THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision

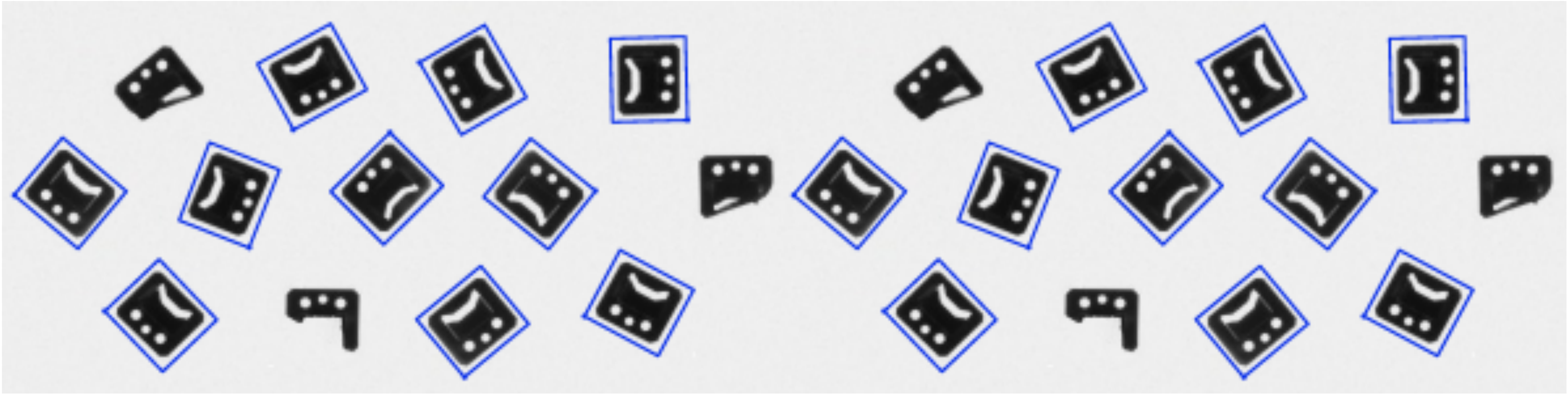


Image Credit: https://docs.adaptive-vision.com/4.7/studio/machine_vision_guide/TemplateMatching.html

Lecture 8: Scaled Representations (cont.), Edge Detection

(unless otherwise stated slides are taken or adopted from **Bob Woodham, Jim Little** and **Fred Tung**)

Menu for Today (**October 2, 2024**)

Topics:

— Imaging **Blending**
— **Scaled** Representations
— Edge **Detection**

Readings:

— **Today's** Lecture: Szeliski 2.3, 3.5, Forsyth & Ponce (2nd ed.) 4.5 - 4.7

Reminders:

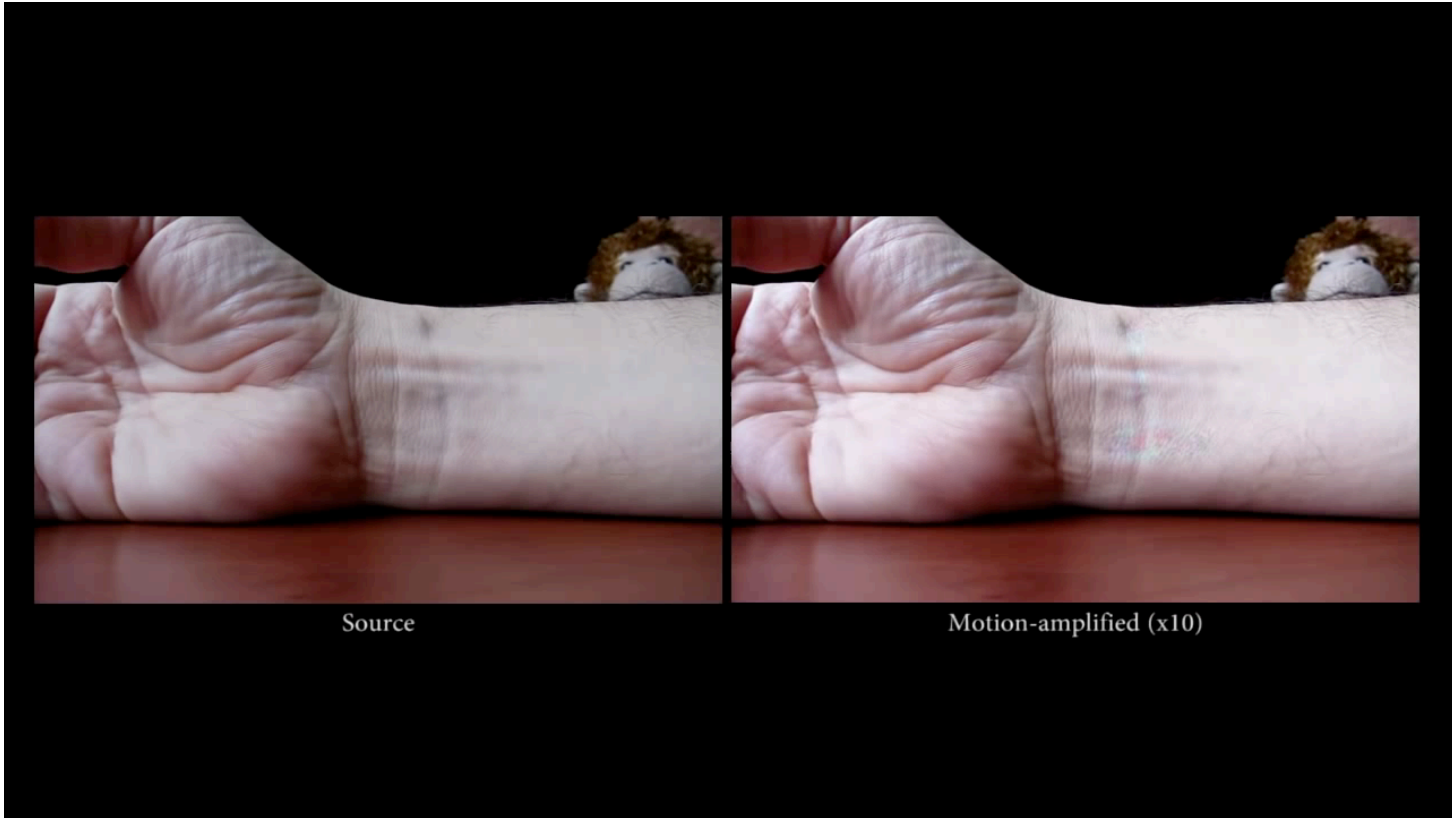
— **Assignment 2**: Scaled Representations, Face Detection and Image Blending
— **Lecture Notes** for last week in the next 1 to 2 days
— **Quiz 2** next Monday

Goal

1. Understand the idea behind **image pyramids**

2. Understand **laplacian pyramids**

Today's "**fun**" Example: Eulerian Video Magnification



Video From: Wu at al., Siggraph 2012

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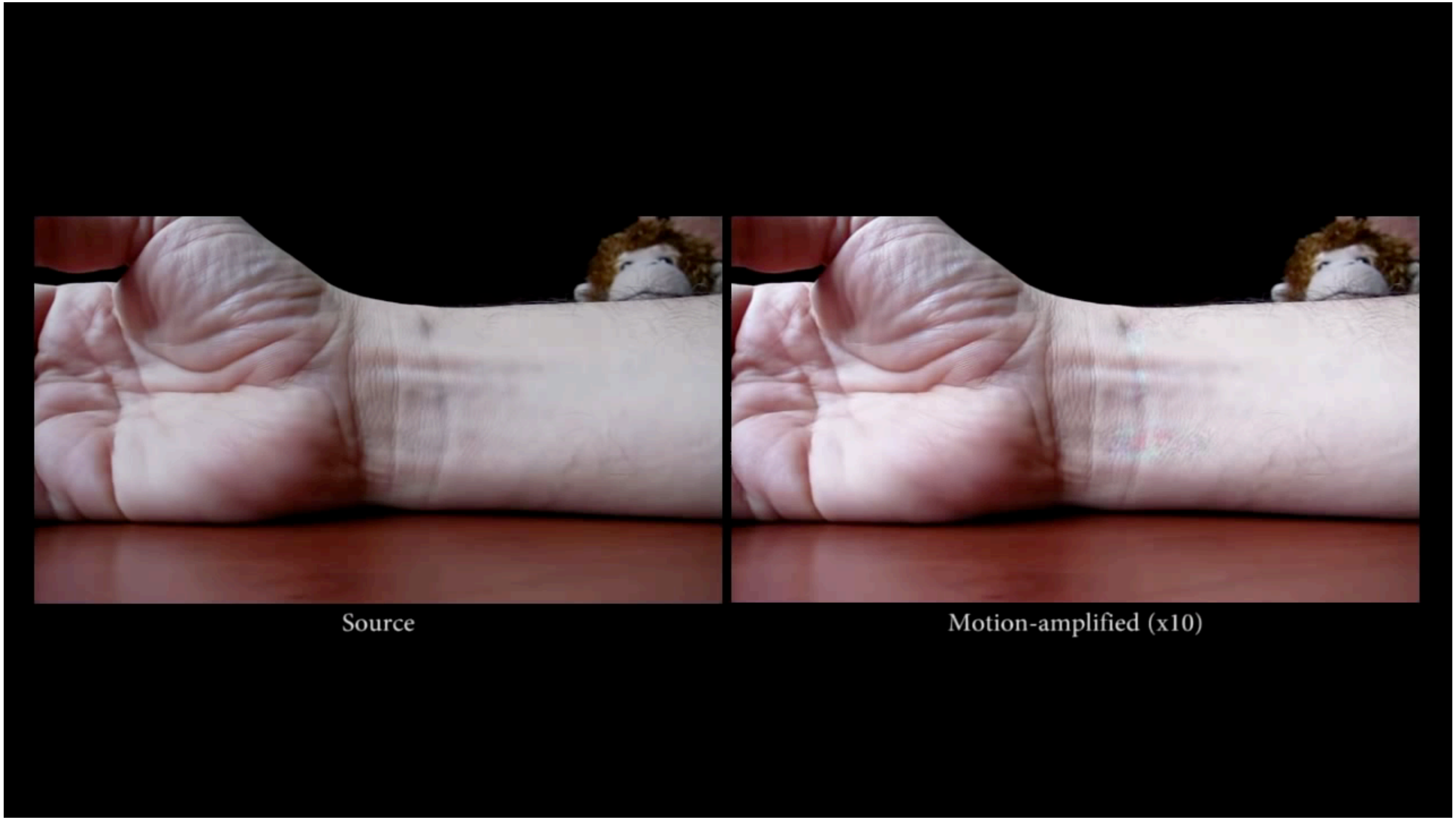

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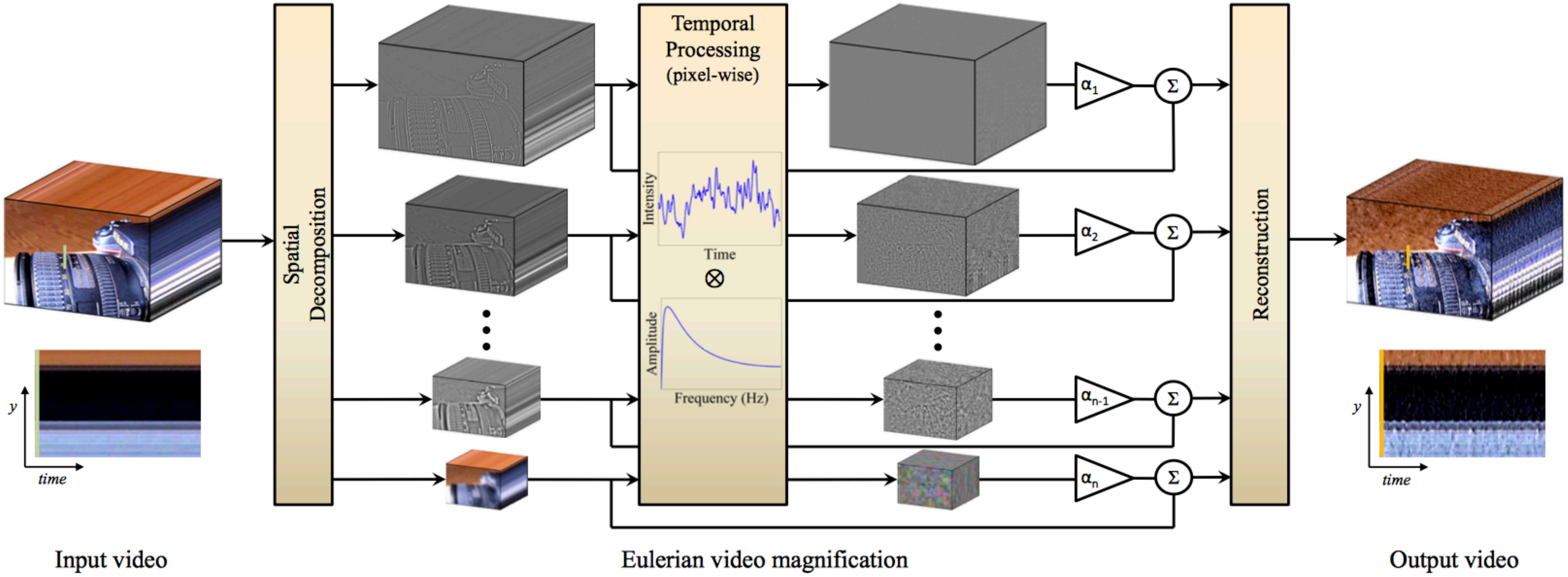
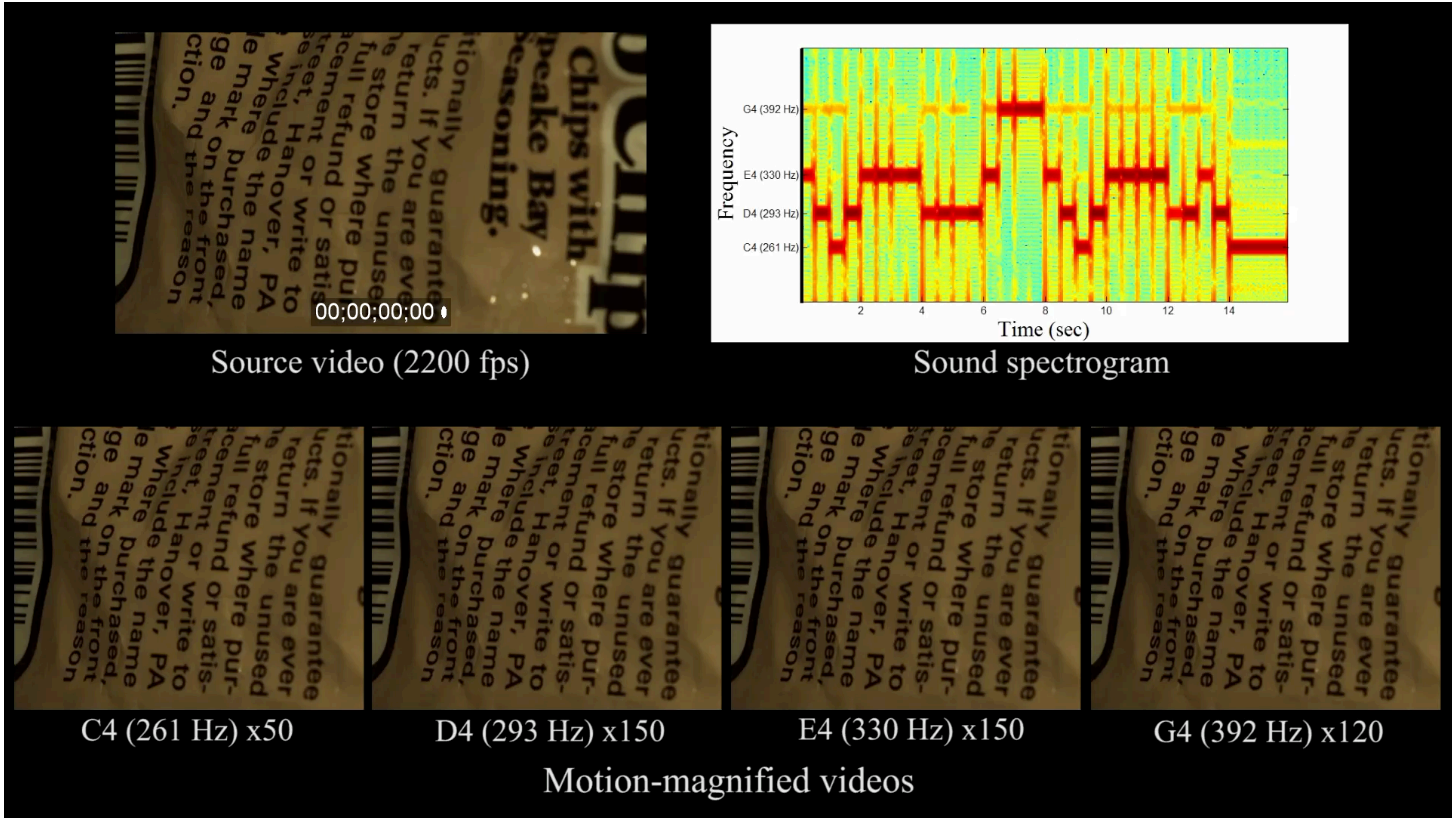


Figure From: Wu at al., Siggraph 2012

Today’s **BONUS “fun”** Example: Visual Microphone



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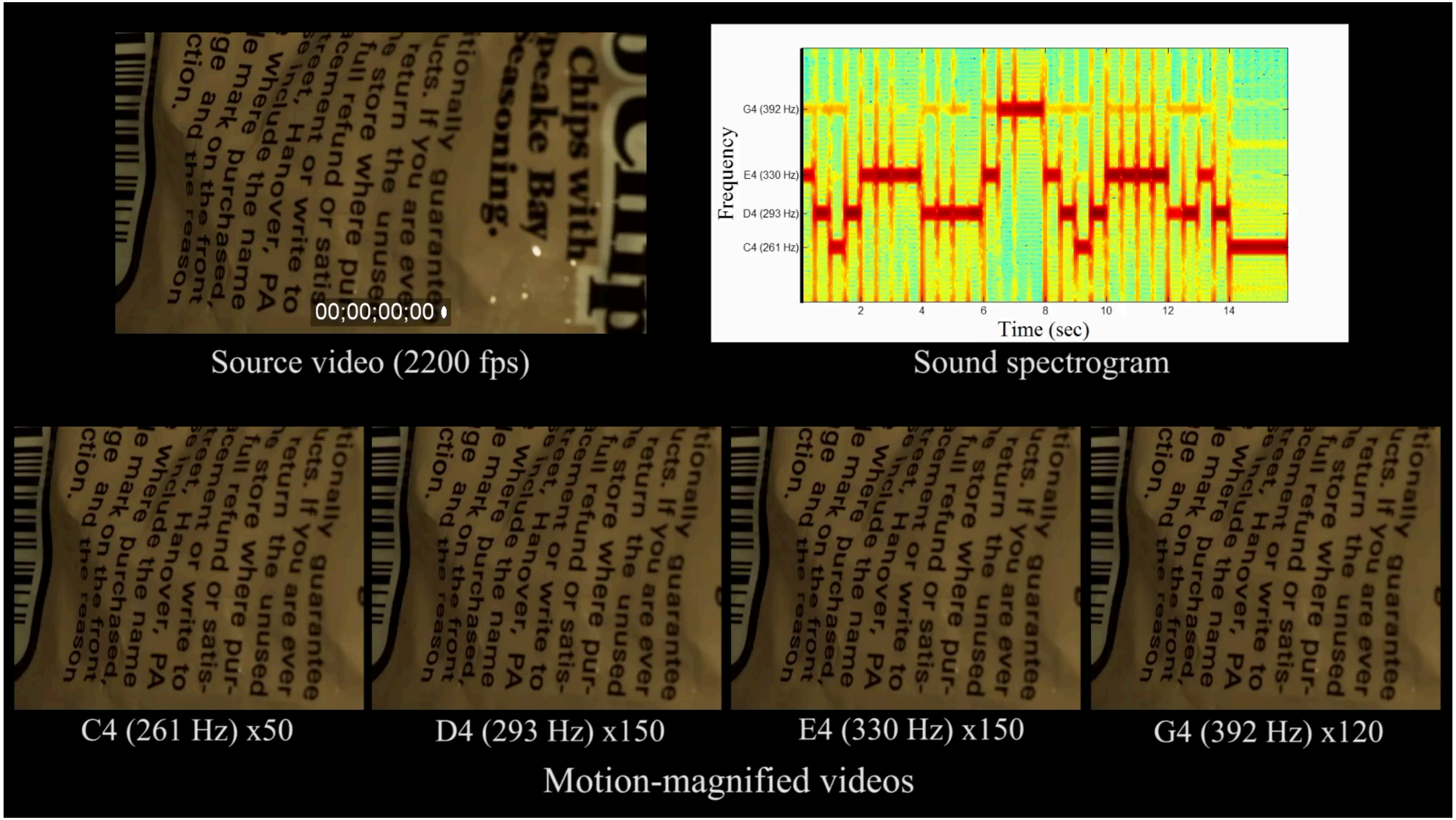
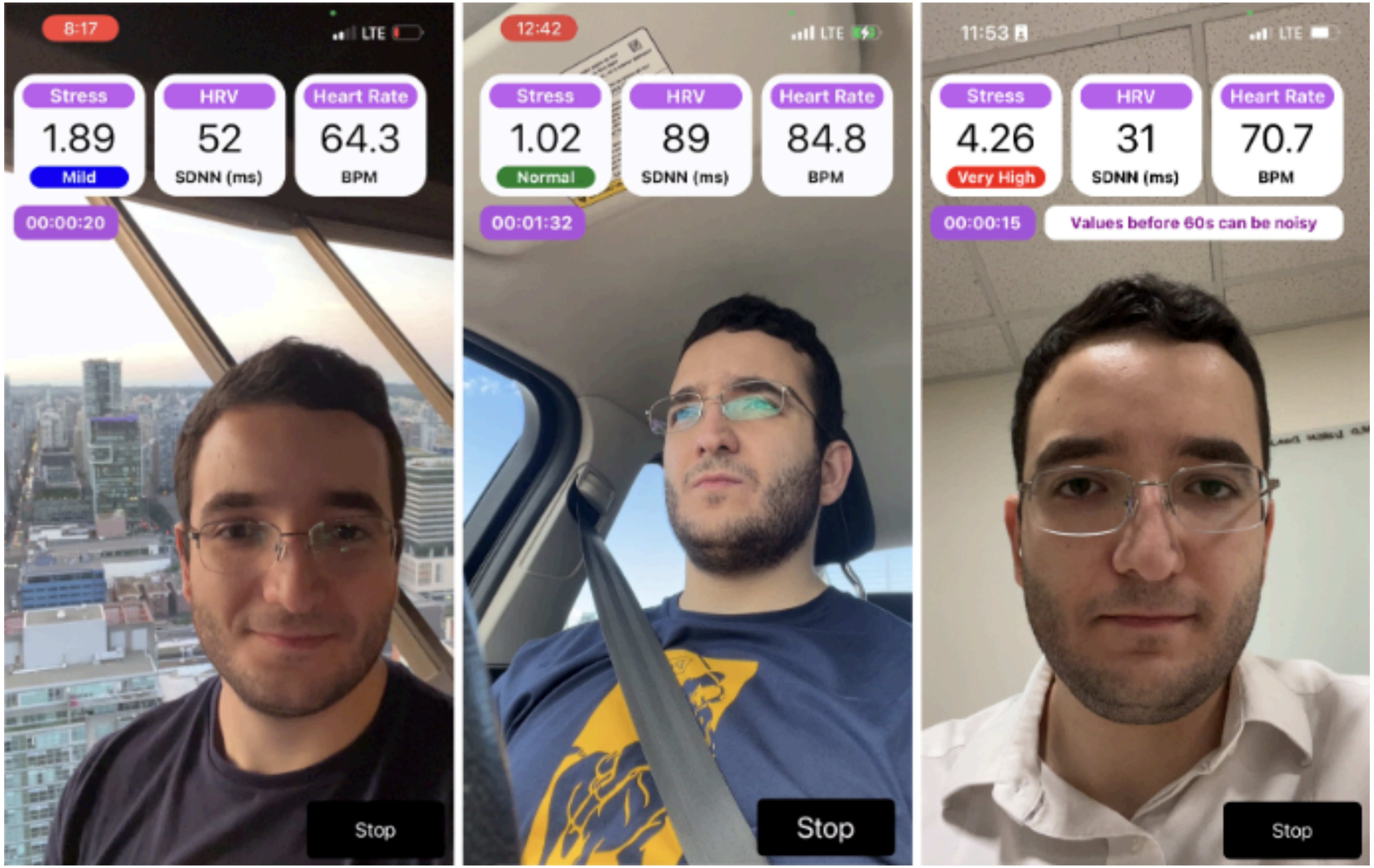
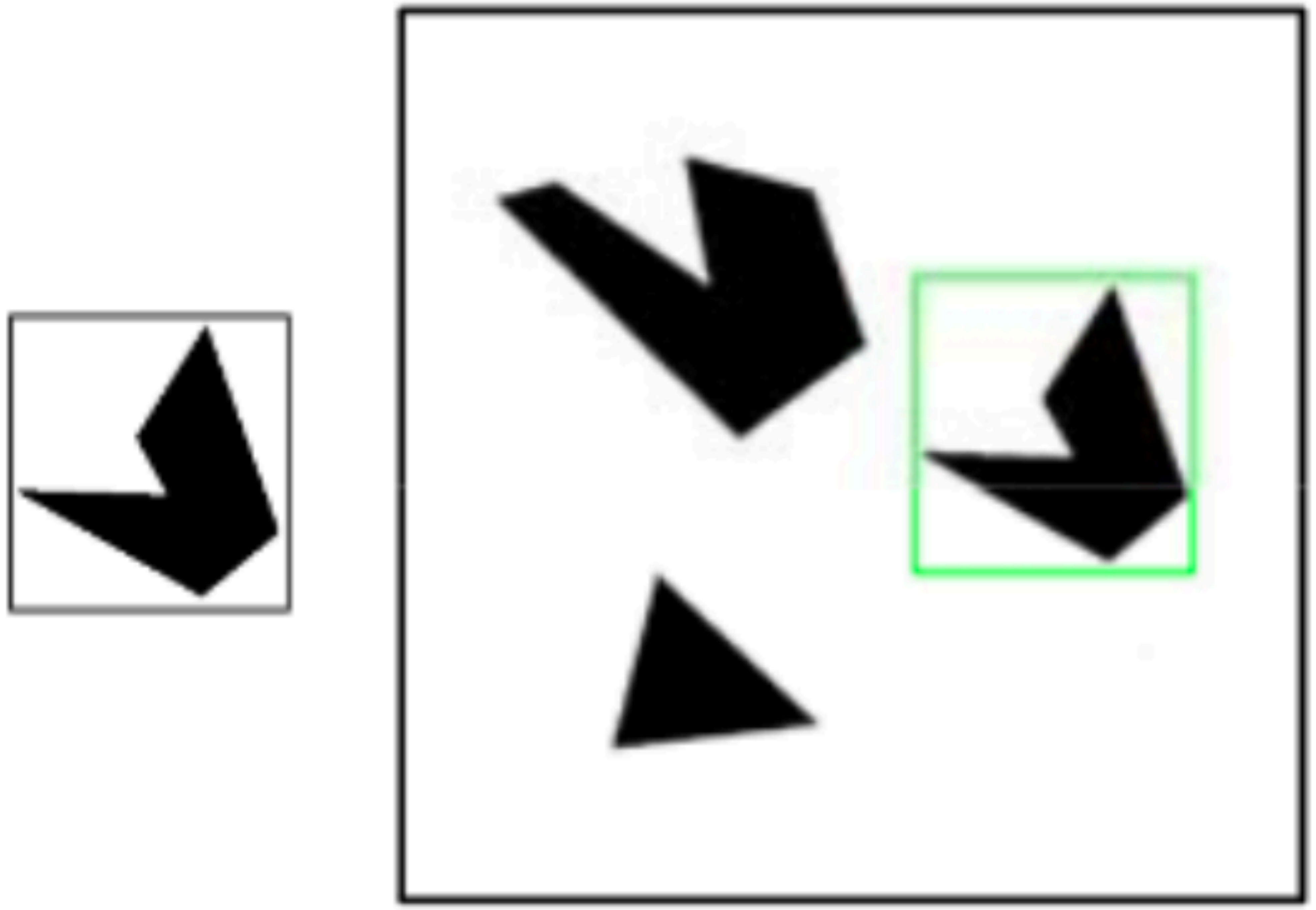


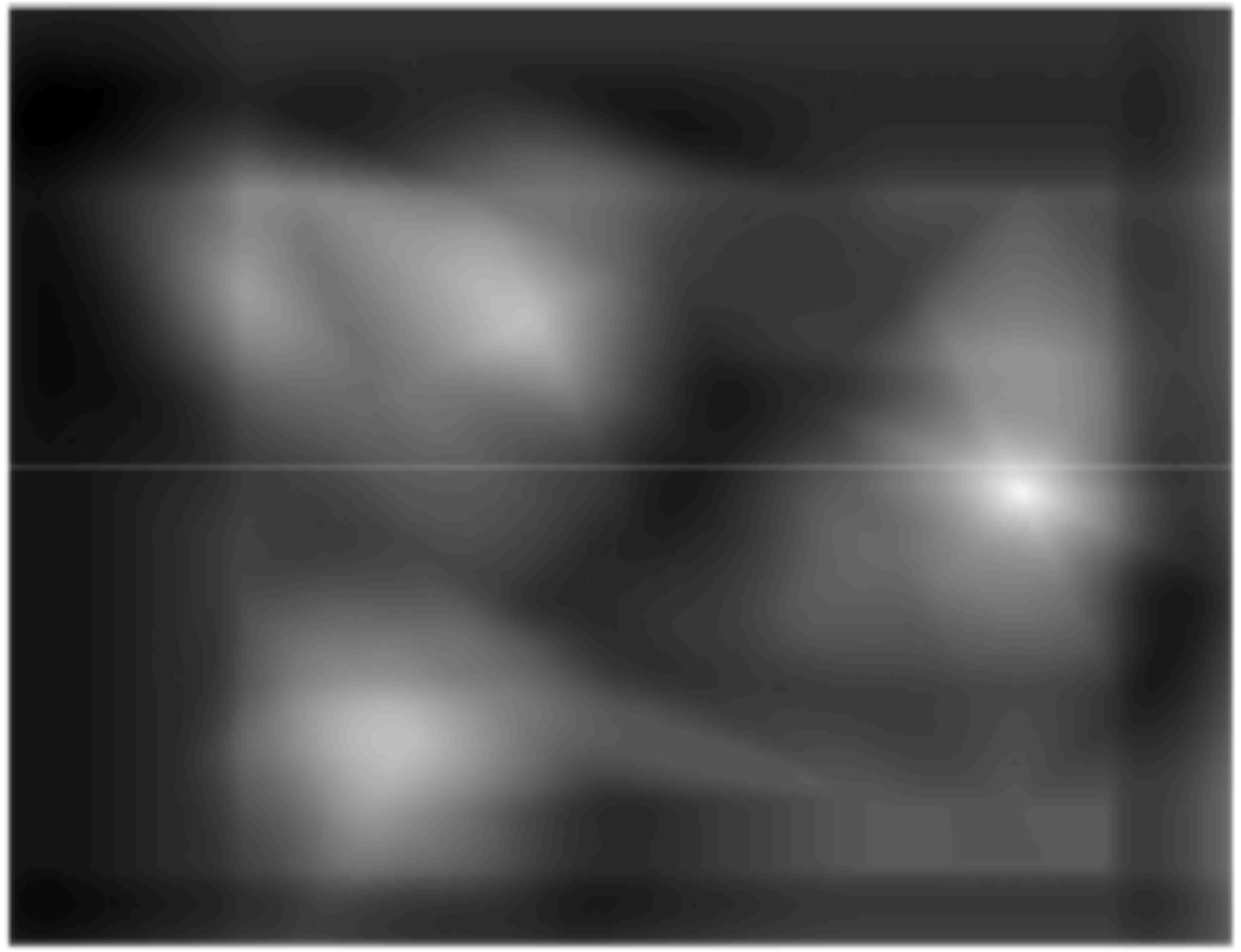
Today's **BONUS "fun"** Example: Beam AI



Lecture 7: Re-cap **Template** Matching



Detected template



Correlation map

Slide Credit: Kristen Grauman

Lecture 7: Re-cap **Template** Matching

Similarity measures between a filter $\mathbf{J}$ local image region $\mathbf{I}$

Correlation, CORR = $\mathbf{I} \cdot \mathbf{J} = \mathbf{I}^T \mathbf{J}$

Normalised Correlation, NCORR = $\dfrac{\mathbf{I}^T \mathbf{J}}{|\mathbf{I}||\mathbf{J}|} = \cos\theta$

Sum Squared Difference, SSD = $|\mathbf{I} - \mathbf{J}|^2$

Normalized correlation varies between –1 and 1, attains the value 1 when the filter and image region are identical (up to a scale factor)

Minimising SSD and maximizing Normalized Correlation
are equivalent if $|\mathbf{I}| = |\mathbf{J}| = 1$

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Sum Squared Difference, SSD = $|\mathbf{I} - \mathbf{J}|^2$ ⟵ **Assignment** 2

Normalized correlation varies between –1 and 1, attains the value 1 when the filter and image region are identical (up to a scale factor)

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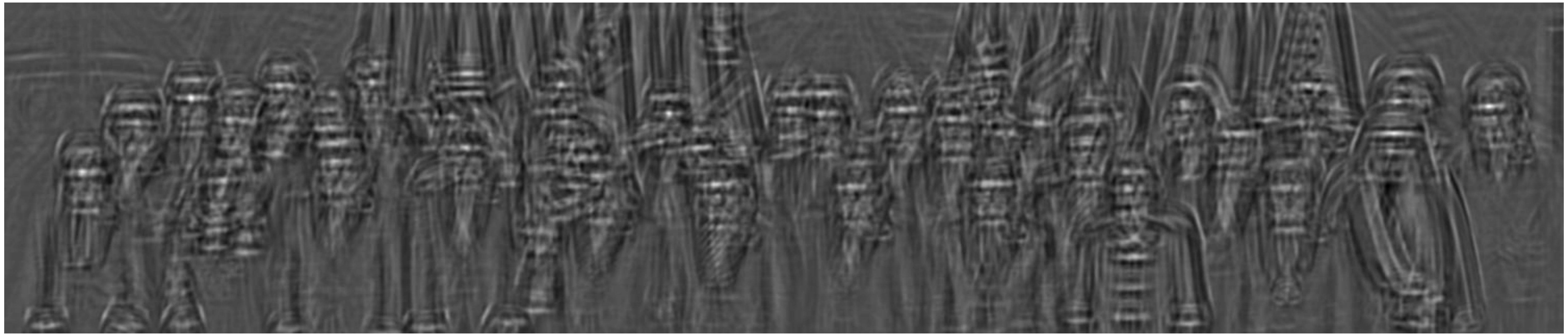
Template Matching

Correlate image with a template

$*$ 

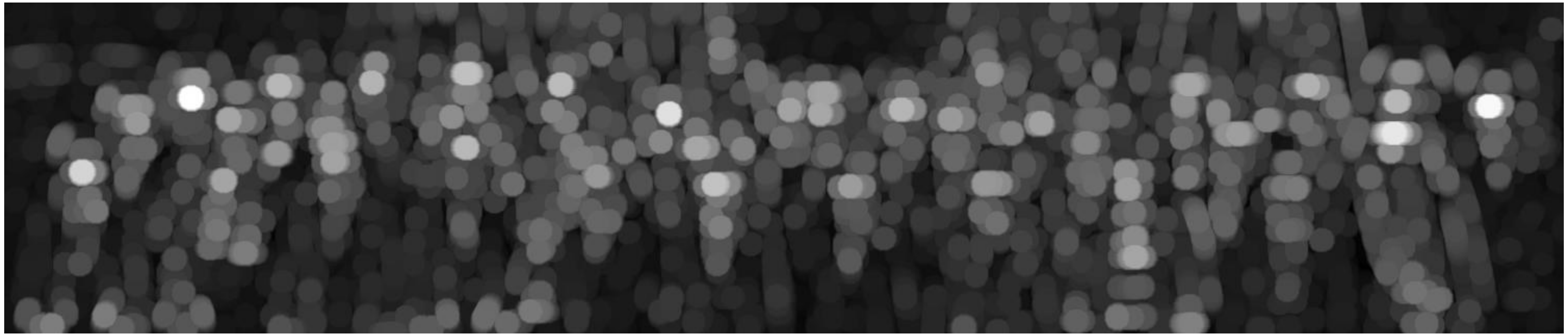


Template Matching

Correlate image with a template

$*$

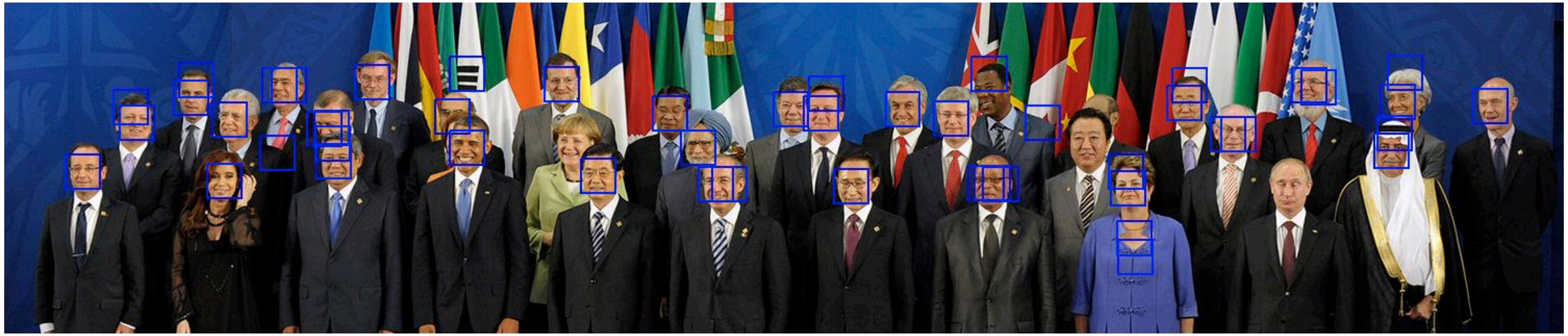
$\longrightarrow$ Non-max suppress $\longrightarrow$



Template Matching

Correlate image with a template

$*$  $\longrightarrow$ Non-max suppress + threshold $\longrightarrow$



Detection Performance

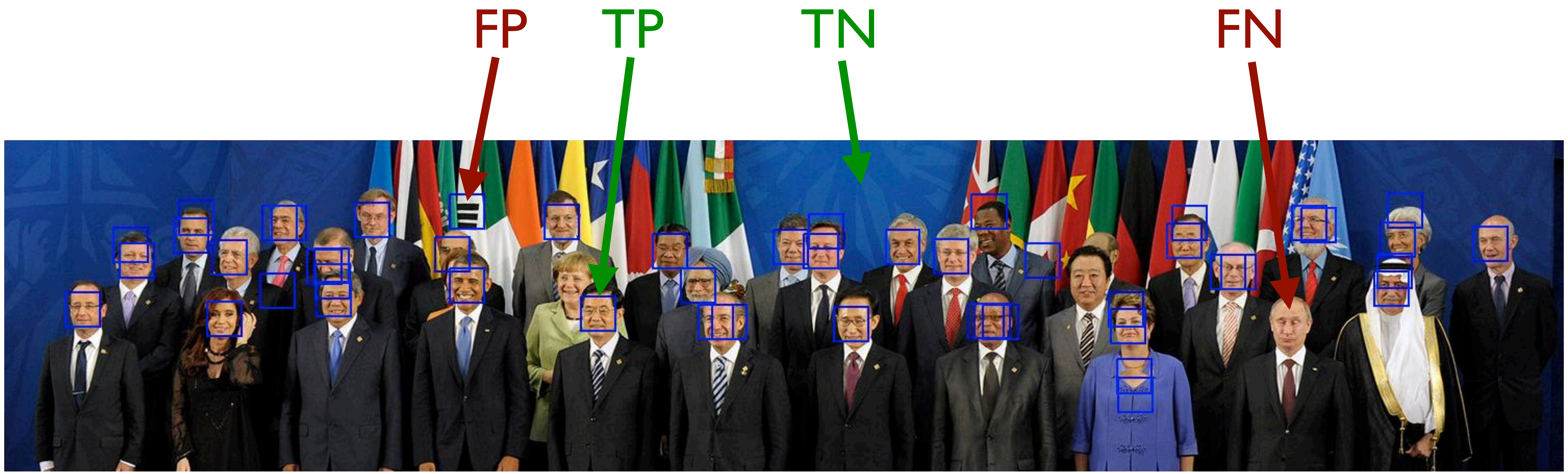
Types of errors in detection:

TP = True positive (true face and detected)

FP = False positive (not face and detected)

TN = True negative (not face and no detection)

FN = False negative (true face and not detected)



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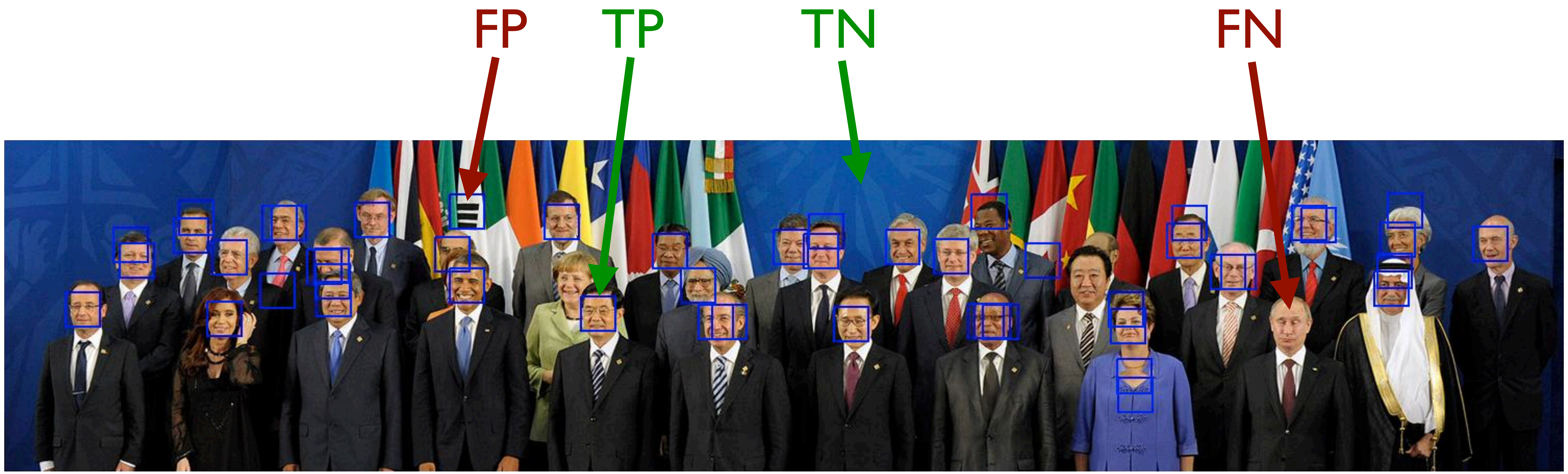
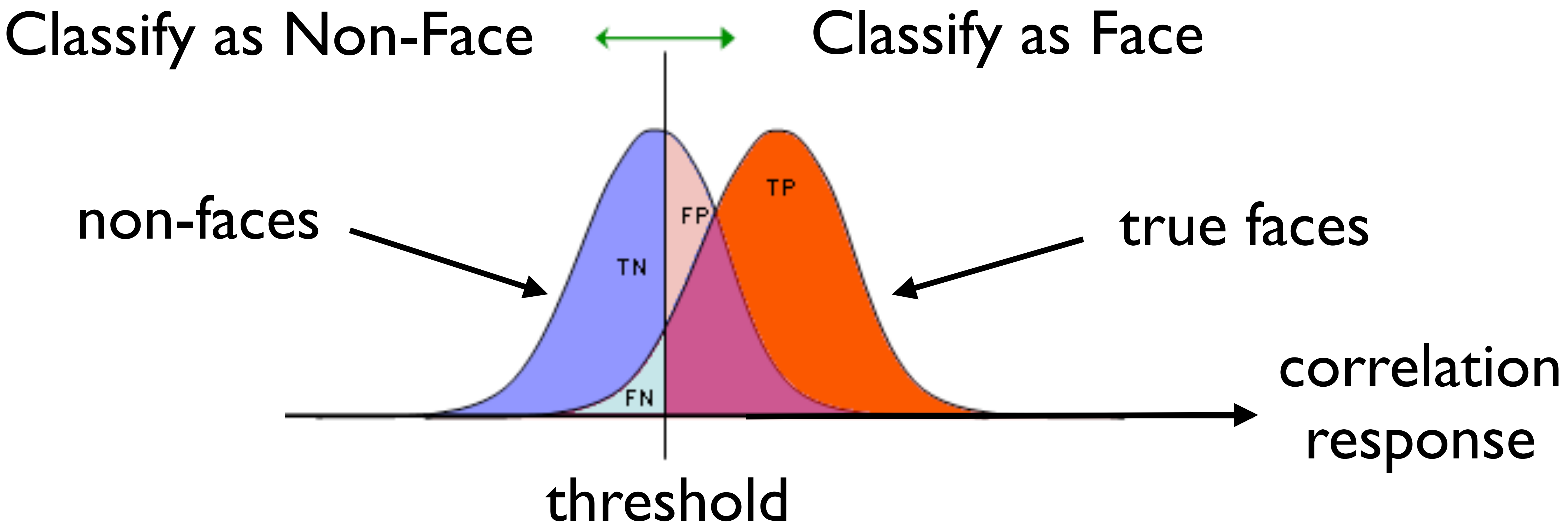
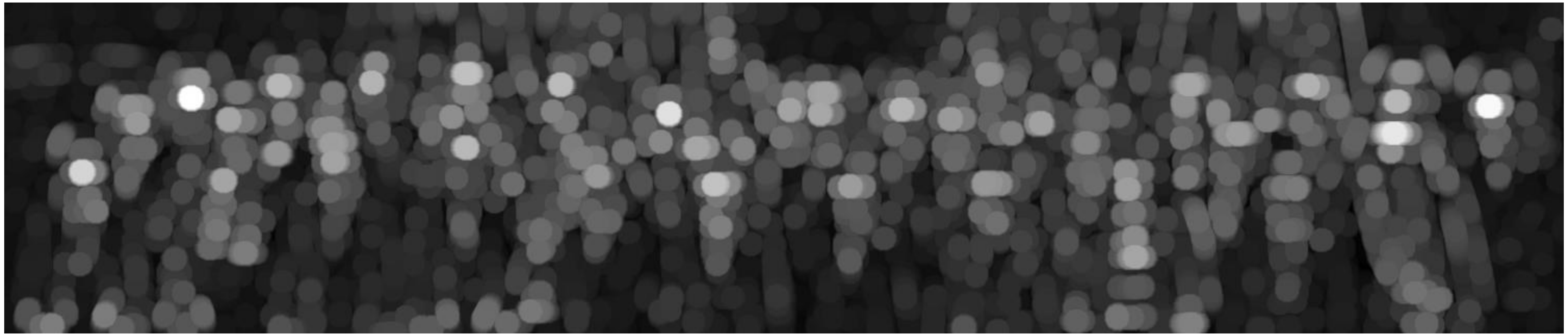


Detection Performance

Depending on where we set the threshold, we can tradeoff between **true positives** and **false positives**:





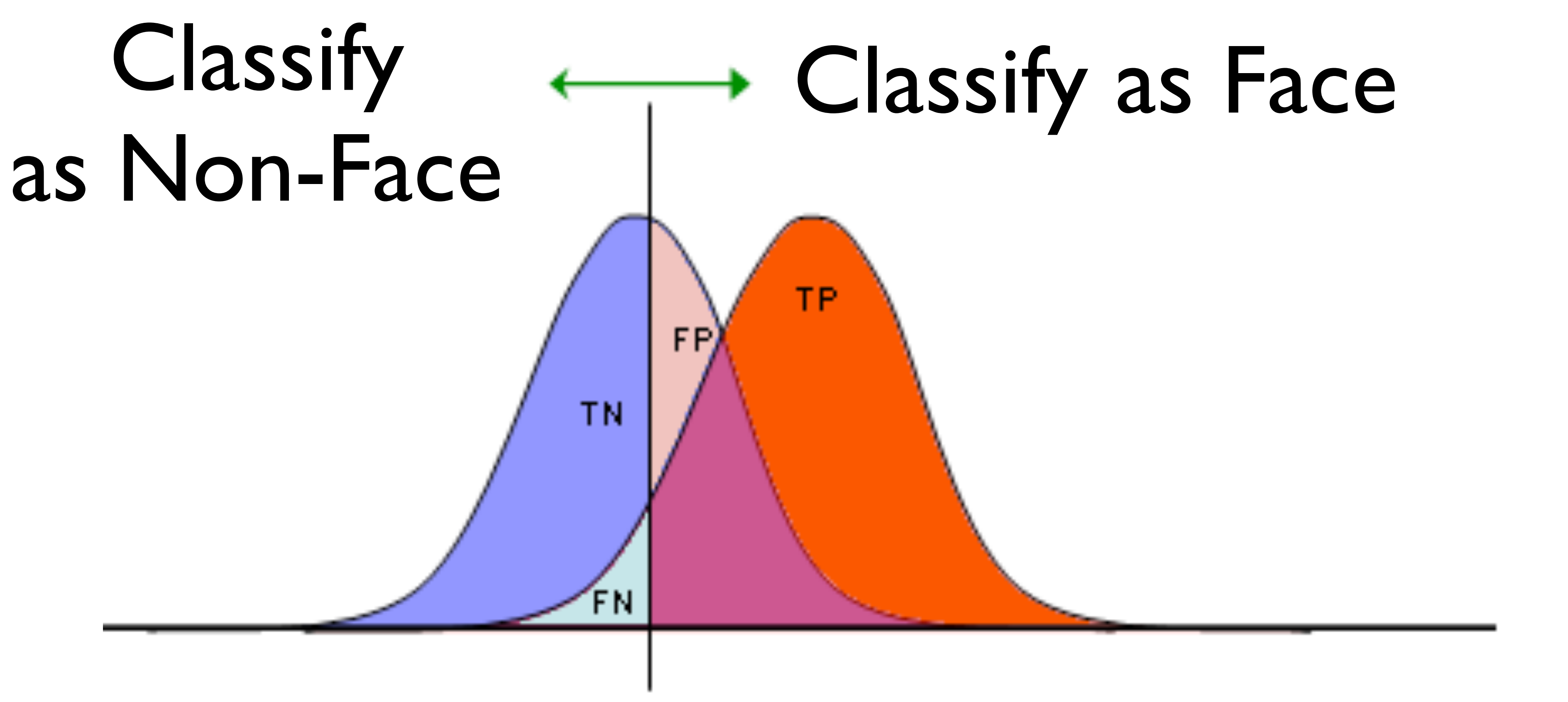
ROC Curves

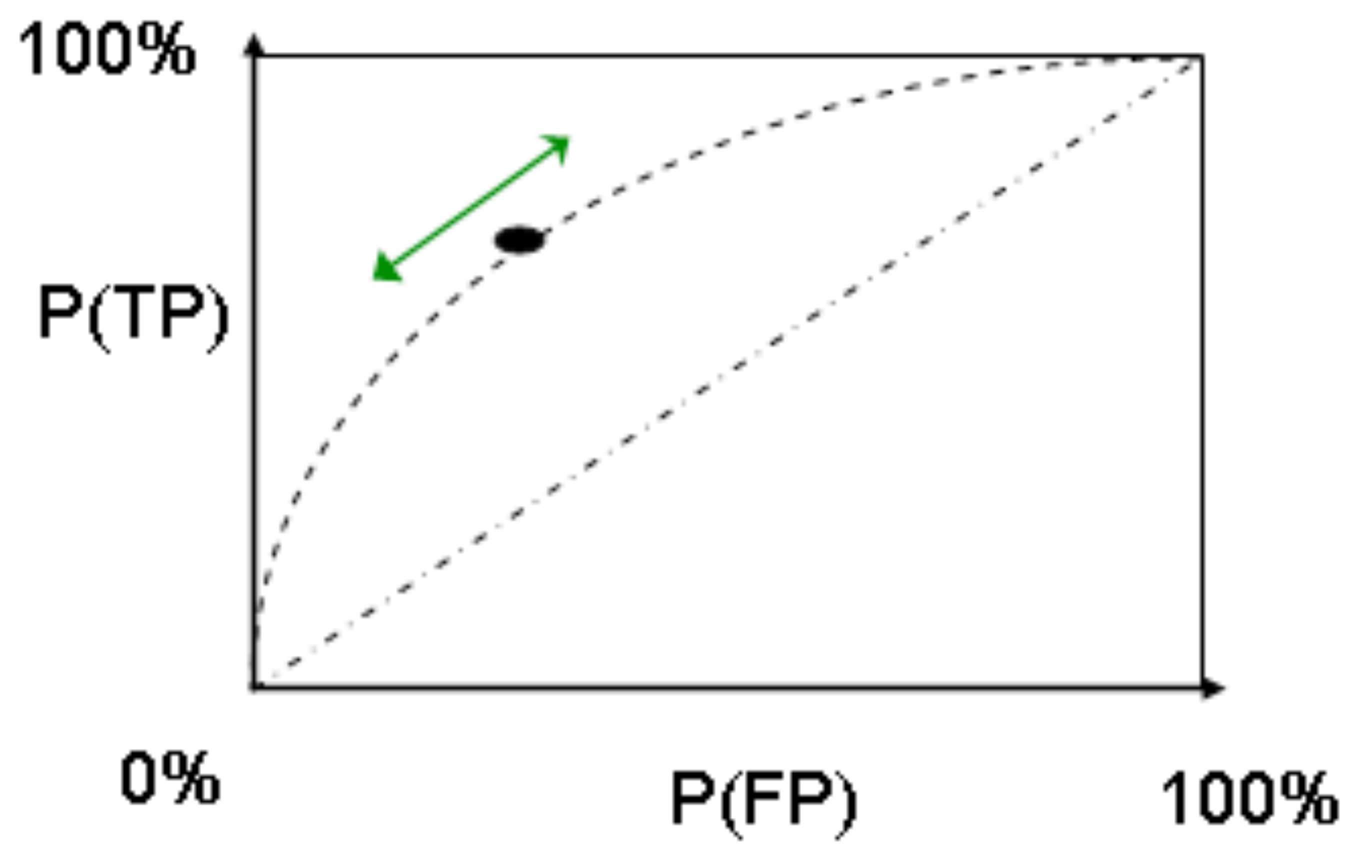
Note that we can easily get 100% true positives (if we are prepared to get 100% false positives as well!)

It is a tradeoff between **true positive rate (TP)** and **false positive rate (FP)**

We can plot a curve of all TP rates vs FP rates by varying the classifier threshold

This is a **Receiver Operating Characteristic (ROC)** curve





red = actual faces, blue = actual non-faces

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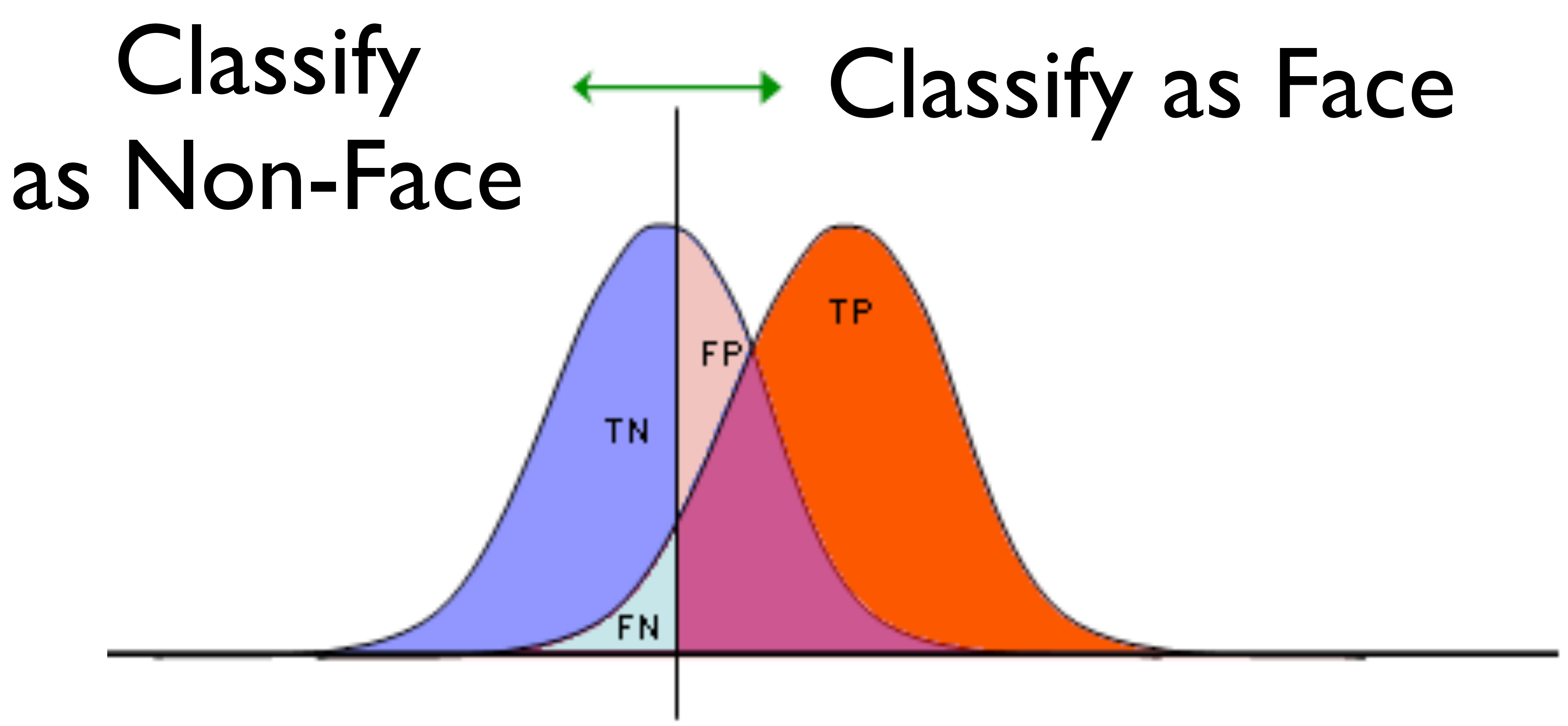

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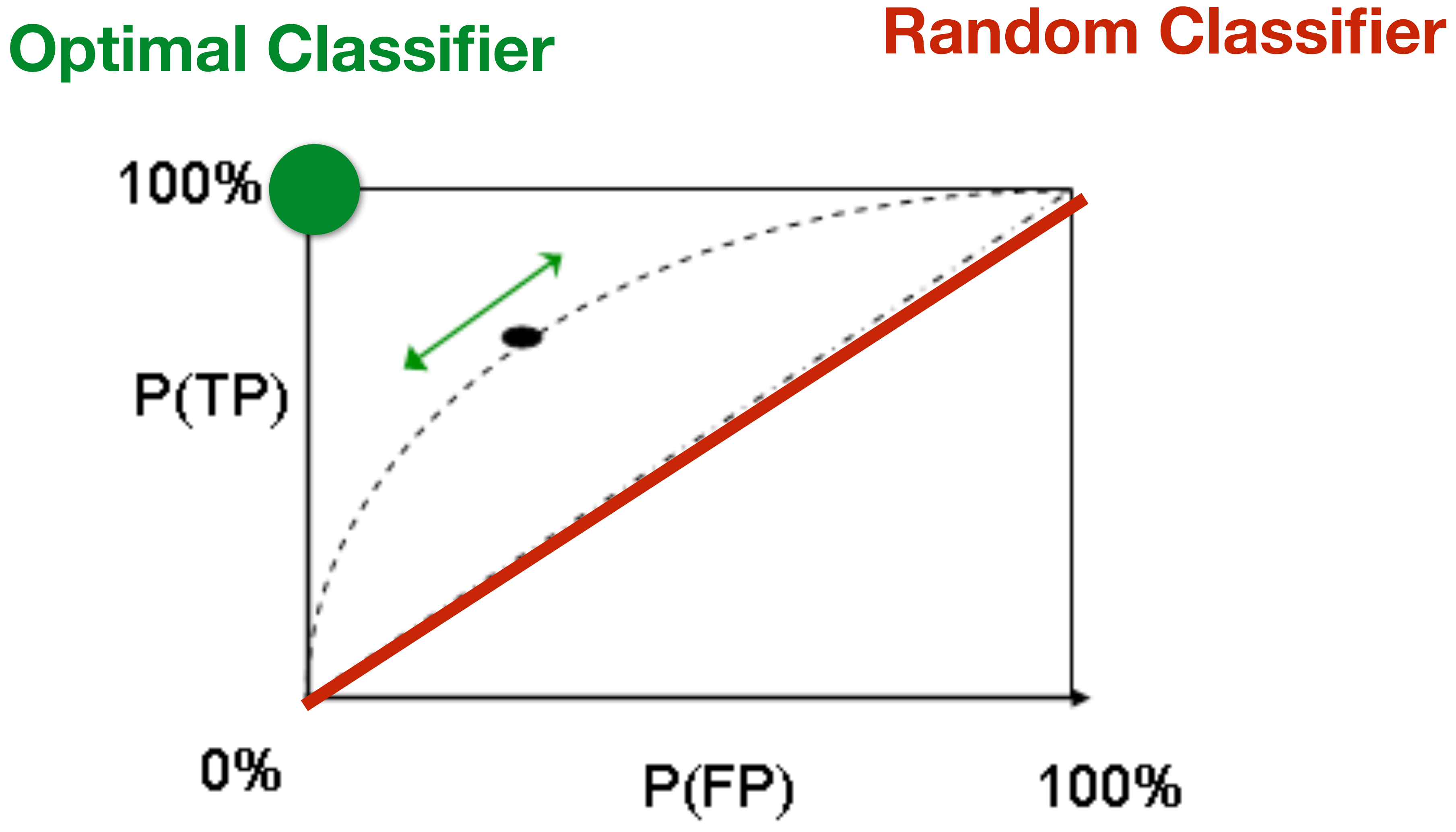

Template Matching

Correlation with a **fixed-sized template** only detects faces at **specific scales**

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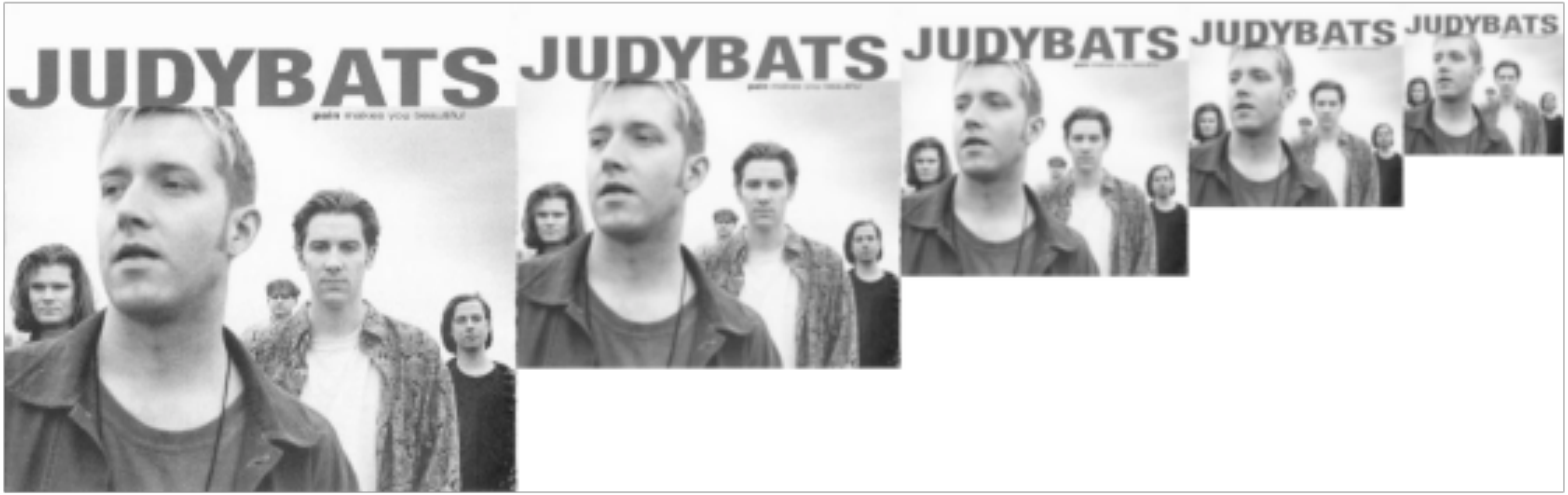
Multi-Scale Template Matching

Solution: form a Gaussian Pyramid and convolve with the template at each scale



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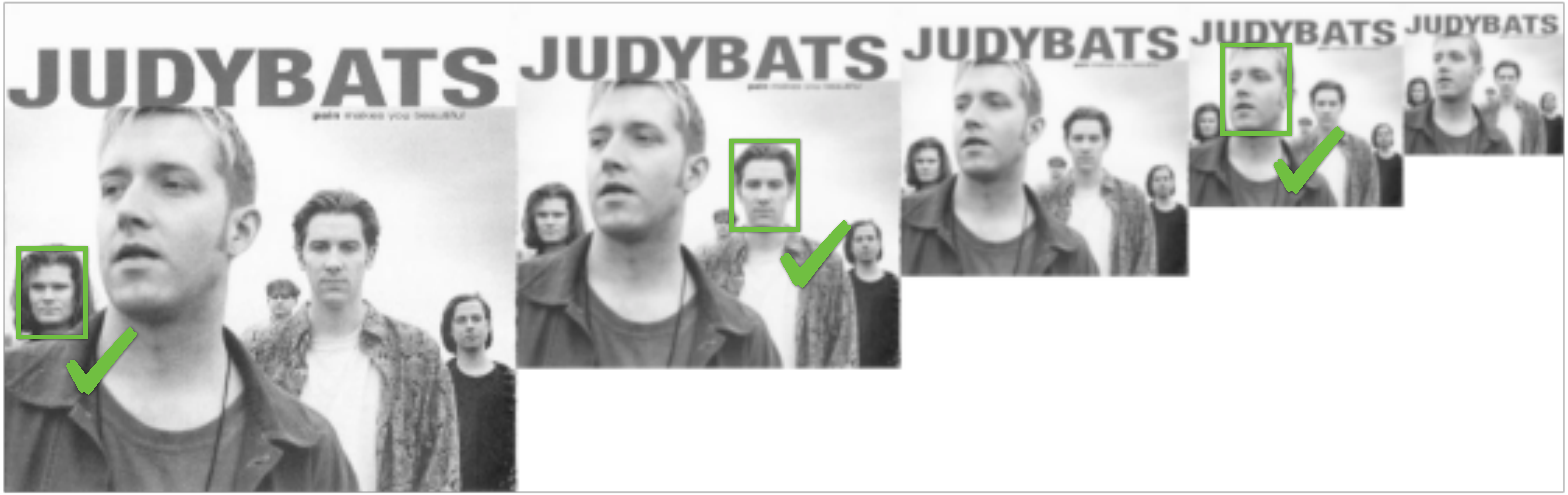

Image **Pyramid**

An **image pyramid** is an efficient way to represent an image at multiple scales

Gaussian vs **Laplacian** Pyramid

   

Shown in opposite order for space

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

$G1$

Blur with a Gaussian kernel, then select every 2nd pixel

$$I_s(x, y) = I(x, y) * g_\sigma(x, y)$$

$G1$

blur

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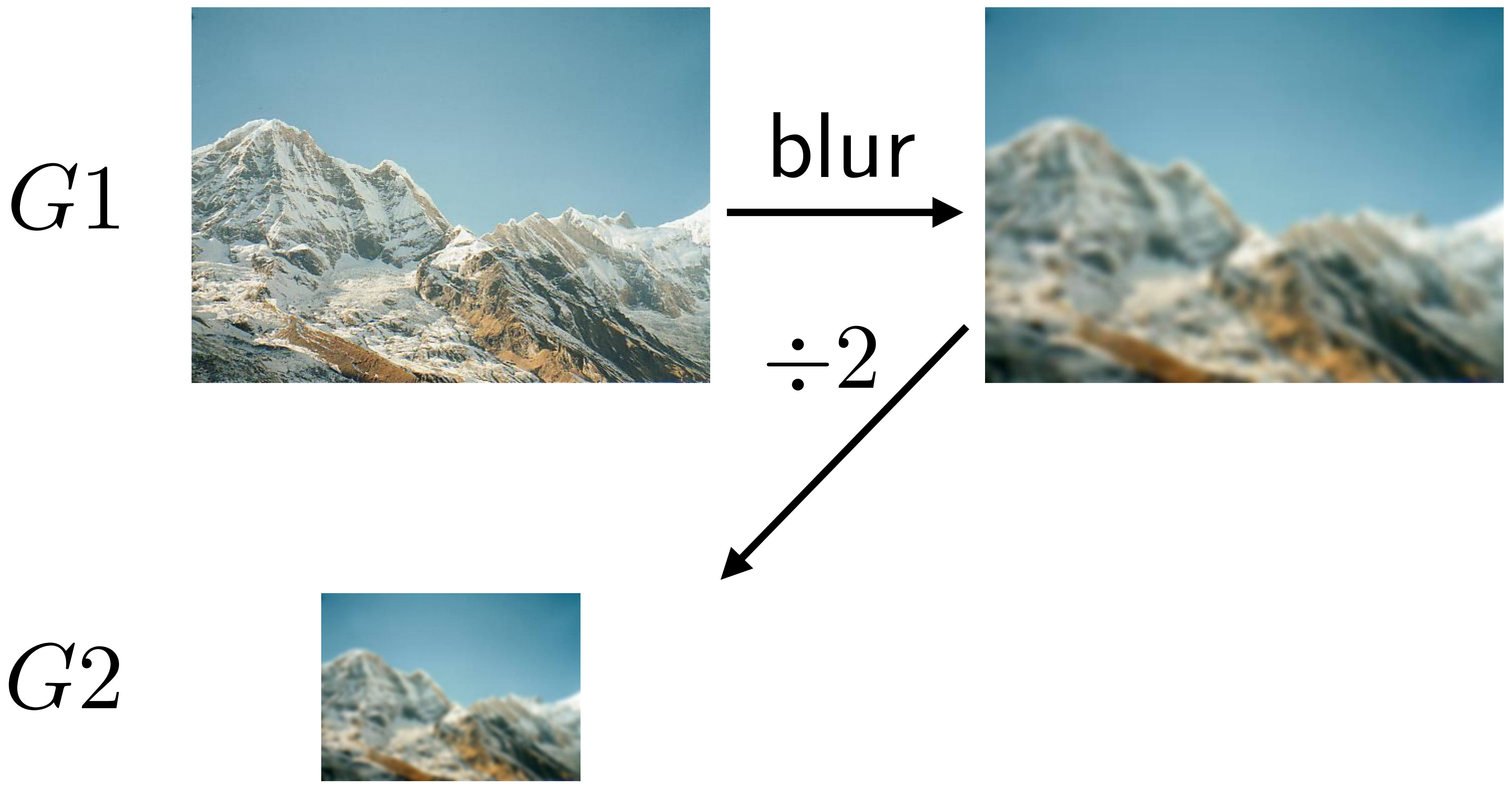

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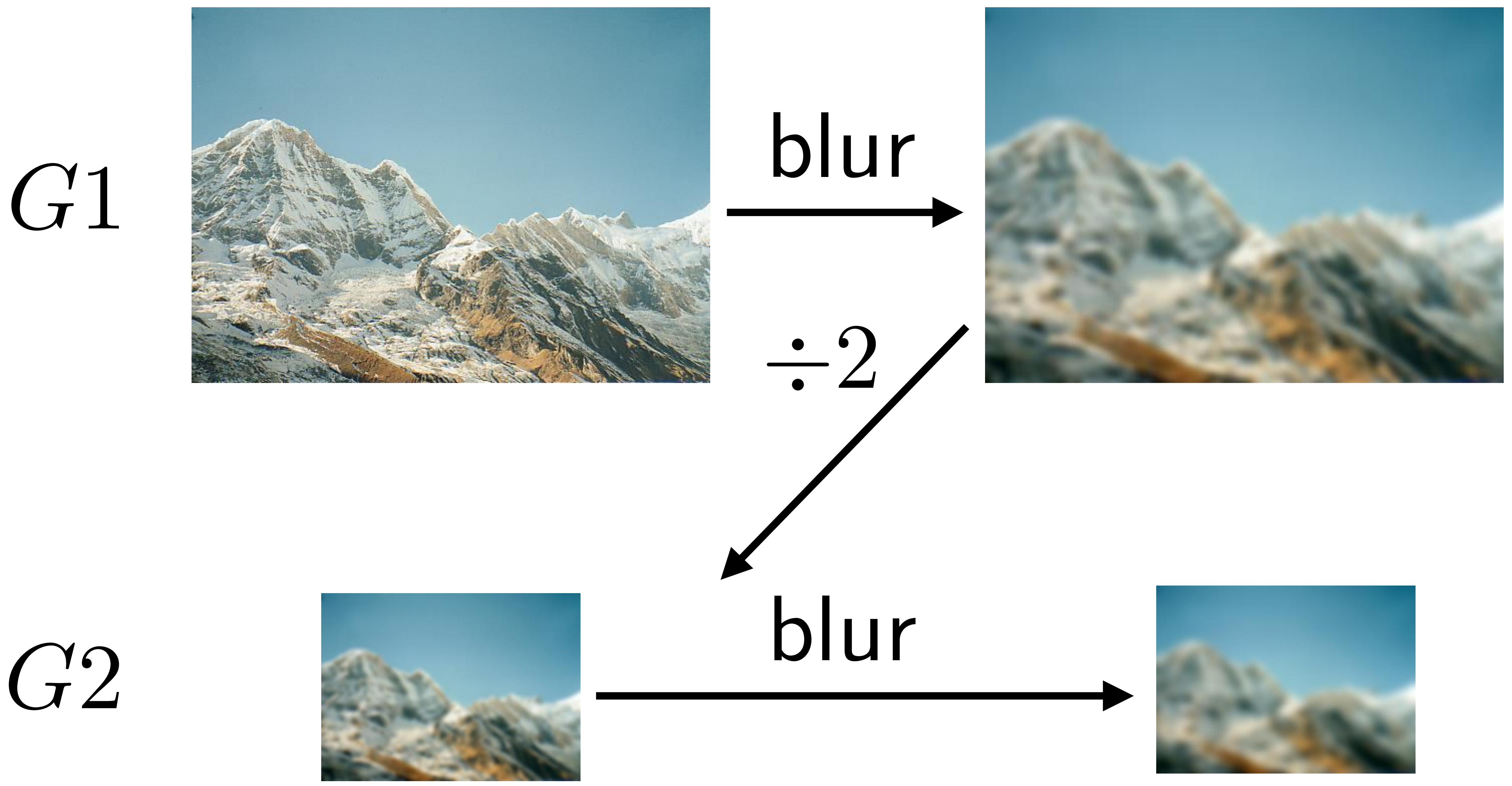

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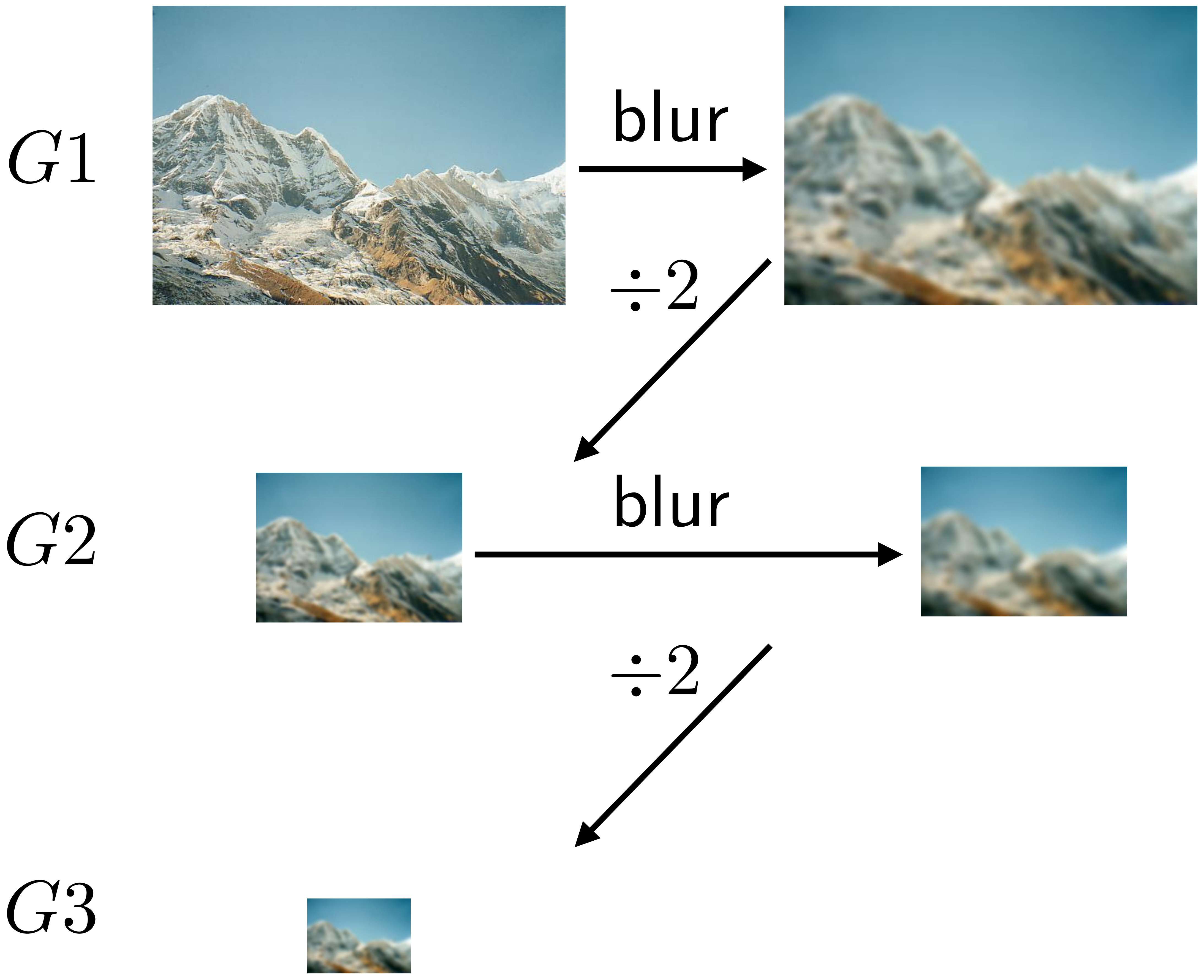

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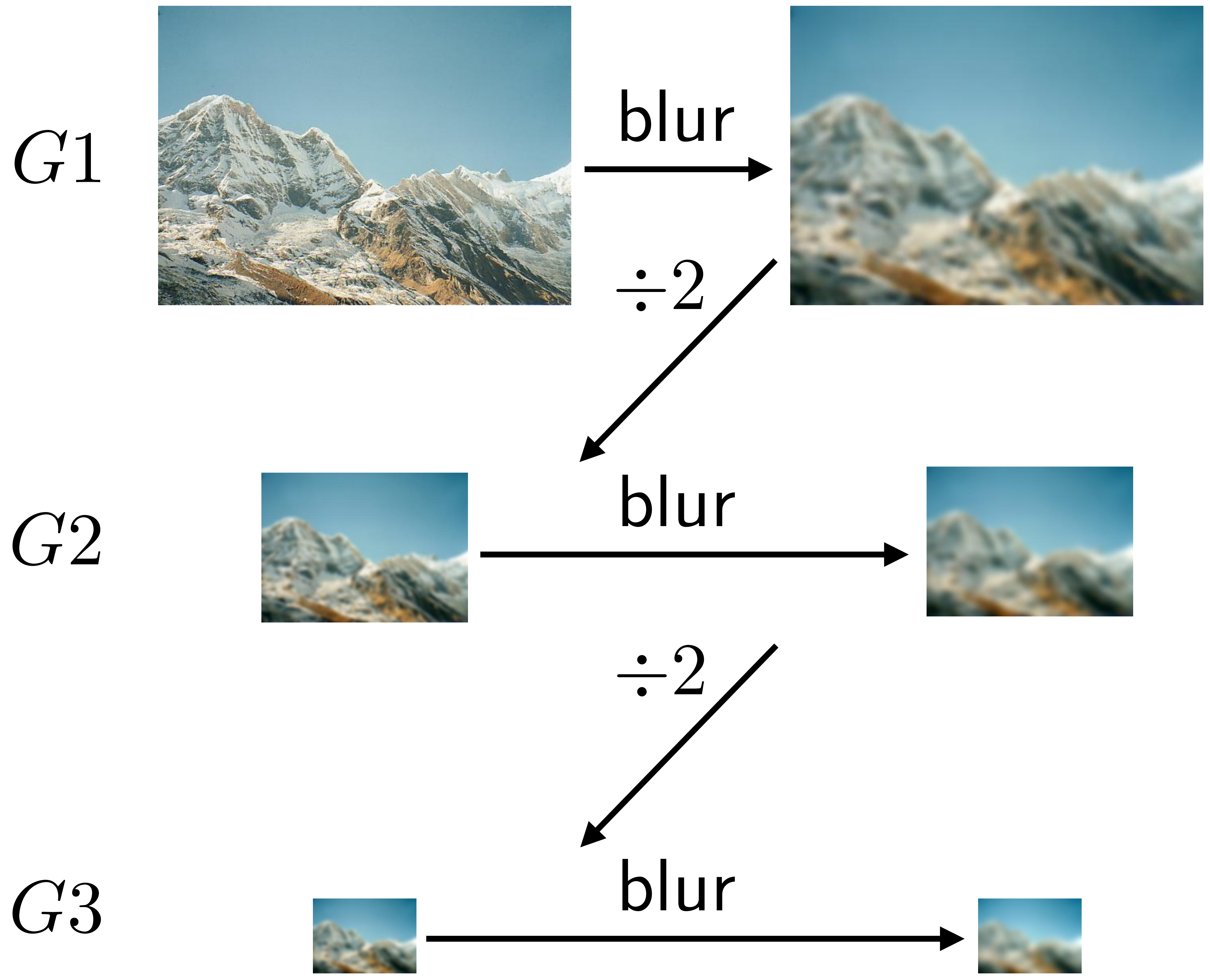

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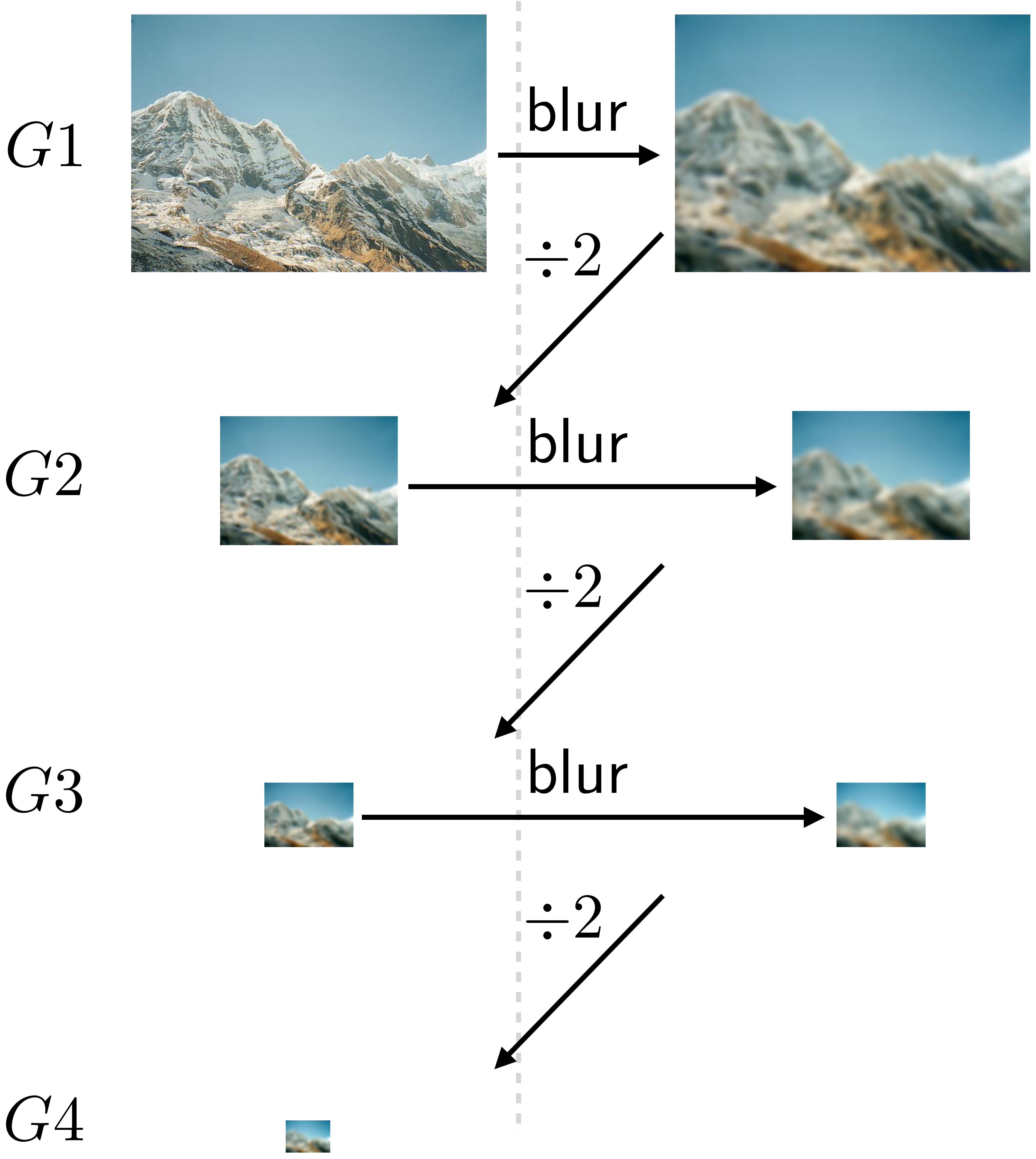

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Gaussian Pyramid

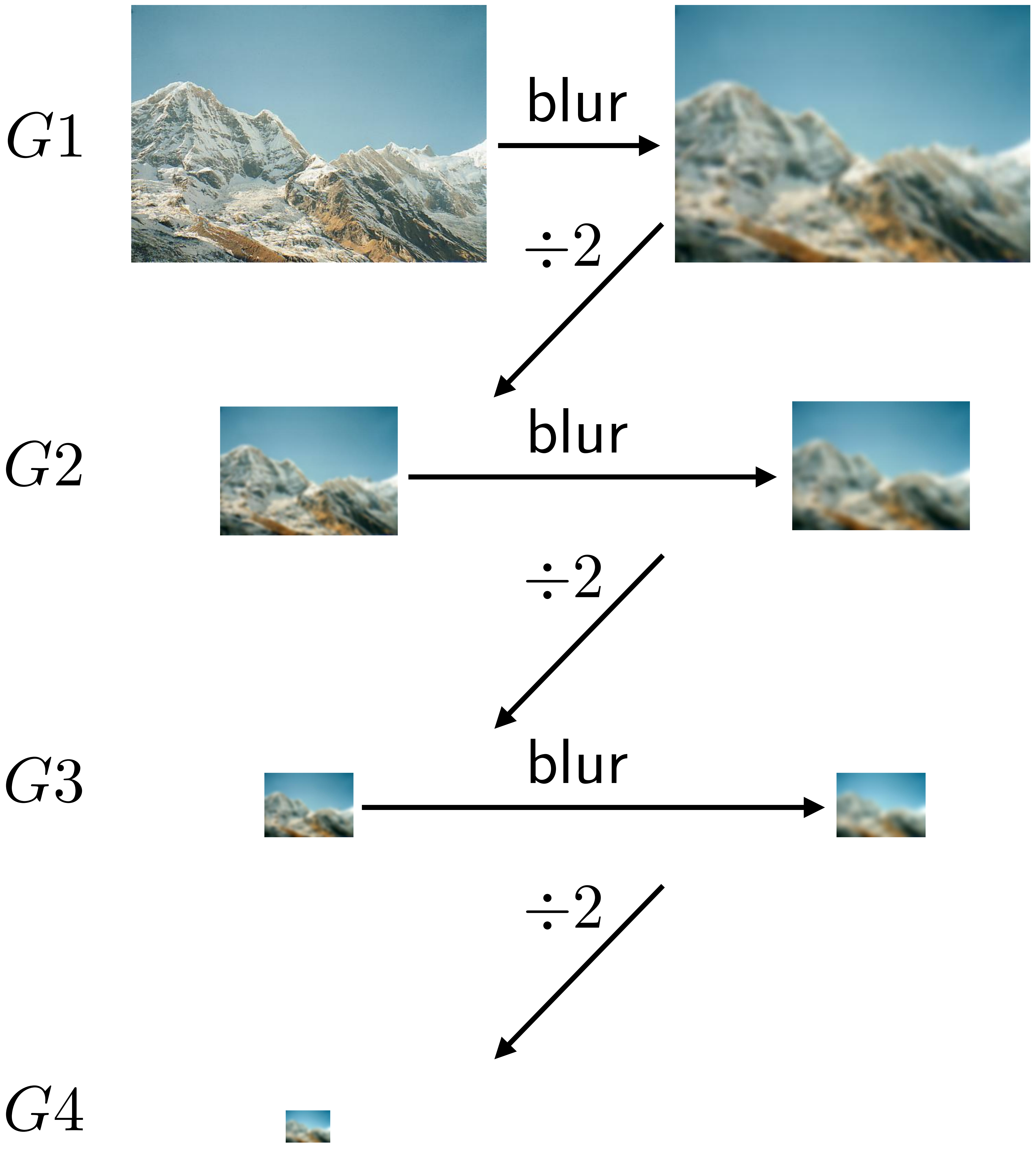
$G1$

$G2$

$G3$

$G4$

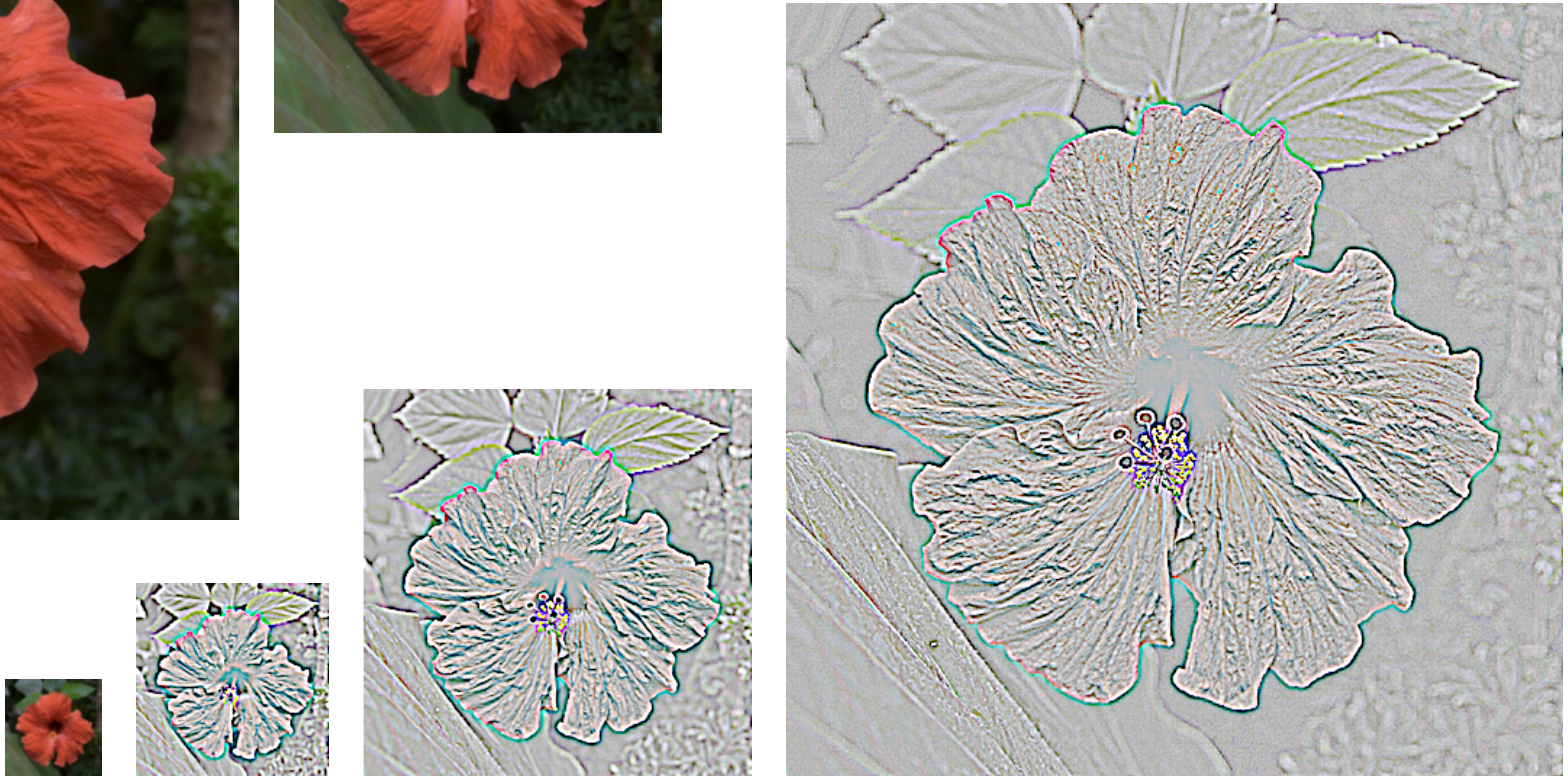
Gaussian Pyramid



Gaussian Pyramid

Gaussian vs **Laplacian** Pyramid

Shown in opposite order for space



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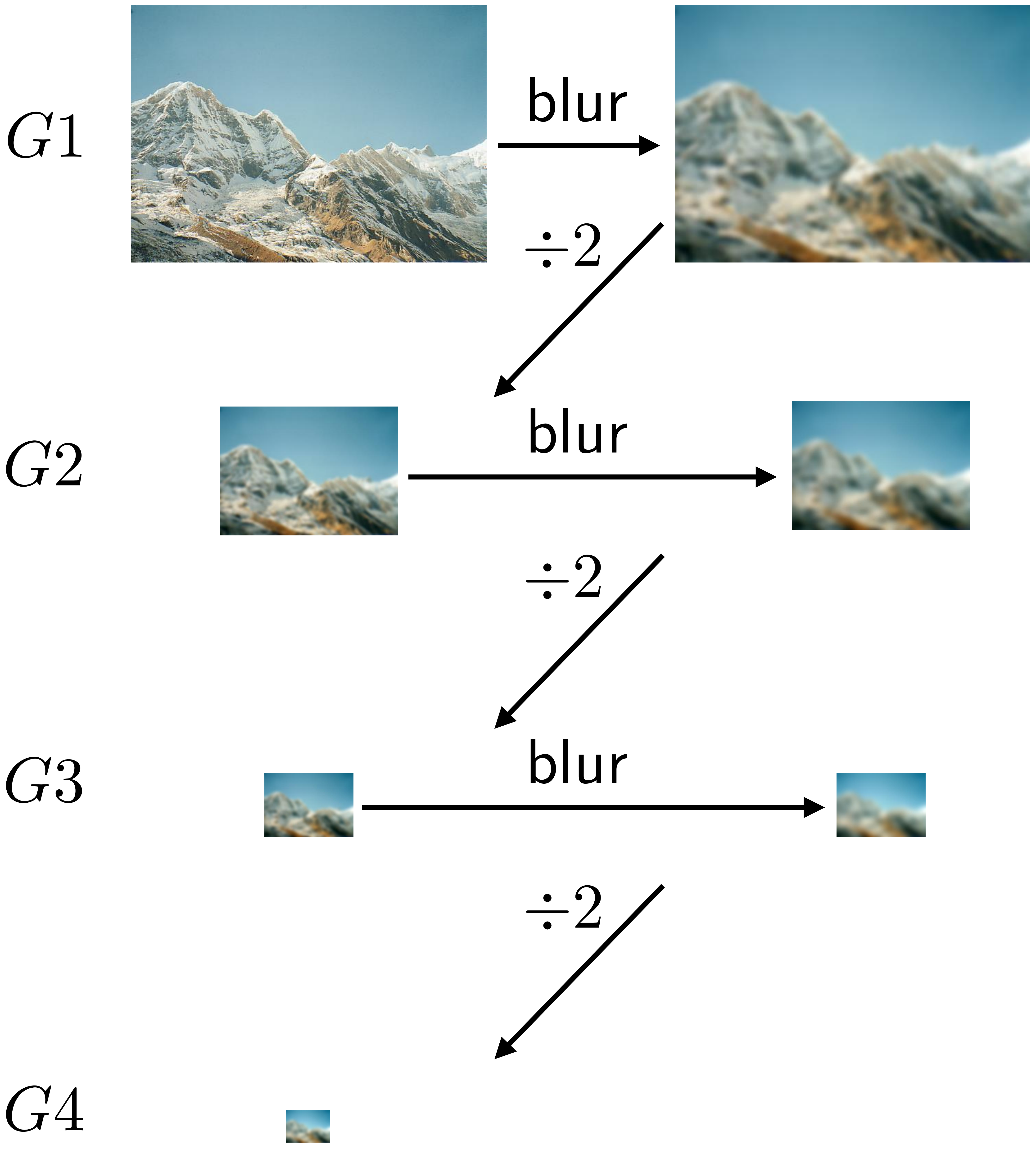
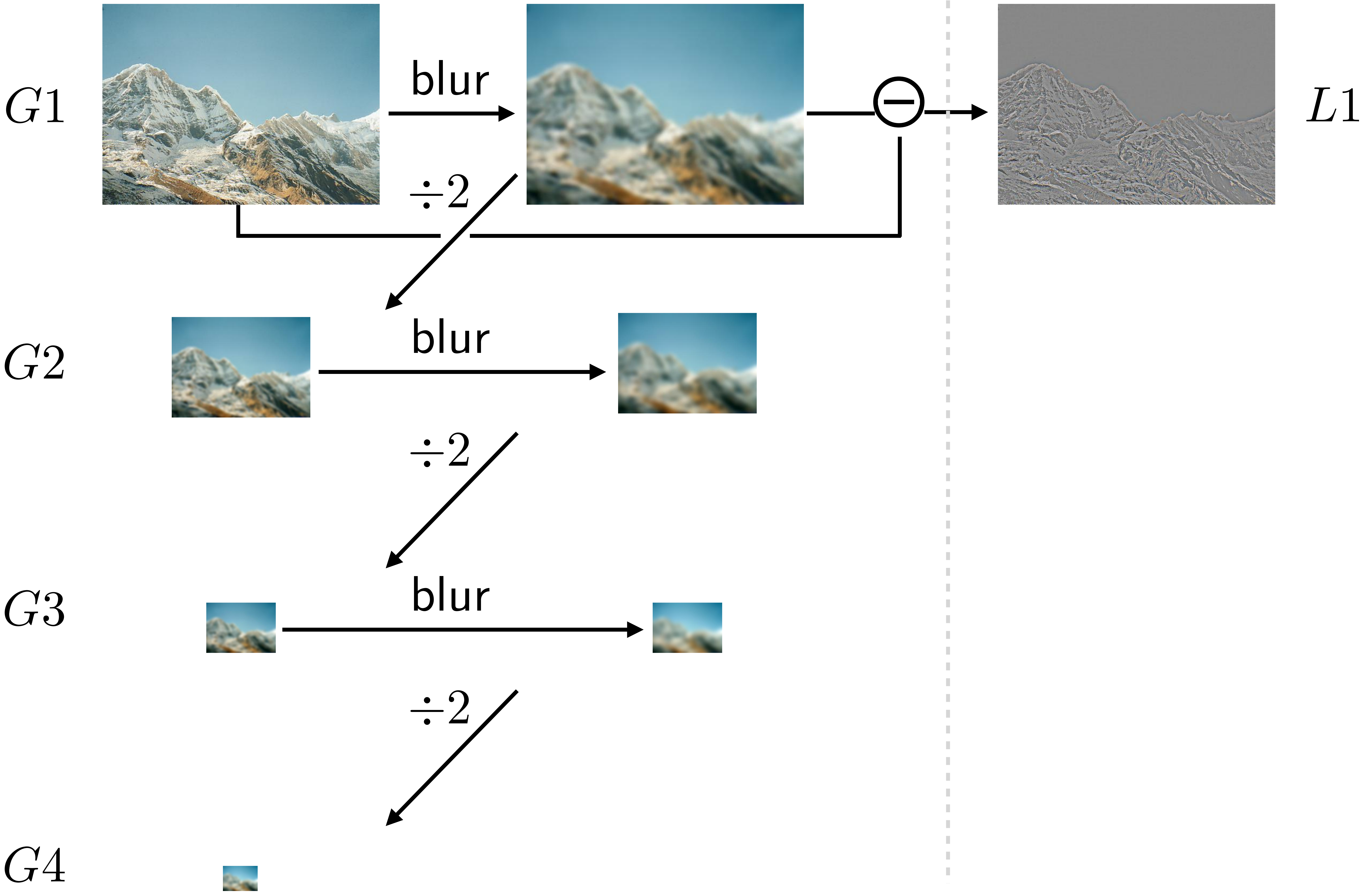
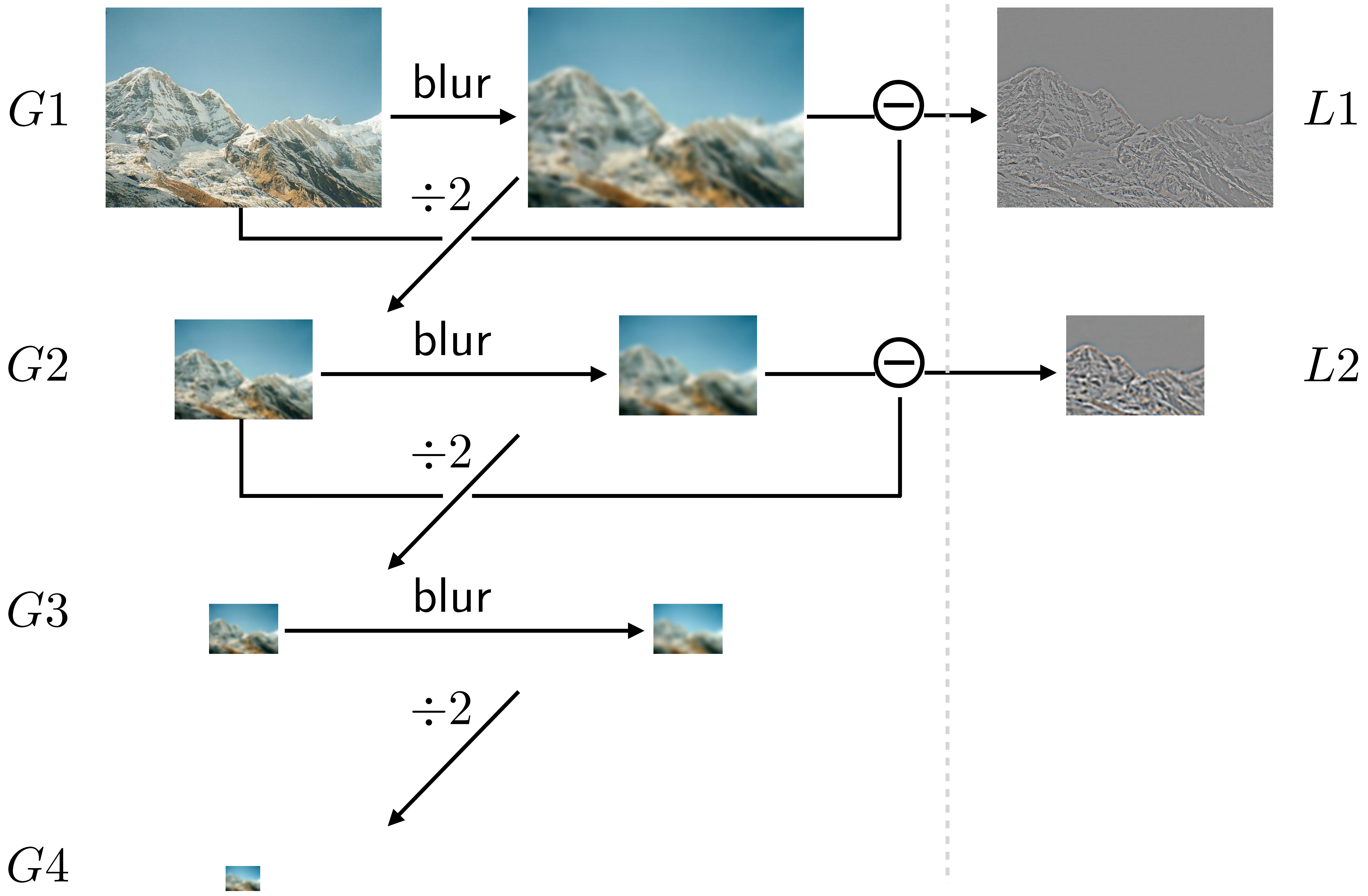


Gaussian Pyramid



Gaussian Pyramid



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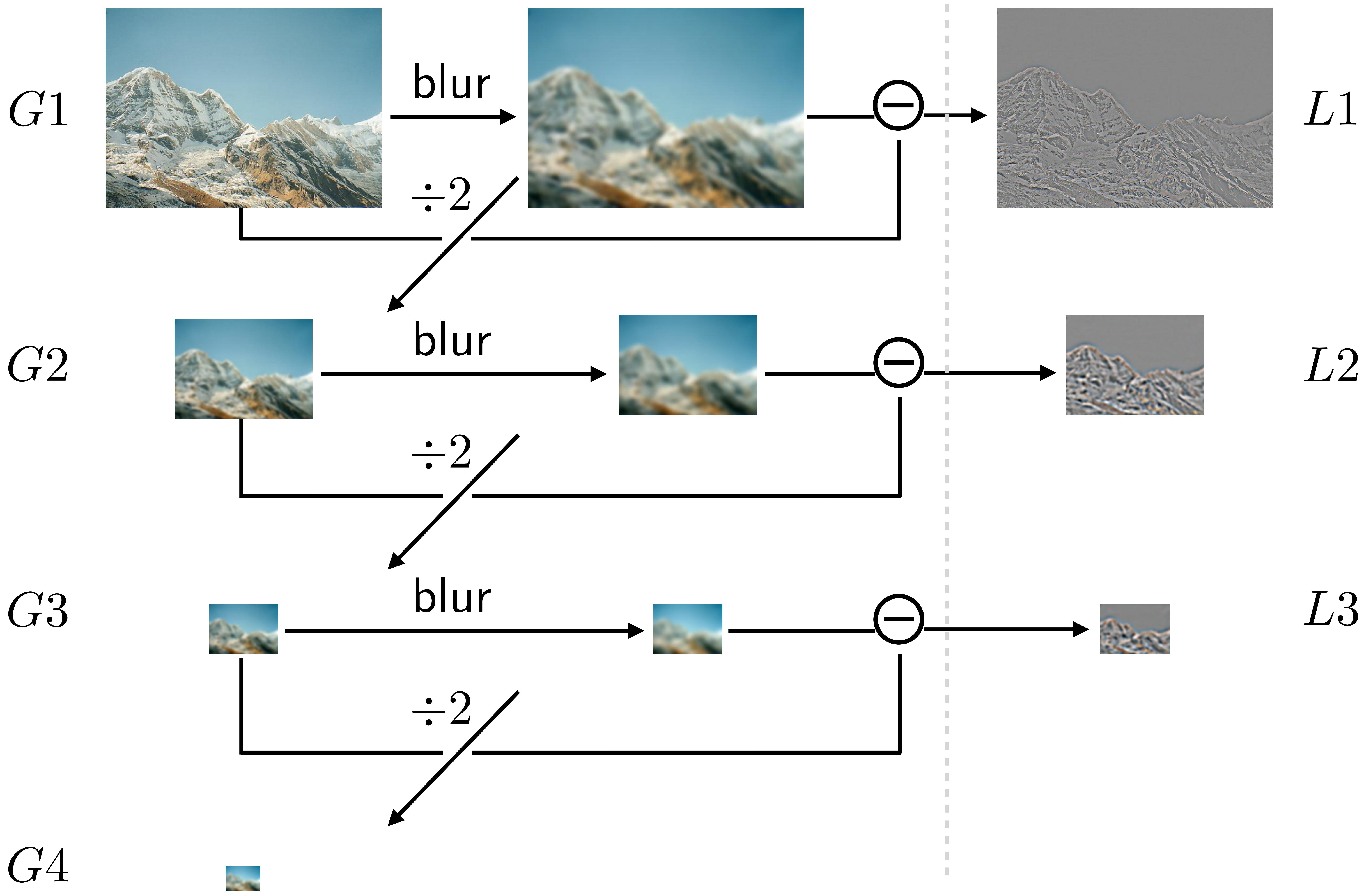

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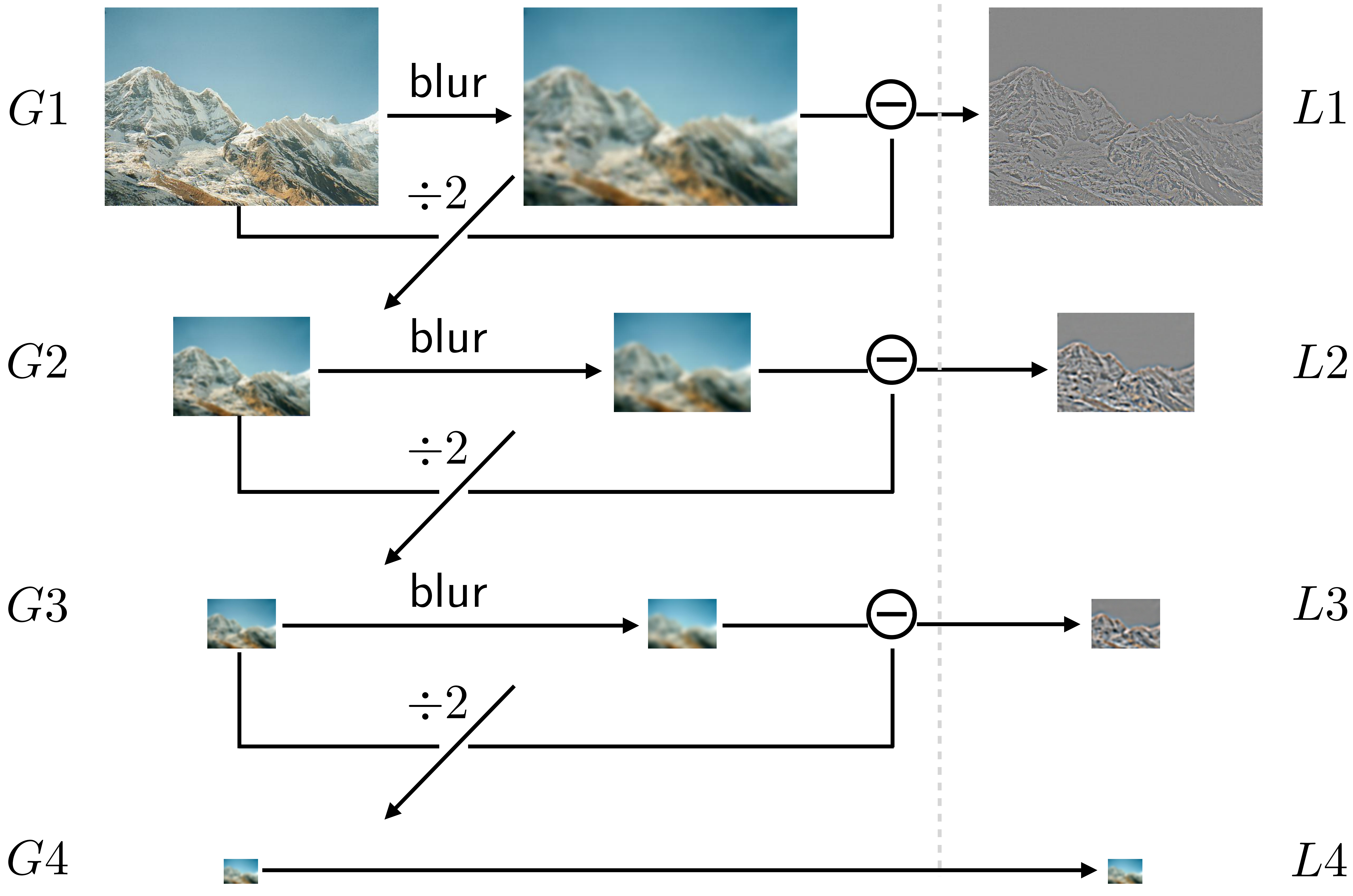

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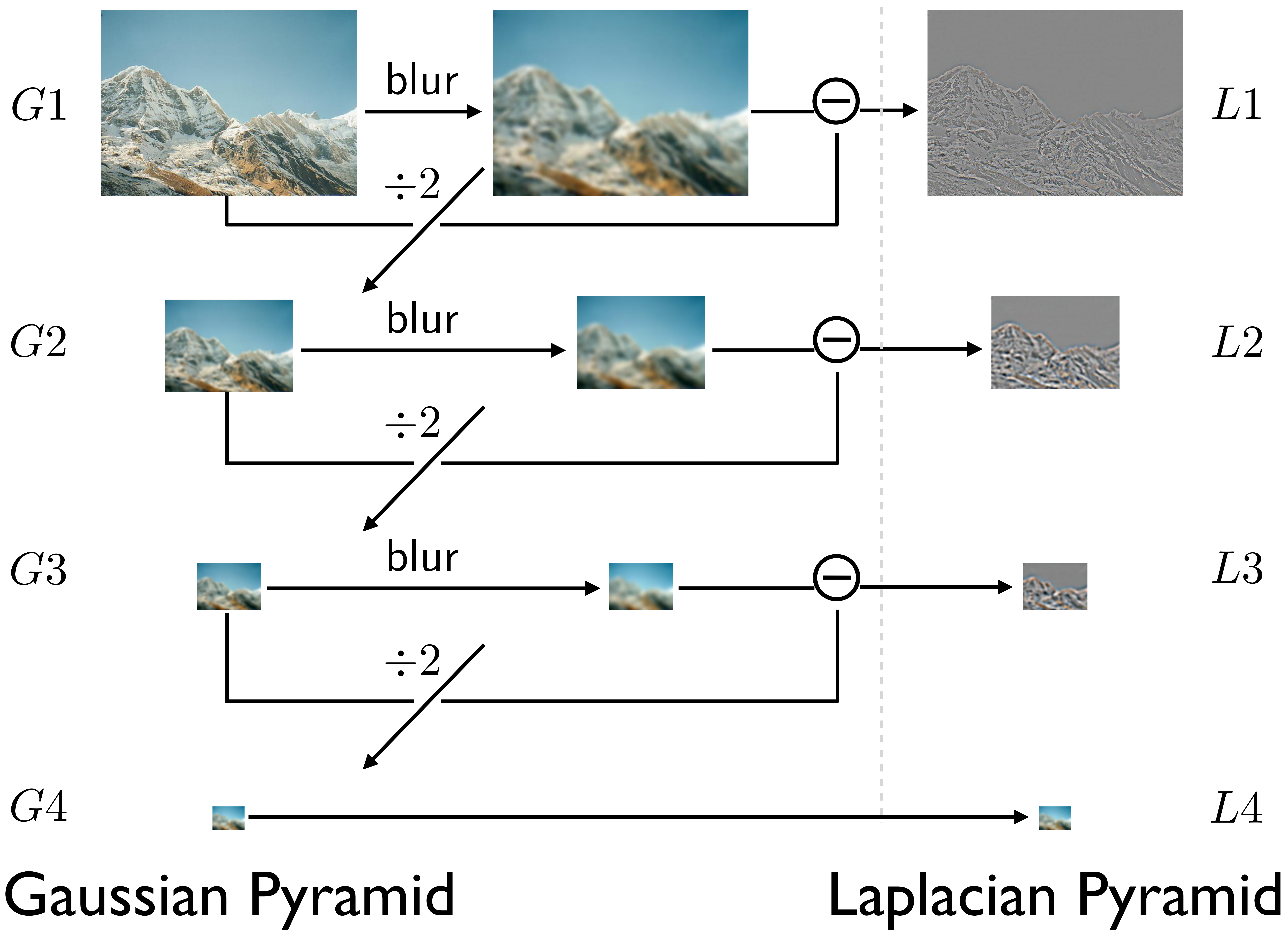
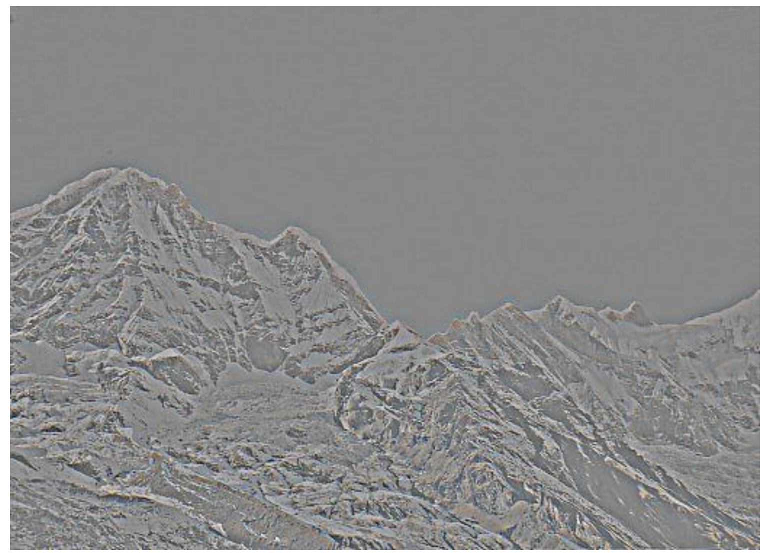
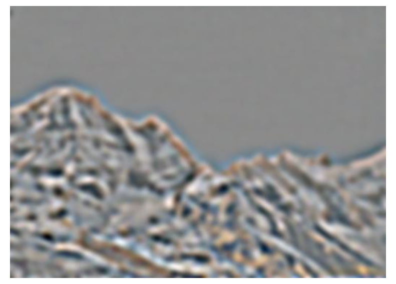
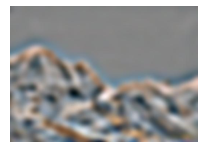

G1
blur
÷2
L1
G2
blur
÷2
L2
G3
blur
÷2
L3
G4
L4
Gaussian Pyramid
Laplacian Pyramid



$L1$



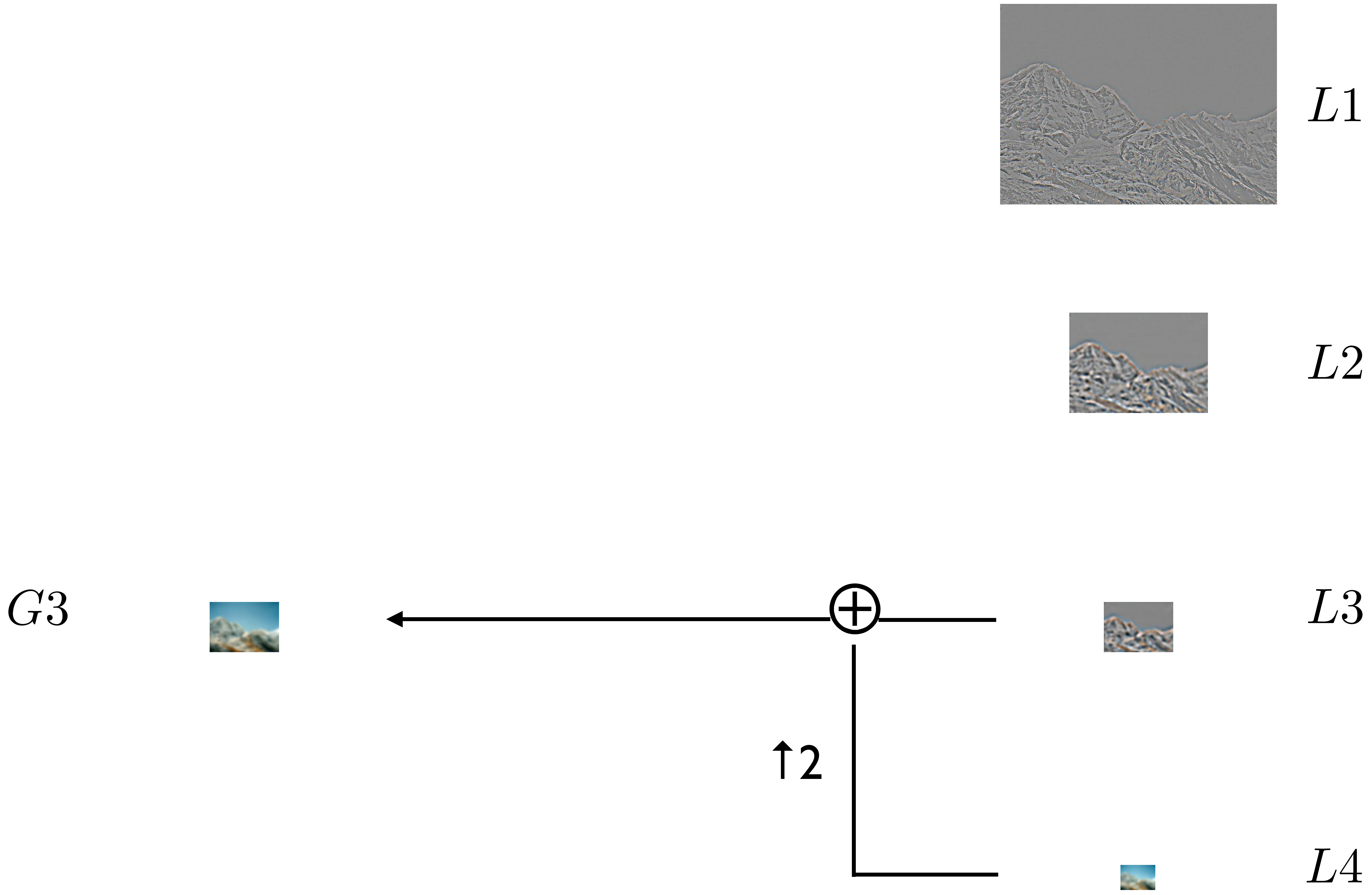
$L2$



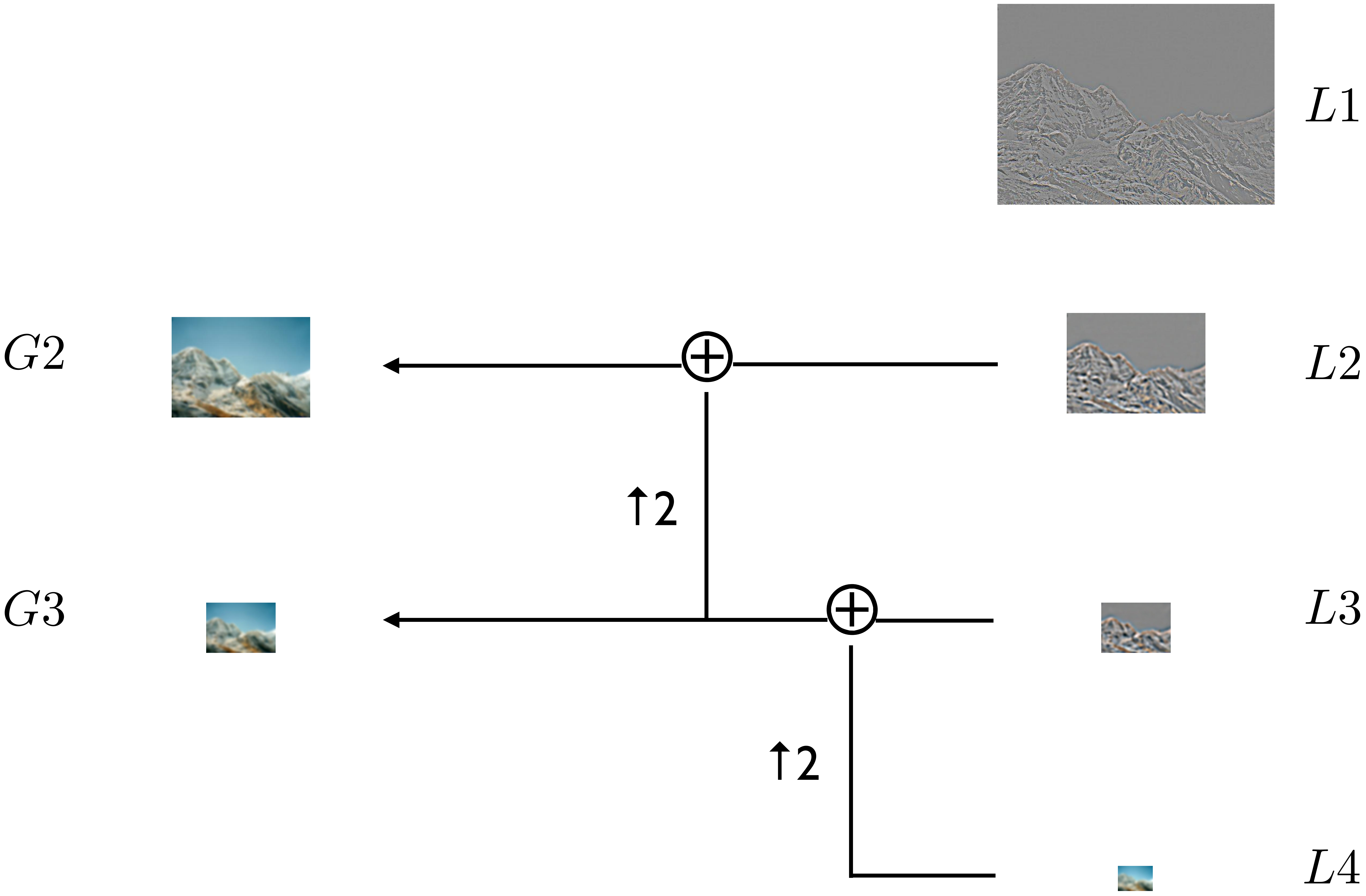
$L3$

$L4$

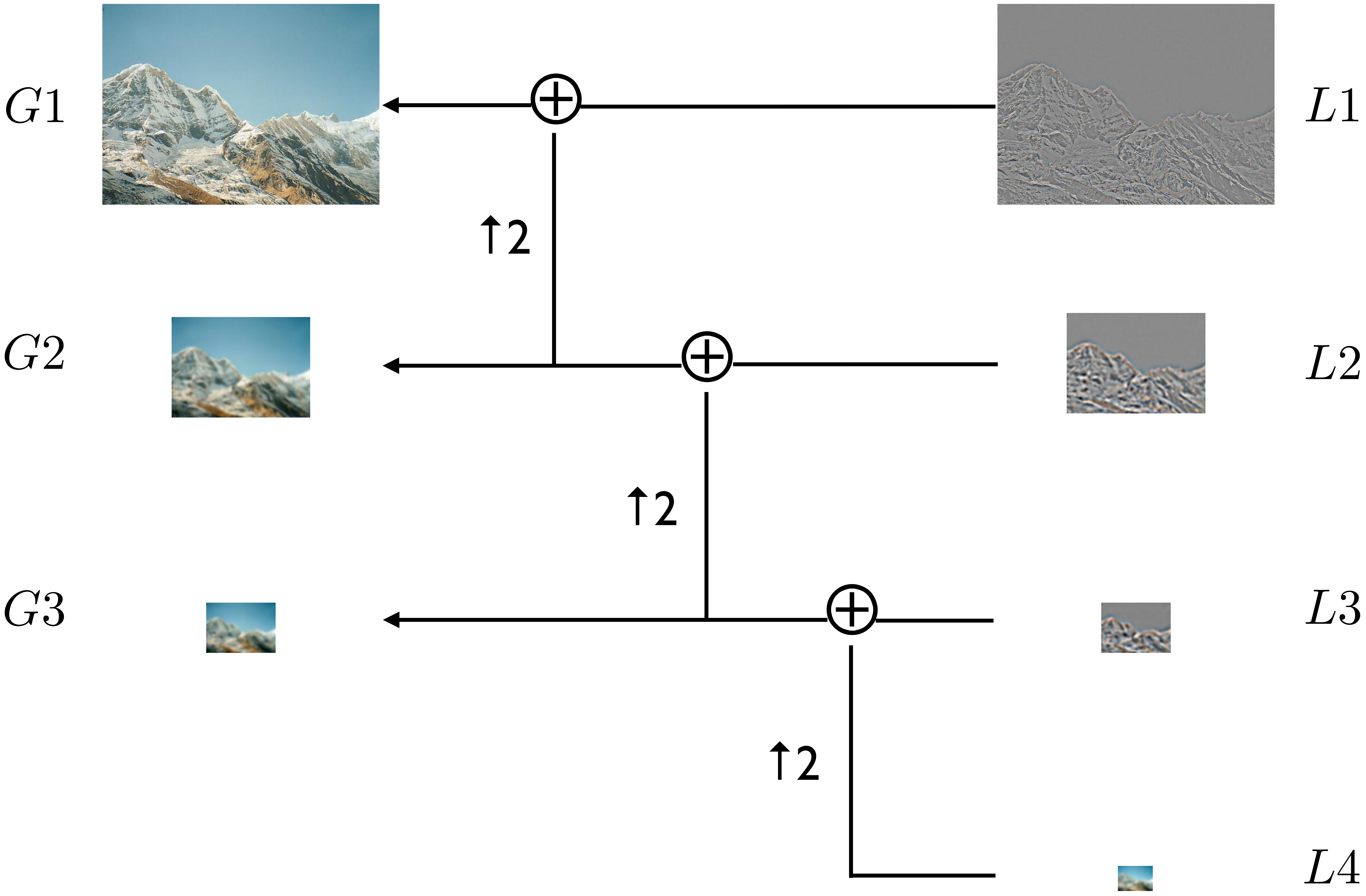
Laplacian Pyramid



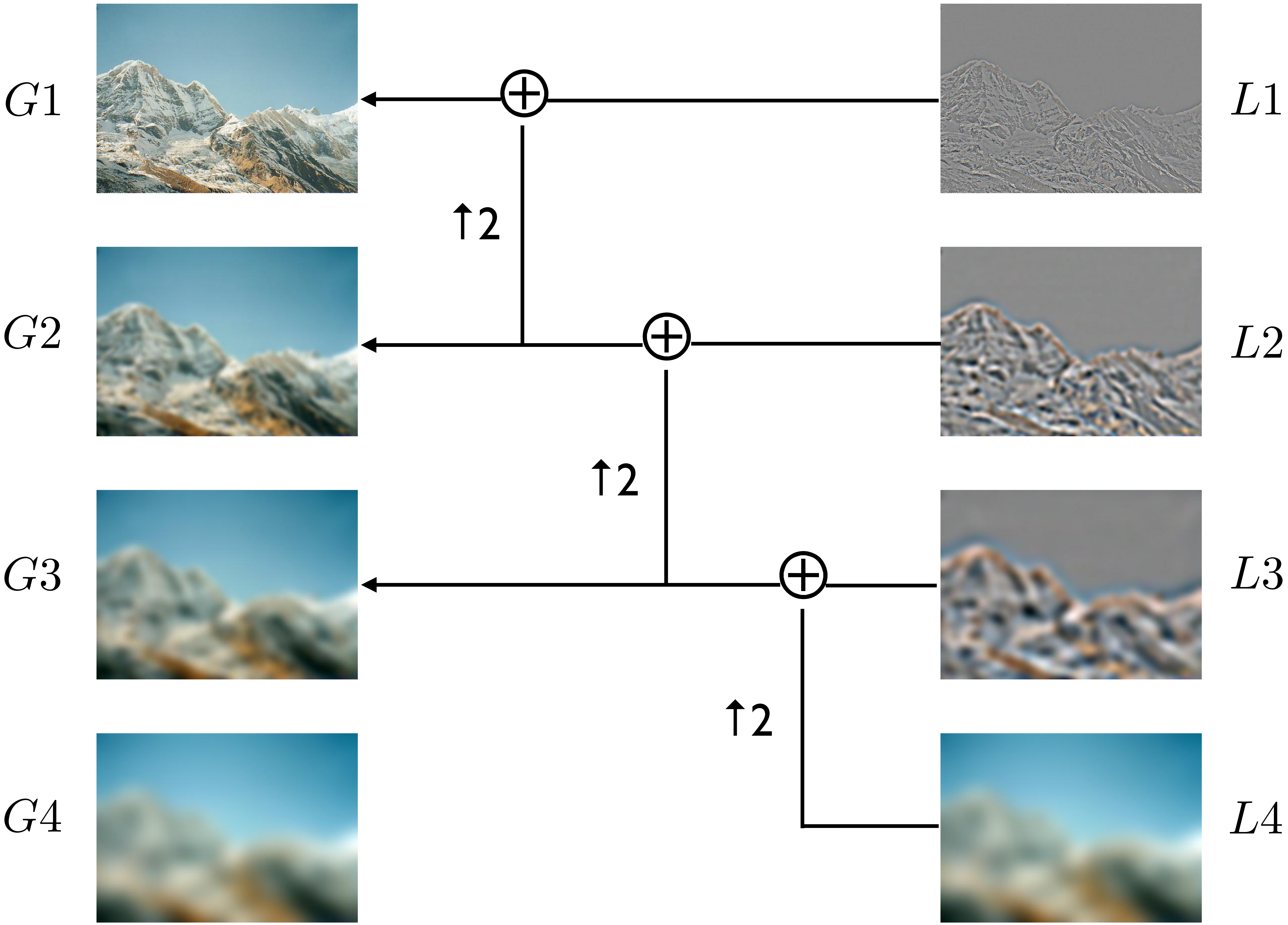
Laplacian Pyramid



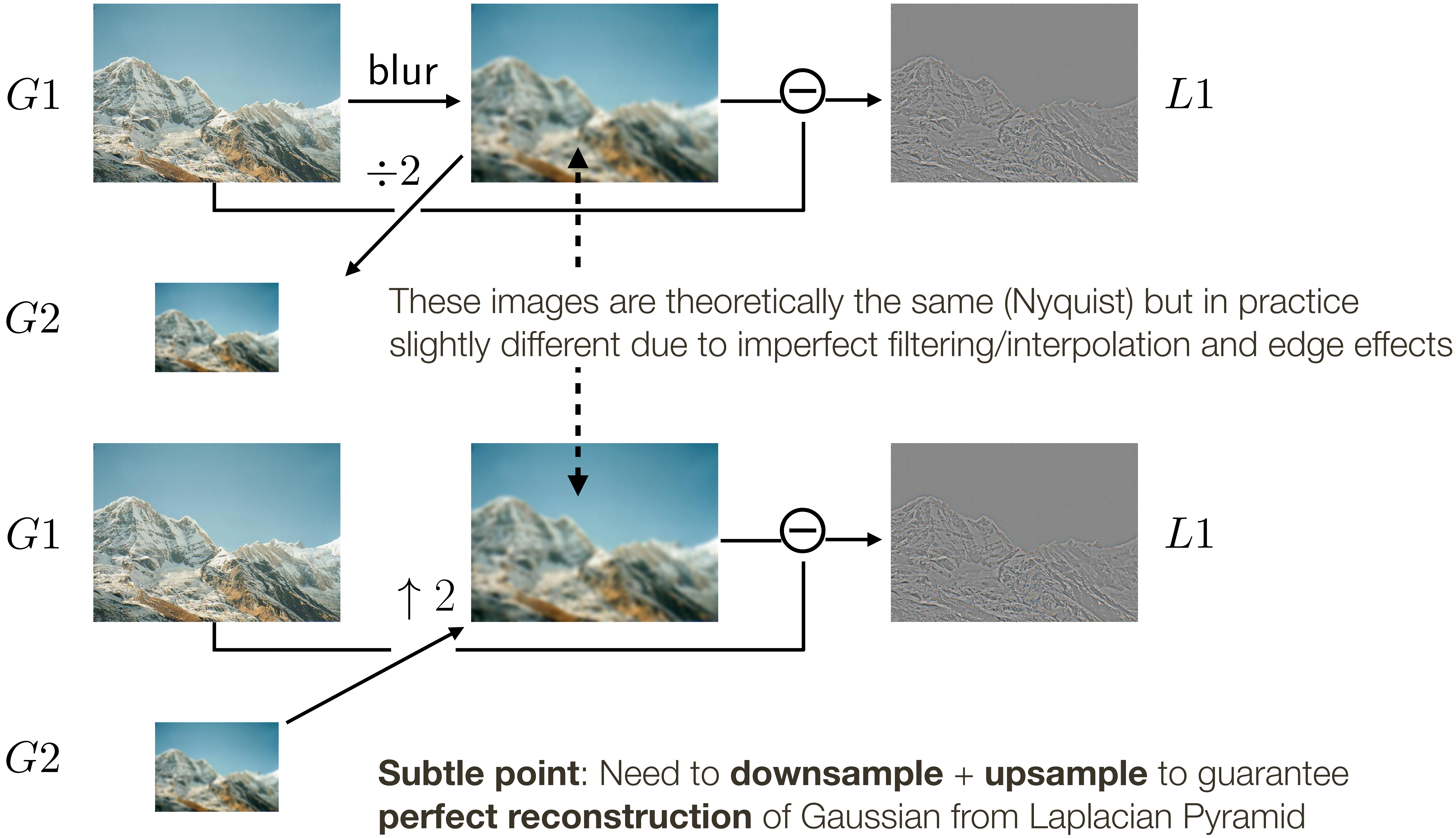
Laplacian Pyramid



Laplacian Pyramid



G1
G2
G3
G4
L1
L2
L3
L4
↑2
↑2
↑2

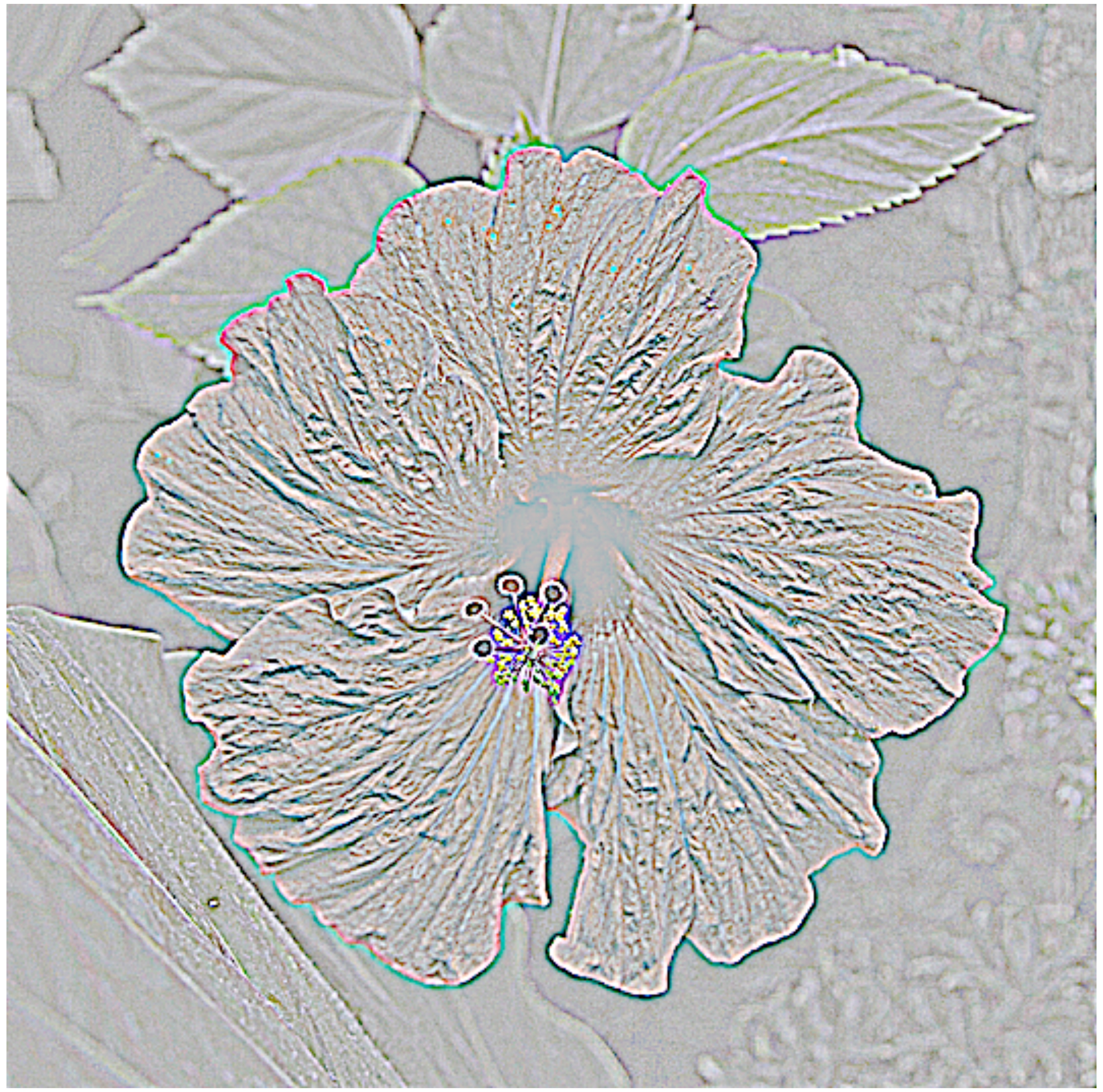


G1
blur
L1
÷2
G2
These images are theoretically the same (Nyquist) but in practice slightly different due to imperfect filtering/interpolation and edge effects
G1
↑ 2
L1
G2
Subtle point: Need to **downsample** + **upsample** to guarantee **perfect reconstruction** of Gaussian from Laplacian Pyramid

Gaussian vs **Laplacian** Pyramid

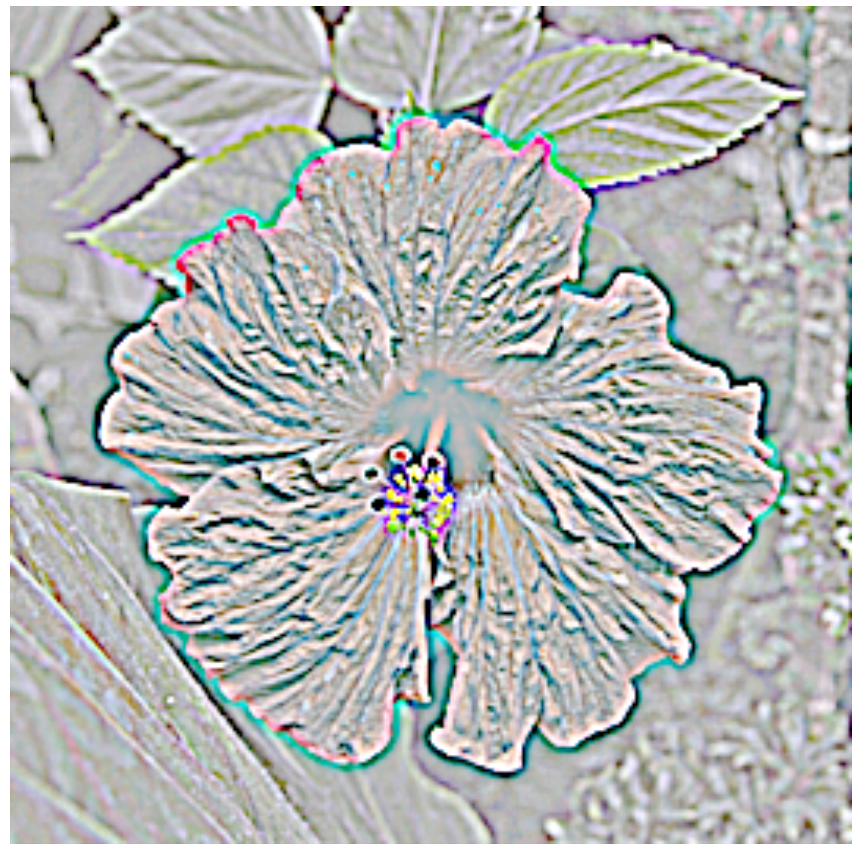



Shown in opposite order for space



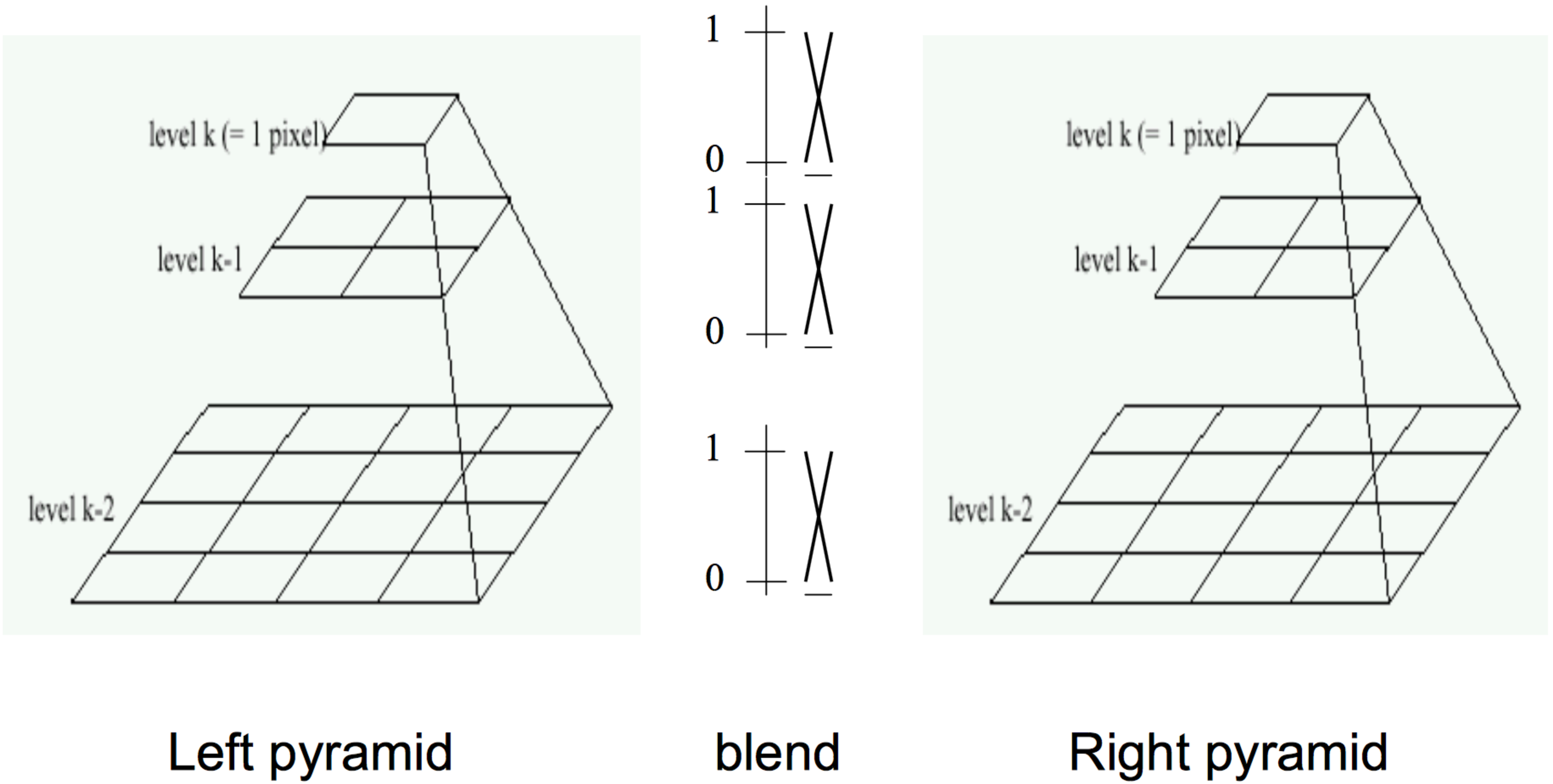
Which one takes more space to store?





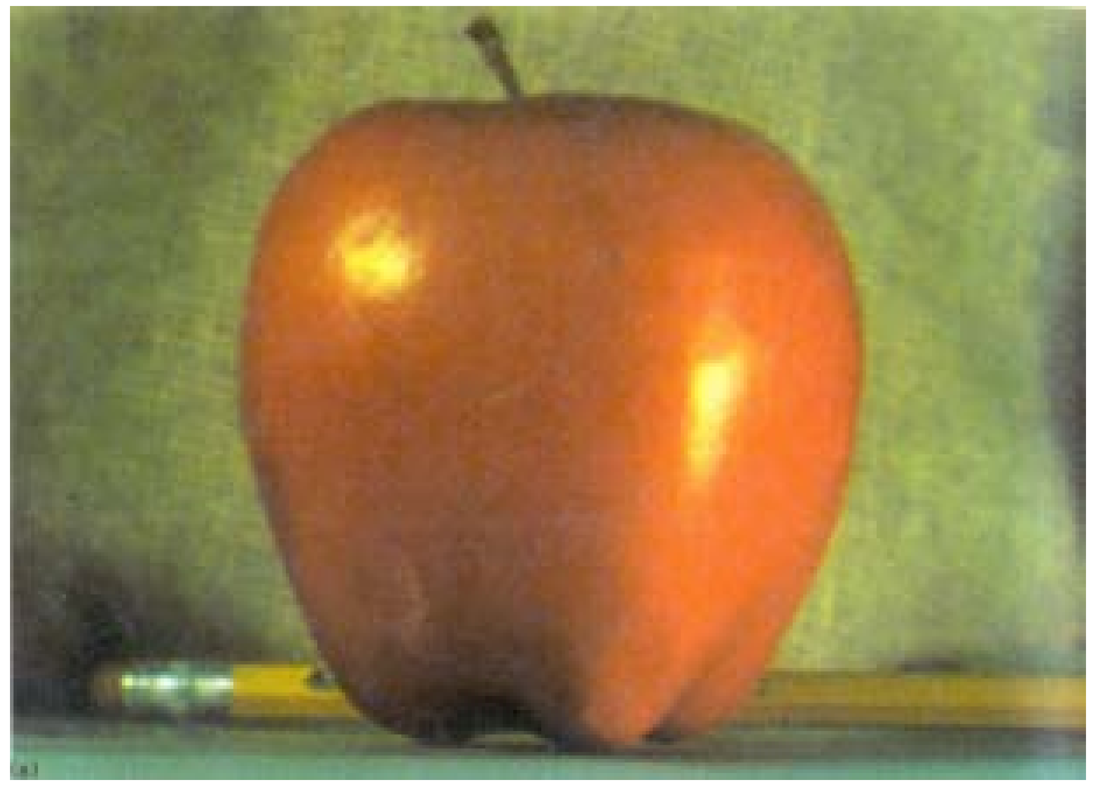
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Application: Image Blending



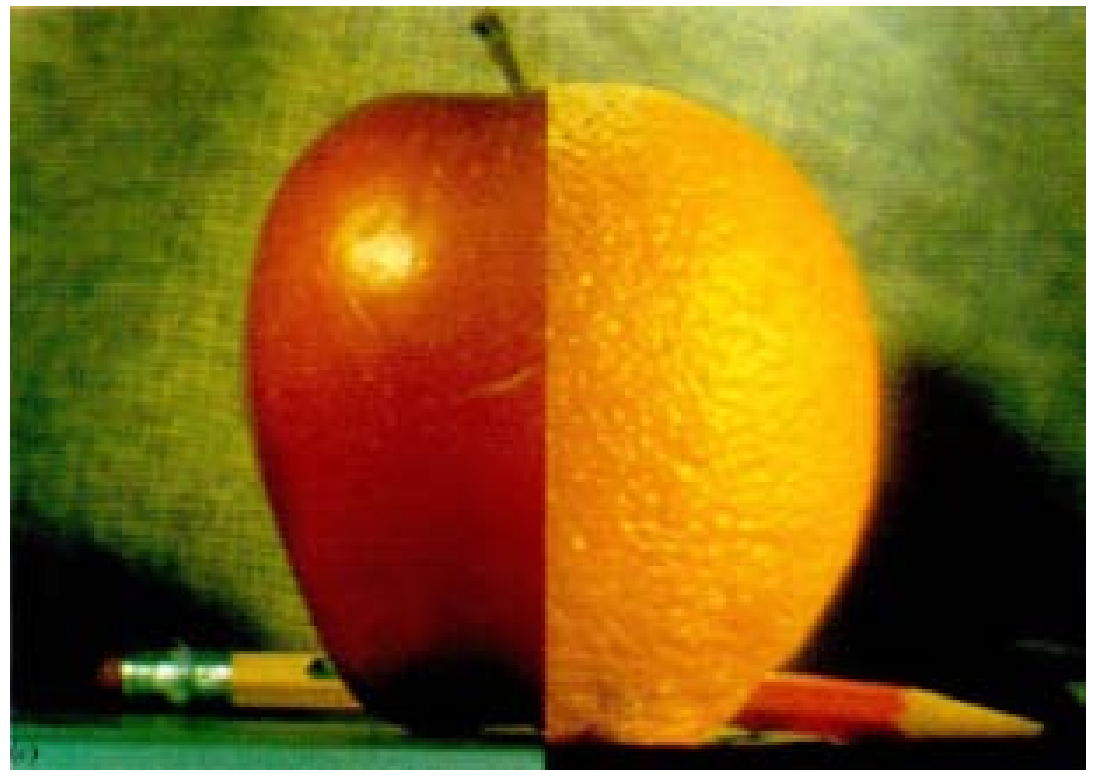
Burt and Adelson, “A multiresolution spline with application to image mosaics,”ACM Transactions on Graphics, 1983, Vol.2, pp.217-236.

Application: Image Pyramid Blending



(a)

(b)



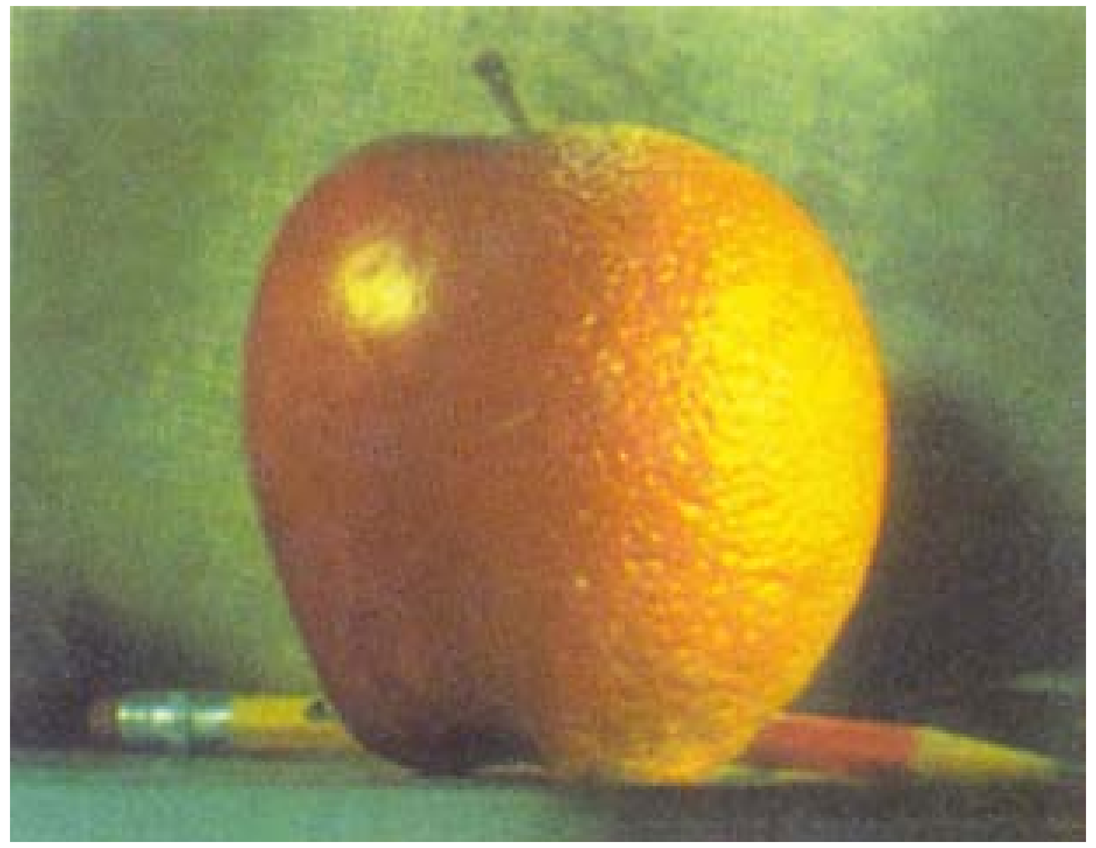


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Image **Blending**

Required for creating **panoramas**

Image **Blending**

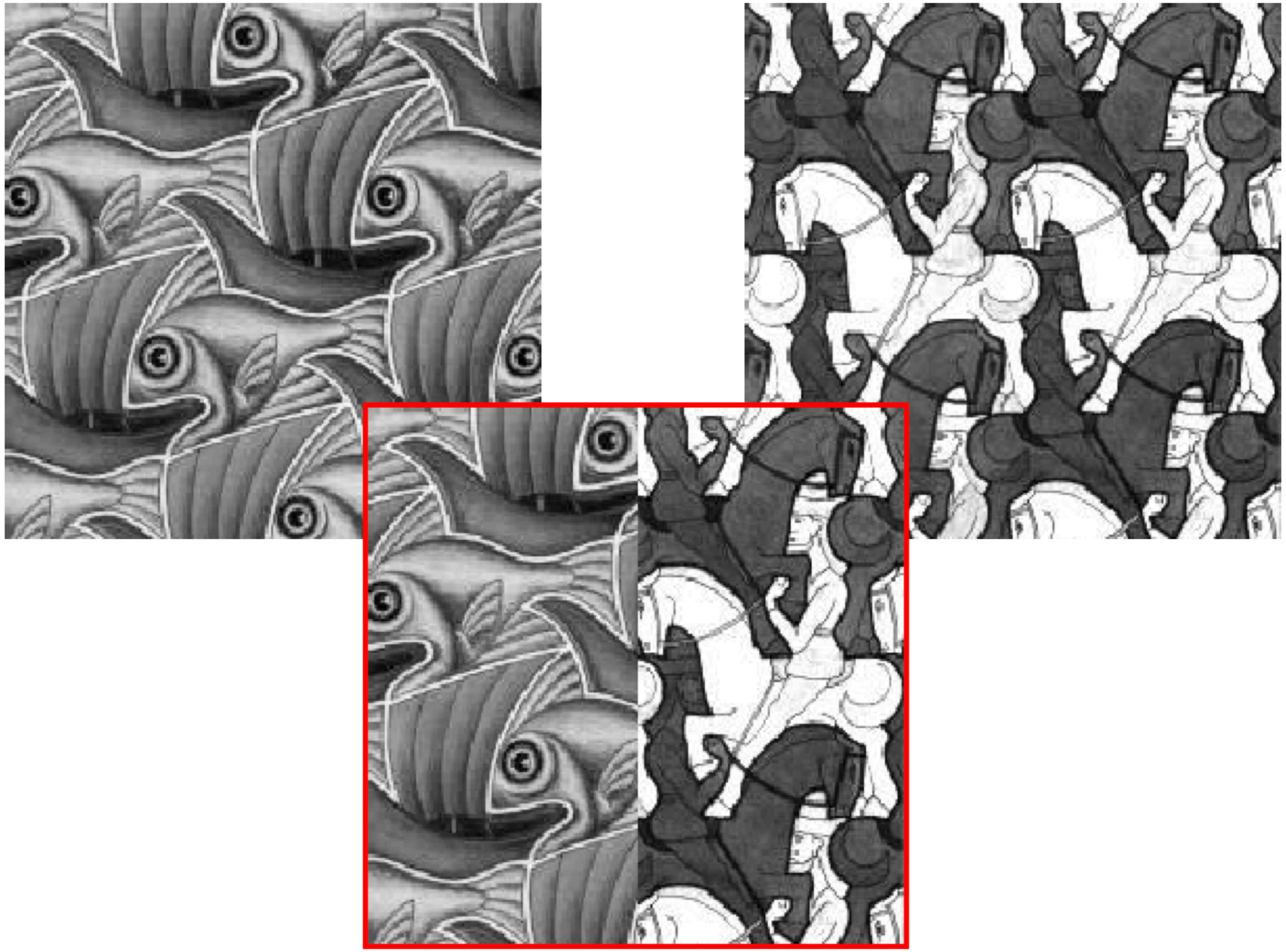
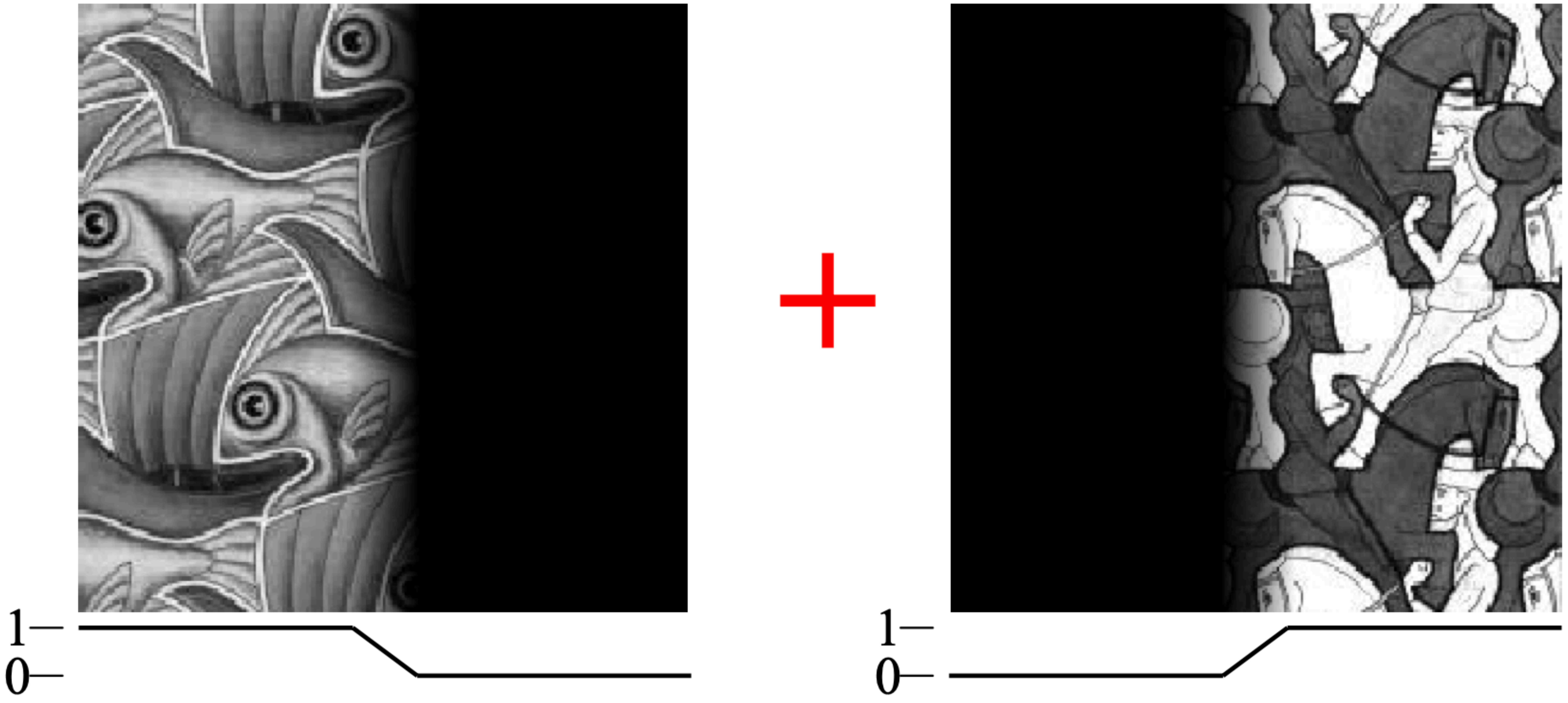
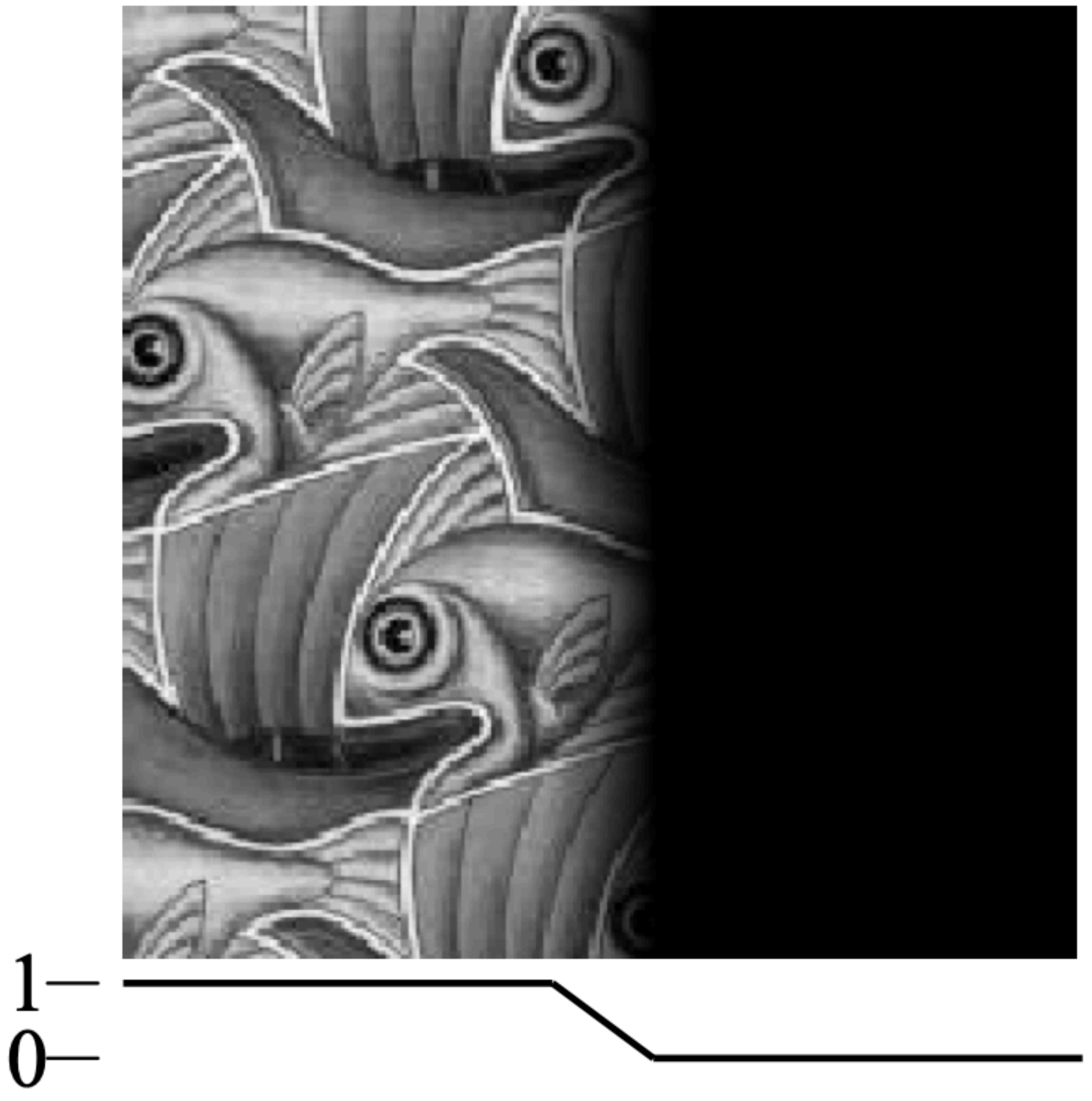


Image **Blending:** Alpha Blending



$$I_{blend} = \alpha I_{left} + (1-\alpha) I_{right}$$

Image **Blending:** Alpha Blending



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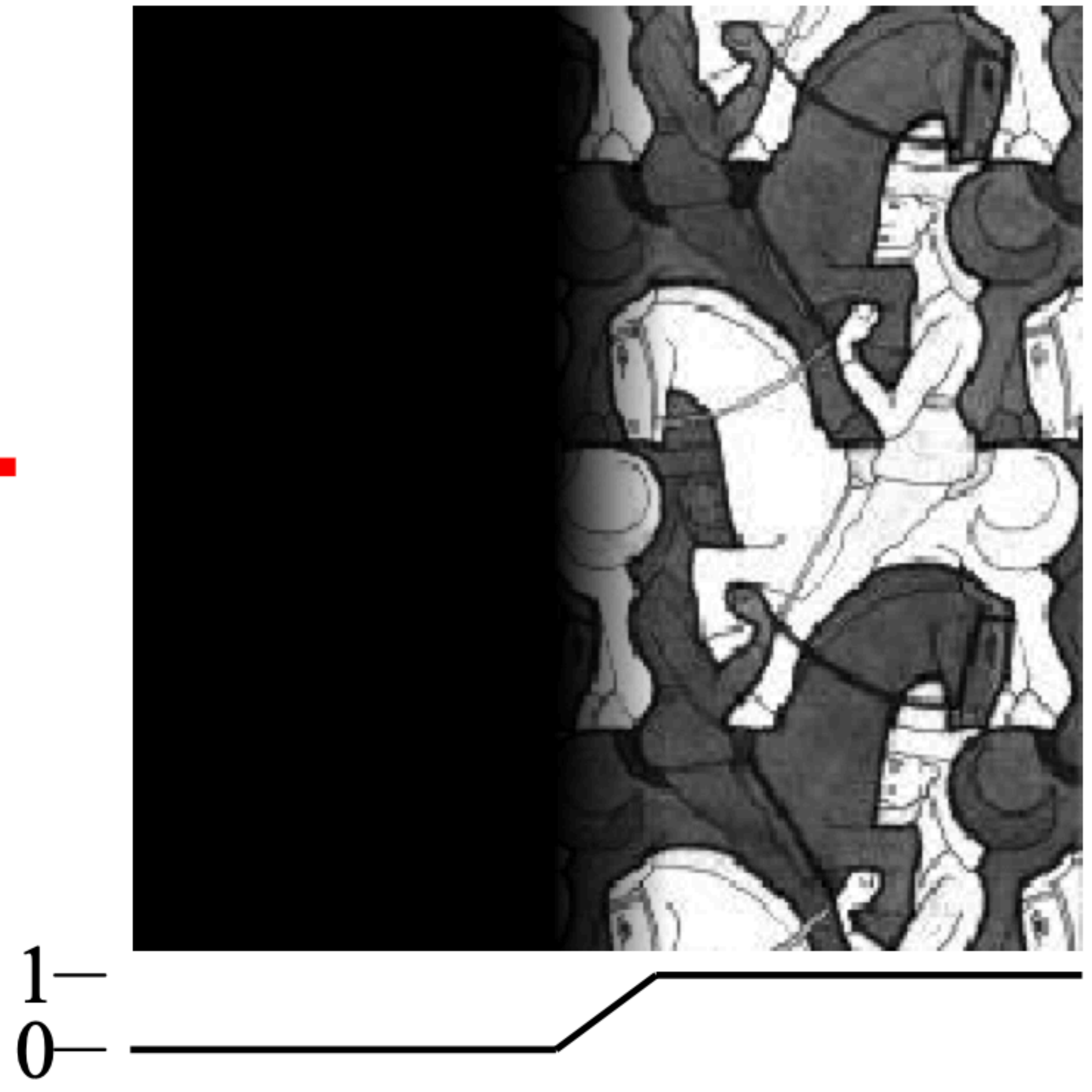

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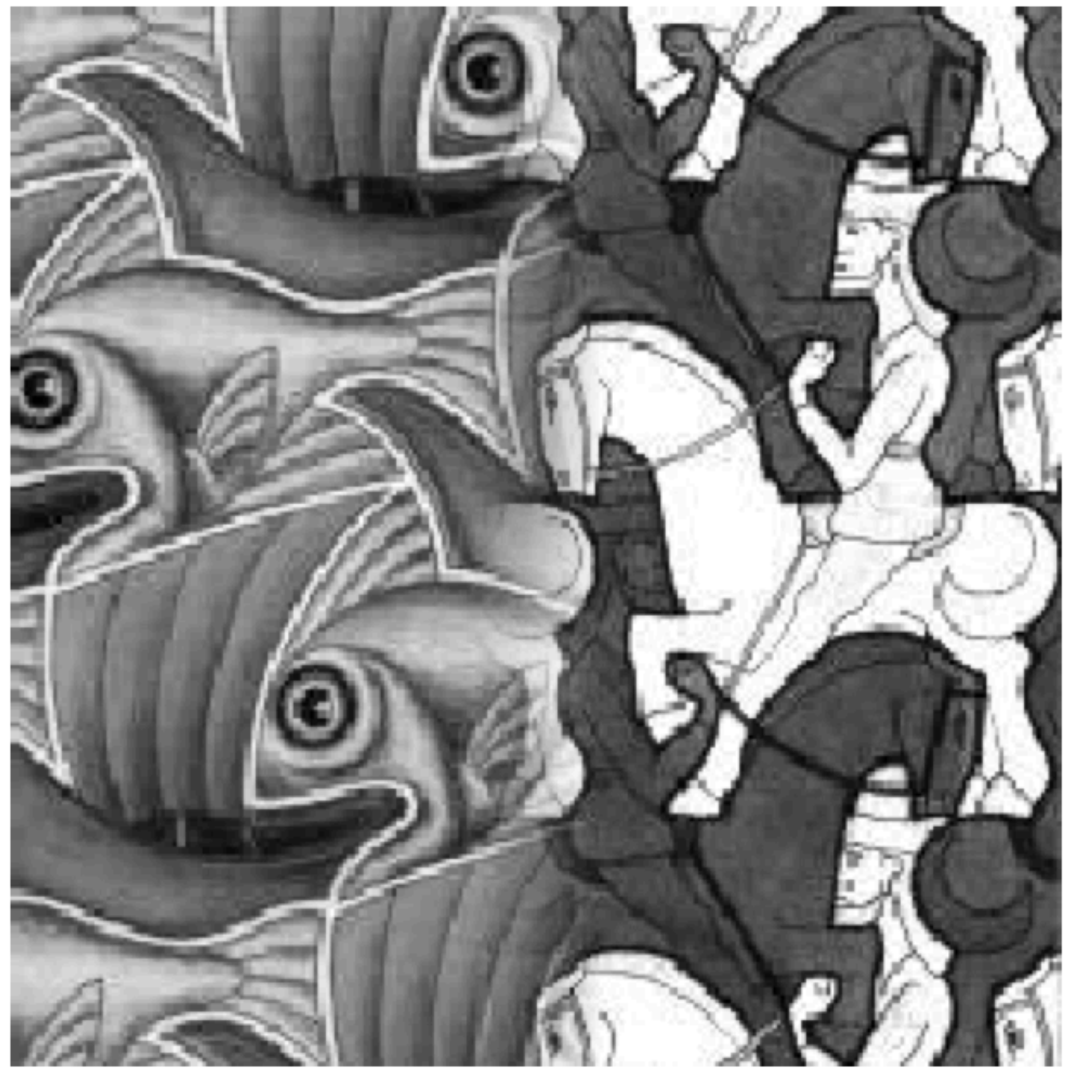


$$I_{blend} = \alpha I_{left} + (1\text{-}\alpha) I_{right}$$

Image **Blending:** Alpha Blending

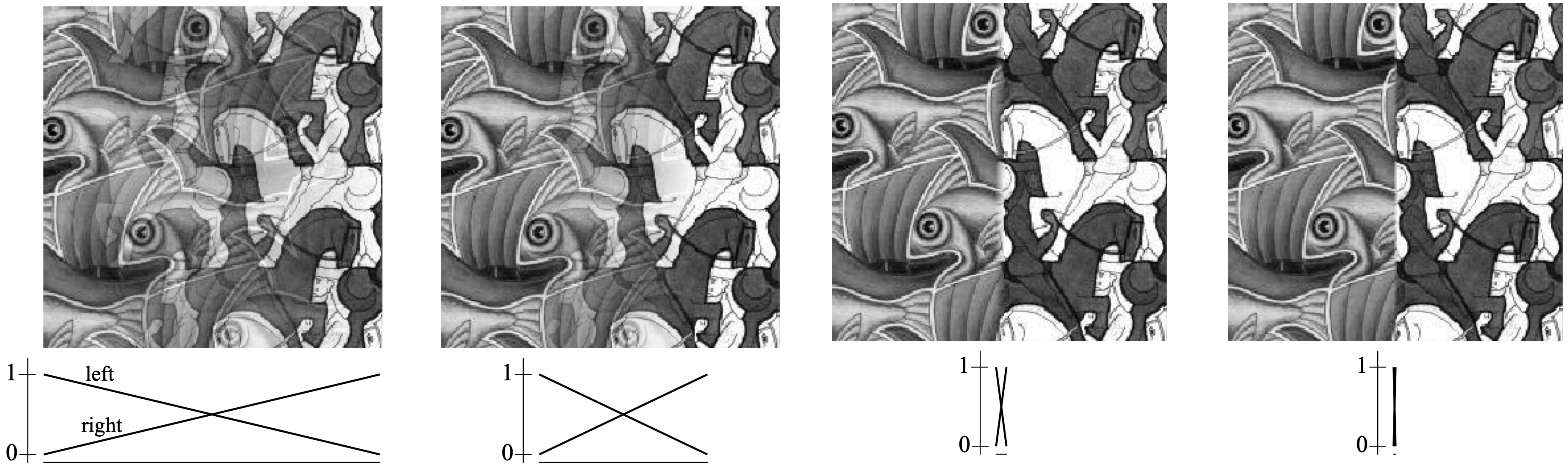


Image **Blending:** Alpha Blending

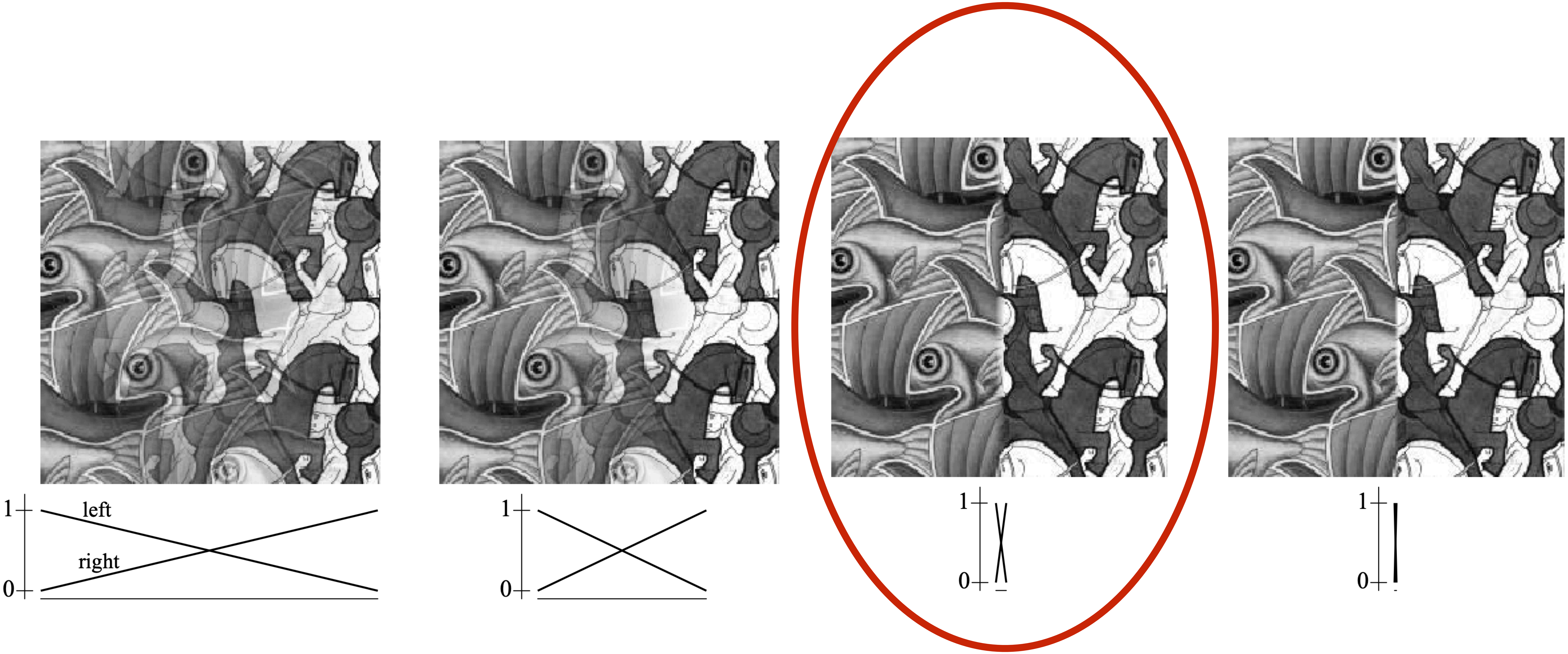
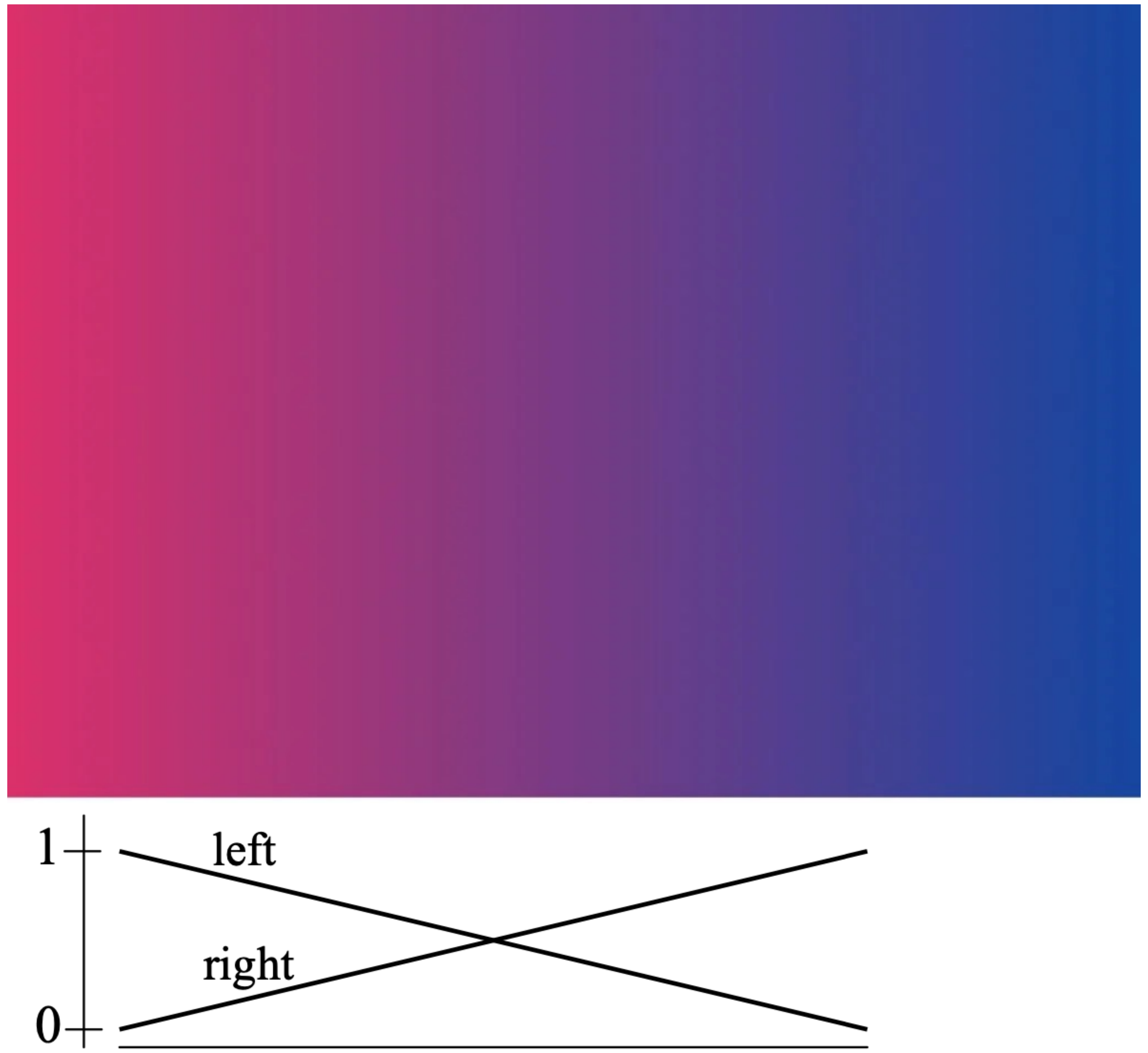
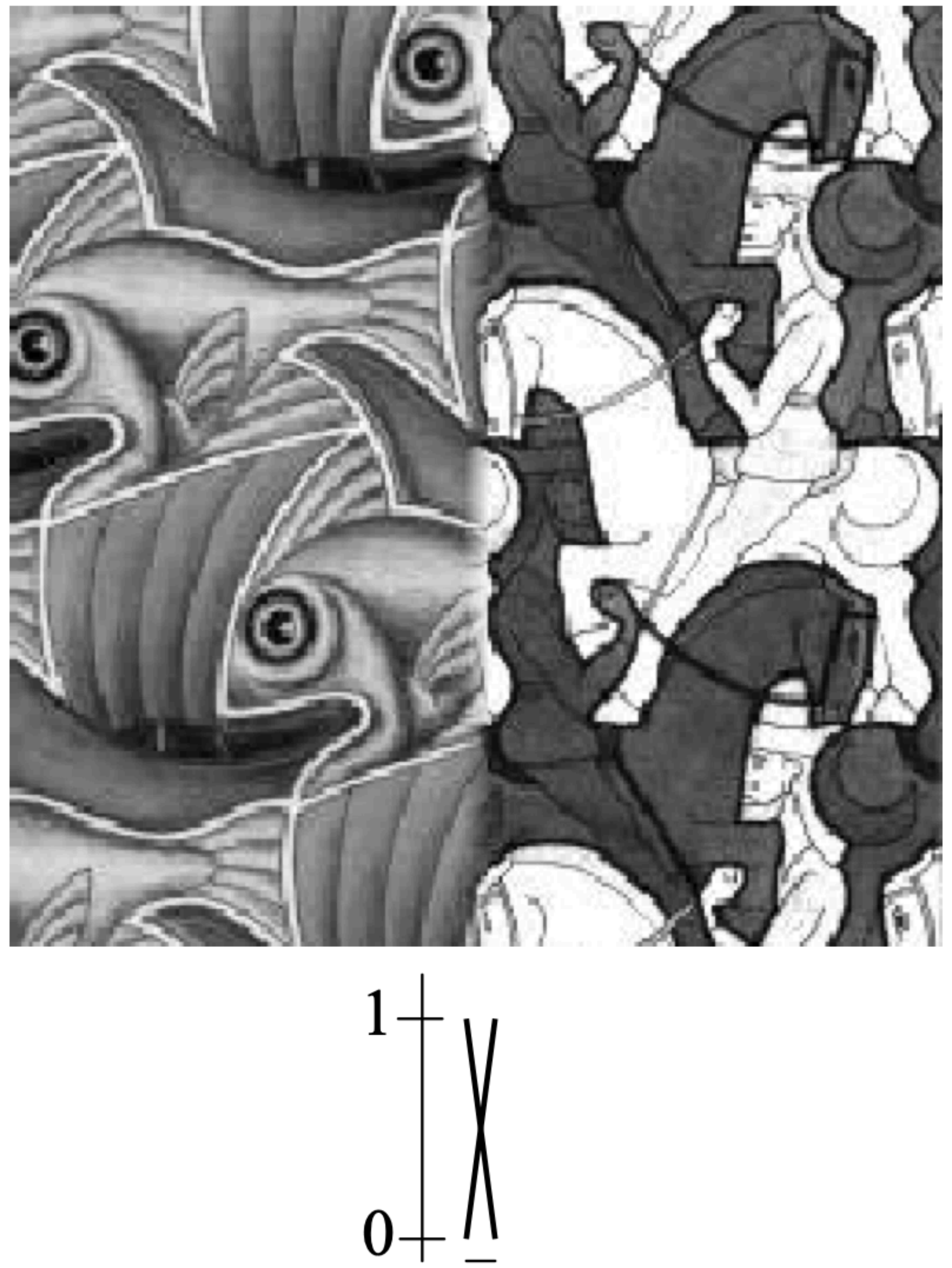


Image **Blending:** Alpha Blending





Application: Image Pyramid Blending

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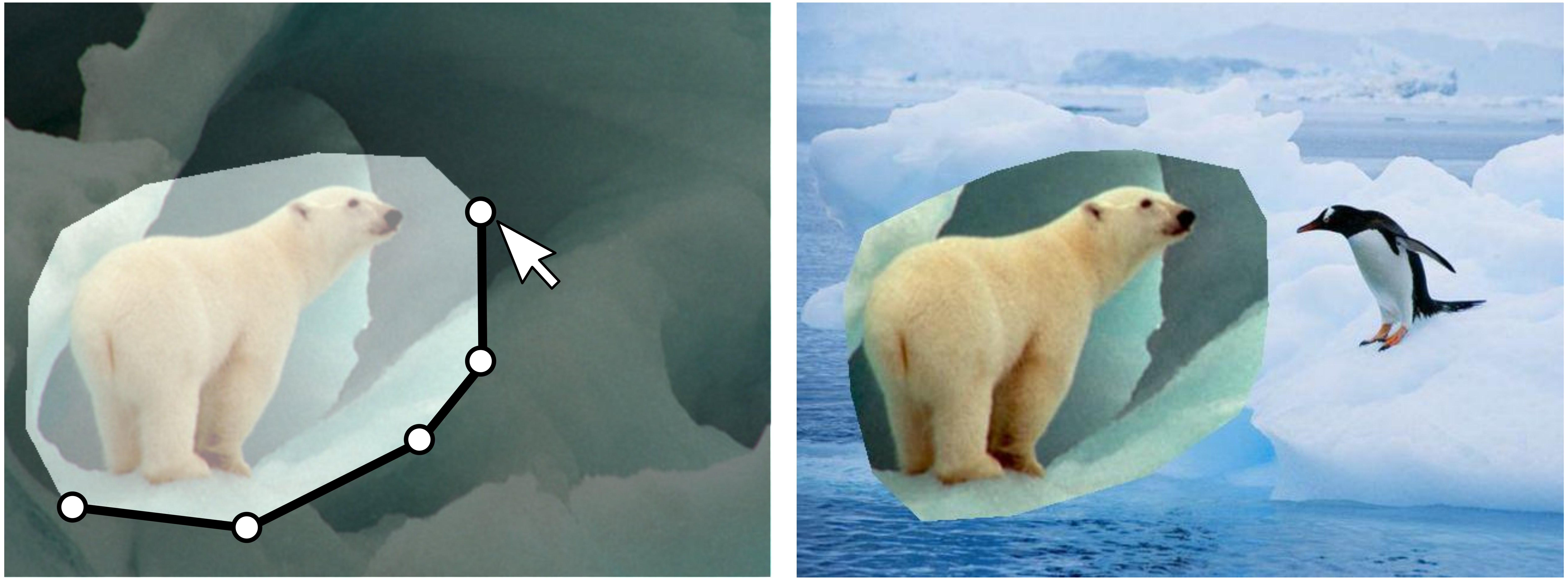
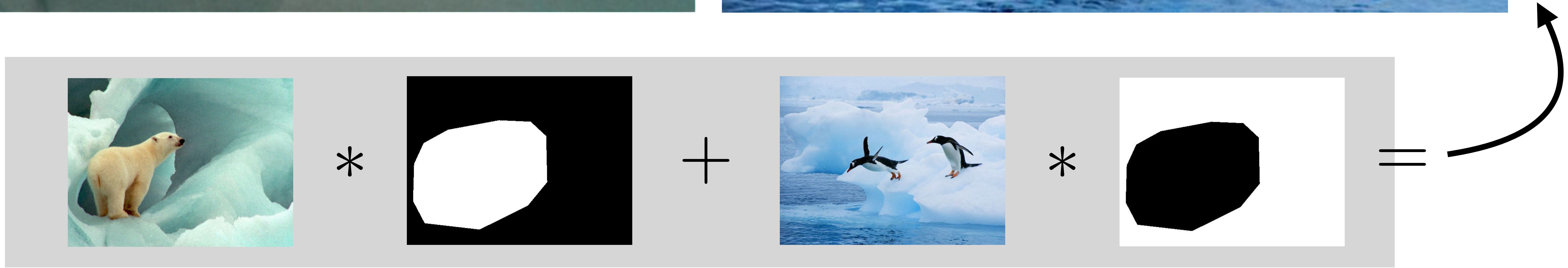
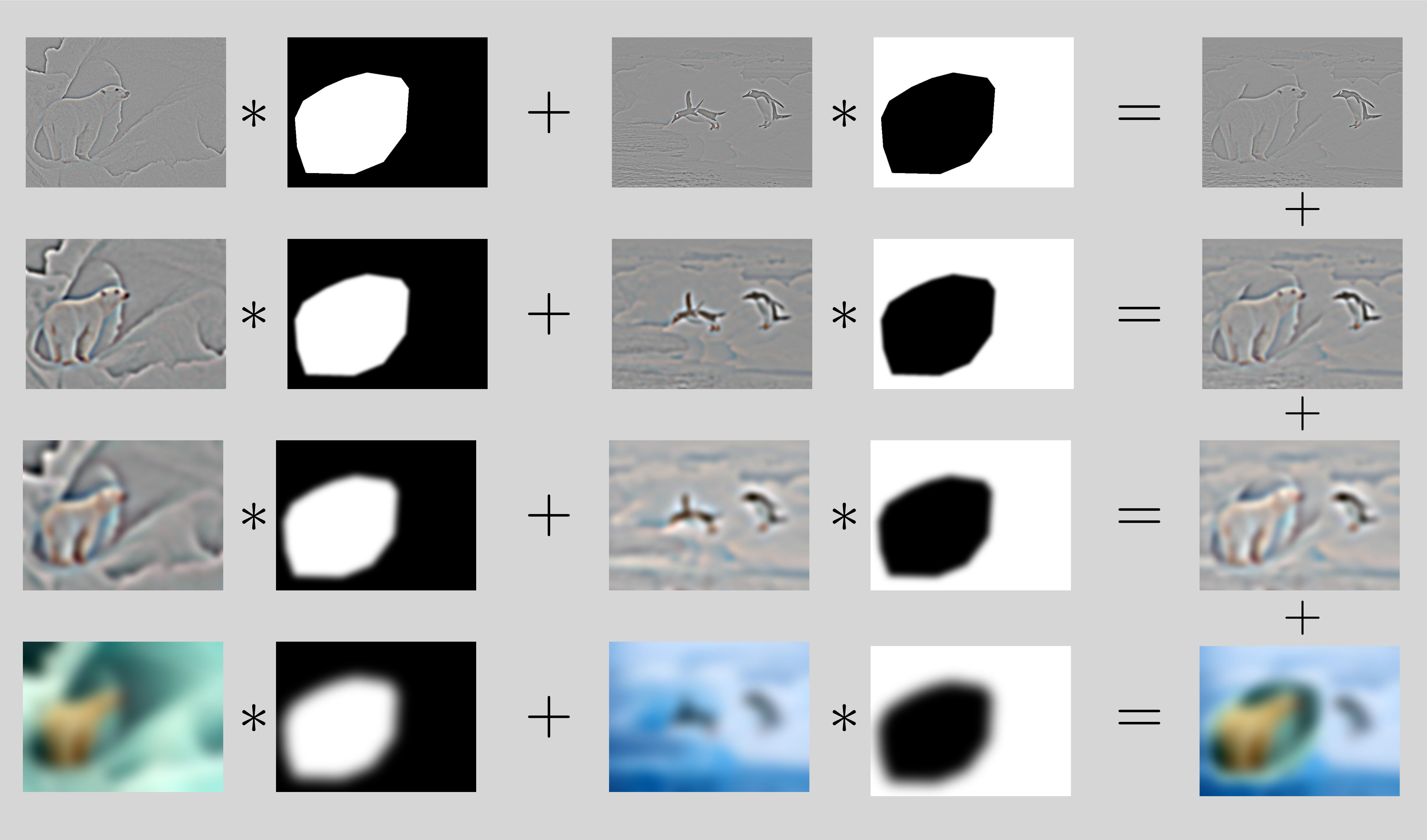
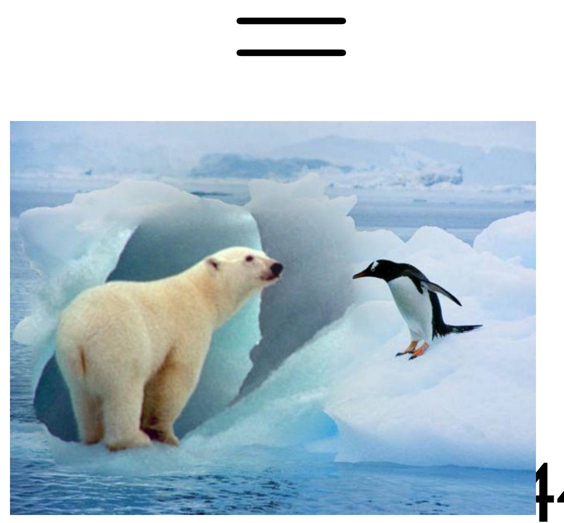




Step 1: Specify an Image Mask





Step 2: blend lower frequency bands over larger spatial ranges, high frequency bands over small spatial ranges

Application: Image Blending

Algorithm:

1. Build Laplacian pyramid LA and LB from images A and B

2. Build a Gaussian pyramid GR from mask image R (the mask defines which image pixels should be coming from A or B)

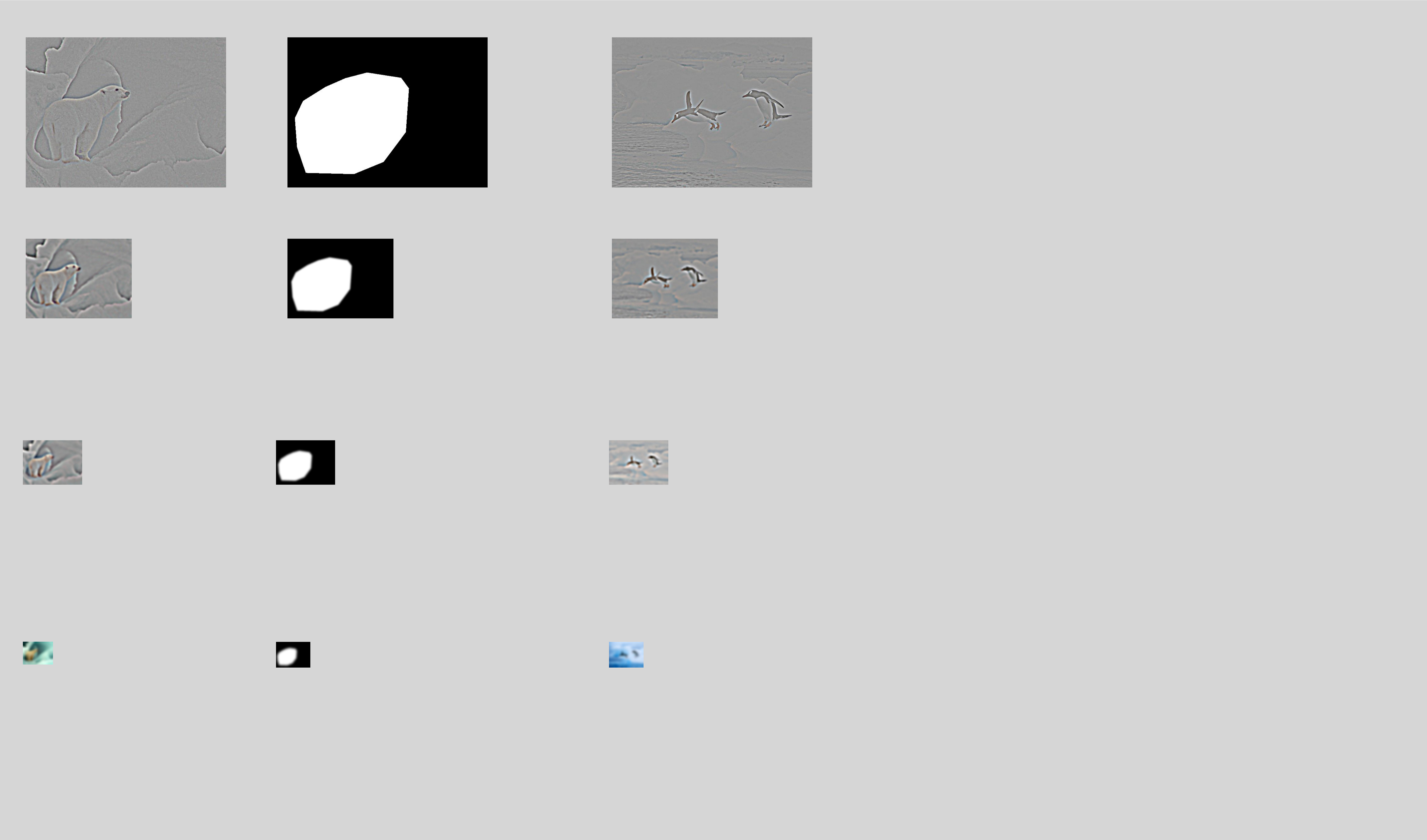
3. From a combined (blended) Laplacian pyramid LS, using nodes of GR as weights: $LS(i,j) = GR(i,j) * LA(i,j) + (1-GR(i,j)) * LB(i,j)$

4. Reconstruct the final blended image from LS

Polar Bear
Laplacian
Pyramid

Polar Bear Laplacian Pyramid

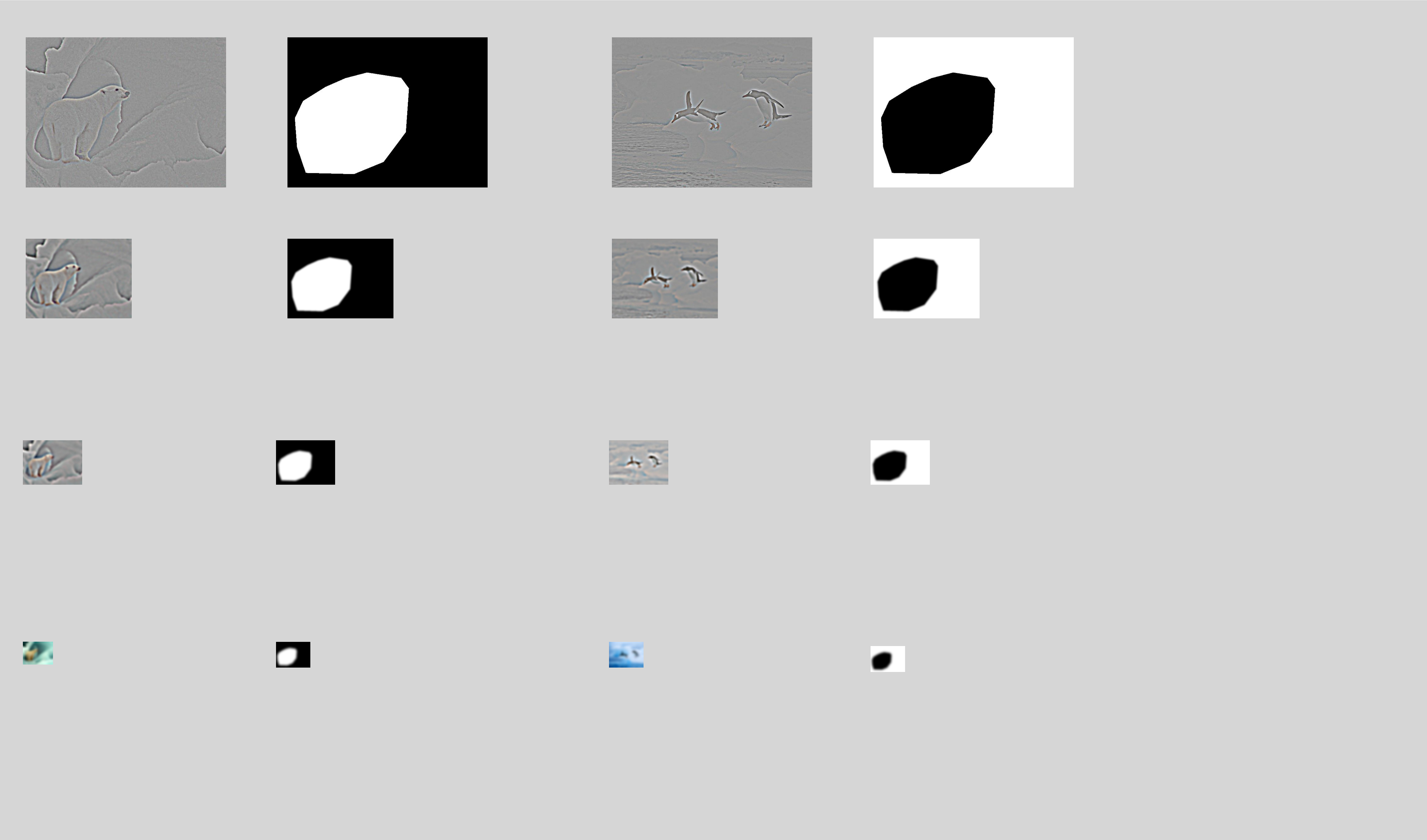
Mask Gaussian Pyramid



Polar Bear Laplacian Pyramid

Mask Gaussian Pyramid

Penguin Laplacian Pyramid

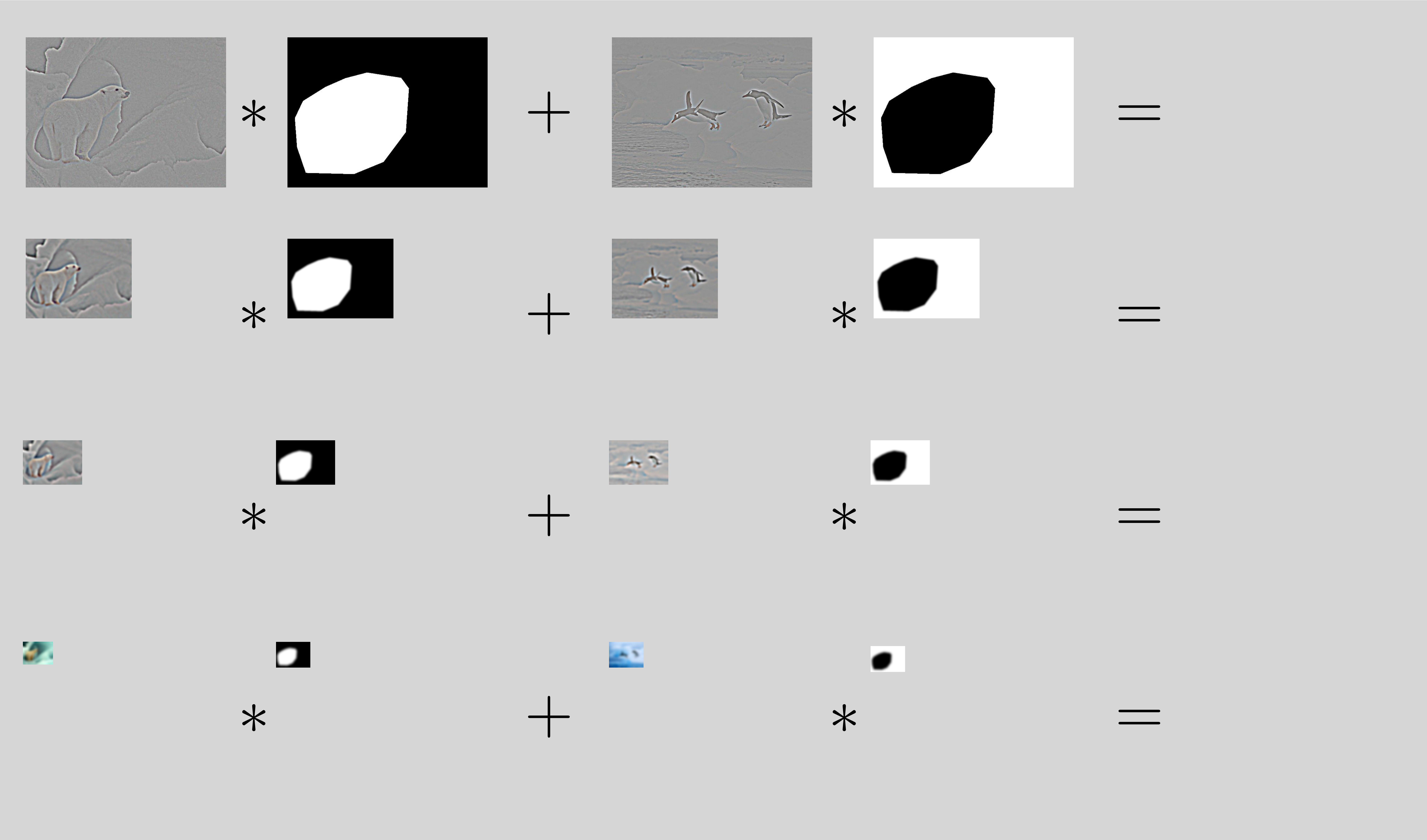


Polar Bear Laplacian Pyramid

Mask Gaussian Pyramid

Penguin Laplacian Pyramid

1 - Mask Gaussian Pyramid

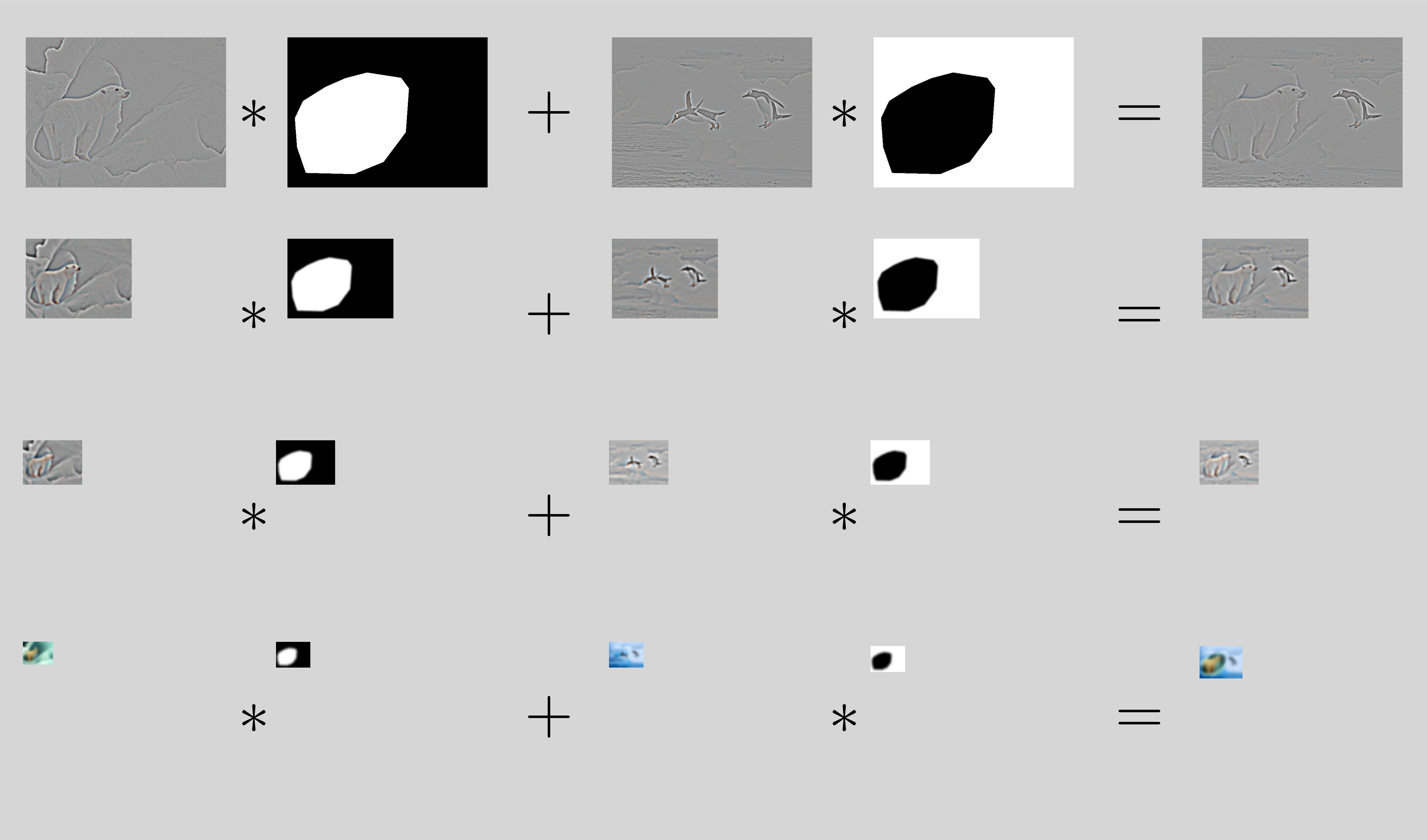


Polar Bear Laplacian Pyramid

Mask Gaussian Pyramid

Penguin Laplacian Pyramid

1 - Mask Gaussian Pyramid



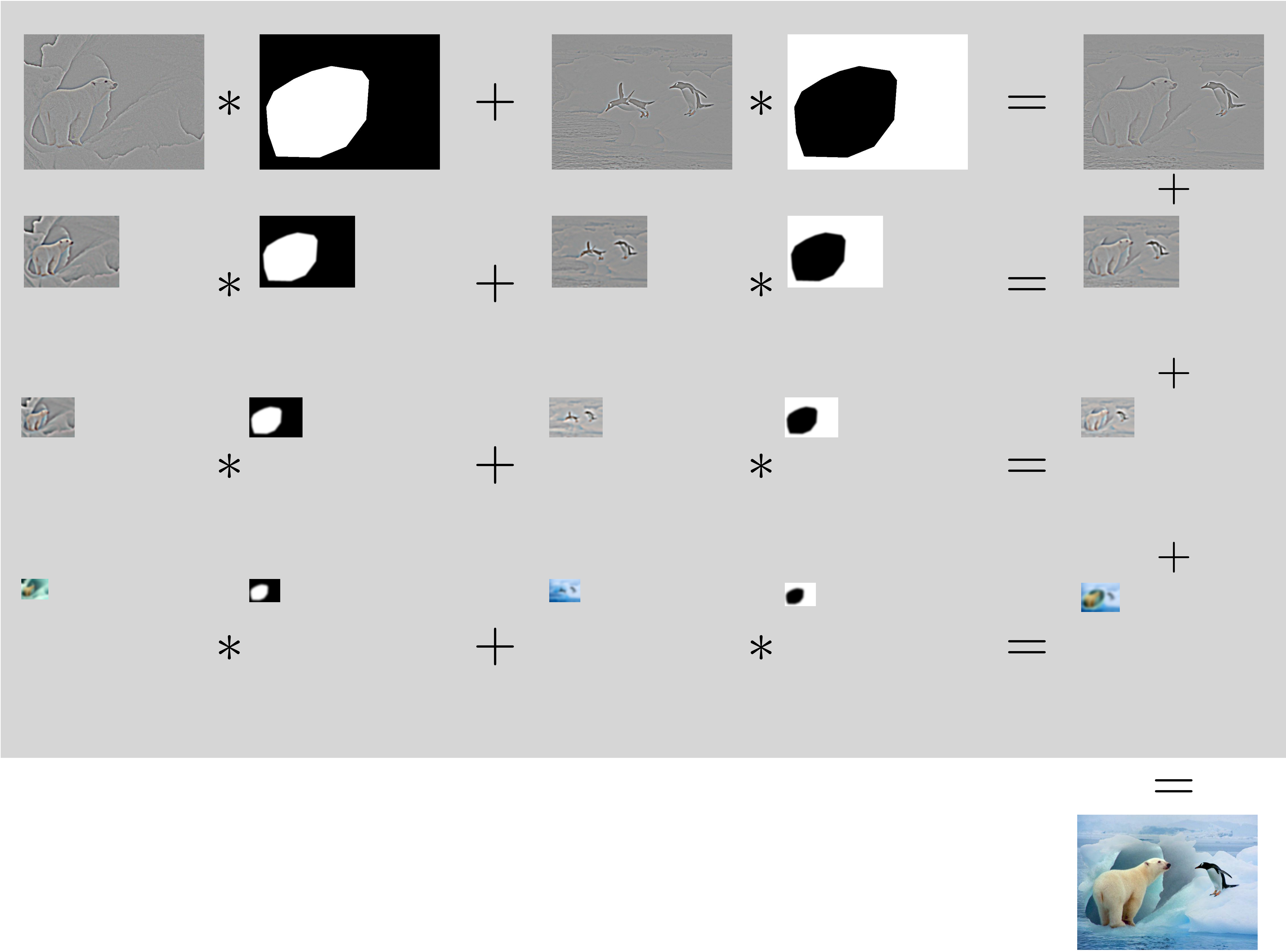
Polar Bear Laplacian Pyramid

Mask Gaussian Pyramid

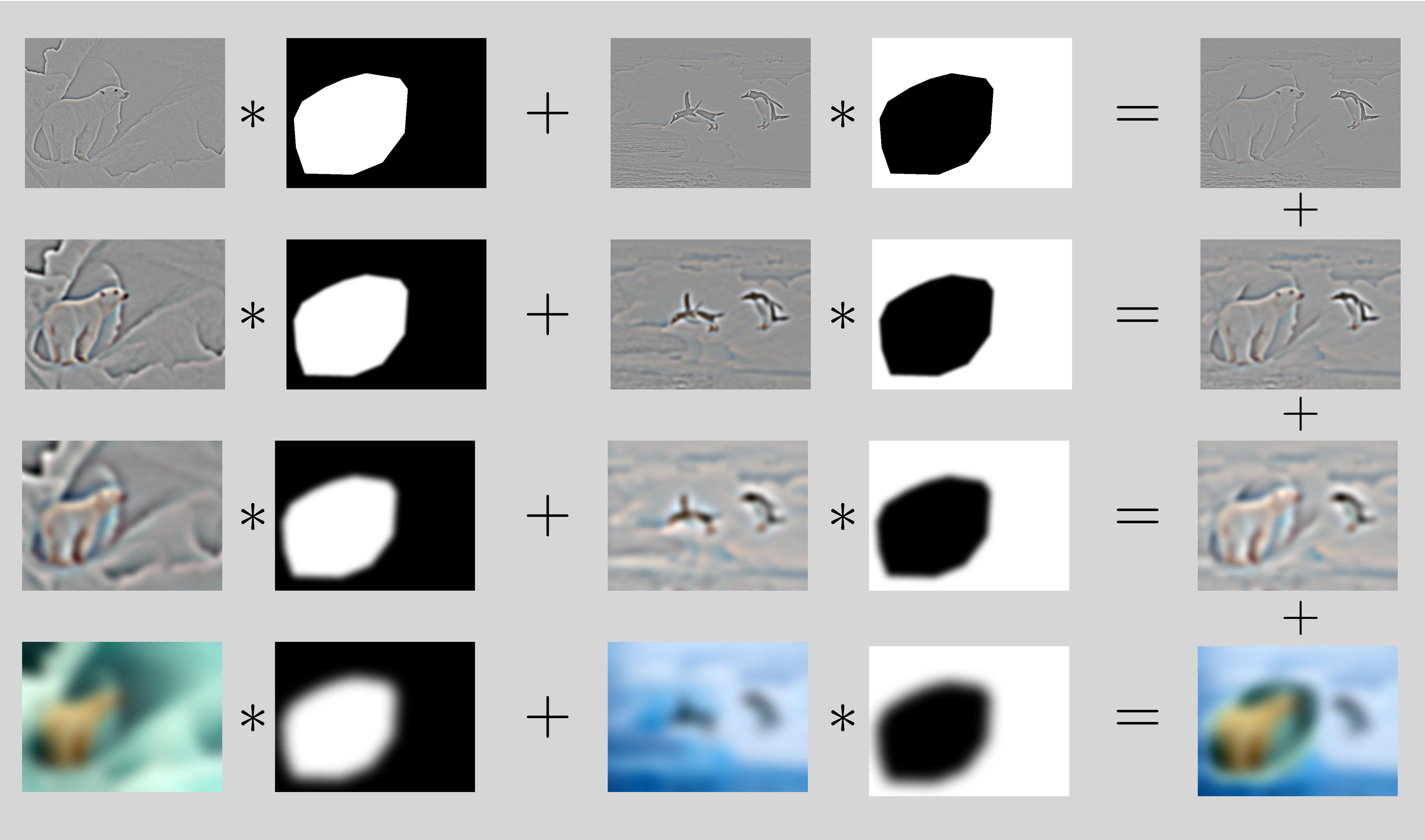
Penguin Laplacian Pyramid

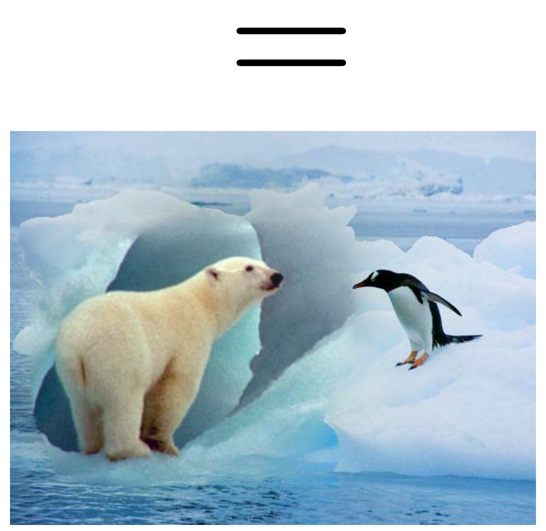
1 - Mask Gaussian Pyramid

Result Pyramid



Reconstruct Result



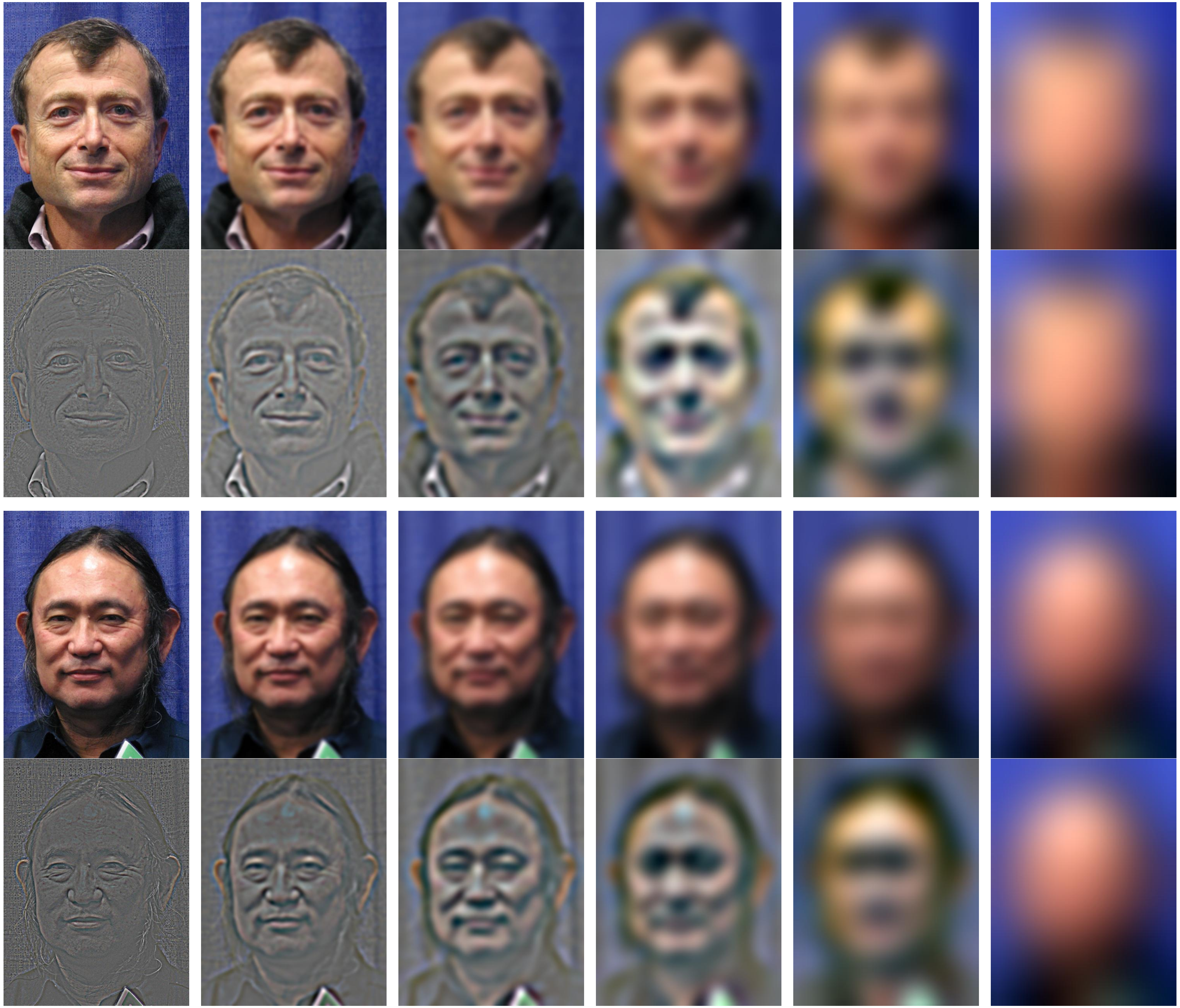


Reconstruct Result


[Jim Kajiya, Andries van Dam]

[Jim Kajiya, Andries van Dam]

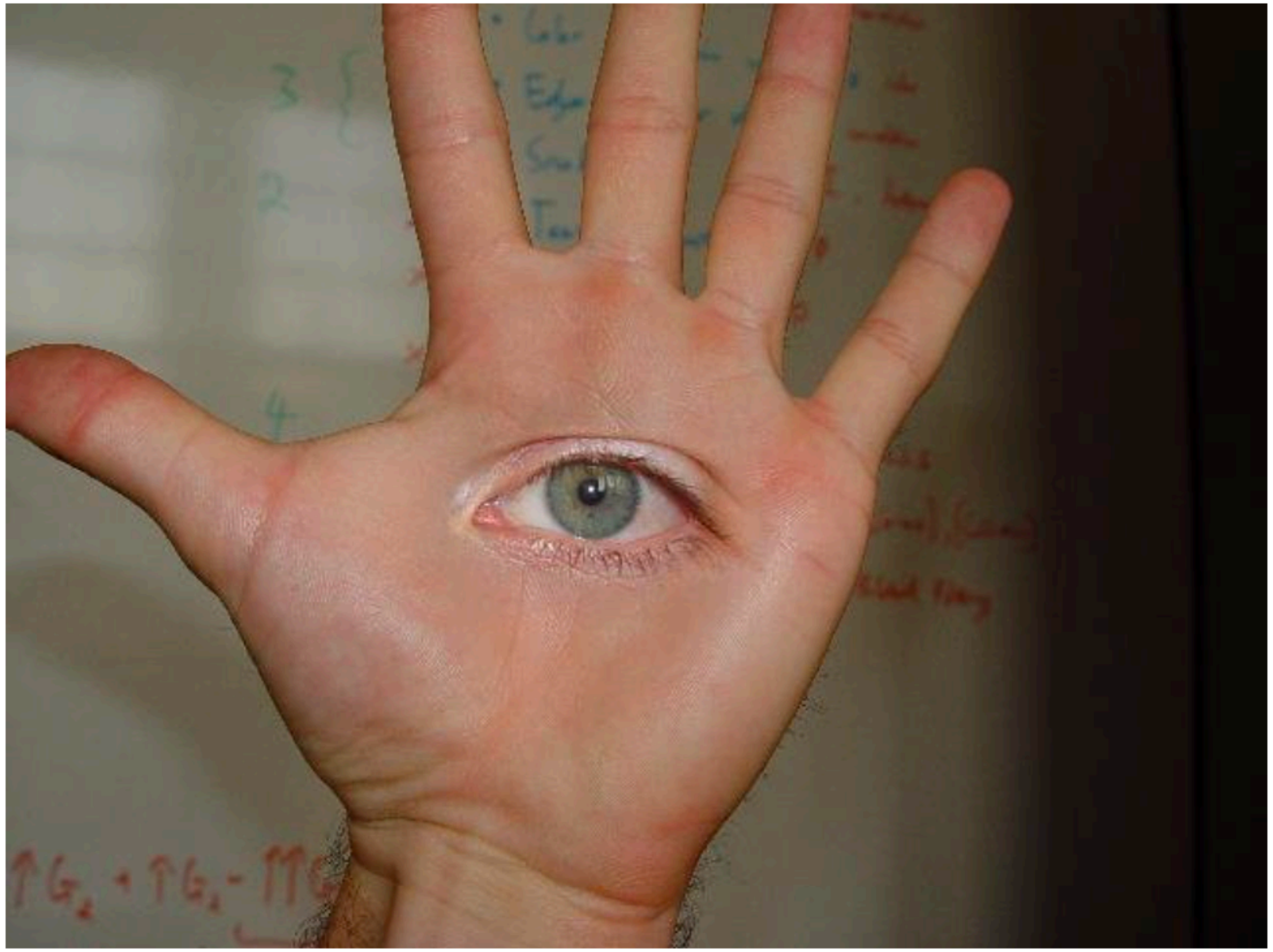


Alpha blend with sharp fall-off

Alpha blend with gradual fall-off

Pyramid Blend

More examples …



© david dmartin (Boston College)

More examples …

© Chris Cameron

Summary: **Scaled Representations**

Gaussian Pyramid

—Each level represents a **low-pass** filtered image at a different scale

—Generated by successive Gaussian blurring and downsampling

—Useful for image resizing, sampling

Laplacian Pyramid

—Each level is a **band-pass** image at a different scale

—Generated by differences between successive levels of a Gaussian Pyramid

—Used for pyramid blending, feature extraction etc.

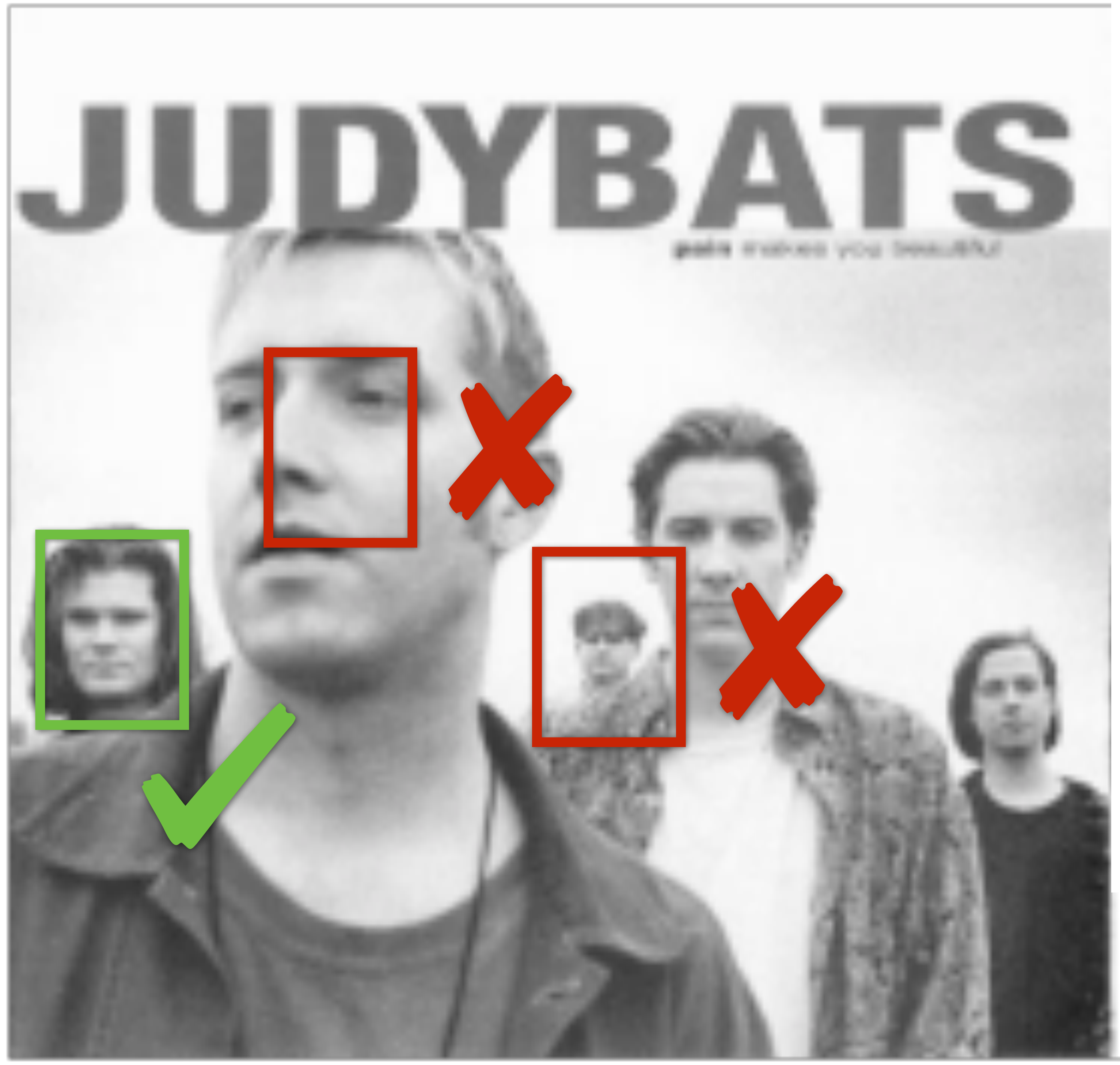
Recap: **Multi-Scale** Template Matching

Correlation with a **fixed-sized image** only detects faces at **specific scales**

= Template

Recap: **Multi-Scale** Template Matching

Correlation with a **fixed-sized image** only detects faces at **specific scales**



= Template

Recap: **Multi-Scale** Template Matching

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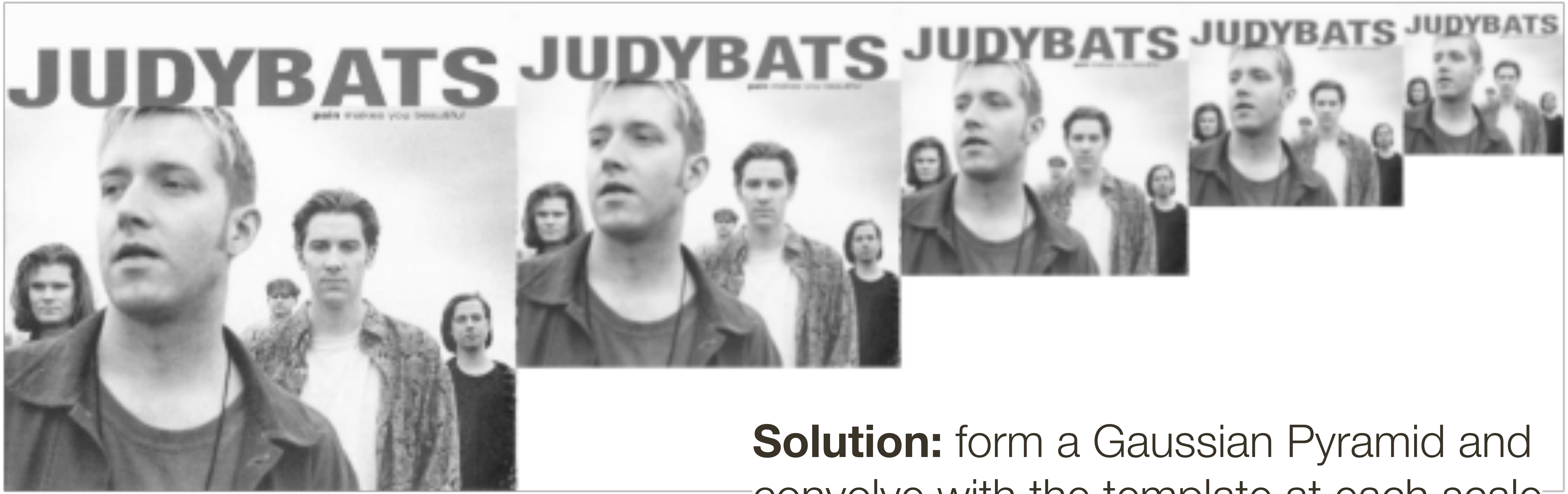

Solution: form a Gaussian Pyramid and convolve with the template at each scale

= Template

Recap: **Multi-Scale** Template Matching

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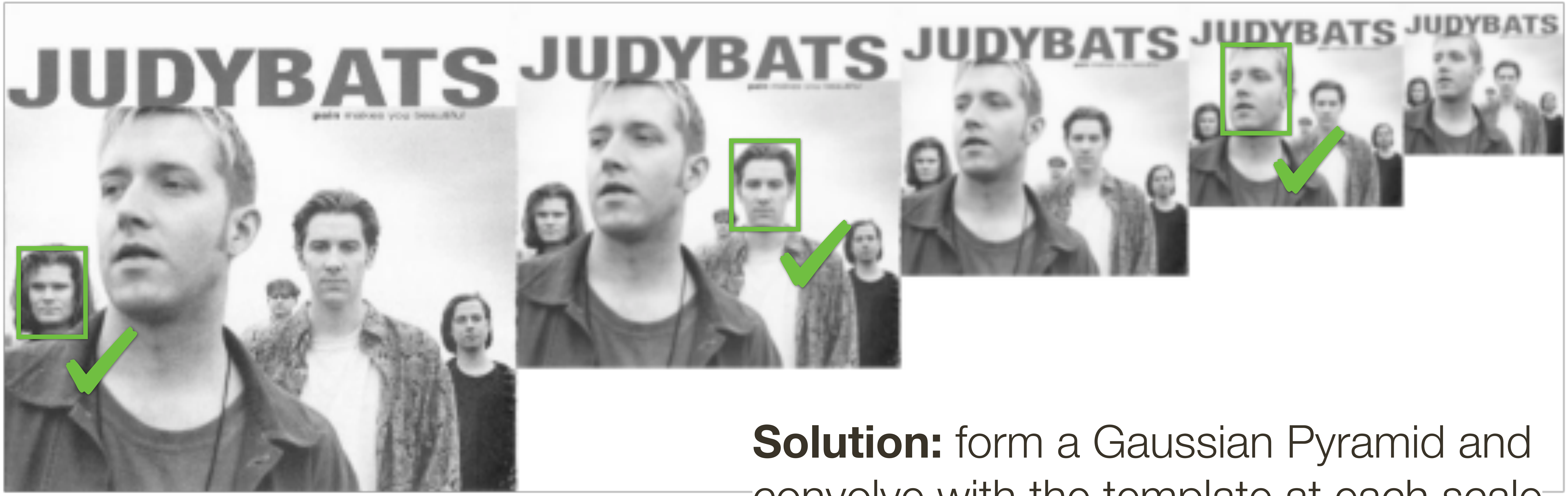

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= Template

Recap: **Multi-Scale** Template Matching

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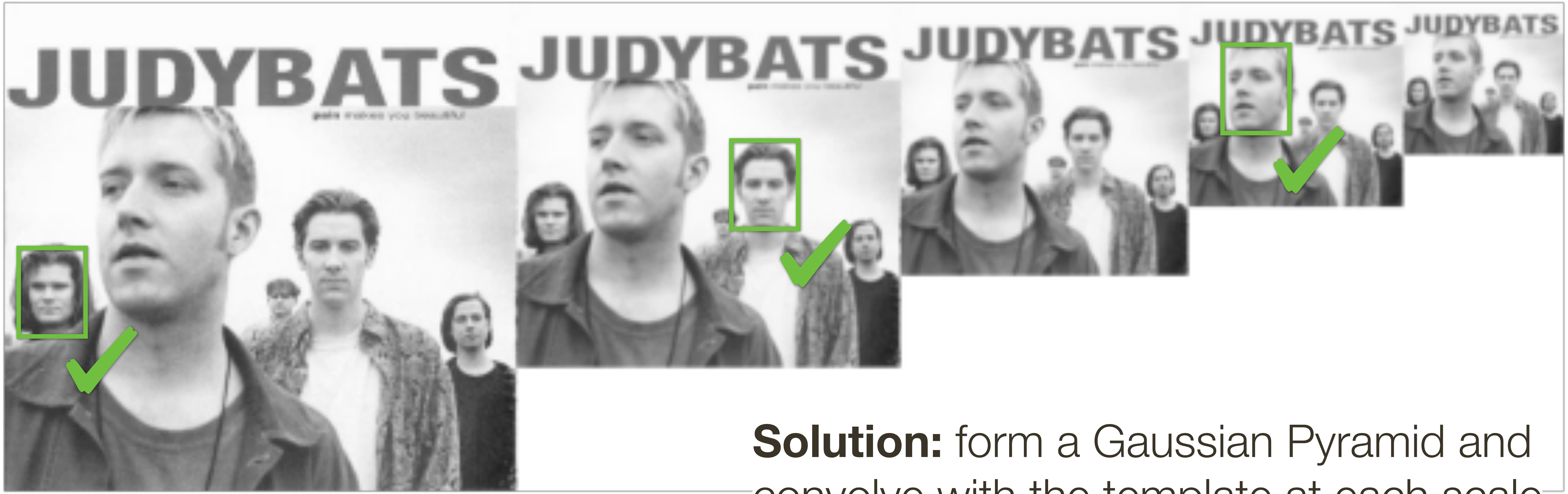


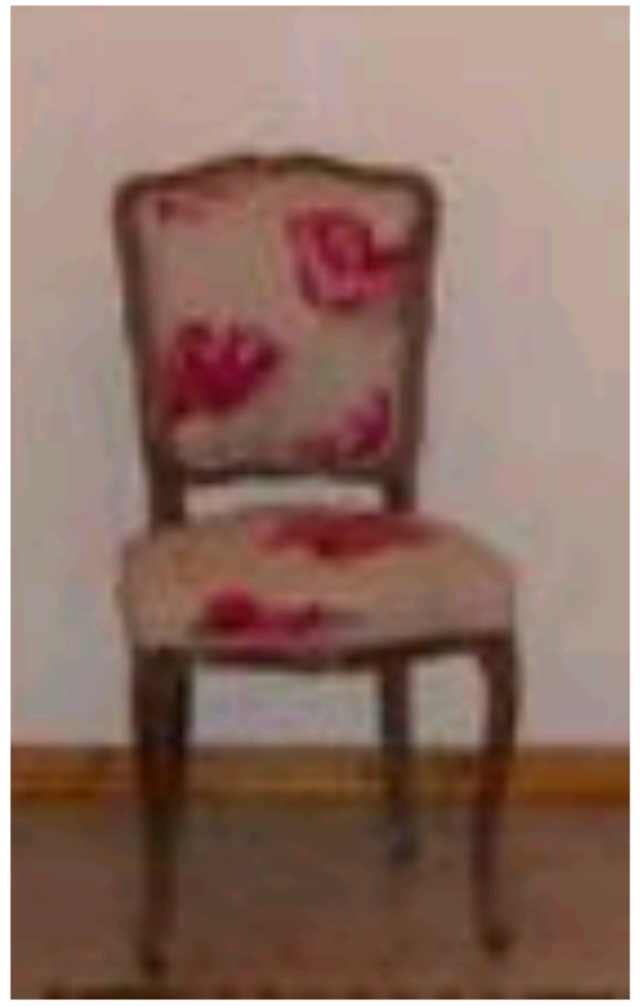
Solution: form a Gaussian Pyramid and convolve with the template at each scale

Q. **Why scale** the **image** and not the **template**?

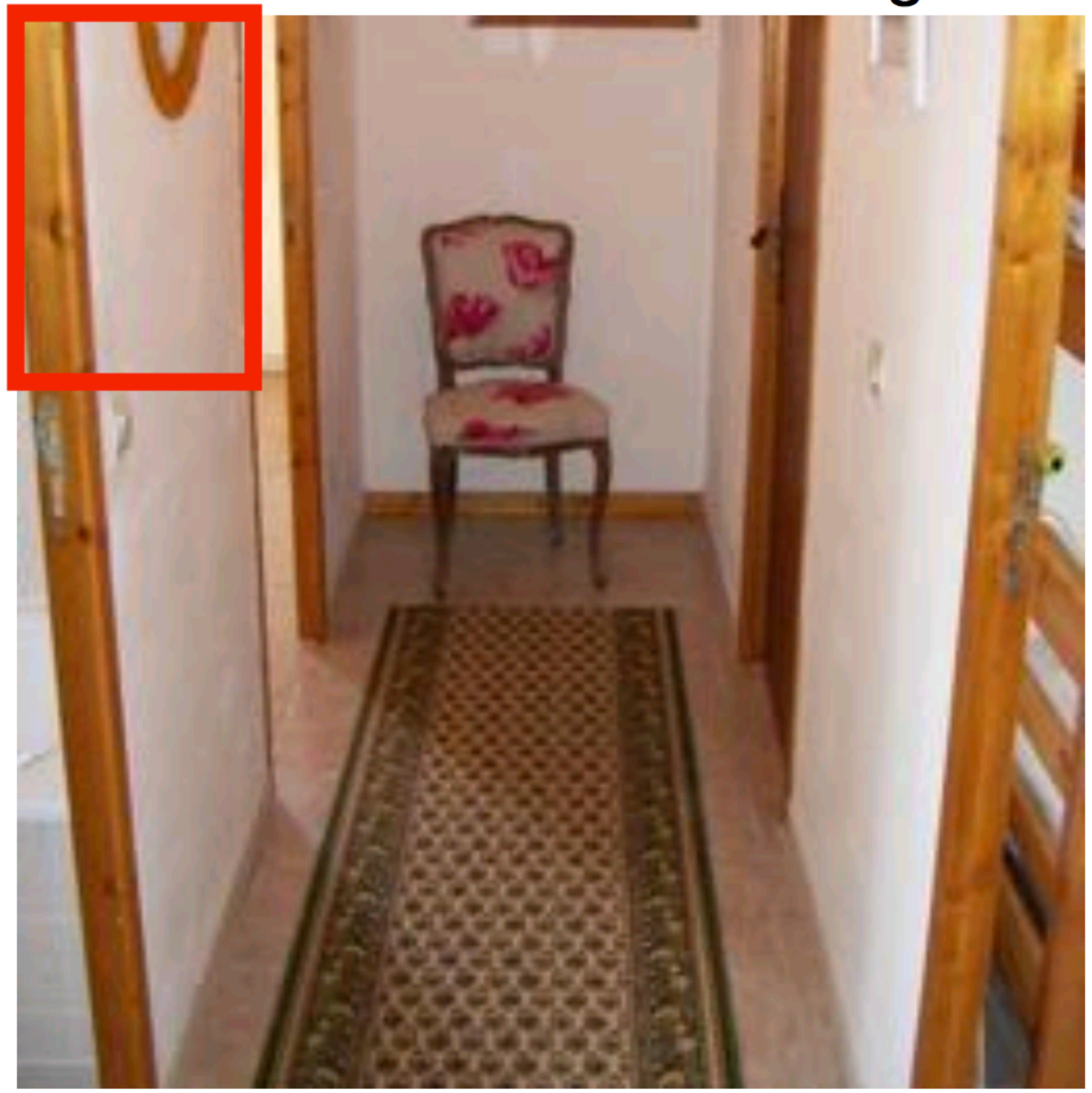
= Template

Improving Template Matching

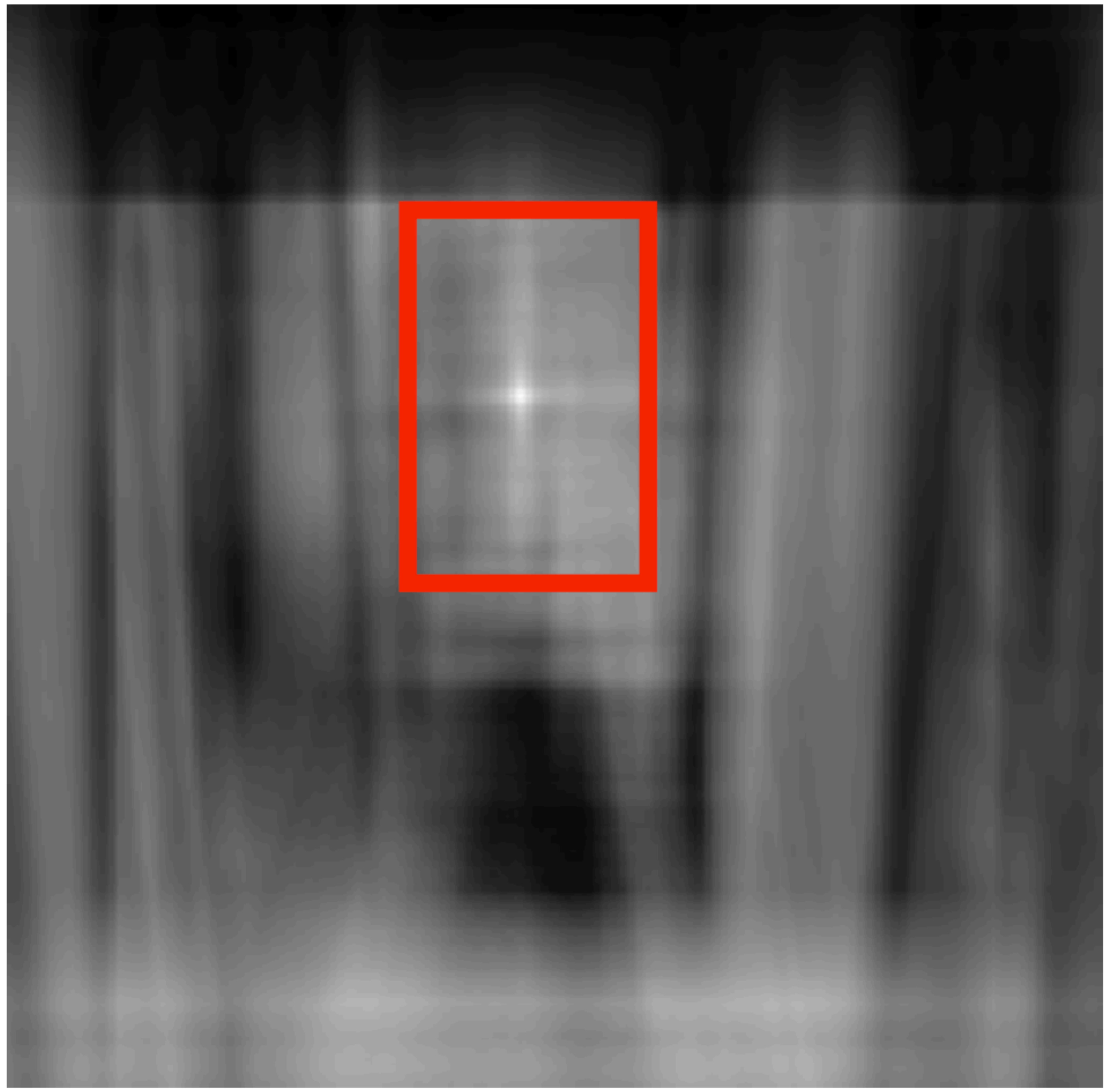
This is a chair



Find the chair in this image

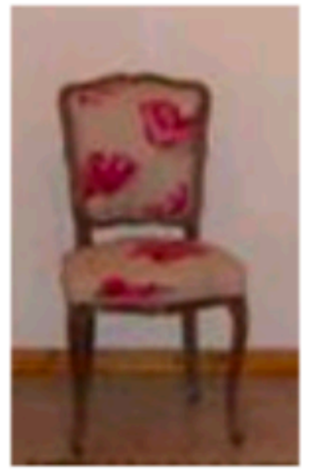


Output of normalized correlation



Slide Credit: Li Fei-Fei, Rob Fergus, and Antonio Torralba

Improving Template Matching



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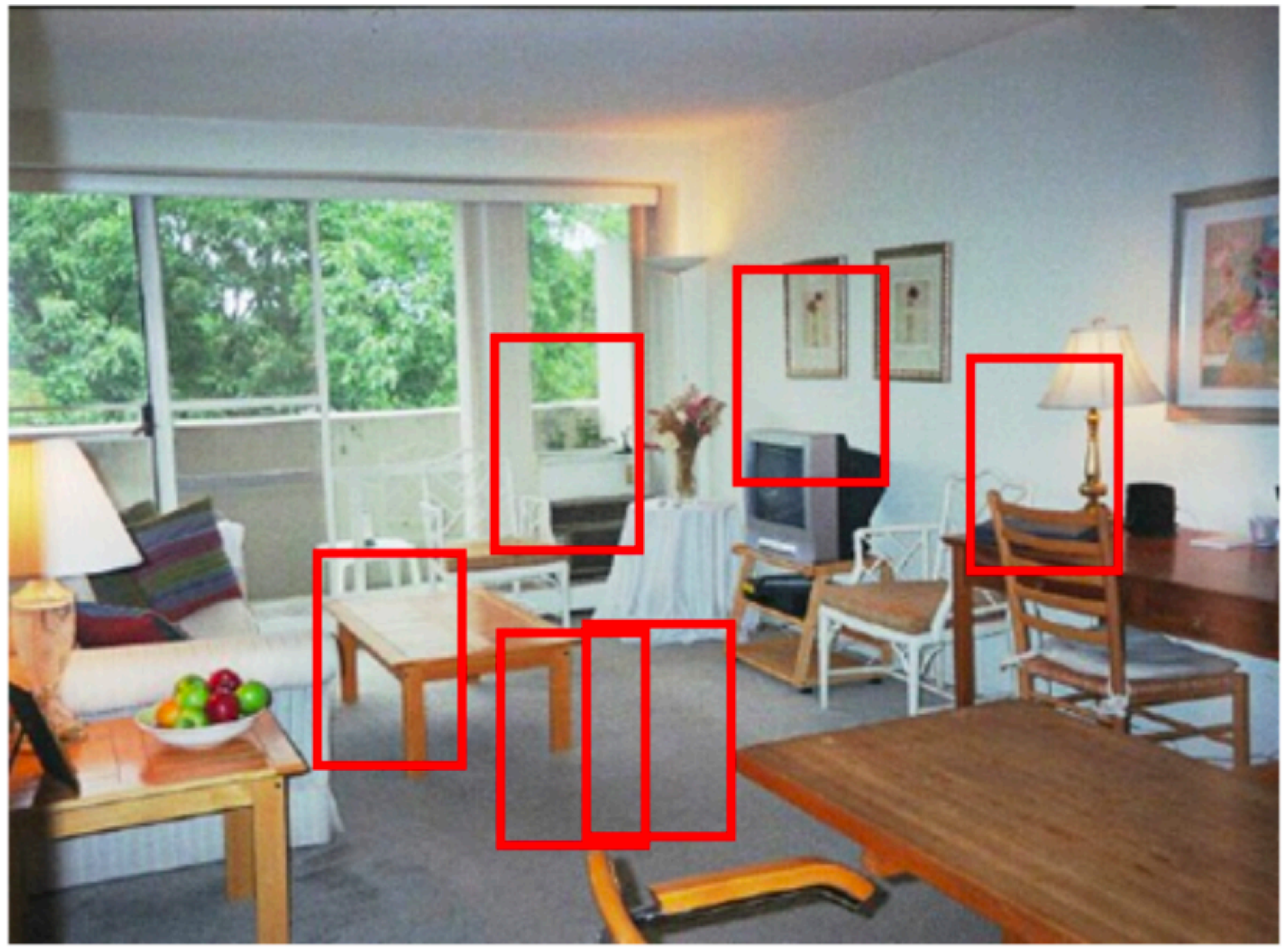
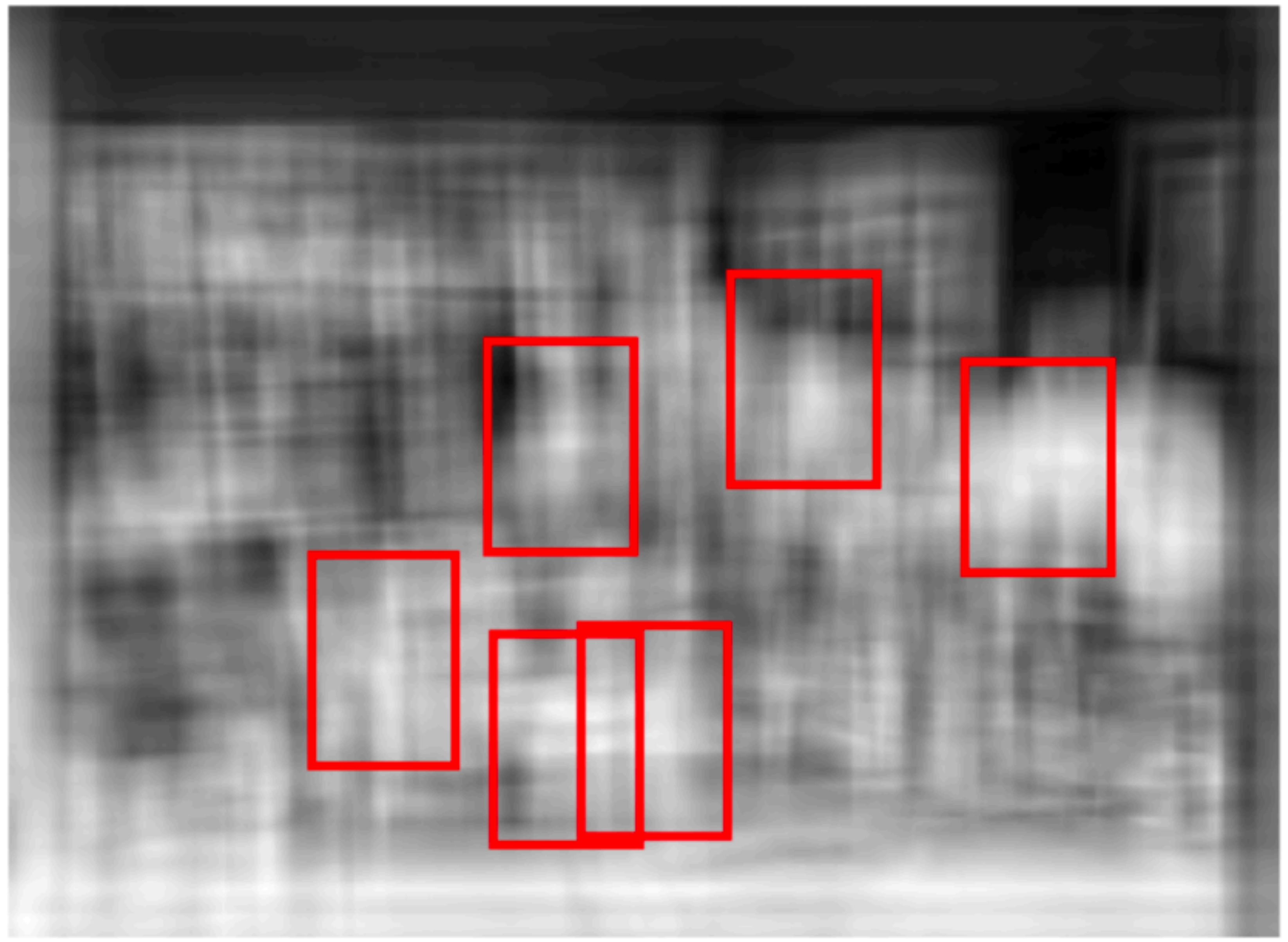




Pretty much garbage
Simple template matching is not going to make it

Slide Credit: Li Fei-Fei, Rob Fergus, and Antonio Torralba

Improving Template Matching

Improved detection algorithms make use of **image features**

These can be **hand coded** or **learned**

From Template Matching to **Local Feature Detection**

Image Template

Test **Image**

From Template Matching to **Local Feature Detection**

Image Template

Edge Template

Test **Image**

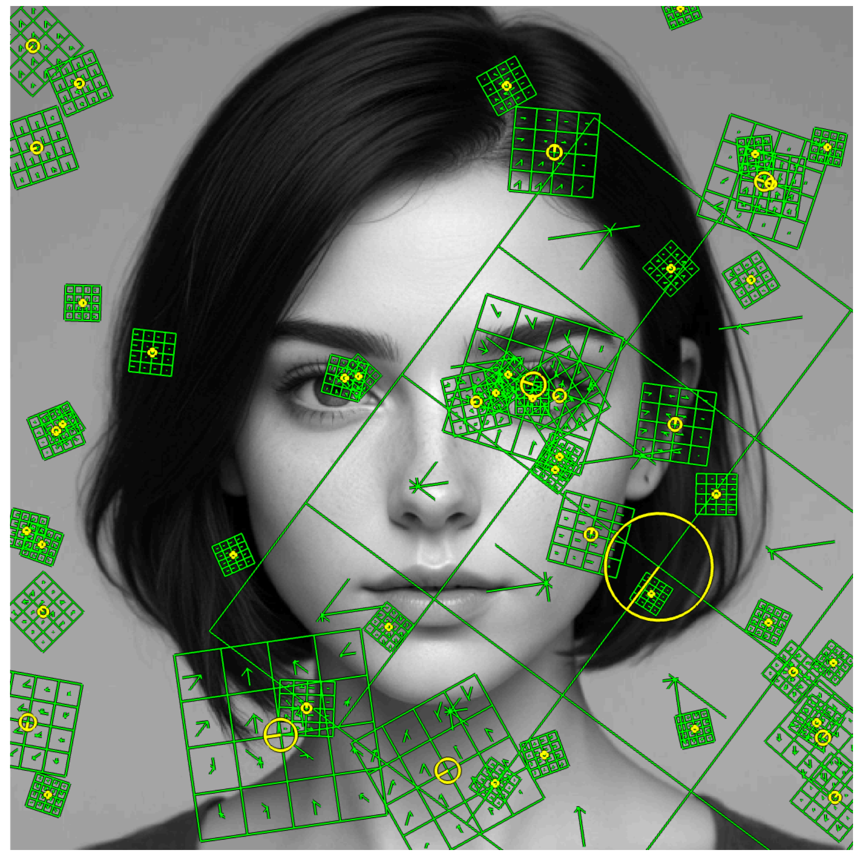
Test **Edge** Image

From Template Matching to **Local Feature Detection**

Image Template

Edge Template

Interest Points



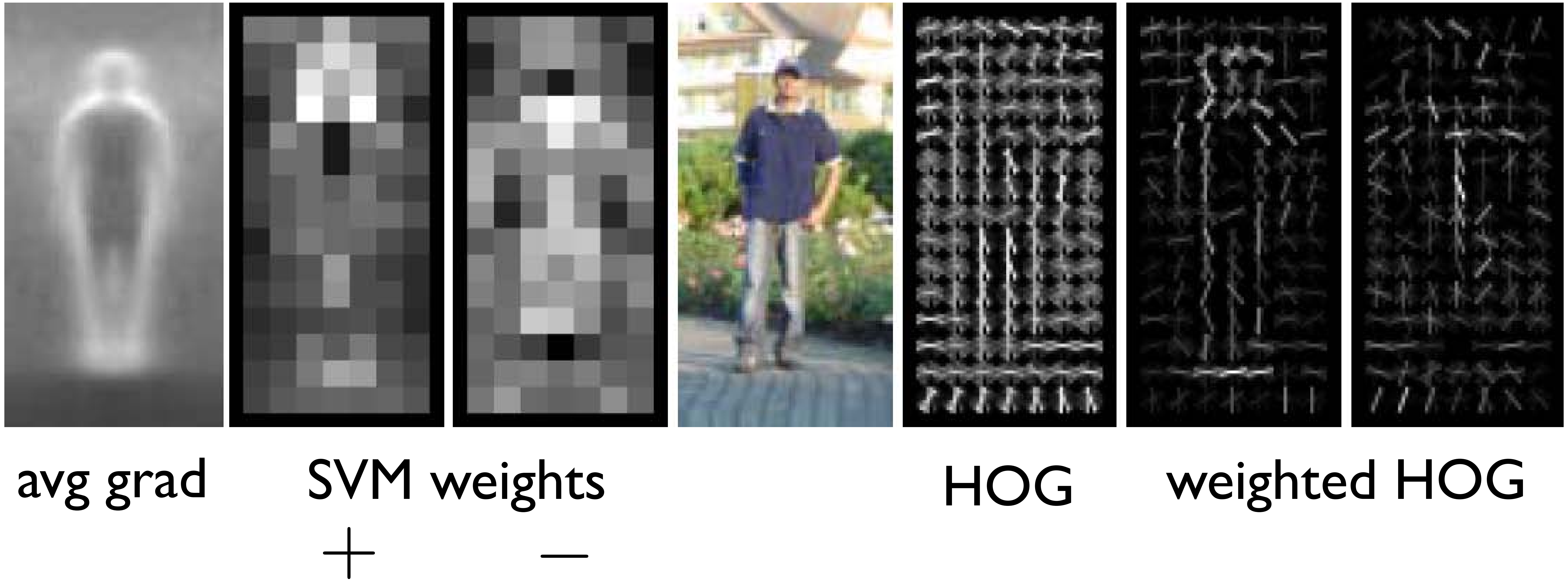
Test **Image**

Test **Edge** Image

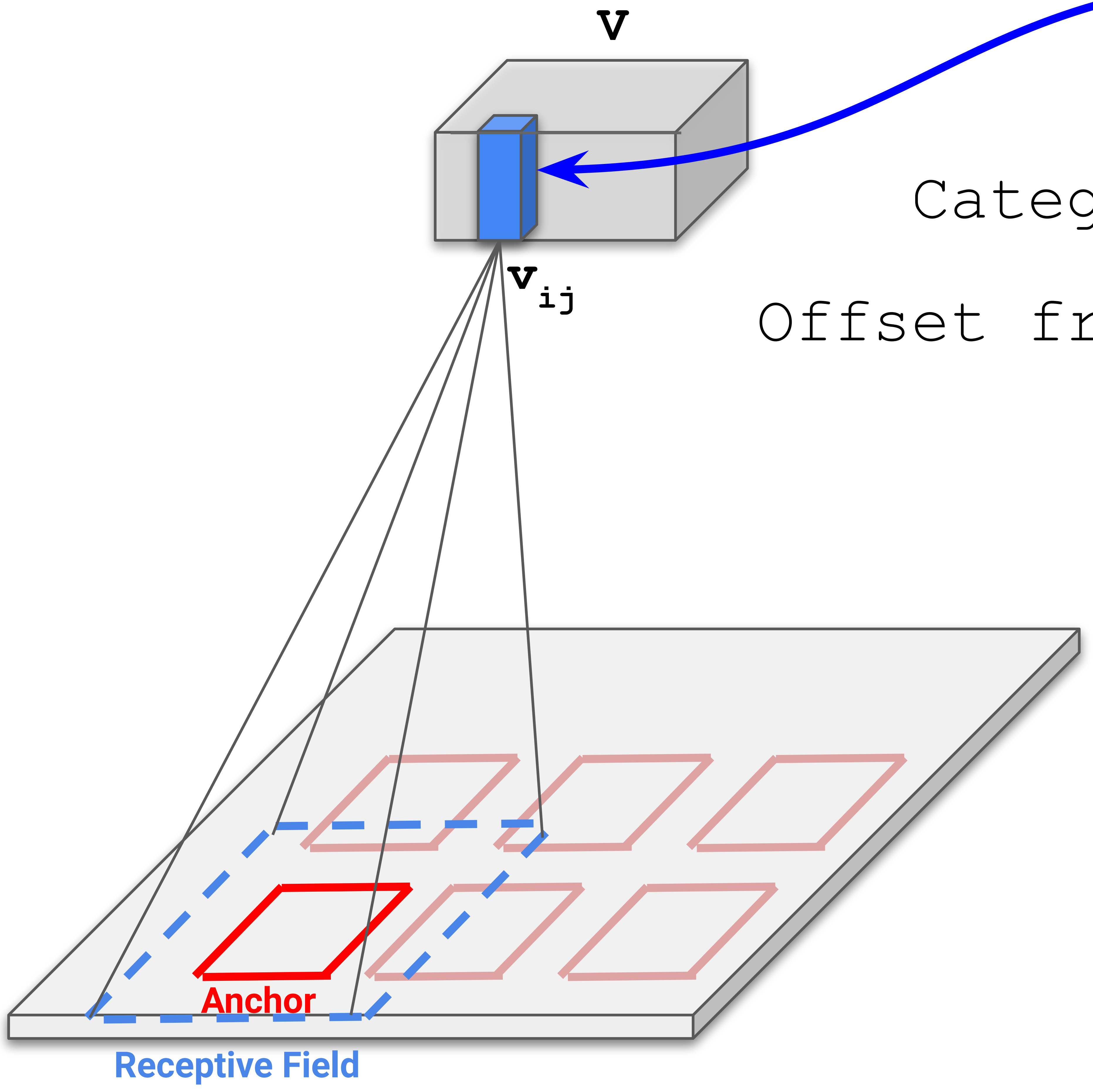
Template Matching with **HoG**

Template matching can be improved by using better features, e.g., Histograms of Gradients (HOG) [Dalal Triggs 2005]

The authors use a Learning-based approach (Support Vector Machine) to find an optimally weighted template



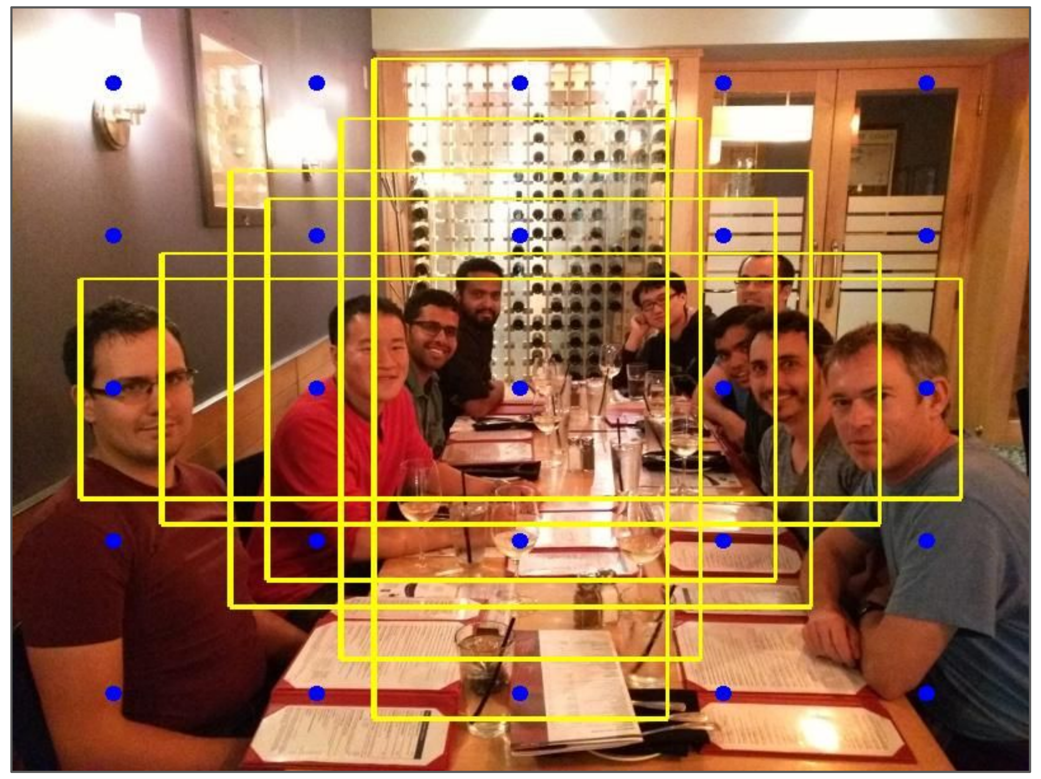
Convnet Object Detection



Think of each feature vector $\mathbf{v}_{ij}$ as corresponding to a sliding window (anchor).

$$\text{Category score} = \text{SoftMax}(W^{cls} \cdot \mathbf{v}_{ij})$$

$$\text{Offset from anchor} = W^{loc} \cdot \mathbf{v}_{ij}$$



— Convnet based object detectors resemble sliding window template matching in feature space

— Architectures typically involve multiple scales and aspect ratios, and regress to a 2D offset in addition to category scores

[Images: Jonathan Huang]

Summary

Template matching as (normalized) correlation. Template matching is not robust to changes in:

— 2D spatial scale and 2D orientation

— 3D pose and viewing direction

— illumination

Scaled representations facilitate

— template matching at multiple scales

— efficient search for image–to–image correspondences

— image analysis at multiple levels of detail

A **Gaussian pyramid** reduces artifacts introduced when sub-sampling to coarser scales

From Template Matching to **Local Feature Detection**

We’ll now shift from global template matching to **local feature detection**

Consider the problem of finding images of an elephant using a template

From Template Matching to **Local Feature Detection**

We’ll now shift from global template matching to **local feature detection**

Consider the problem of finding images of an elephant using a template

An elephant looks different from different viewpoints
— from above (as in an aerial photograph or satellite image)
— head on
— sideways (i.e., in profile)
— rear on

What happens if parts of an elephant are obscured from view by trees, rocks, other elephants?

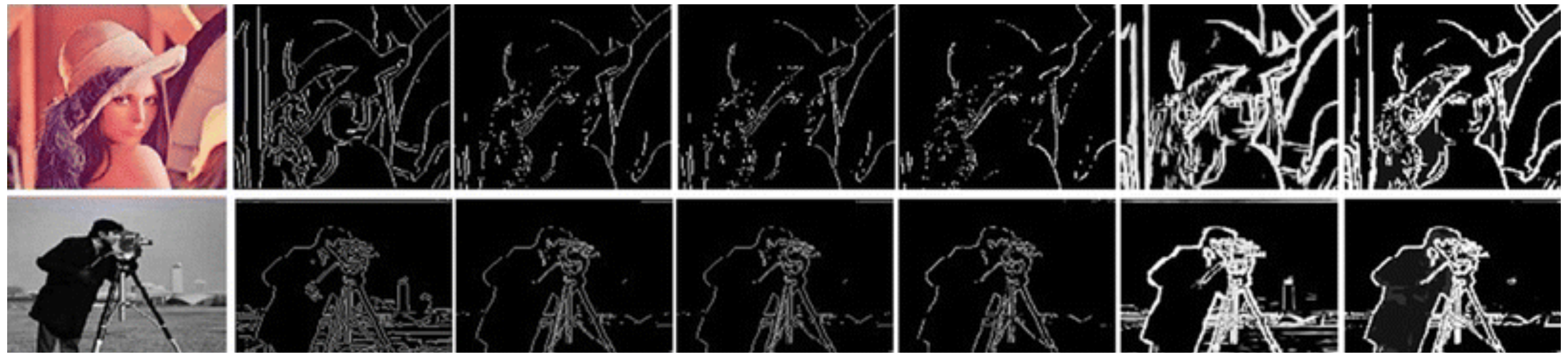
From Template Matching to **Local Feature Detection**

- Move from global template matching to **local template matching**
- Local template matching also called local **feature detection**
- Obvious local features to detect are **edges** and **corners**

Existential **Question**

THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision



Lecture 9: Edge Detection

(unless otherwise stated slides are taken or adopted from **Bob Woodham, Jim Little** and **Fred Tung**)

Edge Detection

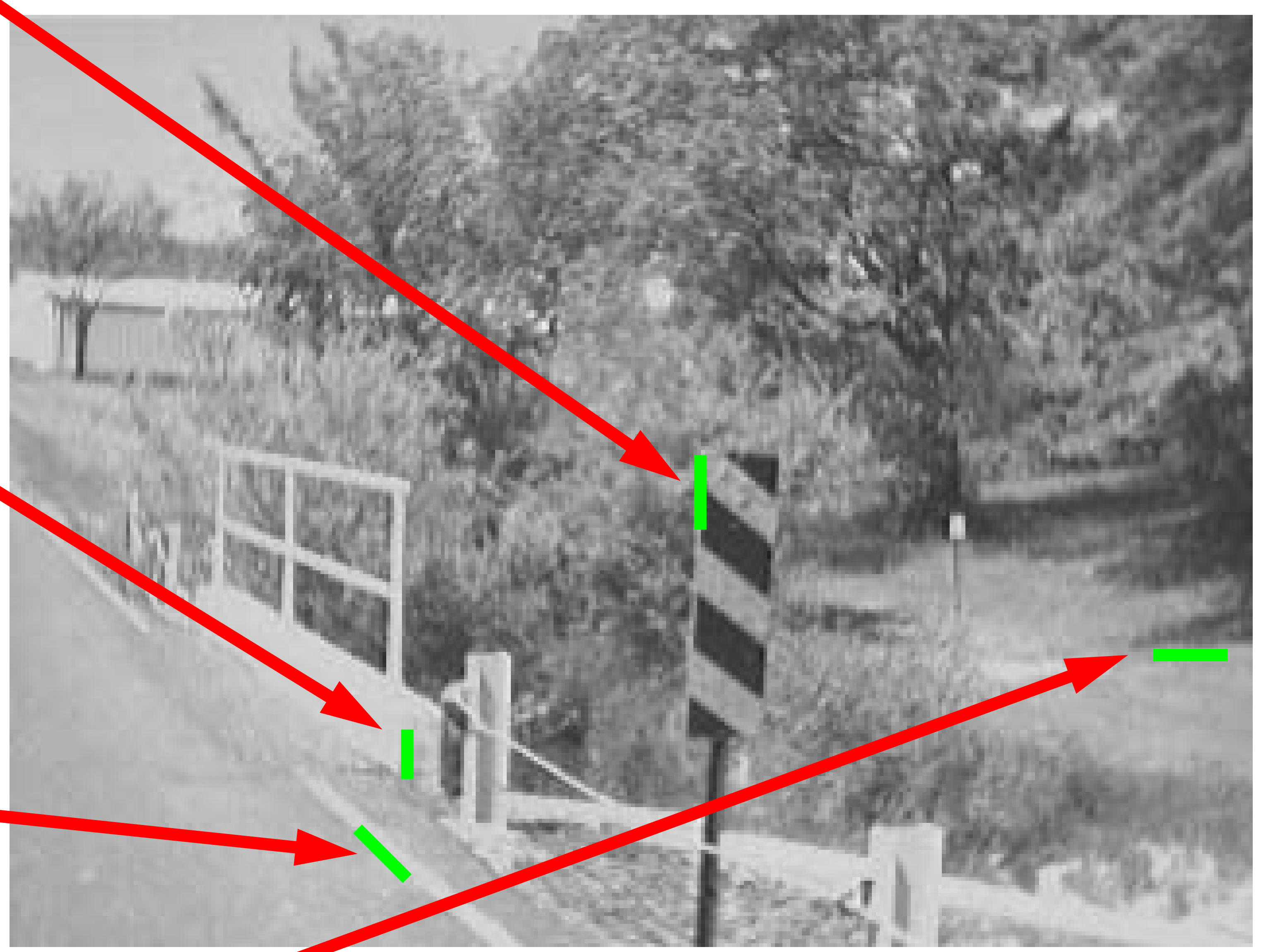
Goal: Identify sudden changes in image intensity

This is where most shape information is encoded

Example: artist's line drawing (but artist also is using object-level knowledge)

What Causes **Edges**?

- Depth discontinuity
- Surface orientation discontinuity
- Reflectance discontinuity (i.e., change in surface material properties)
- Illumination discontinuity (e.g., shadow)



Slide Credit: Christopher Rasmussen

Estimating **Derivatives**

Recall, for a 2D (continuous) function, f(x,y)

$$\frac{\partial f}{\partial x} = \lim_{\epsilon \to 0} \frac{f(x+\epsilon, y) - f(x,y)}{\epsilon}$$

Differentiation is linear and shift invariant, and therefore can be implemented as a convolution

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A (discrete) approximation is

$$\frac{\partial f}{\partial X} \approx \frac{F(X+1, Y) - F(X,Y)}{\Delta X}$$

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-1	1

Estimating **Derivatives**

A (**discrete**) approximation is

$$\frac{\partial f}{\partial X} \approx \frac{F(X+1,Y) - F(X,Y)}{\Delta X}$$

"**forward** difference" implemented as

correlation

-1	1

convolution

1	-1

from **left**

Estimating **Derivatives**

A (**discrete**) approximation is

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1	-1

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Estimating **Derivatives**

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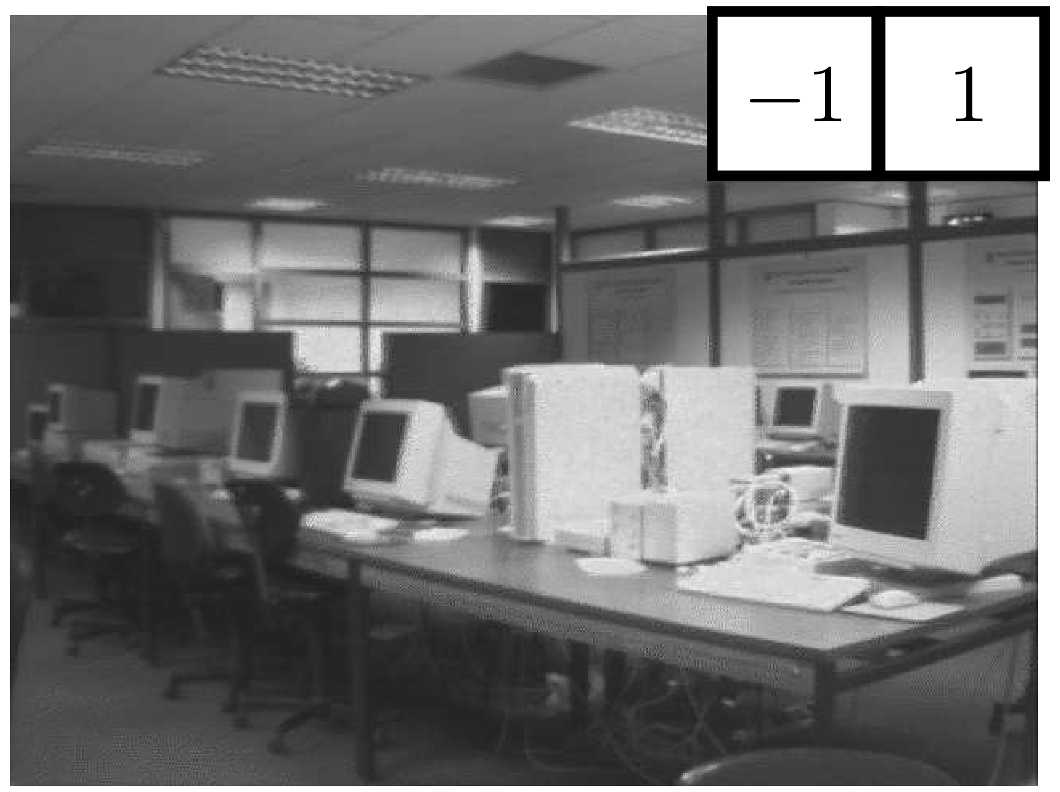
Estimating **Derivatives**



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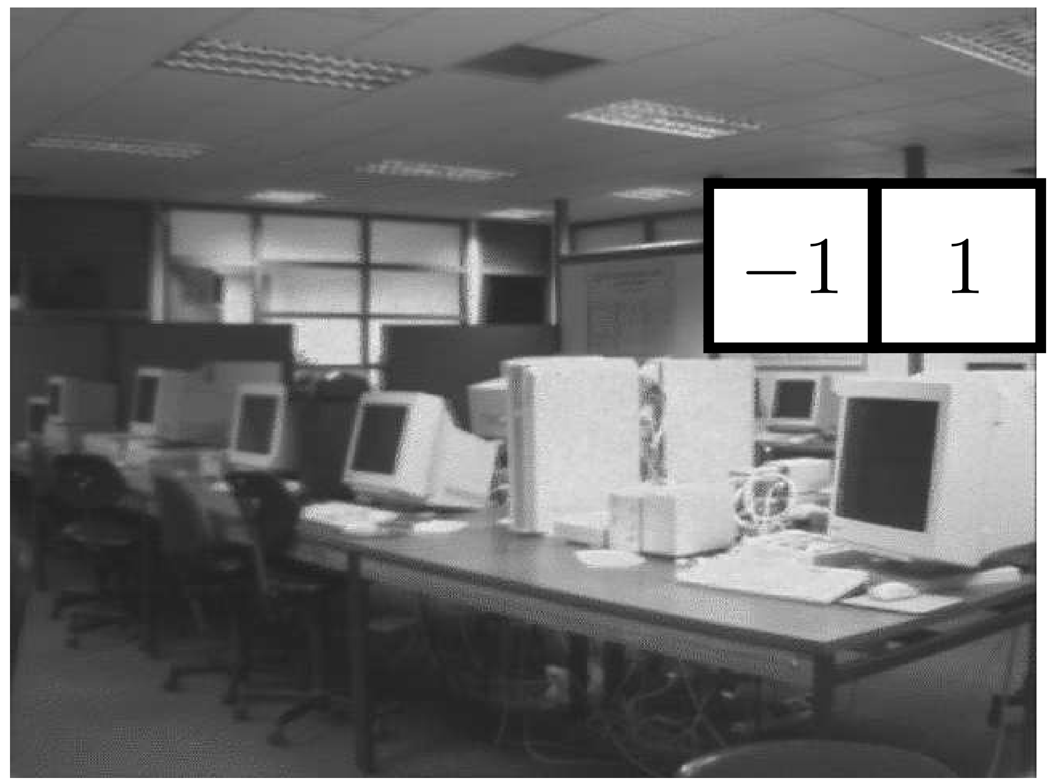
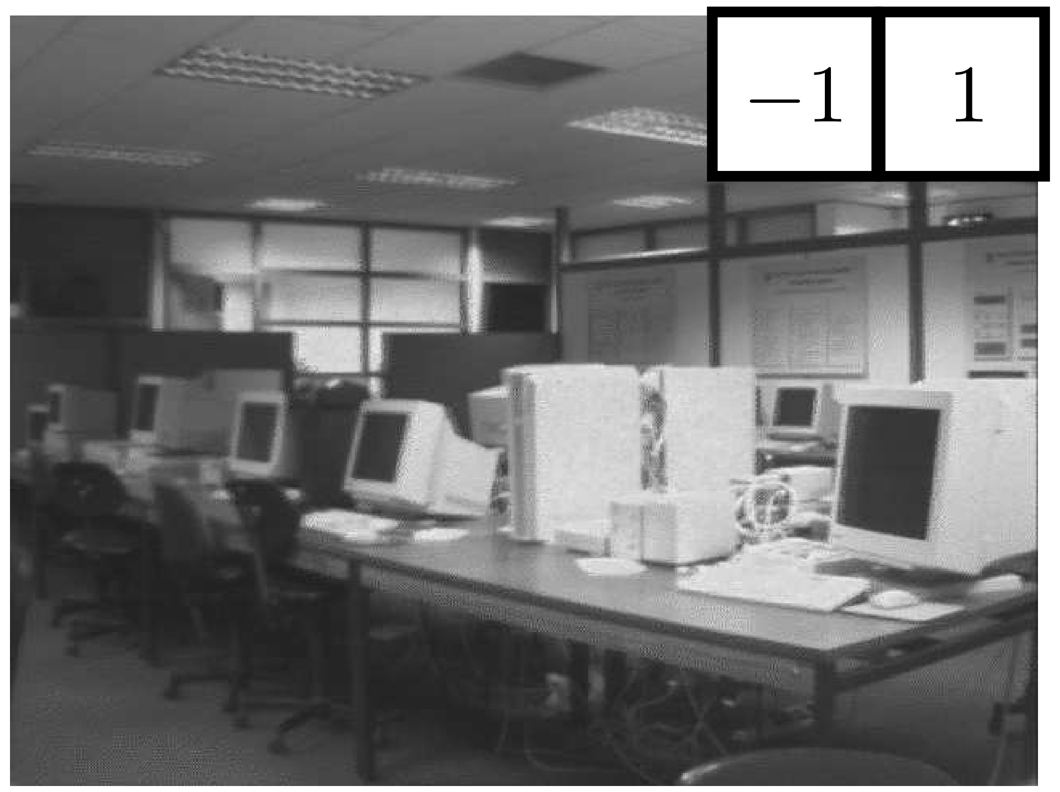
Estimating **Derivatives**





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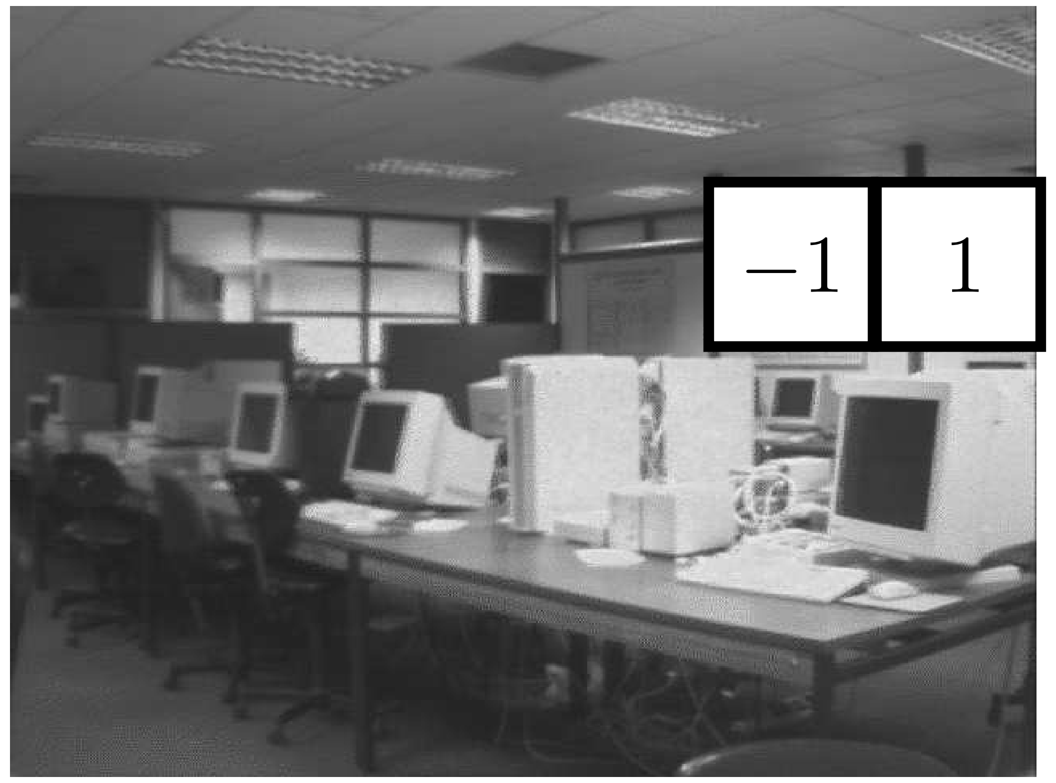

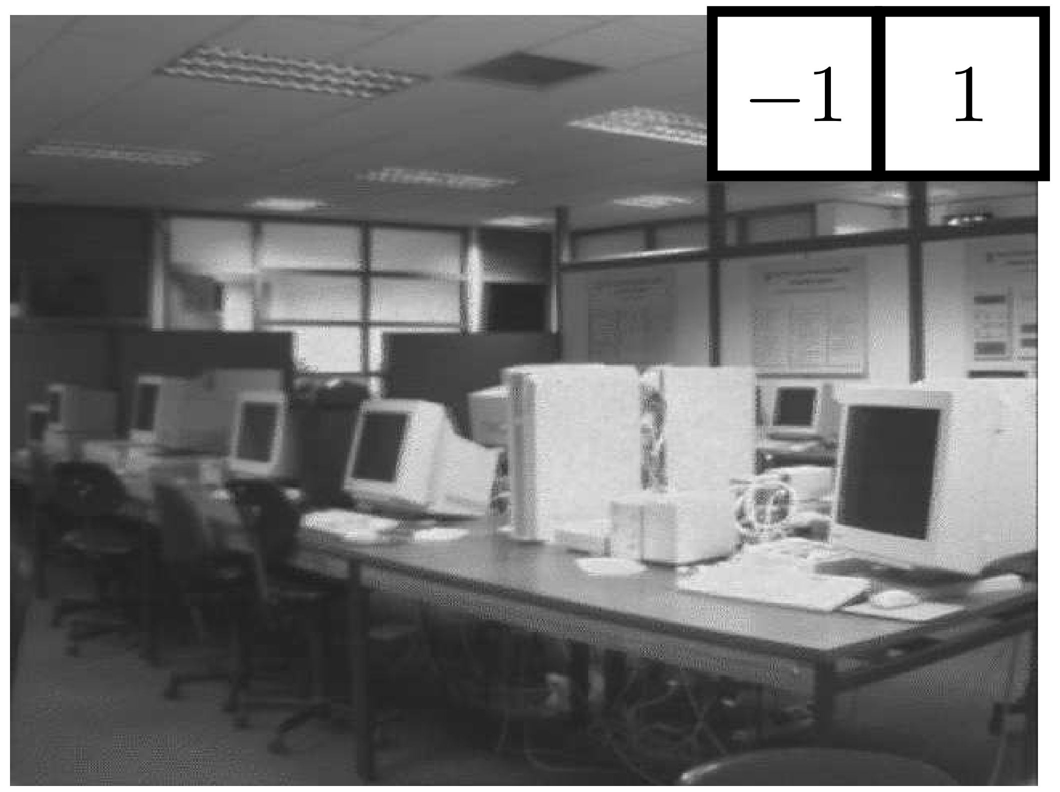

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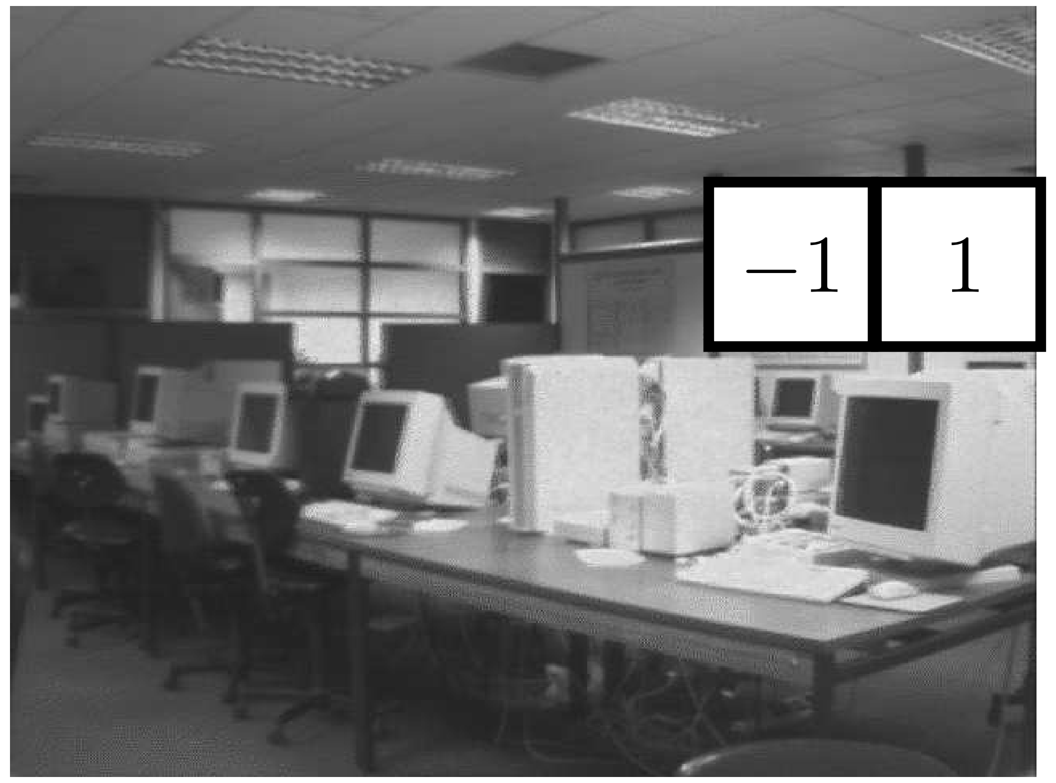
Estimating **Derivatives**



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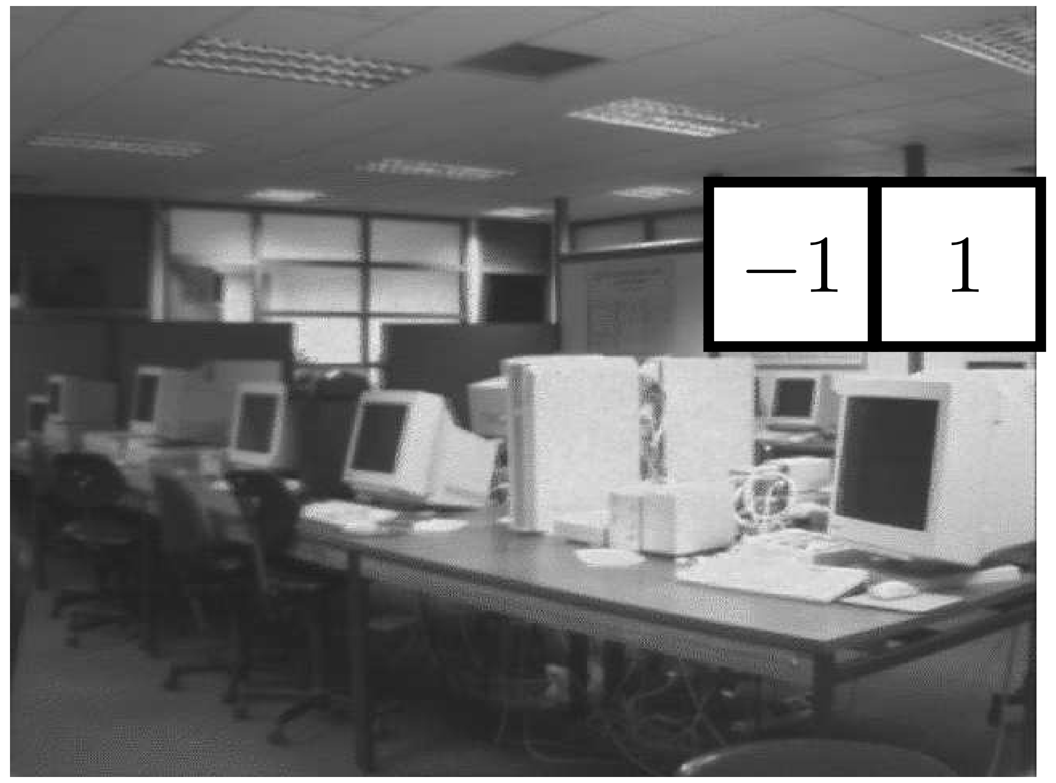
Estimating **Derivatives**



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