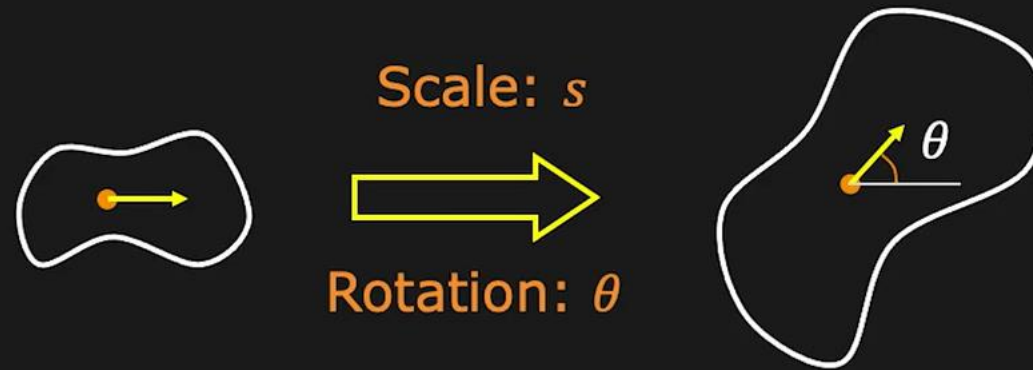
$x_c$	0	0	0	0	0
	0	2	0	1	0
	0	0	4	1	0
	0	2	0	0	0
	0	0	0	1	0

$y_c$

# Results



# Handling Scale and Rotation



Use Accumulation Array:  $A(x_c, y_c, s, \theta)$

$$x_c = x_i \pm r_k^i \cdot s \cos(\alpha_k^i + \theta)$$

$$y_c = y_i \pm r_k^i \cdot s \sin(\alpha_k^i + \theta)$$

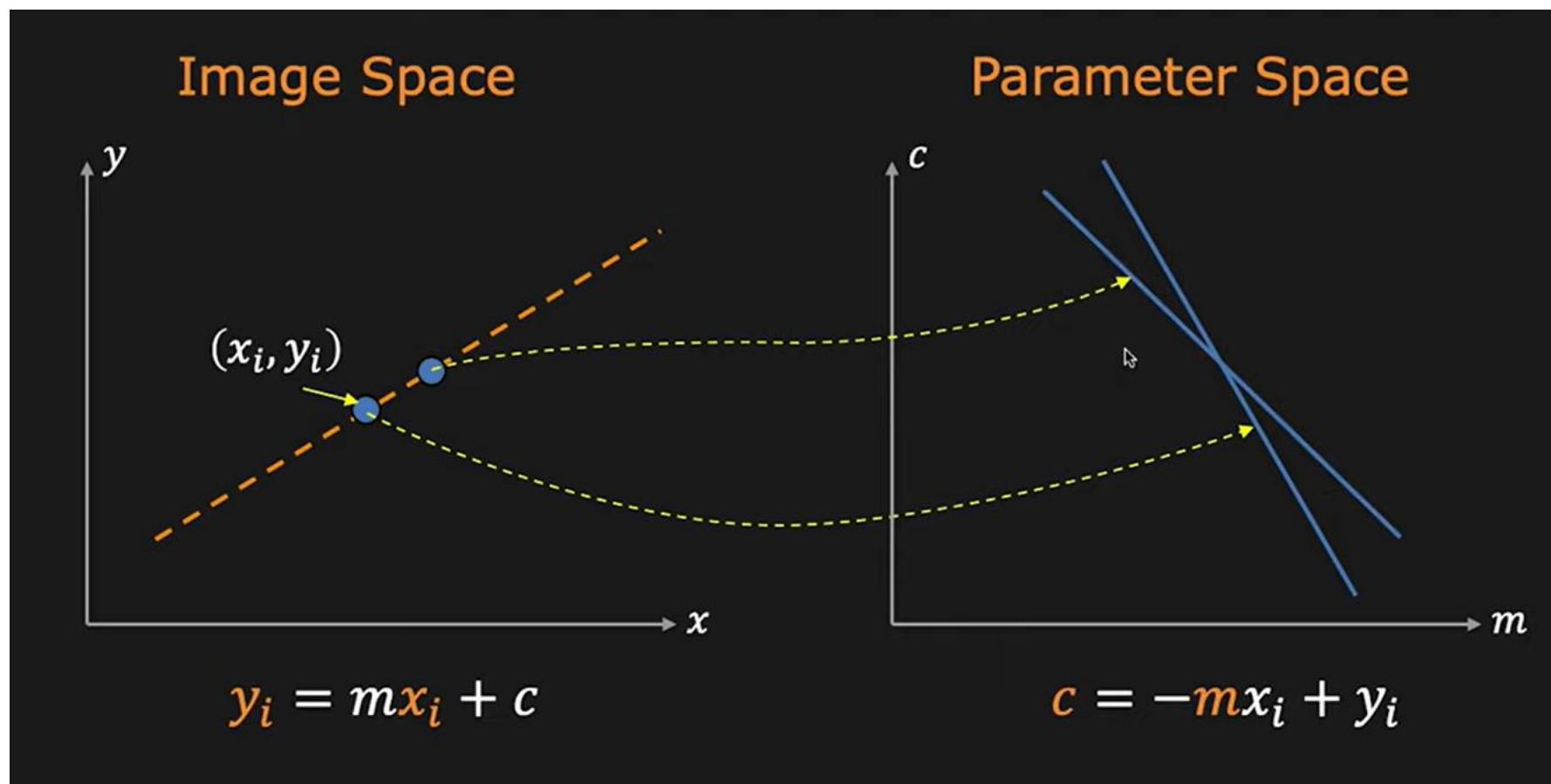
$$A(x_c, y_c, s, \theta) = A(x_c, y_c, s, \theta) + 1$$

**Huge Memory and Computationally Expensive!**

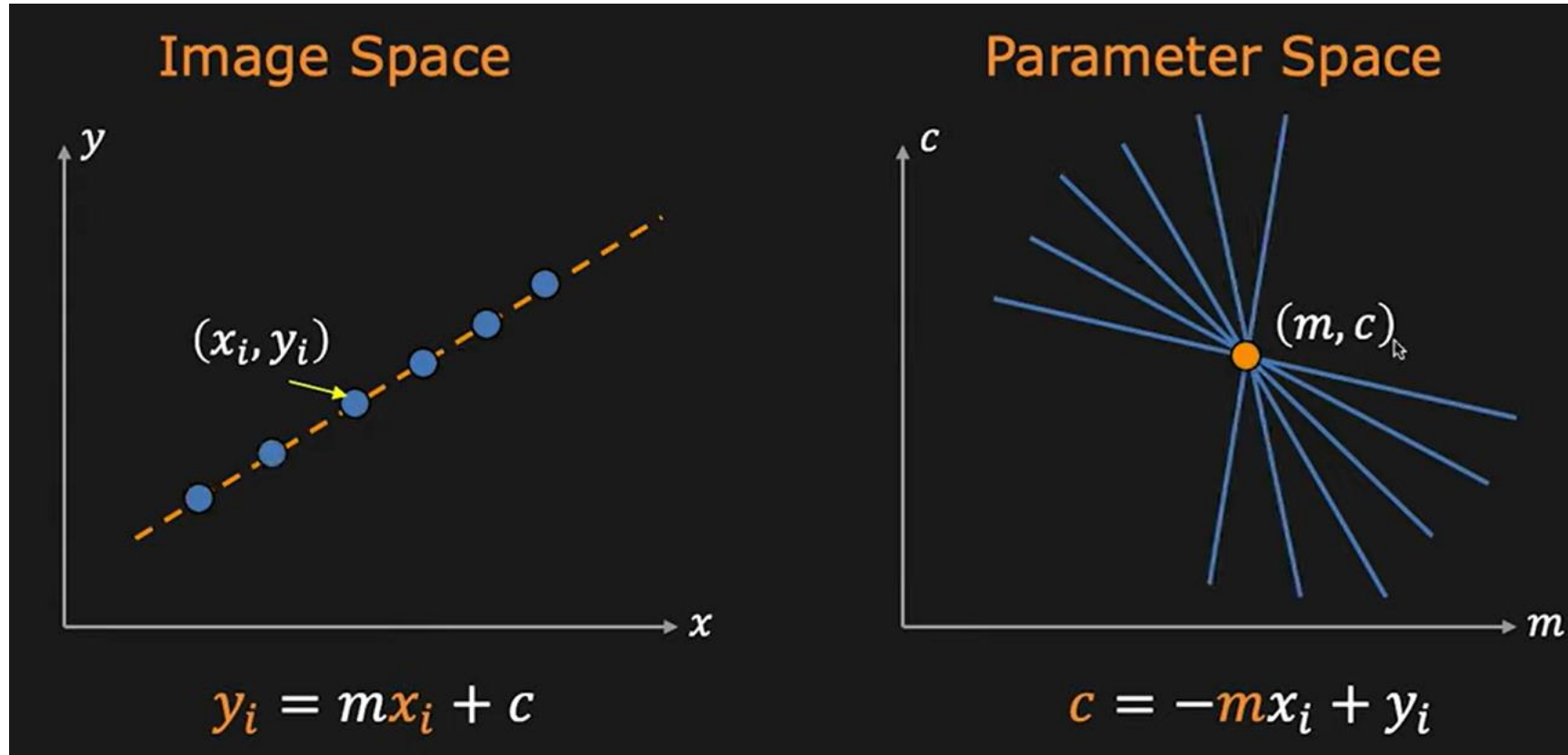
# Hough Transform: Comments

- Works on disconnected edges
- Relatively insensitive to occlusion and noise
- Effective for simple shapes (lines, circles, etc.)
- Complex Shapes: Generalized Hough Transform
- Trade-off between work in image space and parameter space

# Hough Transform: Line Detection (Parameter Space)



# Hough Transform Concept





# Hough Transform Concept

