

Digital Image Processing

Lecture 6 Image Enhancement in Spatial Domain

Fall 2010



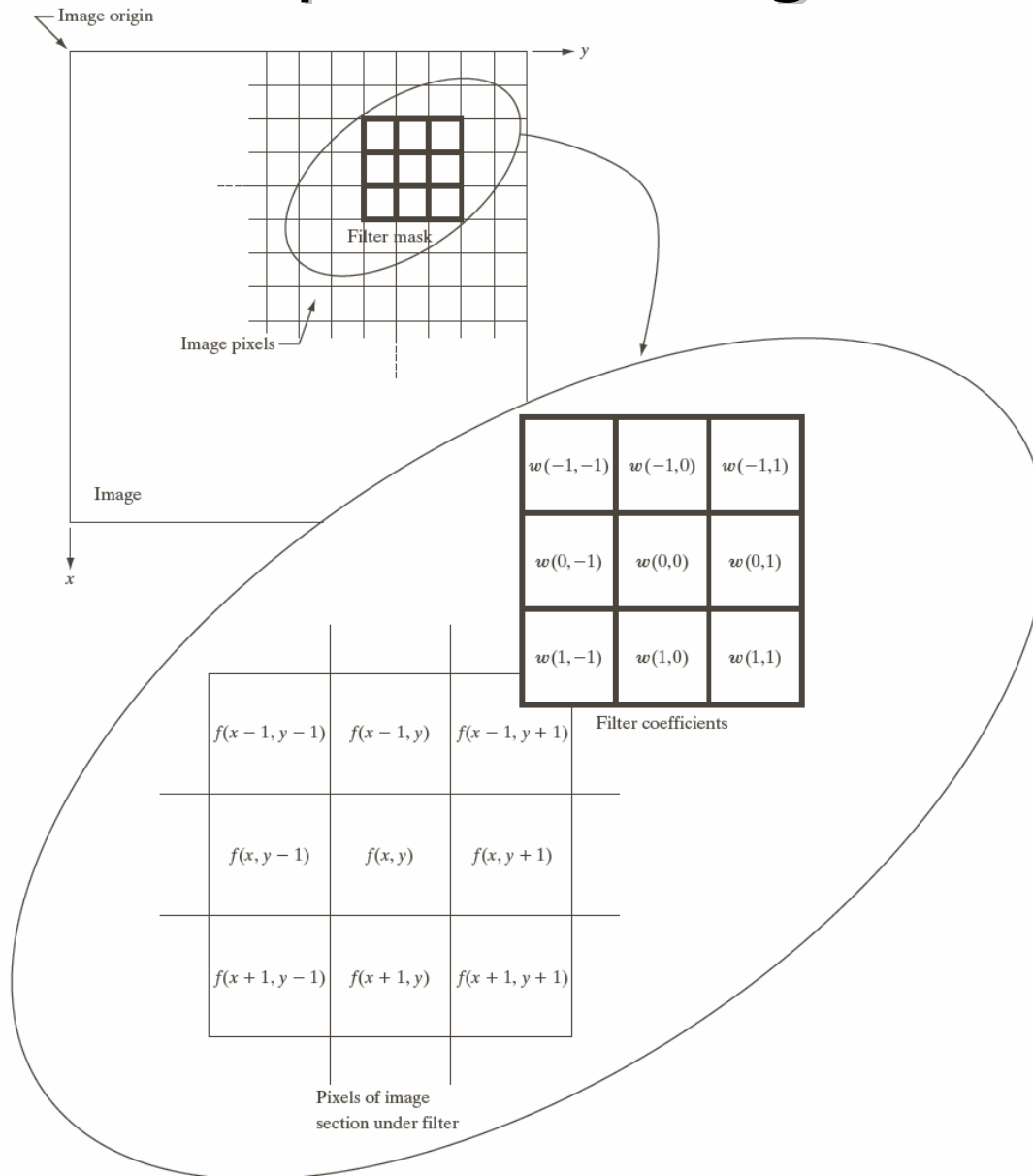
Spatial Filtering

A spatial filter consists of (a) **a neighborhood**, and (b) **a predefined operation**

Linear spatial filtering of an image of size $M \times N$ with a filter of size $m \times n$ is given by the expression

$$g(x, y) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(x + s, y + t)$$

Spatial Filtering



Spatial Correlation

The correlation of a filter $w(x, y)$ of size $m \times n$ with an image $f(x, y)$, denoted as $w(x, y) \star f(x, y)$

$$w(x, y) \star f(x, y) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(x + s, y + t)$$

Spatial Convolution

The convolution of a filter $w(x, y)$ of size $m \times n$ with an image $f(x, y)$, denoted as $w(x, y) \star f(x, y)$

$$w(x, y) \star f(x, y) = \sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(x-s, y-t)$$

	Origin ↙	$f(x, y)$			
0	0	0	0	0	0
0	0	0	0	0	0
0	0	1	0	0	$w(x, y)$ 1 2 3
0	0	0	0	0	4 5 6
0	0	0	0	0	7 8 9

(a)

FIGURE 3.30
Correlation (middle row) and convolution (last row) of a 2-D filter with a 2-D discrete, unit impulse. The 0s are shown in gray to simplify visual analysis.

Smoothing Spatial Filters

Smoothing filters are used for blurring and for noise reduction

Blurring is used in removal of small details and bridging of small gaps in lines or curves

Smoothing spatial filters include linear filters and nonlinear filters.

Spatial Smoothing Linear Filters

The general implementation for filtering an $M \times N$ image with a weighted averaging filter of size $m \times n$ is given

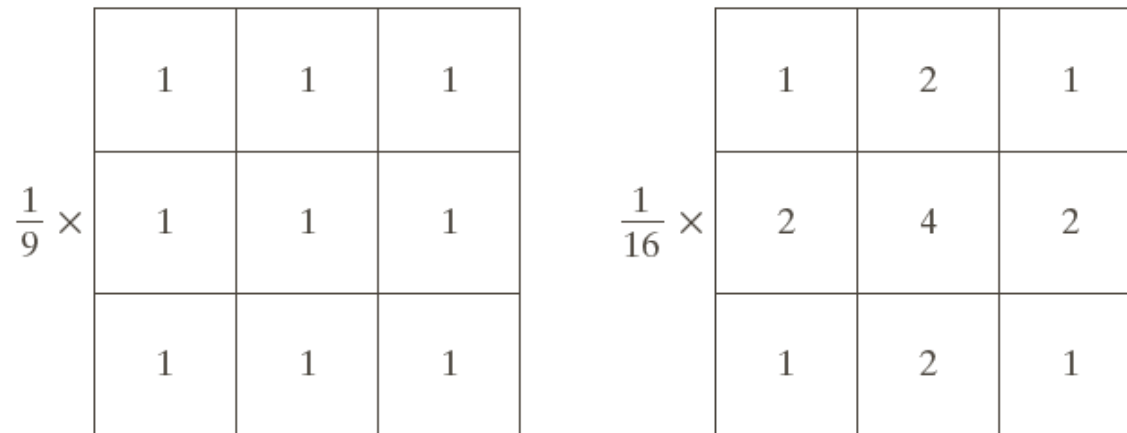
$$g(x, y) = \frac{\sum_{s=-a}^a \sum_{t=-b}^b w(s, t) f(x + s, y + t)}{\sum_{s=-a}^a \sum_{t=-b}^b w(s, t)}$$

where $m = 2a + 1$, $n = 2b + 1$.

Smoothing Spatial Filters

- ▶ used for blurring and for noise reduction
- ▶ blurring is used in preprocessing steps, such as
 - removal of small details from an image prior to object extraction
 - bridging of small gaps in lines or curves
- ▶ noise reduction can be accomplished by blurring with a linear filter and also by a nonlinear filter
- ▶ replacing the value of every pixel in an image by the average of the gray levels in the neighborhood will reduce the "sharp" transitions in gray levels.
- ▶ sharp transitions
 - random noise in the image
 - edges of objects in the image
- ▶ thus, smoothing can reduce noises (desirable) and blur edges (undesirable)

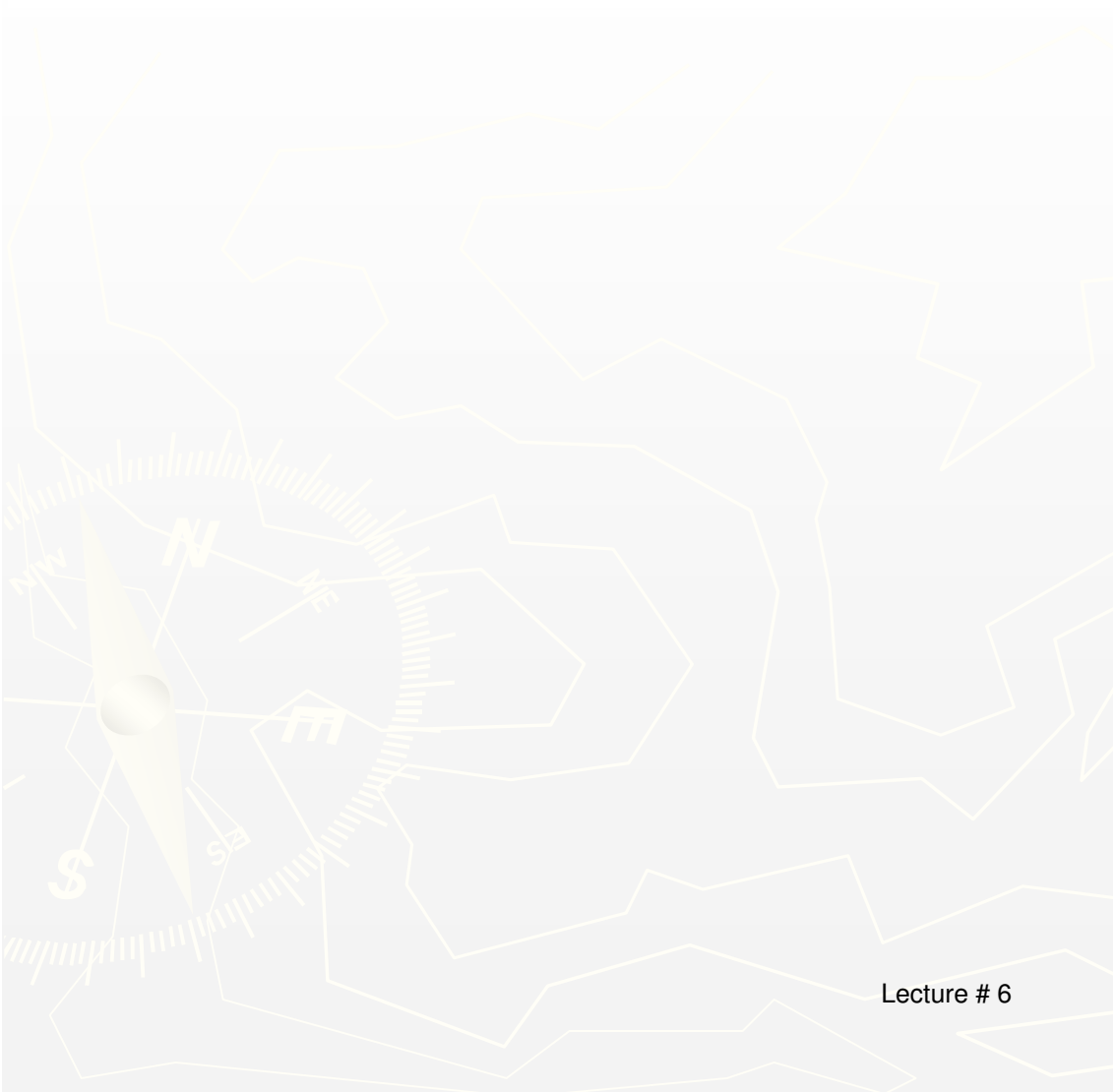
Two Smoothing Averaging Filter Masks



a b

FIGURE 3.32 Two 3×3 smoothing (averaging) filter masks. The constant multiplier in front of each mask is equal to 1 divided by the sum of the values of its coefficients, as is required to compute an average.

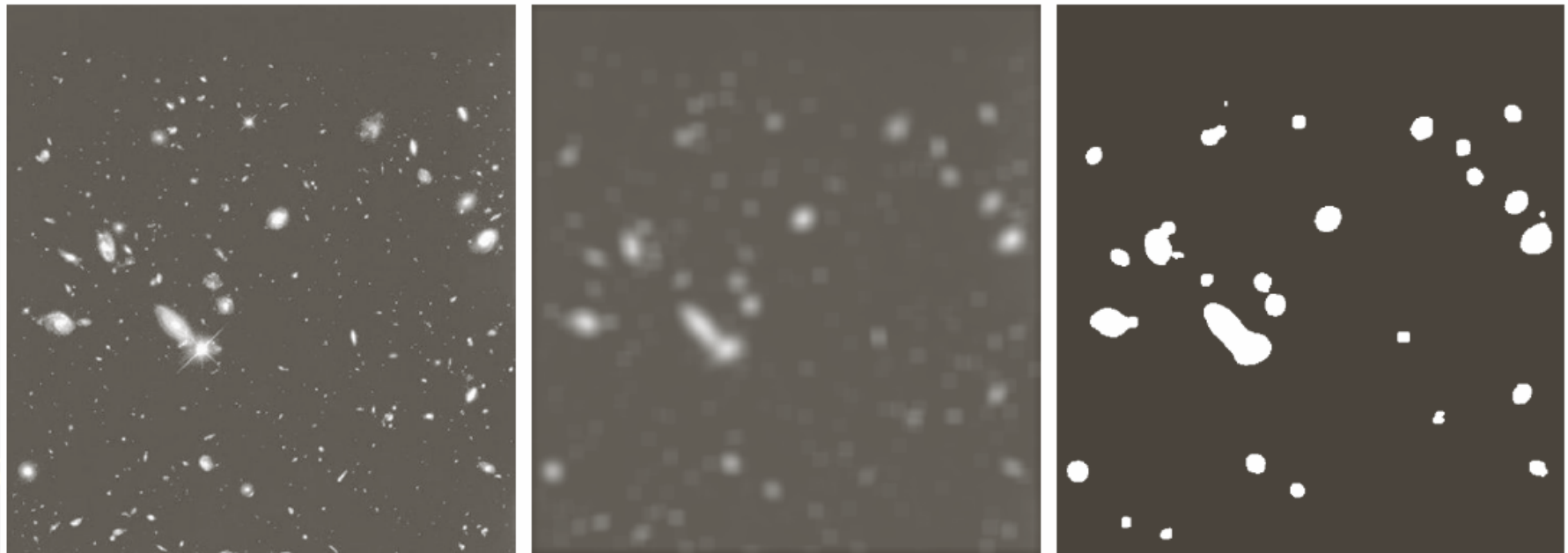
FIGURE 3.33 (a) Original image, of size 500×500 pixels. (b)–(f) Results of smoothing with square averaging filter masks of sizes $m = 3, 5, 9, 15,$ and 35 , respectively. The black squares at the top are of sizes $3, 5, 9, 15, 25, 35, 45,$ and 55 pixels, respectively; their borders are 25 pixels apart. The letters at the bottom range in size from 10 to 24 points, in increments of 2 points; the large letter at the top is 60 points. The vertical bars are 5 pixels wide and 100 pixels high; their separation is 20 pixels. The diameter of the circles is 25 pixels, and their borders are 15 pixels apart; their intensity levels range from 0% to 100% black in increments of 20%. The background of the image is 10% black. The noisy rectangles are of size 50×120 pixels.



a	b
c	d
e	f



Example: Gross Representation of Objects



a b c

FIGURE 3.34 (a) Image of size 528×485 pixels from the Hubble Space Telescope. (b) Image filtered with a 15×15 averaging mask. (c) Result of thresholding (b). (Original image courtesy of NASA.)

Order-statistic (Nonlinear) Filters

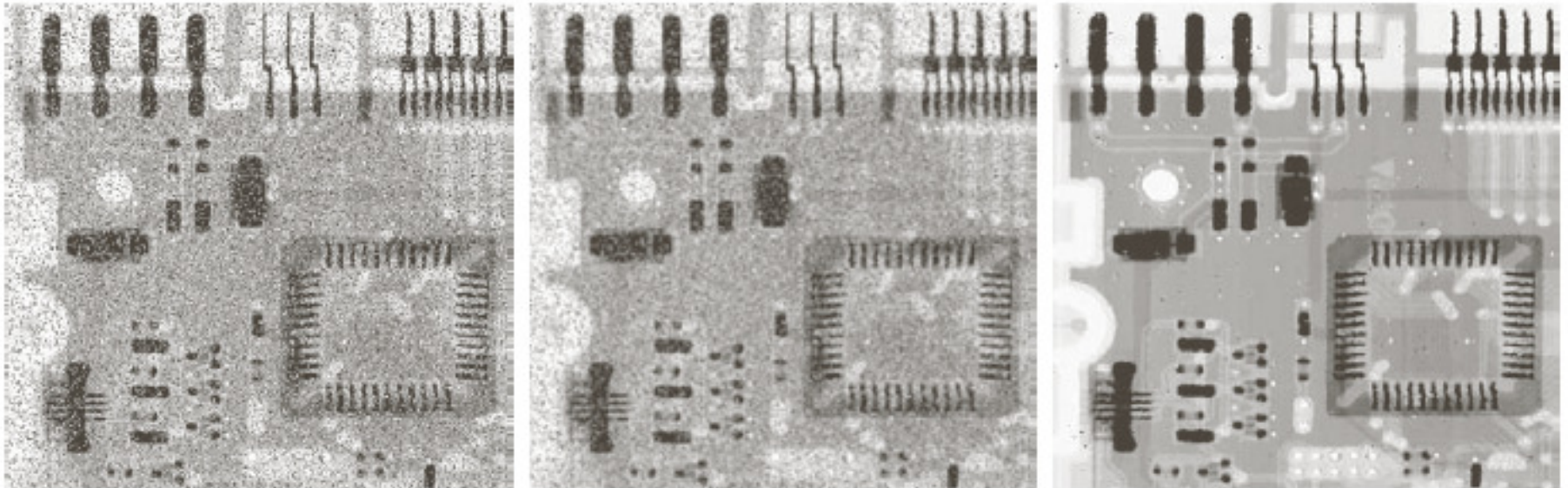
- Nonlinear
- Based on ordering (ranking) the pixels contained in the filter mask
- Replacing the value of the center pixel with the value determined by the ranking result

E.g., median filter, max filter, min filter

Median Filters

- ▶ replaces the value of a pixel by the median of the gray levels in the neighborhood of that pixel (the original value of the pixel is included in the computation of the median)
- ▶ quite popular because for certain types of random noise (impulse noise \Rightarrow salt and pepper noise) , they provide excellent noise-reduction capabilities, with considering less blurring than linear smoothing filters of similar size.

Example: Use of Median Filtering for Noise Reduction



a b c

FIGURE 3.35 (a) X-ray image of circuit board corrupted by salt-and-pepper noise. (b) Noise reduction with a 3×3 averaging mask. (c) Noise reduction with a 3×3 median filter. (Original image courtesy of Mr. Joseph E. Pascente, Lixi, Inc.)

Sharpening Spatial Filters

- ▶ Foundation
- ▶ Laplacian Operator
- ▶ Unsharp Masking and Highboost Filtering
- ▶ Using First-Order Derivatives for Nonlinear Image Sharpening — The Gradient

Sharpening Spatial Filters

- ▶ to highlight fine detail in an image
- ▶ or to enhance detail that has been blurred, either in error or as a natural effect of a particular method of image acquisition.

- ▶ Blurring Vs. Sharpening
 - as we know that blurring can be done in spatial domain by pixel averaging in a neighbors
 - since averaging is analogous to integration
 - thus, we can guess that the sharpening must be accomplished by spatial differentiation.

Derivative operator

- ▶ the strength of the response of a derivative operator is proportional to the degree of discontinuity of the image at the point at which the operator is applied.
- ▶ thus, image differentiation
 - enhances edges and other discontinuities (noise)
 - deemphasizes area with slowly varying gray-level values.

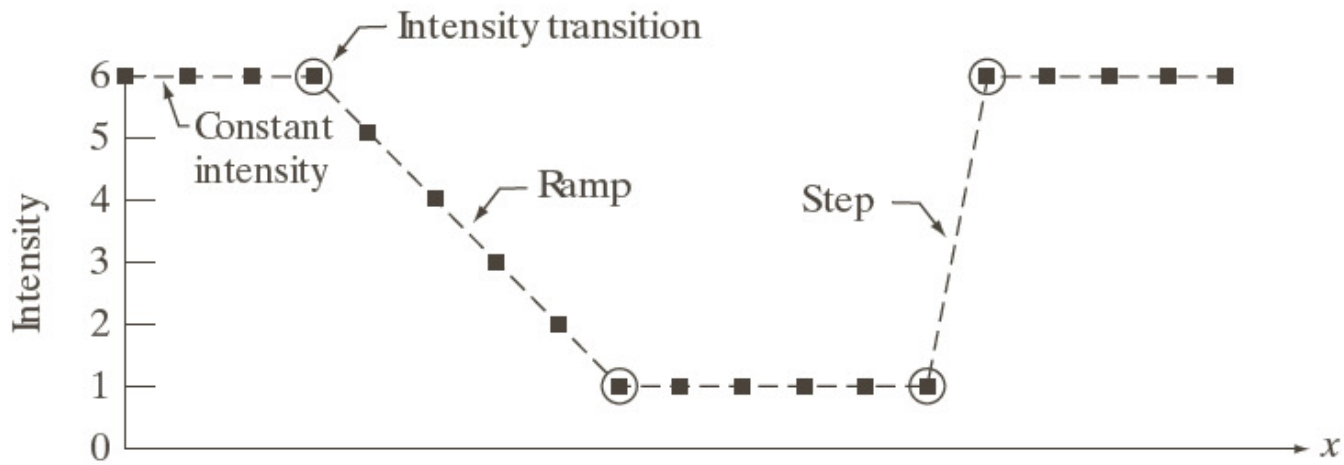
Sharpening Spatial Filters: Foundation

- ▶ The first-order derivative of a one-dimensional function $f(x)$ is the difference

$$\frac{\partial f}{\partial x} = f(x+1) - f(x)$$

- ▶ The second-order derivative of $f(x)$ as the difference

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) - 2f(x)$$



a
b
c

FIGURE 3.36

Illustration of the first and second derivatives of a 1-D digital function representing a section of a horizontal intensity profile from an image. In (a) and (c) data points are joined by dashed lines as a visualization aid.

Sc
lit
1s
21

Sharpening Spatial Filters: Laplace Operator

The second-order isotropic derivative operator is the Laplacian for a function (image) $f(x,y)$

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

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

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

$$\nabla^2 f = f(x+1, y) + f(x-1, y) + f(x, y+1) + f(x, y-1) - 4f(x, y)$$

Sharpening Spatial Filters: Laplace Operator

0	1	0	1	1	1
1	-4	1	1	-8	1
0	1	0	1	1	1
0	-1	0	-1	-1	-1
-1	4	-1	-1	8	-1
0	-1	0	-1	-1	-1

a b
c d

FIGURE 3.37
(a) Filter mask used to implement Eq. (3.6-6).
(b) Mask used to implement an extension of this equation that includes the diagonal terms.
(c) and (d) Two other implementations of the Laplacian found frequently in practice.

Sharpening Spatial Filters: Laplace Operator

Image sharpening in the way of using the Laplacian:

$$g(x, y) = f(x, y) + c \left[\nabla^2 f(x, y) \right]$$

where,

$f(x, y)$ is input image,

$g(x, y)$ is sharpened images,

$c = -1$ if $\nabla^2 f(x, y)$ corresponding to Fig. 3.37(a) or (b)

and $c = 1$ if either of the other two filters is used.



a

b c

d e

FIGURE 3.38

(a) Blurred image of the North Pole of the moon.

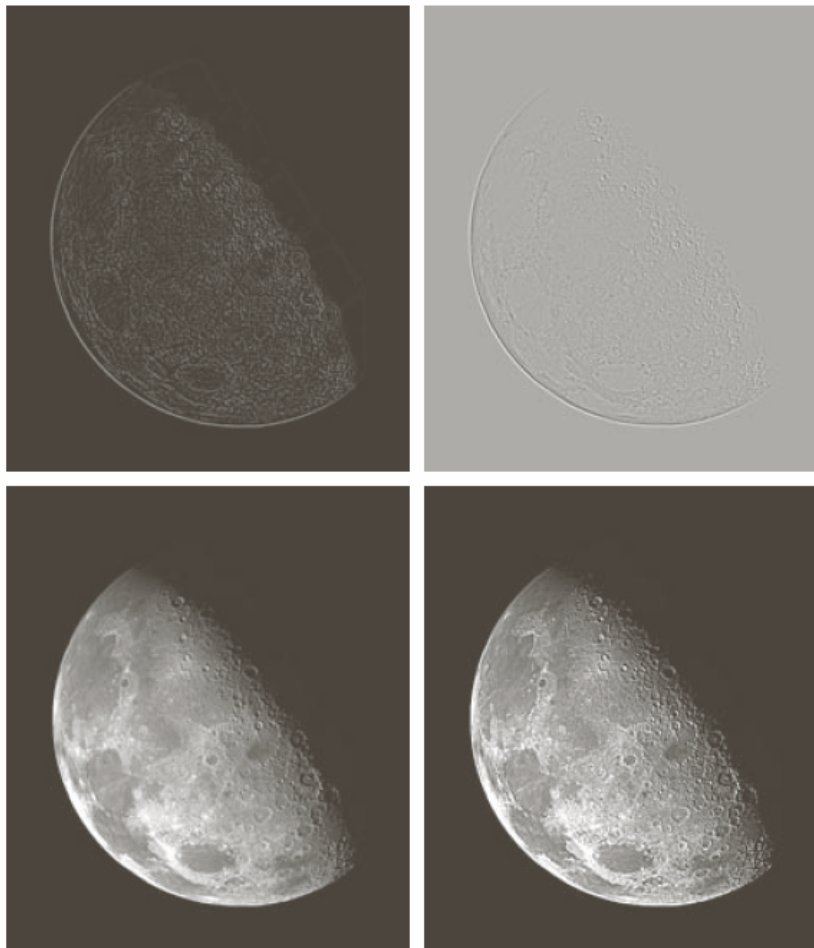
(b) Laplacian without scaling.

(c) Laplacian with scaling.

(d) Image sharpened using the mask in Fig. 3.37(a).

(e) Result of using the mask in Fig. 3.37(b).

(Original image courtesy of NASA.)



Unsharp Masking and Highboost Filtering

▶ Unsharp masking

Sharpen images consists of subtracting an unsharp (smoothed) version of an image from the original image

e.g., printing and publishing industry

▶ Steps

1. Blur the original image
2. Subtract the blurred image from the original
3. Add the mask to the original

Unsharp Masking and Highboost Filtering

Let $\bar{f}(x, y)$ denote the blurred image, unsharp masking is

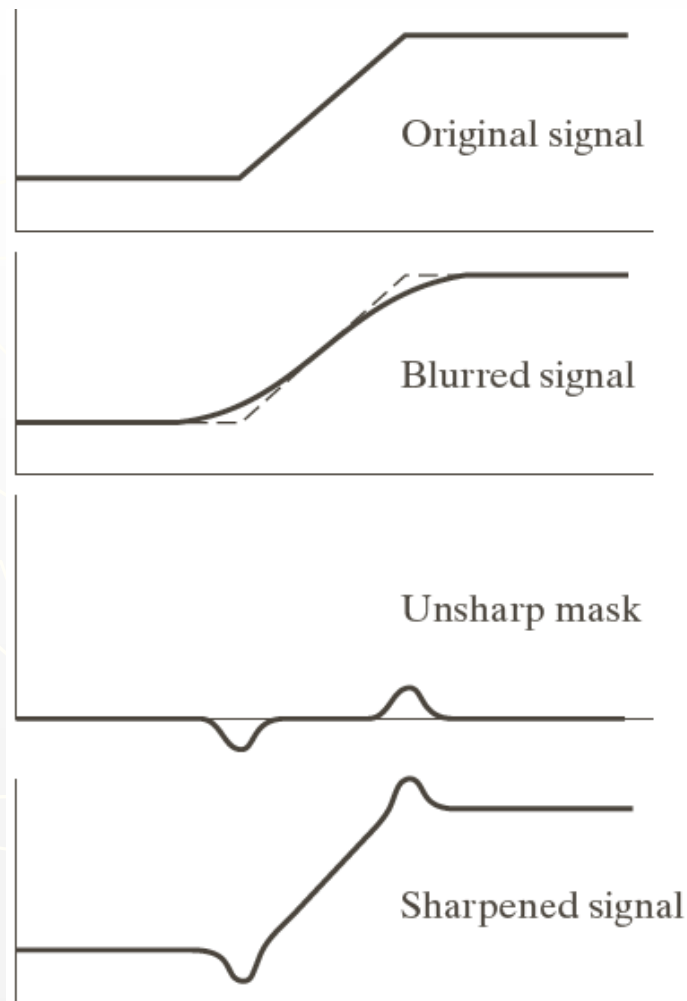
$$g_{mask}(x, y) = f(x, y) - \bar{f}(x, y)$$

Then add a weighted portion of the mask back to the original

$$g(x, y) = f(x, y) + k * g_{mask}(x, y) \quad k \geq 0$$

when $k > 1$, the process is referred to as highboost filtering.

Unsharp Masking: Demo



a
b
c
d

FIGURE 3.39 1-D illustration of the mechanics of unsharp masking. (a) Original signal. (b) Blurred signal with original shown dashed for reference. (c) Unsharp mask. (d) Sharpened signal, obtained by adding (c) to (a).

Unsharp Masking and Highboost Filtering: Example



a
b
c
d
e

FIGURE 3.40

(a) Original image.

(b) Result of blurring with a Gaussian filter.

(c) Unsharp mask. (d) Result of using unsharp masking.

(e) Result of using highboost filtering.

Image Sharpening based on First-Order Derivatives

For function $f(x, y)$, the gradient of f at coordinates (x, y) is defined as

$$\nabla f \equiv \text{grad}(f) \equiv \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

The *magnitude* of vector ∇f , denoted as $M(x, y)$

Gradient Image $M(x, y) = \text{mag}(\nabla f) = \sqrt{g_x^2 + g_y^2}$

Image Sharpening based on First-Order Derivatives

The *magnitude* of vector ∇f , denoted as $M(x, y)$

$$M(x, y) = \text{mag}(\nabla f) = \sqrt{g_x^2 + g_y^2}$$

$$M(x, y) \approx |g_x| + |g_y|$$

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

$$M(x, y) = |z_8 - z_5| + |z_6 - z_5|$$

Image Sharpening based on First-Order Derivatives

Roberts Cross-gradient Operators

$$M(x, y) \approx |z_9 - z_5| + |z_8 - z_6|$$

Sobel Operators

$$M(x, y) \approx |(z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)| \\ + |(z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)|$$

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

Image Sharpening based on First-Order Derivatives

z_1	z_2	z_3
z_4	z_5	z_6
z_7	z_8	z_9

-1	0	0	-1
0	1	1	0

-1	-2	-1	-1	0	1
0	0	0	-2	0	2
1	2	1	-1	0	1

a
b c
d e

FIGURE 3.41

A 3×3 region of an image (the z s are intensity values).

(b)–(c) Roberts cross gradient operators.

(d)–(e) Sobel operators. All the mask coefficients sum to zero, as expected of a derivative operator.

Example

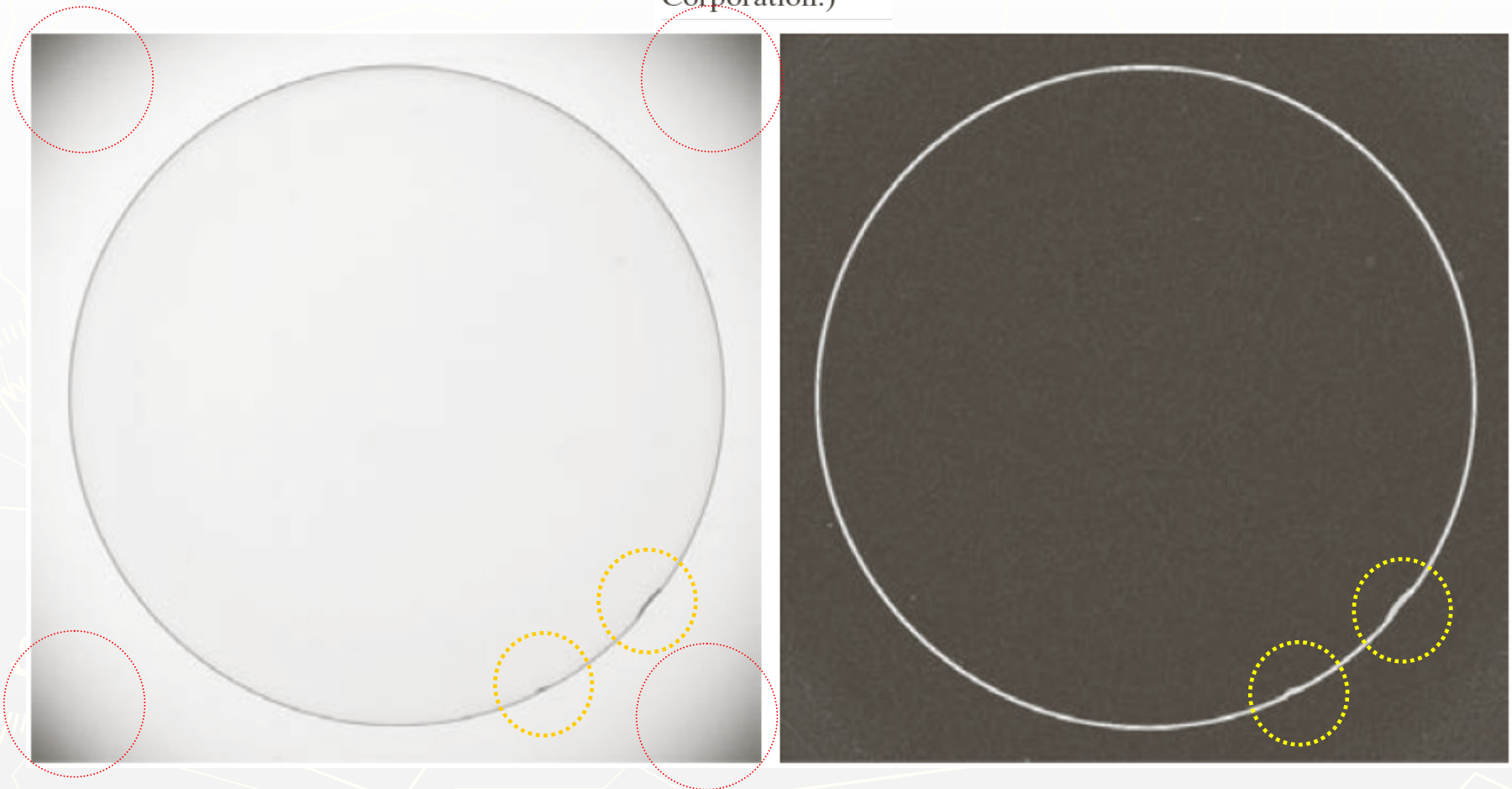
a b

FIGURE 3.42

(a) Optical image of contact lens (note defects on the boundary at 4 and 5 o'clock).

(b) Sobel gradient.

(Original image courtesy of Pete Sites, Perceptics Corporation.)

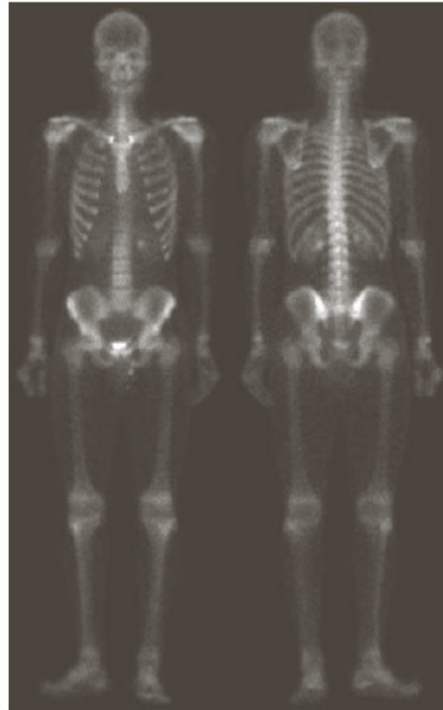


Example:

Combining Spatial Enhancement Methods

Goal:

Enhance the image by sharpening it and by bringing out more of the skeletal detail



a	b
c	d

FIGURE 3.43

(a) Image of whole body bone scan.

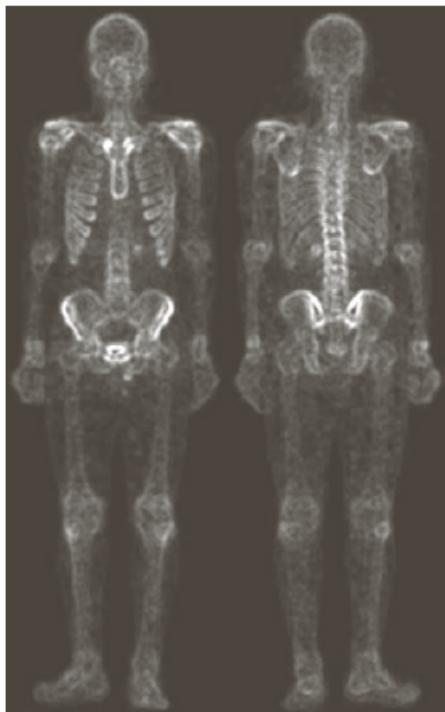
(b) Laplacian of (a). (c) Sharpened image obtained by adding (a) and (b). (d) Sobel gradient of (a).

Example:

Combining Spatial Enhancement Methods

Goal:

Enhance the image by sharpening it and by bringing out more of the skeletal detail



e f
g h

FIGURE 3.43

(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.)