THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision

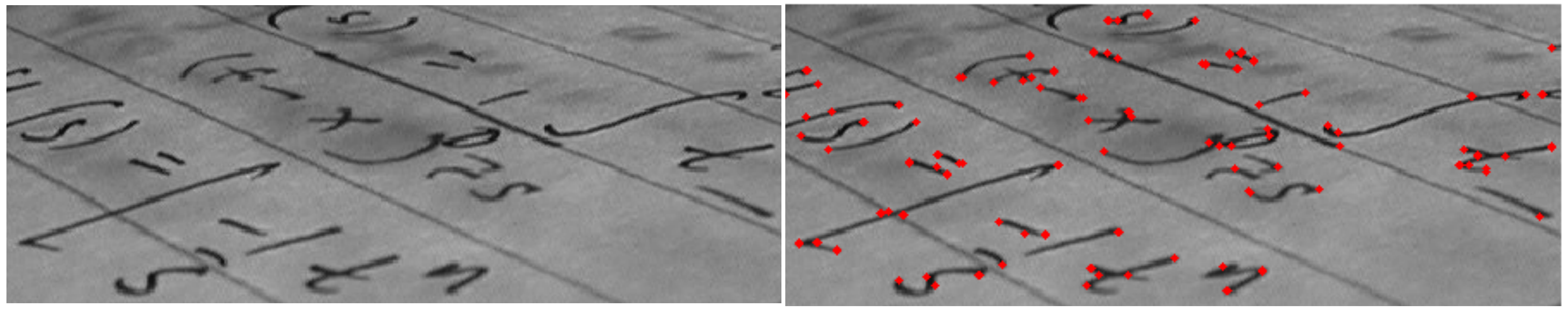


Image Credit: https://en.wikipedia.org/wiki/Corner_detection

Lecture 15: Corner Detection (cont), Texture

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

Menu for Today (**October 14, 2020**)

Topics:

— Harris **Corner** Detector (review)

— **Blob** Detection

— Searching over **Scale**

— **Texture**

Readings:

— **Today's** Lecture: Forsyth & Ponce (2nd ed.) 5.3, 6.1, 6.3

— **Next** Lecture: Forsyth & Ponce (2nd ed.) 3.1-3.3

Reminders:

— **Assignment 2**: Face Detection in a Scaled Representation is due **today**

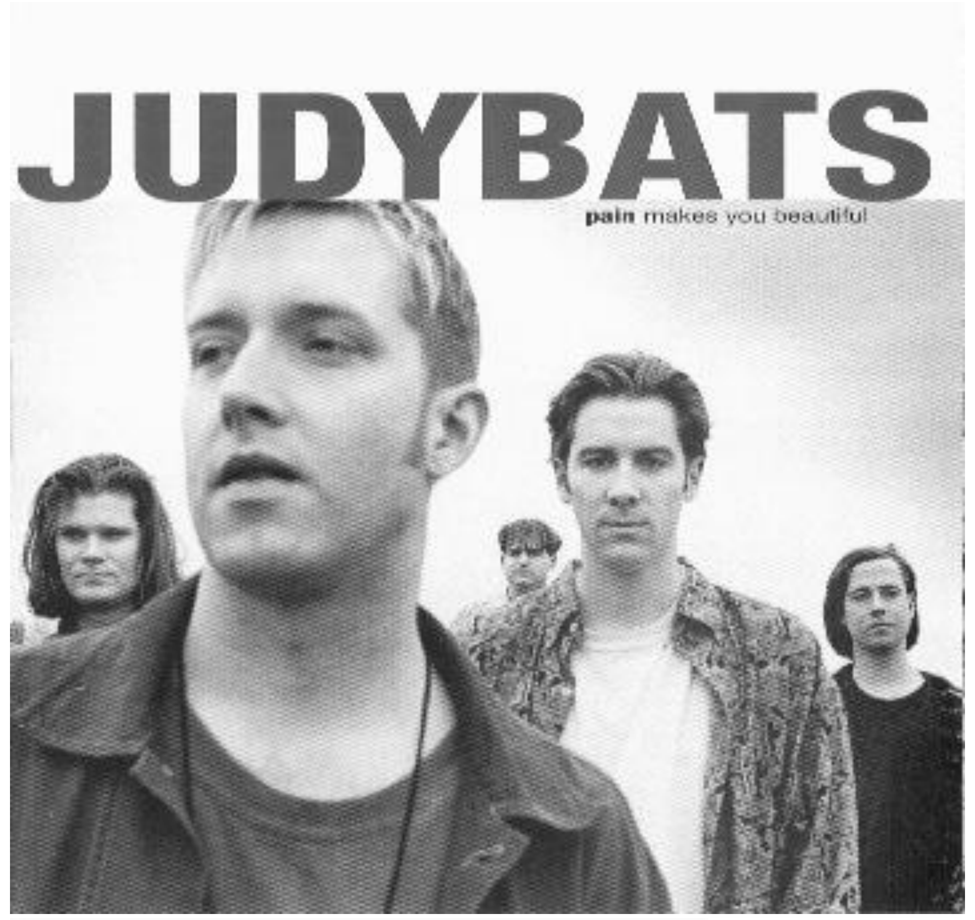
— **Assignment 3:** Texture Synthesis is out **today**

— Study questions for **Midterm** are on Canvas (answers on Friday)

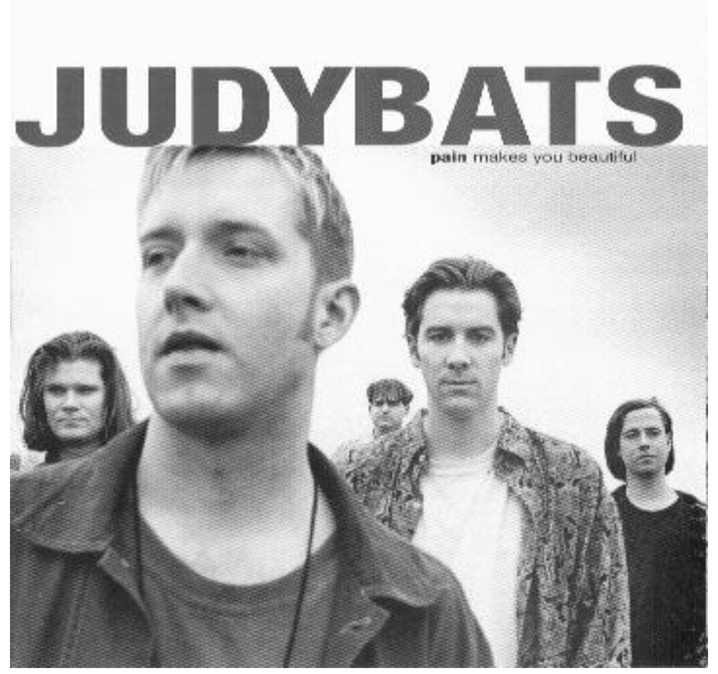
Template matching

Level | **Image** Pyramid (s) | **Template**

0



1



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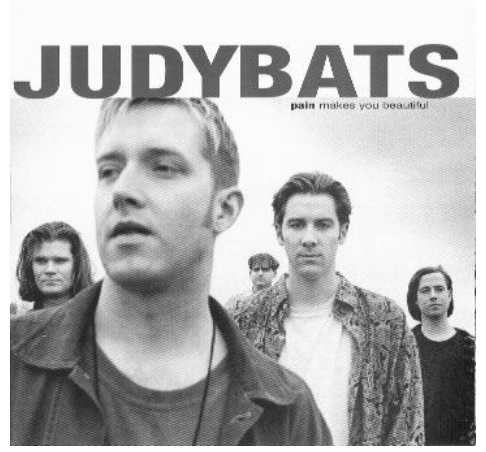


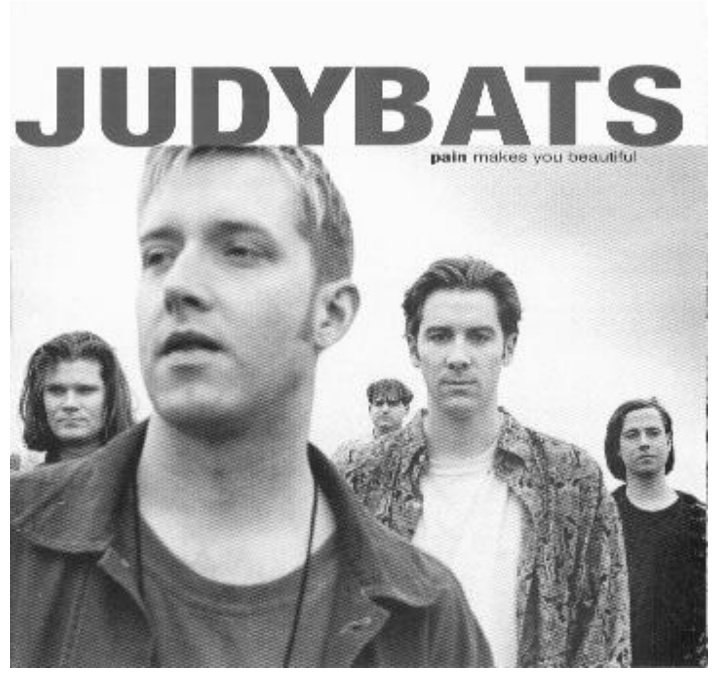
Template matching

Level | **Image** Pyramid (s) | **Template**

0

(x_0, y_0)

1



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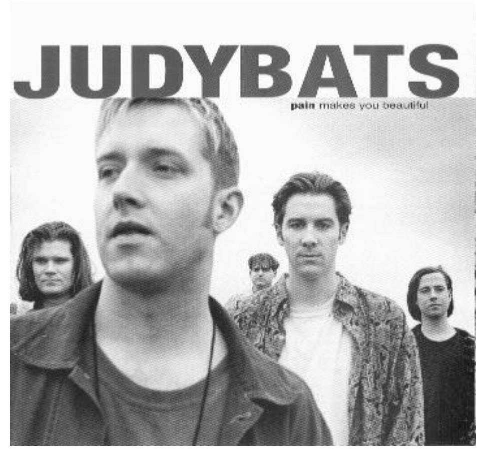


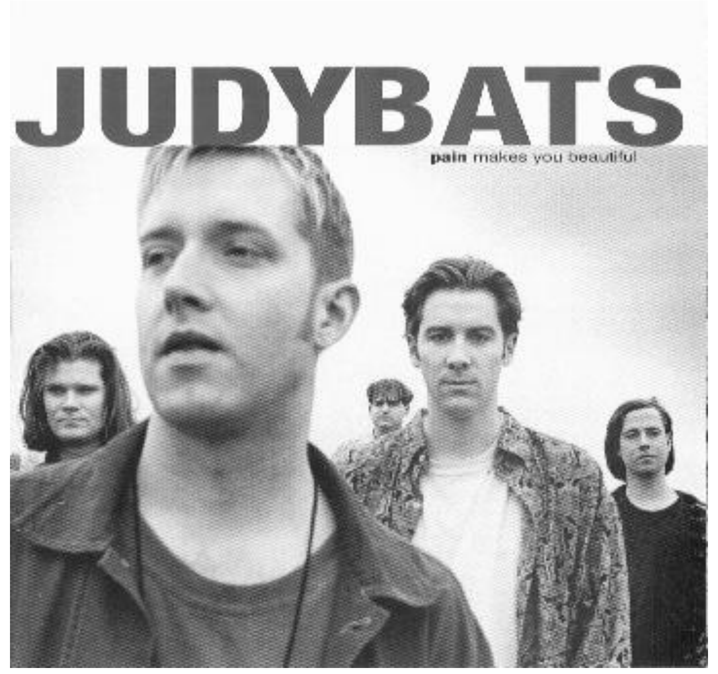
Template matching

Level | **Image** Pyramid (s) | **Template**

0

(x_0, y_0)

1



...

L

(x_L, y_L)

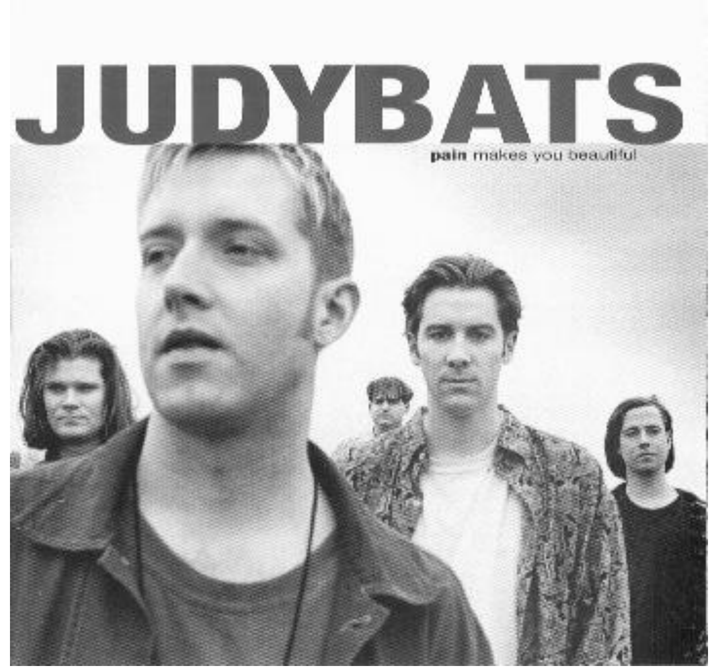
Template matching

Level | **Image** Pyramid (s) | **Template**

0

(x_0, y_0)

1



$$x_L = x_0 s^L$$
$$y_L = y_0 s^L$$

...

L

(x_L, y_L)

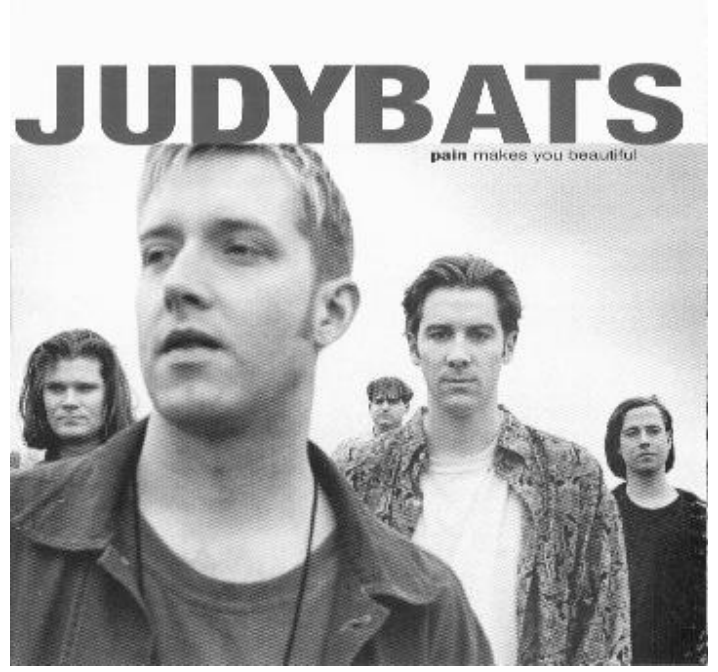
Template matching

Level | **Image** Pyramid (s) | **Template**

0

$(x_0, y_0) \pm (w_0/2, h_0/2)$

1



$$x_L = x_0 s^L \qquad w_L = w_0 s^L$$
$$y_L = y_0 s^L \qquad h_L = h_0 s^L$$

...

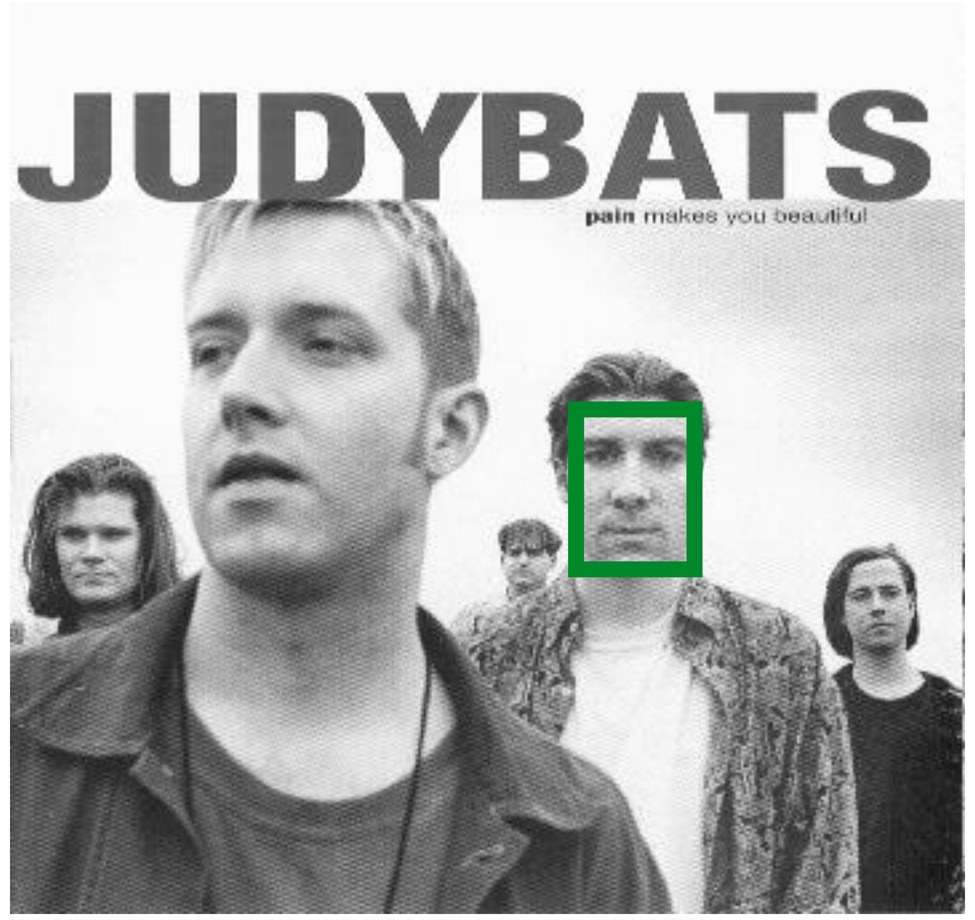
L

$(x_L, y_L) \pm (w_L/2, h_L/2)$

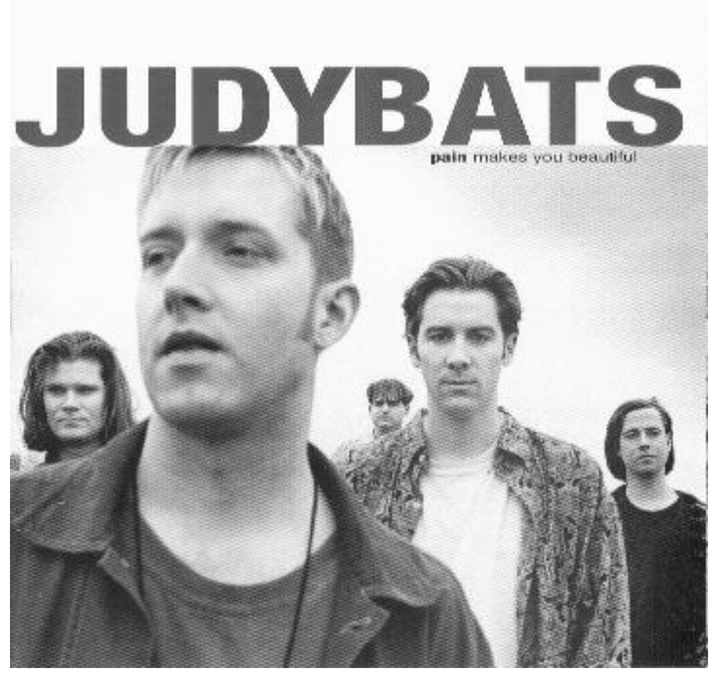
Template matching

Level | **Image** Pyramid (s) | **Template**

0

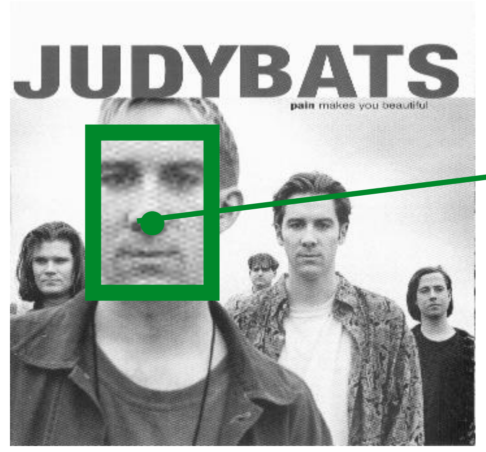


1



...

L

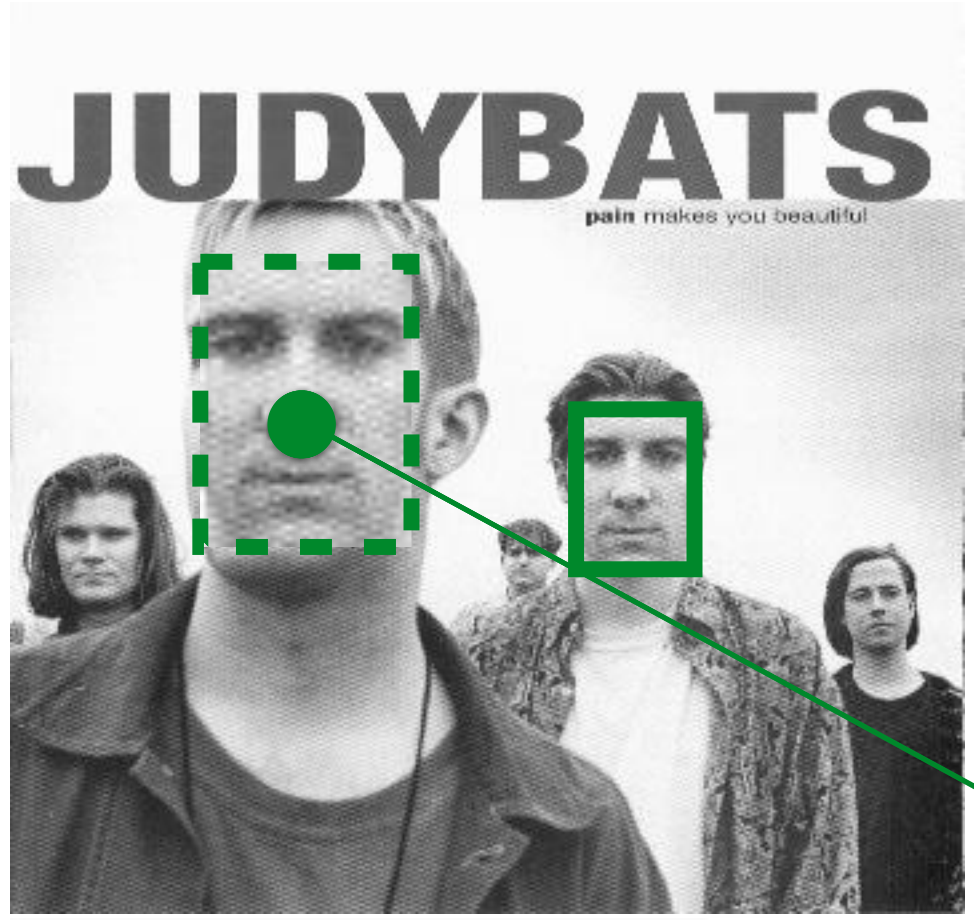


(x_L, y_L)

Template matching

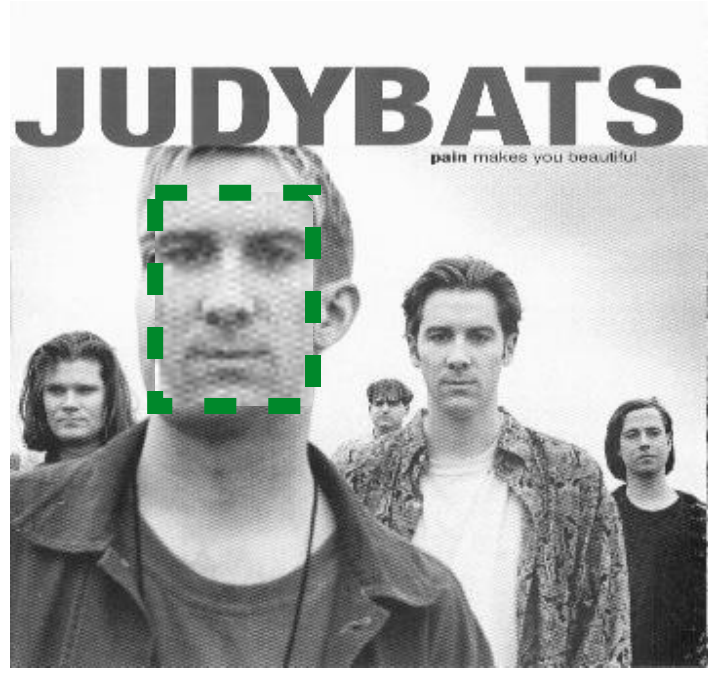
Level **Image** Pyramid (s) **Template**

0



(x_0, y_0)

1



$$x_0 = x_L \times \frac{1}{s^L}$$

$$y_0 = y_L \times \frac{1}{s^L}$$

...

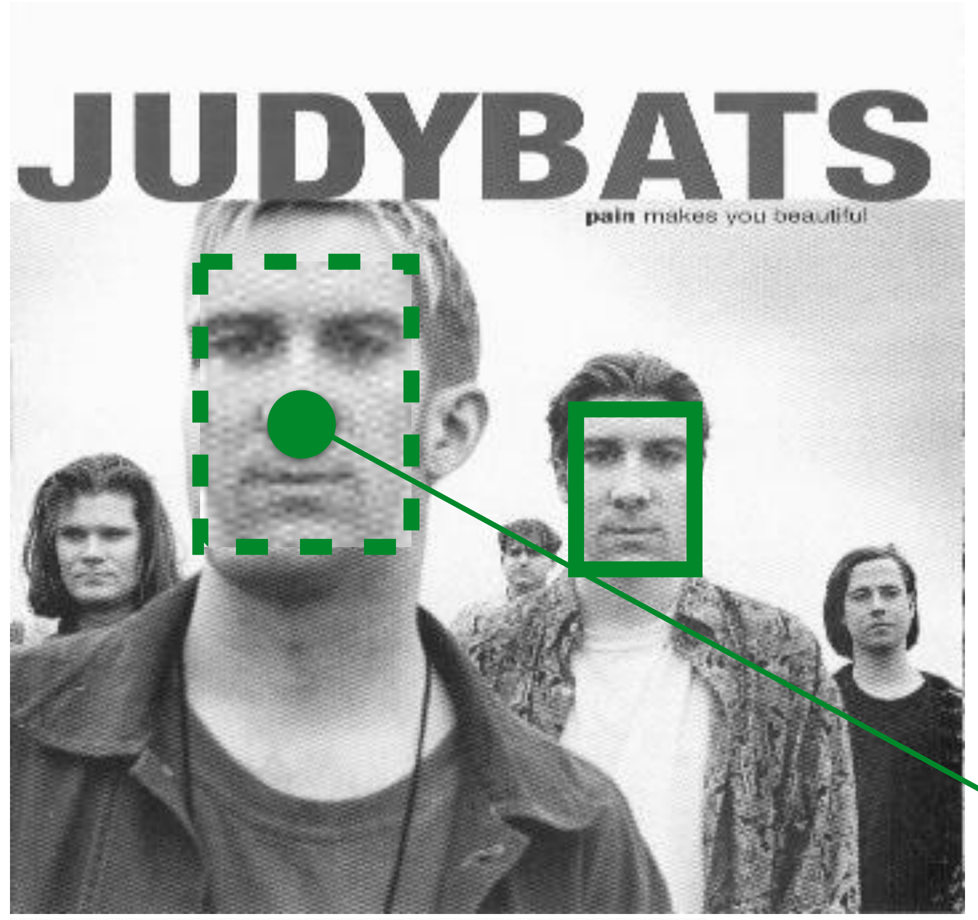
L

(x_L, y_L)

Template matching

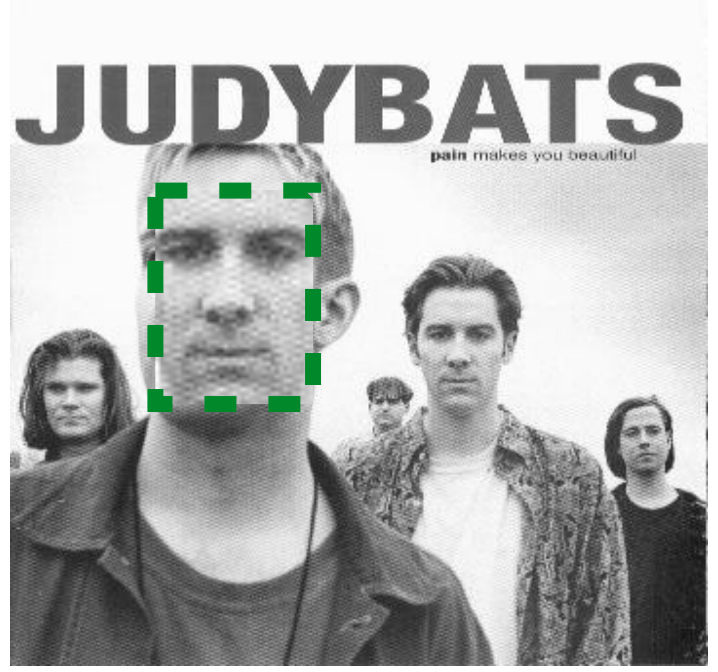
Level | **Image** Pyramid (s) | **Template**

0



$(x_0, y_0) \pm (w_0/2, h_0/2)$

1

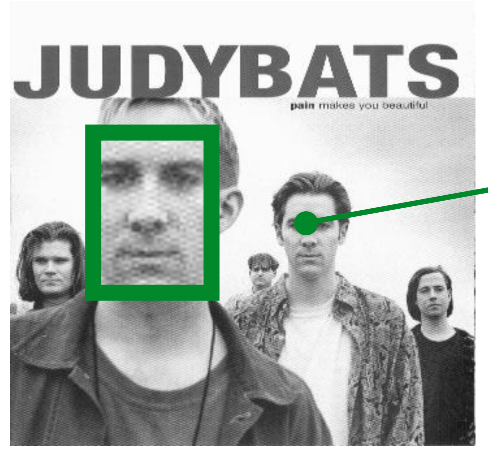


$$x_0 = x_L \times \frac{1}{s^L} \qquad w_0 = w \times \frac{1}{s^L}$$

$$y_0 = y_L \times \frac{1}{s^L} \qquad h_0 = h \times \frac{1}{s^L}$$

...

L

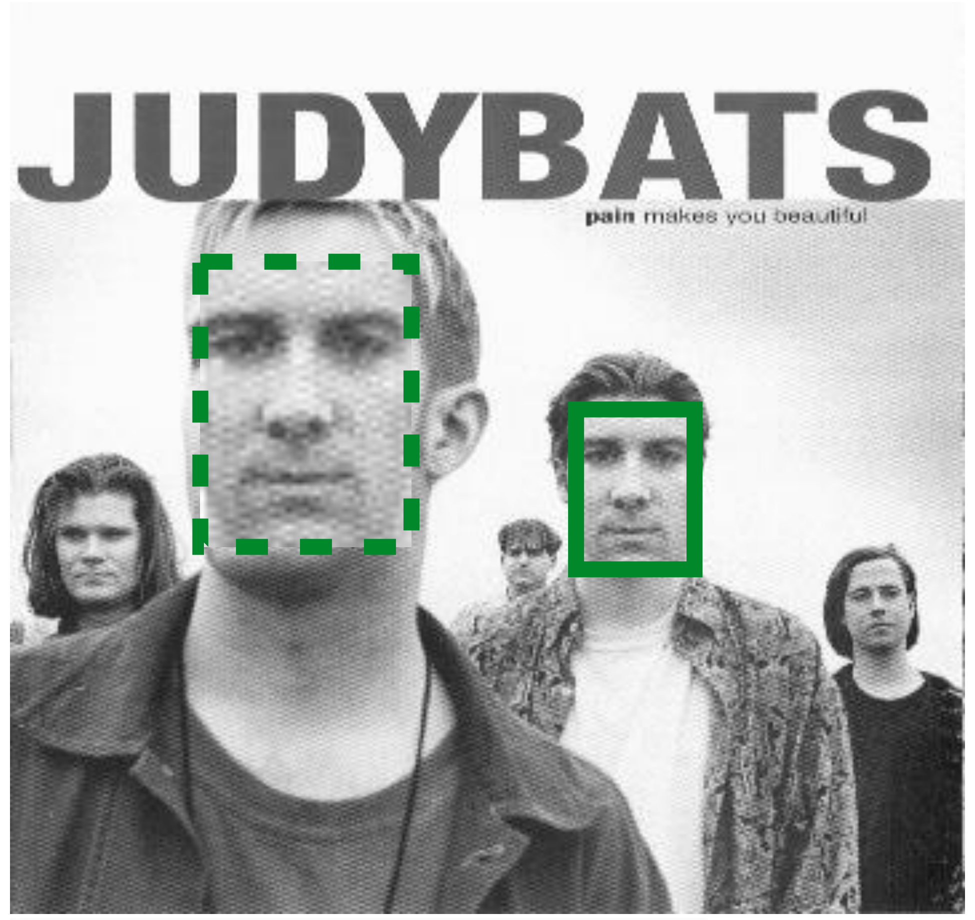


$(x_L, y_L) \pm (w_L/2, h_L/2)$

Template matching

Level | **Image** Pyramid (s) | **Template**

0



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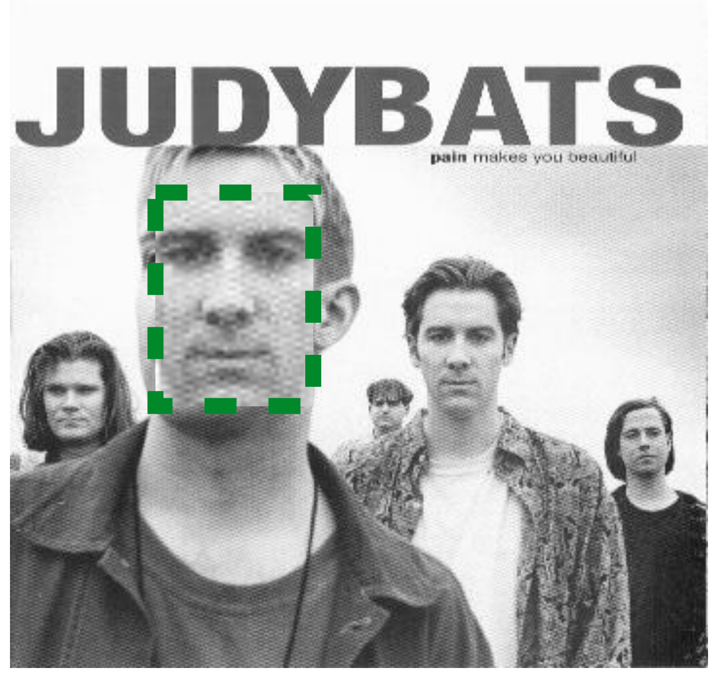

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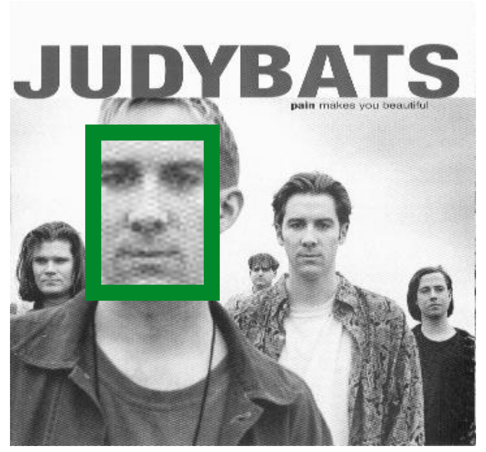
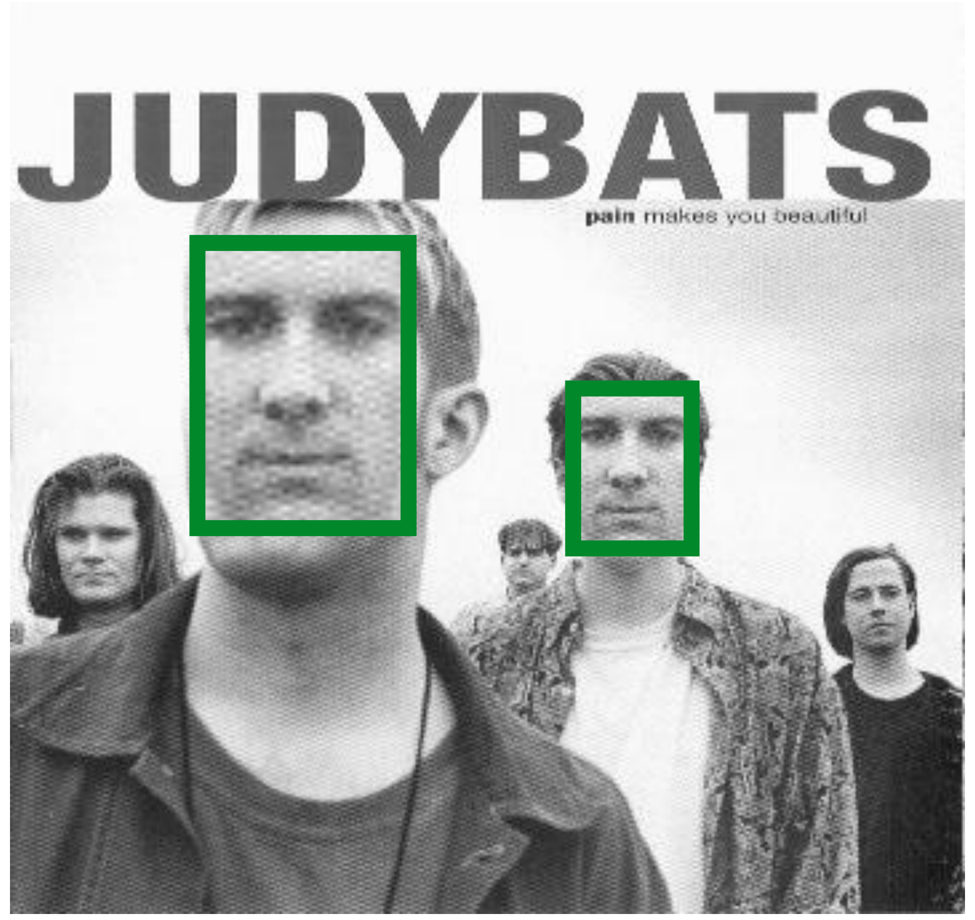


Template Pyramid (1/s) | **Image**

...



Template matching

Level | **Image** Pyramid (s) | **Template**

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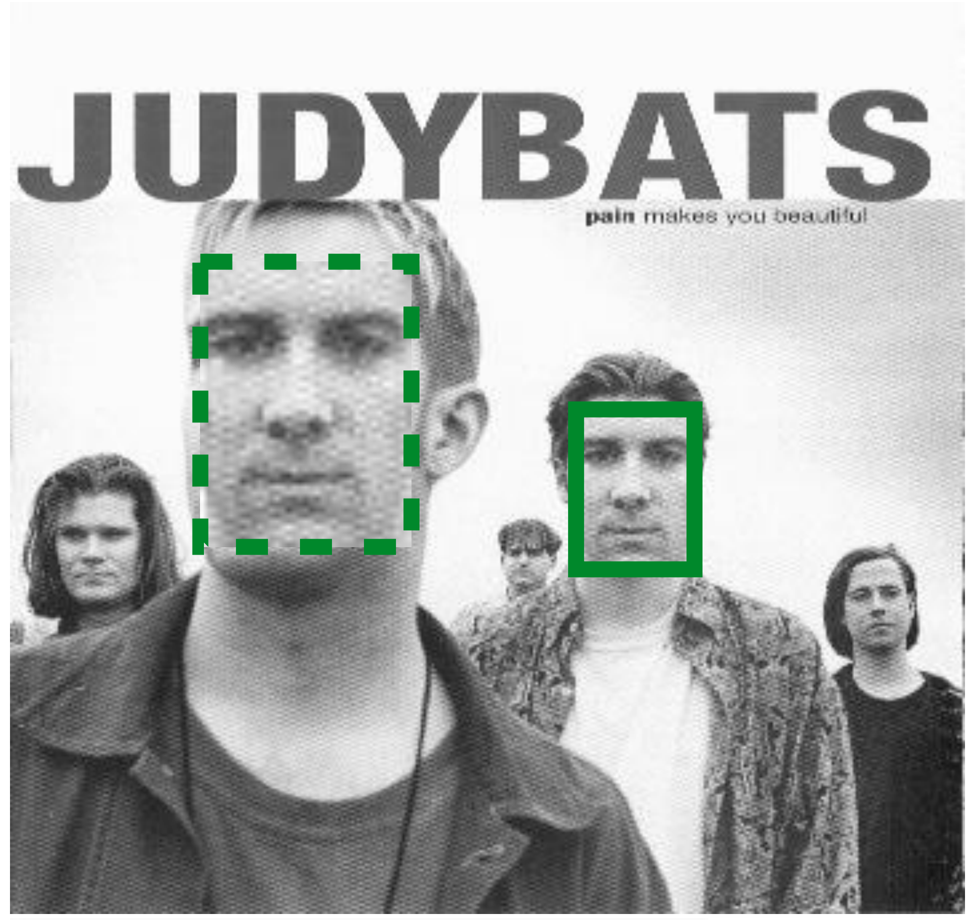
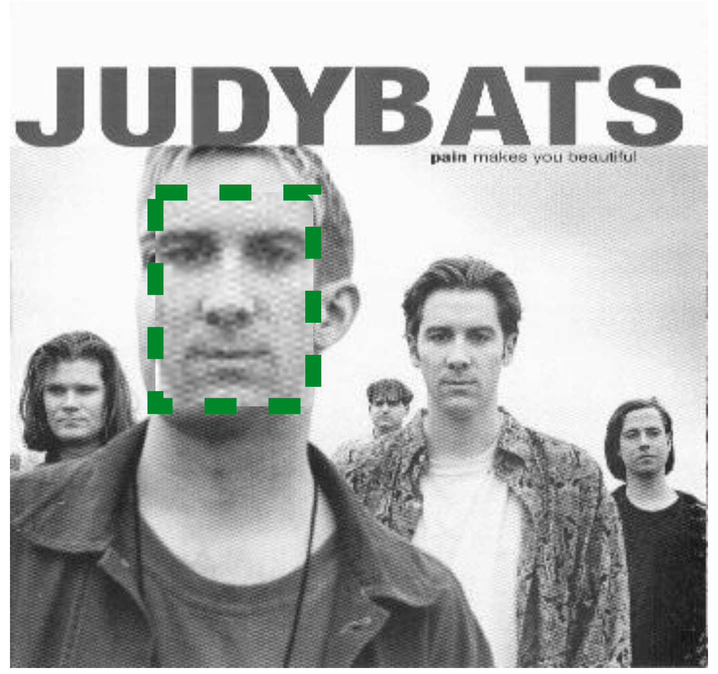


1



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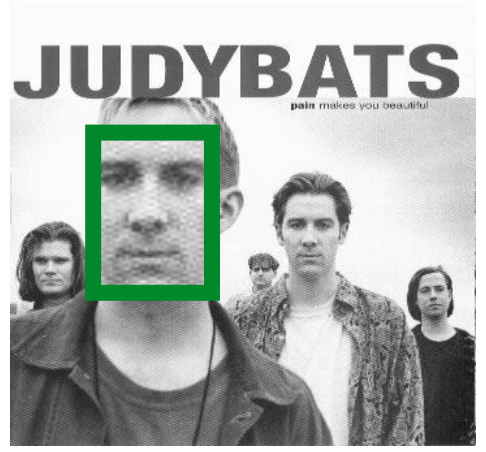
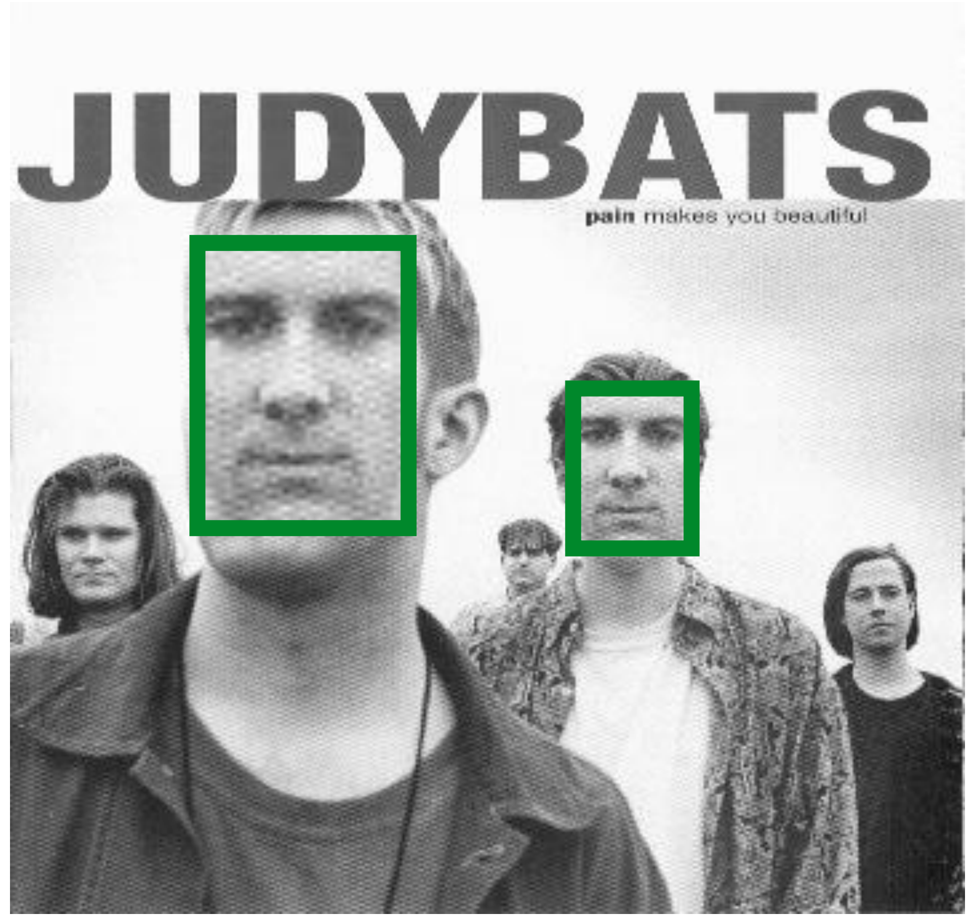


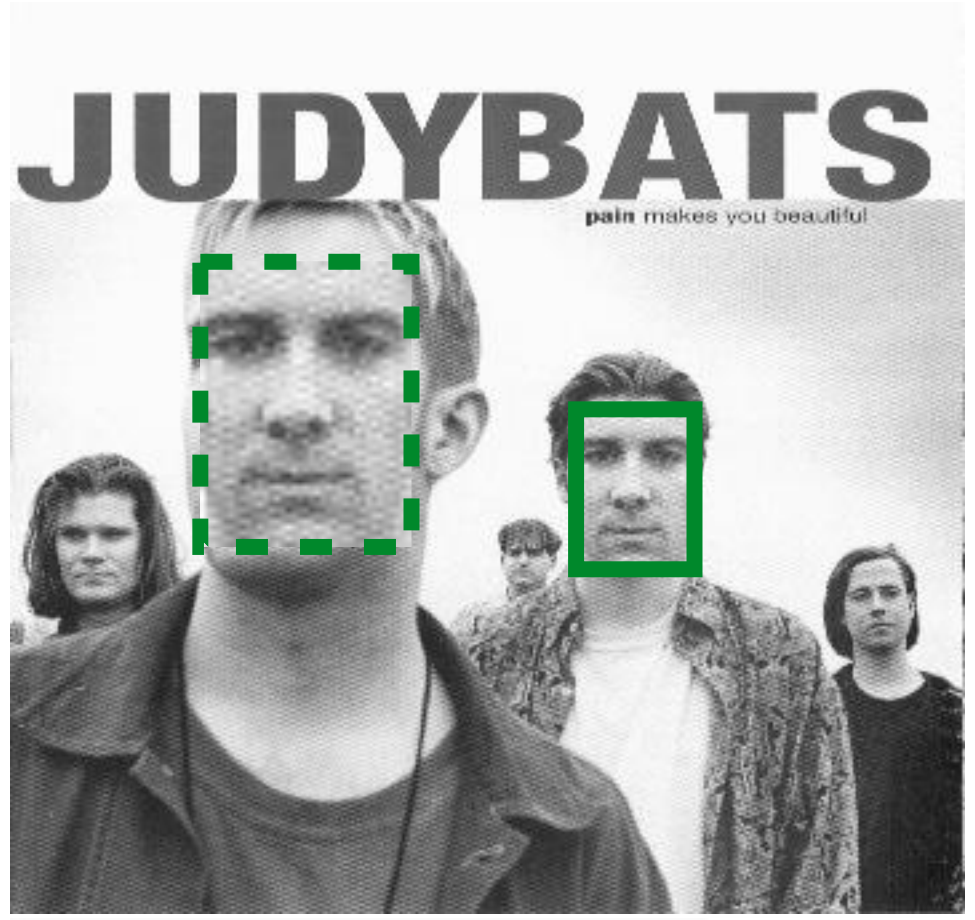
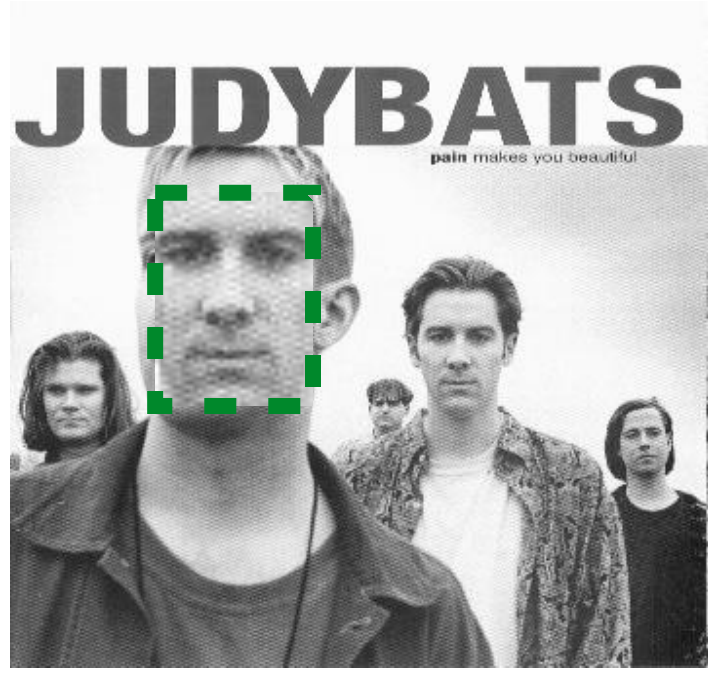
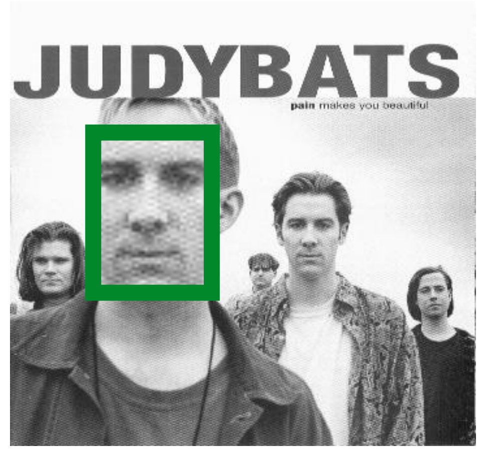
Template Pyramid (1/s) | **Image**

...



Both allow **search over scale**

Template matching

Level	**Image** Pyramid (s)	**Template**
0		 >
1		>
	…	
L		

Faster

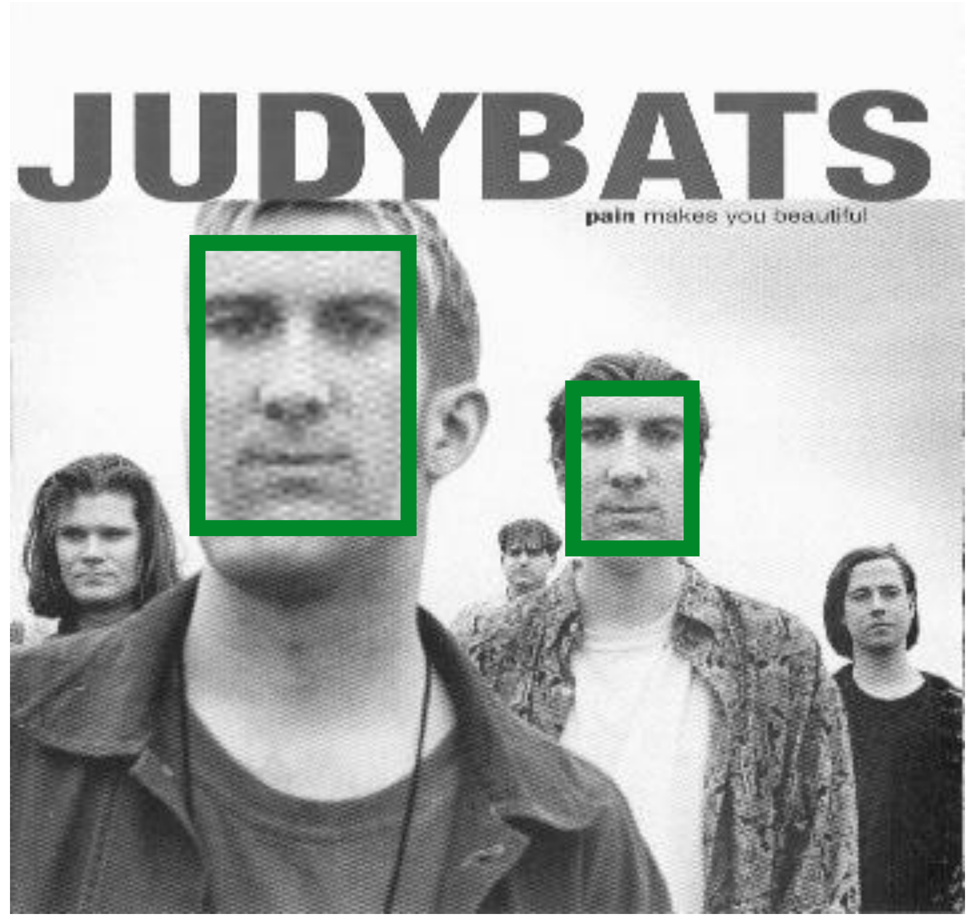
Template Pyramid (1/s)

<

…

<

Image



Slower

Both allow **search over scale**

Template matching

Level | **Image** Pyramid (s) | **Template** Pyramid (s)

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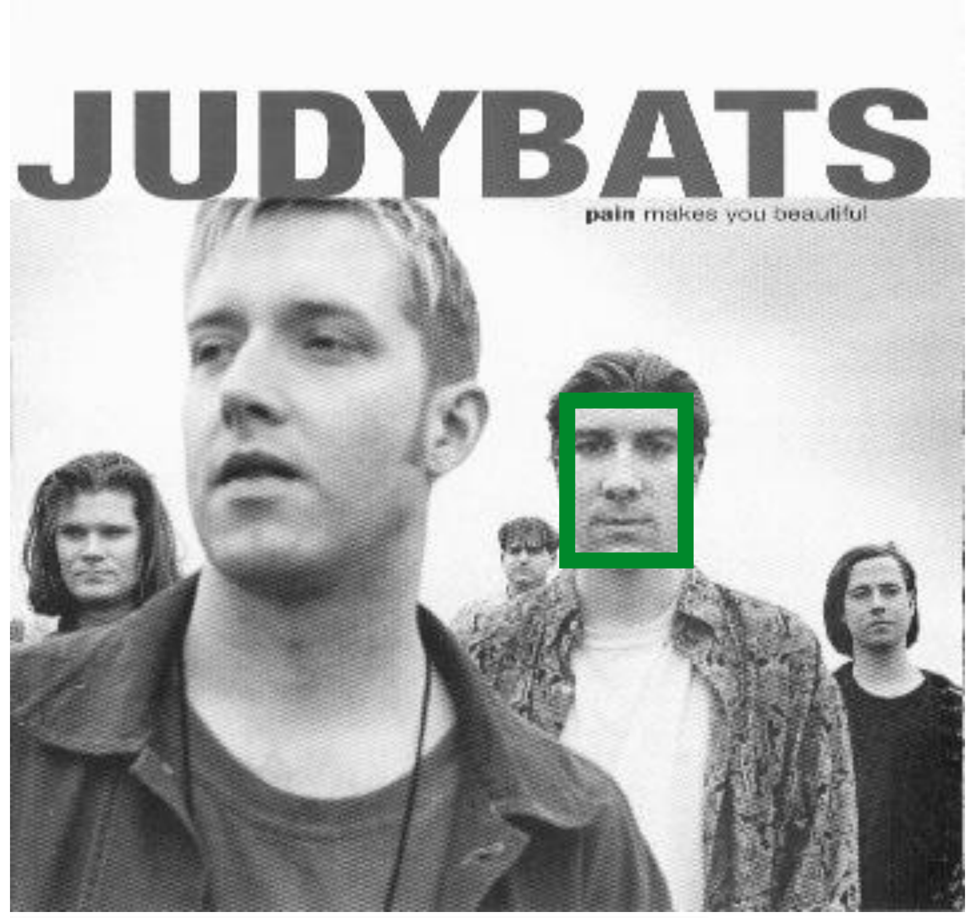
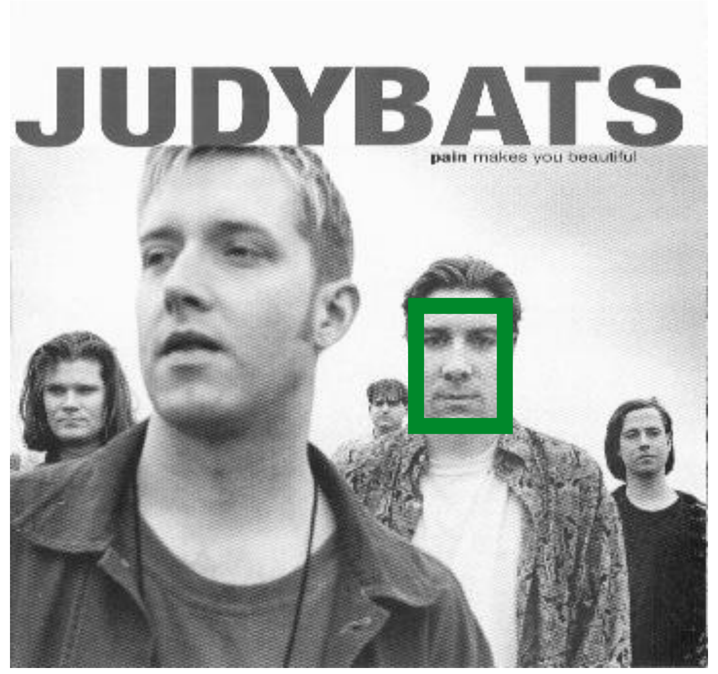


. . .

1



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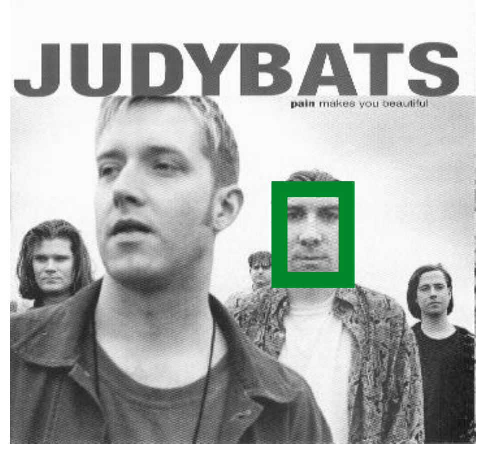
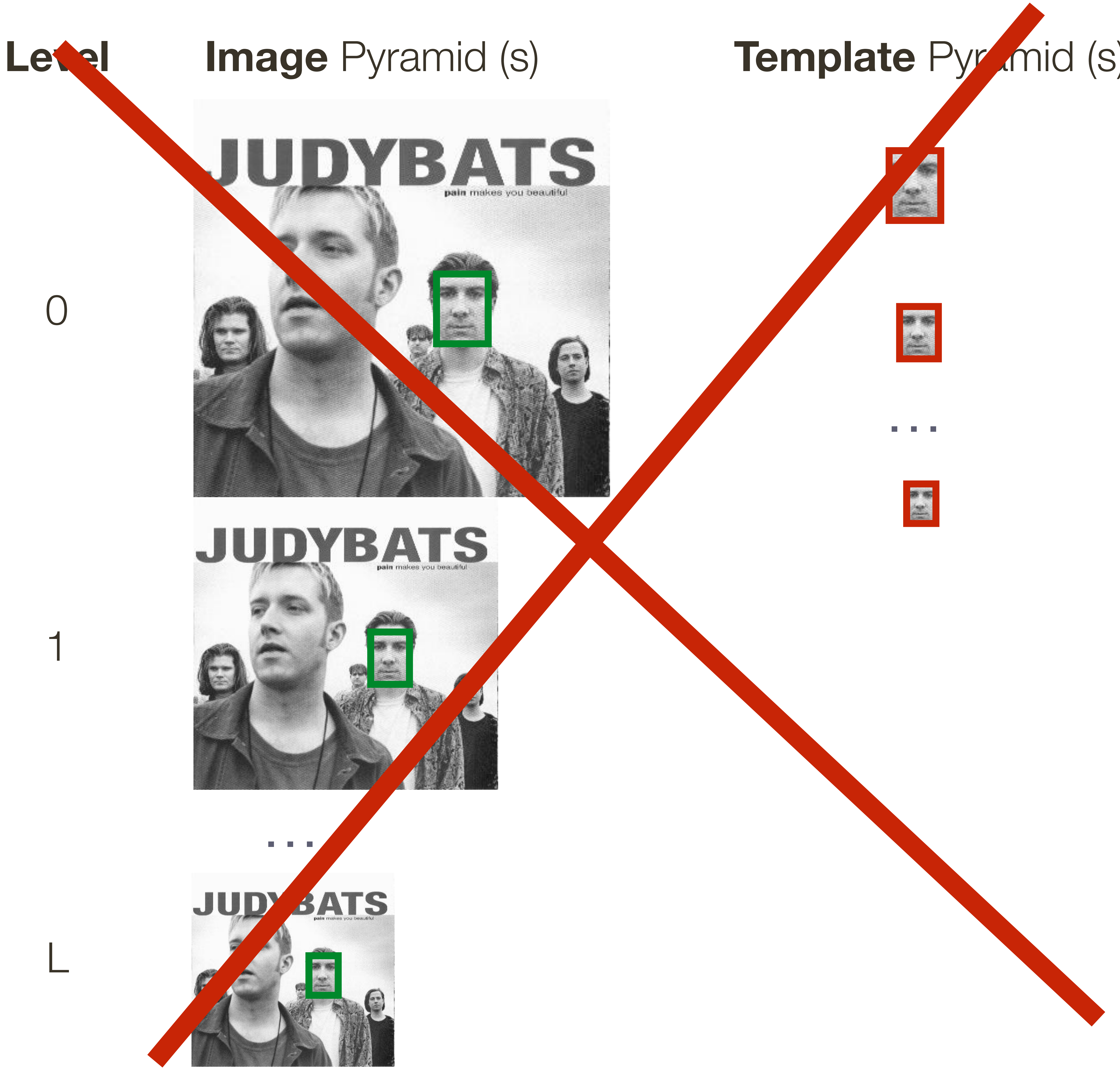
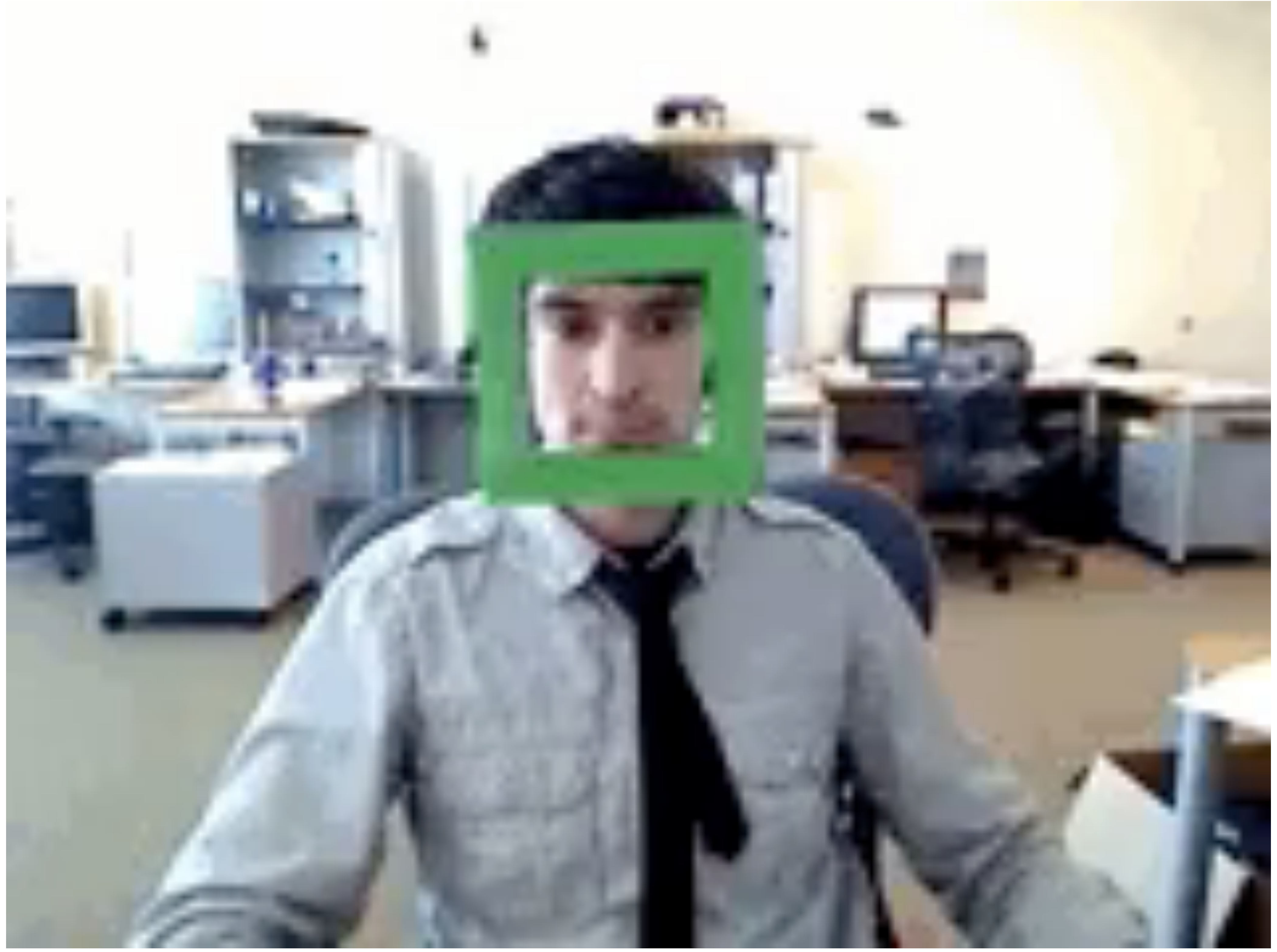


Note: This does not search over scales

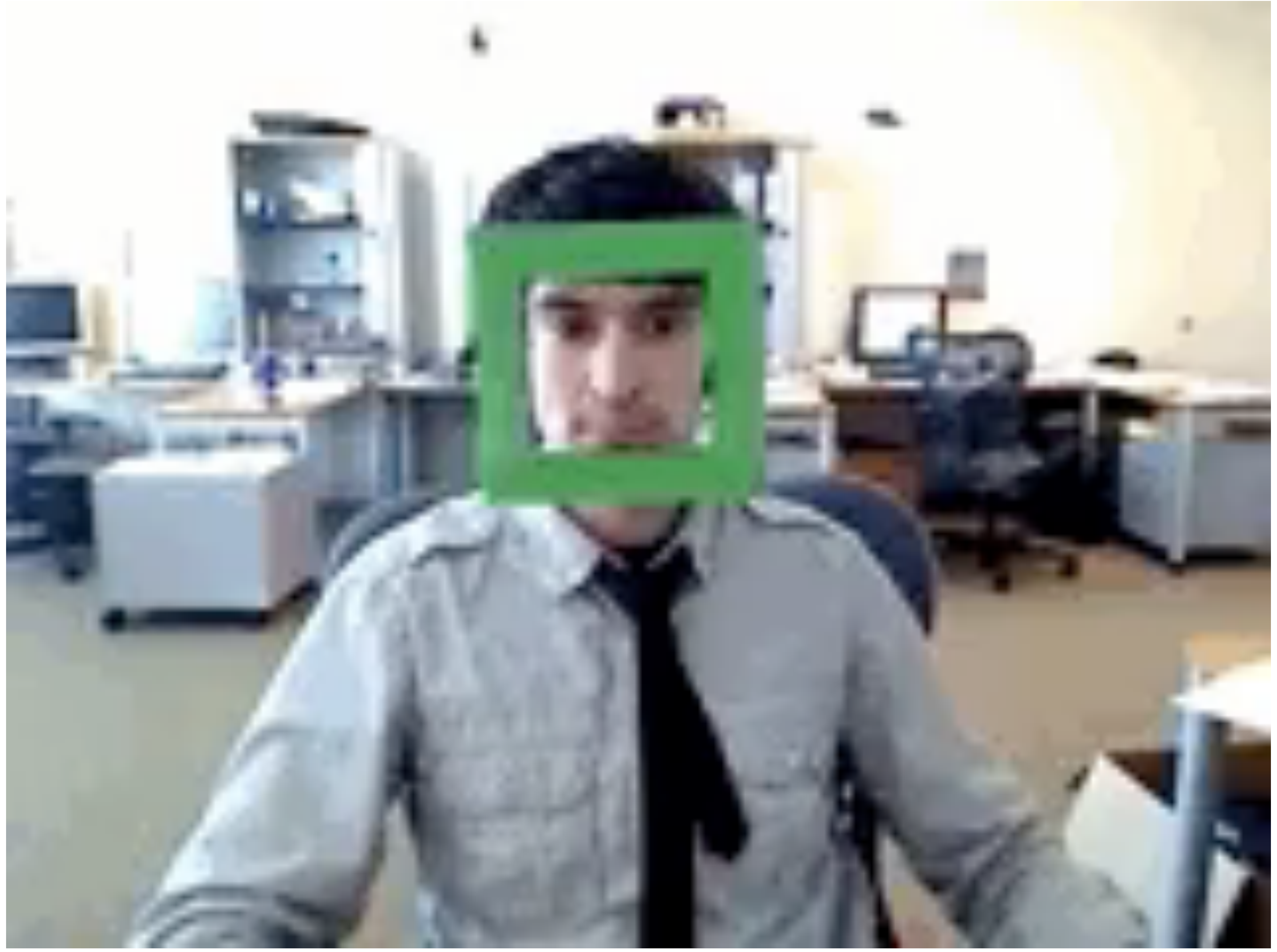
Template matching



Today's "**fun**" Example: Face Detection



Today's "**fun**" Example: Face Detection



Today's "**fun**" Example: Face Detection

Today's "**fun**" Example: Face Detection

Today’s “**fun**” Example: Face Detection

https://www.youtube.com/watch?v=gWjBleSfZBk

Today's "**fun**" Example: Face Detection

https://www.youtube.com/watch?v=gWjBleSfZBk

Lecture 14: Re-cap (Harris Corner Detection)

1. Compute image gradients over small region

2. Compute the covariance matrix

3. Compute eigenvectors and eigenvalues

4. Use threshold on eigenvalues to detect corners

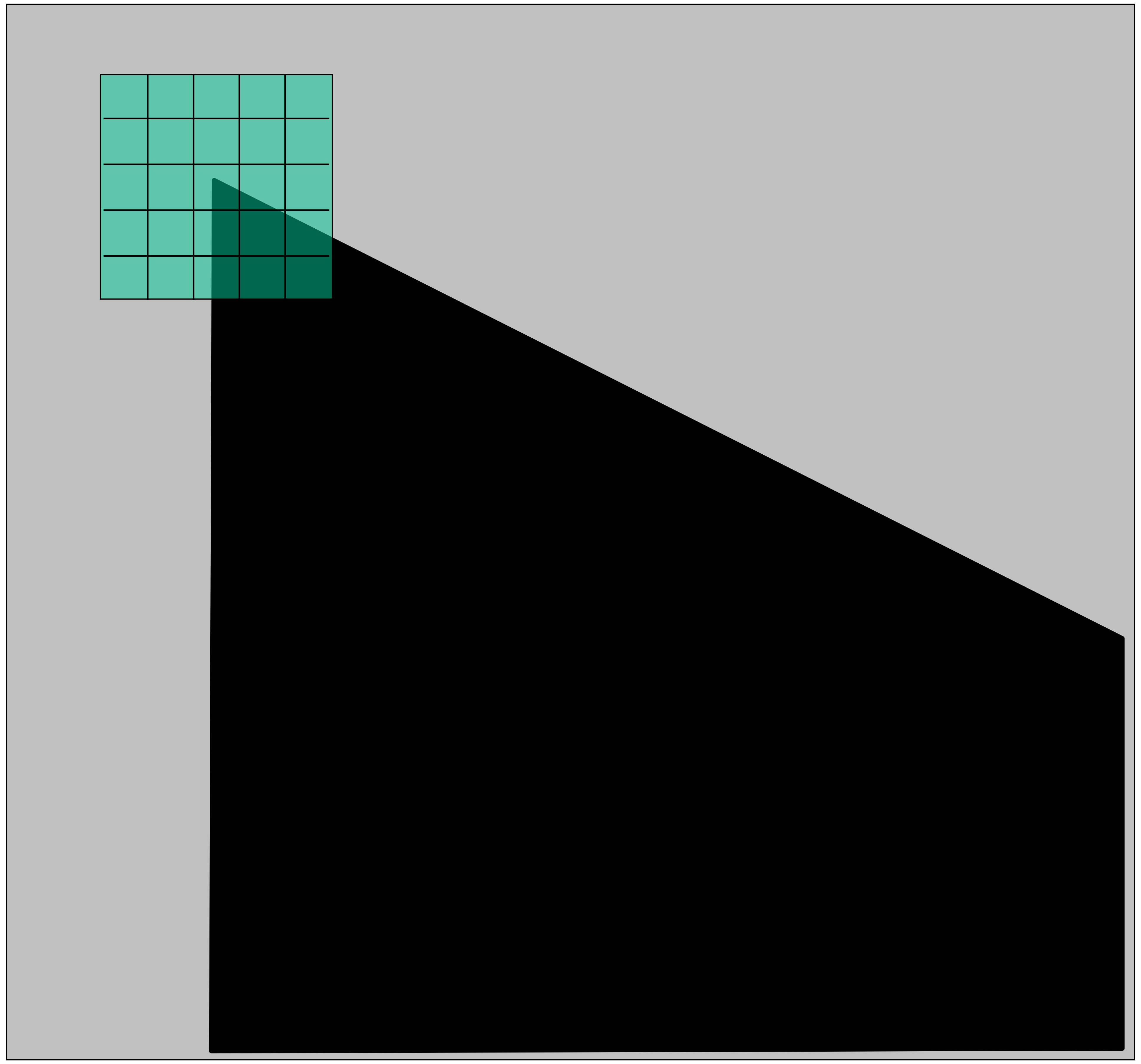
$$I_x = \frac{\partial I}{\partial x} \qquad I_y = \frac{\partial I}{\partial y}$$

$$\begin{bmatrix} \sum\limits_{p \in P} I_x I_x & \sum\limits_{p \in P} I_x I_y \\ \sum\limits_{p \in P} I_y I_x & \sum\limits_{p \in P} I_y I_y \end{bmatrix}$$

Slide Adopted: Ioannis (Yannis) Gkioulekas (CMU)

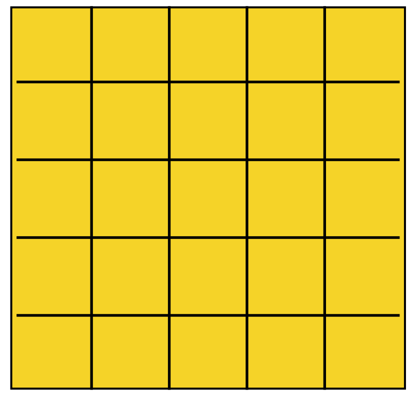
Lecture 14: Re-cap (compute image gradients at patch)

(not just a single pixel)



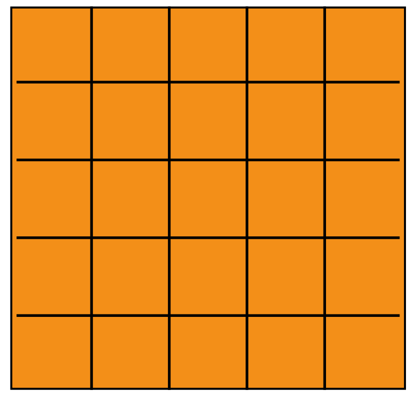
array of x gradients

$$I_x = \frac{\partial I}{\partial x}$$



array of y gradients

$$I_y = \frac{\partial I}{\partial y}$$



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 14: Re-cap (compute the covariance matrix)

Sum over small region around the corner

Gradient with respect to x, times gradient with respect to y

$$C = \begin{bmatrix} \sum_{p \in P} I_x I_x & \sum_{p \in P} I_x I_y \\ \sum_{p \in P} I_y I_x & \sum_{p \in P} I_y I_y \end{bmatrix}$$

Matrix is **symmetric**

Lecture 14: Re-cap

It can be shown that since every C is symmetric:

$$C = \begin{bmatrix} \sum\limits_{p \in P} I_x I_x & \sum\limits_{p \in P} I_x I_y \\ \sum\limits_{p \in P} I_y I_x & \sum\limits_{p \in P} I_y I_y \end{bmatrix} = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

Lecture 14: Re-cap (computing eigenvalues and eigenvectors)

eigenvalue

$$Ce = \lambda e$$

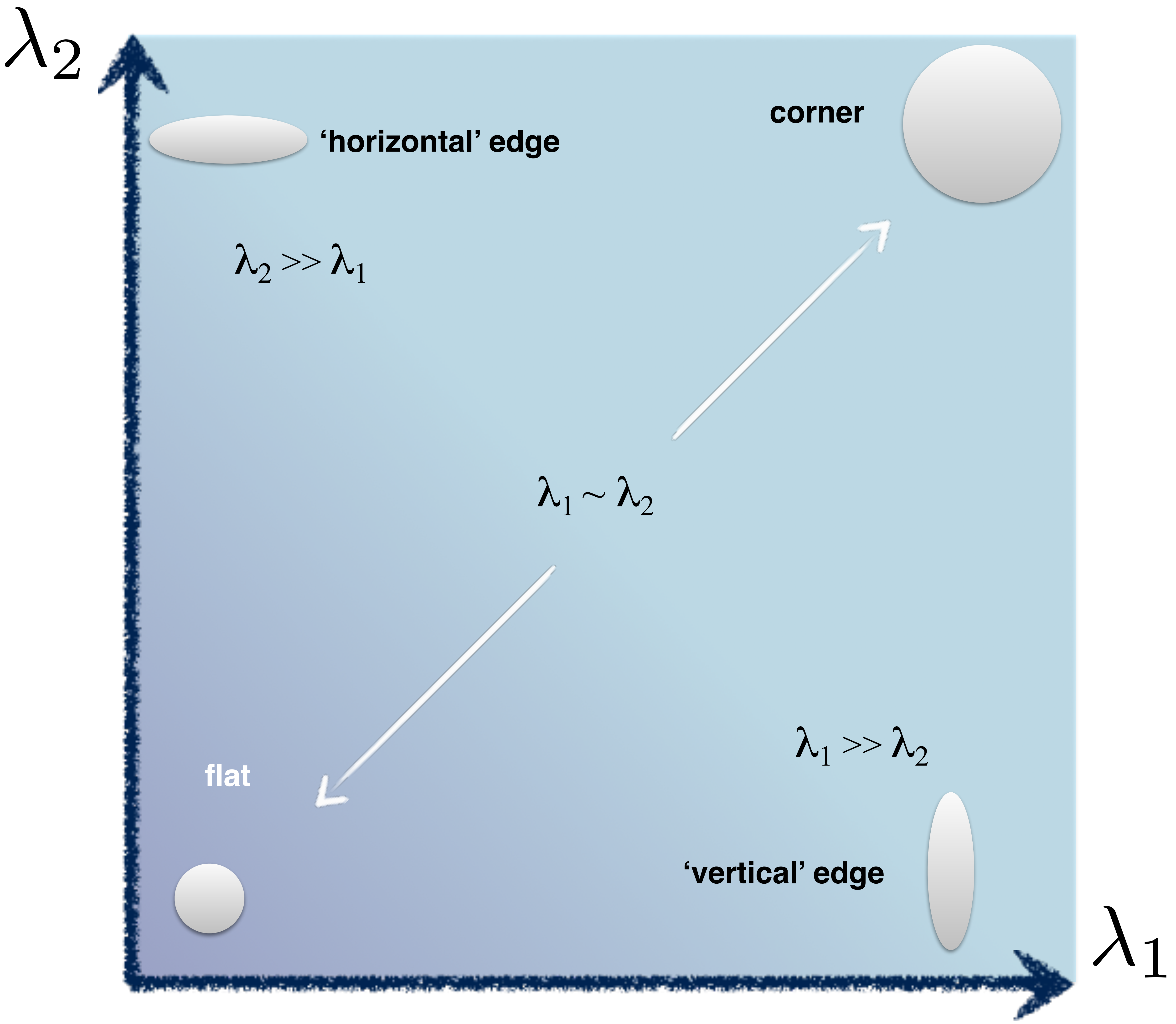
eigenvector

$$(C - \lambda I)e = 0$$

1. Compute the determinant of (returns a polynomial)	$C - \lambda I$
2. Find the roots of polynomial (returns eigenvalues)	$\det(C - \lambda I) = 0$
3. For each eigenvalue, solve (returns eigenvectors)	$(C - \lambda I)e = 0$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 14: Re-cap (interpreting eigenvalues)



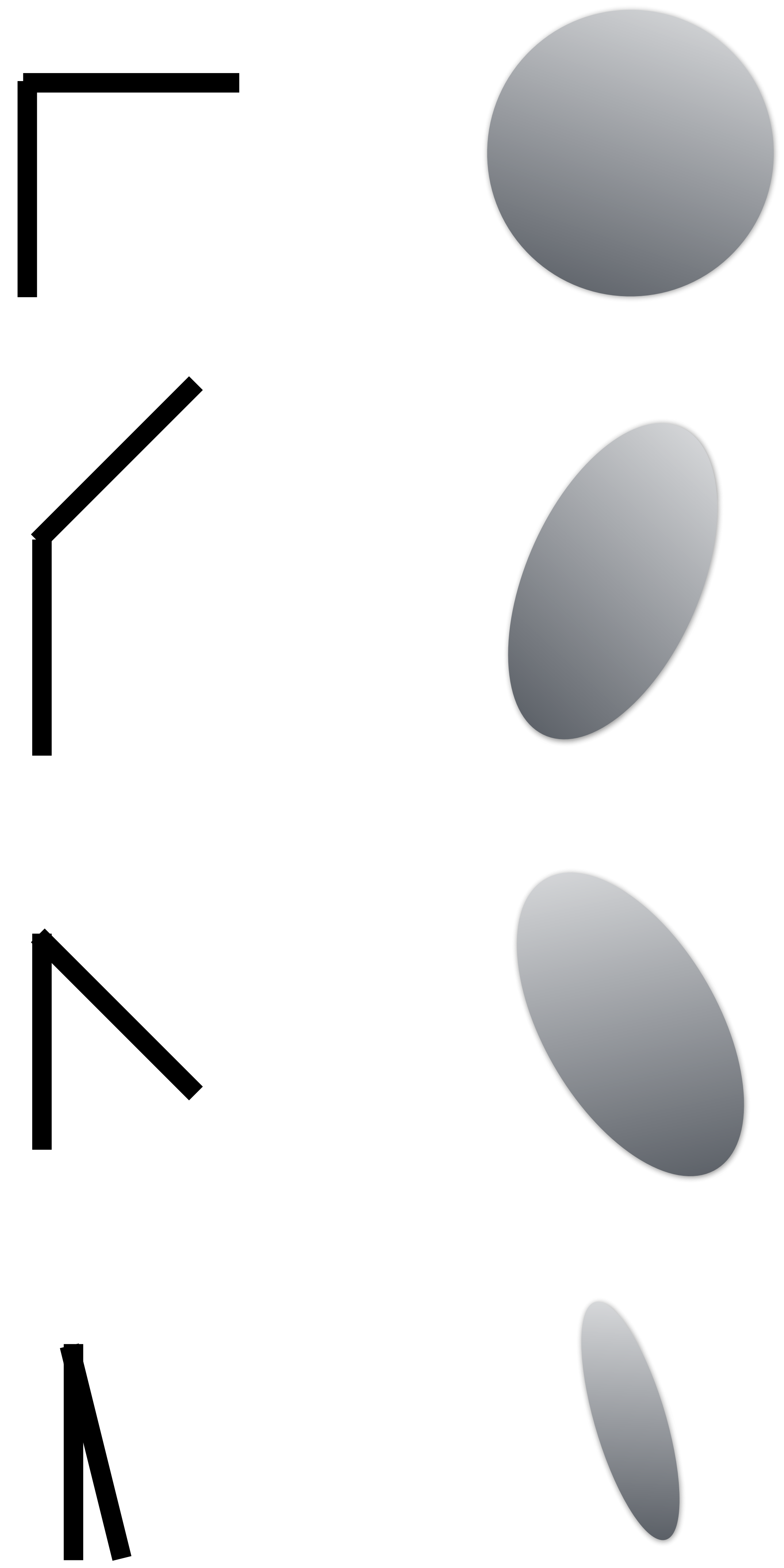
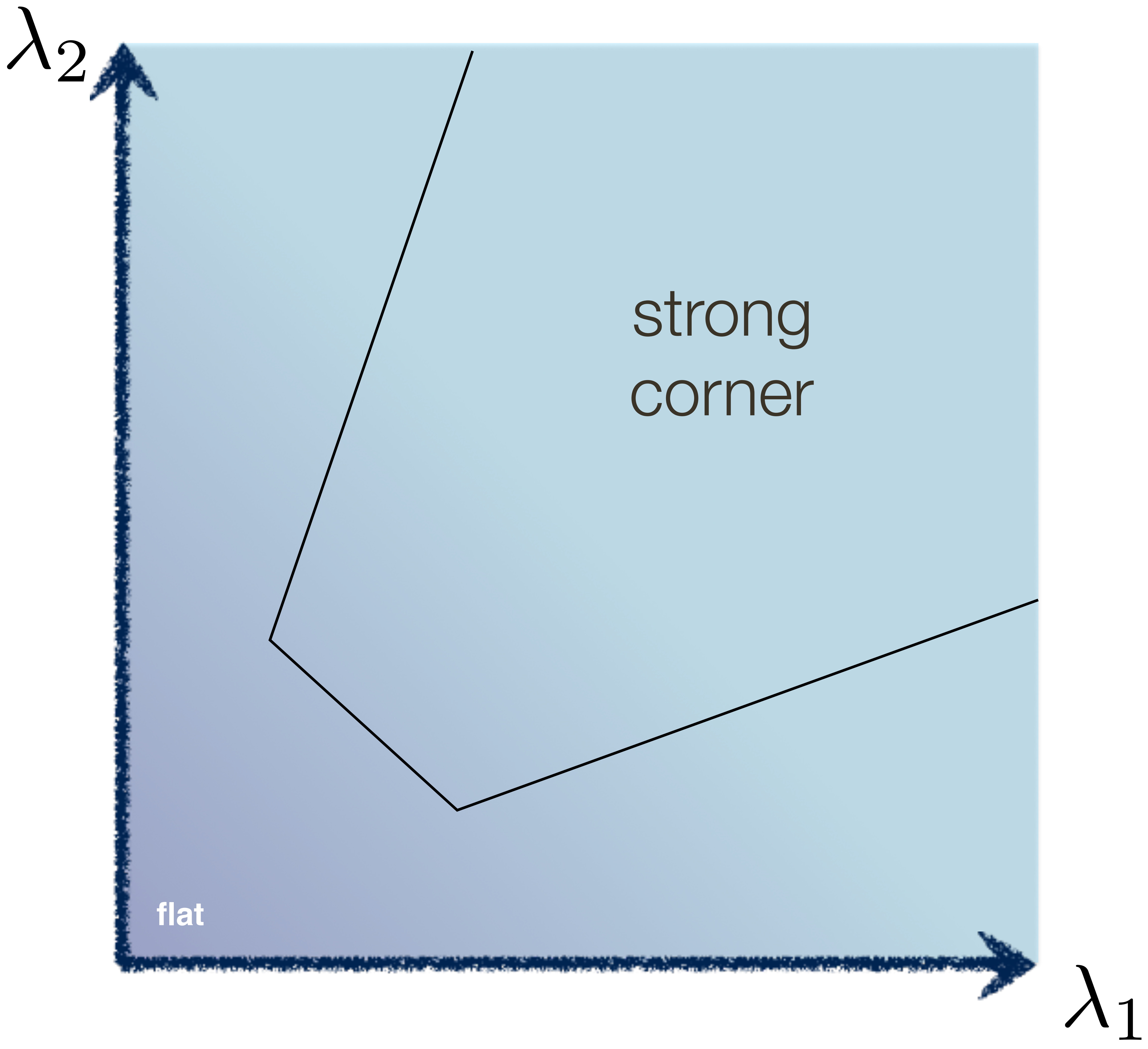


Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 14: Re-cap (**Threshold** on Eigenvalues to **Detect Corners)**



Think of a function to score 'cornerness'

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 14: Re-cap (**Threshold** on Eigenvalues to **Detect Corners)**

Harris & Stephens (1988)

$$\det(C) - \kappa \operatorname{trace}^2(C)$$

Kanade & Tomasi (1994)

$$\min(\lambda_1, \lambda_2)$$

Nobel (1998)

$$\frac{\det(C)}{\operatorname{trace}(C) + \epsilon}$$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Example: Harris Corner Detection

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

Example: Harris Corner Detection

Lets compute a measure of “corner-ness” for the green pixel:

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

Example: Harris Corner Detection

Lets compute a measure of “corner-ness” for the green pixel:

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

Example: Harris Corner Detection

Lets compute a measure of “corner-ness” for the green pixel:

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

(using **backwards** differencing)

0	0	0	0	0	0	
-1	1	0	0	-1	1	
-1	0	0	0	1	0	
-1	0	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	

$$I_x = \frac{\partial I}{\partial x}$$

Example: Harris Corner Detection

Lets compute a measure of “corner-ness” for the green pixel:

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

(using **backwards** differencing)

0	0	0	0	0	0	
-1	1	0	0	-1	1	
-1	0	0	0	1	0	
-1	0	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	

$$I_x = \frac{\partial I}{\partial x}$$

(using **backwards** differencing)

0	-1	0	0	0	-1	0
0	0	-1	-1	-1	1	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

$$I_y = \frac{\partial I}{\partial y}$$

Example: Harris Corner Detection

Lets compute a measure of “corner-ness” for the green pixel:

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

$$\sum \begin{bmatrix} 0 & 0 & 0 \\ 0 & -1 & 1 \\ 0 & 1 & 0 \end{bmatrix} \odot \begin{bmatrix} 0 & 0 & 0 \\ 0 & -1 & 1 \\ 0 & 1 & 0 \end{bmatrix} = 3$$

$$I_x = \frac{\partial I}{\partial x}$$

0	0	0	0	0	0	
-1	1	0	0	-1	1	
-1	0	0	0	1	0	
-1	0	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	

$$I_y = \frac{\partial I}{\partial y}$$

0	-1	0	0	0	-1	0
0	0	-1	-1	-1	1	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Example: Harris Corner Detection

Lets compute a measure of "corner-ness" for the green pixel:

$$\mathbf{C} = \begin{bmatrix} 3 & 2 \\ 2 & 4 \end{bmatrix}$$

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

$$I_x = \frac{\partial I}{\partial x}$$

0	0	0	0	0	0	
-1	1	0	0	-1	1	
-1	0	0	0	1	0	
-1	0	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	

$$I_y = \frac{\partial I}{\partial y}$$

0	-1	0	0	0	-1	0
0	0	-1	-1	-1	1	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Example: Harris Corner Detection

Lets compute a measure of “corner-ness” for the green pixel:

$$\mathbf{C} = \begin{bmatrix} 3 & 2 \\ 2 & 4 \end{bmatrix} => \lambda_1 = 1.4384; \lambda_2 = 5.5616$$

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

$$I_x = \frac{\partial I}{\partial x}$$

0	0	0	0	0	0	
-1	1	0	0	-1	1	
-1	0	0	0	1	0	
-1	0	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	

$$I_y = \frac{\partial I}{\partial y}$$

0	-1	0	0	0	-1	0
0	0	-1	-1	-1	1	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Example: Harris Corner Detection

Lets compute a measure of “corner-ness” for the green pixel:

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

$$\mathbf{C} = \begin{bmatrix} 3 & 2 \\ 2 & 4 \end{bmatrix} => \lambda_1 = 1.4384; \lambda_2 = 5.5616$$

$$\det(\mathbf{C}) - 0.04 \mathrm{trace}^2(\mathbf{C}) = 6.04$$

$$I_x = \frac{\partial I}{\partial x}$$

0	0	0	0	0	0	
-1	1	0	0	-1	1	
-1	0	0	0	1	0	
-1	0	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	

$$I_y = \frac{\partial I}{\partial y}$$

0	-1	0	0	0	-1	0
0	0	-1	-1	-1	1	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Example: Harris Corner Detection

Lets compute a measure of “corner-ness” for the green pixel:

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

$$\mathbf{C} = \begin{bmatrix} 3 & 0 \\ 0 & 0 \end{bmatrix} => \lambda_1 = 3; \lambda_2 = 0$$

$$\det(\mathbf{C}) - 0.04\text{trace}^2(\mathbf{C}) = -0.36$$

$$I_x = \frac{\partial I}{\partial x}$$

0	0	0	0	0	0	
-1	1	0	0	-1	1	
-1	0	0	0	1	0	
-1	0	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	

$$I_y = \frac{\partial I}{\partial y}$$

0	-1	0	0	0	-1	0
0	0	-1	-1	-1	1	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Example: Harris Corner Detection

Lets compute a measure of “corner-ness” for the green pixel:

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

$$\mathbf{C} = \begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix} => \lambda_1 = 3; \lambda_2 = 2$$

$$\det(\mathbf{C}) - 0.04\text{trace}^2(\mathbf{C}) = 5$$

$$I_x = \frac{\partial I}{\partial x}$$

0	0	0	0	0	0	
-1	1	0	0	-1	1	
-1	0	0	0	1	0	
-1	0	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	

$$I_y = \frac{\partial I}{\partial y}$$

0	-1	0	0	0	-1	0
0	0	-1	-1	-1	1	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Harris Corner Detection Review

— Filter image with **Gaussian**

— Compute magnitude of the x and y **gradients** at each pixel

— Construct C in a window around each pixel

— Harris uses a **Gaussian window**

— Solve for product of the λ's

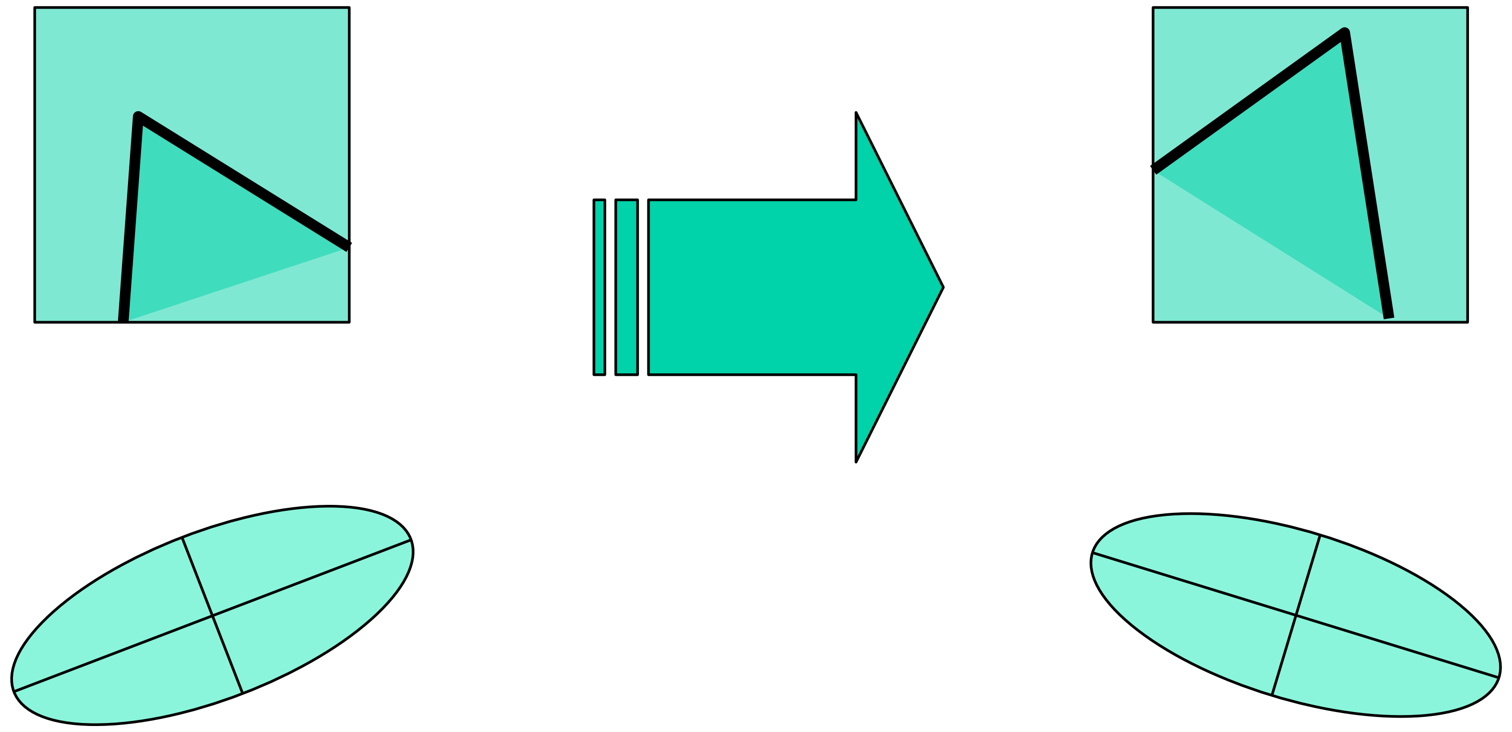
— If λ's both are big (product reaches local maximum above threshold) then we have a corner

— Harris also checks that ratio of λs is not too high

Harris & Stephens (1988)

$$\det(C) - \kappa \operatorname{trace}^2(C)$$

Properties: Rotational Invariance



Ellipse rotates but its shape
(**eigenvalues**) remains the same

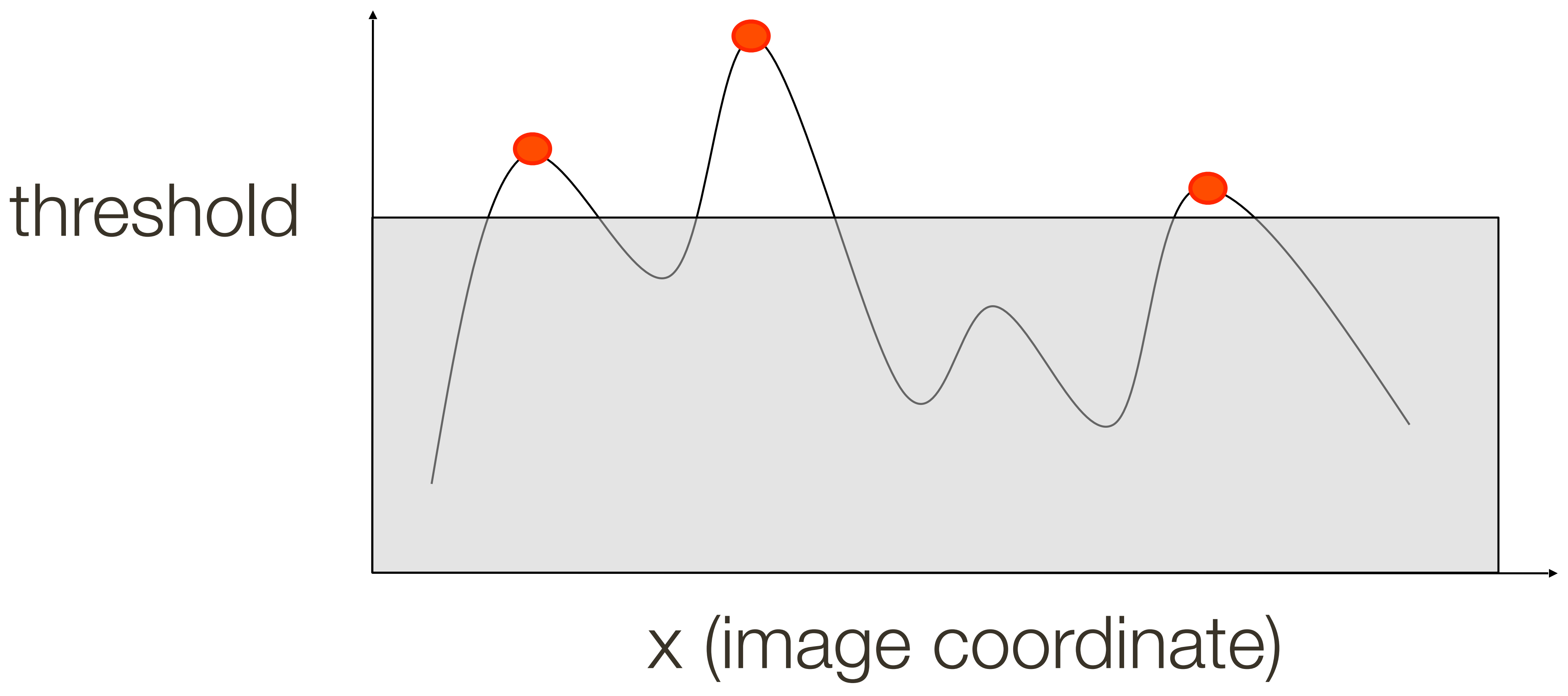
Corner response is **invariant** to image rotation

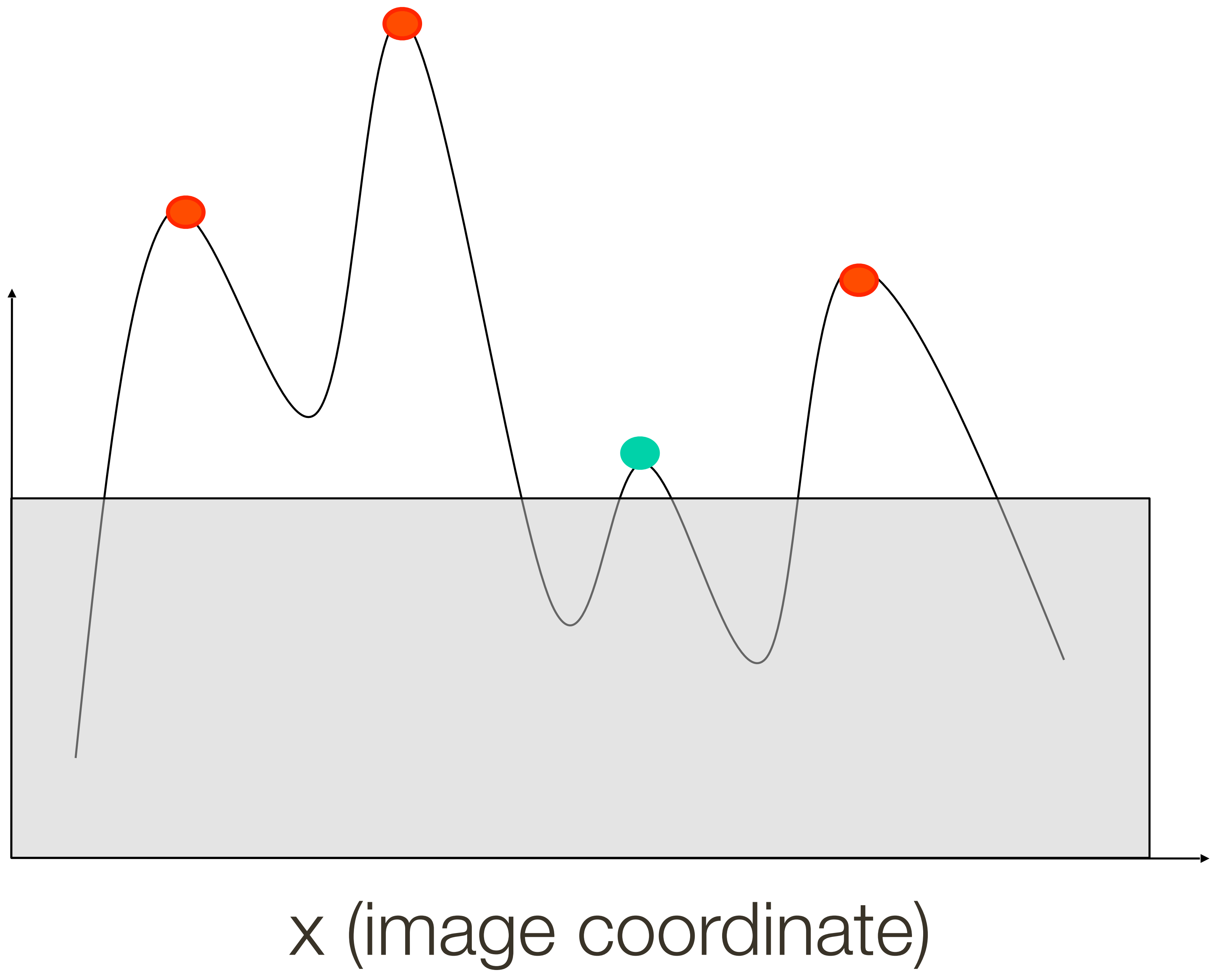
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Properties: (partial) Invariance to Intensity Shifts and Scaling

Only derivatives are used -> Invariance to intensity shifts

Intensity scale could effect performance



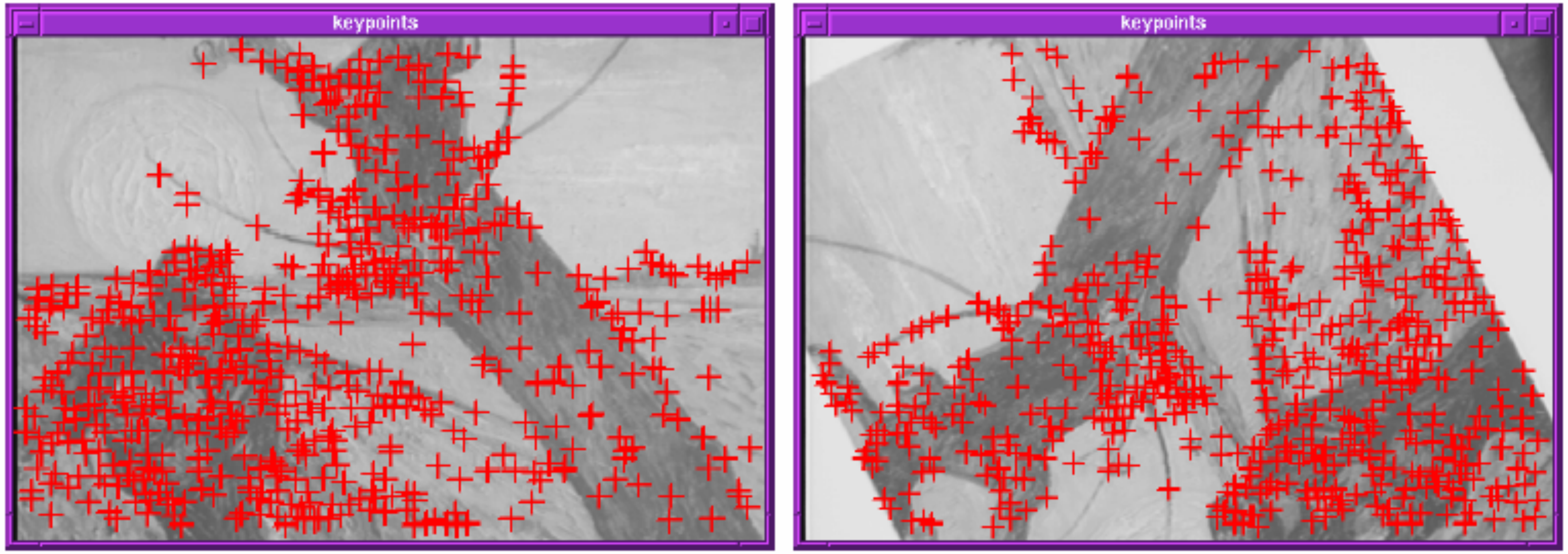


Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Properties: NOT Invariant to Scale Changes

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Example 1:



Example 2: Wagon Wheel (Harris Results)

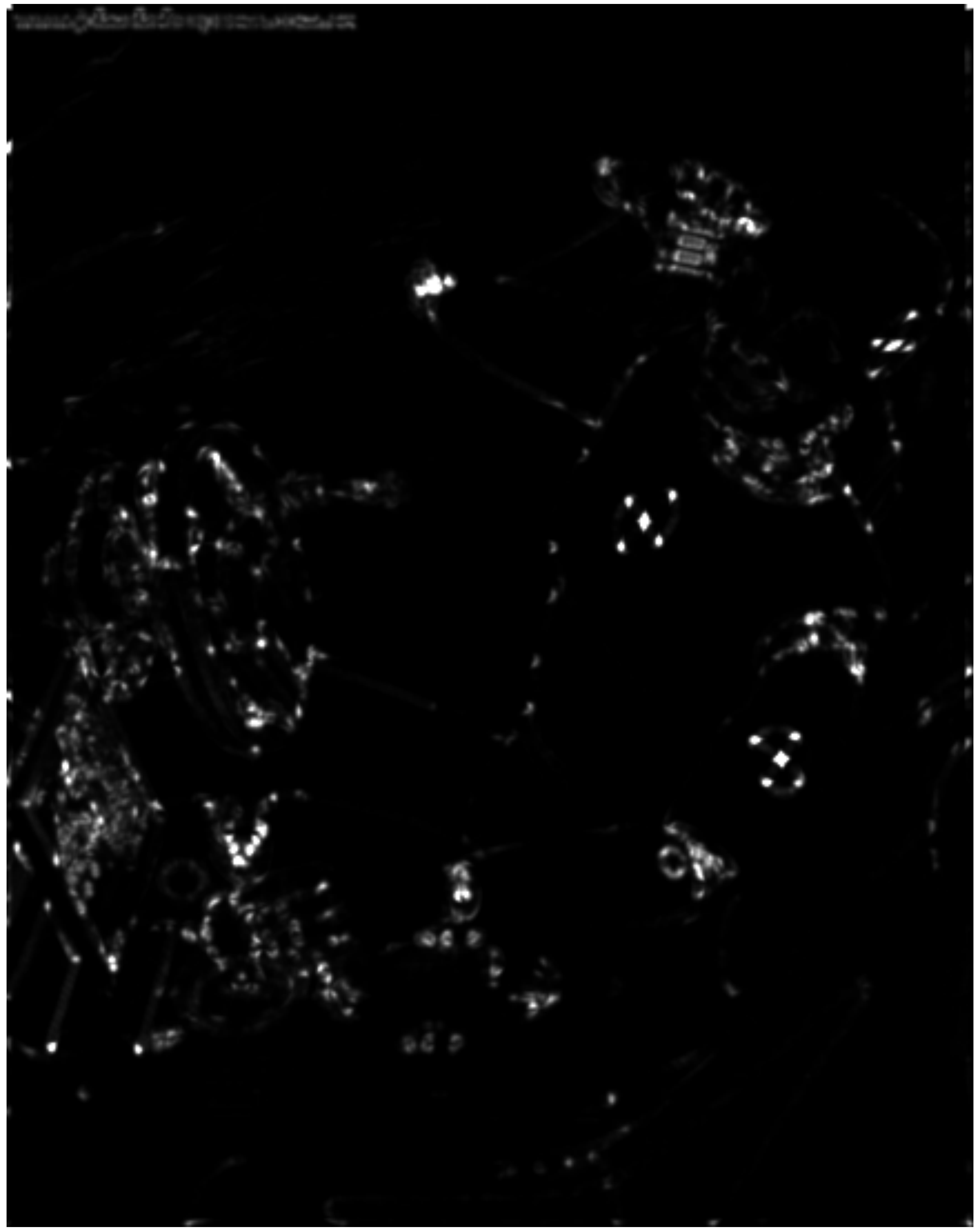
$\sigma = 1$ (219 points)

$\sigma = 2$ (155 points)

$\sigma = 3$ (110 points)

$\sigma = 4$ (87 points)

Example 3: Crash Test Dummy (Harris Result)



corner response image

$\sigma = 1$ (175 points)

Original Image Credit: John Shakespeare, Sydney Morning Herald

Example 2: Wagon Wheel (Harris Results)

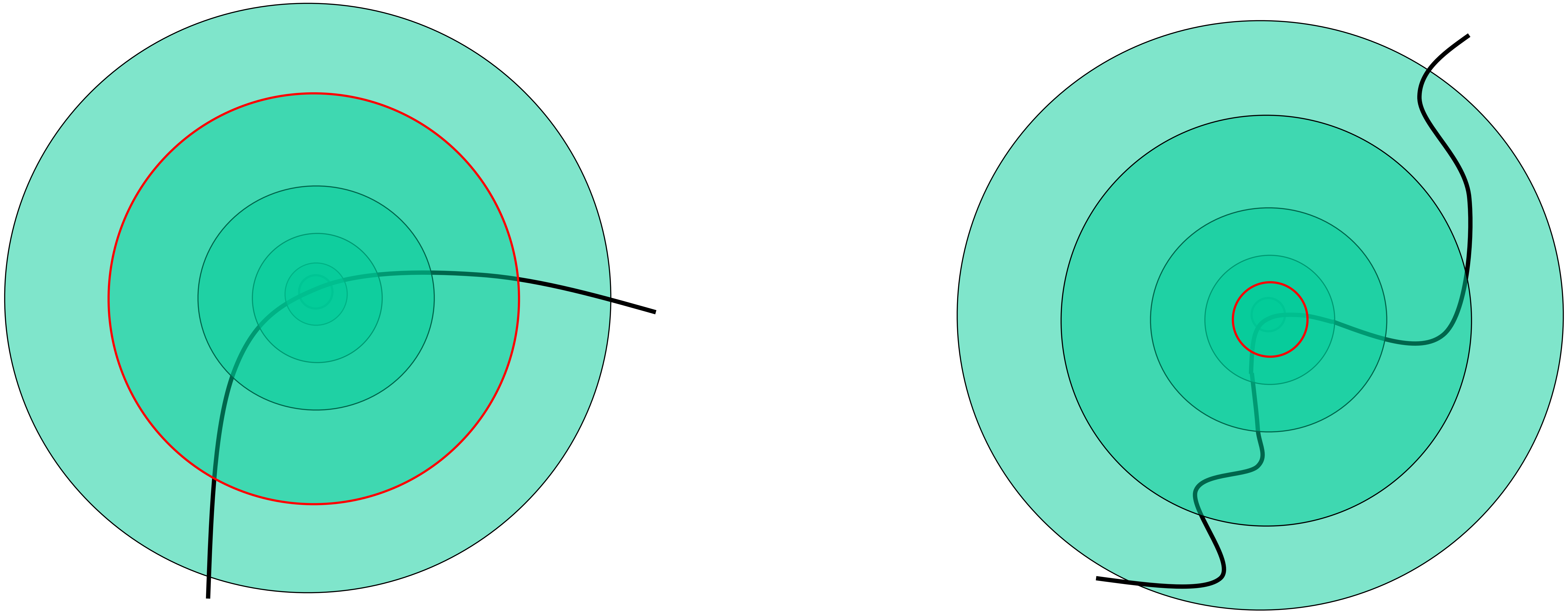
$\sigma = 1$ (219 points)

$\sigma = 2$ (155 points)

$\sigma = 3$ (110 points)

$\sigma = 4$ (87 points)

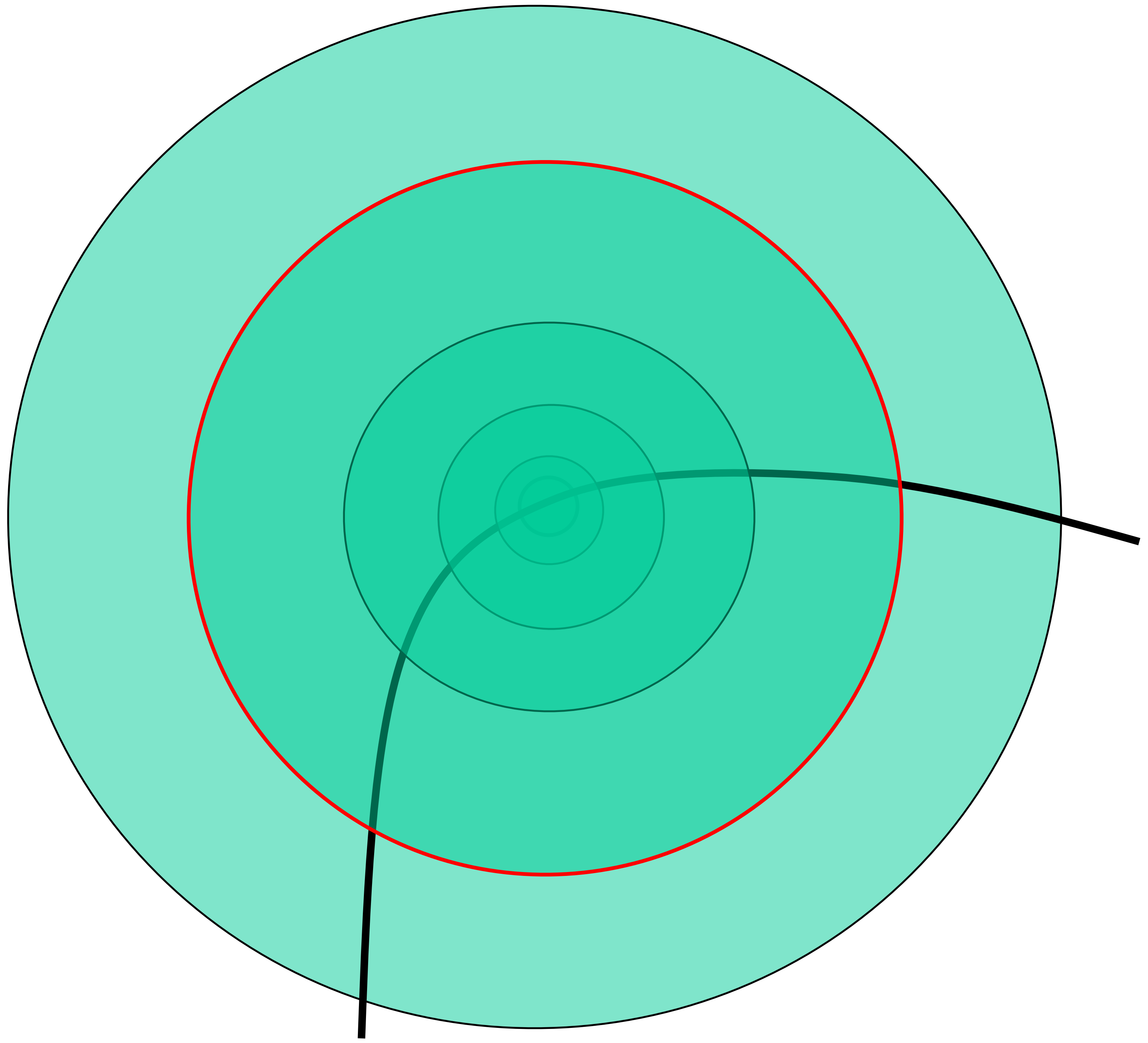
Intuitively …

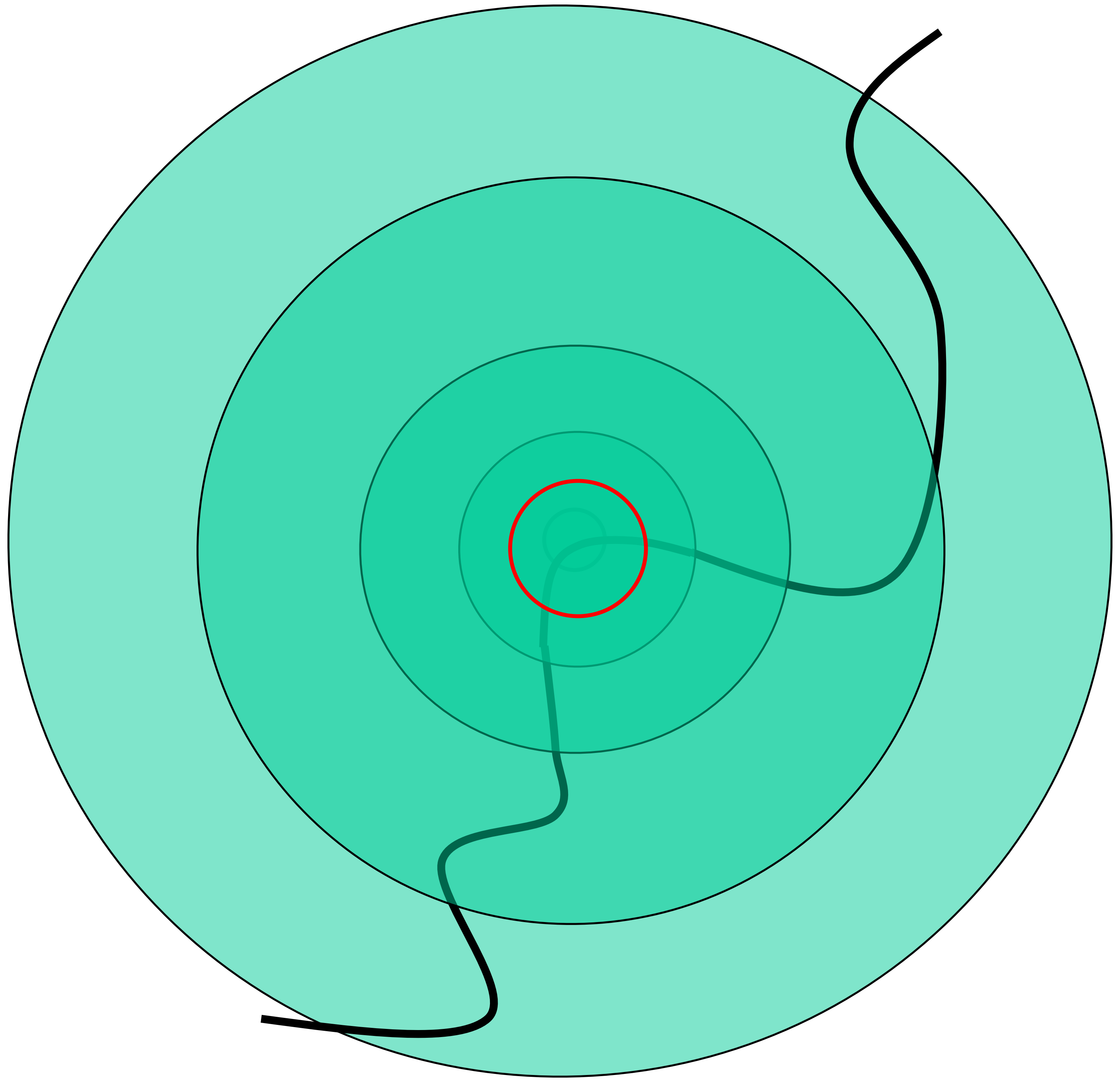


Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Intuitively …

Find local maxima in both **position** and **scale**

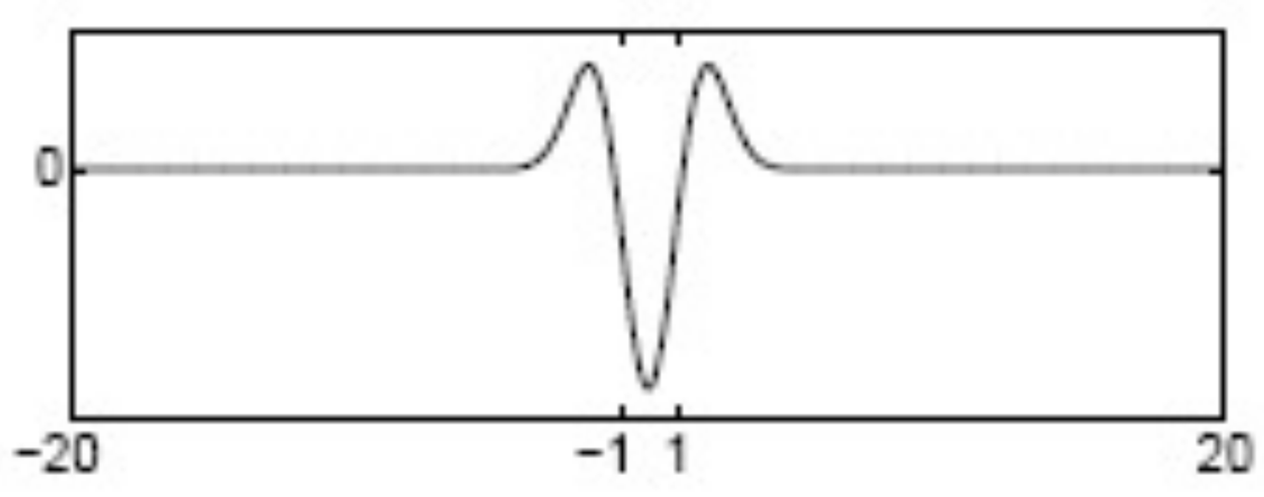




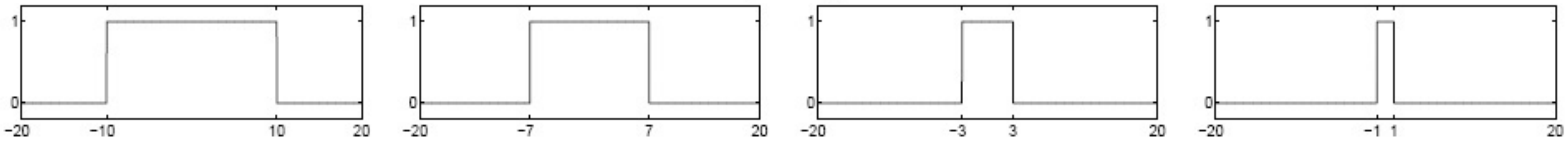
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Formally …

Laplacian filter



Original signal



Convolved with Laplacian ($\sigma = 1$)

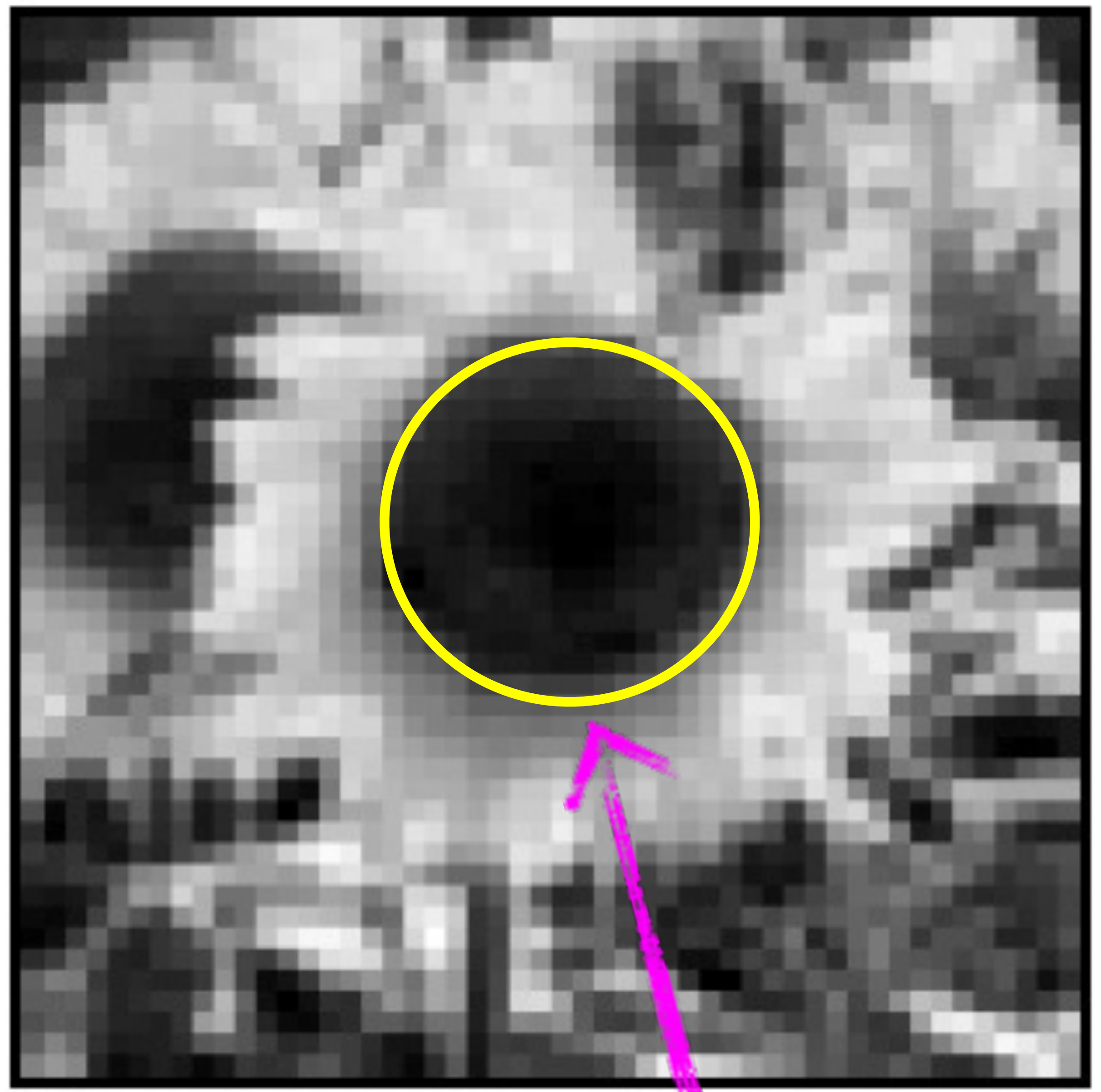
Highest response when the signal has the same **characteristic scale** as the filter

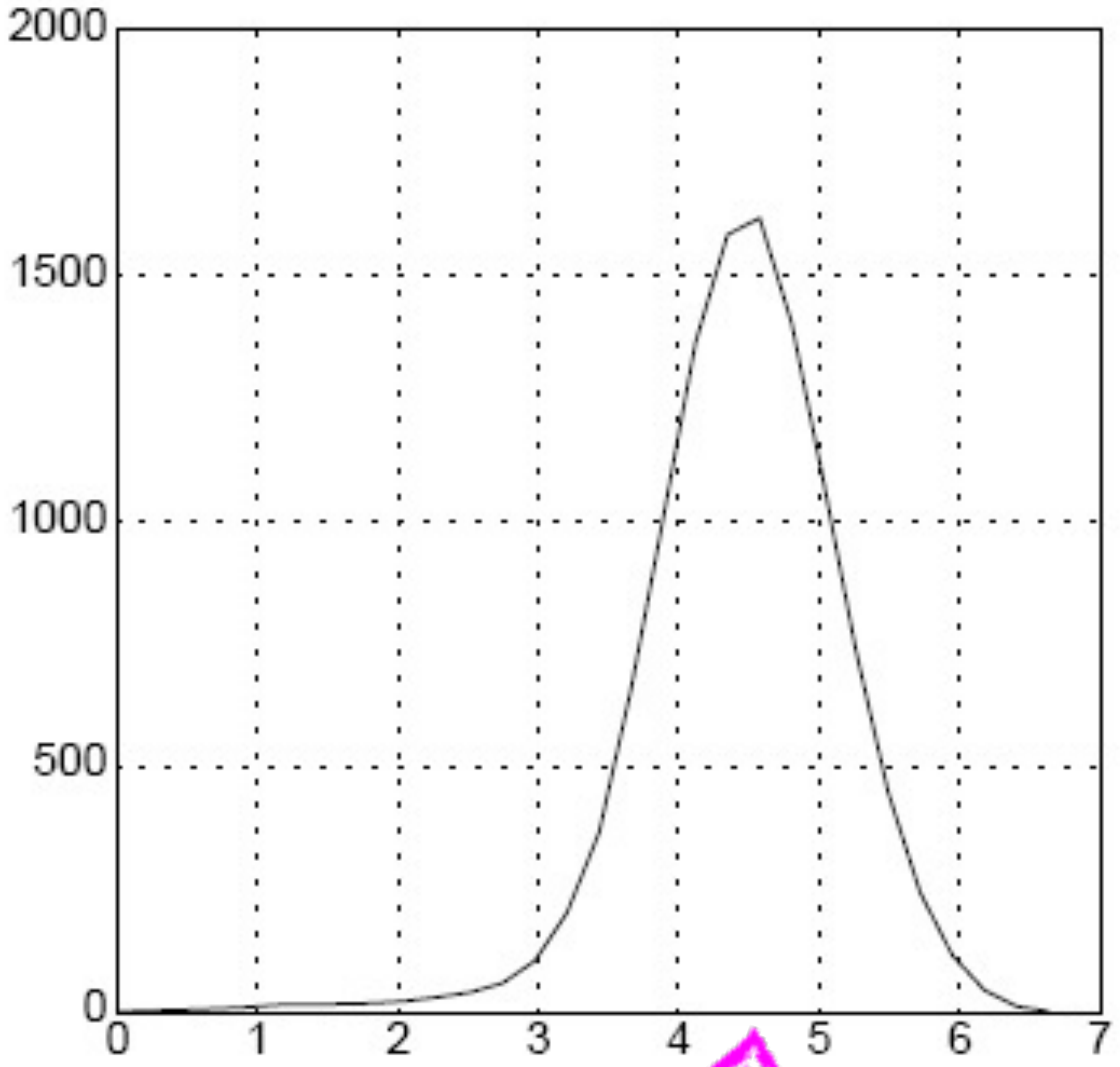
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Characteristic Scale

characteristic scale - the scale that produces peak filter response





characteristic scale

we need to search over characteristic scales

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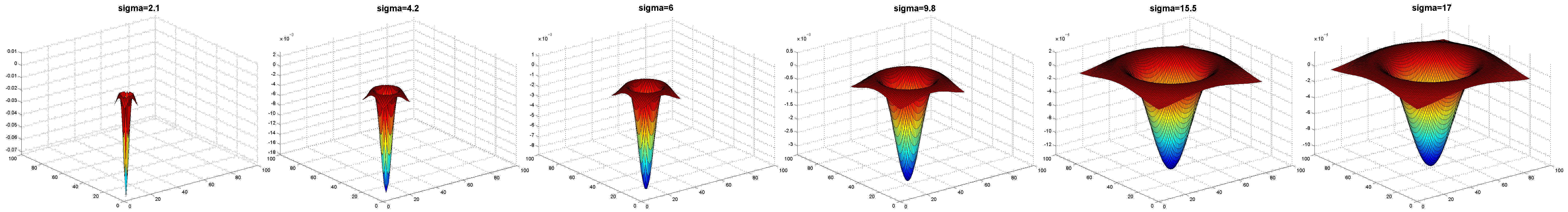
Applying **Laplacian** Filter at Different **Scales**

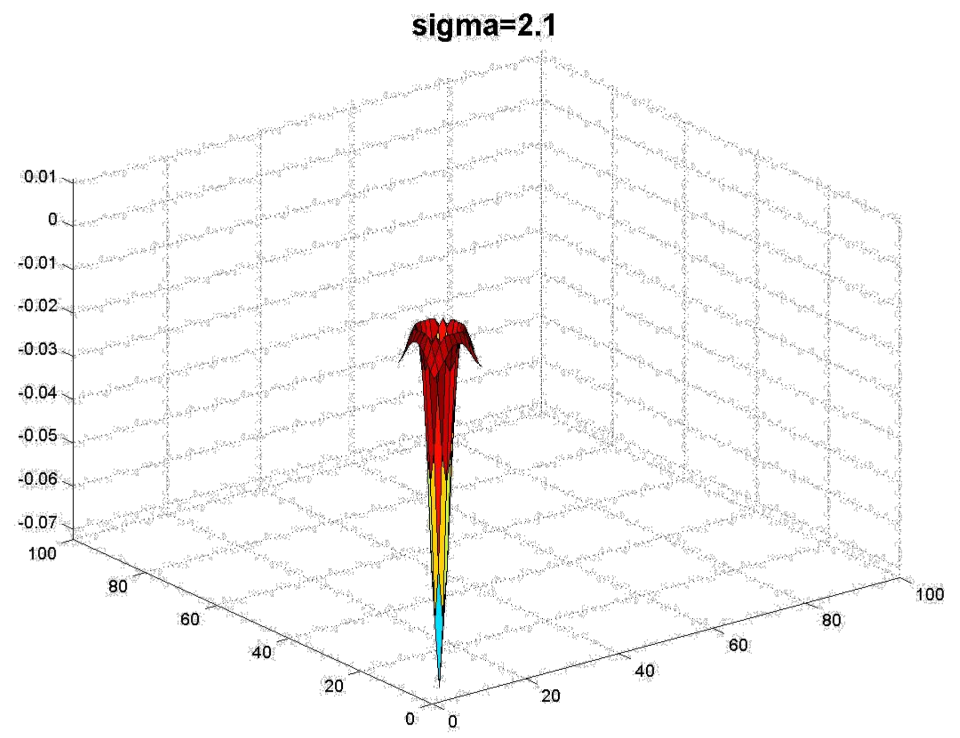


Full size

3/4 size

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

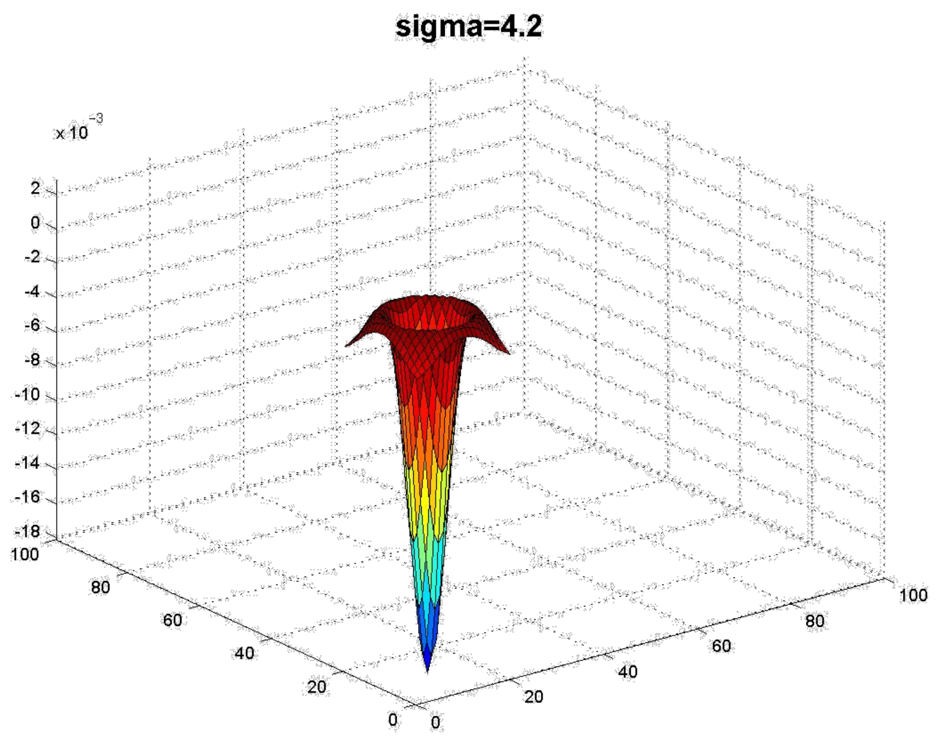
Applying **Laplacian** Filter at Different **Scales**

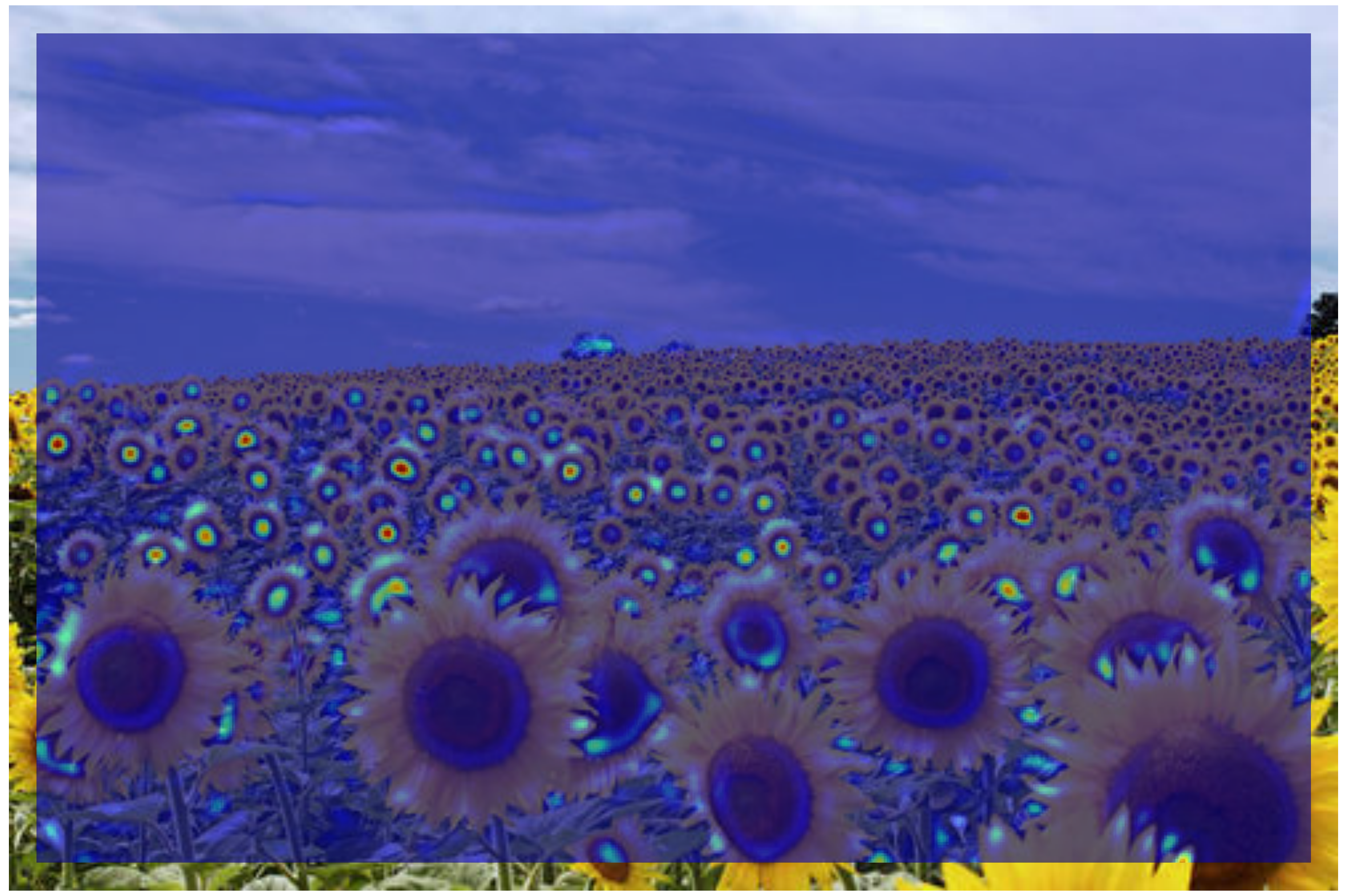


jet color scale
blue: low, red: high

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Applying **Laplacian** Filter at Different **Scales**





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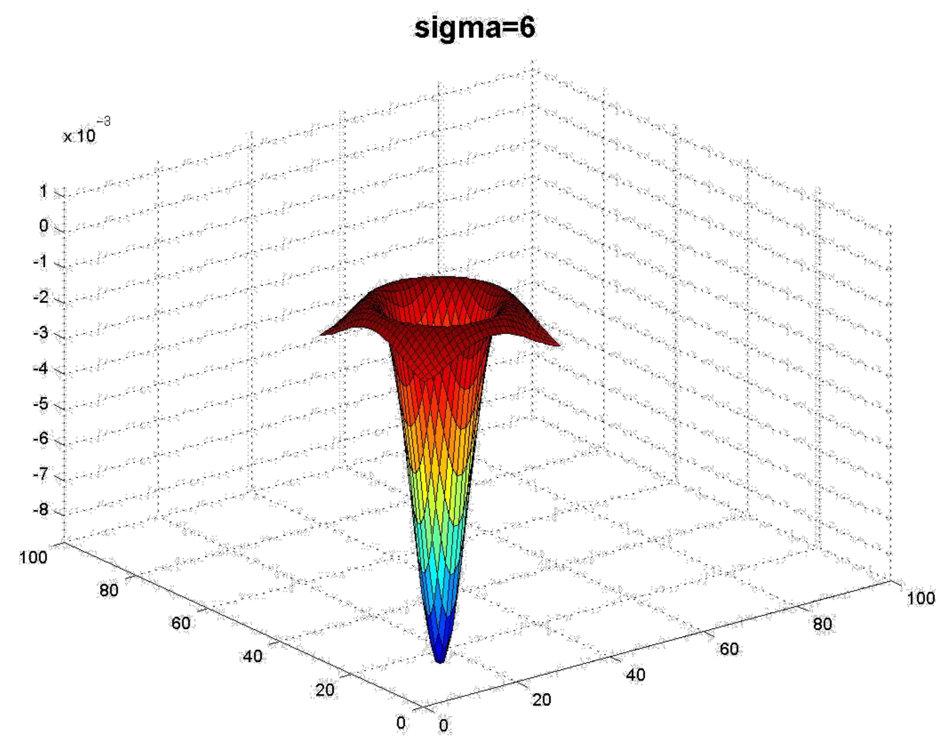
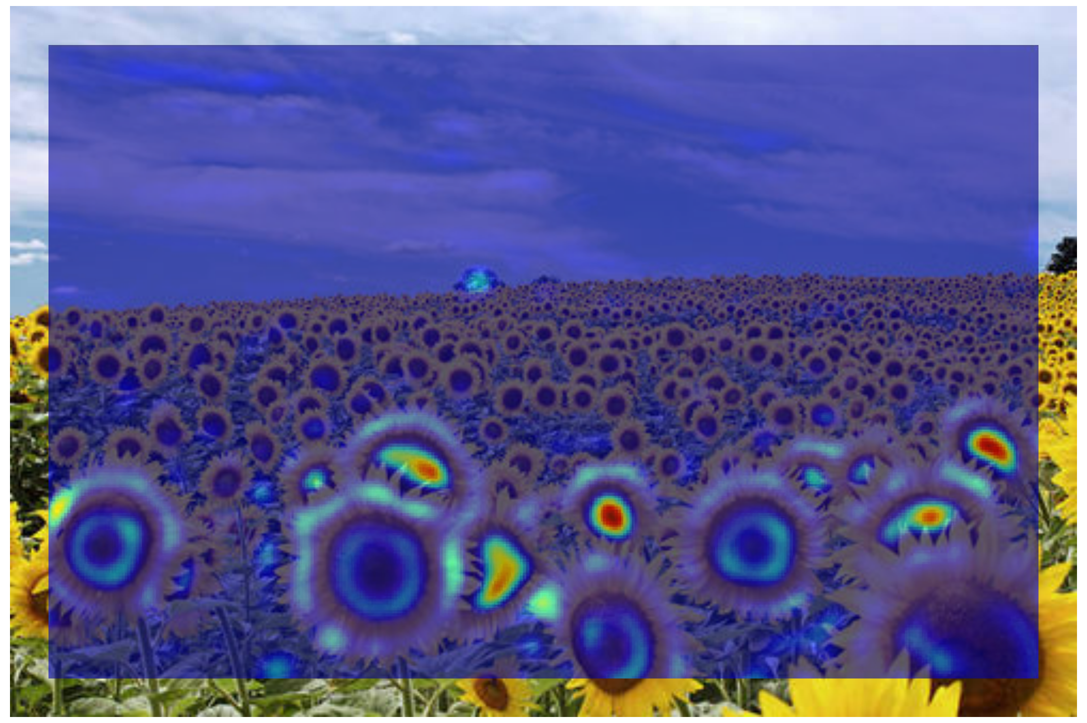
Applying **Laplacian** Filter at Different **Scales**





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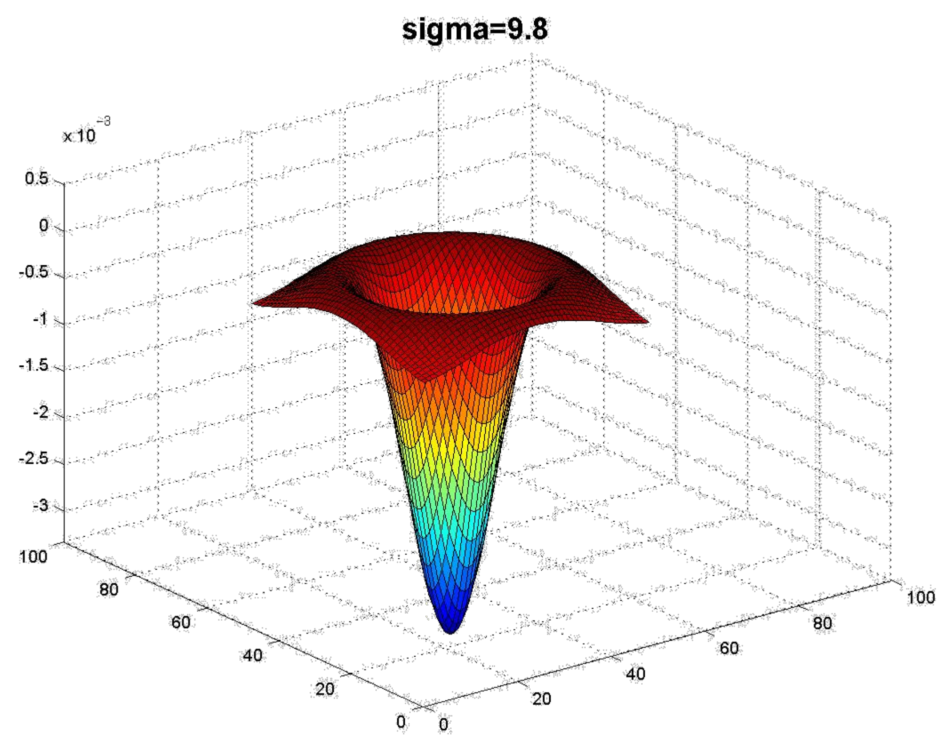
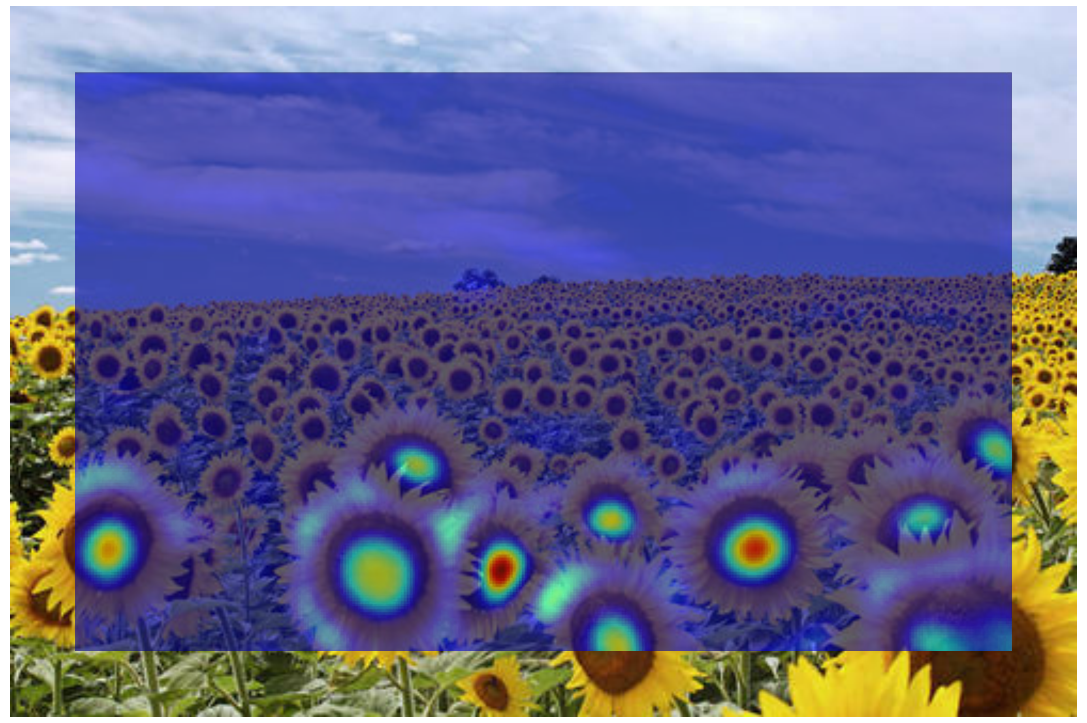
Applying **Laplacian** Filter at Different **Scales**





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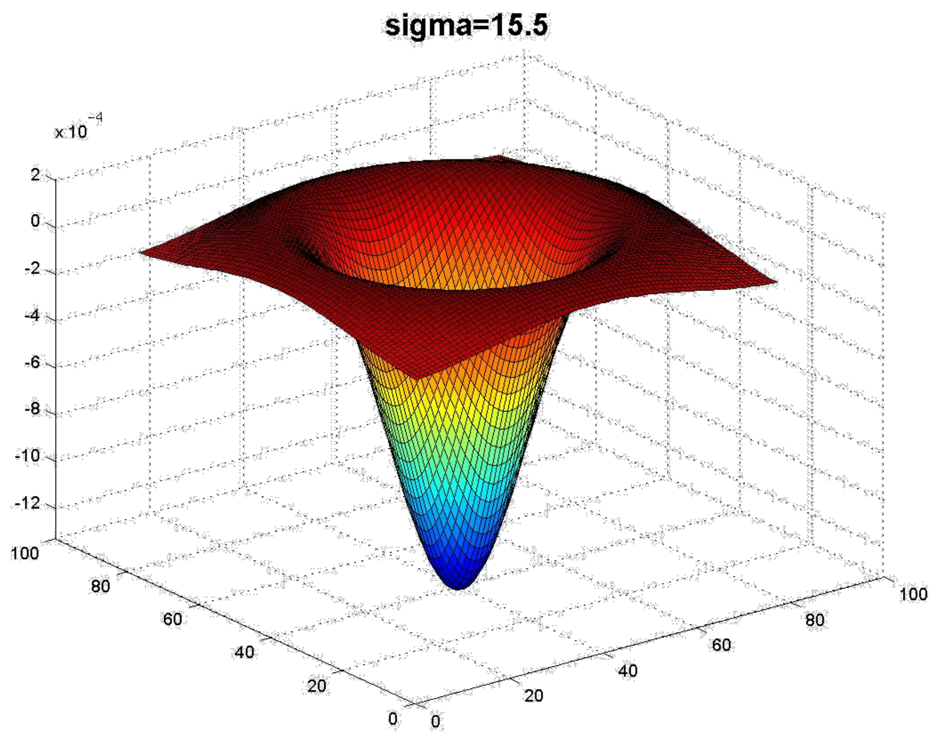
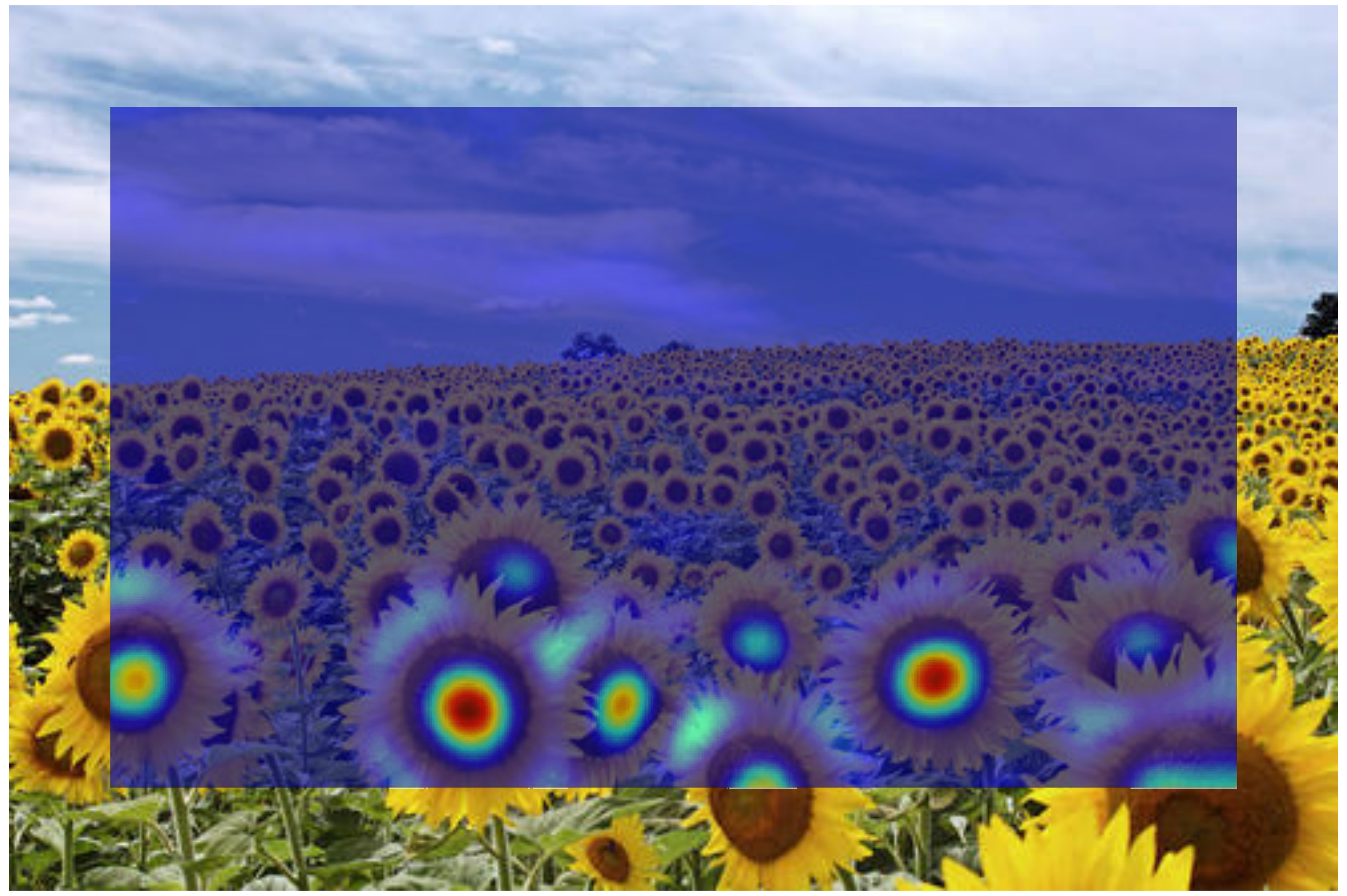
Applying **Laplacian** Filter at Different **Scales**





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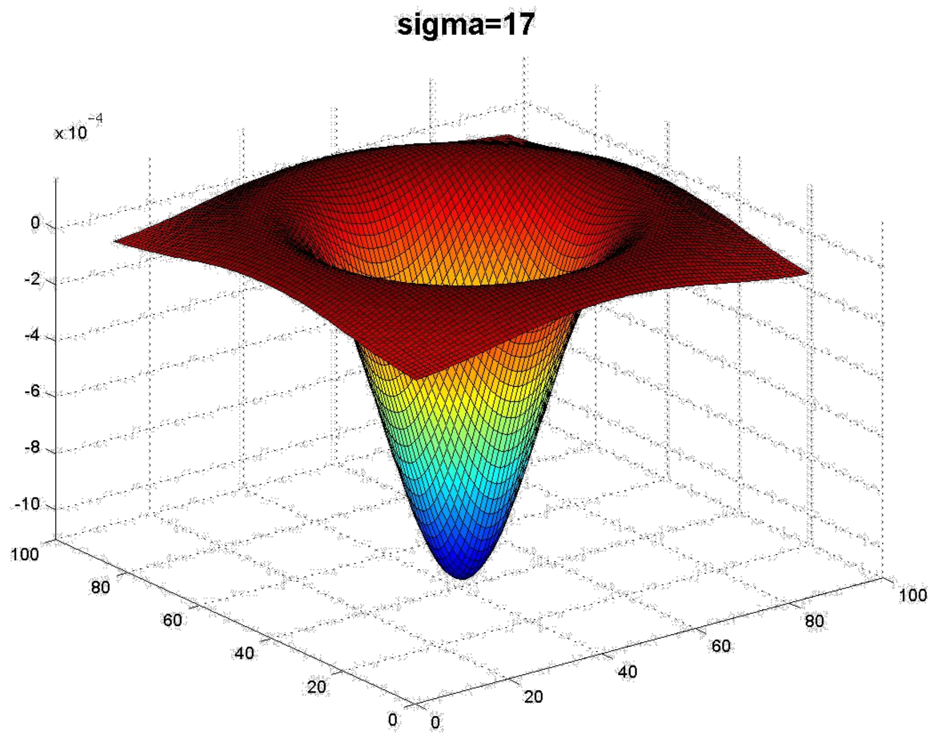
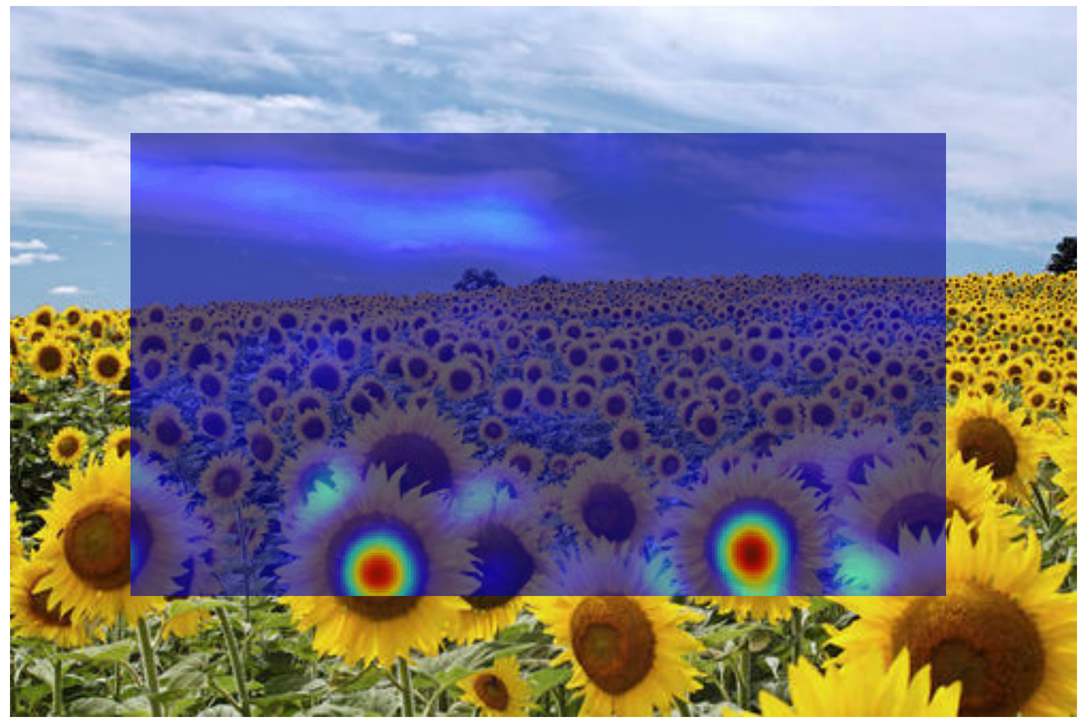
Applying **Laplacian** Filter at Different **Scales**





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Applying **Laplacian** Filter at Different **Scales**

Full size

3/4 size

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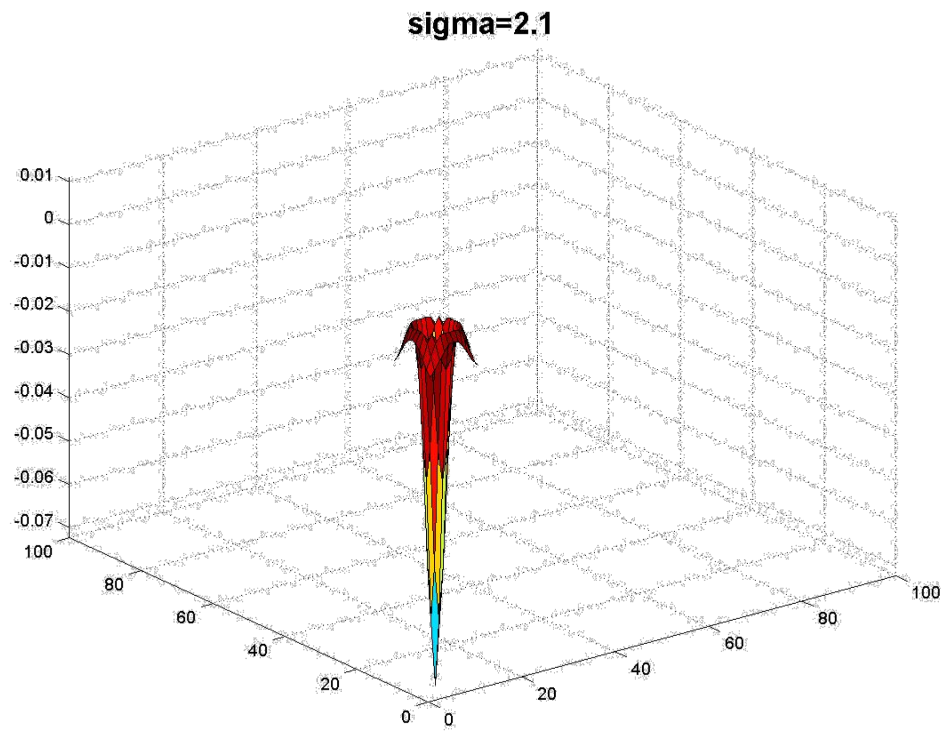
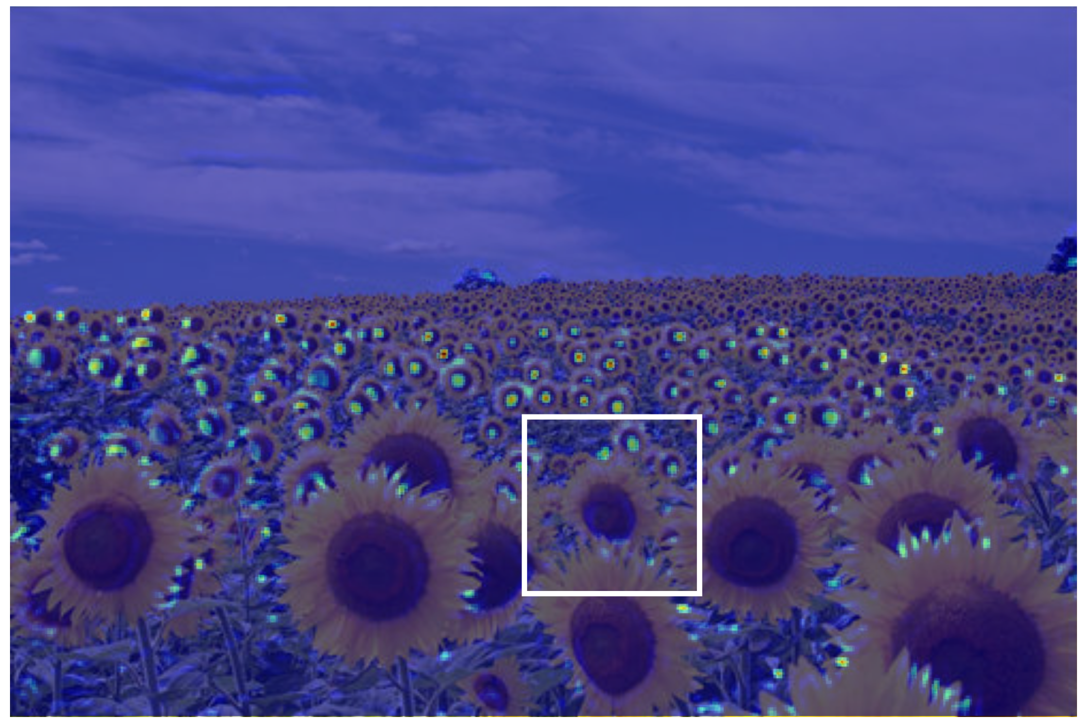
Applying **Laplacian** Filter at Different **Scales**





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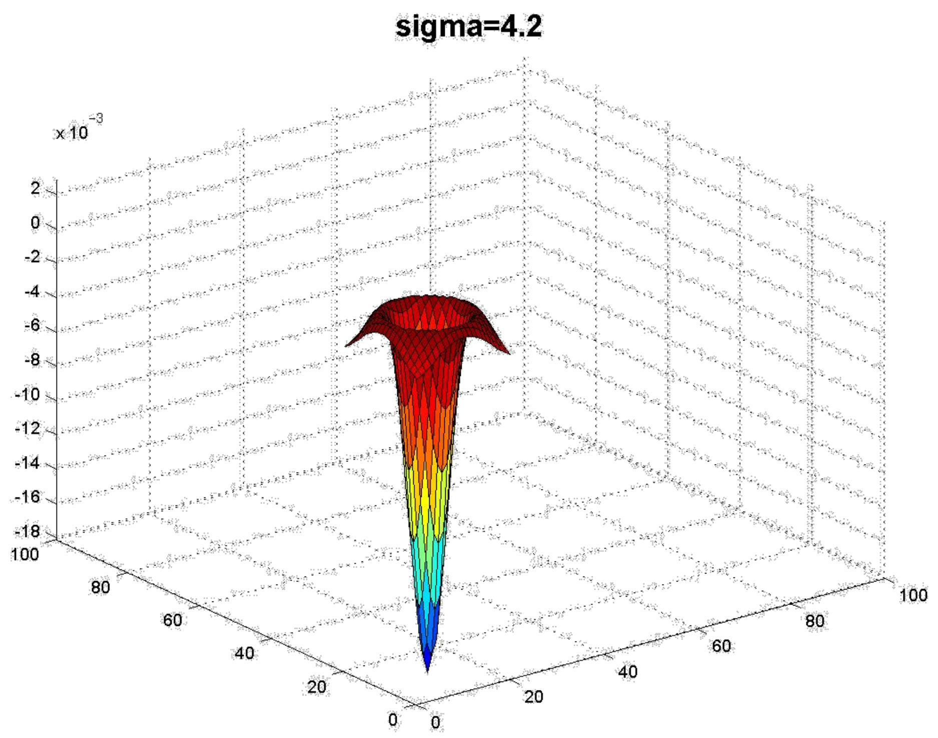
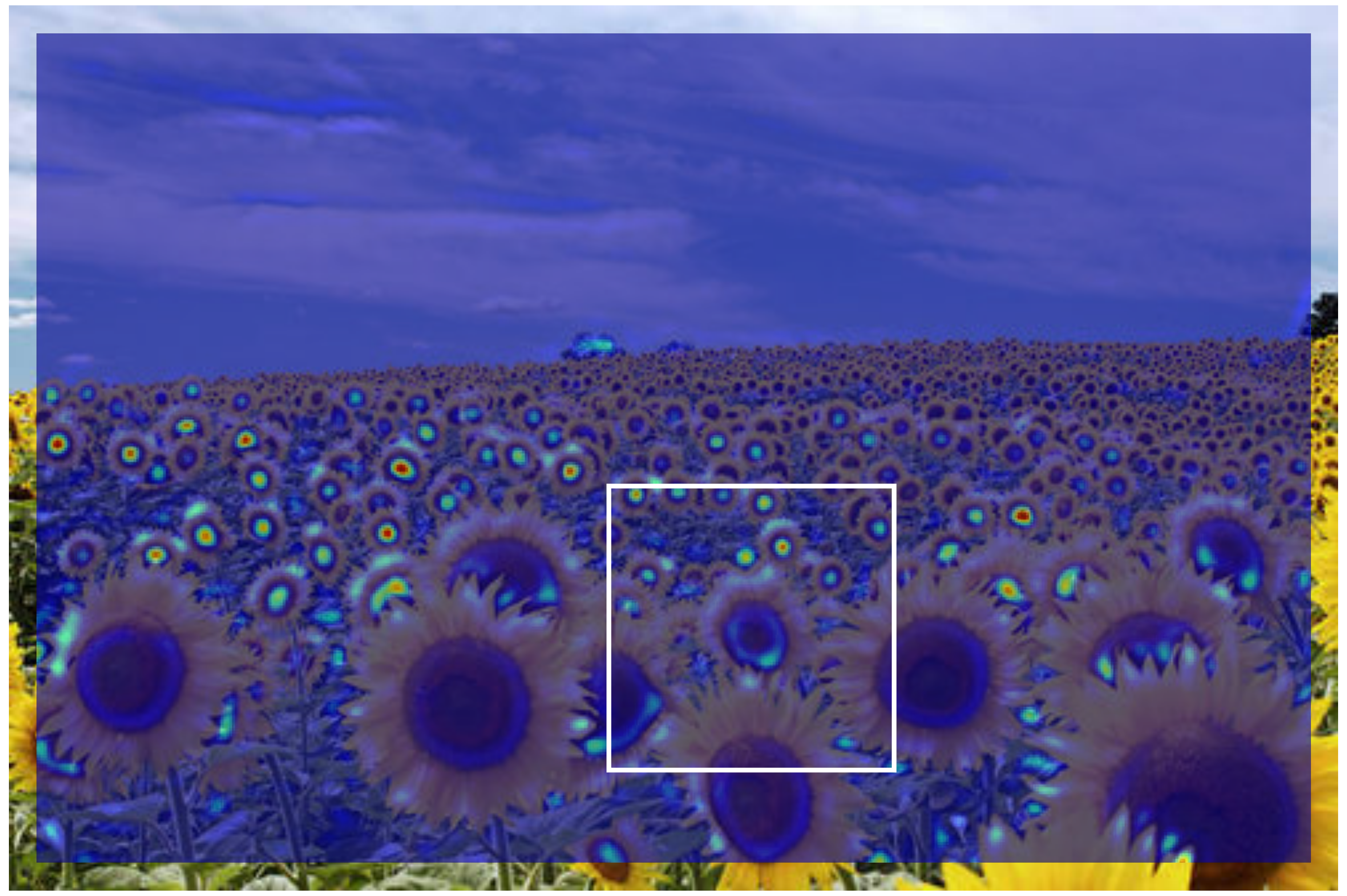
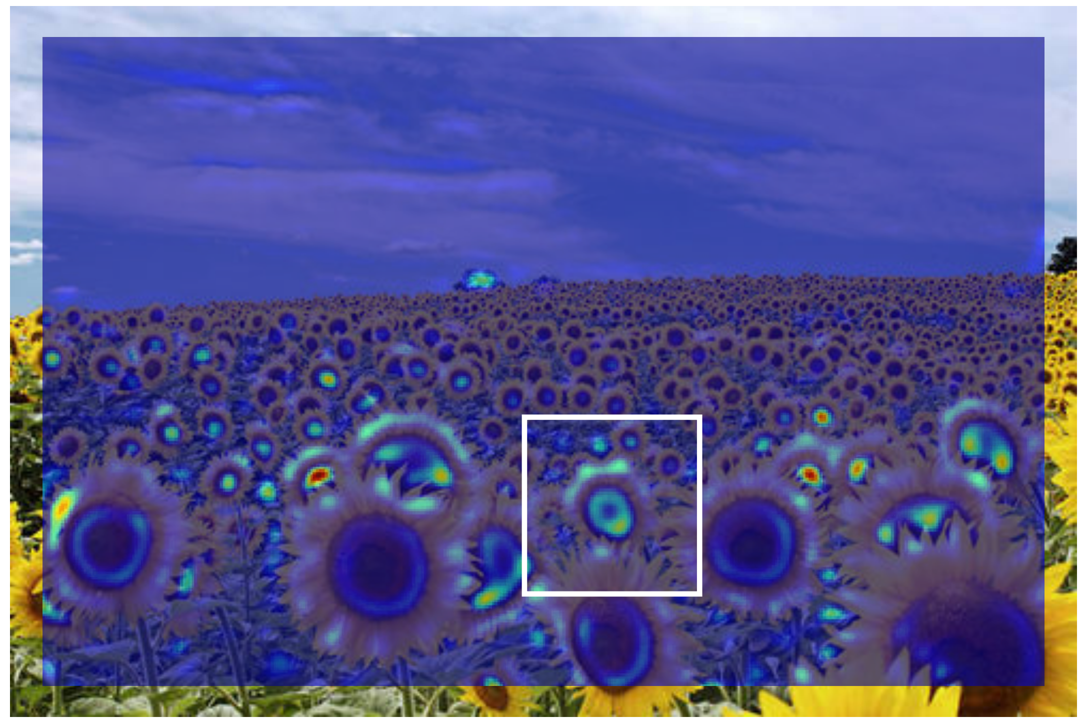
Applying **Laplacian** Filter at Different **Scales**







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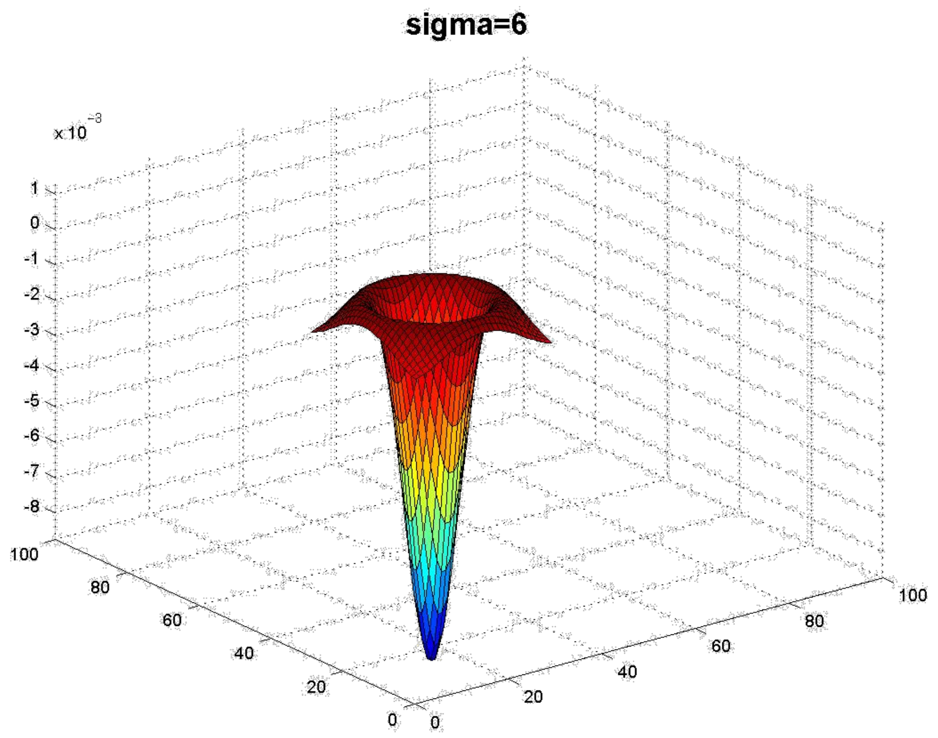

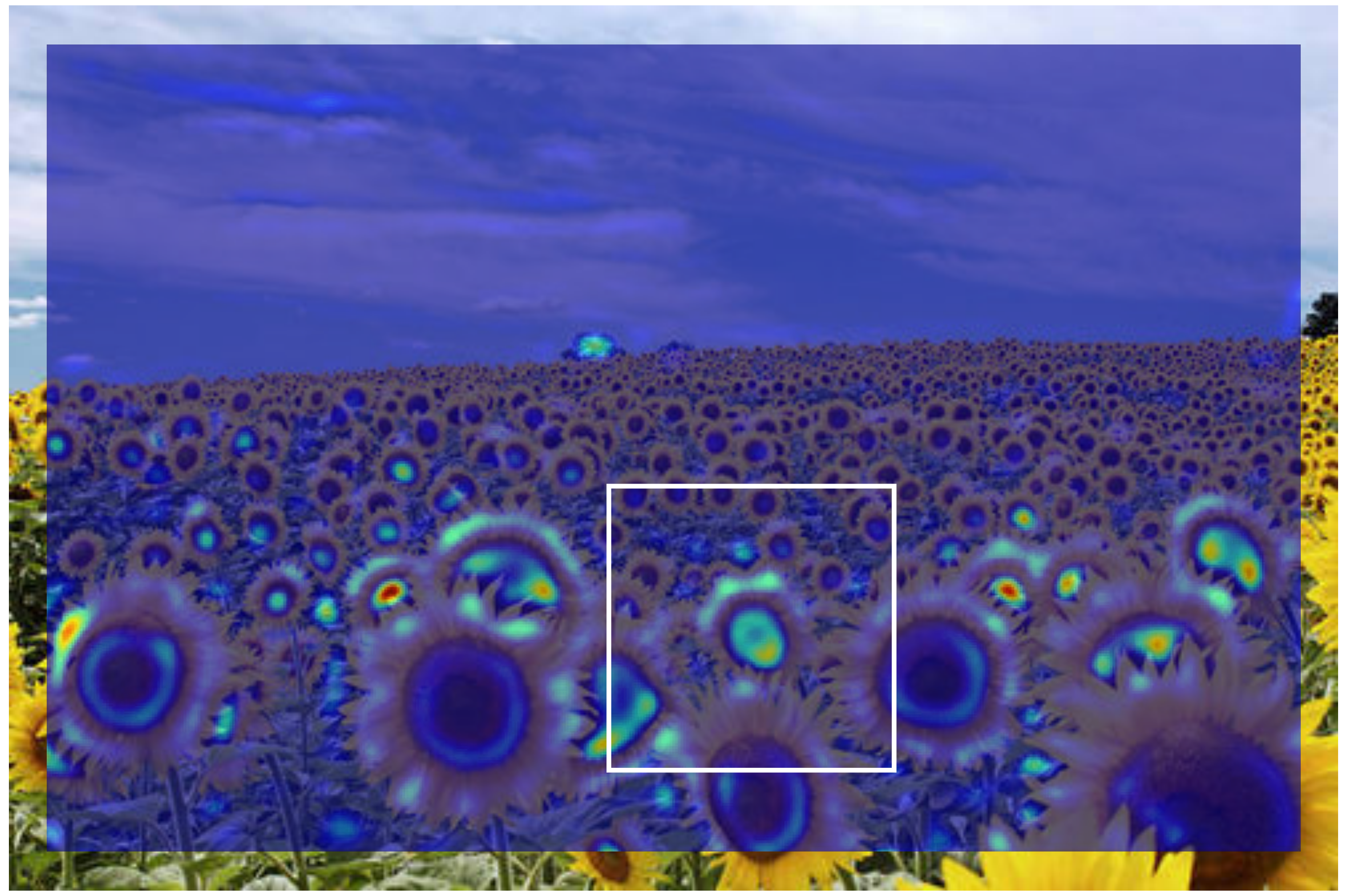

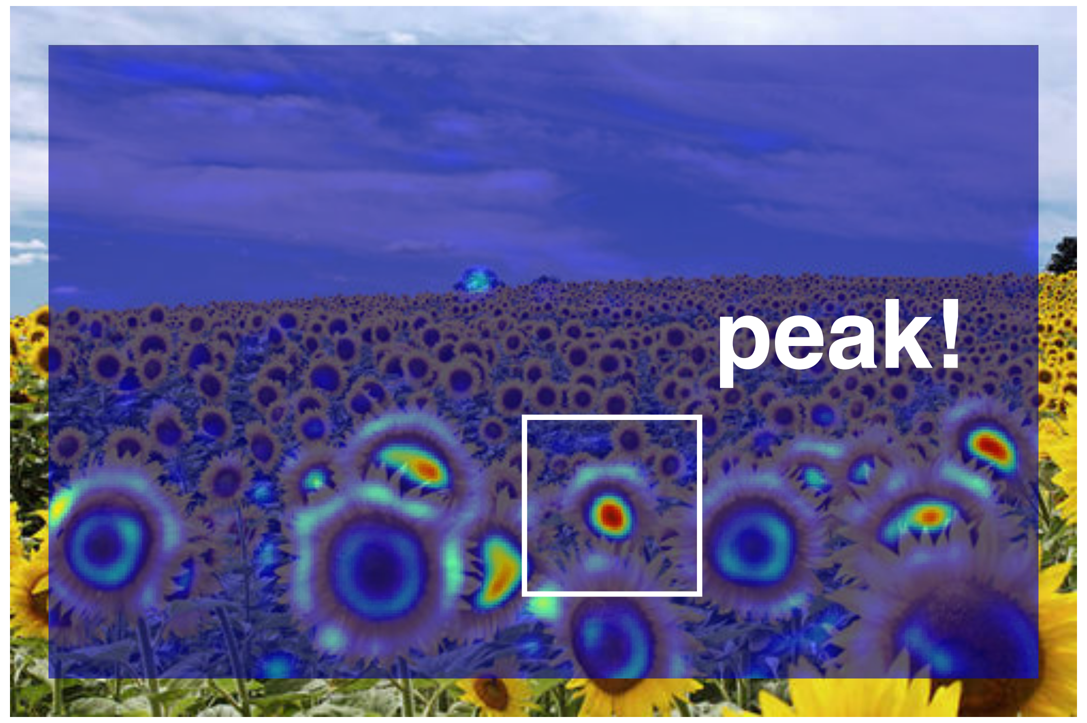

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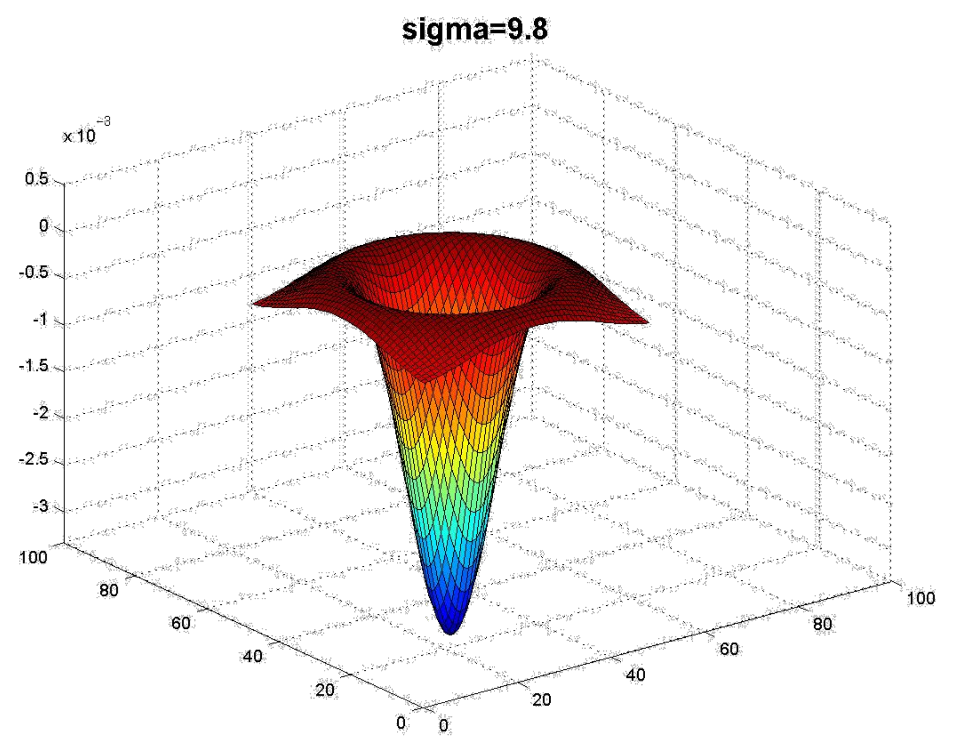
Applying **Laplacian** Filter at Different **Scales**



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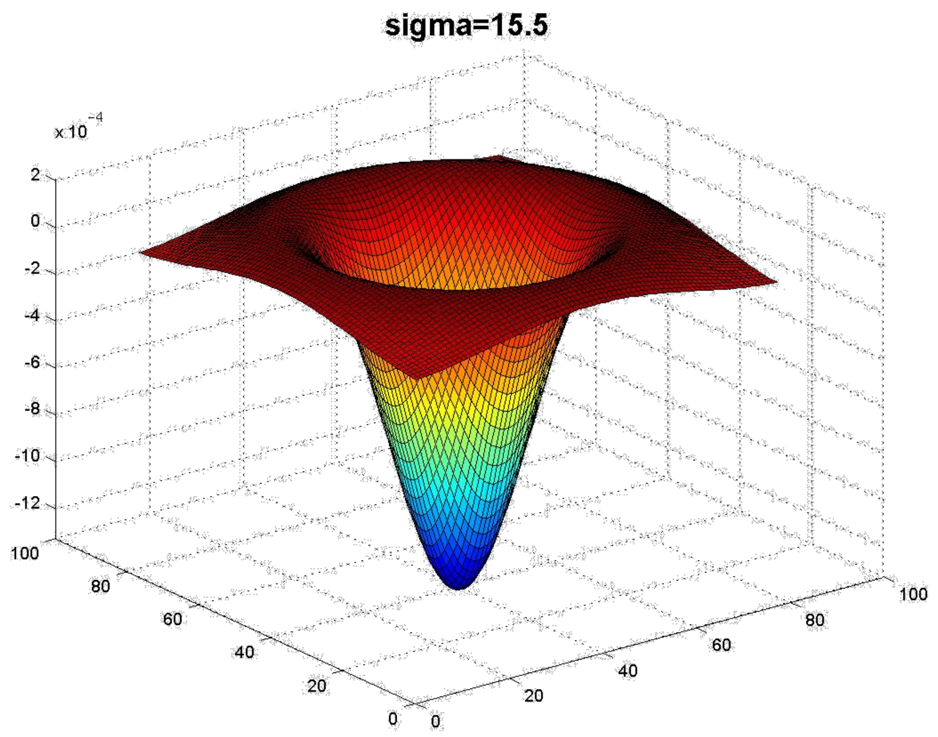

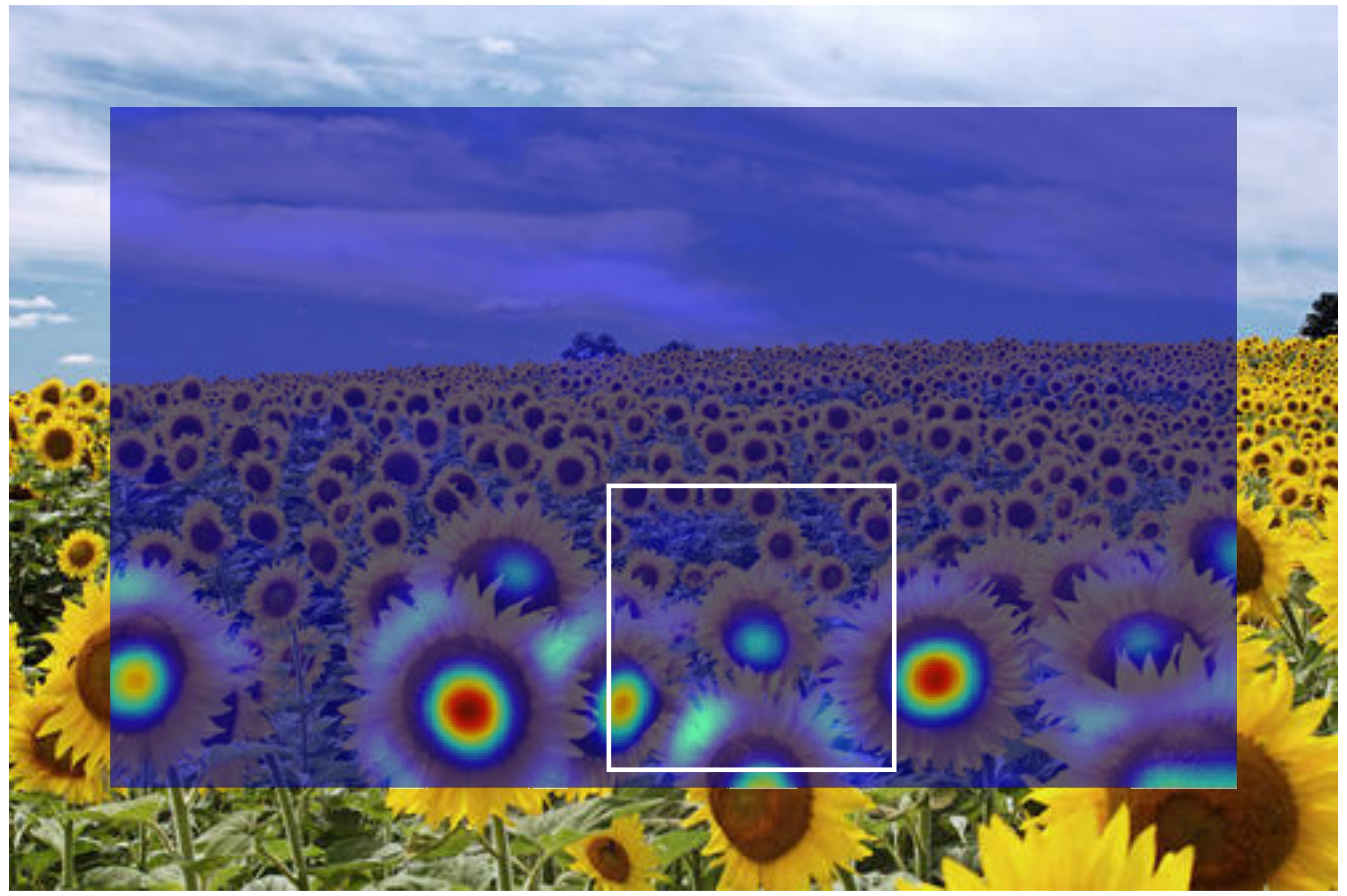

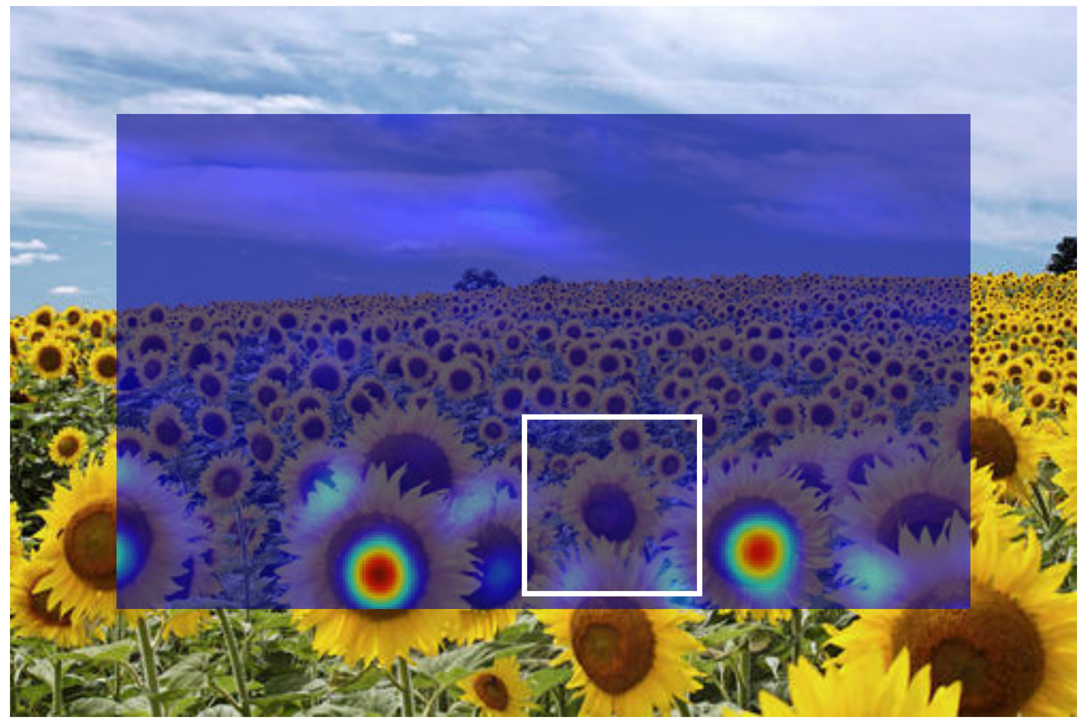

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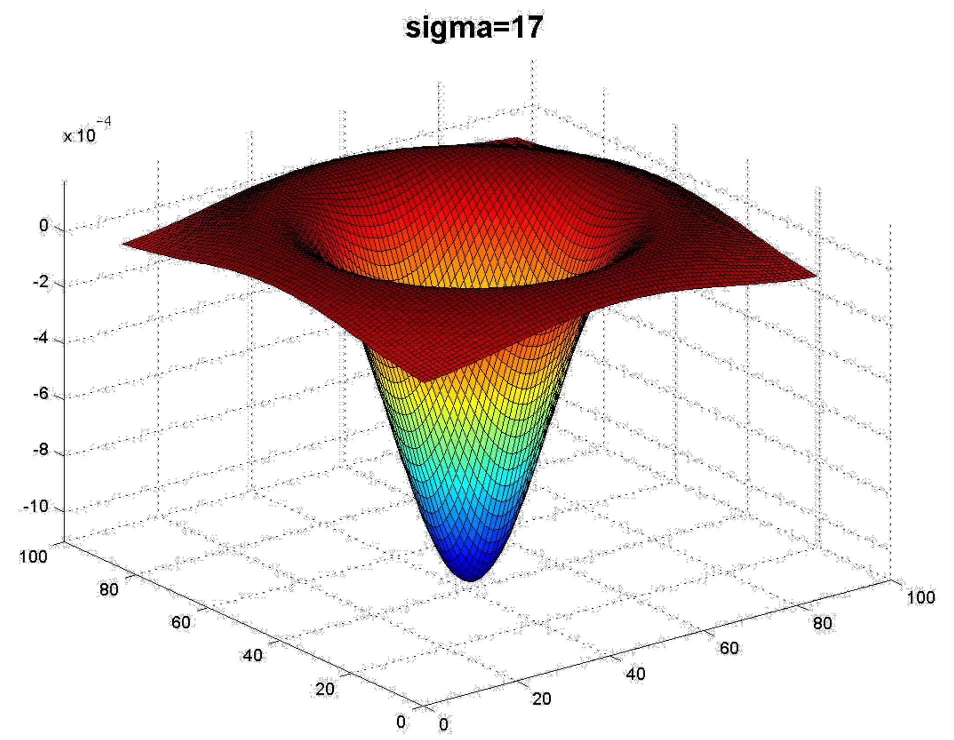
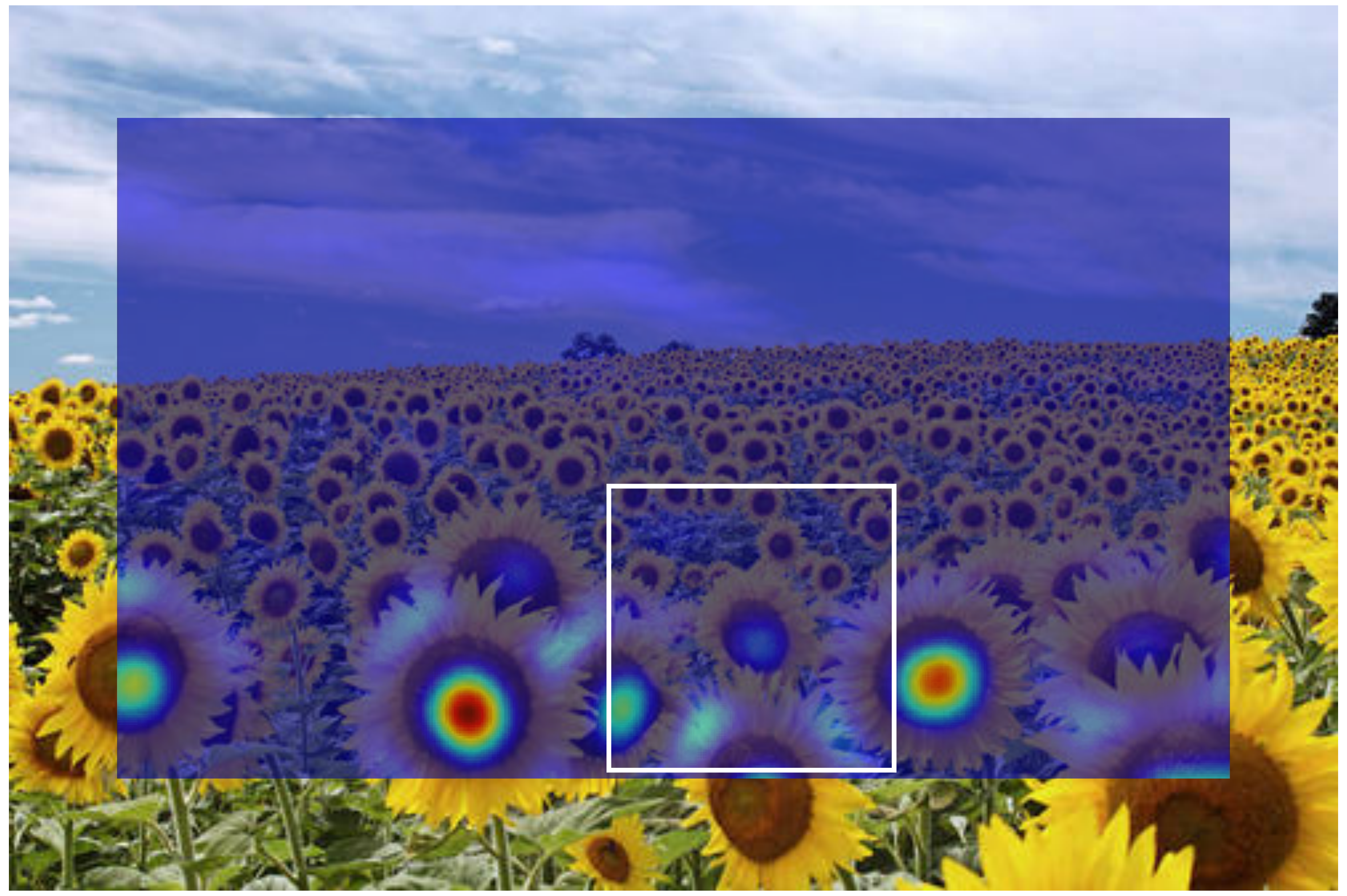
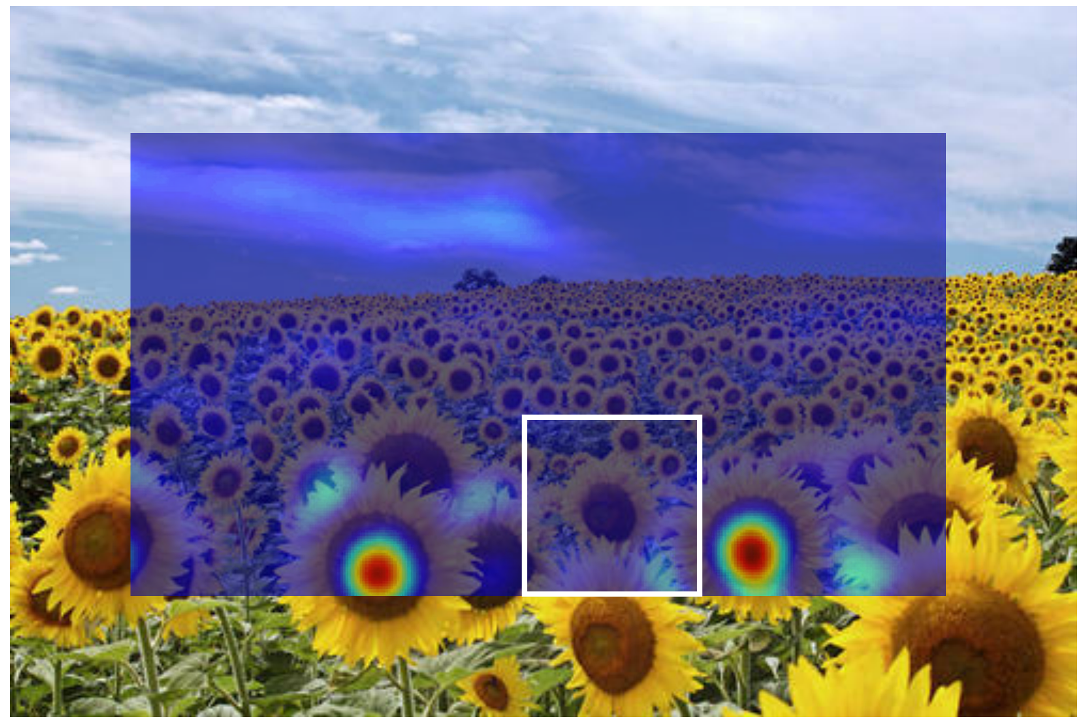
Applying **Laplacian** Filter at Different **Scales**







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Applying **Laplacian** Filter at Different **Scales**

Full size

3/4 size

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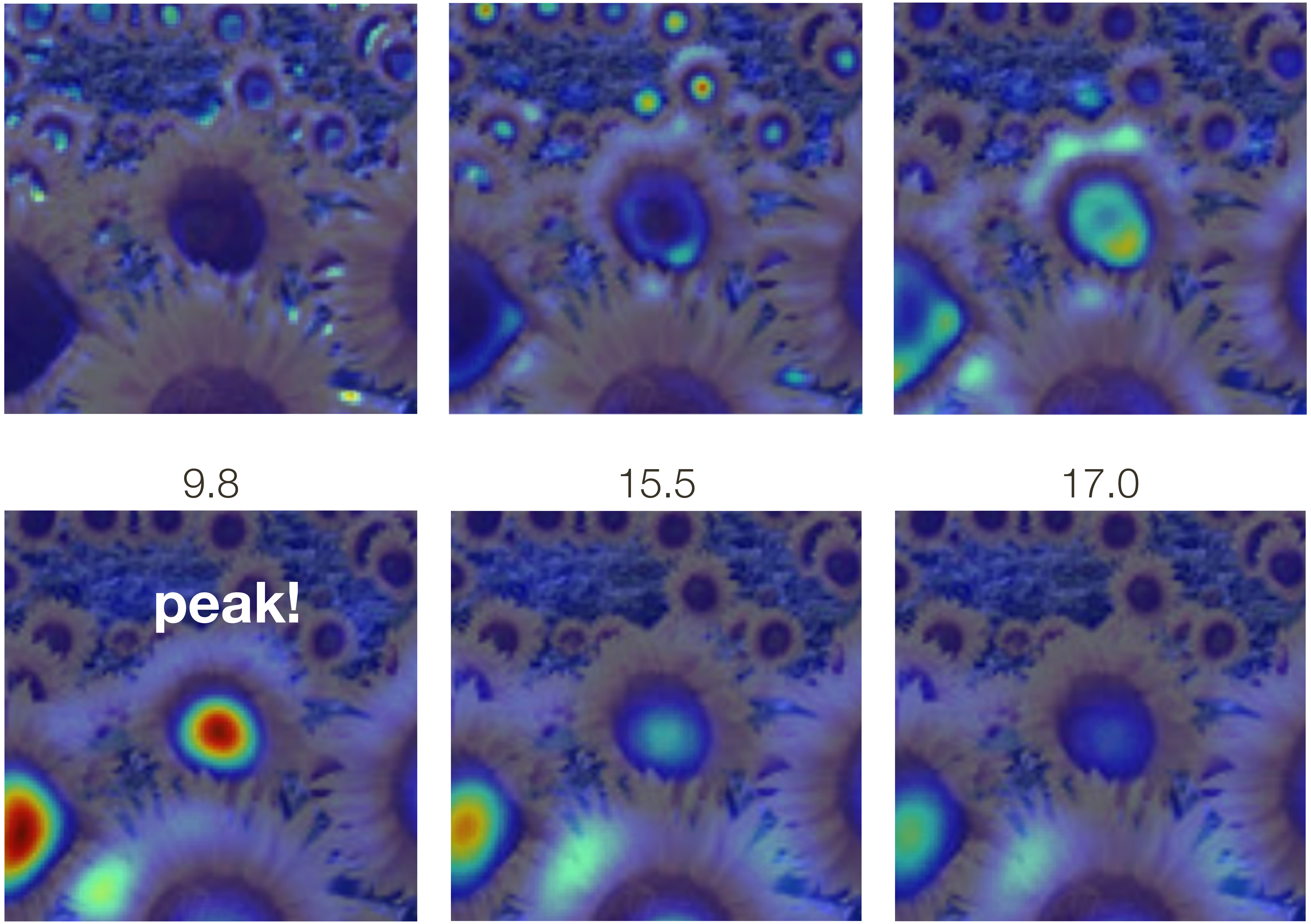
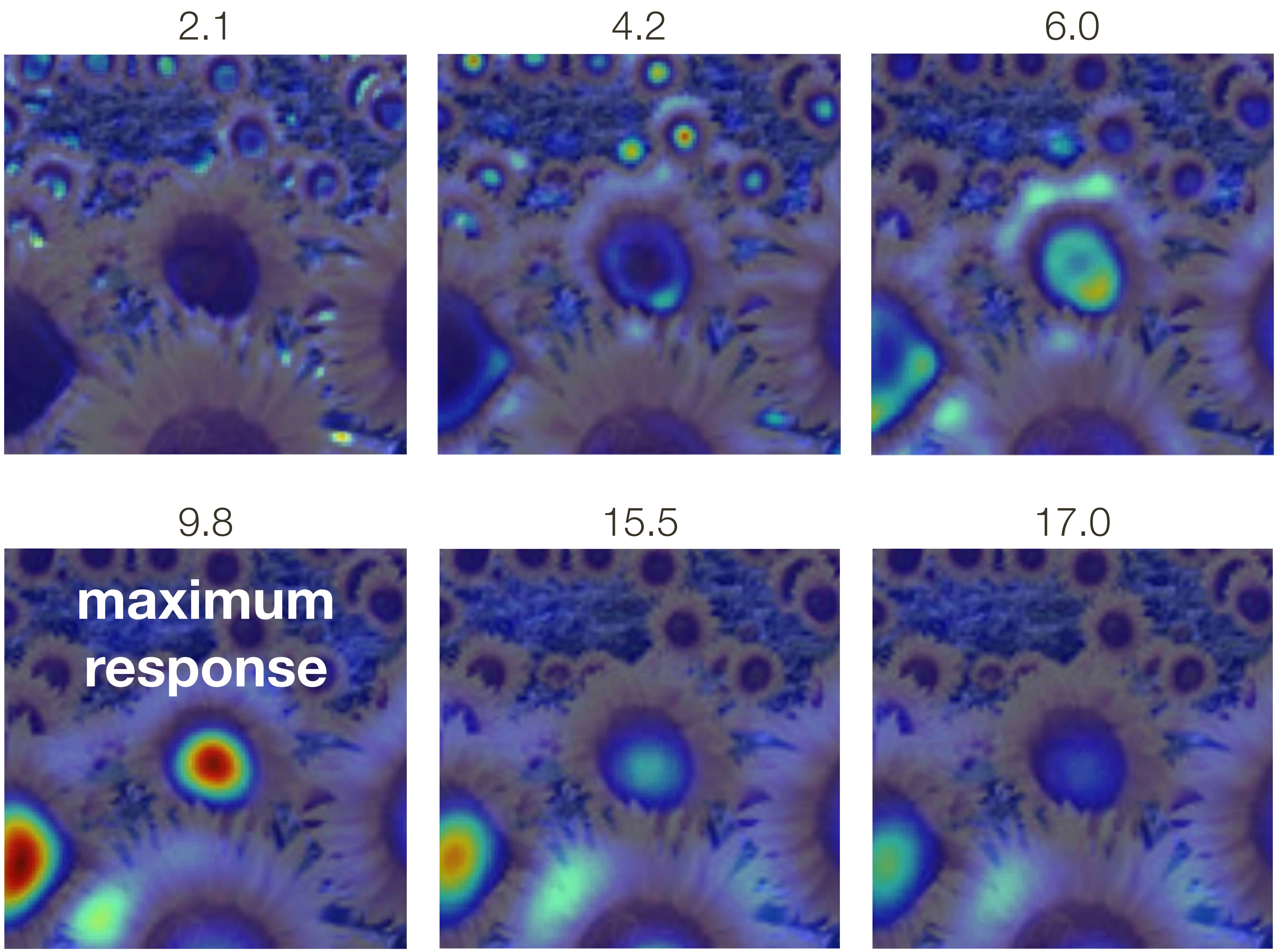
Applying **Laplacian** Filter at Different **Scales**

2.1 | 4.2 | 6.0

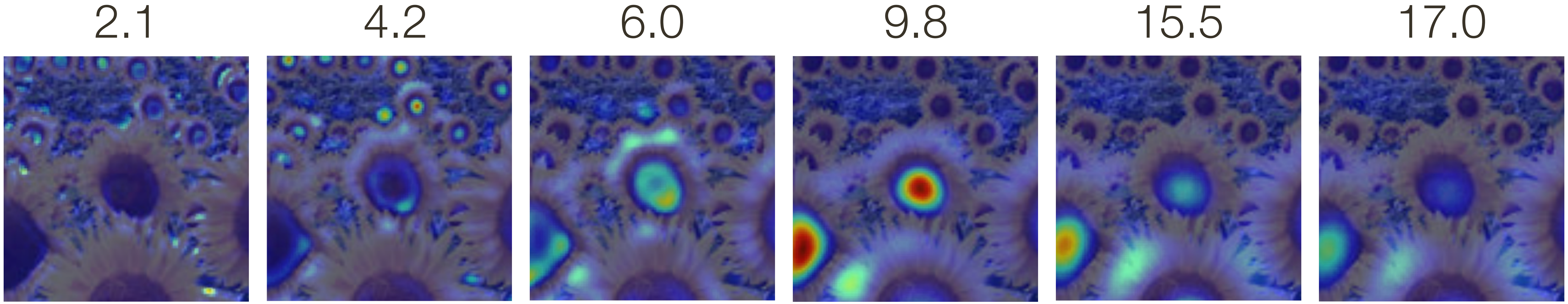
9.8 | 15.5 | 17.0



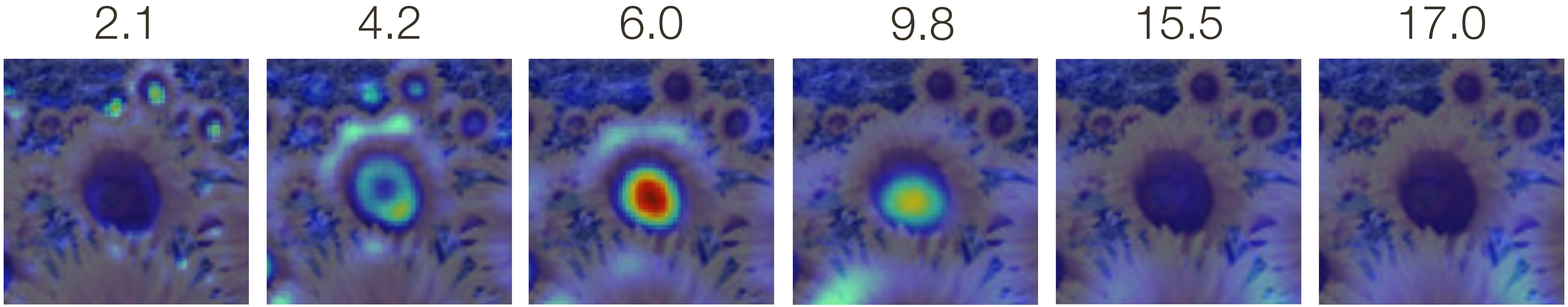
Applying **Laplacian** Filter at Different **Scales**



Optimal **Scale**



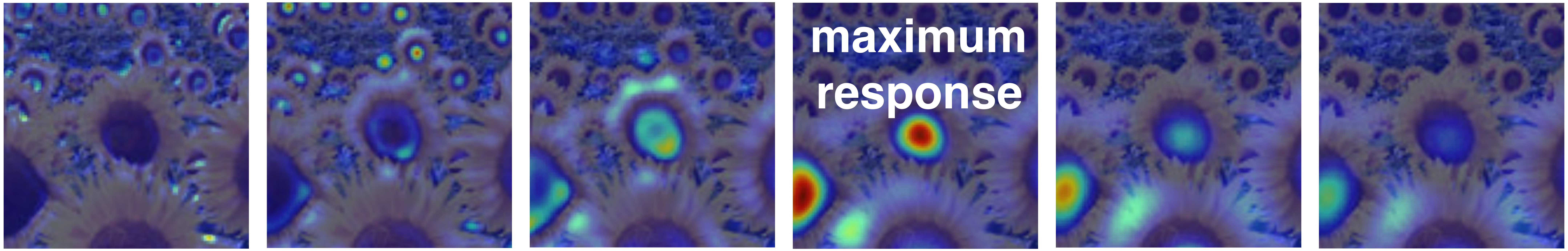
Full size image



3/4 size image

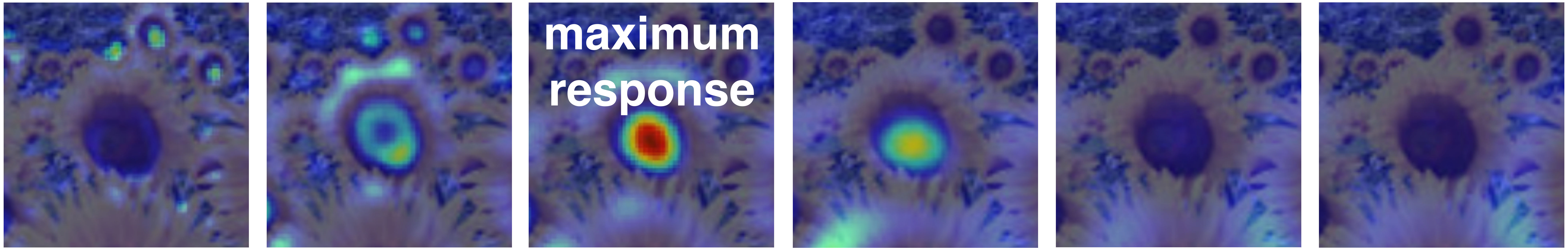
Optimal **Scale**

2.1 4.2 6.0 9.8 15.5 17.0



Full size image

2.1 4.2 6.0 9.8 15.5 17.0



3/4 size image

Implementation

```
For each level of the Gaussian pyramid
compute feature response (e.g. Harris, Laplacian)

For each level of the Gaussian pyramid
    if local maximum and cross-scale
    save scale and location of feature
```

(x, y, s)

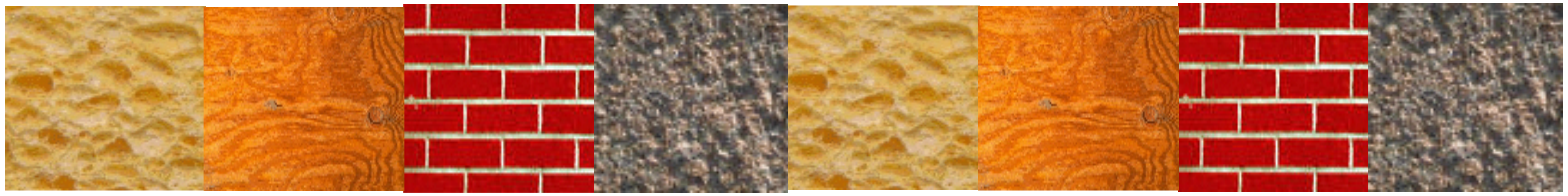
Summary

A **corner** is a distinct 2D feature that can be localized reliably

Edge detectors perform poorly at corners
→ consider corner detection directly

Harris corner detection
— corners are places where intensity gradient direction takes on multiple distinct values
— interpret in terms of autocorrelation of local window
— translation and rotation invariant, but not scale invariant

CPSC 425: Computer Vision



Lecture 15: Texture

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

Texture

What is **texture**?

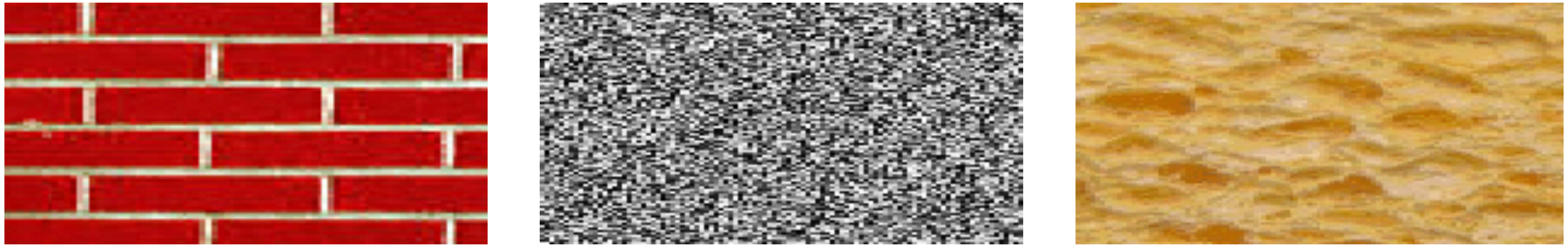


Figure Credit: Alexei Efros and Thomas Leung

Texture is widespread, easy to recognize, but hard to define

Views of large numbers of small objects are often considered textures
— e.g. grass, foliage, pebbles, hair

Patterned surface markings are considered textures
— e.g. patterns on wood

Definition of **Texture**

(Functional) **Definition**:

Texture is detail in an image that is at a scale too small to be resolved into its constituent elements and at a scale large enough to be apparent in the spatial distribution of image measurements

Definition of **Texture**

(Functional) **Definition**:

Texture is detail in an image that is at a scale too small to be resolved into its constituent elements and at a scale large enough to be apparent in the spatial distribution of image measurements

Sometimes, textures are thought of as patterns composed of repeated instances of one (or more) identifiable elements, called **textons**.

— e.g. bricks in a wall, spots on a cheetah

Uses of **Texture**

Texture can be a strong cue to **object identity** if the object has distinctive material properties

Texture can be a strong cue to an **object's shape** based on the deformation of the texture from point to point.

— Estimating surface orientation or shape from texture is known as "**shape from texture**"

Texture

We will look at two main questions:

1. How do we represent texture?
   → Texture **analysis**

2. How do we generate new examples of a texture?
   → Texture **synthesis**

We begin with texture synthesis to set up **Assignment 3**