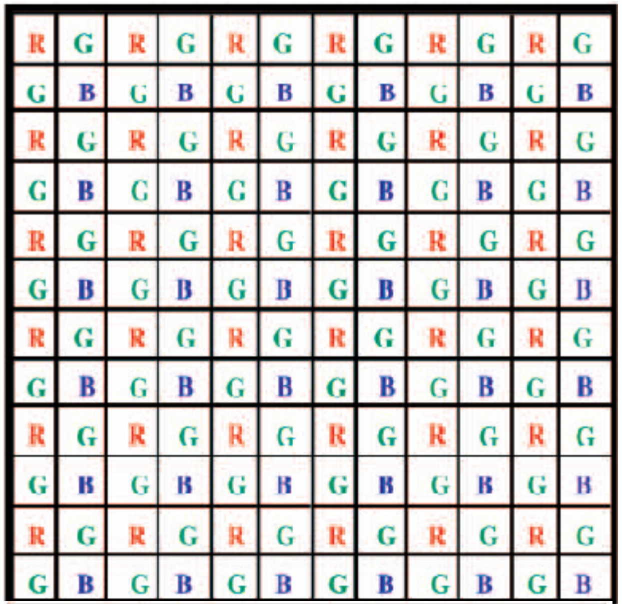
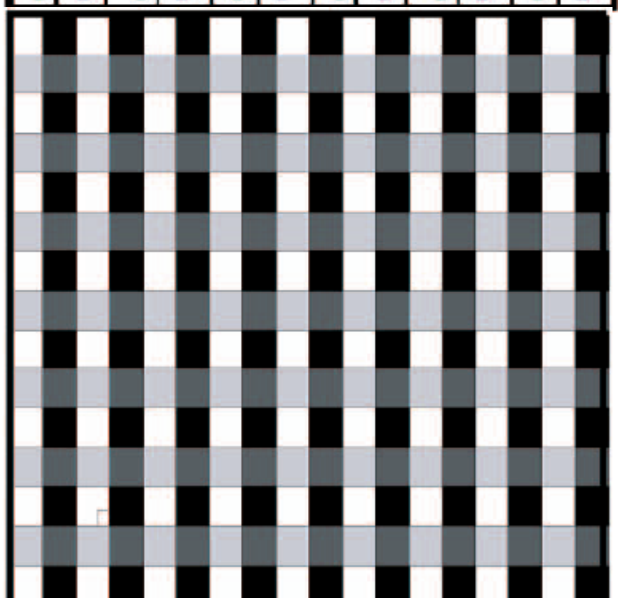
HDR Video

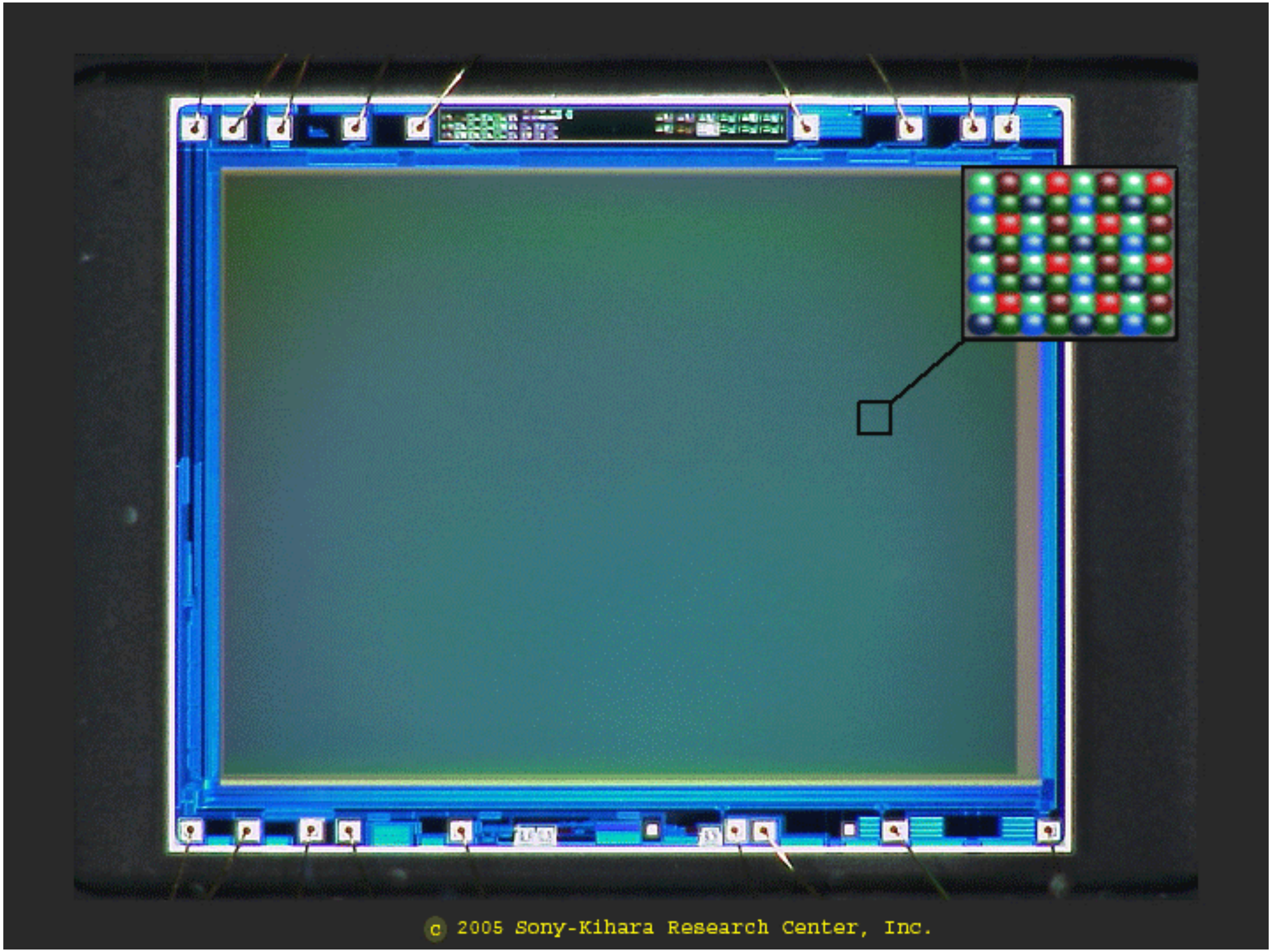

High Dynamic Range Video
Submitted to SIGGRAPH 2003
Paper #125

Assorted pixel (Single Exposure HDR)



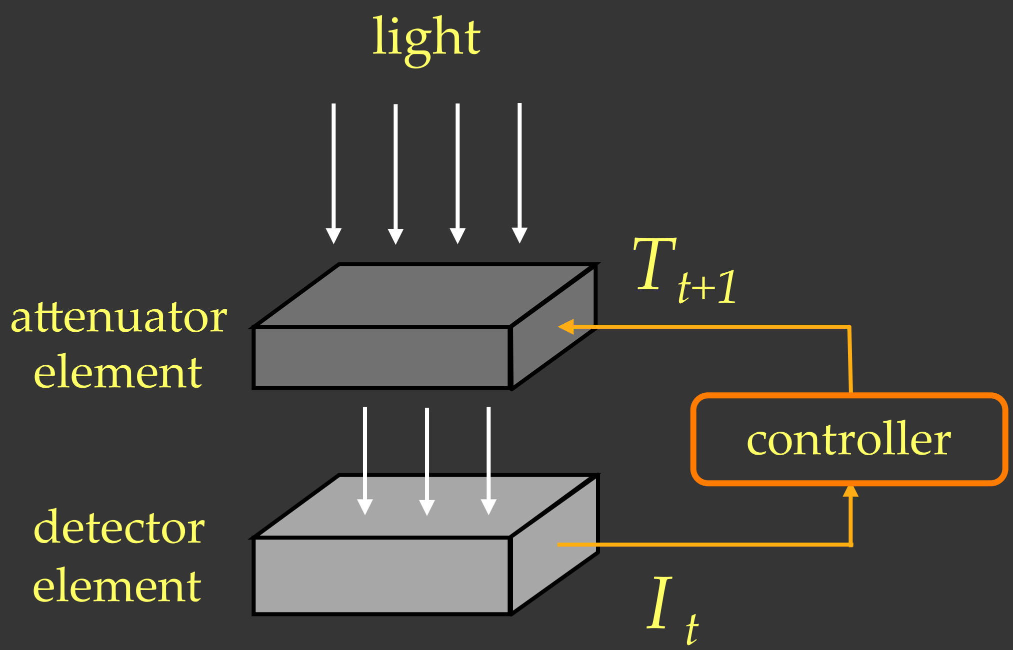


Assorted pixel

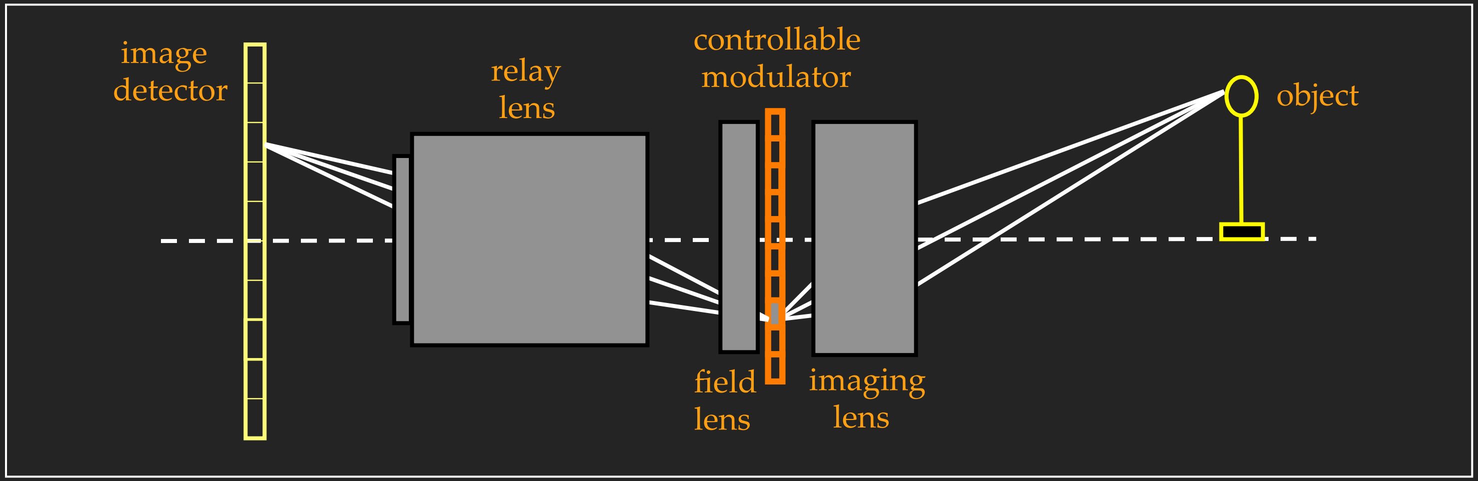


Assorted pixel

Pixel with Adaptive Exposure Control



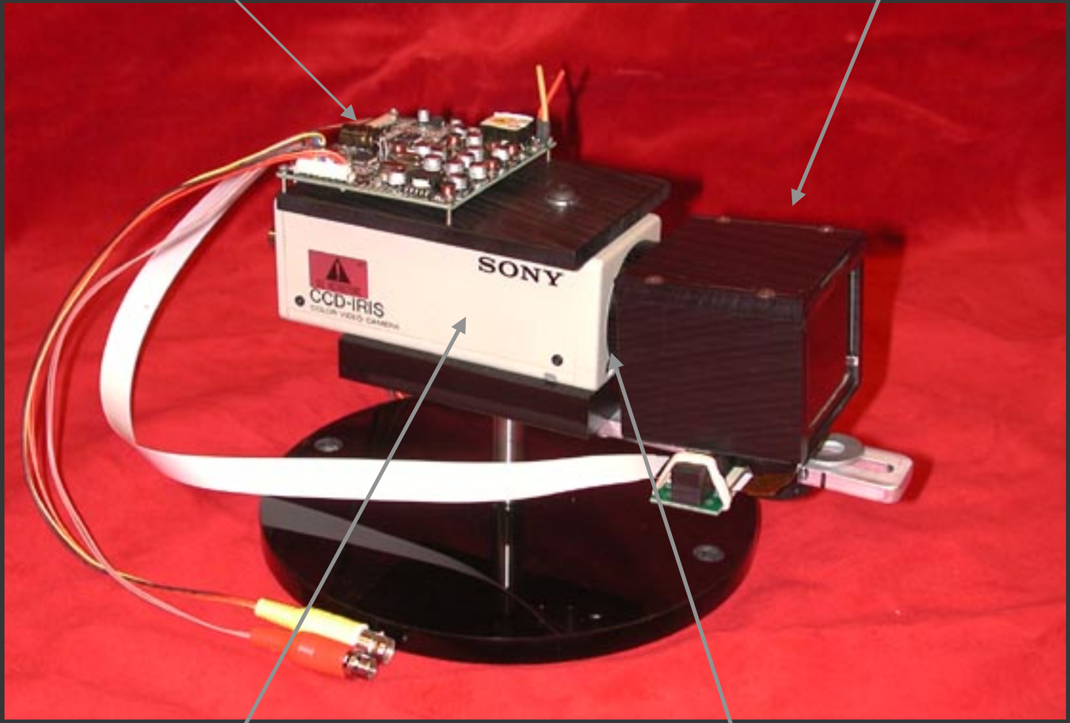
ADR Imaging with Spatial Light Modulator



ADR Camera with LCD Attenuator

LCD Electronics

LCD Attenuator



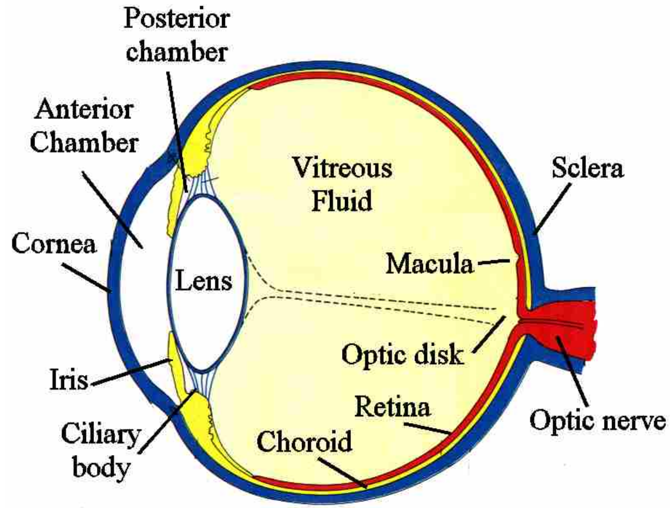
Video Camera

Imaging Lens

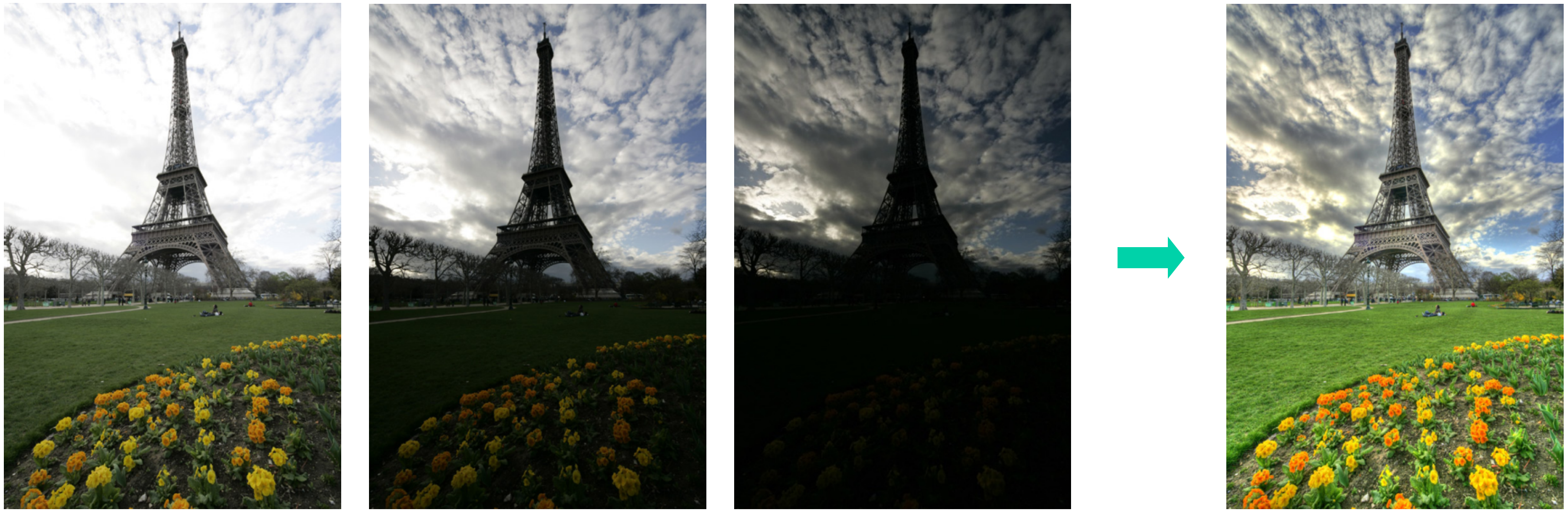
ADAPTIVE DYNAMIC RANGE IMAGING

OPTICAL DYNAMIC ATTENUATION

So far

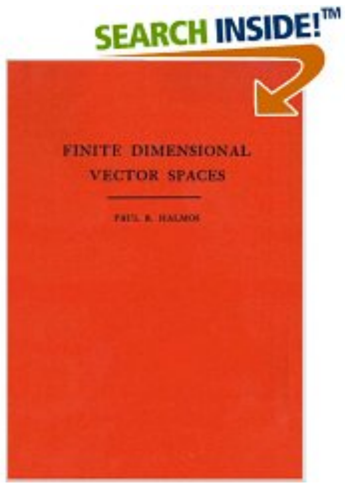


Kimber, D.C.; C.E. Gray, and C.E. Stackpole. (1966). *Anatomy and Physiology*. MacMillan Co., NY. pg 335.

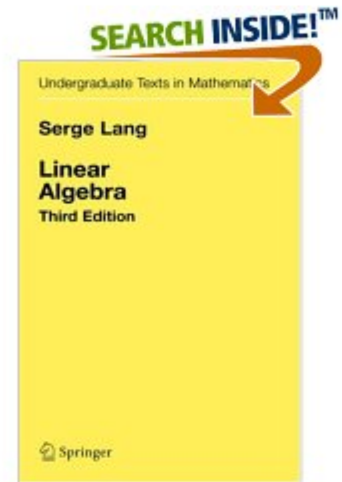


photomatix.com

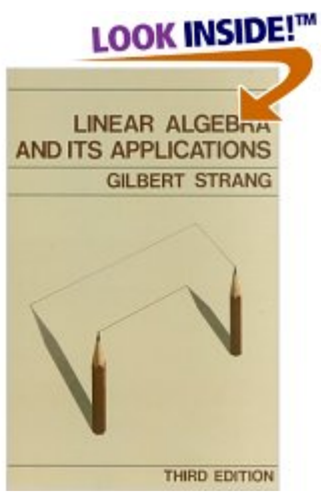
Some books on linear algebra



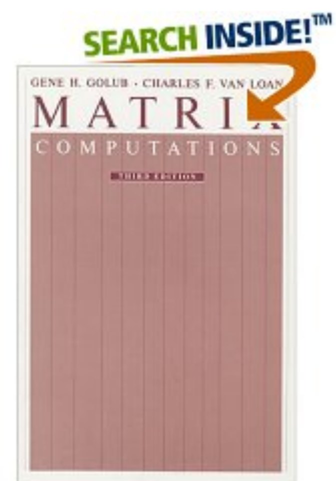
Finite Dimensional Vector Spaces, Paul R. Halmos, 1947



Linear Algebra, Serge Lang, 2004



Linear Algebra and its Applications,
Gilbert Strang, 1988



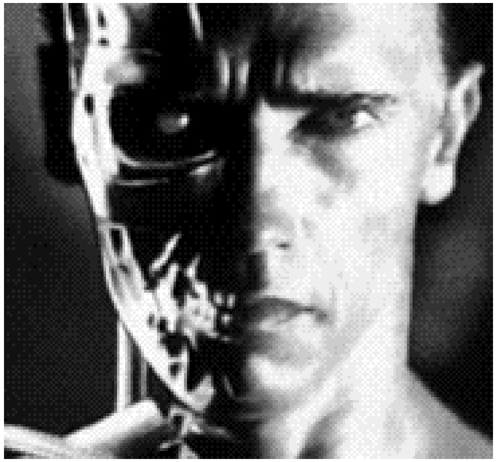
Matrix Computation, Gene H. Golub,
Charles F. Van Loan, 1996

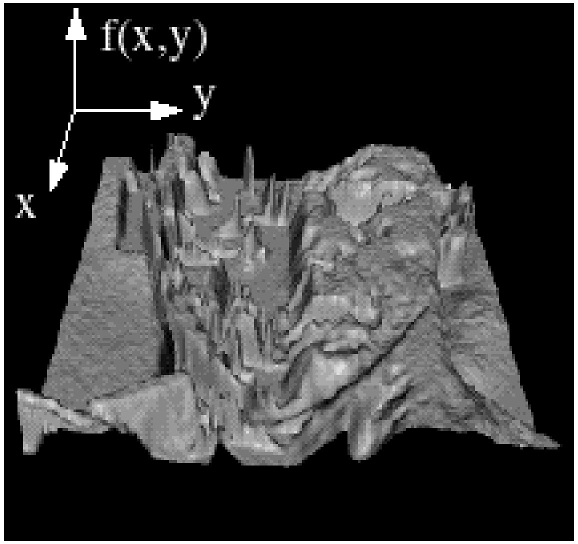
Next

Image Processing: from basic concepts to latest techniques

- Filtering
- Edge detection
- Re-sampling and aliasing
- Image Pyramids (Gaussian and Laplacian)

Image as a discreet function





Represented by a matrix:

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

What is image filtering?

- Modify the pixels in an image based on some function of a local neighborhood of the pixels.

10	5	3
4	5	1
1	1	7

Local image data

Some function $\longrightarrow$

	7	

Modified image data

Linear functions

- Simplest: linear filtering.
  - Replace each pixel by a linear combination of its neighbors.
- The prescription for the linear combination is called the "convolution kernel".

10	5	3
4	5	1
1	1	7

Local image data

0	0	0
0	0.5	0
0	1	0.5

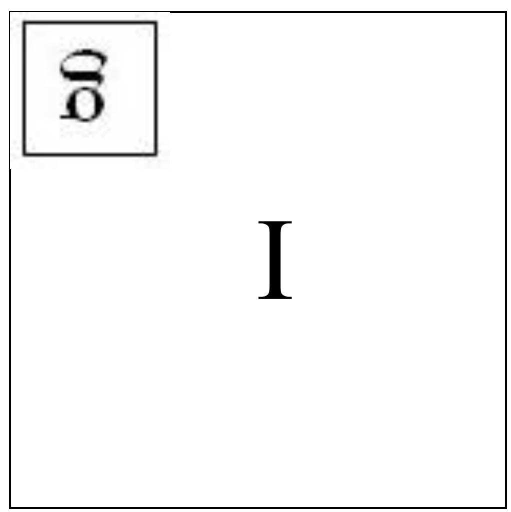
kernel

	7	

Modified image data

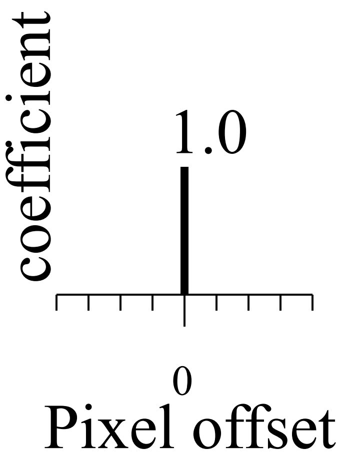
Convolution

$$f[m,n] = I \otimes g = \sum_{k,l} I[m-k, n-l]\, g[k,l]$$



Linear filtering (warm-up slide)

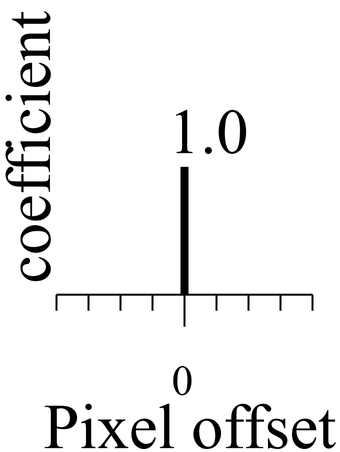
original

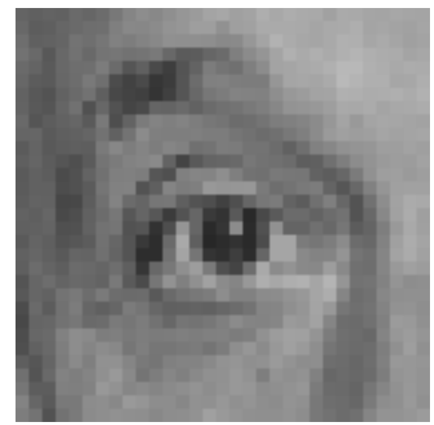


?

Linear filtering (warm-up slide)

original

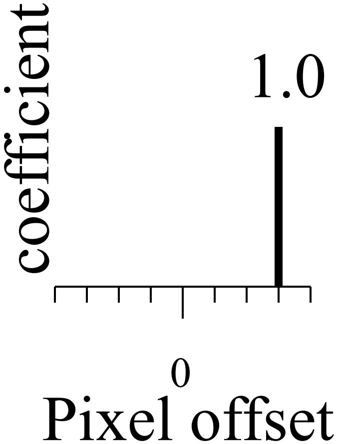




Filtered
(no change)

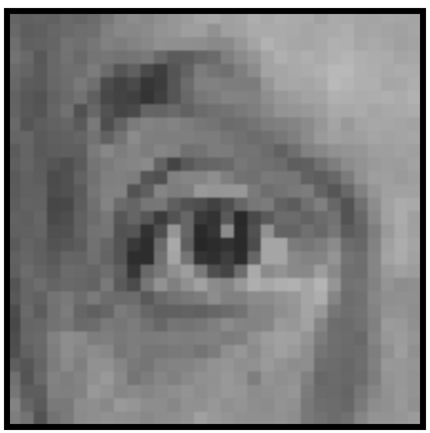
Linear filtering

original

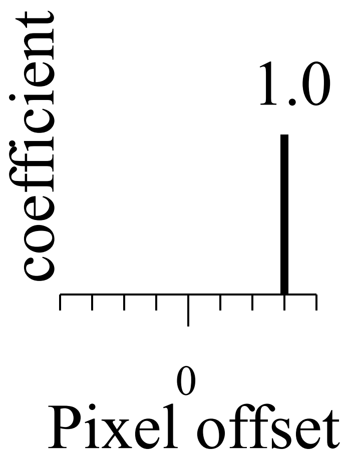


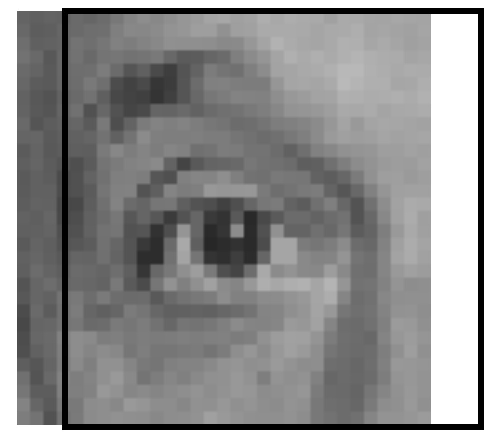
?

shift



original

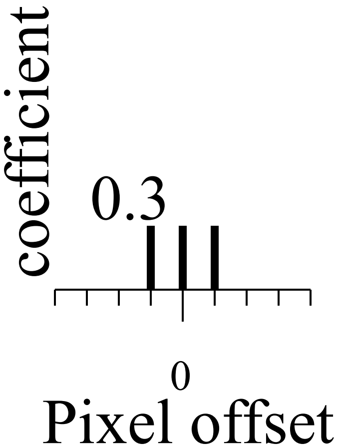




shifted

Linear filtering

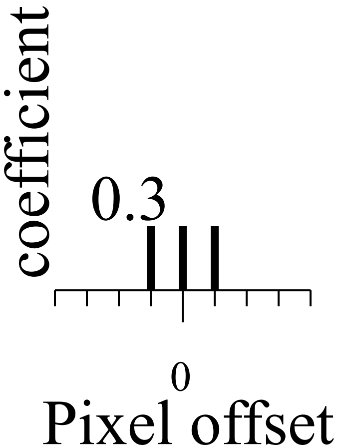
original



?

Blurring

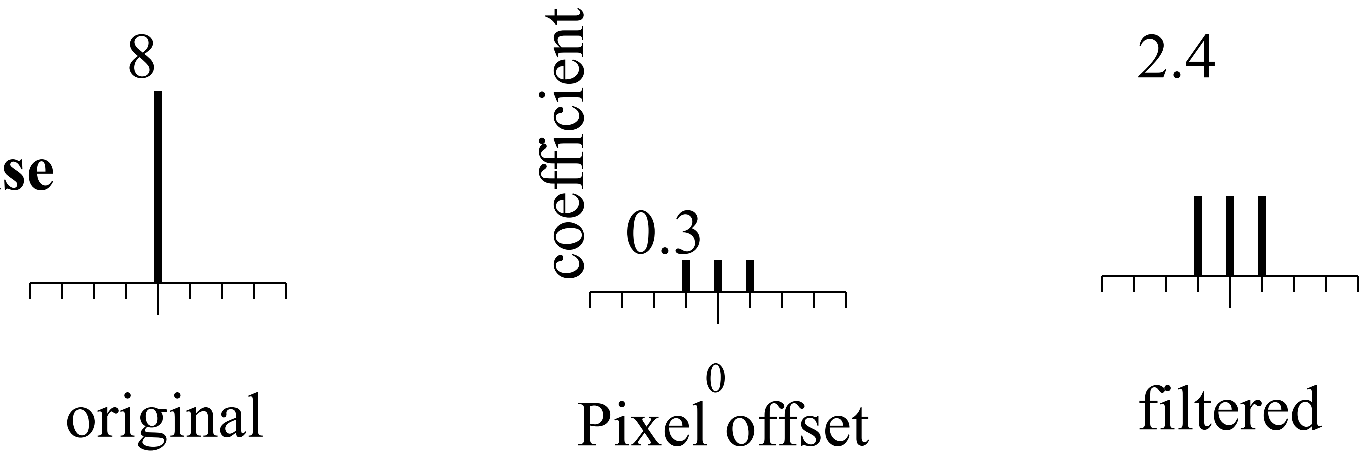
original



Blurred (filter applied in both dimensions).

Blur Examples

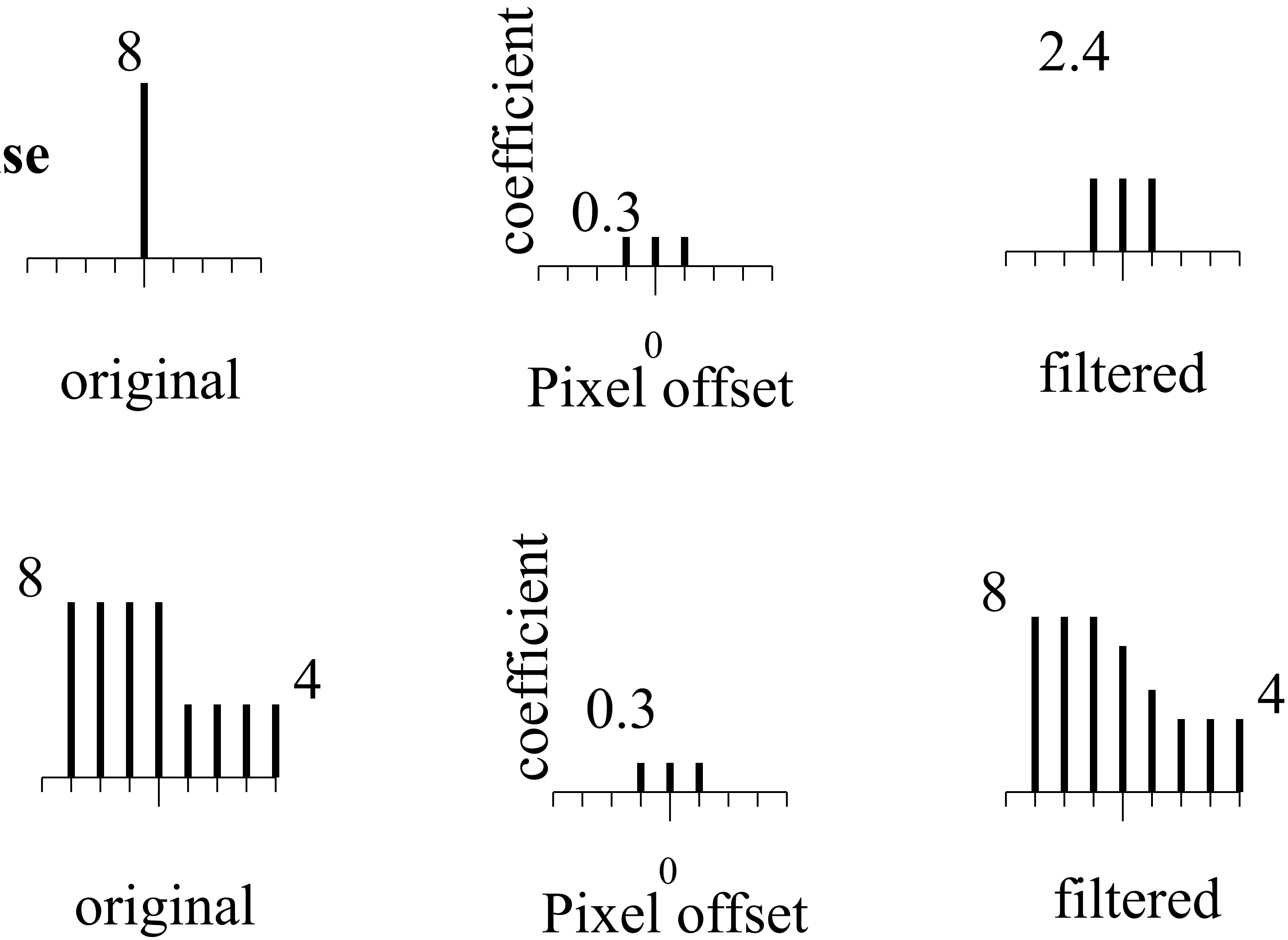
impulse



Blur Examples

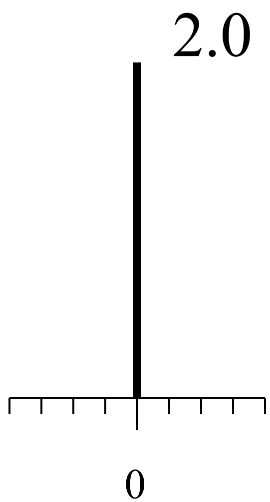
impulse

edge



Linear filtering (warm-up slide)

original



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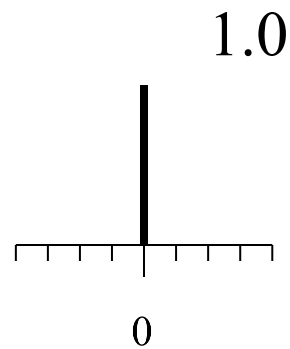

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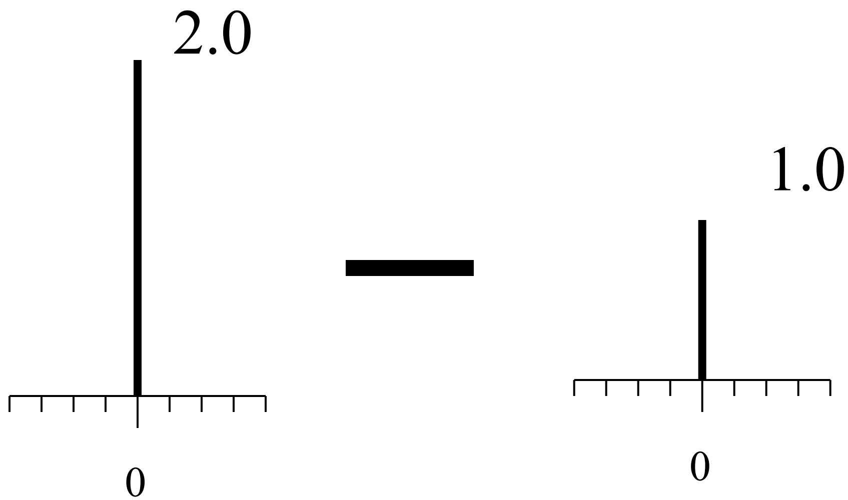
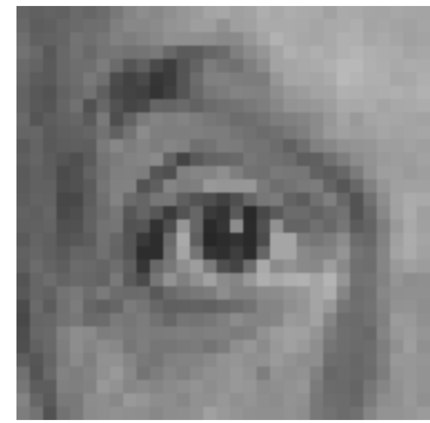
Linear Filtering (no change)

original

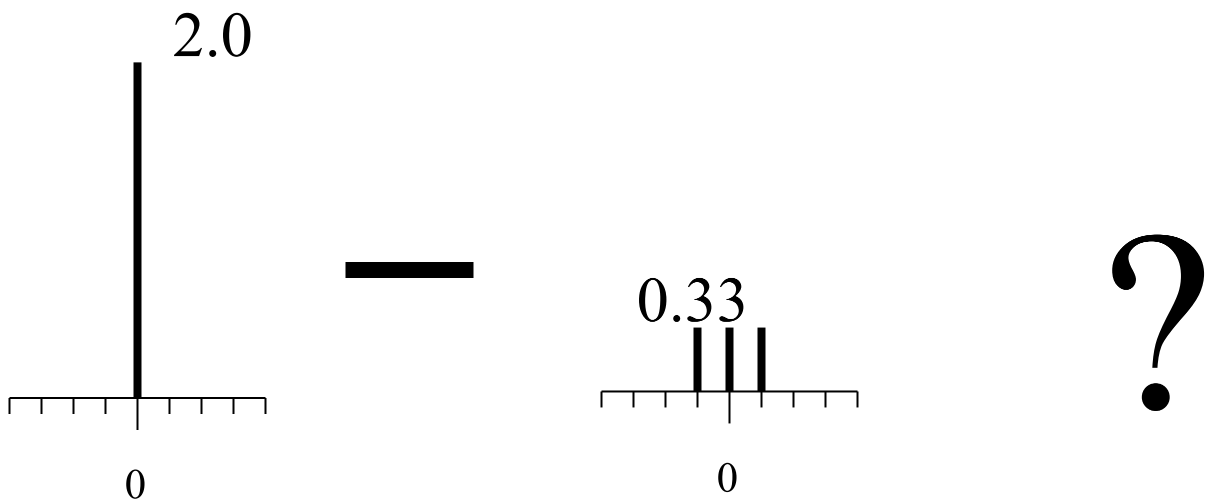




Filtered
(no change)

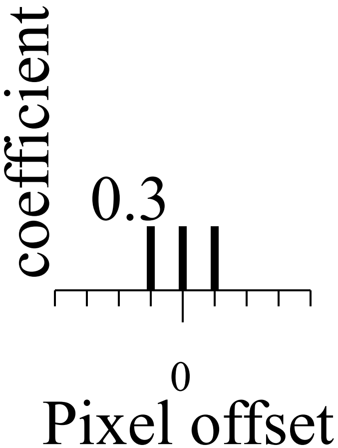
Linear Filtering

original



(remember blurring)

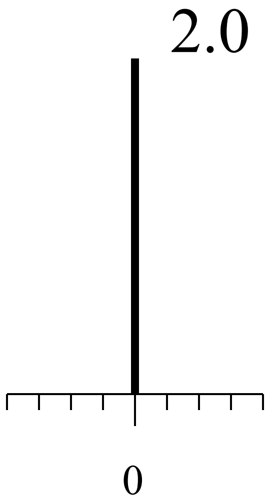
original



Blurred (filter applied in both dimensions).

Sharpening

original



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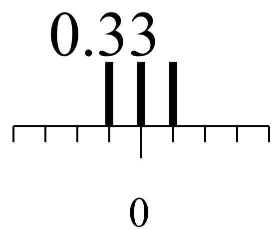
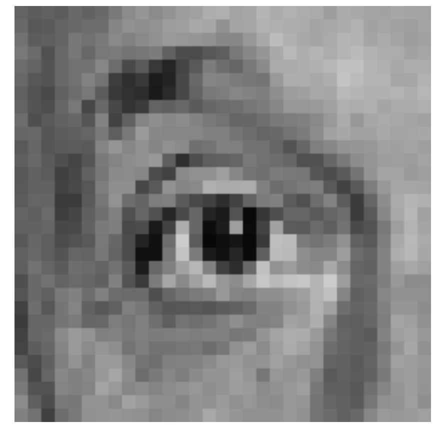
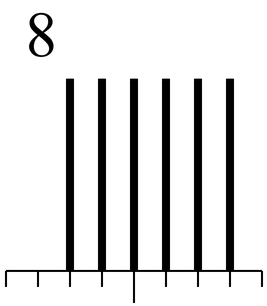


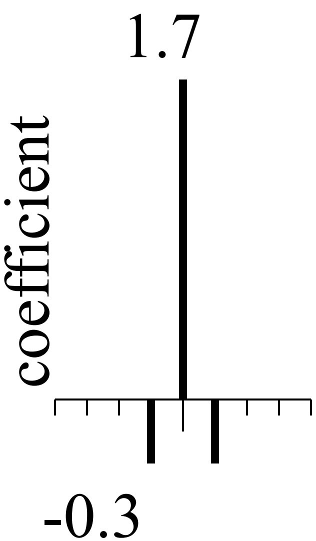


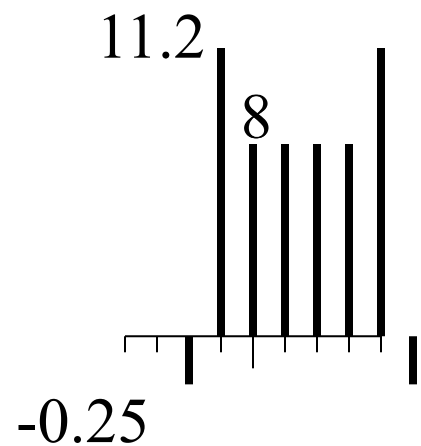
Sharpened
original

Sharpening example



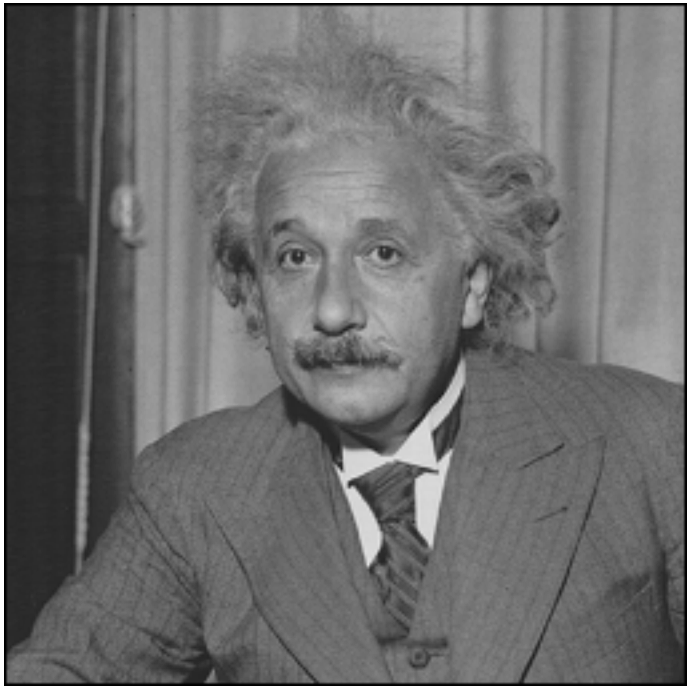
original



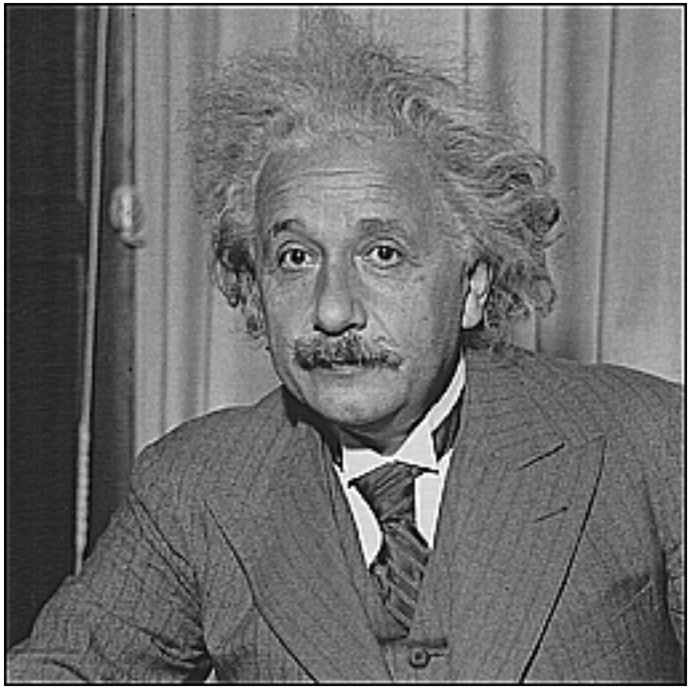


Sharpened
(differences are accentuated; constant areas are left untouched).

Sharpening



before



after

Spatial resolution and color

original

R

G

B

Blurring the G component

original

processed

R

G

B

Blurring the R component

original

processed

R

G

B

Blurring the B component

original

processed

R

G

B

Lab Color Component

L

a

b

A rotation of the color coordinates into directions that are more perceptually meaningful:
L: luminance,
a: red-green,
b: blue-yellow

Bluring L

original

processed

L

a

b

Bluring a

original

processed

L

a

b

Bluring b

original

processed

L

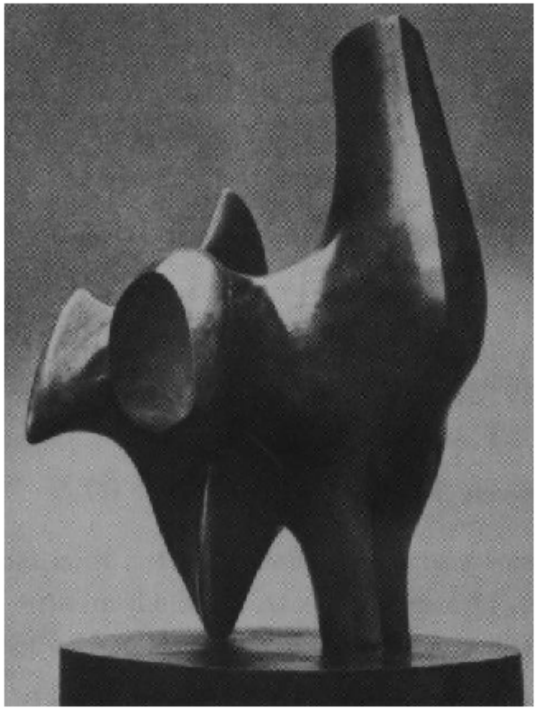
a

b

Application to image compression

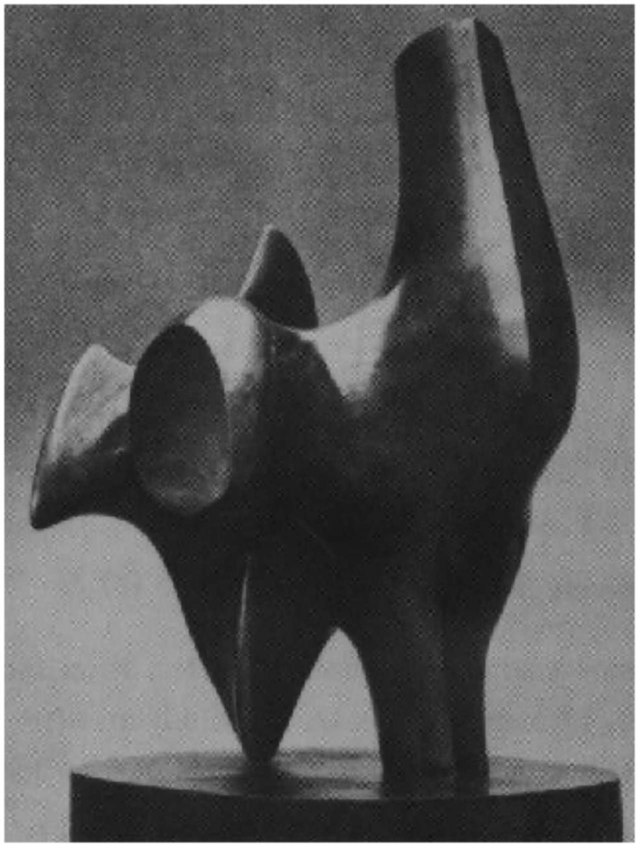
- (compression is about hiding differences from the true image where you can’t see them).

Edge Detection



- Convert a 2D image into a set of curves
  - Extracts salient features of the scene
  - More compact than pixels

How can you tell that a pixel is on an edge?



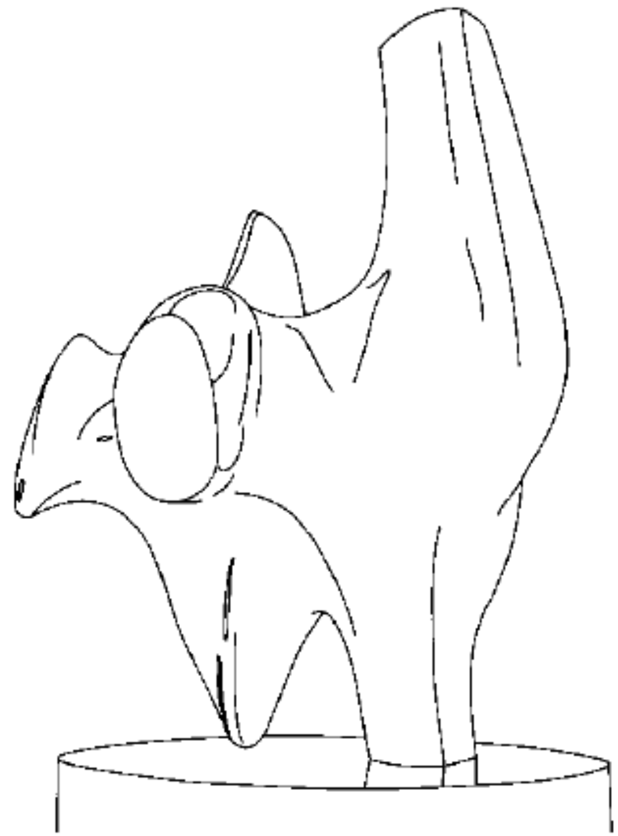
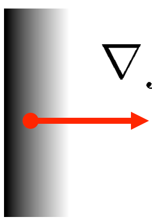


Image gradient

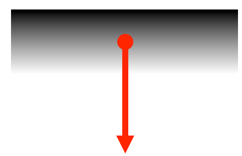
- The gradient of an image:

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

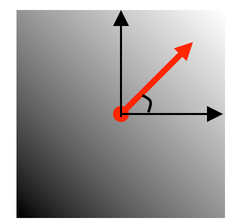
- The gradient points in the direction of most rapid change in intensity



$$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$$



$$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$$



$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

- The gradient direction is given by:

$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

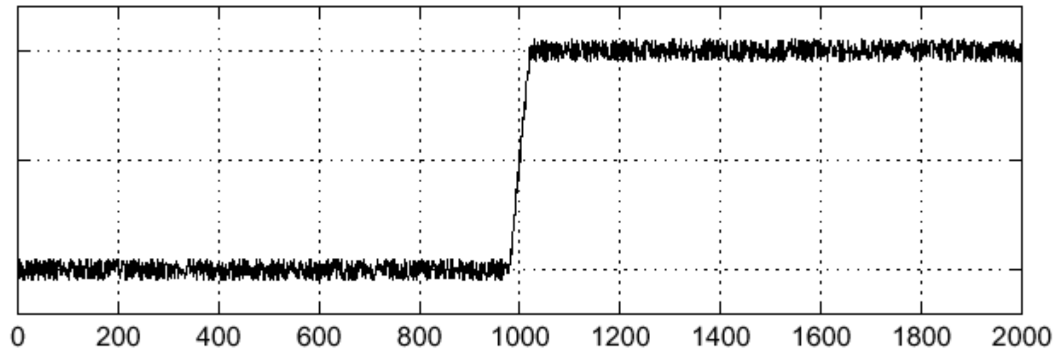
  – how does the gradient relate to the direction of the edge?

- The *edge strength* is given by the gradient magnitude

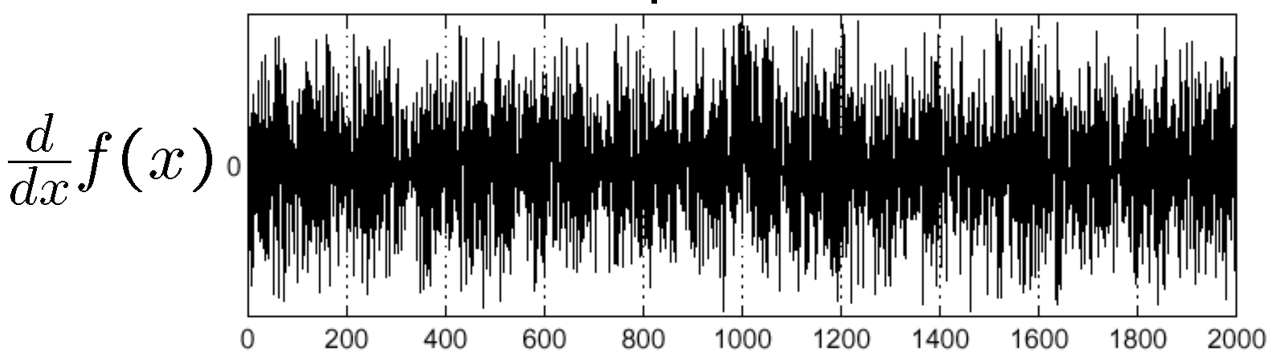
$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Effects of noise

- Consider a single row or column of the image
  - Plotting intensity as a function of position gives a signal

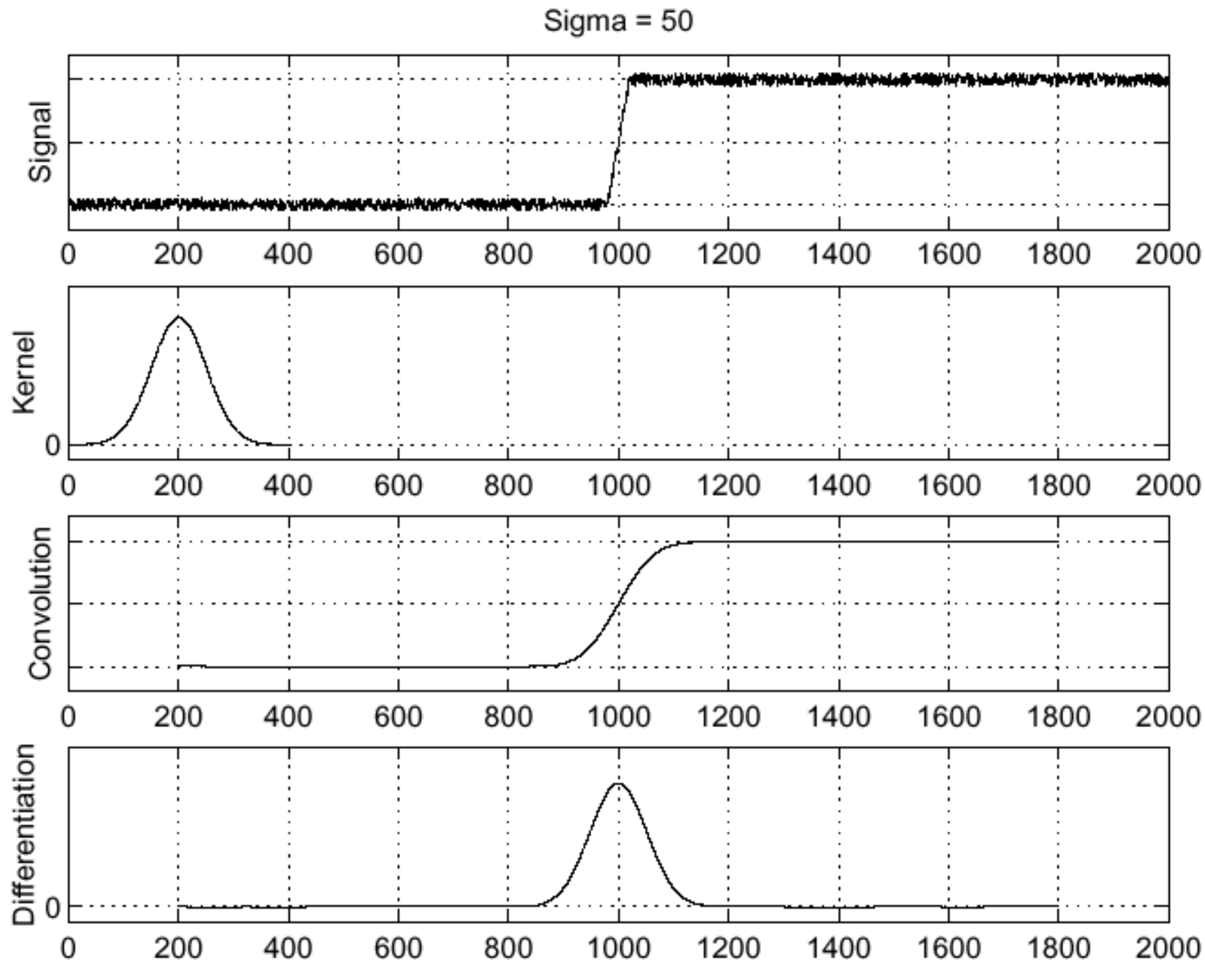


How to compute a derivative?



- Where is the edge?

Solution: smooth first



$$\frac{\partial}{\partial x}(h \star f)$$

- Where is the edge?
- Look for peaks in $\frac{\partial}{\partial x}(h \star f)$

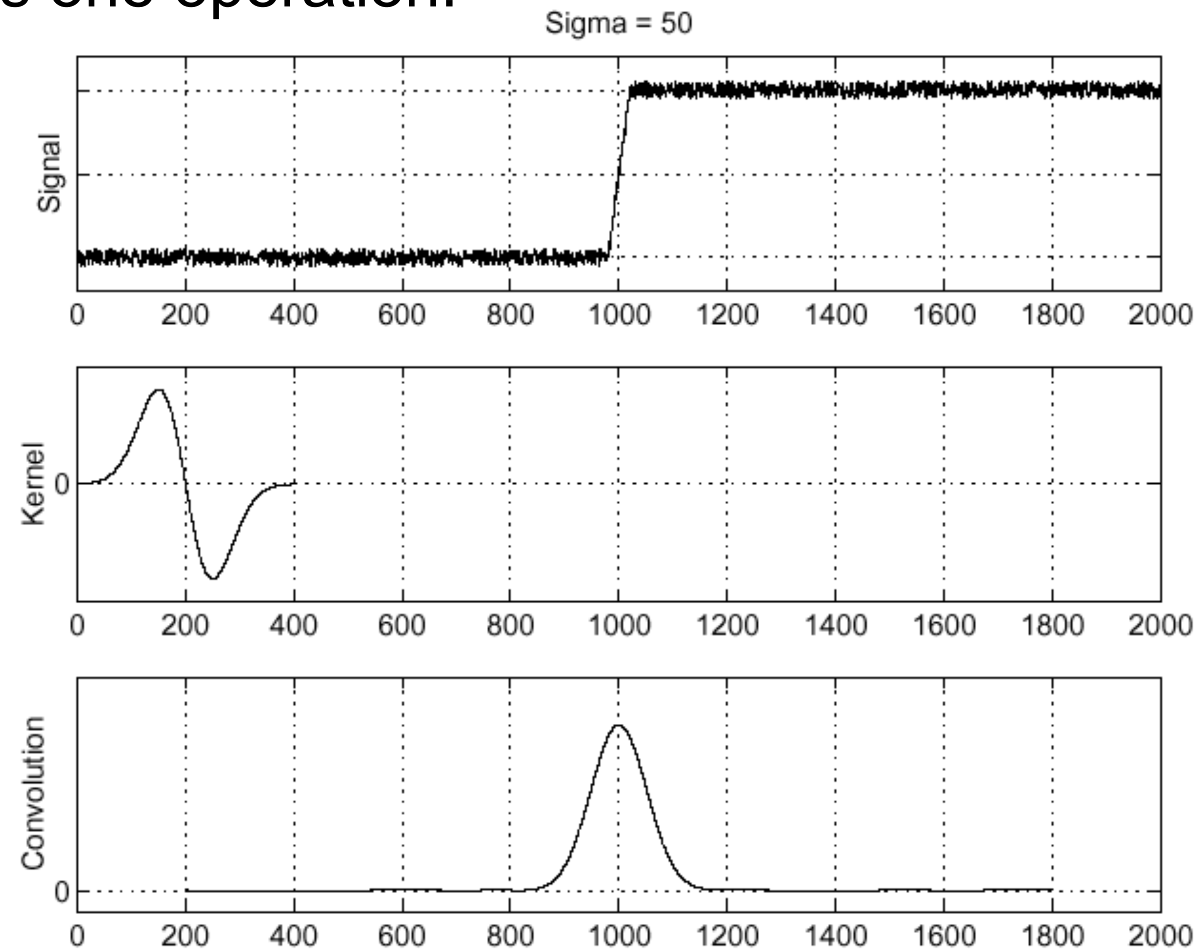
Derivative theorem of convolution

$$\frac{\partial}{\partial x}(h \star f) = (\frac{\partial}{\partial x}h) \star f$$

- This saves us one operation:

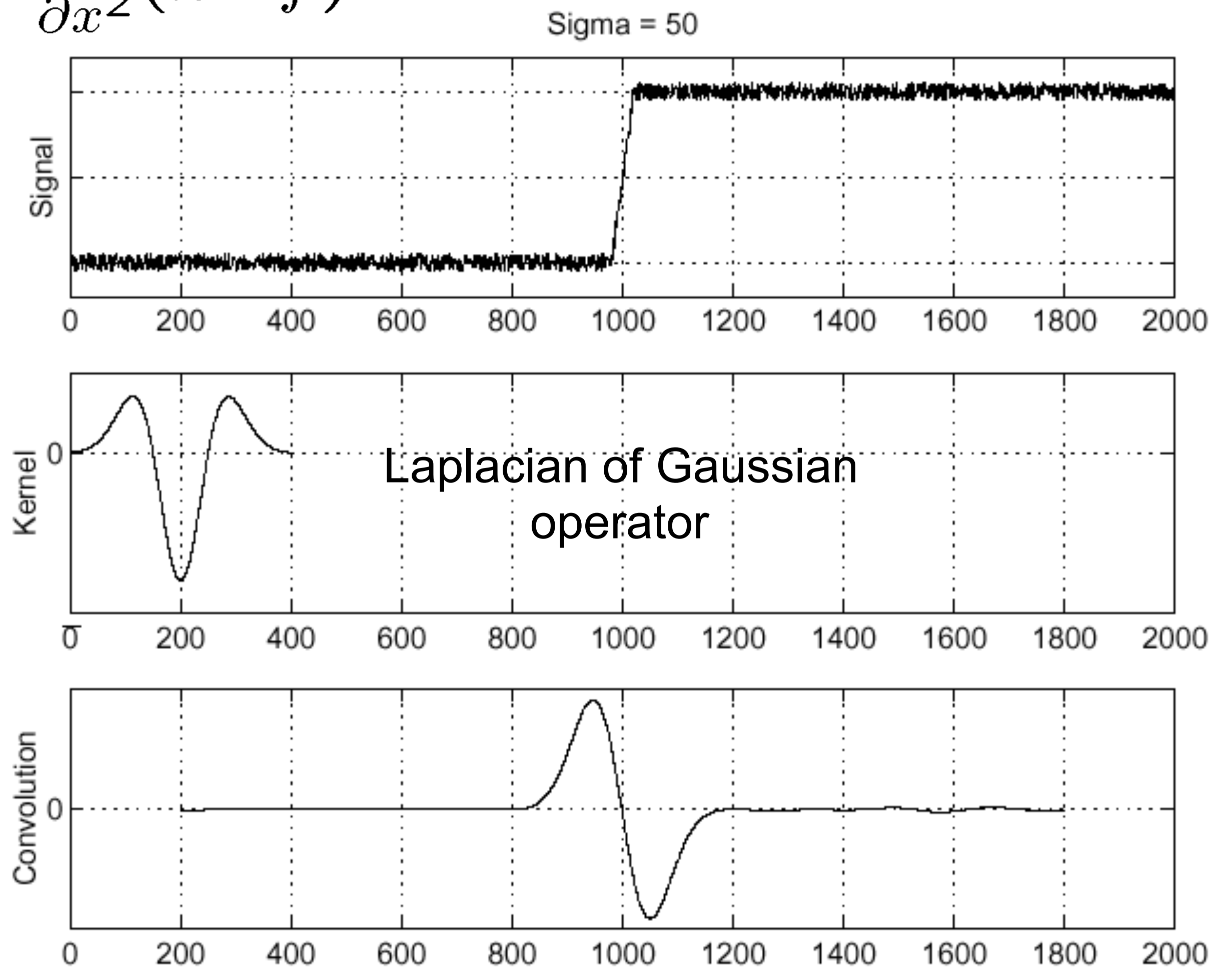
$$\frac{\partial}{\partial x}h$$

$$(\frac{\partial}{\partial x}h) \star f$$



Laplacian of Gaussian

- Consider $\frac{\partial^2}{\partial x^2}(h \star f)$



$$\frac{\partial^2}{\partial x^2}h$$

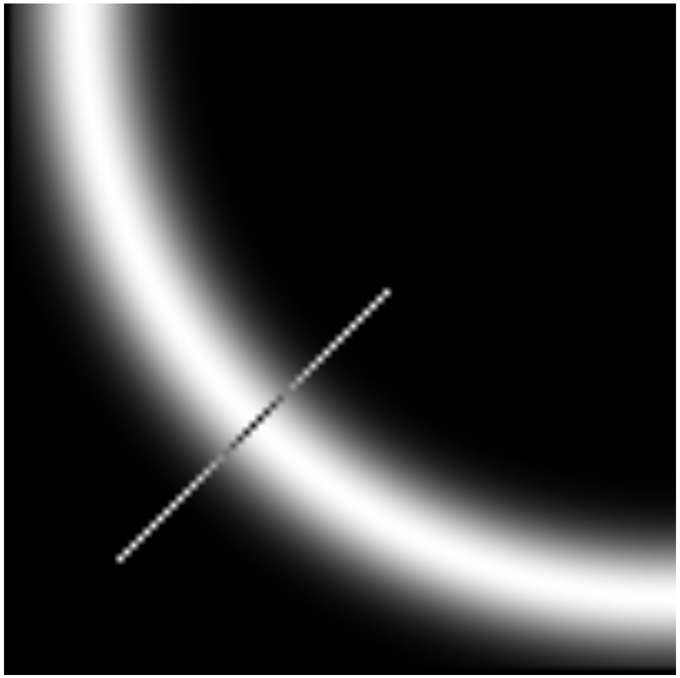
$$\left(\frac{\partial^2}{\partial x^2}h\right) \star f$$

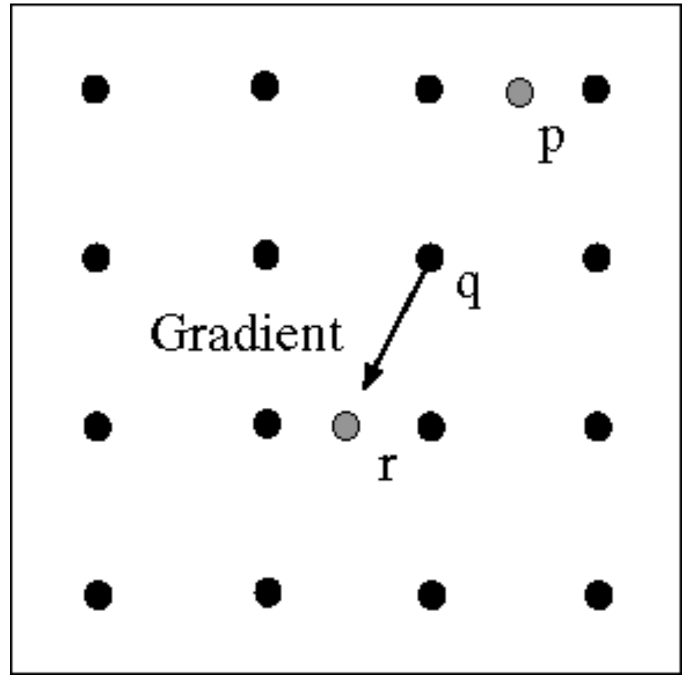
- Where is the edge?
- Zero-crossings of bottom graph

Canny Edge Detector

- Smooth image *I* with 2D Gaussian: $G * I$
- Find local edge normal directions for each pixel $\theta = \arctan \frac{I_y}{I_x}$
- Along this direction, compute image gradient $\left|\nabla(G * I)\right|$
- Locate edges by finding max gradient magnitude (**Non-maximum suppression**)

Non-maximum Suppression





- Check if pixel is local maximum along gradient direction
  - requires checking interpolated pixels p and r

The Canny Edge Detector

original image (Lena)

The Canny Edge Detector

magnitude of the gradient

The Canny Edge Detector

After non-maximum suppression

Canny Edge Detector

original

Canny with $\sigma = 1$

Canny with

- The choice of depends on desired behavior
  - large detects large scale edges
  - small detects fine features

Image Scaling

This image is too big to fit on the screen. How can we reduce it?

How to generate a half-sized version?

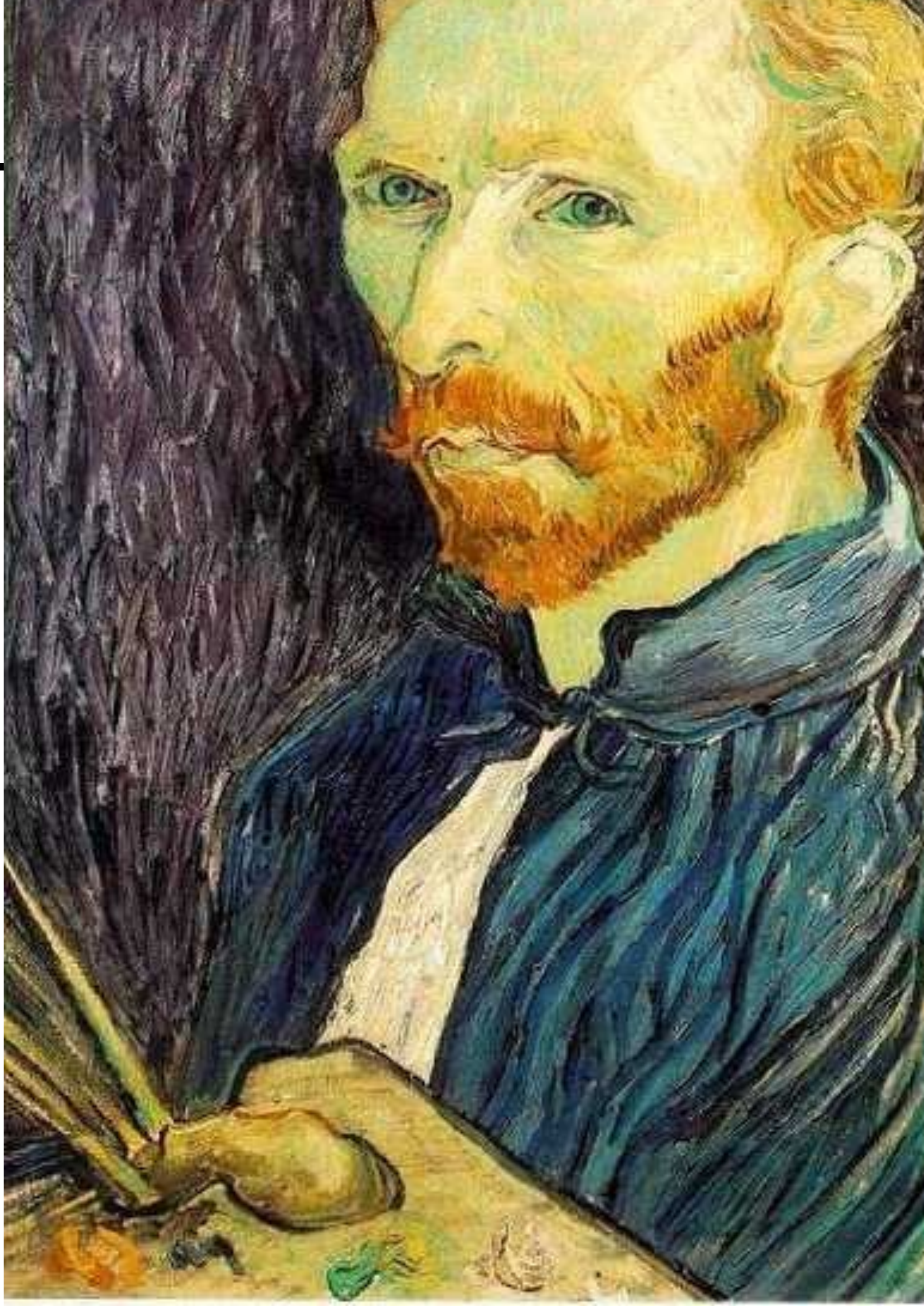
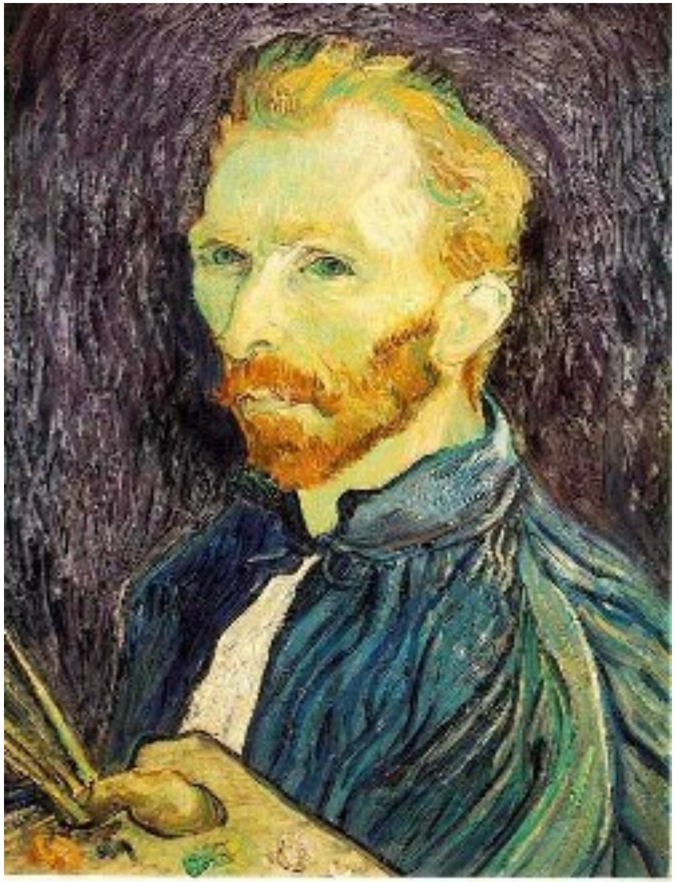


Image sub-sampling

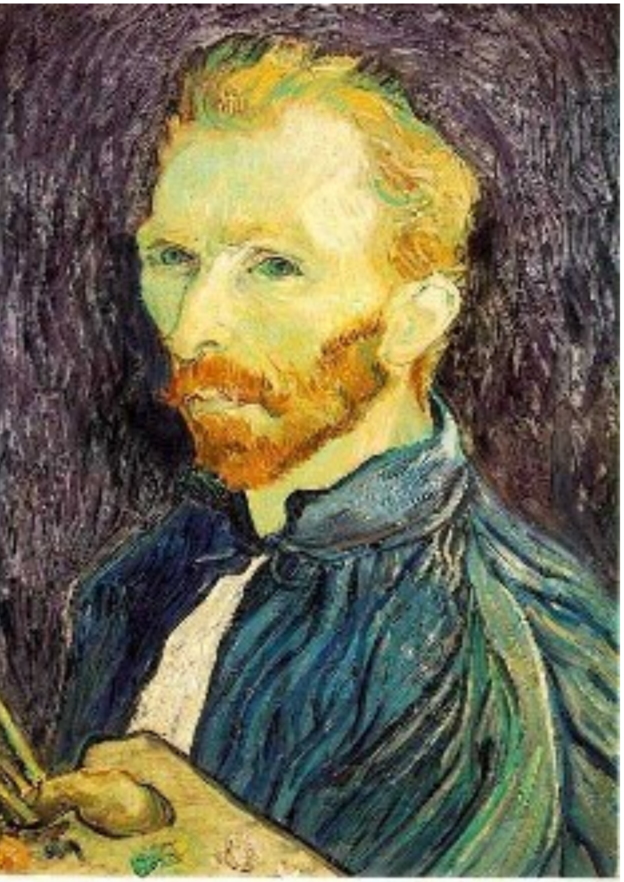


1/4

1/8

Throw away every other row and column to create a 1/2 size image
- called *image sub-sampling*

Image sub-sampling



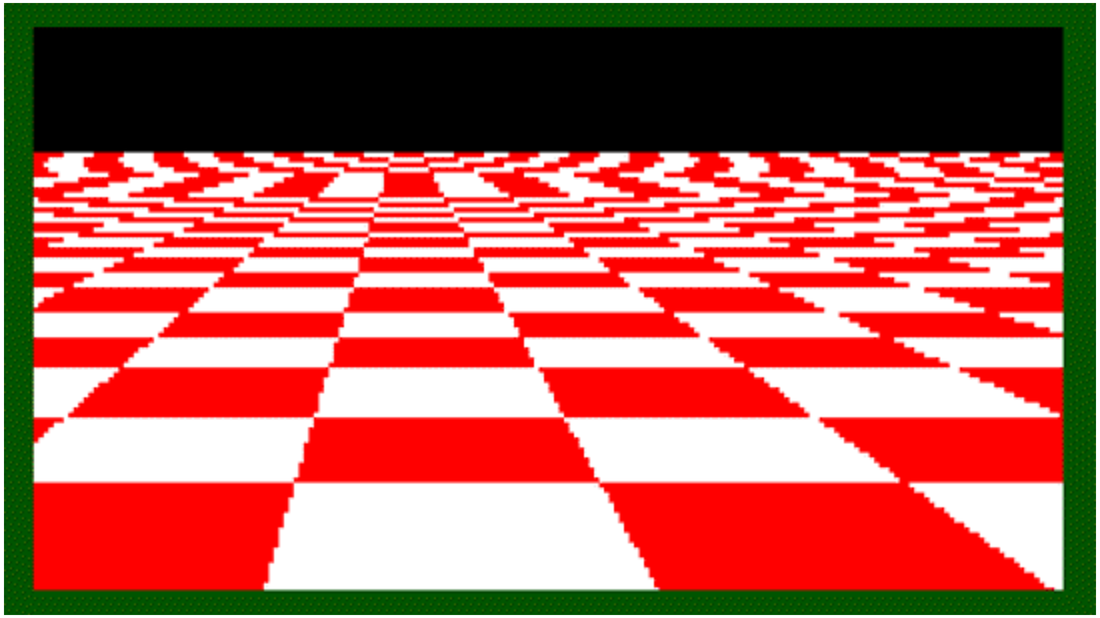
1/2

1/4 (2x zoom)

1/8 (4x zoom)

Why does this look so crufty?

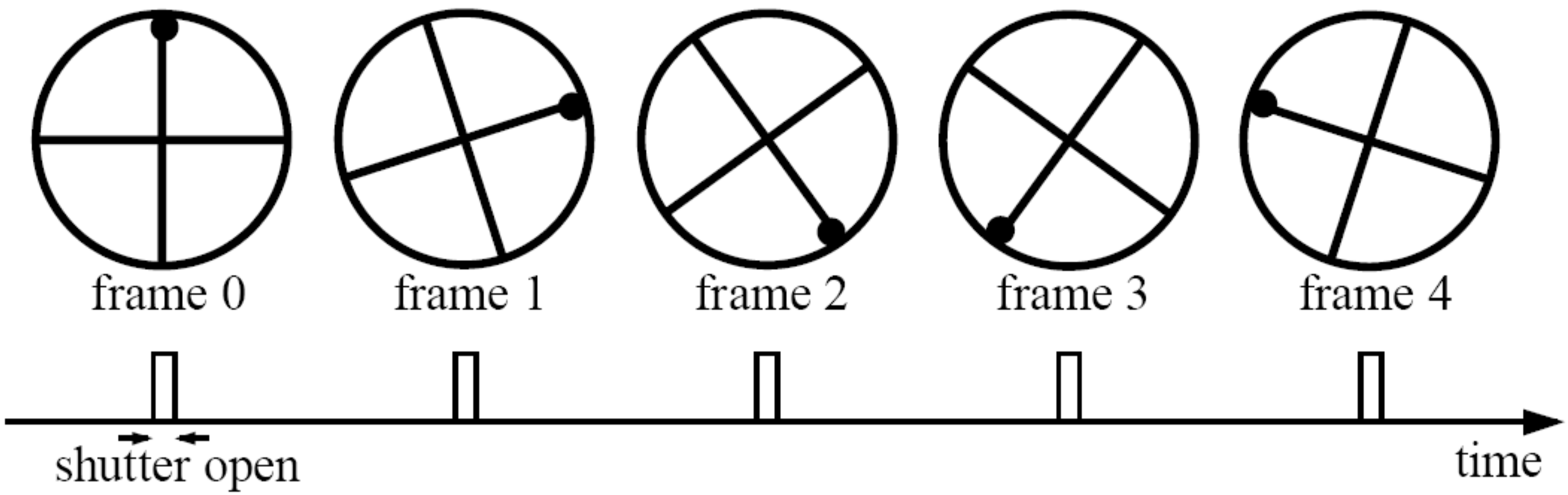
Even worse for synthetic images



Really bad in video

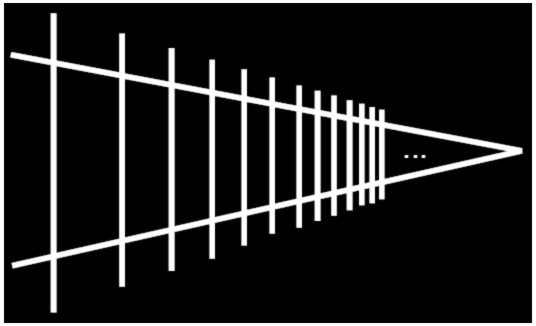
Imagine a spoked wheel moving to the right (rotating clockwise). Mark wheel with dot so we can see what's happening.

If camera shutter is only open for a fraction of a frame time (frame time = 1/30 sec. for video, 1/24 sec. for film):



Without dot, wheel appears to be rotating slowly backwards! (counterclockwise)

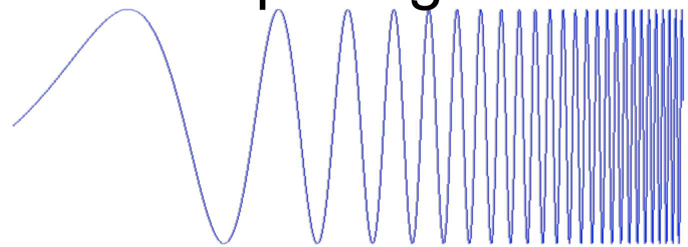
Alias: n., an assumed name



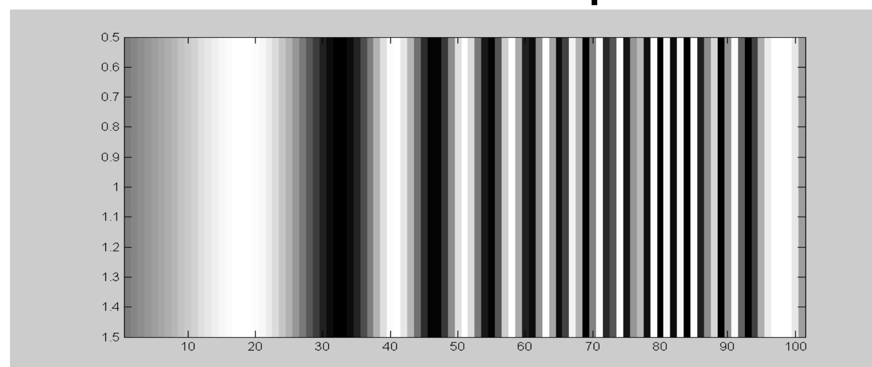
Picket fence receding
Into the distance will
produce aliasing…

WHY?

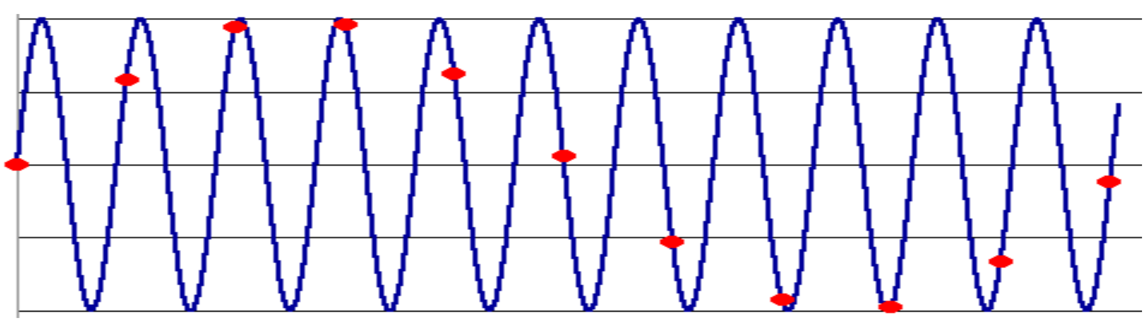
Input signal:



Matlab output:



x = 0:.05:5; imagesc(sin((2.^x).*x))



Aj-aj-aj:
Alias!

Not enough samples

Aliasing

- occurs when your sampling rate is not high enough to capture the amount of detail in your image
- Can give you the wrong signal/image—an *alias*

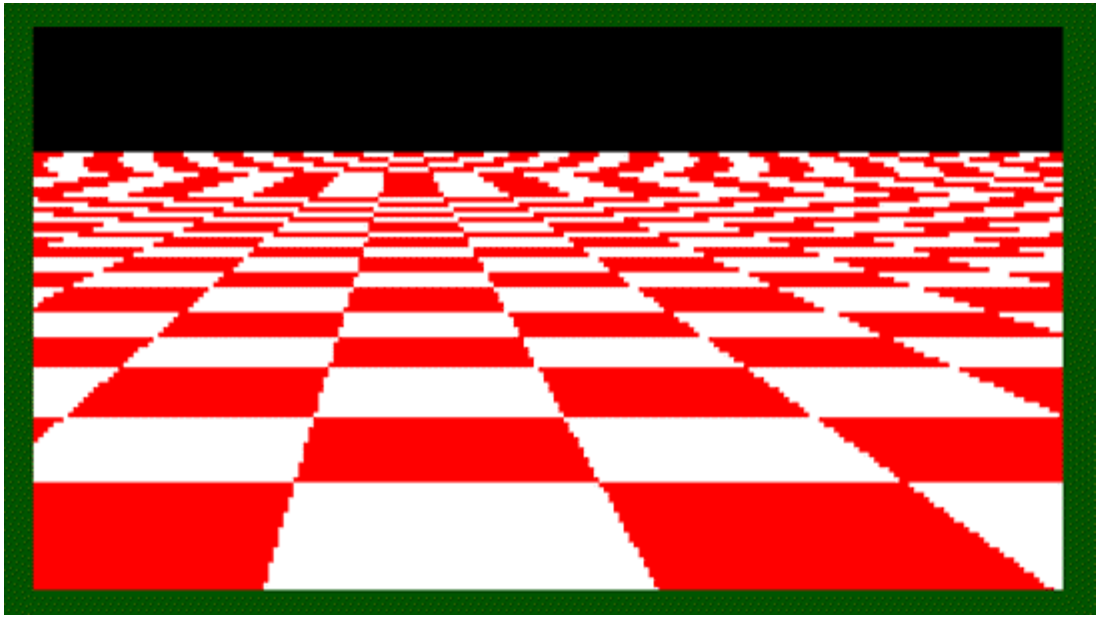
- Where can it happen in images?
- During image synthesis:
  - **sampling** continous singal into discrete signal
  - e.g. ray tracing, line drawing, function plotting, etc.
- During image processing:
  - **resampling** discrete signal at a different rate
  - e.g. Image warping, zooming in, zooming out, etc.

- To do sampling right, need to understand the structure of your signal/image
- Enter Monsieur Fourier…

Antialiasing

- What can be done?

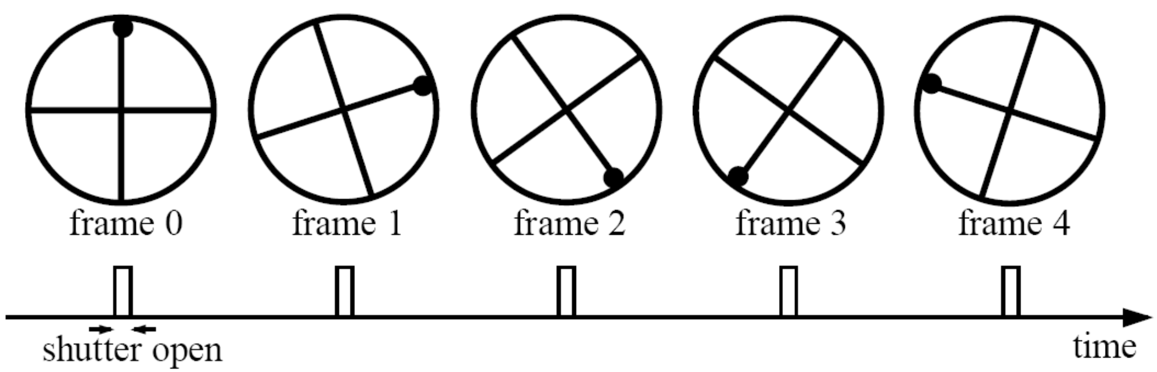
1. Raise sampling rate by *oversampling*
   - *Sample at k times the resolution*



Antialiasing

- What can be done?

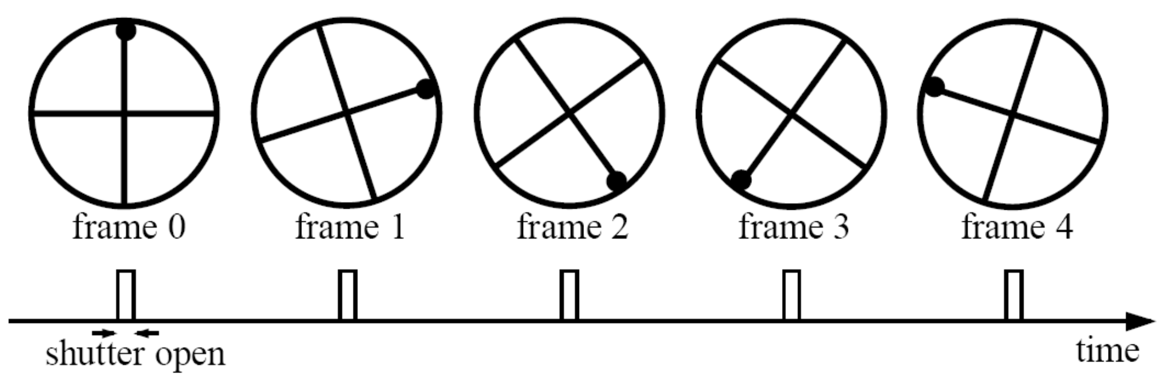
1. Raise sampling rate by *oversampling*
   - *Sample at k times the resolution*



Antialiasing

- What can be done?

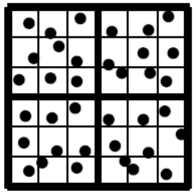
1. Raise sampling rate by *oversampling*
   - *Sample at k times the resolution*
2. Lower the max frequency by *prefiltering*
   - Smooth the signal enough
   - Works on discrete signals



Antialiasing

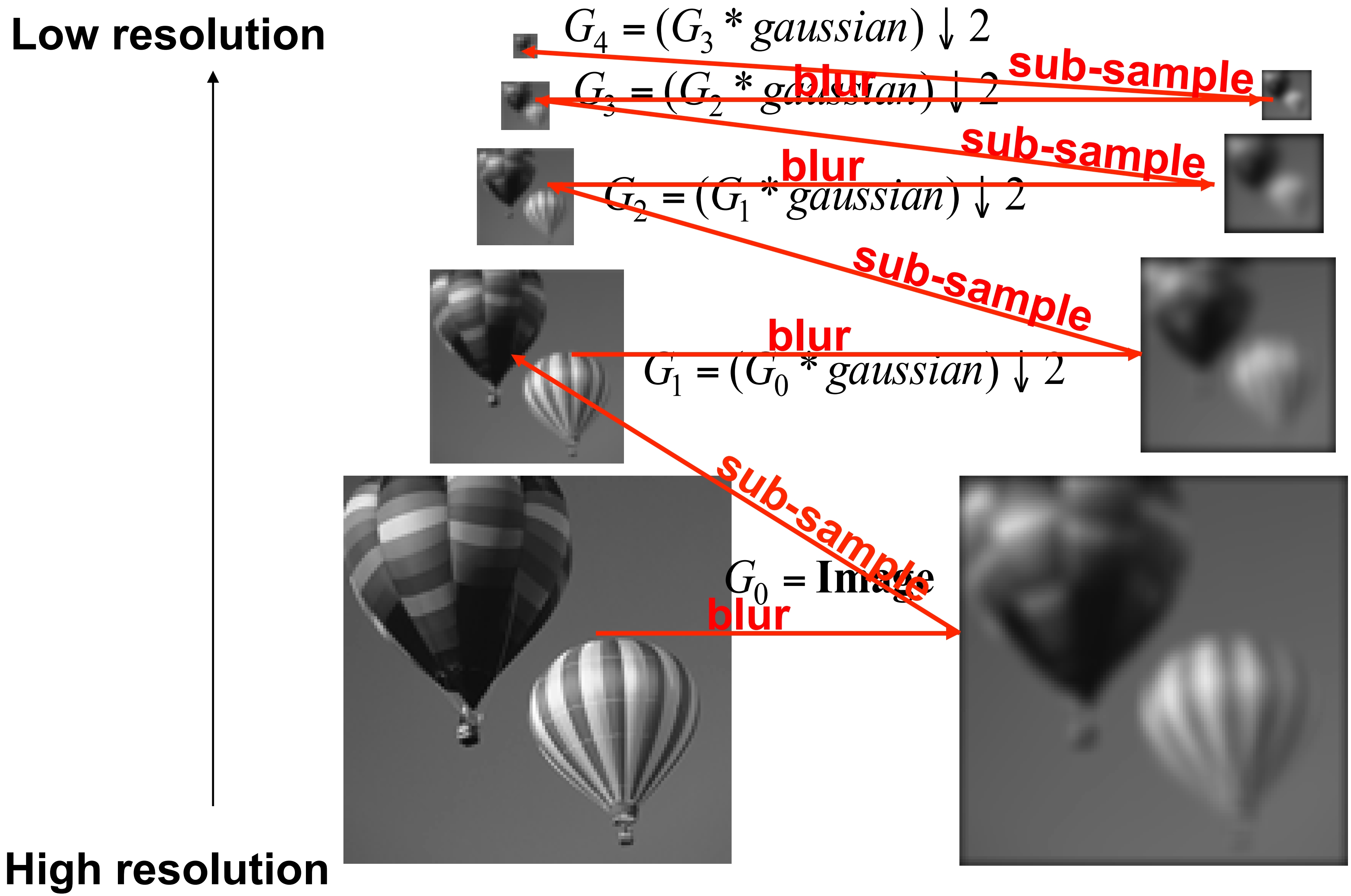
- What can be done?

1. Raise sampling rate by *oversampling*
   - *Sample at k times the resolution*
2. Lower the max frequency by *prefiltering*
   - Smooth the signal enough
   - Works on discrete signals
3. Improve sampling quality with
   better sampling (CS559)

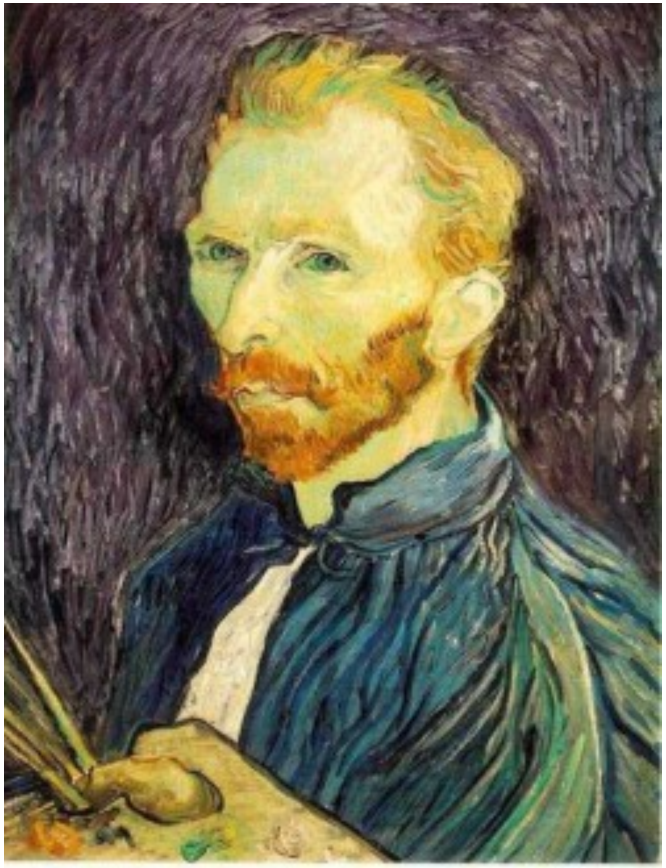


jittered,
9 samples per pixel

The Gaussian Pyramid



Gaussian pre-filtering



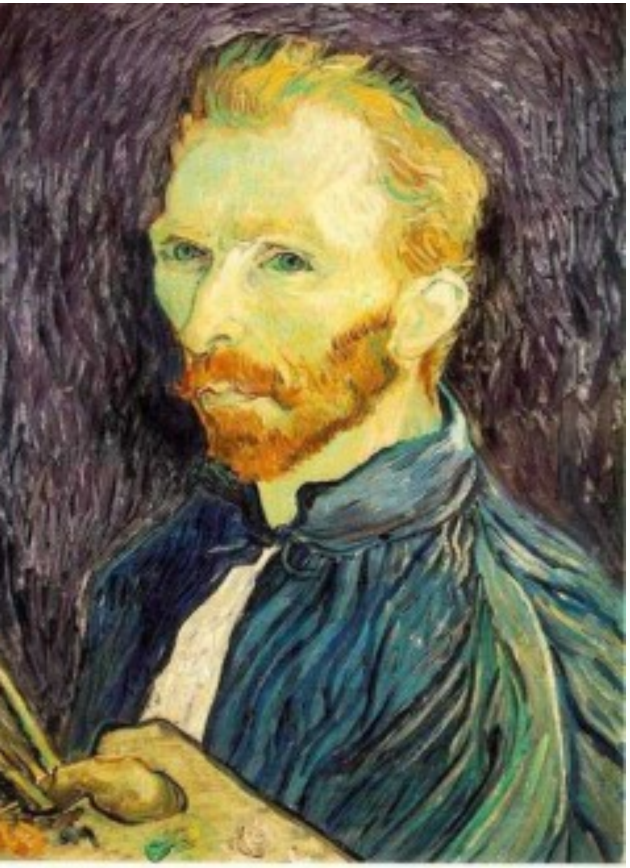
Gaussian 1/2

G 1/4

G 1/8

- Solution: filter the image, *then* subsample

Subsampling with Gaussian pre-filtering



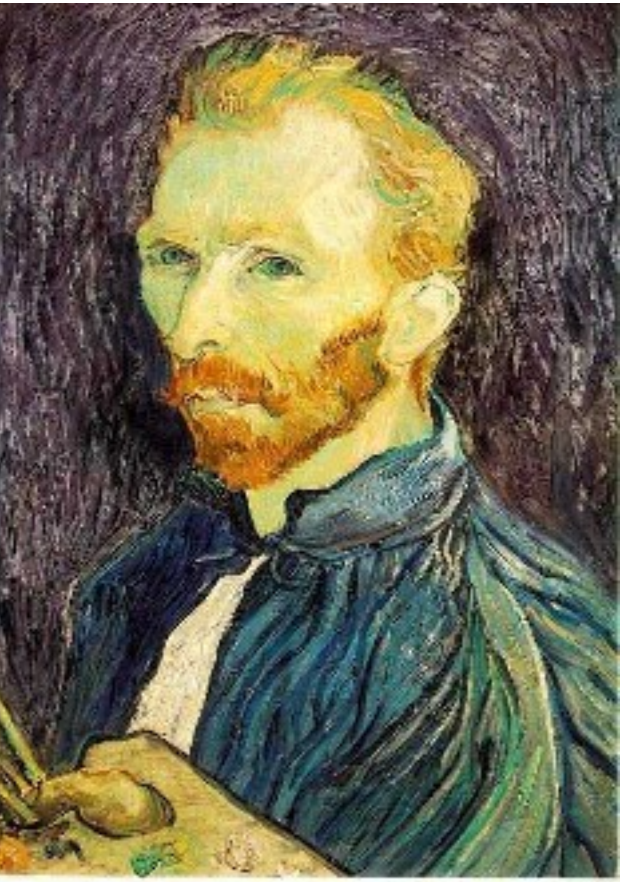
Gaussian 1/2

G 1/4

G 1/8

- Solution: filter the image, *then* subsample

Compare with...

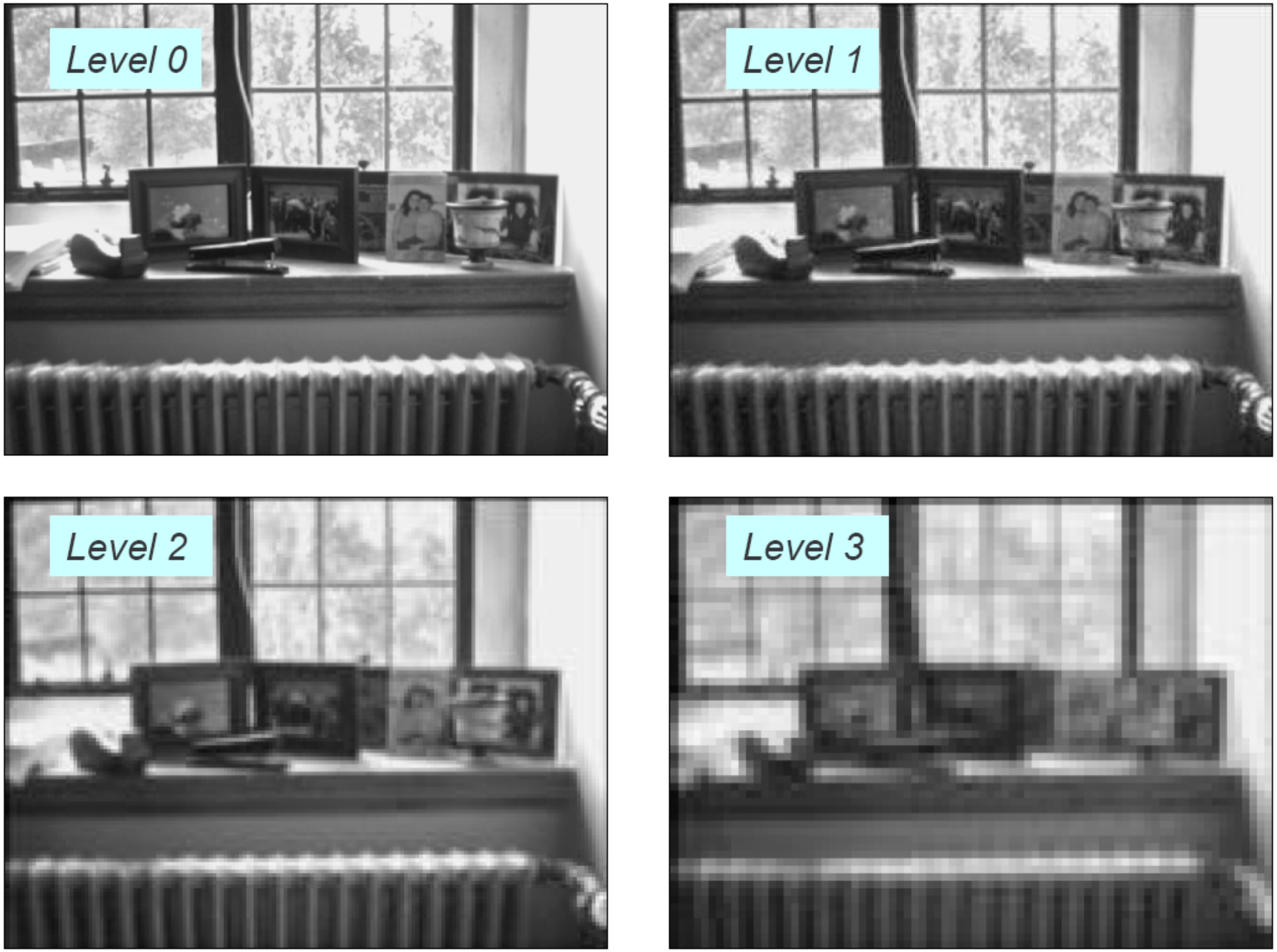


1/2

1/4 (2x zoom)

1/8 (4x zoom)

Pyramids at Same Resolution



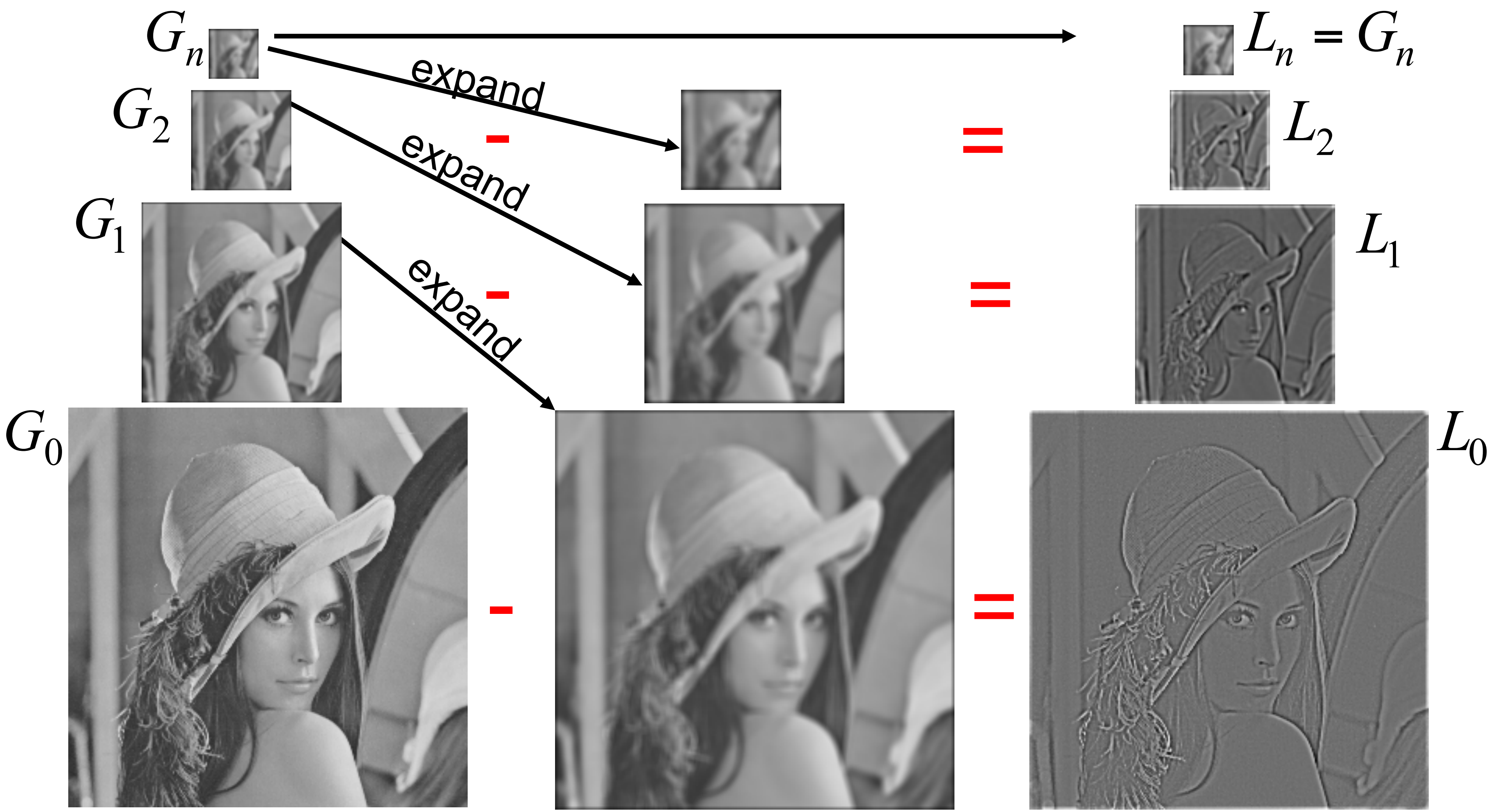
The Laplacian Pyramid

$$L_i = G_i - \text{expand}(G_{i+1})$$

$$G_i = L_i + \text{expand}(G_{i+1})$$

Gaussian Pyramid

Laplacian Pyramid



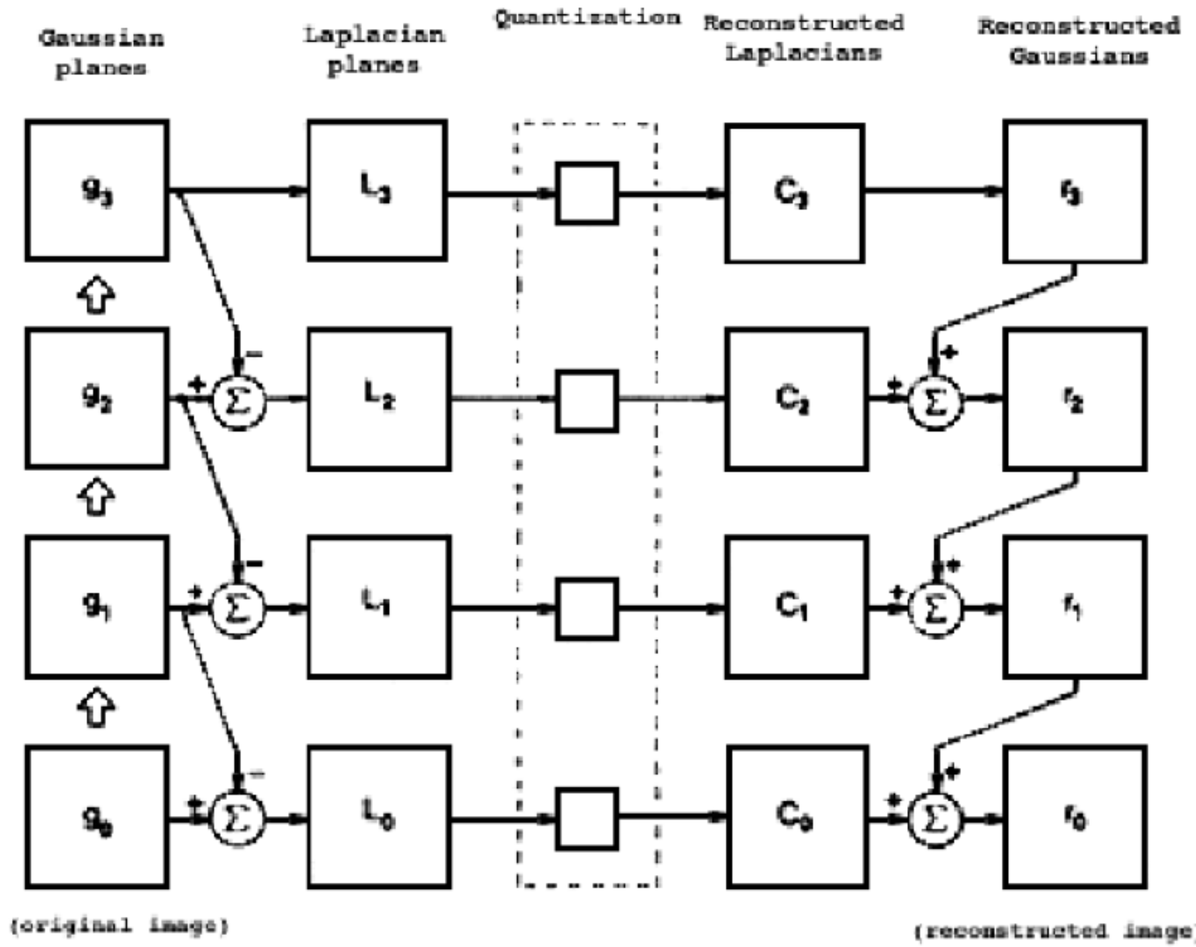


Fig. 10. A summary of the steps in Laplacian pyramid coding and decoding. First, the original image g_0 (lower left) is used to generate Gaussian pyramid levels g_1, g_2, … through repeated local averaging. Levels of the Laplacian pyramid L_0, L_1, … are then computed as the differences between adjacent Gaussian levels. Laplacian pyramid elements are quantized to yield the Laplacian pyramid code C_0, C_1, C_2, …. Finally, a reconstructed image r_0 is generated by summing levels of the code pyramid.

Recap

Image Processing: from basic concepts to latest techniques

- Filtering
- Edge detection
- Re-sampling and aliasing
- Image Pyramids (Gaussian and Laplacian)
- Next …

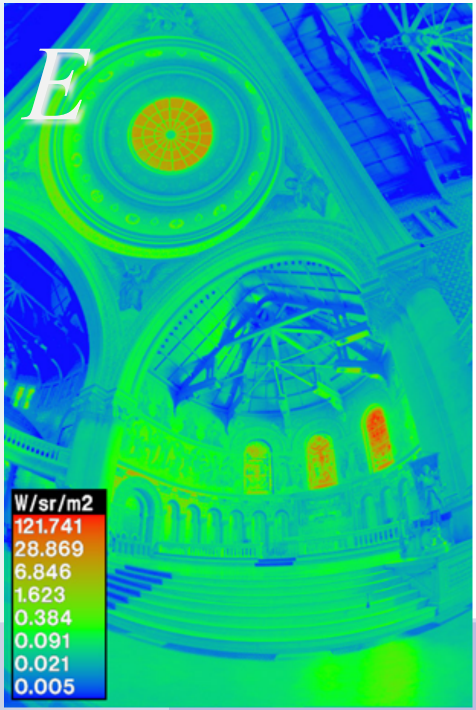
High Dynamic Range Image Reconstruction from Hand-held Cameras

Pei-Ying Lu   Tz-Huan Huang   Meng-Sung Wu
Yi-Ting Cheng   Yung-Yu Chuang

National Taiwan University

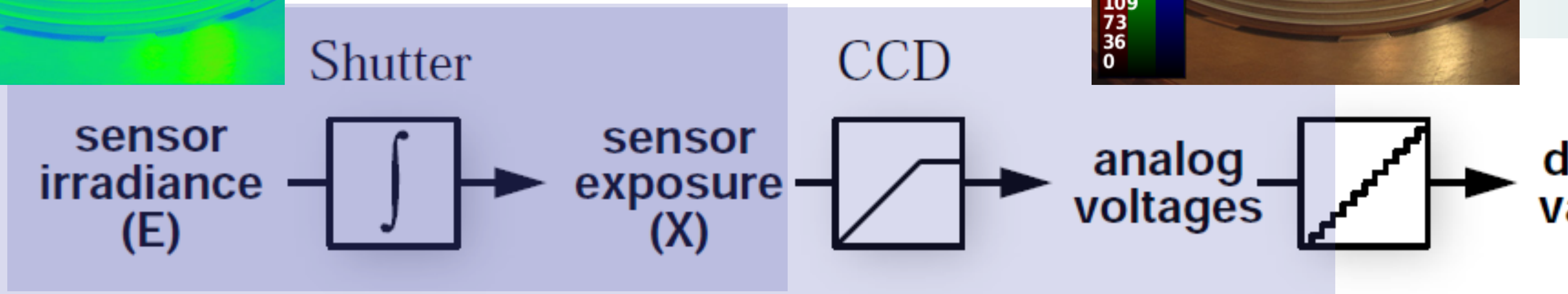
The world is of high dynamic range

Camera pipeline

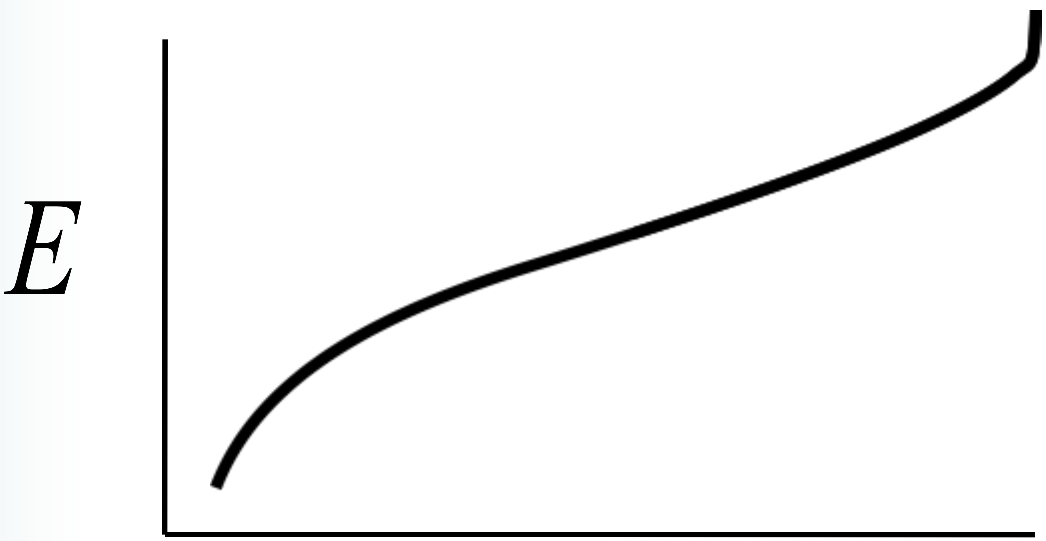


$$X = \int_{t=0}^{\Delta t} E\,dt = E\Delta t$$

$$Z = f(X) = f(E\Delta t)$$



HDR image reconstruction



$$Z_i = f(E\Delta t_i)$$

$$E = f^{-1}(Z_i)/\Delta t_i$$

HDR image reconstruction

- Recovering High Dynamic Range Radiance Maps from Photographs, SIGGRAPH 1997.
- Radiometric Self Calibration, CVPR 2001.
- Estimation-theoretic approach to dynamic range enhancement using multiple exposures, JEI 2003.
- All assume static cameras and thus require tripods.

Images from hand-held camera

- Challenge #1: image mis-alignment

Images from hand-held camera

- Challenge #1: image mis-alignment
- Challenge #2: image blur

A naïve approach

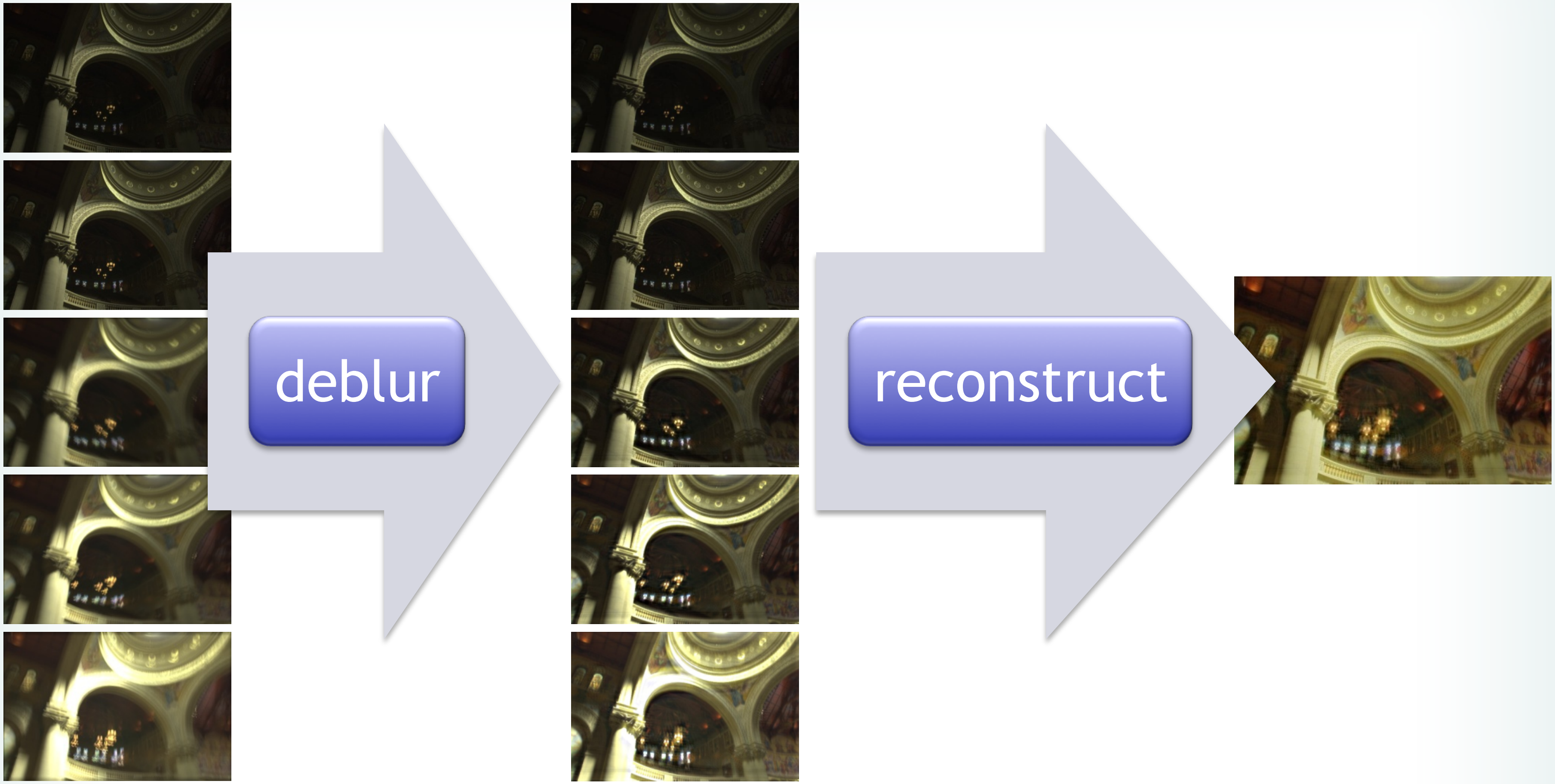
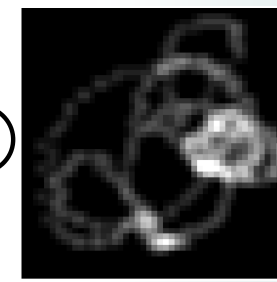


Image blurring process

convolution

=

$\otimes$



blur image

sharp image

blur kernel