

# Image Segmentation

In previous modules we tried to improve the image for better visualization

Now we will try to retrieve some information from image for high level analysis

# Image segmentation

- Division of an image into regions or categories, which correspond to different objects or parts of objects



To represent meaningful areas

Other applications such as number Plate detection, satellite imaging etc.

# Image segmentation



```
graph TD; A[Image segmentation] --> B[Discontinuity based]; A --> C[Similarity based]
```

## Discontinuity based

- Partition is carried out based on abrupt change in intensity values

Focus is on identifying

1. Points
2. Lines
3. Edges

## Similarity based

- Group those pixels which are similar in some sense

Techniques used such as

1. Thresholding
2. Region growing
3. Region splitting and merging

# Discontinuity based image segmentation

- Main focus is to find **isolated points, lines and edges** in the image
- This can be achieved by application of mask like we have discussed in spatial filtering

$$R = w_1 z_1 + w_2 z_2 + \dots + w_9 z_9 = \sum_{i=1}^9 w_i z_i$$

FIGURE 10.1 A  
general  $3 \times 3$   
mask.

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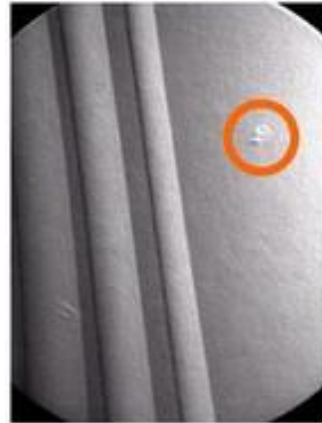
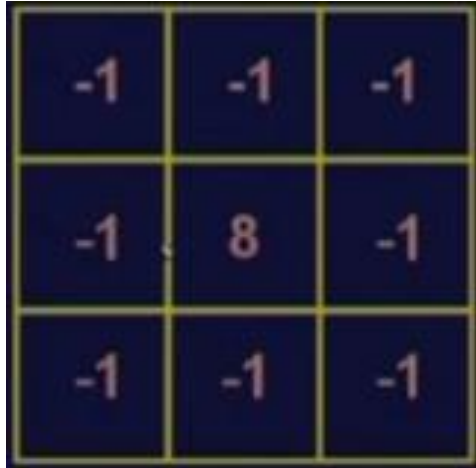
$w_1$	$w_2$	$w_3$
$w_4$	$w_5$	$w_6$
$w_7$	$w_8$	$w_9$

OR

$$R = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(x+s, y+t)$$

# Discontinuity based image segmentation

- Isolated point detection



X-ray image of  
a turbine blade



Result of point  
detection



Result of  
thresholding

$$|R| > T$$

T is threshold value  
(non negative)

# Discontinuity based image segmentation

- Line detection

Moving first mask over entire image  
Detects points lying on horizontal  
line

We can apply all masks over image  
and Find the R value

$$|R_i| > |R_j| \quad \forall \quad i \neq j$$

Then line is having angle more likely  
To the  $i^{\text{th}}$  mask

**FIGURE 10.3** Line masks.

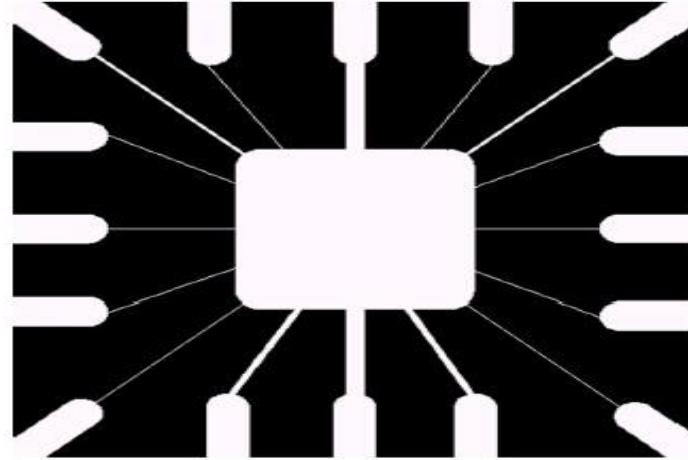
-1	-1	-1	-1	-1	2	-1	2	-1	2	-1	-1
2	2	2	-1	2	-1	-1	2	-1	-1	2	-1
-1	-1	-1	2	-1	-1	-1	2	-1	-1	-1	2
Horizontal			+45°			Vertical			-45°		

# Discontinuity based image segmentation

- Edge detection: Detecting the discontinuity in image
- Edge: Boundary between two regions having distinct intensity values

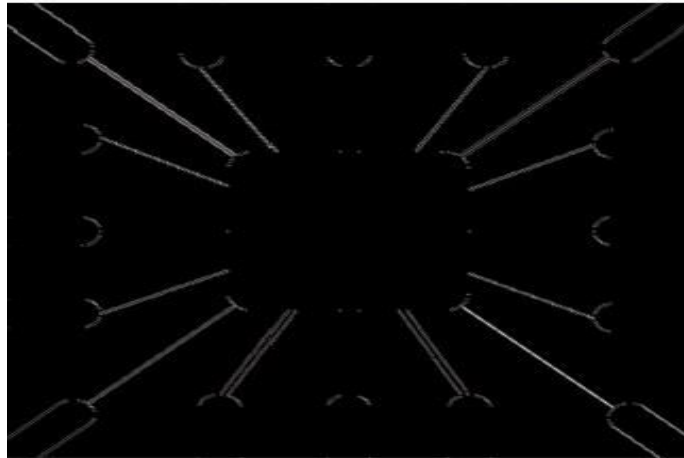


# Detection of Discontinuities Line Detection



a  
b c

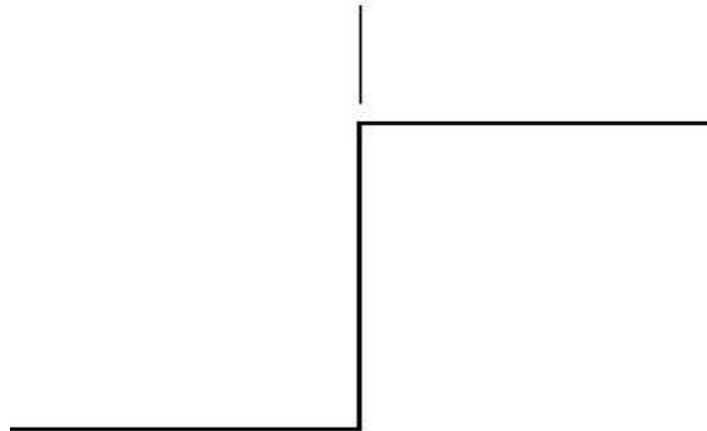
**FIGURE 10.4**  
Illustration of line  
detection.  
(a) Binary wire-  
bond mask.  
(b) Absolute  
value of result  
after processing  
with  $-45^\circ$  line  
detector.  
(c) Result of  
thresholding  
image (b).



# Detection of Discontinuities

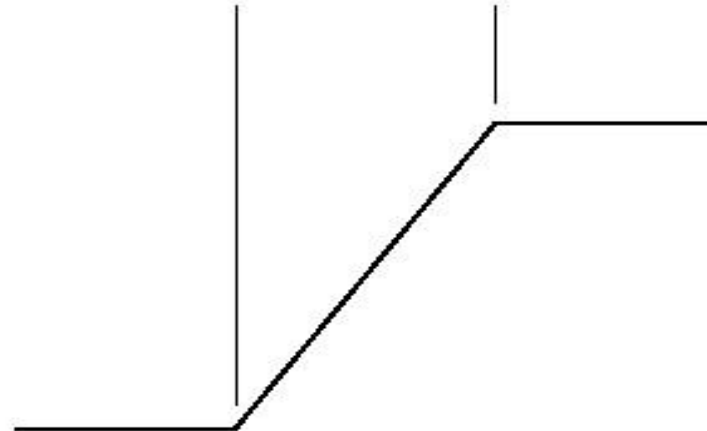
## Edge Detection

Model of an ideal digital edge



Gray-level profile  
of a horizontal line  
through the image

Model of a ramp digital edge



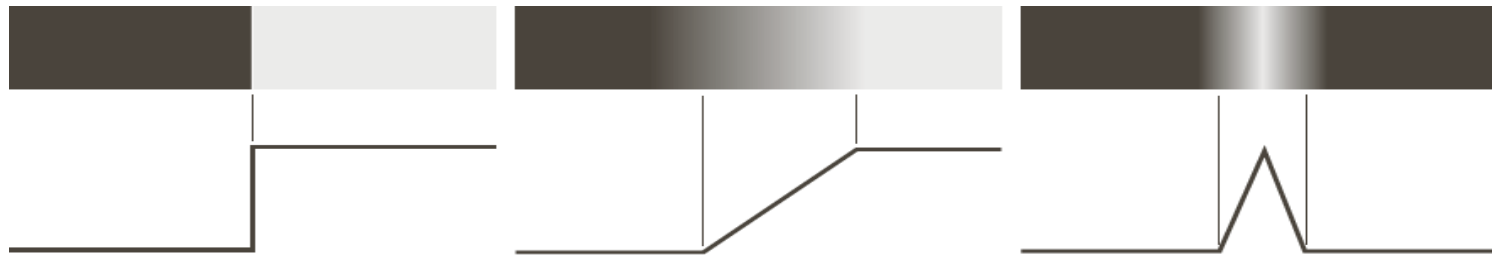
Gray-level profile  
of a horizontal line  
through the image

a b

**FIGURE 10.5**  
(a) Model of an ideal digital edge.  
(b) Model of a ramp edge. The slope of the ramp is proportional to the degree of blurring in the edge.

# Detection of Discontinuities

## Edge Detection



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.

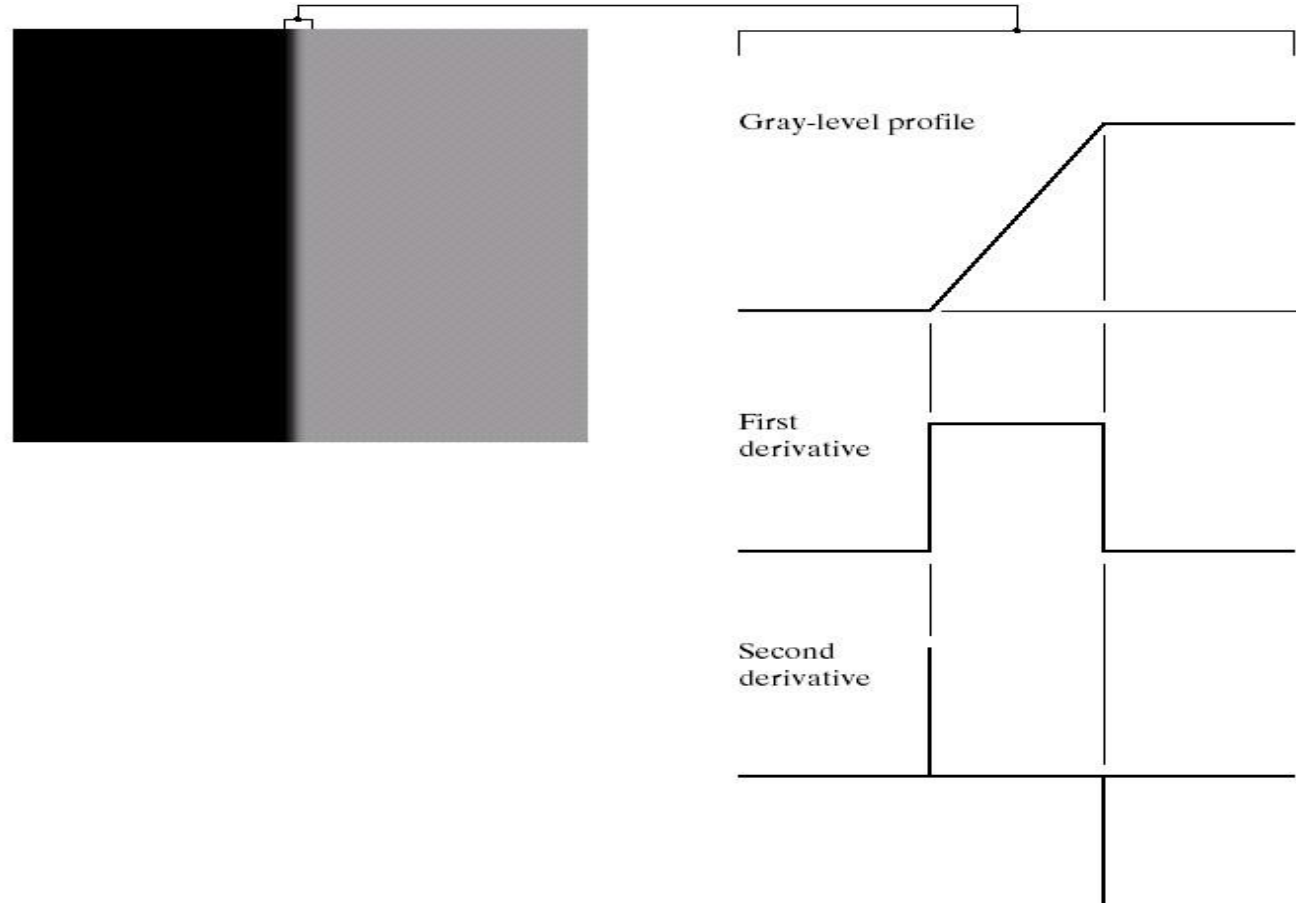
# Detection of Discontinuities

## Edge Detection

a b

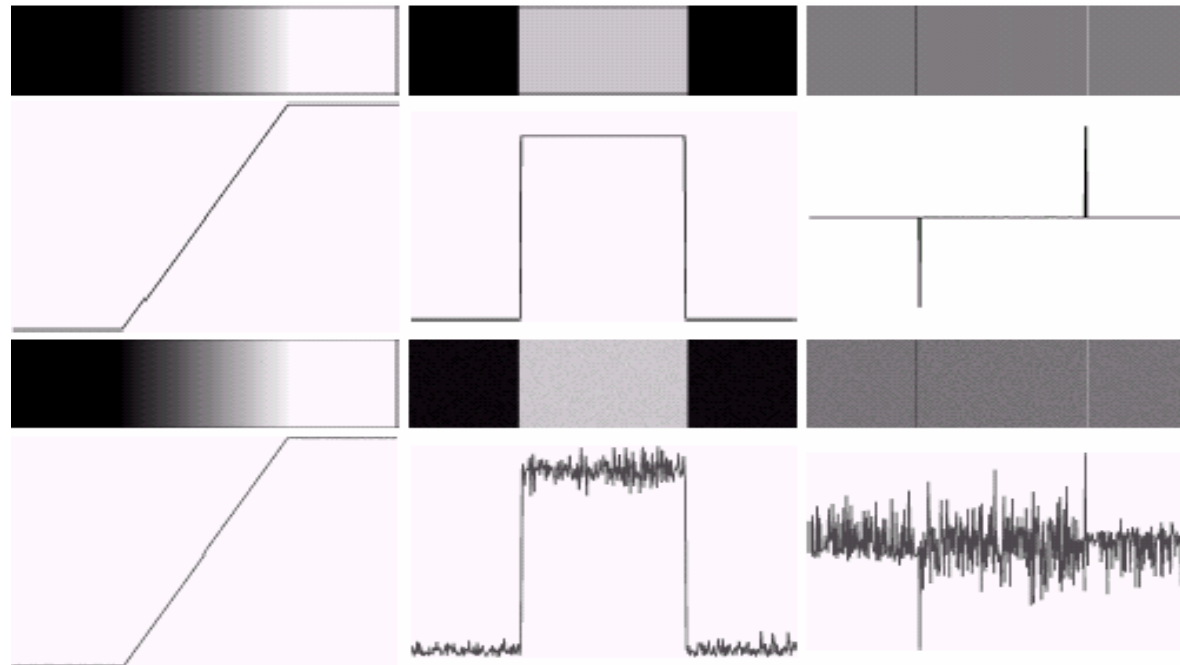
**FIGURE 10.6**

(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.



# Detection of Discontinuities

## Edge Detection



**FIGURE 10.7** 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. Second column: first-derivative images and gray-level profiles. Third column: second-derivative images and gray-level profiles.

a  
b  
c  
d

# Detection of Discontinuities

## Gradient Operators

- First-order derivatives:

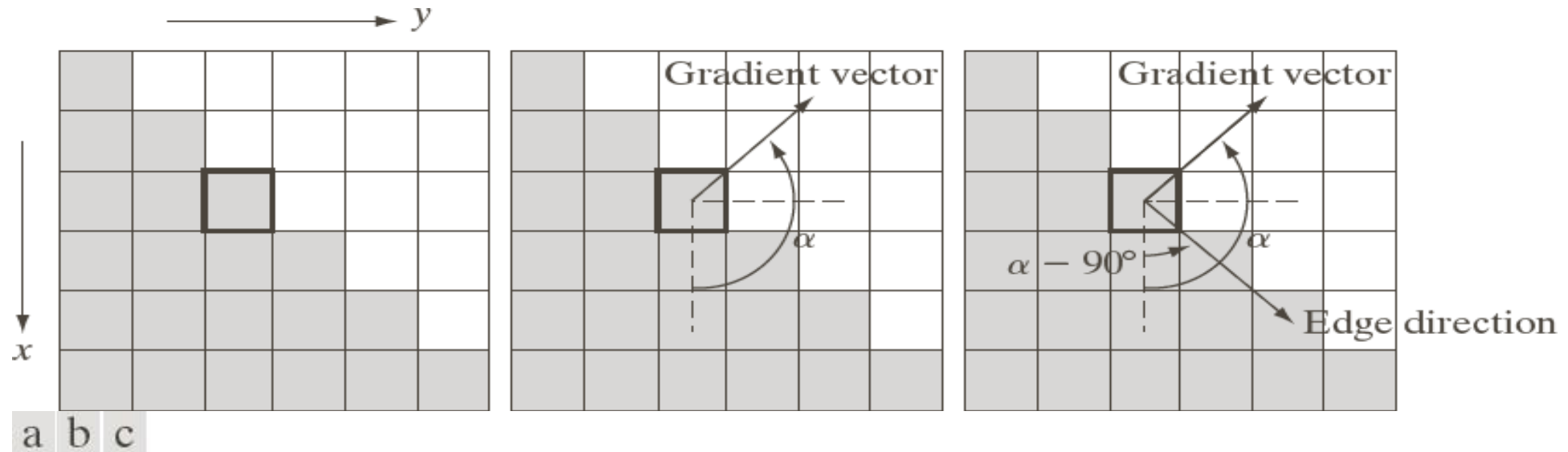
- The gradient of an image  $f(x,y)$  at location  $(x,y)$  is defined as the **vector**:

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

- The **magnitude** of this vector:  $\nabla f = \text{mag}(\nabla \mathbf{f}) = \left[ G_x^2 + G_y^2 \right]^{\frac{1}{2}}$
- The **direction** of this vector:  $\alpha(x, y) = \tan^{-1} \left( \frac{G_x}{G_y} \right)$
- It points in the direction of the greatest rate of change of  $f$  at location  $(x,y)$

# Detection of Discontinuities

## Gradient Operators



**FIGURE 10.12** Using the gradient to determine edge strength and direction at a point. Note that the edge is perpendicular to the direction of the gradient vector at the point where the gradient is computed. Each square in the figure represents one pixel.

# Detection of Discontinuities

## Gradient Operators

Roberts cross-gradient operators



-1	0	0	-1
0	1	1	0

Roberts

Prewitt operators



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

Prewitt

Sobel operators



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

Sobel



# Detection of Discontinuities

## Gradient Operators

Prewitt masks for  
detecting diagonal edges



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

Prewitt

Sobel masks for detecting  
diagonal edges



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

Sobel

a	b
c	d

**FIGURE 10.9** Prewitt and Sobel masks for detecting diagonal edges.

# Edge detection

- Prewitt edge operator

sobel edge operator

<table><tr><td>-1</td><td>-1</td><td>-1</td></tr><tr><td>0</td><td>0</td><td>0</td></tr><tr><td>-1</td><td>-1</td><td>-1</td></tr></table>	-1	-1	-1	0	0	0	-1	-1	-1	<table><tr><td>-1</td><td>0</td><td>-1</td></tr><tr><td>-1</td><td>0</td><td>-1</td></tr><tr><td>-1</td><td>0</td><td>-1</td></tr></table>	-1	0	-1	-1	0	-1	-1	0	-1	<table><tr><td>-1</td><td>-2</td><td>-1</td></tr><tr><td>0</td><td>0</td><td>0</td></tr><tr><td>1</td><td>2</td><td>1</td></tr></table>	-1	-2	-1	0	0	0	1	2	1	<table><tr><td>-1</td><td>0</td><td>1</td></tr><tr><td>-2</td><td>0</td><td>2</td></tr><tr><td>-1</td><td>0</td><td>1</td></tr></table>	-1	0	1	-2	0	2	-1	0	1
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Horizontal	Vertical	Horizontal	Vertical																																				

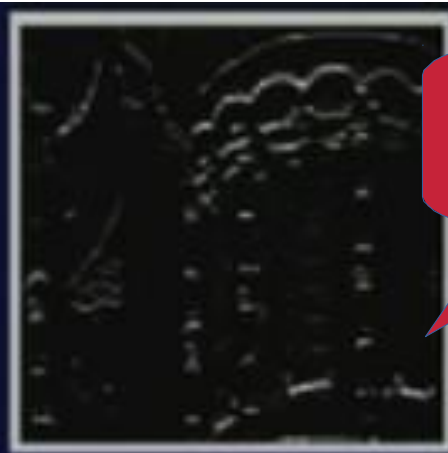
These are first order derivative operators



Input Image



Output Image  
By horizontal  
Sobel operator



Output Image  
By vertical  
Sobel operator



Output Image  
By combined  
Sobel operator



# Detection of Discontinuities

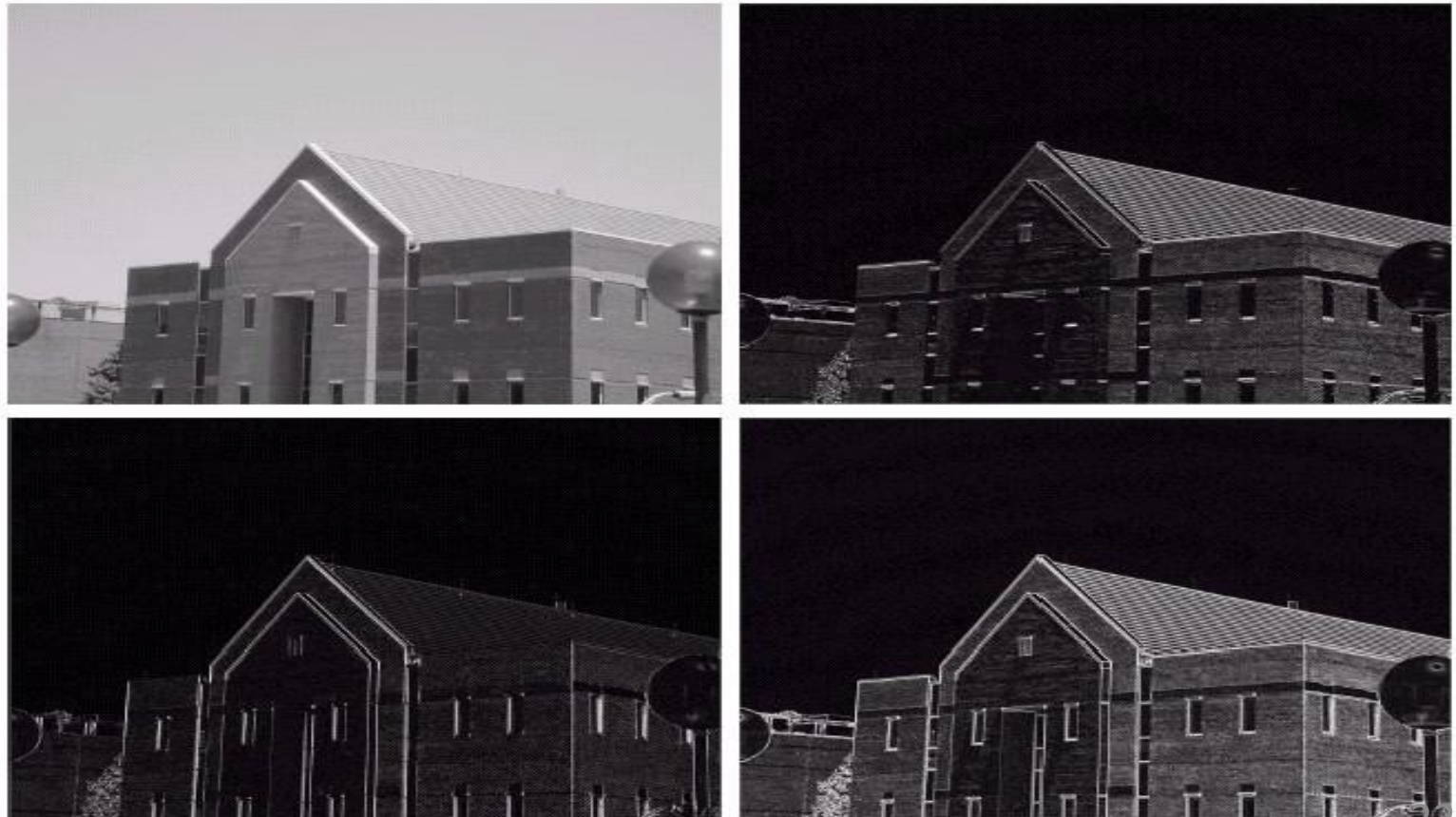
## Gradient Operators: Example

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,  $|G_x| + |G_y|$ .

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



# Detection of Discontinuities

## Gradient Operators: Example

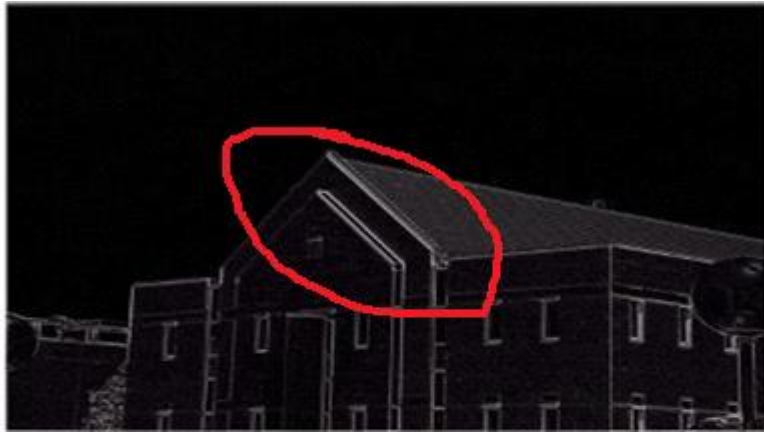


a	b
c	d

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

# Detection of Discontinuities

## Gradient Operators: 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).

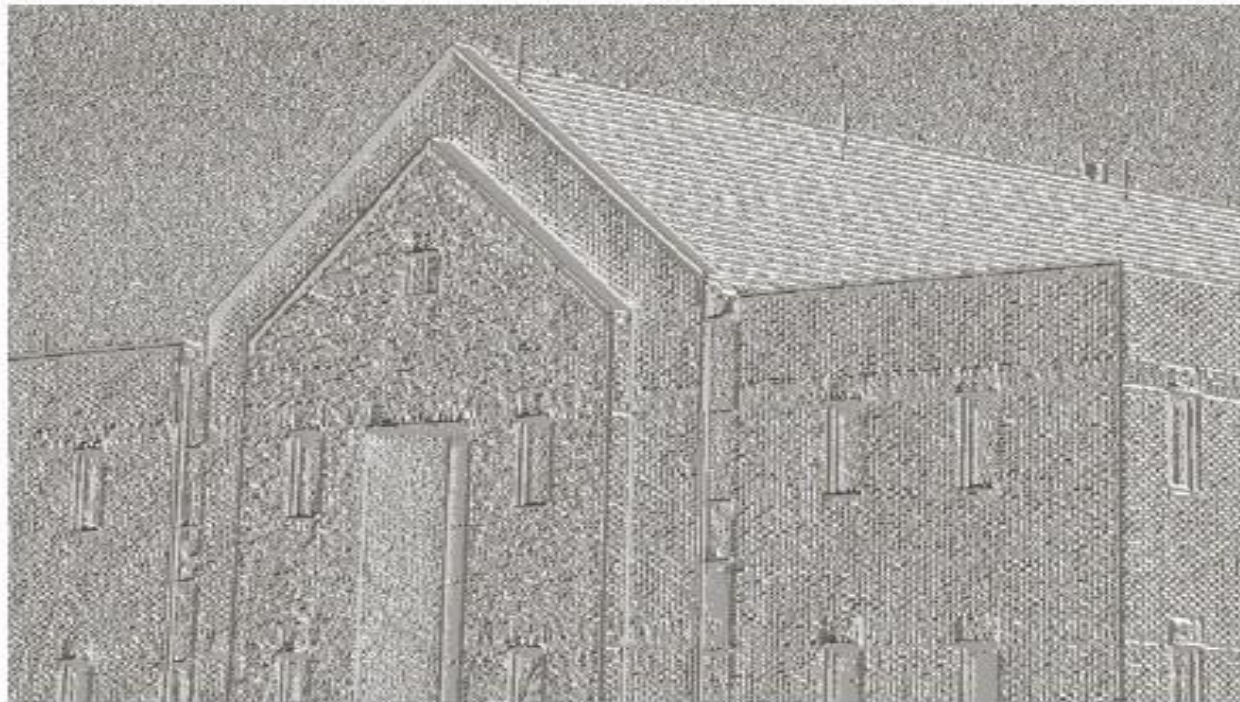
0	1	2
-1	0	1
-2	-1	0

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



# Detection of Discontinuities

## Gradient Operators: Example



**FIGURE 10.17**  
Gradient angle  
image computed  
using  
Eq. (10.2-11).  
Areas of constant  
intensity in this  
image indicate  
that the direction  
of the gradient  
vector is the same  
at all the pixel  
locations in those  
regions.



## Detection of Discontinuities

### Gradient Operators

- Second-order derivatives: (The Laplacian)
  - The Laplacian of an 2D function  $f(x,y)$  is defined as
$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$
  - Two forms in practice:

**FIGURE 10.13**  
Laplacian masks  
used to  
implement  
Eqs. (10.1-14) and  
(10.1-15),  
respectively.

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0	-1	0	-1	-1	-1
-1	4	-1	-1	8	-1
0	-1	0	-1	-1	-1

# Edge detection

- Second derivative operator -Laplacian

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

0	-1	0
-1	4	-1
0	-1	0

- Generally not used, because it is very sensitive to noise
- To reduce the effect of noise first image is smoothened

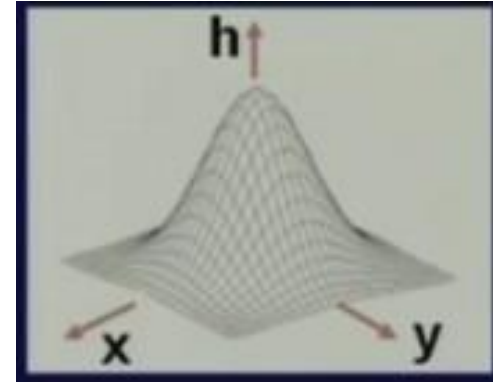
# Edge detection

- For smoothening purpose **Gaussian** operator is used
- After smoothening Laplacian operator is applied
- This is called as **Laplacian of Gaussian** (LoG)
- This will reduce the effect of noise

# Edge detection

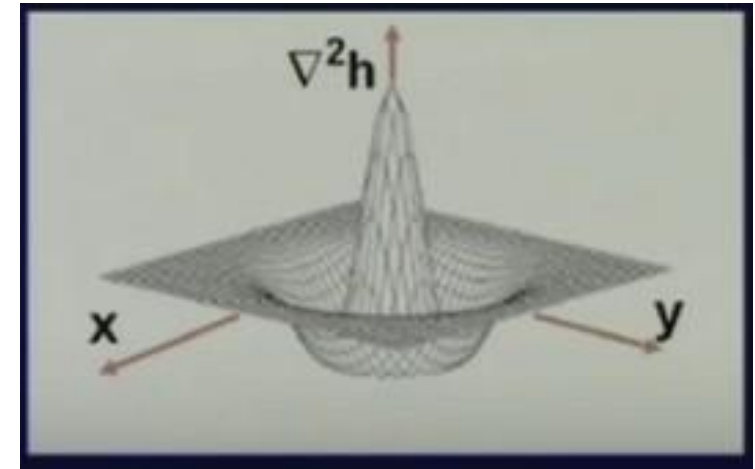
- Gaussian mask:

$$h(x, y) = e^{\frac{-x^2 - y^2}{2\sigma^2}}$$



- Laplacian of Gaussian

$$\nabla^2 h(x, y) = \frac{(x^2 - y^2 - \sigma^2)}{\sigma^4} \cdot e^{\frac{-x^2 - y^2}{2\sigma^2}}$$



Ref: [https://en.wikipedia.org/wiki/Laplace%27s\\_equation](https://en.wikipedia.org/wiki/Laplace%27s_equation)

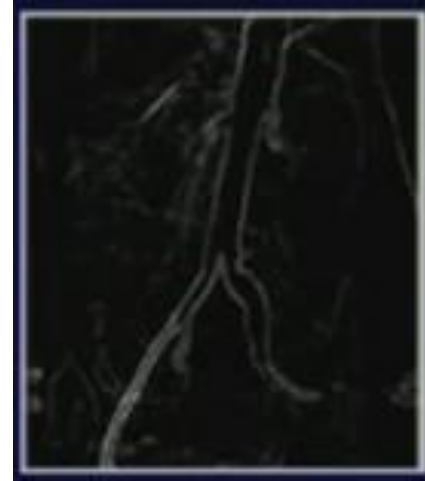
# Edge detection

0	0	-1	0	0
0	-1	-2	-1	0
-1	-2	16	-2	-1
0	-1	-2	-1	0
0	0	-1	0	0

LoG mask



Input Image



Sobel Output  
Image



LoG Output  
Image

LoG identifies location  
Of edge in image