THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision

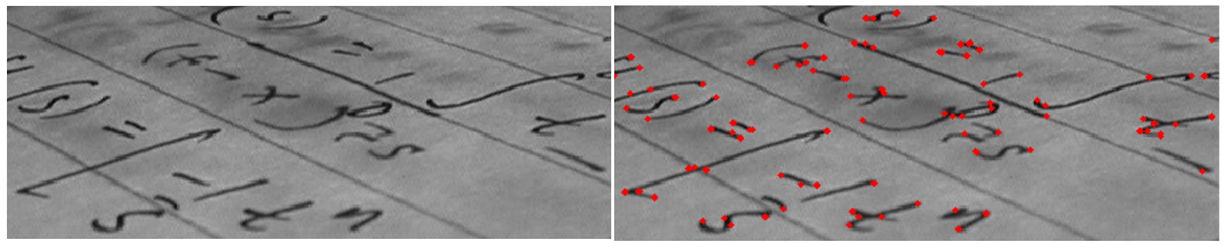


Image Credit: https://en.wikipedia.org/wiki/Corner_detection

Lecture 10: Corner Detection

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

Menu for Today

Topics:

- Corner **Detection**
- Image **Structure**
- **Harris Corner** Detection

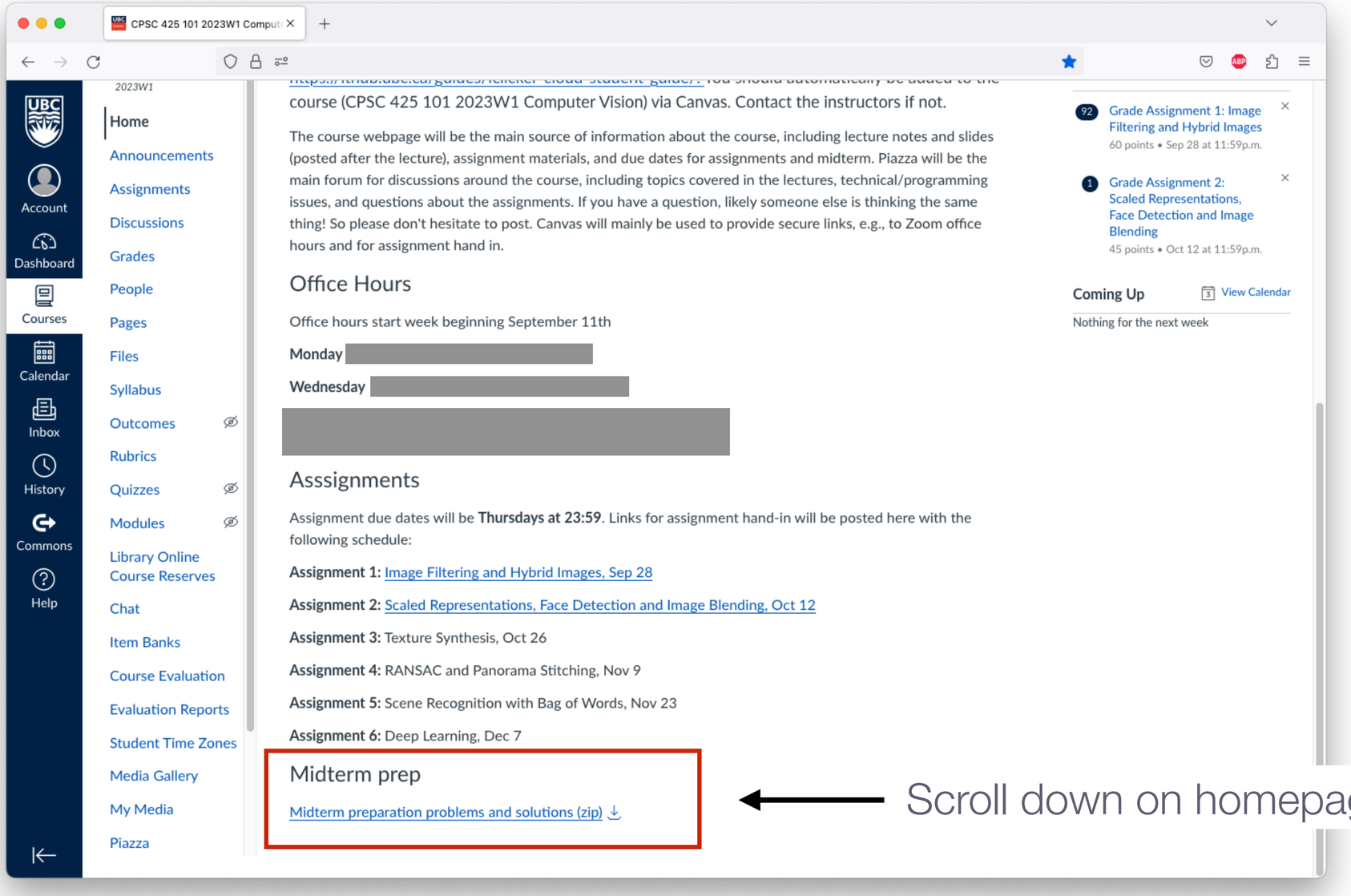
Readings:

- **Today's** Lecture: Szeliski 7.1-7.2, Forsyth & Ponce 5.3.0 - 5.3.1

Reminders:

- **Assignment 2**: Scaled Representations, Face Detection and Image Blending (due **Oct 12** 23:59)
- **Midterm**: **October 19th 5pm** in class, 75 minutes, closed book

Midterm Example Questions + Solutions

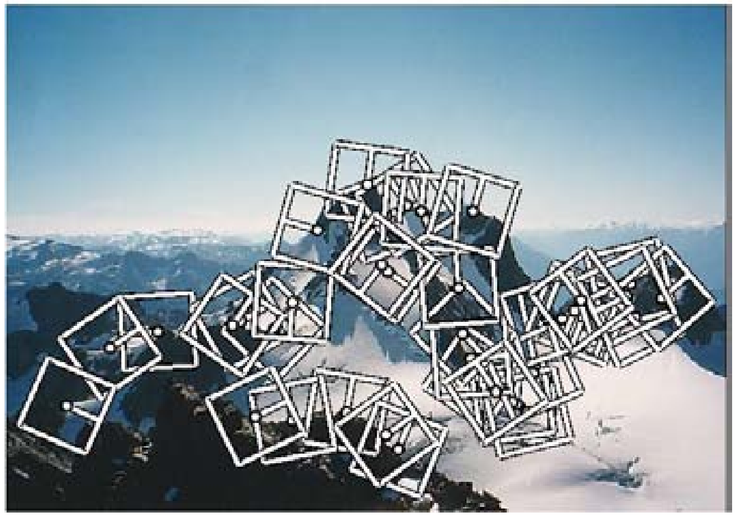


Scroll down on homepage on Canvas

Correspondence Problem

- A basic problem in Computer Vision is to establish matches (correspondences) between images
- This has **many** applications: rigid/non-rigid tracking, object recognition, image registration, structure from motion, stereo...

Feature Detectors



Corners/Blobs

Regions

Edges

Straight Lines

Feature Descriptors

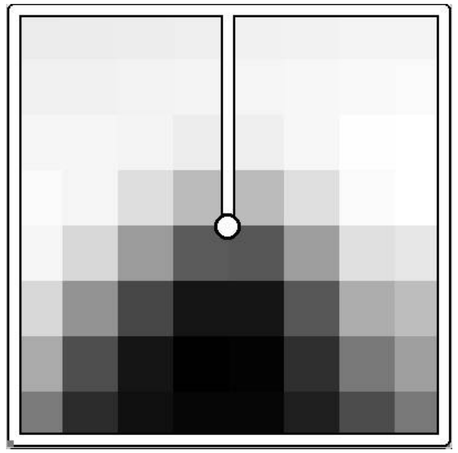
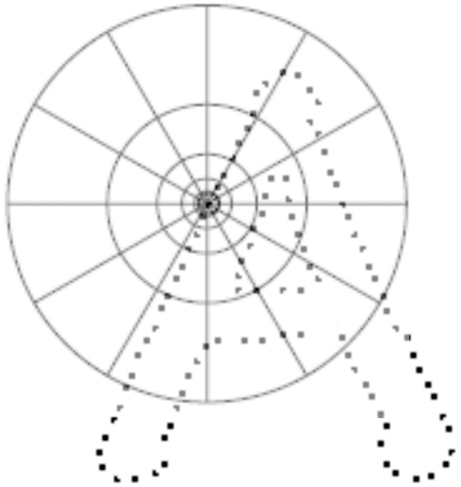
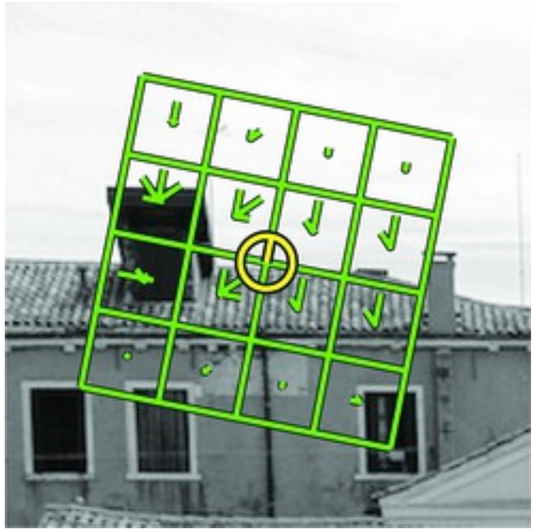


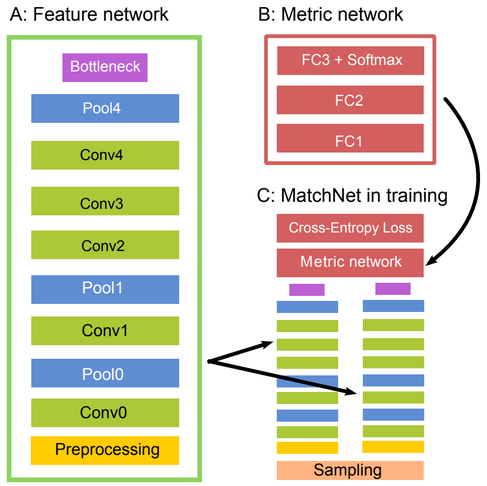
Image Patch



Shape Context



SIFT



Learned Descriptors

What is a **Good Feature Detector**?

Local: features are local, robust to occlusion and clutter

Accurate: precise localization

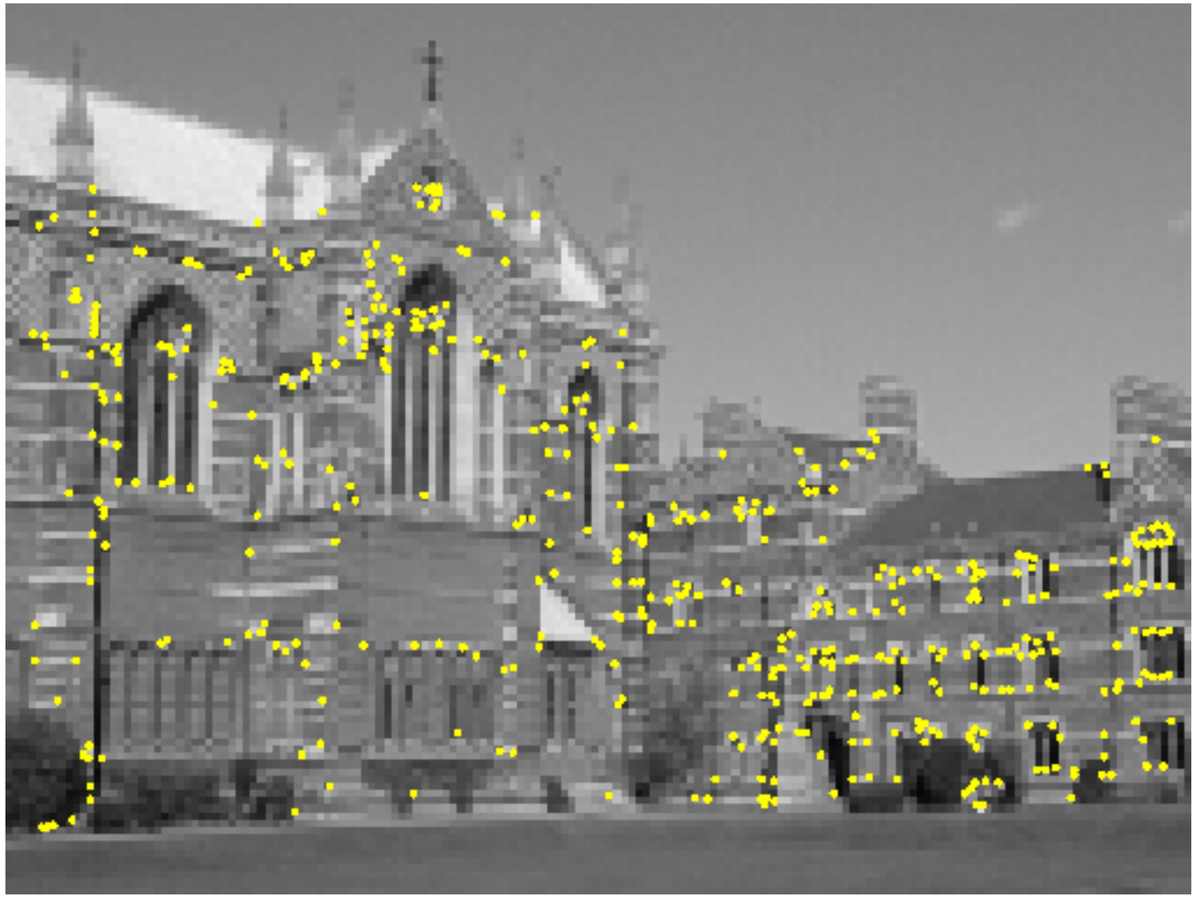
Robust: noise, blur, compression, etc. do not have a big impact on the feature.

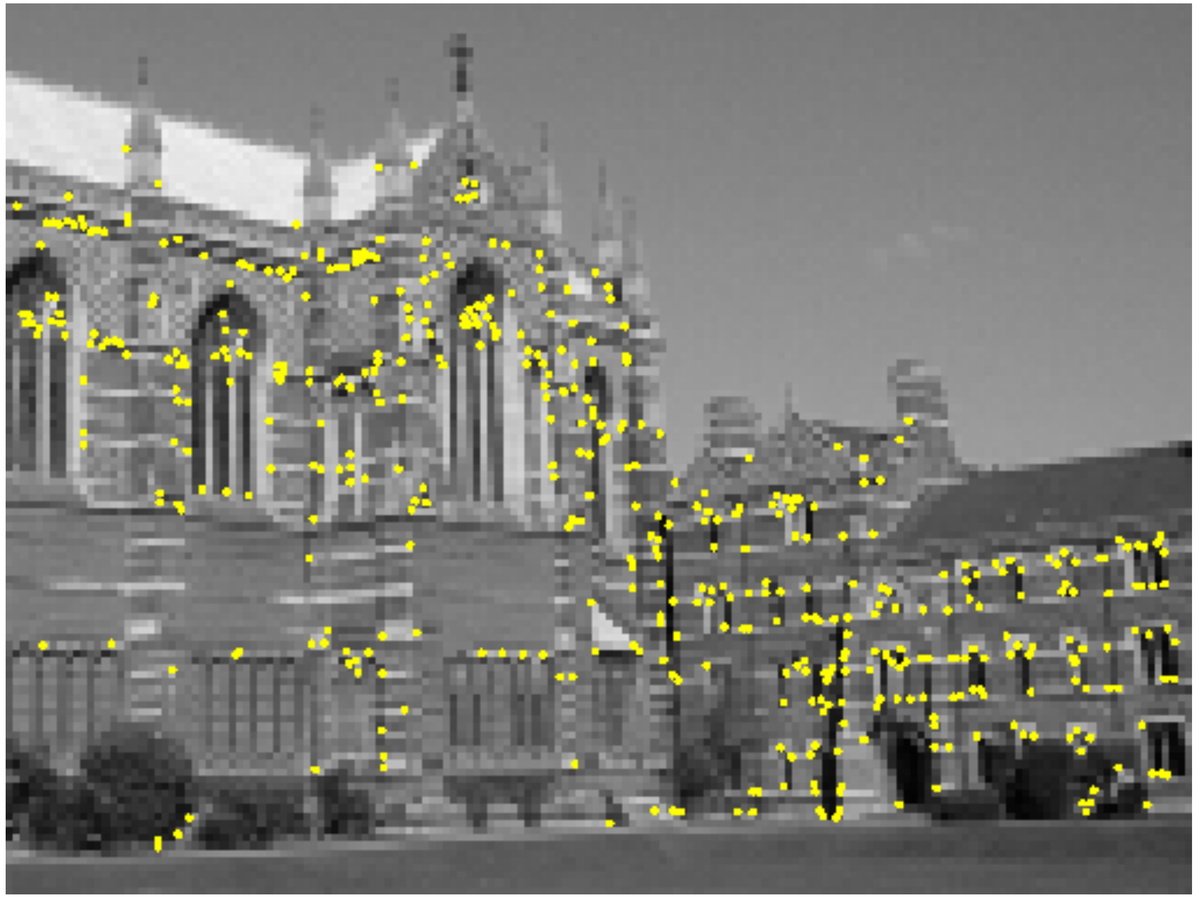
Distinctive: individual features can be easily matched

Efficient: close to real-time performance

Corner Detection

- e.g., Harris corners are peaks of a local similarity function



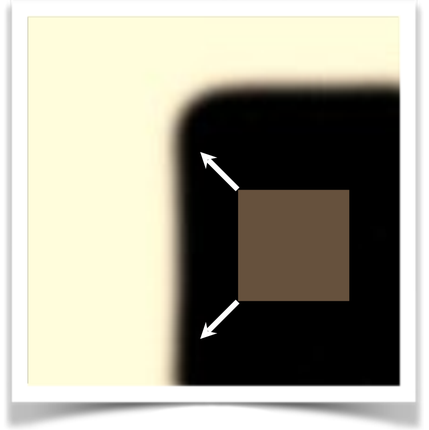


Why are corners **distinct**?

A corner can be **localized reliably**.

Thought experiment:

— Place a small window over a patch of constant image value.



“**flat**” region:

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

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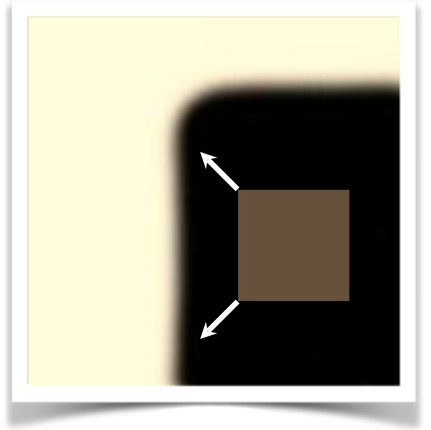
If you slide the window in any direction, the image in the window will not change.



"**flat**" region:
no change in all directions

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Why are corners **distinct**?

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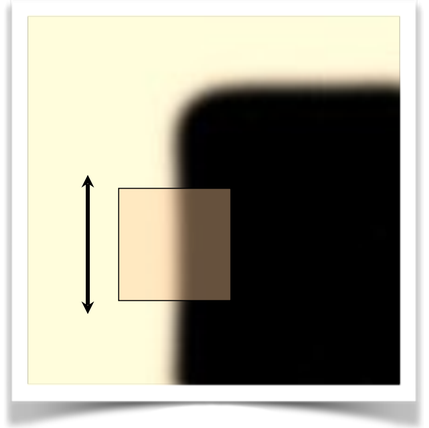
Thought experiment:

— Place a small window over a patch of constant image value.
If you slide the window in any direction, the image in the window will not change.

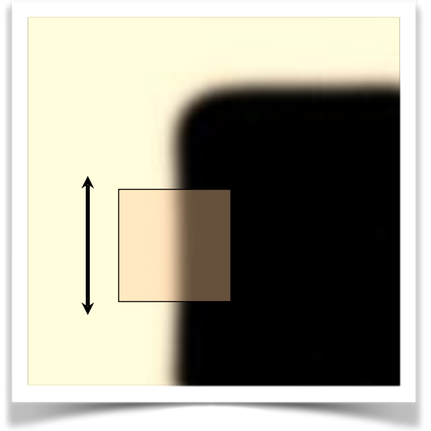
— Place a small window over an edge.



“**edge**”:

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Why are corners **distinct**?



“**edge**”:
no change along
the edge direction

A corner can be **localized reliably**.

Thought experiment:

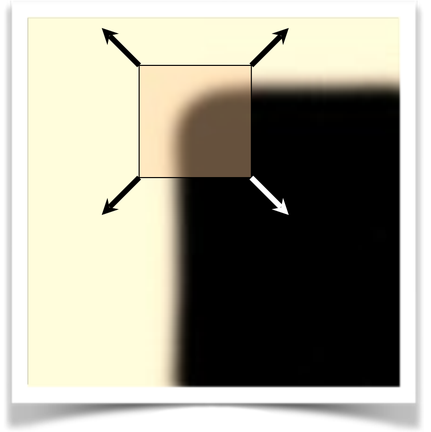
— Place a small window over a patch of constant image value. If you slide the window in any direction, the image in the window will not change.

— Place a small window over an edge. If you slide the window in the direction of the edge, the image in the window will not change

→ Cannot estimate location along an edge (a.k.a., **aperture** problem)

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Why are corners **distinct**?



“**corner**”:

A corner can be **localized reliably**.

Thought experiment:

— Place a small window over a patch of constant image value. If you slide the window in any direction, the image in the window will not change.

— Place a small window over an edge. If you slide the window in the direction of the edge, the image in the window will not change

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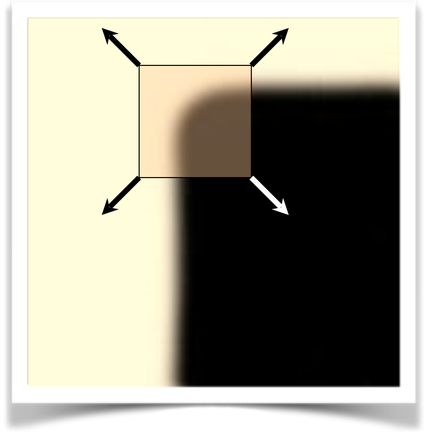
— Place a small window over a corner.

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Why are corners **distinct**?



"**corner**":
significant change
in all directions

A corner can be **localized reliably**.

Thought experiment:

— Place a small window over a patch of constant image value. If you slide the window in any direction, the image in the window will not change.

— Place a small window over an edge. If you slide the window in the direction of the edge, the image in the window will not change

→ Cannot estimate location along an edge (a.k.a., **aperture** problem)

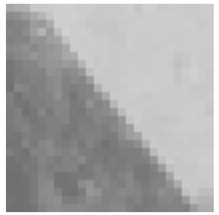
— Place a small window over a corner. If you slide the window in any direction, the image in the window changes.

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

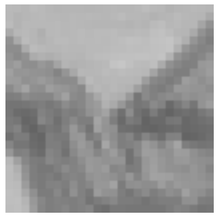
Image Structure

- What kind of structures are present in the image locally?

0D Structure: not useful for matching



1D Structure: edge, can be localised in one direction, subject to the "aperture problem"

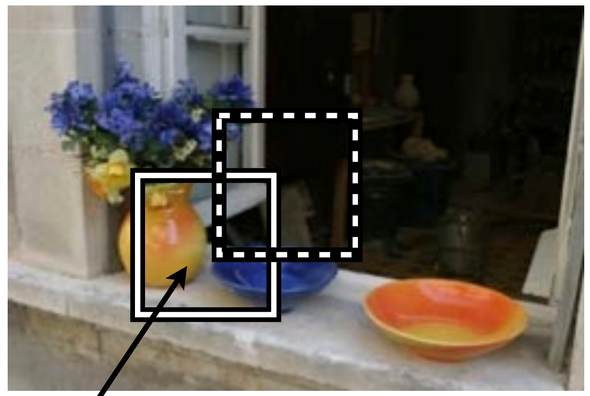


2D Structure: corner, or interest point, can be localised in both directions, good for matching

Edge detectors find contours (1D structure), **Corner** or **Interest point** detectors find points with 2D structure.

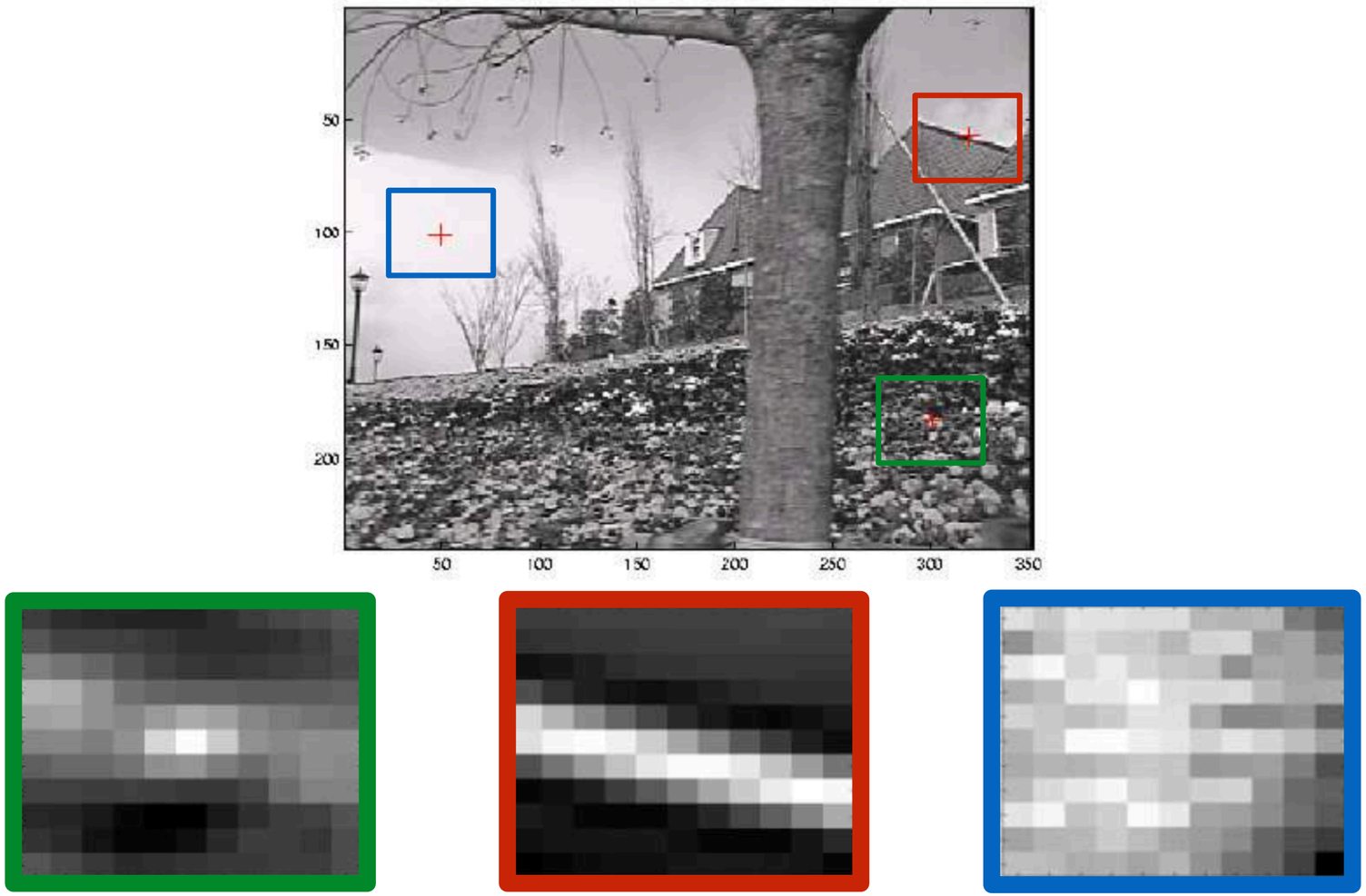
Local SSD Function

- Consider the sum squared difference (SSD) of a patch with its local neighbourhood



$$\text{SSD} = \sum_{\mathcal{R}} |I(\mathbf{x}) - I(\mathbf{x} + \Delta\mathbf{x})|^2$$

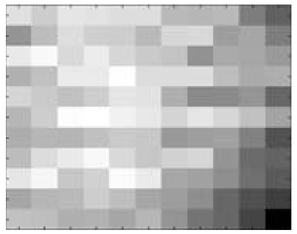
Image Structure

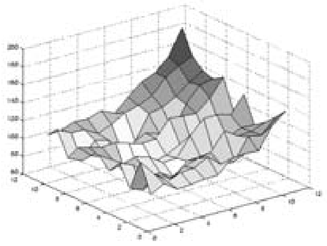


Szeliski, Figure 4.5

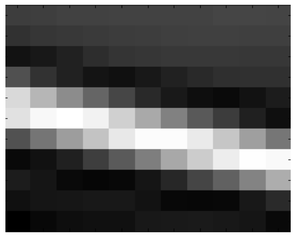
Local SSD Function

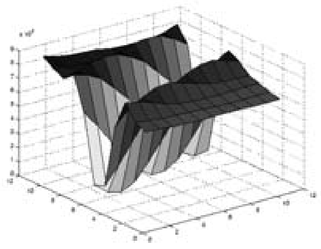
- Consider the local SSD function for different patches



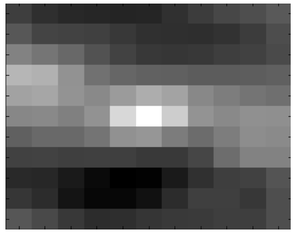


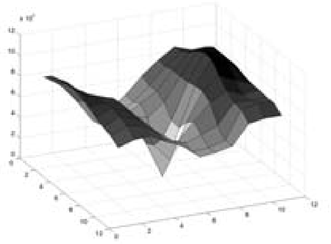
High similarity locally





High similarity along the edge

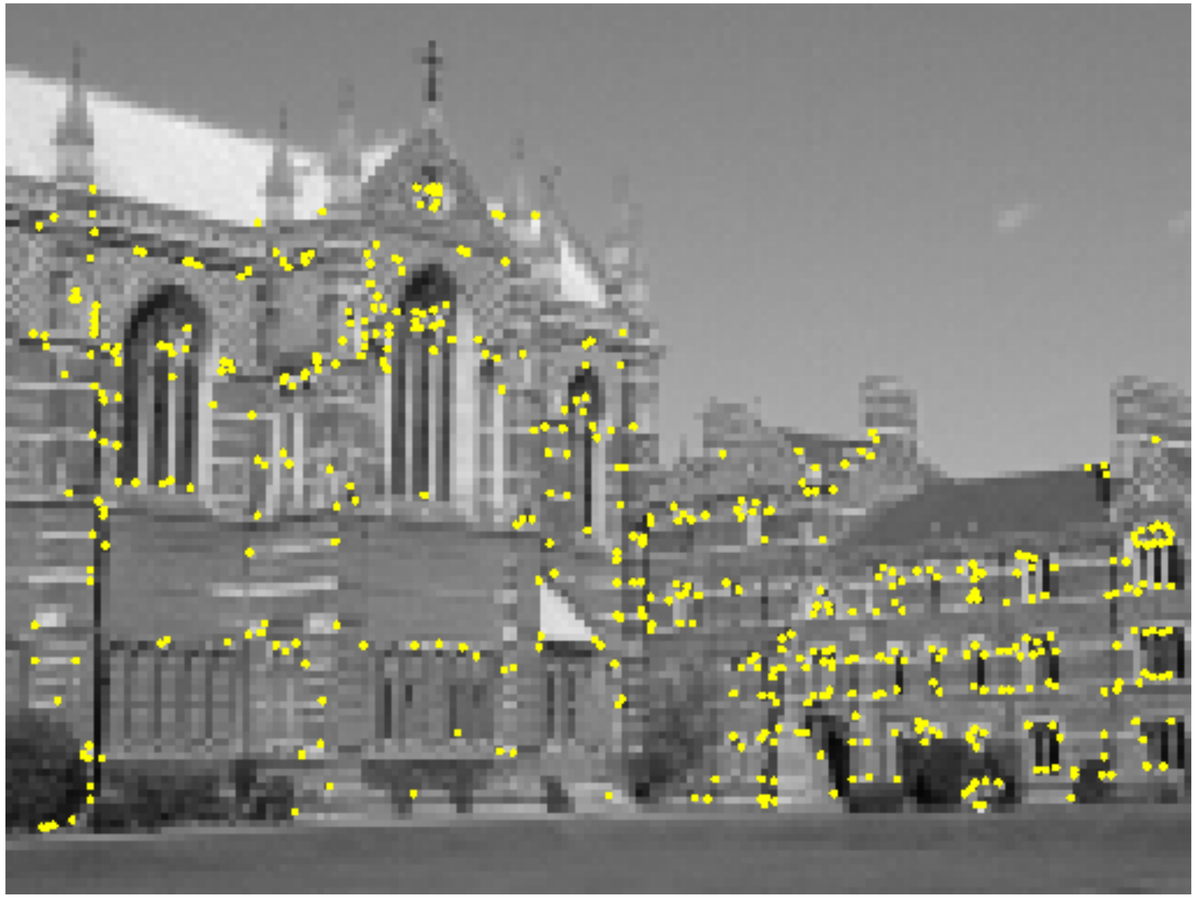


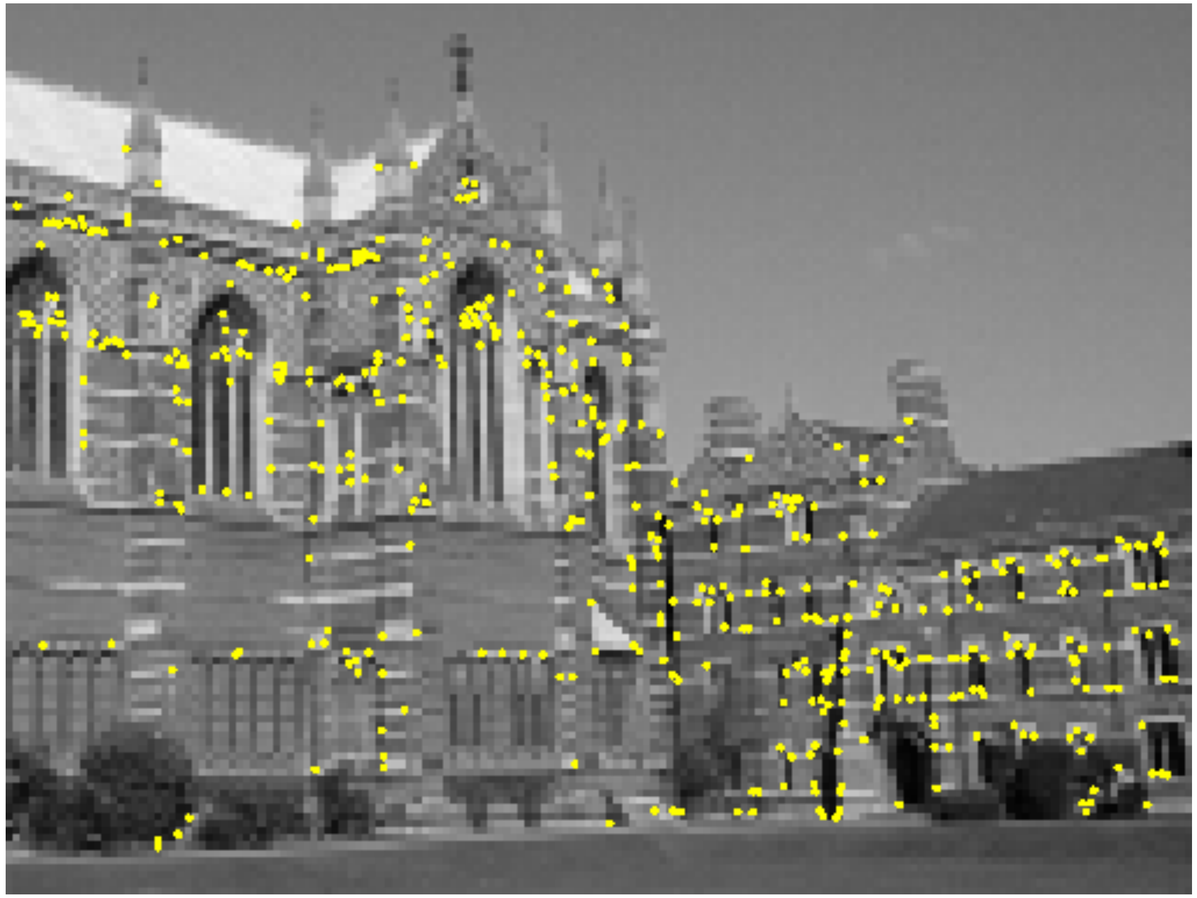


Clear peak in similarity function

Harris Corners

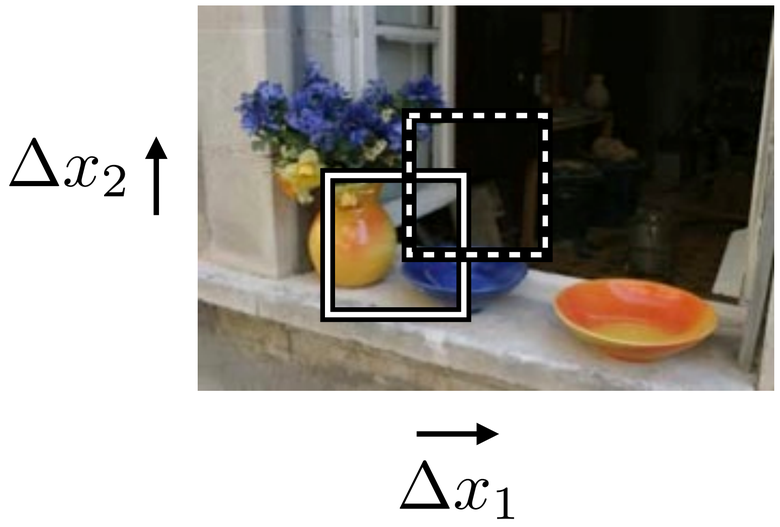
- Harris corners are peaks of a local similarity function





Harris Corners

- We will use a first order approximation to the local SSD function

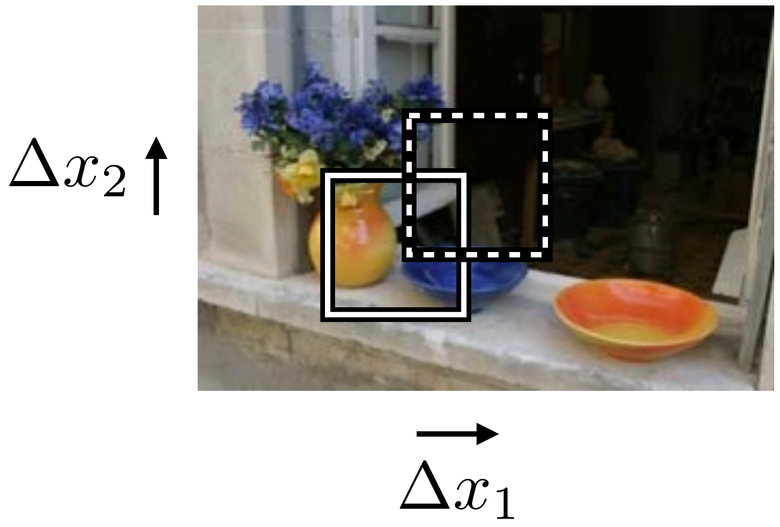


$$\text{SSD} = \sum_{\mathcal{R}} |I(\mathbf{x}) - I(\mathbf{x} + \Delta\mathbf{x})|^2$$

10.1

Harris Corners

- We will use a first order approximation to the local SSD function



$$\text{SSD} = \sum_{\mathcal{R}} |I(\mathbf{x}) - I(\mathbf{x} + \Delta\mathbf{x})|^2$$

$$= \Delta\mathbf{x}^T \mathbf{H} \Delta\mathbf{x}$$

$$\mathbf{H} = \sum_{\mathcal{R}} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Compute the **covariance matrix** (a.k.a. 2nd moment matrix)

Sum over small region around the corner

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

Compute the **covariance matrix** (a.k.a. 2nd moment matrix)

Sum over small region around the corner

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

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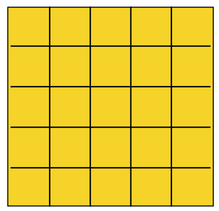
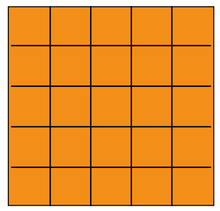
$$\sum_{p \in P} I_x I_y = \text{sum}(\; I_x = \frac{\partial I}{\partial x} \; .* \; I_y = \frac{\partial I}{\partial y} \;)$$

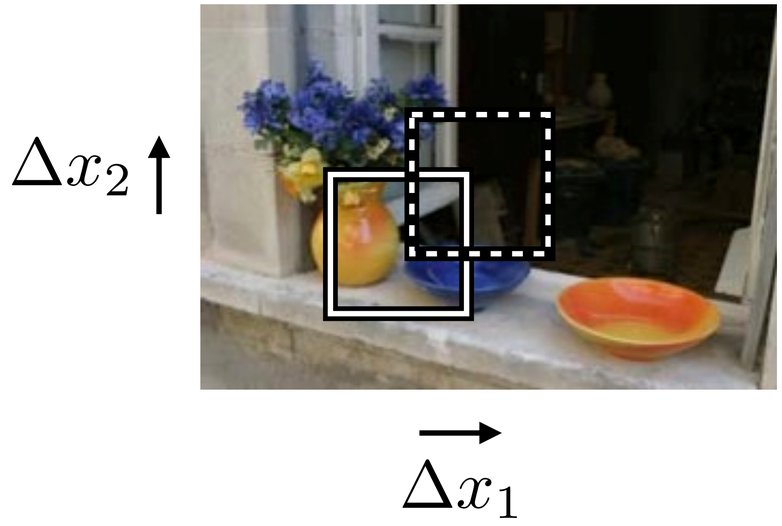


array of x gradients



array of y gradients

Harris Corners



$$\text{SSD} = \sum_{\mathcal{R}} |I(\mathbf{x}) - I(\mathbf{x} + \Delta\mathbf{x})|^2$$

$$= \Delta\mathbf{x}^T \mathbf{H} \Delta\mathbf{x}$$

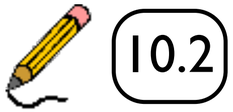
$$\mathbf{H} = \sum_{\mathcal{R}} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

SSD function must be large **for all shifts** $\Delta\mathbf{x}$ for a corner / 2D structure

This implies that **both eigenvalues of** $\mathbf{H}$ must be **large**

Note that $\mathbf{H}$ is a **2x2 matrix**

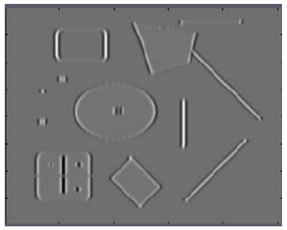
Recap: Computing **Eigenvalues** and **Eigenvectors**



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Harris Corner Detection

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

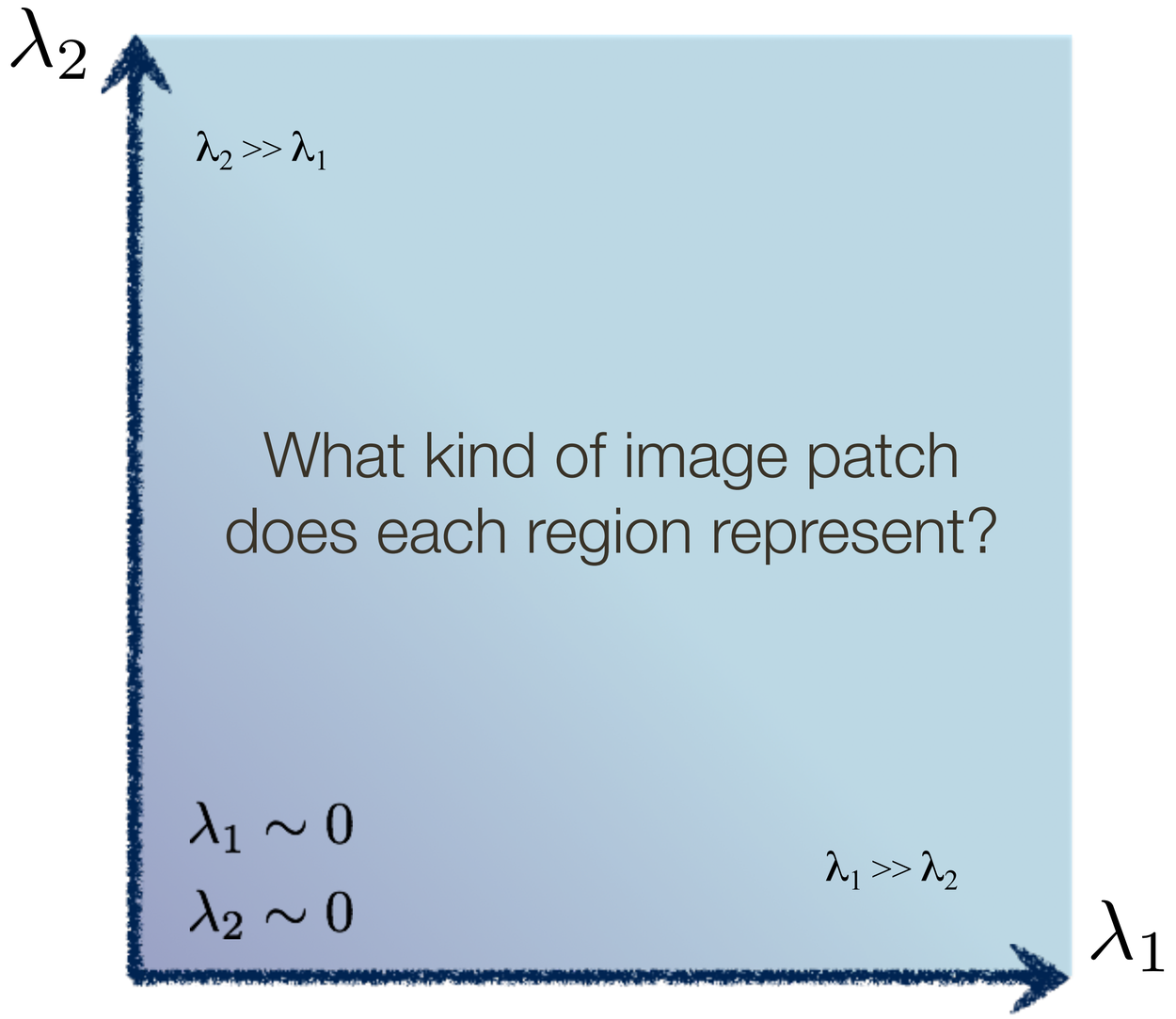


$$\begin{bmatrix} \sum_{p \in P} I_x I_x & \sum_{p \in P} I_x I_y \\ \sum_{p \in P} I_y I_x & \sum_{p \in P} I_y I_y \end{bmatrix}$$

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

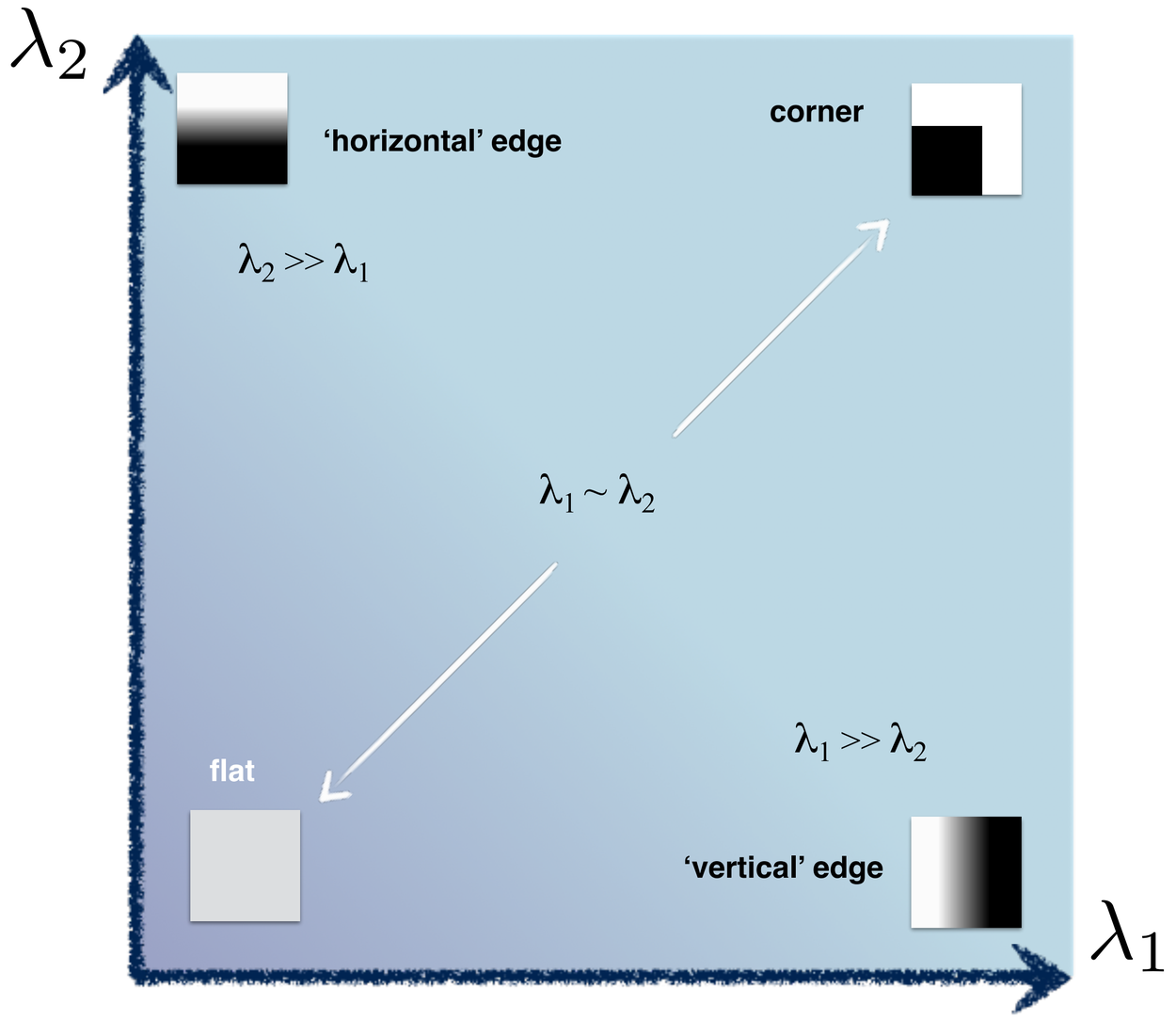
Slide Adopted: Ioannis (Yannis) Gkioulekas (CMU)

Interpreting **Eigenvalues**



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Interpreting **Eigenvalues**



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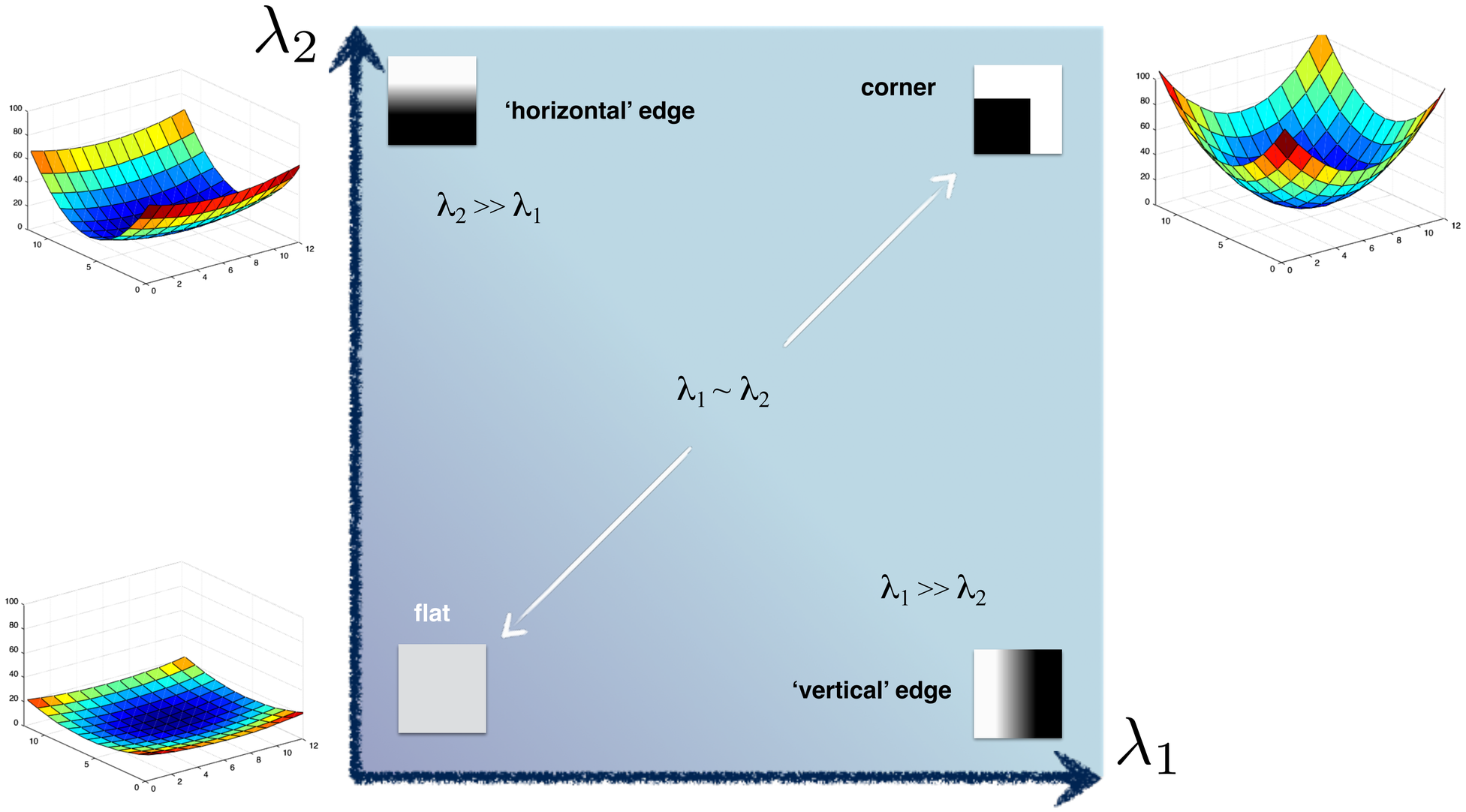
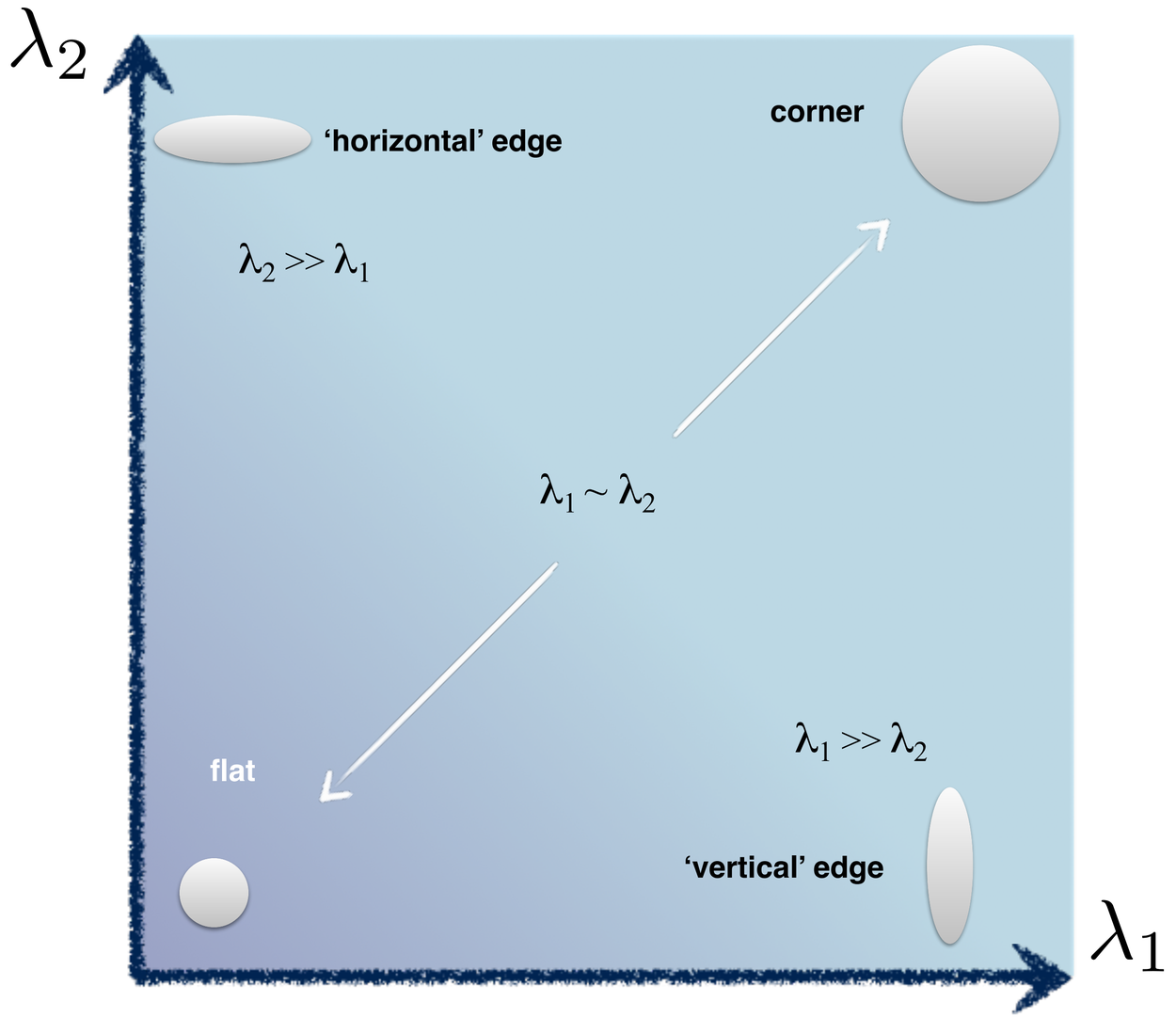
Interpreting **Eigenvalues**



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Interpreting **Eigenvalues**



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Threshold on Eigenvalues to **Detect Corners**

(a function of λ)

Harris & Stephens (1988)

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

Kanade & Tomasi (1994)

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

Nobel (1998)

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

10.3

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Example 1: Wagon Wheel (Harris Results)

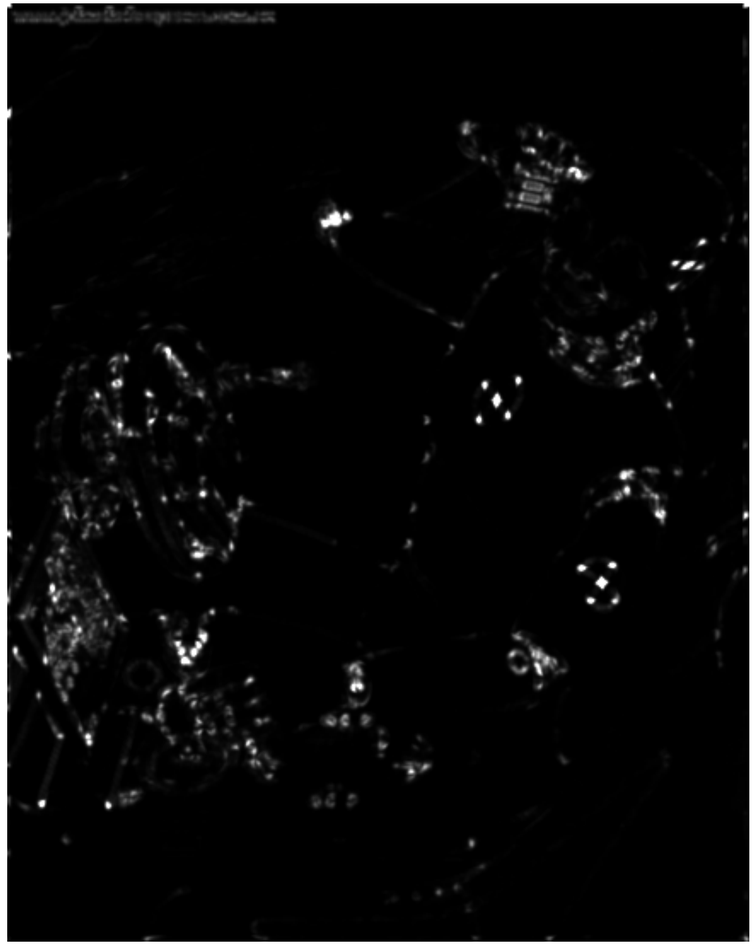
$\sigma = 1$ (219 points)

$\sigma = 2$ (155 points)

$\sigma = 3$ (110 points)

$\sigma = 4$ (87 points)

Example 2: Crash Test Dummy (Harris Result)



corner response image

$\sigma = 1$ (175 points)

Original Image Credit: John Shakespeare, Sydney Morning Herald

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**
- Compute Harris corner strength function $\det(C) - \kappa \mathrm{trace}^2(C)$
- Threshold corner strength function, optionally apply non-maximal suppression

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

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

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	

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

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

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

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

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

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:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

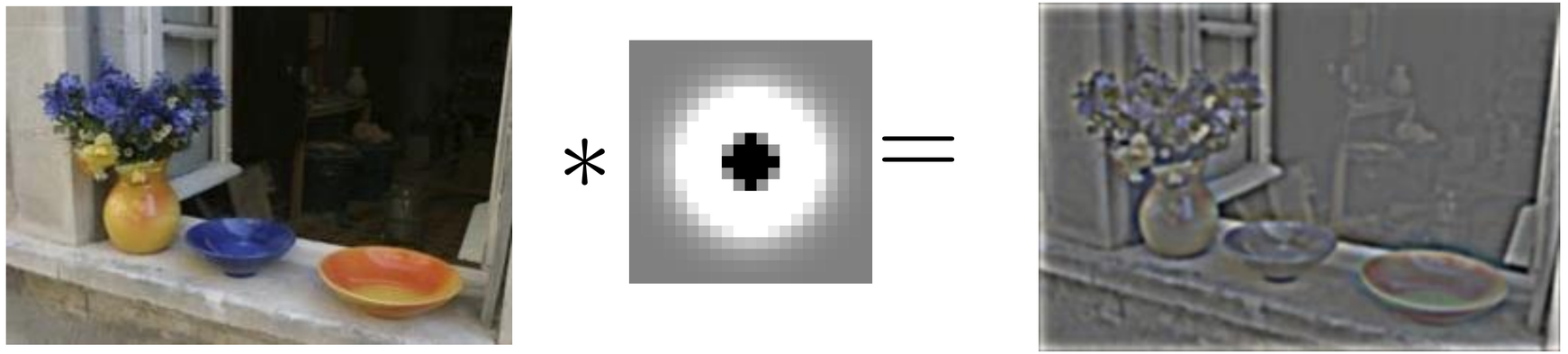
0	0	0	0	0	0	
-1	1	0	0	-1	1	
-1	0	0	0	1	0	
-1	0	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	
0	-1	0	0	1	0	

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

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

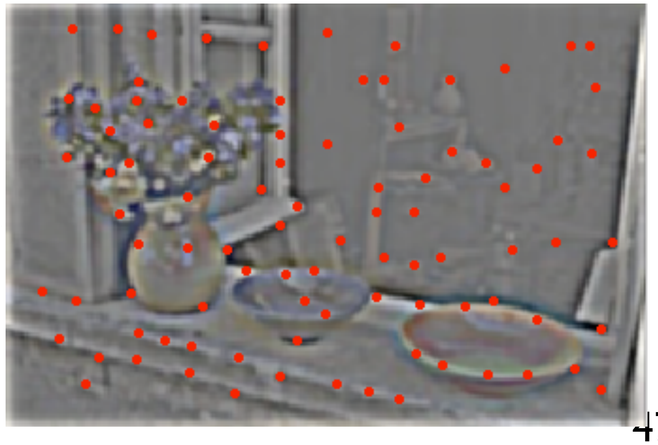
Difference of Gaussian

- DoG = centre-surround filter



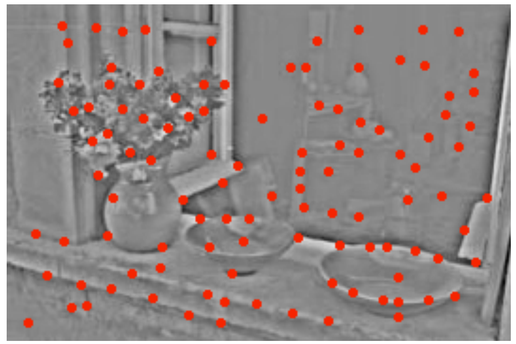
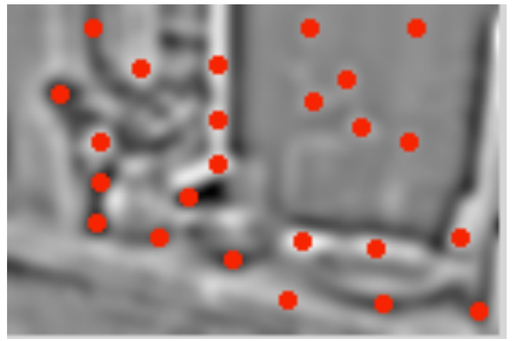
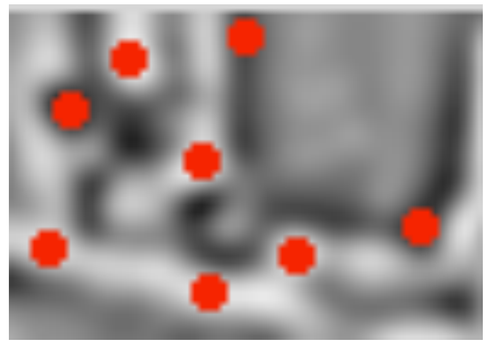
- Find local-maxima of the centre surround response

Non-maximal suppression:
These points are maxima in
a 10 pixel radius



Difference of Gaussian

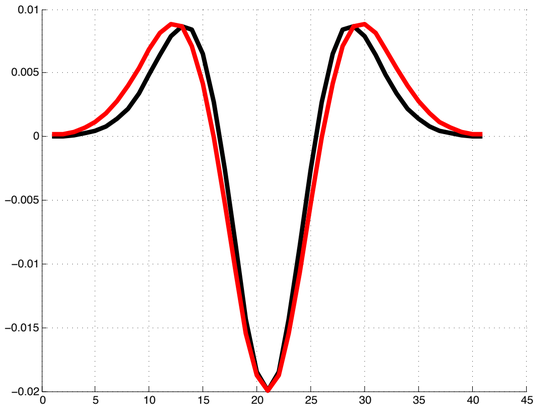
- DoG detects blobs at scale that depends on the Gaussian standard deviation(s)

Note: DOG ≈ Laplacian of Gaussian

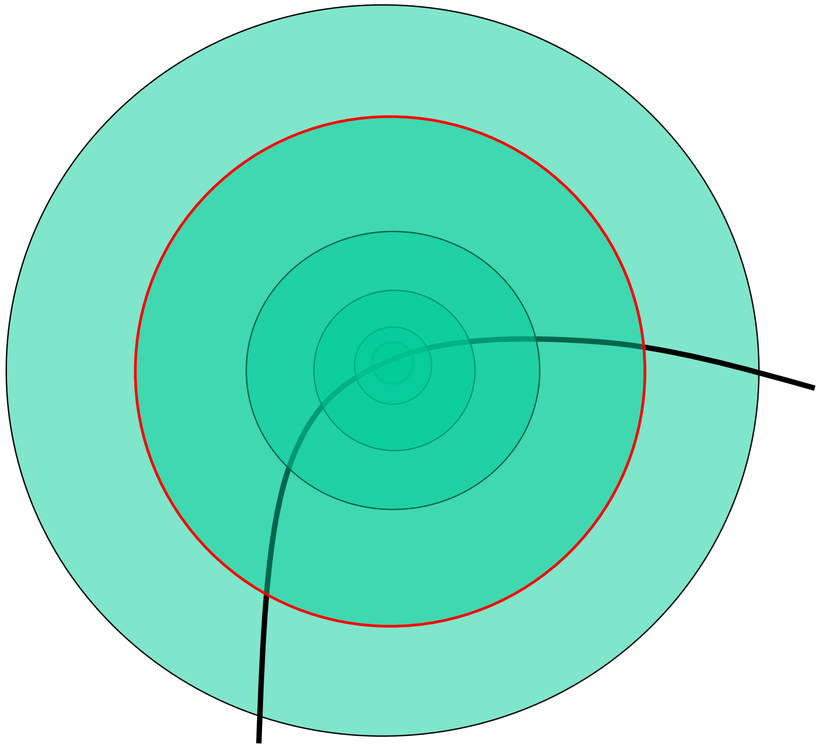
$$\text{red} = [1 \ -2 \ 1] * g(x;\ 5.0)$$

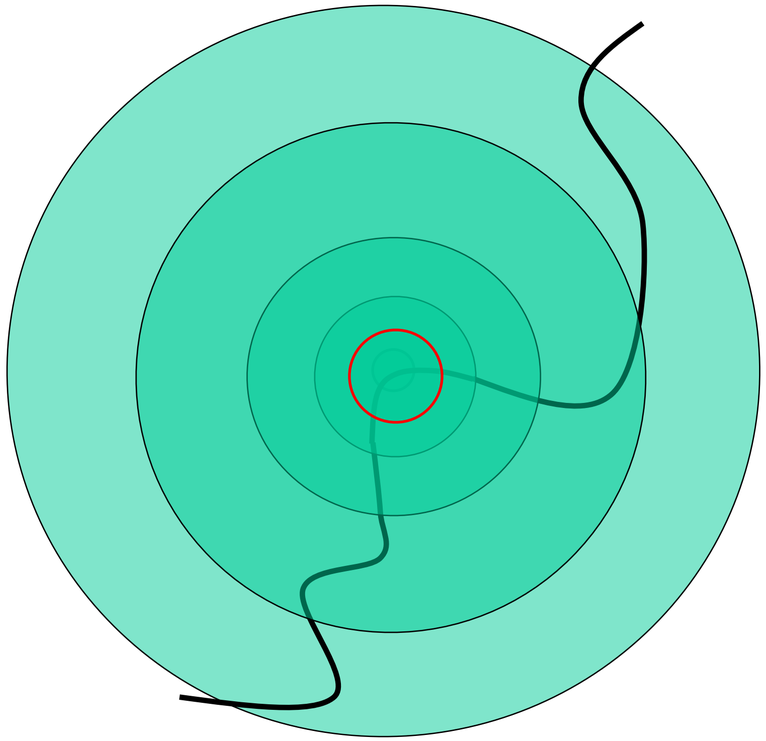
$$\text{black} = g(x;\ 5.0) - g(x;\ 4.0)$$



Scale Invariant Interest Point Detection

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





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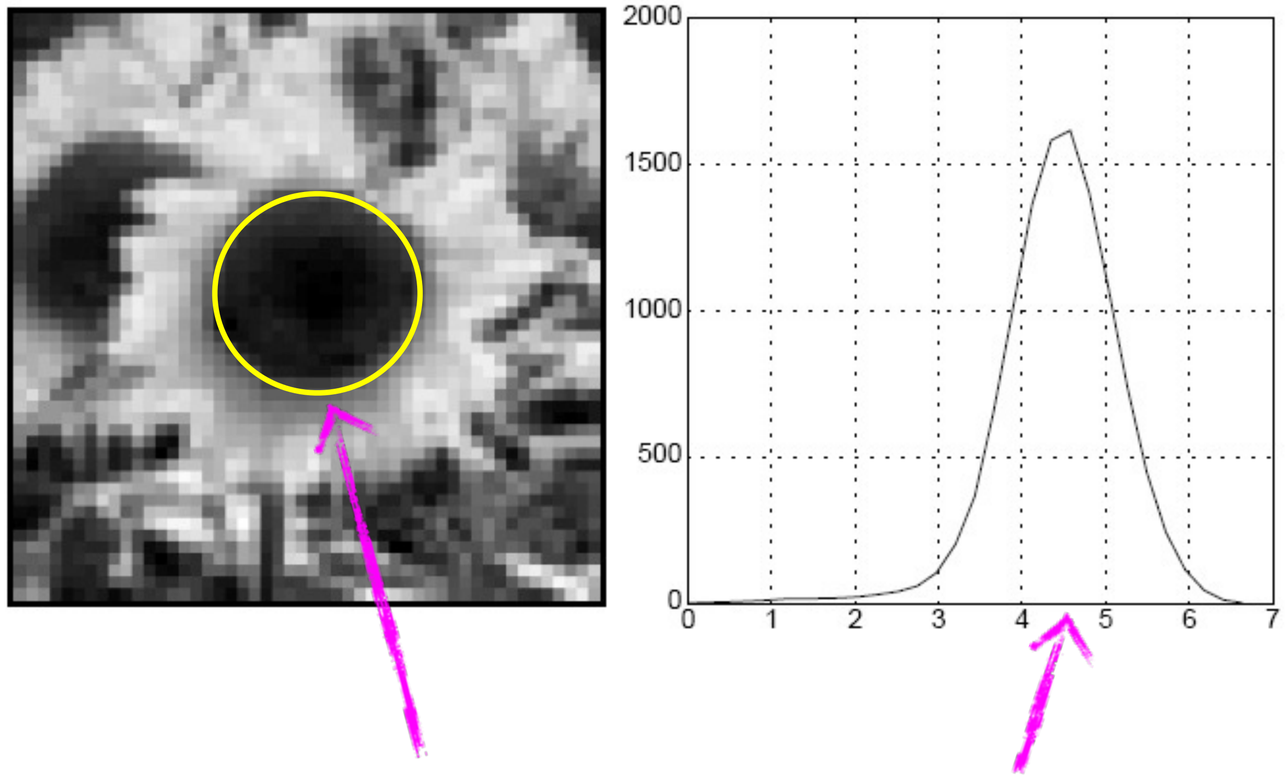
Characteristic Scale

characteristic scale - the scale that produces peak filter response



characteristic scale

we need to search over characteristic scales

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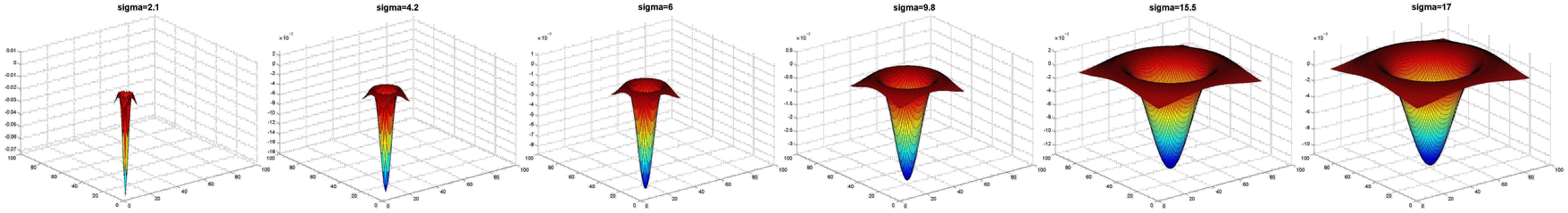
Applying **Laplacian** Filter at Different **Scales**



Full size

3/4 size

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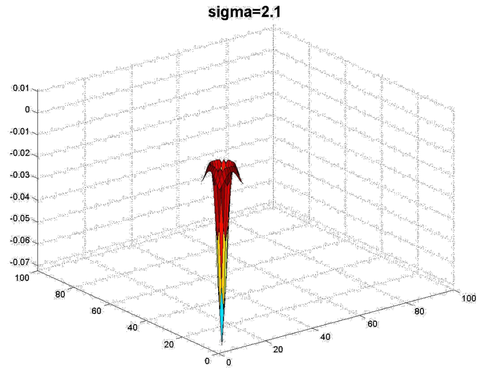
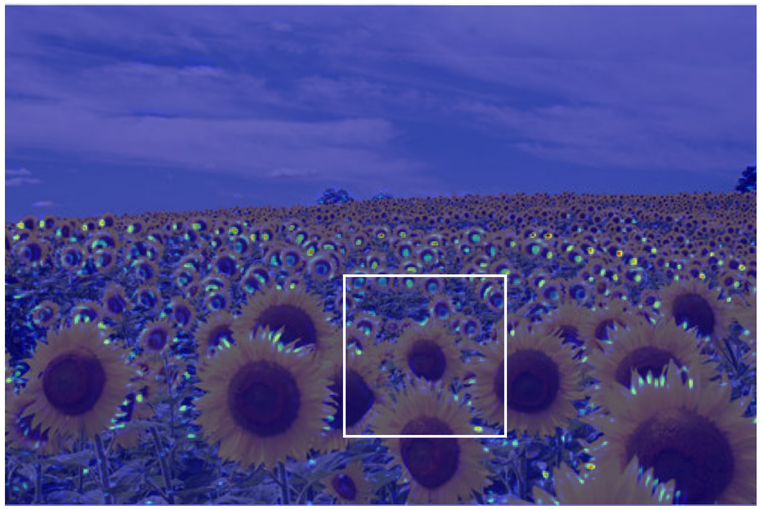
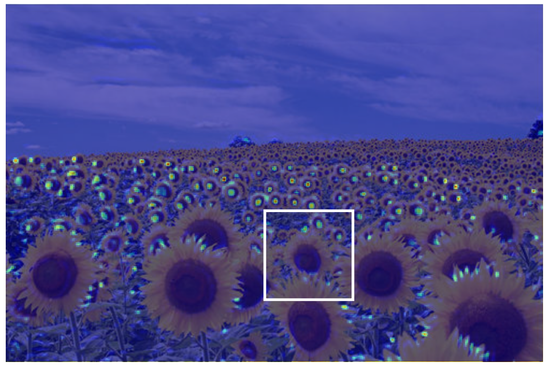
Applying **Laplacian** Filter at Different **Scales**







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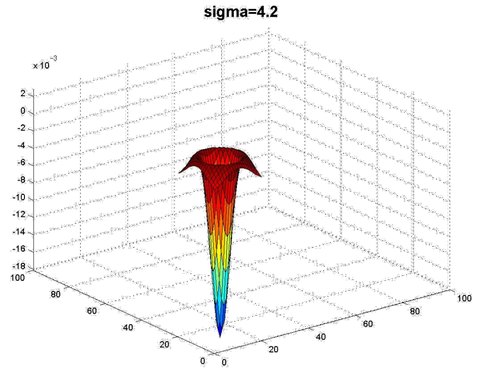
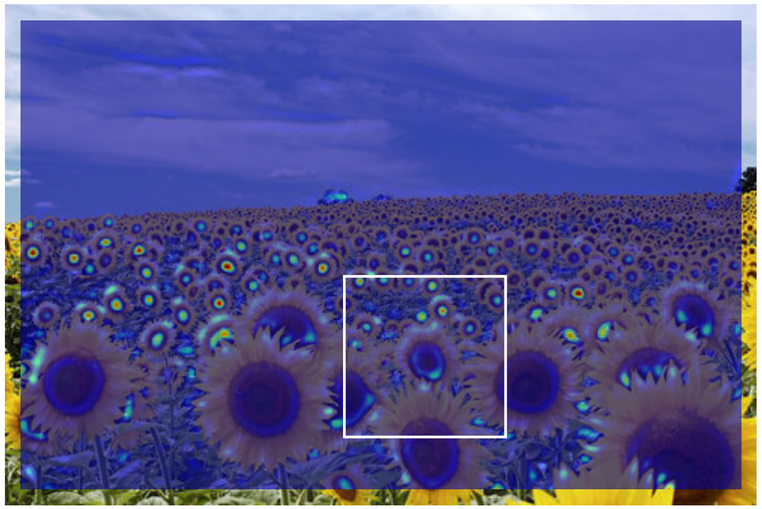
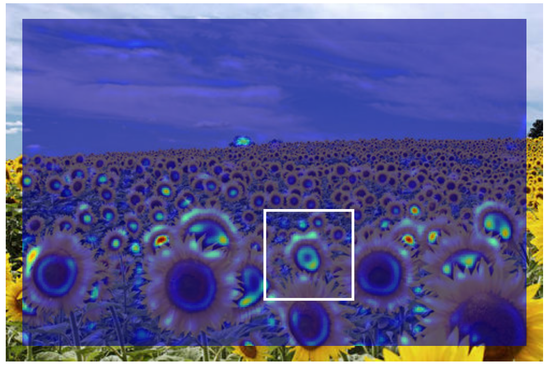
Applying **Laplacian** Filter at Different **Scales**







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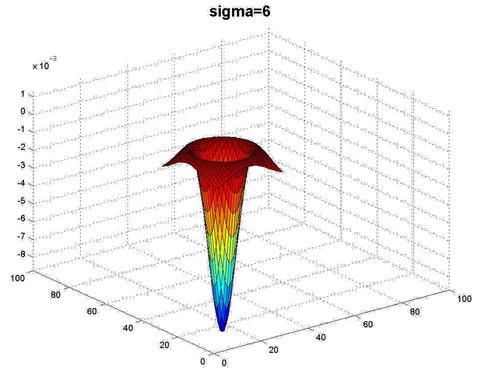
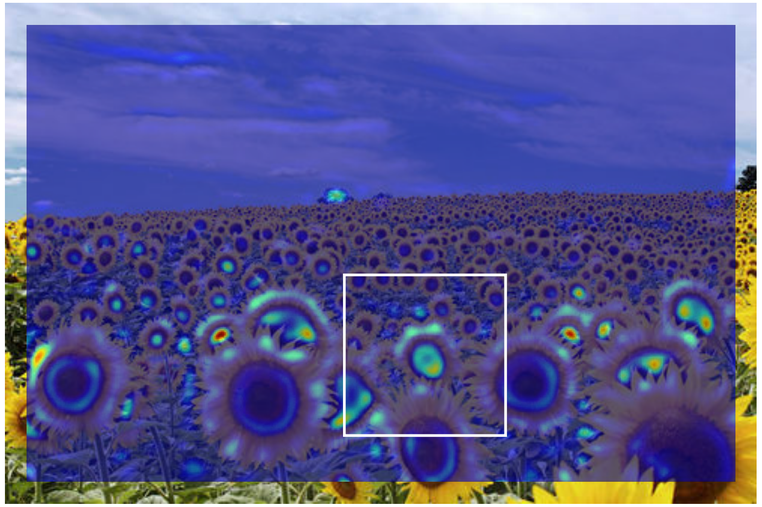
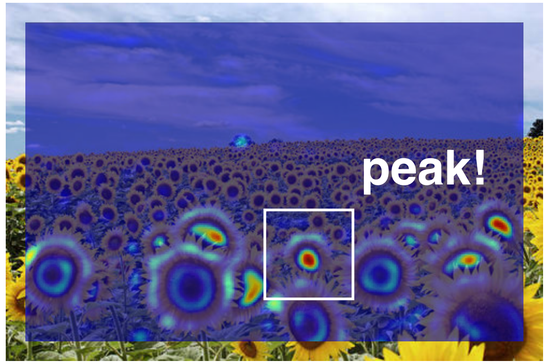
Applying **Laplacian** Filter at Different **Scales**







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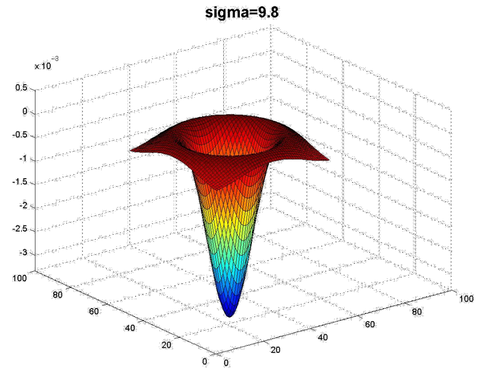
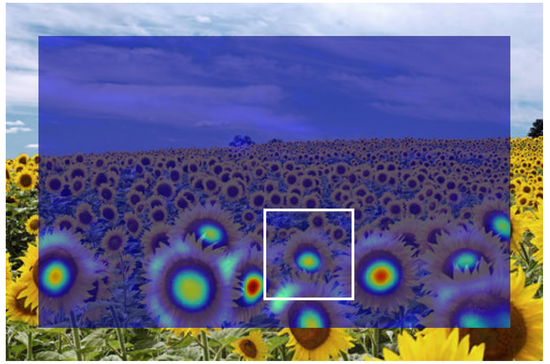
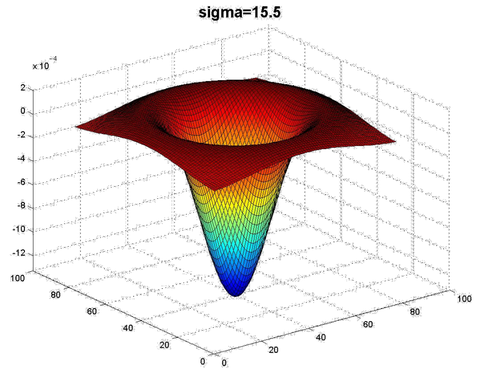
Applying **Laplacian** Filter at Different **Scales**

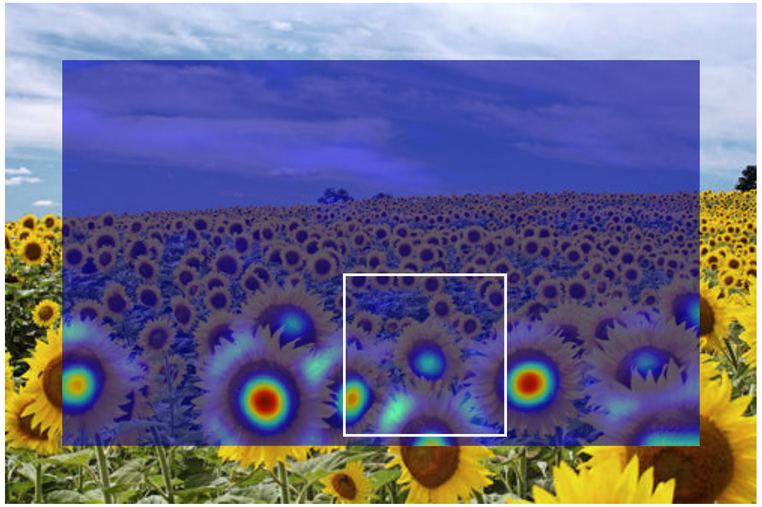


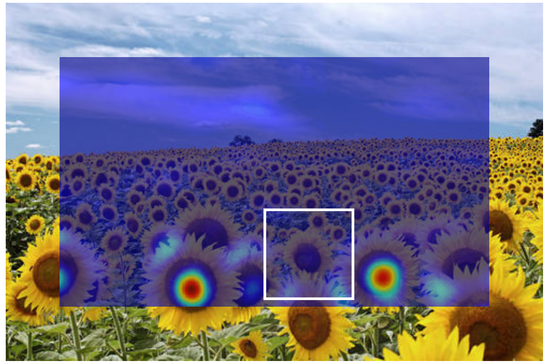


Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

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

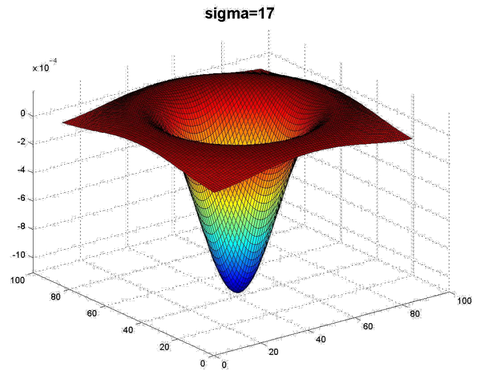


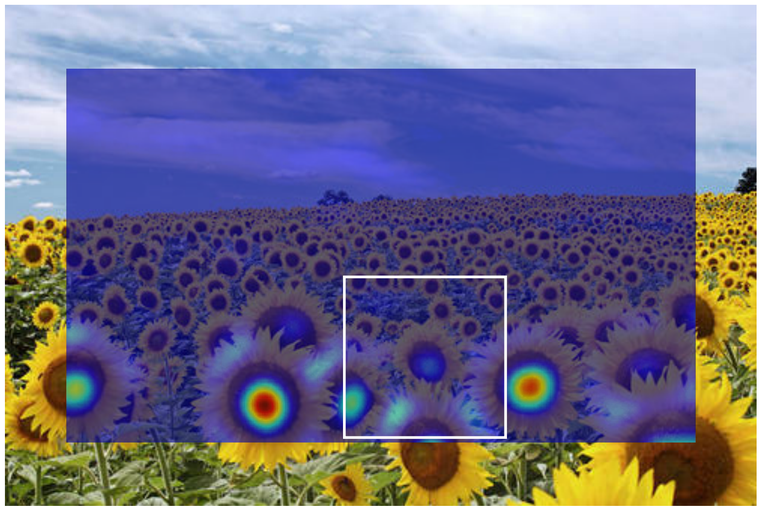


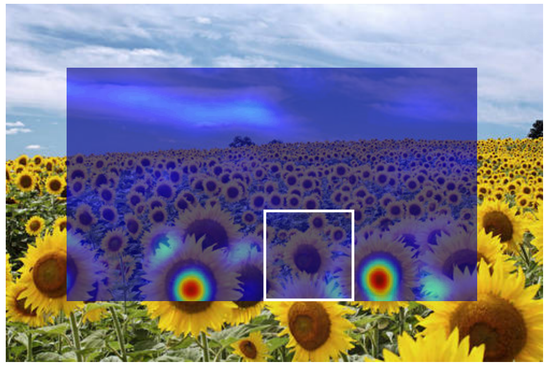


Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

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



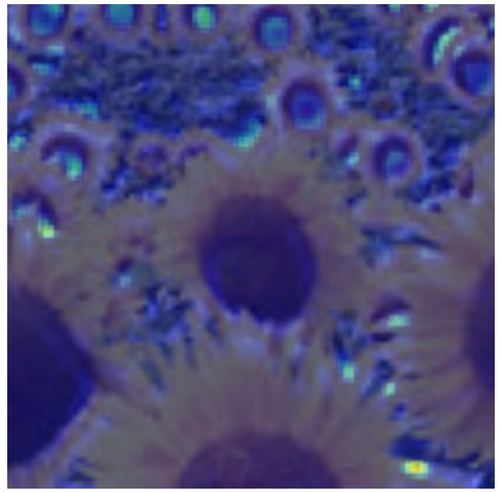




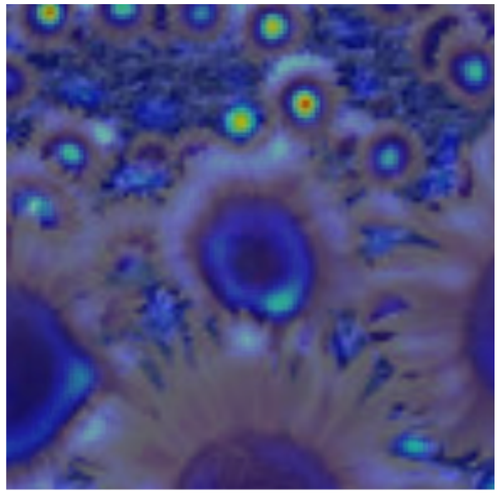
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

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

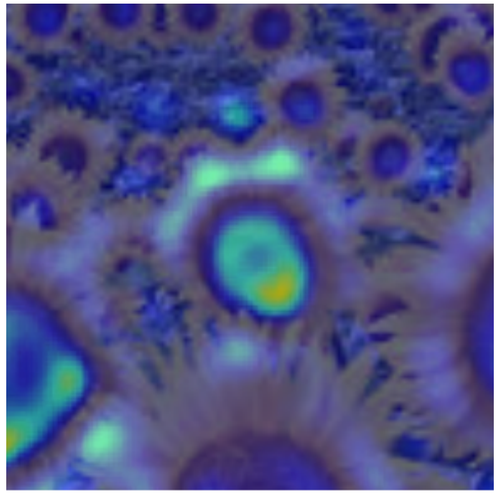
2.1



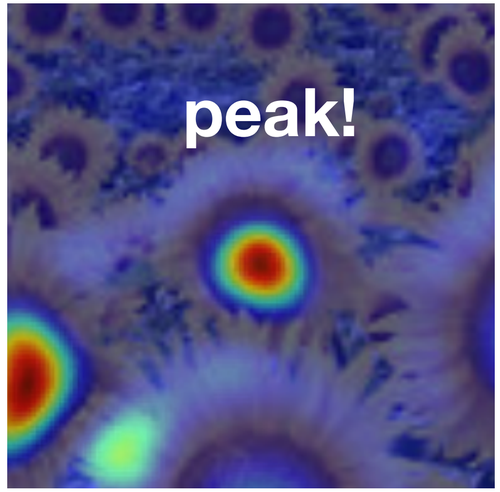
4.2



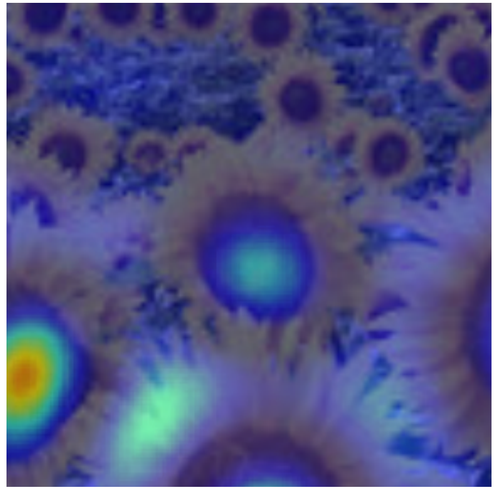
6.0



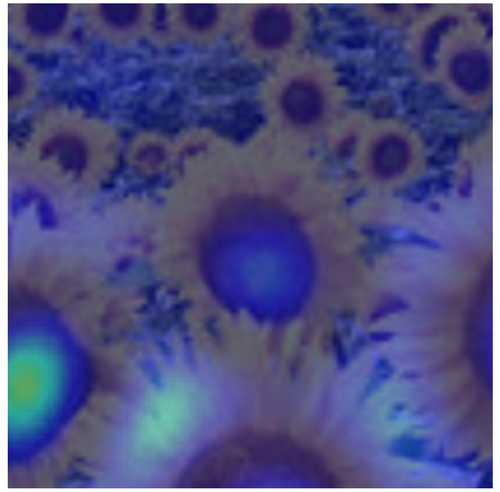
9.8



15.5

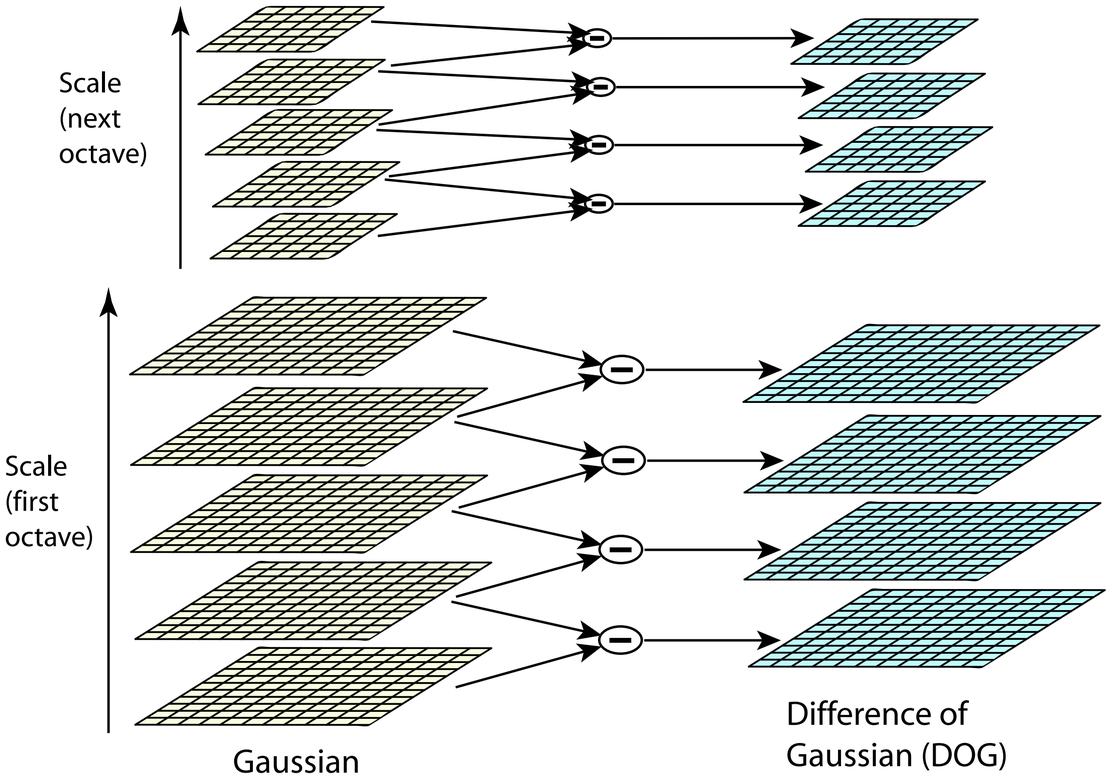


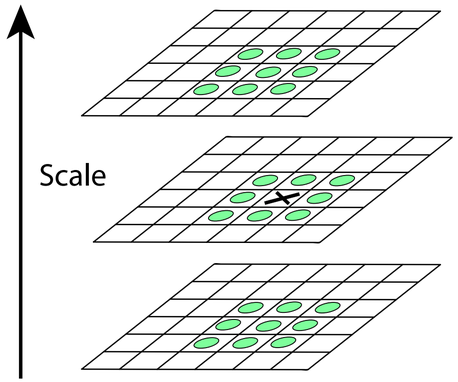
17.0



Scale Selection

- A DOG (Laplacian) Pyramid is formed with multiple scales per ocatve

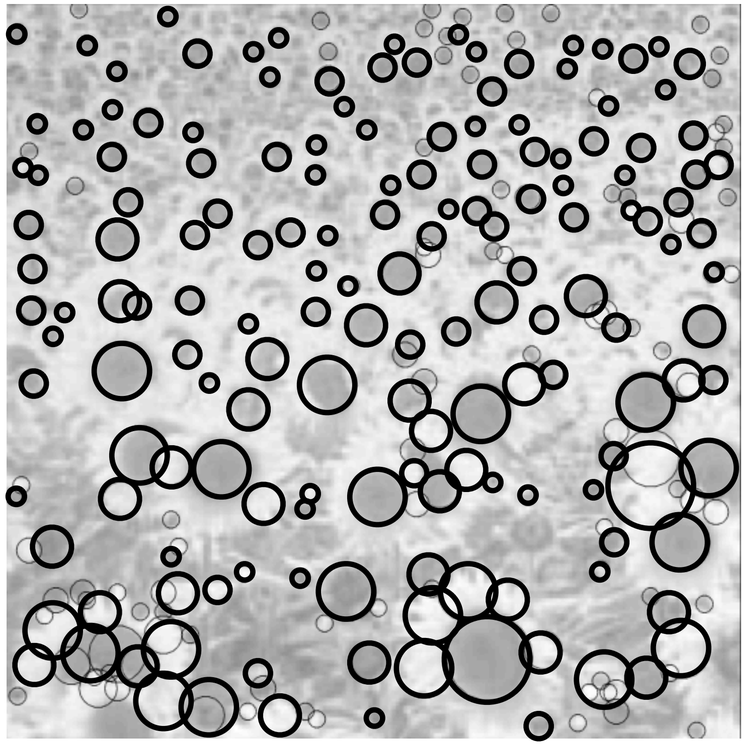


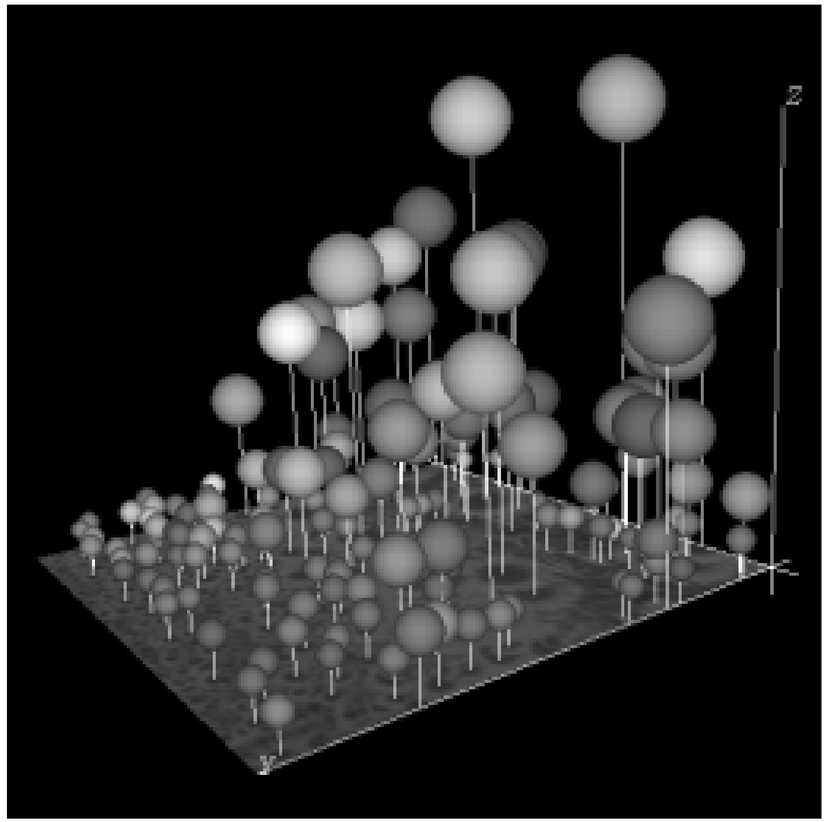


Detections are local maxima in a 3x3x3 scale-space window

Scale Selection

- Maximising the DOG function in scale as well as space performs scale selection





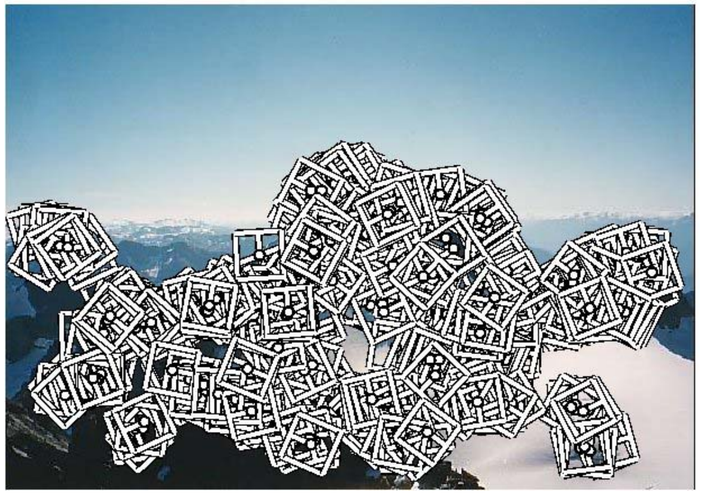
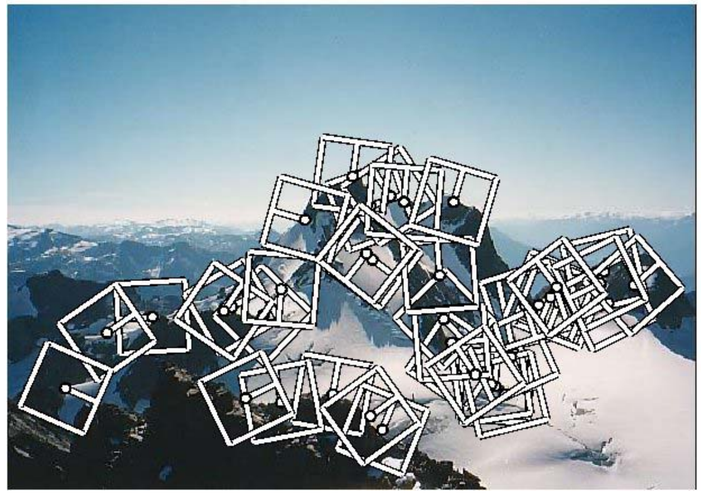
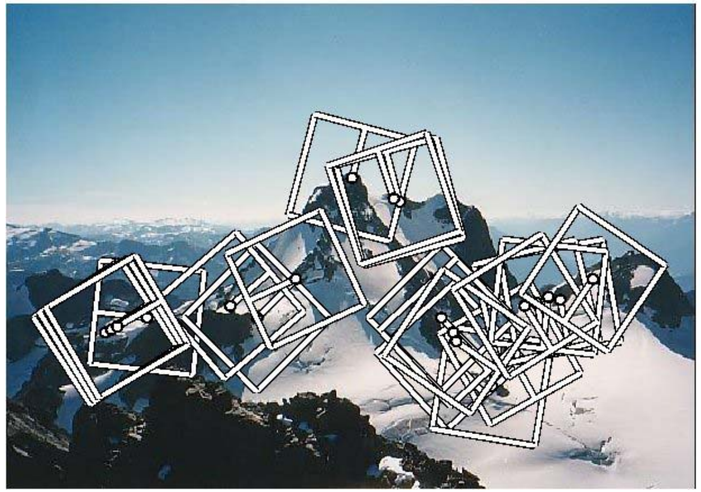
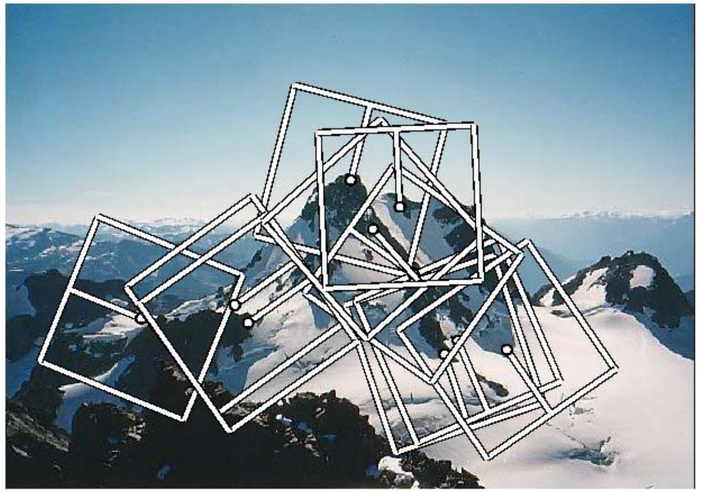
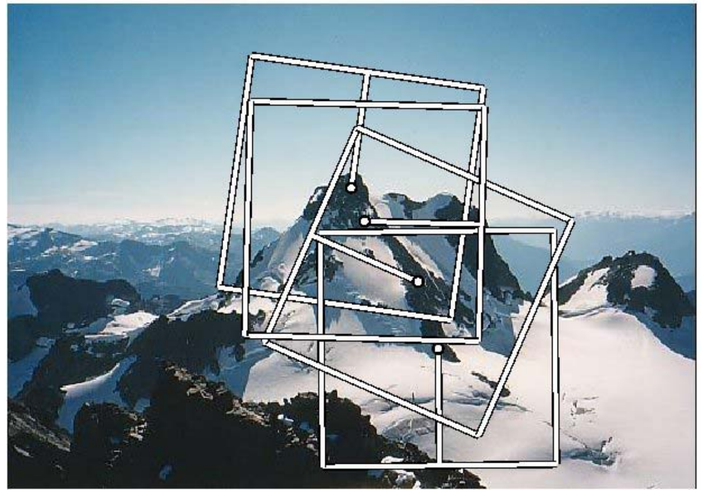
[T. Lindeberg]

Multi-Scale Harris Corners

```
For each level of the Gaussian pyramid
    compute Harris feature response

For each level of the Gaussian pyramid
    if local maximum and cross-scale
    save scale and location of feature (x, y, s)
```

Multi-Scale Harris Corners

Summary

Edges are useful image features for many applications, but suffer from the aperture problem

Canny Edge detector combines edge filtering with linking and hysteresis steps

Corners / Interest Points have 2D structure and are useful for correspondence

Harris corners are minima of a local SSD function

DoG maxima can be reliably located in scale-space and are useful as interest points

Menu for Today

Topics:

- Corner **Detection**
- Image **Structure**
- **Harris Corner** Detection

Readings:

- **Today's** Lecture: Szeliski 7.1-7.2, Forsyth & Ponce 5.3.0 - 5.3.1

Reminders:

- **Assignment 2**: Scaled Representations, Face Detection and Image Blending (due **Oct 12** 23:59)
- **Midterm**: **October 19th 5pm** in class, 75 minutes, closed book