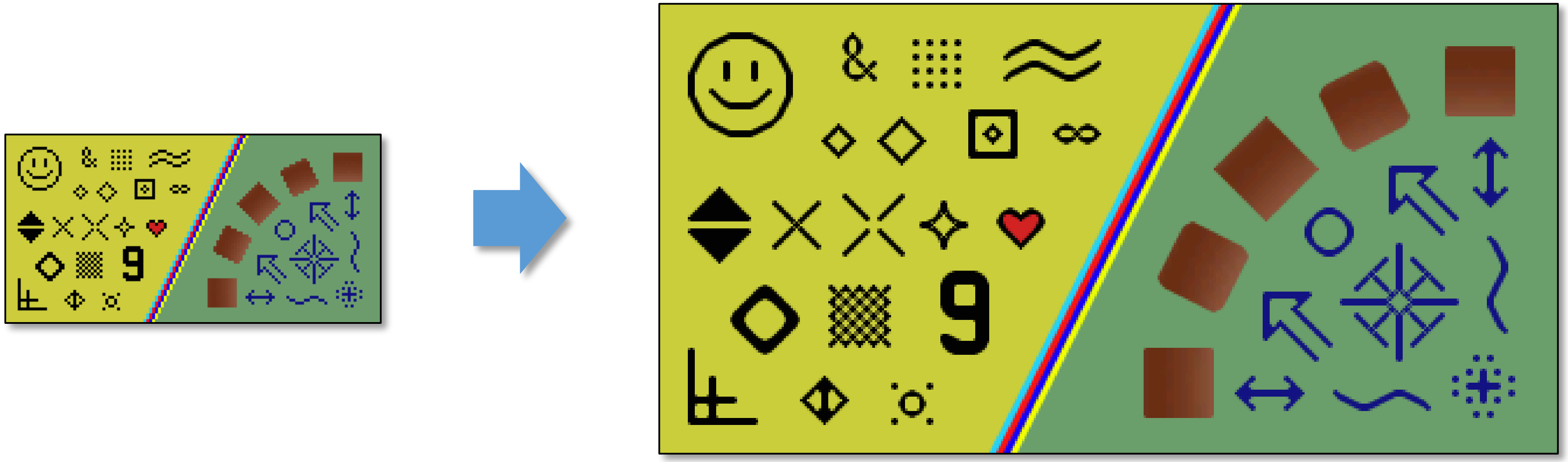
Image Pyramids

Image Resampling & Interpolation



Overview

- Image downsampling.
- Aliasing.
- Gaussian image pyramid.
- Laplacian image pyramid.

Slide Credits

Most of these slides are adapted from:

- Prof. Ioannis Gkioulekas, Carnegie Mellon University, (16-385 Computer Vision, Spring 2019).
- Prof. Noah Snavely, Cornell University(CS5670 Introduction to Computer Vision)

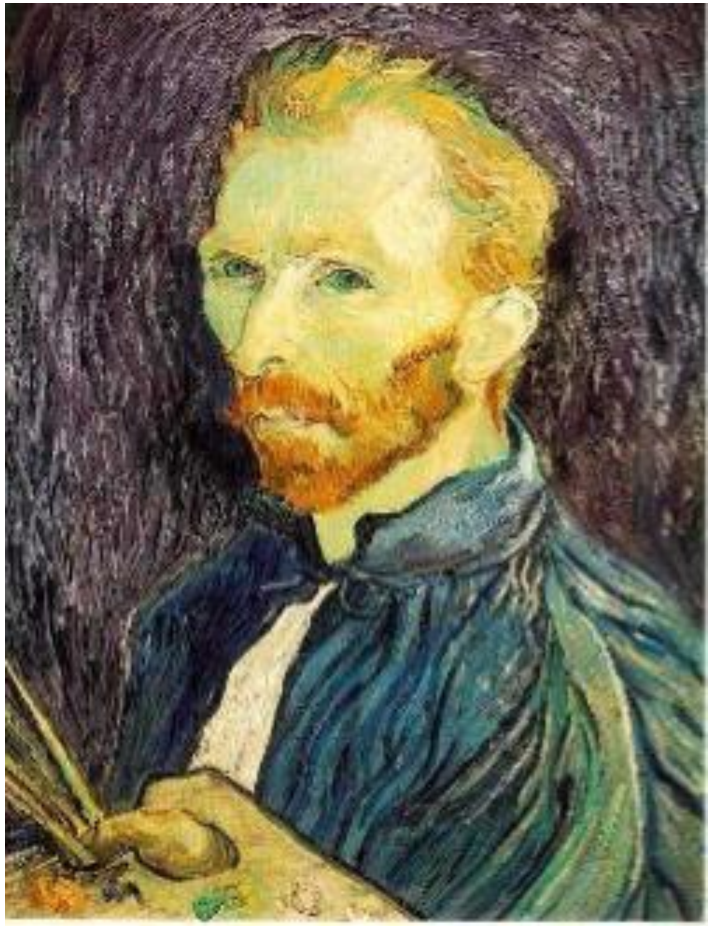
Image downsampling


This image is too big to fit on the screen.
How would you reduce it to half its size?

Naïve image downsampling

Throw away every other row and column to create a 1/2 size image

- called *image sub-sampling*



1/2

delete even rows
delete even columns

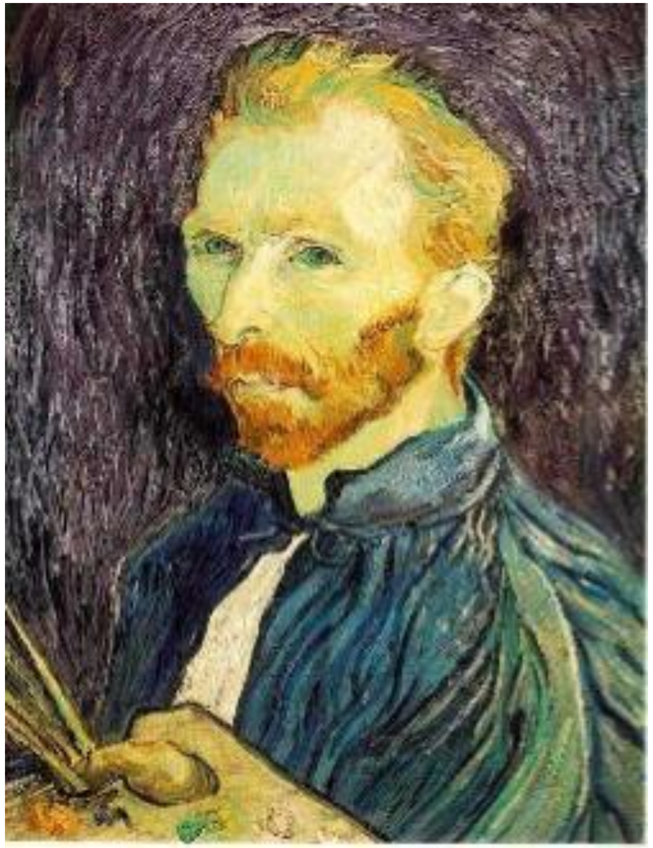
1/4

delete even rows
delete even columns

1/8

What is the problem with this approach?

Naïve image downsampling



1/2

1/4 (2x zoom)

1/8 (4x zoom)

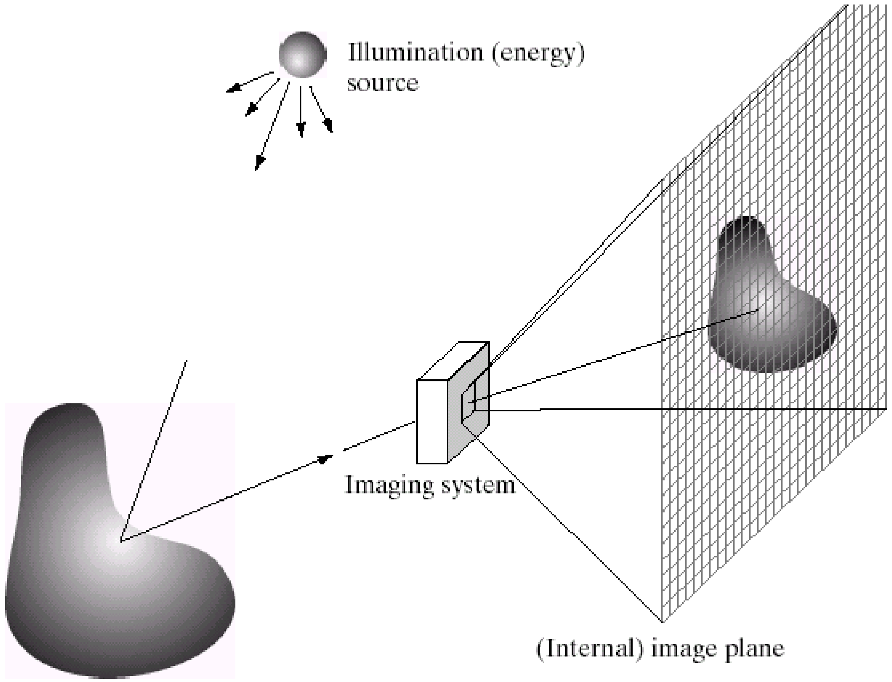
What is the 1/8 image so pixelated (and do you know what this effect is called)?

Image downsampling – another example

What this effect is called? Aliasing

Source: F. Durand

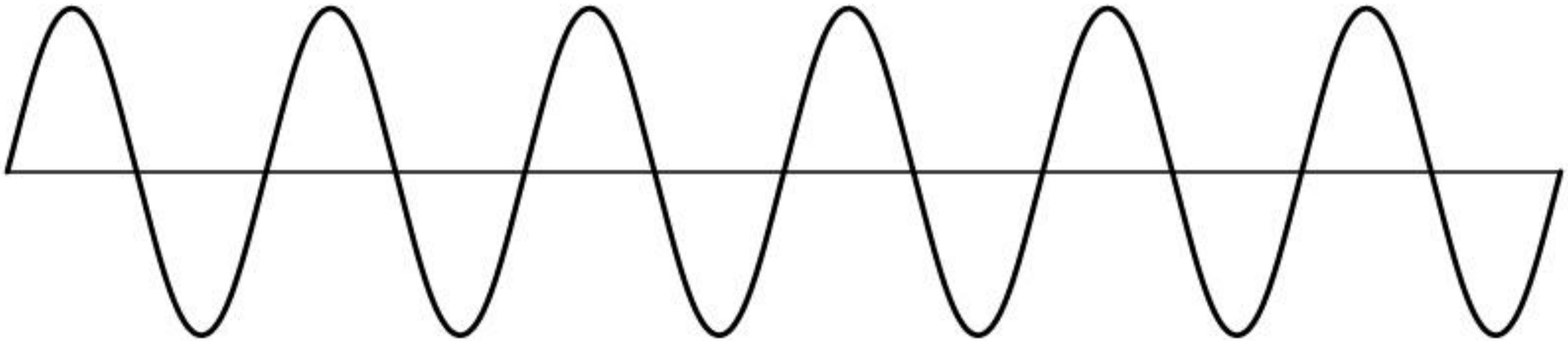
Reminder



Images are a *discrete*, or *sampled*, representation of a *continuous* world

Sampling

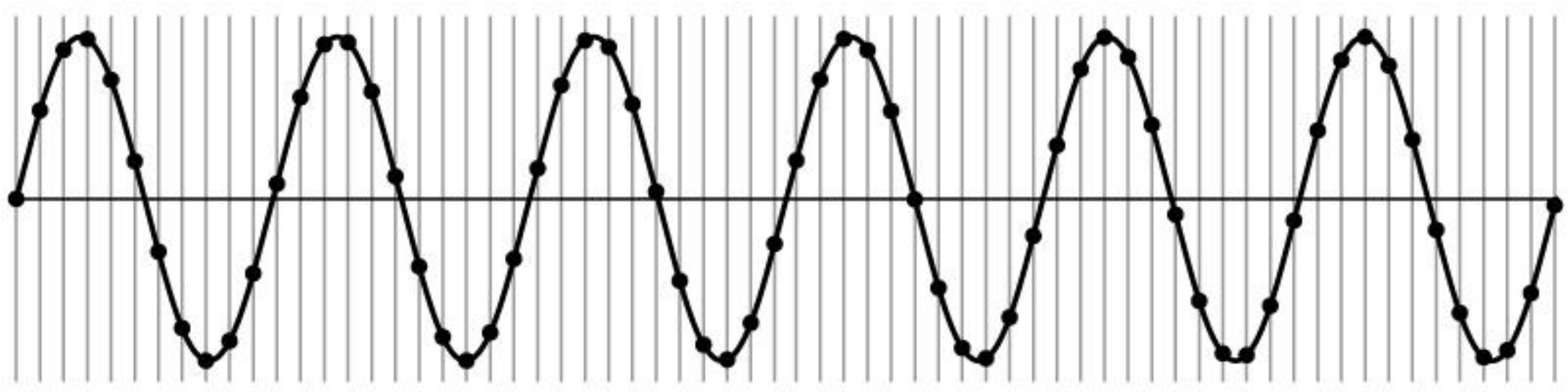
Very simple example: a sine wave



How would you discretize this signal?

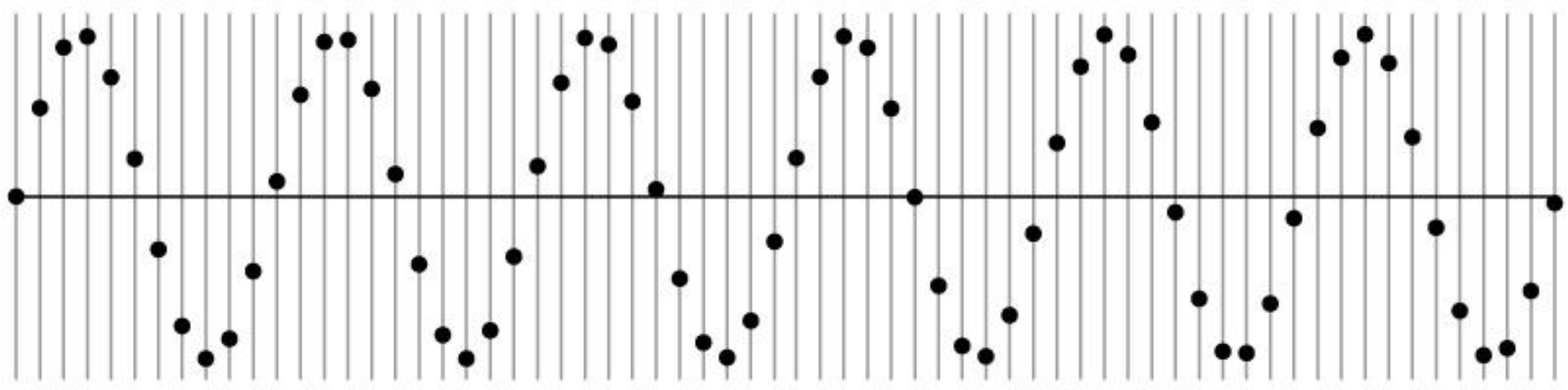
Sampling

Very simple example: a sine wave



Sampling

Very simple example: a sine wave

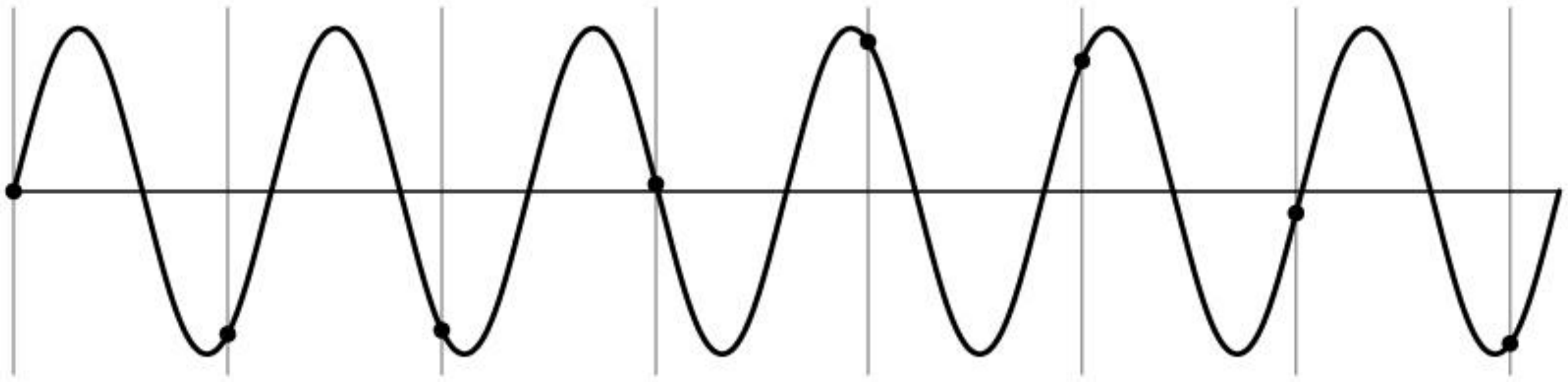


How many samples should I take?

Can I take as *many* samples as I want?

Undersampling

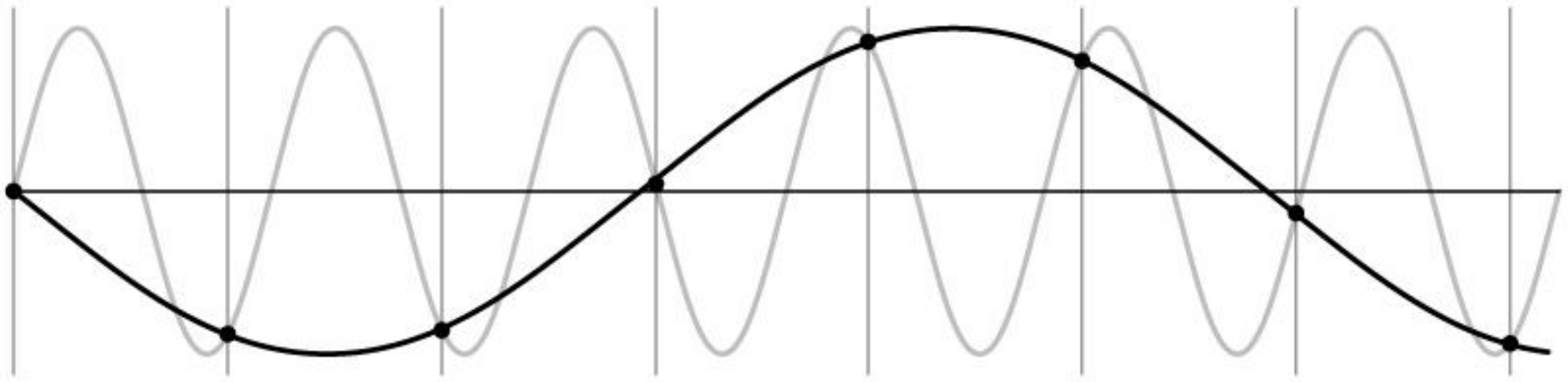
Very simple example: a sine wave



Unsurprising effect: information is lost.

Undersampling

Very simple example: a sine wave

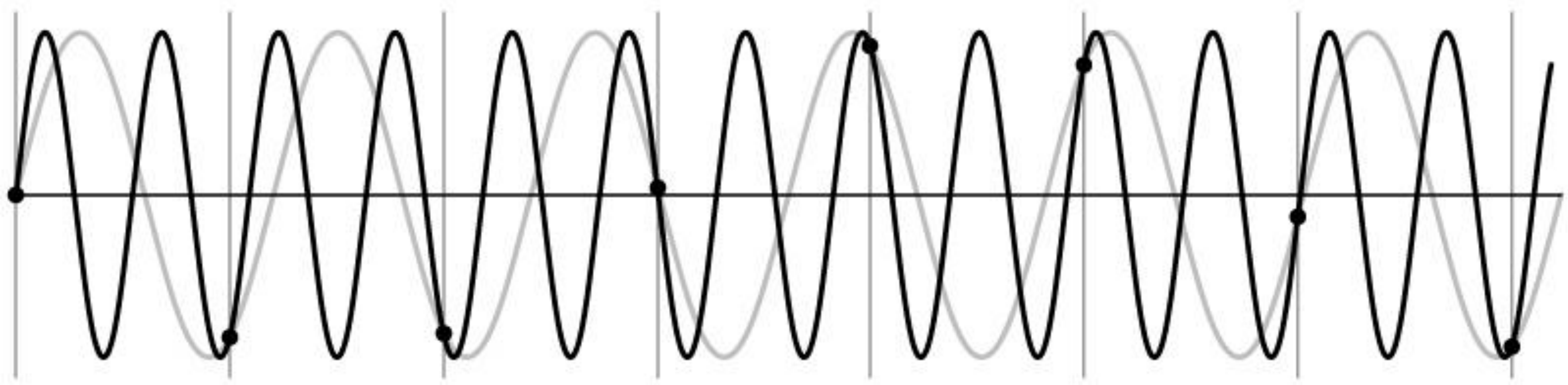


Unsurprising effect: information is lost.

Surprising effect: can confuse the signal with one of *lower* frequency.

Undersampling

Very simple example: a sine wave

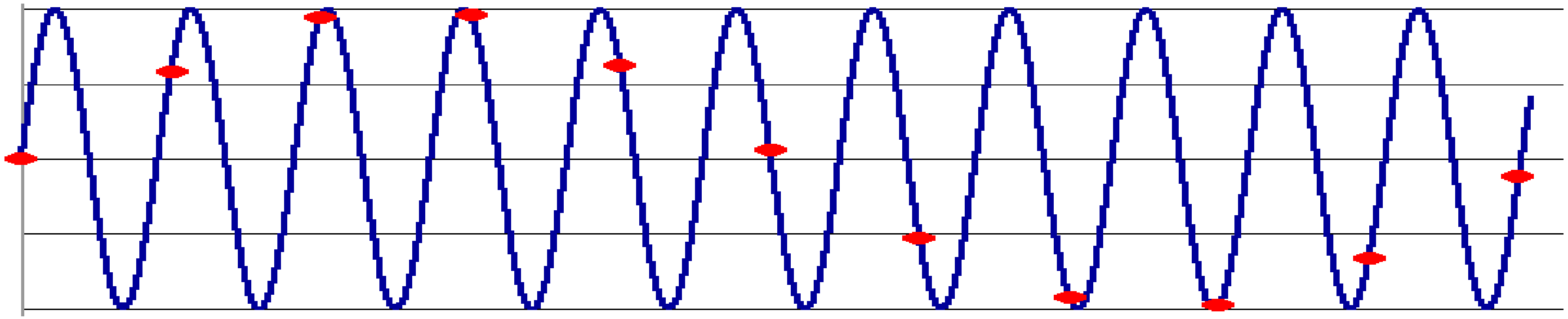


Unsurprising effect: information is lost.

Surprising effect: can confuse the signal with one of *lower* frequency.

Note: we could always confuse the signal with one of *higher* frequency.

Aliasing

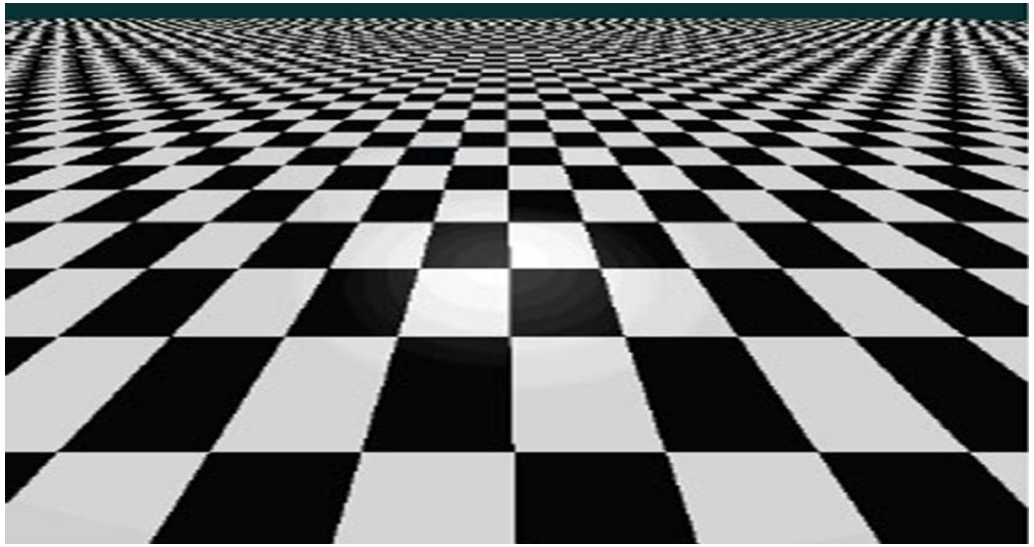


- Occurs when your sampling rate is not high enough to capture the amount of detail in your image
- Can give you the wrong signal/image—an *alias*
- To do sampling right, need to understand the structure of your signal/image
- To avoid aliasing:
  - sampling rate ≥ 2 * max frequency in the image
    - said another way: ≥ two samples per cycle
  - This minimum sampling rate is called the **Nyquist rate**

Source: L. Zhang

Aliasing in photographs

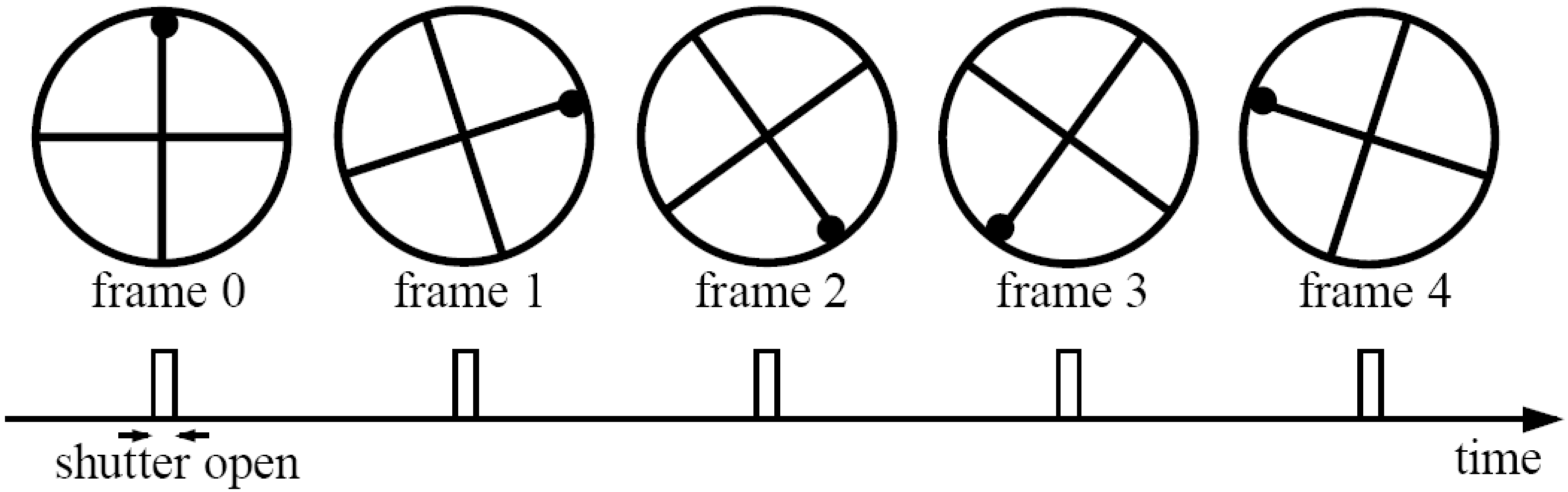
This is also known as “moire”



Temporal aliasing

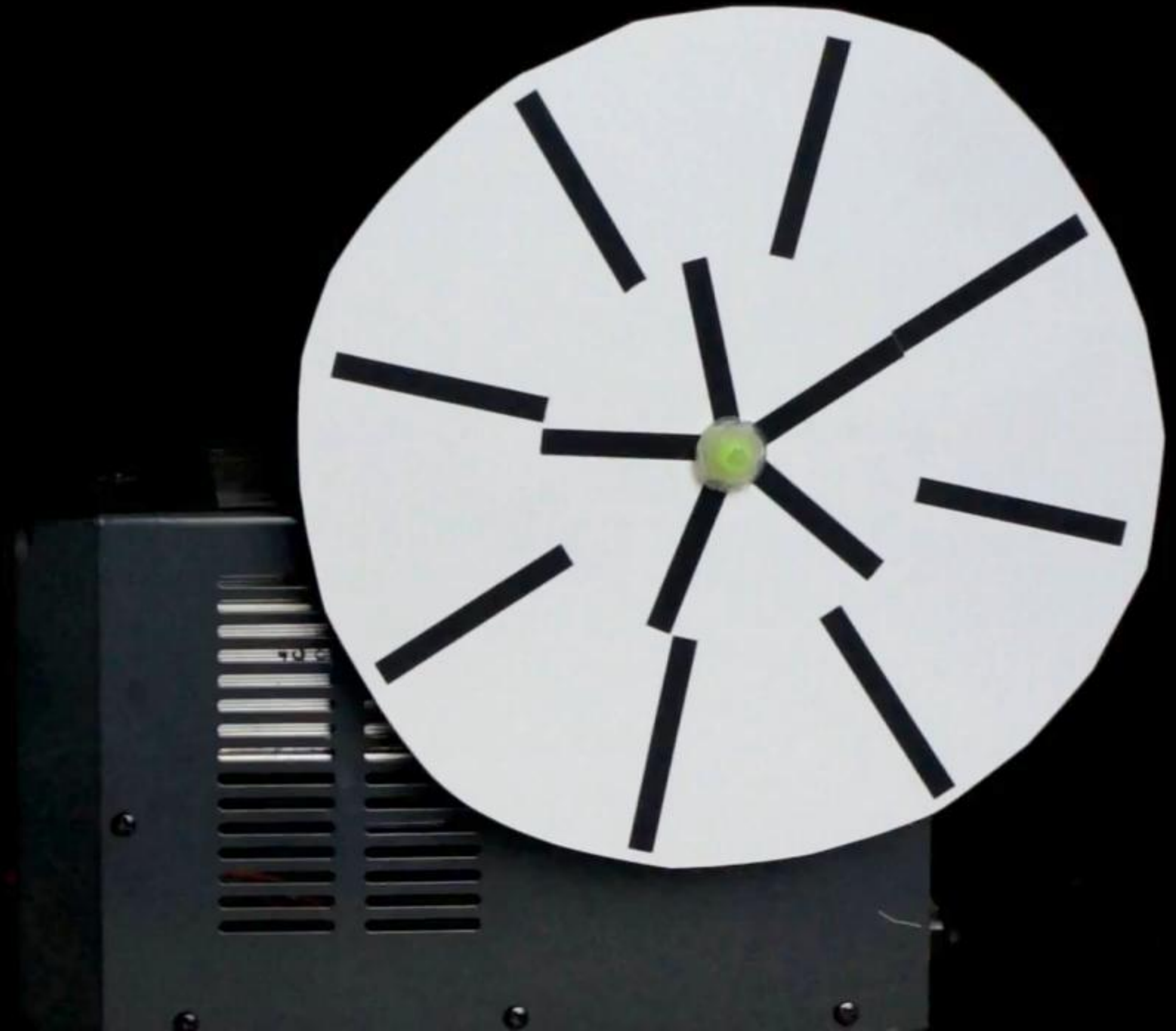
Imagine a spoked wheel moving to the right (rotating clockwise).
Mark wheel with dot so we can see what's happening.

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

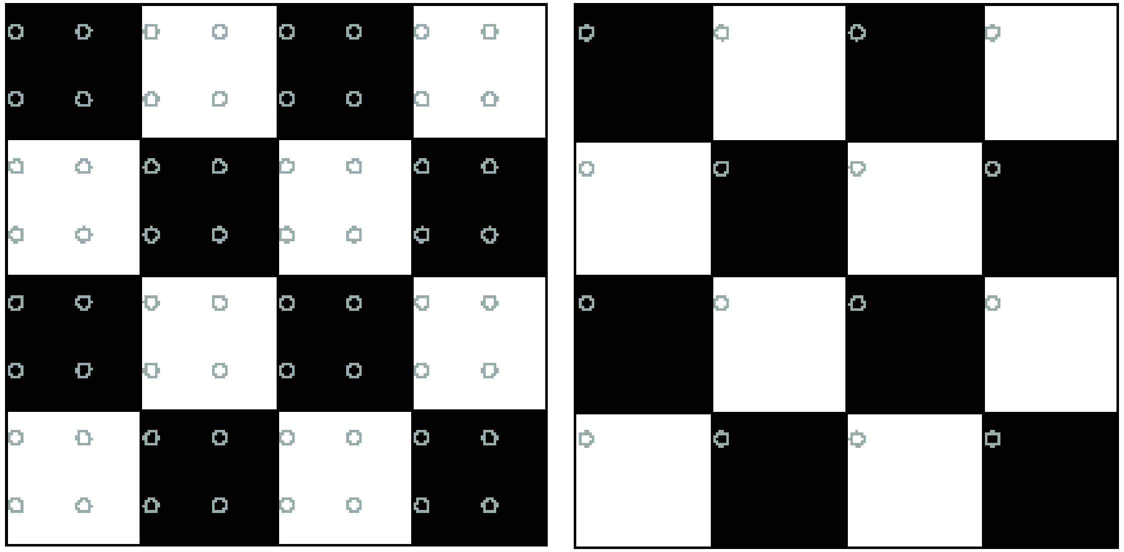


Without dot, wheel appears to be rotating slowly backwards!
(counterclockwise)

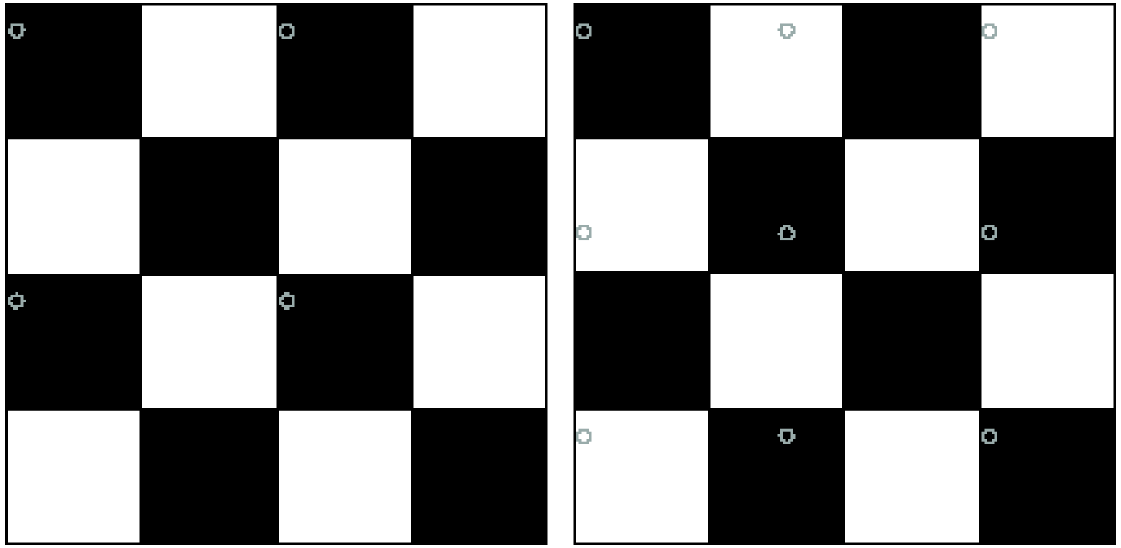
Wagon wheel effect



Nyquist limit – 2D example



Good sampling



Bad sampling

Anti-aliasing

- When downsampling by a factor of two
  - Original image has frequencies that are too high

How would you deal with aliasing?

Approach 1: Oversample the signal

- This is how camera manufacturers started focusing so heavily on number of megapixels.

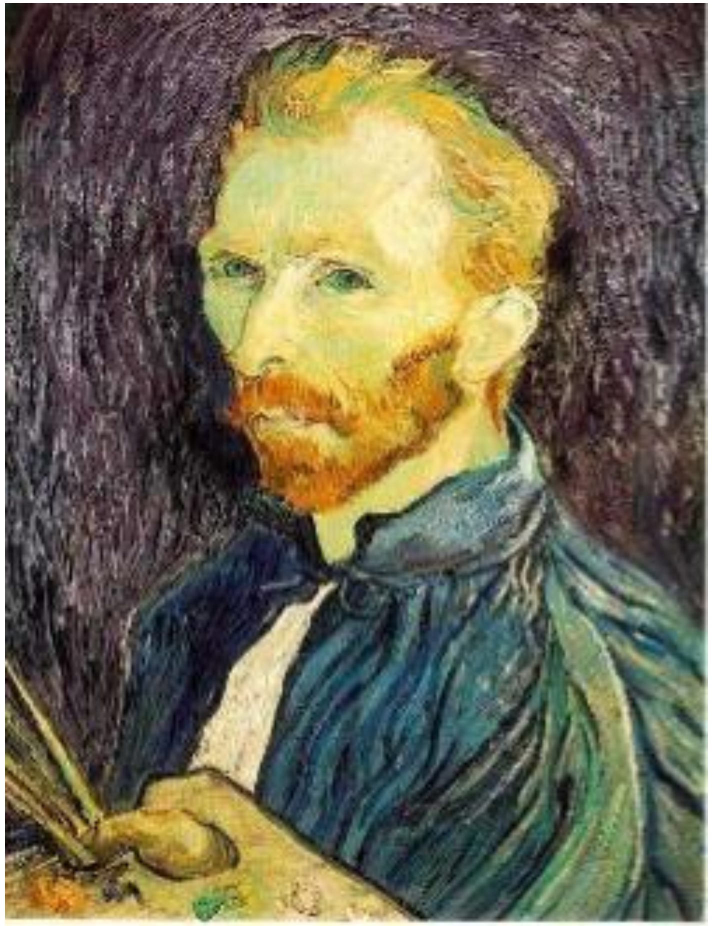
Approach 2: filter the image, *then* subsample

- Remove some of the detail effects that cause aliasing.
- Lose information, but better than aliasing artifacts.

How would you smooth a signal?

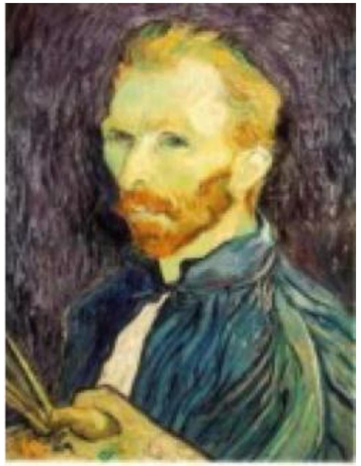
Better image downsampling

Apply a smoothing filter first, then throw away half the rows and columns



1/2

Gaussian filter
delete even rows
delete even columns

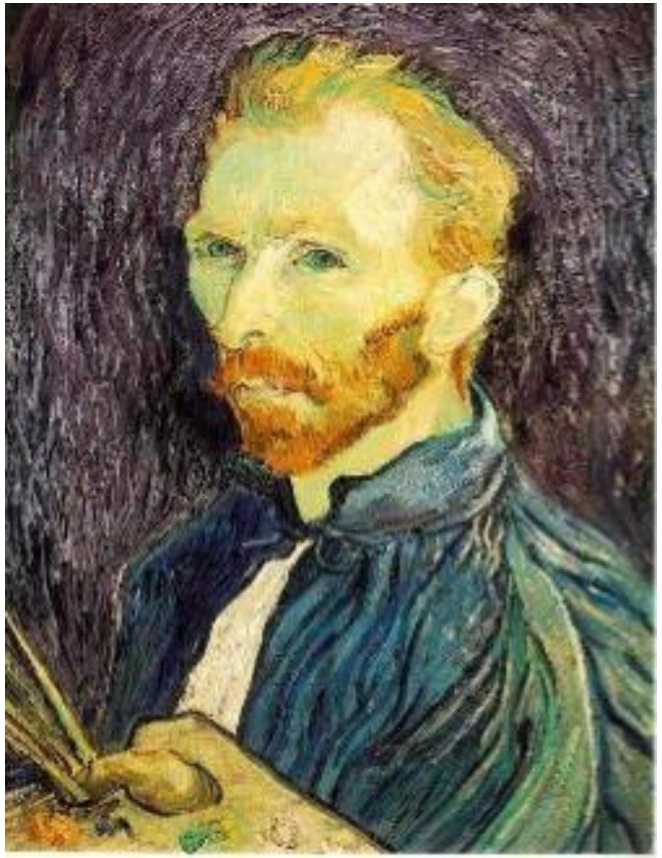


1/4

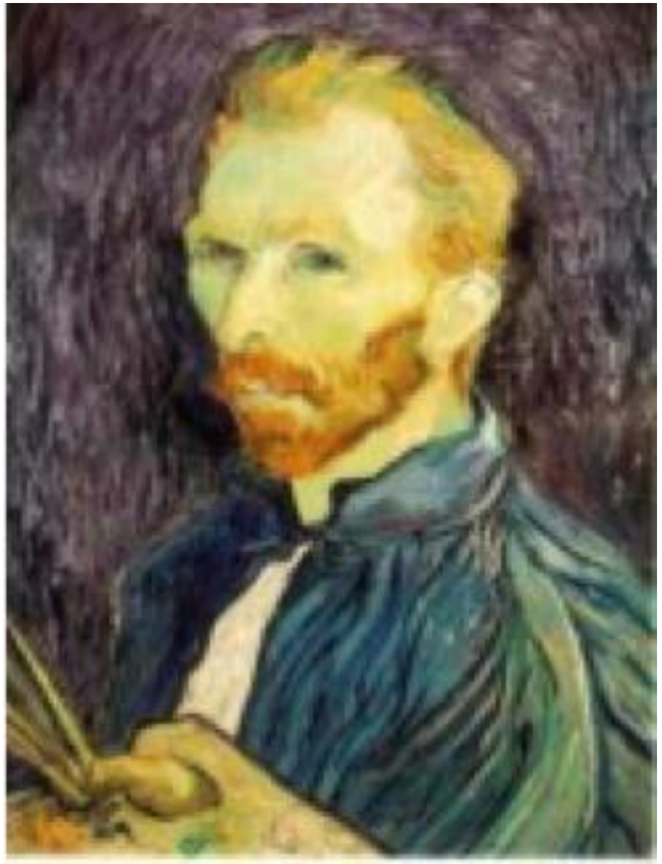
Gaussian filter
delete even rows
delete even columns

1/8

Better image downsampling



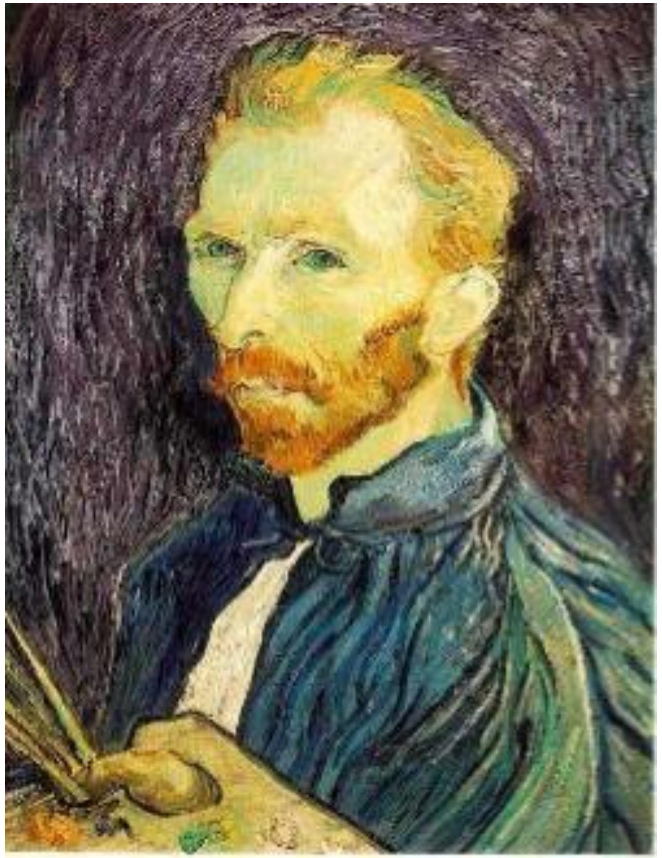
1/2



1/4 (2x zoom)

1/8 (4x zoom)

Compare with Naïve image downsampling



1/2

1/4 (2x zoom)

1/8 (4x zoom)

Anti-aliasing

Question 1: How much smoothing do I need to do to avoid aliasing?

Question 2: How many samples do I need to take to avoid aliasing?

Answer to both: Enough to reach the Nyquist limit.

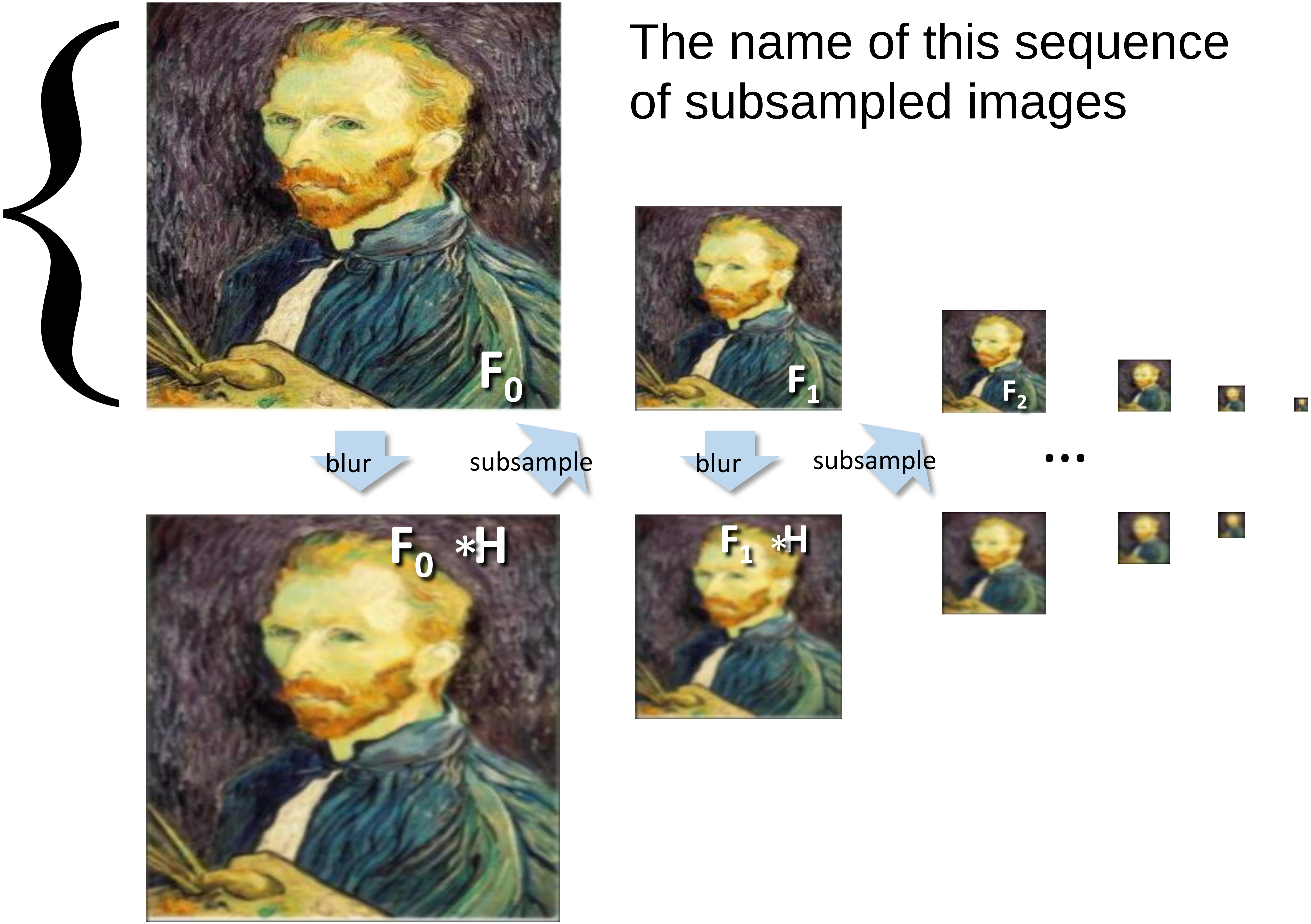
We’ll see what this means soon.

Gaussian pre-filtering

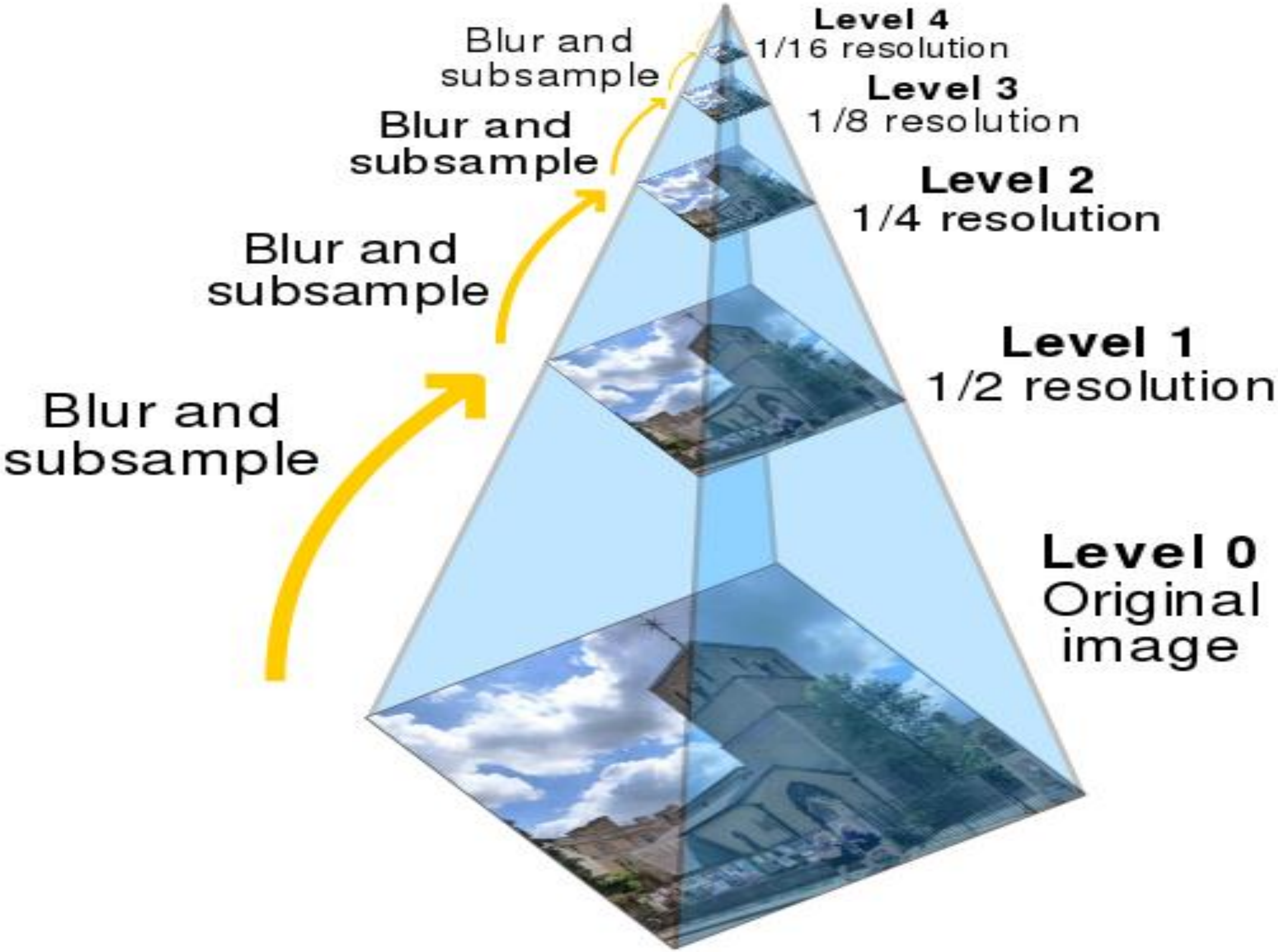
Gaussian image pyramid

Gaussian image pyramid

The name of this sequence of subsampled images



- Solution: filter the image, *then* subsample


Level 4
1/16 resolution
Blur and
subsample
Level 3
1/8 resolution
Blur and
subsample
Level 2
1/4 resolution
Blur and
subsample
Level 1
1/2 resolution
Blur and
subsample
Level 0
Original
image

Constructing a Gaussian pyramid

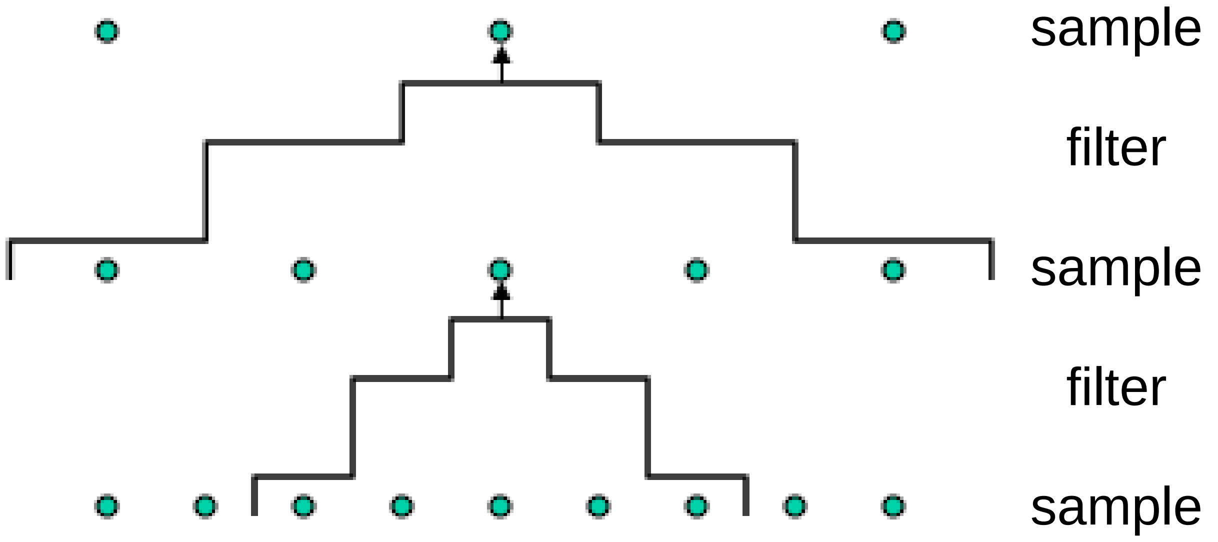
Algorithm

repeat:

filter

subsample

until min resolution reached



Question: How much bigger than the original image is the whole pyramid?

Constructing a Gaussian pyramid

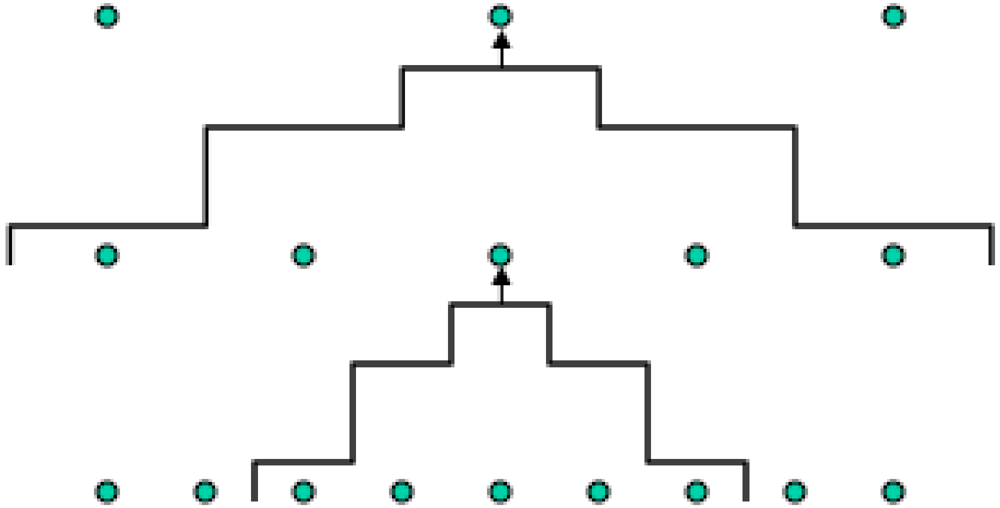
Algorithm

repeat:

filter

subsample

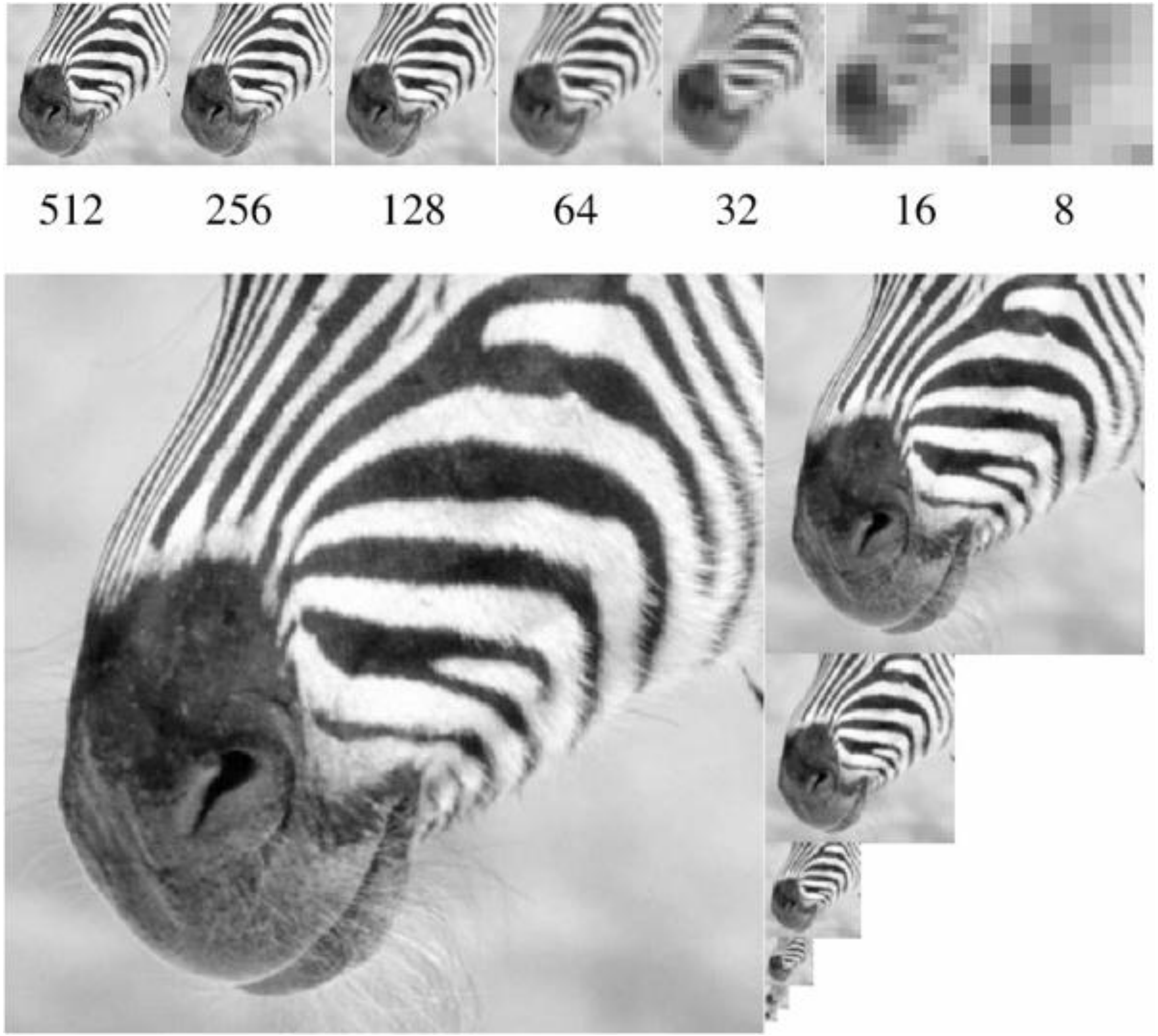
until min resolution reached



Question: How much bigger than the original image is the whole pyramid?

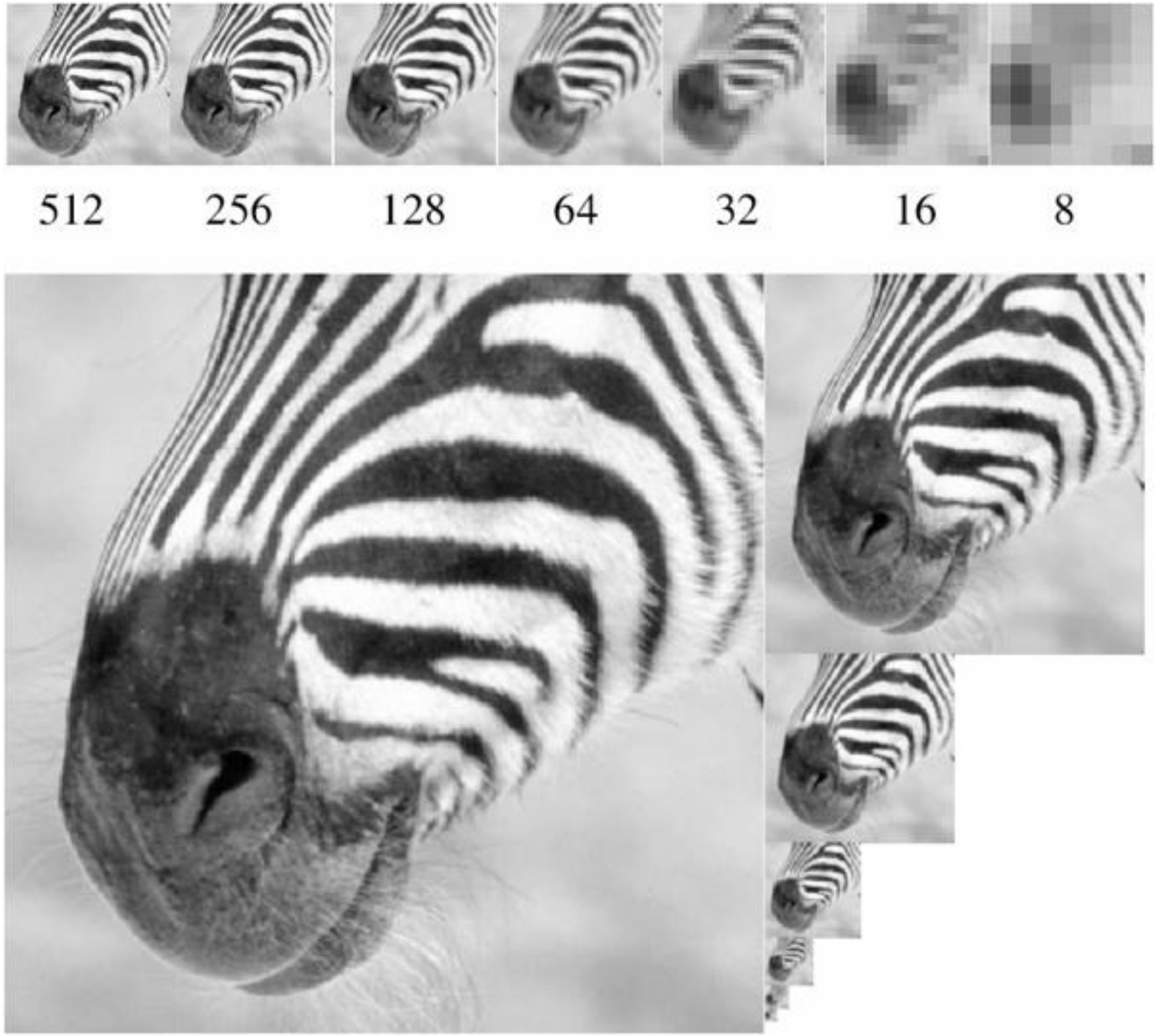
Answer: Just 4/3 times the size of the original image!
(How did I come up with this number?)

Some properties of the Gaussian pyramid



What happens to the details of the image?

Some properties of the Gaussian pyramid

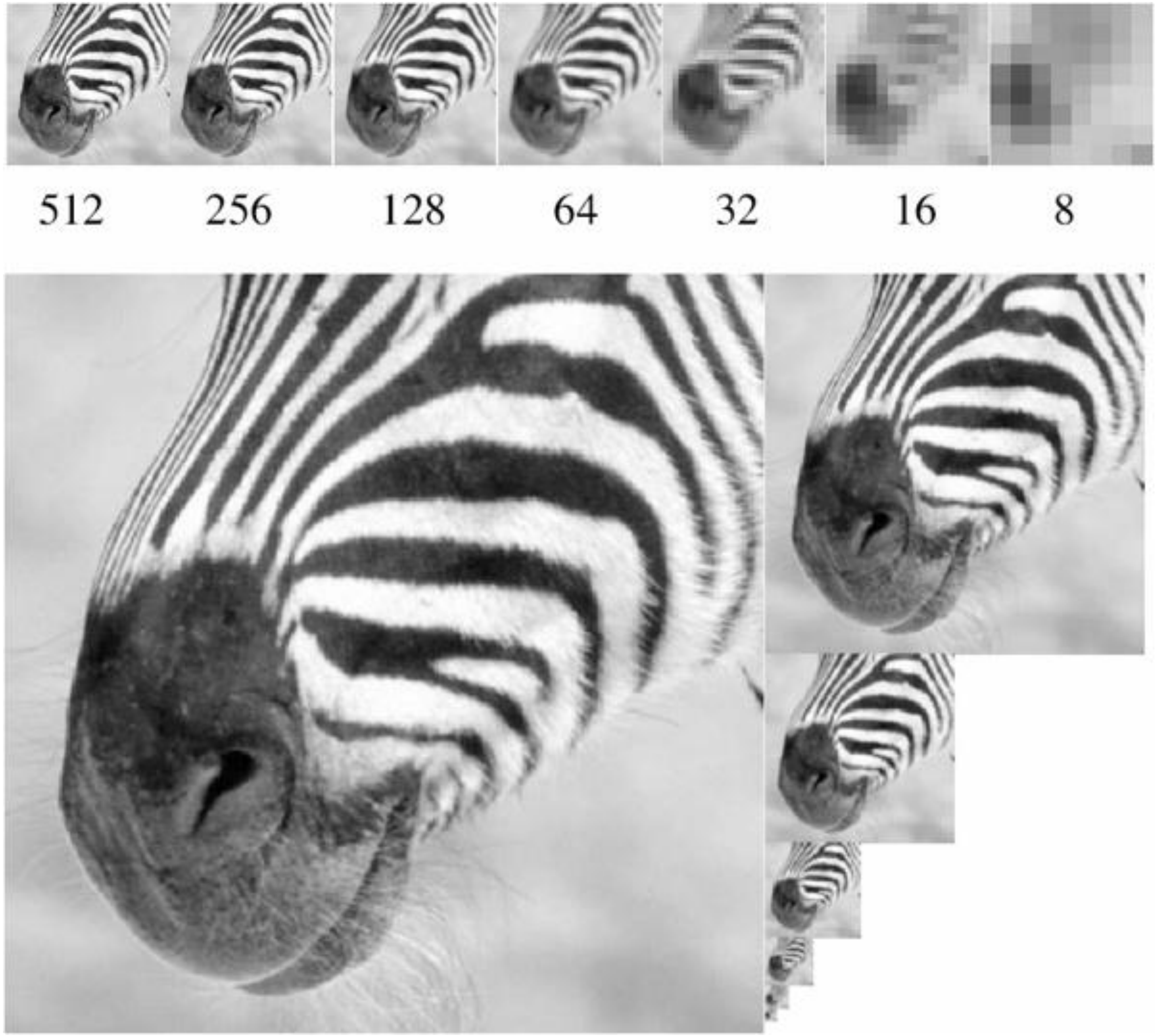


What happens to the details of the image?

- They get smoothed out as we move to higher levels.

What is preserved at the higher levels?

Some properties of the Gaussian pyramid



What happens to the details of the image?

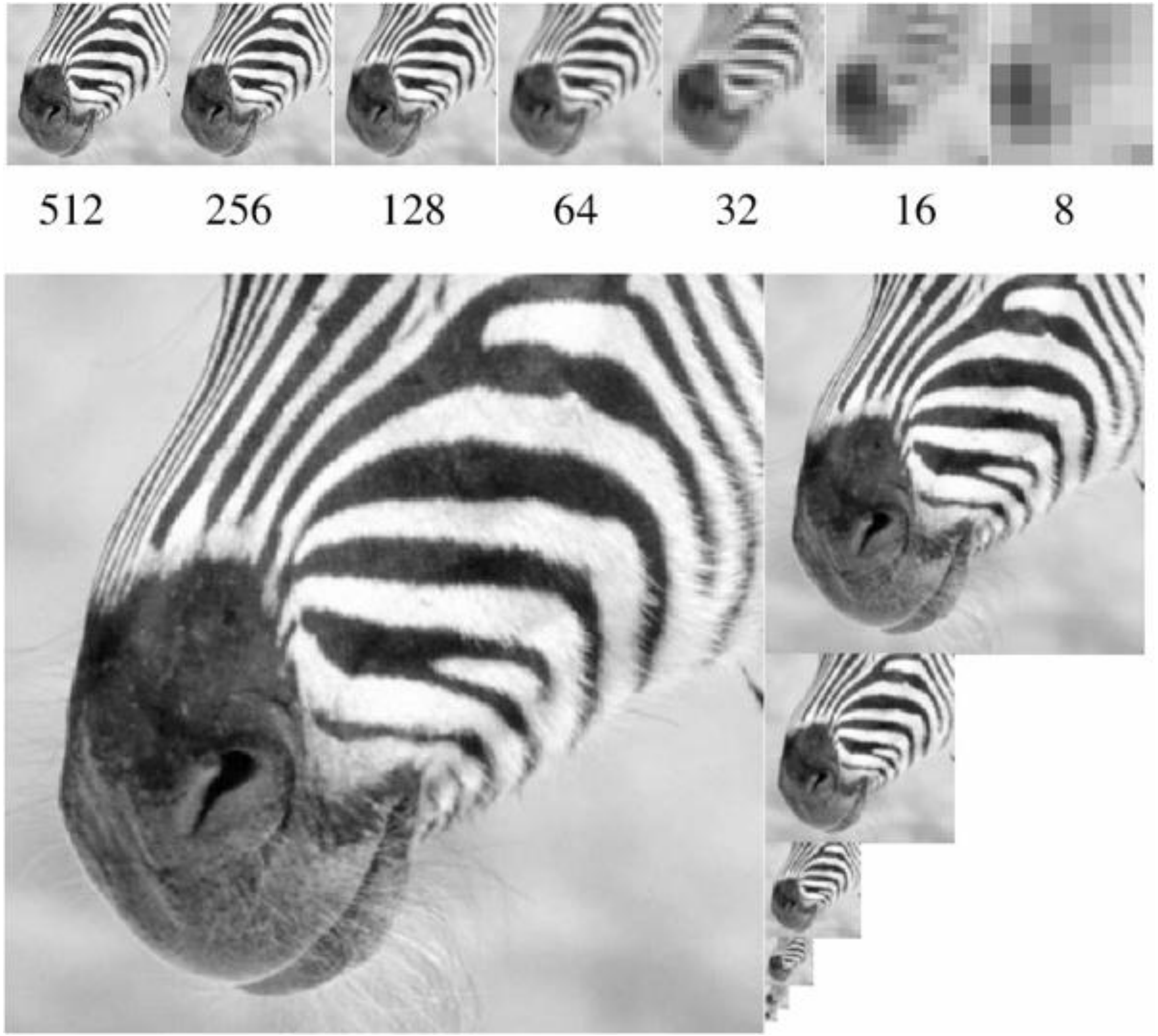
- They get smoothed out as we move to higher levels.

What is preserved at the higher levels?

- Mostly large uniform regions in the original image.

How would you reconstruct the original image from the image at the upper level?

Some properties of the Gaussian pyramid



What happens to the details of the image?

- They get smoothed out as we move to higher levels.

What is preserved at the higher levels?

- Mostly large uniform regions in the original image.

How would you reconstruct the original image from the image at the upper level?

- That’s not possible.

Blurring is lossy

-

=

level 0 | level 1 (before downsampling) | residual

What does the residual look like?

Blurring is lossy

-

=

level 0

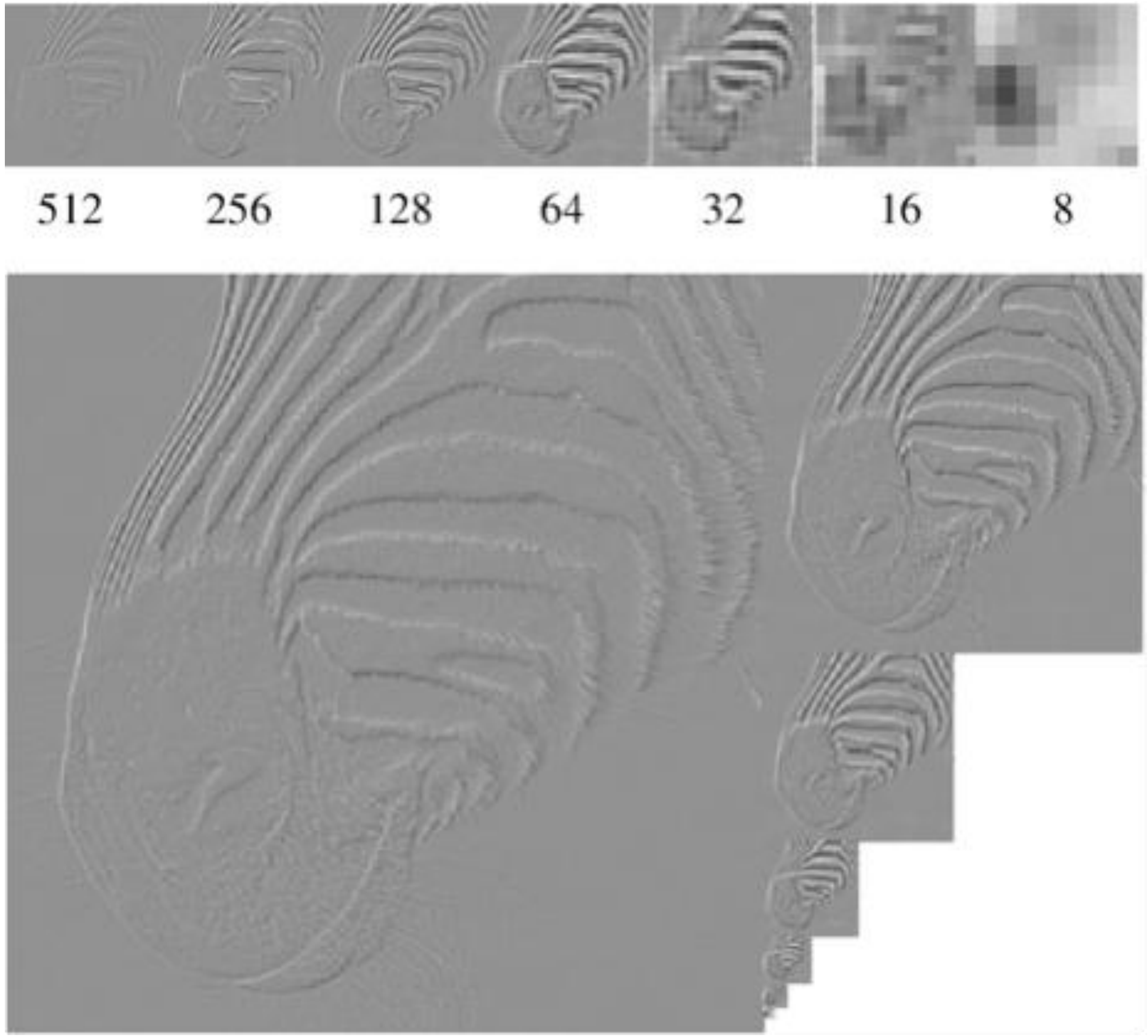
level 1 (before downsampling)

residual

Can we make a pyramid that is lossless?

Laplacian image pyramid

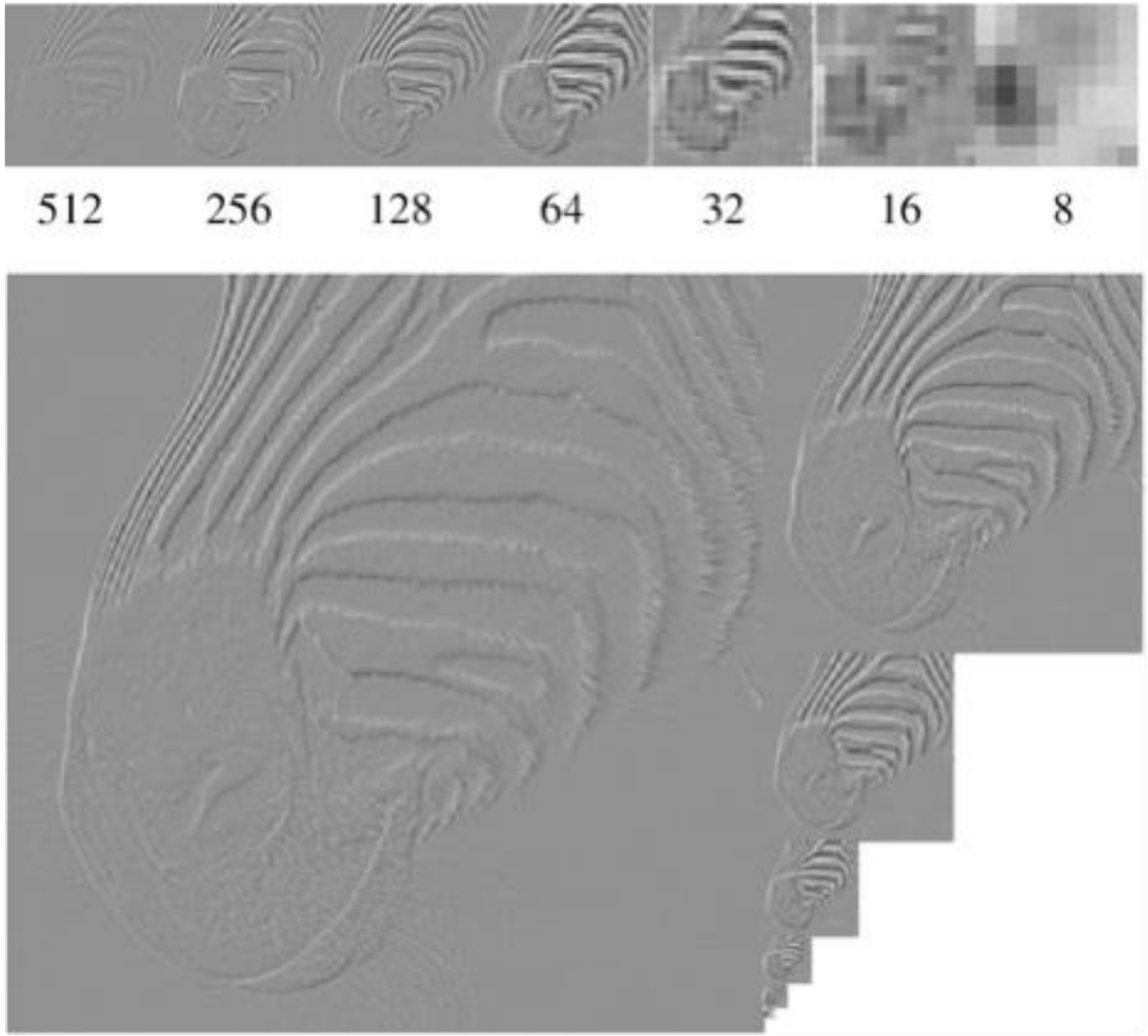
Laplacian image pyramid



At each level, retain the residuals instead of the blurred images themselves.

Can we reconstruct the original image using the pyramid?

Laplacian image pyramid



At each level, retain the residuals instead of the blurred images themselves.

Can we reconstruct the original image using the pyramid?

- Yes we can!

What do we need to store to be able to reconstruct the original image?

Let’s start by looking at just one level

level 0

=

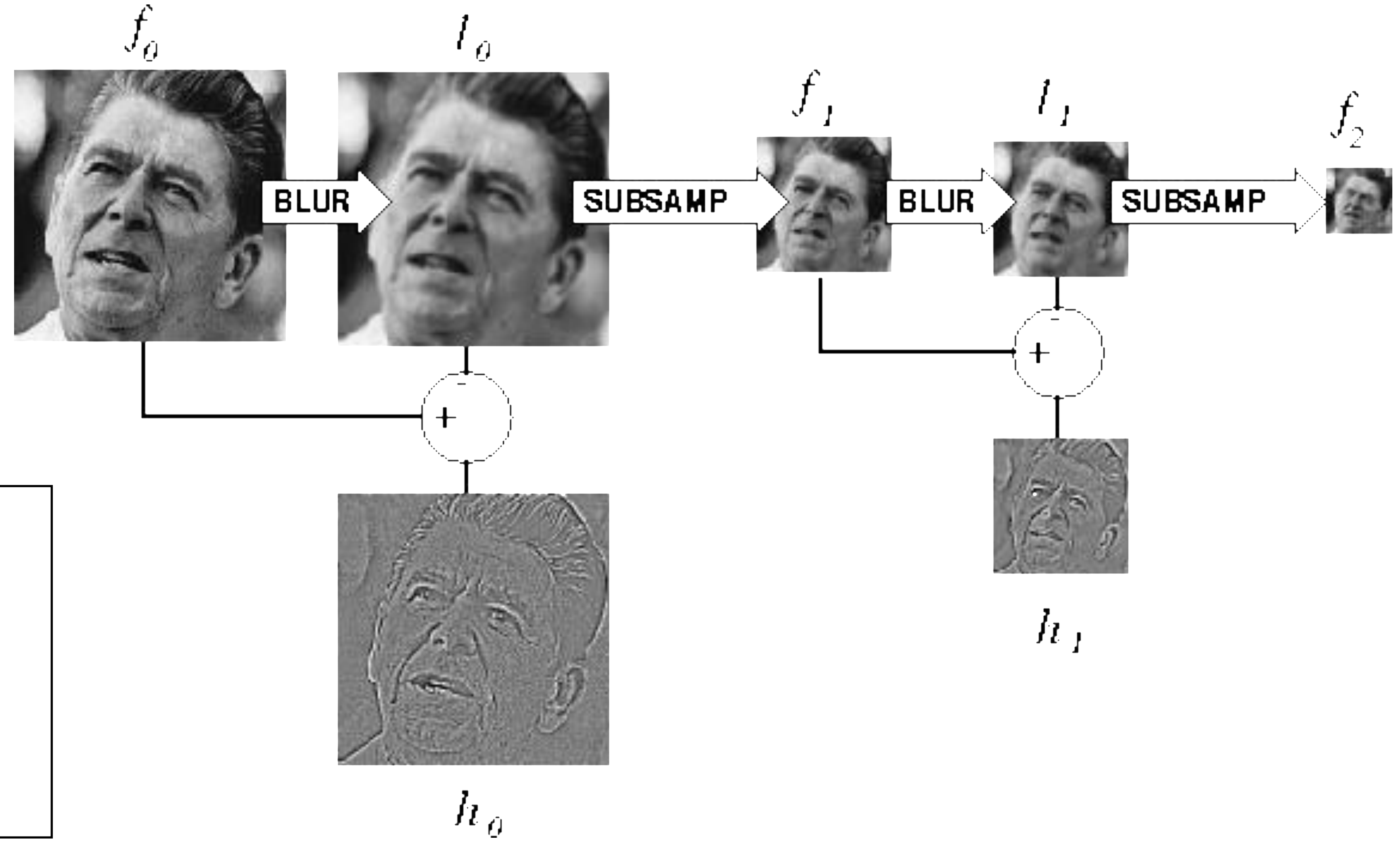
level 1 (upsampled)

+

residual

Does this mean we need to store both residuals and the blurred copies of the original?

Constructing a Laplacian pyramid



Algorithm

repeat:

filter

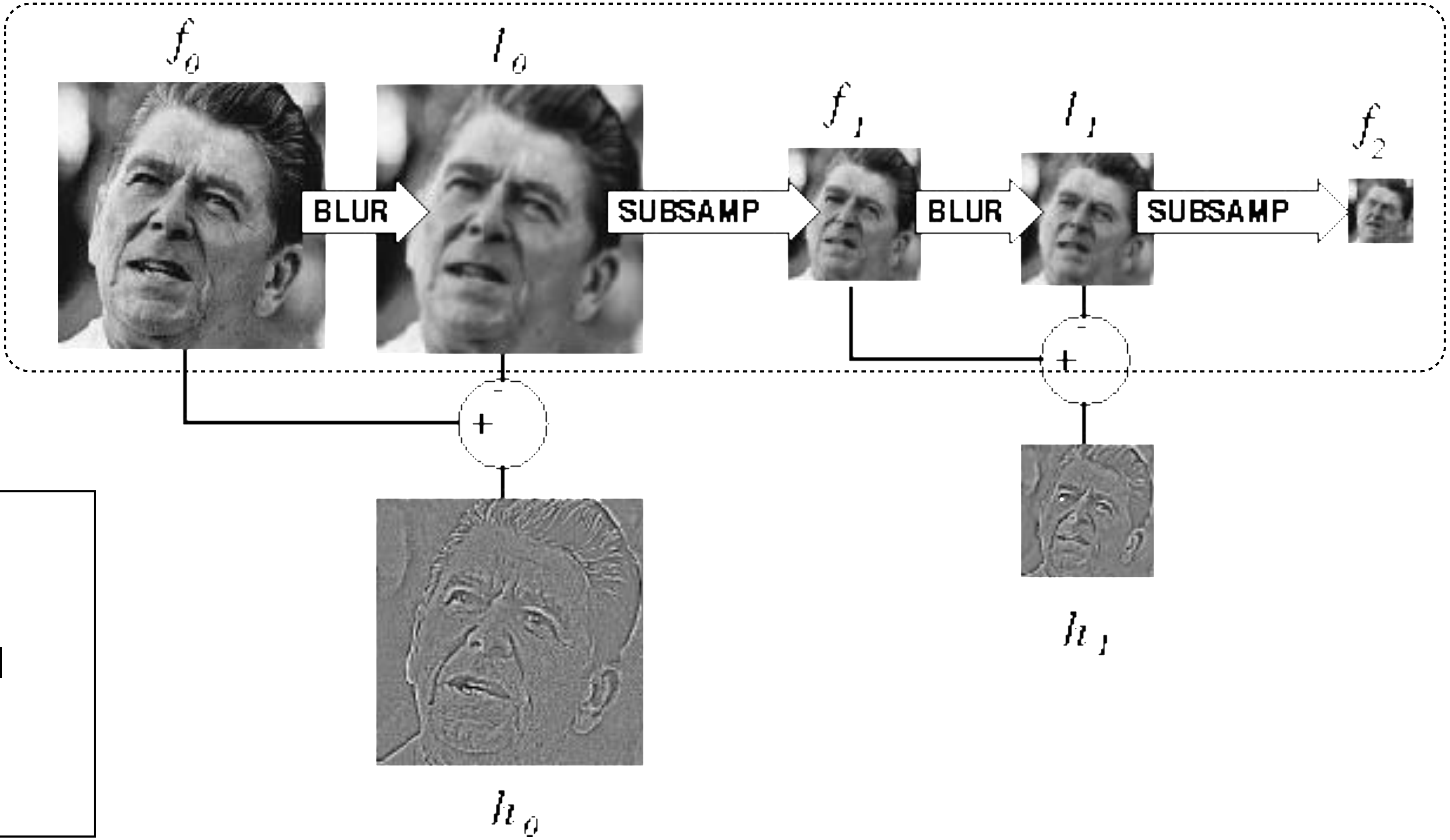
compute residual

subsample

until min resolution reached

Constructing a Laplacian pyramid

What is this part?



Algorithm

repeat:

filter

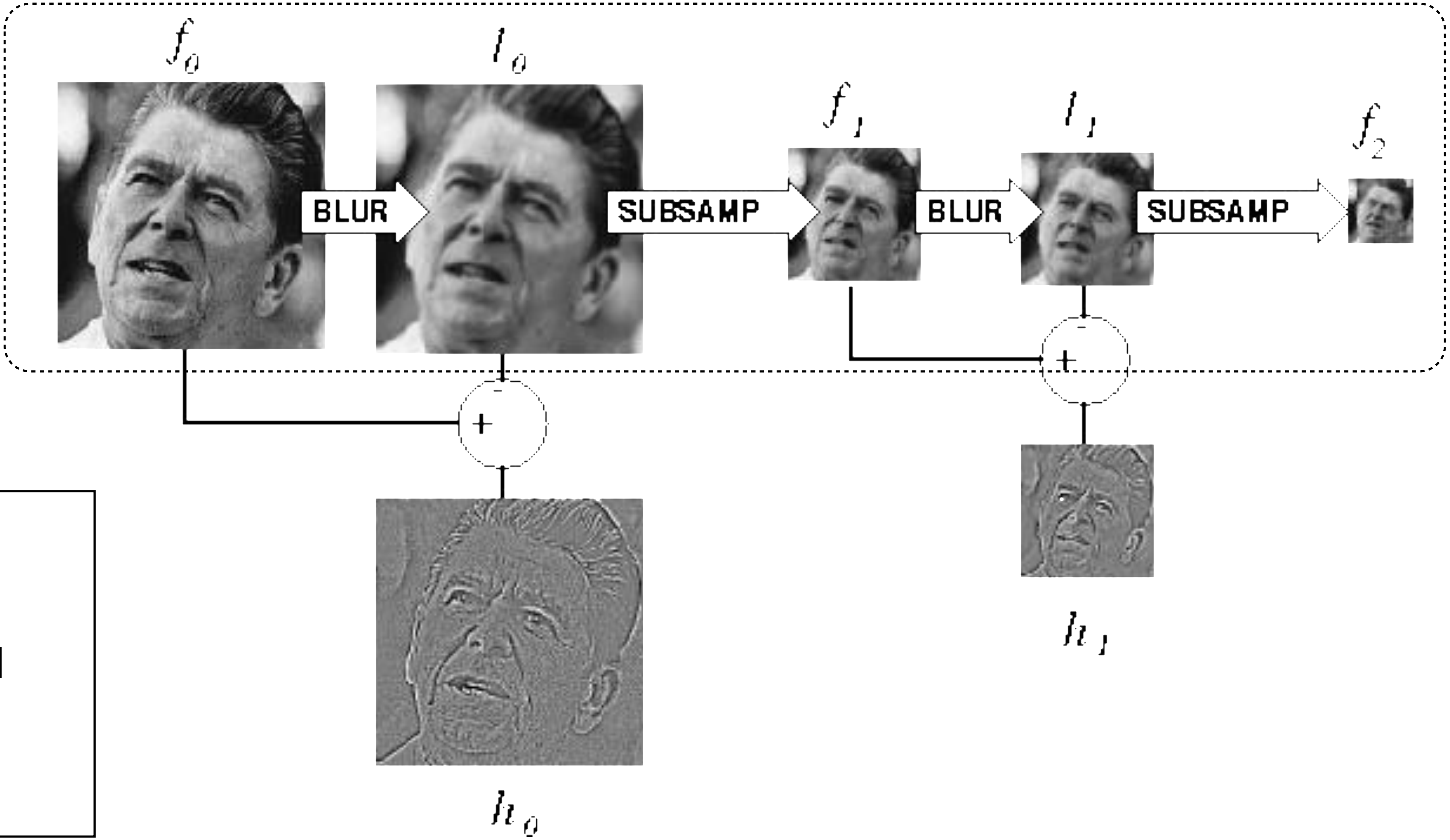
compute residual

subsample

until min resolution reached

Constructing a Laplacian pyramid

It's a Gaussian pyramid.



Algorithm

repeat:

filter

compute residual

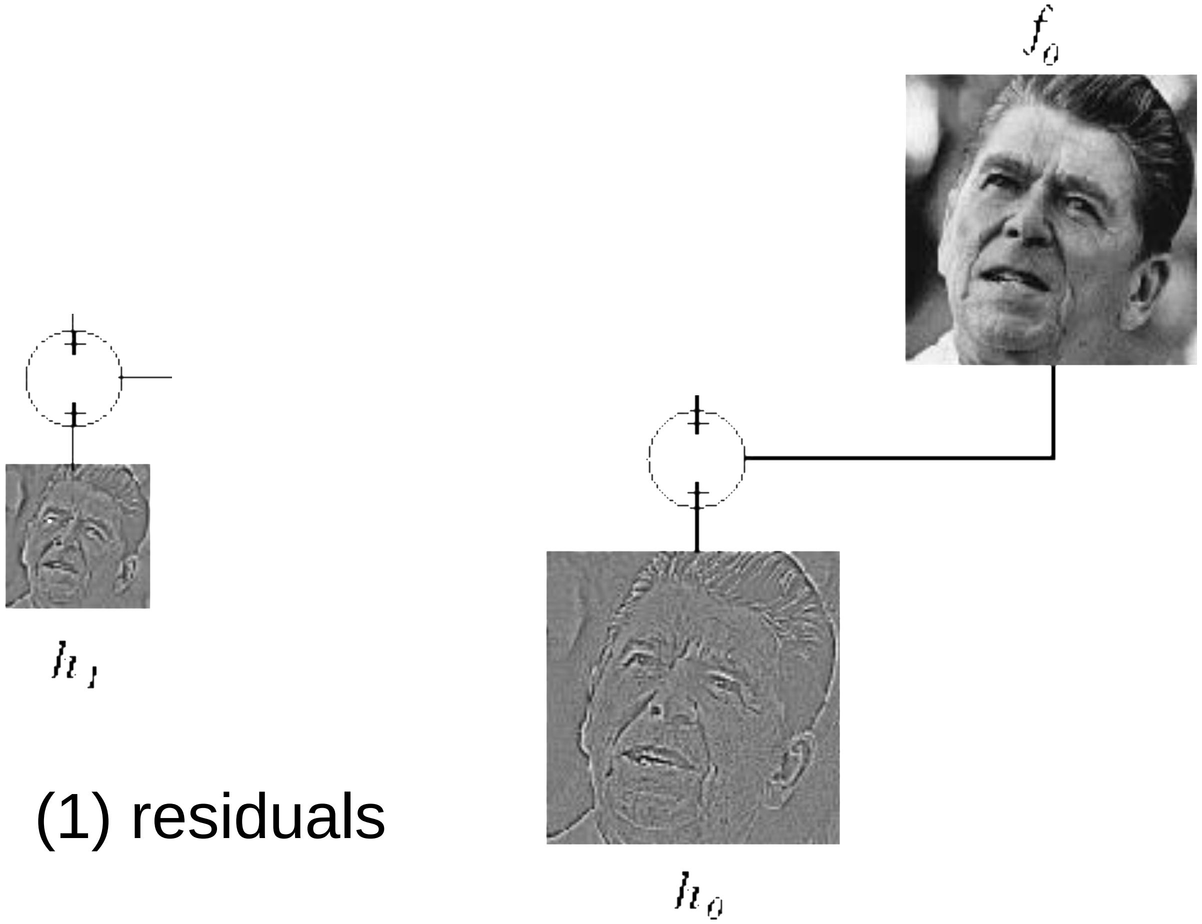
subsample

until min resolution reached

What do we need to construct the original image?

f_0

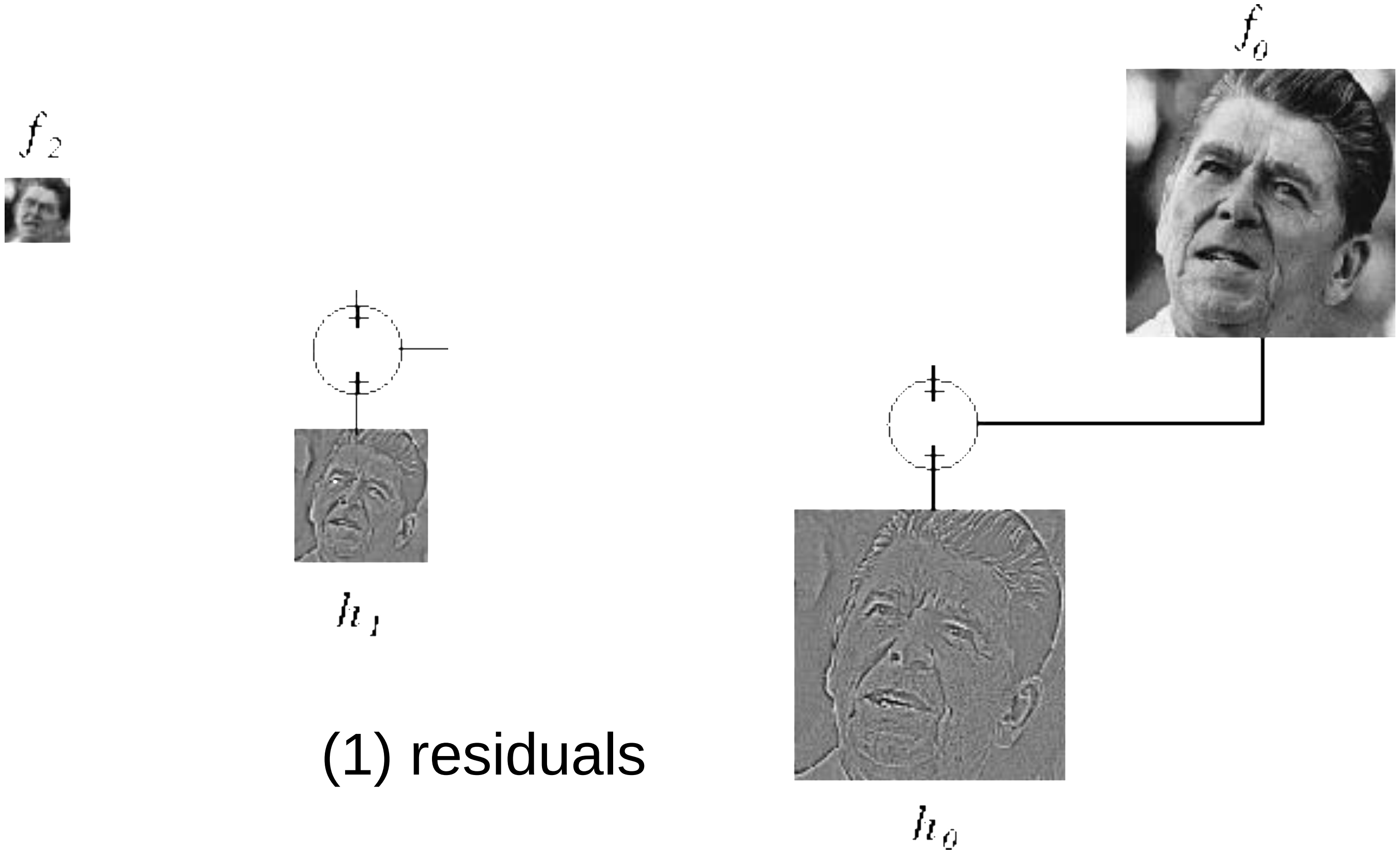
What do we need to construct the original image?



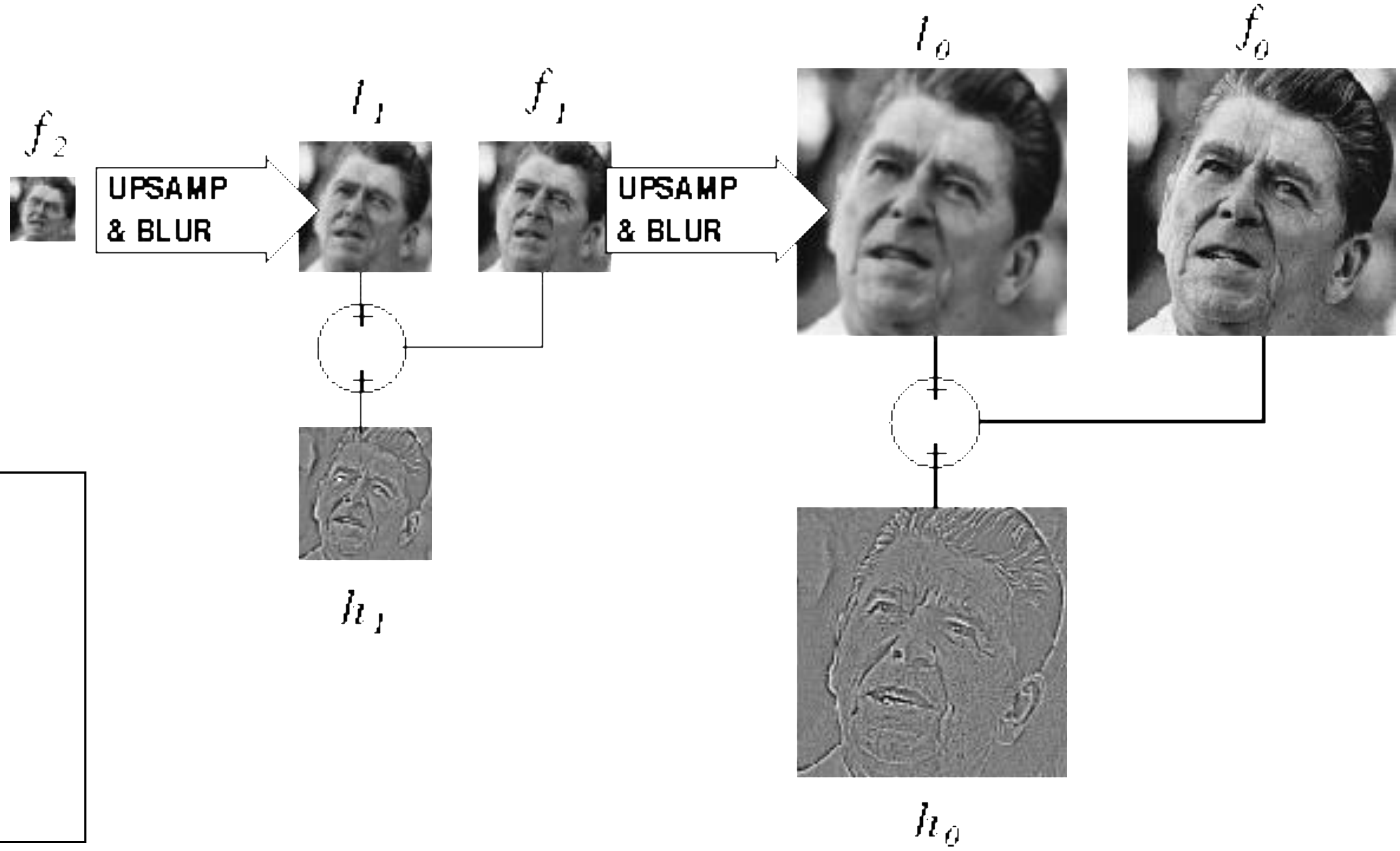
What do we need to construct the original image?

(2) smallest image

(1) residuals



Reconstructing the original image



Algorithm

repeat:

upsample

sum with residual

until orig resolution reached

Gaussian vs Laplacian Pyramid

Shown in opposite order for space.

Which one takes more space to store?

Laplacian pyramid - Still used extensively

Laplacian pyramid - Still used extensively

foreground details enhanced, background details reduced

input image

user-provided mask

Other types of pyramids

Steerable pyramid: At each level keep multiple versions, one for each direction.

Wavelets: Huge area in image processing

What are image pyramids used for?

image compression

multi-scale texture mapping

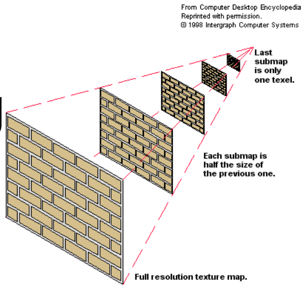
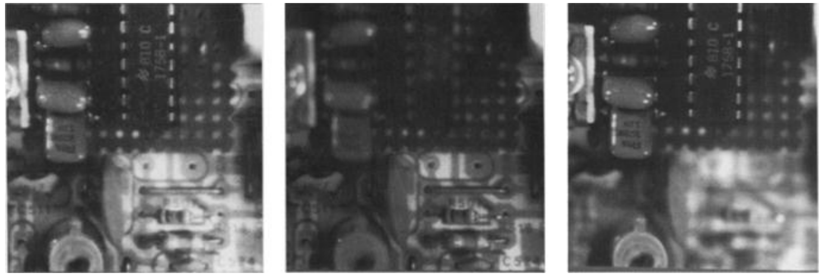
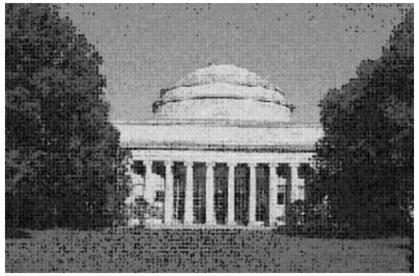


image blending

focal stack compositing

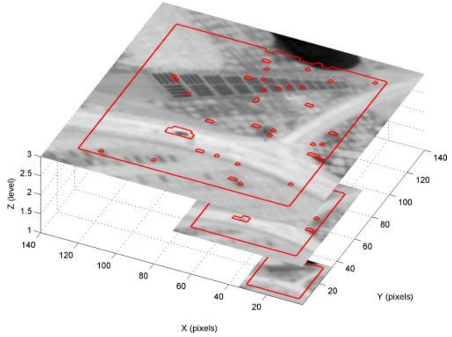


denoising



multi-scale detection

multi-scale registration



Multiresolution Processing
motivation in the context of object recognition

- Images seen as connected regions of similar texture and intensity levels that combine to form objects
- If both small and large objects or low and high contrast objects are present simultaneously- advantageous to study them at several resolutions
- If objects are
  - small in size or low in contrast

    → examine them at high resolution
  - large in size or high in contrast

    → a coarse view is required

- Image with information at different scales or levels of detail (e.g., people vs buildings)
- Analyzing information at the same scale will not be effective.

Multiresolution Processing
motivation in the context of object recognition

- Use windows of different size (i.e., vary scale)

- Alternatively, use the same window size but analyze information at different resolutions:

High resolution

Low resolution

Small size objects should be examined at a high resolution

Large size objects should be examined at a low resolution

Upsampling

- This image is too small for this screen:
- How can we make it 10 times as big?
- Simplest approach:

  repeat each row and column 10 times
- Nearest neighbor interpolation
- Bilinear interpolation
- Bicubic interpolation

Image interpolation

Original image:  x 10

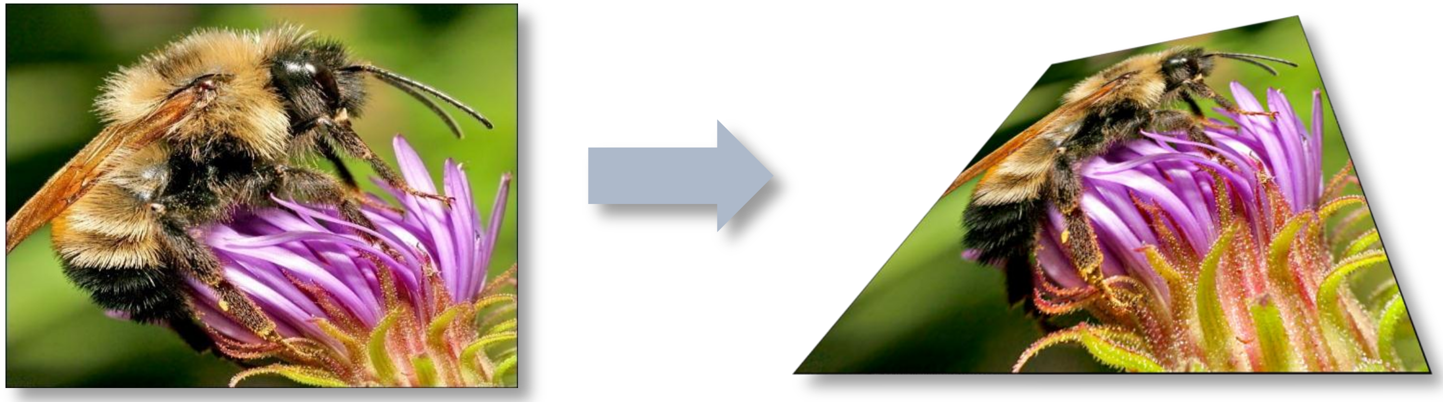

Nearest-neighbor interpolation


Bilinear interpolation


Bicubic interpolation

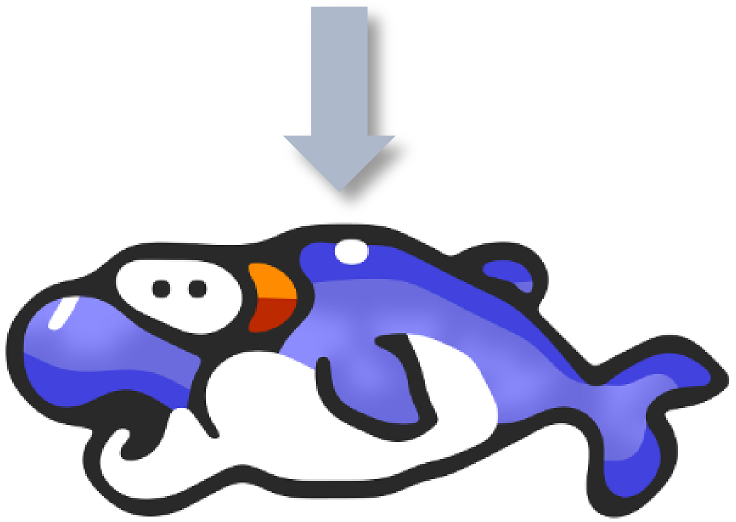
Image interpolation

Also used for *resampling*



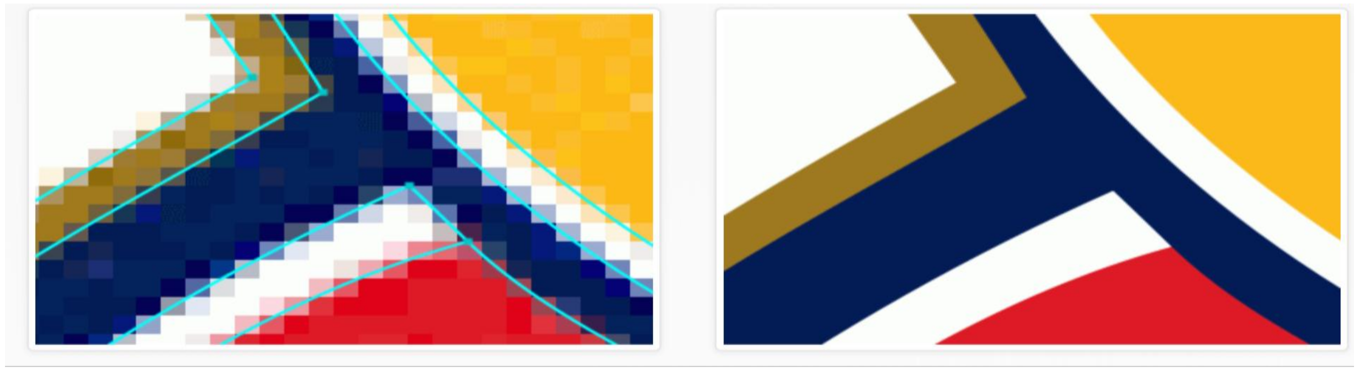
Depixelating Pixel Art

Nearest-neighbor interpolation

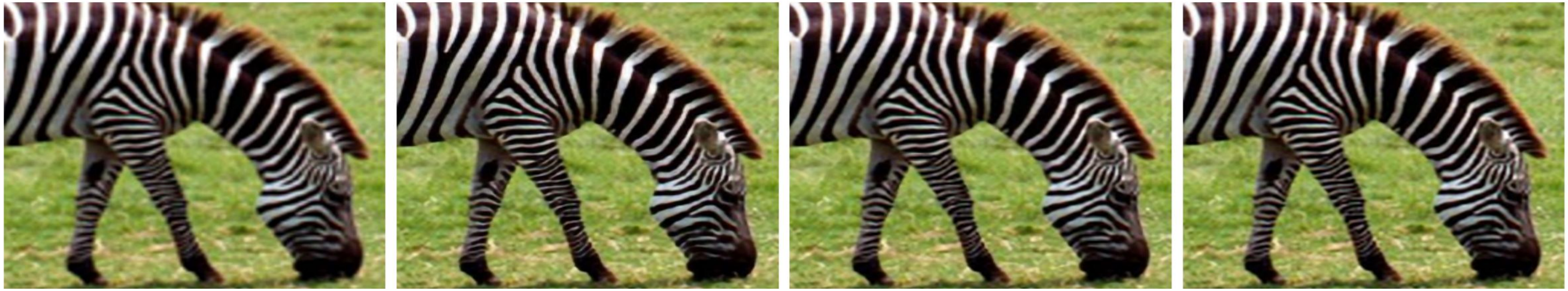


SIGGRAPH 2011

Raster-to-vector graphics



Modern methods



(a) Bicubic (b) SRCNN (c) A+ (d) RAISR

(e) Bicubic (f) SRCNN (g) A+ (h) RAISR

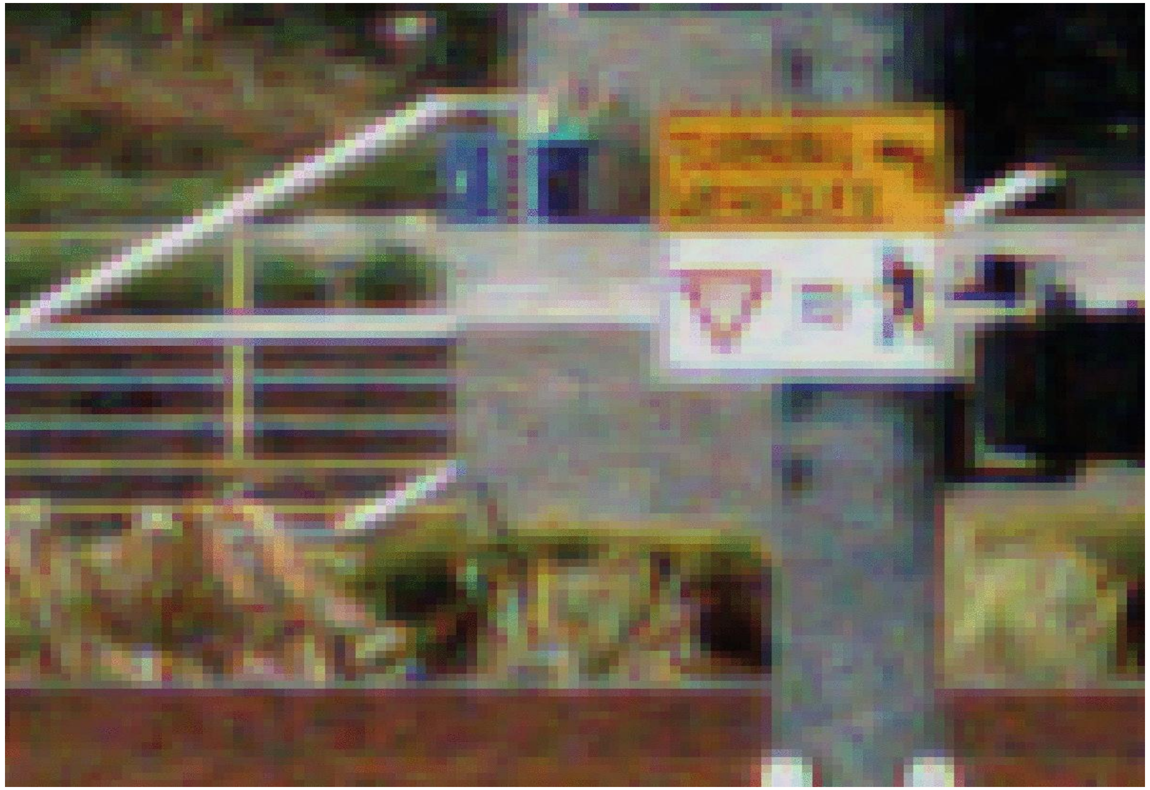
From Romano, et al: RAISR: Rapid and Accurate Image Super Resolution, https://arxiv.org/abs/1606.01299

SRCNN: Image Super-Resolution Using Deep Convolutional Networks

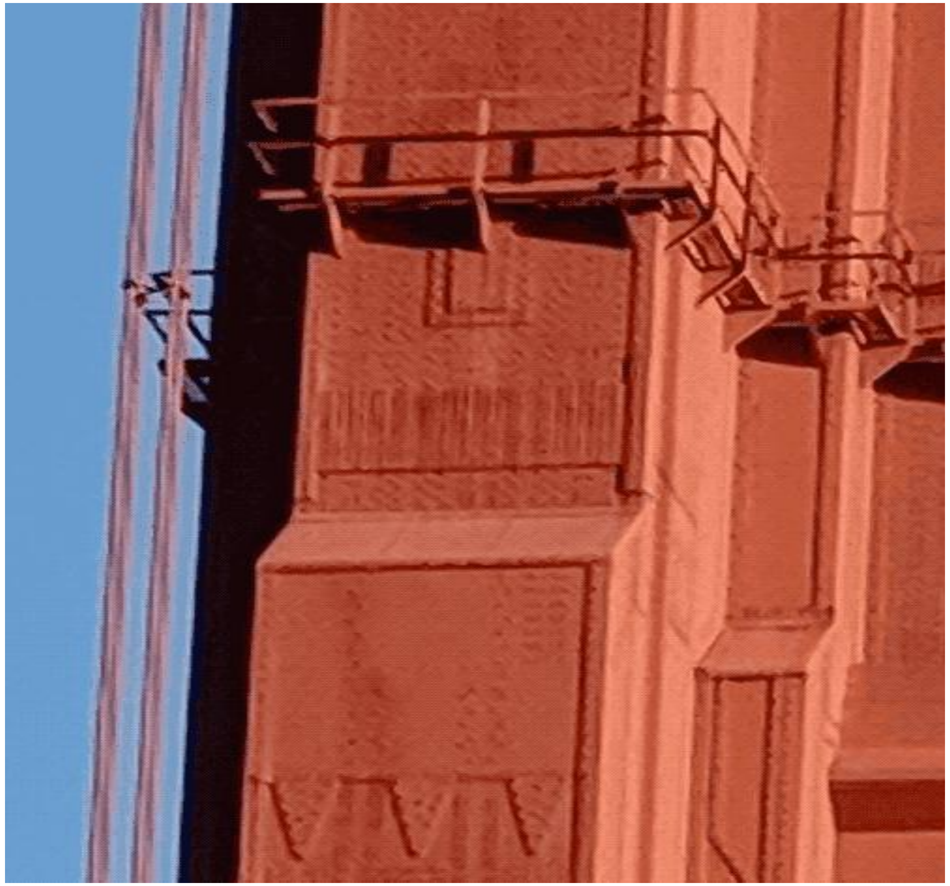
Super-resolution with multiple images

- Can do better upsampling if you have multiple images of the scene taken with small (subpixel) shifts
- Some cellphone cameras (like the Google Pixel line) capture a **burst** of photos
- Can we use that burst for upsampling?

Google Pixel 3 Super Res Zoom



Effect of hand tremor as seen in a cropped burst of photos, after global alignment



Example photo with and without super res zoom (smart burst align and merge)

https://ai.googleblog.com/2018/10/see-better-and-further-with-super-res.html