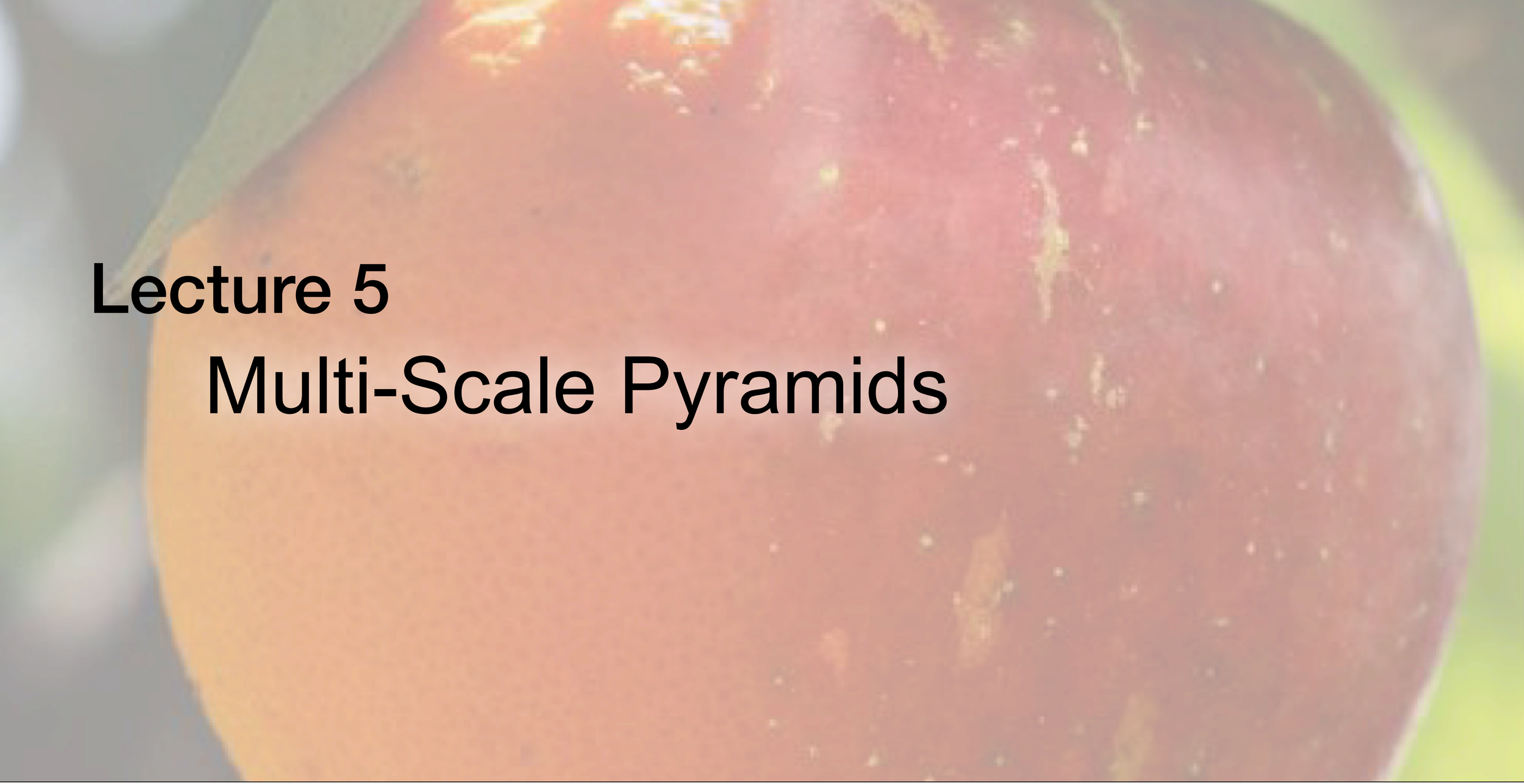


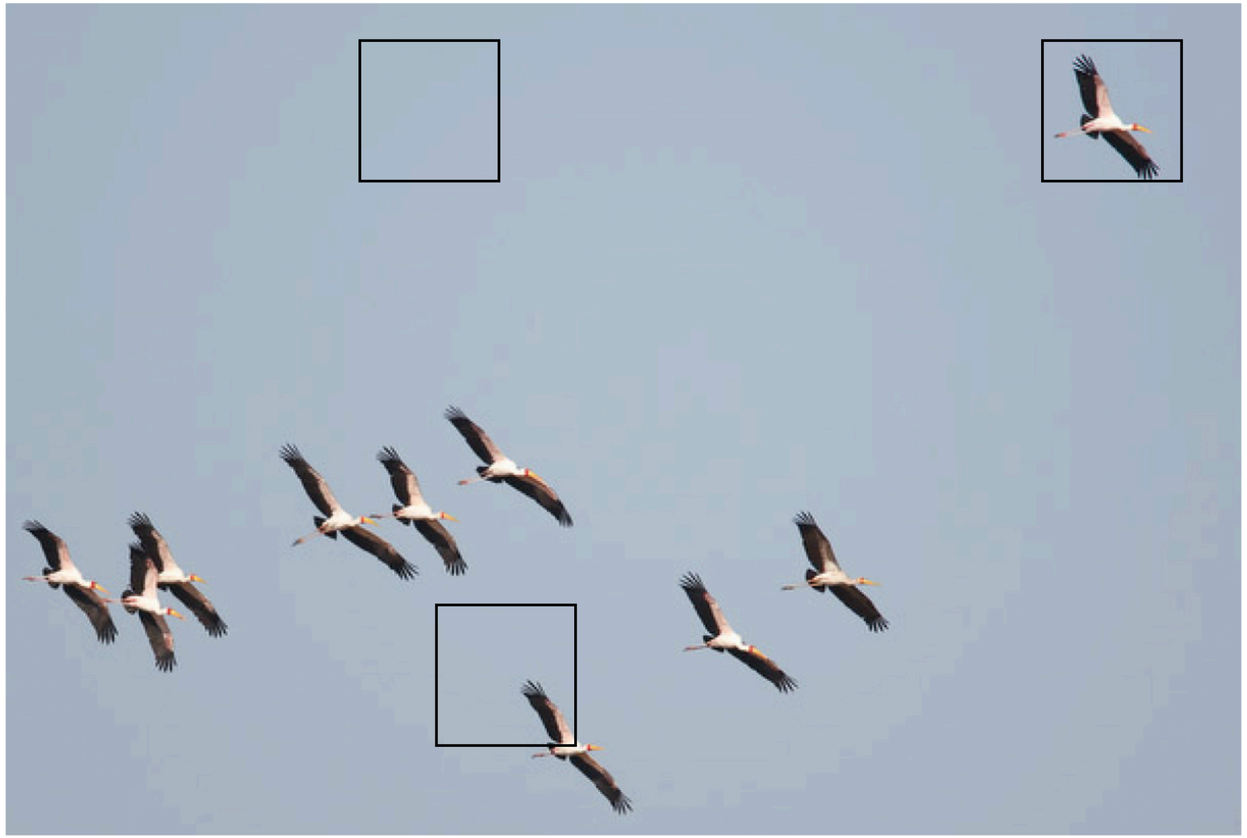
Lecture 5

Multi-Scale Pyramids

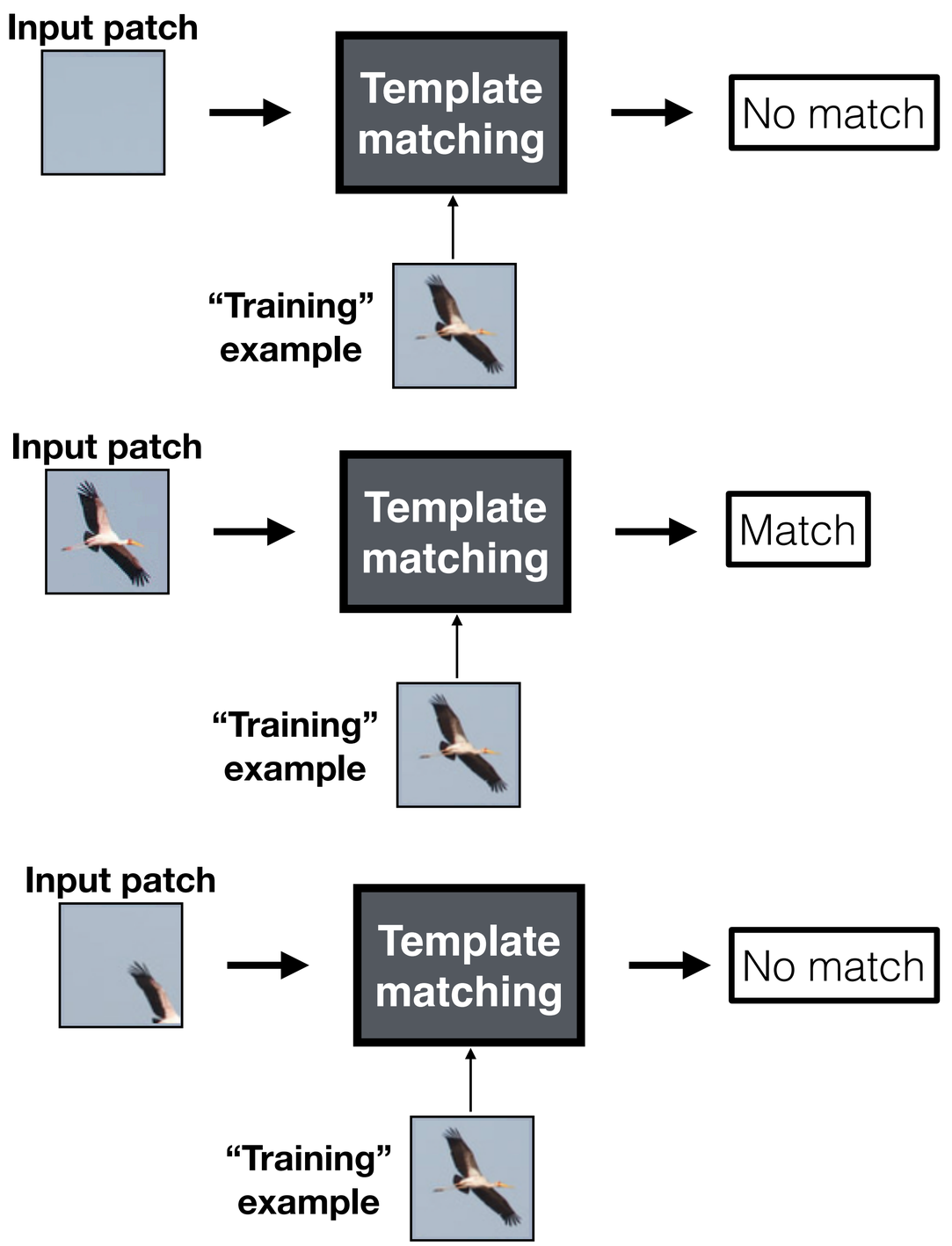
Vincent Sitzmann, Sara Beery, Mina Konaković Luković, Kaiming He

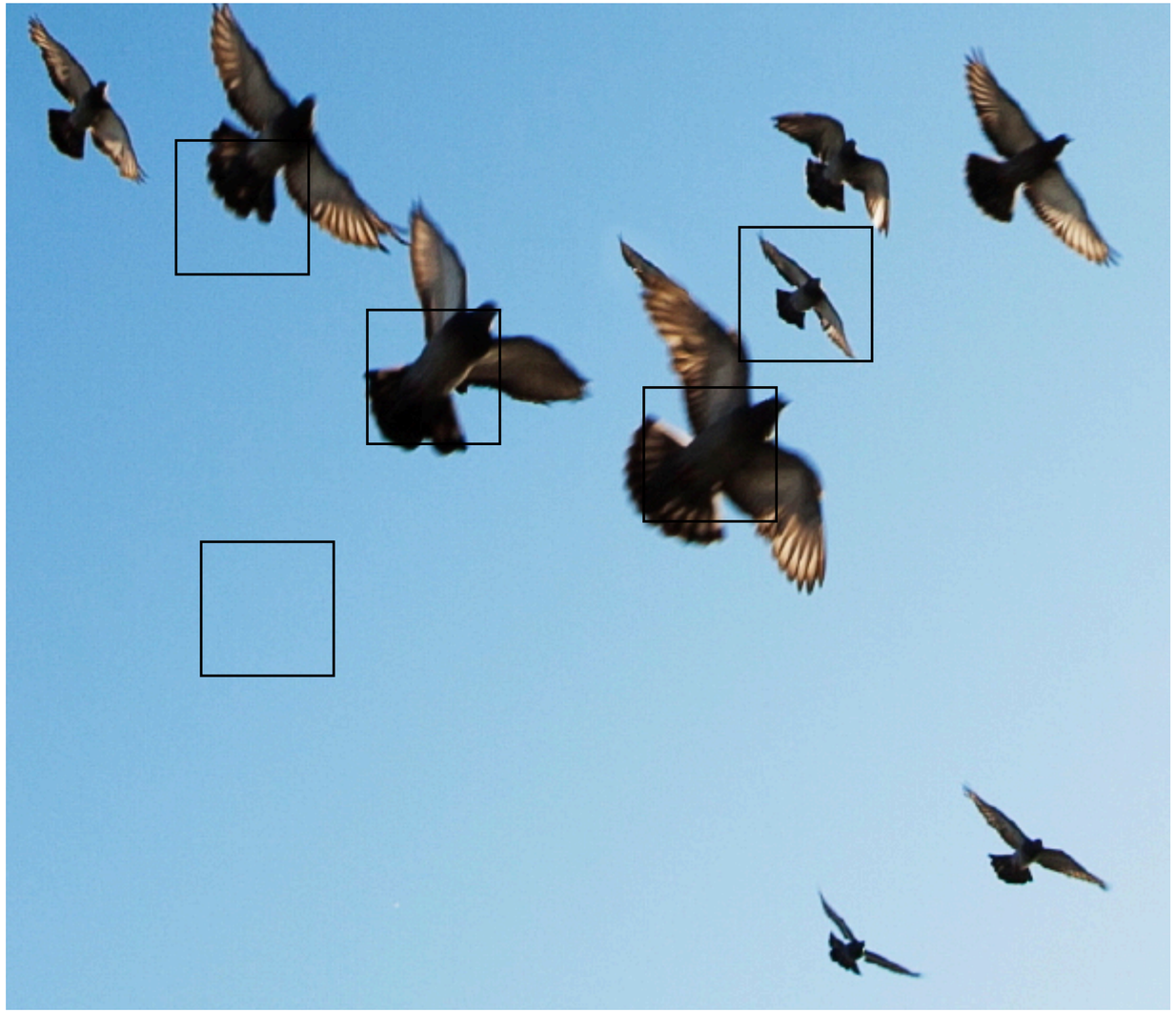
Detecting a pattern in an image

Pattern to detect

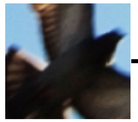


Motivation for translation invariance!



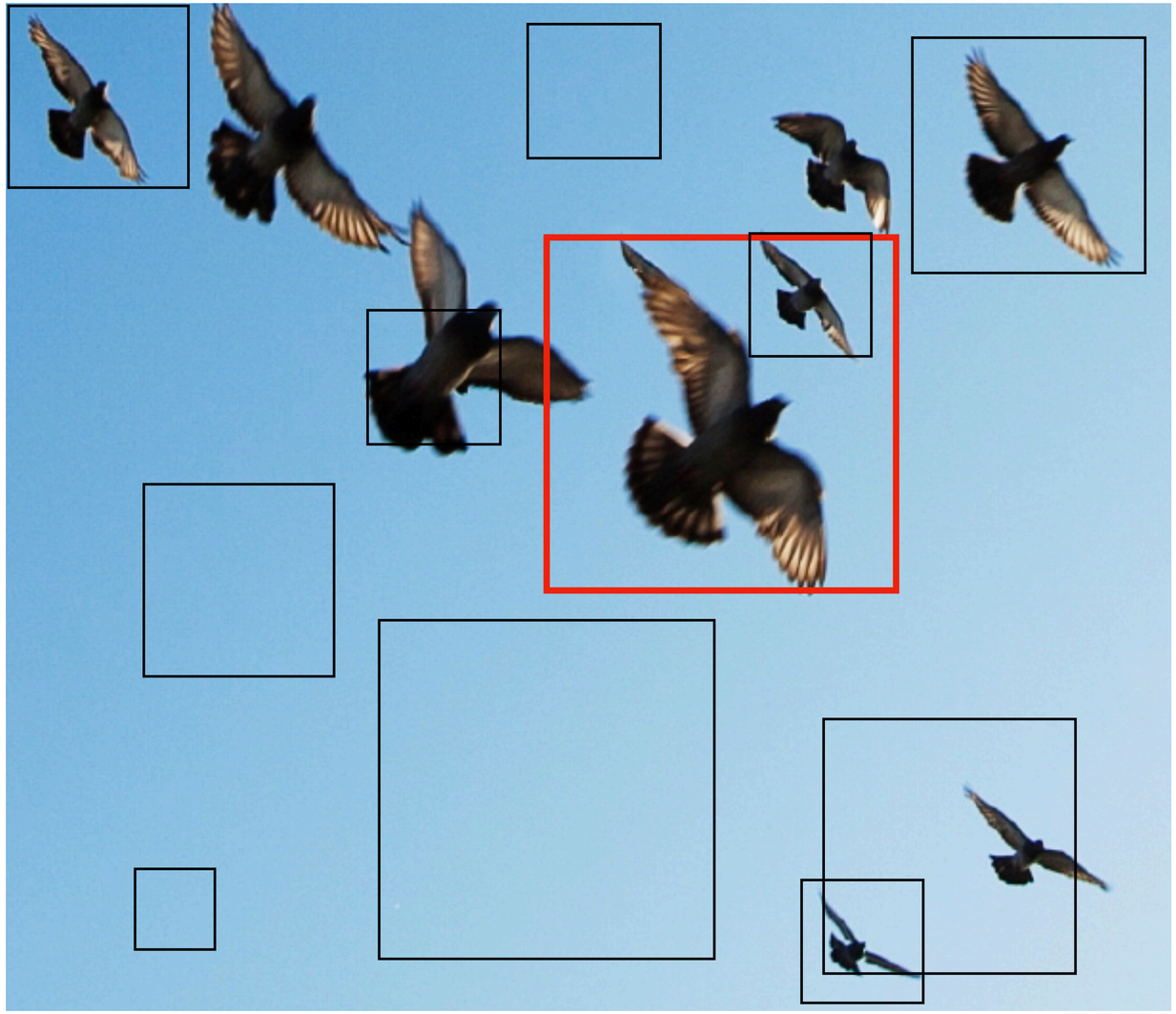


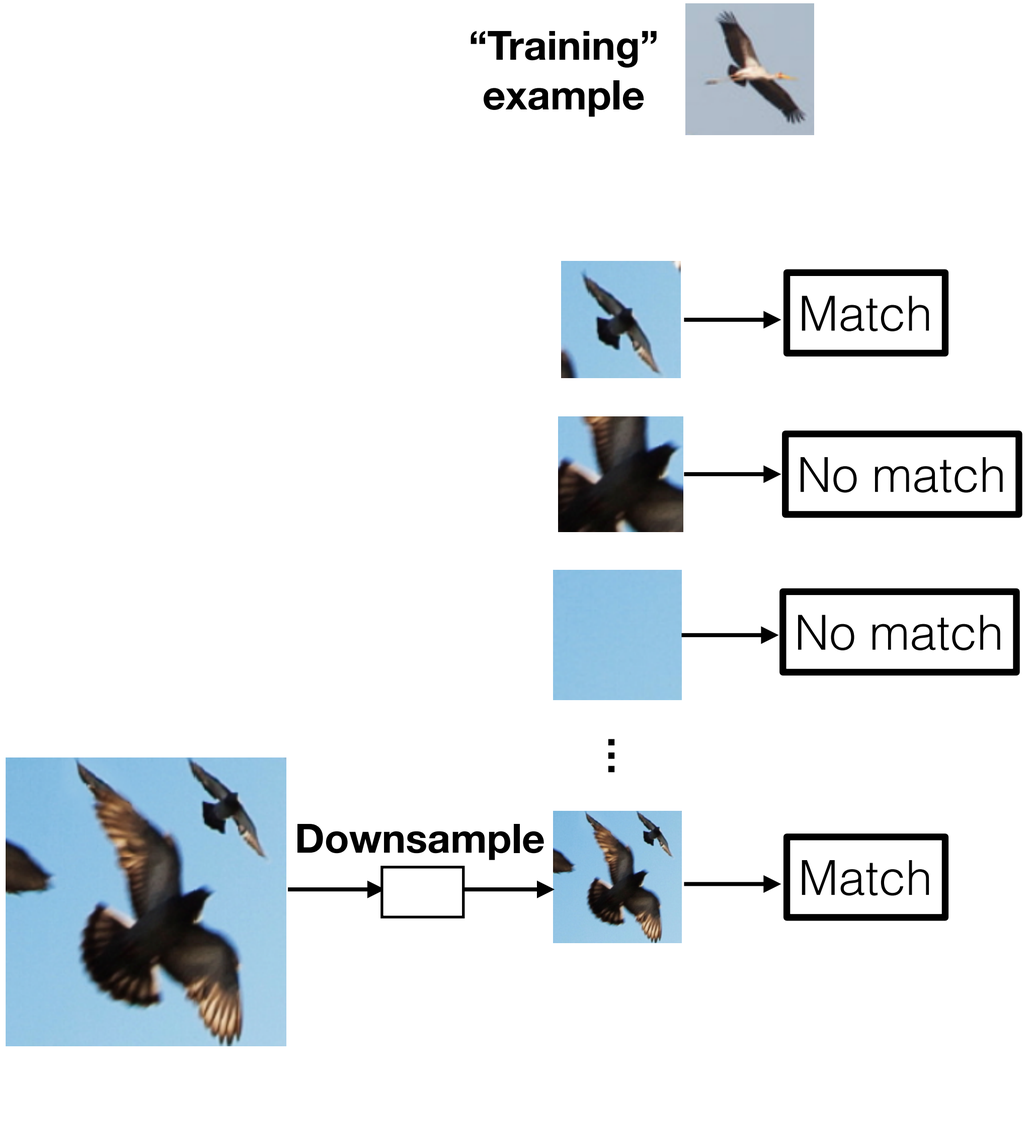
“Training” example



⋮

We need translation and **scale** invariance





Consider all patch location and sizes

Idea: Build Multi-Scale Pyramids

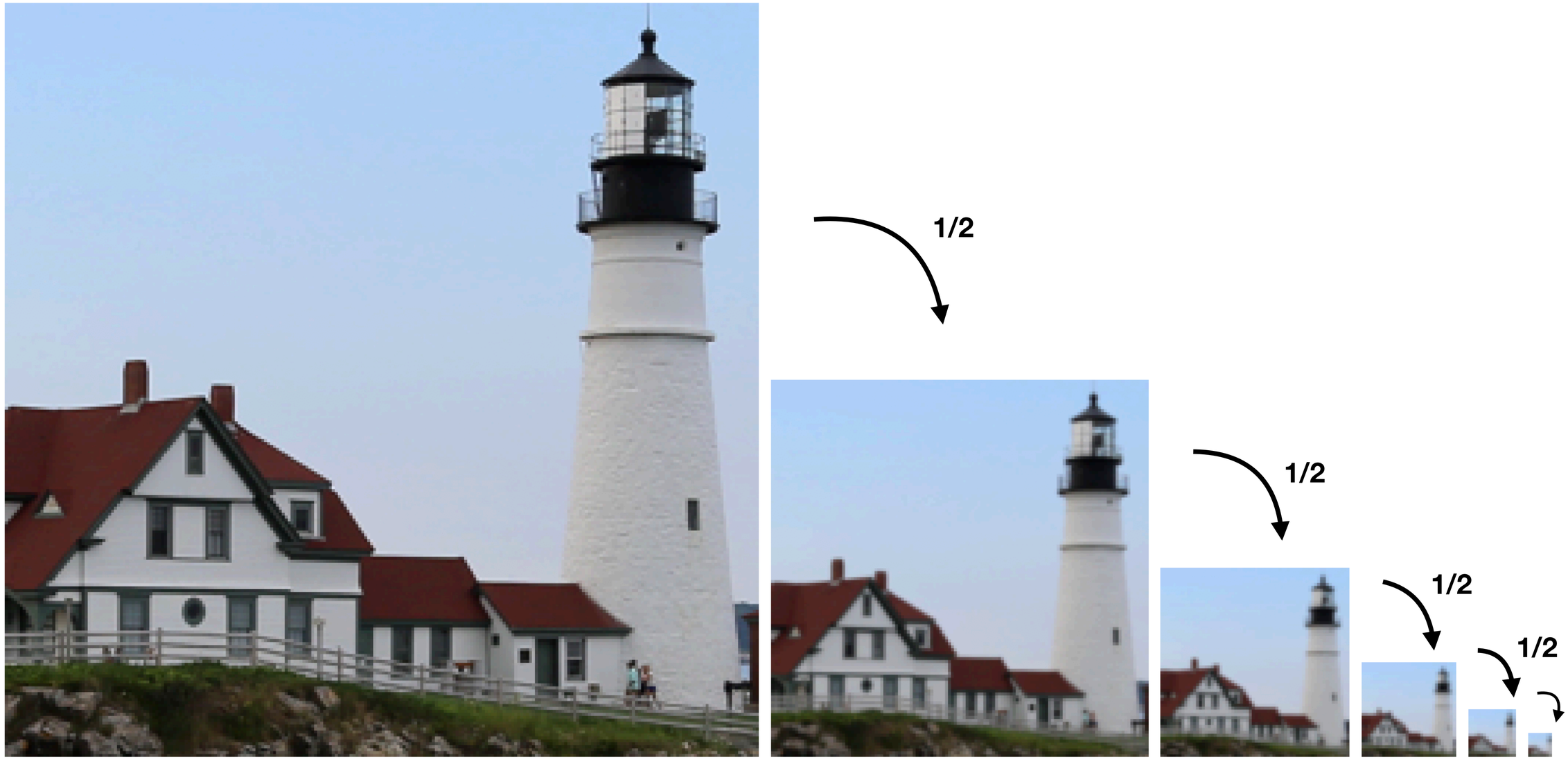
Template

Idea: Build Multi-Scale Pyramids

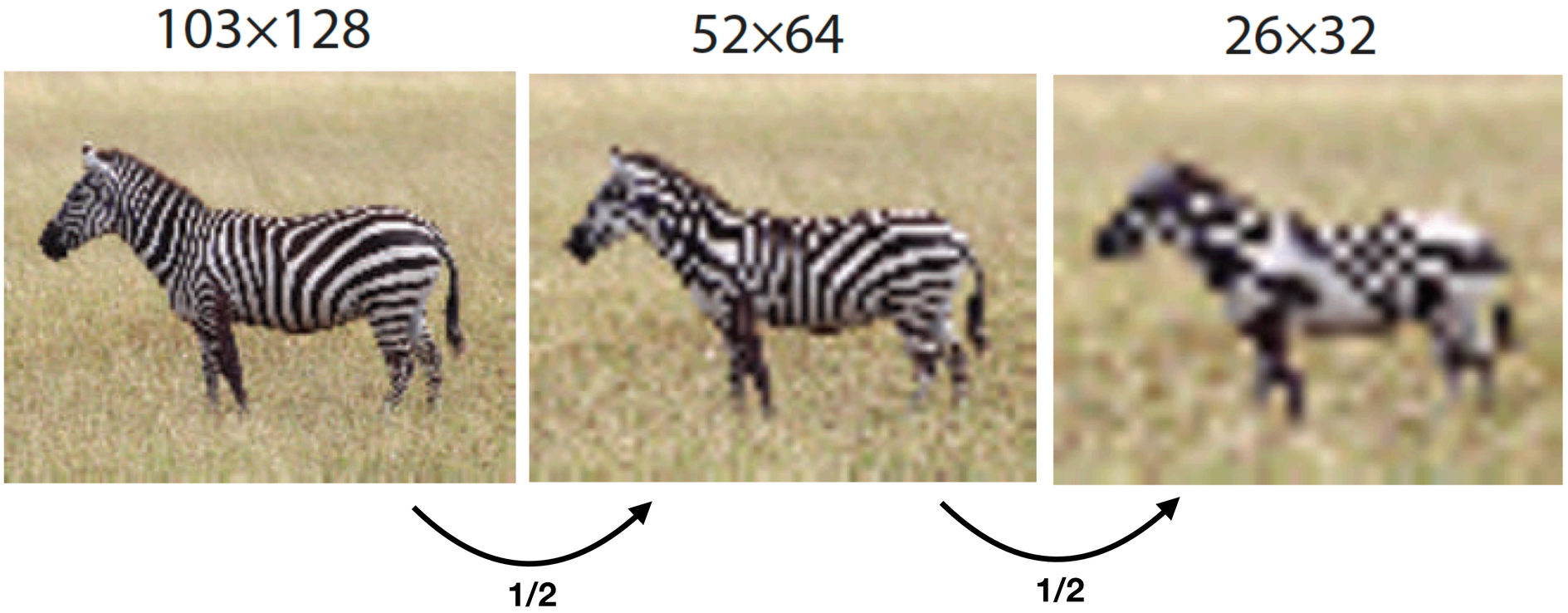
Template

A fast & efficient way to provide scale & translation invariance!

Gaussian Pyramid



Subsampling and aliasing



The Gaussian pyramid

For each level

1. Blur input image with a Gaussian filter

$$[1, 4, 6, 4, 1]$$

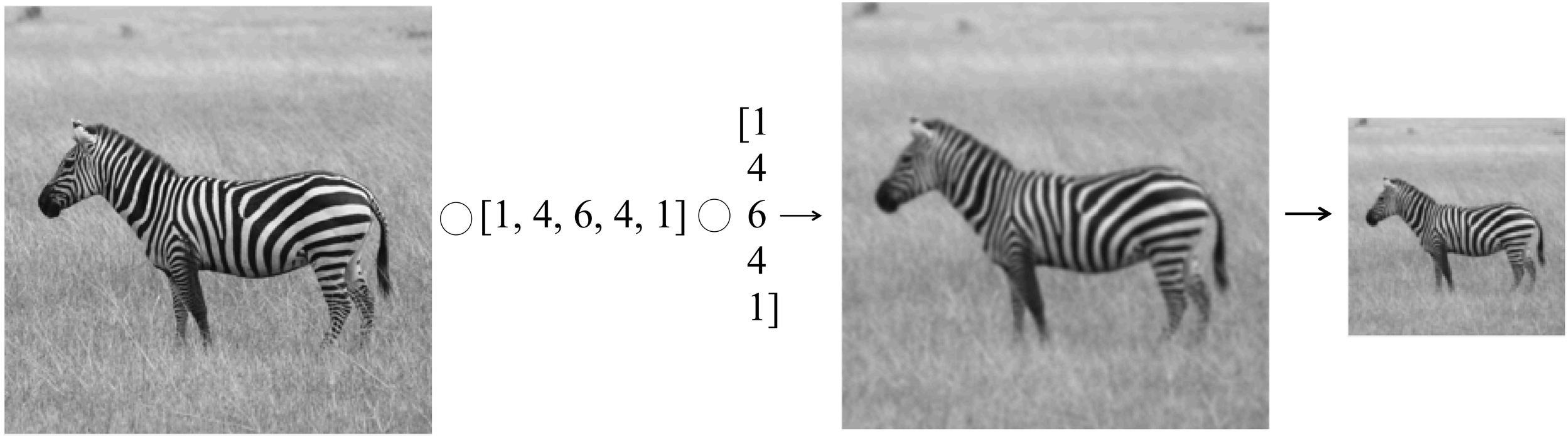
$$\bigcirc\,[1, 4, 6, 4, 1]\,\bigcirc \begin{bmatrix} 1 \\ 4 \\ 6 \\ 4 \\ 1 \end{bmatrix} \rightarrow$$

(The Gaussian filter is approximated with a binomial filter)

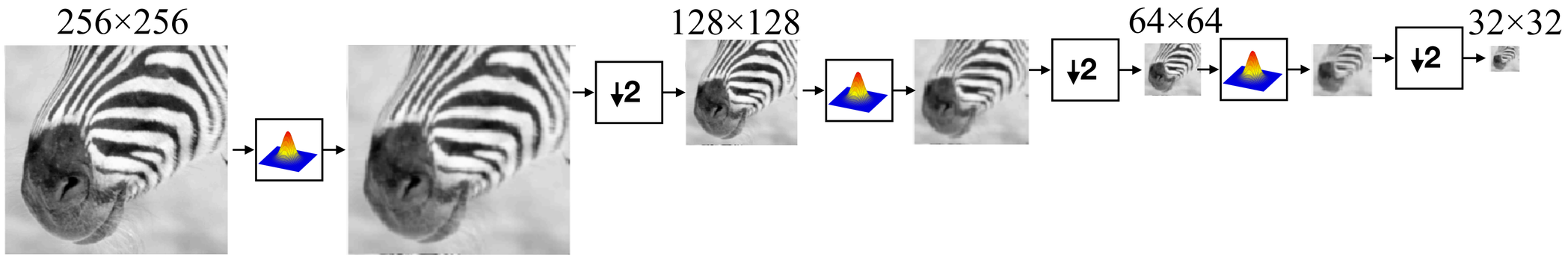
The Gaussian pyramid

For each level

1. Blur input image with a Gaussian filter
2. Downsample image



The Gaussian pyramid



The Gaussian pyramid

512×512

(original image)

256×256

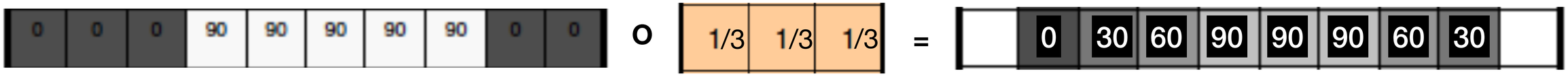
128×128

64×64

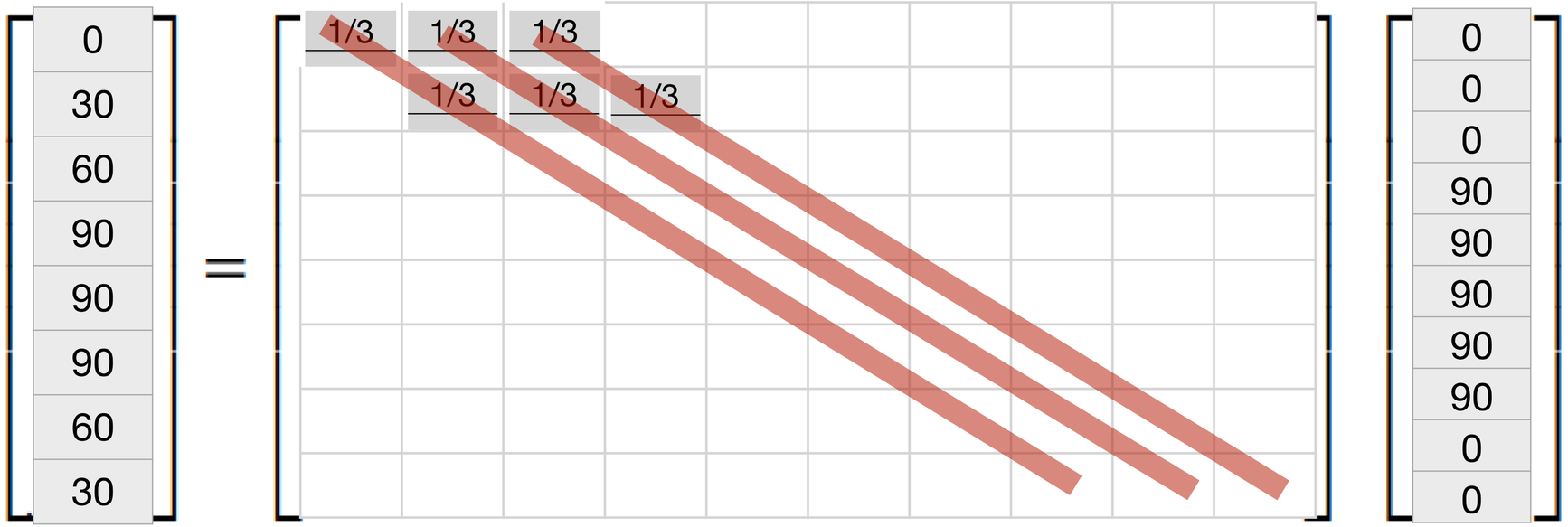
32×32

Convolution as matrix multiplication

In the 1D case, it helps to make explicit the structure of the matrix:



In the 1D case, it helps to make explicit the structure of the matrix:

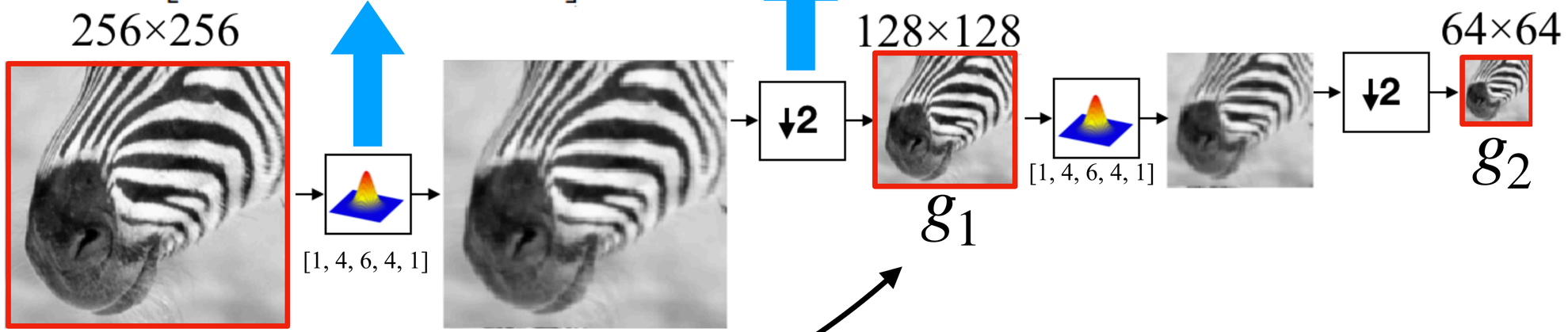


Reminder from Lecture 3

The Gaussian pyramid

$$\frac{1}{16}\begin{bmatrix} 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 \\ 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 \\ 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 \\ 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 \\ 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 \\ 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 \\ 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$



g_0 g_1 g_2

$$g_1 = G_0 g_0$$

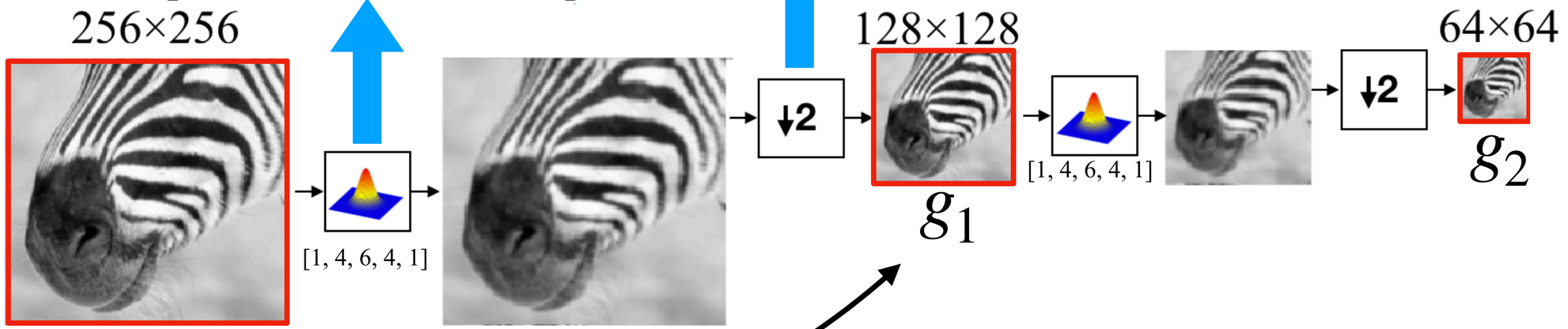
$$G_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \frac{1}{16} \begin{bmatrix} 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 \\ 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 \\ 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 \\ 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 \\ 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 \\ 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 \\ 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 \end{bmatrix}$$

(The arrays shown here are for 1D signals)

The Gaussian pyramid

$$\frac{1}{16}\begin{bmatrix} 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 \\ 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 \\ 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 \\ 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 \\ 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 \\ 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 \\ 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 \end{bmatrix}$$

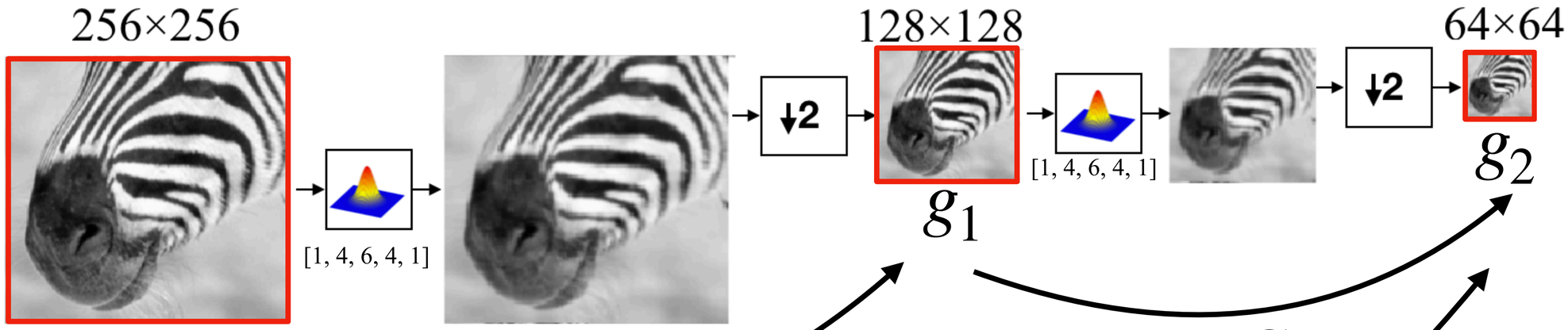
$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$



g_0 g_1 g_2

$$g_1 = G_0 g_0 \qquad G_0 = \frac{1}{16}\begin{bmatrix} 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 \end{bmatrix}$$

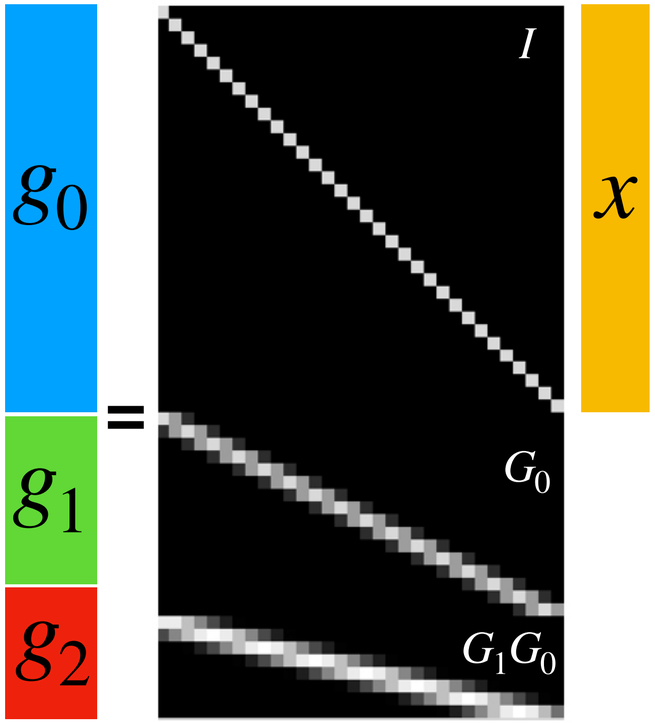
The Gaussian pyramid



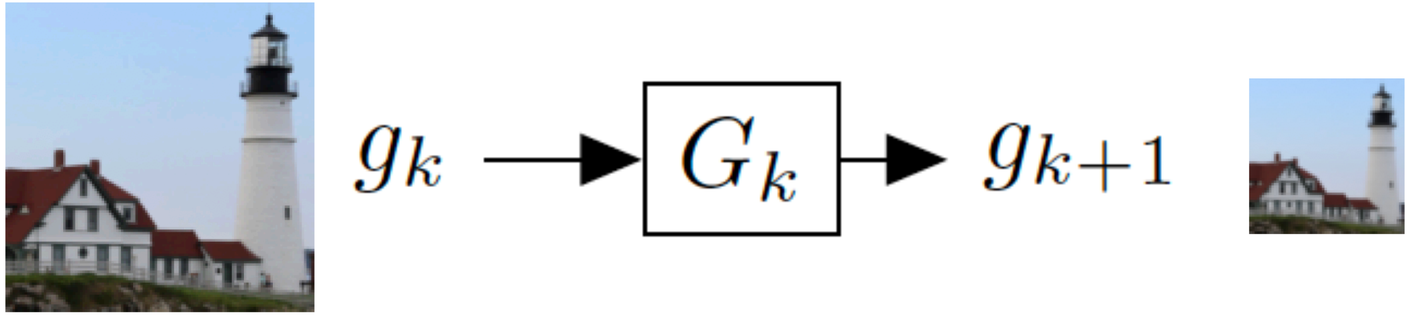
$g_1 = G_0 g_0$

$g_2 = G_1 g_1$

$g_2 = G_1 G_0 g_0$



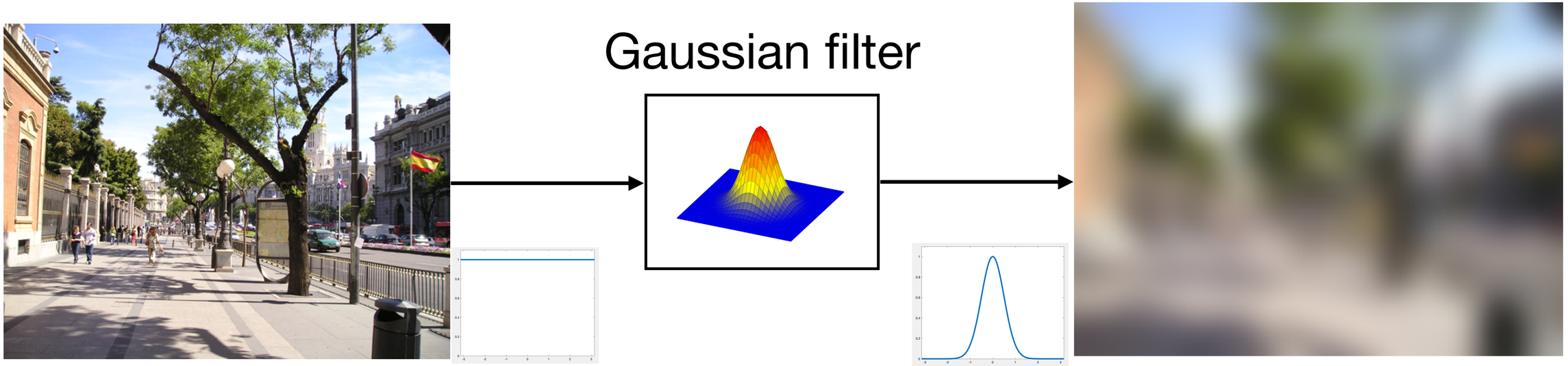
The Gaussian pyramid

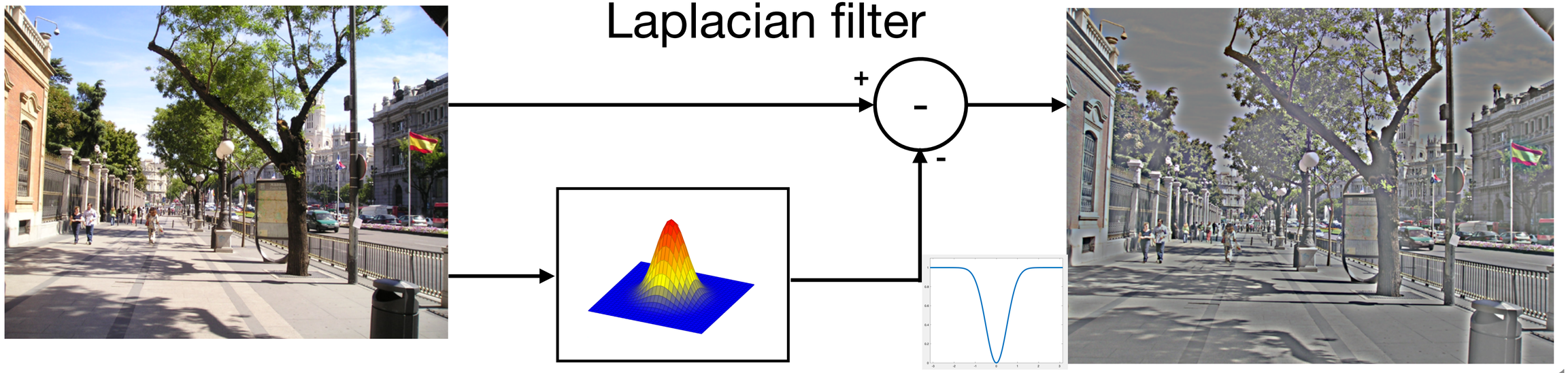


For each level

1. Blur input image with a Gaussian filter
2. Downsample image

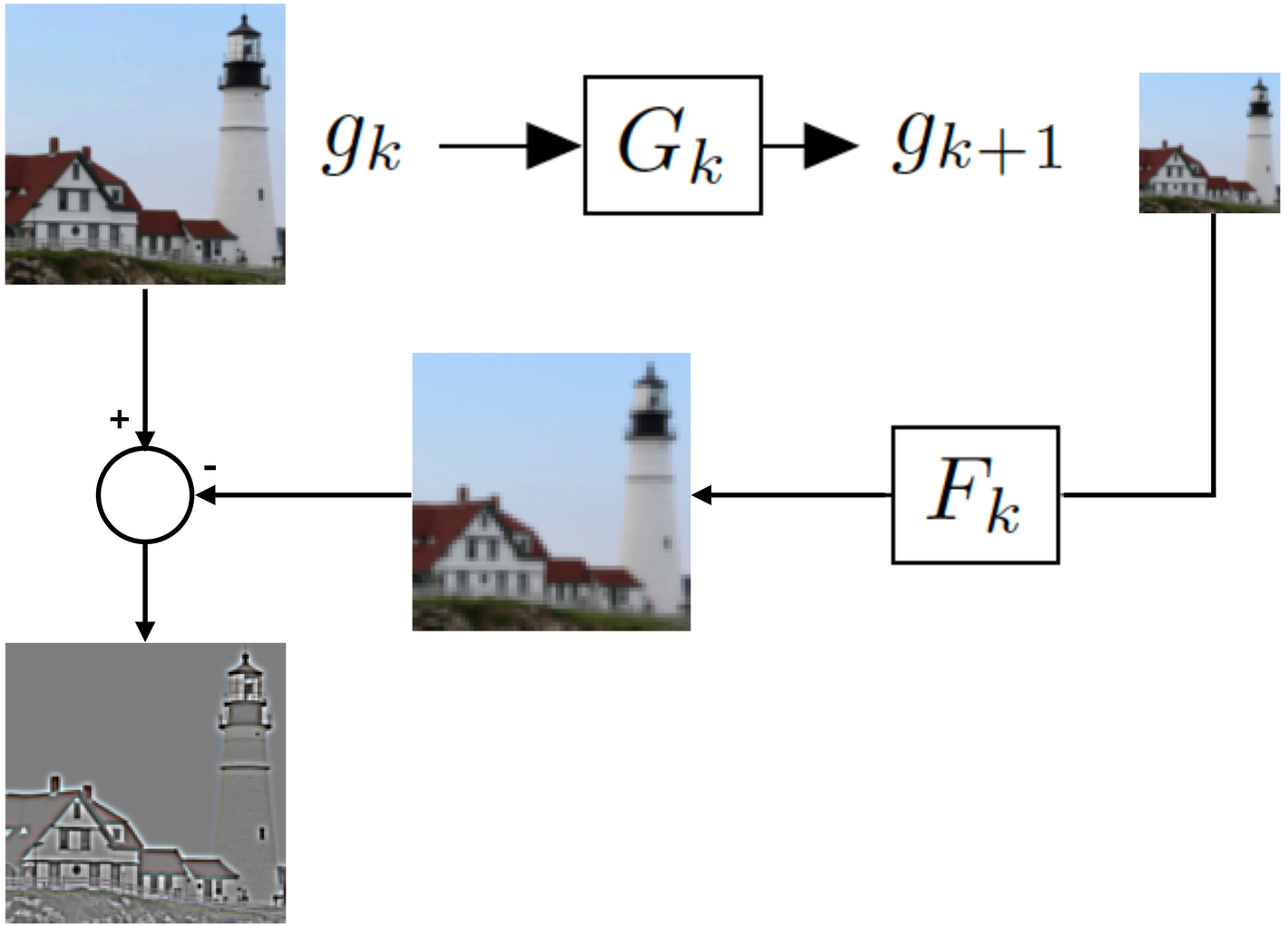
What about the opposite of blurring?



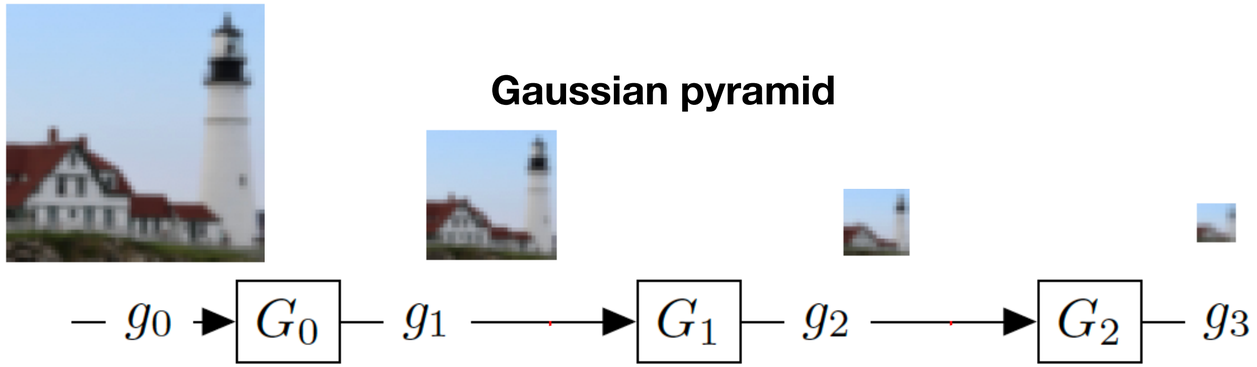


The Laplacian Pyramid

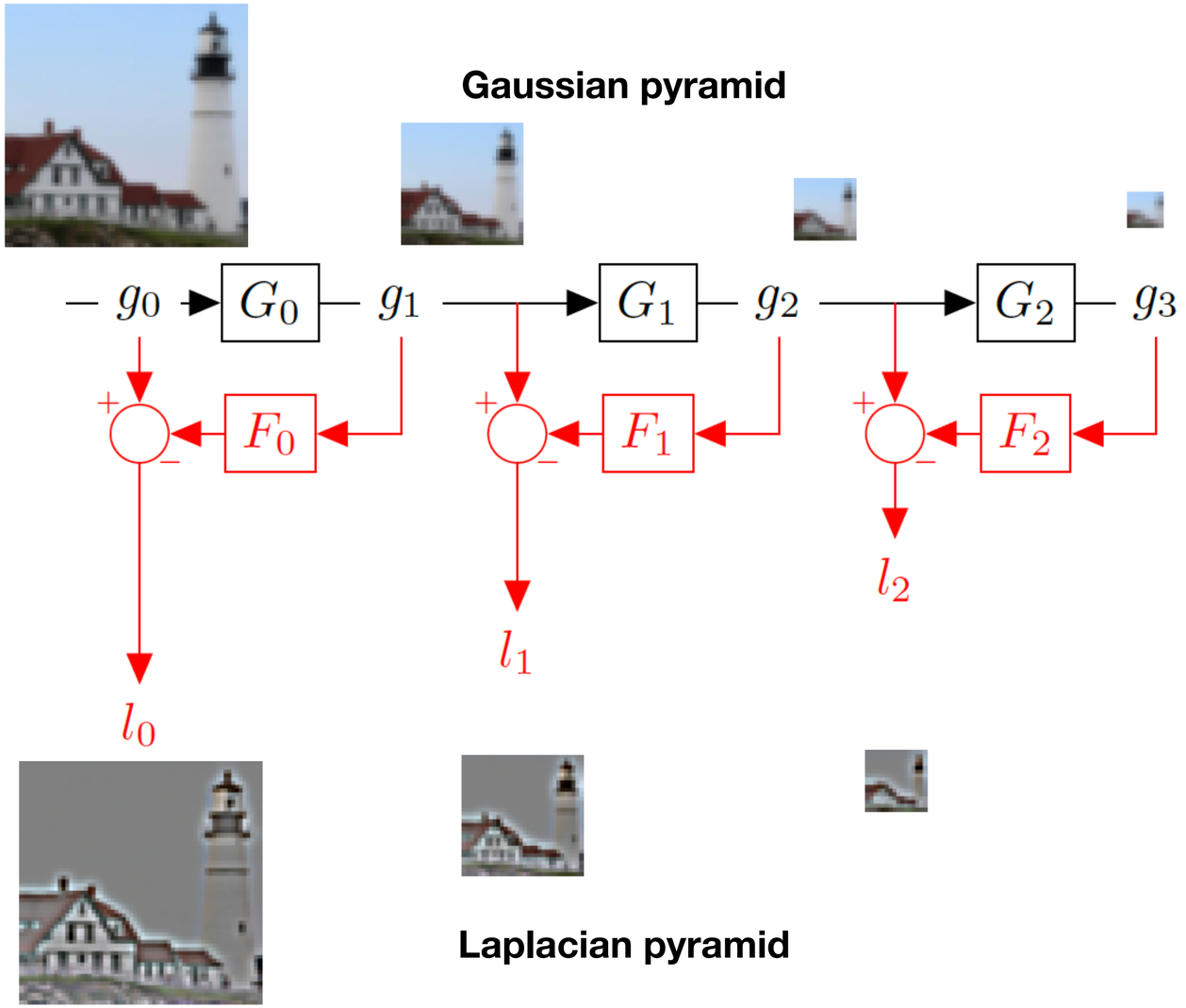
Compute the difference between upsampled Gaussian pyramid level k+1 and Gaussian pyramid level k.



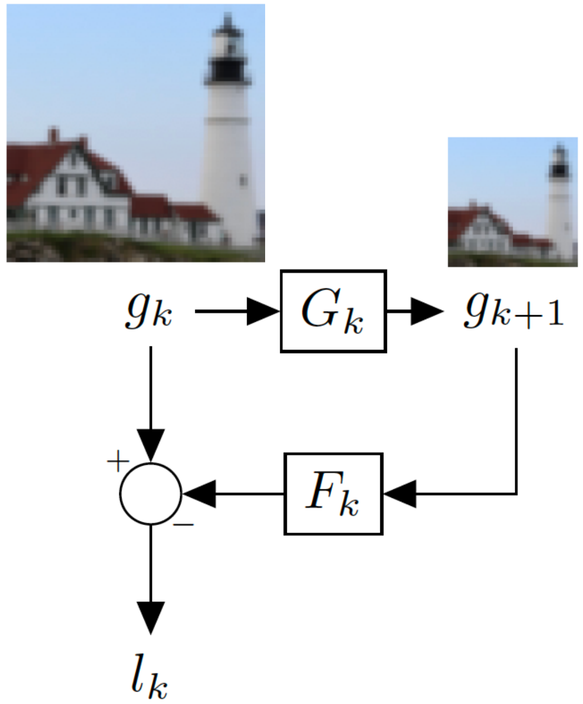
The Laplacian Pyramid



The Laplacian Pyramid



The Laplacian Pyramid



Blurring and downsampling:

$$G_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \frac{1}{16} \begin{bmatrix} 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 \\ 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 \\ 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 \\ 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 \\ 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 \\ 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 \\ 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 \end{bmatrix}$$

(Downsampling by 2)

(blur)

Upsampling and blurring:

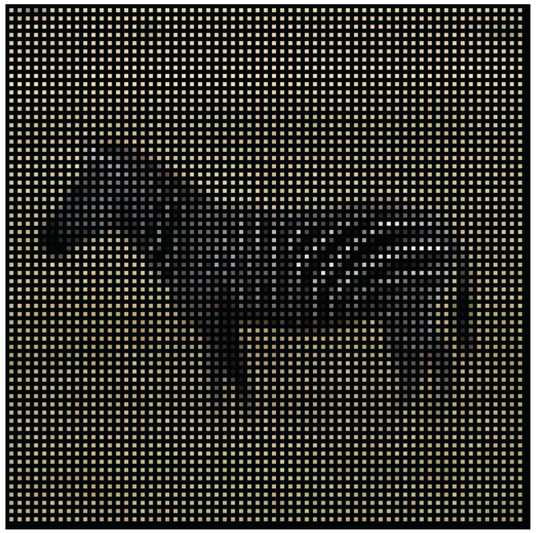
$$F_0 =$$

Upsampling

64x64

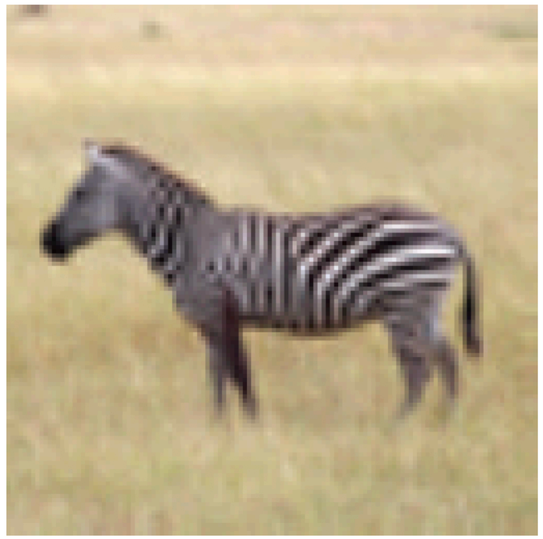
Insert zeros

128x128



$\bigcirc \begin{bmatrix} 0.25 & 0.5 & 0.25 \\ 0.5 & 1 & 0.5 \\ 0.25 & 0.5 & 0.25 \end{bmatrix} =$

128x128



Upsampling

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

$$\bigcirc \begin{bmatrix} 0.25 & 0.5 & 0.25 \\ 0.5 & 1 & 0.5 \\ 0.25 & 0.5 & 0.25 \end{bmatrix} = ?$$

Upsampling

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

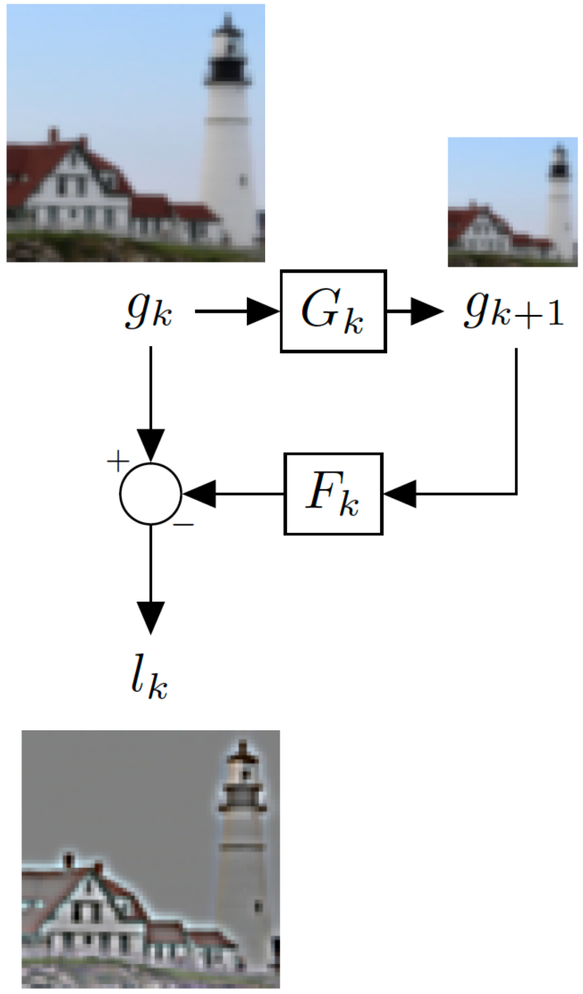
$\bigcirc$

$$\begin{bmatrix} 0.25 & 0.5 & 0.25 \\ 0.5 & 1 & 0.5 \\ 0.25 & 0.5 & 0.25 \end{bmatrix}$$

=

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

The Laplacian Pyramid



Blurring and downsampling:

$$G_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \frac{1}{16} \begin{bmatrix} 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 \\ 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 \\ 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 \\ 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 \\ 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 \\ 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 \\ 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 \end{bmatrix}$$

(Downsampling by 2) (blur)

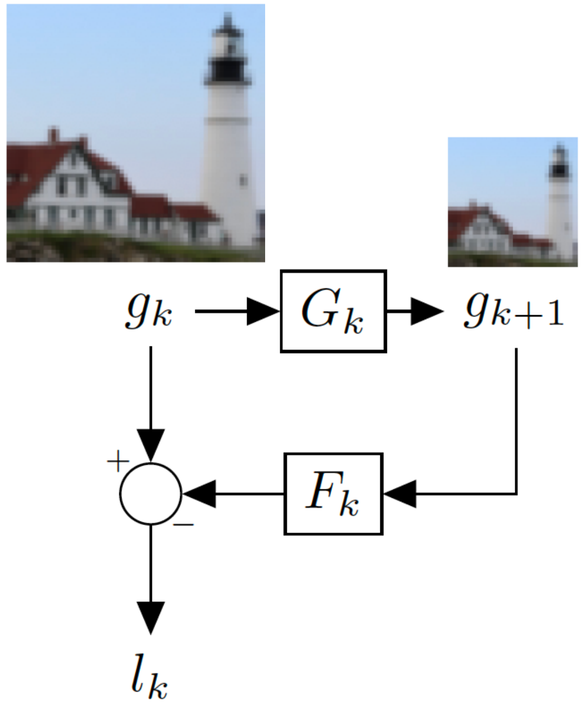
Upsampling and blurring:

$$F_0 = \frac{1}{8} \begin{bmatrix} 6 & 4 & 1 & 0 & 0 & 0 & 0 & 0 \\ 4 & 6 & 4 & 1 & 0 & 0 & 0 & 0 \\ 1 & 4 & 6 & 4 & 1 & 0 & 0 & 0 \\ 0 & 1 & 4 & 6 & 4 & 1 & 0 & 0 \\ 0 & 0 & 1 & 4 & 6 & 4 & 1 & 0 \\ 0 & 0 & 0 & 1 & 4 & 6 & 4 & 1 \\ 0 & 0 & 0 & 0 & 1 & 4 & 6 & 4 \\ 0 & 0 & 0 & 0 & 0 & 1 & 4 & 6 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

(blur) (Upsampling by 2)

$$l_0 = (I_0 - F_0 G_0) g_0$$

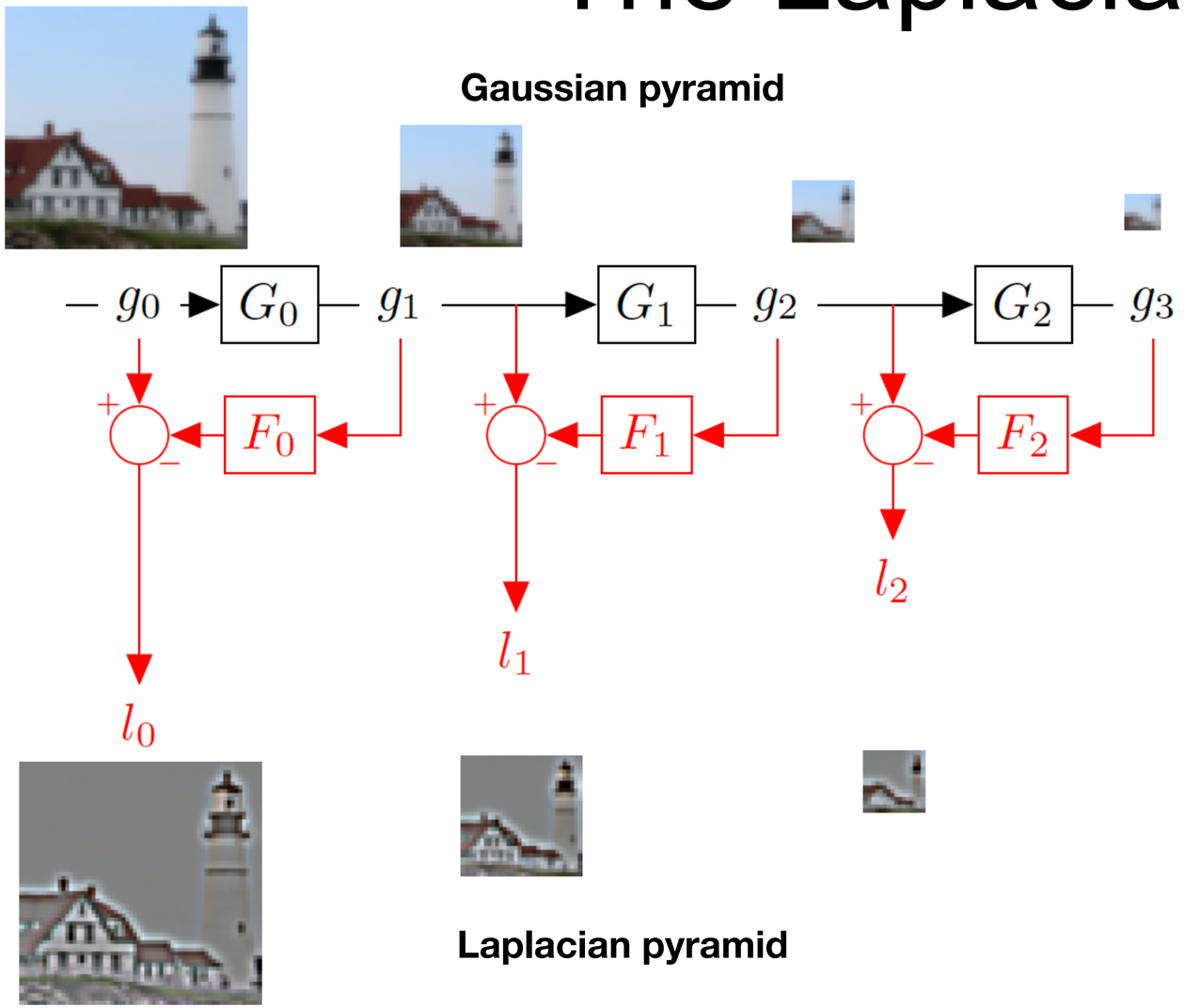
The Laplacian Pyramid

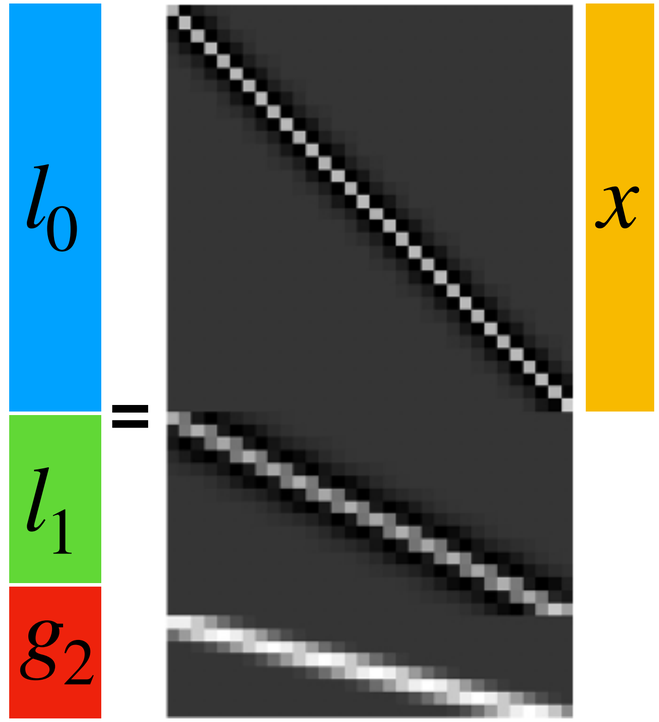


$$l_0 = (I_0 - F_0 G_0) g_0$$

$$= \frac{1}{256} \begin{bmatrix} 182 & -56 & -24 & -8 & -2 & 0 & 0 & 0 \\ -56 & 192 & -56 & -32 & -8 & 0 & 0 & 0 \\ -24 & -56 & 180 & -56 & -24 & -8 & -2 & 0 \\ -8 & -32 & -56 & 192 & -56 & -32 & -8 & 0 \\ -2 & -8 & -24 & -56 & 180 & -56 & -24 & -8 \\ 0 & 0 & -8 & -32 & -56 & 192 & -56 & -32 \\ 0 & 0 & -2 & -8 & -24 & -56 & 182 & -48 \\ 0 & 0 & 0 & 0 & -8 & -32 & -48 & 224 \end{bmatrix} x$$

The Laplacian Pyramid





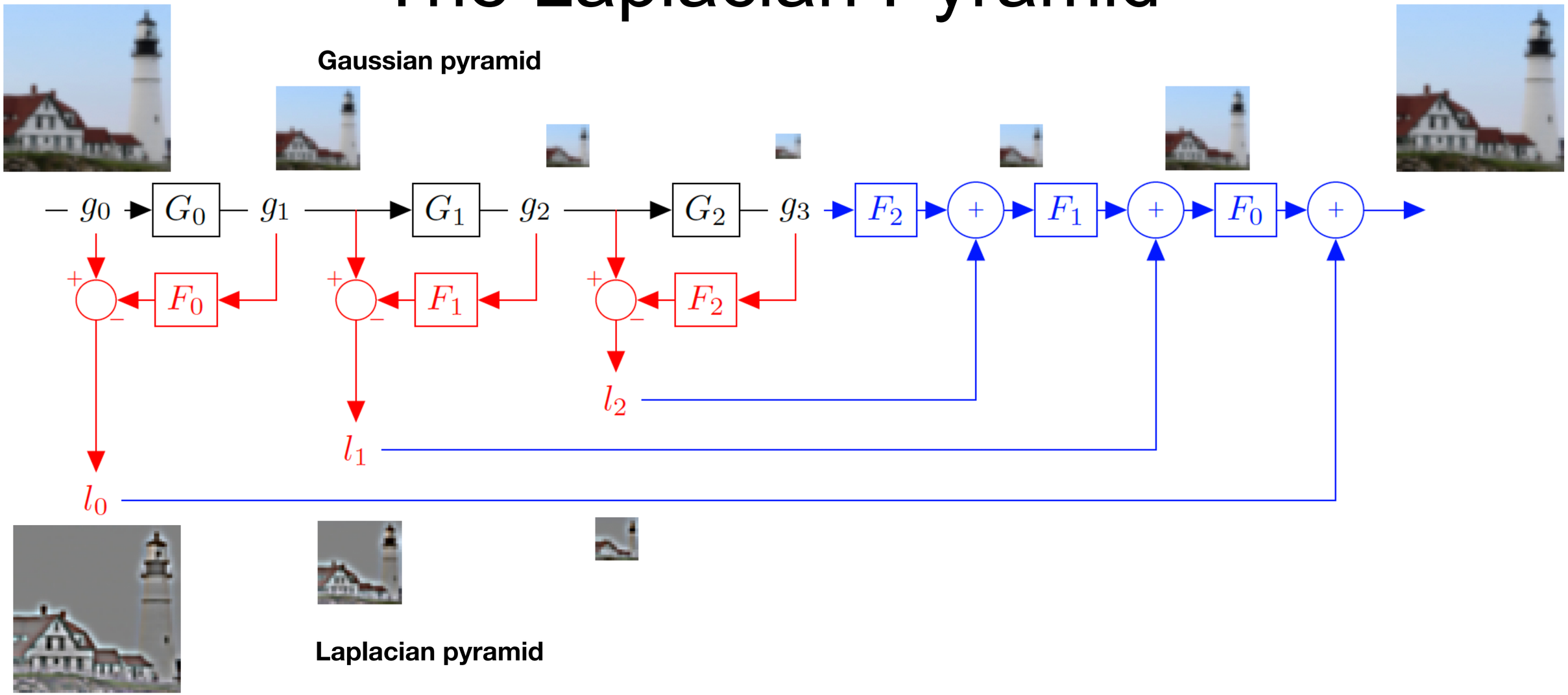
The Laplacian Pyramid

Gaussian residual

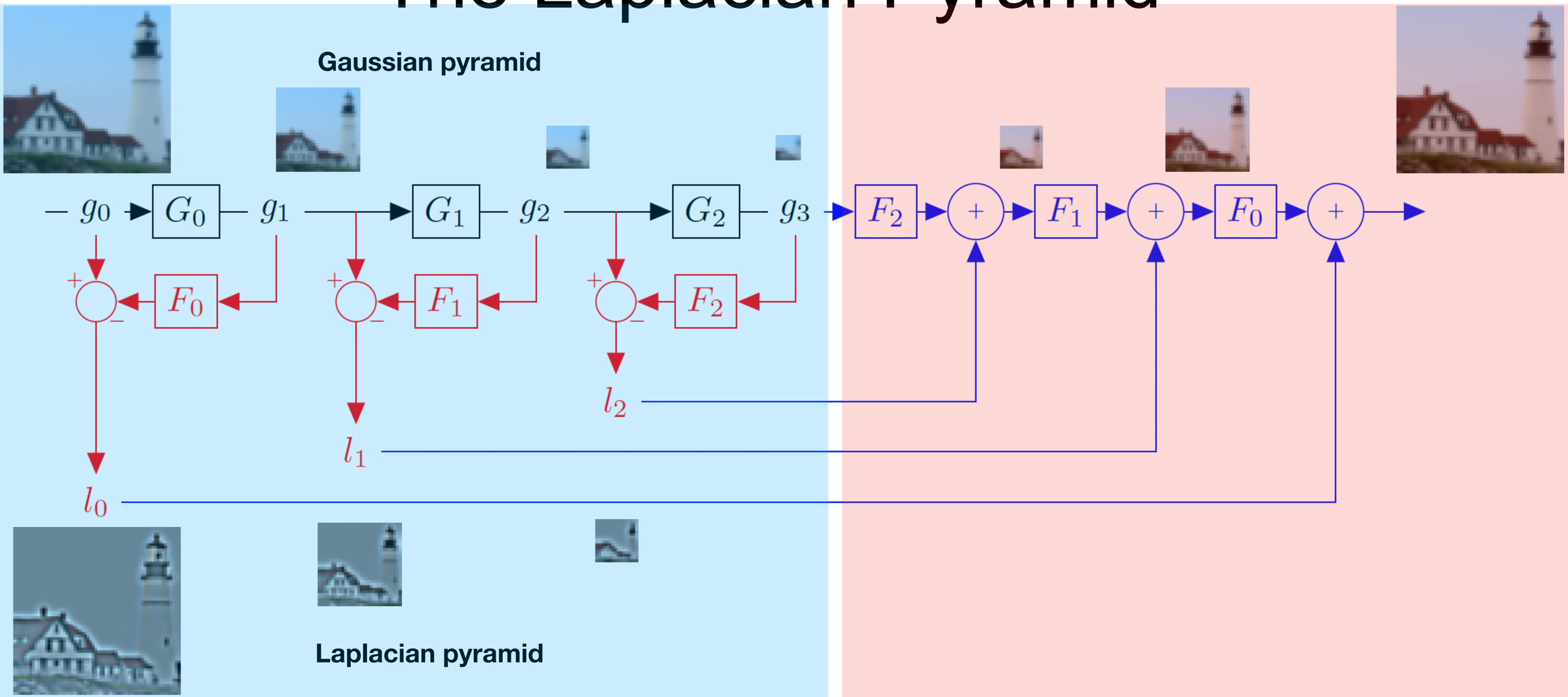
Laplacian pyramid

Can we invert the Laplacian Pyramid?

The Laplacian Pyramid



The Laplacian Pyramid



The Laplacian Pyramid

Laplacian pyramid

Gaussian residual

Laplacian pyramid

Gaussian residual

Laplacian pyramid applications

- Image compression
- Noise removal
- Computing image features (e.g., SIFT)
- Connections to common neural network architectures: ResNets, U-Nets, skip connections in transformers…

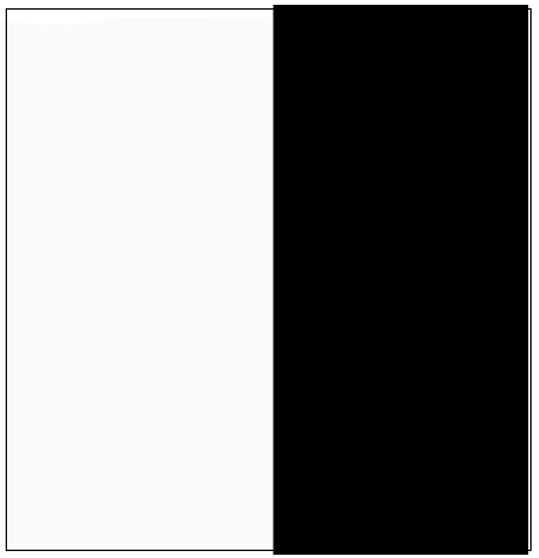
Image Blending

Image Blending

Image Blending

I^A

I^B

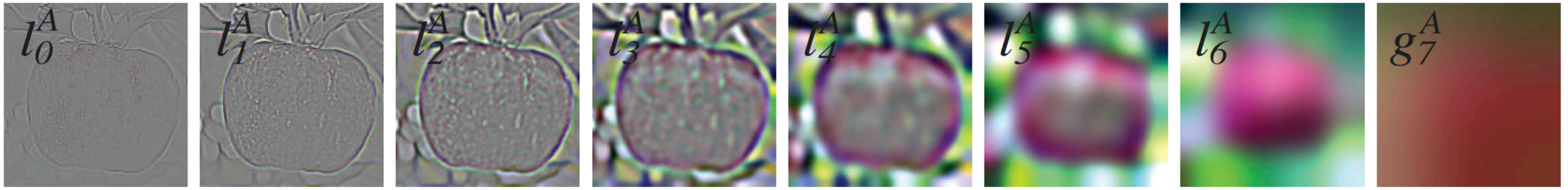


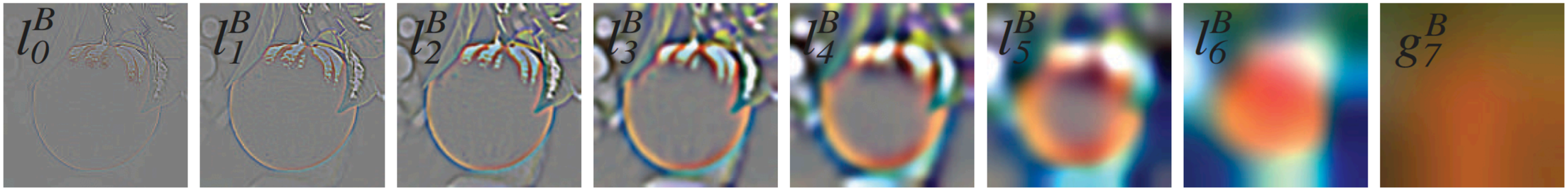
m

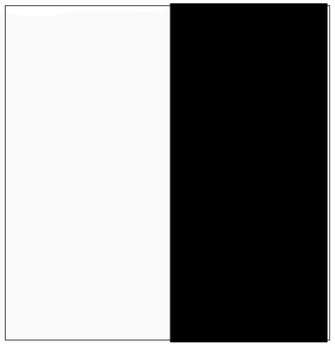
I

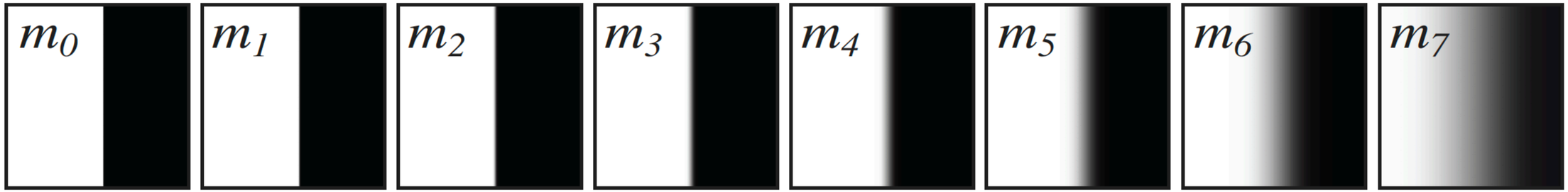
$$I = m * I^A + (1 - m) * I^B$$

Image Blending with the Laplacian Pyramid







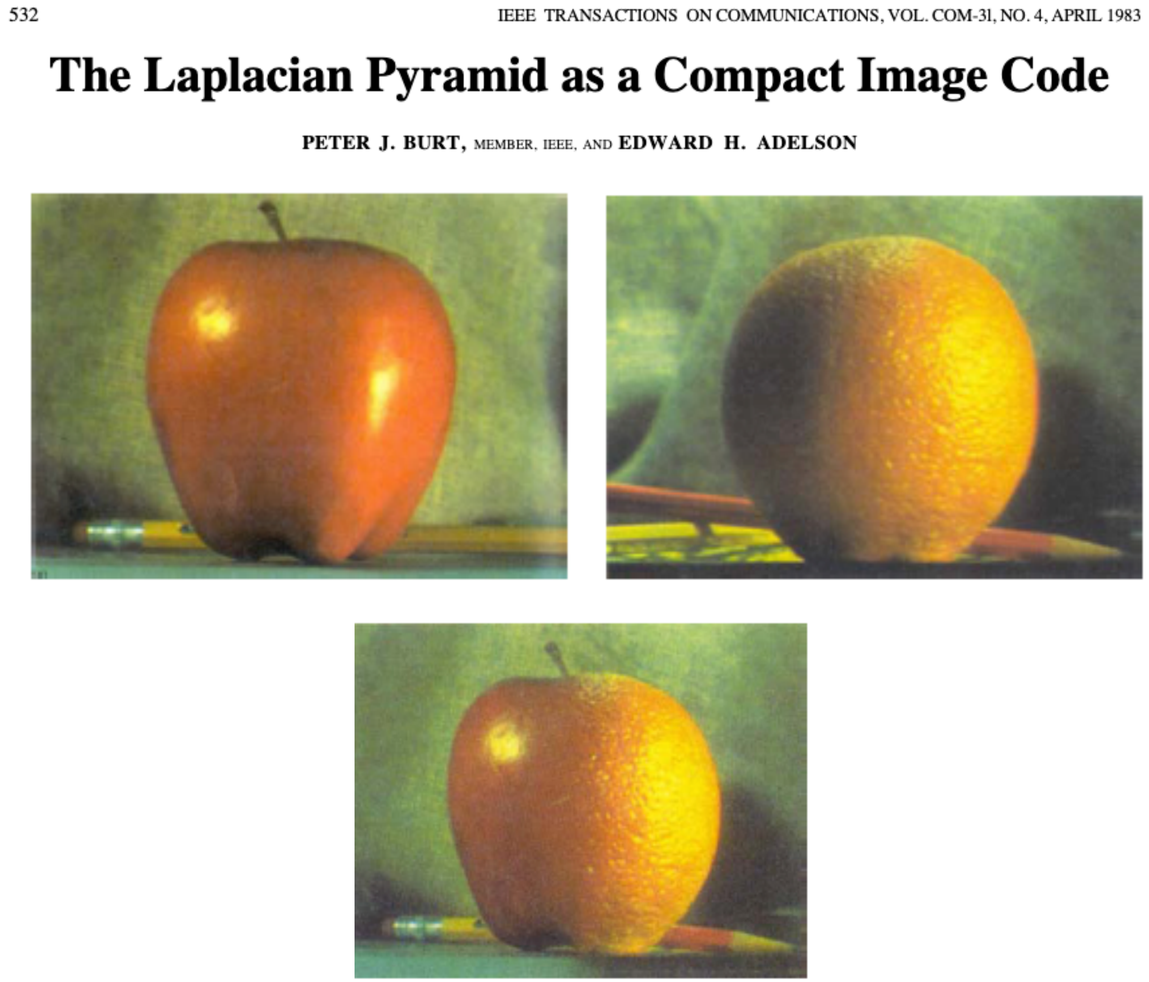


$$l_k = l_k^A * m_k + l_i^B * (1 - m_k)$$

Image Blending with the Laplacian Pyramid

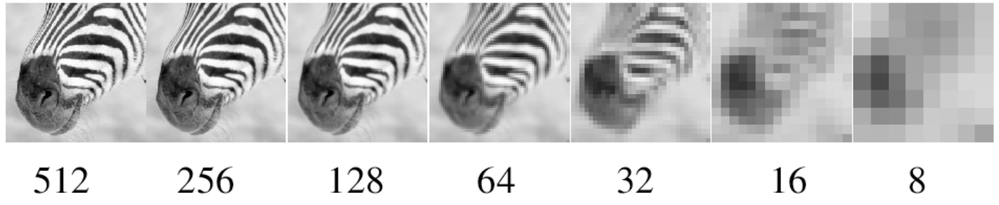
Image Blending with the Laplacian Pyramid

- Build Laplacian pyramid for both images: LA, LB
- Build Gaussian pyramid for mask: G
- Build a combined Laplacian pyramid:
- Collapse L to obtain the blended image

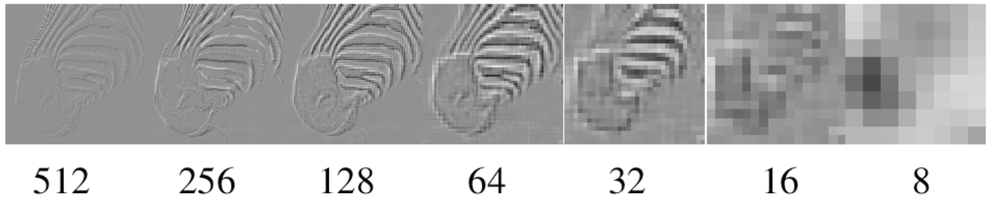


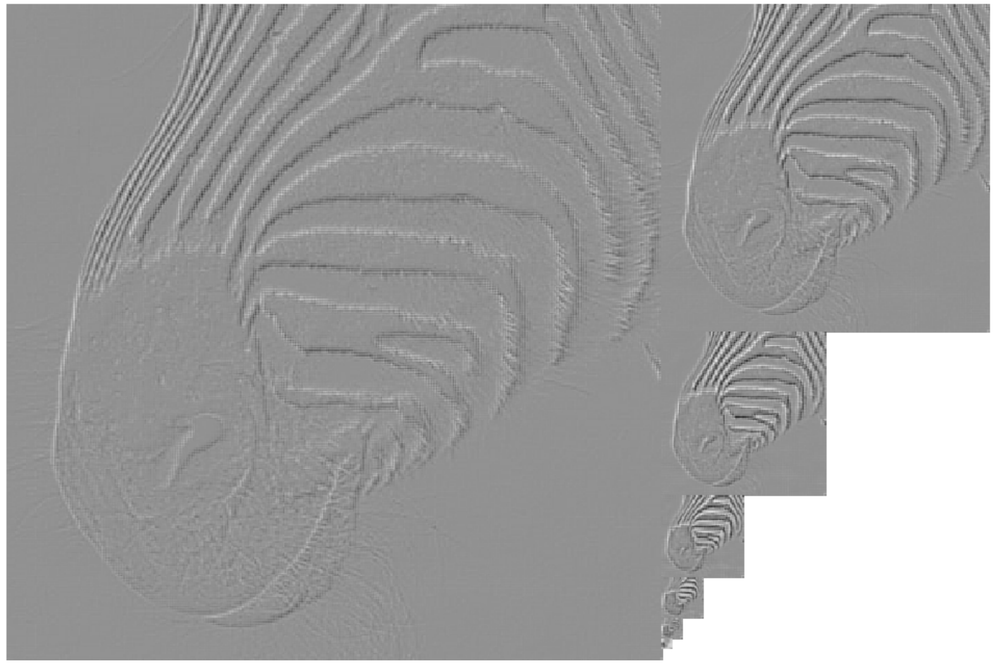
http://persci.mit.edu/pub_pdfs/pyramid83.pdf

Image pyramids



Gaussian Pyr

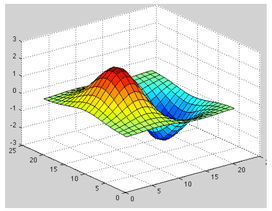


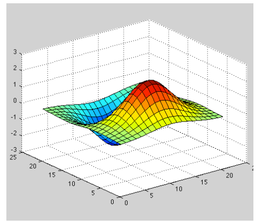


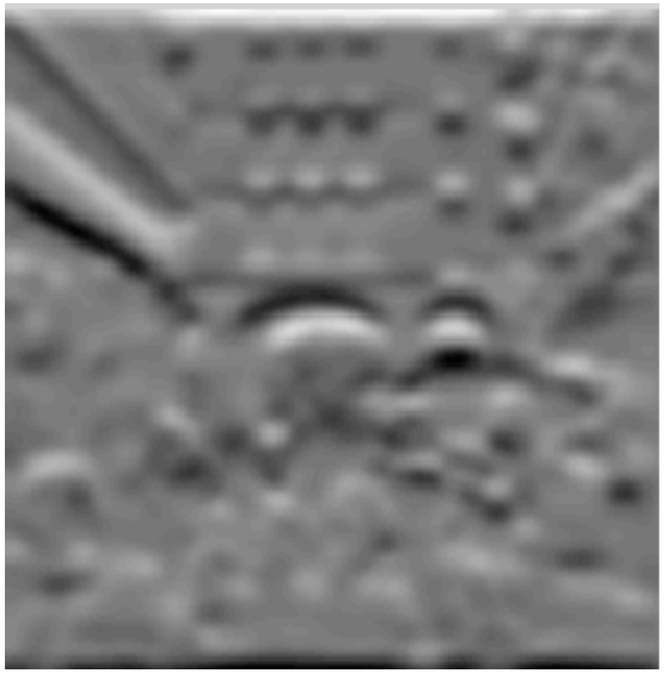
Laplacian Pyr

And many more: QMF, steerable, … Convnets!

Orientations

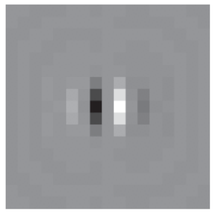


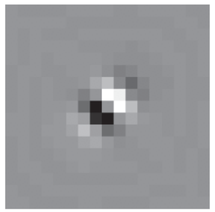


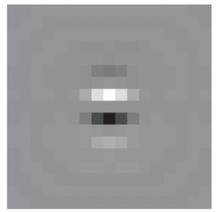


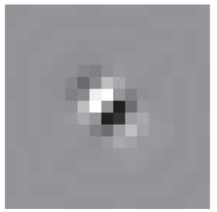
Orientations

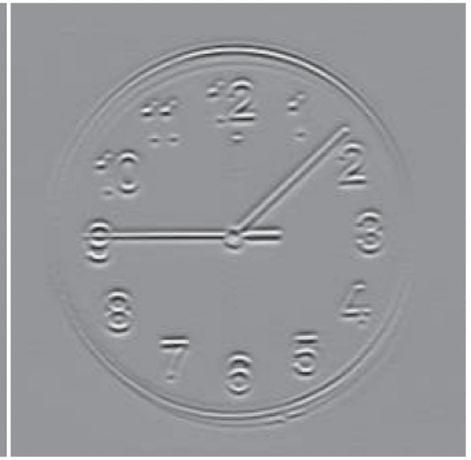
Steerable Pyramid





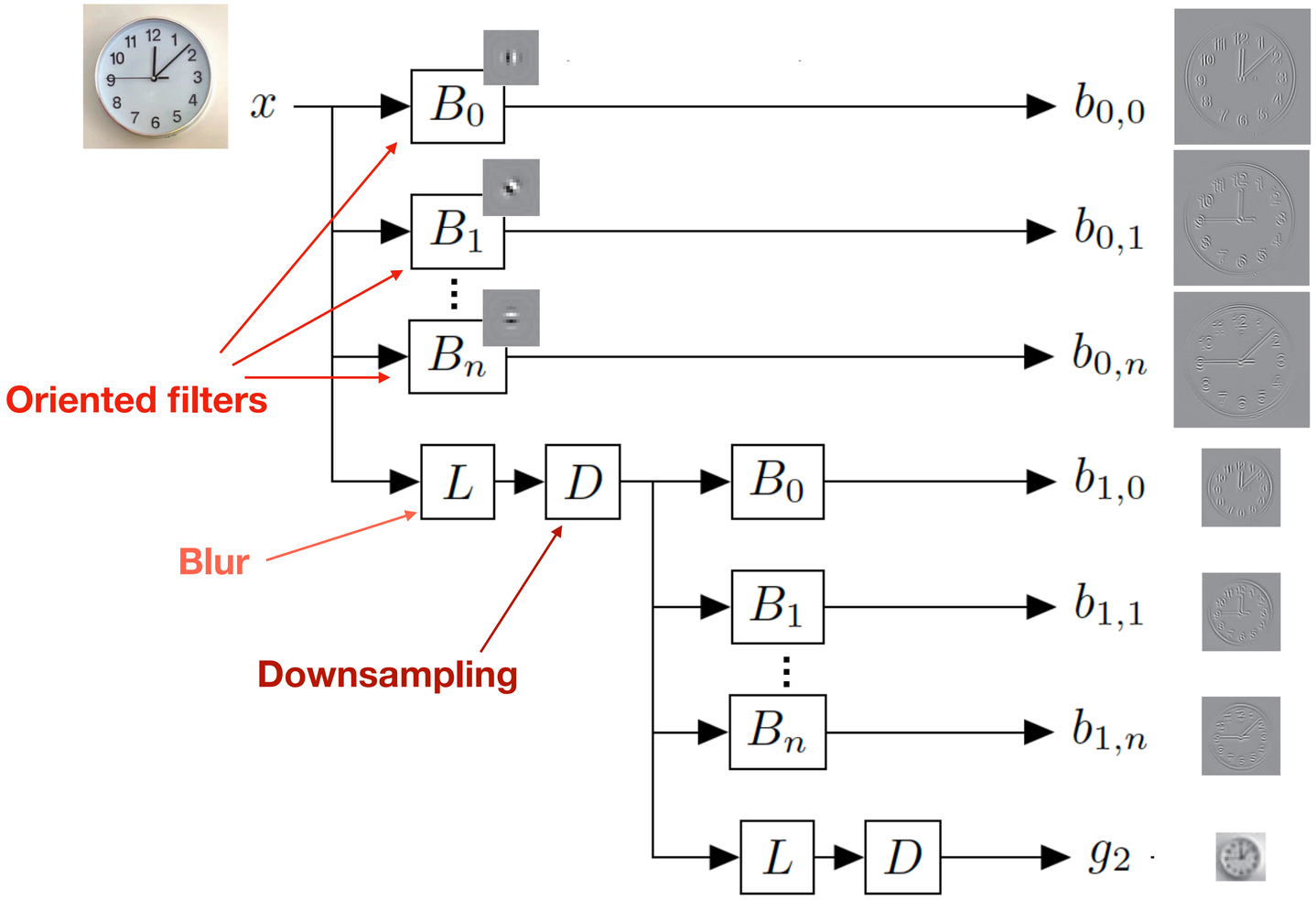


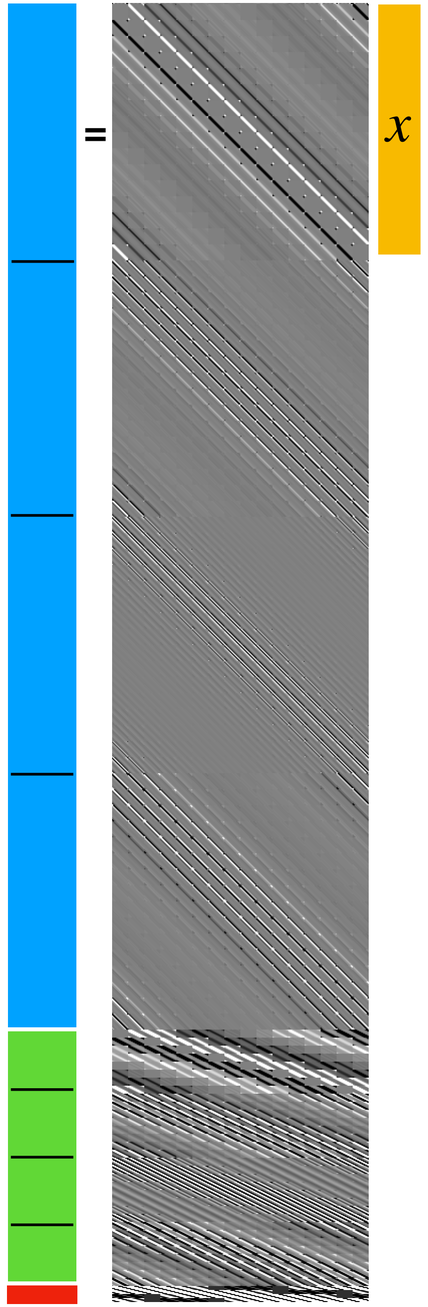




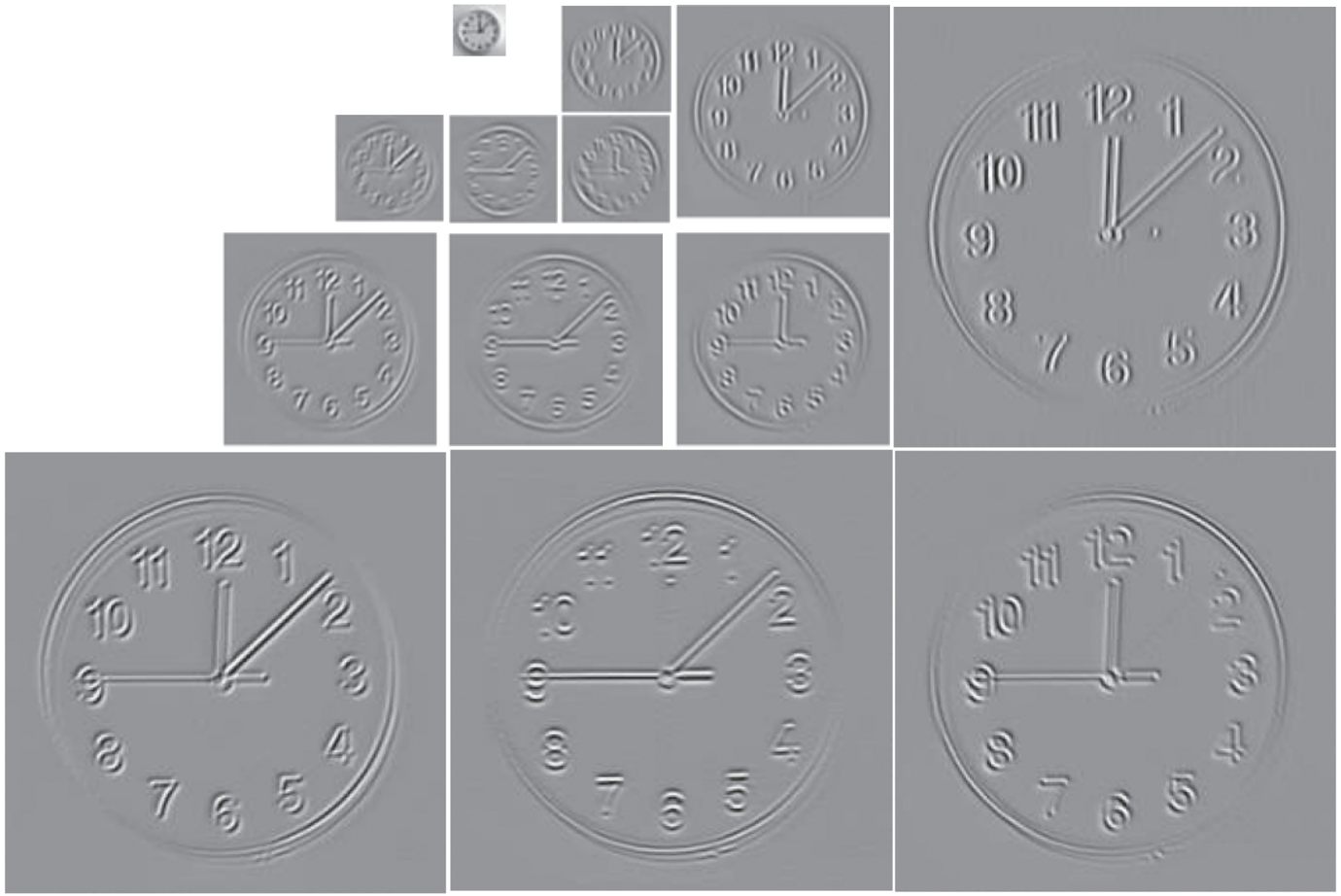
Low pass residual

Steerable Pyramid



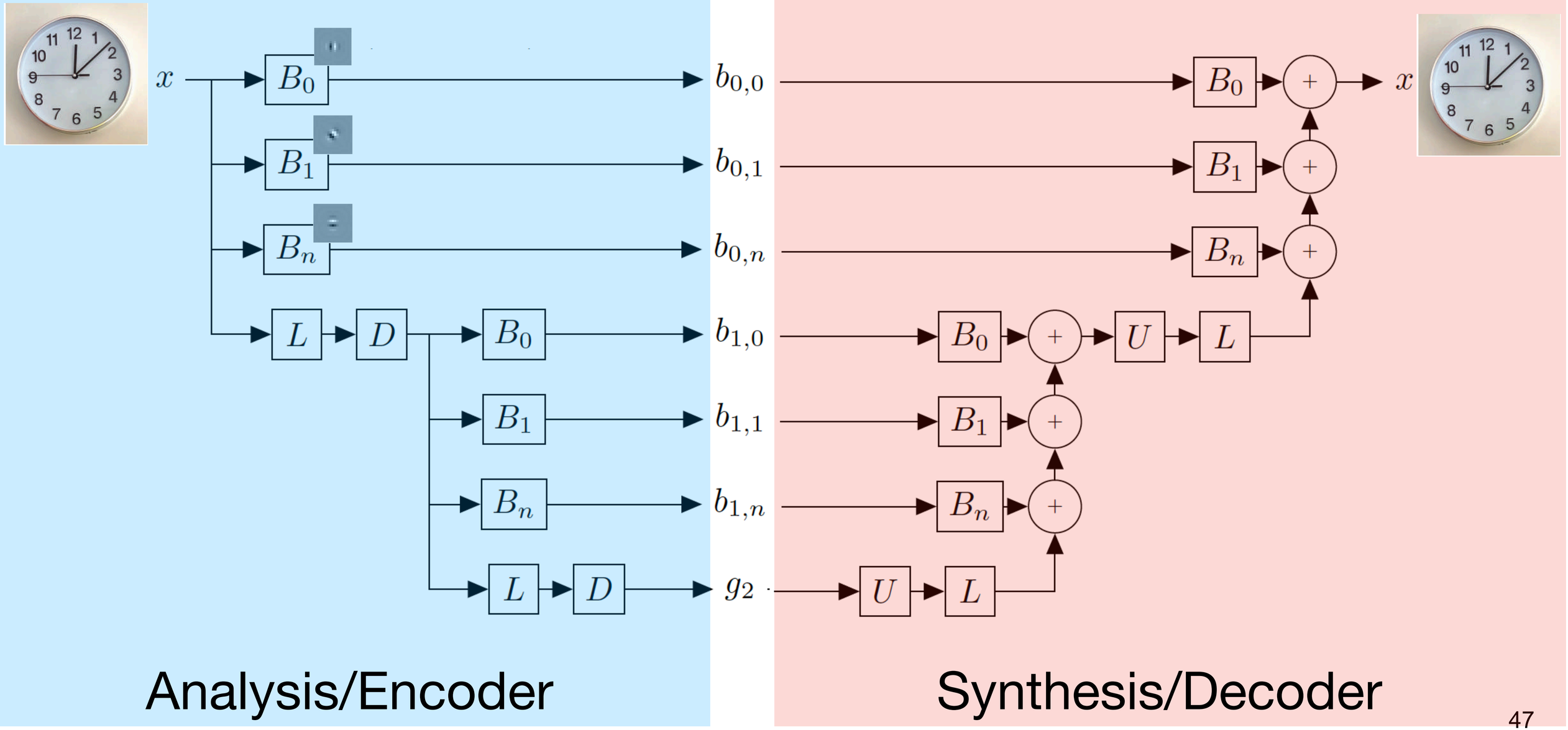


Steerable Pyramid



3 scales, 4 orientations

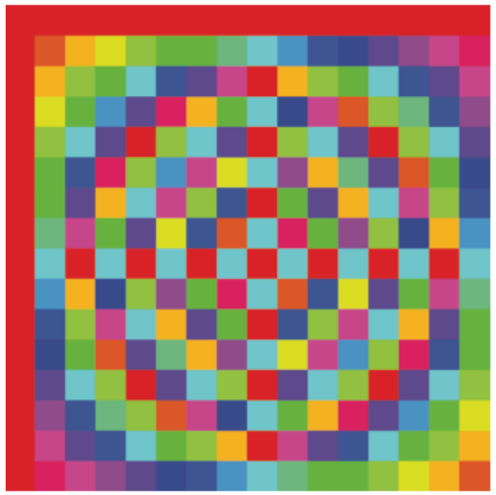
Steerable Pyramid



Visual summary: Linear Image Transforms

Fourier Transform

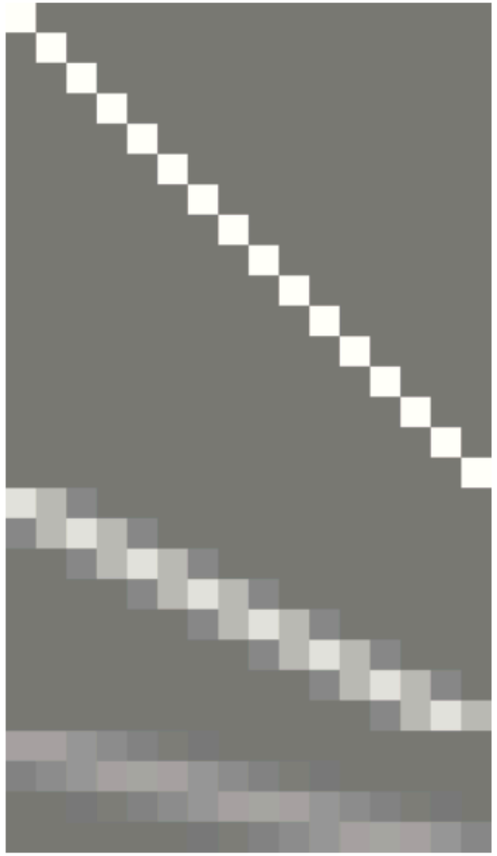
16x16



a) 1D

Gaussian Pyramid

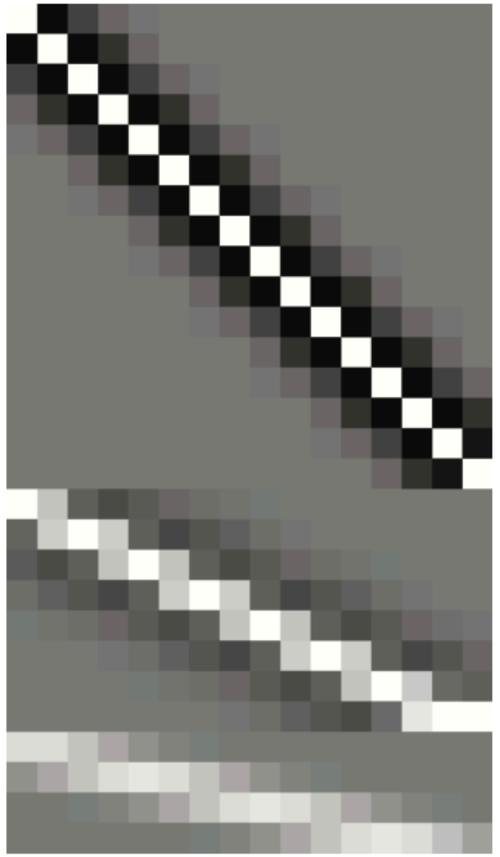
28x16



b) 1D

Laplacian Pyramid

28x16



c) 1D

1297x256

Steerable Pyramid

d) 2D

Steerable pyramid applications

- Texture recognition
- Image compression
- Noise removal
- Computing image features (e.g., SIFT)
- Object recognition

OpenAI

Dall-E 2

An astronaut riding a horse in a photorealistic style

https://openai.com/dall-e-2/

Making textures

Textures

Stationary

Stochastic


SONA·VIE


SANTE BAY FARMS
Organic Red Raspberry Vinaigrette
SANTE BAY FARMS
Organic Spicy Mango Salad Dressing


La Bernardine
La Bernardine
La Bernardine


Bandana's
SPICY BAR-B-Q SAUCE
Bandana's
SWEET & SAUCY BAR-B-Q SAUCE
Bandana's
HOT BAR-B-Q SAUCE
Bandana's
Original BAR-B-Q SAUCE

Nature Vol. 290 12 March 1981

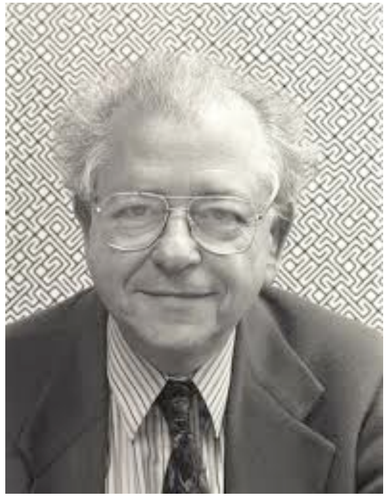
REVIEW ARTICLES

Textons, the elements of texture perception, and their interactions

Bela Julesz

Bell Laboratories, Murray Hill, New Jersey 07974, USA

Research with texture pairs having identical second-order statistics has revealed that the pre-attentive texture discrimination system cannot globally process third- and higher-order statistics, and that discrimination is the result of a few local conspicuous features, called textons. It seems that only the first-order statistics of these textons have perceptual significance, and the relative phase between textons cannot be perceived without detailed scrutiny by focal attention.



Bela Julesz, "Textons, the Elements of Texture Perception, and their Interactions". Nature 290: 91-97. March, 1981.

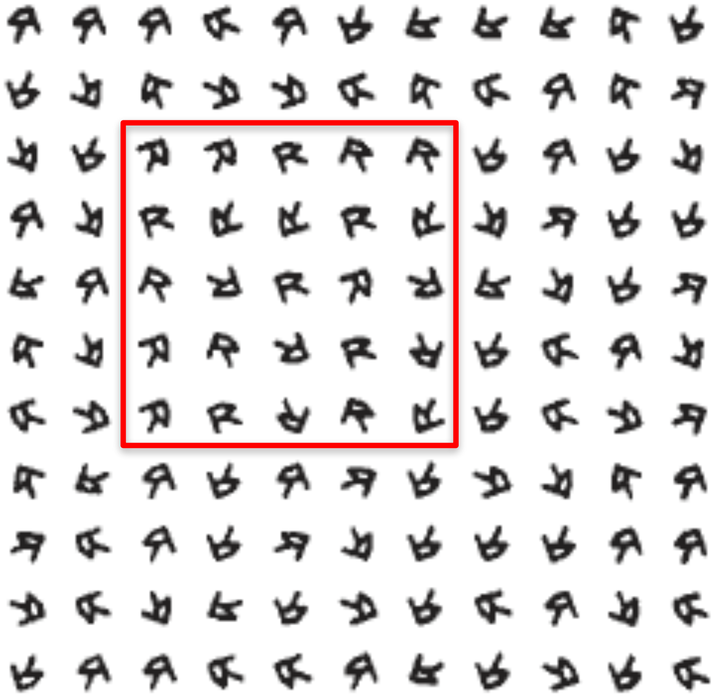
Pre-attentive texture discrimination

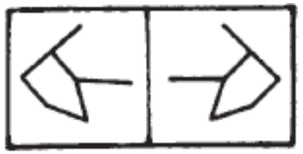
Bela Julesz, "Textons, the Elements of Texture Perception, and their Interactions". Nature 290: 91-97. March, 1981.

Pre-attentive texture discrimination

Bela Julesz, "Textons, the Elements of Texture Perception, and their Interactions". Nature 290: 91-97. March, 1981.

Pre-attentive texture discrimination



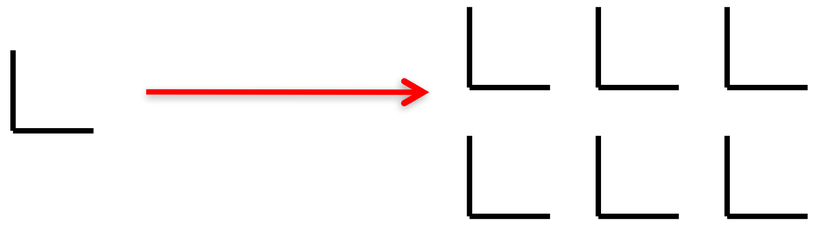


This texture pair is pre-attentively indistinguishable. Why?

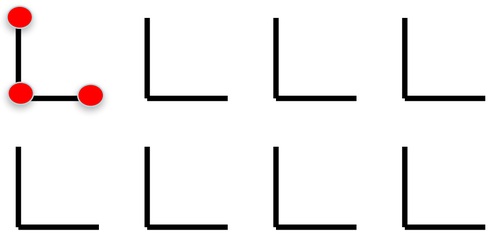
Bela Julesz, "Textons, the Elements of Texture Perception, and their Interactions". Nature 290: 91-97. March, 1981.

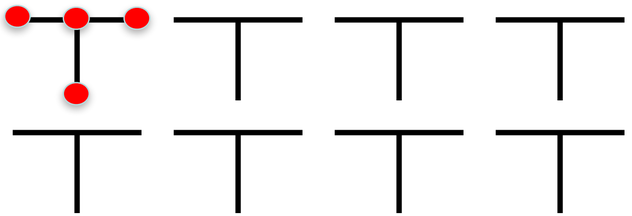
Julesz - Textons

Textons: fundamental texture elements.



Textons might be represented by features such as terminators, corners, and intersections within the patterns…



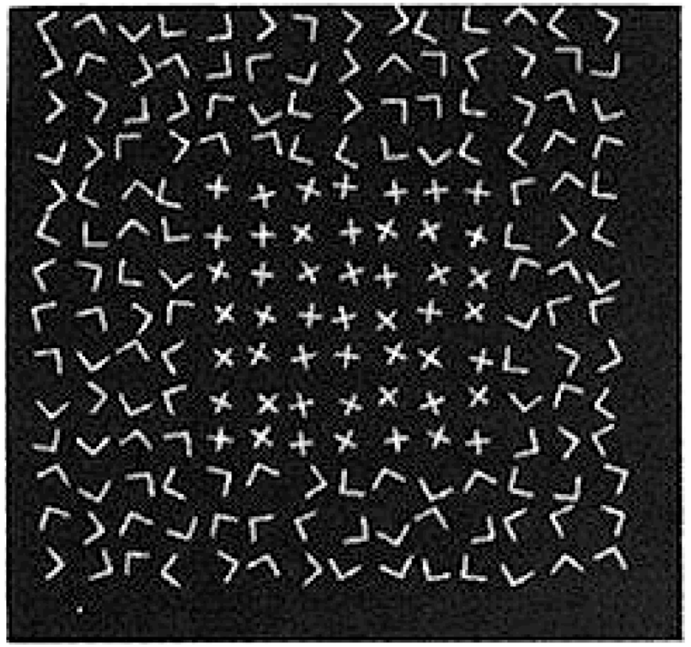


Nature, Vol. 333. No. 6171. pp. 363-364, 26 May 1988

Early vision and texture perception

James R. Bergen* & Edward H. Adelson**

* SRI David Sarnoff Research Center, Princeton,
New Jersey 08540, USA
** Media Lab and Department of Brain and Cognitive Science,



Observation: the Xs look smaller than the Ls.

“We note here that simpler, lower-level mechanisms tuned for size may be sufficient to explain this discrimination.”

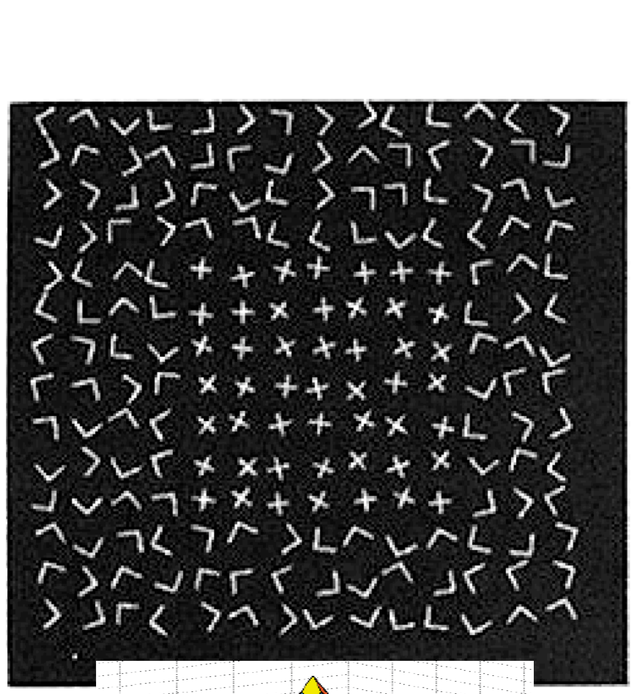
Early vision and texture perception

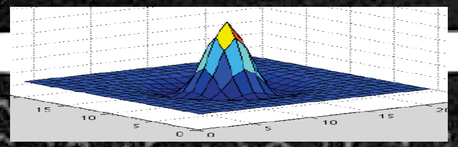
James R. Bergen* & Edward H. Adelson**

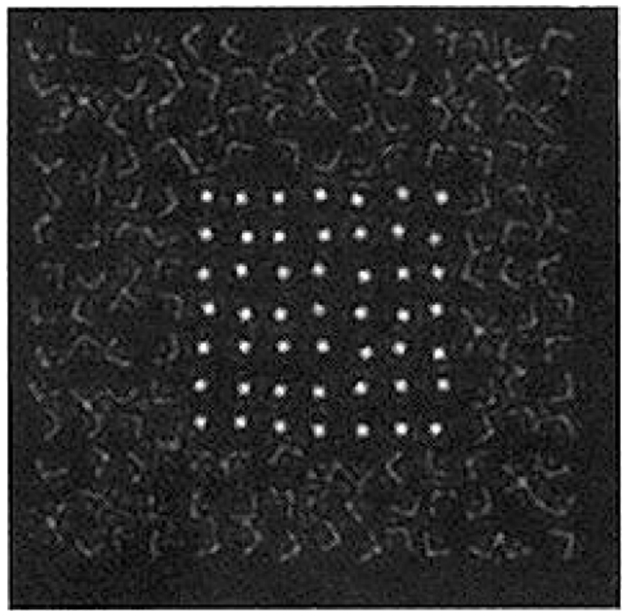
Ls 25% larger

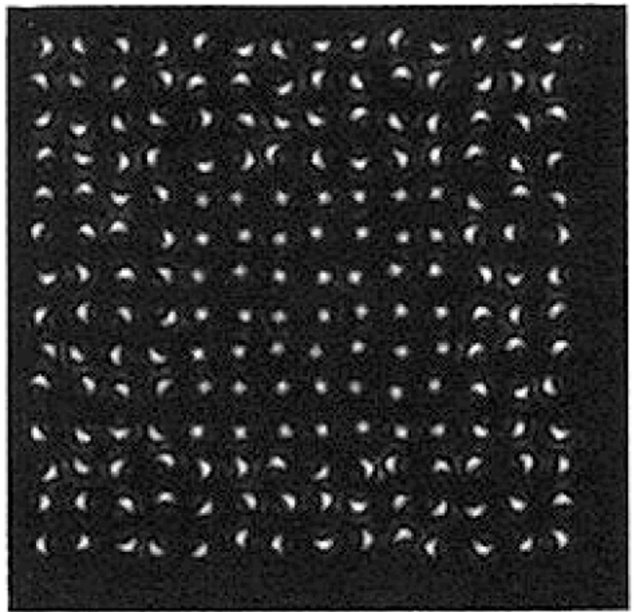
contrast adjusted to keep mean constant

Ls 25% shorter









Pyramid-Based Texture Analysis/Synthesis

David J. Heeger*
Stanford University

James R. Bergen†
SRI David Sarnoff Research Center

Abstract

This paper describes a method for synthesizing images that match the texture appearance of a given digitized sample. This synthesis is completely automatic and requires only the "target" texture as input. It allows generation of as much texture as desired so that any object can be covered. It can be used to produce solid textures for creating textured 3-d objects without the distortions inherent in texture mapping. It can also be used to synthesize texture mixtures, images that look a bit like each of several digitized samples. The approach is based on a model of human texture perception, and has potential to be a practically useful tool for graphics applications.

1 Introduction

Computer renderings of objects with surface texture are more interesting and realistic than those without texture. Texture mapping [15] is a technique for adding the appearance of surface detail by wrapping or projecting a digitized texture image onto a surface. Digitized textures can be obtained from a variety of sources, e.g., cropped from a photoCD image, but the resulting texture chip may not have the desired size or shape. To cover a large object you may need to repeat the texture; this can lead to unacceptable artifacts either in the form of visible seams, visible repetition, or both.

Texture mapping suffers from an additional fundamental problem: often there is no natural map from the (planar) texture image to the geometry/topology of the surface, so the texture may be distorted unnaturally when mapped. There are some partial solutions to this distortion problem [15] but there is no universal solution for mapping an image onto an arbitrarily shaped surface.

An alternative to texture mapping is to create (paint) textures by hand directly onto the 3-d surface model [14], but this process is both very labor intensive and requires considerable artistic skill.

Another alternative is to use computer-synthesized textures so that as much texture can be generated as needed. Furthermore, some of the synthesis techniques produce textures that tile seamlessly.

Using synthetic textures, the distortion problem has been solved in two different ways. First, some techniques work by synthesizing texture directly on the object surface (e.g., [31]). The second solution is to use *solid textures* [19, 23, 24]. A solid texture is a 3-d array of color values. A point on the surface of an object is colored by the value of the solid texture at the corresponding 3-d point. Solid texturing can be a very natural solution to the distortion problem: there is no distortion because there is no mapping. However, existing techniques for synthesizing solid textures can be quite cumbersome. One must learn how to tweak the parameters or procedures of the texture synthesizer to get a desired effect.

This paper presents a technique for synthesizing an image (or solid texture) that matches the appearance of a given texture sample. The key advantage of this technique is that it works entirely from the example texture, requiring no additional information or adjustment. The technique starts with a digitized image and analyzes it to compute a number of texture parameter values. Those parameter values are then used to synthesize a new image (of any size) that looks (in its color and texture properties) like the original. The analysis phase is inherently two-dimensional since the input digitized images are 2-d. The synthesis phase, however, may be either two- or three-dimensional. For the 3-d case, the output is a solid texture such that planar slices through the solid look like the original scanned image. In either case, the (2-d or 3-d) texture is synthesized so that it tiles seamlessly.

2 Texture Models

Textures have often been classified into two categories, deterministic textures and stochastic textures. A deterministic texture is characterized by a set of primitives and a placement rule (e.g., a tile floor). A stochastic texture, on the other hand, does not have easily identifiable primitives (e.g., granite, bark, sand). Many real-world textures have some mixture of these two characteristics (e.g. woven fabric, woodgrain, plowed fields).

Much of the previous work on texture analysis and synthesis can be classified according to what type of texture model was used. Some of the successful texture models include reaction-diffusion [31, 34], frequency domain [17], fractal [9, 18], and statistical/random field [1, 6, 8, 10, 12, 13, 21, 26] models. Some (e.g., [10]) have used hybrid models that include a deterministic (or periodic) component and a stochastic component. In spite of all this work, scanned images and hand-drawn textures are still the principle source of texture maps in computer graphics.

This paper focuses on the synthesis of stochastic textures. Our approach is motivated by research on human texture perception. Current theories of texture discrimination are based on the fact that two textures are often difficult to discriminate when they produce a similar distribution of responses in a bank of (orientation and spatial-frequency selective) linear filters [2, 3, 7, 16, 20, 32]. The method described here, therefore, synthesizes textures by matching distributions (or histograms) of filter outputs. This approach depends on the principle (not entirely correct as we shall see) that all of the spatial information characterizing a texture image can be captured in the first order statistics of an appropriately chosen set of linear filter outputs. Nevertheless, this model (though incomplete) captures an interesting set of texture properties.

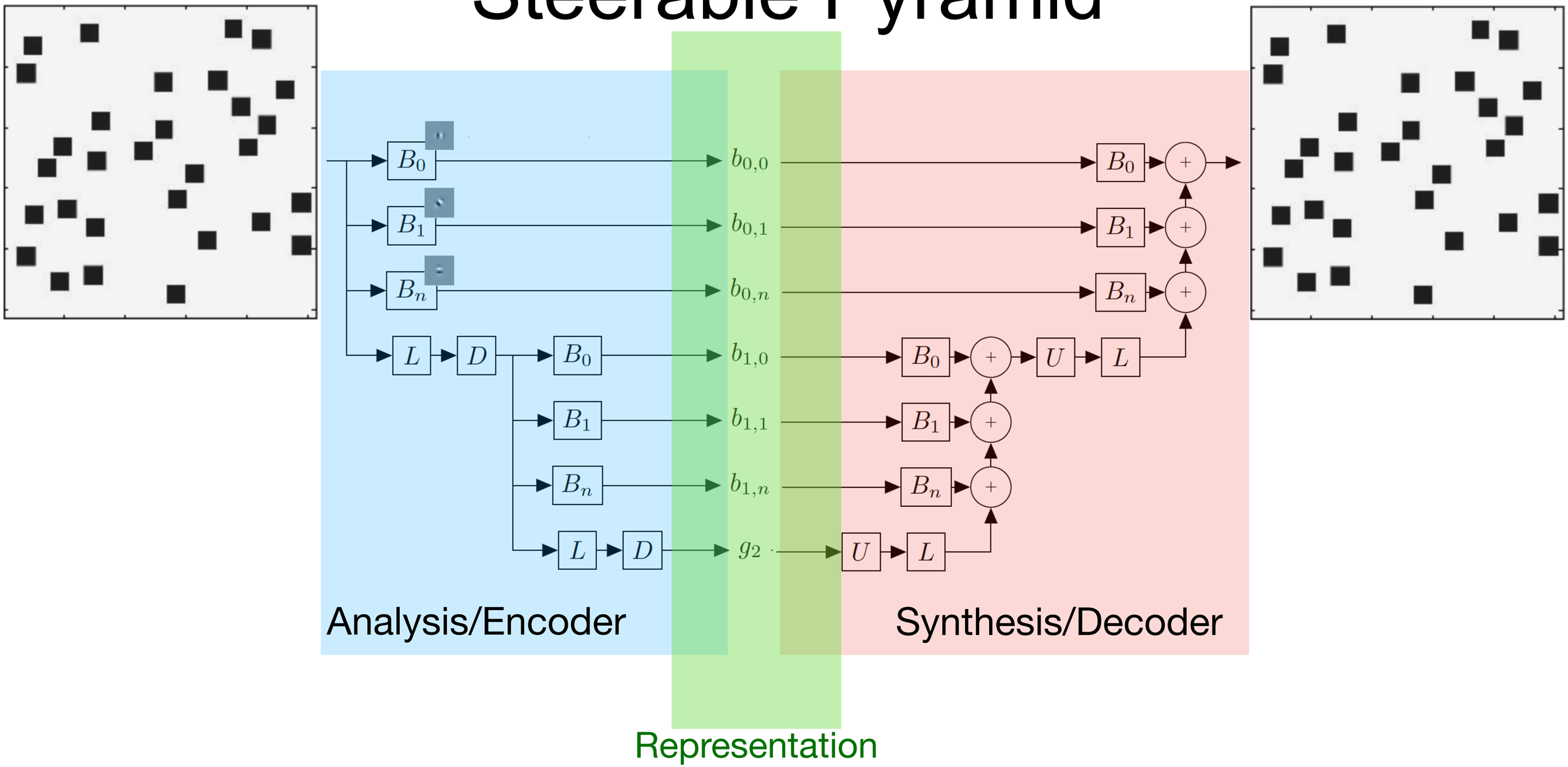
*Department of Psychology, Stanford University, Stanford, CA 94305. heeger@white.stanford.edu http://white.stanford.edu
†SRI David Sarnoff Research Center, Princeton, NJ 08544. jrb@sarnoff.com

Figure 5: (Top Row) Original digitized sample textures: red granite, berry bush, figured maple, yellow coral. (Bottom Rows) Synthetic solid textured teapots.

https://www.cns.nyu.edu/heegerlab/content/publications/Heeger-siggraph95.pdf

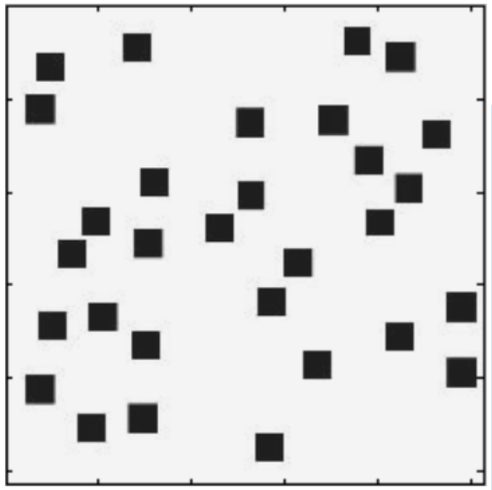
SIGGRAPH 1995

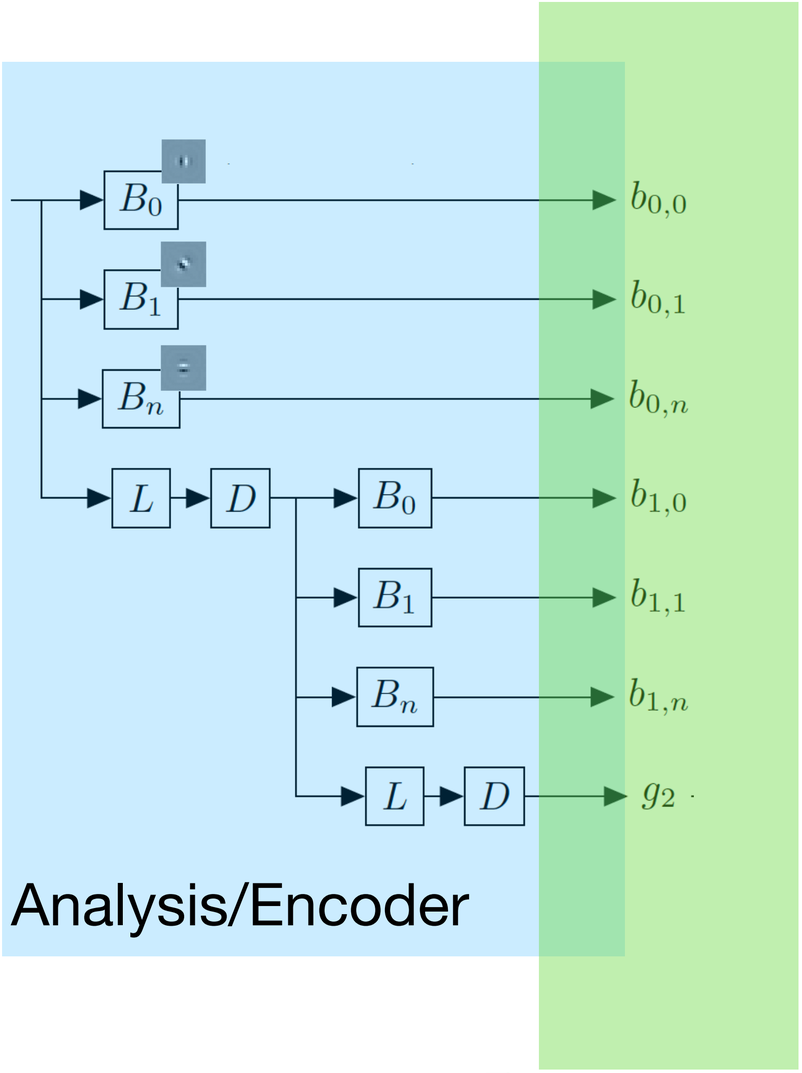
Steerable Pyramid

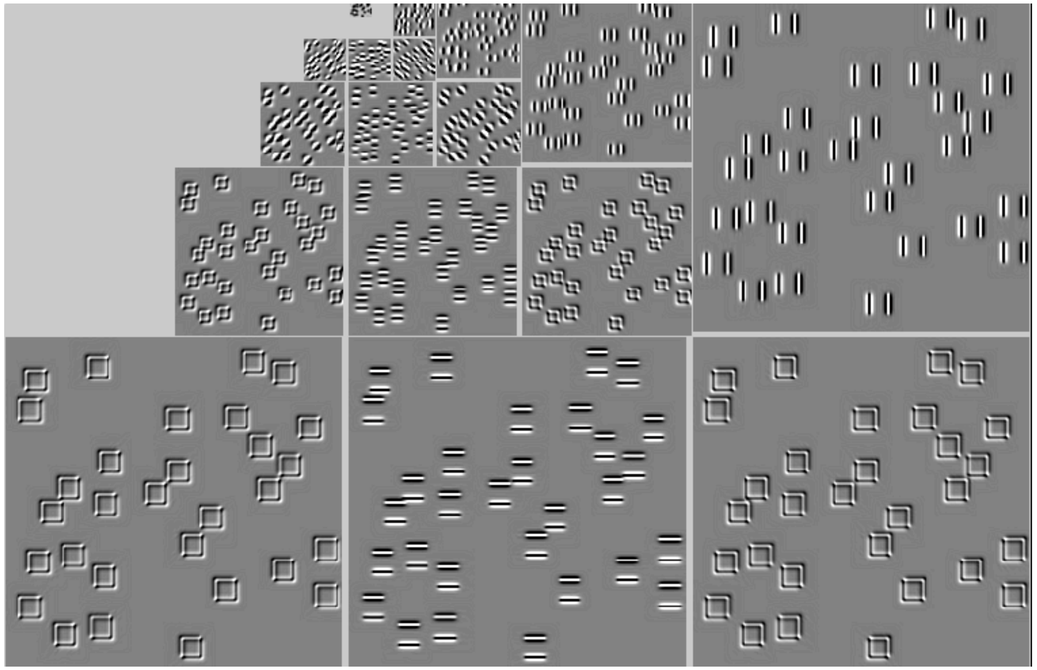


Can we use this representation to generate more samples from the same texture?

Steerable Pyramid

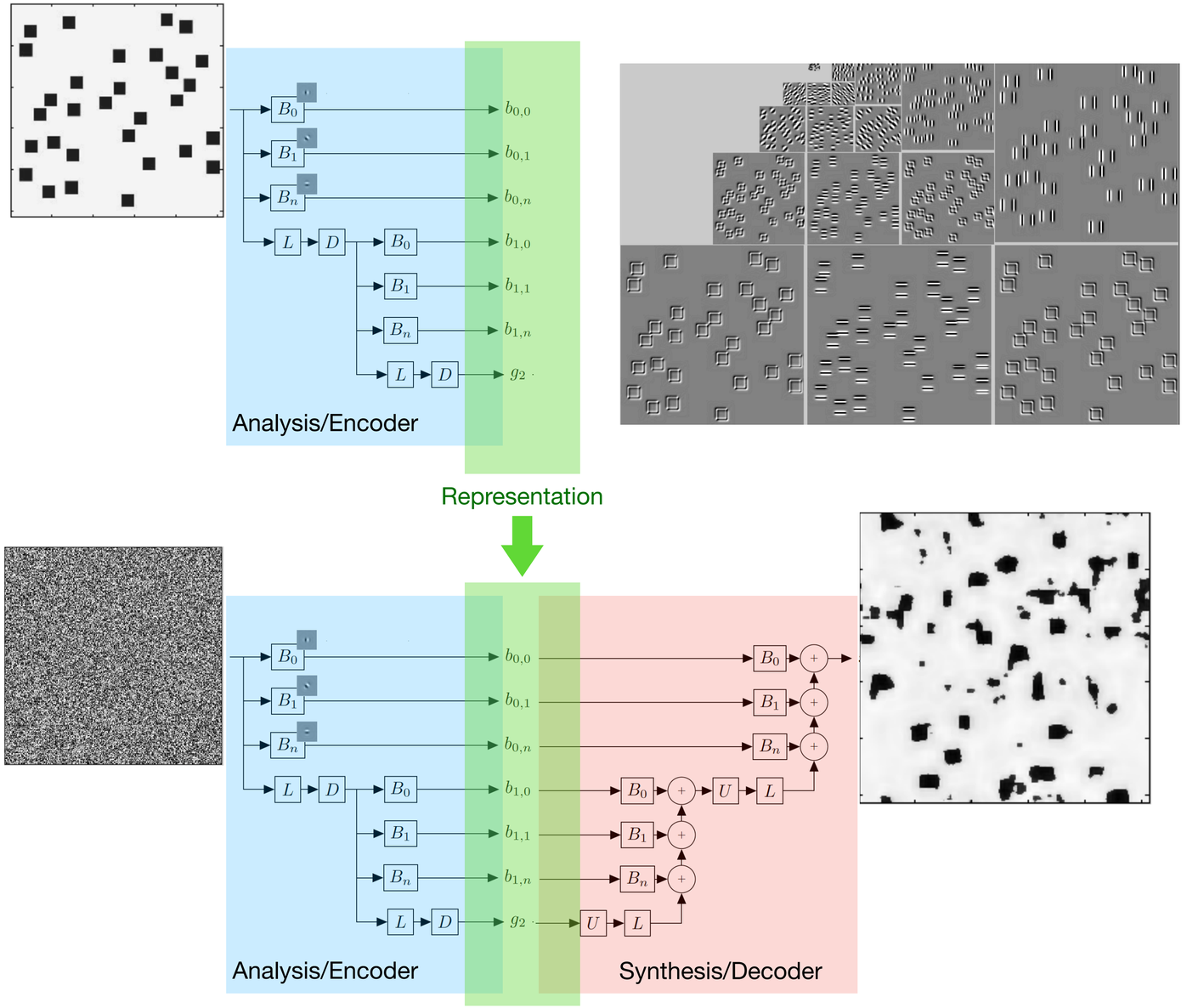






Representation =
Histograms of pixel values
for each subband

Transferring Image Statistics via Representation Matching



Transferring Image Statistics via Representation Matching

```
Match-texture(noise,texture)
  Match-Histogram (noise,texture)
   analysis-pyr = Make-Pyramid (texture)
   Loop for several iterations do
      synthesis-pyr = Make-Pyramid (noise)
      Loop for a-band in subbands of analysis-pyr
           for s-band in subbands of synthesis-pyr
           do
           Match-Histogram (s-band,a-band)
      noise = Collapse-Pyramid (synthesis-pyr)
      Match-Histogram (noise,texture)
```

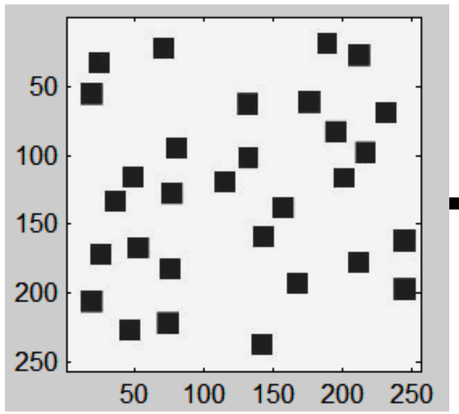
Two main tools:

1- steerable pyramid

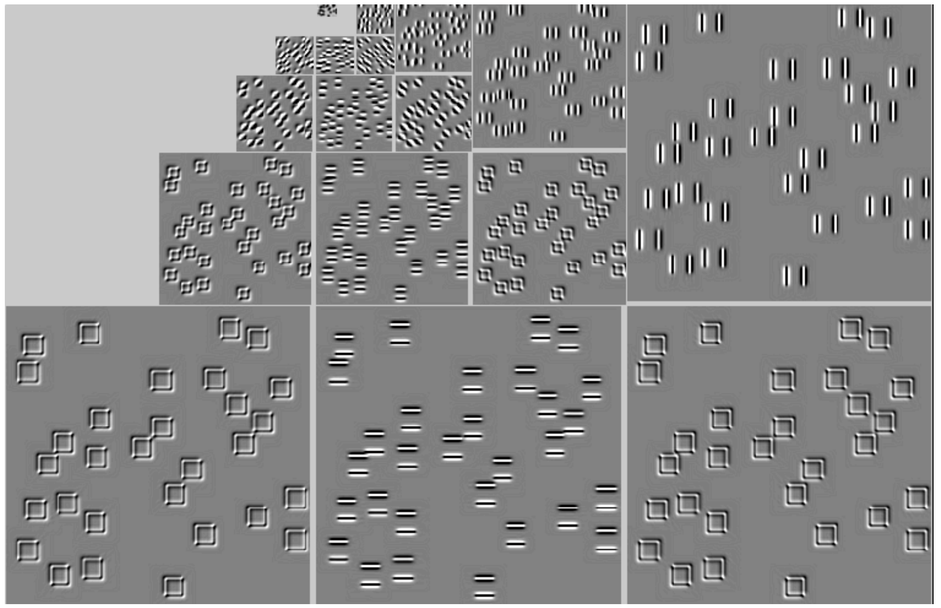
2- matching histograms

1-The steerable pyramid

Input texture



Steerable pyr



Overview of the algorithm

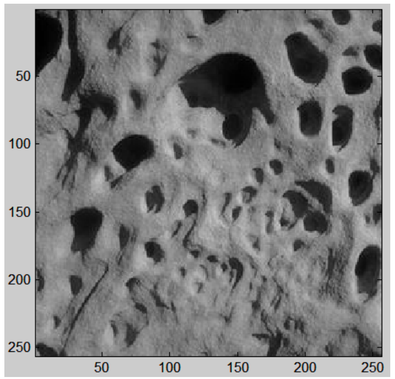
```
Match-texture(noise,texture)
  Match-Histogram (noise,texture)
   analysis-pyr = Make-Pyramid (texture)
   Loop for several iterations do
      synthesis-pyr = Make-Pyramid (noise)
      Loop for a-band in subbands of analysis-pyr
           for s-band in subbands of synthesis-pyr
           do
           Match-Histogram (s-band,a-band)
      noise = Collapse-Pyramid (synthesis-pyr)
      Match-Histogram (noise,texture)
```

Two main tools:

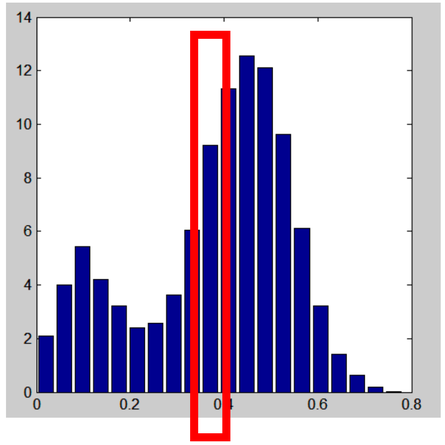
1- steerable pyramid

2- matching histograms

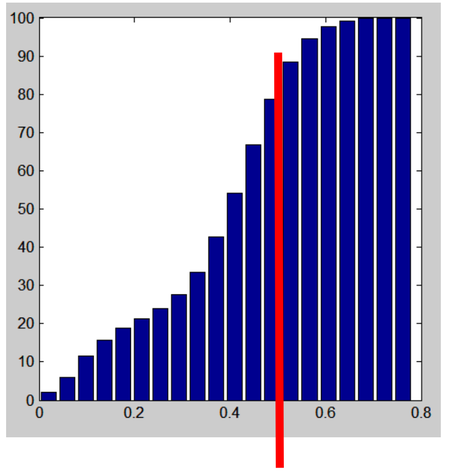
2-Matching histograms



Histogram

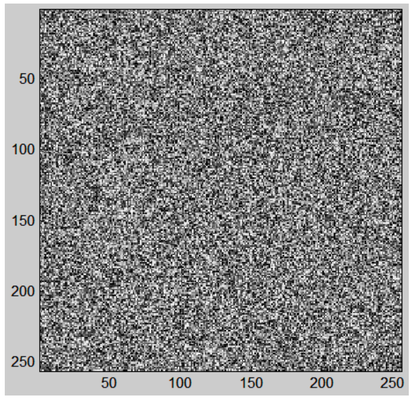


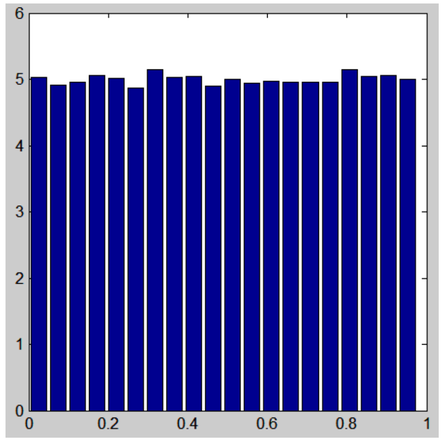
Cumulative distribution

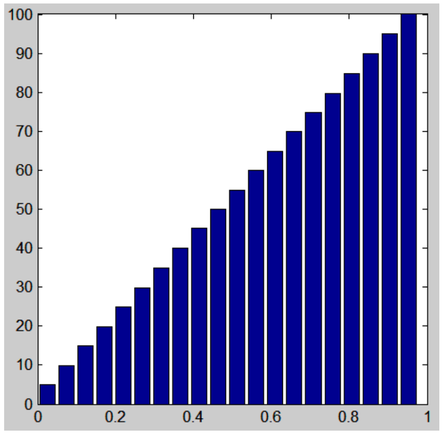


9% of pixels have an intensity value within the range[0.37, 0.41]

75% of pixels have an intensity value smaller than 0.5



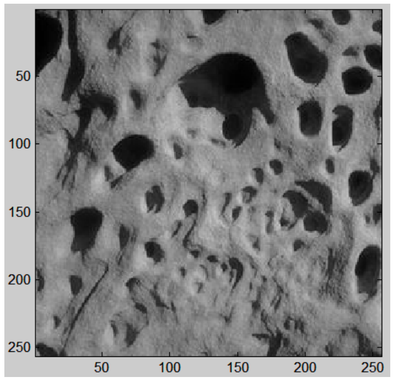


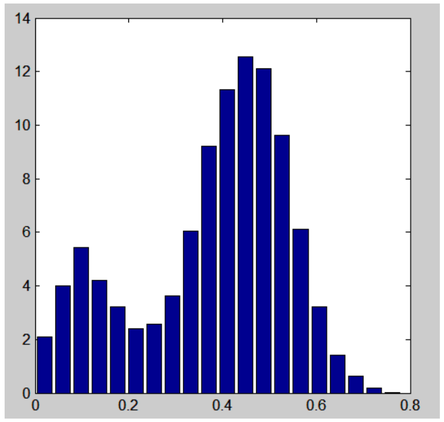


5% of pixels have an intensity value within the range[0.37, 0.41]

2-Matching histograms

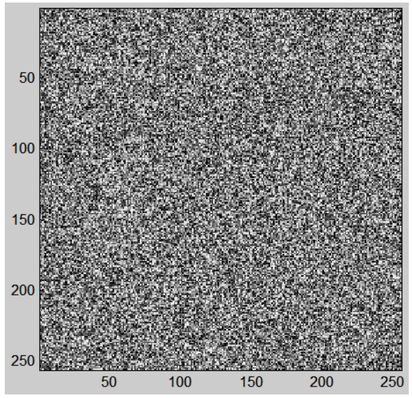
Z[n,m]

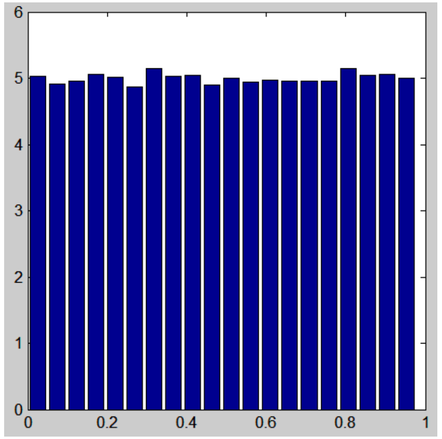




?

Y[n,m]





We look for a transformation
of the image Y

Y' = f (Y)

Such that
Hist(Y) = Hist(f(Z))

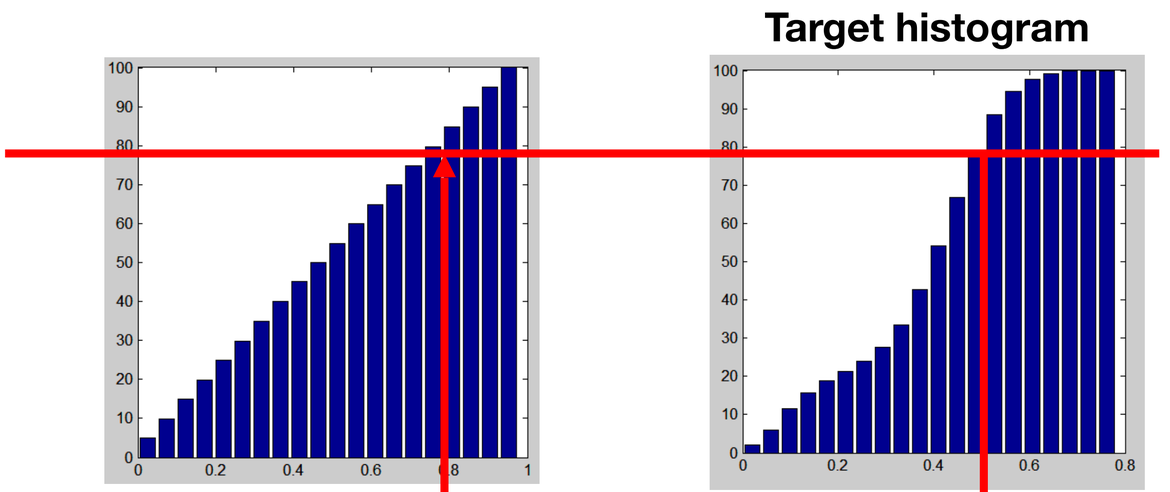
There are infinitely many functions
that can do this transformation.

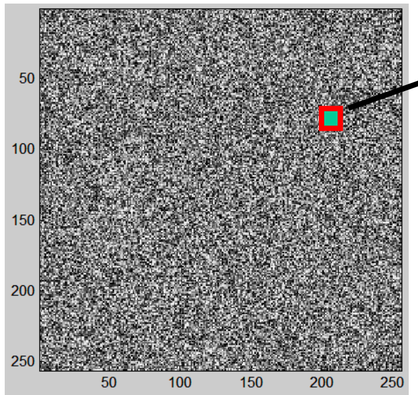
A natural choice is to use **f** being:
- point-wise non linearity
- stationary
- monotonic (most of the time invertible)

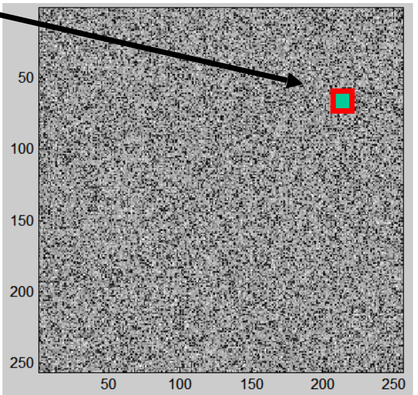
2-Matching histograms

The function f is just a look up table: it says, change all the pixels of value Y into a value f(Y).

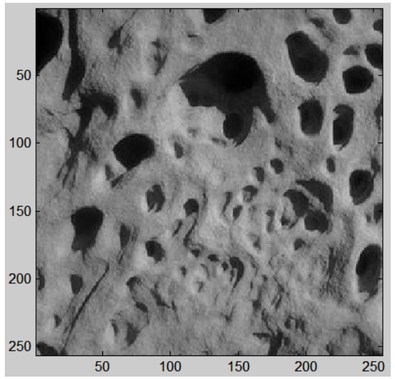
$$Y' = f(Y)$$

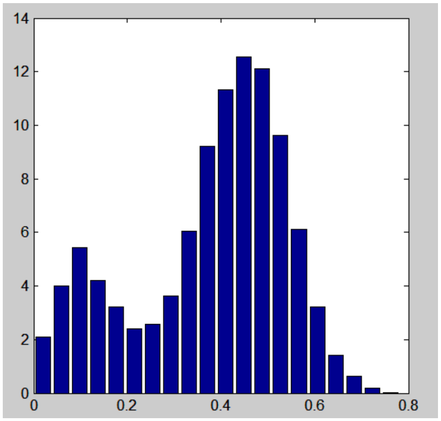


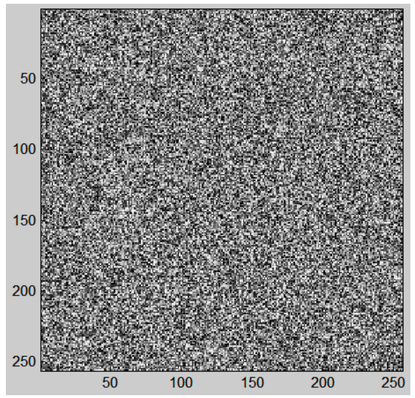




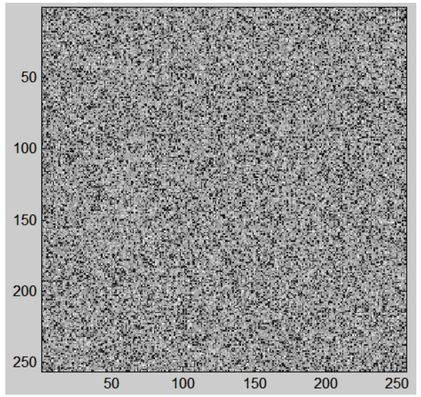
2-Matching histograms

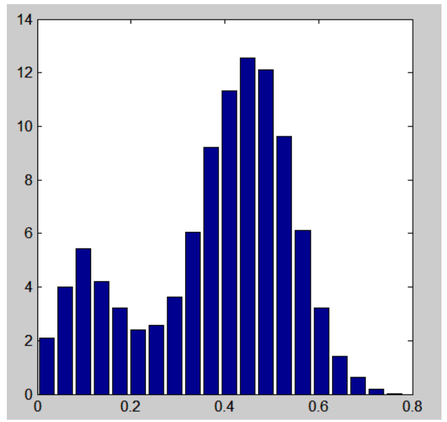




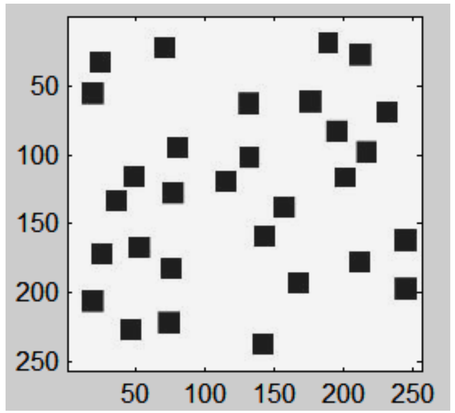


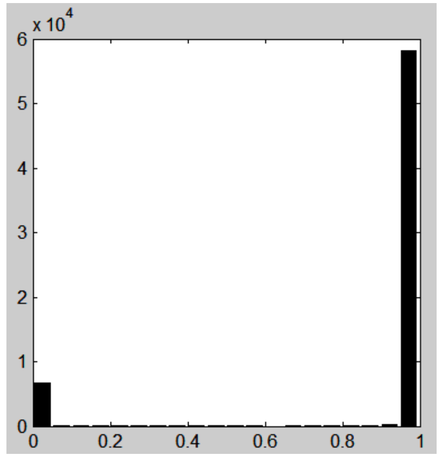
Y' = f (Y)

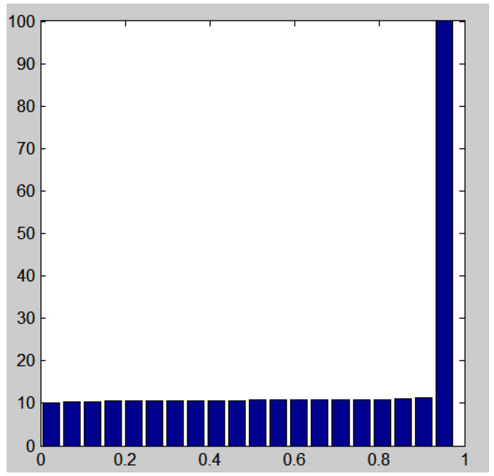




Another example: Matching histograms



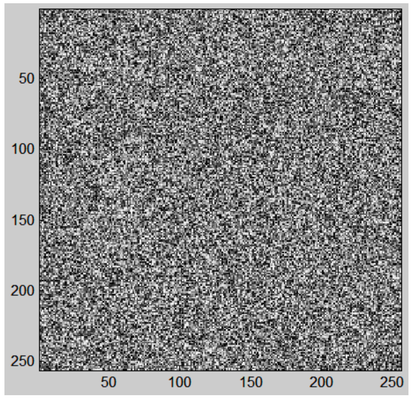


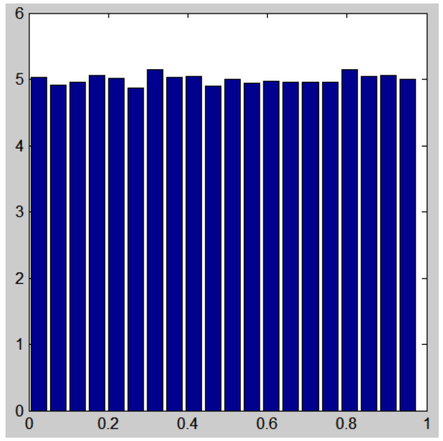


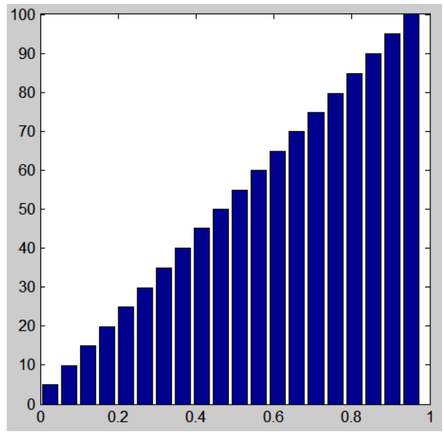
?

?

10% of pixels are black
and 90% are white



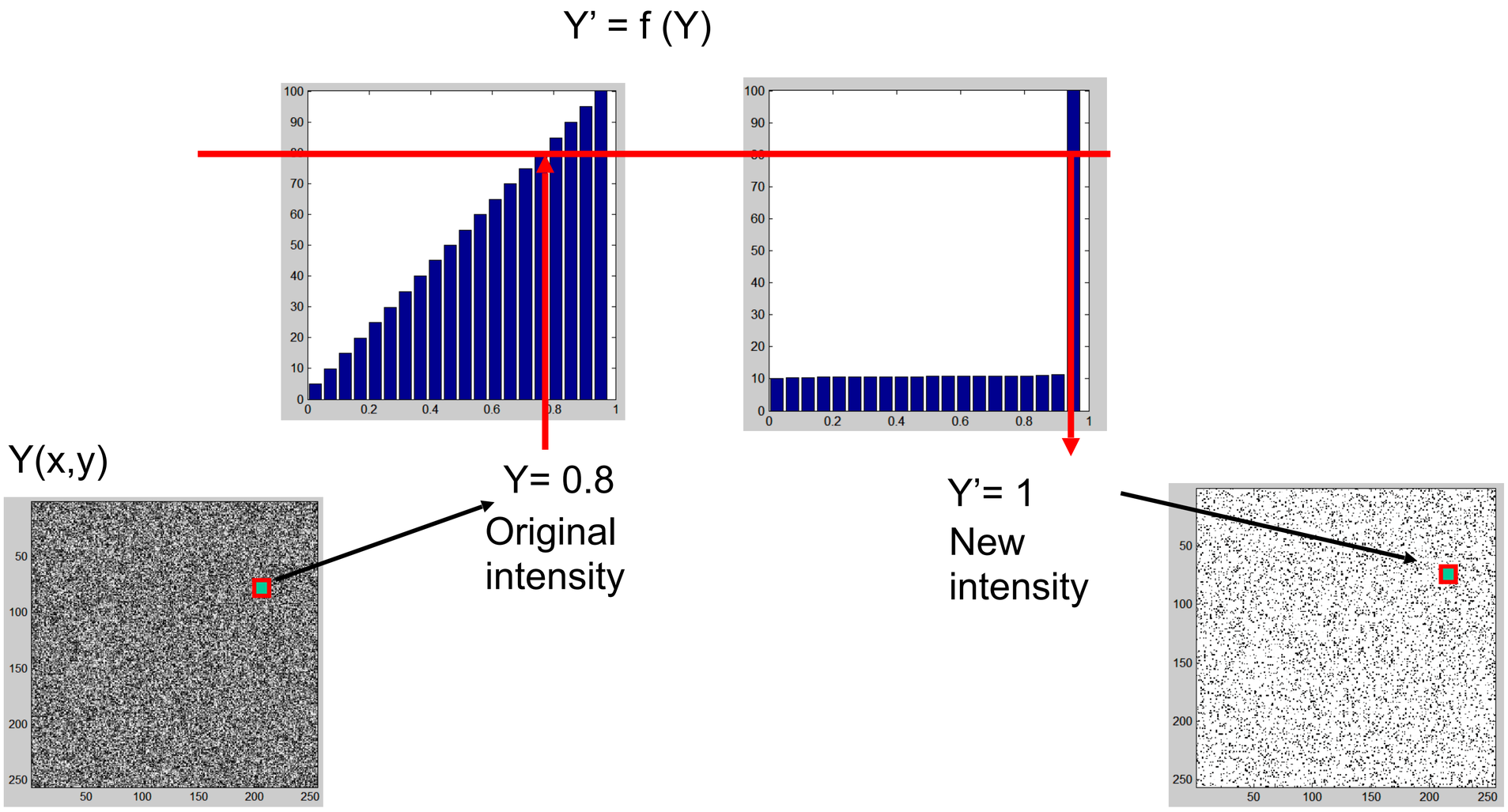




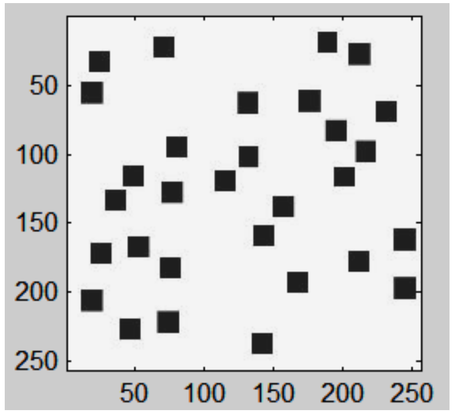
5% of pixels have an intensity value
within the range[0.37, 0.41]

Another example: Matching histograms

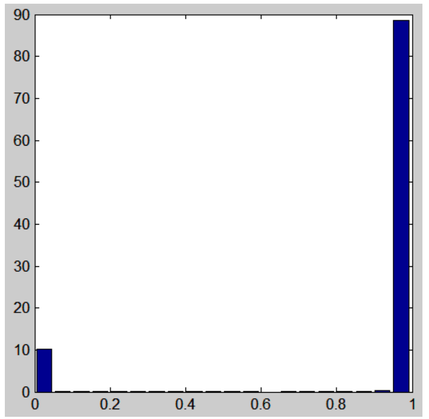
The function f is just a look up table: it says, change all the pixels of value Y into a value f(Y).

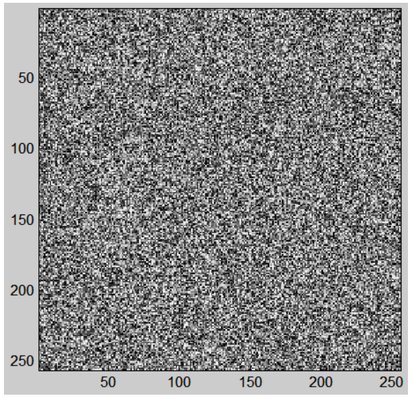


Another example: Matching histograms

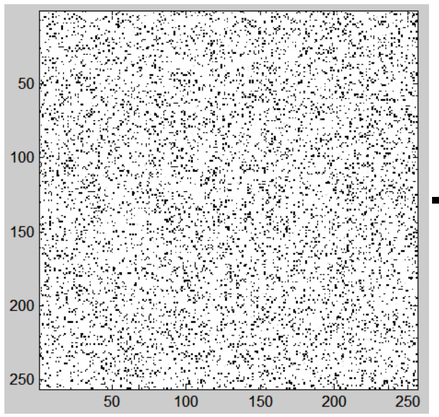


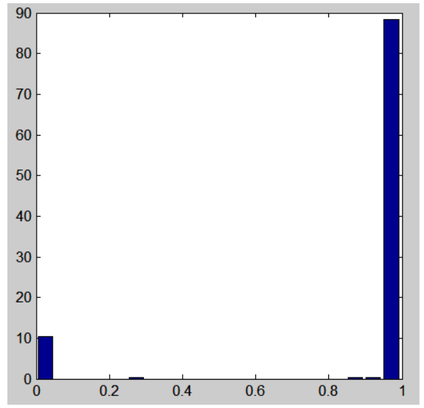
Cumulative distribution





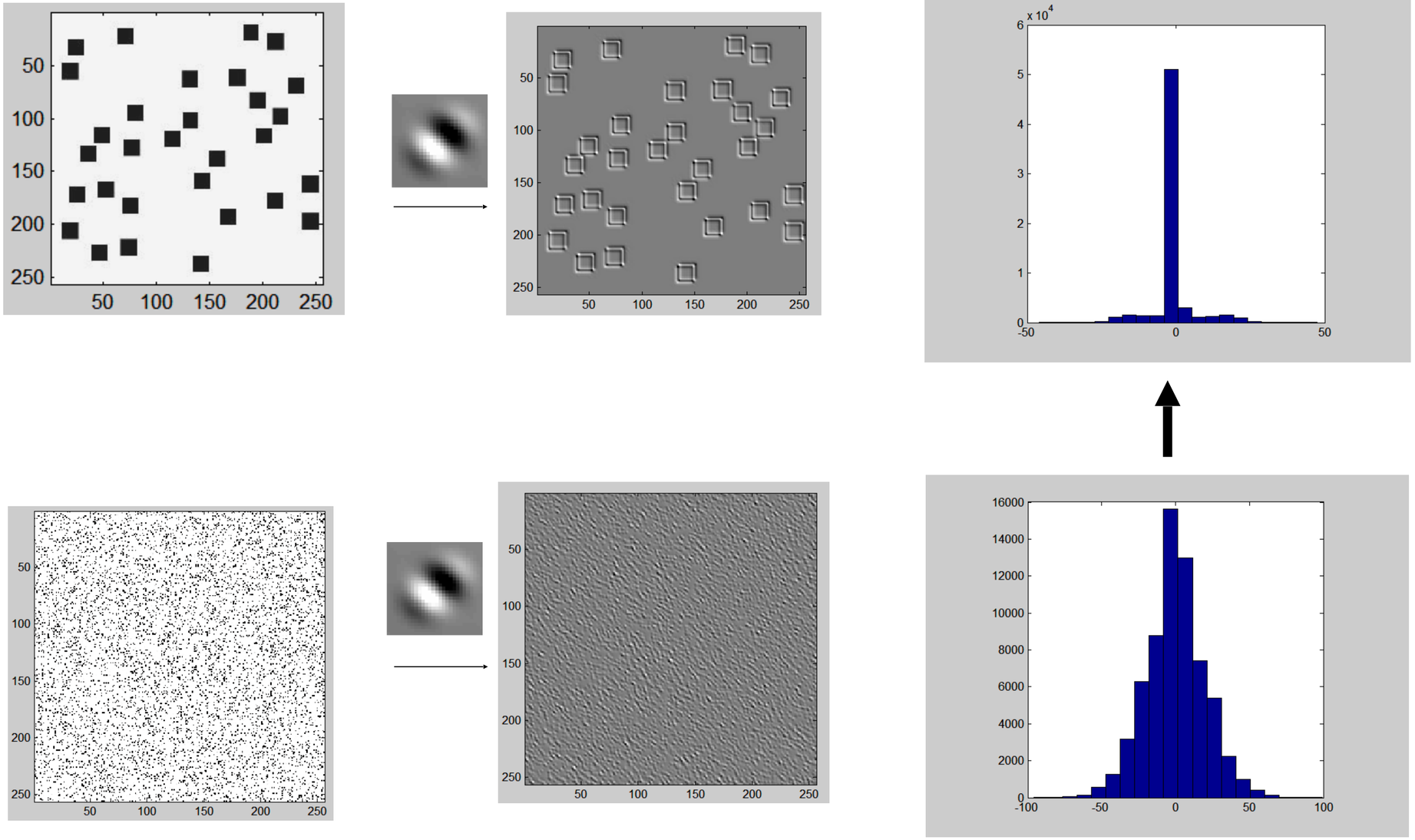
Y’ = f (Y)



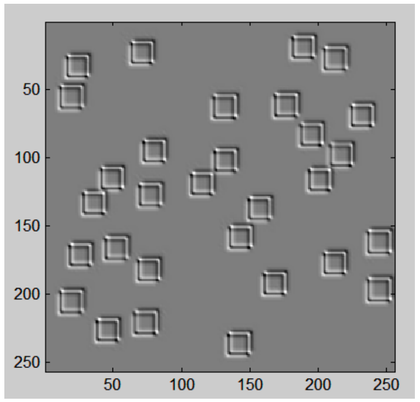


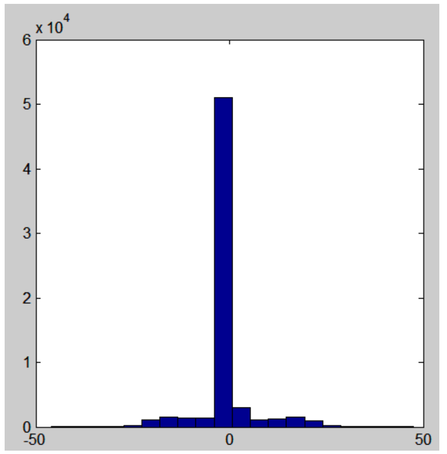
In this example, f is a step function.

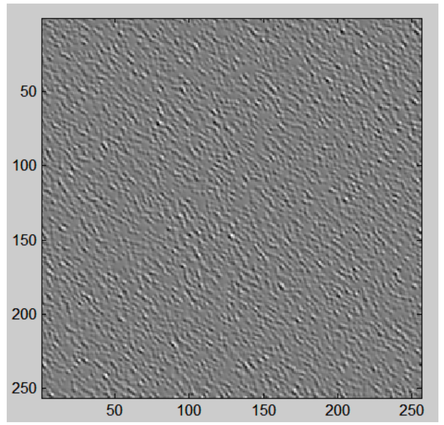
Matching histograms of a subband



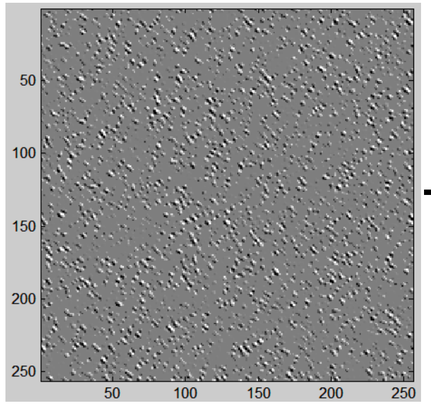
Matching histograms of a subband

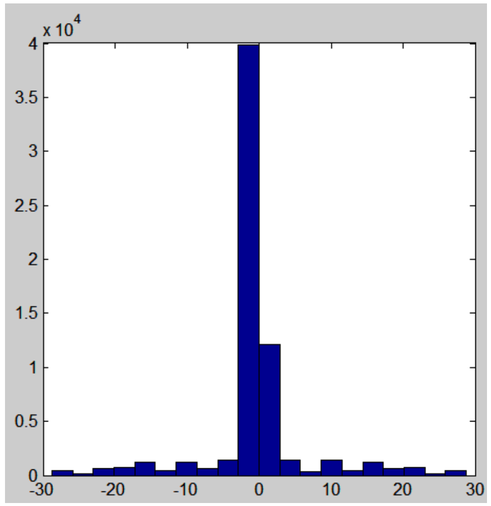






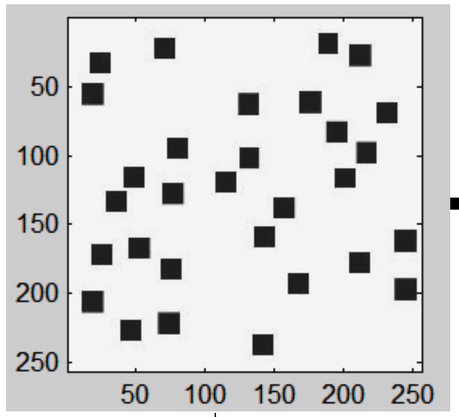
Y’ = f (Y)



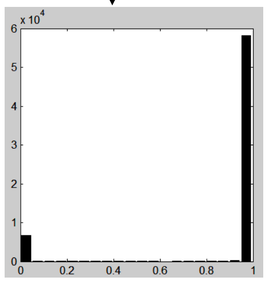


Texture analysis

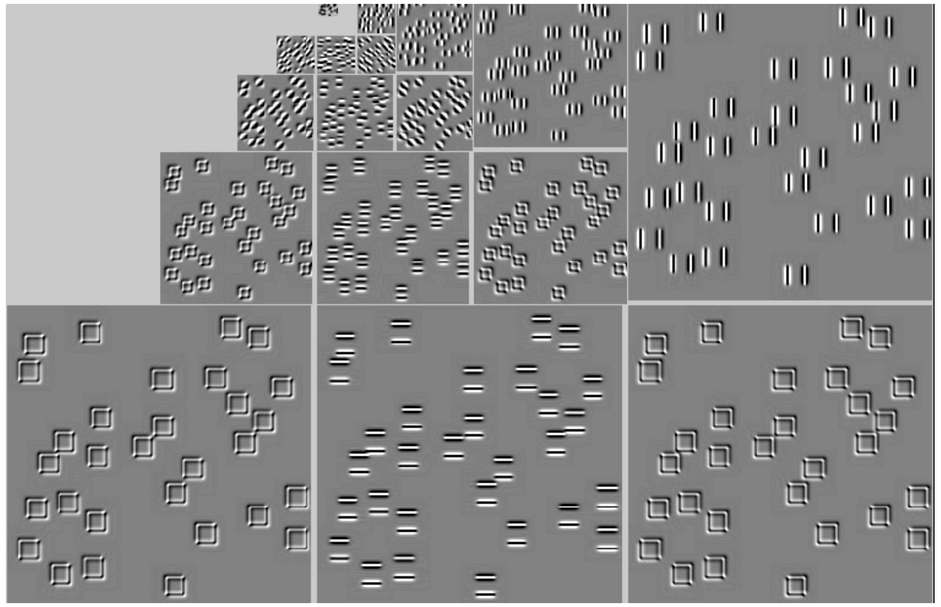
Input texture



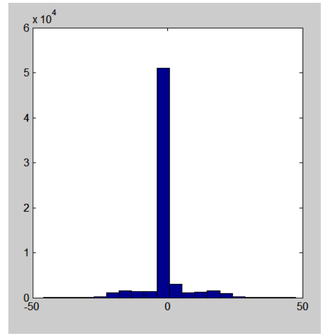
(histogram)



Steerable pyramid



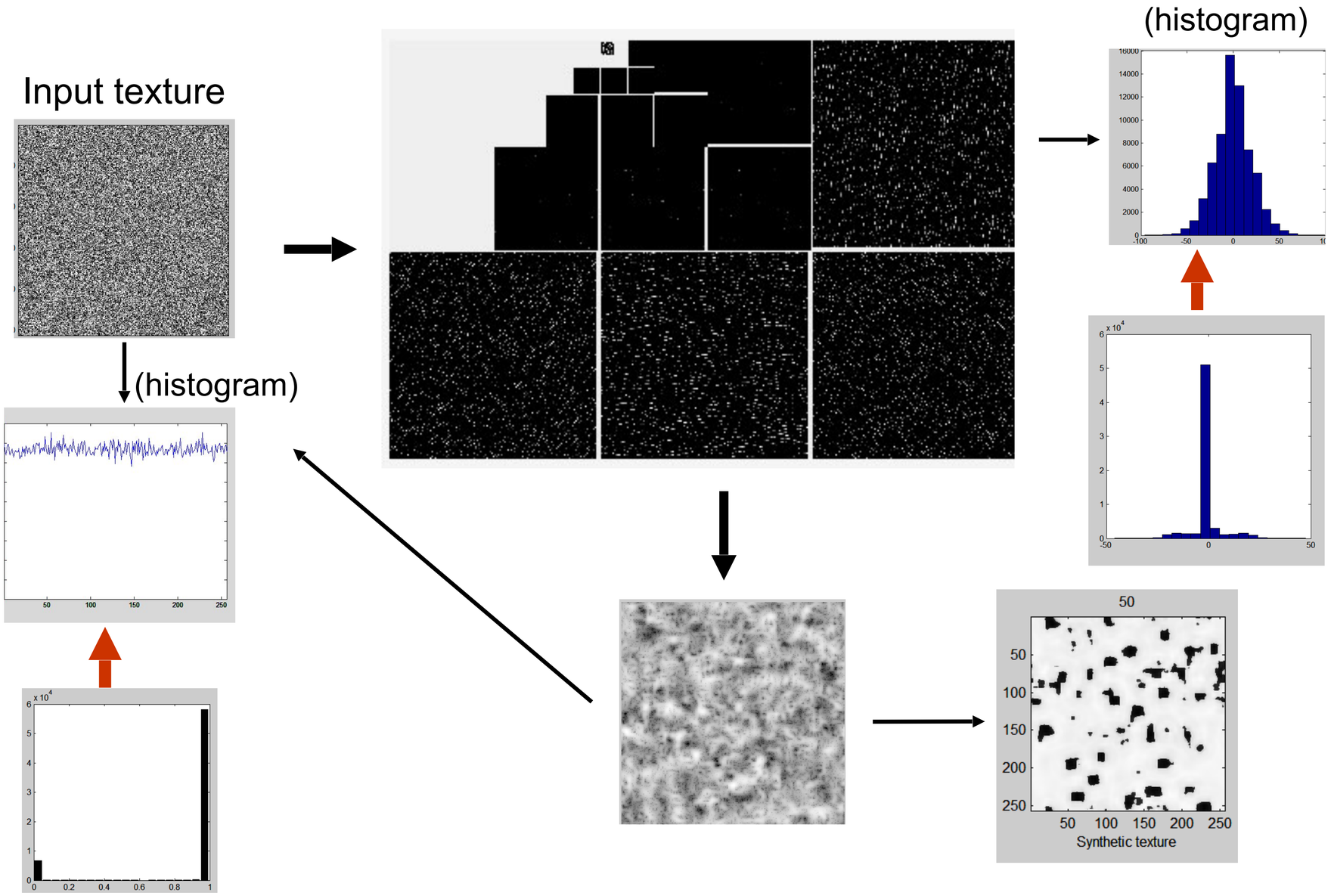
(histogram)



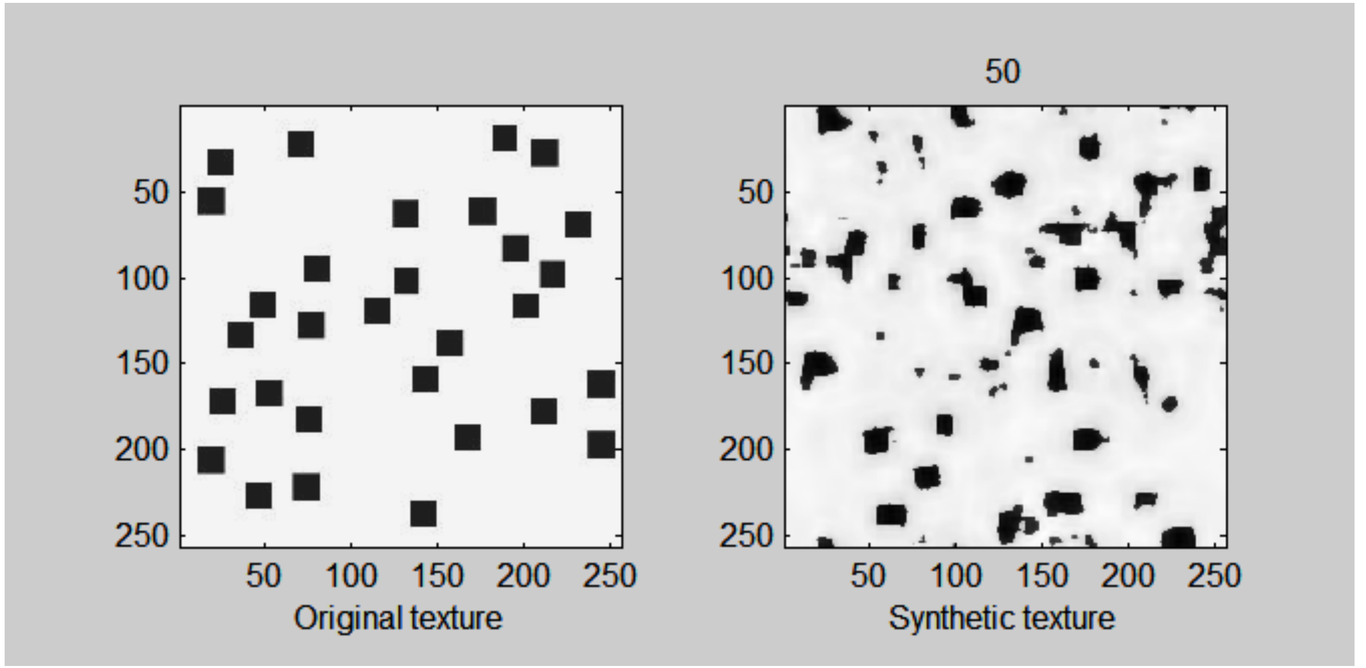
The texture is represented as a collection of marginal histograms.

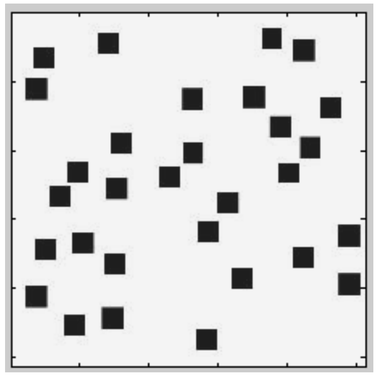
Heeger and Bergen, 1995

Texture synthesis



Why does it work? (sort of)



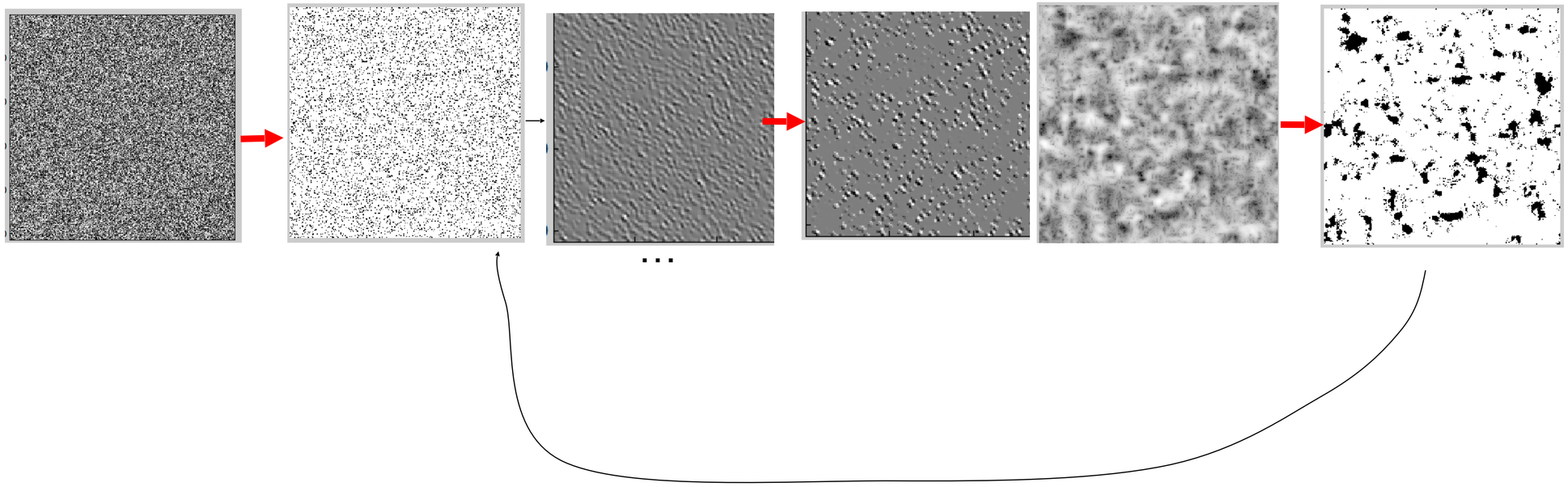


Why does it work? (sort of)

The black and white blocks appear by thresholding (f) a blobby image

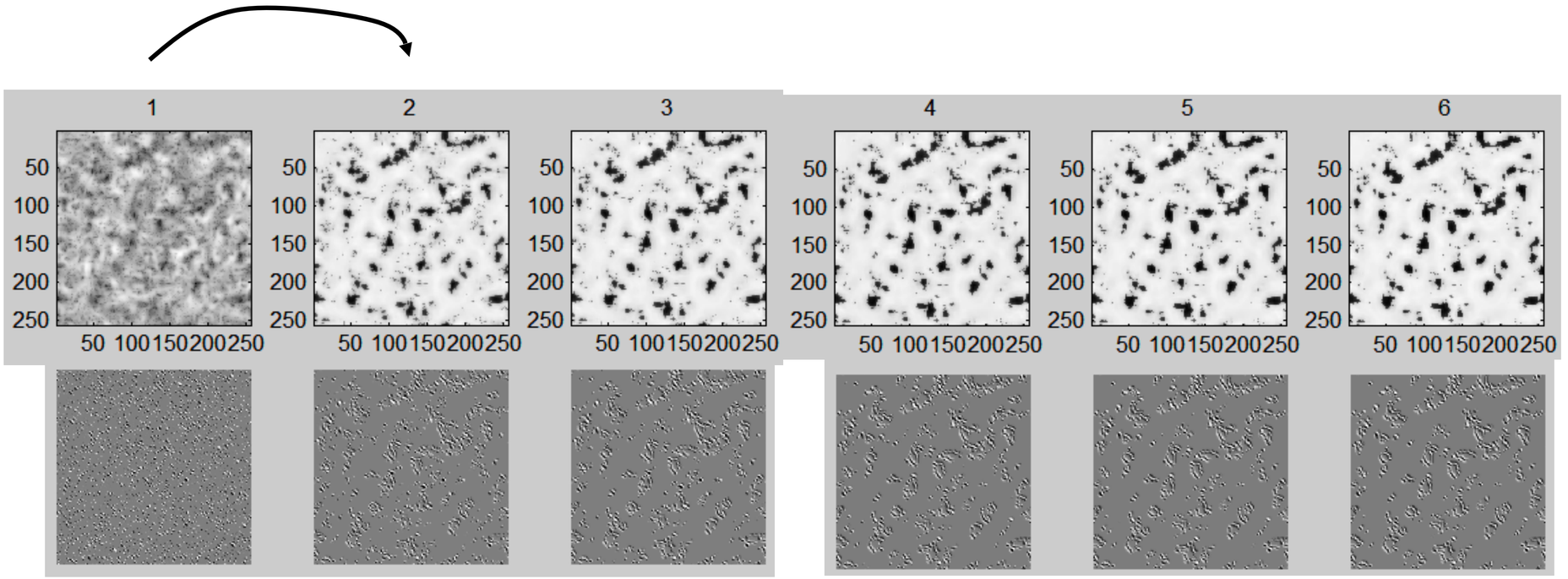
Iteration 0

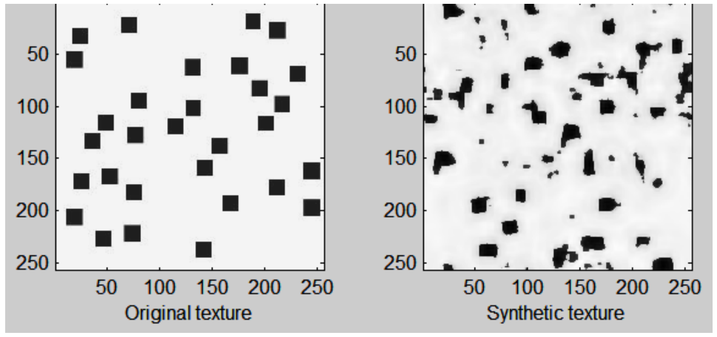
Filter bank



Why does it work? (sort of)

The black and white blocks appear by thresholding (f) a blobby image





Examples from the paper

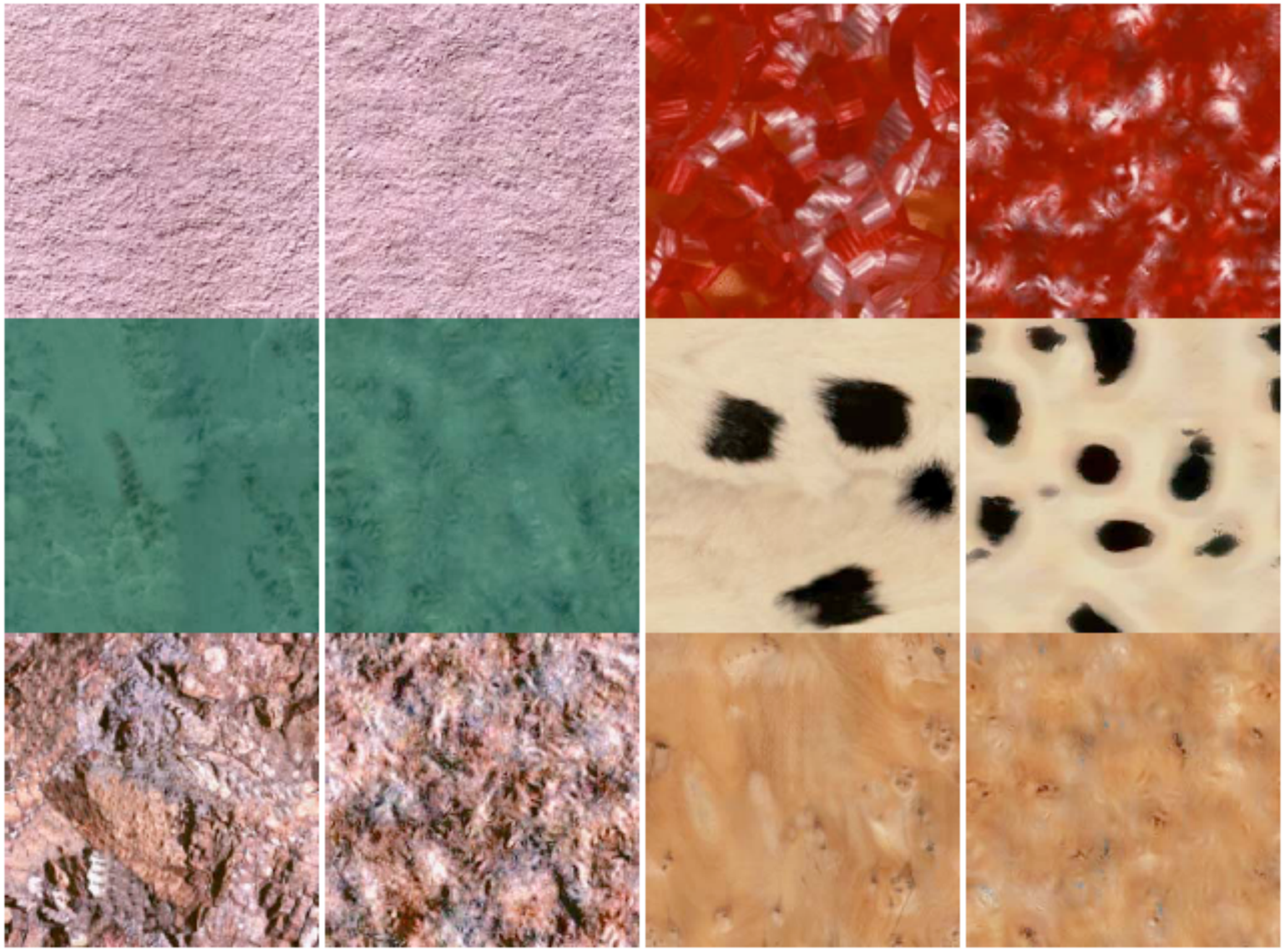


Figure 3: In each pair left image is original and right image is synthetic: stucco, iridescent ribbon, green marble, panda fur, slag stone, figured yew wood.

Heeger and Bergen, 1995

Examples from the paper

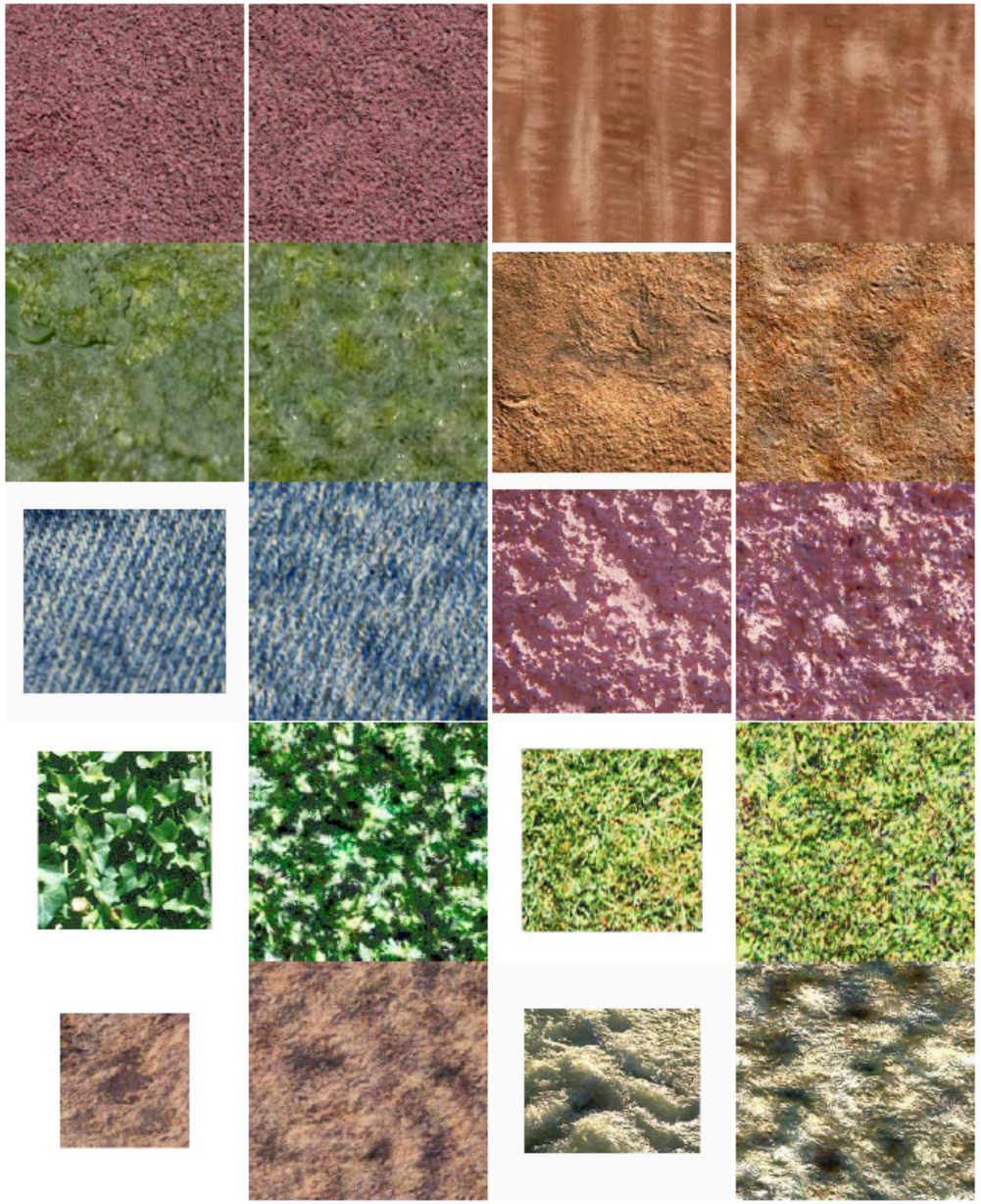
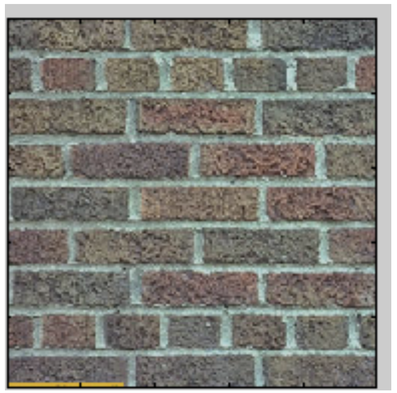


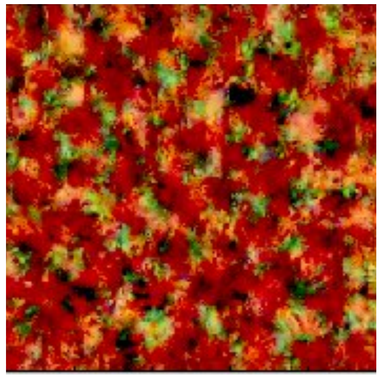
Figure 4: In each pair left image is original and right image is synthetic: red gravel, figured sepele wood, brocolli, bark paper, denim, pink wall, ivy, grass, sand, surf.

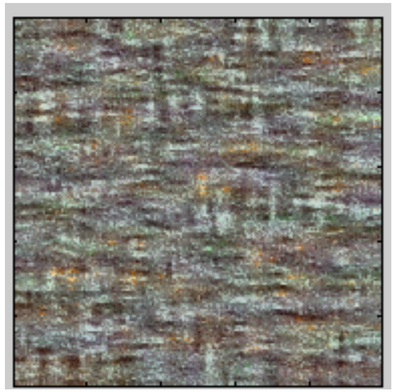
Examples not from the paper

Input texture



Synthetic texture





But, does it really work even when it seems to work?

The main idea: it works by ‘kind of’ projecting a random image into the set of equivalent textures