UNIVERSITÀ DEGLI STUDI DELLA BASILICATA

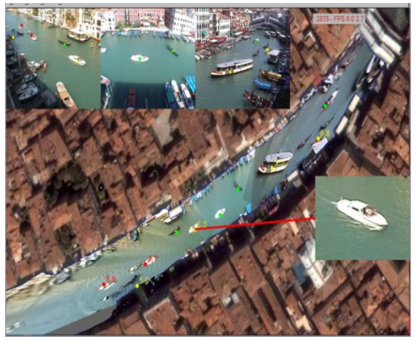
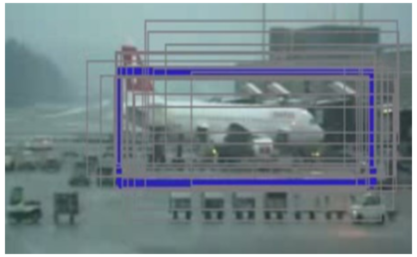
Corso di Sistemi Informativi
A.A. 2019/2020

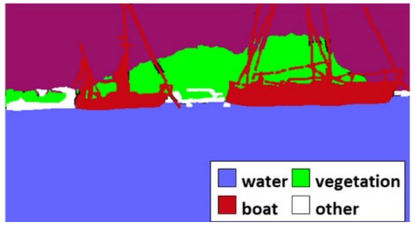
Docente
Domenico Daniele Bloisi

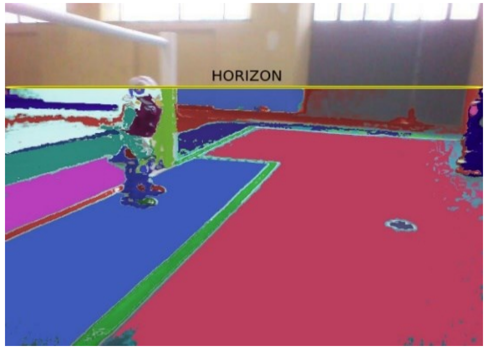
Features

Aprile 2020






Riferimenti

- La maggior parte di queste slide sono adattate da Noah Snavely - CS5670: Computer Vision "Lecture 4: Intro to local features and Harris corner detection“
- Per le slide adattate da altri autori vengono fornite le relative citazioni
- I contenuti fanno riferimento al capitolo 4 del libro "Computer Vision: Algorithms and Applications" di Richard Szeliski, disponibile al seguente indirizzo http://szeliski.org/Book/

Il corso

- Home page del corso
  http://web.unibas.it/bloisi/corsi/visione-e-percezione.html

- Docente: Domenico Daniele Bloisi

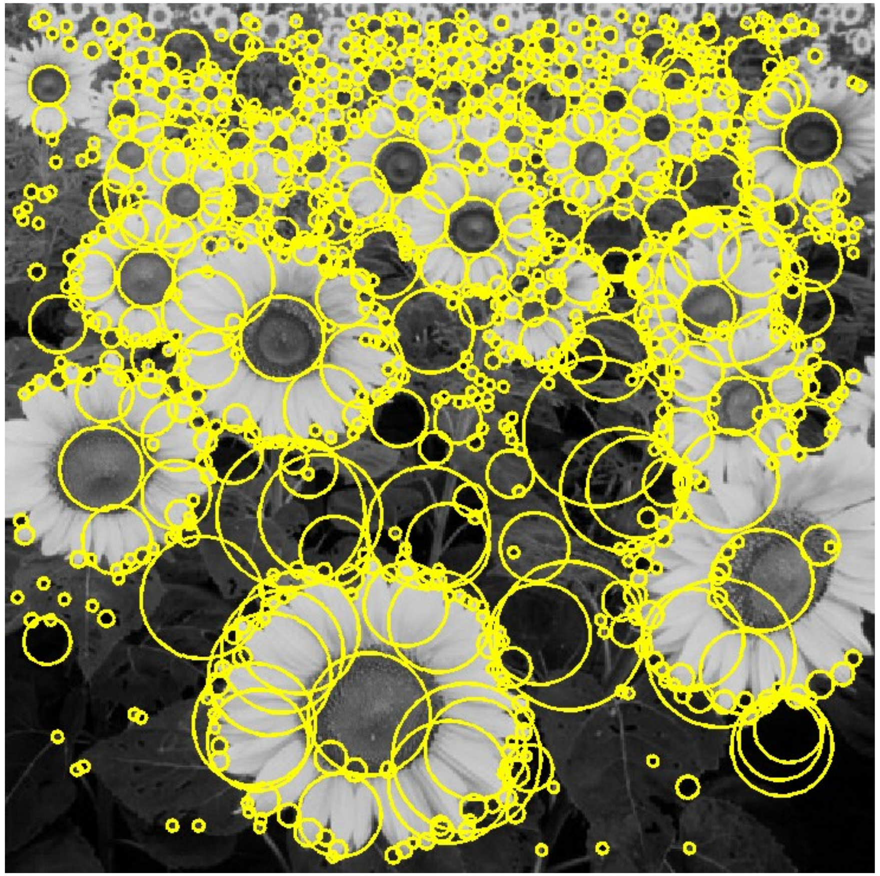
- Periodo: II semestre marzo 2020 – giugno 2020

  Martedì 17:00-19:00 (Aula GUGLIELMINI)
  Mercoledì 8:30-10:30 (Aula GUGLIELMINI)

Feature extraction

corners

blobs



Automatic panoramas

Credit: Matt Brown

Automatic panoramas

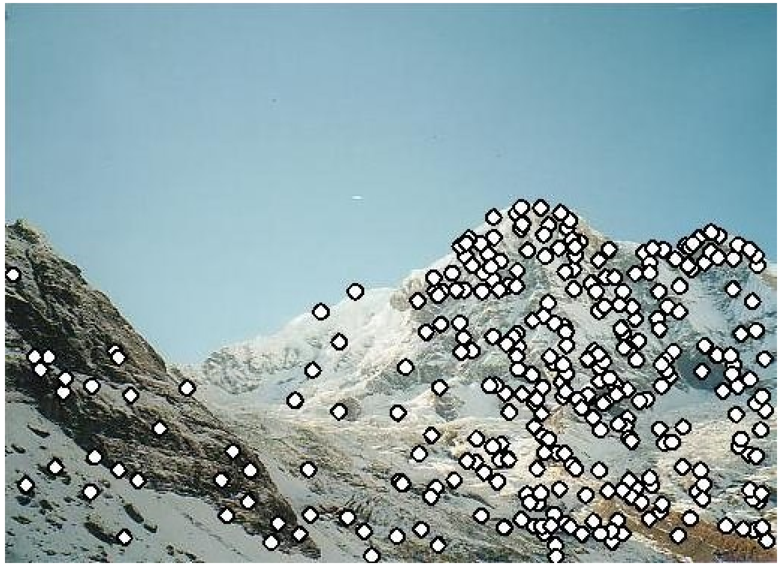
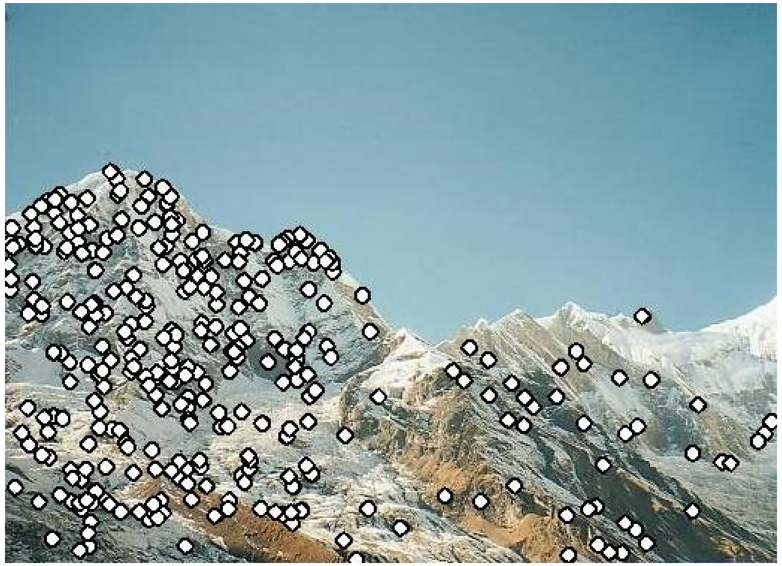
http://gigapan.com

Feature matching

We have two images, how do we combine them?

Feature matching

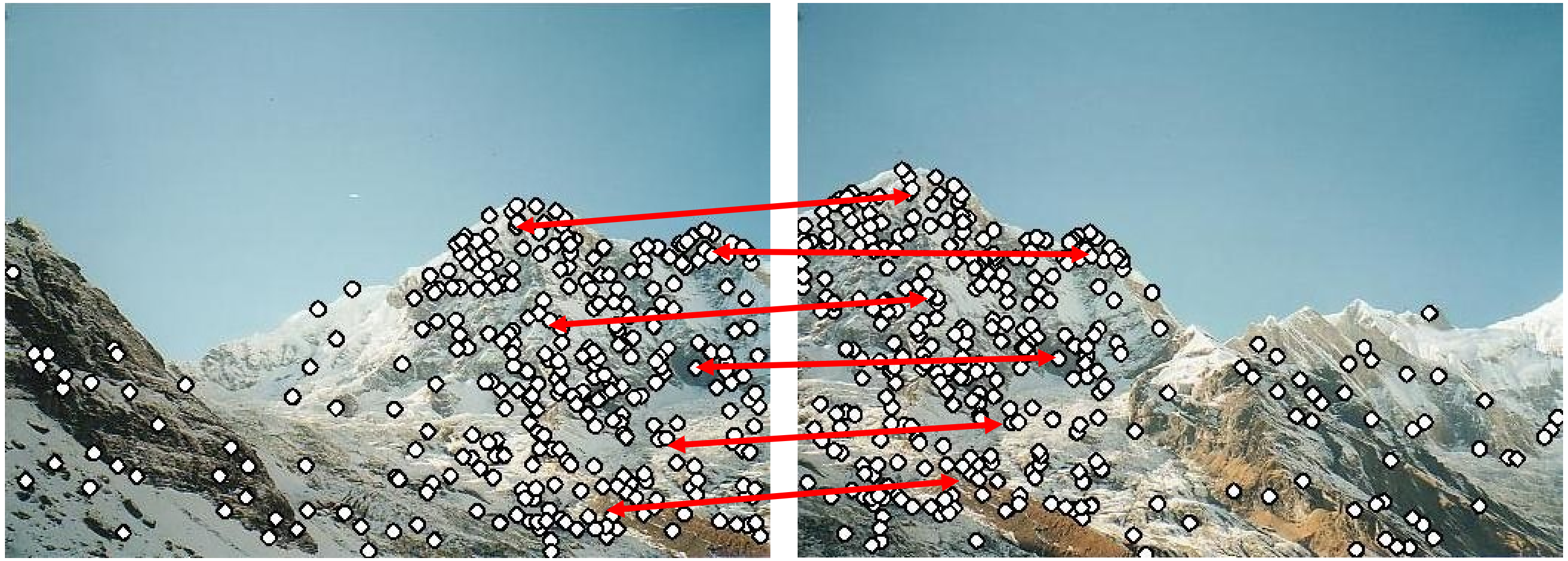
Step 1: extract features

Feature matching

Step 1: extract features

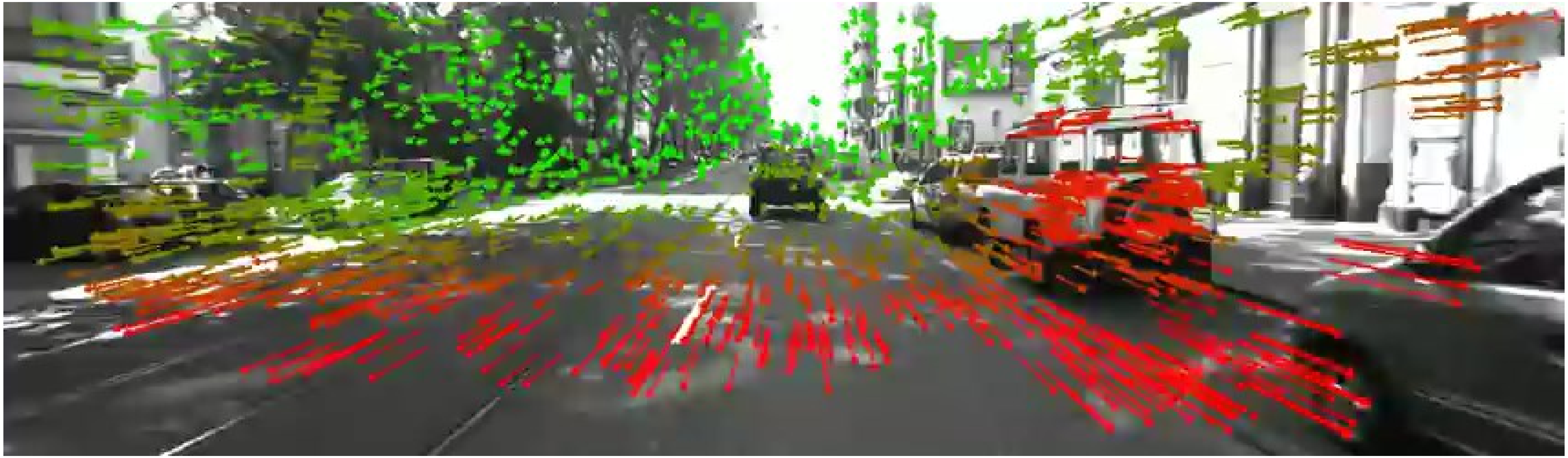
Step 2: match features



Feature matching

Step 1: extract features
Step 2: match features
Step 3: align images

Visual SLAM



https://www.youtube.com/watch?v=DPLh6MoxPAk

Image matching

by Diva Sian

by swashford

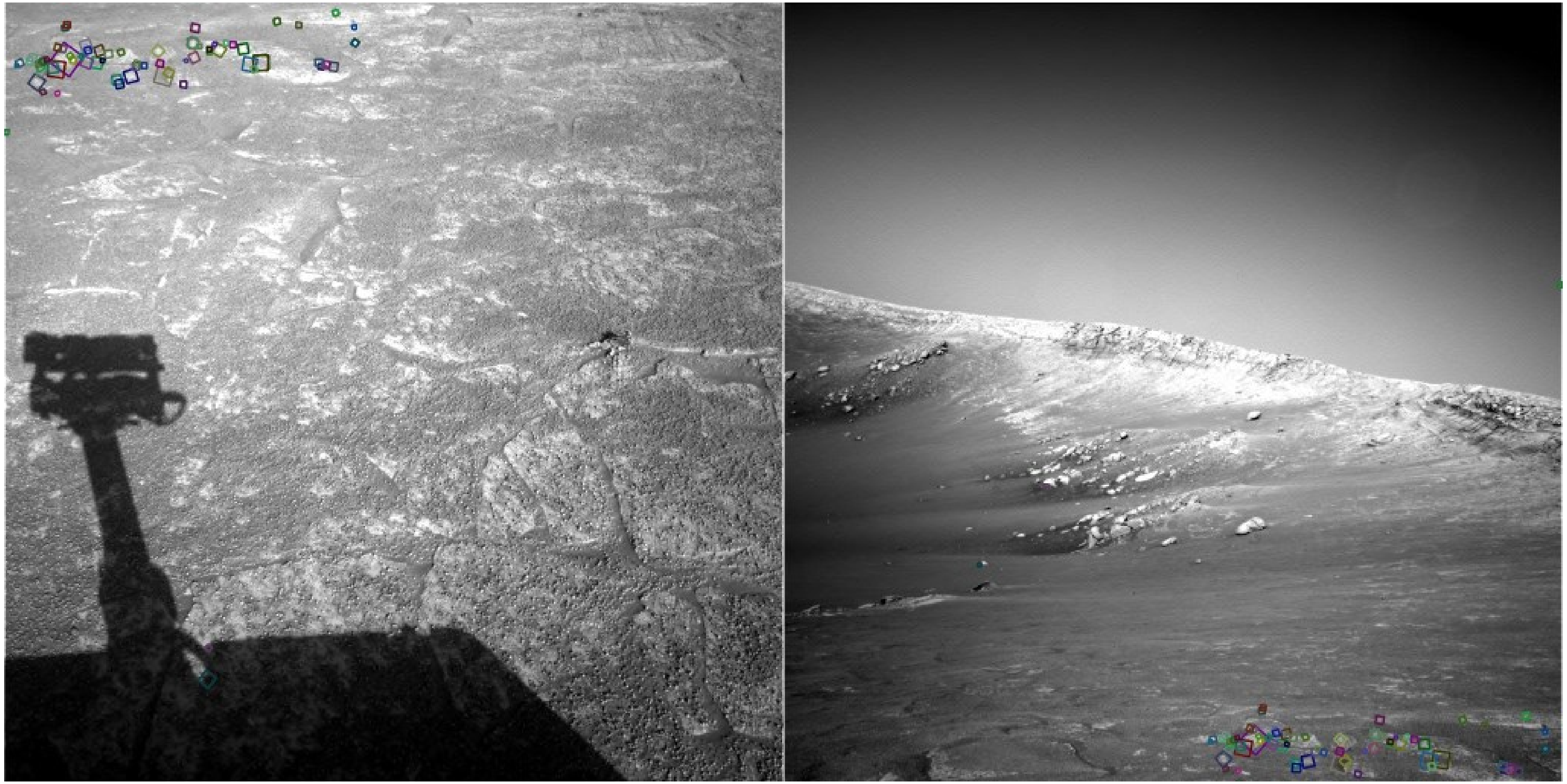
Harder case

by Diva Sian

by scgbt

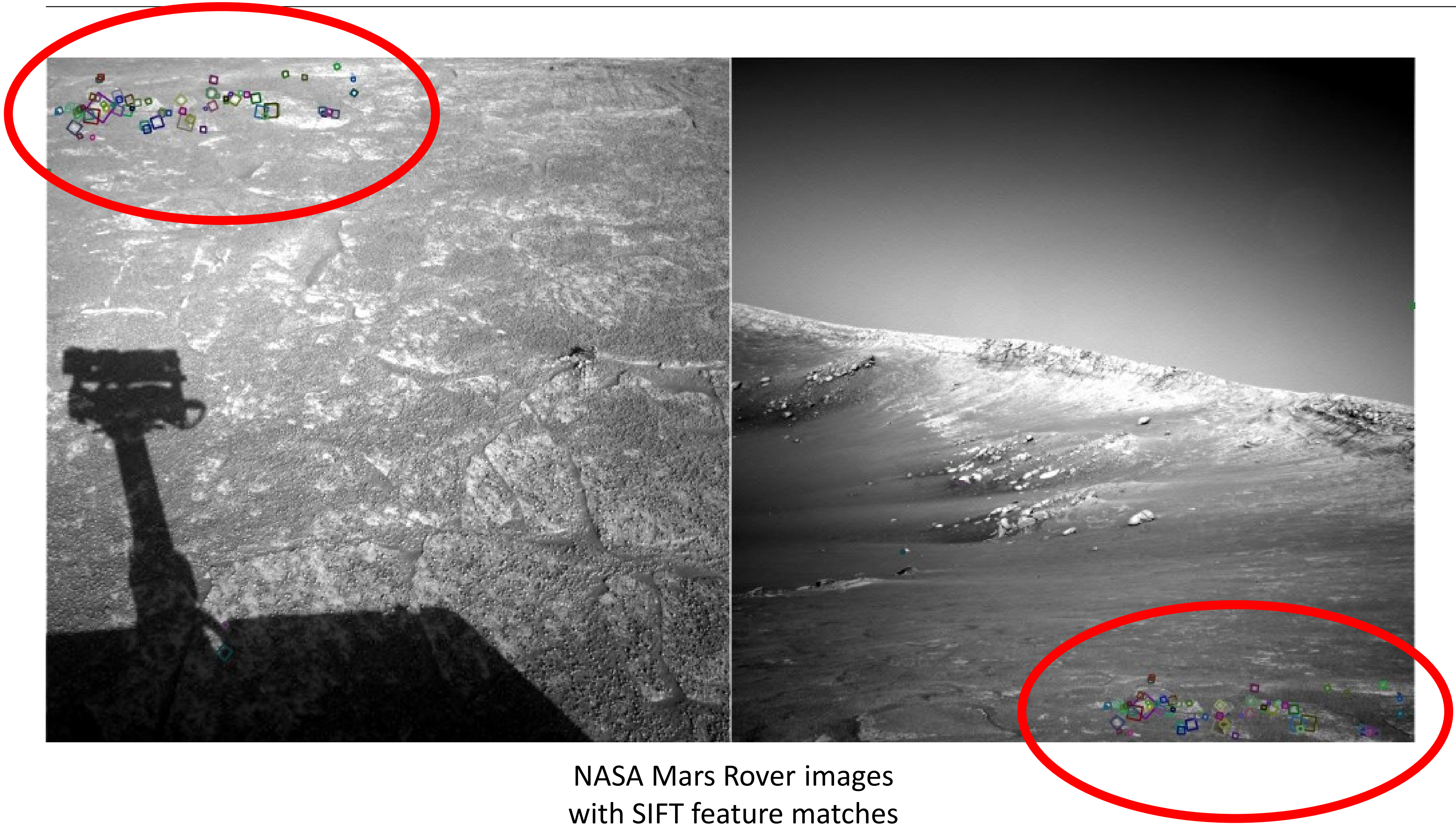
Harder still?

Harder still?



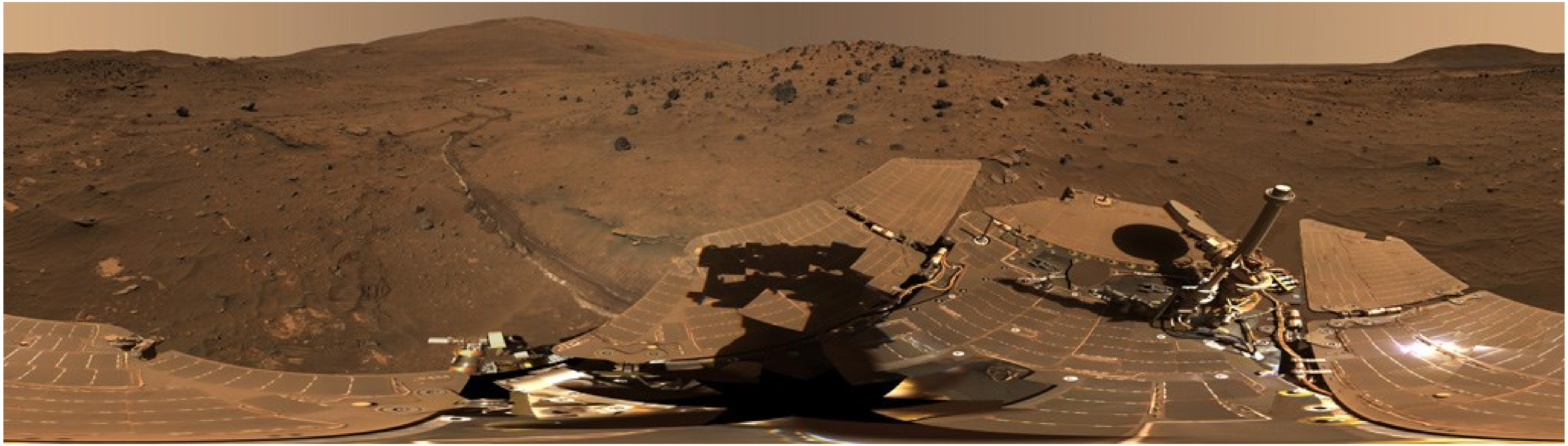
NASA Mars Rover images
with SIFT feature matches

Harder still?



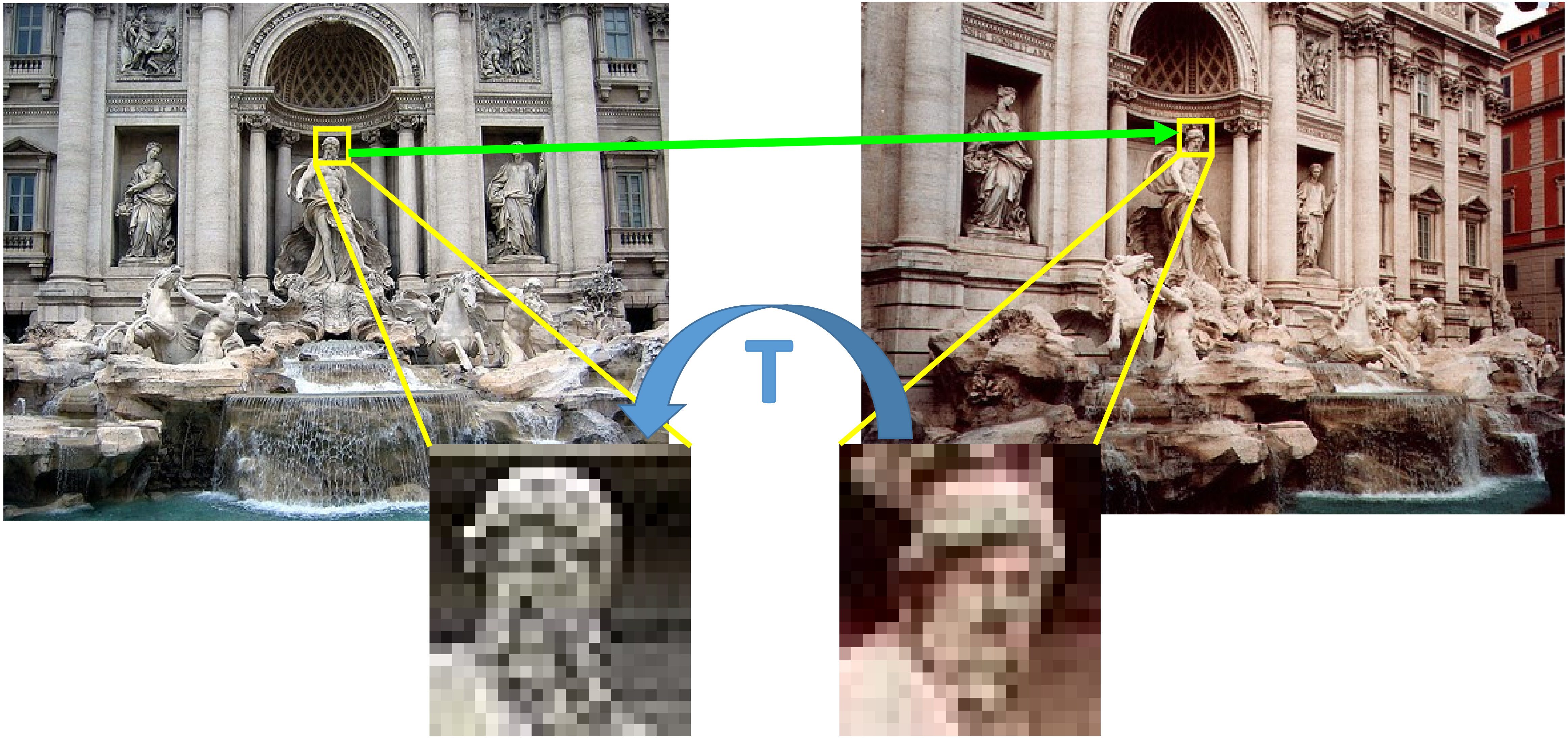
NASA Mars Rover images
with SIFT feature matches

Spirit Mars Rover Panorama



https://mars.nasa.gov/mer/multimedia/panoramas/spirit/

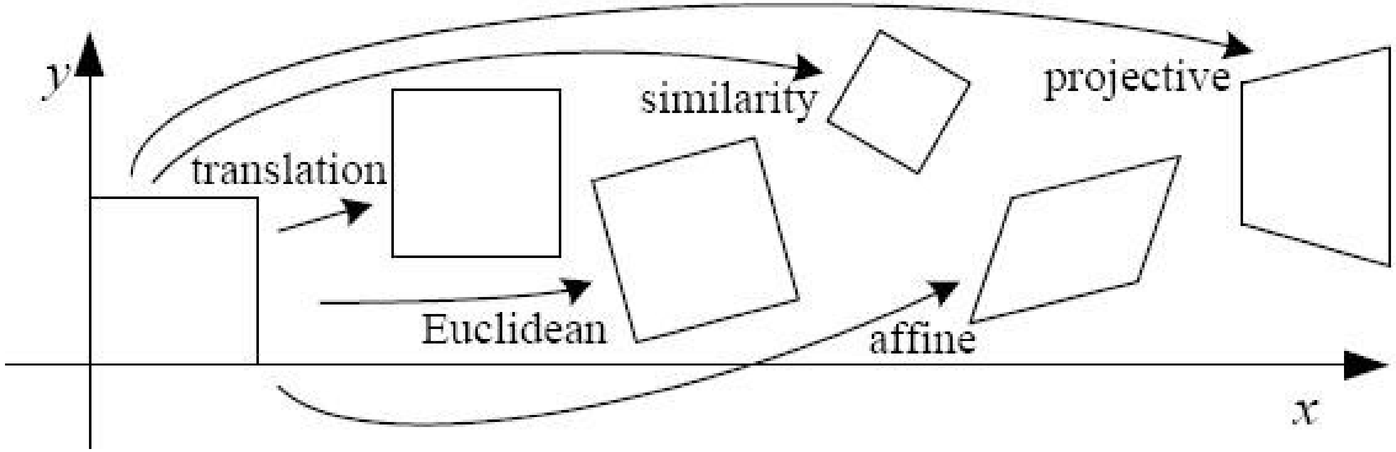
Feature matching



Geometric transformations

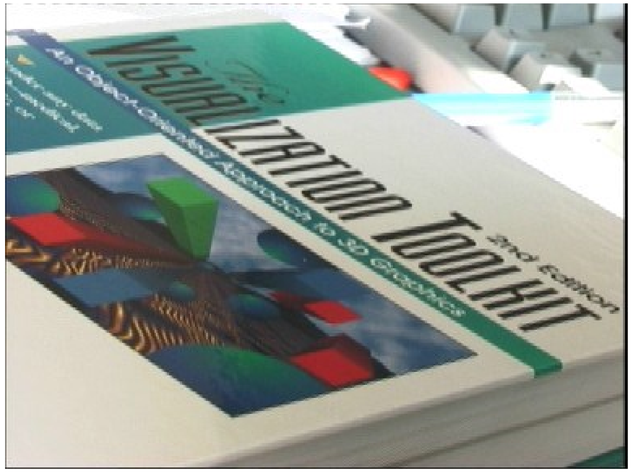
- Translation
- Euclidean (translation + rotation)
- Similarity (translation + rotation + scale)
- Affine transformations
- Projective transformations

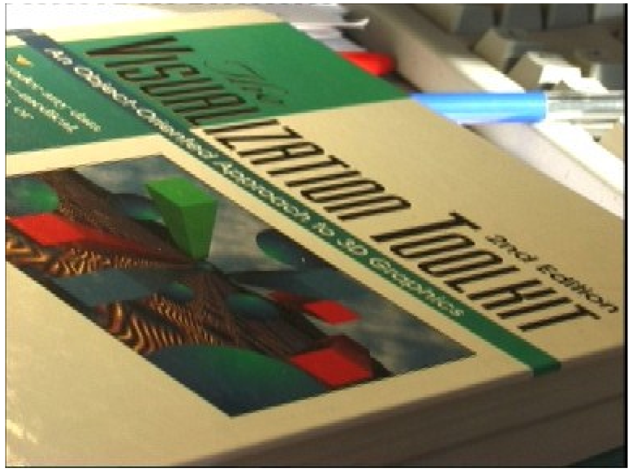
Only holds
for planar patches



http://homes.esat.kuleuven.be/~tuytelaa/tutorial-ECCV06.pdf

Photometric transformations



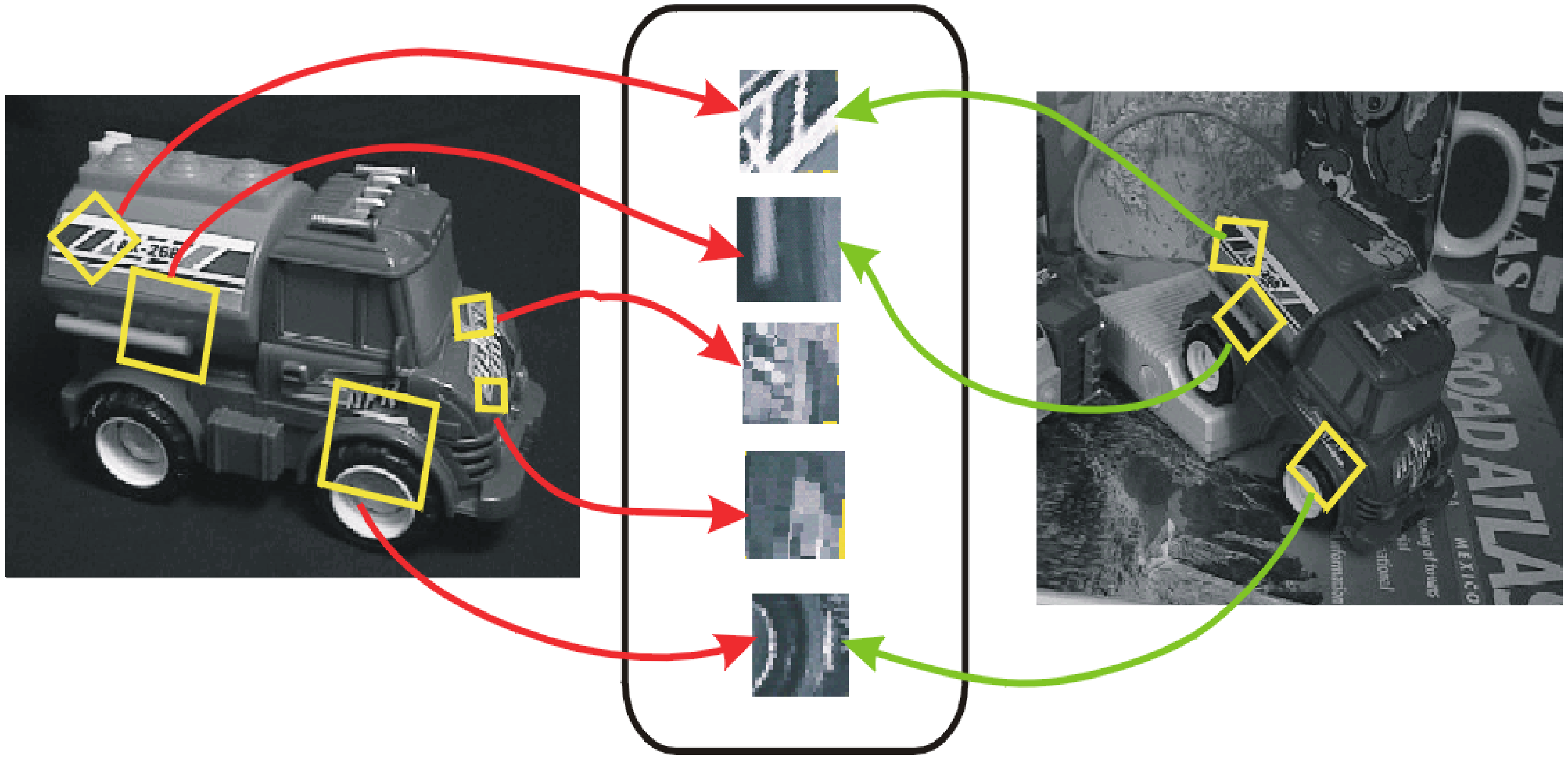


http://homes.esat.kuleuven.be/~tuytelaa/tutorial-ECCV06.pdf

Invariant Local Features

Find features that are invariant to transformations

- geometric invariance: translation, rotation, scale
- photometric invariance: brightness, exposure, …



Feature Descriptors

Advantages of local features

- **Locality**
  features are local, so robust to occlusion and clutter
- **Quantity**
  hundreds or thousands in a single image
- **Distinctiveness**
  can differentiate a large database of objects
- **Efficiency**
  real-time performance achievable

More motivations…

Feature points are used for:

- Image alignment (e.g., mosaics)
- 3D reconstruction
- Motion tracking (e.g. for AR)
- Object recognition
- Image retrieval
- Robot/car navigation
- … other

https://www.youtube.com/watch?v=Kr0W7io5rHw

Approach

1. Feature detection: find it

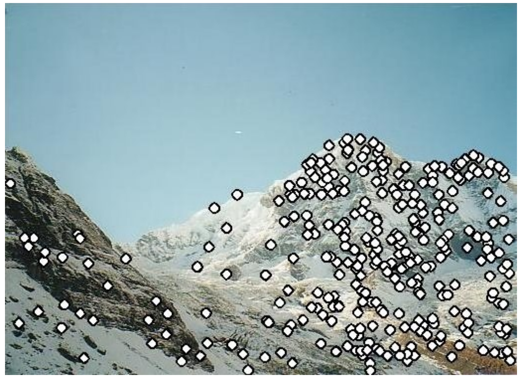
2. Feature descriptor: represent it

3. Feature matching: match it

Feature tracking: track it, when motion

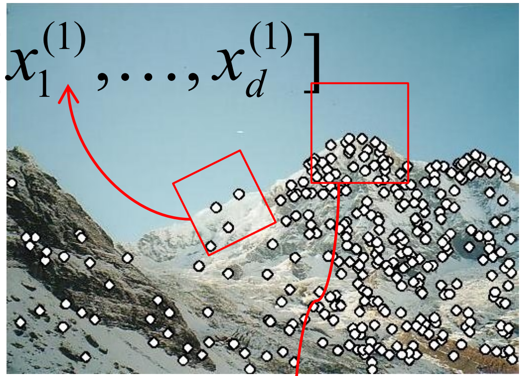
Local features: main components

1) Detection: Identify the interest points



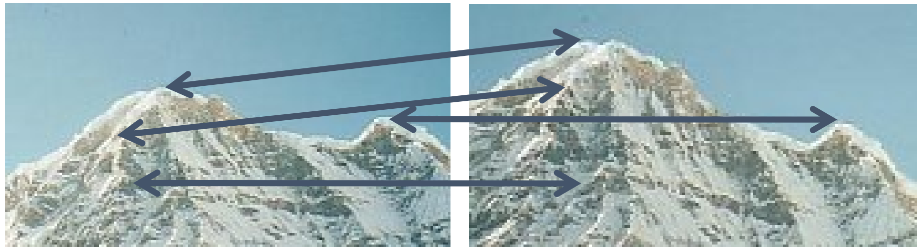
2) Description: Extract vector feature descriptor surrounding each interest point

$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$

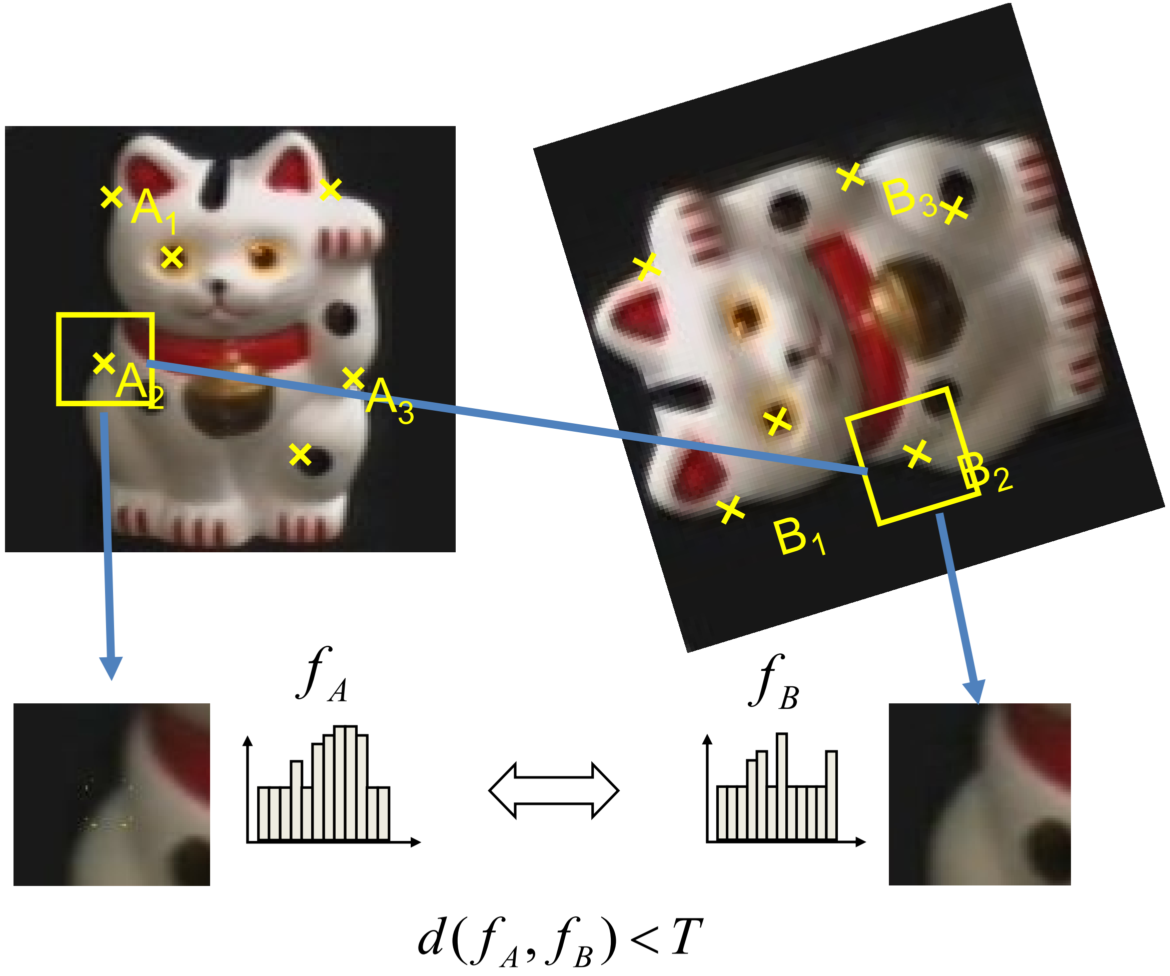


$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

3) Matching: Determine correspondence between descriptors in two views



Overview of Keypoint Matching



1. Find a set of distinctive key-points
2. Define a region around each keypoint
3. Extract and normalize the region content
4. Compute a local descriptor from the normalized region
5. Match local descriptors

K. Grauman, B. Leibe

What points to choose?

Source: Derek Hoiem

Low-texture region?

Gradients have small magnitude

Source: Derek Hoiem

Edge?

Gradients very large or very small

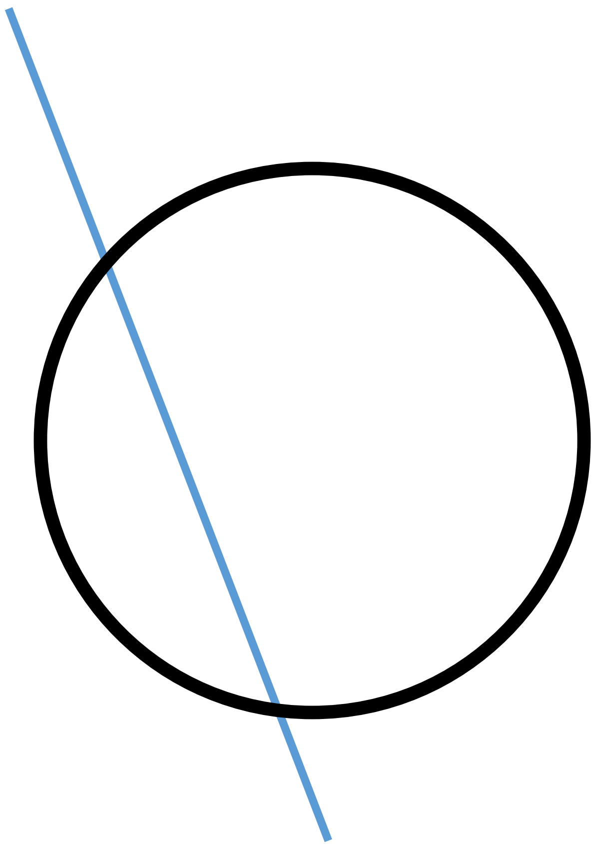
Source: Derek Hoiem

High-texture region?

Gradients are different, large magnitudes

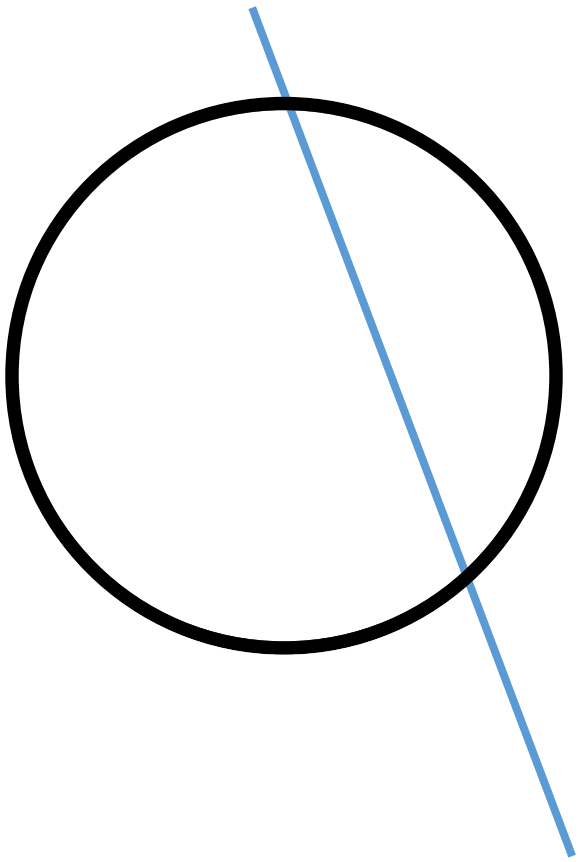
Source: Derek Hoiem

The aperture problem



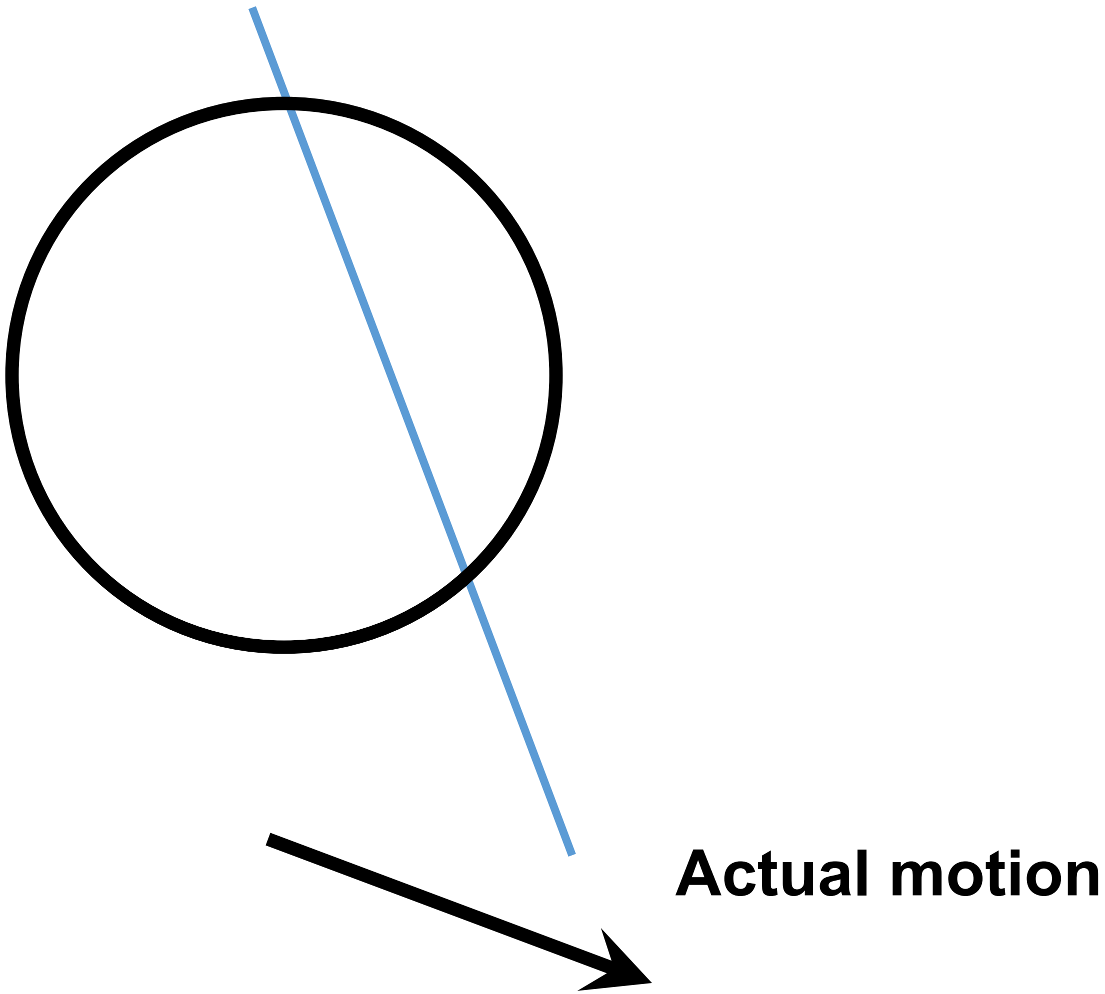
Source: Derek Hoiem

The aperture problem



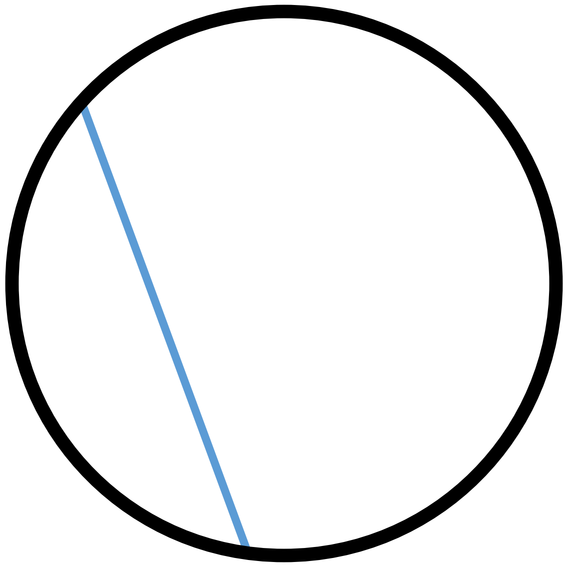
Source: Derek Hoiem

The aperture problem



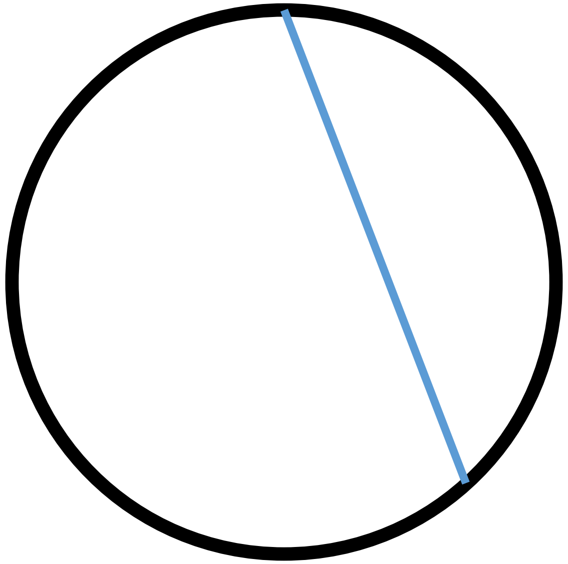
Source: Derek Hoiem

The aperture problem



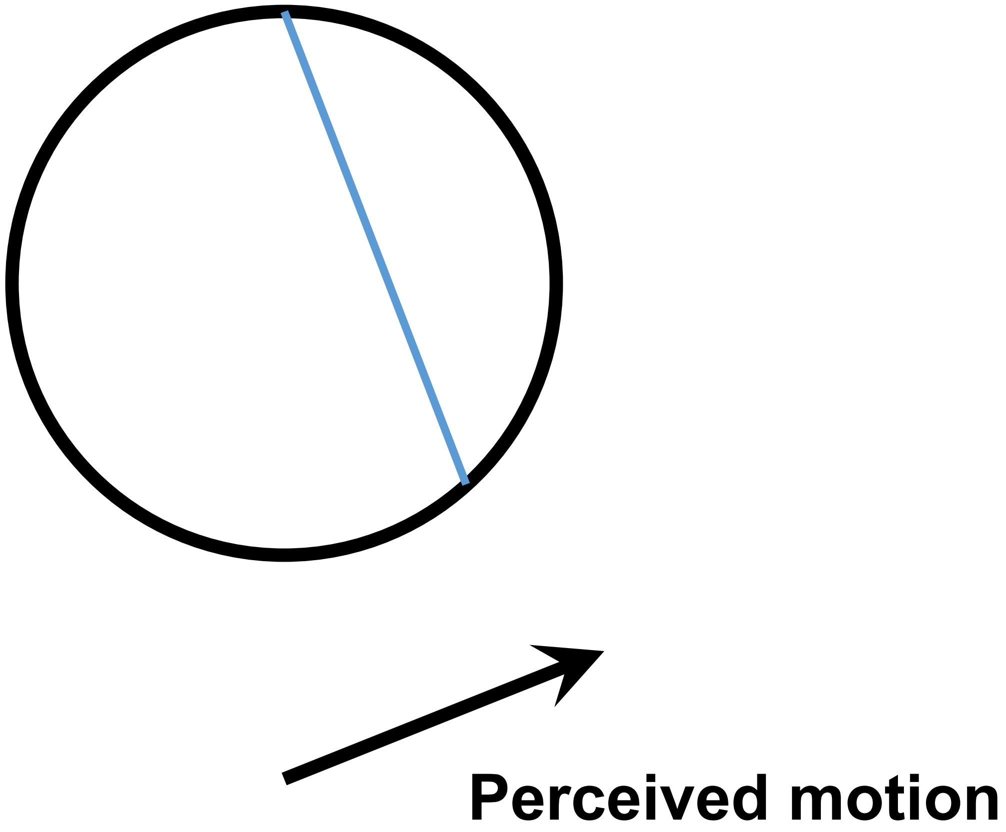
Source: Derek Hoiem

The aperture problem



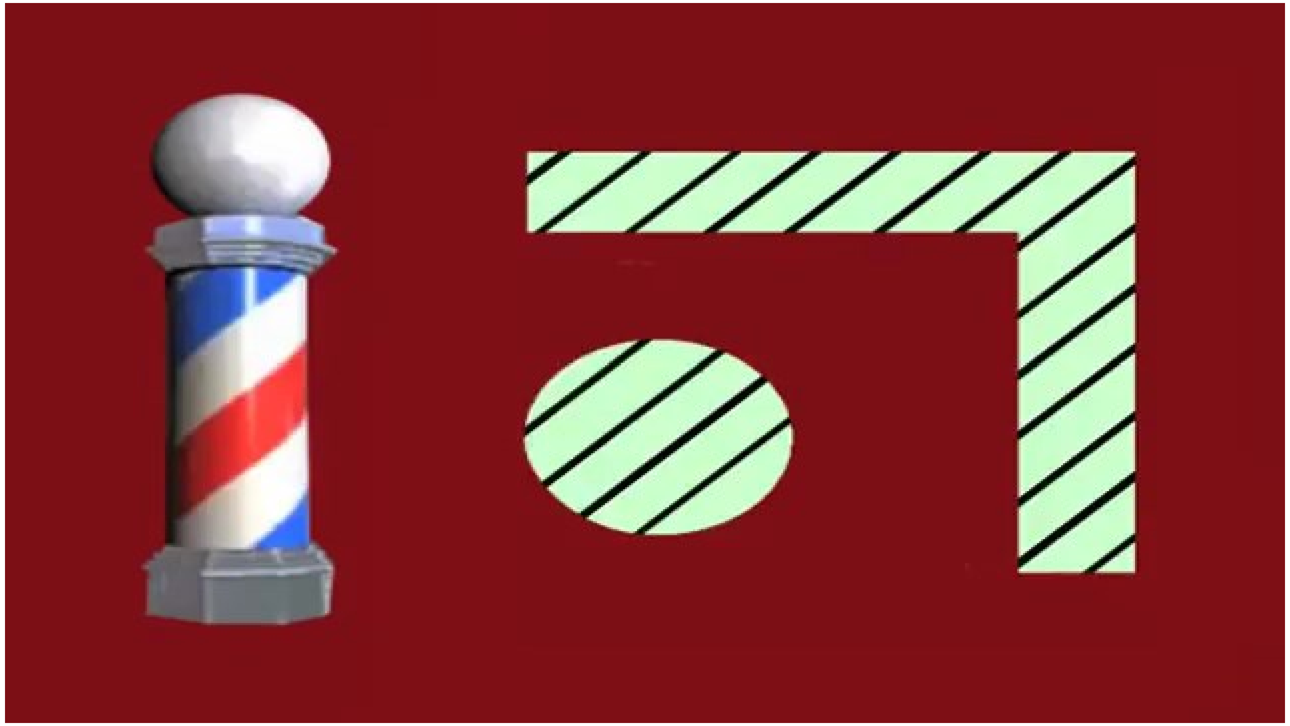
Source: Derek Hoiem

The aperture problem



Source: Derek Hoiem

The barber pole illusion



http://www.opticalillusion.net/wp-content/uploads/2013/07/WedBarb4BB_F8_HQ.mp4?_=1

So, what makes a good feature?

Want uniqueness

Look for image regions that are unusual

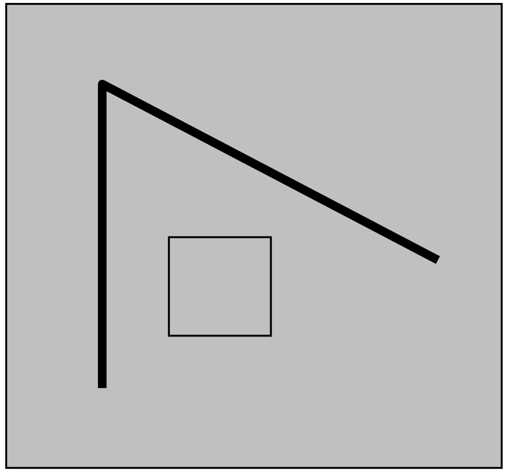
- Lead to unambiguous matches in other images

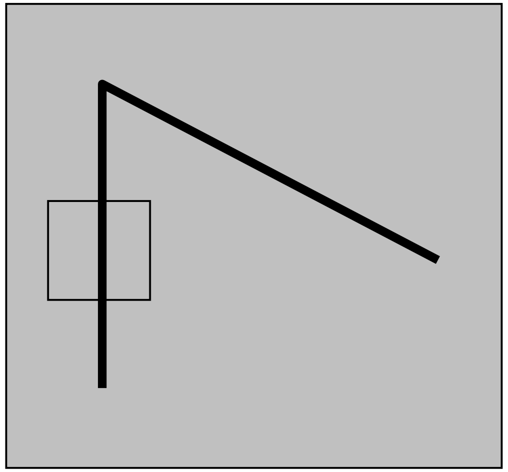
How to define “unusual”?

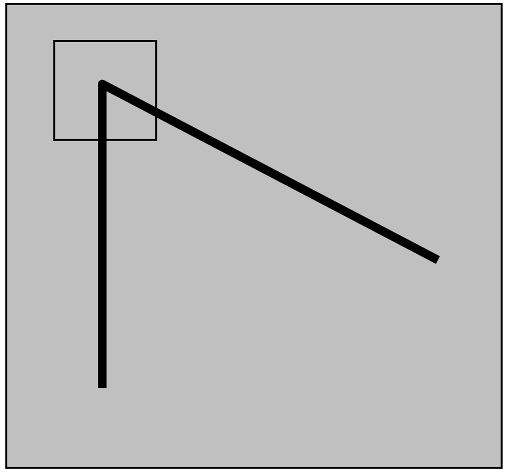
Want uniqueness

Suppose we only consider a small window of pixels

- What defines whether a feature is a good or bad candidate?

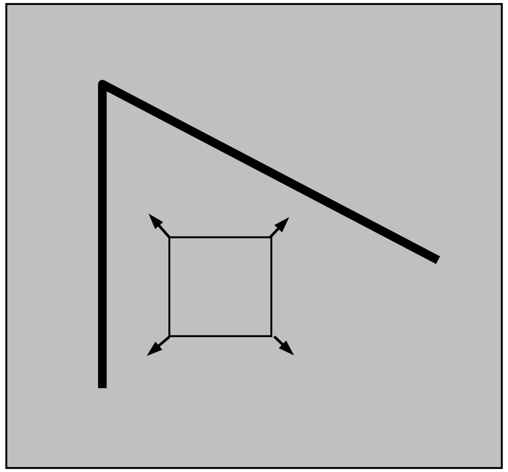




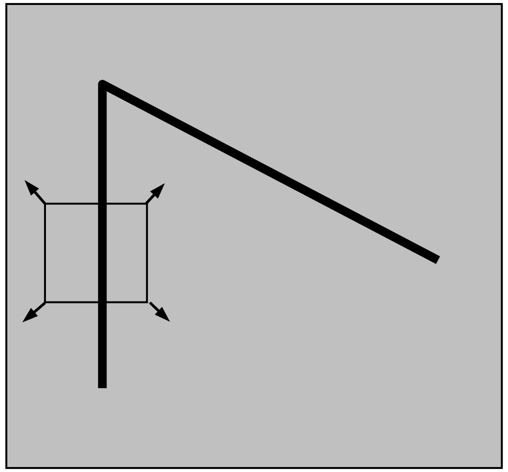


Want uniqueness

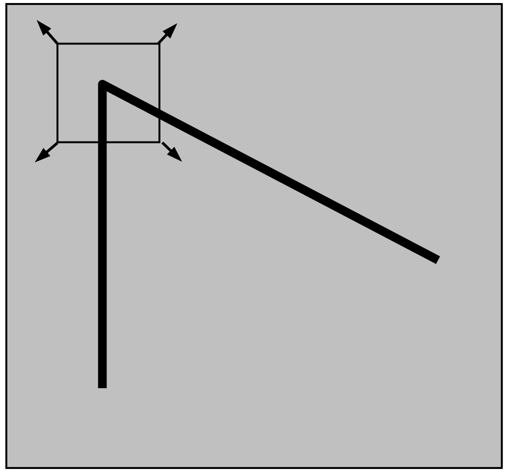
- How does the window change when you shift it?
- Shifting the window in any direction causes a big change



"flat" region:
no change in all directions



"edge":
no change along the edge direction



"corner":
significant change in all directions

Corners

- Textureless patches are nearly impossible to localize

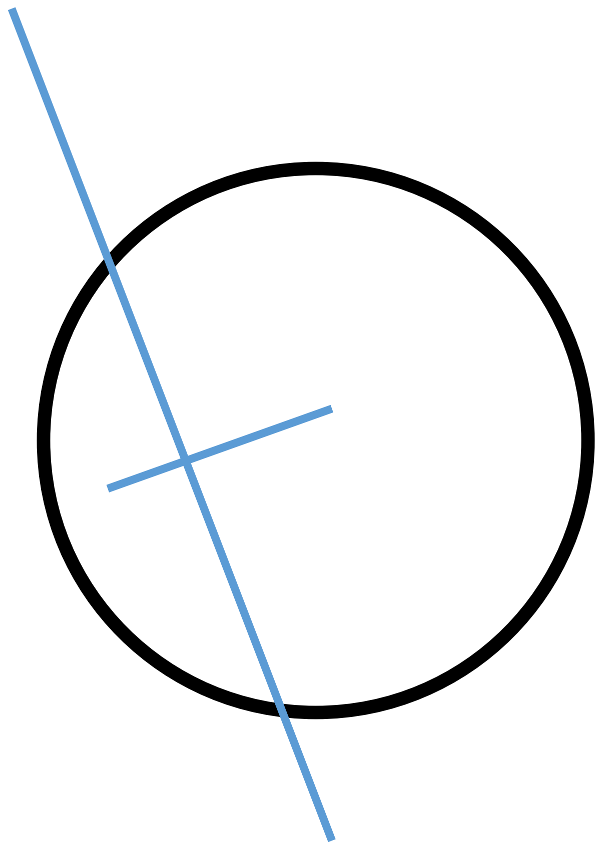
- Patches with large contrast changes (gradients) are easier to localize

- But straight line segments at a single orientation suffer from the aperture problem, i.e., it is only possible to align the patches along the direction normal to the edge direction

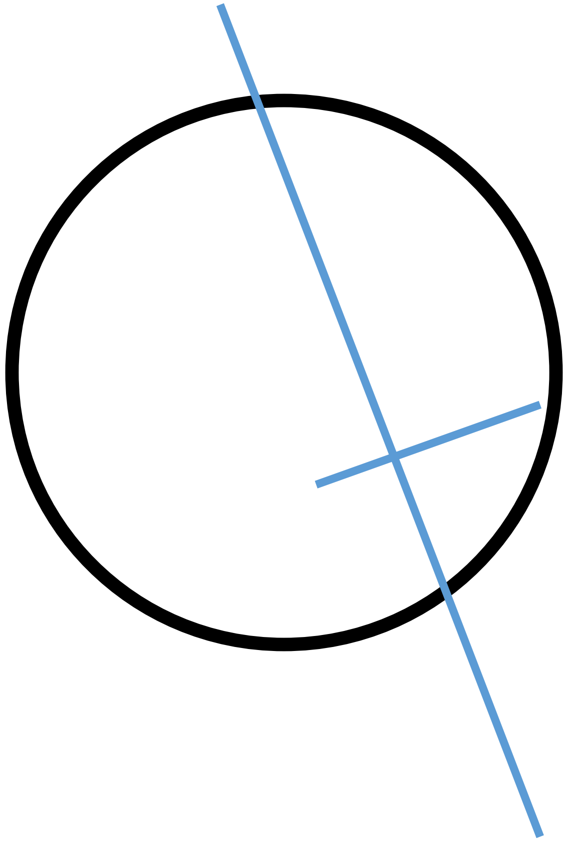
- Gradients in at least two (significantly) different orientations are the easiest, e.g., corners

Source: Raquel Urtasun

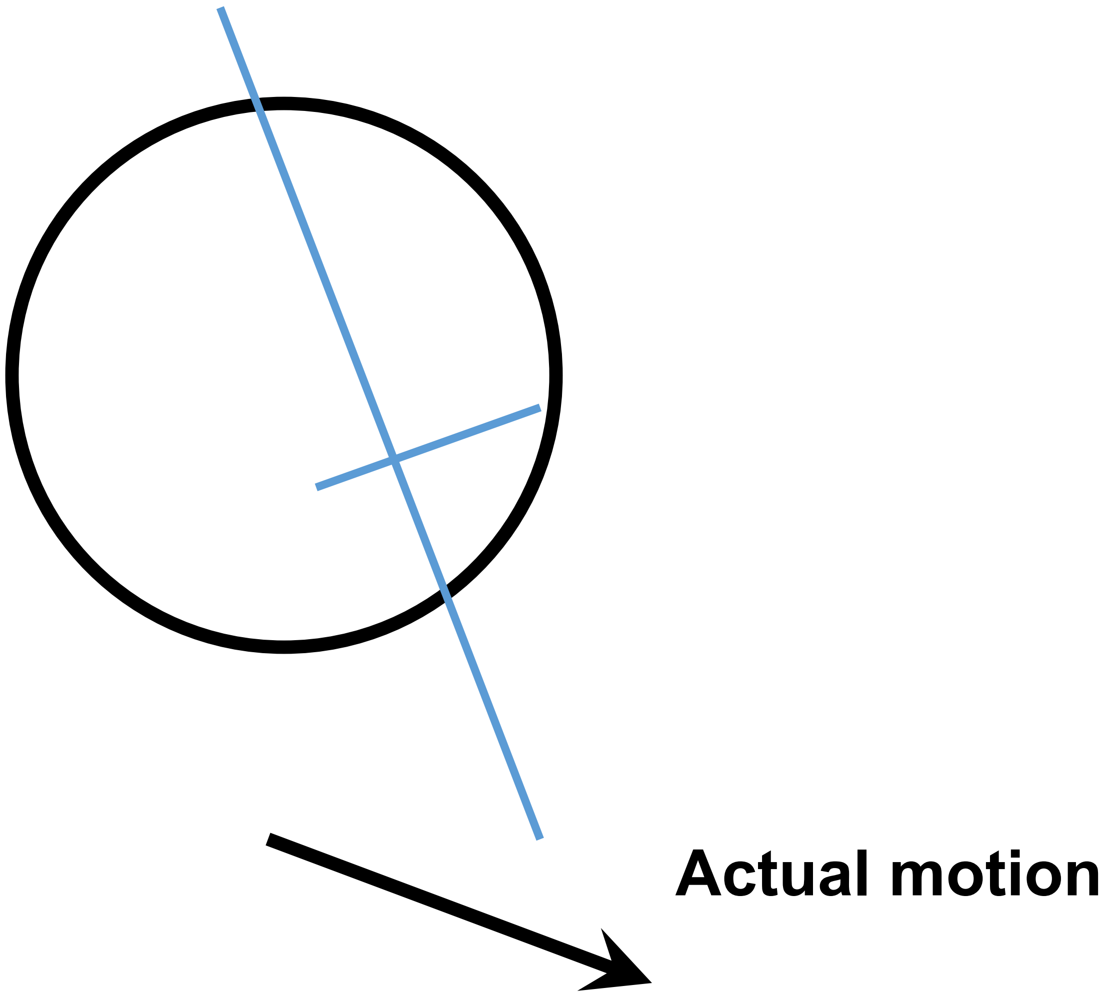
The aperture problem resolved



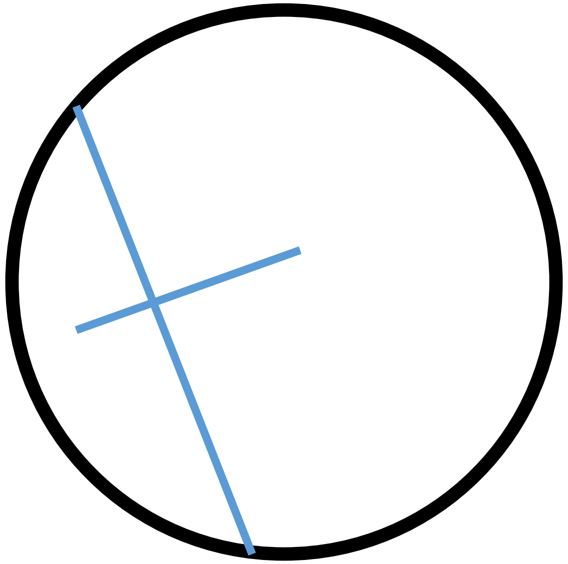
The aperture problem resolved



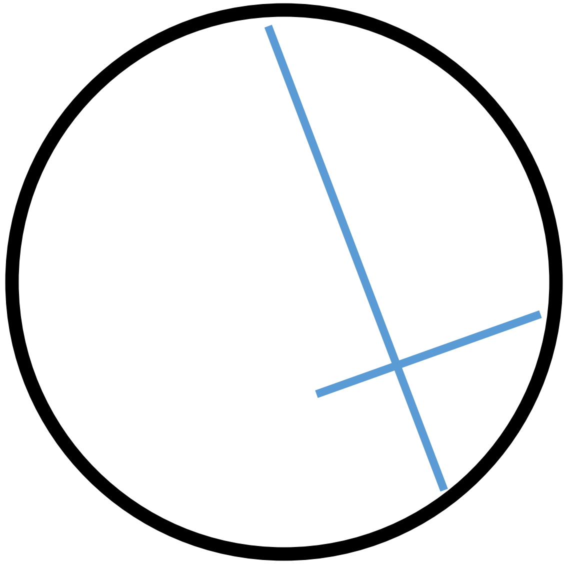
The aperture problem resolved



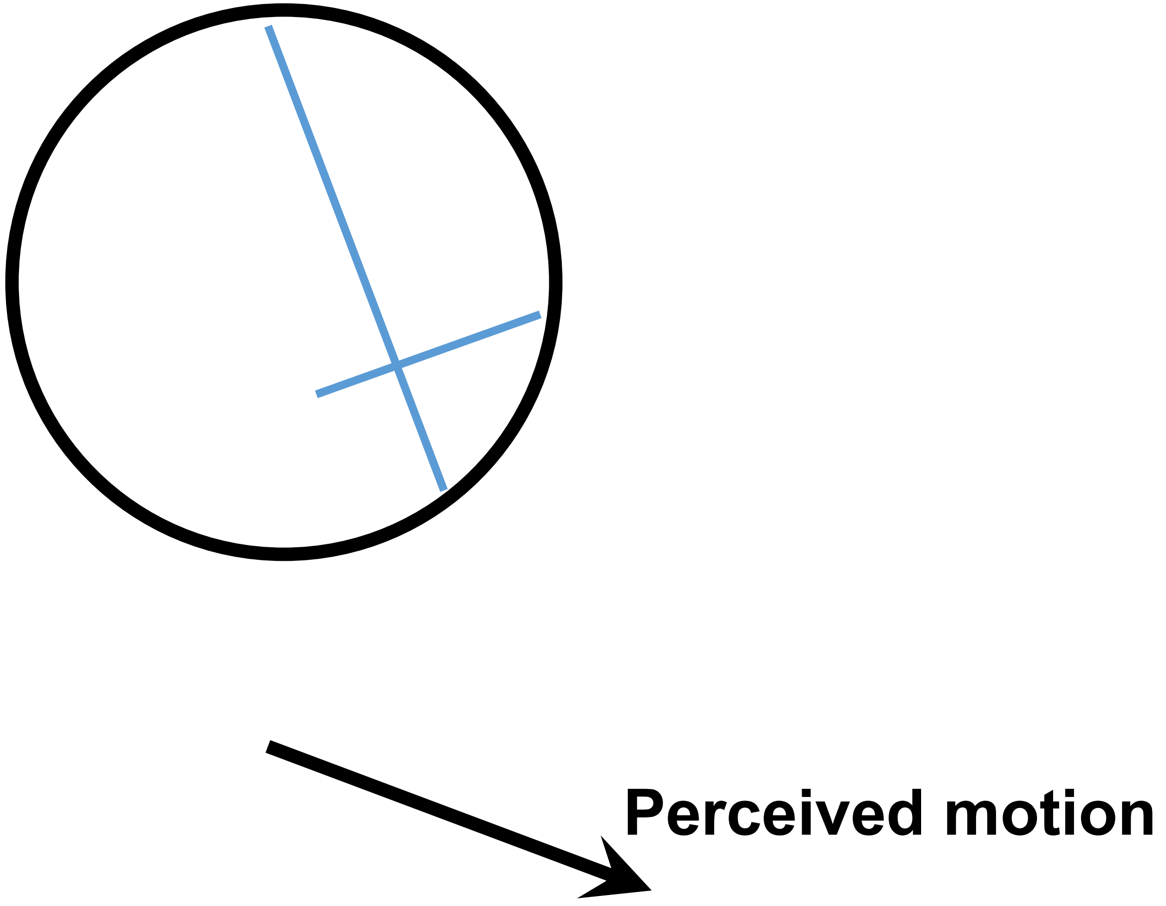
The aperture problem resolved



The aperture problem resolved

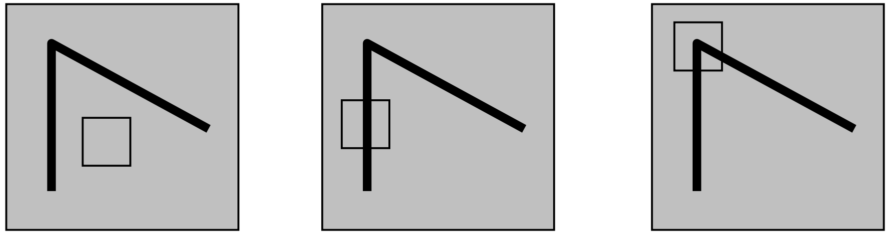


The aperture problem resolved



Harris corner detection

1. Generate a cornerness score for each image window



2. Find points whose surrounding window gave large corner response (f > threshold)

3. Take the points of local maxima, i.e., perform non-maximum suppression

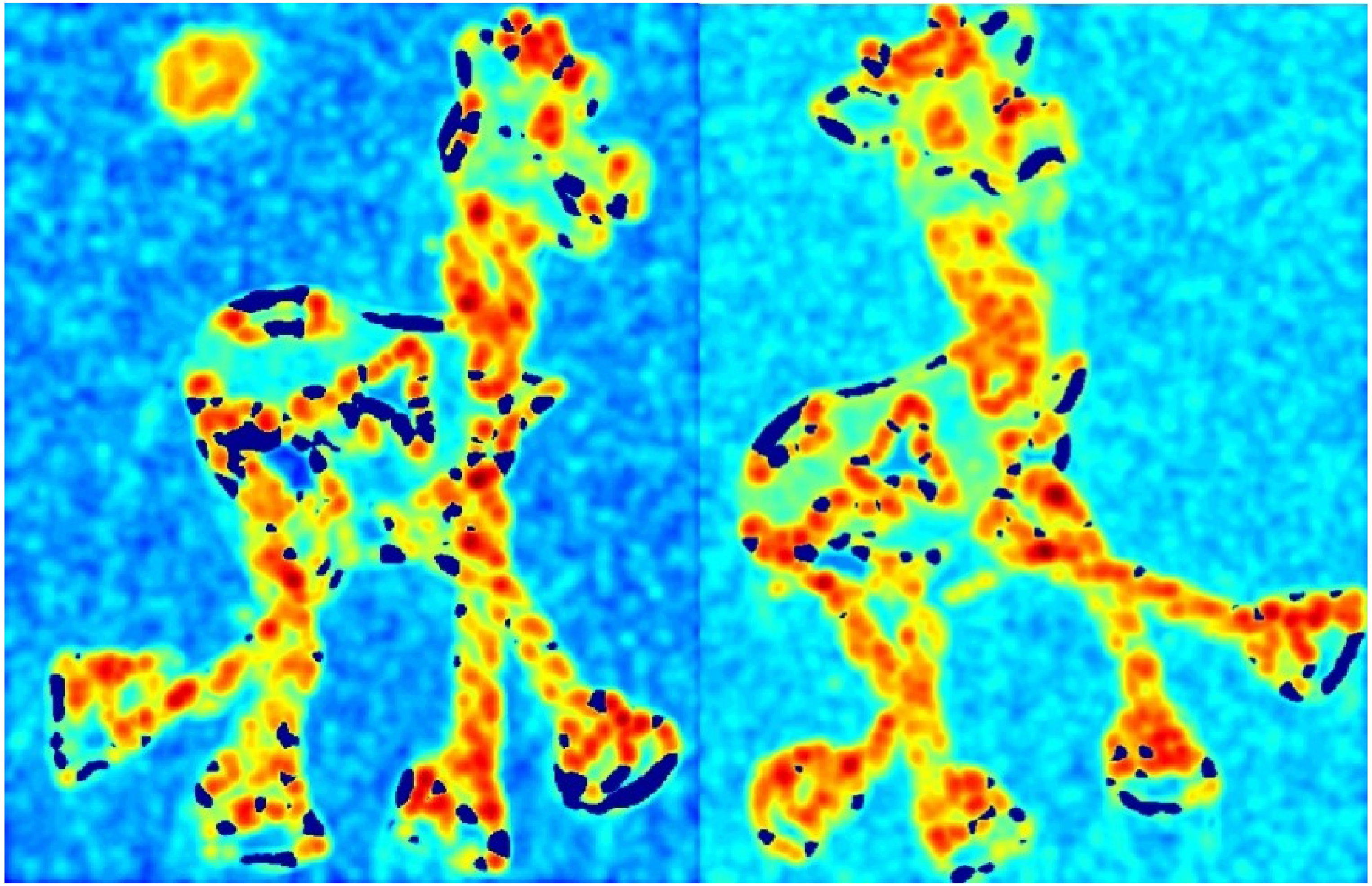
Source: James Hays

Harris detector steps

Source: James Hays

Harris detector steps

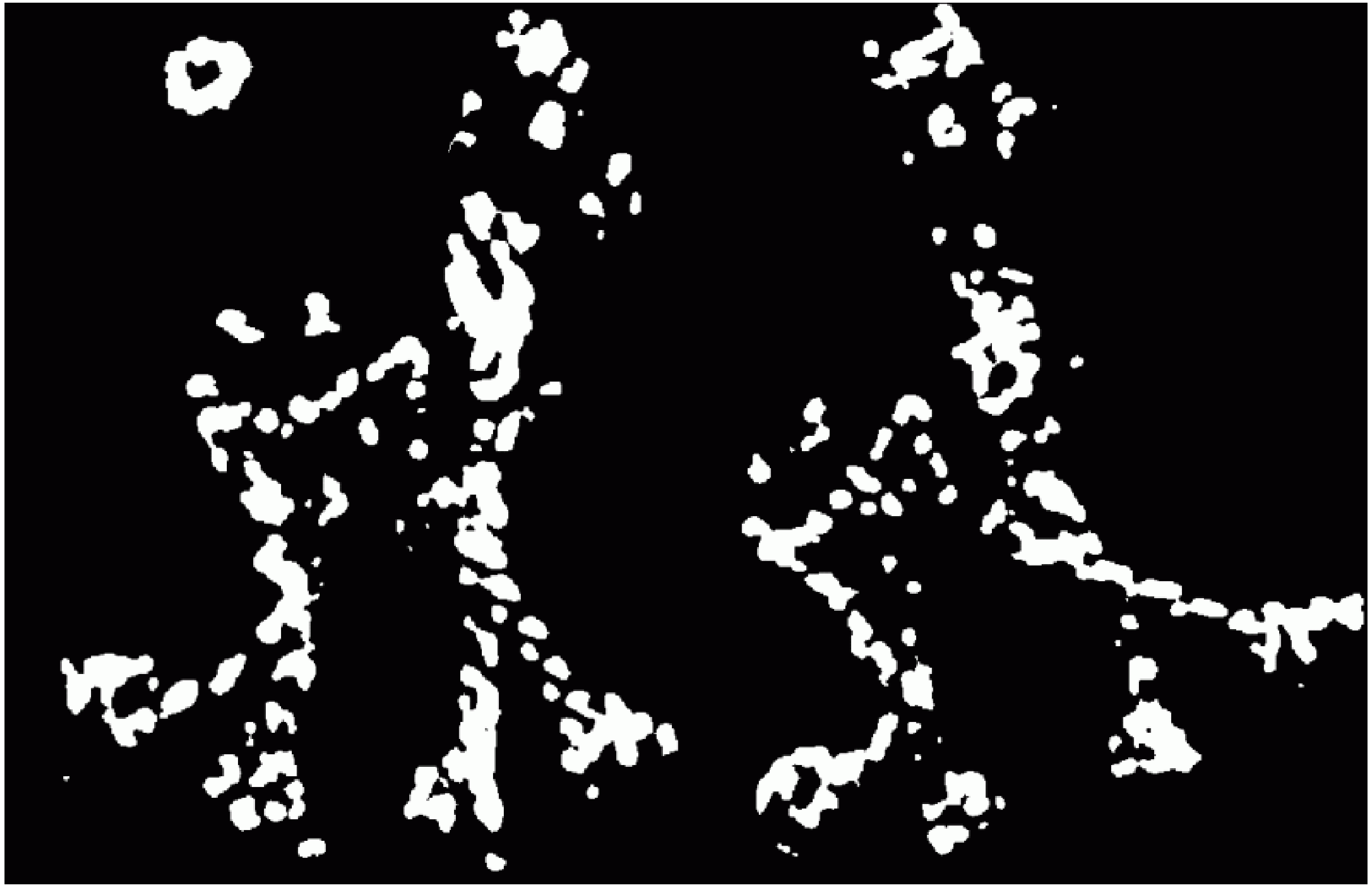
Compute corner response R



Source: James Hays

Harris detector steps

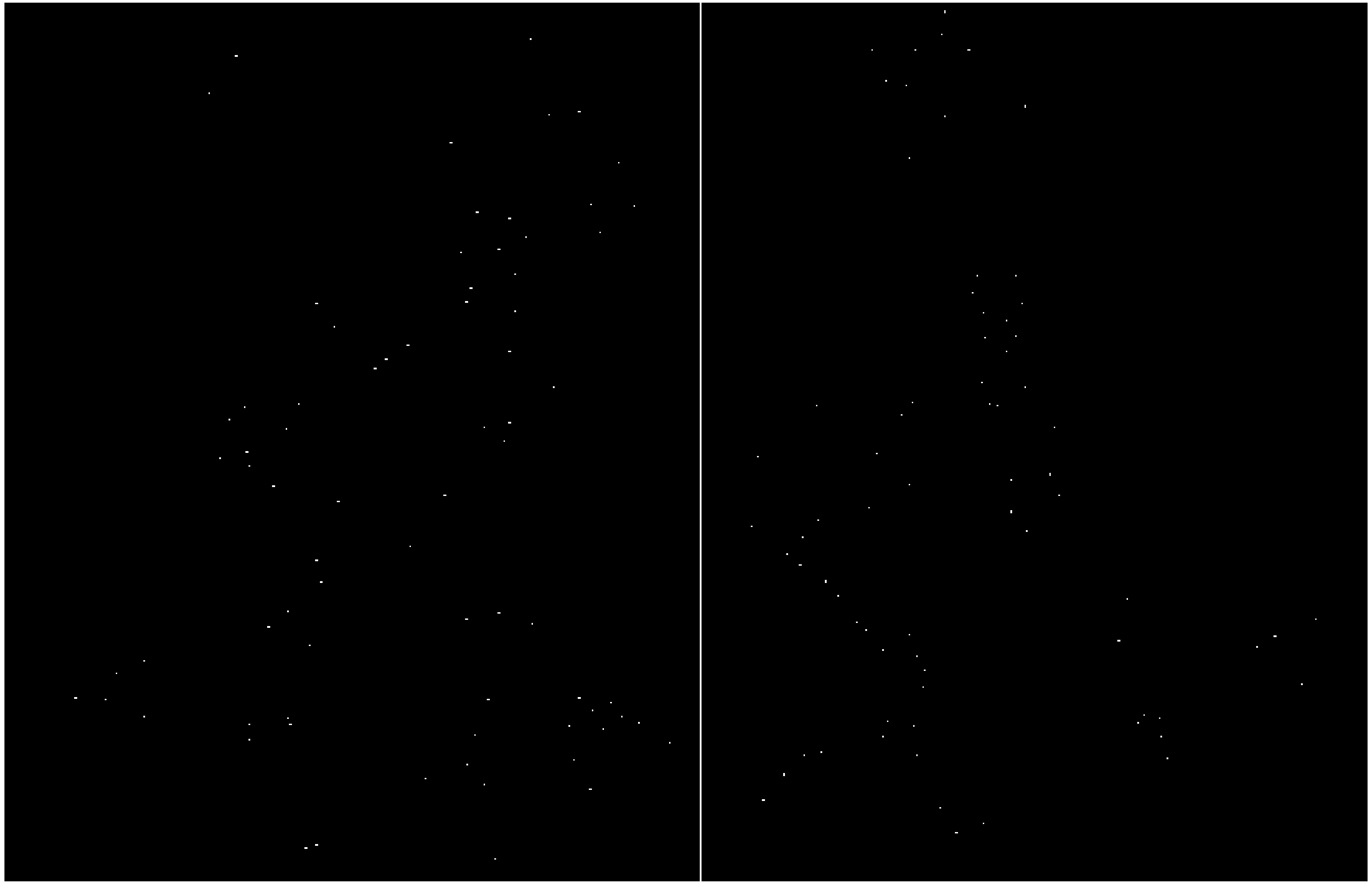
Find points with large corner response: $R >$ threshold



Source: James Hays

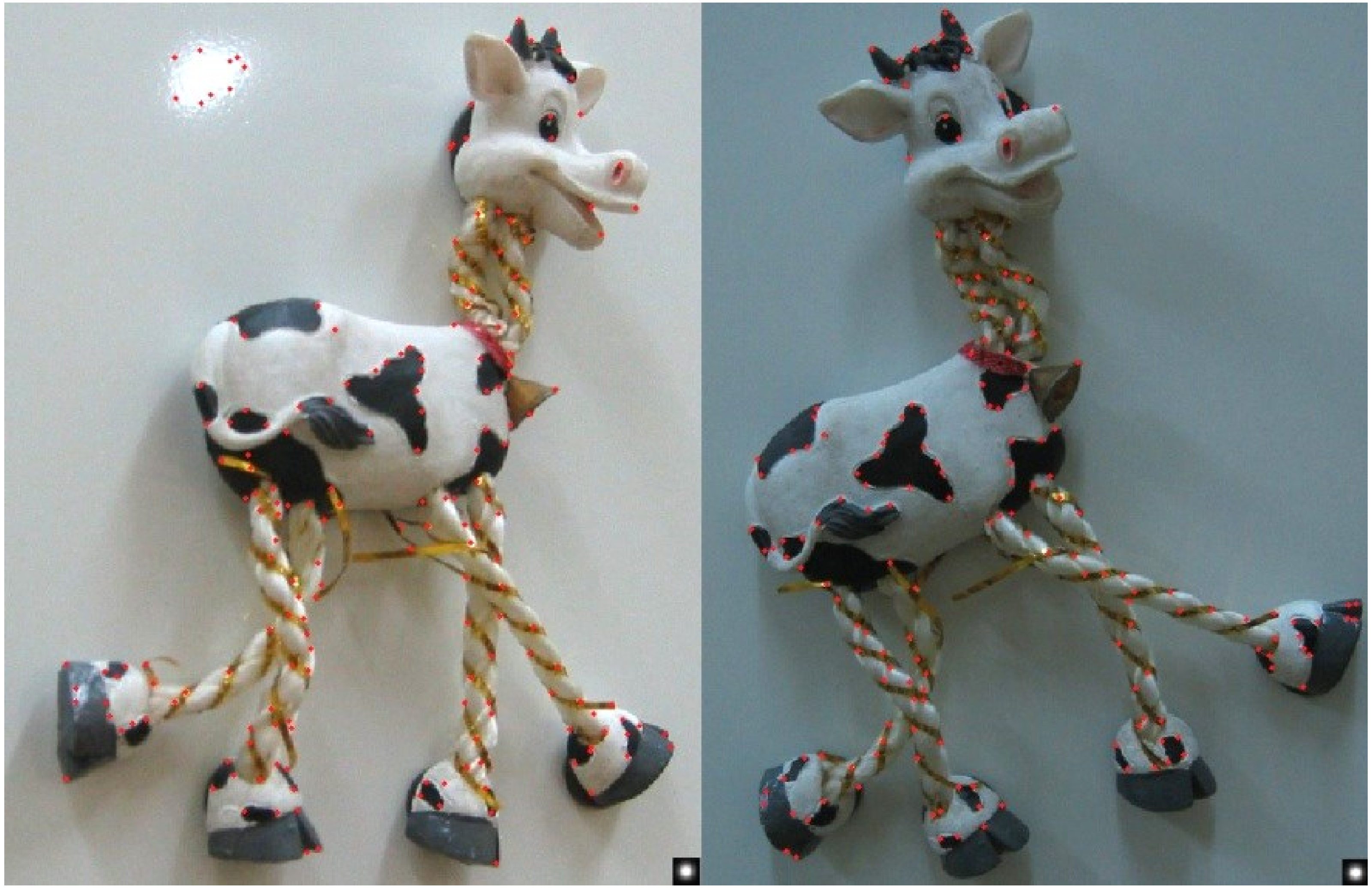
Harris detector steps

Take only the points of local maxima of R



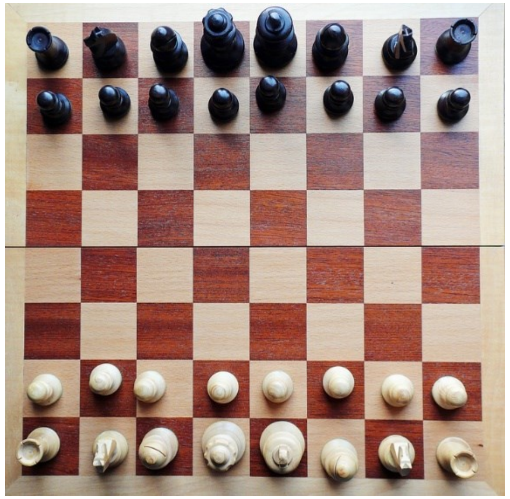
Source: James Hays

Harris detector steps



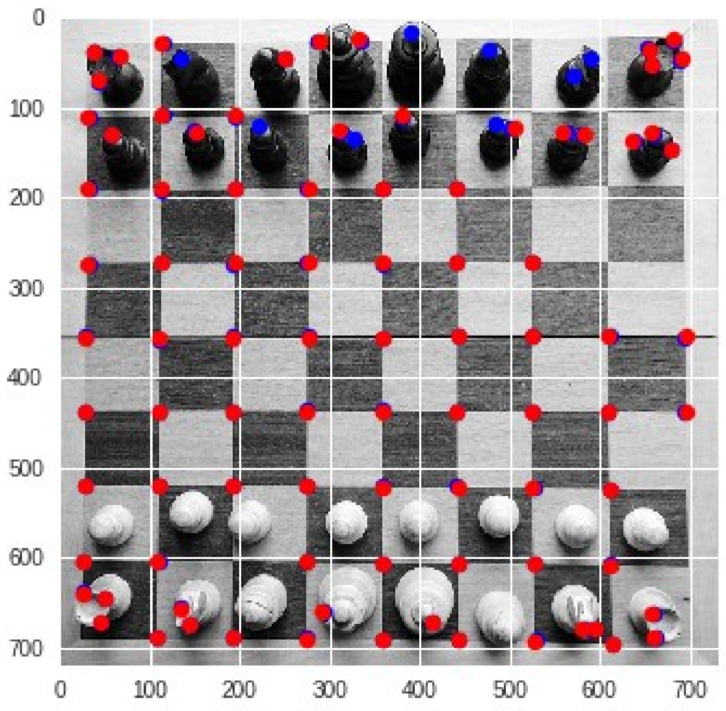
Source: James Hays

Harris corner detection: esempi

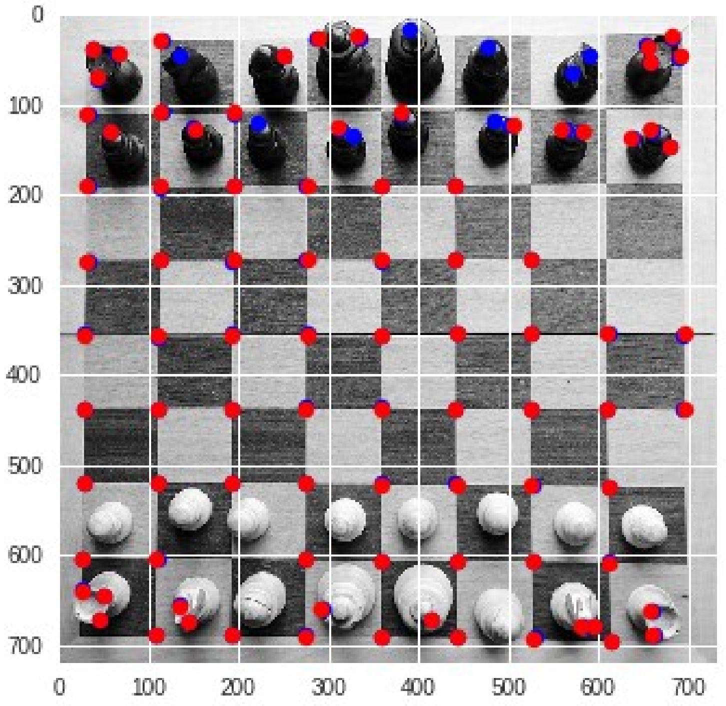


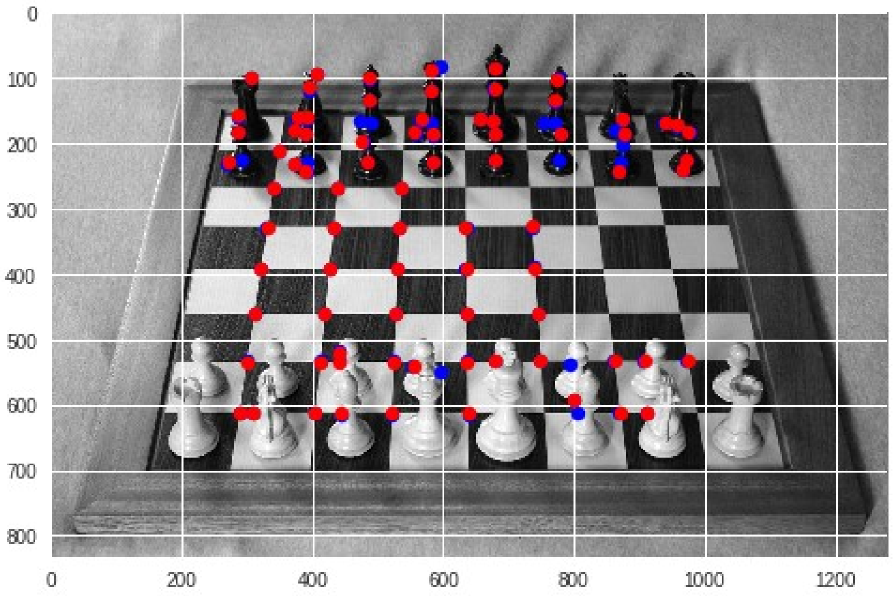
Harris corner detection: esempi

```
from matplotlib import pyplot as plt

import urllib.request

from skimage.io import imread
from skimage.color import rgb2gray
from skimage.feature import corner_harris, corner_subpix, corner_peaks

url = "https://dbloisi.github.io/corsi/images/chessboard-1.jpg"

image = imread(urllib.request.urlopen(url))
image = rgb2gray(image)

coords = corner_peaks(corner_harris(image), min_distance=10)
coords_subpix = corner_subpix(image, coords, window_size=13)

fig, ax = plt.subplots()
ax.imshow(image, interpolation='nearest', cmap=plt.cm.gray)
ax.plot(coords[:, 1], coords[:, 0], '.b', markersize=15)
ax.plot(coords_subpix[:, 1], coords_subpix[:, 0], '.r', markersize=15)
plt.show()
```

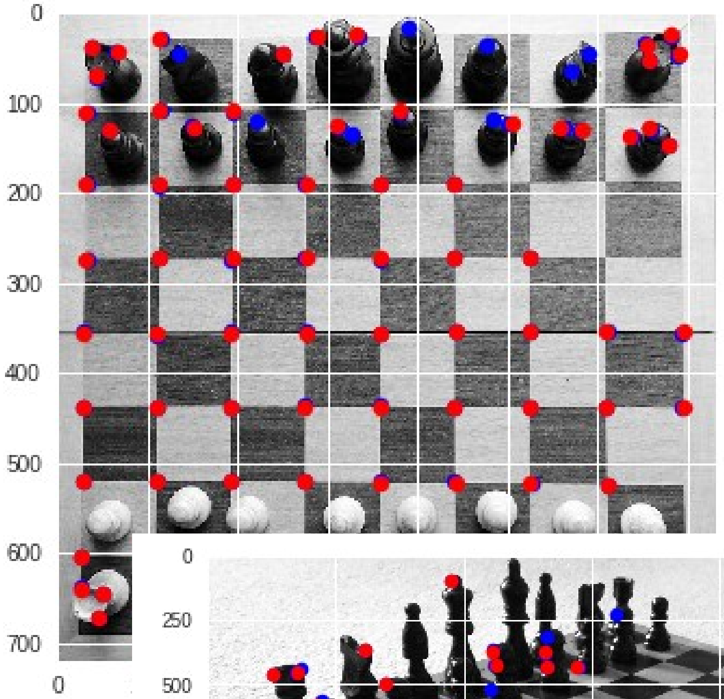


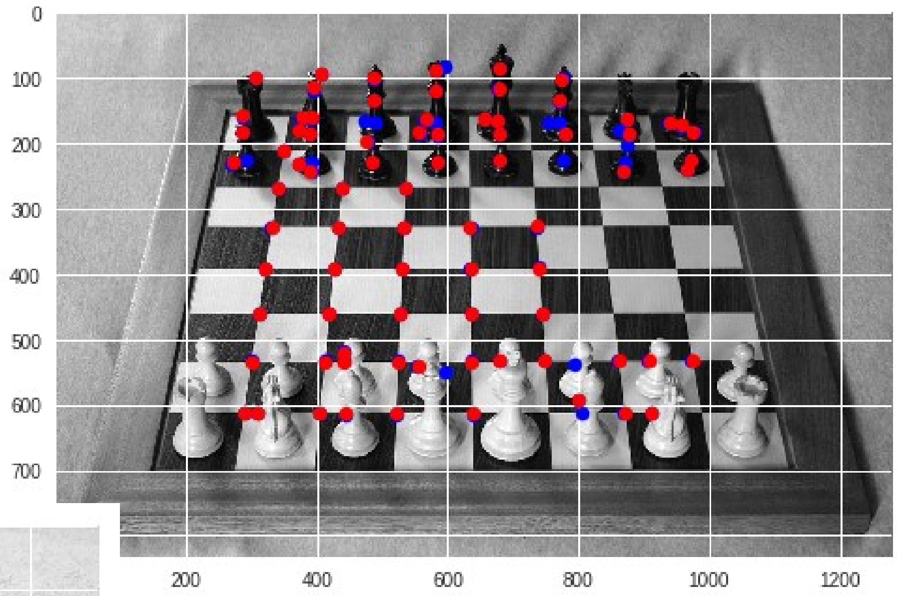
Harris corner detection: esempi

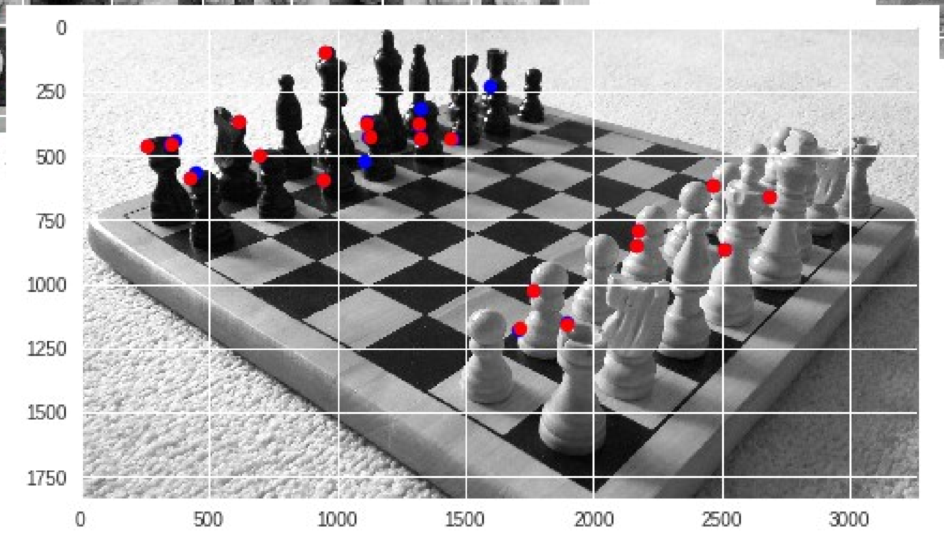




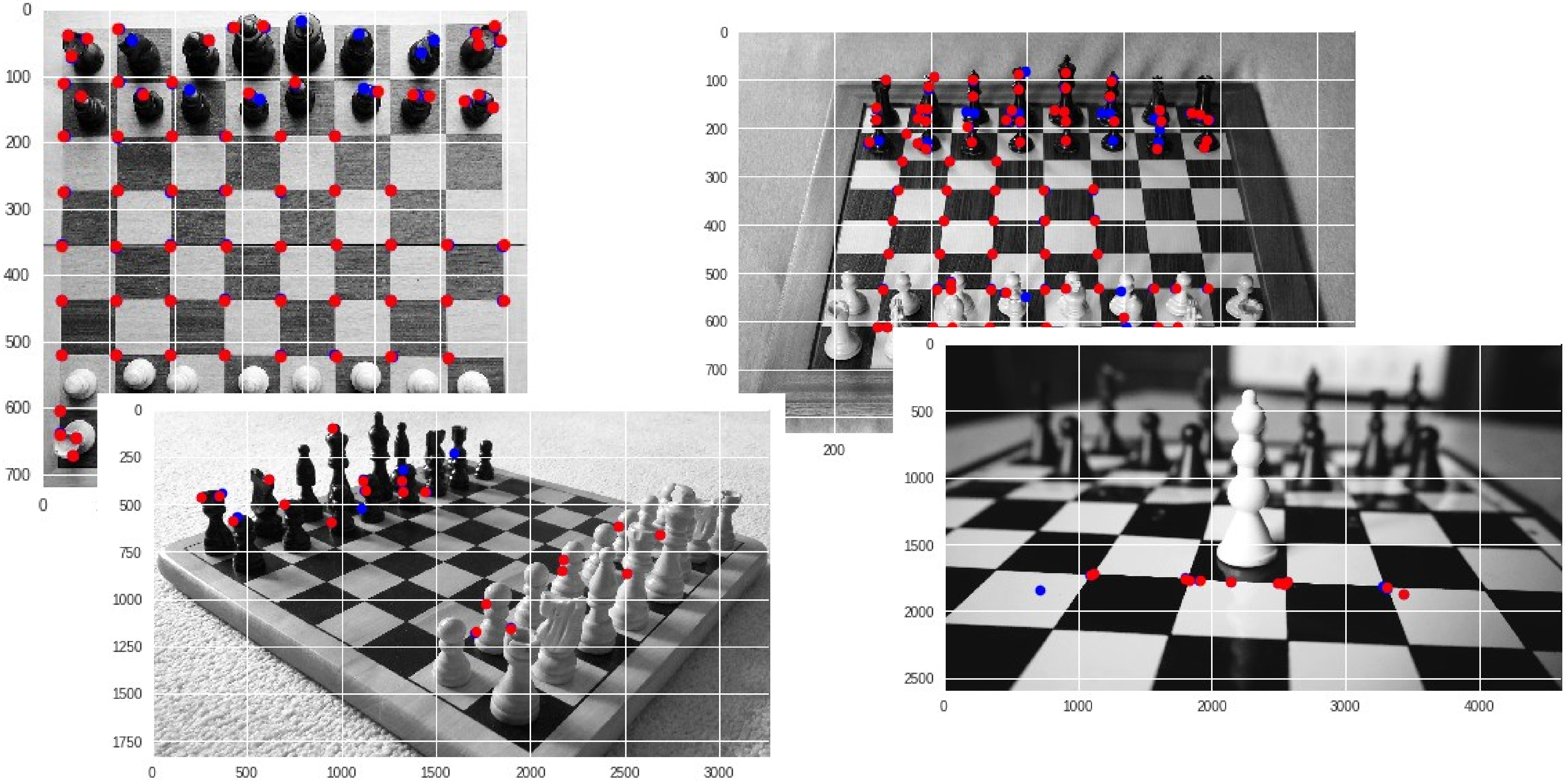
Harris corner detection: esempi







Harris corner detection: esempi



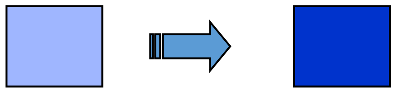
Invariance and covariance

We want corner locations to be *invariant* to photometric transformations and *covariant* to geometric transformations

- **Invariance:** image is transformed and corner locations do not change
- **Covariance:** if we have two transformed versions of the same image, features should be detected in corresponding locations

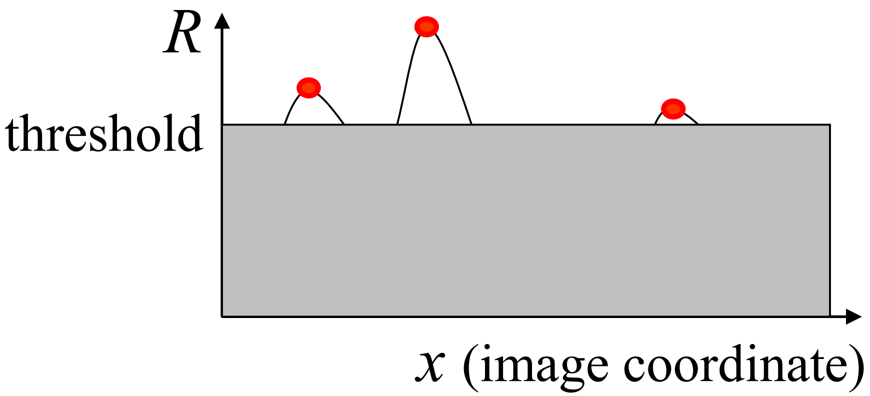
Source: James Hays

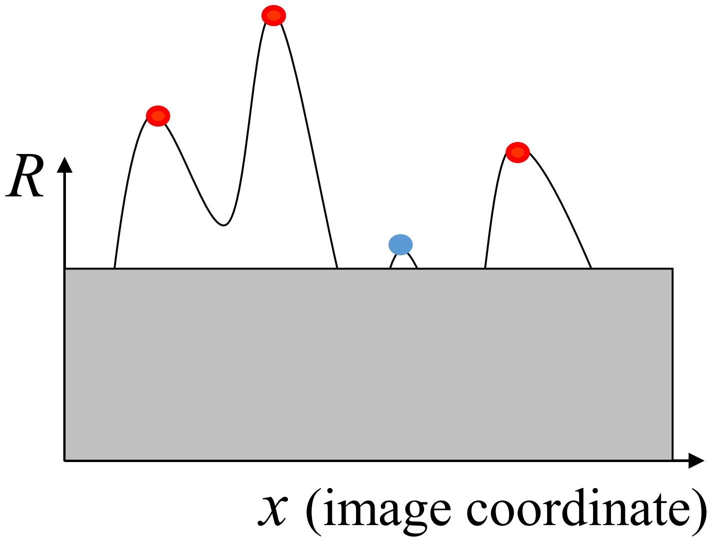
Affine intensity change



$$I \rightarrow a\,I + b$$

- Only derivatives are used ⇨ invariance to intensity shift $I \rightarrow I + b$
- Intensity scaling: $I \rightarrow a\,I$

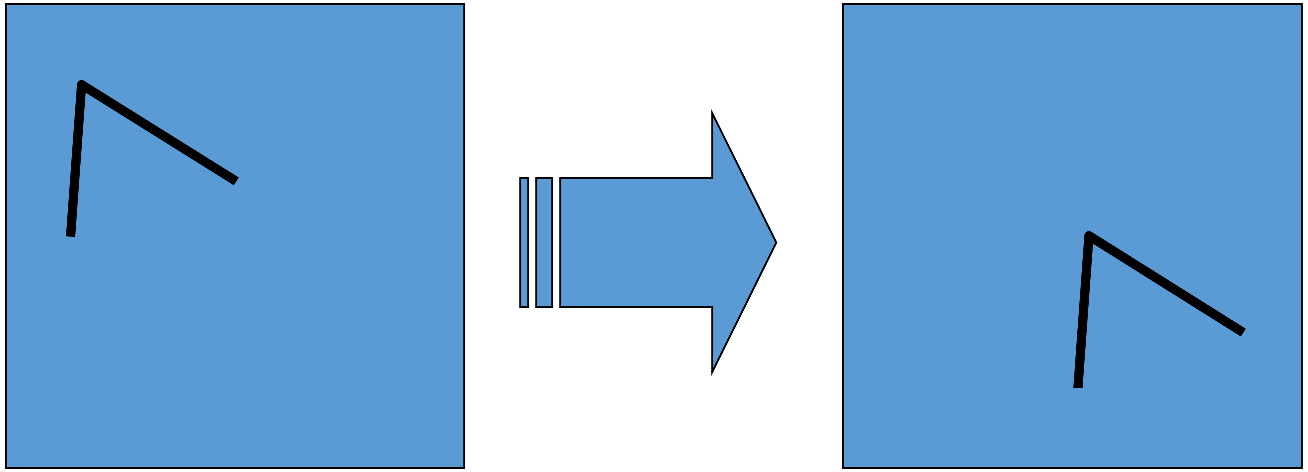




Partially invariant to affine intensity change

Source: James Hays

Translation

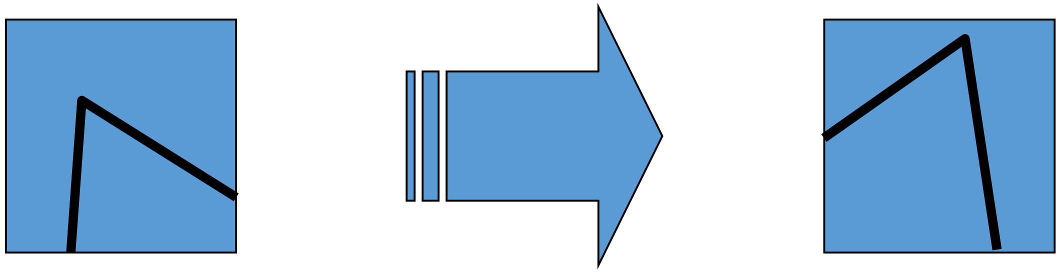


Derivatives and window function are shift-invariant

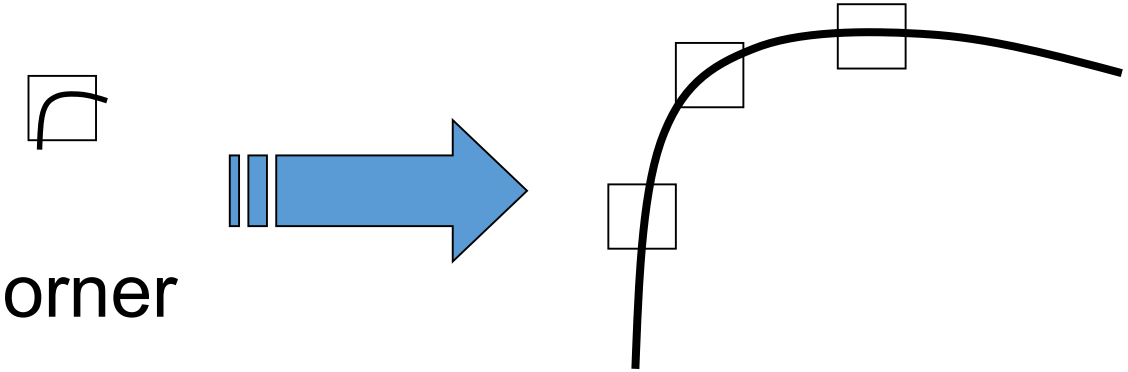
Corner location is covariant w.r.t. translation

Source: James Hays

Rotation and Scaling



Corner location is covariant w.r.t. rotation



Corner

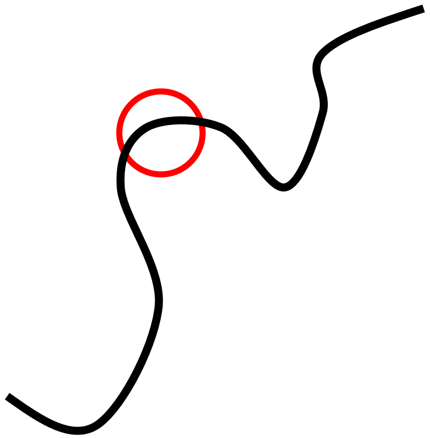
All points will be classified as edges

Corner location is not covariant to scaling!

Source: James Hays

Scale invariant detection

Suppose you're looking for corners

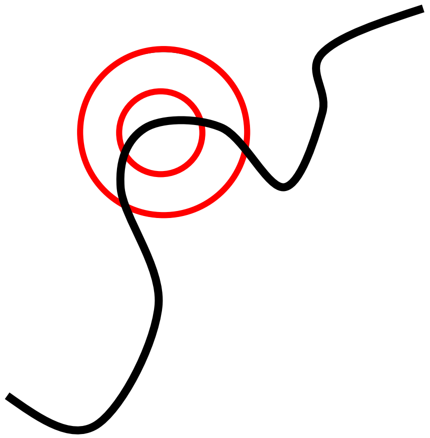


Key idea: find scale that gives local maximum of *f*

- in both position and scale
- One definition of *f*: the Harris operator

Scale invariant detection

Suppose you're looking for corners



Key idea: find scale that gives local maximum of f

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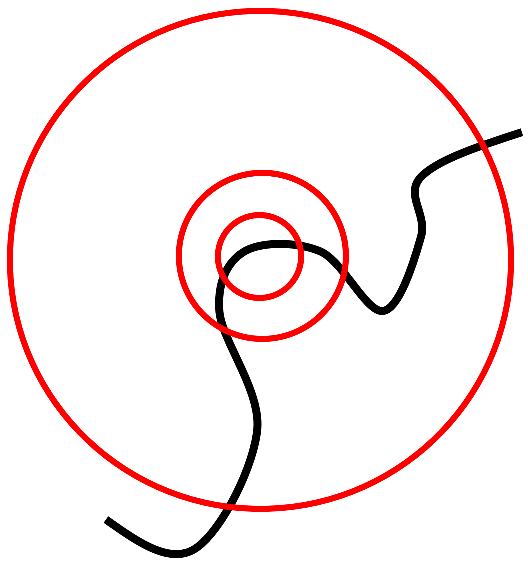
- One definition of f: the Harris operator

Scale invariant detection

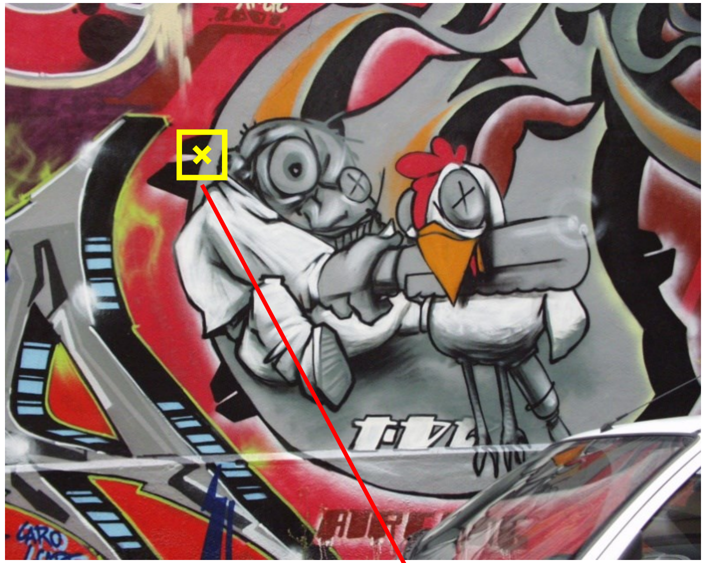
Suppose you're looking for corners



Key idea: find scale that gives local maximum of f

- in both position and scale
- One definition of f: the Harris operator

Scale invariance



$$f(I_{i_1 \ldots i_m}(x,\sigma)) = f(I_{i_1 \ldots i_m}(x',\sigma'))$$

How can we independently select interest points in each image, such that the detections are repeatable across different scales?

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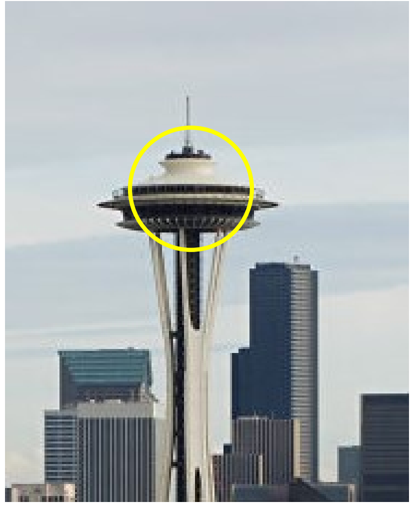
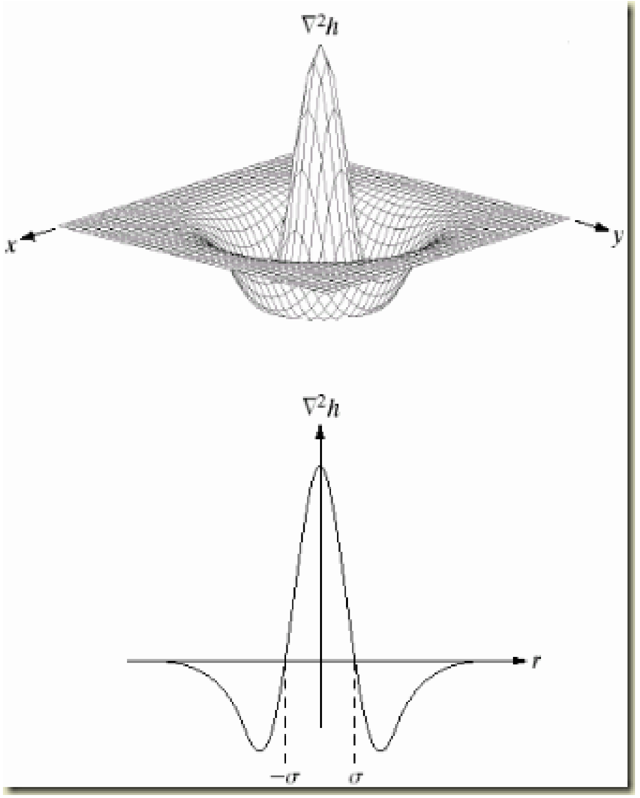
Differences between inside and outside

We can use a Laplacian function

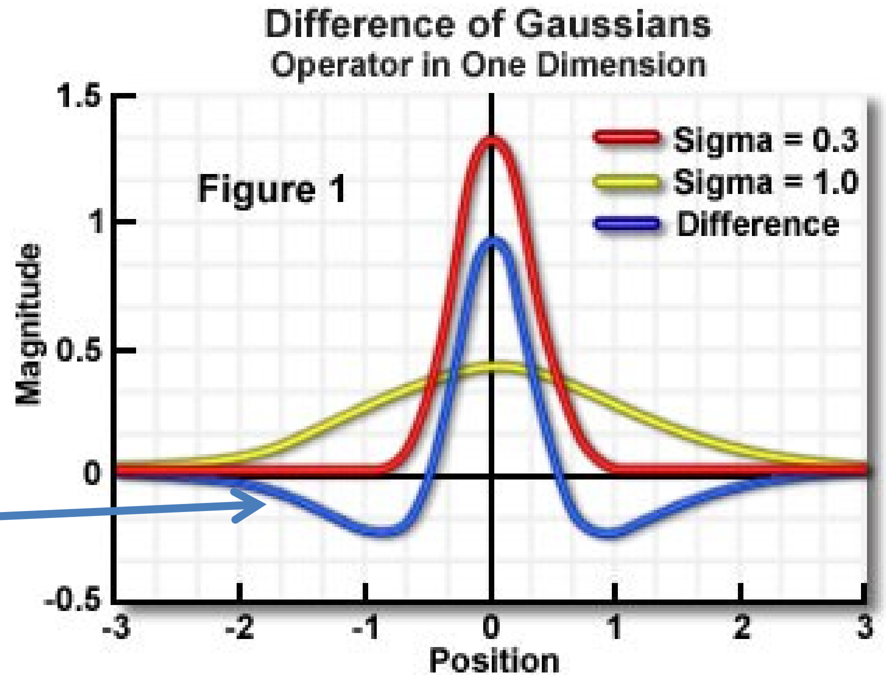




Source: Linda Shapiro

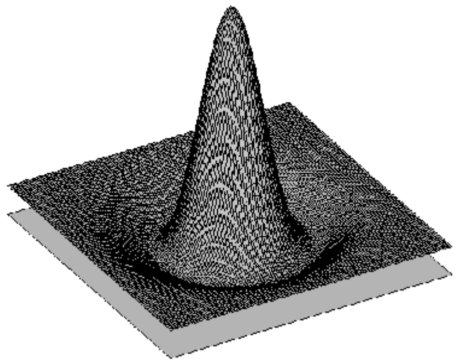
Difference-of-Gaussian (DoG)

In practice, the Laplacian is approximated using a Difference of Gaussian (DoG)



Gaussian is invariant to scale change, i.e., $f * \mathcal{G}_\sigma * \mathcal{G}_{\sigma'} = f * \mathcal{G}_{\sigma''}$ and has several other nice properties [Lindeberg, 1994]

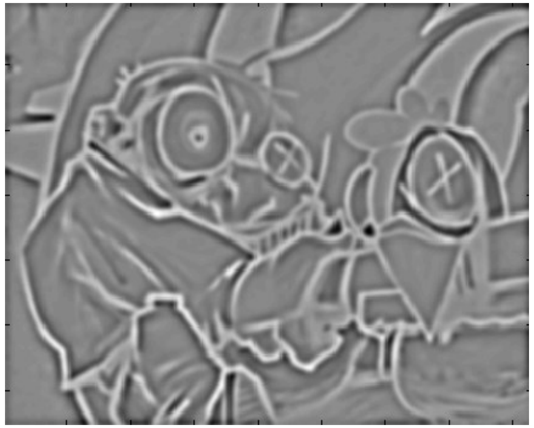
Difference-of-Gaussian (DoG)



G1 **-** **G2** **=** **DoG**

-

=



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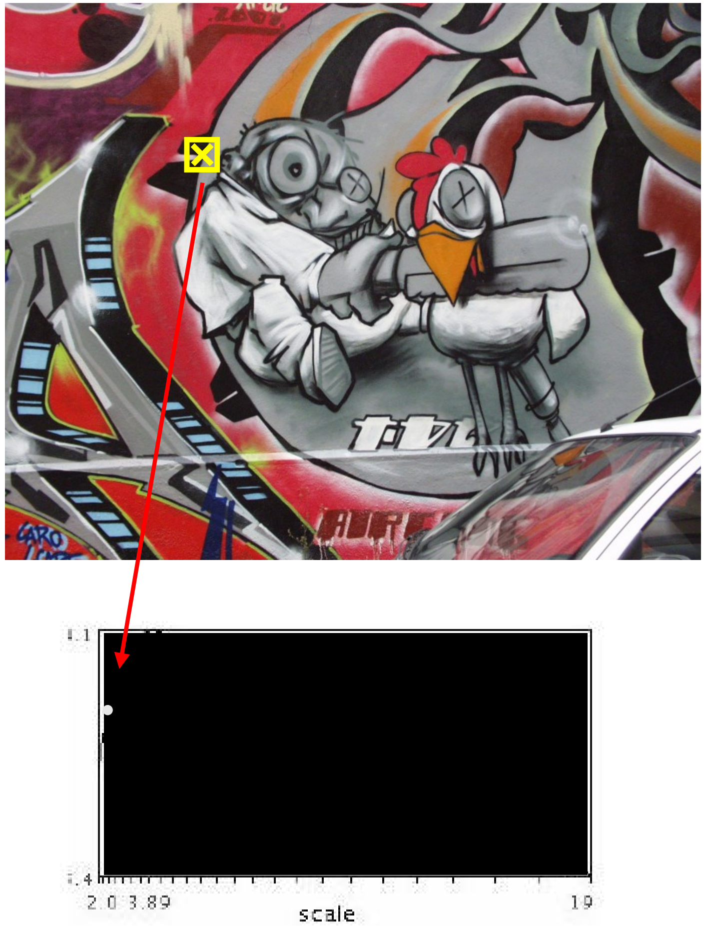
Automatic scale selection

- Function responses for increasing scale (scale signature)



$$f(I_{i_1 \ldots i_m}(x,\sigma))$$

$$f(I_{i_1 \ldots i_m}(x',\sigma))$$

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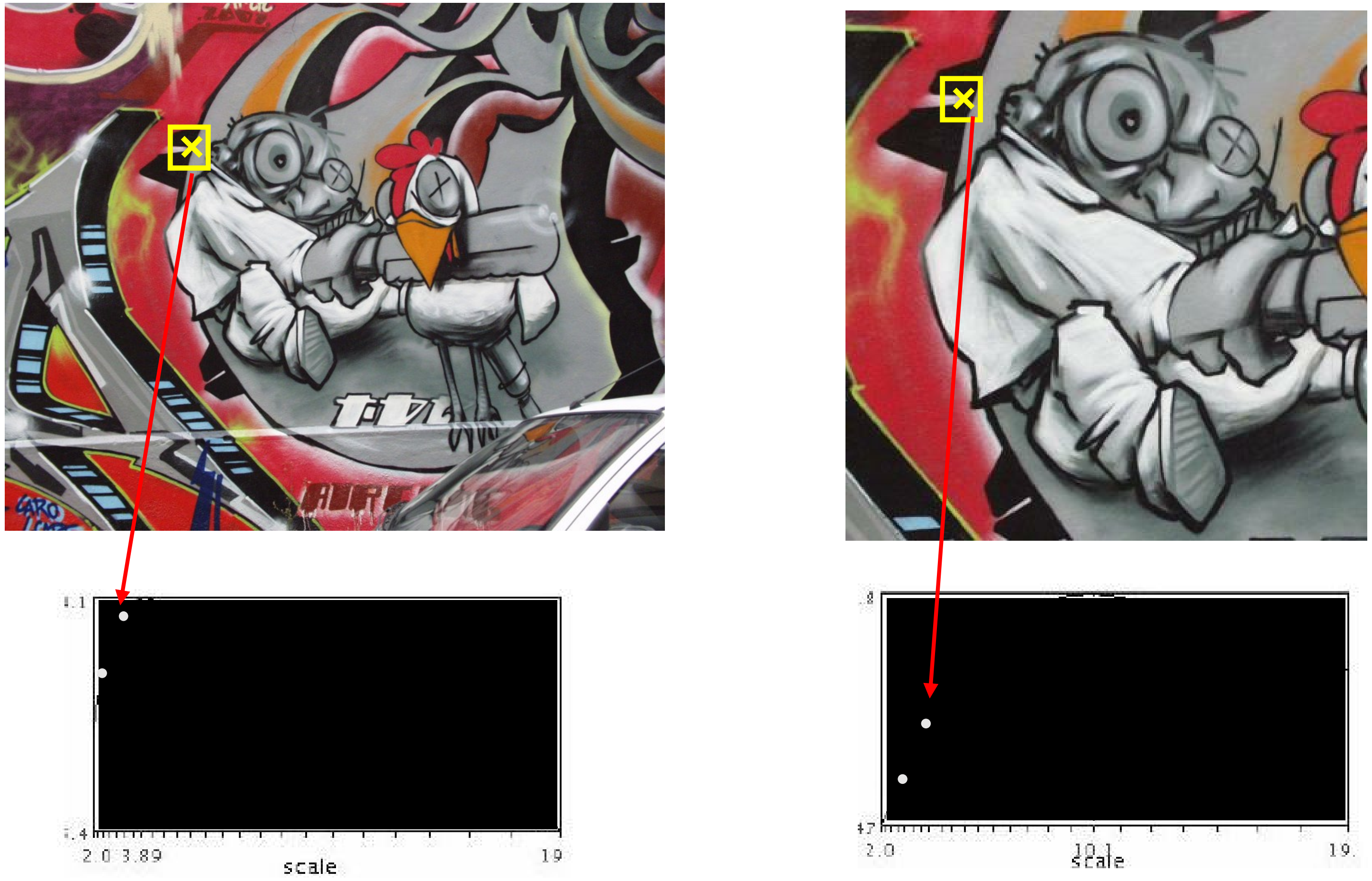
Automatic scale selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \dots i_m}(x,\sigma))$ $\qquad$ $f(I_{i_1 \dots i_m}(x',\sigma))$

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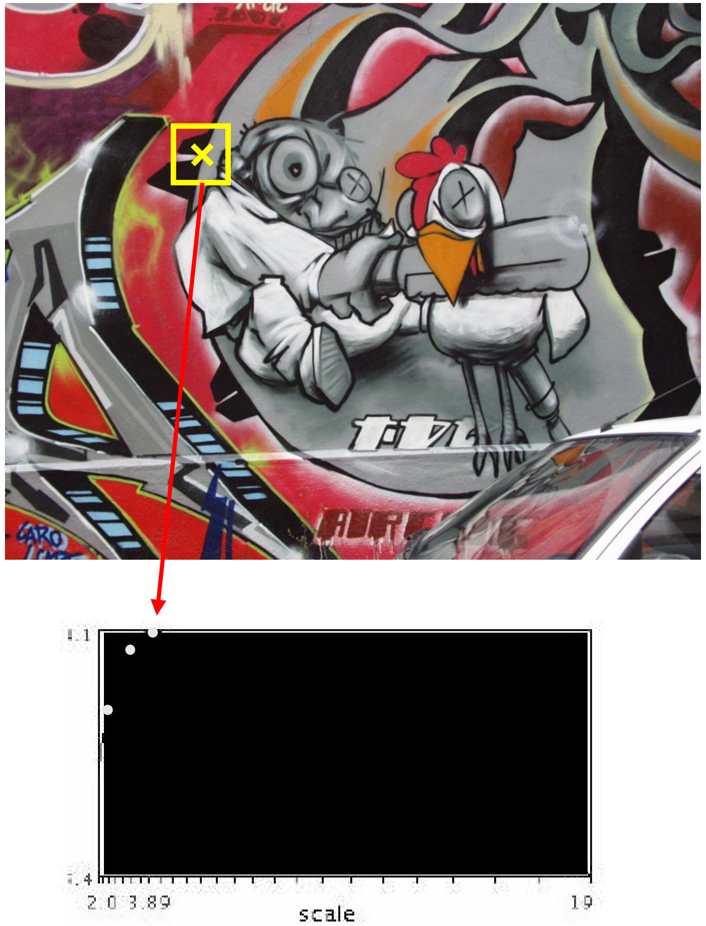
Automatic scale selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \dots i_m}(x, \sigma))$

$f(I_{i_1 \dots i_m}(x', \sigma))$

Automatic scale selection

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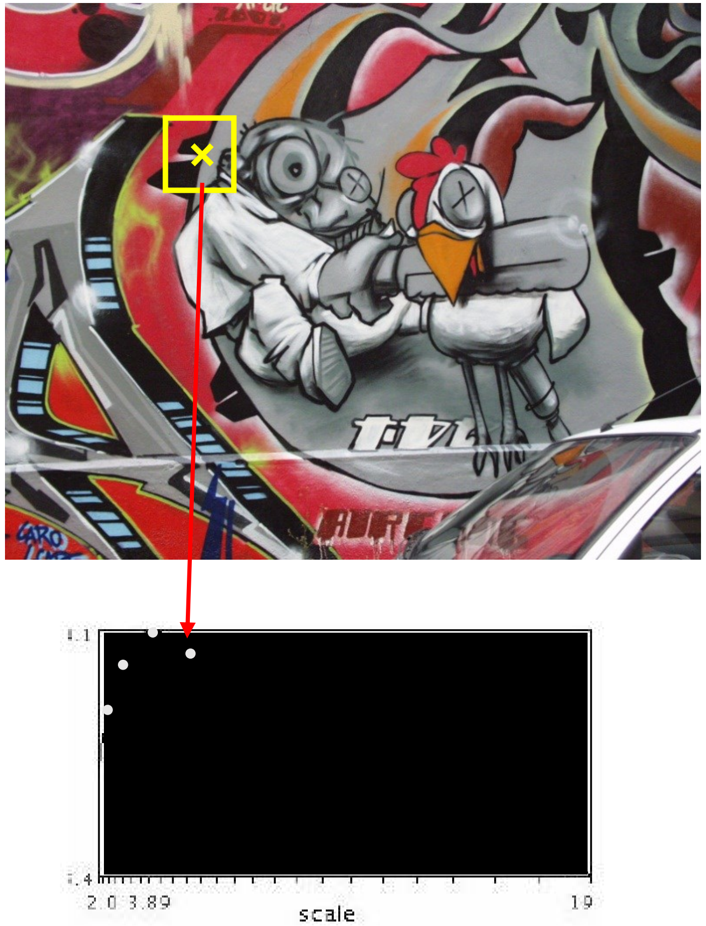

$$f(I_{i_1 \ldots i_m}(x,\sigma))$$

$$f(I_{i_1 \ldots i_m}(x',\sigma))$$

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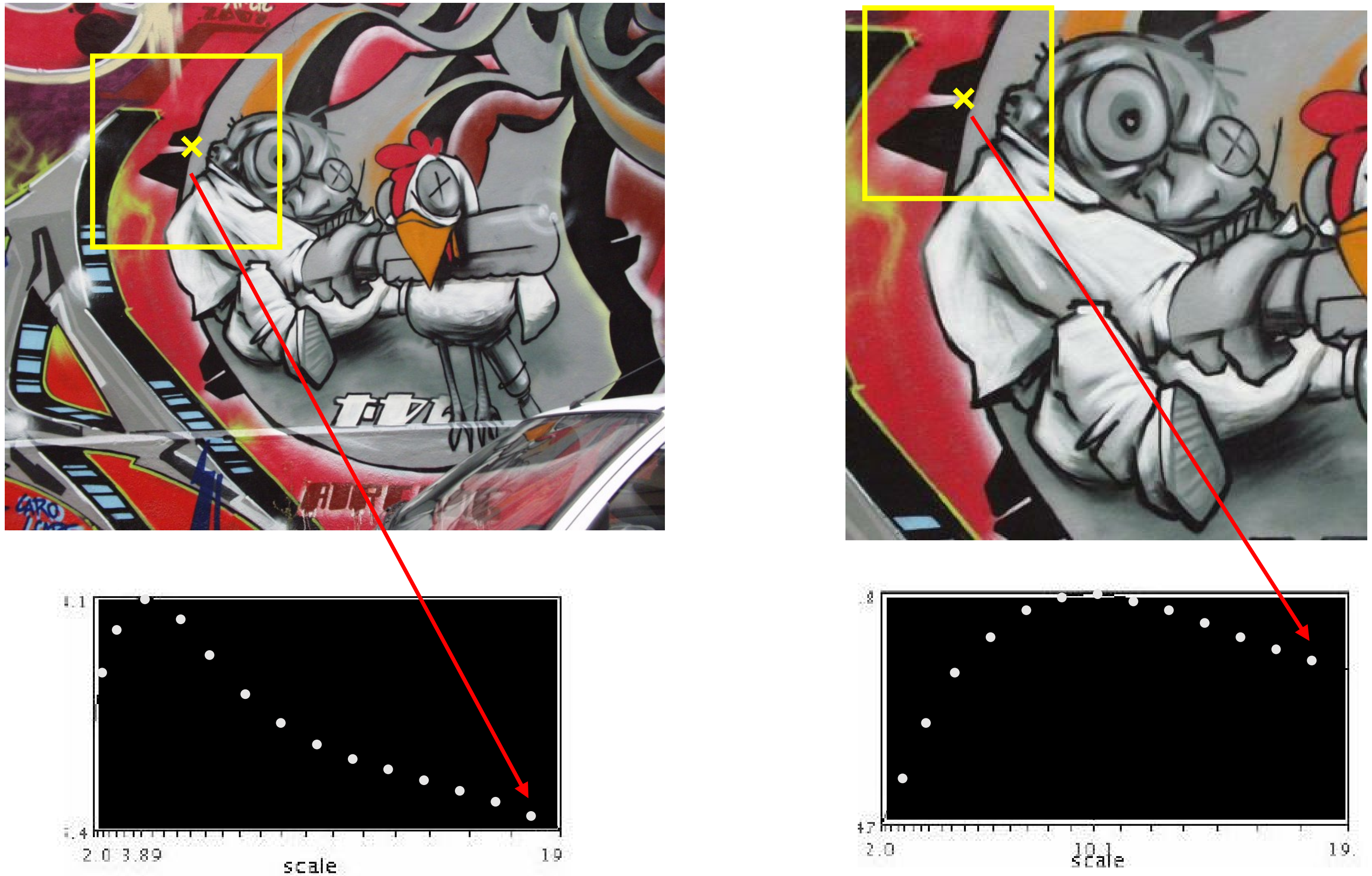
Automatic scale selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x,\sigma))$ $f(I_{i_1 \ldots i_m}(x',\sigma))$

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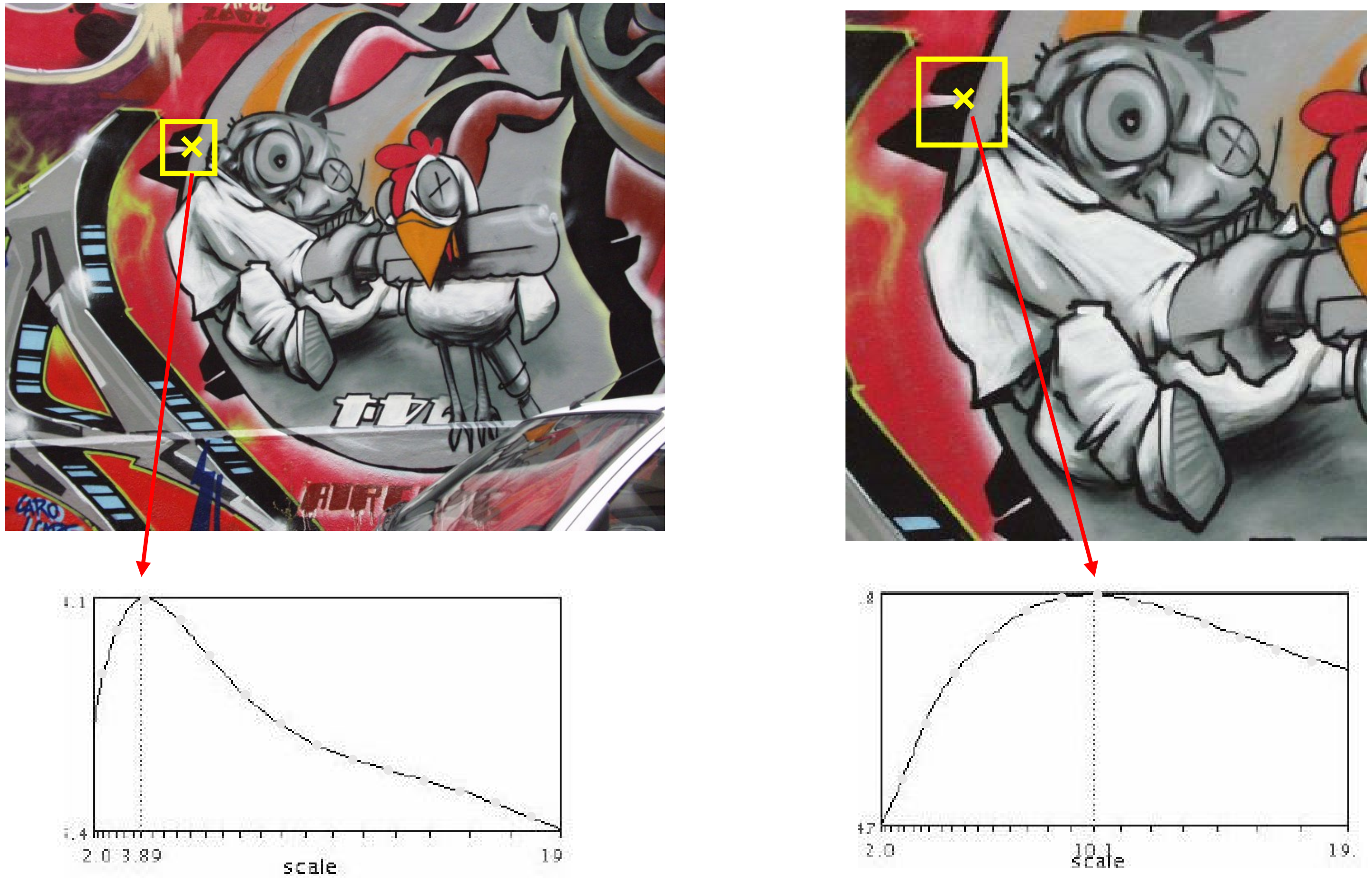
Automatic scale selection

- Function responses for increasing scale (scale signature)



$f(I_{i_1 \ldots i_m}(x,\sigma))$ $\qquad$ $f(I_{i_1 \ldots i_m}(x',\sigma'))$

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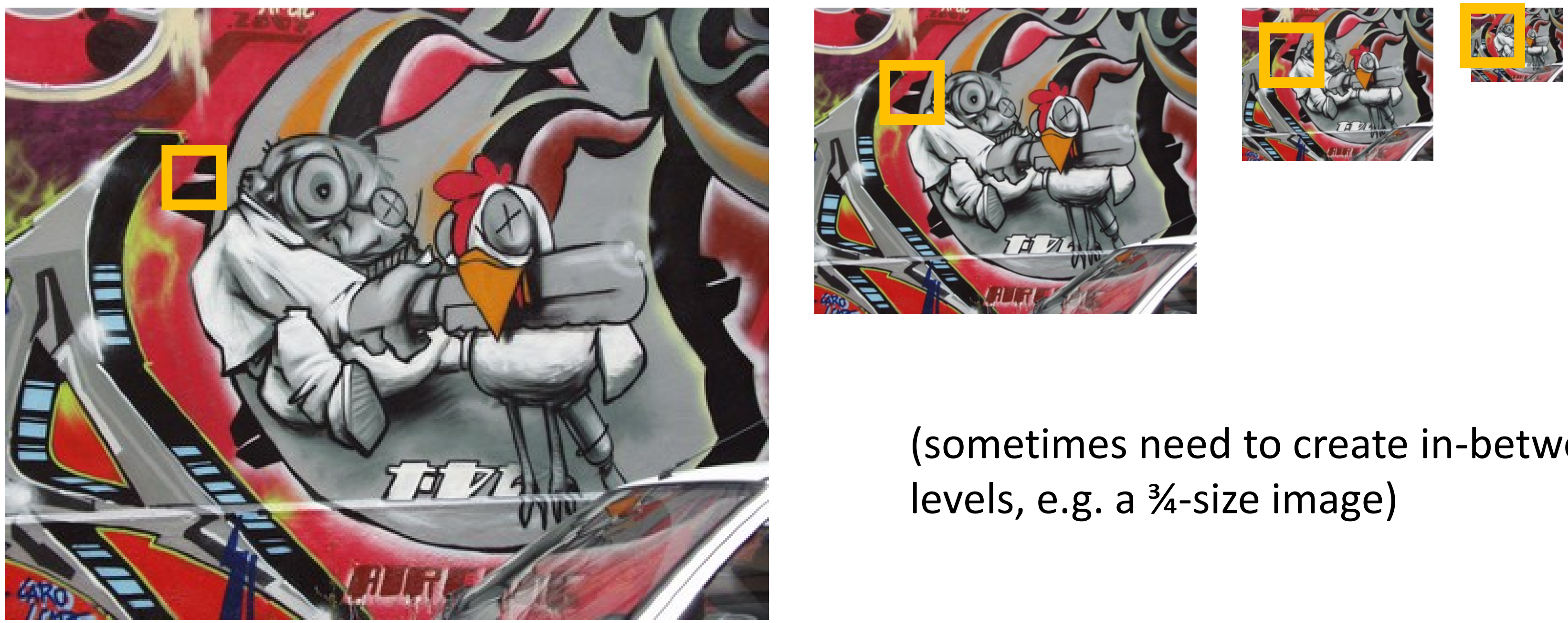
Implementation

- Instead of computing *f* for larger and larger windows, we can implement using a fixed window size with a Gaussian pyramid



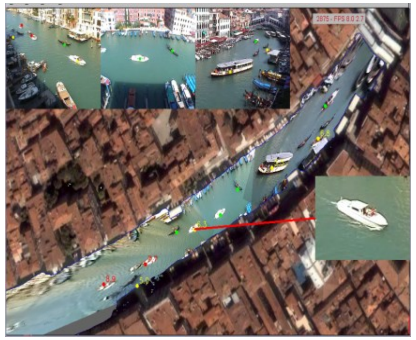
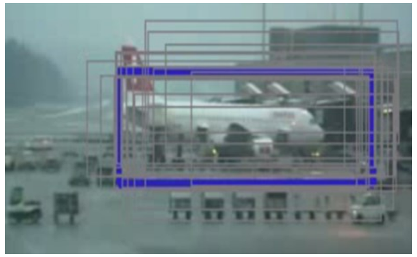
(sometimes need to create in-between levels, e.g. a ¾-size image)

UNIVERSITÀ DEGLI STUDI DELLA BASILICATA



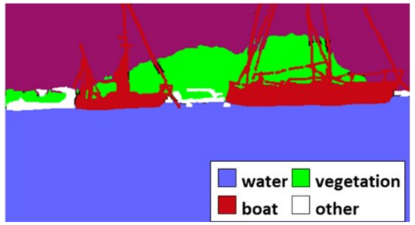
Corso di Sistemi Informativi
A.A. 2019/2020

Docente
Domenico Daniele Bloisi

Features





Aprile 2020