Images and Linear Filters

Class 2

Artificial Vision

Most slides from: Prof. Kristen Grauman, UT-Austin

Today

- What is an image?
  - Types, color vs gray level

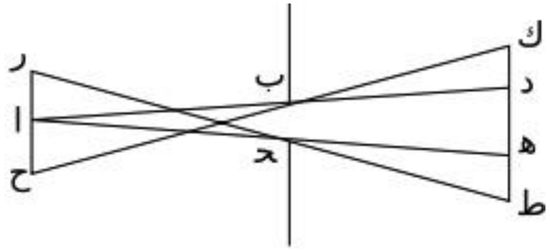
- How to measure the quality of an image?
  - Spatial and photometric resolution
  - Histogram and image contrast enhancement

- How to process by a linear filter
  - Examples: smoothing filters
  - Convolution / correlation
  - Mean and median filters
  - Linear filters with Gaussians

Slide credit: L. Lazebnik

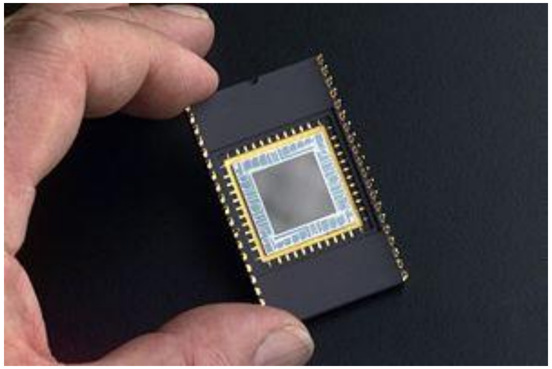
Historical context

- **Pinhole model:** Mozi (470-390 BCE), Aristotle (384-322 BCE)
- **Principles of optics (including lenses):** Alhacen (965-1039 CE)
- **Camera obscure:**
  - [Leonardo da Vinci (1452-1519)]
- **First photo:** Joseph Nicephore Niepce
  - (1822)
- **Cinema** ([Lumière Brothers],
  - 1895)
- **Color Photography** (Lumière Brothers,
  - 1908)
- **Television** (Baird, Farnsworth, Zworykin,
  - 1920s)
- **First consumer camera**:
  - Sony Mavica (1981)
- **First fully digital camera:**
- o Kodak DCS100 (1990)



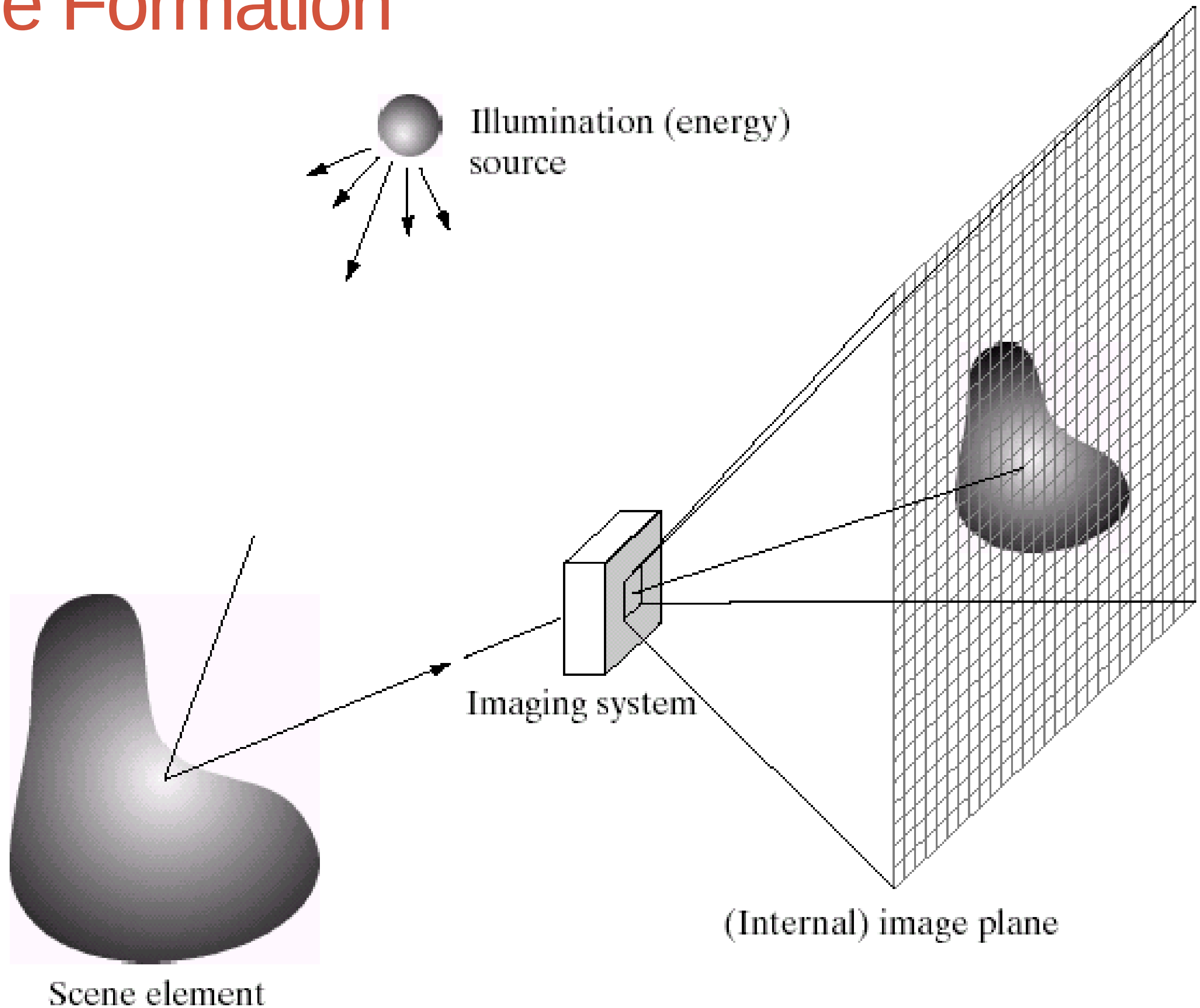
Alhacen's notes

Niepce, "La Table Servie," 1822



CCD chip **K. Grauman**

Image Formation



Slide credit: Derek Hoiem

Analog ameras vs Digital cameras

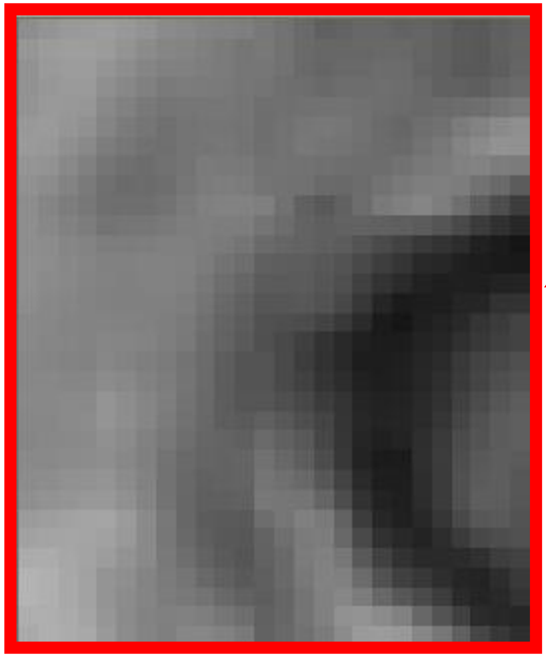
A digital camera replaces film with a sensor array

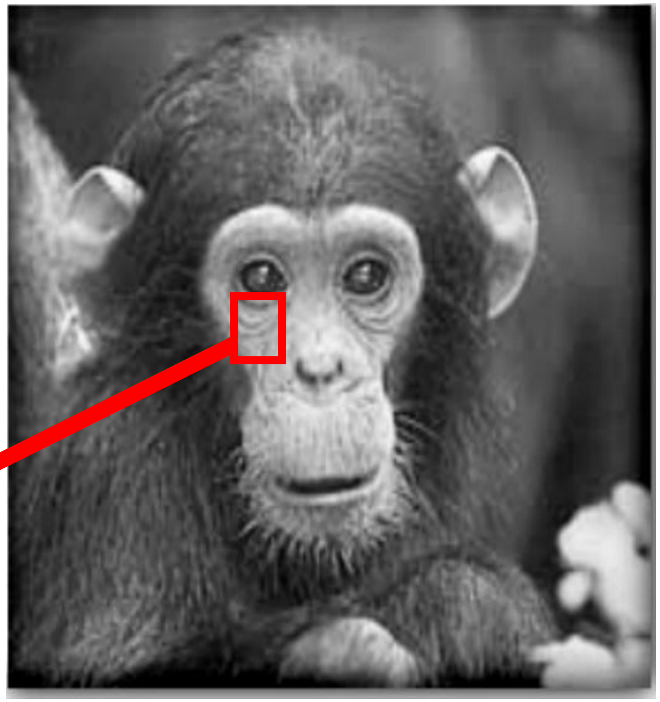
- Each cell in the array is light-sensitive diode that converts photons to electrons

Slide by Steve Seitz

Digital images

Think of images as matrices taken from the CCD array.

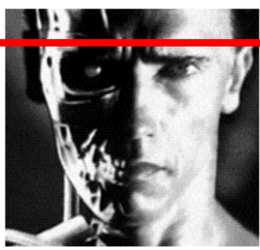


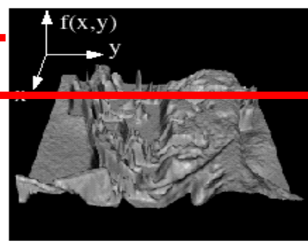


K. Grauman

Digital images

- **Sample** the 2D space on a regular grid
- **Quantize** each sample (round to nearest integer)





j

i

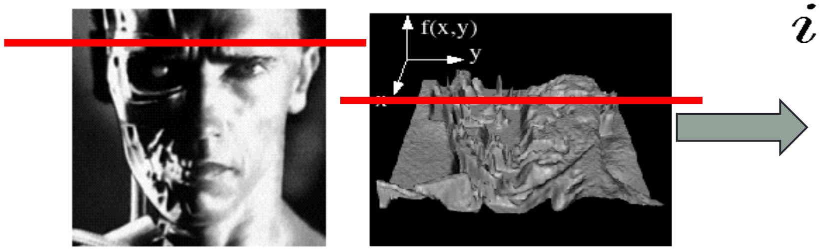
62	79	23	119	120	105	4	0
10	10	9	62	12	78	34	0
10	58	107	46	46	0	0	48
176	135	5	188	191	68	0	49
2	1	1	29	26	37	0	77
0	89	144	147	187	102	62	208
255	252	0	166	123	62	0	31
166	63	127	17	1	0	99	30

2D

Adapted from S. Seitz

Digital images

- Image is represented as a matrix of integer values.

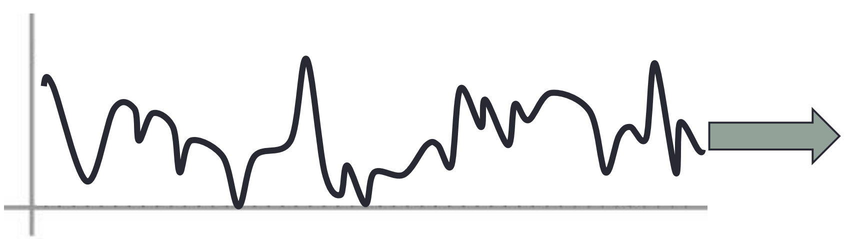


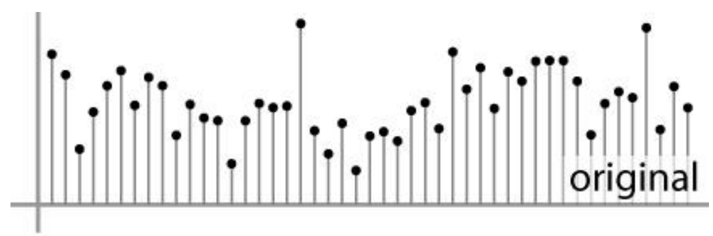
j

i

62	79	23	119	120	105	4	0
10	10	9	62	12	78	34	0
10	58	197	46	46	0	0	48
176	135	5	188	191	68	0	49
2	1	1	29	26	37	0	77
0	89	144	147	187	102	62	208
255	252	0	166	123	62	0	31
166	63	127	17	1	0	99	30

2D



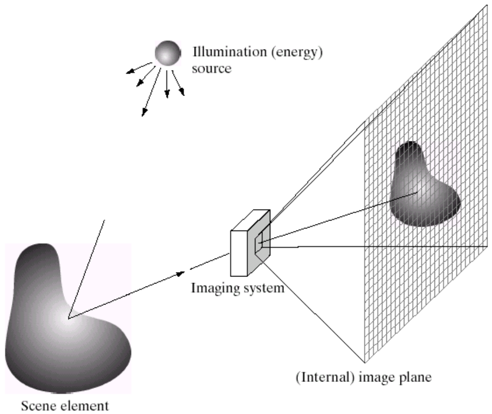


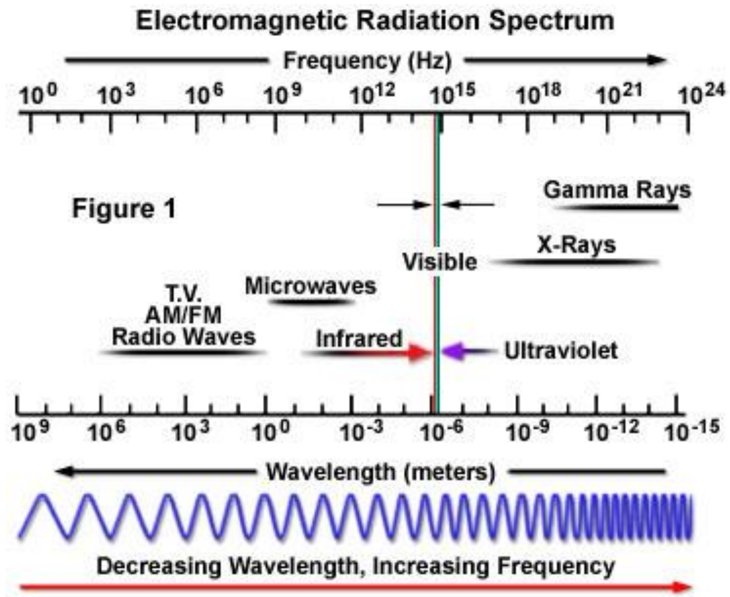
1D

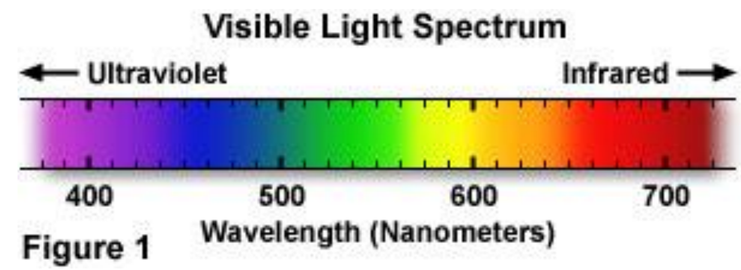
Adapted from S. Seitz

How do we obtain color images?

Light is an energy source that carries coded information about the world, which can be read from a distance through the images!



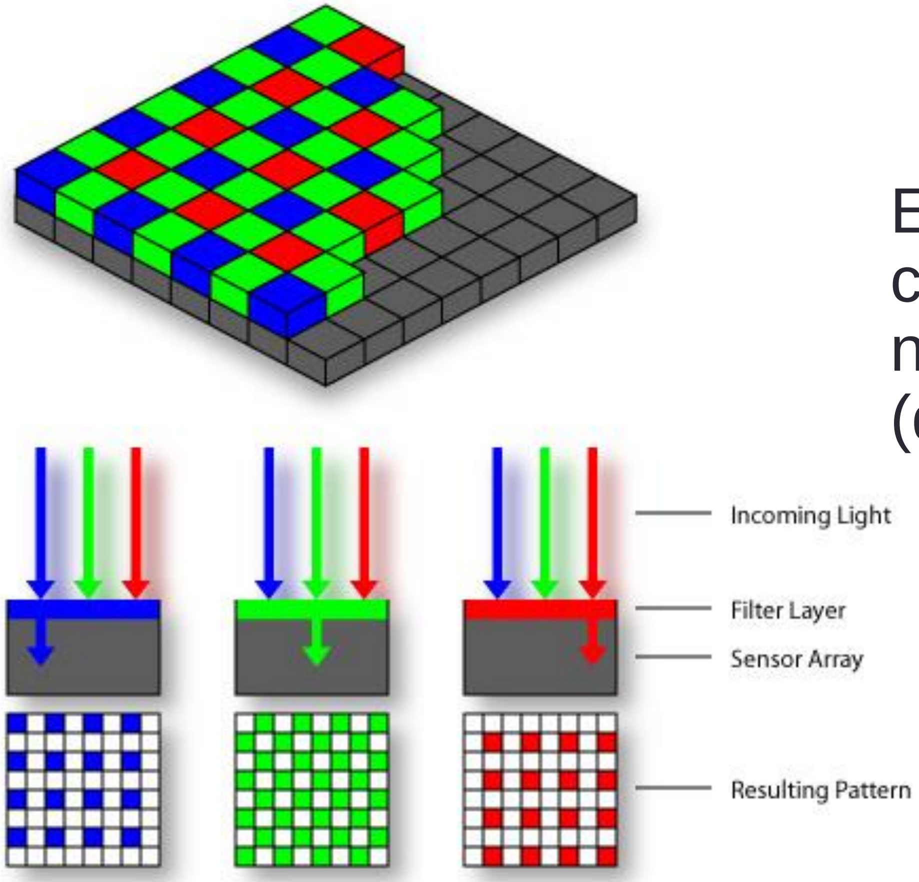




A typical human eye will respond to wavelengths from about 380 to 750 nm.

Color sensing in digital cameras

Bayer grid



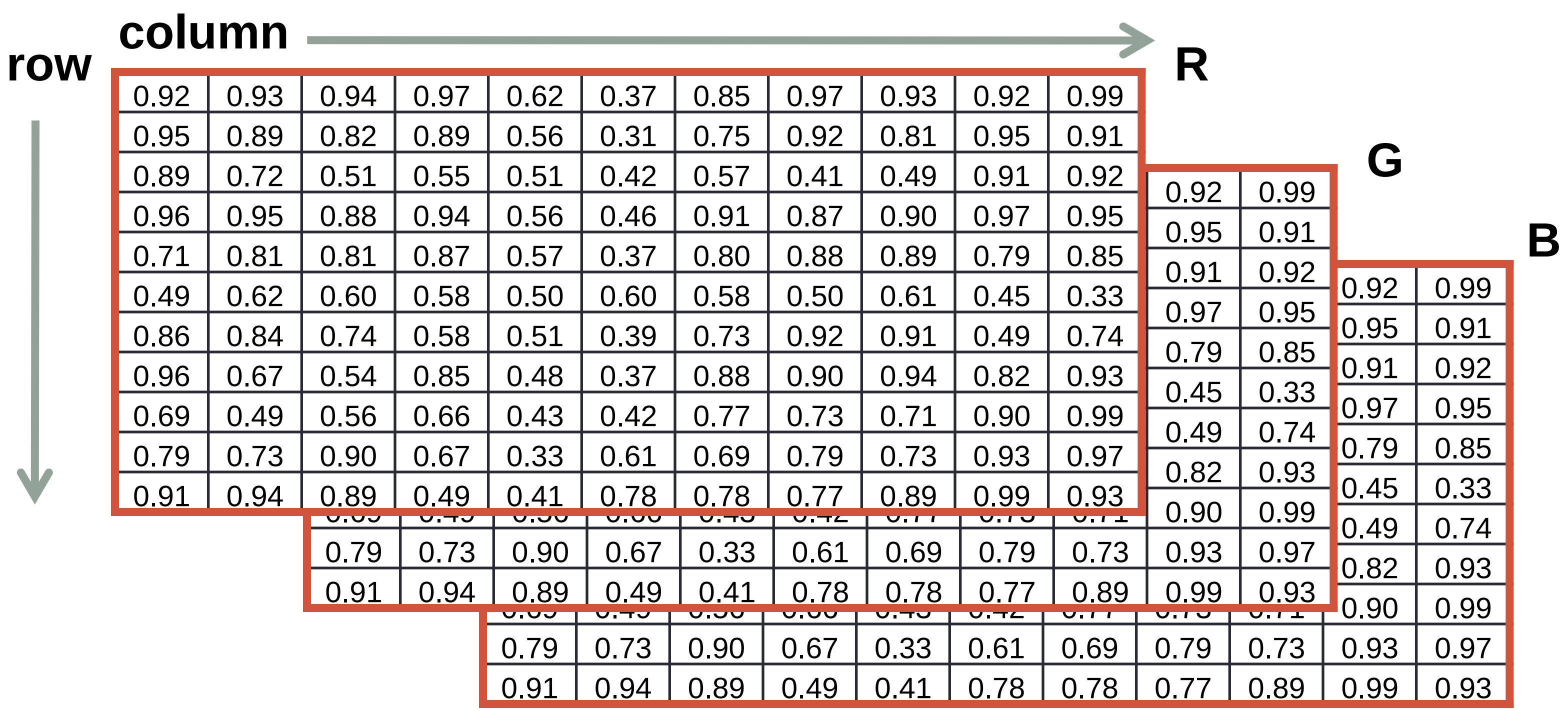
Estimate missing components from neighboring values (demosaicing)

Source: Steve Seitz

Images in Skimage

- Images can be grey-value (1 channel) or color images (3 channels)

- Suppose we have an NxM RGB image called “im”
  - im[0,0,0] = top-left pixel value in R-channel
  - im[y, x, 2] = y pixels down, x pixels to right in the B-channel
  - im[N-1, M-1, 1] = bottom-right pixel in the G-channel



0.92	0.93	0.94	0.97	0.62	0.37	0.85	0.97	0.93	0.92	0.99
0.95	0.89	0.82	0.89	0.56	0.31	0.75	0.92	0.81	0.95	0.91
0.89	0.72	0.51	0.55	0.51	0.42	0.57	0.41	0.49	0.91	0.92
0.96	0.95	0.88	0.94	0.56	0.46	0.91	0.87	0.90	0.97	0.95
0.71	0.81	0.81	0.87	0.57	0.37	0.80	0.88	0.89	0.79	0.85
0.49	0.62	0.60	0.58	0.50	0.60	0.58	0.50	0.61	0.45	0.33
0.86	0.84	0.74	0.58	0.51	0.39	0.73	0.92	0.91	0.49	0.74
0.96	0.67	0.54	0.85	0.48	0.37	0.88	0.90	0.94	0.82	0.93
0.69	0.49	0.56	0.66	0.43	0.42	0.77	0.73	0.71	0.90	0.99
0.79	0.73	0.90	0.67	0.33	0.61	0.69	0.79	0.73	0.93	0.97
0.91	0.94	0.89	0.49	0.41	0.78	0.78	0.77	0.89	0.99	0.93

Slide credit: Derek Hoiem

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Spatial resolution

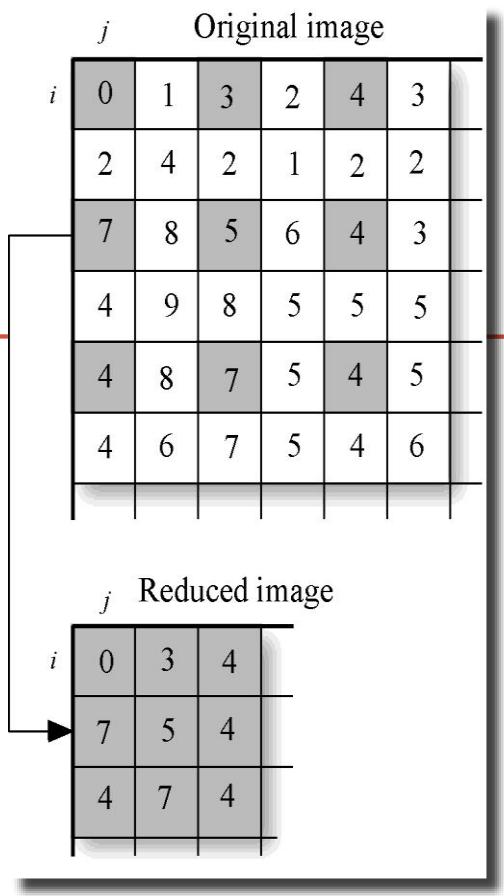
- **Sensor resolution**: size of real-world scene element that images to a single pixel

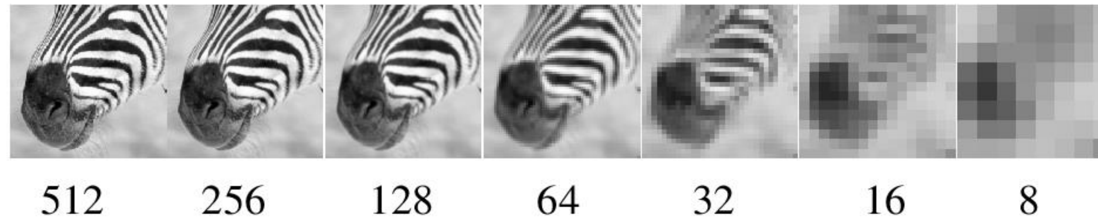
- **Image resolution**: number of pixels

[fig from Mori et al]

It influences what analysis is feasible, it affects best representation choice.

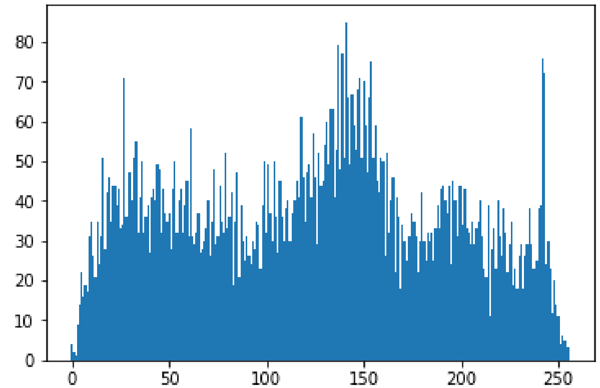
Image reduction






This is actually a black and white

Photometric resolution



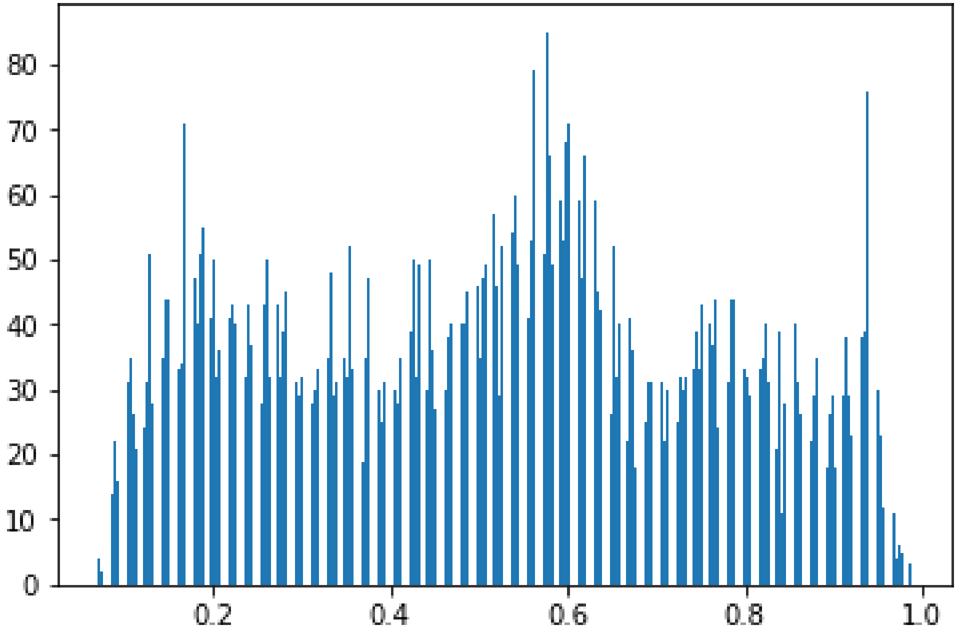
Given an image of type uint8, how many grey levels we can have at most?

A **histogram** of an image represents the frequencies of the image gray levels.

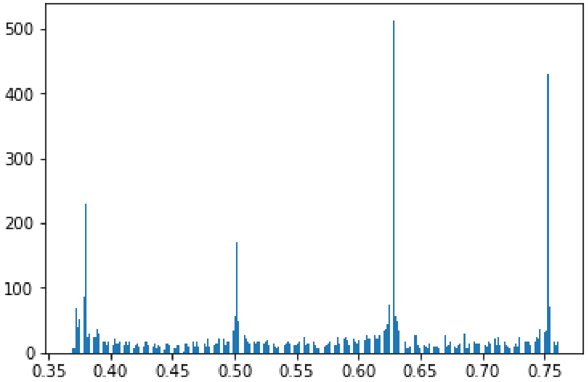
- Does it depend on the spatial distribution? Mayor distribución si hay más píxeles, o viceversa (a no ser que esté normalizado).
- Can it be considered as a measure of image quality? Más o menos distribuido según el nivel de gris.

The number of different grey levels (different pixel values in each color channel) determines the **photometric resolution** of the image.

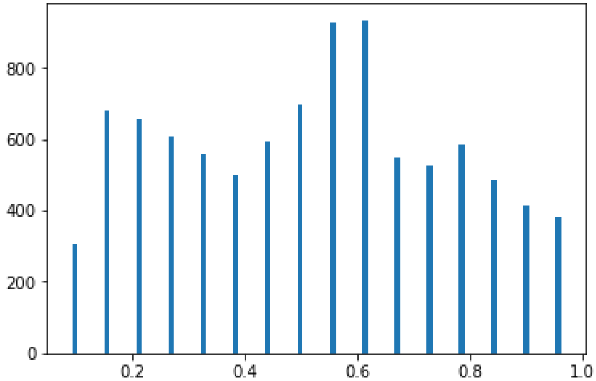
Histogram



Histogram



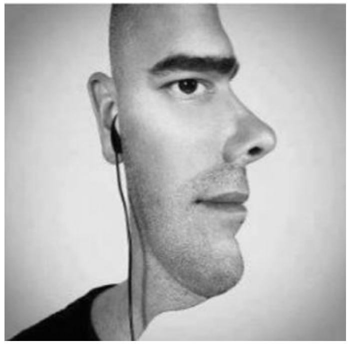
How will the histogram of the right image look?

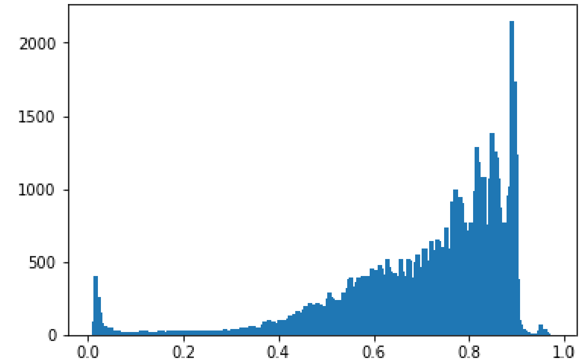


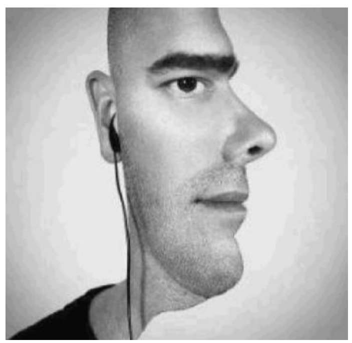
Histogram of 16 bins

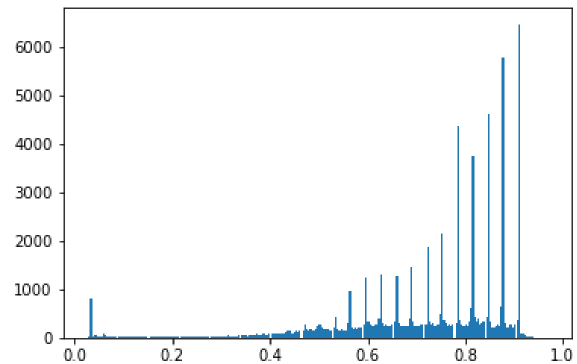
Para cada nivel de gris nos da el # de pixels. Habrá momentos que querremos agrupar varios niveles en grupos (bins).

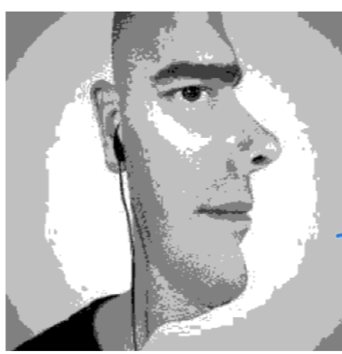
Histogram: How should the histograms look?



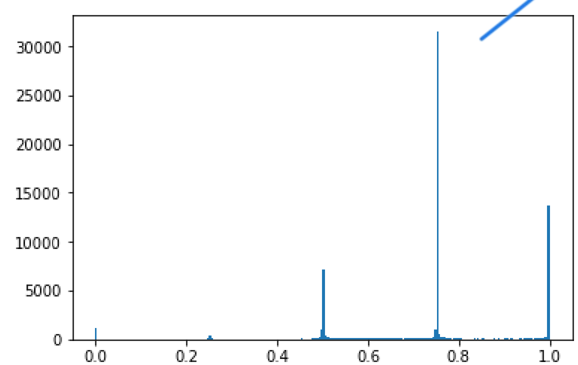






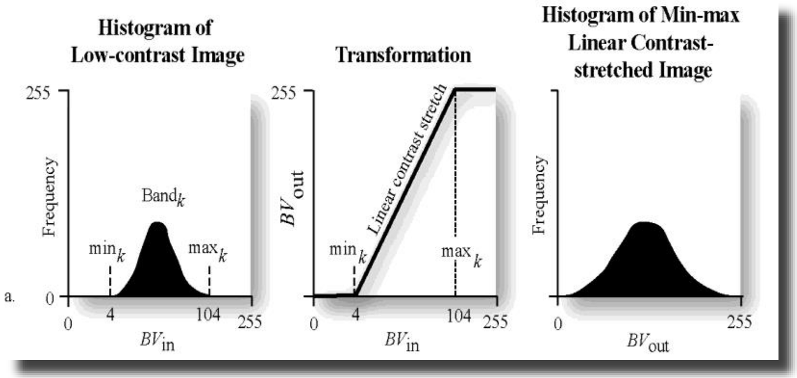


4 niveles de gris



Nos puede dar una idea de la calidad de una imagen (pero hemos de saber cuántos niveles tenemos, etc)

Histogram manipulation for contrast enhancement



Multiply the image to augment its contrast:

$$BV_{out} = \left(\frac{BV_{in} - \min_k}{\max_k - \min_k} \right) quant_k$$

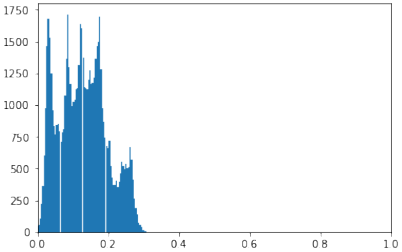
where:

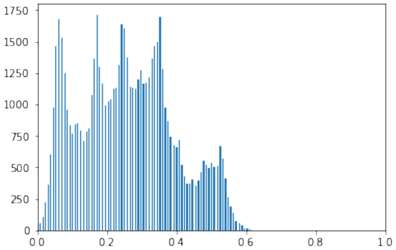
- BV_{in} is the original input brightness value (i.e. the original image)
- $quant_k$ is the range of the brightness values that can be displayed on the CRT (eg 255),
- min_k is the minimum value in the image,
- max_k is the maximum value in the image, and
- BV_{out} is the output brightness value.

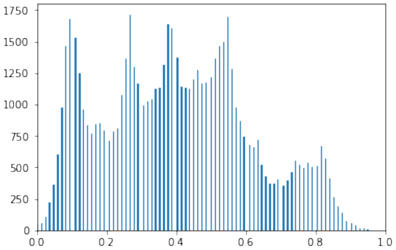
Histogram manipulation for contrast enhancement

$$BV_{out} = \left(\frac{BV_{in} - \min_k}{\max_k - \min_k} \right) quant_k$$









Did we augment the photometric quality really? No hemos aportado + información pero percibimos mejor la imagen.

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- How to process by a linear filter
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Image filtering

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0.89	0.72	0.51	0.55	0.51	0.42	0.57	0.41	0.49	0.91	0.92
0.96	0.95	0.88	0.94	0.56	0.46	0.91	0.87	0.90	0.97	0.95
0.71	0.81	0.81	0.87	0.57	0.37	0.80	0.88	0.89	0.79	0.85
0.49	0.62	0.60	0.58	0.50	0.60	0.58	0.50	0.61	0.45	0.33
0.86	0.84	0.74	0.58	0.51	0.39	0.73	0.92	0.91	0.49	0.74
0.96	0.67	0.54	0.85	0.48	0.37	0.88	0.90	0.94	0.82	0.93
0.69	0.49	0.56	0.66	0.43	0.42	0.77	0.73	0.71	0.90	0.99
0.79	0.73	0.90	0.67	0.33	0.61	0.69	0.79	0.73	0.93	0.97
0.91	0.94	0.89	0.49	0.41	0.78	0.78	0.77	0.89	0.99	0.93

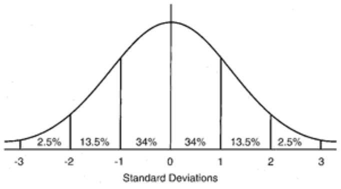
- **Filtering**: Compute a function of the local neighborhood at each pixel in the image
  - Function specified by a “filter” or mask saying how to combine values from neighbors.

- Uses of filtering:
  - Enhance an image (denoise, etc)
  - Extract information (edges, etc)
  - Detect patterns (template matching)

Adapted from Derek Hoiem

Common types of noise

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




Original

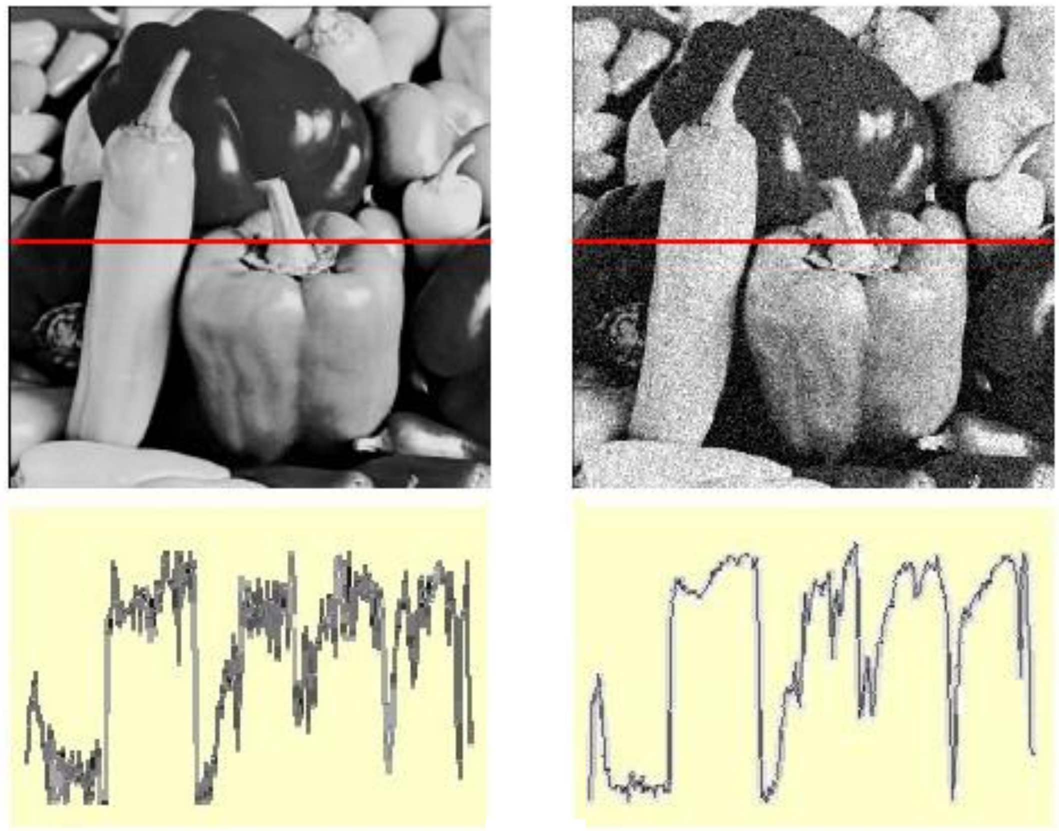

Salt and pepper noise


Impulse noise


Gaussian noise

Source: S. Seitz

Gaussian noise



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

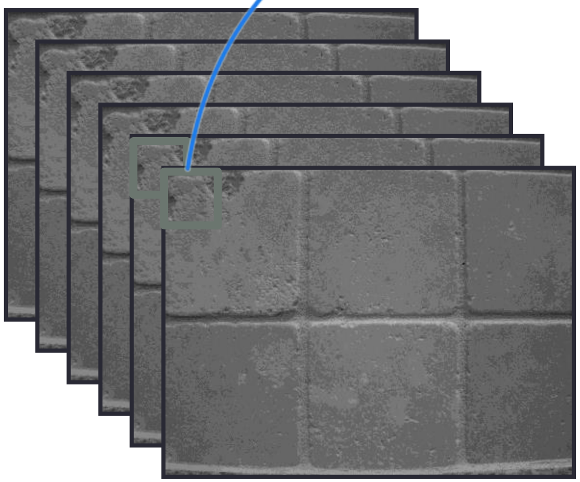
Gaussian i.i.d. ("white") noise:
$\eta(x,y) \sim \mathcal{N}(\mu,\sigma)$

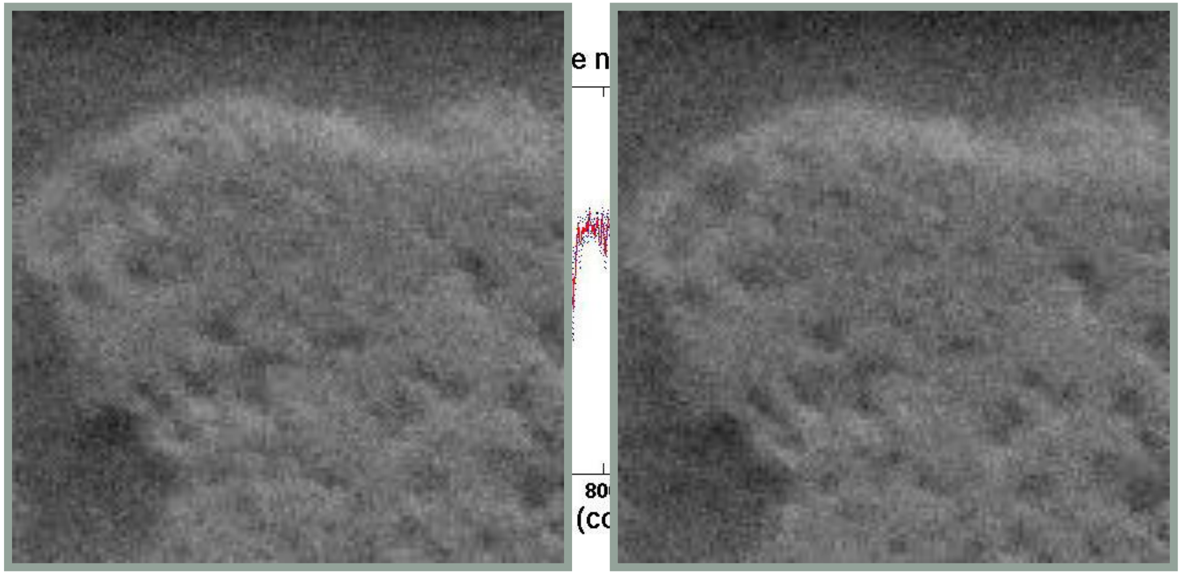
What is the impact of sigma (var) parameter?

Fig: M. Hebert

Motivation: noise reduction

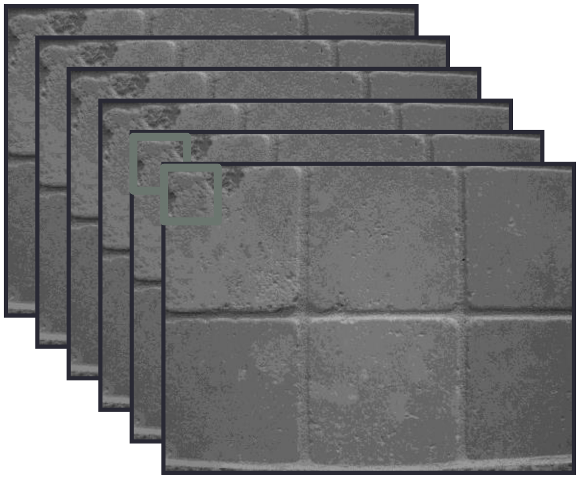
Hacemos un promedio.

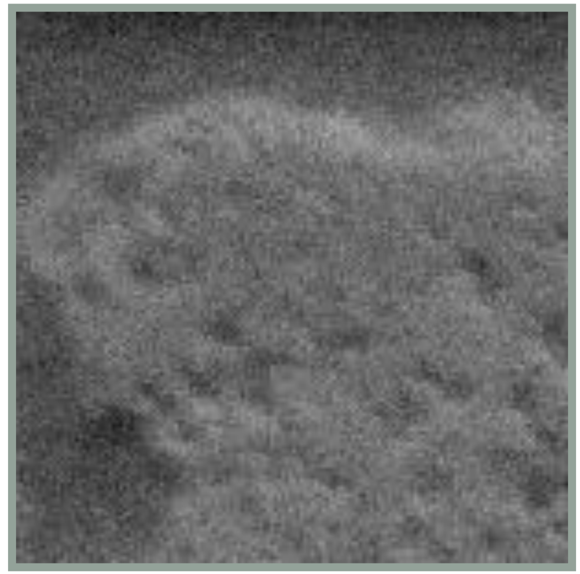


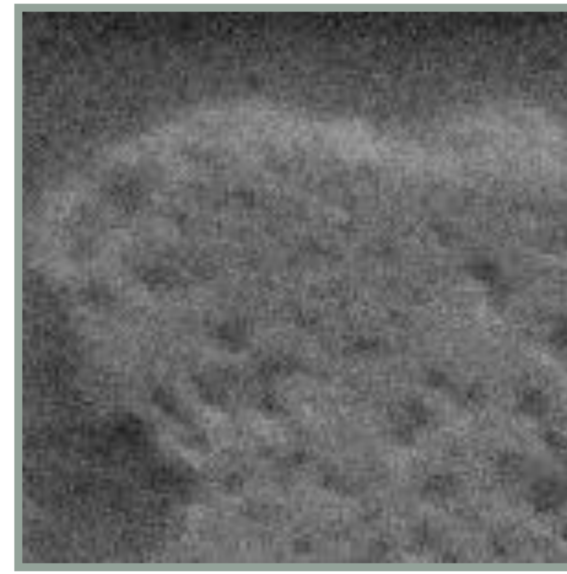


- Even multiple images of the **same static scene** will not be identical.

Motivation: noise reduction







- Even multiple images of the same static scene will not be identical.
- How could we reduce the noise, i.e., give an estimate of the true intensities?
  - Take the average of the grey values per pixel.

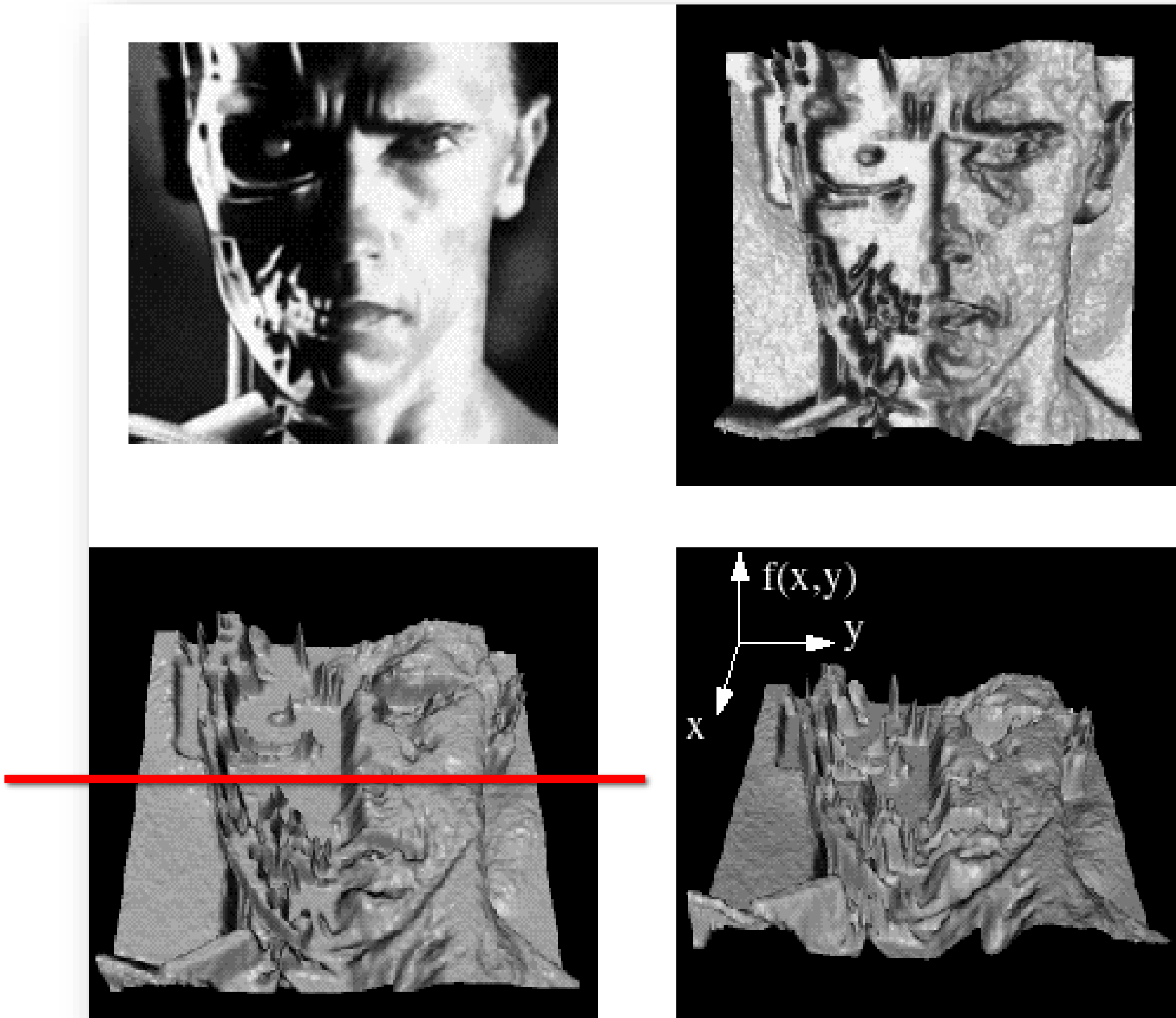
- **What if there's only one image?**

First attempt at a solution

- Let's replace each pixel with an average of all the values in its neighborhood
- Assumptions:
  - Expect pixels to be like their neighbors
  - Expect noise processes to be independent from pixel to pixel

Que no dependa de la posición en la imagen

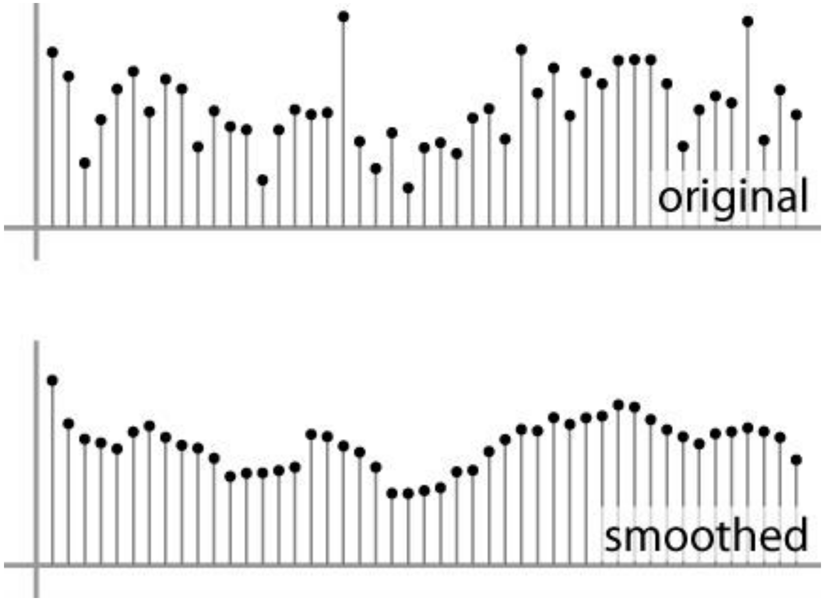
Remember: an image is a matrix & topographic map



First attempt at a solution

- Let's replace each pixel with an average of all the values in its neighborhood

- Moving average in 1D:



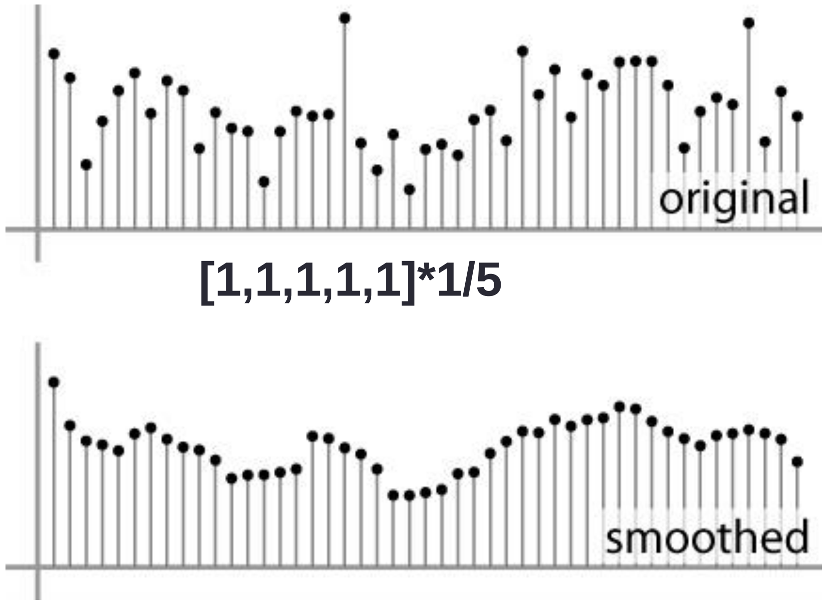
Source: S. Marschner

First attempt at a solution

- What is the average value?
- (F[i-2]+F[i-1]+F[i]+F[i+1]+ F[i+2])/5

vecinos vecinos

- For each pixel i, multiply its neighbourhood by a mask:
  - [1,1,1,1,1]*1/5= [1/5,1/5,1/5,1/5,1/5,1/5]



Definition: Convolution

$$(F*G)[i]=\sum_{m=-M}^{M} F[i-m]g[m]$$

Source: S. Marschner

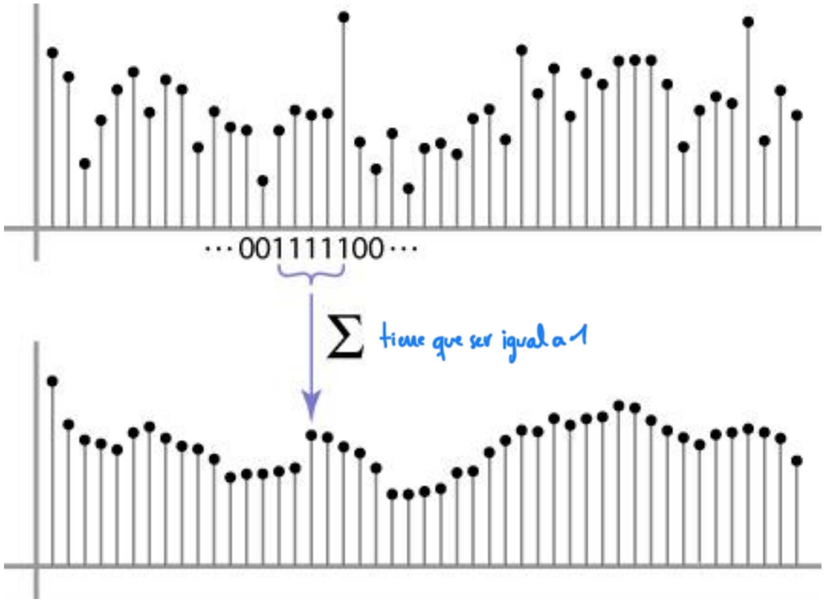
Weighted Moving Average – Mean filter

Estamos dando el mismo peso a todos los pixels.

- *Weights* [1, 1, 1, 1, 1] / 5

El pixel i debería tener el mayor peso

- Why are we dividing by 5? Porque tenemos 5 valores.

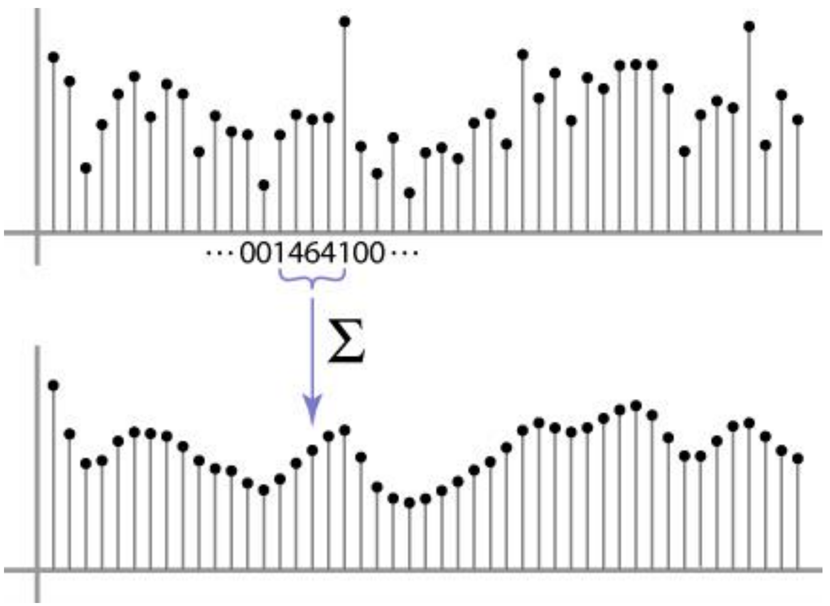


Can we add weights to our moving average? Why?

Source: S. Marschner

Weighted Moving Average

- Non-uniform weights [1, 4, 6, 4, 1] / 16



- What is the difference with the previous one?

Source: S. Marschner

Moving Average in 2D

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

	0								

Source: S. Seitz

Moving Average in 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10							

Source: S. Seitz

Moving Average in 2D

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

	0	10	20						

Source: S. Seitz

Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20	30					

Source: S. Seitz

Moving Average in 2D

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$G[x, y]$

	0	10	20	30	30				

Source: S. Seitz

Moving Average in 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

Source: S. Seitz

Linear filter

$F[x, y] \otimes H[u, v]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

a	b	c
d	e	f
g	h	i

“box filter”

$$G = H \otimes F$$

Convolution

la Σ de los coeficientes ha de ser = 1.

$$df[i,j] = a * f[i-1, j-1] + b * f[i-1, j] + c * f[i-1, j+1] +$$
$$d * f[i, j-1] + e * f[i, j] + f * f[i, j+1] +$$
$$g * f[i+1, j-1] + h * f[i+1, j] + i * f[i+1, j+1]$$

Para cada pixel.

Linear filter

- Normalization: divide the mask by (a+b+c+d+e+f+g+h+i)

$F[x, y]$ $\otimes$ $H[u, v]$ $G[x, y]$

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$H[u, v]$

a	b	c
d	e	f
g	h	i

"box filter"

***1/(a+b+c+d+e+f+g+h+i)**

$G[x, y]$

	0	10	20	30	30				

$$G = H \otimes F$$

Convolutional filtering

Say the averaging window size is (2k+1) x (2k+1):

$$G[i,j] = \underbrace{\frac{1}{(2k+1)^2}}_{\text{Attribute uniform weight to each pixel}} \underbrace{\sum_{u=-k}^{k} \sum_{v=-k}^{k} F[i+u, j+v]}_{\text{Loop over all pixels in neighborhood around image pixel F[i,j]}}$$

Convolutional filtering

Now generalize to allow **different weights** depending on neighboring pixel's relative position:

Máscara

Por este término no tenemos que normalizar porque sabemos que es igual a 1.

$$G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} \underbrace{H[u,v]}_{\textit{Non-uniform weights}} F[i+u, j+v]$$

Convolutional filtering

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

This is called **convolution**, denoted as: $G = H \otimes F$

Filtering an image: replace each pixel with a linear combination of its neighbors.

The filter "**kernel**" or "**mask**" *H*[*u*,*v*] is the prescription for the weights in the linear combination.

Mean filter

- What values do belong in the kernel *H* for the moving average example?

$F[x,y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$\otimes$

$H[u,v]$

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & ? & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

“box filter”

$G[x,y]$

	0	10	20	30	30				

$$G = H \otimes F$$

Mean filter

- Normalization: why do we need to divide the mask by 9?

$F[x, y]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$\otimes$

$H[u, v]$

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & ? & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

"box filter"

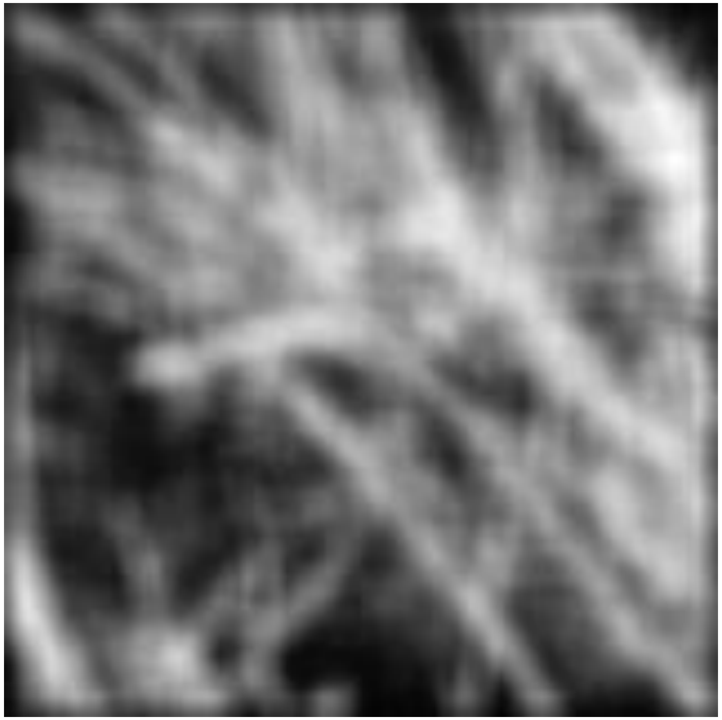
$G[x, y]$

	0	10	20	30	30				

$$G = H \otimes F$$

Smoothing by averaging

original



filtered

What is the effect if the filter size was 5 x 5 instead of 3 x 3?

Filtering an impulse signal

What is the result of filtering the impulse signal (image) *F* with the arbitrary kernel *H*?

0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

$F[x, y]$

$\otimes$

a	b	c
d	e	f
g	h	i

$H[u, v]$

			?			

$G[x, y]$

Practice with linear filters

Original

0	0	0
0	1	0
0	0	0

?

Source: D. Lowe

Practice with linear filters

0	0	0
0	1	0
0	0	0

Original

Filtered (no change)

Source: D. Lowe

Practice with linear filters

Original

0	0	0
0	0	1
0	0	0

?

Source: D. Lowe

Practice with linear filters

Original

0	0	0
0	0	1
0	0	0

Shifted left by 1 pixel with correlation

Source: D. Lowe

Practice with linear filters

Original

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

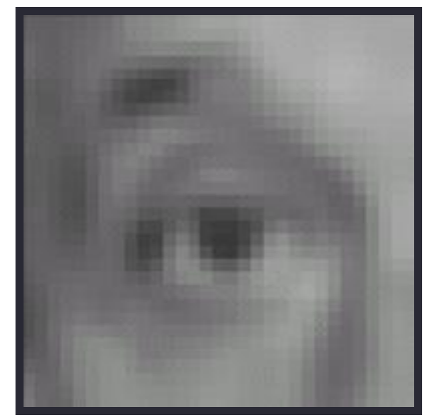
?

Source: D. Lowe

Practice with linear filters

Original

$$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$



Blur (with a box filter)

Source: D. Lowe

Practice with linear filters

Original

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad ?$$

Source: D. Lowe

Properties of convolution

- **Shift invariant:**
  - Operator behaves the same everywhere, i.e. the value of the output depends on the pattern in the image neighborhood, not the position of the neighborhood.
- **Superposition:**
  - $h * (f1 + f2) = (h * f1) + (h * f2)$

Smoothing with a rectangular filter

I[x,y]

A

h[i,j]

=

f[x,y]

$$\text{Mask}=1/25* \begin{matrix} 1,1,1,1,1 \\ 1,1,1,1,1 \\ 1,1,1,1,1 \\ 1,1,1,1,1 \\ 1,1,1,1,1 \end{matrix}$$

Smoothing with a rectangular filter

I[x,y]

A =

h[i,j]

f[x,y]

Mask= 1/5*[1,1,1,1,1]

Ha suavizado demasiado.

Smoothing with a rectangular filter

I[x,y]

A

h[i,j]

=

f[x,y]

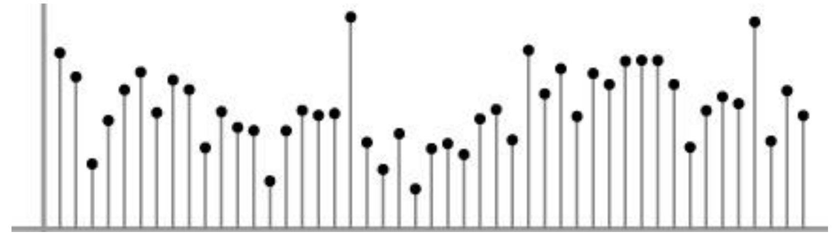
Mask=1/5* 1, 1, 1, 1, 1

Today

- What is an image?
  - Types, color vs gray level
- How to measure the quality of an image?
  - Spatial and photometric resolution
  - Histogram and image contrast enhancement
- How to process by a linear filter
  - Examples: smoothing filters
  - Convolution / correlation
  - Mean and median filters
  - Linear filters with Gaussians

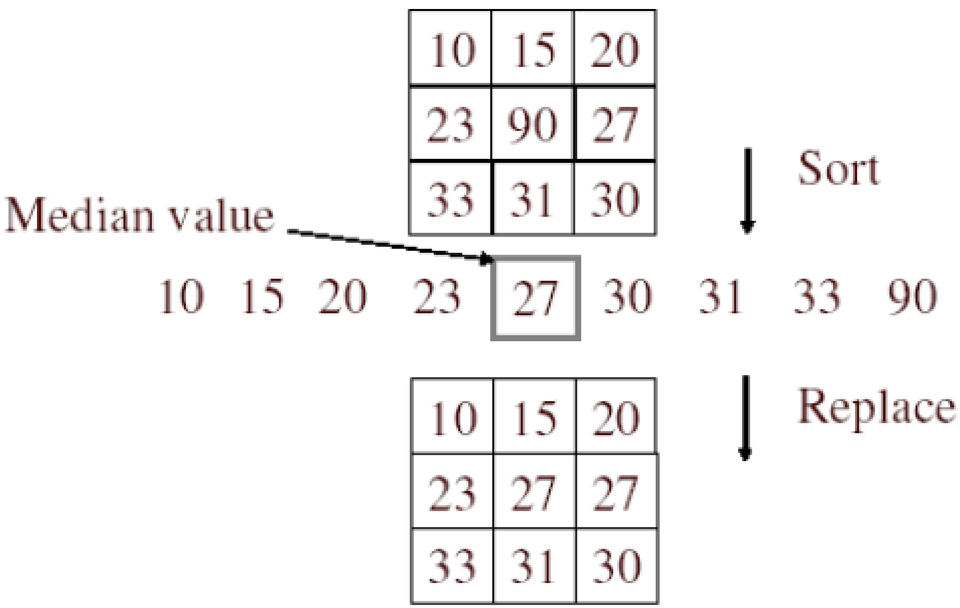
Median filter

What is the behavior of the mean filter in the impulse noise pixels?



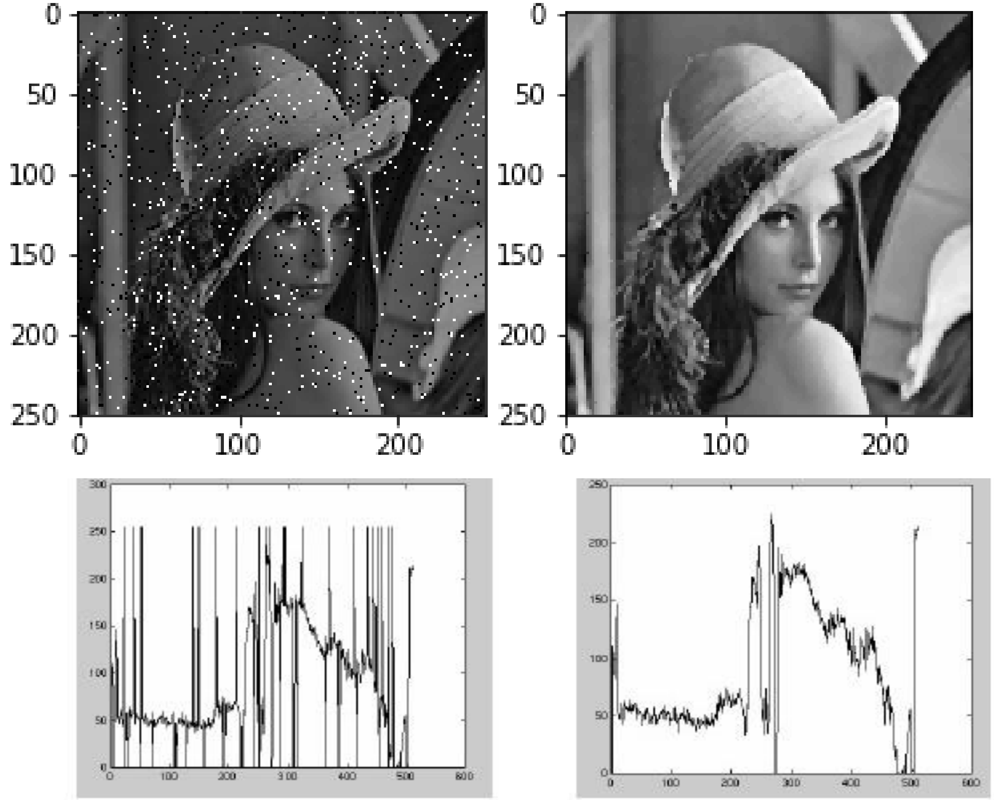
- No new pixel values introduced
- Removes spikes: good for impulse, salt & pepper noise

•Non-linear filter (it can be proved)



Median filter

Salt and pepper noise



Median filtered

Plots of a row of the image

Source: M. Hebert

Median filter vs Mean filter

Introduce the captions of the images

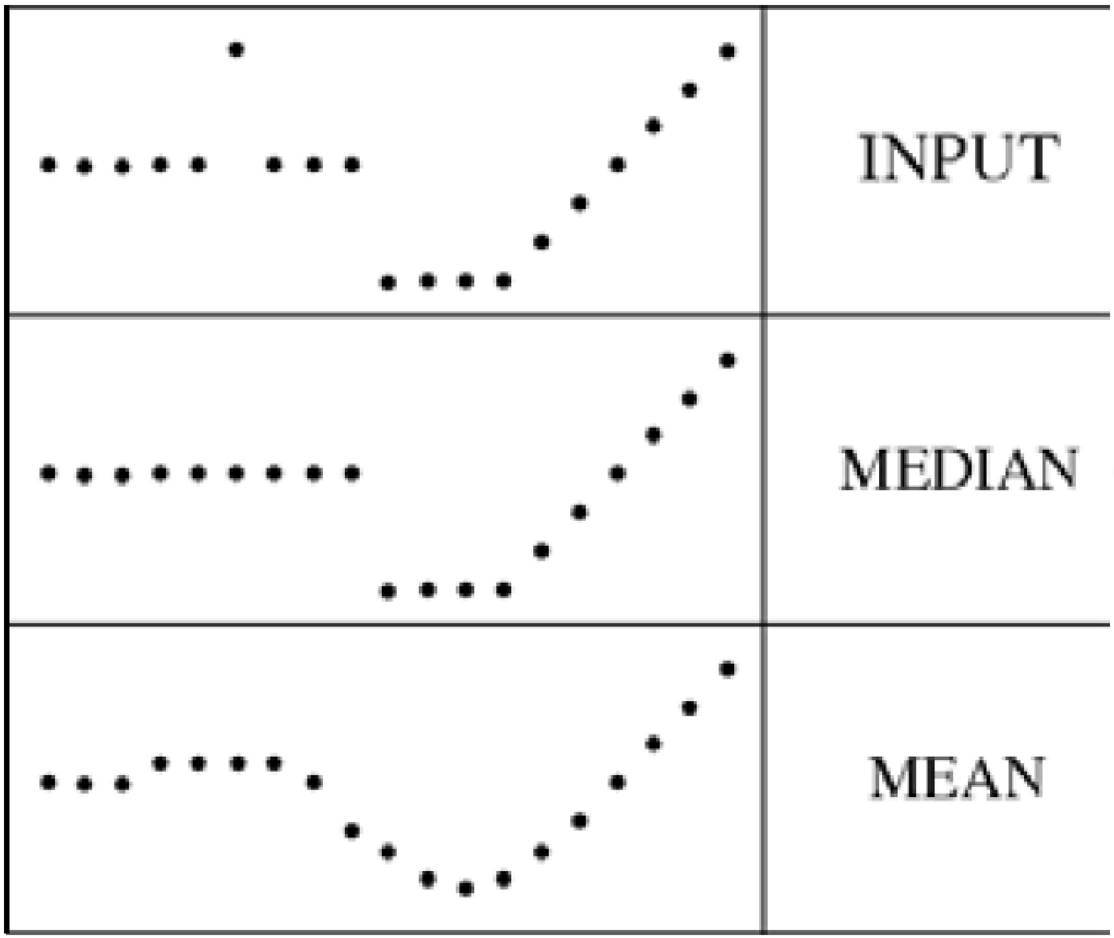
Mediana

Promedio

Source: M. Hebert

Median filter

- Median filter is edge preserving



más costosa a nivel de tiempo

What would be the result of a mean filter?

Today

- What is an image?
  - Types, color vs gray level

- How to measure the quality of an image?
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  - Histogram and image contrast enhancement

- How to process by a linear filter
  - Examples: smoothing filters
  - Convolution / correlation
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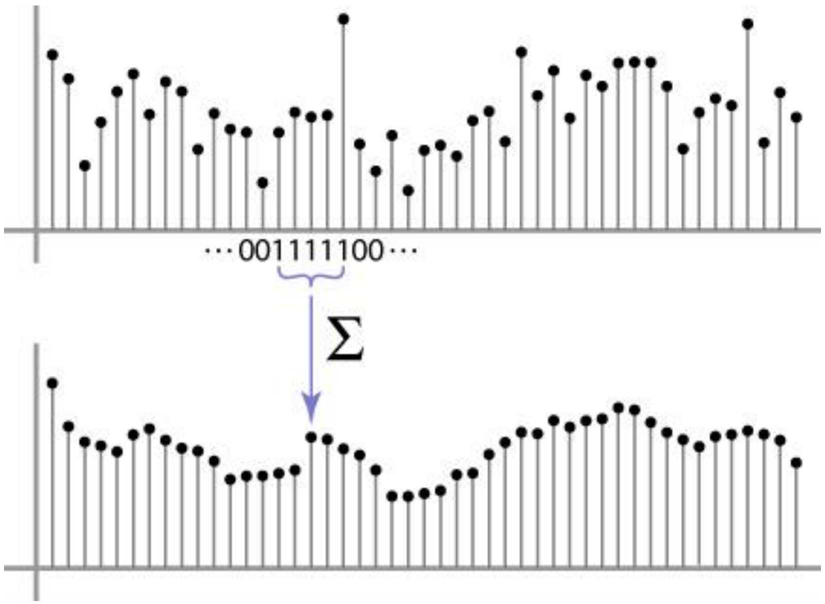
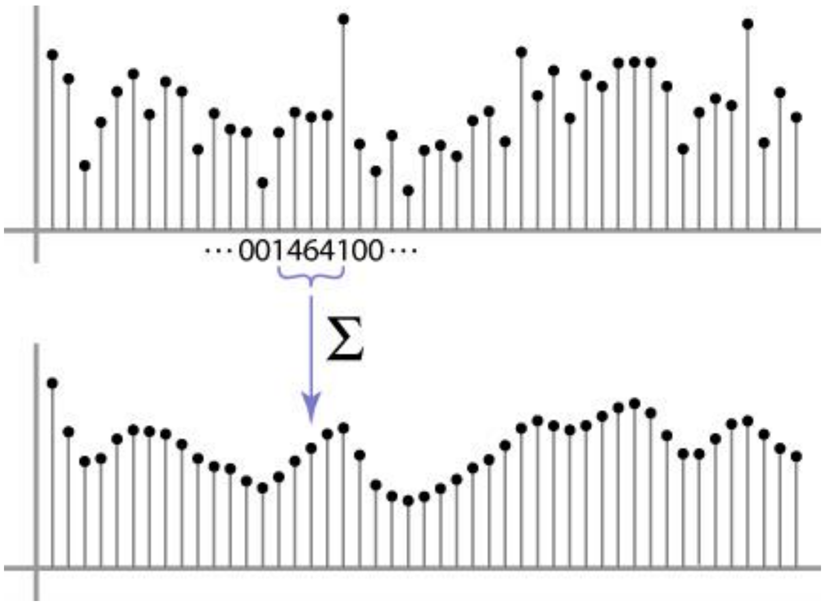
  - Linear filters with Gaussians

Weighted Moving Average

- *Weights* [1, 1, 1, 1, 1] / 5
- **Non-uniform weights [1, 4, 6, 4, 1] / 16**





Adding weights to our moving average? Why?

Source: S. Marschner

Gaussian filter

- What if we want nearest neighboring pixels to have the most influence on the output?

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$F[x, y]$$

$$\frac{1}{16}$$

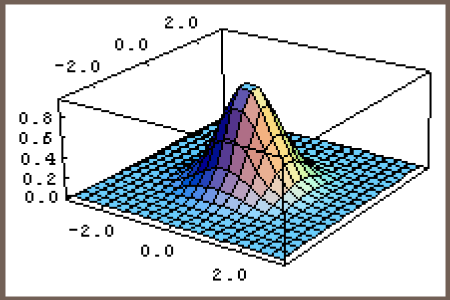
1	2	1
2	4	2
1	2	1

$$H[u, v]$$

This kernel is an approximation of a 2D Gaussian function:

$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$

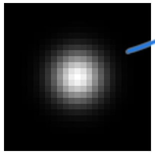
mayor sigma → gaussiana + ancha



Removes high-frequency components from the image ("low-pass filter").

Source: S. Seitz

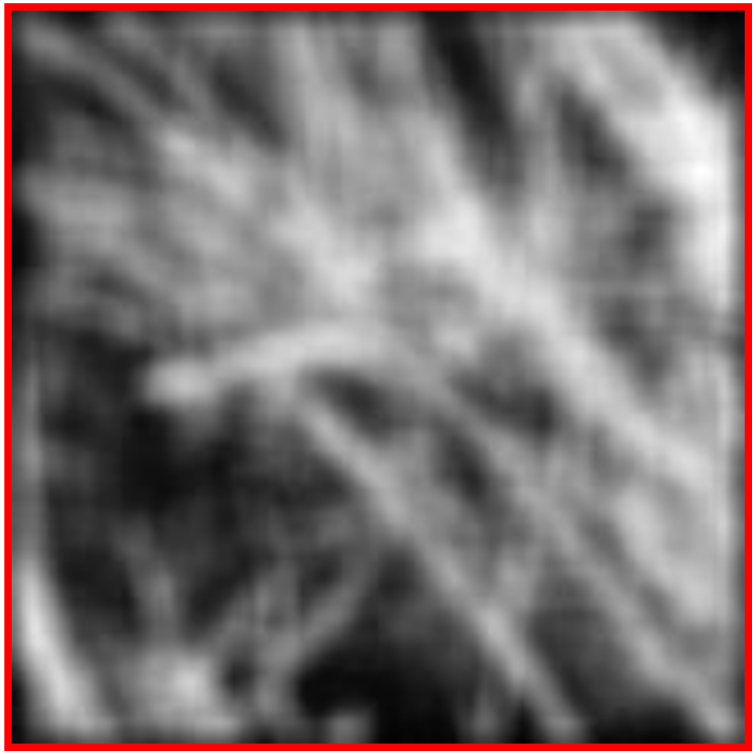
Smoothing with a Gaussian



Gaussiana + ancha = máscara + ancha

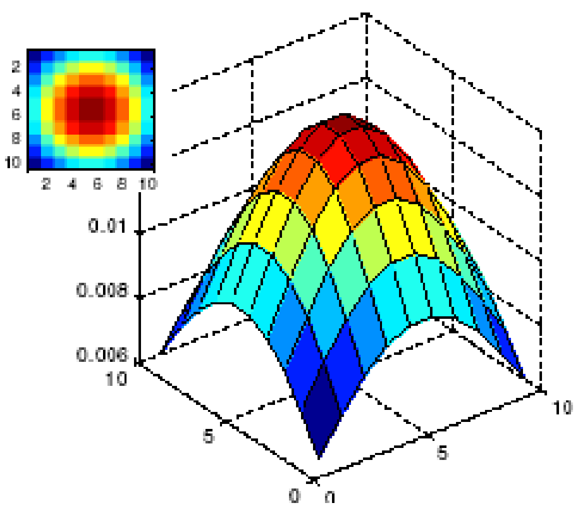
↓

promedio en un área + grande

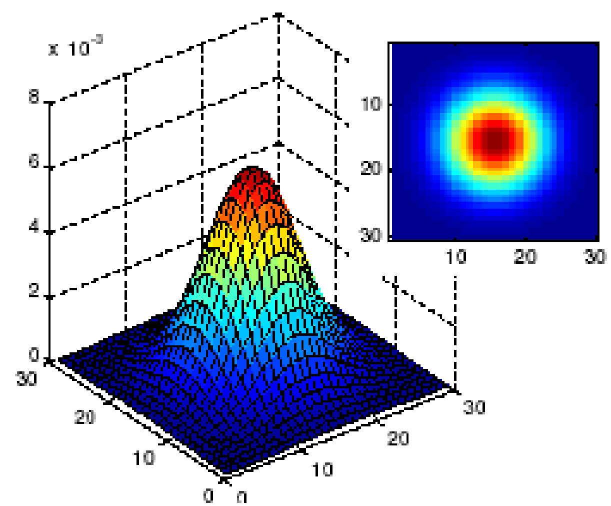


Gaussian filters

- What parameters do matter here?
- **Size** of kernel or mask
  - Note, Gaussian function has infinite support, but discrete filters use finite kernels



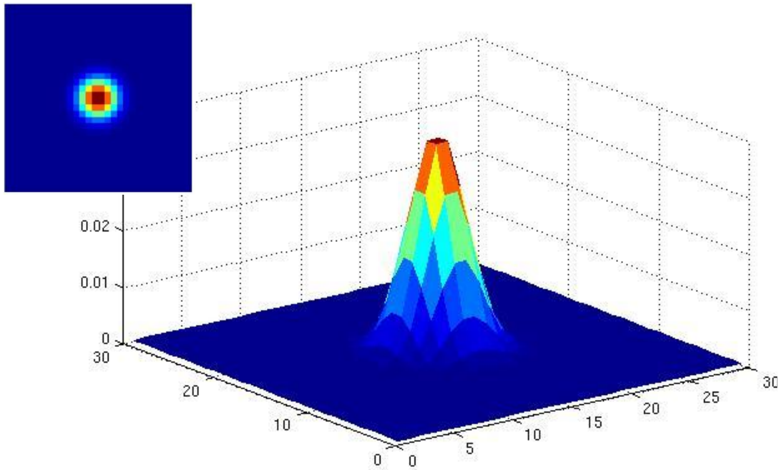
σ = 5 with 10 x 10 kernel



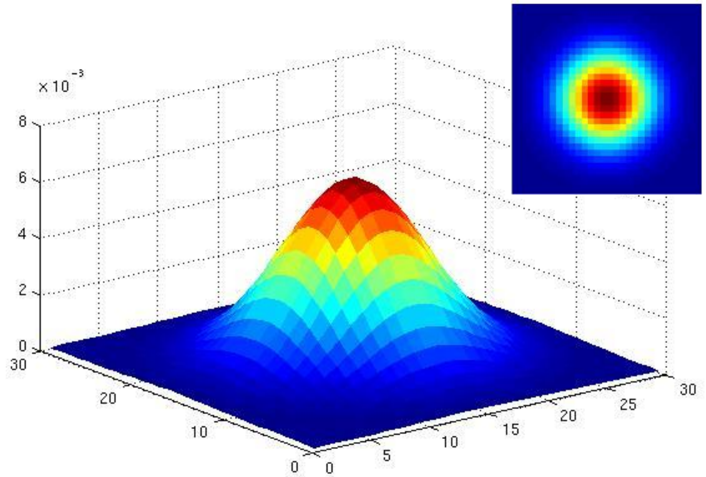
σ = 5 with 30 x 30 kernel

Gaussian filters

- What parameters do matter here?
- **Variance** of Gaussian: determines extent of smoothing



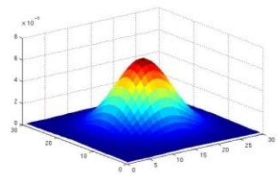
σ = 2 with 30 x 30 kernel

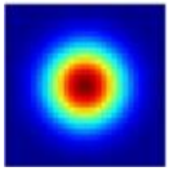


σ = 5 with 30 x 30 kernel

Smoothing with a Gaussian filter

Applying a smoothing operation with a Gaussian with sigma=1



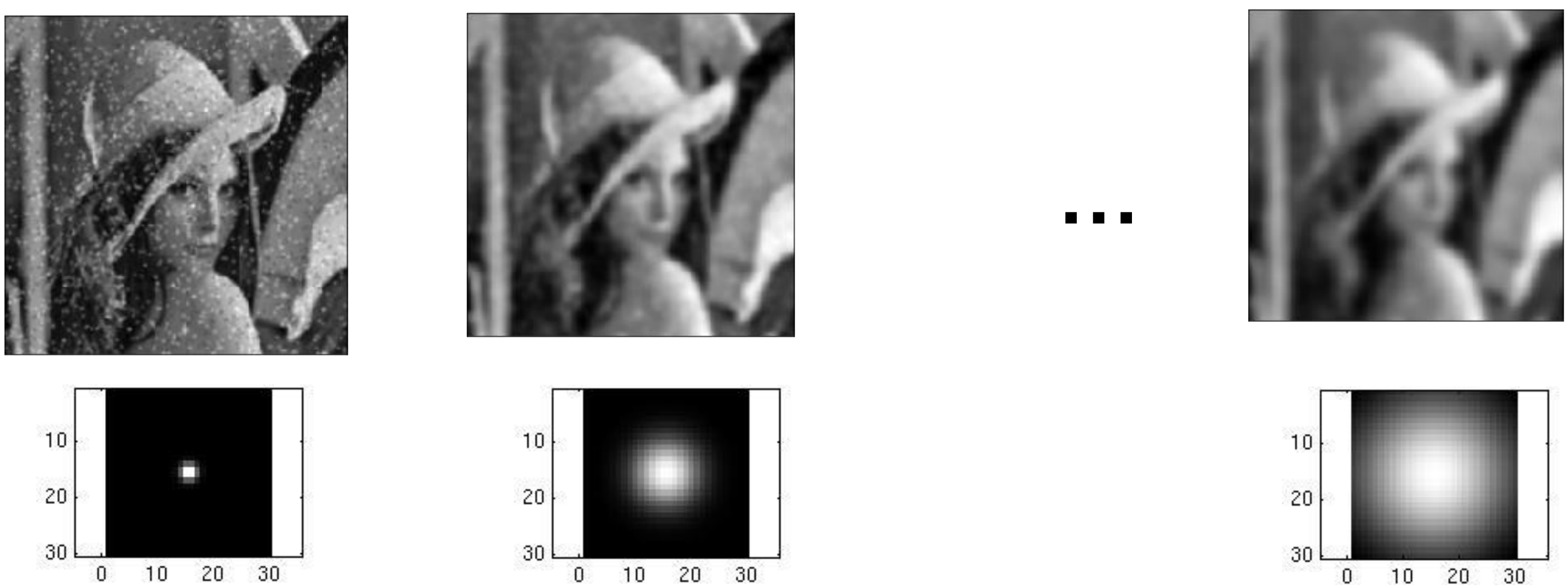


Gaussian filter

output

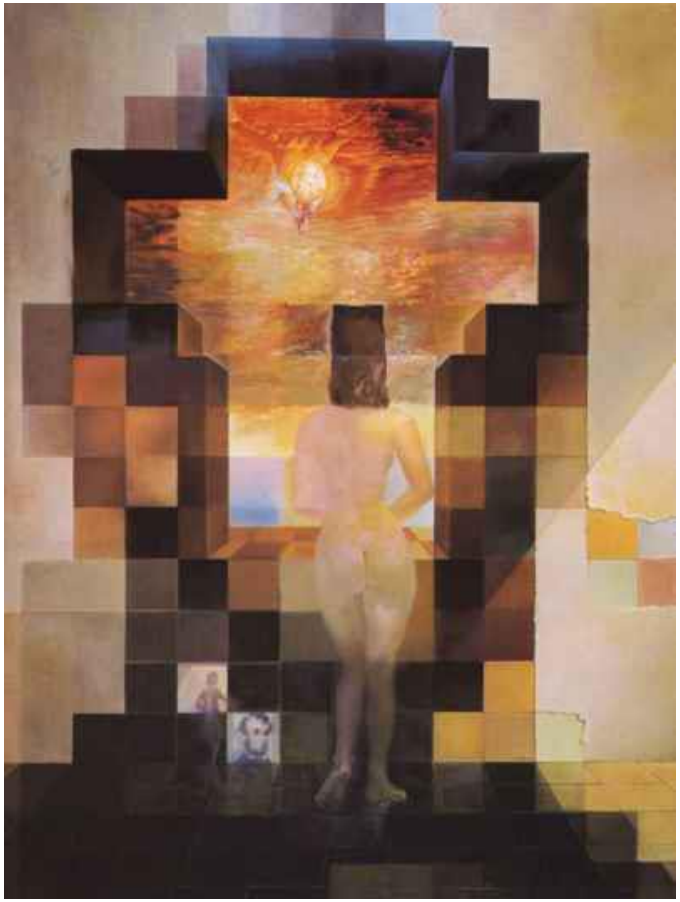
Smoothing with a Gaussian filter

Parameter σ is the “scale” / “width” / “spread” of the Gaussian kernel, and controls the amount of smoothing.

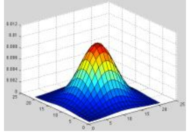


Applying Gaussian smothing with different sigma parameters

Local vs global analysis



Dali



Summary

- Digital images: resolution, “noise”
- Histograms
  - – a tool to visualize the statistical distribution of grey levels of pixels
- Linear filters and convolution useful for
  - Enhancing images (smoothing, removing noise)
    - Box filter
    - Impact of scale / width of smoothing filter
- Gaussians – how to use analytical functions to control processing scale
- Next: convolutions for image Gradient estimation

Properties of smoothing filters

- Smoothing
  - Values positive
  - Sum to 1 → constant regions same as input
  - Amount of smoothing proportional to mask size
  - Remove "high-frequency" components; "low-pass" filter
- Test:

  → espacial no porque no cambiamos el tamaño

  - Smoothing can improve fotamétrica. resolution and quality
  - Smoothing does not improve .spatial resolution
  - ..Spatial....... resolution affects the speed of the algorithms
  - ..Fotométrica..... resolution does not affect the speed of the algorithms.