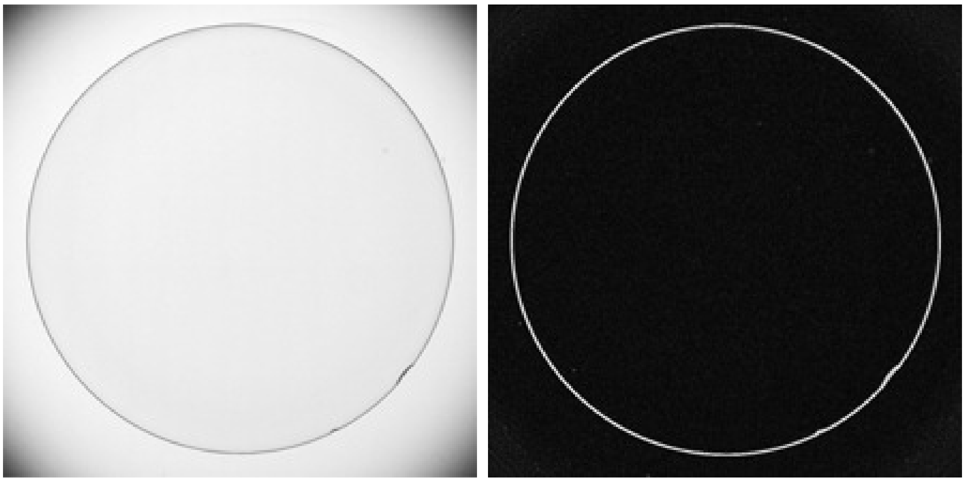


a b

FIGURE 3.45 Optical image of contact lens (note defects on the boundary at 4 and 5 o'clock). (b) Sobel gradient. (Original image courtesy of Mr. Pete Sites, Perceptics Corporation.)

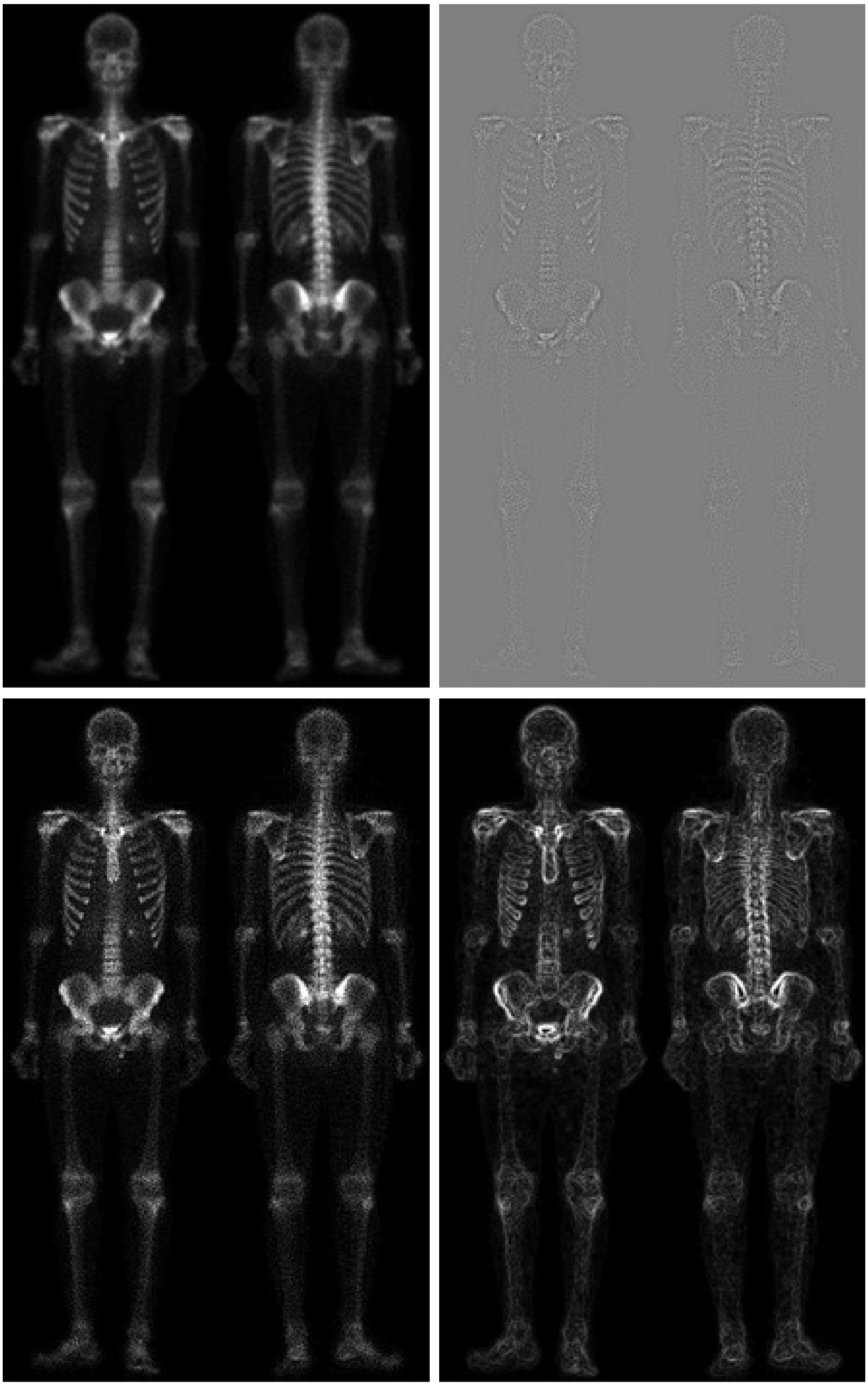
defects in the lens boundary seen at 4 and 5 o'clock. Figure 3.45(b) shows the gradient obtained using Eq. (3.7-14) with the two Sobel masks in Figs. 3.44(d) and (e). The edge defects also are quite visible in this image, but with the added advantage that constant or slowly varying shades of gray have been eliminated, thus simplifying considerably the computational task required for automated inspection. Note also that the gradient process highlighted small specs that are not readily visible in the gray-scale image (specs like these can be foreign matter, air pockets in a supporting solution, or miniscule imperfections in the lens). The ability to enhance small discontinuities in an otherwise flat gray field is another important feature of the gradient. ■

3.8 Combining Spatial Enhancement Methods

With a few exceptions, like combining blurring with thresholding in Section 3.6.1, we have focused attention thus far on individual enhancement approaches. Frequently, a given enhancement task will require application of several complementary enhancement techniques in order to achieve an acceptable result. In this section we illustrate by means of an example how to combine several of the approaches developed in this chapter to address a difficult enhancement task.

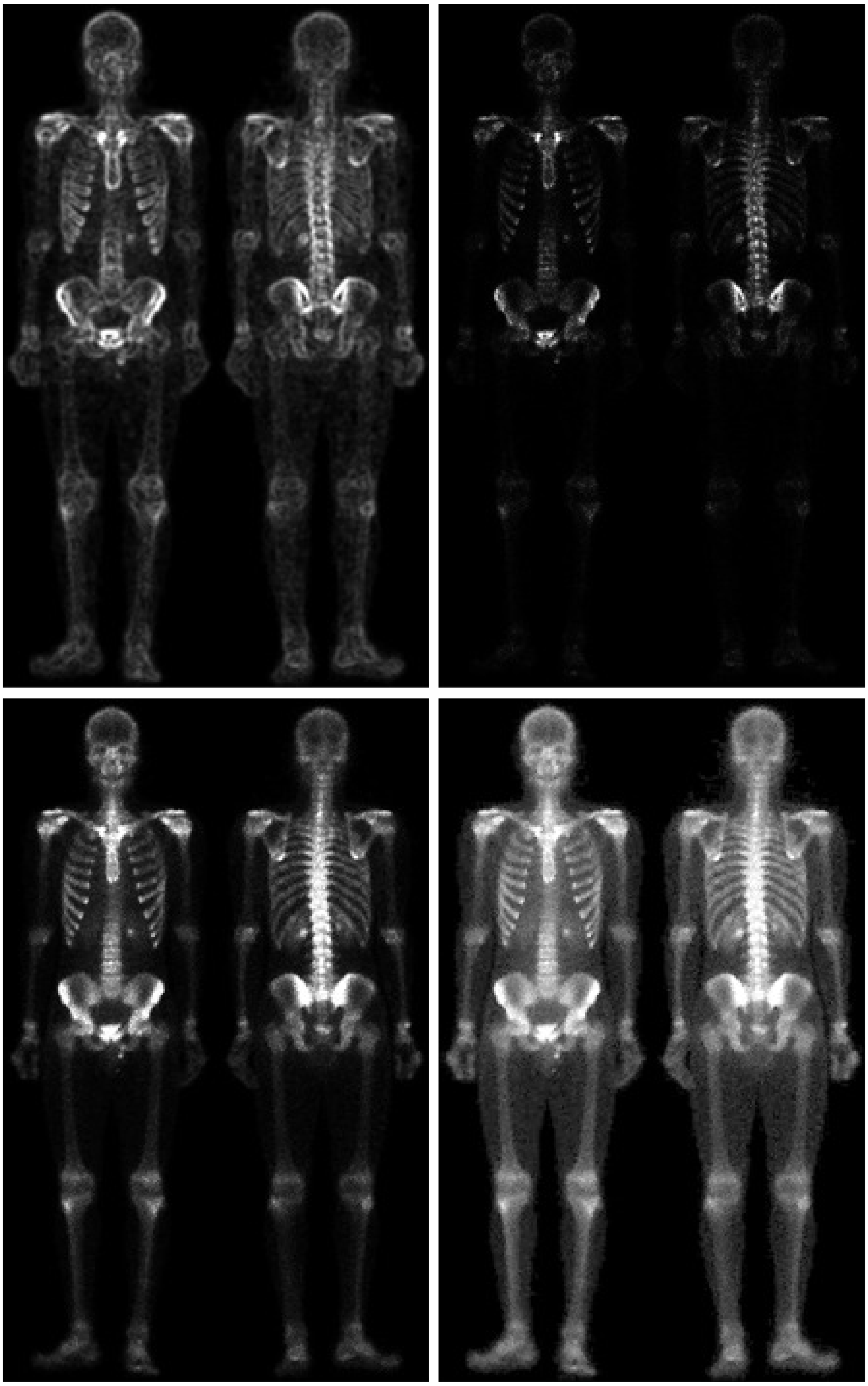
The image shown in Fig. 3.46(a) is a nuclear whole body bone scan, used to detect diseases such as bone infection and tumors. Our objective is to enhance this image by sharpening it and by bringing out more of the skeletal detail. The narrow dynamic range of the gray levels and high noise content make this image difficult to enhance. The strategy we will follow is to utilize the Laplacian to highlight fine detail, and the gradient to enhance prominent edges. For reasons that will be explained shortly, a smoothed version of the gradient image will be used to mask the Laplacian image (see Section 3.4 regarding masking). Finally, we will attempt to increase the dynamic range of the gray levels by using a gray-level transformation.

Figure 3.46 (b) shows the Laplacian of the original image, obtained using the mask in Fig. 3.39(d). This image was scaled (for display only) using the same technique as in Fig. 3.40. We can obtain a sharpened image at this point



a b
c d

FIGURE 3.46
(a) Image of whole body bone scan.
(b) Laplacian of (a). (c) Sharpened image obtained by adding (a) and (b). (d) Sobel of (a).



e	f
g	h

FIGURE 3.46 *(Continued)* (e) Sobel image smoothed with a 5×5 averaging filter. (f) Mask image formed by the product of (c) and (e). (g) Sharpened image obtained by the sum of (a) and (f). (h) Final result obtained by applying a power-law transformation to (g). Compare (g) and (h) with (a). (Original image courtesy of G.E. Medical Systems.)

simply by adding Figs. 3.46(a) and (b), which are an implementation of the second line in Eq. (3.7-5) (we used a mask with a positive center coefficient). Just by looking at the noise level in (b), we would expect a rather noisy sharpened image if we added Figs. 3.46(a) and (b), a fact that is confirmed by the result shown in Fig. 3.46(c). One way that comes immediately to mind to reduce the noise is to use a median filter. However, median filtering is a nonlinear process capable of removing image features. This is unacceptable in medical image processing.

An alternate approach is to use a mask formed from a smoothed version of the gradient of the original image. The motivation behind this is straightforward and is based on the properties of first- and second-order derivatives explained in Section 3.7.1. The Laplacian, being a second-order derivative operator, has the definite advantage that it is superior in enhancing fine detail. However, this causes it to produce noisier results than the gradient. This noise is most objectionable in smooth areas, where it tends to be more visible. The gradient has a stronger response in areas of significant gray-level transitions (gray-level ramps and steps) than does the Laplacian. The response of the gradient to noise and fine detail is lower than the Laplacian's and can be lowered further by smoothing the gradient with an averaging filter. The idea, then, is to smooth the gradient and multiply it by the Laplacian image. In this context, we may view the smoothed gradient as a mask image. The product will preserve details in the strong areas while reducing noise in the relatively flat areas. This process can be viewed roughly as combining the best features of the Laplacian and the gradient. The result is added to the original to obtain a final sharpened image, and could even be used in boost filtering.

Figure 3.46(d) shows the Sobel gradient of the original image, computed using Eq. (3.7-14). Components G_x and G_y were obtained using the masks in Figs. 3.44(d) and (e), respectively. As expected from our discussion in Section 3.7.1, edges are much more dominant in this image than in the Laplacian image. The smoothed gradient image shown in Fig. 3.46(e) was obtained by using an averaging filter of size 5×5. The two gradient images were scaled for display in the same manner as the two Laplacian images. Because the smallest possible value of a gradient image is 0, the background is black in the scaled gradient images, rather than gray as in the scaled Laplacian. The fact that Figs. 3.46(d) and (e) are much brighter than Fig. 3.46(b) is again evidence that the gradient of an image with significant edge content has values that are higher in general than in a Laplacian image.

The product of the Laplacian and smoothed-gradient image is shown in Fig. 3.46(f). Note the dominance of the strong edges and the relative lack of visible noise, which is the key objective behind masking the Laplacian with a smoothed gradient image. Adding the product image to the original resulted in the sharpened image shown in Fig. 3.46(g). The significant increase in sharpness of detail in this image over the original is evident in most parts of the image, including the ribs, spinal chord, pelvis, and skull. This type of improvement would not have been possible by using the Laplacian or gradient alone.

The sharpening procedure just discussed does not affect in an appreciable way the dynamic range of the gray levels in an image. Thus, the final step in our enhancement task is to increase the dynamic range of the sharpened image. As we discussed in some detail in Sections 3.2 and 3.3, there are a number of gray-level transformation functions that can accomplish this objective. We do know from the results in Section 3.3.2 that histogram equalization is not likely to work well on images that have dark gray-level distributions like our images have here. Histogram specification could be a solution, but the dark characteristics of the images with which we are dealing lend themselves much better to a power-law transformation. Since we wish to spread the gray levels, the value of γ in Eq. (3.2-3) has to be less than 1. After a few trials with this equation we arrived at the result shown in Fig. 3.46(h), obtained with $\gamma = 0.5$ and $c = 1$. Comparing this image with Fig. 3.46(g), we see that significant new detail is visible in Fig. 3.46(h). The areas around the wrists, hands, ankles, and feet are good examples of this. The skeletal bone structure also is much more pronounced, including the arm and leg bones. Note also the faint definition of the outline of the body, and of body tissue. Bringing out detail of this nature by expanding the dynamic range of the gray levels also enhanced noise, but Fig. 3.46(h) represents a significant visual improvement over the original image.

The approach just discussed is representative of the types of processes that can be linked in order to achieve results that are not possible with a single technique. The way in which the results are used depends on the application. The final user of the type of images shown in this section is likely to be a radiologist. For a number of reasons that are beyond the scope of our discussion, physicians are unlikely to rely on enhanced results to arrive at a diagnosis. However, enhanced images are quite useful in highlighting details that can serve as clues for further analysis in the original image or sequence of images. In other areas, the enhanced result may indeed be the final product. Examples are found in the printing industry, in image-based product inspection, in forensics, in microscopy, in surveillance, and in a host of other areas where the principal objective of enhancement is to obtain an image with a higher content of visual detail.

Summary

The material presented in this chapter is representative of spatial domain techniques commonly used in practice for image enhancement. This area of image processing is a dynamic field, and new techniques and applications are reported routinely in professional literature and in new product announcements. For this reason, the topics included in this chapter were selected for their value as fundamental material that would serve as a foundation for understanding the state of the art in enhancement techniques, as well as for further study in this field. In addition to enhancement, this chapter served the purpose of introducing a number of concepts, such as filtering with spatial masks, that will be used in numerous occasions throughout the remainder of the book. In the following chapter, we deal with enhancement from a complementary viewpoint in the frequency domain. Between these two chapters, the reader will have developed a solid foundation for the terminology and some of the most fundamental tools used in image processing. The fact that these tools were introduced in the context of image enhancement is likely to aid in the understanding of how they operate on digital images.