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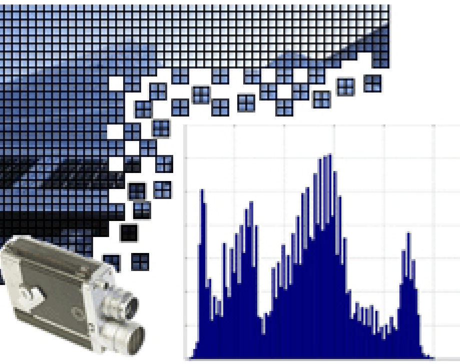

6.869 Advances in Computer Vision: Learning and Interfaces

Spring 2005

Tuesday and Thursday; 2:30 to 4:00pm in 36-153

Announcements

Course Information

- Syllabus
- Problem Sets and Exams
- Grading and Requirements
- Internet Resources

Contacts

http://courses.csail.mit.edu/6.869

Course Calendar

Lecture	Date	Description	Readings	Assignments	Materials
1	2/1	Course Introduction Cameras and Lenses	Req: FP 1.1, 2.1, 2.2, 2.3, 3.1, 3.2	PS0 out	
2	2/3	Image Filtering	Req: FP 7.1 - 7.6		
3	2/8	Image Representations: Pyramids	Req: FP 7.7, 9.2		
4	2/10	Image Statistics		PS0 due	
5	2/15	Texture	Req: FP 9.1, 9.3, 9.4	PS1 out	
6	2/17	Color	Req: FP 6.1-6.4		
7	2/22	Guest Lecture: Context in vision			
8	2/24	Guest Lecture: Medical Imaging		PS1 due	
9	3/1	Multiview Geometry	Req: Mikolajczyk and Schmid; FP 10	PS2 out	
10	3/3	Local Features	Req: Shi and Tomasi; Lowe		

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http://courses.csail.mit.edu/6.869/syllabus.html Go

Course Calendar

Lecture	Date	Description	Readings	Assignments	Materials
2	2/3	Image Filtering	Req: FP 7.1 - 7.6		
3	2/8	Image Representations: Pyramids	Req: FP 7.7, 9.2		

Today

Reading

- Related to today's lecture:
  - Chapters 7.7, 9.2, Forsyth&Ponce..
  - Adelson article on pyramid representations, posted on web site.

Spatial resolution and color

original

R

G

B

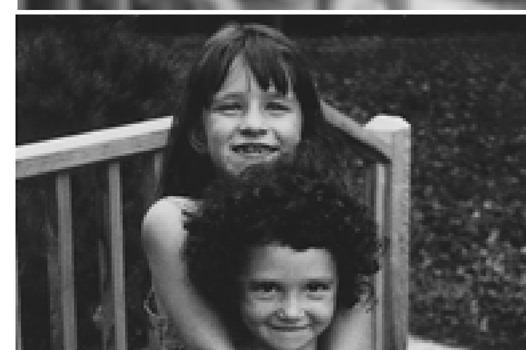
Blurring the G component

original

processed

R

G



B

Blurring the R component

original

processed

R

G

B

Blurring the B component

original

processed

R

G

B

From W. E. Glenn, in Digital Images and Human Vision, MIT Press, edited by Watson, 1993

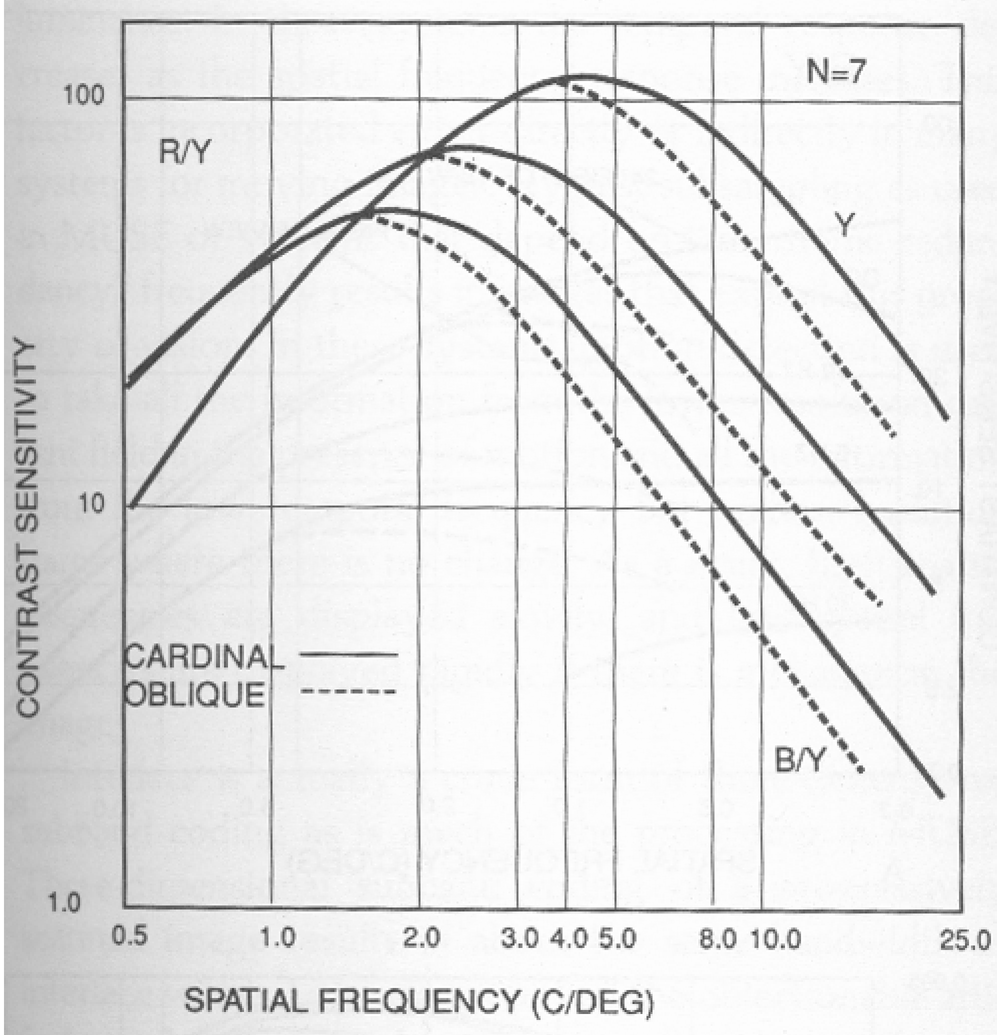


Figure 6.1
Contrast sensitivity threshold functions for static luminance gratings (Y) and isoluminance chromaticity gratings (R/Y,B/Y) averaged over seven observers.

Lab color components

L

a

b

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

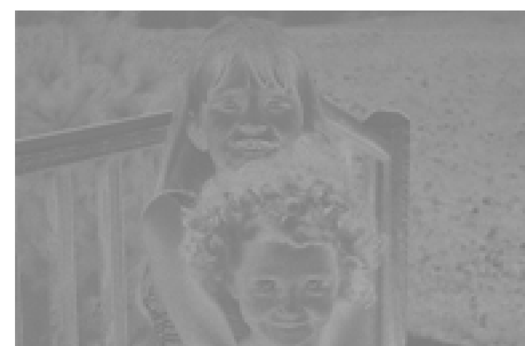
Blurring the L Lab component

original

processed

L

a

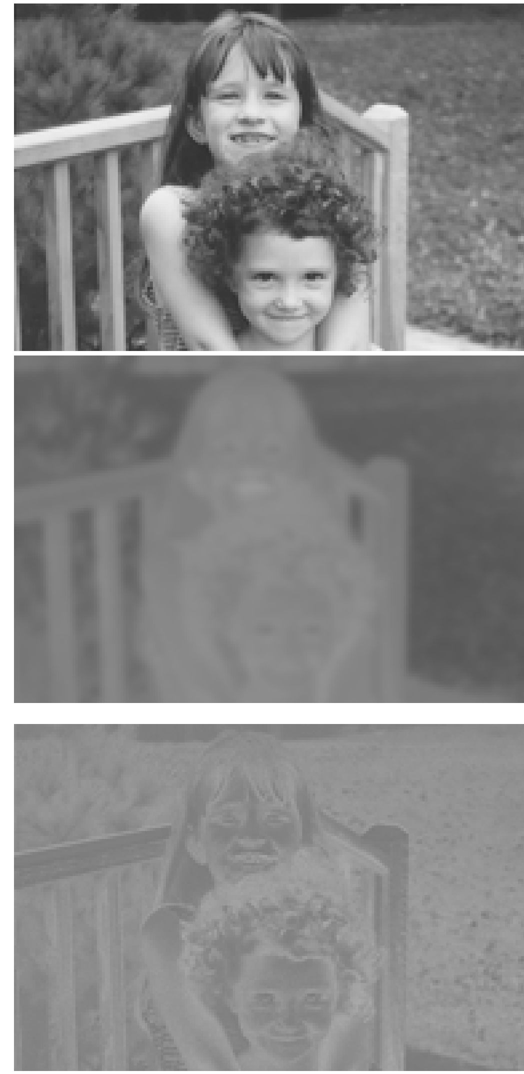


b

Blurring the a Lab component

original

processed



L

a

b

Blurring the b Lab component

original

processed

L

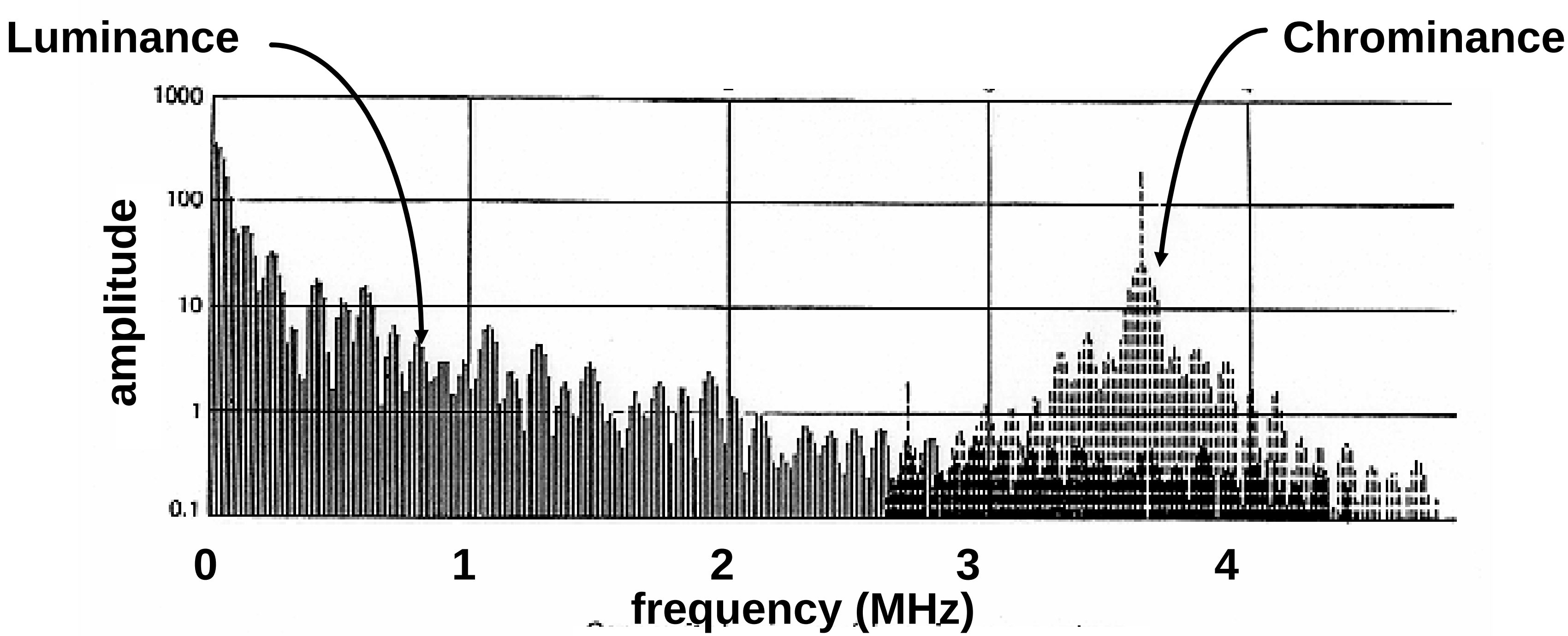
a

b

Application to image compression

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

Bandwidth (transmission resources) for the components of the television signal

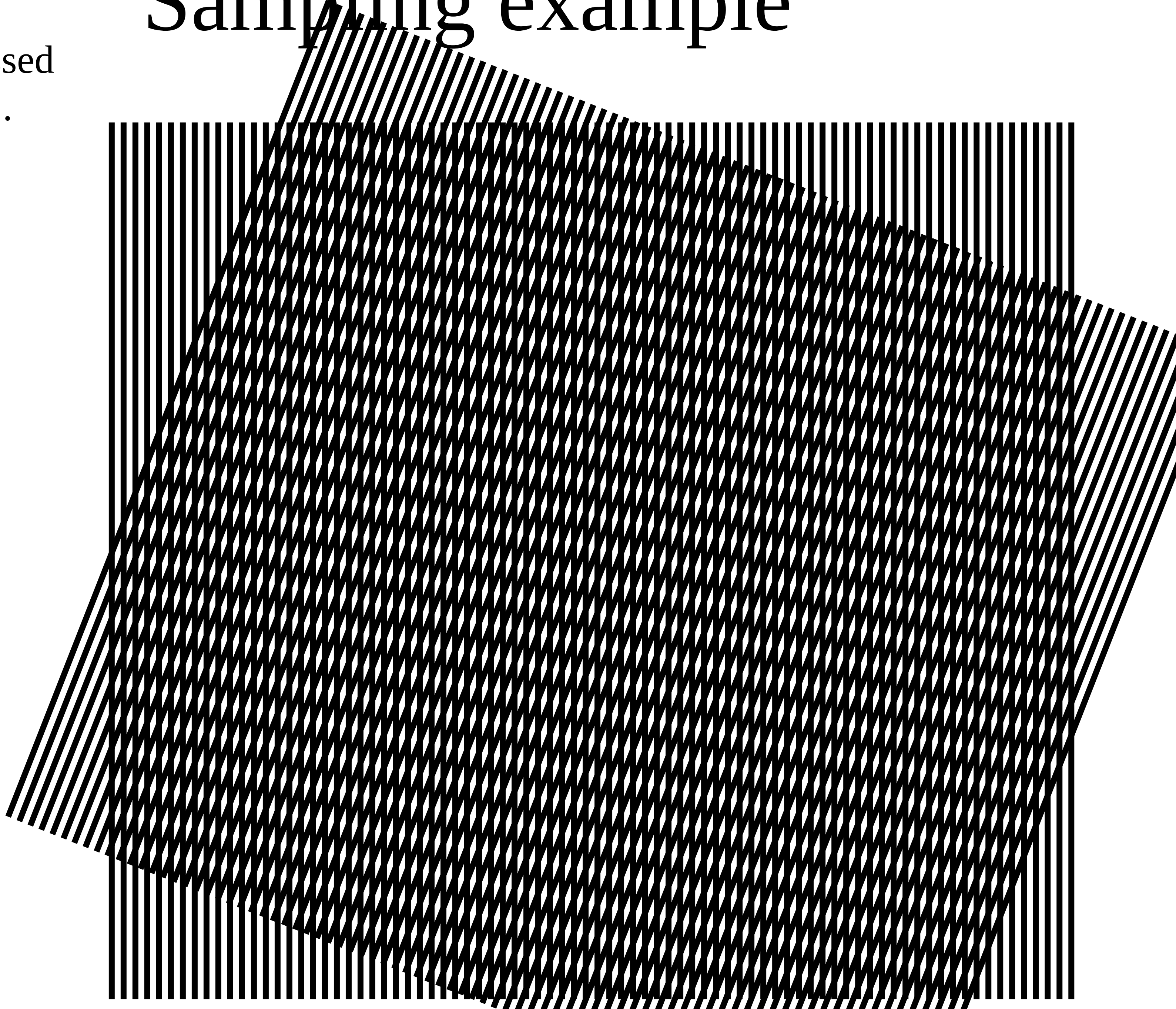


Understanding image perception allowed NTSC to add color to the black and white television signal (with some, but limited, incompatibility artifacts).

Sampling and aliasing

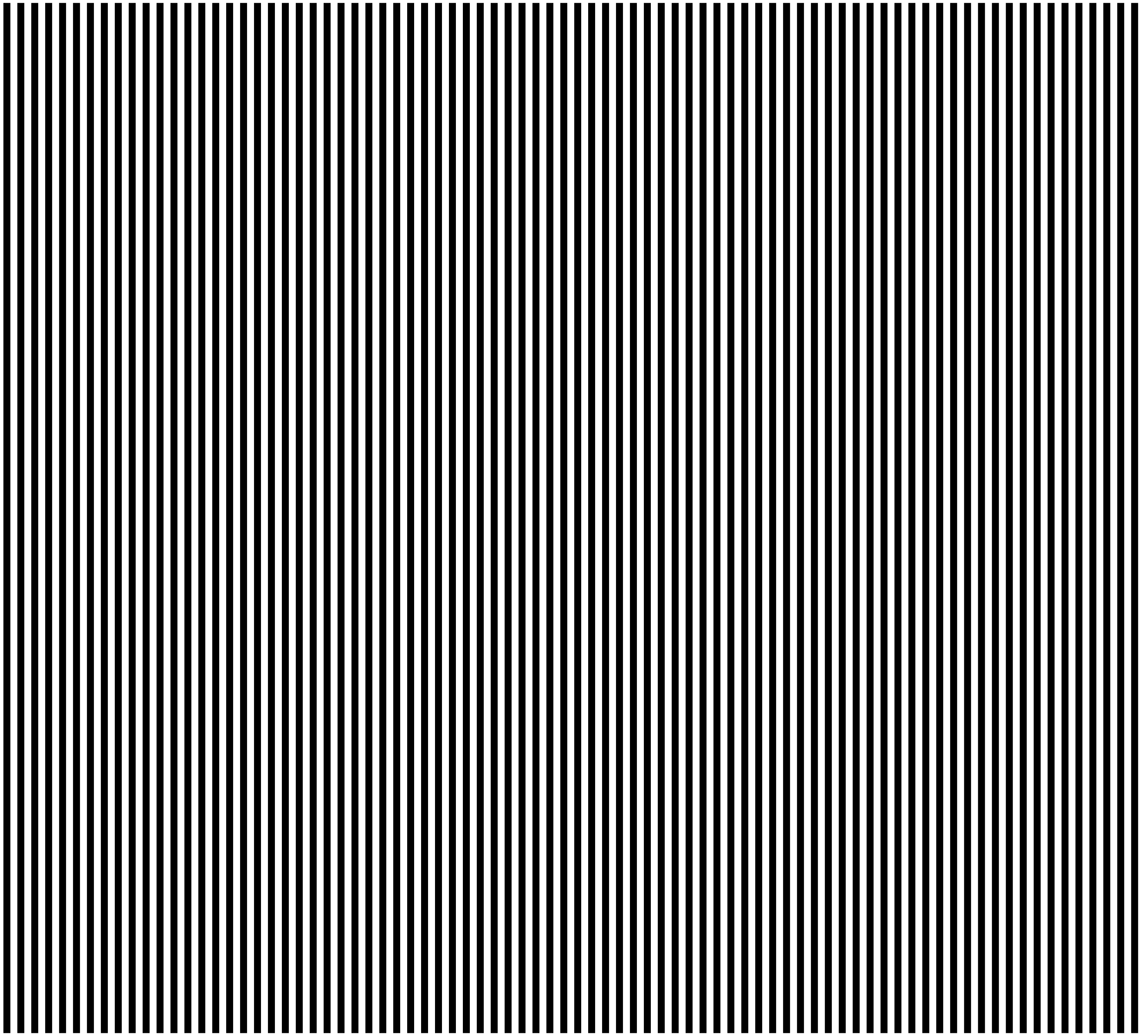
Sampling example

Analyze crossed gratings…



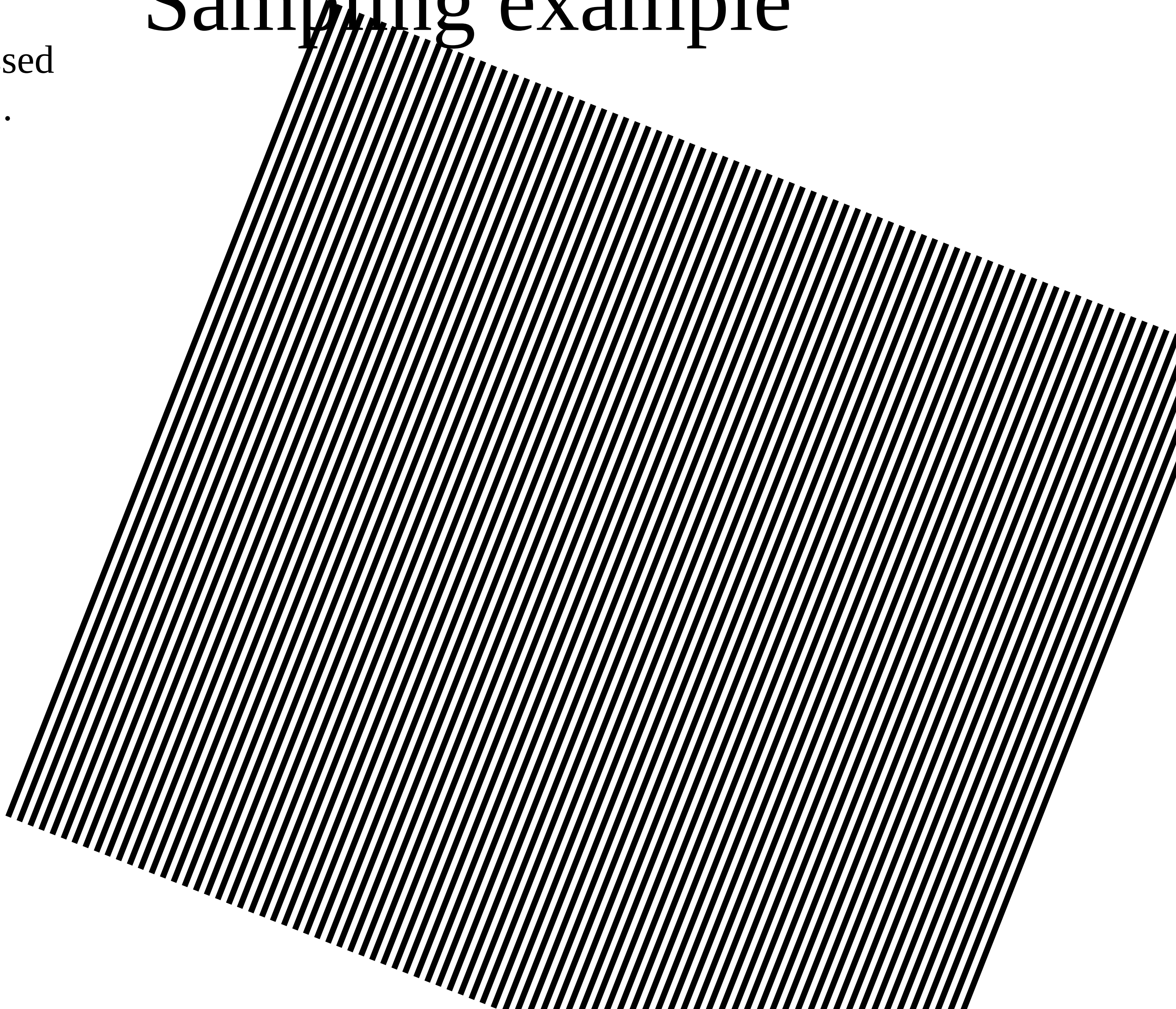
Sampling example

Analyze crossed gratings…



Sampling example

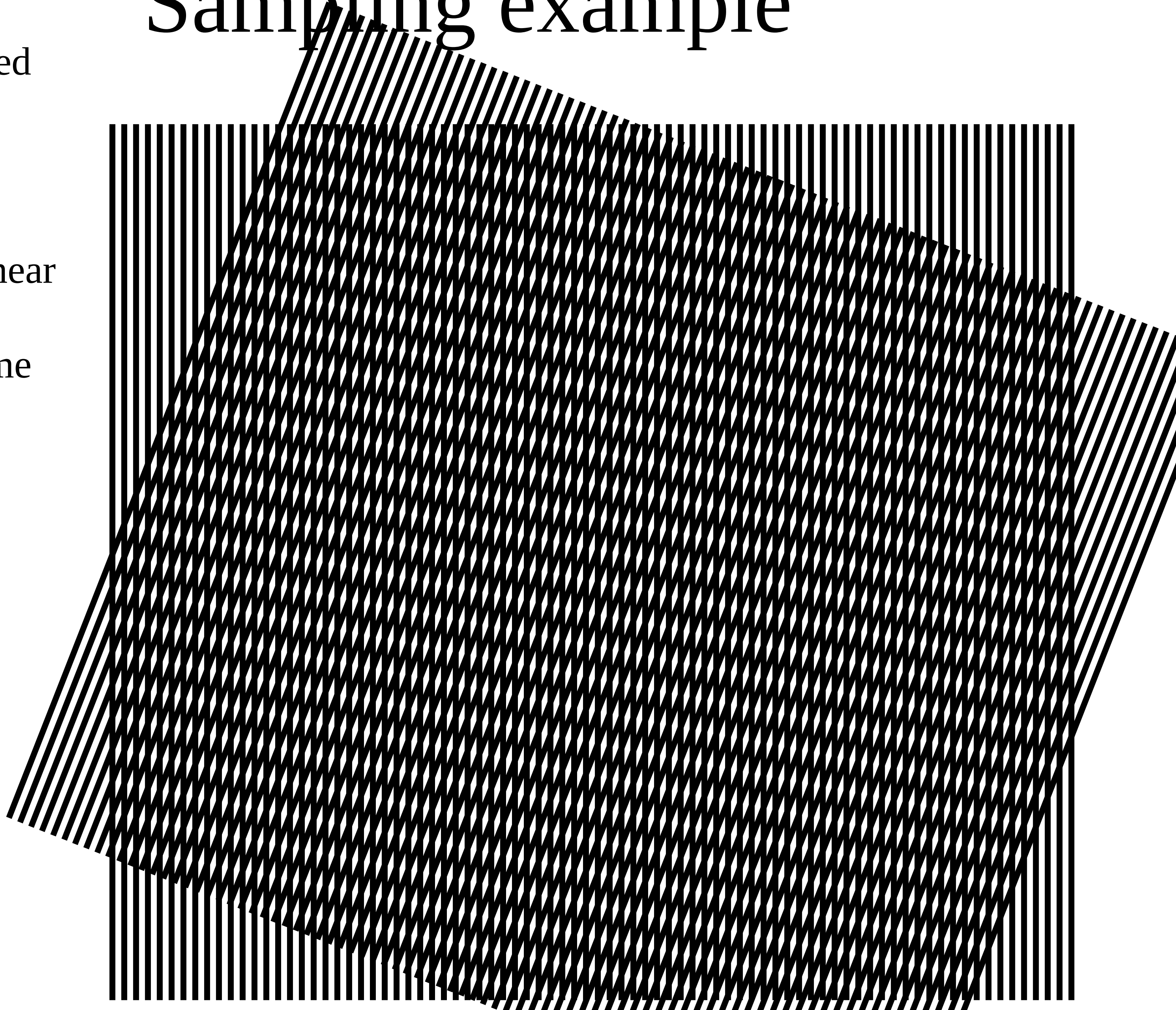
Analyze crossed gratings…

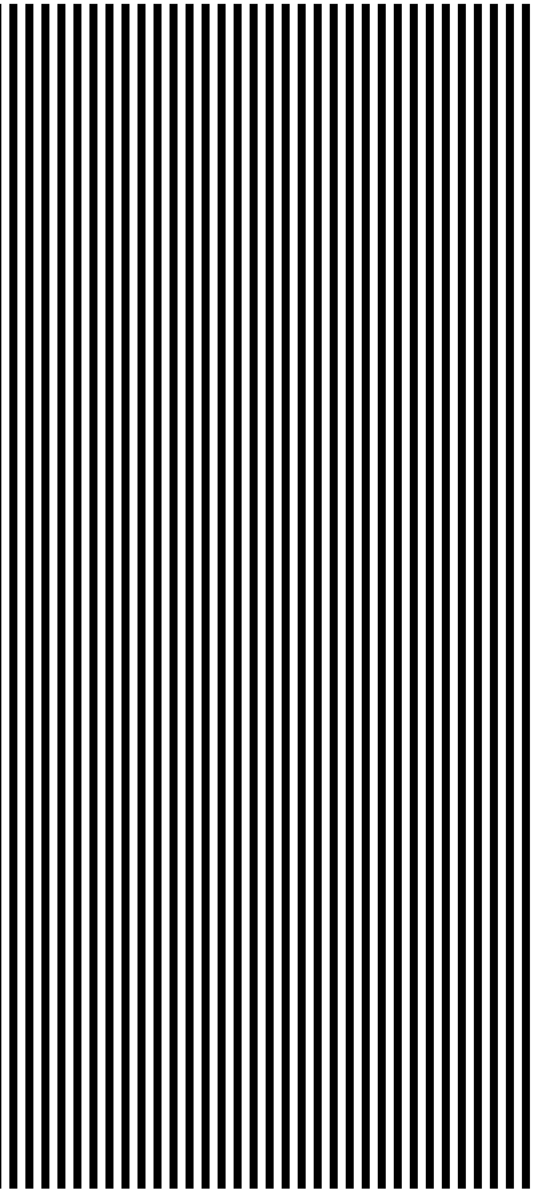


Sampling example

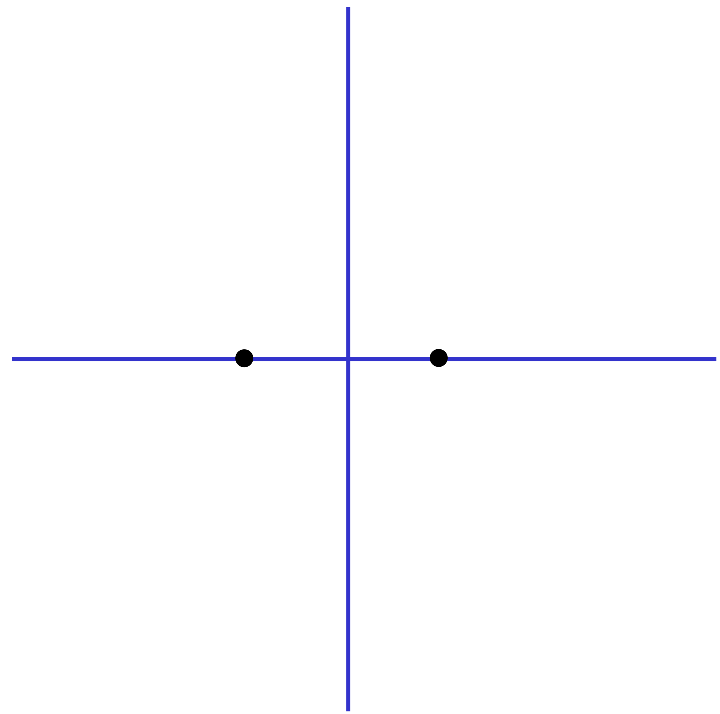
Analyze crossed gratings…

Where does perceived near horizontal grating come from?

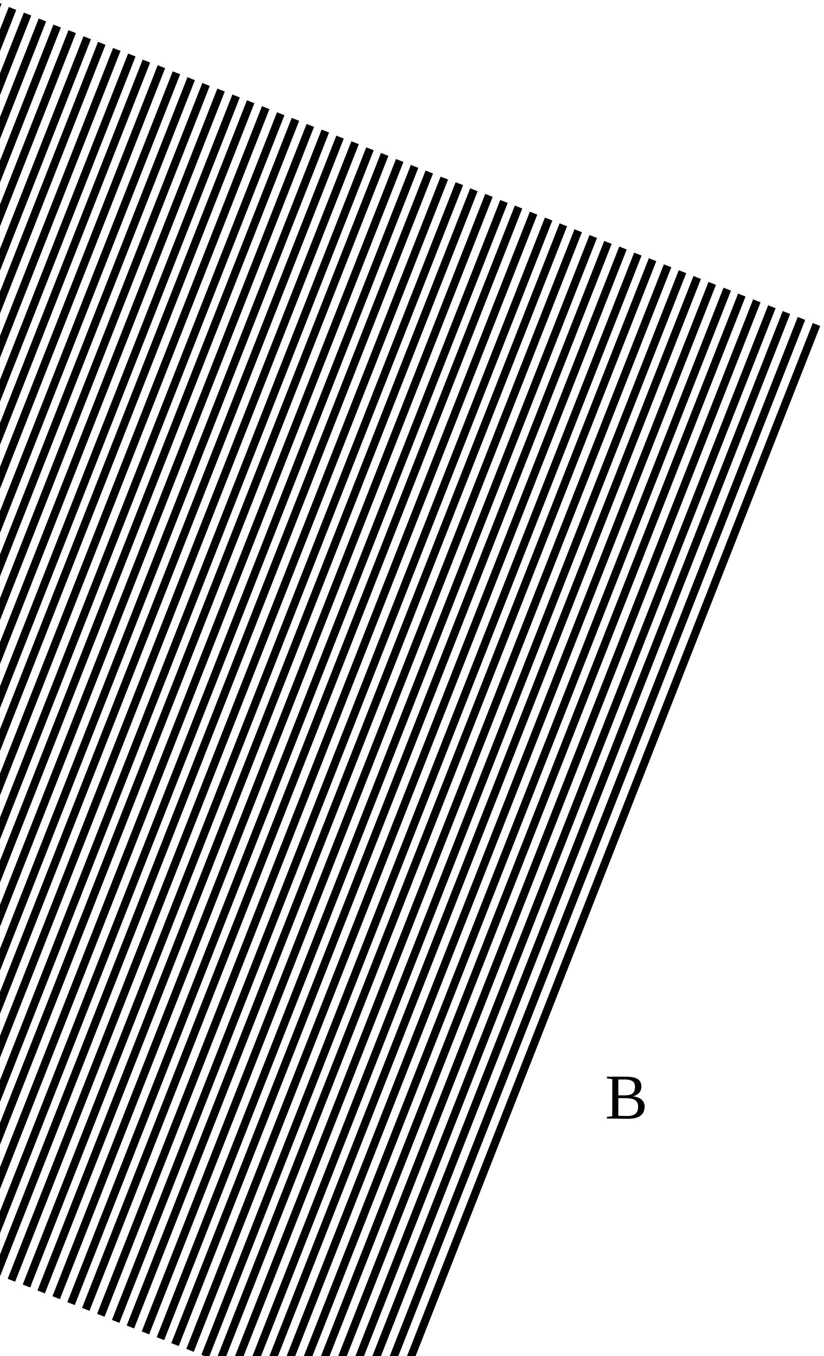




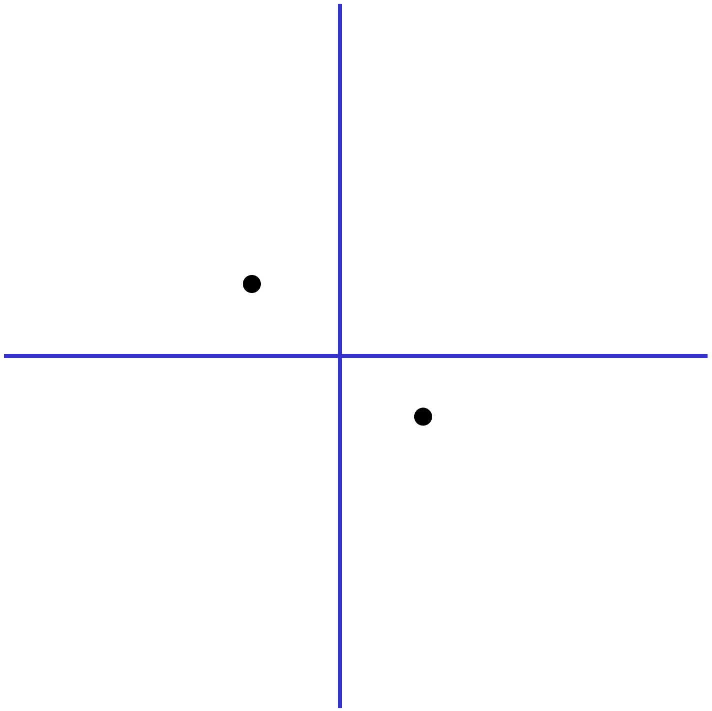
A



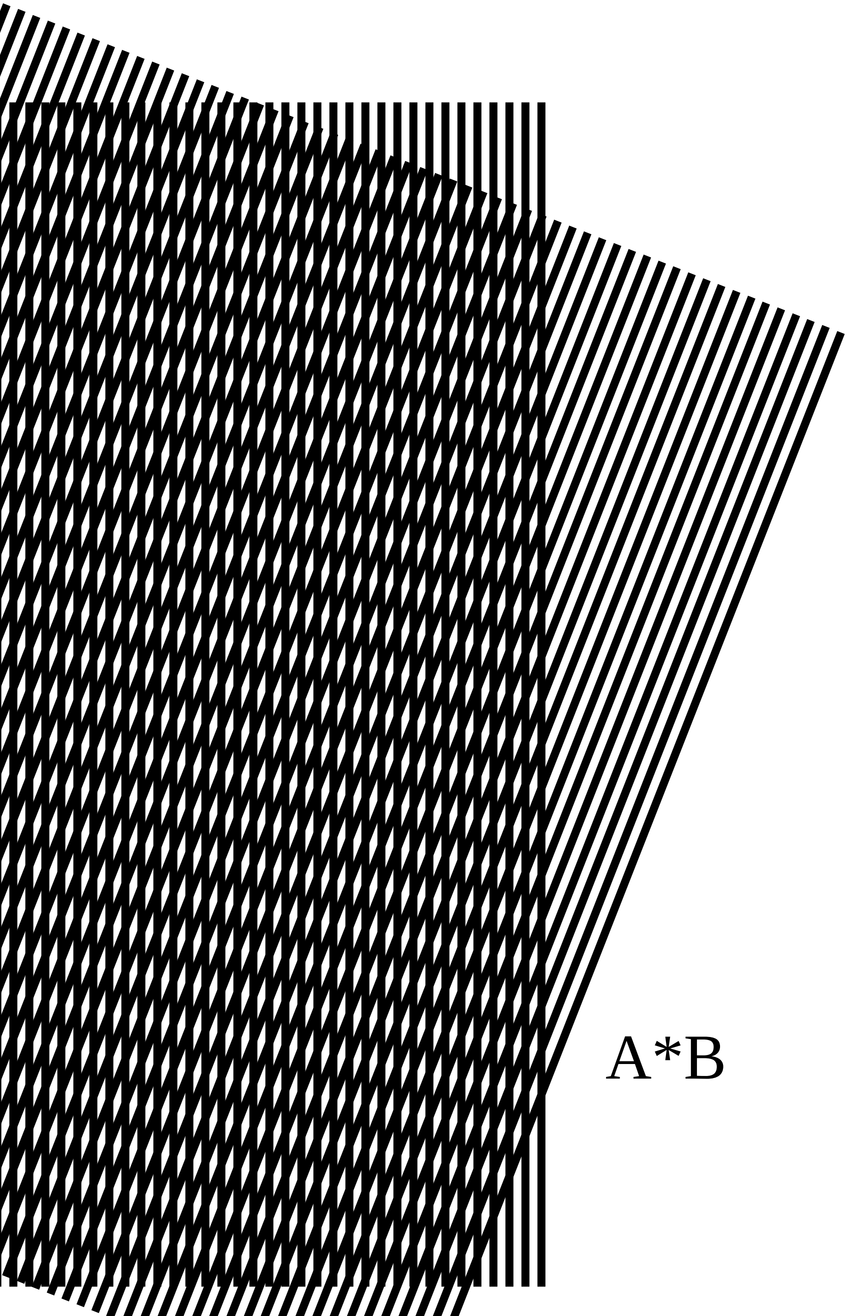
F(A)



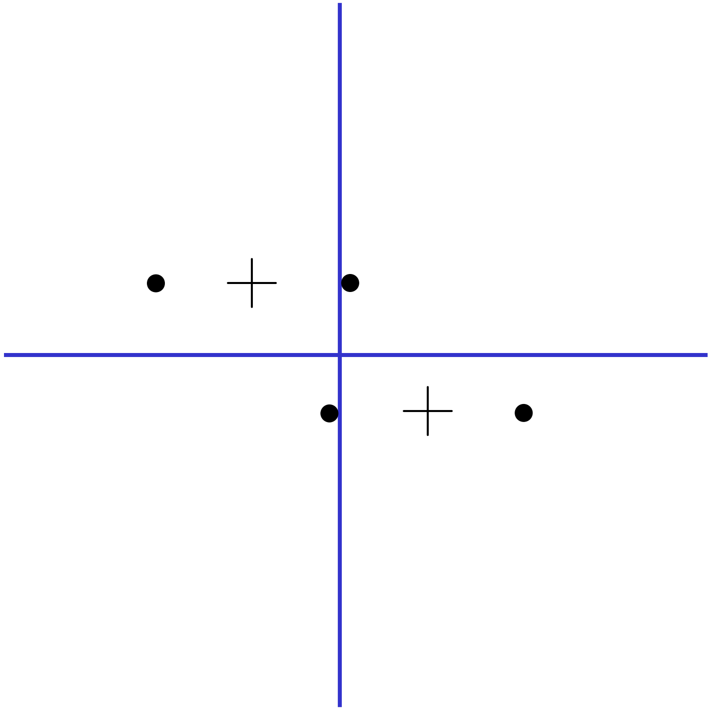
B



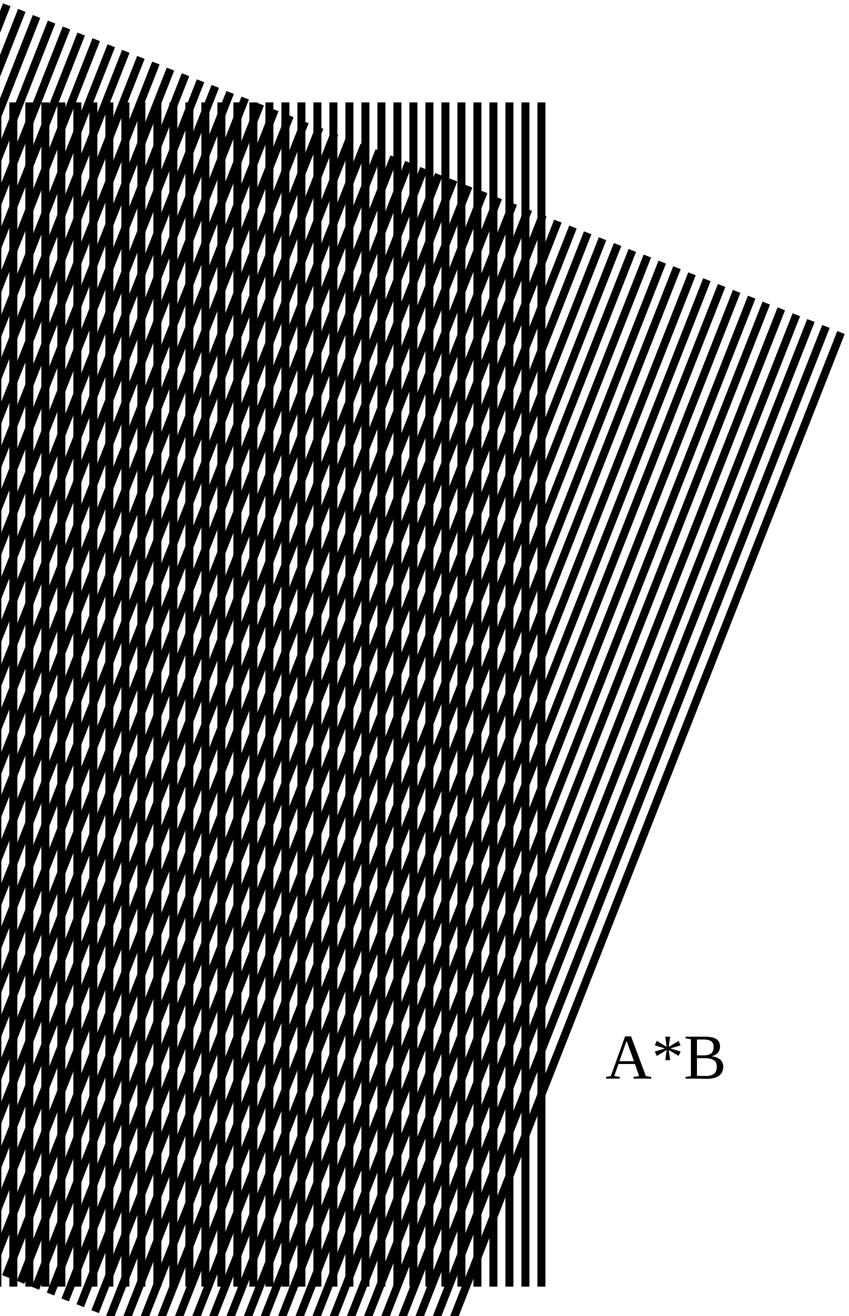
F(B)



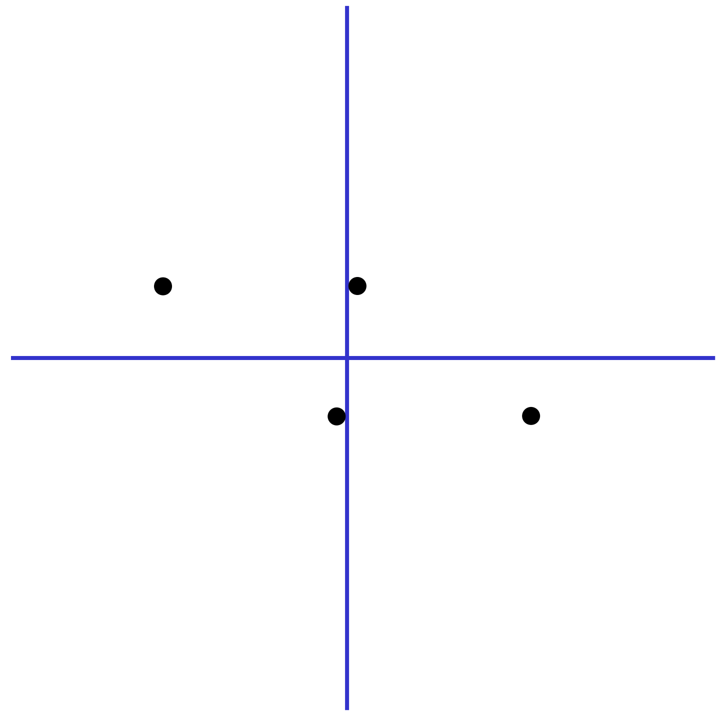
A*B



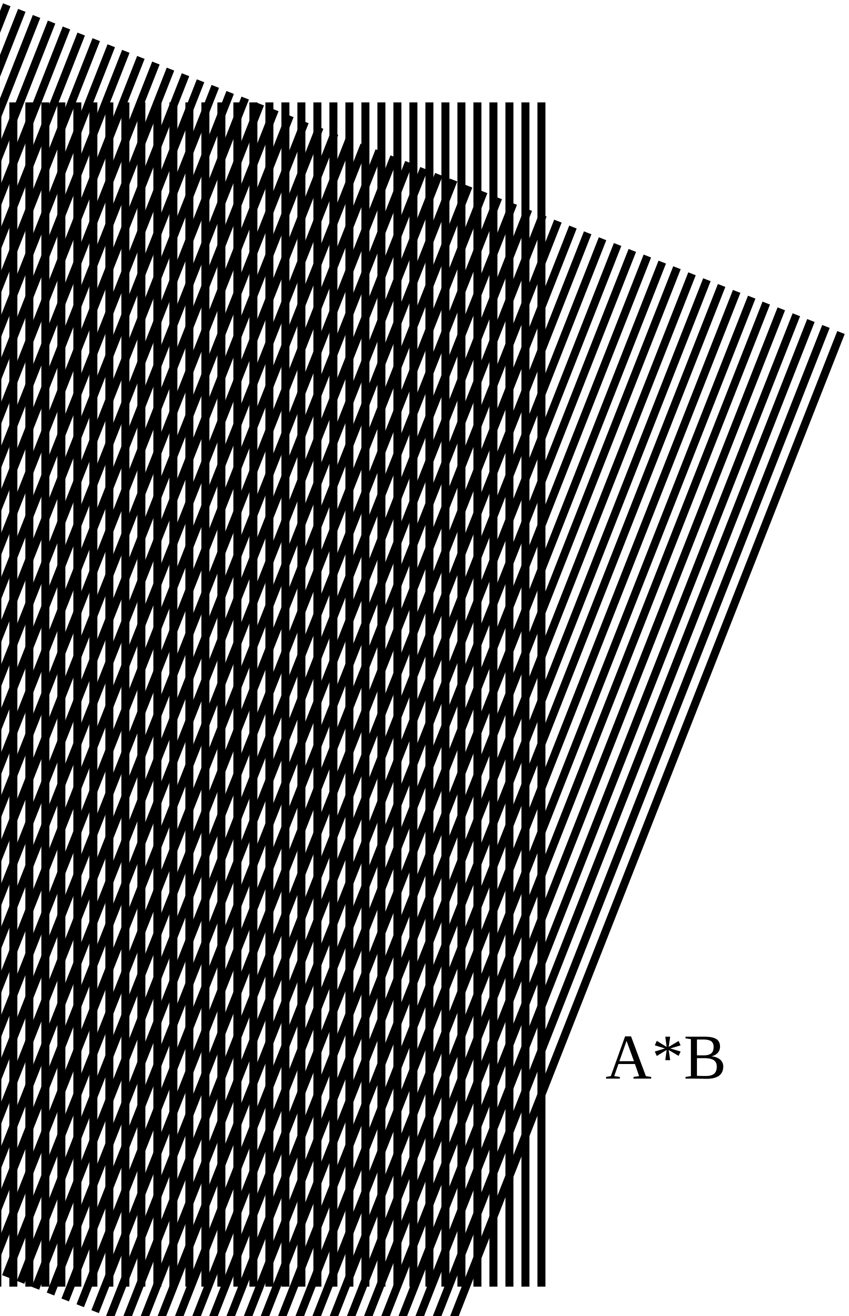
F(A)**F(B)



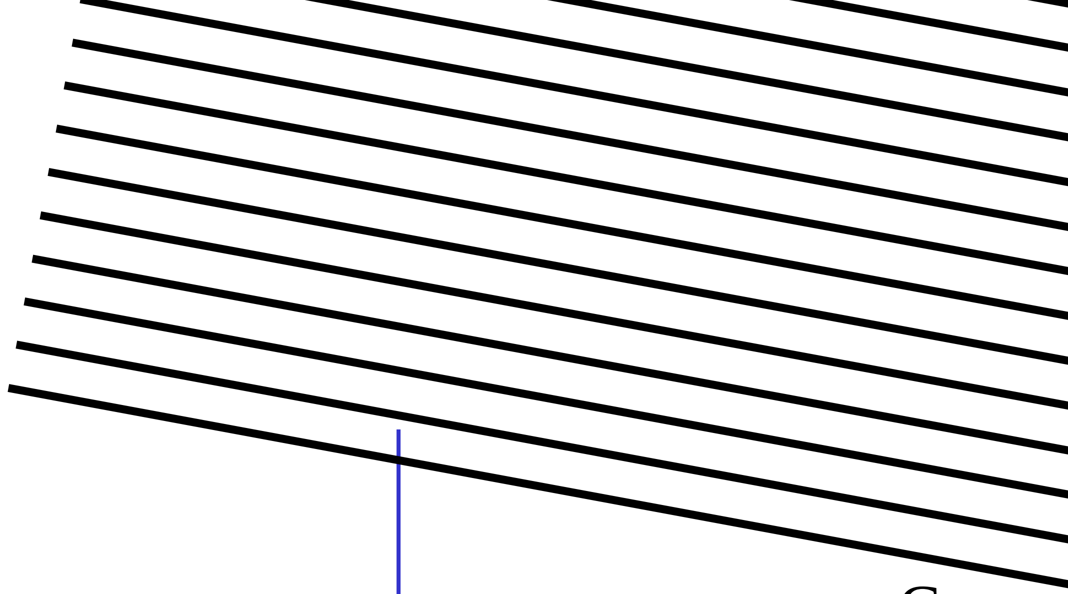
A*B



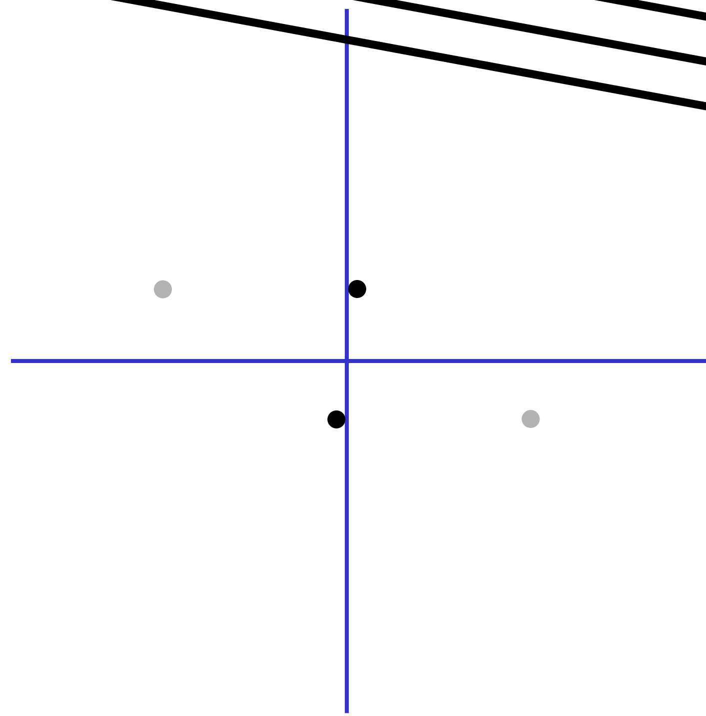
F(A)**F(B)



A*B



C

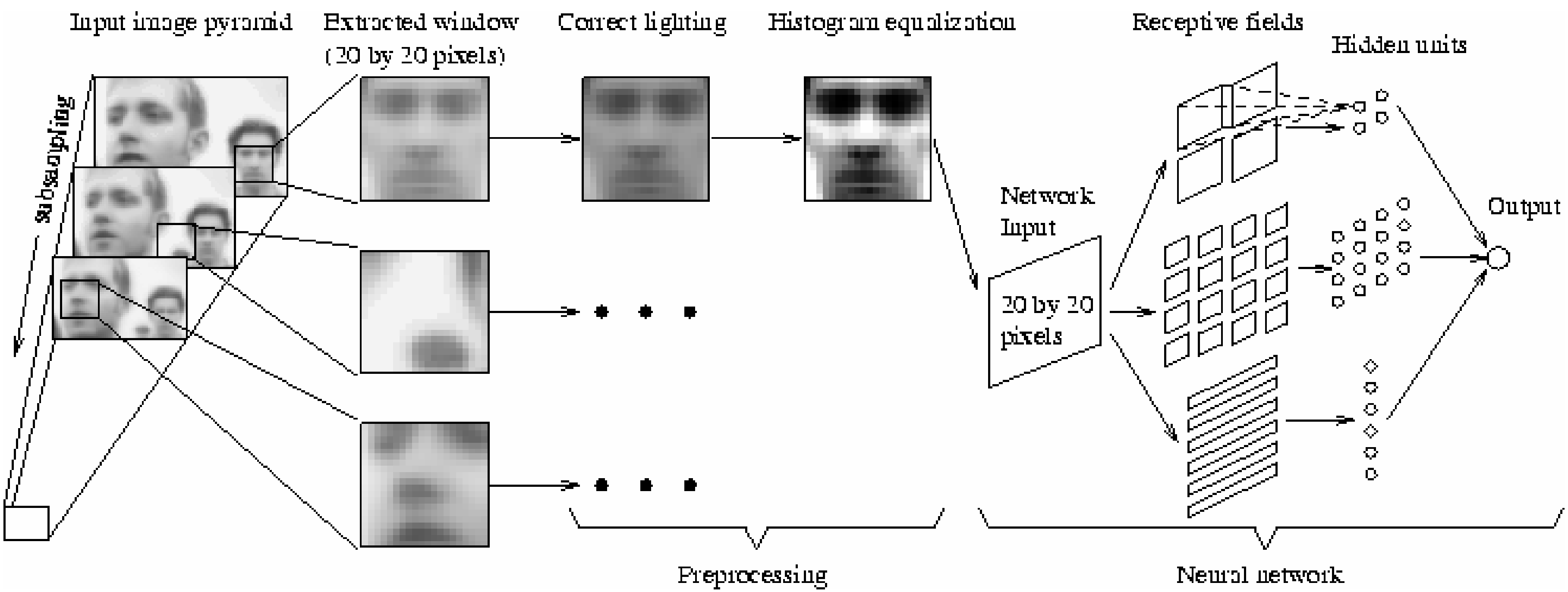


Lowpass(F(A)**F(B))
~=F(C)

Scaled representations

- Big bars (resp. spots, hands, etc.) and little bars are both interesting
  - Stripes and hairs, say
- Inefficient to detect big bars with big filters
  - And there is superfluous detail in the filter kernel
- Alternative:
  - Apply filters of fixed size to images of different sizes
  - Typically, a collection of images whose edge length changes by a factor of 2 (or root 2)
  - This is a pyramid (or Gaussian pyramid) by visual analogy

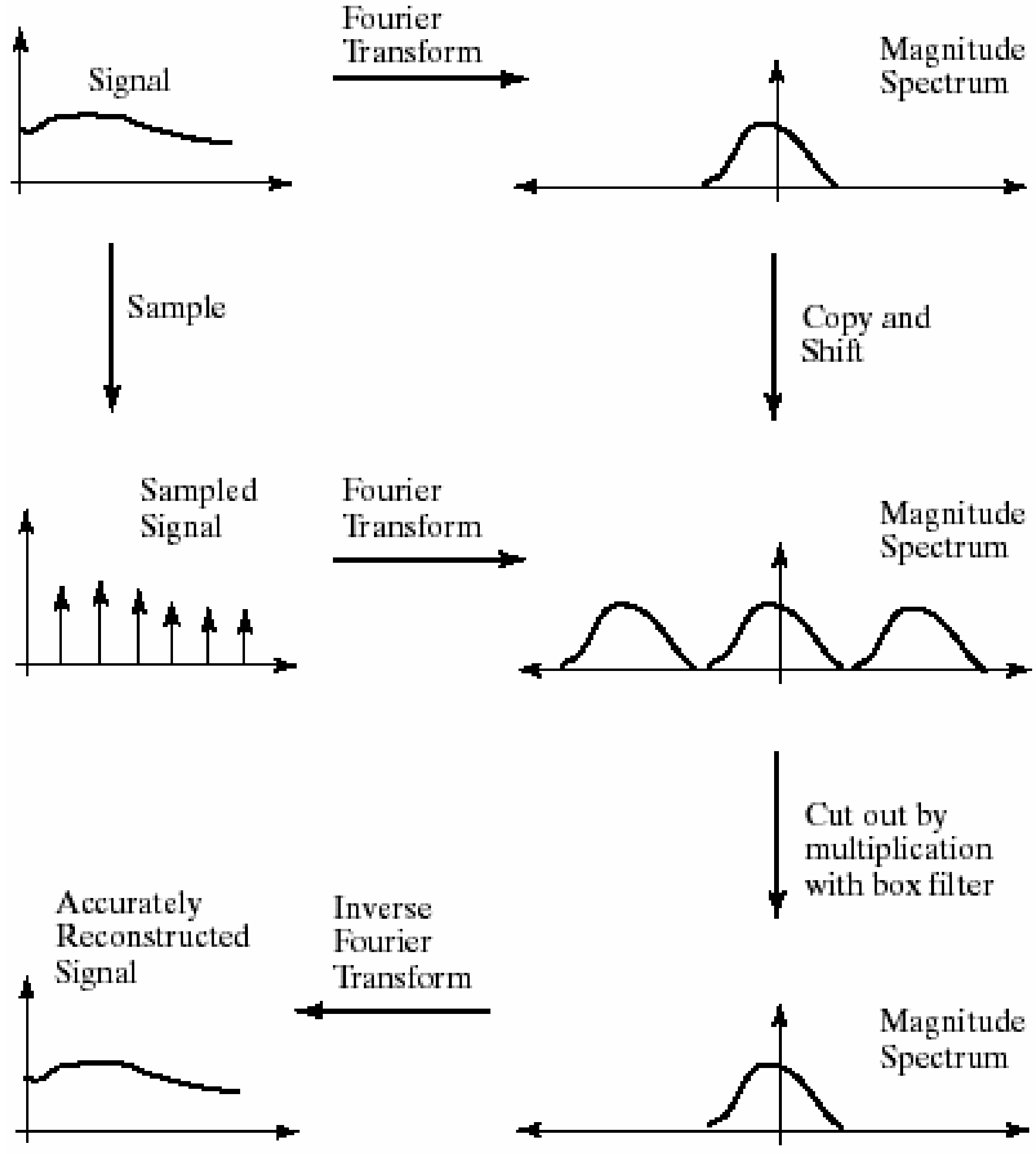
Example application: CMU face detector

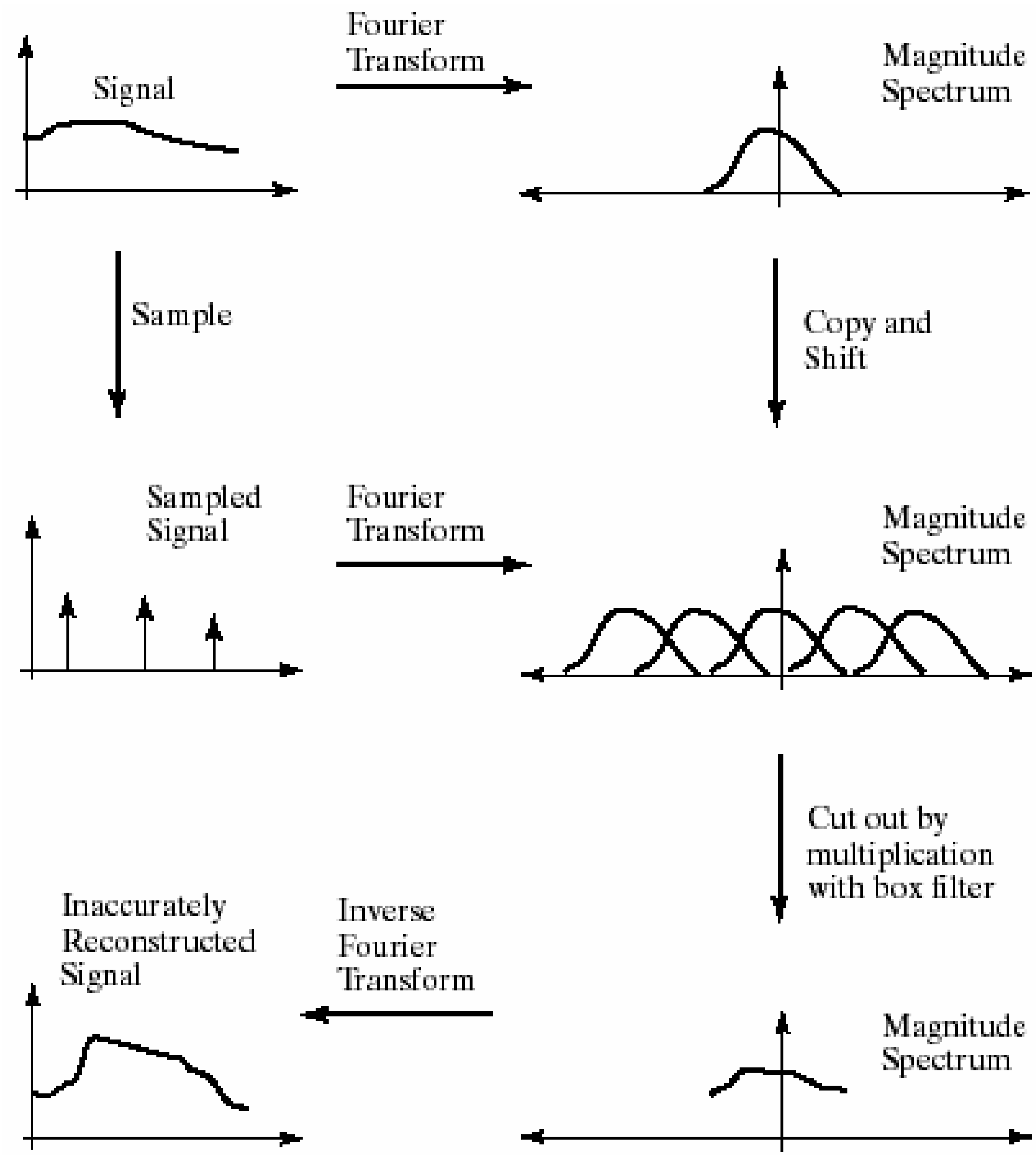


From: http://www.ius.cs.cmu.edu/IUS/har2/har/www/CMU-CS-95-158R/

Aliasing

- Can’t shrink an image by taking every second pixel
- If we do, characteristic errors appear
  - In the next few slides
  - Typically, small phenomena look bigger; fast phenomena can look slower
  - Common phenomenon
    - Wagon wheels rolling the wrong way in movies
    - Checkerboards misrepresented in ray tracing
    - Striped shirts look funny on colour television


Signal
Fourier Transform
Magnitude Spectrum
Sample
Copy and Shift
Sampled Signal
Fourier Transform
Magnitude Spectrum
Cut out by multiplication with box filter
Accurately Reconstructed Signal
Inverse Fourier Transform
Magnitude Spectrum

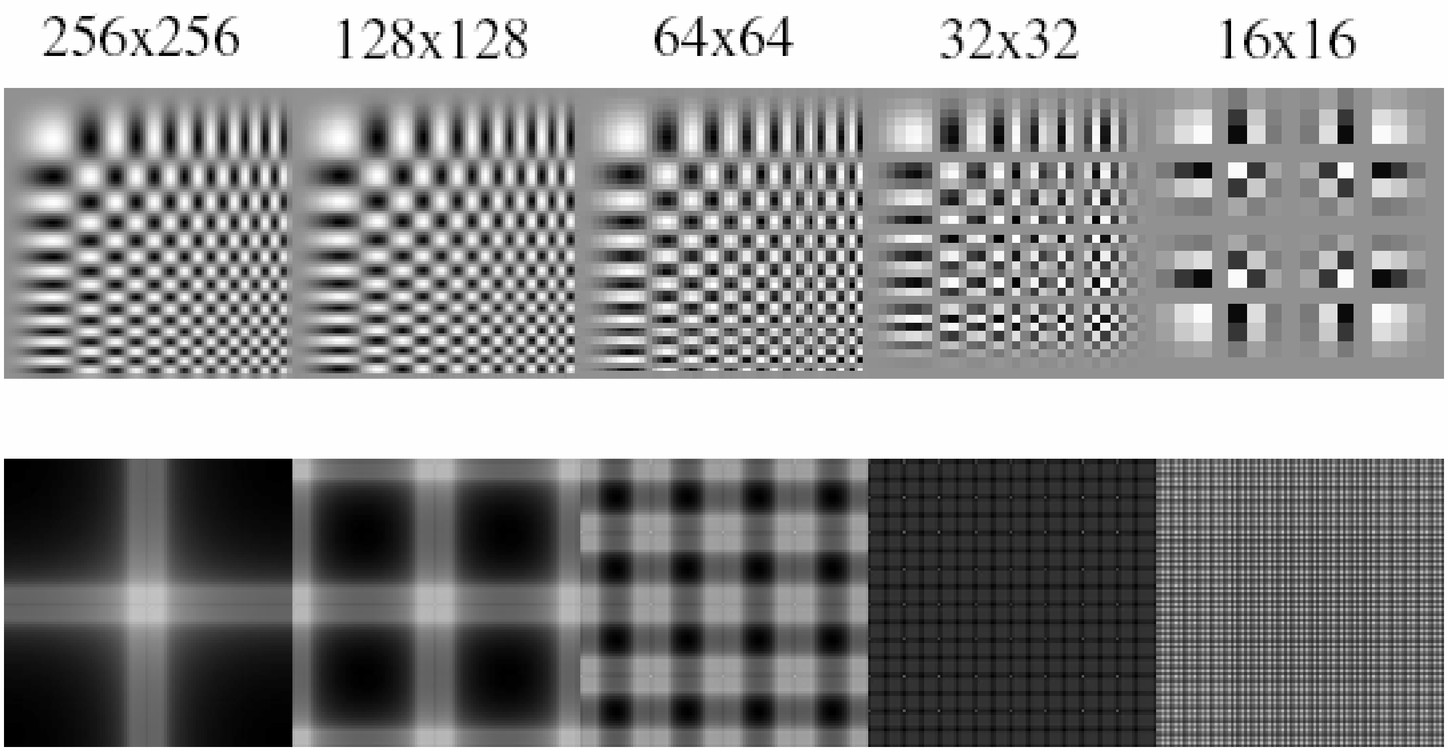


Fourier Transform
Signal
Magnitude Spectrum
Sample
Copy and Shift
Sampled Signal
Fourier Transform
Magnitude Spectrum
Cut out by multiplication with box filter
Inaccurately Reconstructed Signal
Inverse Fourier Transform
Magnitude Spectrum

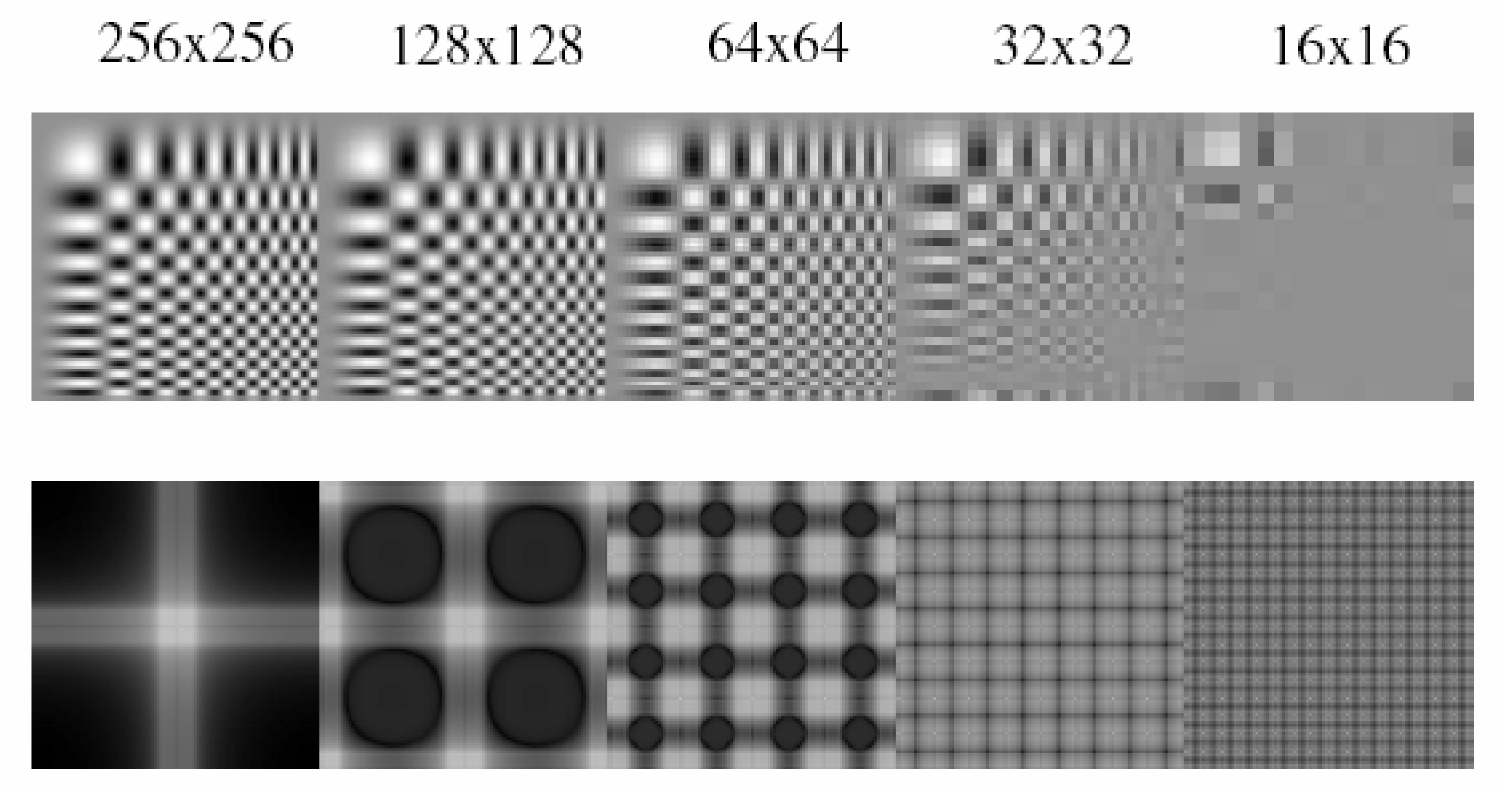
Smoothing as low-pass filtering

- The message of the FT is that high frequencies lead to trouble with sampling.
- Solution: suppress high frequencies before sampling
  - multiply the FT of the signal with something that suppresses high frequencies
  - or convolve with a low-pass filter
- A filter whose FT is a box is bad, because the filter kernel has infinite support
- Common solution: use a Gaussian
  - multiplying FT by Gaussian is equivalent to convolving image with Gaussian.

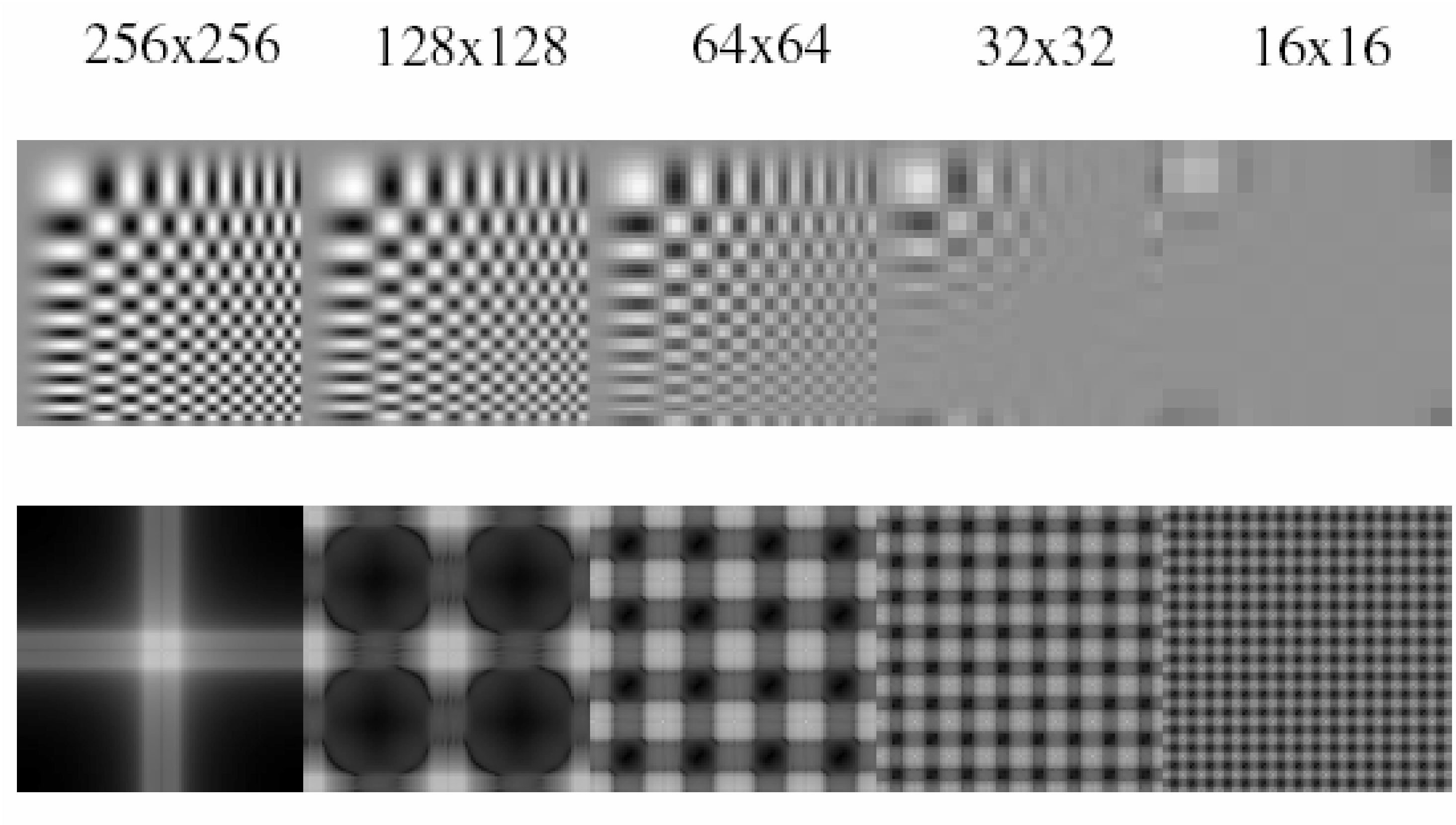
Sampling without smoothing. Top row shows the images, sampled at every second pixel to get the next; bottom row shows the magnitude spectrum of these images.



Sampling with smoothing. Top row shows the images. We get the next image by smoothing the image with a Gaussian with sigma 1 pixel, then sampling at every second pixel to get the next; bottom row shows the magnitude spectrum of these images.



Sampling with smoothing. Top row shows the images. We
get the next image by smoothing the image with a Gaussian with sigma 1.4 pixels,
then sampling at every second pixel to get the next; bottom row
shows the magnitude spectrum of these images.



Matlab

Subsample image in matlab.

The Gaussian pyramid

- Smooth with gaussians, because
  - a gaussian*gaussian=another gaussian
- Synthesis
  - smooth and sample
- Analysis
  - take the top image
- Gaussians are low pass filters, so repn is redundant

Convolution and subsampling as a matrix multiply (1-d case)

U1 =

1	4	6	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	4	6	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	4	6	4	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	4	6	4	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	4	6	4	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	4	6	4	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	1	4	6	4	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	4	6	4	1	0

Next pyramid level

U2 =

1	4	6	4	1	0	0	0
0	0	1	4	6	4	1	0
0	0	0	0	1	4	6	4
0	0	0	0	0	0	1	4

b * a, the combined effect of the two pyramid levels

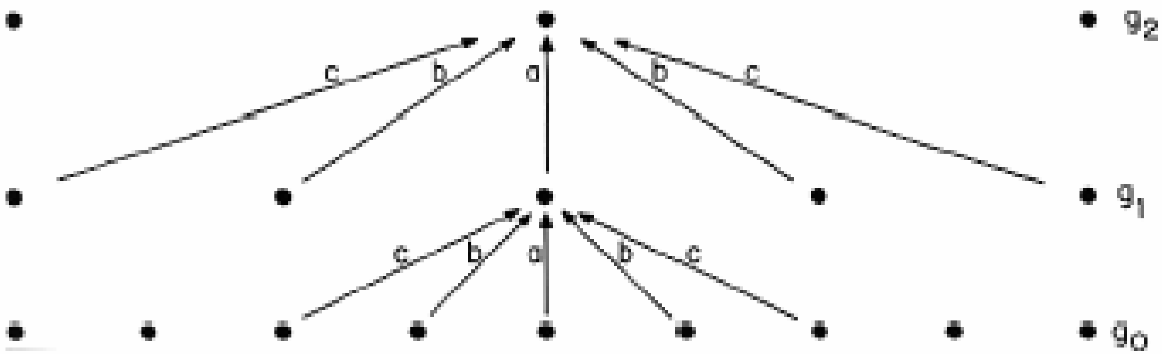
```
>> U2 * U1

ans =

     1     4    10    20    31    40    44    40    31    20    10     4     1     0     0     0     0     0     0     0
     0     0     0     0     1     4    10    20    31    40    44    40    31    20    10     4     1     0     0     0
     0     0     0     0     0     0     0     0     1     4    10    20    31    40    44    40    30    16     4     0
     0     0     0     0     0     0     0     0     0     0     0     0     1     4    10    20    25    16     4     0
```

The computational advantage of pyramids

GAUSSIAN PYRAMID



g_0 = IMAGE

g_L = REDUCE $[g_{L-1}]$

Fig 1. A one-dimensional graphic representation of the process which generates a Gaussian pyramid Each row of dots represents nodes within a level of the pyramid. The value of each node in the zero level is just the gray level of a corresponding image pixel. The value of each node in a high level is the weighted average of node values in the next lower level. Note that node spacing doubles from level to level, while the same weighting pattern or "generating kernel" is used to generate all levels.

http://www-bcs.mit.edu/people/adelson/pub_pdfs/pyramid83.pdf

IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. COM-31, NO. 4, APRIL 1983

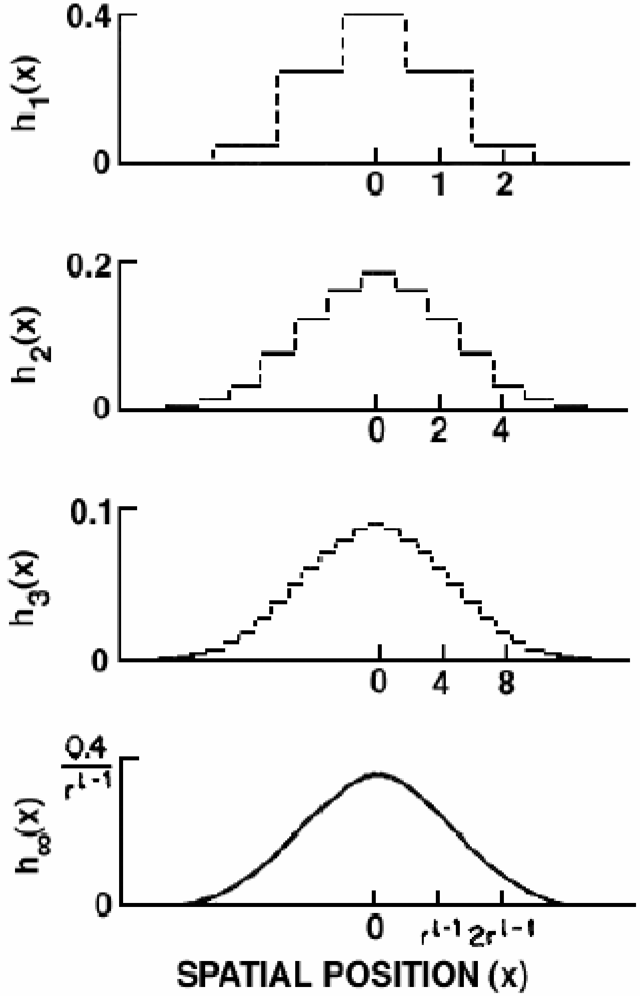
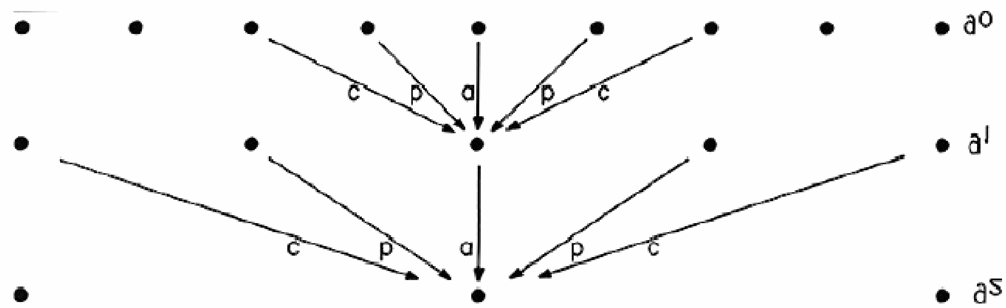


Fig. 2. The equivalent weighting functions $h_l(x)$ for nodes in levels 1, 2, 3, and infinity of the Gaussian pyramid. Note that axis scales have been adjusted by factors of 2 to aid comparison Here the parameter a of the generating kernel is 0.4, and the resulting equivalent weighting functions closely resemble the Gaussian probability density functions.



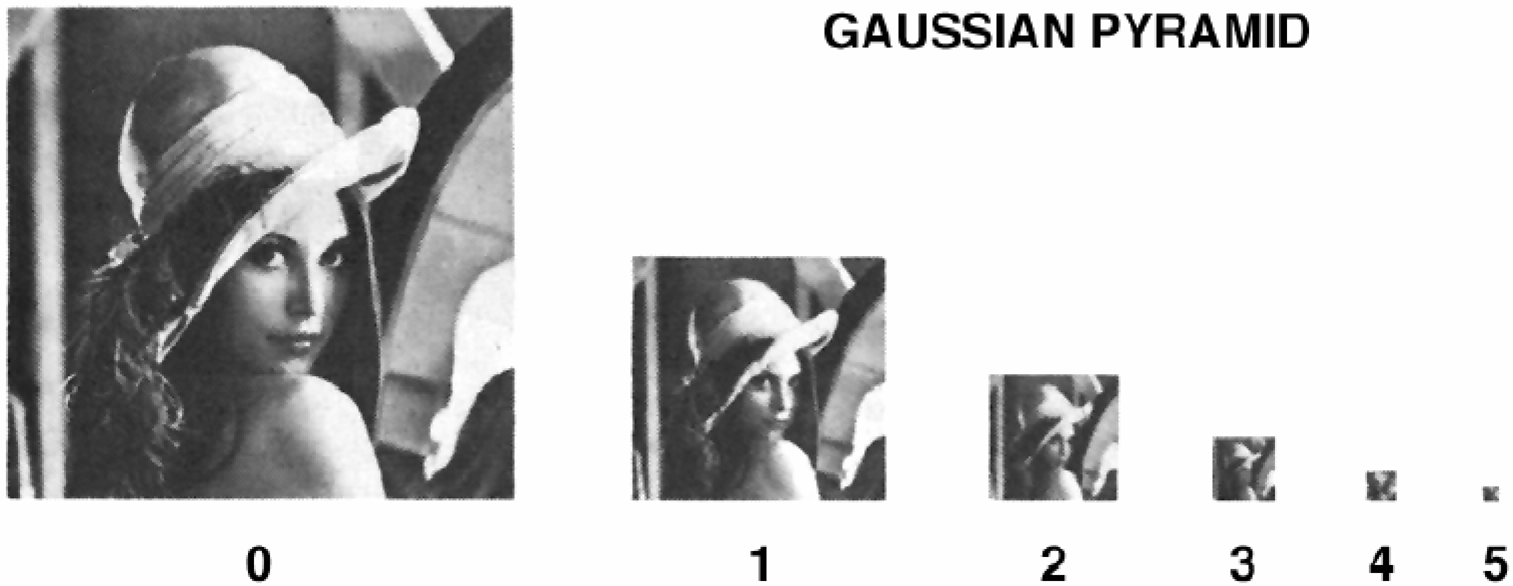


Fig. 4. First six levels of the Gaussian pyramid for the "Lady" image The original image, level 0, meusures 257 by 257 pixels and each higher level array is roughly half the dimensdons of its predecessor. Thus, level 5 measures just 9 by 9 pixels.

IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. COM-31, NO. 4, APRIL 1983

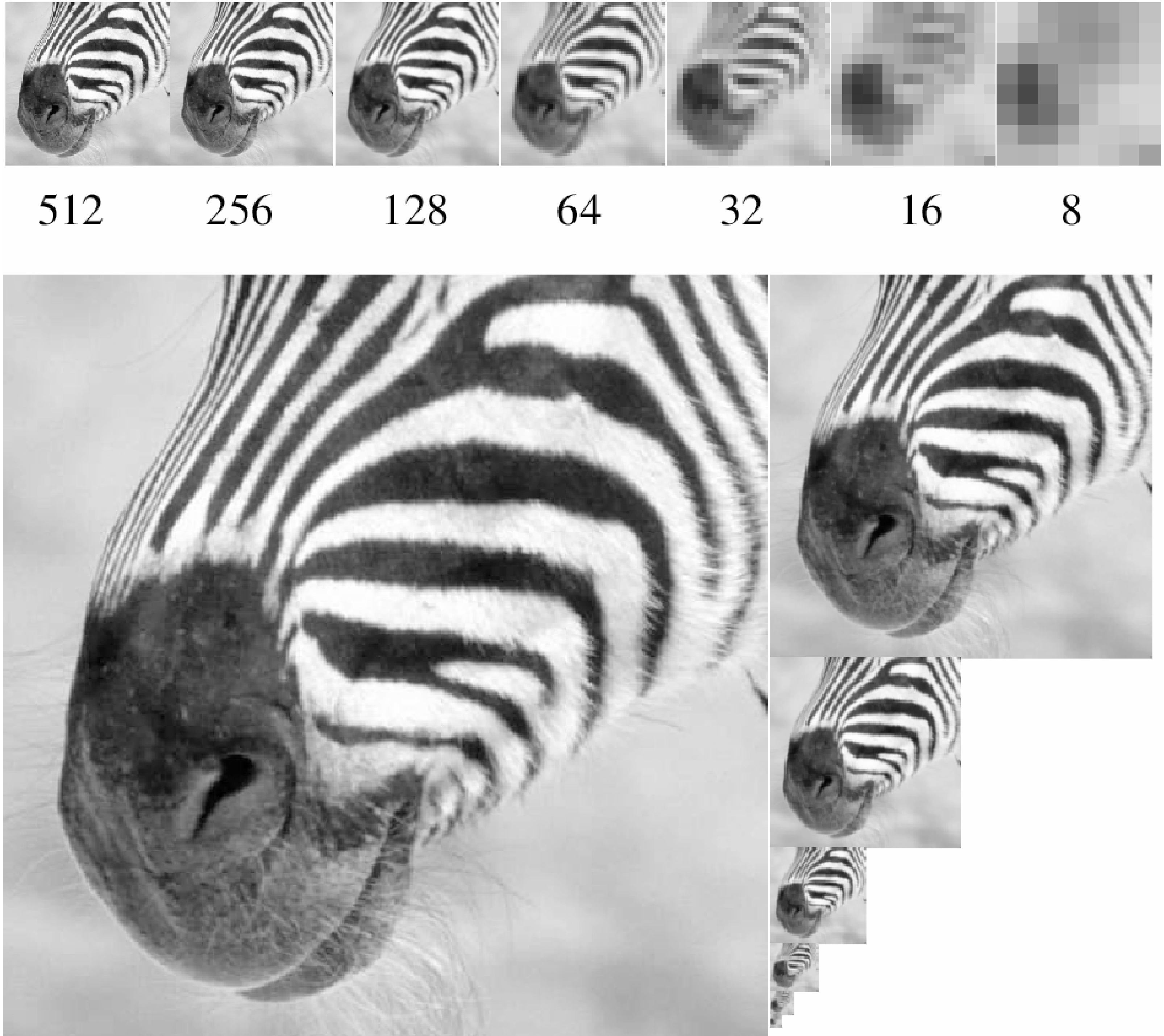

512
256
128
64
32
16
8

Image pyramids

- Gaussian
- Laplacian
- Wavelet/QMF
- Steerable pyramid

Image pyramids

- Gaussian
- Laplacian
- Wavelet/QMF
- Steerable pyramid

The Laplacian Pyramid

- Synthesis
  - preserve difference between upsampled Gaussian pyramid level and Gaussian pyramid level
  - band pass filter - each level represents spatial frequencies (largely) unrepresented at other levels
- Analysis
  - reconstruct Gaussian pyramid, take top layer

Laplacian pyramid algorithm

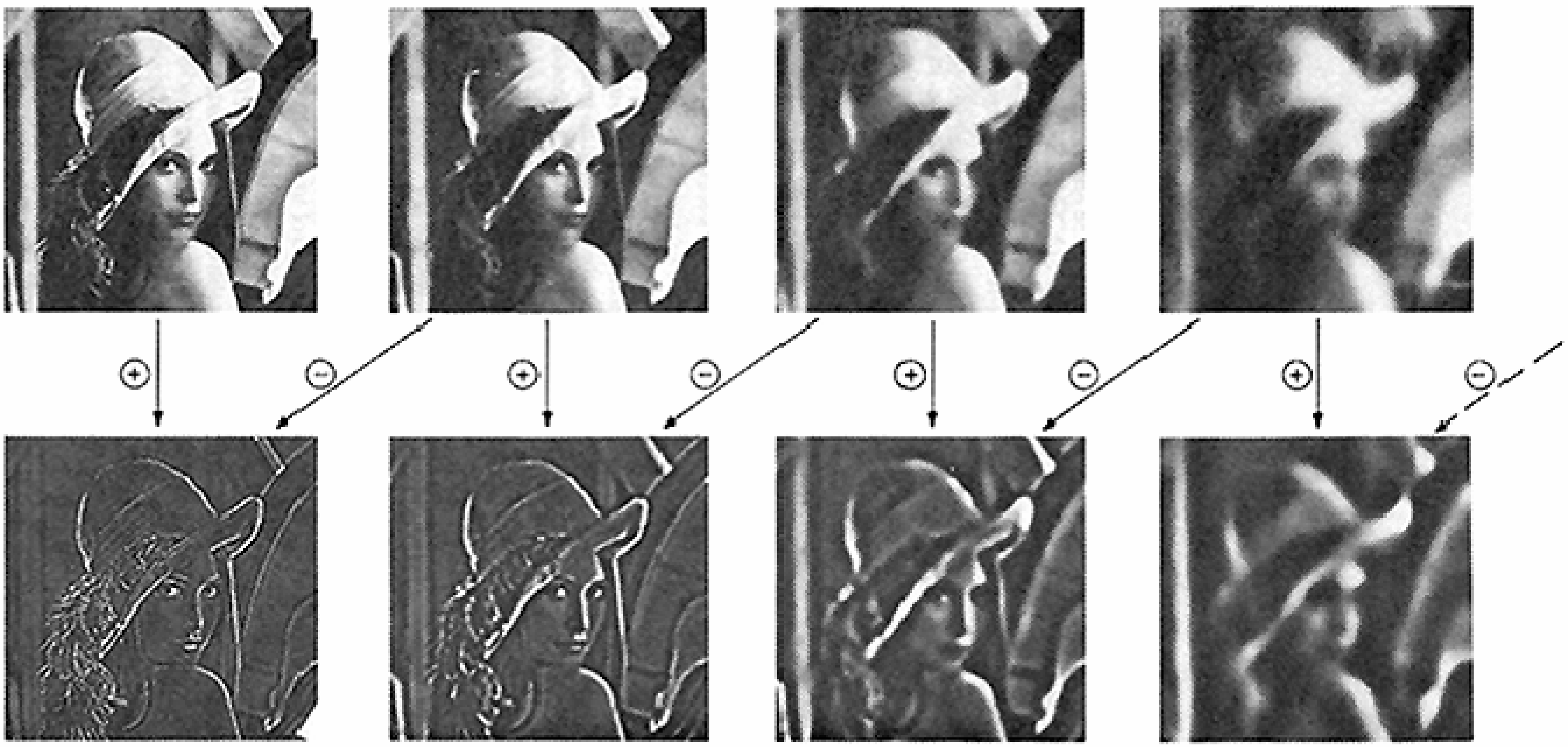
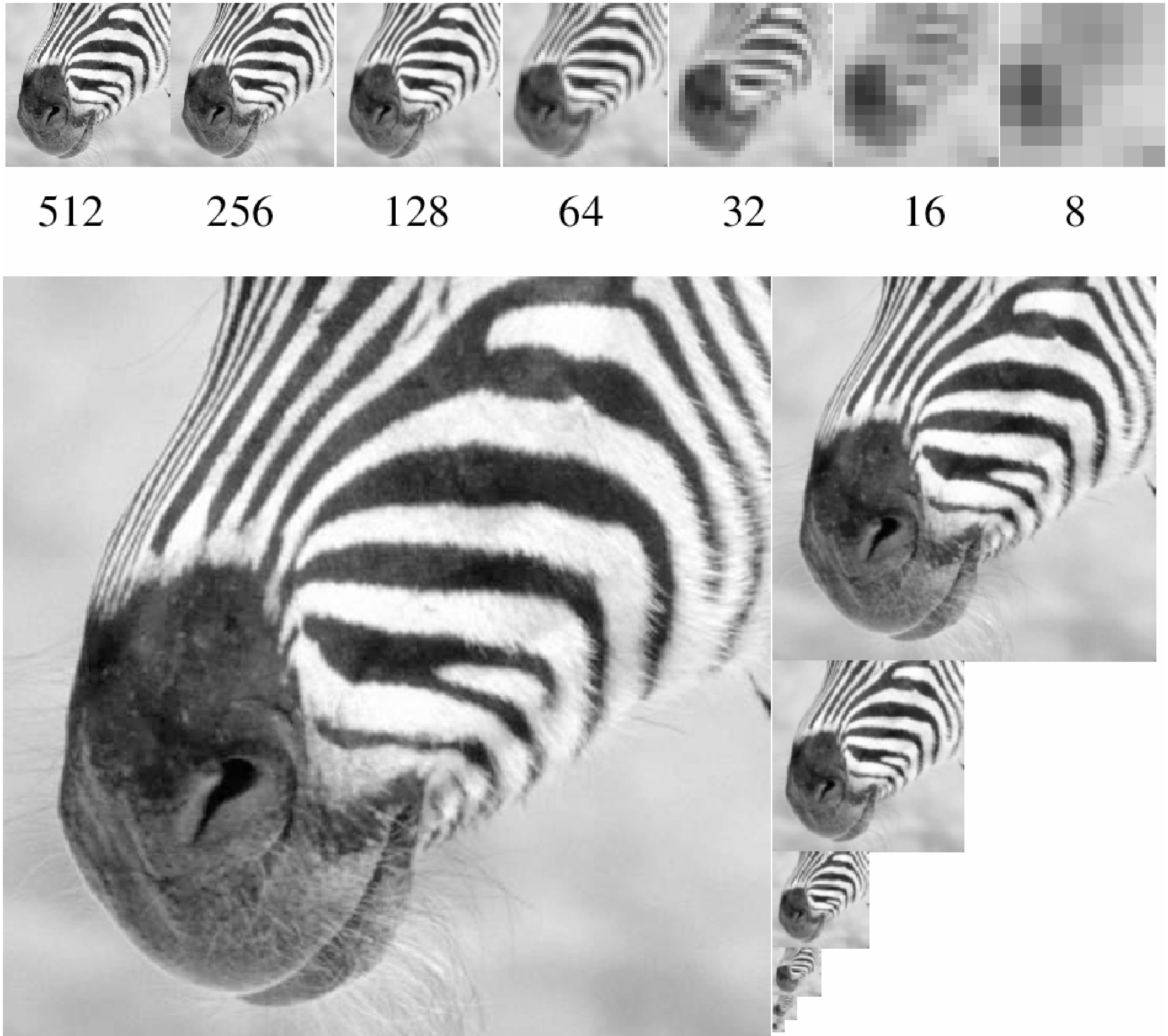
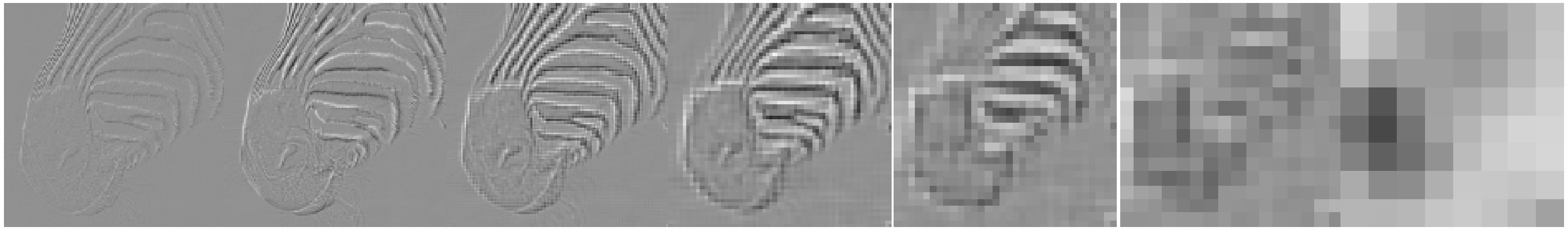


Fig 5. First four levels of the Gaussian and Laplacian pyramid. Gaussian images, upper row, were obtainedby expanding pyramid arrays (Fig. 4) through Gaussian interpolation. Each level of the Laplacian pyramid is the difference between the corresponding and next higher levels of the Gaussian pyramid.

http://www-bcs.mit.edu/people/adelson/pub_pdfs/pyramid83.pdf

IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. COM-31, NO. 4, APRIL 1983


512
256
128
64
32
16
8



512 256 128 64 32 16 8

Application to image compression

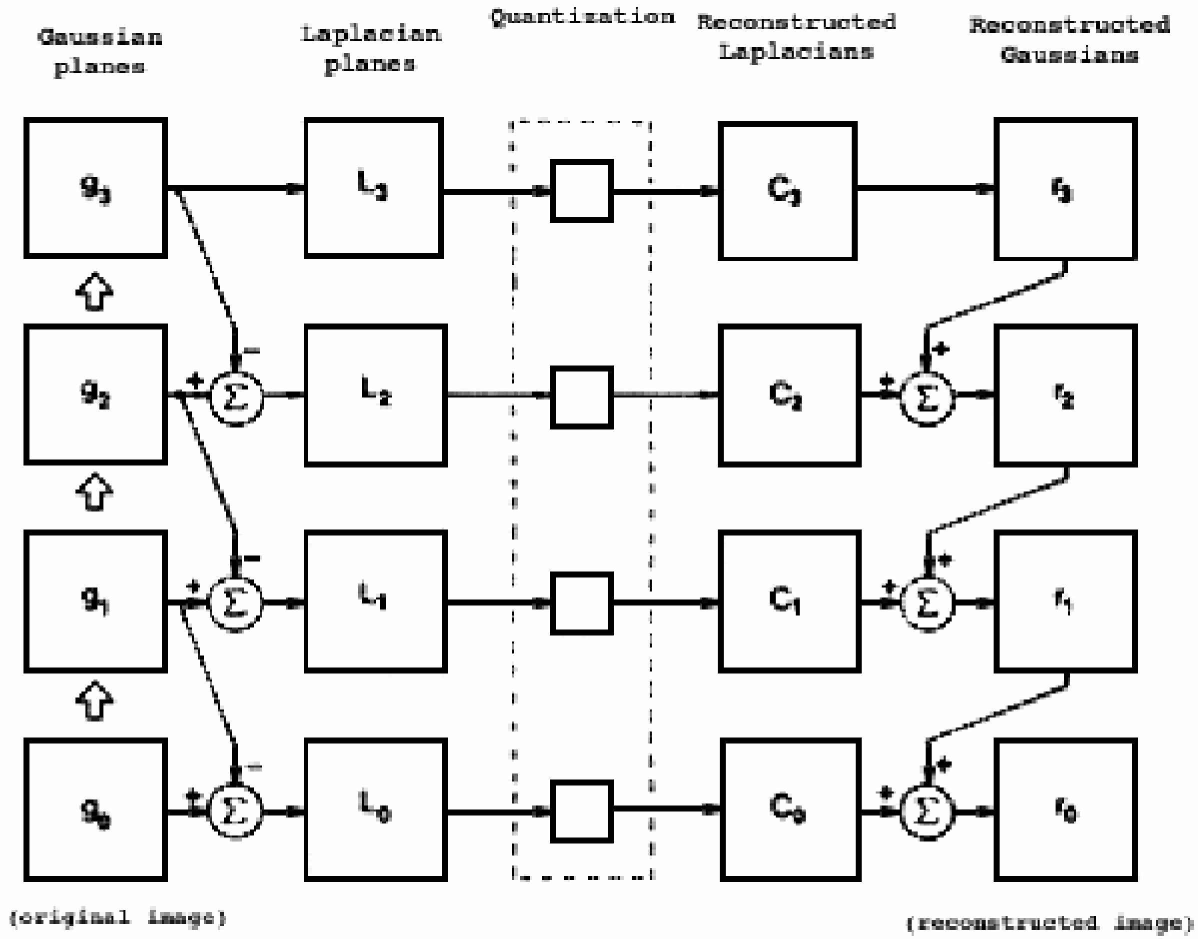


Fig. 10. A summary of the steps in Laplacian pyramid coding and decoding. First, the original image g_0 (lower left) is used to generate Gaussian pyramid levels g_1, g_2, … through repeated local averaging. Levels of the Laplacian pyramid L_0, L_1, … are then computed as the differences between adjacent 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.

http://www-bcs.mit.edu/people/adelson/pub_pdfs/pyramid83.pdf

IEEE TRANSACTIONS ON COMMUNICATIONS, VOL. COM-31, NO. 4, APRIL 1983

Matlab manipulations with gaussian and laplacian pyramids

Image pyramids

- Gaussian
- Laplacian
- Wavelet/QMF
- Steerable pyramid

What is a good representation for image analysis?

(Goldilocks and the three representations)

- Fourier transform domain tells you "what" (textural properties), but not "where". In space, this representation is too spread out.
- Pixel domain representation tells you "where" (pixel location), but not "what". In space, this representation is too localized
- Want an image representation that gives you a local description of image events—what is happening where. That representation might be "just right".

Wavelets/QMF's

transformed image

$$\vec{F} = U\vec{f}$$

Vectorized image

Fourier transform, or
Wavelet transform, or
Steerable pyramid transform

U =

$$\begin{matrix} 1 & 1 \\ 1 & -1 \end{matrix}$$

```
>> inv(U)

ans =

    0.5000    0.5000
    0.5000   -0.5000
```

U =

$$
\begin{matrix}
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & -1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & -1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & -1
\end{matrix}
$$

```
>> inv(U)

ans =

    0.5000    0.5000         0         0         0         0         0         0
    0.5000   -0.5000         0         0         0         0         0         0
         0         0    0.5000    0.5000         0         0         0         0
         0         0    0.5000   -0.5000         0         0         0         0
         0         0         0         0    0.5000    0.5000         0         0
         0         0         0         0    0.5000   -0.5000         0         0
         0         0         0         0         0         0    0.5000    0.5000
         0         0         0         0         0         0    0.5000   -0.5000
```

Matlab examples of Haar wavelet representation

- Frequency characteristics of the high and low-pass representations

Simoncelli and Adelson, in “Subband coding”, Kluwer, 1990.

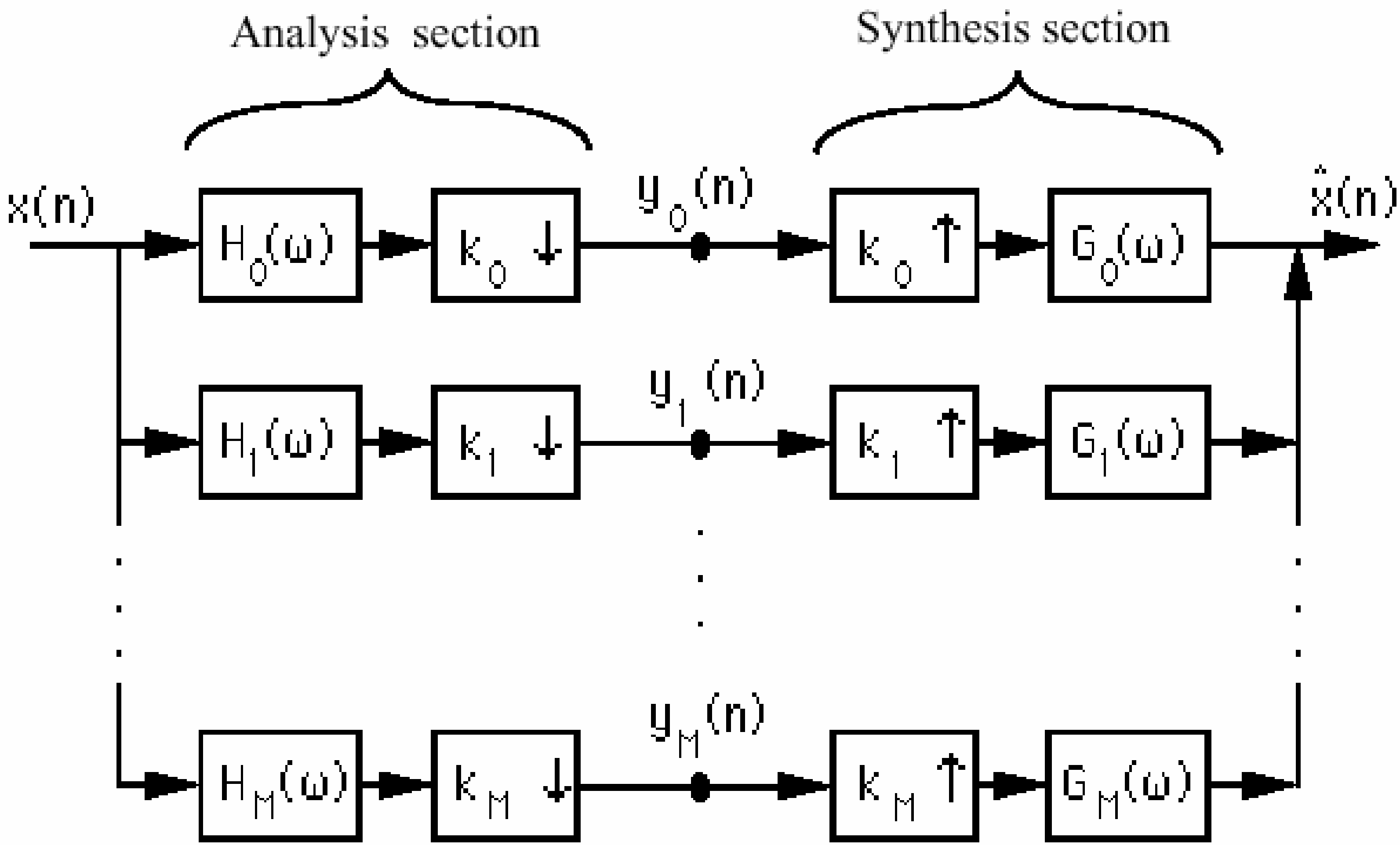


Figure 4.2: An analysis/synthesis filter bank.

Simoncelli and Adelson, in “Subband coding”, Kluwer, 1990.

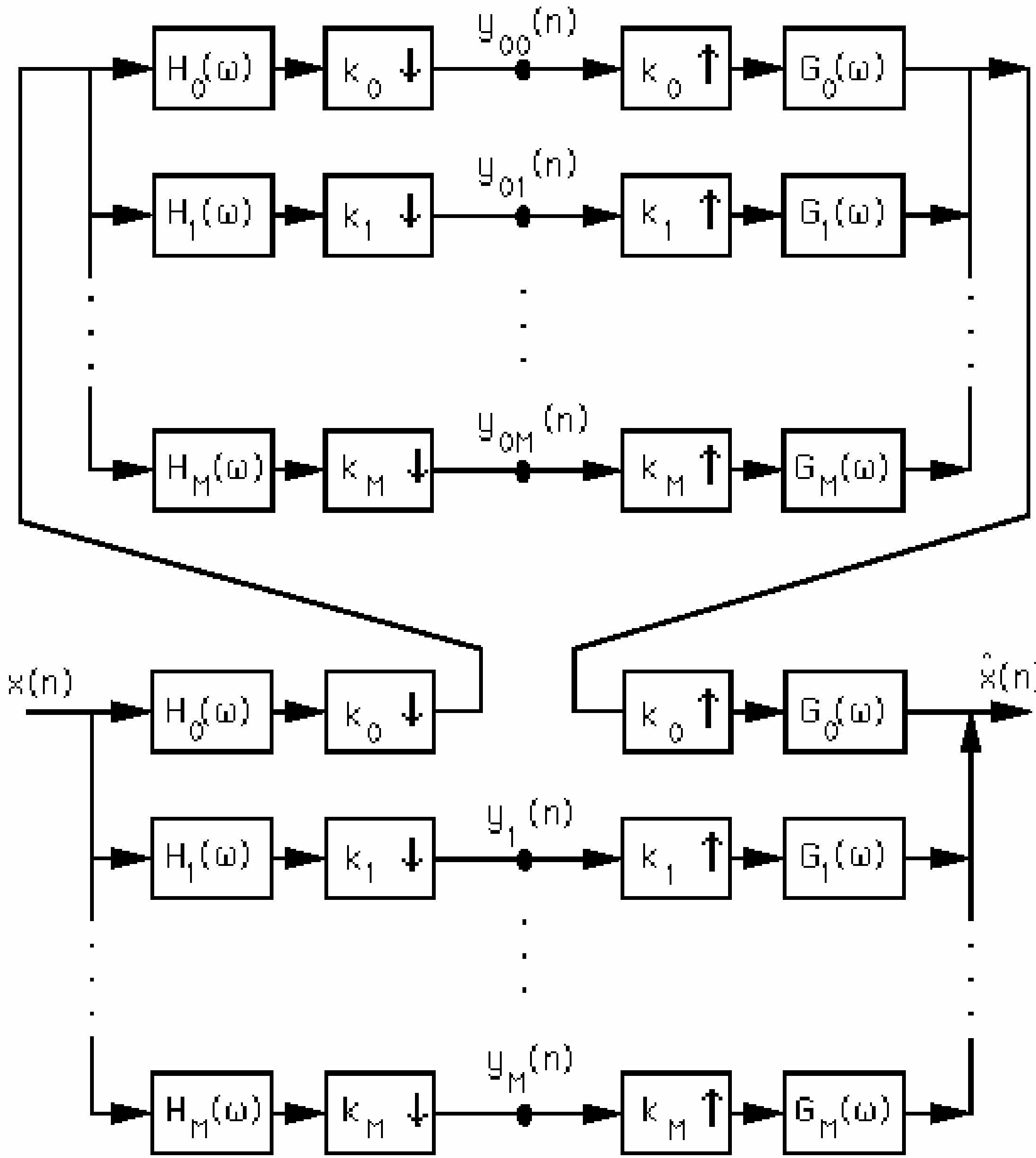


Figure 4.3: A non-uniformly cascaded analysis/synthesis filter bank.

Simoncelli and Adelson, in “Subband coding”, Kluwer, 1990.

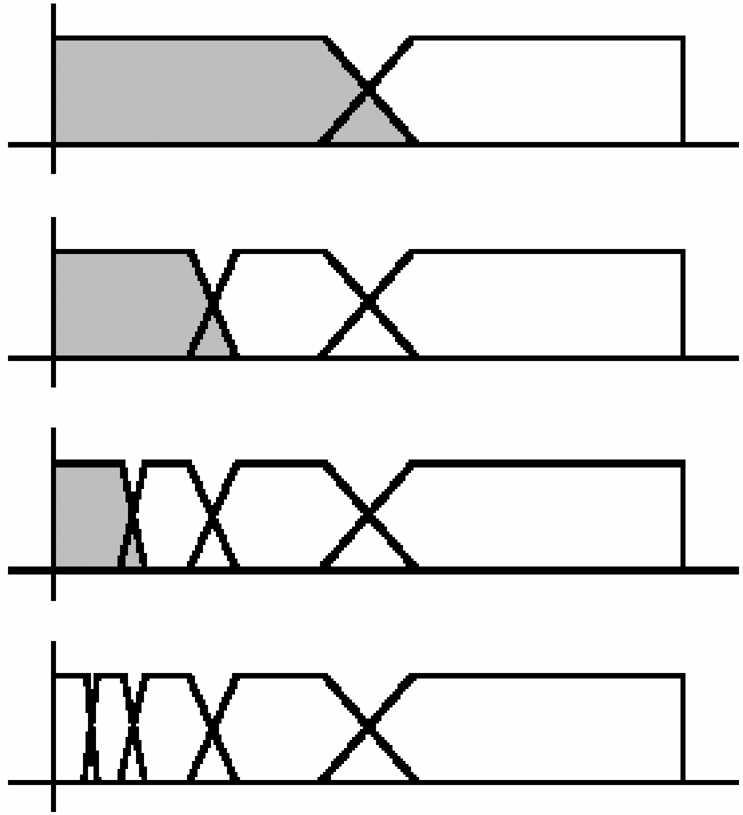


Figure 4.4: Octave band splitting produced by a four-level pyramid cascade of a two-band A/S system. The top picture represents the splitting of the two-band A/S system. Each successive picture shows the effect of re-applying the system to the lowpass subband (indicated in grey) of the previous picture. The bottom picture gives the final four-level partition of the frequency domain. All frequency axes cover the range from 0 to π.

n	QMF-5	QMF-9	QMF-13
0	0.8593118	0.7973934	0.7737113
1	0.3535534	0.41472545	0.42995453
2	-0.0761025	-0.073386624	-0.057827797
3		-0.060944743	-0.09800052
4		0.02807382	0.039045125
5			0.021651438
6			-0.014556438

Table 4.1: Odd-length QMF kernels. Half of the impulse response sample values are shown for each of the normalized lowpass QMF filters (All filters are symmetric about $n = 0$). The appropriate highpass filters are obtained by delaying by one sample and multiplying with the sequence $(-1)^n$.

Simoncelli and Adelson, in “Subband coding”, Kluwer, 1990.

To create 2-d filters, apply the 1-d filters separably in the two spatial dimensions

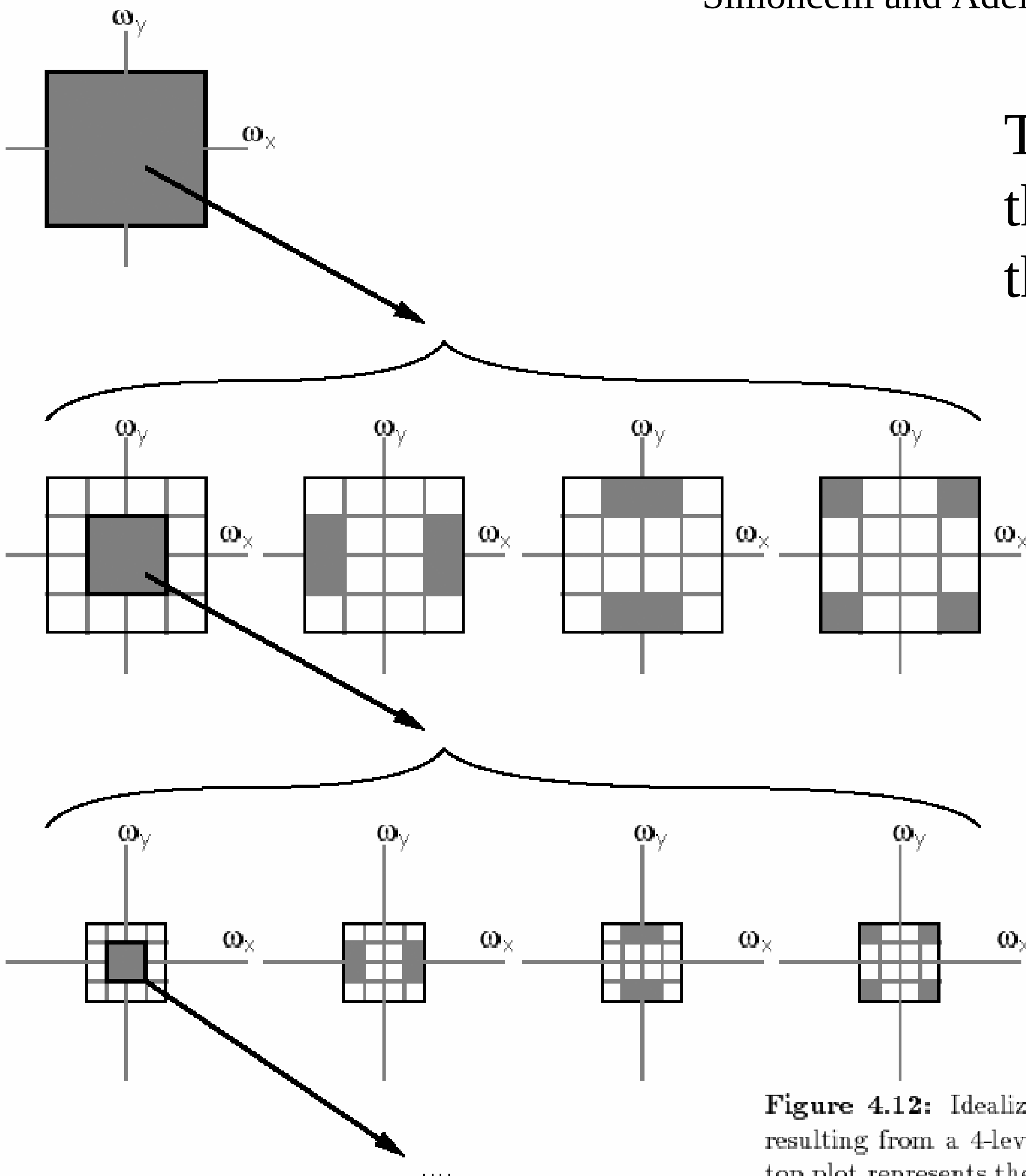
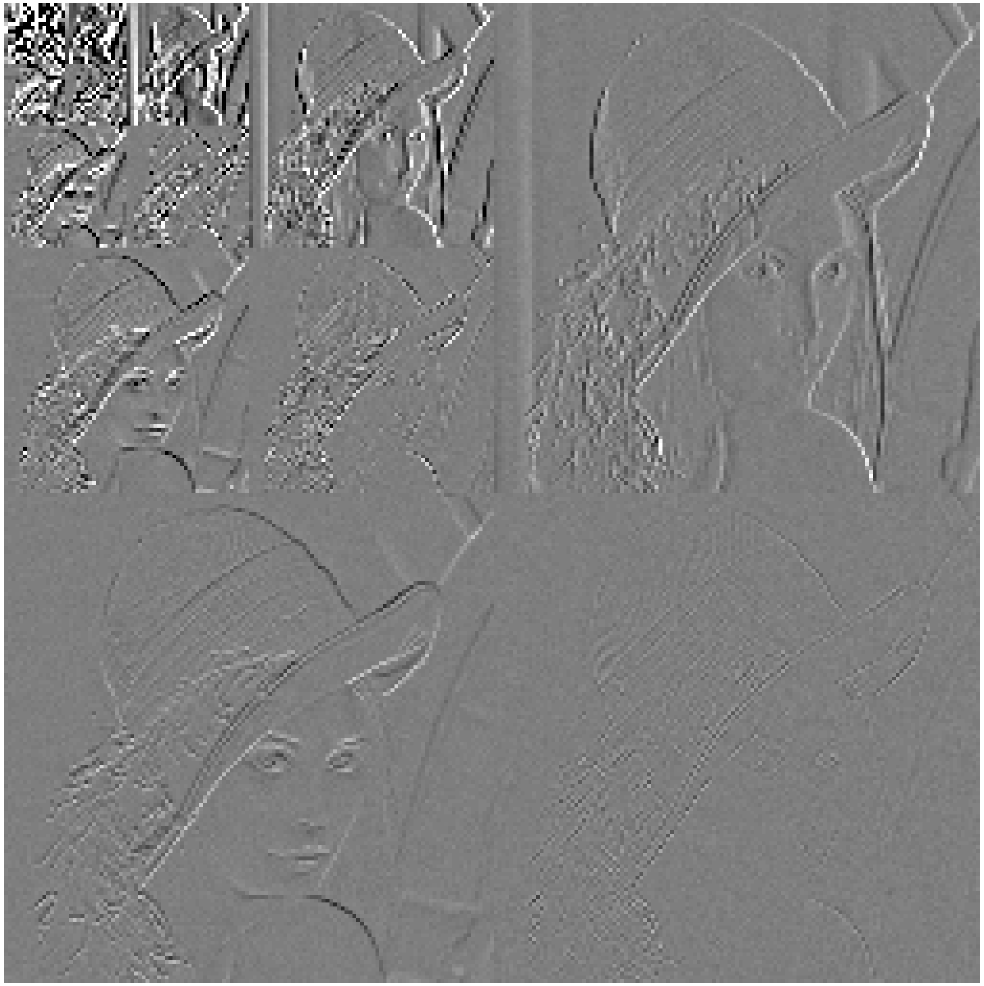


Figure 4.12: Idealized diagram of the partition of the frequency plane resulting from a 4-level pyramid cascade of separable 2-band filters. The top plot represents the frequency spectrum of the original image, with axes ranging from $-\pi$ to π. This is divided into four subbands at the next level. On each subsequent level, the lowpass subband (outlined in bold) is subdivided further.

Wavelet/QMF representation



Good and bad features of wavelet/QMF filters

- Bad:
  - Aliased subbands
  - Non-oriented diagonal subband
- Good:
  - Not overcomplete (so same number of coefficients as image pixels).
  - Good for image compression (JPEG 2000)

Image pyramids

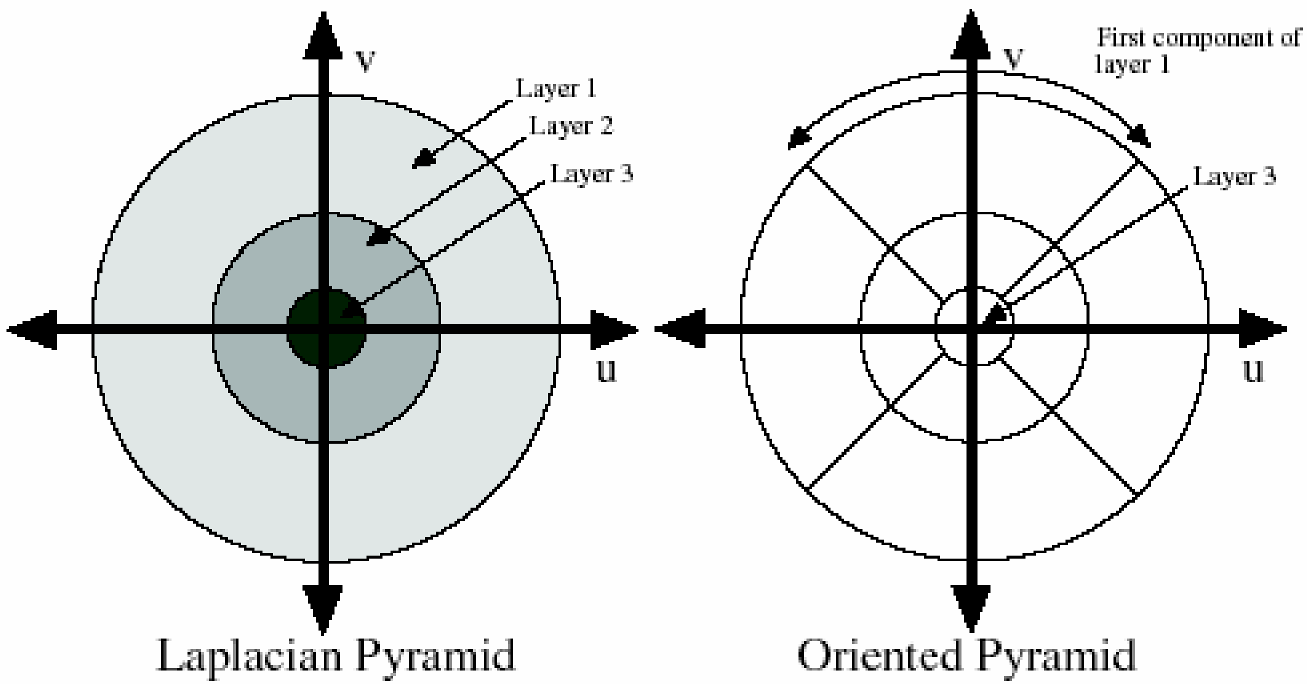
- Gaussian
- Laplacian
- Wavelet/QMF
- Steerable pyramid

Steerable pyramids

- Good:
  - Oriented subbands
  - Non-aliased subbands
  - Steerable filters
- Bad:
  - Overcomplete
  - Have one high frequency residual subband, required in order to form a circular region of analysis in frequency from a square region of support in frequency.

Oriented pyramids

- Laplacian pyramid is orientation independent
- Apply an oriented filter to determine orientations at each layer
  - by clever filter design, we can simplify synthesis
  - this represents image information at a particular scale and orientation


v
Layer 1
Layer 2
Layer 3
u
Laplacian Pyramid
v
First component of
layer 1
Layer 3
u
Oriented Pyramid

	Laplacian Pyramid	Dyadic QMF/Wavelet	Steerable Pyramid
self-inverting (tight frame)	no	yes	yes
overcompleteness	$4/3$	1	$4k/3$
aliasing in subbands	perhaps	yes	no
rotated orientation bands	no	only on hex lattice [9]	yes

Table 1: Properties of the Steerable Pyramid relative to two other well-known multi-scale representations.

http://www.cns.nyu.edu/ftp/eero/simoncelli95b.pdf

Simoncelli and Freeman, ICIP 1995

But we need to get rid of the corner regions before starting the recursive circular filtering

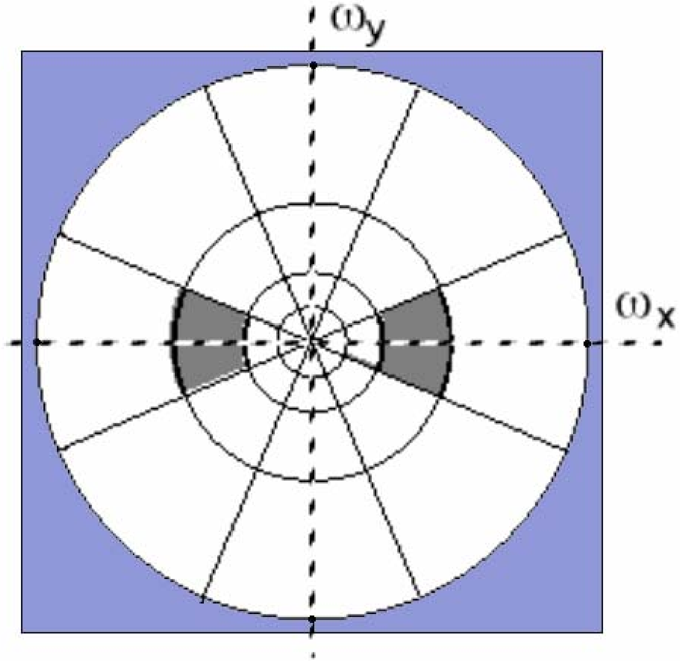
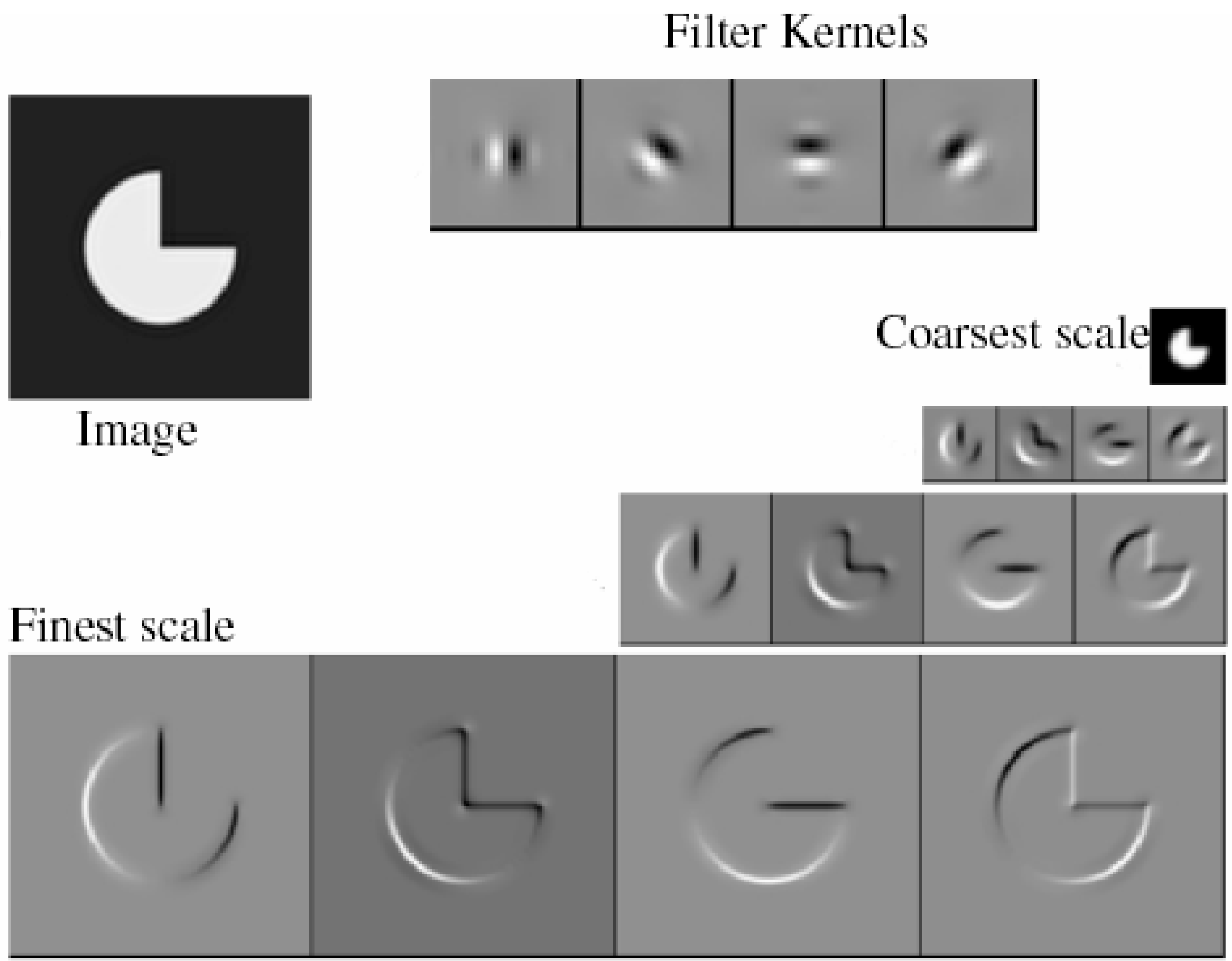


Figure 1. Idealized illustration of the spectral decomposition performed by a steerable pyramid with $k = 4$. Frequency axes range from $-\pi$ to π. The basis functions are related by translations, dilations and *rotations* (except for the initial highpass subband and the final lowpass subband). For example, the shaded region corresponds to the spectral support of a single (vertically-oriented) subband.

http://www.cns.nyu.edu/ftp/eero/simoncelli95b.pdf

Simoncelli and Freeman, ICIP 1995



Reprinted from “Shiftable MultiScale Transforms,” by Simoncelli et al., IEEE Transactions on Information Theory, 1992, copyright 1992, IEEE

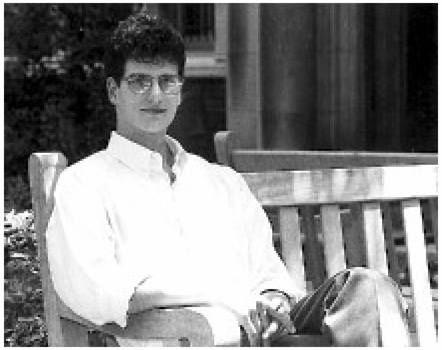
Matlab resources for pyramids (with tutorial)

http://www.cns.nyu.edu/~eero/software.html

Eero P. Simoncelli

Associate Investigator,
Howard Hughes Medical Institute

Associate Professor,
Neural Science and Mathematics,
New York University



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Publicly Available Software Packages

- Texture Analysis/Synthesis - Matlab code is available for analyzing and synthesizing visual textures. README | Contents | ChangeLog | Source code (UNIX/PC, gzip'ed tar file)
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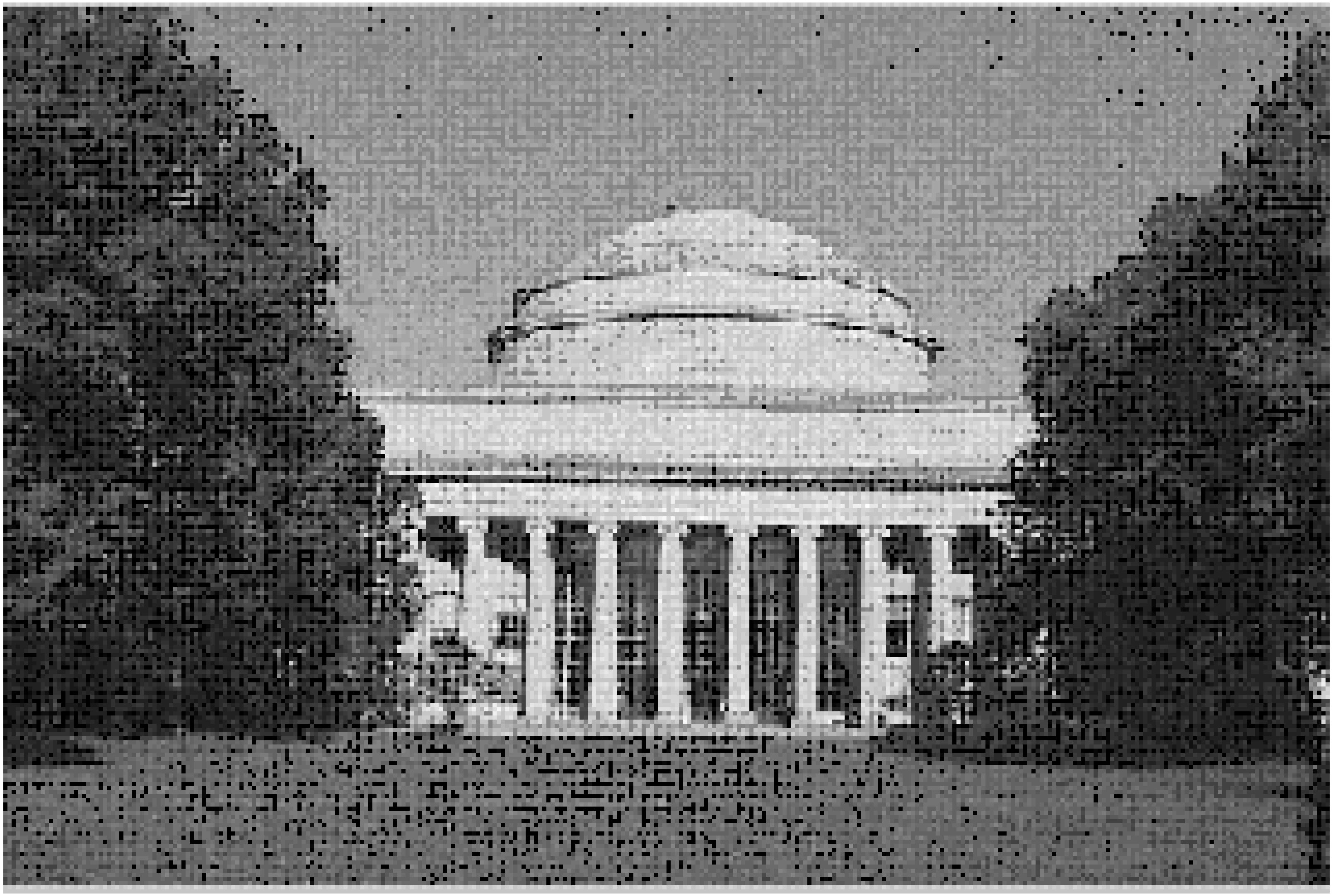
- EPIC - Efficient Pyramid (Wavelet) Image Coder. C source code available.
- OBVIUS [Object-Based Vision & Image Understanding System]: README / ChangeLog / Doc (225k) / Source Code (2.25M).
- CL-SHELL [Gnu Emacs <-> Common Lisp Interface]: README / Change Log / Source Code (119k).

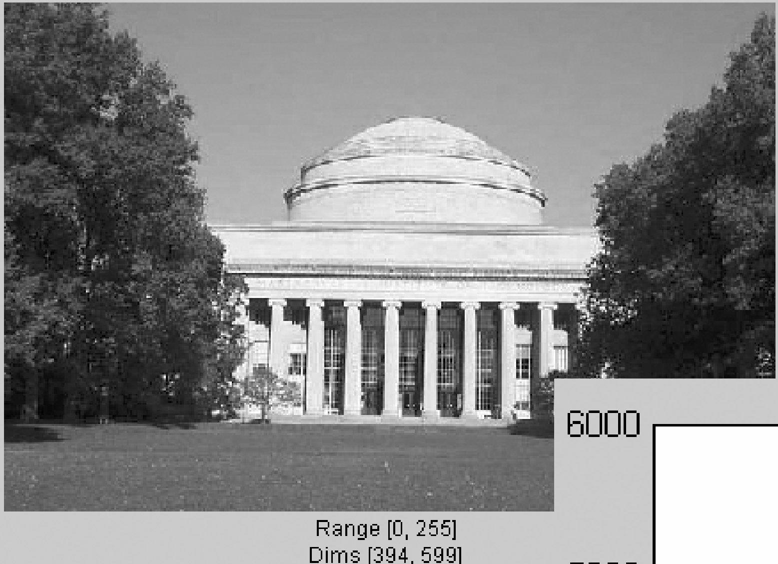
An application of image pyramids: noise removal

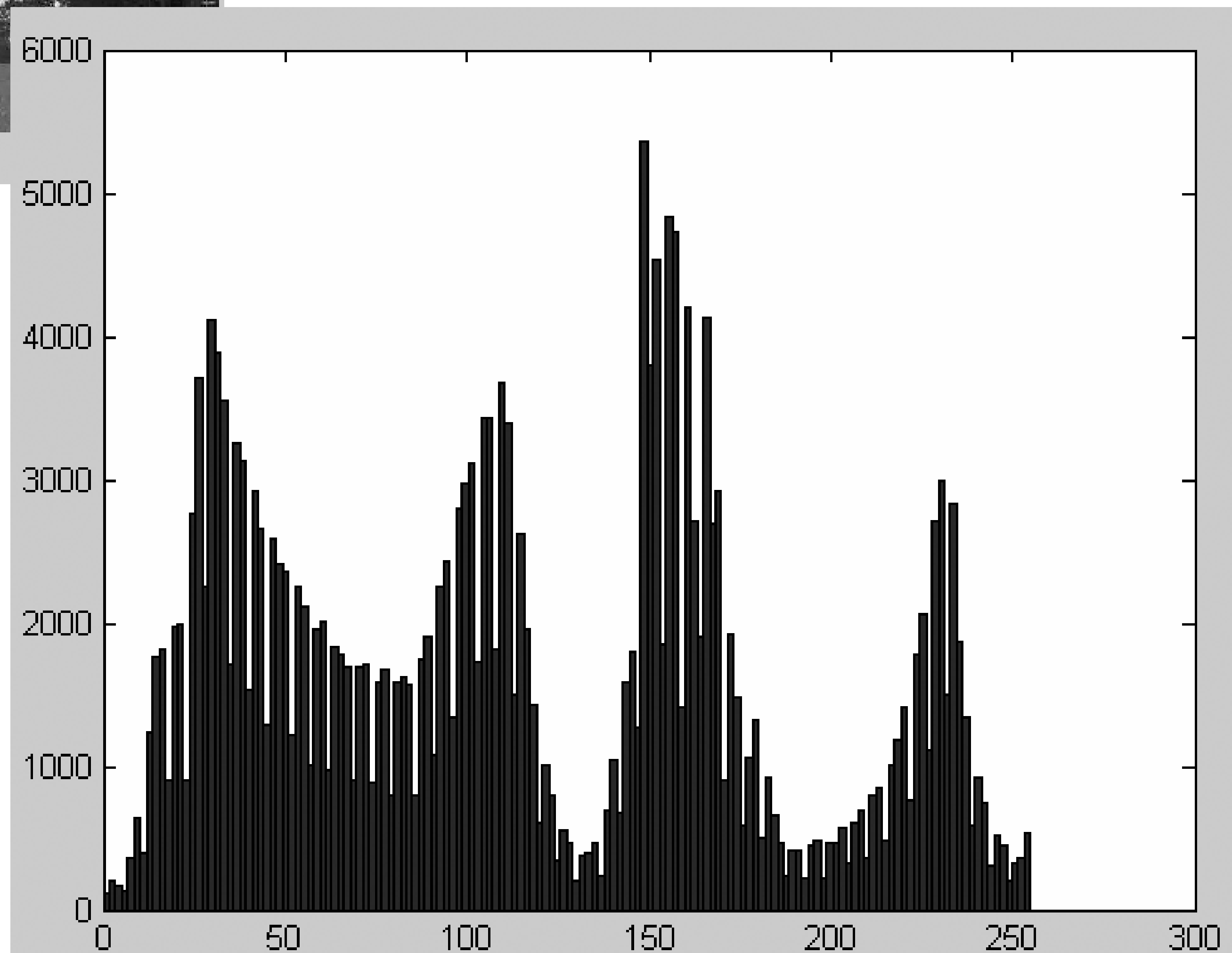
Image statistics (or, mathematically, how can you tell image from noise?)



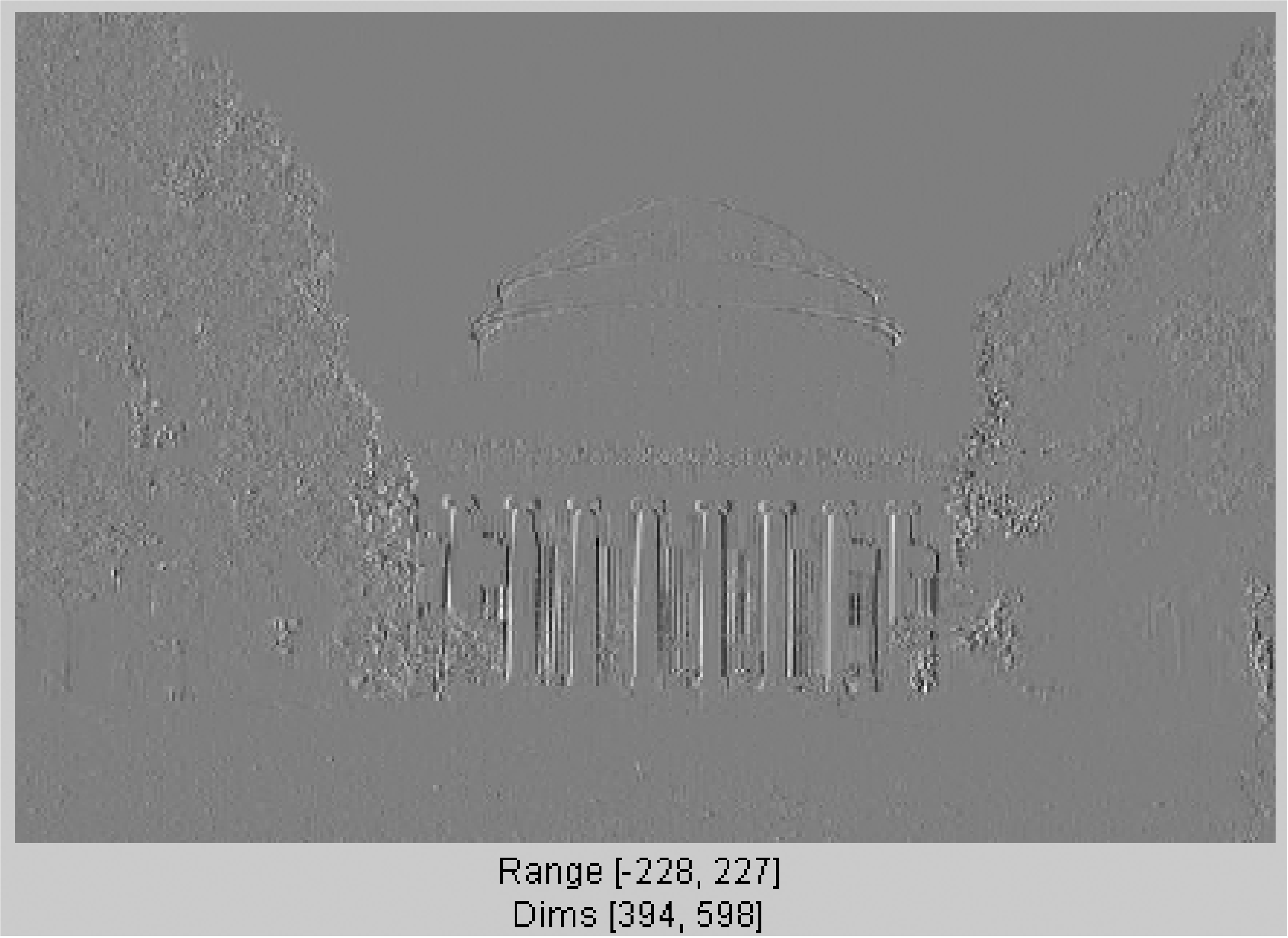
Range [0, 255]
Dims [394, 599]

Pixel representation
image histogram

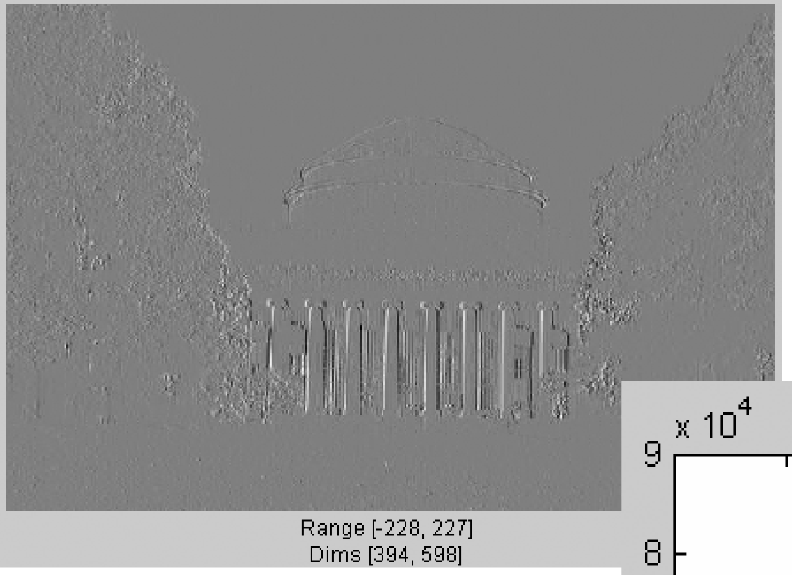


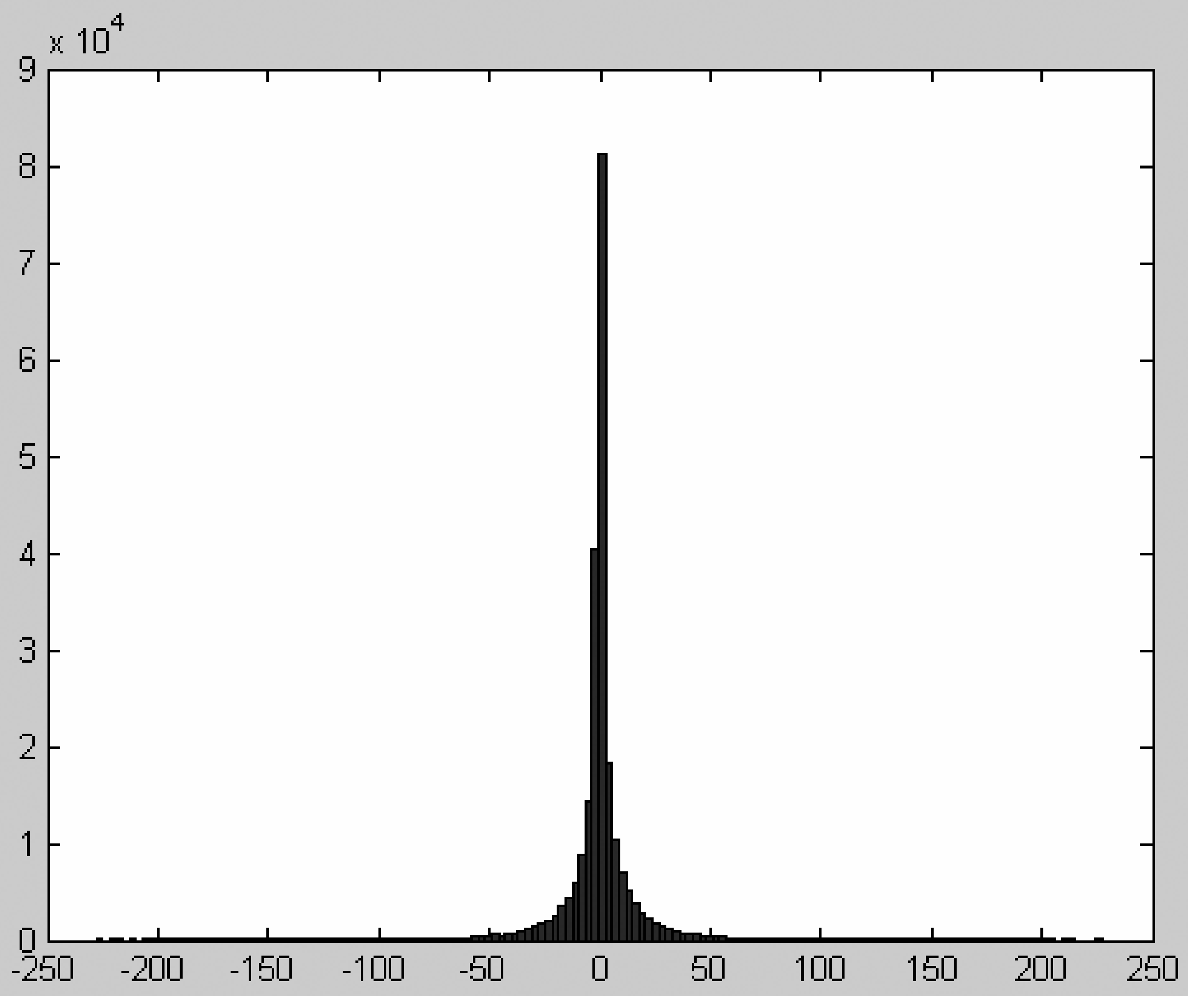


bandpass filtered image

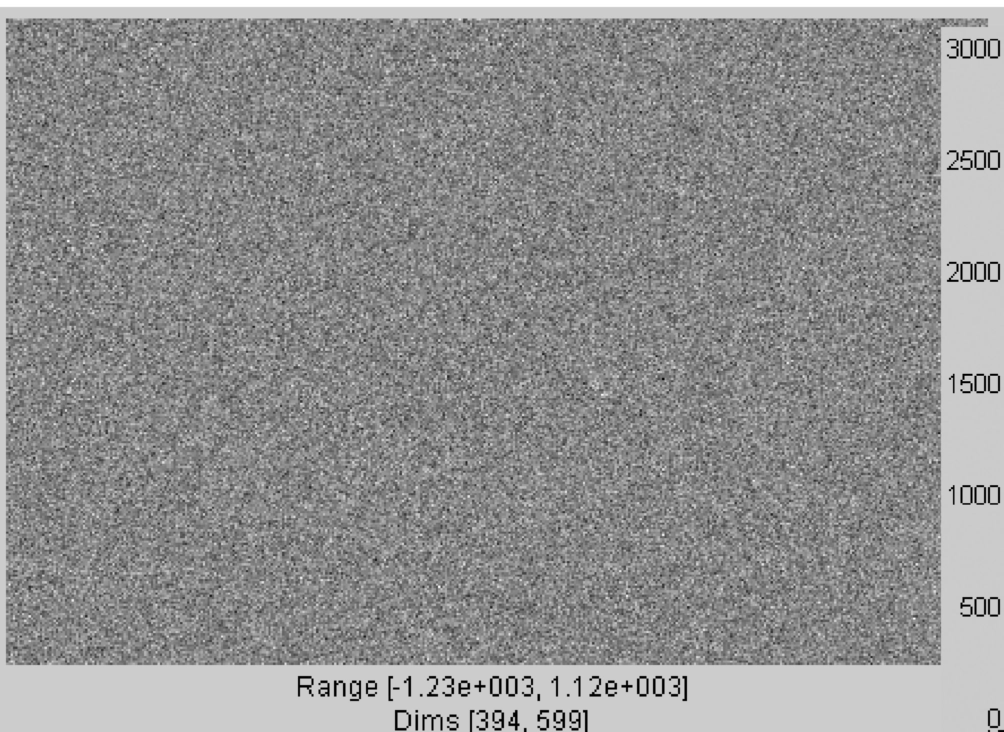


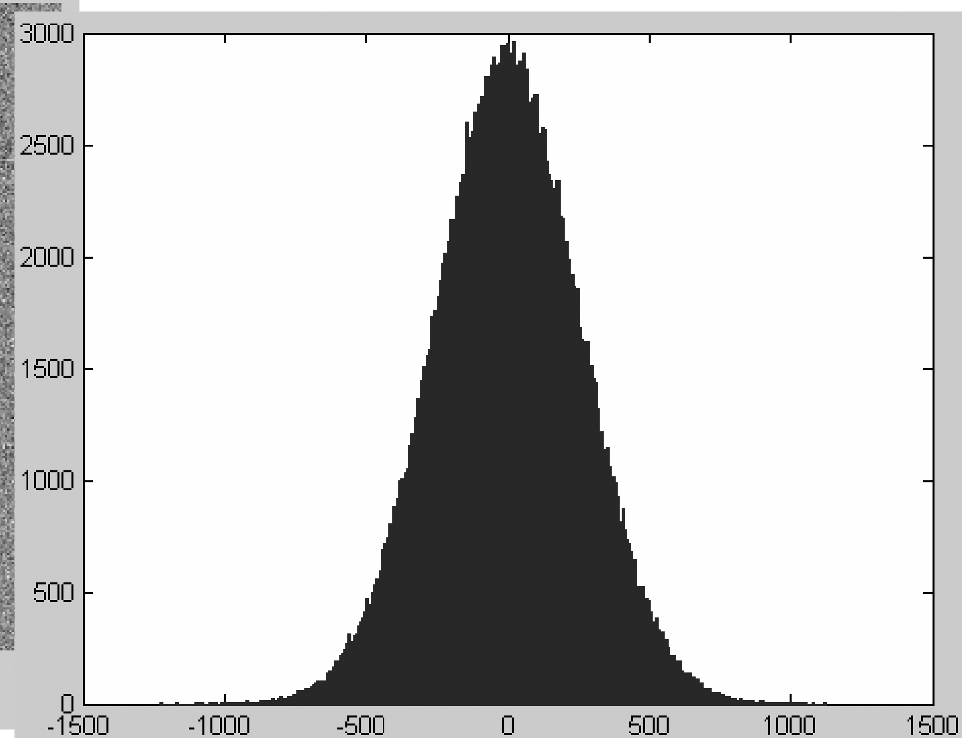
bandpassed representation image histogram



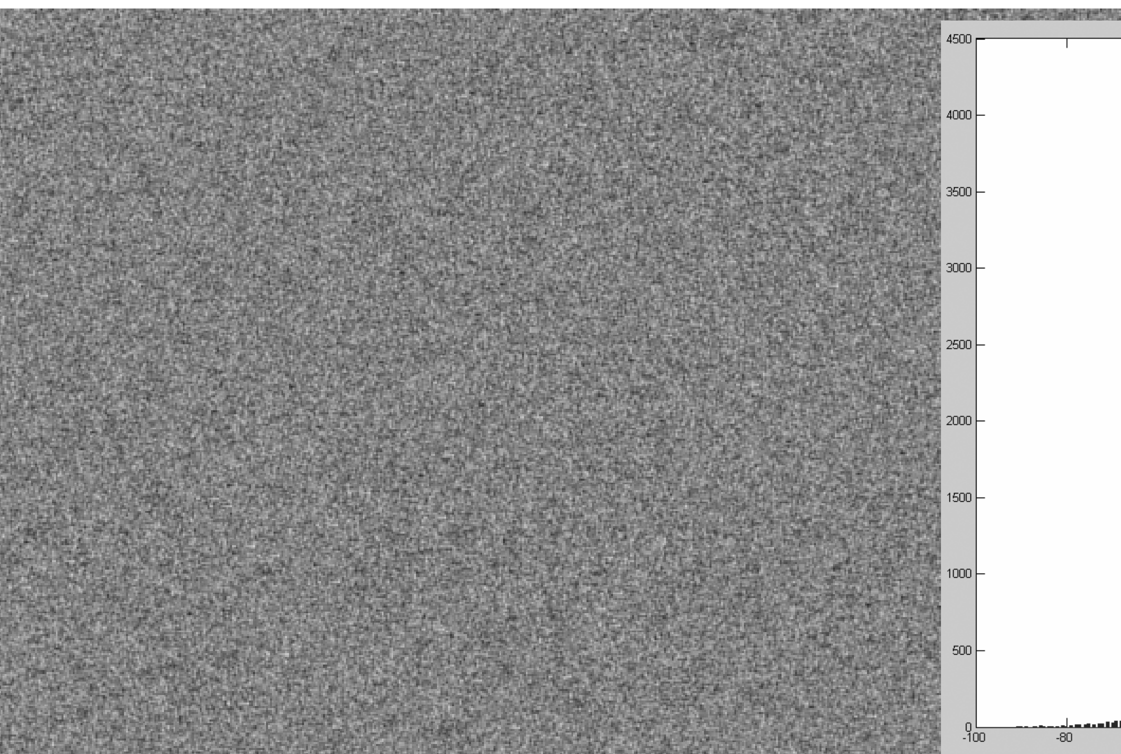


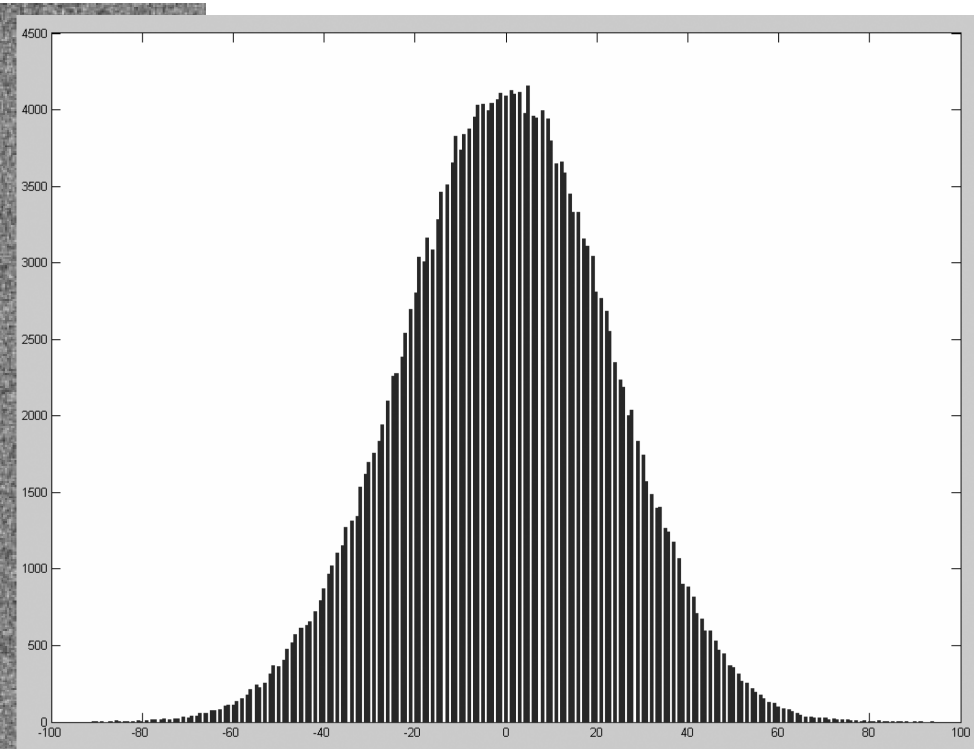
Pixel domain noise image and histogram



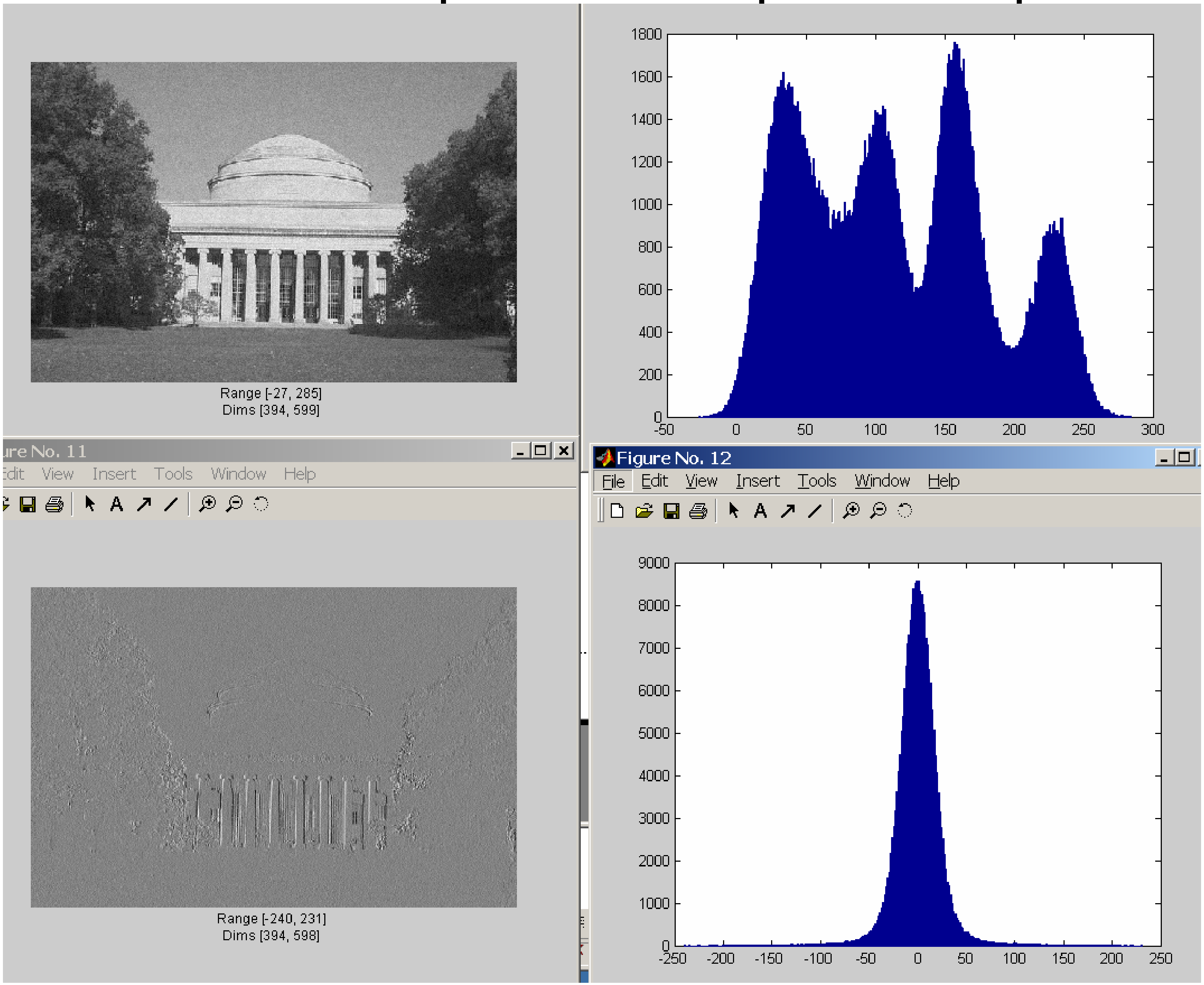


Bandpass domain noise image and histogram





Noise-corrupted full-freq and bandpass images



Bayes theorem

$$P(x, y) = P(x|y)\,P(y)$$

so

$$P(x|y)\,P(y) = P(y|x)\,P(x)$$

and

$$P(x|y) = P(y|x)\,P(x)\,/\,P(y)$$

- x: The parameters you want to estimate
- y: What you observe
- $P(y|x)$: Likelihood function
- $P(x)$: Prior probability
- $P(y)$: Constant w.r.t. parameters x.

Bayesian MAP estimator for clean bandpass coefficient values

Let x = bandpassed image value before adding noise.

Let y = noise-corrupted observation.

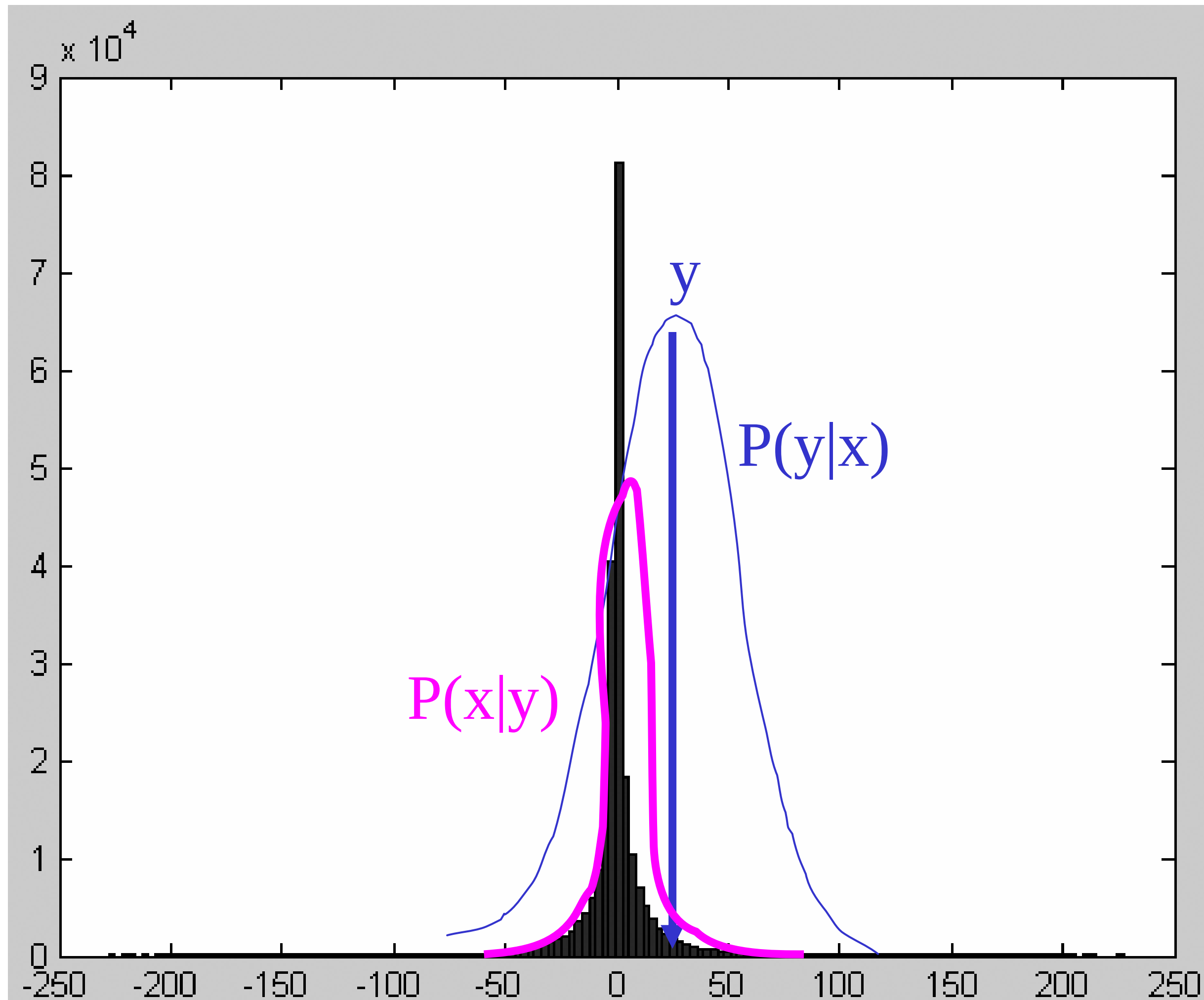
By Bayes theorem

P(x|y) = k P(y|x) P(x)

P(x)

P(y|x)

P(x|y)



Bayesian MAP estimator

Let x = bandpassed image value before adding noise.

Let y = noise-corrupted observation.

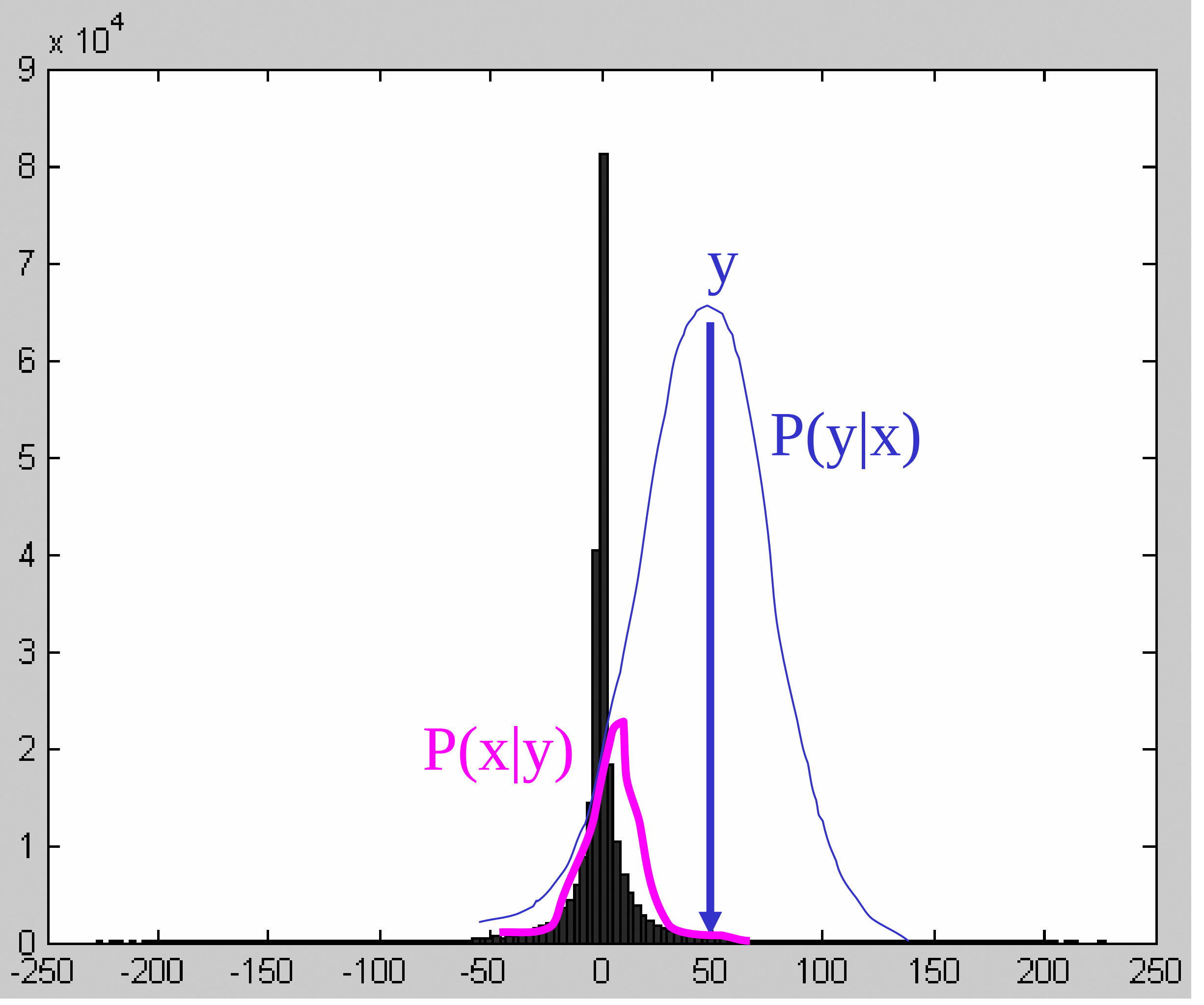
By Bayes theorem

P(x|y) = k P(y|x) P(x)

P(x)

P(y|x)

P(x|y)



Bayesian MAP estimator

Let x = bandpassed image value before adding noise.

Let y = noise-corrupted observation.

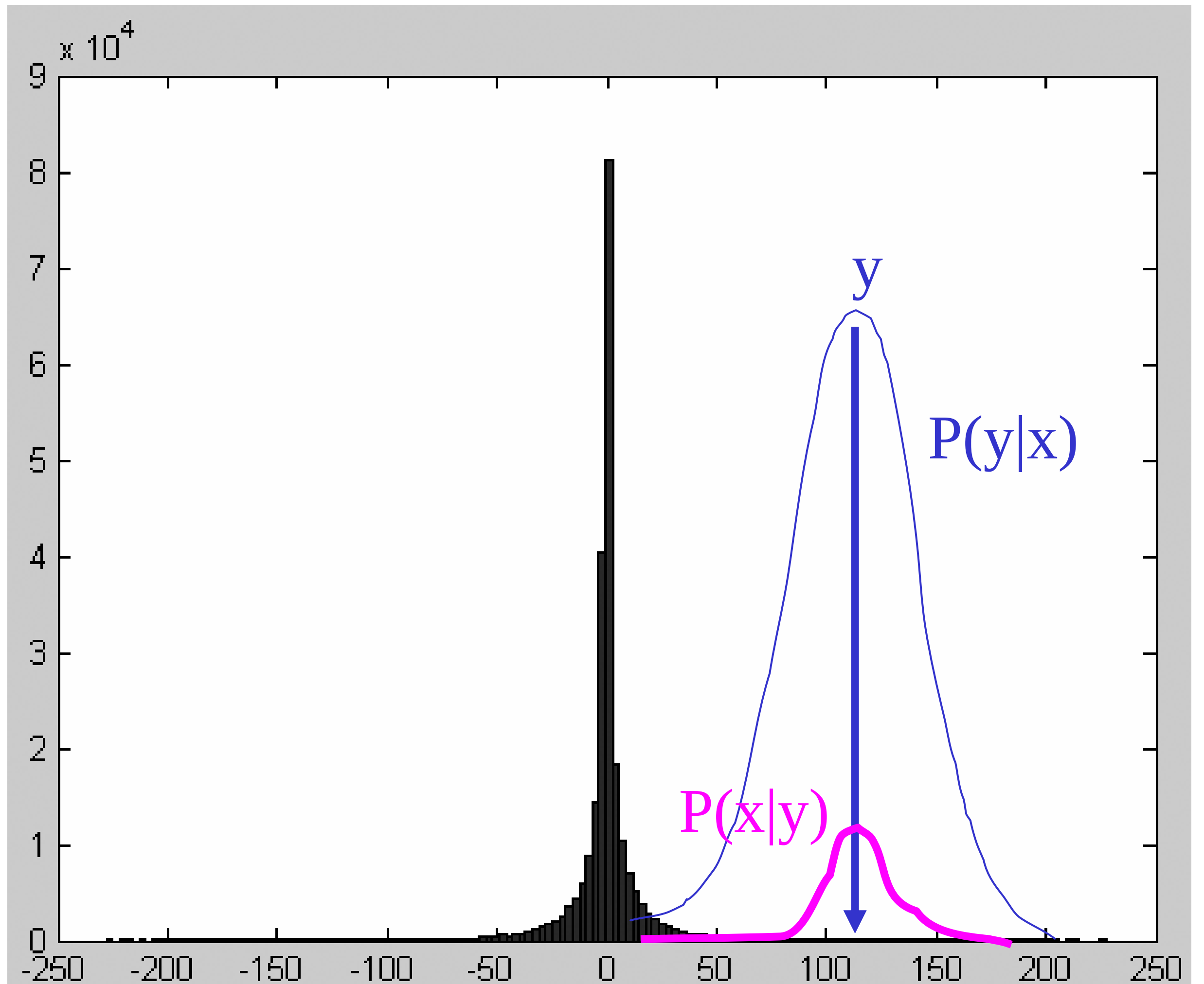
By Bayes theorem

P(x|y) = k P(y|x) P(x)

P(x)

P(y|x)

P(x|y)



MAP estimate, $\hat{x}$, as function of observed coefficient value, y

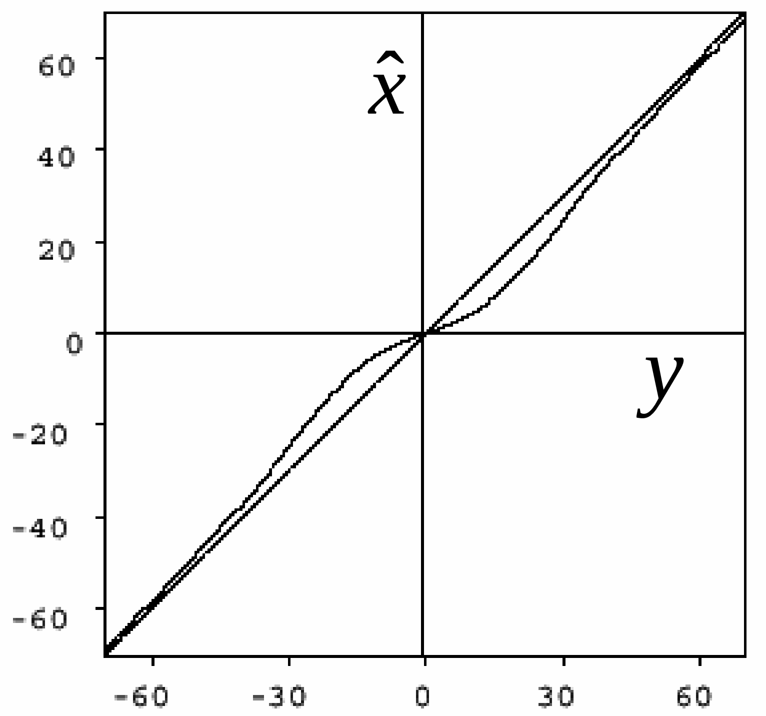


Figure 2: Bayesian estimator (symmetrized) for the signal and noise histograms shown in figure 1. Superimposed on the plot is a straight line indicating the identity function.

http://www-bcs.mit.edu/people/adelson/pub_pdfs/simoncelli_noise.pdf **Simoncelli and Adelson, Noise Removal via Bayesian Wavelet Coring**

Noise removal results

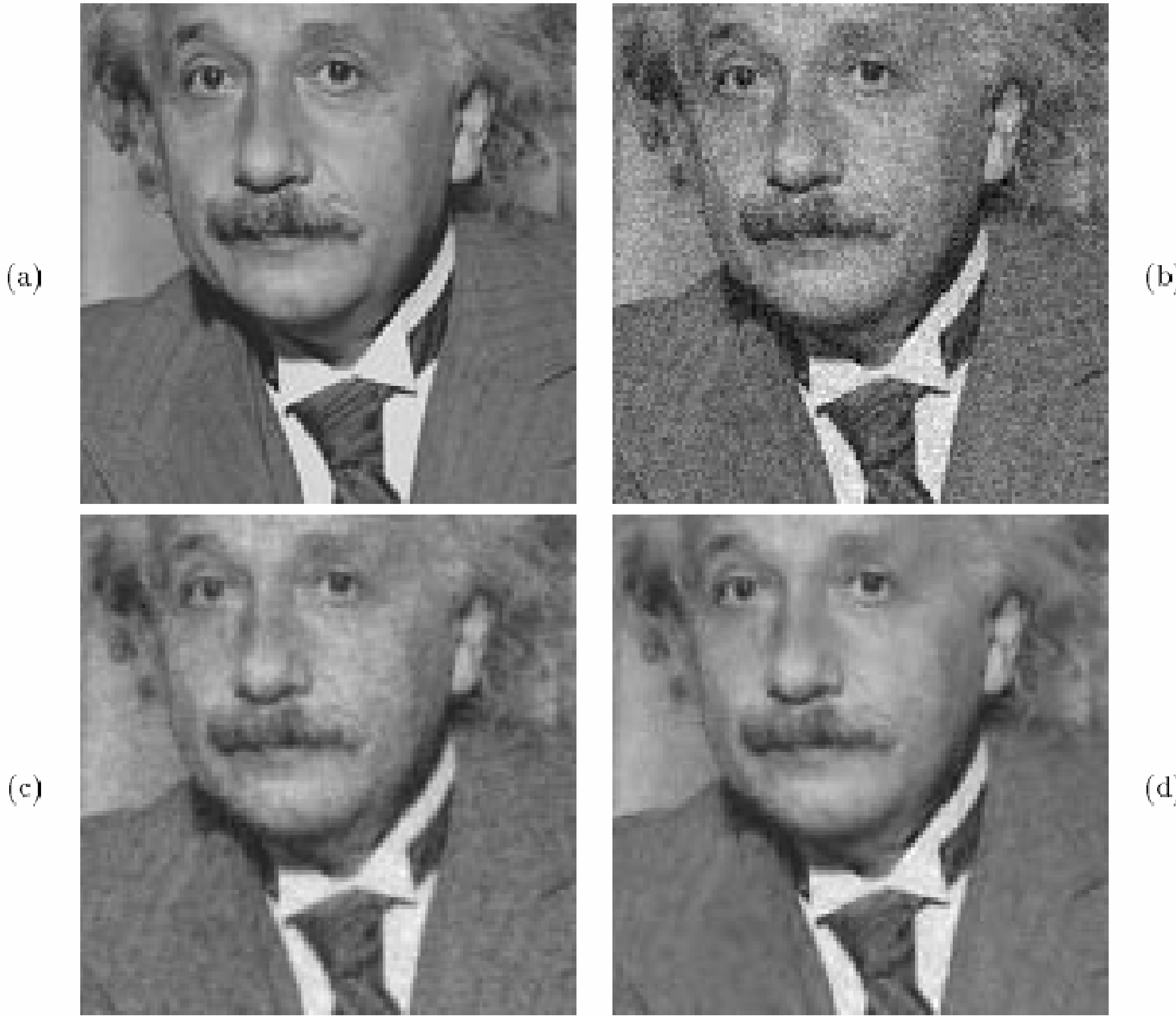


Figure 4: Noise reduction example. (a) Original image (cropped). (b) Image contaminated with additive Gaussian white noise (SNR = 9.00dB). (c) Image restored using (semi-blind) Wiener filter (SNR = 11.88dB). (d) Image restored using (semi-blind) Bayesian estimator (SNR = 13.82dB).

http://www-bcs.mit.edu/people/adelson/pub_pdfs/simoncelli_noise.pdf

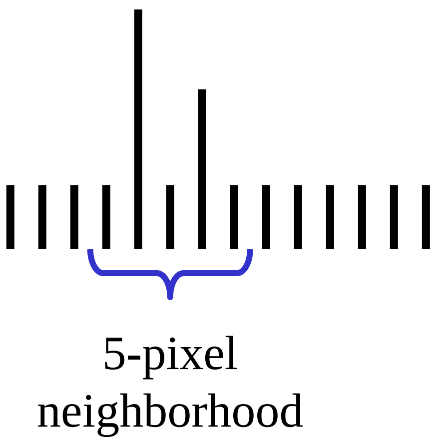
Simoncelli and Adelson, Noise Removal via Bayesian Wavelet Coring

Non-linear filtering example

Median filter

Replace each pixel by the median over N pixels (5 pixels, for these examples).
Generalizes to “rank order” filters.

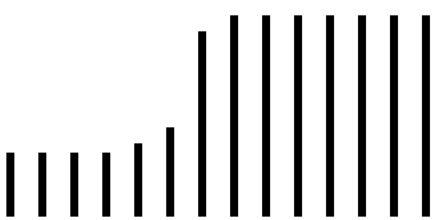
In:



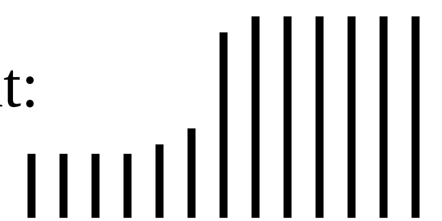
Out:

Spike noise is removed

In:



Out:



Monotonic edges remain unchanged

Degraded image

Radius 1 median filter

Radius 2 median filter

CCD color sampling

Color sensing, 3 approaches

- Scan 3 times (temporal multiplexing)
- Use 3 detectors (3-ccd camera, and color film)
- Use offset color samples (spatial multiplexing)

Typical errors in temporal multiplexing approach

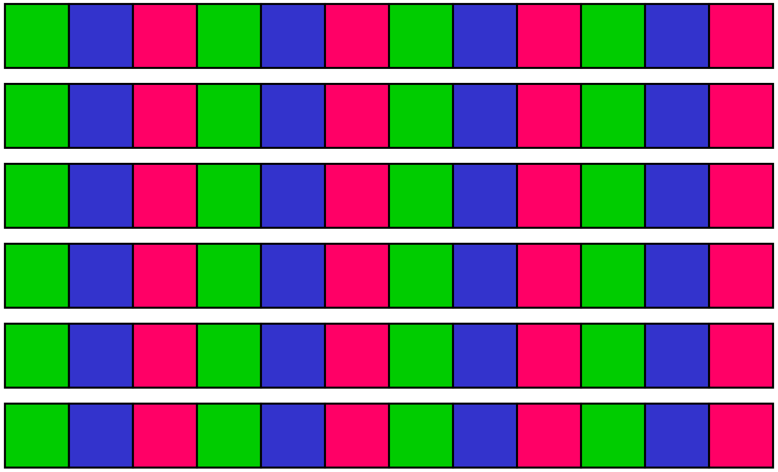
- Color offset fringes

Typical errors in spatial multiplexing approach.

- Color fringes.

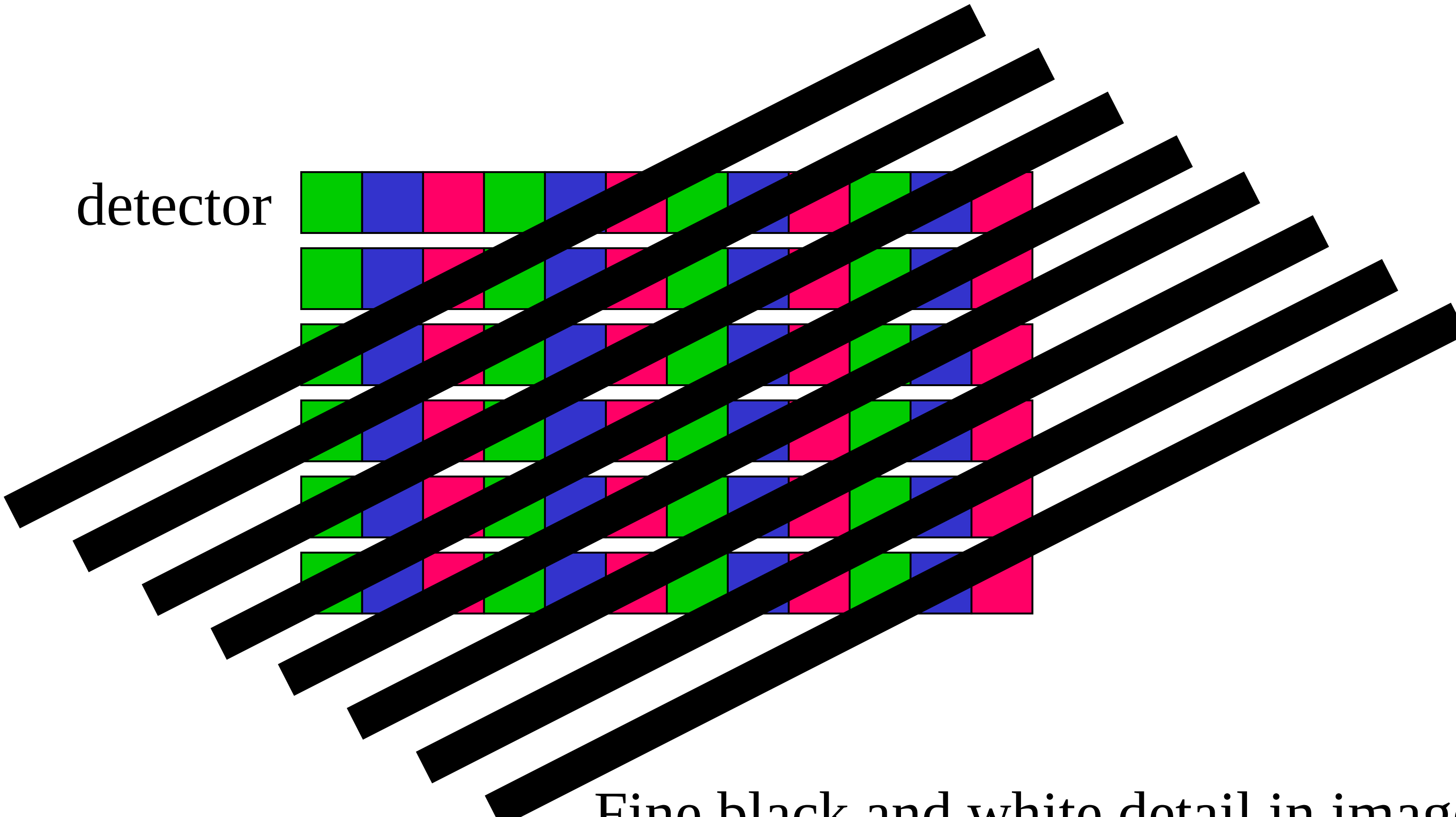
CCD color filter pattern

detector



The cause of color moire

detector

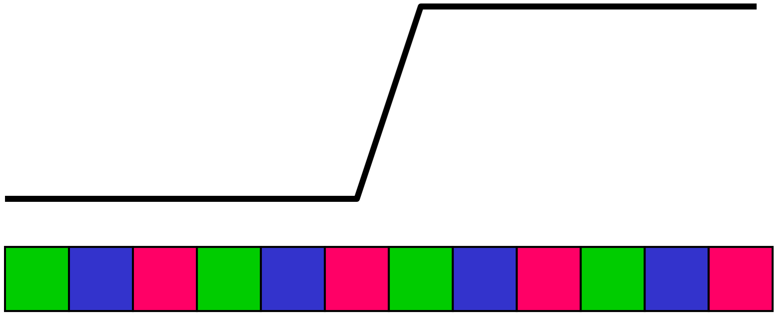


Fine black and white detail in image
mis-interpreted as color information.

Black and white edge falling on color CCD detector

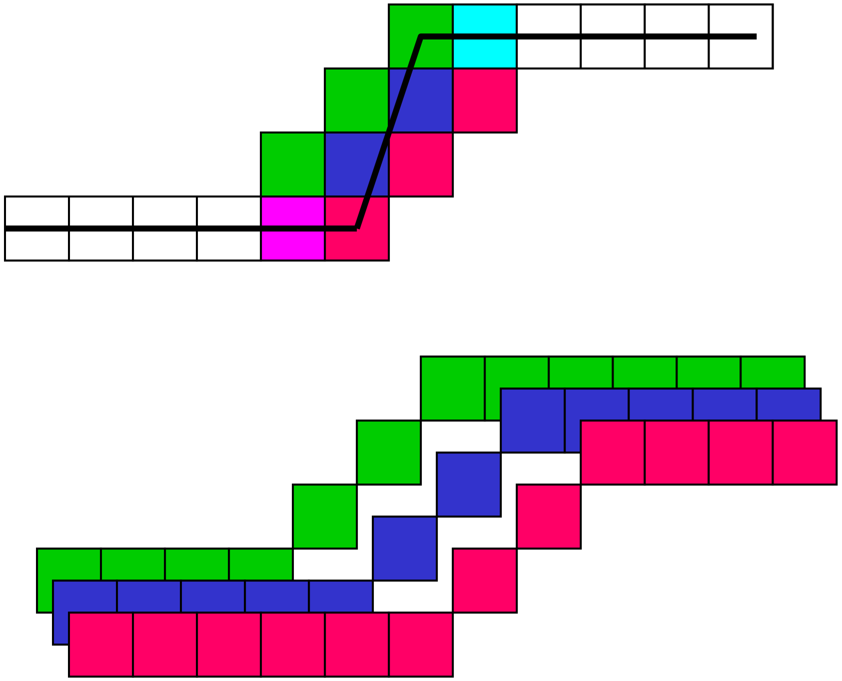
Black and white image (edge)

Detector pixel colors



Color sampling artifact

Interpolated pixel colors,
for grey edge falling on colored
detectors (linear interpolation).

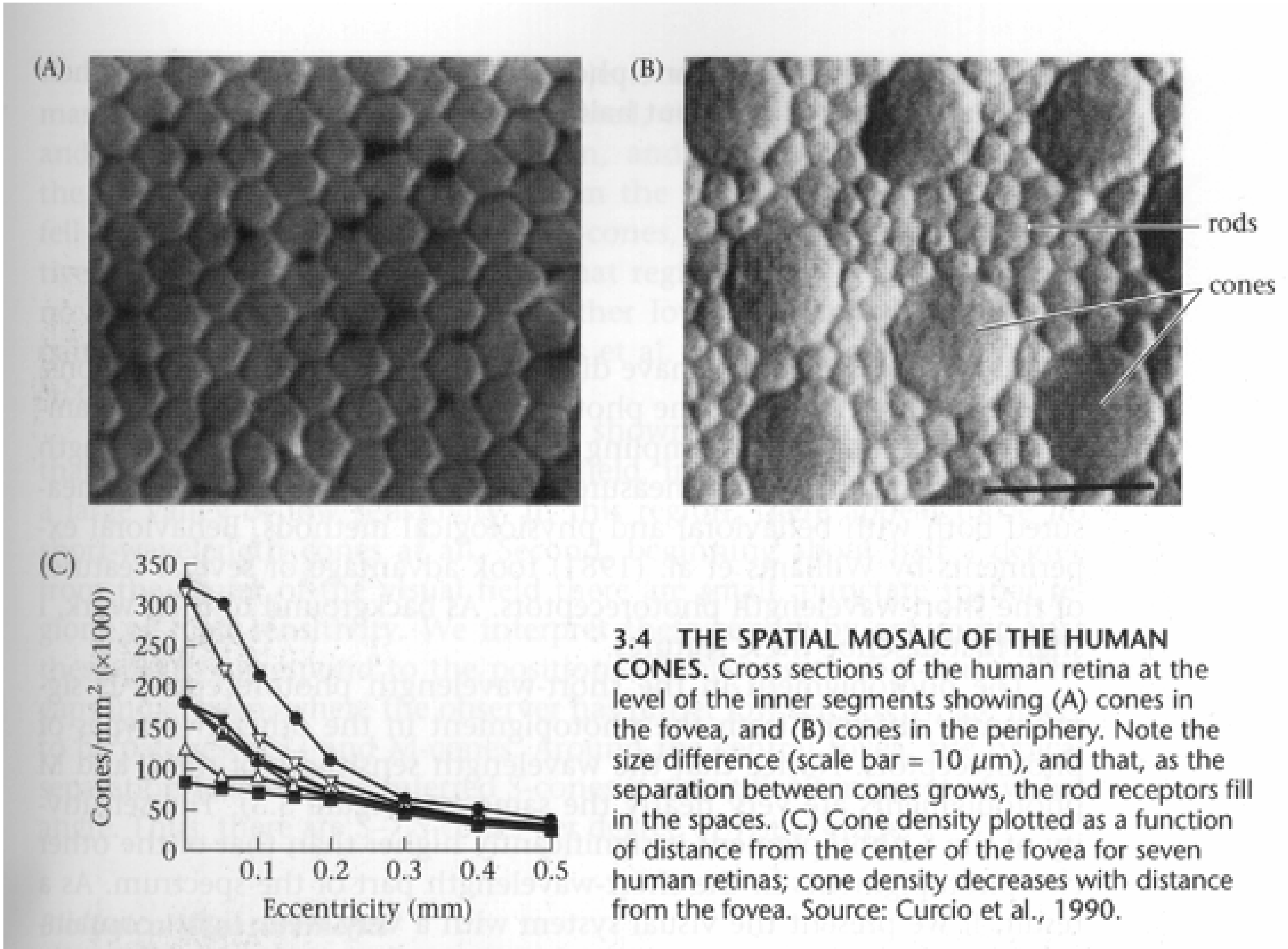


Typical color moire patterns

Blow-up of electronic camera image. Notice spurious colors in the regions of fine detail in the plants.

Color sampling artifacts

Human Photoreceptors

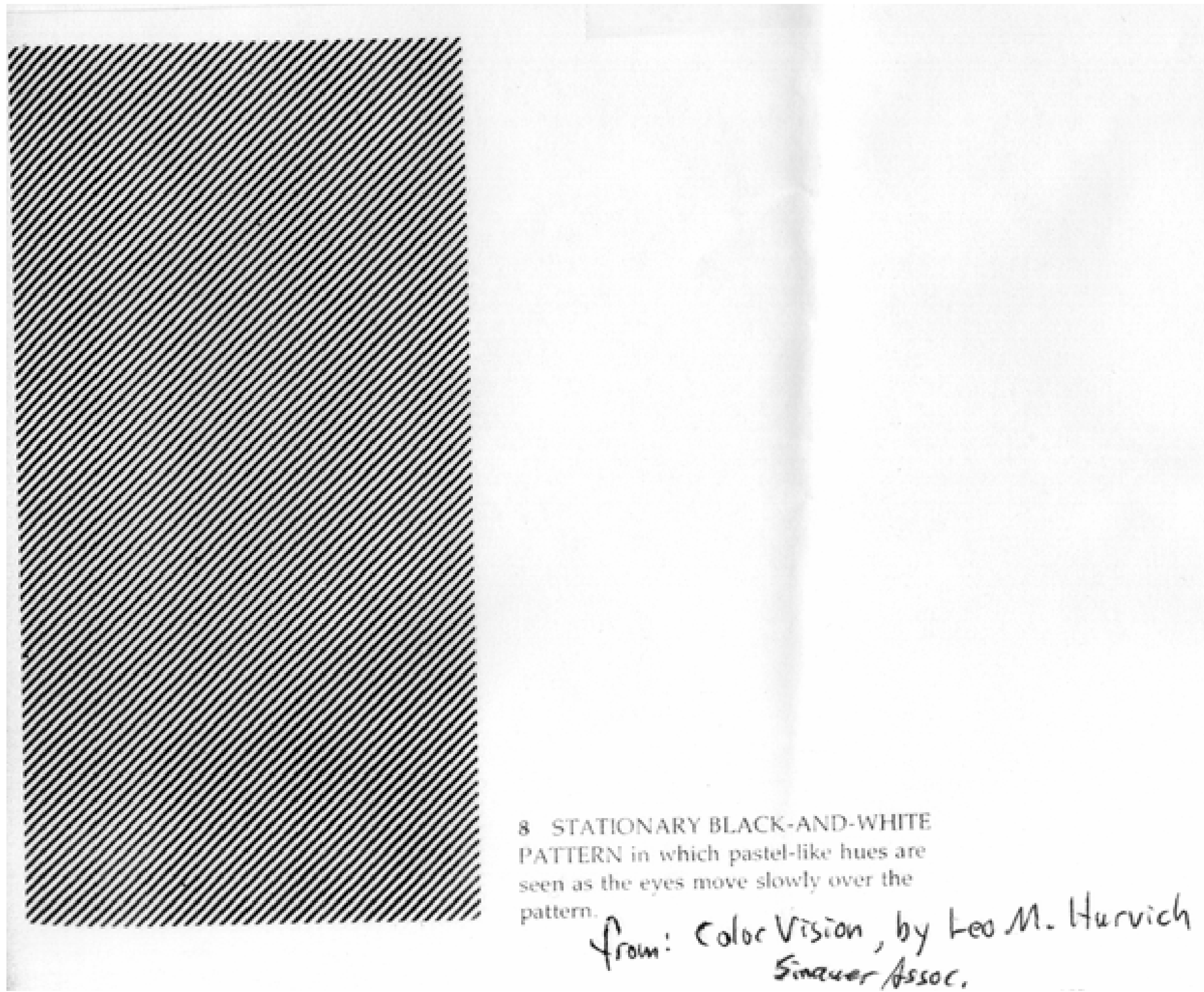


3.4 THE SPATIAL MOSAIC OF THE HUMAN CONES. Cross sections of the human retina at the level of the inner segments showing (A) cones in the fovea, and (B) cones in the periphery. Note the size difference (scale bar = 10 μm), and that, as the separation between cones grows, the rod receptors fill in the spaces. (C) Cone density plotted as a function of distance from the center of the fovea for seven human retinas; cone density decreases with distance from the fovea. Source: Curcio et al., 1990.

(From Foundations of Vision, by Brian Wandell, Sinauer Assoc.)

Brewster's colors example (subtle).

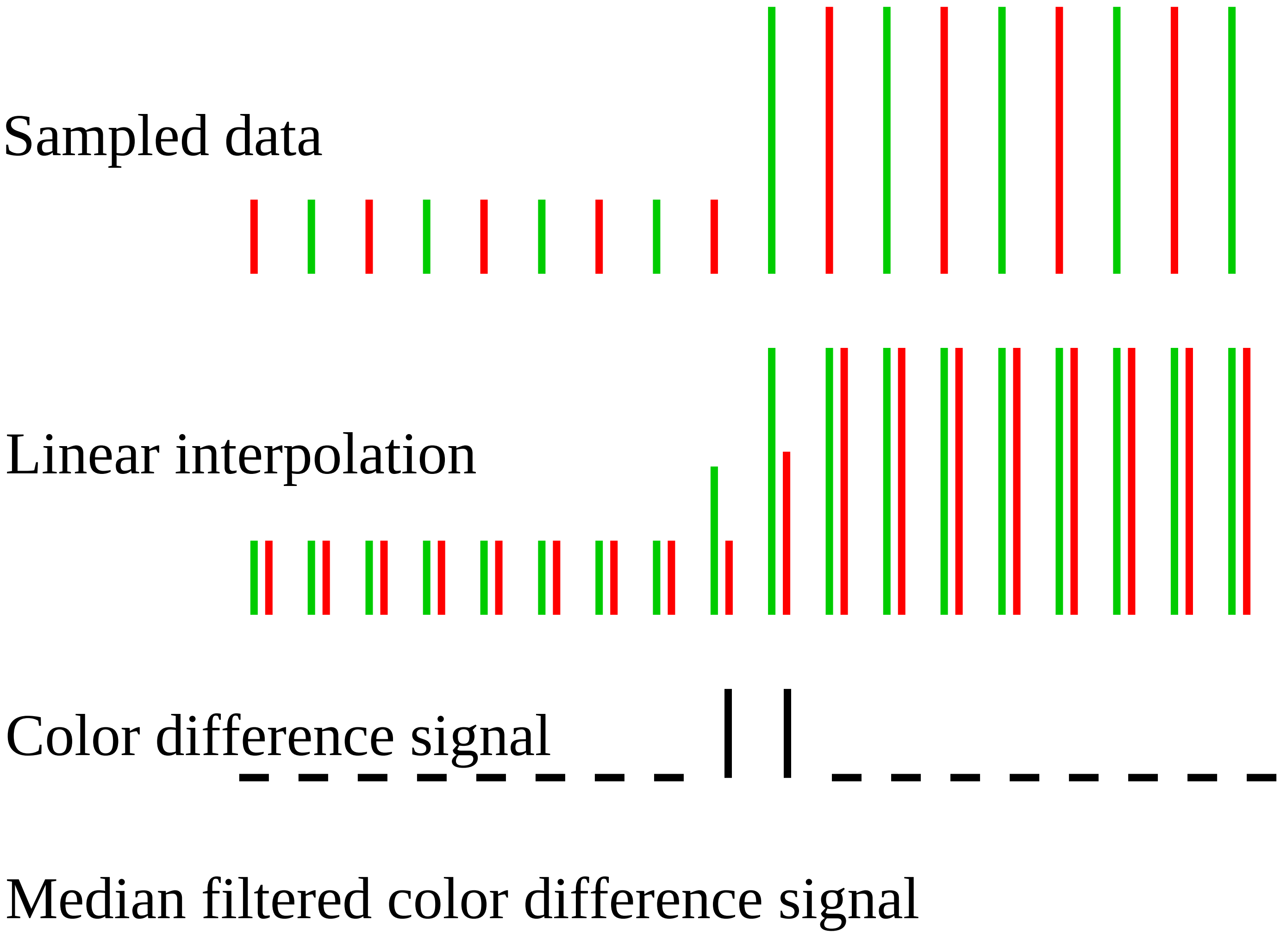
Scale relative to human photoreceptor size: each line covers about 7 photoreceptors.



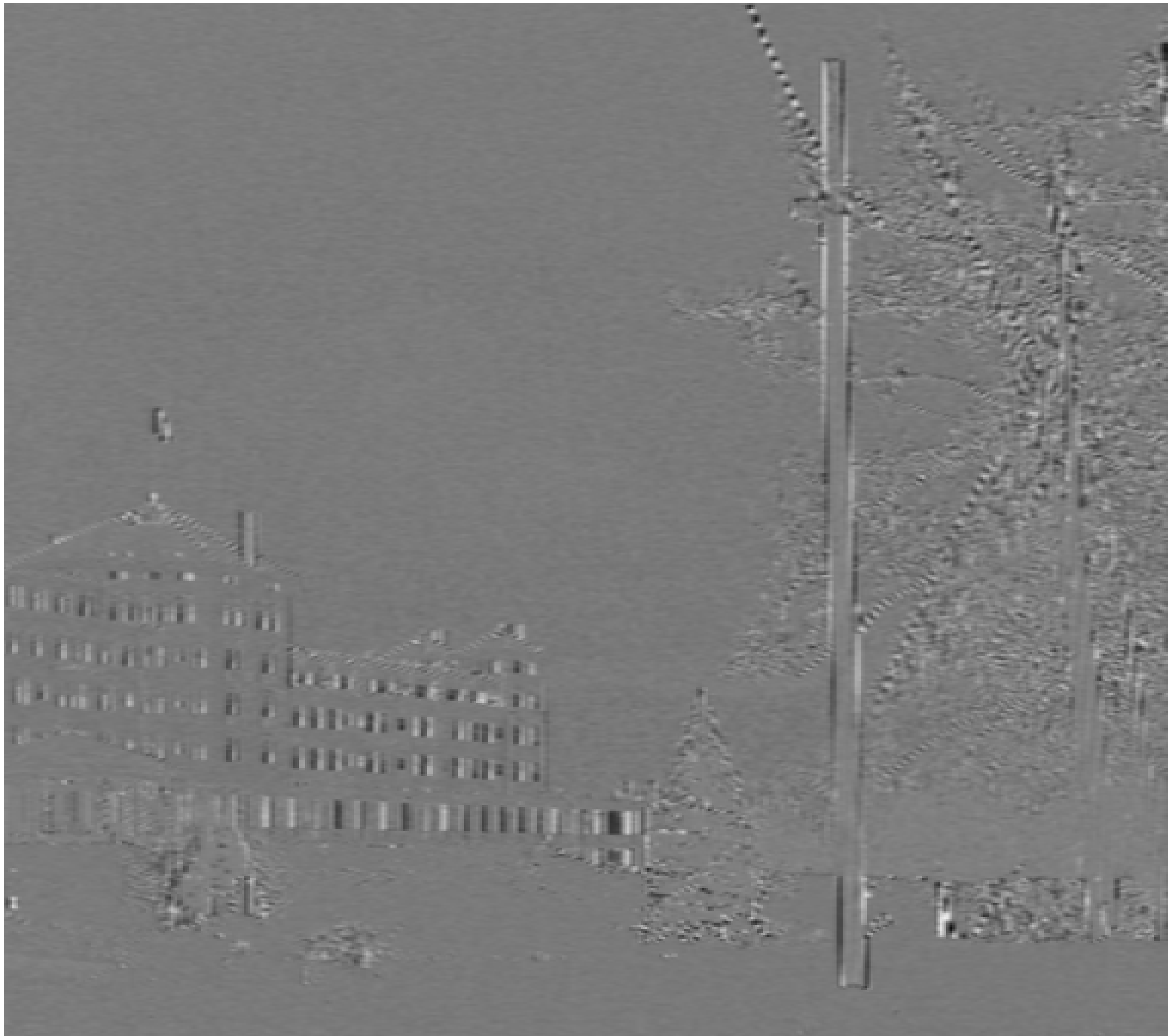
Median Filter Interpolation

- Perform first interpolation on isolated color channels.
- Compute color difference signals.
- Median filter the color difference signal.
- Reconstruct the 3-color image.

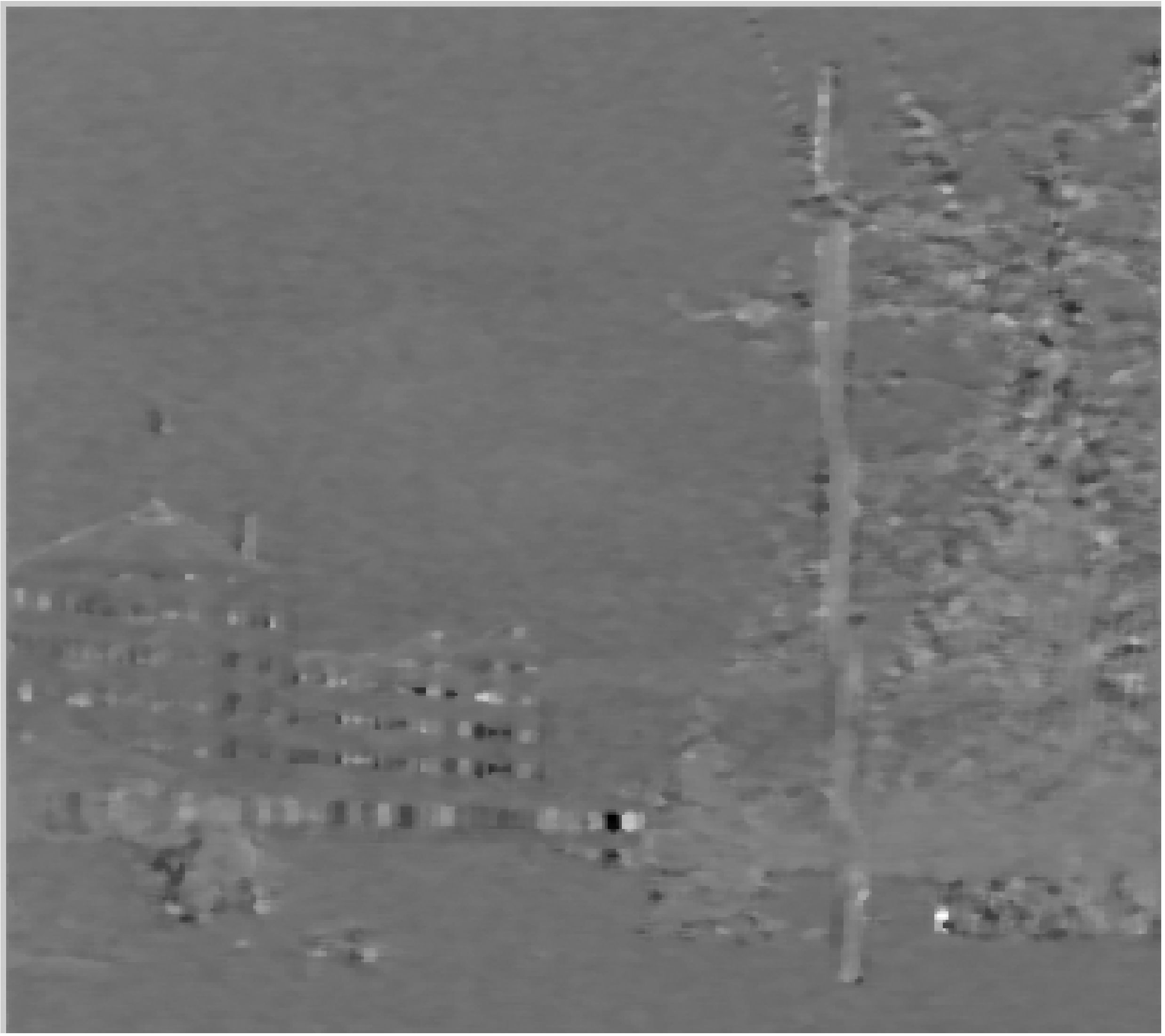
Two-color sampling of BW edge



R-G, after linear interpolation



R – G, median filtered (5x5)



Recombining the median filtered colors

Linear interpolation

Median filter interpolation

Didn’t get a chance to show:

Local gain control.

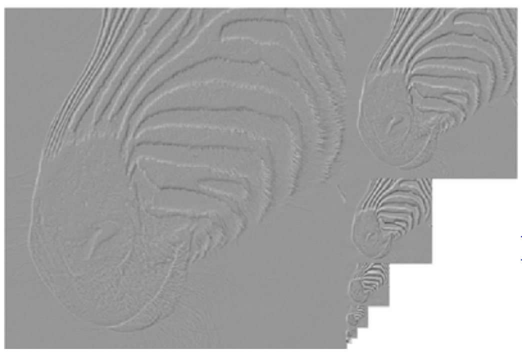
- Summary of pyramid representations

Image pyramids

- Gaussian

Progressively blurred and subsampled versions of the image. Adds scale invariance to fixed-size algorithms.

- Laplacian

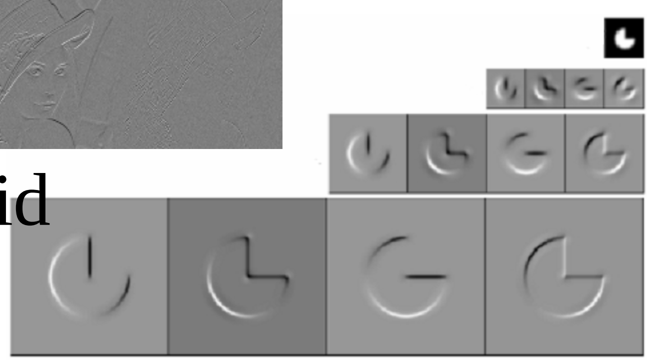


Shows the information added in Gaussian pyramid at each spatial scale. Useful for noise reduction & coding.

- Wavelet/QMF

Bandpassed representation, complete, but with aliasing and some non-oriented subbands.

- Steerable pyramid



Shows components at each scale and orientation separately. Non-aliased subbands. Good for texture and feature analysis.

Linear image transformations

- In analyzing images, it's often useful to make a change of basis.

transformed image

$$\vec{F} = U\vec{f}$$

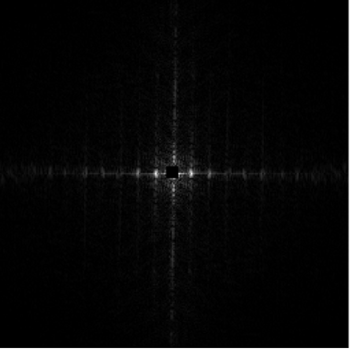
Vectorized image

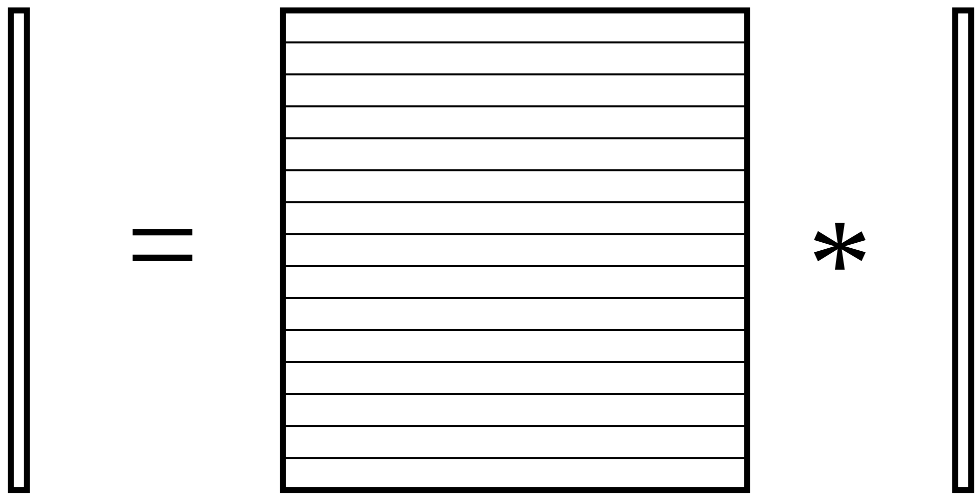
Fourier transform, or
Wavelet transform, or
Steerable pyramid transform

Schematic pictures of each matrix transform

- Shown for 1-d images
- The matrices for 2-d images are the same idea, but more complicated, to account for vertical, as well as horizontal, neighbor relationships.

Fourier transform



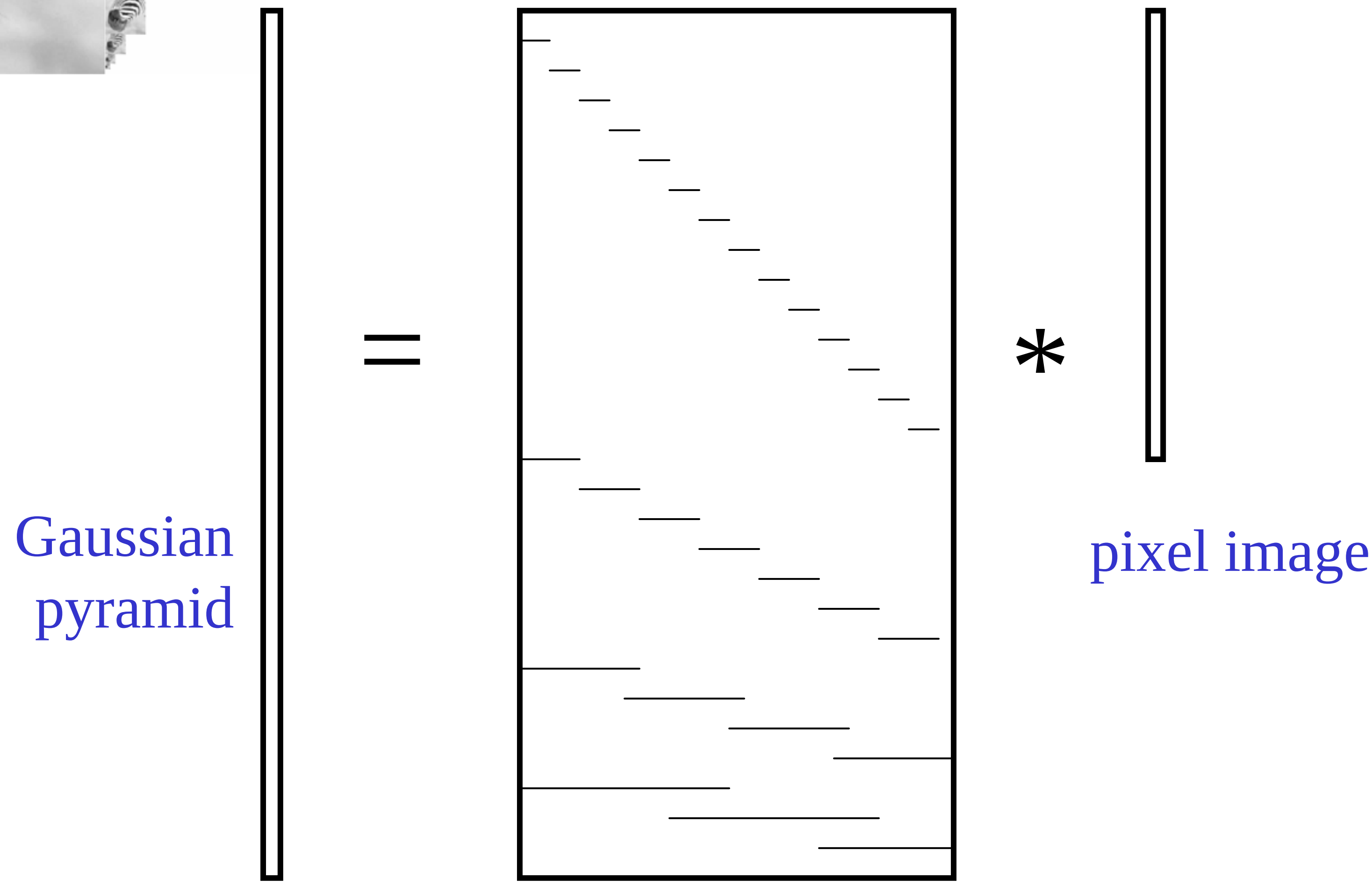


Fourier transform

Fourier bases are global: each transform coefficient depends on all pixel locations.

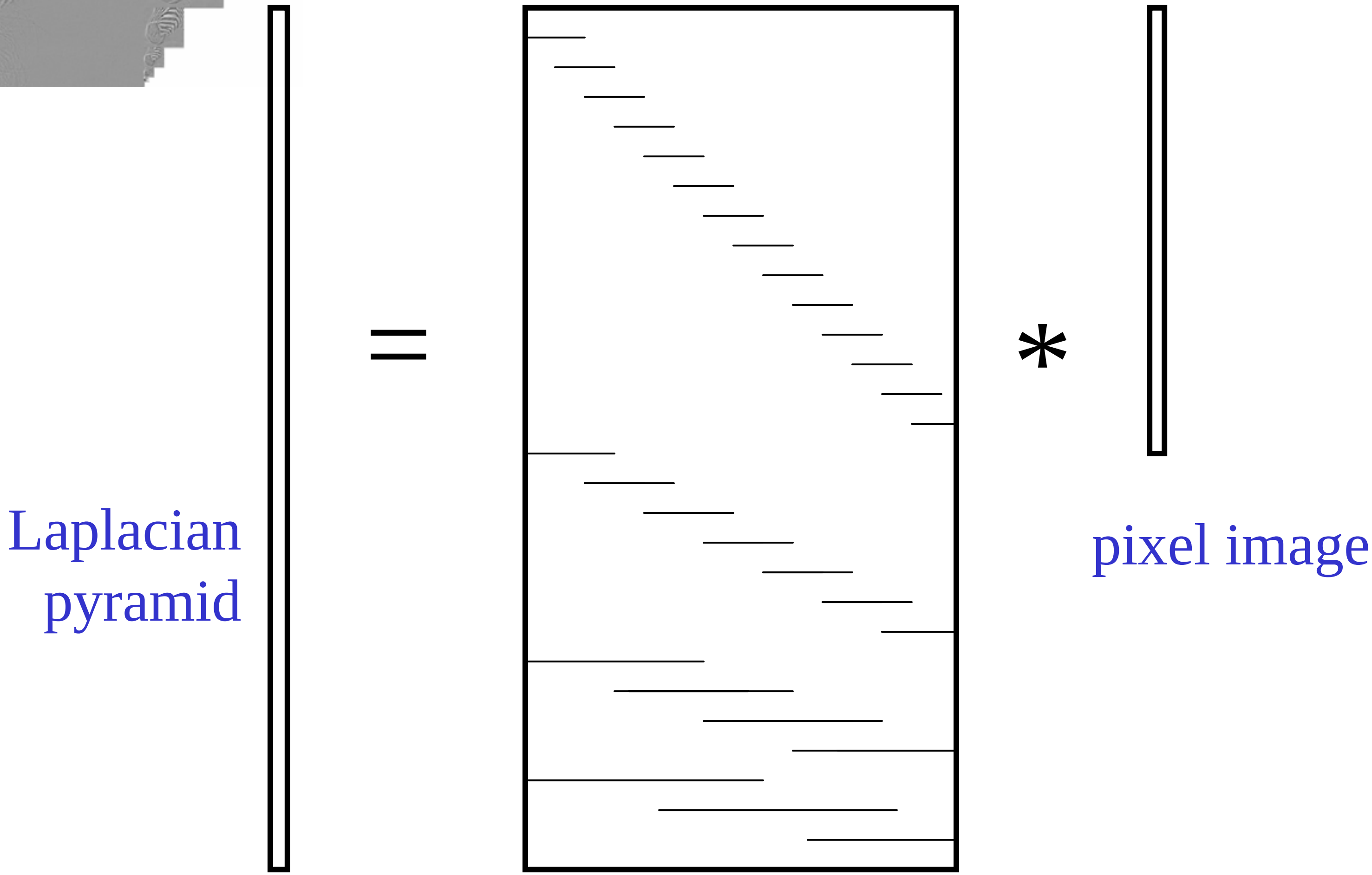
pixel domain image

Gaussian pyramid



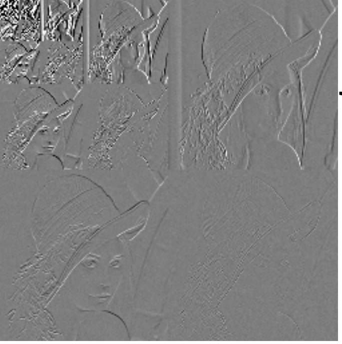
Overcomplete representation.
Low-pass filters, sampled
appropriately for their blur.

Laplacian pyramid

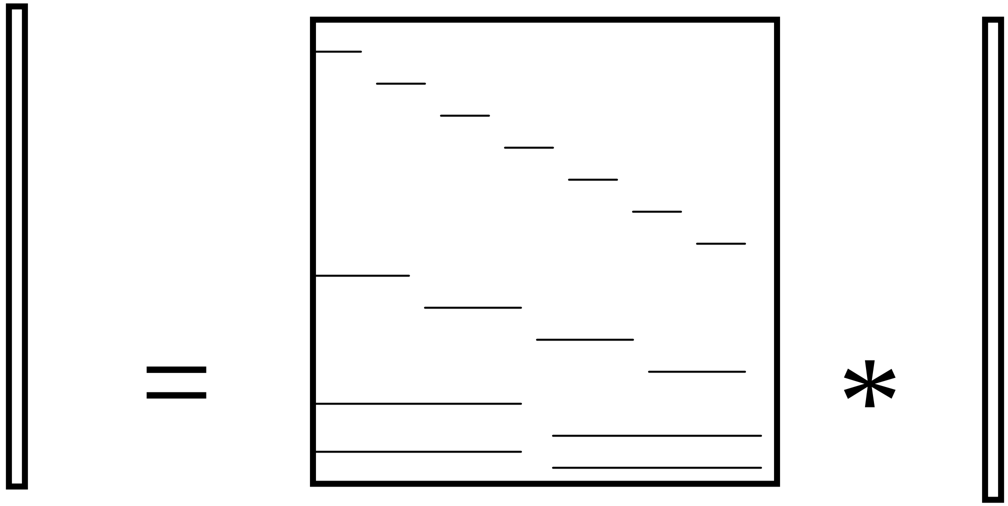


Overcomplete representation.
Transformed pixels represent
bandpassed image information.

Wavelet (QMF) transform



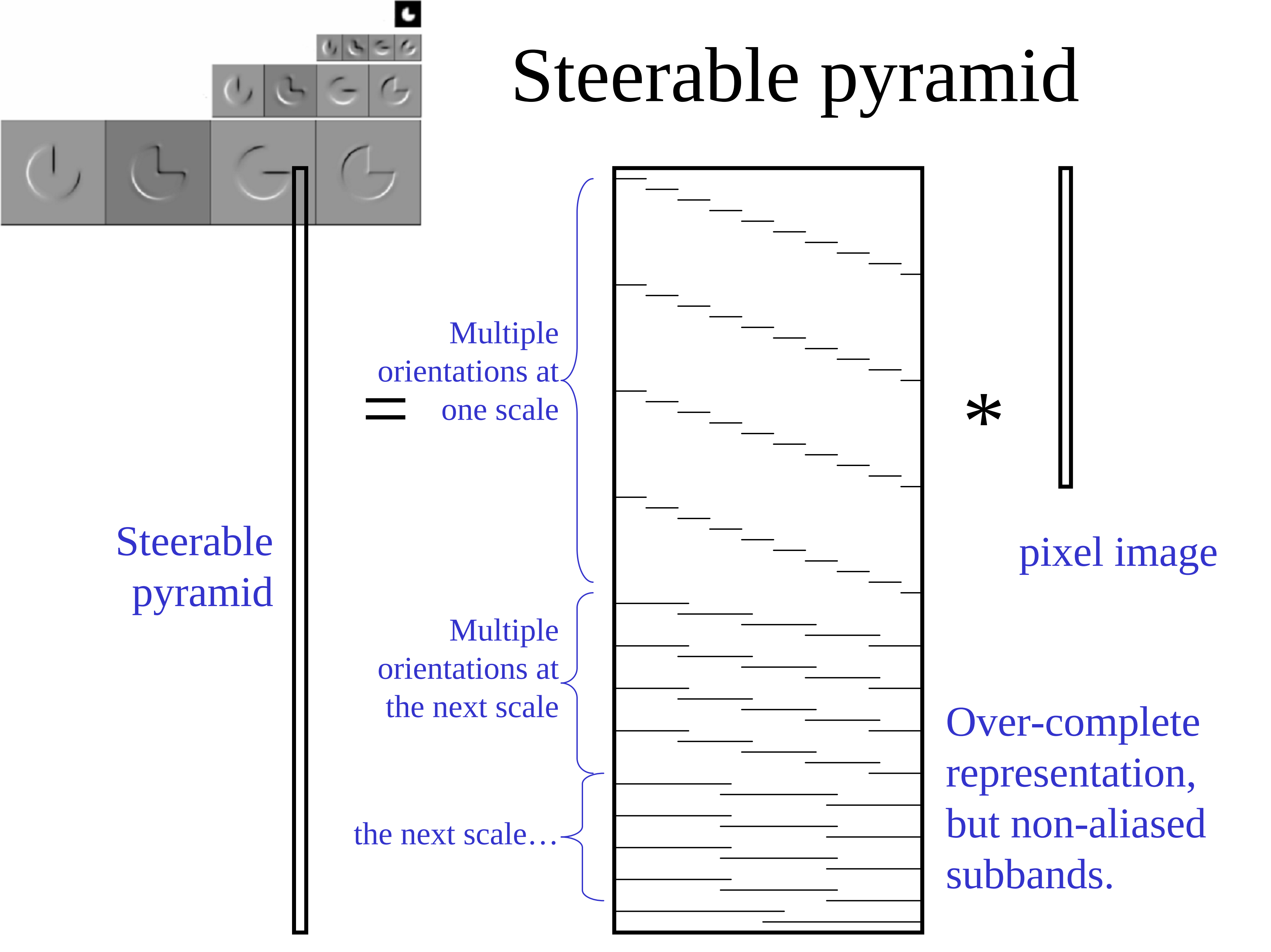
Wavelet pyramid



Ortho-normal transform (like Fourier transform), but with localized basis functions.

pixel image

Steerable pyramid



Matlab resources for pyramids (with tutorial)

http://www.cns.nyu.edu/~eero/software.html

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- The Steerable Pyramid, an (approximately) translation- and rotation-invariant multi-scale image decomposition. MatLab (see above) and C implementations are available.
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- EPIC - Efficient Pyramid (Wavelet) Image Coder. C source code available.
- OBVIUS [Object-Based Vision & Image Understanding System]: README / ChangeLog / Doc (225k) / Source Code (2.25M).
- CL-SHELL [Gnu Emacs <-> Common Lisp Interface]: README / Change Log / Source Code (119k).

Why use these representations?

- Handle real-world size variations with a constant-size vision algorithm.
- Remove noise
- Analyze texture
- Recognize objects
- Label image features

end