Robot Vision: Features

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Outline

- The importance of feature matching
- Image similarity and viewpoint changes
- Challenges
- Properties of detectors and descriptors
- Detectors
  - What locations would be good
  - Point detectors (concept of Harris and FAST)
  - Blob detectors (DOG)

Image features

- The term “feature” or “image feature” is used with some variety of meaning.

- Set of properties, description of an image region (in this case including a specific location) or the whole image
- Strictly speaking the term “feature” only means a description, but any description needs a location. So the wider definition also means a location and region
- “Feature points” are the detected point locations in images that are used for image matching or geometric algorithms.
- Image features are a combination of the results of a detector method and a descriptor method.

The importance of feature matches

- Geometric algorithms need point correspondences i.e. image feature matches
- The quality of feature matches determines the outcome of geometric algorithms.
  - Location accuracy of feature matches
  - Correctness of feature matches (mis-matches)

- Image classification, image indexing, image search, image interpretation also need feature points and feature matches.

Image similarity and viewpoint changes

Image similarity and viewpoint changes






Two challenges

- How to select proper points (detectors)
- How to compute the similarity of image patches (descriptor)

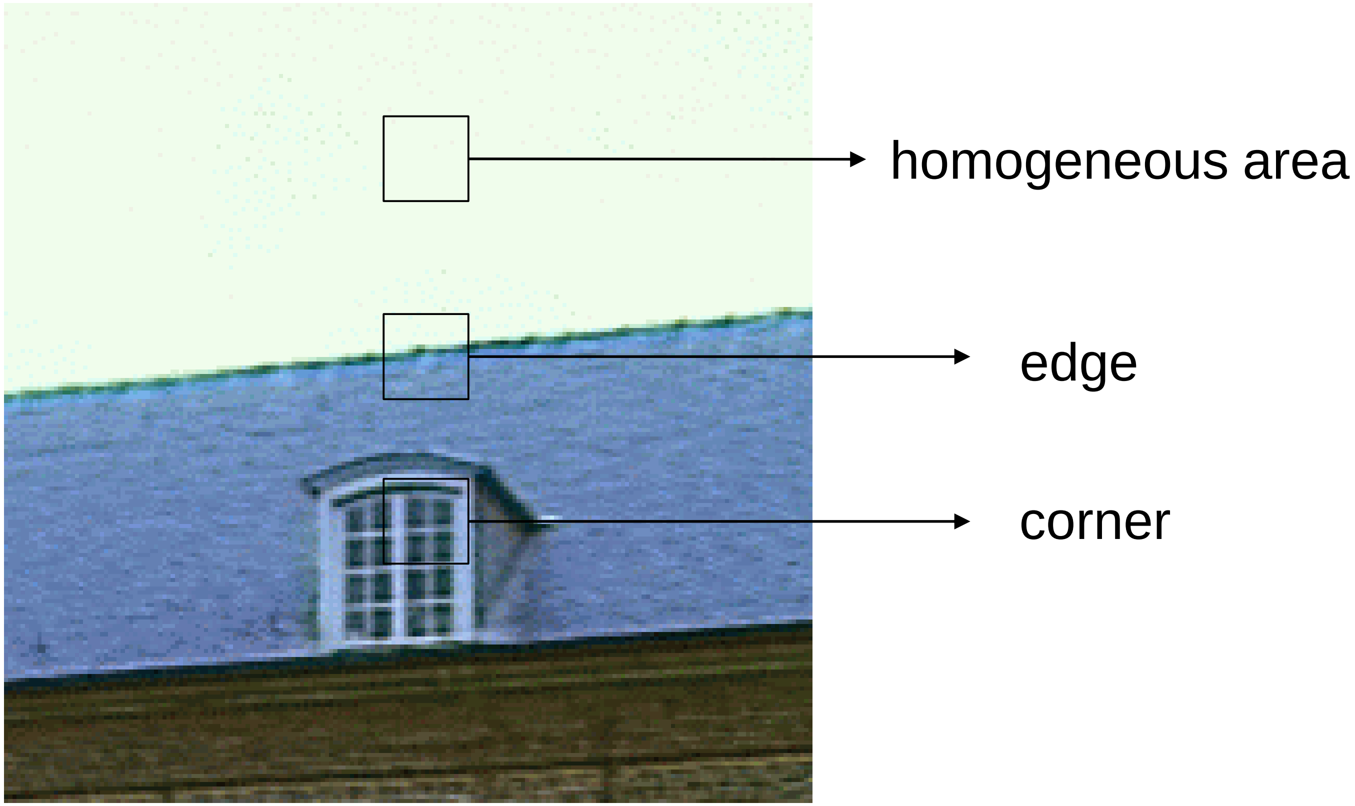
Properties of detectors

- Accurate localization
- Useful locations
- High repeatability detection

Properties of descriptors

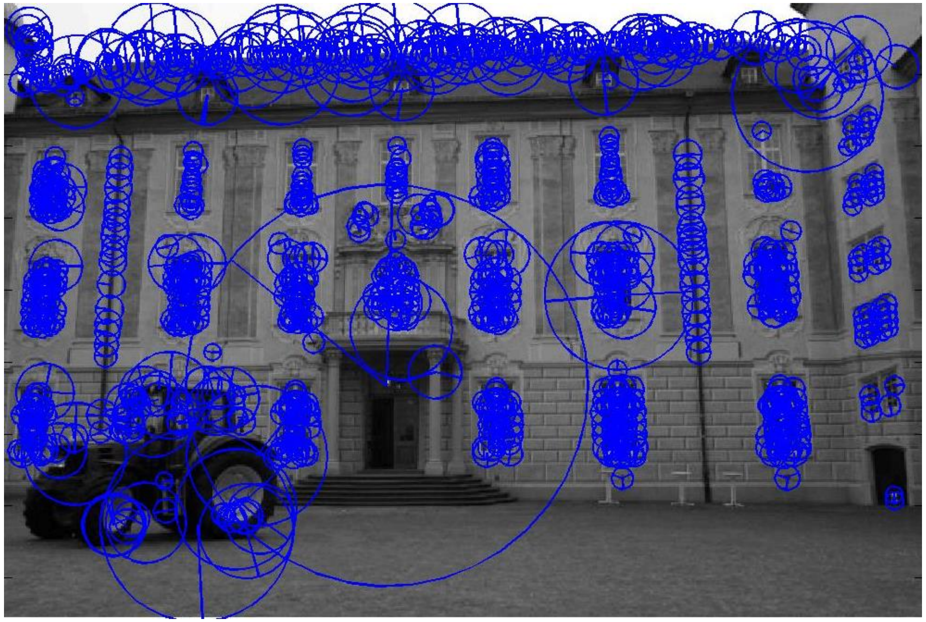
- Discriminative
- Descriptive
- Compact descriptions
- Invariance to image changes (brightness, rotation)

Detectors: Which locations would be good



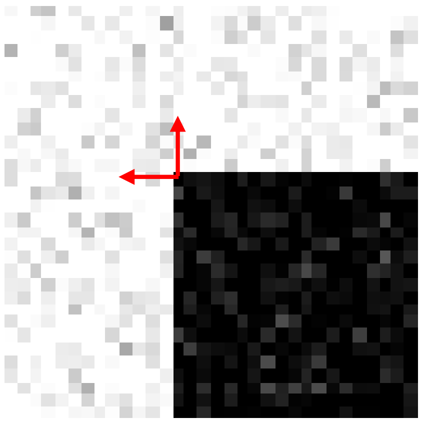
Detectors

- Point detectors
  - Harris corners
  - FAST corners
- Blob detectors
  - DOG points



Harris corners

- Looks for locations in an image where the SSD changes strongly

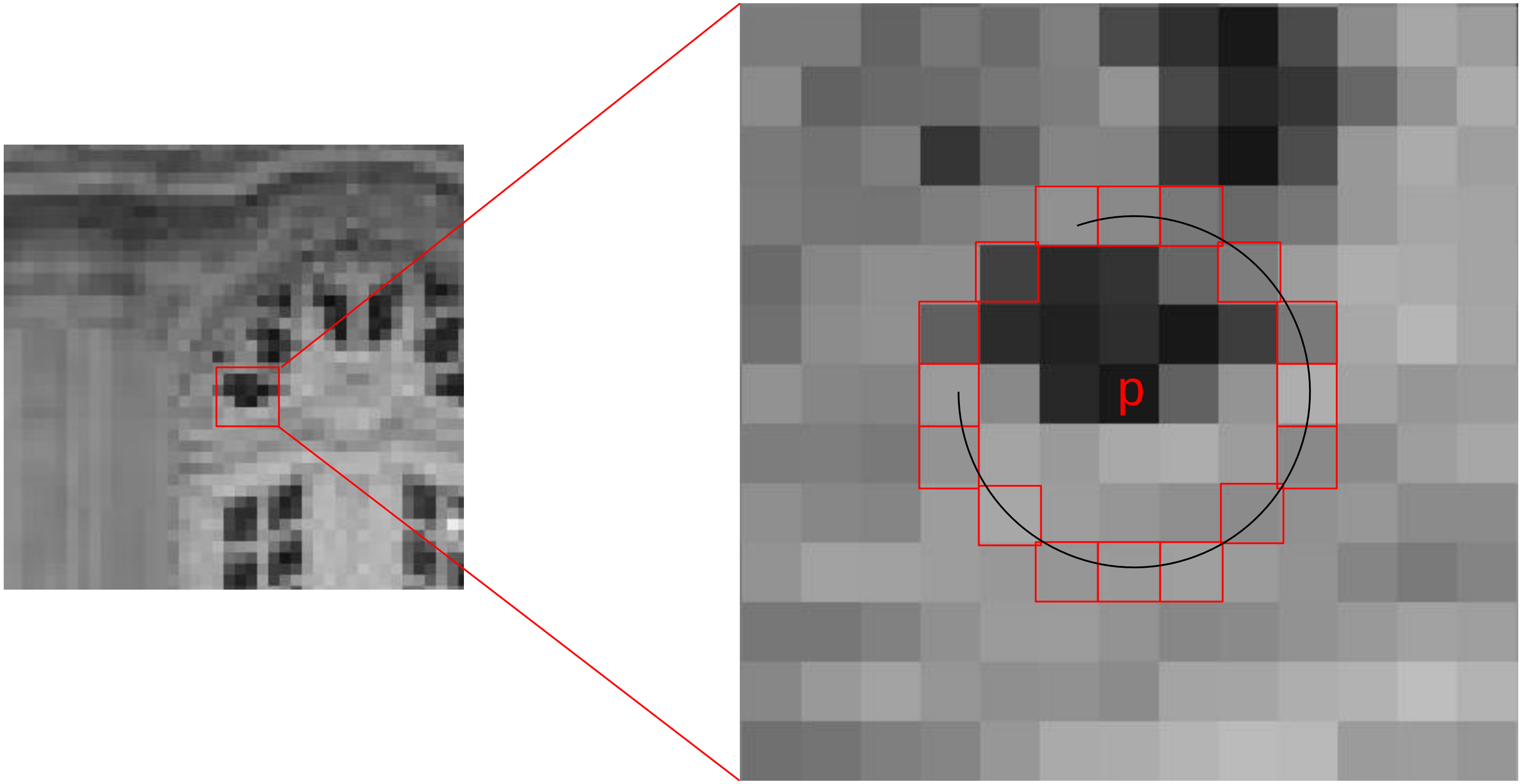


$$f(x,y) = \sum_{(x_k,y_k)\in W} \left(I(x_k,y_k) - I(x_k+\Delta x, y_k+\Delta y)\right)^2$$

$$f(x,y) \approx \begin{pmatrix} \Delta x & \Delta y \end{pmatrix} M \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix}$$

$$M = \sum_{(x,y)\in W} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = \begin{bmatrix} \sum_{(x,y)\in W} I_x^2 & \sum_{(x,y)\in W} I_x I_y \\ \sum_{(x,y)\in W} I_x I_y & \sum_{(x,y)\in W} I_y^2 \end{bmatrix}$$

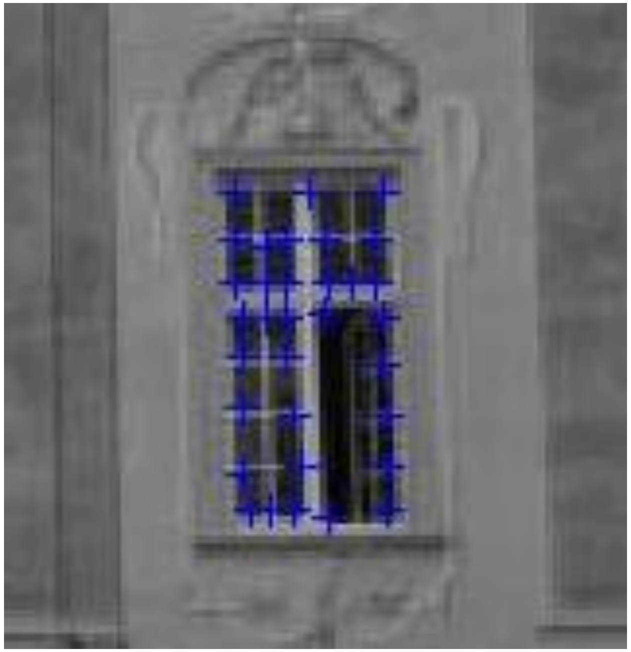
FAST corners

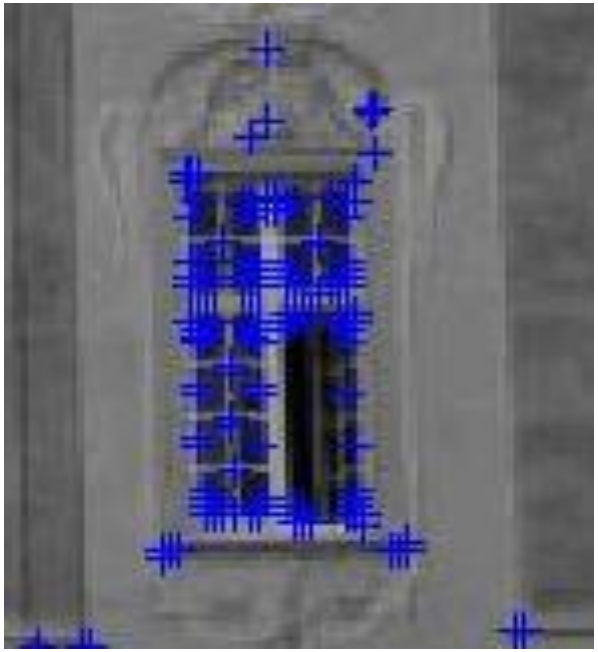


- Count the number N of contiguos pixels around a center pixel p that are brighter than the center pixel. If N >= than some threshold this point is a feature location.

Harris corners vs. Fast corners

Harris corners vs. Fast corners



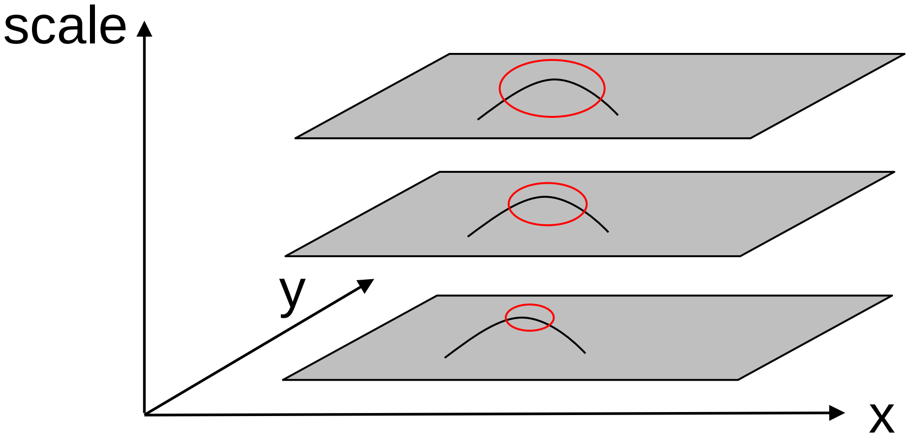


- Slower to compute
- Better control of number of detections with threshold

- Fast to compute
- Many detections
- Many corners next to each other

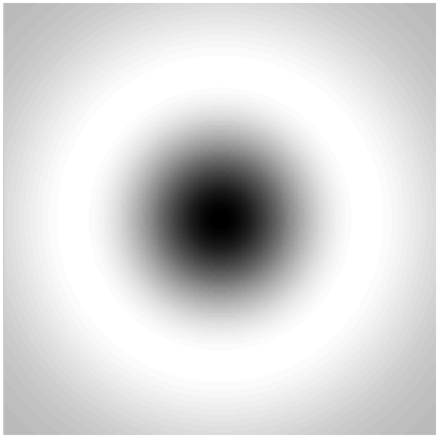
Difference of Gaussian (DOG) points

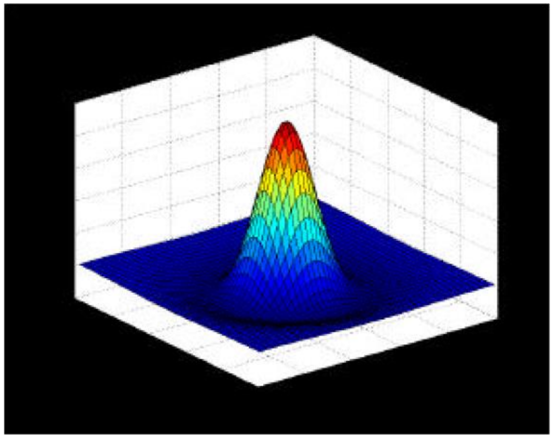
- Is a Blob detector, detections are not necessarily on image corners
- Is a scale invariant detector, high repeatability even for images of different scales (image resolution)
- Processes images at different resolutions (scales) and then selects a feature location in x,y **and** a specific scale s which has a high value for the sum of the squares of the second derivatives in all directions (Laplacian)



DOG filter mask

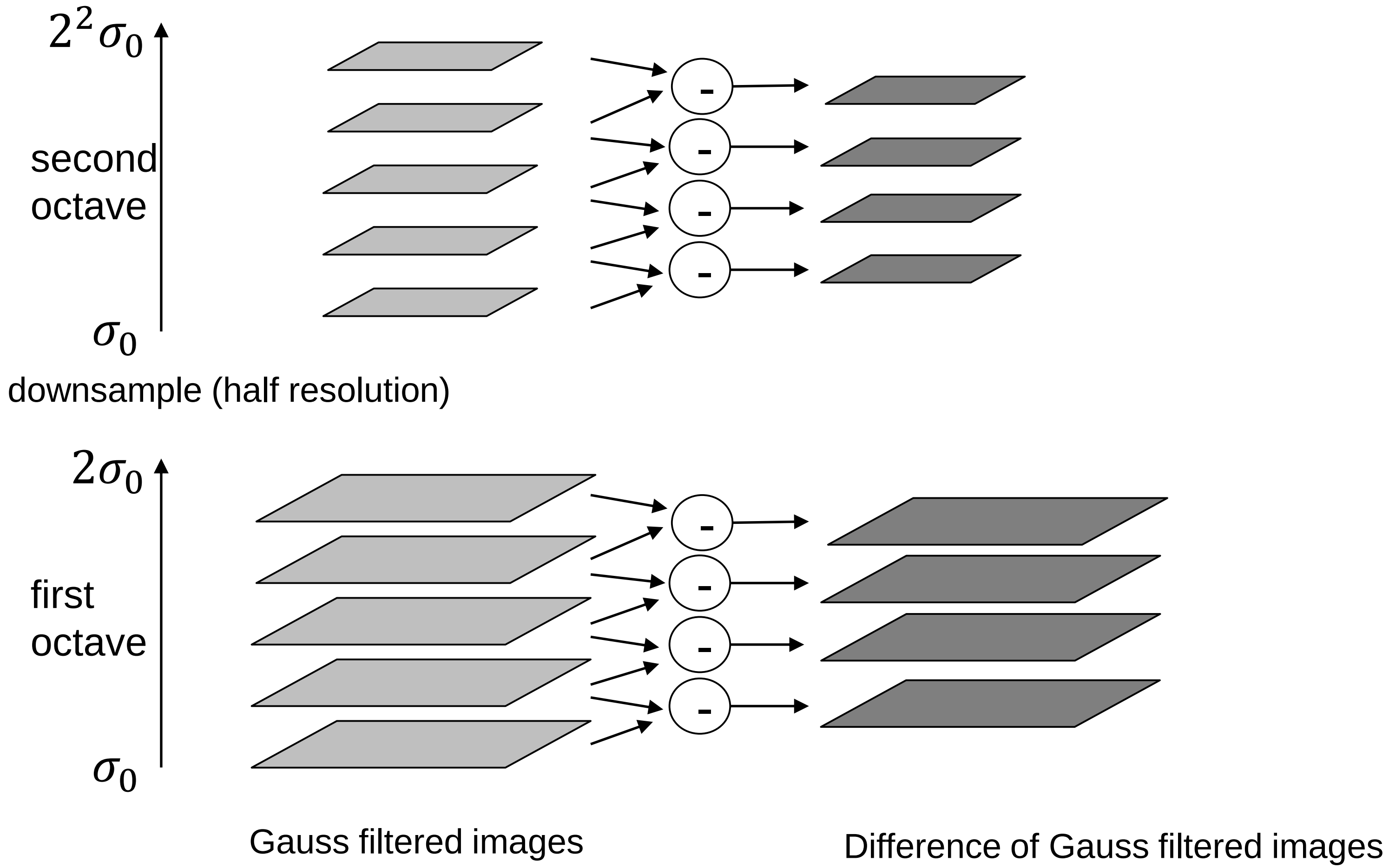
- Filter mask is composed of the subtraction of two Gaussian filter masks
- Is an approximation of the Laplace operator (Laplacian of Gaussian, LOG) which is a blob detector





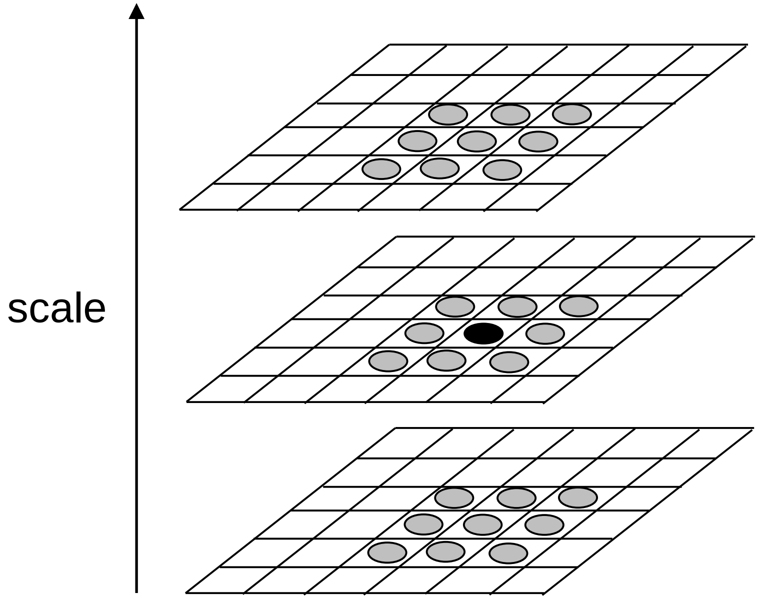
$$\mathrm{DOG}(x,y) = \frac{1}{k} e^{-\frac{x^2+y^2}{(k\sigma)^2}} - e^{-\frac{x^2+y^2}{\sigma^2}}$$

Computation of DOG's measure



Selection of extrema

- Extrema are selected in 3D (x,y,scale)
- Center pixel needs to be larger or smaller than it‘s 26 neighbors



DOG feature points