3.3.3 Local Histogram Processing

The histogram processing methods discussed in the previous two sections are *global*, in the sense that pixels are modified by a transformation function based on the intensity distribution of an entire image. Although this global approach is suitable for overall enhancement, there are cases in which it is necessary to enhance details over small areas in an image. The number of pixels in these areas may have negligible influence on the computation of a global transformation whose shape does not necessarily guarantee the desired local enhancement. The solution is to devise transformation functions based on the intensity distribution in a neighborhood of every pixel in the image.

The histogram processing techniques previously described are easily adapted to local enhancement. The procedure is to define a neighborhood and move its center from pixel to pixel. At each location, the histogram of the points in the neighborhood is computed and either a histogram equalization or histogram specification transformation function is obtained. This function is then used to map the intensity of the pixel centered in the neighborhood. The center of the neighborhood region is then moved to an adjacent pixel location and the procedure is repeated. Because only one row or column of the neighborhood changes during a pixel-to-pixel translation of the neighborhood, updating the histogram obtained in the previous location with the new data introduced at each motion step is possible (Problem 3.12). This approach has obvious advantages over repeatedly computing the histogram of all pixels in the neighborhood region each time the region is moved one pixel location. Another approach used sometimes to reduce computation is to utilize nonoverlapping regions, but this method usually produces an undesirable "blocky" effect.

EXAMPLE 3.10: Local histogram equalization.

■ Figure 3.26(a) shows an 8-bit, 512×512 image that at first glance appears to contain five black squares on a gray background. The image is slightly noisy, but the noise is imperceptible. Figure 3.26(b) shows the result of global histogram equalization. As often is the case with histogram equalization of smooth, noisy regions, this image shows significant enhancement of the noise. Aside from the noise, however, Fig. 3.26(b) does not reveal any new significant details from the original, other than a very faint hint that the top left and bottom right squares contain an object. Figure 3.26(c) was obtained using local histogram equalization with a neighborhood of size 3×3. Here, we see significant detail contained within the dark squares. The intensity values of these objects were too close to the intensity of the large squares, and their sizes were too small, to influence global histogram equalization significantly enough to show this detail. ■

3.3.4 Using Histogram Statistics for Image Enhancement

Statistics obtained directly from an image histogram can be used for image enhancement. Let r denote a discrete random variable representing intensity values in the range $[0, L - 1]$, and let $p(r_i)$ denote the normalized histogram

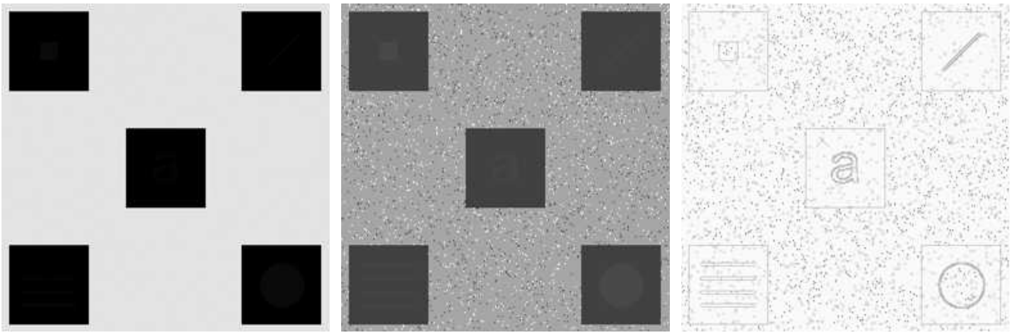

FIGURE 3.26 (a) Original image. (b) Result of global histogram equalization. (c) Result of local histogram equalization applied to (a), using a neighborhood of size 3×3.

component corresponding to value r_i. As indicated previously, we may view $p(r_i)$ as an estimate of the probability that intensity r_i occurs in the image from which the histogram was obtained.

As we discussed in Section 2.6.8, the nth moment of r about its mean is defined as

$$\mu_n(r) = \sum_{i=0}^{L-1} (r_i - m)^n p(r_i) \tag{3.3-17}$$

where m is the mean (average intensity) value of r (i.e., the average intensity of the pixels in the image):

We follow convention in using m for the mean value. Do not confuse it with the same symbol used to denote the number of rows in an $m \times n$ neighborhood, in which we also follow notational convention.

$$m = \sum_{i=0}^{L-1} r_i p(r_i) \tag{3.3-18}$$

The second moment is particularly important:

$$\mu_2(r) = \sum_{i=0}^{L-1} (r_i - m)^2 p(r_i) \tag{3.3-19}$$

We recognize this expression as the intensity variance, normally denoted by σ^2 (recall that the standard deviation is the square root of the variance). Whereas the mean is a measure of average intensity, the variance (or standard deviation) is a measure of contrast in an image. Observe that all moments are computed easily using the preceding expressions once the histogram has been obtained from a given image.

When working with only the mean and variance, it is common practice to estimate them directly from the sample values, without computing the histogram. Appropriately, these estimates are called the *sample mean* and *sample variance*. They are given by the following familiar expressions from basic statistics:

$$m = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \tag{3.3-20}$$