



# ZJU-UIUC Institute

Zhejiang University / University of Illinois at Urbana-Champaign Institute



# ECE 470: Introduction to Robotics

## Lecture 24

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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

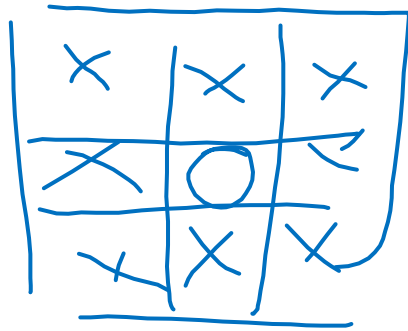
- Common techniques to manipulate, enhance & analyse images

## III. Robot Vision Applications

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

# Image Processing

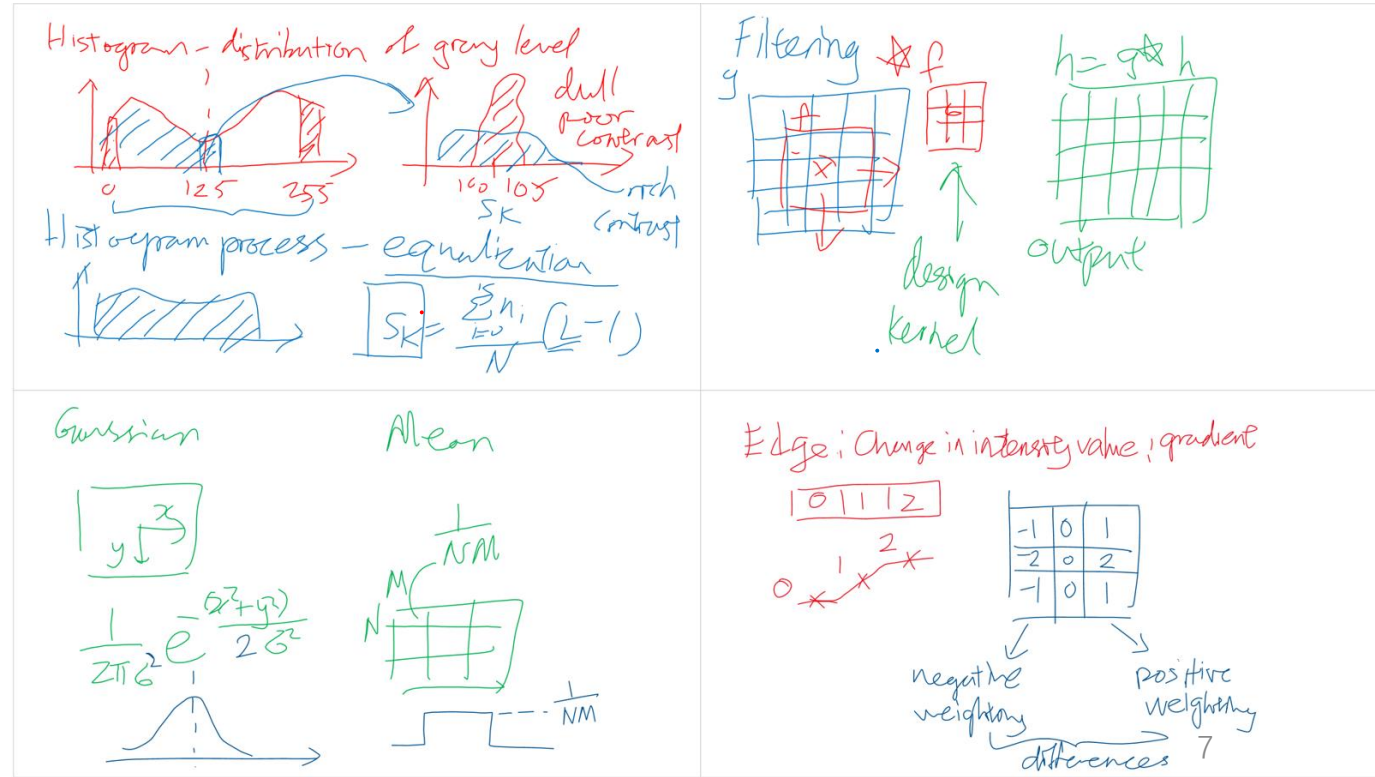
- Thresholding & Histogram Processing
- Filtering
- Feature Detect & Extract
  - Edges & Corners
  - Lines, shapes, interest points

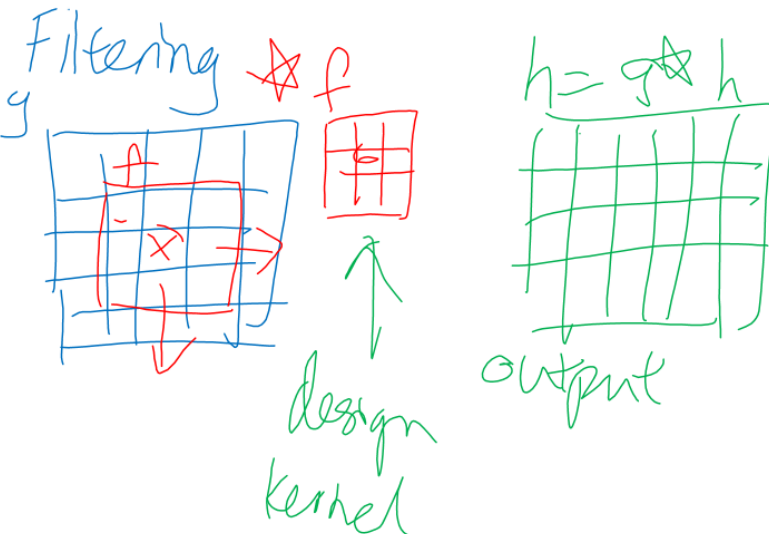
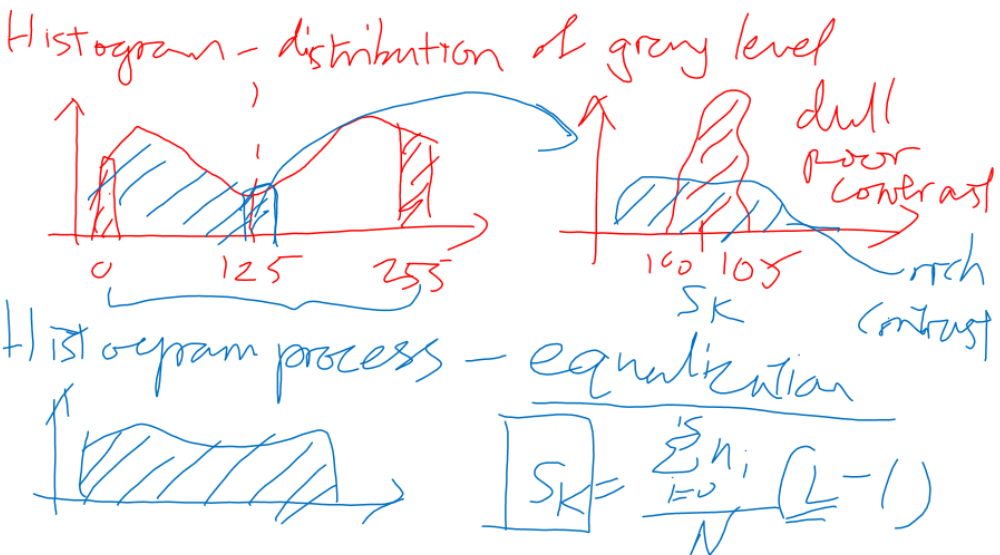


## Overview of Robot Vision

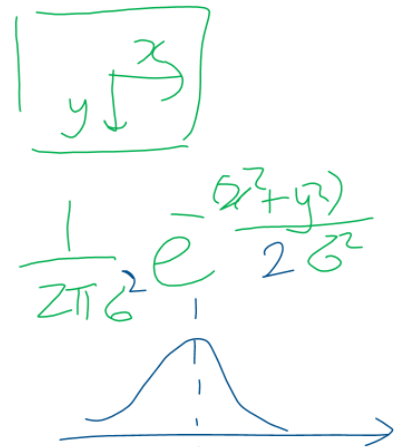
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Draft

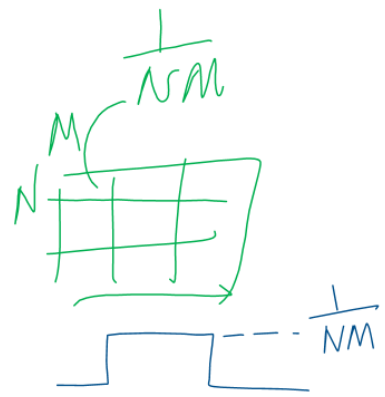




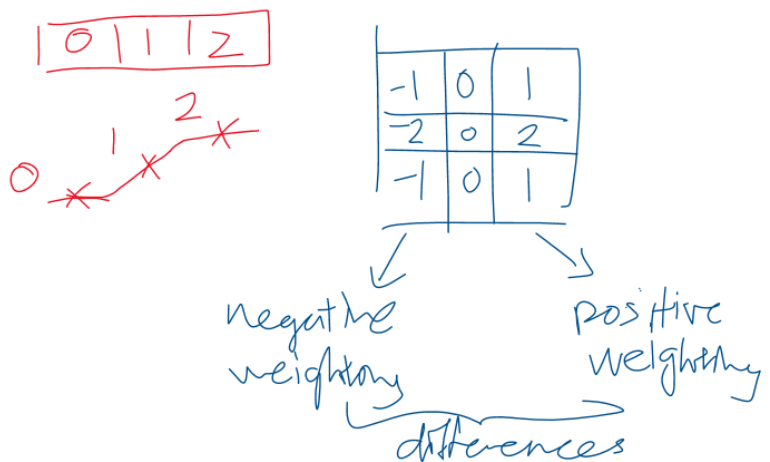
Gaussian



Mean



Edge: Change in intensity value; gradient



# Image Processing

- Thresholding & Histogram Processing
- Filtering
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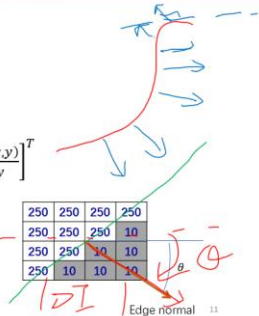
## Edge Detection

- Edges are locations with high image gradient or derivative
- A simple edge detection:
  - Compute gradient magnitude at each pixel
  - If the gradient magnitude exceeds a threshold, report as an edge point
- The derivative of each pixel can be estimated using finite difference method:
  - $\frac{\partial I}{\partial x} = \frac{I(x+1,y) - I(x-1,y)}{2}$
  - $\frac{\partial I}{\partial y} = \frac{I(x,y+1) - I(x,y-1)}{2}$

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## Gradient Vector

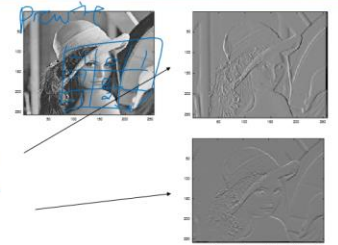
- $\frac{\partial I(x,y)}{\partial x} = \frac{I(x+1,y) - I(x-1,y)}{2}$
- $\frac{\partial I(x,y)}{\partial y} = \frac{I(x,y+1) - I(x,y-1)}{2}$
- Gradient Vector:  $\nabla I(x,y) = \left[ \frac{\partial I(x,y)}{\partial x}, \frac{\partial I(x,y)}{\partial y} \right]^T$
- $|\nabla I(x,y)| = \sqrt{\left( \frac{\partial I(x,y)}{\partial x} \right)^2 + \left( \frac{\partial I(x,y)}{\partial y} \right)^2}$
- $\theta(x,y) = \tan^{-1} \left( \frac{\partial I(x,y)}{\partial y} / \frac{\partial I(x,y)}{\partial x} \right)$



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## Sobel operator

- $\frac{\partial I(x,y)}{\partial x} = \frac{I(x+1,y) - I(x-1,y)}{2}$
- $\frac{\partial I(x,y)}{\partial y} = \frac{I(x,y+1) - I(x,y-1)}{2}$
- Sobel Operator:
  - $\frac{\partial I(x,y)}{\partial x} = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * A$
  - $\frac{\partial I(x,y)}{\partial y} = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} * A$
- where A is the source image and \* denotes the 2-dimensional convolution operation



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# Canny Edge Detection (····· Last Lecture)

- Canny edge detection is probably the most used and taught edge detection algorithm
- Involves 5 steps:
  1. Apply Gaussian filter to smoothen the image in order to remove the noise
  2. Find the intensity gradients of the image
  3. Apply non-maximum suppression to get rid of spurious response to edge detection
  4. Apply edge detection using two threshold value
  5. Finalize edge detection by hysteresis
- J. Canny, "A Computational Approach to Edge Detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 8, no. 6, 1986.

# Canny Edge Detection

- Step (1): Apply Gaussian filter

# 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
- Question: Does this give you a sharper image?

*Not this step*



# Canny Edge Detection

- Step (2): Find the intensity gradients of the image

# Canny Edge Detection

- Step (2): Find the intensity gradients of the image

- $\frac{\partial I(x,y)}{\partial x} = \frac{I(x+1,y) - I(x-1,y)}{2}$

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- Gradient Vector:  $\nabla I(x,y) = \left[ \frac{\partial I(x,y)}{\partial x}, \frac{\partial I(x,y)}{\partial y} \right]^T$

- $|\nabla I(x,y)| = \sqrt{\left( \frac{\partial I(x,y)}{\partial x} \right)^2 + \left( \frac{\partial I(x,y)}{\partial y} \right)^2}$

- $\theta(x,y) = \tan^{-1} \left( \frac{\partial I(x,y)}{\partial y} / \frac{\partial I(x,y)}{\partial x} \right)$

## Application Example



# Canny Edge Detection

- Step (2): Find the intensity gradients of the image

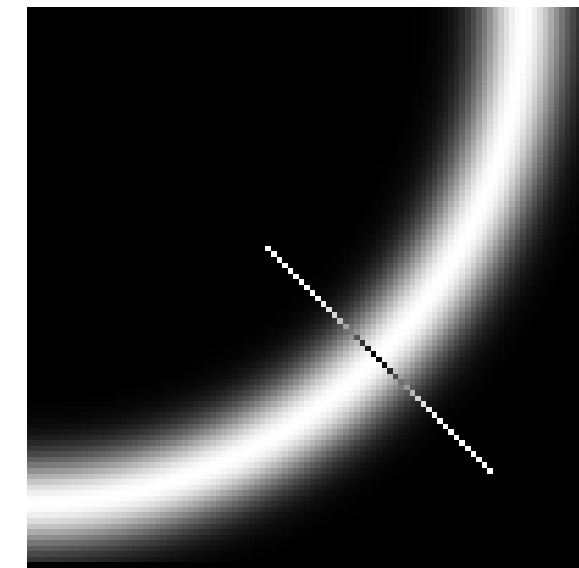
$$\begin{aligned} \bullet \frac{\partial I(x,y)}{\partial x} &= \frac{I(x+1,y) - I(x-1,y)}{2} \\ \bullet \frac{\partial I(x,y)}{\partial y} &= \frac{I(x,y+1) - I(x,y-1)}{2} \end{aligned}$$

*Handwritten notes:*  $\Delta$  in  $x$ -direction (above the first equation),  $y$ -direction (above the second equation)

- Gradient Vector:  $\nabla I(x,y) = \left[ \frac{\partial I(x,y)}{\partial x}, \frac{\partial I(x,y)}{\partial y} \right]^T$

- $|\nabla I(x,y)|$  =  $\sqrt{\left(\frac{\partial I(x,y)}{\partial x}\right)^2 + \left(\frac{\partial I(x,y)}{\partial y}\right)^2}$

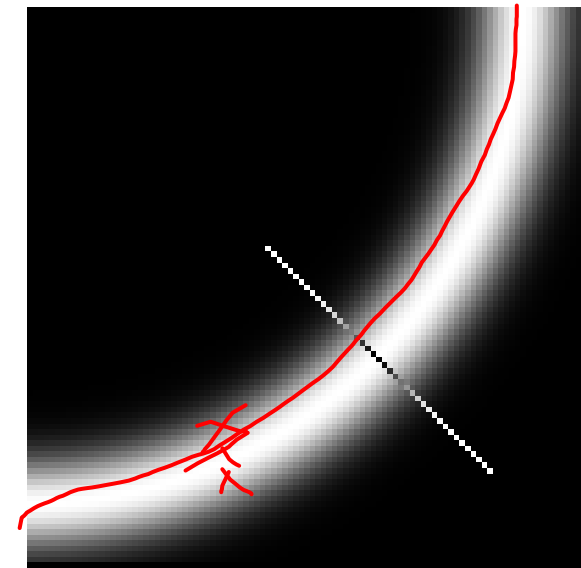
- $\theta(x,y)$  =  $\tan^{-1} \left( \frac{\partial I(x,y)}{\partial y} / \frac{\partial I(x,y)}{\partial x} \right)$



# Canny Edge Detection

- How do we precisely localize the edge?

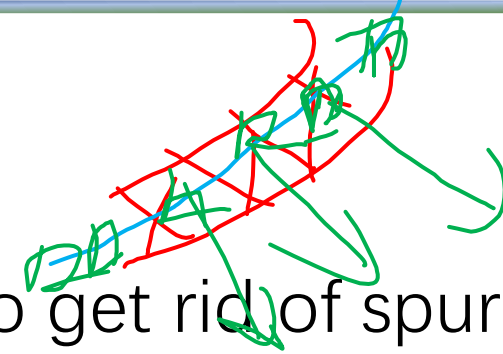
*Thinning of the edge*



# Canny Edge Detection

- Step (3): Apply non-maximum suppression to get rid of spurious response to edge detection
- Non-maximum suppression is an edge thinning technique

# Canny Edge Detection



- Step (3): Apply non-maximum suppression to get rid of spurious response to edge detection
- Non-maximum suppression is an edge thinning technique
  - Close to the center of the true edge
  - non-maximum suppression can help to suppress all the gradient values to 0 except the local maximal, which indicates location with the sharpest change of intensity value
  - Compare the edge strength of the current pixel with the edge strength of the pixel in the positive and negative gradient directions
  - If the edge strength of the current pixel is the largest compared to the other pixels in the mask with the same direction, the value will be preserved. Otherwise, the value will be suppressed.

# Canny Edge Detection

- Step (4): Apply edge detection using two threshold value  $K_H$  and  $K_L$

$$\bullet \text{ Edge}(x, y) = \begin{cases} E_{strong} & \text{if } |\nabla I(x, y)| > K_H \\ E_{average} & \text{if } K_L \leq |\nabla I(x, y)| \leq K_H \\ E_{weak} & \text{if } |\nabla I(x, y)| < K_L \end{cases}$$

# Canny Edge Detection

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✓ → definitely edge

→ definitely Not



# Canny Edge Detection

- Step (4): Apply edge detection using two threshold value  $K_H$  and  $K_L$

$$Edge(x, y) = \begin{cases} E_{strong} & \text{if } |\nabla I(x, y)| > K_H \\ E_{average} & \text{if } K_L \leq |\nabla I(x, y)| \leq K_H \\ E_{weak} & \text{if } |\nabla I(x, y)| < K_L \end{cases}$$

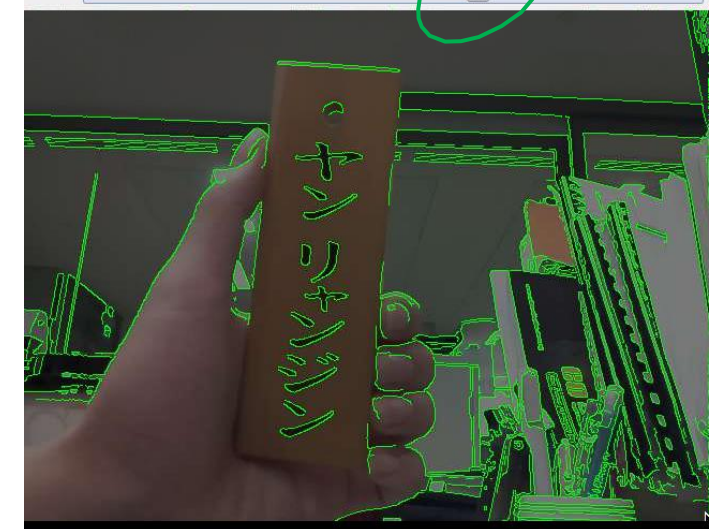
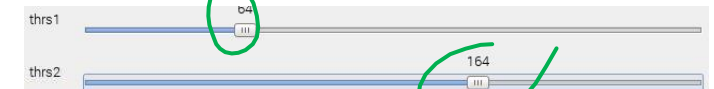
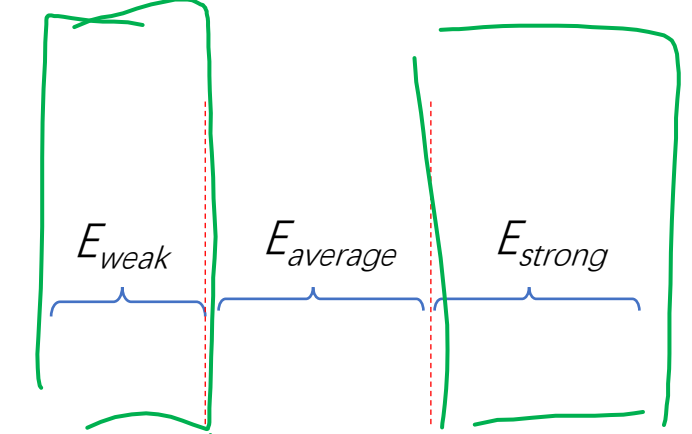
edge.py

cv2.Canny(image, thrs1, thrs2, size)

decided by  
developer (user)

$K_L$   
 $K_H$

✓ *Merged* ✓

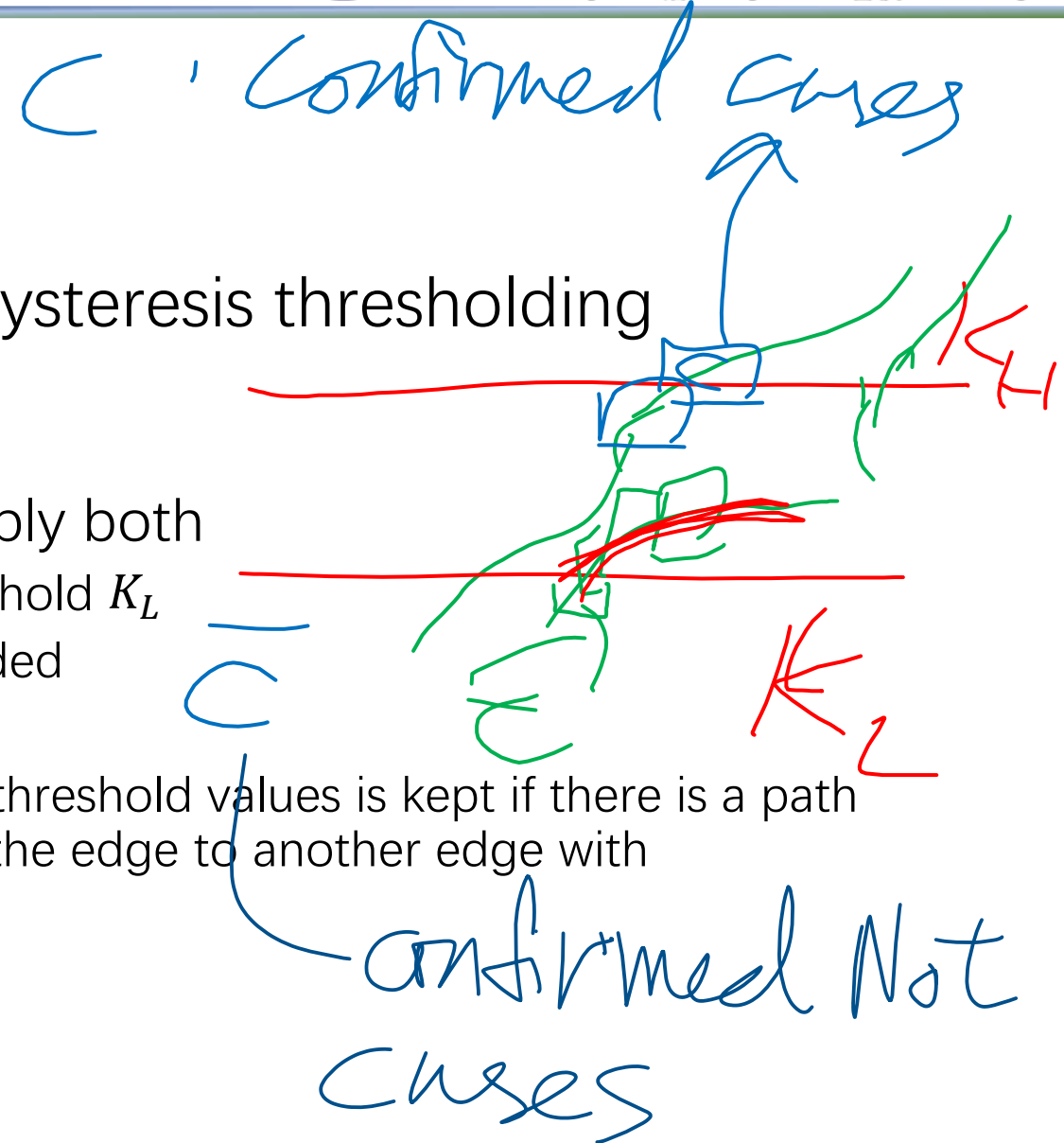


# Canny Edge Detection

- 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  $> K_H$

# Canny Edge Detection

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# Edge Detection

Original



# Edge Detection

Original



Sobel Operator



Canny Algorithm



discontinuous

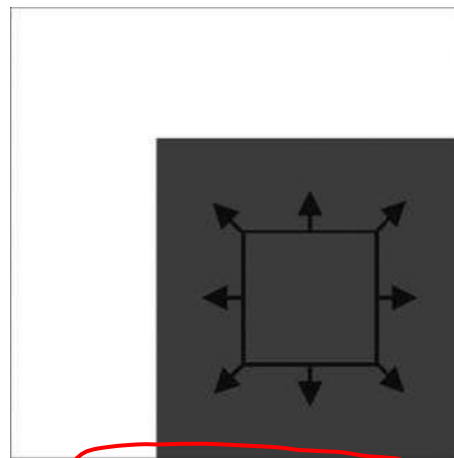
continuous  
edge

# Image Processing

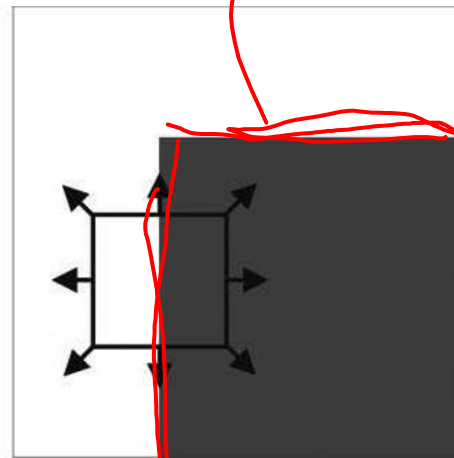
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# Corner Detection

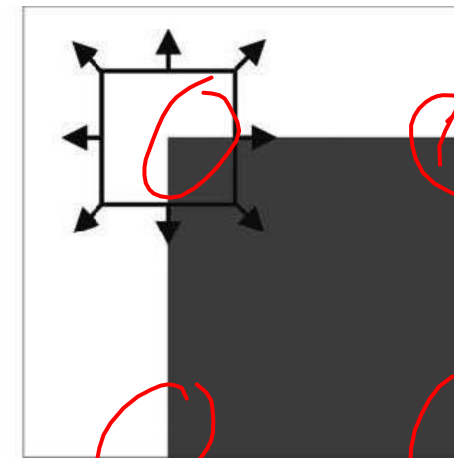
- Corner detection are used for many image feature extraction
  - Because corners are features with high repeatability



Flat region



Edge



Corner

Interest pt



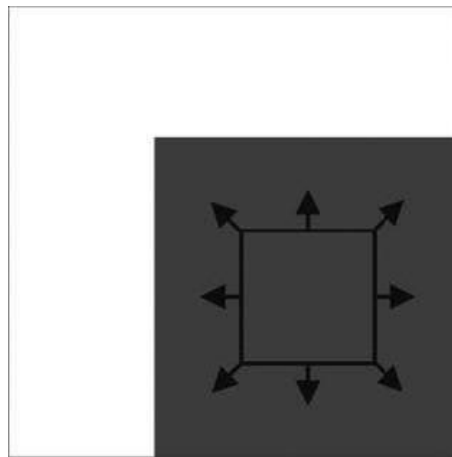
corner

blob

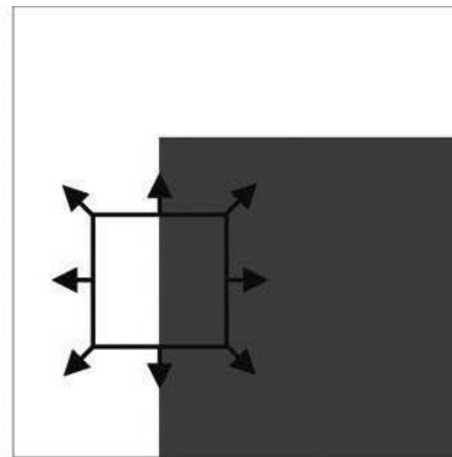
o

# Corner Detection

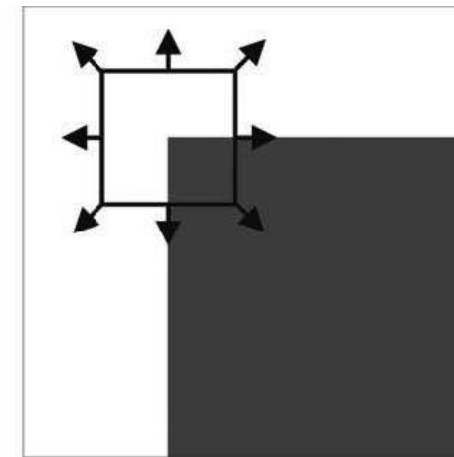
- Basic idea of corner detection: large change in appearance
  - Flat region: no change
  - Edge: no change along edge
  - Corner: significant change in more than one direction



Flat region



Edge



Corner



# Harris Corner Detector

- Consider taking an image patched centered on  $(u, v)$  and shifting it by  $(x, y)$ , the sum of square differences SSD between these two patches is:

$$SSD(x, y) = \sum_u \sum_v [I(u, v) - I(u + x, v + y)]^2$$

- Using first-order Taylor expansion,

$$I(u + x, v + y) \approx I(u, v) + I_x(u, v)x + I_y(u, v)y$$

- Hence, SSD becomes

$$\begin{aligned} SSD(x, y) &\approx \sum_u \sum_v [I_x(u, v)x + I_y(u, v)y]^2 \\ &= \sum_u \sum_v [I_x^2 x^2 + 2xyI_xI_y + I_y^2 y^2] \end{aligned}$$

# Harris Corner Detector

$$\begin{aligned} SSD(x, y) &= \sum_u \sum_v [I_x^2 x^2 + 2xyI_xI_y + I_y^2 y^2]^2 \\ &= \sum_u \sum_v [x \quad y] \begin{bmatrix} I_x^2 & I_xI_y \\ I_xI_y & I_y^2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \\ &= [x \quad y] \sum_u \sum_v \begin{bmatrix} I_x^2 & I_xI_y \\ I_xI_y & I_y^2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \end{aligned}$$

- $SSD(x, y) = [x \quad y]M \begin{bmatrix} x \\ y \end{bmatrix}$
- Since  $M$  is symmetric, we can rewrite the matrix as:

$$M = A^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} A$$

- where  $\lambda_1$  and  $\lambda_2$  are the eigenvalues of  $M$

# Harris Corner Detector

$$\begin{aligned}
 SSD(x, y) &= \sum_u \sum_v [I_x^2 x^2 + 2xyI_x I_y + I_y^2 y^2]^2 \\
 &= \sum_u \sum_v [x \quad y] \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \\
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 \end{aligned}$$

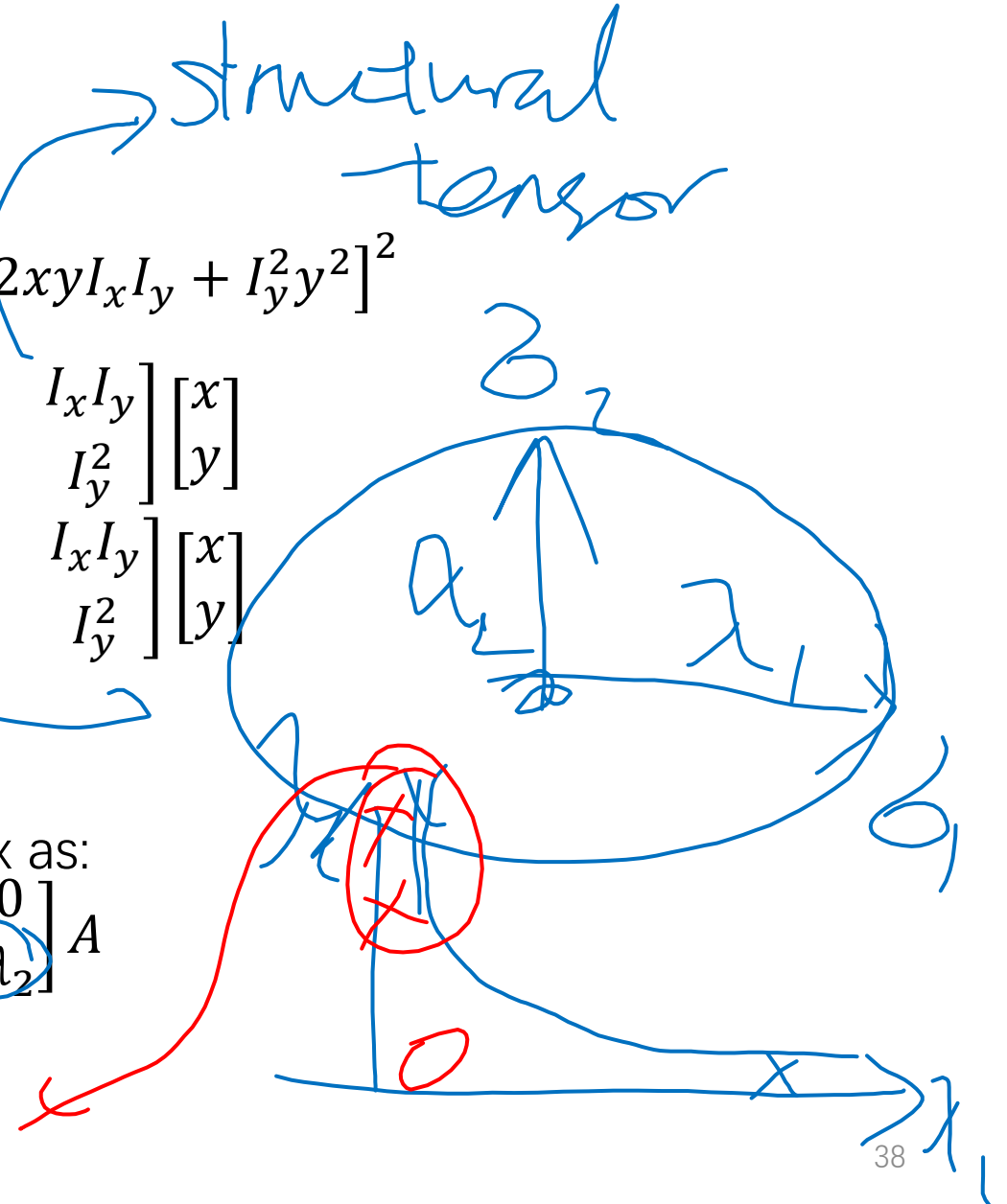
structural tensor

- $SSD(x, y) = [x \quad y] M \begin{bmatrix} x \\ y \end{bmatrix}$
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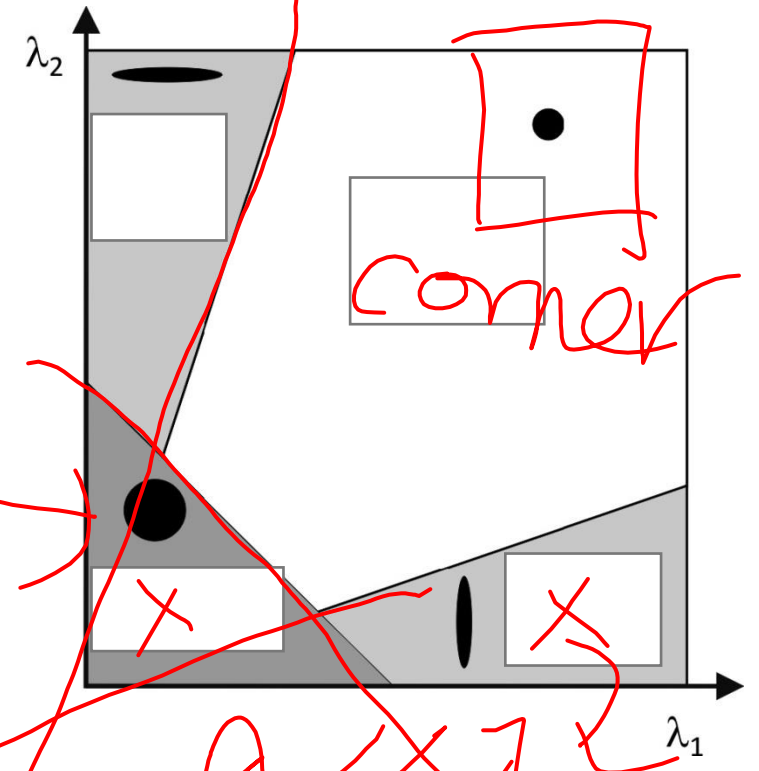
edge in  $\theta_2$



# Harris Corner Detector

flat region  
wide lab

- As mentioned, a corner is characterized by a large variation of SSD in all direction, the larger the variation in that direction
- Both  $\lambda$  are small means flat region
- One strong and one weak  $\lambda$  means edge
- Two strong  $\lambda$  means corner



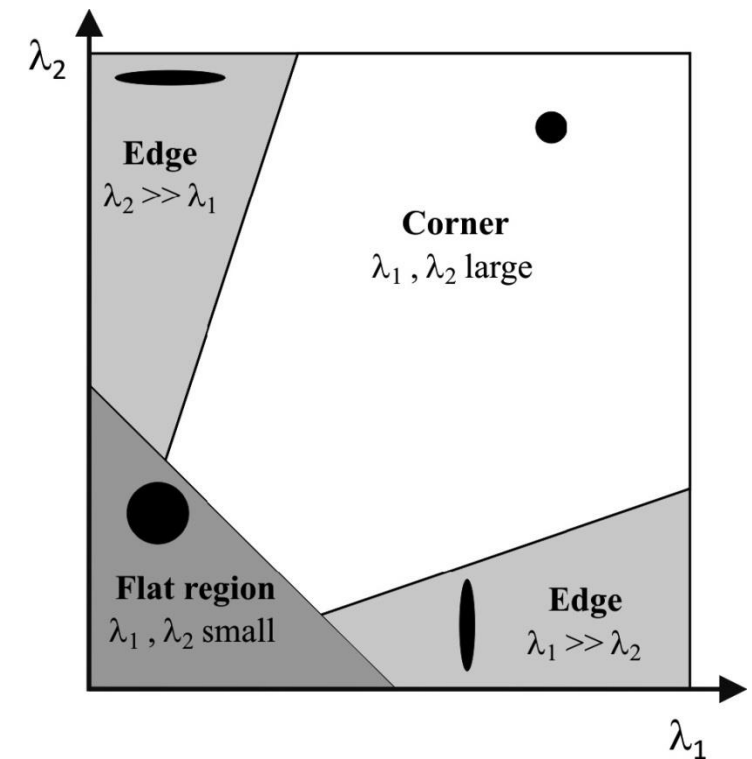
# Harris Corner Detector

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Quick way of Calculating Corner Response:

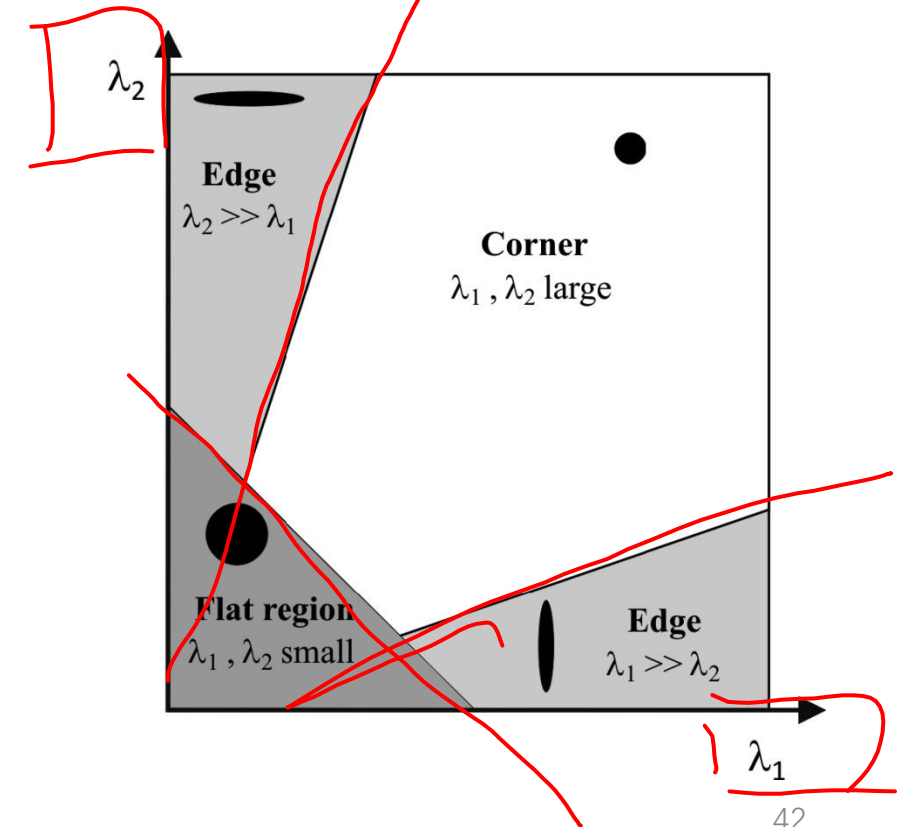
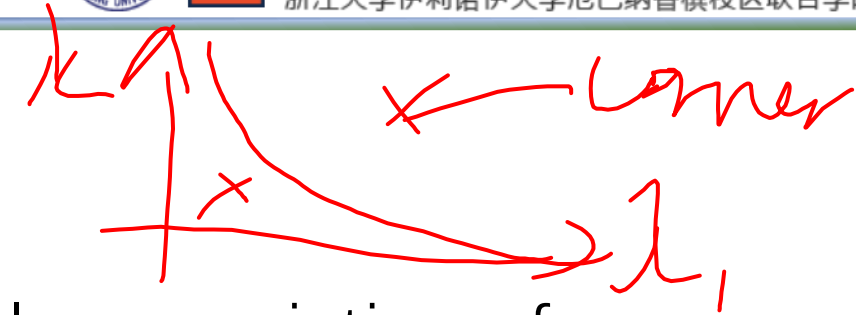
$$R = \lambda_1 \lambda_2 - k \cdot (\lambda_1 + \lambda_2)^2 = \det(M) - k \cdot \text{tr}(M)^2$$

where  $k$  is an empirically determined constant;  $k \in [0.04, 0.06]$  .



# Harris Corner Detector

- As mentioned, a corner is characterized by a large variation of SSD in all direction, the larger the variation in that direction
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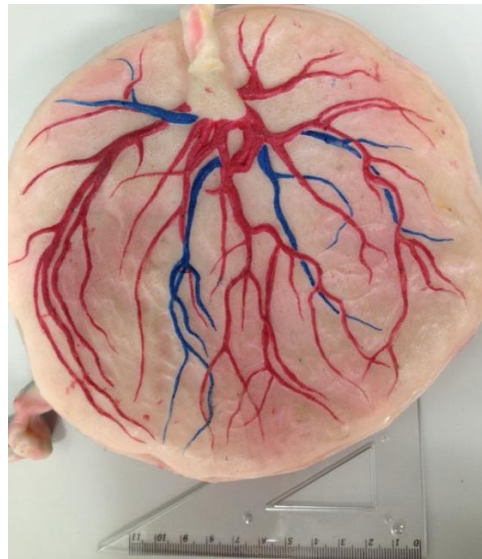
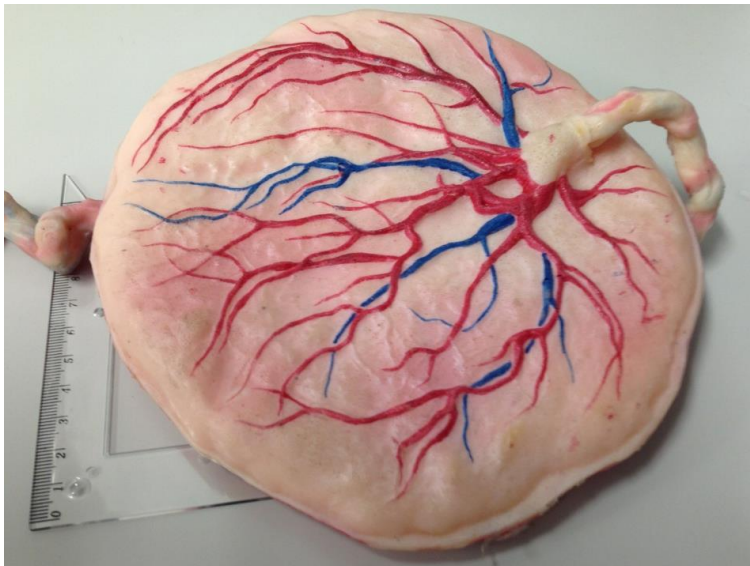
Quick way of Calculating Corner Response:

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# Match two images

- Are these objects the same?
  - Pixel to pixel comparison might not work

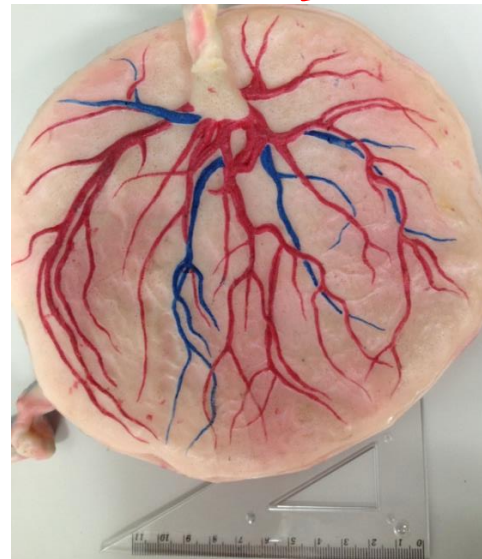
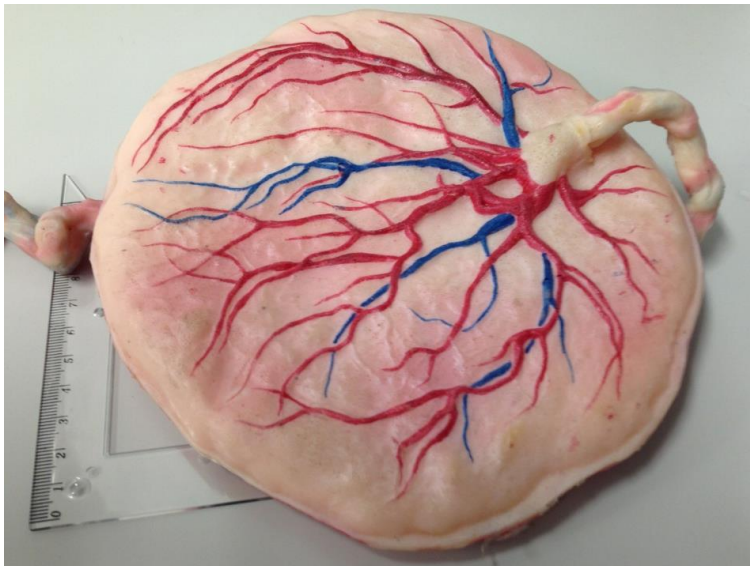




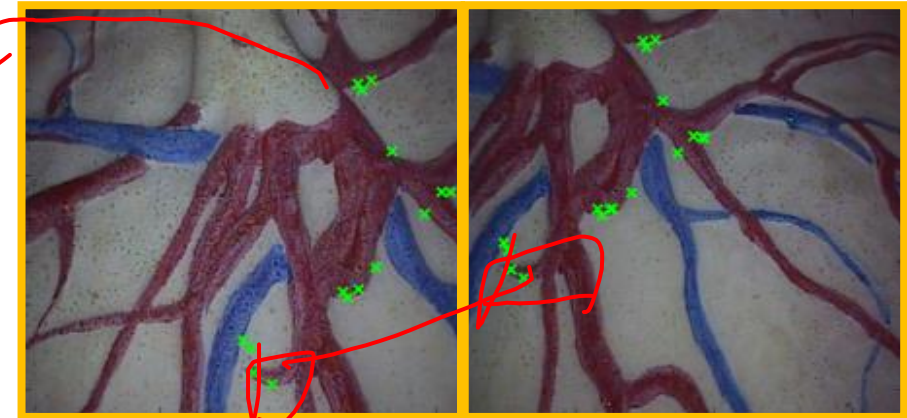
# Match two images

- Are these objects the same?
  - Pixel to pixel comparison might not work

Feature detected can be  
interest pt (Feature  
Descriptor)



Descriptor





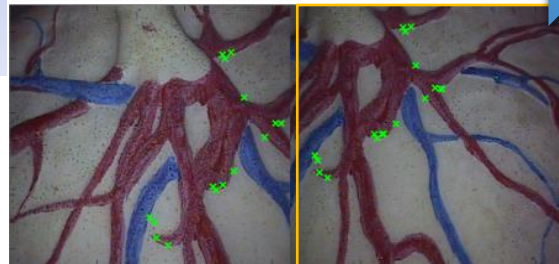
# Match two images

- Feature matching
- Detect; Describe; Match; Transform (for image mapping)

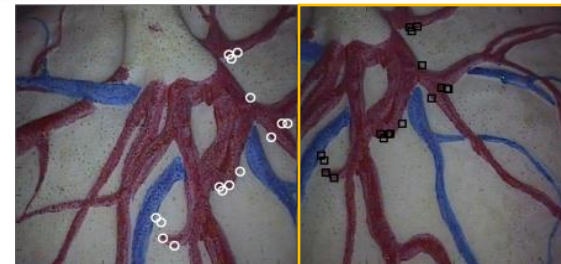
Feature Detection, Description,  
& Matching

Feature Matches

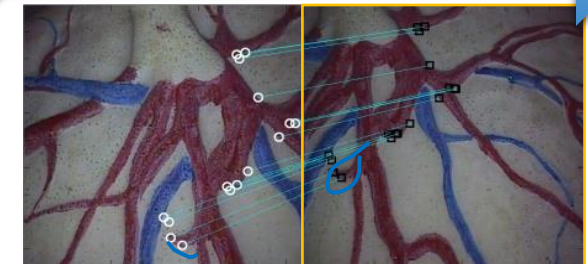
Detect



Describe



Match



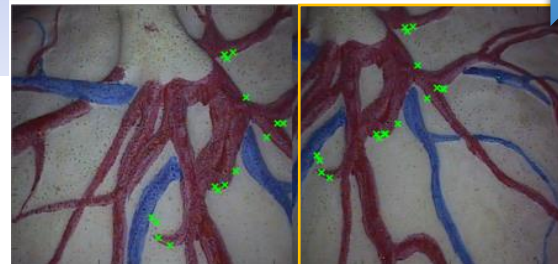
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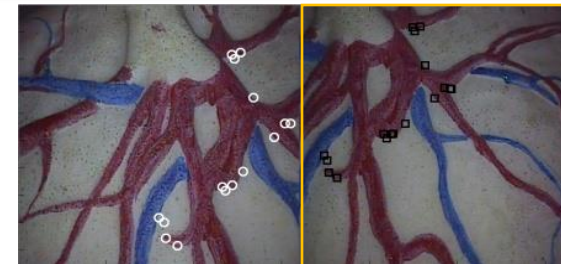
Feature Detection, Description,  
& Matching

Feature Matches

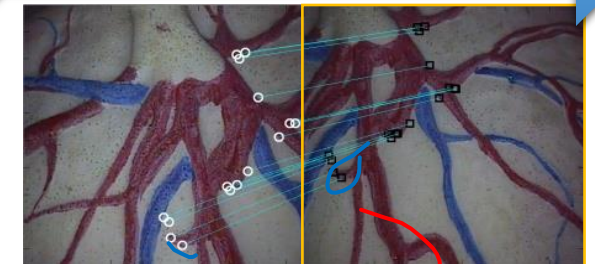
Detect



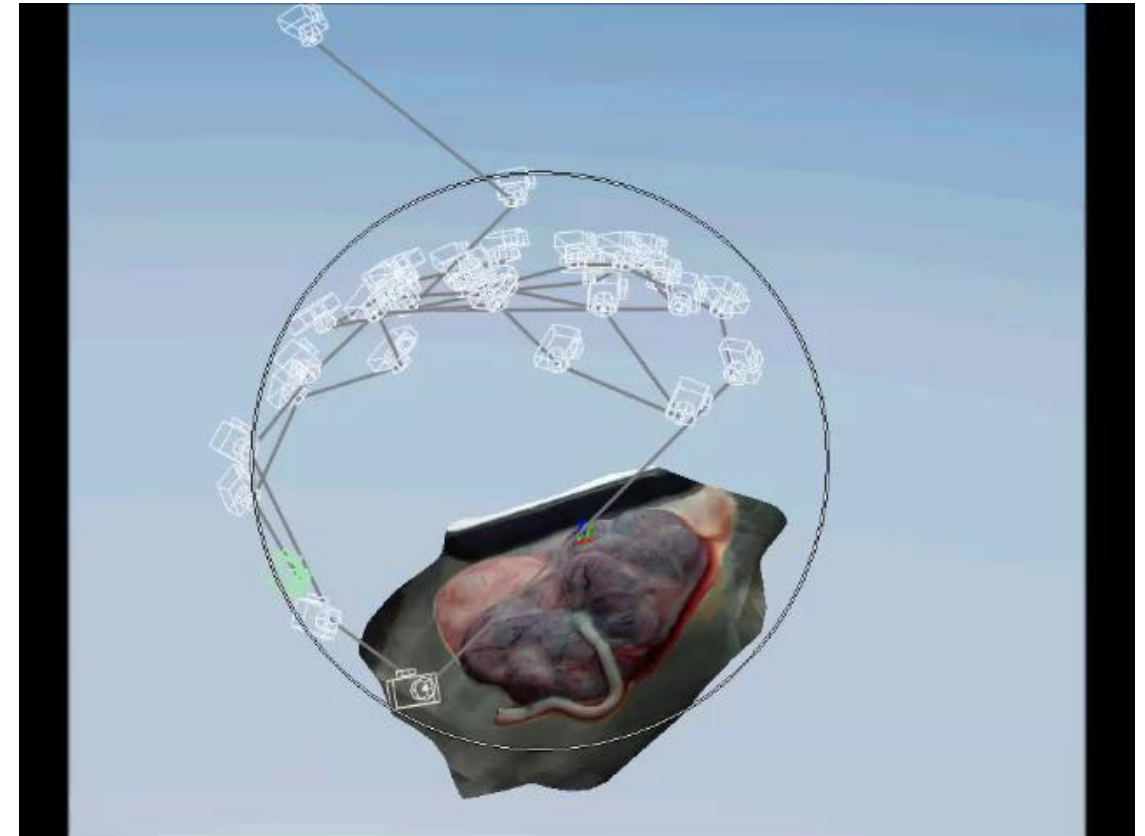
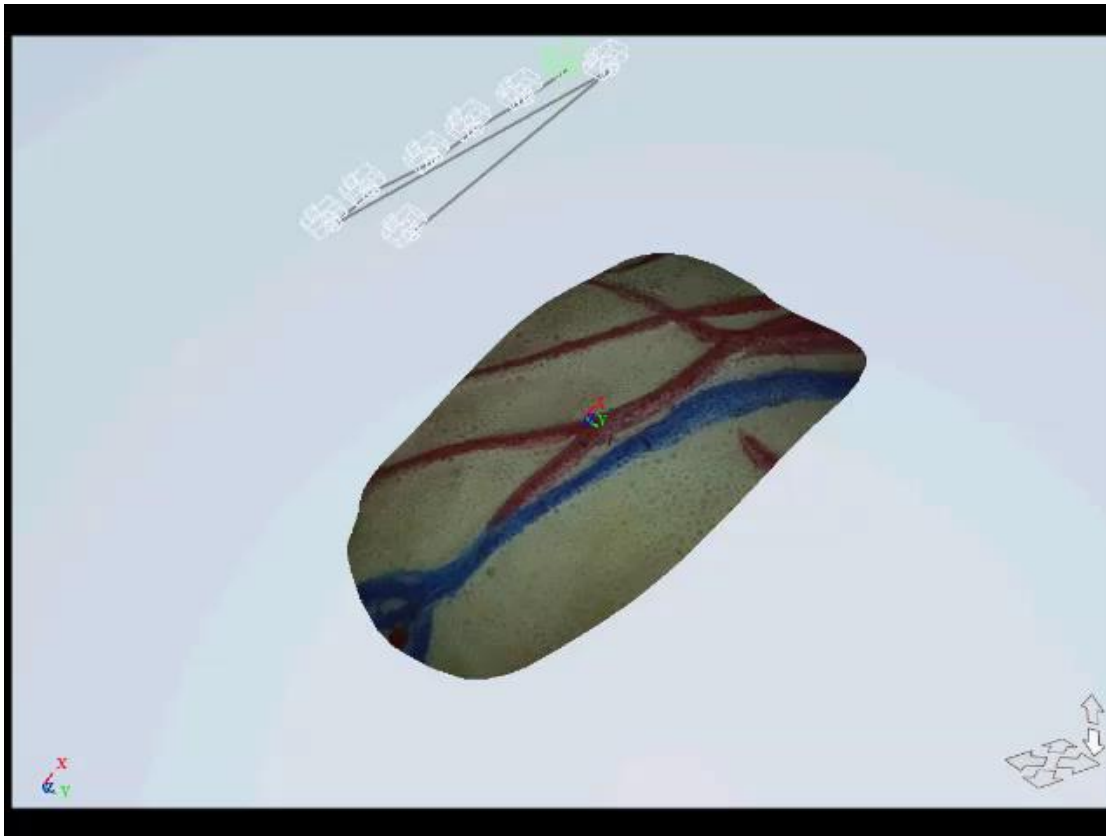
Describe



Match

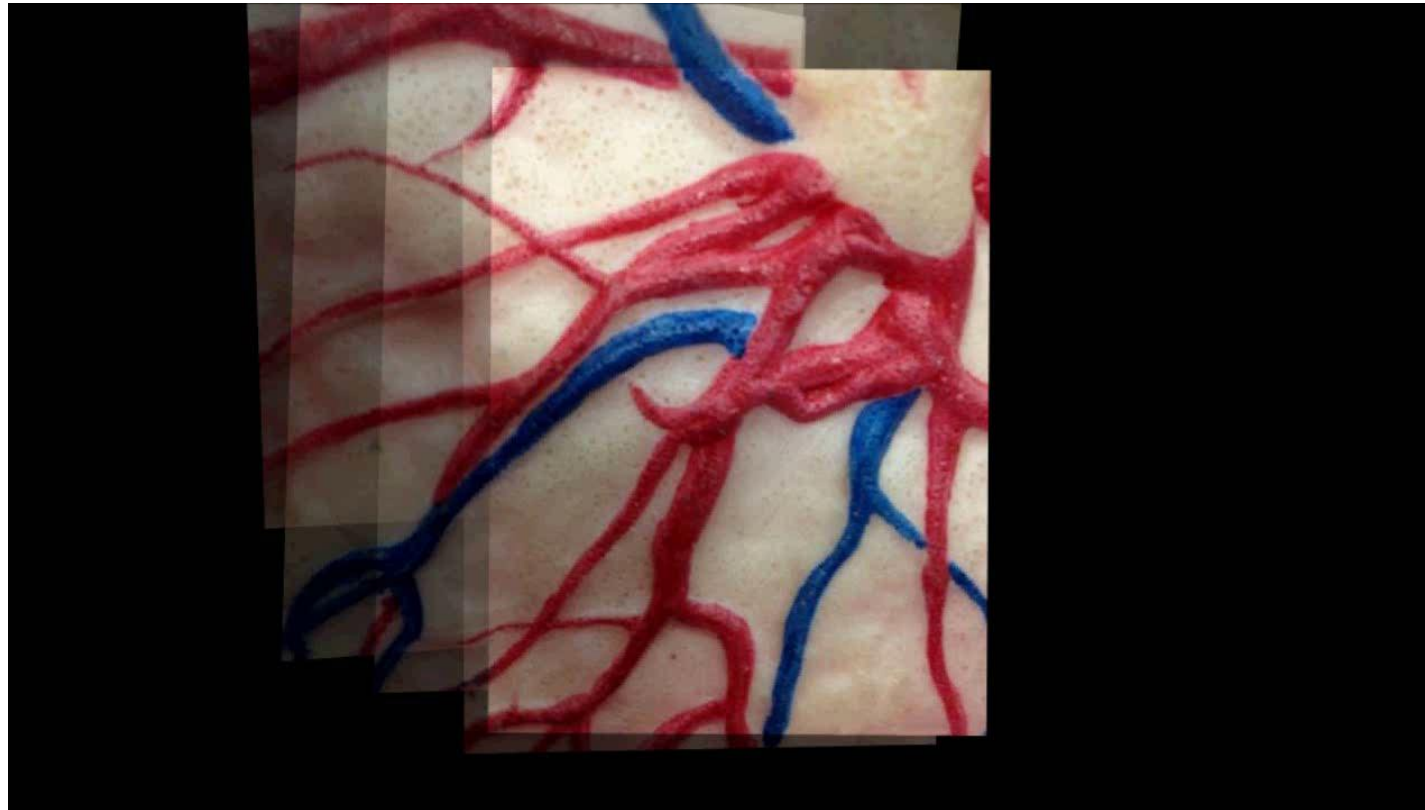


# Example of Applications in Corner Detection

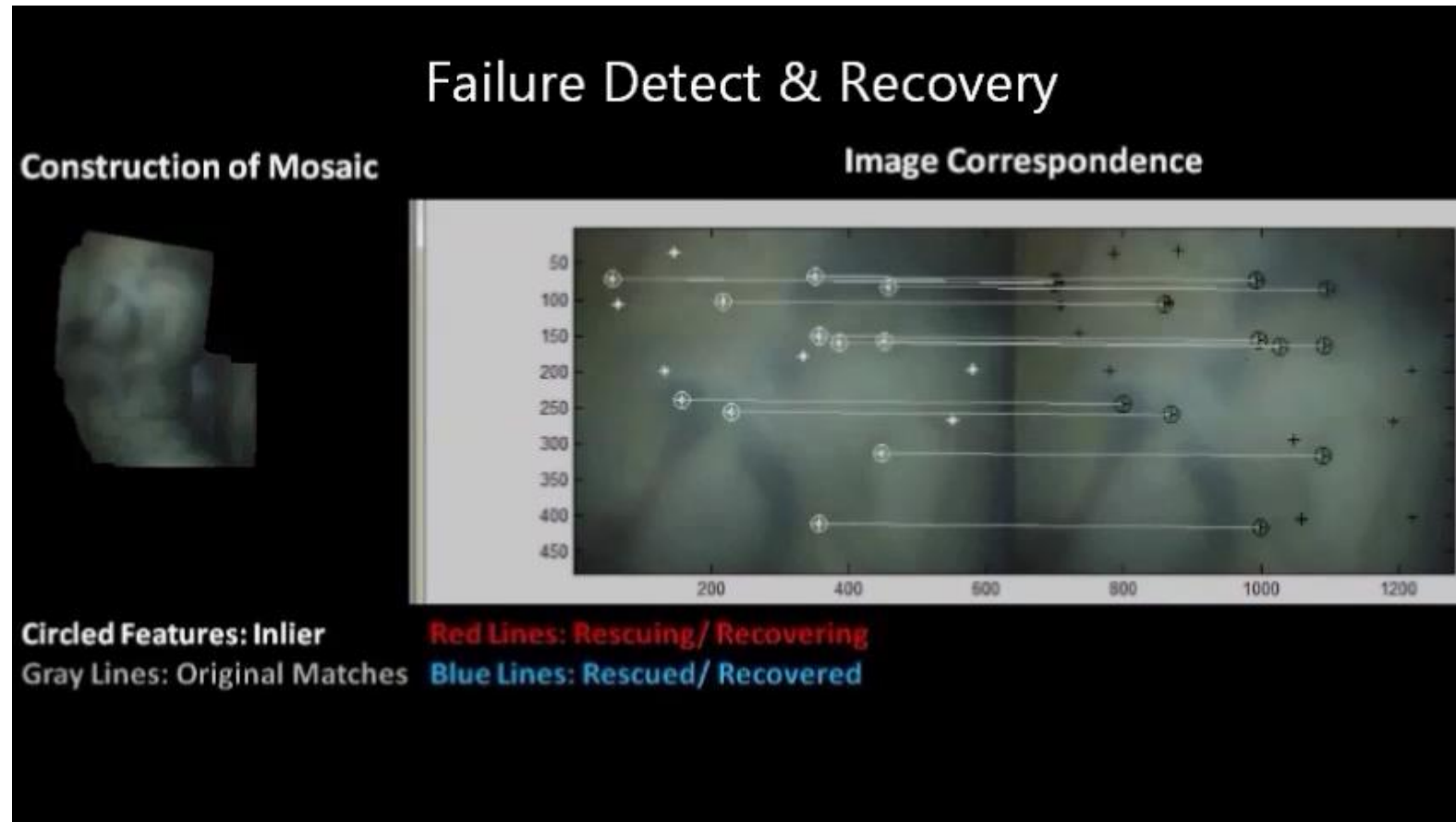


# Example of Applications in Corner Detection

- Microsoft Photosynth



# Dealing with Failure



Yang, L., et al. (2015). "Towards scene adaptive image correspondence for placental vasculature mosaic in computer assisted fetoscopic procedures." *Int J of Med Robot* **12**(3): 375--386.

# Image Processing

- Image Enhancement
  - ☒ Thresholding & Histogram Processing
  - ☒ Filtering
- Image Analysis
  - ☒ Feature Detection
    - ☒ Edges
    - ☒ Interest points- Corners
    - Lines & Shapes
    - Target Tracking