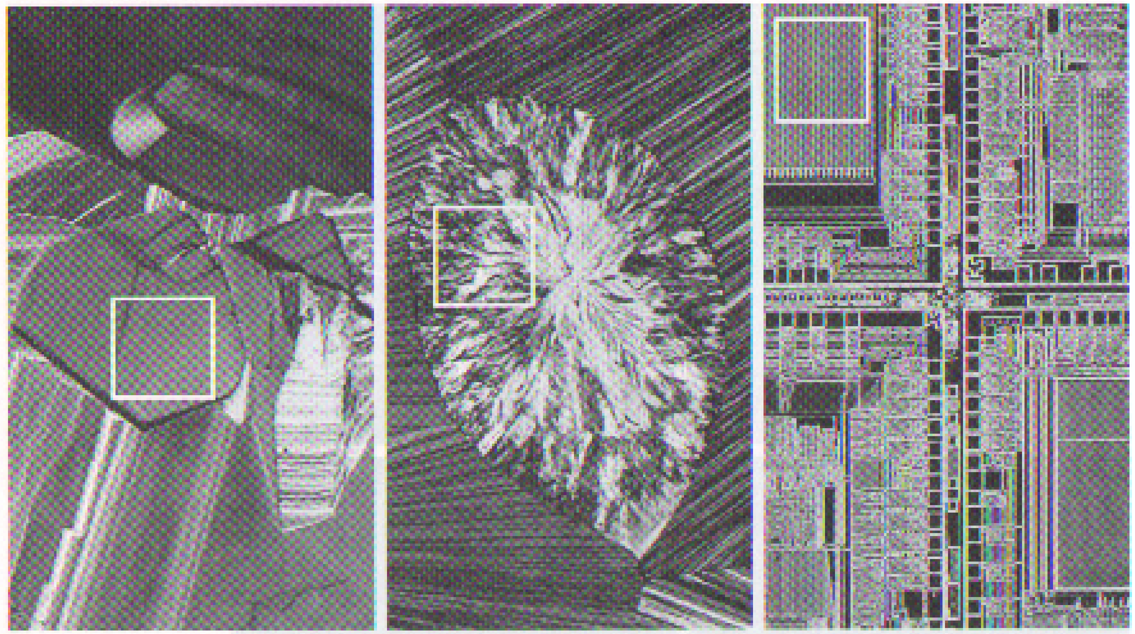

a b c

FIGURE 11.22 The white squares mark, from left to right, smooth, coarse, and regular textures. These are optical microscope images of a superconductor, human cholesterol, and a microprocessor. (Courtesy of Dr. Michael W. Davidson, Florida State University.)

grainy, and so on. Structural techniques deal with the arrangement of image primitives, such as the description of texture based on regularly spaced parallel lines. Spectral techniques are based on properties of the Fourier spectrum and are used primarily to detect global periodicity in an image by identifying high-energy, narrow peaks in the spectrum.

Statistical approaches

One of the simplest approaches for describing texture is to use statistical moments of the gray-level histogram of an image or region. Let z be a random variable denoting gray levels and let $p(z_i)$, $i = 0, 1, 2, \ldots, L-1$, be the corresponding histogram, where L is the number of distinct gray levels. From Eq. (3.3-18), the nth moment of z about the mean is

$$\mu_n(z) = \sum_{i=0}^{L-1} (z_i - m)^n p(z_i) \tag{11.3-4}$$

where m is the mean value of z (the average gray level):

$$m = \sum_{i=0}^{L-1} z_i p(z_i). \tag{11.3-5}$$

Note from Eq. (11.3-4) that $\mu_0 = 1$ and $\mu_1 = 0$. The second moment [the *variance* $\sigma^2(z) = \mu_2(z)$] is of particular importance in texture description. It is a measure of gray-level contrast that can be used to establish descriptors of relative smoothness. For example, the measure

$$R = 1 - \frac{1}{1 + \sigma^2(z)} \tag{11.3-6}$$

is 0 for areas of constant intensity (the variance is zero there) and approaches 1 for large values of $\sigma^2(z)$. Because variance values tend to be large for gray-scale images with values, for example, in the range 0 to 255, it is a good idea to normalize the variance to the interval [0, 1] for use in Eq. (11.3-6). This is done simply by dividing $\sigma^2(z)$ by $(L-1)^2$ in Eq. (11.3-6). The standard deviation, $\sigma(z)$, also is used frequently as a measure of texture because values of the standard deviation tend to be more intuitive to many people.

The third moment,

$$\mu_3(z) = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i), \tag{11.3-7}$$

is a measure of the skewness of the histogram while the fourth moment is a measure of its relative flatness. The fifth and higher moments are not so easily related to histogram shape, but they do provide further quantitative discrimination of texture content. Some useful additional texture measures based on histograms include a measure of "uniformity," given by

$$U = \sum_{i=0}^{L-1} p^2(z_i), \tag{11.3-8}$$

and an *average entropy* measure, which the reader might recall from basic information theory, or from our discussion in Chapter 8, is defined as

$$e = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i). \tag{11.3-9}$$

Because the p's have values in the range [0, 1] and their sum equals 1, measure U is maximum for an image in which all gray levels are equal (maximally uniform), and decreases from there. Entropy is a measure of variability and is 0 for a constant image.

EXAMPLE 11.6: Texture measures based on histograms.

■ Table 11.2 summarizes the values of the preceding measures for the three types of textures highlighted in Fig. 11.22. The mean just tells us the average gray level of each region and is useful only as a rough idea of intensity, not really texture. The standard deviation is much more informative; the numbers clearly show that the first texture has significantly less variability in gray level (it is smoother) than the other two textures. The coarse texture shows up clearly in this measure. As expected, the same comments hold for R, because it measures essentially the same thing as the standard deviation. The third moment generally is useful for determining the degree of symmetry of histograms and whether they are skewed to the left (negative value) or the right (positive value).