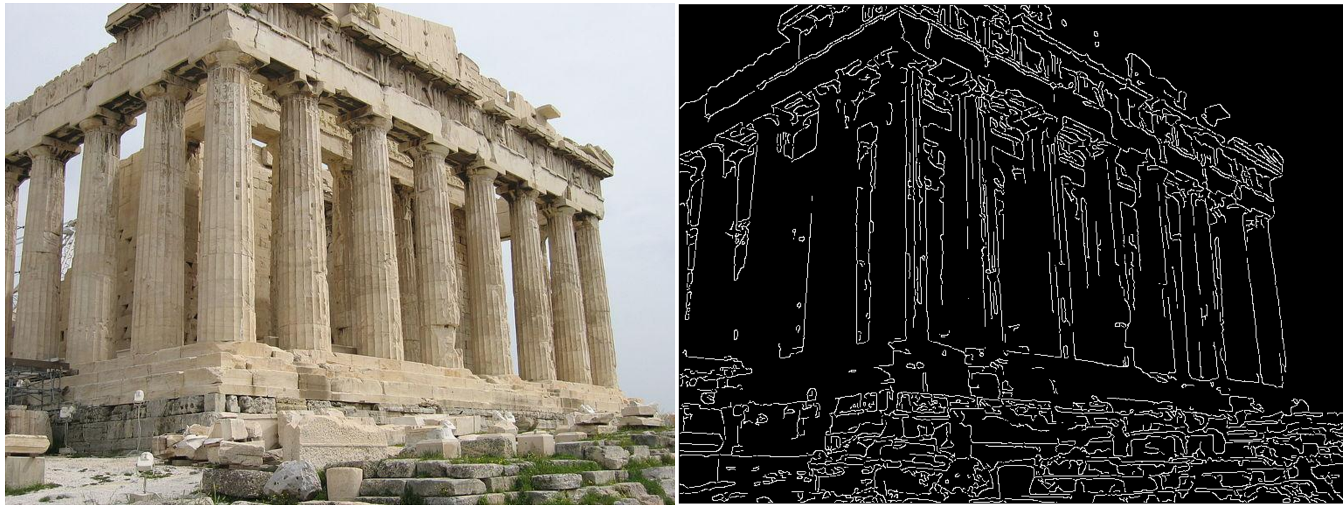
Perception | **Edges & Points**
Autonomous Mobile Robots

Margarita Chli – University of Edinburgh

Paul Furgale, Marco Hutter, Martin Rufli, Davide Scaramuzza, Roland Siegwart

Edge Detection

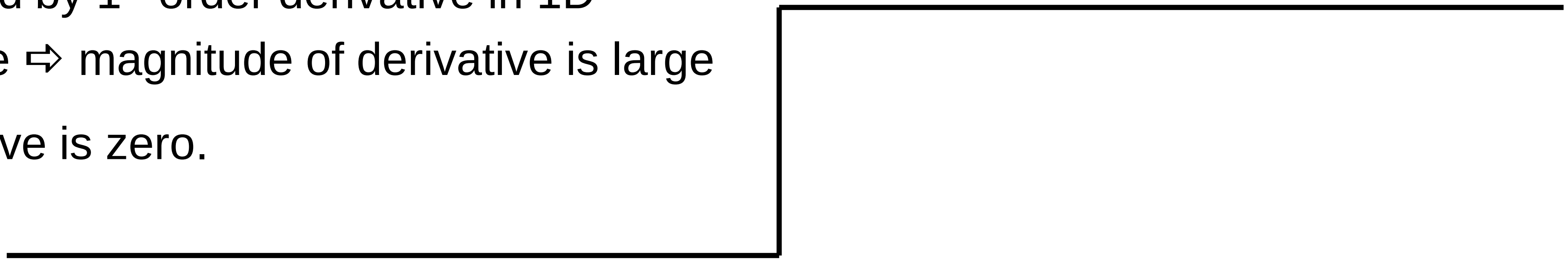
- Edge contours in the image correspond to important scene contours.
- Ultimate goal of edge detection: an idealized line drawing.



Parthenon by Tim Bekaert, Wikimedia Commons

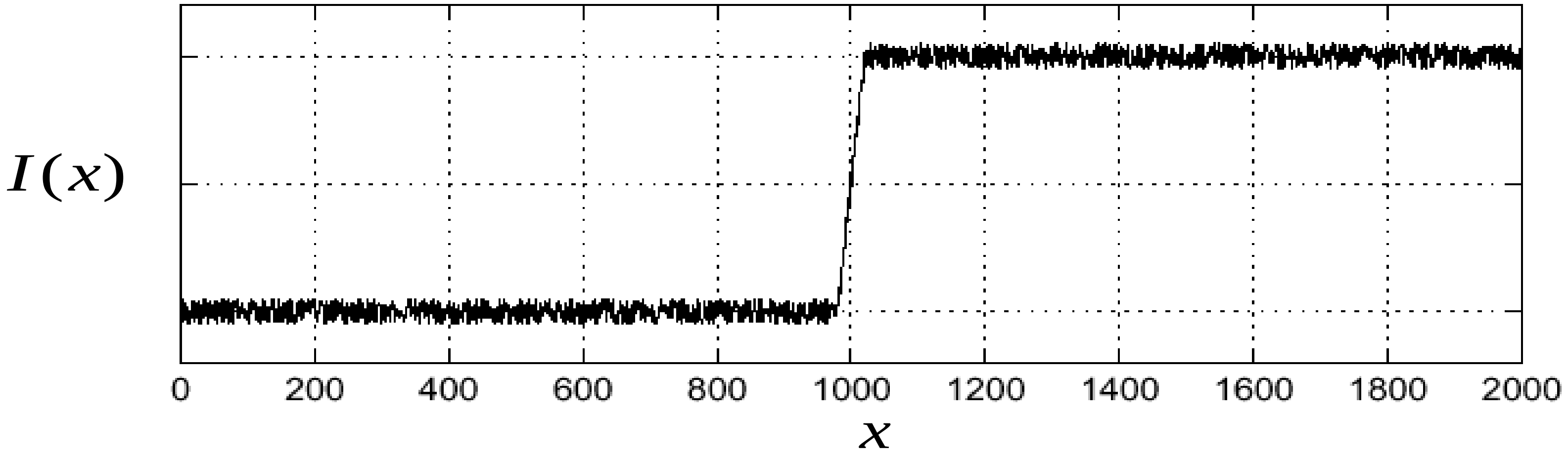
- Edges correspond to sharp changes of intensity

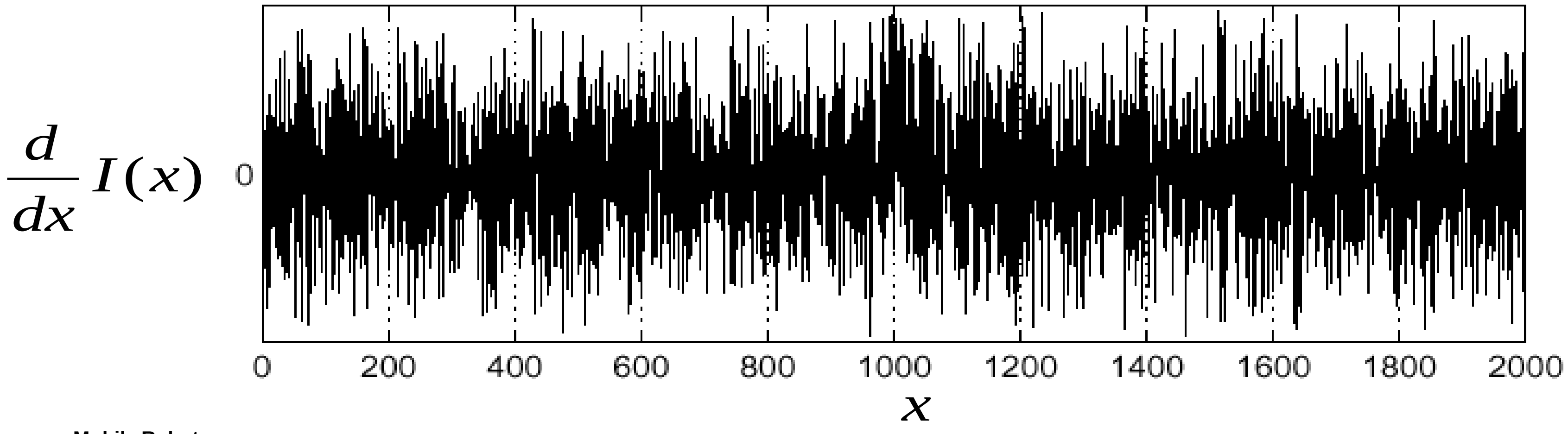
- Change is measured by 1st order derivative in 1D
- Big intensity change ➪ magnitude of derivative is large
- Or 2nd order derivative is zero.



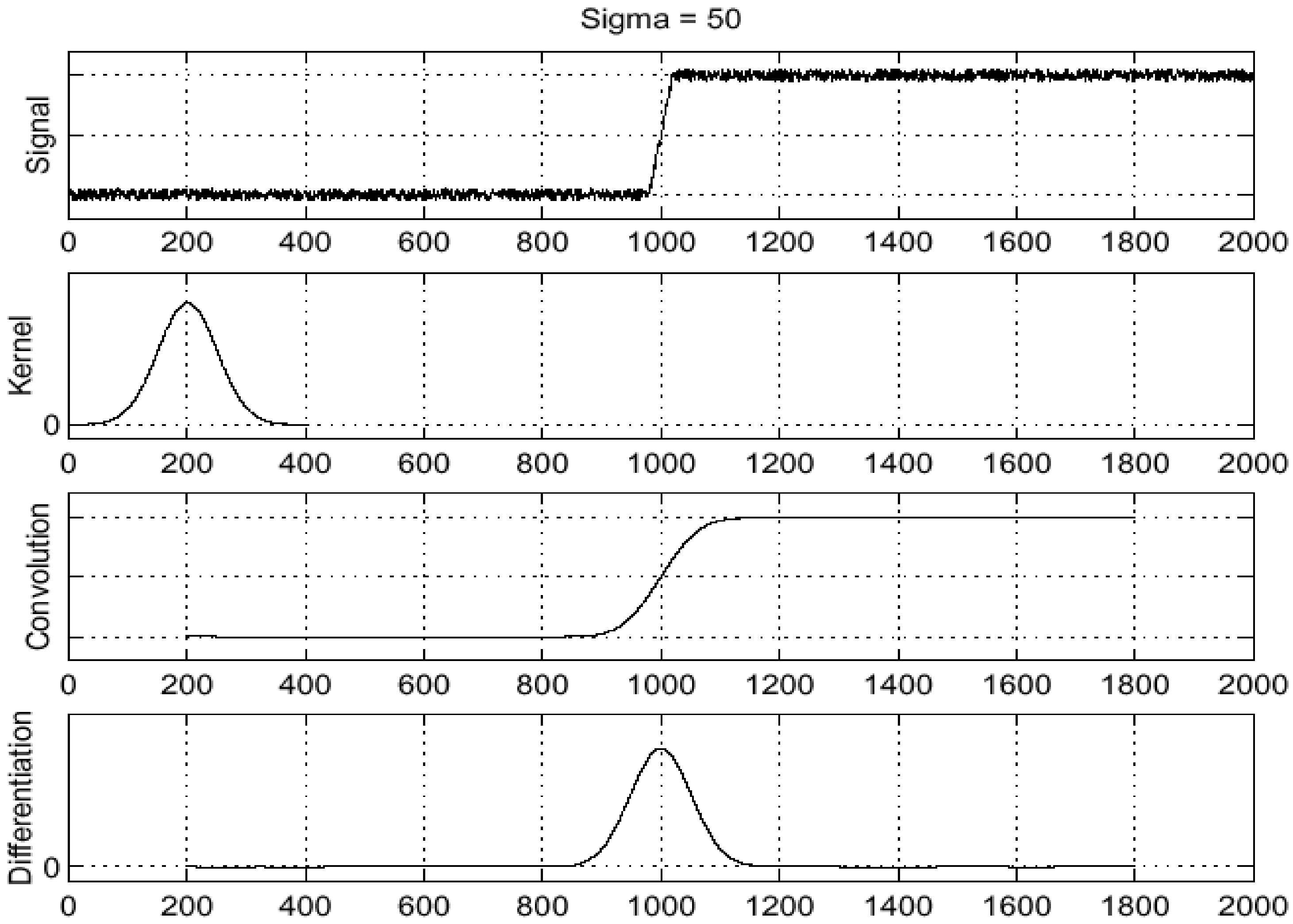
Edge Detection | 1D edge detection

- Image intensity shows an obvious change





Edge Detection | solution: smooth first



$$I(x)$$

$$G_\sigma(x)$$

$$s(x) = I(x) * G_\sigma(x)$$

$$s'(x) = \frac{d}{dx}\left(s(x)\right)$$

Edges occur at maxima/minima of $s'(x)$

Edge Detection | derivative theorem of convolution

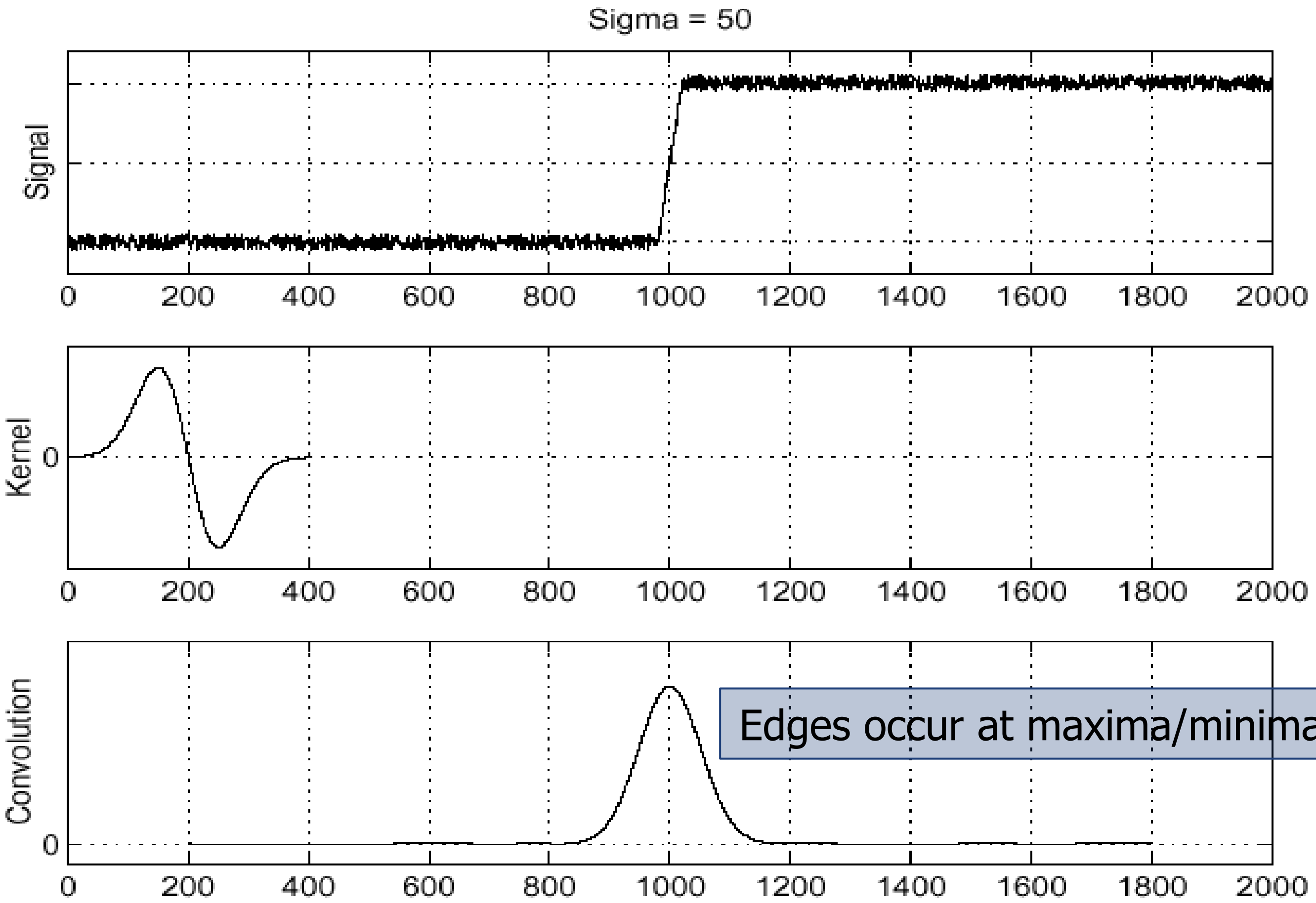
- $$s'(x) = \frac{d}{dx}\left(G_\sigma(x) * I(x)\right) = G'_\sigma(x) * I(x)$$

- This saves us one operation:

$$I(x)$$

$$G'_\sigma(x) = \frac{d}{dx} G_\sigma(x)$$

$$s'(x) = G'_\sigma(x) * I(x)$$



Edges occur at maxima/minima of $s'(x)$

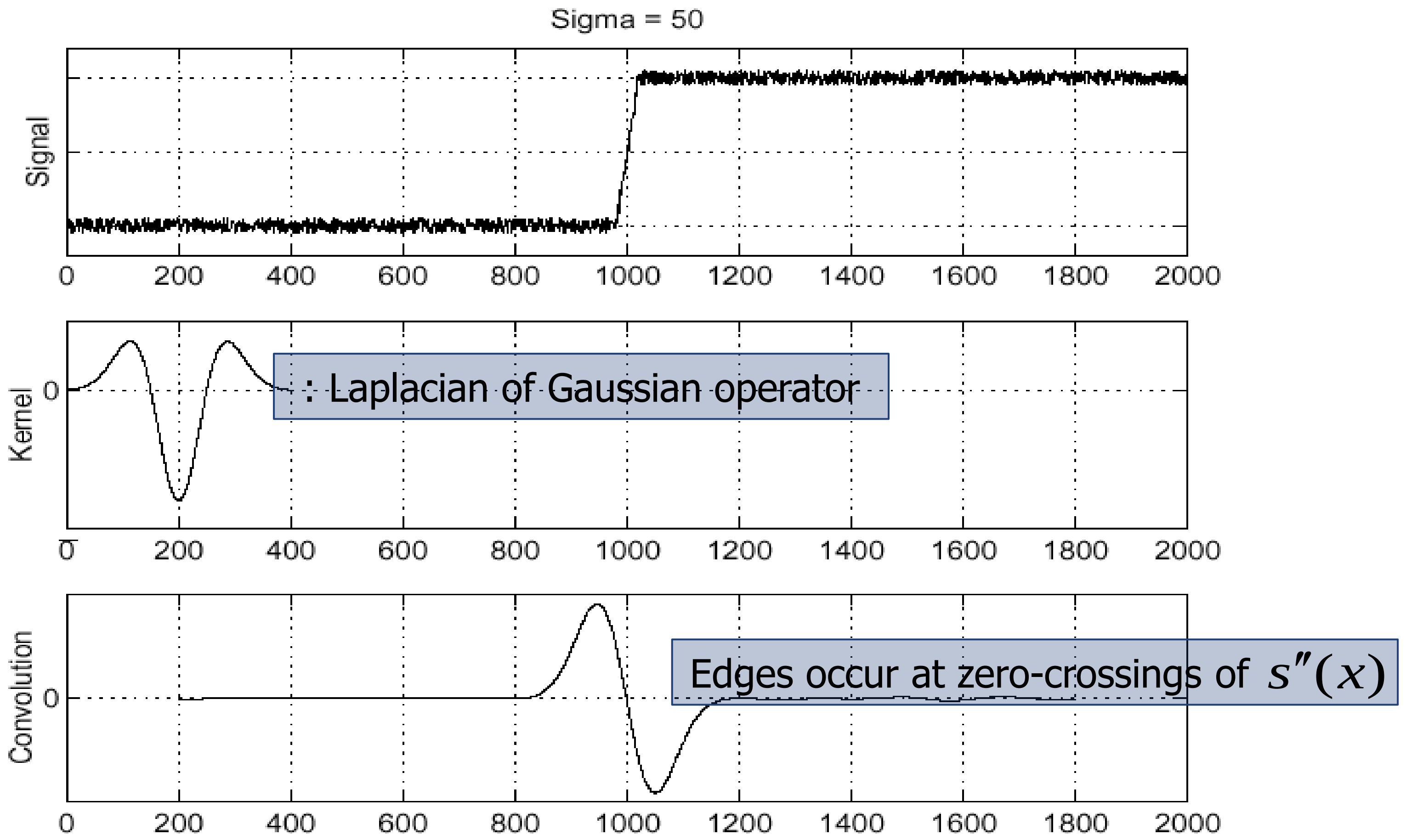
Edge Detection | zero-crossings

- Locations of Maxima/minima in $s'(x)$ are equivalent to zero-crossings in $s''(x)$

$$I(x)$$

$$G''_\sigma(x) = \frac{d^2}{dx^2} G_\sigma(x)$$

$$s''(x) = G''_\sigma(x) * I(x)$$



Edge Detection | 2D Edge detection

Usually use a separable filter such that:

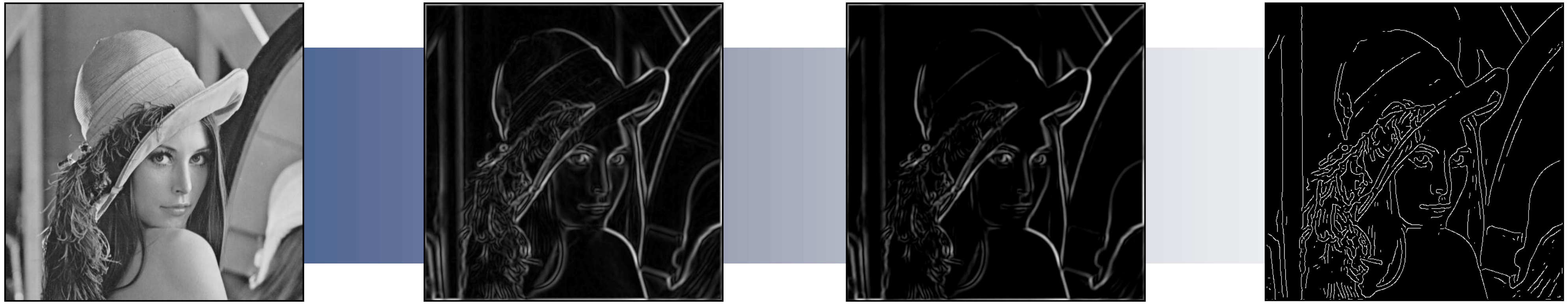
$$G_\sigma(x,y) = G_\sigma(x)G_\sigma(y)$$

- Find gradient of smoothed image in both directions

$$\nabla S = \nabla(G_\sigma * I) = \begin{bmatrix} \dfrac{\partial(G_\sigma * I)}{\partial x} \\ \dfrac{\partial(G_\sigma * I)}{\partial y} \end{bmatrix} = \begin{bmatrix} \dfrac{\partial G_\sigma}{\partial x} * I \\ \dfrac{\partial G_\sigma}{\partial y} * I \end{bmatrix} = \begin{bmatrix} G'_\sigma(x)G_\sigma(y) * I \\ G_\sigma(x)G'_\sigma(y) * I \end{bmatrix}$$

- Discard pixels with $|\nabla S|$ (i.e. edge strength), below a certain below a certain threshold
- **Non-maximal suppression**: identify local maxima of $|\nabla S|$ ⇨ detected edges

I : Original image ("Lenna") | $|\nabla S|$: Edge strength | Thresholding $|\nabla S|$ | Non-maximal suppression ⇨ **edge image**



Point Features | example: create a panorama

Generated using **AUTOSTITCH** (freeware)

Images from [Brown and Lowe, ICCV 2003]

How to create a panorama:

- detect corresponding points across images in order to align them

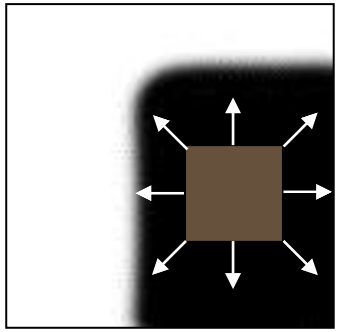
We need to:
- detect the same points independently in different images ⇨ repeatable detector
- identify the correct correspondence of each point ⇨ reliable & distinctive descriptor

- Point features used in robot navigation, object/place recognition, 3D reconstruction, …

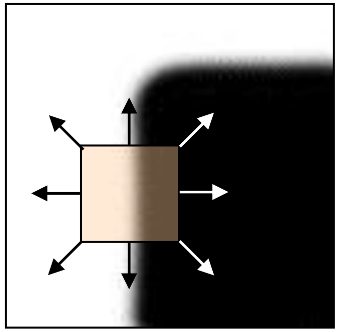
Point Features | harris corner detection [Harris and Stephens, Alvey Vision Conference 1988]

Teddy Bear by Polimerek, Wikimedia Commons.

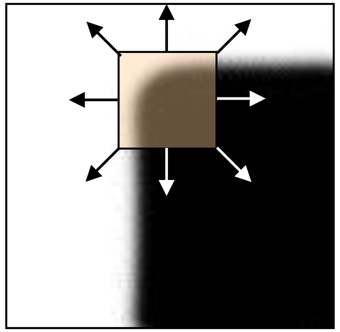
- How do we identify corners?
- Key: around a corner, the image gradient has **two or more** dominant directions
- Shifting a window in **any direction** should give a **large change** in intensity in at least 2 directions



"flat" region:
no intensity change



"edge":
no change along the edge direction



"corner":
significant change in at least 2 directions

Point Features | how do we implement this?

- Two image patches of size P one centered at (x, y) and one centered at $(x+\Delta x, y+\Delta y)$

  The Sum of Squared Differences between them is:

$$SSD(\Delta x, \Delta y) = \sum_{x,y \in P} \left(I(x,y) - I(x+\Delta x, y+\Delta y) \right)^2$$

- Let $I_x = \frac{\partial I(x,y)}{\partial x}$ and $I_y = \frac{\partial I(x,y)}{\partial y}$. Approximating with a 1st order Taylor expansion:

$$I(x+\Delta x, y+\Delta y) \approx I(x,y) + I_x(x,y)\Delta x + I_y(x,y)\Delta y$$

- This produces the approximation

$$SSD(\Delta x, \Delta y) \approx \sum_{x,y \in P} \left(I_x(x,y)\Delta x + I_y(x,y)\Delta y \right)^2$$

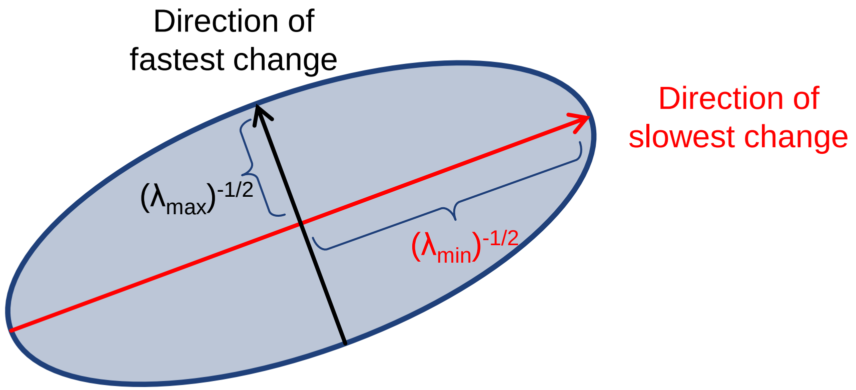
- Which can be written in a matrix form as $SSD(\Delta x, \Delta y) \approx \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} M \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$

Point Features | how do we implement this?

$$SSD(\Delta x, \Delta y) \approx [\Delta x \quad \Delta y] M \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

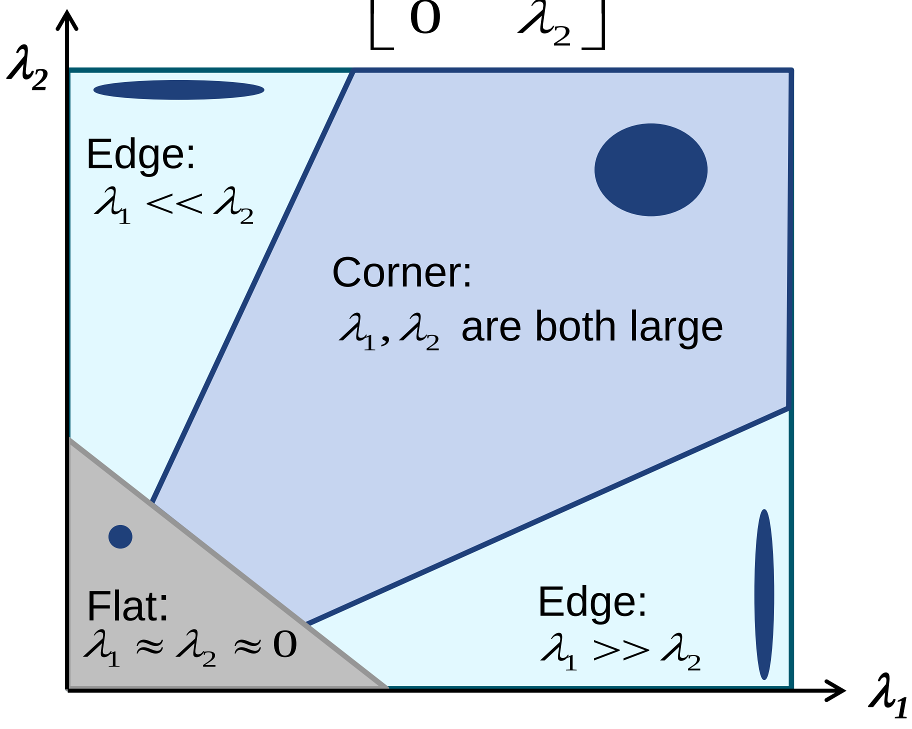
- ***M*** is the "second moment matrix" $M = \sum_{x,y \in P} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$
- Since ***M*** is symmetric ⇨ if λ_1 and λ_2: the eingenvalues of ***M*** ⇨ $M = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$
- The Harris detector analyses λ_1 and λ_2 to decide if we are in presence of a corner or not ⇨ i.e. looks for large intensity changes in at least 2 directions
- Visualize ***M*** as an **ellipse** with axis-lengths determined by λ_1 and λ_2, and orientation determined by ***R:***

$$[\Delta x \quad \Delta y] M \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix} = const$$



Point Features | corner response function

$$M = R^{-1}\begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$



Does the patch P describe a corner or not?

- **No structure:** $\lambda_1 \approx \lambda_2 \approx 0$
  SSD is almost constant in all directions, so it's a **flat** region
- **1D structure:** $\lambda_1 >> \lambda_2$ is large (or vice versa)
  SSD has a large variation only in one direction, which is the one perpendicular to the **edge**.
- **2D structure:** λ_1, λ_2 are both large
  SSD has large variations in all directions and then we are in presence of a **corner**.

Computation of λ_1 and λ_2 is expensive ⇨ use "**cornerness function**" instead:

$$C = \lambda_1\lambda_2 - \kappa(\lambda_1 + \lambda_2)^2 = det(M) - \kappa \cdot trace^2(M)$$

k= between 0.04 and 0.15

- Last step of Harris corner detector: extract local minima of the cornerness function

Point Features | harris corner properties

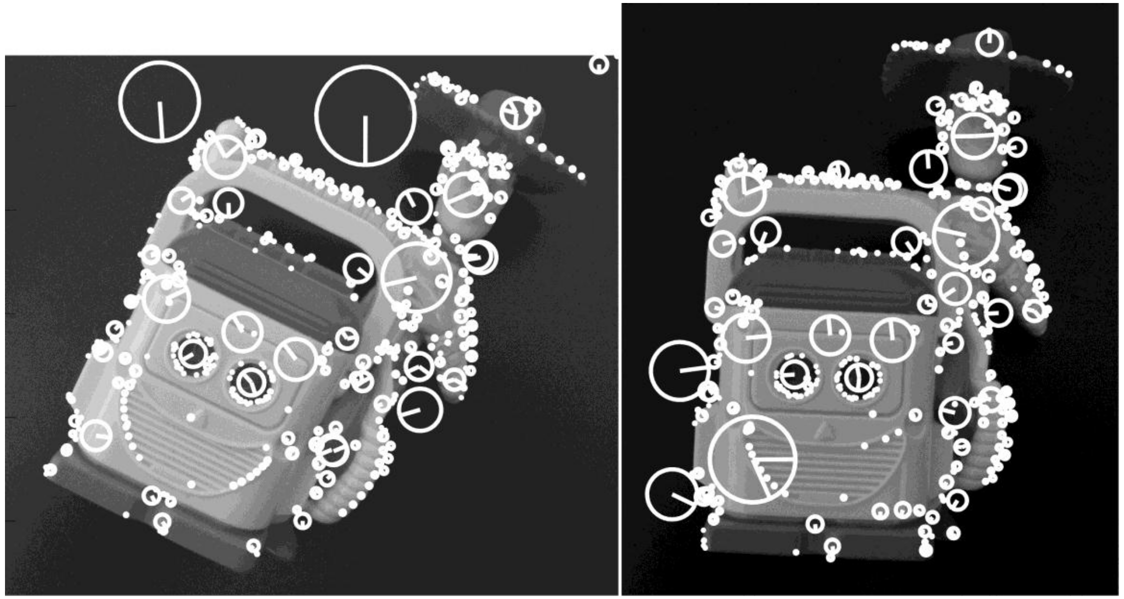
- Harris detector: probably the most widely used & known corner detector
- The detection is invariant to
  - Rotation
  - Linear intensity changes
  - **note:** to make the matching invariant to these we need a suitable descriptor and matching criterion (e.g. SSD on patches is not rotation- or affine- invariant)
- The detection is NOT invariant to
  - Scale changes
- Geometric affine changes: an image transformation which distorts the neighborhood of the corner, can distort its '*cornerness*' response

Point Features | SIFT features [Lowe, IJCV 2004]

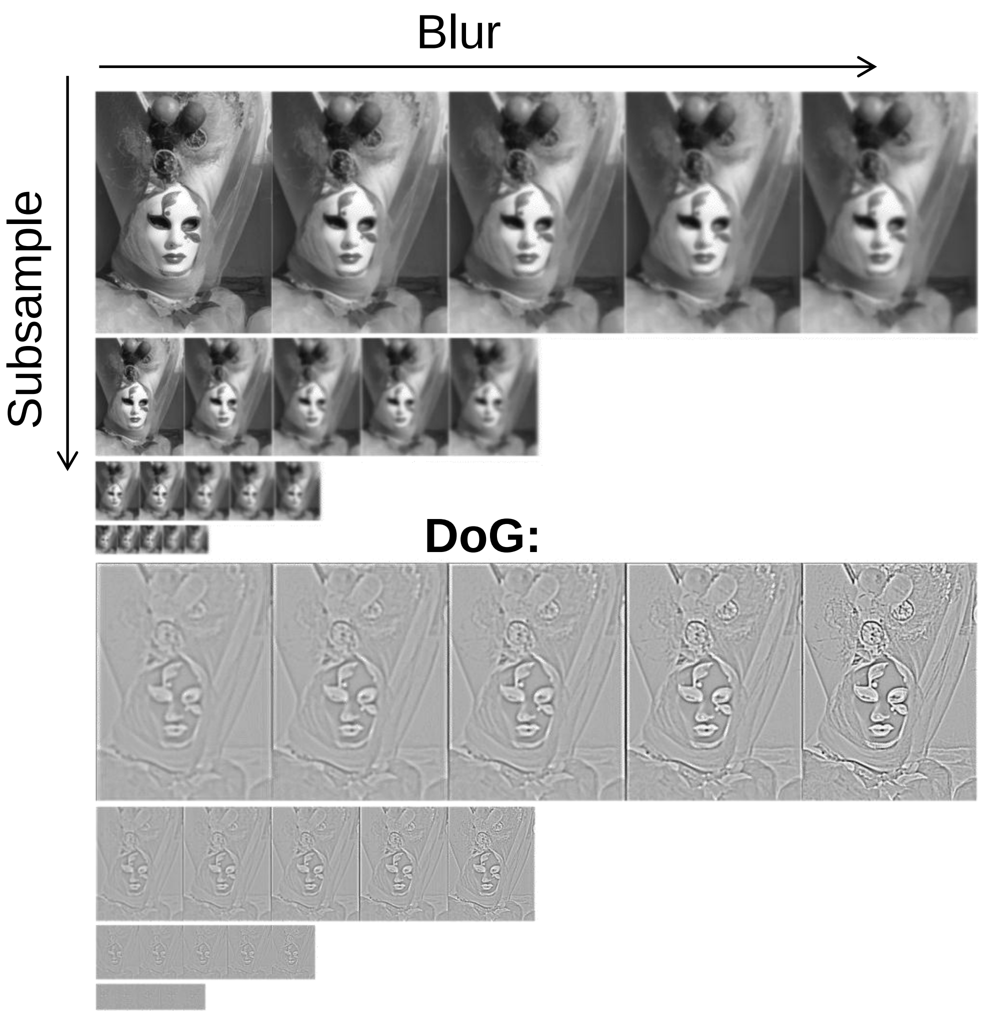
- SIFT: **S**cale **I**nvariant **F**eature **T**ransform
- SIFT features are reasonably **invariant** to changes in:
rotation, scaling, small changes in viewpoint, illumination
- Very powerful in capturing + describing **distinctive** structure, but also **computationally demanding**

Main SIFT stages:

1. Extract keypoints + scale
2. Assign keypoint orientation
3. Generate keypoint descriptor

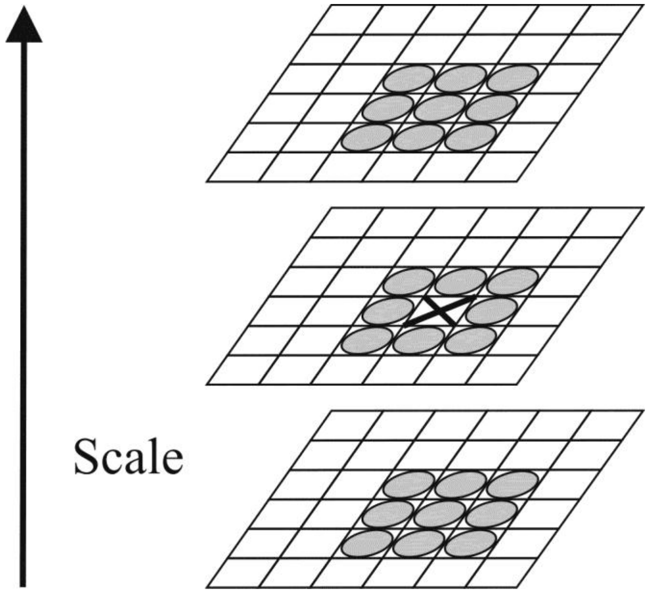


Point Features | SIFT detector (keypoint location + scale)



Keypoint detection

1. Scale-space pyramid: subsample and blur original image
2. Difference of Gaussians (DoG) pyramid: subtract successive smoothed images
3. Keypoints: local extrema in the DoG pyramid



Point Features | SIFT orientation and descriptor

Keypoint orientation (to achieve **rotation invariance**)

- Sample intensities around the keypoint
- Compute a histogram of orientations of intensity gradients
- **Keypoint orientation = histogram peak**

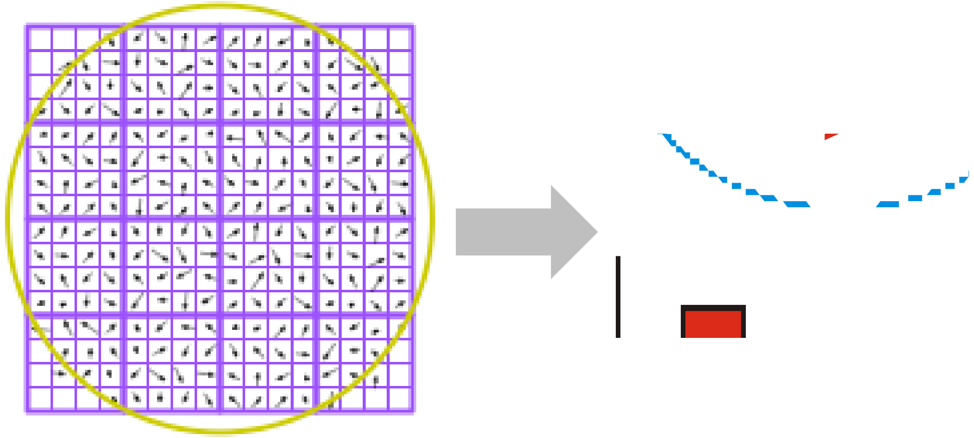
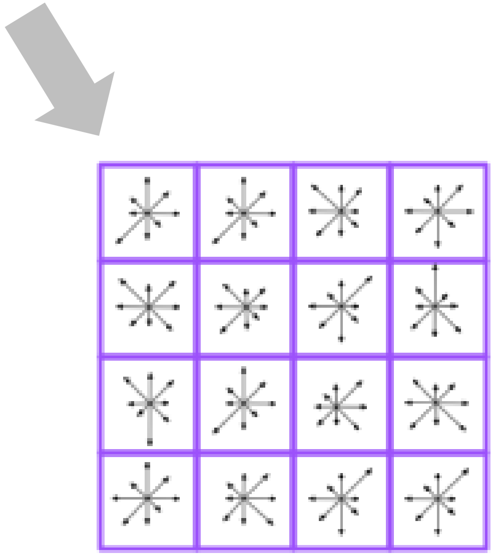


Image gradients

Keypoint descriptor

- SIFT descriptor: 128-long vector
- Describe all gradient orientations **relative to the Keypoint Orientation**
- Divide keypoint neighborhood in 4×4 regions &
compute orientation histograms along 8 directions
- SIFT descriptor: concatenation of all 4×4×8 (=128) values



Keypoint descriptor

Features for Robotics | FAST detector [Rosten et al., PAMI 2010]

- FAST: **F**eatures from **A**ccelerated **S**egment **T**est
- Studies intensity of pixels on circle around candidate pixel C
- Area centered at C is a FAST corner if a set of N contiguous pixels on a circle are significantly darker/brighter than C

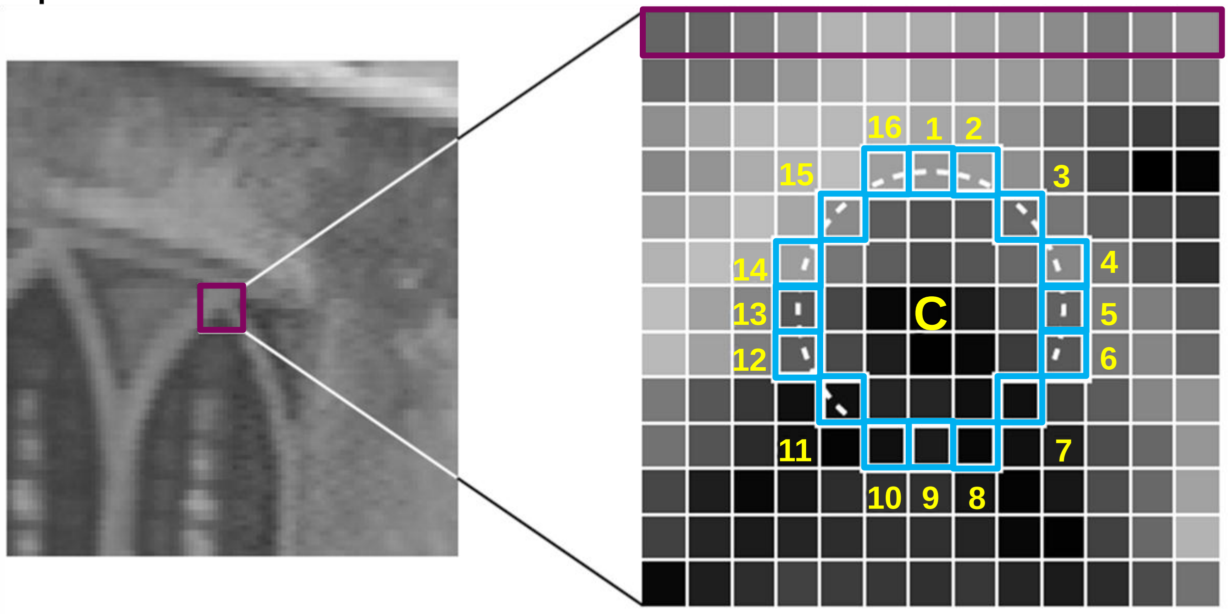


Image from [Rosten et al., PAMI 2010]

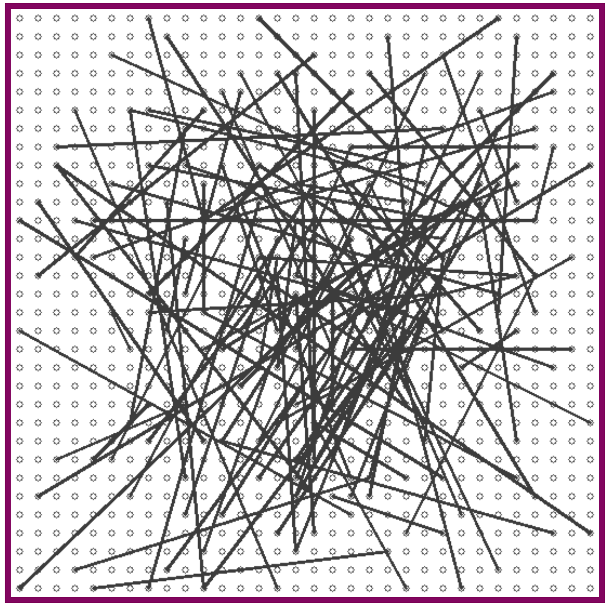
- Typical FAST mask: test for **12** contiguous pixels on a **16**-pixel circle
- **Very fast detector**

Features for Robotics | BRIEF descriptor [Calonder et. al, ECCV 2010]

- BRIEF: **B**inary **R**obust **I**ndependent **E**lementary **F**eatures
- Goal: high speed (in description and matching)

- BRIEF **Binary** descriptor =
  concatenation of simple intensity tests between random pixel pairs
- Pattern of random pixel pairs: pre-selected

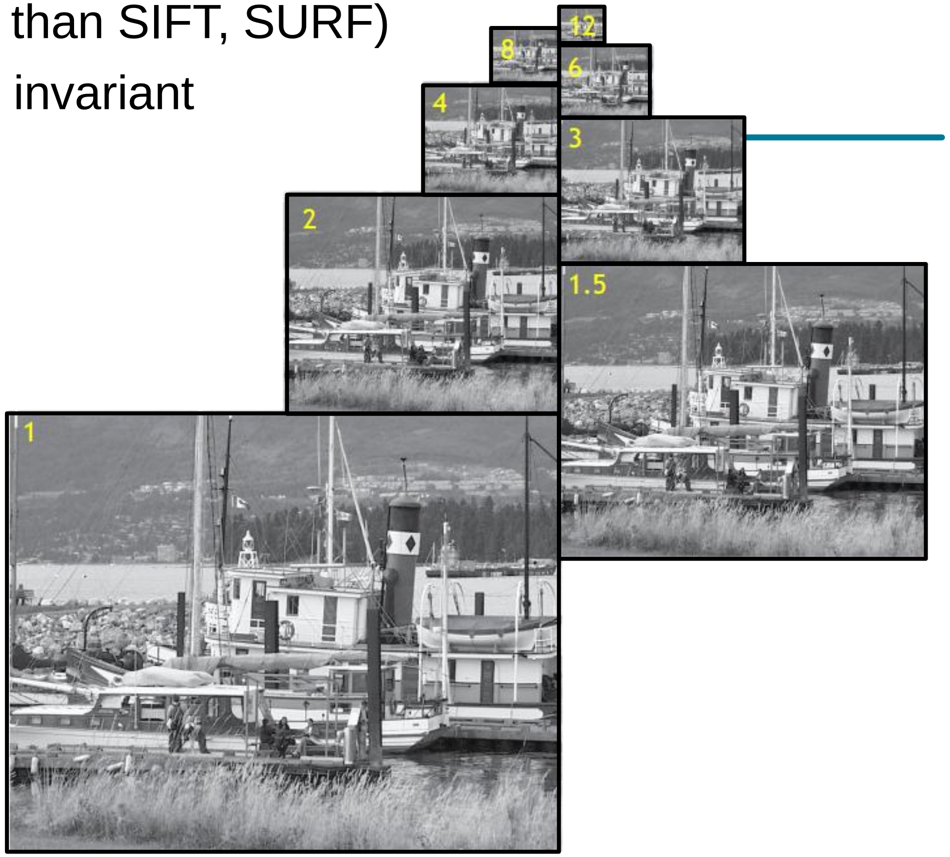
- Not scale/rotation invariant (extensions exist…)
- Allows **very fast** Hamming Distance matching:
  count the number of bits that are different in the descriptors matched

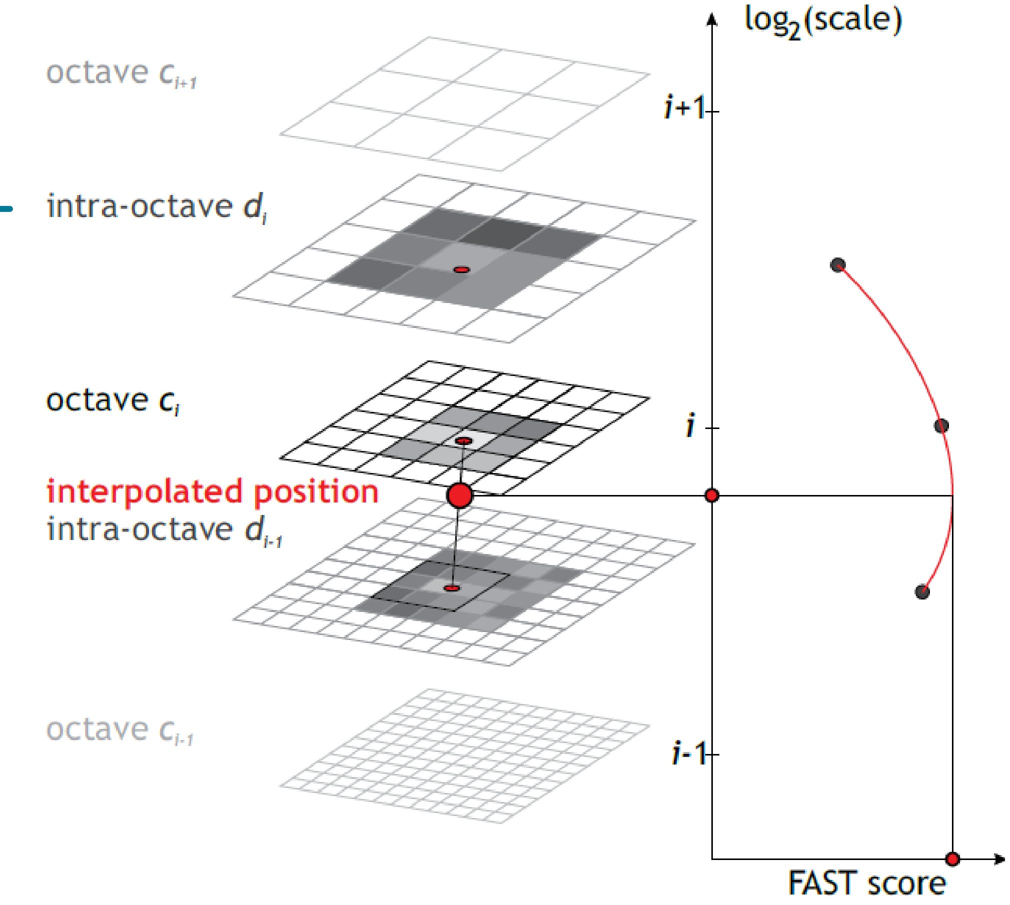


Pattern for intensity pair samples generated randomly

Features for Robotics | BRISK detector [Leutenegger et al., ICCV 2011]

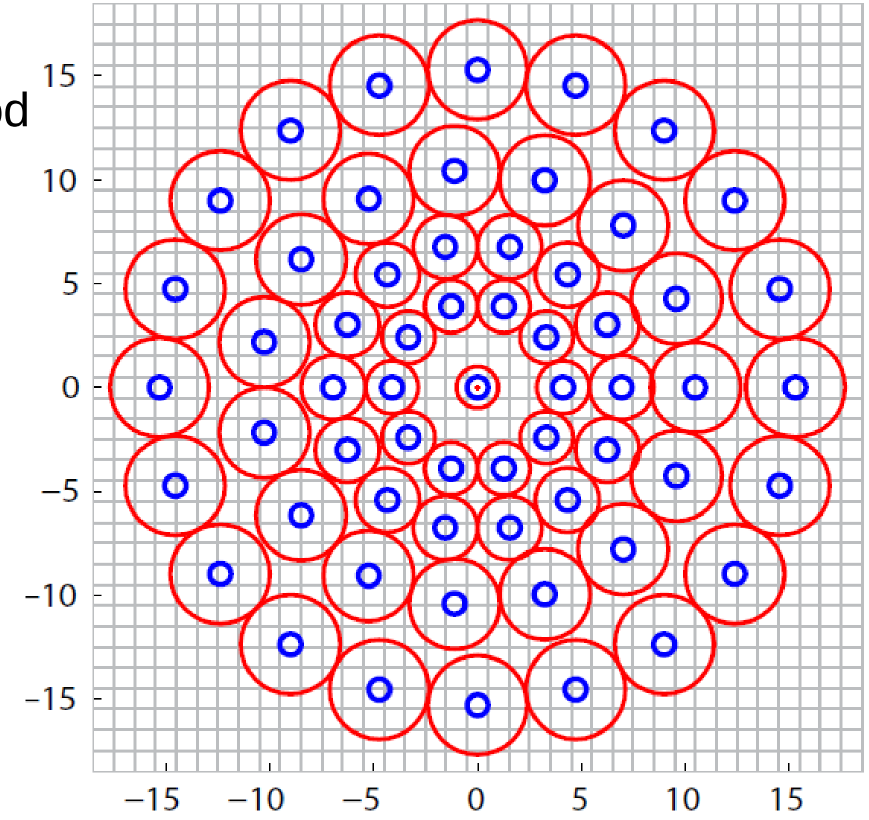
- BRISK: **B**inary **R**obust **I**nvariant **S**calable **K**eypoints
- Detect corners in scale-space based on FAST
- High-speed (faster than SIFT, SURF)
- Rotation and scale invariant





Features for Robotics | BRISK decriptor

- **Binary**, formed by pairwise intensity comparisons (like BRIEF)
- **Pattern** defines intensity comparisons in the keypoint neighborhood
- Red circles: size of the smoothing kernel applied
- Blue circles: smoothed pixel value used
- Compare short- and long-distance pairs for orientation assignment & descriptor formation
- Detection and descriptor speed: ≈10 times faster than SURF (and even faster than SIFT)
- Slower than BRIEF, but scale- and rotation- invariant



BRISK sampling pattern

Features for Robotics | BRISK in action

Open-source code for FAST, BRIEF, BRISK and many more, available at the [OpenCV library]