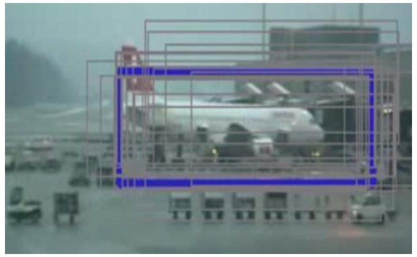
UNIVERSITÀ DEGLI STUDI DELLA BASILICATA

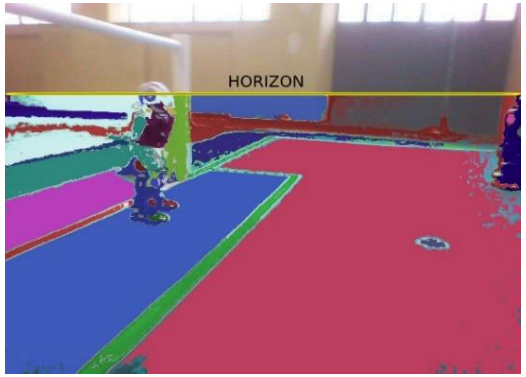


Corso di Visione e Percezione

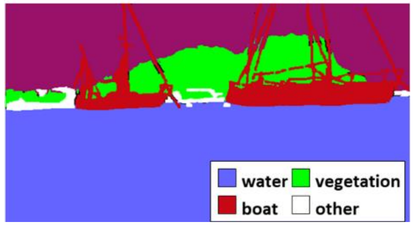
Docente
Domenico D. Bloisi

Features



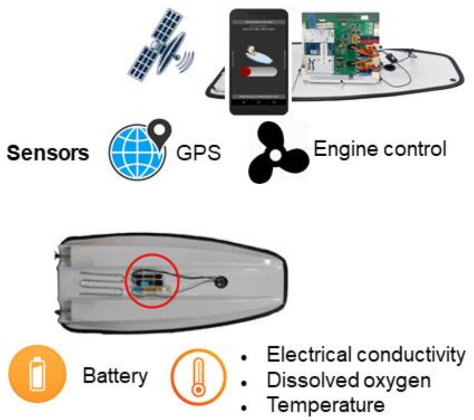


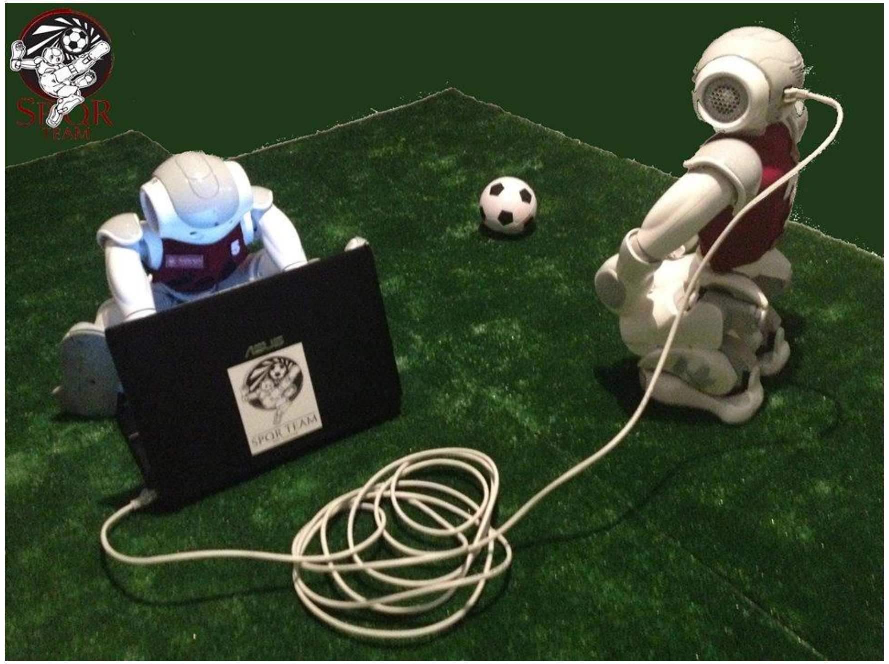


Domenico Daniele Bloisi

- Professore Associato
  Dipartimento di Matematica, Informatica ed Economia
  Università degli studi della Basilicata
  http://web.unibas.it/bloisi

- SPQR Robot Soccer Team
  Dipartimento di Informatica, Automatica e Gestionale Università degli studi di Roma “La Sapienza”
  http://spqr.diag.uniroma1.it





UNIBAS Wolves https://sites.google.com/unibas.it/wolves

- UNIBAS WOLVES is the robot soccer team of the University of Basilicata. Established in 2019, it is focussed on developing software for NAO soccer robots participating in RoboCup competitions.

- UNIBAS WOLVES team is twinned with SPQR Team at Sapienza University of Rome.

Informazioni sul corso

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

- Docente: Domenico Daniele Bloisi

- Periodo: II semestre marzo 2022 – giugno 2022

  - Martedì dalle 15:00 alle 17:00 (Aula Copernico)
  - Mercoledì dalle 8:30 alle 10:30 (Aula Copernico)

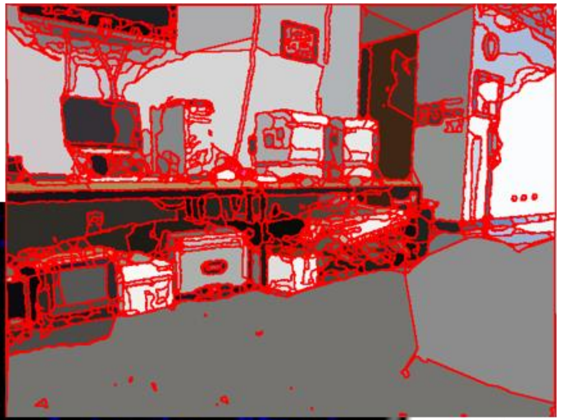
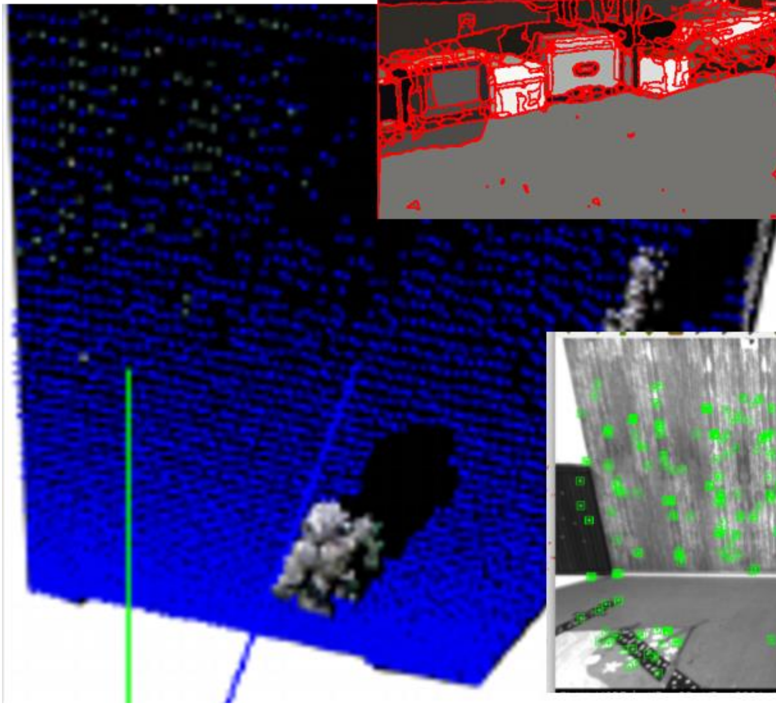
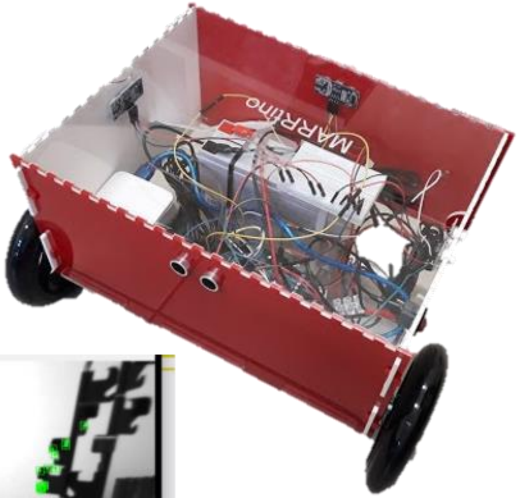
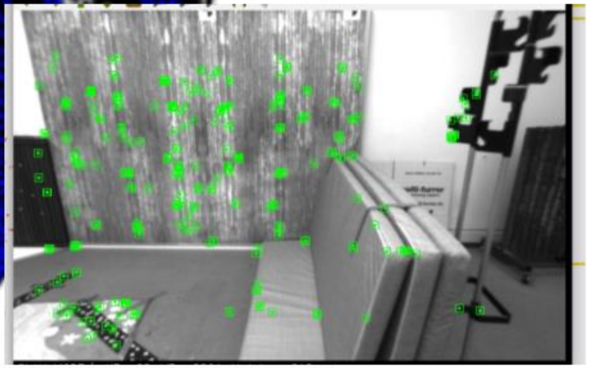
Ricevimento

- Durante il periodo delle lezioni:
  Mercoledì dalle 11:00 alle 12:30 → Edificio 3D, II piano, stanza 15
  Si invitano gli studenti a controllare regolarmente la bacheca degli avvisi per eventuali variazioni
- Al di fuori del periodo delle lezioni:
  da concordare con il docente tramite email

Per prenotare un appuntamento inviare una email a
domenico.bloisi@unibas.it

Programma – Visione e Percezione

- Introduzione al linguaggio Python
- Elaborazione delle immagini con Python
- Percezione 2D – OpenCV
- Introduzione al Deep Learning
- ROS
- Il paradigma publisher and subscriber
- Simulatori
- Percezione 3D - PCL

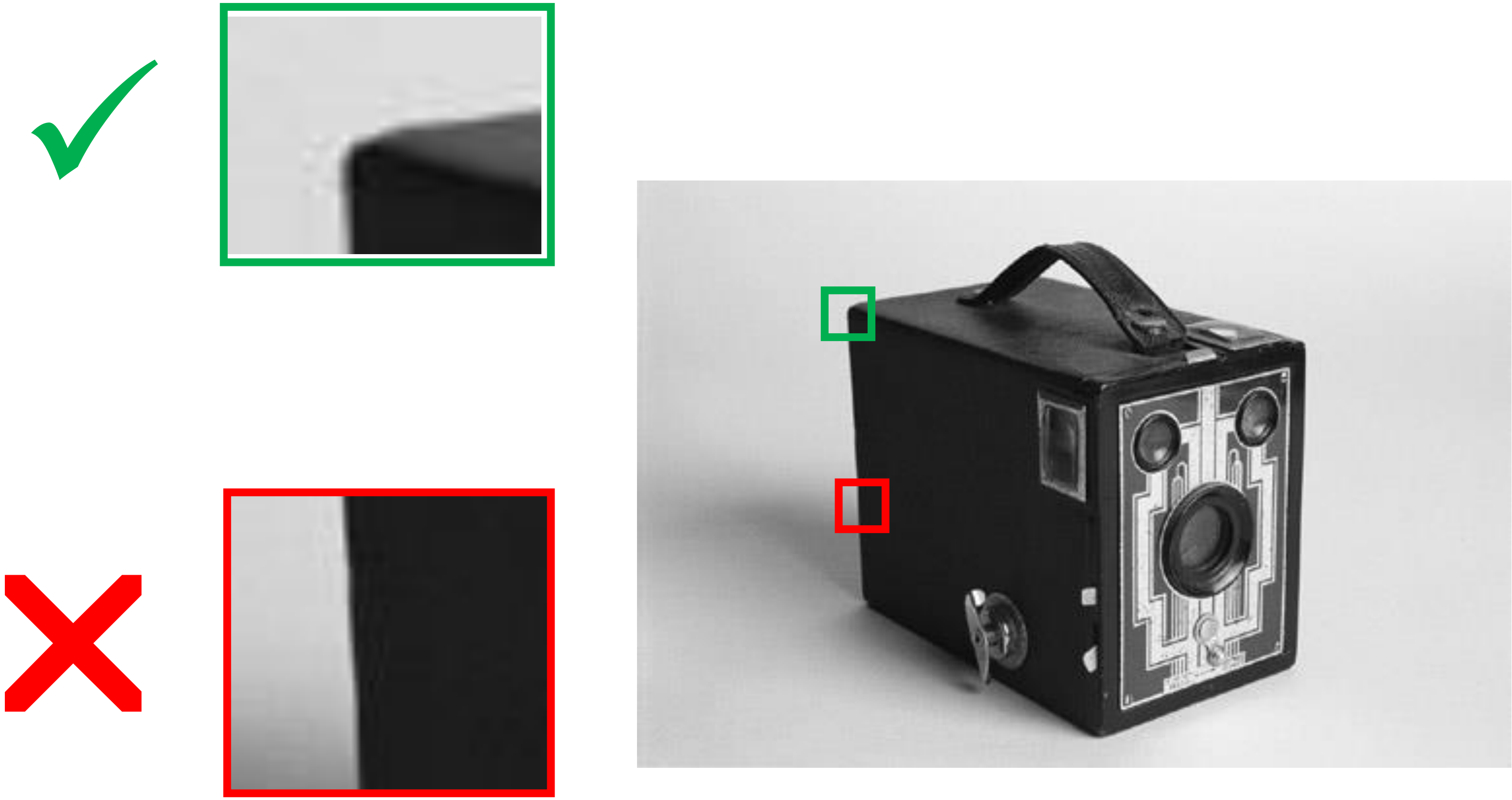





Riferimenti

- 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/

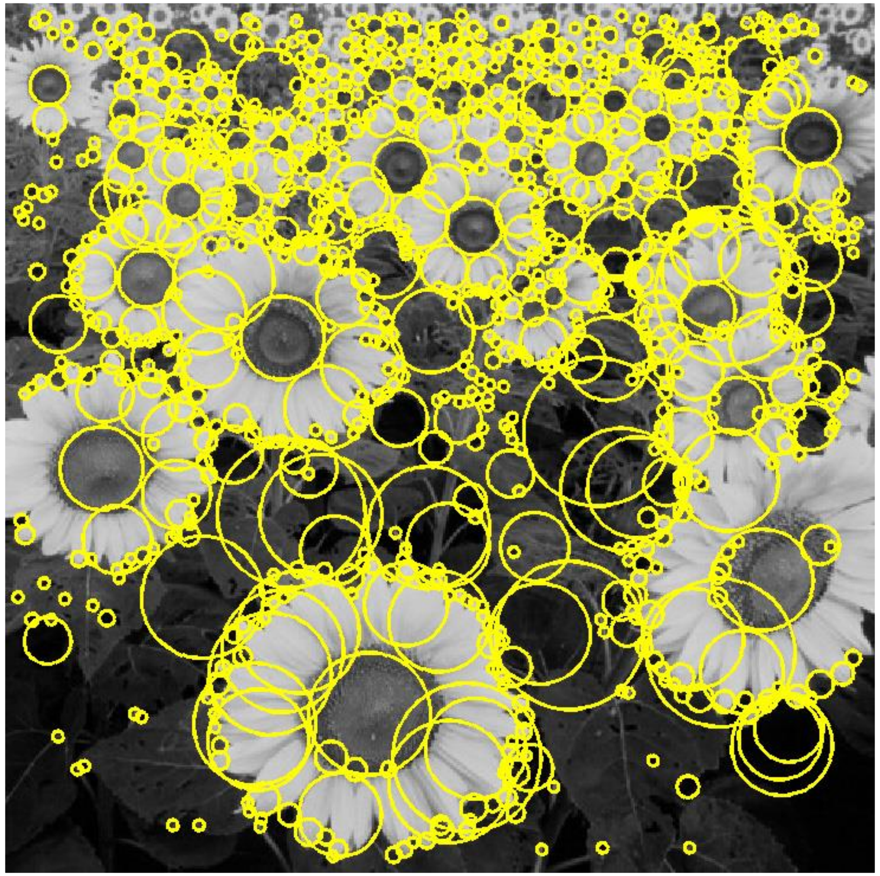
Corners

Large gradients in more than one direction



Adapted from CSc 83020 3-D Computer Vision – Ioannis Stamos

Blobs



A blob is a region of an image in which some properties like intensity or colour are approximately constant

Distinctive Features

- A point is distinctive when it looks different from its neighbors

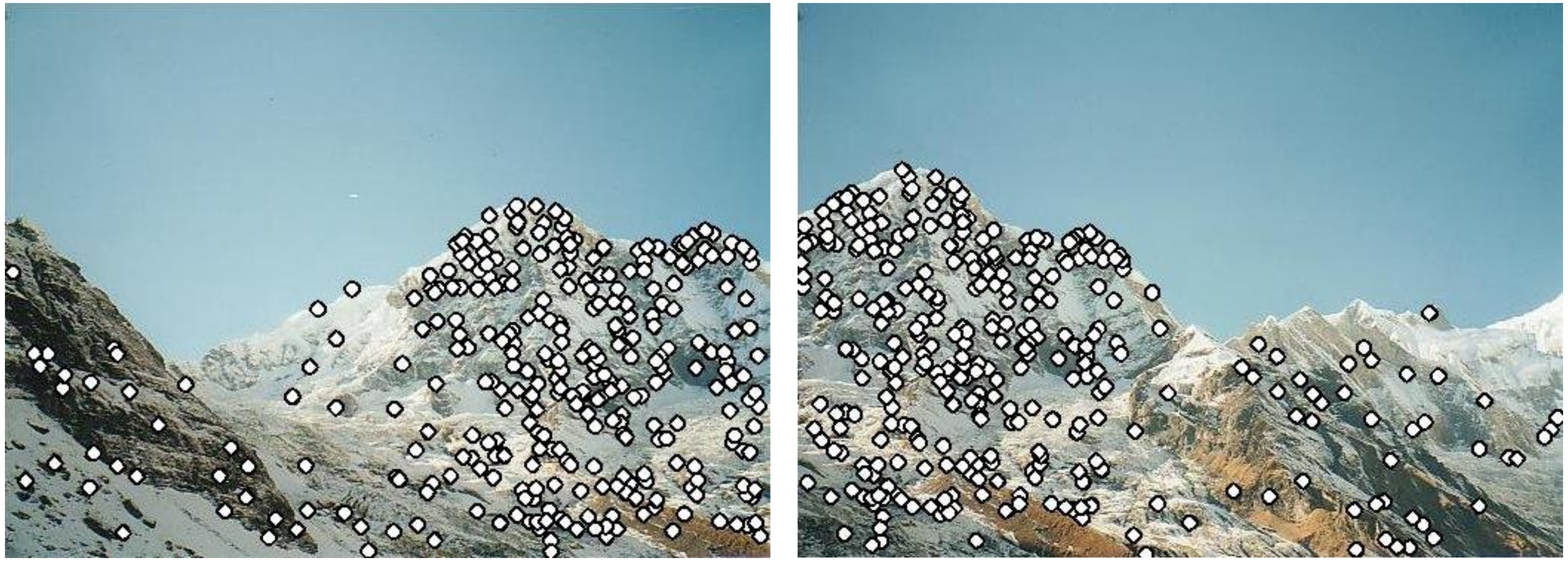
- A blob also looks different from neighbors at different scales

Feature matching

We have two images, how do we combine them?

Feature matching

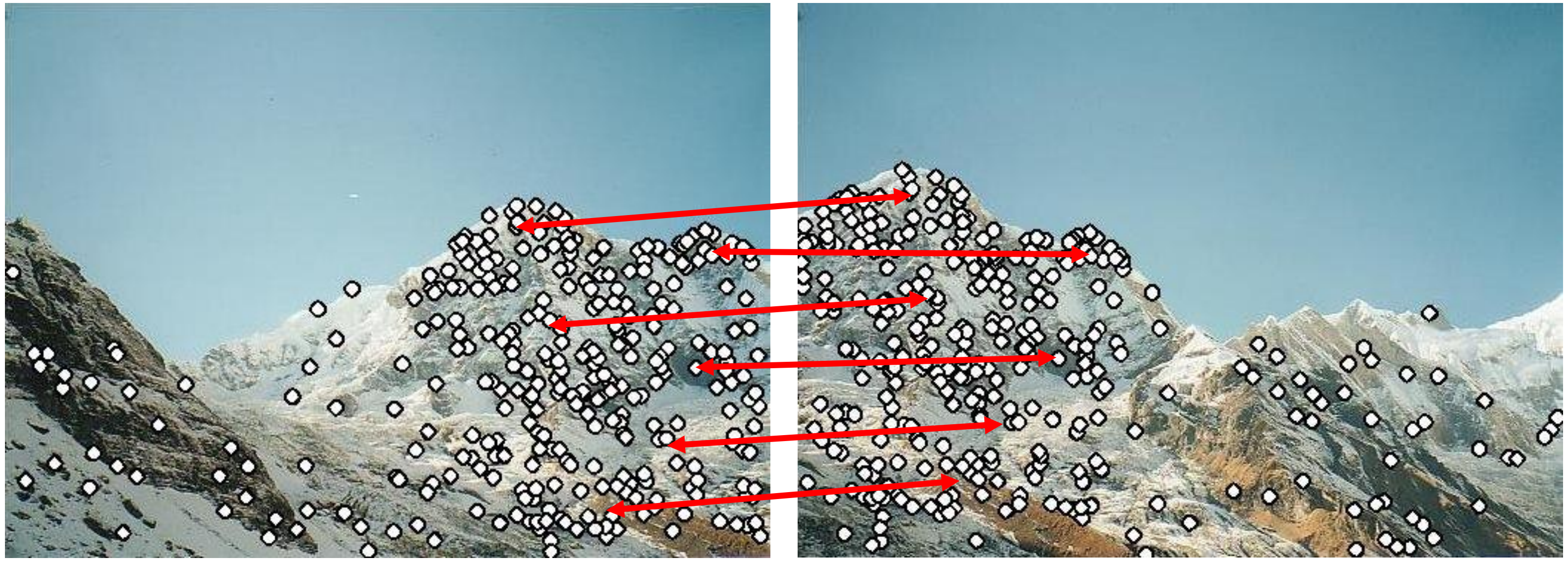
Step 1: extract features



Feature matching

Step 1: extract features

Step 2: match features



Feature matching

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

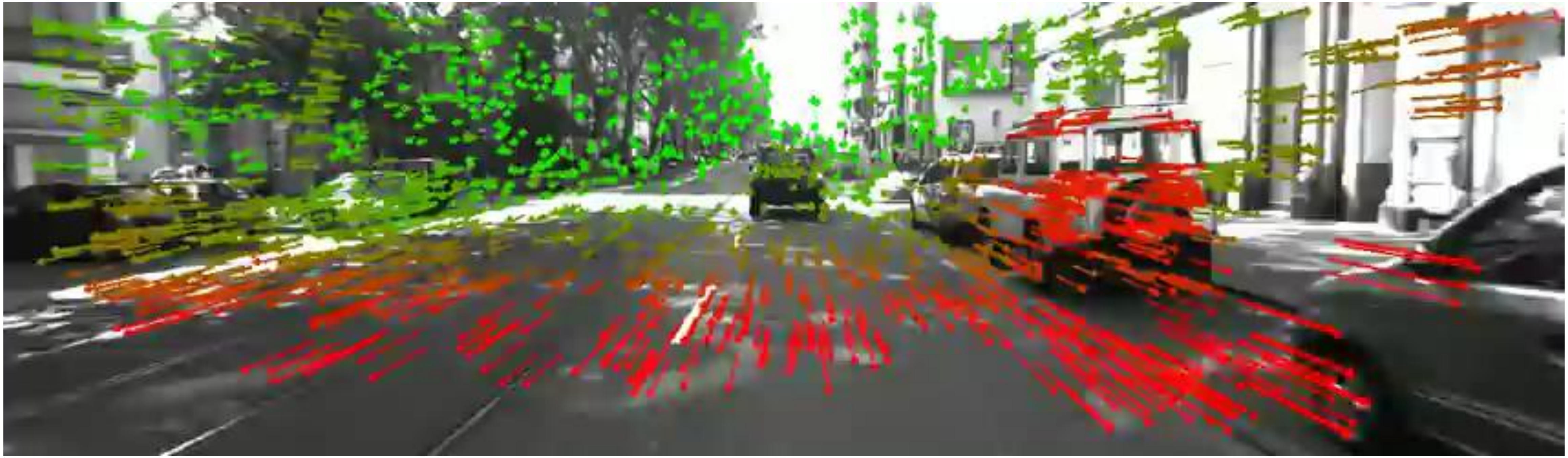
Automatic panoramas

Credit: Matt Brown

Automatic panoramas

http://gigapan.com

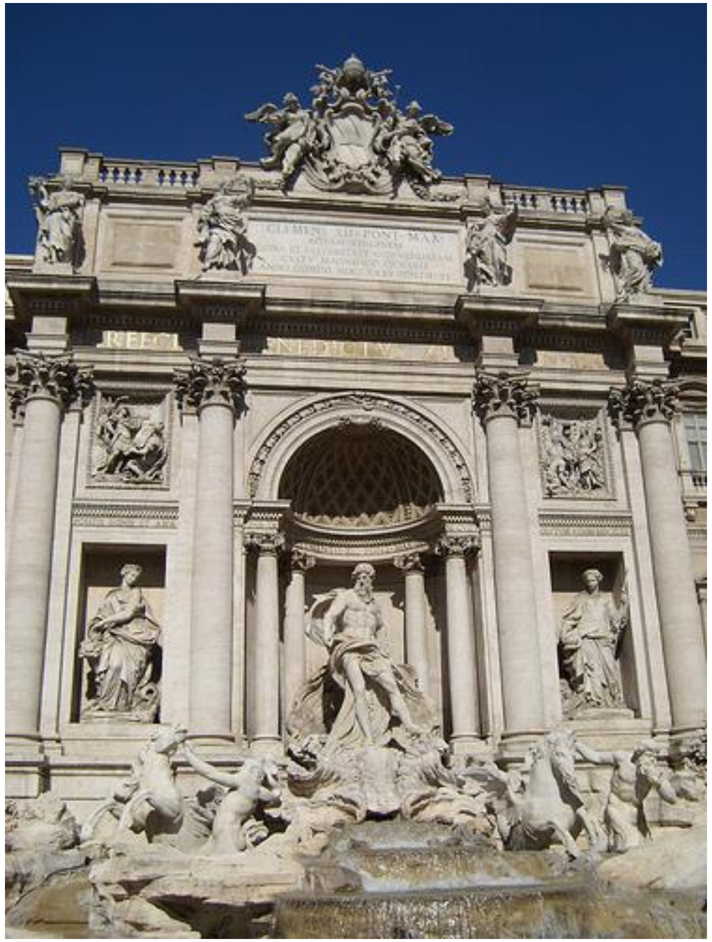
Visual SLAM



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

Image matching

by Diva Sian



by swashford

Harder case

by Diva Sian

by scgbt

Image Matching Challenge

https://www.cs.ubc.ca/research/image-matching-challenge/

Image matching on Mars

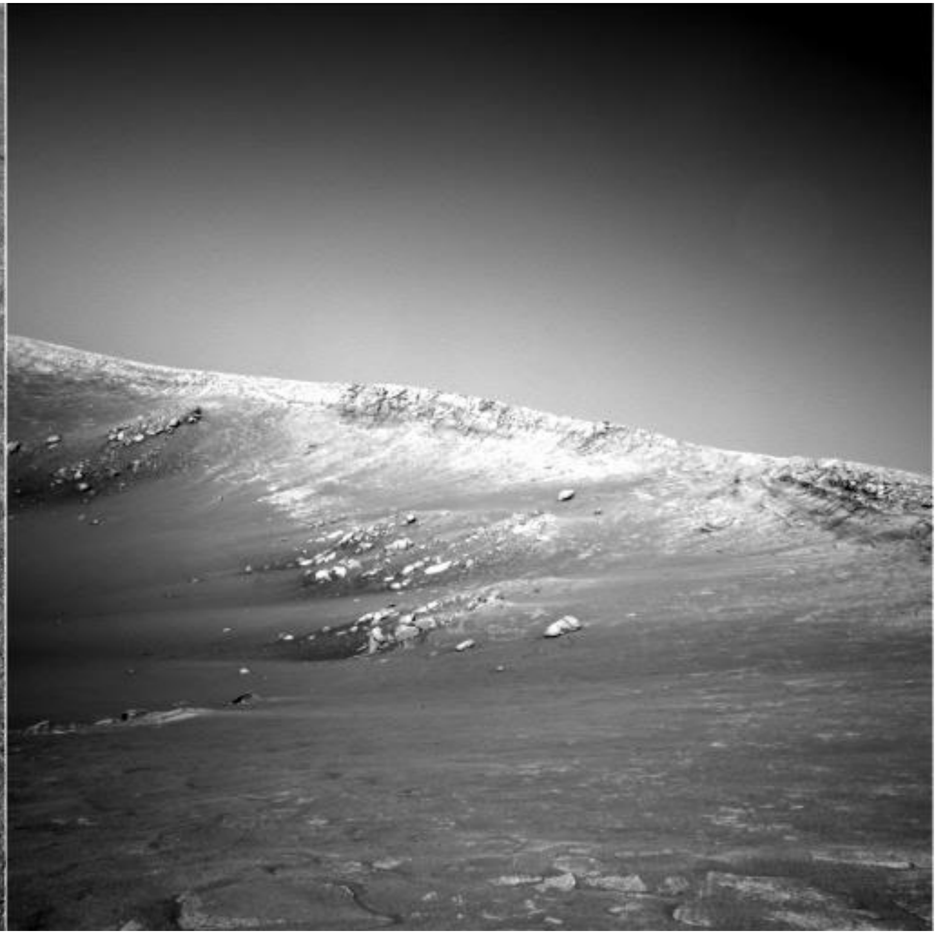
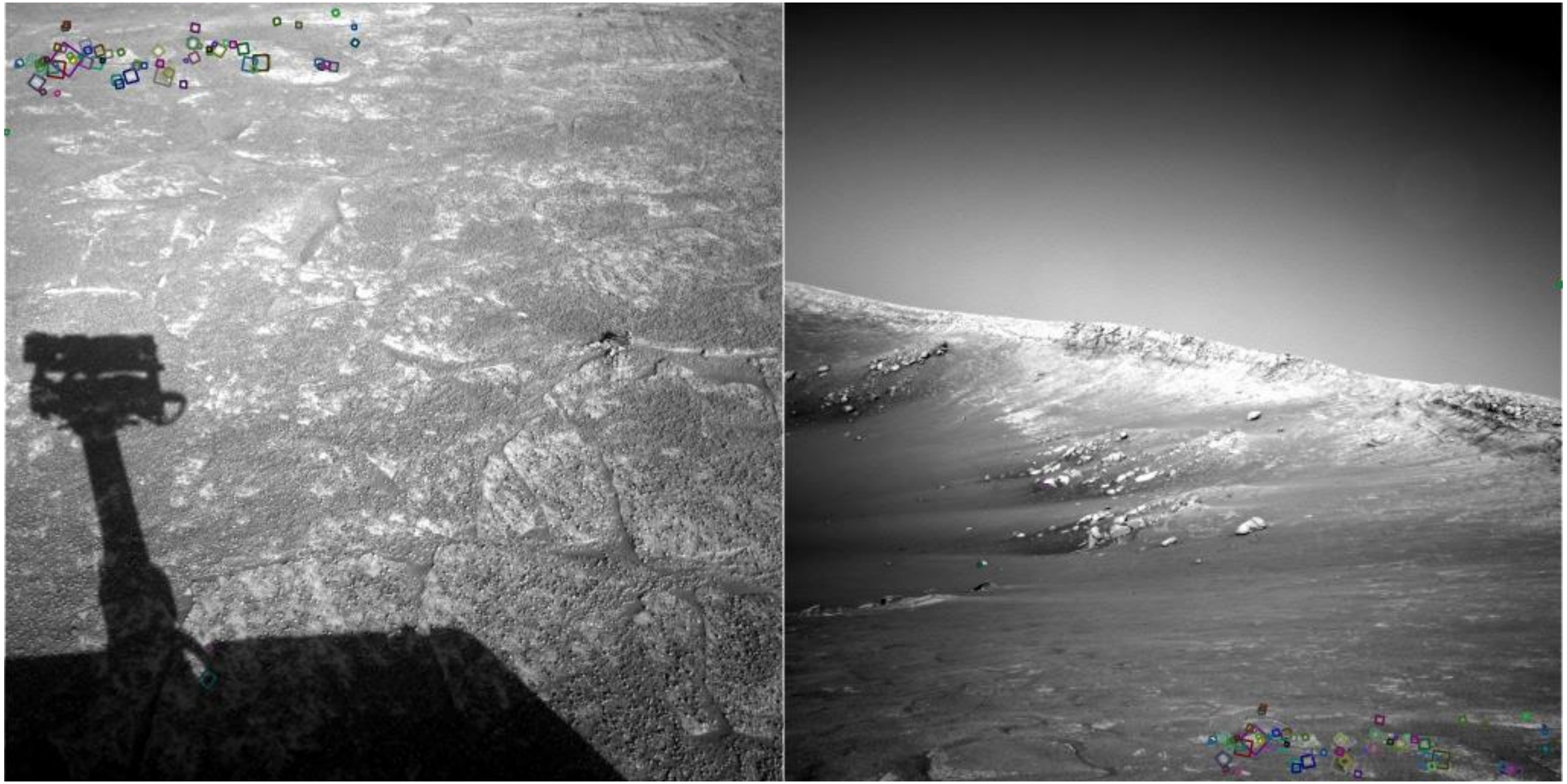
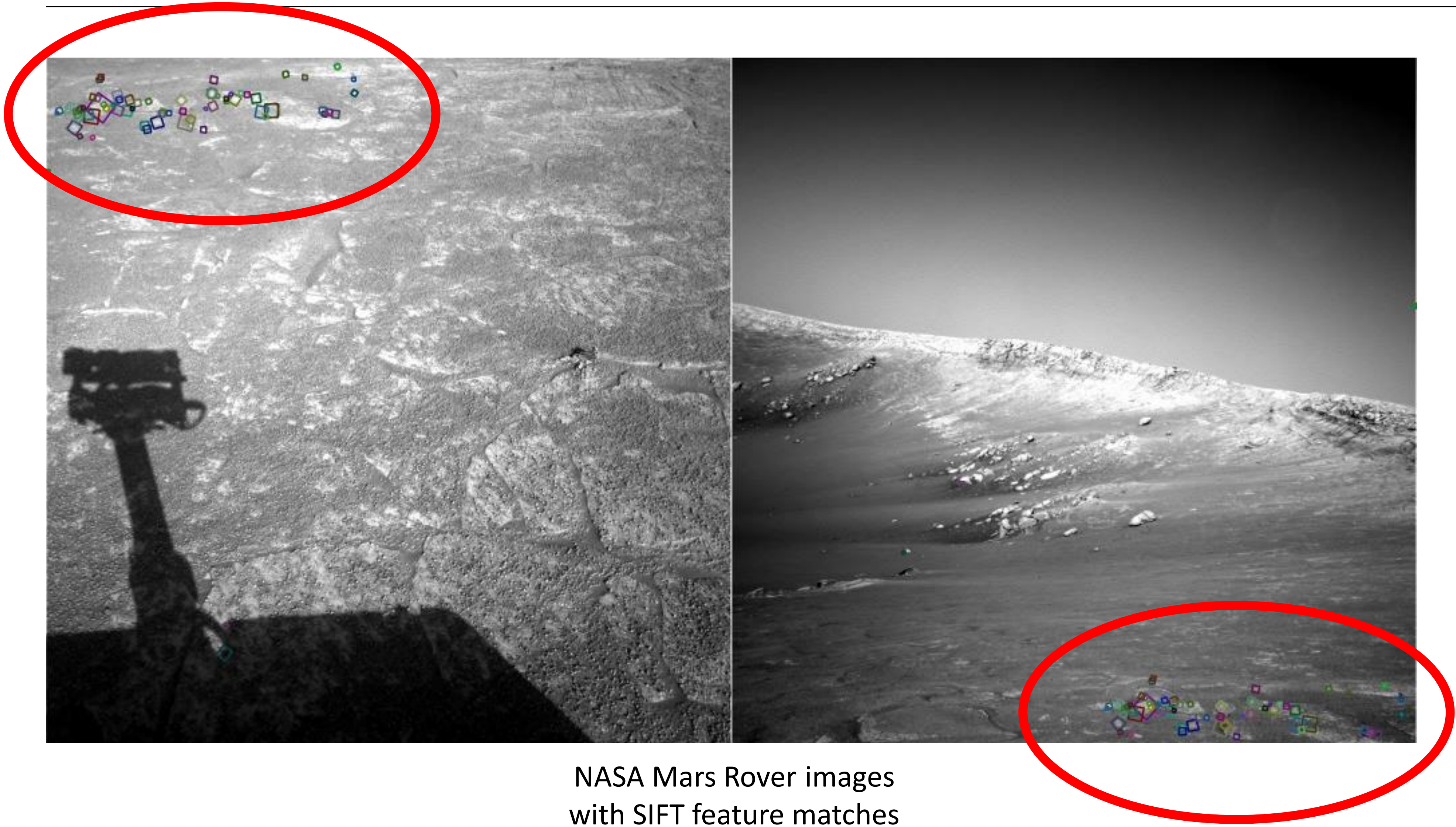
 

Image matching on Mars



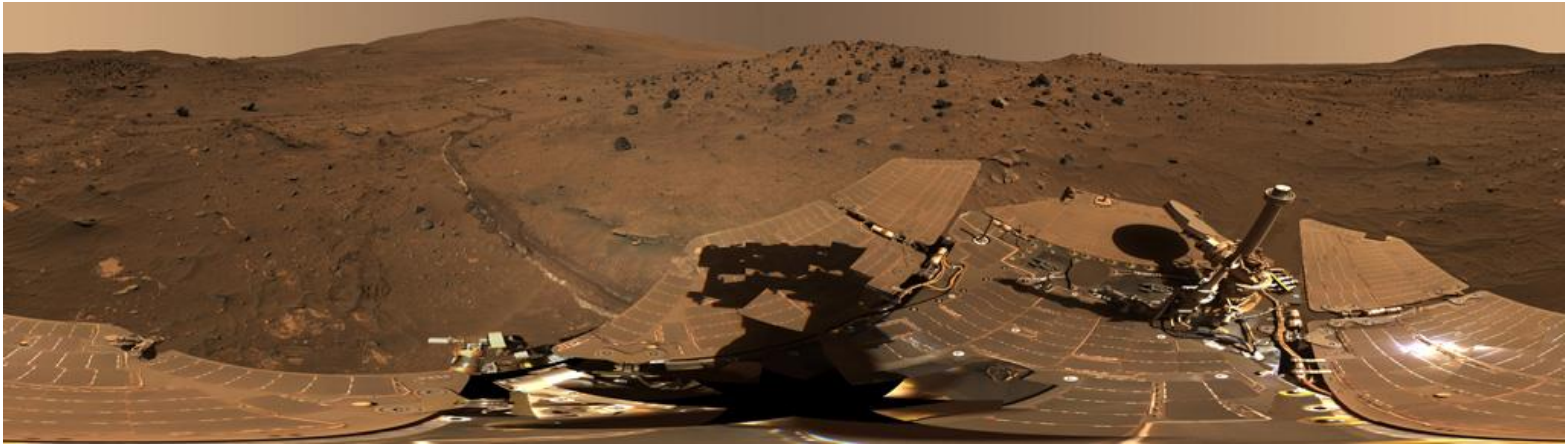
NASA Mars Rover images
with SIFT feature matches

Image matching on Mars



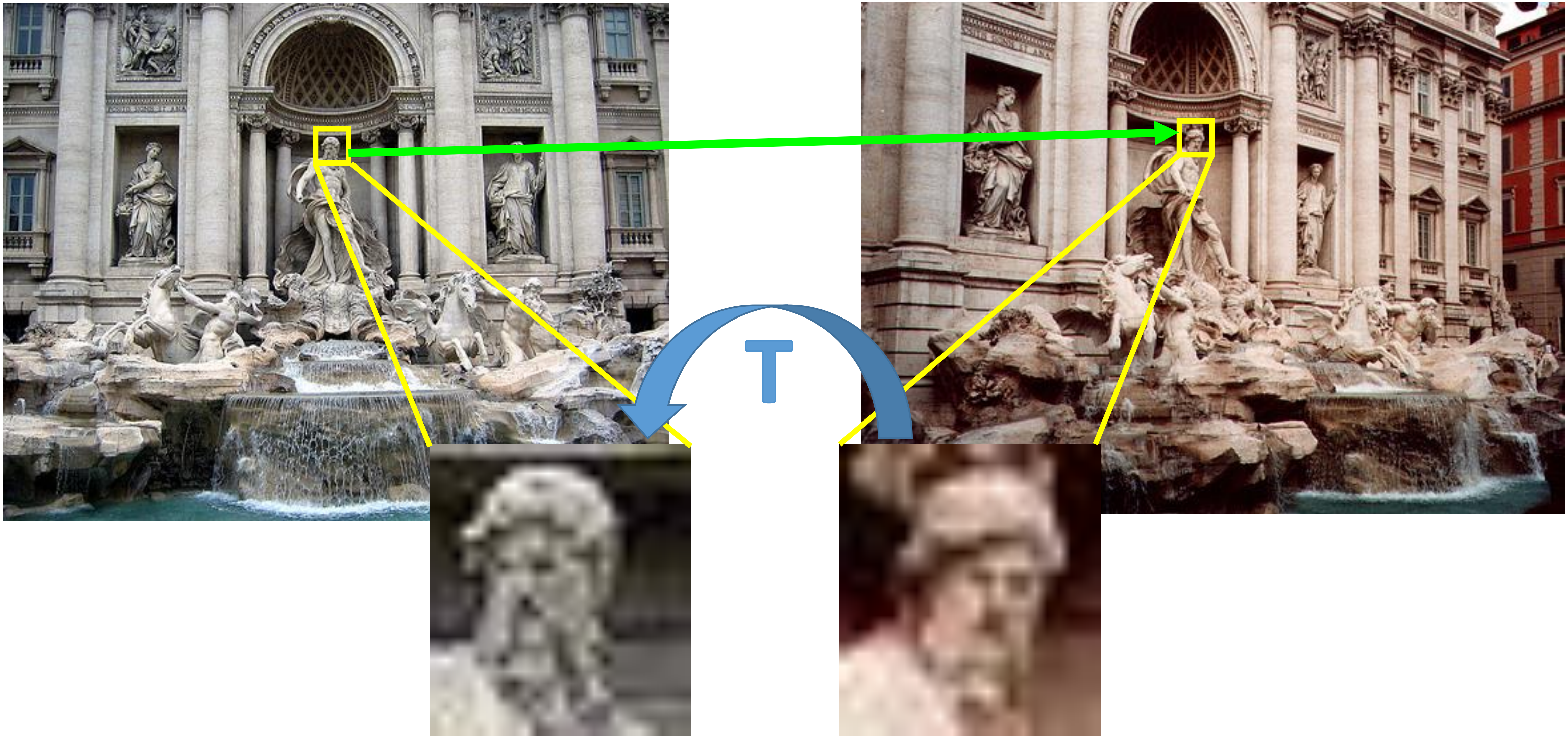
NASA Mars Rover images
with SIFT feature matches

Spirit Mars Rover Panorama



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

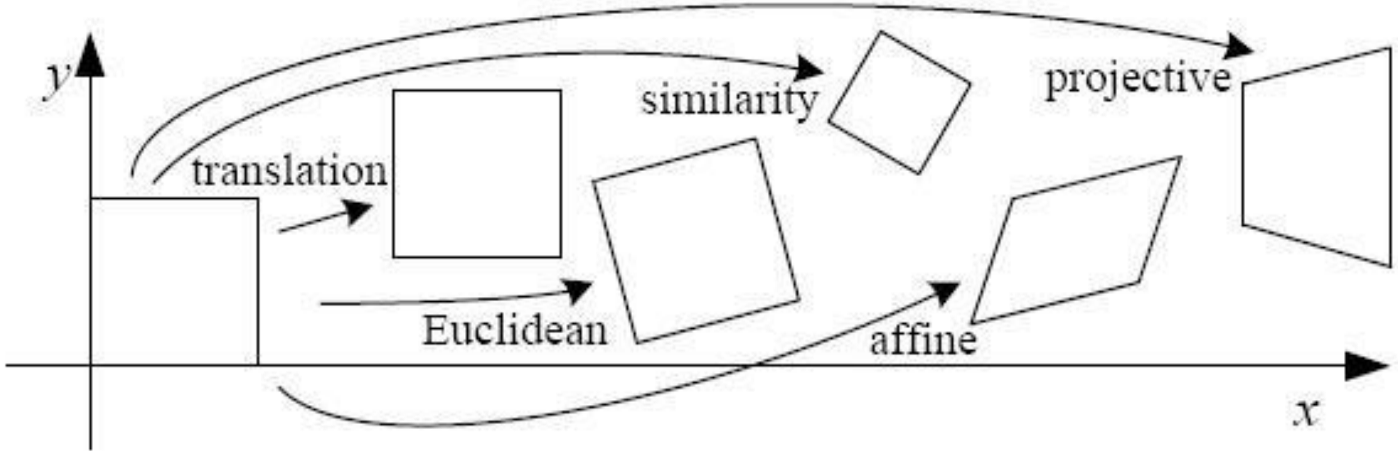
Challenges in feature matching



Geometric transformations

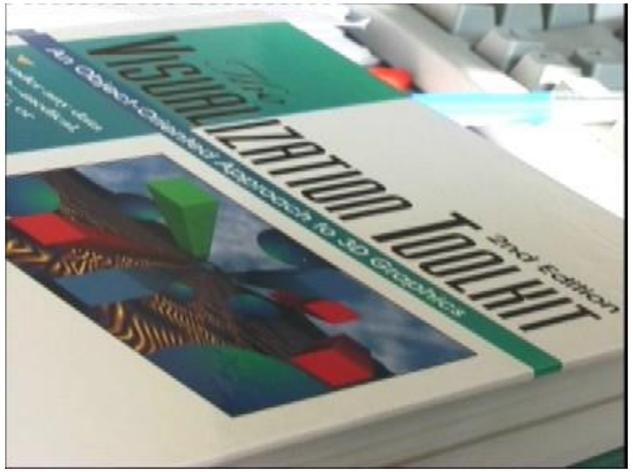
- Translation
- Euclidean (translation + rotation)
- Similarity (translation + rotation + scale)
- Affine transformations
- Projective transformations

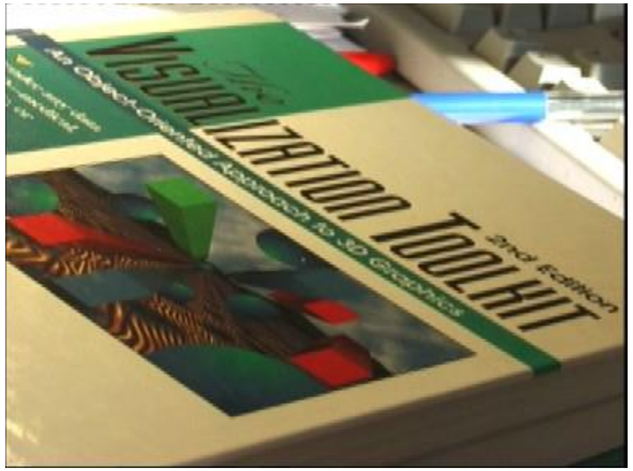
Only holds
for planar patches



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

Photometric transformations



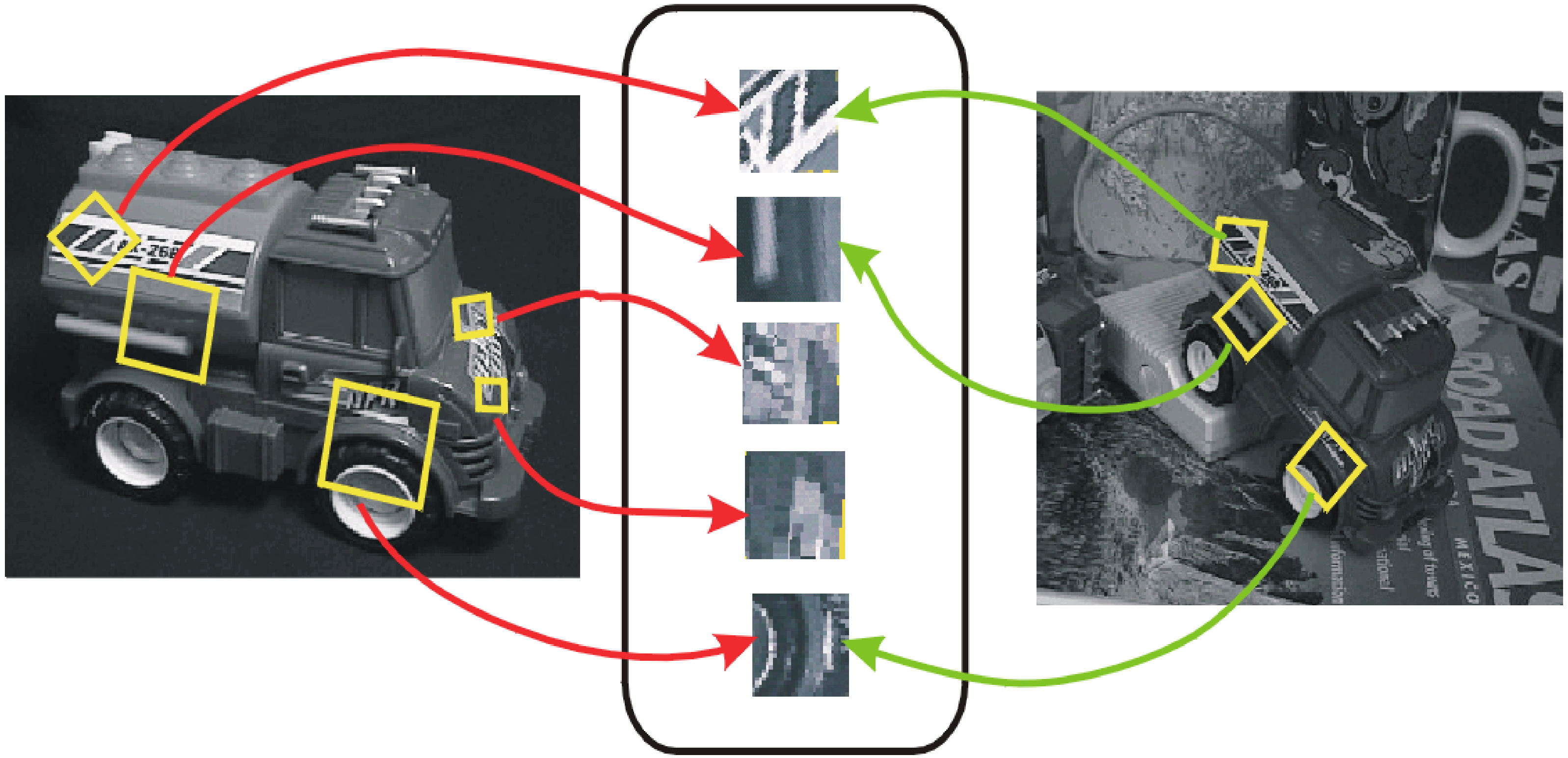


http://homes.esat.kuleuven.be/~tuytelaa/tutorial-ECCV06.pdf

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

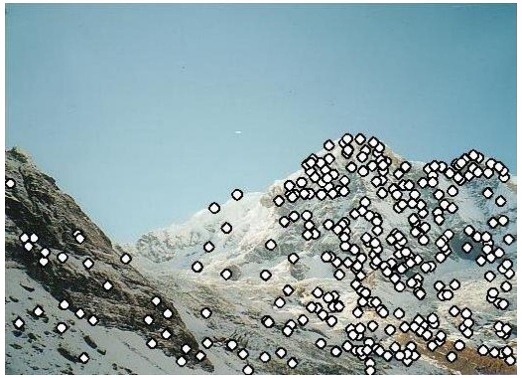
2. Feature descriptor: represent it

3. Feature matching: match it

Feature tracking: track it, when motion

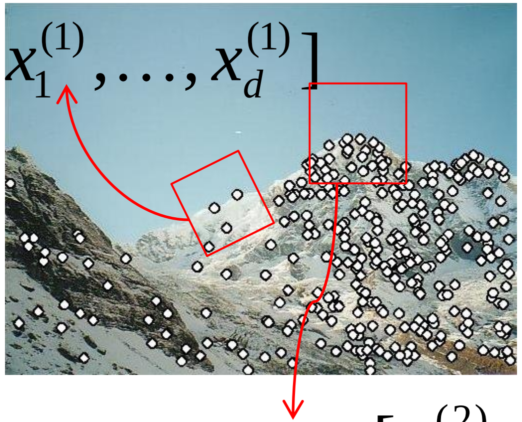
Local features: main components

1) Detection: Identify the interest points



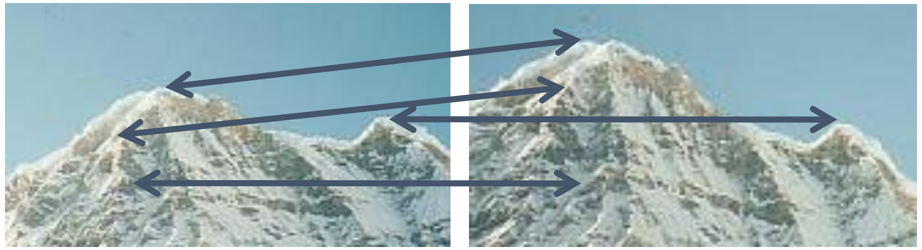
2) Description: Extract vector feature descriptor surrounding each interest point

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

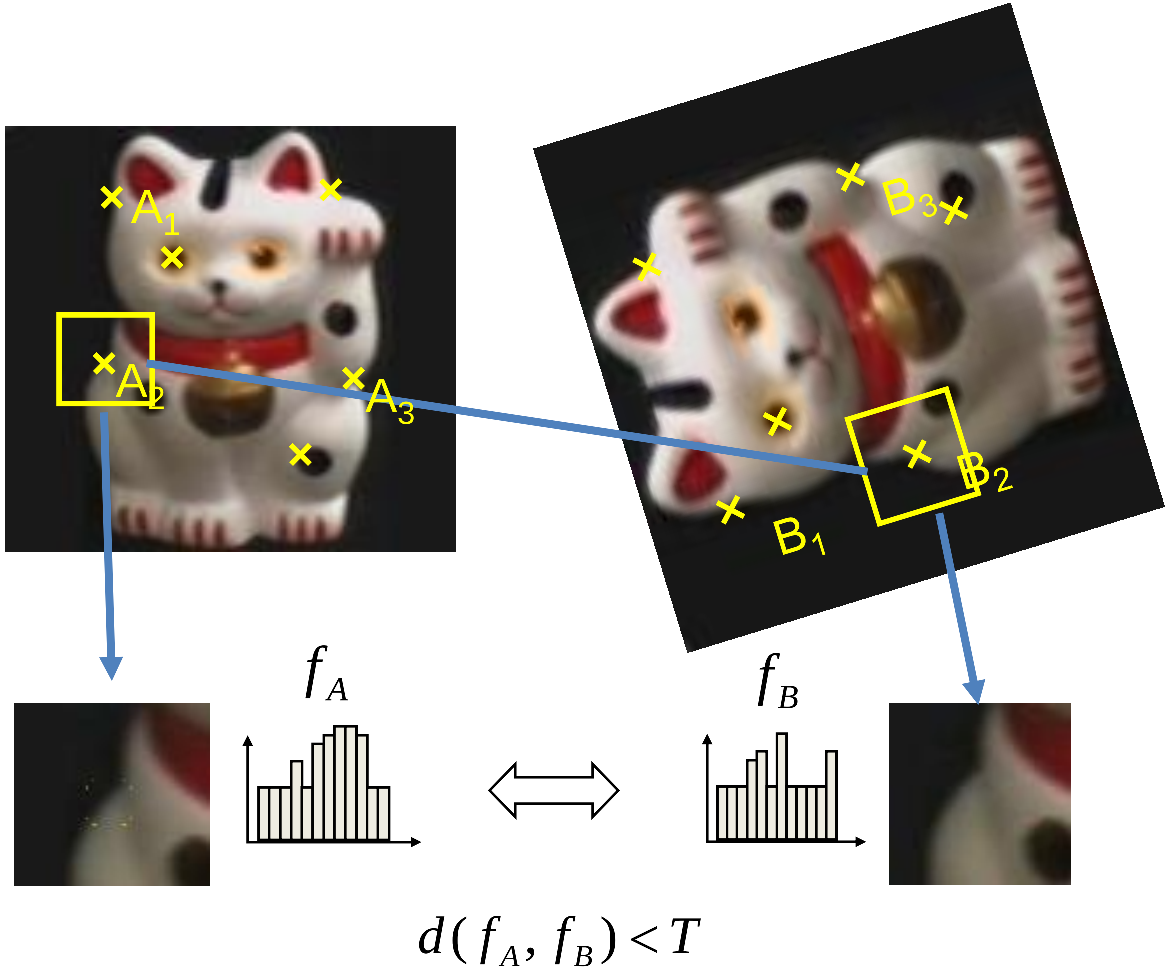


$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

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?

NO

- Textureless patches are nearly impossible to localize
- Gradients have small magnitude

Source: Derek Hoiem

Edge?

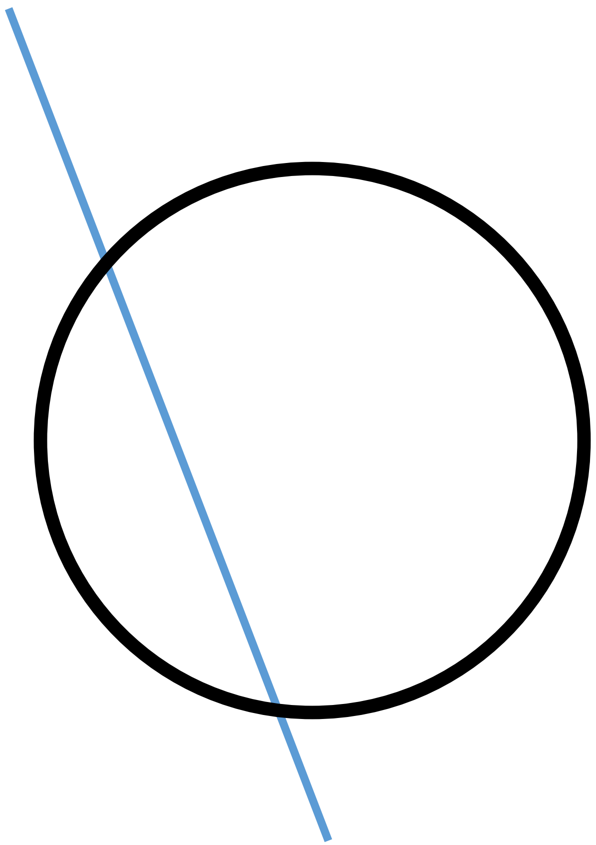
Gradients very large (or very small)

NO

- 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

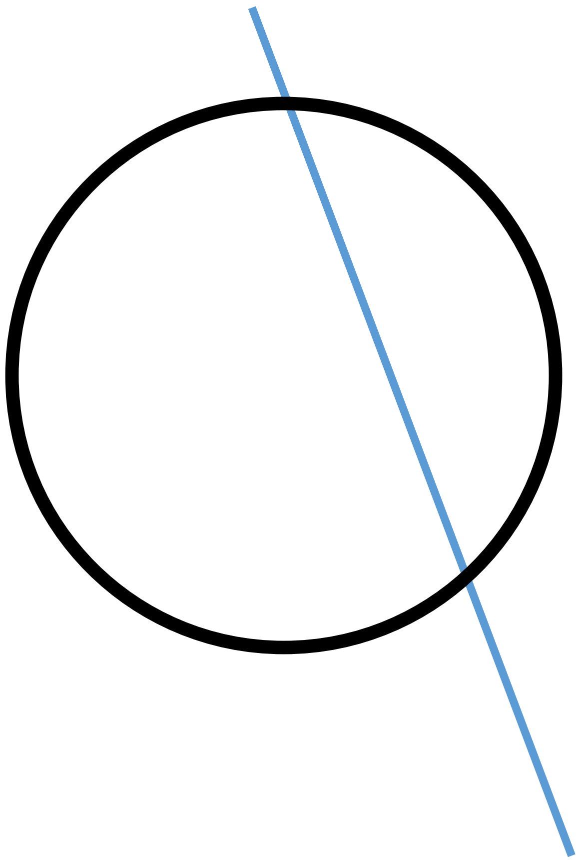
Source: Derek Hoiem

The aperture problem



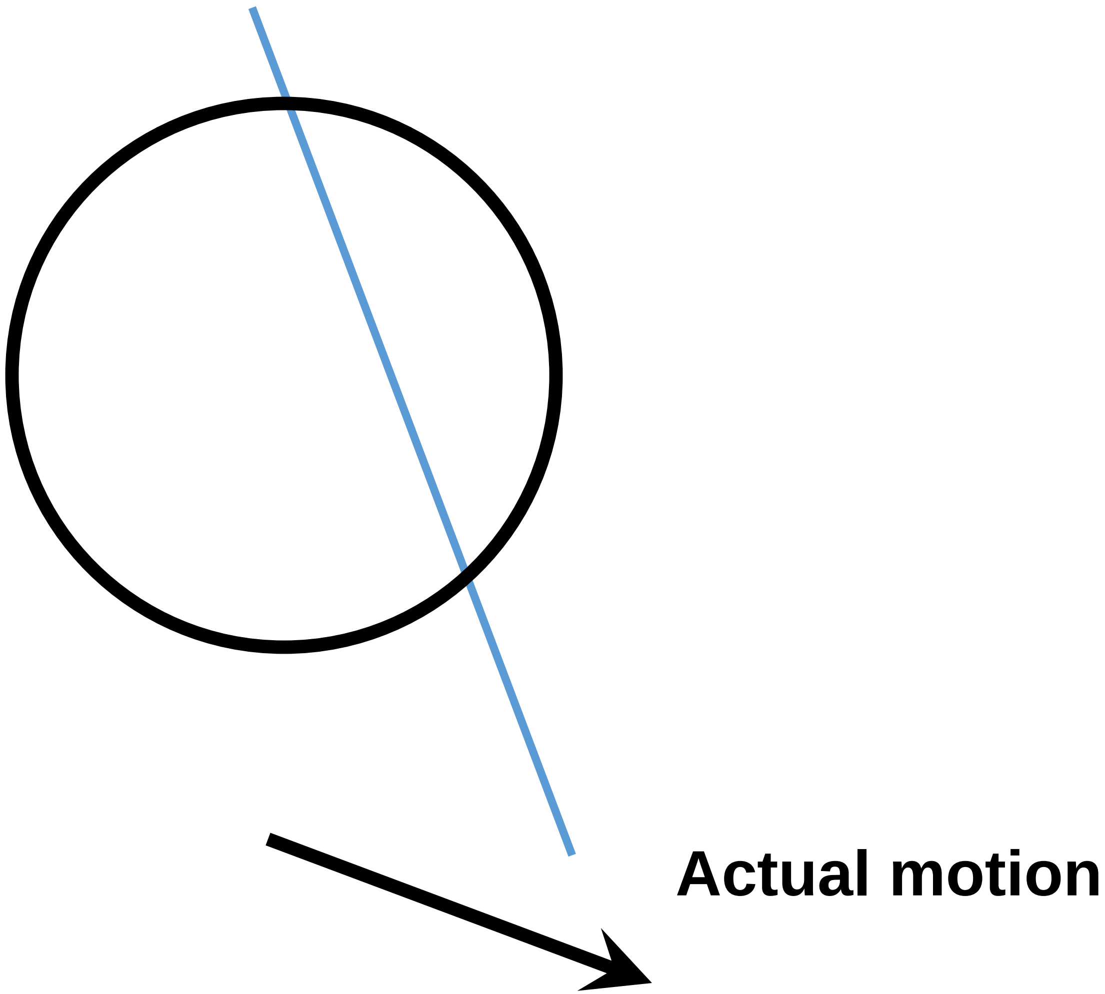
Source: Derek Hoiem

The aperture problem



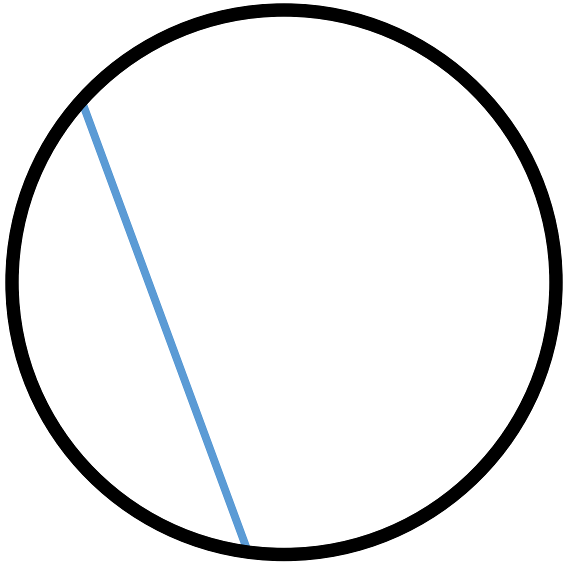
Source: Derek Hoiem

The aperture problem



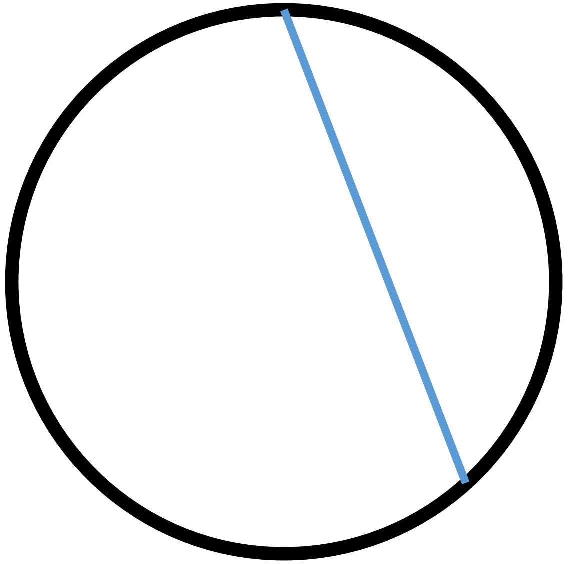
Source: Derek Hoiem

The aperture problem



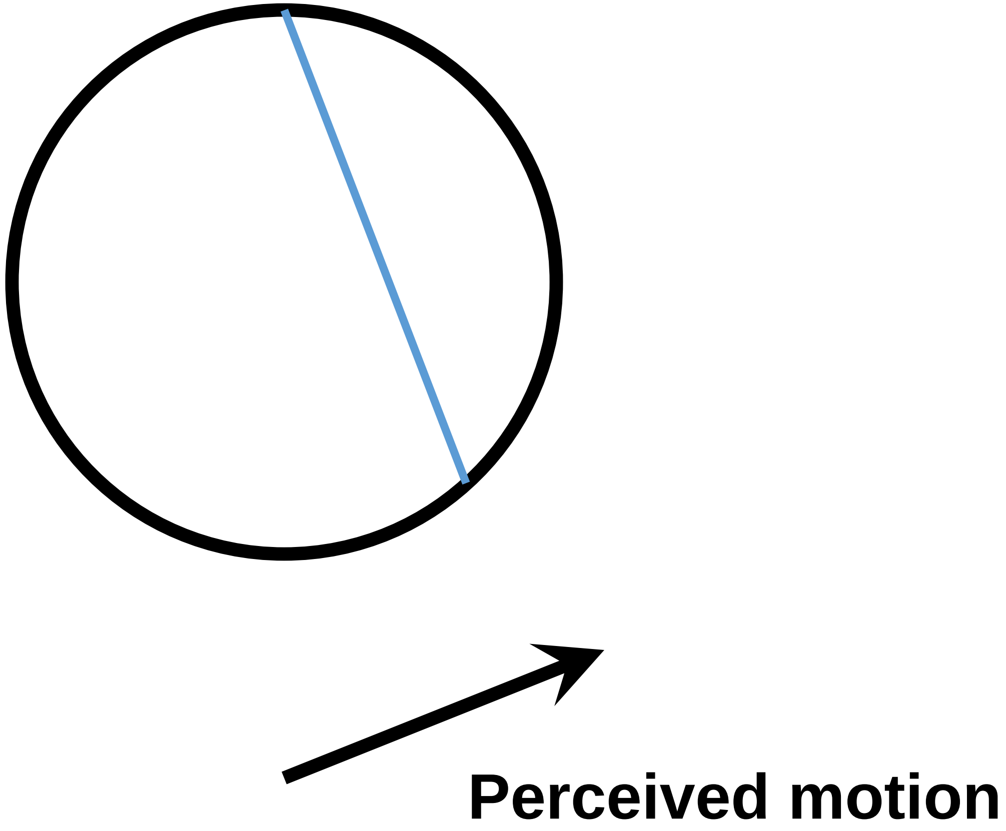
Source: Derek Hoiem

The aperture problem



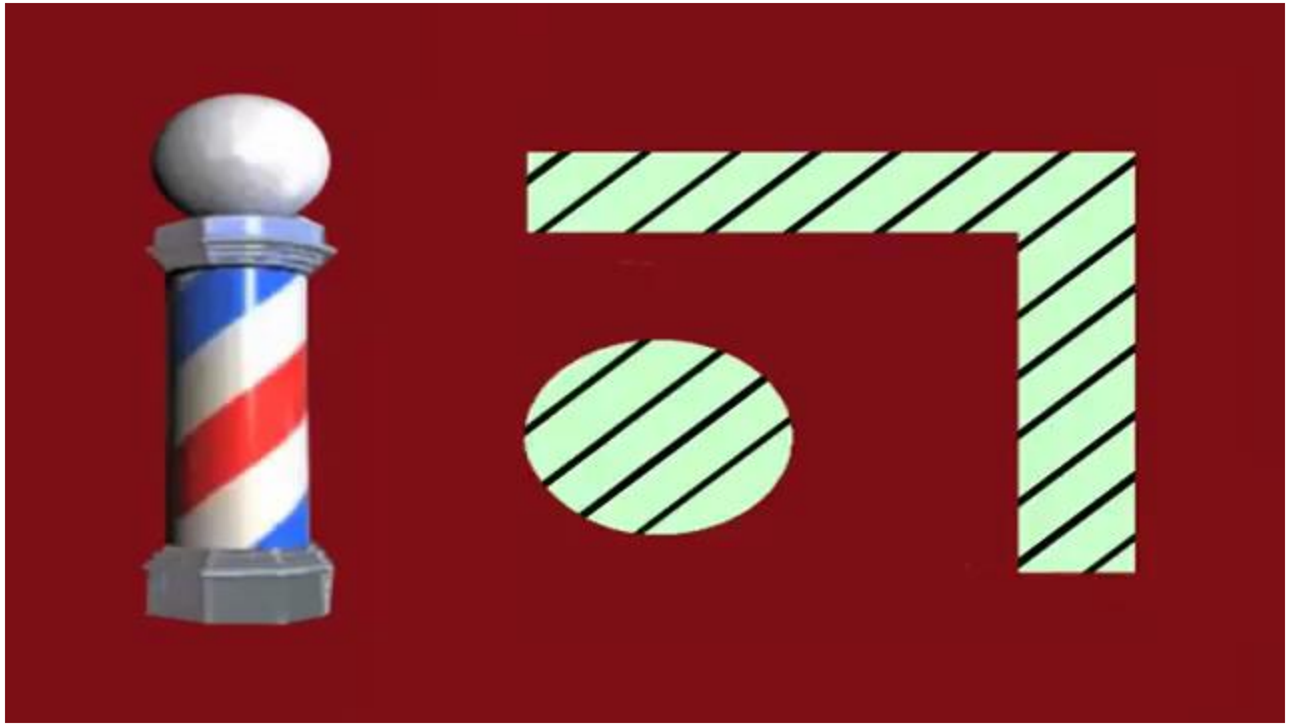
Source: Derek Hoiem

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

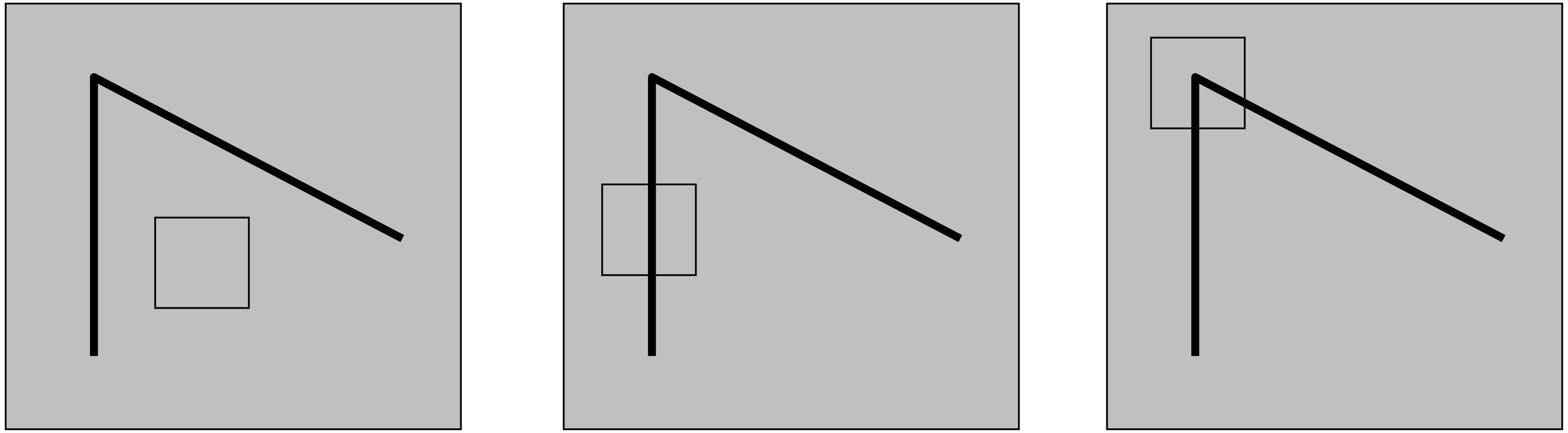
- Lead to unambiguous matches in other images

How to define “unusual”?

Want uniqueness

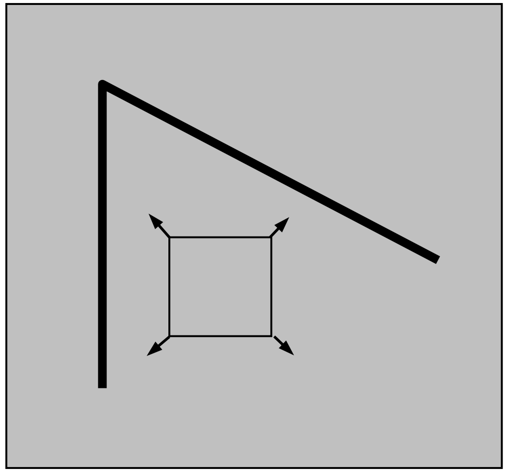
Suppose we only consider a small window of pixels

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

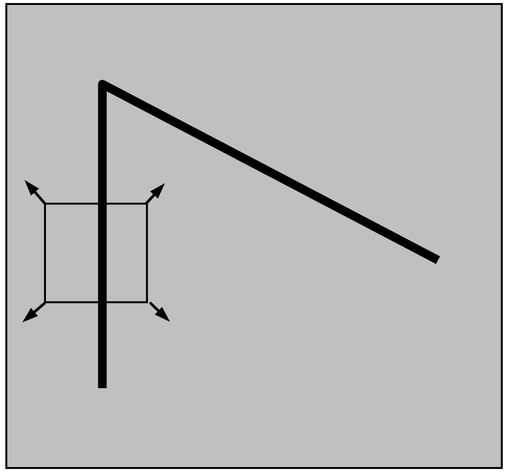


Want uniqueness

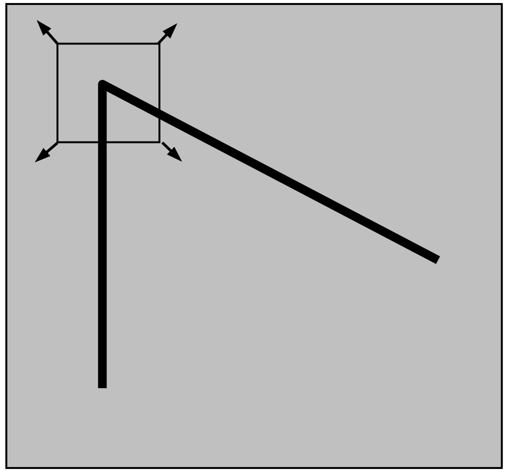
- How does the window change when you shift it?
- Shifting the window in any direction causes a big change



"flat" region:
no change in all directions



"edge":
no change along the edge direction



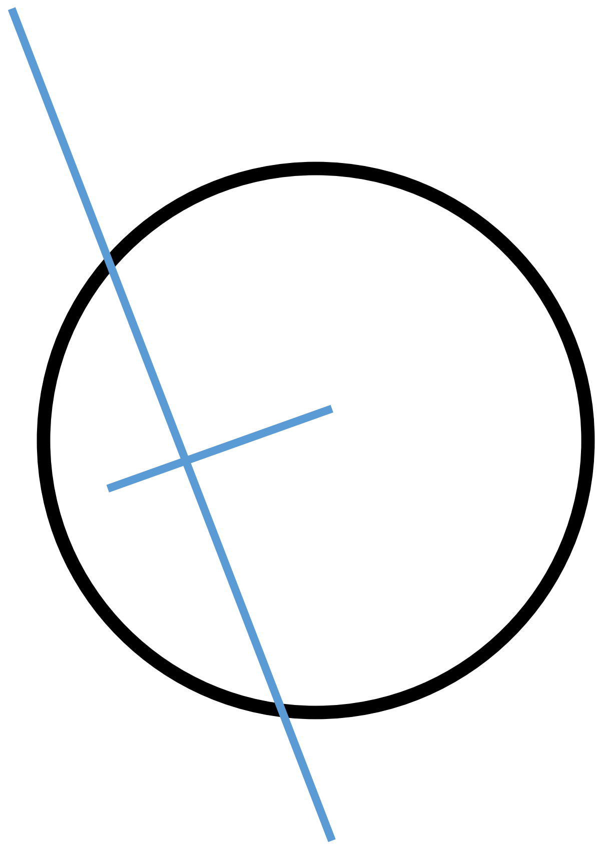
"corner":
significant change in all directions

Corners

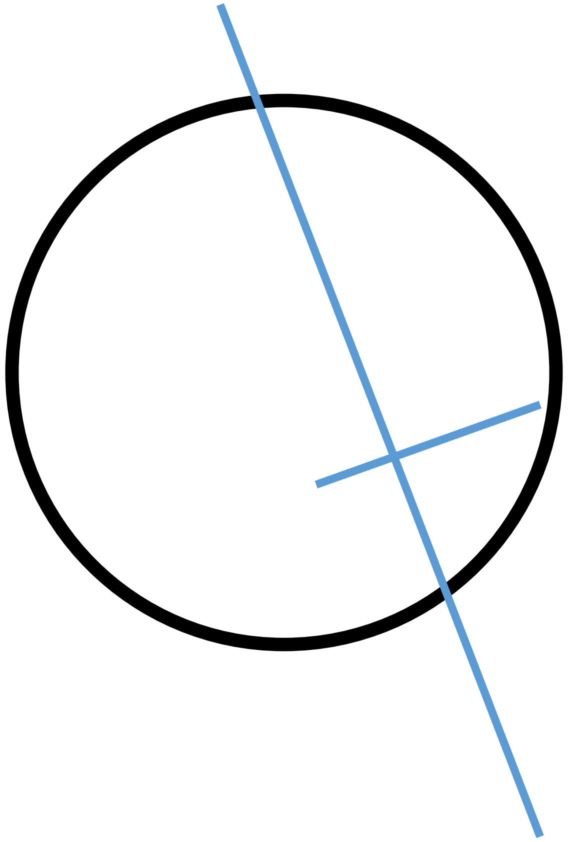
- Textureless patches are nearly impossible to localize
- Patches with large contrast changes (gradients) are easier to localize
- But straight line segments at a single orientation suffer from the aperture problem, i.e., it is only possible to align the patches along the direction normal to the edge direction
- Gradients in at least two (significantly) different orientations are the easiest, e.g., corners

Source: Raquel Urtasun

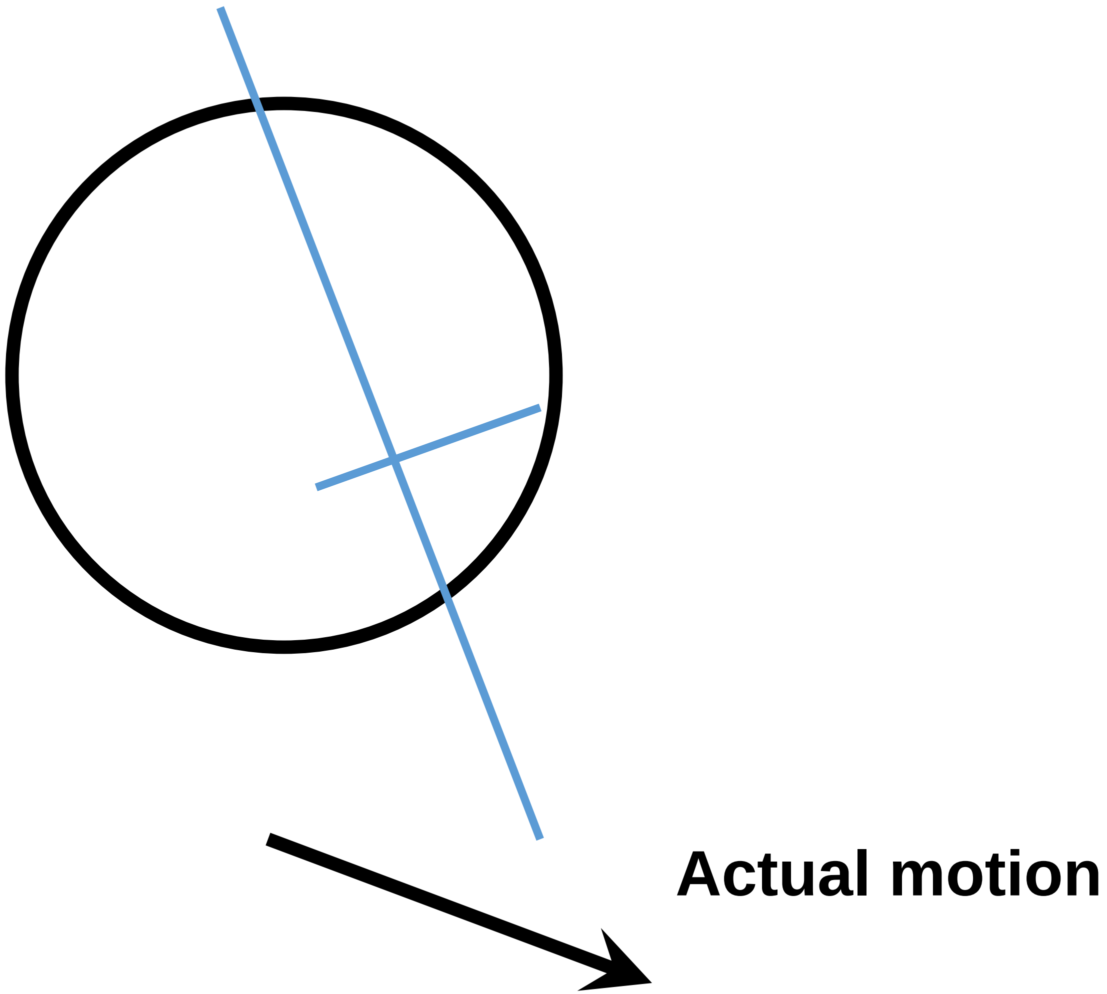
The aperture problem resolved



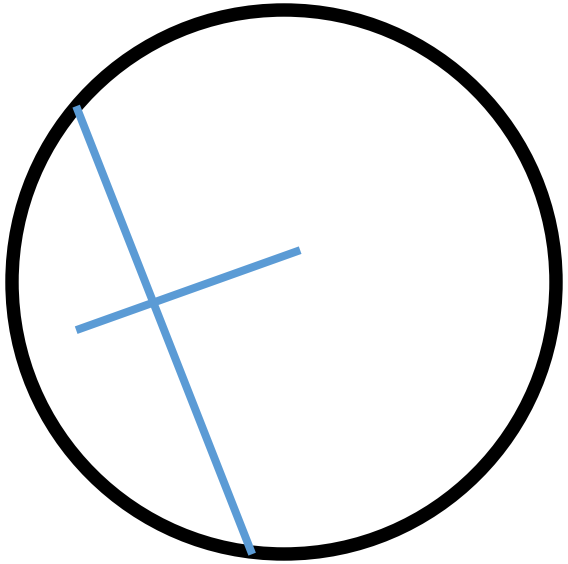
The aperture problem resolved



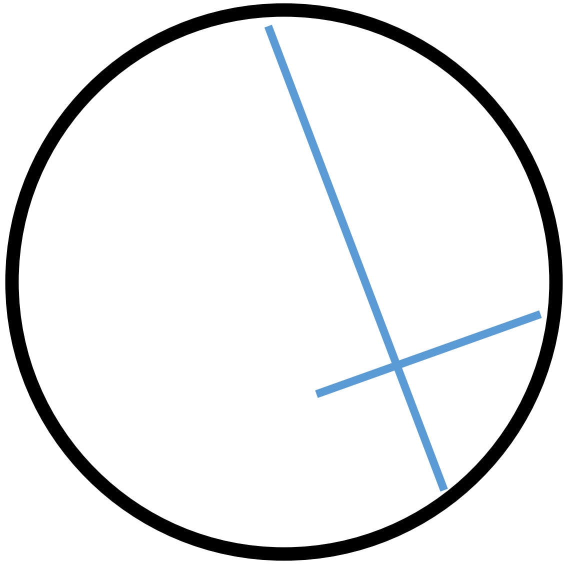
The aperture problem resolved



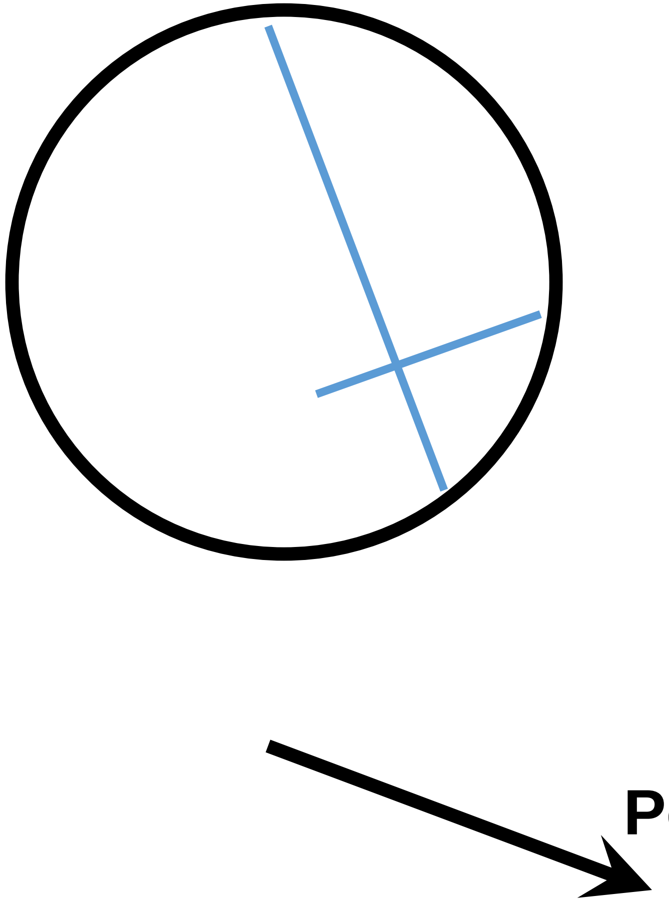
The aperture problem resolved



The aperture problem resolved



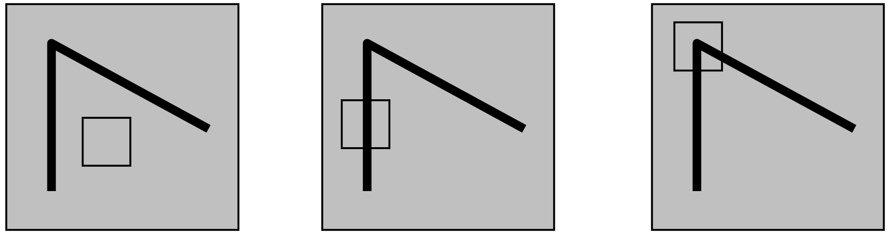
The aperture problem resolved



Perceived motion

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

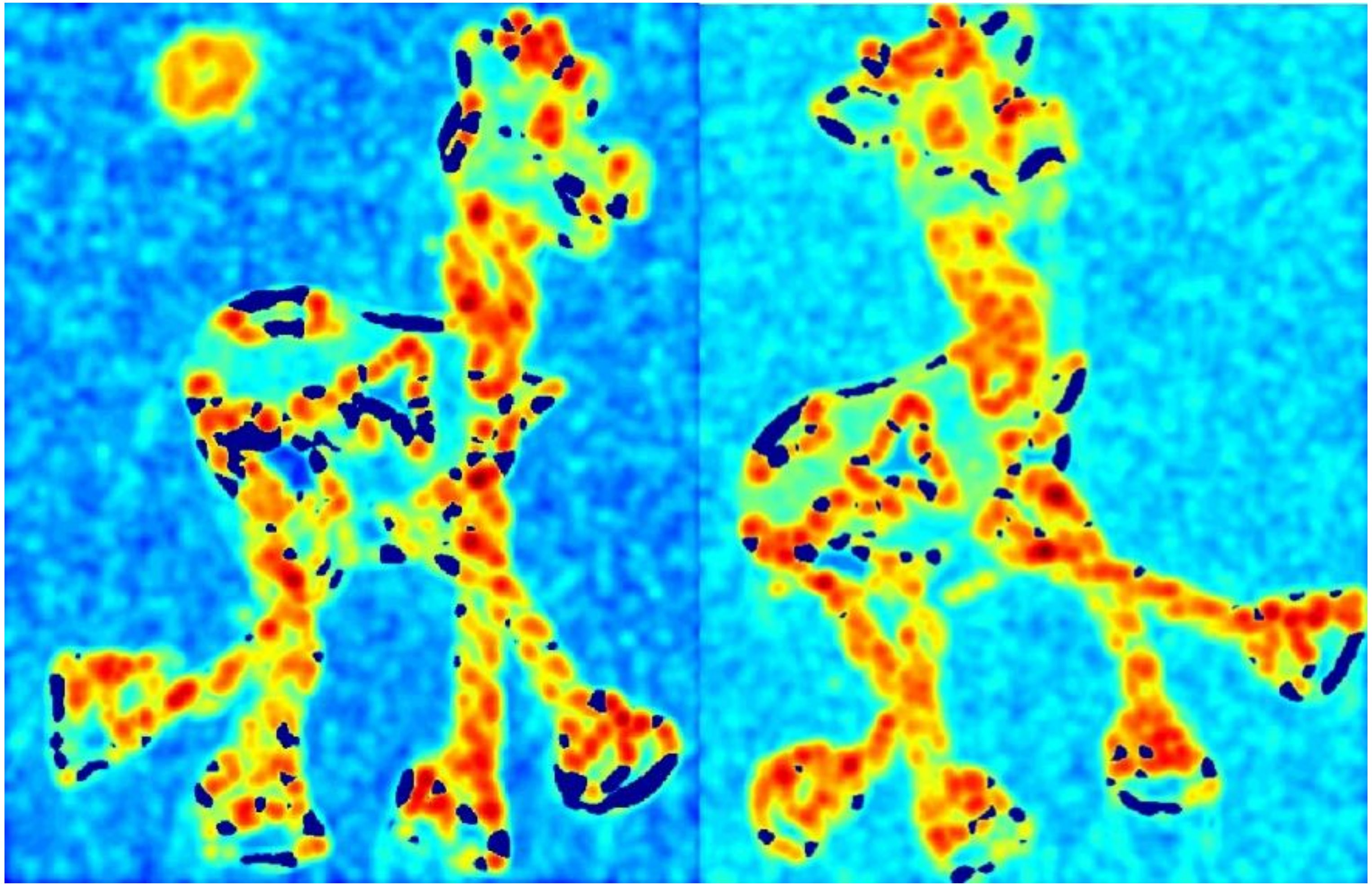
Source: James Hays

Harris detector steps

Source: James Hays

Harris detector steps

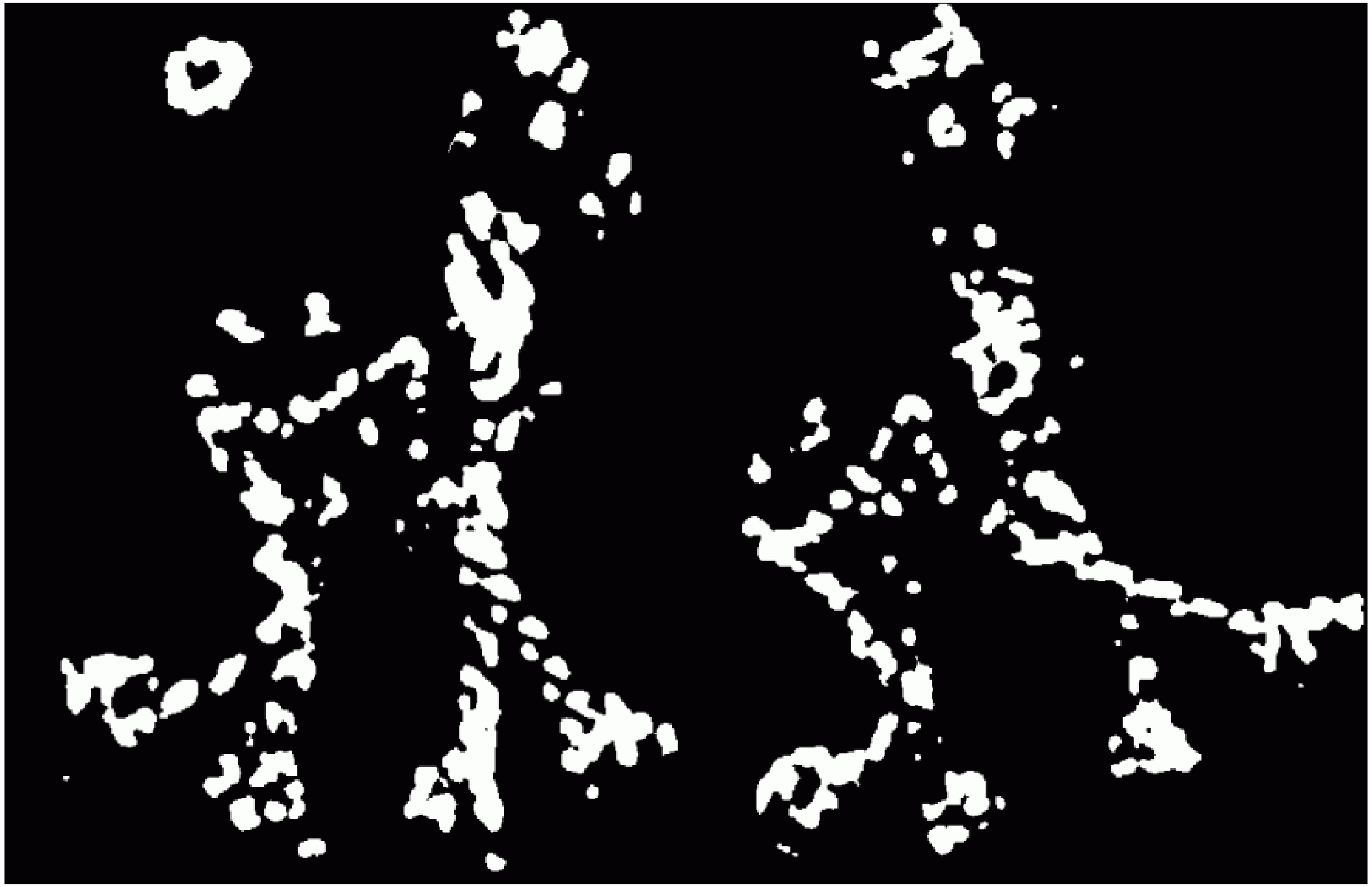
Compute corner response R



Source: James Hays

Harris detector steps

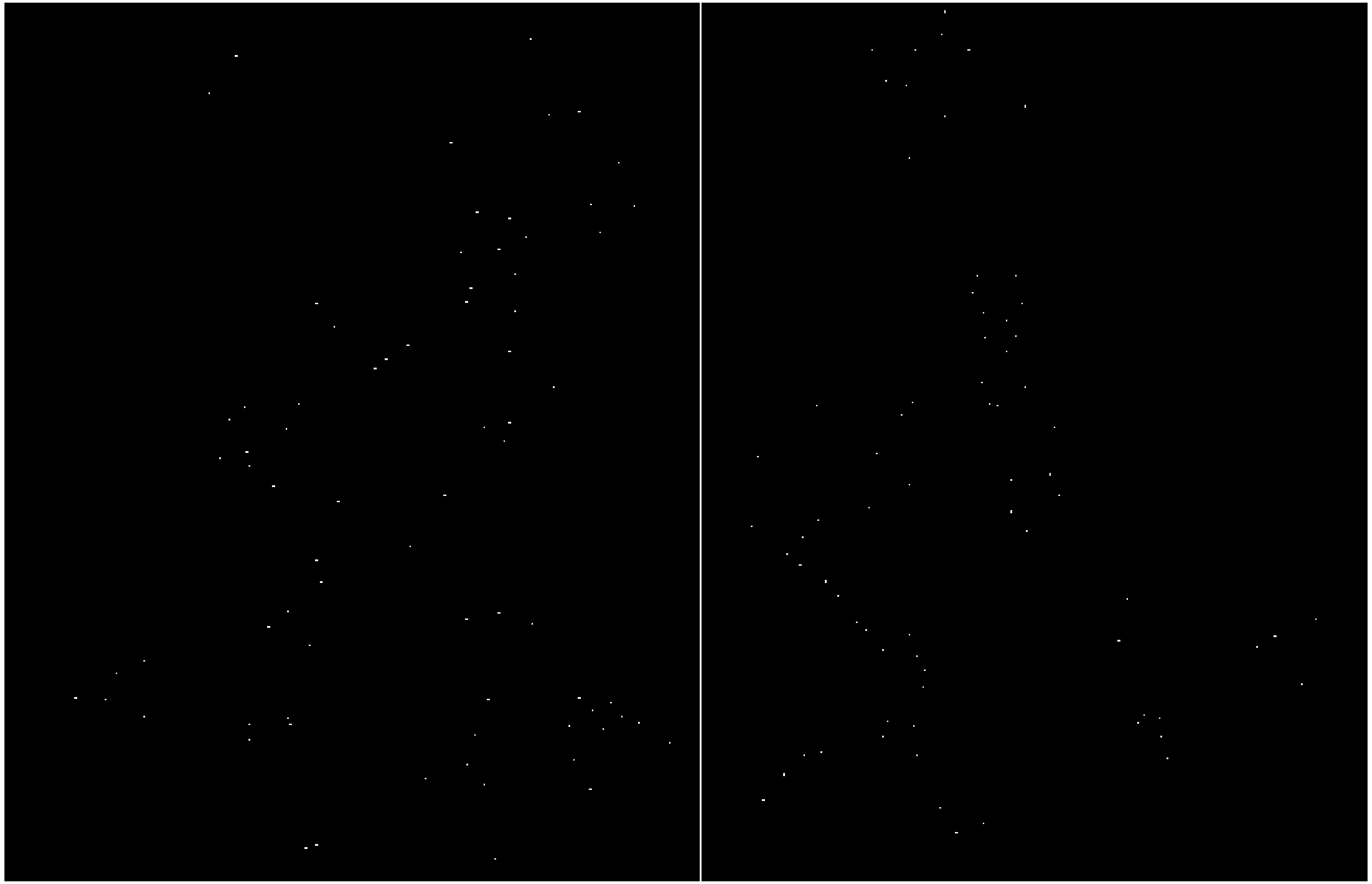
Find points with large corner response: R > threshold



Source: James Hays

Harris detector steps

Take only the points of local maxima of R

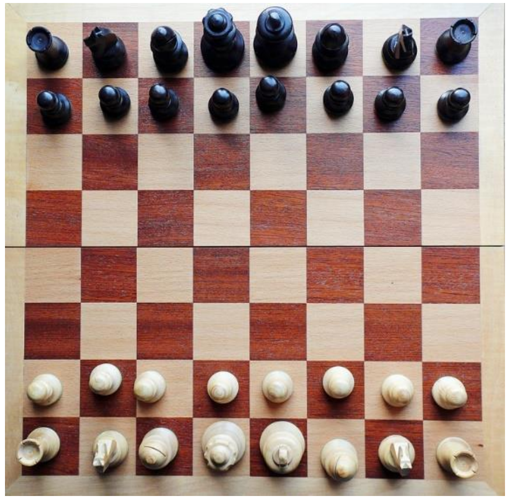


Source: James Hays

Harris detector steps

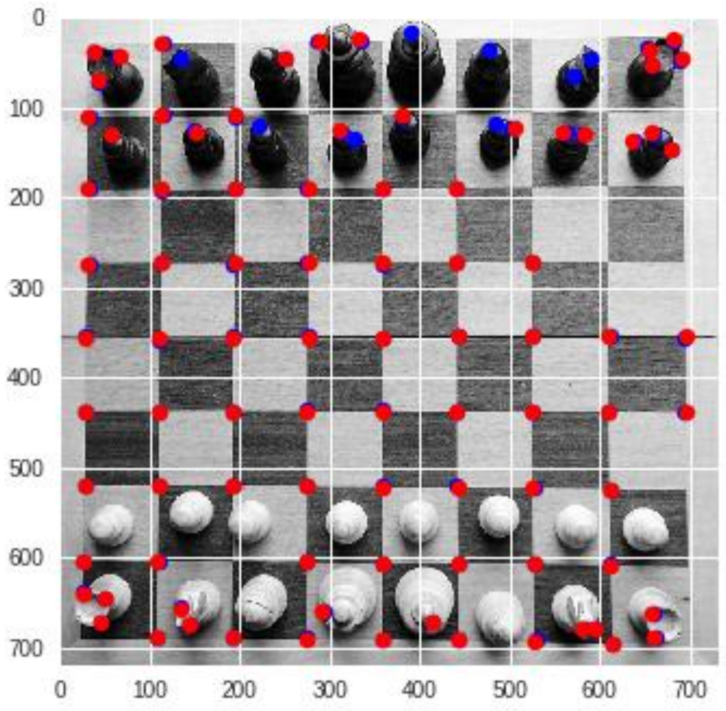
Source: James Hays

Harris corner detection: esempi

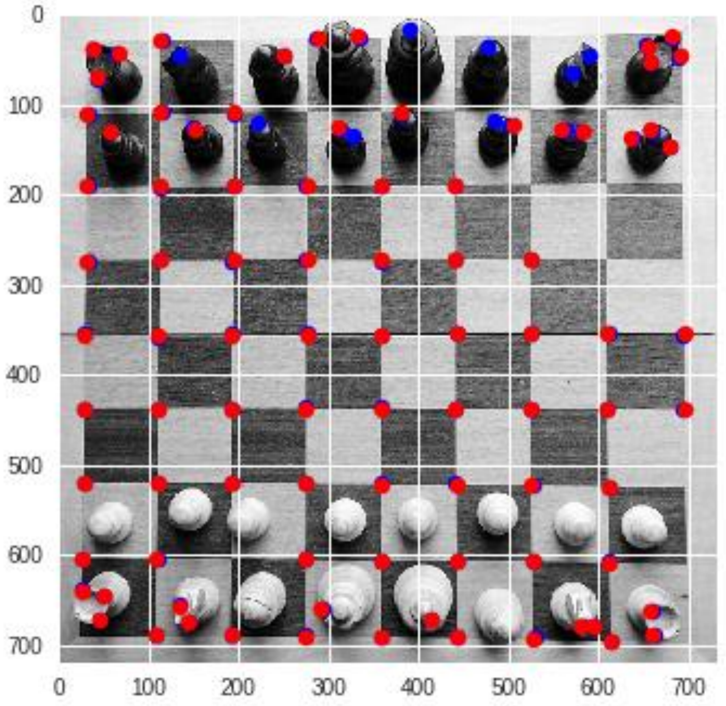


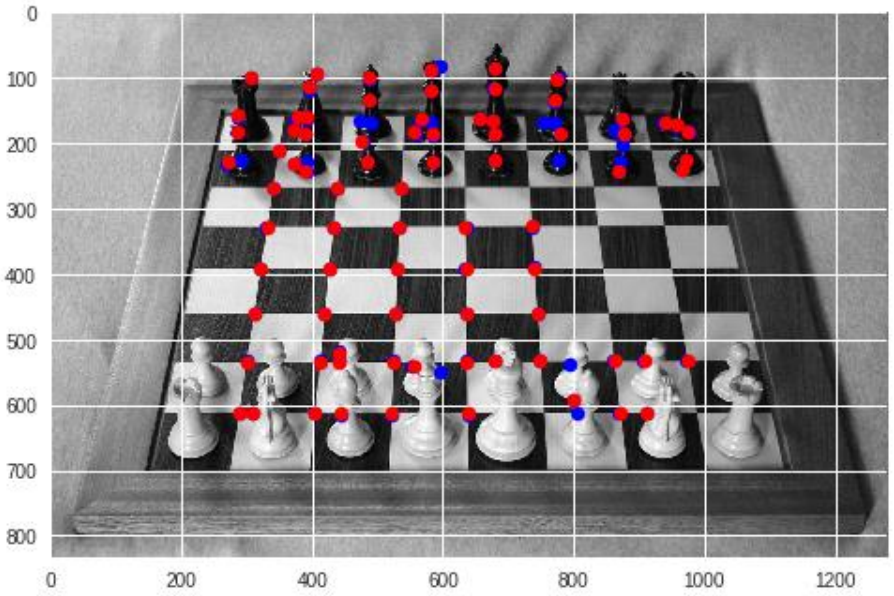

Harris corner detection: esempi

```python
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()
```

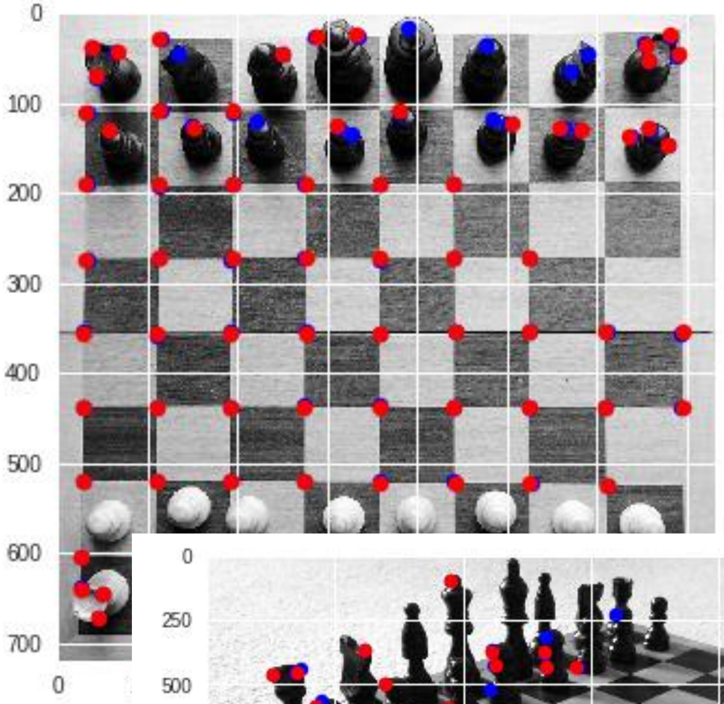


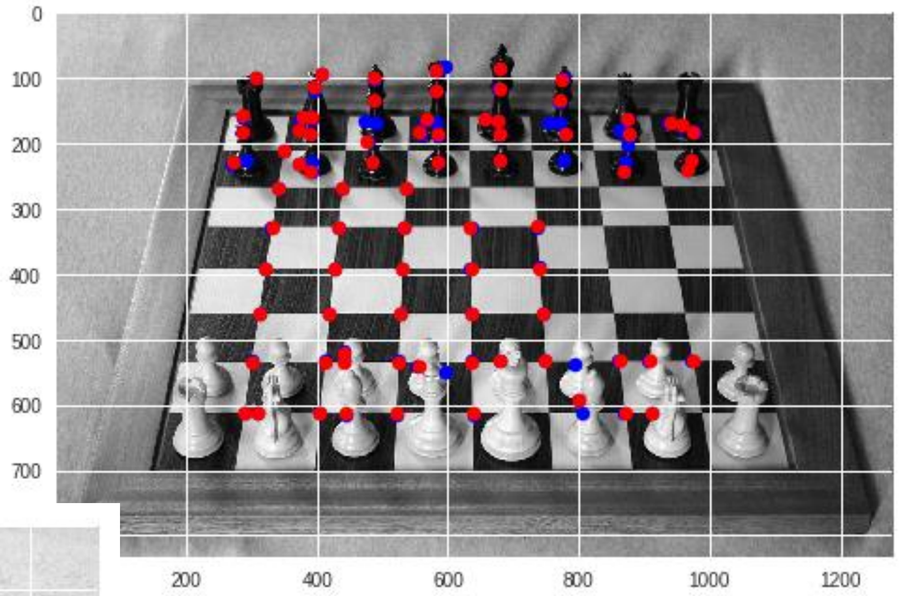
Harris corner detection: esempi

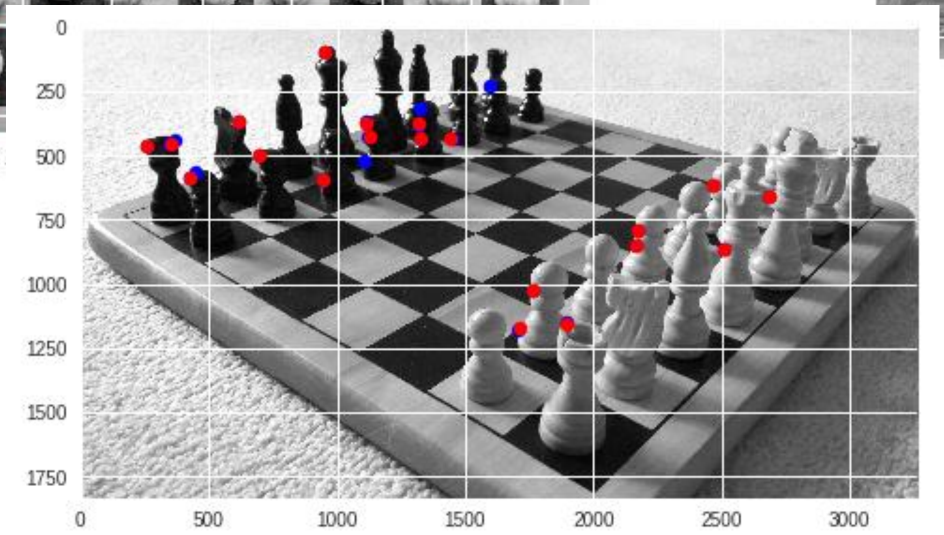




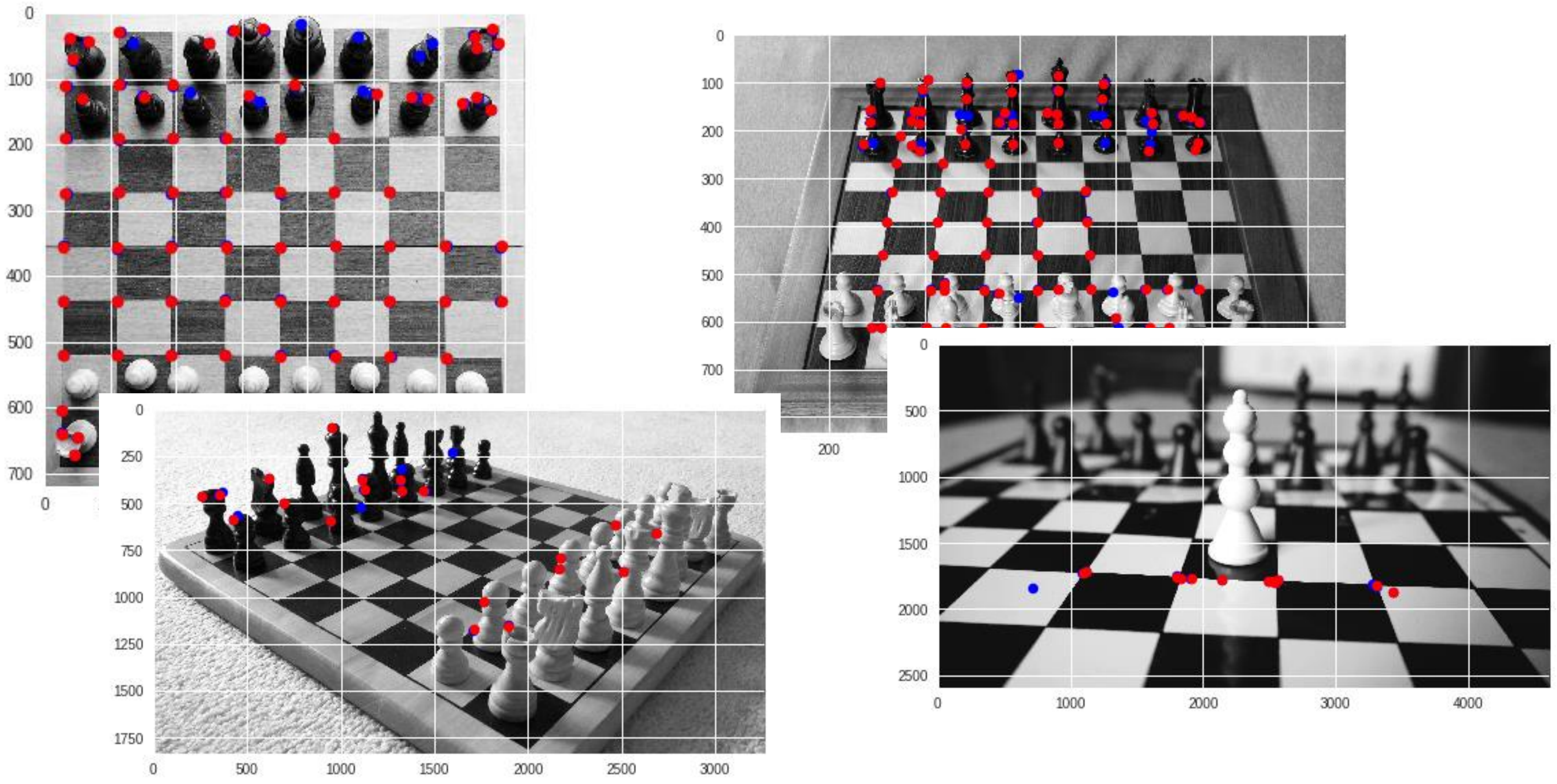
Harris corner detection: esempi







Harris corner detection: esempi



Invariance and covariance of corner locations

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

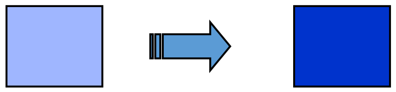
Source: James Hays

Invariance and covariance of corner locations

Invariance: image is transformed and corner locations do not change

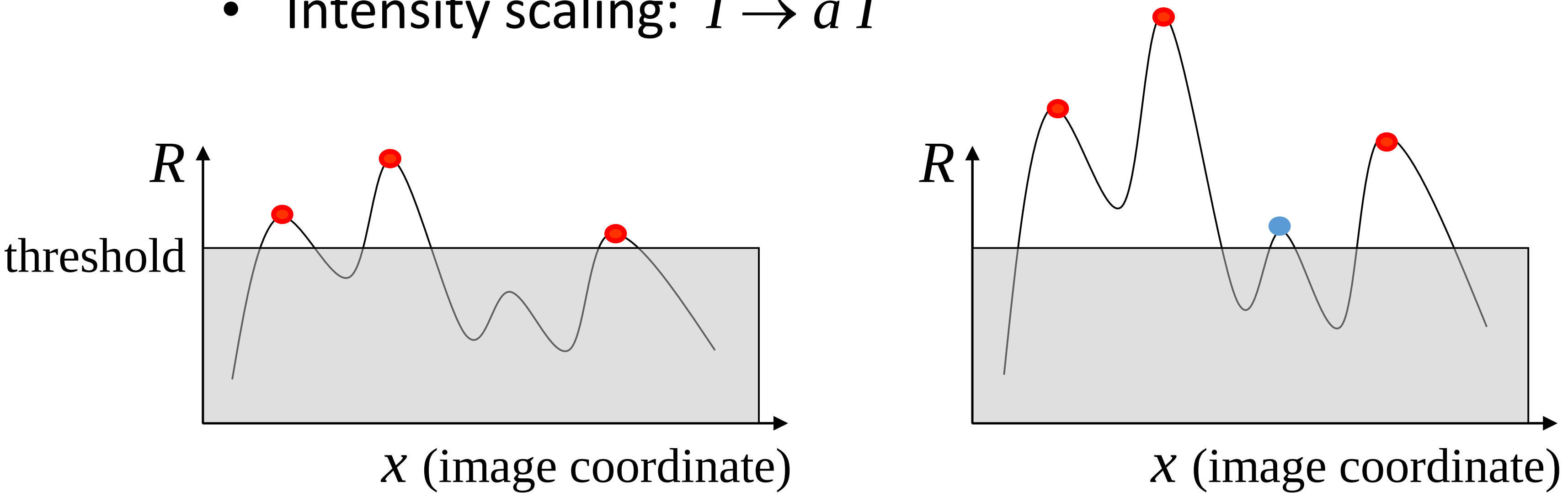
Covariance: if we have two transformed versions of the same image, features should be detected in corresponding locations

Affine intensity change



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

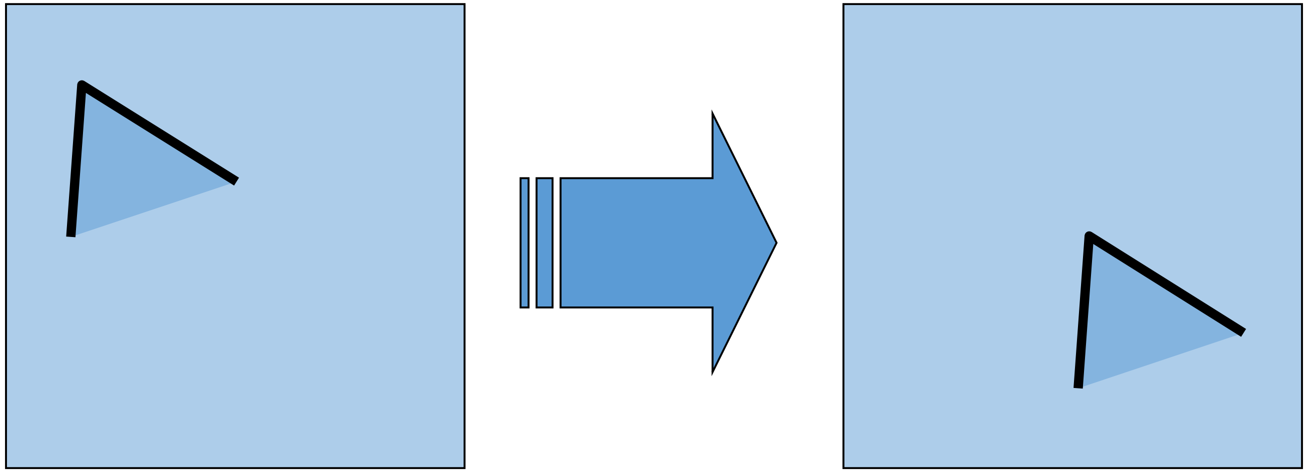
- Only derivatives are used ➡ invariance to intensity shift $I \rightarrow I + b$
- Intensity scaling: $I \rightarrow a\,I$



Partially invariant to affine intensity change

Source: James Hays

Translation

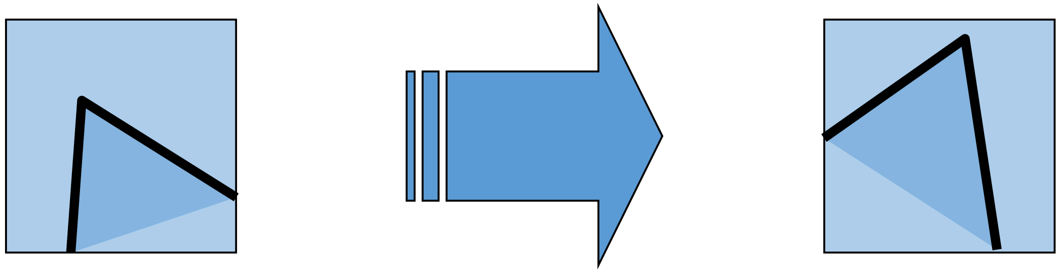


Derivatives and window function are shift-invariant

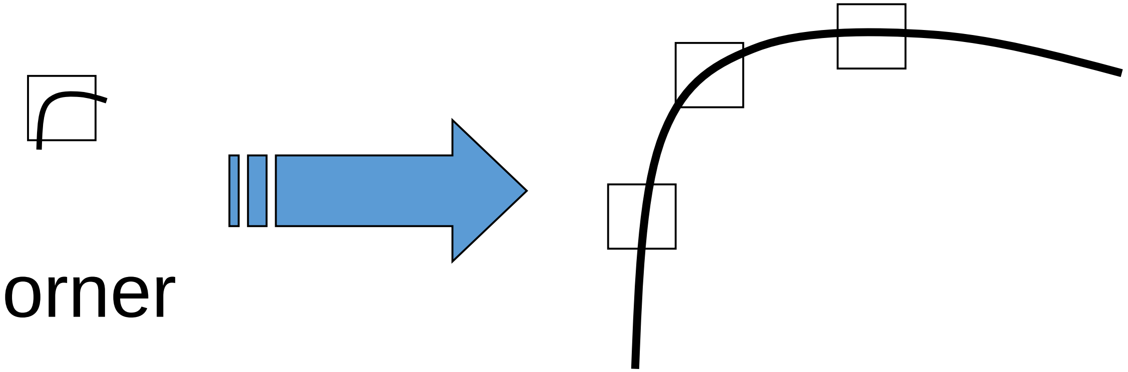
Corner location is covariant w.r.t. translation

Source: James Hays

Rotation and Scaling



Corner location is covariant w.r.t. rotation



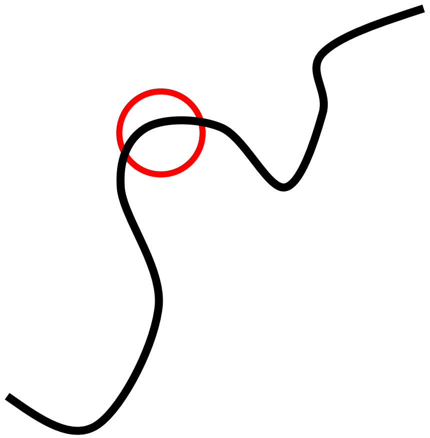
All points will be classified as edges

Corner location is not covariant to scaling!

Source: James Hays

Scale invariant detection

Suppose you're looking for corners

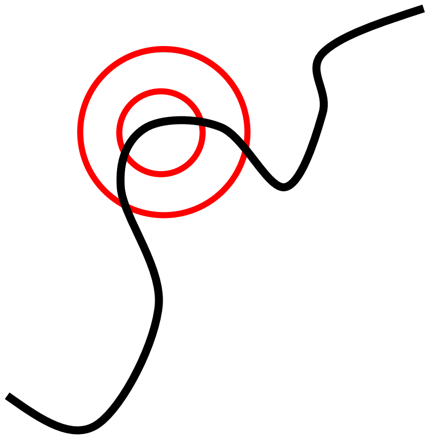


Key idea: find scale that gives local maximum of *f*

- 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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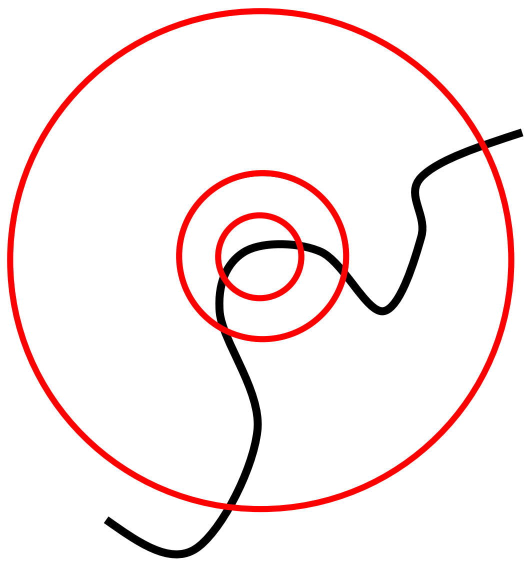
Scale invariant detection

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

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

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

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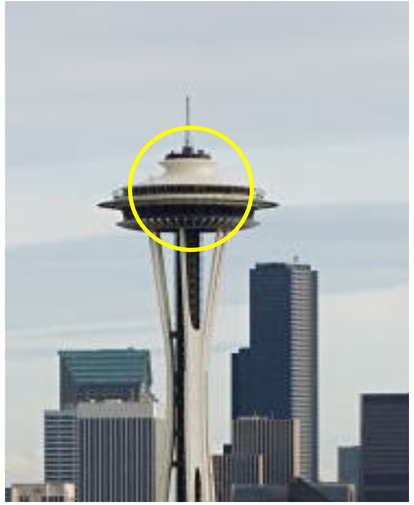
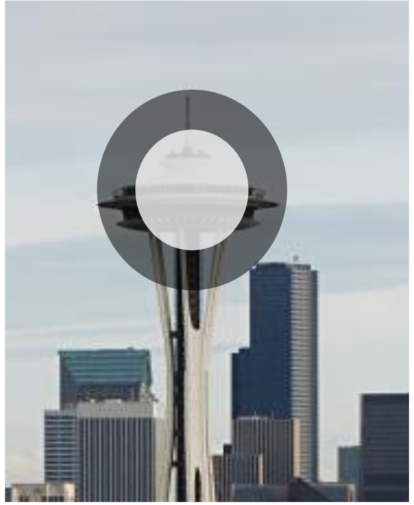
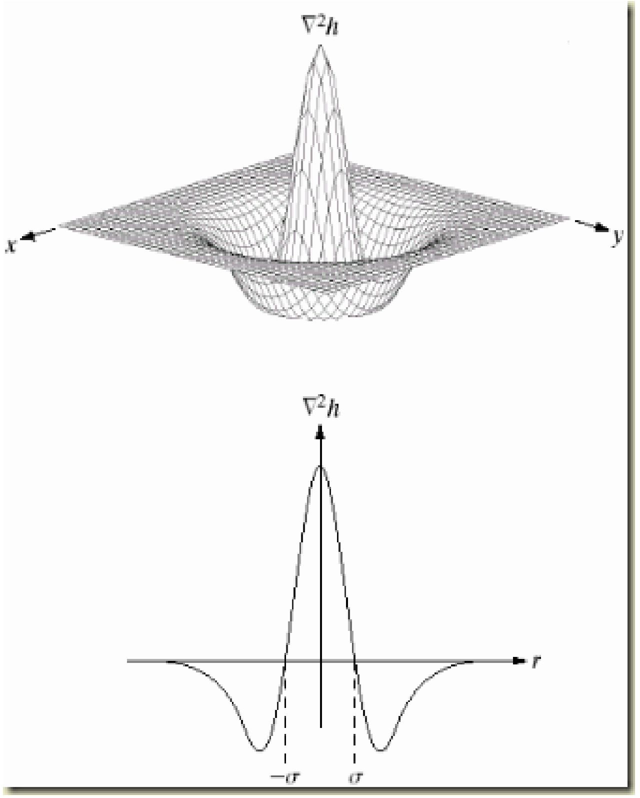
Differences between inside and outside

We can use a Laplacian function



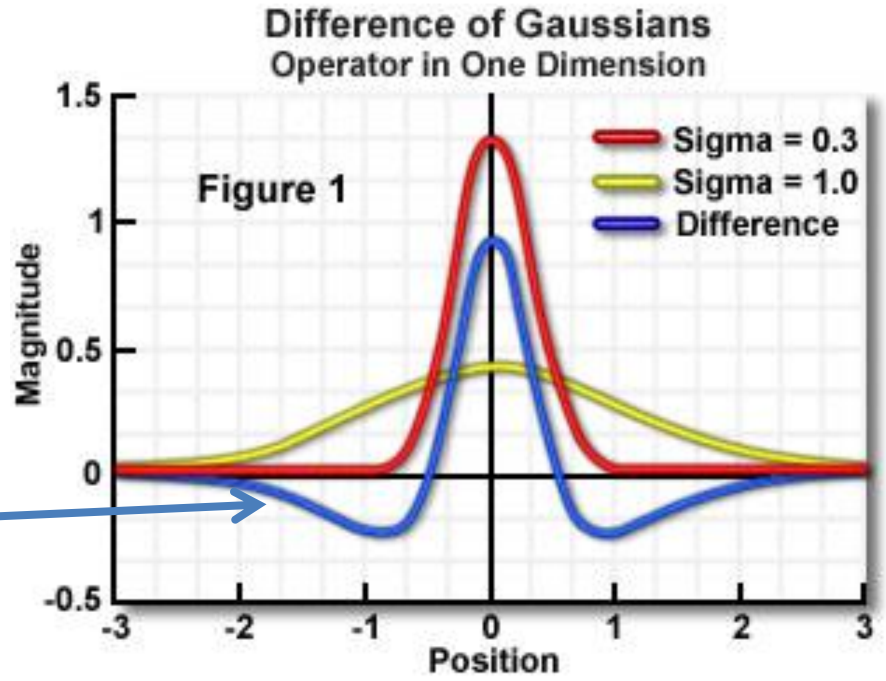




Source: Linda Shapiro

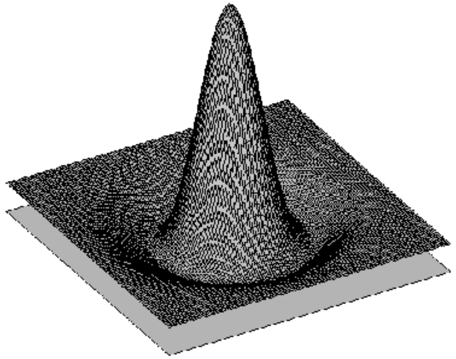
Difference-of-Gaussian (DoG)

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]

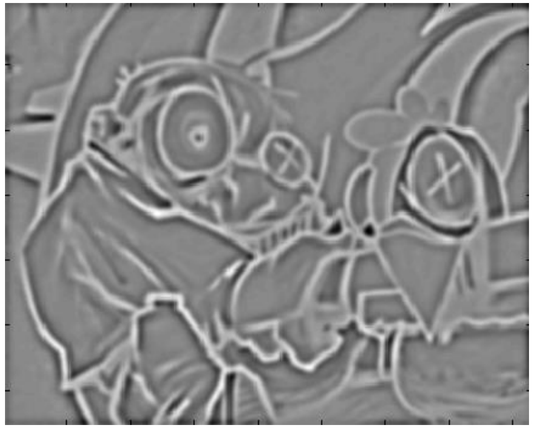
Difference-of-Gaussian (DoG)



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

-

=



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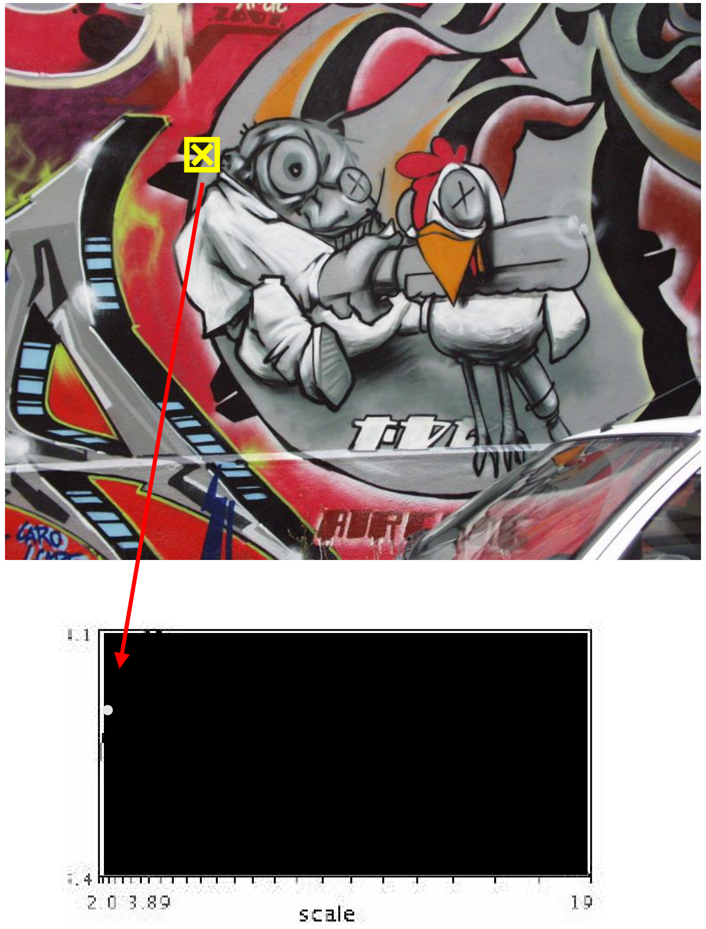
Automatic scale selection

- 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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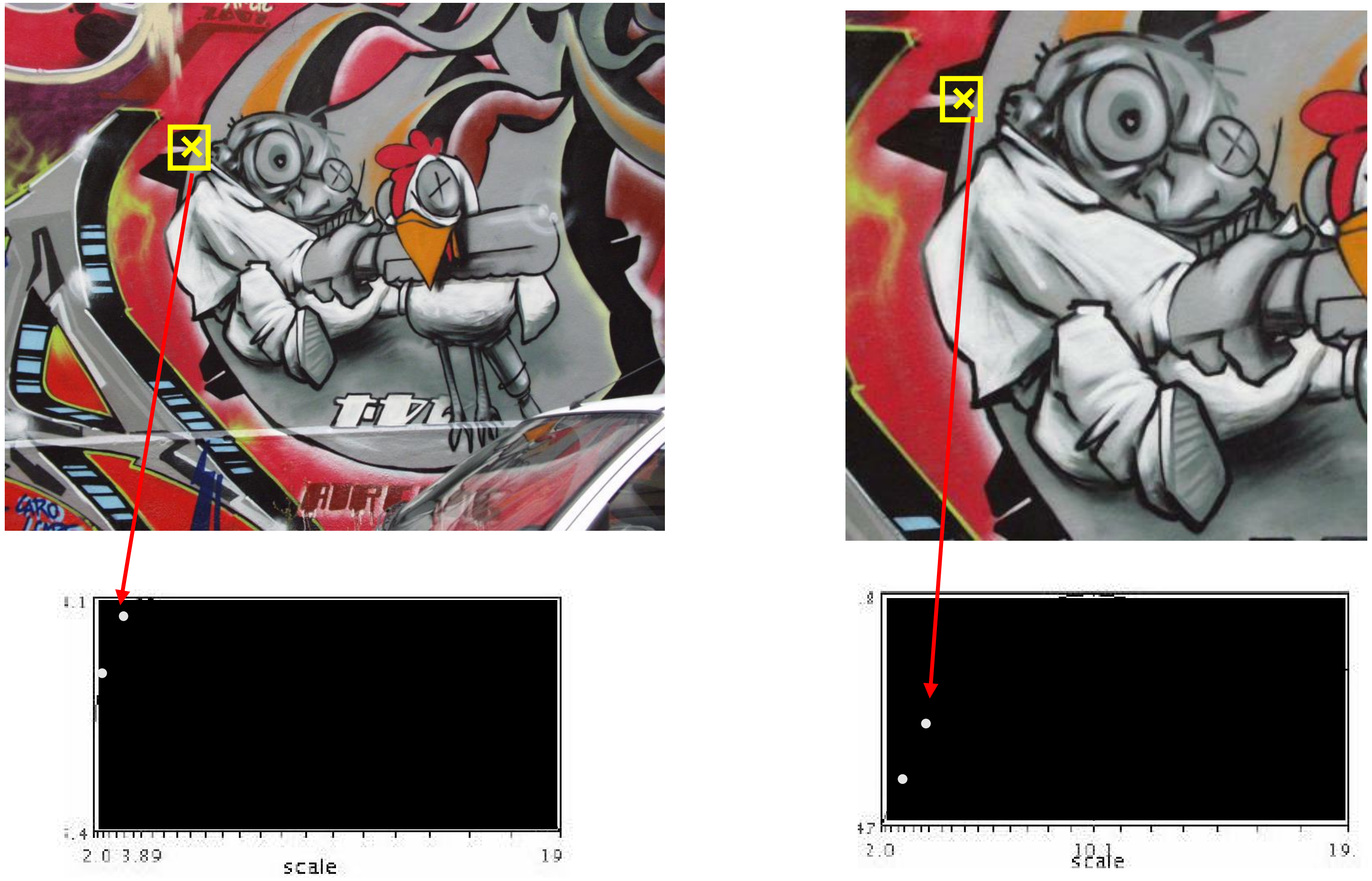
Automatic scale selection

- Function responses for increasing scale (scale signature)



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

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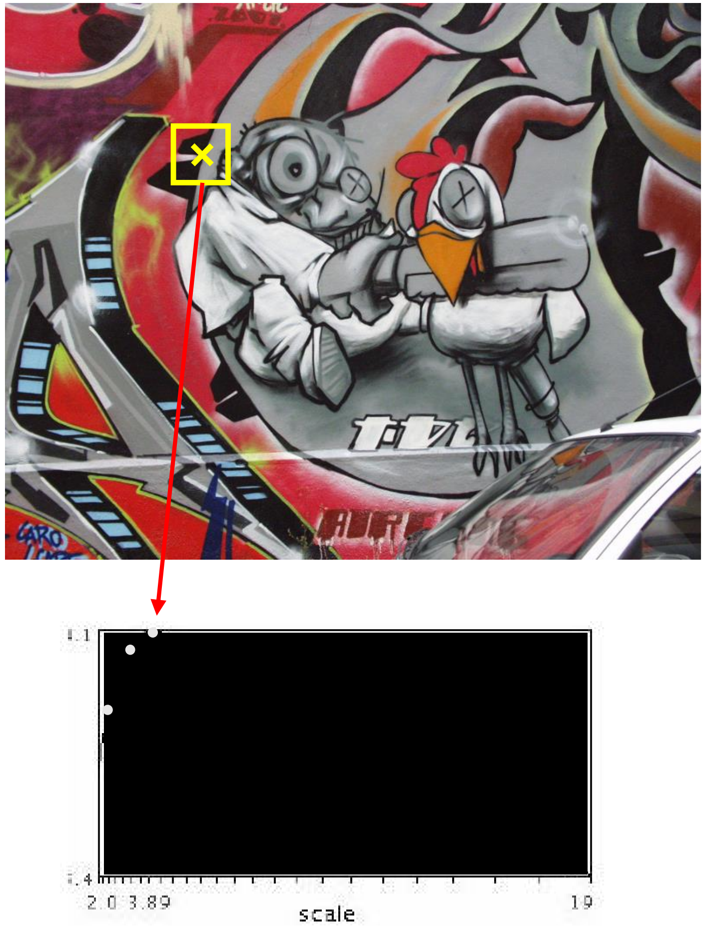
Automatic scale selection

- Function responses for increasing scale (scale signature)



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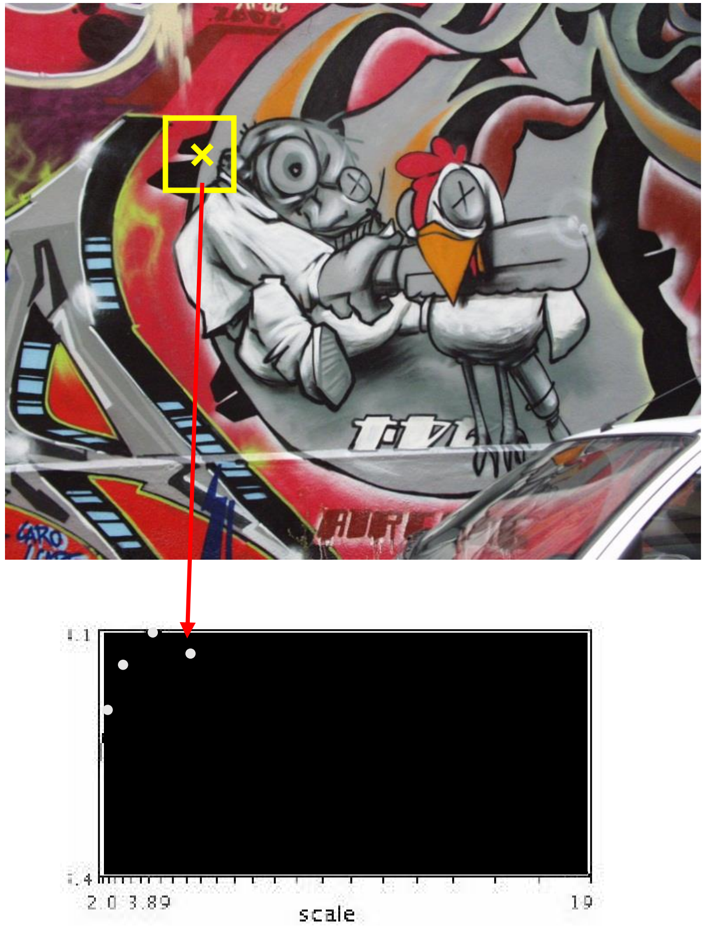

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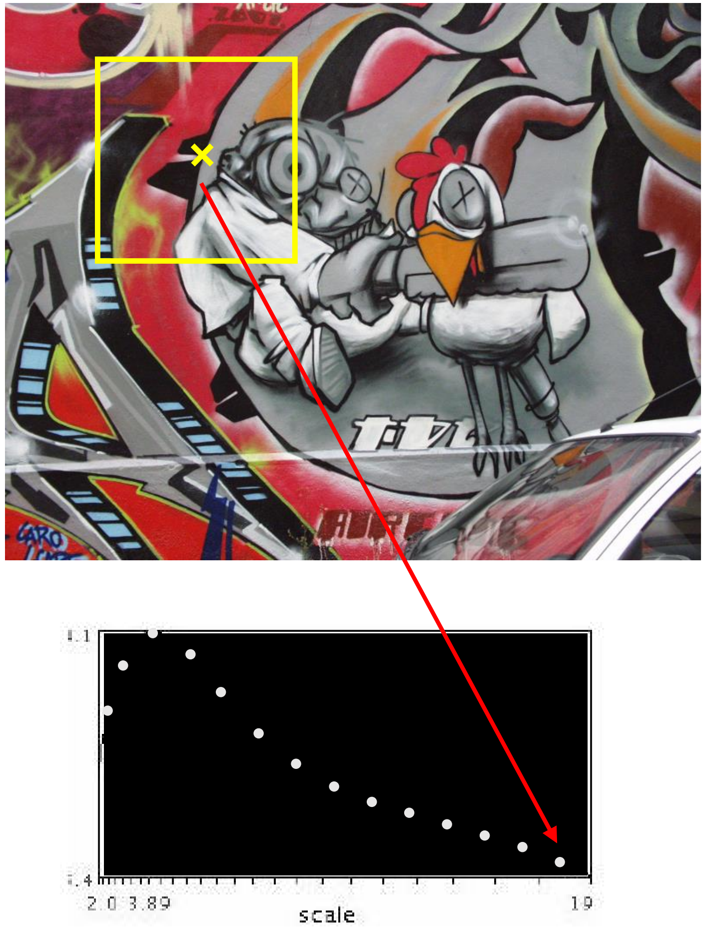
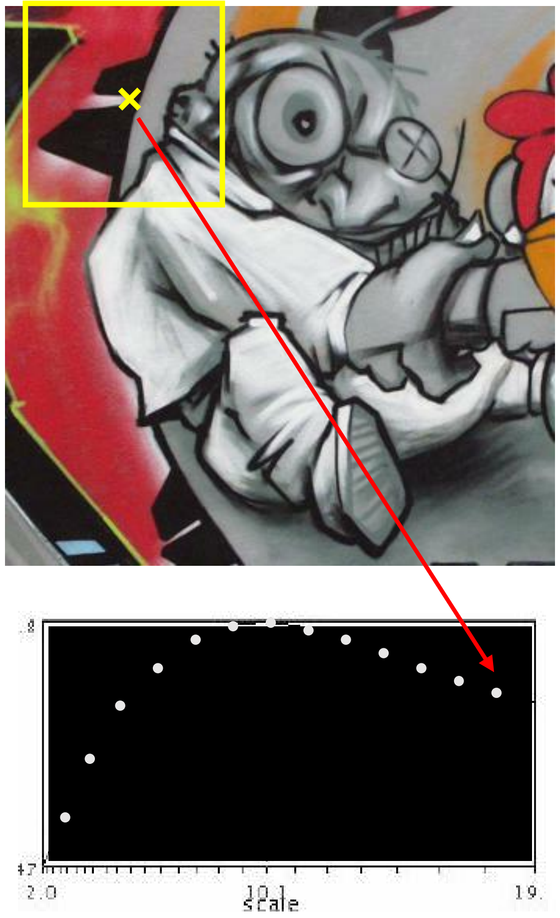


$f(I_{i_1 \ldots i_m}(x,\sigma))$



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

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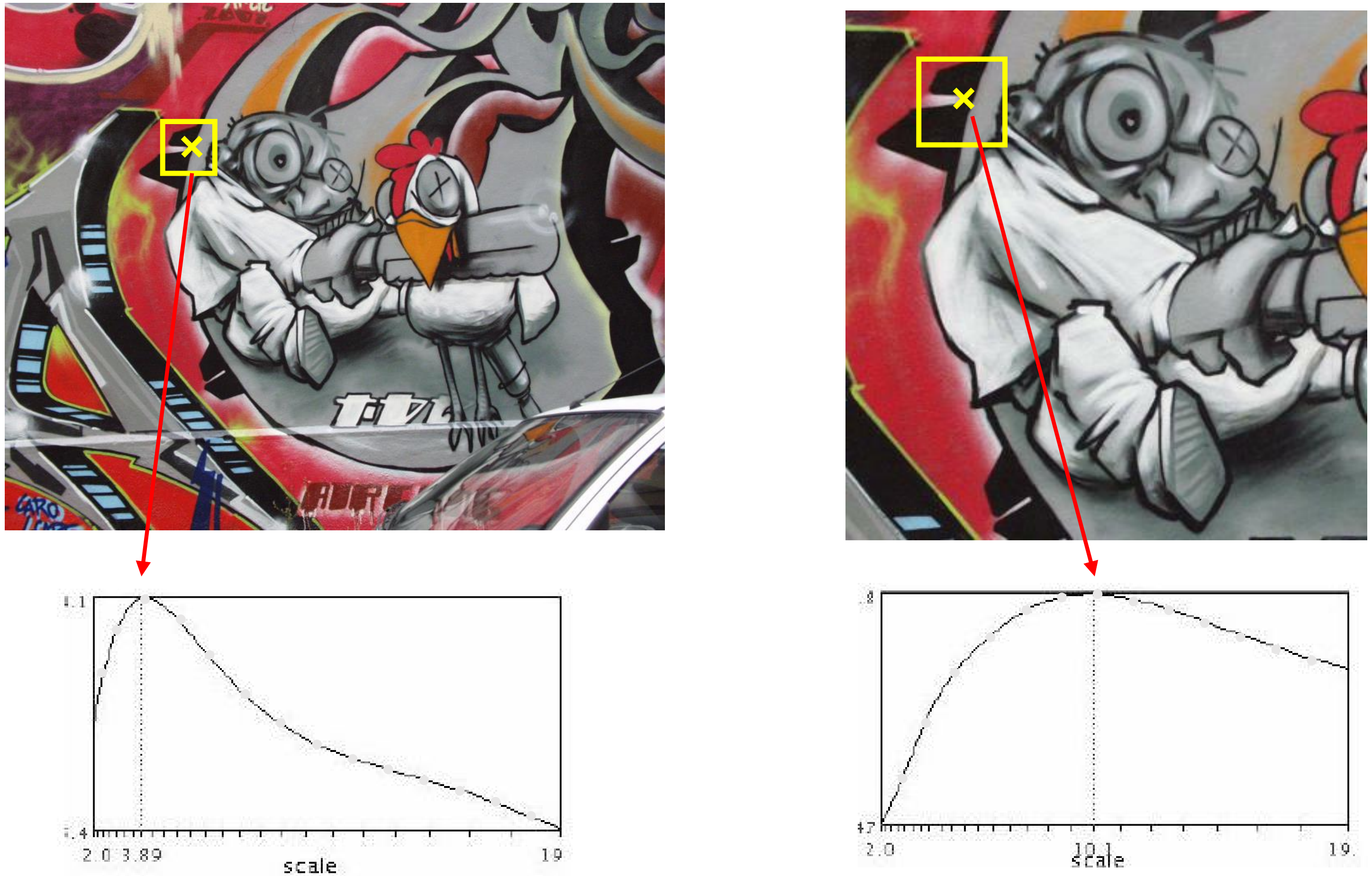
Automatic scale selection

- Function responses for increasing scale (scale signature)



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

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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 Visione e Percezione

Docente
Domenico D. Bloisi

Features