



# **SNS COLLEGE OF ENGINEERING**

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**An Autonomous Institution**

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Approved by AICTE, New Delhi & Affiliated to Anna University, Chennai

## **DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING**

**COURSE NAME : 19EC513 – IMAGE PROCESSING AND COMPUTER  
VISION**

**III YEAR / V SEMESTER**

**Unit III- IMAGE COMPRESSION AND IMAGE SEGMENTATION**

**Topic : Edge models – Basic edge detection**



## Edge Models



- Edge detection is the approach used most frequently for segmenting images based on abrupt (local) changes in intensity. We begin by introducing several ways to model edges and then discuss a number of approaches for edge detection. Edge models are classified according to their intensity profiles. A step edge involves a transition between two intensity levels occurring ideally over the distance of 1 pixel.
- a section of a vertical step edge and a horizontal intensity profile through the edge. Step edges occur, for example, in images generated by a computer for use in areas such as solid modeling and animation. These clean, ideal edges can occur over the distance of 1 pixel, provided that no additional processing (such as smoothing) is used to make them look “real.” Digital step edges are used frequently as edge models in algorithm development.



## Basic Edge Detection



As illustrated in the previous section, detecting changes in intensity for the purpose of finding edges can be accomplished using first- or second-order derivatives. We discuss first-order derivatives in this section and work with second order derivatives

The image gradient and its properties The tool of choice for finding edge strength and direction at location of an image, is the gradient, denoted by and defined as the vector

$$\nabla f = \text{grad}(f) = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (10.2-9)$$

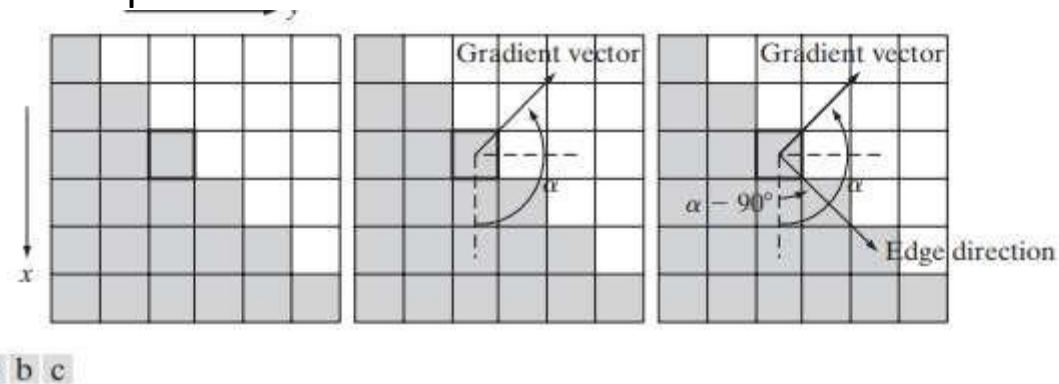
This vector has the important geometrical property that it points in the direction of the greatest rate of change of at location The magnitude (length) of vector denoted as where

$$M(x, y) = \text{mag}(\nabla f) = \sqrt{g_x^2 + g_y^2} \quad (10.2-10)$$

is the value of the rate of change in the direction of the gradient vector. Note that and are images of the same size as the original, created when and are allowed to vary over all pixel locations in It is common practice to refer to the latter image as the gradient image, or simply as the gradient when the meaning is clear. The summation, square, and square root operations are array operations,. The direction of the gradient vector is given by the angle

$$\alpha(x, y) = \tan^{-1} \left[ \frac{g_y}{g_x} \right] \quad (10.2-11)$$

measured with respect to the x-axis. As in the case of the gradient image, also is an image of the same size as the original created by the array division of image by image. The direction of an edge at an arbitrary point  $(x, y)$  is orthogonal to the direction, of the gradient vector at the point.



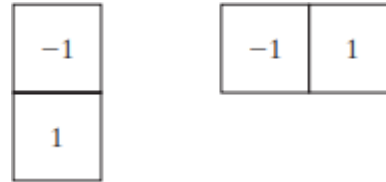
**FIGURE 10.12** Using the gradient to determine edge strength and direction at a point. Note that the edge is perpendicular to the direction of the gradient vector at the point where the gradient is computed. Each square in the figure represents one pixel.

Gradient operators Obtaining the gradient of an image requires computing the partial derivatives and at every pixel location in the image. We are dealing with digital quantities, so a digital approximation of the partial derivatives over a neighborhood about a point is required.



$$g_x = \frac{\partial f(x, y)}{\partial x} = f(x + 1, y) - f(x, y) \quad (10.2-12)$$

$$g_y = \frac{\partial f(x, y)}{\partial y} = f(x, y + 1) - f(x, y) \quad (10.2-13)$$



These two equations can be implemented for all pertinent values of and by filtering with the 1-D masks in Fig. 10.13. When diagonal edge direction is of interest, we need a 2-D mask. The Roberts cross-gradient operators (Roberts [1965]) are one of the earliest attempts to use 2-D masks with a diagonal preference. Consider the region in Fig. 10.14(a). The Roberts operators are based on implementing the diagonal differences

$$g_x = \frac{\partial f}{\partial x} = (z_9 - z_5) \quad (10.2-14)$$

$$g_y = \frac{\partial f}{\partial y} = (z_8 - z_6) \quad (10.2-15)$$

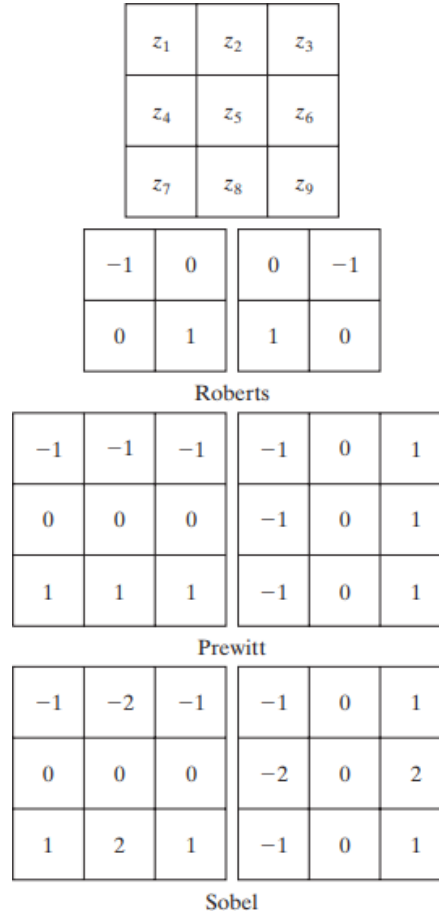


FIGURE : A region of an image (the z's are intensity values) and various masks used to compute the gradient at the point labeled z5



These derivatives can be implemented by filtering an image with the masks in Figs. 10.14(b) and (c). Masks of size are simple conceptually, but they are not as useful for computing edge direction as masks that are symmetric about the center point, the smallest of which are of size These masks take into account the nature of the data on opposite sides of the center point and thus carry more information regarding the direction of an edge. The simplest digital approximations to the partial derivatives using masks of size are given by

$$g_x = \frac{\partial f}{\partial x} = (z_7 + z_8 + z_9) - (z_1 + z_2 + z_3) \quad (10.2-16)$$

$$g_y = \frac{\partial f}{\partial y} = (z_3 + z_6 + z_9) - (z_1 + z_4 + z_7) \quad (10.2-17)$$

In these formulations, the difference between the third and first rows of the region approximates the derivative in the x-direction, and the difference between the third and first columns approximate the derivative in the y-direction. Intuitively, we would expect these approximations to be more accurate than the approximations obtained using the Roberts operators. Equations (10.2-16) and (10.2-17) can be implemented over an entire image by filtering with the two masks in Figs. 10.14(d) and (e). These masks are called the Prewitt operators (Prewitt [1970]). A slight variation of the preceding two equations uses a weight of 2 in the center coefficient:

$$g_x = \frac{\partial f}{\partial x} = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3) \quad (10.2-18)$$

$$g_y = \frac{\partial f}{\partial y} = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7) \quad (10.2-19)$$

It can be shown (Problem 10.10) that using a 2 in the center location provides image smoothing. Figures 10.14(f) and (g) show the masks used to implement Eqs. (10.2-18) and (10.2-19). These masks are called the Sobel operators (Sobel [1970]). The Prewitt masks are simpler to implement than the Sobel masks, but, the slight computational difference between them typically is not an issue. The fact that the Sobel masks have better noise-suppression (smoothing) characteristics makes them preferable because, as mentioned in the previous section, noise suppression is an important issue when dealing with derivatives. Note that the coefficients of all the masks in Fig. 10.14 sum to zero, thus giving a response of zero in areas of constant intensity, as expected of a derivative operator

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





The masks just discussed are used to obtain the gradient components and at every pixel location in an image. These two partial derivatives are then used to estimate edge strength and direction. Computing the magnitude of the gradient requires that and be combined in the manner shown in Eq. (10.2- 10). However, this implementation is not always desirable because of the computational burden required by squares and square roots. An approach used frequently is to approximate the magnitude of the gradient by absolute values:

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

This equation is more attractive computationally, and it still preserves relative changes in intensity levels. The price paid for this advantage is that the resulting filters will not be isotropic (invariant to rotation) in general. However, this is not an issue when masks such as the Prewitt and Sobel masks are used to compute and because these masks give isotropic results only for vertical and horizontal edges. Results would be isotropic only for edges in those two directions, regardless of which of the two equations is used. In addition, Eqs. (10.2-10) and (10.2-20) give identical results for vertical and horizontal edges when the Sobel or Prewitt masks are used (Problem 10.8). It is possible to modify the masks in Fig. 10.14 so that they have their strongest responses along the diagonal directions. Figure 10.15 shows the two additional Prewitt and Sobel masks needed for detecting edges in the diagonal directions



a b  
c d

**FIGURE 10.16**

(a) Original image of size  $834 \times 1114$  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,  $|g_x| + |g_y|$ .



THANK YOU !!!