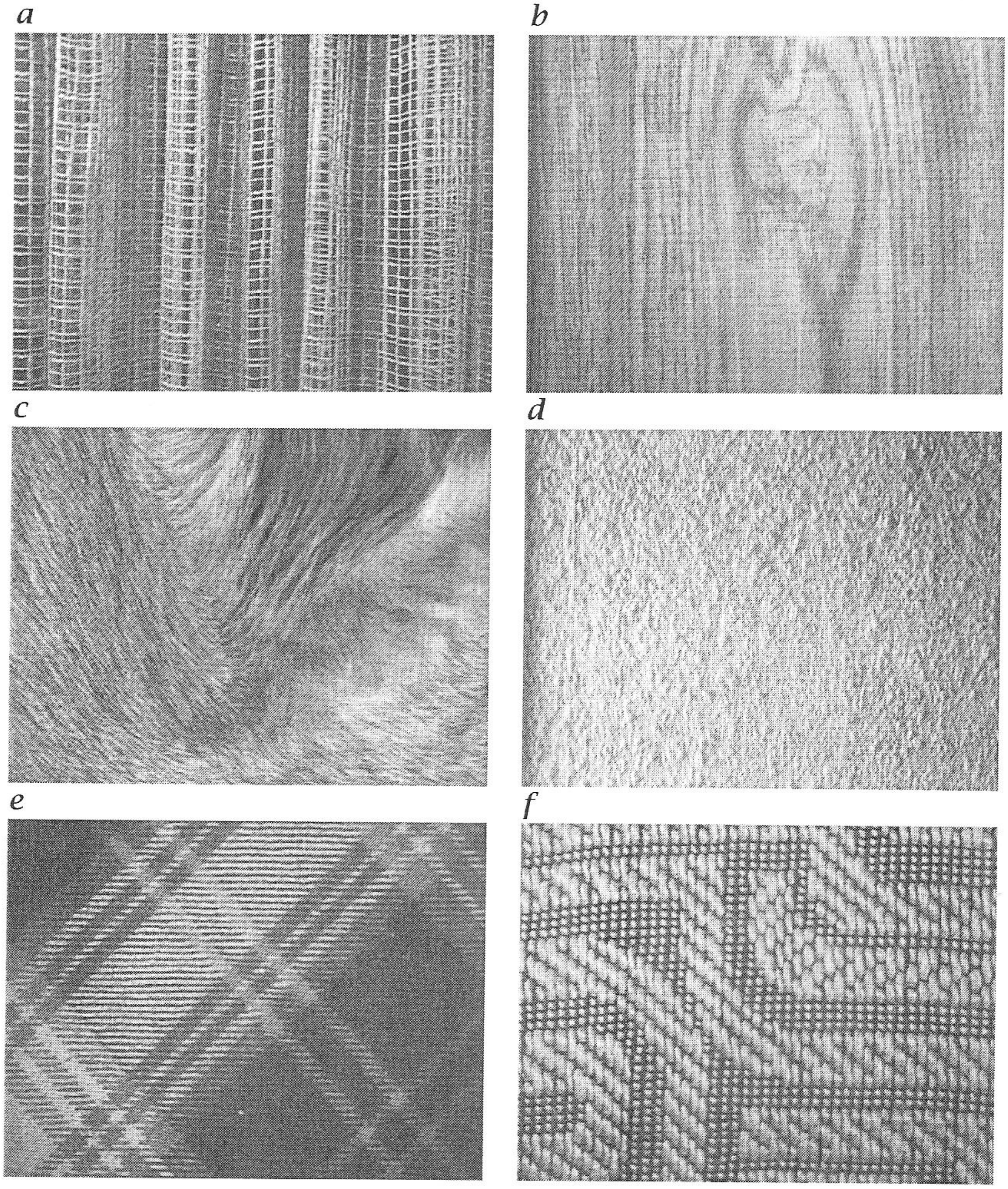

Figure 12.1: *Examples of textures:* ***a*** *curtain;* ***b*** *wood;* ***c*** *dog fur;* ***d*** *woodchip paper;* ***e, f*** *clothes.*

Textures may be organized in a *hierarchical* manner, i. e., they may look quite different at different scales. A good example is the curtain shown in Fig. 12.1a. On the finest scale our attention is focused on the individual threads (Fig. 12.2a). Then the characteristic scale is the thick-

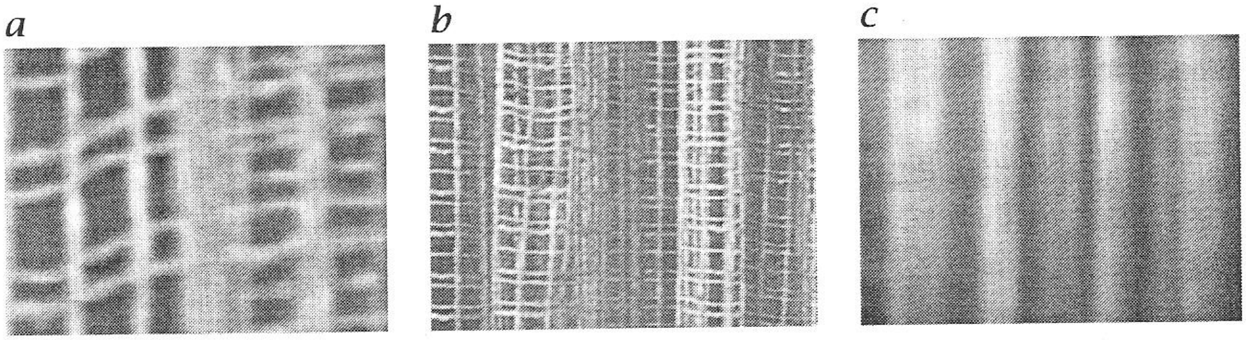

Figure 12.2: Hierarchical organization of texture demonstrated by showing the image of the curtain in Fig. 12.1a at different resolutions.

the local orientation is well distributed. Finally, at an even coarser level, we no longer recognize the individual meshes, but observe the folds of the curtain (Fig. 12.2c). They are characterized by yet another characteristic scale, showing the period of the folds and their orientation. These considerations emphasize the importance of *multiscale texture analysis*. Thus multiscale data structures as discussed in the first part of this book (Chap. 5) are essential for texture analysis.

Generally, two classes of texture parameters are of importance. Texture parameters may or may not be rotation and scale invariant. This classification is motivated by the task we have to perform.

Imagine a typical industrial or scientific application in which we want to recognize objects that are randomly oriented in the image. We are not interested in the orientation of the objects but in their distinction from each other. Therefore, texture parameters that depend on orientation are of no interest. We might still use them but only if the objects have a characteristic shape which then allows us to determine their orientation. We can use similar arguments for scale-invariant features. If the objects of interest are located at different distances from the camera, the texture parameter used to recognize them should also be scale invariant. Otherwise the recognition of the object will depend on distance. However, if the texture changes its characteristics with the scale — as in the example of the curtain in Fig. 12.1a — the scale-invariant texture features may not exist at all. Then the use of textures to characterize objects at different distances becomes a difficult task.

In the examples above, we were interested in the objects themselves but not in their orientation in space. The orientation of surfaces is a key feature for another image processing task, the reconstruction of a

In the simplest case, we can select a mask and compute the parameters only from the pixels contained in this window W. The *variance operator*, for example, is then given by

$$V_{mn} = \frac{1}{P-1} \sum_{m',n' \in W} \left(G_{m-m',n-n'} - \langle G \rangle_{mn} \right)^2 . \qquad (12.1)$$

The sum runs over the P image points of the window. The expression $\langle G \rangle_{mn}$ denotes the mean of the gray values at the point $[m,n]^T$, computed over the same window W:

$$\langle G \rangle_{mn} = \frac{1}{P} \sum_{m',n' \in W} G_{m-m',n-n'} . \qquad (12.2)$$

It is important to note that the variance operator is nonlinear. However, it resembles the general form of a neighborhood operation — a convolution. Combining (12.1) and (12.2), we can show the variance operator is a combination of linear convolution and nonlinear point operations

$$V_{mn} = \frac{1}{P-1} \left[\sum_{m',n' \in M} G^2_{m-m',n-n'} - \left(\frac{1}{P} \sum_{m',n' \in M} G_{m-m',n-n'} \right)^2 \right], \qquad (12.3)$$

or, in operator notation,

$$\mathcal{V} = \mathcal{R}(\mathcal{I} \cdot \mathcal{I}) - (\mathcal{R} \cdot \mathcal{R}). \qquad (12.4)$$

The operator $\mathcal{R}$ denotes a smoothing over all the image points with a box filter of the size of the window W. The operator $\mathcal{I}$ is the identity operator. Therefore the operator $\mathcal{I} \cdot \mathcal{I}$ performs a nonlinear point operation, namely the squaring of the gray values at each pixel. Finally, the variance operator subtracts the square of a smoothed gray value from the smoothed squared gray values.

From discussions on smoothing in Sect. 10.3 we know that a box filter is not an appropriate smoothing filter. Thus we obtain a better variance operator if we replace the box filter $\mathcal{R}$ with a binomial filter $\mathcal{B}$

$$\mathcal{V} = \mathcal{B}(\mathcal{I} \cdot \mathcal{I}) - (\mathcal{B} \cdot \mathcal{B}). \qquad (12.5)$$

We know the variance operator to be isotropic. It is also scale independent if the window is larger than the largest scales in the textures and if no fine scales of the texture disappear because the objects are located further away from the camera. This suggests that a scale-invariant

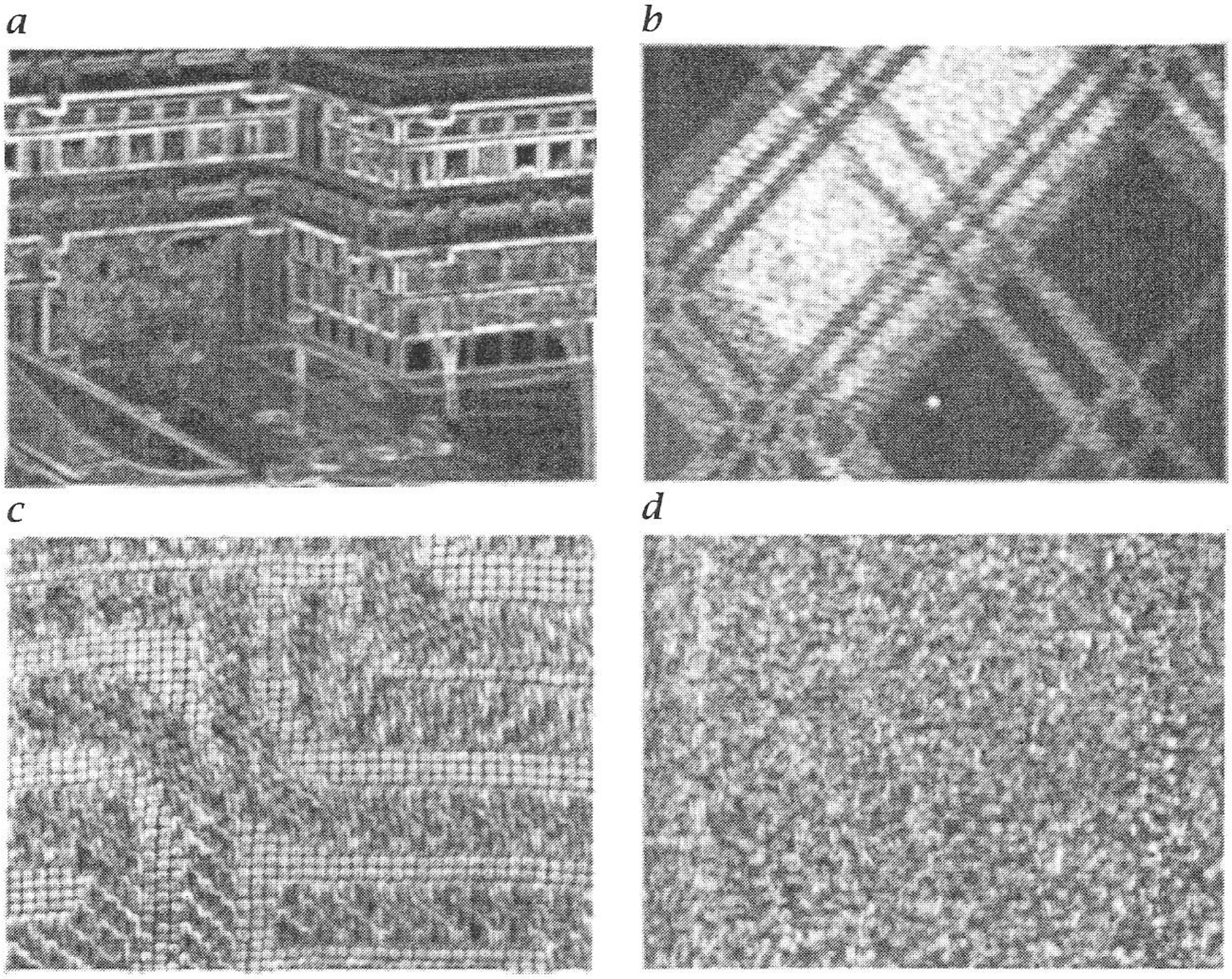

***Figure 12.3:** Variance operator applied to different images: **a** Fig. 10.6a; **b** Fig. 12.1e; **c** Fig. 12.1f; **d** Fig. 12.1d.*

out to be an isotropic edge detector, since the original image contains areas with more or less uniform gray values.

The other three examples in Fig. 12.3 show variance images from textured surfaces. The variance operator can distinguish the areas with the fine horizontal stripes in Fig. 12.1e from the more uniform surfaces. They appear as uniform bright areas in the variance image (Fig. 12.3b). The variance operator cannot distinguish between the two textures in Fig. 12.3c. Since the resolution is still finer than the characteristic repetition scale of the texture, the variance operator does not give a uniform estimate of the variance in the texture. The chipwood paper (Fig. 12.3d) also gives a non-uniform response to the variance operator since the pattern shows significant random fluctuations.

12.2.2 Higher Moments

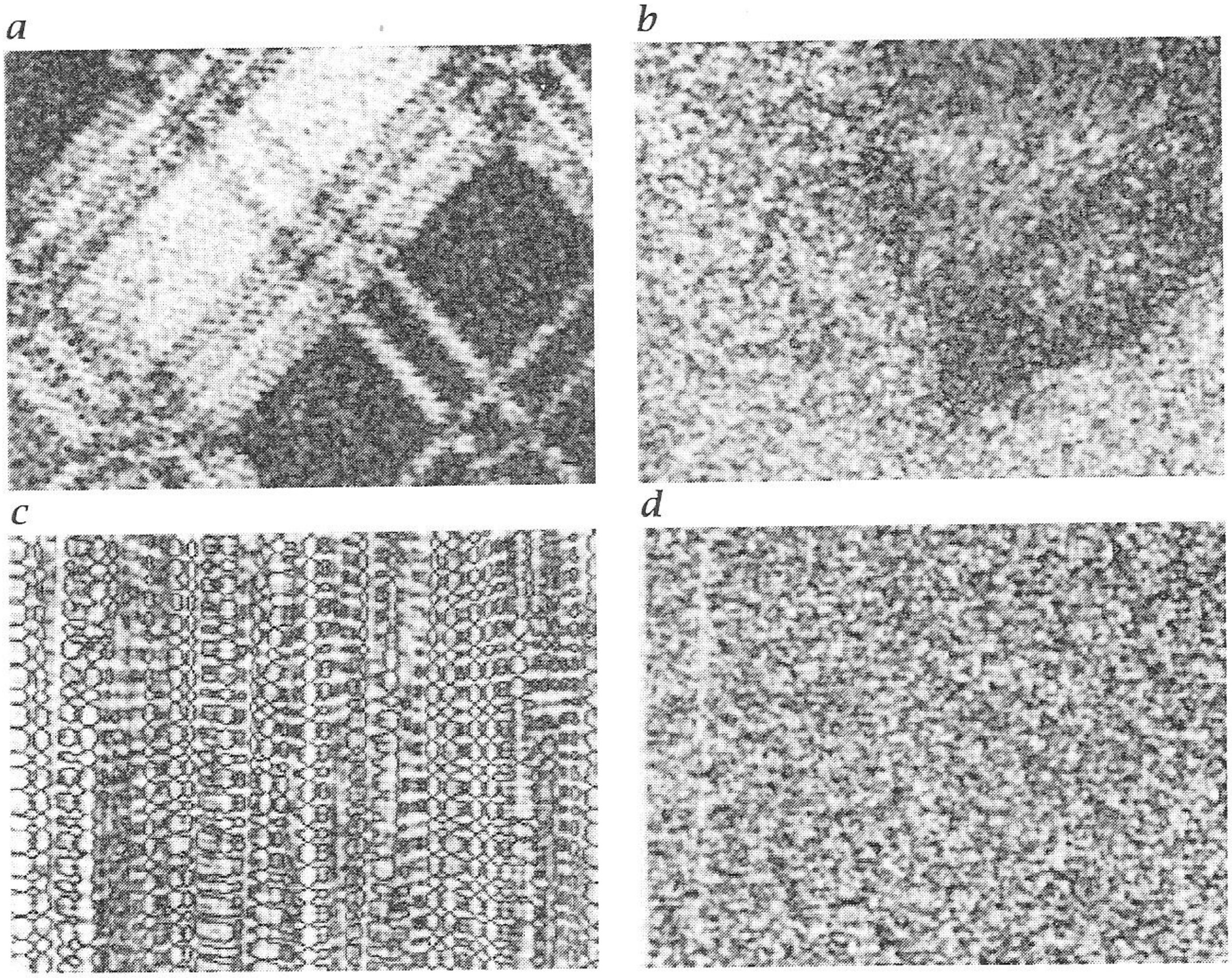

Figure 12.4: Coherence of local orientation of **a** *piece of cloth with regions of horizontal stripes (Fig. 12.1e),* **b** *dog fur (Fig. 12.1c),* **c** *curtain (Fig. 12.1a), and* **d** *woodchip wall paper (Fig. 12.1d) (For a complete analysis of the local orientation, see* ***exercise 12.2****).*

tion. The significance of this approach may be illustrated with examples of two quite different gray value distributions, a normal and a bimodal distribution:

$$p(g) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{g - \langle g \rangle}{2\sigma^2}\right), \quad p'(g) = \frac{1}{2}\left(\delta(\langle g \rangle + \sigma) + \delta(\langle g \rangle - \sigma)\right).$$

Both distributions show the same mean and variance but differ in higher-order moments.

12.3 Rotation and Scale Variant Texture Features

12.3.1 Local Orientation

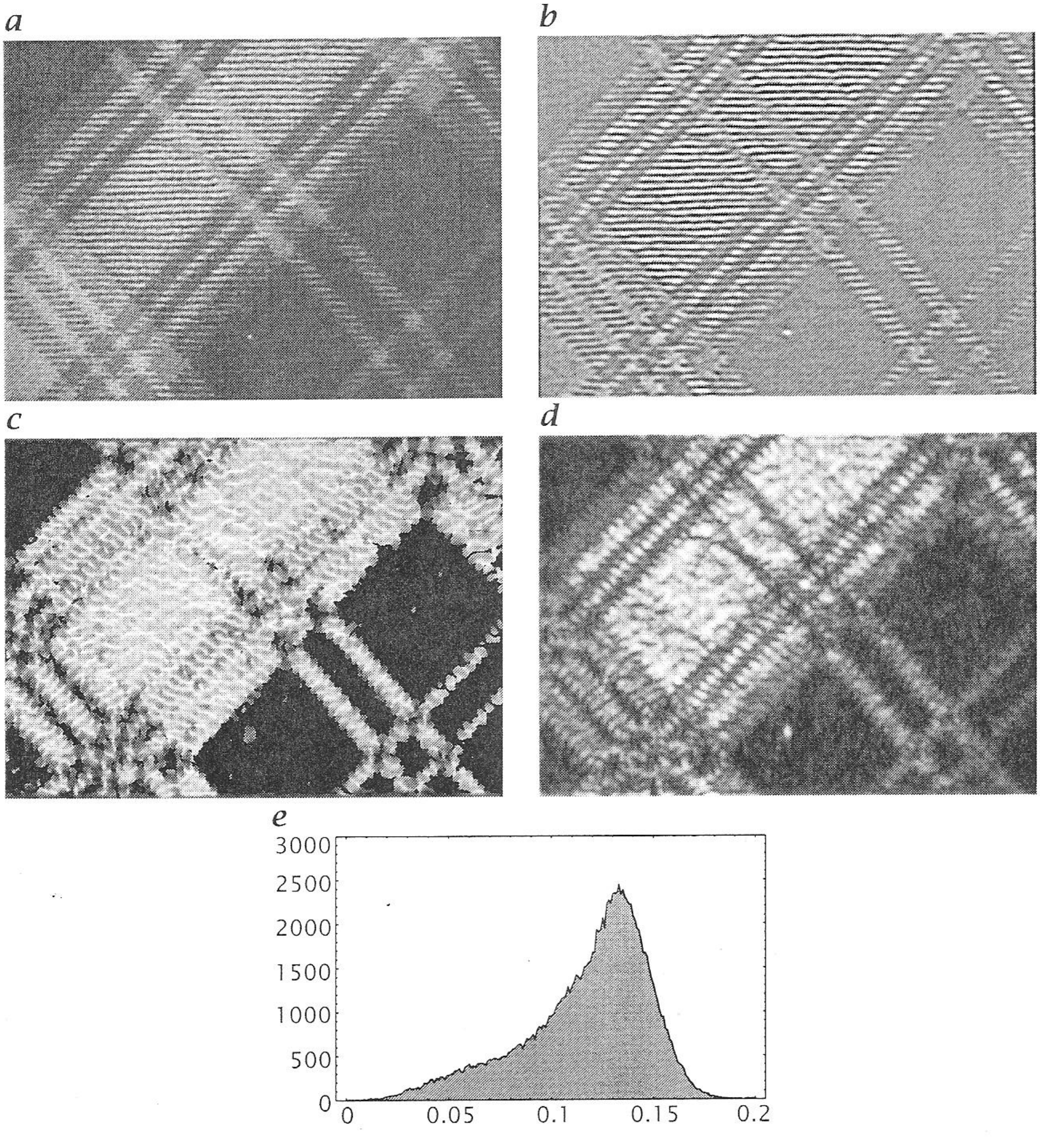

Figure 12.5: *Determination of the characteristic scale of a texture by computation of the local wave number:* ***a*** *original texture,* ***b*** *directional bandpass using the levels one and two of the vertical component of a directiopyramidal decomposition,* ***c*** *estimate of the local wave number (all structures below a certain threshold are masked to black),* ***d*** *amplitude of the local wave number, and* ***e*** *histogram of the local wave number distribution (units: number of periods per pixel).*

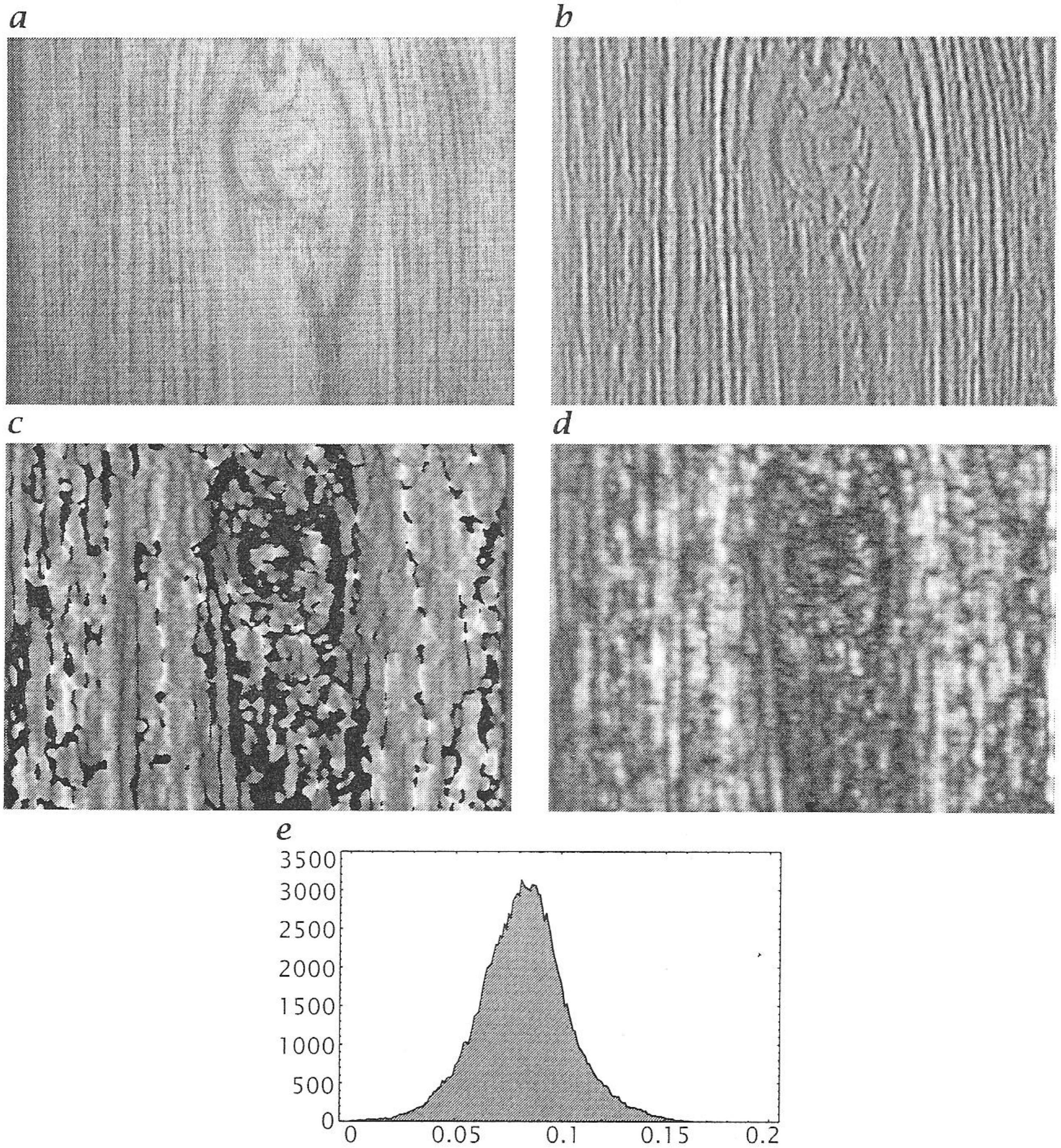

Figure 12.6: *Determination of the characteristic scale of a texture by computation of the local wave number:* ***a*** *original texture,* ***b*** *directional bandpass using the levels one and two of the vertical component of a directiopyramidal decomposition,* ***c*** *estimate of the local wave number (all structures below a certain threshold are masked to black),* ***d*** *amplitude of the local wave number, and* ***e*** *histogram of the local wave number distribution (units: number of periods per pixel).*

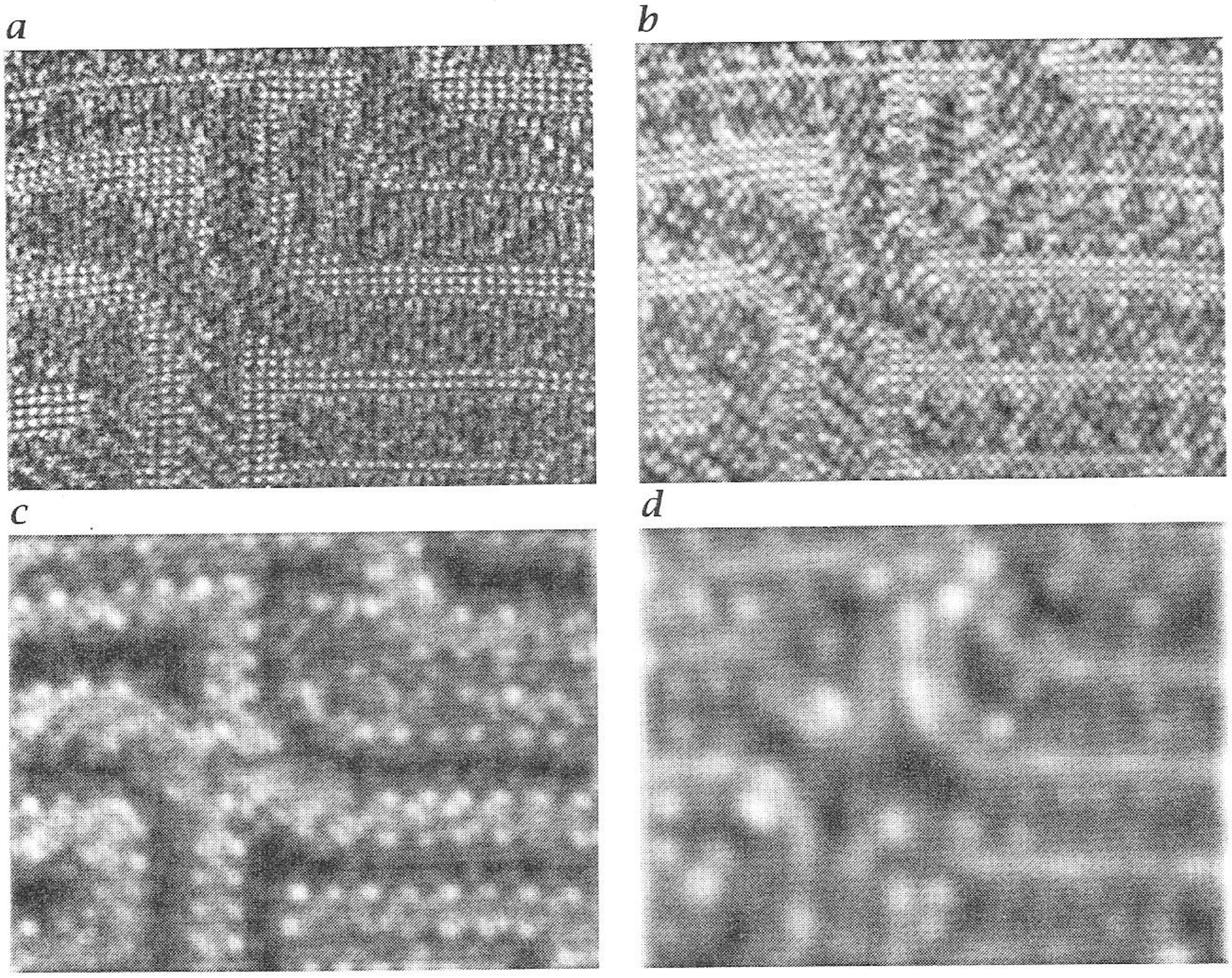

Figure 12.7: Application of the variance operator to levels 0 to 3 of the Laplace pyramid of the image from Fig. 12.1f.

the areas in which no significant amplitudes of the bandpass filtered image are present. If the masking is not performed, the estimate of the local wave number will be significantly distorted. With the masking a quite narrow distribution of the local wave number is found with a peak at a wave number of 0.085.

12.3.3 Pyramidal Texture Analysis

The Laplace pyramid is an alternative to the local wave number operator, because it results in a bandpass decomposition of the image. This decomposition does not compute a local wave number directly, but we can obtain a series of images which show the texture at different scales.

The variance operator takes a very simple form with a Laplace pyramid, since the mean gray value, except for the coarsest level, is zero:

$$\mathcal{V} = \mathcal{B}(\mathcal{L}^{(p)} \cdot \mathcal{L}^{(p)}). \qquad (12.6)$$