Lecture 5. Features and Fitting

Local invariant features

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CS131 Computer Vision: Foundations and Applications

CS 131 Roadmap

Pixels	Segments	Images	Videos	Web
Convolutions Edges Features	Resizing Segmentation Clustering	Recognition Detection Machine learning	Motion Tracking	Neural networks Convolutional neural networks

What will we learn today?

- Local invariant features
  - Motivation
  - General approach and requirements

Some background reading:
Rick Szeliski, Chapter 4.1.1; David Lowe, IJCV 2004

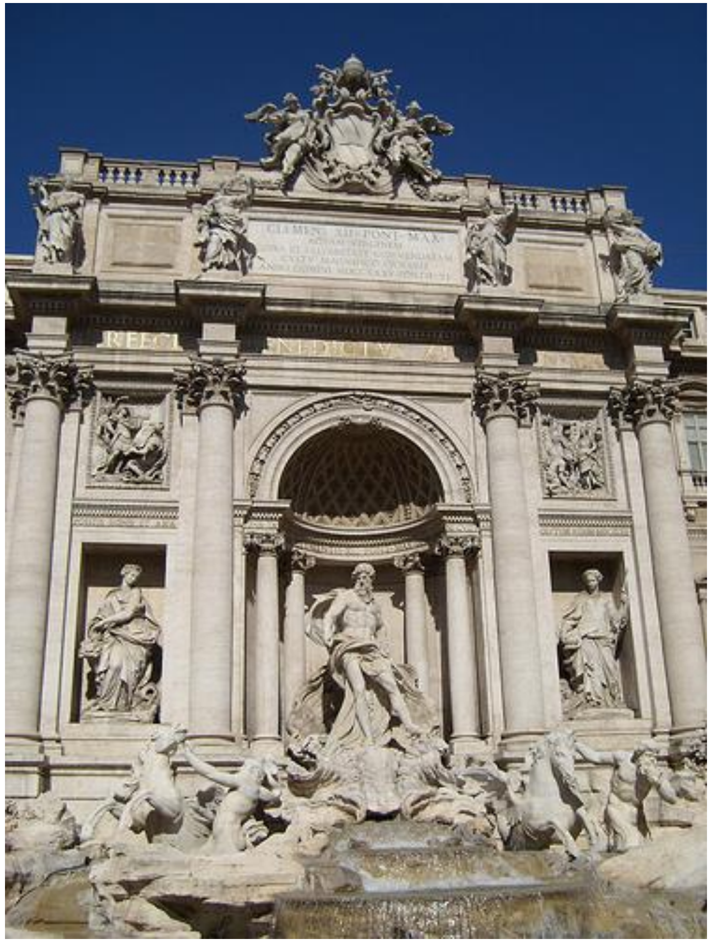
Image matching: a challenging problem

Template

Query Image

Image matching: a challenging problem

by Diva Sian



by swashford

Slide credit: Steve Seitz

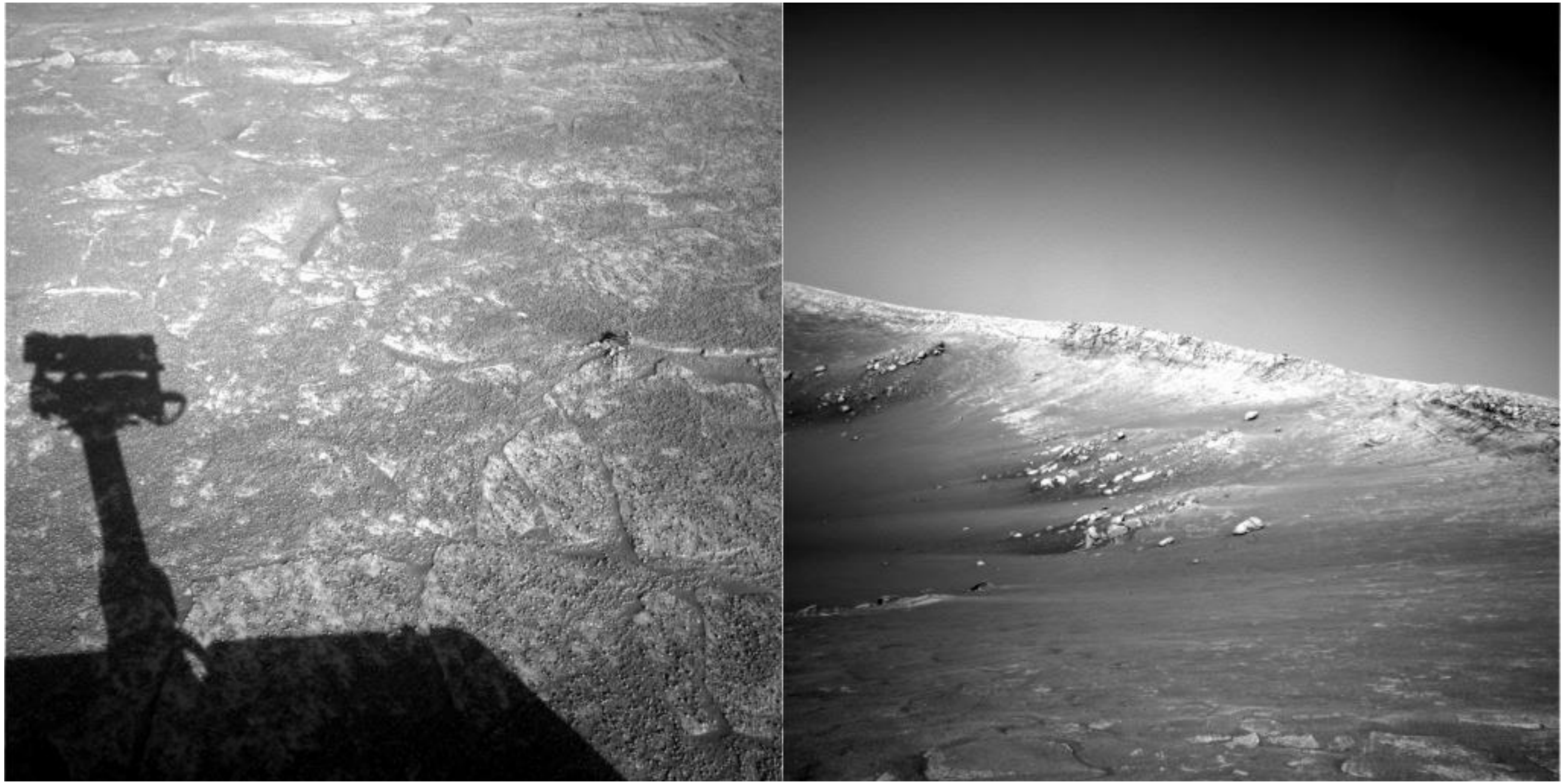
Harder Case

by Diva Sian

by scgbt

Slide credit: Steve Seitz

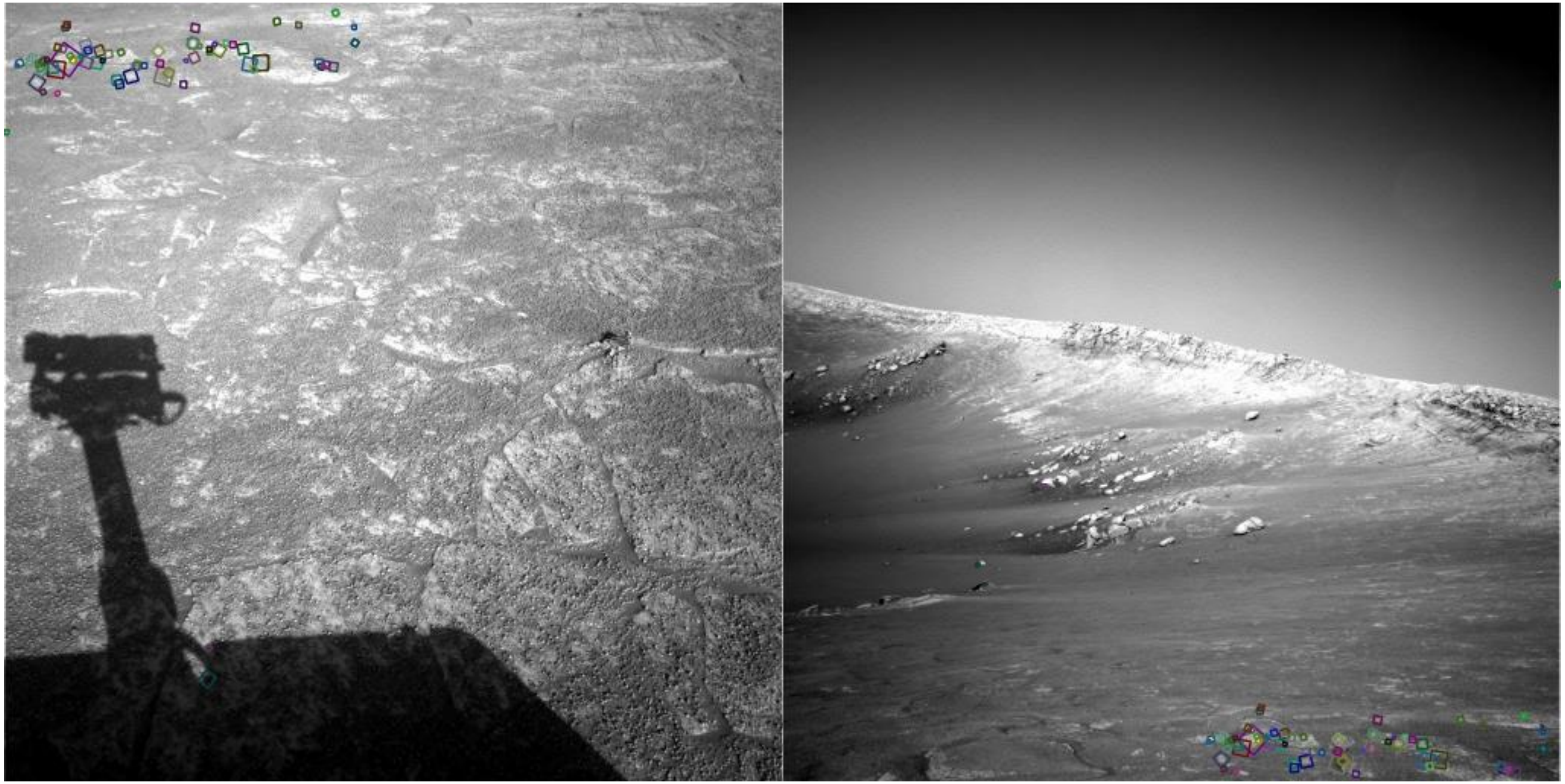
Harder Still?



NASA Mars Rover images

Slide credit: Steve Seitz

Answer Below (Look for tiny colored squares)

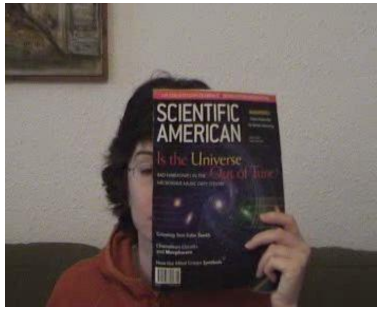


NASA Mars Rover images with SIFT feature matches
(Figure by Noah Snavely)

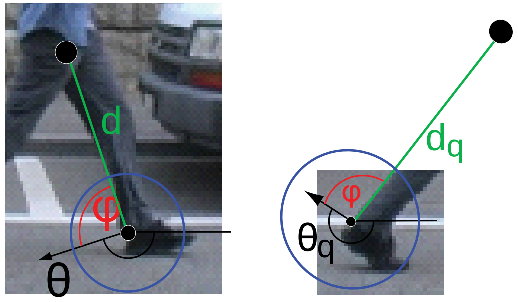
Slide credit: Steve Seitz

Motivation for using local features

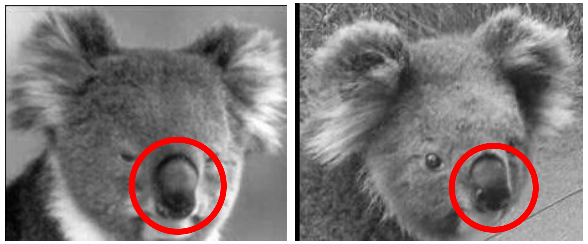
- Global representations have major limitations
- Instead, describe and match only local regions
- Increased robustness to
  - Occlusions



  - Articulation



  - Intra-category variations



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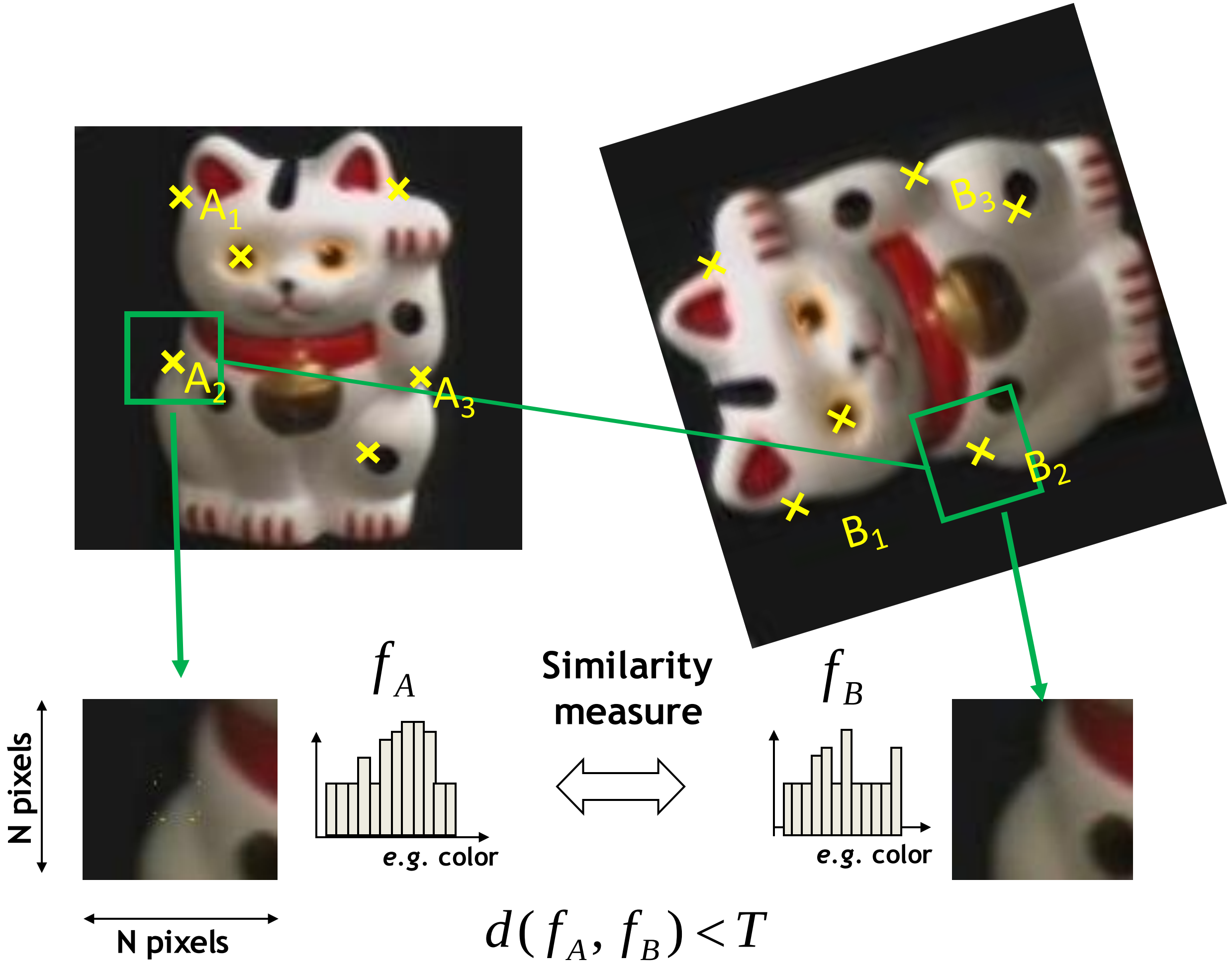
General Approach



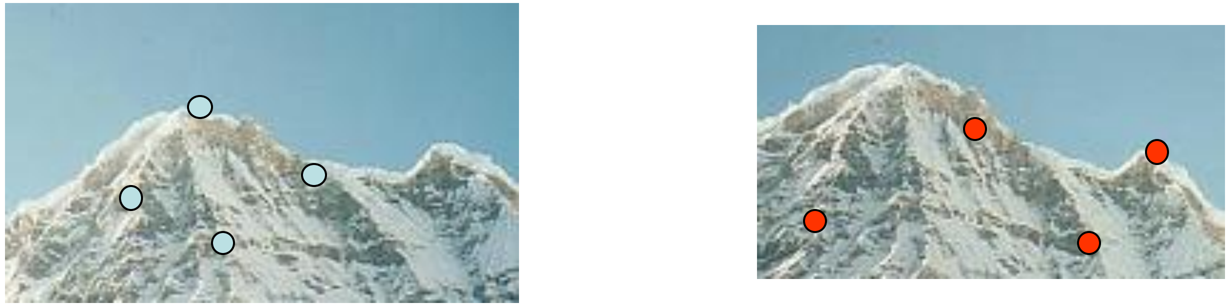
$$d(f_A, f_B) < T$$

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

Slide credit: Bastian Leibe

Common Requirements

- Problem 1:
  - Detect the same point *independently* in both images



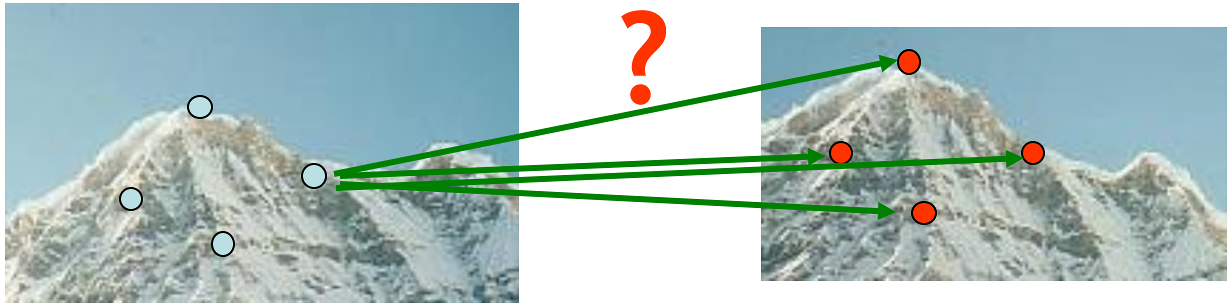
No chance to match!

We need a repeatable detector!

Slide credit: Darya Frolova, Denis Simakov

Common Requirements

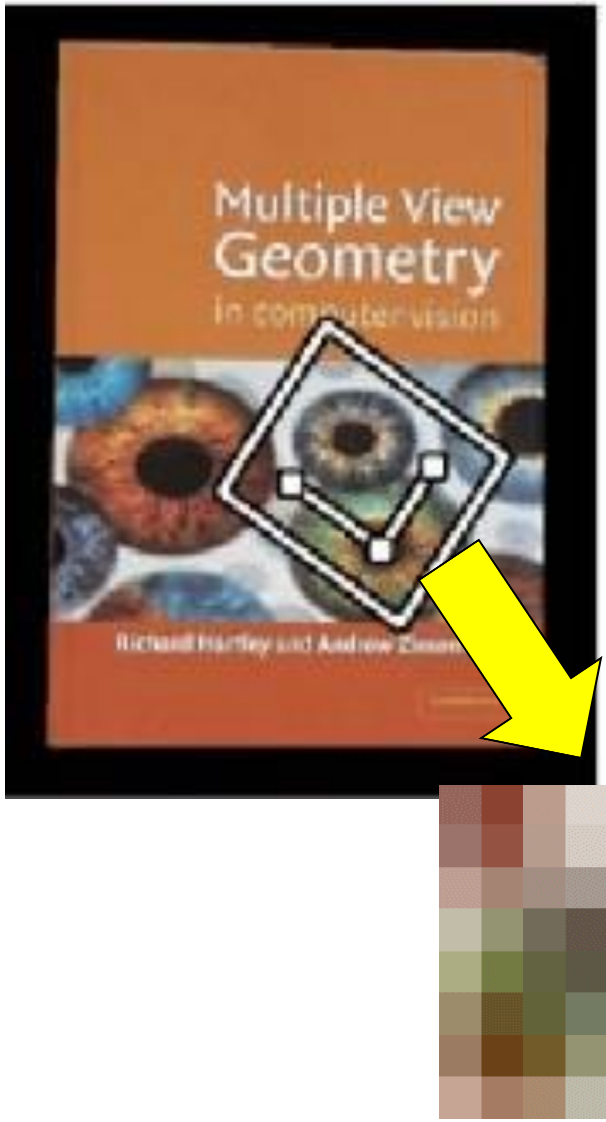
- Problem 1:
  - Detect the same point *independently* in both images
- Problem 2:
  - For each point correctly recognize the corresponding one



We need a reliable and distinctive descriptor!

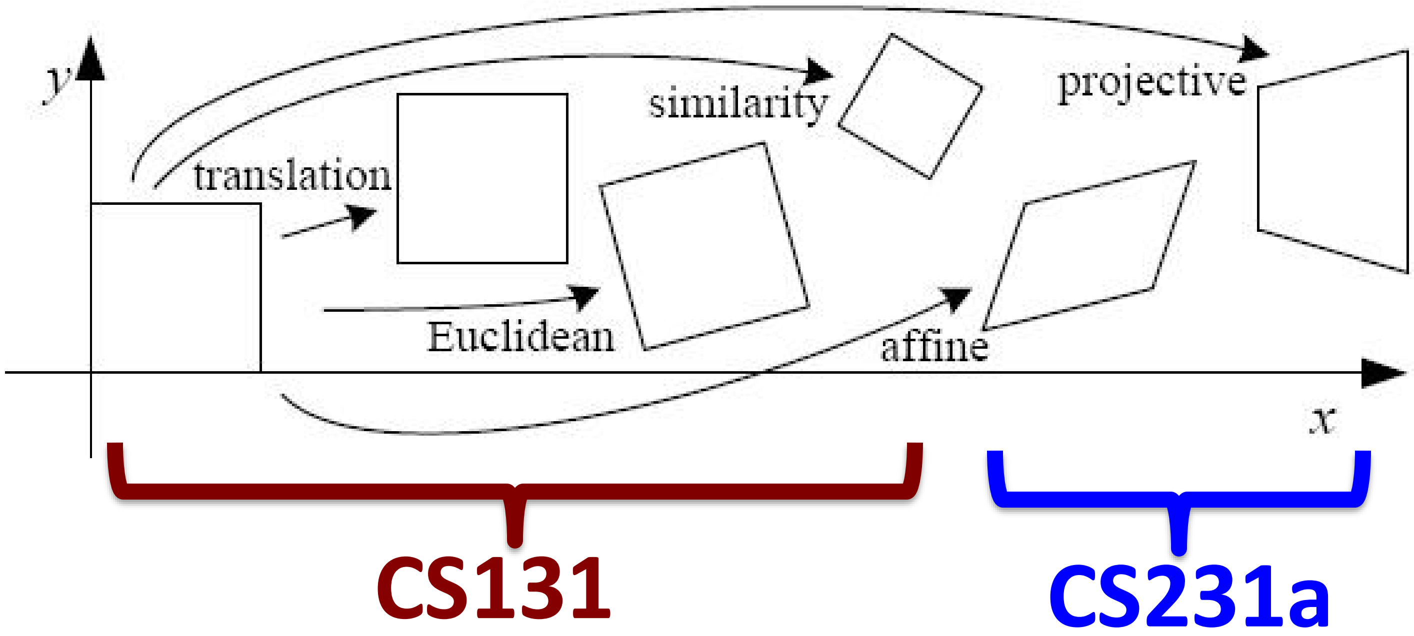
Slide credit: Darya Frolova, Denis Simakov

Feature Invariances: Geometric Transformations



Slide credit: Steve Seitz

Levels of Geometric Invariance



Slide credit: Bastian Leibe

Feature Invariances: Photometric Transformations

- Often modeled as a linear transformation:
  - Scaling + Offset

Slide credit: Tinne Tuytelaars

Requirements for Local Features

- Region extraction needs to be repeatable and accurate
  - Invariant to translation, rotation, scale changes
  - Robust or covariant to out-of-plane (≈affine) transformations
  - Robust to lighting variations, noise, blur, quantization
- Locality: Features are local, therefore robust to occlusion and clutter.
- Quantity: We need a sufficient number of regions to cover the object.
- Distinctivenes : The regions should contain "interesting" structure.
- Efficiency: Close to real-time performance.

Slide credit: Bastian Leibe

Many Existing Feature Detectors Available

• Hessian & Harris	[Beaudet '78], [Harris '88]
• Laplacian, DoG	[Lindeberg '98], [Lowe '99]
• Harris-/Hessian-Laplace	[Mikolajczyk & Schmid '01]
• Harris-/Hessian-Affine	[Mikolajczyk & Schmid '04]
• EBR and IBR	[Tuytelaars & Van Gool '04]
• MSER	[Matas '02]
• Salient Regions	[Kadir & Brady '01]
• Others…	

- *Those detectors have become a basic building block for many applications in Computer Vision.*

Slide credit: Bastian Leibe

Summary

- Local invariant features
  - Motivation
  - General approach and requirements