



# Image Resampling and Pyramids



# Text Aliasing

The screenshot shows two separate windows of the gv viewer application. Both windows display the same document content: "Chapter 1: Introduction" followed by the heading "1 Introduction". Below the heading, there is a block of text about the library's fundamental purpose and a bulleted list of software packages maintained by the user.

**gv: kpathsea.dvi**

Chapter 1: Introduction

## 1 Introduction

This manual corresponds to version 3.2 of the Kpathsea 1

The library's fundamental purpose is to return a filename user, similar to what shells do when looking up program names.

The following software, all of which we maintain, uses the

- Dvilkj (see the ‘dvilkj’ man page)
- Dvipsk (see section “Introduction” in Dvips: A DVI d
- GNU font utilities (see section “Introduction” in GNU
- Web2c (see section “Introduction” in Web2c: A TeX in
- Xdvik (see the ‘xdvi’ man page)

**gv: kpathsea.pdf**

Chapter 1: Introduction

## 1 Introduction

This manual corresponds to version 3.2 of the Kpathsea 1

The library's fundamental purpose is to return a filename user, similar to what shells do when looking up program names.

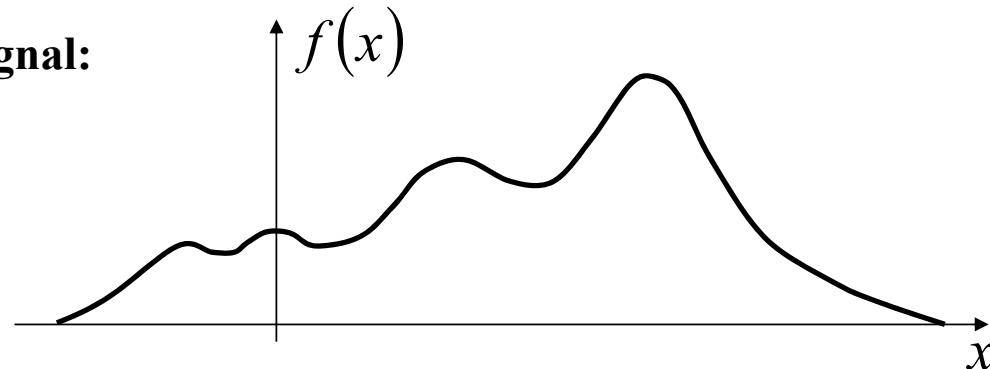
The following software, all of which we maintain, uses the

- Dvilkj (see the ‘dvilkj’ man page)
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- GNU font utilities (see section “Introduction” in GNU
- Web2c (see section “Introduction” in Web2c: A TeX in
- Xdvik (see the ‘xdvi’ man page)

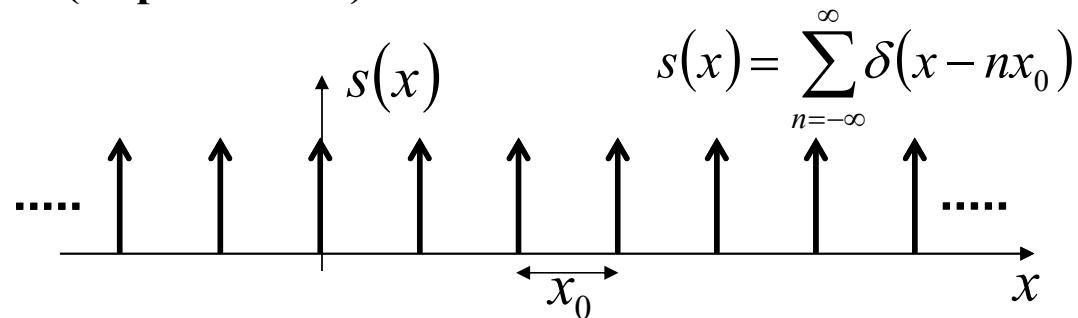


# RECAP - Sampling Theorem

Continuous signal:



Shah function (Impulse train):



Sampled function:

$$f_s(x) = f(x)s(x) = f(x) \sum_{n=-\infty}^{\infty} \delta(x - nx_0)$$



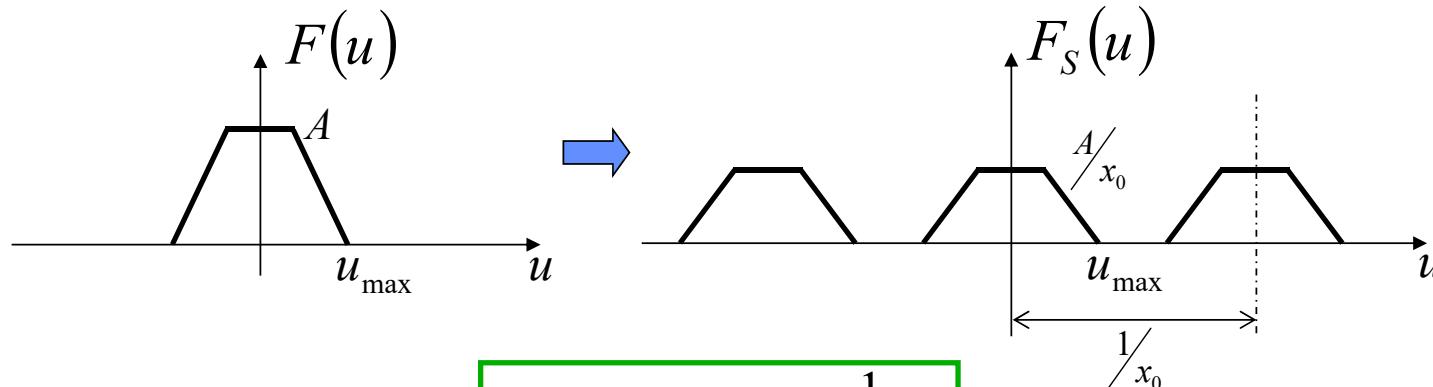
# RECAP - Sampling Theorem

Sampled function:

$$f_s(x) = f(x)s(x) = f(x) \sum_{n=-\infty}^{\infty} \delta(x - nx_0)$$

Sampling frequency  $\frac{1}{x_0}$

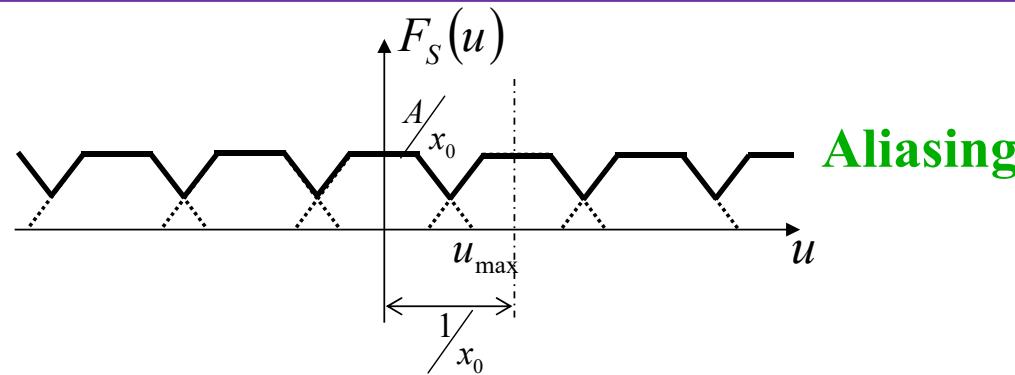
$$F_S(u) = F(u) * S(u) = F(u) * \frac{1}{x_0} \sum_{n=-\infty}^{\infty} \delta\left(u - \frac{n}{x_0}\right)$$



Only if  $u_{max} \leq \frac{1}{2x_0}$



If  $u_{\max} > \frac{1}{2x_0}$



When can we recover  $F(u)$  from  $F_S(u)$ ?

Only if  $u_{\max} \leq \frac{1}{2x_0}$  (Nyquist Frequency)

We can use

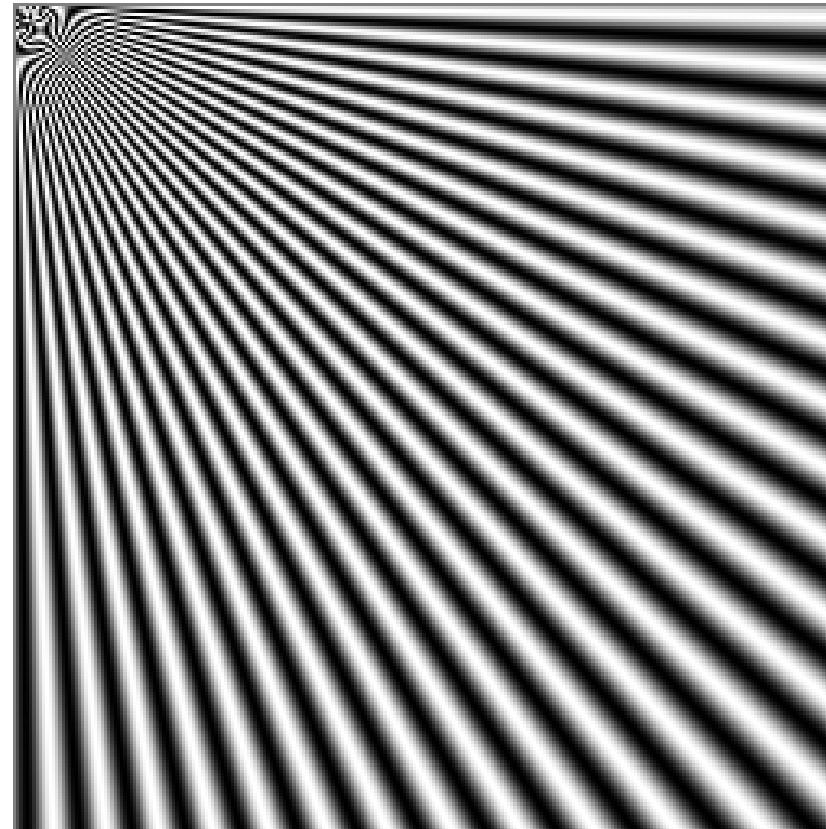
$$C(u) = \begin{cases} x_0 & |u| < \frac{1}{2x_0} \\ 0 & \text{otherwise} \end{cases}$$

Then  $F(u) = F_S(u)C(u)$  and  $f(x) = \text{IFT}[F(u)]$

Sampling frequency must be greater than  $2u_{\max}$



# Aliasing

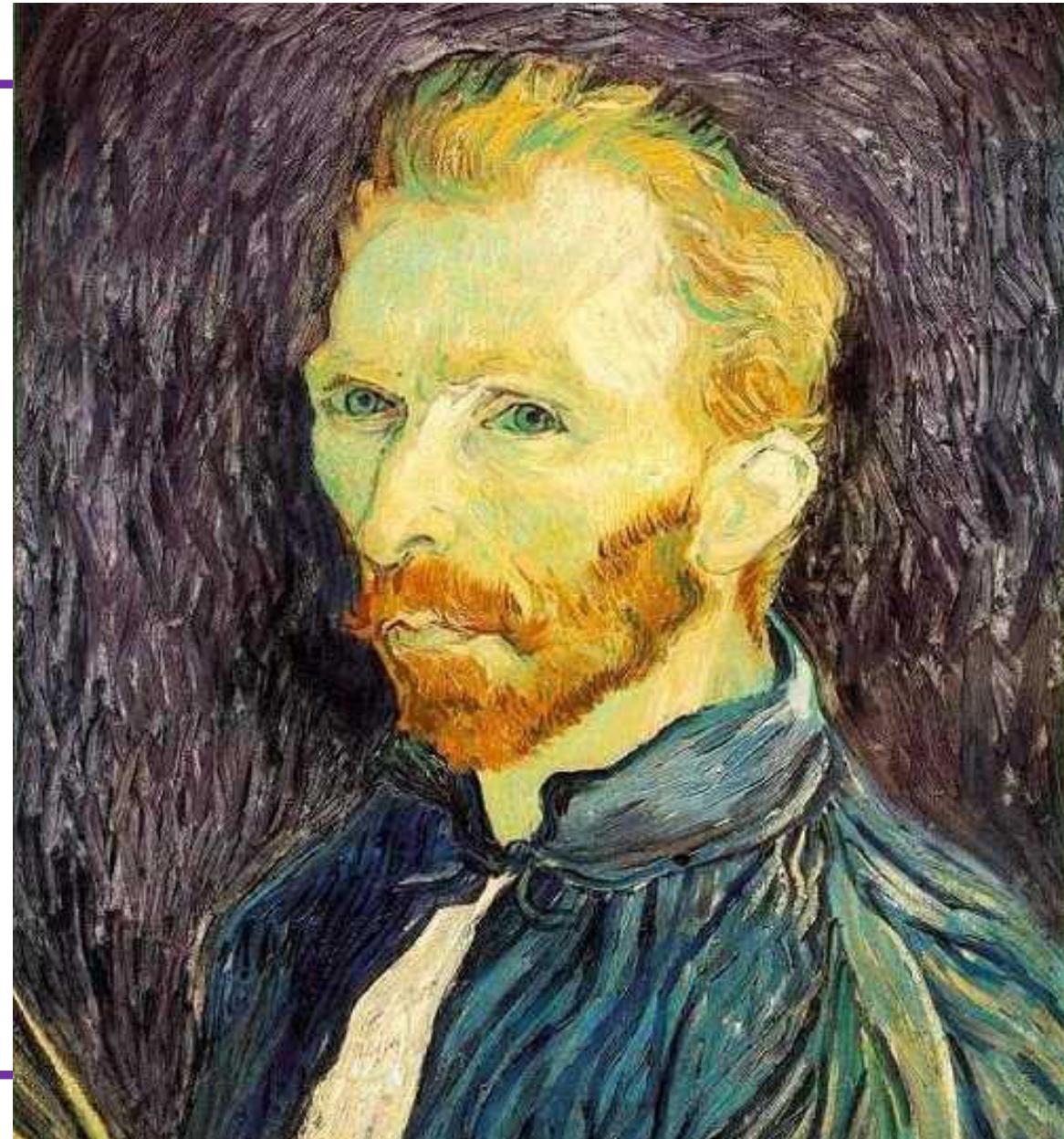




# Image Scaling

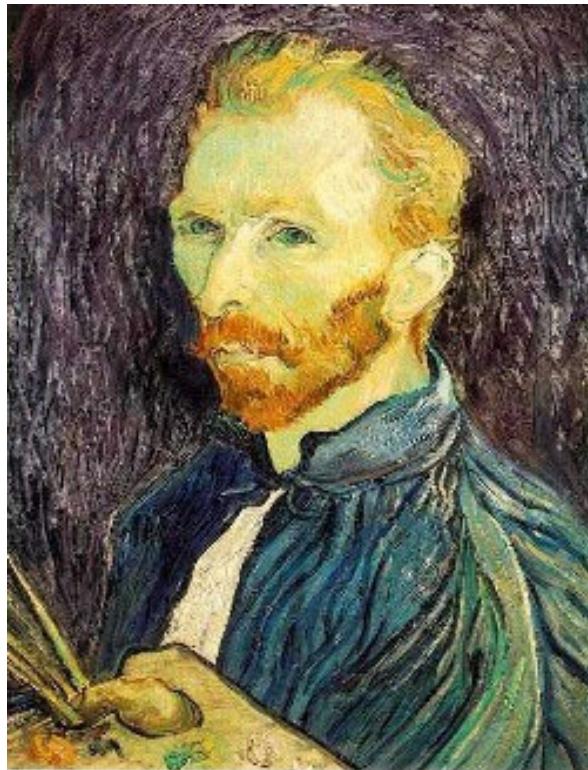
**This image is too big to fit on the screen. How can we reduce it?**

**How to generate a half-sized version?**





# Image Sub-Sampling



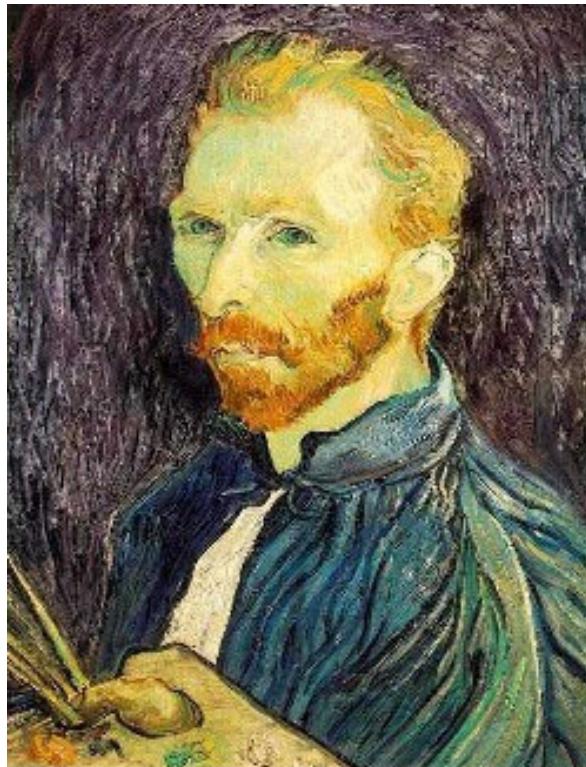
1/4

1/8

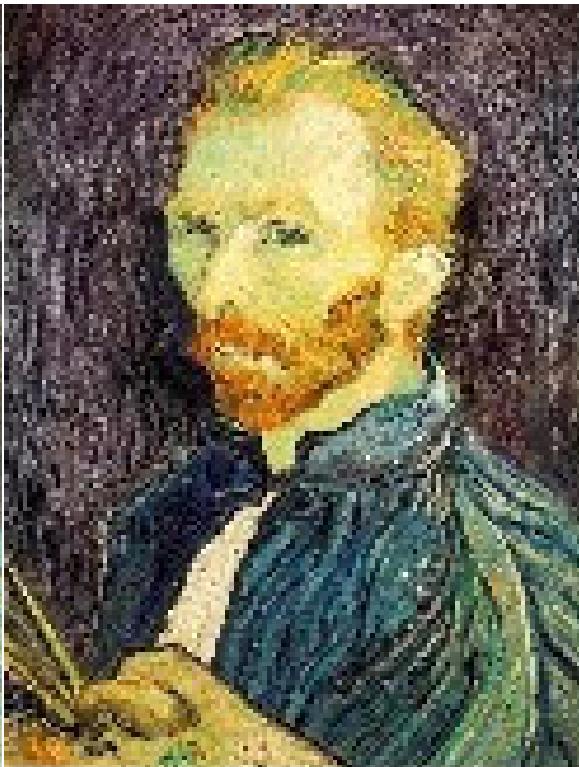
**Throw away every other row and  
column to create a  $1/2$  size image  
- called *image sub-sampling***



# Image Sub-Sampling



**1/2**



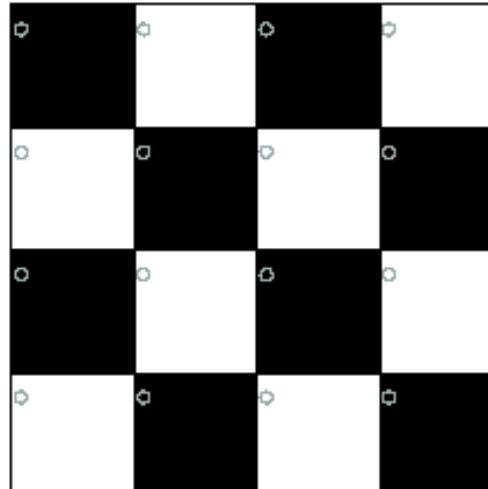
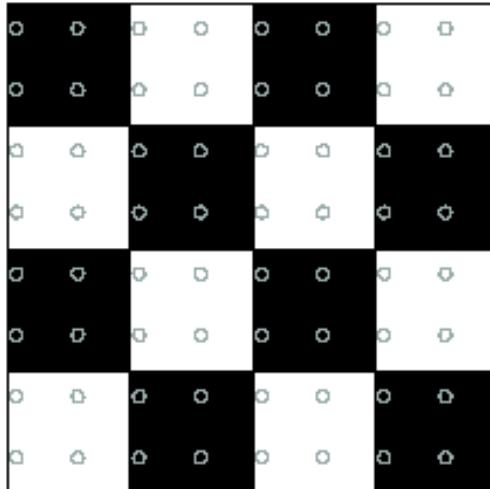
**1/4 (2x zoom)**



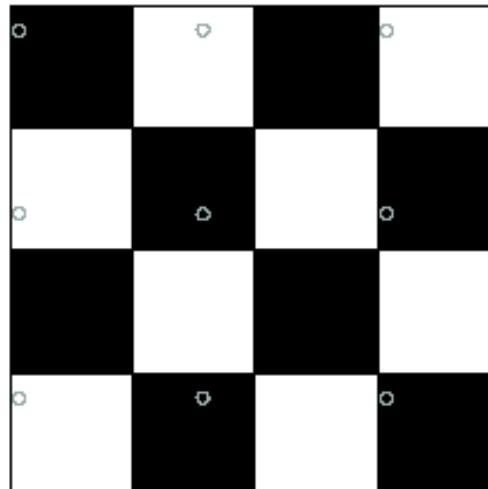
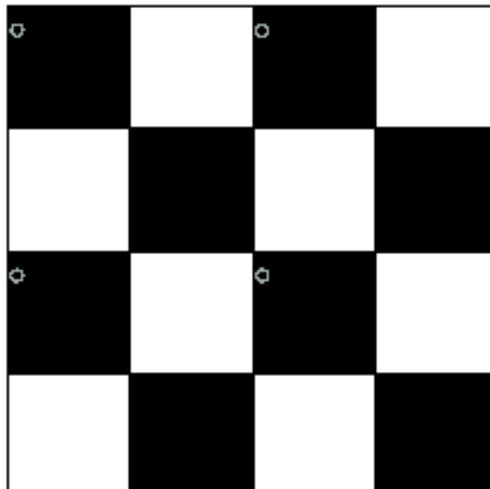
**1/8 (4x zoom)**



# Good and Bad Sampling



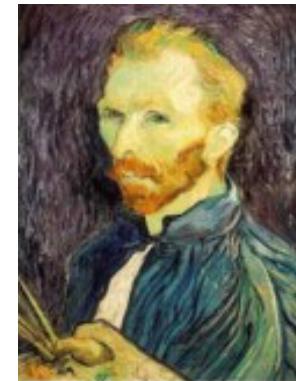
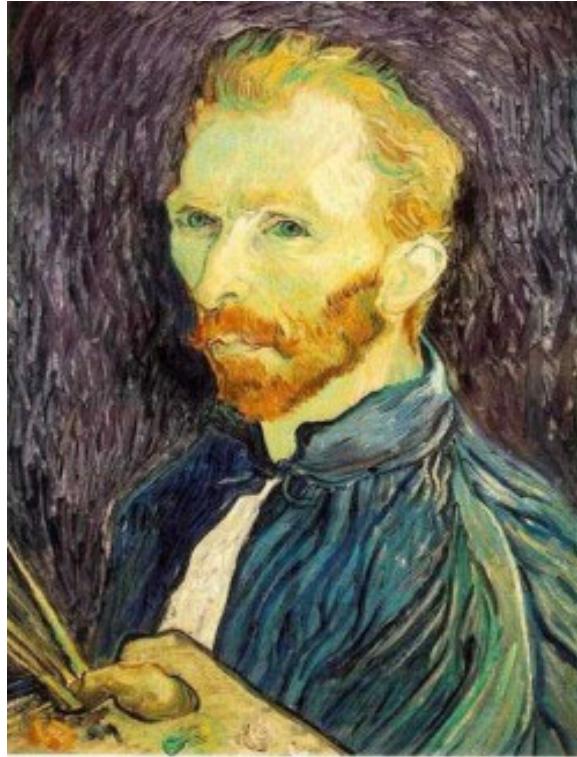
**Good sampling:**  
•Sample often or,  
•Sample wisely



**Bad sampling:**  
•see aliasing in action!



# Sub-Sampling with Gaussian Pre-Filtering



G 1/4



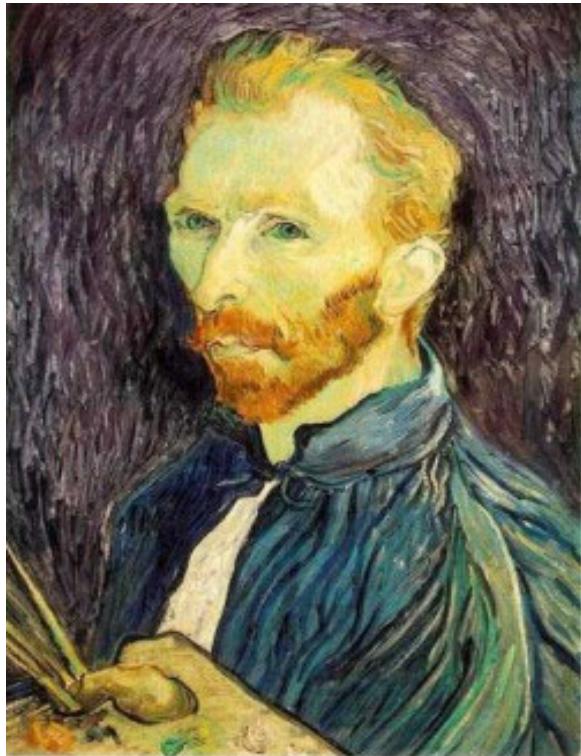
G 1/8

**Gaussian 1/2**

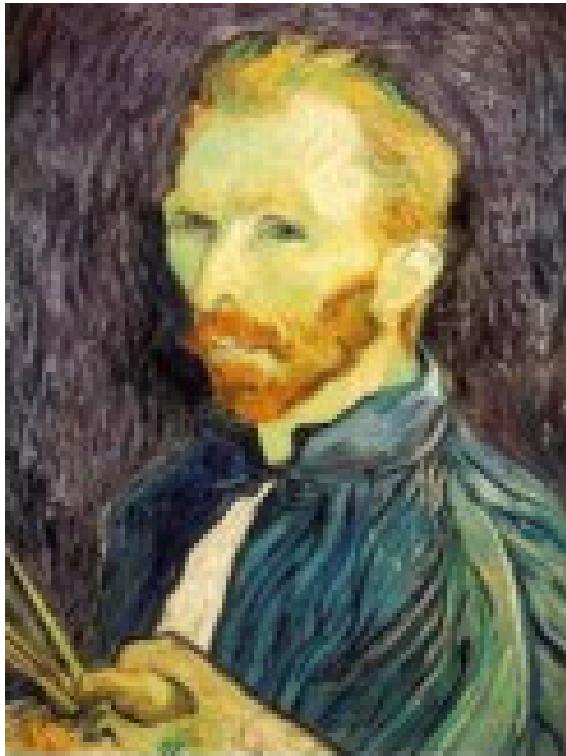
- **Solution: filter the image, *then* subsample**
  - Filter size should double for each  $\frac{1}{2}$  size reduction. Why?



## Sub-Sampling with Gaussian Pre-Filtering



**Gaussian 1/2**



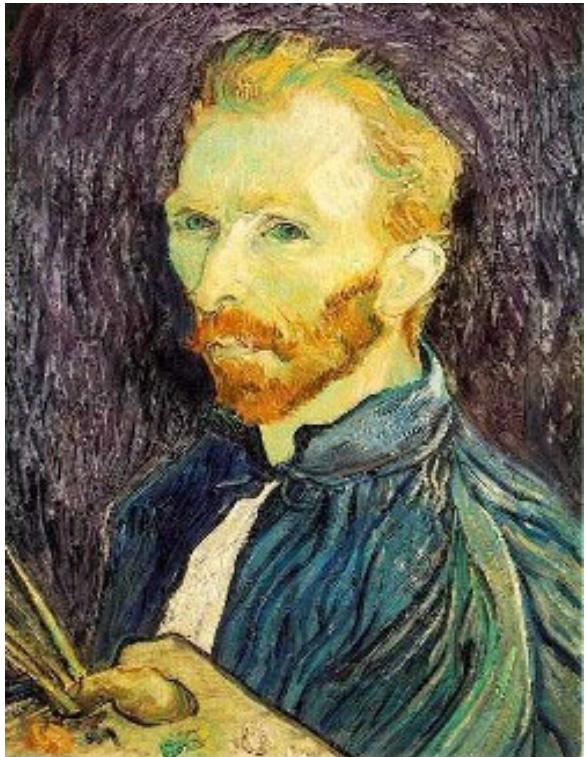
**G 1/4**



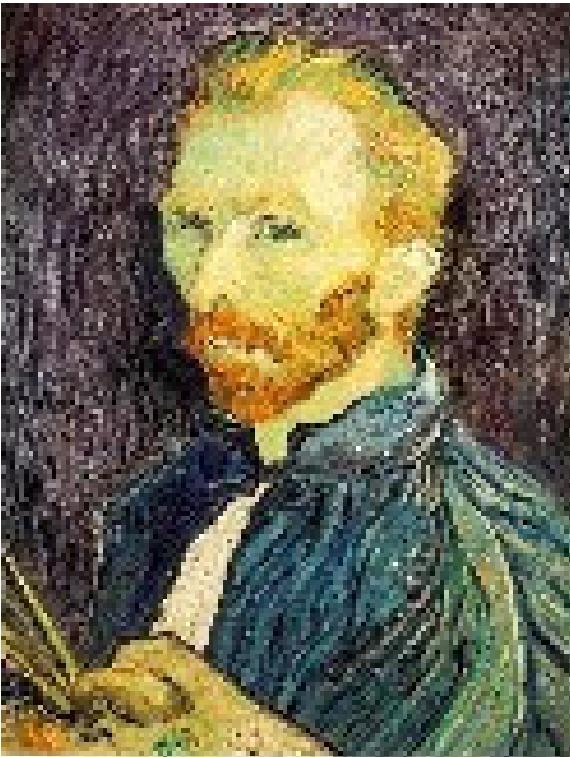
**G 1/8**



## Compare with...



**1/2**



**1/4 (2x zoom)**

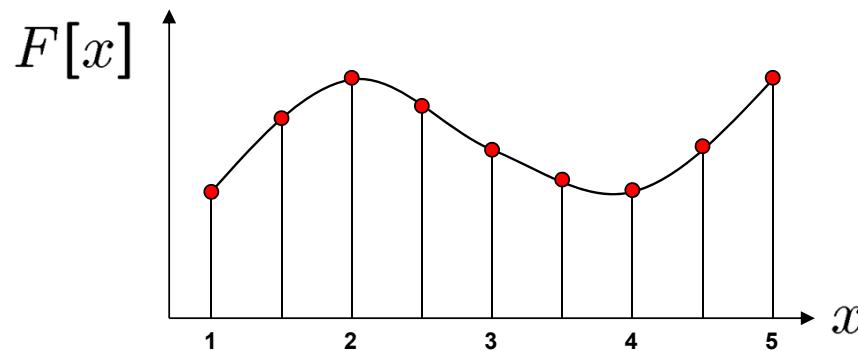


**1/8 (4x zoom)**



# Image Resampling

- What about arbitrary scale reduction?
- How can we increase the size of the image?



- **Recall how a digital image is formed**

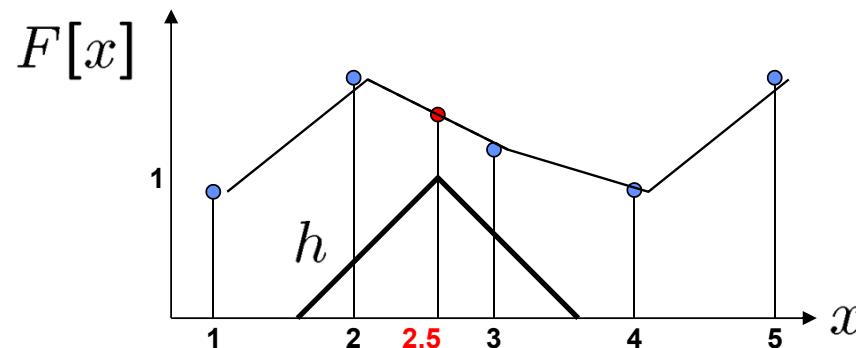
$$F[x, y] = \text{quantize}\{f(xd, yd)\}$$

- **It is a discrete point-sampling of a continuous function**
- **If we could somehow reconstruct the original function, any new image could be generated, at any resolution and scale**



# Image Resampling

- So what to do if we don't know  $f$ 
  - Answer: guess an approximation  $\tilde{f}$
  - Can be done in a principled way: filtering

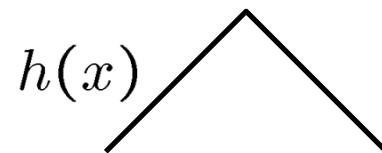


- Image reconstruction
  - Convert  $F$  to a continuous function
$$f_F(x) = F\left(\frac{x}{d}\right) \text{ when } \frac{x}{d} \text{ is an integer, 0 otherwise}$$
  - Reconstruct by convolution:
$$\tilde{f} = h \otimes f_F$$

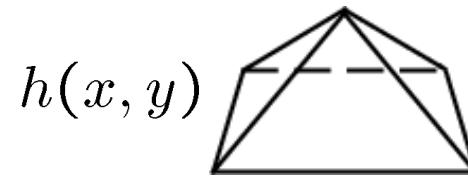


# Resampling filters

- What does the 2D version of this hat function look like?



performs  
linear interpolation



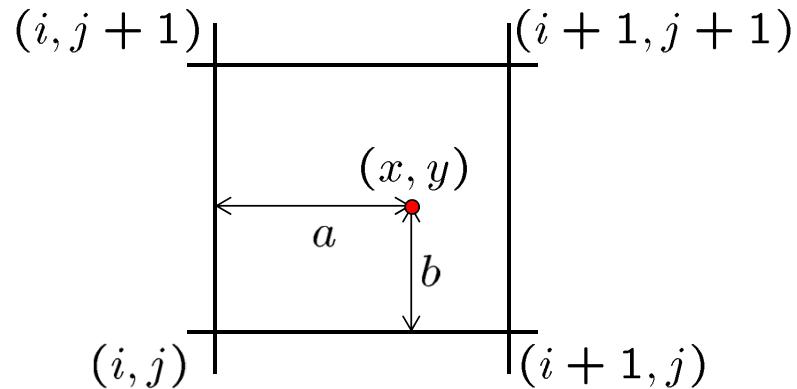
performs  
bilinear interpolation

- **Better filters give better resampled images**
  - Bicubic is common choice



# Bilinear interpolation

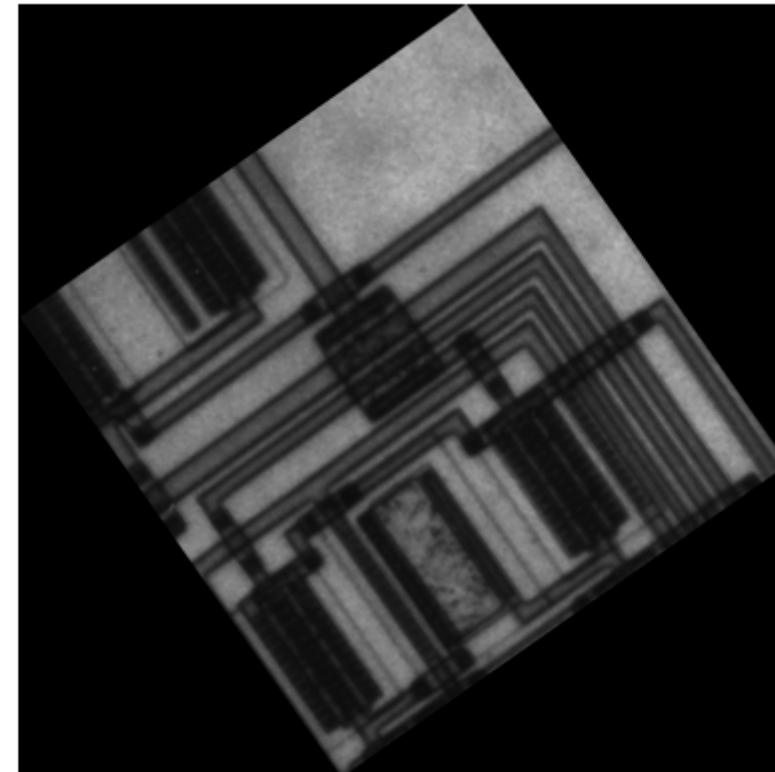
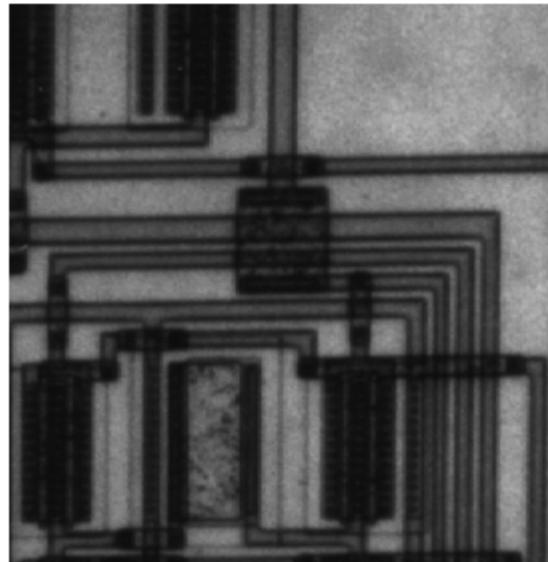
- A common method for resampling images



$$\begin{aligned} F(x, y) = & (1 - a)(1 - b) F(i, j) \\ & + a(1 - b) F(i + 1, j) \\ & + ab F(i + 1, j + 1) \\ & + (1 - a)b F(i, j + 1) \end{aligned}$$



# Image Rotation





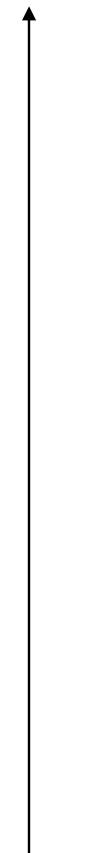
## Multi-Resolution Image Representation

- Fourier domain tells us “what” (frequencies, sharpness, texture properties), but not “where”.
- Spatial domain tells us “where” (pixel location) but not “what”.
- We want a image representation that gives a local description of image “events” – what is happening where.
- Naturally, think about representing images across varying scales.



# Multi-resolution Image Pyramids

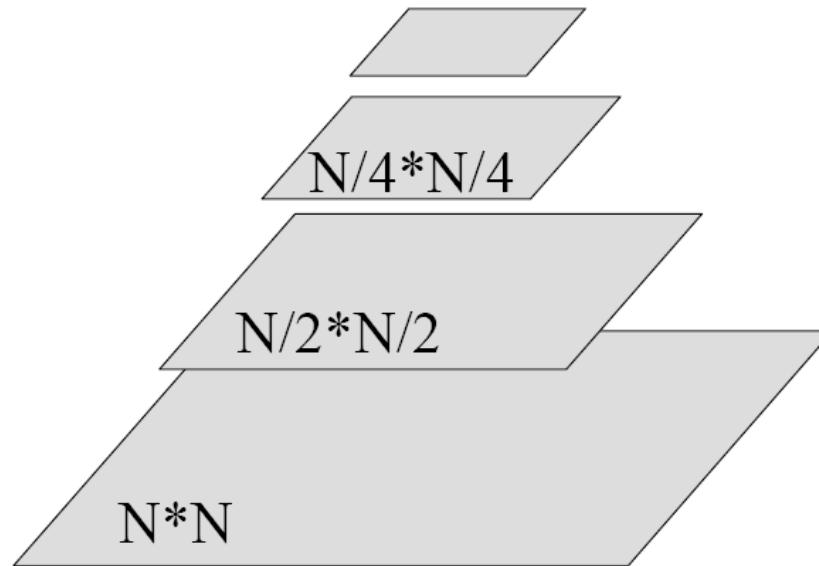
Low resolution



High resolution



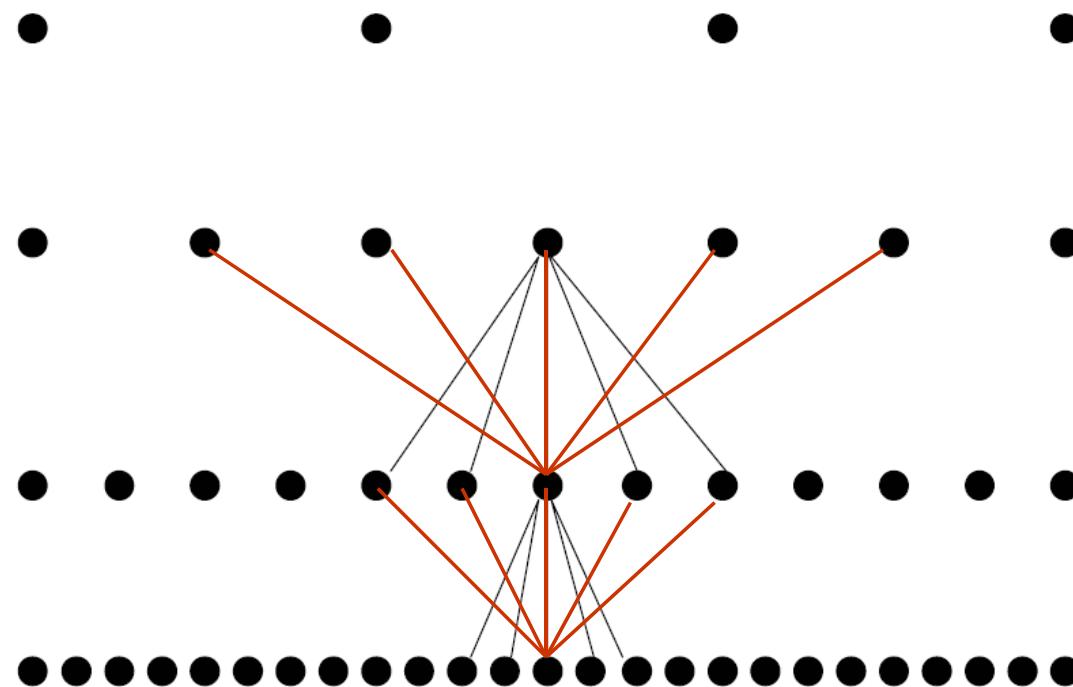
# Space Required for Pyramids

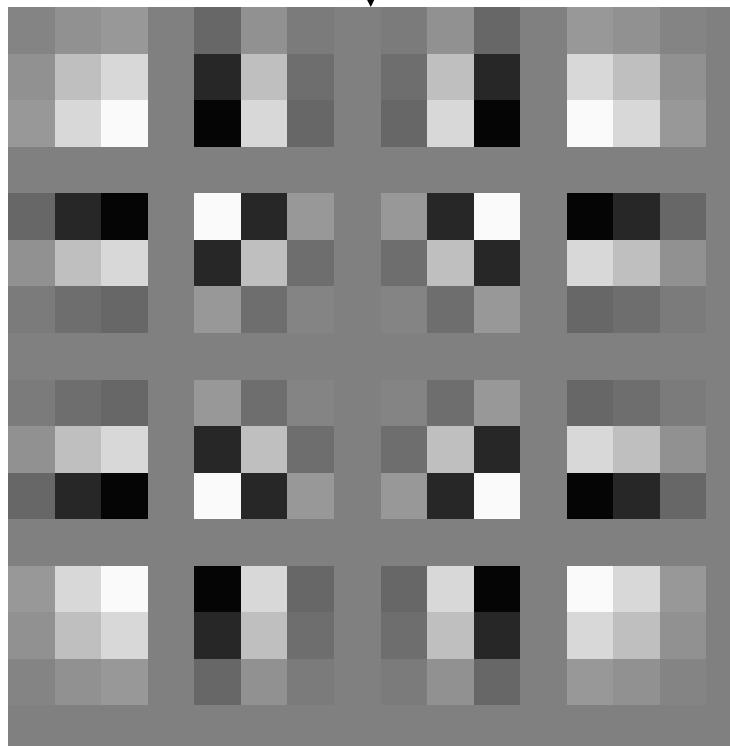
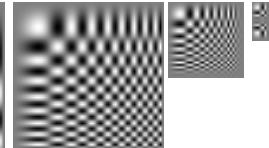
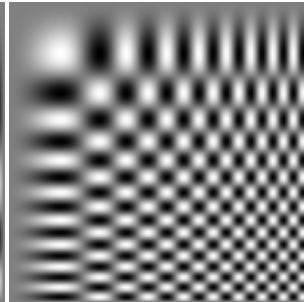
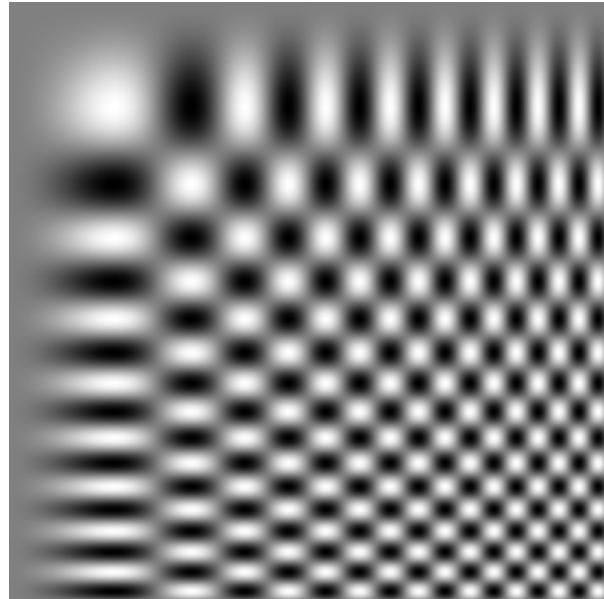


$$N^2 + \frac{1}{4}N^2 + \frac{1}{16}N^2 + \dots = 1\frac{1}{3}N^2$$



# Pyramid Construction





**Constructing a pyramid by taking every second pixel leads to layers that badly misrepresent the top layer**



## Even worse for synthetic images





# Downsampling



\*

1	4	6	4	1
4	16	24	16	4
6	24	36	24	6
4	16	24	16	4
1	4	6	4	1



Subsample





# Expansion



Expand  
Image



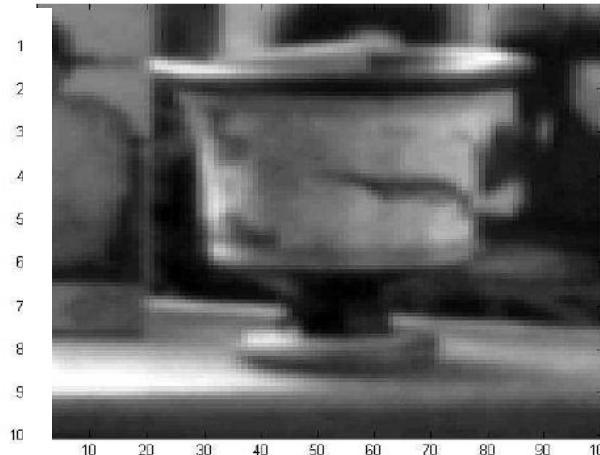
Interpolation



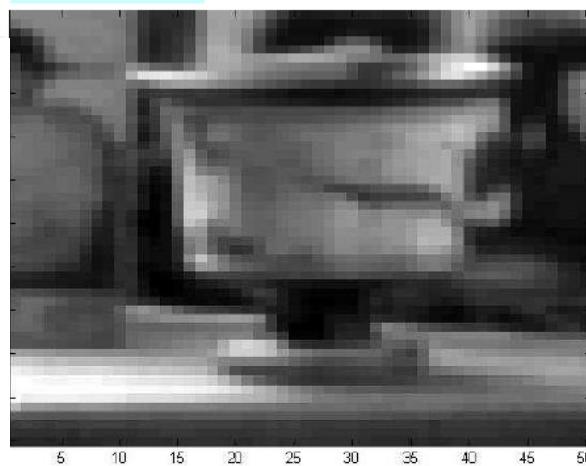


# Interpolation Results

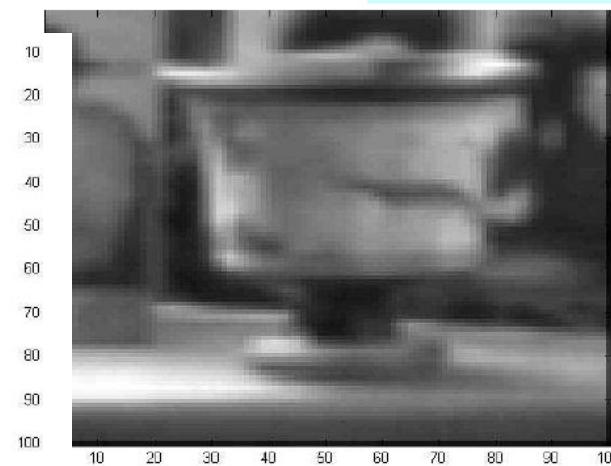
Original  
Image



Nearest  
Neighbor



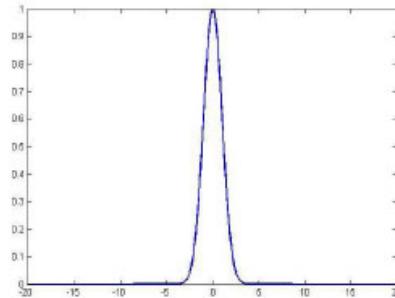
Bilinear  
Interpolation



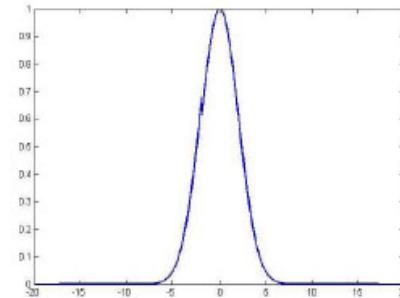


# The Gaussian Pyramid

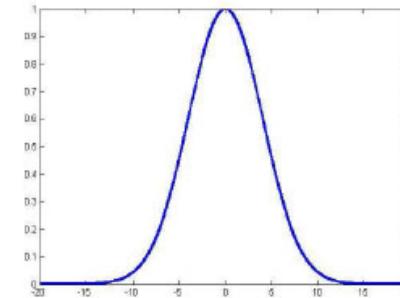
- Smooth with Gaussians because
  - a Gaussian\*Gaussian=another Gaussian
- Synthesis
  - smooth and downsample
- Gaussians are low pass filters, so repetition is redundant
- Kernel width doubles with each level



Level 1



Level 2



Level 3

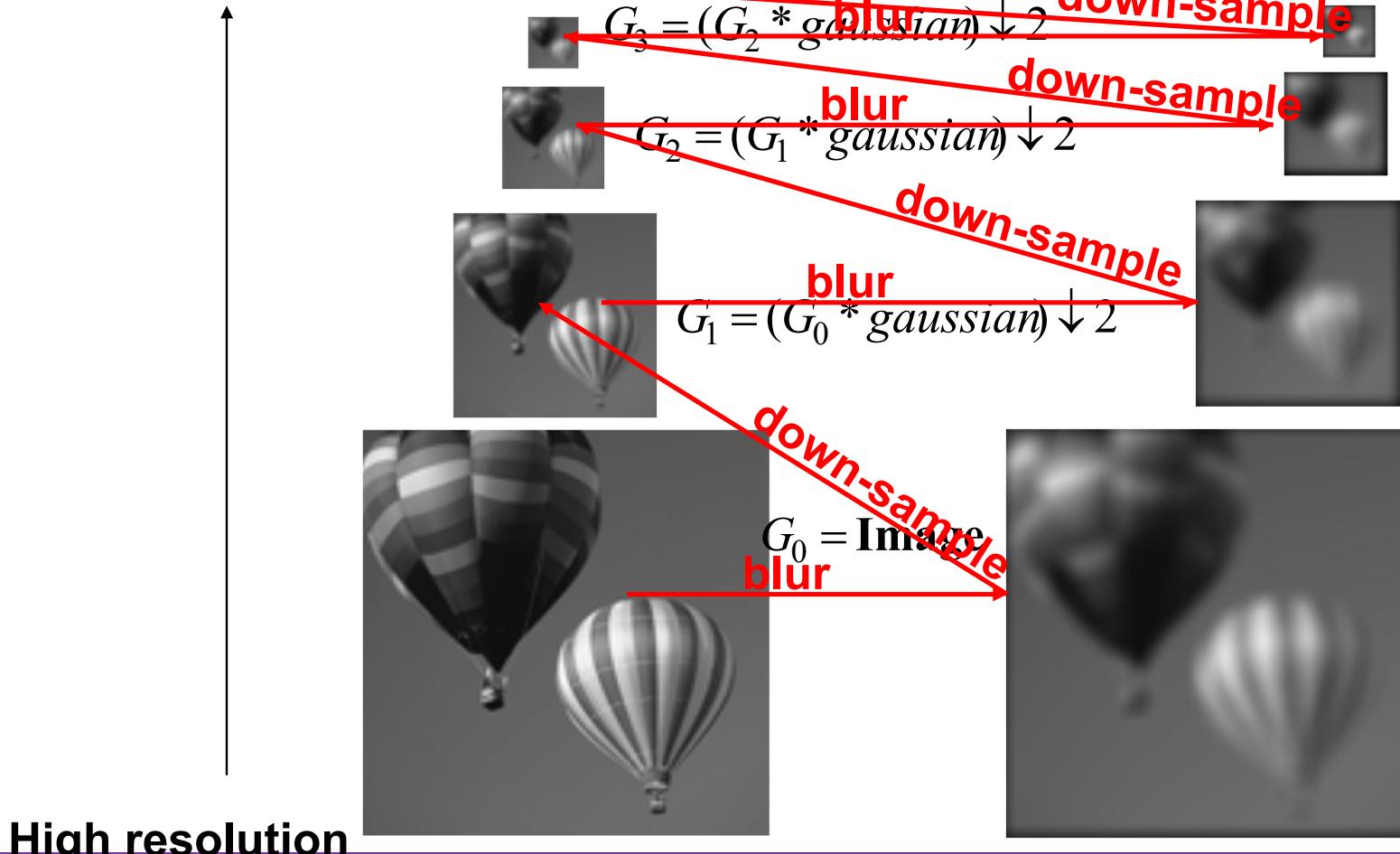


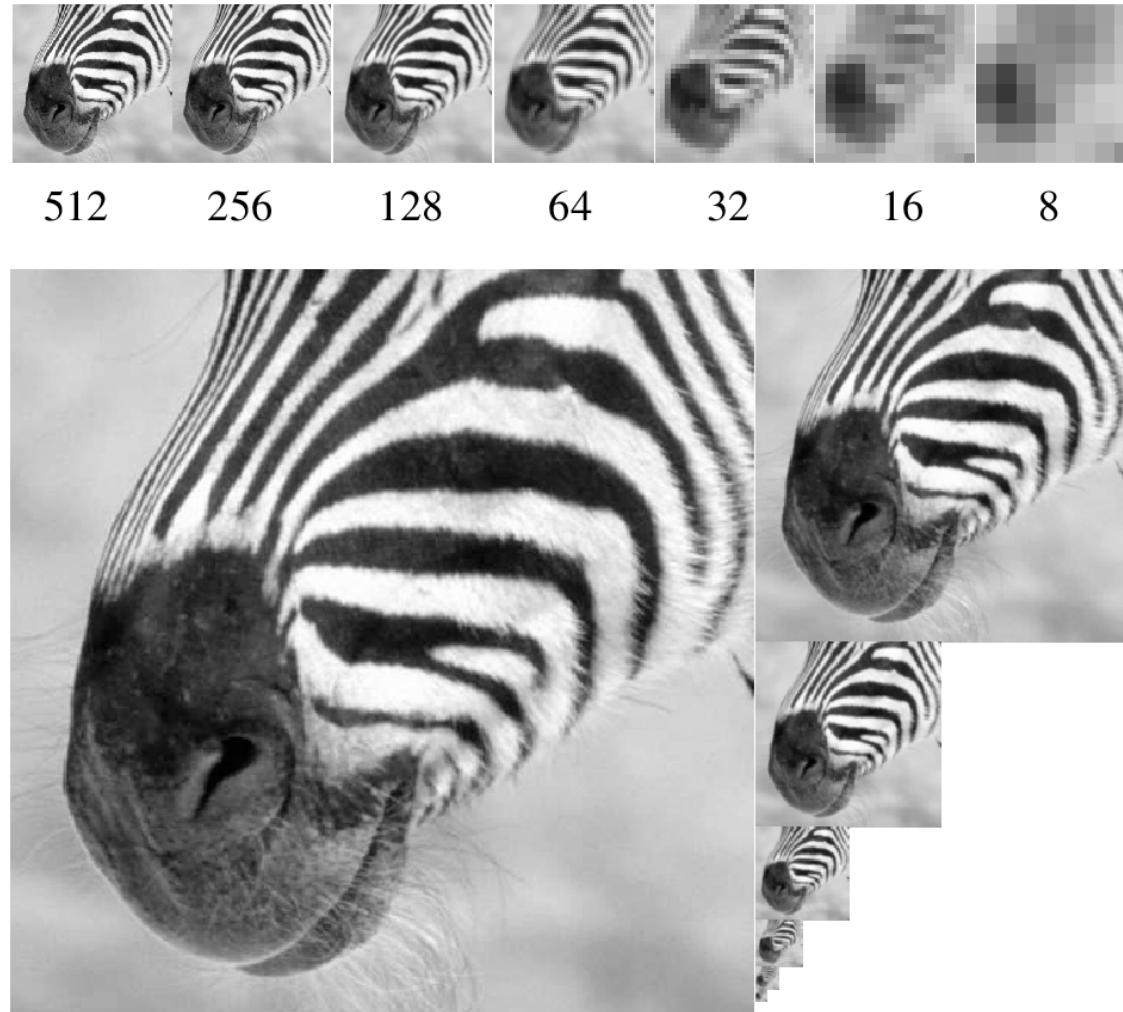
## Smoothing as low-pass filtering

- High frequencies lead to trouble with sampling.
- Suppress high frequencies before sampling !
  - truncate high frequencies in FT
  - or convolve with a low-pass filter
- Common solution: use a Gaussian
  - multiplying FT by Gaussian is equivalent to convolving image with Gaussian.



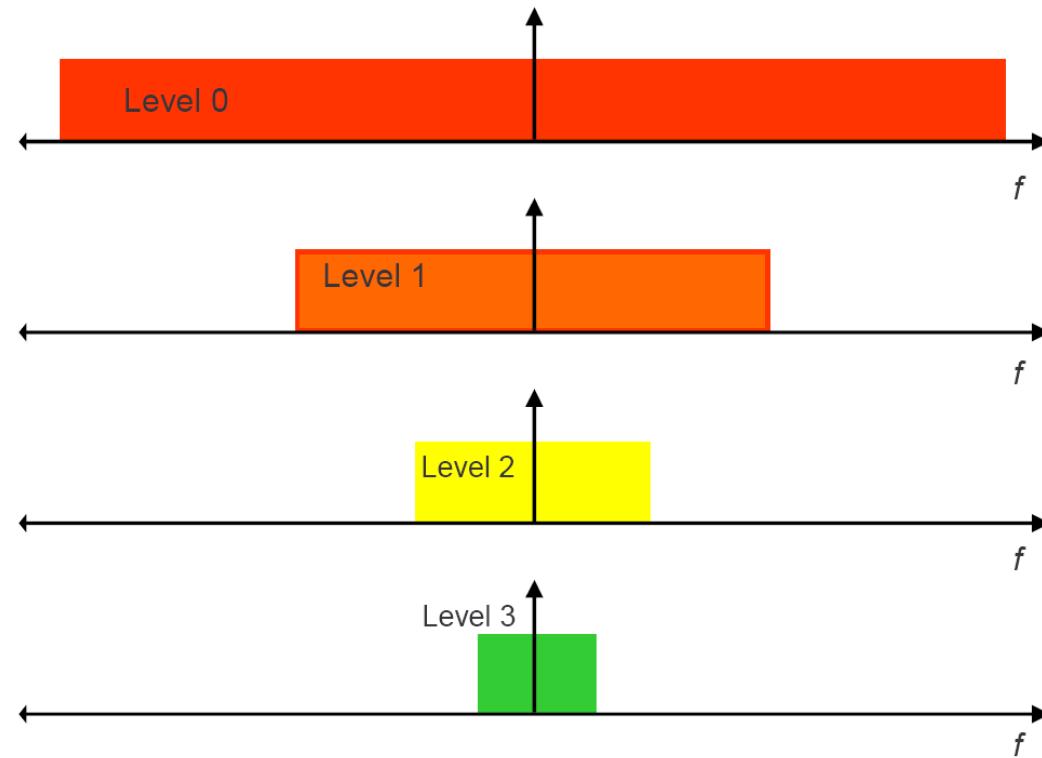
**Low resolution**





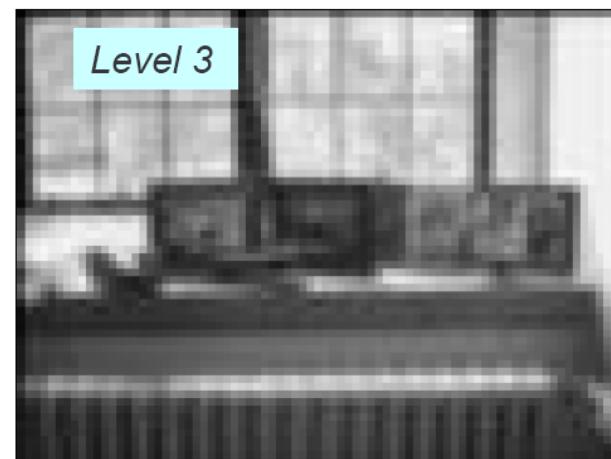


## Gaussian Pyramid Frequency Composition





# Pyramids at Same Resolution



BRIAN LEVYON



## Difference of Gaussians (DoG)

- Laplacian of Gaussian can be approximated by the difference between two different Gaussians

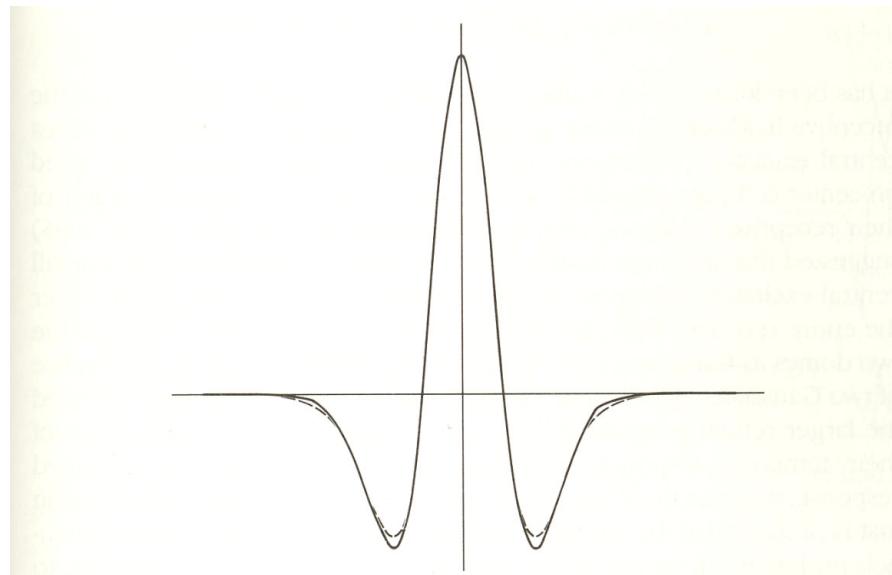
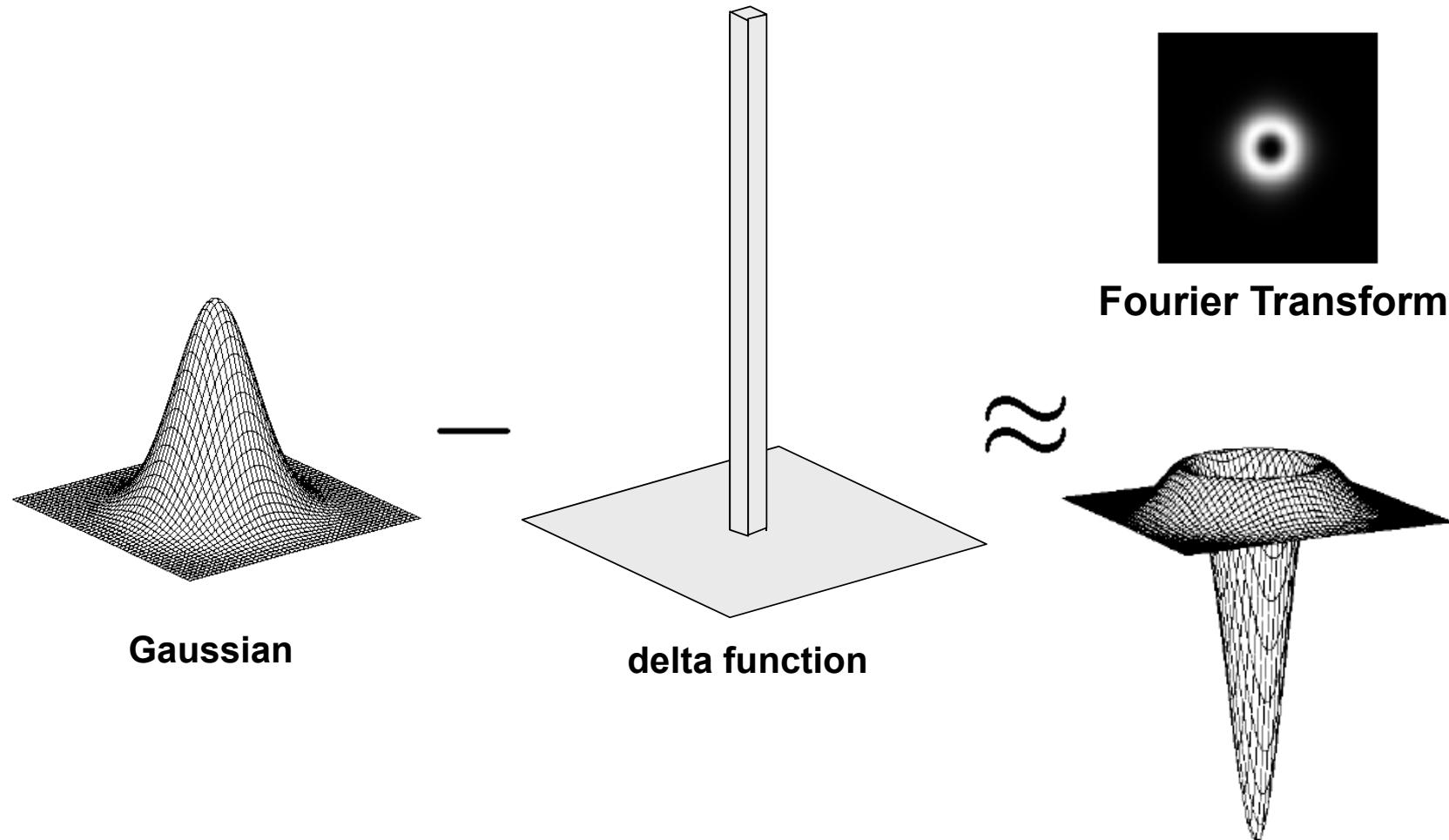
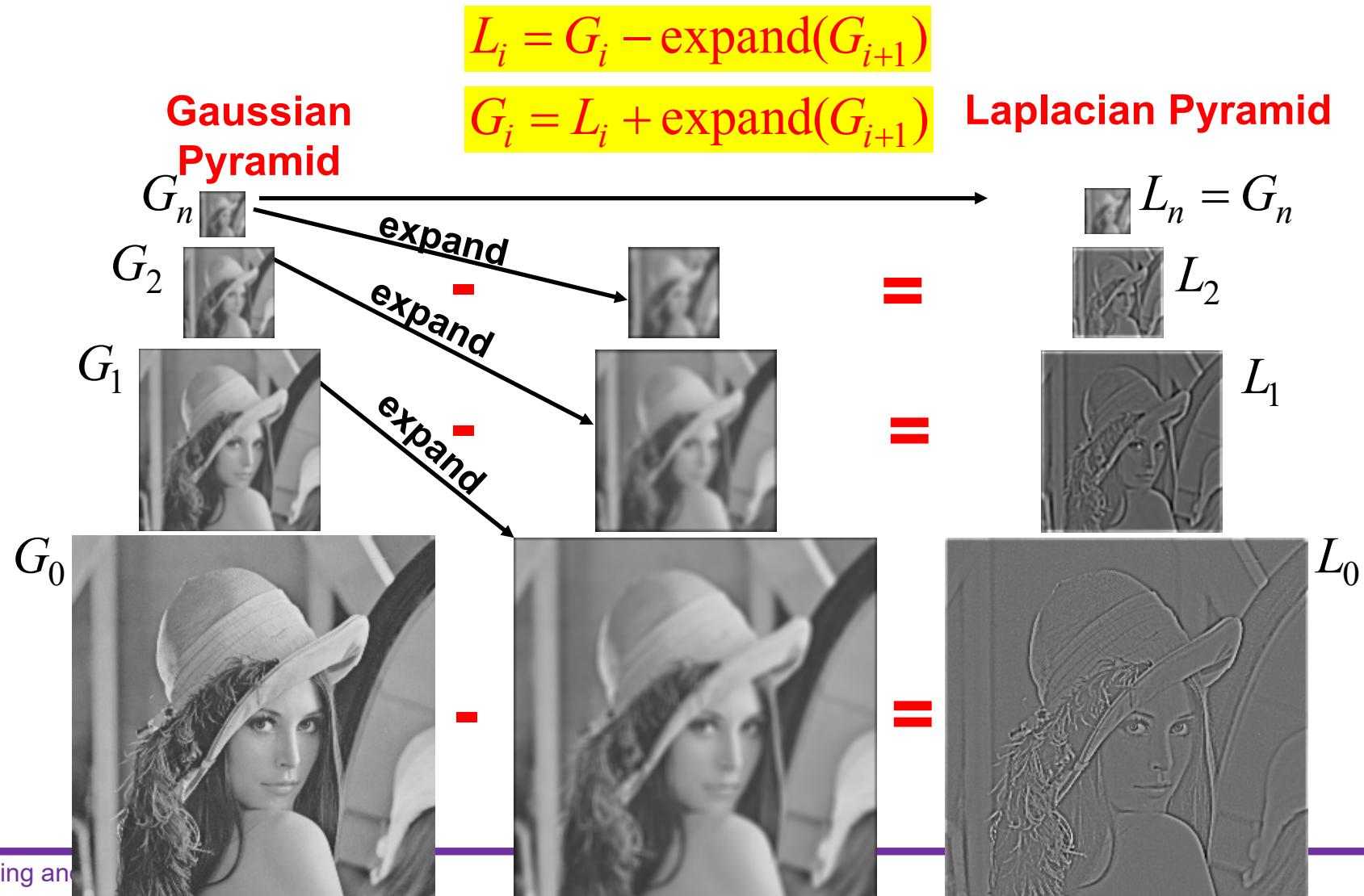


Figure 2–16. The best engineering approximation to  $\nabla^2 G$  (shown by the continuous line), obtained by using the difference of two Gaussians (DOG), occurs when the ratio of the inhibitory to excitatory space constraints is about 1:1.6. The DOG is shown here dotted. The two profiles are very similar. (Reprinted by permission from D. Marr and E. Hildreth, “Theory of edge detection,” *Proc. R. Soc. Lond. B* 204, pp. 301–328.)



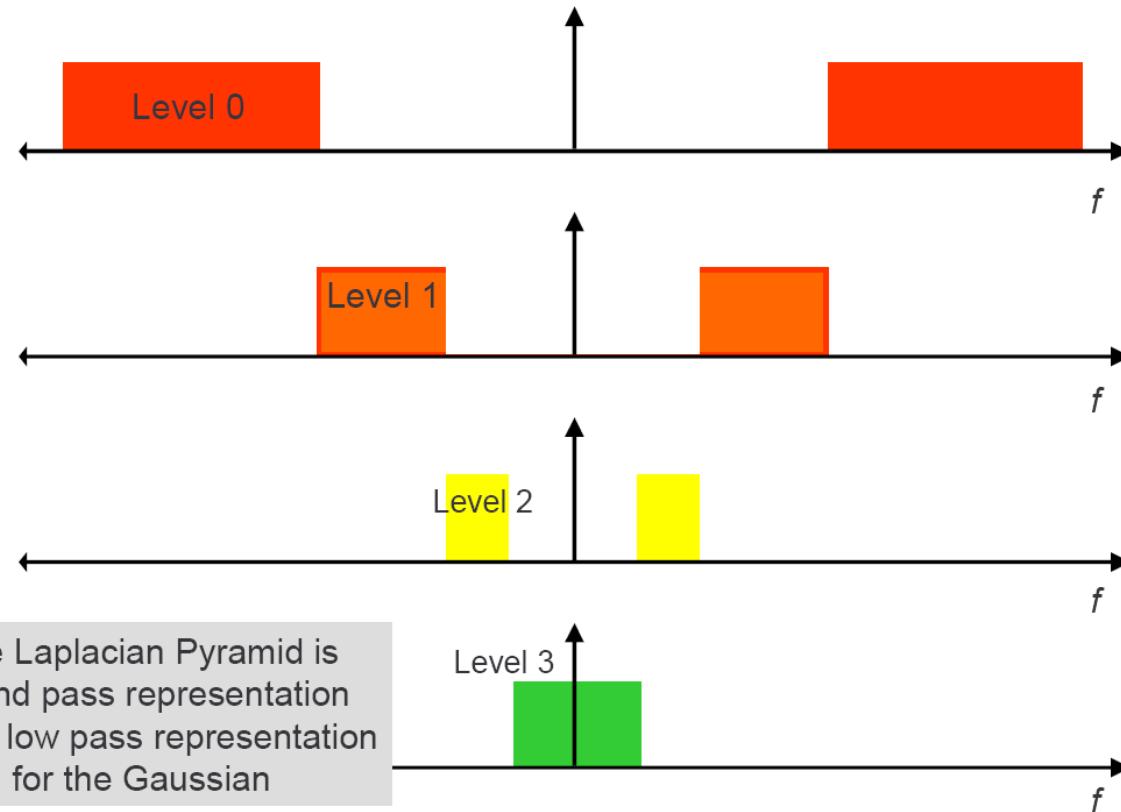
# Gaussian – Image filter







## Laplacian Pyramid Frequency Composition





# Applications of Image Pyramids

- Coarse-to-Fine strategies for computational efficiency.
- Search for correspondence
  - look at coarse scales, then refine with finer scales
- Edge tracking
  - a “good” edge at a fine scale has parents at a coarser scale
- Control of detail and computational cost in matching
  - e.g. finding stripes
  - very important in texture representation
- Image Blending and Mosaicing
- Data compression



# Edge Detection using Pyramids

**Coarse-to-fine strategy:**

- Do edge detection at higher level.
- Consider edges of finer scales only near the edges of higher scales.

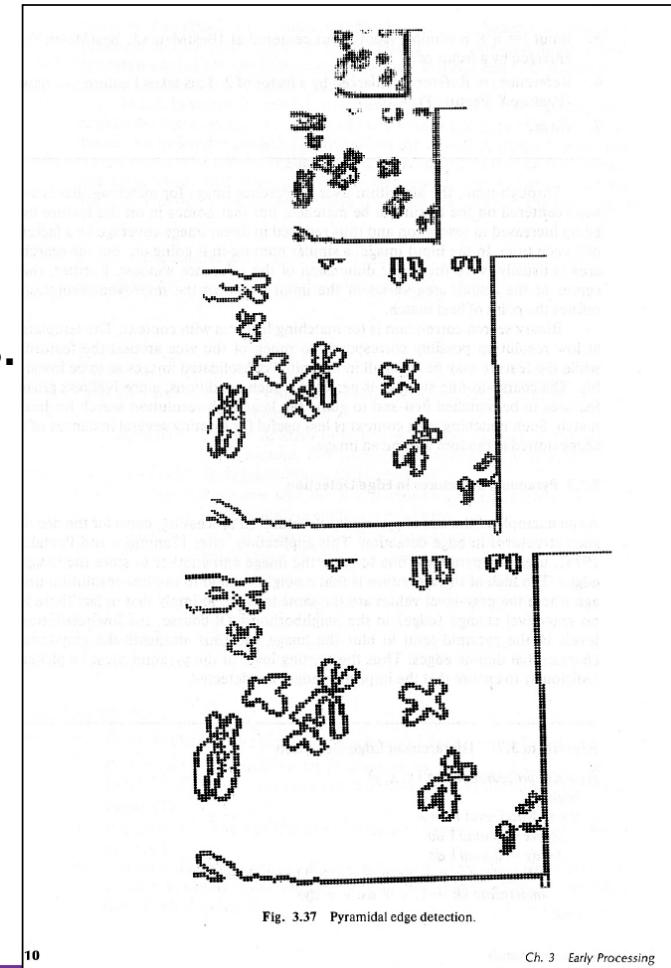


Fig. 3.37 Pyramidal edge detection.

10

Ch. 3 Early Processing

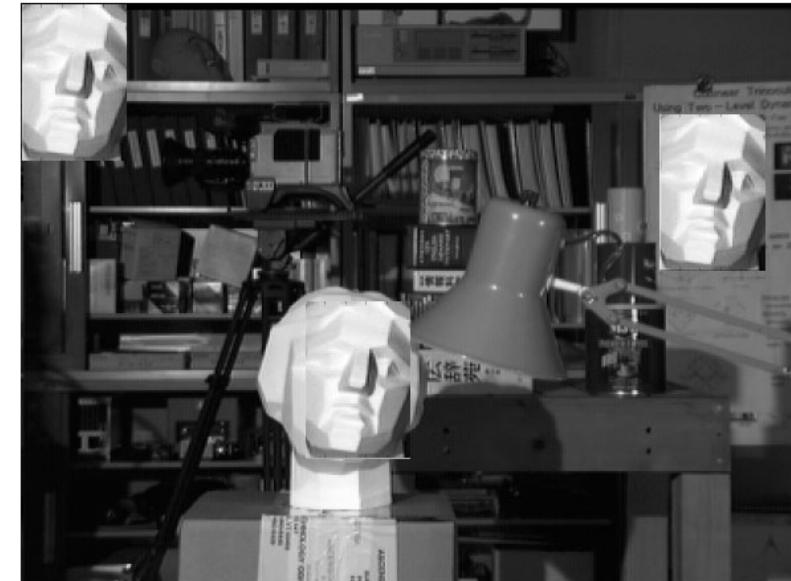


# Fast Template Matching

*Template*



*Search Region*



- For an  $m \times n$  image...
- For a  $p \times q$  template...
- The complexity of the 2D pattern recognition task is  $O(mnpq)$  😞
- This gets even worse for a family of templates (e.g., to address scale and/or rotational effects)



# Fast Template Matching

*Template*



*Search Region*

Original Image



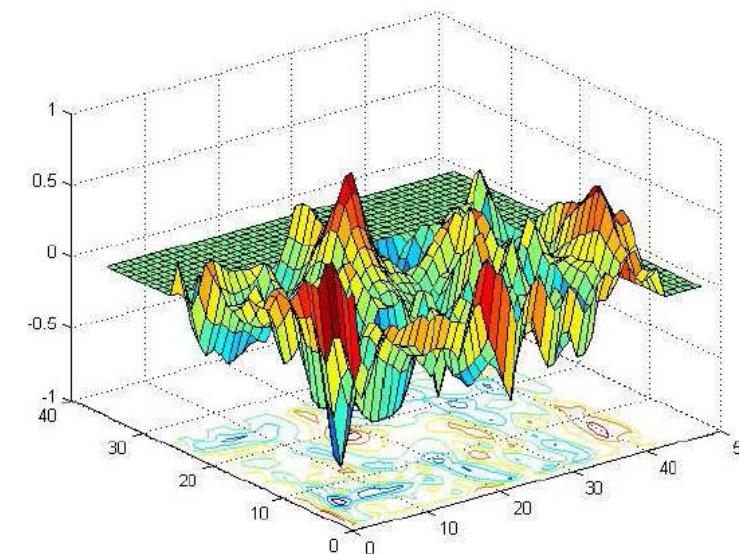
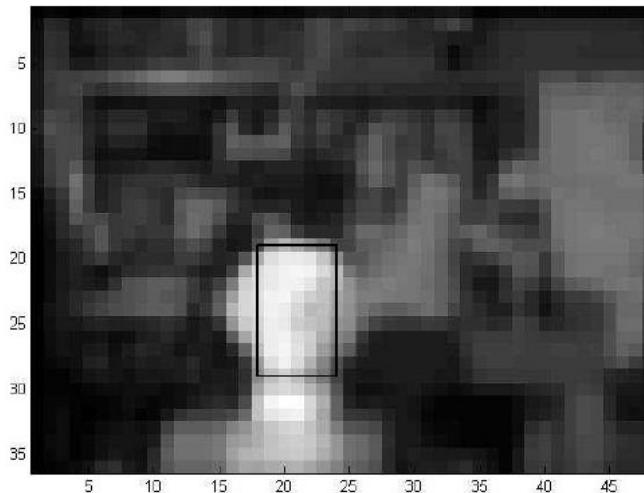


- Multi-resolution template matching
  - reduce resolution of both template and image by creating an **image pyramid**
  - match small template against small image
  - identify locations of strong matches
  - expand the image and template, and match higher resolution template selectively to higher resolution image
  - iterate on higher and higher resolution images
- Issue:
  - how to choose detection thresholds at each level
    - too low will lead to too much cost
    - too high will miss match



## Level 3 Search

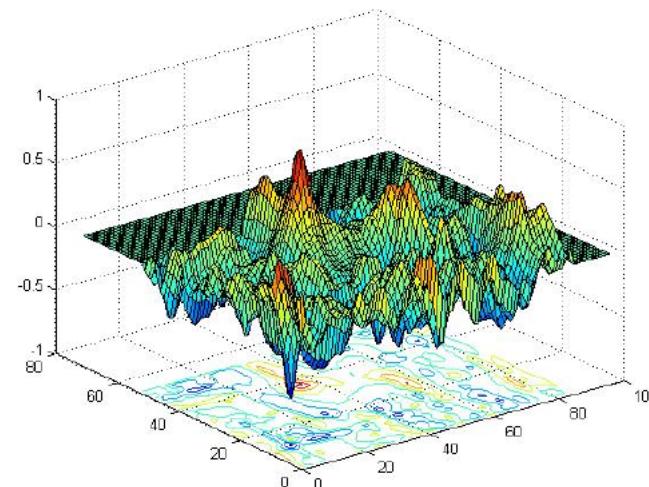
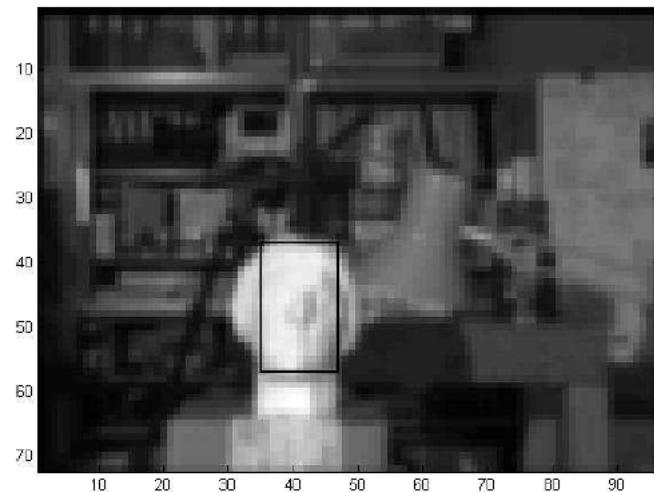
- At the lowest pyramid level, we search the entire image with the correlation template





## Level 2 Search

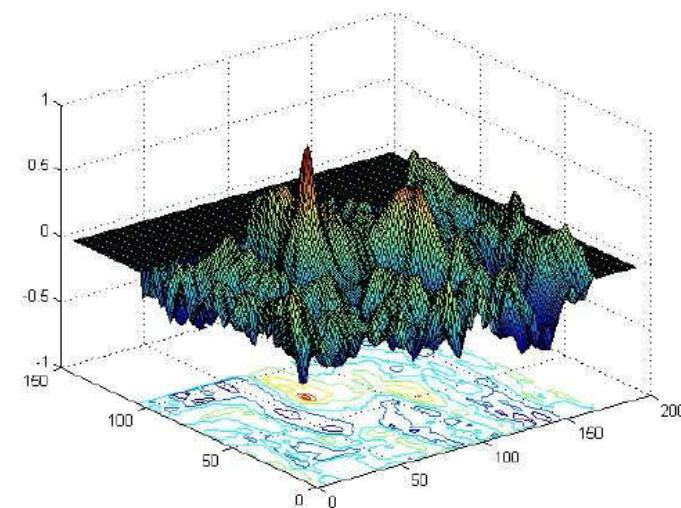
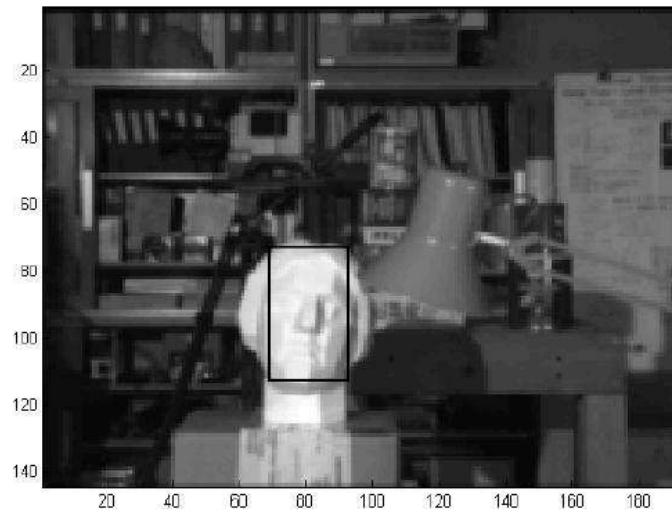
- Subsequent searches are constrained to a neighborhood of only several pixels in the x and y directions





## Level 1 Search

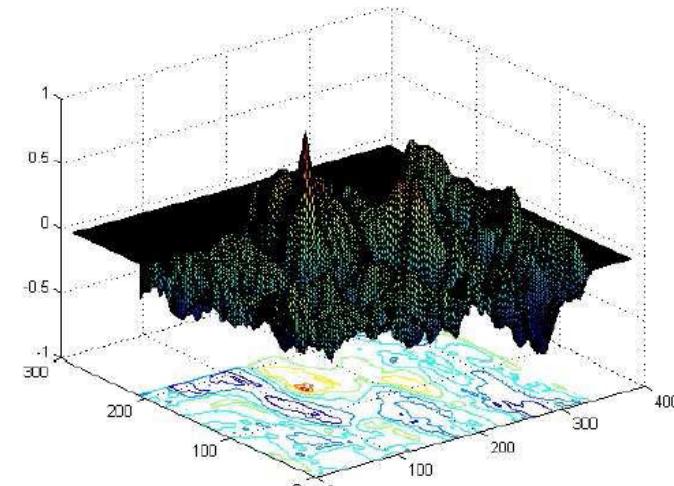
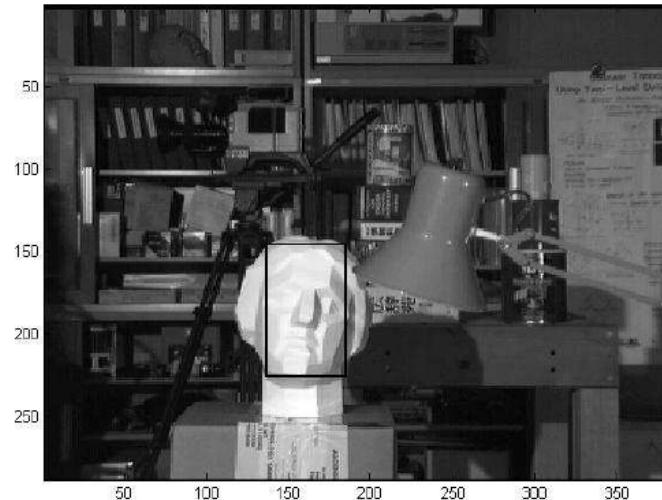
- Subsequent searches are constrained to a neighborhood of only several pixels in the x and y directions





## Level 0 Search

- In the end, the total time (in Matlab) was reduced from  $\approx 31$  seconds to  $\approx 0.5$  seconds while obtaining the same template match





# Image Blending and Mosaicing

- Given two images  $A$  and  $B$
- Construct Laplacian Pyramid  $L_a$  and  $L_b$
- Create a third Laplacian Pyramid  $L_c$  where for each level  $l$

$$L_c(i, j) = \begin{cases} L_a(i, j) & \text{if } i < \text{width}/2 \\ (L_a(i, j) + L_b(i, j))/2 & \text{if } i = \text{width}/2 \\ L_b(i, j) & \text{if } i > \text{width}/2 \end{cases}$$

- Sum all levels  $L_c$  in to get the blended image

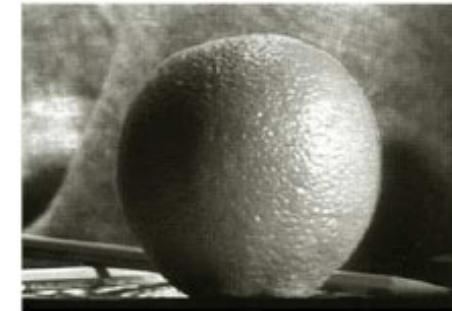
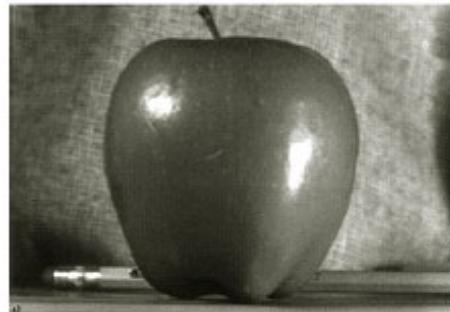
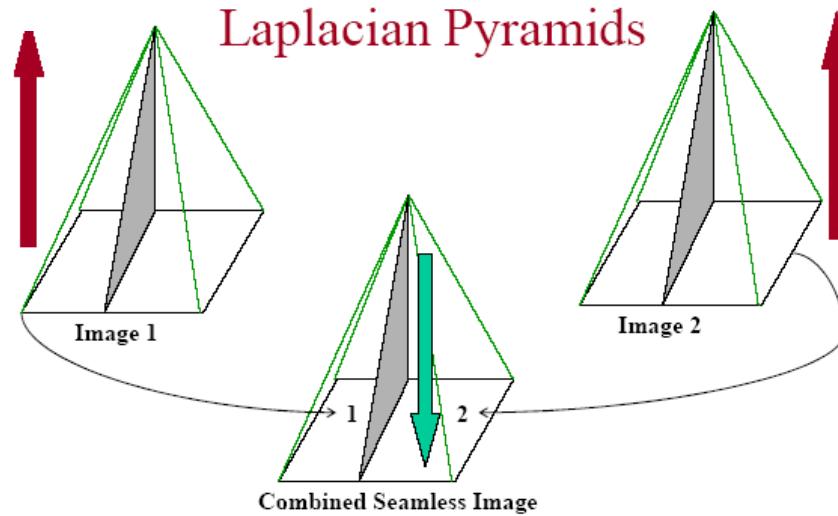
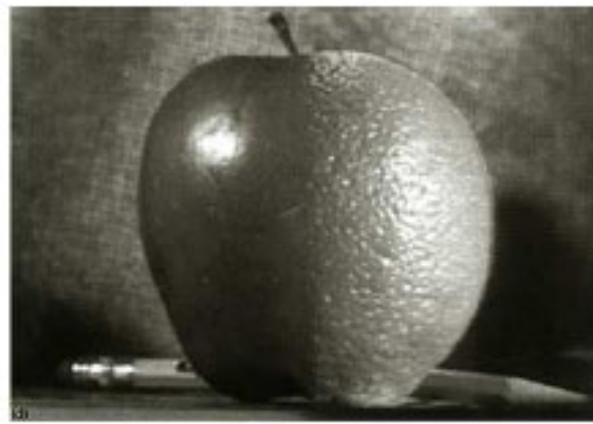
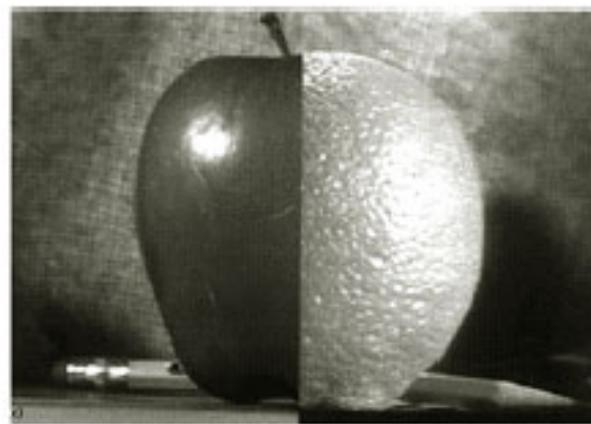
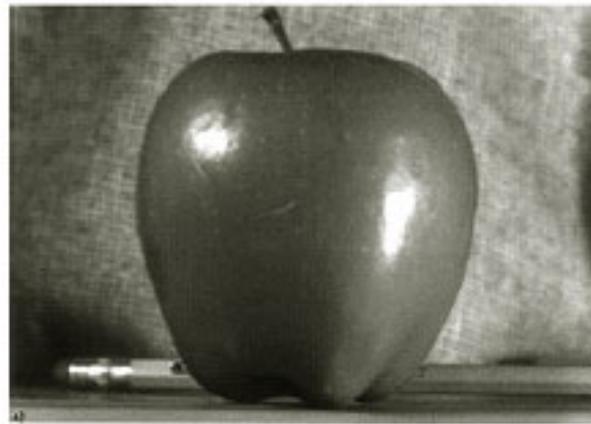


Image Merging with  
Laplacian Pyramids





# Blending Apples and Oranges



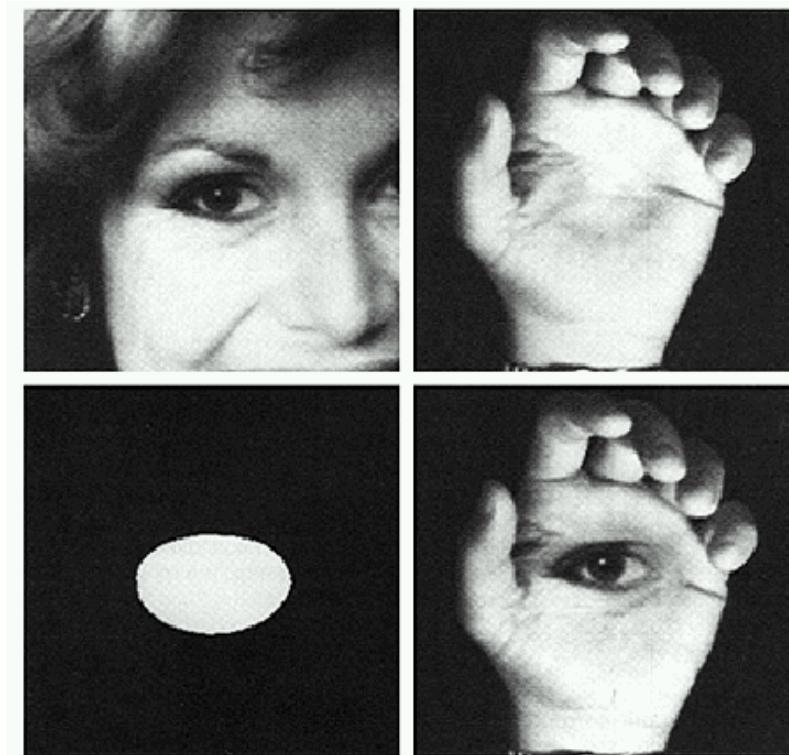


# Pyramid blending of Regions

- Given two images  $A$  and  $B$ , and a mask  $M$
- Construct Laplacian Pyramids  $L_a$  and  $L_b$
- Construct a Gaussian Pyramid  $G_m$
- Create a third Laplacian Pyramid  $L_c$  where for each level  $l$

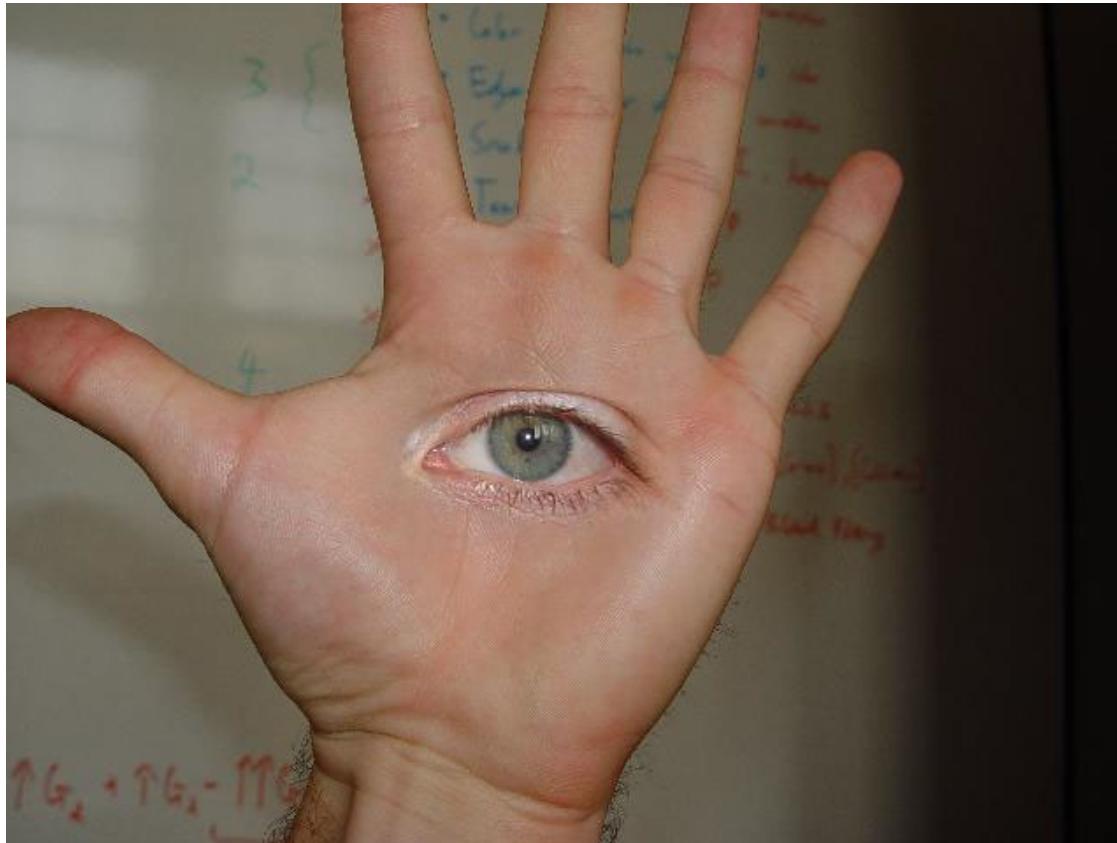
$$L_c(i, j) = G_m(i, j)L_a(i, j) + (1 - G_m(i, j))L_b(i, j)$$

- Sum all levels  $L_c$  in to get the blended image



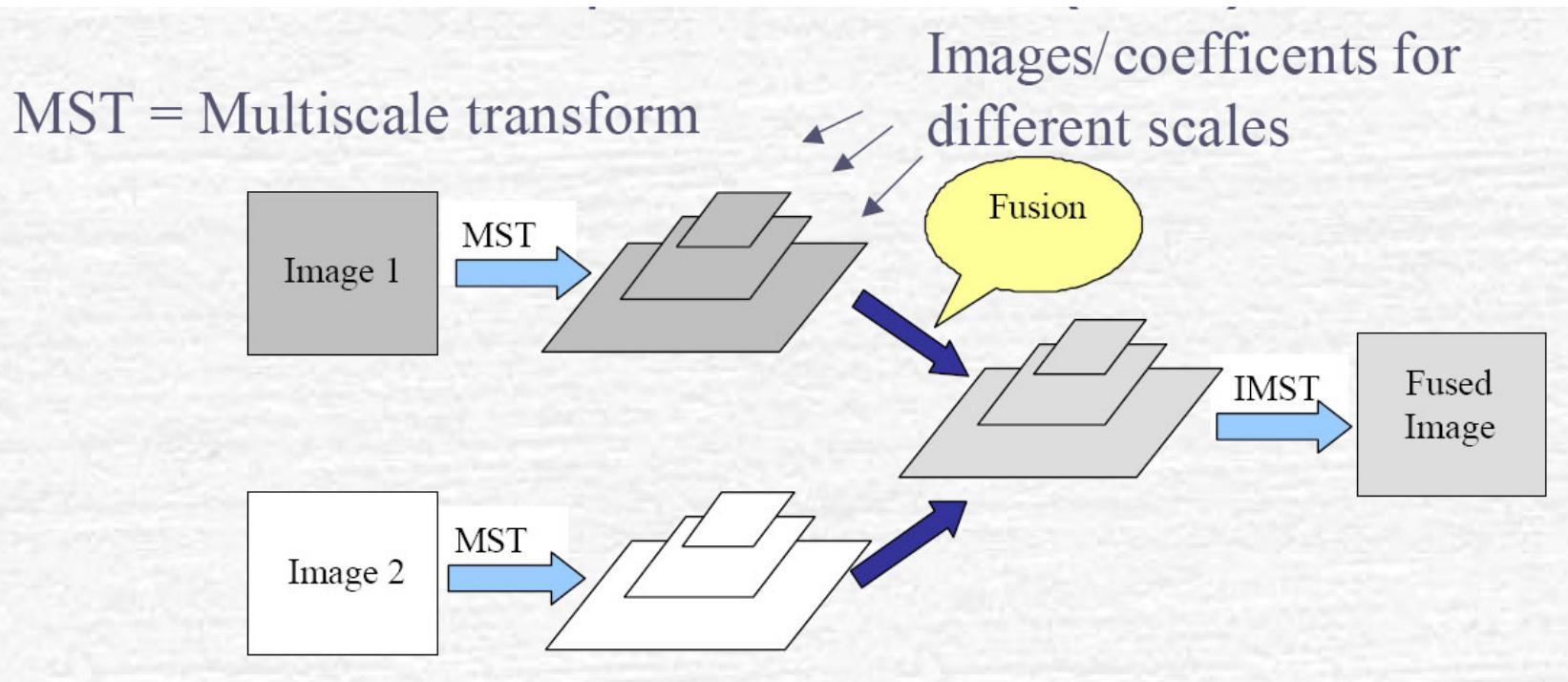


# Horror Photo





# Image Fusion



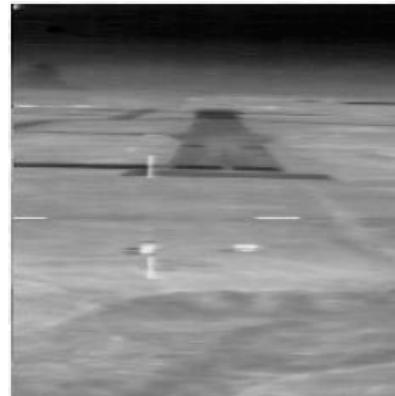
**Multi-scale Transform (MST)**

= Obtain Pyramid from Image

**Inverse Multi-scale Transform (IMST)** = Obtain Image from Pyramid



# Multi-Sensor Fusion

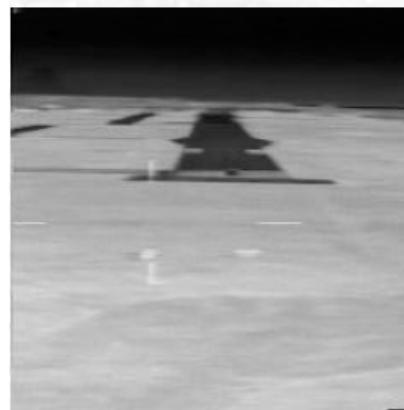


Long Wave



Medium Wave

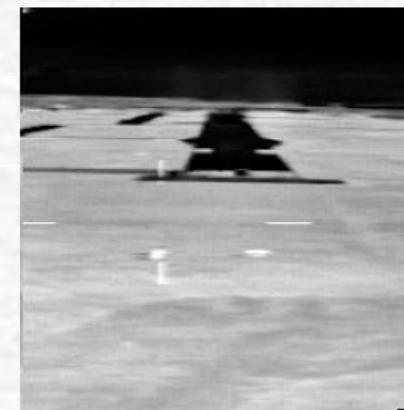
**Matlab  
Impyramid()**



Averaging



Selecting Maximum



Laplacian Fusion