Scale Invariant Feature Transform
SIFT Descriptor

SIFT citation

- Cited 34442 (google scholar, 30.3.2016)
- Cited 34663 (google scholar, 14.4.2016)

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Object recognition from local scale-invariant features DG Lowe International Conference on Computer Vision, 1999, 1150-1157	10914	1999
Perceptual Organization and Visual Recognition DG Lowe Kluwer Academic Publishers, Boston	1628 *	1985
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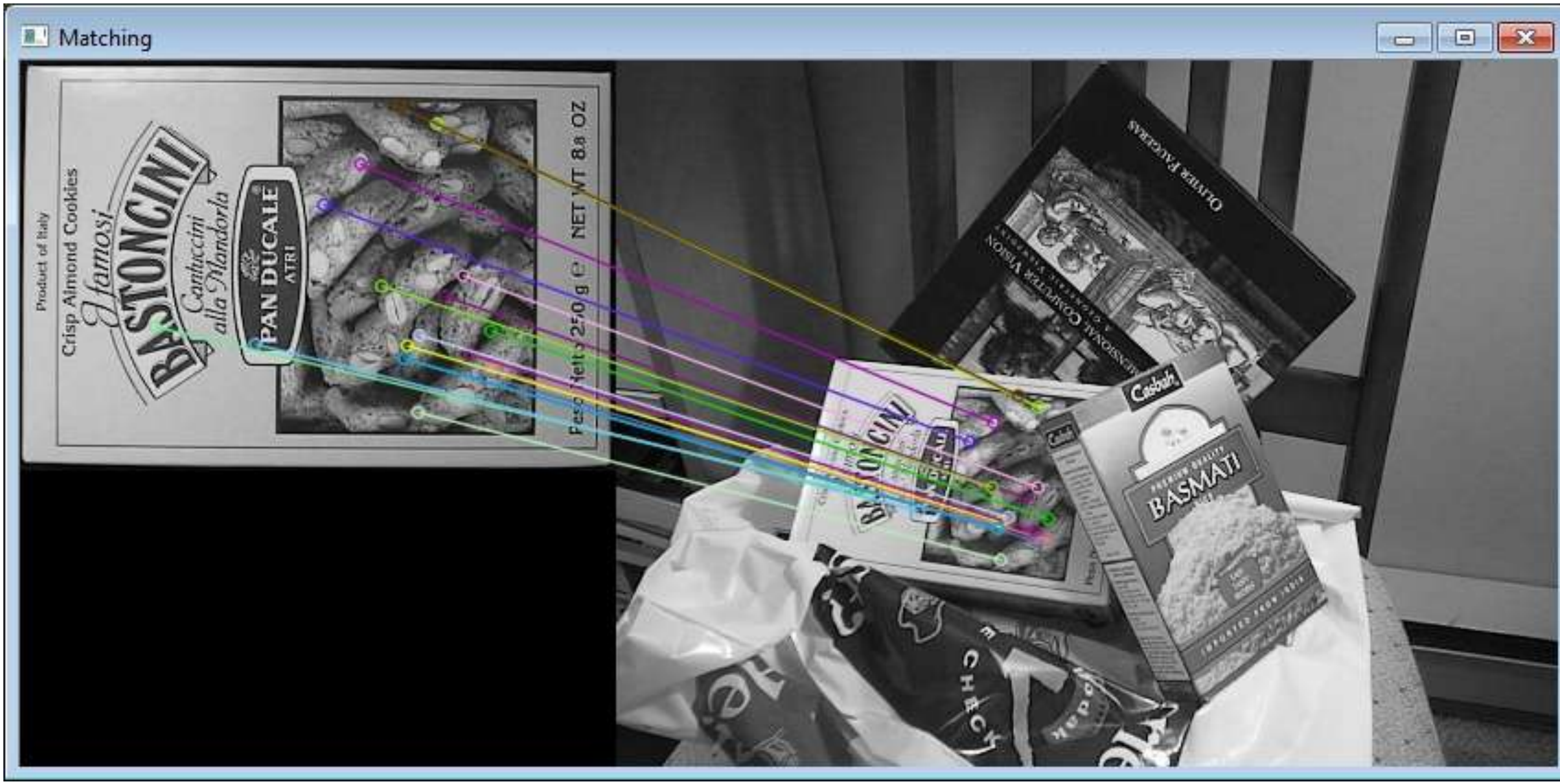
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Outline

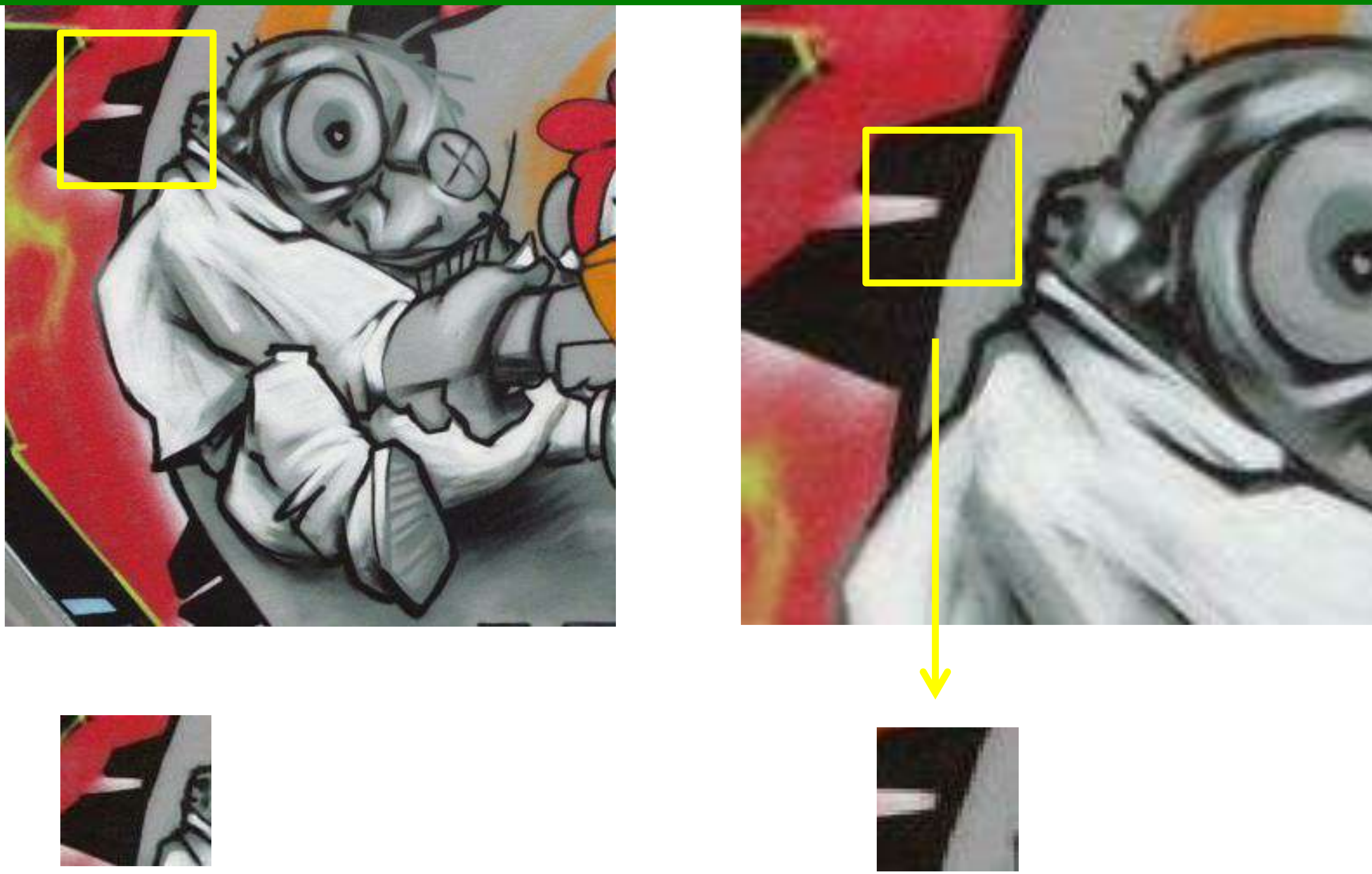
- Automatic scale selection
- SIFT Descriptor

Local Descriptors

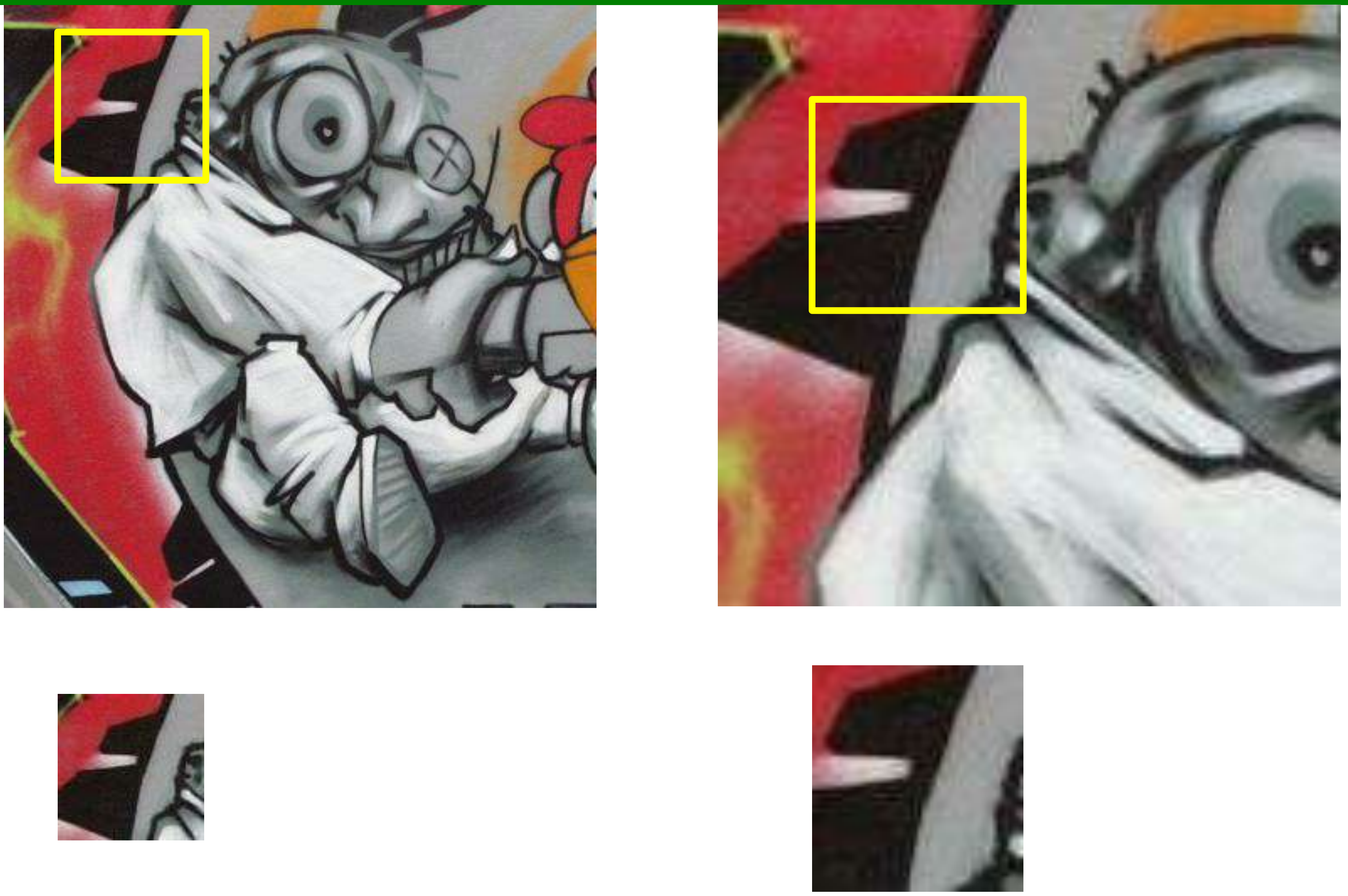
- The ideal descriptor should be
  - Robust
  - Distinctive
  - Compact
  - Efficient

- Most available descriptors focus on edge/gradient information
  - Capture texture information
  - Color rarely used

Exhaustive search (Multi-scale approach)

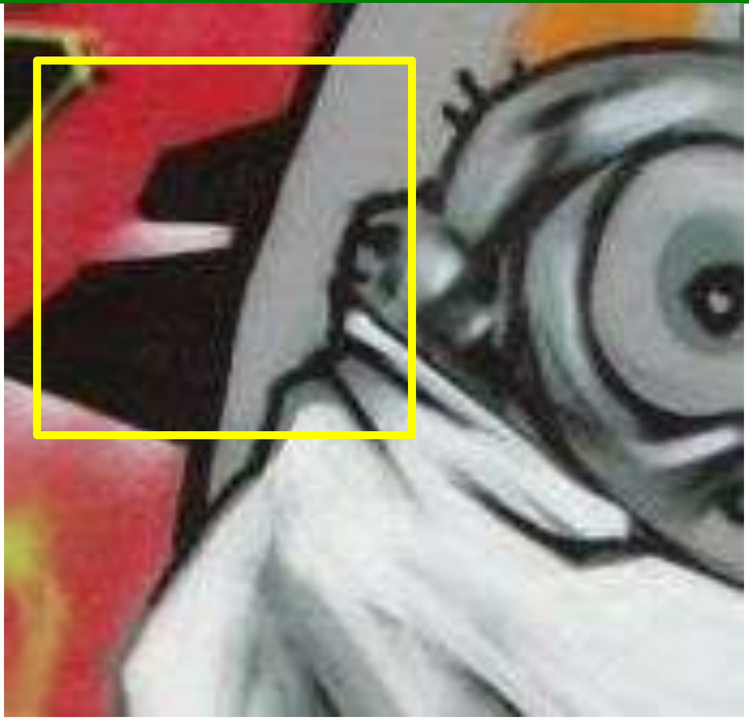


Exhaustive search (Multi-scale approach)

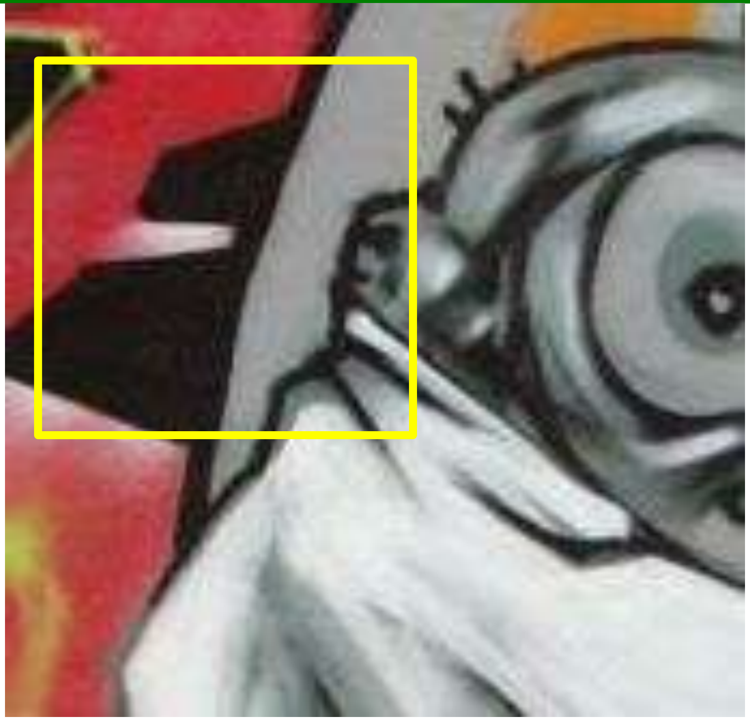


Exhaustive search (Multi-scale approach)

Exhaustive search (Multi-scale approach)



Invariance
Extract patch frrom each image individually

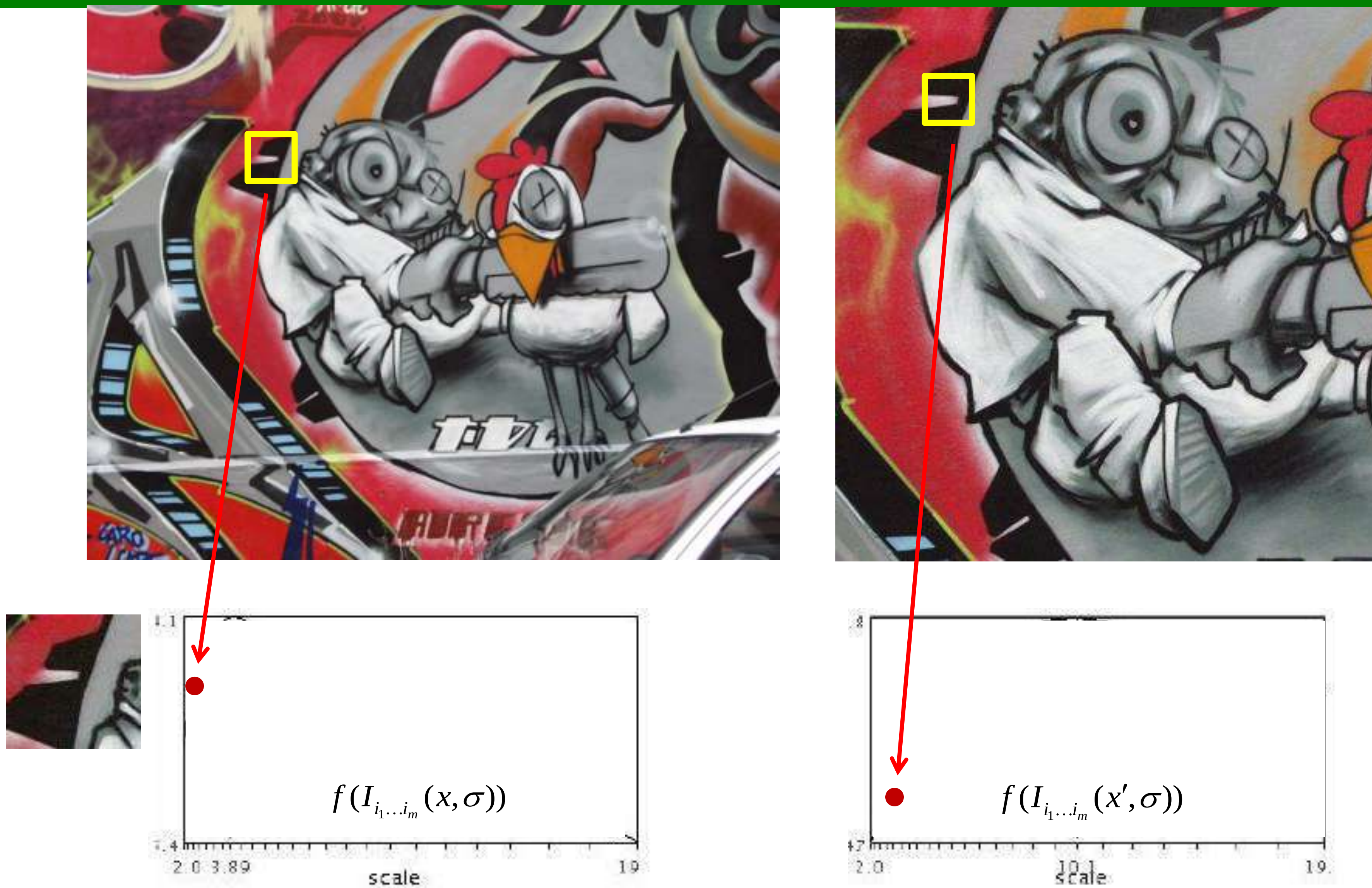


Automatic scale selection

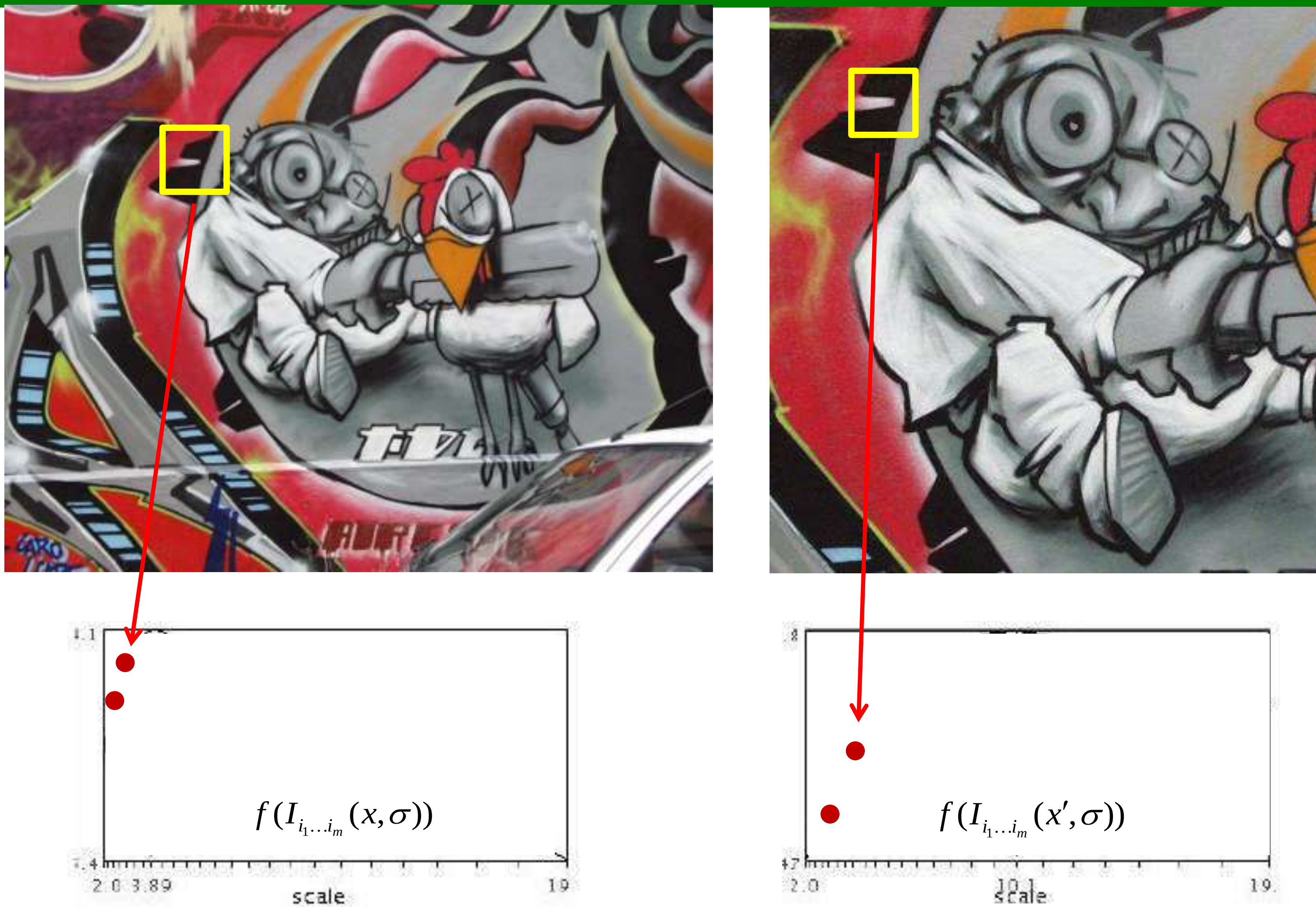
$$f(I_{i_1\ldots i_m}(x,\sigma)) = f(I_{i_1\ldots i_m}(x',\sigma'))$$

How to find corresponding patch sizes?

Automatic scale selection
Function responses for increasing scale



Automatic scale selection



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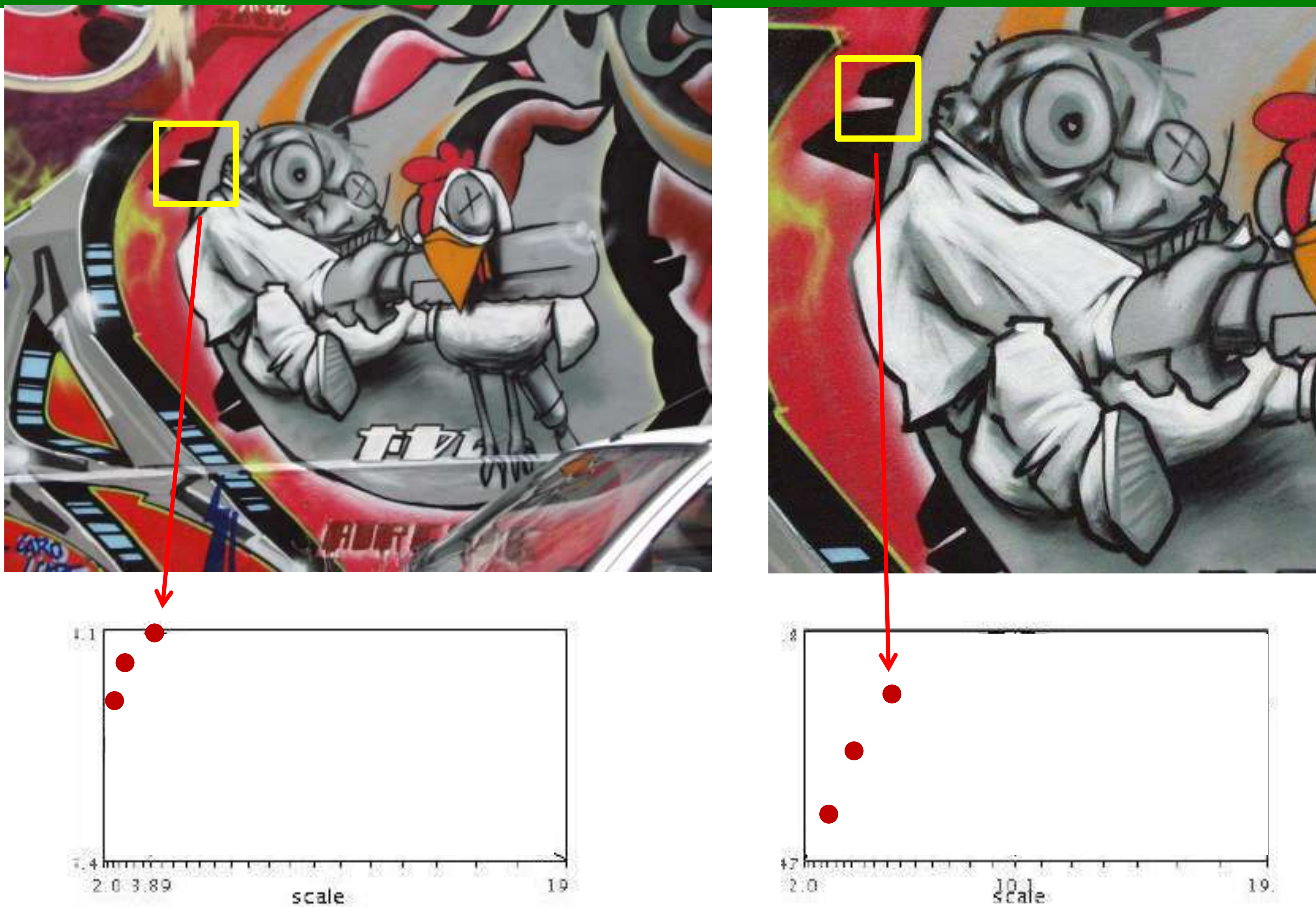

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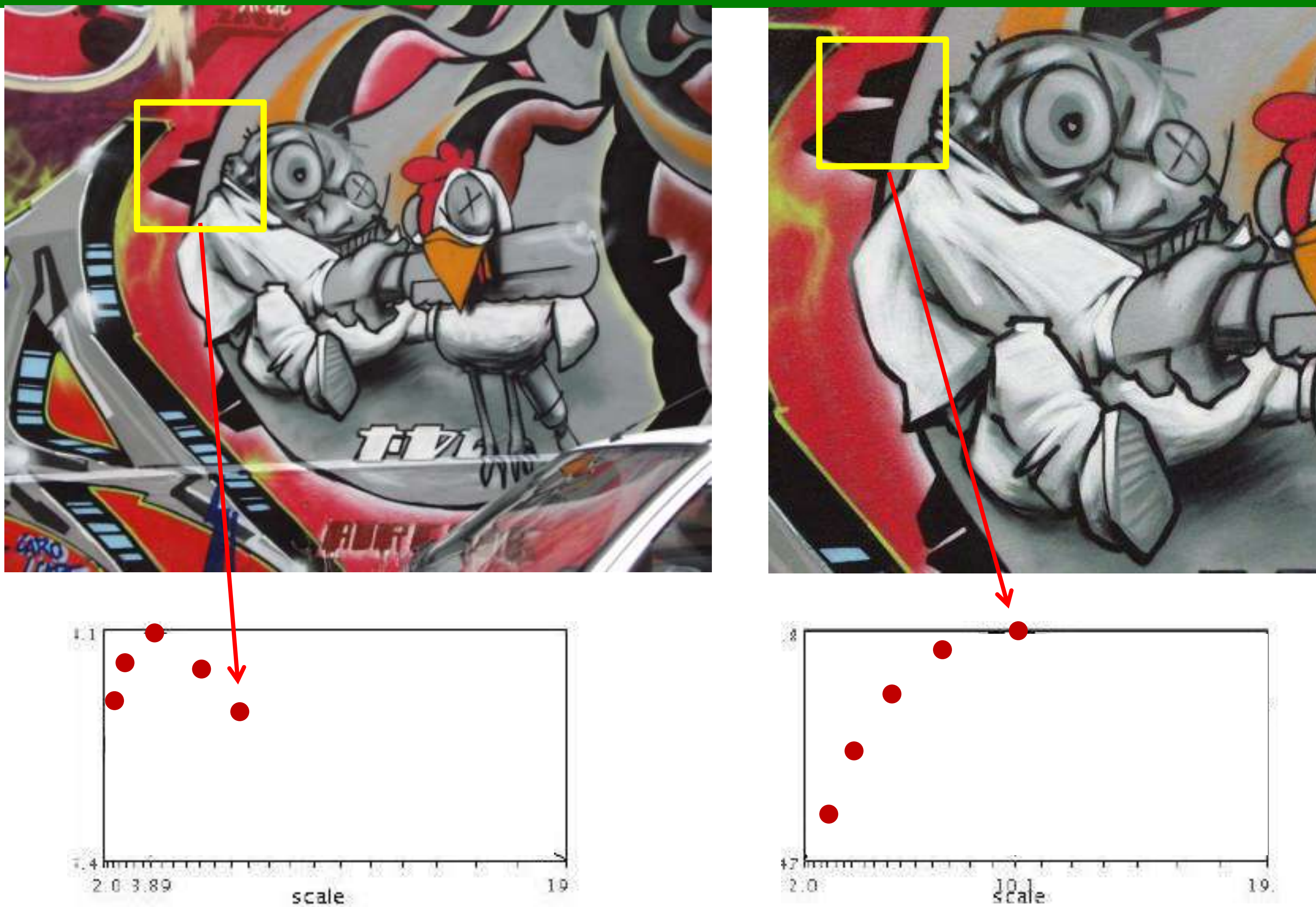
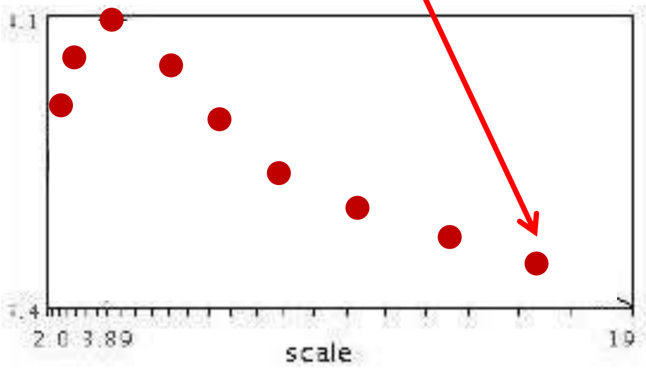
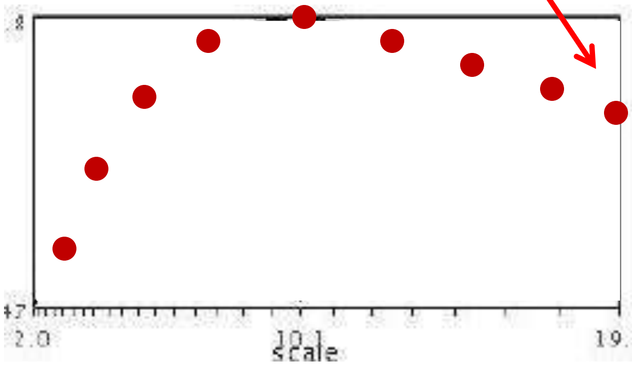


Automatic scale selection





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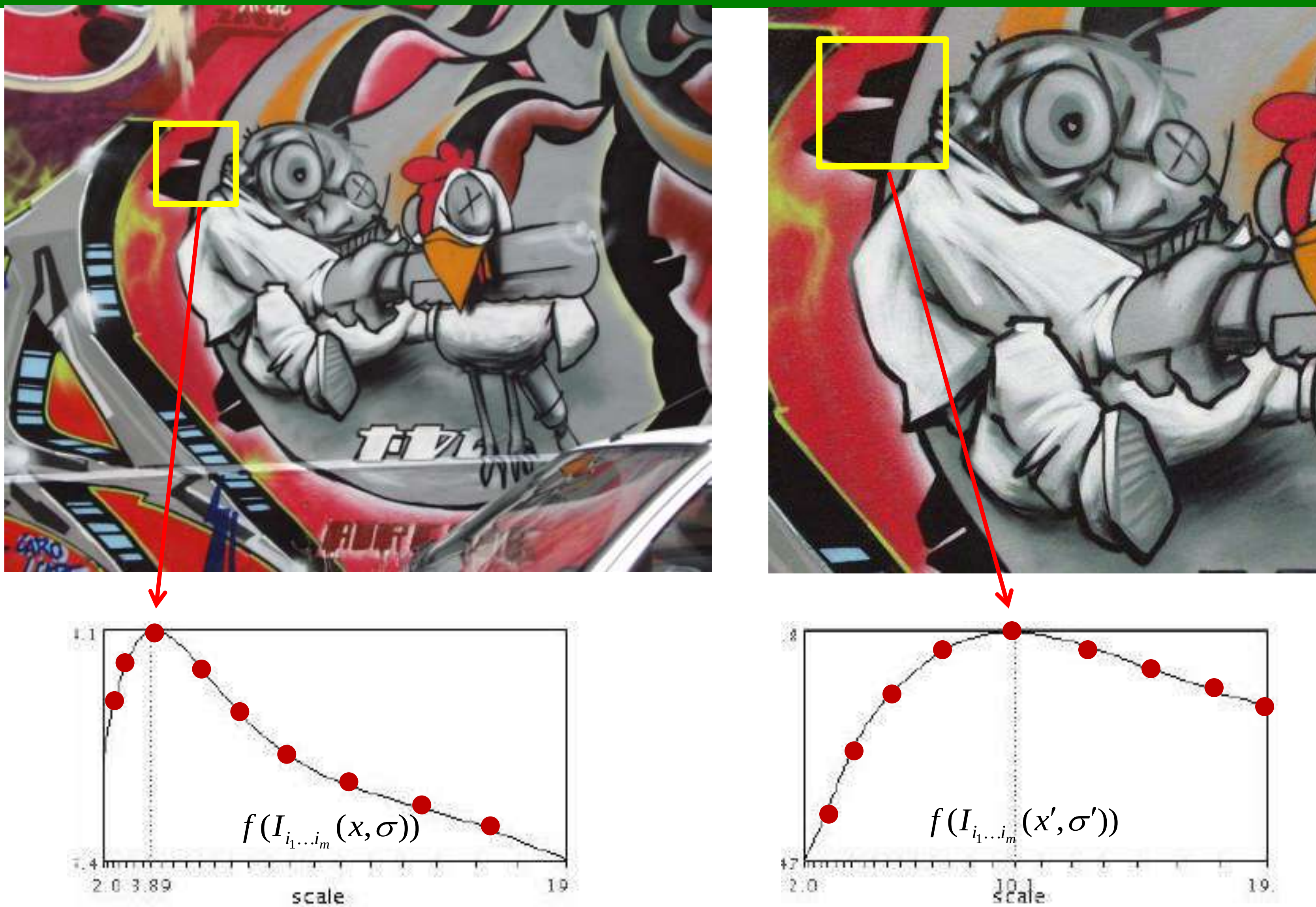
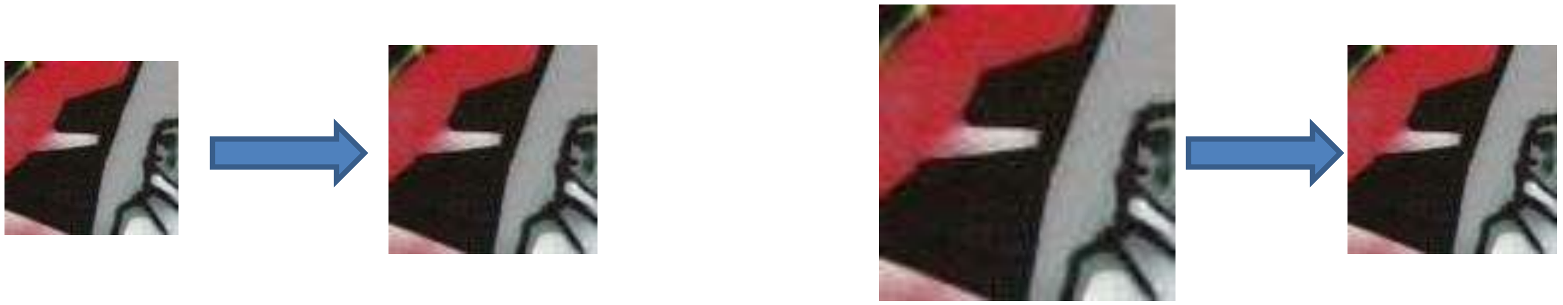


Automatic scale selection



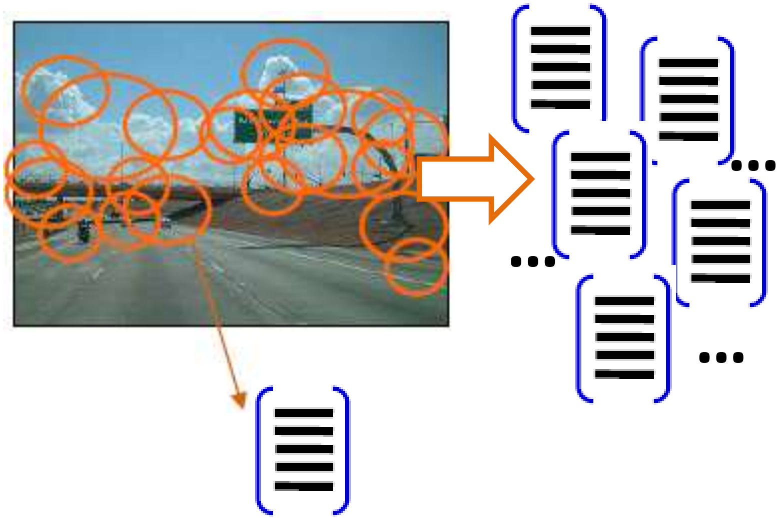
- Normalize: rescale to fixed size

Outline

- Automatic scale selection
- SIFT Descriptor

What is SIFT?

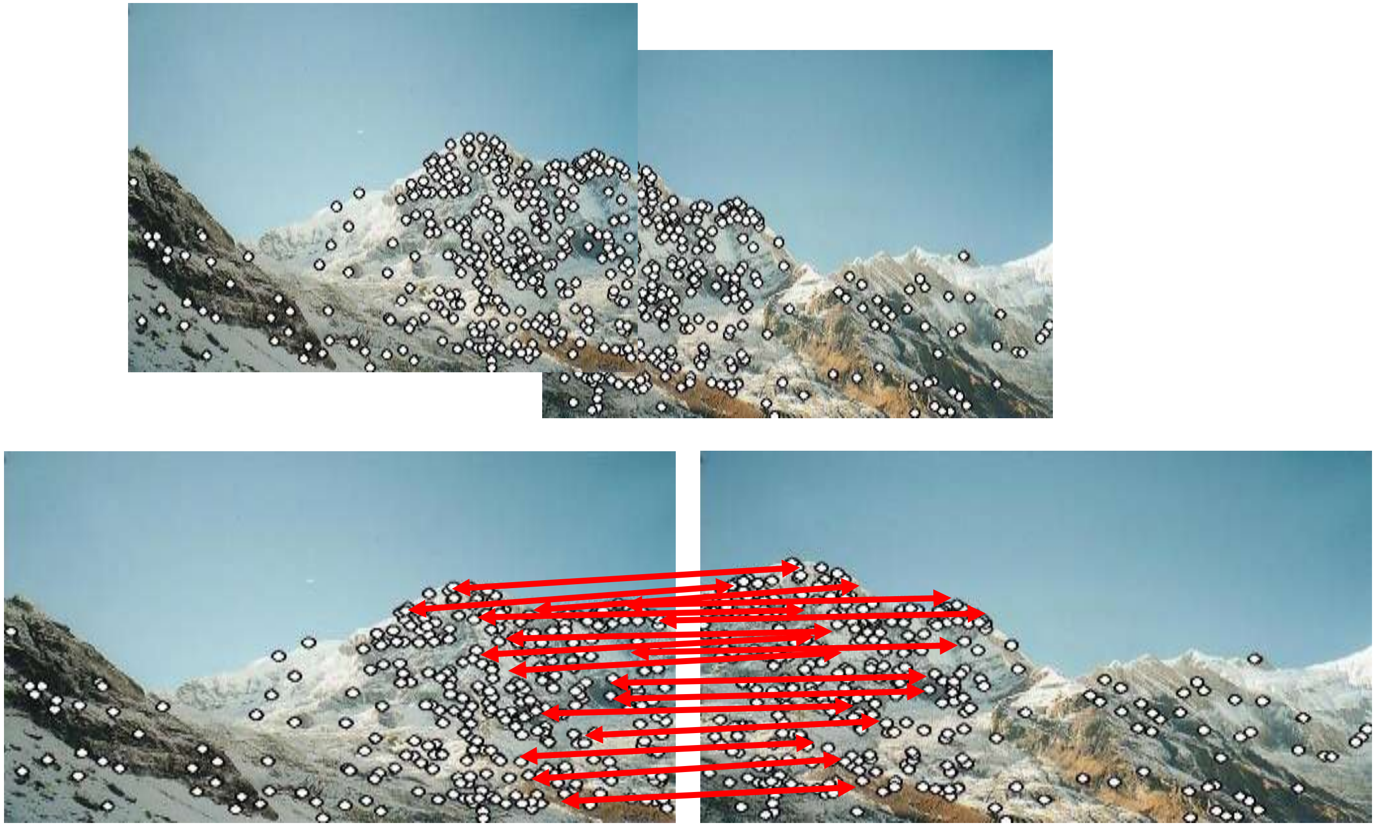
- Scale Invariant Feature Transform (SIFT) is an approach for detecting and extracting ***local features*** from an image.



What is SIFT?

- Originally proposed for panorama stitching

Panorama stitching



How to detect *which features* to match?

Slide credit: Prof. Grauman

Applications

- Object recognition
- Robot localization and mapping
- 3D scene modeling, recognition and tracking
- Human action recognition
- Analyzing the human brain in 3D magnetic resonance images
- ……

What is SIFT?

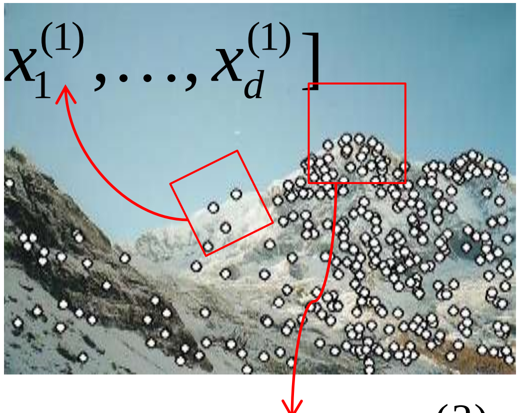
- SIFT feature descriptors are reasonably ***invariant*** to
  - scaling
  - rotation
  - image noise
  - changes in illumination
  - small changes in viewpoint

Local features: main components

1) **Detection:** Identify the interest points

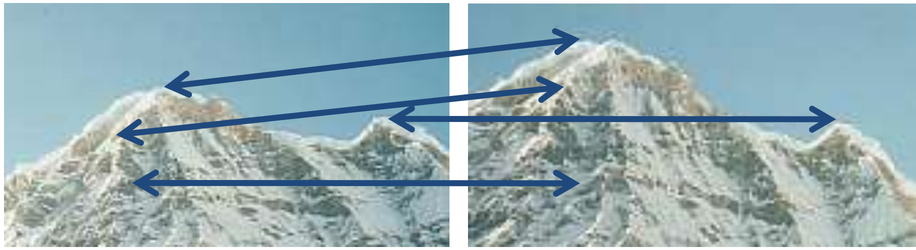
2) **Description**: Extract a feature descriptor surrounding each interest point.

$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$



$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

3) **Matching:** Determine correspondence between descriptors in two views



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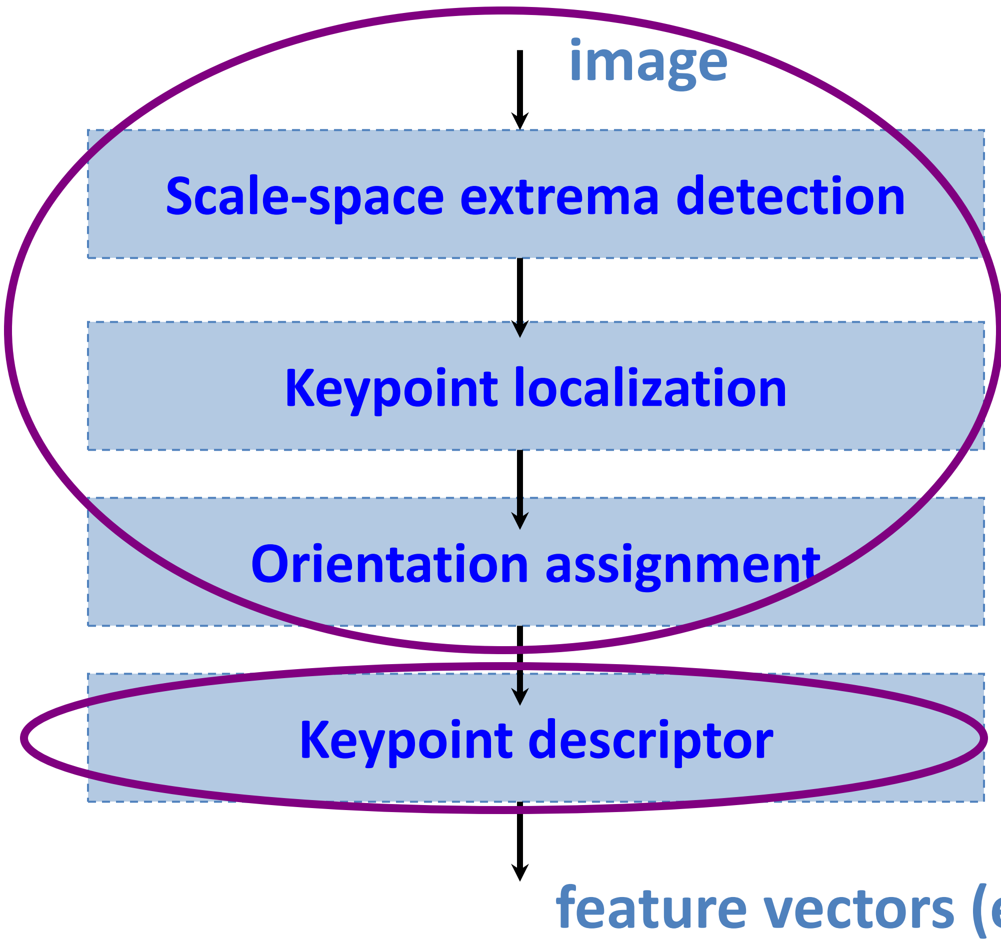
SIFT: Overview

- Major stages of SIFT computation

Interest point detector
+
descriptor



Identify potential interest points
(location, scale)

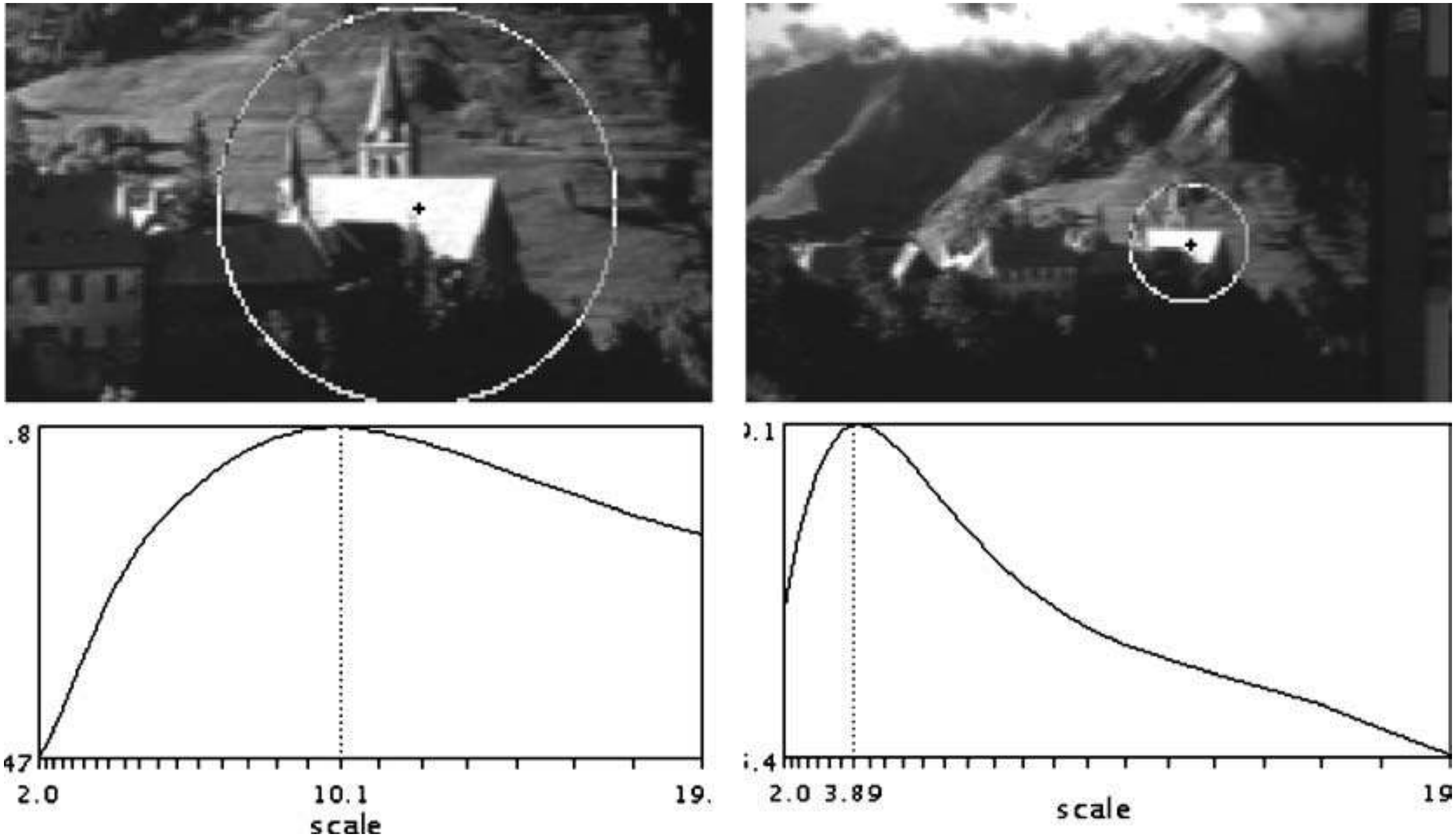
Localize candidate keypoints
Reduced sets of (location, scale)

Identify the dominant orientations
(location, scale, orientation)

Build a descriptor based on
histogram of gradients in local
neighborhood

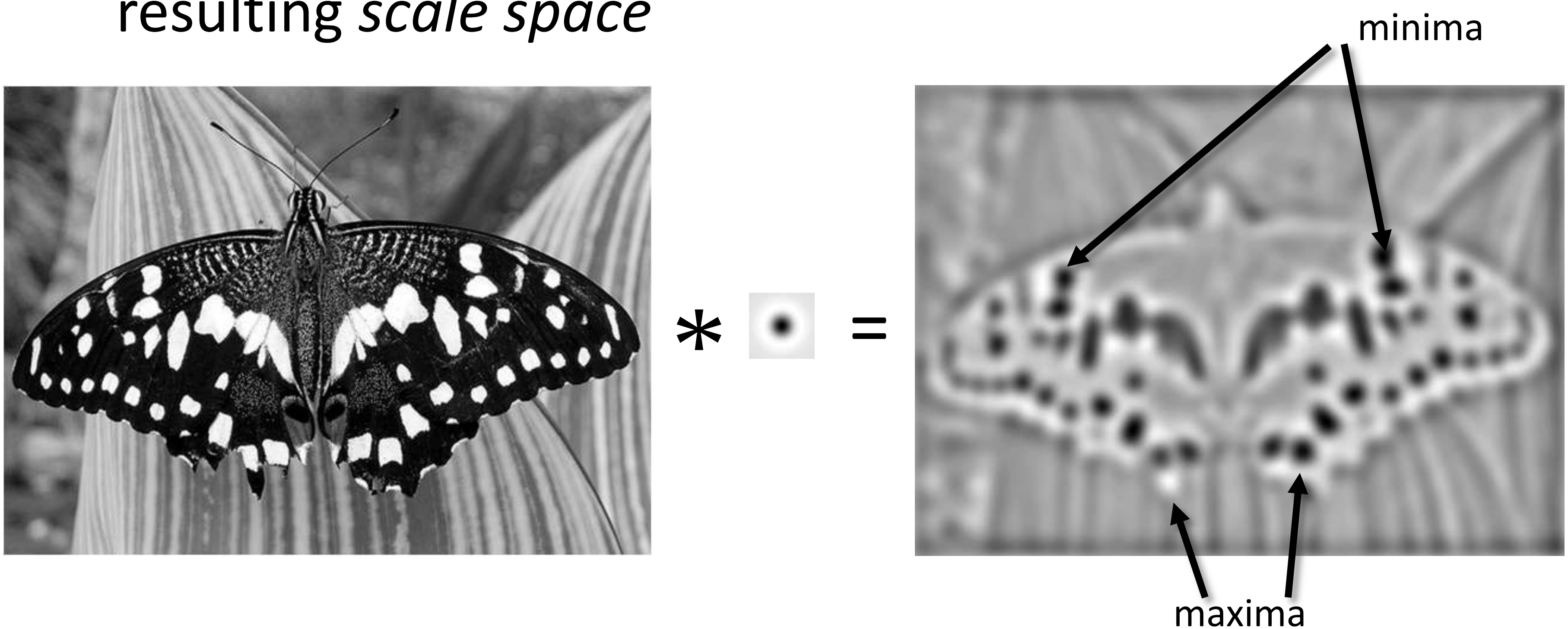
Keypoint detection with scale selection

- We want to extract keypoints with characteristic scale that is *covariant* with the image transformation



Basic idea → Blob detection

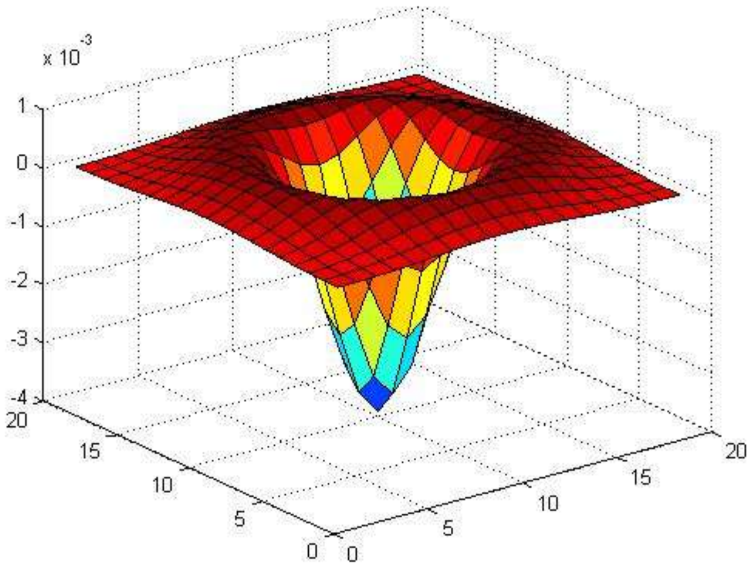
- Convolve the image with a “blob filter” at multiple scales and look for extrema of filter response in the resulting *scale space*

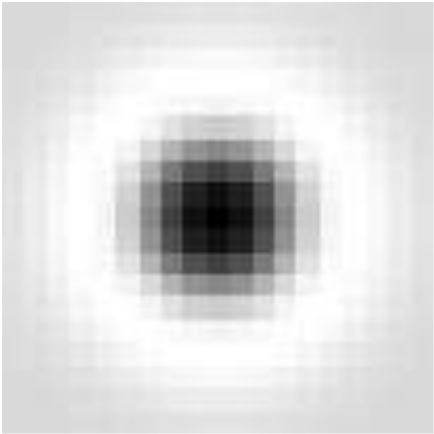


- Find maxima *and minima* of blob filter response in space *and scale*

Blob filter

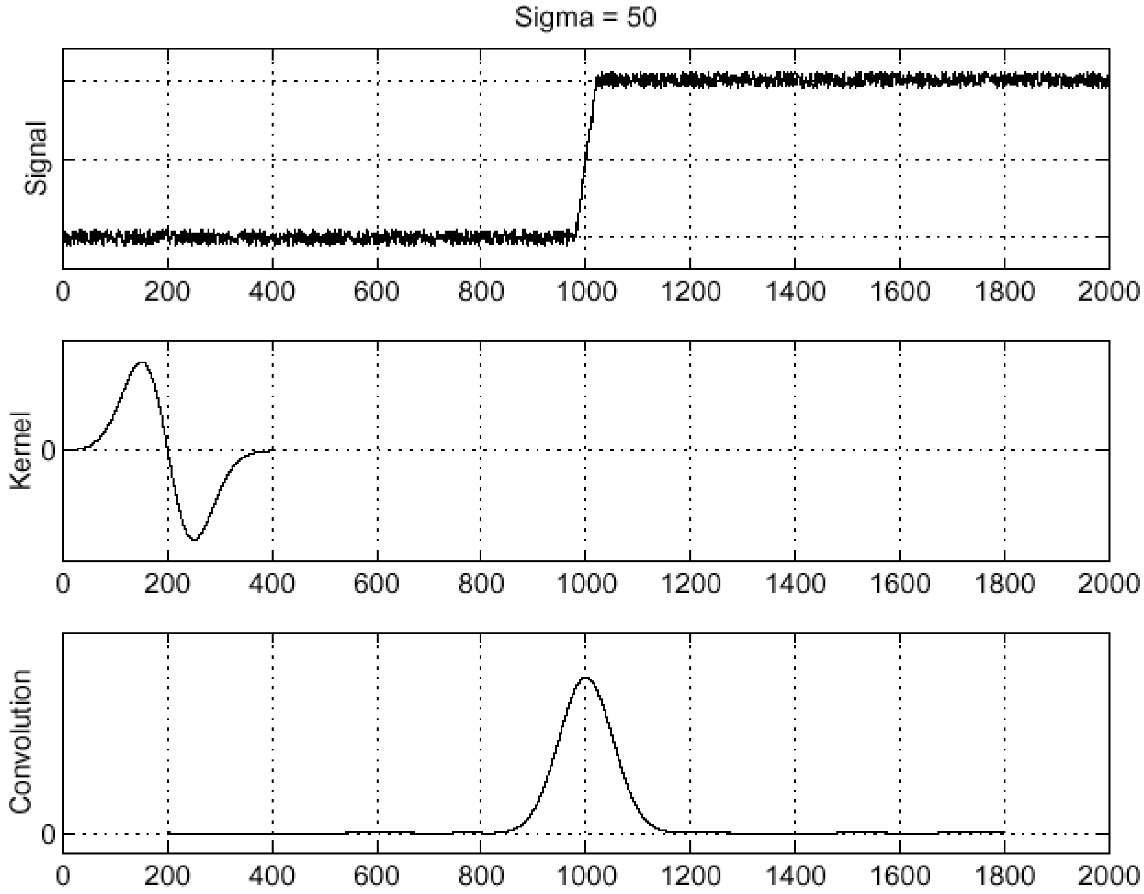
- Laplacian of Gaussian: Circularly symmetric operator for blob detection in 2D





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

Recall: Edge detection



f

Edge

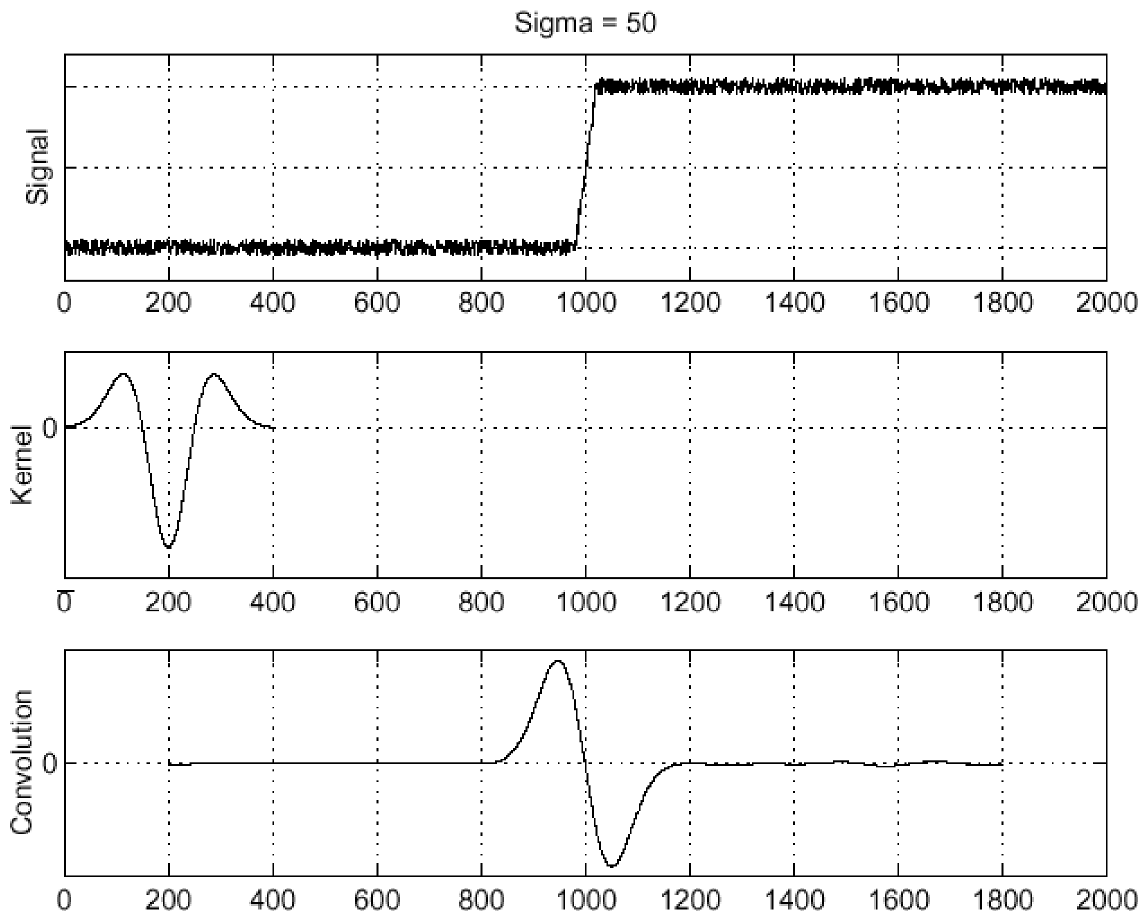
$\frac{d}{dx} g$

Derivative of Gaussian

$f * \frac{d}{dx} g$

Edge = maximum of derivative

Edge detection, Take 2



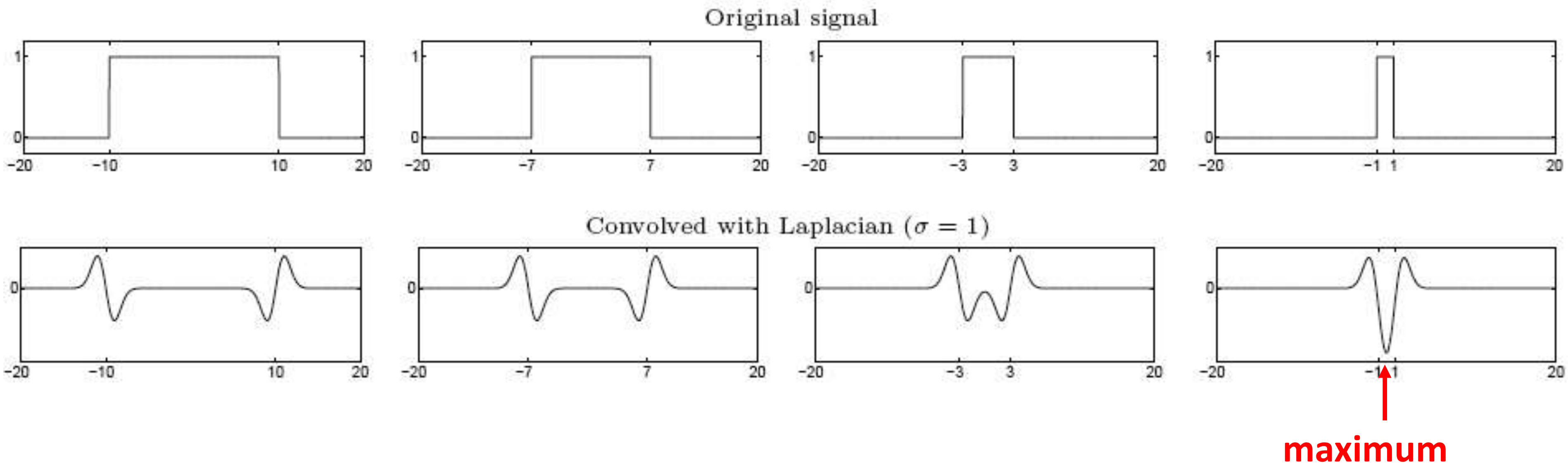
f — Edge

$\frac{d^2}{dx^2} g$ — Second derivative of Gaussian (Laplacian)

$f * \frac{d^2}{dx^2} g$ — Edge = zero crossing of second derivative

From edges to blobs

- 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

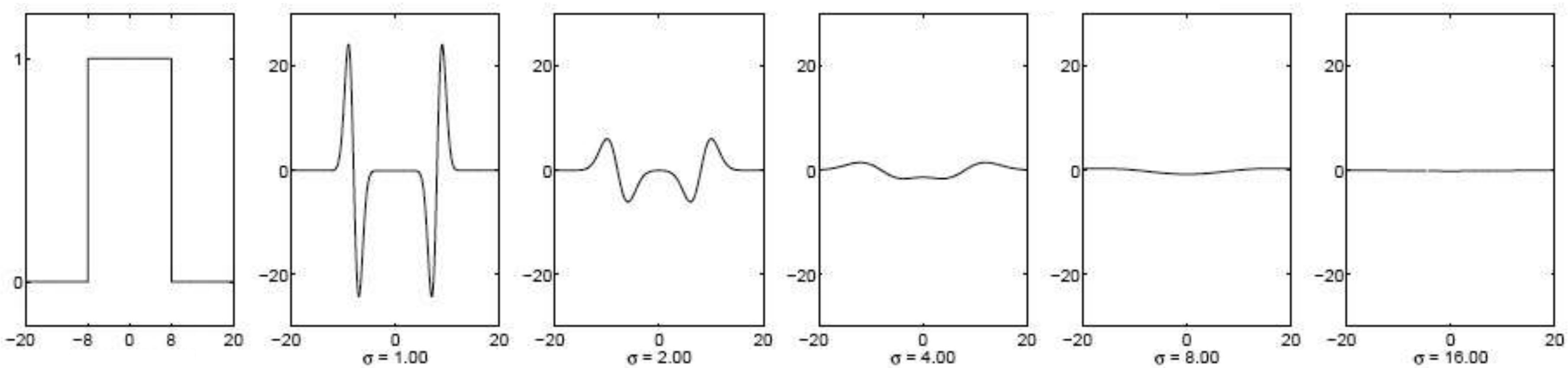
Scale normalization

- The response of a derivative of Gaussian filter to a perfect step edge decreases as σ increases
- To keep response the same (scale-invariant), must multiply Gaussian derivative by σ
- Laplacian is the second Gaussian derivative, so it must be multiplied by σ^2

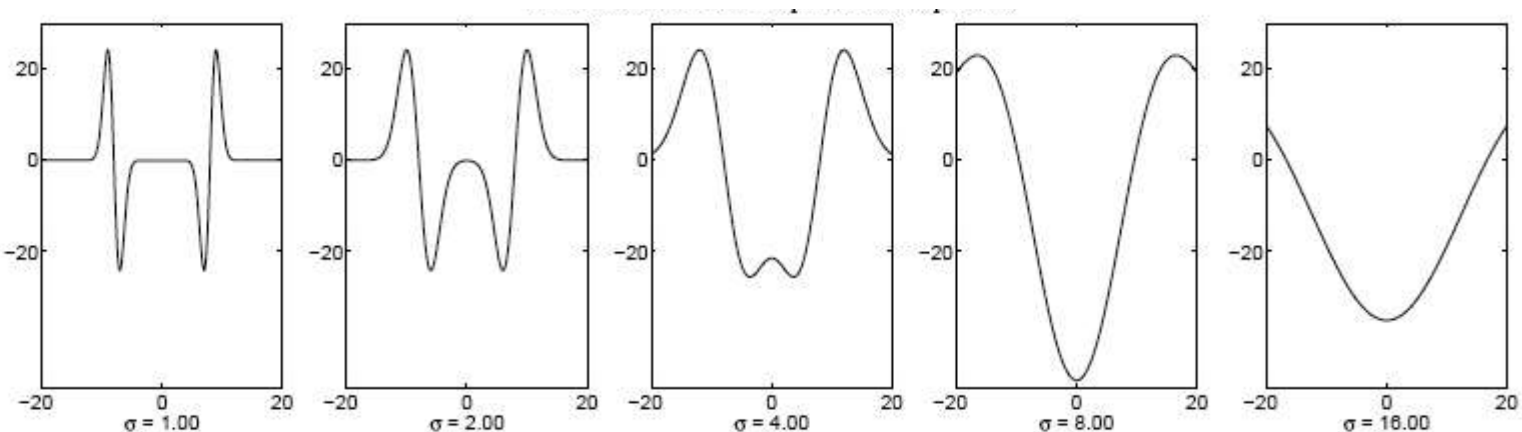
Effect of scale normalization

Original signal

Unnormalized Laplacian response



Scale-normalized Laplacian response

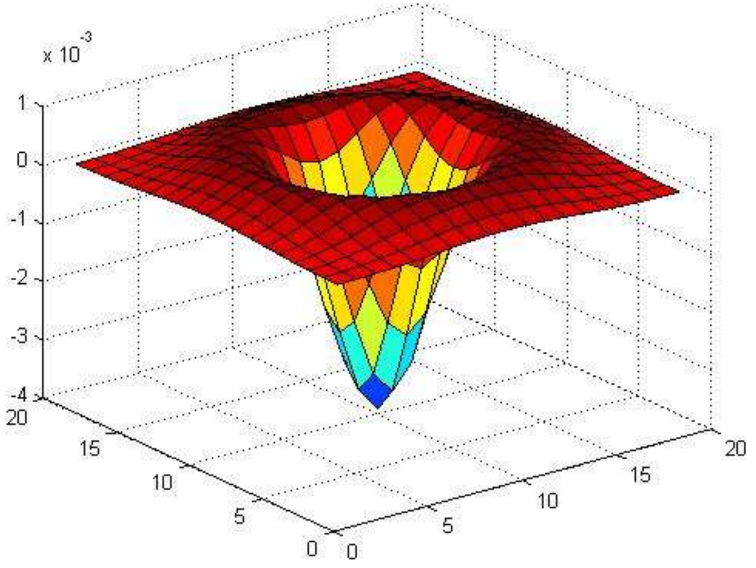


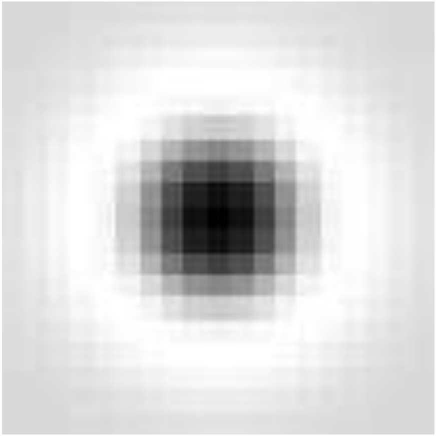
maximum

Blob detection in 2D

- *Scale-normalized* Laplacian of Gaussian:

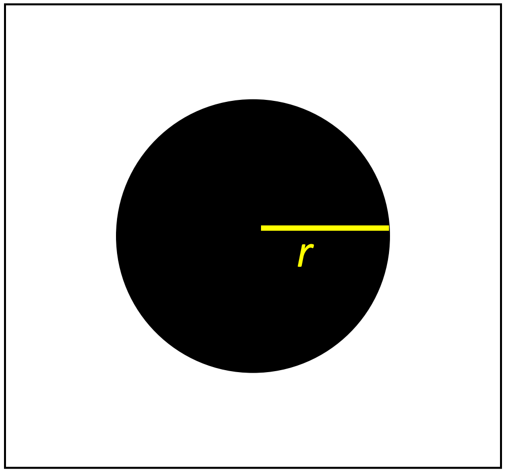
$$\nabla^2_{\text{norm}} g = \sigma^2 \left(\frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2} \right)$$





Blob detection in 2D

- At what scale does the Laplacian achieve a maximum response to a binary circle of radius r?



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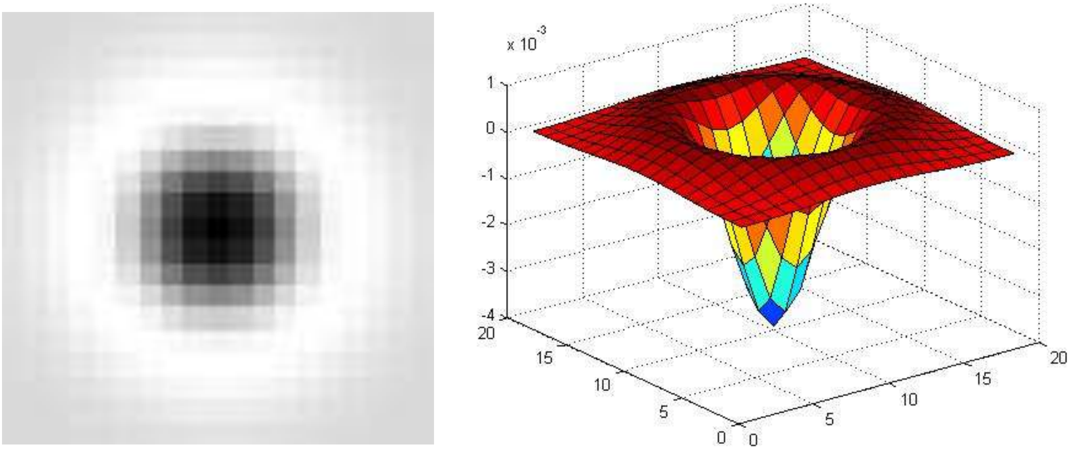


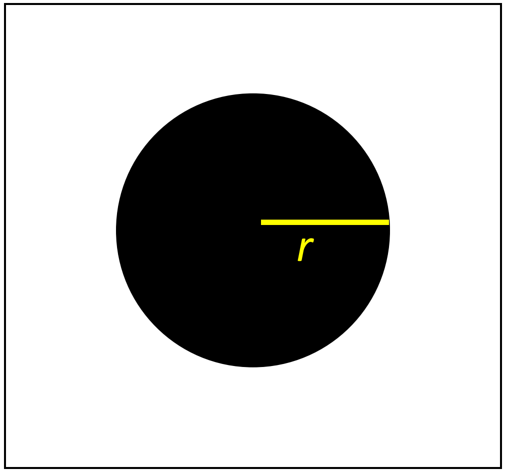
Laplacian

Blob detection in 2D

- At what scale does the Laplacian achieve a maximum response to a binary circle of radius r?
- To get maximum response, the zeros of the Laplacian have to be aligned with the circle
- The Laplacian is given by (up to scale):

$$(x^2 + y^2 - 2\sigma^2)\, e^{-(x^2+y^2)/2\sigma^2}$$

- Therefore, the maximum response occurs at $\sigma = r / \sqrt{2}.$



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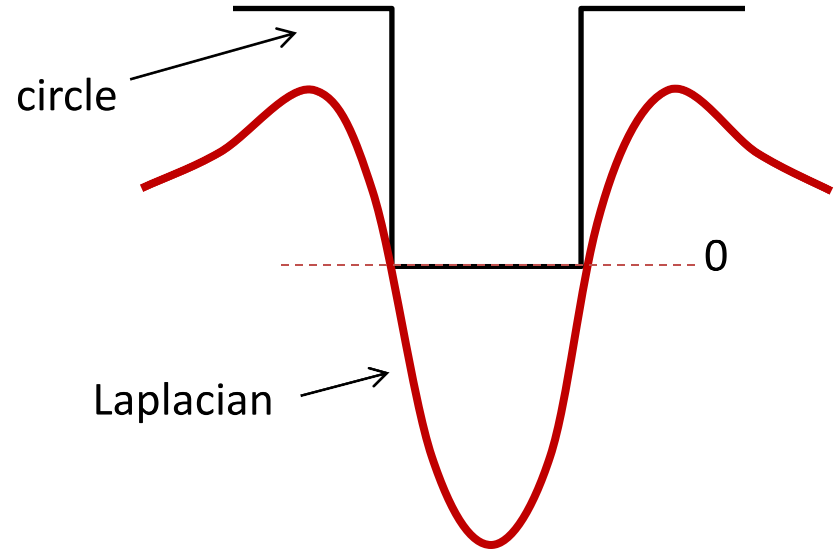


Scale-space blob detector

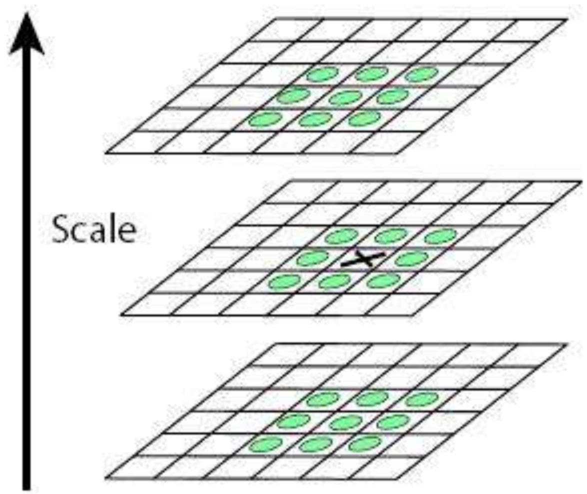
1. Convolve image with scale-normalized Laplacian at several scales

Scale-space blob detector: Example

sigma = 11.9912

Scale-space blob detector

1. Convolve image with scale-normalized Laplacian at several scales
2. Find maxima of squared Laplacian response in scale-space



Efficient implementation

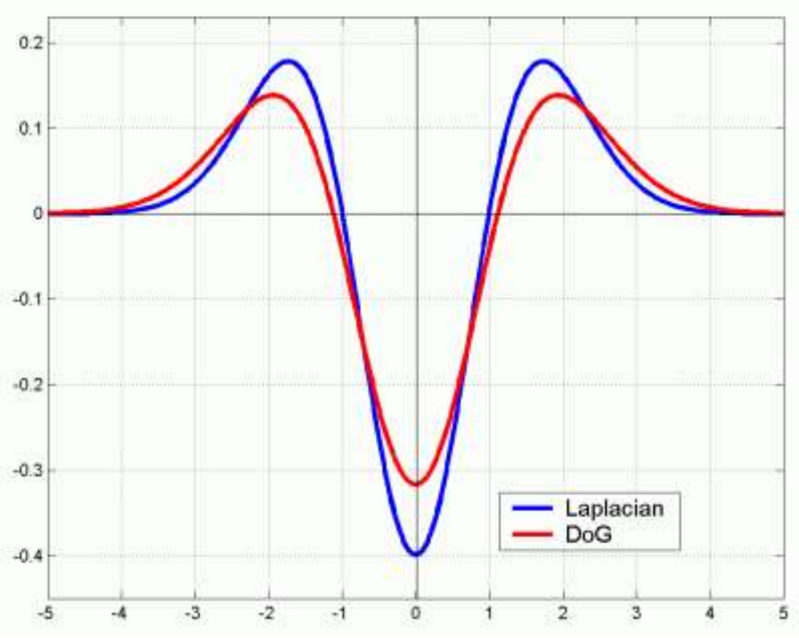
- Approximating the Laplacian with a difference of Gaussians:

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

(Laplacian)

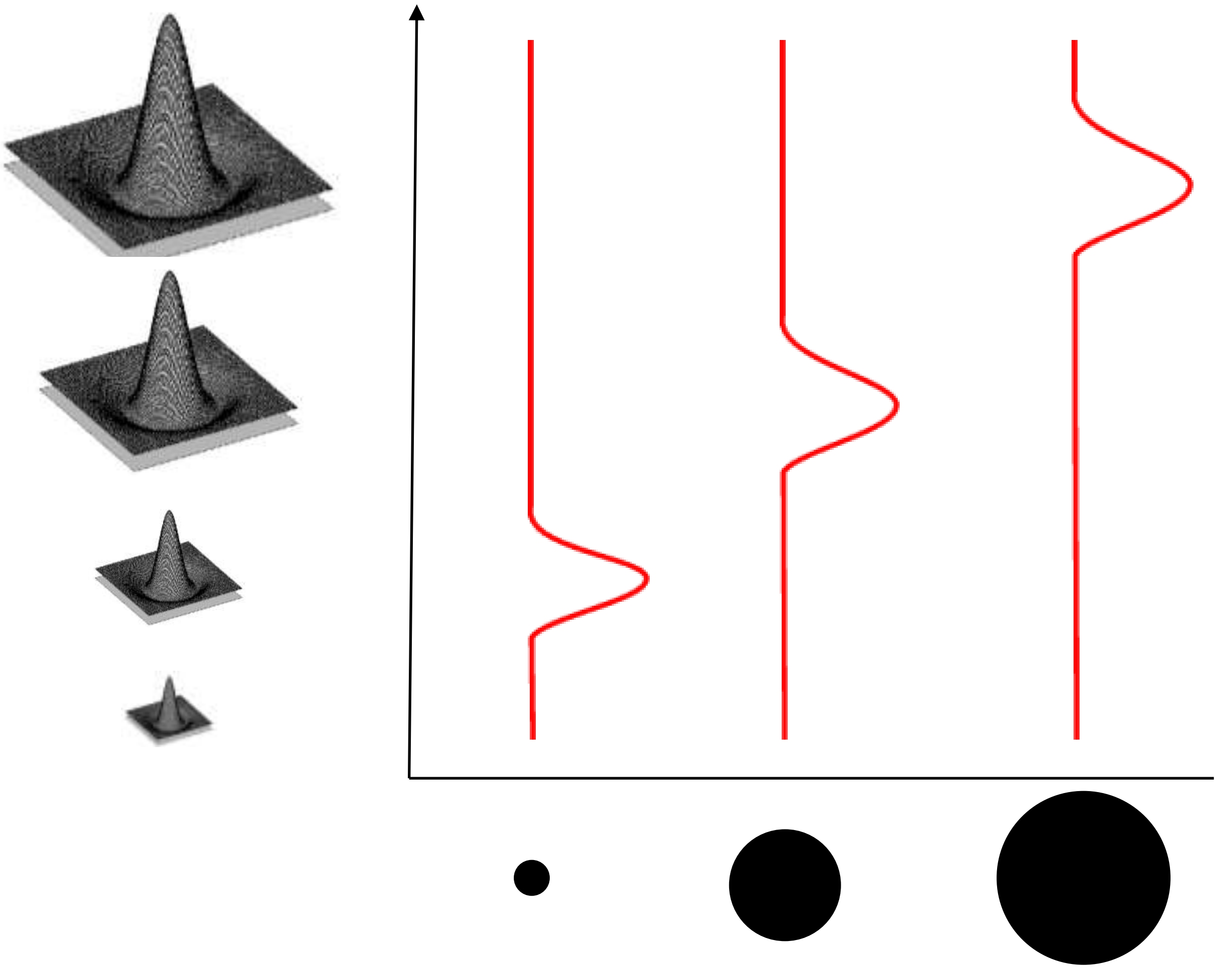
$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

(Difference of Gaussians)



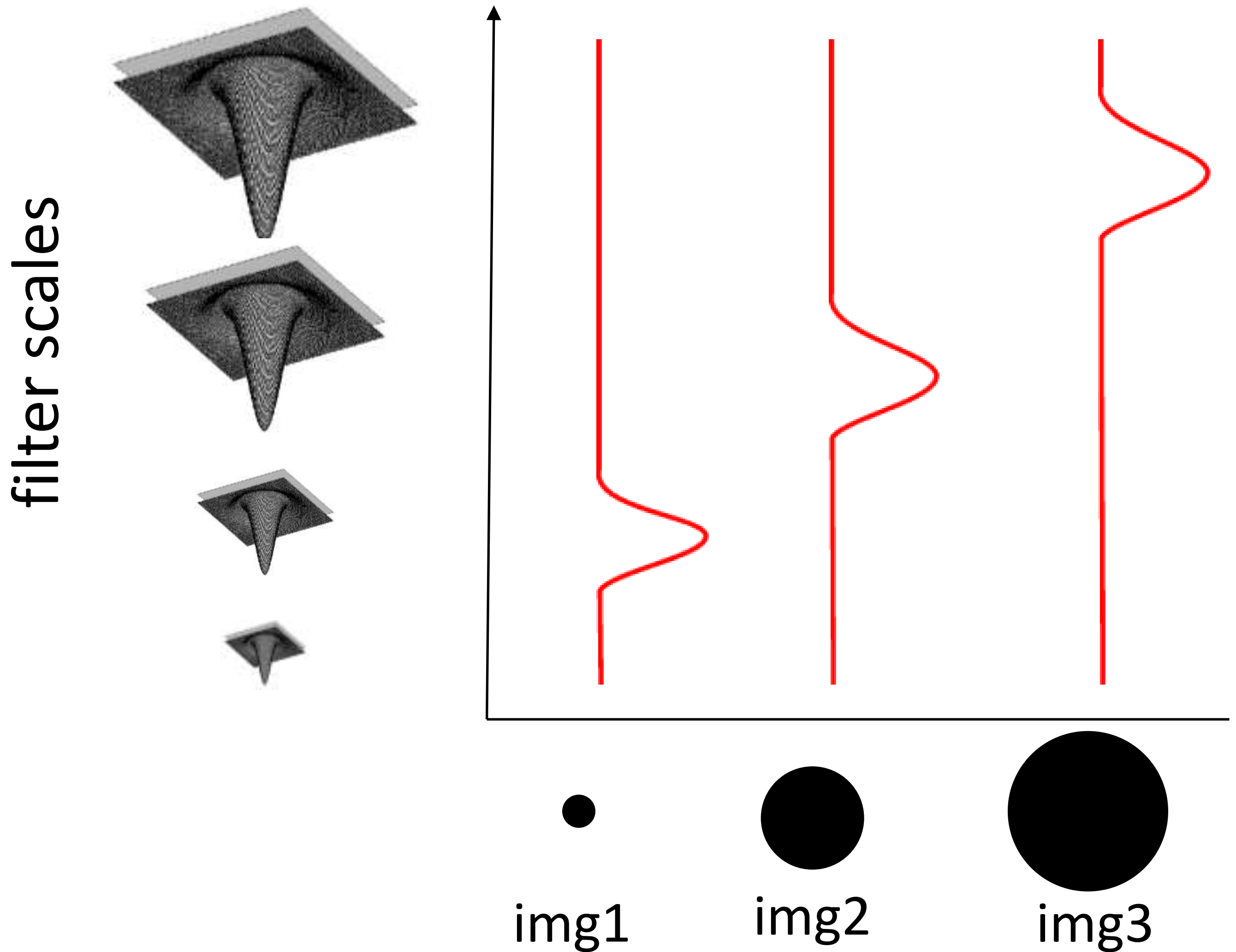
Useful Signature Function

- Difference-of-Gaussian = "blob" detector



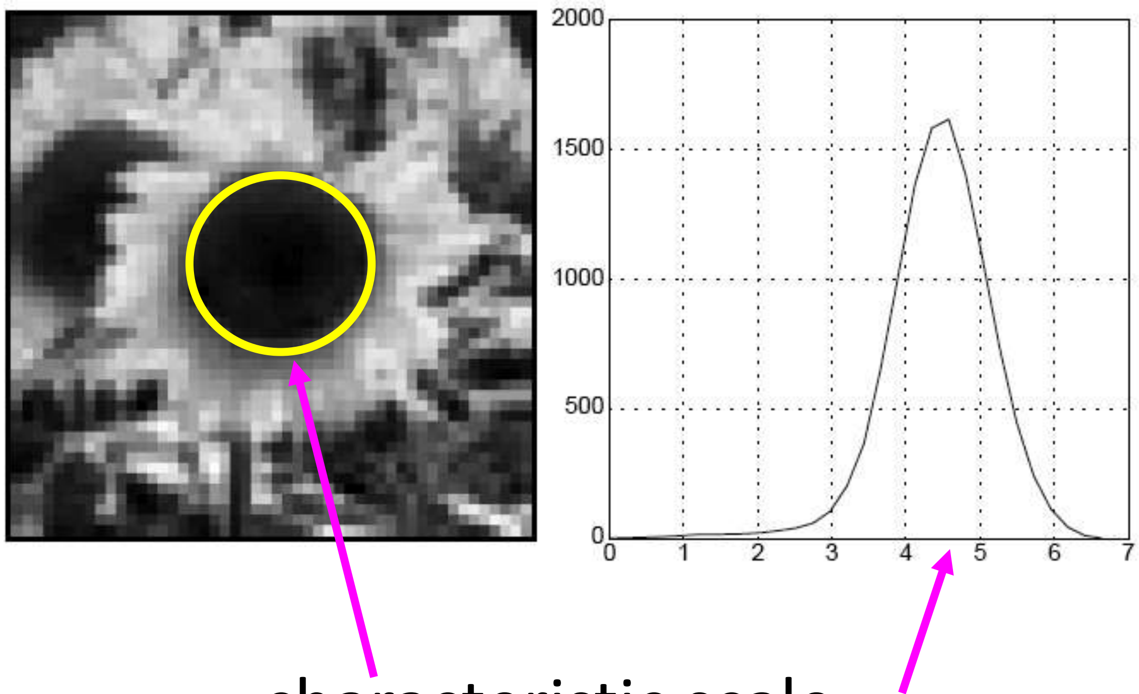
Laplacian of Gaussian

- Difference-of-Gaussian = "blob" detector



Blob detection in 2D

- We define the *characteristic scale* as the scale that produces peak of Laplacian response



characteristic scale

Slide credit: Lana Lazebnik

Exa

Original image at
¾ the size

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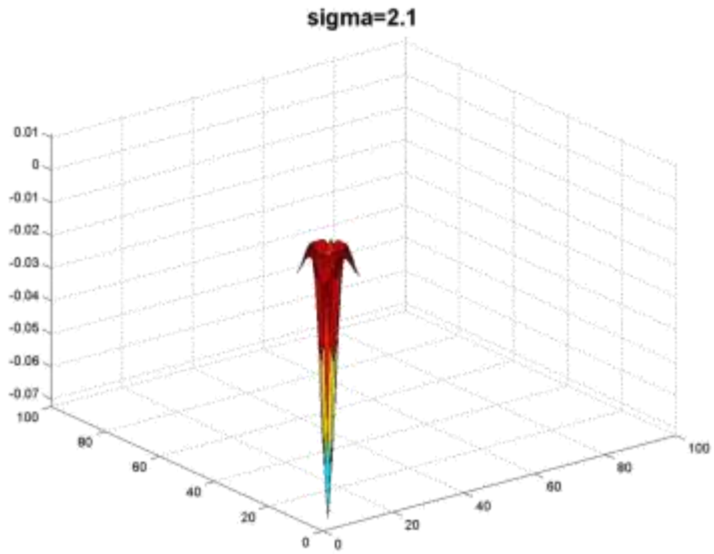
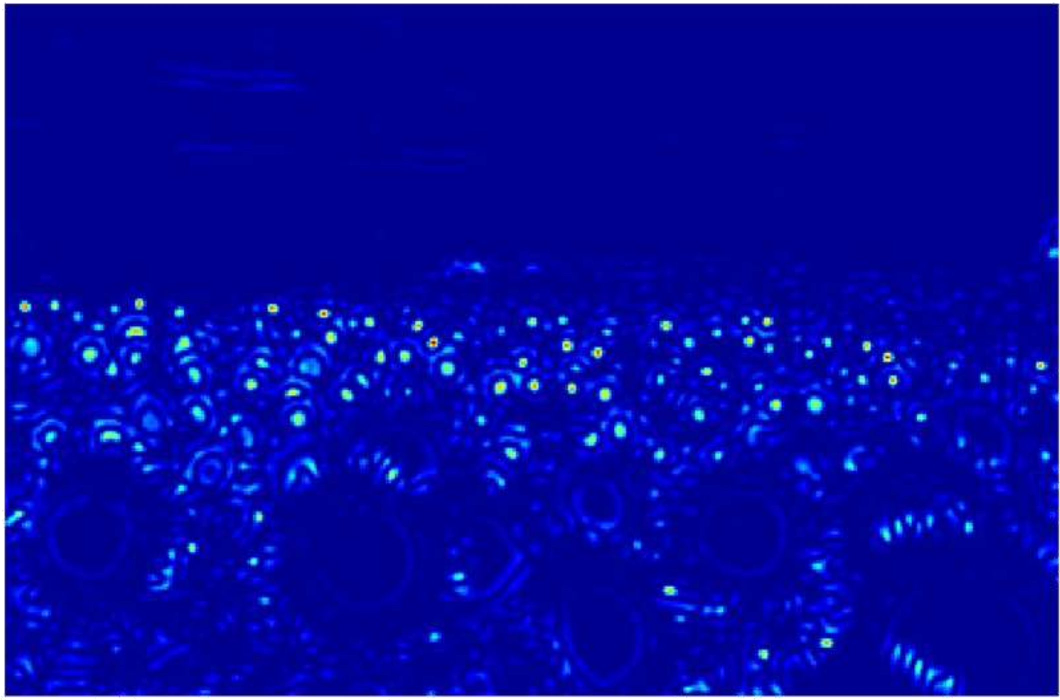
Example





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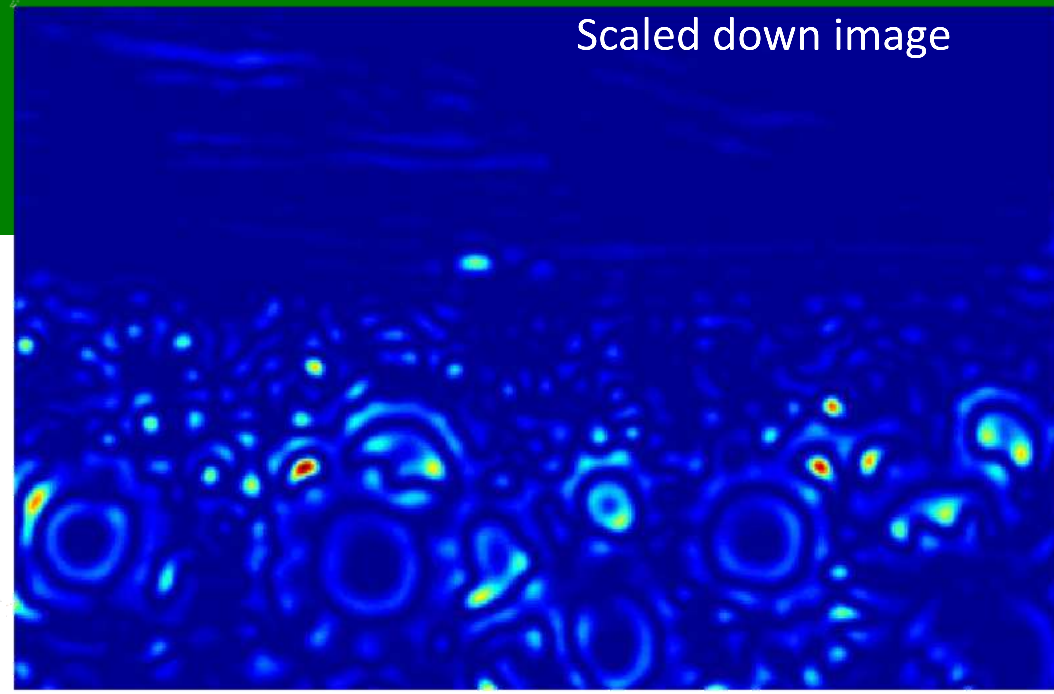

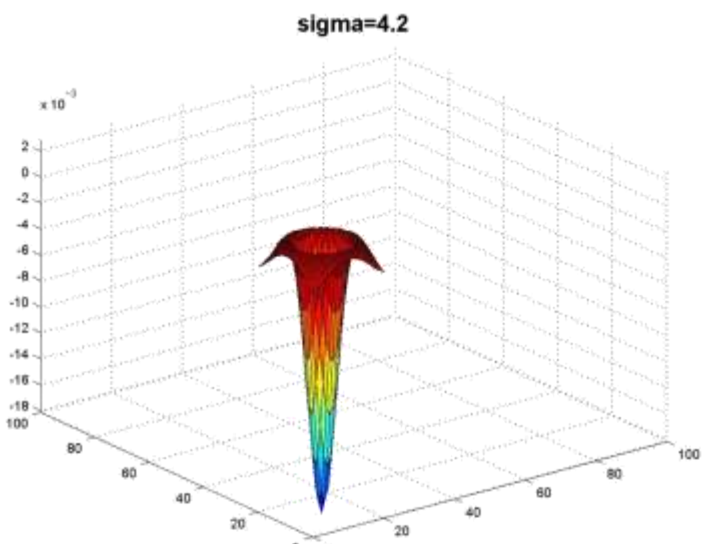

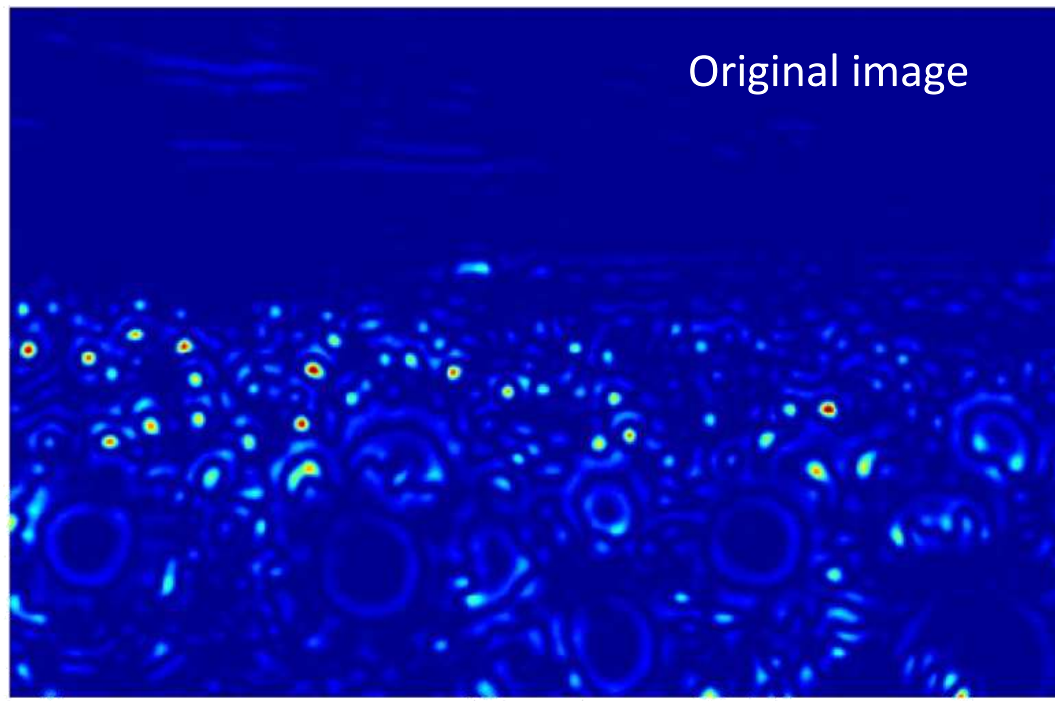

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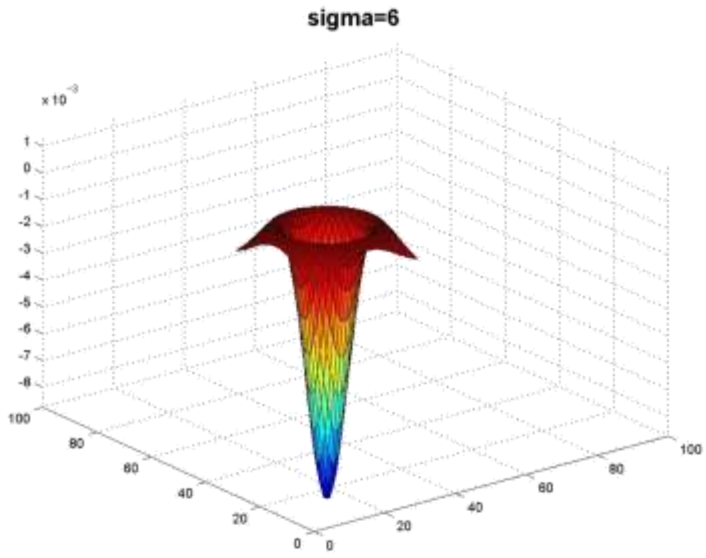
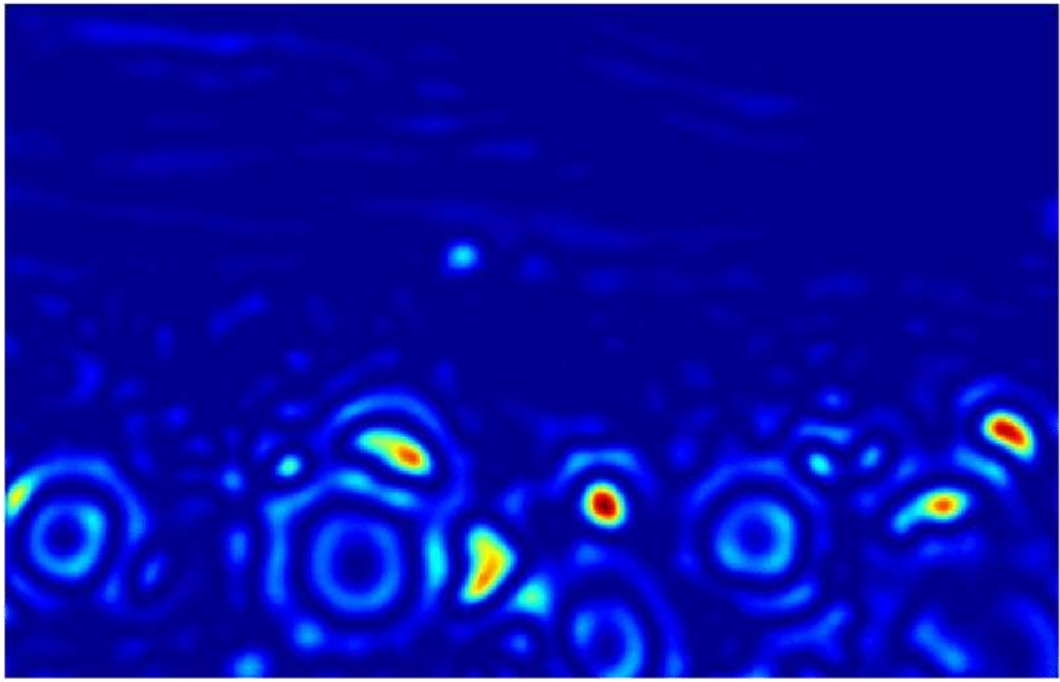
Example





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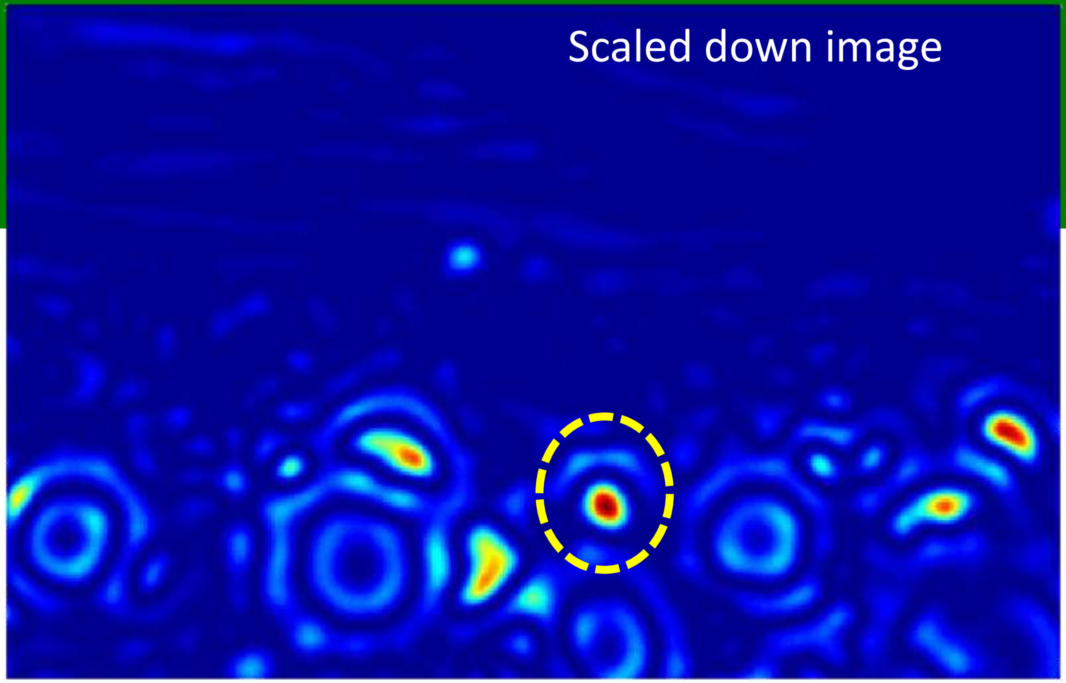

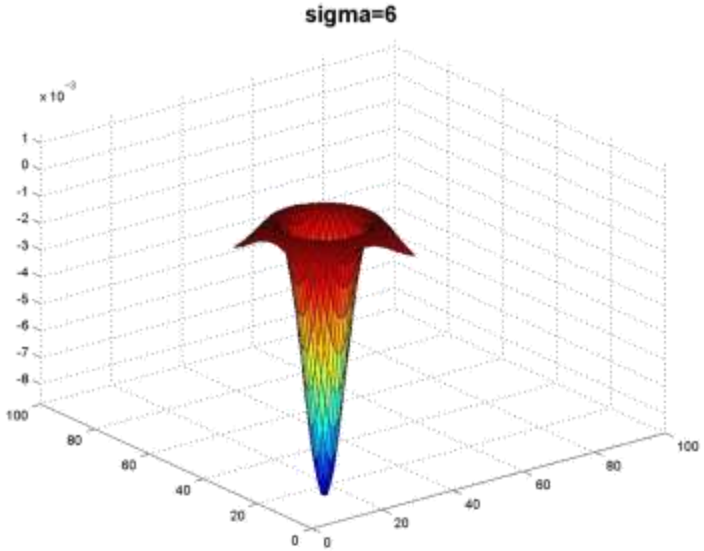

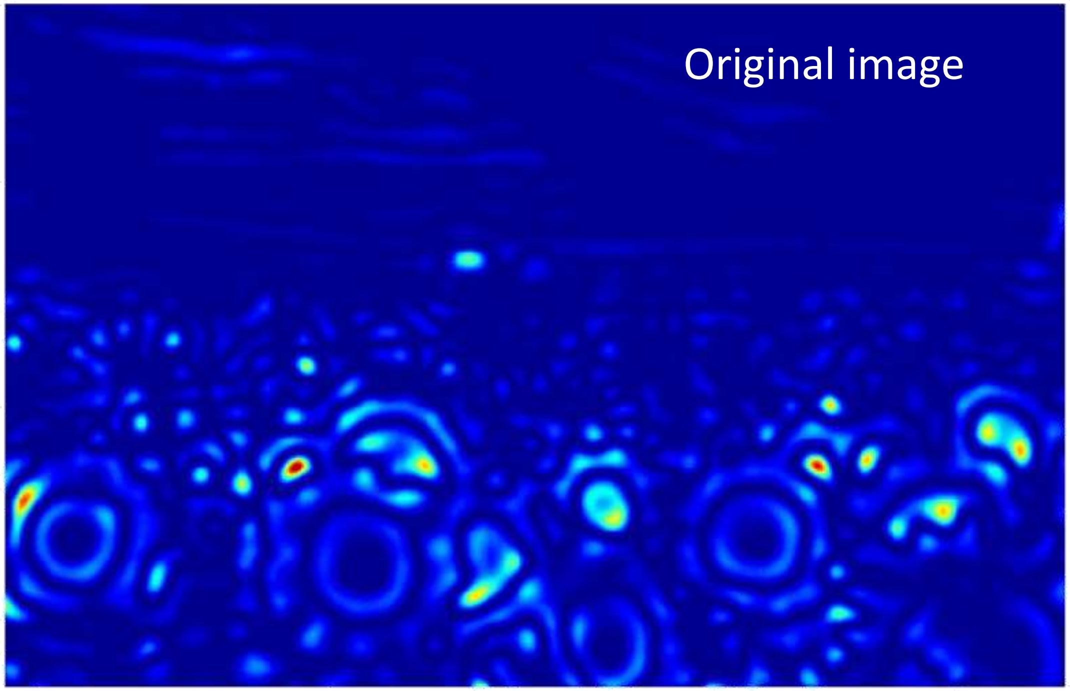

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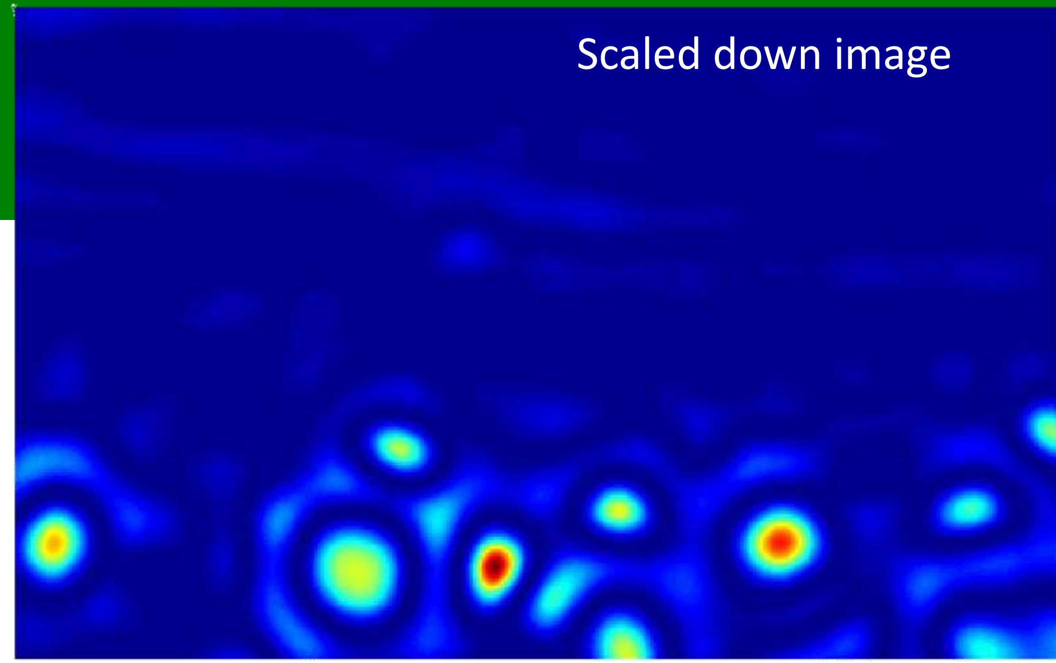

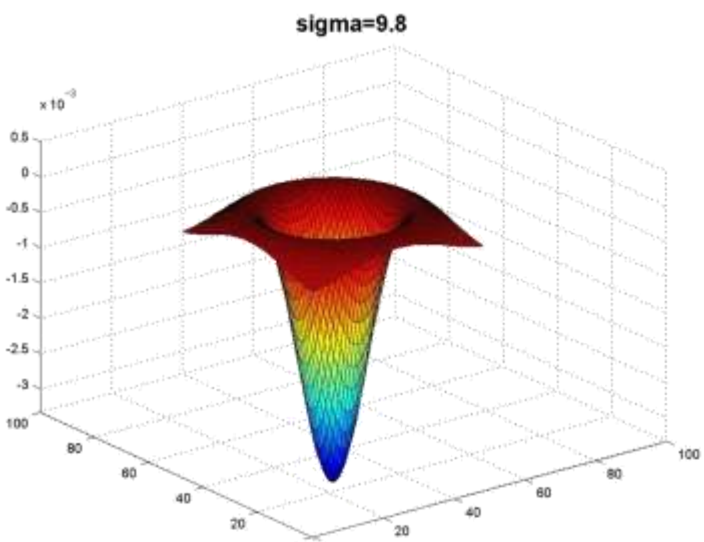

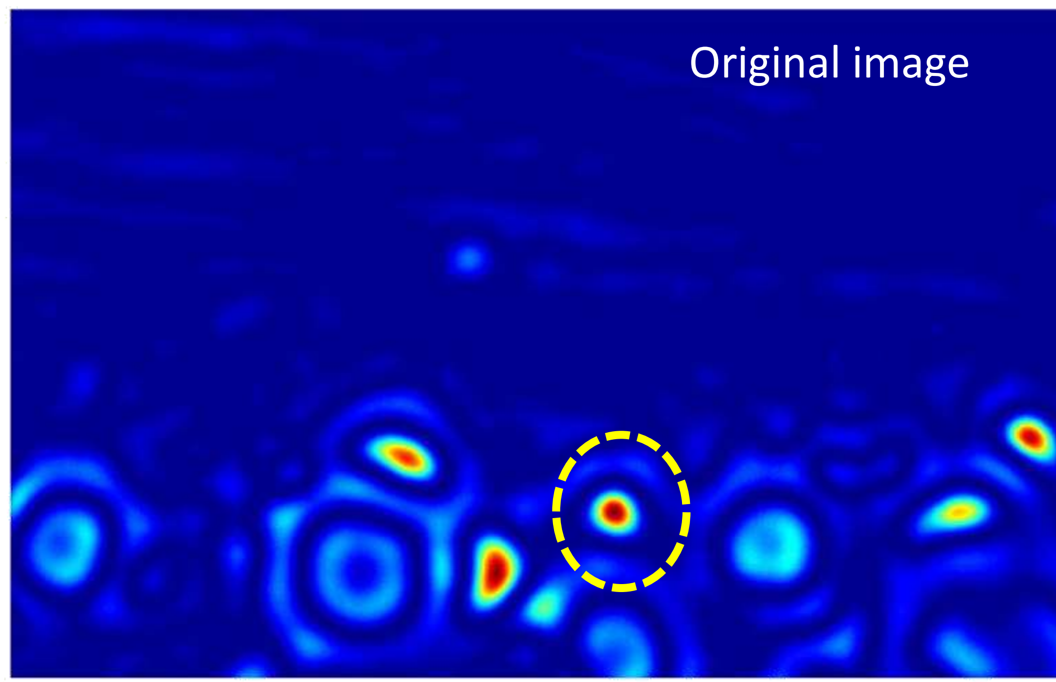

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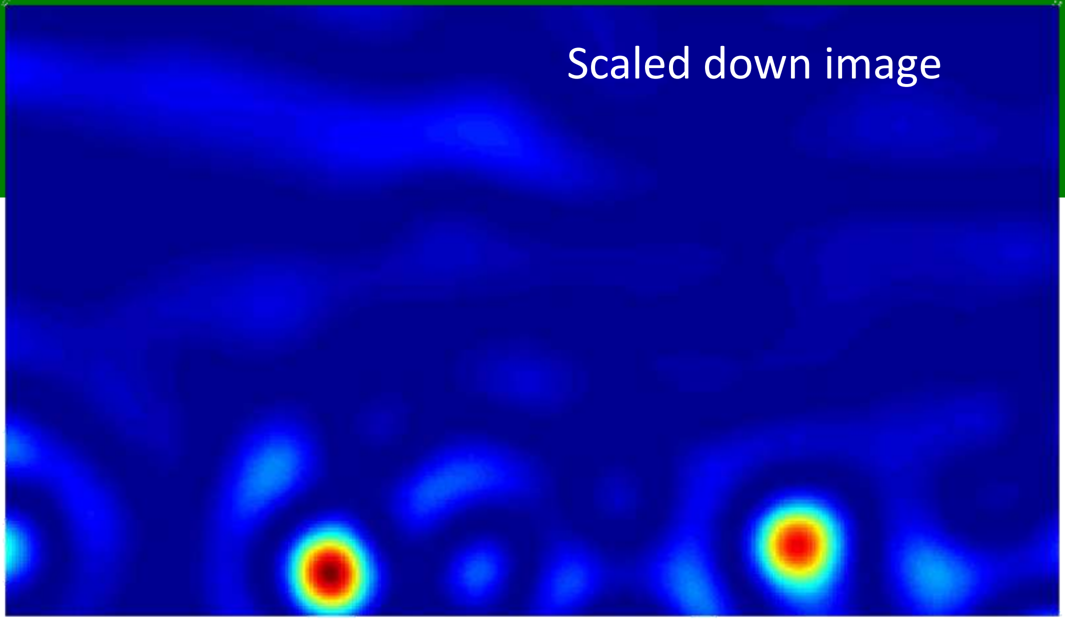
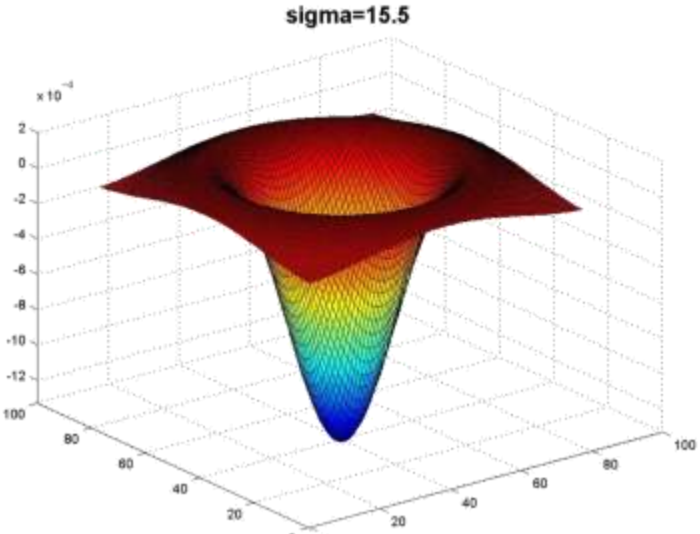
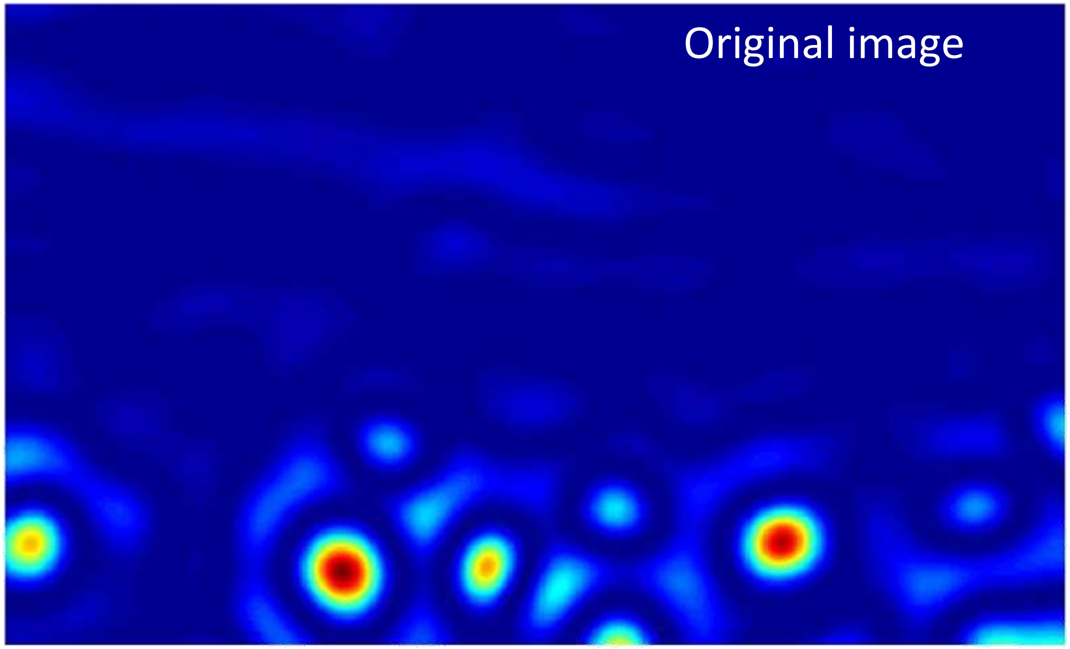
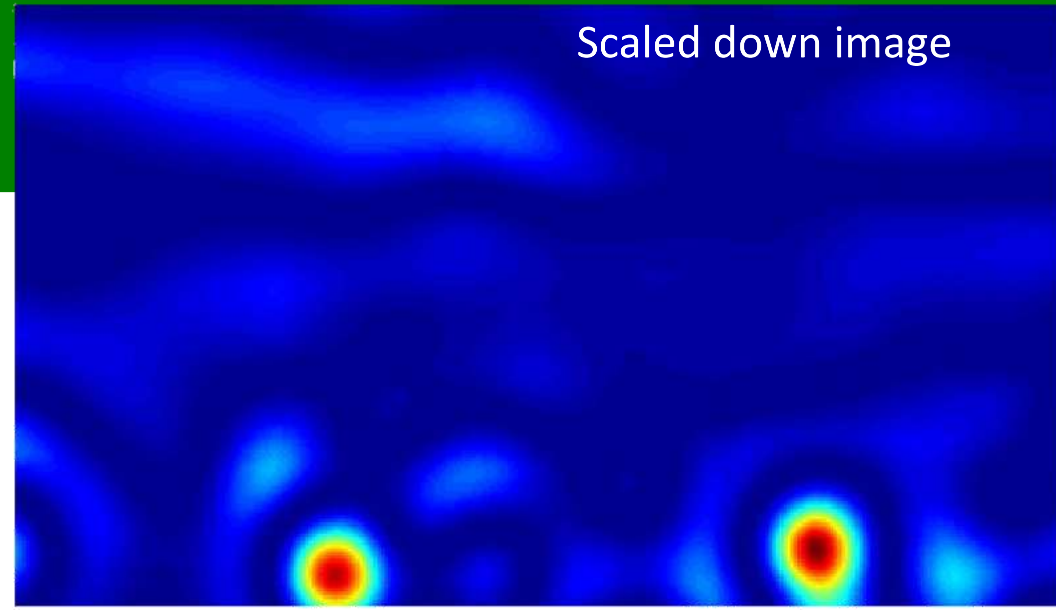
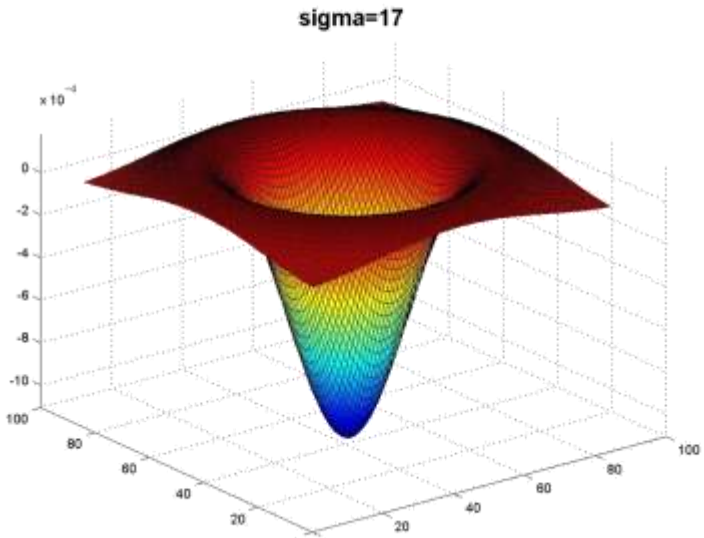


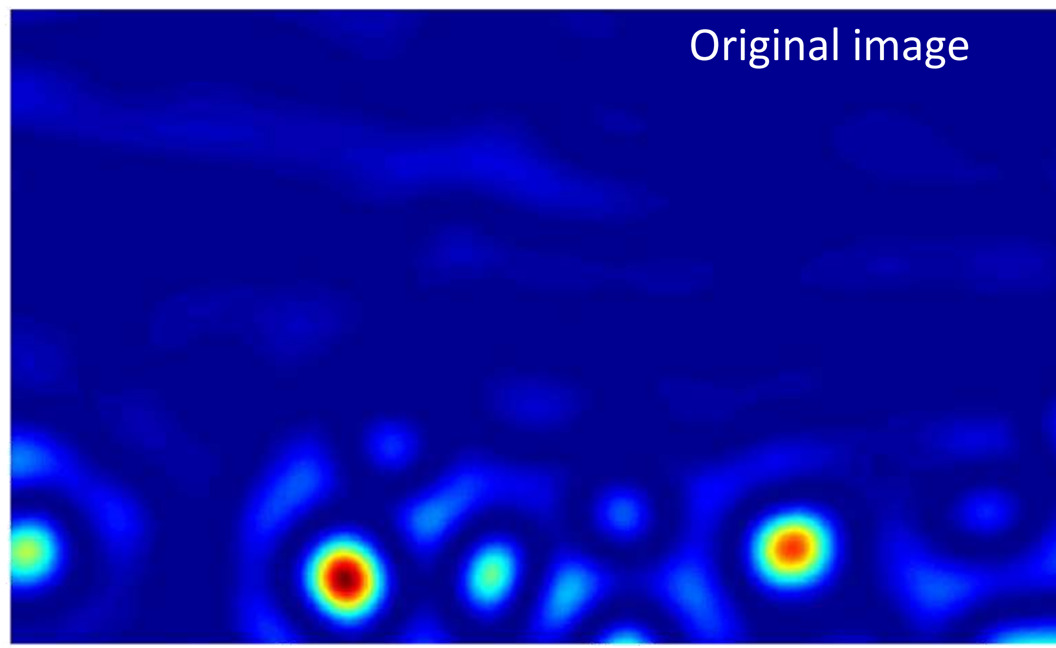




Slide credit: Kristen Grauman



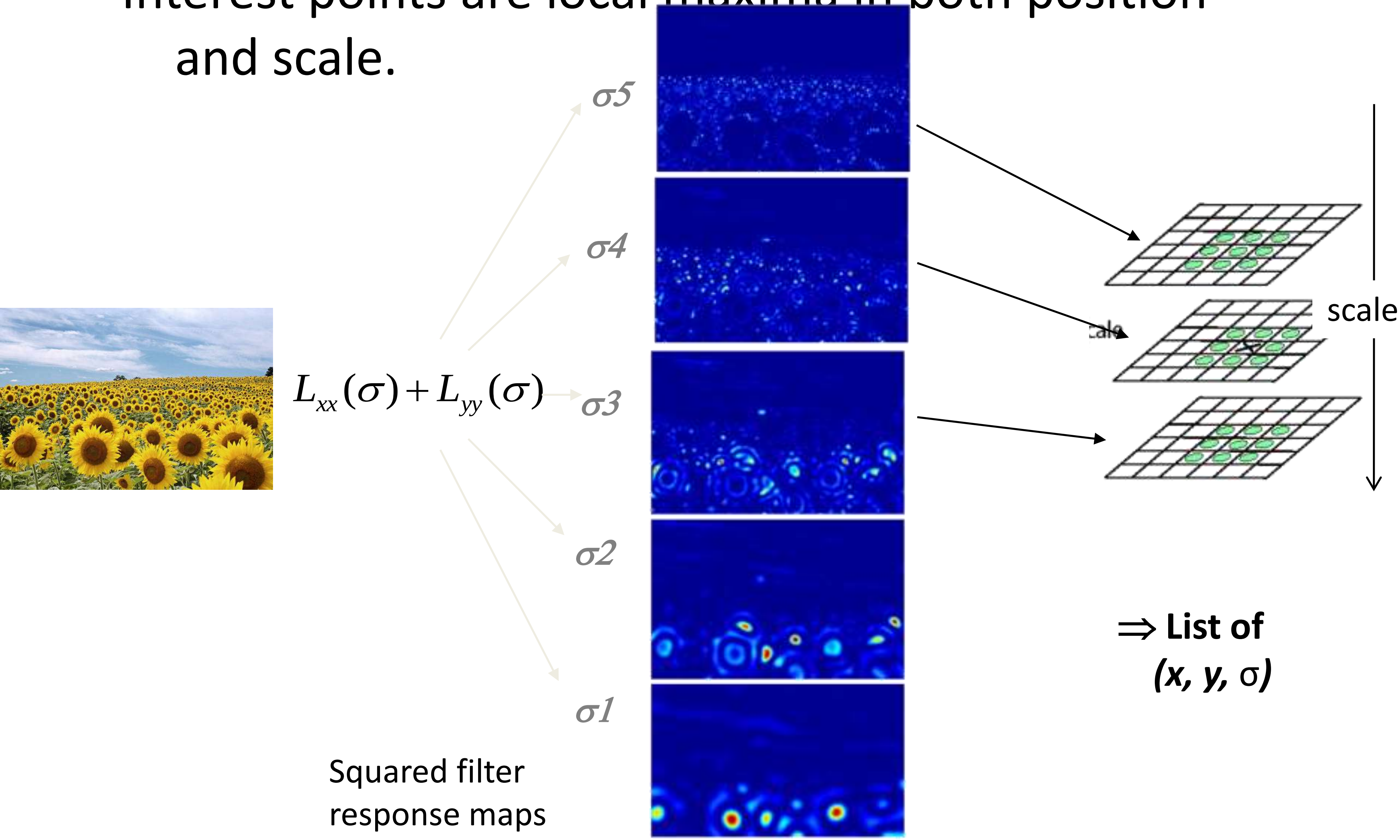




Slide credit: Kristen Grauman

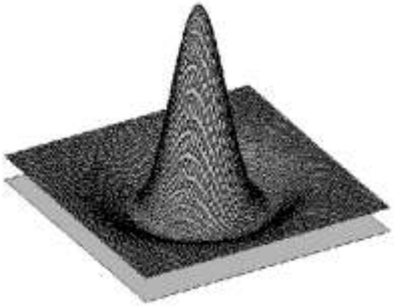
Scale invariant interest points

Interest points are local maxima in both position and scale.



⇒ **List of *(x, y, σ)***

Difference-of-Gaussian (DoG)



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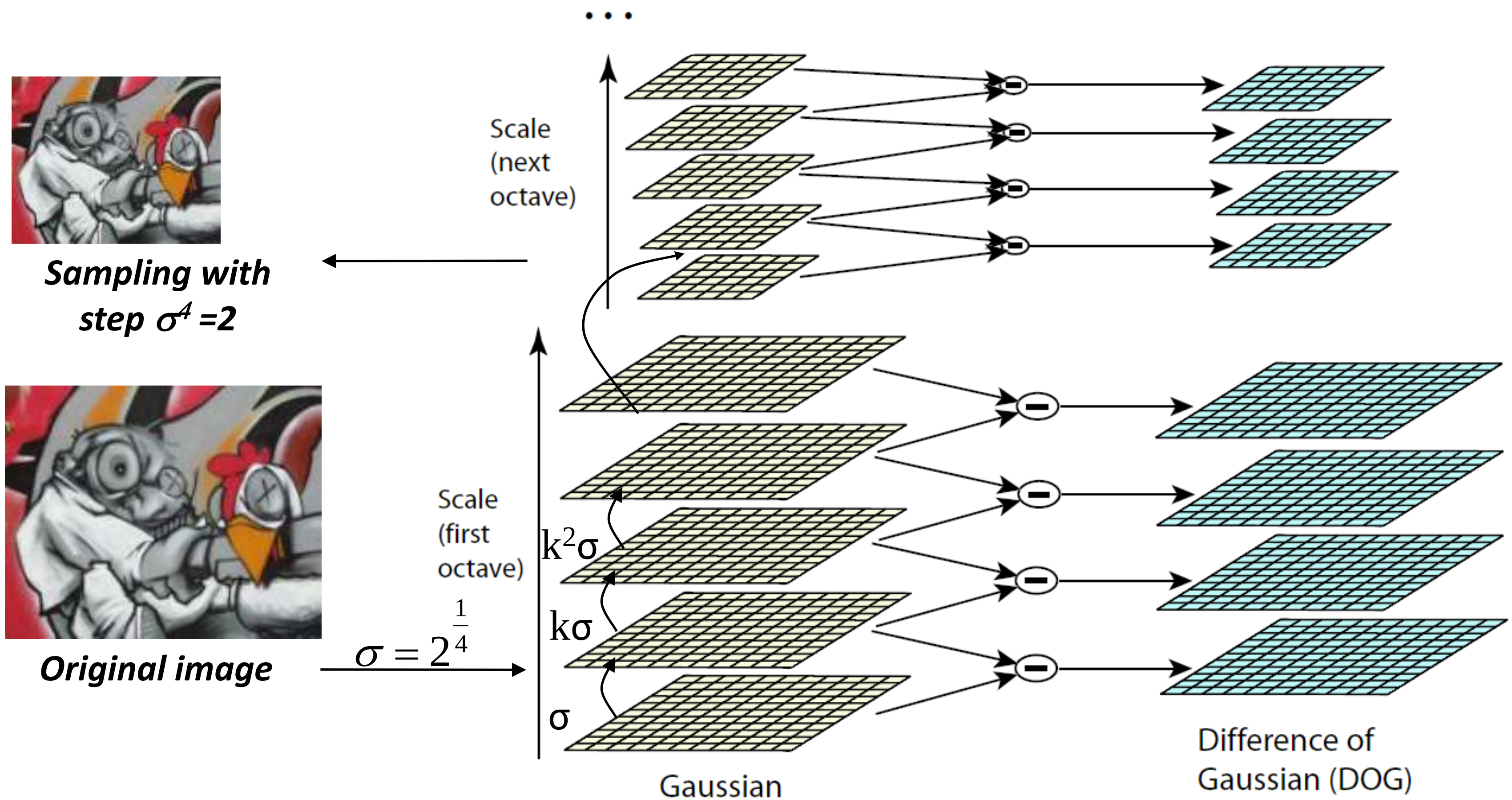
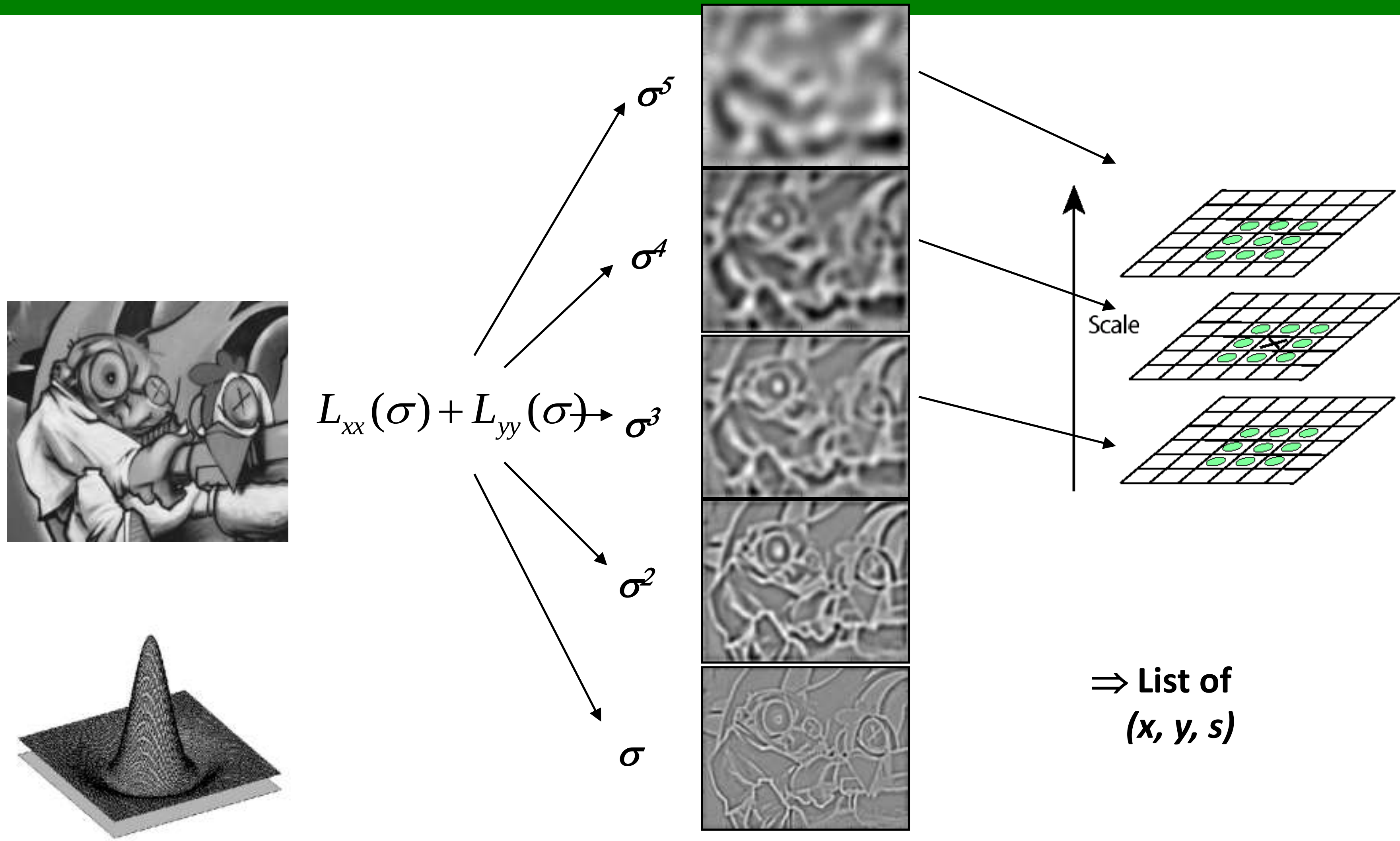
=

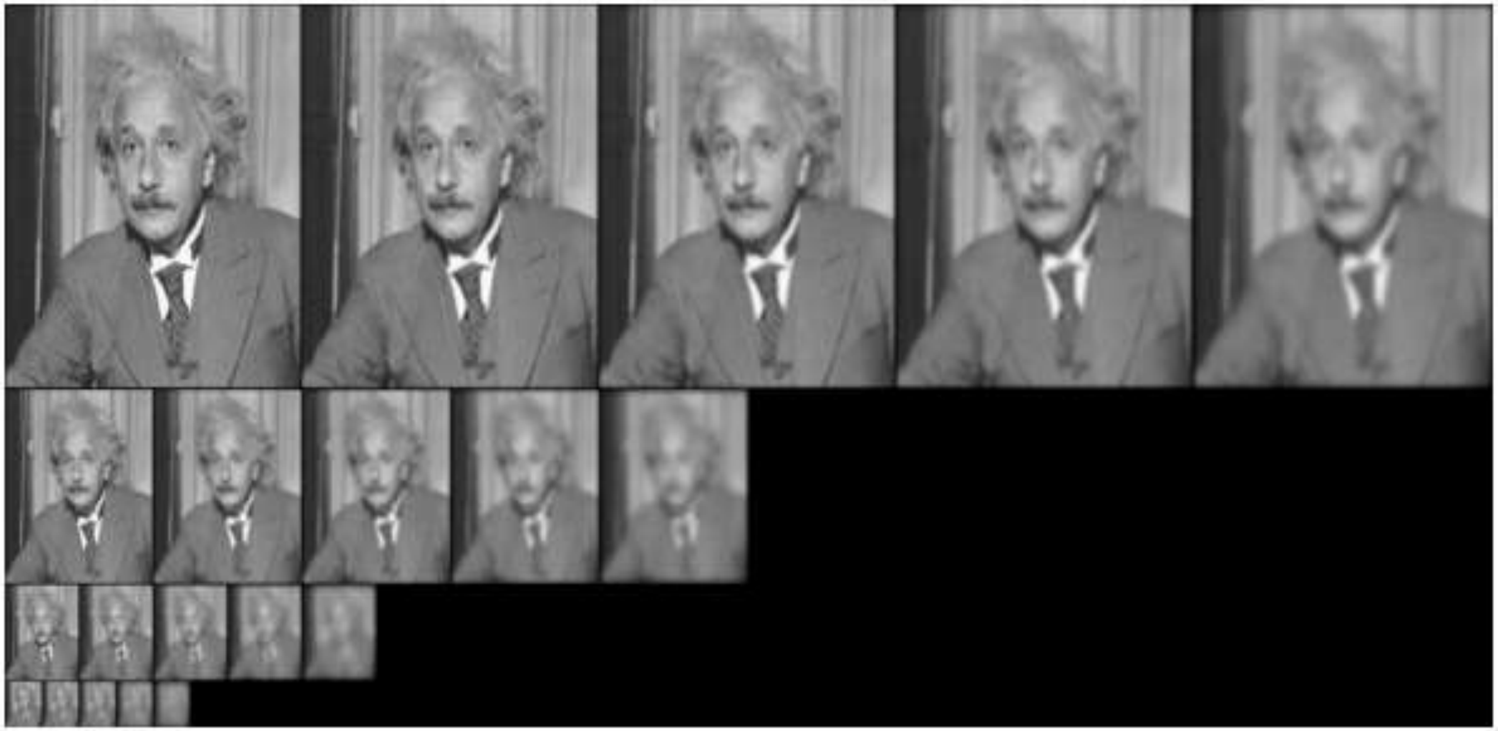
DoG – Efficient Computation

- Computation in Gaussian scale pyramid



Find local maxima in position-scale space of Difference-of-Gaussian

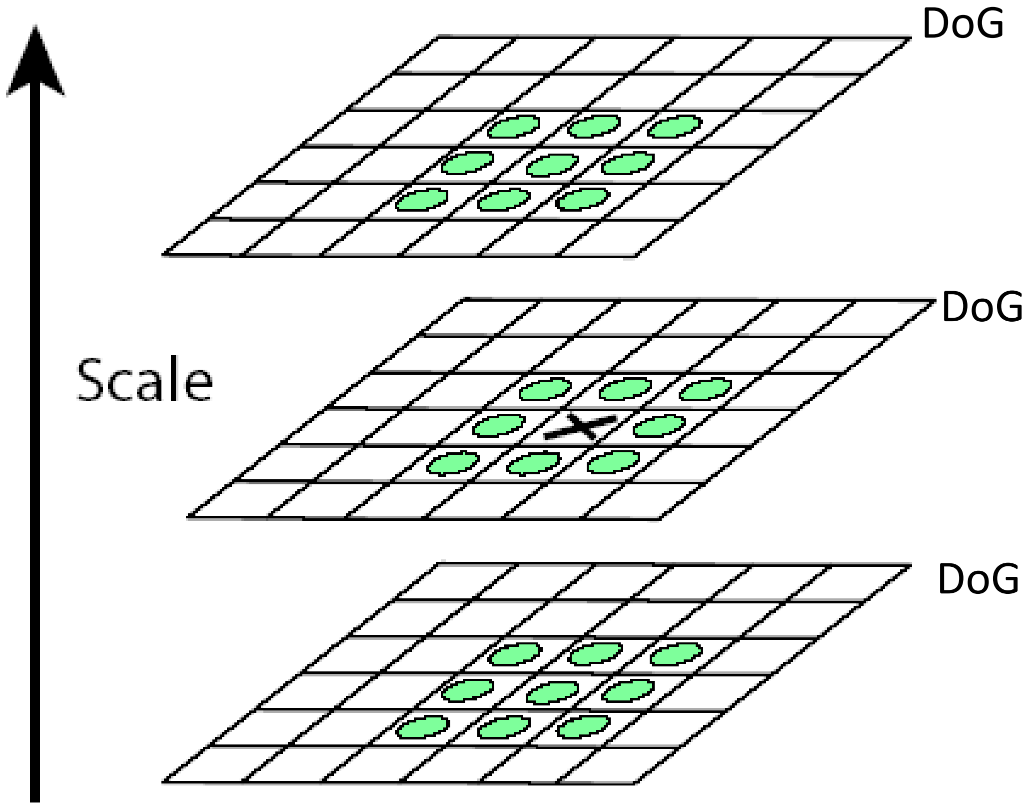




Gaussian images

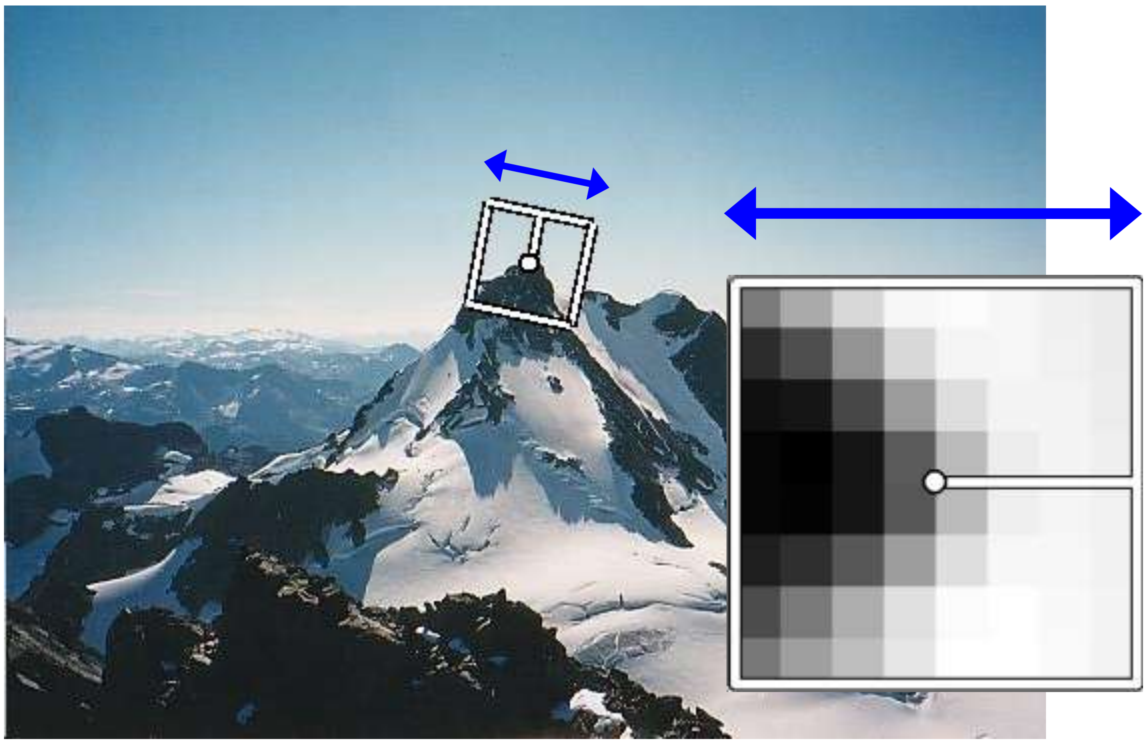
DoG images

Scale-space extrema detection



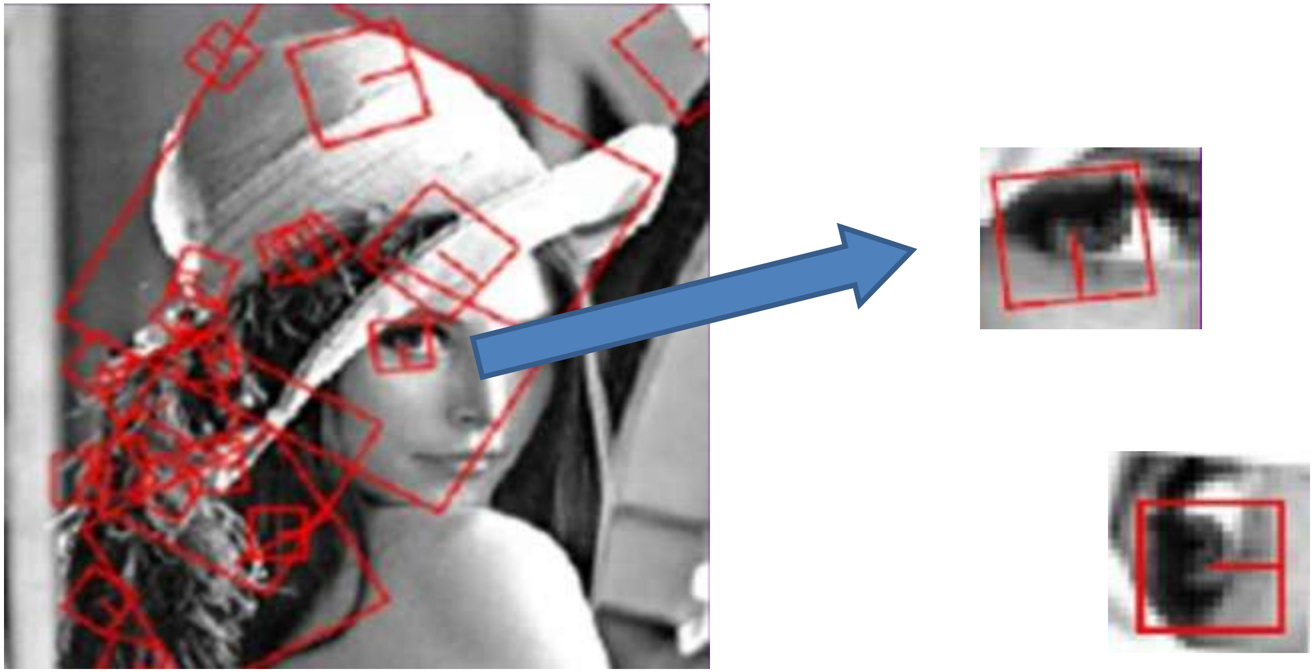
If ***X*** is the *largest* or the *smallest* of all of its neighbors, ***X*** is called a ***keypoint***.

Making descriptor rotation invariant



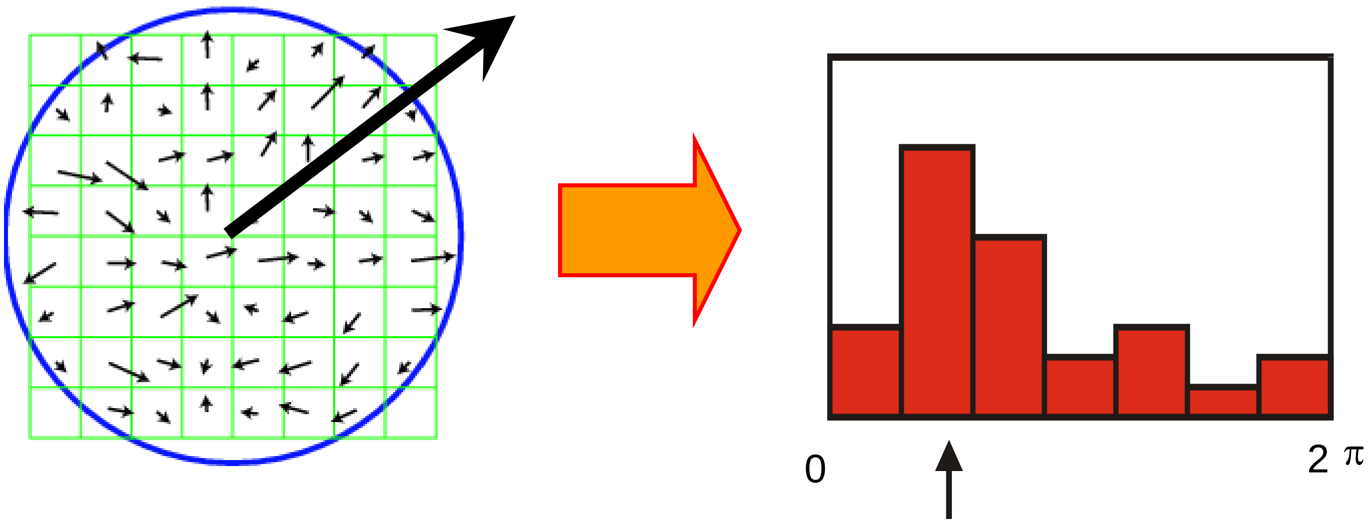
- Rotate patch according to its *dominant* gradient orientation
- This puts the patches into a canonical orientation.

Orientation assignment



Eliminating rotation ambiguity

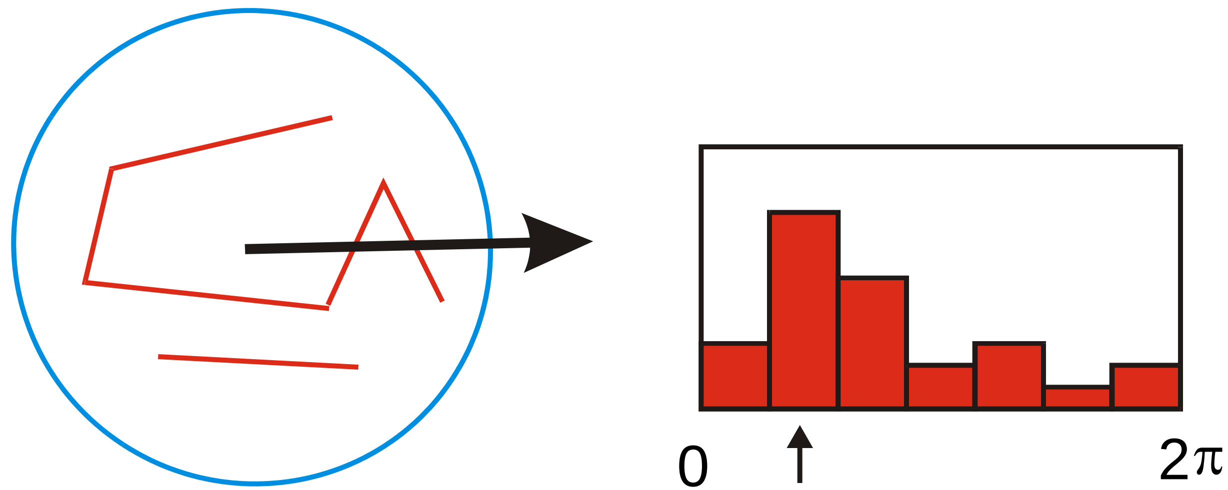
- To assign a unique orientation to circular image windows:
  - Create histogram of local gradient directions in the patch
  - Assign canonical orientation at peak of smoothed histogram



Orientation Normalization

[Lowe, SIFT, 1999]

- Compute orientation histogram
- Select dominant orientation
- Normalize: rotate to fixed orientation



Orientation assignment

- To achieve invariance to ***rotation***
- Compute gradient magnitude and orientation for each image sample *L*(x, y, σ)

$$m = \sqrt{(L_{x+1,y} - L_{x-1,y})^2 + (L_{x,y+1} - L_{x,y-1})^2}$$

$$\theta = \tan^{-1}((L_{x,y+1} - L_{x,y-1})/(L_{x+1,y} - L_{x-1,y}))$$

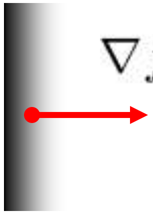
- Form an ***orientation histogram*** from the gradient orientations of sample points within a region around the keypoint, weighted by its gradient magnitude and a Gaussian-weighted window
- Detect the highest peak

Review: Image gradient

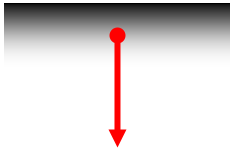
The gradient of an image:

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

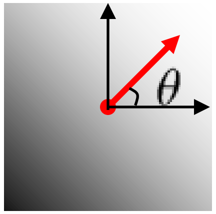
The gradient points in the direction of most rapid change in intensity



$$\nabla f = \left[\frac{\partial f}{\partial x}, 0\right]$$



$$\nabla f = \left[0, \frac{\partial f}{\partial y}\right]$$



$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

The **gradient direction** is given by:

$$\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$$

The **gradient magnitude** is given by:

$$||\nabla f|| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

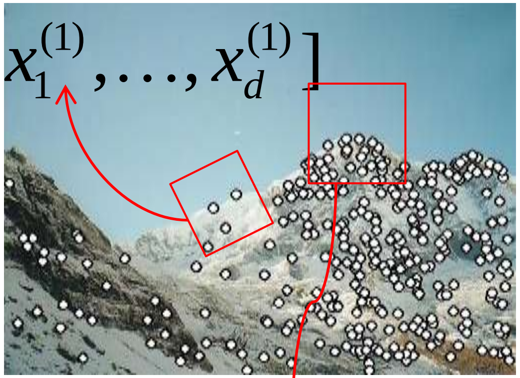
Local features: main components

1) Detection: Identify the interest points

2) **Description**: Extract a feature descriptor surrounding each interest point.

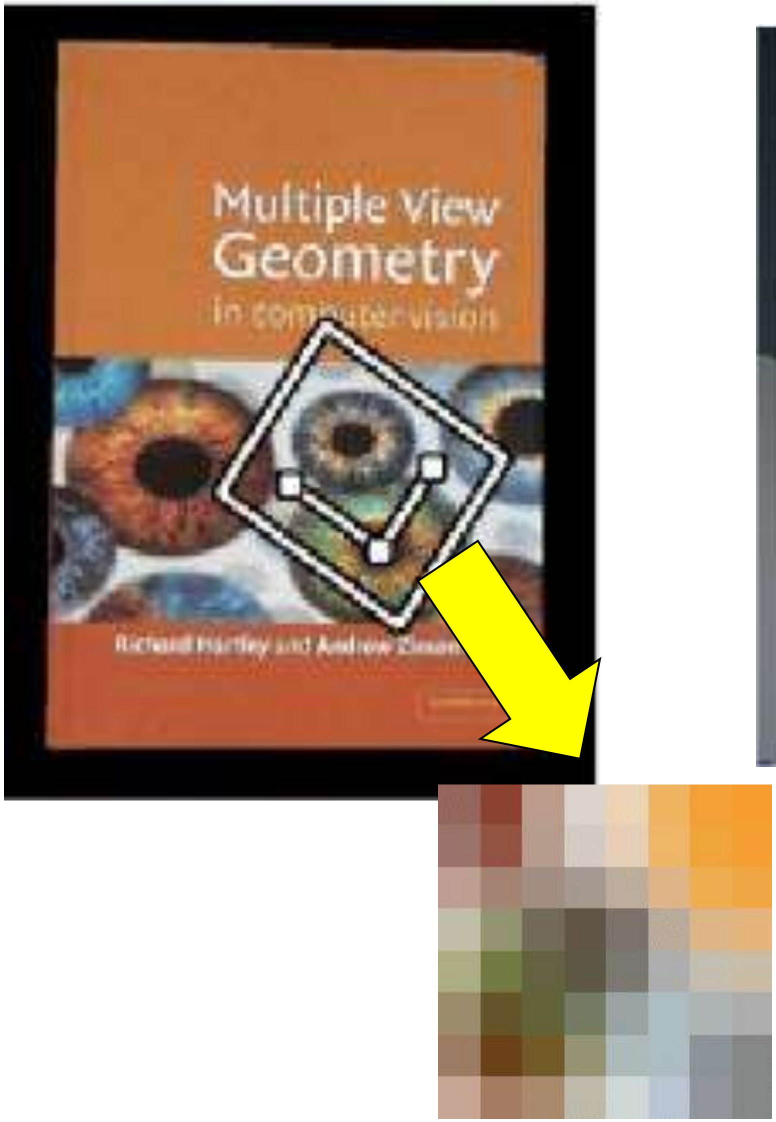
3) Matching: Determine correspondence between descriptors in two views

$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$



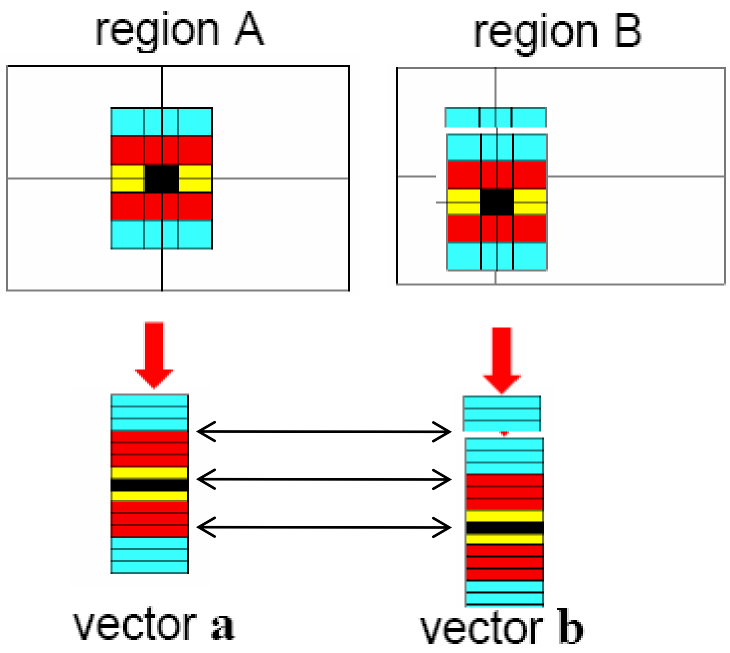
$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

Geometric transformations



e.g. scale,
translation,
rotation

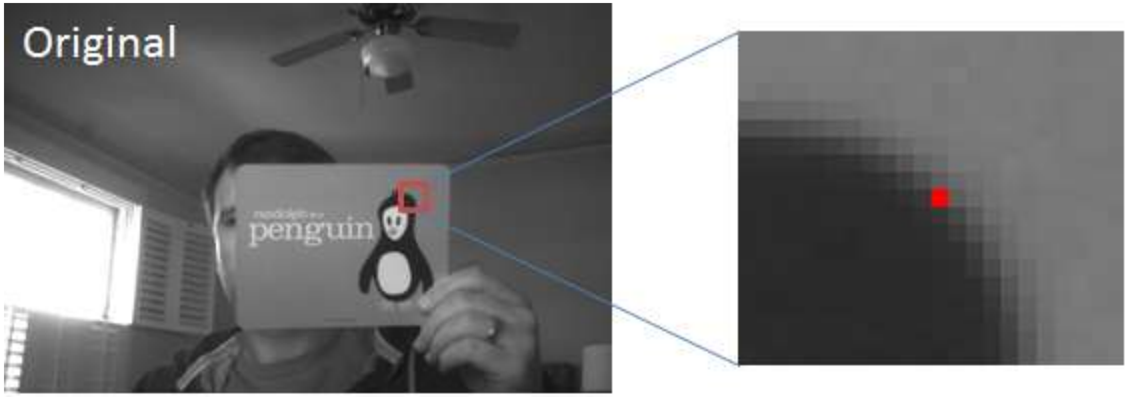
Raw patches as local descriptors



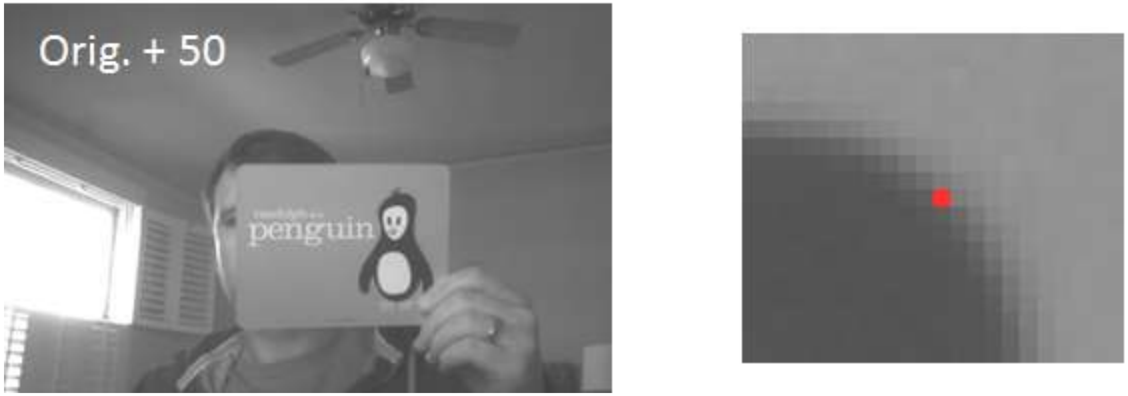
- The simplest way to describe the neighborhood around an interest point is to use *intensities* to form a feature vector.
- But this is very sensitive to even small shifts, rotations.

Gradient vectors

- The first image shows a pixel, highlighted in red, in the original image.

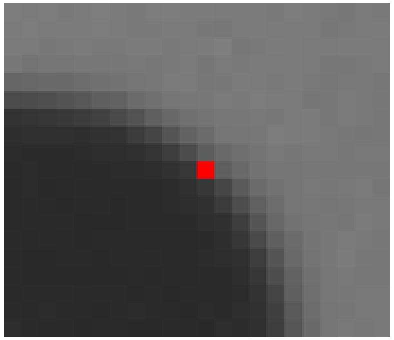


- In the second image, all pixel values have been increased by 50.



Gradient vectors

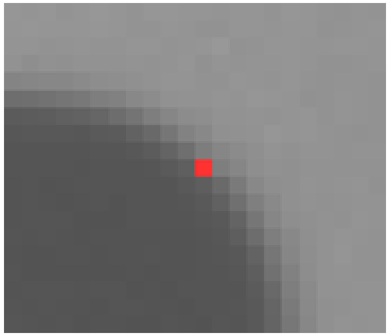
-1	0	1



	93	
56		94
	55	

$$\nabla f = \begin{bmatrix} 38 \\ 38 \end{bmatrix}$$

$$|\nabla f| = \sqrt{(38)^2 + (38)^2} = 53.74$$



	143	
106		144
	105	

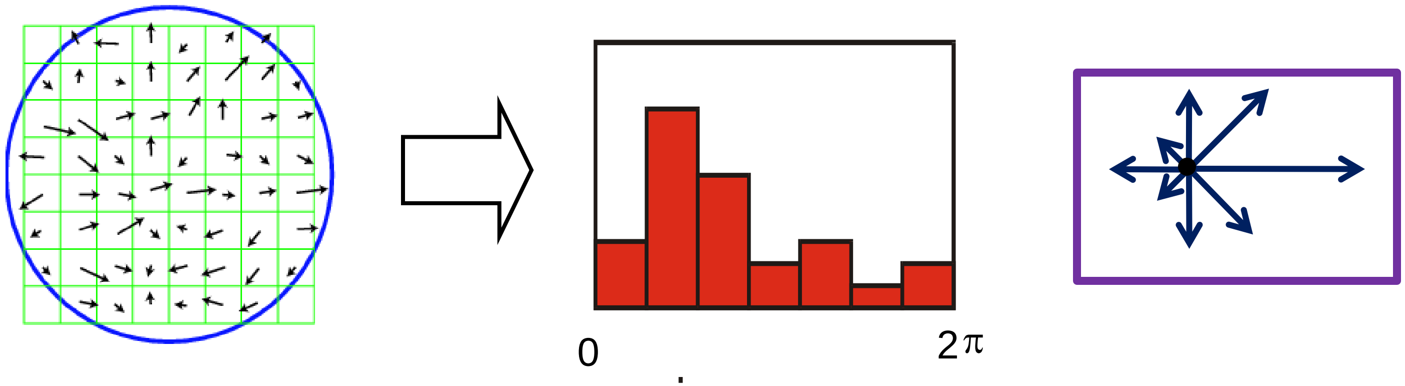
$$\nabla f = \begin{bmatrix} 38 \\ 38 \end{bmatrix}$$

$$|\nabla f| = \sqrt{(38)^2 + (38)^2} = 53.74$$

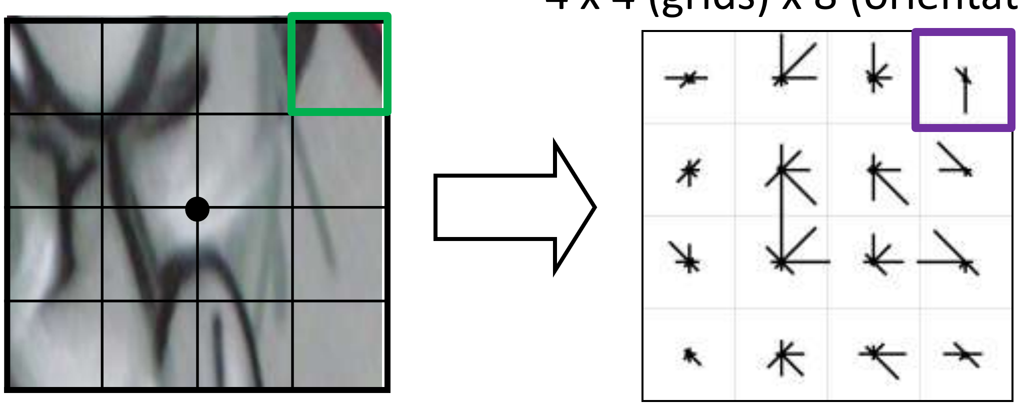
- The gradient vectors are equivalent in the first and second images

Local image descriptor

- Why does SIFT have some illumination invariance?

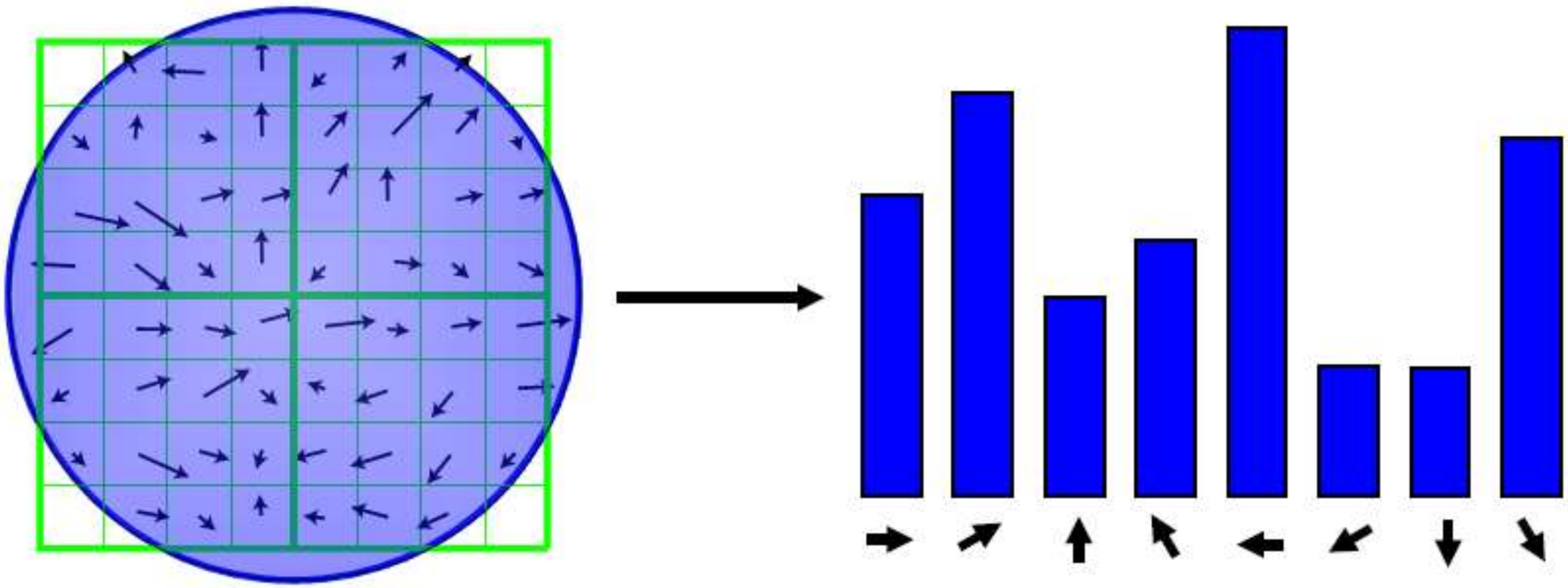


4 x 4 (grids) x 8 (orientations)



Gradient histogram

- 8 (orientations)



SIFT descriptors

- Inspiration: complex neurons in the primary visual cortex

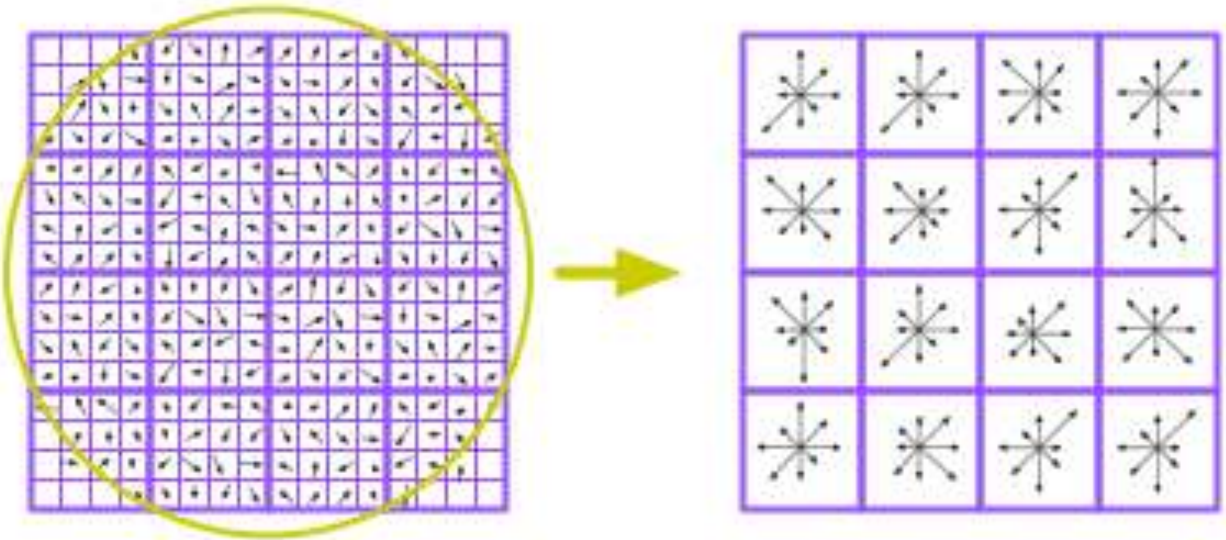


Image gradients Keypoint descriptor

Use a 4x4 grid computed from a 16x16 sample array
128-d = 4 x 4 x 8 (orientations)

D. Lowe. **[Distinctive image features from scale-invariant keypoints.]()** *IJCV* 2004.

621 128

Number of keypoints
Feature dimension

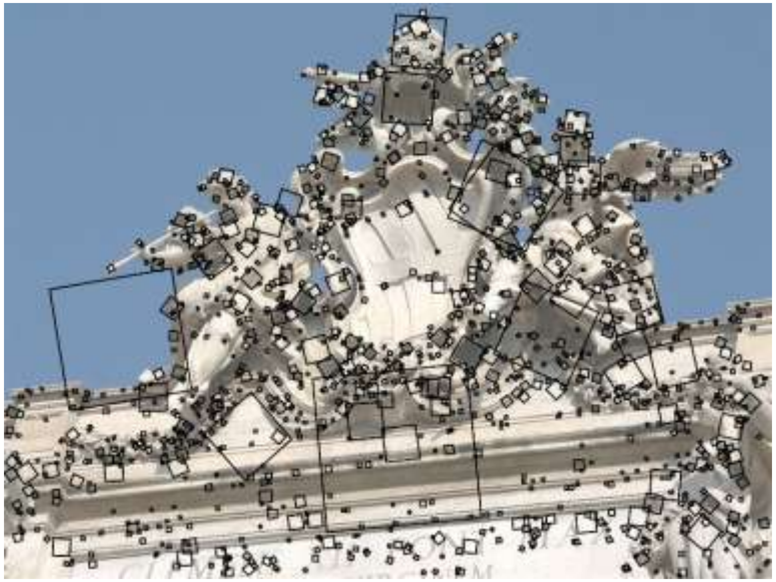
162.38 155.79 44.30 2.615
7 6 0 0 0 0 0 1 58 63 1 0 7 6 1 8 8 9 0 0
24 42 39 14 0 0 0 0 0 0 7 2 44 7 0 0 23 22 6
69 137 64 0 0 0 0 11 137 55 12 0 0 2 25 137
112 0 0 0 0 3 17 30 6 34 1 0 0 20 51 137 89
137 89 0 0 0 15 115 102
137 47 0 0 4 37 26 43 0 0 0 0 19 45 4 0 0 0 0
0 0 16 137 53 33 2 0 0 0 56 137 51 57 2 0 0
0 3 14 35 0 0 0 0 0 0 2 0 0

282.47 185.76 27.80 2.009
0 0 0 0 0 0 0 0 1 41 13 1 0 12 4 0 5 17 15 16
17 83 35 16 19 0 0 1 2 13 24 104 0 1 9 0 0 0
0 0 22 127 127 5 0 0 0 1 127 127 75 16 6 0 0
70 55 2 0 1 0 0 25 127 1 1 9 0 0 1 1 2 115 22
49 4 0 0 0 68
127 127 30 4 0 0 0 58 67 127 69 0 0 0 5 20 2
0 0 0 4 65 5 2 85 50 6 0 1 15 2 30 56 93 53
19 0 0 4 41 22 127 86 1 0 2 17 20
……….

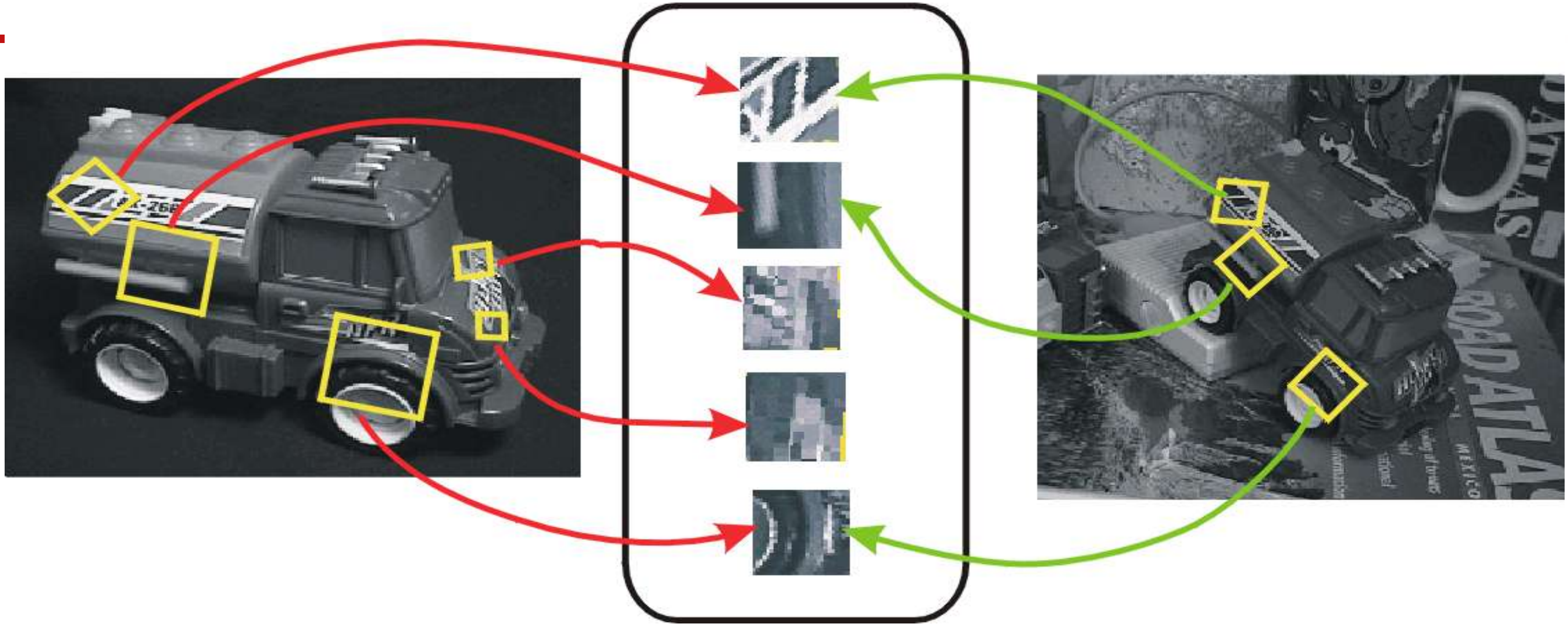
row col scale orientation (-pi~pi)
128 integers (0~255)

SIFT features

- Detected features with characteristic scales and orientations:



From feature detection to feature description



- Description is *invariant*:

  features(transform(image)) = features(image)

Details of Lowe's SIFT algorithm

- Run DoG detector
  - Find maxima in location/scale space
  - Remove edge points
- Find all major orientations
  - Bin orientations into 36 bin histogram
    - Weight by gradient magnitude
    - Weight by distance to center (Gaussian-weighted mean)
  - Return orientations within 0.8 of peak
    - Use parabola for better orientation fit
- For each (x,y,scale,orientation), create descriptor:
  - Sample 16x16 gradient mag. and rel. orientation
  - Bin 4x4 samples into 4x4 histograms
  - Threshold values to max of 0.2, divide by L2 norm
  - Final descriptor: 4x4x8 normalized histograms

$$\mathbf{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

$$\frac{\mathrm{Tr}(\mathbf{H})^2}{\mathrm{Det}(\mathbf{H})} < \frac{(r+1)^2}{r}$$

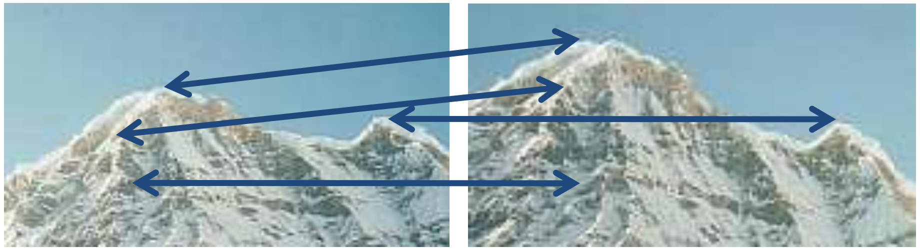
Lowe IJCV 2004

Local features: main components

1) **Detection:** Identify the interest points

2) **Description:** Extract a feature descriptor surrounding each interest point.

3) **Matching:** Determine correspondence between descriptors in two views



Properties of SIFT

Extraordinarily robust detection and description technique

- Can handle changes in viewpoint
  - Up to about 60 degree out-of-plane rotation
- Can handle significant changes in illumination
  - Sometimes even day vs. night
- Fast and efficient—can run in real time
- Lots of code available