



# Image Segmentation I

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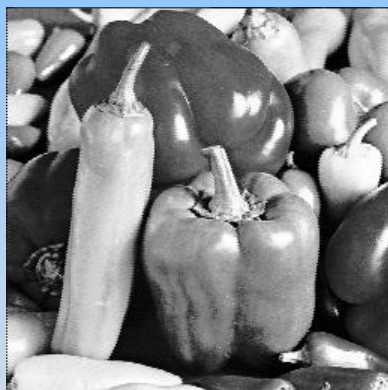
# Preview

- Segmentation is to subdivide an image into its component regions or objects.
- Segmentation should stop when the objects of interest in an application have been isolated.



# Preview

- Example





# Preview

- Segmentation algorithms generally are based on one of 2 basis properties of intensity values
  - *discontinuity* : to partition an image based on sharp changes in intensity (such as edges)
  - *similarity* : to partition an image into regions that are similar according to a set of predefined criteria.



# Topic

## Edge Detection

- Gradient-based methods
- Canny edge detector
- Hough transform





# Detection of Discontinuities

- Detect the three basic types of gray-level discontinuities

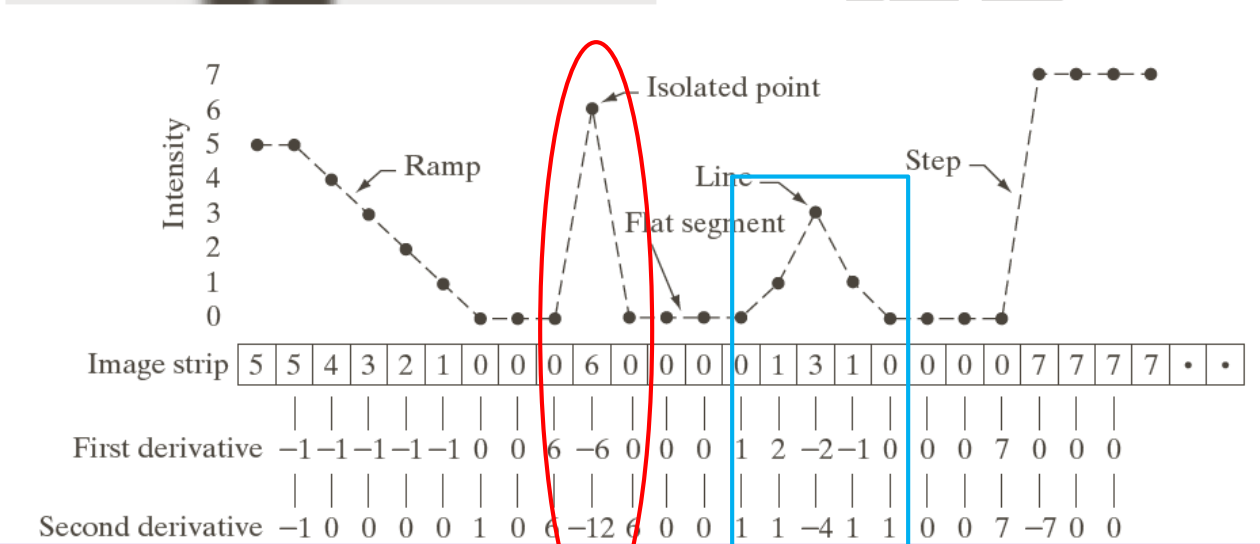
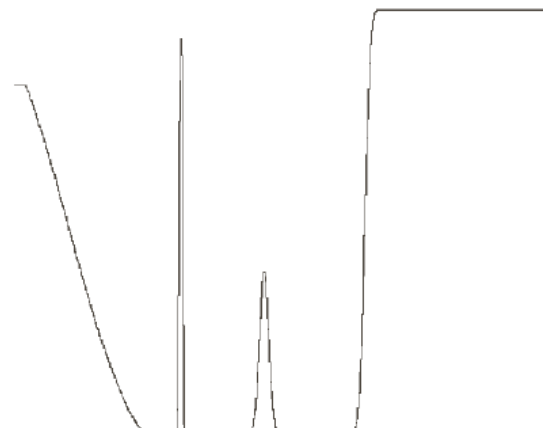
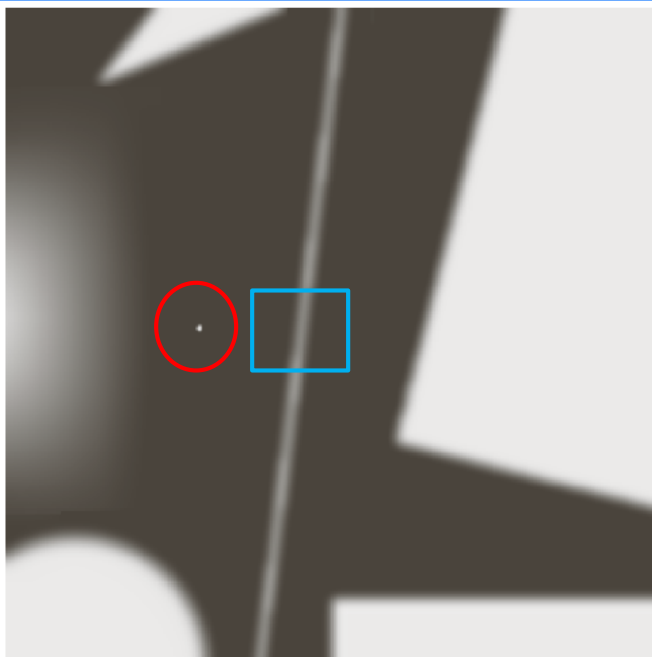
*points , lines , edges*



# Detection of Discontinuities

- What are their characteristics of points, lines, and edges ?









# Detection of Discontinuities

- We can arrive at the following conclusions:
  1. 1-st order derivatives usually produce **thicker edges**;
  2. 2-nd order derivatives have a **stronger** response to fine details, such as thin lines, isolated points, and noise.
  3. 2-nd order derivatives produce a **double-edge** response at ramp and step transitions in intensity.



-1	-1	-1
-1	8	-1
-1	-1	-1

# Point Detection

A point can be detected at the location where has a stronger 2-nd derivatives, which can be implemented by convolving with the mark and having response:

$$|R| \geq T$$

where

T is a nonnegative threshold

R is the sum of products of the coefficients with the gray levels contained in the region encompassed by the mark.



# Line Detection

-1	-1	-1	-1	-1	2	-1	2	-1	2	-1	-1
2	2	2	-1	2	-1	-1	2	-1	-1	2	-1
-1	-1	-1	2	-1	-1	-1	2	-1	-1	-1	2
Horizontal			$+45^\circ$			Vertical			$-45^\circ$		

- Horizontal mask will result with max response when a line passed through the middle row of the mask with a constant background.
- the similar idea is used with other masks.
- note: the preferred direction of each mask is weighted with a larger coefficient (i.e., 2) than other possible directions.

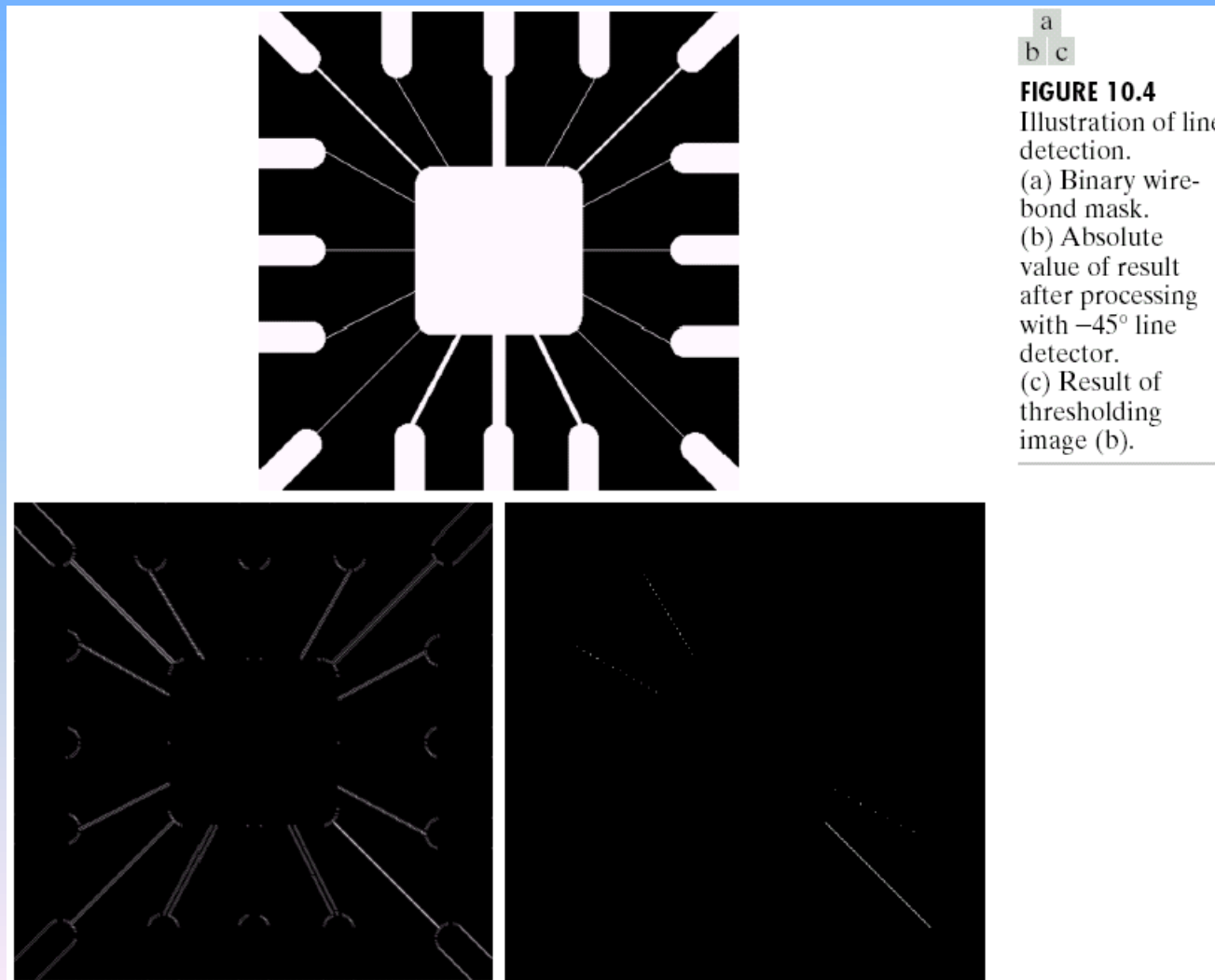


# Line Detection

- If we are interested in detecting all lines in an image in one direction, we simply run corresponding mask through the image and threshold the absolute value of the result.
- The points that are left are the **strongest responses**, which, for lines **one pixel thick**, correspond closest to the direction defined by the mask.



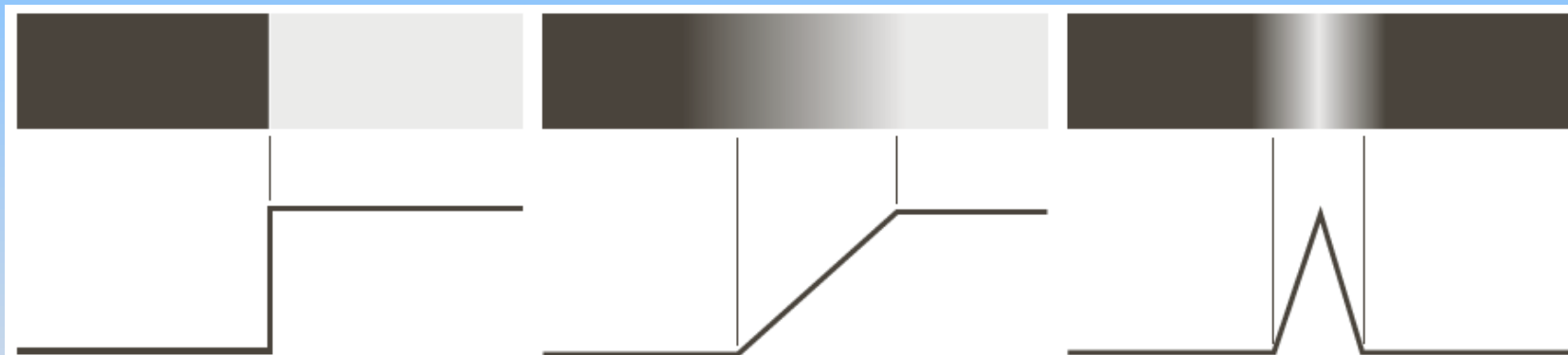
# Example





# Focus on Edge

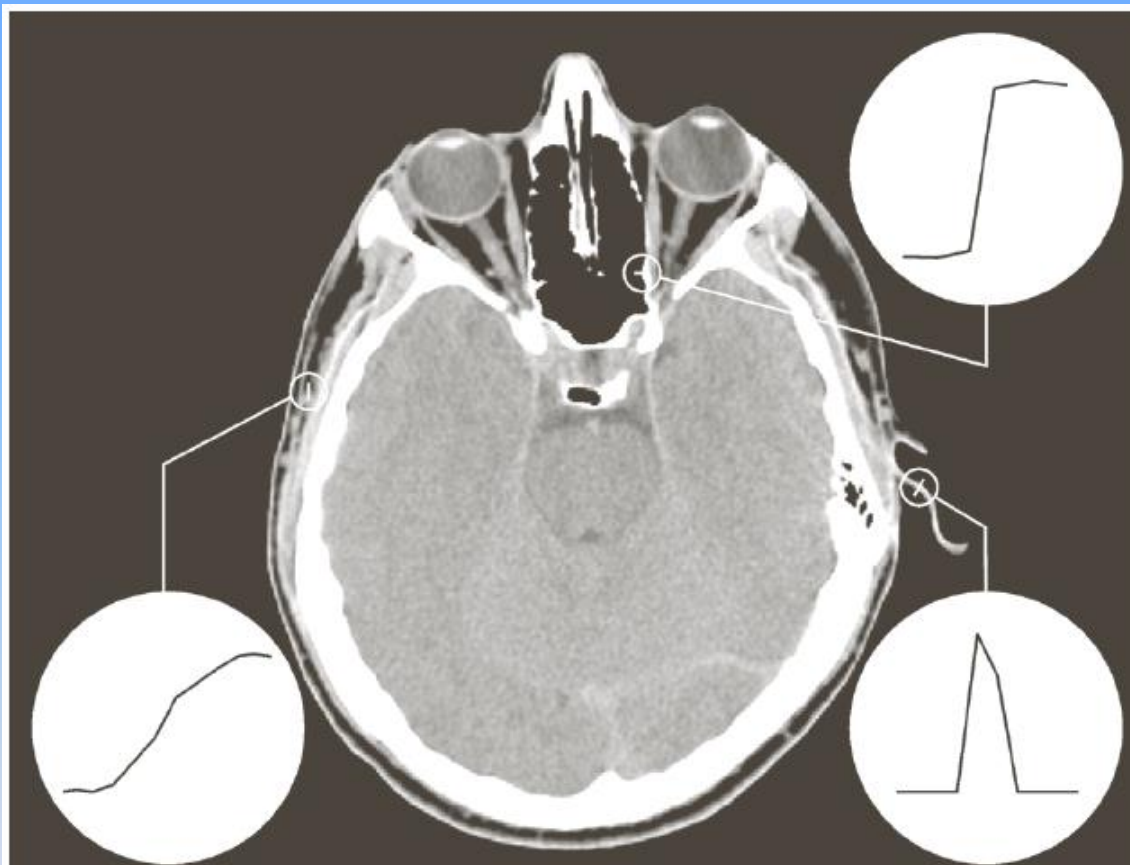
- What is an edge ?



a b c

**FIGURE 10.8**

From left to right, models (ideal representations) of a step, a ramp, and a roof edge, and their corresponding intensity profiles.



**FIGURE 10.9** A  $1508 \times 1970$  image showing (zoomed) actual ramp (bottom, left), step (top, right), and roof edge profiles. The profiles are from dark to light, in the areas indicated by the short line segments shown in the small circles. The ramp and “step” profiles span 9 pixels and 2 pixels, respectively. The base of the roof edge is 3 pixels. (Original image courtesy of Dr. David R. Pickens, Vanderbilt University.)

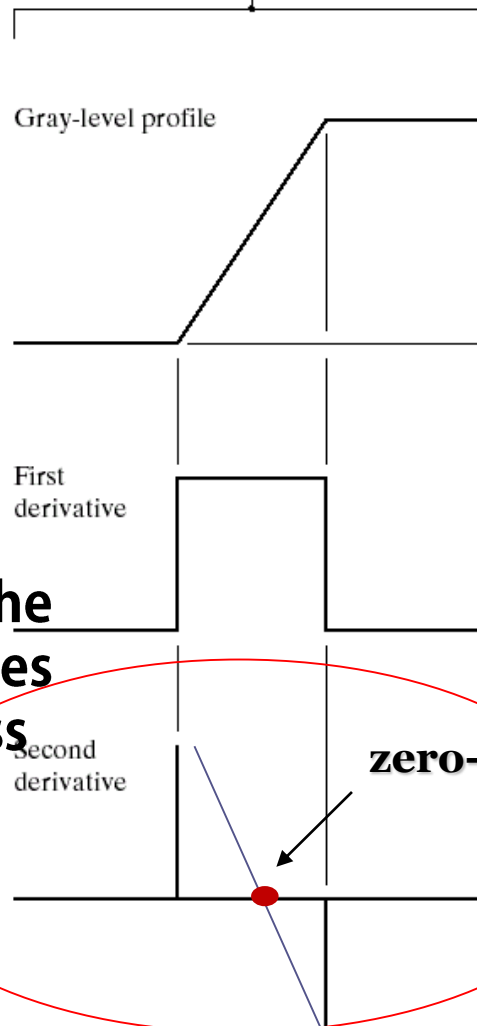


# Character of an edge

a b

**FIGURE 10.6**

(a) Two regions separated by a vertical edge.  
 (b) Detail near the edge, showing a gray-level profile, and the first and second derivatives of the profile.



**An imaginary straight line joining the extreme positive and negative values of the second derivative would cross zero near the midpoint of the edge**





## Review the conclusions:

- We can arrive at the following conclusions:

1. *1-st order derivatives usually produce **thicker edges**;*
2. 2-nd order derivatives have a **stronger** response to fine detail, such as thin lines, isolated points, and noise.
3. *2-nd order derivatives produce a **double-edge response** at ramp and step transitions in intensity.*



# Edge detection

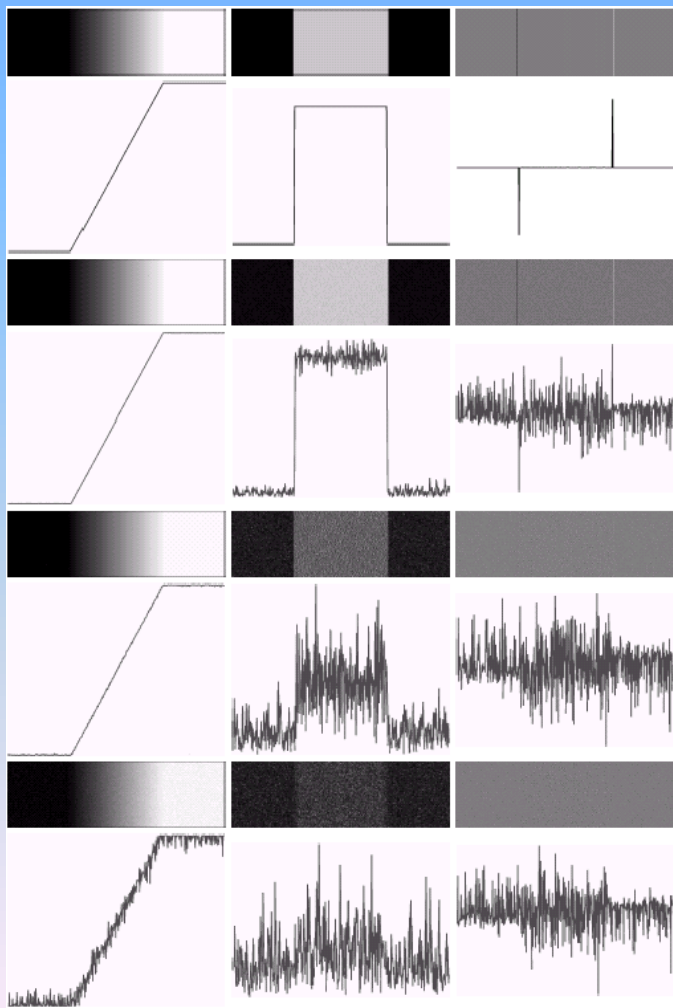
- We find a way to detect edges! Yeh!  
Just use 1-st derivatives or zero-crossing points of 2-nd derivatives.

## Really?





## How about noisy image?



First column: images and gray-level profiles of a ramp edge corrupted by random Gaussian noise of mean 0 and  $\sigma = 0.0, 0.1, 1.0$  and  $10.0$ , respectively.

### *Notation:*

Fairly little noise can have such a significant impact on the two key derivatives used for edge detection in images

***Image smoothing is necessary!***



# Gradient-based edge detection

- Procedure:
  1. *Image smoothing for noise reduction.*
  2. *Detection of edge points.* Using 1-st or 2-nd derivatives.
  3. *Edge localization.* To select from the candidate edge points that are true members of edge set.



$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

# 1-st order Gradient Operator

- First derivatives are implemented using the **magnitude of the gradient**.

$$\begin{aligned} \nabla f &= \text{mag}(\nabla f) = [G_x^2 + G_y^2]^{1/2} \\ &= \left[ \left( \frac{\partial f}{\partial x} \right)^2 + \left( \frac{\partial f}{\partial y} \right)^2 \right]^{1/2} \end{aligned}$$

commonly approx.

$$\nabla f \approx |G_x| + |G_y|$$

the magnitude becomes nonlinear



# Gradient Masks

$z_1$	$z_2$	$z_3$
$z_4$	$z_5$	$z_6$
$z_7$	$z_8$	$z_9$

-1	0	0	-1
0	1	1	0

Roberts

-1	-1	-1	-1	0	1
0	0	0	-1	0	1
1	1	1	-1	0	1

Prewitt

-1	-2	-1	-1	0	1
0	0	0	-2	0	2
1	2	1	-1	0	1

Sobel



# Diagonal edges detect mask

0	1	1	-1	-1	0
-1	0	1	-1	0	1
-1	-1	0	0	1	1

Prewitt

0	1	2	-2	-1	0
-1	0	1	-1	0	1
-2	-1	0	0	1	2

Sobel



# Example

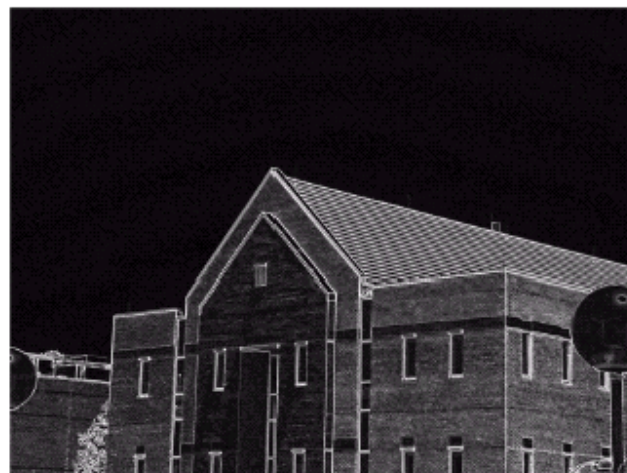
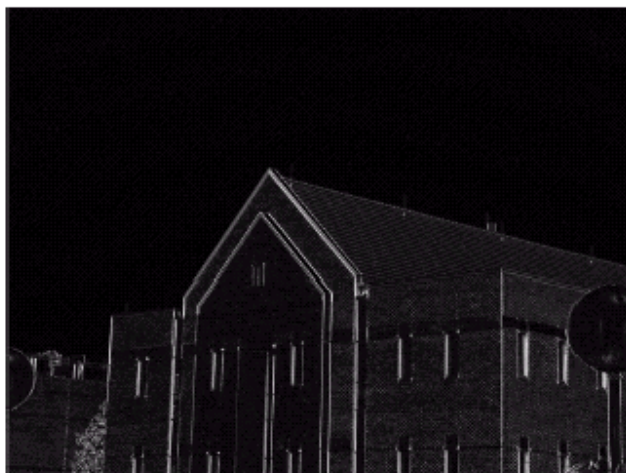
a b  
c d

**FIGURE 10.10**

(a) Original image. (b)  $|G_x|$ , component of the gradient in the  $x$ -direction.

(c)  $|G_y|$ , component in the  $y$ -direction.

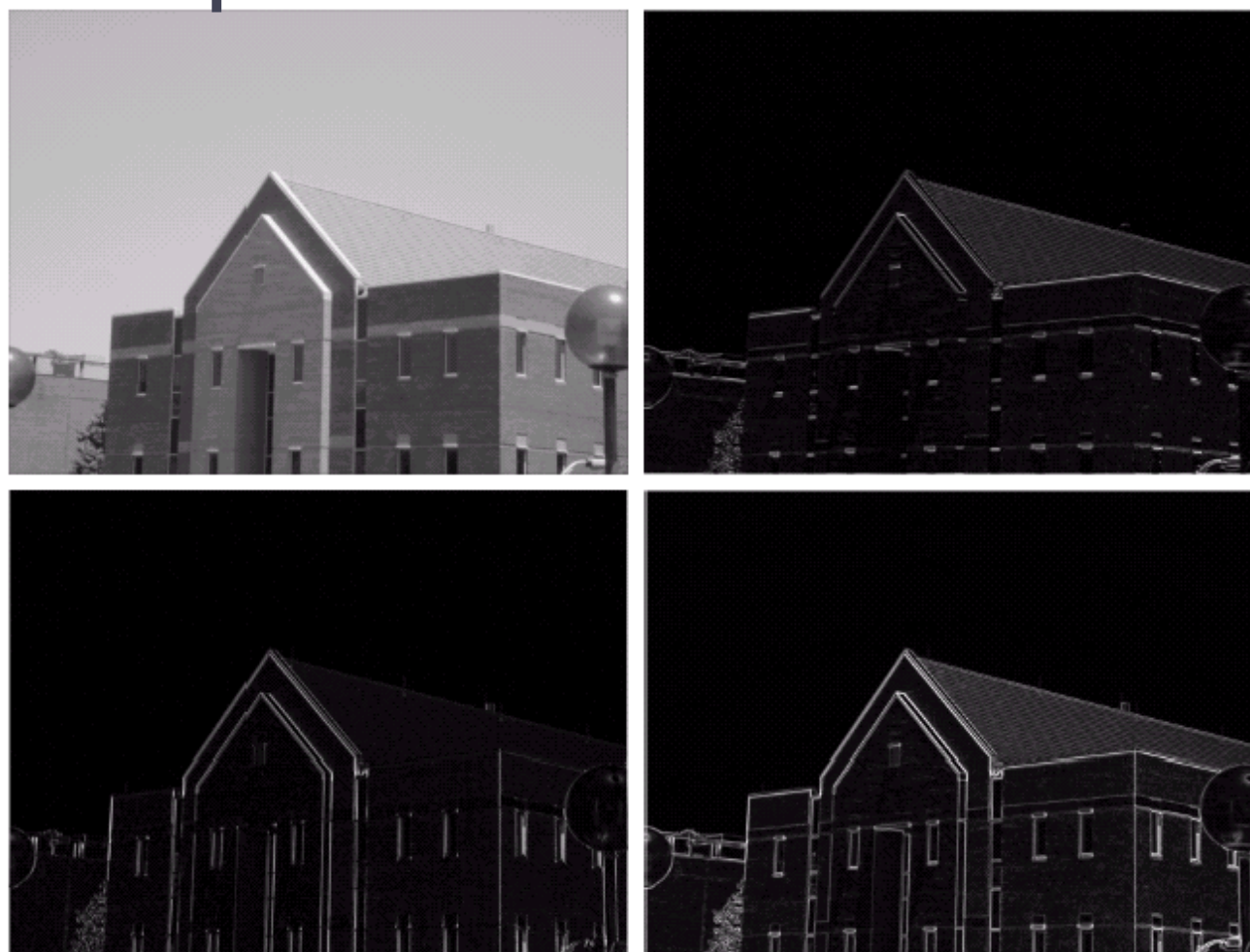
(d) Gradient image,  $|G_x| + |G_y|$ .







## Example



a	b
c	d

**FIGURE 10.11**  
 Same sequence as in Fig. 10.10, but with the original image smoothed with a  $5 \times 5$  averaging filter.



# Example



a b

**FIGURE 10.12**  
Diagonal edge  
detection.

(a) Result of using  
the mask in  
Fig. 10.9(c).

(b) Result of using  
the mask in  
Fig. 10.9(d). The  
input in both cases  
was Fig. 10.11(a).



## 2-nd order gradient operator

- Laplacian

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

$$\nabla^2 f = [f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) - 4f(x, y)]$$



## 2-nd order gradient operator

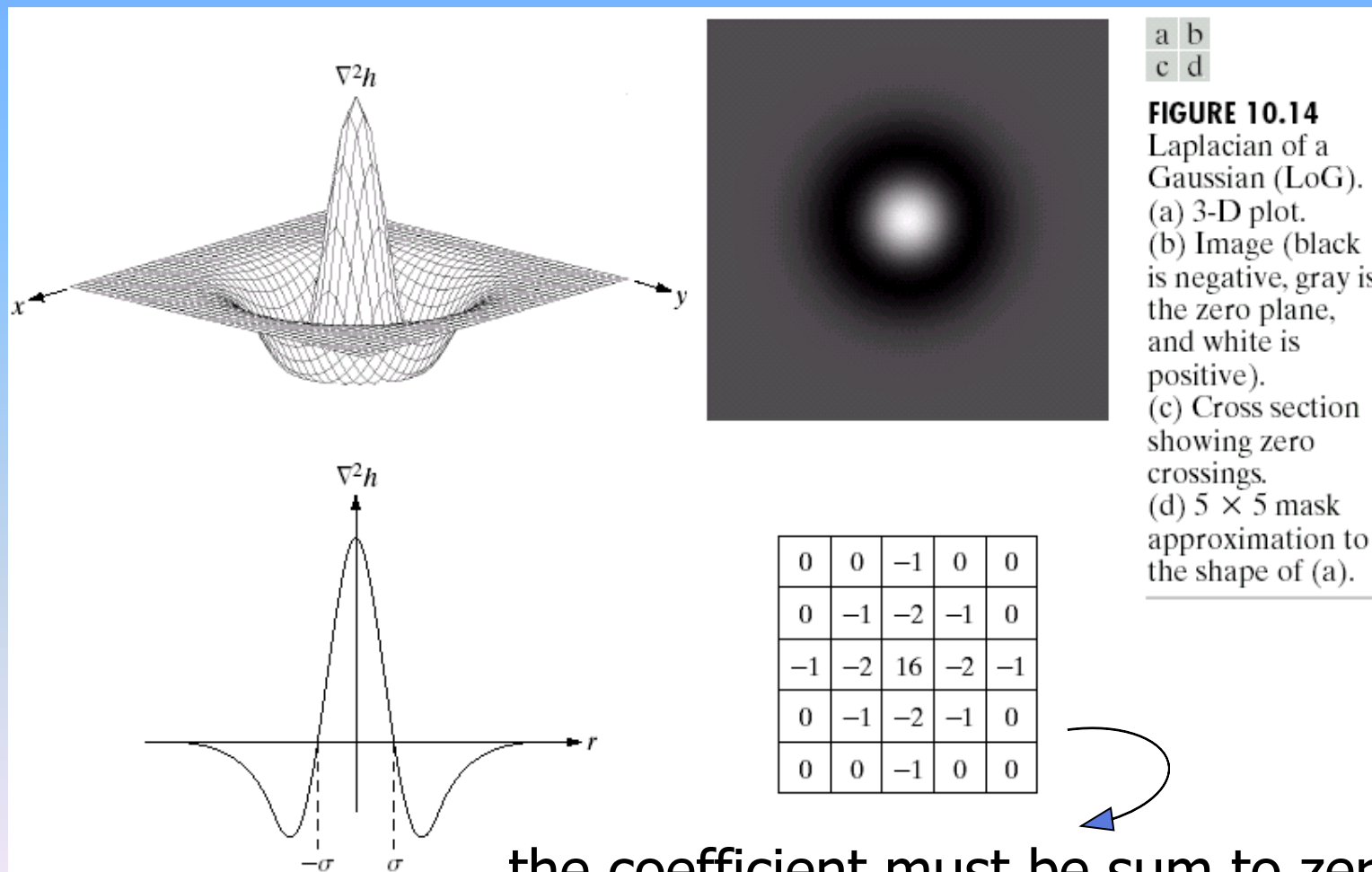
- Laplacian of Gaussian (LoG)
  1. First using Gaussian function to smooth image, then applying Laplacian operator.

According to linear property, we can change the order.

$$\nabla^2(G(x, y) * I(x, y)) = (\nabla^2 G(x, y)) * I(x, y)$$



# LoG



the coefficient must be sum to zero



## 2-nd order gradient operator

- Laplacian of Gaussian (LoG)
  2. Calculate the zero-crossing points.
  3. Threshold.



## 2-nd order gradient operator

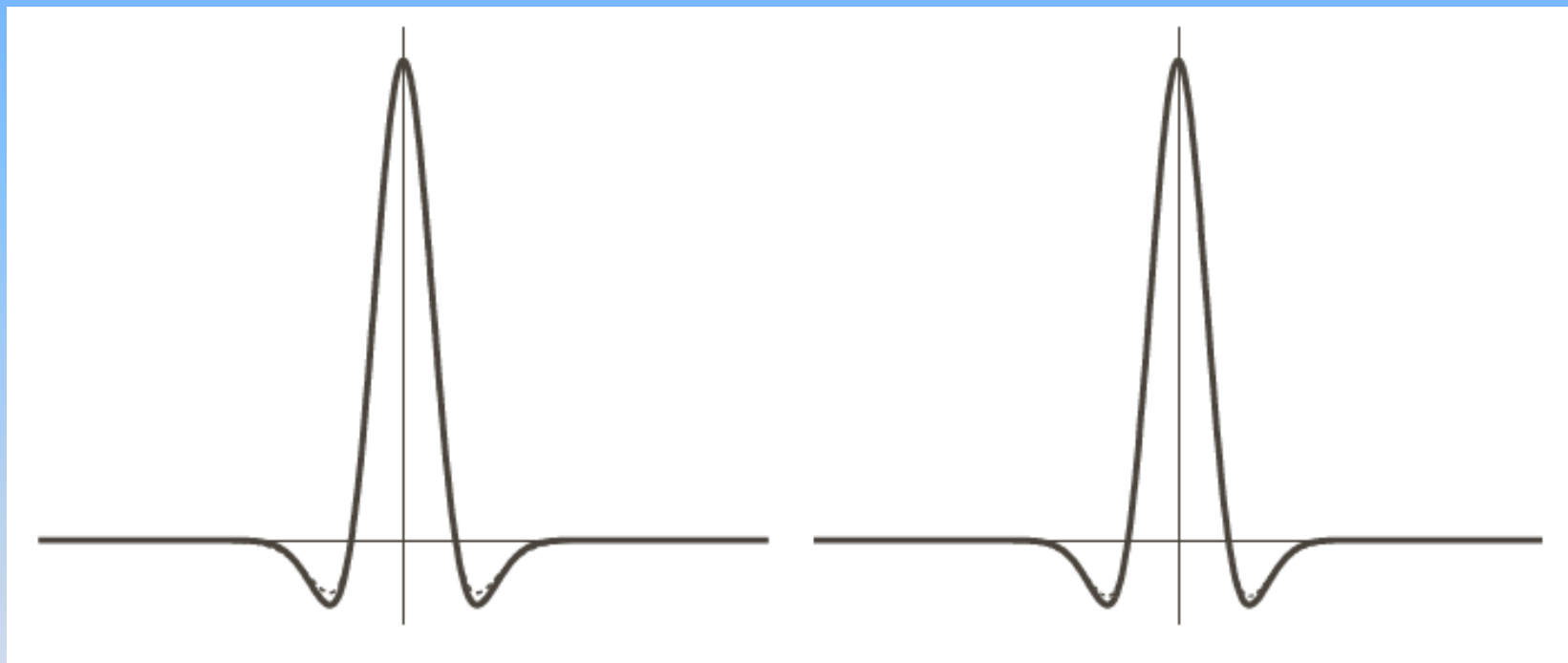
- Difference of Gaussian (DoG)

LoG is complicated, we can approximate the LoG filtering by a DoG operator.

$$DoG(x, y) = \frac{1}{2\pi\sigma_1^2} \exp\left(-\frac{x^2 + y^2}{2\sigma_1^2}\right) - \frac{1}{2\pi\sigma_2^2} \exp\left(-\frac{x^2 + y^2}{2\sigma_2^2}\right)$$



## 2-nd order gradient operator



a b

**FIGURE 10.23**

(a) Negatives of the LoG (solid) and DoG (dotted) profiles using a standard deviation ratio of 1.75:1.

(b) Profiles obtained using a ratio of 1.6:1.





# Canny Edge Detector

- The optimal one:

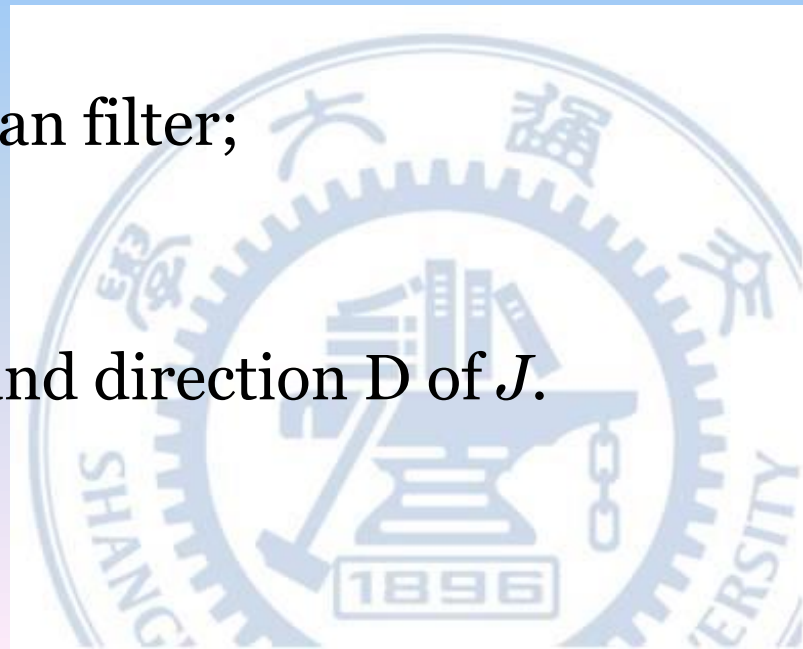
So far, canny operator has been considered as the best of edge detector.

- Four Steps:

1. Image smoothing using Gaussian filter;

$$J = I * G$$

2. Calculating the magnitude  $M$  and direction  $D$  of  $J$ .





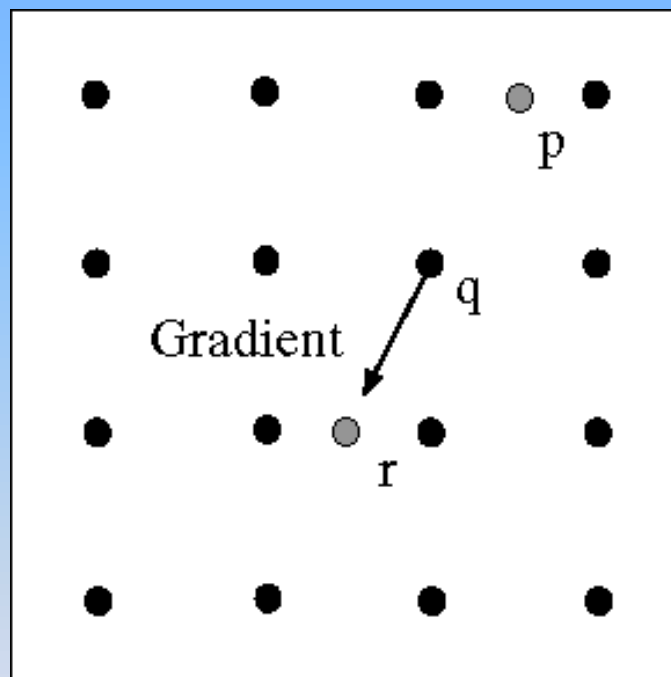
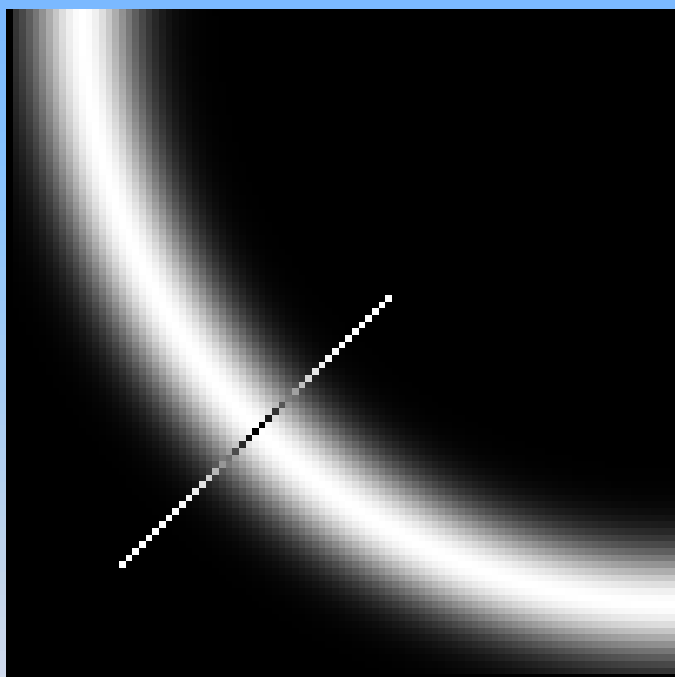
# Canny Edge Detector

## 3. Non-maxima suppression

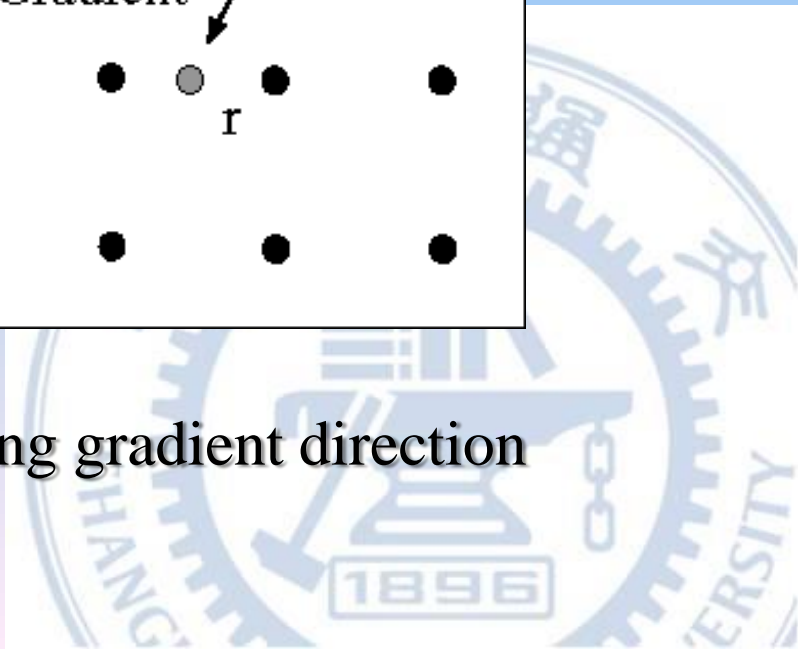
- Let  $d_1, d_2, d_3, d_4$  denote four basic edge directions  $(0^\circ, 45^\circ, 90^\circ, 135^\circ)$ , then for each point  $(x, y)$  in  $D$ :
  - I. find direction  $d_k$  which best approximates the direction of  $D(x, y)$ .
  - II. Along the direction  $d_k$ , check the two neighbors of pixel  $[x, y]$  in  $M$ . If  $M[x, y]$  is greater than both of its neighbors, set  $I[x, y] = M[x, y]$ ; otherwise,  $I[x, y] = 0$ .



# Canny Edge Detector



Check if pixel is local maximum along gradient direction





# Canny Edge Detector

- Double threshold and edge link

Choose two thresholds  $T_h$  and  $T_l$  such that  $T_h > T_l$ , and threshold  $I$  with  $T_h$  and  $T_l$  respectively:

$$I_H(x, y) = I(x, y) \geq T_h$$

$$I_L(x, y) = I(x, y) \geq T_l$$

Then eliminate from  $I_L$  all the nonzero pixels from  $I_H$  :

$$I_L(x, y) = I_L(x, y) - I_H(x, y)$$



# Canny Edge Detector

- Double threshold and edge link

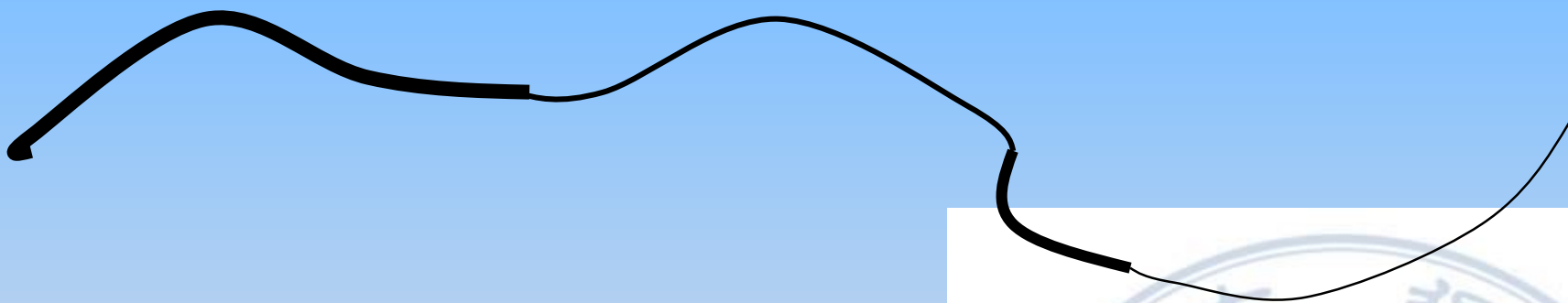
After the thresholding operation, all strong pixels in  $I_H$  are assumed to be valid edge pixels and marked immediately.

However, such pixels have gaps, we link edge as follows:

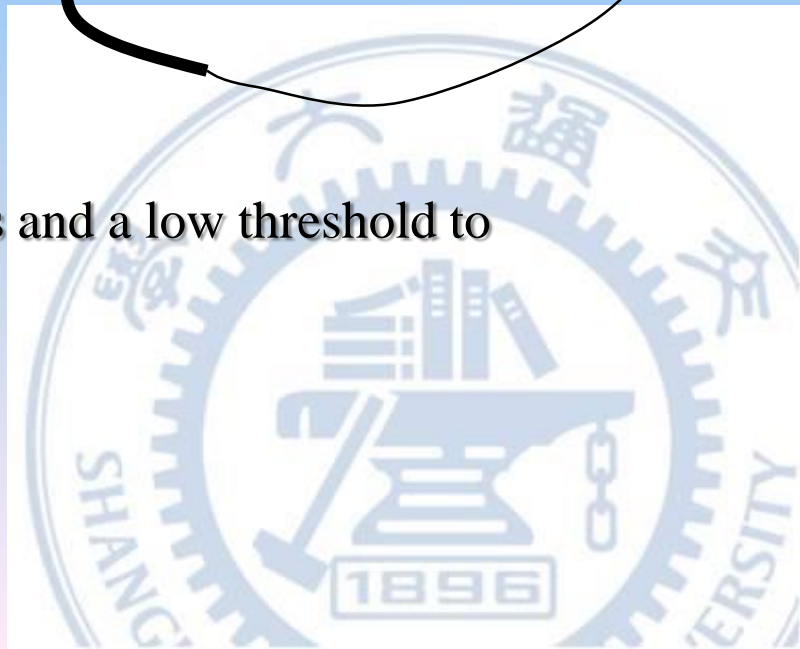
- (a) Locate the next unvisited edge pixel  $p$  in  $I_H$ .
- (b) Mark as valid edge pixels all the weak pixels in  $I_L$  that are connected to  $p$ .
- (c) If all nonzero pixels in  $I_H$  have been visited, go to (d), else to (a).
- (d) Set to zero all pixels in  $I_L$  that are not marked as valid edge pixels.



# Hysteresis thresholding



Use a high threshold to start edge curves and a low threshold to continue them.





# Canny Edge Detector

## Effect of $\sigma$ (Gaussian Kernel Size)



original


 Canny with  $\sigma = 1$ 

 Canny with  $\sigma = 2$ 

The choice of  $\sigma$  depends on desired behavior

- large  $\sigma$  detects large scale edges
- small  $\sigma$  detects fine features





# Hough Transform

Edge detection yields sets of pixels lying on edge. We use Hough transform to link them.





# Hough Transform

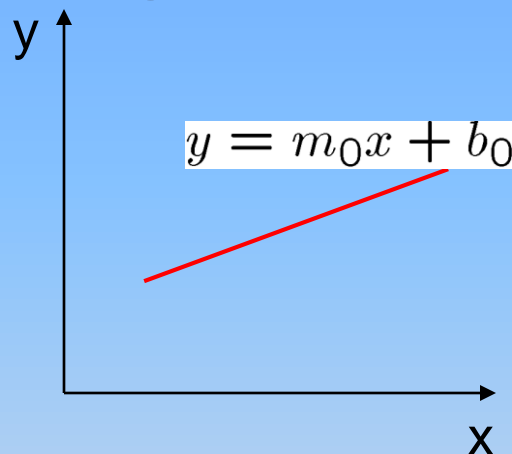
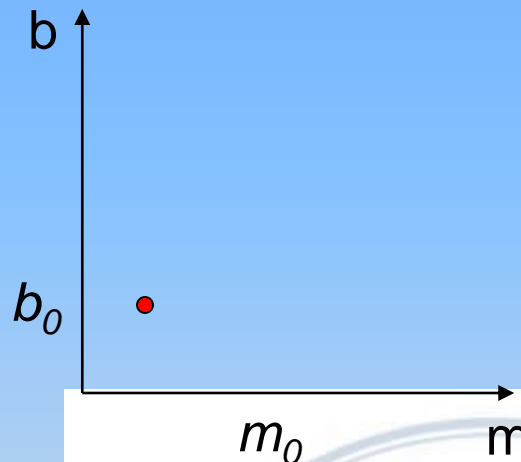
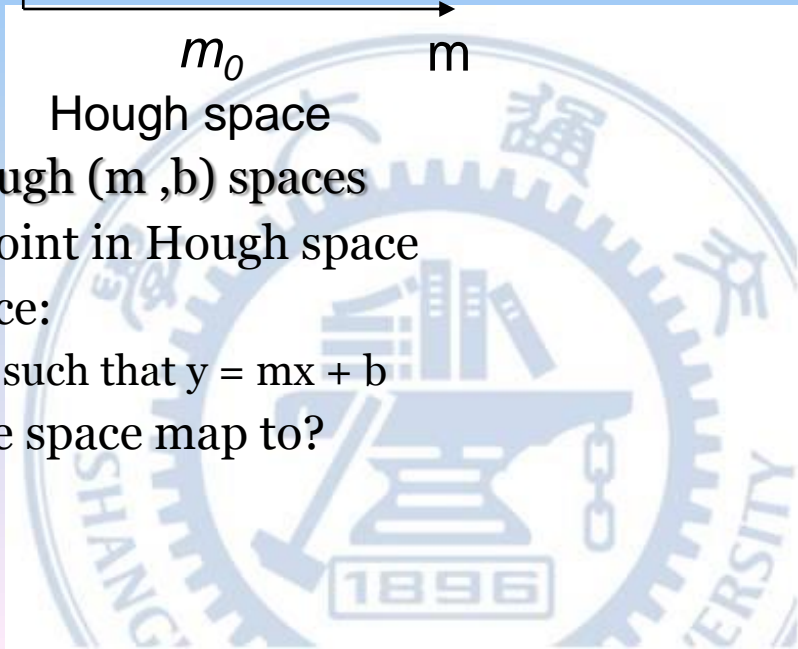


image space



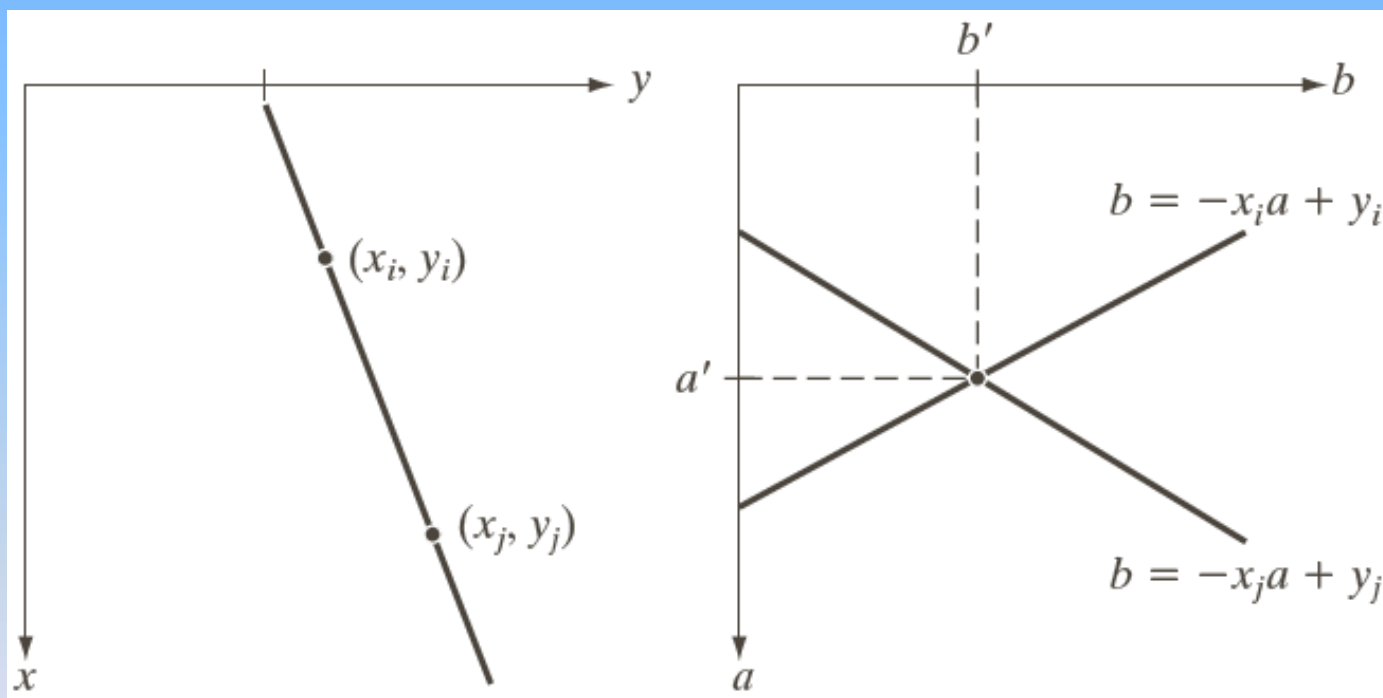
Hough space

- Connection between image  $(x, y)$  and Hough  $(m, b)$  spaces
  - A line in the image corresponds to a point in Hough space
  - To go from image space to Hough space:
    - given a set of points  $(x, y)$ , find all  $(m, b)$  such that  $y = mx + b$
  - What does a point  $(x_0, y_0)$  in the image space map to?





# Hough Transform



a b

**FIGURE 10.31**  
 (a) *xy*-plane.  
 (b) Parameter space.

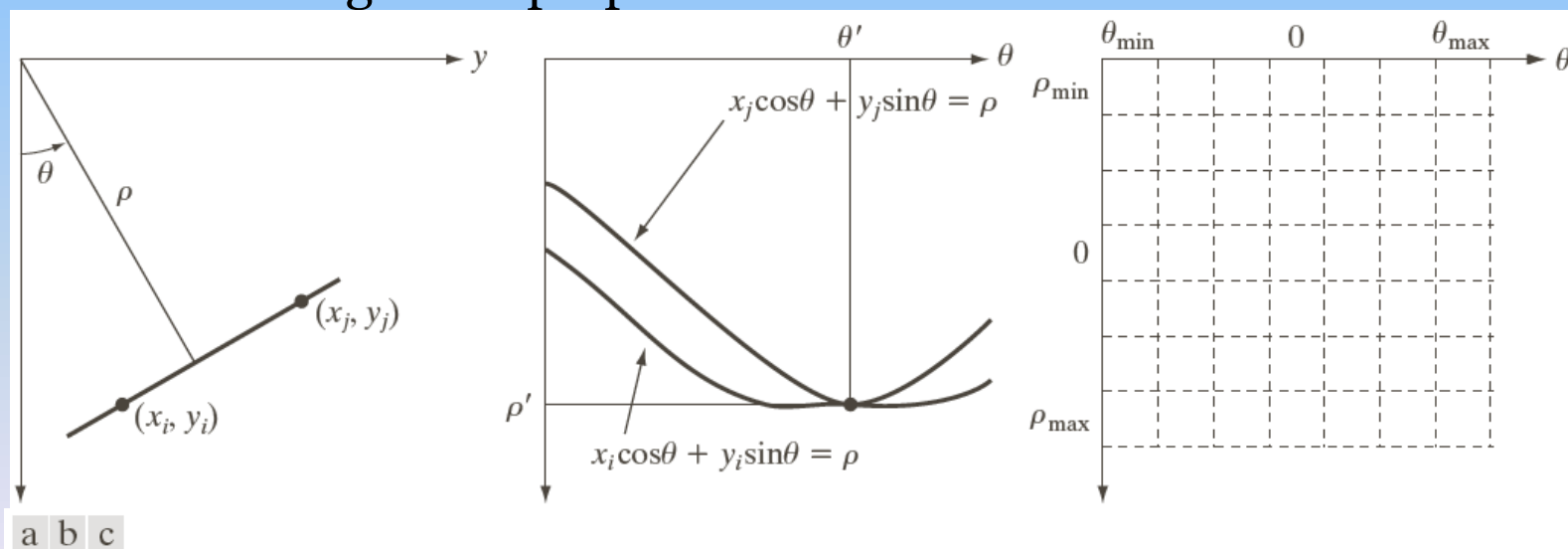


# Hough Transform Algorithm

- Typically use a different parameterization

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

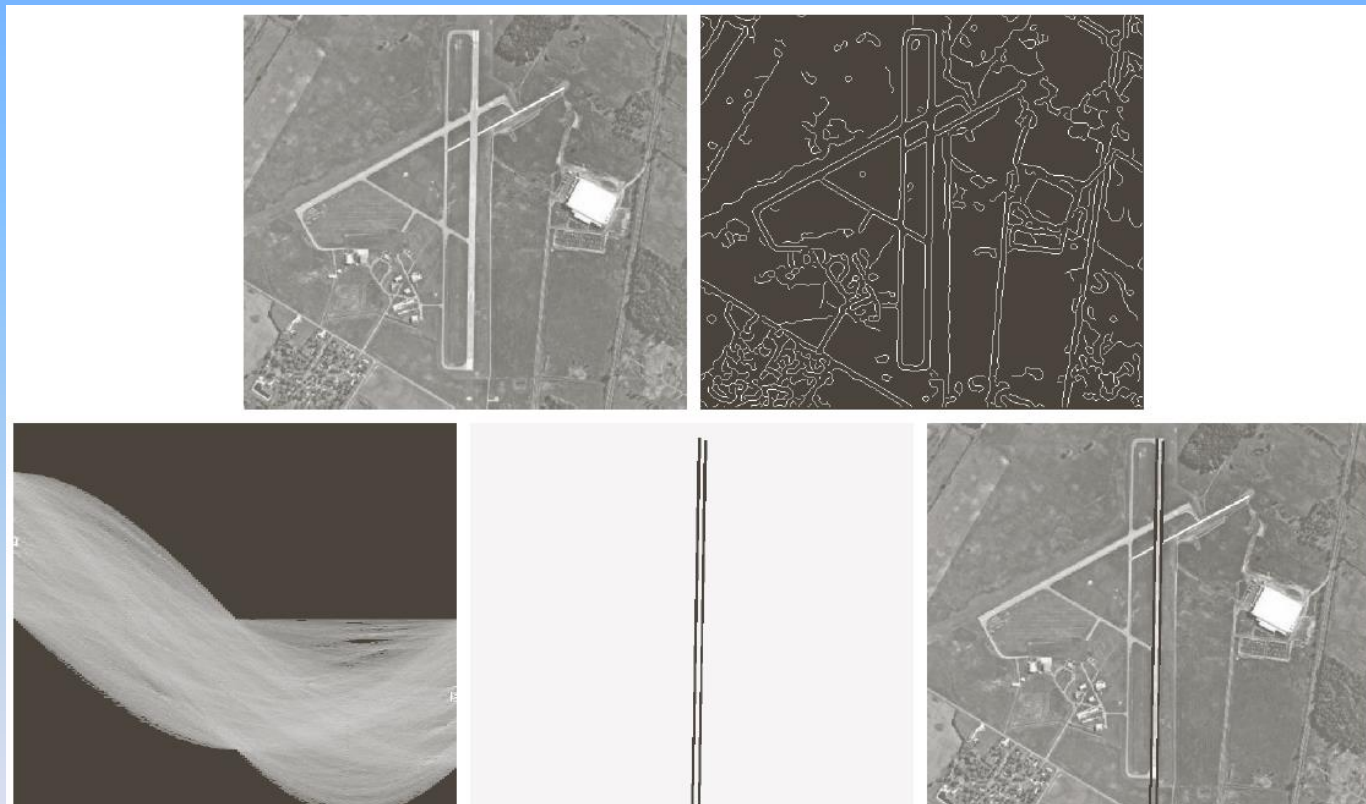
- $d$  is the perpendicular distance from the line to the origin
- $\theta$  is the angle this perpendicular makes with the x axis



**FIGURE 10.32** (a)  $(\rho, \theta)$  parameterization of line in the  $xy$ -plane. (b) Sinusoidal curves in the  $\rho\theta$ -plane; the point of intersection  $(\rho', \theta')$  corresponds to the line passing through points  $(x_i, y_i)$  and  $(x_j, y_j)$  in the  $xy$ -plane. (c) Division of the  $\rho\theta$ -plane into accumulator cells.



# Example



a	b
c	d e

**FIGURE 10.34** (a) A  $502 \times 564$  aerial image of an airport. (b) Edge image obtained using Canny's algorithm. (c) Hough parameter space (the boxes highlight the points associated with long vertical lines). (d) Lines in the image plane corresponding to the points highlighted by the boxes). (e) Lines superimposed on the original image.



# Considering question

- Problem 10.23 (don't need to hand in)



**IVM**

<http://ivm.sjtu.edu.cn>

*Image, Video, and Multimedia Communications Laboratory*



# Thank You!

