

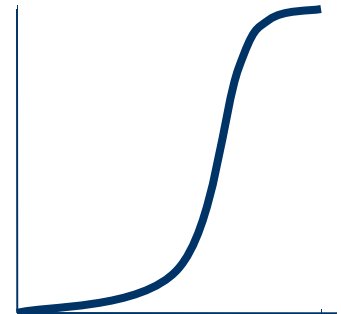
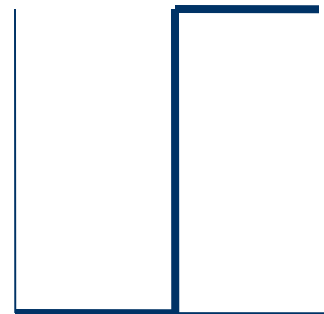
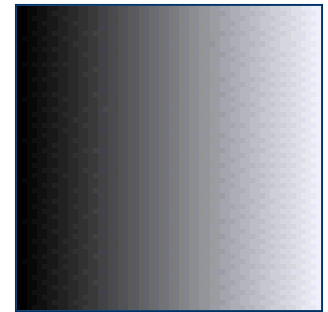
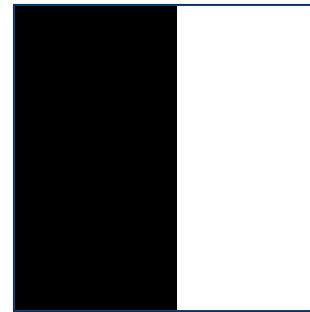
Edge Detection

courtesy: Longin Jan Latecki

- What are edges in an image?
- Edge Detection
- Edge Detection Methods
- Edge Operators
- Matlab Program
- Performance

What are edges in an image?

- ◆ Edges are those places in an image that correspond to object boundaries.
- ◆ Edges are pixels where image brightness changes abruptly.



Brightness vs. Spatial Coordinates

More About Edges

- ◆ An edge is a property attached to an individual pixel and is calculated from the image function behavior in a neighborhood of the pixel.
- ◆ It is a **vector variable** (**magnitude** of the gradient, **direction** of an edge) .

Image To Edge Map



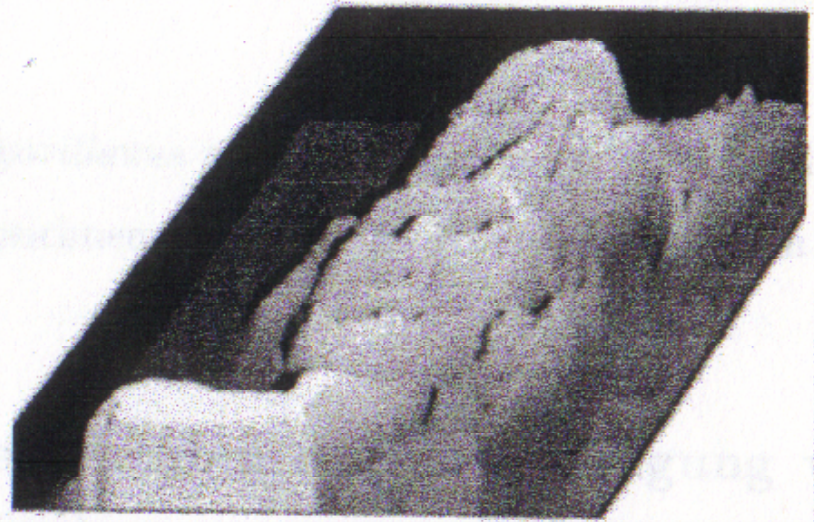
Edge Detection

- ◆ Edge information in an image is found by looking at the relationship a pixel has with its neighborhoods.
- ◆ If a pixel's gray-level value is similar to those around it, there is probably not an edge at that point.
- ◆ If a pixel's has neighbors with widely varying gray levels, it may present an edge point.

Edge Detection Methods

- ◆ Many are implemented with convolution mask and based on discrete approximations to differential operators.
- ◆ Differential operations measure the rate of change in the image brightness function.
- ◆ Some operators return orientation information. Other only return information about the existence of an edge at each point.

**A 2D grayvalue - image is
a 2D \rightarrow 1D function**



Edge detectors

- locate sharp changes in the intensity function
- edges are pixels where brightness changes abruptly.

- Calculus describes changes of continuous functions using derivatives; an image function depends on two variables - partial derivatives.
- A change of the image function can be described by a gradient that points in the direction of the largest growth of the image function.
- An edge is a property attached to an individual pixel and is calculated from the image function behavior in a neighborhood of the pixel.
- It is a **vector variable**:
magnitude of the gradient and **direction**

- The gradient direction gives the direction of maximal growth of the function, e.g., from black ($f(i,j)=0$) to white ($f(i,j)=255$).
- This is illustrated below; closed lines are lines of the same brightness.
- Boundary and its parts (edges) are perpendicular to the direction of the gradient.

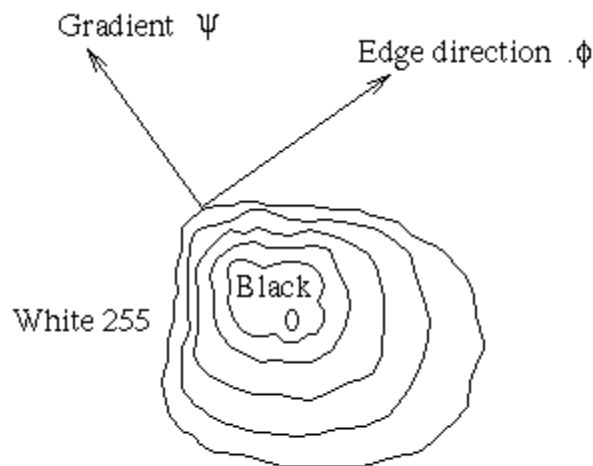


Figure 4.16 Gradient direction and edge direction.

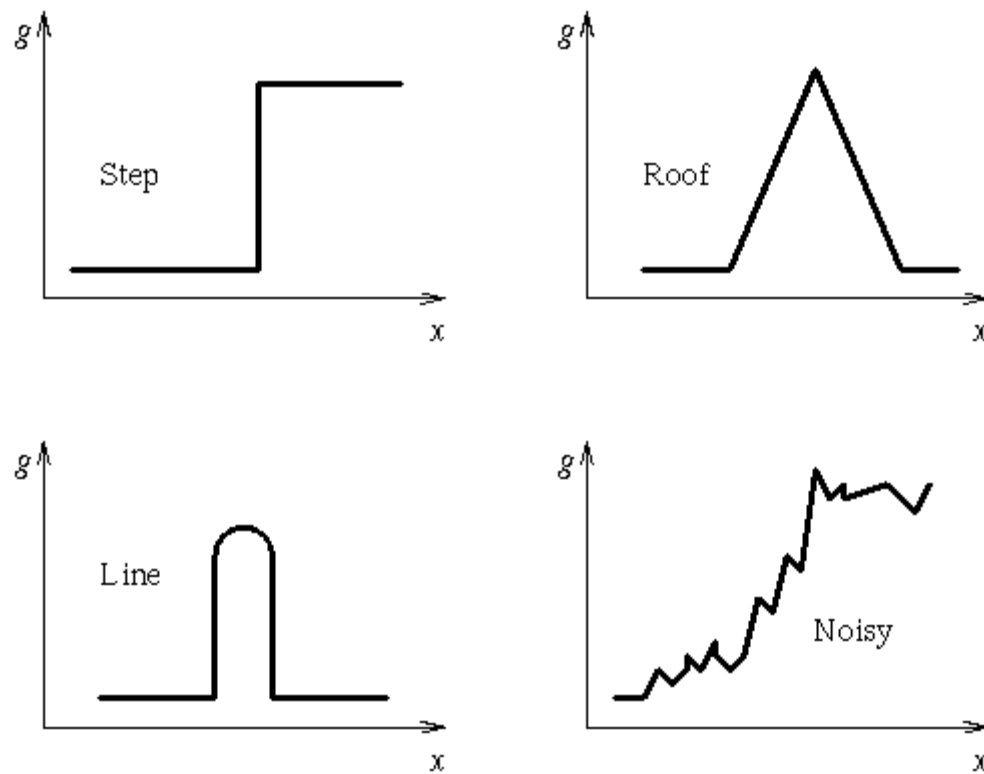


Figure 4.17 Typical edge profiles.

- The gradient magnitude and gradient direction are continuous image functions, where $\arg(x,y)$ is the angle (in radians) from the x-axis to the point (x,y) .

$$|\mathit{grad} g(x, y)| = \sqrt{\left(\frac{\partial g}{\partial x}\right)^2 + \left(\frac{\partial g}{\partial y}\right)^2} \quad (4.35)$$

$$\psi = \mathit{arg}\left(\frac{\partial g}{\partial x}, \frac{\partial g}{\partial y}\right) \quad (4.36)$$

- A digital image is discrete in nature, derivatives must be approximated by **differences**.
- The first differences of the image g in the vertical direction (for fixed i) and in the horizontal direction (for fixed j)
- n is a small integer, usually 1.

$$\begin{aligned}\Delta_i g(i, j) &= g(i, j) - g(i - n, j) \\ \Delta_j g(i, j) &= g(i, j) - g(i, j - n)\end{aligned}\tag{4.39}$$

The value n should be chosen small enough to provide a good approximation to the derivative, but large enough to neglect unimportant changes in the image function.

Roberts Operator

- ◆ Mark edge point only
- ◆ No information about edge orientation
- ◆ Work best with binary images
- ◆ Primary disadvantage:
 - High sensitivity to noise
 - Few pixels are used to approximate the gradient

Roberts Operator (Cont.)

- ◆ First form of Roberts Operator

$$\sqrt{[I(r, c) - I(r - 1, c - 1)]^2 + [I(r, c - 1) - I(r - 1, c)]^2}$$

- ◆ Second form of Roberts Operator

$$|I(r, c) - I(r - 1, c - 1)| + |I(r, c - 1) - I(r - 1, c)|$$

$$h_1 = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

$$h_2 = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$$

Prewitt Operator

- ◆ Looks for edges in both horizontal and vertical directions, then combine the information into a single metric.

$$y = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \quad x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

$$\text{Edge Magnitude} = \sqrt{x^2 + y^2} \quad \text{Edge Direction} = \tan^{-1} \left[\frac{y}{x} \right]$$

Sobel Operator

- ◆ Similar to the Prewitt, with different mask coefficients:

$$y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

$$x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$\text{Edge Magnitude} = \sqrt{x^2 + y^2} \quad \text{Edge Direction} = \tan^{-1} \left[\frac{y}{x} \right]$$

Kirsch Compass Masks

- ◆ Taking a single mask and rotating it to 8 major compass orientations: N, NW, W, SW, S, SE, E, and NE.
- ◆ The edge magnitude = The maximum value found by the convolution of each mask with the image.
- ◆ The edge direction is defined by the mask that produces the maximum magnitude.

Kirsch Compass Masks (Cont.)

- ◆ The Kirsch masks are defined as follows:

$$E = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \quad NE = \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \quad N = \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad NW = \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

$$W = \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad SW = \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \quad S = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \quad SE = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

- ◆ EX: If NE produces the maximum value, then the edge direction is Northeast

Robinson Compass Masks

- ◆ Similar to the Kirsch masks, with mask coefficients of 0, 1, and 2:

$$E = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad NE = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix} \quad N = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad NW = \begin{bmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{bmatrix}$$

$$W = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \quad SW = \begin{bmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{bmatrix} \quad S = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad SE = \begin{bmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix}$$

- Sometimes we are interested only in edge magnitudes without regard to their orientations.
 - The **Laplacian** may be used.
-
- The Laplacian has the same properties in all directions and is therefore invariant to rotation in the image.

$$\nabla^2 (x, y) = \frac{\partial^2 g(x, y)}{\partial x^2} + \frac{\partial^2 g(x, y)}{\partial y^2} \quad (4.37)$$

- The Laplace operator is a very popular operator approximating the second derivative which gives the gradient magnitude only.

Laplacian Operators

- ◆ Edge magnitude is approximated in digital images by a convolution sum.
- ◆ The sign of the result (+ or -) from two adjacent pixels provide edge orientation and tells us which side of edge brighter

Laplacian Operators (Cont.)

- ◆ Masks for 4 and 8 neighborhoods

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \qquad \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

- ◆ Mask with stressed significance of the central pixel or its neighborhood

$$\begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix} \qquad \begin{bmatrix} -2 & 1 & -2 \\ 1 & 4 & 1 \\ -2 & 1 & -2 \end{bmatrix}$$

Performance

- ◆ Please try the following link [Matlab demo](#).
To run type EDgui
- ◆ Sobel and Prewitt methods are very effectively providing good edge maps.
- ◆ Kirsch and Robinson methods require more time for calculation and their results are not better than the ones produced by Sobel and Prewitt methods.
- ◆ Roberts and Laplacian methods are not very good as expected.

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- Gradient operators can be divided into **three** categories

I. Operators approximating derivatives of the image function using differences.

- rotationally invariant (e.g., Laplacian) need one convolution mask only. Individual gradient operators that examine small local neighborhoods are in fact convolutions and can be expressed by convolution masks.

- approximating first derivatives use several masks, the orientation is estimated on the basis of the best matching of several simple patterns. Operators which are able to detect edge direction. Each mask corresponds to a certain direction.

II. Operators based on the zero crossings of the image function second derivative (e.g., Marr-Hildreth or Canny edge detector).

III. Operators which attempt to match an image function to a parametric model of edges. Parametric models describe edges more precisely than simple edge magnitude and direction and are much more computationally intensive.

The categories II and III will not be covered here;