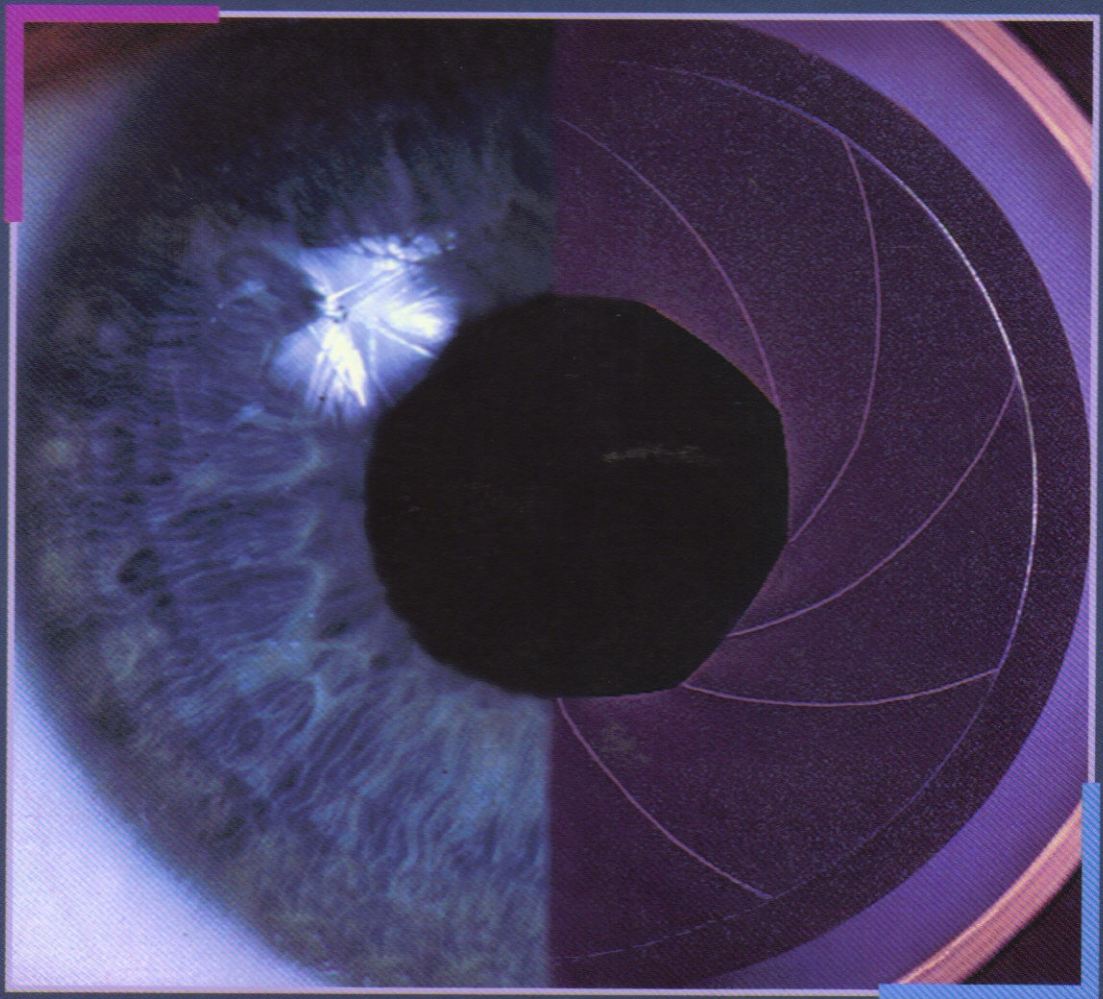
MACHINE VISION



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MACHINE VISION

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Machine Vision

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Chapter 5

Edge Detection

The early stages of vision processing identify features in images that are relevant to estimating the structure and properties of objects in a scene. Edges are one such feature. Edges are significant local changes in the image and are important features for analyzing images. Edges typically occur on the boundary between two different regions in an image. Edge detection is frequently the first step in recovering information from images. Due to its importance, edge detection continues to be an active research area. This chapter covers only the detection and localization of edges. Basic concepts in edge detection will be discussed. Several common edge detectors will be used to illustrate the basic issues in edge detection. Algorithms for combining edges into contours are discussed in Chapter 6.

An edge in an image is a significant local change in the image intensity, usually associated with a discontinuity in either the image intensity or the first derivative of the image intensity. Discontinuities in the image intensity can be either (1) *step* discontinuities, where the image intensity abruptly changes from one value on one side of the discontinuity to a different value on the opposite side, or (2) *line* discontinuities, where the image intensity abruptly changes value but then returns to the starting value within some short distance. However, step and line edges are rare in real images. Because of low-frequency components or the smoothing introduced by most sensing devices, sharp discontinuities rarely exist in real signals. Step edges become *ramp* edges and line edges become *roof* edges, where intensity changes are not instantaneous but occur over a finite distance. Illustrations of these edge profiles are shown in Figure 5.1.

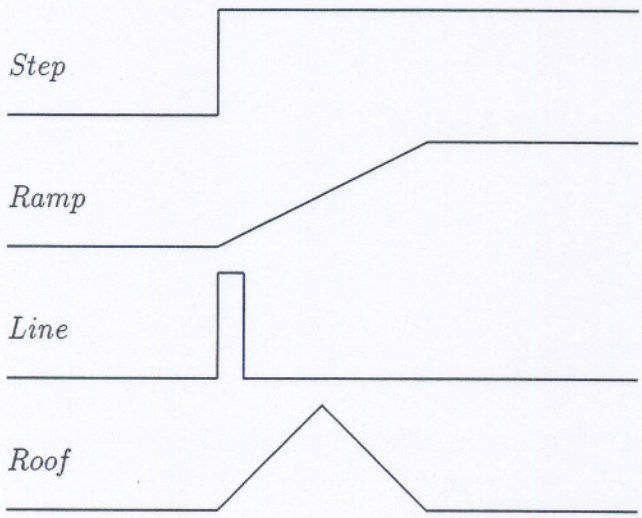

Figure 5.1: One-dimensional edge profiles.

It is also possible for an edge to have both step and line characteristics. For example, a surface that changes orientation from one flat surface to another will produce a step edge; but if the surface has a specular component of reflectance and if the surface corner is rounded, there can be a highlight due to the specular component as the surface orientation of the rounded corner passes the precise angle for specular reflection. The edge profile generated by such a situation looks like a step edge with a superimposed line edge. There are also edges associated with changes in the first derivative of the image intensity. For example, mutual reflection from the sides of a concave corner generate roof edges. Edges are important image features since they may correspond to significant features of objects in the scene. For example, the boundary of an object usually produces step edges because the image intensity of the object is different from the image intensity of the background.

This chapter will deal almost exclusively with step edges, although many of the ideas can be adapted to other types of image intensity changes. The profile of an ideal step edge and the profile of a real image that provides some examples of step edges are displayed in Figure 5.2. By definition, an edge is a significant local change in the image intensity. The plot shows step

previous chapter. The threshold values used for detection are given in the captions.

Figure 5.4 shows results of all the edge detection methods discussed so far, from the simple 1×2 gradient approximation up to the Prewitt operator. Figure 5.5 shows the results of the edge detectors when the filtering step is omitted. The next set of images (Figure 5.6) shows the results of edge detection on the same image now with additive Gaussian noise, $\sigma = 12$. The filter used was the same Gaussian filter as used in the previous figure. The final series of images (Figure 5.7) shows the results of edge detection on the same noisy image. However, for these images the filtering step was again omitted. Note the many false edges detected as a result of the noise.

5.3 Second Derivative Operators

The edge detectors discussed earlier computed the first derivative and, if it was above a threshold, the presence of an edge point was assumed. This results in detection of too many edge points. (Notice the thick lines after thresholding in Figures 5.4 to 5.7.) A better approach would be to find only the points that have local maxima in gradient values and consider them edge points, as shown in Figure 5.8. This means that at edge points, there will be a peak in the first derivative and, equivalently, there will be a zero crossing in the second derivative. Thus, edge points may be detected by finding the zero crossings of the second derivative of the image intensity.

There are two operators in two dimensions that correspond to the second derivative: the Laplacian and second directional derivative.

5.3.1 Laplacian Operator

The second derivative of a smoothed step edge is a function that crosses zero at the location of the edge (see Figure 5.8). The Laplacian is the two-dimensional equivalent of the second derivative. The formula for the Laplacian of a function $f(x, y)$ is

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}. \tag{5.18}$$

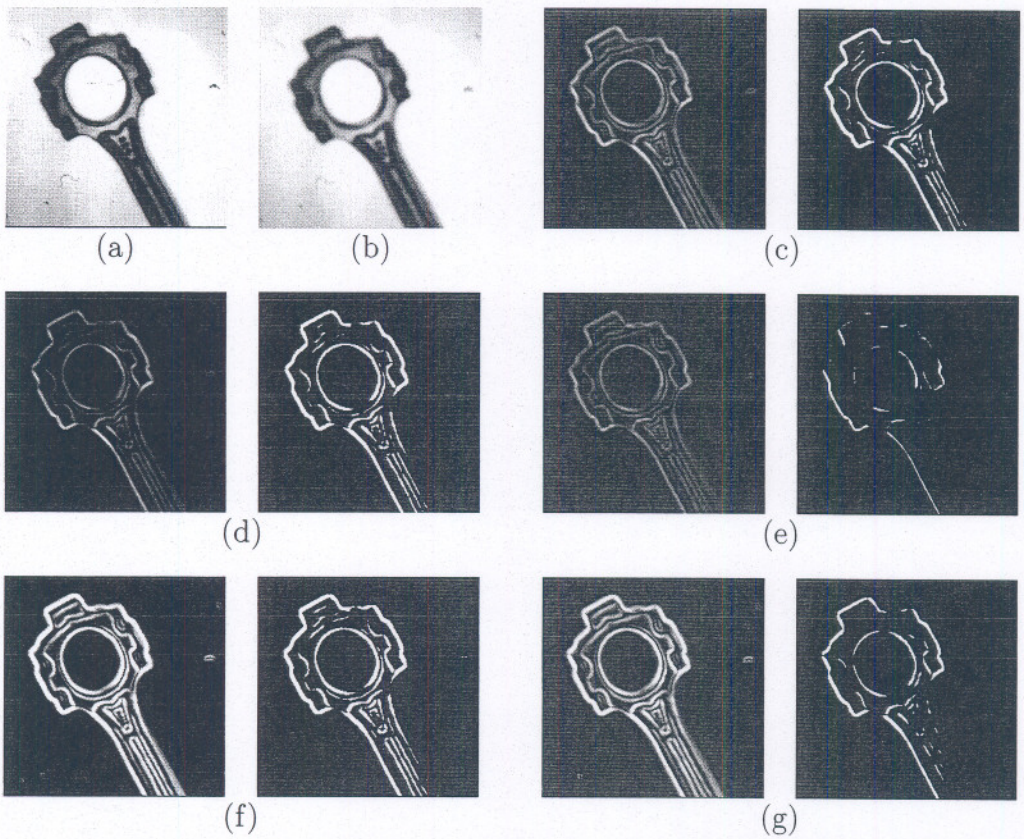

Figure 5.4: A comparison of various edge detectors. (a) Original image. (b) Filtered image. (c) Simple gradient using 1×2 and 2×1 masks, $T = 32$. (d) Gradient using 2×2 masks, $T = 64$. (e) Roberts cross operator, $T = 64$. (f) Sobel operator, $T = 225$. (g) Prewitt operator, $T = 225$.

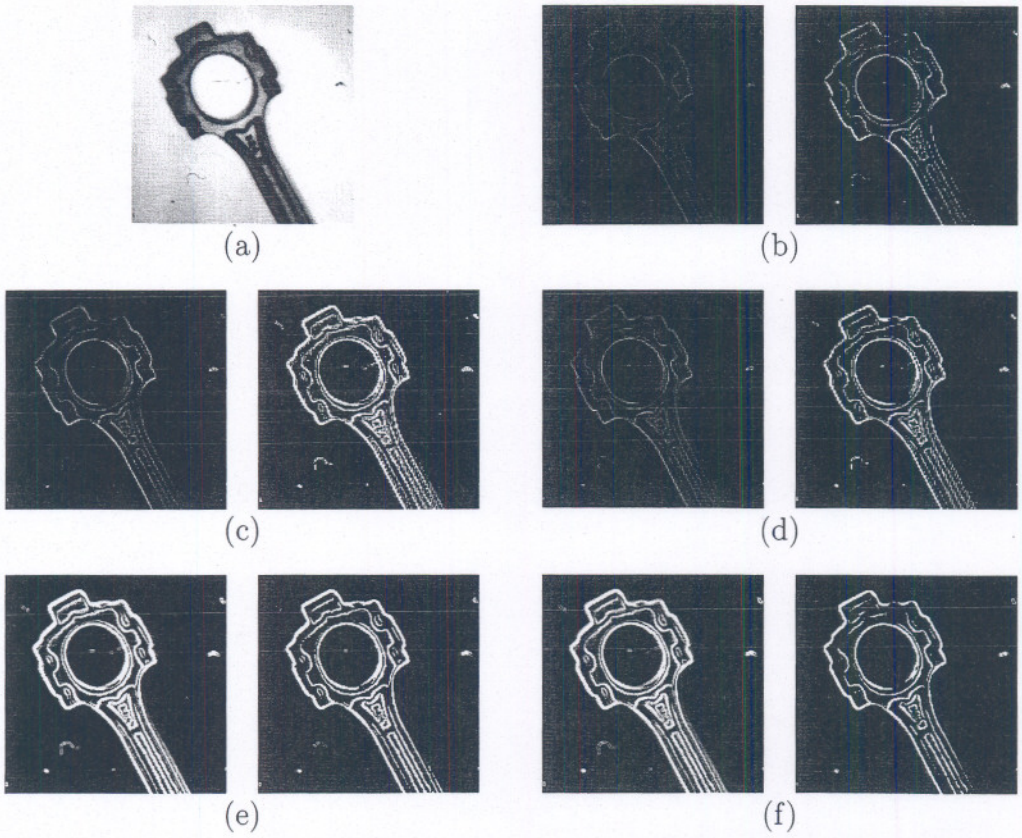

Figure 5.5: A comparison of various edge detectors without filtering. (a) Original image. (b) Simple gradient using 1×2 and 2×1 masks, $T = 64$. (c) Gradient using 2×2 masks, $T = 64$. (d) Roberts cross operator, $T = 64$. (e) Sobel operator, $T = 225$. (f) Prewitt operator, $T = 225$.

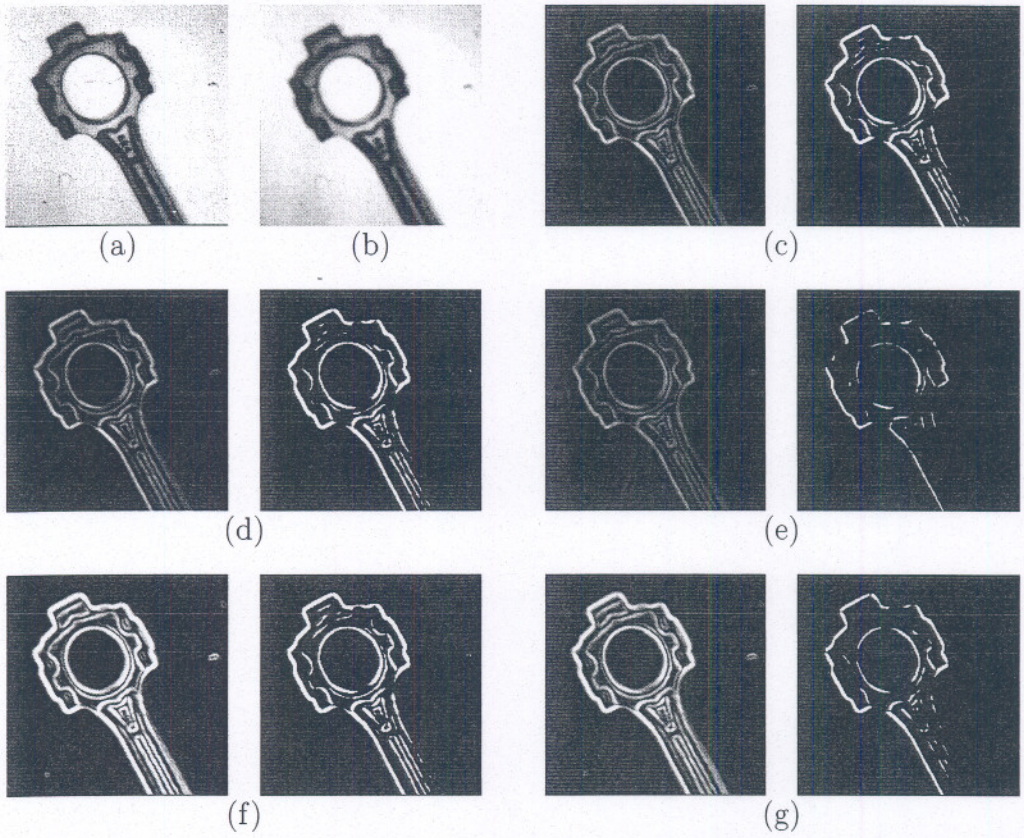

Figure 5.6: A comparison of various edge detectors on a noisy image. (a) Noisy image. (b) Filtered image. (c) Simple gradient using 1×2 and 2×1 masks, $T = 32$. (d) Gradient using 2×2 masks, $T = 64$. (e) Roberts cross operator, $T = 64$. (f) Sobel operator, $T = 225$. (g) Prewitt operator, $T = 225$.

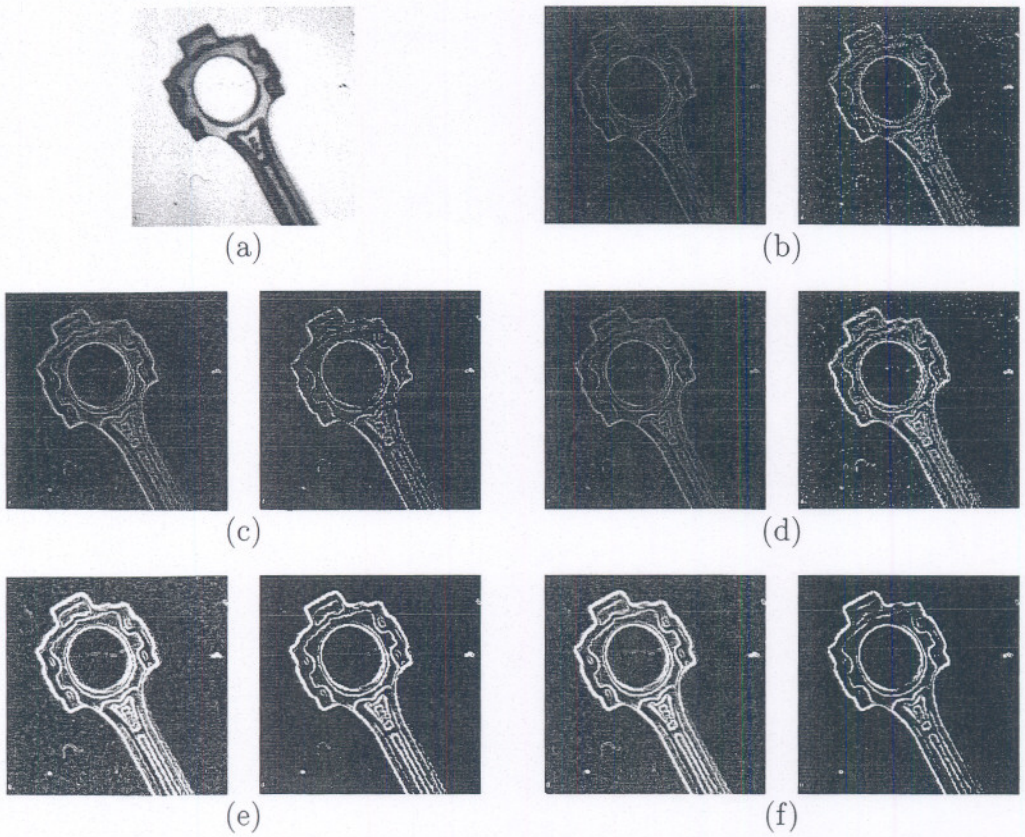

Figure 5.7: A comparison of various edge detectors on a noisy image without filtering. (a) Noisy image. (b) Simple gradient using 1×2 and 2×1 masks, $T = 64$. (c) Gradient using 2×2 masks, $T = 128$. (d) Roberts cross operator, $T = 64$. (e) Sobel operator, $T = 225$. (f) Prewitt operator, $T = 225$.

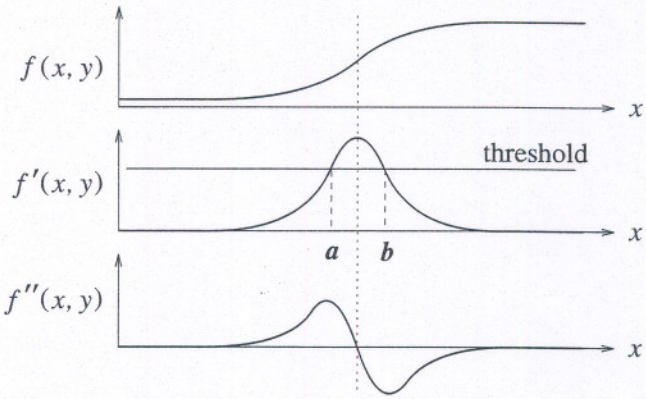

Figure 5.8: If a threshold is used for detection of edges, all points between a and b will be marked as edge pixels. However, by removing points that are *not* a local maximum in the first derivative, edges can be detected more accurately. This local maximum in the first derivative corresponds to a zero crossing in the second derivative.

The second derivatives along the x and y directions are approximated using difference equations:

$$\begin{aligned}
\frac{\partial^2 f}{\partial x^2} &= \frac{\partial G_x}{\partial x} && (5.19)\\
&= \frac{\partial\,(f[i,j+1]-f[i,j])}{\partial x} && (5.20)\\
&= \frac{\partial f[i,j+1]}{\partial x} - \frac{\partial f[i,j]}{\partial x} && (5.21)\\
&= (f[i,j+2]-f[i,j+1]) - (f[i,j+1]-f[i,j]) && (5.22)\\
&= f[i,j+2] - 2f[i,j+1] + f[i,j]. && (5.23)
\end{aligned}$$

However, this approximation is centered about the pixel $[i, j+1]$. Therefore, by replacing j with $j-1$, we obtain

$$\frac{\partial^2 f}{\partial x^2} = f[i,j+1] - 2f[i,j] + f[i,j-1], \qquad (5.24)$$

which is the desired approximation to the second partial derivative centered about $[i, j]$. Similarly,

$$\frac{\partial^2 f}{\partial y^2} = f[i+1, j] - 2f[i, j] + f[i-1, j]. \tag{5.25}$$

By combining these two equations into a single operator, the following mask can be used to approximate the Laplacian:

$$\nabla^2 \approx \begin{array}{|c|c|c|} \hline 0 & 1 & 0 \\ \hline 1 & -4 & 1 \\ \hline 0 & 1 & 0 \\ \hline \end{array} \tag{5.26}$$

Sometimes it is desired to give more weight to the center pixels in the neighborhood. An approximation to the Laplacian which does this is

$$\nabla^2 \approx \begin{array}{|c|c|c|} \hline 1 & 4 & 1 \\ \hline 4 & -20 & 4 \\ \hline 1 & 4 & 1 \\ \hline \end{array} \tag{5.27}$$

The Laplacian operator signals the presence of an edge when the output of the operator makes a transition through zero. Trivial zeros (uniform zero regions) are ignored. In principle, the zero crossing location can be estimated to subpixel resolution using linear interpolation, but the result may be inaccurate due to noise.

Consider the example shown in Figure 5.9. This figure shows the result of the Laplacian on an image with a simple step edge. A single row of the resulting image is:

0	0	0	6	−6	0	0	0

In this example, the zero crossing, corresponding to the edge in the original image, lies halfway between the two center pixels. The edge should be marked at either the pixel to the left or the pixel to the right of the edge, as long as it is marked consistently throughout the image. In most cases, however, the zero crossing rarely lies exactly between two pixels, and the actual edge

2	2	2	2	2	8	8	8	8	8
2	2	2	2	2	8	8	8	8	8
2	2	2	2	2	8	8	8	8	8
2	2	2	2	2	8	8	8	8	8
2	2	2	2	2	8	8	8	8	8
2	2	2	2	2	8	8	8	8	8

A sample image containing a vertical step edge.

0	0	0	6	−6	0	0	0
0	0	0	6	−6	0	0	0
0	0	0	6	−6	0	0	0
0	0	0	6	−6	0	0	0

Figure 5.9: The response of the Laplacian to a vertical step edge.

location must be determined by interpolating the pixel values on either side of the zero crossing.

Now consider the example in Figure 5.10. This figure shows the response of the Laplacian to a ramp edge. A single row of the output of the Laplacian is

0	0	0	3	0	−3	0	0

The zero crossing directly corresponds to a pixel in the image. Again, this is an ideal situation, and the actual edge location should be determined by interpolation.

5.3.2 Second Directional Derivative

The second directional derivative is the second derivative computed in the direction of the gradient. The operator is implemented using the formula

$$\frac{\partial^2}{\partial n^2} = \frac{f_x^2 f_{xx} + 2 f_x f_y f_{xy} + f_y^2 f_{yy}}{f_x^2 + f_y^2} \tag{5.28}$$