ZJU-UIUC Institute

Zhejiang University / University of Illinois at Urbana-Champaign Institute

# ECE 470: Introduction to Robotics

## Lecture 25

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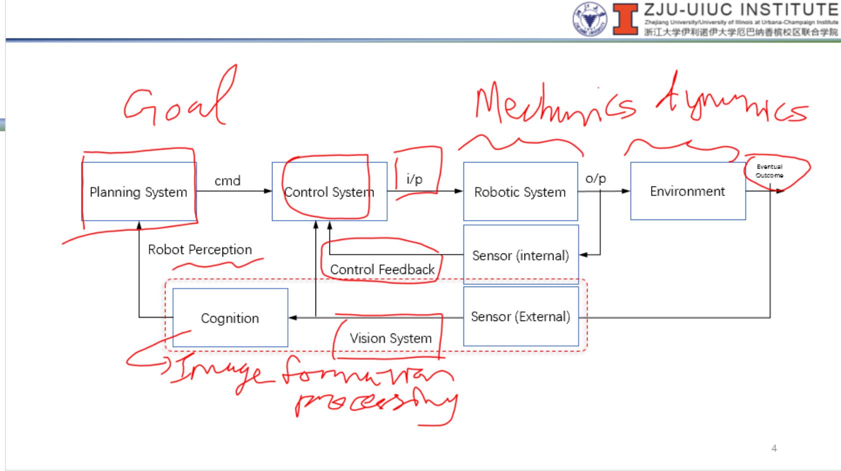
# Overview of Robot Vision




## O. Introduction to Robot Vision

- **What is Robot Vision?**

## I. Image Formation

- The science behind machine vision (+ represent as a form of signal)

## II. Image Processing

- Common techniques to manipulate, enhance & <u>analyse images</u>

## III. Robot Vision Applications

- 3D Vision; Photogrammetry; Vision-based techniques in robotics- visual servo, pose estimation, localization, mapping, navigation

# Image Processing

- ☑Thresholding & Histogram Processing
- ☑ Filtering
- ☑ Edge & Corner Detection
- Interest Points/ Feature Description
- Lines & Shapes

Represent → extra (neighborhood Info)

# Recap: Canny Edge Detection

- Involves 5 steps:
  1. Apply Gaussian filter: remove the noise
  2. Find the intensity gradients of the image
  3. Apply non-maximum suppression: remove spurious response
  4. Apply edge detection using two threshold value
  5. Finalize edge detection by hysteresis

$\nabla^2$



## Canny Edge Detection

- Step (1): Apply Gaussian filter to smooth the image in order to remove the noise
  - Edge detection are easily affected by image noise
  - A Gaussian filter is applied to convolve with the image
    - $h(x, y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$
  - This will smooth the image to reduce the effects of obvious noise on the edge detector





## Canny Edge Detection

$\boxed{1 \mid 0 \mid 1 \mid 2}$

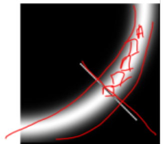
- Step (2): Find the intensity gradients of the image
  - $\frac{\partial I(x,y)}{\partial x} = \frac{I(x+1,y)-I(x-1,y)}{2}$ $\Delta x$
  - $\frac{\partial I(x,y)}{\partial y} = \frac{I(x,y+1)-I(x,y-1)}{2}$ $\Delta y$
  - Gradient Vector: $\nabla I(x,y) = \left[\frac{\partial I(x,y)}{\partial x}, \frac{\partial I(x,y)}{\partial y}\right]^T$
  - mag → $|\nabla I(x,y)| = \sqrt{\left(\frac{\partial I(x,y)}{\partial x}\right)^2 + \left(\frac{\partial I(x,y)}{\partial y}\right)^2}$
  - ang → $\theta(x,y) = \tan^{-1}\left(\frac{\partial I(x,y)}{\partial y} / \frac{\partial I(x,y)}{\partial x}\right)$





## Canny Edge Detection

- Step (3): Apply non-maximum suppression to get rid of spurious response to edge detection
  - compare values along the gradient vector to retain only the maximum





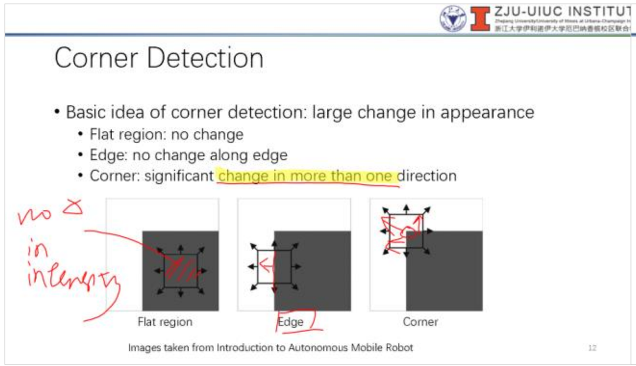
## Canny Edge Detection

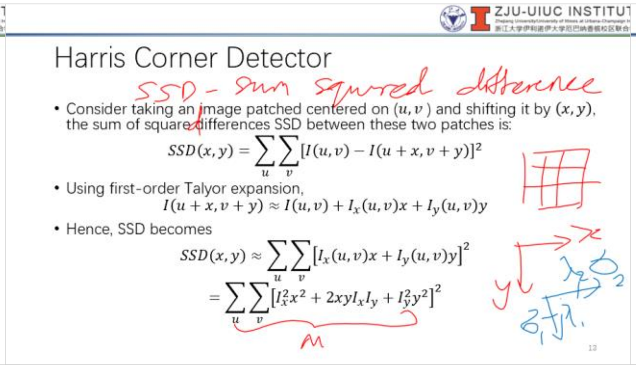
- Step (4): Apply edge detection using two threshold value $K_H$ and $K_L$
  - $Edge(x,y) = \begin{cases} E_{strong} & if\ |\nabla I(x,y)| > K_H \\ \boxed{E_{average} \quad if\ K_L \le |\nabla I(x,y)| \le K_H} \\ E_{weak} & if\ |\nabla I(x,y)| < K_L \end{cases}$ marginal case
- Step (5): Finalize edge detection by hysteresis thresholding
  - Small $K$ means more details
  - High $K$ includes more noise
  - Hysteresis Thresholding allows us to apply both
    - Keep both high threshold $K_H$ and low threshold $K_L$
    - Any edges with magnitude < $K_L$ are discarded
    - Any edges with magnitude > $K_H$ are kept
    - An edge with magnitude between the two threshold values is kept if there is a path of edges with magnitude > $K_L$ connecting the edge to another edge with magnitude ≥ $K_H$

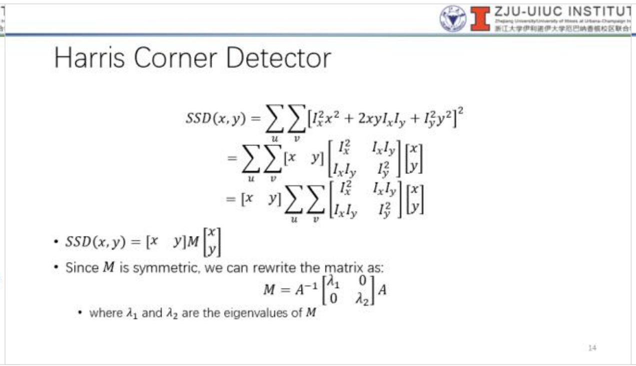
# Recap: Harris Corner Detection

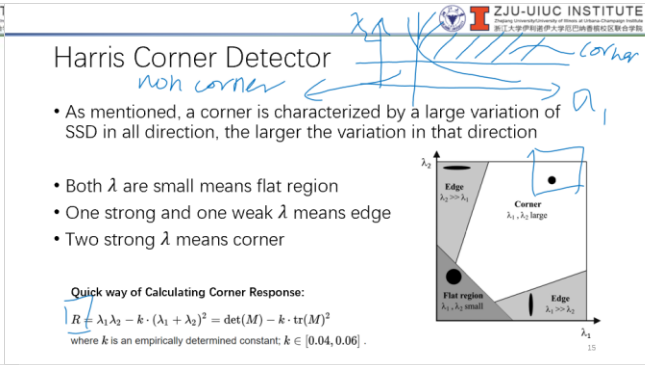
- Involves 5 steps:
  1. Apply Gaussian filter: remove the noise
  2. Find the intensity gradients of the image
  3. Apply non-maximum suppression: remove spurious response
  4. Apply edge detection using two threshold value
  5. Finalize edge detection by hysteresis

Looking at the Detector as an operation



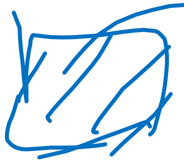



# Feature Extraction

- (Local) Features
  - (Locally) Unique structures e.g. Edges, Corners, Blobs, flat region
- Detector
  - Methods for deciding if a pixel is associated with particular a feature e.g. Canny, Harris, LoG

$I(u,v)$



- Descriptor
  - Representations of (local) features

# Feature Extraction

- Ideal features should be
  - Repeatable
    - Robustly detectable in different viewpoints and imaging conditions (e.g. noise)
  - Distinctive
    - Uniquely representable for comparison
  - Localizable
    - Provide spatial information

# Feature Extraction

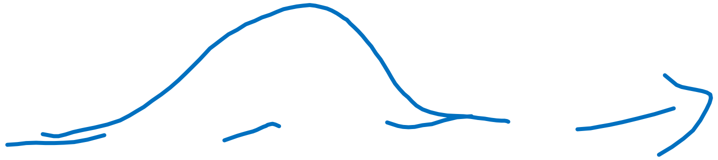
- Detector
  - Methods for deciding if a pixel is associated with particular a feature e.g. Canny, Harris, LoG

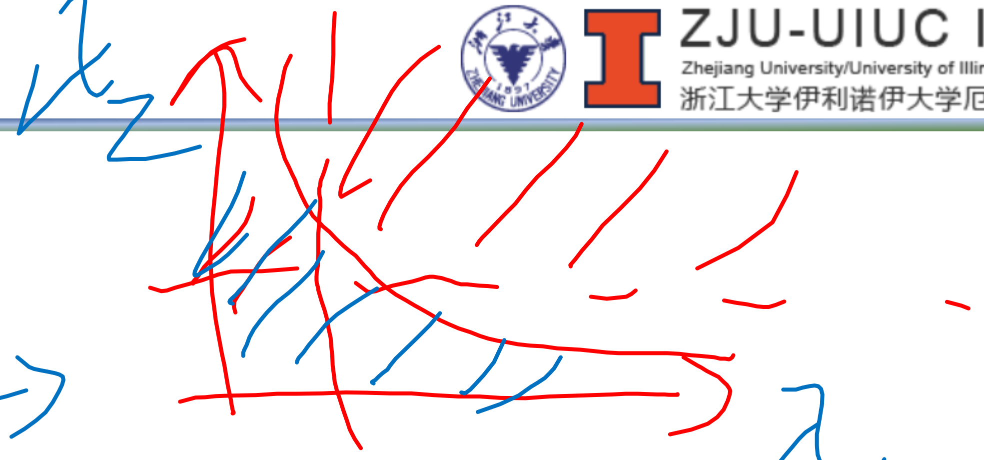
| Detector | Feature Type | Function | Scale Independent |
|---|---|---|---|
| FAST [1] | Corner | detectFASTFeatures | No |
| Minimum eigenvalue algorithm [4] | Corner | detectMinEigenFeatures | No |
| Corner detector [3] | Corner | detectHarrisFeatures | No |
| SURF [11] | Blob | detectSURFFeatures | Yes |
| KAZE [12] | Blob | detectKAZEFeatures | Yes |
| BRISK [6] | Corner | detectBRISKFeatures | Yes |
| MSER [8] | Region with uniform intensity | detectMSERFeatures | Yes |
| ORB [13] | Corner | detectORBFeatures | No |

https://www.mathworks.com/help/vision/ug/local-feature-detection-and-extraction.html#bulf47t-4

Scale-space σ

# Feature Extraction





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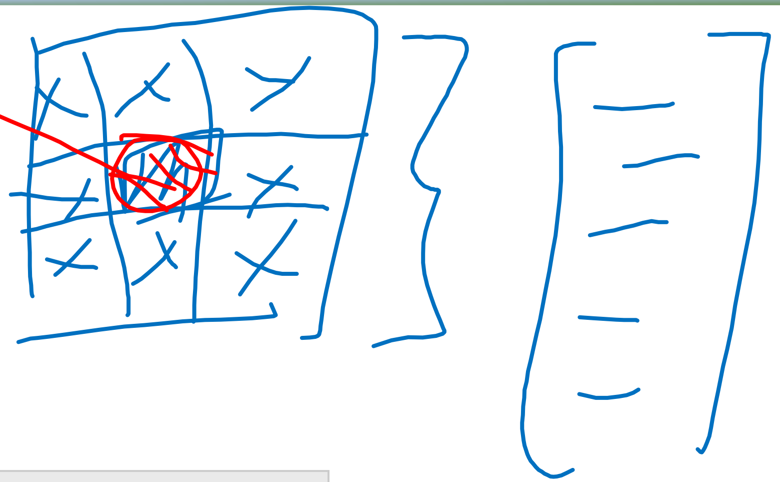
Speed up Robust Feature

https://www.mathworks.com/help/vision/ug/local-feature-detection-and-extraction.html#bulf47t-4

feature

# Feature Extraction

Block



- Descriptor
  - Representations of (local) features

| Descriptor | Binary | Function and Method | Invariance | | Typical Use | |
|---|---|---|---|---|---|---|
| | | | Scale | Rotation | Finding Point Correspondences | Classification |
| HOG | No | `extractHOGFeatures(I, ...)` | No | No | No | Yes |
| LBP | No | `extractLBPFeatures(I, ...)` | No | Yes | No | Yes |
| SURF | No | `extractFeatures(I,points,'Method','SURF')` | Yes | Yes | Yes | Yes |
| KAZE | No | `extractFeatures(I,points,'Method','KAZE')` | Yes | Yes | Yes | Yes |
| FREAK | Yes | `extractFeatures(I,points,'Method','FREAK')` | Yes | Yes | Yes | No |
| BRISK | Yes | `extractFeatures(I,points,'Method','BRISK')` | Yes | Yes | Yes | No |
| ORB | Yes | `extractFeatures(I,points,'Method','ORB')` | No | Yes | Yes | No |
| • Block<br>• Simple pixel neighborhood around a keypoint | No | `extractFeatures(I,points,'Method','Block')` | No | No | Yes | Yes |

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# Feature Extraction Practical Consideration

- Select appropriate types of feature-detector-descriptor
  - Based on
  - Nature of scenes
  - Application context
  - Operation requirement

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- Select appropriate types of feature-detector-descriptor
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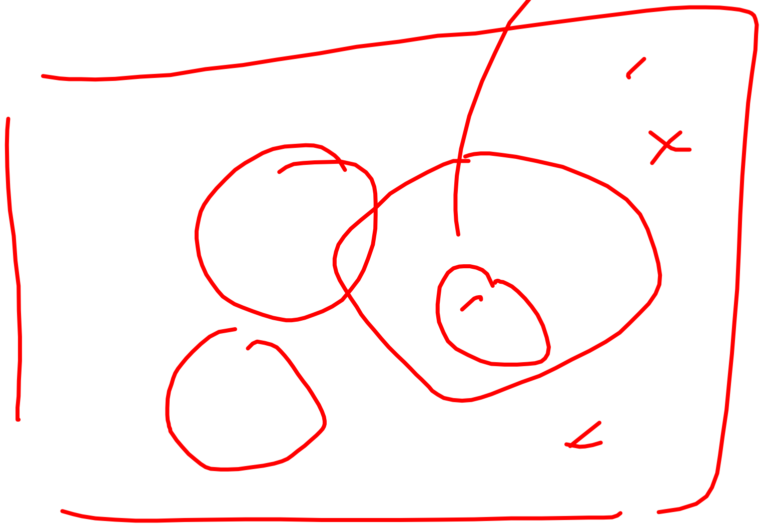
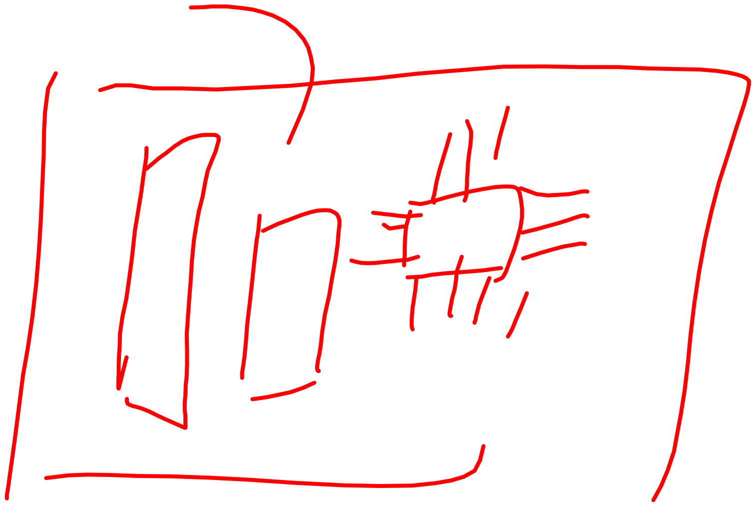
cell

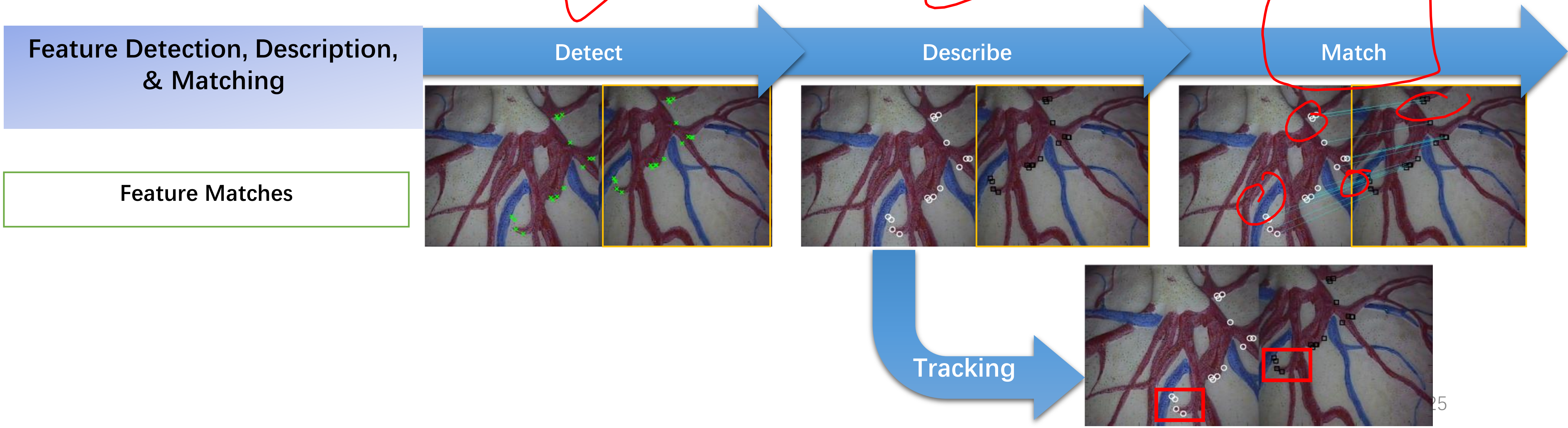
PCB





# Feature Matching

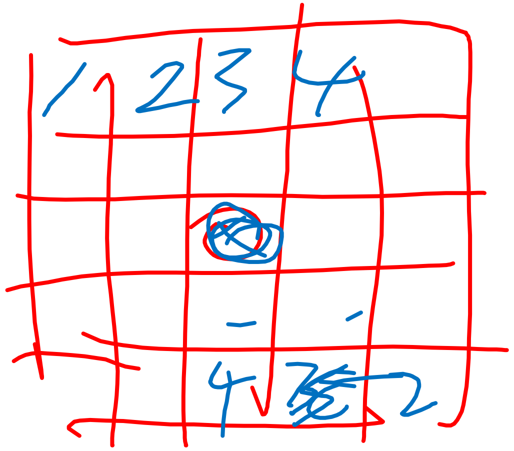
- Given views of the same scene, how to match the features?
  - Detect; Describe; Match; Transform (for image mapping) or Tracking (Visual tracking)

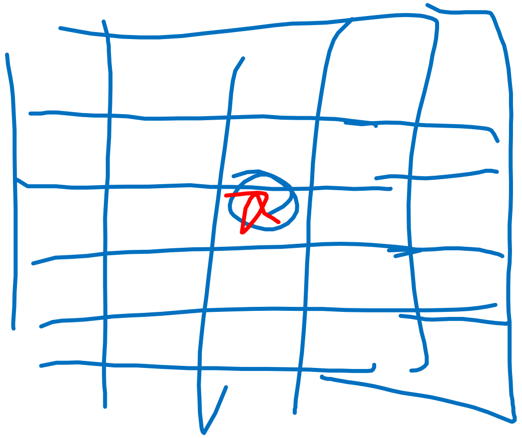


# Similarity Scores between image patches

Measure

- How do we measure the similarity/ difference?





# Similarity Score

- Sum of Squared Difference (SSD)

SSD between two image patches $I_1$ *and* $I_2$

$$w_{SSD}(x,y)=\sum_{p}^{P}\sum_{q}^{Q}\left[I_1(p,q)-I_2(p,q)\right]^2$$

Recall in corner detection, we look at change of patch $I$ centered on $(p,q)$ and itself when shifted by $(x,y)$, we used SSD to represent the change

$$w_{SSD}(x,y)=\sum_{p}^{P}\sum_{q}^{Q}\left[I(p,q)-I(p+x,q+y)\right]^2$$

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$$w_{SSD}(x,y)=\sum_{p}^{P}\sum_{q}^{Q}[I(p,q)-I(p+x,q+y)]^2$$

# Similarity Score

- Normalized Cross-correlation (NCC)

For a $U$ x $V$ image and $P$ x $Q$ patch, the cross-correlation $w_{cc}(u,v)$ at a particular image coordinates $(u, v)$ of a template patch $g(p,q)$ and the image $f(p,q)$ is

$$w_{cc}(u,v) = \sum_{p=0}^{P} \sum_{q=0}^{Q} g(p,q) f(p+u, q+v)$$

To reduce the over sensitivity toward intensity variant, normalized cross-correlation coefficient (Similarity Score),

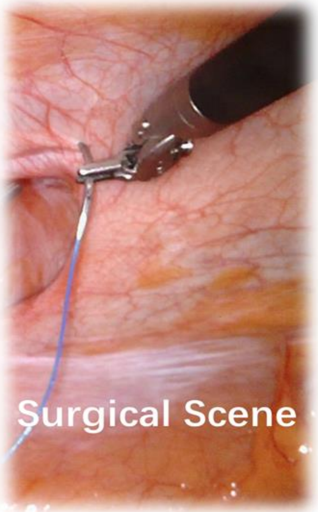
$$w_{ncc}(u,v) = \frac{\sum_{p=0}^{P} \sum_{q=0}^{Q} \left(g(p,q)-\bar{g}\right)\left(f(p+u,q+v)-\bar{f}(u,v)\right)}{\left[\left(\sum_{p=0}^{P} \sum_{q=0}^{Q} \left(g(p,q)-\bar{g}\right)^2\right)\left(\sum_{p=0}^{P} \sum_{q=0}^{Q} \left(f(p+u,q+v)-\bar{f}(u,v)\right)^2\right)\right]^{0.5}}$$

is used where $\bar{g}$ *and* $\bar{f}$ denotes the mean intensity in the template and overlapping region, respectively.

# Detection of Line and Shape

circle
triangle
polygons

- After detecting the edges and local interest points, how do we detect lines and other geometries?
- A problem of pattern recognition

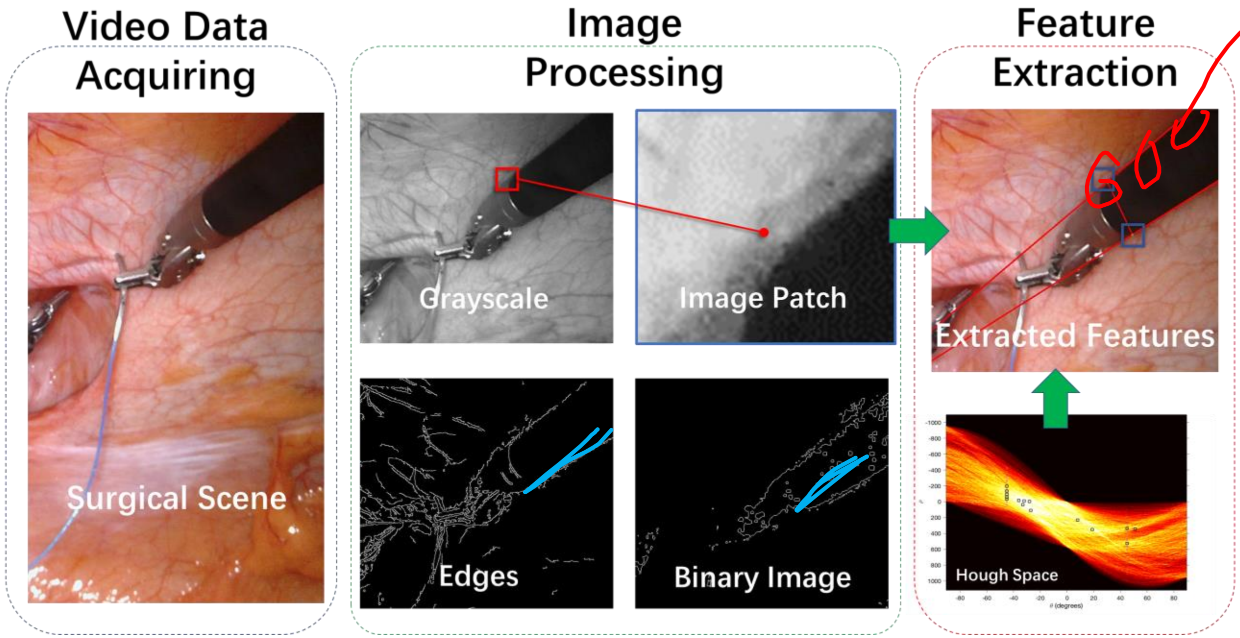


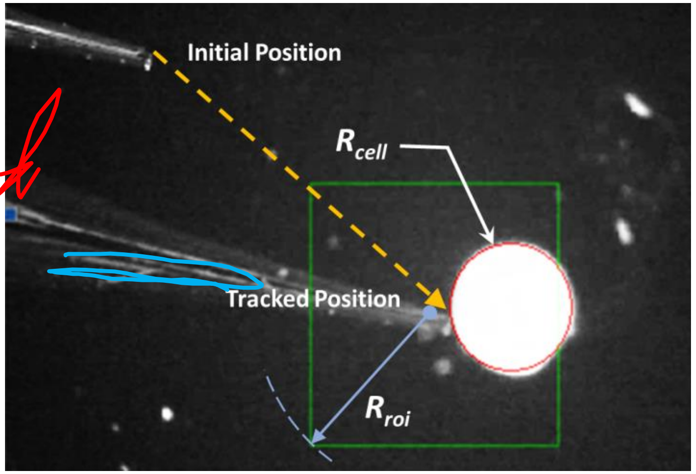

Huang, J., Li, X., Kesavadas, T. and Yang, L., 2019, July. Feature Extraction of Video Data for Automatic Visual Tool Tracking in Robot Assisted Surgery. In *Proceedings of the 2019 4th International Conference on Robotics, Control and Automation* (pp. 121-127).

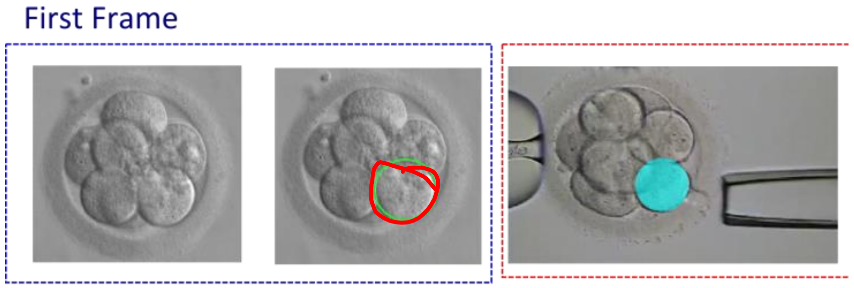
# Detection of Line and Shape

- After detecting the edges and local interest points, how do we detect lines and other geometries?
- A problem of pattern recognition

associated with IMU




Circle detection



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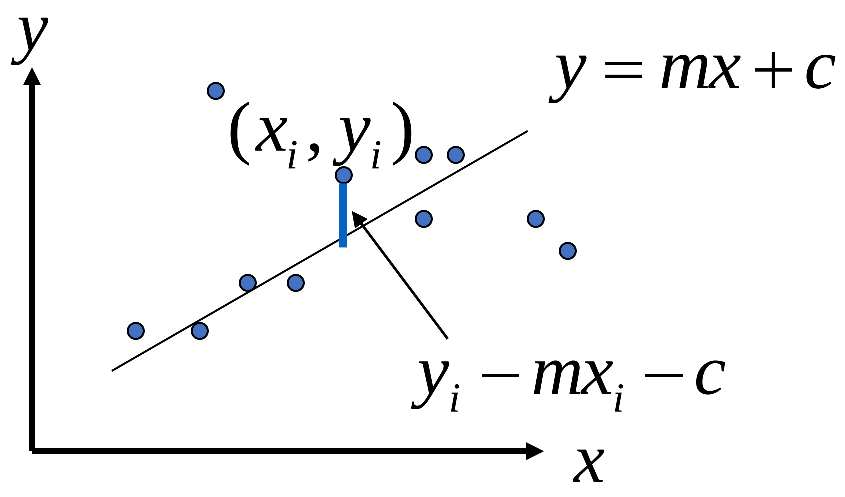
# Fitting lines to edges using least square

ECE 470

- Given:
  - Many edges $(x_i, y_i)$
  - Equation of line: $y = mx + c$
  - Parameters: $m\ , c$

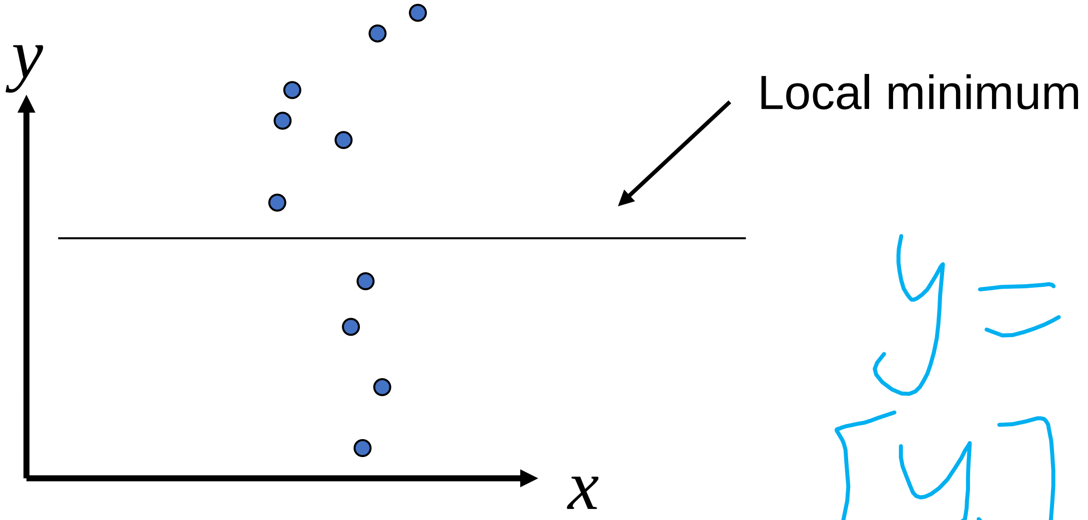



- Objective function is to minimize average square distance:
  - $E = \sum \frac{(y_i - mx_i - c)^2}{N}$
- Using $\frac{\partial E}{\partial m} = 0$ & $\frac{\partial E}{\partial c} = 0$

$$c = \bar{y} - m\,\bar{x}$$

$$m = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2}$$

# Fitting lines to edges using least square




$$y = mx + c$$

$$\begin{bmatrix} y \\ 1 \end{bmatrix} = \begin{bmatrix} m & c \end{bmatrix} \begin{bmatrix} x \\ 1 \end{bmatrix}$$

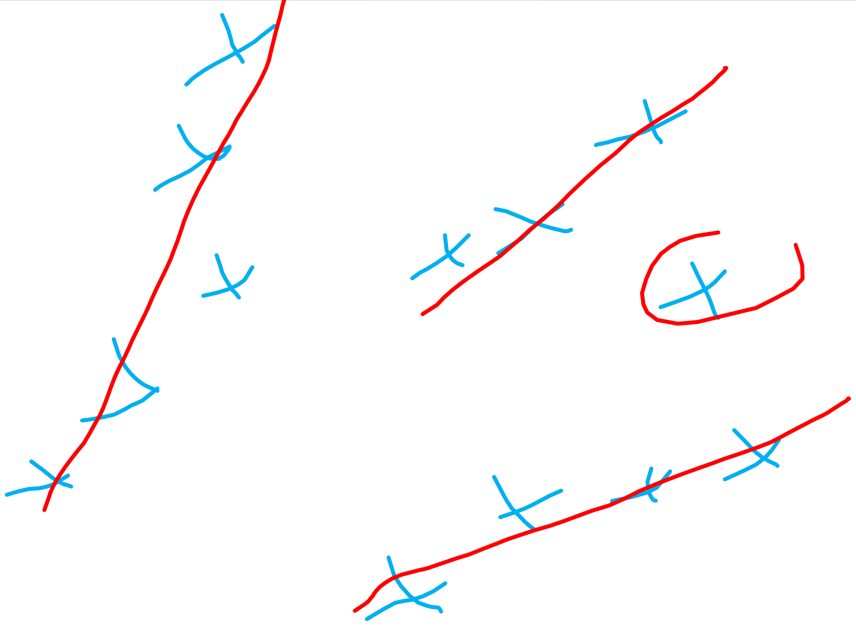
- Possible Solution: Hough Transformation

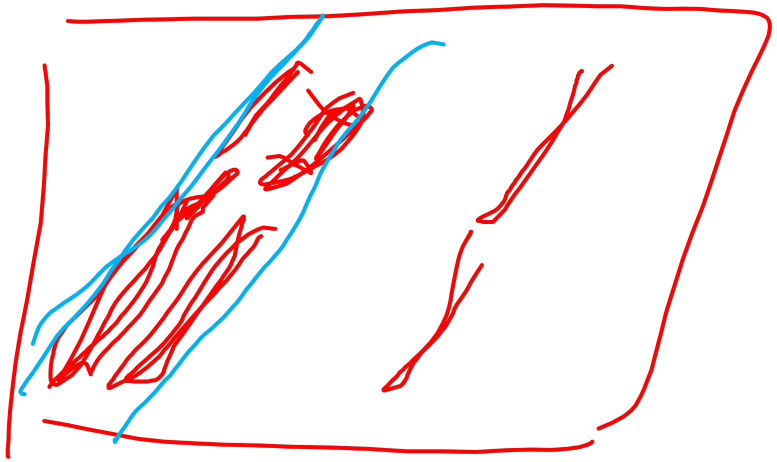
# Hough Transform

- Ability to detect edges
- What about lines? Shapes (eg: circle)?

- Hough Transform
  - Elegant method for direct object recognition
  - Edges need not be connected
  - Key idea: edges “vote” for the possible model

$\rho\theta$ 坐标

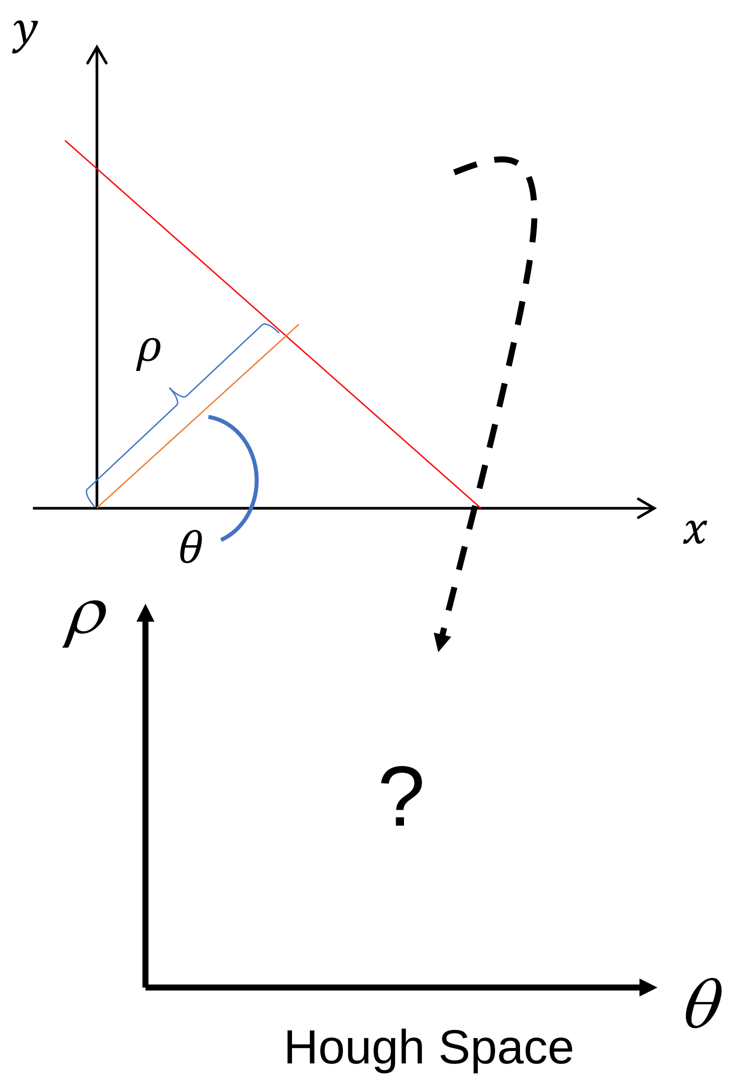




# Hough Space – $(\boldsymbol{\rho}, \boldsymbol{\theta})$ space

- $\rho = x\cos\theta + y\sin\theta$
- $y = \frac{\rho}{\sin\theta} - \frac{x}{\tan\theta}$

- Line equation: $\rho = x\cos\theta + y\sin\theta$
  - Parameters: $\rho$ and $\theta$
  - Where $0 \le \theta \le 2\pi$



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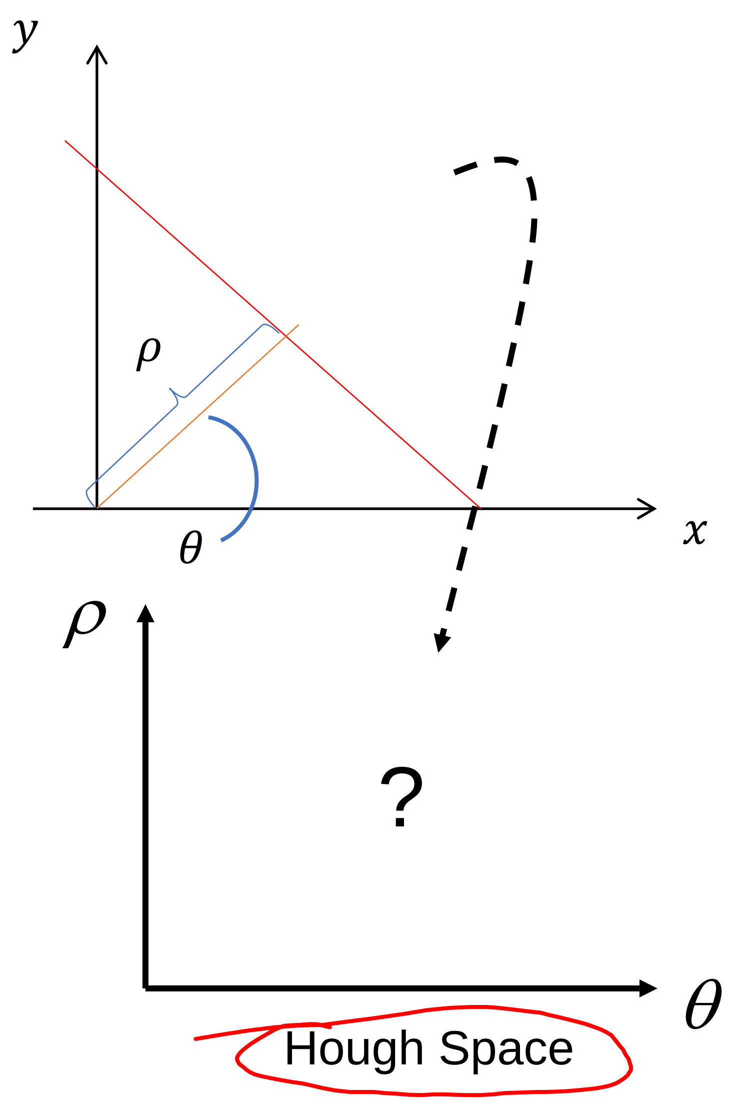

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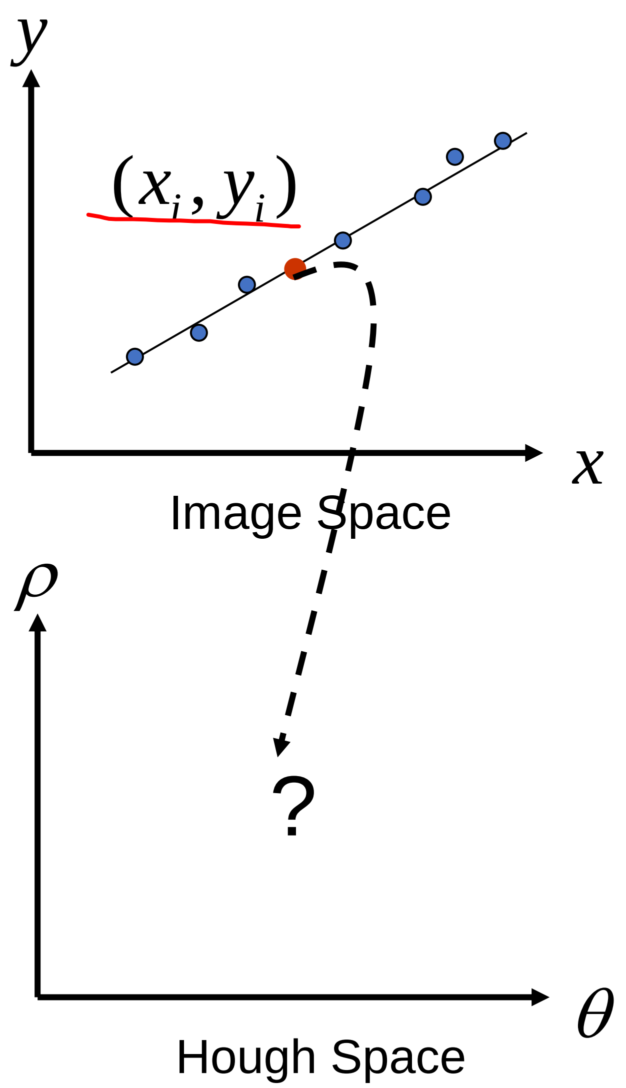
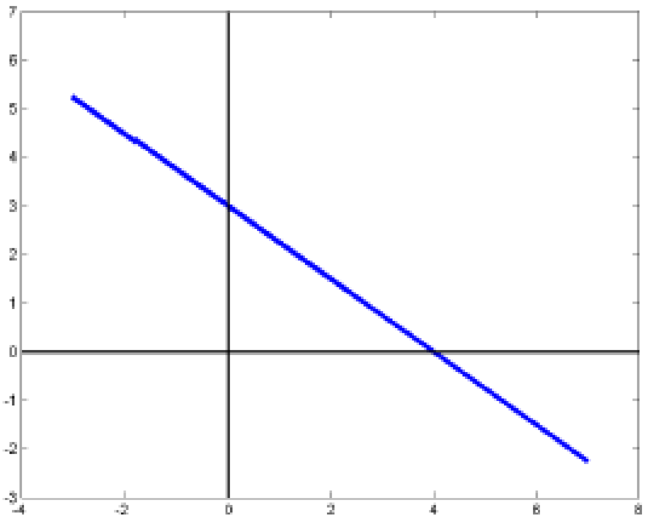
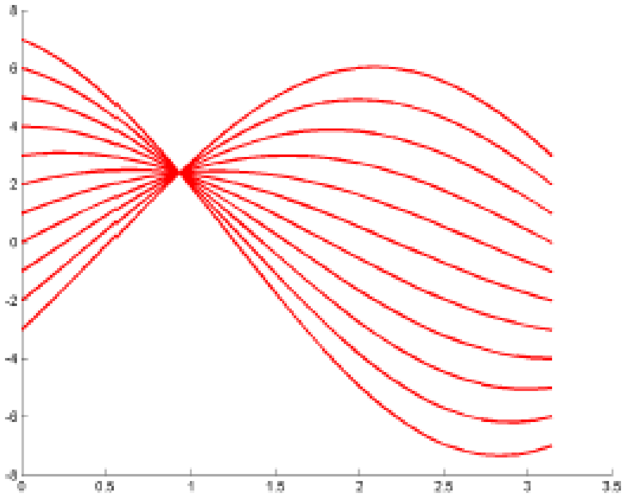
- How to map onto the Hough Space (sometimes also known as parameter space)?
  - $\rho = x_i\cos\theta + y_i\sin\theta$
  - Sinusoid curve



# Hough Space – $(\boldsymbol{\rho}, \boldsymbol{\theta})$ space

- $\rho = x\cos\theta + y\sin\theta$
- Points in picture → sinusoids in parameter space
- Points in parameter space → lines in picture
- There will be a unique intersection point if the points in the picture form a straight line





But how to choose the solution if there are noise?

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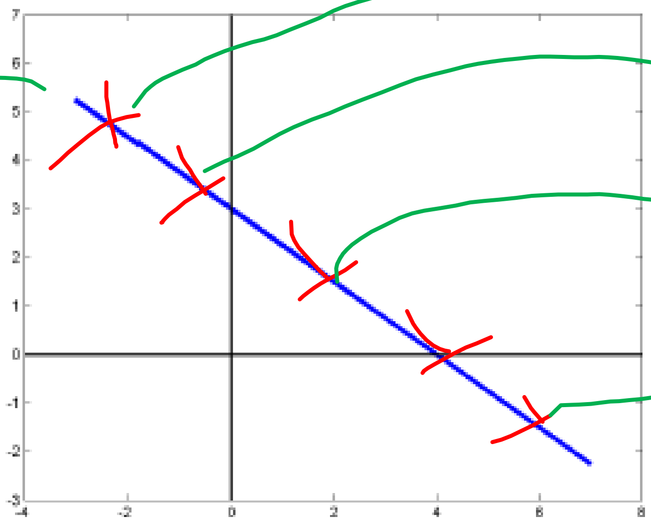
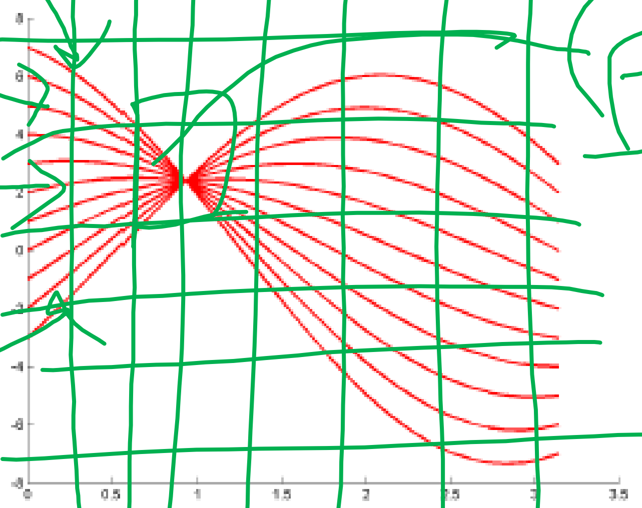




$(\rho, \theta)$

But how to choose the solution if there are noise?

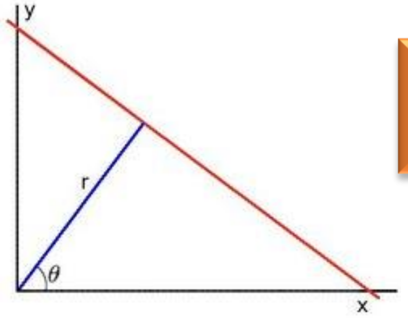
# Quantizing parameter space and Voting

- Discretize the $(\rho, \theta)$ space
  - For each point $(x_i, y_i)$, compute only for a finite set of angles $\theta = \theta_1, \theta_2, \dots, \theta_N$
  - For each $\theta_j$, obtain $\rho_{ij} = x_i \cos\theta_j + y_i \sin\theta_j$
- Create a matrix, called the accumulator matrix
  - Each column corresponds to angles $\theta = \theta_1, \theta_2, \dots, \theta_N$
  - Each row corresponds to the “bins” (intervals) of the resulting distance $\rho$
- Voting:
  - For each point in the image and for each $\theta_j$, compute the $\rho_{ij}$, and increment the corresponding element of the accumulator matrix
  - Highest value means highest “vote”

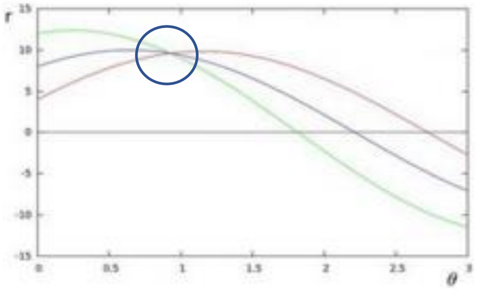
# Quantizing parameter space and Voting

- Voting (continue)
  - If more than one line, you can set a threshold value (number of vote) to obtain more lines
  - For example, if number of votes (ie value in that element) is more than the threshold value, then consider that $(\rho, \theta)$ to be a line

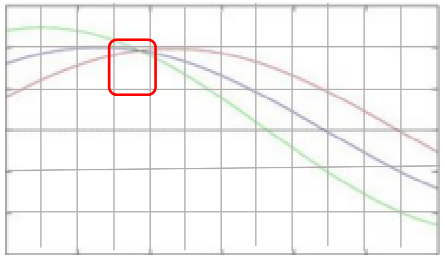
**Cartesian Coord.** → **Polar Coord.** → **Discrete Polar Coord**




**Feature Extraction**




**Discretize Coord. Space**



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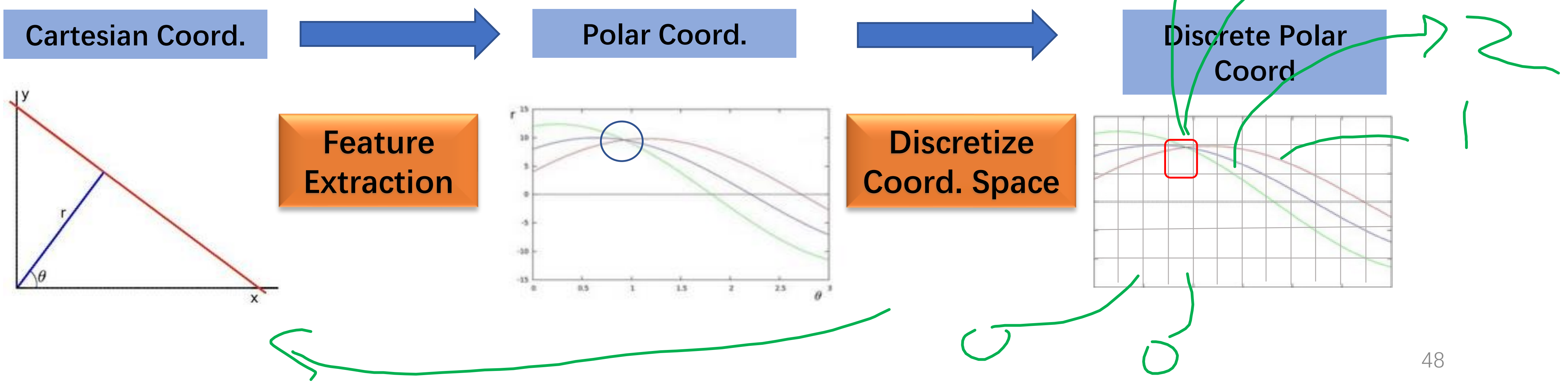
  - If more than one line, you can set a threshold value (number of vote) to obtain more lines
  - For example, if number of votes (ie value in that element) is more than the threshold value, then consider that $(\rho, \theta)$ to be a line

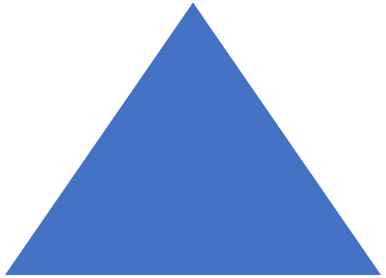


# Case Problem (1)

Using what you have learnt, design an algorithm that is capable of identifying the following simple blocks on white background.

1)Rectangle

2)Triangle



Solution

# Case Problem (1) Solution

- Stage (1): **Edge detection** using Canny edge detection
  - Apply Gaussian filter to smoothen the image in order to remove the noise
  - Find the intensity gradients vector of the image
    - $|\nabla I(x,y)| = \sqrt{\left(\frac{\partial I(x,y)}{\partial x}\right)^2 + \left(\frac{\partial I(x,y)}{\partial y}\right)^2}$
    - $\theta(x,y) = \tan^{-1}\left(\frac{\partial I(x,y)}{\partial y} / \frac{\partial I(x,y)}{\partial x}\right)$
  - Apply non-maximum suppression to get rid of spurious response to edge detection
  - Apply edge detection using two threshold value $K_H$ and $K_L$
    - $Edge(x,y) = \begin{cases} E_{strong} & if \ \ |\nabla I(x,y)| > K_H \\ E_{average} & if \ \ K_L \leq |\nabla I(x,y)| \leq K_H \\ E_{weak} & if \ \ |\nabla I(x,y)| < K_L \end{cases}$ Finalize edge detection by hysteresis
    - Any edges with magnitude < $K_L$ are discarded
    - Any edges with magnitude > $K_H$ are kept
    - An edge with magnitude between the two threshold values is kept if there is a path of edges with magnitude > $K_L$ connecting the edge to another edge with magnitude > $K_H$

# Case Problem (1) Solution

- Stage (2): Hough Transformation – **line detection**
  - Use $\rho = x\cos\theta + y\sin\theta$
  - Map it onto the Hough space – $(\rho, \theta)$ space
  - Intersection point exist if the points in the picture form a straight line
  - As more than one line is involved, various $(\rho, \theta)$ are considered to be a line number if number of votes is more than the threshold value

# Case Problem (1) Solution

- Stage (2): Hough Transformation - **voting**
  - Discretize the $(\rho, \theta)$ space
    - For each point $(x_i, y_i)$, compute only for a finite set of angles $\theta = \theta_1, \theta_2, \dots, \theta_N$
    - For each $\theta_j$, obtain $\rho_{ij} = x_i \cos\theta_j + y_i \sin\theta_j$
  - Create a matrix, called the accumulator matrix
    - Each column corresponds to angles $\theta = \theta_1, \theta_2, \dots, \theta_N$
    - Each row corresponds to the "bins" (intervals) of the resulting distance $\rho$
  - Voting:
    - For each point in the image and for each $\theta_j$, compute the $\rho_{ij}$, and increment the corresponding element of the accumulator matrix
    - Highest value means highest "vote"

# Case Problem (1) Solution

- Stage (3) – Shape identification
  - Rectangle:
    - 4 vertices
    - All angles are ~ 90 degrees apart
      - Checked using $\theta$
  - Triangle
    - 3 vertices

# FYI: Digit Recognition

- Contour is used in the digit recognition program

1AB

# Detection of other shapes

- Hough Transform can be generalized to find other shapes like circles and ellipses.
- However, the computational complexity increases
  - More computational time is required

# Hough circle transform

- Equation of circle:

$$(x-a)^2+(y-b)^2=R^2$$

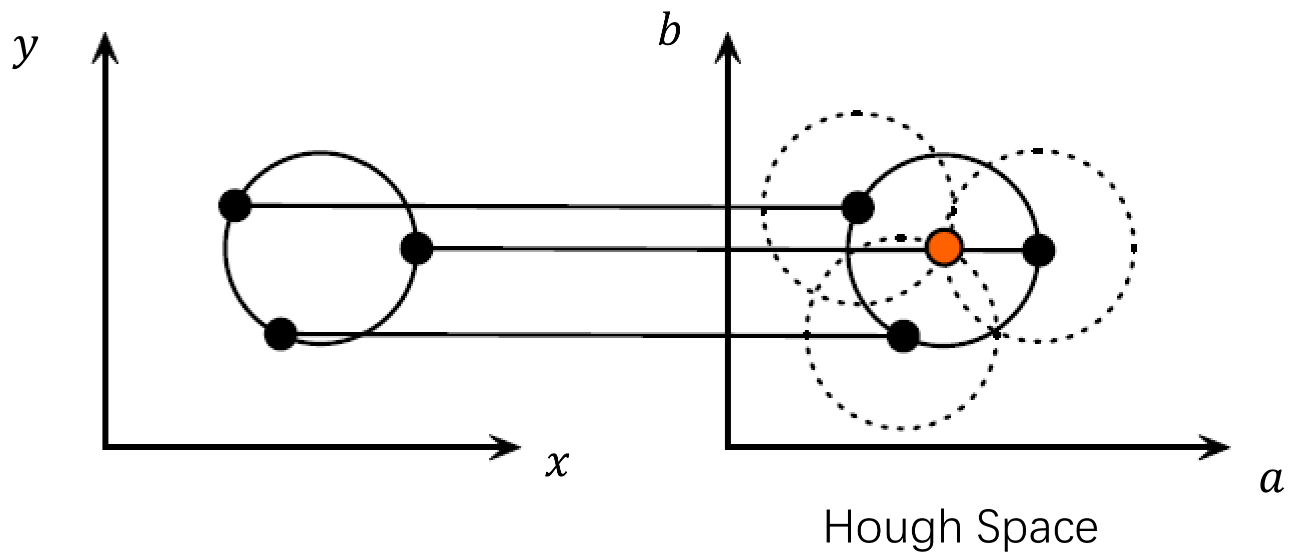
  - $(a,b)$ is the center of the circle
  - $R$ is the radius of the circle
- Parameters: $a,b,R$
- Rewriting the equation:

$$(a-x)^2+(b-y)^2=R^2$$

# Circle with known $\boldsymbol{R}$

$$(a-x)^2+(b-y)^2=R^2$$

- Parameters: $a, b$
- Points (edge) in picture → circle in parameter space
- Points in parameter space → circle in picture
- Like line detection, discretization and voting are used
- Example:

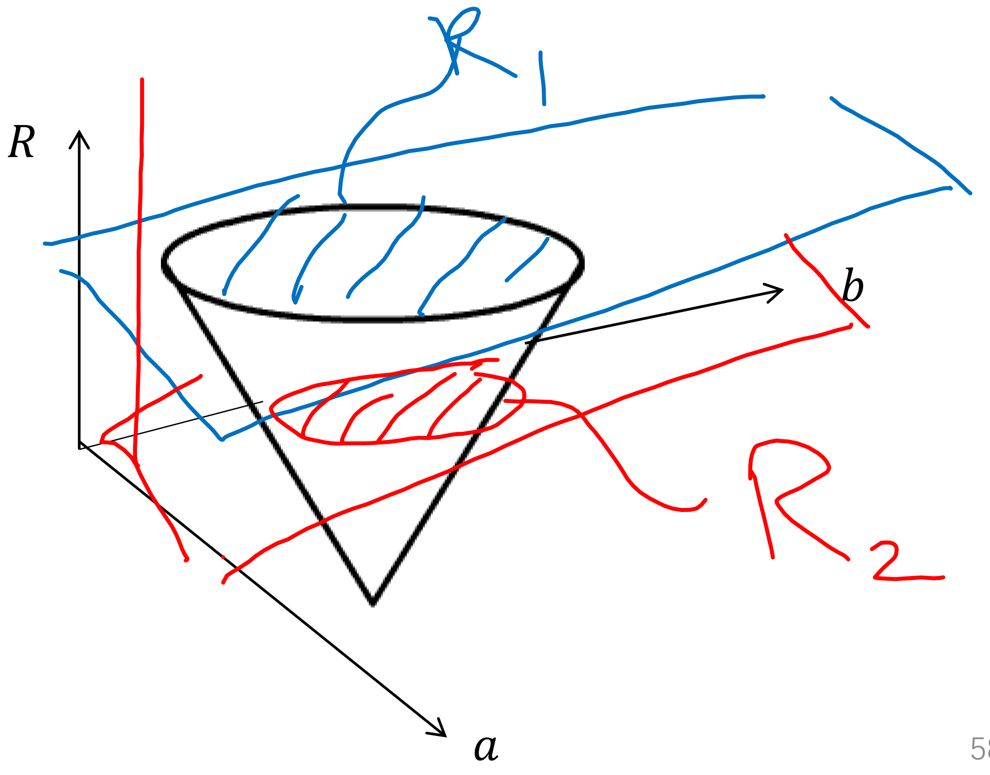


# Circle with unknown *R*

- Parameters: $a, b$, $R$
- Points (edge) in picture $\boxed{\leftrightarrow}$ conical surface in parameter space
- Additional computational time

Pixelization

Voxelization



# Application: Extraction of Blastomere

- Embryo Biopsy
- 8-cell stage
- Tracking of the extraction of blastomere for biopsy