SNS COLLEGE OF ENGINEERING

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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 : Image segmentation : detection of isolated points and line detection

Image Segmentation

Segmentation subdivides an image into its constituent regions or objects .The level of detail to which the subdivision is carried depends on the problem being solved .That is, segmentation should stop when the objects or regions of interest in an application have been detected. For example, in the automated inspection of electronic assemblies, interest lies in analyzing images of products with the objective of determining the presence or absence of specific anomalies, such as missing components or broken connection paths. There is no point in carrying segmentation past the level of detail required to identify those elements.
Segmentation of nontrivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures. For this reason, considerable care should be taken to improve the probability of accurate segmentation.

The focus of this section is on segmentation methods that are based on detecting sharp, local changes in intensity.The three types of image features in which we are interested are isolated points, lines, and edges

Detection of isolated points

We know that point detection should be based on the second derivative.

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

where the partials are obtained using Eq. (10.2-2):

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

and

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

The Laplacian is then

$$\begin{aligned}\nabla^2 f(x, y) = {} & f(x + 1, y) + f(x - 1, y) + f(x, y + 1) \\ & + f(x, y - 1) - 4f(x, y)\end{aligned} \qquad (10.2\text{-}7)$$

As explained in that section, we can extend Eq. (10.2-7) to include the diagonal terms, and use the mask in Fig. 3.37(b). Using the Laplacian mask in Fig. 10.4(a), which is the same as the mask in Fig. 3.37(b), we say that a point has been detected at the location on which the mask is centered if the absolute value of the response of the mask at that point exceeds a specified threshold. Such points are labeled 1 in the output image and all others are labeled 0, thus producing a binary image. In other words, the output is obtained using the following expression:

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

(10.2-8) where is the output image, is a nonnegative threshold, and is given by Eq. (10.2-3). This formulation simply measures the weighted differences between a pixel and its 8-neighbors. Intuitively, the idea is that the intensity of an isolated point will be quite different from its surroundings and thus will be easily detectable by this type of mask. The only differences in intensity that are considered of interest are those large enough (as determined by) to be considered isolated points. Note that, as usual for a derivative mask, the coefficients sum to zero, indicating that the mask response will be zero in areas of constant intensity.

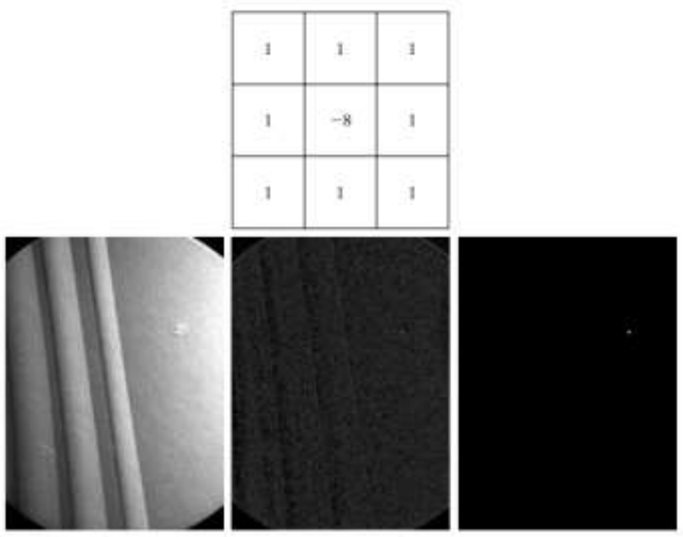

FIGURE (a) Point detection (Laplacian) mask. (b) X-ray image of turbine blade with a porosity. The porosity contains a single black pixel. (c) Result of convolving the mask with the image. (d) Result of using Eq.(10.2-8) showing a single point (the point was enlarged to make it easier to see). (Original image courtesy of X-TEK Systems, Ltd.

We illustrate segmentation of isolated points in an image with the aid of Fig. 10.4(b), which is an X-ray image of a turbine blade from a jet engine. The blade has a porosity in the upper-right quadrant of the image, and there is a single black pixel embedded within the porosity. Figure 10.4(c) is the result of applying the point detector mask to the X-ray image, and Fig. 10.4(d) shows the result of using Eq. (10.2-8) with equal to 90% of the highest absolute pixel value of the image in Fig. 10.4(c). The single pixel is clearly visible in this image (the pixel was enlarged manually to enhance its visibility). This type of detection process is rather specialized, because it is based on abrupt intensity changes at single-pixel locations that are surrounded by a homogeneous background in the area of the detector mask. When this condition is not satisfied, other methods discussed in this chapter are more suitable for detecting intensity changes.

Line detection

The next level of complexity is line detection. Based on the discussion in Section 10.2.1, we know that for line detection we can expect second derivatives to result in a stronger response and to produce thinner lines than first derivatives.Thus, we can use the Laplacian mask in Fig. 10.4(a) for line detection also, keeping in mind that the double-line effect of the second derivative must be handled properly.

Figure 10.5(a) shows a (binary) portion of a wire-bond mask for an electronic circuit, and Fig. 10.5(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. 10.5(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 the image in Fig. 10.5(d) shows, this approach results in thinner lines, which are considerably more useful. Note in Figs. 10.5(b) through (d) that when the lines are wide with respect to the size of the Laplacian mask, the lines are separated by a zero "valley."

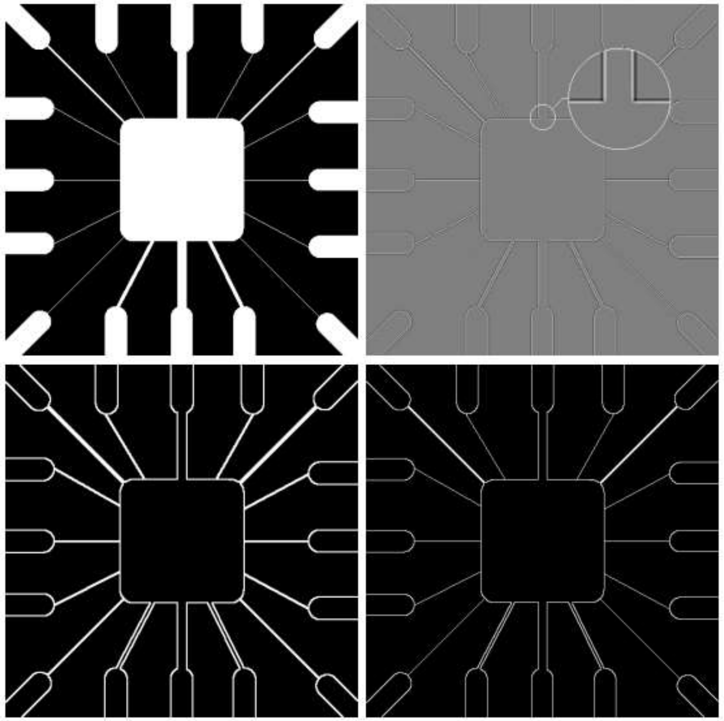

FIGURE 10.5 (a) Original image. (b) Laplacian image; the magnified section shows the positive/negative double-line effect characteristic of the Laplacian. (c) Absolute value of the Laplacian. (d) Positive values of the Laplacian

This is not unexpected. For example, when the filter is centered on a line of constant intensity 5 pixels wide, the response will be zero, thus producing the effect just mentioned. When we talk about line detection, the assumption is that lines are thin with respect to the size of the detector. Lines that do not satisfy this assumption are best treated as regions and handled by the edge detection methods

THANK YOU !!!