Local Image Features

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Last few lectures!

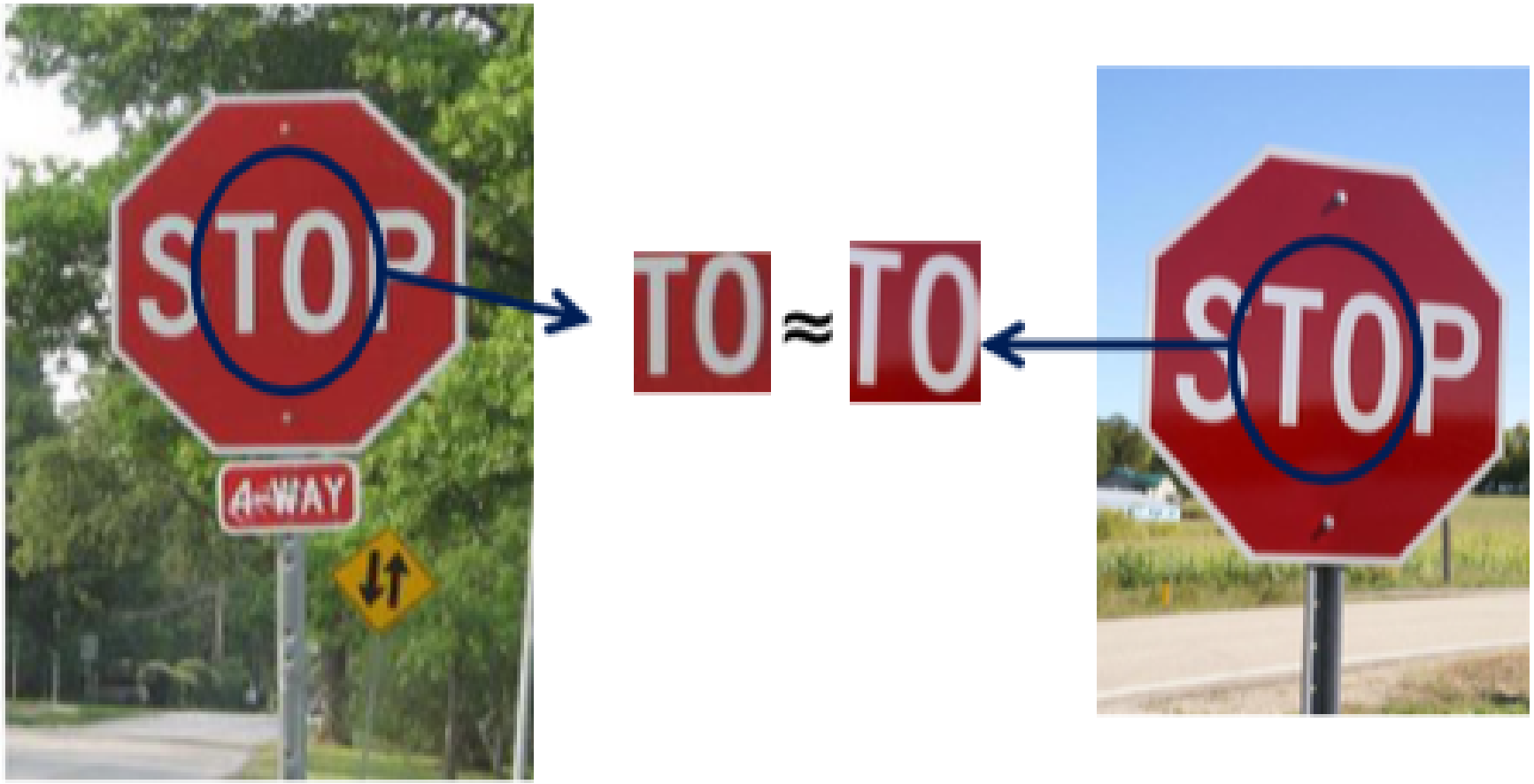
- Image filtering:
  - Smooth/sharpen based upon different kernel
- Template matching:
  - Filter kernels "look like" the features they enhance
  - Use normalized cross-correlation to "match" kernel response
- Image gradients:
  - Can convolve using several finite-difference kernels
  - Noise is amplified in image derivative
  - Smooth with Gaussian $\Longrightarrow$ take a derivative of Gaussian kernel and then convolve to get image derivative
- Edge detection:
  - Magnitude of the image gradient "enhances" large deviations in intensity (edges)
  - Edge direction is determine by the direction of the gradient
  - Use non-maximum suppression and hysteresis thresholding to create a binary edge map
  - Can use other techniques to "pull out" interesting features (Hough transform)

Today! (and next few lectures)

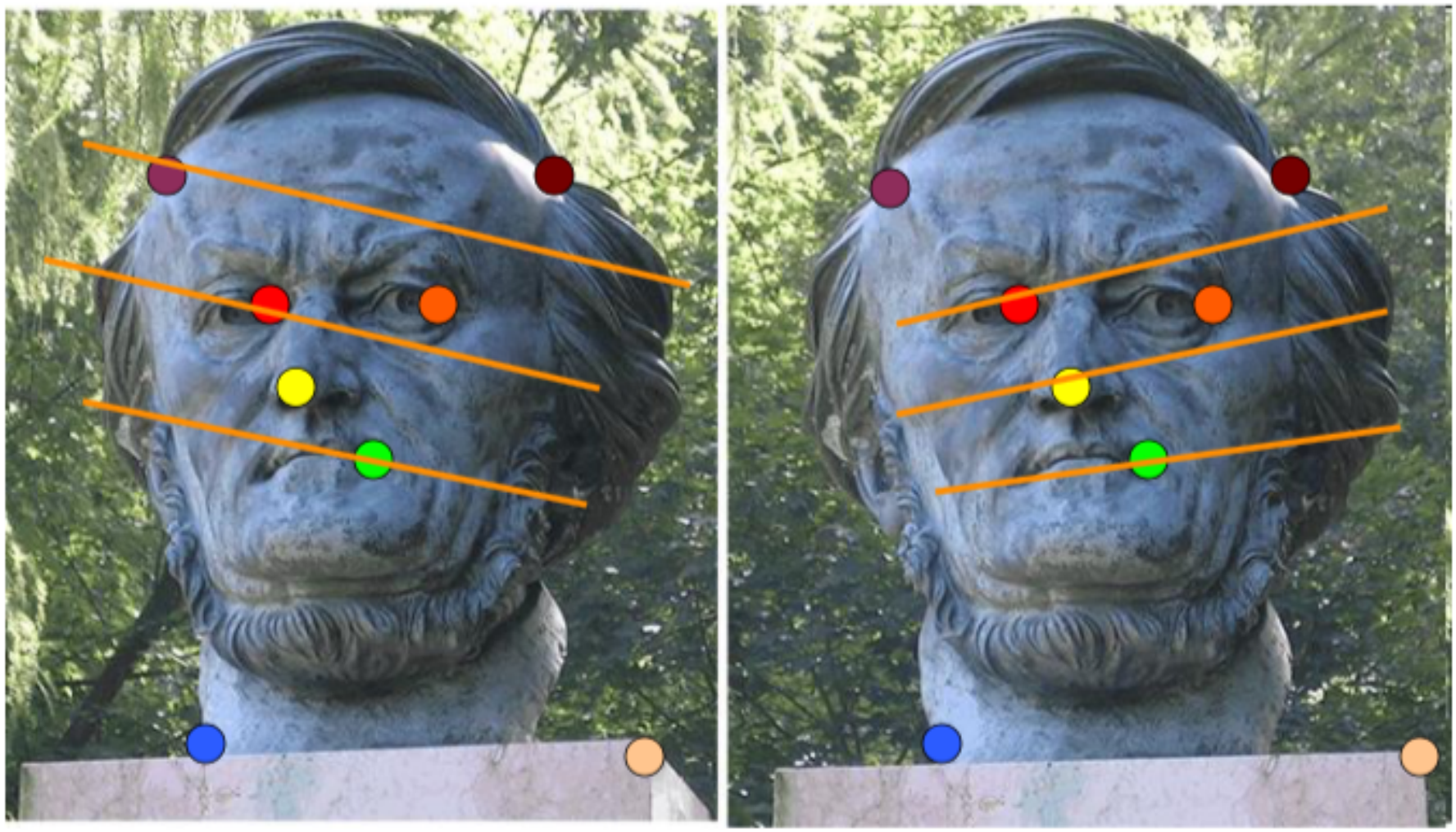
- Image features (filters $\longrightarrow$ edges $\longrightarrow$ corners)
  - How to extract local invariant features
    - Sometimes referred to as: interest points, key points, etc.
- Description:
  - How to develop a "description" of said features for later correspondence
- Feature matching:
  - How to match features across multiple images

Correspondence across different views/scale/aspect/etc.

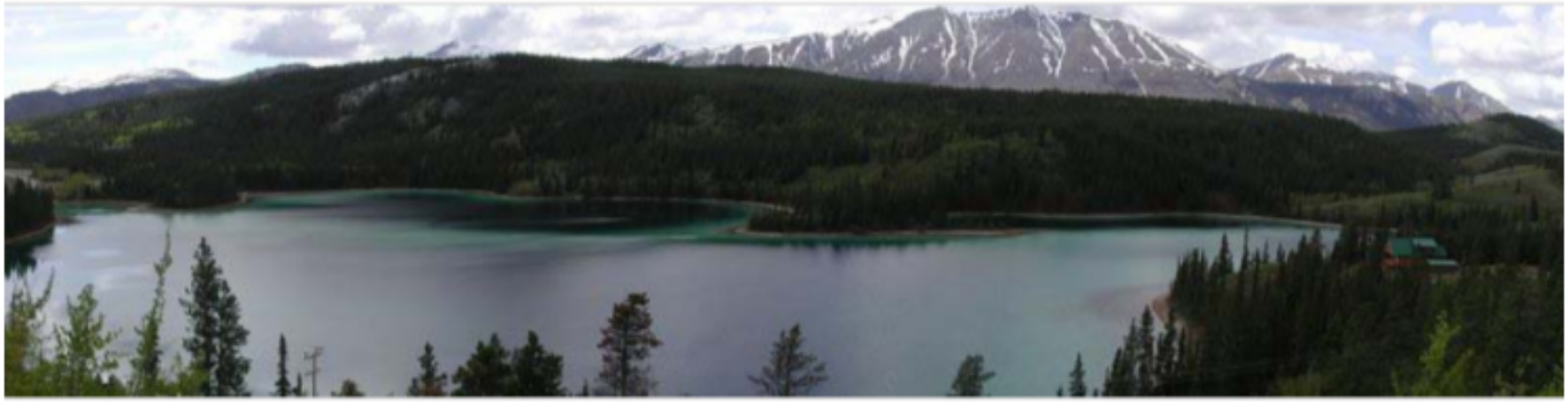
- Correspondence: matching points, patches, edges, or regions across images.



Example: Estimate the "fundamental matrix" between views (3D reconstruction)

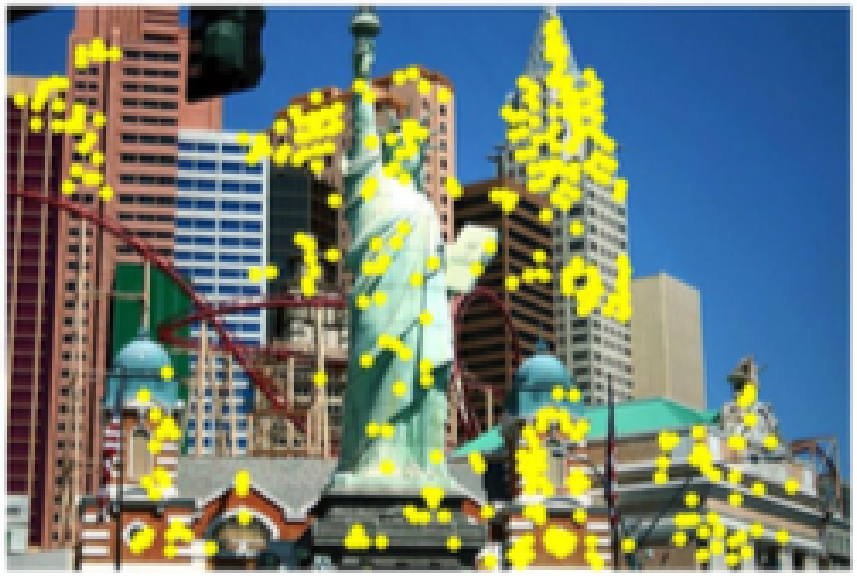


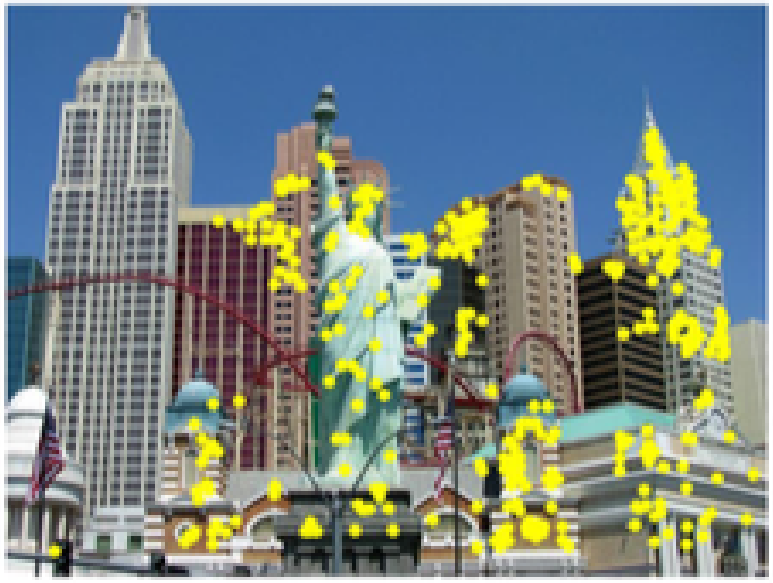
Example: Image alignment (project 3)



Features build the foundation of computer vision

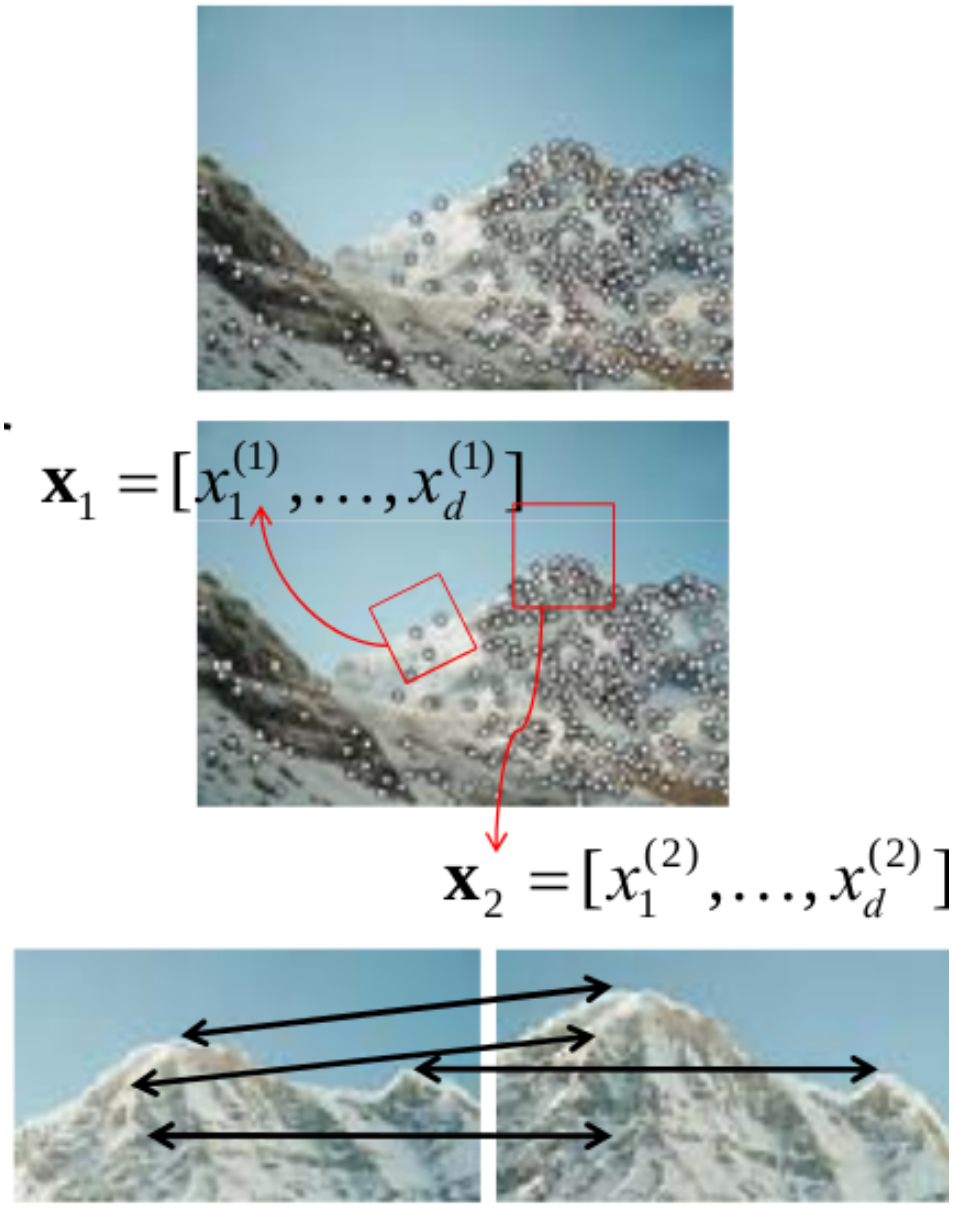
- Many application areas:
  - Motion tracking (surveillance/recon.)
  - Robotics (learning, motion planning, interaction, etc.)
  - Recognition/Classification
  - etc.





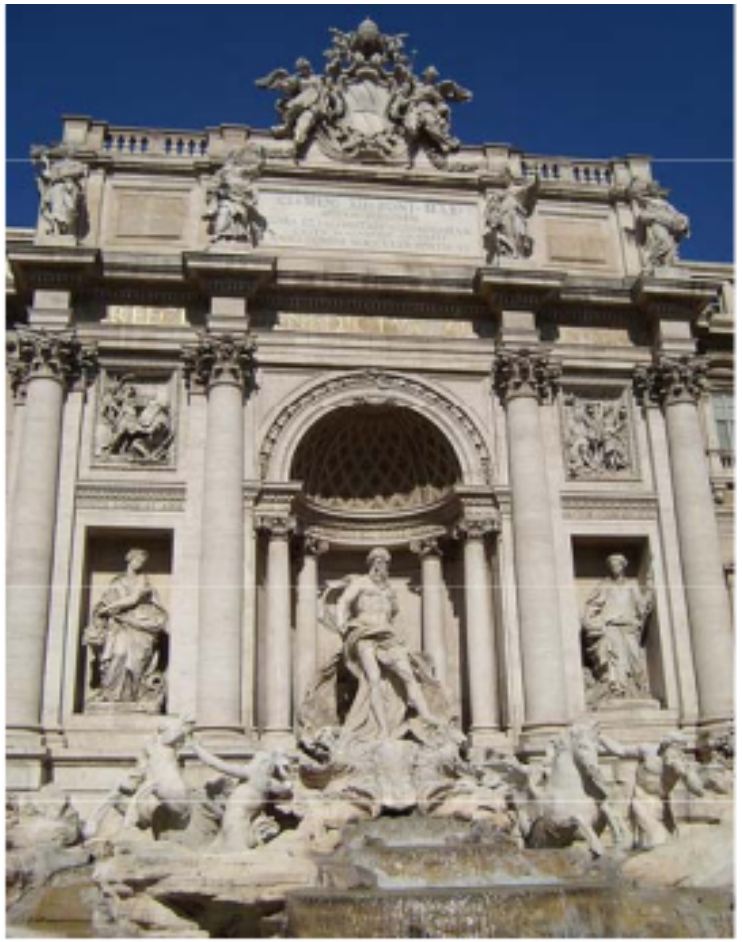
Local features: main components

- Detection:
  - Identify points of interest.
- Description:
  - Extract a feature descriptor surrounding each interest point.
- Matching:
  - Determine correspondence between descriptors from multiple views.



How do we match subsequent images???

by Diva Sian



by swashford

How do we match subsequent images???

by Diva Sian

by scgbt

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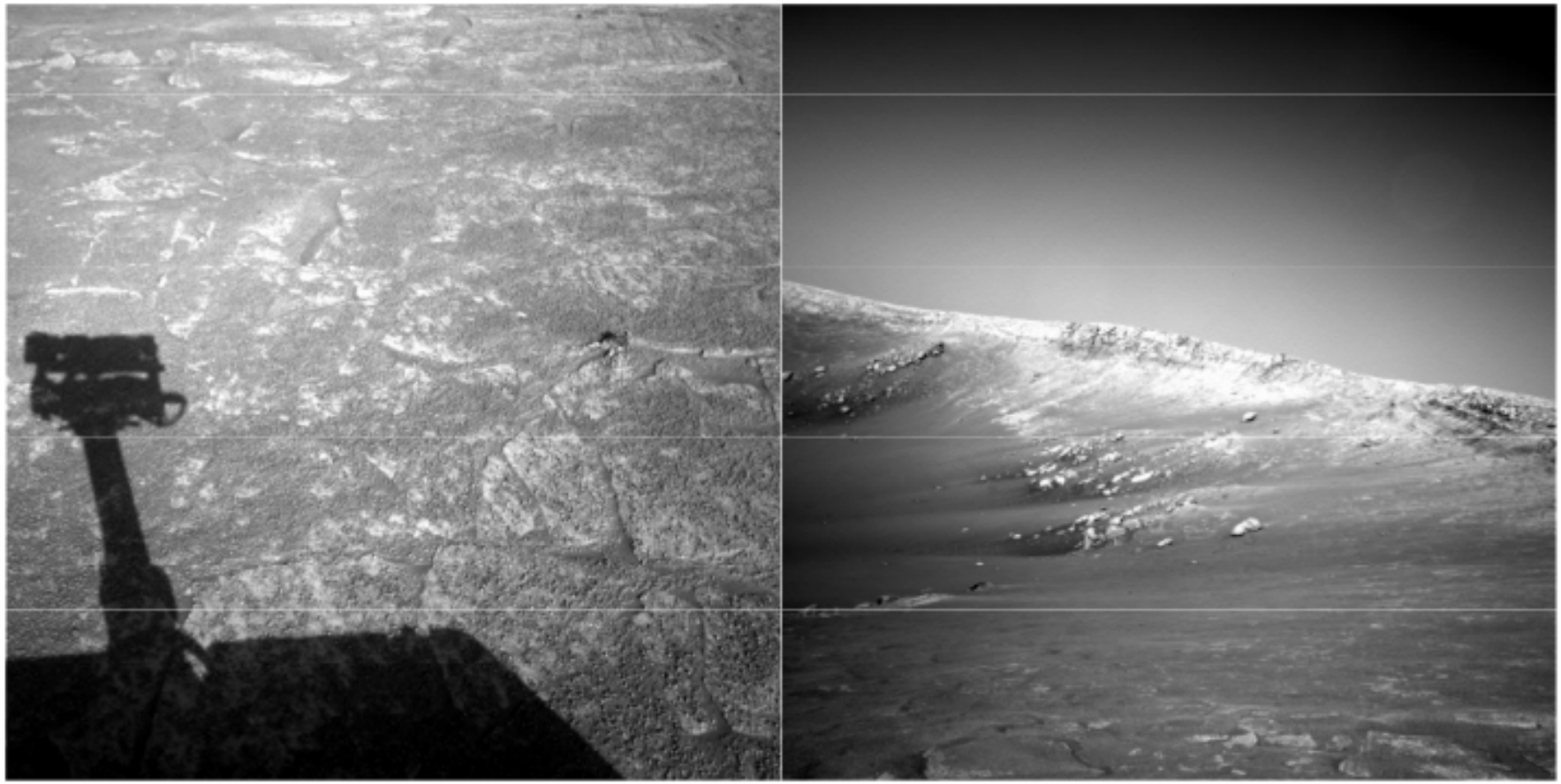

NASA Mars Rover images

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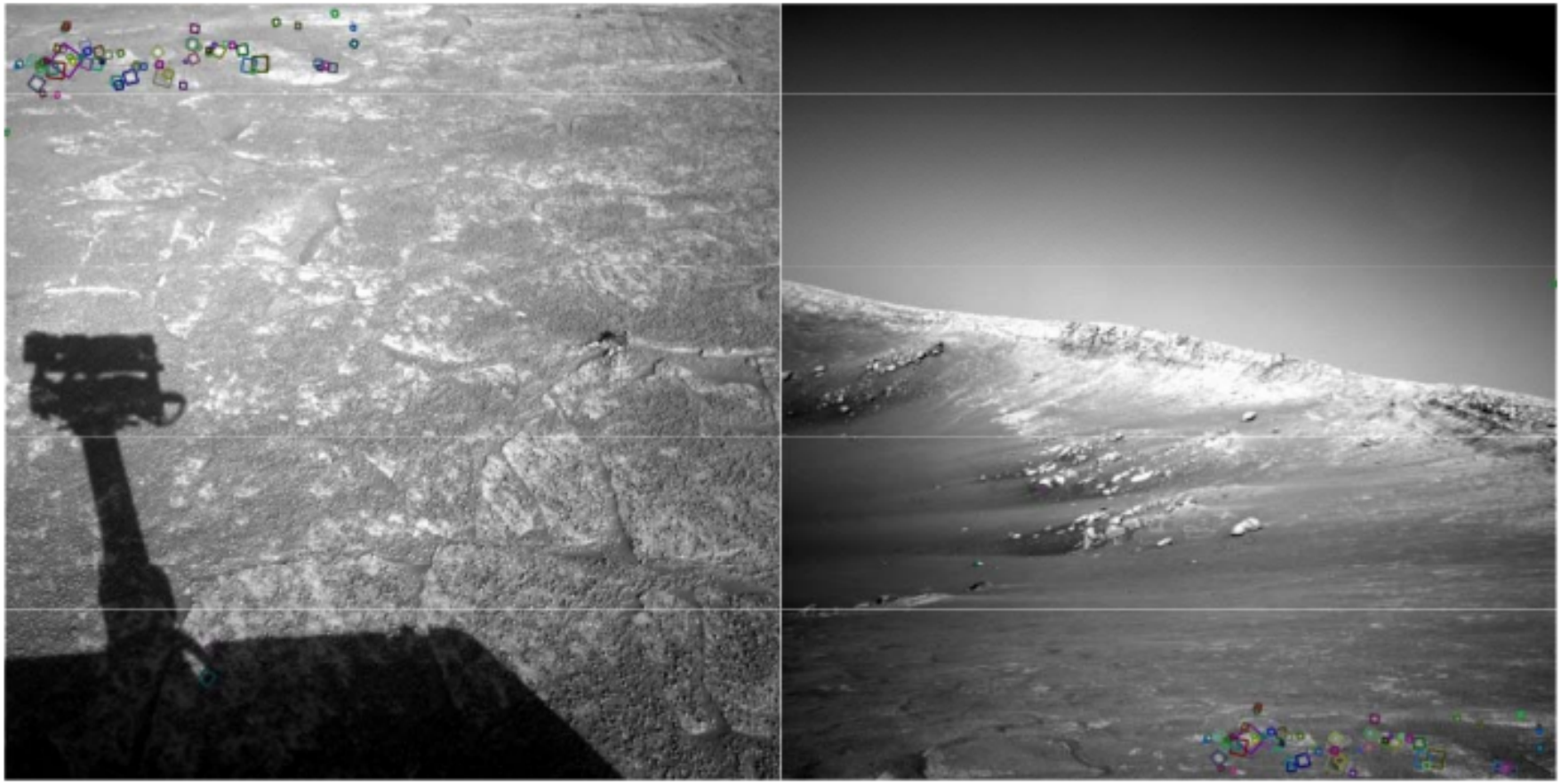


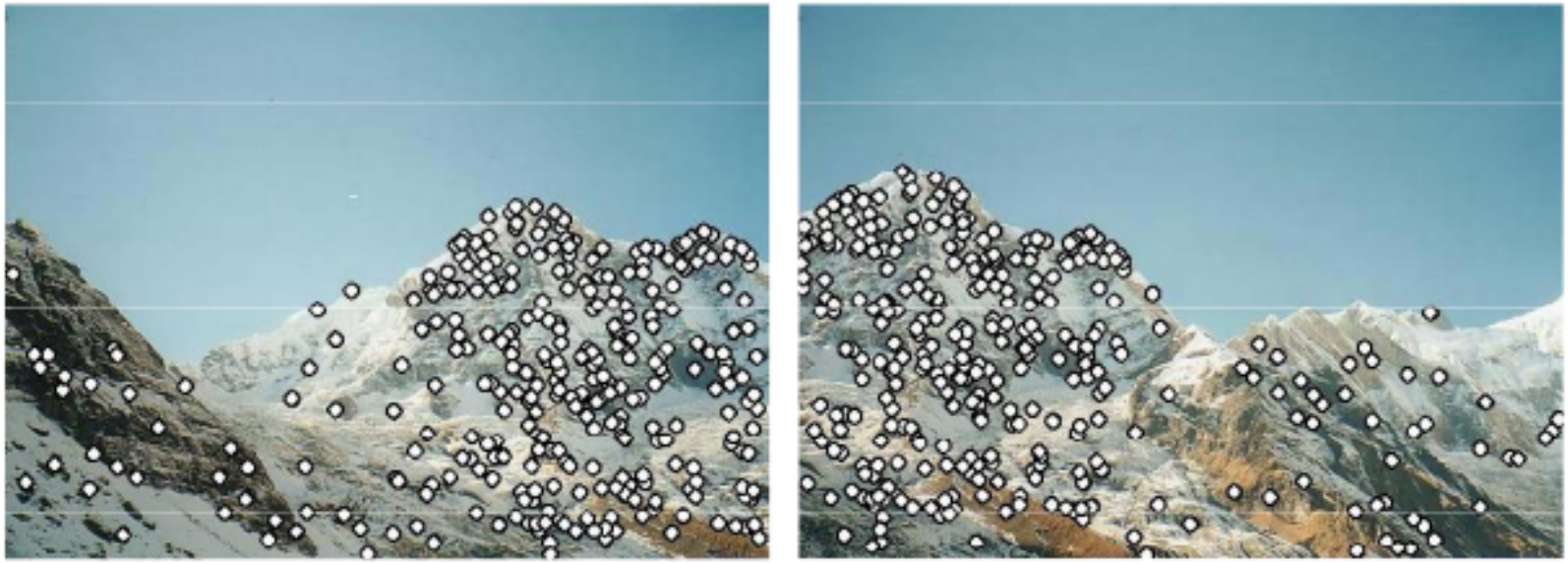
NASA Mars Rover images
with SIFT feature matches
Figure by Noah Snavely

Suppose we wish to align two images into a panoramic!

- First, look for local features in the images that match well!
- How would we do this by "eying" it?

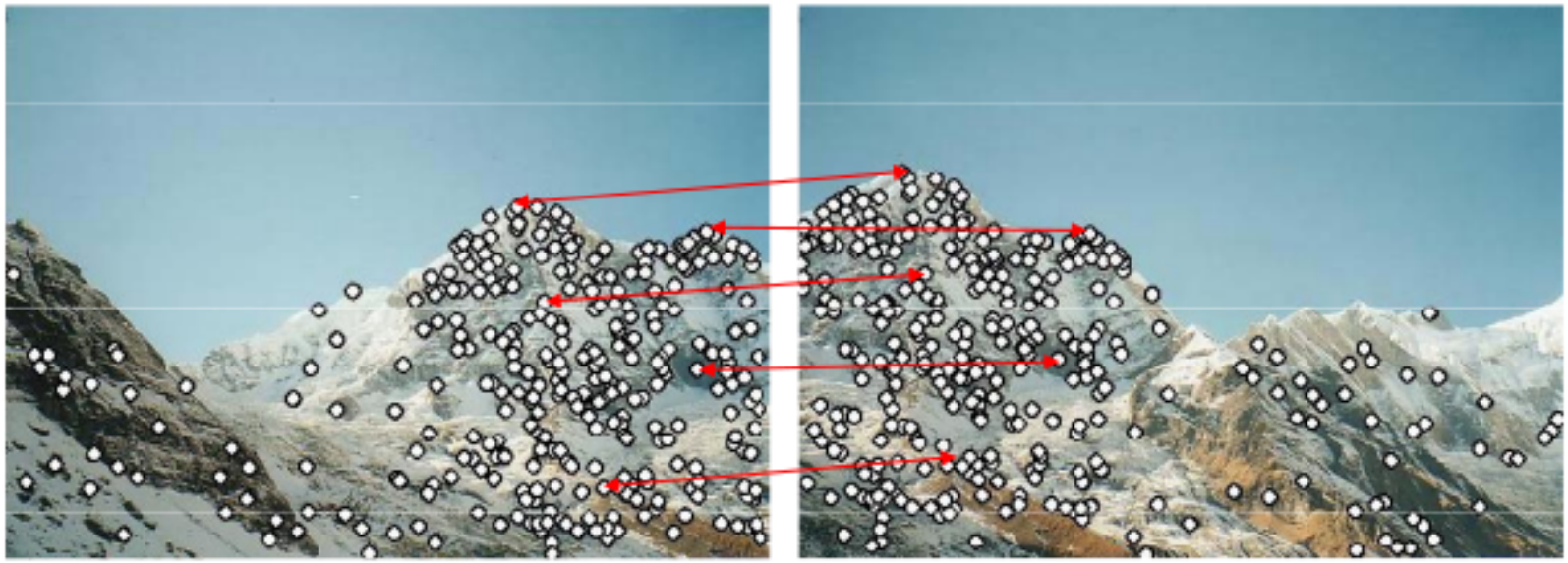
Local features and alignment

1. Detect a lot of features in both images



Local features and alignment

1. Detect a lot of features in both images
2. Find corresponding pairs

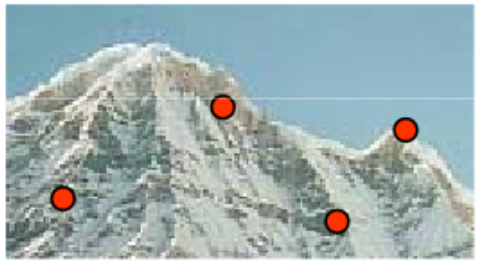


Local features and alignment

1. Detect a lot of features in both images
2. Find corresponding pairs
3. Use these pairs to align the images

Easier said than done!

- Problem 1:
  - Detect the **same** point **independently** in both images



no chance to match!

- We need a repeatable detector

Easier said than done!

- Problem 2:
  - For each feature detected, correctly recognize the corresponding point

- We need a reliable and distinctive descriptor

Our detector and descriptor should have some *invariant* properties!

- Geometric transformations: (rotation, scale, projections, affine shifts, etc.)

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- Photometric properties: (illumination, color space, etc.)

Figure from T. Tuytelaars ECCV 2006 tutorial

Our detector and descriptor should have some *invariant* properties!

- Geometric transformations: (rotation, scale, projections, affine shifts, etc.)
- Photometric properties: (illumination, color space, etc.)
- Other: (noise, blur, compression, etc.)

Figure from T. Tuytelaars ECCV 2006 tutorial

Invariant local features

Subset/subregions within the image designed to be invariant to common geometric and photometric changes.

- Basic steps involved:
  1. Detect distinctive interest points within the image
  2. Extract invariant descriptors to describe said interest points

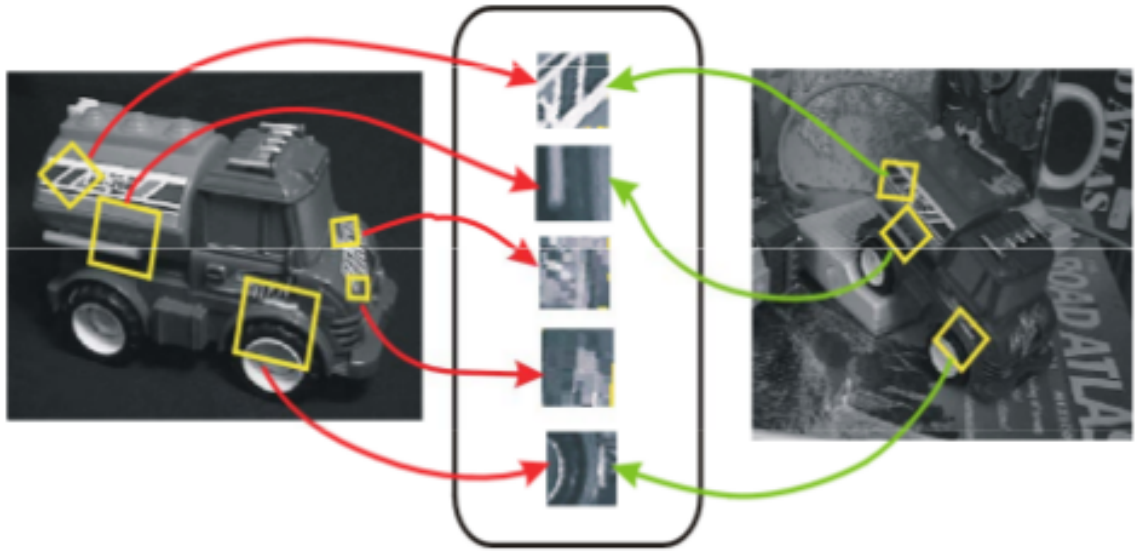


Figure: David Lowe

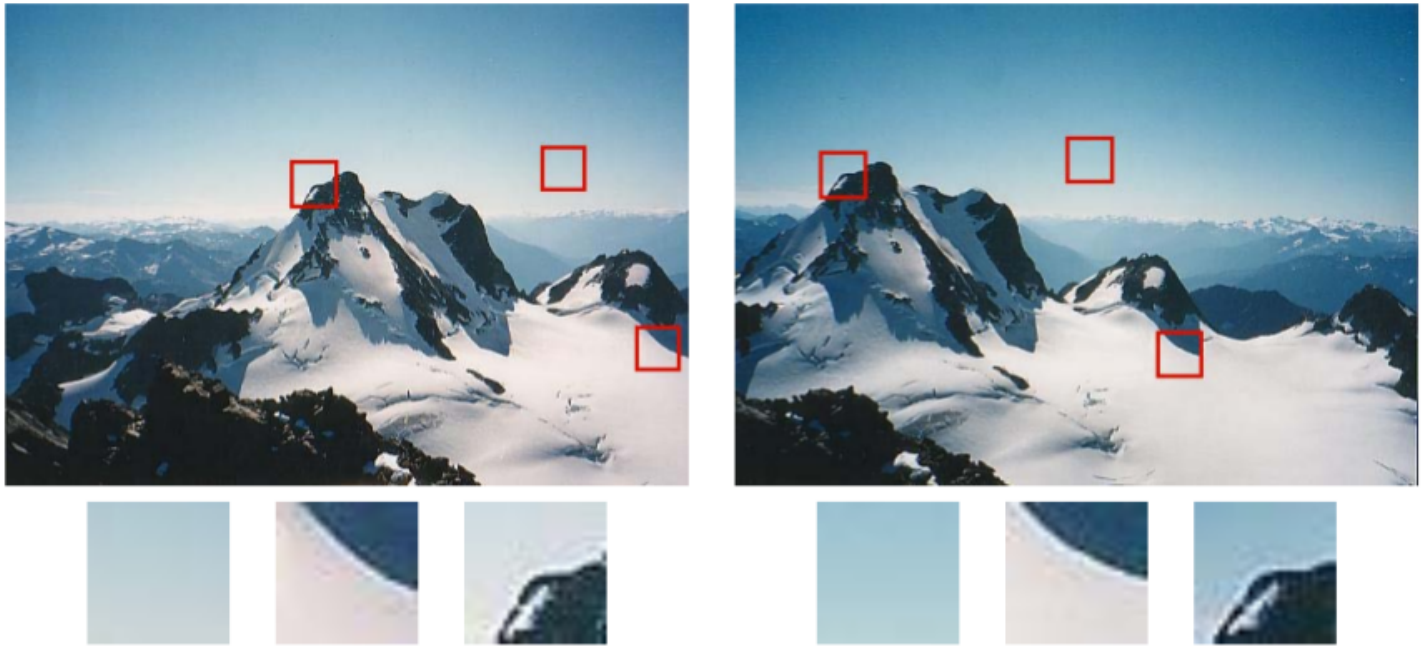
Main questions to be answered

How will these "interest" points be computed?

- What are considered to be salient features that we can **detect** in multiple images?
- How do we **describe** a local region?
- How do we establish **correspondences**, i.e., compute matches?

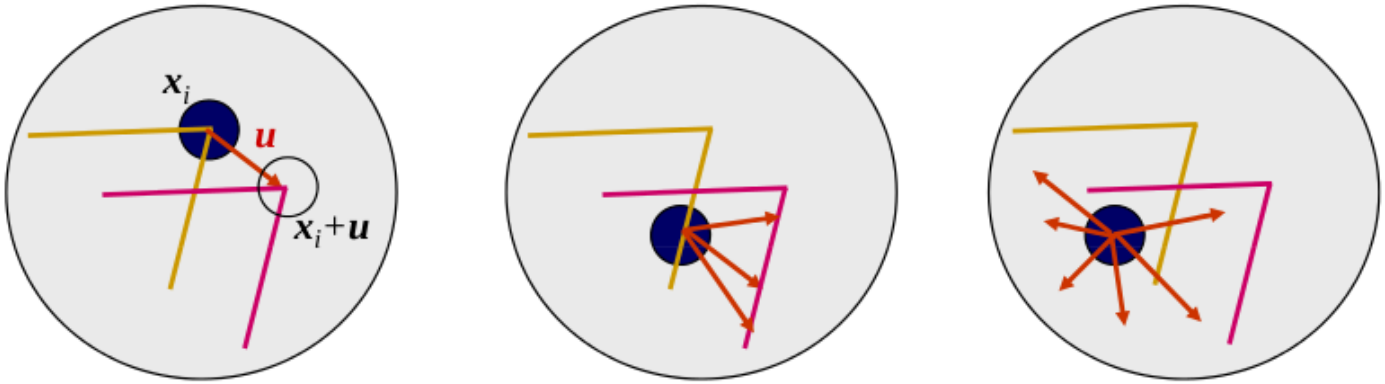
How can we find key features?

- Textureless patches can't be localized!



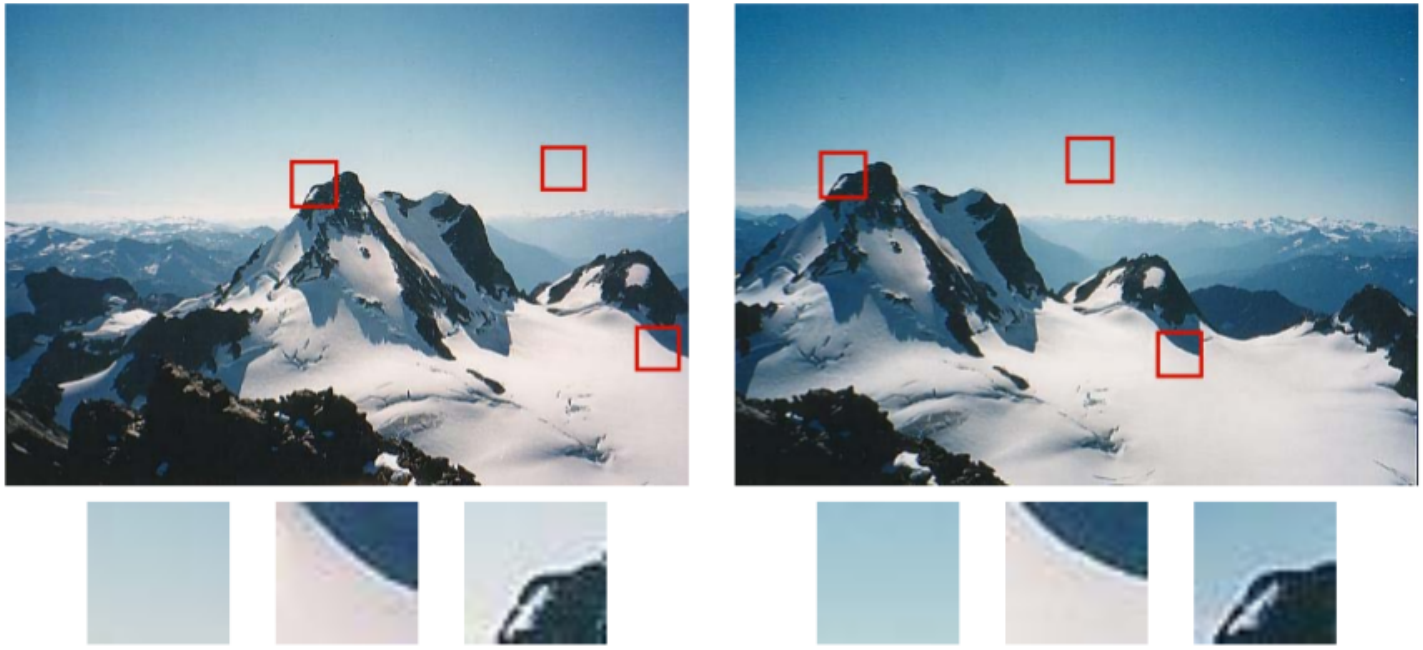
How can we find key features?

- Textureless patches can't be localized!
- Patches with large gradients do better
  - Straight line segments (single gradient directions) suffer from the aperture problem



How can we find key features?

- Textureless patches can't be localized!
- Patches with large gradients do better
  - Straight line segments (single gradient directions) suffer from the aperture problem
- As we just saw, patches with gradients in at least two (significantly) different orientations are a good place to start!



How do we know what a good feature is?

- Consider a small patch I_0 in an image
- We can compare this patch with a translated version of itself (by some Δu)
- Auto-correlation:

$$E_{AC}(\Delta u) = \sum_i w(x_i)[I_0(x_i - \Delta u) - I_0(x_i)]^2$$

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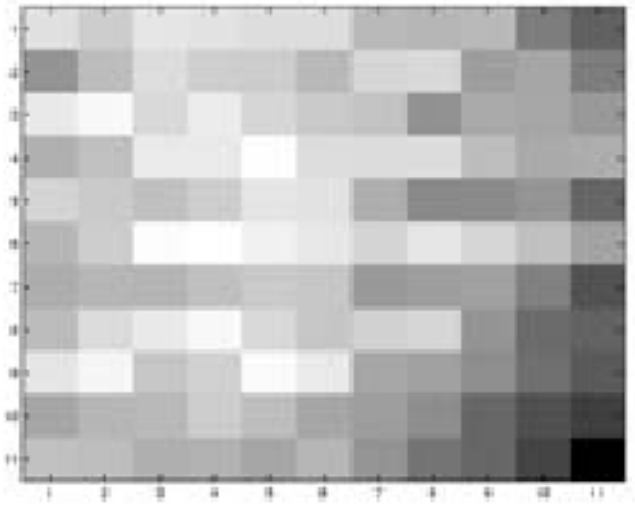

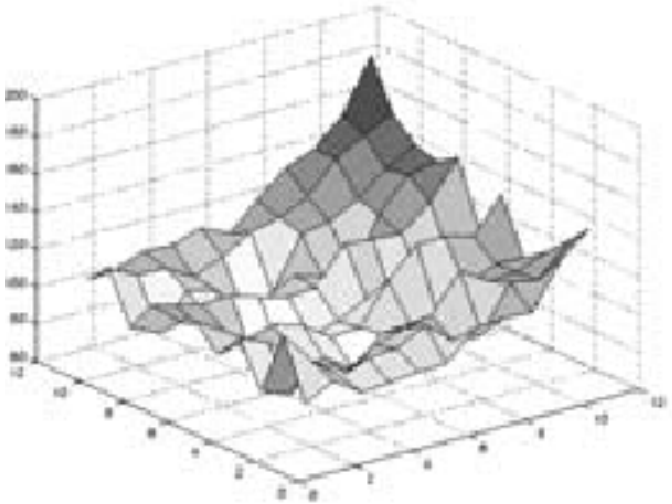

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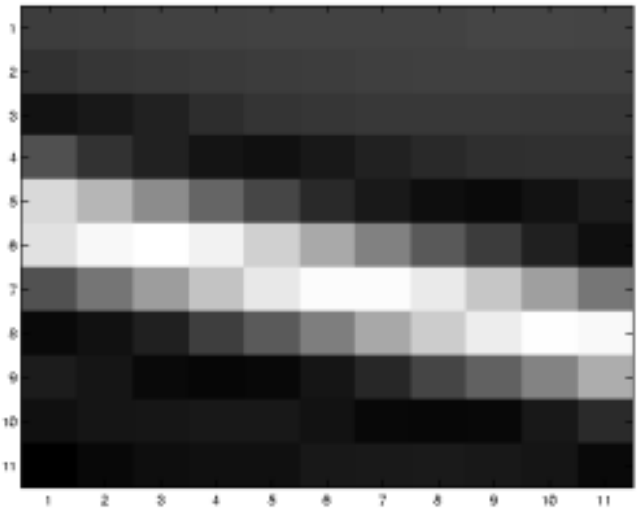

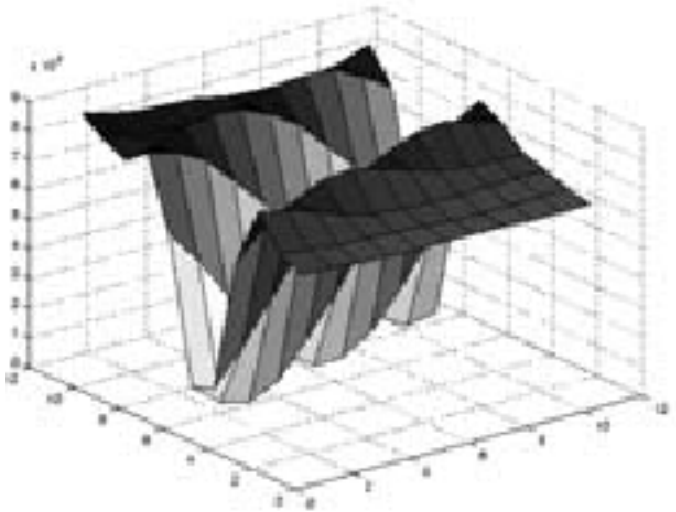

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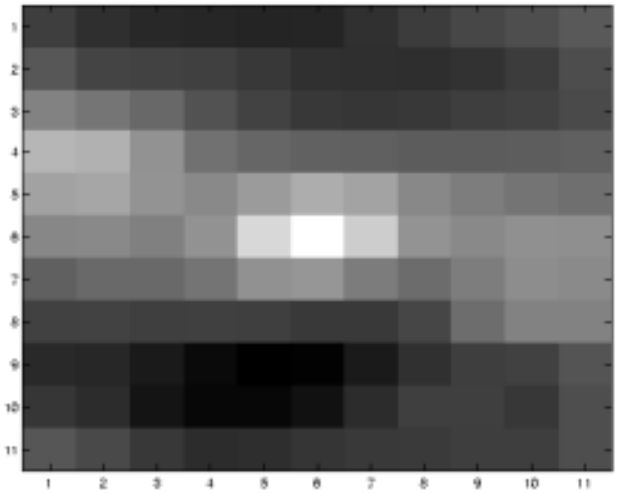

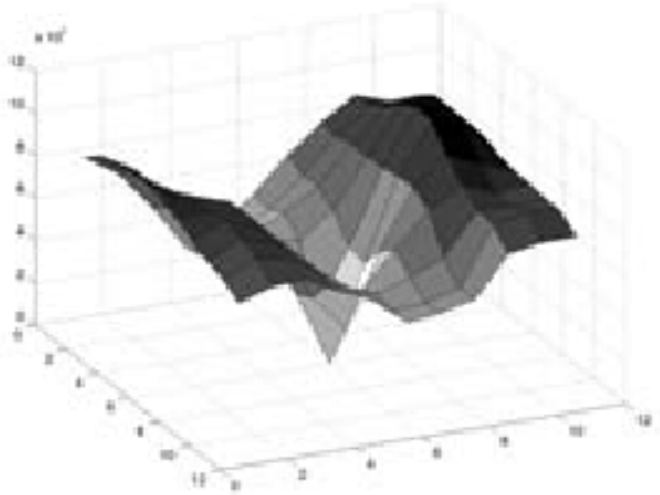

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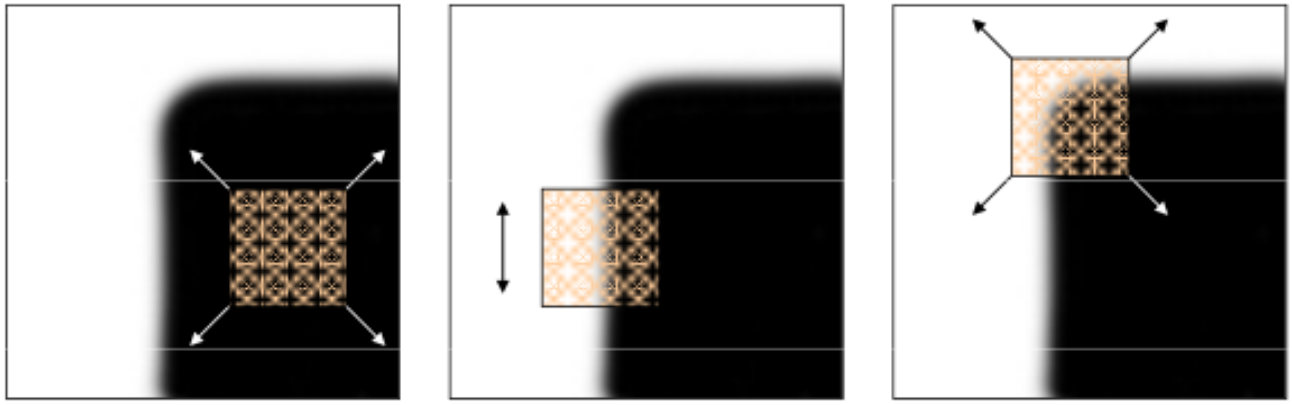
- Good features have gradients in multiple directions!
- Corners are a good place to start!

Finding corners

- **Key property:** in the region around a corner, the image gradient has *at least* two dominant directions!
- Corners are repeatable and distinctive (read the paper by Harris and Stephens)

Corners as distinctive interest points

- We should easily identify the point by "looking" through a small window
- Shifting the window in **any** direction should result in a **large** intensity change



"flat" region: no change in all directions

"edge": no change along the edge direction

"corner": significant change in all directions

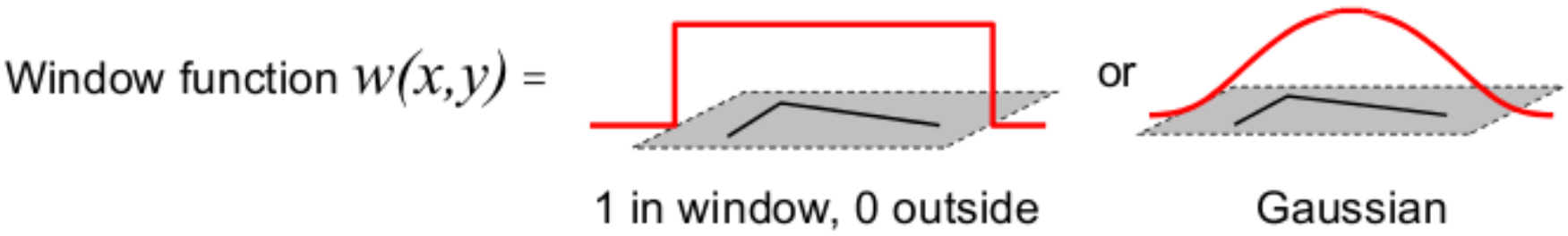
Source: A. Efros

Harris corners

- Being more specific, let Δu in the auto-correlation be represented by a shift $[u, v]$
- Then our auto-correlation becomes:

$$E(u,v) = \sum_{x,y} \underbrace{w(x,y)}_{\text{window}} [\underbrace{I(x+u, y+v)}_{\text{Shifted intensity}} - \underbrace{I(x,y)}_{\text{Intensity}}]^2$$

where



Harris corners

- Note that a Taylor series expansion of $I(x+u, y+v)$ yields:

$$I(x+u, y+v) \approx I(x,y) + \nabla I(x,y) \cdot [u,v].$$

Recall:

$$\nabla I(x,y) = \left[\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right](x,y)$$

is the image gradient.

Plugging this in and simplifying (p.g. 212 in your text):

$$\begin{aligned} E(u,v) &\approx \sum_{x,y} w(x,y)[\nabla I(x,y) \cdot [u,v]]^2 \\ &= [u,v] H [u,v]^T \end{aligned}$$

where H is the 2×2 Harris matrix (a.k.a the auto-correlation matrix)

$$H = w * \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = \begin{bmatrix} w * I_x^2 & w * I_x I_y \\ w * I_x I_y & w * I_y^2 \end{bmatrix}$$

Hessian corners

- So, what exactly does this mean and what is this $w(x, y)$?
- First, note that the matrix H looks very similar to the image Hessian [Beaudet78]

$$\text{Hessian}(I) = \begin{bmatrix} I_{xx} & I_{xy} \\ I_{xy} & I_{yy} \end{bmatrix}$$

and $\det(\text{Hessian}(I)) = I_{xx}I_{yy} - I_{xy}^2$

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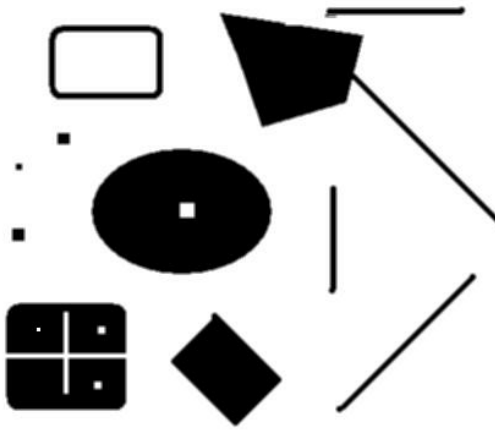

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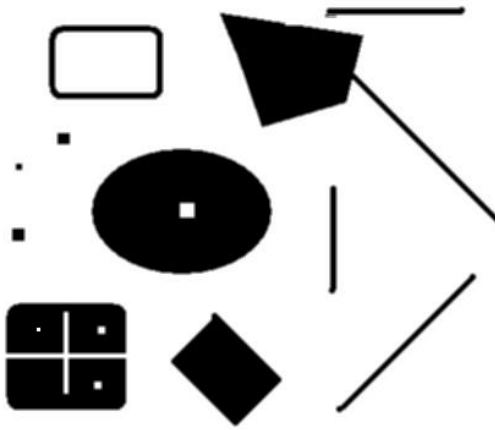

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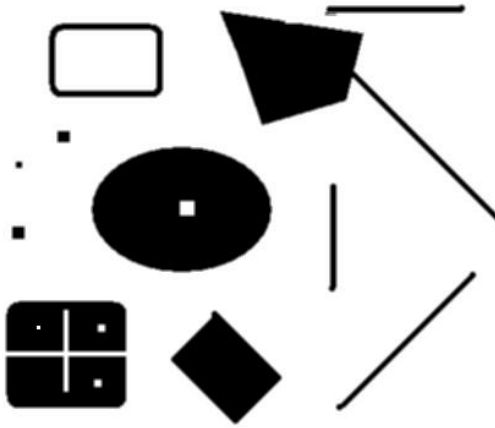

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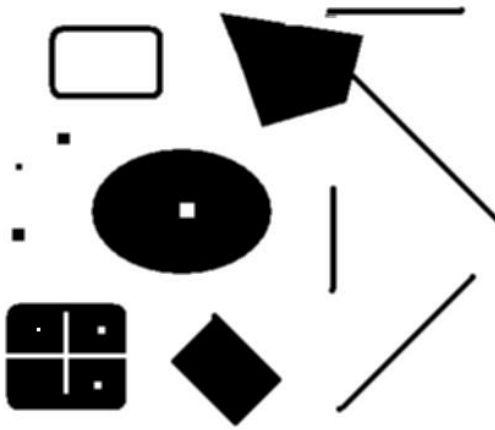

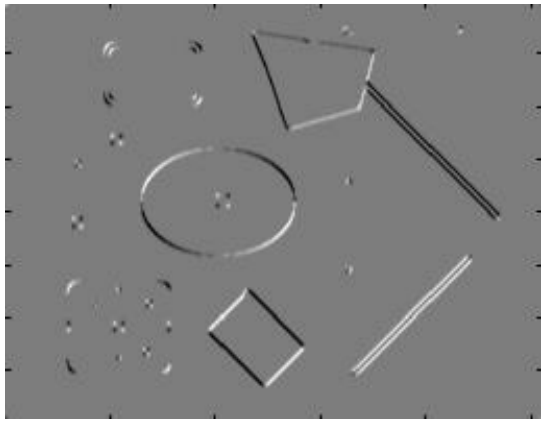

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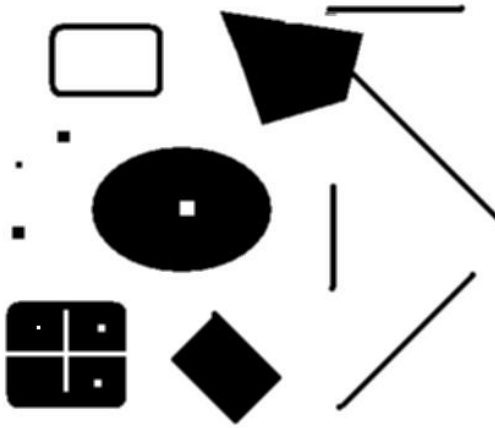
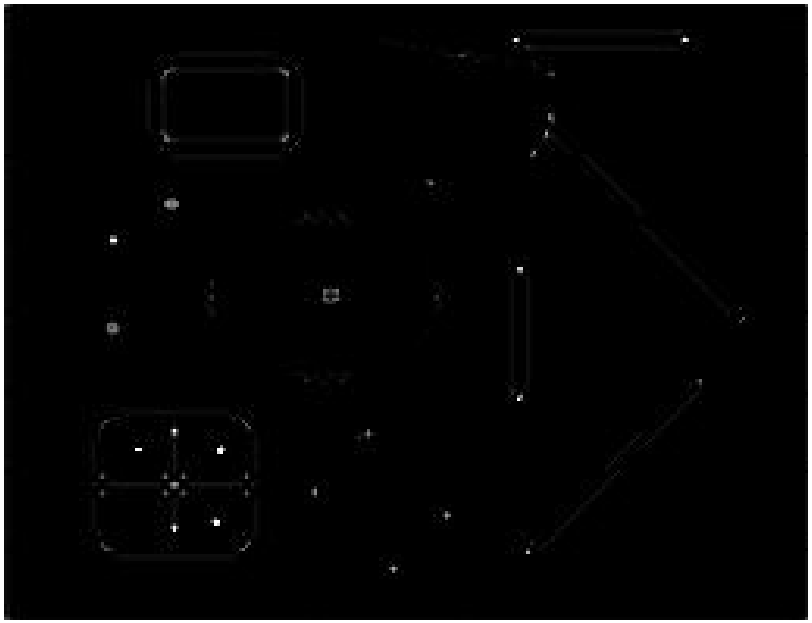
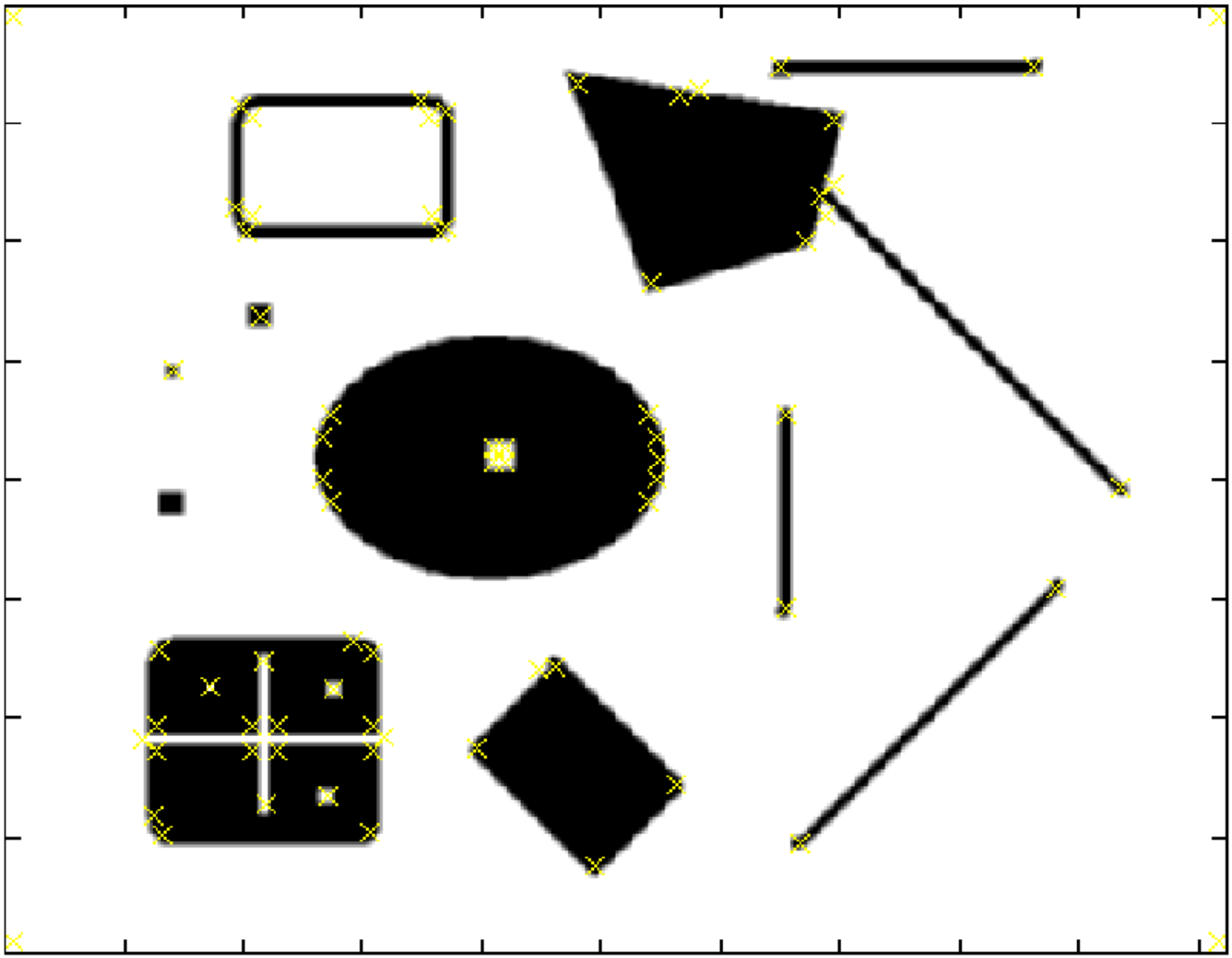




Hessian corners



Harris corners

- So, how is the Harris detector different?
- The Harris matrix (auto-correlation matrix) is the second moment matrix!

$$H = w * \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

- What does this mean??? (example)

Lets formulate this mathematically

1. Given some image $I \in [0,1]^{m \times n}$
2. Define the Gaussian kernel G_{σ_1} and compute the image derivatives as:

$$\left\{ I_x = I * \frac{\partial G_{\sigma_1}}{\partial x}, \quad I_y = I * \frac{\partial G_{\sigma_1}}{\partial y} \right\} \in \mathbb{R}^{m \times n}$$

3. Compute the three images

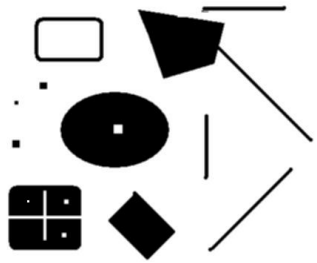
$$\left\{ I_x^2, \ I_y^2, \text{ and } I_x I_y \right\} \in \mathbb{R}^{m \times n}$$

   by performing the **Hadamard product**
4. Filter I_x^2, I_y^2, and $I_x I_y$ by convolving them with some G_{σ_2} where in general $\sigma_2 > \sigma_1$ (this is our window function convolved with H)
5. Compute the corner strength function at each (x, y) (Harris used this but there are others):

$$G_{\sigma_2}(I_x^2)G_{\sigma_2}(I_y^2) - [G_{\sigma_2}(I_x I_y)]^2 - \alpha[G_{\sigma_2}(I_x^2) + G_{\sigma_2}(I_y^2)]^2, \quad \alpha \in [0.04, 0.08]$$

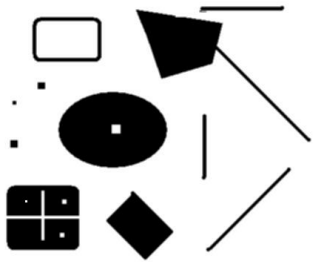
Example of the Harris corner process

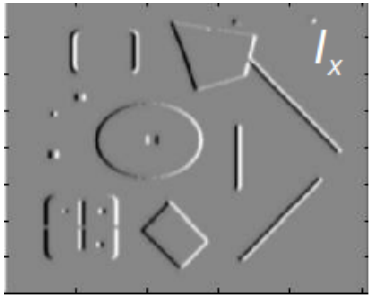
1. Consider our test image
   $I \in [0,1]^{m \times n}$

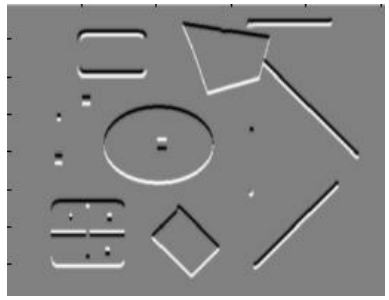


Example of the Harris corner process

1. Consider our test image $I \in [0,1]^{m \times n}$
2. Compute the image derivatives I_x, I_y

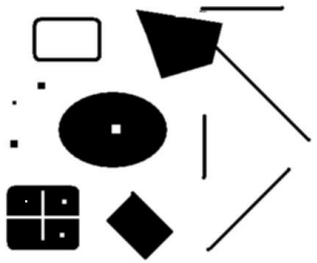


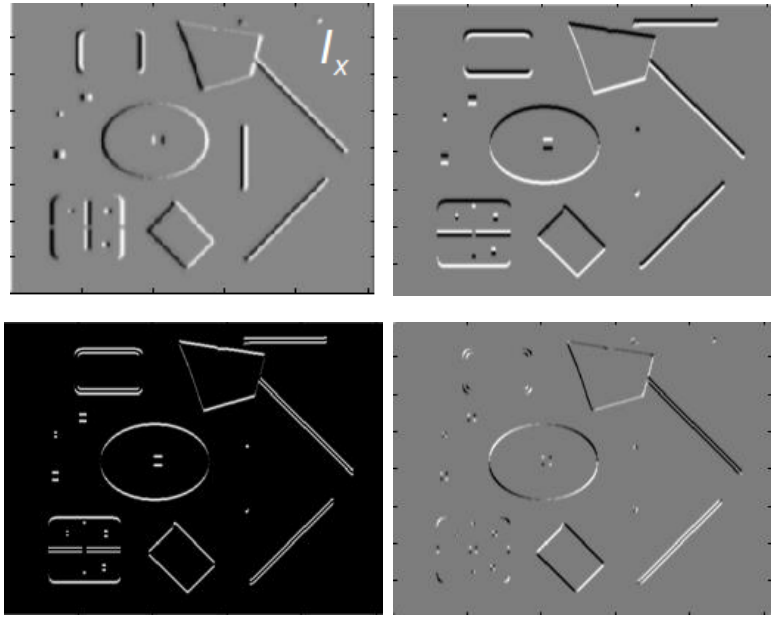




Example of the Harris corner process

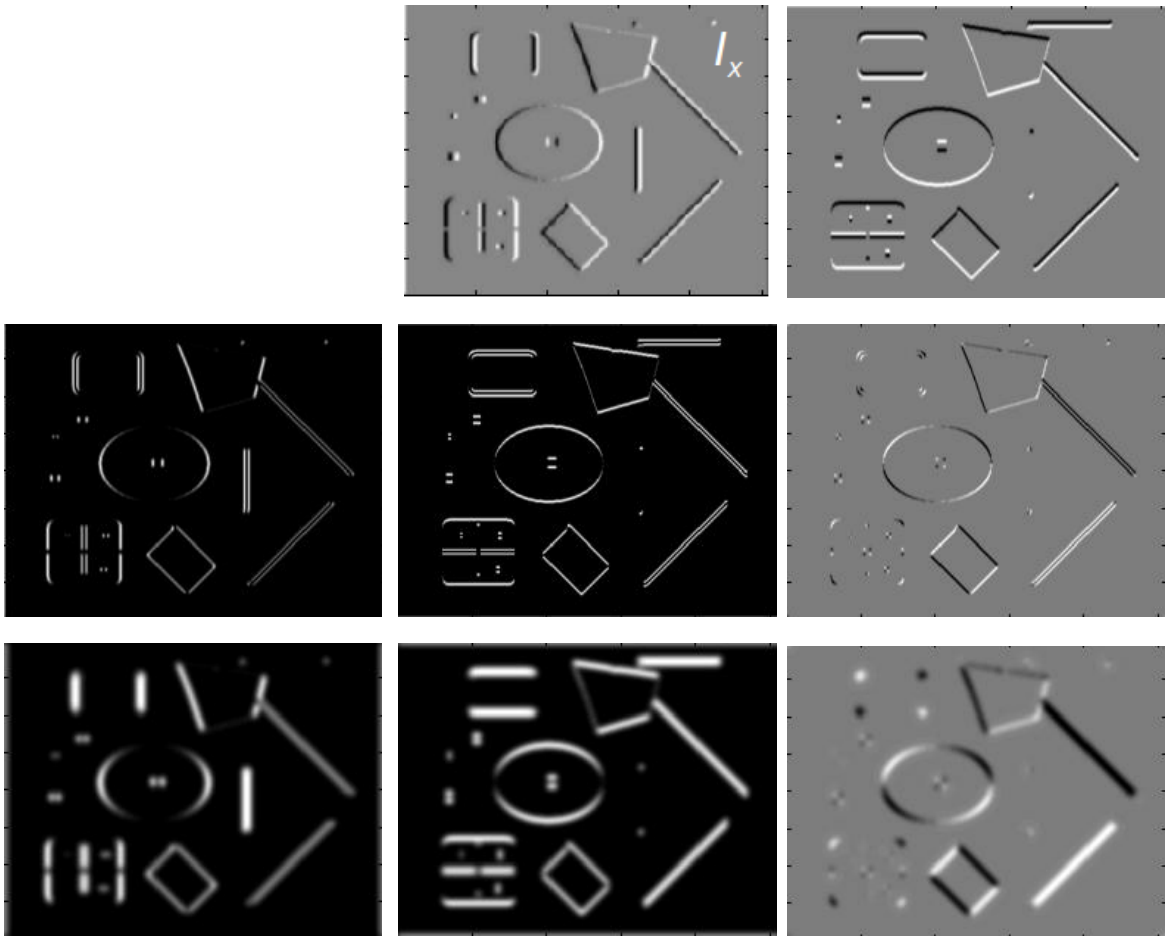
1. Consider our test image $I \in [0,1]^{m \times n}$
2. Compute the image derivatives I_x, I_y
3. Square them and compute $I_x I_y$





Example of the Harris corner process

1. Consider our test image $I \in [0,1]^{m \times n}$
2. Compute the image derivatives I_x, I_y
3. Square them and compute $I_x I_y$
4. Gauss filter I_x^2, I_y^2, and $I_x I_y$



Example of the Harris corner process

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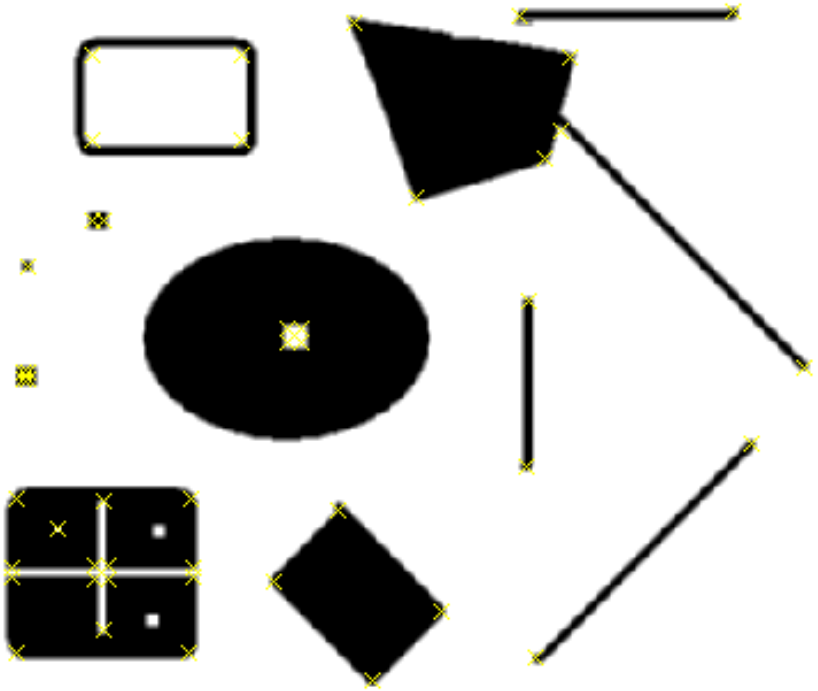
4. Gauss filter I_x^2, I_y^2, and $I_x I_y$
5. Compute a corner strength function

$$G_{\sigma_2}(I_x^2)G_{\sigma_2}(I_y^2) - [G_{\sigma_2}(I_x I_y)]^2 - \alpha[G_{\sigma_2}(I_x^2) + G_{\sigma_2}(I_y^2)]^2$$

Example of the Harris corner process



1. Consider our test image $I \in [0,1]^{m \times n}$
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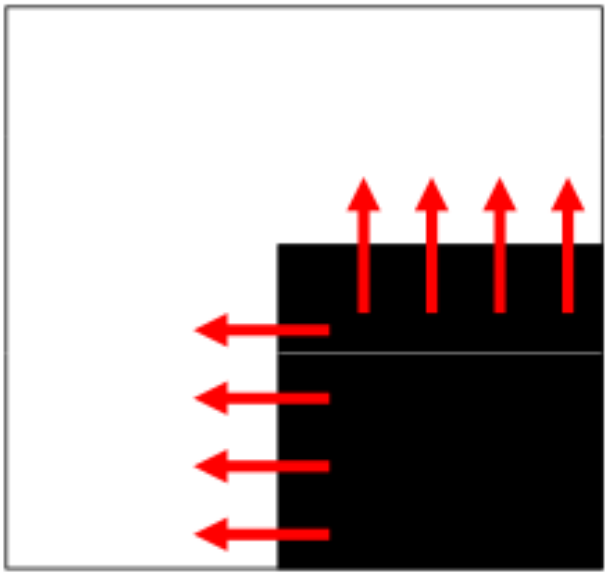
What does this matrix reveal?

- Consider a corner that happens to exactly align with the image axis



What does this matrix reveal?

- Consider a corner that happens to exactly align with the image axis
  - In this case, there is no $I_x I_y$ component! (why???)

$$H = w * \begin{bmatrix} I_x^2 & 0 \\ 0 & I_y^2 \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$

- Dominant gradient directions align with the x or y axis
- If λ_i is close to 0, then this is **not** a corner $\rightarrow$ look for locations where both λ_i are large

What does this matrix reveal?

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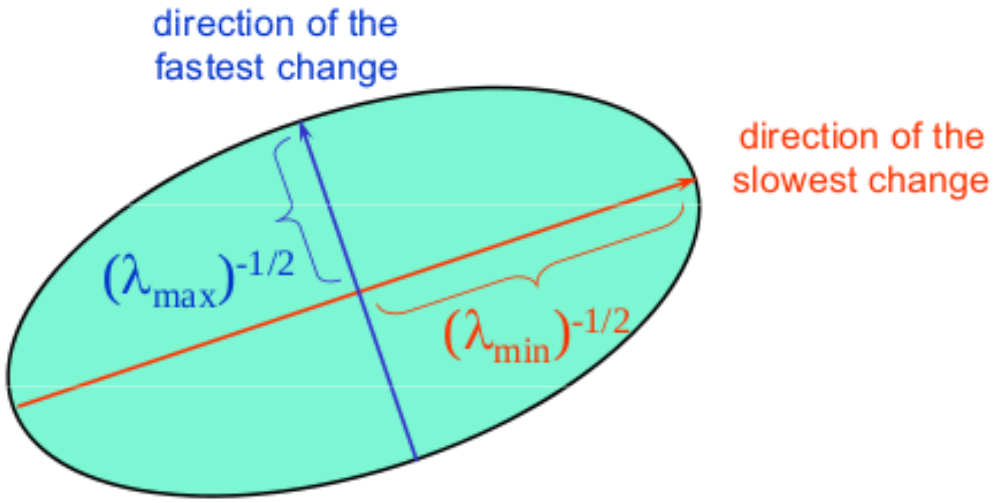
- Dominant gradient directions align with the x or y axis
- If λ_i is close to 0, then this is **not** a corner $\rightarrow$ look for locations where both λ_i are large
- What if the corner is NOT aligned with the image axis?

General case

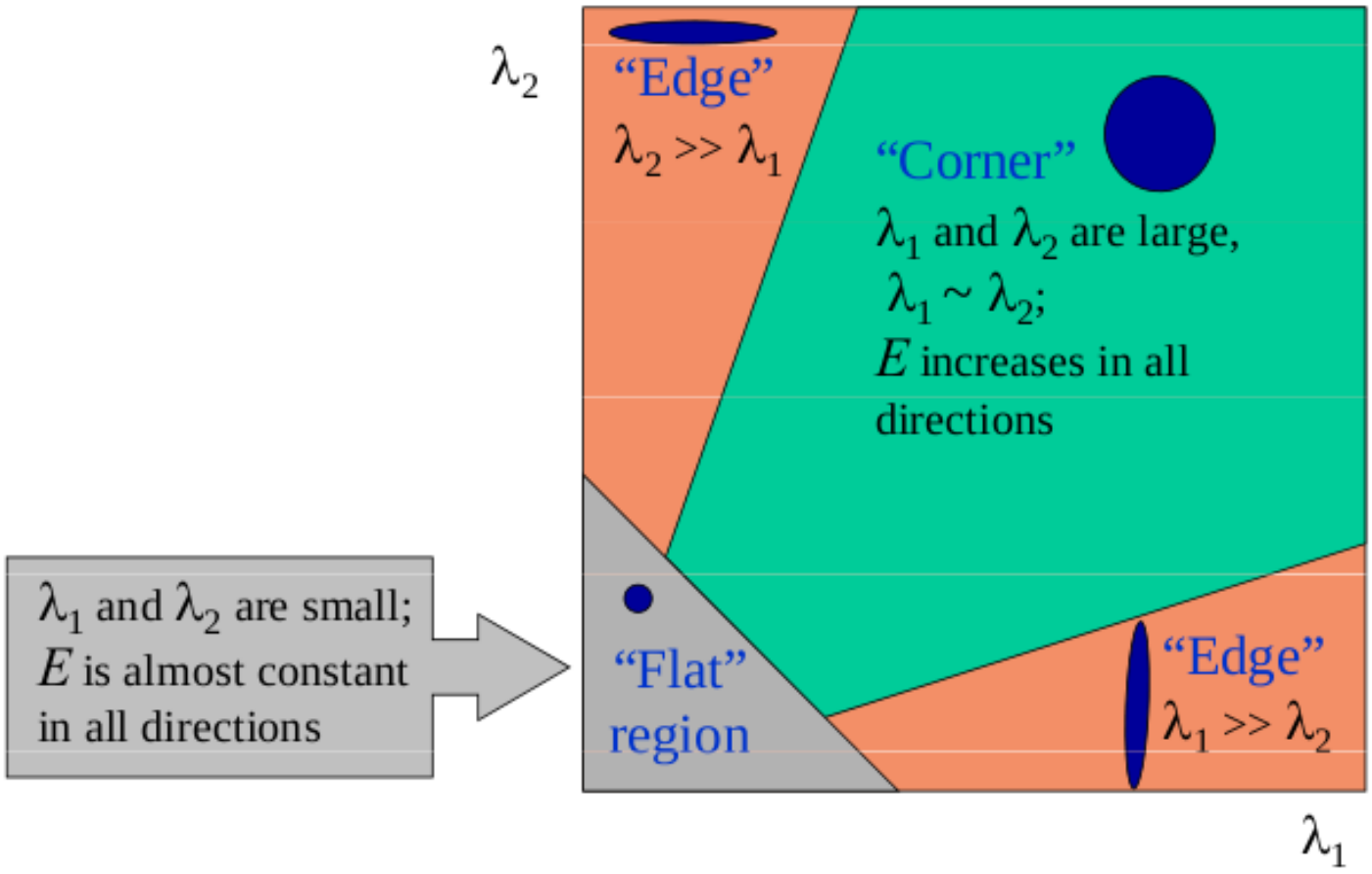
- Note that H is symmetric
  - $\Longrightarrow$ we can visualize H as an ellipse whose axis lengths are determined by the eigenvalues and whose eigenvectors define the principle axis

$$H = w * \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = R^T \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

where R is a rotation matrix (determines the orientation of the ellipse)



How do we interpret the eigenvalues of H?



Corner response function(s)

1. Harris and Stephens:

$$C(H) = \det(H) - \alpha \text{trace}(A)^2 = \lambda_1\lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

$(\alpha \in [0.04 - 0.06])$

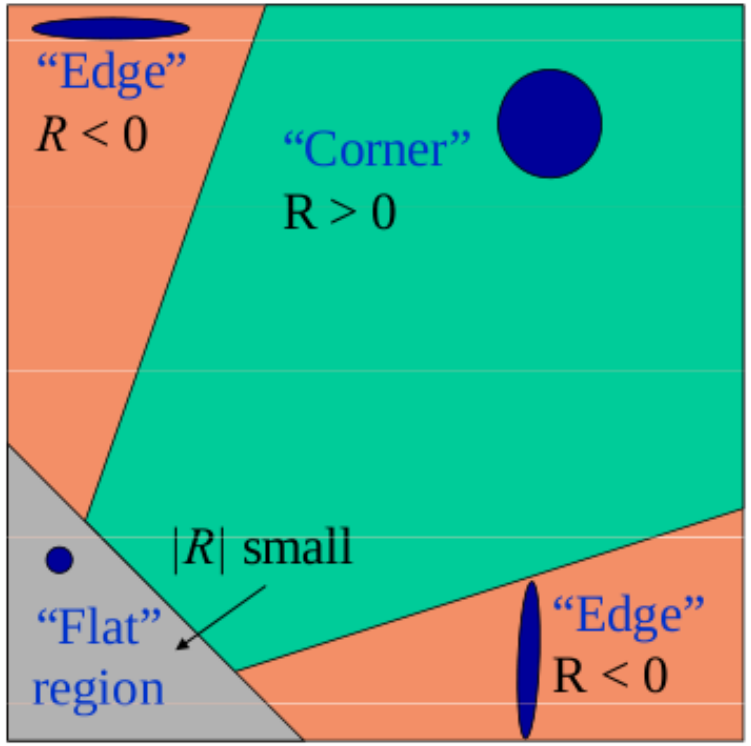
2. Triggs:

$$C(H) = \lambda_1 - \alpha\lambda_2$$

$(\alpha = 0.05)$

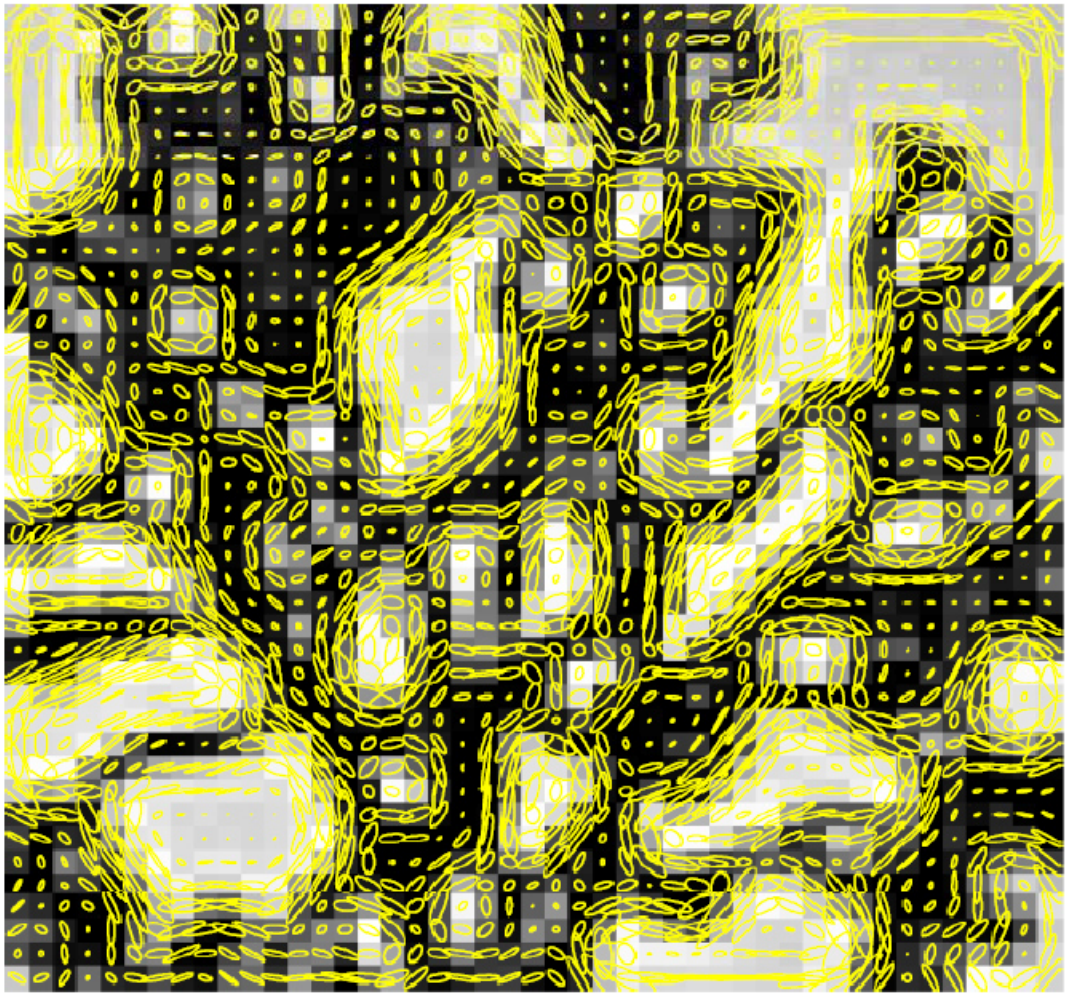
3. Brown, Szeliski, and Winder:

$$C(H) = \frac{\det(H)}{\text{trace}(A)} = \frac{\lambda_1\lambda_2}{\lambda_1 + \lambda_2}$$



Example

Example



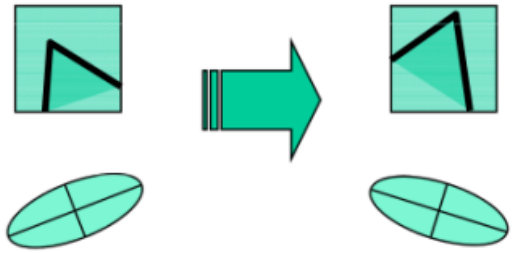
Harris detector Alg. summary

Harris Algorithm:

1. Compute I_x and I_y by convolving the original image with a derivative of Gaussian kernel
2. Compute the three images corresponding to I_x^2, I_y^2, and $I_x I_y$
3. Convolve each of these images with a larger Gaussian
4. Compute the corner strength according to one of the corner strength functions
5. Find the maxima above a threshold and report as detected features
6. (optionally) apply non-maximum suppression to ensure feature is a local maxima

What are the invariance properties of the Harris corner detector?

- Rotation invariance

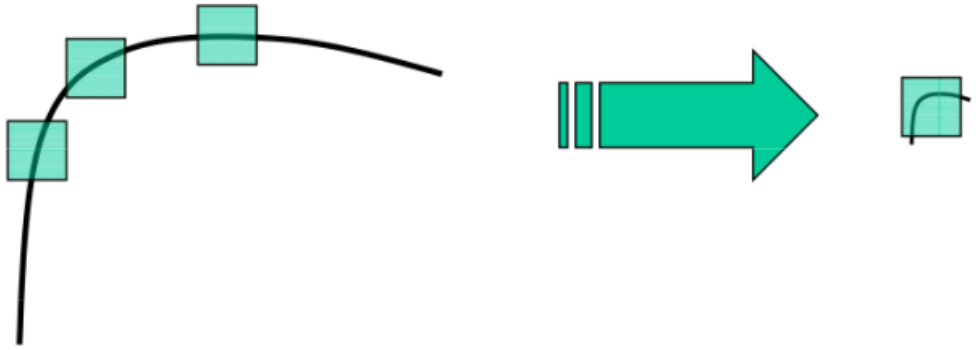


Ellipse rotates but its shape (i.e. eigenvalues) remains the same

- The corner response $C(H)$ is invariant to image rotation!

What are the invariance properties of the Harris corner detector?

- Scale invariance



All points will be classified as edges

Corner !

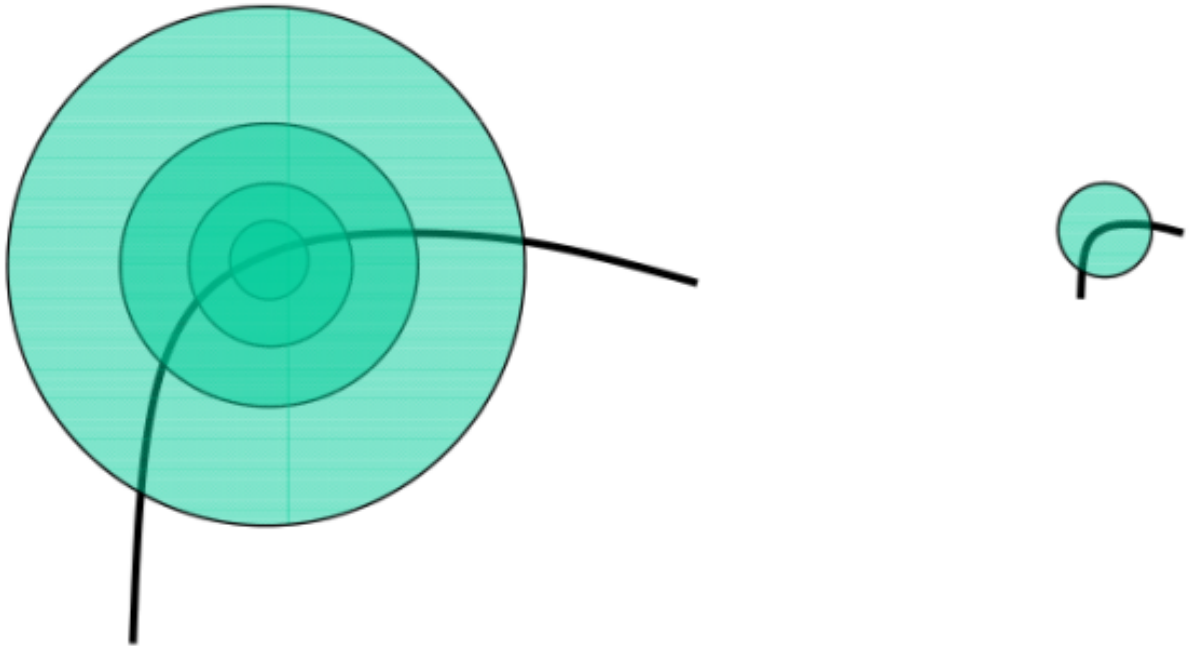
- The corner response $C(H)$ is NOT invariant to image scale!

Scale invariance!

- How can we detect **scale invariant** feature points?

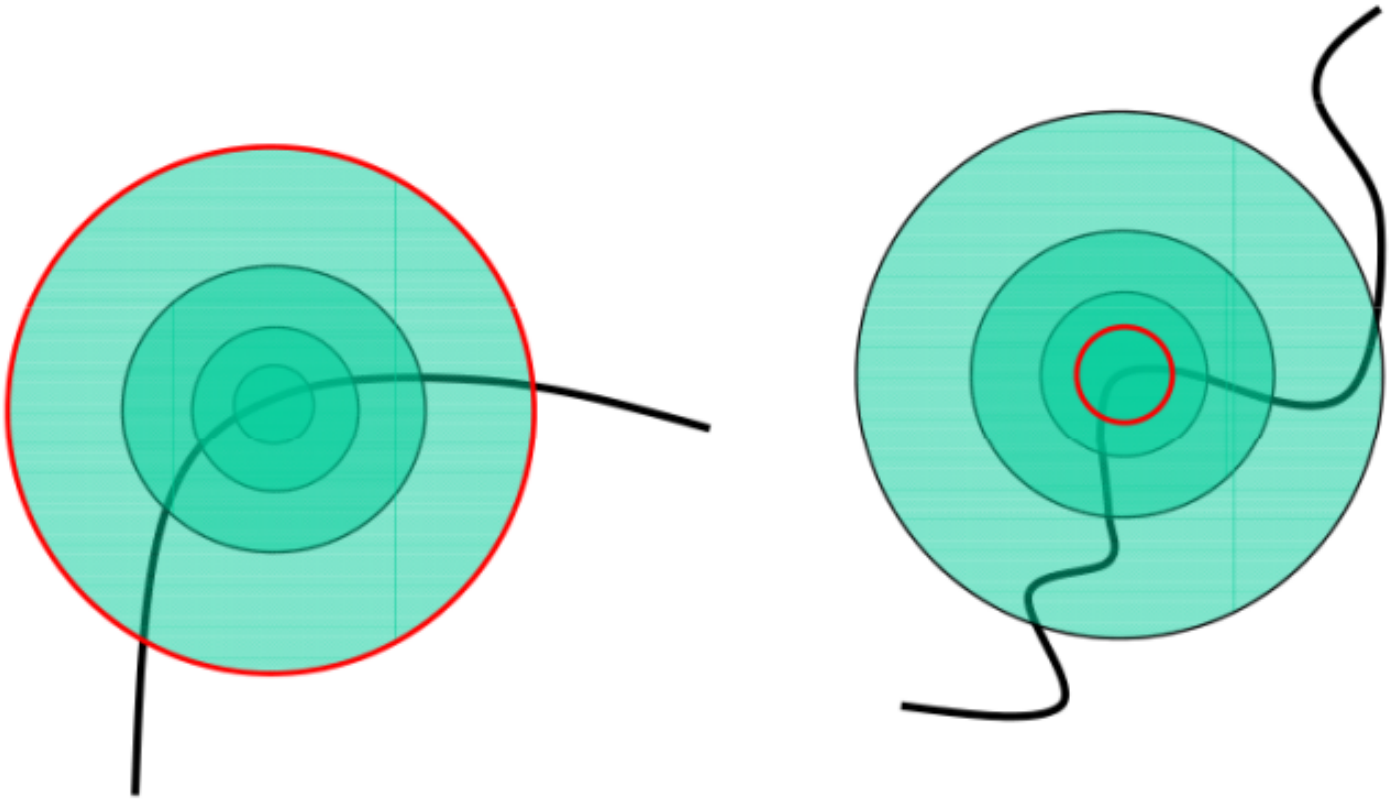
Scale invariance!

- How can we detect **scale invariant** feature points?
- Consider regions of different size patches around the potential feature point
- The regions of corresponding sizes will look the same in both images



Scale invariance!

- Issue: how do we choose the correct patch size in each image independently?



Scale invariance!

- Solution 1: Exhaustive search across all scales

Scale invariance!

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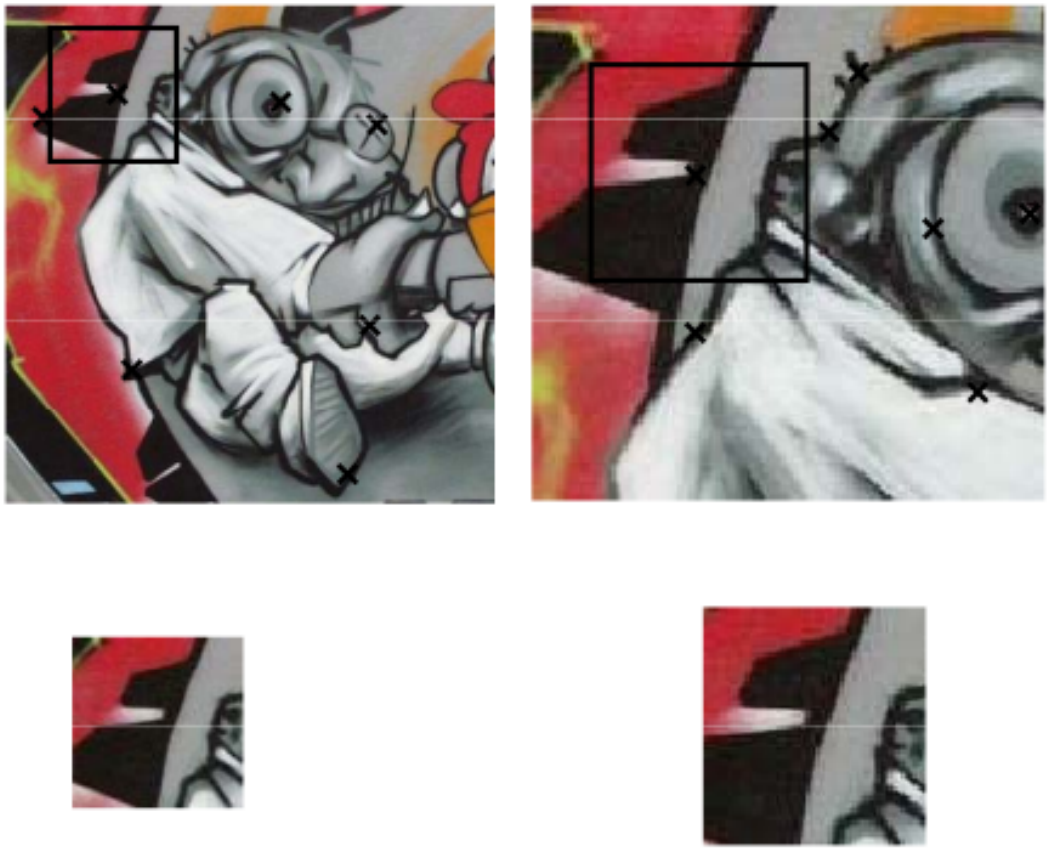


Scale invariance!

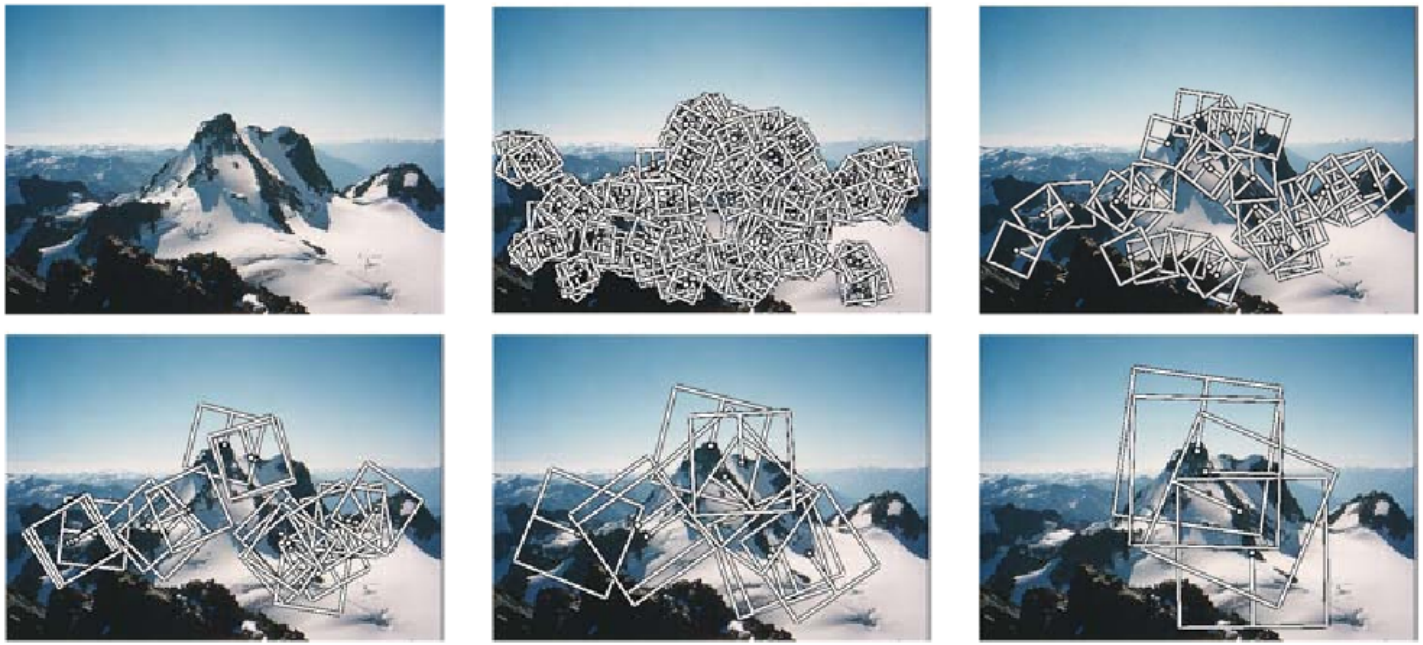
- Solution 1: Exhaustive search across all scales

Scale invariance!

- Solution 1: Exhaustive search across all scales
- Extract a patch from each image individually (your feature list now becomes FL$= [x, y, \text{scale}]$)

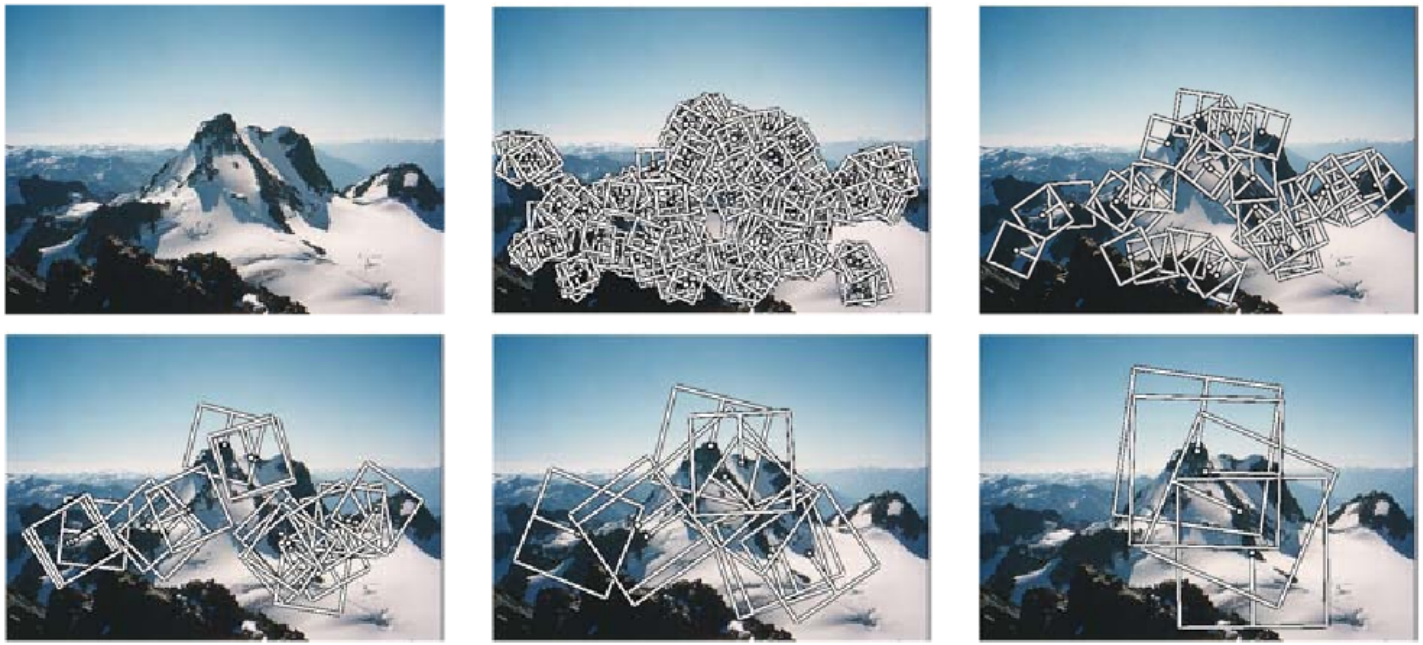
Scale invariance!

- Solution 1: Exhaustive search across all scales



Scale invariance!

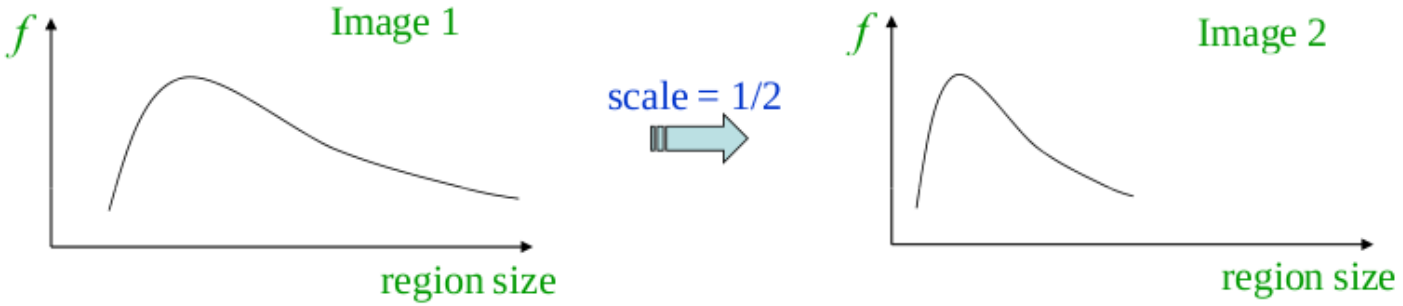
- Solution 1: Exhaustive search across all scales



- Issue: we have to search across all possible scales! We would prefer to select the scale automatically.

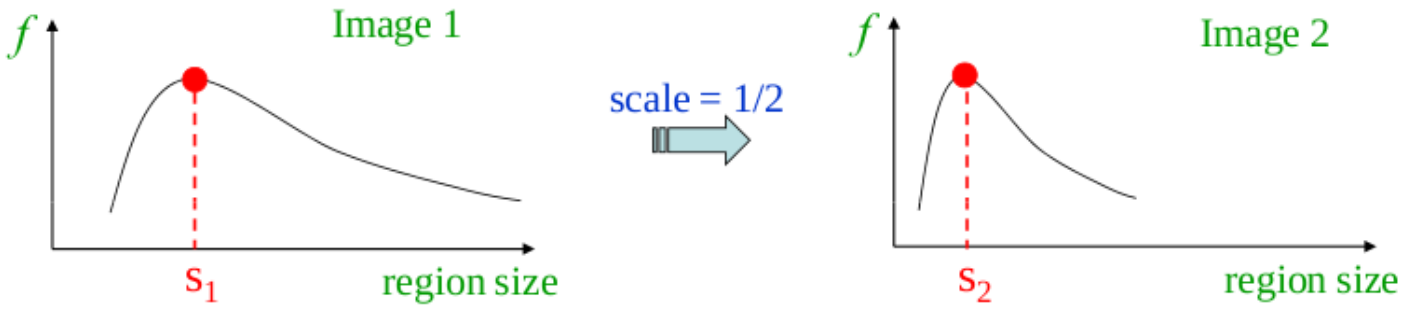
Scale invariance!

- Solution 2: Automatic scale selection
  - Design a function on the patch which is scale invariant (the same for corresponding regions, even at different scales)
    - A good example of such a function is the average intensity. For corresponding regions (even at different scales) this will remain the same.
  - For any given point in an image, we can compute this function as we vary the size of the region (patch) surrounding the interest point



Scale invariance!

- Solution 2: Automatic scale selection
  - Common approach:
    - Take a local max of this function $\Longrightarrow$ the region size for which the maximum is achieved should be invariant to image scale!
  - Important: this scale invariant region size is found in each image **independently**!



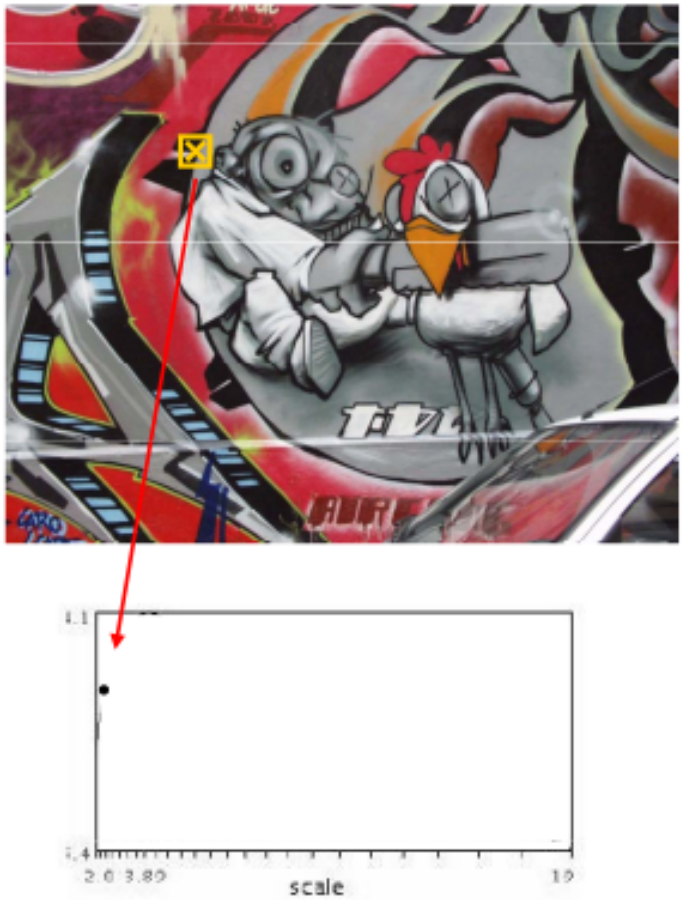
Automatic scale selection

- The same operator response if the patch contains the same image up to a scale factor!

$$f(I_{i_1 \ldots i_m}(x, \sigma)) = f(I_{i_1 \ldots i_m}(x', \sigma'))$$

Automatic scale selection

- Function response for increasing scale (scale signature)

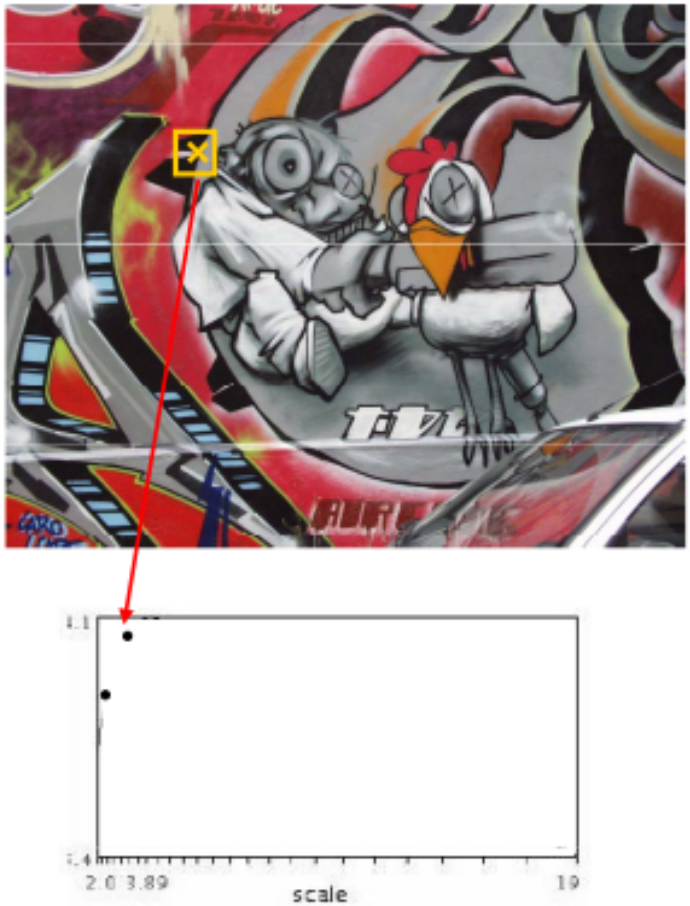


$f(I_{i_1 \ldots i_m}(x, \sigma))$

$f(I_{i_1 \ldots i_m}(x', \sigma))$

Automatic scale selection

- Function response for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x, \sigma))$

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Automatic scale selection

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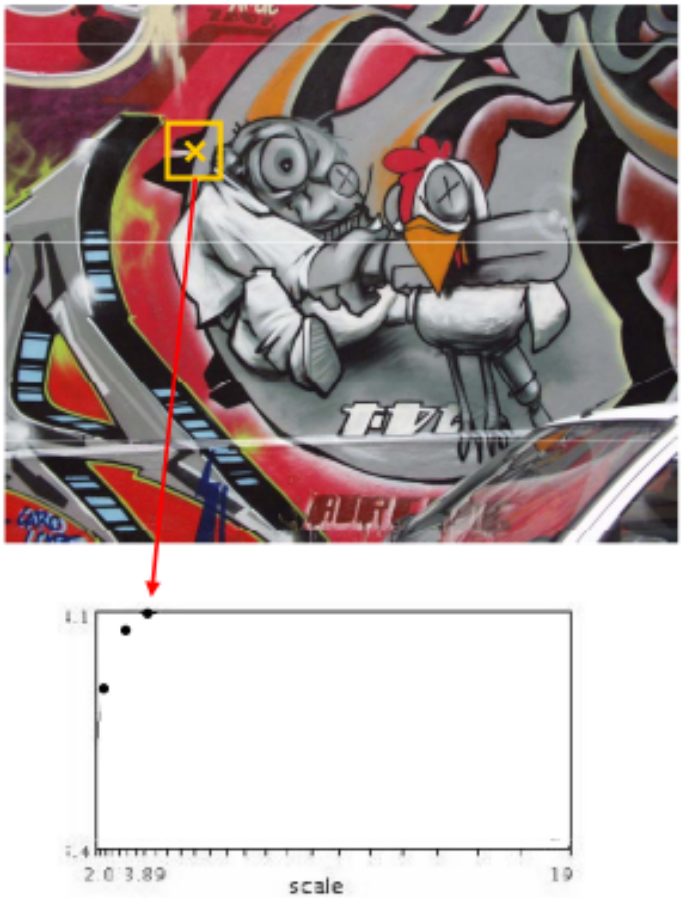
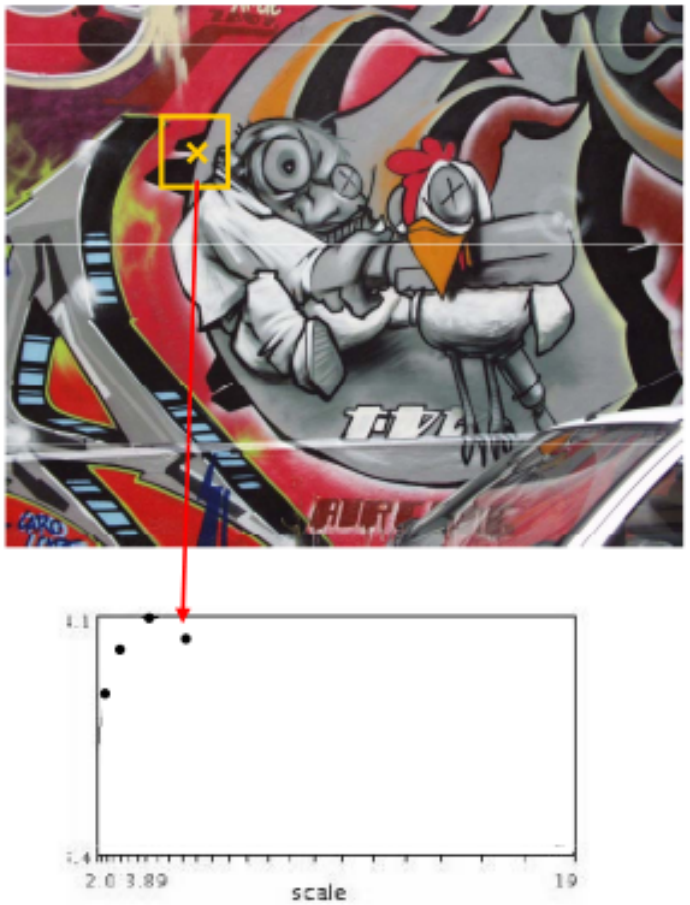


$f(I_{i_1 \ldots i_n}(x, \sigma))$

$f(I_{i_1 \ldots i_m}(x', \sigma))$

Automatic scale selection

- Function response for increasing scale (scale signature)



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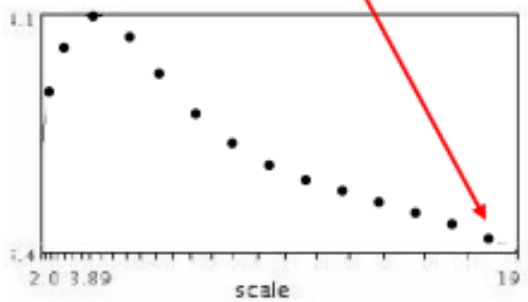
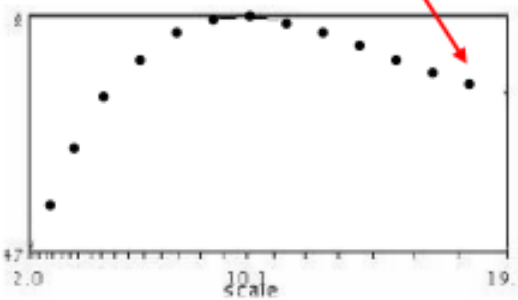
Automatic scale selection

- Function response for increasing scale (scale signature)



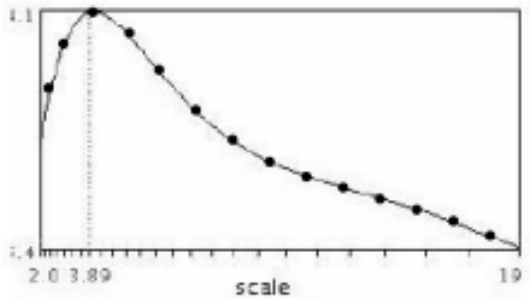
$f(I_{i_1 \ldots i_n}(x, \sigma))$



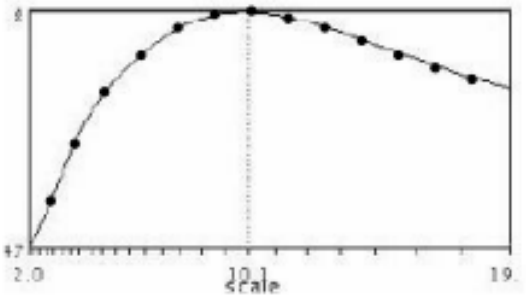
$f(I_{i_1 \ldots i_m}(x', \sigma))$

Automatic scale selection

- Function response for increasing scale (scale signature)



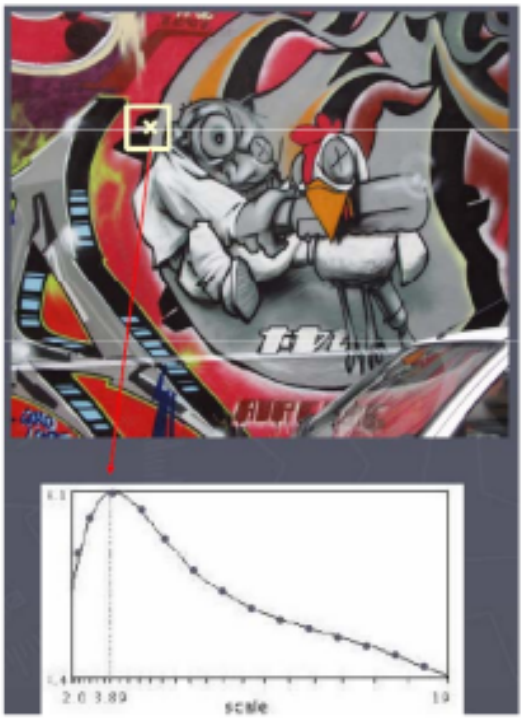
$f(I_{i_1 \ldots i_m}(x, \sigma))$

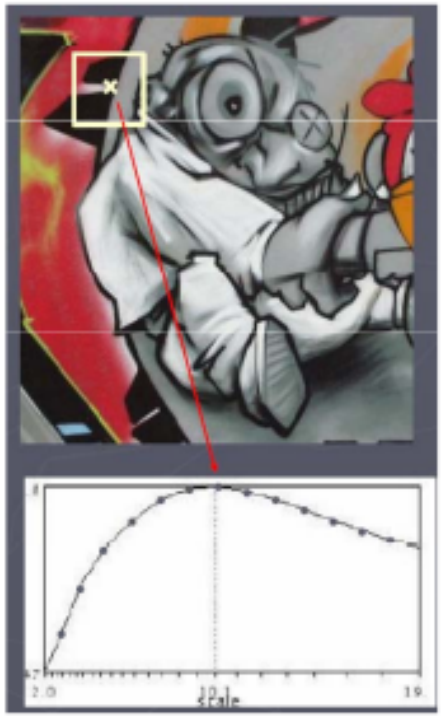


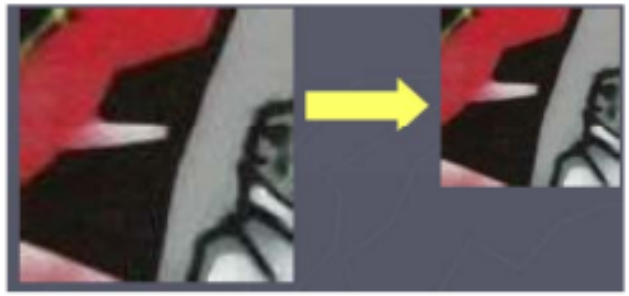
$f(I_{i_1 \ldots i_m}(x', \sigma'))$

Scale selection

- Use the scale determined by the detector to compute a descriptor in a normalized frame!

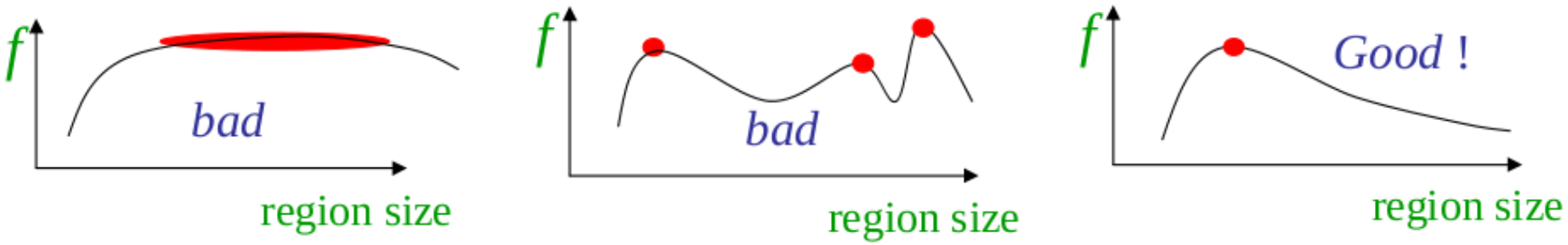






So what function do we use? i.e., what is a good signature function?

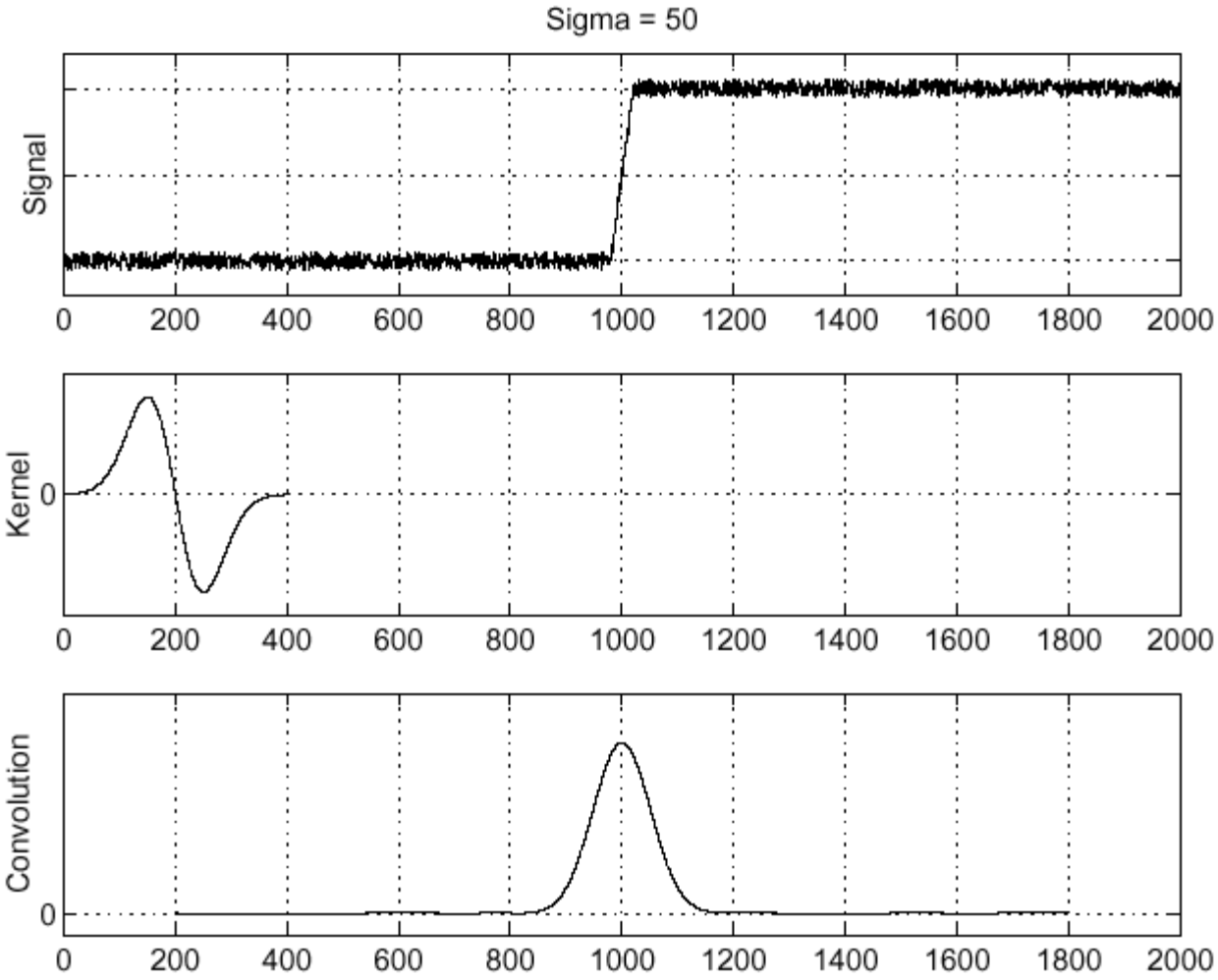
- A "good" function for scale detection is one that has a single **stable** sharp peak



- For usual images: a good function would be one that responds to contrast (sharp local intensity change)

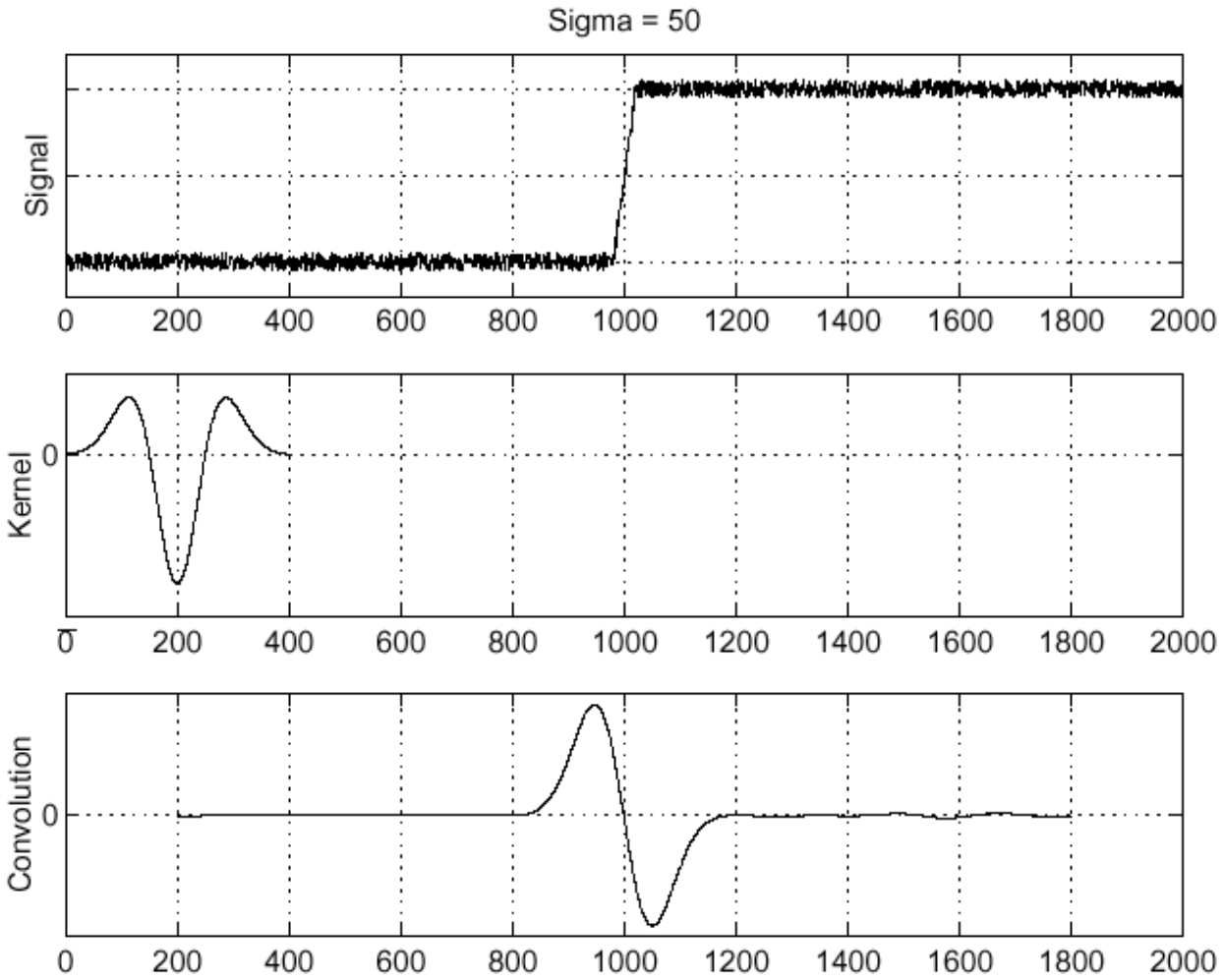
So what function do we use? $\rightarrow$ Recall edge detection!

- f
- $\frac{\partial}{\partial x} g$
- $f * \frac{\partial}{\partial x} g$



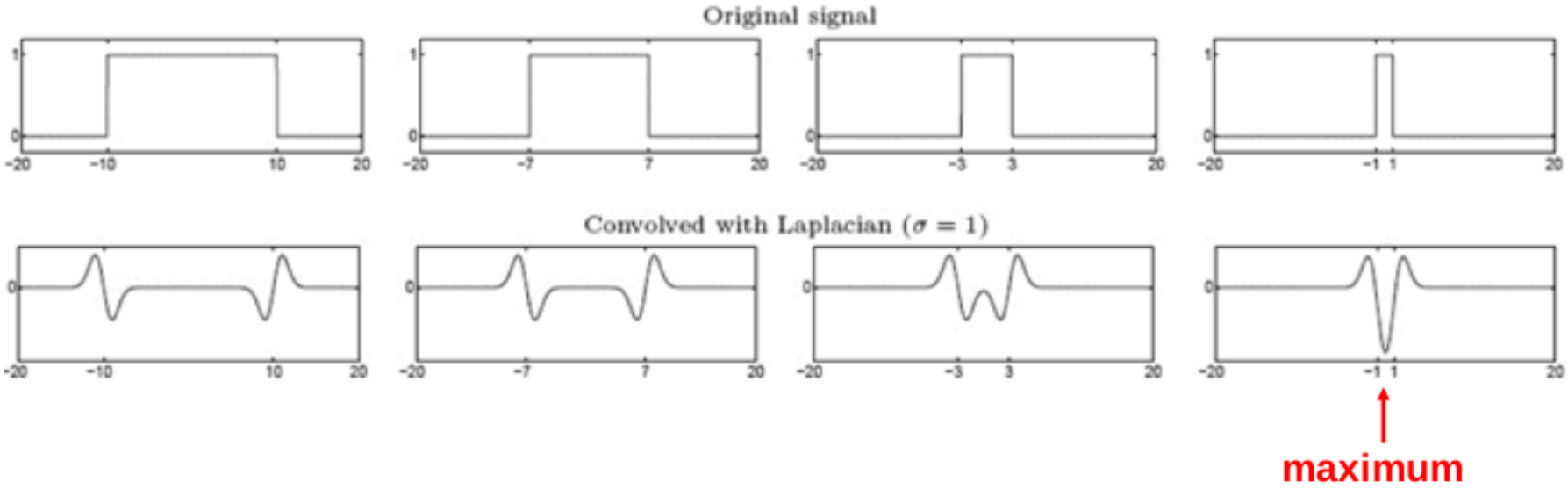
So what function do we use? $\rightarrow$ Recall edge detection!

- f
- $\frac{\partial^2}{\partial x^2} g$
- $f * \frac{\partial^2}{\partial x^2} g$



From edge detection to ripple detection

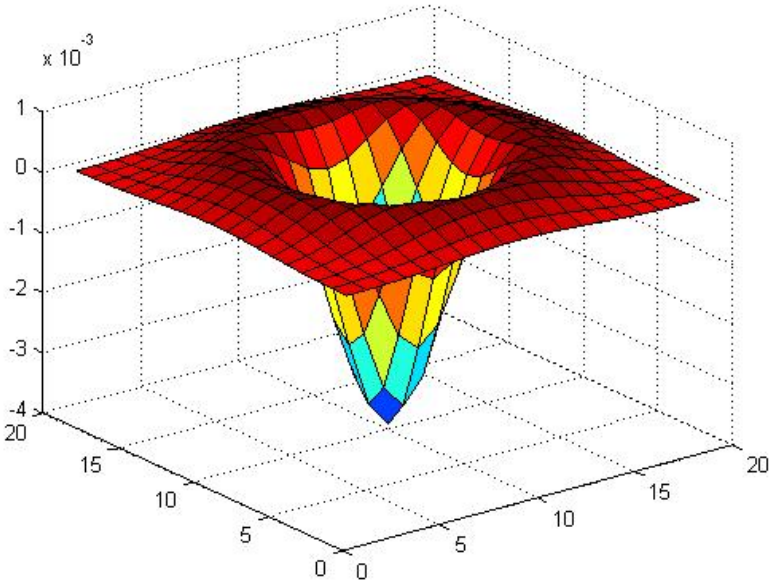
- Edge = ripple
- Blob = superposition of two ripples

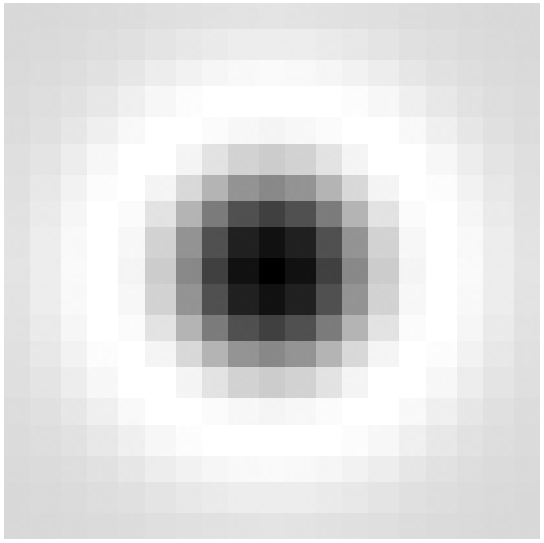


- **Spatial selection:** the **magnitude** of the Laplacian response will achieve a maximum at the center of the blob (provided the scale of the Laplacian is "matched" to the scale of the blob)

Blob detection - 2D

- Laplacian of Gaussian: Circularly symmetric kernel for blob detection in 2D

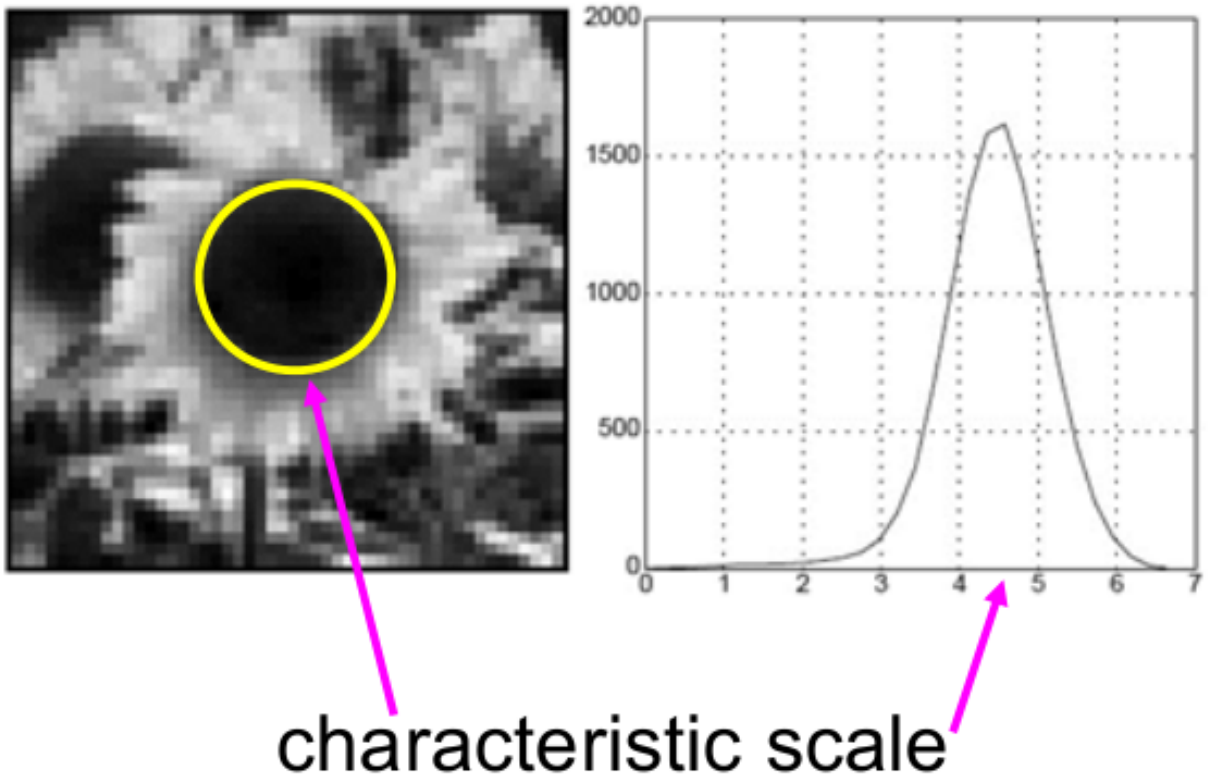




$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

Blob detection - 2D

- Define the *characteristic scale* as the scale that produces a peak of the Laplacian response (squared!)

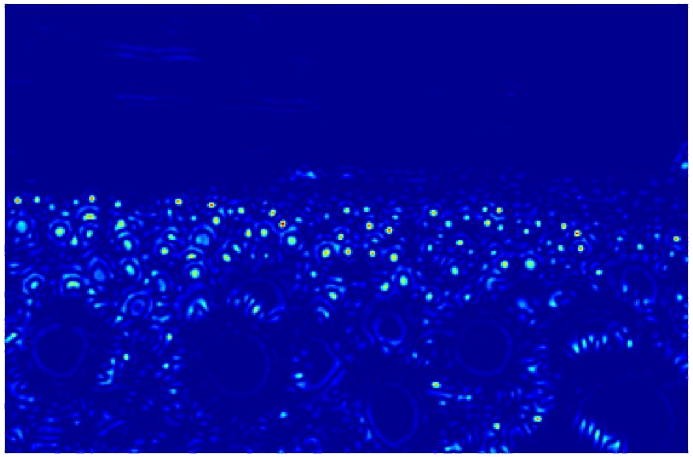


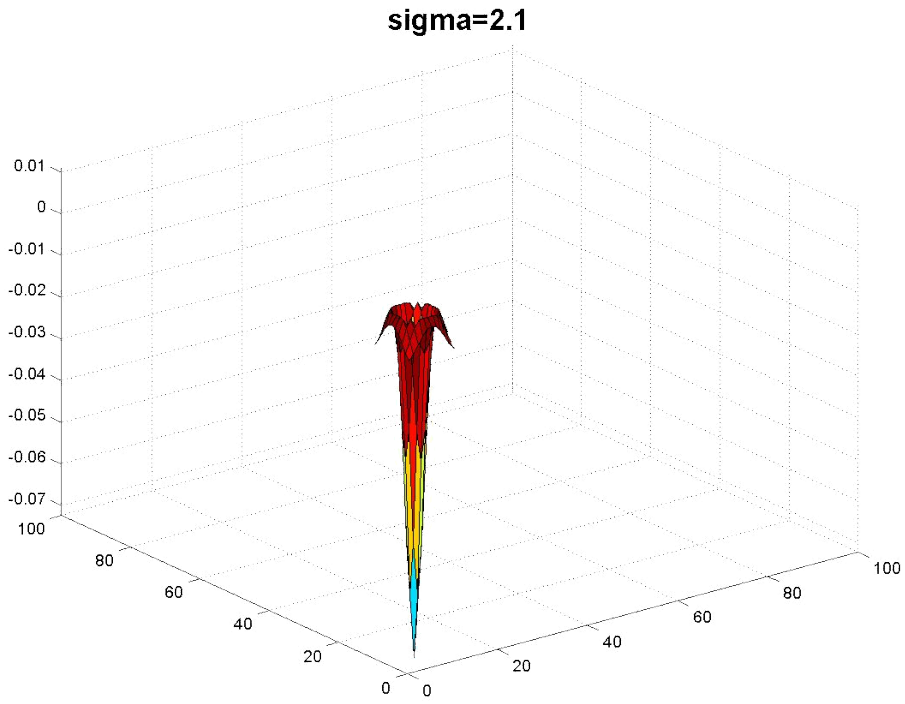
Example

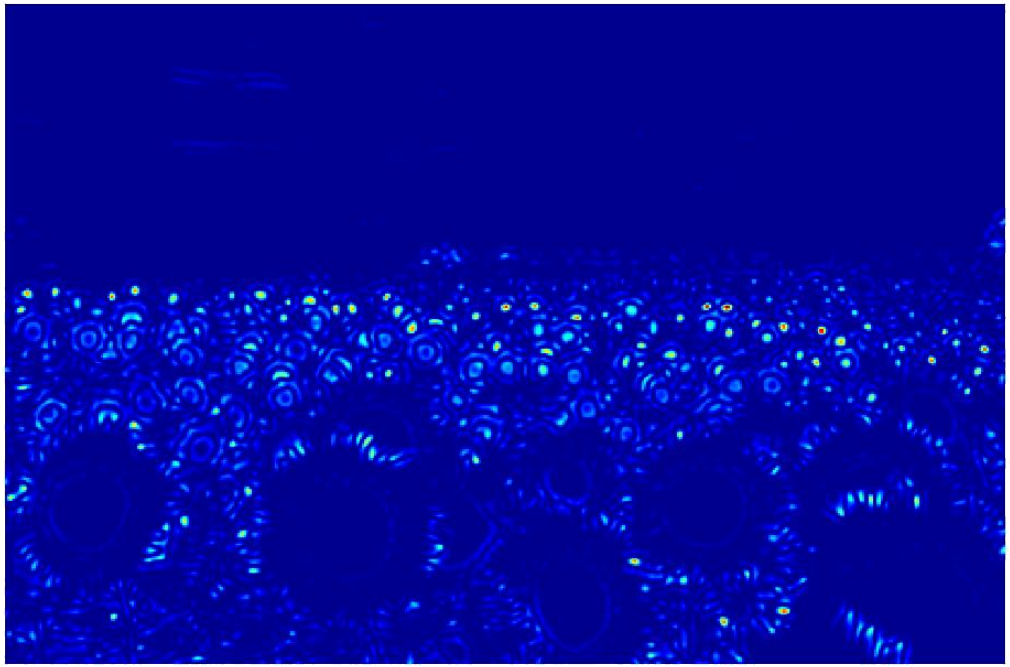
- Original image at 3/4 scale!

Example

- Original image at 3/4 scale!

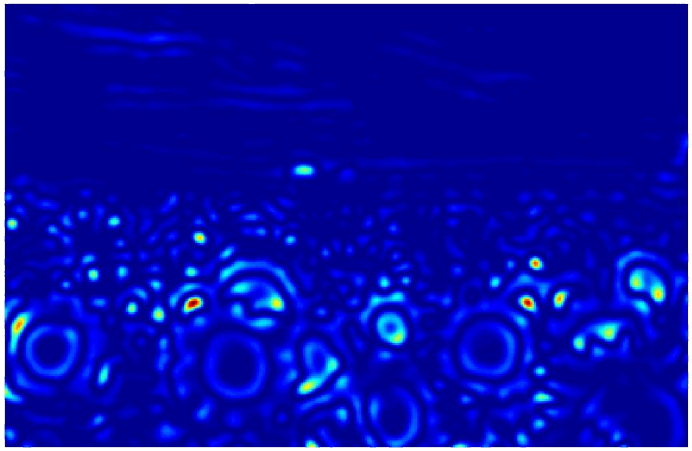


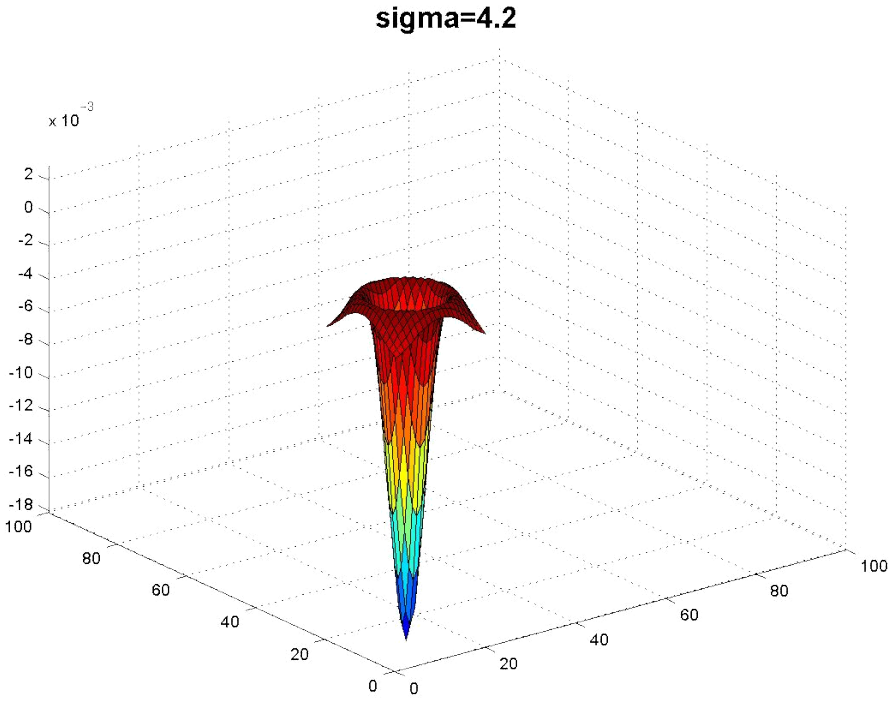


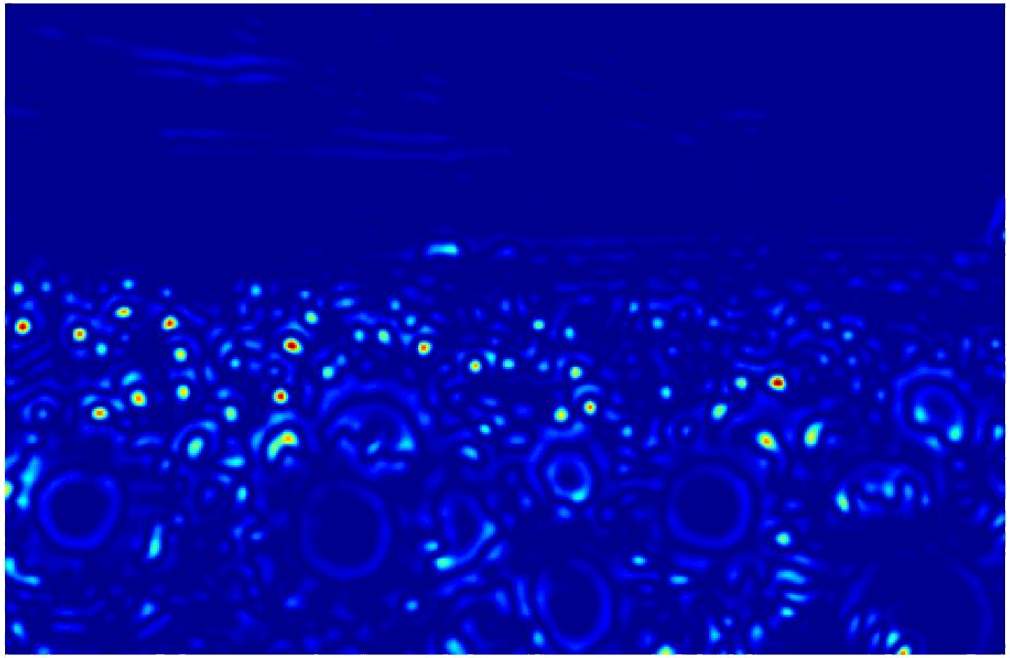


Example

- Original image at 3/4 scale!

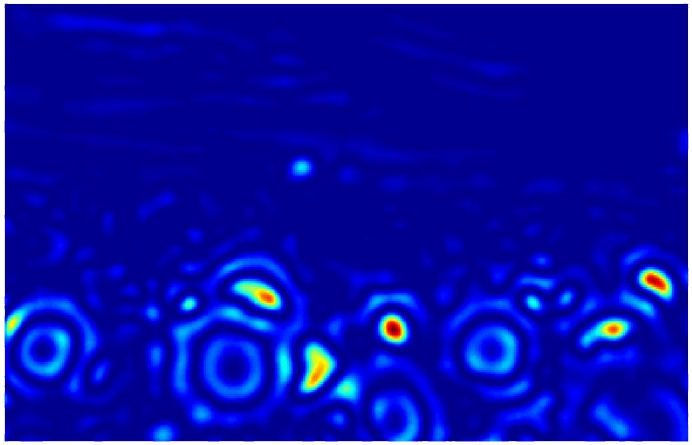


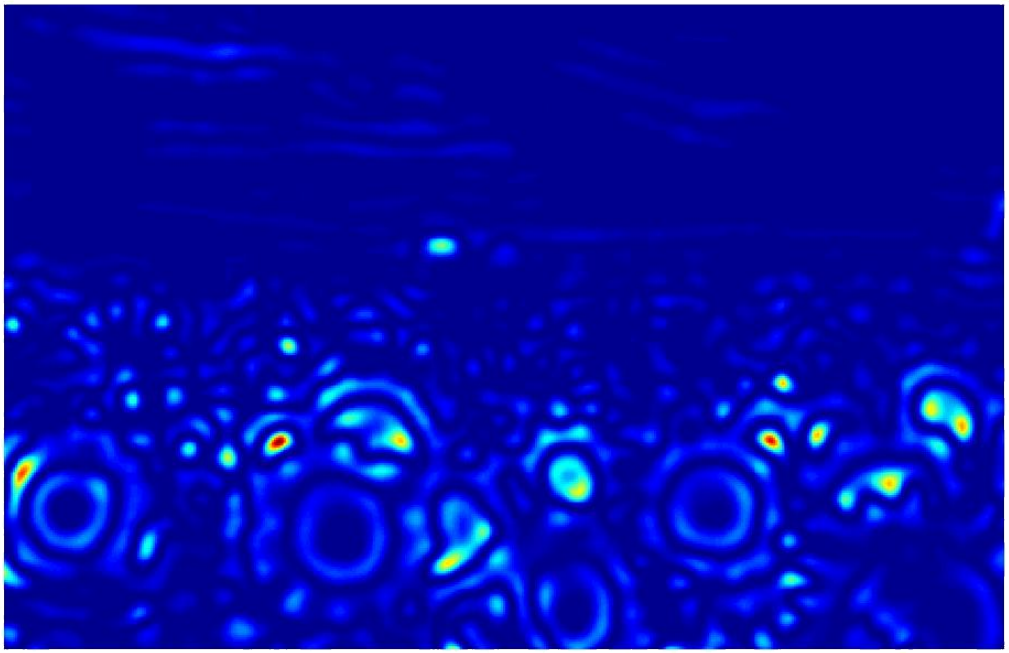


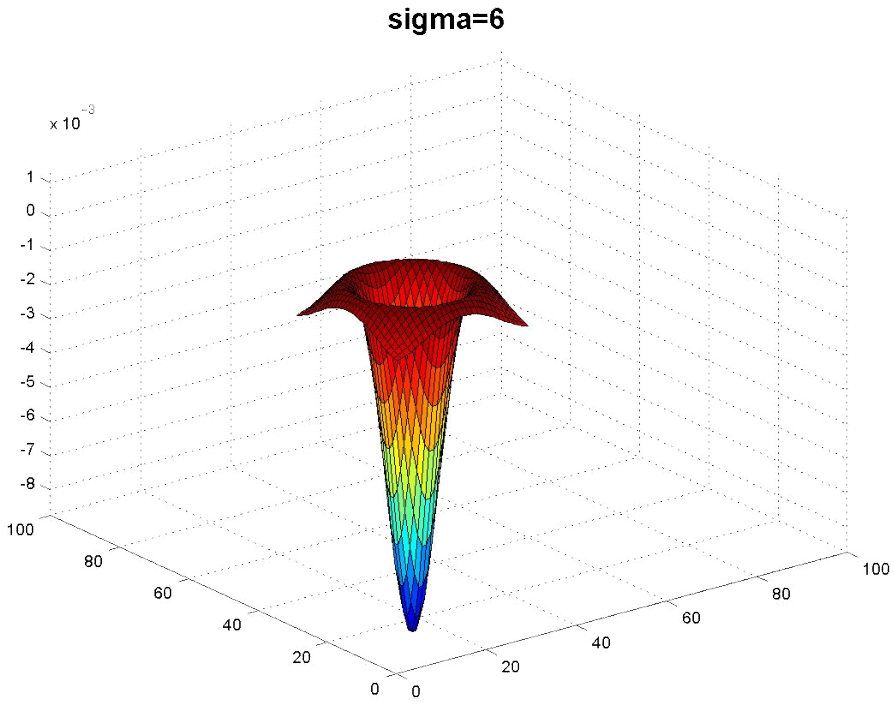


Example

- Original image at 3/4 scale!







Example

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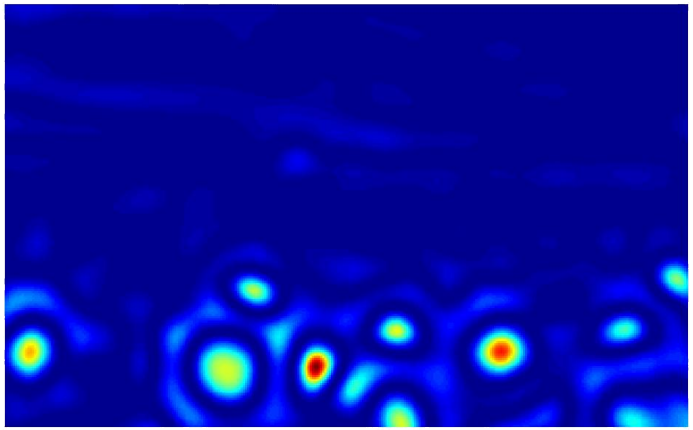

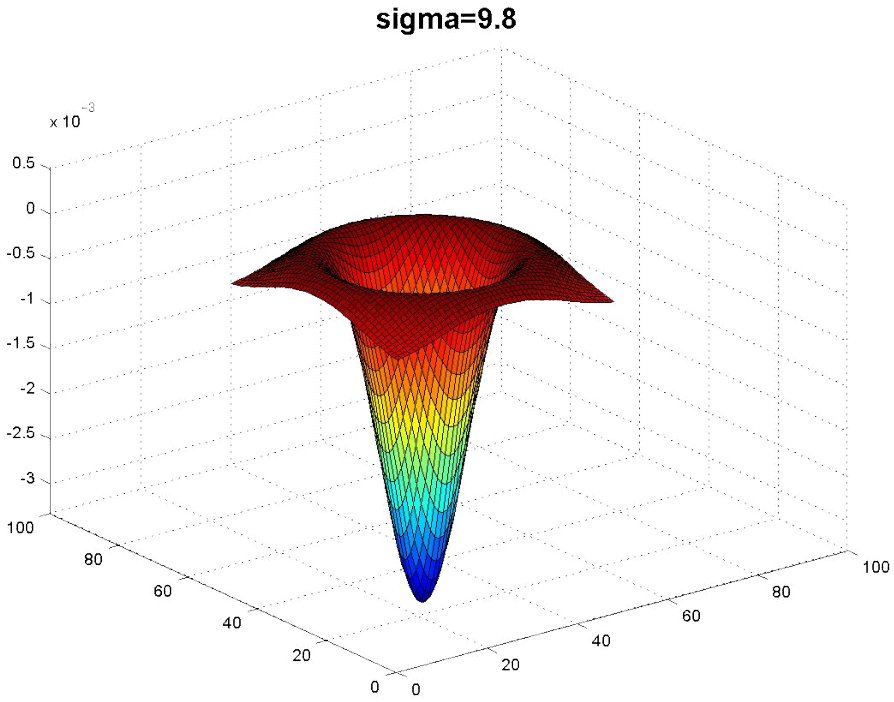

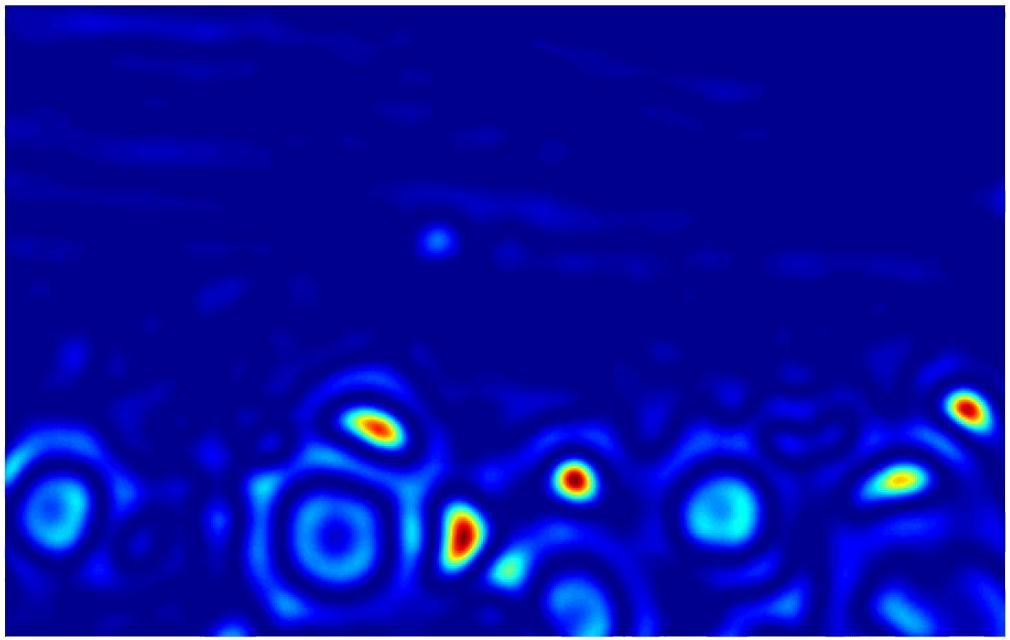

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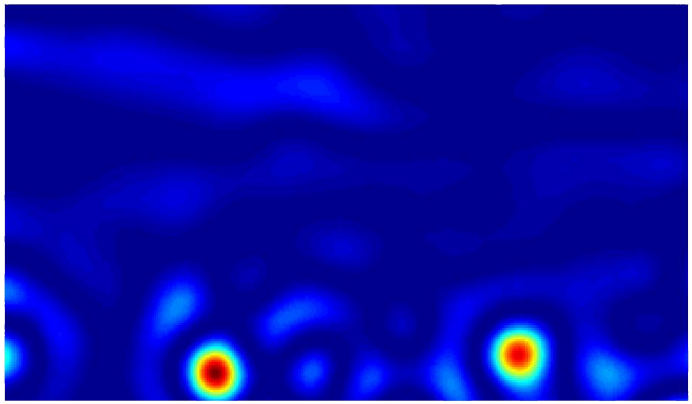
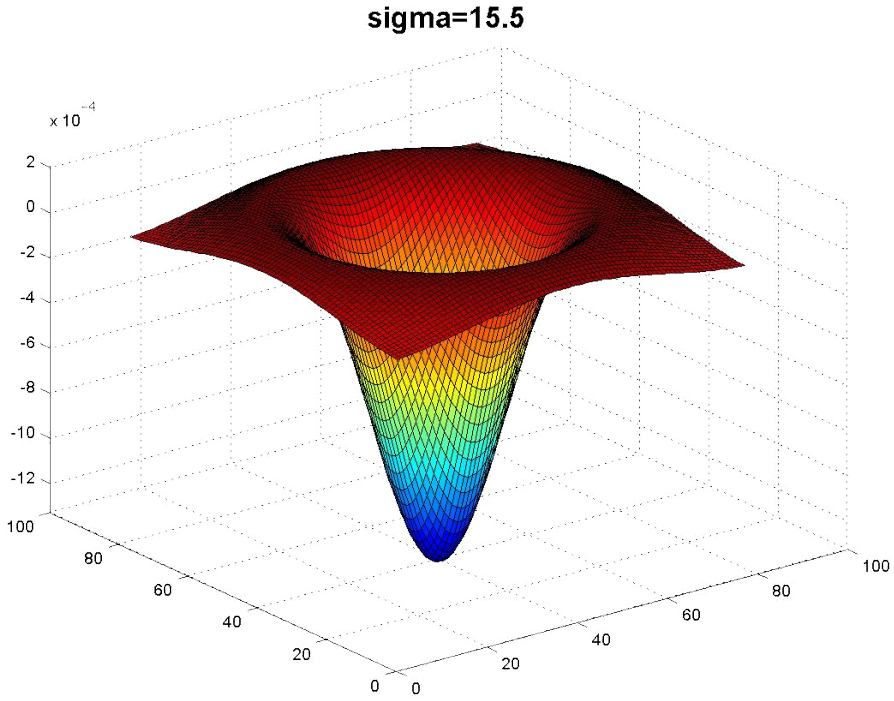
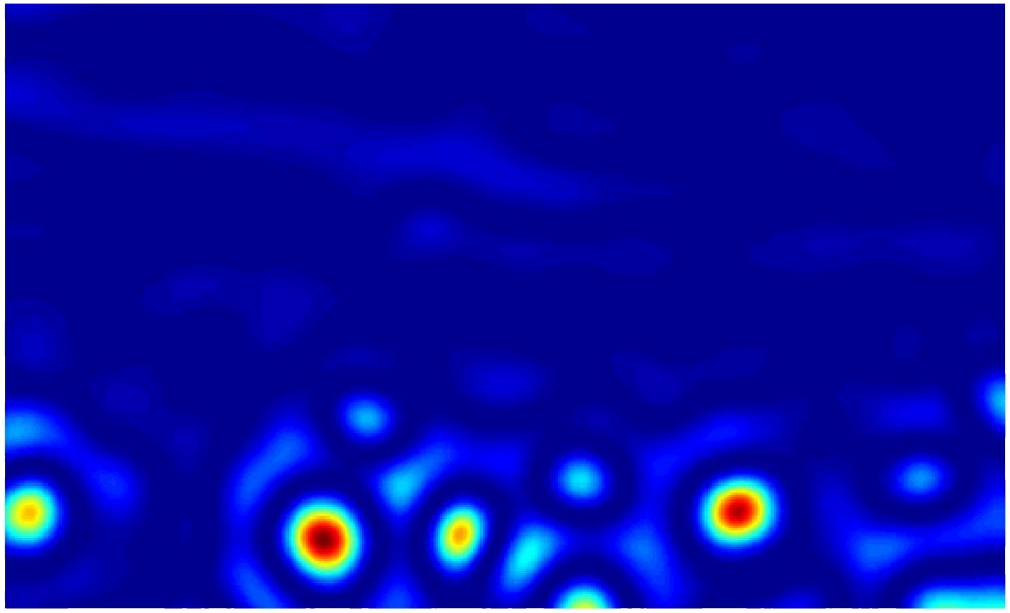
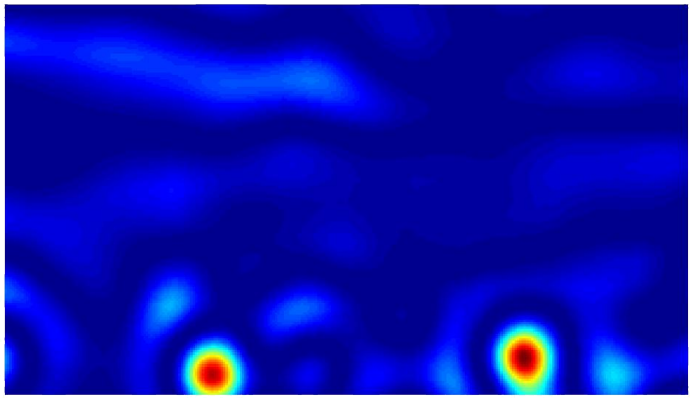


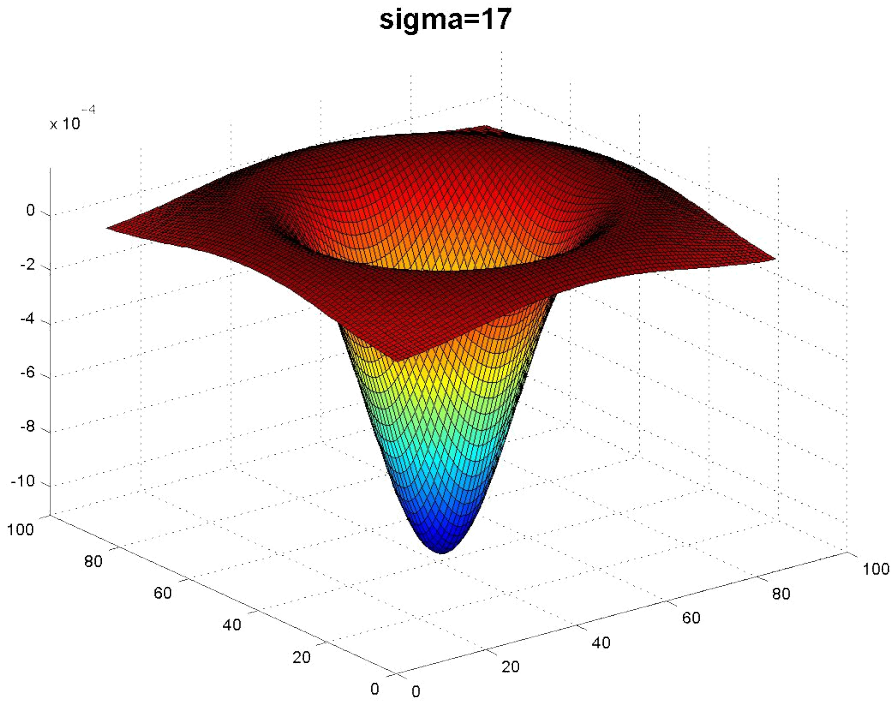


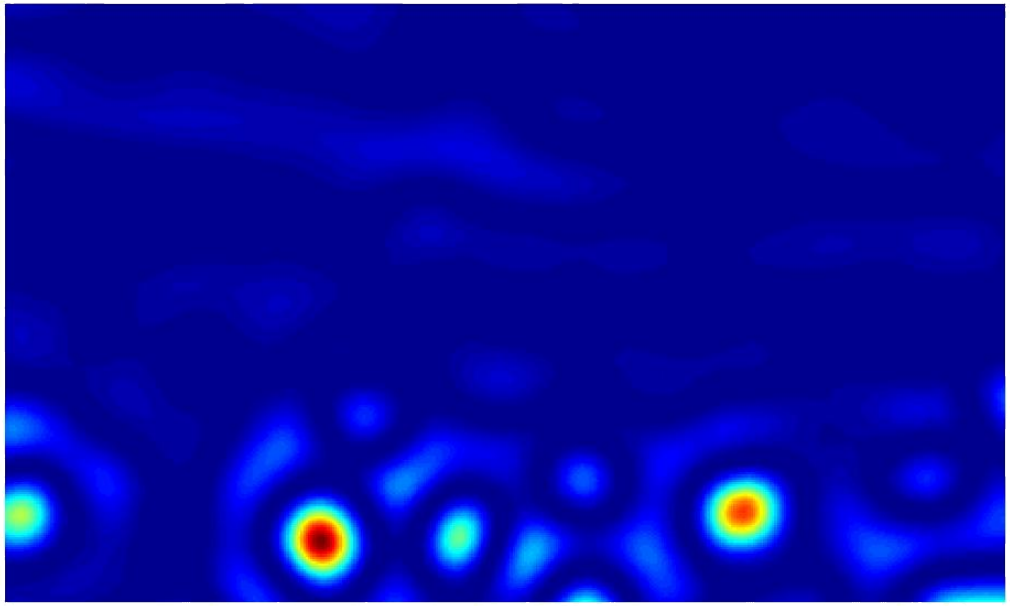


Example

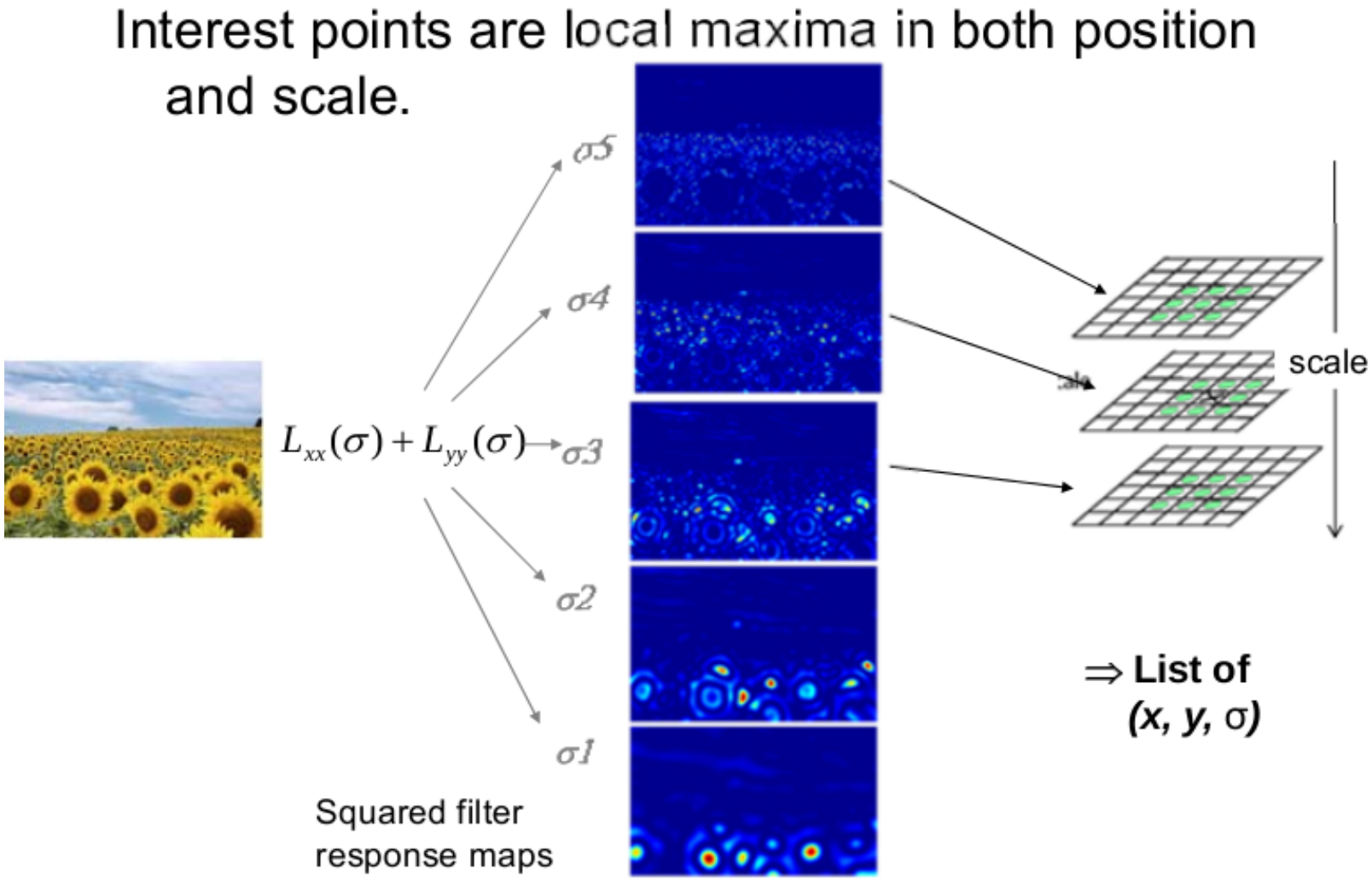
- Original image at 3/4 scale!







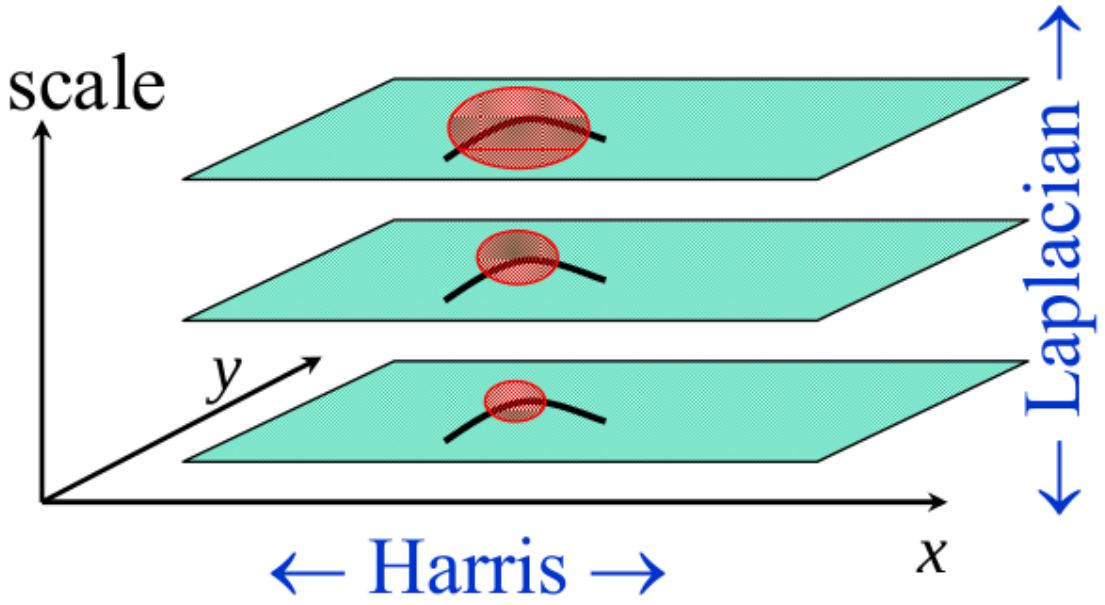
Scale invariant interest points → Harris-Laplacian



Scale invariant feature detector → Harris-Laplacian

Harris-Laplacian

- Find local maximum of:
  - Harris corner detector in space (image coordinates)
  - Laplacian in scale



Scale space feature detector: Example

Let's have a look at this Laplacian kernel!

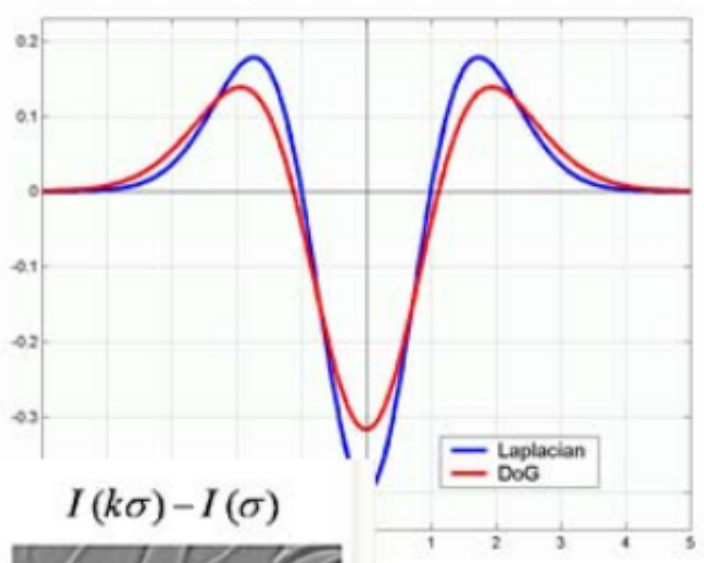
We can approximate the Laplacian with a difference of Gaussians; more efficient to implement.

$$L = \sigma^2 \left(G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma) \right)$$

(Laplacian)

$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

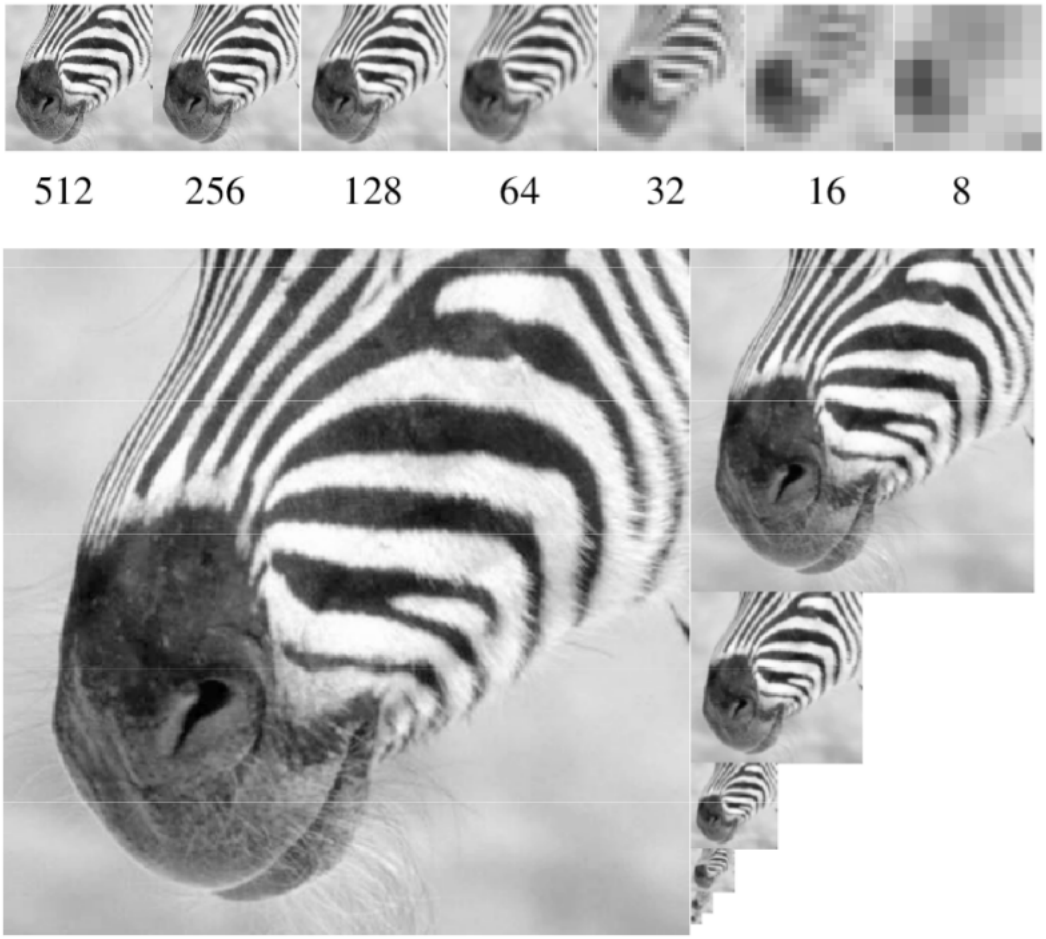
(Difference of Gaussians)



$I(k\sigma)$ $I(\sigma)$ $I(k\sigma) - I(\sigma)$

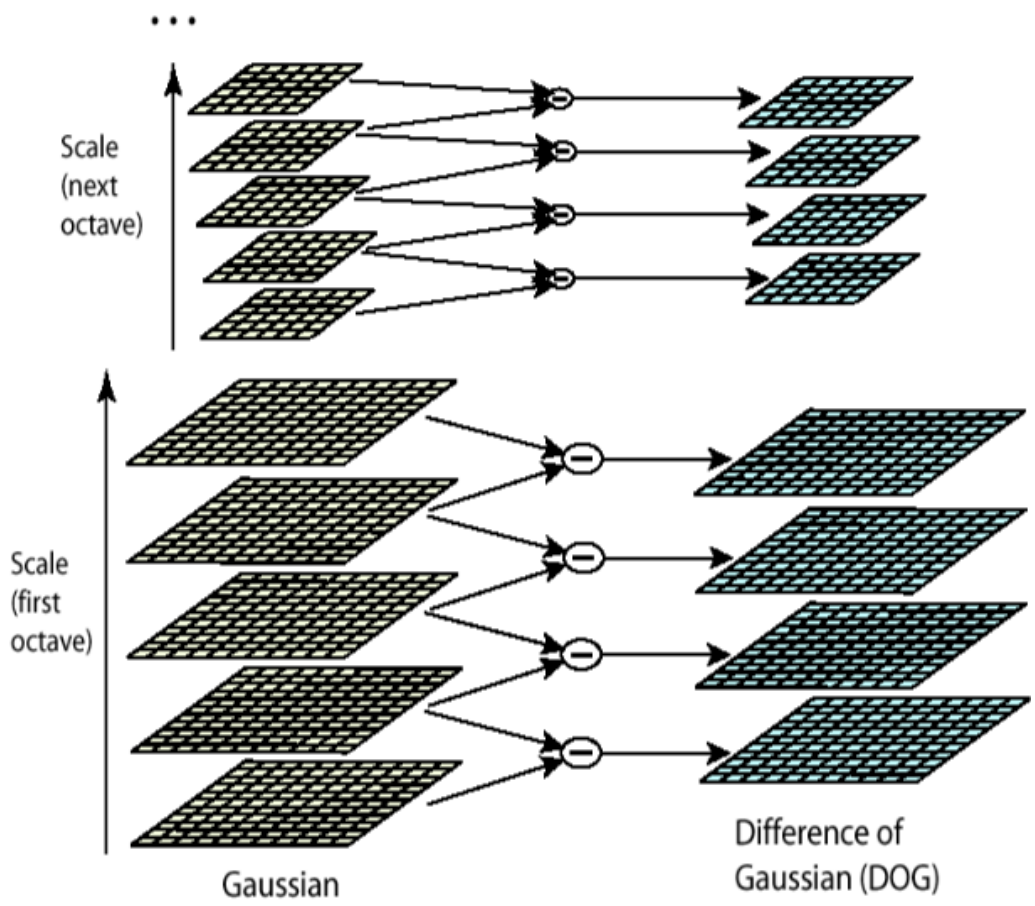
The Scale Invariant Feature Transform (SIFT)

1. Construct an image pyramid at 3-4 scales (octaves - refer to your text)



The Scale Invariant Feature Transform (SIFT)

1. Construct an image pyramid at 3-4 scales (octaves - refer to your text)
2. Convolve each image at different scales with a Gaussian kernel $G(x, y, k\sigma)$ (k is selected so we get a fixed number of blurred images/octave)



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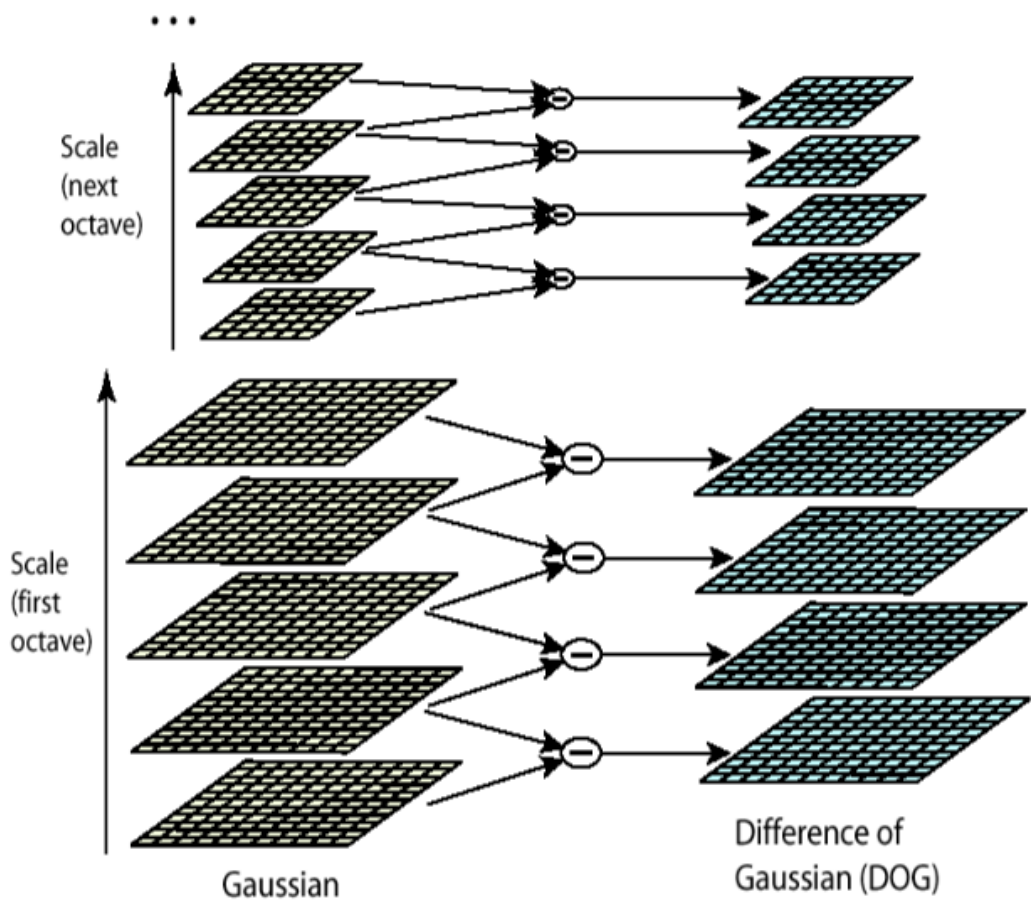
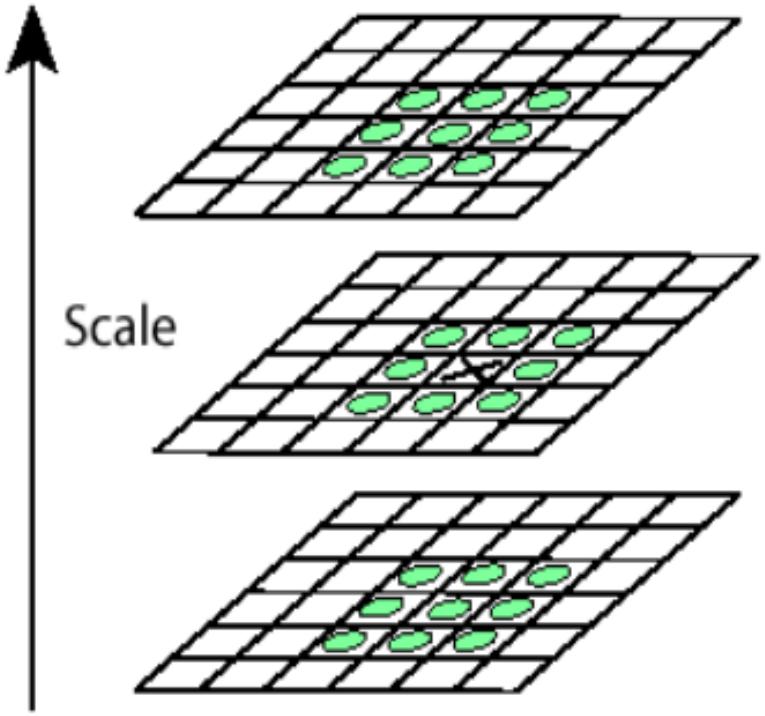
3. At each octave, compute the set of DoG images



The Scale Invariant Feature Transform (SIFT)

1. Construct an image pyramid at 3-4 scales (octaves - refer to your text)
2. Convolve each image at different scales with a Gaussian kernel $G(x, y, k\sigma)$ (k is selected so we get a fixed number of blurred images/octave)
3. At each octave, compute the set of DoG images
4. Find local maxima or minima in the DoG images across scale
   - Compare to 8-neighbors + 18 neighbors at diff. scales
   - If local max/min = candidate keypoint



The Scale Invariant Feature Transform (SIFT)

1. For each candidate point:
   - Interpolate for sub-pixel localization
     - Taylor series expansion, differentiate, set to zero and solve for the true max/min
     - Improves robustness and stability of the feature

$$
\begin{aligned}
I(x,y) \quad \approx \quad & I(x_0,y_0) + [(x-x_0),(y-y_0)]\,\nabla I(x_0,y_0)^T \\
& + \frac{1}{2}\left([(x-x_0),(y-y_0)]\,\nabla^2 I(x_0,y_0)\,[(x-x_0),(y-y_0)]^2\right) \\
& + o(\cdot)
\end{aligned}
$$

   - Remove low-contrast keypoints (using the Gaussian image at the closest scale set a threshold - again at the sub-pixel level!)
   - Remove edge keypoints (the same as the Harris detector - 1 big gradient and 1 small gradient $\implies$ edge)

The Scale Invariant Feature Transform (SIFT)

- Assign the keypoint an orientation
  - Keypoint orientation: Gradient orientation histogram computed in the neighborhood (using the Gaussian image at the closest scale)
  - The contribution of each neighboring pixel is weighted by the gradient magnitude and a Gaussian window ($\sigma = 1.5$ times the scale)
- Keep keypoints for maximum hist direction as well as directions within 80% of the max (relative to the keypoint orientation $\rightarrow$ rotation invariance)
- In Lowe's paper, he used 10° bins at this stage

Note: This is only the keypoint (feature) not the descriptor!

SIFT example - single scale!

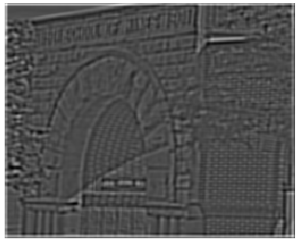
SIFT example - single scale!

SIFT example - single scale!

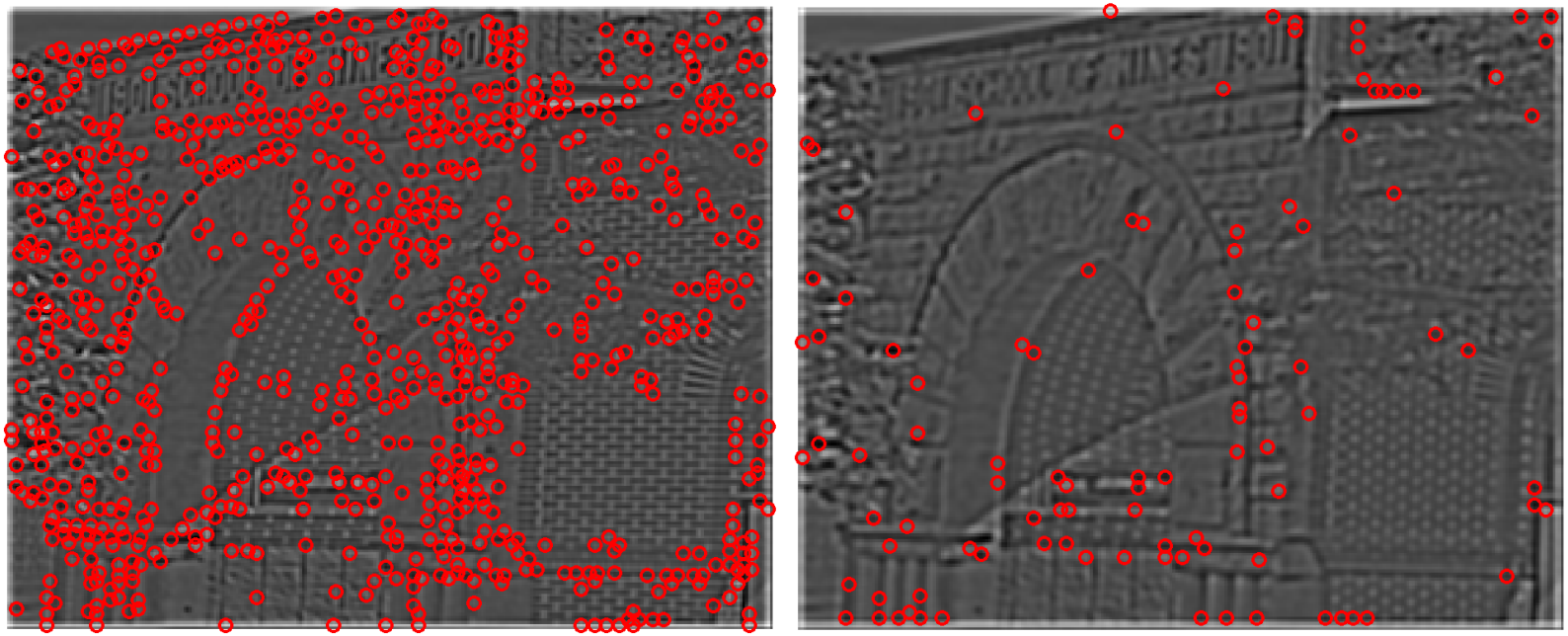




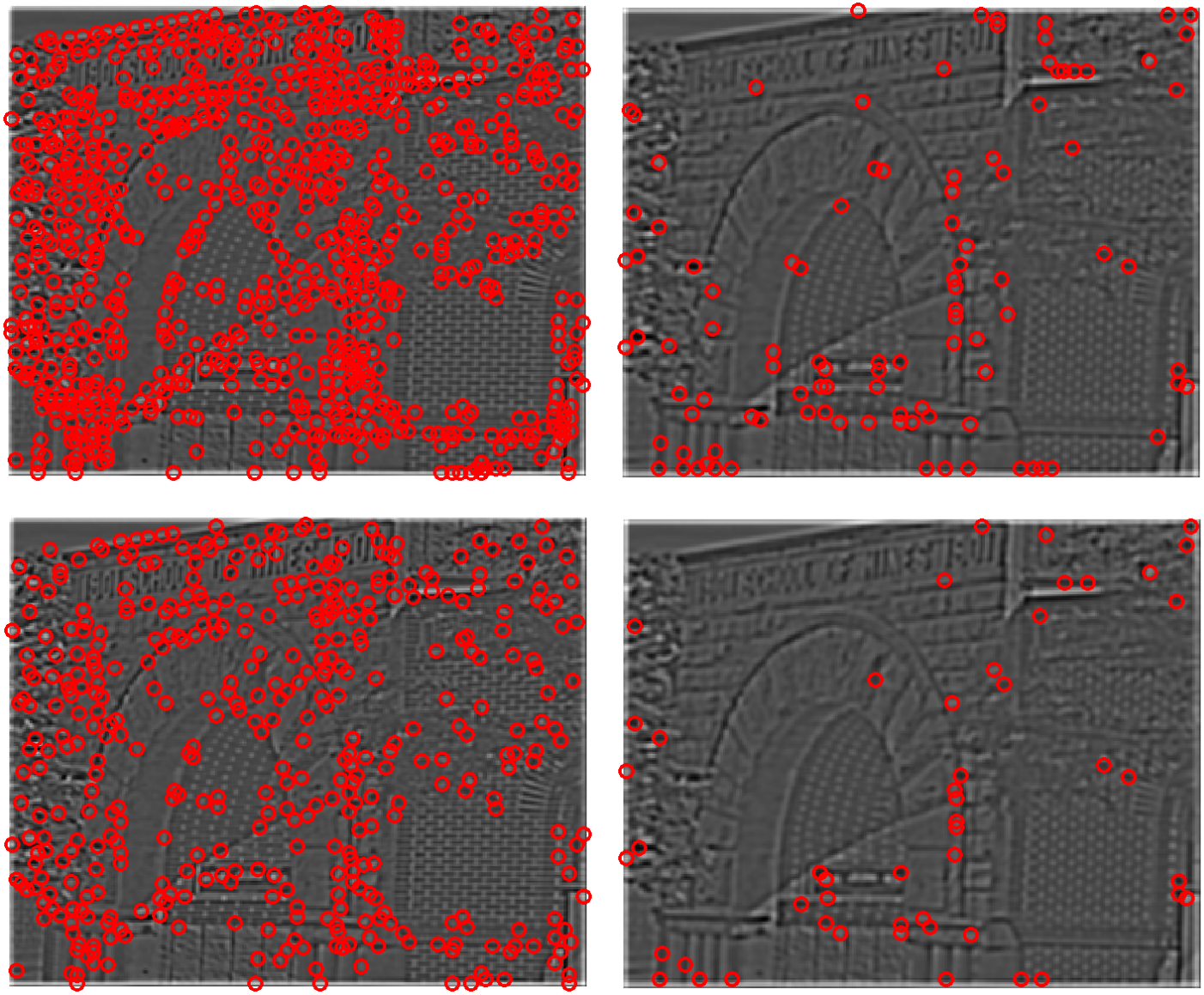


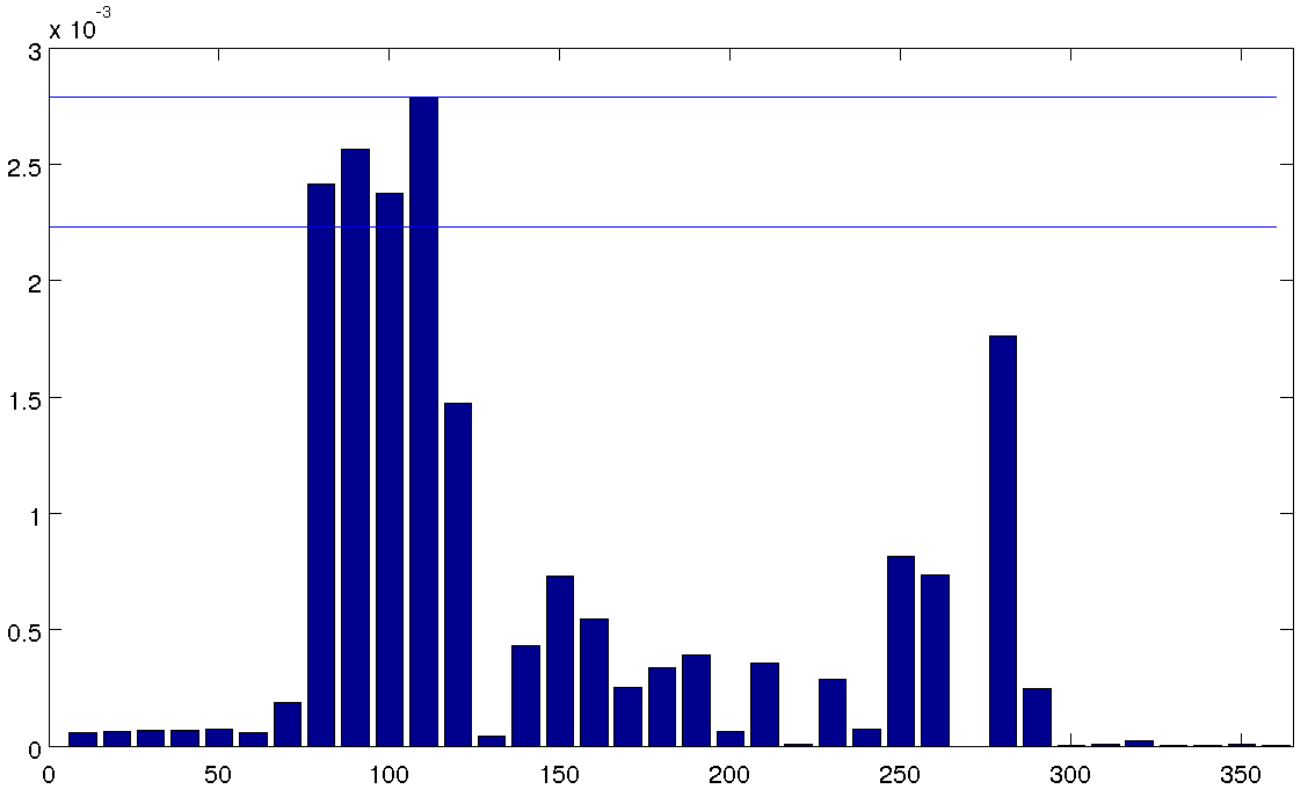

SIFT example - single scale!



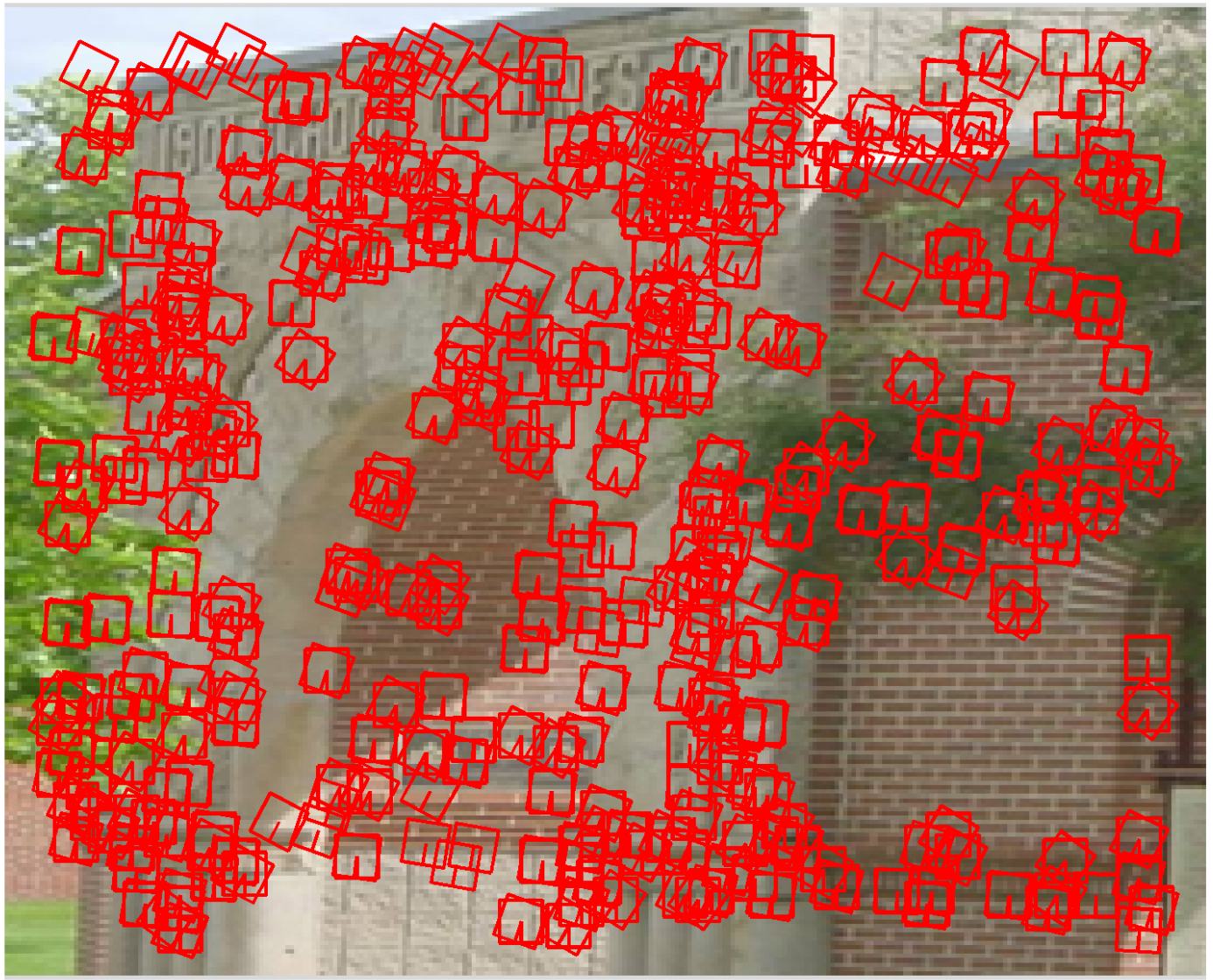
SIFT example - single scale!



SIFT example - single scale!



SIFT example - single scale!



Slide credits

- Prof. Trever Darrell
- Prof. Kristen Grauman
- Forsyth and Ponce
- Rich Szeliski