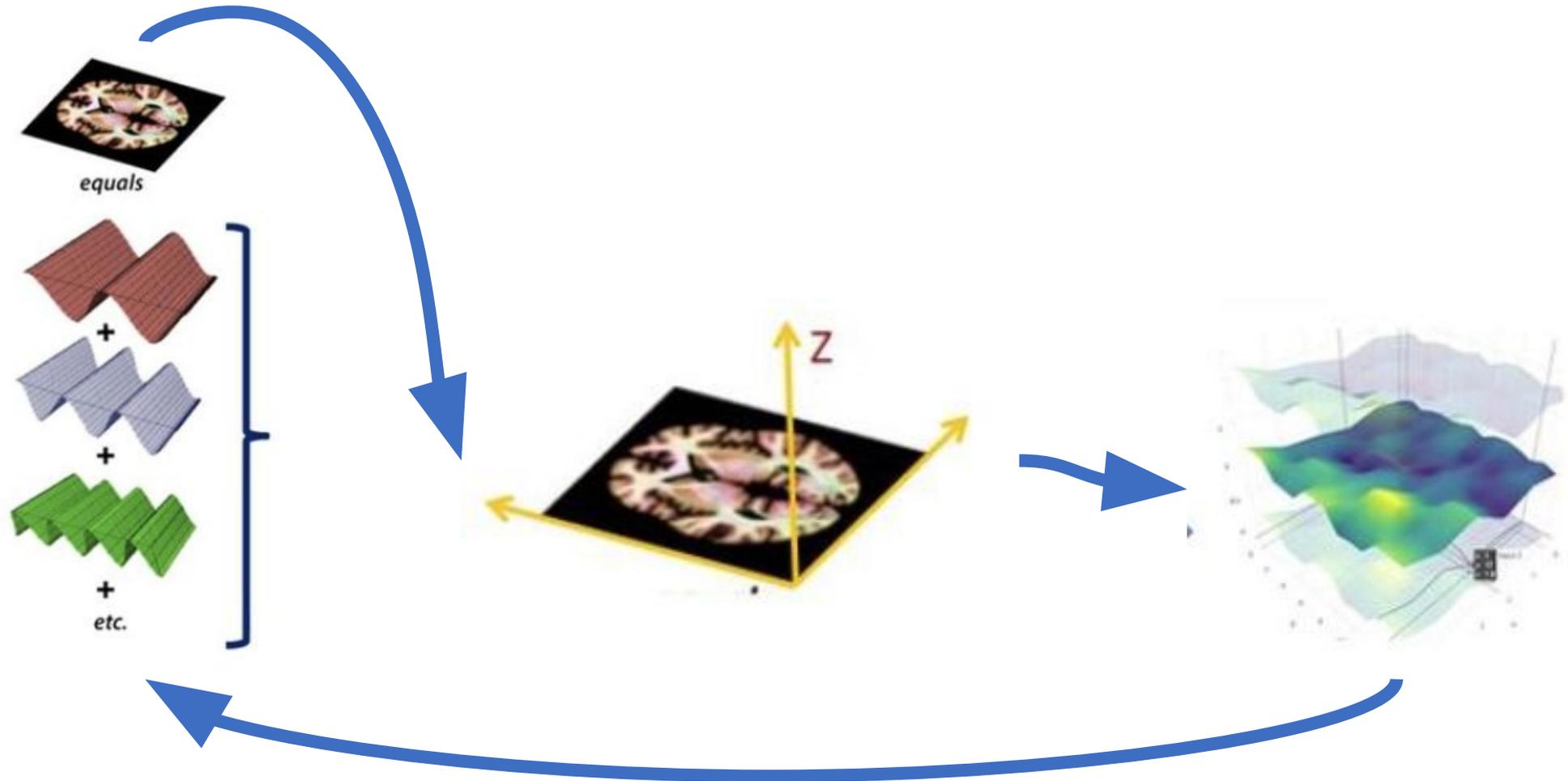


# Discussion 3 – Pyramids & FFT

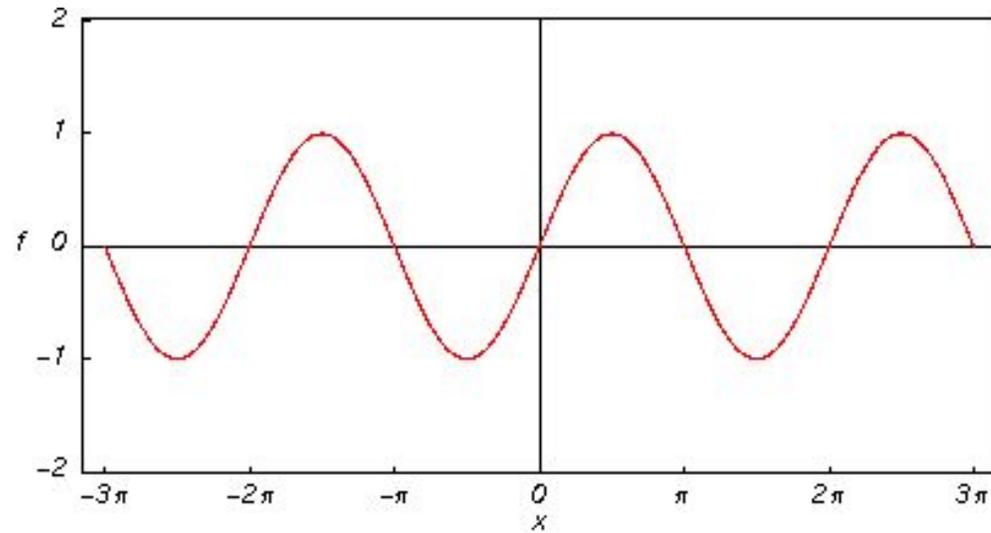
EECS 442 - Fall 2023

# 2D Fourier Transform

# 2D Fourier Transform



# 2D Fourier Transform



- Amplitude
- Frequency
- Phase
- Direction

# Pairs of Fourier Transforms

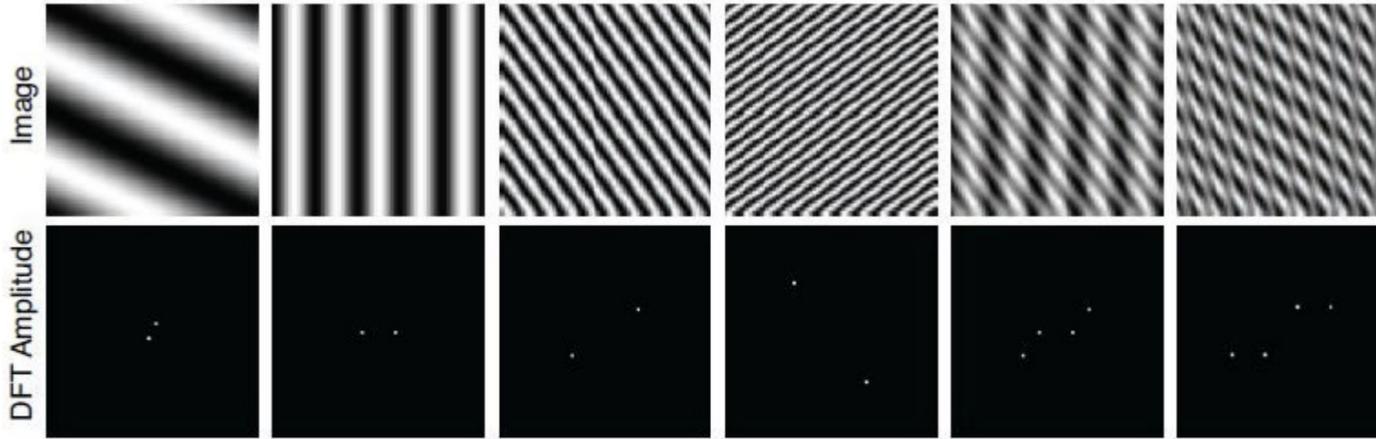


Figure 2.6: Some two-dimensional Fourier transform pairs. Images are  $64 \times 64$  pixels. The waves are *cos* with frequencies  $(1, 2)$ ,  $(5, 0)$ ,  $(10, 7)$ ,  $(11, -15)$ . The last two examples show the sum of two waves and the product.

$$X(m) = \sum_{n=0}^{N-1} x(n) [\cos(2\pi nm/N) - i \sin(2\pi nm/N)]$$

- $X(m)$ :  $m^{\text{th}}$  output of DFT, e.g. ,  $X(0), X(1), \dots, X(m)$
- $x(n)$ : Input samples, e.g. ,  $x(0), x(1), \dots, x(n)$
- $i$ : Imaginary numbers line
- $N$ : length of Input

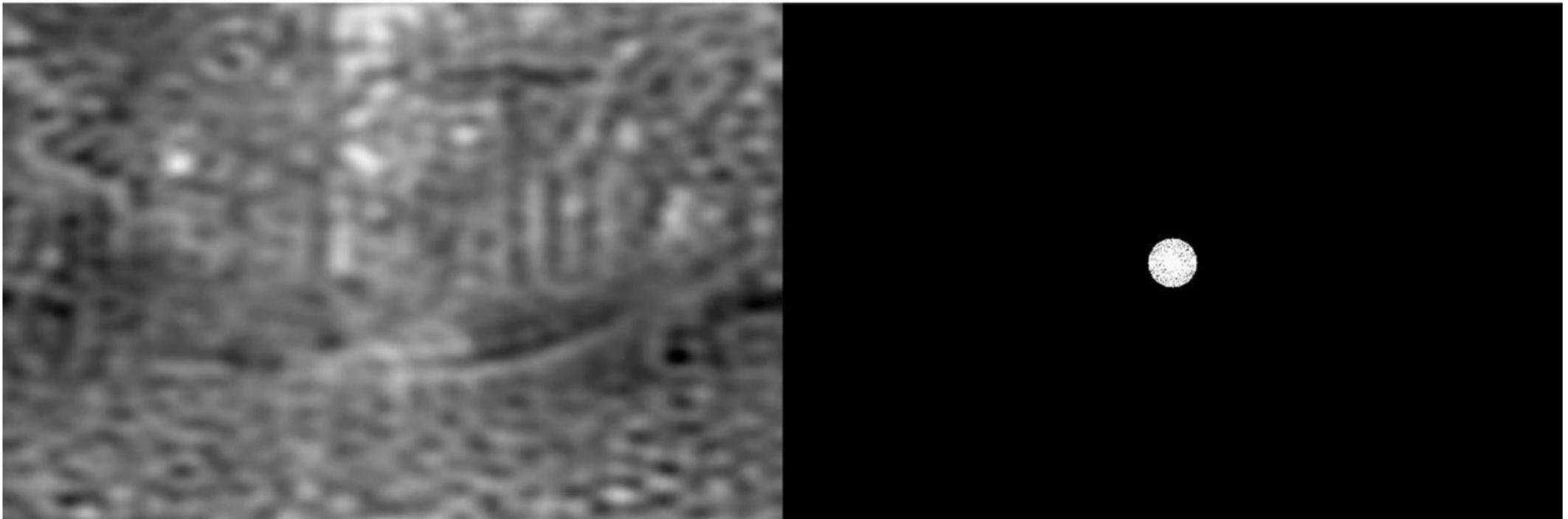
$$X_{\text{mag}}(m) = |X(m)| = \sqrt{X_{\text{real}}(m)^2 + X_{\text{imag}}(m)^2}$$

$$X_{\phi}(m) = \tan^{-1} \left( \frac{X_{\text{imag}}(m)}{X_{\text{real}}(m)} \right)$$

$$f(m) = \frac{mf_s}{N}$$

# Reconstruct an image, low frequency to high

0.5%



Image

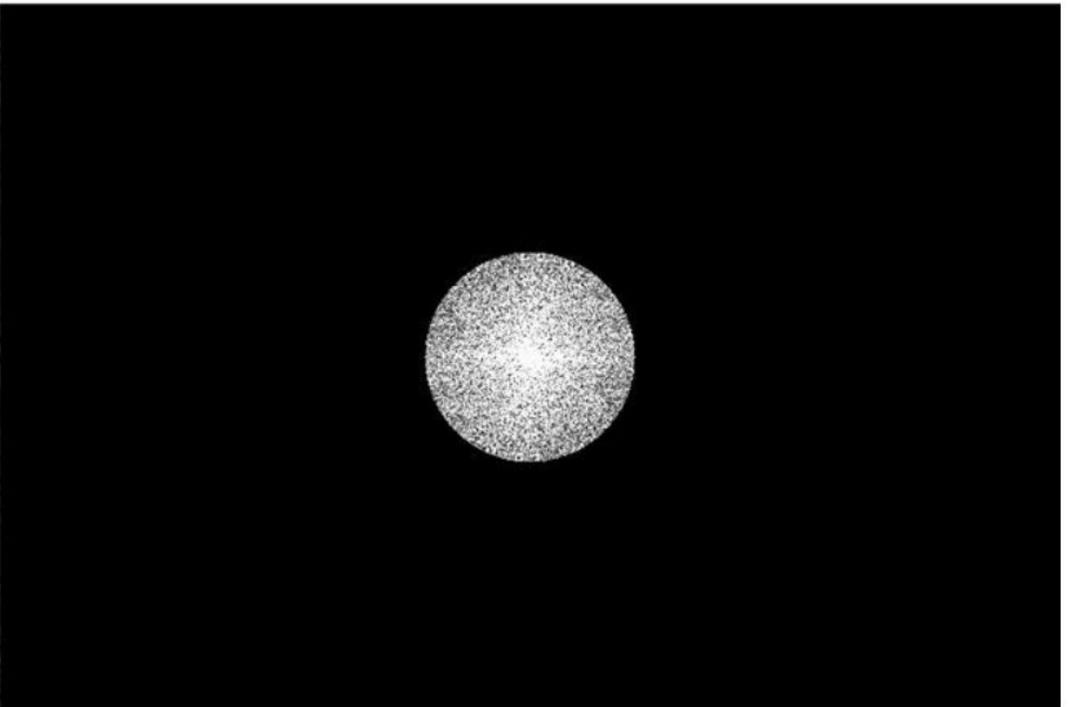
DFT

# Reconstruct an image, low frequency to high

4.6%



Image



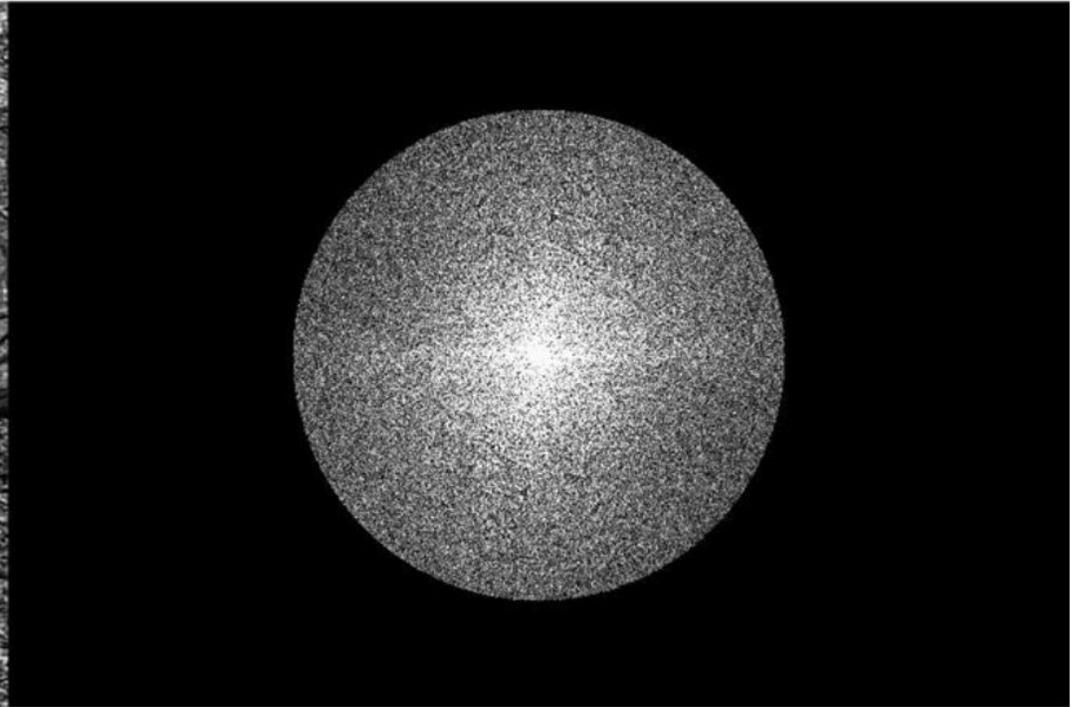
DFT

# Reconstruct an image, low frequency to high

25.2%

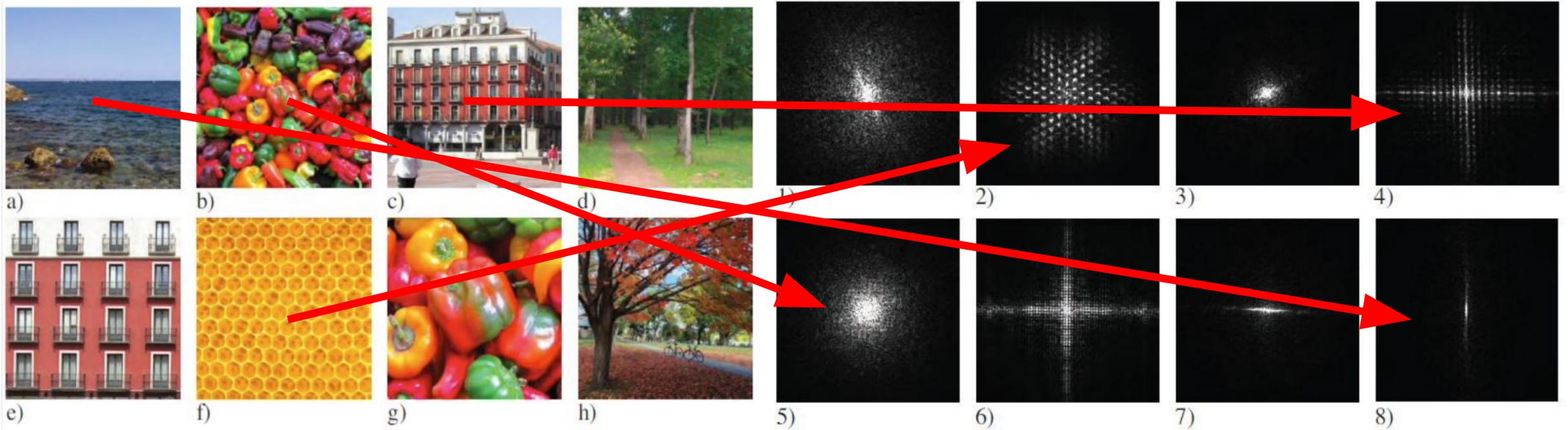


Image



DFT

# Fourier Matching Game



Match each image (a-h) with its corresponding Fourier transform magnitude (1-8)

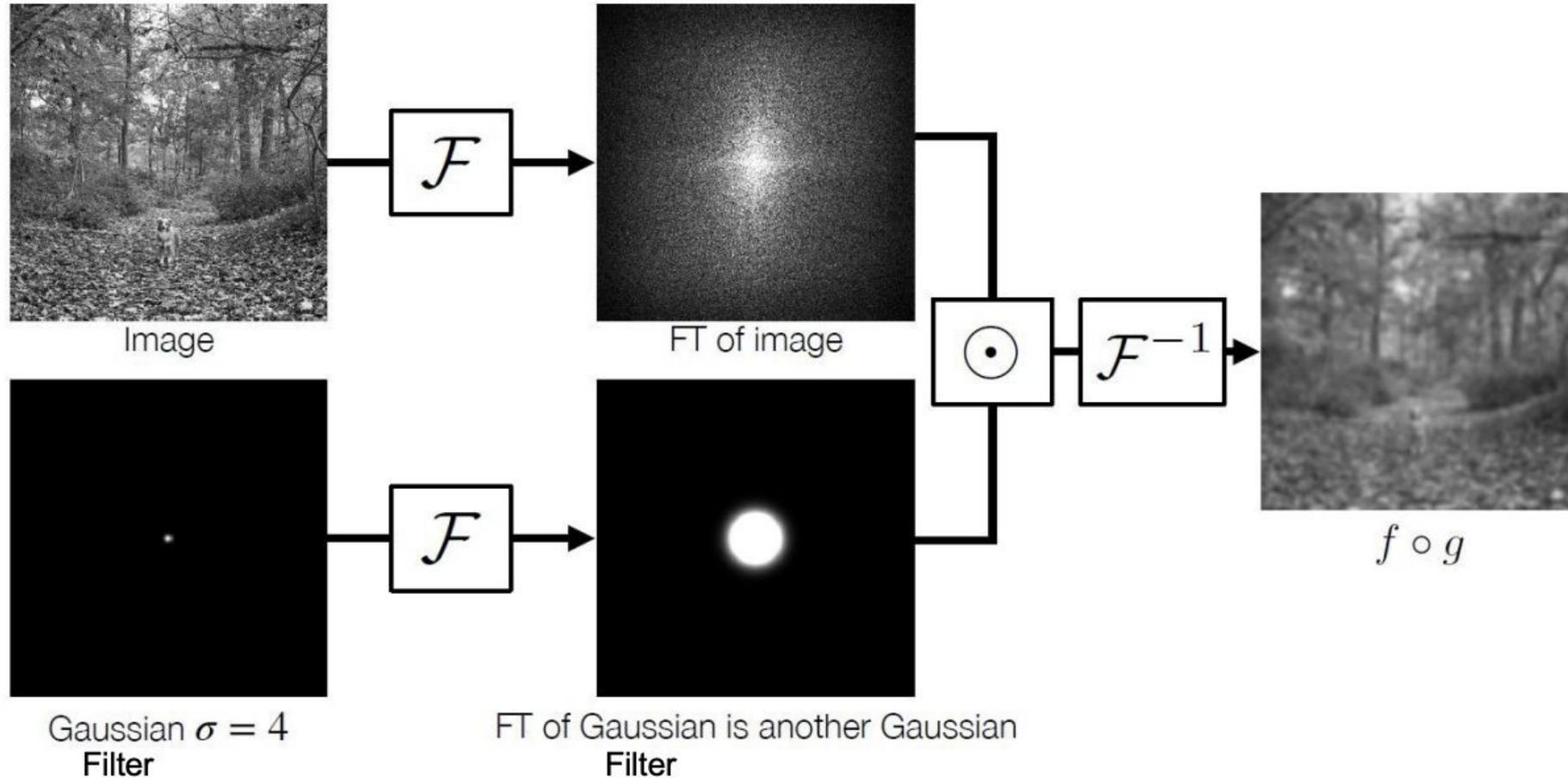
# Convolution Theorem of Fourier Transform

- 2D Fourier transform is separable (just like Gaussian)
- Computable in  $O(n \log n)$  (using FFT)
- Convolution Theorem: convolution is pointwise multiplication in the Fourier domain!

$$\mathcal{F}\{f \circledast g\} = \mathcal{F}\{f\} \odot \mathcal{F}\{g\}$$

- Useful trick for fast convolutions, especially for large filters

# Convolution Theorem Example



# Convolution Theorem – Why it matters?

## Conv in space domain

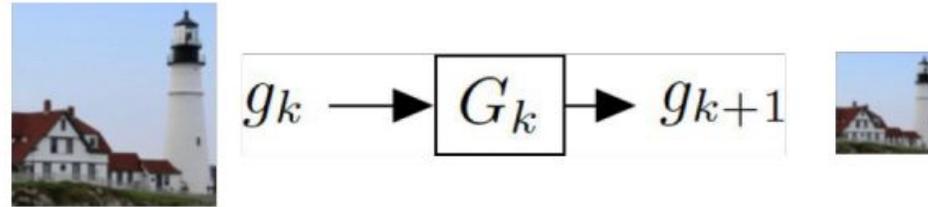
- Convolve the whole image with a filter
- Expensive to compute
- $O(n^4)$  for 2D convolution

## Conv in frequency domain

- FFT + Pointwise multiplications
- Much faster to compute
- $O(n^2 \log^2(n))$  for 2D FFT

# Gaussian & Laplacian Pyramids

# Gaussian Pyramid Logic



For each level

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



blur  
→

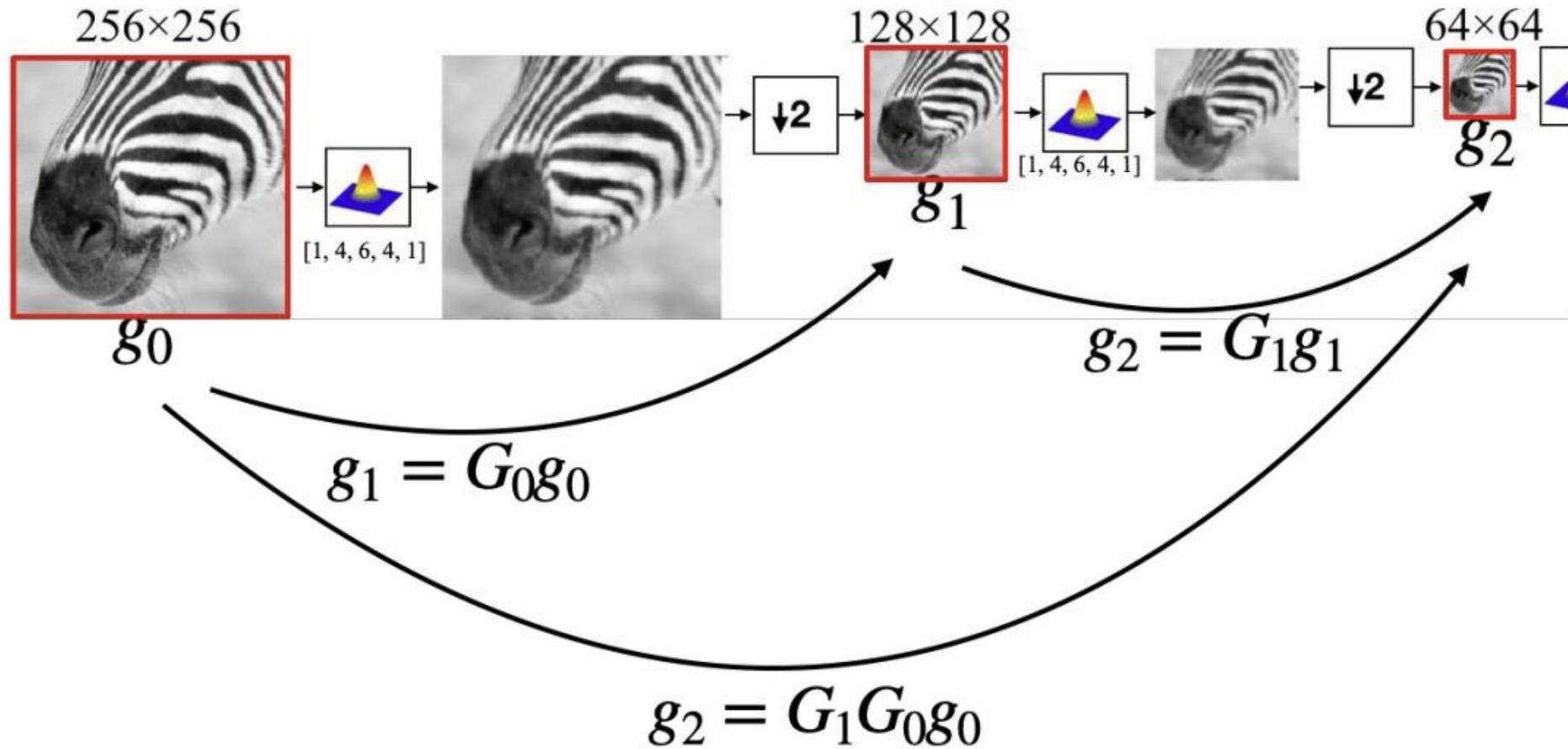


downsample  
→



What is  $G_k$ ?  
The operation including both blur  
and downsample

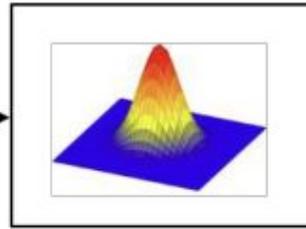
# Gaussian Pyramid



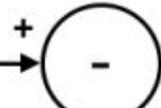
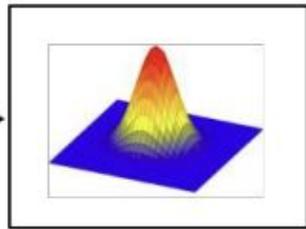
# Use of Laplacian



Gaussian filter  
(a.k.a. "low pass")

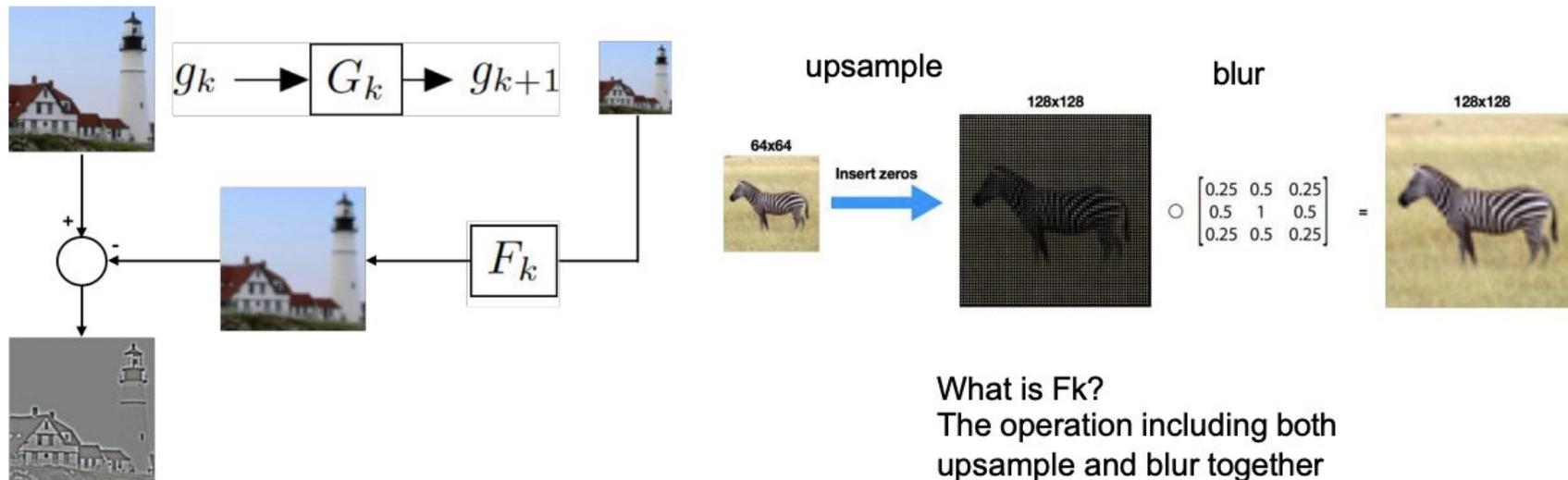


Approx. Laplacian  
(a.k.a. "high pass")

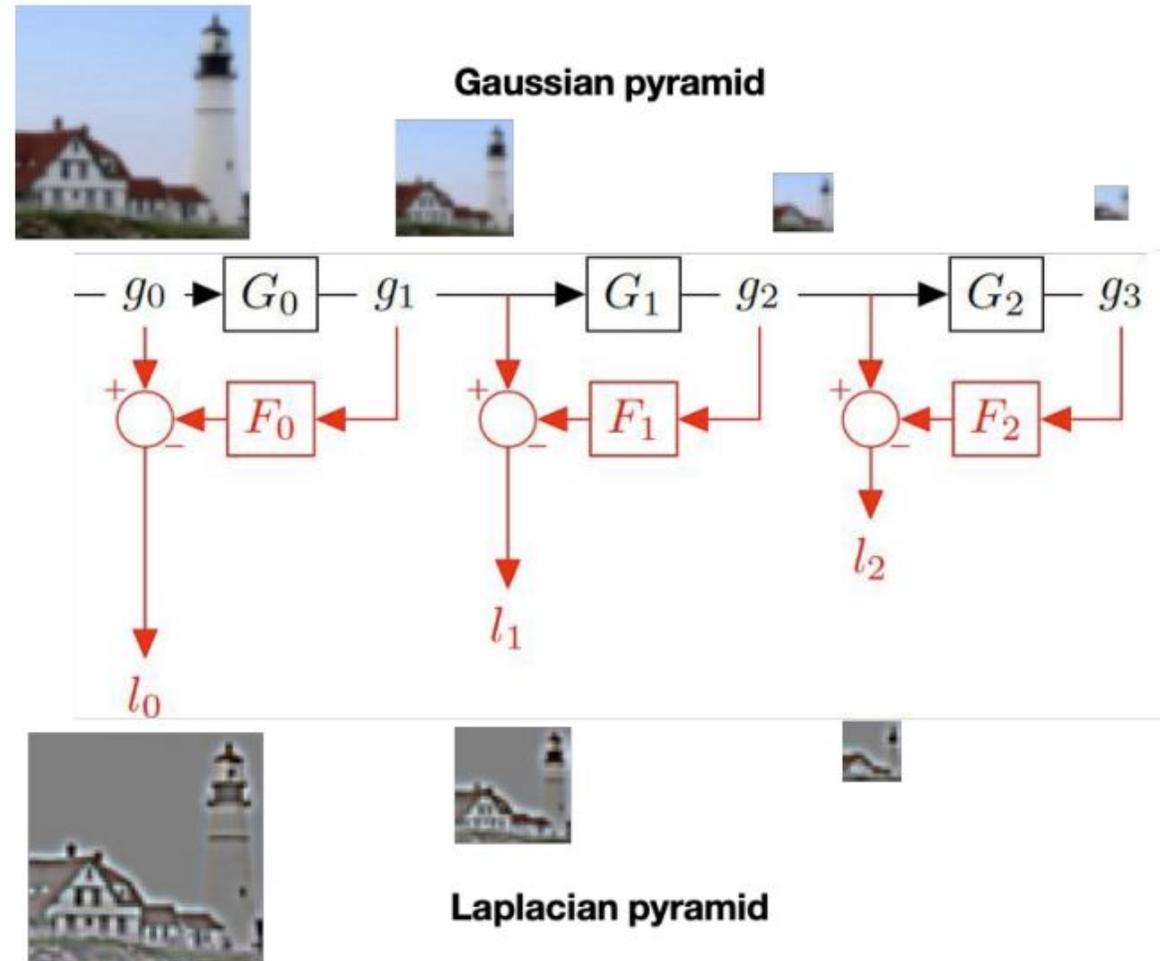


# Laplacian Pyramid

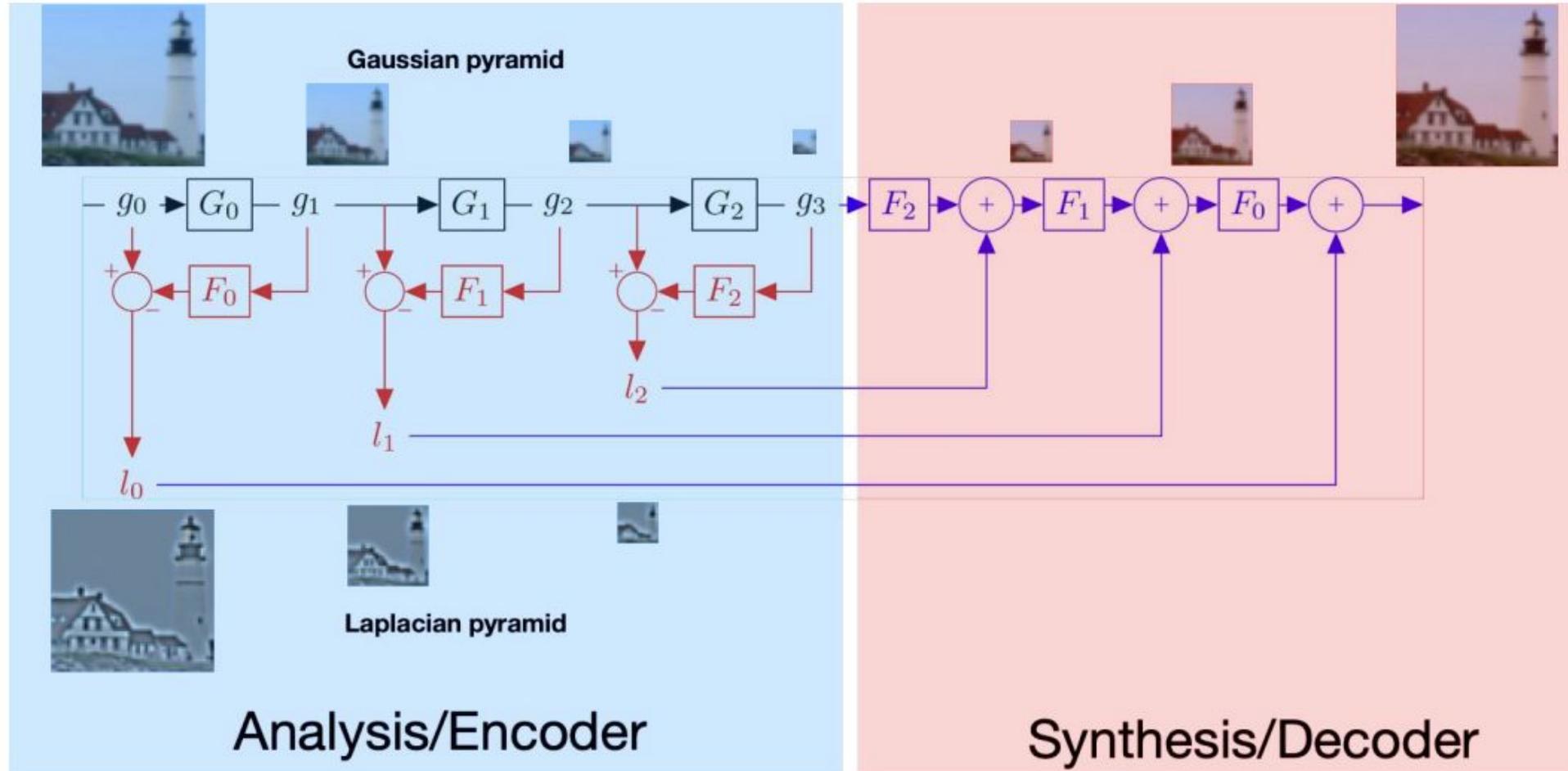
1. Upsample the Gaussian pyramid at level  $k+1$
2. Blur the upsampled Gaussian pyramid at level  $k+1$
3. The difference of Gaussian pyramid at level  $k$  and result from the 2nd step is the Laplacian pyramid



# Laplacian Pyramid



# Gaussian & Laplacian Pyramid



# Gaussian & Laplacian Pyramid - Applications

- Texture synthesis
- Image compression
- Noise removal
- Computing image “keypoints”

# Image Blending (PS2)

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

