Feature Detection

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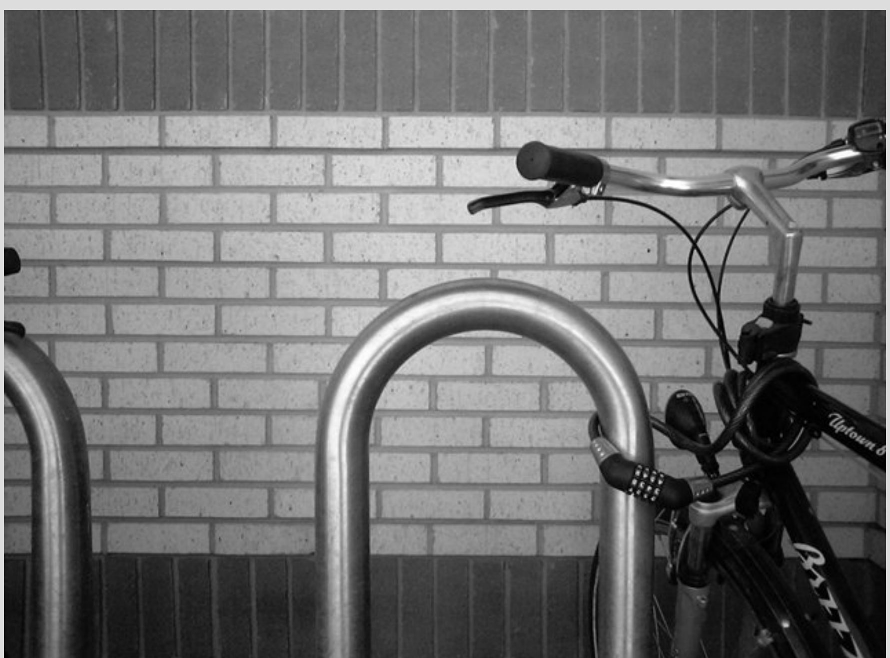
Introduction

- image features are distinct image parts
- feature detection often is first operation to define image parts to process later
- finding corresponding features in pictures necessary for object recognition
- Multi-Image-Panoramas need to be “stitched” together at according image features
- the description of a feature is as important as the extraction

Types of image features

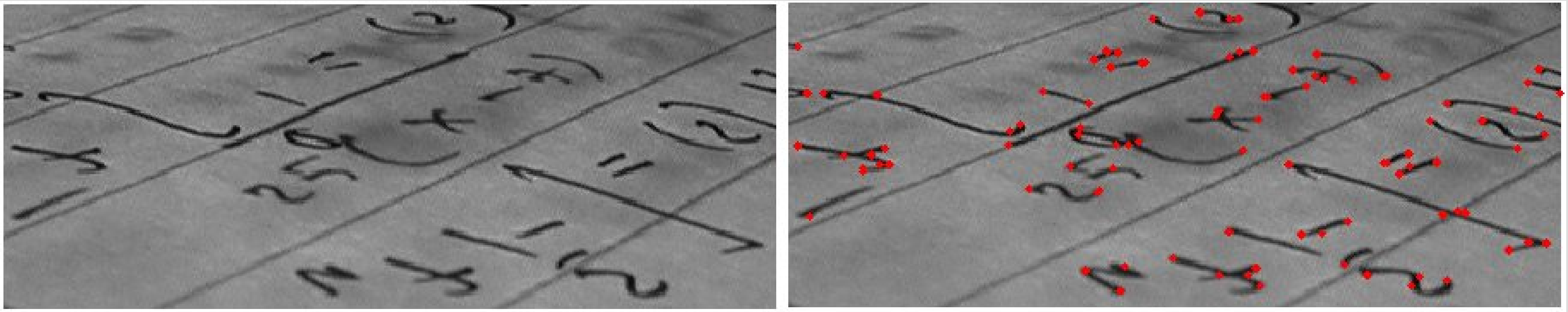
Edges

- sharp changes in brightness
- most algorithms use the first derivative of the intensity
- different methods: (one or two thresholds etc.)



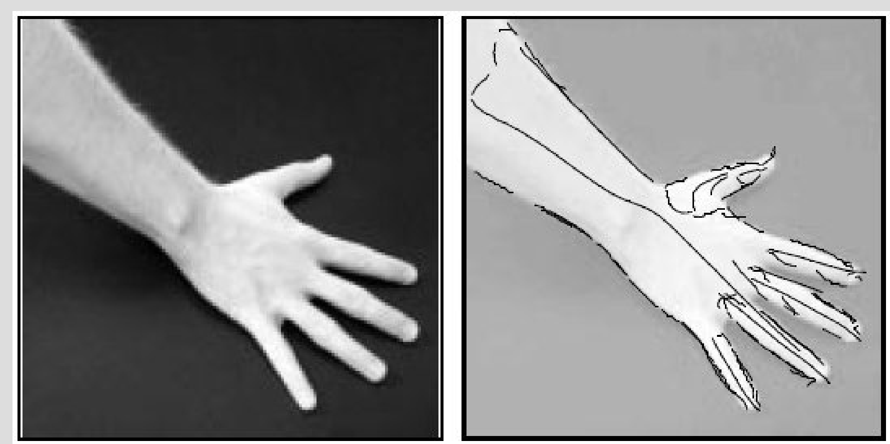
Types of image features
Corners

- point with two dominant and different edge directions in its neighbourhood
- Moravec Detector: similarity between patch around pixel and overlapping patches in the neighbourhood is measured
- low similarity in all directions indicates corner



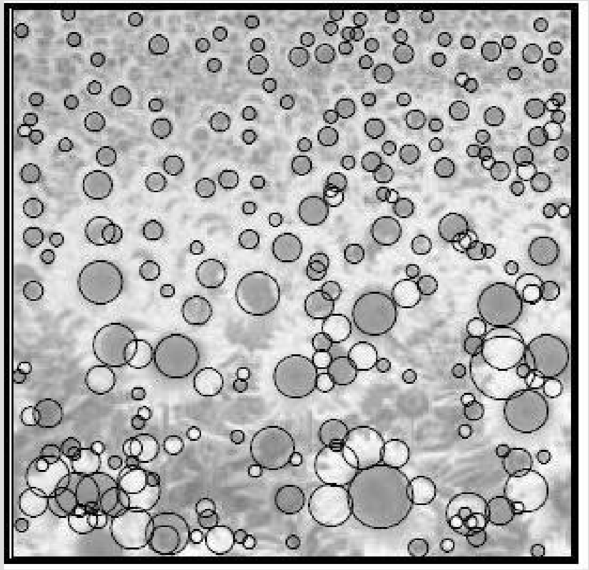
Types of image features
Ridges

- curves which points are local maxima or minima in at least one dimension
- quality depends highly on the scale
- used to detect roads in aerial images or veins in 3D magnetic resonance images



Types of image features
Blobs

- points or regions brighter or darker than the surrounding
- SIFT uses a method for blob detection



SIFT

- SIFT = Scale-invariant feature transform
- first published in 1999 by David Lowe
- Method to extract and describe distinctive image features
- feature descriptors are invariant to image scale and rotation
- robust against change of viewpoint, noise and illumination change

Scale-space extrema detection

- blob detection is very sensitive to scale
- image is represented by a family of smoothed images known as scale space
- Scale Space of an Image I(x,y) is a function $L(x,y,\sigma)$

$$L(x,y,\sigma)=G(x,y,\sigma)*I(x,y) \text{ where}$$

$$G(x,y,\sigma)=\frac{1}{2\cdot\pi\cdot\sigma^2}\cdot e^{-(x^2+y^2)/(2\cdot\sigma^2)}$$

Scale-space extrema detection

scale space example:

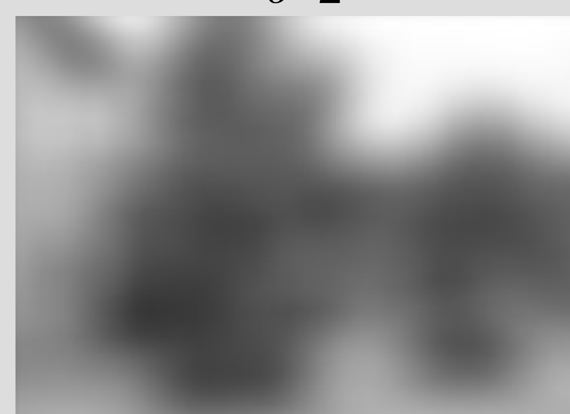
original image

σ=1

σ=2

σ=4

σ=8

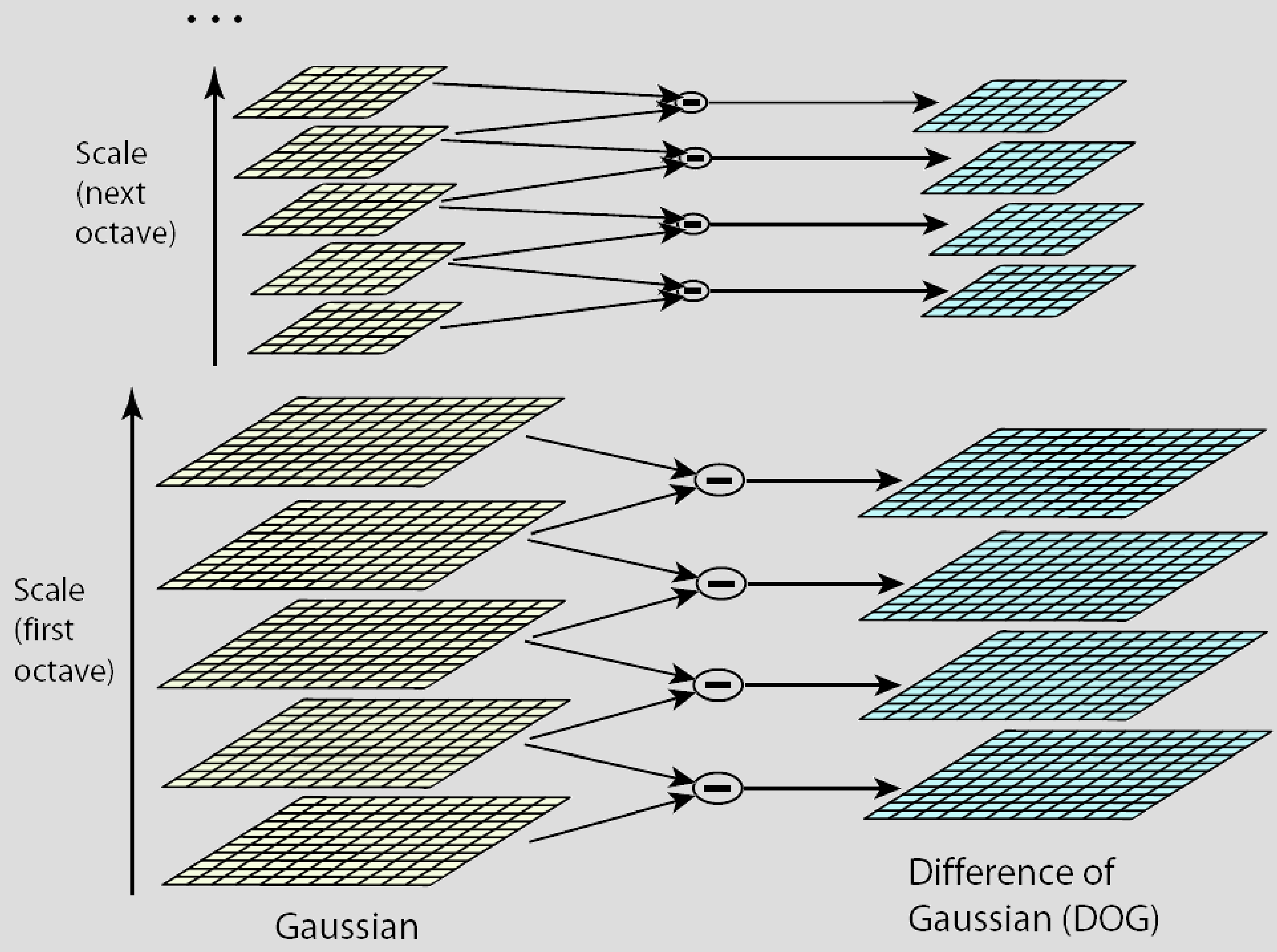


σ=16

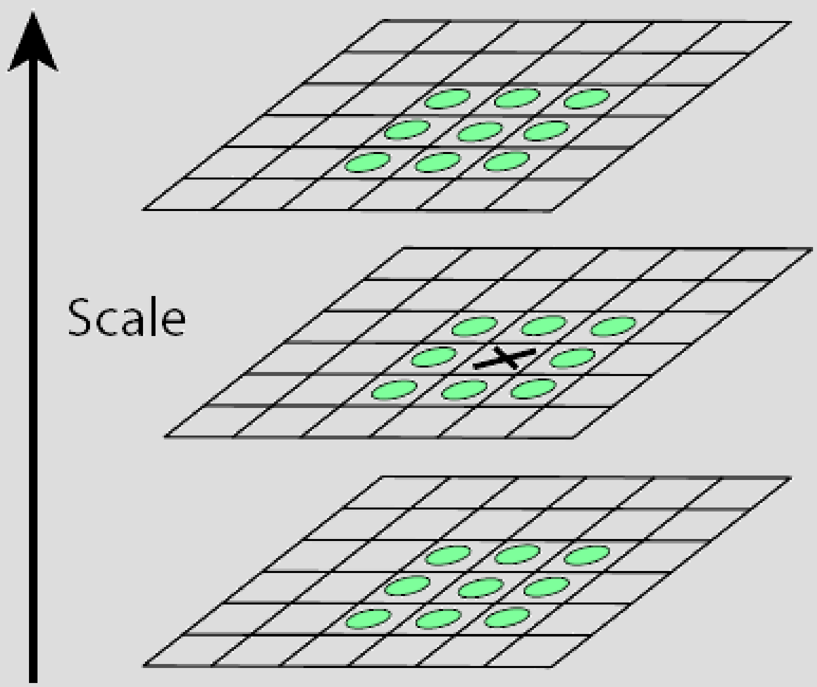
Scale-space extrema detection

- blobs are minima or maxima of the scale normalized Laplacian of Gaussian: $\sigma^2(L_{xx}+L_{yy})$
- this function is almost identical to the difference of Gaussian:
- $G(x,y,k\sigma)-G(x,y,\sigma) \approx (k-1)\sigma^2(L_{xx}+L_{yy})$, where (k-1) is constant and can be omitted

Scale-space extrema detection



Scale-space extrema detection



- each pixel in a DoG image is compared to its neighbours in its own and adjacent scales
- a pixel is only selected if it's darker or brighter than all his neighbours

Keypoint localization

- not all extrema in scale space are usefull keypoints
- especially points with low contrast are very sensitive to noise and shouldn't be used
- DoG is very sensitive to edges even if the point's location along the edge is poorly localized

Keypoint localization

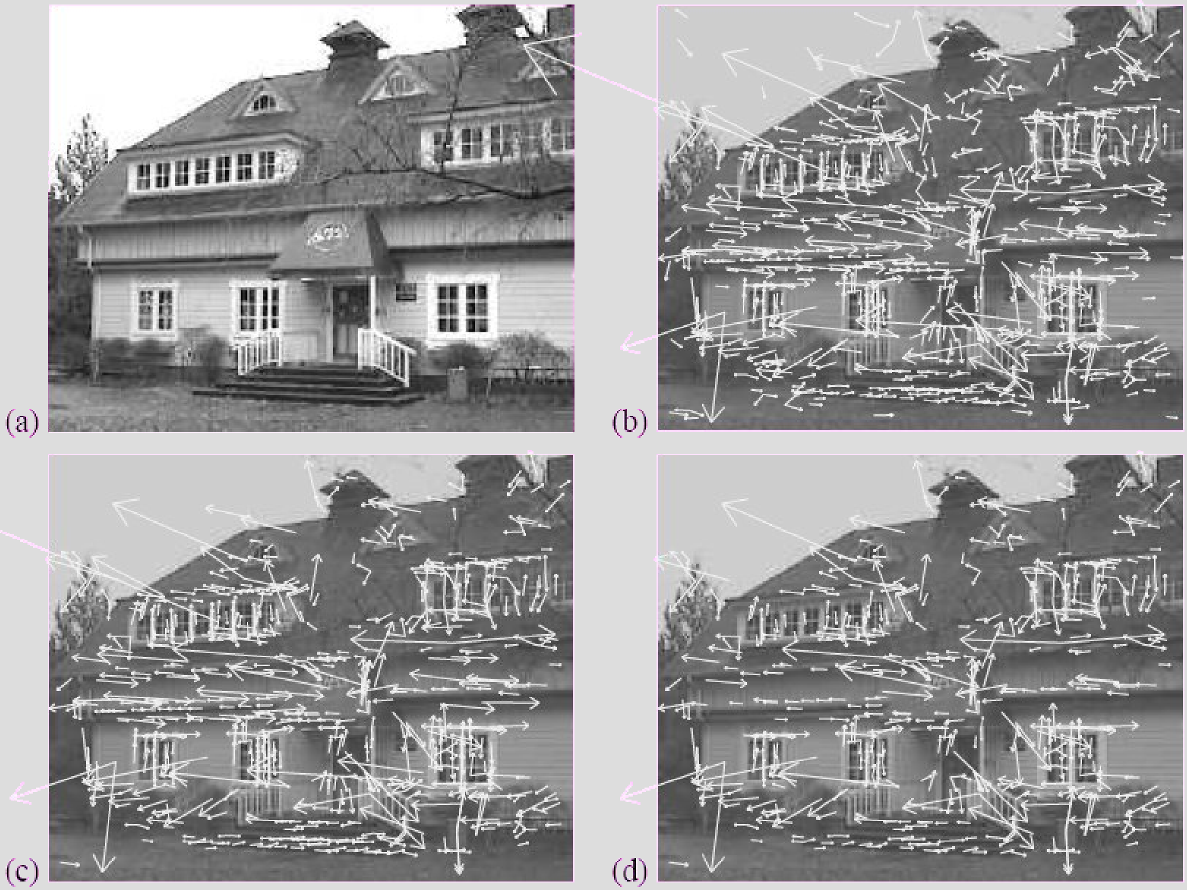
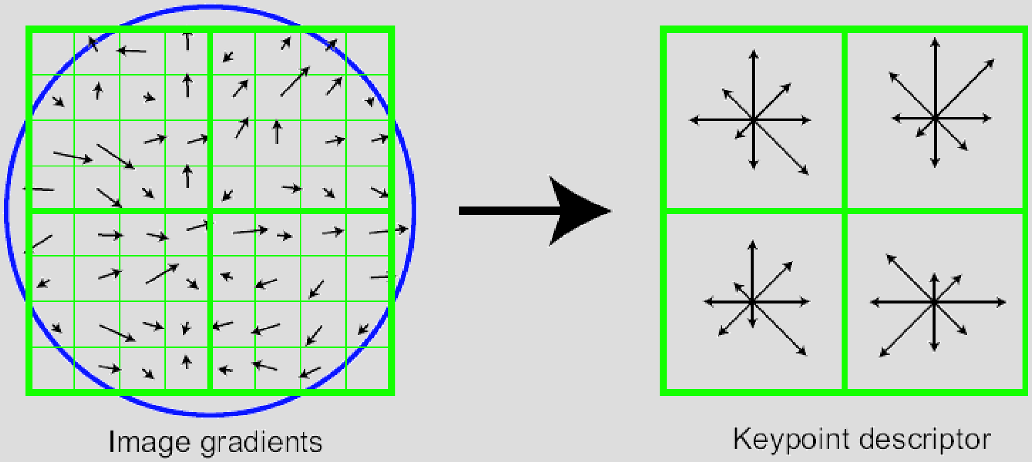


Figure 5: This fi gure shows the stages of keypoint selection. (a) The 233x189 pixel original image. (b) The initial 832 keypoints locations at maxima and minima of the difference-of-Gaussian function. Keypoints are displayed as vectors indicating scale, orientation, and location. (c) After applying a threshold on minimum contrast, 729 keypoints remain. (d) The fi nal 536 keypoints that remain following an additional threshold on ratio of principal curvatures.

Orientation assignment

- to achieve invariance to image rotation each keypoint gets one or more orientations assigned
- a orientation histogram with 36 bins is formed from the gradient orientations of pixels around the keypoint
- each sample is weighted by the magnitude of its gradient and a Gaussian window
- the maximum of this histogram and any other local peak within 80% of it is used to generate a keypoint

Keypoint descriptor



- neighbourhood is divided into subregions
- coordinates and orientations are rotated relative to the keypoint orientation
- orientation histograms with 8 bins are computed for each one

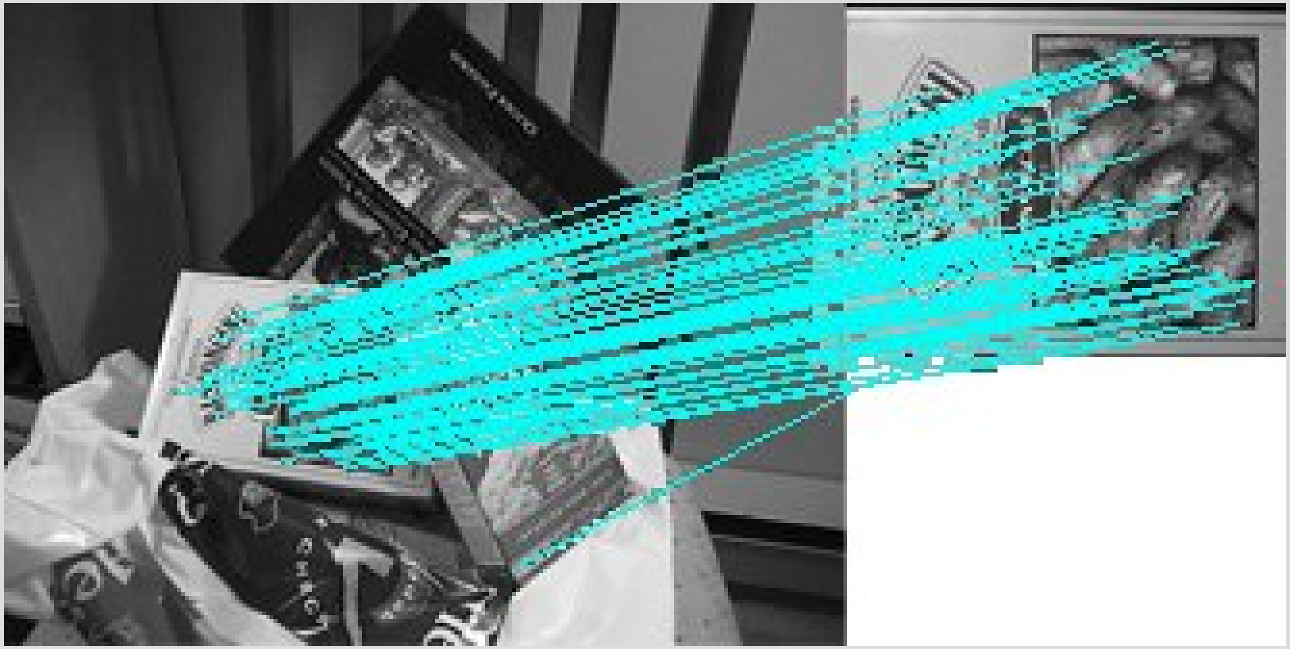
Keypoint Descriptor

The Descriptor is independent of changes in

- **rotation:** coordinates and orientations relative to the keypoint orientation
- **contrast:** the descriptor vector is normalized
- **brightness:** wouldn't effect the gradients because they are calculated from pixel-differences

Examples

Examples



Examples

Resources

- [1] ***Lowe, David G.:*** *Distinctive image features from scale-invariant keypoints 2004*
- ***[2] Lindeberg, Tony:*** *Edge detection and ridge detection with automatic scale selection 1998*
- ***[3] Lindeberg, Tony:*** *Feature Detection with Automatic Scale Selection 1998*
- *[4] en.wikipedia.org*

Image sources:

- **[1] Slide 12,13,15,17**
- **[2] Slide 6**
- **[3] Slide 7**
- **[4] Slide 4, 5, 10**
- **http://www.cs.ubc.ca/~lowe/keypoints/ Slide 19,20**
- **http://web.engr.oregonstate.edu/~hess/index.html Slide 21**