Image Features

Deep Learning and Image Processing

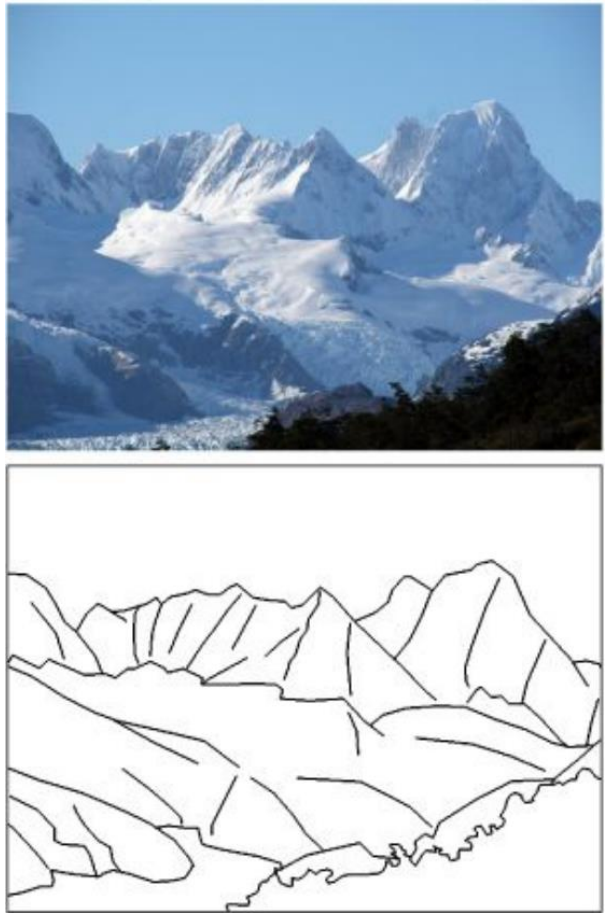
From Edges to Boundaries

edge: image location of rapid change in intensity
(caused by discontinuities of surface, depth, or illumination)

edges encode most shape and semantic information

to detect edge pixels: image derivatives (see sharpening filters)

follow-up steps:
→edge linking (connect edge pixels to edge segments)
→boundary detection
→non-semantic image segmentation and object recognition

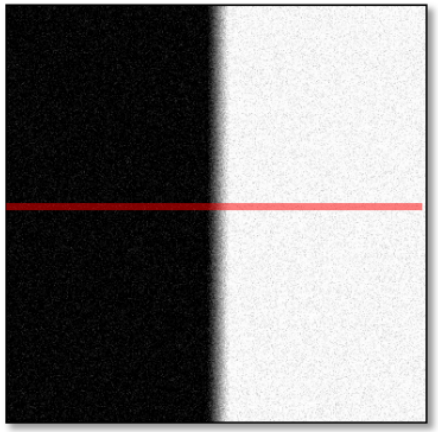


Canny Edge Detector

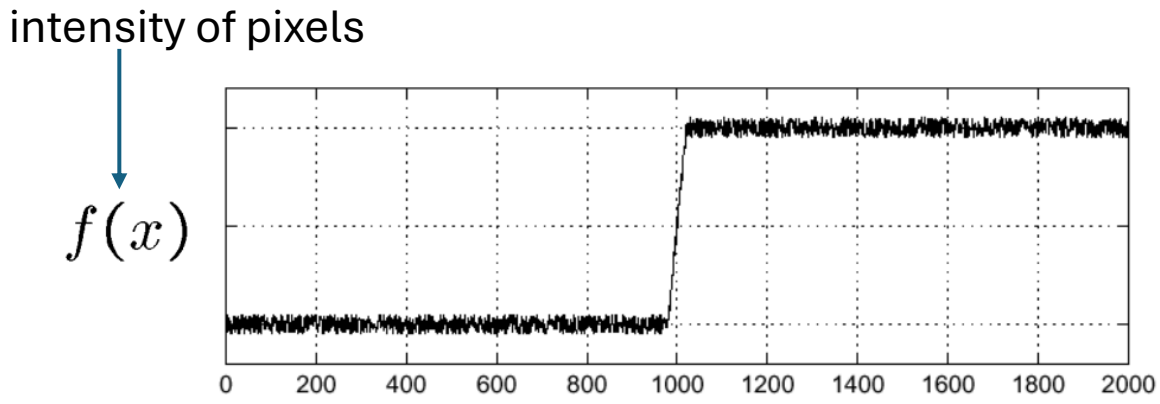
Noise Complications for Edge Detection

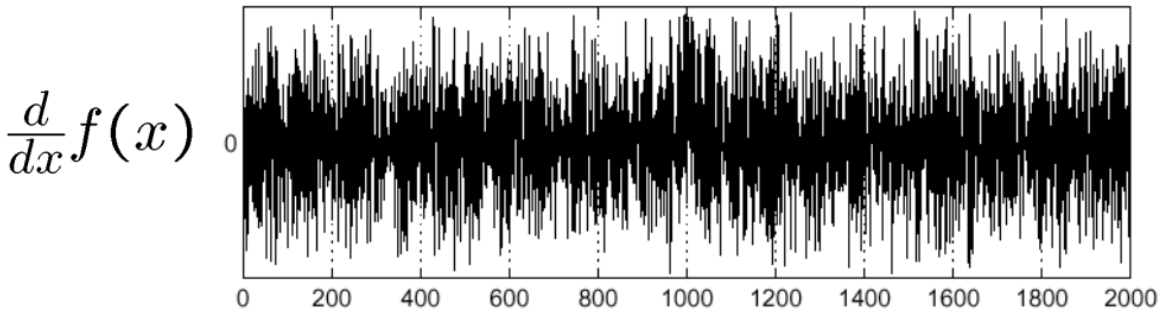
image derivatives accentuate high frequencies (high-pass filter)

→ amplification of noise (proportion of noise to signal larger at high frequencies)



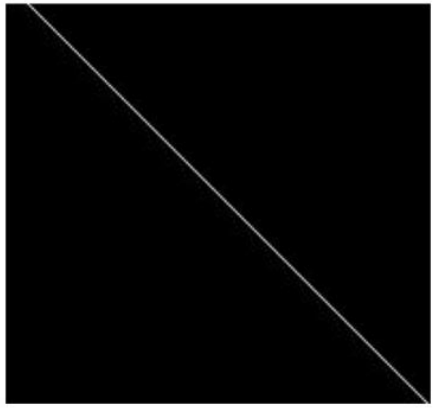
Noisy input image





Need for Band-Pass Filter

Image with Edge



Edge Location

idea:
blurring (low-pass filter) before derivation (high-pass filter)

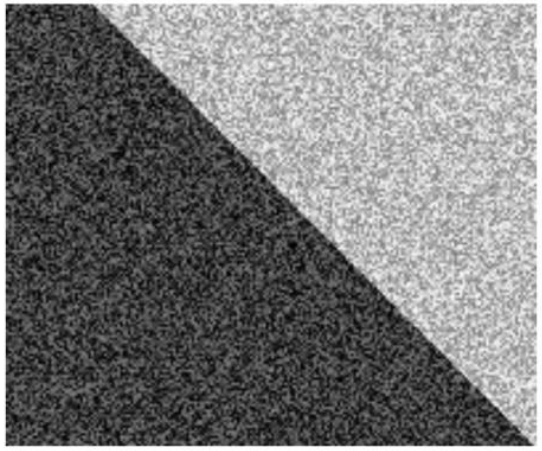
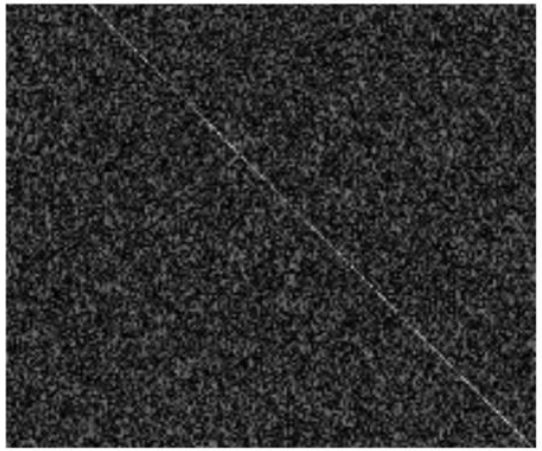
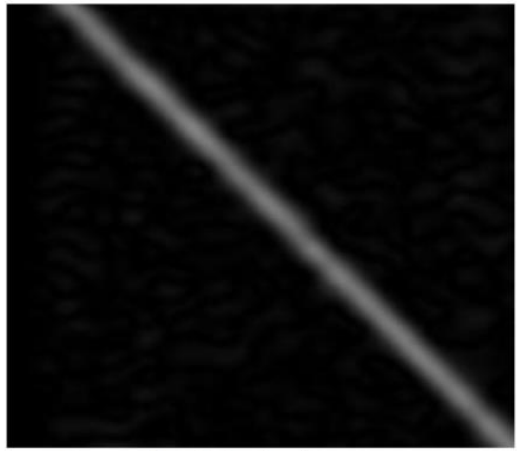


Image + Noise



Derivatives detect edge *and* noise



Smoothed derivative removes noise, but blurs edge

edge detector should be isotropic:
need for circularly symmetric smoothing filter
→ Gaussian is only separable one

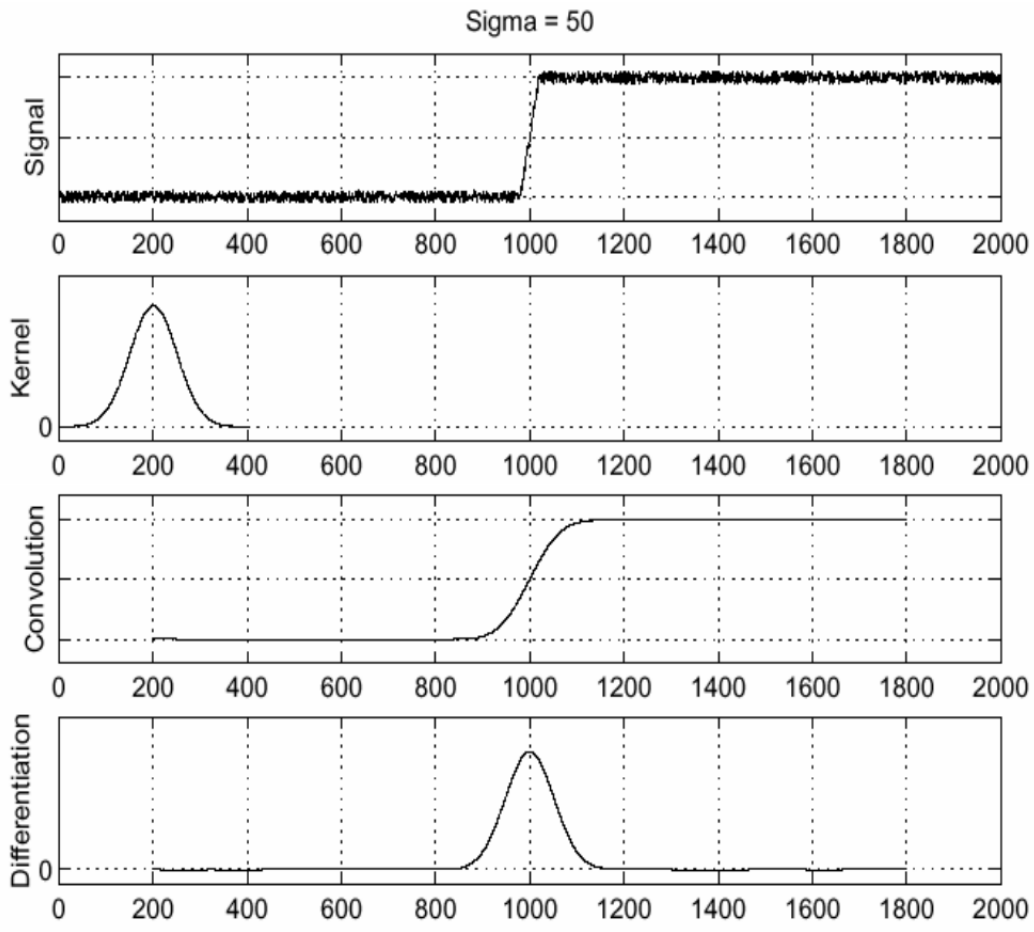
Gradient with Gaussian Smoothing

f

G

$f * G$

$\frac{d}{dx}(f * G)$

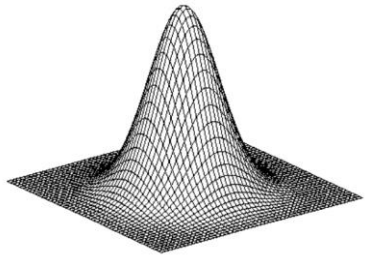


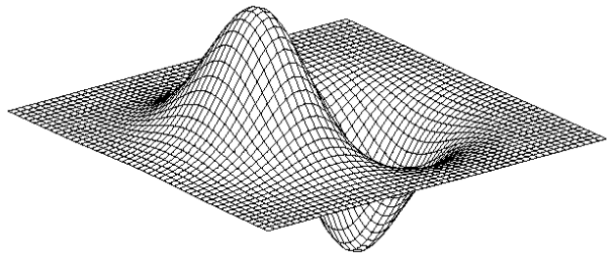
→

to find edges, look for peaks in first-order derivatives

same result, but more efficient:

$$\frac{d}{dx}(f * G) = f * \frac{dG}{dx}$$

$\frac{d}{dx}$  =



$\frac{d}{dy}$ accordingly

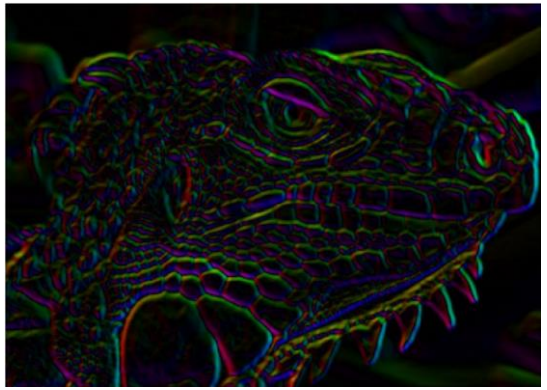
Edge Strength and Orientation

gradient magnitude (edge strength):

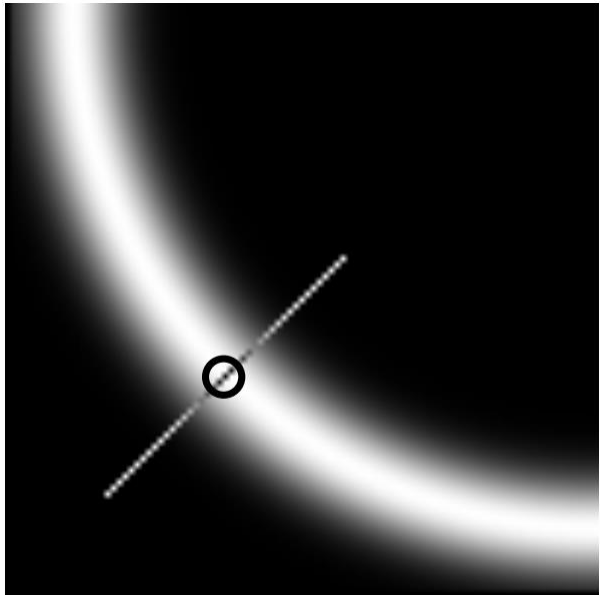
$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

gradient direction (perpendicular to edge orientation):

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



Non-Maximum Suppression



only detect as edge pixel if local maximum along gradient direction (using interpolation between pixels)

→ thin the edges

(can be done with Laplacian zero-crossings)

gradient magnitude:

before

after

Thresholding

still need to decide for each pixel if edge pixel or not
→ generate binary image by thresholding gradient magnitudes

problem: thresholding can lead to many disconnected edges
also, choice of threshold value can be difficult:

high threshold: few edges

low threshold: many edges

Hysteresis: Edge Tracking

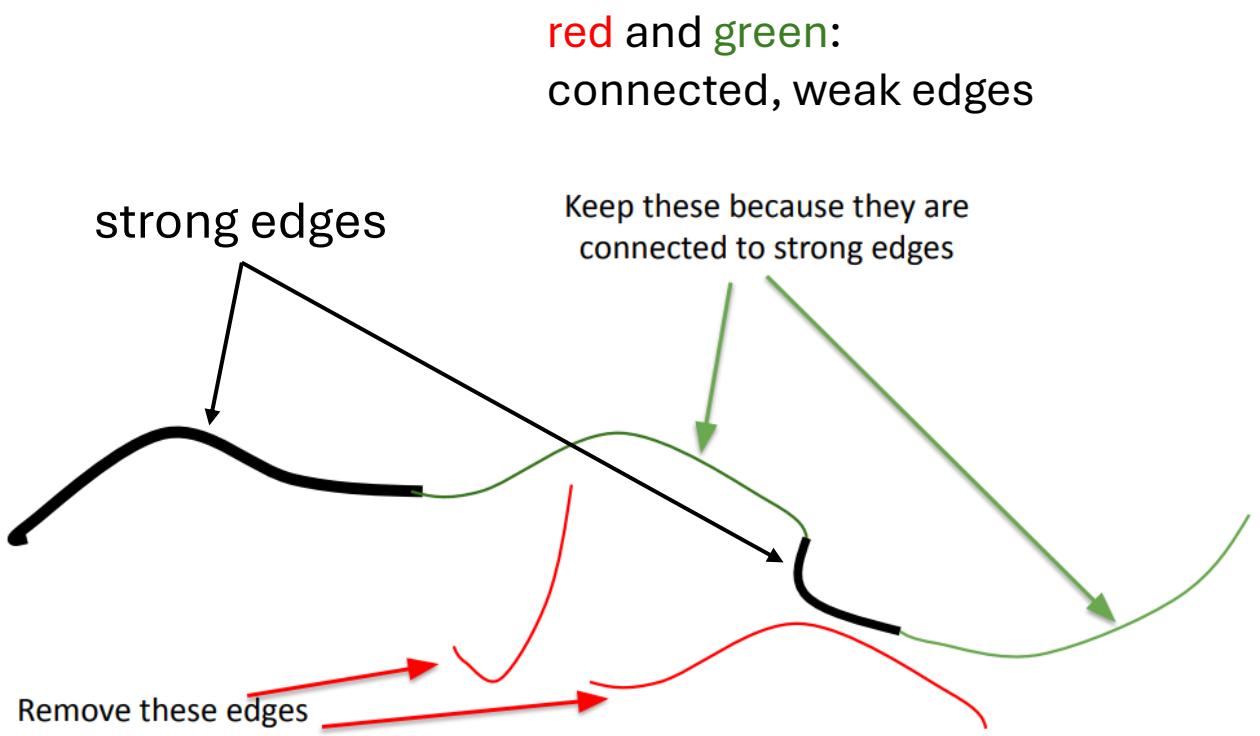
define two thresholds t_1 and t_2:

$\|\nabla f\| < t_1$ no edge pixel

$\|\nabla f\| > t_2$ strong edge → edge pixel

$t_1 < \|\nabla f\| < t_2$ weak edge → uncertain

for weak edges, decide on neighborhood:



Putting It Together: Canny Edge Detector

- smoothing by Gaussian filter
- calculate magnitude and direction of gradient image
- non-maximum suppression (reduce to single-pixel edges)
- hysteresis (binary edge image with linked edge pixels)

Scale Space

besides threshold values, one more important parameter in Canny edge detector: used standard deviation of Gaussian smoothing filter

- broad Gaussians detects large-scale edges
- narrow Gaussians detect fine edges

→ can be combined to detect and select edges at different scales

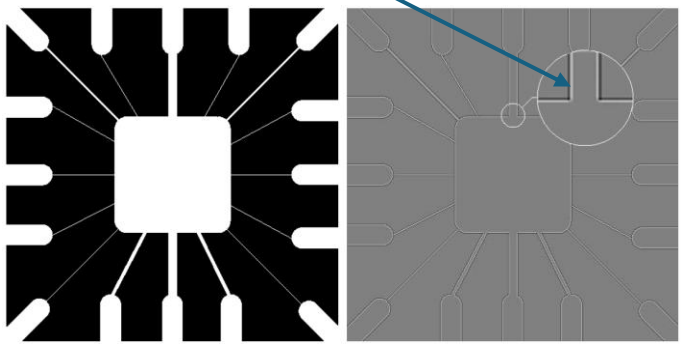
original Canny with $\sigma = 1$ Canny with $\sigma = 2$

Marr-Hildreth Edge Detector

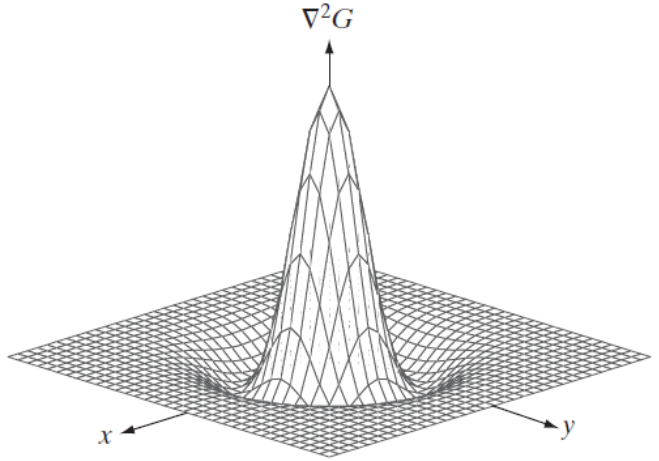
Alternative: Laplacian of Gaussian (LoG)

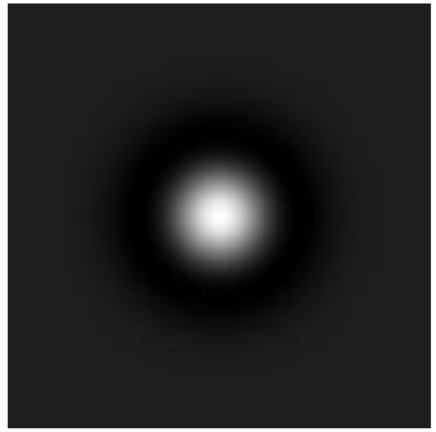
use same idea of smoothing by Gaussian filter before Laplacian
$\nabla^2(f * G) = f * \nabla^2 G$

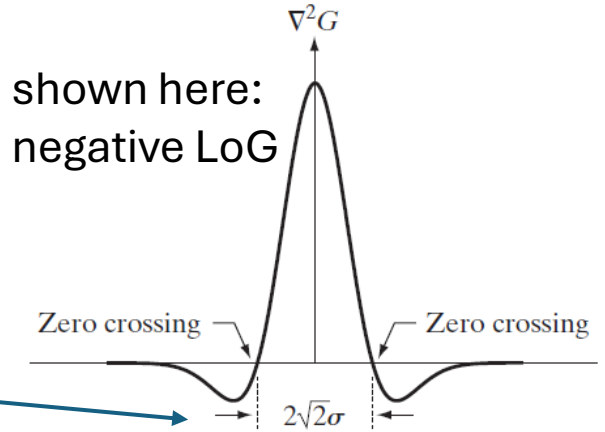
Laplacian:
zero-crossings at edges



f $\nabla^2 f$







shown here:
negative LoG

0	0	−1	0	0
0	−1	−2	−1	0
−1	−2	16	−2	−1
0	−1	−2	−1	0
0	0	−1	0	0

approximated
LoG filter

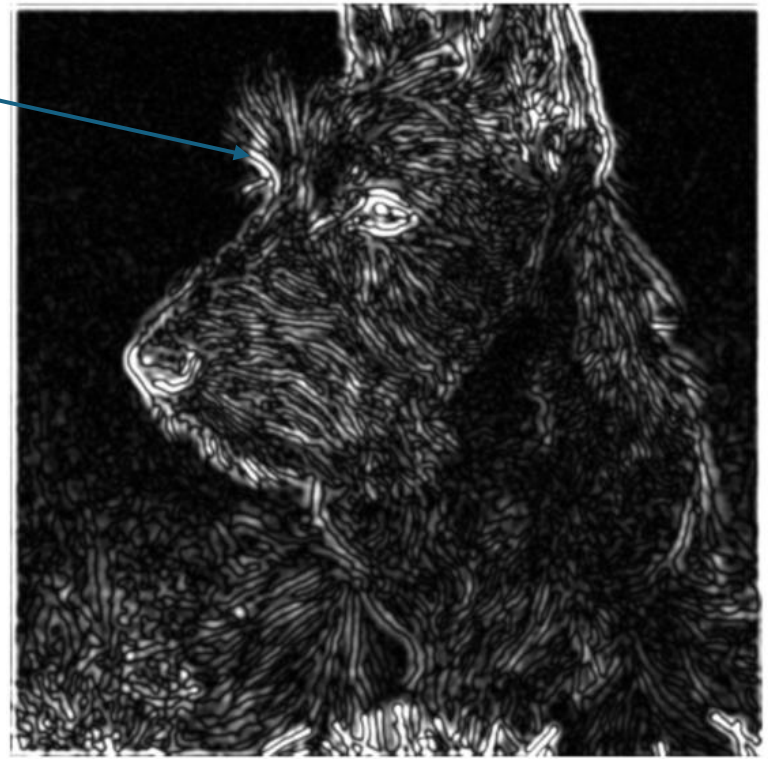
scale of edge detection defined by σ

Zero-Crossings for Edge Detection

use zero-crossings for edge detection
(instead of maxima for gradient)

effect of Gaussian smoothing:

LoG



Laplacian

zero-crossings also thresholded:

Image (I)

Laplacian
(0 maps to 128)

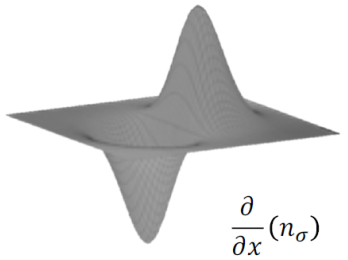
Laplacian
"Zero Crossings"

LoG vs Derivative of Gaussian

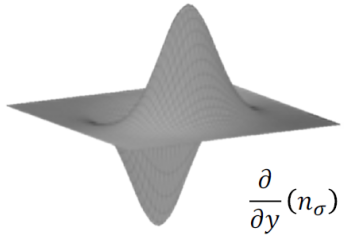
LoG

derivative of Gaussian

Derivative of Gaussian (∇G)

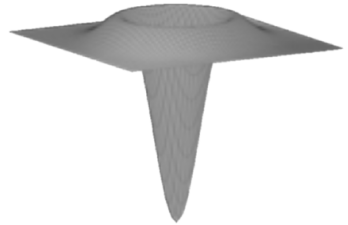


$\frac{\partial}{\partial x}(n_\sigma)$



$\frac{\partial}{\partial y}(n_\sigma)$

Laplacian of Gaussian ($\nabla^2 G$)



$\frac{\partial^2}{\partial x^2}(n_\sigma) + \frac{\partial^2}{\partial y^2}(n_\sigma)$

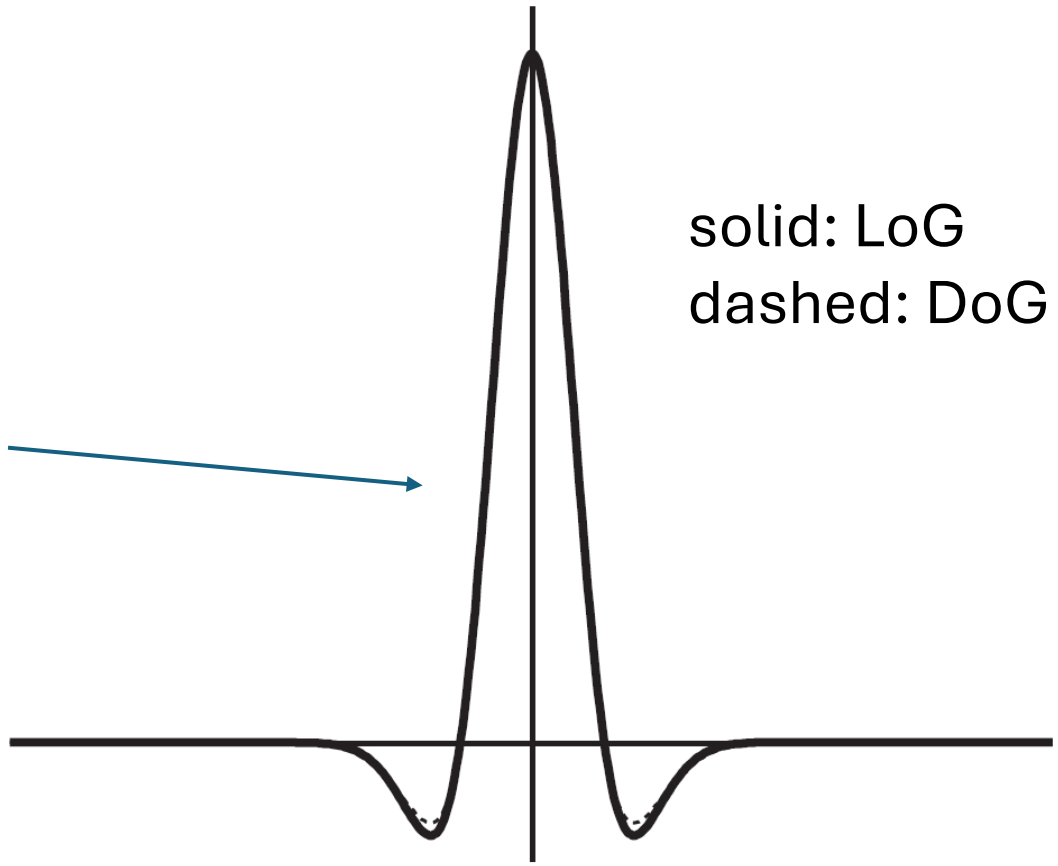
Inverted "Sombrero"
(Mexican Hat)

- Laplacian provides only edge location, no strength or direction
- but requires only one convolution instead of two

Difference of Gaussians (DoG)

difference of two Gaussians with different σ as approximation to LoG

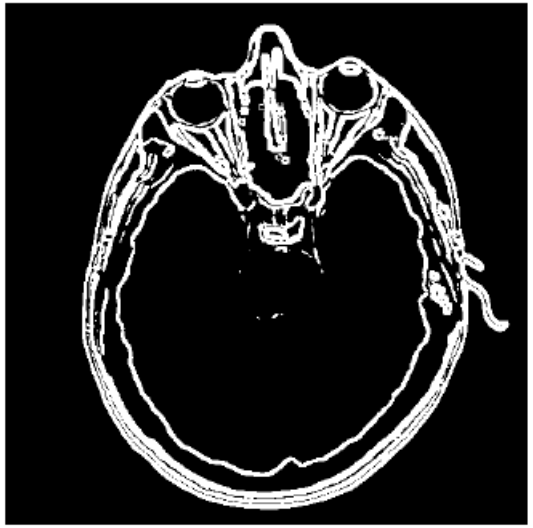
→ less complex and faster



Marr-Hildreth edge detector

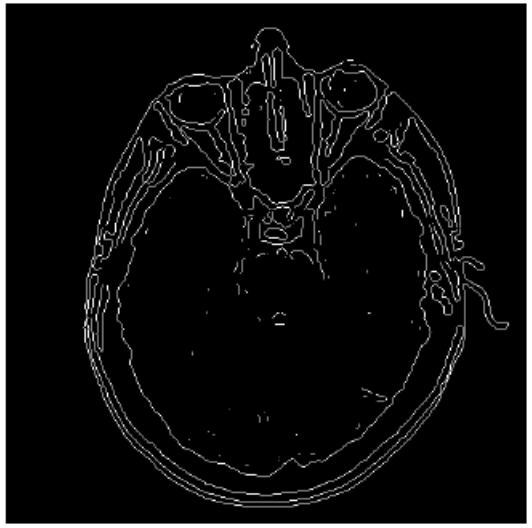
Comparison of Edge Detectors

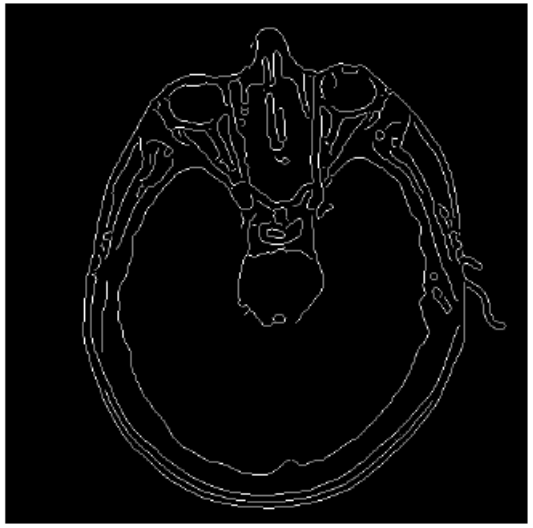
original



thresholded gradient of smoothed image

Marr-Hildreth edge detector





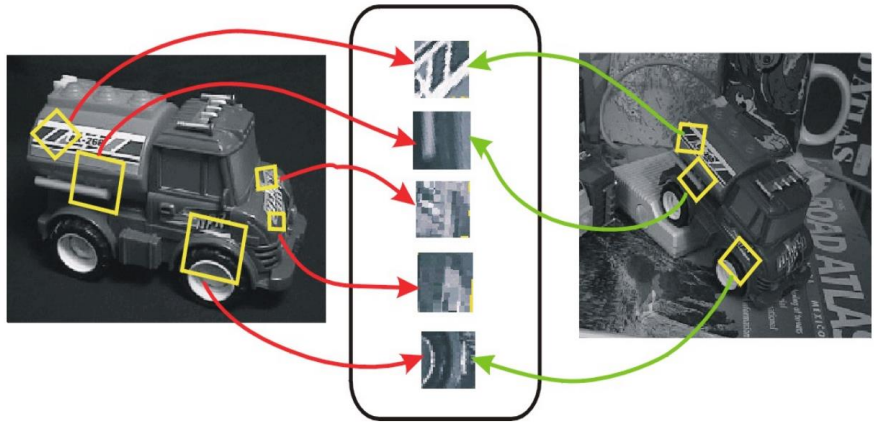
Canny edge detector

Local Features

Keypoint Detection & Matching

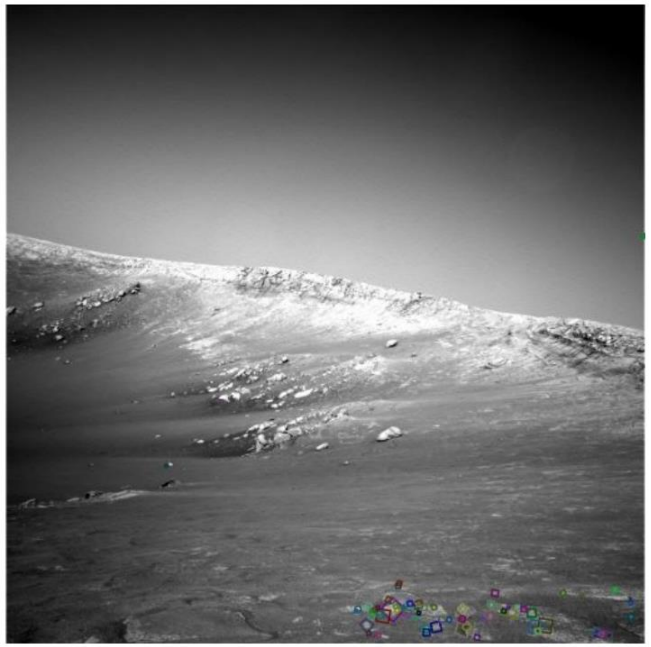
different stages:

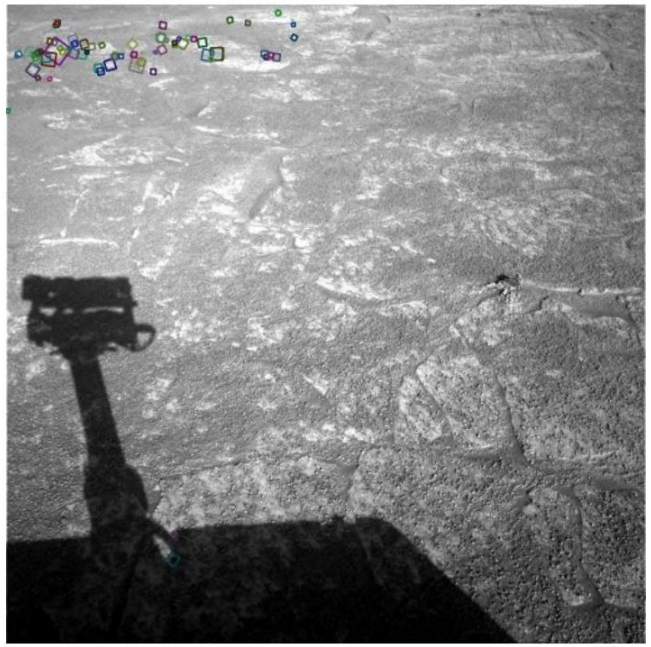
- **feature detection**: search for distinguishing keypoints (aka interest points) in images
- **feature description**: construct (invariant) descriptors/features from regions (pixel patches) around detected keypoint locations
- **feature matching**: search for matching keypoints (correspondences) in other images



Why Local Keypoint Features for Instance Recognition?

often non-obvious shapes



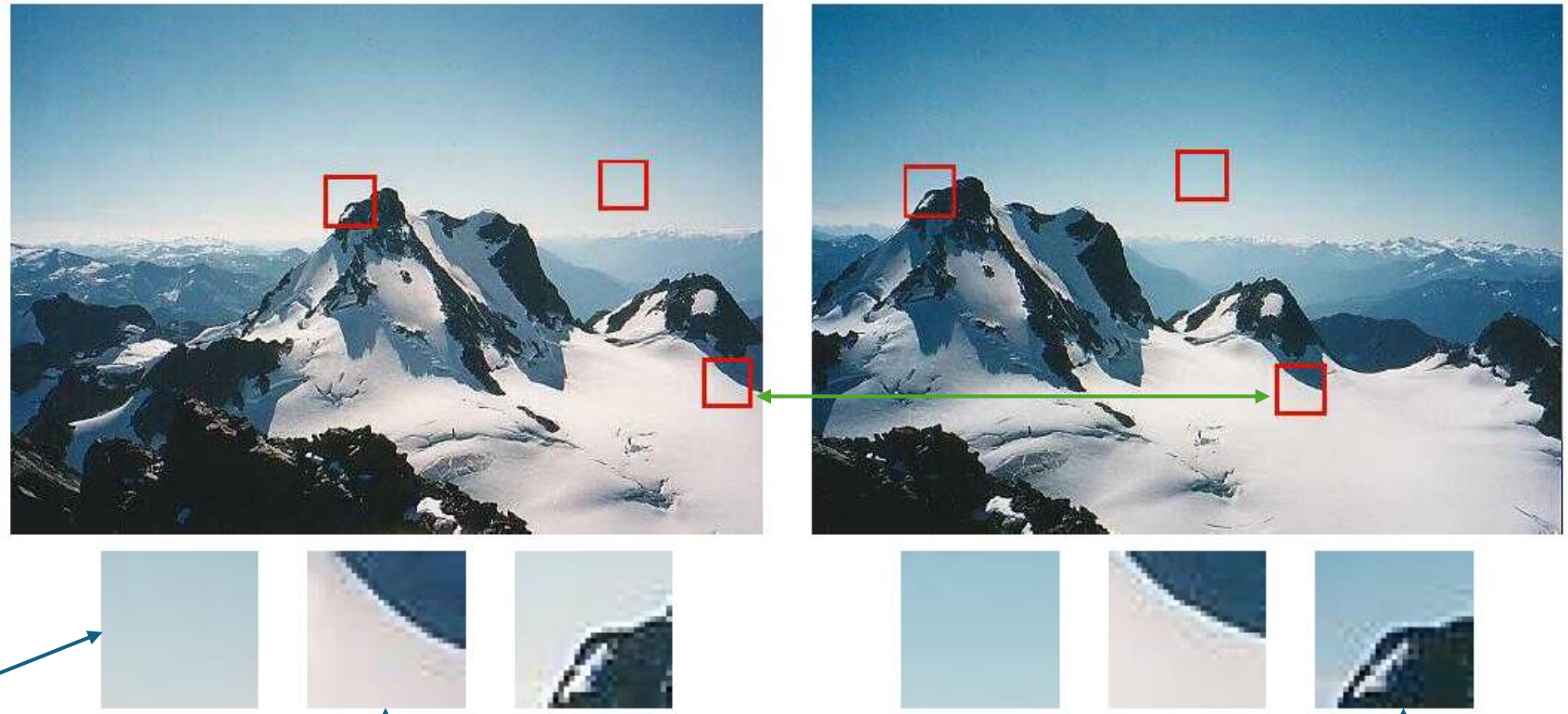


NASA Mars Rover images with SIFT feature matches

at different scales, under perspective changes and with partial observability

→ matching predefined shapes or large patches very difficult

Good and Bad Keypoints



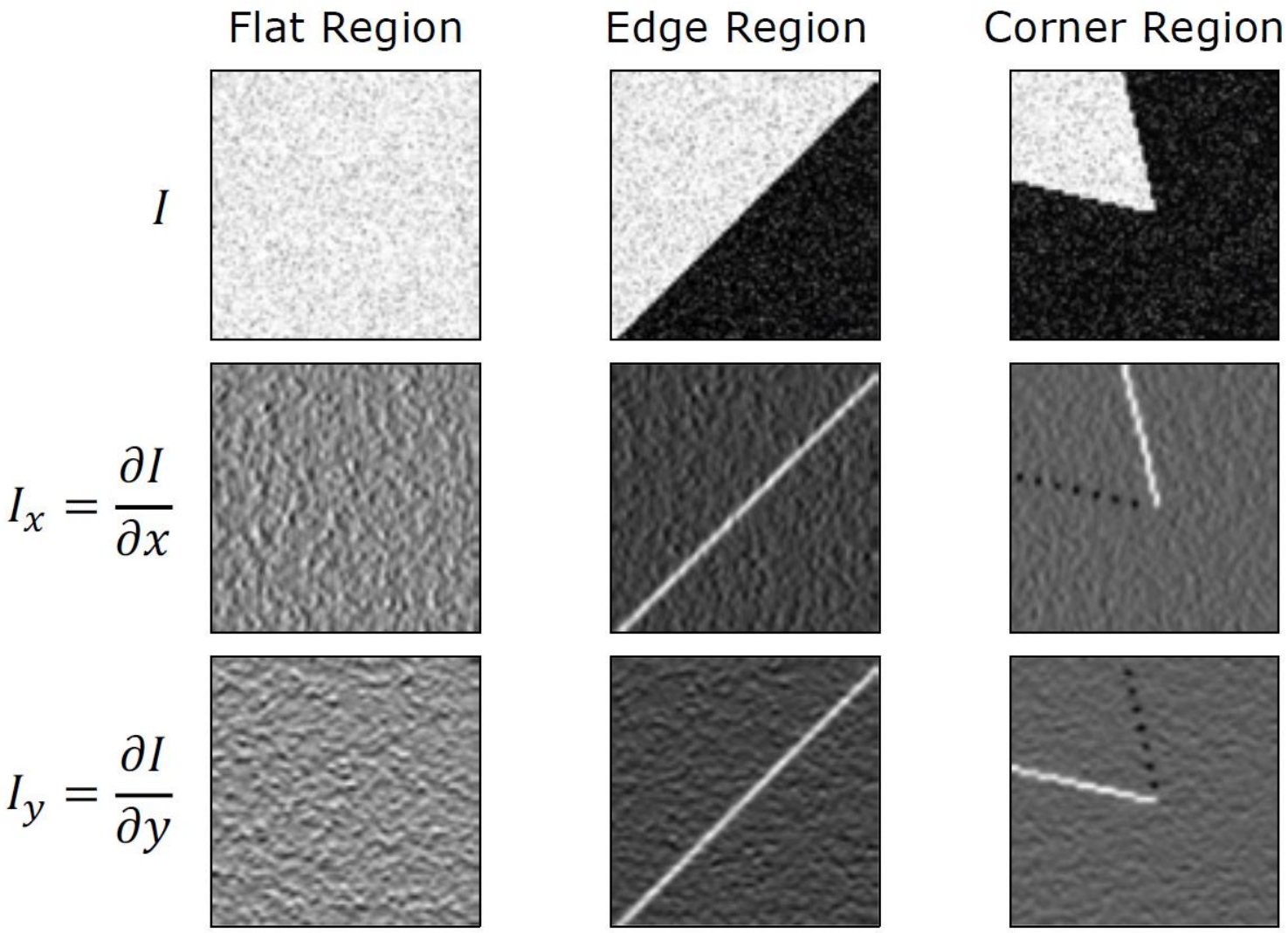
flat regions cannot be localized

edges are difficult to localize

corners are interesting candidates

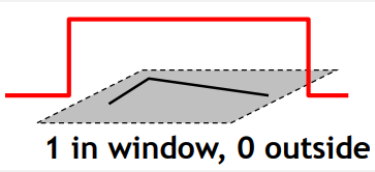
Feature Detection

Harris Corner Detector

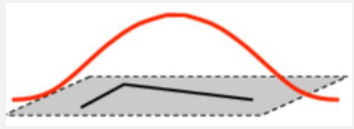


1. define a small window and shift over image
2. for each region calculate image gradients

discrete convolution with weighting kernel w:



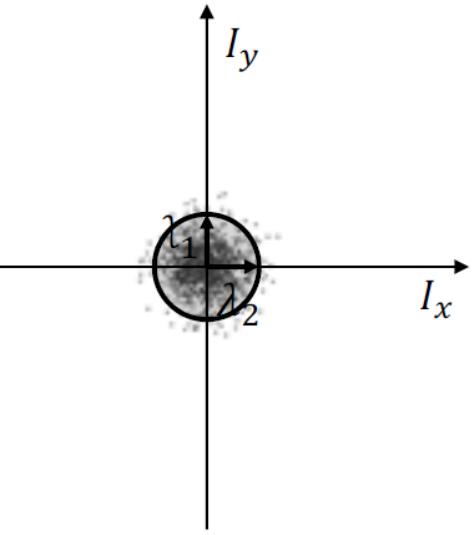
or better: Gaussian
→ rotation invariant



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

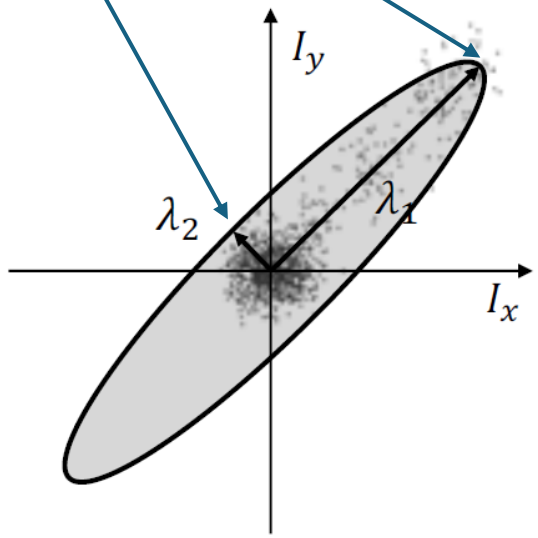
directions of maximum variance

Flat Region



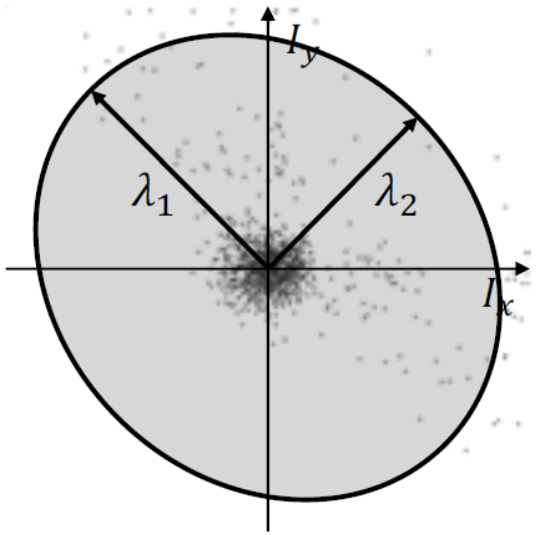
$\lambda_1 \sim \lambda_2$
Both are Small

Edge Region



$\lambda_1 \gg \lambda_2$
λ_1 is Large
λ_2 is Small

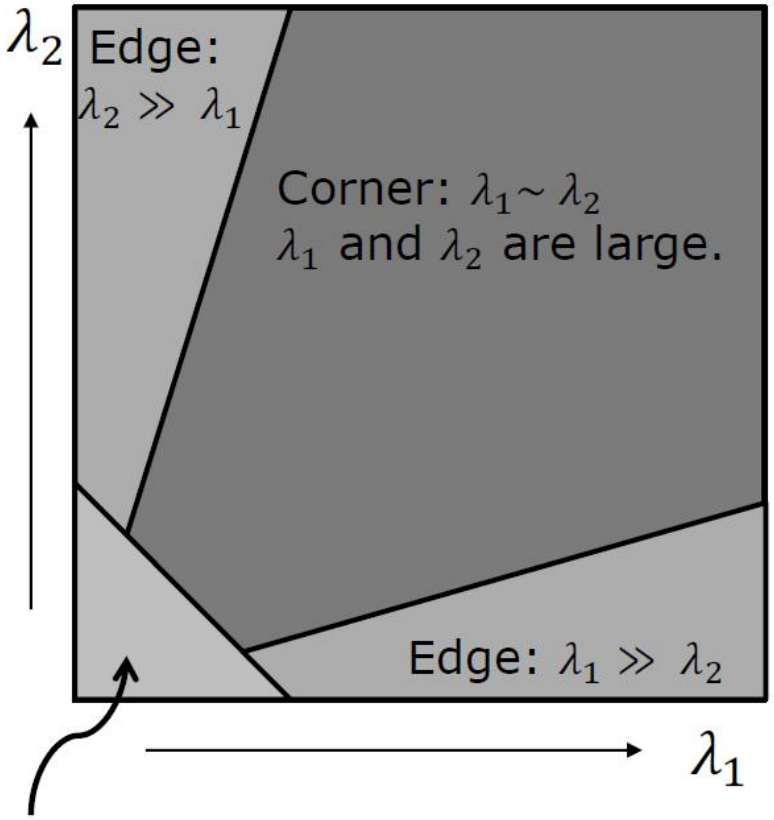
Corner Region



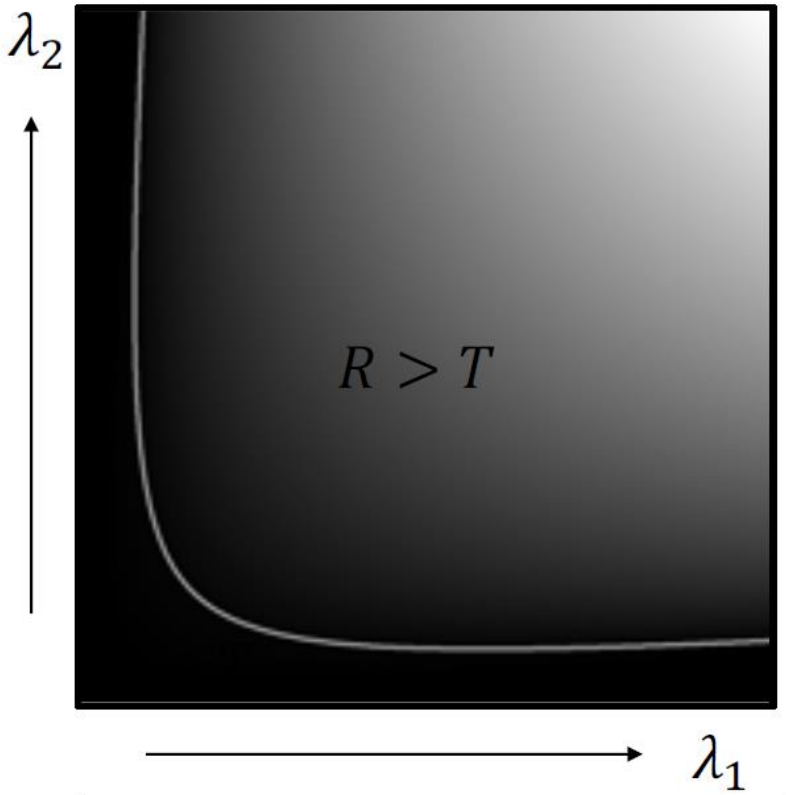
$\lambda_1 \sim \lambda_2$
Both are Large

3. build covariance matrix of image gradients and calculate its eigenvalues λ_1 and λ_2 (aka **P**rincipal **C**omponent **A**nalysis)

response function R



Flat: $\lambda_1 \sim \lambda_2$
λ_1 and λ_2 are small.



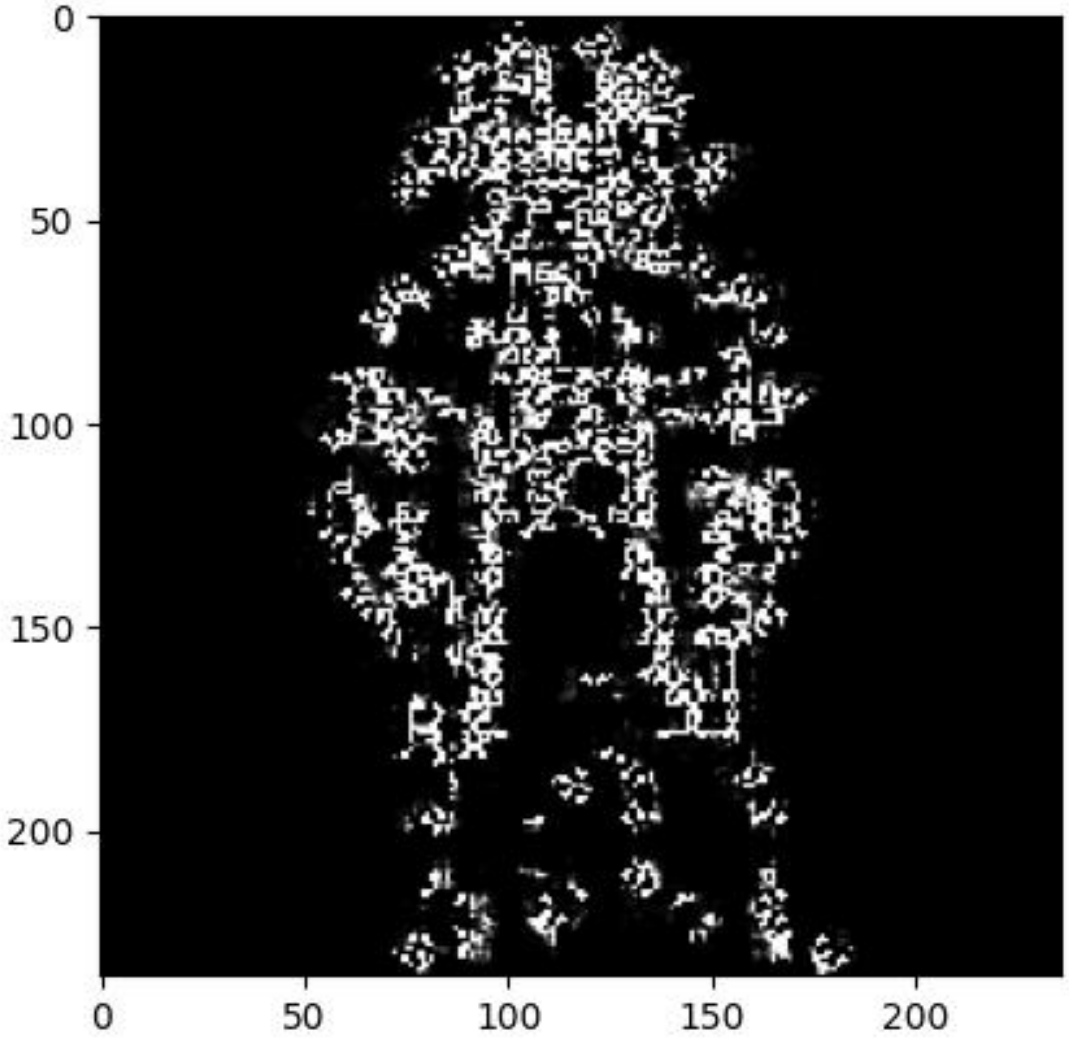
$$R = \lambda_1\lambda_2 - k(\lambda_1 + \lambda_2)^2$$

where: $0.04 \leq k \leq 0.06$

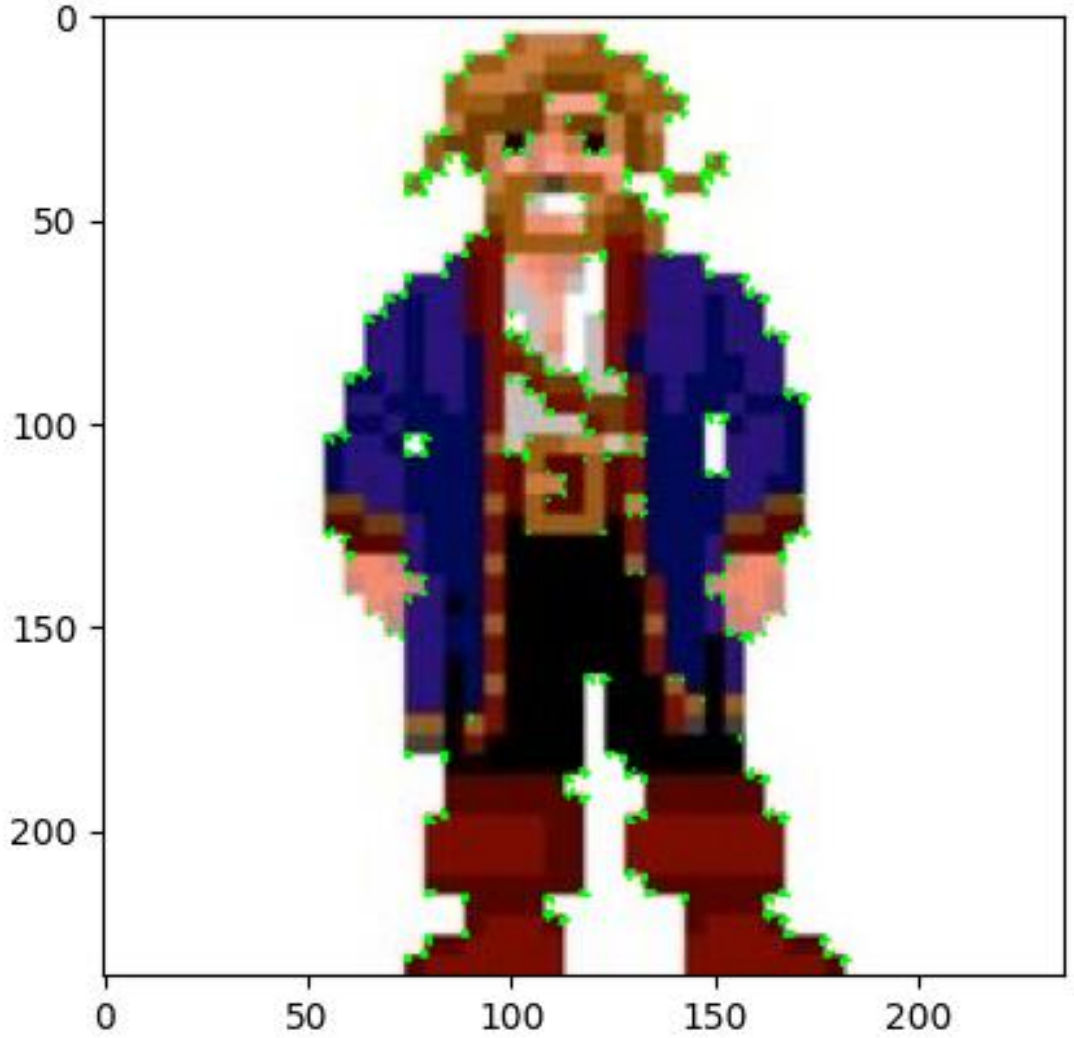
alternative:
use the smaller eigenvalue
as response function

4. use threshold on eigenvalues for corner detection
5. perform non-maximum suppression

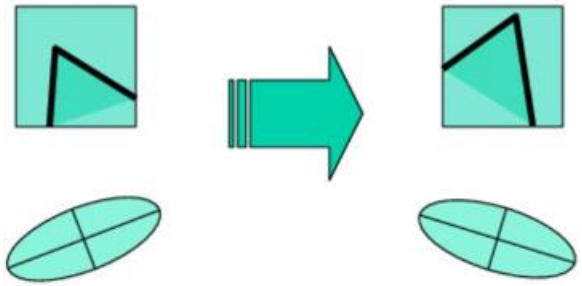
response function:



thresholded response:

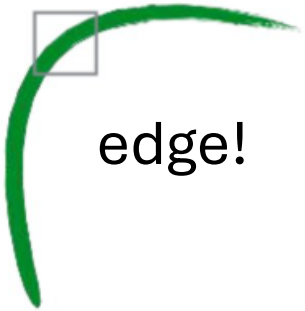


corner response rotation invariant



eigenvalues stay the same

but not scale invariant



edge!

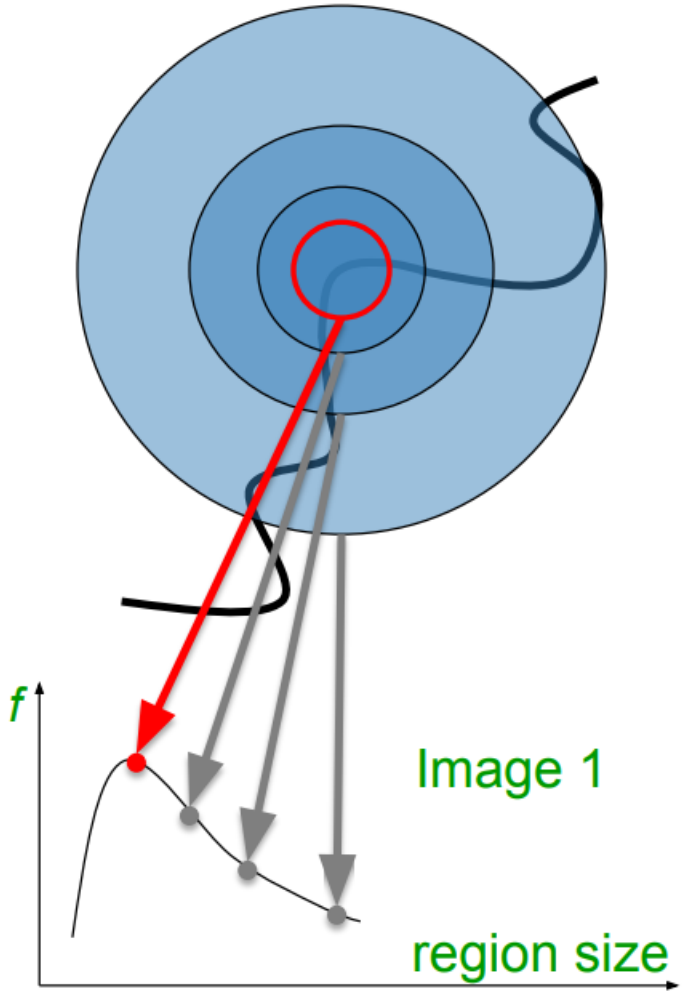
corner!

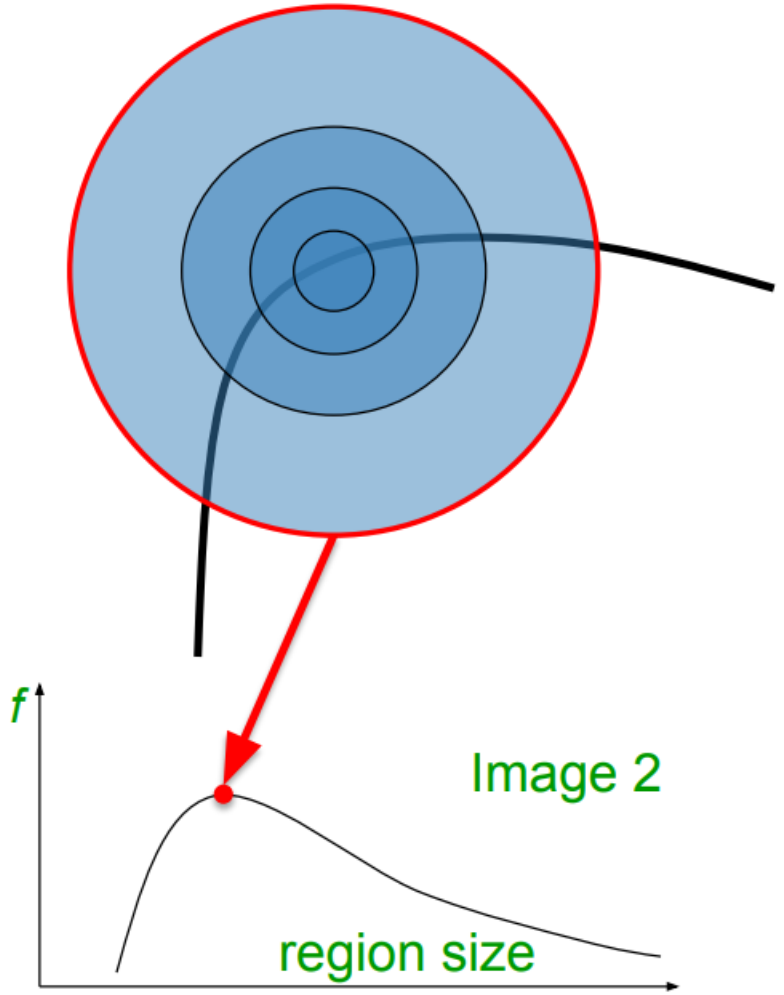
important for detection in images with different sizes or at positions with different depths

Scale-Invariant Keypoint Detection

→ need to detect keypoints at the right scale for each image

→ search for both position and scale

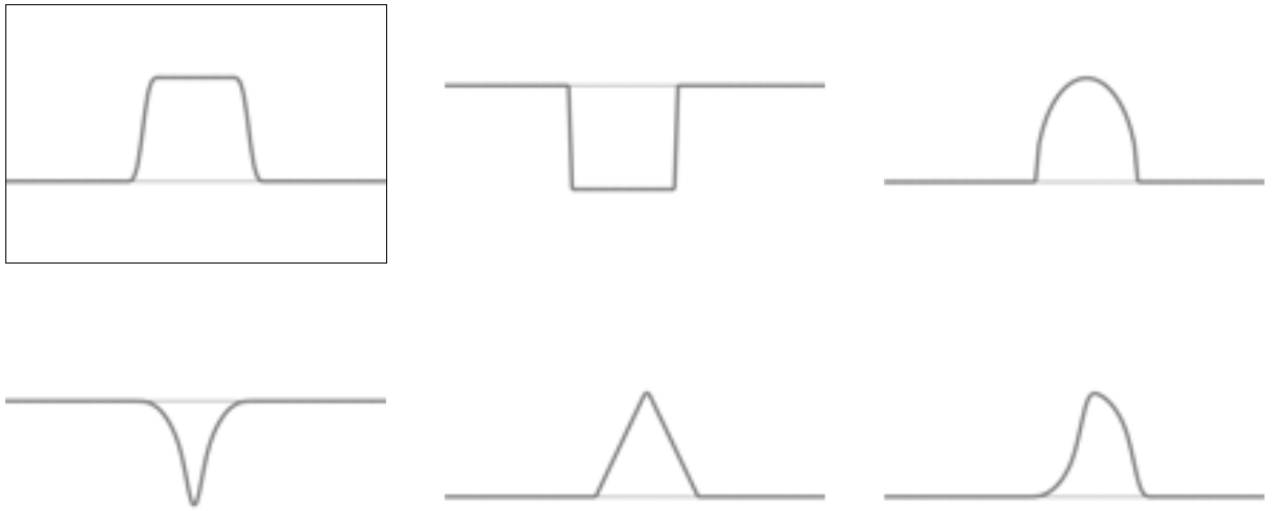




Additional Keypoint-Detection Requirements

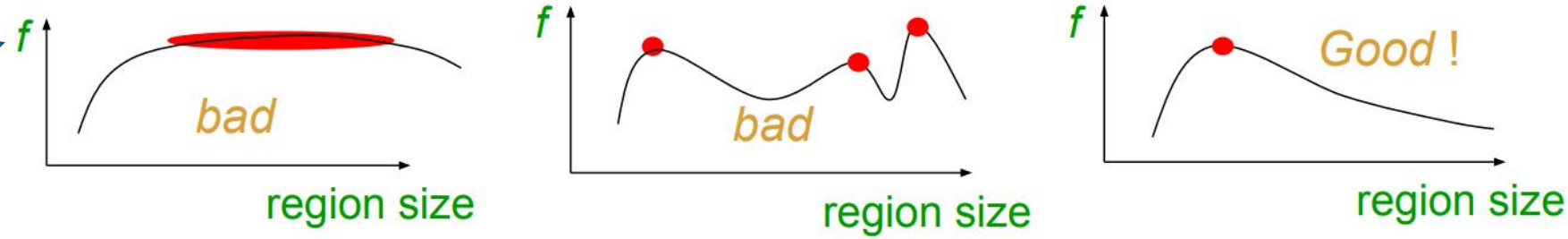
corners often not descriptive enough for complex objects (e.g., smoother regions)

→ need to detect not only corners, but all kinds of **blobs** (keypoint as center of blob region)

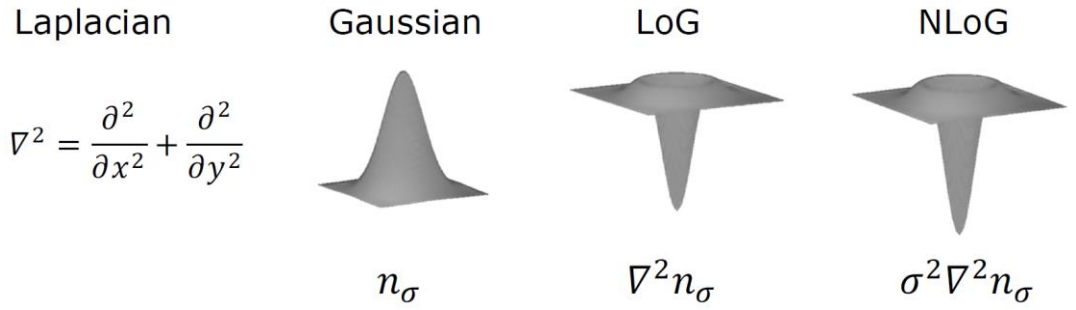


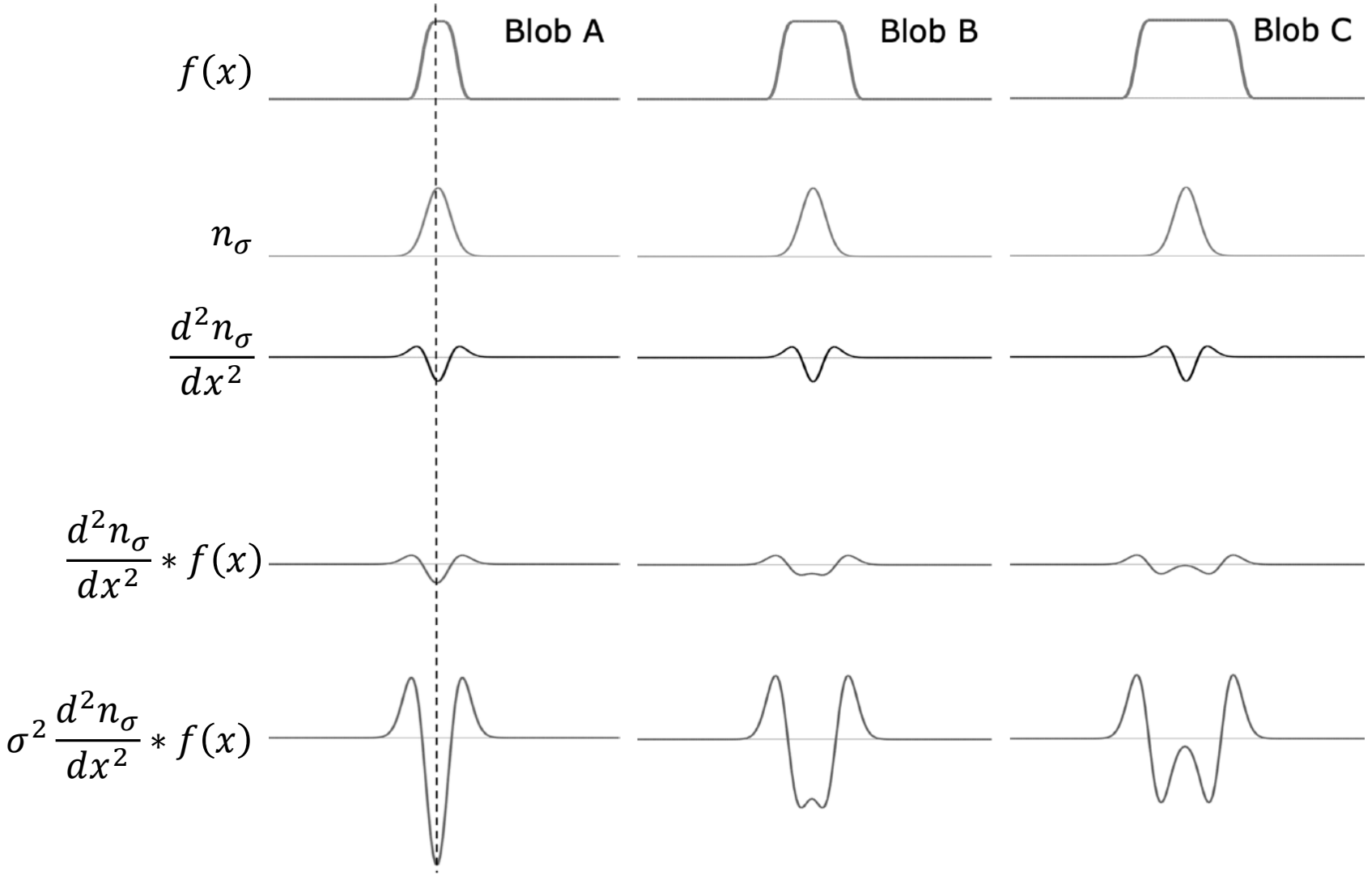
and it must be possible to find the right scale for the blob to be detected:

response of blob detector

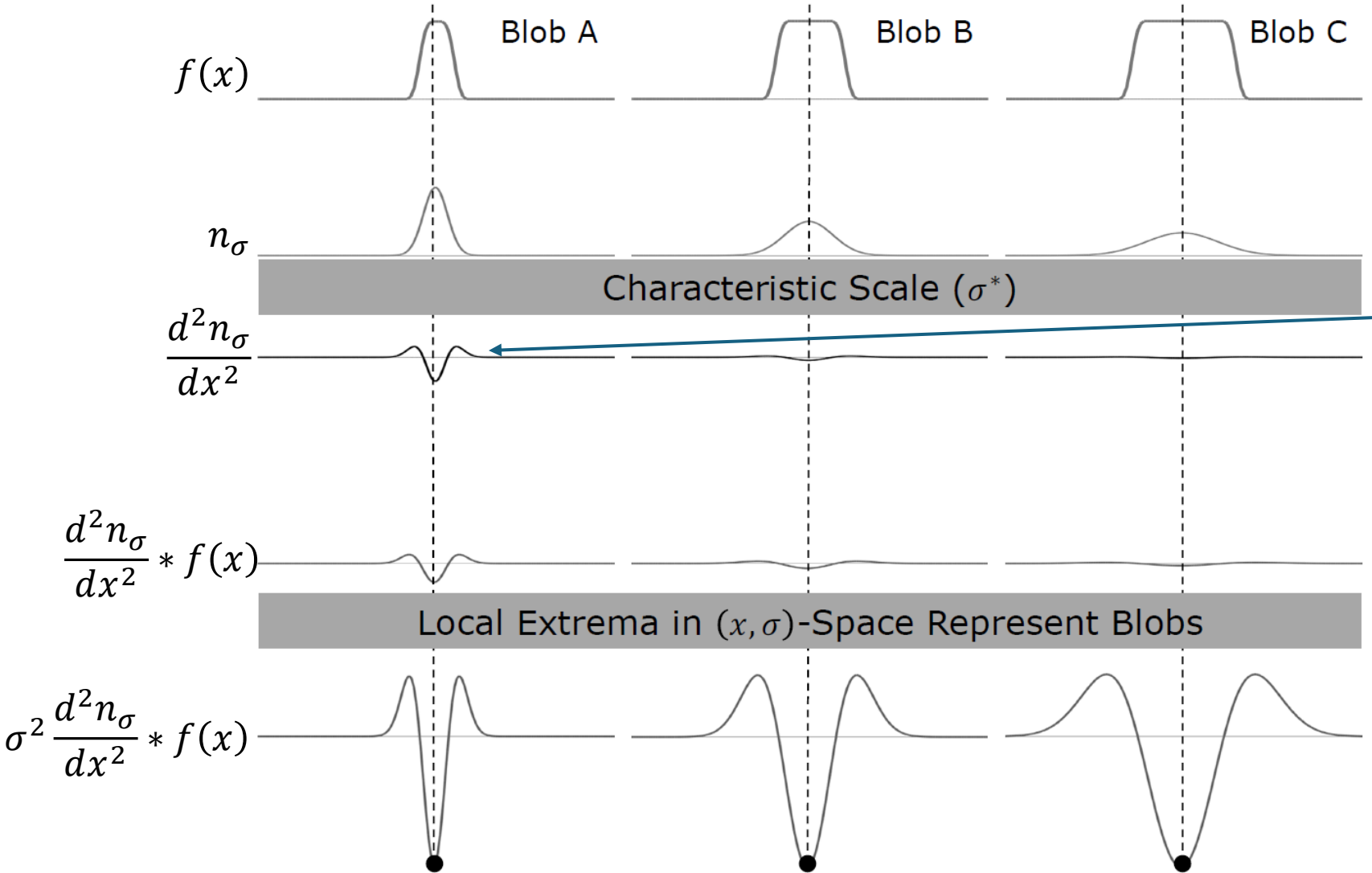


LoG Operator





Detect Blobs at Different Sizes



example: LoG filter for $\sigma = 1.4$

$$\begin{bmatrix} 0 & 0 & 1 & 2 & 2 & 2 & 1 & 0 & 0 \\ 0 & 1 & 3 & 5 & 5 & 5 & 3 & 1 & 0 \\ 1 & 3 & 5 & 3 & 0 & 3 & 5 & 3 & 1 \\ 2 & 5 & 3 & -12 & -23 & -12 & 3 & 5 & 2 \\ 2 & 5 & 0 & -23 & -40 & -23 & 0 & 5 & 2 \\ 2 & 5 & 3 & -12 & -23 & -12 & 3 & 5 & 2 \\ 1 & 3 & 5 & 3 & 0 & 3 & 5 & 3 & 1 \\ 0 & 1 & 3 & 5 & 5 & 5 & 3 & 1 & 0 \\ 0 & 0 & 1 & 2 & 2 & 2 & 1 & 0 & 0 \end{bmatrix}$$

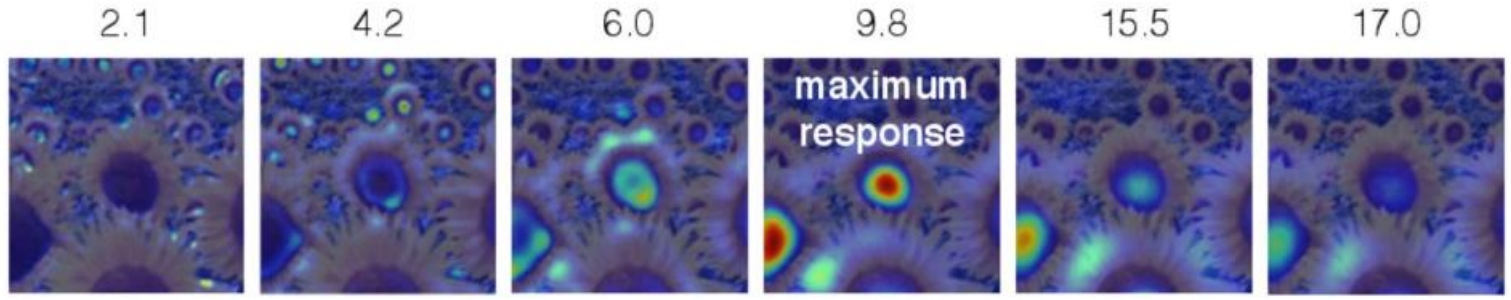
need larger filter for larger σ

→ need to compute this at many scales

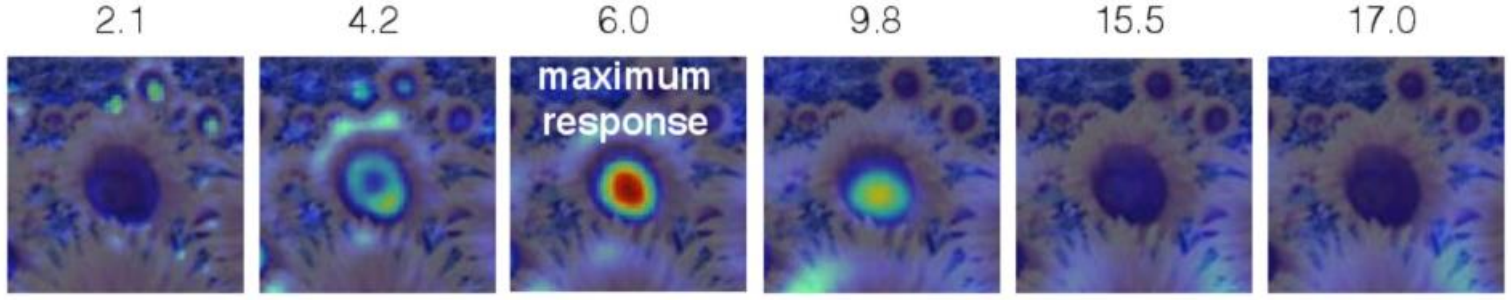
Full size

3/4 size

σ



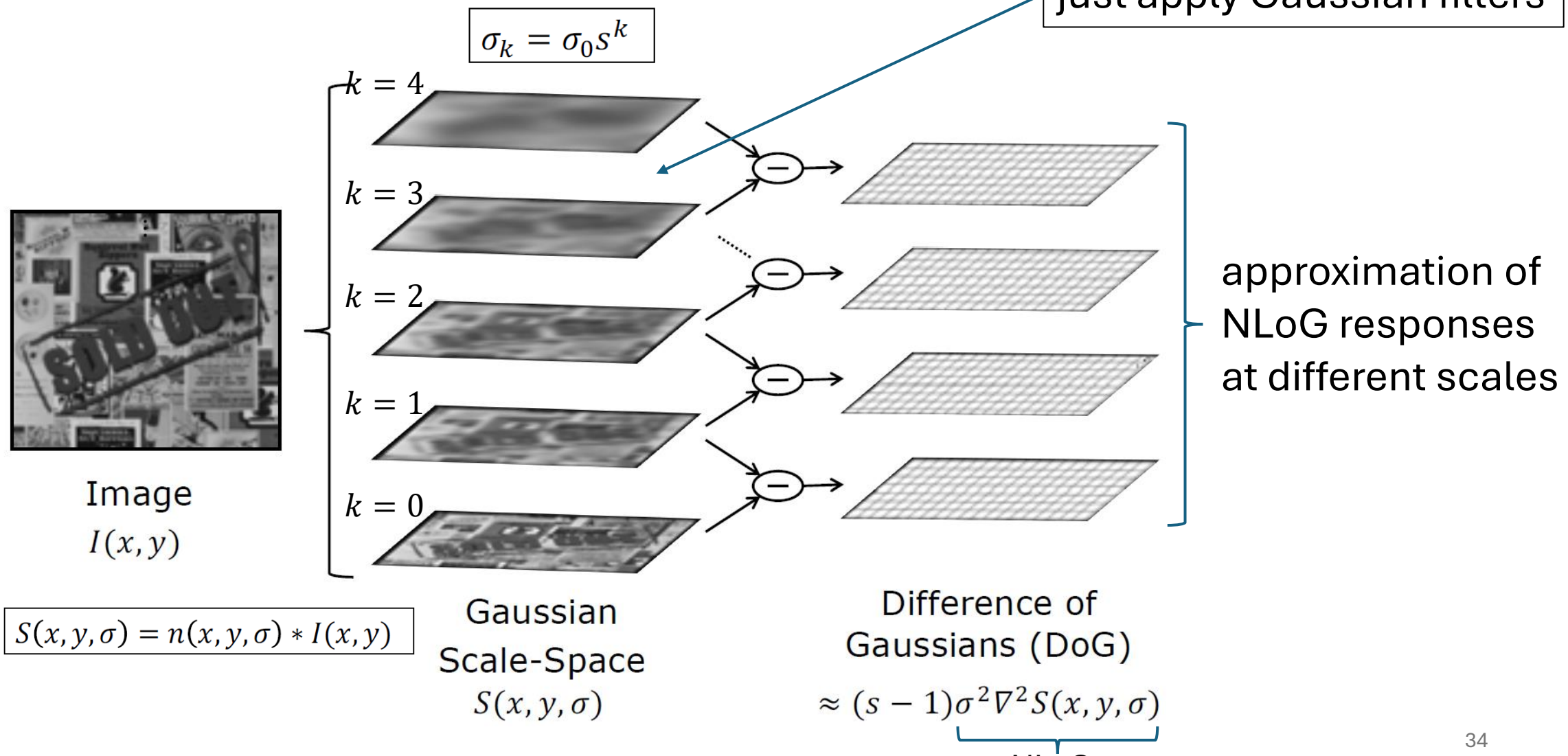
Full size image



3/4 size image

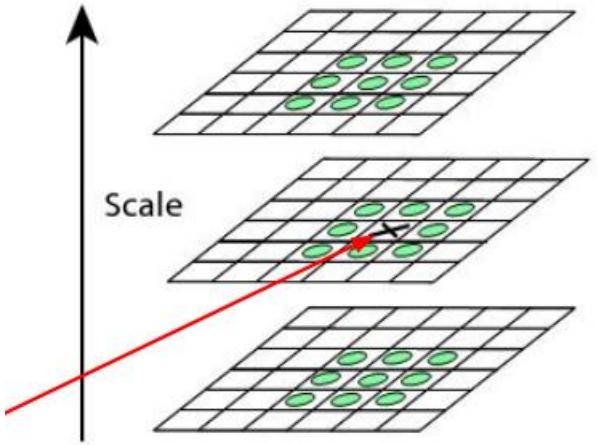
multiple scales via Gaussian filters with different σ

DoG as Approximation of LoG

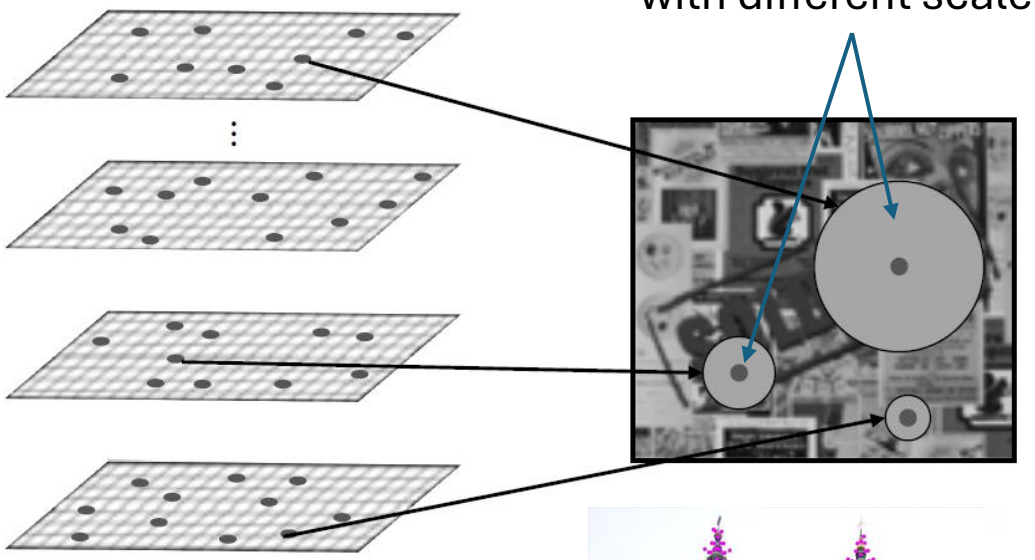


Scale Invariant Feature Transform (SIFT) Detector

look at $3 \times 3 \times 3$ neighborhoods

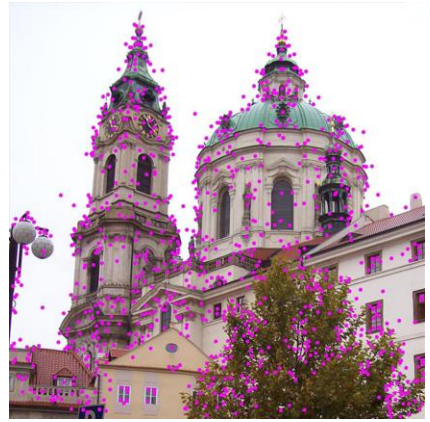


detect as keypoint if center is extrema in this pixel-scale volume



detected keypoints with different scales

SIFT Interest Points



Feature Description & Matching

Motivation

feature descriptor:

simplified representation of an image containing only its most important information

raw pixel intensities difficult to interpret

(→ deep learning)

Local Patches as Features

extract patches around keypoints

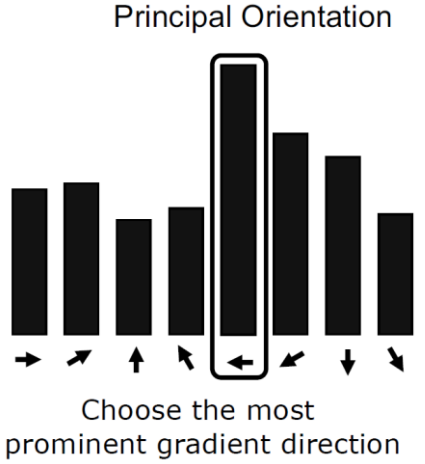
→ descriptor: vector summarizing content of these patches

simplest descriptor: just raw intensity values of pixels in patch (template matching)

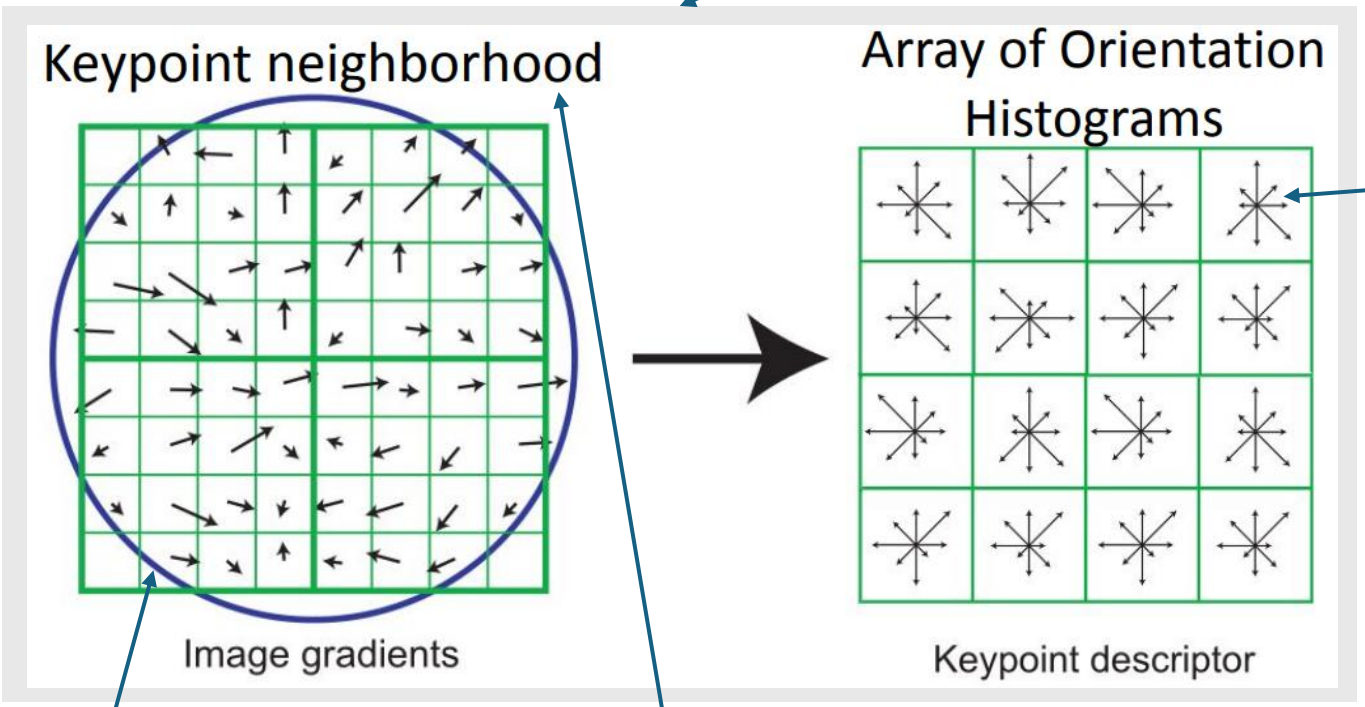
but need to be invariant to translation, rotation, scale, (illumination)

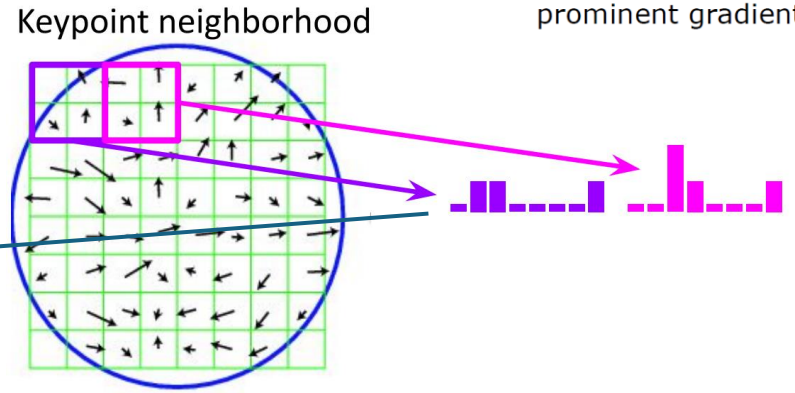
SIFT Descriptor

rotation invariance:
rotate gradients relative to the keypoint's principal orientation before calculating the descriptor



16 × 16 square window around detected keypoint
(8 × 8 shown here for visualization)





SIFT descriptor is vector of length 128:

- 4 × 4 histograms per keypoint
- 8 orientation bins per histogram

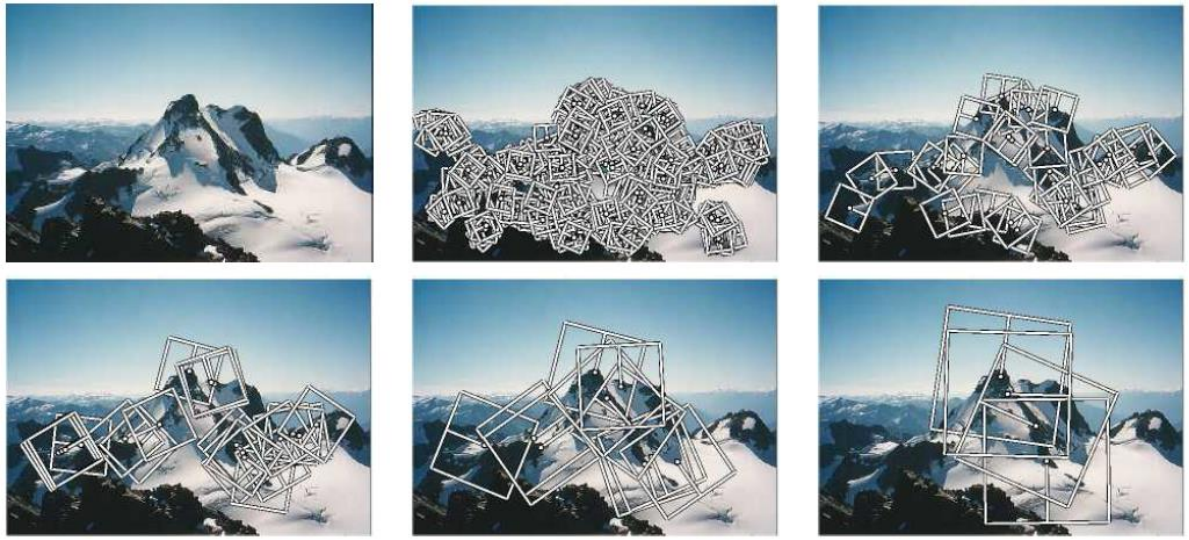
weighted by Gaussian fall-off function

using the image of the detected scale (i.e., smoothed with corresponding Gaussian filter) for this keypoint

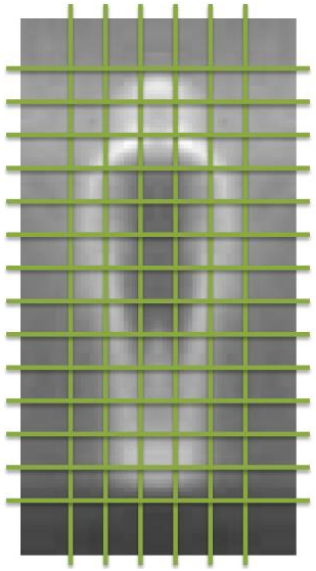
Many Other Feature Detectors/Descriptors

- MOPS: simple normalized intensity patches
- SURF, ORB: similar to SIFT, but faster
- HOG: used for larger image regions, particularly suited for human detection
- …

Multi-scale **O**riented **P**atche**S**:



Histogram of **O**riented **G**radients:



counting occurrences of gradient orientations in localized portions of an image

features covering entire image (instead of just local patches)

Feature Matching

goal: for each keypoint in a given image, find nearest neighbor in other image

(or rank different potential matches)

→ look for smallest distance d between the corresponding feature descriptors $\boldsymbol{f}$ (vectors) in image 1 and 2

several possible distance metrics, e.g., L2:

$$d = \sqrt{(\boldsymbol{f}_1 - \boldsymbol{f}_2)^2}$$

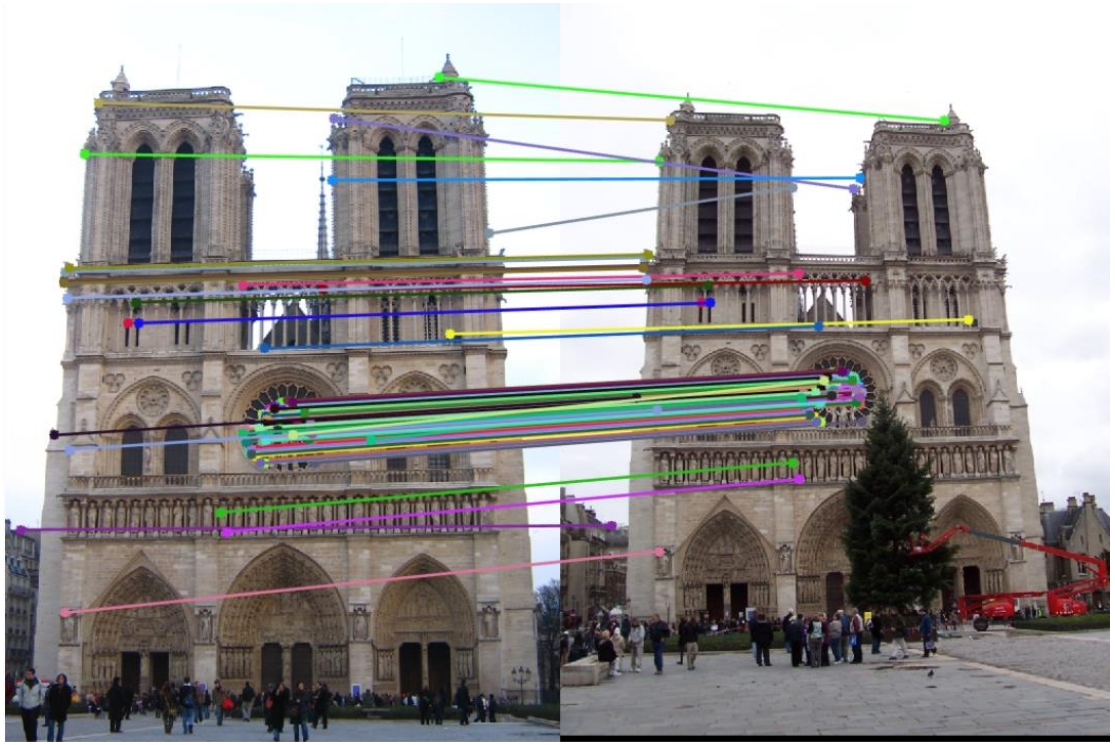
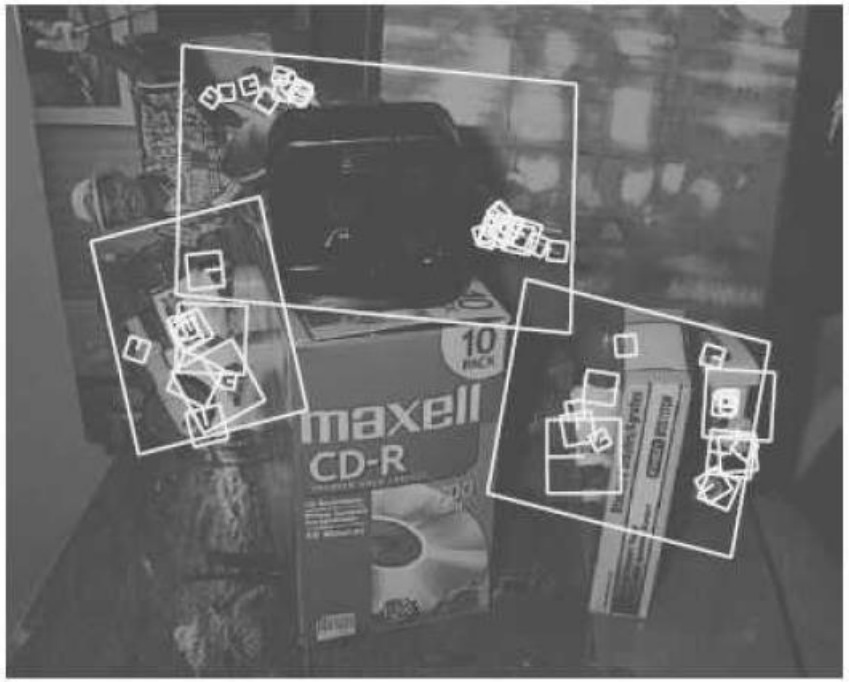


image alignment: homography …

Object Recognition

two database images to be recognized:

using SIFT features



approach: extract featues and compare against stored object features in database (successful if defined number of feature matches found), subsequent match verification by geometric alignment

works well for instance recognition (e.g., specific car), but class recognition (e.g, cars in general) requires more abstraction → ML

Facial Recognition with Eigenfaces

alternative approach for instance recognition: eigenimages

most popular example: individual face images expressed as combination of basis images (called eigenfaces)

PCA (unsupervised ML) on large training set of face images, use principal components (eigenvectors with largest eigenvalues) as basis images

identification: compare vectors of eigenface components (projections to eigenspace), typically using ~100 eigenfaces

some eigenfaces: