EEE-6512: Image Processing and Computer Vision

October 16, 2018

Lecture #8: Segmentation I

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Reminder: Exam #2 October 23

Topics:

- Chapter #4: Frequency Domain Filtering
- Chapter #7: Color Image Processing
- Chapter #9: Morphological Image Processing
- Chapter #10: Image Segmentation
  - Preliminaries
  - Point, Line, Edge Detection *
  - Thresholding *

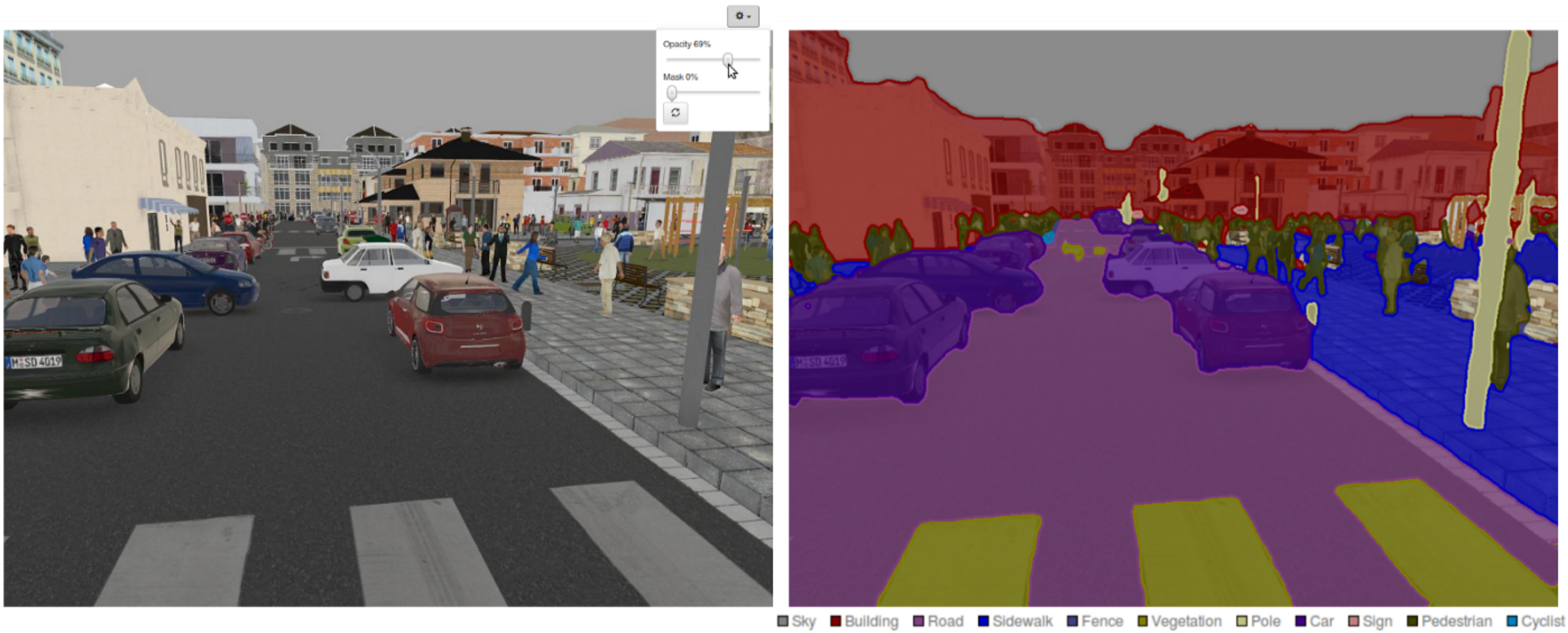
Reminder: Exam #2 October 23

- Same format as Exam #1
- 15 – 20 questions
- 1 – 2 extra credit questions
- Calculator allowed

Why is image segmentation important?

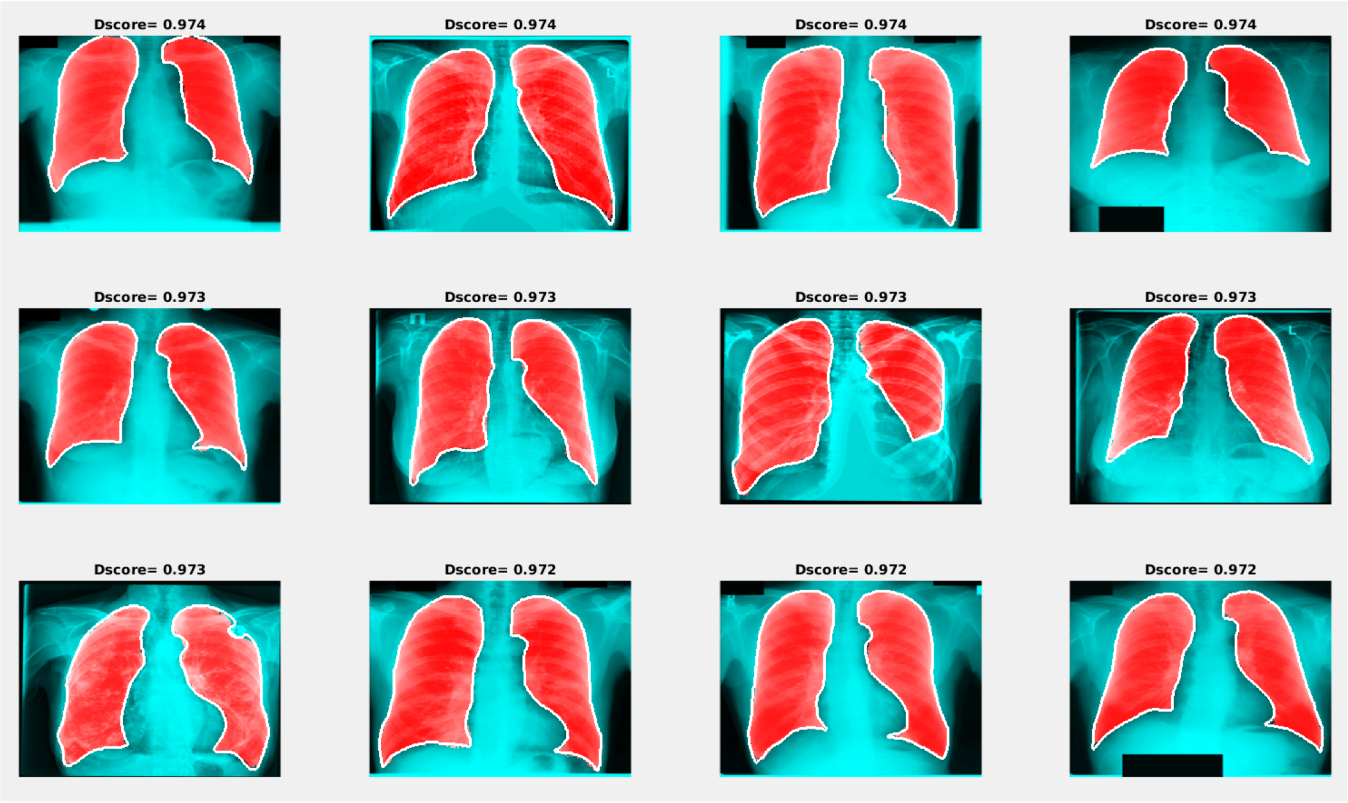
- Important image processing step used everywhere we want to analyze the contents of an image.
- The output of image segmentation is locations of meaningful objects of the image.

Image Segmentation Examples



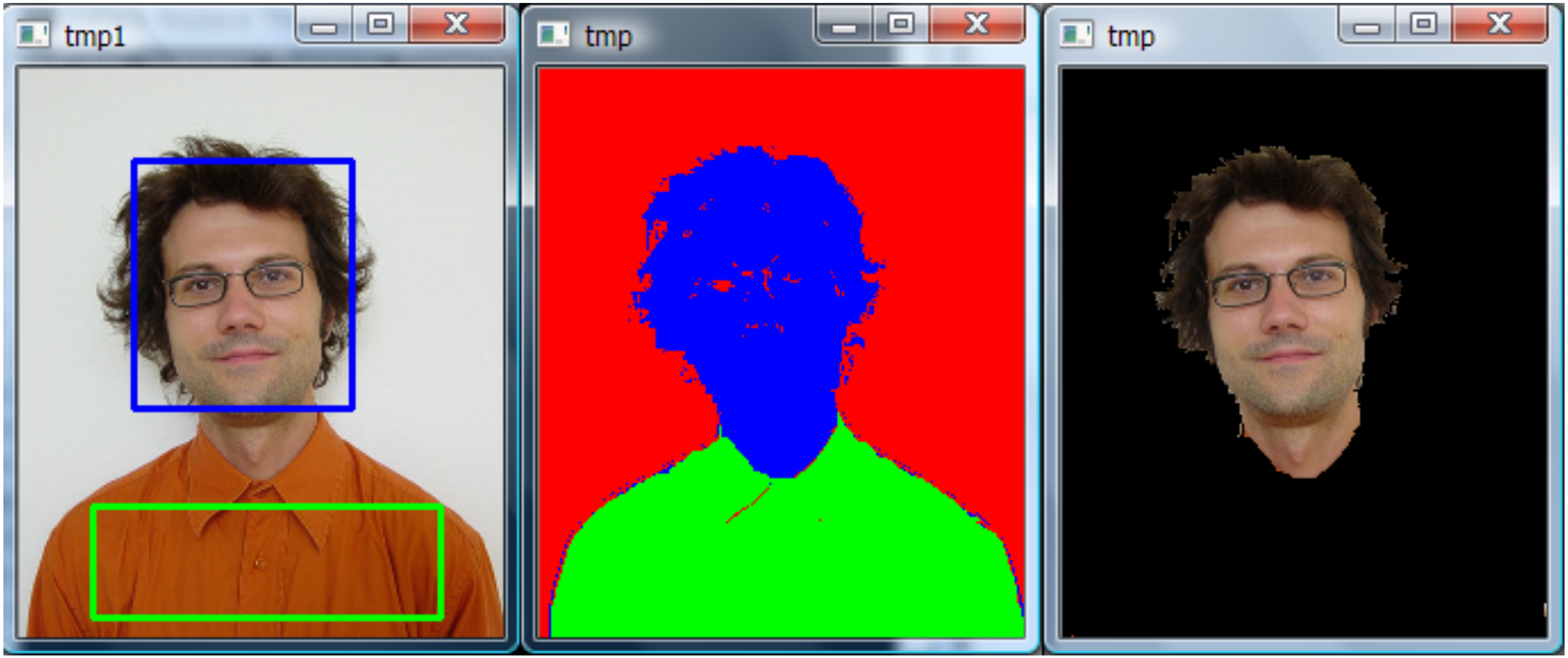
Semantic Segmentation

Image Segmentation Examples (cont.)



Segmentation of x-ray images

Image Segmentation Examples (cont.)



Segementation Based on Graph-cuts

Outline

- Fundamentals
- Point, Line, and Edge Detection
- Thresholding

Fundamentals

- Let R represent the entire spatial region occupied by an image. Image segmentation is a process that partitions R into *n* sub-regions, R_1, R_2, …, R_n, such that

(a) $\bigcup_{i=1}^{n} R_i = R.$

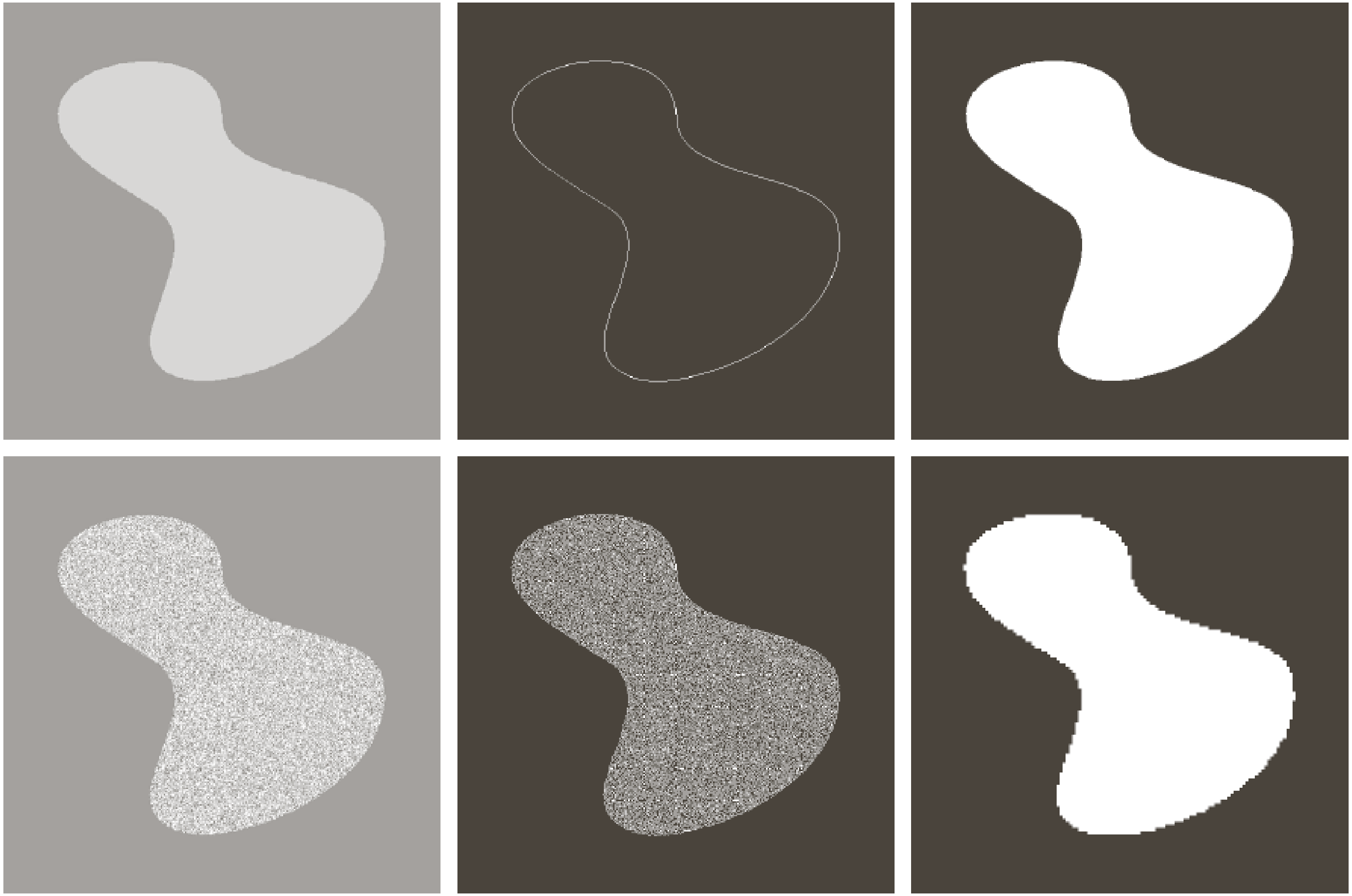
(b) R_i is a connected set. $i = 1,\ 2,\ \ldots,\ n.$

(c) $R_i \cap R_j = \Phi.$

(d) $\llbracket\ (R_i) = \text{TRUE}$ for $i = 1,\ 2,\ \ldots,\ n.$

(e) $\llbracket\ (R_i \cup R_j) = \text{FALSE}$ for any adjacent regions

R_i and R_j.



a b c
d e f

FIGURE 10.1 (a) Image containing a region of constant intensity. (b) Image showing the boundary of the inner region, obtained from intensity discontinuities. (c) Result of segmenting the image into two regions. (d) Image containing a textured region. (e) Result of edge computations. Note the large number of small edges that are connected to the original boundary, making it difficult to find a unique boundary using only edge information. (f) Result of segmentation based on region properties.

Point, Line, and Edge Detection

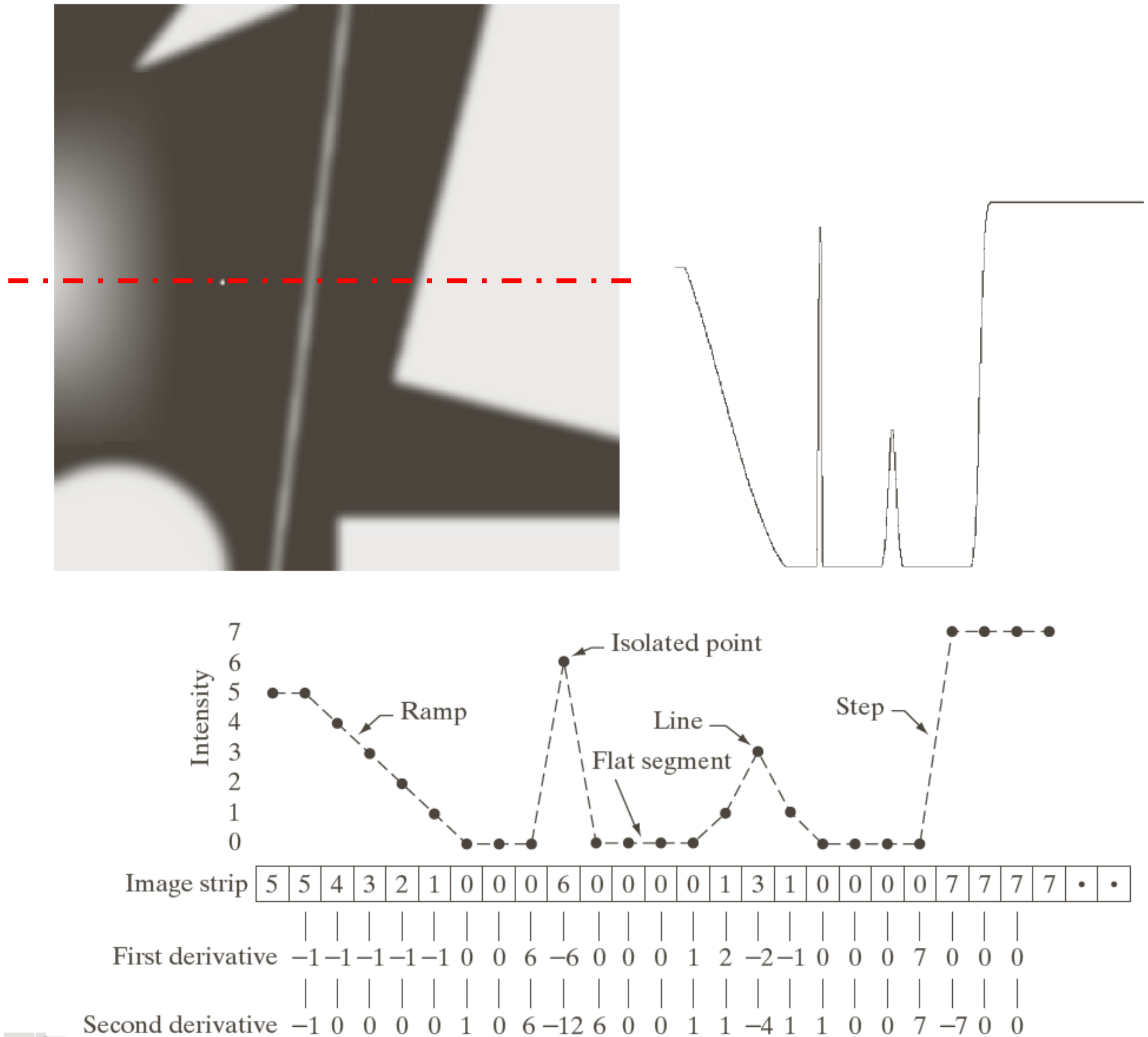
Background

- First-order derivative

$$\frac{\partial f}{\partial x} = f'(x) = f(x+1) - f(x)$$

- Second-order derivative

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) - 2f(x)$$



a b
c

FIGURE 10.2 (a) Image. (b) Horizontal intensity profile through the center of the image, including the isolated noise point. (c) Simplified profile (the points are joined by dashes for clarity). The image strip corresponds to the intensity profile, and the numbers in the boxes are the intensity values of the dots shown in the profile. The derivatives were obtained using Eqs. (10.2-1) and (10.2-2).

Characteristics of First and Second Order Derivatives

- First-order derivatives generally produce thicker edges in image
- Second-order derivatives have a stronger response to fine detail, such as thin lines, isolated points, and noise
- Second-order derivatives produce a double-edge response at ramp and step transition in intensity
- The sign of the second derivative can be used to determine whether a transition into an edge is from light to dark or dark to light

Detection of Isolated Points

- The Laplacian

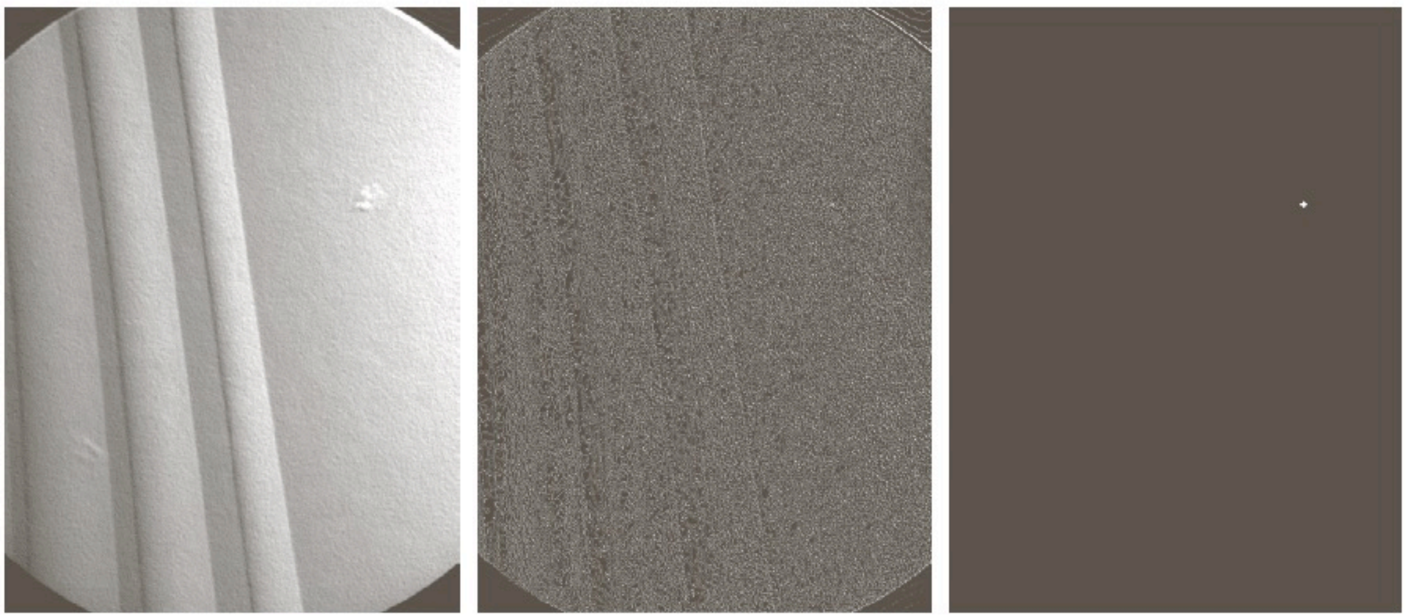
$$\nabla^2 f(x,y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

$$= f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1)$$

$$-4f(x,y)$$

$$g(x,y) = \begin{cases} 1 & \text{if } |R(x,y)| \geq T \\ 0 & \text{otherwise} \end{cases} \qquad R = \sum_{k=1}^{9} w_k z_k$$

1	1	1
1	−8	1
1	1	1



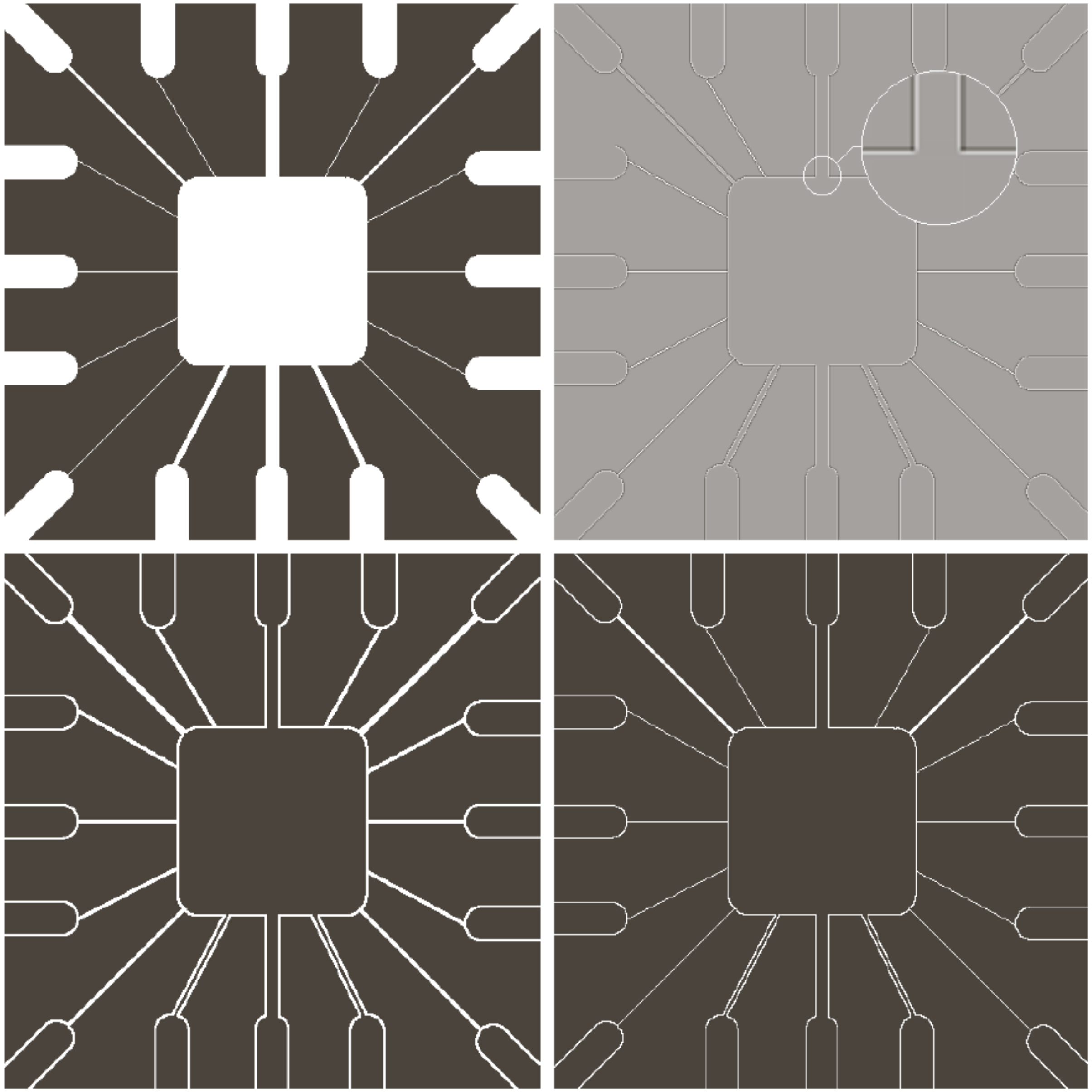
a
b c d

FIGURE 10.4 (a) Point detection (Laplacian) mask. (b) X-ray image of turbine blade with a porosity. The porosity contains a single black pixel. (c) Result of convolving the mask with the image. (d) Result of using Eq. (10.2-8) showing a single point (the point was enlarged to make it easier to see). (Original image courtesy of X-TEK Systems, Ltd.)

Line Detection

- Second derivatives to result in a stronger response and to produce thinner lines than first derivatives

- Double-line effect of the second derivative must be handled properly



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 Line in Specified Directions

Horizontal

−1	−1	−1
2	2	2
−1	−1	−1

+45°

2	−1	−1
−1	2	−1
−1	−1	2

Vertical

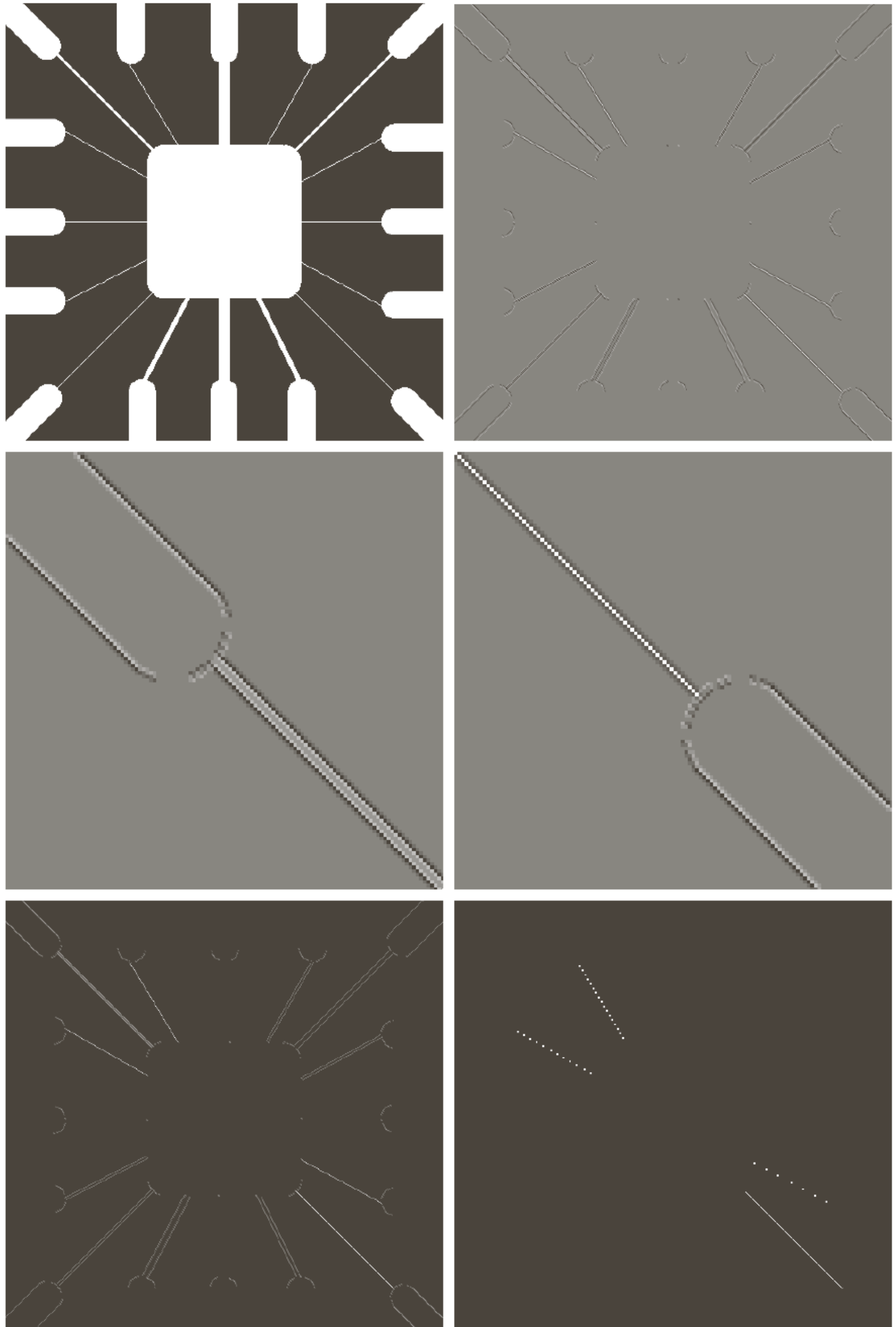
−1	2	−1
−1	2	−1
−1	2	−1

−45°

−1	−1	2
−1	2	−1
2	−1	−1

FIGURE 10.6 Line detection masks. Angles are with respect to the axis system in Fig. 2.18(b).

- Let R_1, R_2, R_3, and R_4 denote the responses of the masks in Fig. 10.6. If, at a given point in the image, $|R_k|>|R_j|$, for all $j \neq k$, that point is said to be more likely associated with a line in the direction of mask k.

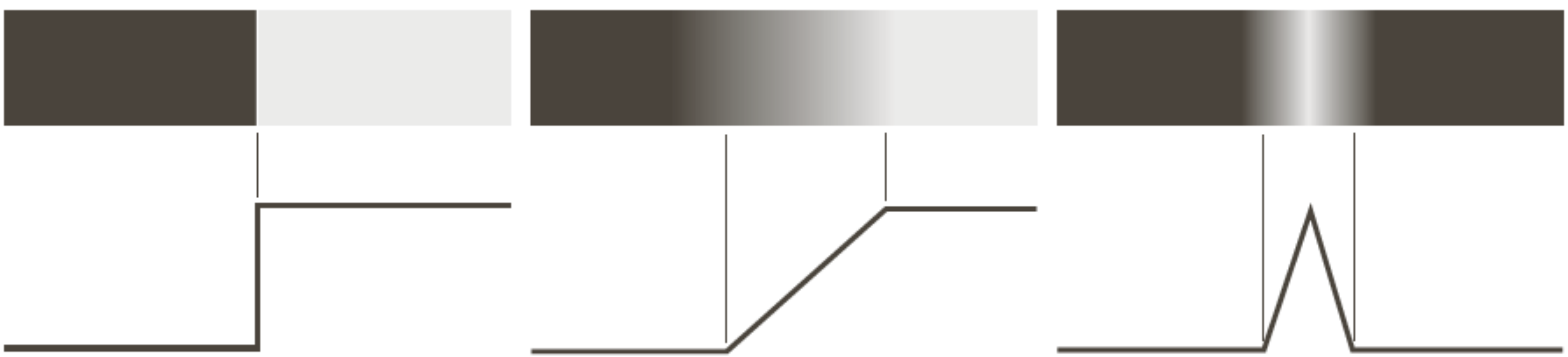


a	b
c	d
e	f

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 Detection

- Edges are pixels where the brightness function changes abruptly
- Edge models



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.

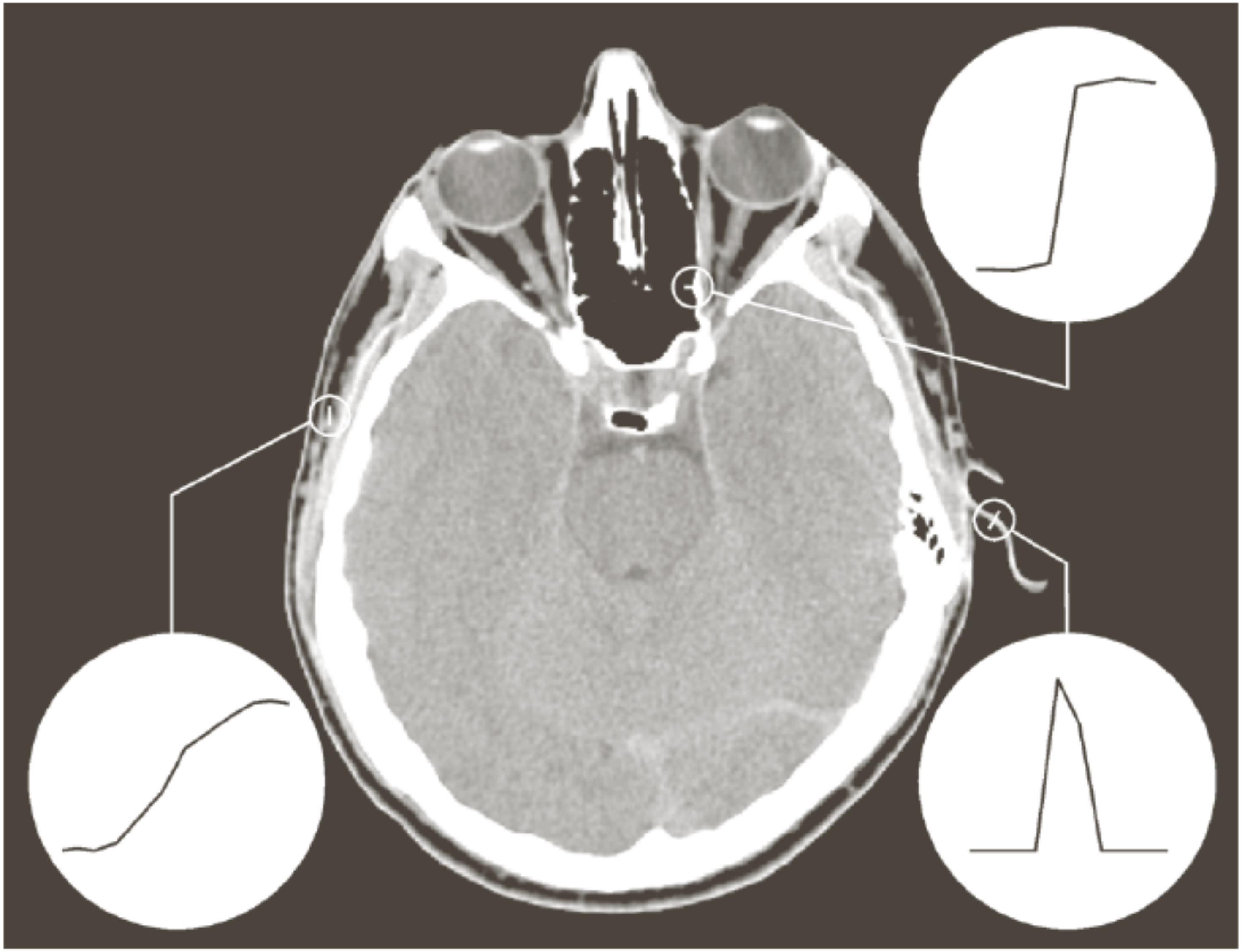
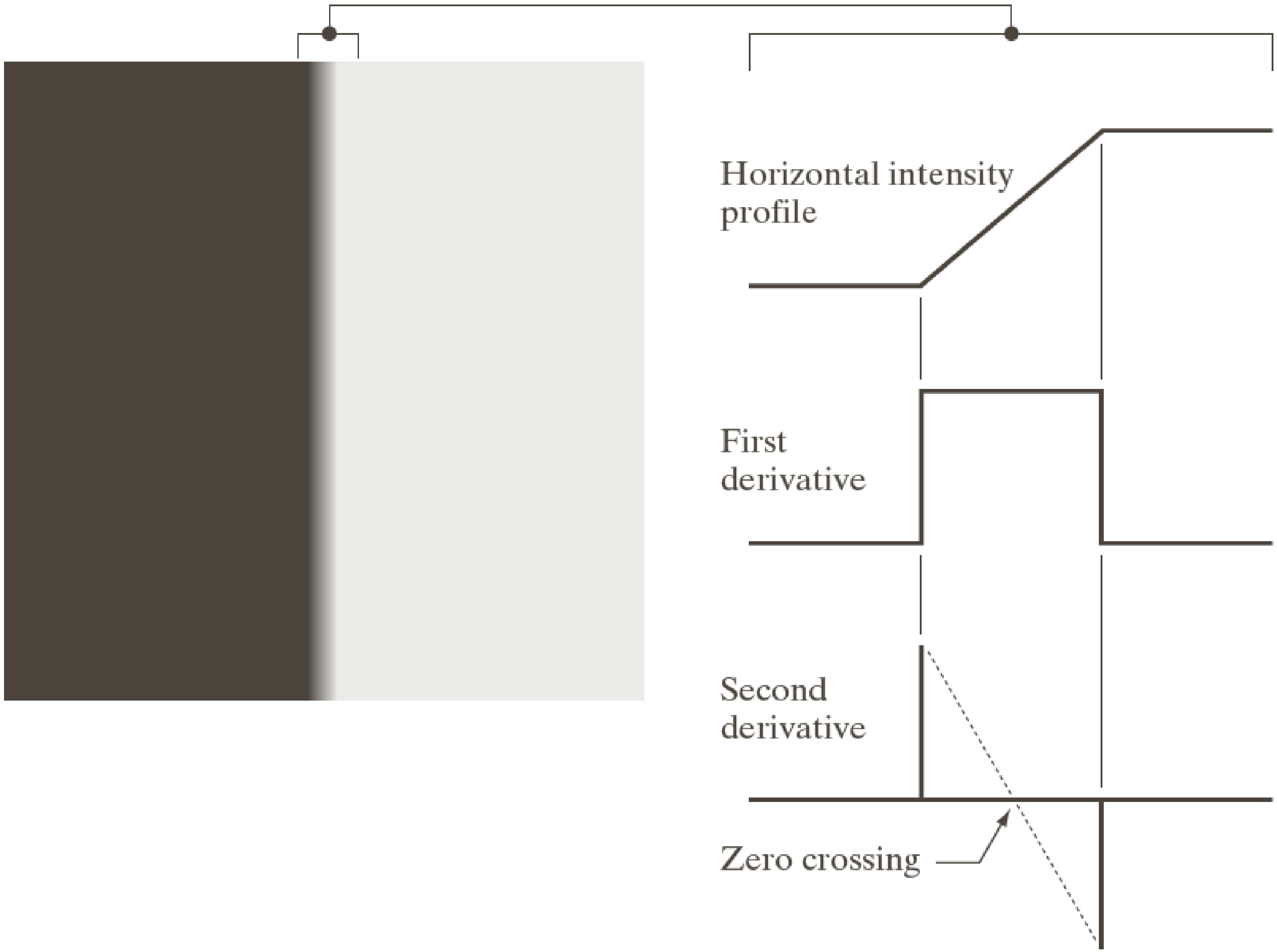


FIGURE 10.9 A 1508 × 1970 image showing (zoomed) actual ramp (bottom, left), step (top, right), and roof edge profiles. The profiles are from dark to light, in the areas indicated by the short line segments shown in the small circles. The ramp and "step" profiles span 9 pixels and 2 pixels, respectively.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



a b

FIGURE 10.10
(a) Two regions of constant intensity separated by an ideal vertical ramp edge.
(b) Detail near the edge, showing a horizontal intensity profile, together with its first and second derivatives.

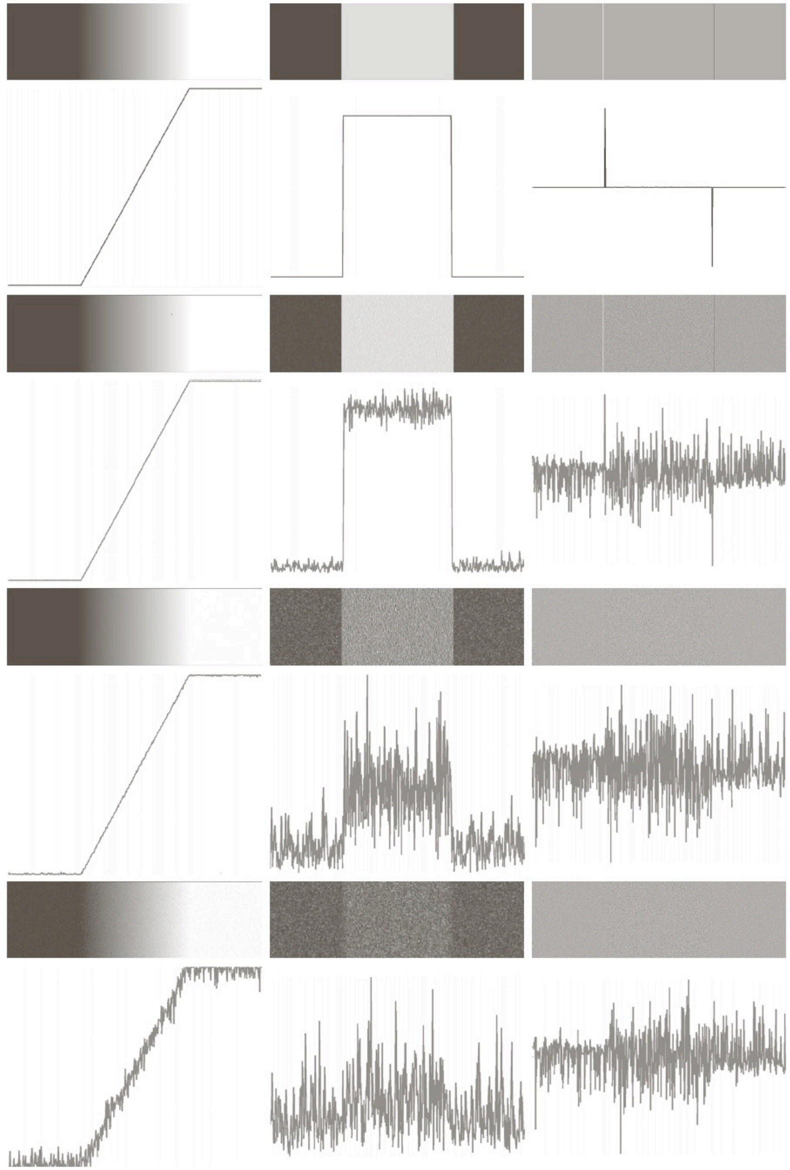


FIGURE 10.11 First column: Images and intensity profiles of a ramp edge corrupted by random Gaussian noise of zero mean and standard deviations of 0.0, 0.1, 1.0, and 10.0 intensity levels, respectively. Second column: First-derivative images and intensity profiles. Third column: Second-derivative images and intensity profiles.

Typical Steps Performed for Edge Detection

1. Image smoothing for noise reduction
2. Detection of edge points
3. Edge localization

Basic Edge Detection by Using First-Order Derivative

Edge normal: $\nabla f \equiv grad(f) = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f}{\partial x} \\ \dfrac{\partial f}{\partial y} \end{bmatrix}$

Edge unit normal: $\nabla f \,/\, \text{mag}(\nabla f)$

Edge Direction: $\alpha(x,y) = \tan^{-1}[g_y(x,y)/g_x(x,y)]$

In practice,sometimes the magnitude is approximated by

$$\text{mag}(\nabla f) = \left|\frac{\partial f}{\partial x}\right| + \left|\frac{\partial f}{\partial y}\right| \text{ or } \text{mag}(\nabla f) = \max\left(\left|\frac{\partial f}{\partial x}\right|, \left|\frac{\partial f}{\partial y}\right| \right)$$

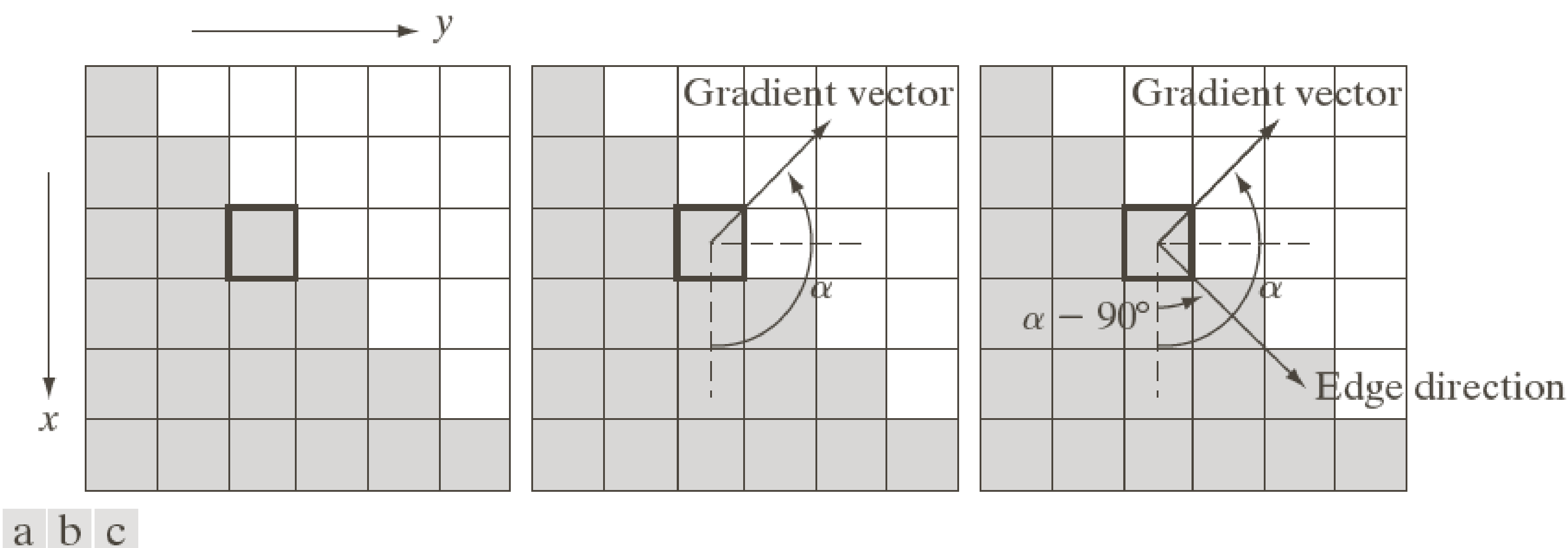


FIGURE 10.12 Using the gradient to determine edge strength and direction at a point. Note that the edge is perpendicular to the direction of the gradient vector at the point where the gradient is computed. Each square in the figure represents one pixel.

a b

−1
1

−1	1

FIGURE 10.13 One-dimensional masks used to implement Eqs. (10.2-12) and (10.2-13).

- Kernels used for computing g_x and g_y
- Capture changes in the x and y directions but what about diagonal edge detection?
- A 2D mask is necessary

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

a
b c
d e
f g

FIGURE 10.14 A 3×3 region of an image (the z's are intensity values) and various masks used to compute the gradient at the point labeled z_5.

0	1	1		−1	−1	0
−1	0	1		−1	0	1
−1	−1	0		0	1	1

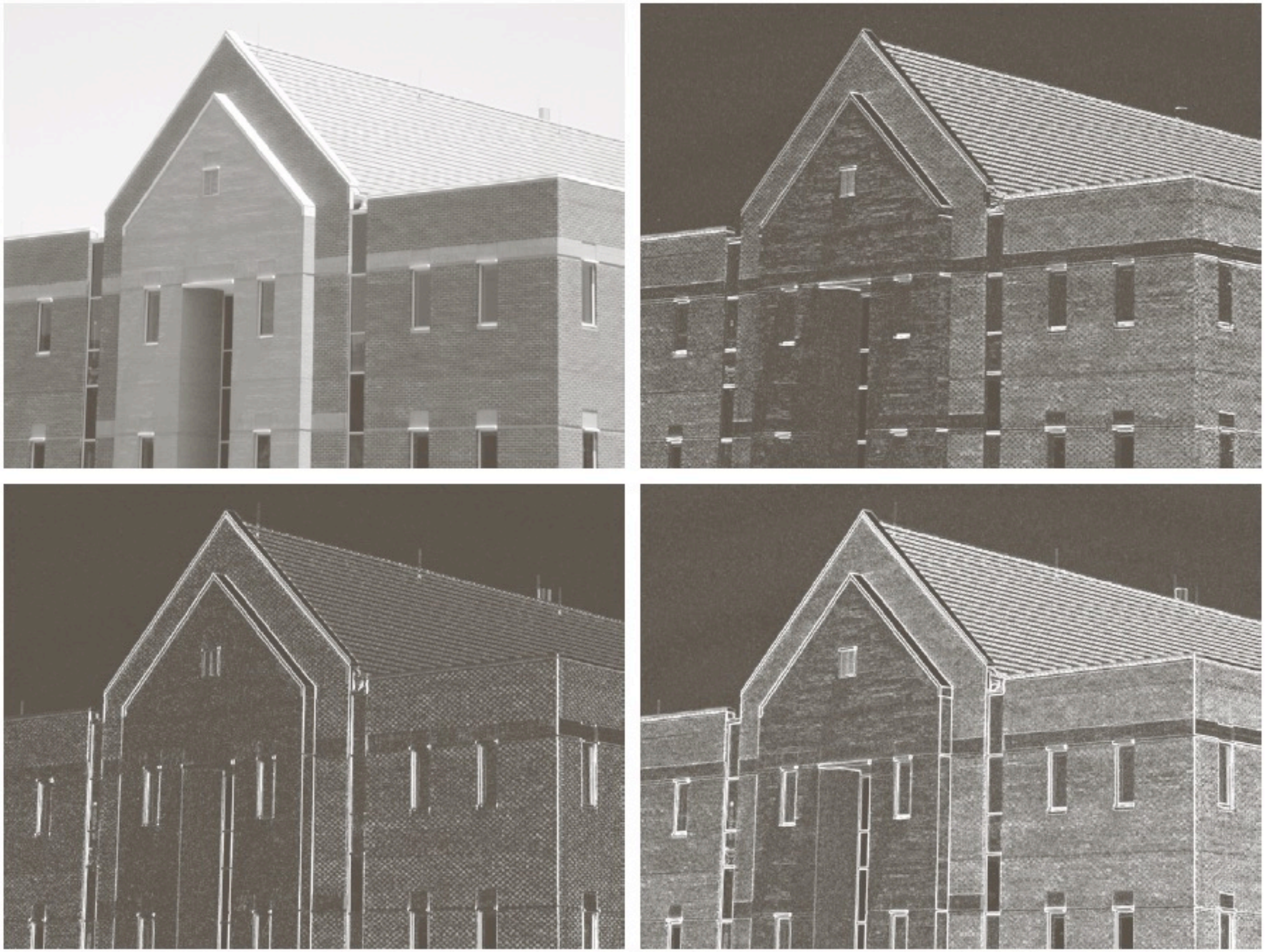
Prewitt

0	1	2		−2	−1	0
−1	0	1		−1	0	1
−2	−1	0		0	1	2

Sobel

a	b
c	d

FIGURE 10.15 Prewitt and Sobel masks for detecting diagonal edges.



a b
c d

FIGURE 10.16 (a) Original image of size 834×1114 pixels, with intensity values scaled to the range $[0, 1]$. (b) $|g_x|$, the component of the gradient in the x-direction, obtained using the Sobel mask in Fig. 10.14(f) to filter the image. (c) $|g_y|$, obtained using the mask in Fig. 10.14(g). (d) The gradient image, $|g_x| + |g_y|$.

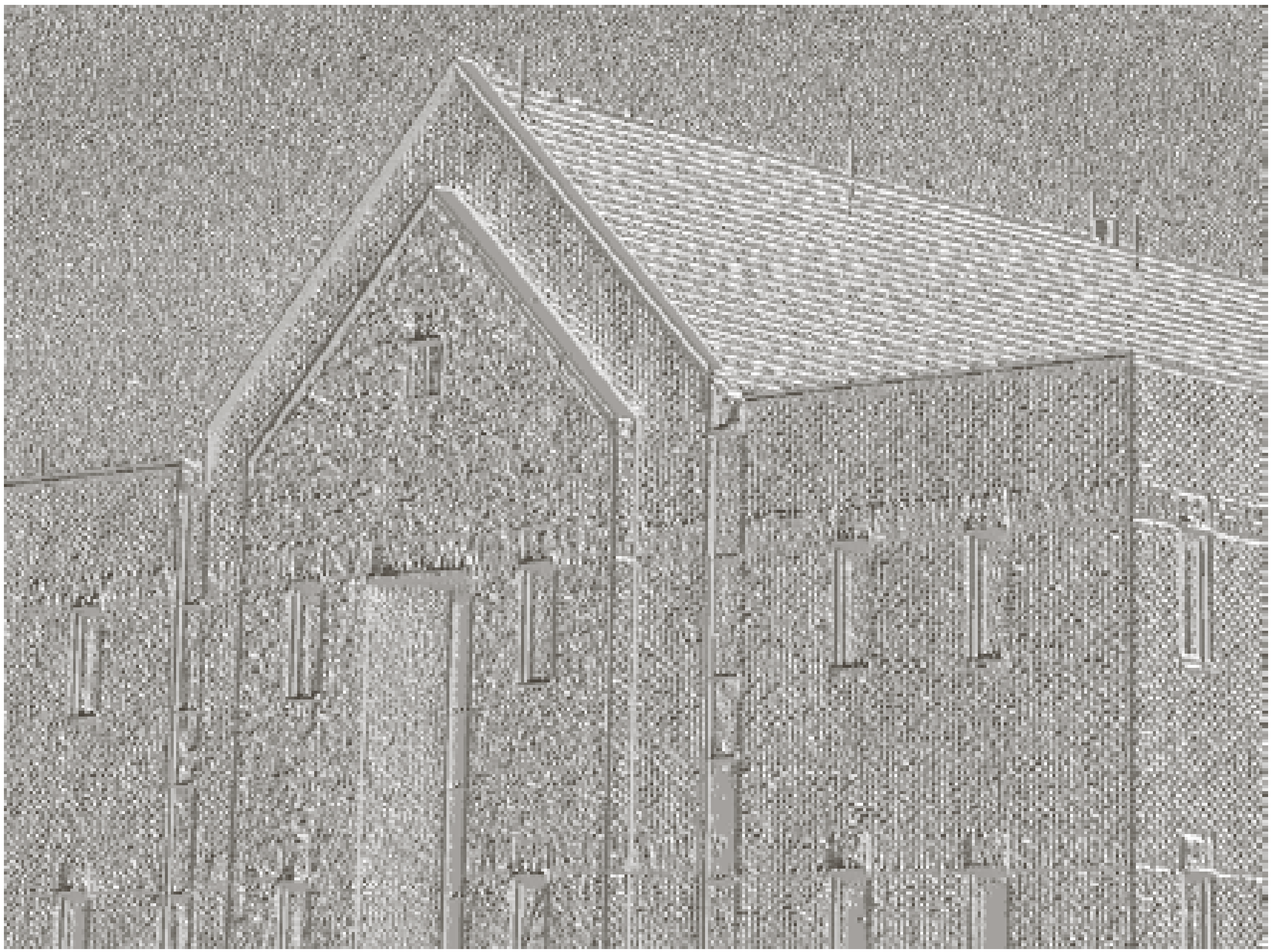
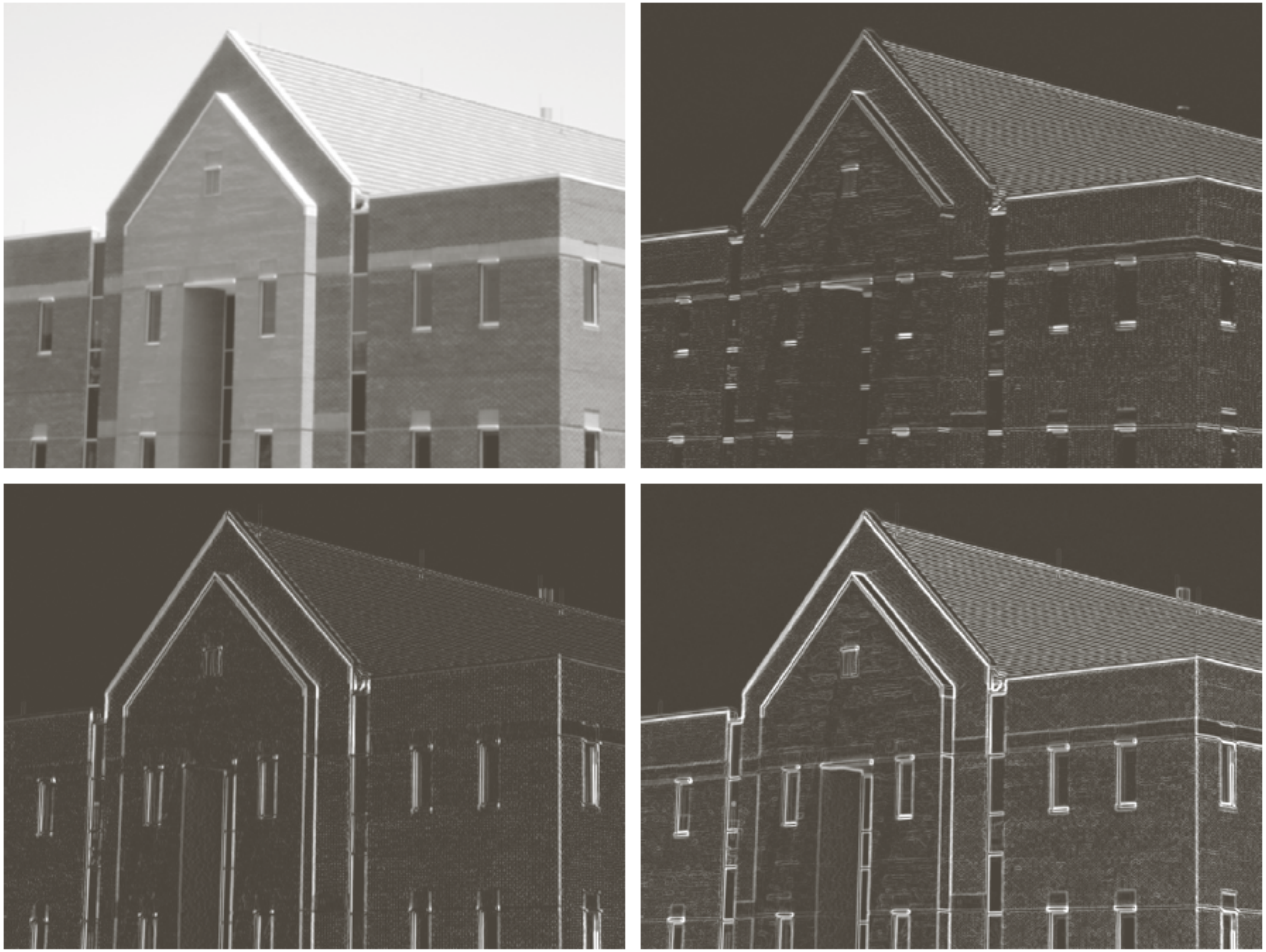


FIGURE 10.17 Gradient angle image computed using Eq. (10.2-11). Areas of constant intensity in this image indicate that the direction of the gradient vector is the same at all the pixel locations in those regions.



a	b
c	d

FIGURE 10.18 Same sequence as in Fig. 10.16, but with the original image smoothed using a 5×5 averaging filter prior to edge detection.

Kirsch Compass Kernel

a	b	c	d
e	f	g	h

FIGURE 10.15 Kirsch compass kernels. The edge direction of strongest response of each kernel is labeled below it.

−3	−3	5
−3	0	5
−3	−3	5

N

−3	5	5
−3	0	5
−3	−3	−3

NW

5	5	5
−3	0	−3
−3	−3	−3

W

5	5	−3
5	0	−3
−3	−3	−3

SW

5	−3	−3
5	0	−3
5	−3	−3

S

−3	−3	−3
5	0	−3
5	5	−3

SE

−3	−3	−3
−3	0	−3
5	5	5

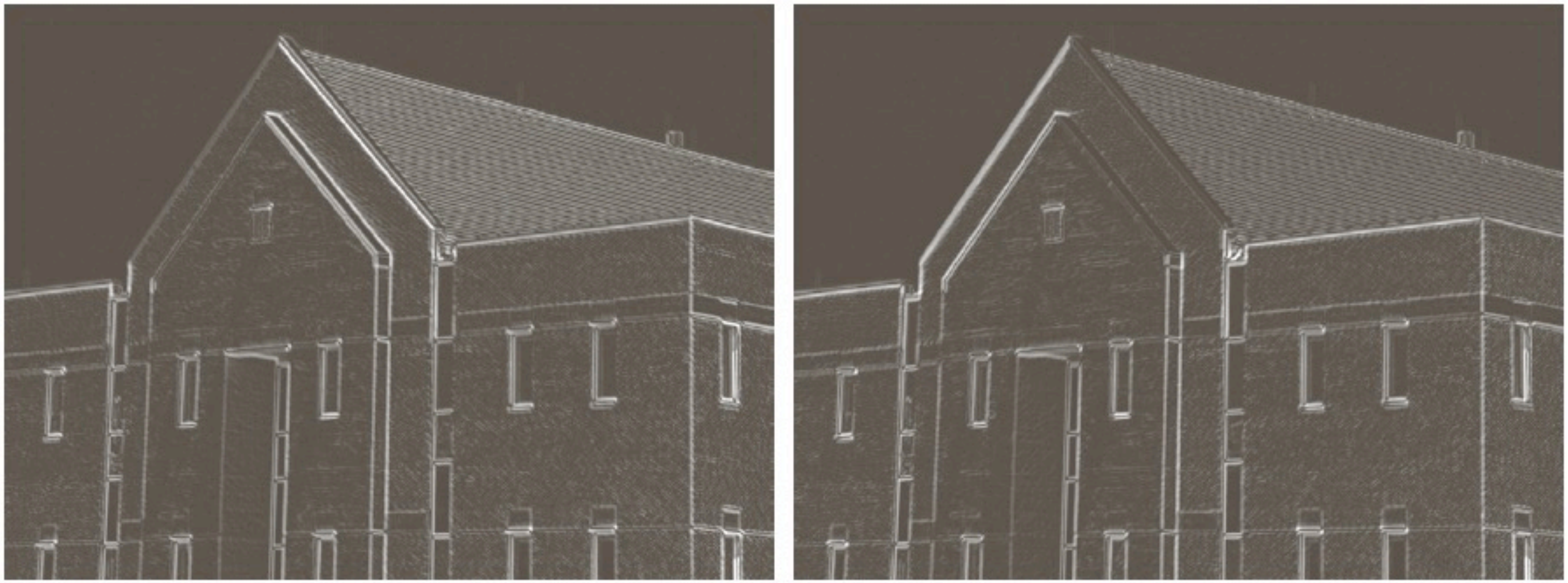
E

−3	−3	−3
−3	0	5
−3	5	5

NE

- Are designed to detect edge direction and magnitude in all eight compass directions.
- Rather than compute the magnitude and direction using the previous formulas, convolve with all eight kernels and assign magnitude to points as the one which gave the highest response.

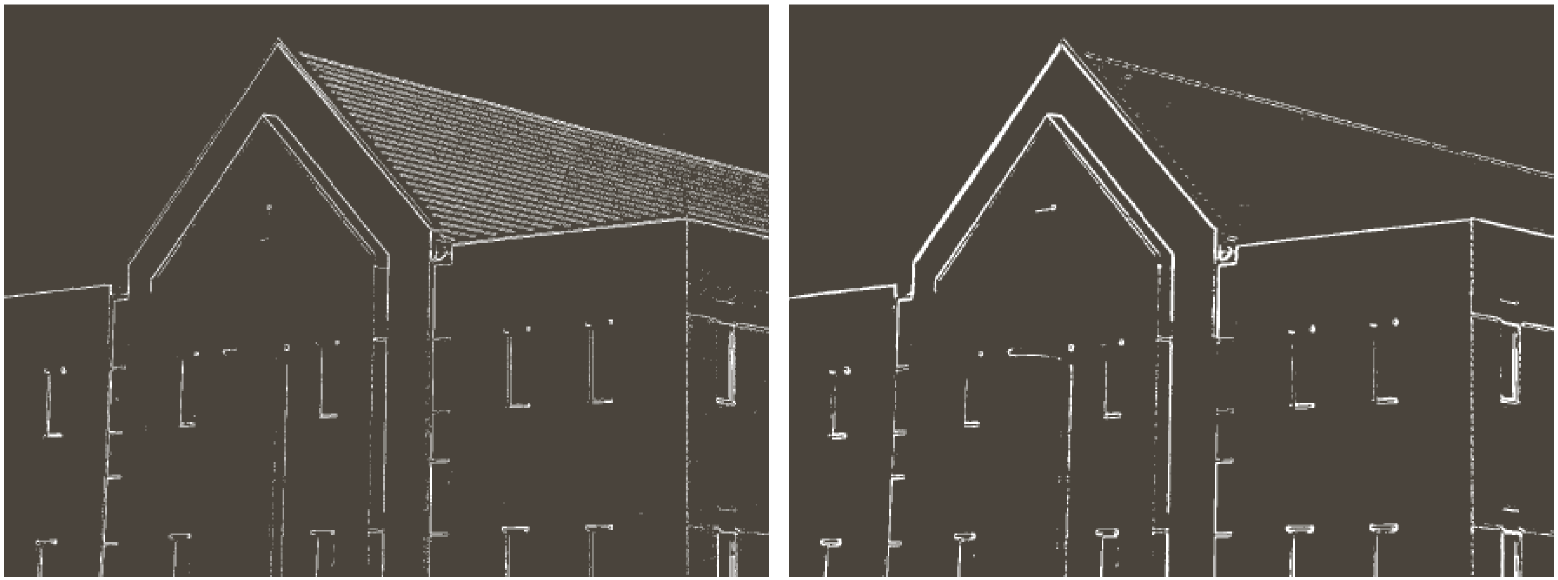
Kirsch Kernel Result



a b

FIGURE 10.19 Diagonal edge detection. (a) Result of using the mask in Fig. 10.15(c). (b) Result of using the mask in Fig. 10.15(d). The input image in both cases was Fig. 10.18(a).

Combining the Gradient with Thresholding



a b

FIGURE 10.20 (a) Thresholded version of the image in Fig. 10.16(d), with the threshold selected as 33% of the highest value in the image; this threshold was just high enough to eliminate most of the brick edges in the gradient image. (b) Thresholded version of the image in Fig. 10.18(d), obtained using a threshold equal to 33% of the highest value in that image.

Advanced Techniques for Edge Detection

Edge Detection Ideas

- The basic edge detection methods is based on simple filtering without taking note of image characteristic and other information
- More advanced techniques make attempt to improve the simple detection by taking into account factors such as noise, scaling, etc.
- We will discuss two advanced methods
  - Marr-Hildreth [1980]
  - Canny [1986]

Edge Detection Ideas

- Intensity changes are not independent of image scale, implying that detection requires using operators of different sizes.

- Sudden intensity changes will give rise to a peak or trough in the first derivative or equivalently, to a zero crossing in the second derivative.

Edge Detection Ideas (cont.)

The previous ideas suggest that an operator used for edge detection should have two salient features

- It should be a differential operator capable of computing the digital approximation of the first or second derivative at every point in the image.
- It should be capable of being “tuned” to act at any desired scale, so that large operators can be used to detect blurry edges and small operators to detect sharply focused fine detail.

Advanced Techniques for Edge Detection

The Marr-Hildreth edge detector

$$G(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}}, \;\; \sigma: \text{space constant.}$$

Laplacian of Gaussian (LoG)

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

$$= \frac{\partial}{\partial x}\left[\frac{-x}{\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}\right] + \frac{\partial}{\partial y}\left[\frac{-y}{\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}\right]$$

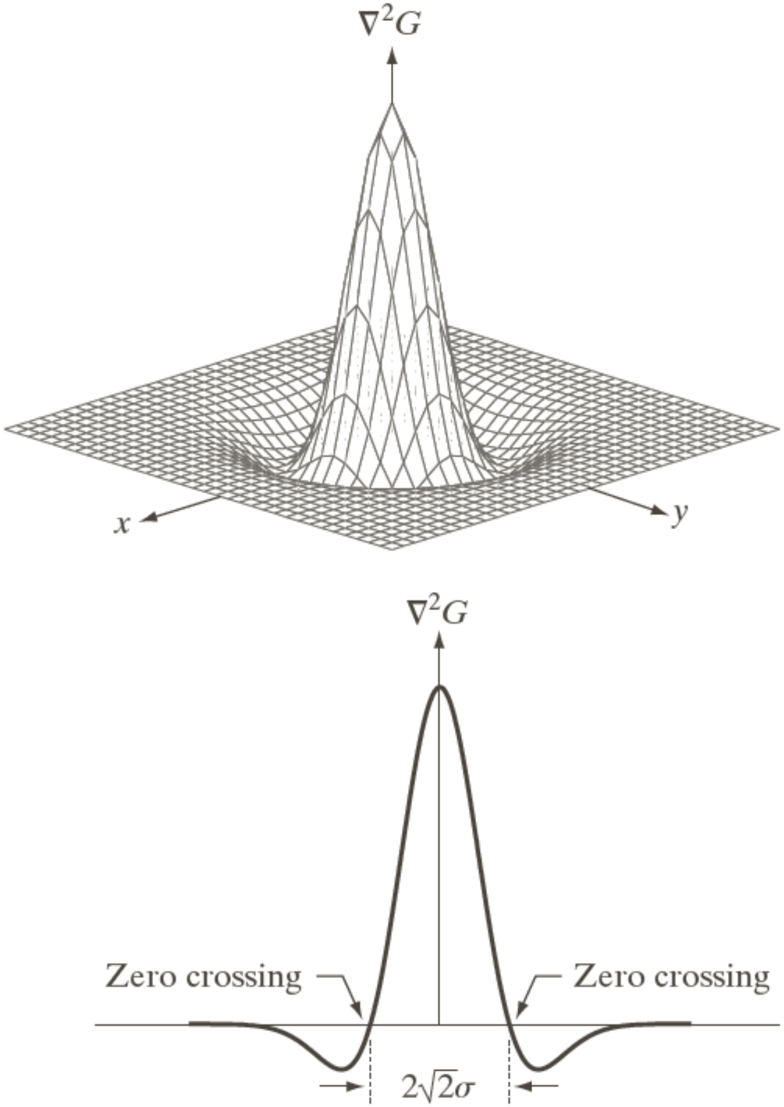
$$= \left[\frac{x^2}{\sigma^4} - \frac{1}{\sigma^2}\right] e^{-\frac{x^2+y^2}{2\sigma^2}} + \left[\frac{y^2}{\sigma^4} - \frac{1}{\sigma^2}\right] e^{-\frac{x^2+y^2}{2\sigma^2}}$$

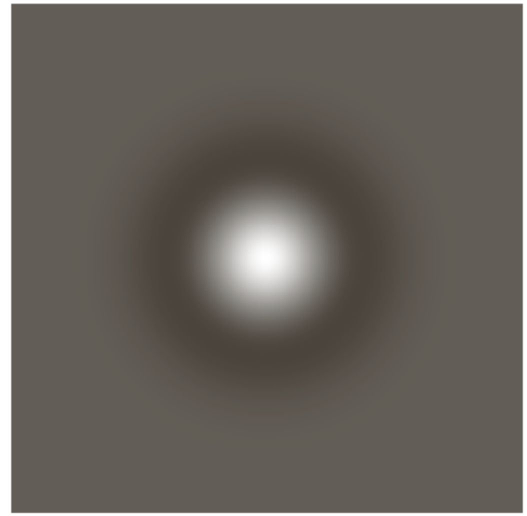
$$= \left[\frac{x^2 + y^2 - \sigma^2}{\sigma^4}\right] e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Marr-Hildreth edge detector

- The Gaussian part of the operator blurs the image, the reducing the intensity of structures (including noise) at scales smaller than σ. Less likely to introduce ringing.

- Operator is isotropic so the application of multiple kernels to calculate the strongest response not necessary.





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.

Marr-Hildreth Algorithm

1. Filter the input image with an nxn Gaussian lowpass filter. N is the smallest odd integer greater than or equal to 6σ

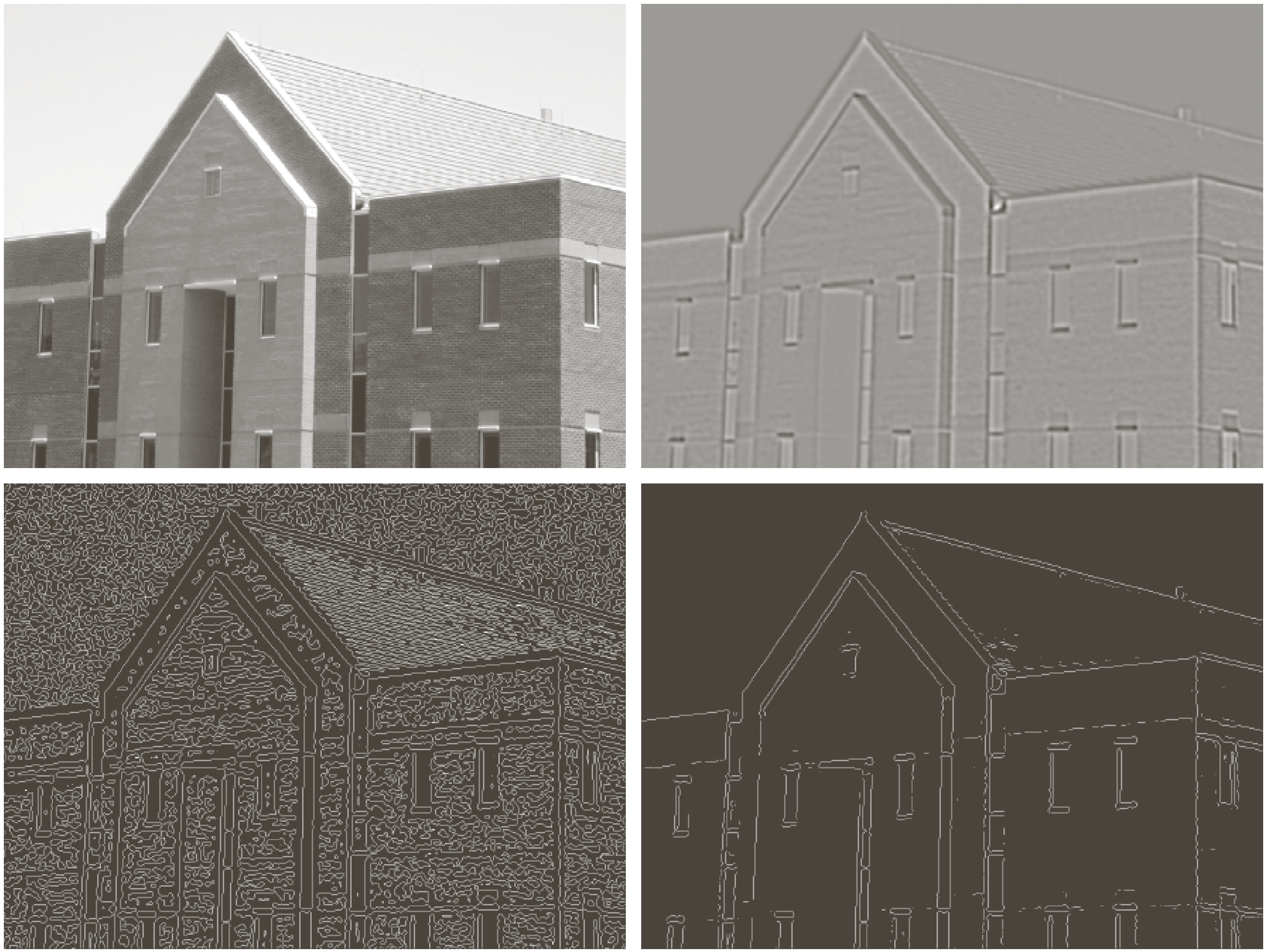
2. Compute the Laplacian of the image resulting from step1

3. Find the zero crossing of the image from step 2

$$g(x,y) = \nabla^2 \left[G(x,y) \star f(x,y) \right]$$

Marr-Hildreth Algorithm

- To find a zero crossing it is possible to use a 3x3 mask that checks sign changes around a pixel (At least two of opposing neighbor signs must differ.
  - Test four cases: left/right, up/down, and two diagonals
  - Check for opposing signs of neighbors as well as if the absolute value of their difference exceeds a specified threshold.
- Sometimes it is recommended to use the algorithm with different σ values and then to combine the results.



a b
c d

FIGURE 10.22
(a) Original image of size 834 × 1114 pixels, with intensity values scaled to the range [0, 1]. (b) Results of Steps 1 and 2 of the Marr-Hildreth algorithm using $\sigma = 4$ and $n = 25$. (c) Zero crossings of (b) using a threshold of 0 (note the closed-loop edges). (d) Zero crossings found using a threshold equal to 4% of the maximum value of the image in (b). Note the thin edges.

The Canny Edge Detector

Using numerical optimization it was determined that the optimal step edge detector is the first derivative of a Gaussian.

Objectives

- **Low error rate**
  The edges detected must be as close as possible to the true edge
- **Edge points should be well localized**
  The edges located must be as close as possible to the true edges
- **Single edge point response**
  The number of local maxima around the true edge should be minimum

The Canny Edge Detector: Algorithm (1)

Let $f(x, y)$ denote the input image and $G(x, y)$ denote the Gaussian function:

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

We form a smoothed image, $f_s(x, y)$ by convolving G and f:

$$f_s(x, y) = G(x, y) \bigstar f(x, y)$$

The Canny Edge Detector: Algorithm(2)

Compute the gradient magnitude and direction (angle):

$$M(x, y) = \sqrt{{g_x}^2 + {g_y}^2}$$

and

$$\alpha(x, y) = \arctan(g_y / g_x)$$

where $g_x = \partial f_s / \partial x$ and $g_y = \partial f_s / \partial y$

Note: any of the filter mask pairs in Fig.10.14 can be used to obtain g_x and g_y

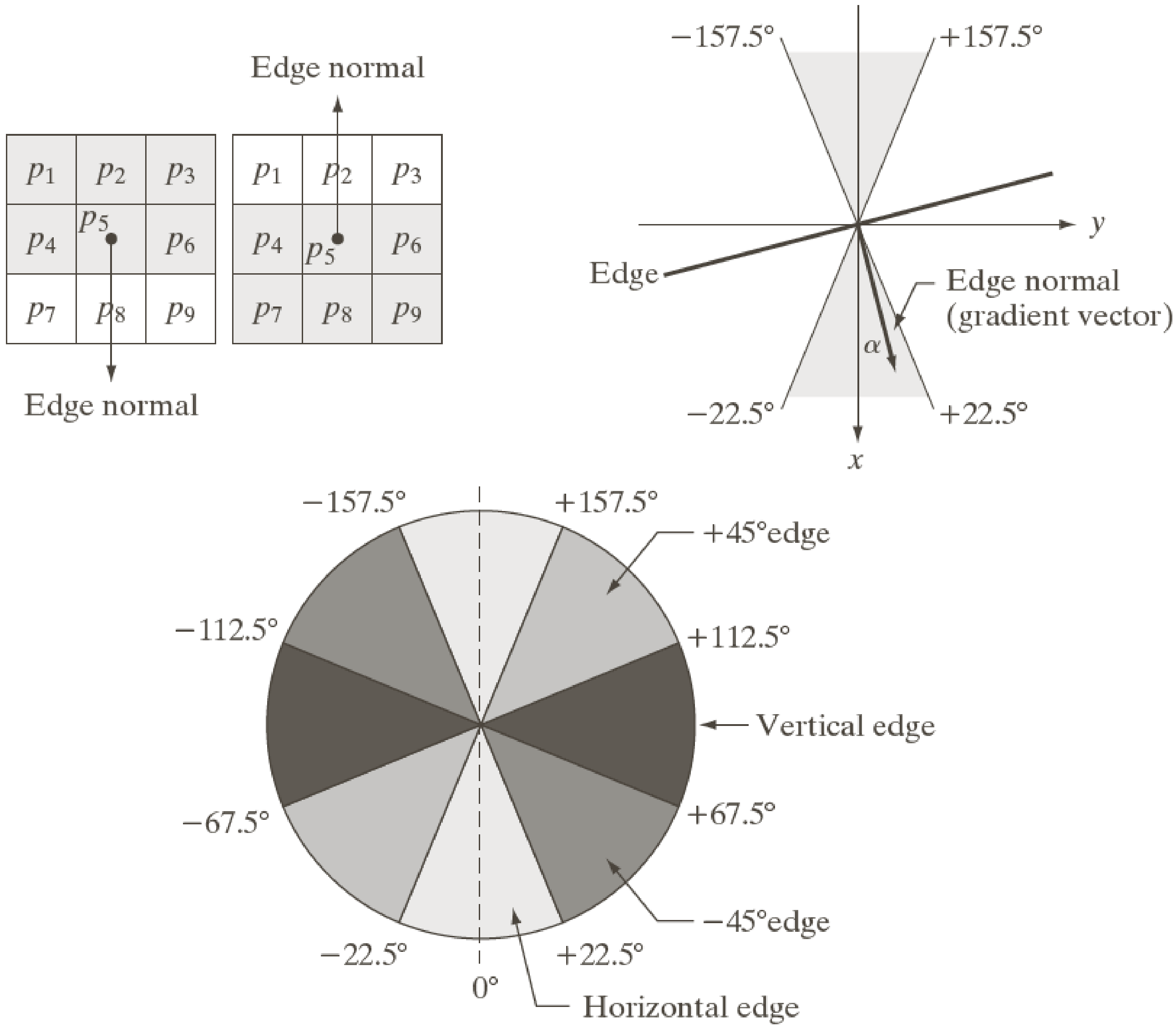
The Canny Edge Detector: Algorithm(3)

The gradient $M(x, y)$ typically contains wide ridge around local maxima. Next step is to thin those ridges.

Nonmaxima suppression:

Let d_1, d_2, d_3, and d_4 denote the four basic edge directions for a 3×3 region: horizontal, -45°, vertical,+45°, respectively.

1. Find the direction d_k that is closest to $\alpha(x, y)$.
2. If the value of $M(x, y)$ is less than at least one of its two neighbors along d_k, let $g_N(x, y) = 0$ (suppression); otherwise, let $g_N(x, y) = M(x, y)$



a b
c

FIGURE 10.24 (a) Two possible orientations of a horizontal edge (in gray) in a 3 × 3 neighborhood. (b) Range of values (in gray) of α, the direction angle of the *edge normal*, for a horizontal edge. (c) The angle ranges of the edge normals for the four types of edge directions in a 3 × 3 neighborhood. Each edge direction has two ranges, shown in corresponding shades of gray.

The Canny Edge Detector: Algorithm(4)

The final operation is to threshold $g_N(x, y)$ to reduce false edge points.

<u>Hysteresis thresholding</u>:

$$g_{NH}(x, y) = g_N(x, y) \geq T_H$$
$$g_{NL}(x, y) = g_N(x, y) \geq T_L$$

and

$$g_{NL}(x, y) = g_{NL}(x, y) - g_{NH}(x, y)$$

The Canny Edge Detector: Algorithm(5)

Depending on the value of T_H, the edges in $g_{NH}(x, y)$ typically have gaps. Longer edges are formed using the following procedure:

(a). Locate the next unvisited edge pixel, p, in $g_{NH}(x, y)$.

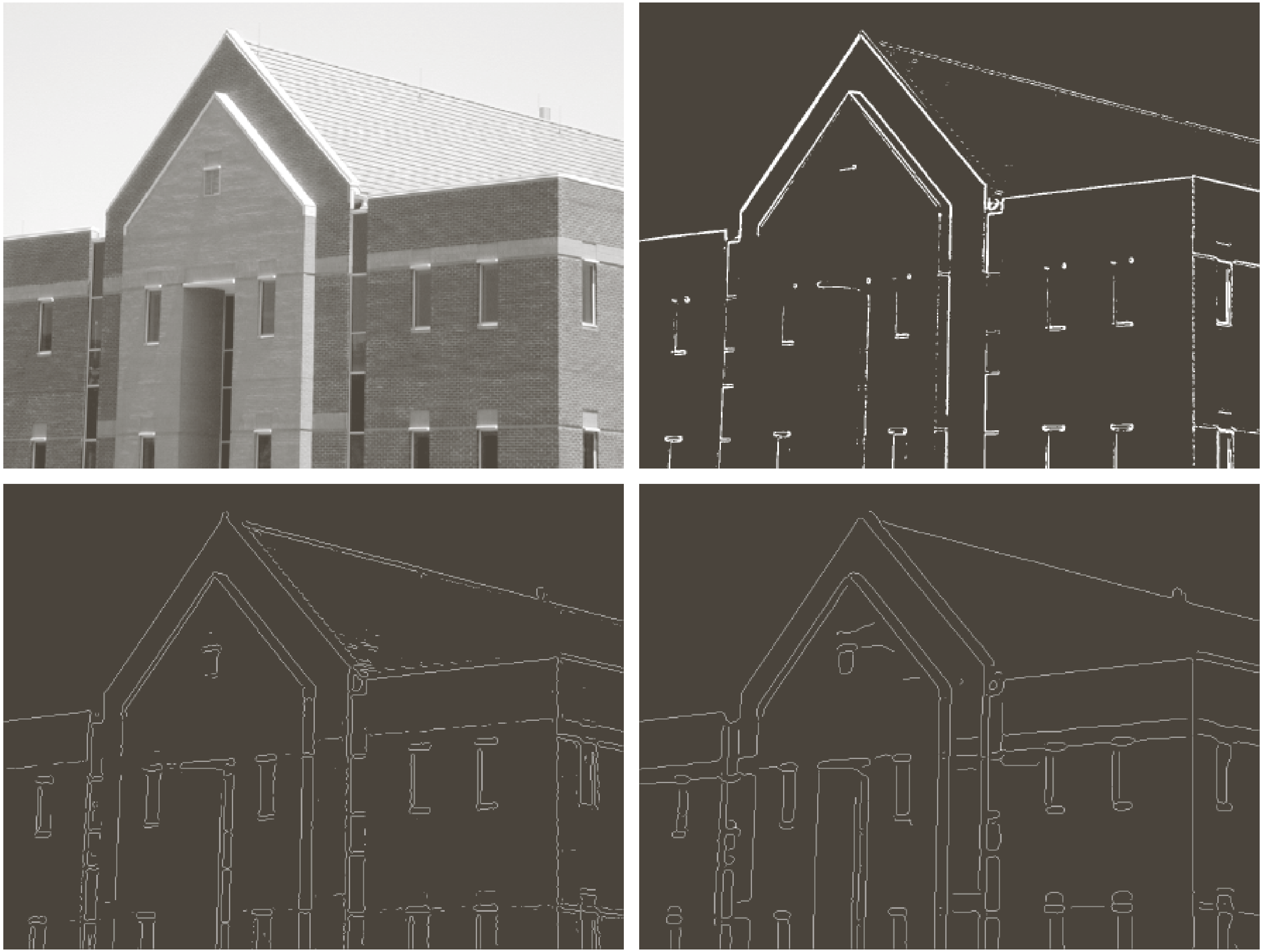
(b). Mark as valid edge pixel all the weak pixels in $g_{NL}(x, y)$ that are connected to p using 8-connectivity.

(c). If all nonzero pixel in $g_{NH}(x, y)$ have been visited go to step (d), esle return to (a).

(d). Set to zero all pixels in $g_{NL}(x, y)$ that were not marked as valid edge pixels.

The Canny Edge Detection: Summary

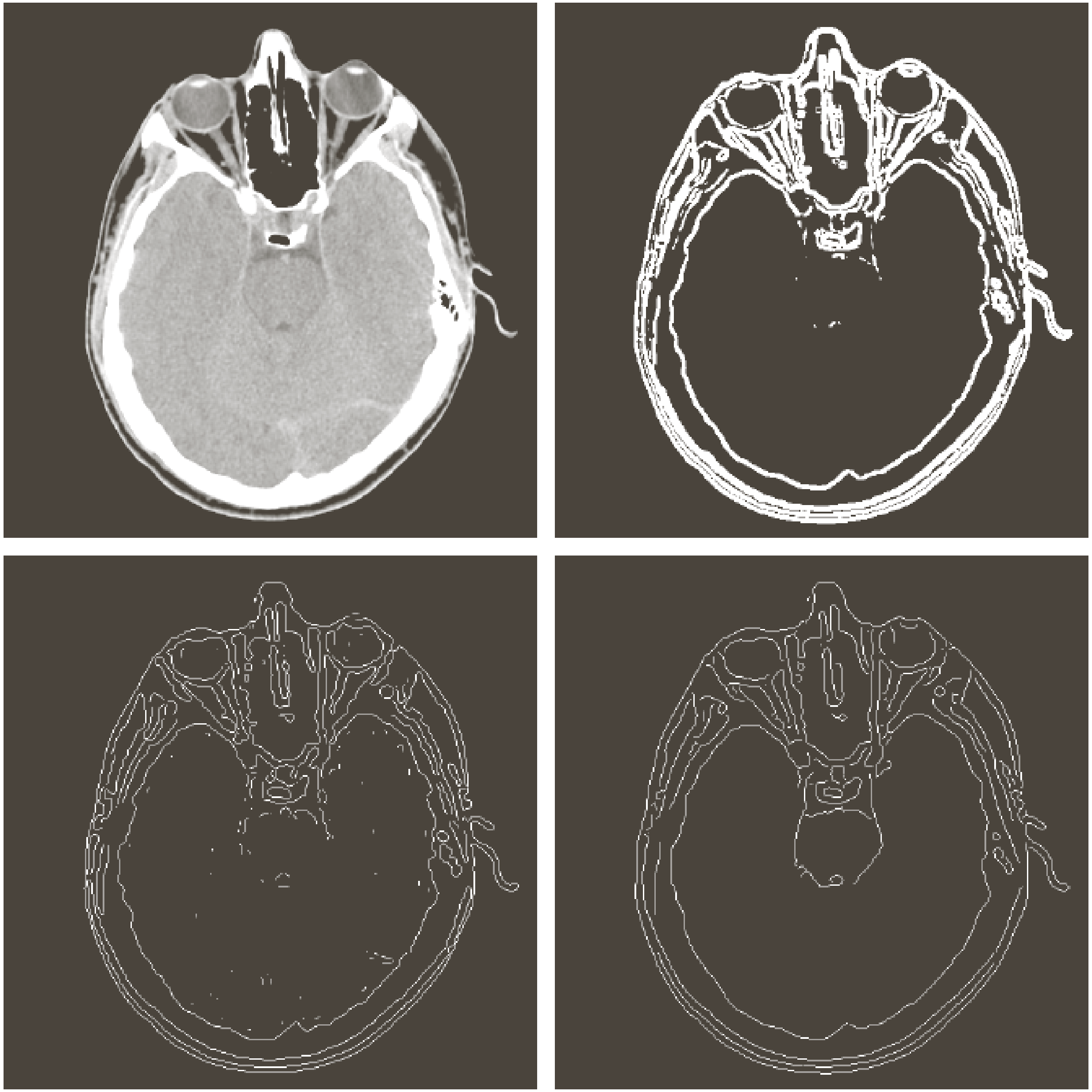
- Smooth the input image with a Gaussian filter
- Compute the gradient magnitude and angle images
- Apply nonmaxima suppression to the gradient magnitude image
- Use double thresholding and connectivity analysis to detect and link edges



a	b
c	d

FIGURE 10.25
(a) Original image of size 834 × 1114 pixels, with intensity values scaled to the range [0, 1].
(b) Thresholded gradient of smoothed image.
(c) Image obtained using the Marr-Hildreth algorithm.
(d) Image obtained using the Canny algorithm. Note the significant improvement of the Canny image compared to the other two.

$T_L = 0.04; T_H = 0.10; \sigma = 4$ and a mask of size 25×25



a	b
c	d

FIGURE 10.26 (a) Original head CT image of size 512 × 512 pixels, with intensity values scaled to the range [0, 1]. (b) Thresholded gradient of smoothed image. (c) Image obtained using the Marr-Hildreth algorithm. (d) Image obtained using the Canny algorithm. (Original image courtesy of Dr. David R. Pickens, Vanderbilt University.)

$T_L = 0.05; T_H = 0.15; \sigma = 2$ and a mask of size 13×13

Canny Edge Detector

- Canny edge detector exhibits best performance compared other methods.

- Implementation is significantly more complex than previous approaches.

Edge Linking and Boundary Detection

Edge Linking and Boundary Detection

- Edge detection typically is followed by linking algorithms designed to assemble edge pixels into meaningful edges and/or region boundaries

- Two approaches to edge linking
  Local processing
  Global processing (Hough Transform)

Local Processing

- Analyze the characteristics of pixels in a small neighborhood about every point (x,y) that has been declared an edge point

- All points that similar according to predefined criteria are linked, forming an edge of pixels.

 Establishing similarity: (1) the strength (magnitude) and (2) the direction of the gradient vector.

 A pixel with coordinates (s,t) in S_{xy} is linked to the pixel at (x,y) if both magnitude and direction criteria are satisfied.

Local Processing

Let S_{xy} denote the set of coordinates of a neighborhood centered at point (x, y) in an image. An edge pixel with coordinate (s,t) in S_{xy} is similar in *magnitude* to the pixel at (x, y) if

$$\left|M(s,t) - M(x, y)\right| \leq E$$

An edge pixel with coordinate (s,t) in S_{xy} is similar in *angle* to the pixel at (x, y) if

$$\left|\alpha(s,t) - \alpha(x, y)\right| \leq A$$

Local Processing: Steps (1)

1. Compute the gradient magnitude and angle arrays, M(x,y) and $\alpha(x,y)$, of the input image f(x,y)

2. Form a binary image, g, whose value at any pair of coordinates (x,y) is given by

$$g(x,y)=\begin{cases}1 & \text{if } M(x,y)>T_M \text{ and } \alpha(x,y)=A\pm T_A \\ 0 & \text{otherwise}\end{cases}$$

T_M : threshold $\quad A$: specified angle direction

T_A: a "band" of acceptable directions about A

Local Processing: Steps (2)

3. Scan the rows of g and fill (set to 1) all gaps (sets of 0s) in each row that do not exceed a specified length, K.

4. To detect gaps in any other direction, rotate g by this angle and apply the horizontal scanning procedure in step 3.

FIGURE 10.27 (a) A 534×566 image of the rear of a vehicle. (b) Gradient magnitude image. (c) Horizontally connected edge pixels. (d) Vertically connected edge pixels. (e) The logical OR of the two preceding images. (f) Final result obtained using morphological thinning. (Original image courtesy of Perceptics Corporation.)

Questions?

Slide Credits

Images taken from Digital Image Processing by Gonzalez and Woods Text.

Material taken from Jen-Chang Liu lecture slides

Material taken from Stanley Birchfield lecture slides