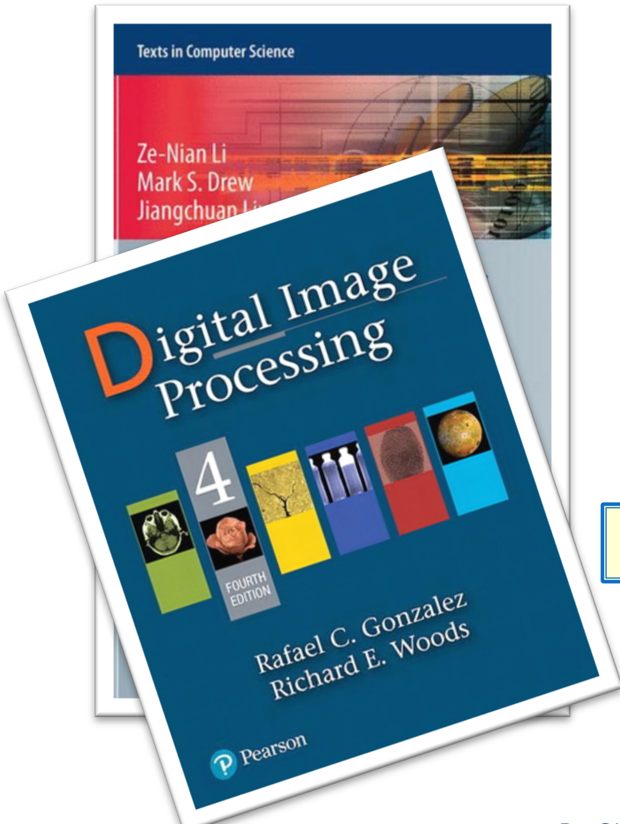
MULTIMEDIA

Dr Siba HAIDAR • INFO430 • 2019-2020

Textbook: Fundamentals of Multimedia • Z.-N. Li et al.

Course Outline



1. Introduction to multimedia
2. Digital representation of graphics and images
3. Colors in images and video
4. Fundamental Concepts in Video
5. Lossless compression algorithms
6. Lossy compression algorithms (JPEG)
7. Video Coding (MPEG)
8. Introduction to Image Processing

Background Photo:
The Starry Night

INTRODUCTION TO IMAGE PROCESSING

Chapter Outline

- Introduction to Image Processing

1. Histogram
2. Histogram Transformation
3. Linear Filtering – Part I
4. Smoothing spatial filters
5. Sharpening spatial filters

Background Photo:
The Milk Maid

Histogram

Example of histogram for a grayscale image

- For each gray level, count the number of pixels referring to it
- For each level, draw the bar graph of the number of pixels
- (possibility of grouping nearby levels into a single class)

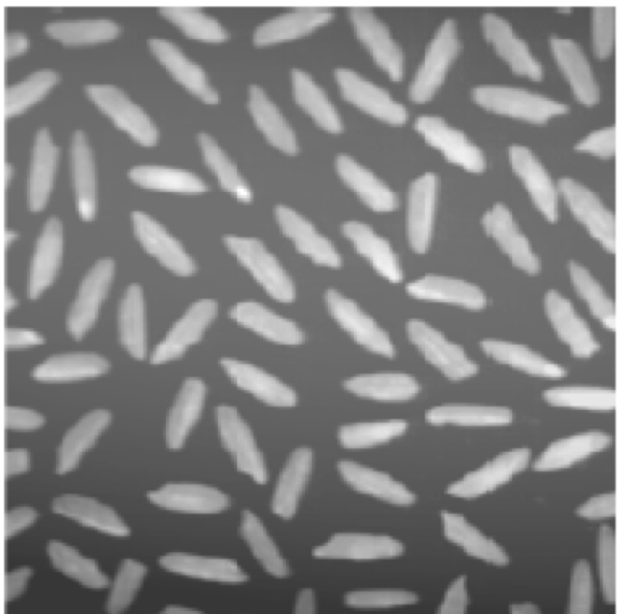
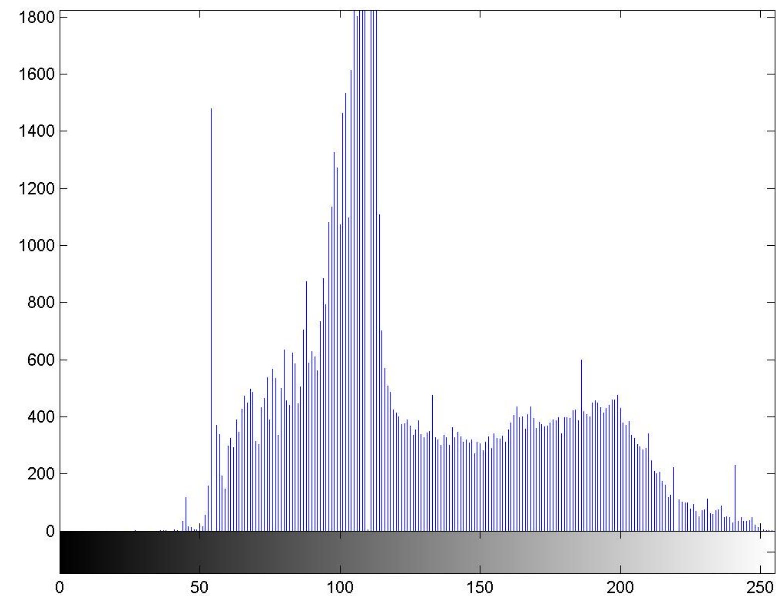


Image 256 × 256 pixels - 8 bits



Pixel population for each gray level [0; 255]

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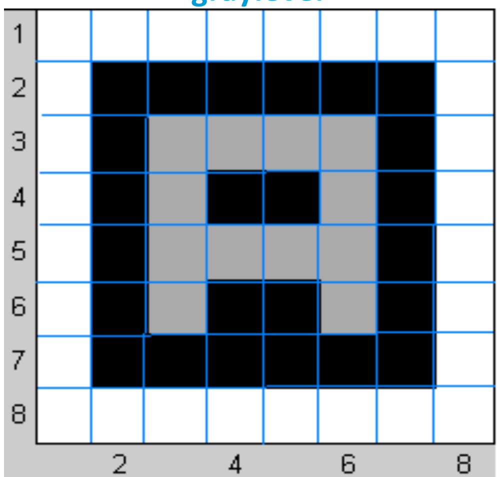
Simple example of histogram calculation for an image

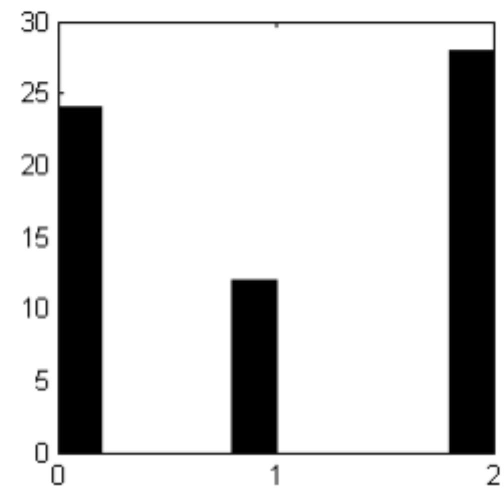
Image "A" in graylevel



Matrix of luminance values of pixels in image "A"

2	2	2	2	2	2	2	2
2	0	0	0	0	0	0	2
2	0	1	1	1	1	0	2
2	0	1	0	0	1	0	2
2	0	1	1	1	1	0	2
2	0	1	0	0	1	0	2
2	0	0	0	0	0	0	2
2	2	2	2	2	2	2	2

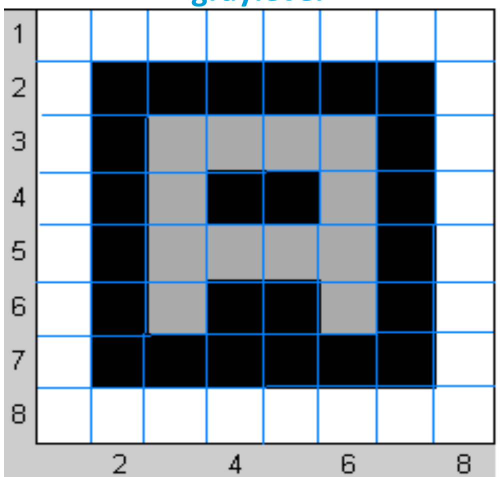
Histogram of "A"



- Image "A" has 3 different levels of gray: 0, 1 and 2.
- Count the number of pixels for each gray level, using the luminance values matrix.
- Levels 0, 1 and 2 are respectively represented by 24, 12 and 28 pixels ➔ representation of this population of pixels on the histogram.

Cumulative histogram of an image

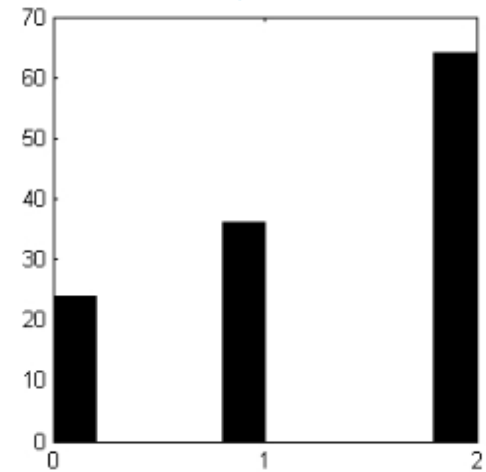
Image "**A**" in graylevel



Matrix of luminance values of pixels in image "**A**"

2	2	2	2	2	2	2	2
2	0	0	0	0	0	0	2
2	0	1	1	1	1	0	2
2	0	1	0	0	1	0	2
2	0	1	1	1	1	0	2
2	0	1	0	0	1	0	2
2	0	0	0	0	0	0	2
2	2	2	2	2	2	2	2

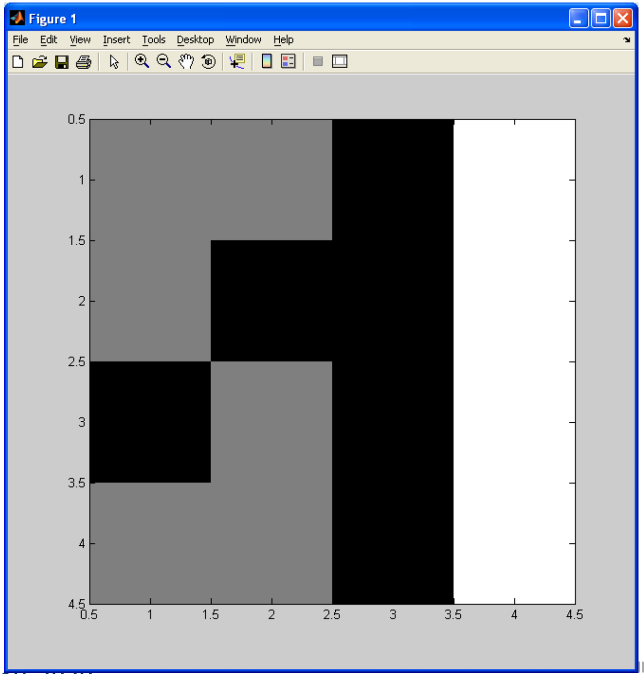
Cumulative Histogram of "**A**"



- *useful for some image processing such as histogram equalization (→ contrast enhancement)*

function imhist

```
>> n=0; b=1; g=127/255;
>> M=[g g n b;g n n b;n g n b;g g n b];
>> imagesc(M)
>>imhist(M,3)
```



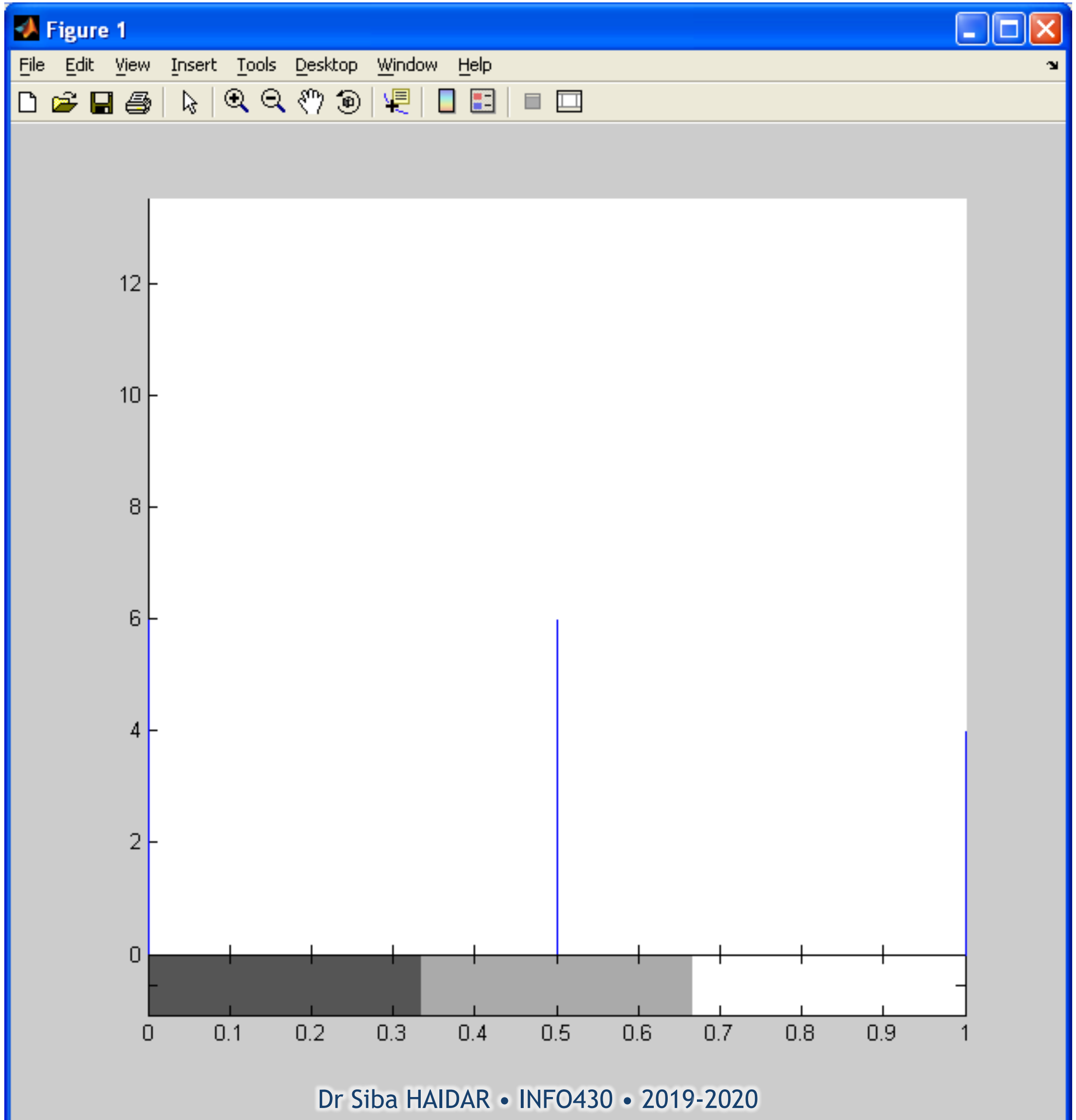


Figure 1
File Edit View Insert Tools Desktop Window Help
12
10
8
6
4
2
0
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

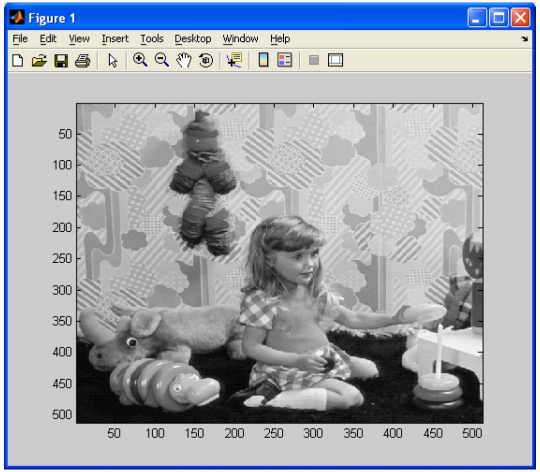


Figure 1
File Edit View Insert Tools Desktop Window Help
50 100 150 200 250 300 350 400 450 500
50 100 150 200 250 300 350 400 450 500

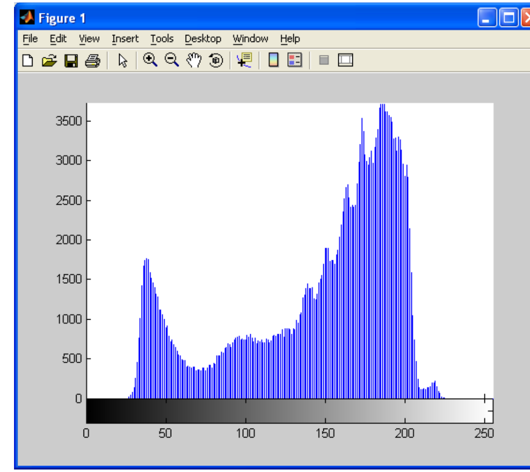


Figure 1
File Edit View Insert Tools Desktop Window Help
0 500 1000 1500 2000 2500 3000 3500
0 50 100 150 200 250

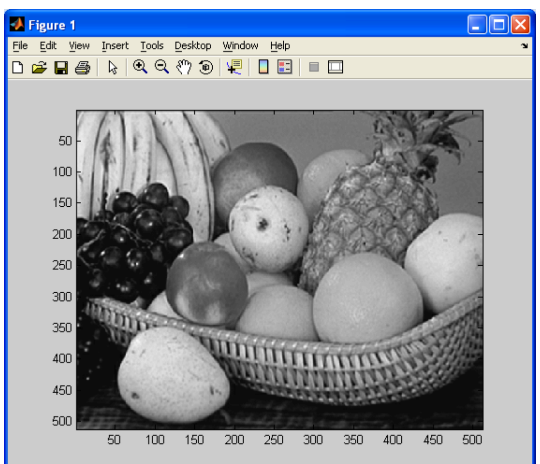


Figure 1
File Edit View Insert Tools Desktop Window Help
50 100 150 200 250 300 350 400 450 500
50 100 150 200 250 300 350 400 450 500

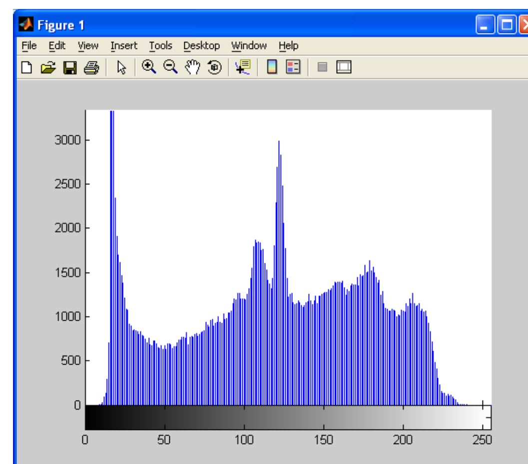
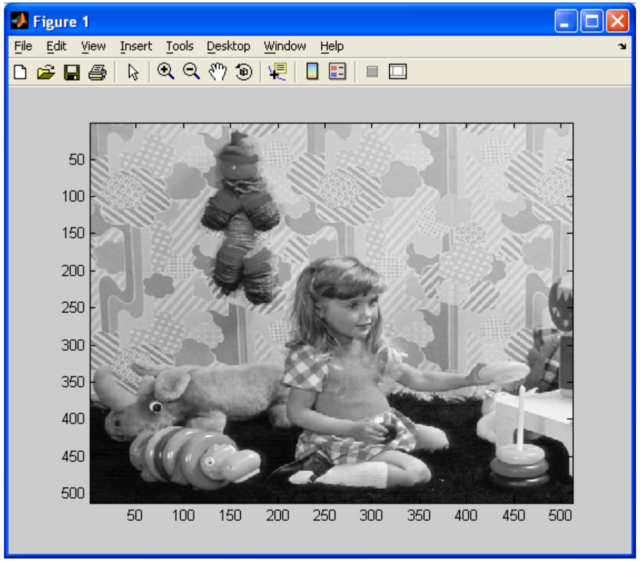
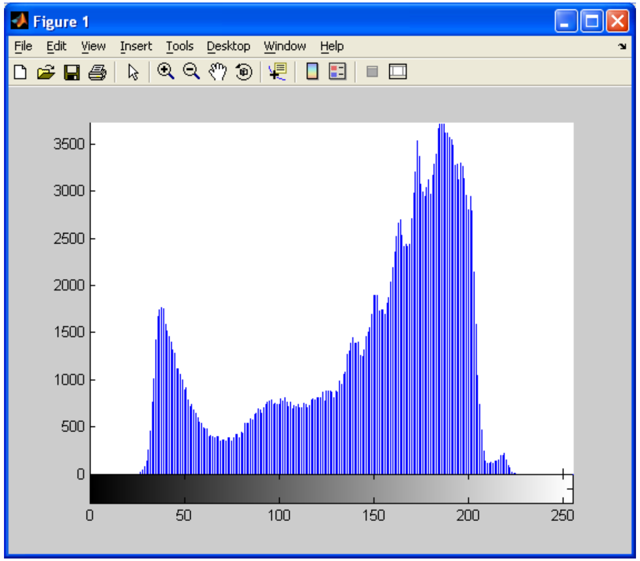
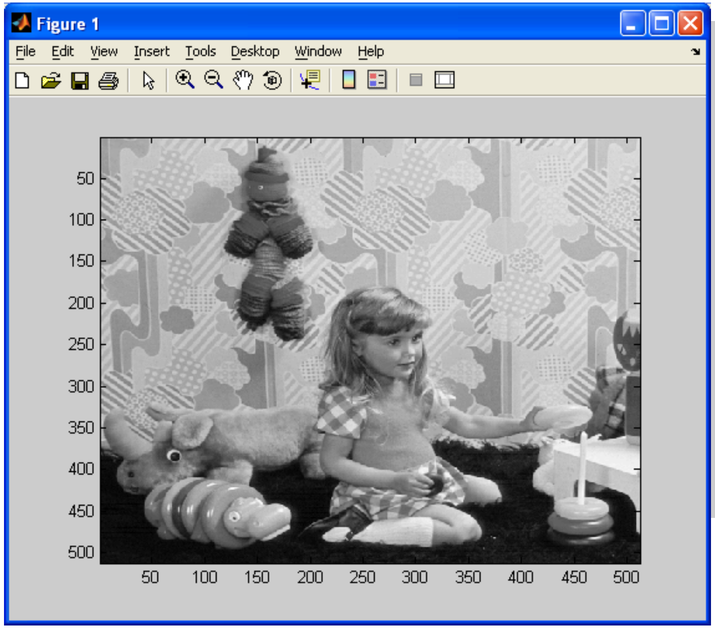


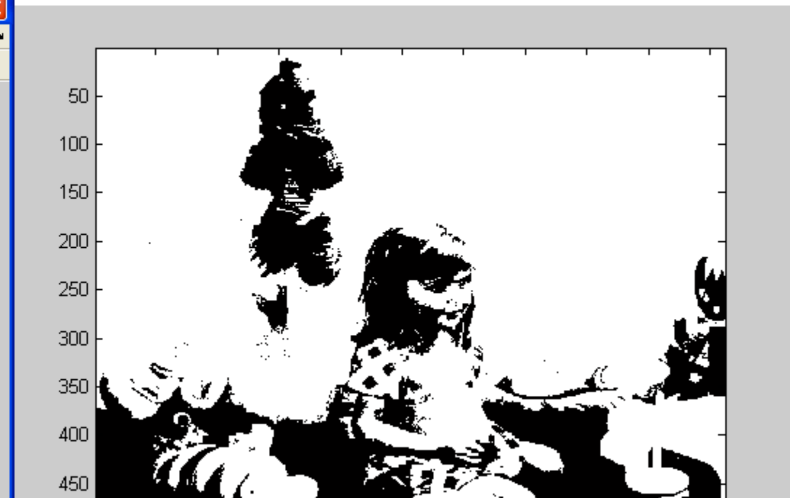
Figure 1
File Edit View Insert Tools Desktop Window Help
0 500 1000 1500 2000 2500 3000
0 50 100 150 200 250

Binarisation im2bw







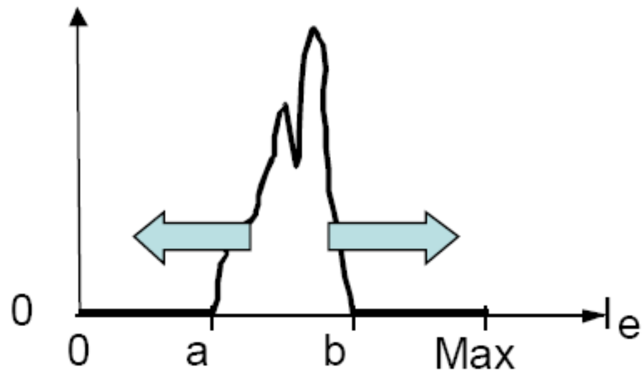


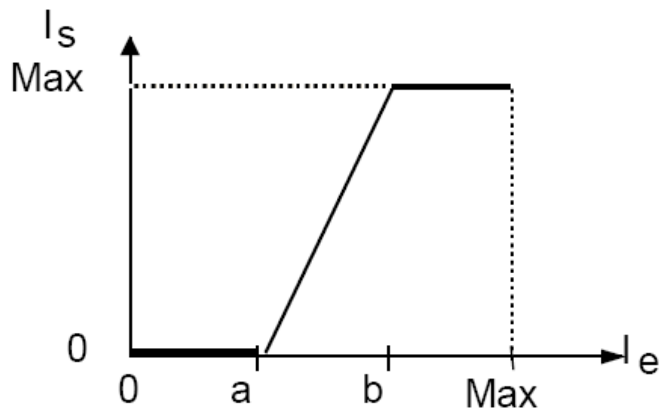
- ImBinaire=im2bw(Im,128/255)
;
- imshow(ImBinaire);

Background Photo:
[The Milk Maid]

Histogram Transformation

Contrast enhancement by histogram stretching





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Histogram normalization

- *D : dynamique*
- *Nmin : la plus petite valeur dans l'image*
- *Nmax : la plus grande valeur dans l'image*

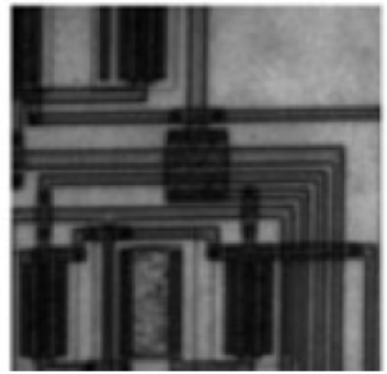
$$f_{new}[x,y]=(f[x,y]-Nmin)\cdot\frac{2^D-1}{Nmax-Nmin}$$

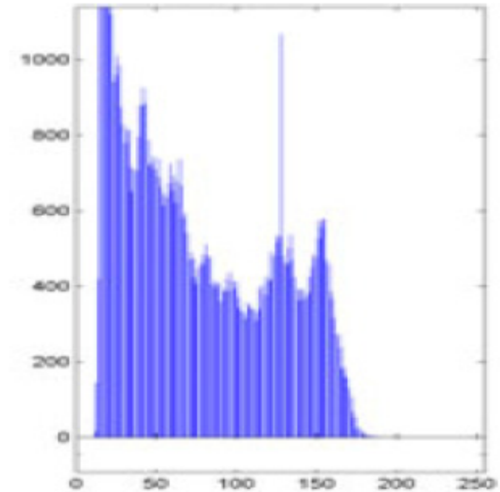
Pour rendre la normalisation moins sensible aux valeurs marginales (outliers), on utilise généralement un paramètre β, $0<\beta<1$, *et on prend :*

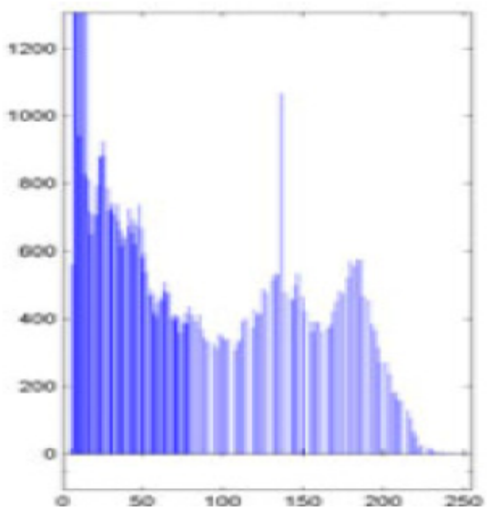
$$Nmin \in HC^{-1}(\beta)$$
$$Nmax \in HC^{-1}(1-\beta)$$

Exemple : imadjust

Image originale







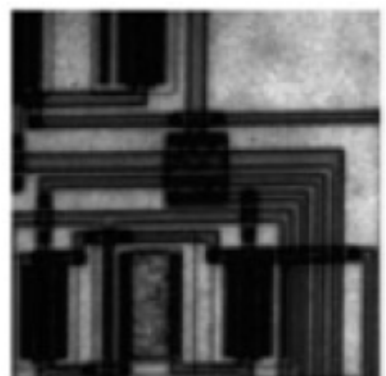


Image contrastée

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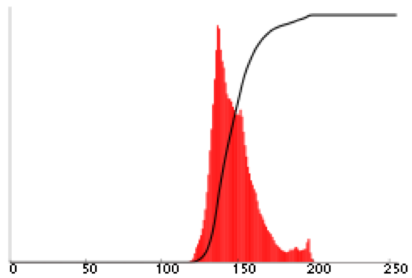
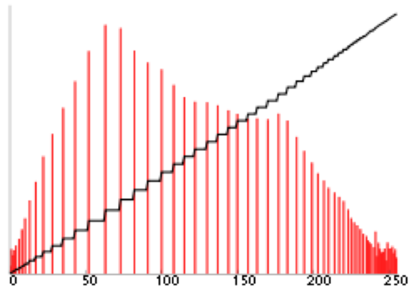
Histogram equalization

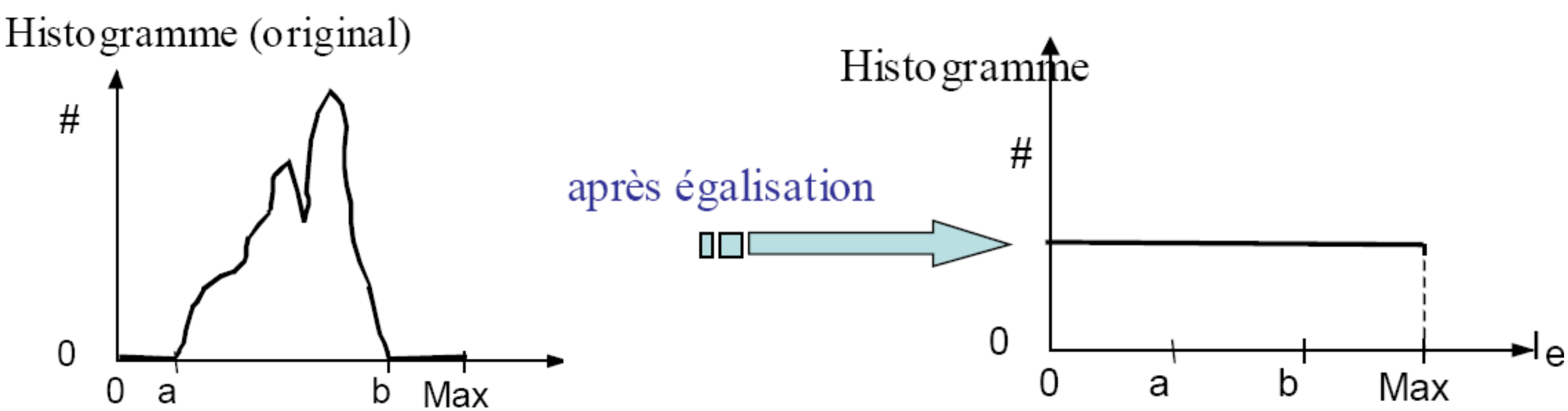
- In image processing, histogram equalization is a method of adjusting the contrast of a digital image that uses the histogram.
- It consists of applying a transformation on each pixel of the image, and therefore of obtaining a new image from an independent operation on each of the pixels. This transformation is constructed from the cumulative histogram of the starting image.
- The histogram equalization makes it possible to better distribute the intensities over the whole range of possible values, by "spreading" the histogram.
- The equalization is interesting for images in which all, or only a part, is of low contrast (all the pixels are of close intensity).
- The method is fast, easy to implement, and completely automatic (i.e. no settings).


0
50
100
150
200
250


0
50
100
150
200
250

Histogram equalization (histeq)

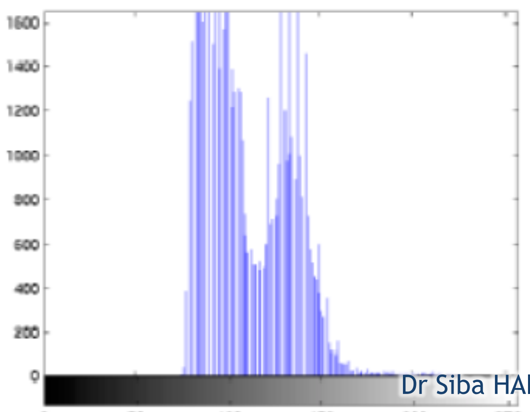
- stretching with uniform distribution of gray levels

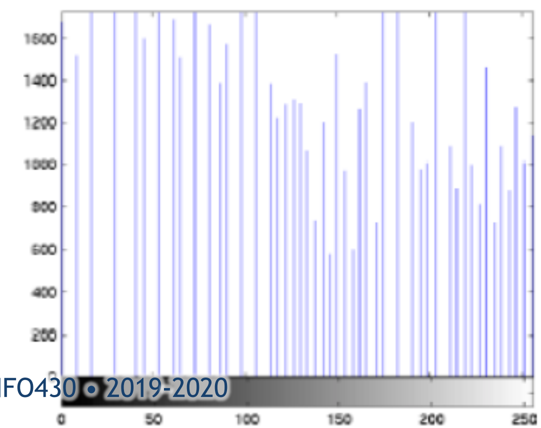


Histogram equalization effect

Image originale et son histogramme

Image et son histogramme après égalisation





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Original - Étirement d’histogramme - Égalisation

- *contrast enhancement is more pronounced with histogram equalization, allowing detection of structures in the shade*
- *any gray level is represented strongly stretched*
- *any level of gray is poorly represented merged with other levels close*

Background Photo:
The Milk Maid

Linear Filtering – Part I

from Selim Aksoy

Importance of neighborhood

- Both zebras and dalmatians have black and white pixels in similar numbers.
- The difference between the two is the characteristic appearance of small group of pixels rather than individual pixel values.

Adapted from Pinar Duygulu, Bilkent University

Outline

- We will discuss neighborhood operations that work with the values of the image pixels in the neighborhood.
- Spatial domain filtering

- there is also:
  - Frequency domain filtering
  - Image enhancement
  - Finding patterns

Spatial domain filtering

- What is the value of the center pixel?

3	3	3
3	3	3
3	3	3

- What assumptions are you making to infer the center value?

3	4	3
2	3	3
3	4	2

Spatial domain filtering

- Some neighborhood operations work with
  - the values of the image pixels in the neighborhood, and
  - the corresponding values of a subimage that has the same dimensions as the neighborhood.
- The subimage is called a filter (or mask, kernel, template, window).
- The values in a filter subimage are referred to as coefficients, rather than pixels.

Spatial domain filtering

- Operation: modify the pixels in an image based on some function of the pixels in their neighborhood.
- Simplest: linear filtering (replace each pixel by a linear combination of its neighbors).
- Linear spatial filtering is often referred to as "convolving a mask with an image".
- Filter masks are sometimes called convolution masks (or convolution kernels).

Spatial domain filtering

- Filtering process:
  - Masks operate on a neighborhood of pixels.
  - The filter mask is centered on a pixel.
  - The mask coefficients are multiplied by the pixel values in its neighborhood and the products are summed.

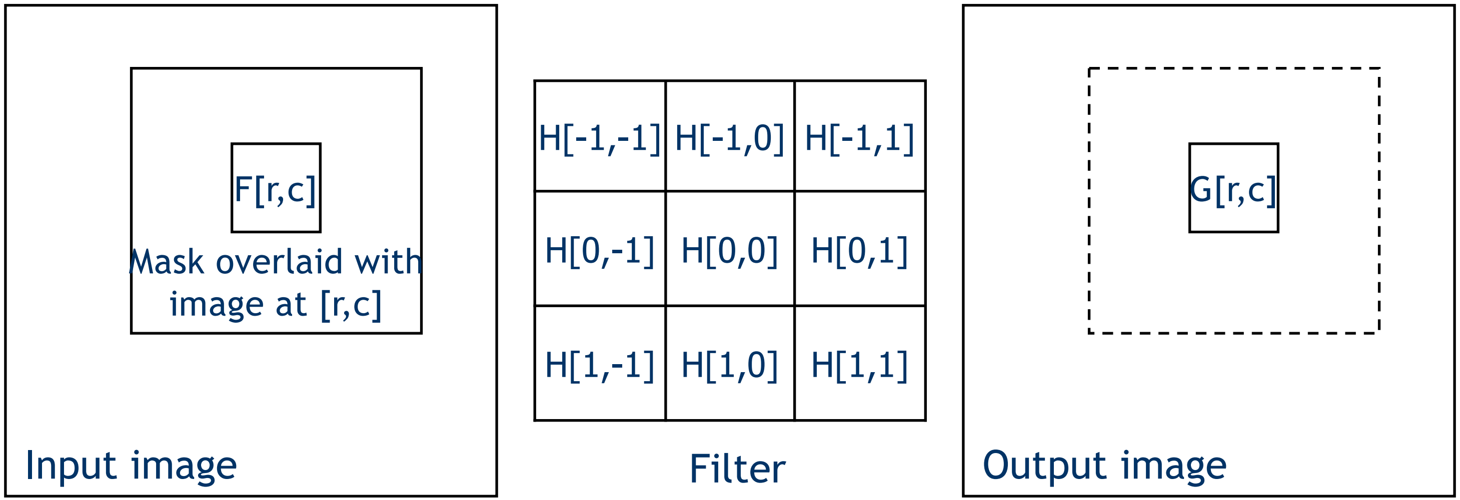
$$G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u,v] F[i+u, j+v]$$

  - The result goes into the corresponding pixel position in the output image.
  - This process is repeated by moving the filter mask from pixel to pixel in the image.

Spatial domain filtering

- This is called the cross-correlation operation and is denoted by

$$G = H \otimes F$$



- Be careful about indices, image borders and padding during implementation.

Background Photo:
[The Milk Maid]

Smoothing spatial filters

Smoothing spatial filters

- Often, an image is composed of
  - some underlying ideal structure, which we want to detect and describe,
  - together with some random noise or artifact, which we would like to remove.
- Smoothing filters are used for blurring and for noise reduction.
- Linear smoothing filters are also called averaging filters.

Smoothing spatial filters

$$\frac{1}{9} \times \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad \frac{1}{16} \times \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

Averaging (mean) filter

Weighted average

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Smoothing spatial filters

I

10	11	10	0	0	1
9	10	11	1	0	1
10	9	10	0	2	1
11	10	9	10	9	11
9	10	11	9	99	11
10	9	9	11	10	10

F

1/9

1	1	1
1	1	1
1	1	1

O

X	X	X	X	X	X
X	10				X
X					X
X					X
X					X
X	X	X	X	X	X

1/9.(10x1 + 11x1 + 10x1 + 9x1 + 10x1 + 11x1 + 10x1 + 9x1 + 10x1) =
1/9.(90) = 10

Adapted from Octavia Camps, Penn State

Smoothing spatial filters

I

10	11	10	0	0	1
9	10	11	1	0	1
10	9	10	0	2	1
11	10	9	10	9	11
9	10	11	9	99	11
10	9	9	11	10	10

F

1/9

1	1	1
1	1	1
1	1	1

O

X	X	X	X	X	X
X					X
X					X
X					X
X				20	X
X	X	X	X	X	X

$$1/9.(10x1 + 9x1 + 11x1 + 9x1 + 99x1 + 11x1 + 11x1 + 10x1 + 10x1) =$$
$$1/9.(180) = 20$$

Adapted from Octavia Camps, Penn State

Smoothing spatial filters

- Common types of noise:
  - Salt-and-pepper noise: contains random occurrences of black and white pixels.
  - Impulse noise: contains random occurrences of white pixels.
  - Gaussian noise: variations in intensity drawn from a Gaussian normal distribution.

Original

Salt and pepper noise

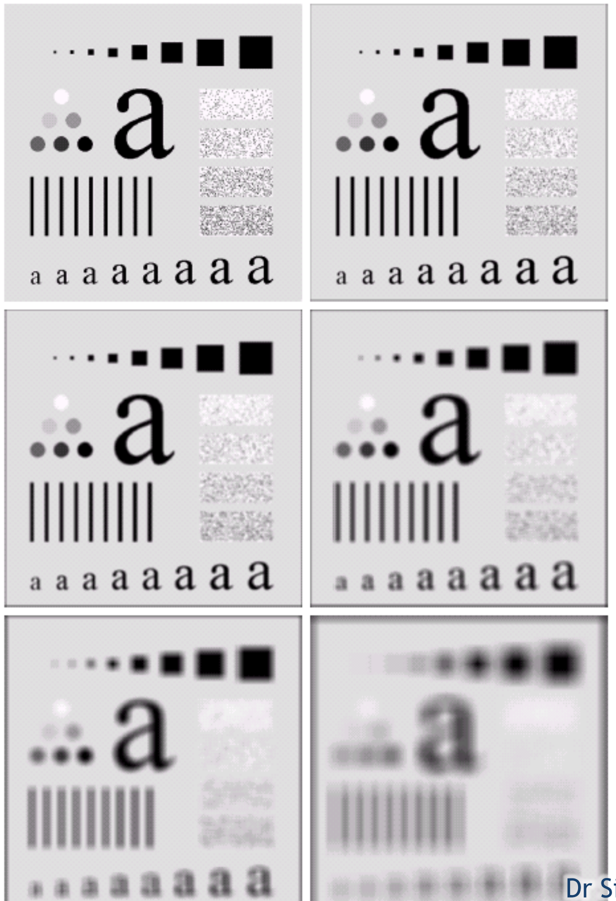
Impulse noise

Gaussian noise

Adapted from Linda Shapiro, U of Washington

Adapted from Linda Shapiro, U of Washington

Smoothing spatial filters

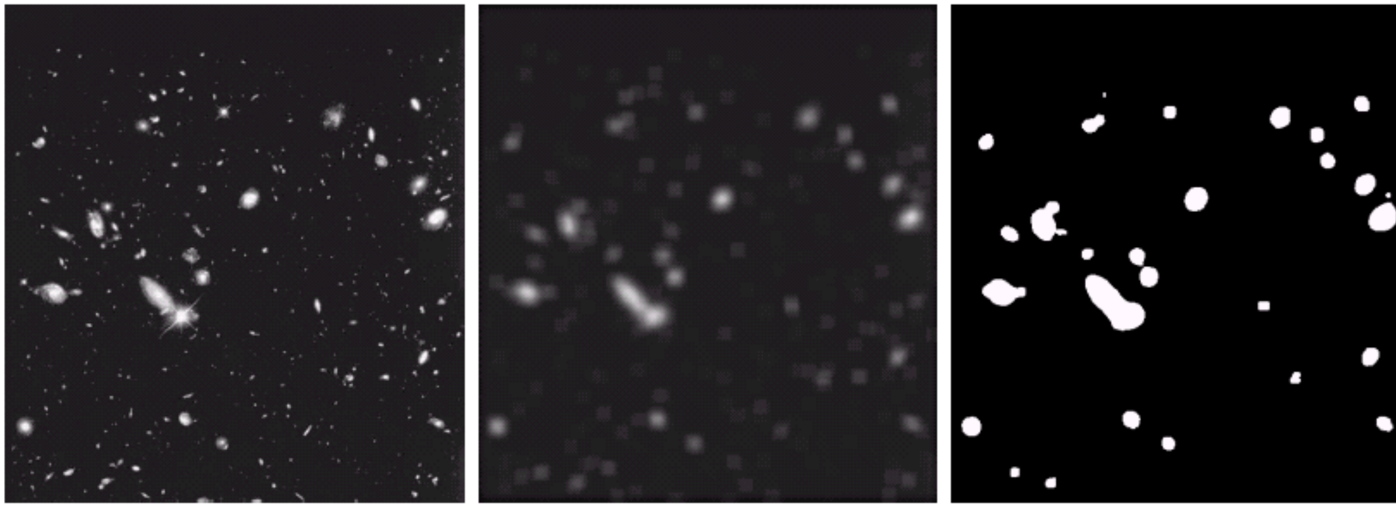


a	b
c	d
e	f

FIGURE 3.35 (a) Original image, of size 500 × 500 pixels. (b)–(f) Results of smoothing with square averaging filter masks of sizes $n = 3, 5, 9, 15,$ 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 gray 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.

Adapted from Gonzales and Woods

Smoothing spatial filters



a b c

FIGURE 3.36 (a) Image from the Hubble Space Telescope. (b) Image processed by a 15 × 15 averaging mask. (c) Result of thresholding (b). (Original image courtesy of NASA.)

Adapted from Gonzales and Woods

Smoothing spatial filters

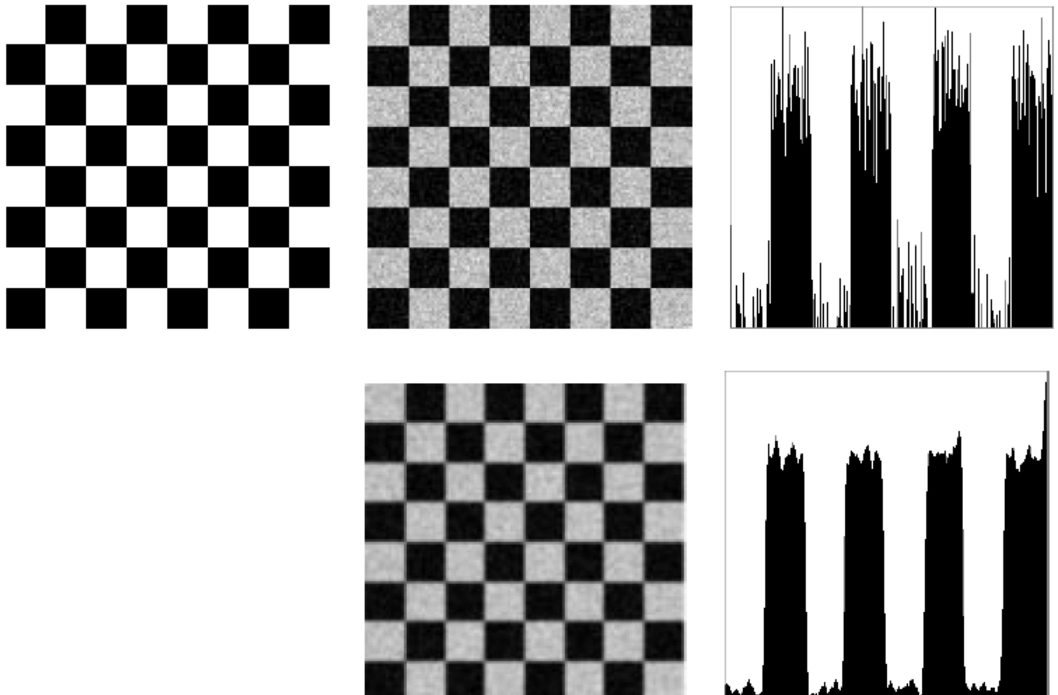
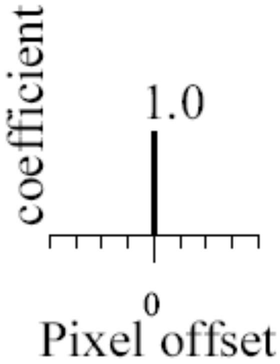


Figure 5.7: Ideal image of checkerboard (top left) with pixel values of 0 in the black squares and 255 in the white squares; (top center) image with added Gaussian noise of standard deviation 30; (top right) pixel values in a horizontal row 100 from the top of the noisy image; (bottom center) noise averaged using a 5x5 neighborhood centered at each pixel; (bottom right) pixels across image row 100 from the top.

apiro and Stockman

Smoothing spatial filters

original

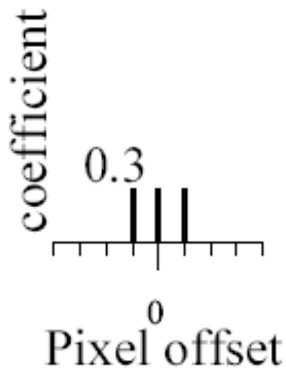


Filtered
(no change)

Adapted from Darrell and Freeman, MIT

Smoothing spatial filters

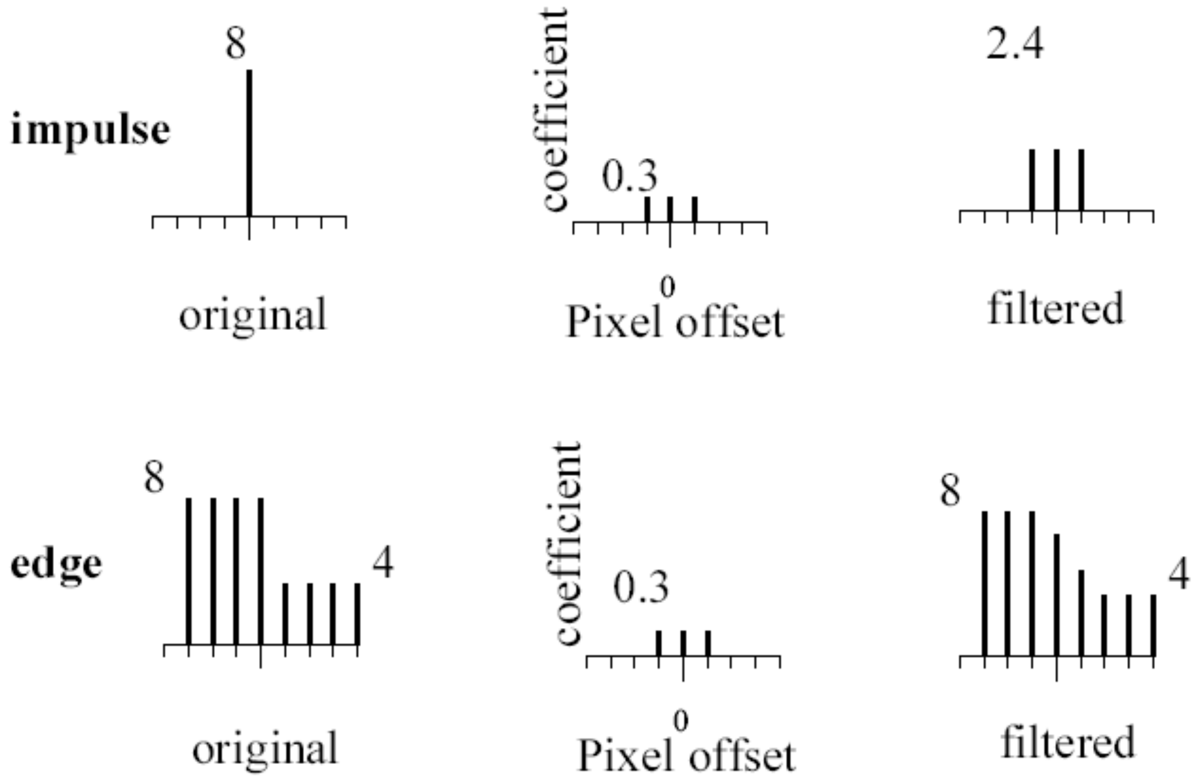
original



Blurred (filter applied in both dimensions).

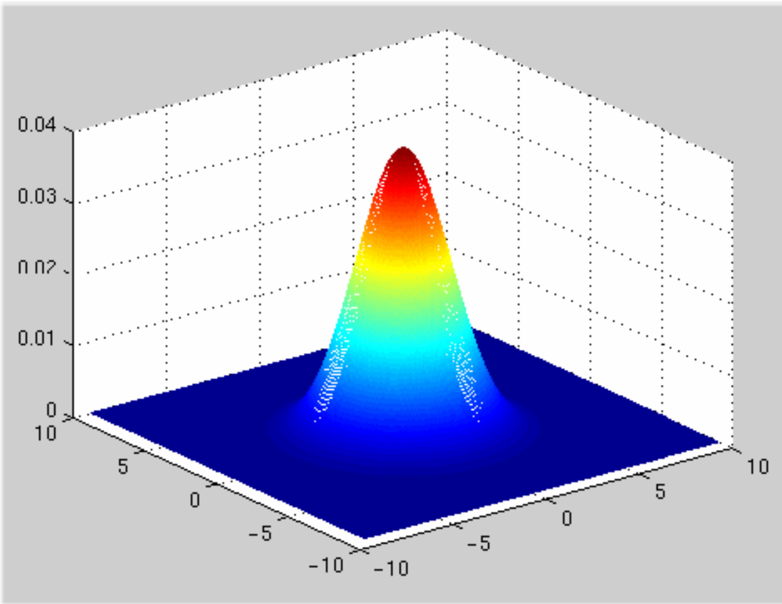
Adapted from Darrell and Freeman, MIT

Smoothing spatial filters



Adapted from Darrell and Freeman, MIT

Smoothing spatial filters



$$G_\sigma(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(x^2+y^2)}{2\sigma^2}\right)$$

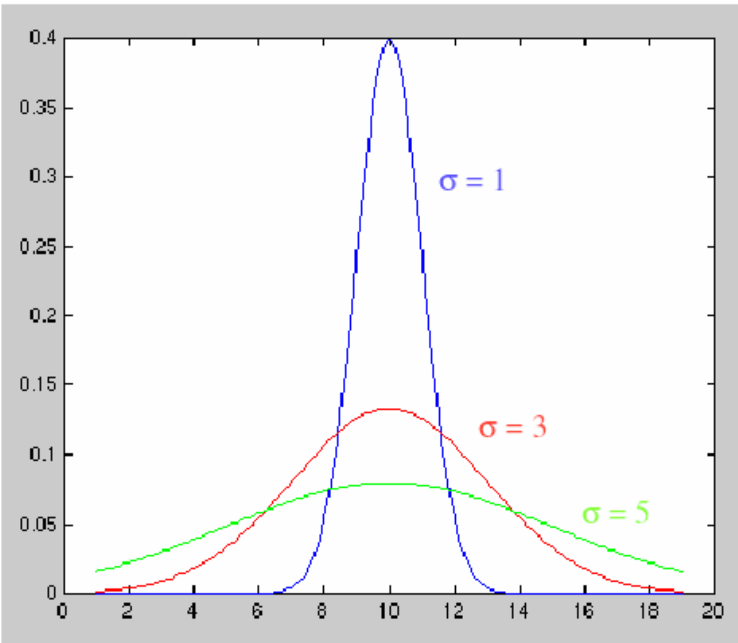
A weighted average that weighs pixels at its center much more strongly than its boundaries.

2D Gaussian filter

Adapted from Martial Hebert, CMU

Smoothing spatial filters

Effect of σ



- If σ is small: smoothing will have little effect.
- If σ is larger: neighboring pixels will have larger weights resulting in consensus of the neighbors.
- If σ is very large: details will disappear along with the noise.

Adapted from Martial Hebert, CMU

Smoothing spatial filters

Result of blurring using a uniform local model.

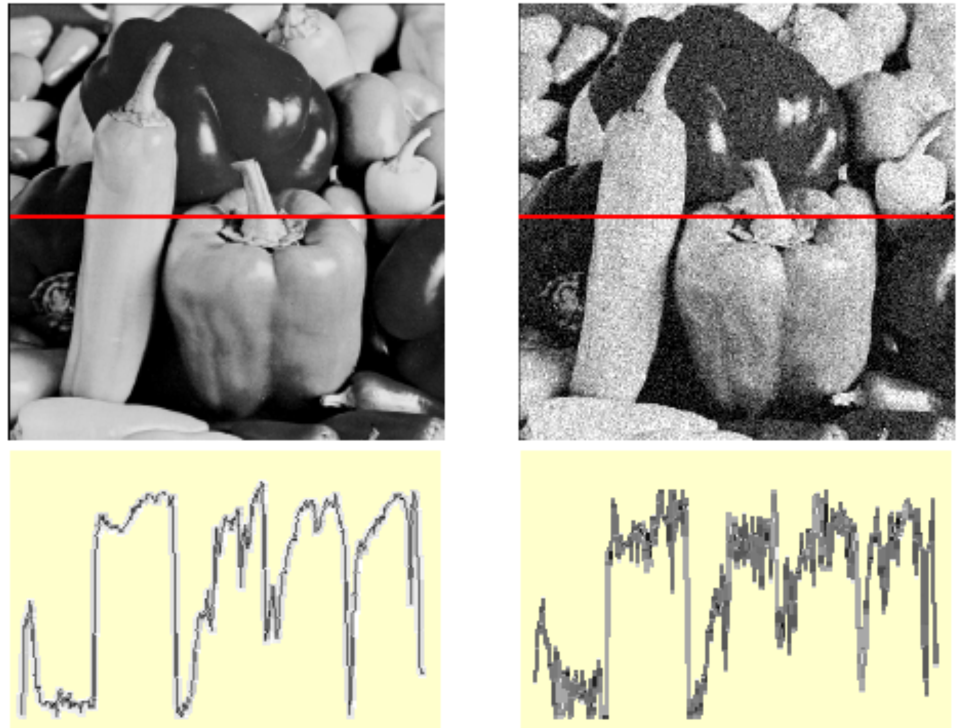
Produces a set of narrow horizontal and vertical bars – ringing effect.

Result of blurring using a Gaussian filter.

Adapted from David Forsyth, UC Berkeley

Smoothing spatial filters

Image Noise

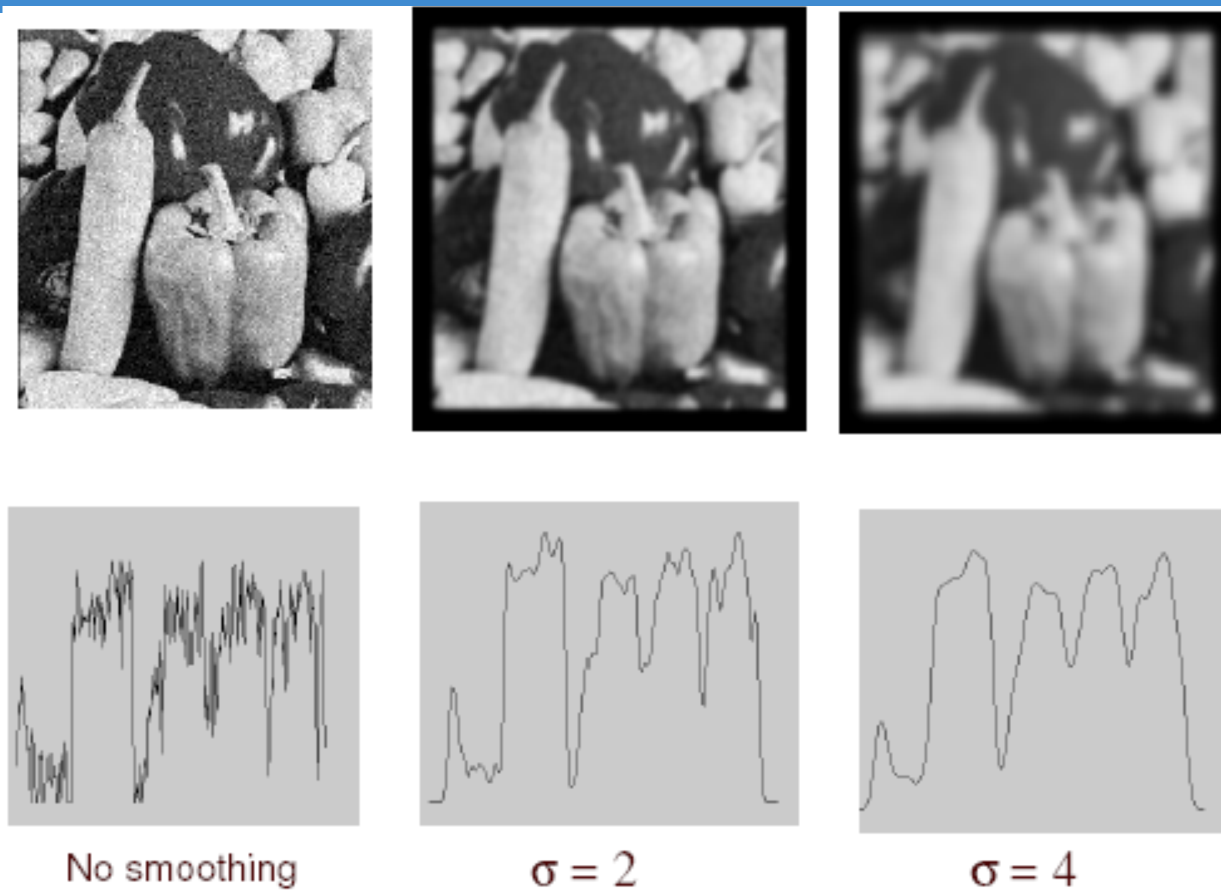


$$f(x,y) = \overbrace{\tilde{f}(x,y)}^{\text{Ideal Image}} + \overbrace{\eta(x,y)}^{\text{Noise process}}$$

Gaussian i.i.d. ("white") noise:
$\eta(x,y) \sim \mathcal{N}(\mu,\sigma)$

Adapted from Martial Hebert, CMU

Smoothing spatial filters

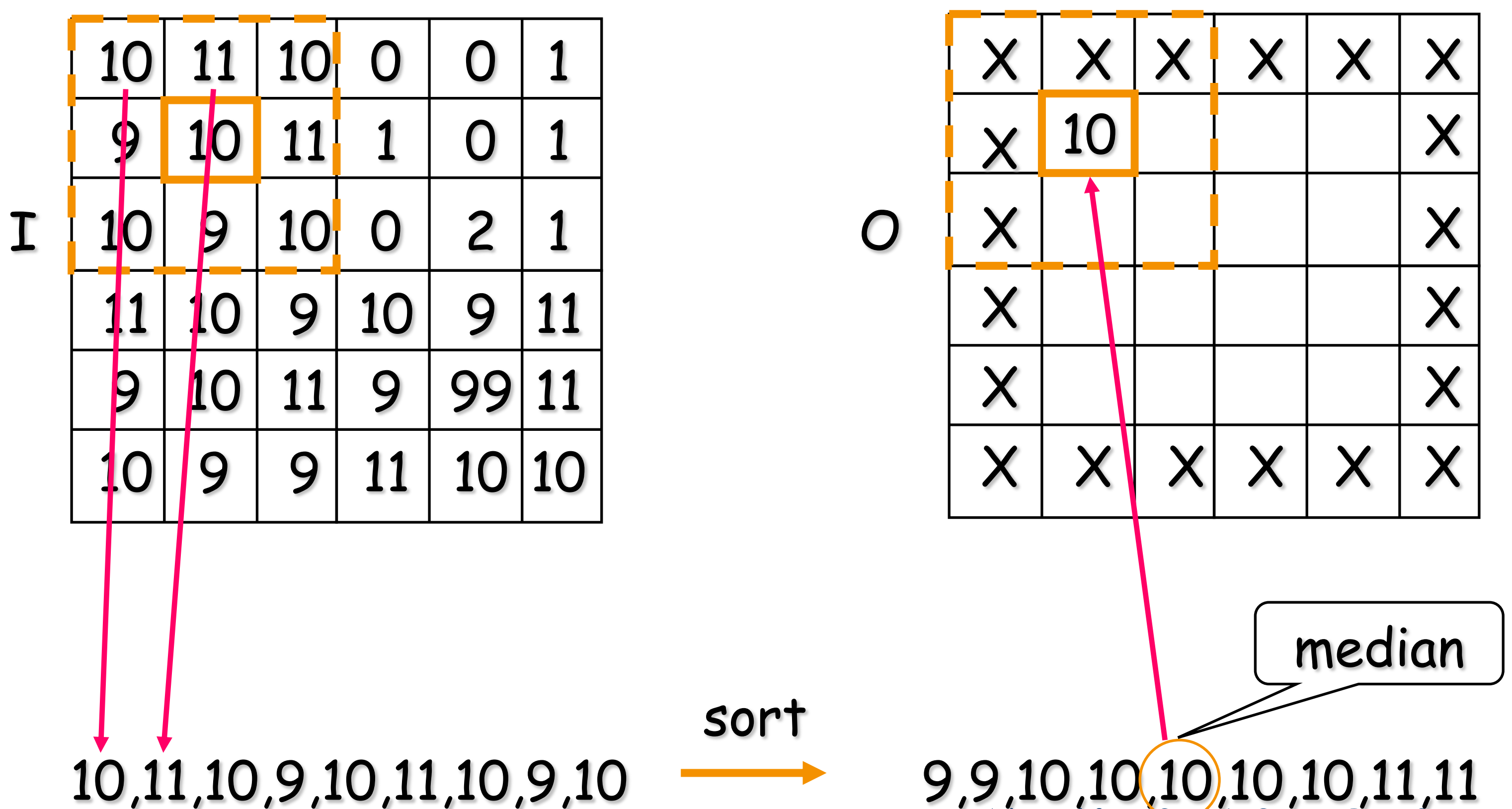


Adapted from Martial Hebert, CMU

Order-statistic filters

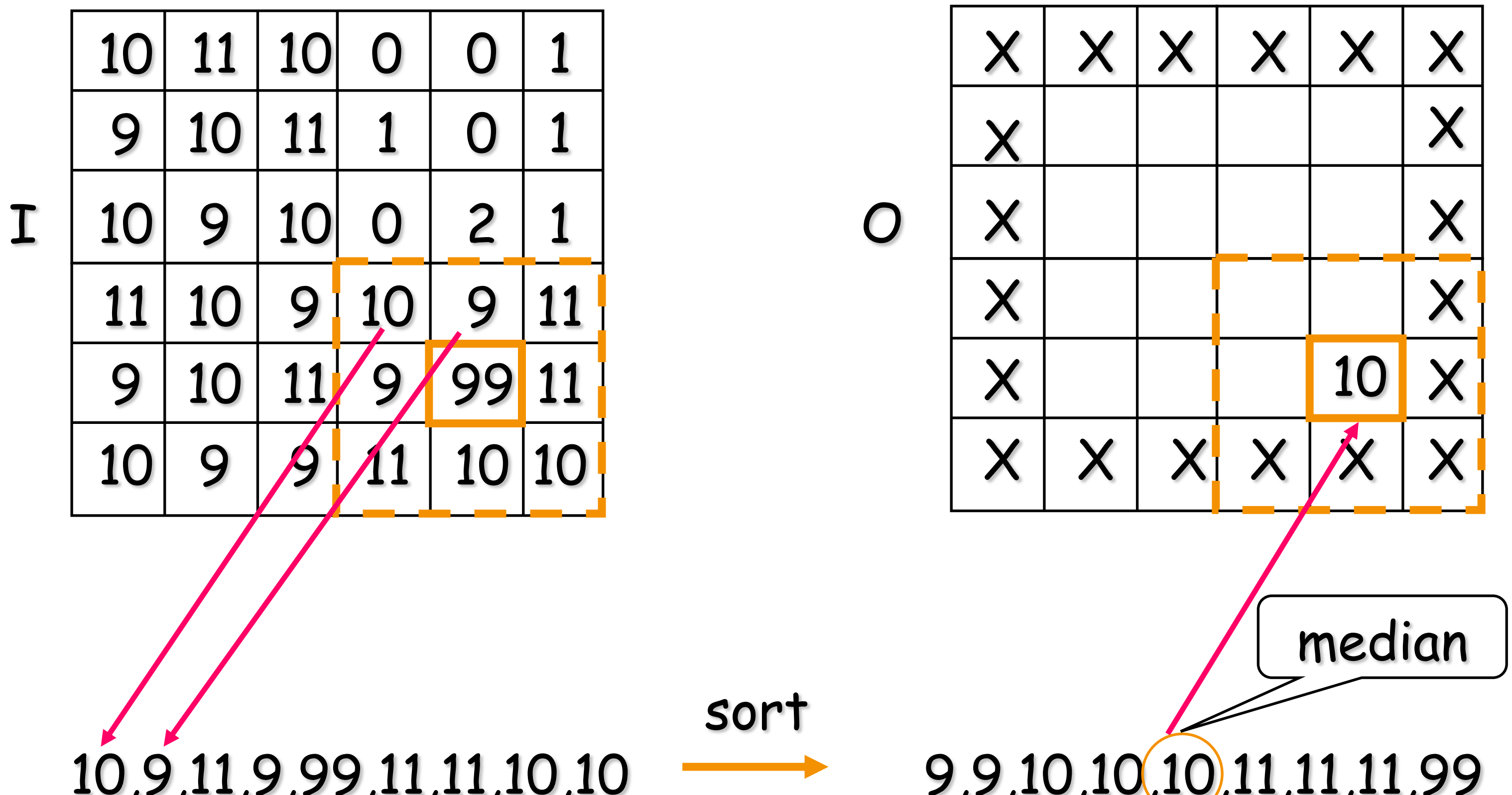
- Order-statistic filters are nonlinear spatial filters whose response is based on
  - ordering (ranking) the pixels contained in the image area encompassed by the filter, and then
  - replacing the value of the center pixel with the value determined by the ranking result.
- The best-known example is the median filter.
- It is particularly effective in the presence of impulse or salt-and-pepper noise, with considerably less blurring than linear smoothing filters.

Order-statistic filters



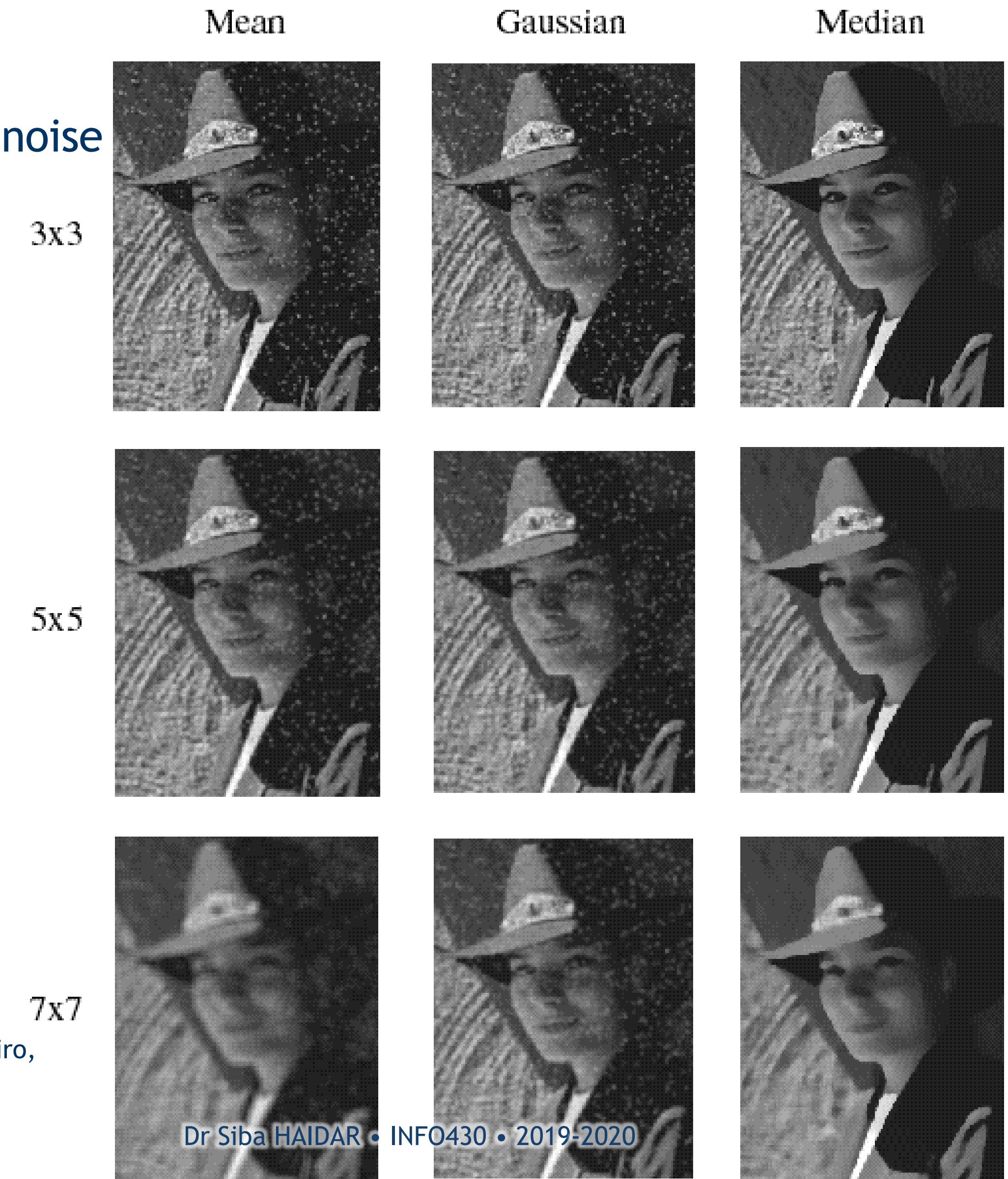
Adapted from Octavia Camps, Penn State

Order-statistic filters



Adapted from Octavia Camps, Penn State

Salt-and-pepper noise

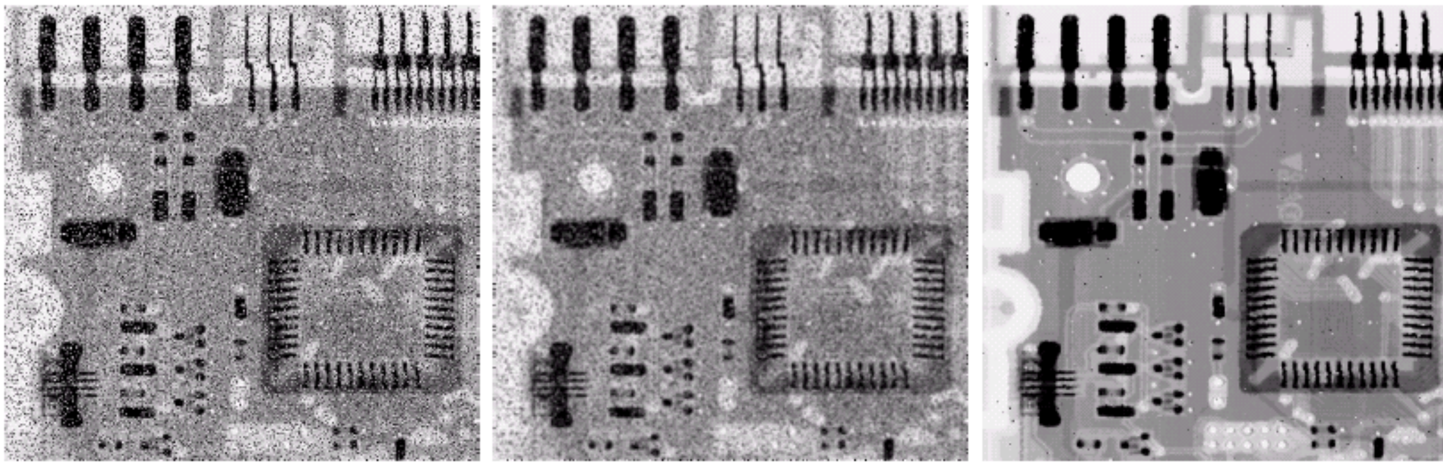


Adapted from Linda Shapiro, U of Washington

Gaussian noise

Adapted from Linda Shapiro, U of Washington

Order-statistic filters



a b c

FIGURE 3.37 (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.)

Adapted from Gonzales and Woods

Order-statistic filters

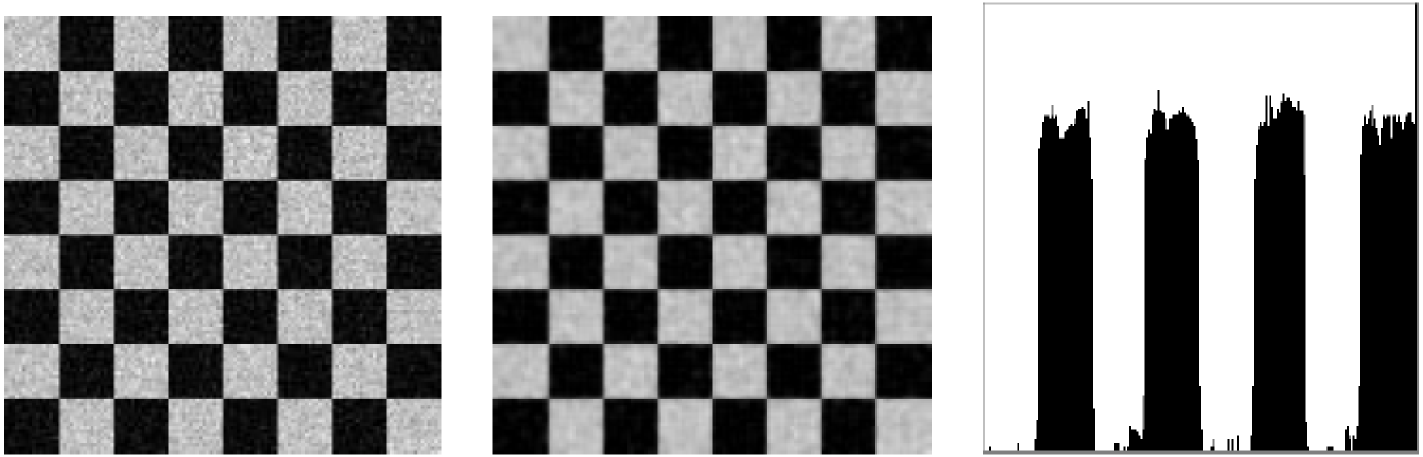
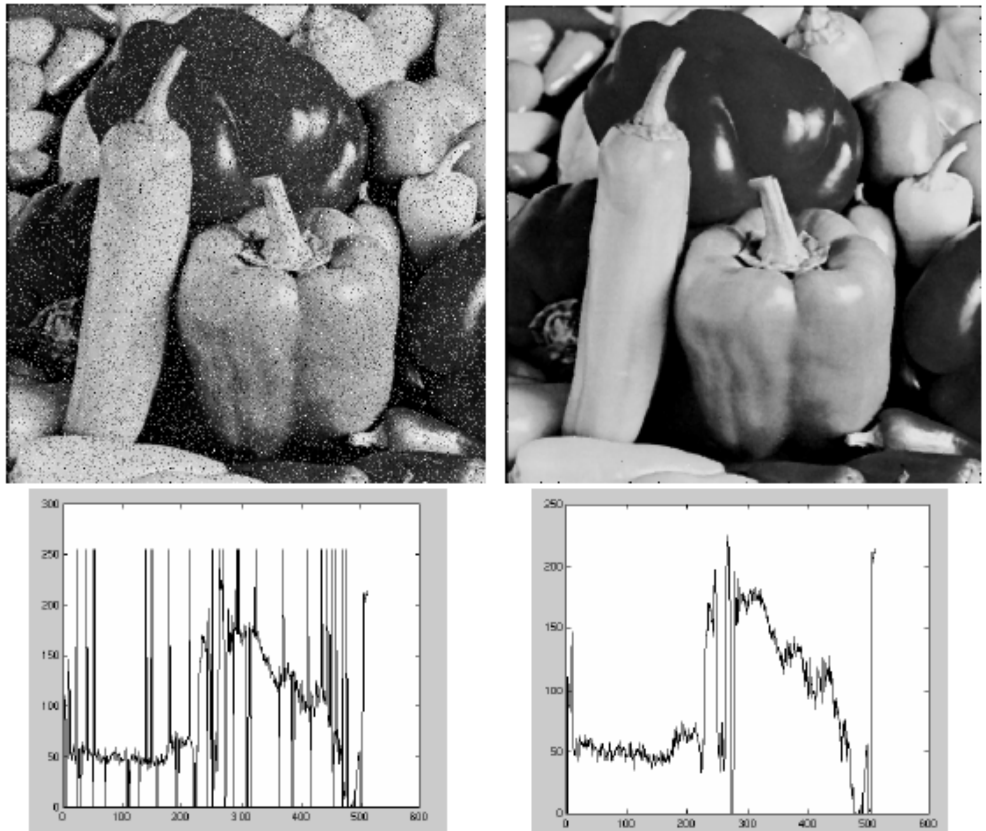


Figure 5.8: (Left) Noisy checkerboard image; (center) result of setting output pixel to the median value of a 5x5 neighborhood centered at the pixel; (right) display of pixels across image row 100 from the top; compare to Figure 5.7.

Adapted from Shapiro and Stockman

Order-statistic filters

Effect of median filter on salt and pepper noise



Adapted from Martial Hebert, CMU

Background Photo:
The Milk Maid

Sharpening spatial filters

Sharpening spatial filters

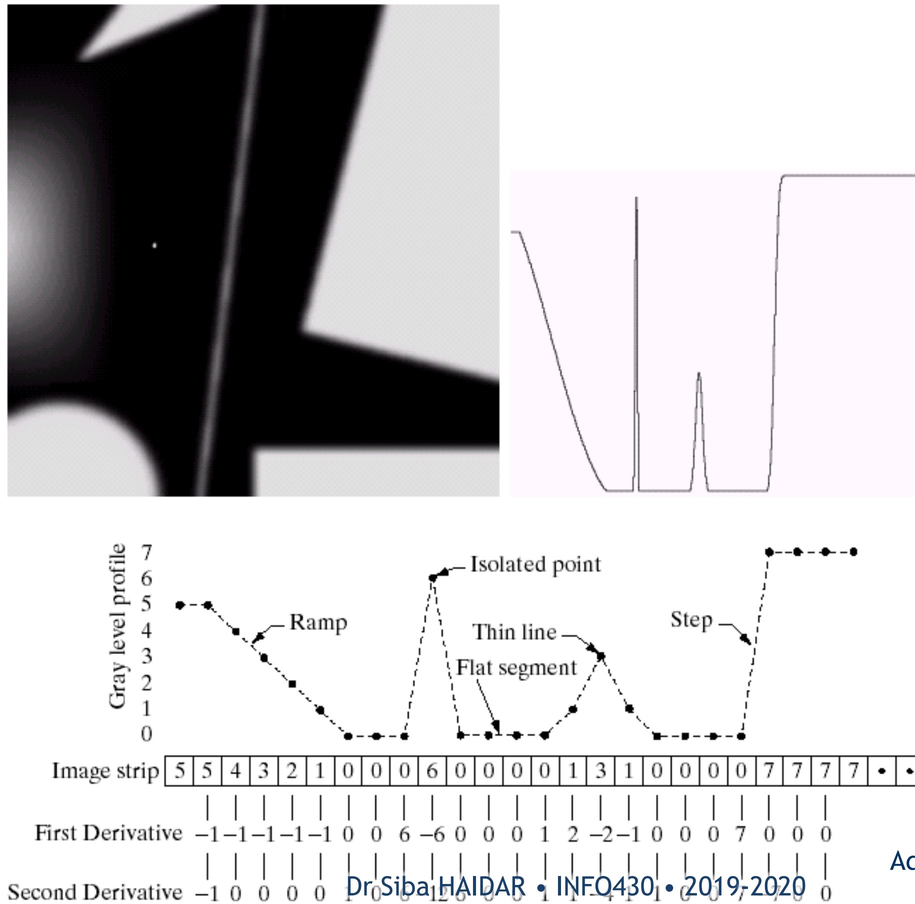
- Objective of sharpening is to highlight or enhance fine detail in an image.
- Since
  - smoothing (averaging) is analogous to integration,
  - sharpening can be accomplished by spatial differentiation.
- First-order derivative of 1D function f(x)

$$f(x+1) - f(x).$$

- Second-order derivative of 1D function f(x)

$$f(x+1) - 2f(x) + f(x-1).$$

Sharpening spatial filters



a b
c

FIGURE 3.38
(a) A simple image. (b) 1-D horizontal gray-level profile along the center of the image and including the isolated noise point.
(c) Simplified profile (the points are joined by dashed lines to simplify interpretation).

Adapted from Gonzales and Woods

Sharpening spatial filters

- Observations:
  - First-order derivatives generally produce thicker edges in an image.
  - Second-order derivatives have a stronger response to fine detail (such as thin lines or isolated points).
  - First-order derivatives generally have a stronger response to a gray level step.
  - Second-order derivatives produce a double response at step changes in gray level.

Sharpening spatial filters

- *Laplacian* of a function (image) $f(x, y)$ of two variables x and y

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

is a second-order derivative operator.

(a)

0	1	0
1	−4	1
0	1	0

(b)

1	1	1
1	−8	1
1	1	1

(c)

0	−1	0
−1	4	−1
0	−1	0

(d)

−1	−1	−1
−1	8	−1
−1	−1	−1

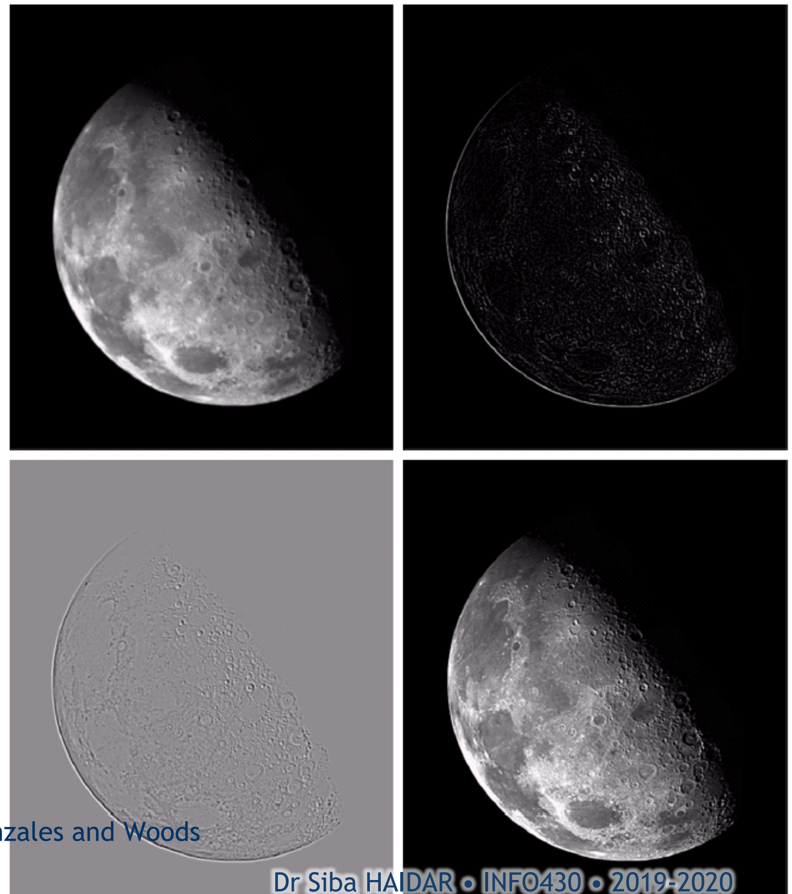
a b
c d

FIGURE 3.39 (a) Filter mask used to implement the digital Laplacian, as defined in Eq. (3.7-4). (b) Mask used to implement an extension of this equation that includes the diagonal neighbors. (c) and (d) Two other implementations of the Laplacian.

Sharpening spatial filters

a b
c d

FIGURE 3.40
(a) Image of the North Pole of the moon.
(b) Laplacian-filtered image.
(c) Laplacian image scaled for display purposes.
(d) Image enhanced by using Eq. (3.7-5).
(Original image courtesy of NASA.)



Adapted from Gonzales and Woods

Sharpening spatial filters

- For a function $f(x, y)$, the *gradient* at (x, y) is defined as

$$\nabla f = \left[\frac{\partial f}{\partial x} \; \frac{\partial f}{\partial y} \right]^T$$

where its magnitude can be used to implement first-order derivatives.

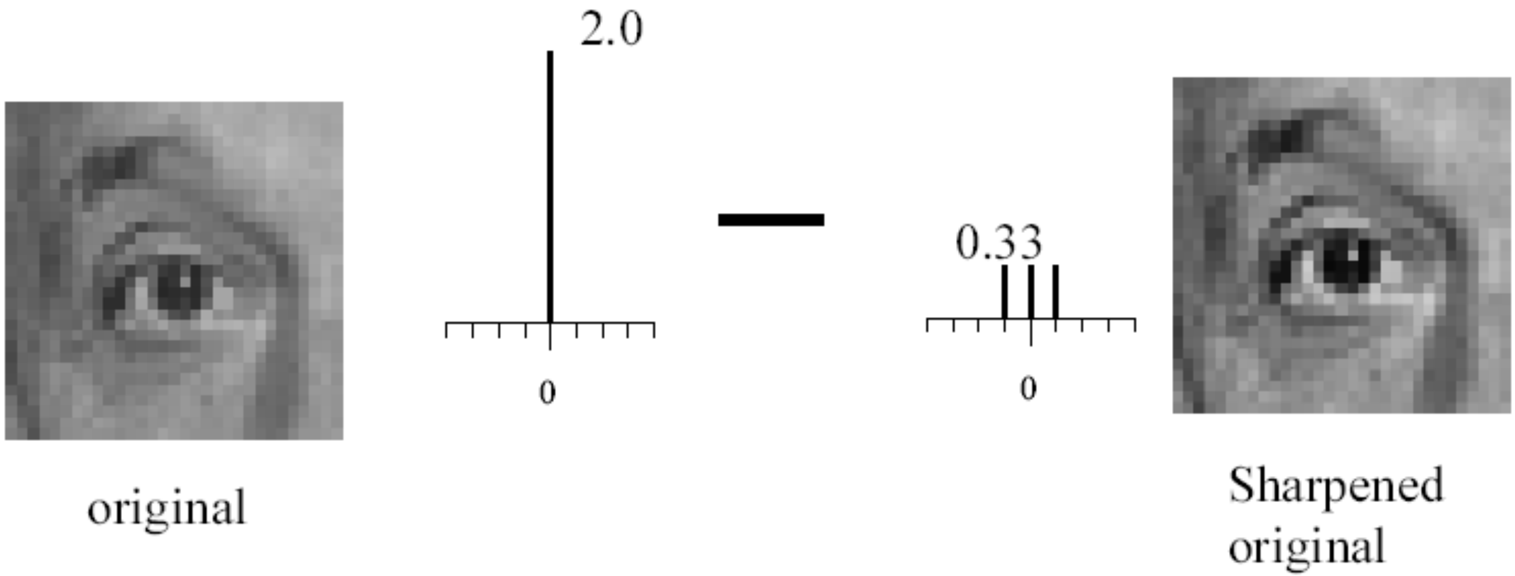
Robert's cross-gradient operators

−1	0	0	−1
0	1	1	0

Sobel gradient operators

−1	−2	−1	−1	0	1
0	0	0	−2	0	2
1	2	1	−1	0	1

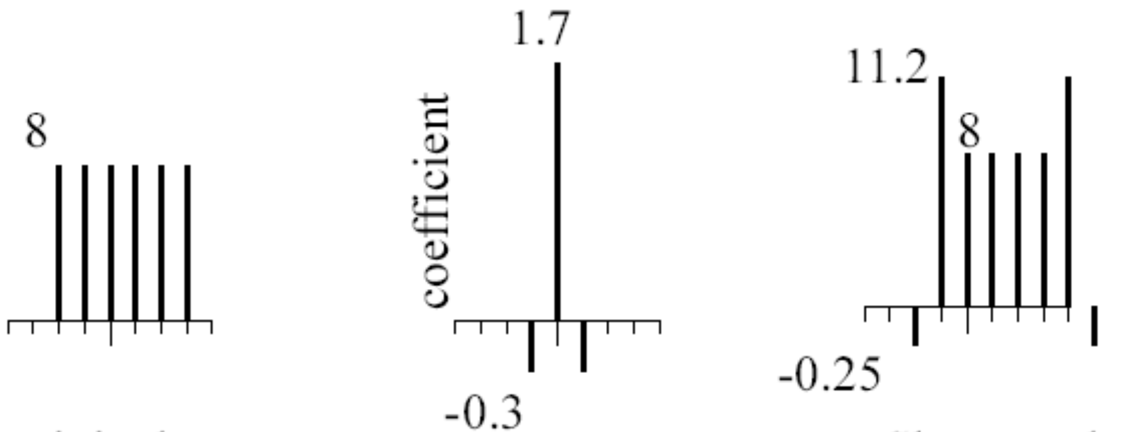
Sharpening spatial filters



High-boost filtering

Adapted from Darrell and Freeman, MIT

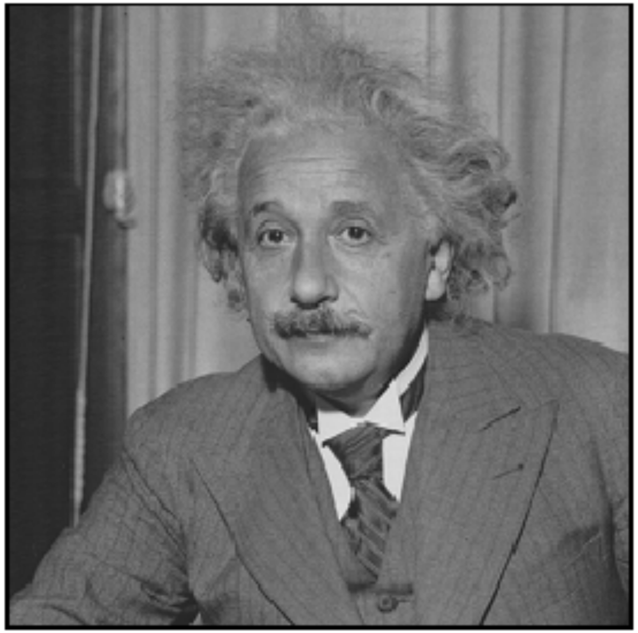
Sharpening spatial filters



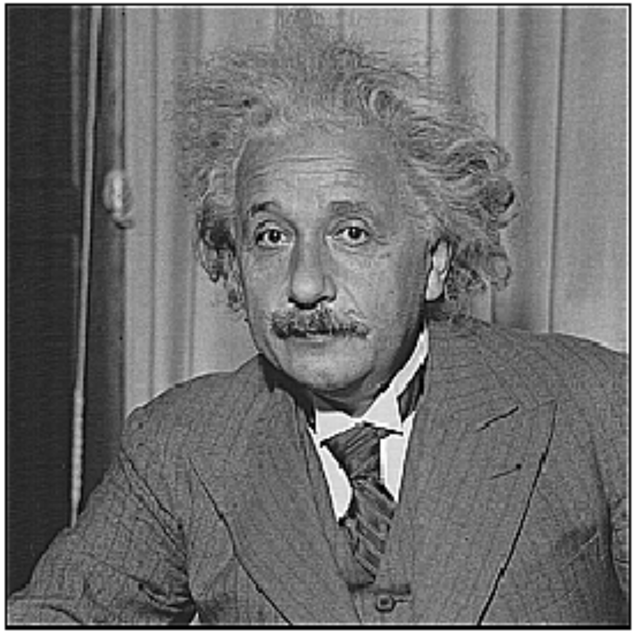
Sharpened
(differences are
accentuated; constant
areas are left untouched).

Adapted from Darrell and Freeman, MIT

Sharpening spatial filters



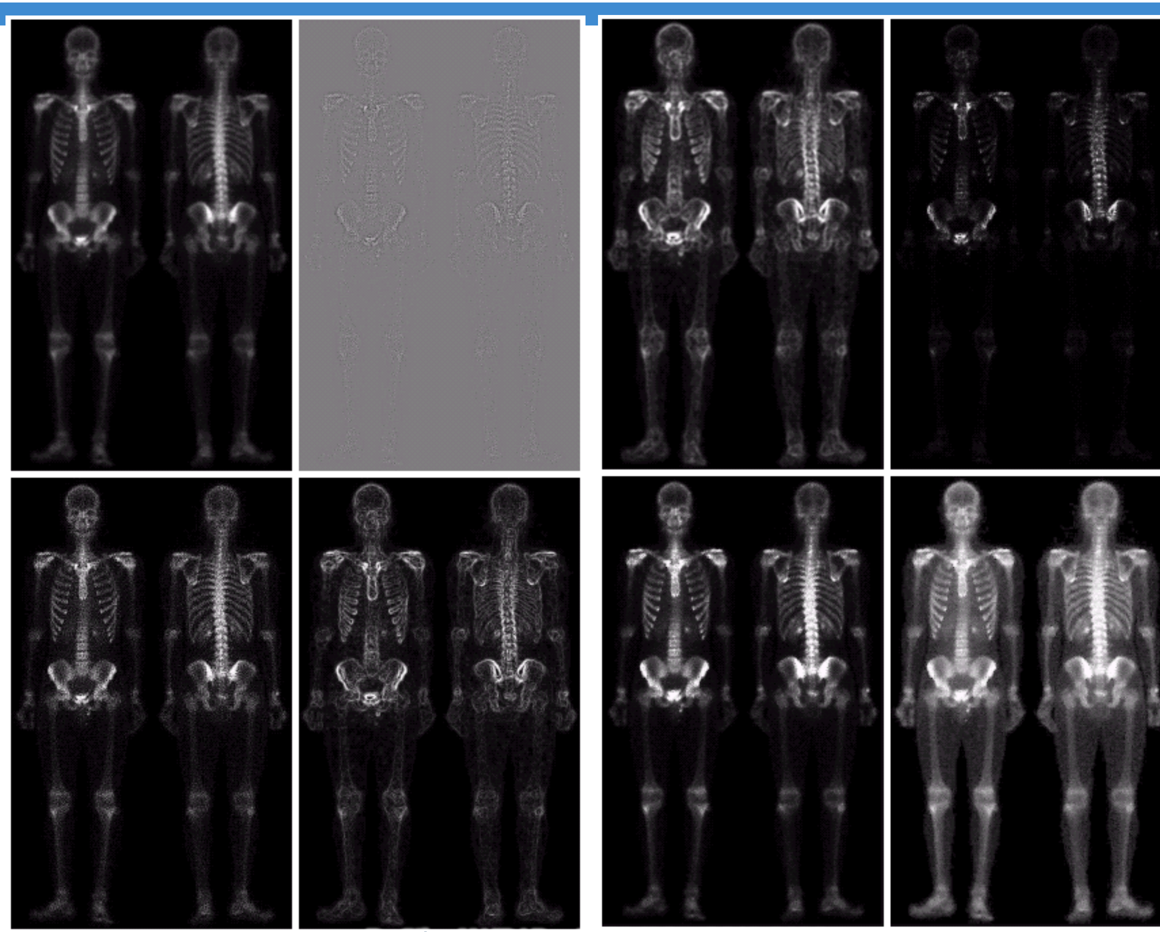
before



after

Adapted from Darrell and Freeman, MIT

Combining spatial enhancement methods



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.)

References

- Selim Aksoy course webpage for year 2007
  - CS 484, Image Analysis, Spring 2007
  - http://www.cs.bilkent.edu.tr/~saksoy/courses/cs484-Spring2007/#Lectures
  - Linear Filtering Part I
    - ***this current presentation in his own***
- Book: Digital Image Processing, Gonzalez and Woods
  - Chapter 3: Image Enhancement in the Spatial Domain