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IT4130 - Image Understanding and Processing

Lecture 06 – Edge Detection

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Sessional outcomes

- Points, Lines and Edges
- Point detection
- Line detection
- Edge models
- Edge detection
  - First Order
  - Laplacian
  - Laplacian of Gaussian

Point, Line and Edges

- Edge pixels
  - Pixels where intensity changes abruptly.
- Edges
  - Sets of connected edge pixels.
- Line
  - Edge segment where the intensity on either side are higher or lower.
- point
  - A line with one pixel.

Revision

- First order and second order derivatives
  - Thin\thick edges
  - Double edge response
  - Transitions from light to dark and dark to light

a b
c

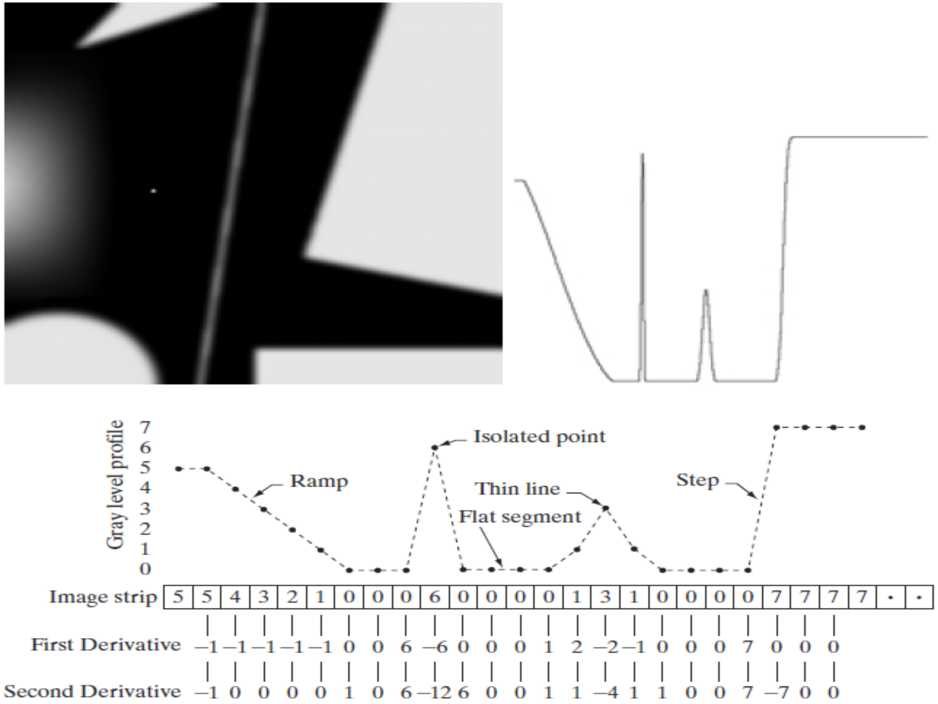
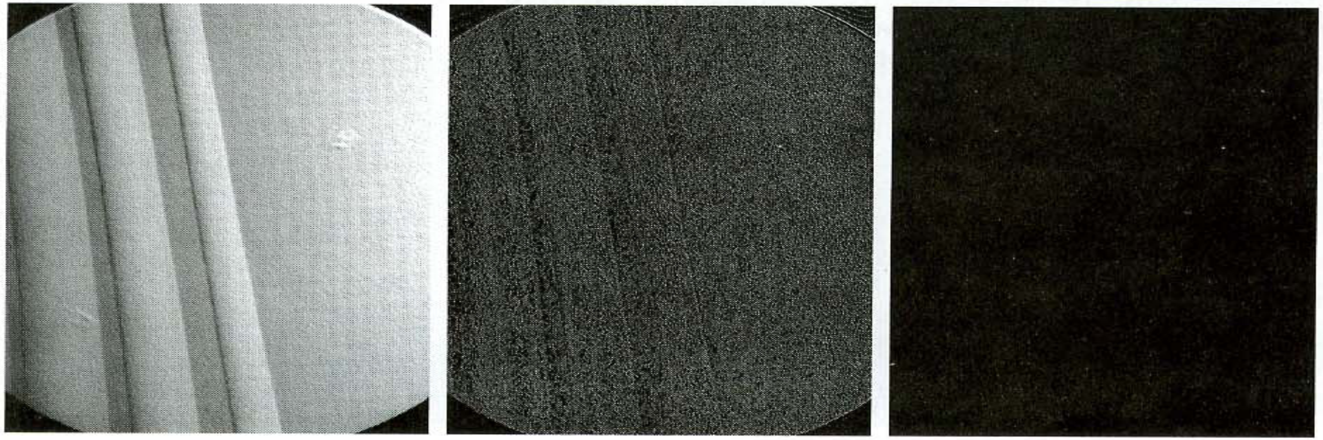


FIGURE 3.38 (a) A simple image. (b) 1-D horizontal gray-level profile along the center of the image and including the isolated noise point. (c) Simplified profile (the points are joined by dashed lines to simplify interpretation).

Point detection

- Use Laplacian
  - Basic
  - General
- Sum of the coefficients is zero
- R is given by the weighted difference between a pixel and its neighborhood
- a pixel is selected if R>= Threshold

−1	−1	−1
−1	8	−1
−1	−1	−1



a
b c d

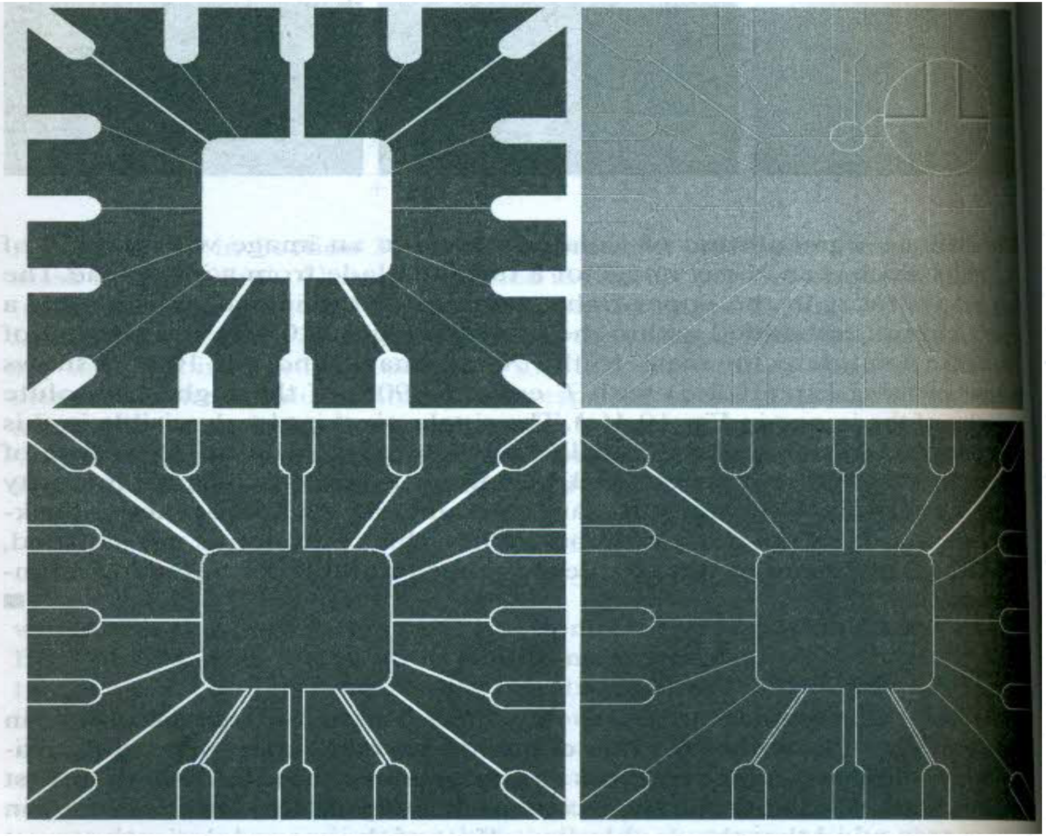
FIGURE 10.2 (a) Point detection mask. (b) X-ray image of a turbine blade with a porosity. (c) Result of point detection. (d) Result of using Eq. (10.1-2). (Original image courtesy of X-TEK Systems Ltd.)

Line detection

- Use Laplacian
- Absolute values
  - Doubles the thickness
- Positive values only
  - Thinner lines
- More suitable to thinner lines

a b
c d

FIGURE 10.5
(a) Original image.
(b) Laplacian image; the magnified section shows the positive/negative double-line effect characteristic of the Laplacian.
(c) Absolute value of the Laplacian.
(d) Positive values of the Laplacian.



Detecting directed lines

- Compute the thresholds T_1, T_2, T_3, T_4
- Procedure
  - Run the mask
  - Threshold the absolute value of the result

FIGURE 10.3 Line masks.

Horizontal

−1	−1	−1
2	2	2
−1	−1	−1

+45°

−1	−1	2
−1	2	−1
2	−1	−1

Vertical

−1	2	−1
−1	2	−1
−1	2	−1

−45°

2	−1	−1
−1	2	−1
−1	−1	2

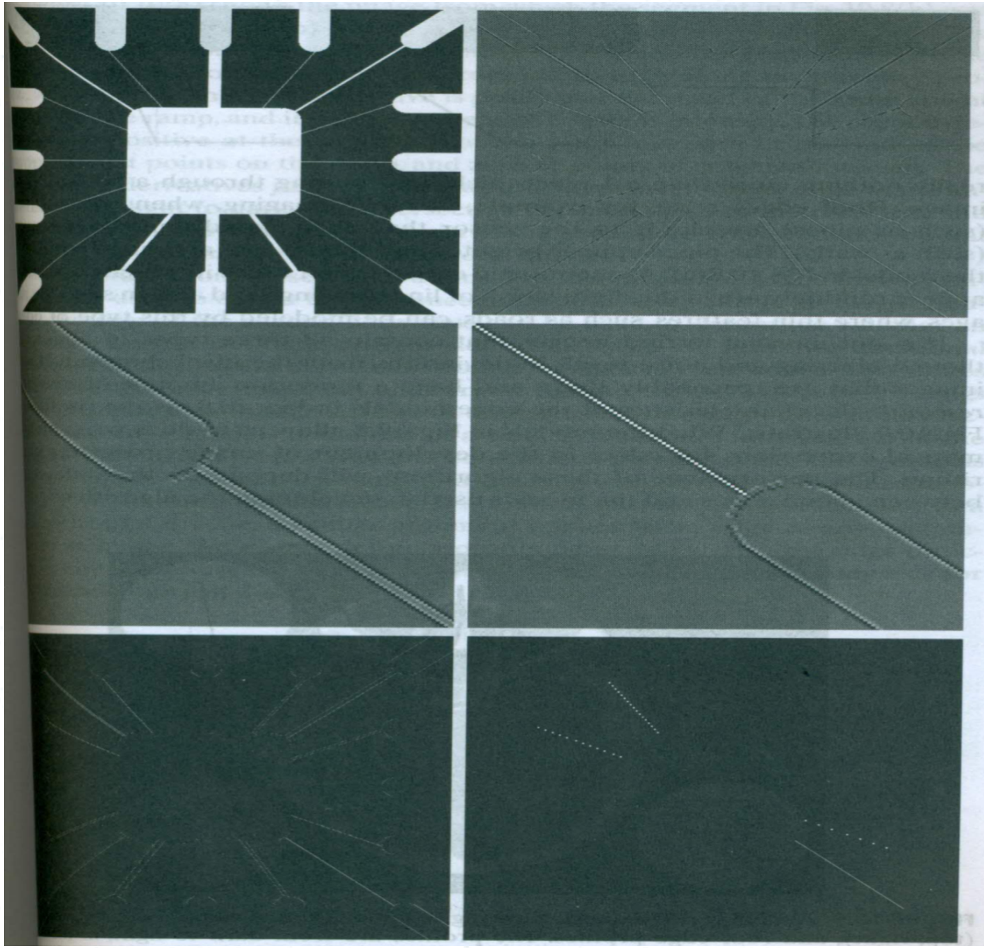


FIGURE 10.7 (a) Image of a wire-bond template. (b) Result of processing with the +45° line detector mask in Fig. 10.6. (c) Zoomed view of the top left region of (b). (d) Zoomed view of the bottom right region of (b). (e) The image in (b) with all negative values set to zero. (f) All points (in white) whose values satisfied the condition $g \geq T$, where g is the image in (e). (The points in (f) were enlarged to make them easier to see.)

Edge models

1. Step edge:
   - Transition between two intensity levels over one pixel
   - Ideal in computer generated images

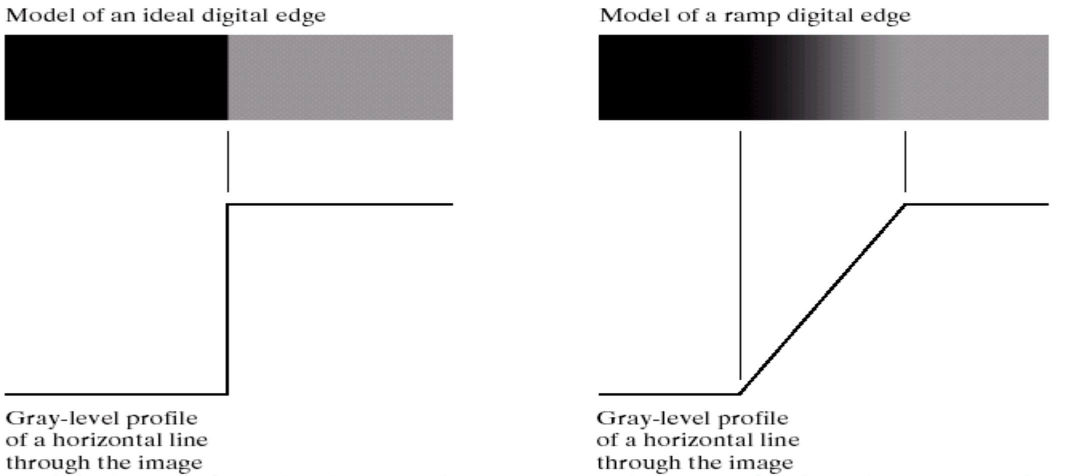
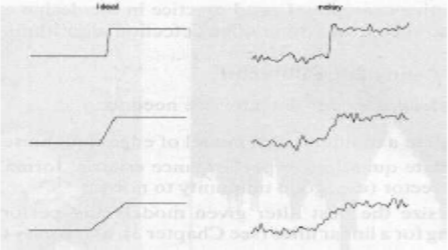
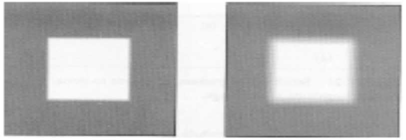


FIGURE 10.5 (a) Model of an ideal digital edge. (b) Model of a ramp edge. The slope of the ramp is proportional to the degree of blurring in the edge.

Edge models

2. <u>Ramp edge:</u>
   - Results in blurred and noisy images
   - a step edge where the intensity change occurs over a finite distance.
   - Ramp slope is inversely proportional to the degree of blurring

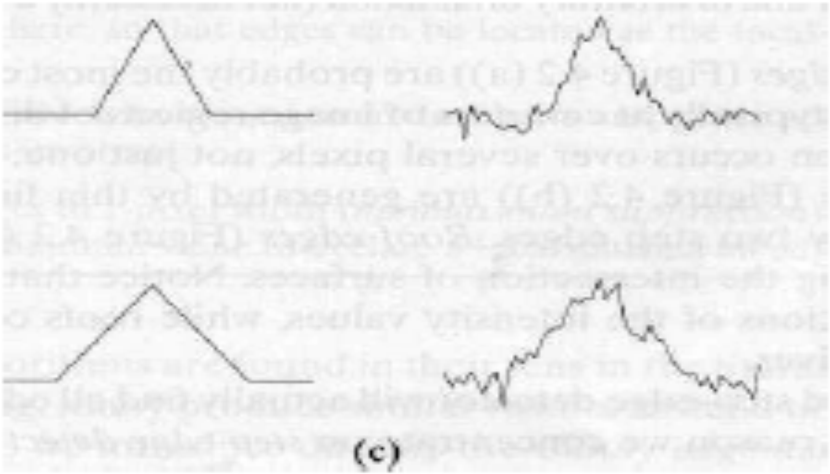




Edge models

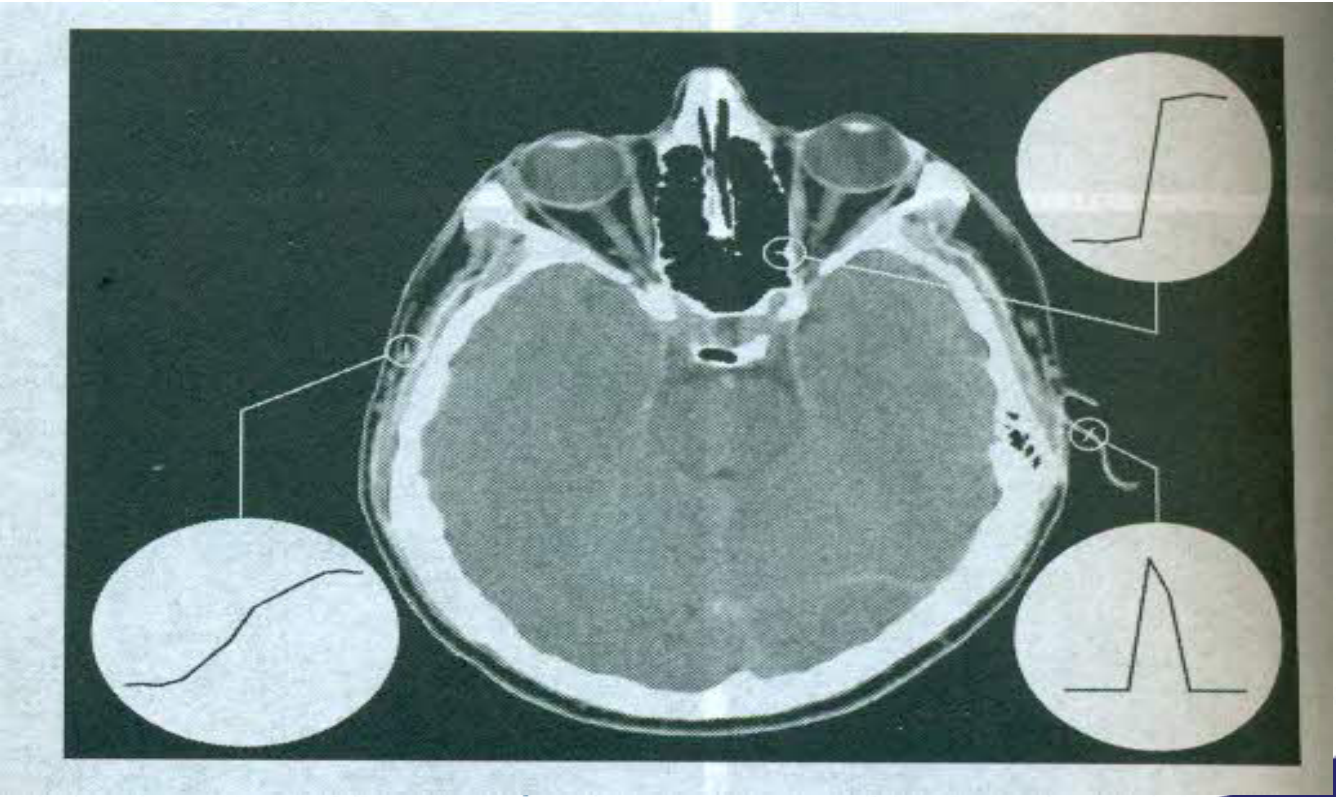
3. Roof edge:

- intensity change occurs over a finite distance.
- generated usually by the intersection of surfaces
- When thin objects are closer to the sensor than the background.



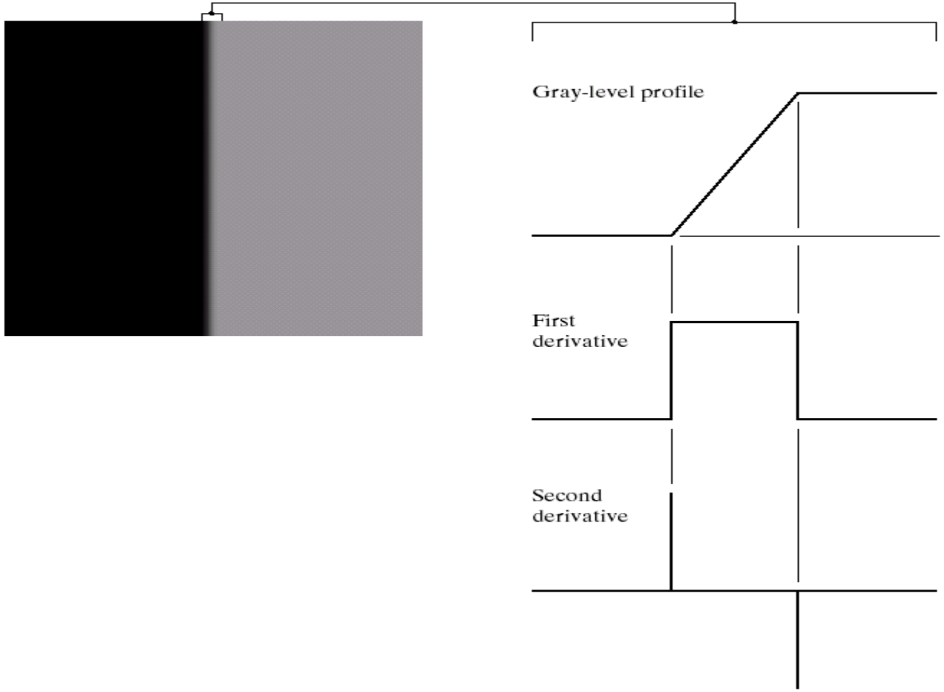
(c)

Example



Edge detection

- Presence
  - FOD
- Color
  - Sign of SOD



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.

Edge strength and direction

- Gradient

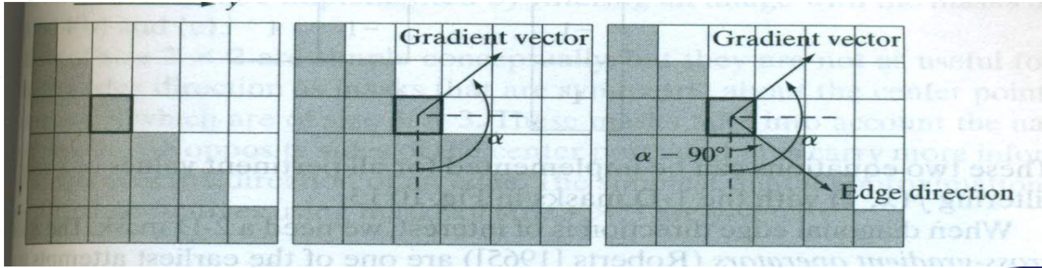
$$\nabla \mathbf{f} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f}{\partial x} \\ \dfrac{\partial f}{\partial y} \end{bmatrix}$$

$$\nabla f = \mathrm{mag}(\nabla \mathbf{f}) = [G_x^2 + G_y^2]^{1/2} \qquad \nabla f \approx |G_x| + |G_y|$$

- Strength

$$\alpha(x, y) = \tan^{-1}\left(\frac{G_y}{G_x}\right)$$

- Direction – orthogonal to the gradient vector



First Order Gradient operators

−1
1

−1	1

0	1	1
−1	0	1
−1	−1	0

−1	−1	0
−1	0	1
0	1	1

Prewitt

0	1	2
−1	0	1
−2	−1	0

−2	−1	0
−1	0	1
0	1	2

Sobel

a	
b	c
d	e
f	g

FIGURE 10.8 A 3 × 3 region of an image (the z's are gray-level values) and various masks used to compute the gradient at point labeled z_5.

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
0	0	0
1	1	1

−1	0	1
−1	0	1
−1	0	1

Prewitt

−1	−2	−1
0	0	0
1	2	1

−1	0	1
−2	0	2
−1	0	1

Sobel

Example - 1

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 - 2

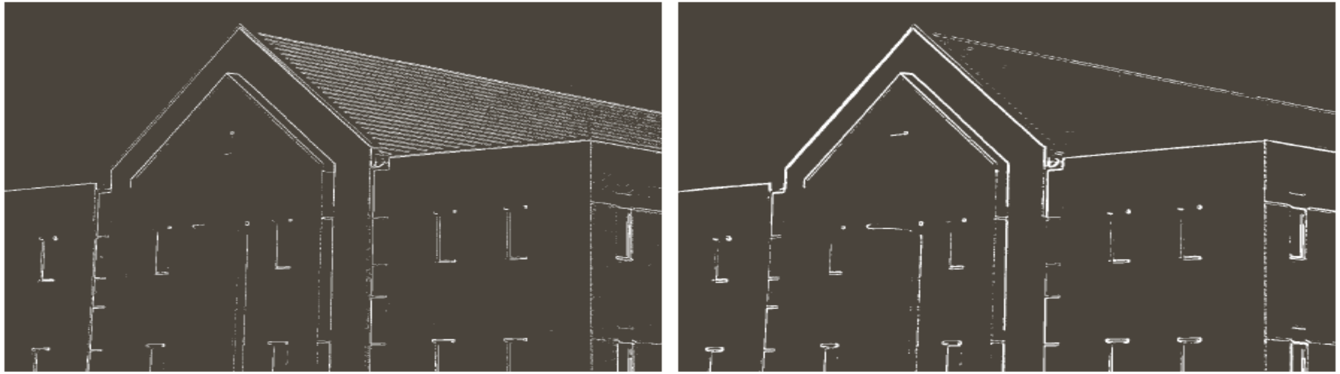
a	b
c	d

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

Example -3 & 4

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).



Noisy edges

Noisy Image (A+10*randn(512))

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- Effect of noise
  - SOD more sensitive
- Steps in edge detection
  - Smoothing
  - Edge points
  - Edge localization

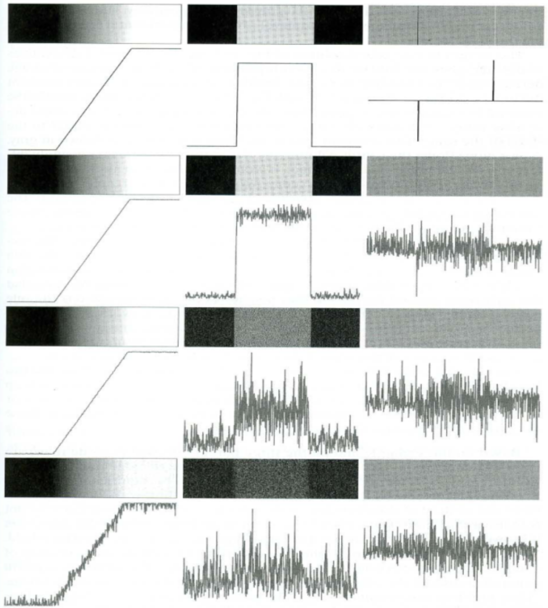


FIGURE 10.7 First column: images and gray-level profiles of a ramp edge corrupted by random Gaussian noise of mean 0 and σ = 0.0, 0.1, 1.0, and 10.0, respectively. Second column: first-derivative images and gray-level profiles. Third column: second-derivative images and gray-level profiles.

Laplacian in practice

- Although the Laplacian responds to changes in intensity, it is seldom used in edge detection for several reasons
  - As a second derivative operator it is typically unacceptably sensitive to noise
  - The Laplacian produces double edges
  - Unable to detect direction
- As such, the Laplacian is used in the secondary role of detector for establishing whether a pixel is on the light or dark side of an edge

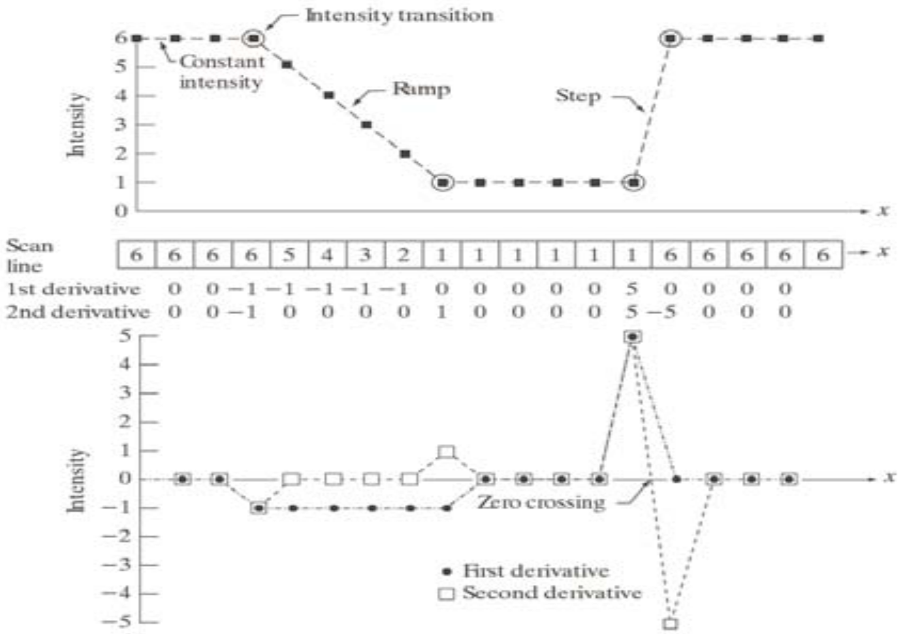
Second order derivative operators

0	1	0
1	−4	1
0	1	0

1	1	1
1	−8	1
1	1	1

0	−1	0
−1	4	−1
0	−1	0

−1	−1	−1
−1	8	−1
−1	−1	−1



Advanced Techniques for Edge Detection

- The Marr-Hildreth edge detector
  - Gaussian kernel

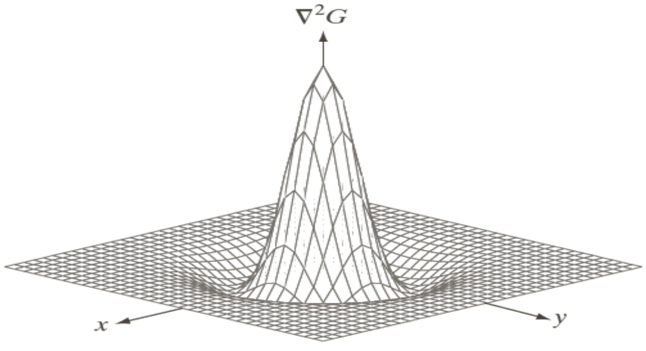
$$G_\sigma(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} exp[-\frac{x^2+y^2}{2\sigma^2}]$$

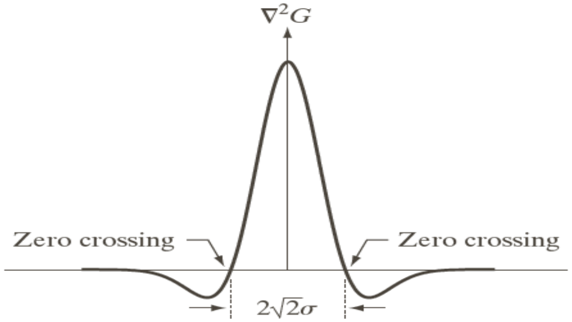
$$\frac{\partial}{\partial x} G_\sigma(x,y) = \frac{\partial}{\partial x} e^{-(x^2+y^2)/2\sigma^2} = -\frac{x}{\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$$

$$\frac{\partial^2}{\partial^2 x} G_\sigma(x,y) = \frac{x^2}{\sigma^4} e^{-(x^2+y^2)/2\sigma^2} - \frac{1}{\sigma^2} e^{-(x^2+y^2)/2\sigma^2} = \frac{x^2-\sigma^2}{\sigma^4} e^{-(x^2+y^2)/2\sigma^2}$$

$$LoG \triangleq \triangle G_\sigma(x,y) = \frac{\partial^2}{\partial x^2} G_\sigma(x,y) + \frac{\partial^2}{\partial y^2} G_\sigma(x,y) = \frac{x^2+y^2-2\sigma^2}{\sigma^4} e^{-(x^2+y^2)/2\sigma^2}$$

  - Laplacian of Gaussian





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

a	b
c	d

FIGURE 10.21 (a) Three-dimensional plot of the *negative* of the LoG. (b) Negative of the LoG displayed as an image. (c) Cross section of (a) showing zero crossings. (d) 5×5 mask approximation to the shape in (a). The negative of this mask would be used in practice.

Laplacian of Gaussian

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Laplacian of Gaussian

- Underlying concepts
  - Reduces noise
  - Less artifacts than averaging
  - Isotropic
- Implementation
  - LoG * f
  - Laplacian{Gaussian * f}

Marr-Hildreth Algorithm process

1. Filter the input image with an n x n Gaussian lowpass filter.
   - N >= 6σ
2. Compute the Laplacian of the image resulting from step1
3. Find the zero crossing of the image from step 2
   - Based on 3x3 neighborhood and thresholding