IMAGE SEGMENTATION

IMAGE SEGMENTATION

- ✓ It is a stage of transition from image processing methods whose inputs and outputs are images, to methods in which the inputs are images but the outputs are attributes extracted from those images.

IMAGE SEGMENTATION CONCEPT

- ✓ Segmentation refers to the process of partitioning an image into multiple regions.
- ✓ Regions : A group of connected pixels with similar properties.
  - ✓ Regions are used to interpret images.
  - ✓ A region may correspond to a particular object, or different parts of an object.

SEGMENTATION-REQUIREMENT

In most cases, segmentation should provide a set of regions having the following properties

- Connectivity and compactness
- Regularity of boundaries
- Homogeneity in terms of color or texture
- Differentiation from neighbor regions

NEED FOR SEGMENTATION

- ✓ The goal of segmentation is to simplify the representation of an image into something that is more meaningful and easier to analyze.
- ✓ Image segmentation is typically used to locate objects and boundaries in images.
- ✓ For correct interpretation, image must be partitioned into regions that correspond to objects or parts of an object.

BASIC FORMULATION

Let R represent the entire image region. We want to partition R into n sub regions, R1, R2, ... Rn, such that:

- $\bigcup_{i=1}^{n} R_i = R$
- R_i is a connected set, i =1,2,....,n.
- $R_i \cap R_j = \varnothing$ for all i and j, $i \neq j$
- $Q(R_i) =$ TRUE for i = i = 1, 2,...,n
- $Q(R_i \cup R_j) =$ False , $i \neq j$

BASIC FORMULATION

- segmentation must be complete
  - all pixels must belong to a region
- pixels in a region must be connected
- regions must be disjoint
- $Q(R_i)$ states that pixels in a region must all share the same property
  - The logic predicate $Q(R_i)$ over a region must return True
- indicates that regions are different in the sense of the predicate Q.

BASIC PROPERTIES OF SEGMENTATION

Segmentation is based on basic properties of intensity values

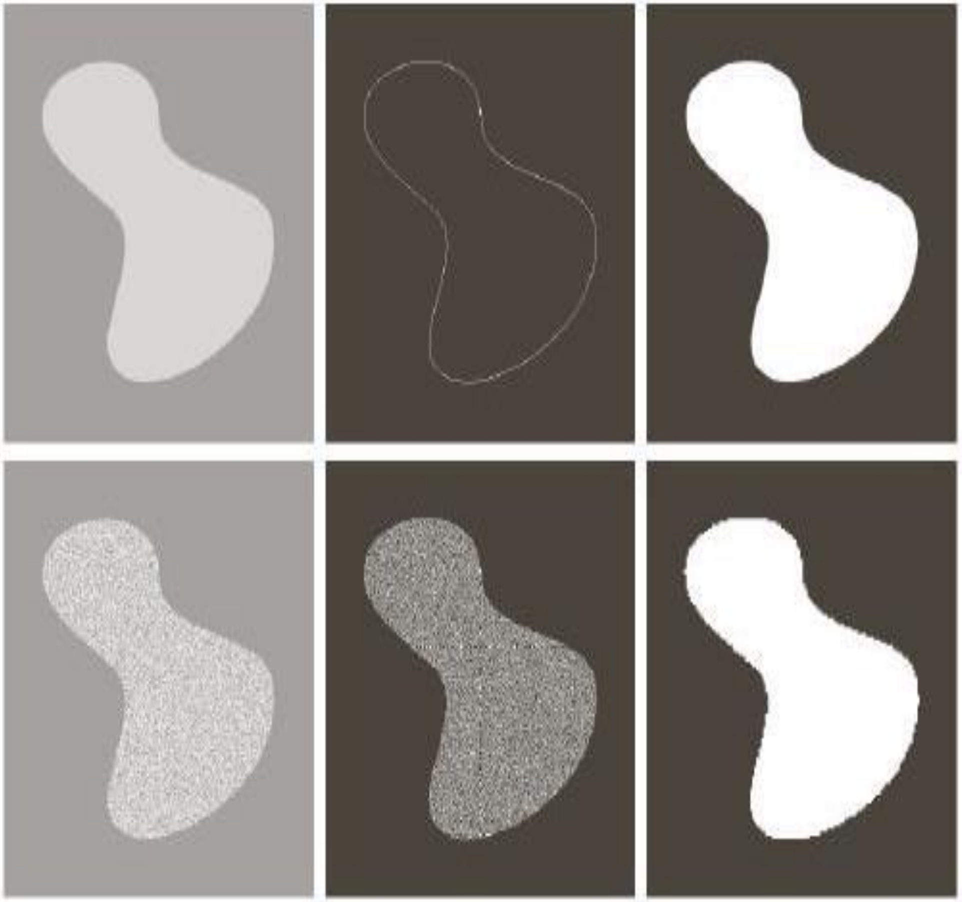
✓ Discontinuity

- partitioning based on abrupt change in intensity
- Example : point detection, Line detection, edge detection

✓ Similarity

- partitioning into regions based on similarity according to a set of predefined criteria.
- Example : Thresholding, Clustering, Region growing, Split and merge

SEGMENTATION - EXAMPLE



(a) Image of a constant intensity region.
(b) Boundary based on intensity discontinuities.
(c) Result of segmentation.
(d) Image of a texture region.
(e) Result of intensity discontinuity computations (note the large number of small edges).
(f) Result of segmentation based on region properties.

SEGMENTATION-EXAMPLE

- ✓ Figure (a) shows an image of a region of constant intensity superimposed on a darker background, also of constant intensity.
- ✓ These two regions comprise the overall image.
- ✓ Figure (b) shows the result of computing the boundary of the inner region based on intensity discontinuities.
- ✓ Points on the inside and outside of the boundary are black (zero) because there are no discontinuities in intensity in those regions.
- ✓ To segment the image, we assign one level (say, white) to the pixels on or inside the boundary, and another level (e.g., black) to all points exterior to the boundary. Figure (c) shows the result of such a procedure.

SEGMENTATION-EXAMPLE

- ✓ Region-based segmentation- Figure (d) is similar to Fig. (a), but the intensities of the inner region form a textured pattern.
- ✓ Figure (e) shows the result of computing intensity discontinuities in this image. The numerous spurious changes in intensity make it difficult to identify a unique boundary for the original image because many of the nonzero intensity changes are connected to the boundary, so edge-based segmentation is not a suitable approach.
- ✓ However, the outer region is constant, so all we need to solve this segmentation problem is a predicate that differentiates between textured and constant regions.
- ✓ The standard deviation of pixel values is a measure that accomplishes this because it is nonzero in areas of the texture region, and zero otherwise.
- ✓ Figure (f) shows the result of dividing the original image into subregions of size 8 × 8.
- ✓ Each subregion was then labeled white if the standard deviation of its pixels was positive (i.e., if the predicate was TRUE), and zero otherwise.
- ✓ The result has a "blocky" appearance around the edge of the region because groups of 8 × 8 squares were labeled with the same intensity (smaller squares would have given a smoother region boundary).

DISCONTINUITY AND SIMILARITY

- ✓ **Discontinuity- 3 ways of finding**
  - Isolated point
  - Line detection
  - Edge detection
- ✓ **Similarity**
  - Thresholding
  - Region growing
  - Region Split
  - Region merge

POINT , LINE AND EDGE DETECTION

- ✓ *Edge pixels* are pixels at which the intensity of an image changes abruptly, and *edges* (or *edge segments*) are sets of connected edge pixels
- ✓ *Edge detectors* are local image processing tools designed to detect edge pixels.
- ✓ A *line* may be viewed as a (typically) thin edge segment in which the intensity of the background on either side of the line is either much higher or much lower than the intensity of the line pixels.
- ✓ Lines give rise to so-called "roof edges."
- ✓ Finally, an *isolated point* may be viewed as a foreground (background) pixel surrounded by background (foreground) pixels.

TO DETERMINE DISCONTINUITIES

Use filtering

✓ **Spatial – Not Feasible**

✓ **Sharpening**

- First order derivatives
- Second order derivatives

IMAGE DERIVATIVES

a b
c

FIGURE 10.2
(a) Image.
(b) Horizontal intensity profile that includes the isolated point indicated by the arrow.
(c) Subsampled profile; the dashes were added for clarity. The numbers in the boxes are the intensity values of the dots shown in the profile. The derivatives were obtained using Eqs. (10-4) for the first derivative and Eq. (10-7) for the second.

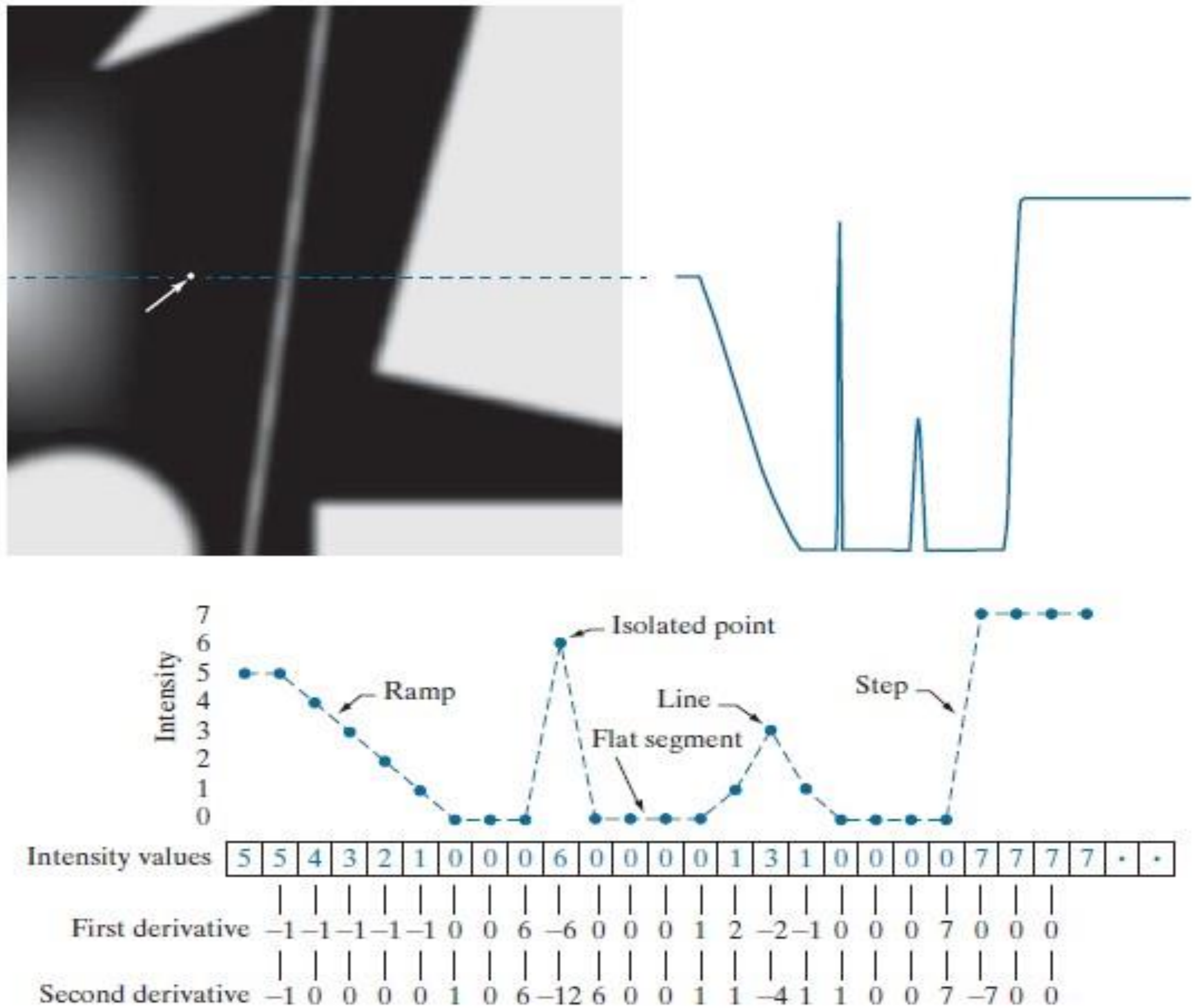


IMAGE DERIVATIVES

- ✓ Figure (b) shows a horizontal intensity profile (scan line) through the center of the image, including the isolated point.
- ✓ Transitions in intensity between the solid objects and the background along the scan line show two types of edges: *ramp edges* (on the left) and *step edges* (on the right).
- ✓ Intensity transitions involving thin objects such as lines often are referred to as *roof edges*.

HOW THE FIRST- AND SECOND-ORDER DERIVATIVES BEHAVE AS THEY ENCOUNTER A POINT, A LINE, AND THE EDGES OF OBJECTS

(1) First-order derivatives generally produce thicker edges.

(2) Second-order derivatives have a stronger response to fine detail, such as thin lines, isolated points, and noise.

(3) Second-order derivatives produce a double-edge response at ramp and step transitions in intensity.

(4) 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

- ✓ Point detection should be based on the second derivative using the Laplacian:
- ✓ A point has been detected at a location (x, y) on which the kernel is centered if the absolute value of the response of the filter at that point exceeds a specified threshold.
- ✓ Such points are labeled 1 and all others are labeled 0 in the output image, thus producing a binary image

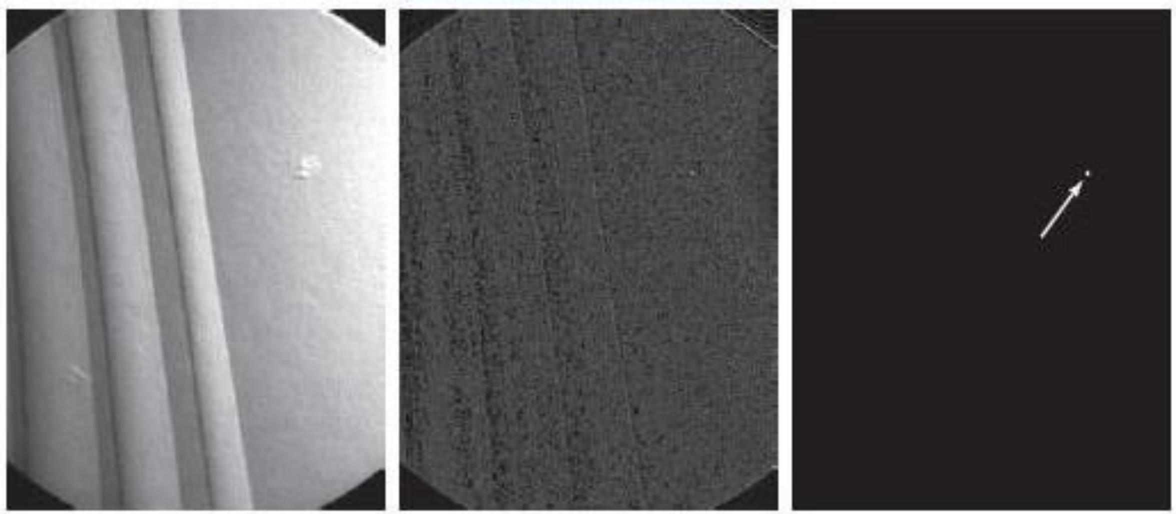
POINT DETECTION

a
b c d

FIGURE 10.4
(a) Laplacian kernel used for point detection.
(b) X-ray image of a turbine blade with a porosity manifested by a single black pixel.
(c) Result of convolving the kernel with the image.
(d) Result of using Eq. (10-15) was a single point (shown enlarged at the tip of the arrow). (Original image courtesy of X-TEK Systems, Ltd.)

1	1	1
1	−8	1
1	1	1

$$g(x,y) = \begin{cases} 1 & \text{if } |Z(x,y)| > T \\ 0 & \text{otherwise} \end{cases}$$



LINE DETECTION

- ✓ For line detection , second order derivatives result in a stronger filter response, and to produce thinner lines than first derivatives

−1	−1	−1
2	2	2
−1	−1	−1

Horizontal

2	−1	−1
−1	2	−1
−1	−1	2

+45°

−1	2	−1
−1	2	−1
−1	2	−1

Vertical

−1	−1	2
−1	2	−1
2	−1	−1

−45°

a b c d

FIGURE 10.6 Line detection kernels. Detection angles are with respect to the axis system in Fig. 2.19, with positive angles measured counterclockwise with respect to the (vertical) x-axis.

LINE DETECTION

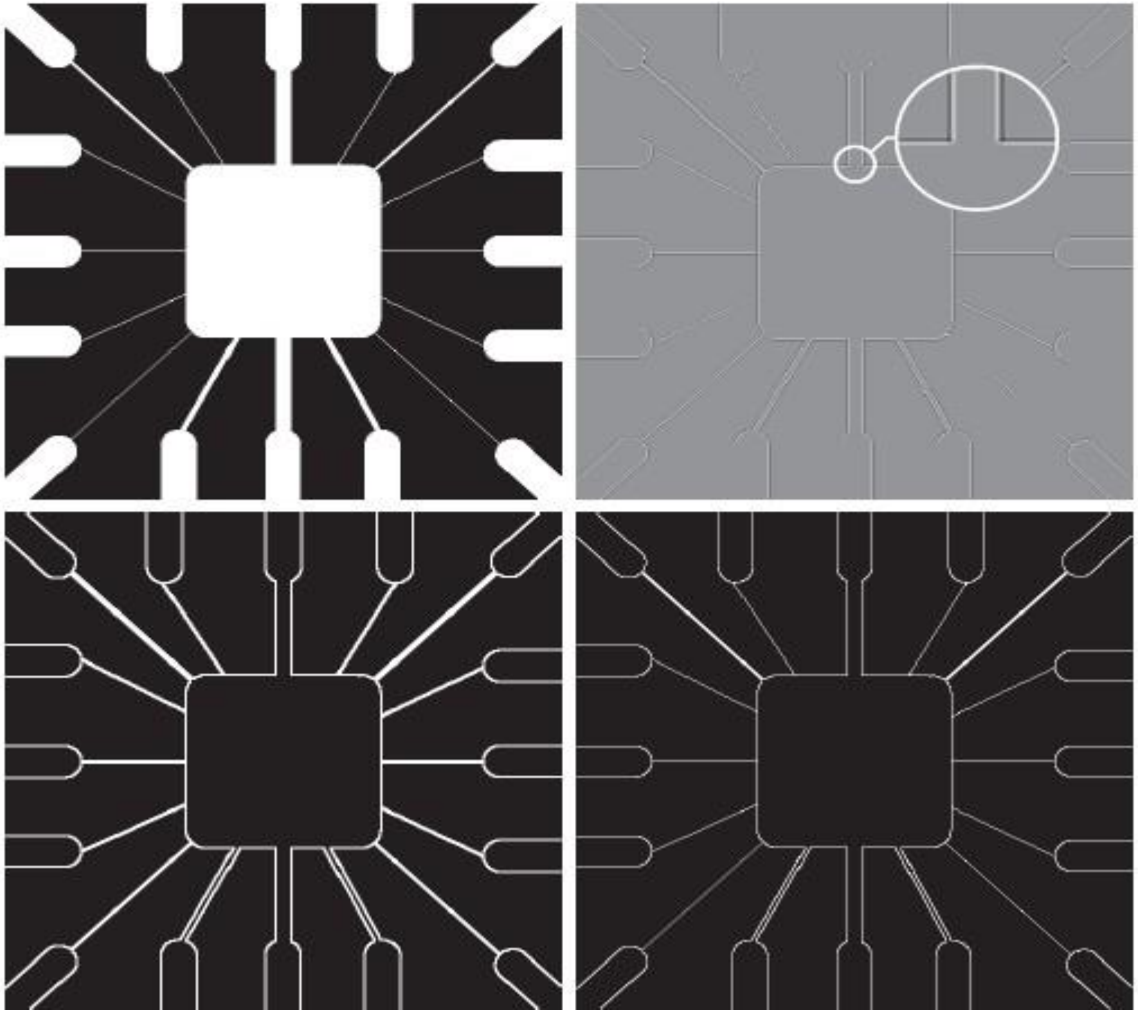
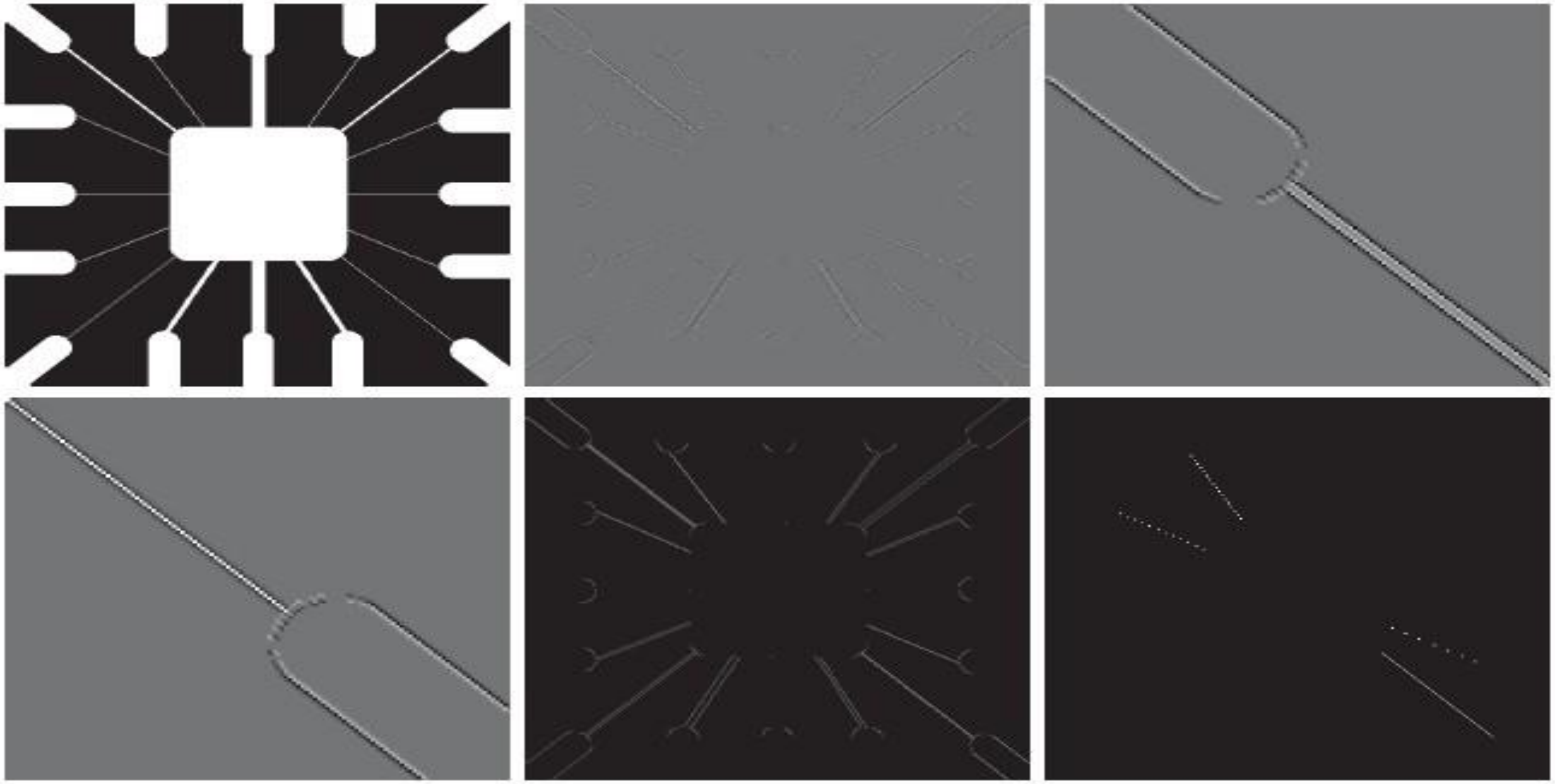


FIGURE 10.5
(a) Original image.
(b) Laplacian image; the magnified section shows the positive/negative double-line effect characteristic of the Laplacian.
(c) Absolute value of the Laplacian.
(d) Positive values of the Laplacian.

LINE DETECTION

- ✓ Figure (a) shows a 486 × 486 (binary) portion of a wire-bond mask for an electronic circuit, and
- ✓ Fig. (b) shows its Laplacian image. Because the Laplacian image contains negative values scaling is necessary for display.
- ✓ As the magnified section shows, mid gray represents zero, darker shades of gray represent negative values, and lighter shades are positive.
- ✓ The double-line effect is clearly visible in the magnified region.
- ✓ At first, it might appear that the negative values can be handled simply by taking the absolute value of the Laplacian image.
- ✓ However, as Fig. (c) shows, this approach doubles the thickness of the lines.
- ✓ A more suitable approach is to use only the positive values of the Laplacian (in noisy situations we use the values that exceed a positive threshold to eliminate random variations about zero caused by the noise).
- ✓ As Fig. (d) shows, this approach results in thinner lines that generally are more useful.

LINE DETECTION



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 kernel 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 $g > T$, where g is the image in (e) and $T = 254$ (the maximum pixel value in the image minus 1). (The points in (f) were enlarged to make them easier to see.)

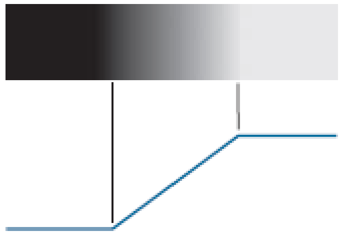
EDGE MODELS

- Edge detection is an approach used frequently for segmenting images based on abrupt (local) changes in intensity.

- Edge models are classified according to their intensity profiles.

- A *step edge* is characterized by a transition between two intensity levels occurring ideally over the distance of one pixel.

EDGE MODELS



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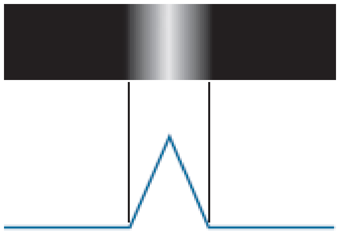
- ✓ In practice, digital images have edges that are blurred and noisy, with the degree of blurring determined principally by limitations in the focusing mechanism (e.g., lenses in the case of optical images), and the noise level determined principally by the electronic components of the imaging system.
- ✓ In such situations, edges are more closely modeled as having an intensity *ramp* profile.
- ✓ The slope of the ramp is inversely proportional to the degree to which the edge is blurred.
- ✓ In this model, we no longer have a single “edge point” along the profile.
- ✓ Instead, an edge point now is any point contained in the ramp, and an edge segment would then be a set of such points that are connected.

EDGE MODELS



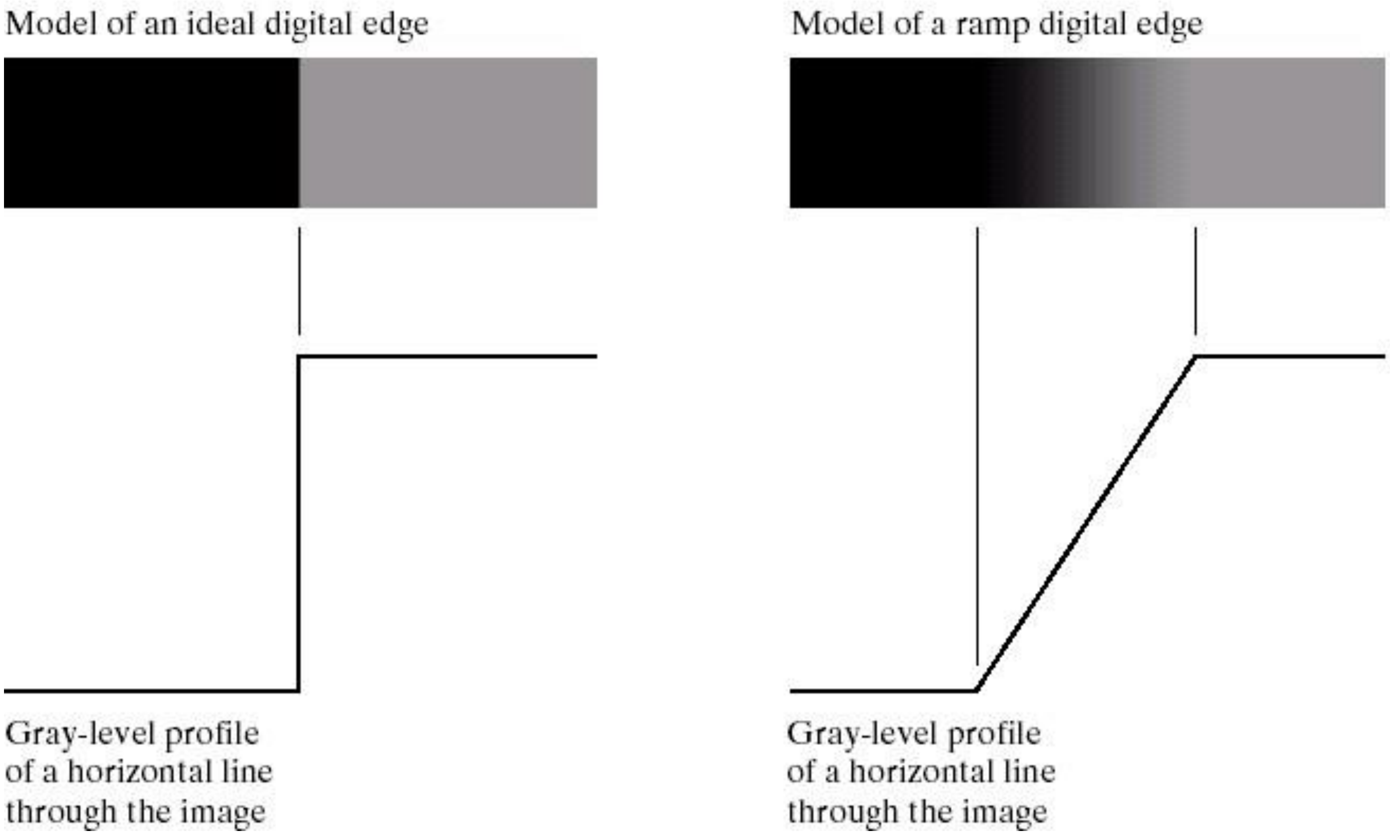
- ✓ Roof edges are models of lines through a region, with the base (width) of the edge being determined by the thickness and sharpness of the line.

- ✓ Roof edges arise, for example, in range imaging, when thin objects (such as pipes) are closer to the sensor than the background (such as walls).

- ✓ The pipes appear brighter and thus create an image similar to the model in Fig. (c).

- ✓ Other areas in which roof edges appear routinely are in the digitization of line drawings and also in satellite images, where thin features, such as roads, can be modeled by this type of edge.

Detection of Discontinuities
Edge Detection



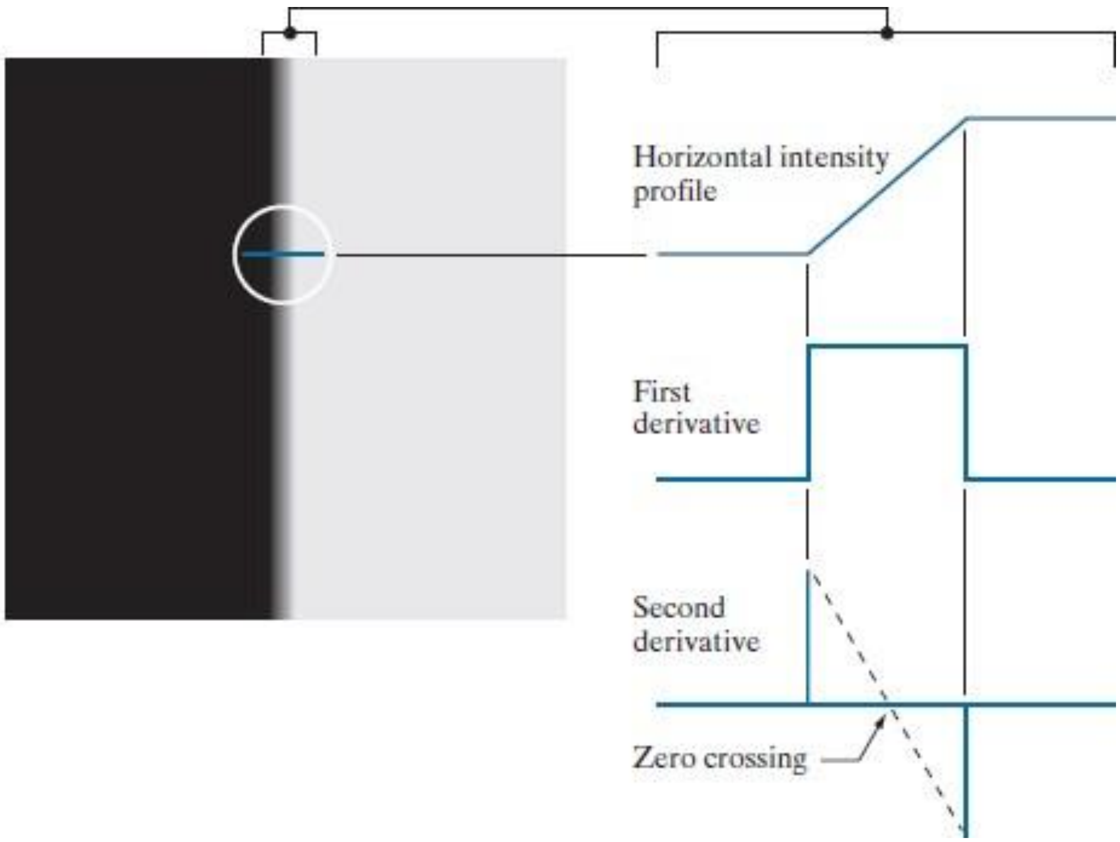
a b

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.

IDEAL RAMP EDGE

a b

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



IDEAL RAMP EDGE

- ✓ Figure (b) shows a horizontal intensity profile.
- ✓ Moving from left to right along the intensity profile, we note that the first derivative is positive at the onset of the ramp and at points on the ramp, and it is zero in areas of constant intensity.
- ✓ The second derivative is positive at the beginning of the ramp, negative at the end of the ramp, zero at points on the ramp, and zero at points of constant intensity.
- ✓ The signs of the derivatives would be reversed for an edge that transitions from light to dark.
- ✓ The intersection between the zero intensity axis and a line extending between the extrema of the second derivative marks a point called the *zero crossing* of the second derivative.

IDEAL RAMP EDGE – CONCLUDING REMARKS

Magnitude of the first derivative can be used to detect the presence of an edge at a point in an image.

The *sign* of the second derivative can be used to determine whether an edge pixel lies on the dark or light side of an edge.

Two additional properties of the second derivative around an edge are:

(1)it produces two values for every edge in an image; and

(2)its zero crossings can be used for locating the centers of thick edges

STEPS FOR EDGE DETECTION

The three steps performed typically for edge detection are:

1. *Image smoothing for noise reduction*.
2. *Detection of edge points.*
   - is a local operation that extracts from an image all points that are potential edge-point candidates.

3. *Edge localization.*
   - The objective of this step is to select from the candidate points only the points that are members of the set of points comprising an edge.

DETECTION OF DISCONTINUITIES – GRADIENT OPERATORS

First-order derivatives to determine edge strength and direction:

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

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

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

- The magnitude of this vector:

This is the *value* of the rate of change in the direction of the gradient vector at point (*x*, *y*).

$$M(x,y) \approx |g_x| + |g_y|$$

- The direction of this vector:

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

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

- ✓ Sobel kernels have better noise-suppression (smoothing) characteristics makes them preferable.

DETECTION OF DISCONTINUITIES – GRADIENT OPERATORS

Prewitt masks for detecting diagonal edges

+45 degree

0	1	1
−1	0	1
−1	−1	0

-45 degree

−1	−1	0
−1	0	1
0	1	1

Prewitt

Sobel masks for detecting diagonal edges

0	1	2
−1	0	1
−2	−1	0

−2	−1	0
−1	0	1
0	1	2

Sobel

a	b
c	d

FIGURE 10.9 Prewitt and Sobel masks for detecting diagonal edges.

DETECTION OF DISCONTINUITIES – GRADIENT OPERATORS- KRISH COMPASS KERNELS

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

DETECTION OF DISCONTINUITIES – GRADIENT OPERATORS

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 5×5 averaging filter.

DETECTION OF DISCONTINUITIES – GRADIENT OPERATORS - EXAMPLE

- ✓ The original image in Fig. (a) is of reasonably high resolution, and at the distance the image was acquired, the contribution made to image detail by the wall bricks is significant.
- ✓ This level of fine detail often is undesirable in edge detection because it tends to act as noise, which is enhanced by derivative computations and thus complicates detection of the principal edges.
- ✓ One way to reduce fine detail is to smooth the image prior to computing the edges., hence the original image smoothed first using a 5 × 5 averaging filter.
- ✓ The response of each kernel now shows almost no contribution due to the bricks, with the results being dominated mostly by the principal edges in the image.

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

Second-order derivatives: (The Laplacian)

- The Laplacian of an 2D function $f(x,y)$ is defined as

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

0	−1	0
−1	4	−1
0	−1	0

−1	−1	−1
−1	8	−1
−1	−1	−1