

Scale-space image processing

- Corresponding image features can appear at different scales



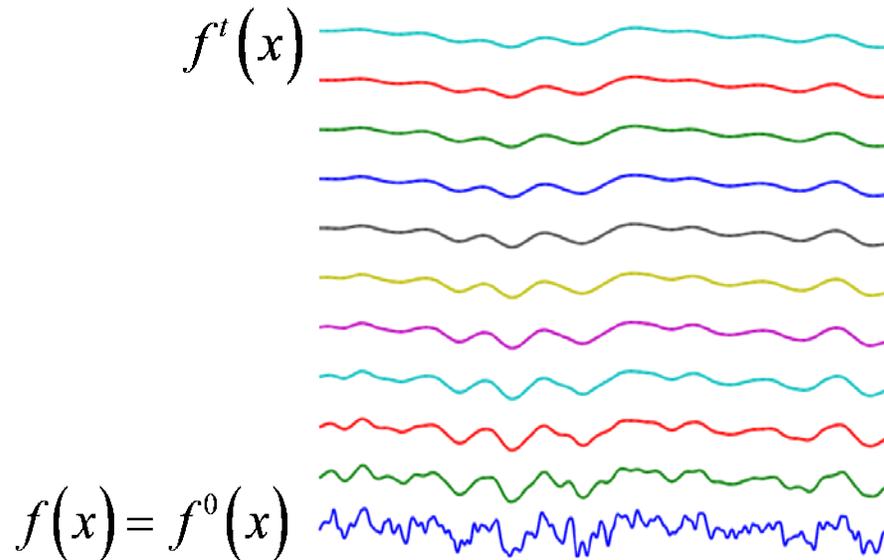
- Like shift-invariance, ***scale-invariance*** of image processing algorithms is often desirable.
- Scale-space representation is useful to process an image in a manner that is both shift-invariant and scale-invariant

Scale-space image processing

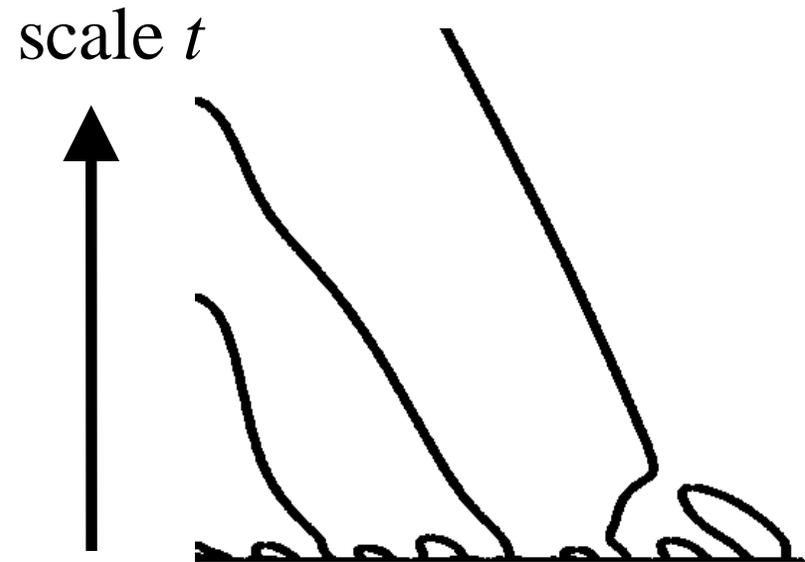
- Scale-space theory
- Laplacian of Gaussian (LoG) and Difference of Gaussian (DoG)
- Scale-space edge detection
- Scale-space keypoint detection
 - Harris-Laplacian
 - SIFT detector
 - SURF detector

Scale-space representation of a signal

Parametric family of signals $f^t(x)$ where fine-scale information is successively attenuated



Successive smoothing
with a Gaussian filter



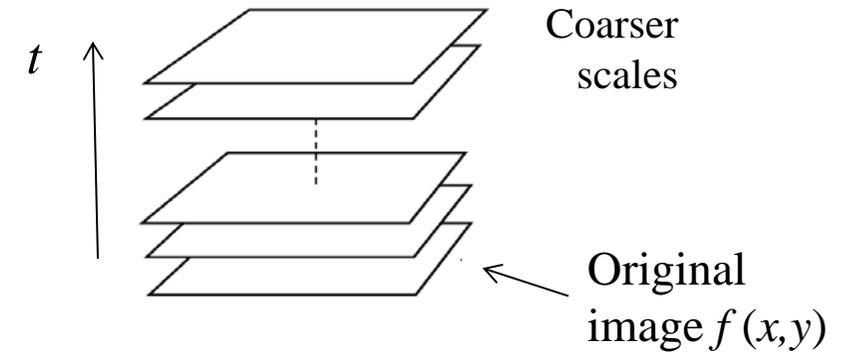
Zero-crossings of 2nd derivative $f''(x)$
Fewer edges at coarser scales



Scale-space representation of images

- Parametric family of images smoothed by Gaussian filter

$$f^t(x, y) = g^t(x, y) * f(x, y); t \geq 0 \quad \text{with} \quad g^t(x, y) = \frac{1}{2\pi t} \exp\left(-\frac{x^2 + y^2}{2t}\right)$$
$$F^t(\omega_x, \omega_y) = G^t(\omega_x, \omega_y) F(\omega_x, \omega_y) \quad \text{with} \quad G^t(\omega_x, \omega_y) = \exp\left(-\frac{t}{2}(\omega_x^2 + \omega_y^2)\right)$$



- Shift-invariance

$$f^t(x - \Delta x, y - \Delta y) = g^t(x, y) * f(x - \Delta x, y - \Delta y)$$

- Rotation-invariance

$$f^t(x \cos \theta - y \sin \theta, x \sin \theta + y \cos \theta) = g^t(x, y) * f(x \cos \theta - y \sin \theta, x \sin \theta + y \cos \theta)$$

Scale-space representation of images (cont.)

- Commutative semigroup property

$$\begin{aligned} f^{t_1+t_2}(x, y) &= g^{t_1}(x, y) * f^{t_2}(x, y) = g^{t_2}(x, y) * f^{t_1}(x, y) \\ &= g^{t_1}(x, y) * g^{t_2}(x, y) * f(x, y) \end{aligned}$$

- Separability

$$\begin{aligned} g^t(x, y) &= \frac{1}{2\pi t} \exp\left(-\frac{x^2 + y^2}{2t}\right) = \frac{1}{\sqrt{2\pi t}} \exp\left(-\frac{x^2}{2t}\right) \cdot \frac{1}{\sqrt{2\pi t}} \exp\left(-\frac{y^2}{2t}\right) \\ G^t(\omega_x, \omega_y) &= \exp\left(-\frac{t}{2}(\omega_x^2 + \omega_y^2)\right) = \exp\left(-\frac{t}{2}\omega_x^2\right) \exp\left(-\frac{t}{2}\omega_y^2\right) \end{aligned}$$

Scale-space representation of images (cont.)

- Non-creation of local extrema (for $f(x, y)$ and all of its partial derivatives) since $g^t(x, y) \geq 0$ and unimodal.
- Solution to diffusion equation (heat equation)

$$\frac{\partial}{\partial t} f^t(x, y) = \frac{1}{2} \nabla^2 f^t(x, y)$$

$$\begin{aligned} \frac{\partial}{\partial t} F^t(\omega_x, \omega_y) &= \frac{\partial}{\partial t} G^t(\omega_x, \omega_y) F(\omega_x, \omega_y) \\ &= \frac{\partial}{\partial t} \exp\left(-\frac{t}{2}(\omega_x^2 + \omega_y^2)\right) F(\omega_x, \omega_y) \\ &= -\frac{1}{2}(\omega_x^2 + \omega_y^2) \exp\left(-\frac{t}{2}(\omega_x^2 + \omega_y^2)\right) F(\omega_x, \omega_y) \\ &= -\frac{1}{2}(\omega_x^2 + \omega_y^2) F^t(\omega_x, \omega_y) \end{aligned}$$

t = 0.07 sec

$$\frac{\partial}{\partial t} f^t(x, y) = \frac{1}{2} \nabla^2 f^t(x, y)$$

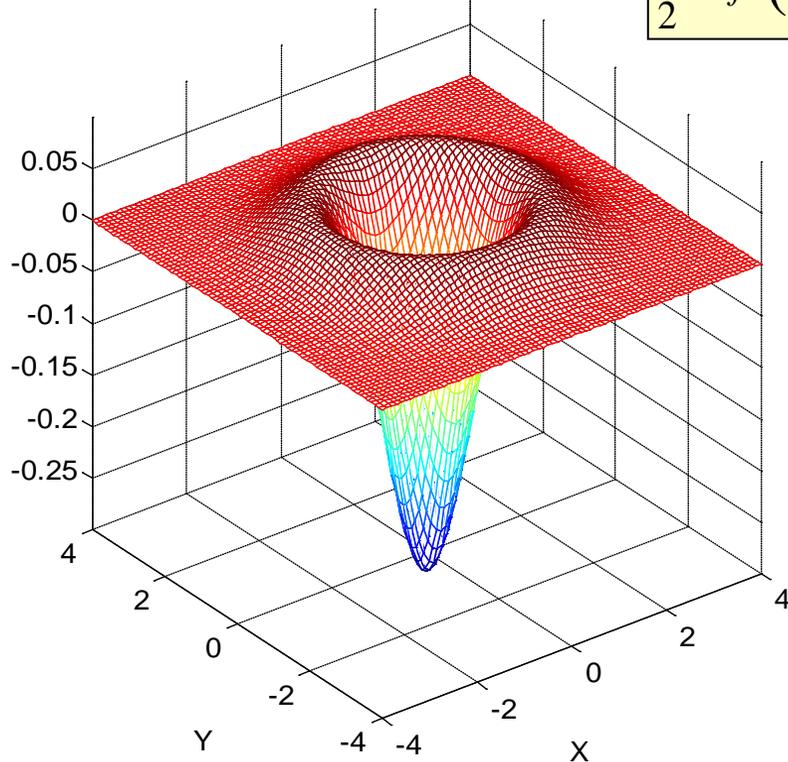


LoG vs. DoG

Laplacian of Gaussian

$$t = \sigma^2 = 1$$

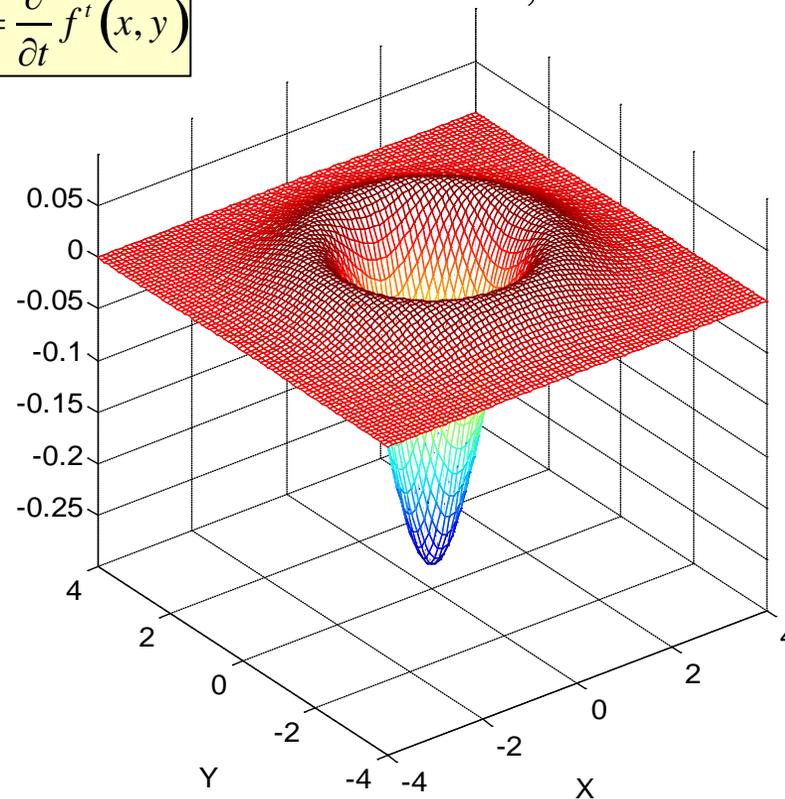
$$\frac{1}{2} \nabla^2 f'(x, y) = \frac{\partial}{\partial t} f'(x, y)$$



$$LoG(x, y) = -\frac{1}{\pi t^2} \left(1 - \frac{x^2 + y^2}{2t} \right) e^{-\frac{x^2 + y^2}{2t}}$$

Difference of Gaussians

$$t = \sigma^2 = 1, k = 1.1$$



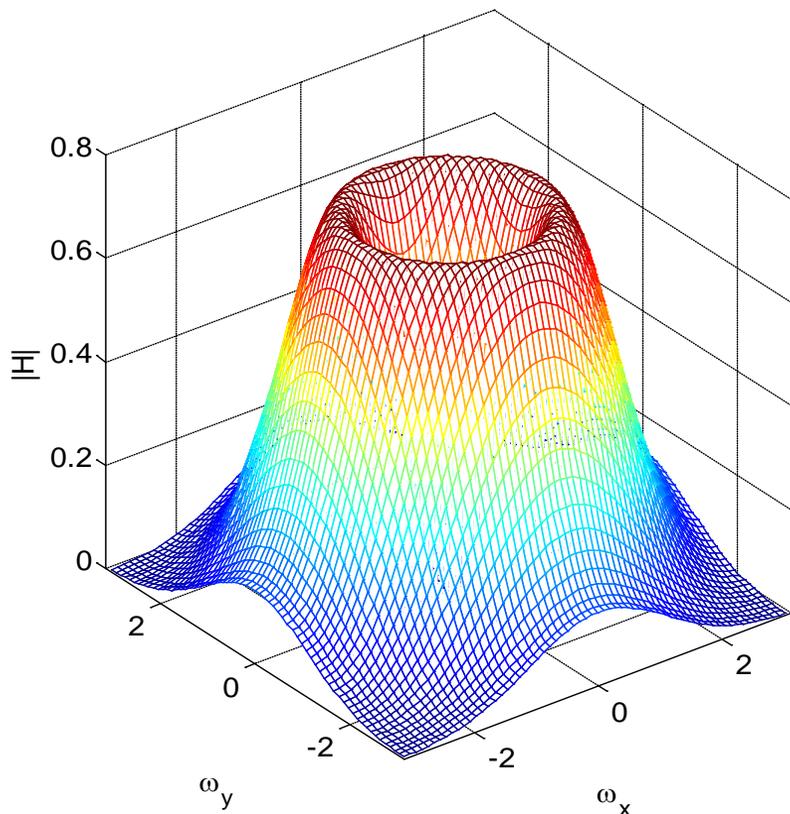
$$DoG(x, y) = \frac{1}{(k-1)t} \left(g^{k^2 t}(x, y) - g^t(x, y) \right)$$



LoG vs. DoG (cont.)

Laplacian of Gaussian

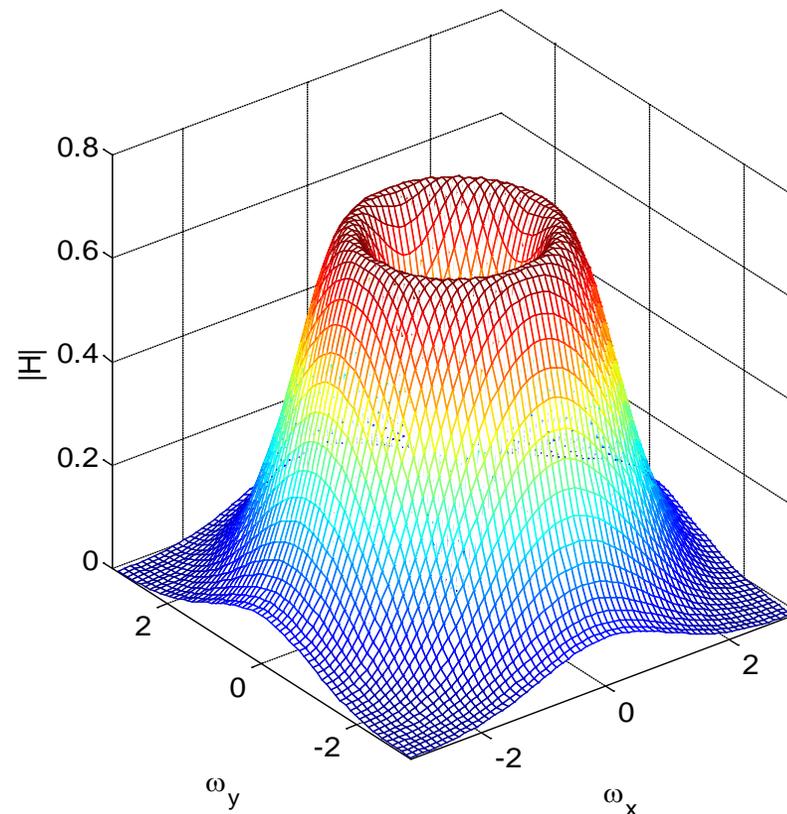
$$t = \sigma^2 = 1$$



$$H(\omega_x, \omega_y) = -(\omega_x^2 + \omega_y^2)G^t(\omega_x, \omega_y)$$

Difference of Gaussians

$$t = \sigma^2 = 1, k = 1.1$$



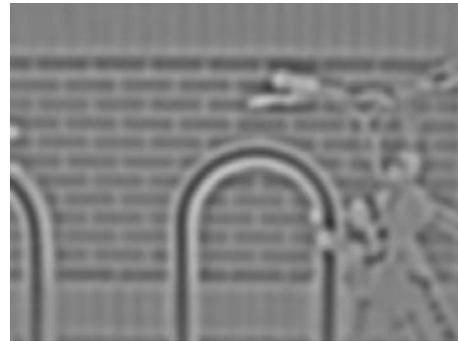
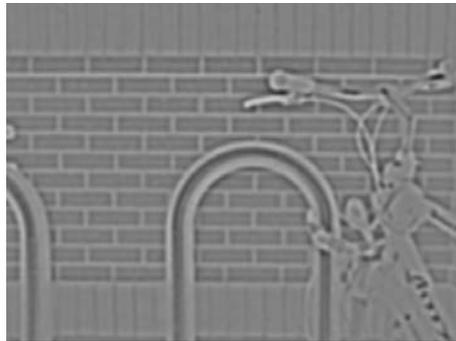
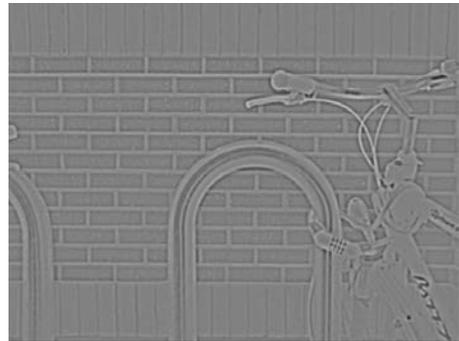
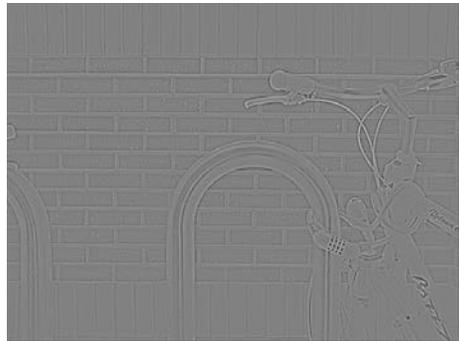
$$H(\omega_x, \omega_y) = \frac{1}{(k-1)t} \left[G^{k^2 t}(\omega_x, \omega_y) - G^t(\omega_x, \omega_y) \right]$$



Scale space: Laplacian images



$$f^t(x, y)$$



$$t \cdot \nabla^2 f^t(x, y)$$

t = 1

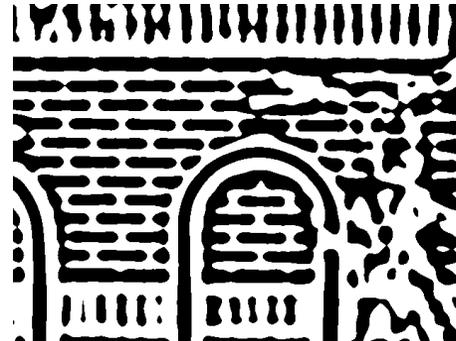
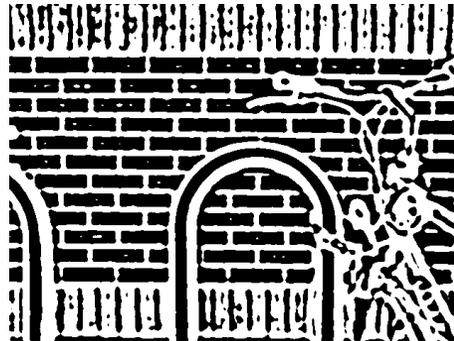
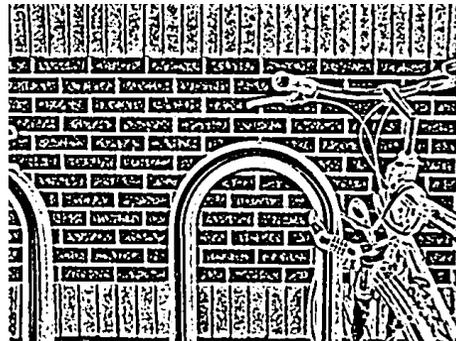
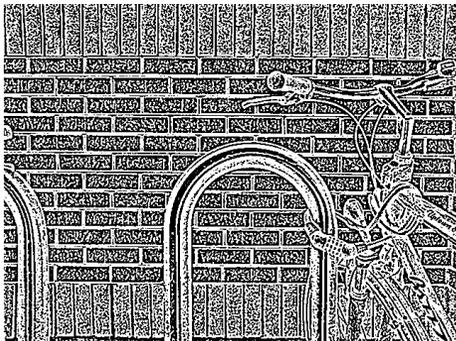
t = 4

t = 16

t = 64



Scale space: Binarized Laplacian images



$t = 1$

$t = 4$

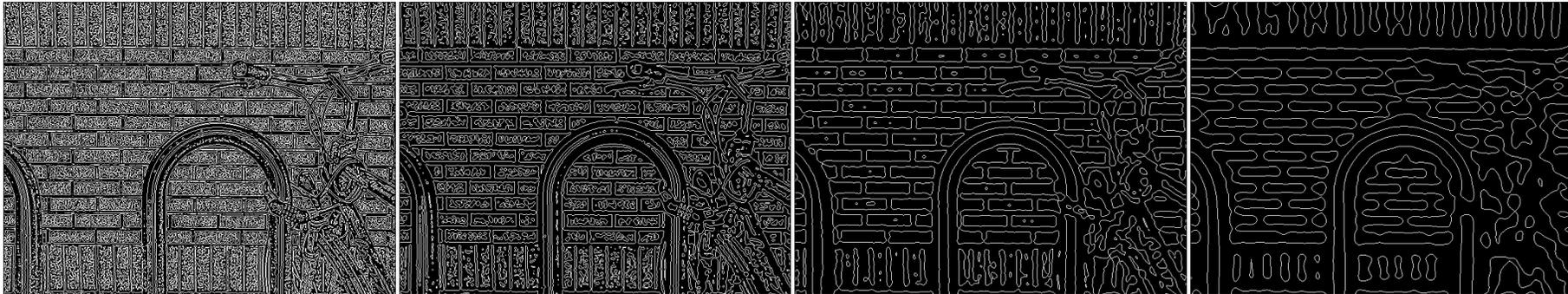
$t = 16$

$t = 64$



Scale space: edge detection

Zero crossings of Laplacian images



$t = 1$

$t = 4$

$t = 16$

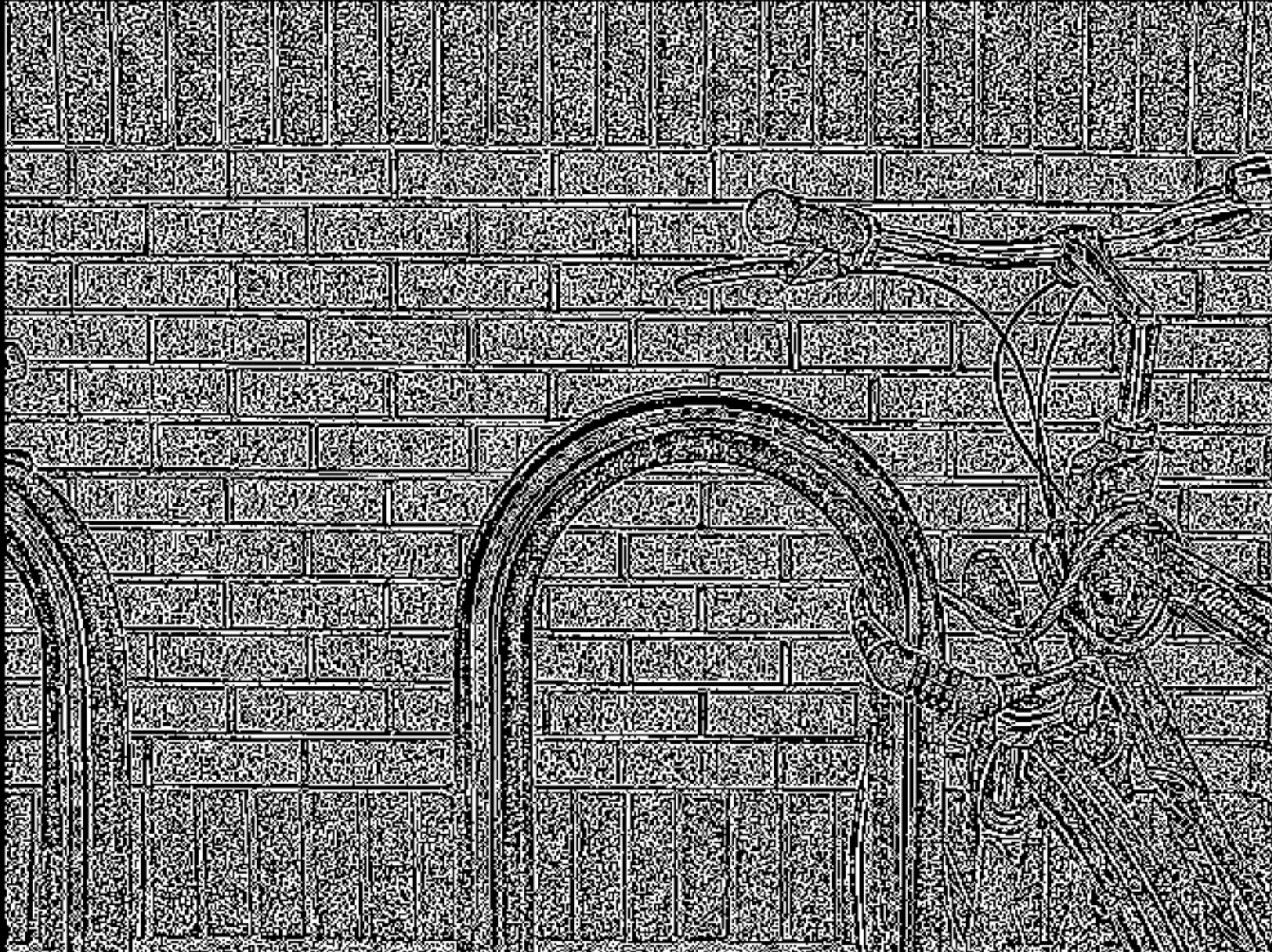
$t = 64$

Low-gradient-magnitude edges removed



Laplacian zero-crossings

$t = 0.07$ sec



Keypoint detection with automatic scale selection

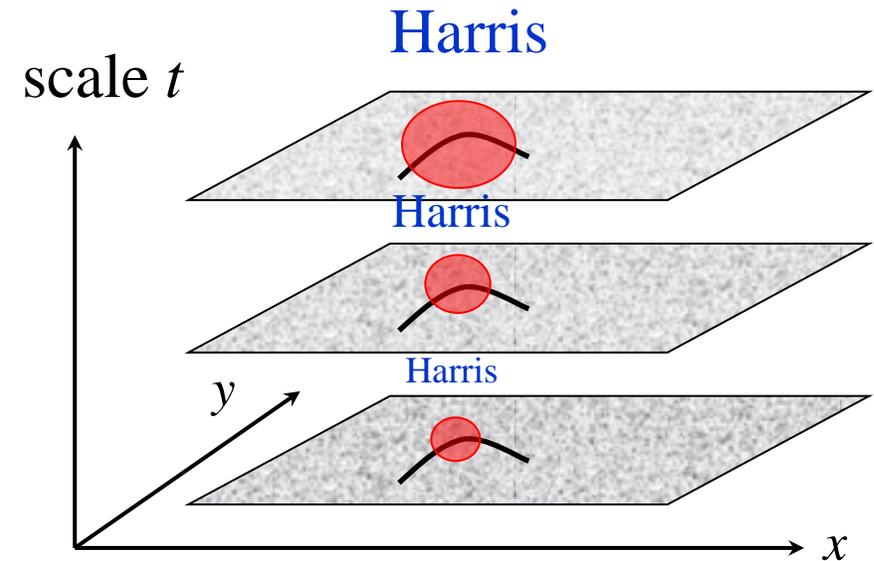
- Scale-space representation provides all scales; which scale is best for keypoint detection?

- *Harris-Laplacian*

1. Detect Harris corners at some initial scale
2. For each Harris corner x_h, y_h detect characteristic scale

$$t_h = \arg \max_t |t \cdot \nabla^2 f^t(x_h, y_h)|$$

3. Apply Harris detector in a spatial neighborhood at scale t_h to refine keypoint location x_h, y_h
4. Repeat 2. and 3. until convergence



Keypoint detection with automatic scale selection

Harris-Laplacian example (150 strongest peaks)

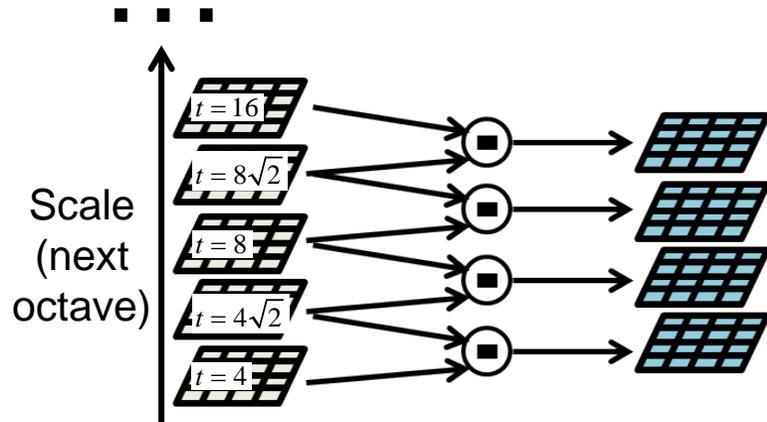


Keypoint detection with automatic scale selection

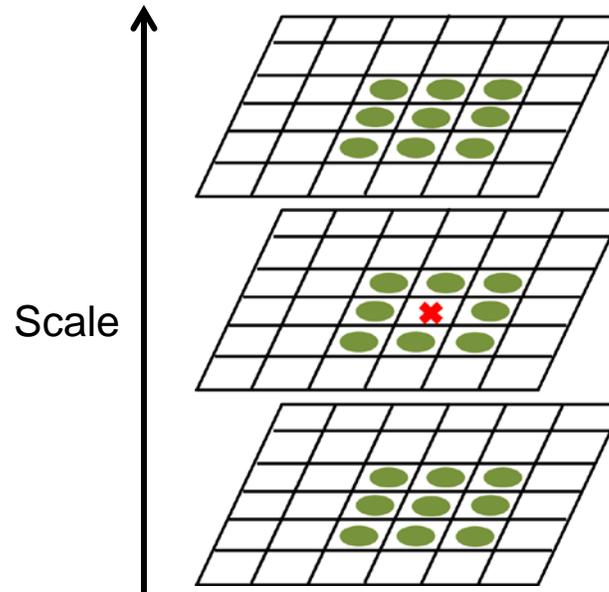
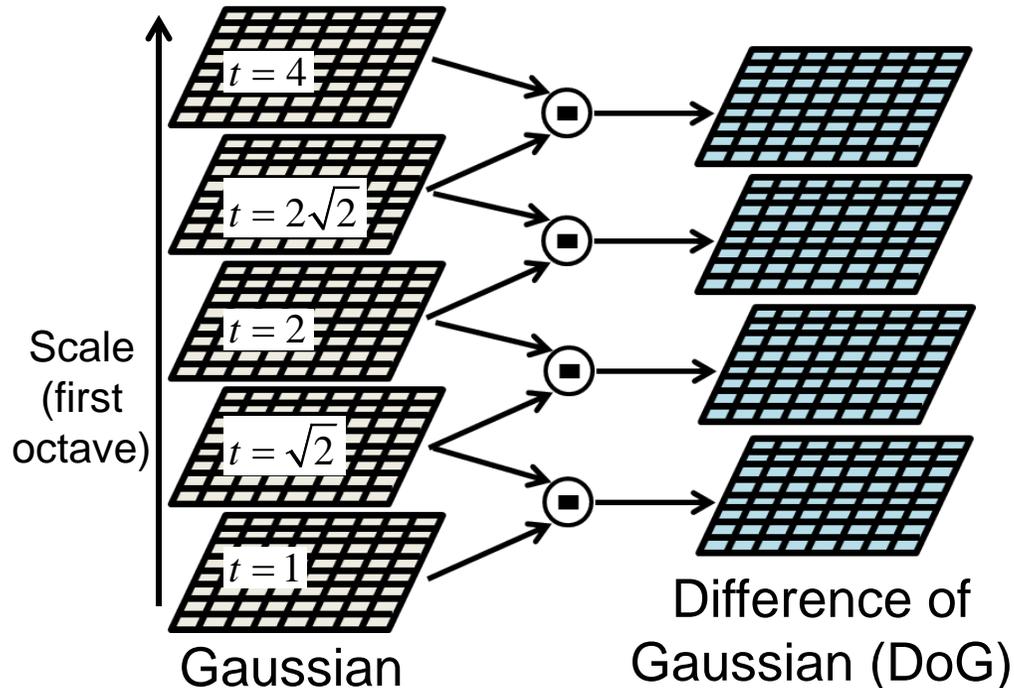
Harris-Laplacian example (200 strongest peaks)



SIFT keypoint detection

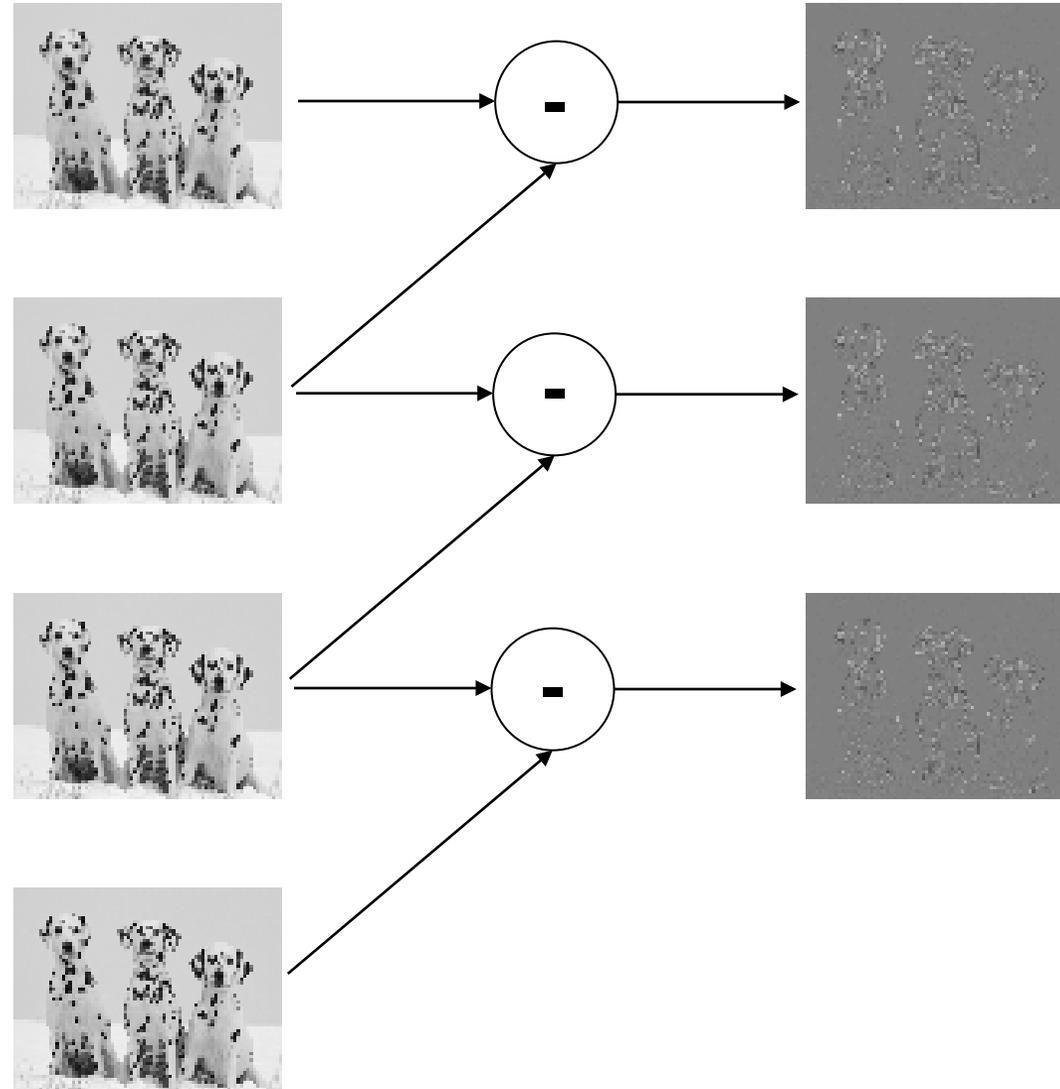


- SIFT - Scale-Invariant Feature Transform
- Decompose image into DoG scale-space representation
- Detect minima and maxima locally and across scales
- Fit 3-d quadratic function to localize extrema with sub-pixel/sub-scale accuracy [Brown, Lowe, 2002]
- Eliminate edge responses based on Hessian

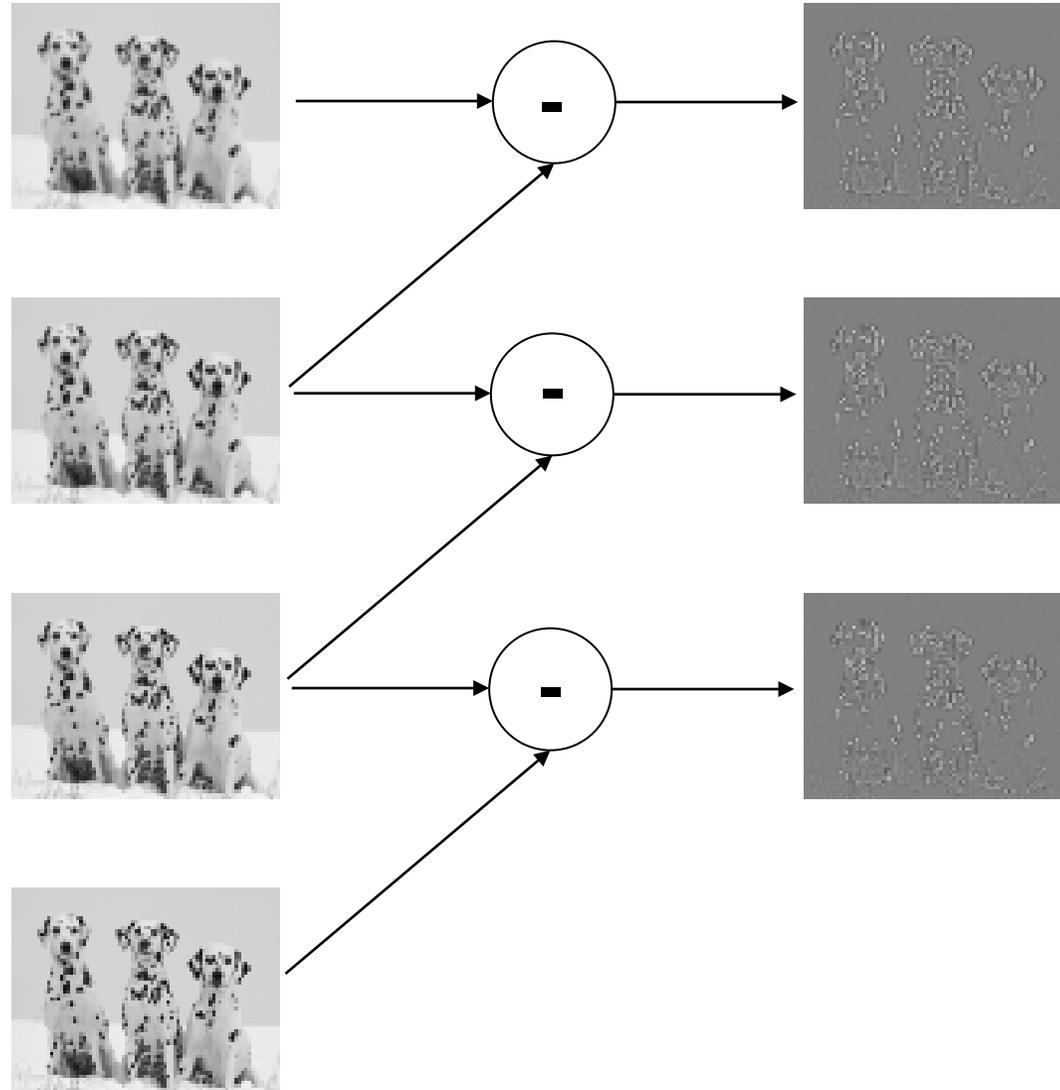


[Lowe, 1999, 2004]

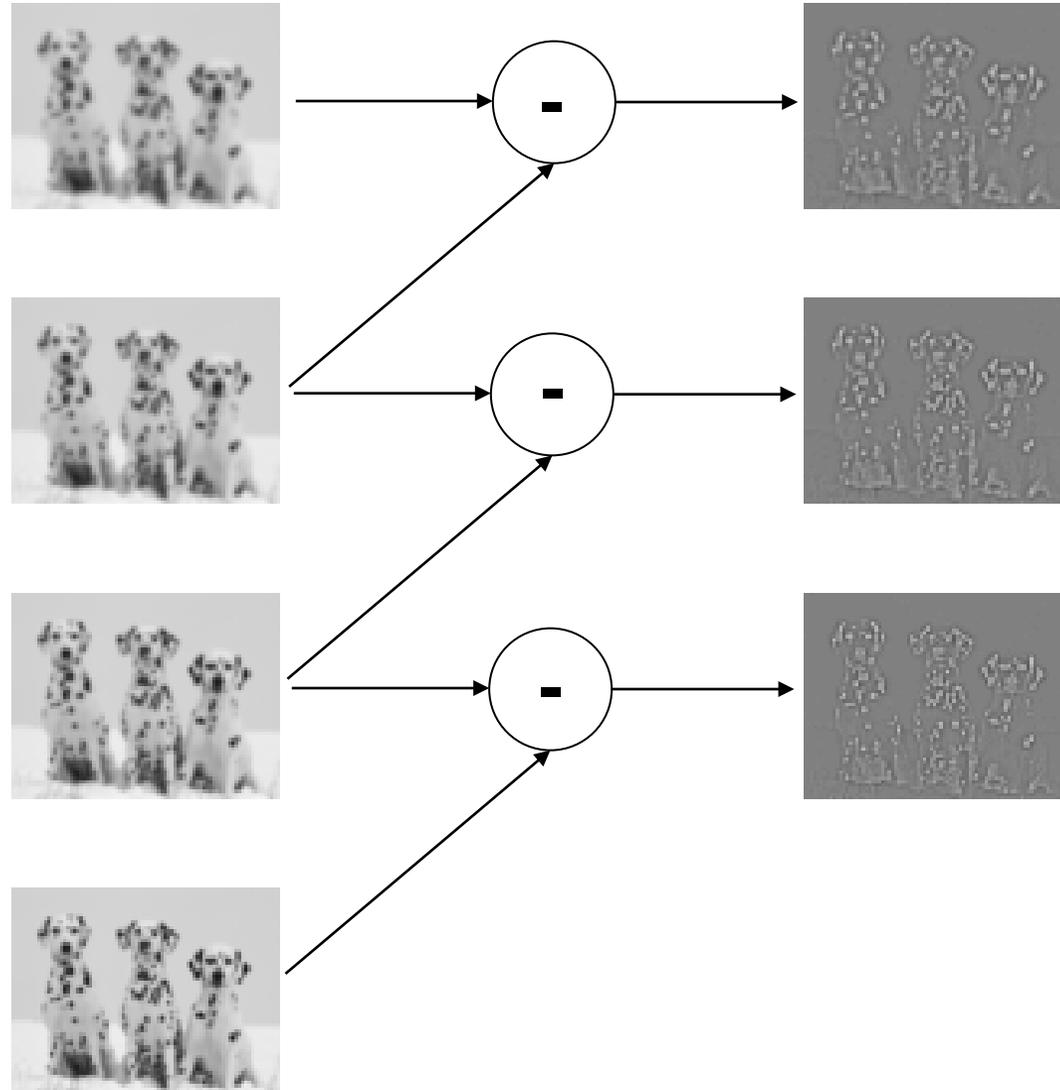
SIFT scale space pyramid: octave 1



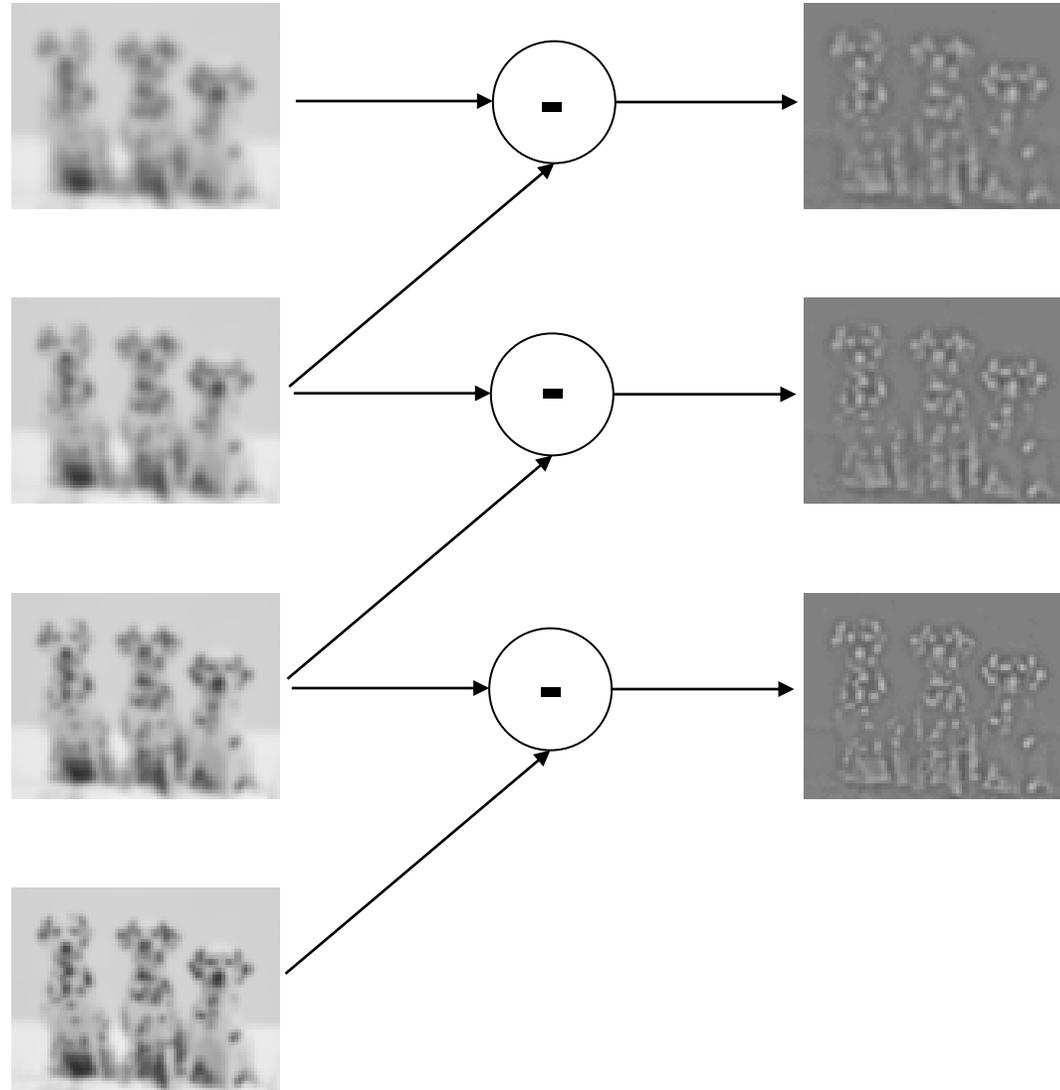
SIFT scale space pyramid: octave 2



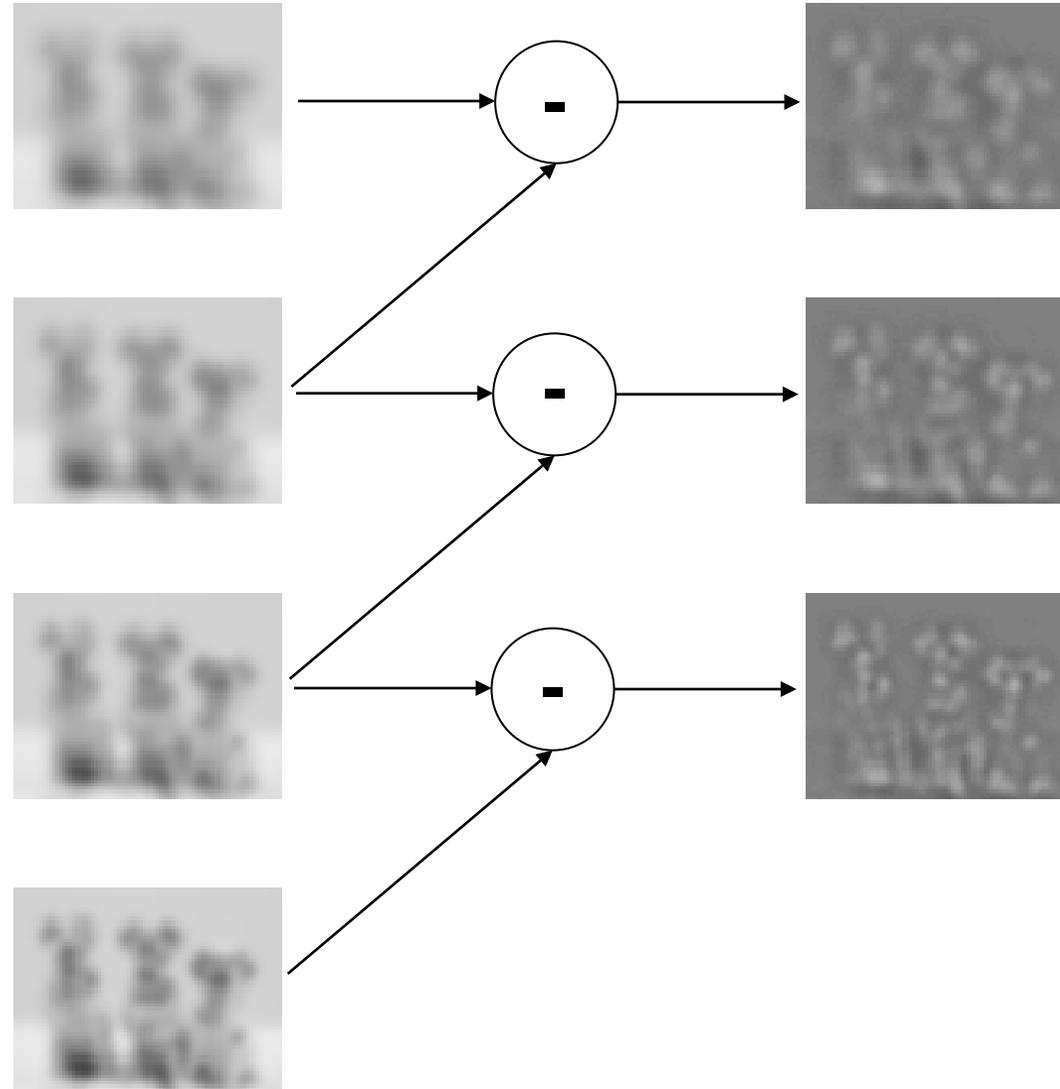
SIFT scale space pyramid: octave 3



SIFT scale space pyramid: octave 4



SIFT scale space pyramid: octave 5



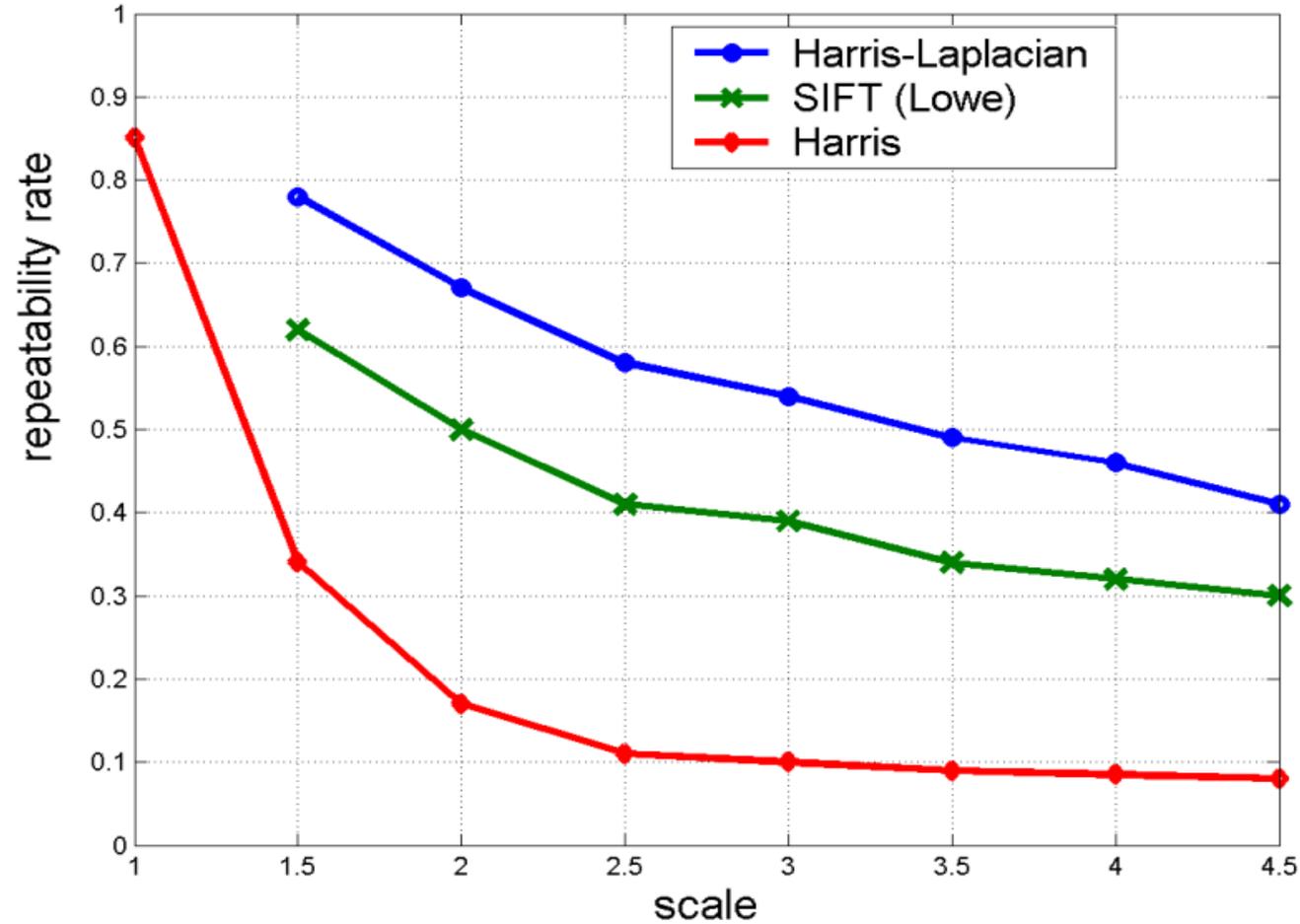
SIFT keypoints



SIFT keypoints

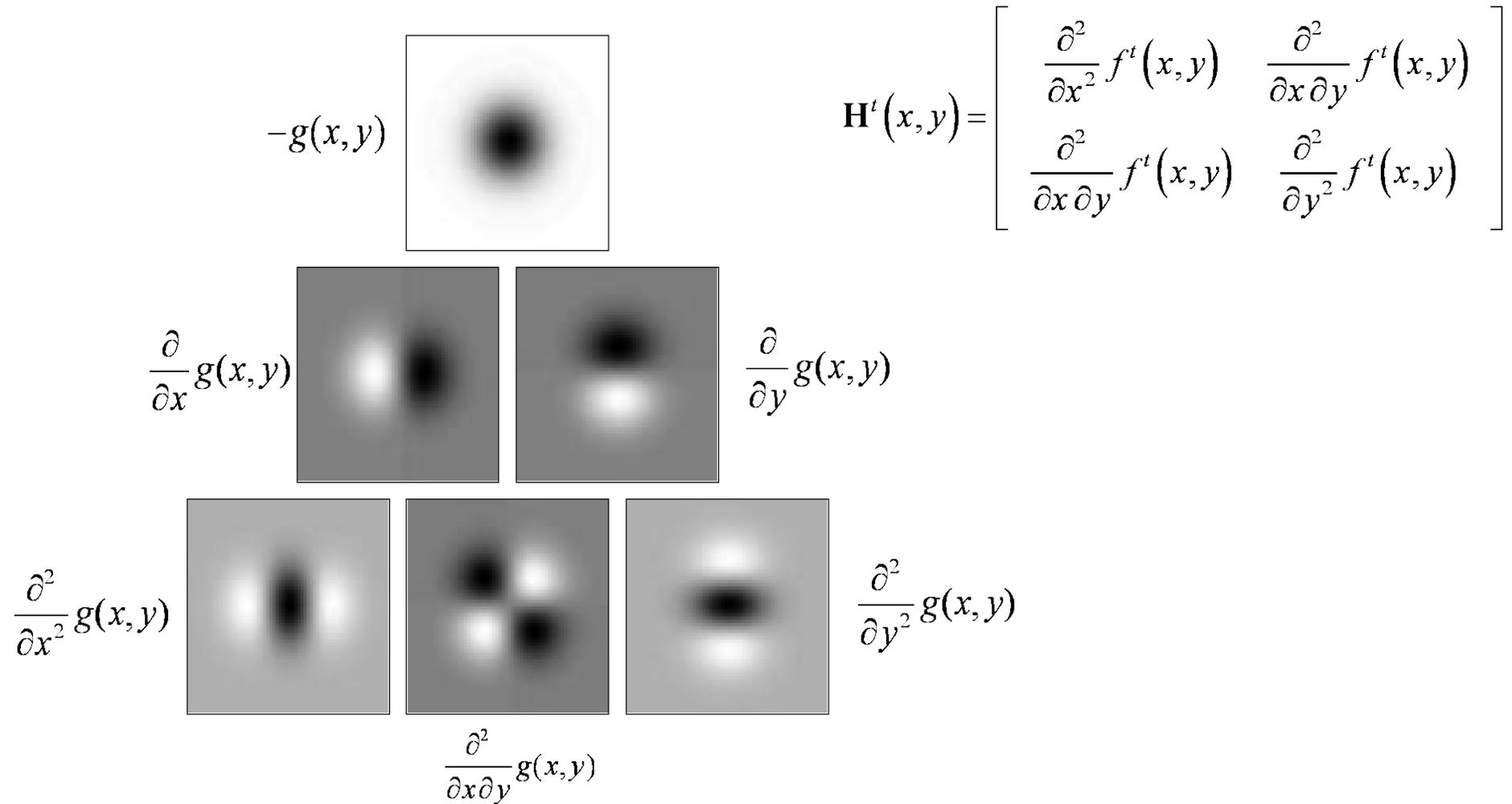


Robustness against scaling



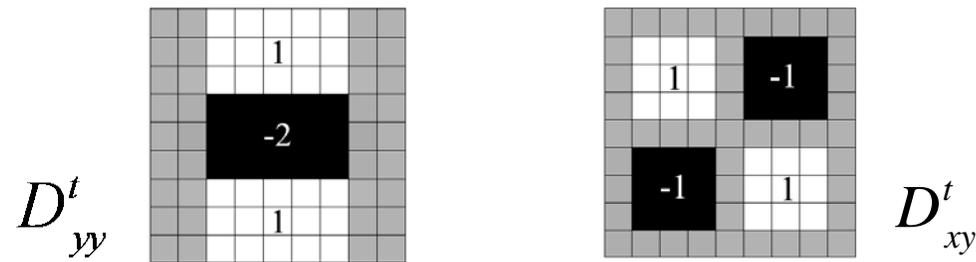
[Mikolajczyk, Schmid, 2001]

Hessian keypoints in scale space



SURF keypoint detection

- SURF – Speeded Up Robust Features [*Bay, Tuytelaars, Van Gool, ECCV 2006*]
- No subsampling – all resolution levels at full spatial resolution
- Simple approximation of scale space Gaussian derivatives using integral images



- Determinant of Hessian

$$\det(\mathbf{H}^t) \approx D^t_{xx} D^t_{yy} - \left(0.9 D^t_{xy}\right)^2$$

- Non-maximum suppression in 3x3x3 $[x, y, t]$ neighborhood
- Interpolation of maximum of $\det(\mathbf{H})$ in image space x, y and scale t

SURF keypoints



SIFT keypoints



SURF keypoints



SIFT keypoints

