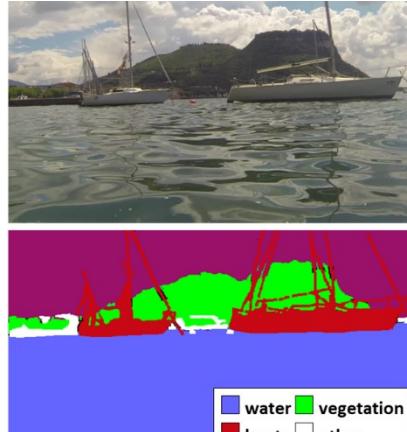
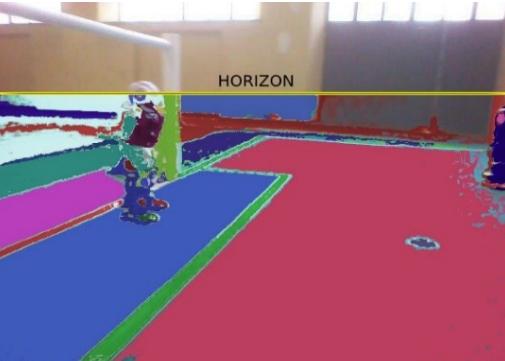




UNIVERSITÀ DEGLI STUDI
DELLA BASILICATA

Corso di Visione e Percezione

Feature Descriptors



Docente

Domenico D. Bloisi

Domenico Daniele Bloisi

- Ricercatore RTD B

Dipartimento di Matematica, Informatica
ed Economia

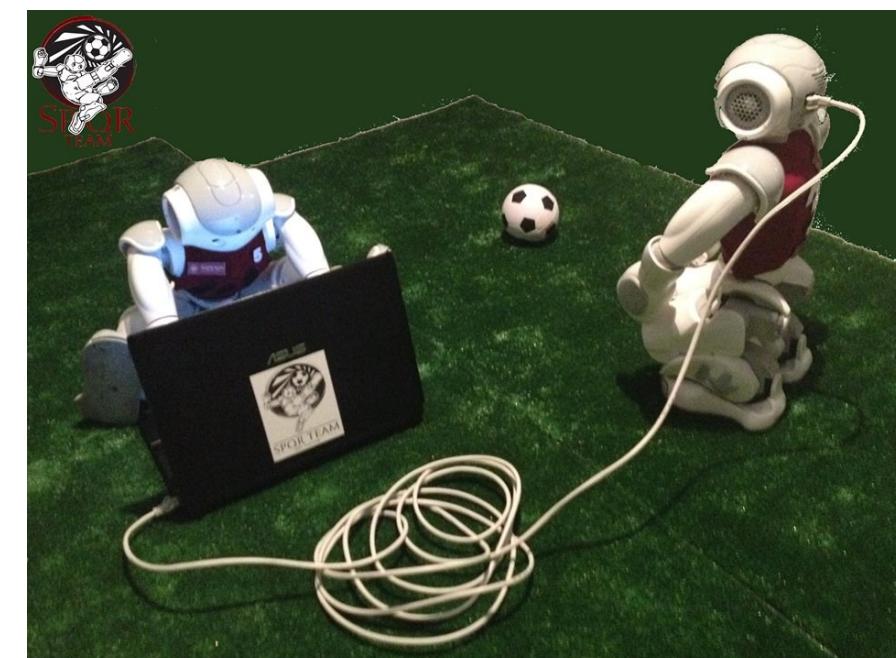
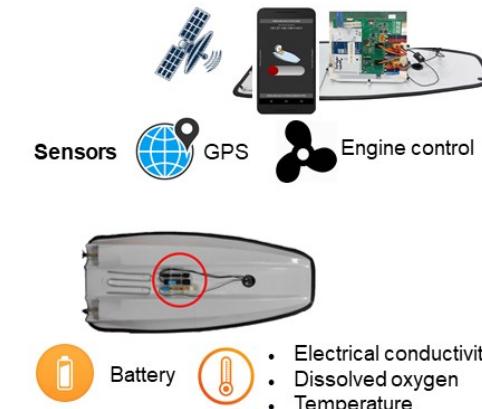
Università degli studi della Basilicata

<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>



Informazioni sul corso

- Home page del corso
<http://web.unibas.it/bloisi/corsi/visione-e-percezione.html>
- Docente: Domenico Daniele Bloisi
- Periodo: **Il semestre** marzo 2021 – giugno 2021

Martedì 17:00-19:00 (Aula COPERNICO)

Mercoledì 8:30-10:30 (Aula COPERNICO)



Codice corso Google Classroom:

<https://classroom.google.com/c/Njl2MjA4MzgzNDFa?cjc=xgolays>

Ricevimento

- Su appuntamento tramite Google Meet

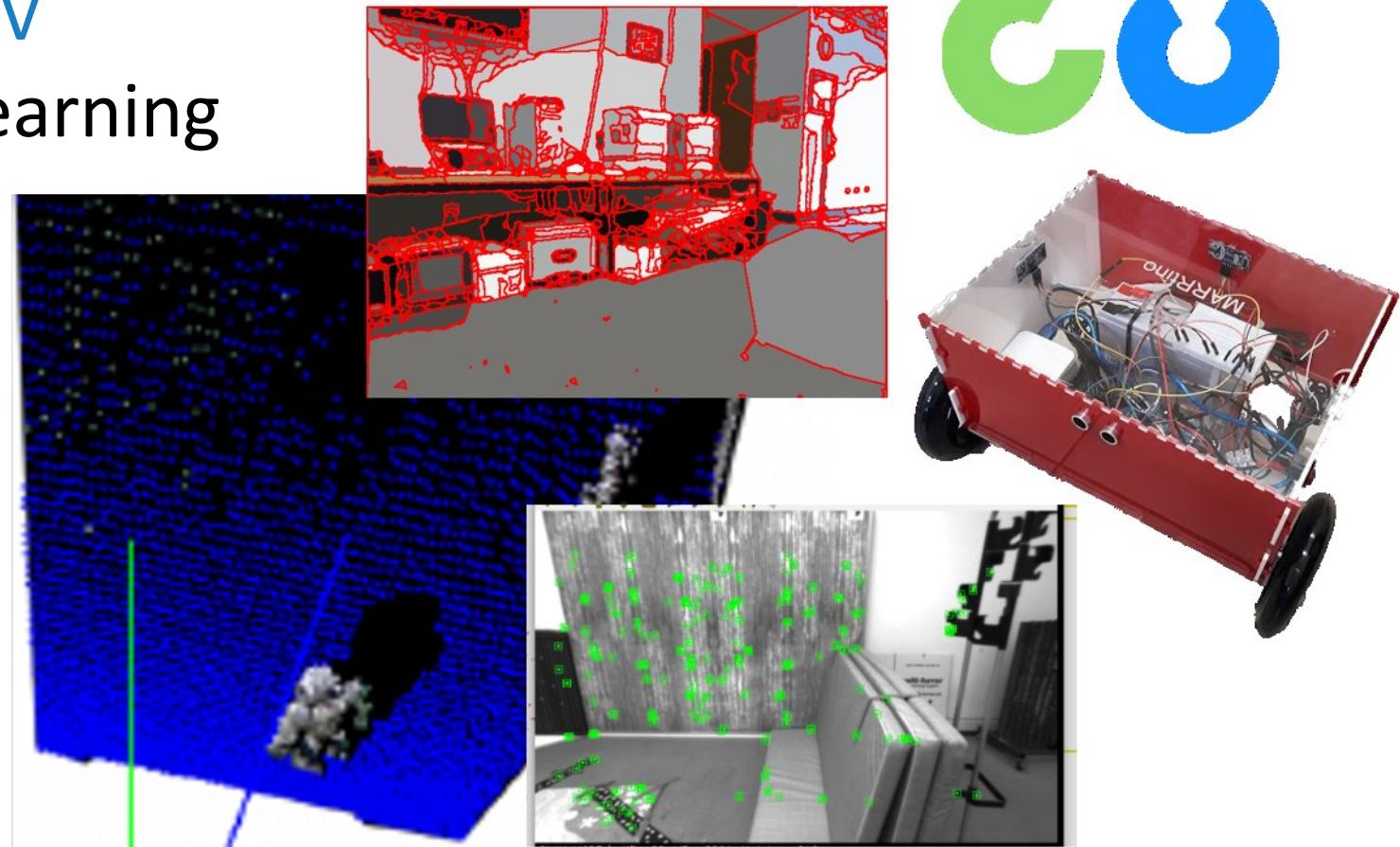
Per prenotare un appuntamento inviare
una email a

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



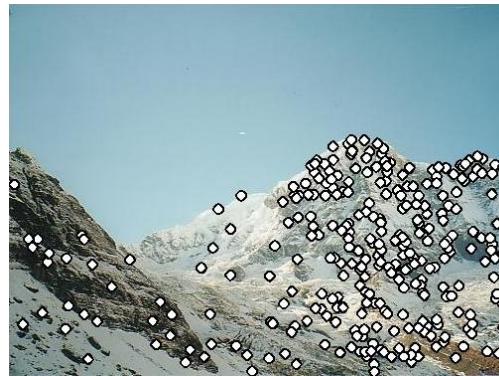
Riferimenti

- Queste slide sono adattate da
Noah Snavely - CS5670: Computer Vision
"Lecture 5: Feature descriptors and matching"
- 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/>

Local features: main components

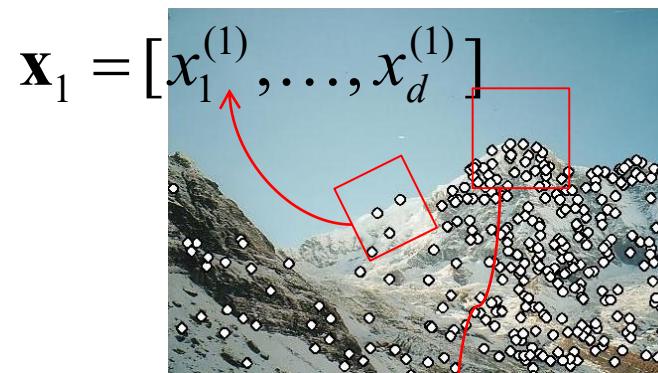
1) Detection:

Identify the interest points



2) Description:

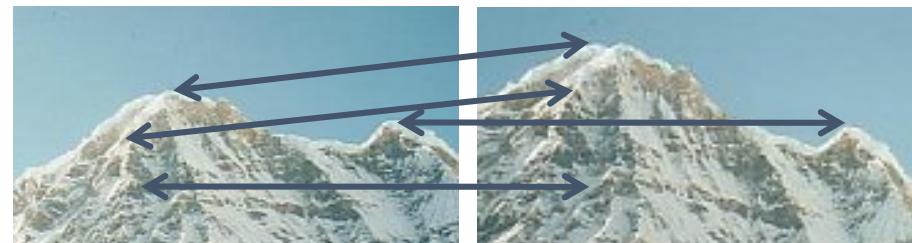
Extract vector feature descriptor surrounding each interest point



3) Matching:

Determine correspondence between descriptors in two views

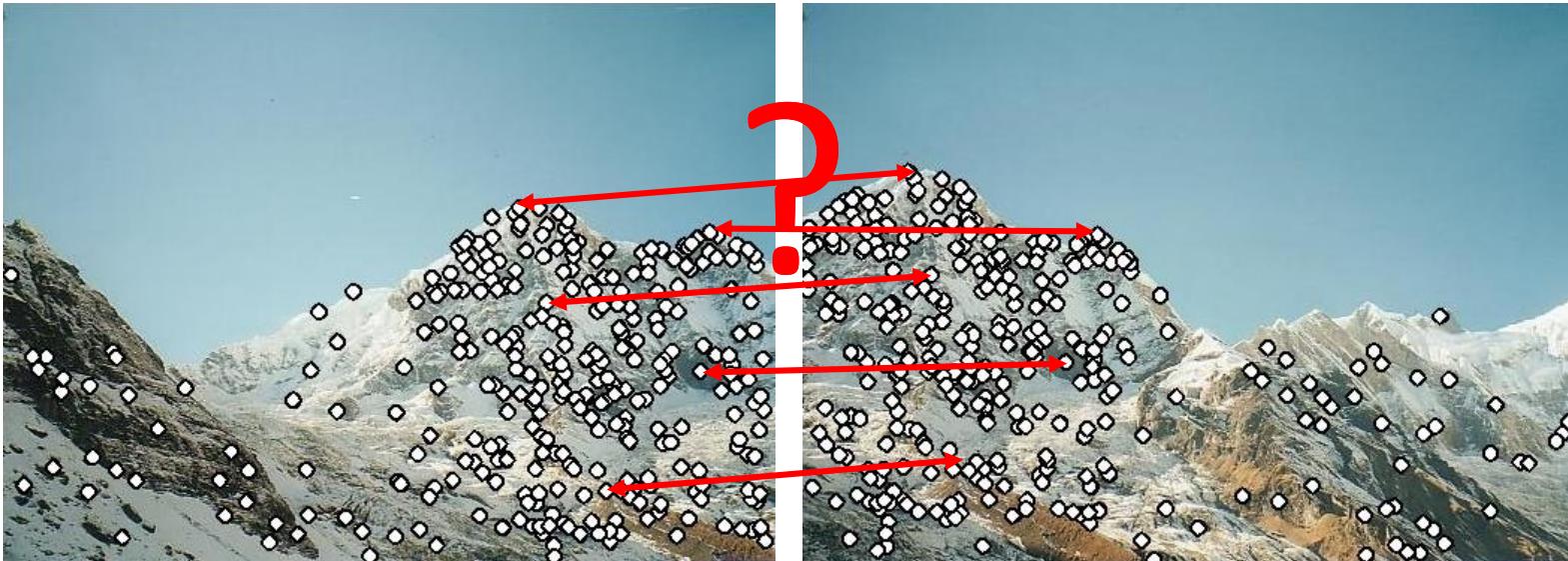
$$\mathbf{x}_2 = [x_1^{(2)}, \dots, x_d^{(2)}]$$



Feature descriptors

We know how to detect good points

Next question: **How to match them?**



Answer: Come up with a *descriptor* for each point,
find similar descriptors between the two images

Come capire se due descrittori sono simili?

Lots of possibilities:

- Simple option:
 - match square windows around the point
- Better option:
 - use invariant and discriminative descriptors
(SIFT, SURF, BRIEF, BRISK, ORB, ...)

Invariance vs. discriminability

Invariance:

Descriptor should **not change** even if image is transformed

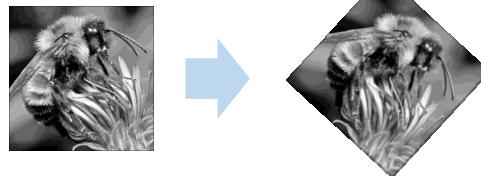
Discriminability:

Descriptor should be highly **unique** for each point

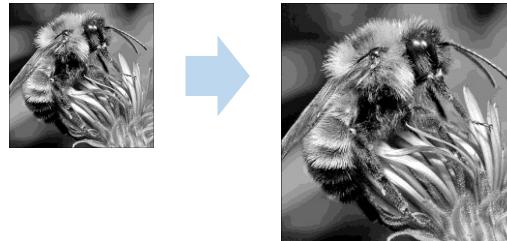
Image transformations

Geometric

Rotation



Scale

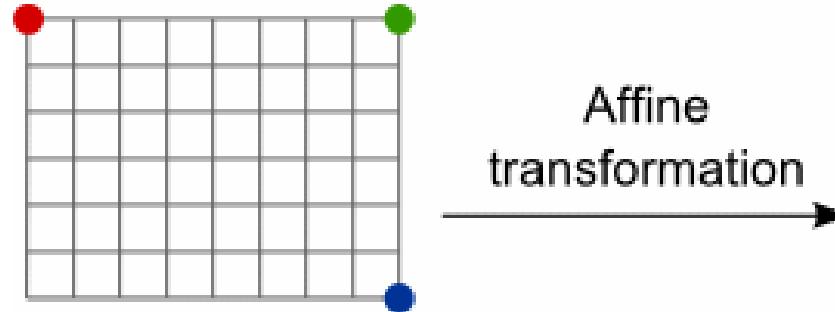


Photometric

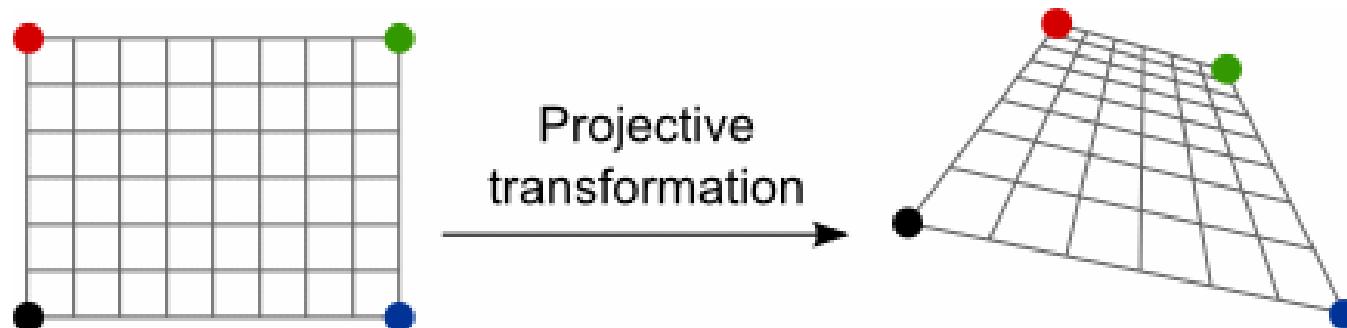
Intensity change



Image transformations



Affine transformations
preserve parallelism



Projective
transformations
do not preserve
parallelism, length,
and angle

Invariant descriptors

- We looked at invariant / covariant **detectors**
- Most feature **descriptors** are also designed to be invariant to
 - Translation, 2D rotation, scale
- They can usually also handle
 - Limited 3D rotations (SIFT works up to about 60 degrees)
 - Limited affine transforms (some are fully affine invariant)
 - Limited illumination/contrast changes

Rotation invariance for feature descriptors

- Find dominant orientation of the image patch
- Rotate the patch according to this angle

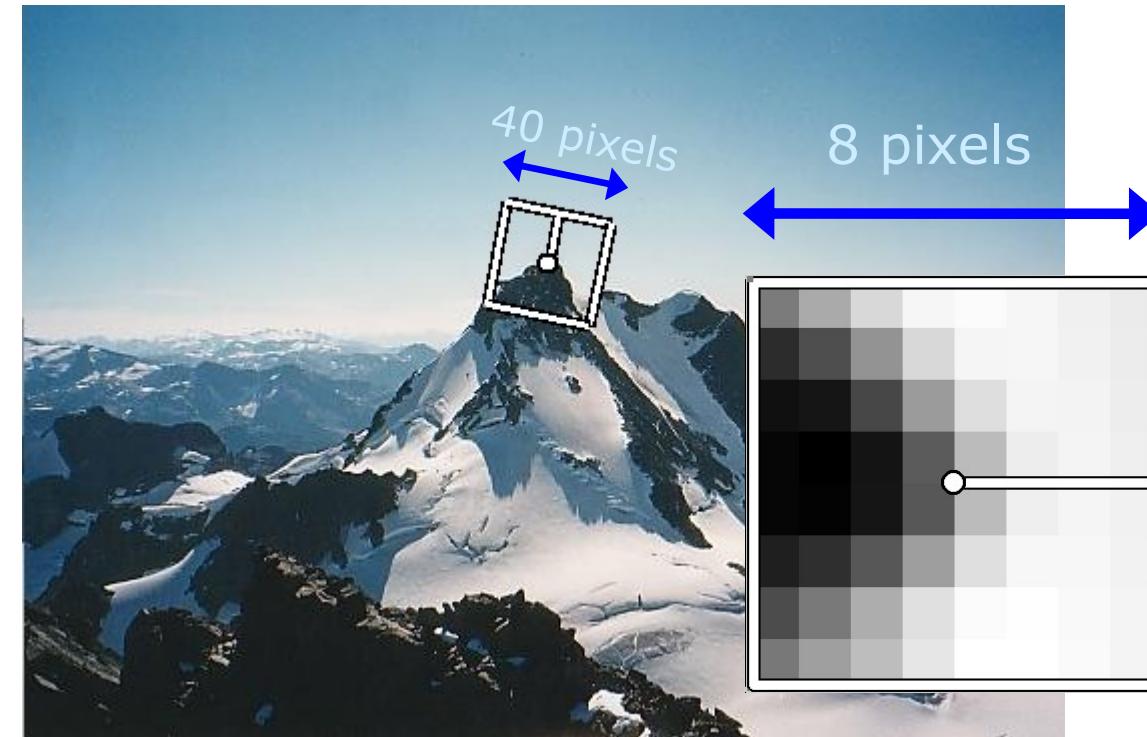


Figure by Matthew Brown

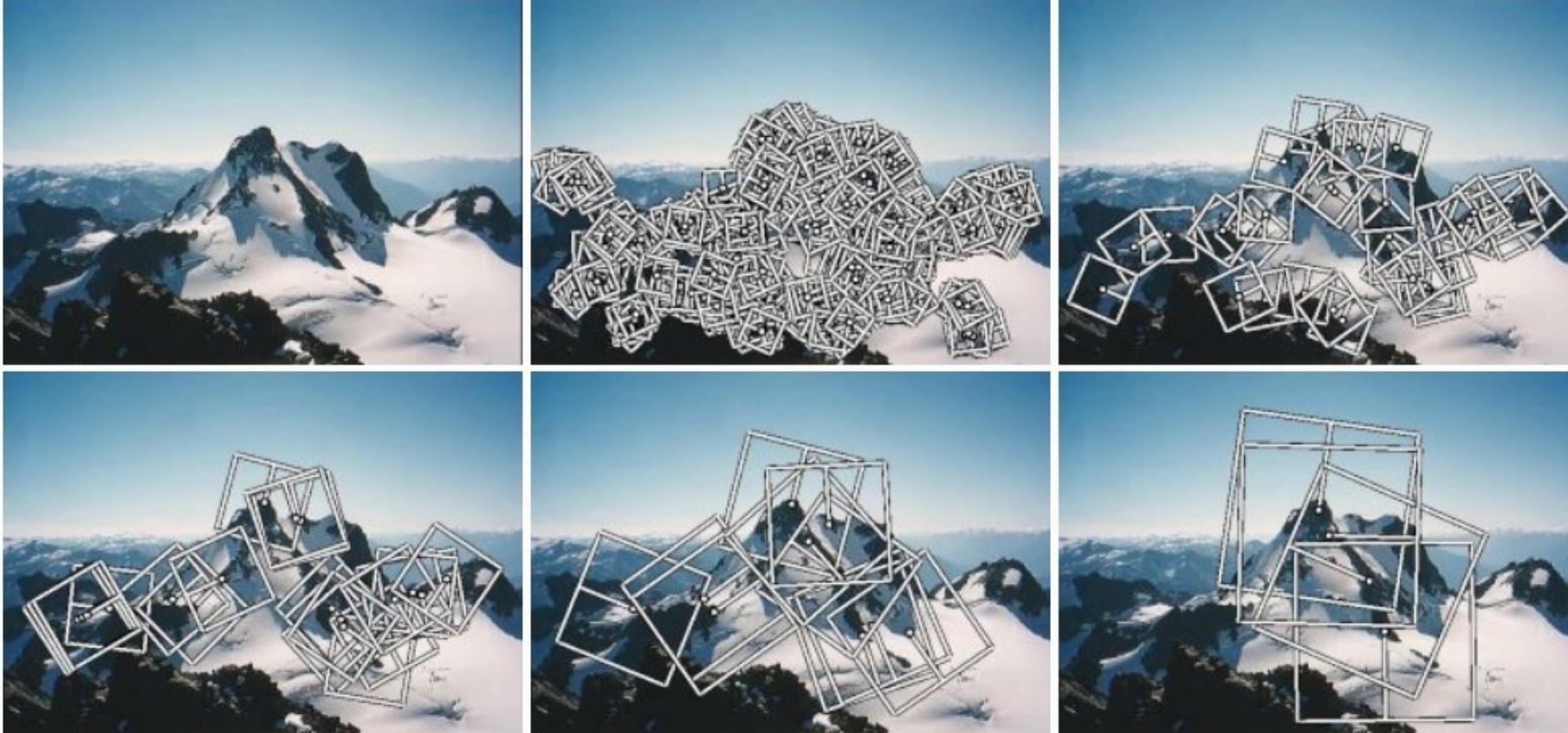
Multiscale Oriented PatcheS descriptor

Take 40x40 square window around detected feature

- Scale to 1/5 size (using prefiltering)
- Rotate to horizontal
- Sample 8x8 square window centered at feature
- Intensity normalize the window by subtracting the mean, dividing by the standard deviation in the window (to obtain bias/gain normalised intensity values)



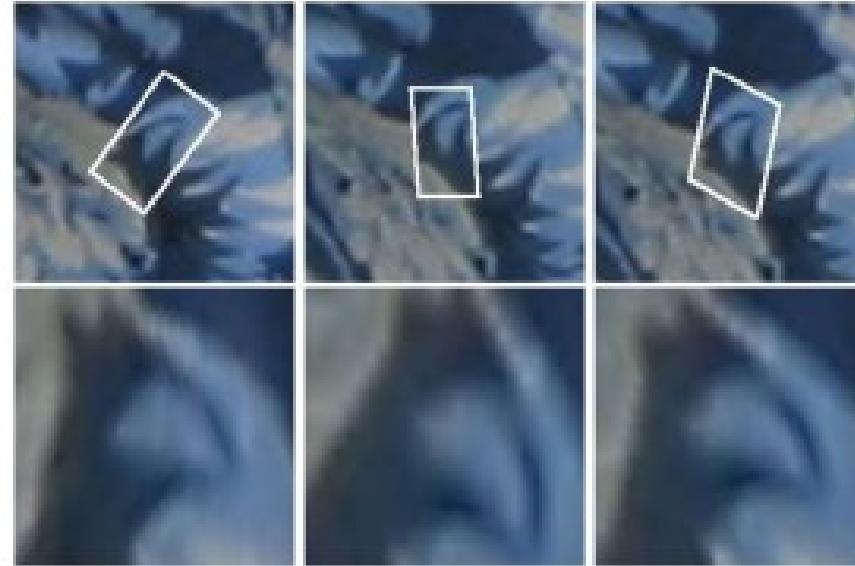
Detection at multiple scales



Multi-scale Oriented Patches (MOPS) extracted at 5 pyramid levels

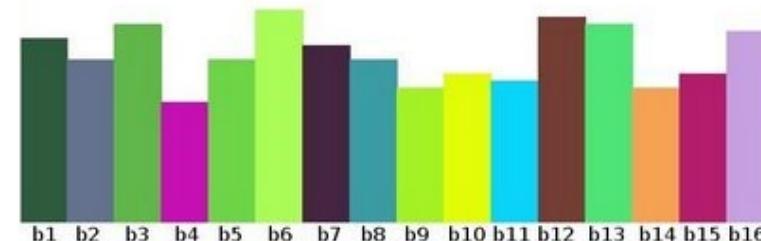
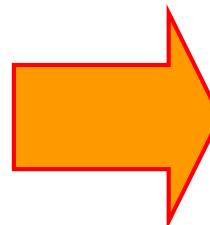
Svantaggi delle patches come descrittori

- Disadvantage of patches as descriptors:
 - Small shifts can affect matching score a lot



Histograms as descriptors

254	143	203	176	109	229	177	220	192	9	229	142	138	64	0	63	28	8	88	82
27	68	231	75	141	107	149	210	13	239	141	35	68	242	110	208	244	0	33	88
54	42	17	215	230	254	47	41	98	160	55	253	235	47	122	208	76	110	152	100
9	166	192	71	104	193	88	171	37	233	18	147	174	1	143	211	178	188	192	68
179	20	238	192	190	132	41	248	22	134	83	133	110	254	176	238	188	234	51	204
232	25	0	163	174	129	61	30	110	189	0	173	197	163	153	43	22	87	68	118
235	35	151	185	129	81	239	170	195	94	38	21	67	101	58	37	196	149	52	154
155	242	54	0	104	109	189	47	130	254	225	158	31	181	121	15	128	35	252	205
223	114	79	129	147	6	201	68	89	107	58	44	253	84	38	1	62	5	231	218
55	168	237	188	80	101	131	241	68	133	124	151	111	28	190	4	240	78	117	145
152	155	229	76	90	217	219	105	116	77	38	49	2	9	214	181	205	116	135	33
182	94	176	199	20	149	57	223	232	113	32	45	177	15	31	179	100	118	208	81
224	118	124	172	75	29	69	180	167	195	41	44	8	170	158	101	131	31	28	112
238	83	38	7	83	69	173	183	98	237	67	227	18	218	248	237	75	192	201	146
88	195	224	207	140	22	31	118	234	34	182	110	23	47	68	242	189	152	116	248
140	37	101	230	246	145	122	64	27	58	229	1	225	143	91	100	98	90	40	195
251	4	178	139	121	95	97	174	249	182	77	115	223	188	182	82	65	252	83	196
179	180	223	230	87	182	148	78	176	19	17	4	184	176	183	102	83	81	132	206
173	137	185	242	181	181	214	49	74	238	197	37	98	102	15	217	148	8	102	188
85	9	17	222	18	210	70	21	78	241	184	216	93	93	208	102	153	212	119	47



Scale Invariant Feature Transform

Basic idea:

- Take 16x16 square window around detected feature
- Compute edge orientation (angle of the gradient - 90°) for each pixel
- Throw out weak edges (threshold gradient magnitude)
- Create histogram of surviving edge orientations

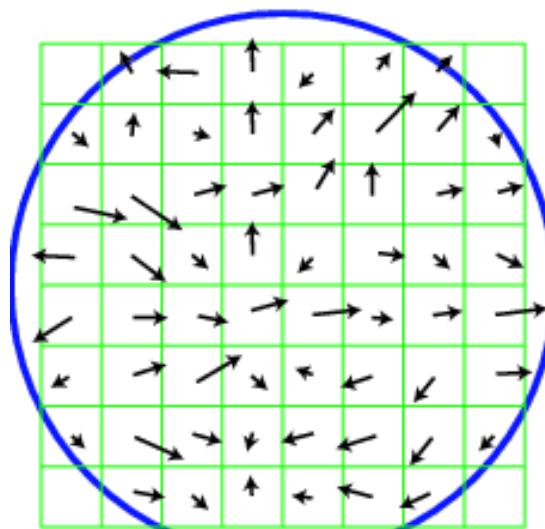
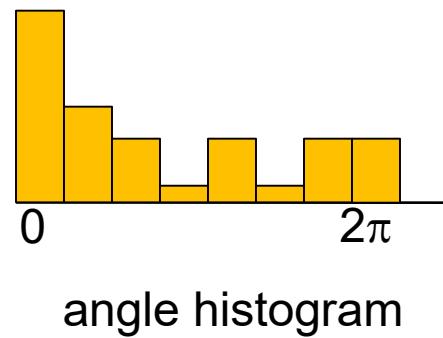
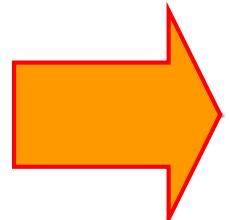
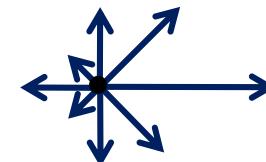


Image gradients

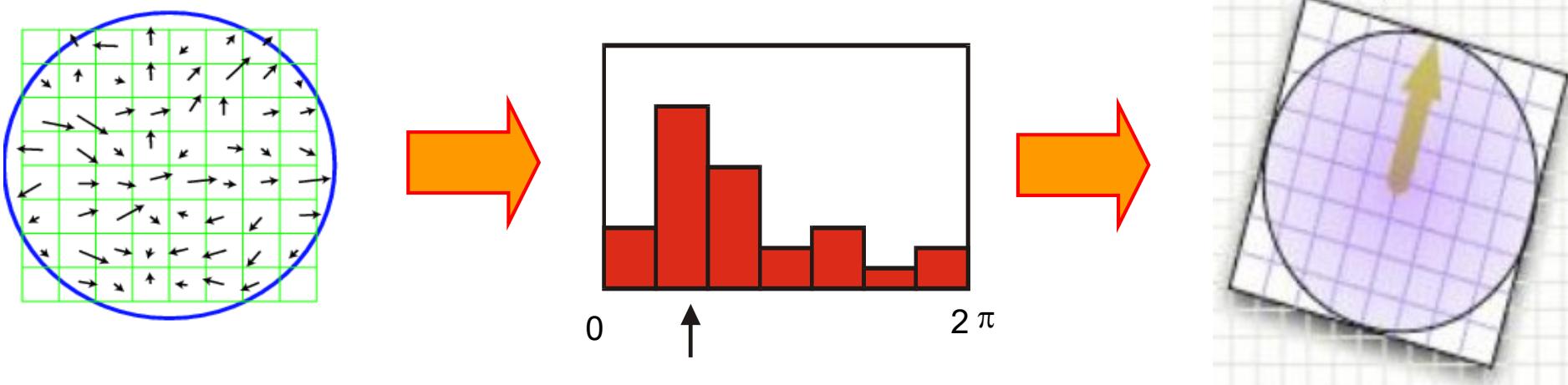


angle histogram



Finding a reference orientation

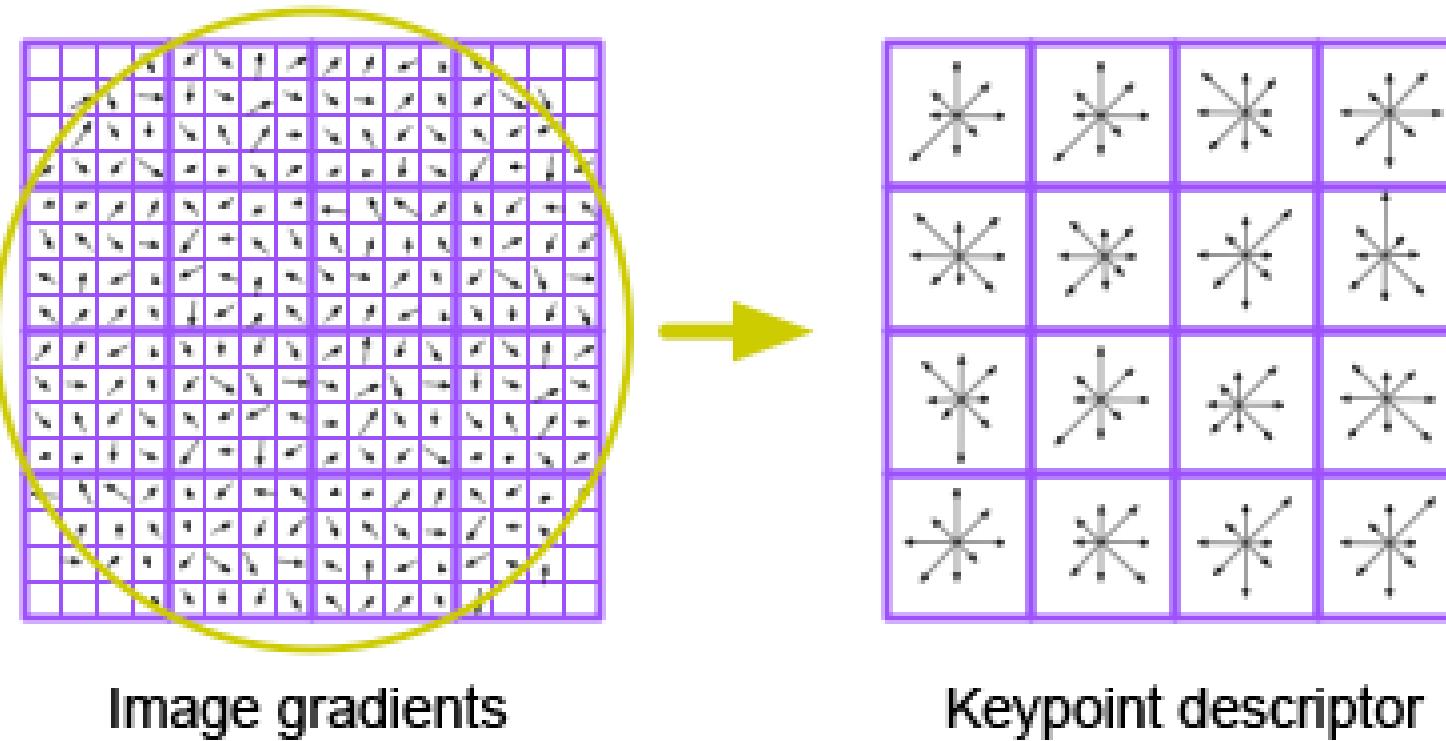
Assign reference orientation at peak of smoothed histogram



SIFT descriptor

Full version

- Divide the 16x16 window into a 4x4 grid of cells
- Compute an orientation histogram for each cell
- 16 cells * 8 orientations = 128 dimensional descriptor



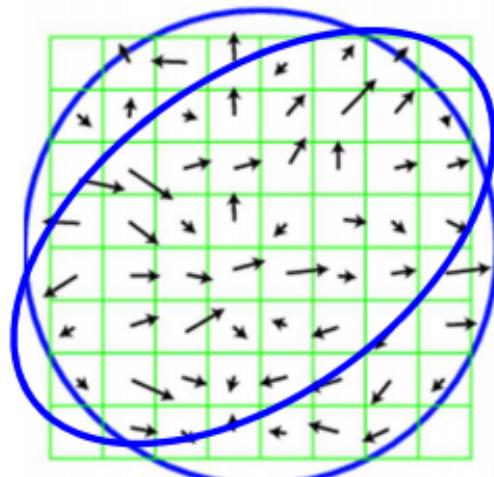
What about 3D rotations?

Affine transformation approximates viewpoint changes for roughly planar objects and roughly orthographic cameras



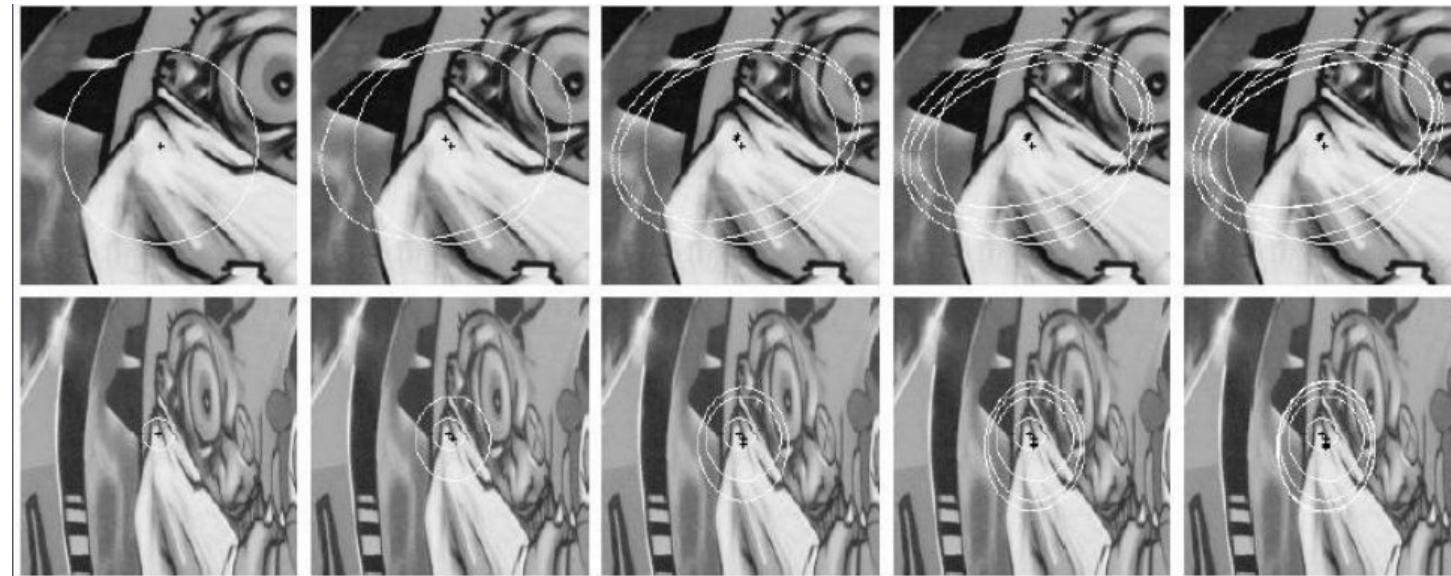
Affine adaptation

- Problem:
 - Determine the characteristic shape of the region.
 - Assumption: shape can be described by “local affine frame”.
- Solution: iterative approach
 - Use a circular window to compute second moment matrix.
 - Compute eigenvectors to adapt the circle to an ellipse.
 - Recompute second moment matrix using new window and iterate...

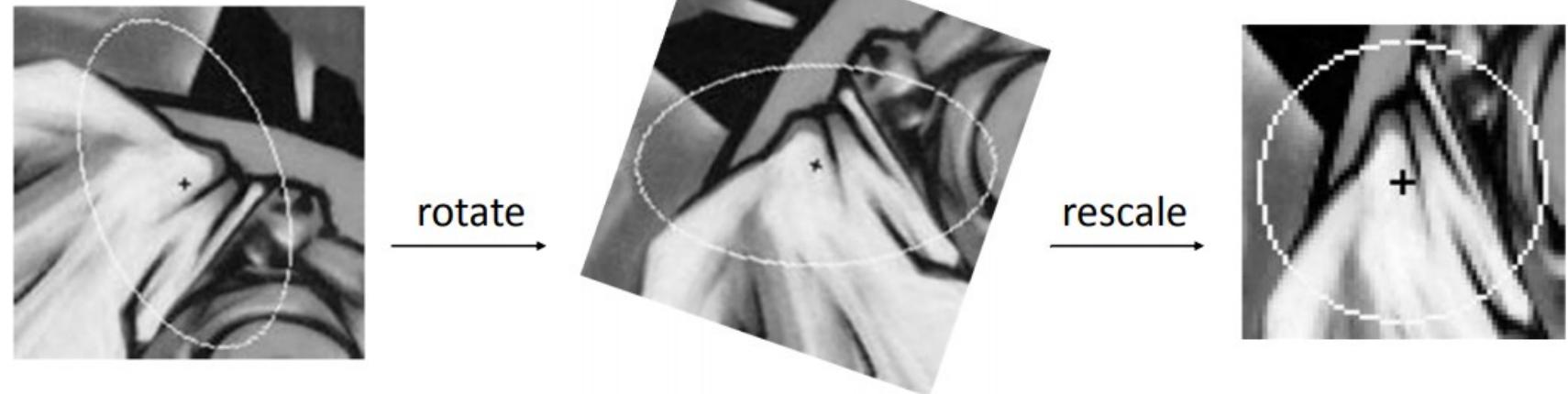


Affine normalization ('deskewing')

Iterative
Affine
Adaptation



- Rotate the ellipse's main axis to horizontal
- Scale the x axis, such that it forms a circle

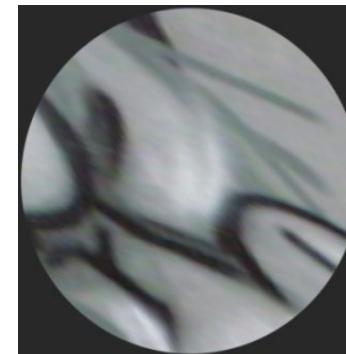


Summary: Affine-Inv. Feature Extraction

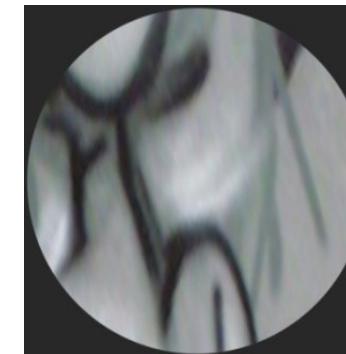
Extract affine regions



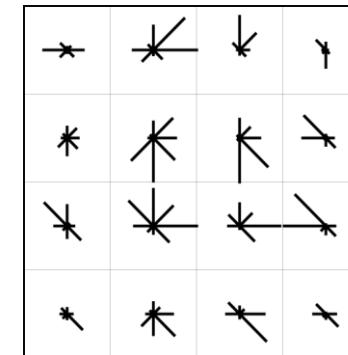
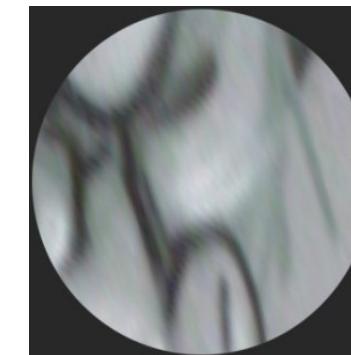
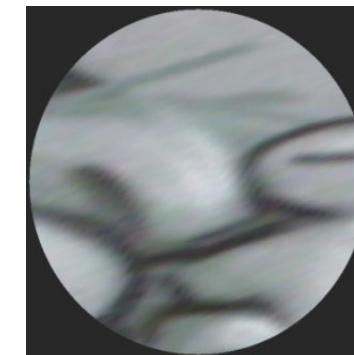
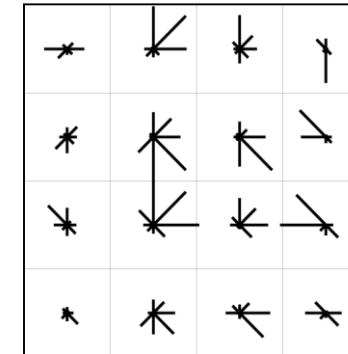
Normalize regions



Eliminate rotational ambiguity



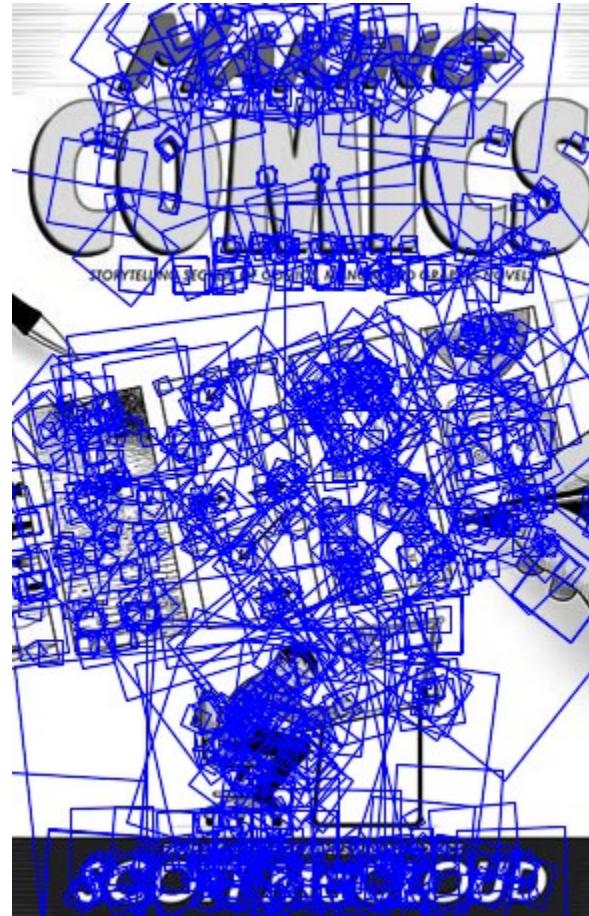
Compare descriptors



SIFT example



sift

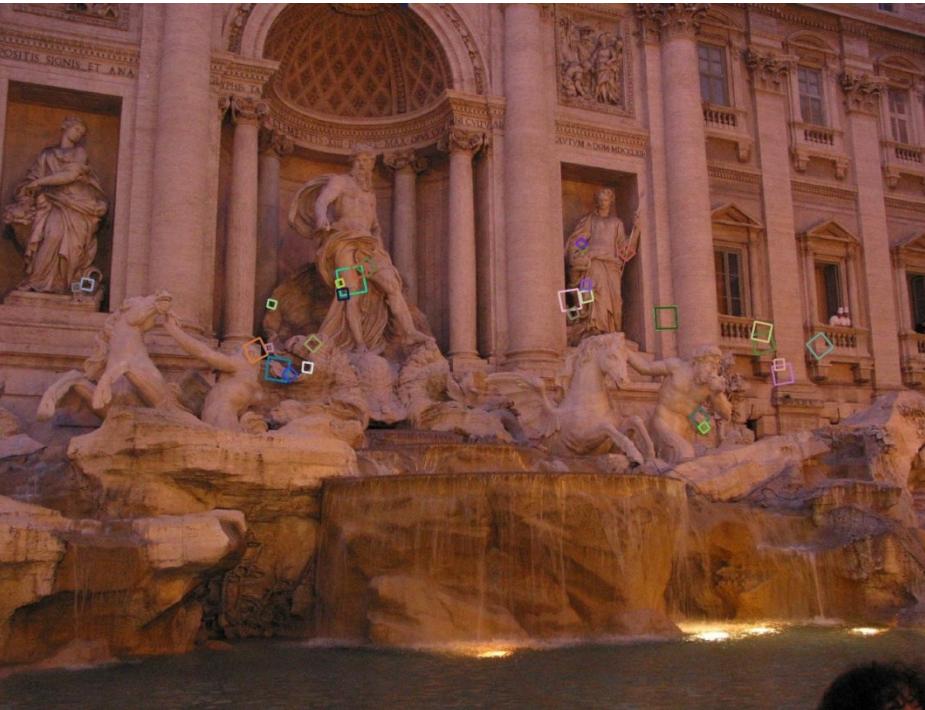


868 SIFT features

Properties of SIFT

Extraordinarily robust matching technique

- Can handle changes in viewpoint
 - Up to about 60 degree out of plane rotation
- Can handle significant changes in illumination
 - Sometimes even day vs. night (below)
- Fast and efficient—can run in real time



Storia dei feature descriptor

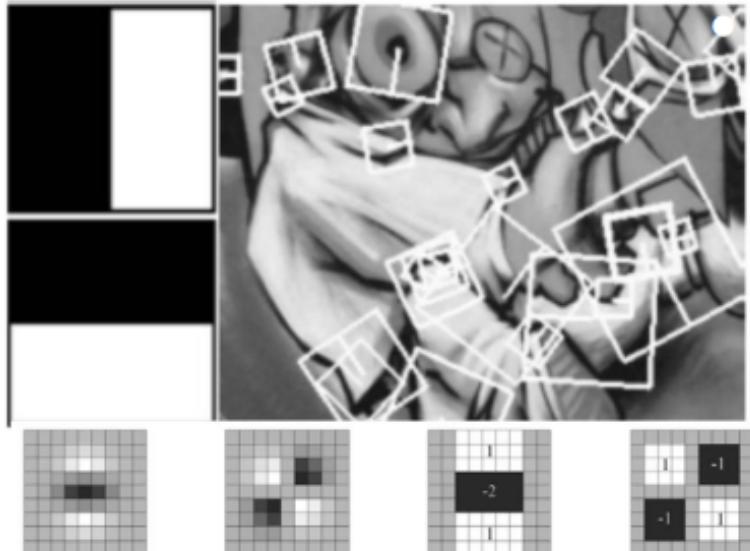
Traditional (slower, accurate):

- 1999 Scale Invariant Feature Transform (Lowe)
- 2006 Speeded Up Robust Features (Bay, Tuytelaars, Van Gool)

Binary (faster, real time, smartphone, performance):

- 2010 Binary Robust Independent Elementary Features (Michael Calonder et al.)
- 2011 Binary Robust Invariant Scalable Keypoints (Leutenegger, Chli, Siegwart)
- 2011 Oriented FAST and Rotated BRIEF (Ethan Rublee et al.)

SURF Speeded Up Robust Features



Fast approximation of SIFT idea

Efficient computation by 2D box filters & integral images
⇒ 6 times faster than SIFT

Equivalent quality for object identification

<http://www.vision.ee.ethz.ch/~surf>

GPU implementation available

Feature extraction @ 100Hz
(detector + descriptor, 640×480 img)

<http://homes.esat.kuleuven.be/~ncorneli/gpusurf/>

<http://www.vision.ee.ethz.ch/~surf>

[Bay, ECCV'06], [Cornelis, CVGPU'08]

Source: Fei-Fei Li

(some) Features descriptors in OpenCV

- SIFT (Scale Invariant Feature Transform)
 - SURF (Speeded Up Robust Features)
 - BRISK (Binary Robust Invariant Scalable Keypoints)
 - BRIEF (Binary Robust Independent Elementary Features)
 - ORB (Oriented FAST and Rotated BRIEF)
- 
- NON FREE
but the patent expired in
the year 2020

SIFT – Example



OpenCV

Version 4.5.1

surf.pnng



BRIEF – Example



```
import cv2 as cv
import numpy as np
import matplotlib.pyplot as plt
import urllib.request

url = "https://dbloisi.github.io/corsi/images/castelmezzano-panorama.jpg"

url_response = urllib.request.urlopen(url)
numpy_img = np.array(bytearray(url_response.read()), dtype=np.uint8)
img = cv.imdecode(numpy_img, -1)

gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)

star = cv.xfeatures2d.StarDetector_create()

brief = cv.xfeatures2d.BriefDescriptorExtractor_create()

kp = star.detect(gray, None)

kp, des = brief.compute(gray, kp)

img = cv.drawKeypoints(gray, kp, None,
                       flags=cv.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

plt.axis('off')
plt.imshow(img)

cv.imwrite('brief.png', img)
```

brief.png



BRISK – Example



```
import cv2 as cv
import numpy as np
import matplotlib.pyplot as plt
import urllib.request

url = "https://dbloisi.github.io/corsi/images/castelmezzano-panorama.jpg"

url_response = urllib.request.urlopen(url)
numpy_img = np.array(bytearray(url_response.read()), dtype=np.uint8)
img = cv.imdecode(numpy_img, -1)

gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)

brisk = cv.BRISK_create(thresh=60, octaves=3, patternScale=1.0)

kp = brisk.detect(gray, None)

kp, des = brisk.compute(gray, kp)

img = cv.drawKeypoints(gray, kp, None,
                       flags=cv.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

plt.axis('off')
plt.imshow(img)

cv.imwrite('brisk.png', img)
```

brisk.png



ORB – Example

```
import cv2 as cv
import numpy as np
import matplotlib.pyplot as plt
import urllib.request

url = "https://dbloisi.github.io/corsi/images/castelmezzano-panorama.jpg"

url_response = urllib.request.urlopen(url)
numpy_img = np.array(bytearray(url_response.read()), dtype=np.uint8)
img = cv.imdecode(numpy_img, -1)

gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)

orb = cv.ORB_create()

kp = orb.detect(gray, None)

kp, des = orb.compute(gray, kp)

img = cv.drawKeypoints(gray, kp, None,
                       flags=cv.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

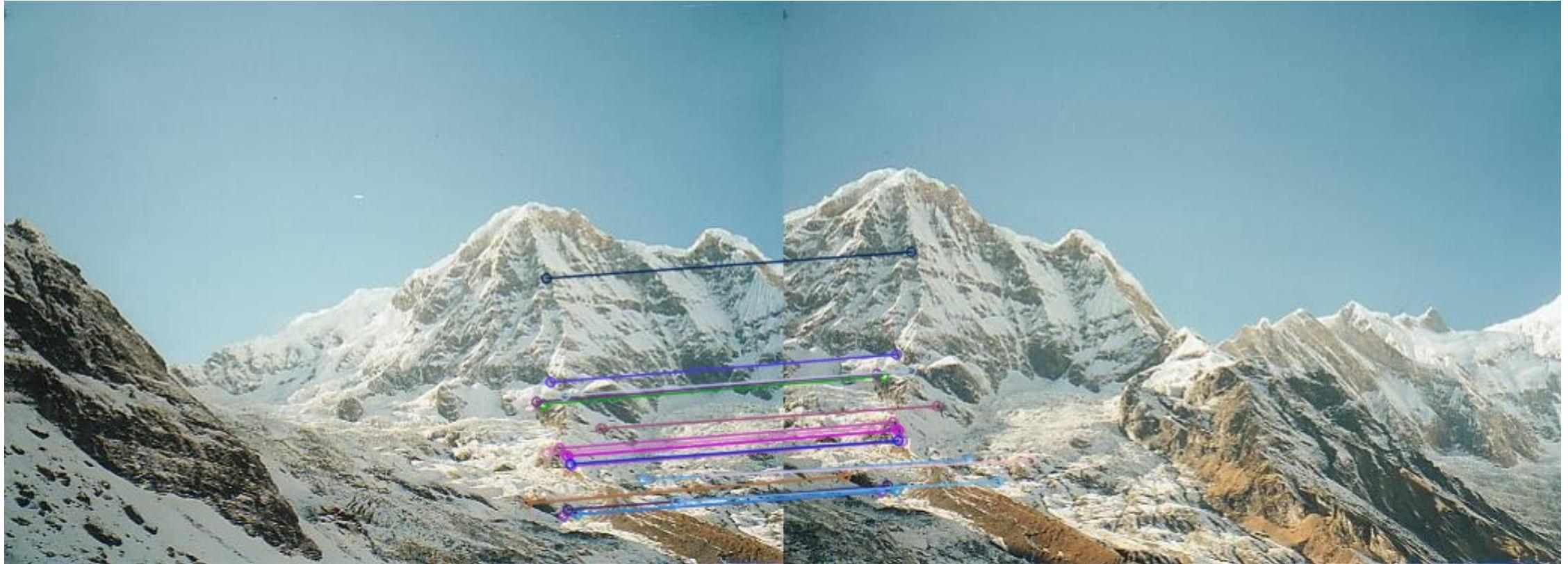
plt.axis('off')
plt.imshow(img)

cv.imwrite('orb.png', img)
```

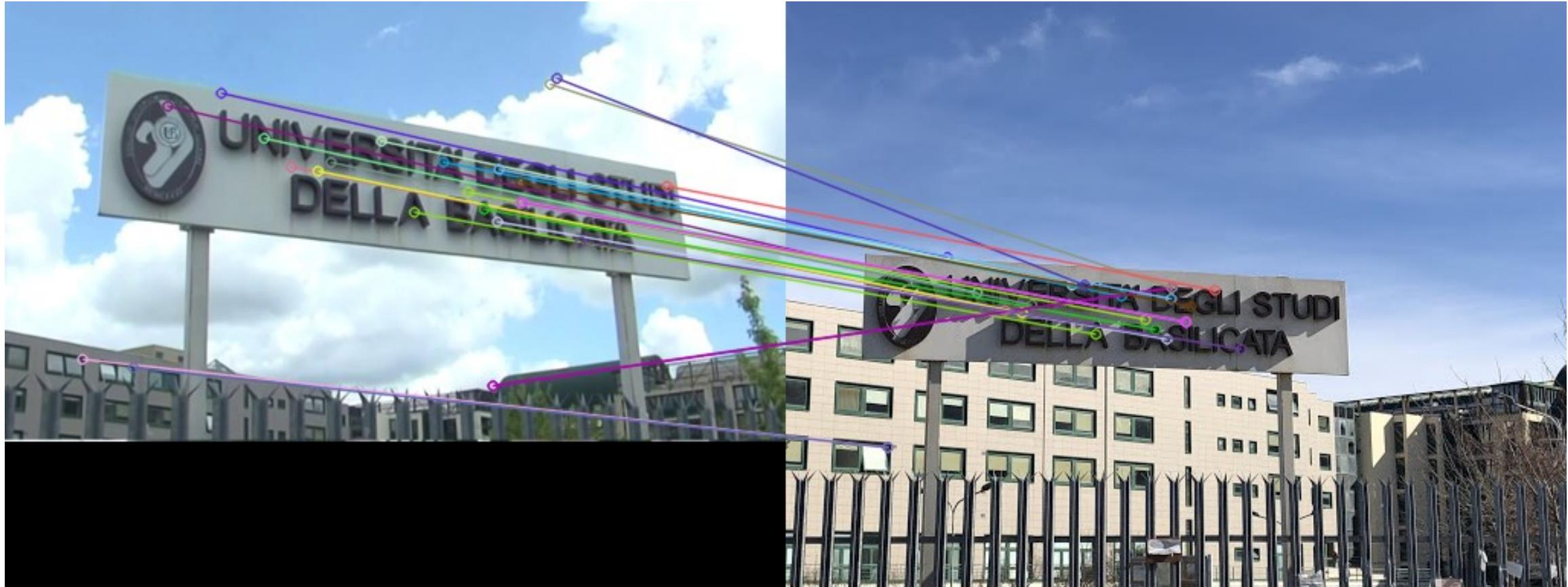
Orb.png



Feature matching



Feature matching

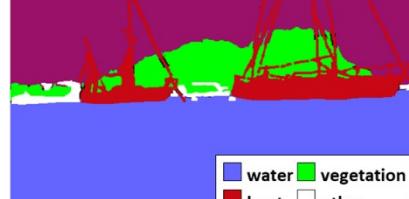
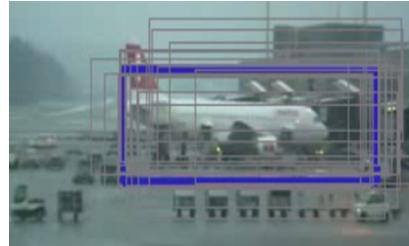
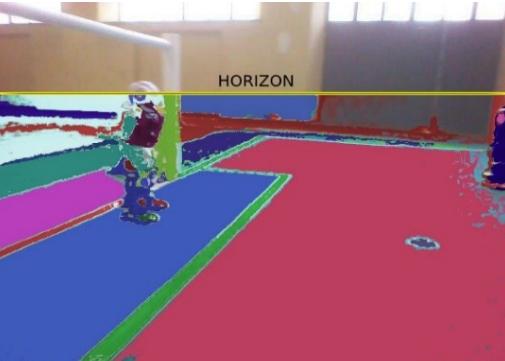




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