Computer Vision
(Summer Semester 2020)

Lecture 5, Part 1

Feature Descriptors (1)

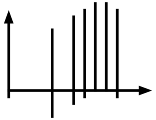
Feature Descriptors and Matching

- How to find out the ‘right’ scale of an interest point?
- SIFT: scale-invariant image descriptor
- Feature matching

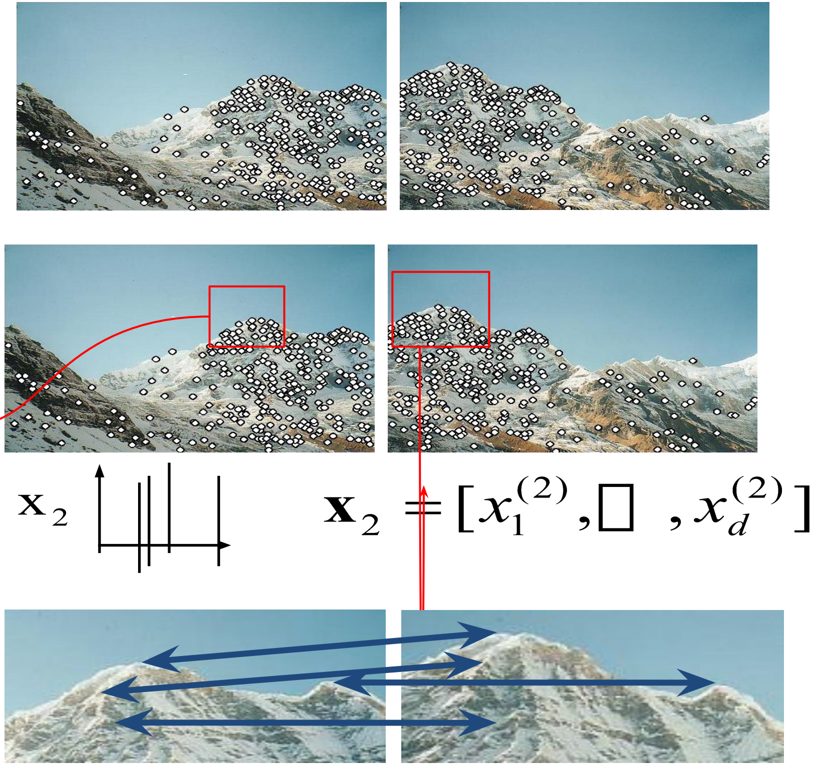
Note: The core of these slides stems from the class CSCI 1430: “Introduction to Computer Vision” by James Tompkin, Fall 2017, Brown University.

Local features: main components

1) **Detection (harris corner):**
   Find a set of distinctive key points.
2) Description:
   Extract feature descriptor around each interest point as vector.

$\mathbf{x}_1$ 

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



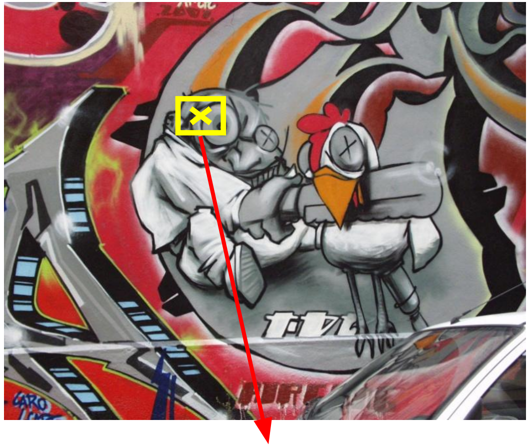
$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

3) Matching:
   Compute distance between feature vectors to find correspondence.

$$d(\mathrm{x}_1, \mathrm{x}_2) < T$$

HOW CAN THE ‘SCALE’ OF A FEATURE POINT BE MODELED?

Automatic Scale Selection



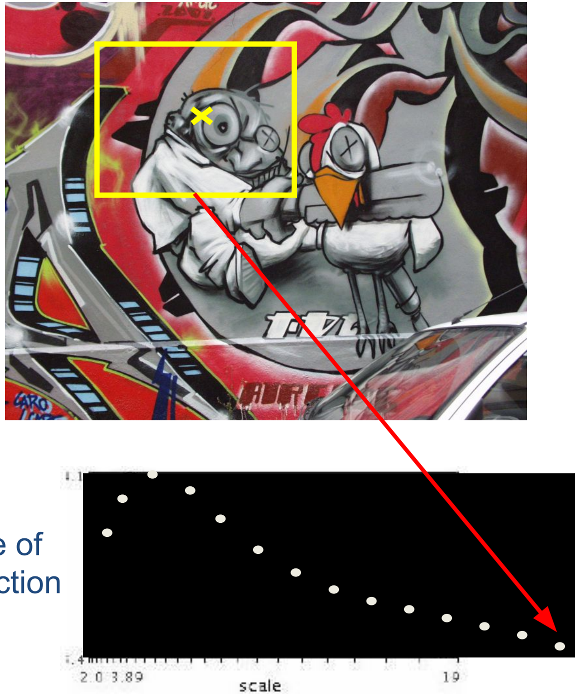
$$f(I_{i1 \to im}(x, \sigma)) = f(I_{i1 \to im}(x', \sigma'))$$

How to find patch sizes at which *f* response is equal?

What is a good *f* ?

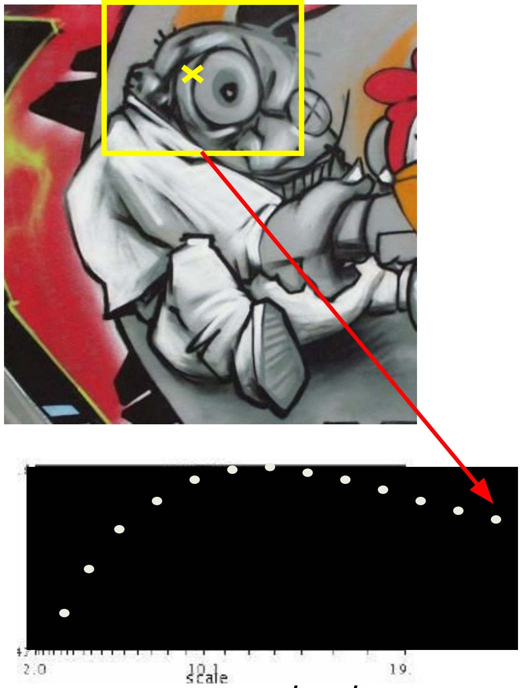
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



Response of some function *f*

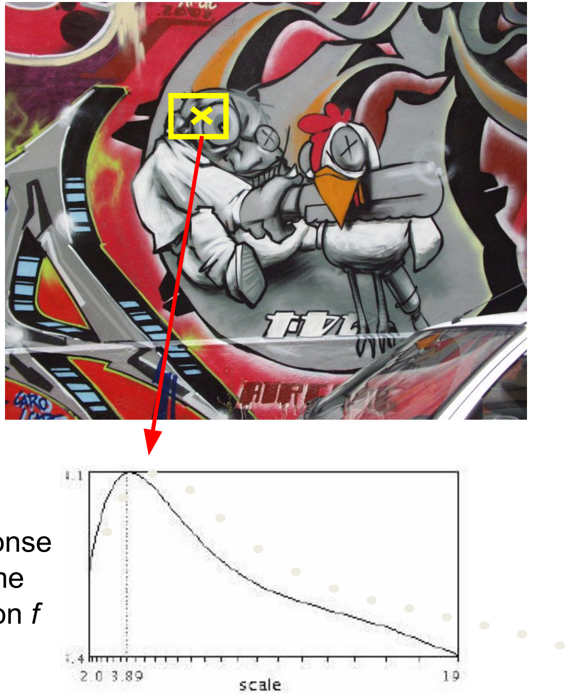
$$f(I_{i1 \to im}(x, \sigma))$$



$$f(I_{i1 \to im}(x', \sigma'))$$

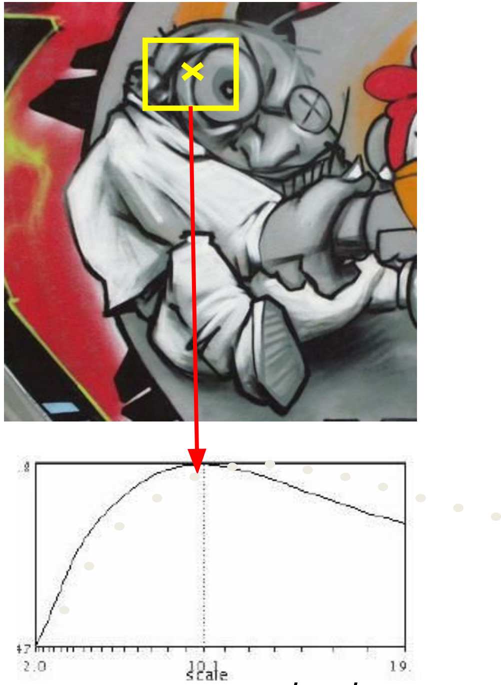
Automatic Scale Selection

- Function responses for increasing scale (scale signature)



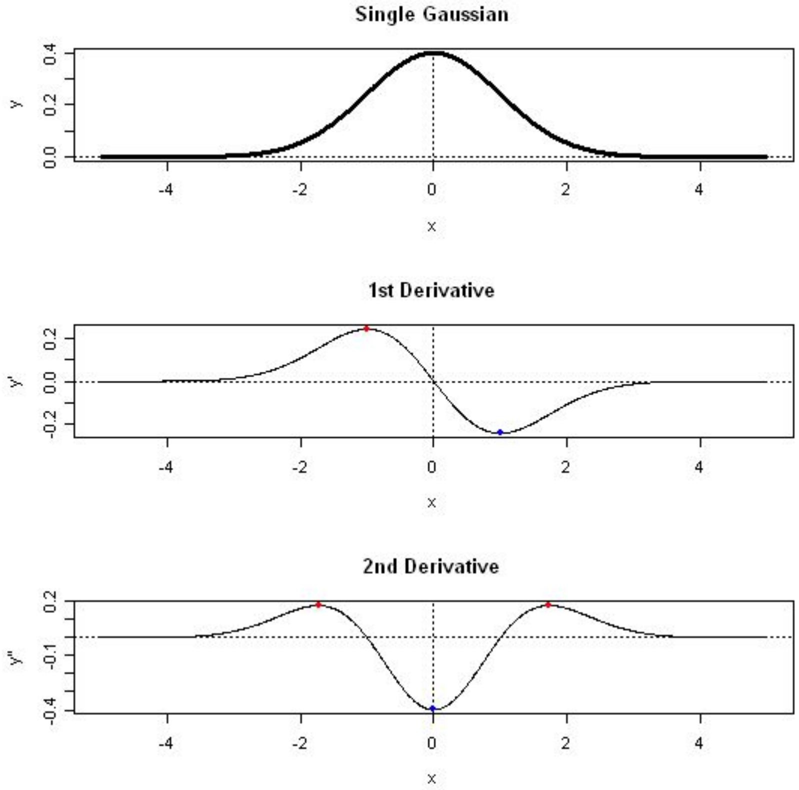
Response of some function *f*

$f(I_{i1\rightarrow im}(x, \sigma))$

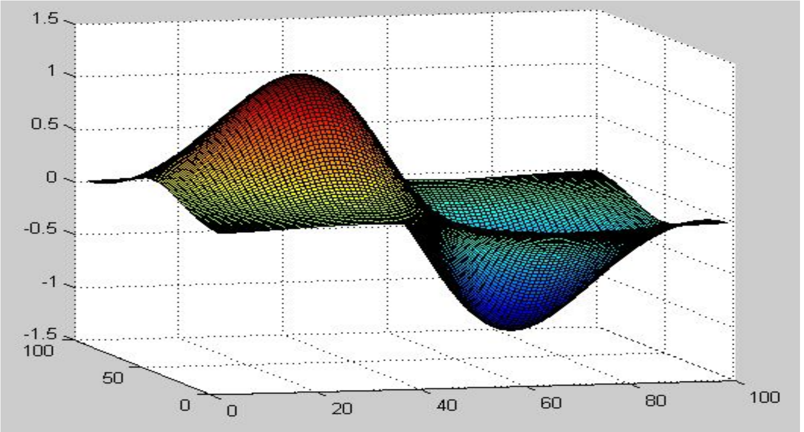


$f(I_{i1\rightarrow im}(x', \sigma'))$

What Is A Useful Signature Function *f* ?



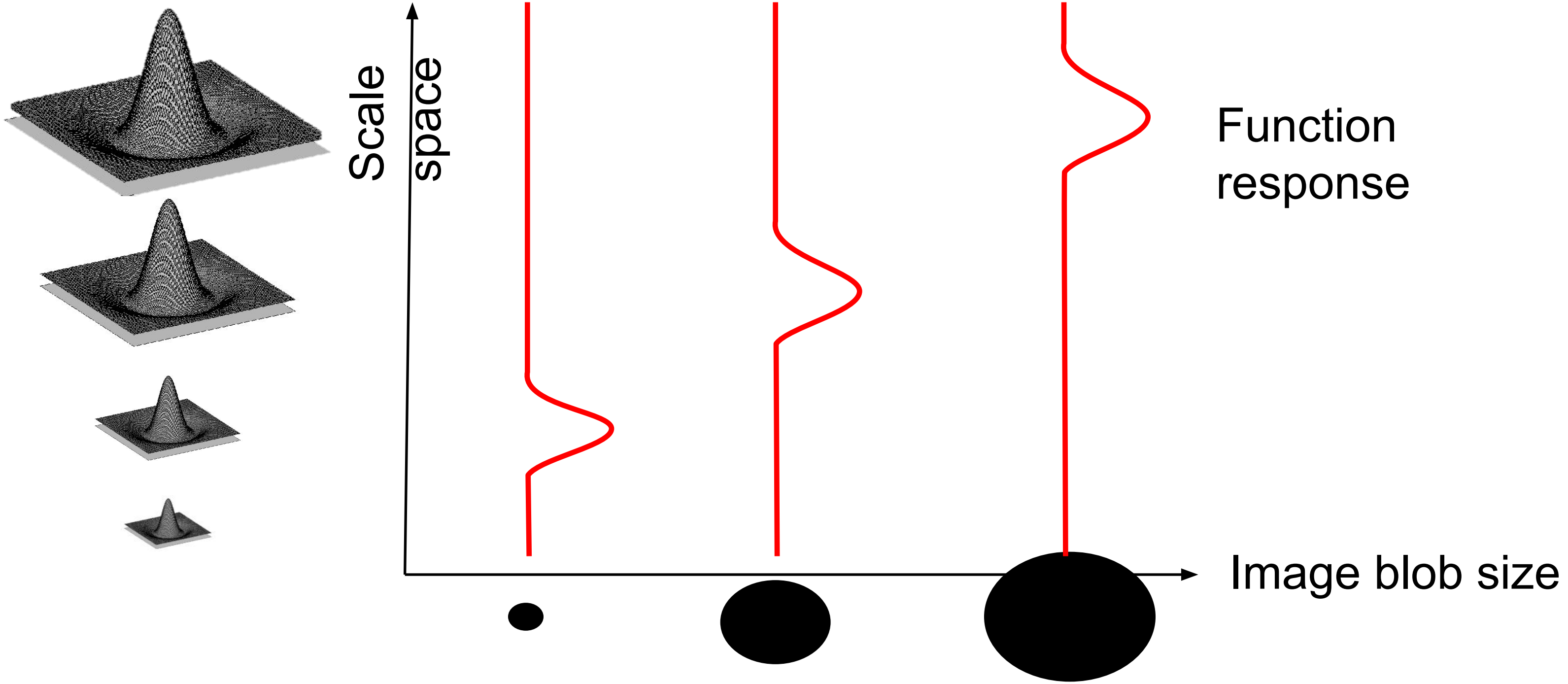
1st Derivative of Gaussian



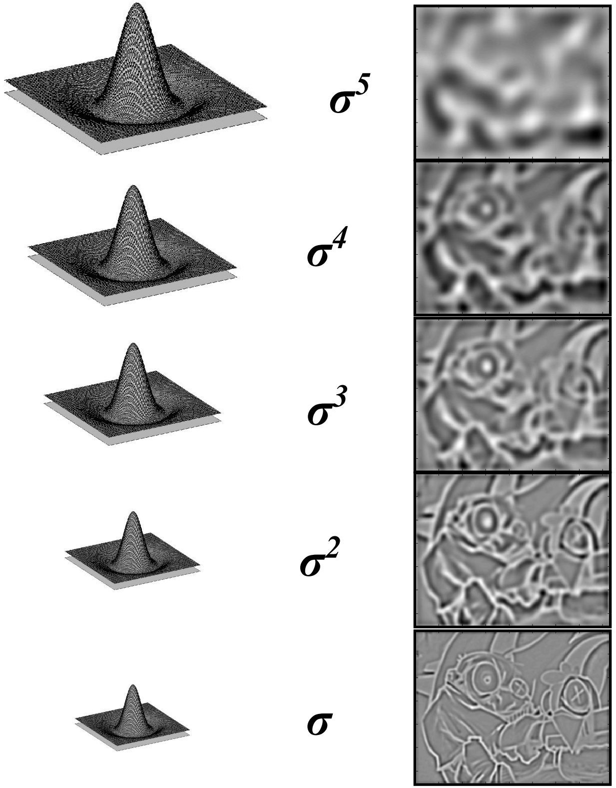
(Laplacian of Gaussian)

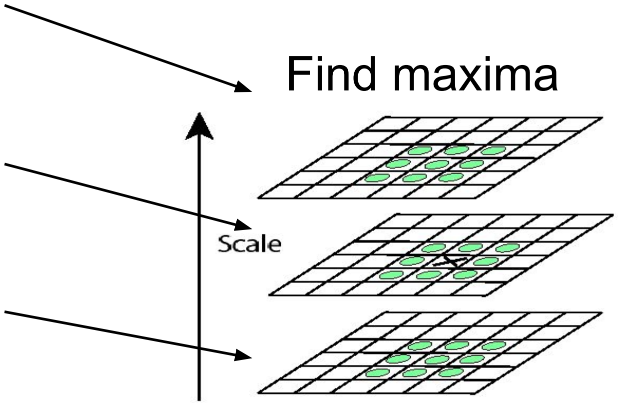
What Is A Useful Signature Function *f* ?

- “Blob” detector is common for corners
  - - Laplacian (2nd derivative) of Gaussian (LoG)



Find local maxima in position-scale space

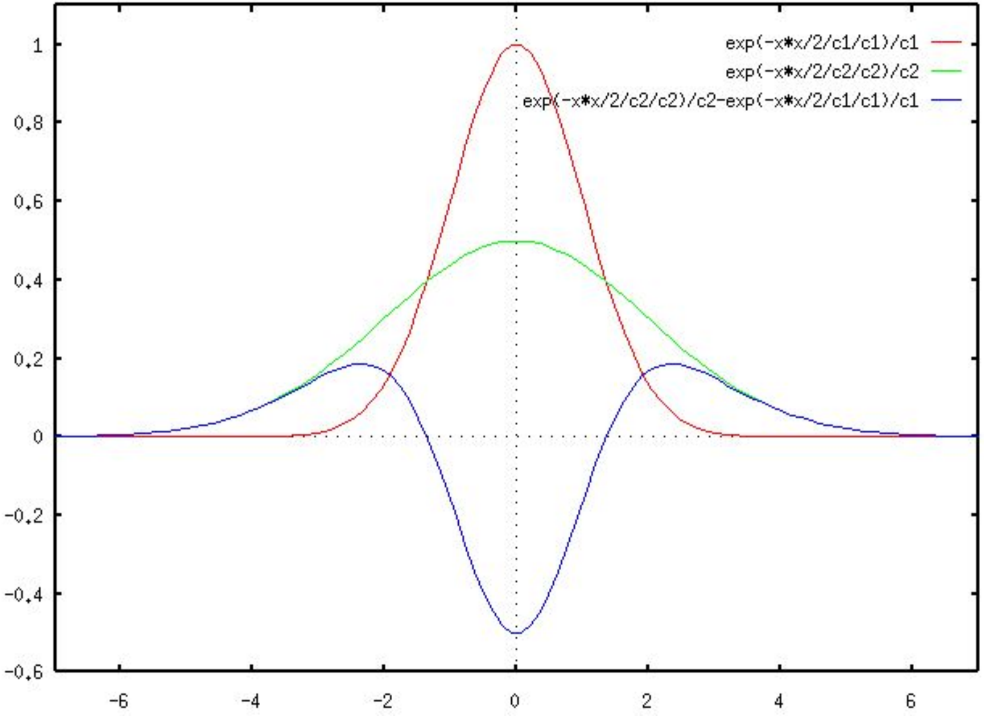




⇒ List of
(x, y, s)

Alternative approach

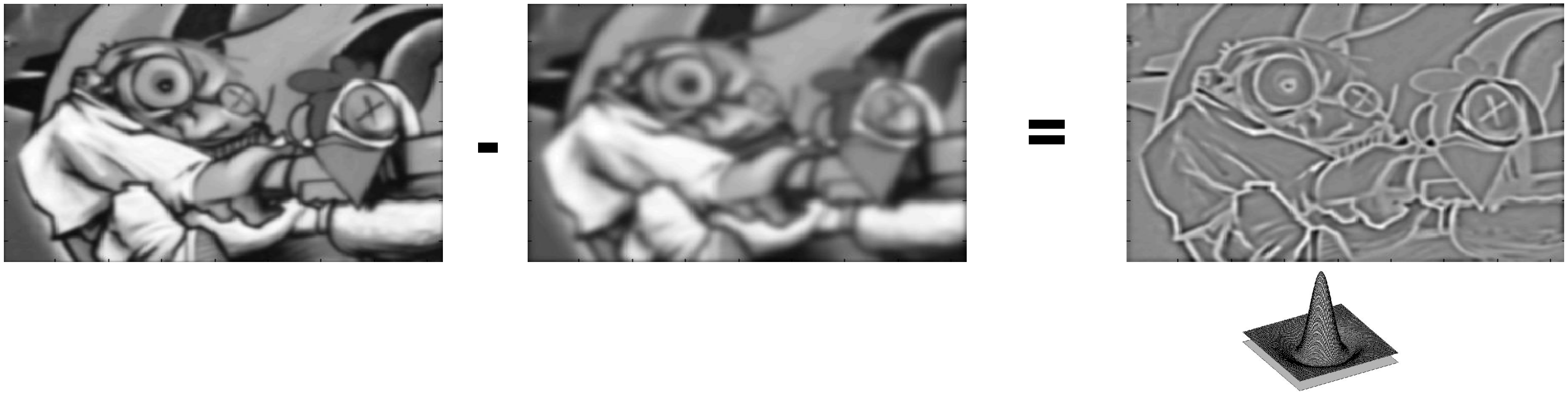
Approximate LoG with Difference-of-Gaussian (DoG).



Alternative approach

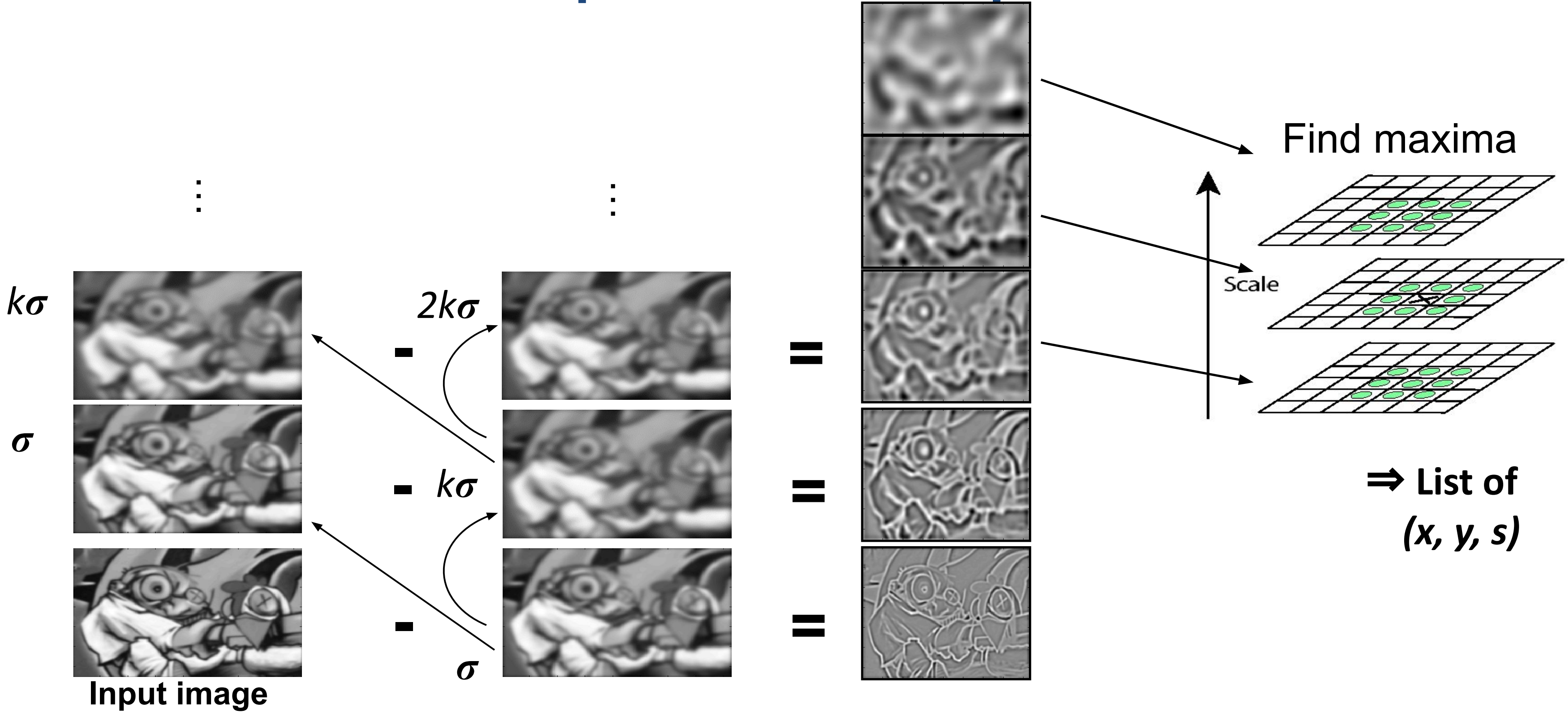
Approximate LoG with Difference-of-Gaussian (DoG).

1. Blur image with σ Gaussian kernel
2. Blur image with $k\sigma$ Gaussian kernel
3. Subtract 2. from 1.



K.Grauman, B.Leibe

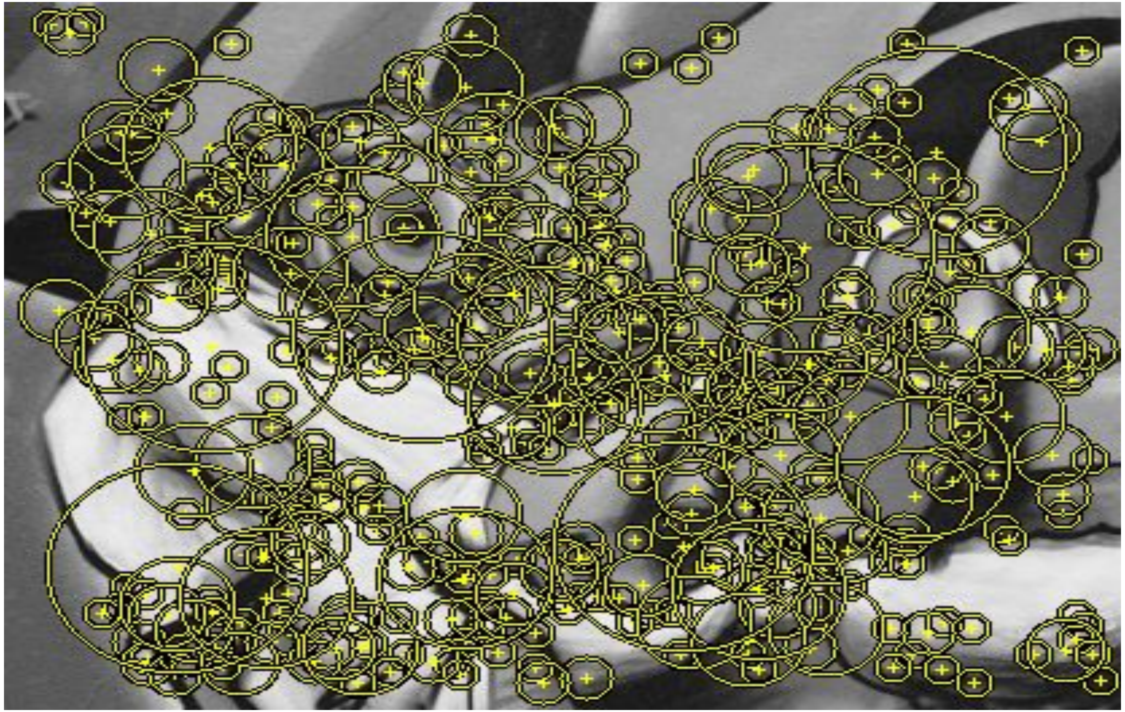
Find local maxima in position-scale space of DoG



⇒ List of (x, y, s)

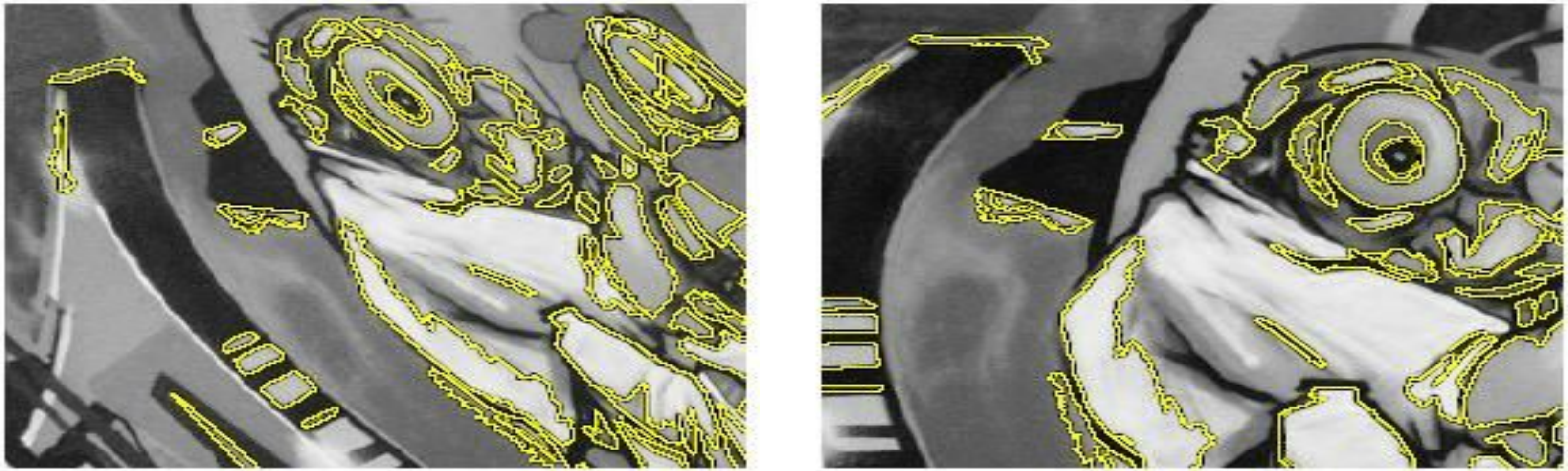
Results: Difference-of-Gaussian

- Larger circles = larger scale
- Descriptors with maximal scale response



Maximally Stable Extremal Regions [Matas '02]

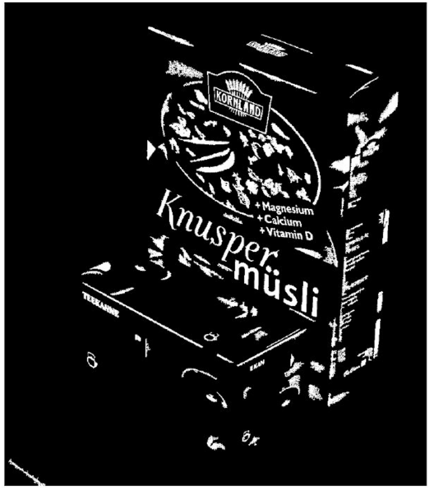
- Based on Watershed segmentation algorithm
- Select regions that stay stable over a large parameter range



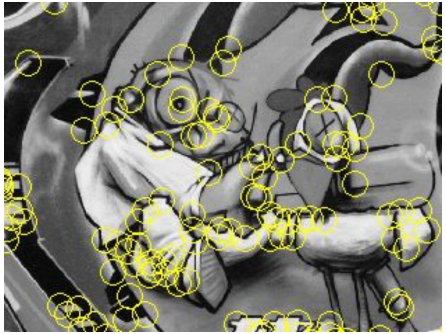
Review: Interest points

- Keypoint detection: repeatable and distinctive
  - Corners, blobs, stable regions
  - Harris, DoG, MSER

(a) Gray scale input image



(b) Detected MSERs



Review: Choosing an interest point detector

- Why choose?
  - Collect more points with more detectors, for more possible matches

- What do you want it for (*application specific*)?
  - Precise localization in x-y: **Harris**
  - Good localization in scale: **Difference of Gaussian**
  - Flexible region shape: **MSER**

Review: Choosing an interest point detector

- Best choice often application dependent
  - Harris-/Hessian-Laplace/DoG work well for many natural categories
  - MSER works well for buildings and printed things

- There have been extensive evaluations/comparisons
  - [Mikolajczyk et al., IJCV’05, PAMI’05]
  - All detectors/descriptors shown here work well

Comparison of Keypoint Detectors

Table 7.1 Overview of feature detectors.

Feature Detector	Corner	Blob	Region	Rotation invariant	Scale invariant	Affine invariant	Repeatability	Localization accuracy	Robustness	Efficiency
Harris	√			√			+++	+++	+++	++
Hessian		√		√			++	++	++	+
SUSAN	√			√			++	++	++	+++
Harris-Laplace	√	(√)		√	√		+++	+++	++	+
Hessian-Laplace	(√)	√		√	√		+++	+++	+++	+
DoG	(√)	√		√	√		++	++	++	++
SURF	(√)	√		√	√		++	++	++	+++
Harris-Affine	√	(√)		√	√	√	+++	+++	++	++
Hessian-Affine	(√)	√		√	√	√	+++	+++	+++	++
Salient Regions	(√)	√		√	√	(√)	+	+	++	+
Edge-based	√			√	√	√	+++	+++	+	+
MSER			√	√	√	√	+++	+++	++	+++
Intensity-based			√	√	√	√	++	++	++	++
Superpixels			√	√	(√)	(√)	+	+	+	+

 Tuytelaars M 2008