Digital Image Processing
15CS753

MODULE-4

Image Segmentation

- **Module – 4 Image Segmentation:**
- Introduction, Detection of isolated points, line detection,
- Edge detection, Edge linking,
- Region based segmentation- Region growing,
- split and merge technique,
- local processing, regional processing,
- Hough transform,
- Segmentation using Threshold.

8 Hours

Image Segmentation

- Introduction:
- So far we saw image processing methods whose input and output are images, but now let us see those methods in which the inputs are images, but the **outputs are attributes extracted** from those images
- Segmentation subdivides an image into its constituent regions or objects.
- The level to which the subdivision is carried depends on the problem being solved.
    - Segmentation should stop when the objects of interest have been isolated.
- Segmentation accuracy determines the eventual success or failure of computerized analysis procedures.
- Hence, care should be taken to improve the probability of segmentation.

Image Segmentation

- In industrial inspection applications, at least some measure of control over the environment is possible at times.
- The experienced image processing system designer invariably pays considerable attention to such opportunities.
- In other applications, such as autonomous target acquisition, the system designer has no control of the environment.
- Then the usual approach is to focus on selecting the types of sensors which could enhance the objects of interest while diminishing the contribution of irrelevant image detail.
- E.g. : the use of infrared imaging by the military to detect objects with strong heat signatures, such as equipment and troops in motion.

Image Segmentation

- Image segmentation algorithms are based on one of two basic properties of intensity values:
  - Discontinuity and
  - Similarity.
- **Discontinuity:**
- Approach is to partition an image based on abrupt changes in intensity, such as edges in an image.
- **Similarity:**
- These are based on partitioning an image into regions that are similar according to a set of predefined criteria.

Image Segmentation

- The segmentation algorithms for monochrome images are based on either discontinuity or similarity of pixel intensities
- In first category assumption is that boundaries of regions are sufficiently different from each other and from the background to allow boundary detection based on local intensity discontinuity
- E.g. Edge based segmentation
- In the second category, idea is to partition the image into regions that are similar according to a set of predefined criteria
- E.g.: region based segmentation
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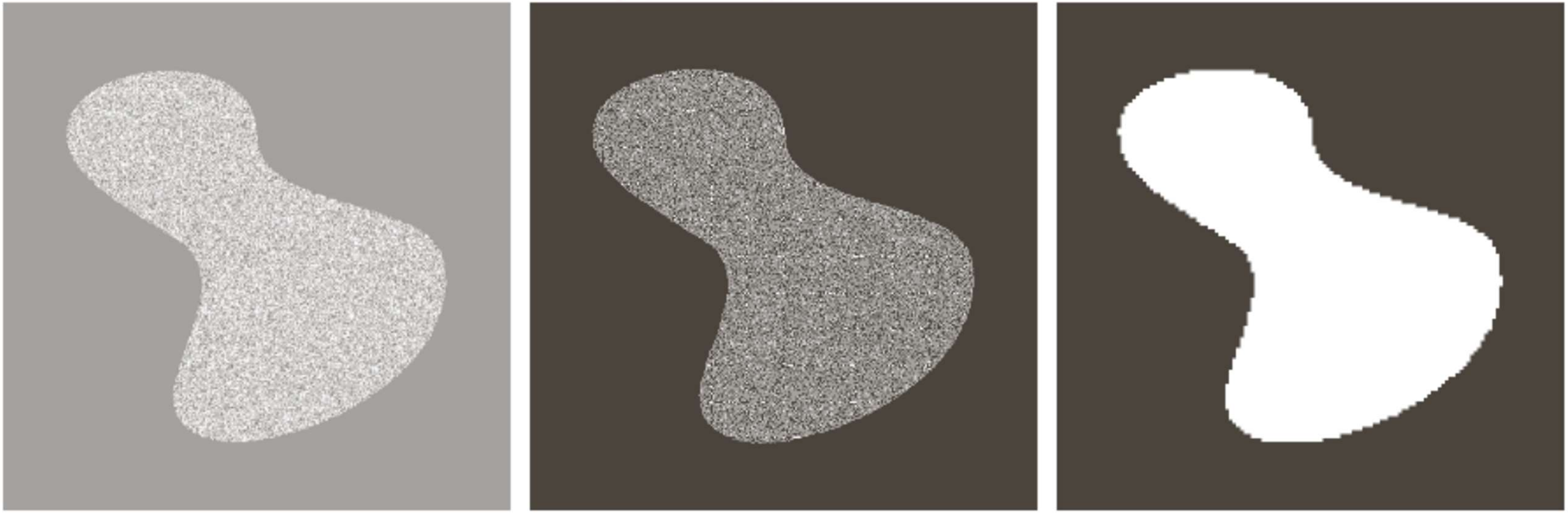
Image Segmentation

Image Segmentation

- (a) shows an image having a region of constant intensity superimposed on darker background.
- These two region comprise the entire image
- (b) shows the result of computing boundary of the inner region based on intensity discontinuity
- Points inside and outside the boundary are zero because there are no discontinuities in those regions.
- To segment the image, we assign one level (say white) to the pixels on or interior to boundary and another level (black) to the pixels exterior to boundary
- This is shown in (c)

Image Segmentation



- These three images represent region based segmentation
- In first image inner region intensities form texture pattern

Image Segmentation

- Next figure shows the result of computing edges of the previous image
- Due to the continuously varying intensities it is difficult to detect unique boundary. Thus edge based segmentation is not suitable
- But we see that, outer region is of uniform intensities
- So to do segmentation, we need to differentiate between constant region and textured region
- We may compute standard deviation of pixels to achieve this
- This is because, SD is non-zero in texture region and zero in constant region
- The original image may be subdivided into region of 4X4 and labeled white if the SD of the pixels are positive and zero otherwise.
- This can be seen as shown in the figure

Image Segmentation

- Point line and edge detection:
- Using the segmentation methods which are based on detecting sharp local intensity changes we can extract three features – isolated points, lines and edges
- Edge pixels are those at which intensity of an image function changes abruptly
- Edge - connected set of edge pixels.
- Edge detectors - local image processing methods used to detect edge pixels
- A line - an edge element, in which intensity of the background on the either side of the line is either much larger or much lower than the line pixel intensity

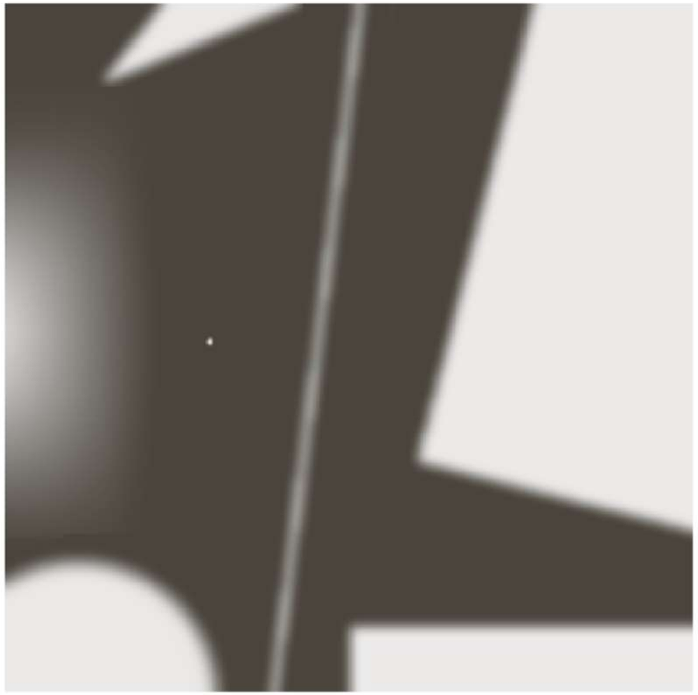
Image Segmentation

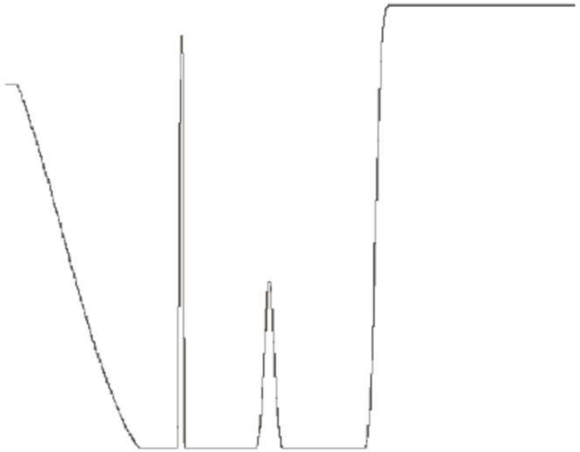
- Background:
- Basics of derivatives
- The rules to be satisfied
- Equations for first and second order derivatives

$$\frac{\partial f}{\partial x} = f'(x) = f(x+1) - f(x) \qquad (10.2\text{-}1)$$

$$\frac{\partial^2 f}{\partial x^2} = f''(x) = f(x+1) + f(x-1) - 2f(x) \qquad (10.2\text{-}2)$$

- E.g.:





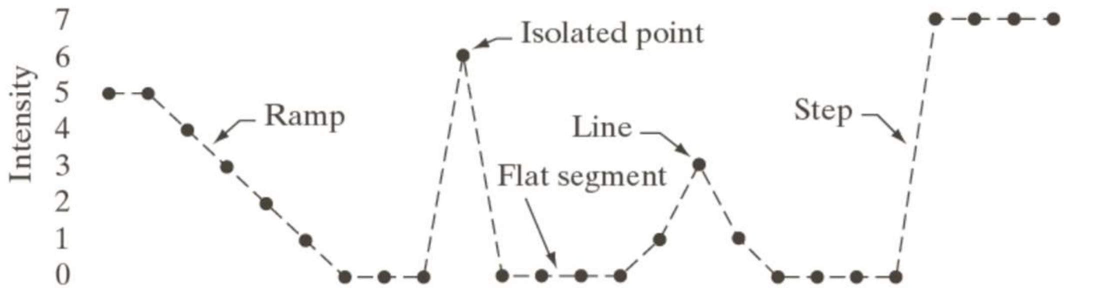


Image strip	5	5	4	3	2	1	0	0	0	6	0	0	0	0	1	3	1	0	0	0	0	7	7	7	7	•	•
First derivative		−1	−1	−1	−1	−1	0	0	6	−6	0	0	0	1	2	−2	−1	0	0	0	7	0	0	0			
Second derivative		−1	0	0	0	0	1	0	6	−12	6	0	0	1	1	−4	1	1	0	0	7	−7	0	0			

Image Segmentation

- Figure has
- Solid objects, straight line and single noise point
- Horizontal Intensity profile of a scan line is shown in (b)
- We can notice ramp edges and step edges
- (c) shows how simplified view of profile to analyze numerically how 1st and 2nd order derivatives behave as they encounter noise point, line and edge
  - Transition in ramp – 4 pixel,
  - Transition on noise point – 1 pixel
  - Transition on line 3 - pixels and
  - Transition on step – adjacent pixels
- By using the properties of derivatives we can see that, first order derivative is non-zero at the onset and along the ramp

Image Segmentation

- 2^{nd} order derivative is non-zero only at the onset and end of the ramp
- Since the edges of digital images show this type of transition, we can say that 1^{st} order derivatives produce thick edges and second order derivatives produce fine edges
- For noise point, magnitude of 2^{nd} order derivative is larger than 1^{st} order derivative
- Reason is 2^{nd} order derivatives are more capable of enhancing fine details
- Similar arguments hold good for line which is also thin in this case
- 2^{nd} order derivative in both ramp and step has opposite signs as it transitions into and out of edge.
- This double edge effect can be used to detect the edges.

Image Segmentation

- Detection of isolated points
- Point detection could be based on 2nd derivative
- So we can use Laplacian equation seen earlier

$$\nabla^2 f(x, y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \qquad (10.2\text{-}4)$$

- where partial derivatives are obtained as below

$$\frac{\partial^2 f(x, y)}{\partial x^2} = f(x + 1, y) + f(x - 1, y) - 2f(x, y) \qquad (10.2\text{-}5)$$

$$\frac{\partial^2 f(x, y)}{\partial y^2} = f(x, y + 1) + f(x, y - 1) - 2f(x, y) \qquad (10.2\text{-}6)$$

Image Segmentation

- Then the Laplacian will be

$$\nabla^2 f(x, y) = f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) - 4f(x, y) \tag{10.2-7}$$

- This expression can be implemented using the mask (a) shown below

0	1	0
1	−4	1
0	1	0

1	1	1
1	−8	1
1	1	1

- (b) represents the mask with diagonal terms

Image Segmentation

- The Laplacian mask is as shown below

1	1	1
1	−8	1
1	1	1

- Using this mask we can say that a point is detected at location (x, y) on which mask is centered, if the absolute value of the response of the mask at that point exceeds the specified threshold.
- All such points are labeled as 1 and all other are with 0 resulting in binary image
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Image Segmentation

- The output is obtained by using the expression

$$g(x, y) = \begin{cases} 1 & \text{if } |R(x, y)| \geq T \\ 0 & \text{otherwise} \end{cases} \qquad (10.2\text{-}8)$$

- where g is output image,
- T – non-negative threshold
- R is the response given by

$$R = w_1z_1 + w_2z_2 + \cdots + w_9z_9$$
$$= \sum_{k=1}^{9} w_kz_k$$

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

Image Segmentation

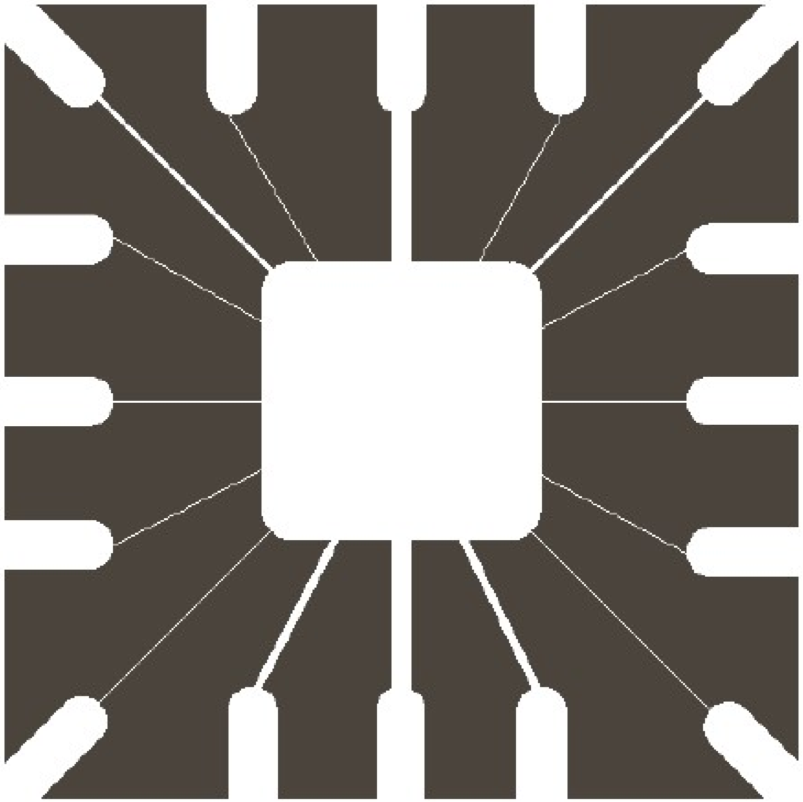
- Line detection:
- We have seen that, second order derivative produces stronger response and could result in thinner line than 1st order derivative.
- Thus we can use Laplacian mask used for point detection here also

1	1	1
1	−8	1
1	1	1

- But care is to be given to handle the double line effect similar to double edge of point detection

Image Segmentation

- Let us go through an example to see how line detection is done
- Consider the 486 x 486 binary image shown below
- When this is applied with Laplacian mask we get the output as



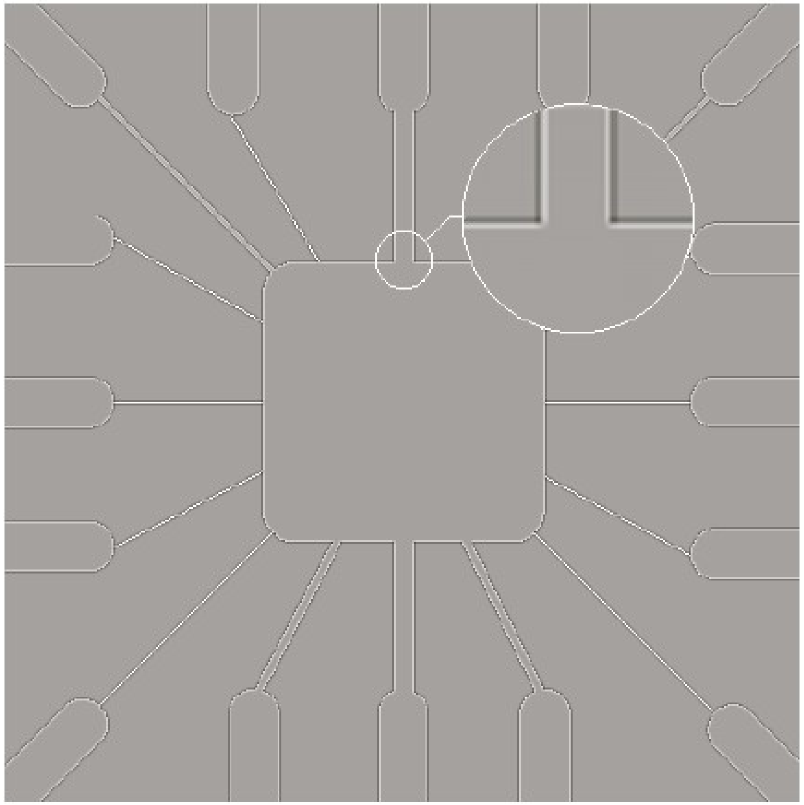


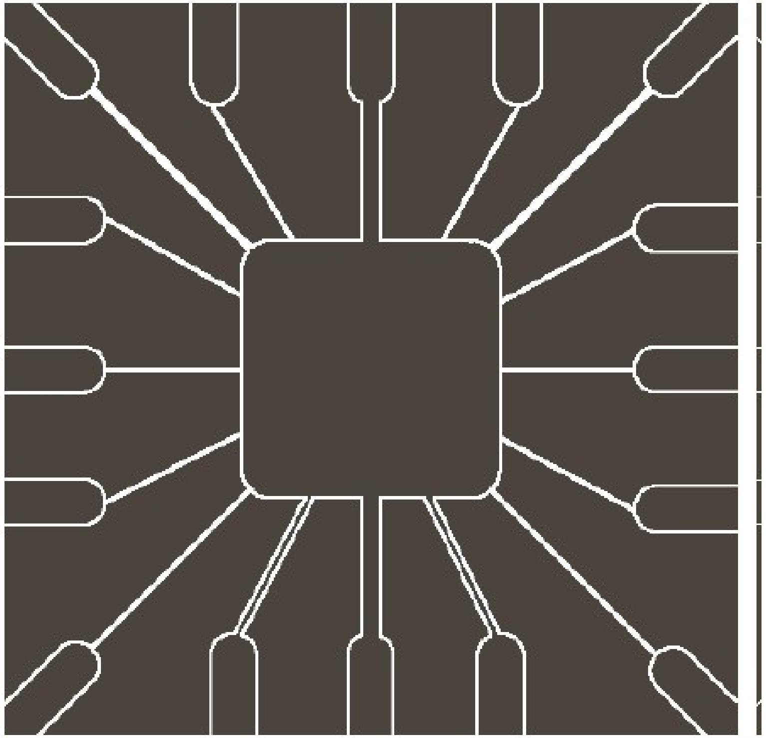
Image Segmentation

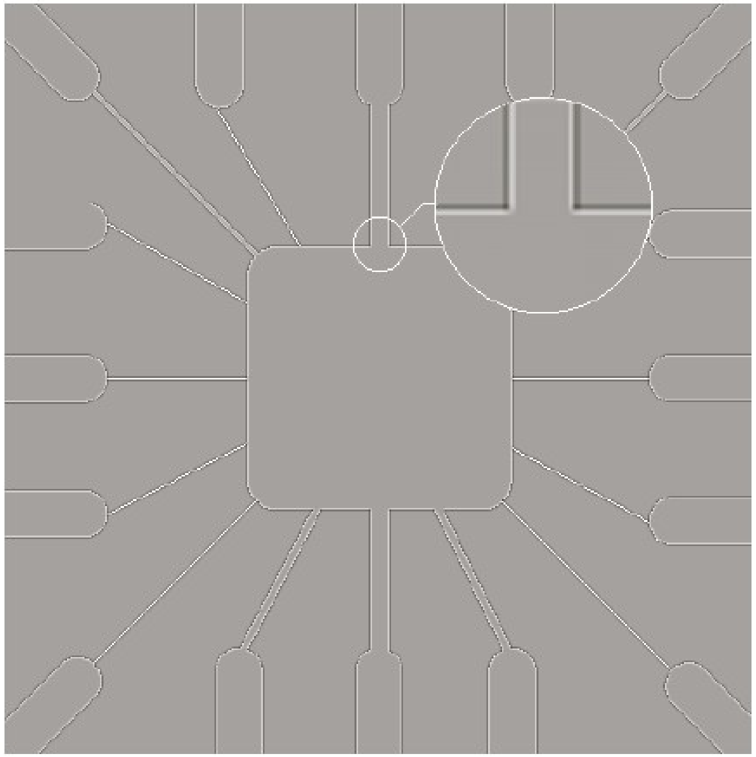
- If a mask has sum of all coefficients zero, then when such a mask is convolved with an image, the resulting image pixels' sum also will be zero.
- This indicates that, resulting image pixels contain both negative and positive values.
- But for displaying binary image negative pixel values need to be scaled.
- As it can be seen in the magnified section, mid gray represents zero, darker gray represents negative values and lighter shade represents positive values.
- We can also see double line effect in the magnified region of the image

- How to avoid the effect of negative pixel values??

Image Segmentation

- Option 1 – take the absolute value of Laplacian image
- Result will be as shown below

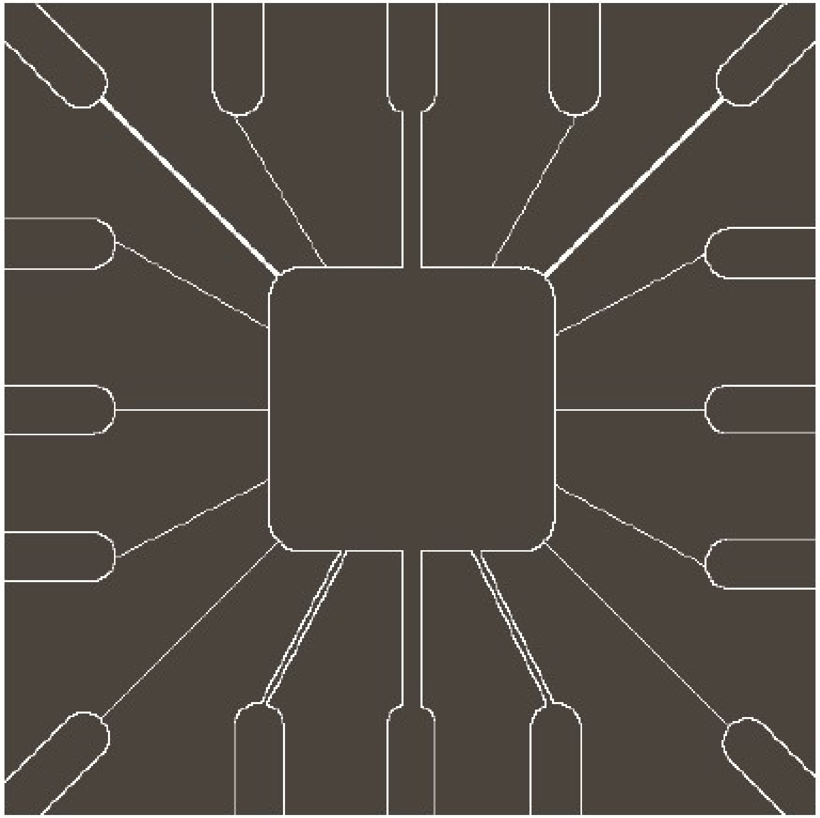




- This results in line thickness being doubled.

Image Segmentation

- Option 2 – to use only positive values of Laplacian image
- Resulting image shown below



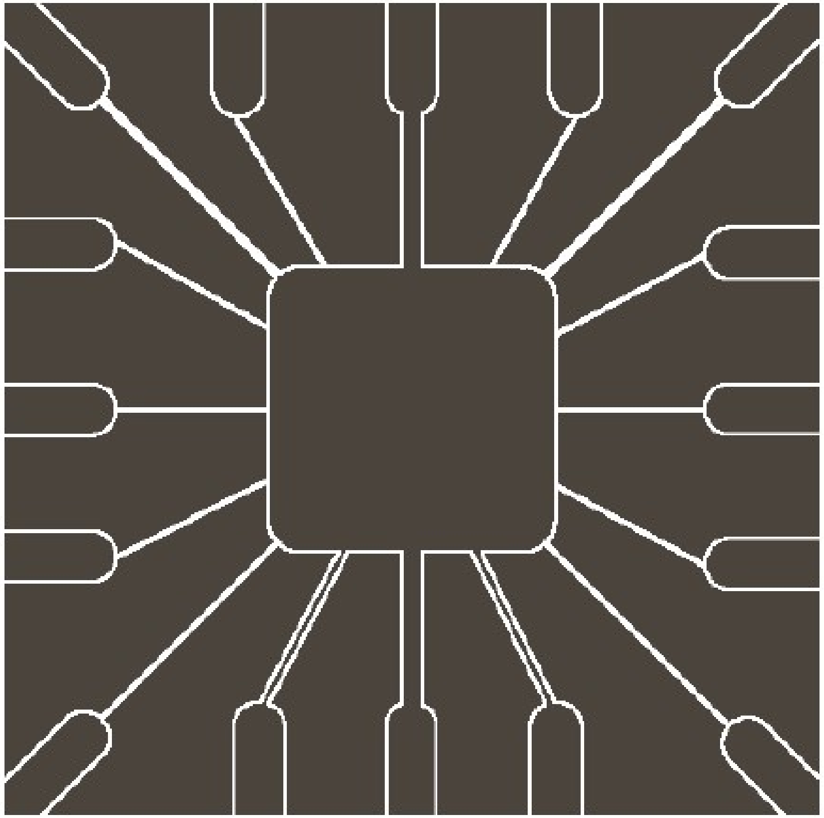


Image Segmentation

- Laplacian mask seen earlier is isotropic- its response is independent of directions (vertical, horizontal and two diagonals)
- But in reality lines may not be always in these four directions
- Consider the following masks

−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°

Image Segmentation

- Suppose that an image with constant background, containing various lines is filtered with first mask.
- The maximum response would occur at image locations where the horizontal line is passed through the middle row of the mask
- Similarly second mask gives best response to line which are oriented +45°, third mask for vertical lines and last mask for -45°.
- Let Rl, R2 , R3 , and R4 denote the responses of the masks in Fig. from left to right, where the R's are given by

$$R = w_1 z_1 + w_2 z_2 + \cdots + w_9 z_9 = \sum_{k=1}^{9} w_k z_k$$

where z_k is the gray level of the pixel associated with mask coefficient w_k

Image Segmentation

- Suppose that the four masks are run individually through an image.
- If, at a certain point in the image, $|R_i| > |R_j|$, for all j != i, that point is said to be more likely associated with a line in the direction of mask i.
- E.g.:
- if at a point in the image, |R1|> |Rj| for j = 2, 3, 4… that particular point is said to be more likely associated with a horizontal line.
- Alternatively, we may be interested in detecting lines in a specified direction.
- In this case, we would use the mask associated with that direction and threshold its output as per the equation
- .

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

Image Segmentation

- In other words, if we are interested in detecting all the lines in an image in the direction defined by a given mask, we run the 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.
- The following example illustrates this procedure.

...age Segmentation

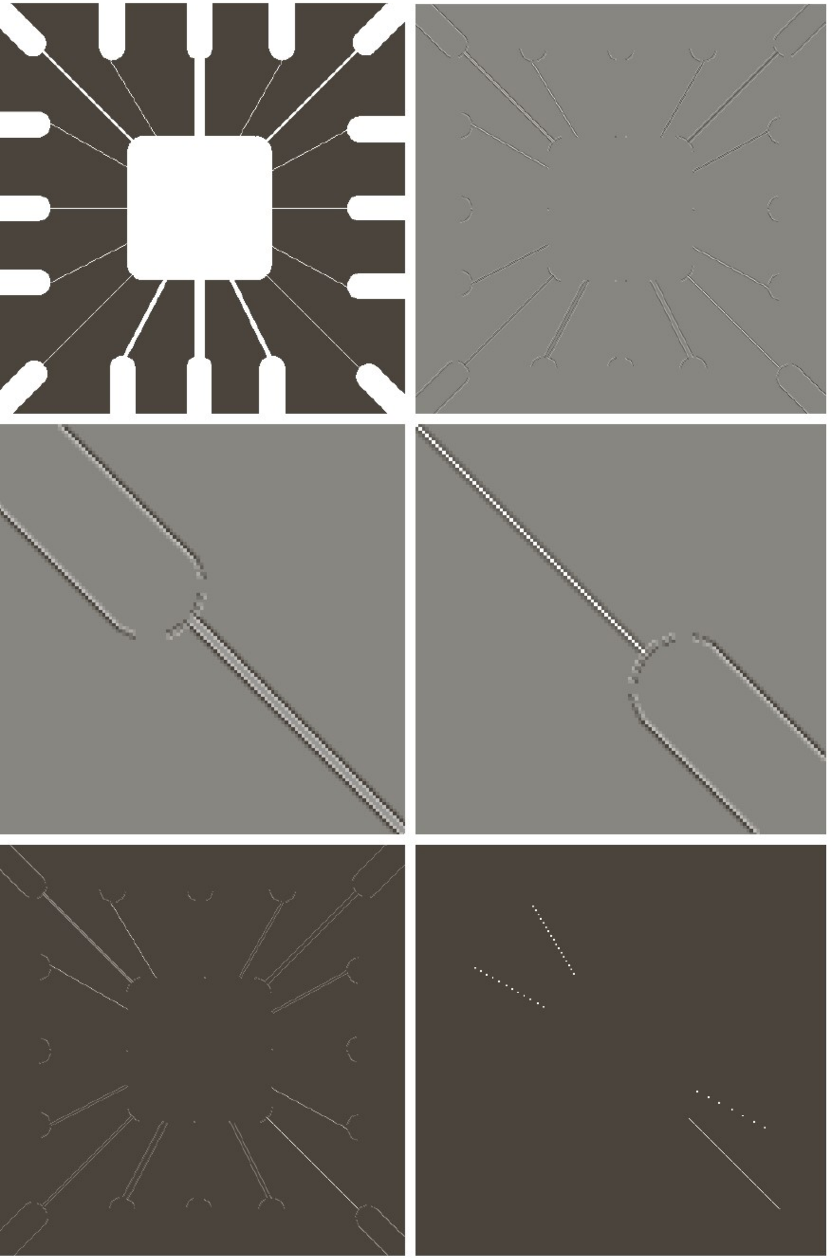


Image Segmentation

- Edge models:
- Classified according to their intensity profiles
- **Step edge**: transition between two intensities occur ideally over a distance of one pixel
- Figure below shows the section of vertical step edge and horizontal intensity profile along the edge

- These clean ideal edges occur over distance of 1 pixel
- They need no processing (smoothing) to make them look “real”

Image Segmentation

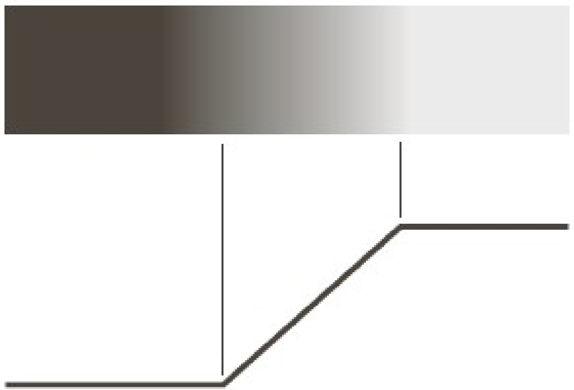
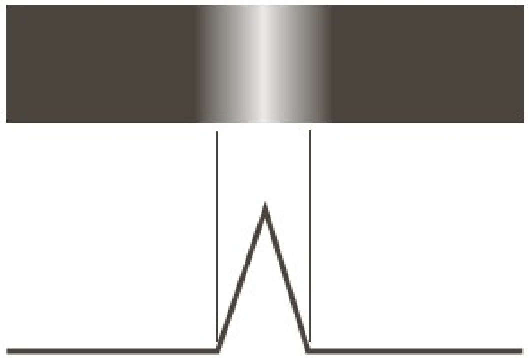
- **Ramp edge:** In practice, images contain edges that are blurred and noisy
- Degree of blurring depends on focusing mechanism such as lenses and degree of noise depends on electronic components of imaging system
- In these cases, edges are modeled as ramp as shown below
- 
- Here thee will not be any thin path (1 pixel)
- Instead, edge point is any point contained in the ramp and edge segment would be set of connected edge points

Image Segmentation

- **Roof edge**: These have characteristics as shown in figure below



- These are models of lines through a region with base of the roof edge is determined by the thickness and sharpness of the line
- If the base thickness is 1 pixel, then edge will be one line running through the region
- E.g.: in range imaging, when thin objects are closer to the sensors than the background. (pipe and wall- pipes appear bright and create

Image Segmentation

- Note that, single image may contain all three types of edges
- There may be a little deviation from the ideal shape due to noise and blurring
- The ideal edge models discussed allow us to write mathematical expressions to develop edge detection algorithms
- Performance of these algorithms depend on differences between actual edge and the model used in developing algorithm
- E.g. :

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.)

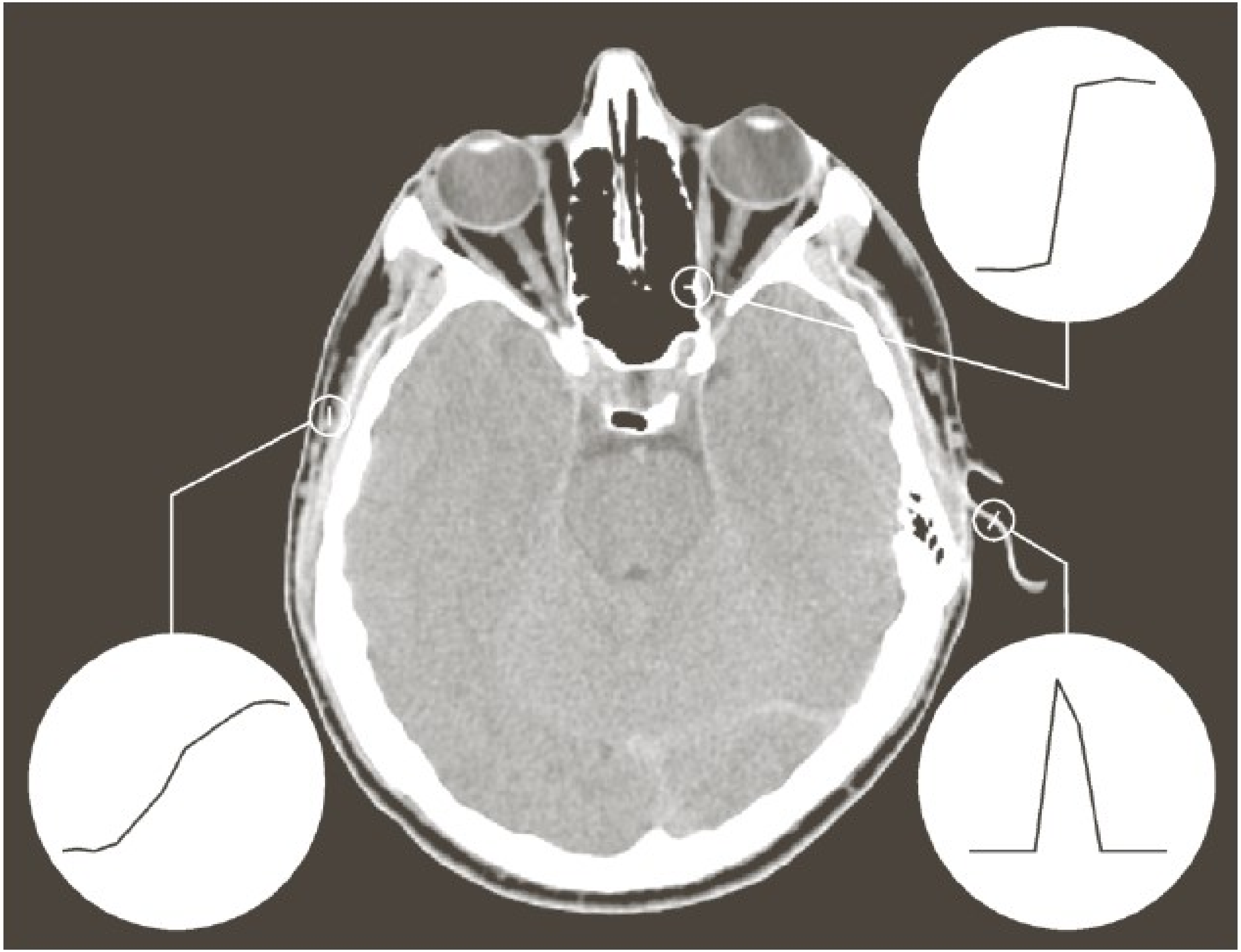


Image Segmentation

- Consider the following image from which ramp edge model is derived
- Its intensity profile is as shown
- First and second derivatives are shown in the figure

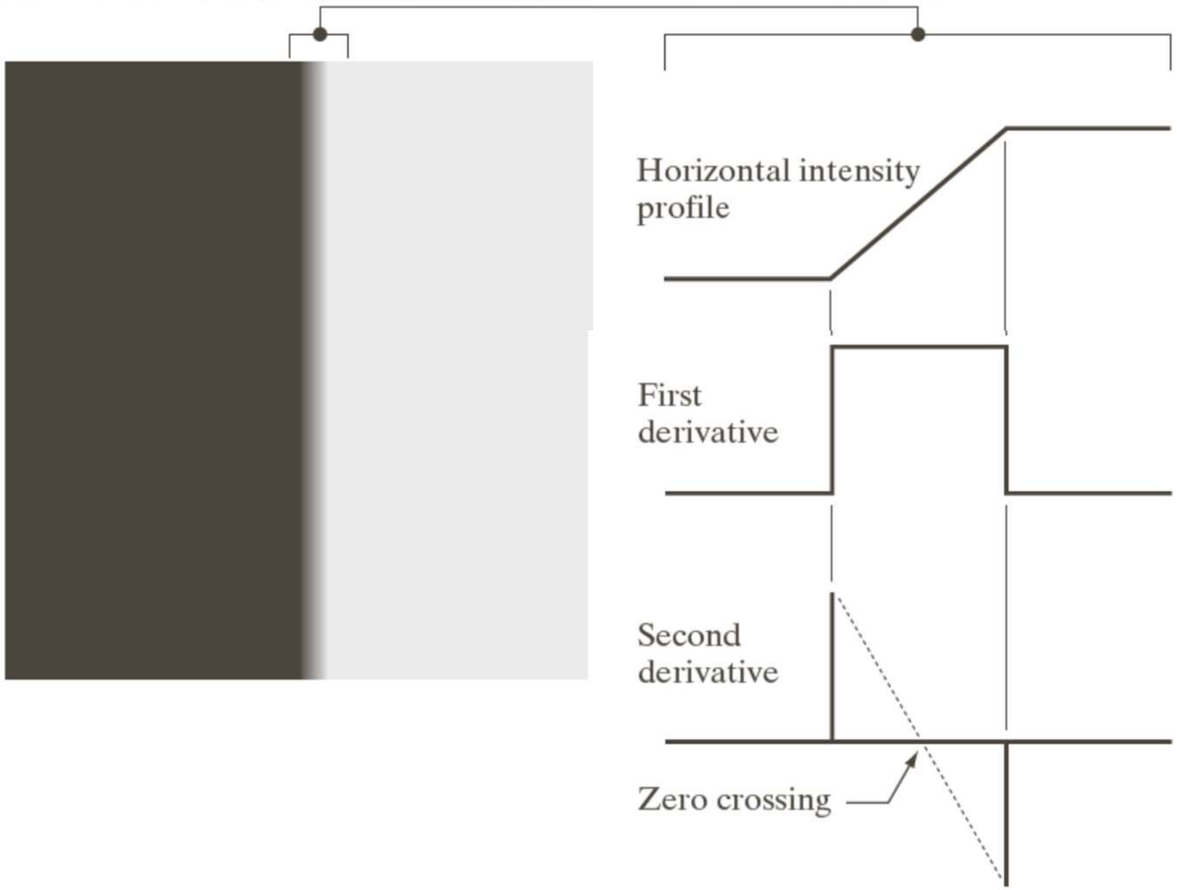


Image Segmentation

- As we move from left to right along the intensity profile, we see that 2st derivative is positive at the onset of ramp and along the ramp too.
- And it is zero at area of constant intensity
- 2^{nd} derivative is positive at the beginning of the ramp and negative at the end of the ramp, zero along the ramp and also zero at constant intensity
- Sign of the derivative will be reversed at the edge that transitions from light to dark
- The intersection of the line extending between extrema of 2^{nd} derivative and line representing zero intensity is called zero crossing
-

Image Segmentation

- We can see that, magnitude of 1st derivative is used to detect the presence of the edge
- Similarly, sign of the 2nd derivative is useful to detect whether the edge pixel is on the darker side or lighter side of the edge
- In addition, 2nd derivative produces two values for every edge which is undesirable and zero crossings can be used to locate the center of the thick edges
-

age Segmentation

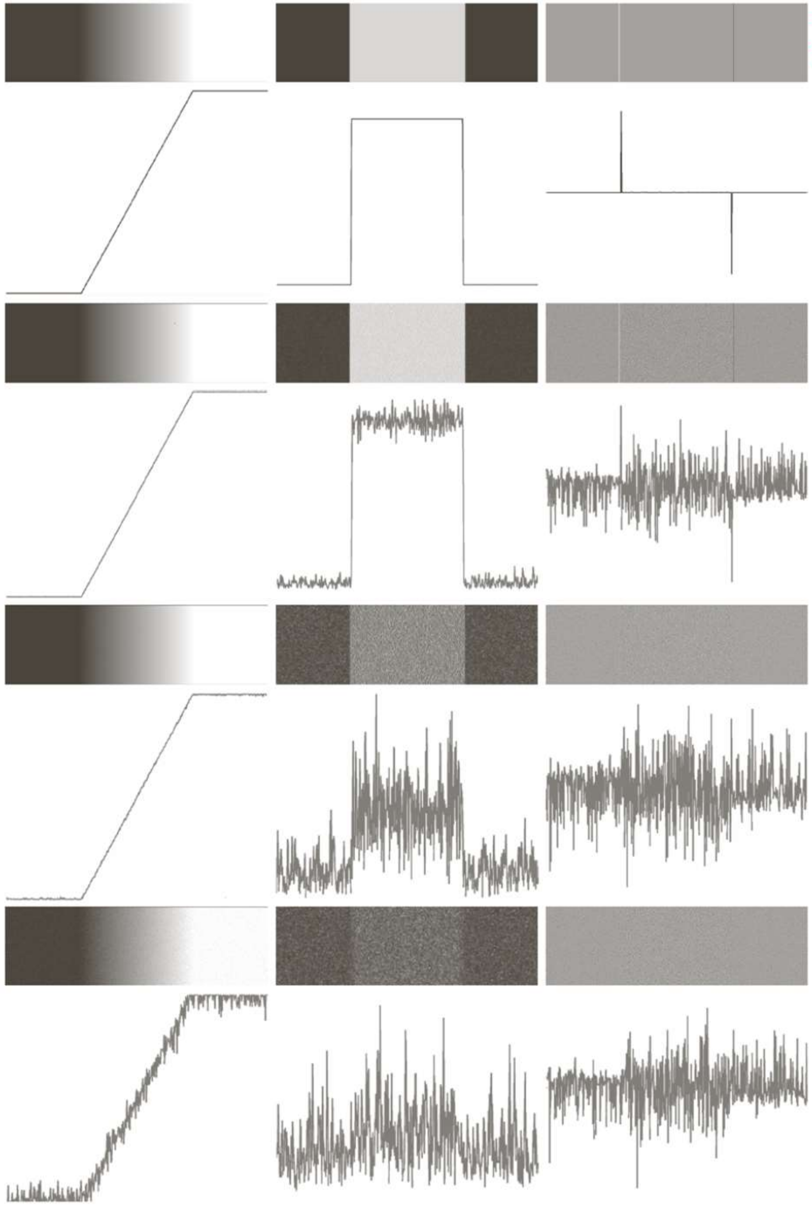


FIGURE 10.11 First column: Images and intensity profiles of a ramp edge corrupted by random Gaussian noise of zero mean and standard deviations of 0.0, 0.1, 1.0, and 10.0 intensity levels, respectively. Second column: First-derivative images and intensity profiles. Third column: Second-derivative images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

Image Segmentation

- Fundamental steps in edge detection

1. *Image smoothing for noise reduction.* The need for this step is amply illustrated by the results in the second and third columns of Fig. 10.11.
2. *Detection of edge points.* As mentioned earlier, this is a local operation that extracts from an image all points that are potential candidates to become edge points.
3. *Edge localization.* The objective of this step is to select from the candidate edge points only the points that are true members of the set of points comprising an edge.

Image Segmentation

- Continued…