Blob Detection

Slides adapted from Lana Lazebnik

Features

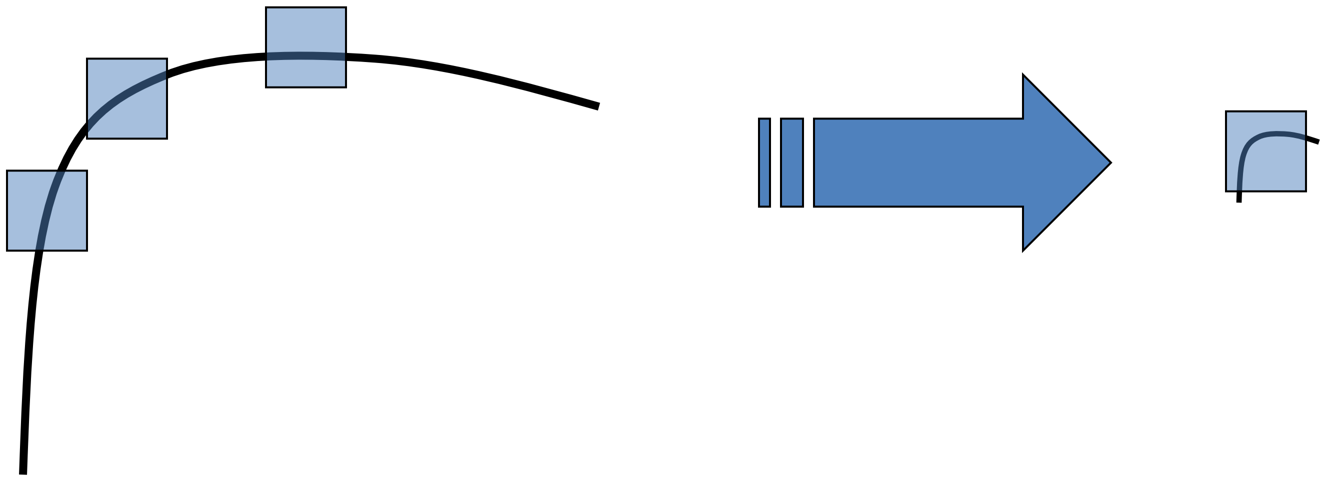
- We want to find the most "interesting" pixels in an image
  - Called image features or interest points
- Our progression…
  - Edge points (high gradient magnitude)
  - Corner points (high magnitudes in multiple directions)

- Issue: Scale-invariance
  - Today: Blobs or regions

Harris Corner Detector

- Affine Intensity Invariant? Sort of
- Rotation covariant? Yes
- Translation covariant? Yes

- Scale covariant? No



All points will be classified as edges

Corner !

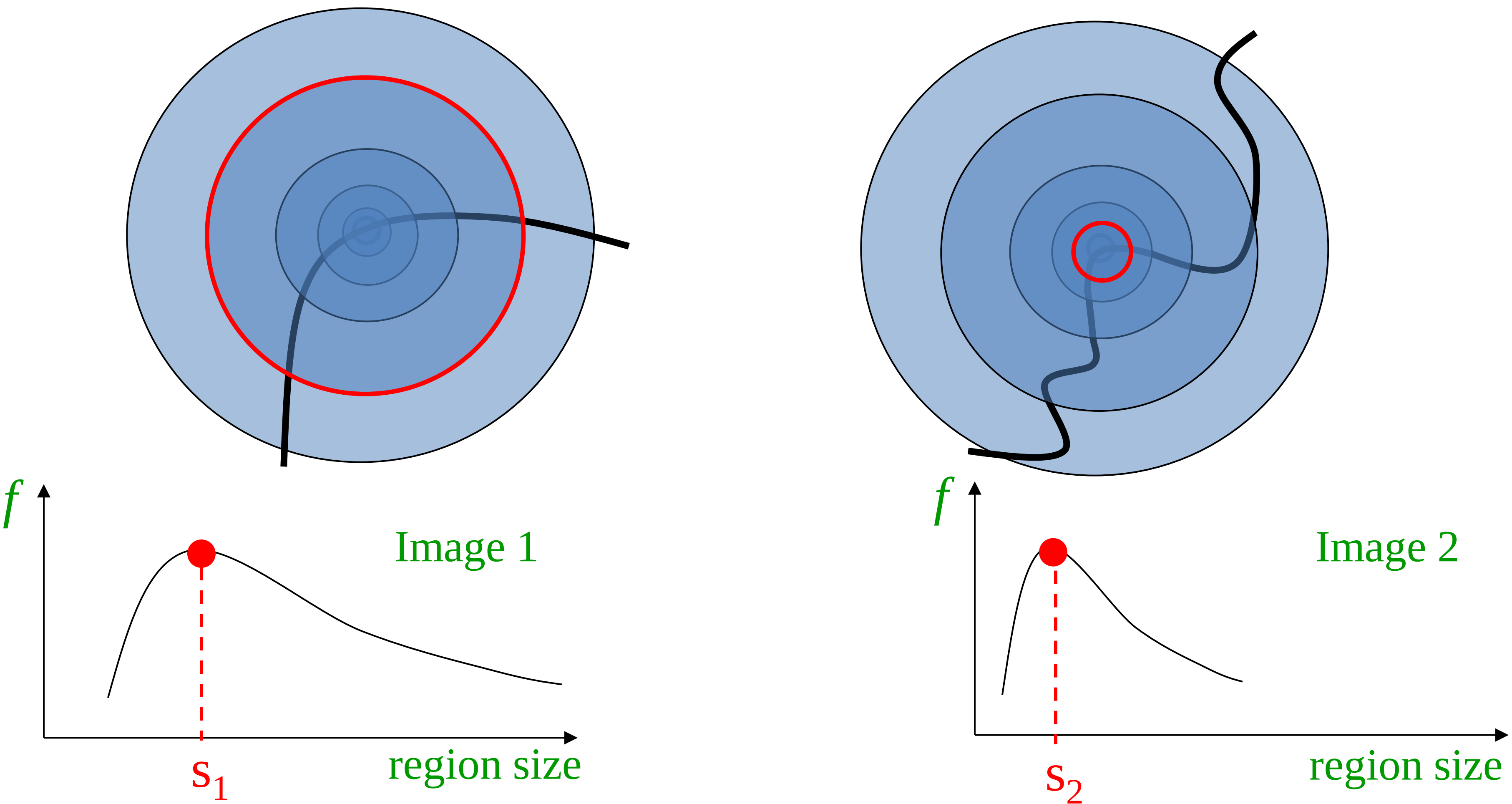
Scale invariant interest points

How can we independently select interest points in each image, such that the detections are repeatable across different scales?

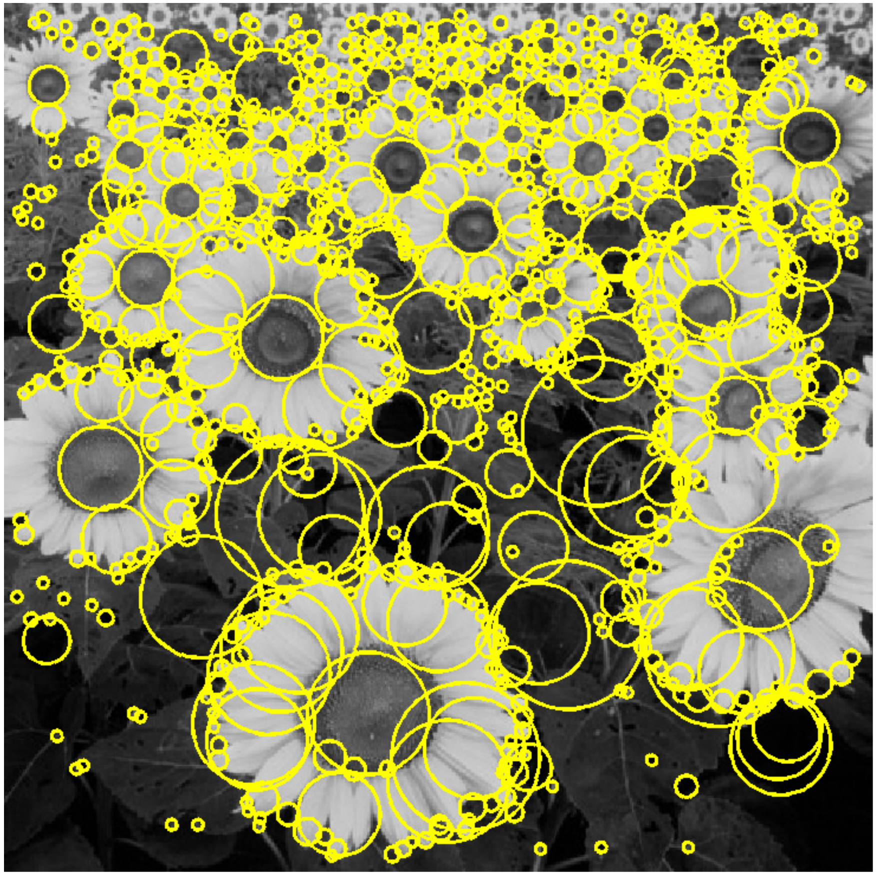
Automatic Scale Selection

Intuition:

- Find scale that gives local maxima of some function *f* in both position and scale.



Scale-invariant features: Blobs



Recall: Edge detection

$$f$$

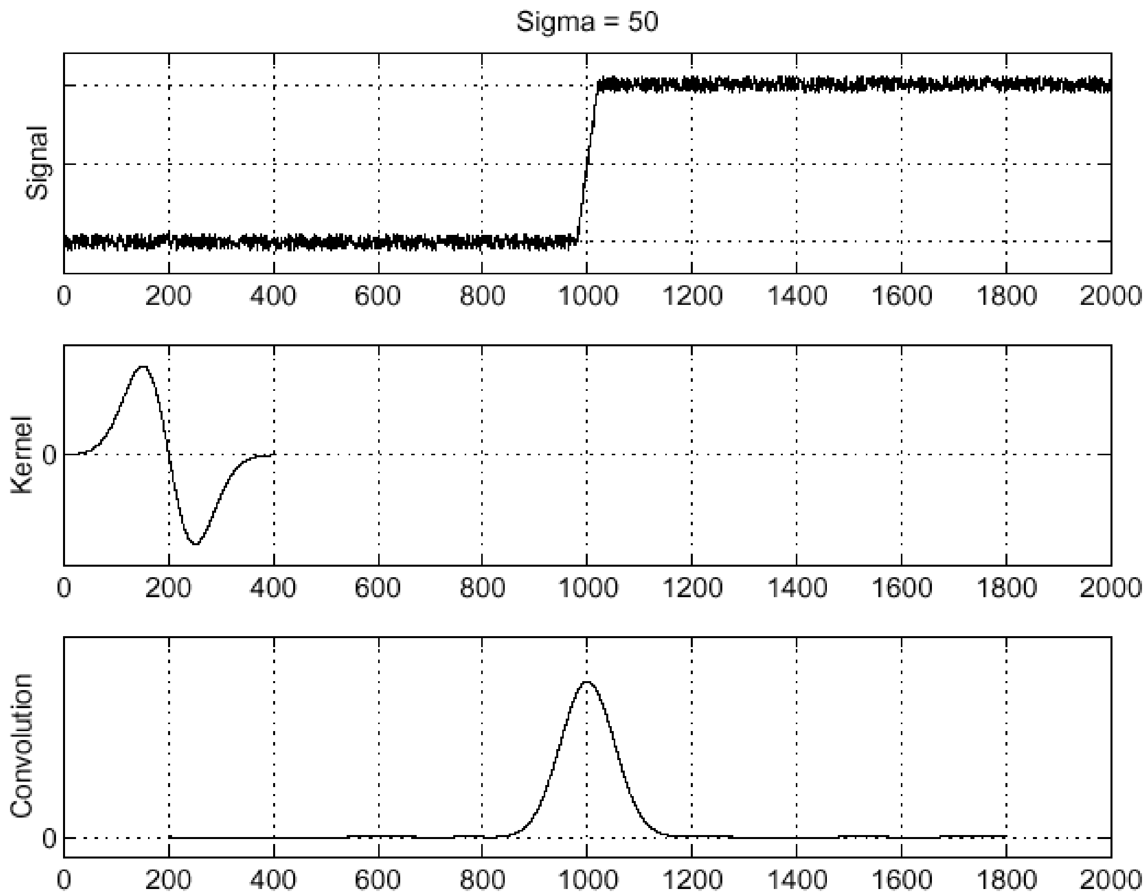
Edge

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

Derivative of Gaussian

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

Edge = maximum of derivative



Source: S. Seitz

Edge detection, Take 2

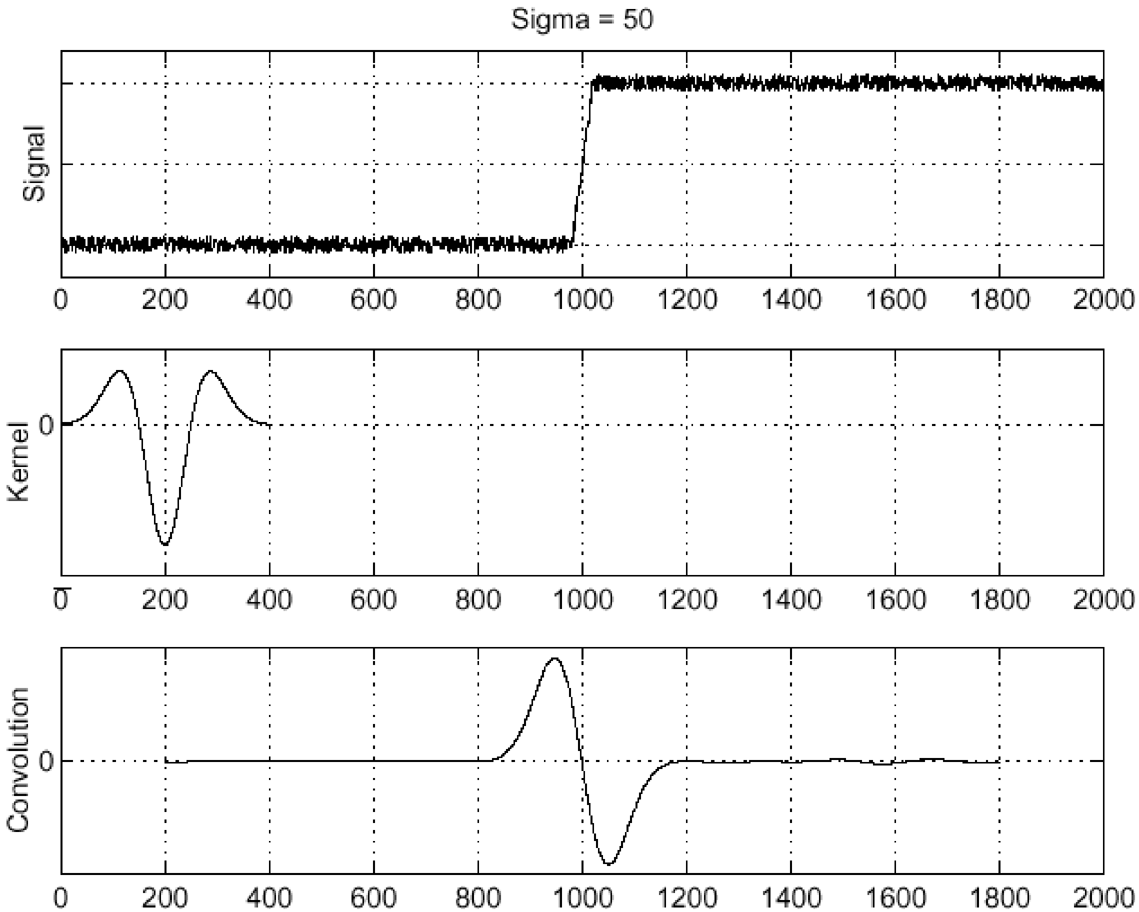
f — Edge

$$\frac{d^2}{dx^2} g$$

Second derivative of Gaussian (Laplacian)

$$f * \frac{d^2}{dx^2} g$$

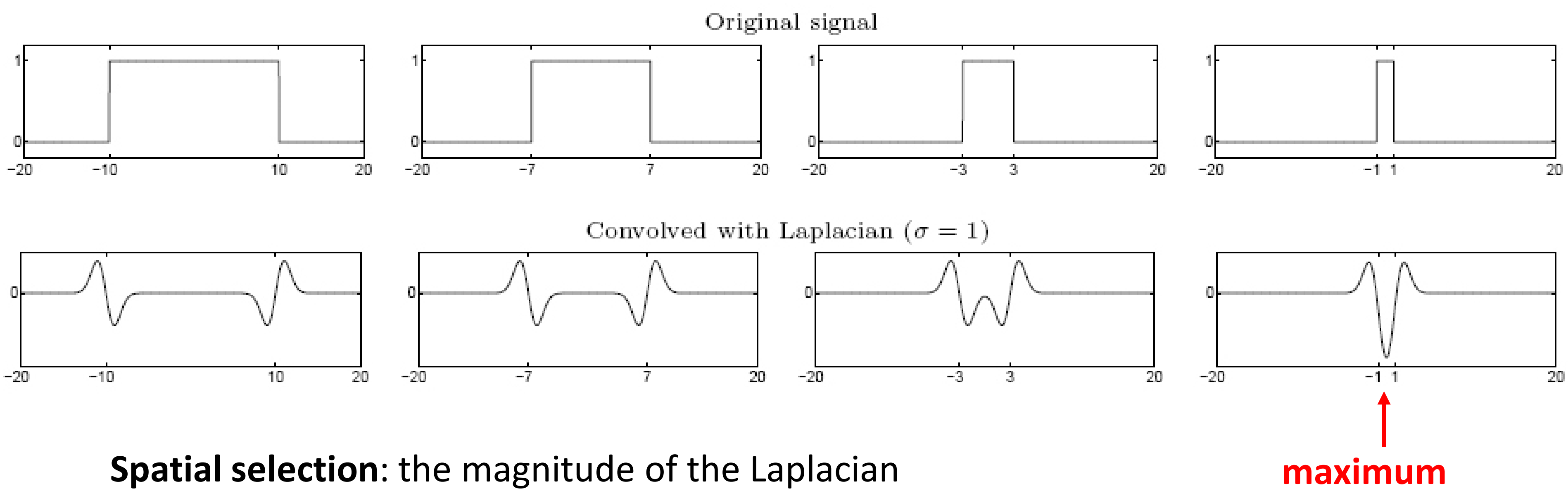
Edge = zero crossing of second derivative



Source: S. Seitz

From Edges to Blobs

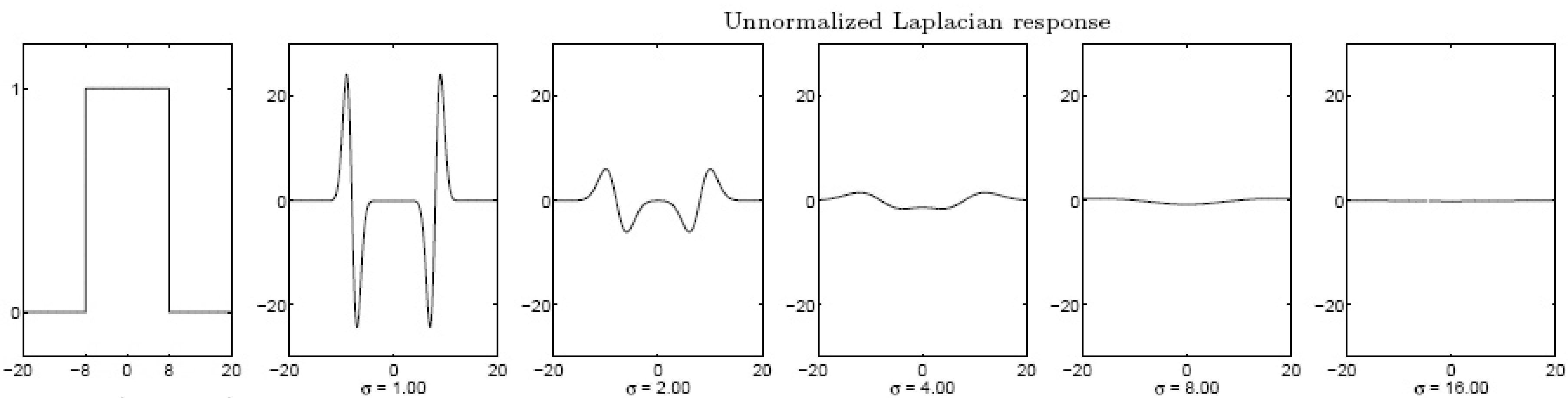
- Edge = ripple
- Blob = superposition of two ripples



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 selection

- We want to find the characteristic scale of the blob by convolving it with Laplacians at several scales and looking for the maximum response
- However, Laplacian response decays as scale increases:



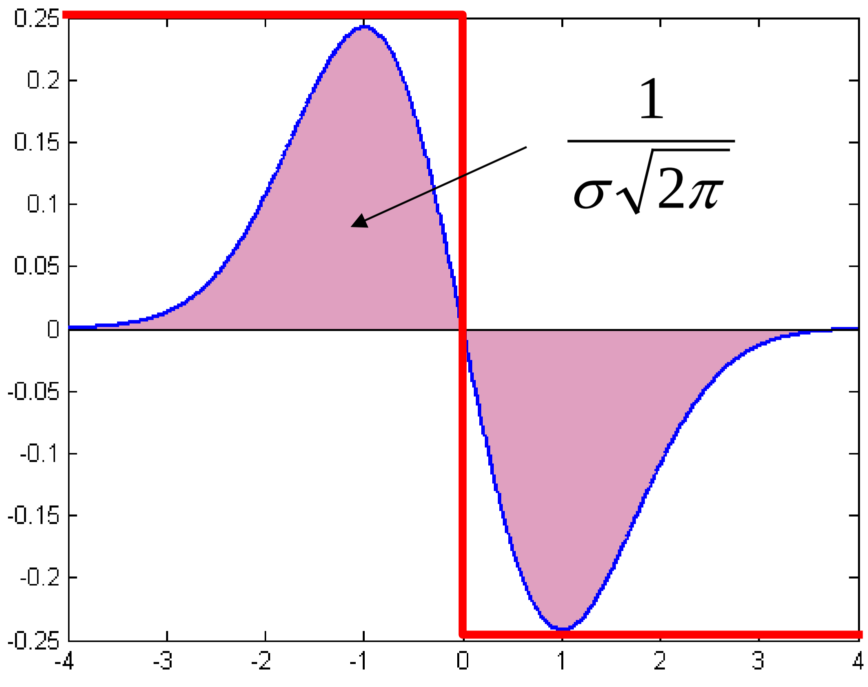
original signal (radius=8)

increasing σ

Why does this happen?

Scale normalization

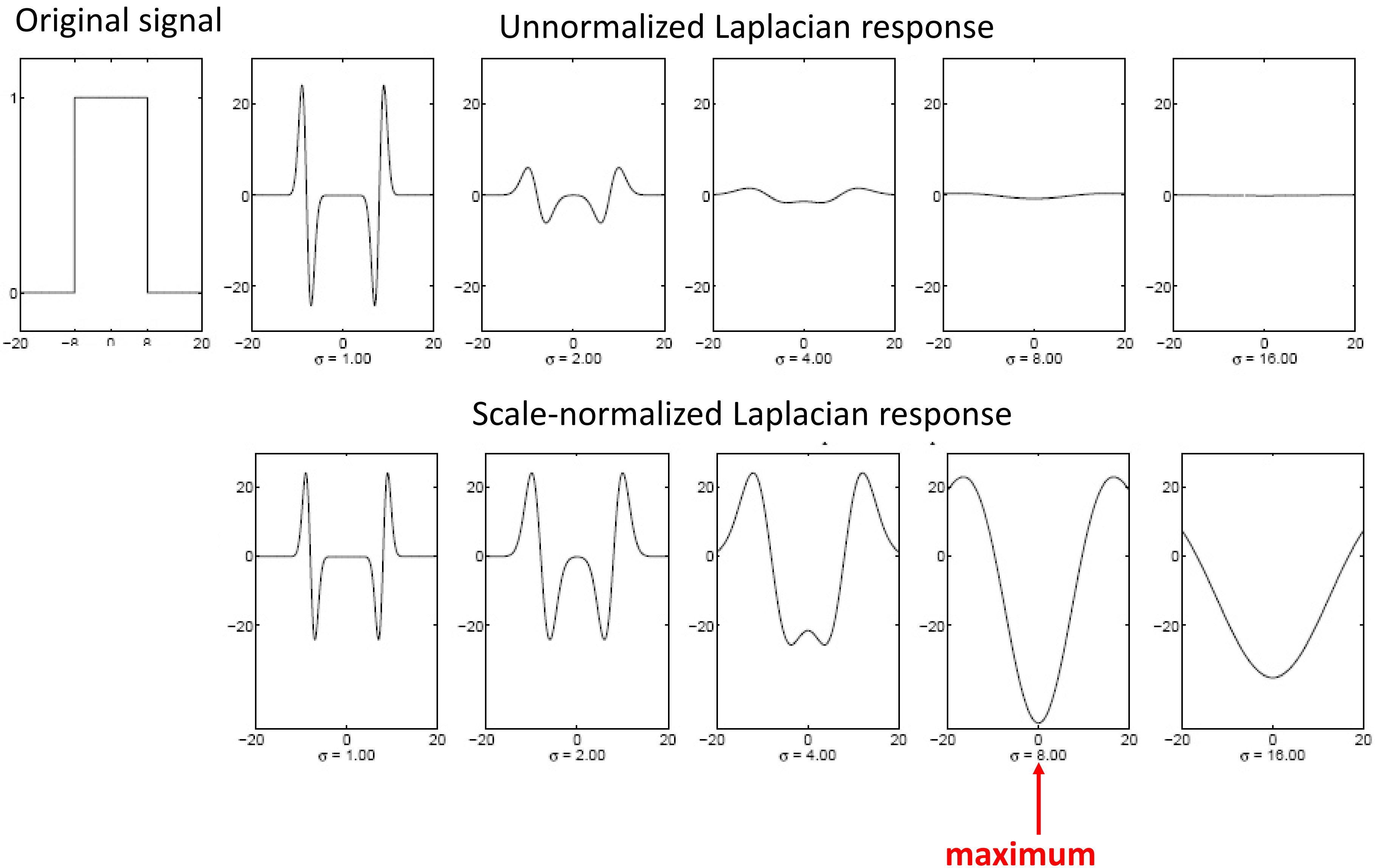
- The response of a derivative of Gaussian filter to a perfect step edge decreases as σ increases



Scale normalization

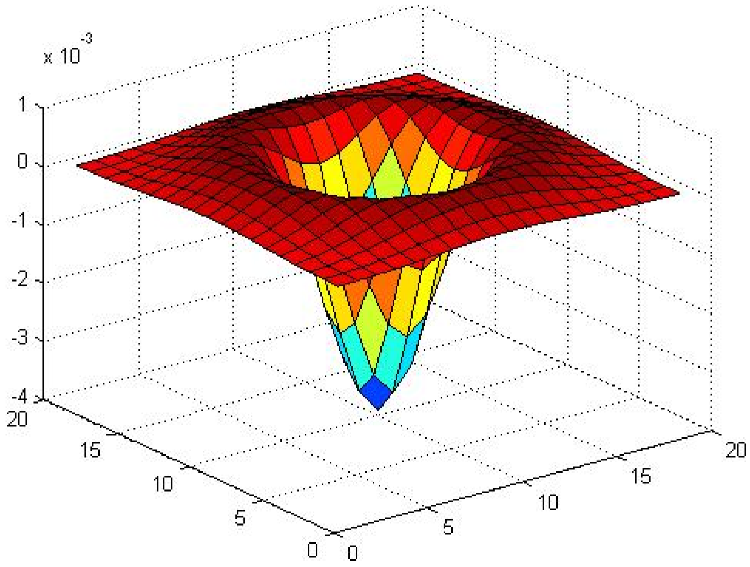
- The response of a derivative of Gaussian filter to a perfect step edge decreases as σ increases
- To keep response the same (scale-invariant), must multiply Gaussian derivative by σ
- Laplacian is the second Gaussian derivative, so it must be multiplied by σ^2

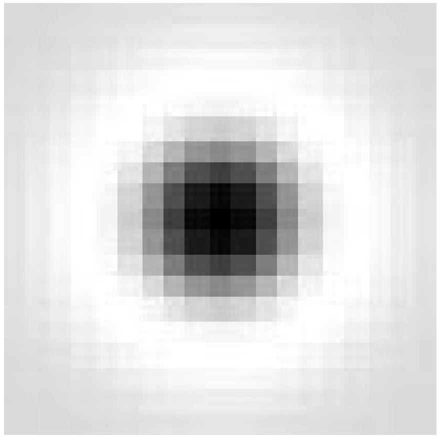
Effect of scale normalization



Blob detection in 2D

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

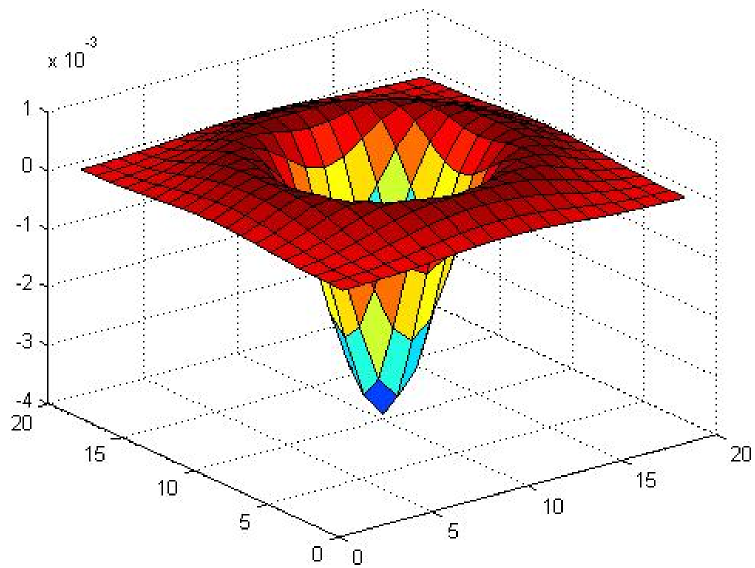


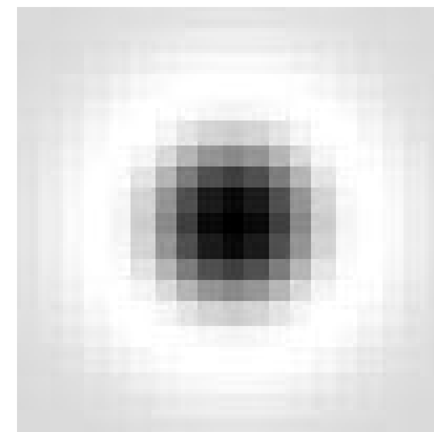


$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

Blob detection in 2D

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



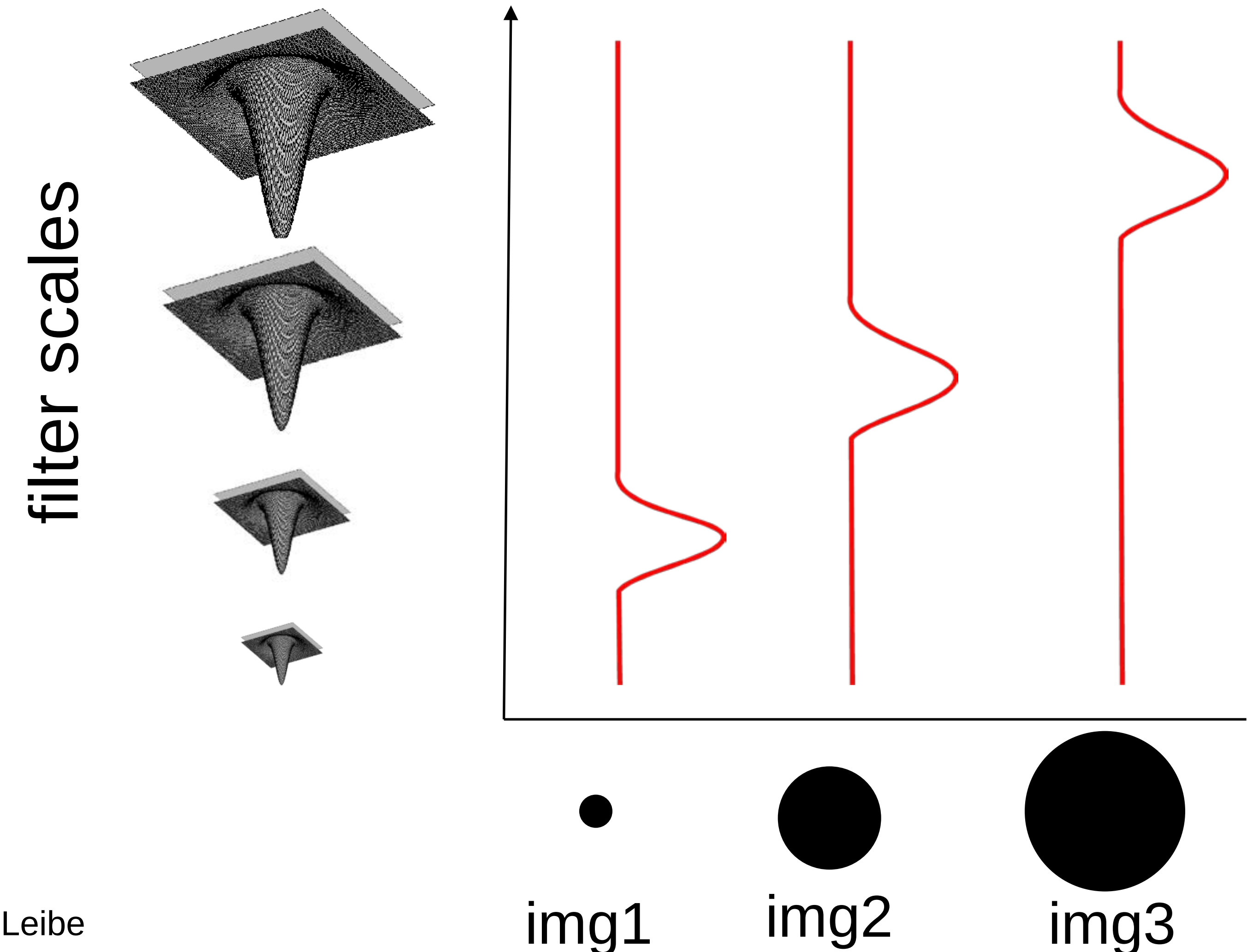


Scale-normalized:

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

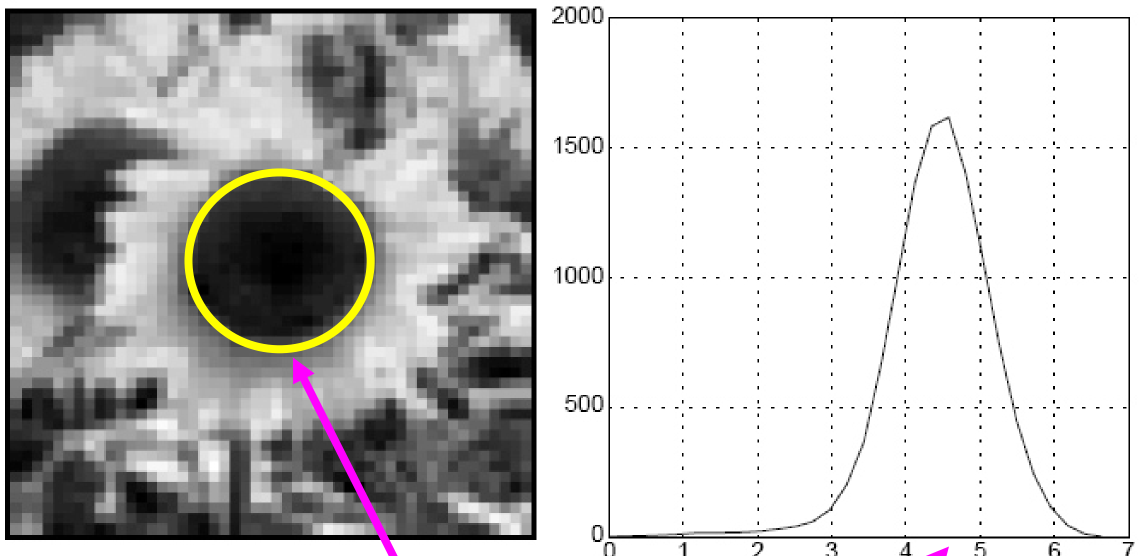
Blob detection in 2D: scale selection

- Laplacian-of-Gaussian = "blob" detector $\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$



Characteristic scale

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

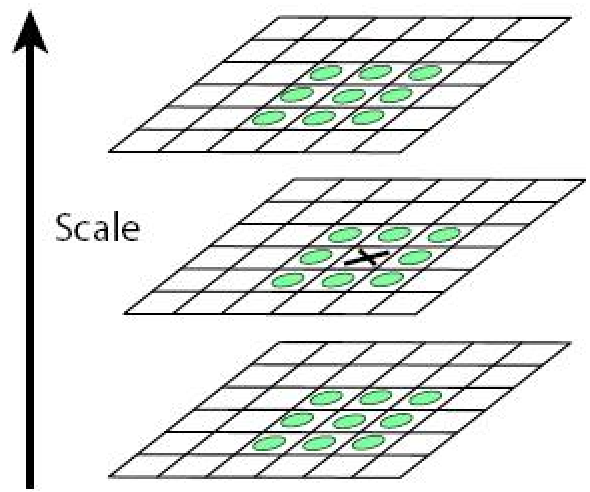


characteristic scale

T. Lindeberg (1998). ["Feature detection with automatic scale selection."](#) *International Journal of Computer Vision* **30** (2): pp 77--116.

Scale-Space Blob Detector

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

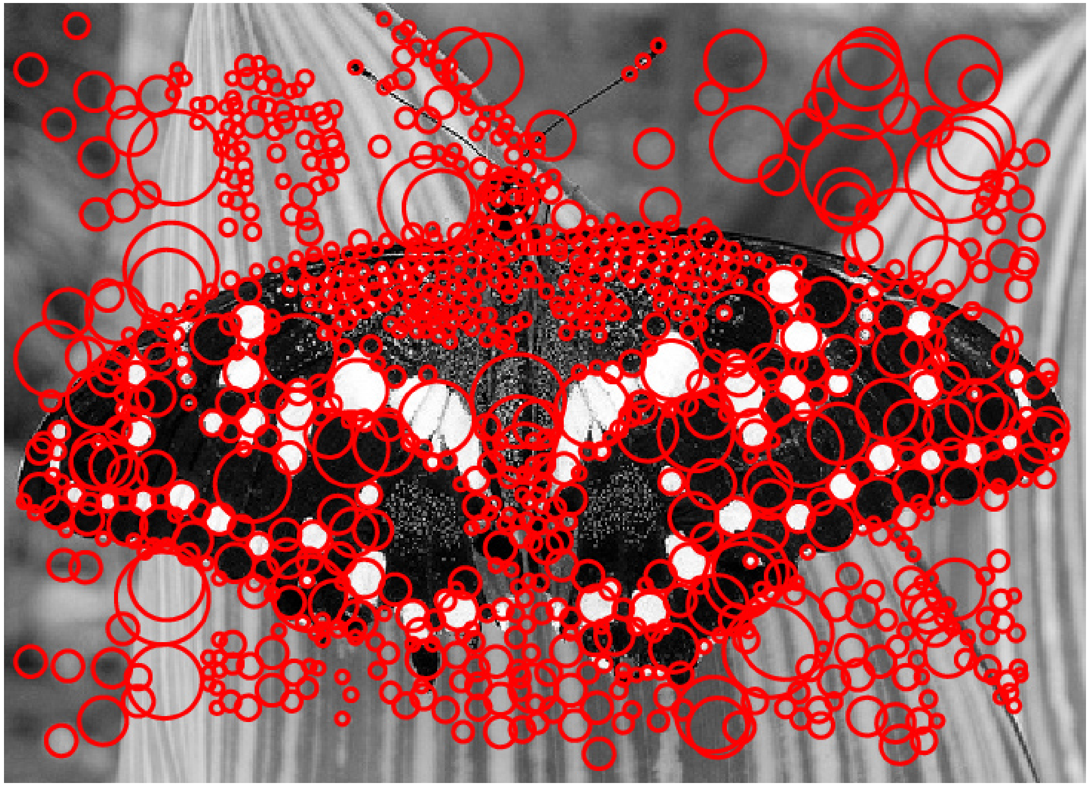


Scale-space blob detector: Example

Scale-space blob detector: Example

sigma = 11.9912

Scale-space blob detector: Example



Efficient Implementation

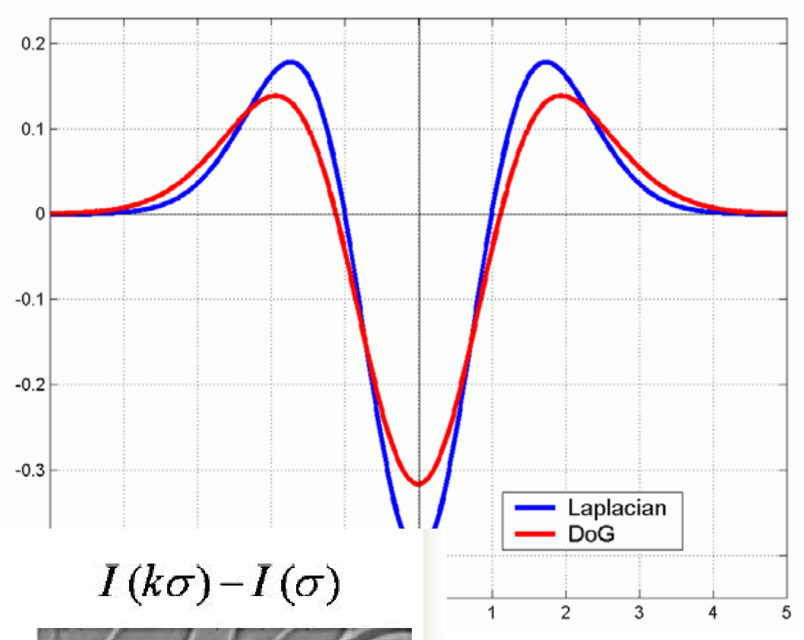
- Approximating the Laplacian with a difference of Gaussians:

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

(Laplacian)

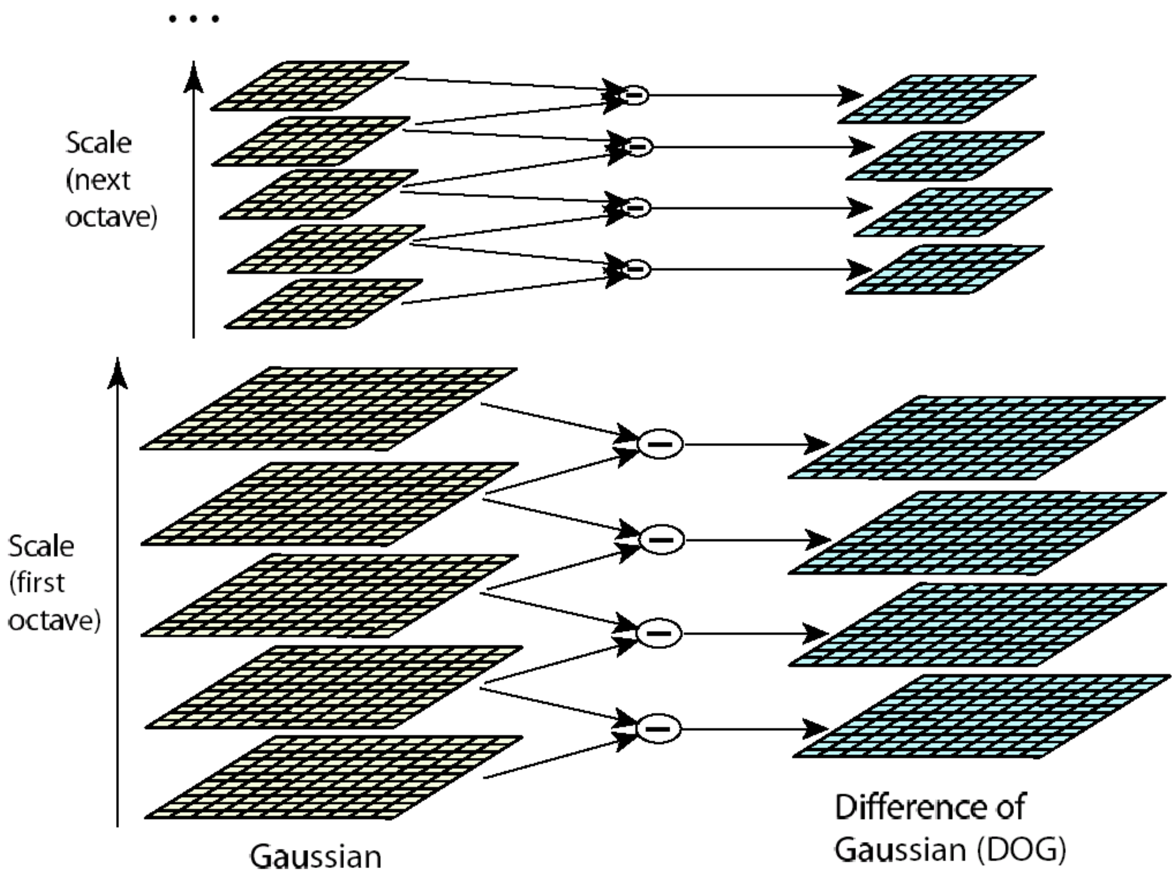
$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

(Difference of Gaussians)



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

Efficient implementation



David G. Lowe. ["Distinctive image features from scale-invariant keypoints."]() *IJCV* 60 (2), pp. 91-110, 2004.

Feature Matching

- We can now find multiple interest points (edges, corners, blobs) in images
- How do we match a feature in one image to a feature in another?
  - We'll start to find out next class…