



Digital Image Processing

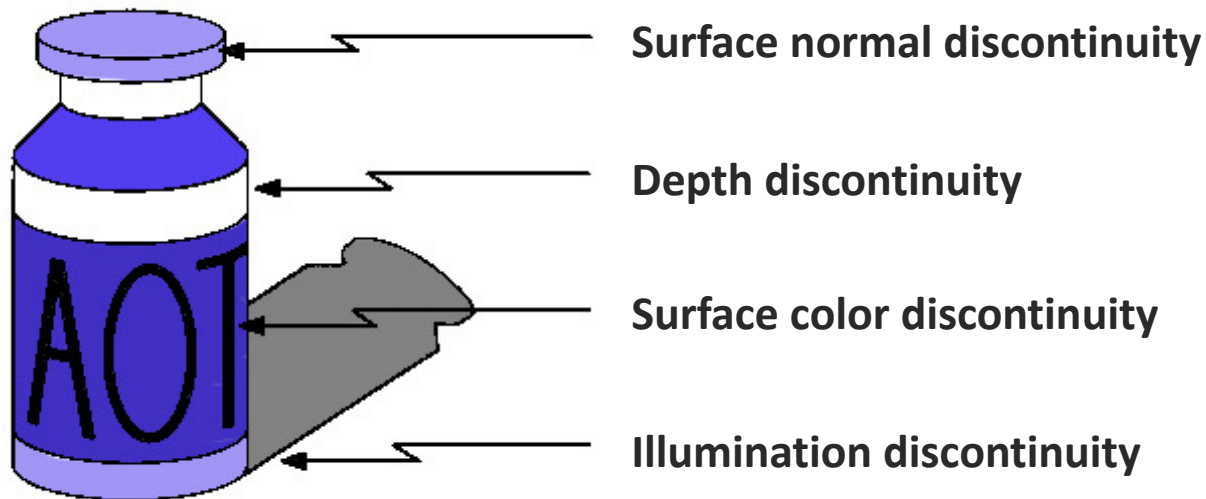
Edge Crispening

Ming-Sui (Amy) Lee

Lecture 03

[Edges]

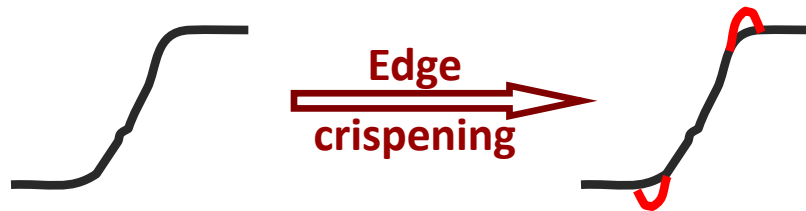
- Edges are caused by a variety of factors



Edge Crispening

■ Motivation

- A photograph with accentuated edges look more appealing



$$H = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

- Edge \rightarrow high frequency
- High pass filtering

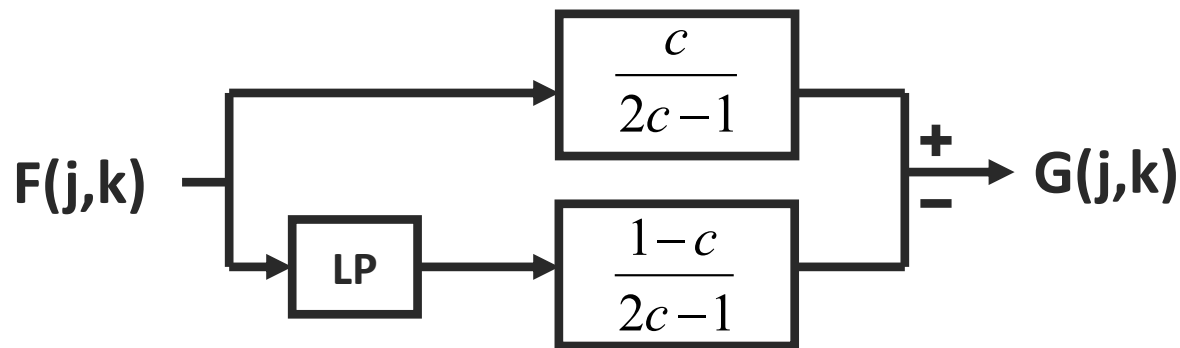
$$H = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

\rightarrow amplify the noise at the same time

Edge Crispening

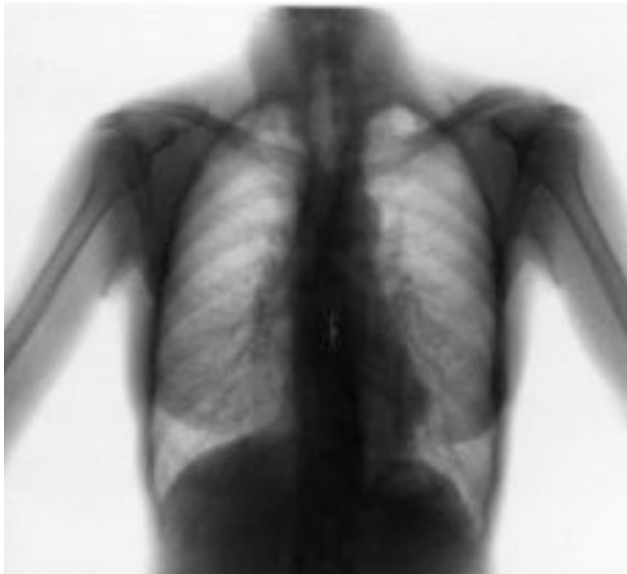
■ Unsharp Masking

- Appropriate combination of all-pass and low-pass filters

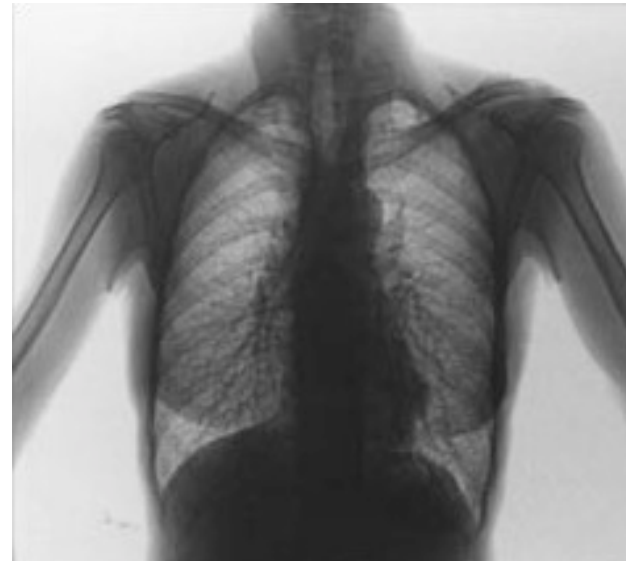


$$G(j,k) = \frac{c}{2c-1} F(j,k) - \frac{1-c}{2c-1} F_L(j,k), \quad \text{where } \frac{3}{5} \leq c \leq \frac{5}{6}$$

Edge Crispening



Original image



After sharpening
 $L=7, c=0.6$



(a) Normal resolution



(b) Low resolution



(c) Unsharp masking



Edge Detection

Edge Detection

■ Motivation

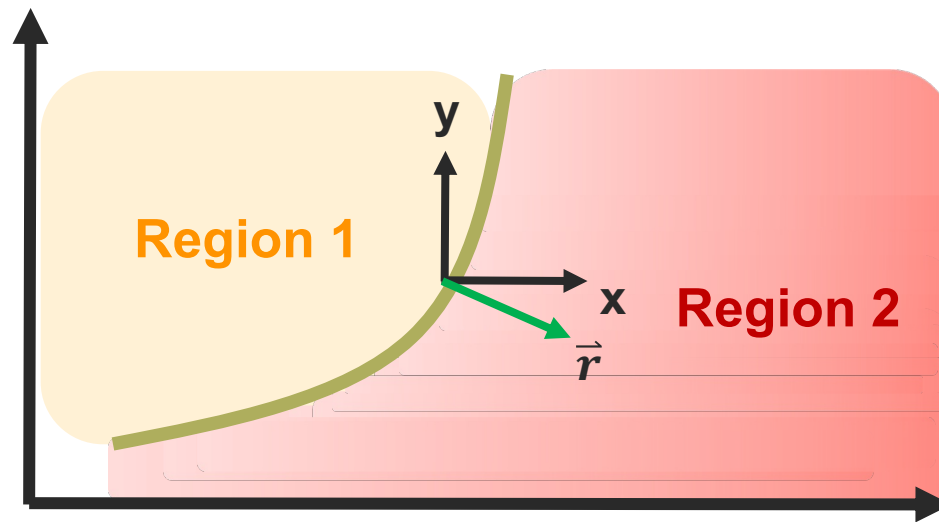
- Human eyes are more sensitive to edges
- Characterize object boundaries
- Fundamental step in image analysis
 - Segmentation, registration, identification, etc.

■ Edge description

- Model-based methods
 - Rarely used
- Non-parametric approaches
 - 1st and 2nd order derivatives

Edge Detection (1st order)

■ Orthogonal gradient generation



$$\frac{dF}{dr} = \frac{\partial F}{\partial x} \frac{\partial x}{\partial r} + \frac{\partial F}{\partial y} \frac{\partial y}{\partial r} = \begin{pmatrix} \frac{\partial F}{\partial x} & \frac{\partial F}{\partial y} \end{pmatrix} \cdot \begin{pmatrix} \frac{\partial x}{\partial r} \\ \frac{\partial y}{\partial r} \end{pmatrix} = \begin{pmatrix} \frac{\partial F}{\partial x} & \frac{\partial F}{\partial y} \end{pmatrix} \cdot \begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix}$$

Edge Detection (1st order)

■ Orthogonal gradient generation

- When $\begin{pmatrix} \frac{\partial F}{\partial x} \\ \frac{\partial F}{\partial y} \end{pmatrix}$ (gradient direction) is parallel to $\begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix}$

$\left\| \frac{dF}{dr} \right\|$ has maximum value

$$\Rightarrow \left\| \frac{dF}{dr} \right\| = \left\| \begin{pmatrix} \frac{\partial F}{\partial x} \\ \frac{\partial F}{\partial y} \end{pmatrix} \right\| = \sqrt{\left(\frac{\partial F}{\partial x} \right)^2 + \left(\frac{\partial F}{\partial y} \right)^2} \quad \theta = \tan^{-1} \left(\frac{\frac{\partial F}{\partial y}}{\frac{\partial F}{\partial x}} \right)$$

Magnitude

Orientation

Edge Detection (1st order)

■ Discrete case

○ Approximation I – 3 points

A_0	A_1	A_2
A_7	$F(j, k)$	A_3
A_6	A_5	A_4

■ Row gradient

$$\frac{\partial F}{\partial x}(j, k) \cong F(j, k) - F(j, k-1) = G_R(j, k)$$

■ Column gradient

$$\frac{\partial F}{\partial y}(j, k) \cong F(j, k) - F(j+1, k) = G_C(j, k)$$

$$\Rightarrow G(j, k) = \sqrt{G_R^2(j, k) + G_C^2(j, k)} \quad \theta(j, k) = \tan^{-1} \left(\frac{G_C(j, k)}{G_R(j, k)} \right)$$

Edge Detection (1st order)

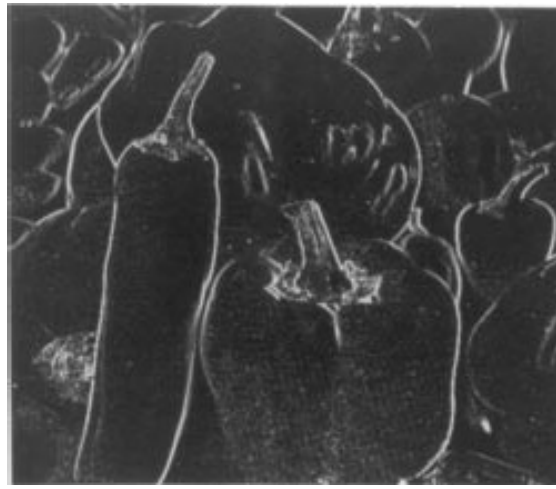
■ Example

$$G_R(j, k) = F(j, k) - F(j, k - 1)$$

$$G_C(j, k) = F(j, k) - F(j + 1, k)$$



Original image



Horizontal magnitude



Vertical magnitude

Edge Detection (1st order)

■ Discrete case

○ Approximation II – 4 points

○ Roberts cross differentiation (0~90→45~135)

A_0	A_1	A_2
A_7	$F(j, k)$	A_3
A_6	A_5	A_4

■ Row gradient

$$G_1(j, k) = F(j, k) - F(j+1, k+1)$$

■ Column gradient

$$G_2(j, k) = F(j, k+1) - F(j+1, k)$$

$$\Rightarrow G(j, k) = \sqrt{G_1^2(j, k) + G_2^2(j, k)} \quad \theta(j, k) = \tan^{-1} \left(\frac{G_2(j, k)}{G_1(j, k)} \right) + \frac{\pi}{4}$$

Edge Detection (1st order)

■ Discrete case

○ Approximation III – 9points

A_0	A_1	A_2
A_7	$F(j, k)$	A_3
A_6	A_5	A_4

■ Row gradient

$$G_R(j, k) = \frac{1}{K+2} [(A_2 + KA_3 + A_4) - (A_0 + KA_7 + A_6)]$$

■ Column gradient

$$G_C(j, k) = \frac{1}{K+2} [(A_0 + KA_1 + A_2) - (A_6 + KA_5 + A_4)]$$

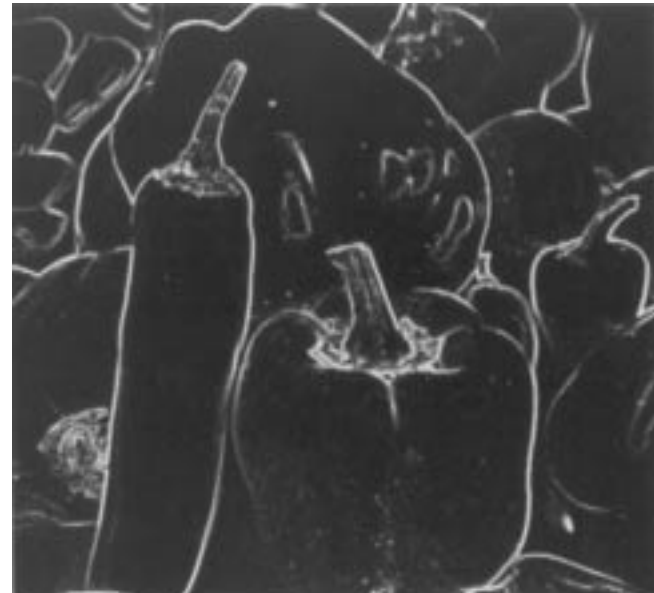
$$\Rightarrow G(j, k) = \sqrt{G_R^2(j, k) + G_C^2(j, k)} \quad \theta(j, k) = \tan^{-1} \left(\frac{G_C(j, k)}{G_R(j, k)} \right)$$

■ K=1: Prewitt Mask ; K=2: Sobel Mask

Edge Detection (1st order)



Roberts magnitude



Roberts square root

Edge Detection (1st order)



- Compute row and column gradients
- ◆ Analyze the statistics of the magnitude (histogram)

- Pick a threshold T
- If $G(j,k) \geq T$
 - set it as an edge point
 - otherwise (If $G(j,k) < T$)
 - non-edge point
- Q: How to select T ?
- ◆ Examine the cumulative distribution function

Canny Edge Detector

■ Why Canny?

○ Good Detection

- The optimal detector must minimize the probability of false positives as well as false negatives

○ Good Localization

- The edges detected must be as close as possible to the true edges

○ Single Response Constraint

- The detector must return one point only for each edge point

Canny Edge Detector

■ Five Steps:

- **Noise reduction**
- Compute gradient magnitude and orientation
- Non-maximal suppression
- Hysteretic thresholding
- Connected component labeling method



Smooth the image
with a Gaussian filter



Example:

5x5 Gaussian filter with $\sigma = 1.4$

$$F_{NR} = \frac{1}{159} \begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} * F$$



Canny Edge Detector

■ Five Steps:

- Noise reduction
- **Compute gradient magnitude and orientation**
- Non-maximal suppression
- Hysteretic thresholding
- Connected component labeling method

$$G(j,k) = \sqrt{G_R^2(j,k) + G_C^2(j,k)}$$

$$\theta(j,k) = \tan^{-1} \left(\frac{G_C(j,k)}{G_R(j,k)} \right)$$



Magnitude

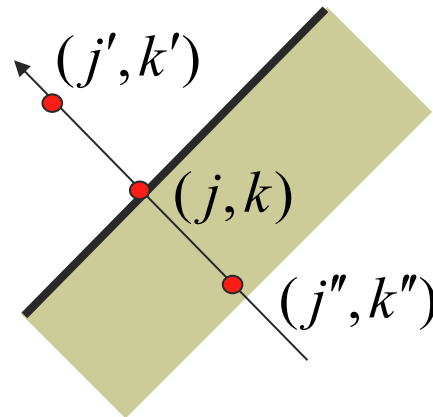
Canny Edge Detector

■ Five Steps:

- Noise reduction
- Compute gradient magnitude and orientation
- **Non-maximal suppression**
- Hysteretic thresholding
- Connected component labeling method

Search the nearest neighbors (j',k') and (j'',k'') along the edge normal

$$G_N(j,k) = \begin{cases} G(j,k) & \text{if } G(j,k) > G(j',k') \\ & \text{and } G(j,k) > G(j'',k'') \\ 0 & \text{otherwise} \end{cases}$$



Canny Edge Detector

■ Five Steps:

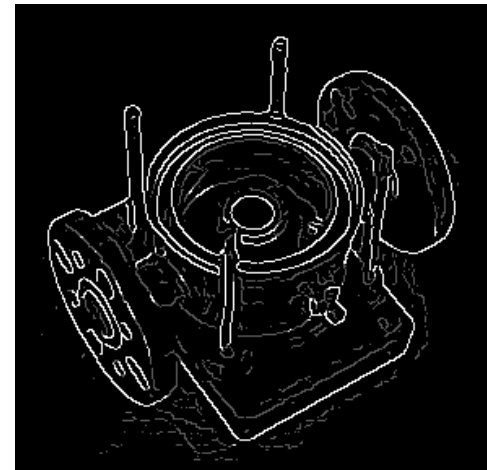
- Noise reduction
- Compute gradient magnitude and orientation
- Non-maximal suppression
- **Hysteretic thresholding**
- Connected component labeling method

Label each pixels according to two threshold: T_H, T_L

$G_N(x, y) \geq T_H$ Edge Pixel

$T_H > G_N(x, y) \geq T_L$ Candidate Pixel

$G_N(x, y) < T_L$ Non-edge Pixel

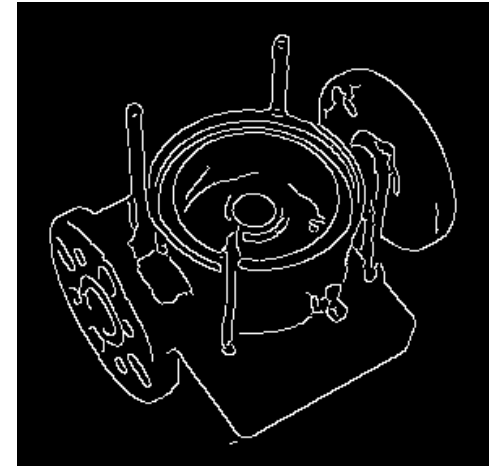


Canny Edge Detector

■ Five Steps:

- Noise reduction
- Compute gradient magnitude and orientation
- Non-maximal suppression
- Hysteretic thresholding
- **Connected component labeling method**

If a candidate pixel is connected to an edge pixel directly or via another candidate pixel then it is declared as an edge pixel



Edge Map

Canny Edge Detector



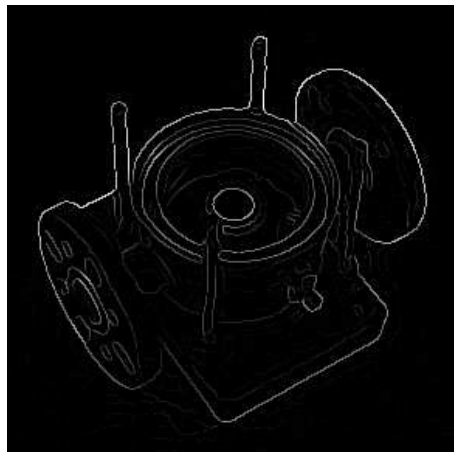
Input



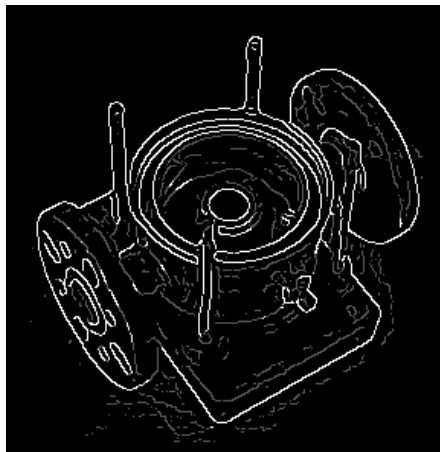
Step 1



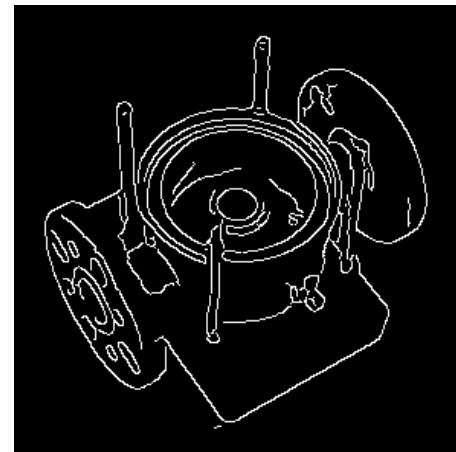
Step 2



Step 3



Step 4



Step 5

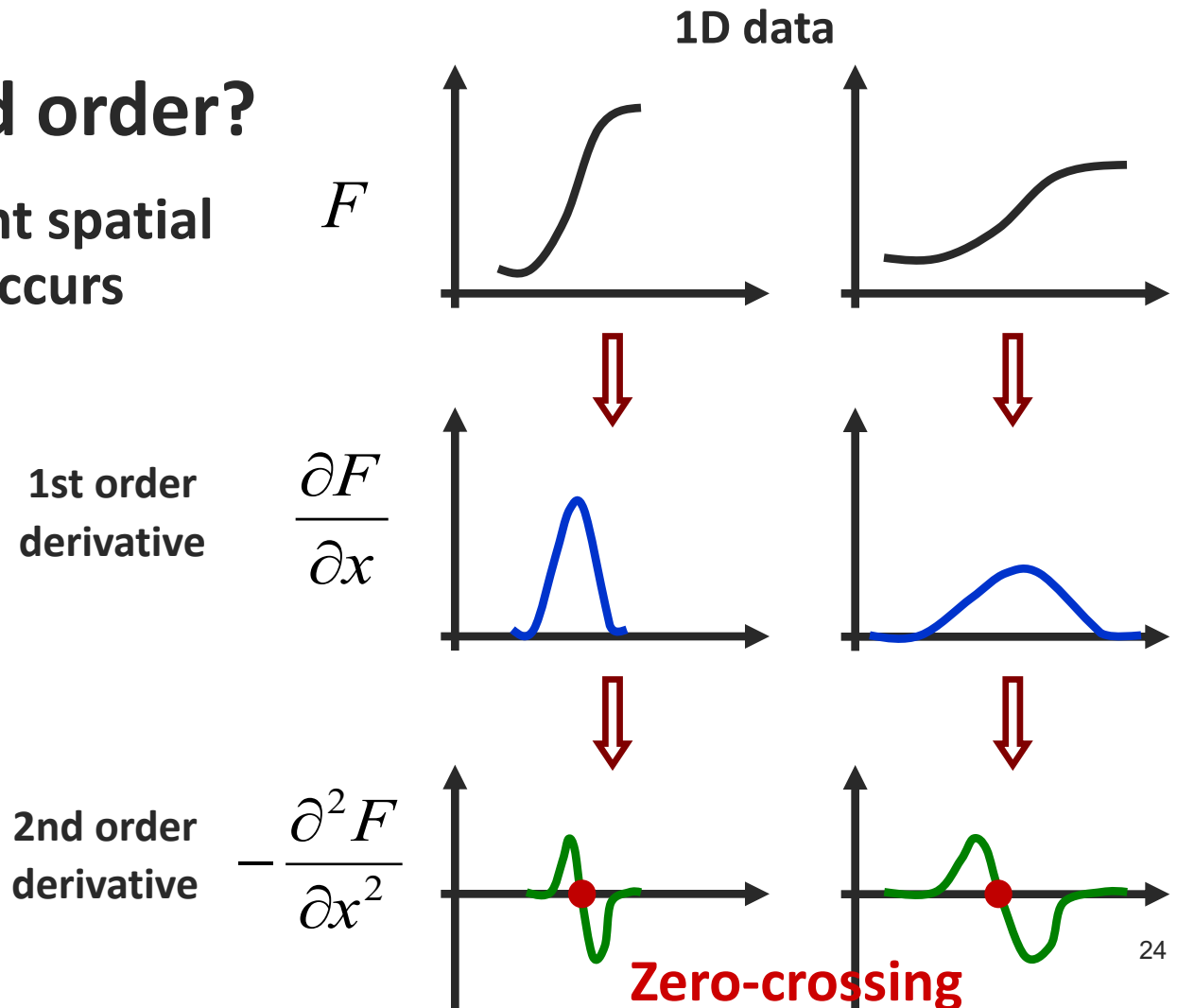


Edge Detection – Part II

Edge Detection (2nd order)

■ Why 2nd order?

- Significant spatial change occurs



Edge Detection (2nd order)

■ Laplacian Generation

$$\nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} \quad \Rightarrow \quad \nabla^2 F(x, y) = \frac{\partial^2 F(x, y)}{\partial x^2} + \frac{\partial^2 F(x, y)}{\partial y^2}$$

■ Discrete Approximation

$$-\frac{\partial^2}{\partial x^2} \cong [-1 \quad 2 \quad -1] \quad \Rightarrow \quad 2f(x) - (f(x+h) + f(x-h))$$

○ By Taylor series expansion

$$\begin{aligned} & 2f(x) - (f(x+h) + f(x-h)) \\ = & 2f(x) - \left[f(x) + hf'(x) + \frac{h^2}{2} f''(x) + f(x) + (-h)f'(x) + \frac{h^2}{2} f''(x) + \dots \right] \\ \cong & -h^2 f''(x) \end{aligned}$$

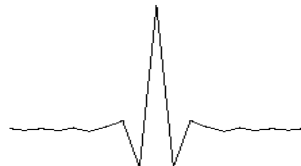
Edge Detection (2nd order)

■ Discrete Approximation

$$-\frac{\partial^2}{\partial x^2} \cong \begin{bmatrix} -1 & 2 & -1 \end{bmatrix} \quad -\frac{\partial^2}{\partial y^2} \cong \begin{bmatrix} -1 & 2 & -1 \end{bmatrix}^T$$

○ combine together

$$-\nabla^2 \cong \frac{1}{4} \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}; \quad \nabla^2 \cong \frac{1}{4} \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

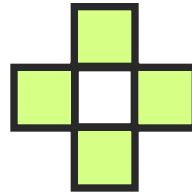


Edge Detection (2nd order)

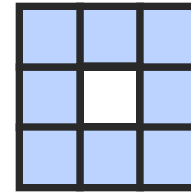
■ Laplacian impulse response

○ four-neighbor

$$H = \frac{1}{4} \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



4-neighbor



8-neighbor

○ eight-neighbor

$$H = \frac{1}{8} \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

non-separable

$$H = \frac{1}{8} \begin{bmatrix} -2 & 1 & -2 \\ 1 & 4 & 1 \\ -2 & 1 & -2 \end{bmatrix}$$

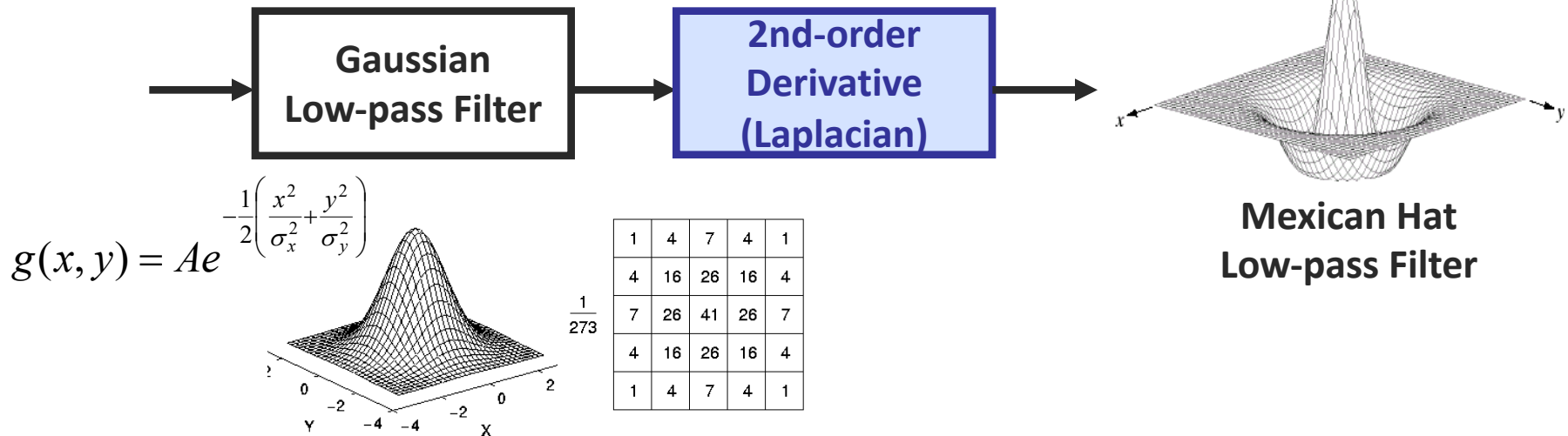
separable

$$H_1 = \frac{1}{8} \begin{bmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 2 & -1 \end{bmatrix}$$

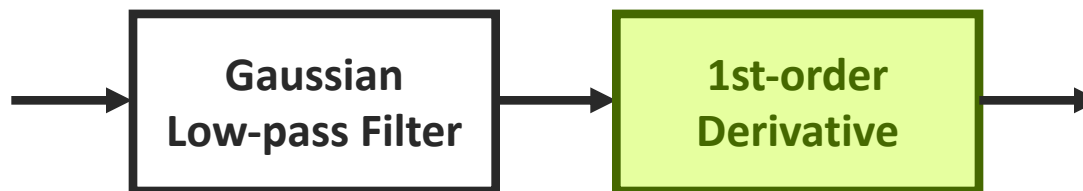
$$H_2 = \frac{1}{8} \begin{bmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{bmatrix}$$

Edge Detection (2nd order)

■ Laplacian of Gaussian (LOG)

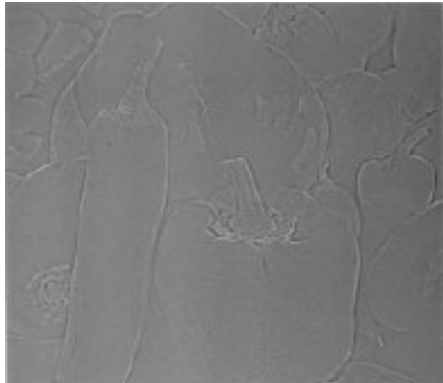


■ Difference of Gaussians (DOG)



Edge Detection (2nd order)

■ Examples



Four-neighbor



Eight-neighbor



Separable
eight-neighbor



Laplacian of
Gaussian (LOG)

Are we done yet?

Edge Detection (2nd order)

■ 2nd Order Edge Detection



○ How to detect zero-crossing?

- many ways

Edge Detection (2nd order)

■ Zero-crossing



3 steps:

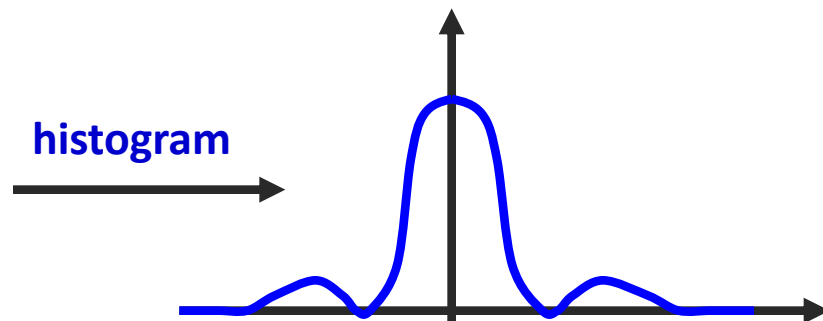
- Generate the histogram of G
- Set up a threshold to separate zero and non-zero, output as G'
- For $G'(j,k)=0$, decide whether (j,k) is a zero-crossing point

Edge Detection (2nd order)

■ Zero-crossing

○ 3 steps:

- **Generate the histogram of G**
- Set up a threshold to separate zero and non-zero to get G'
- For $G'(j,k)=0$, decide whether (j,k) is a zero-crossing point



Edge Detection (2nd order)

■ Zero-crossing

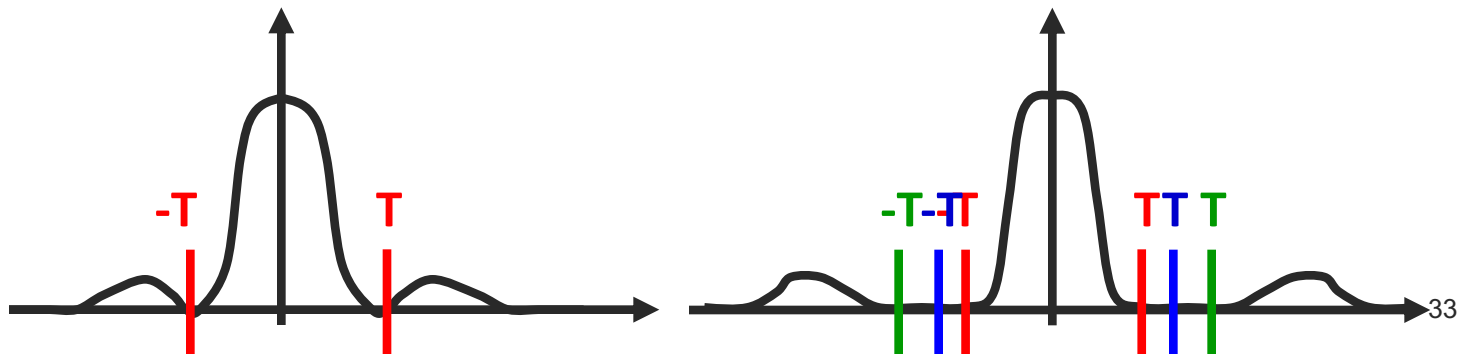
○ 3 steps:

■ Generate the histogram of G

■ **Set up a threshold to separate zero and non-zero to get G'**

$$|G(j,k)| \leq T \Rightarrow G'(j,k) = 0$$

■ For $G'(j,k)=0$, decide whether (j,k) is a zero-crossing point



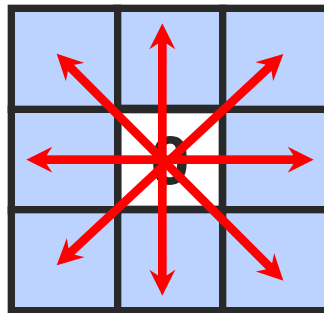
Edge Detection (2nd order)

■ Zero-crossing

○ 3 steps:

- Generate the histogram of G
- Set up a threshold to separate zero and non-zero to get G'
- For $G'(j,k)=0$, decide whether (j,k) is a zero-crossing point → edge map

$$G'(j,k) = 0$$



e.g. $\{-1,0,1\}$

Edge Detection (2nd order)

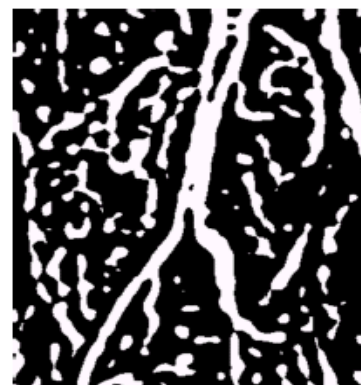
■ Example



Original



Laplacian



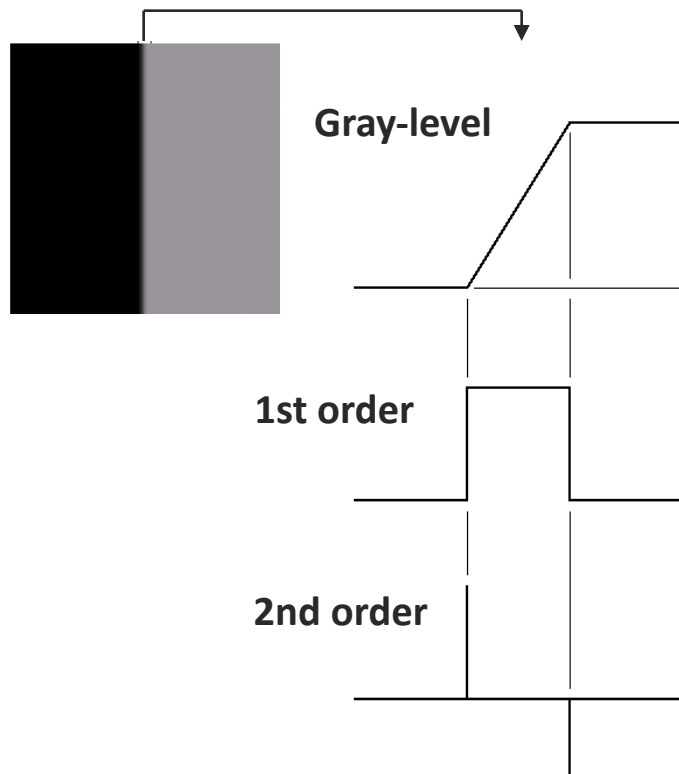
Thresholded



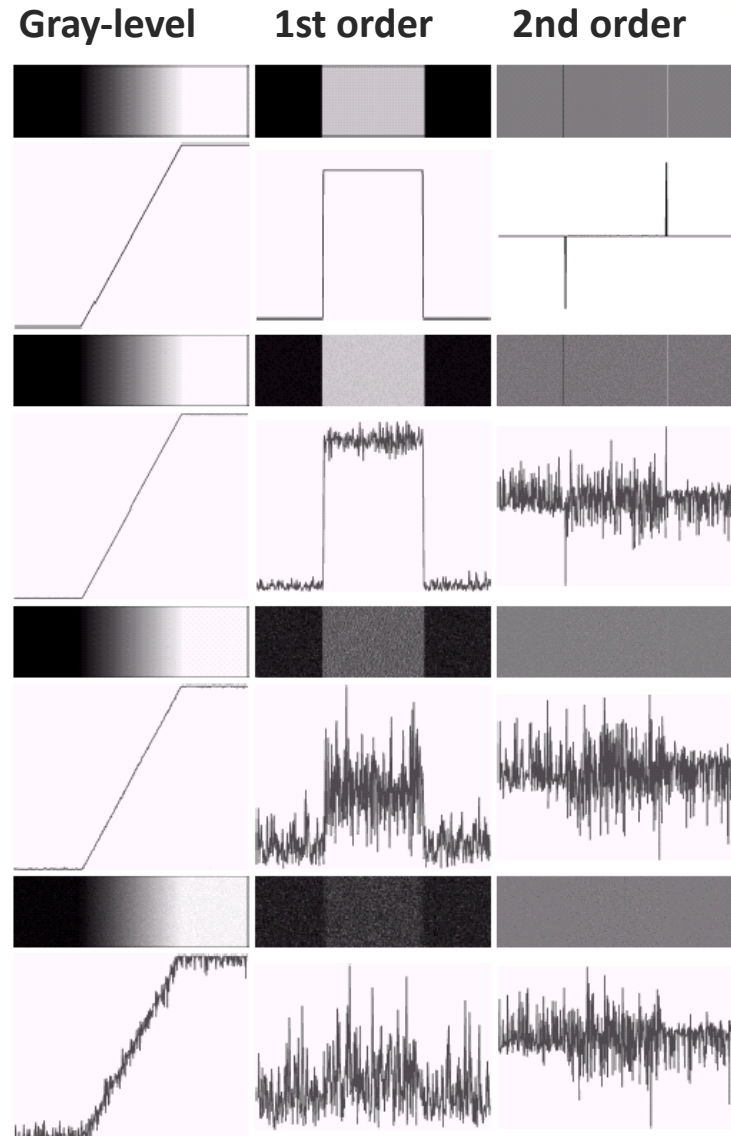
Edge map

Edge Detection

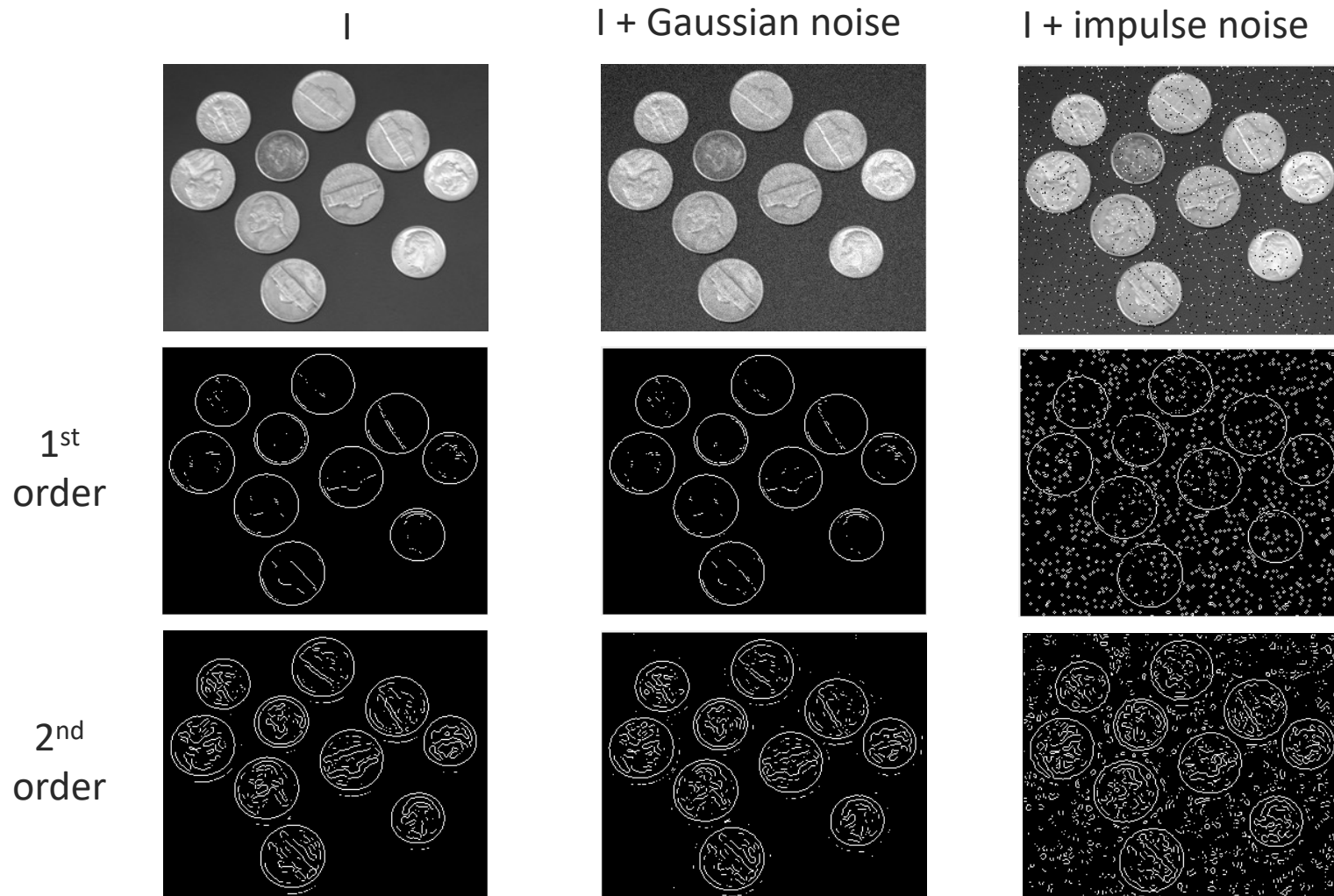
Noisy image



“Pre-processing”

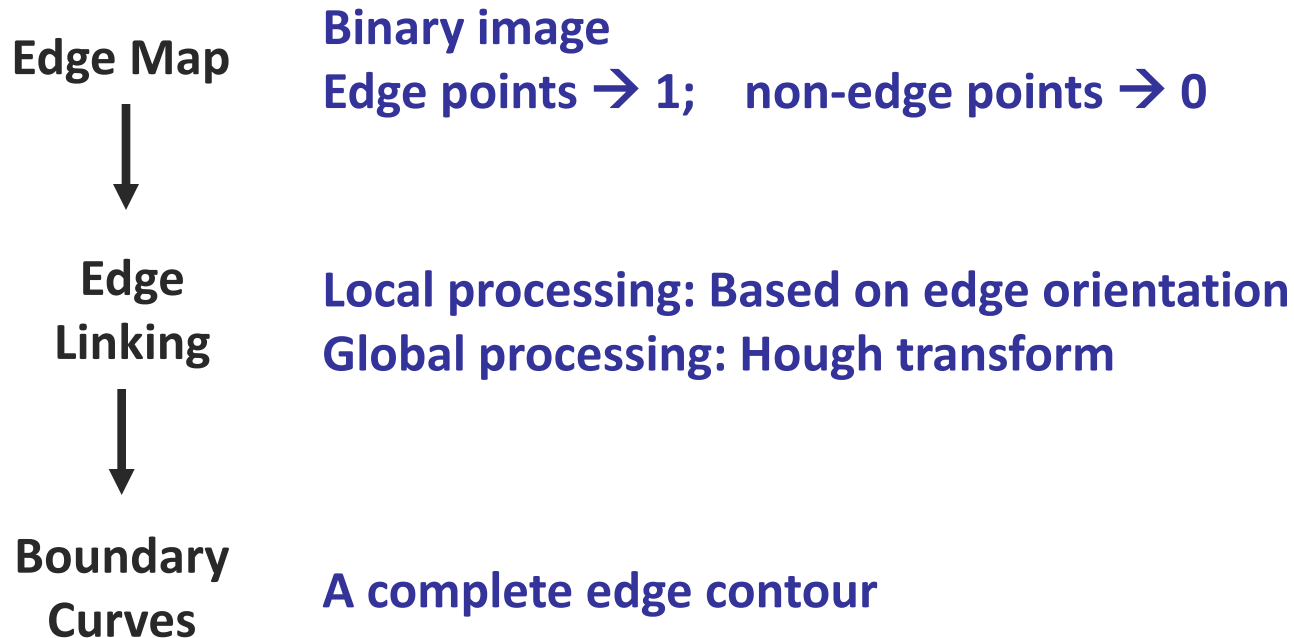


Edge Detection



Edge Detection

■ Post-Processing



How can we detect lines?

■ Option 1:

- Search for the line at every possible position/orientation

■ Option 2:

- Hough transform
 - performed after edge detection
- Advantages
 - tolerant of gaps in the edges
 - relatively unaffected by noise
 - unaffected by occlusion in the image

Hough Transform

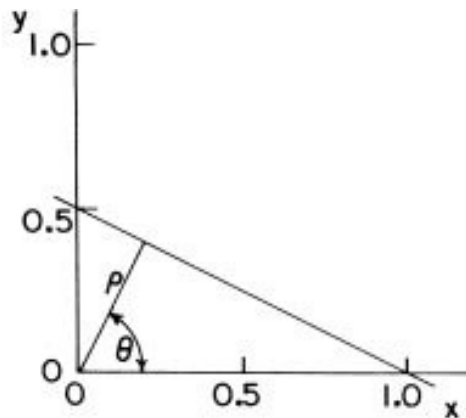
- A straight line can be represented as

$$y = mx + b$$

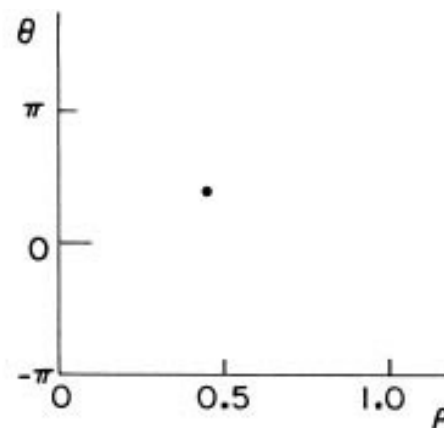
- fails in case of vertical lines

- A more useful representation is

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



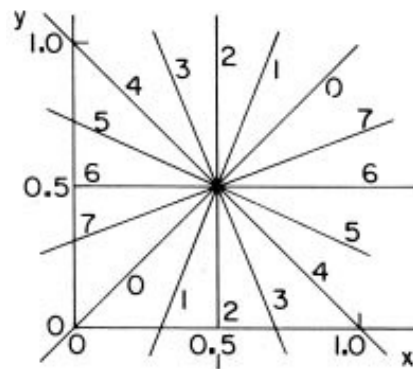
(a) Parametric line



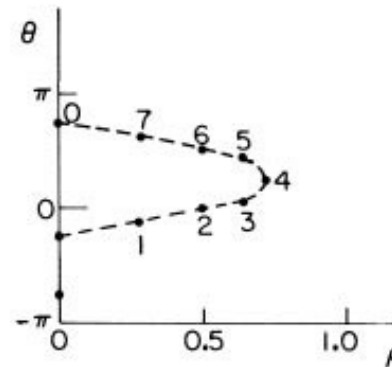
(b) Hough transform of (a)

Hough Transform

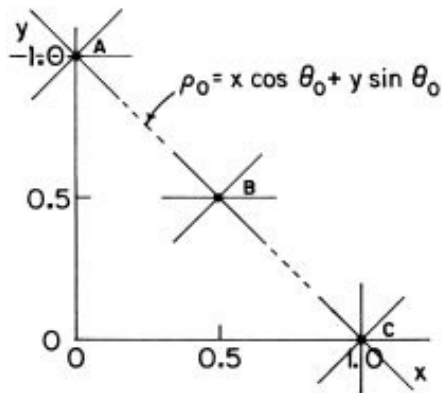
$$\rho = x \cos \theta + y \sin \theta$$



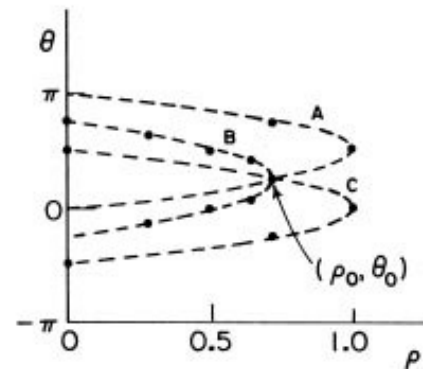
(c) Family of lines, common point



(d) Hough transform of (c)



(e) Colinear points



(f) Hough transform of (e)

A decorative graphic consisting of a thin gold circle on the left side. A horizontal bar, colored with a gold-to-white gradient, extends from the circle across the top of the slide. A large black left square bracket is positioned on the left side of the bar, and a large gold right square bracket is on the right side.

Review

Review

■ Noise Cleaning

- Uniform noise → low-pass filtering
- Impulse noise → non-linear filtering
- Mixed noise → ?

■ Edge Crispening

- Unsharp masking

■ Edge Detection

- 1st-order edge detection -- threshold
- 2nd-order edge detection -- zero-crossing