



Perception for Autonomous Systems 31392:

Image Feature Detection and Description

Lecturer: Evangelos Boukas—PhD

10 Feb. 2020 DTU Electrical Engineering

DTU

Image Features

Feature Detection:

Find the most "prominent" Points (areas) in an image.

The ones which are likely to be detected in other images, as well

• Feature Description:

Create a "unique" descriptor fingerprint for each Feature point

• Feature Matching:

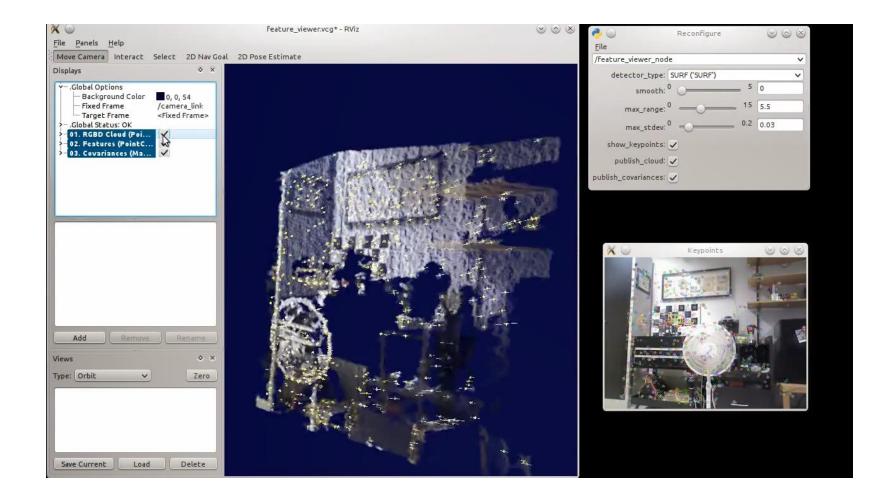
Find correspondences among different images





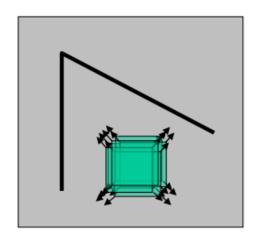


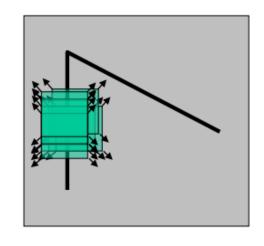
A quick view

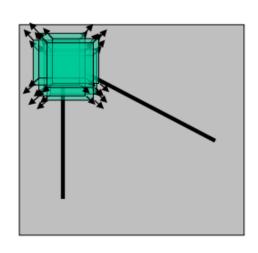




Corners are great for features







Lines not so, why

"flat" region: no change in all directions

"edge": no change along the edge direction

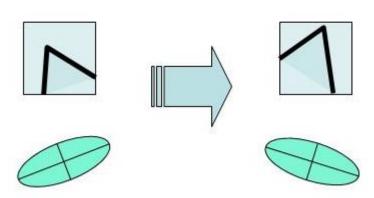
"corner": significant change in all directions

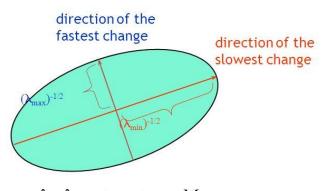


Harris can discriminate among edge, flat and corners



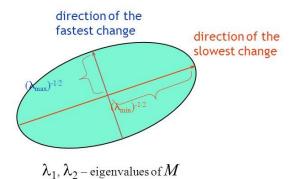
Linear algebra





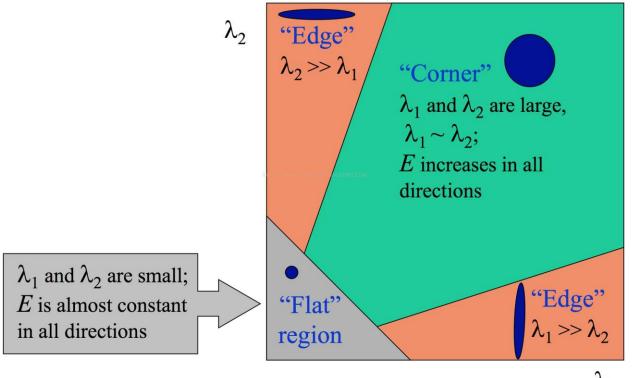


So how are these eigenvalues useful?





So how are these eigenvalues useful?



Mikolajczyk, K., and Schmid, C., "A performance evaluation of local descriptors",

IEEE Transactions on Pattern Analysis and Machine Intelligence, 10, 27, pp 1615--1630, 2005.



• So how are these eigenvalues useful?



 λ_1

Mikolajczyk, K., and Schmid, C., "A performance evaluation of local descriptors",

IEEE Transactions on Pattern Analysis and Machine Intelligence, 10, 27, pp 1615--1630, 2005.



Feature Detection: Scale Space Theory

- So we can find corners.
- But how descriptive are these corners?
 - Not really,
 - Think that the roof of a building has corners
 - And you desk has corners...
- Finally a revelation:

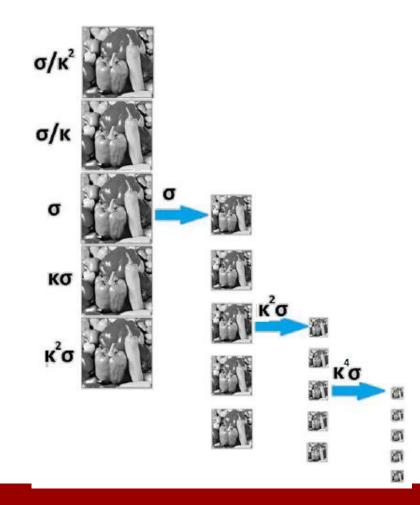
Lindeberg, T. 1994. Scale-space theory: A basic tool for analysing structures at different scales. Journal of Applied Statistics, 21(2):224-270

Lindeberg, Tony (1998). "Feature detection with automatic scale selection". International Journal of Computer Vision 30 (2): 79–116.



Feature Detection: Scale Space Theory

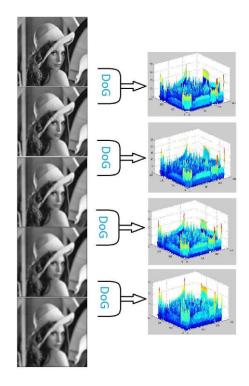
- We should be able to find these points which are prominent in different scales
- Create octaves with different scale among them
- Different blur level (Gaussian) in them





Feature Detection: Difference of Gaussians

- The main point is the difference of Gaussians
- We can then do this on our scale-space:







The mother of Features - SIFT

- Ok, we've seen how we can find interest points, but how about matching??
- David Lowe published the most influential paper in computer vision:

Lowe, D. Distinctive Image Features from Scale-Invariant Keypoints.International Journal of Computer Vision, 60, 2, pp 91-110 (2004).

- How many people do you think have cited this?
- 60000!!!!



Contains all:

- Detection
- Description
- Matching

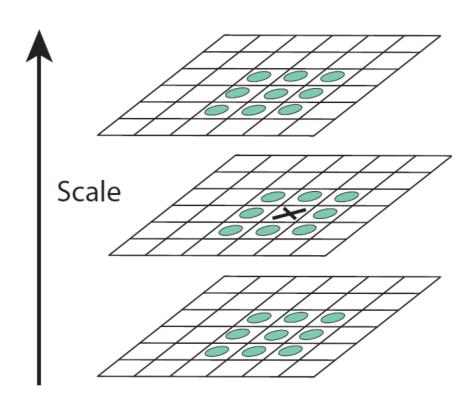
Main Feature is that it is robust in:

- Change of Translation
- Change in Scale
- Change in Rotation
- Change in 3D View Point
- Change in Illumination



Detection

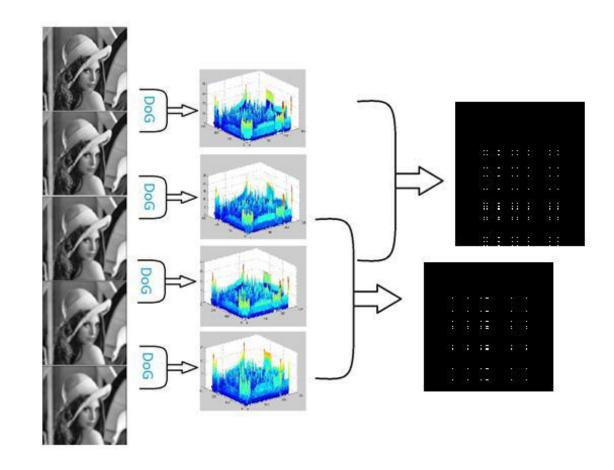
- Use DoG on Scale Space
 - Only the maximum or minimum in a neighborhood are considered
 - All octaves are investigated





Detection

- Use DoG on Scale Space
 - Only the maximum or minimum in a neighborhood are considered
 - All octaves are investigated
- · Specifically,
 - In groups of 3
 - 2 Set of Points from each octave
 - 4 octaves -> 8 set of Points





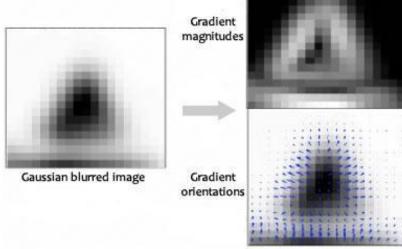
Description

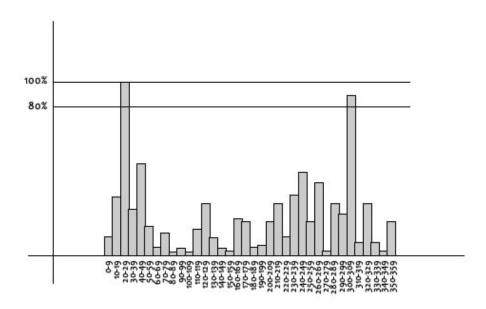
- Orientation:
 - Based on the gradient

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$

$$\theta(x,y) = \tan^{-1}((L(x,y+1) - L(x,y-1))/(L(x+1,y) - L(x-1,y)))$$

- Create a histogram of orientations Consisting of 36 bins (every 10 degrees)
- Fingerprint

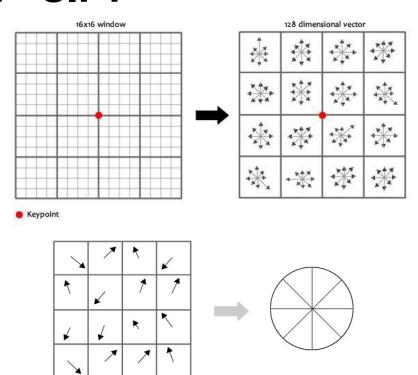


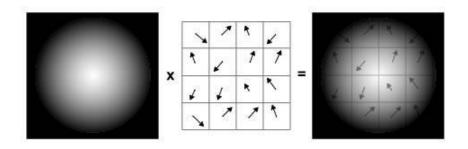




Description

- Orientation
- Fingerprint:
 - Assume a 16 x 16 area around each Key Point
 - Create histogram with 8 bins (as before)
 - This gives out 128 values
 - Note that the values are scaled for proximity







Matching

- Given some features from (let's say) 2 Images:
- Lowe proposed the ALL-ALL Euclidean distance:

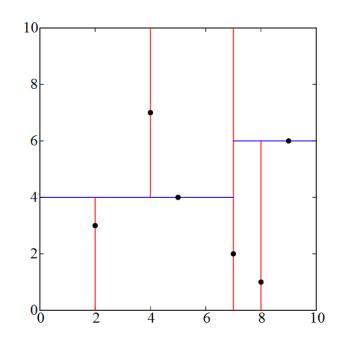
$$d(p,q) = \sqrt{(p1-q1)^2 + (p2-q2)^2 + (p3-q3)^2 + \dots + (pi-qi)^2 + \dots + (pn-qn)^2}$$

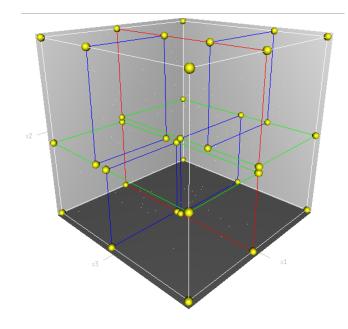
- For a 640x640 image we can get even 1000 features
- With 128 values each feature, you see how this can get ugly quickly



Matching

- So our hero, proposed the usage of Kd-Trees:
- Creation:
 - You split the space in half based on distance
 - Then again
 - Then again,....
- Search:
 - Start from top
 - Is it closer to 1 than 2?
 - Go in 1
 - Is it closer to 1.1 than 1.2?
 - Go in 1.1
 - GO On until you find a feature







Feature points and areas

- A multitude of features have been proposed (specific for each application):
 - SIFT
 - SURF
 - BRISK
 - FREAK
 - MSER
 - ORB

— ...

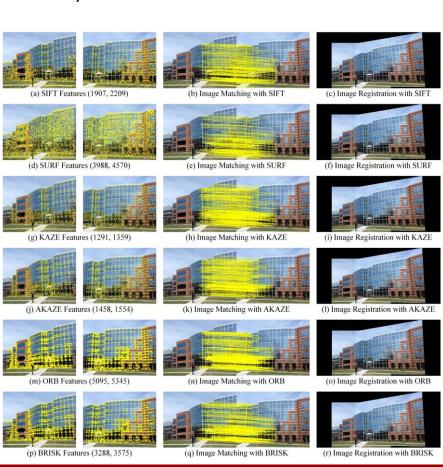
10 Feb. 2020 **DTU Electrical Engineering** 18



Feature points and areas

- A multitude of features have been proposed (specific for each application):
 - SIFT
 - SURF
 - BRISK
 - FREAK
 - MSER
 - ORB

 - Patches A special case to research





What applications do the Features have?

- More or less everything..
- Motion Estimation
- Localization
- Mapping
- Photogrammetry
- Image Retrieval
- Machine Learning
 - Object Detection
 - & Recognition
- Autonomous Driving
- More or less everything!



What applications do the Features have?

- More or less everything..
- Motion Estimation
- Localization
- Mapping
- Photogrammetry
- Image Retrieval
- Machine Learning
 - Object Detection
 - & Recognition
- Autonomous Driving
- More or less everything!





Image Feature Detection and Description

- What did we learn?
 - Is that a good feature?
 - How to get scale and rotational invariance in the features we get?
 - How to detect points of interest?
 - How to describe the feature of points so,
 - We can match them across multiple images.
 - How can we use features?

20 10 Feb. 2020 **DTU Electrical Engineering**



Perception for Autonomous Systems 31392:

Image Feature Detection and Description

Lecturer: Evangelos Boukas—PhD

10 Feb. 2020 DTU Electrical Engineering 21