Feature Detection and Matching

Chul Min Yeum
Assistant Professor
Civil and Environmental Engineering
University of Waterloo, Canada

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UNIVERSITY OF WATERLOO
FACULTY OF ENGINEERING

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Two Major Challenges in Computer Vision

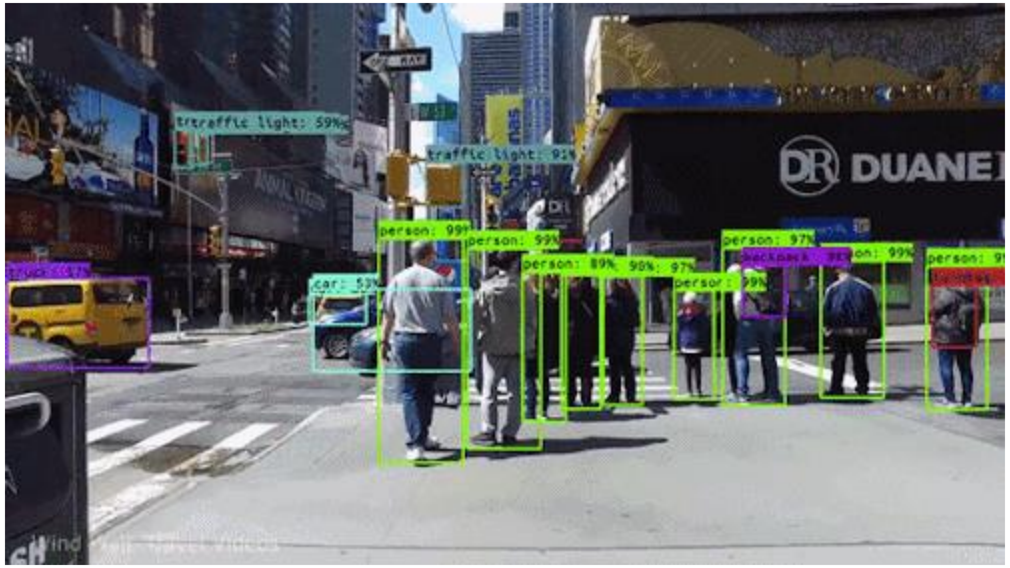
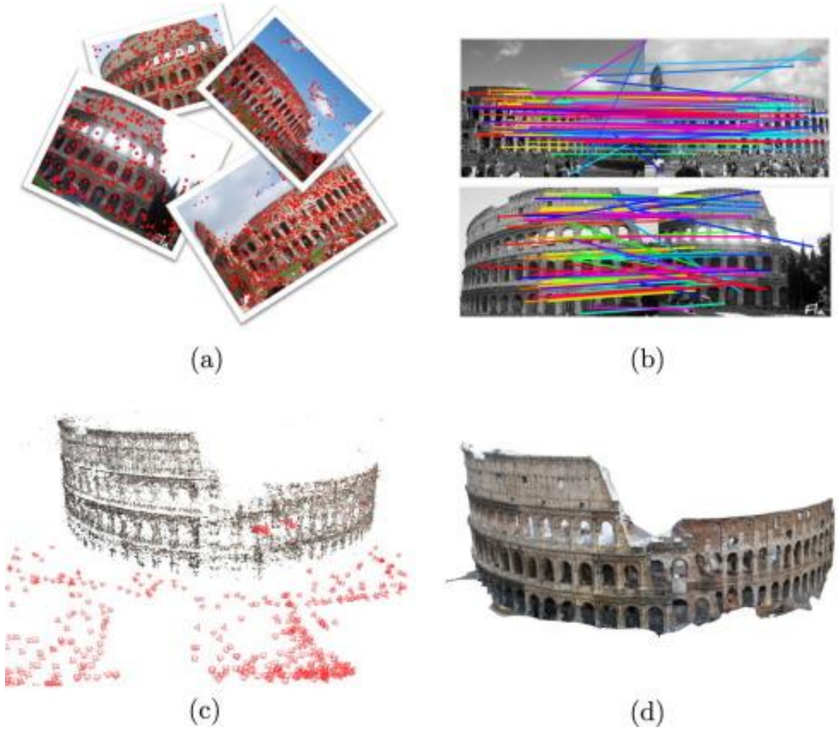


Image recognition



Feature matching

Why We Extract Features? Extracting Features

Motivation: panorama stitching

- We have two images
- How do we combine them?

Why We Extract Features? Extracting Features (Continue)

Motivation: panorama stitching

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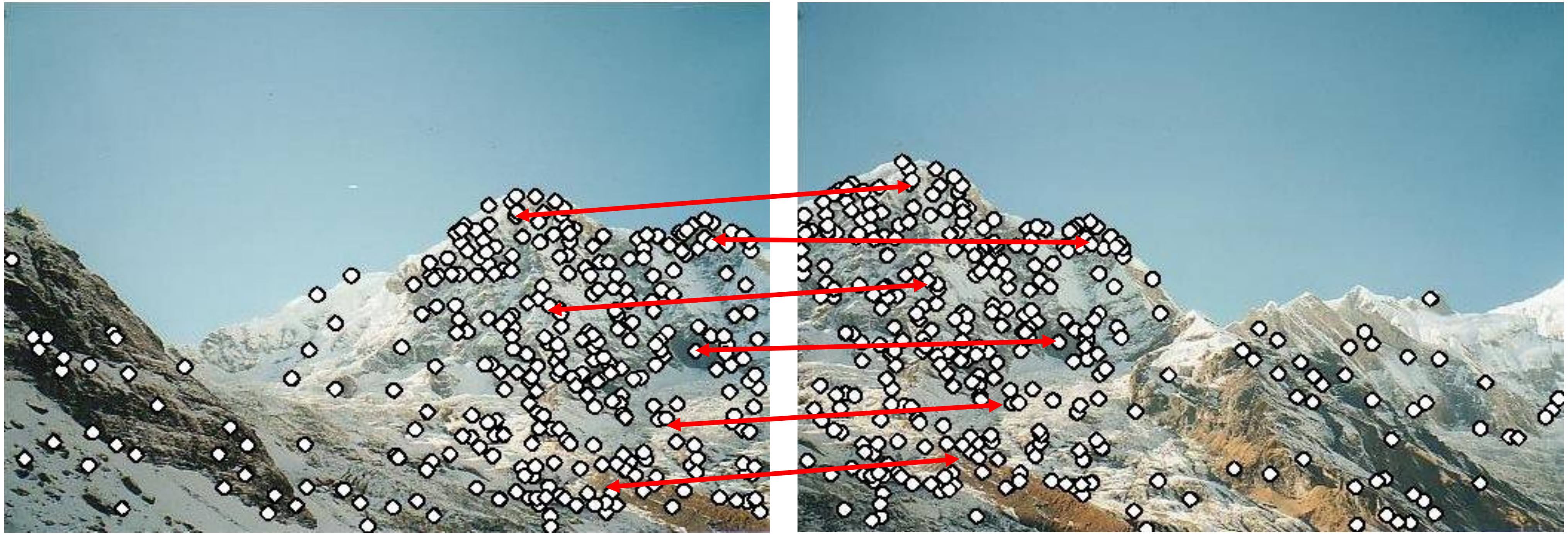
– How do we combine them?



Why We Extract Features? Extracting Features (Continue)

Motivation: panorama stitching

- We have two images
- How do we combine them?

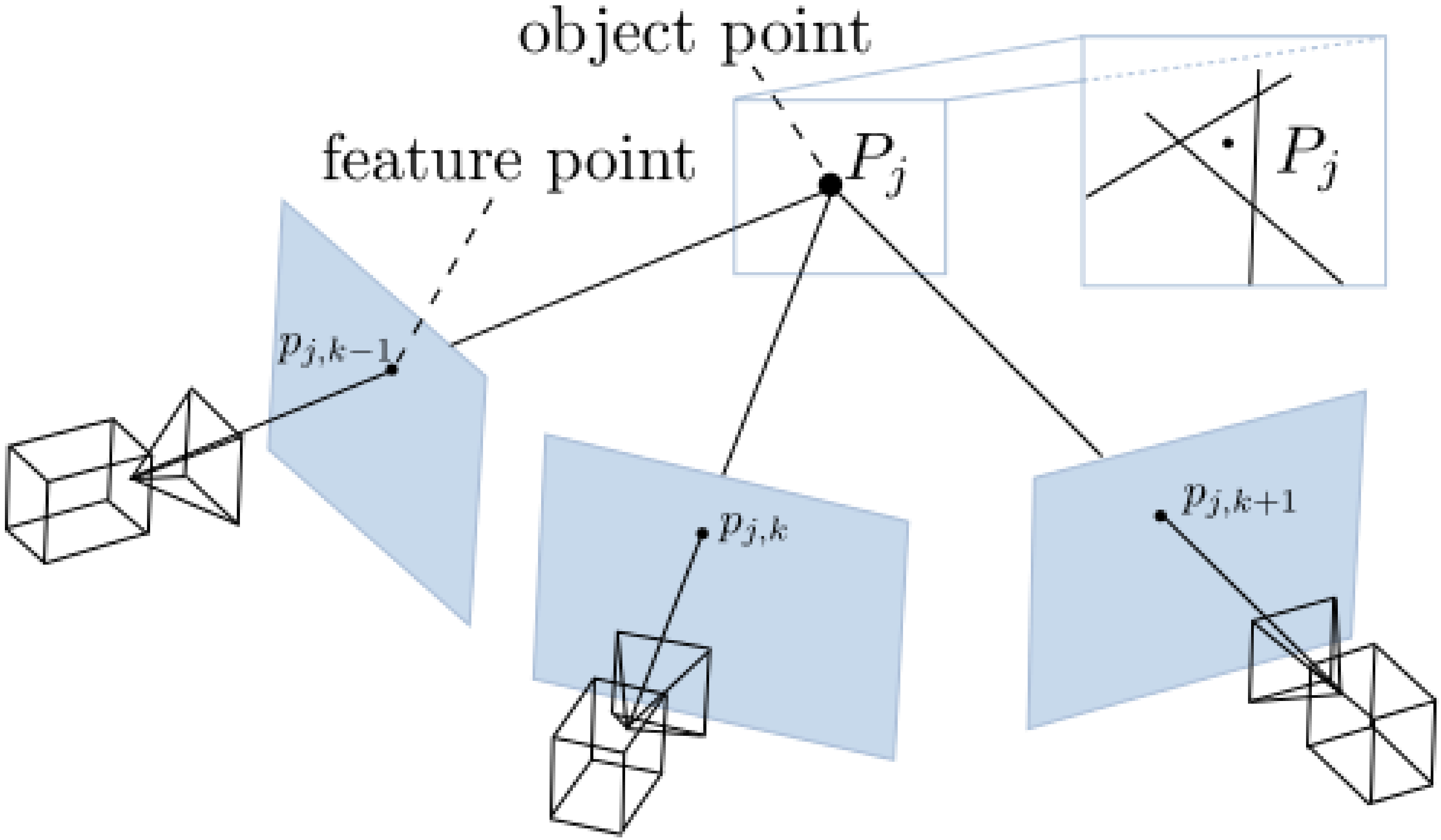
Example: Automatic Panoramas

A large volume collected images from drone

Orthophoto(10,000 × 3,656) geometrically connected to each collected images

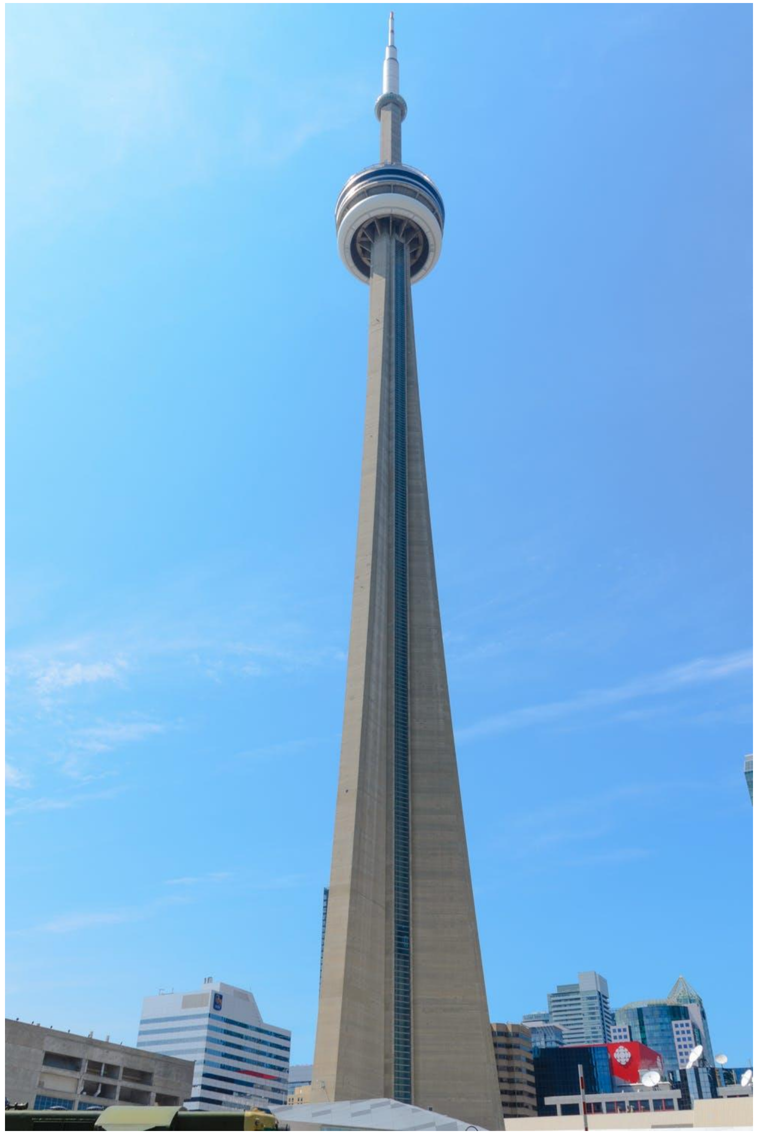
Jongseong Choi, Chul Min Yeum, Shirley J. Dyke, and Mohammad R. Jahanshahi, “Computer-Aided Approach for Rapid Post-Event Visual Evaluation of a Building Façade,” Sensors, 18, 3017 (2018).

Example: Multi-view Geometry



Streo-camera

Image Matching



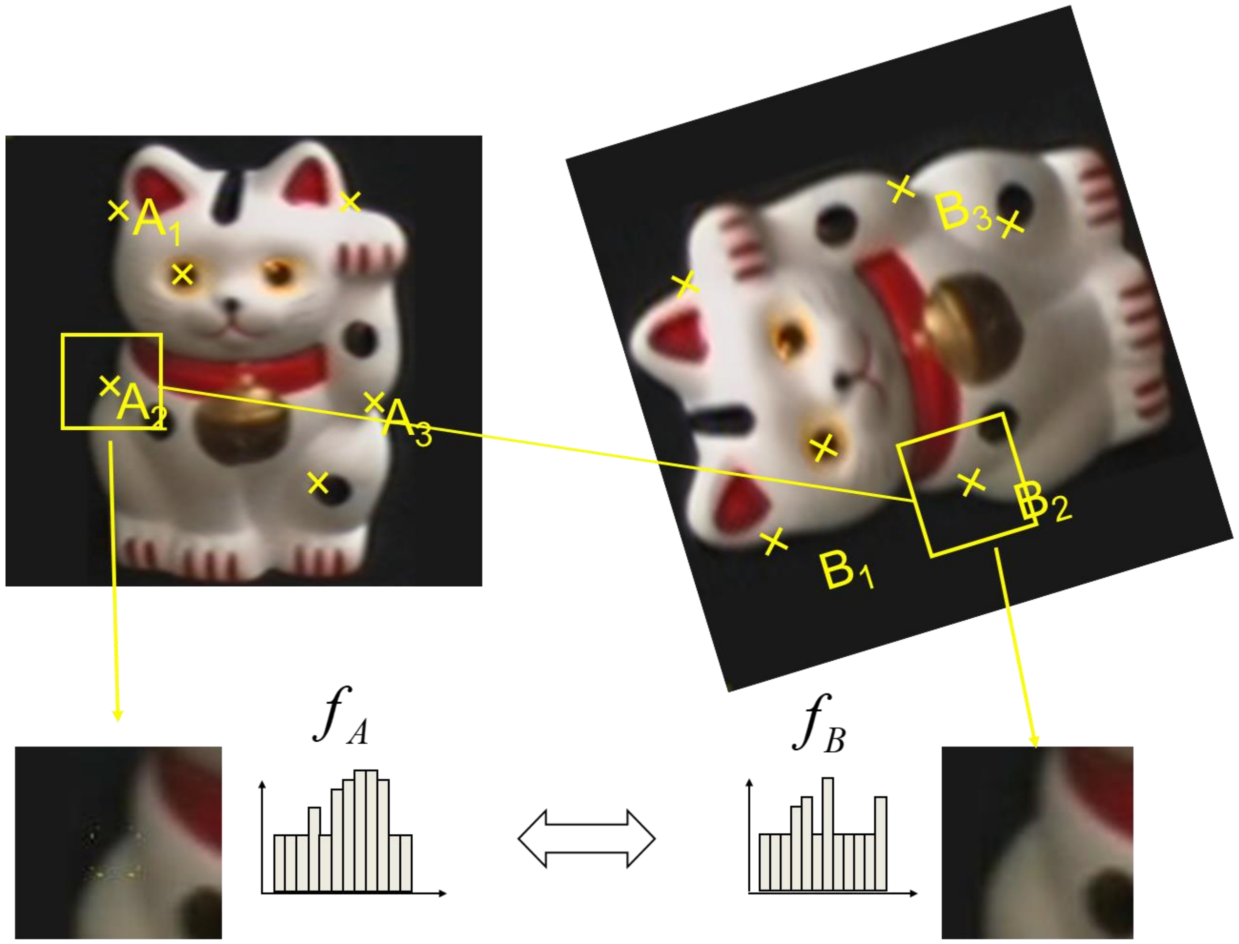
What are Features (Keypoints)?

- A feature is an prominent point that is selected based on a certain criteria, such as edge, corner, or blob.
- This is represented in terms of the coordinates of the image points by pixel or sub-pixel.
- The feature likely contain and preserve the distinctive local regional information.
- Note: “interest points” = “keypoints”, also sometimes called “features”

Many applications:

- Object/motion tracking: which points are good to track?
- Object recognition: find patches likely to tell us something about object category
- 3D scene reconstruction: find correspondences across different views

Overview of Feature Matching



f_A $\Leftrightarrow$ f_B

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

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**

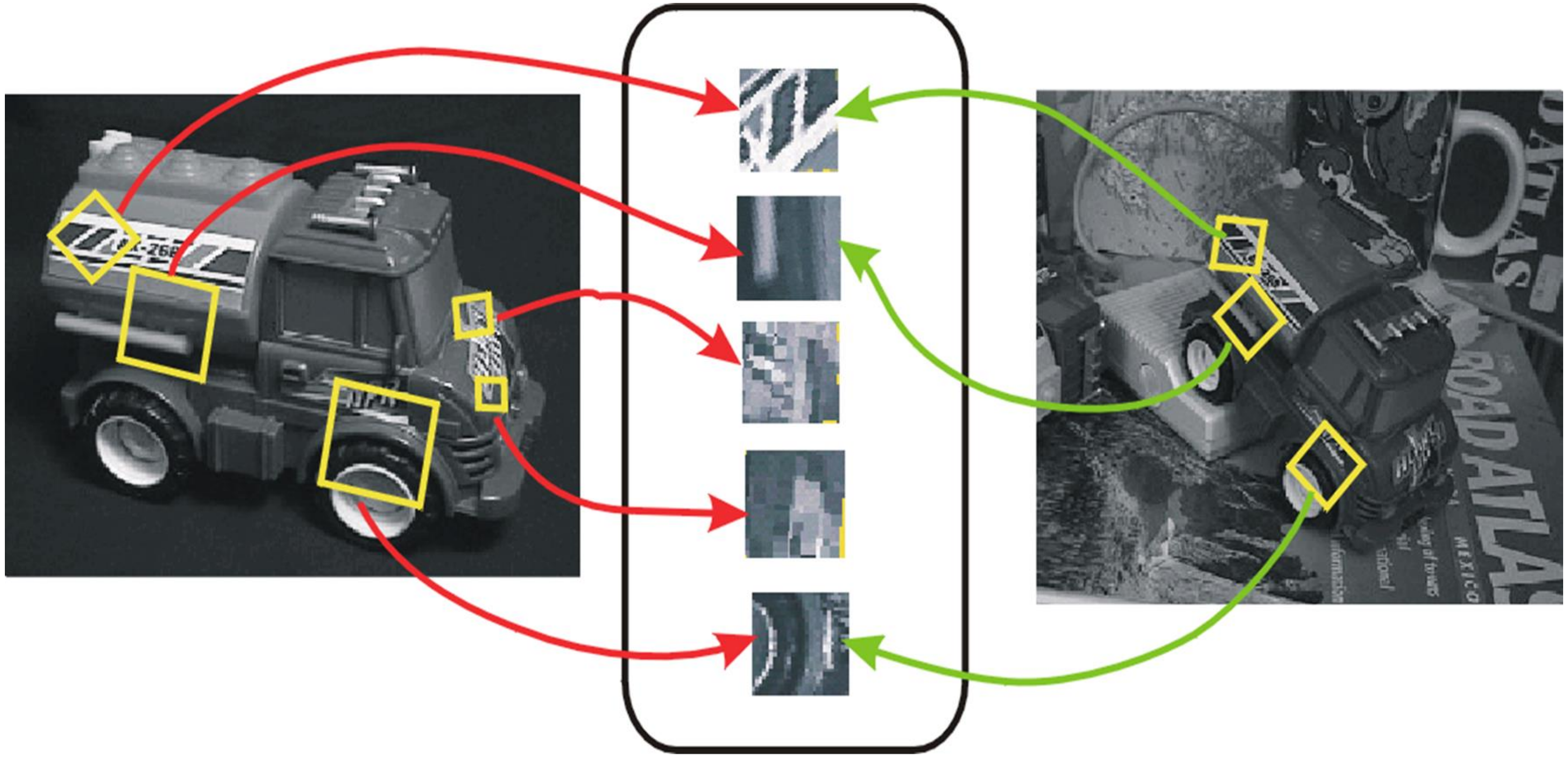
<u>Local?</u>

BEST Features !!

Detect points that are *repeatable* and *distinctive*

Invariant Local Features

Image content is transformed into local feature coordinates that are <u>invariant to translation, rotation, scale, and other imaging parameters</u>



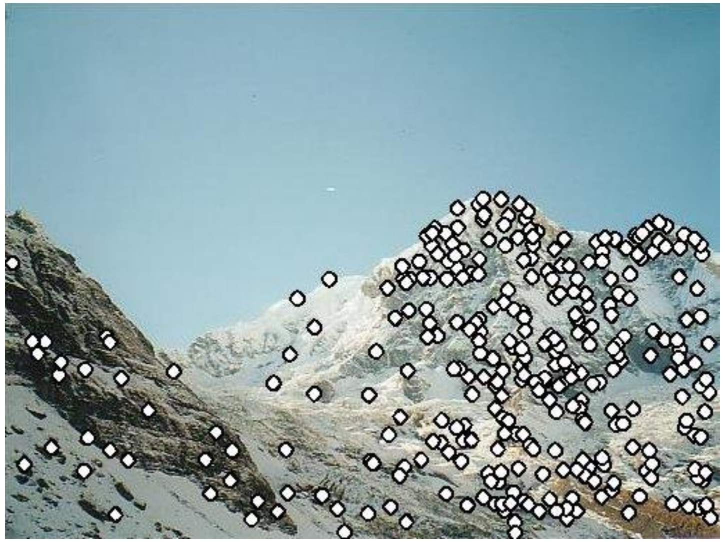
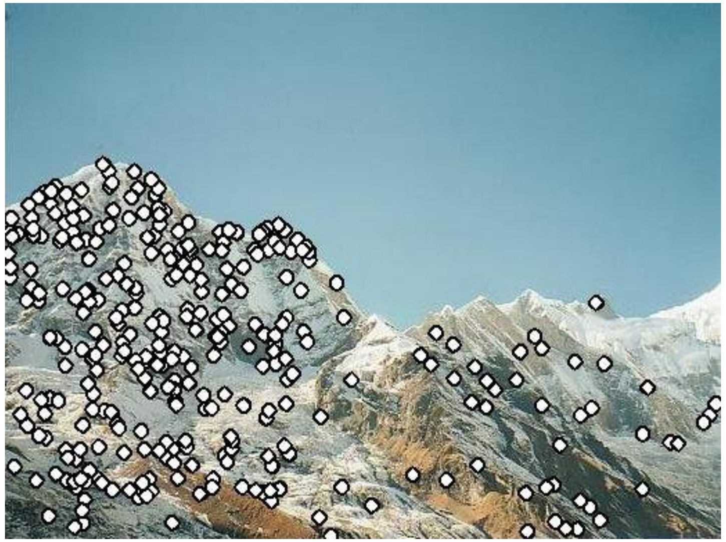
Characteristic of Good Features

Repeatability: The same feature can be found in several images despite geometric and photometric transformations

Saliency: Each feature is distinctive

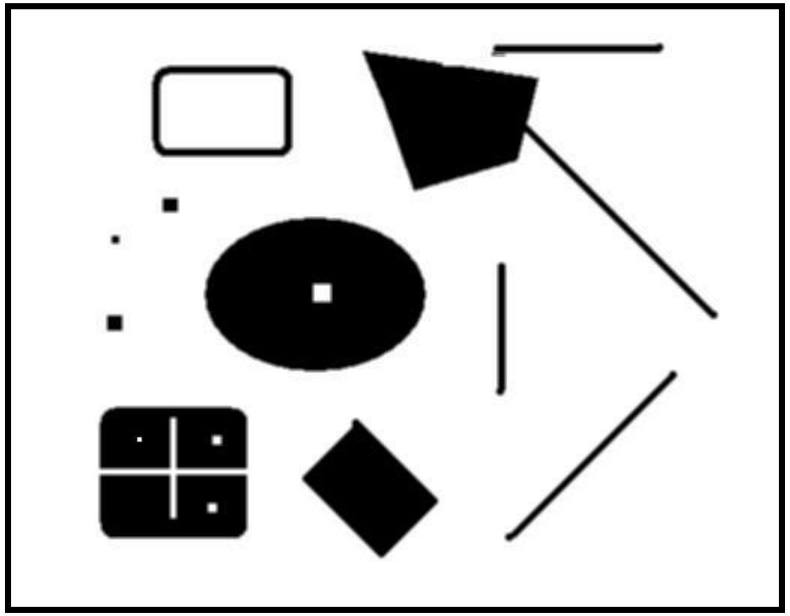
Compactness and efficiency: Many fewer features than image pixels

Locality: A feature occupies a relatively small area of the image; robust to clutter and occlusion

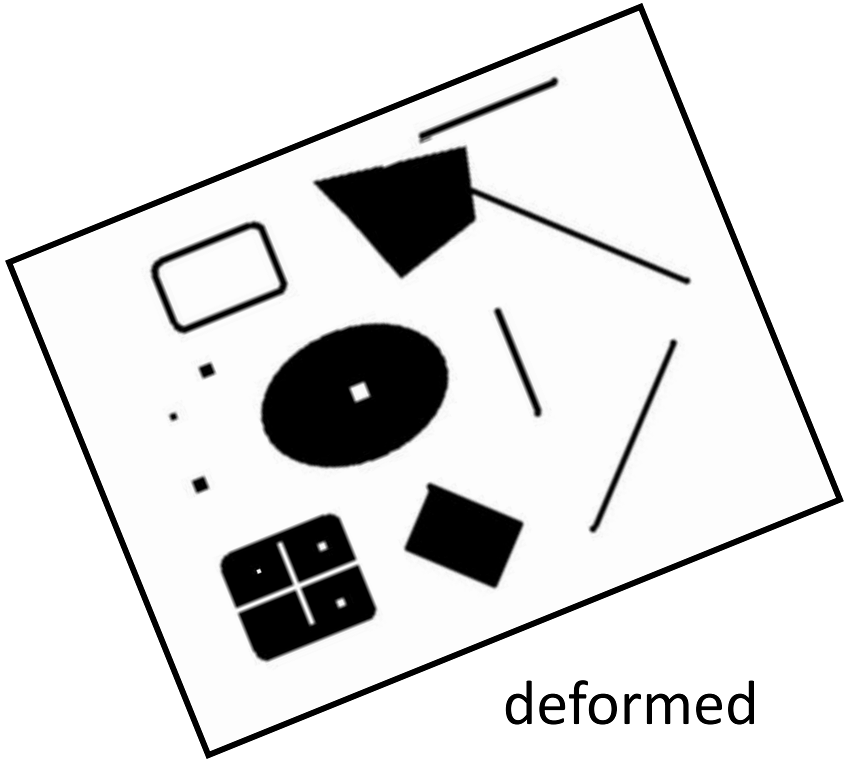



Example: Keypoints/Features

Suppose you have to click on some point, go away and come back after I deform the image, and click on the same points again. Which points would you choose?



original

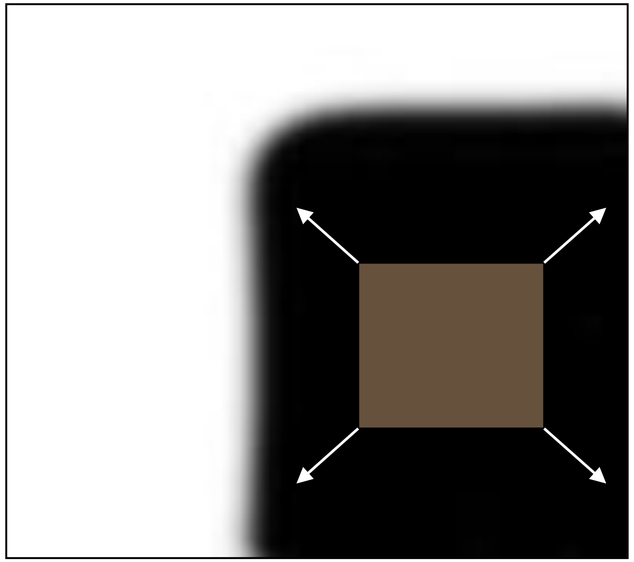


deformed

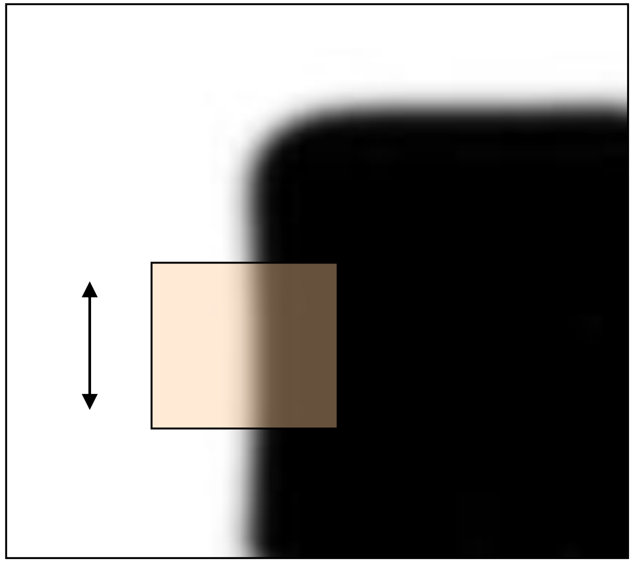
What Points would You Choose?

Corner Detection: Basic Idea

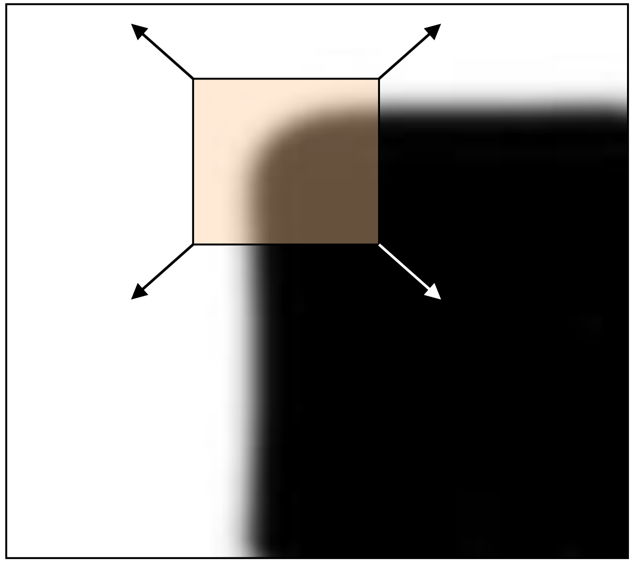
- We should easily recognize the point by looking through a small window
- Shifting a window in *any direction* should give *a* *large change* in intensity



Flat region
no change in all directions



Edge
no change along the edge direction

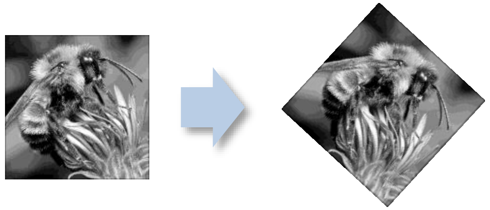


Corner
significant change in all directions

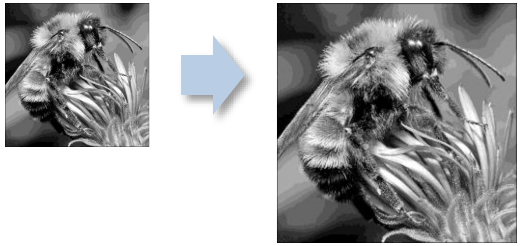
Image Transformations

- Geometric

Rotation

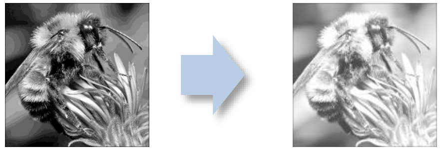


Scale



- Photometric

Intensity change



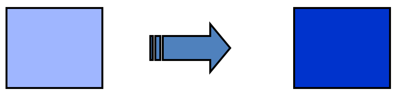
Invariance and Covariance

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

Invariance: images are transformed and corner locations do not change

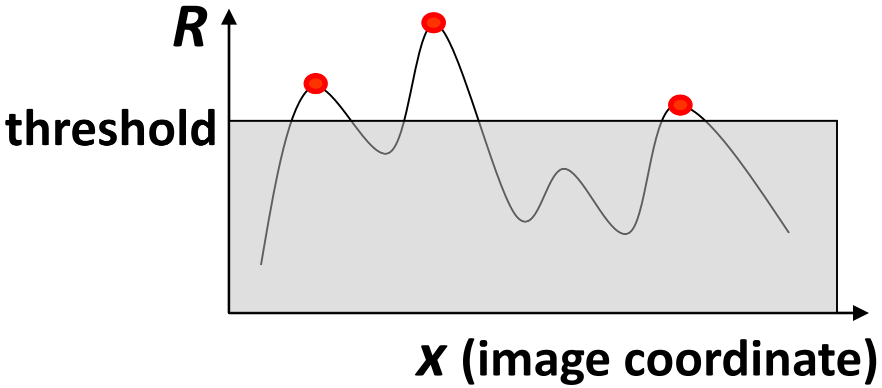
Covariance: if we have two transformed versions of the same image, features should be detected in corresponding locations

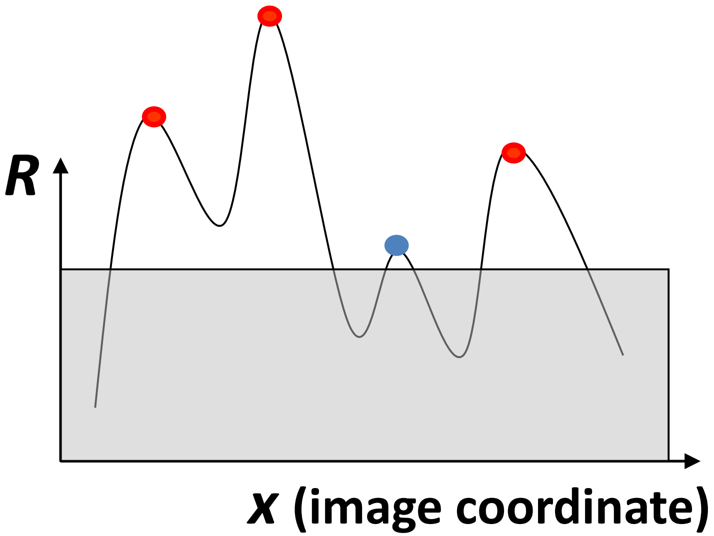
Intensity Change



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

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

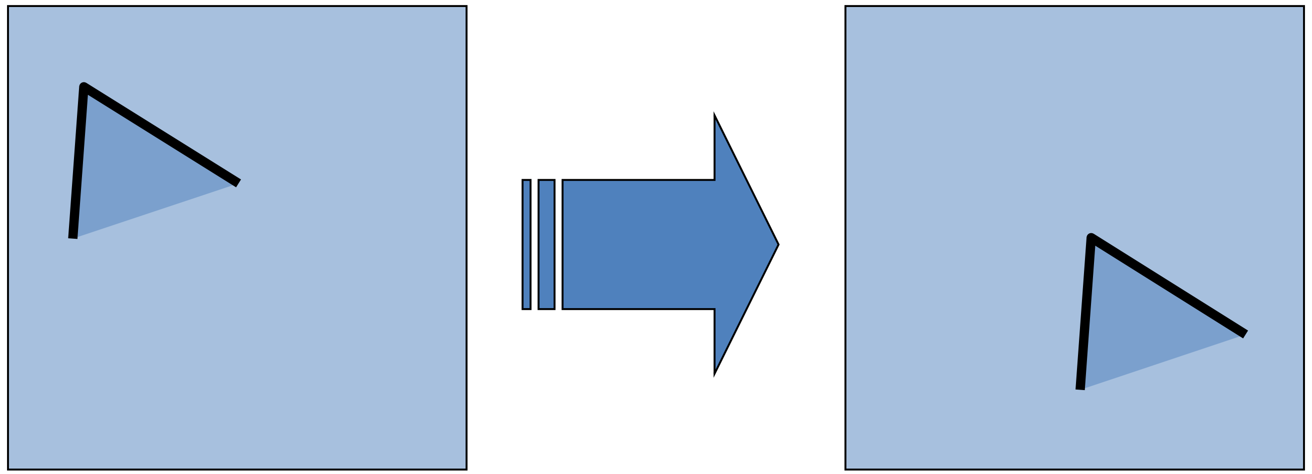




***Partially invariant* to intensity change**

Source: James Hayes

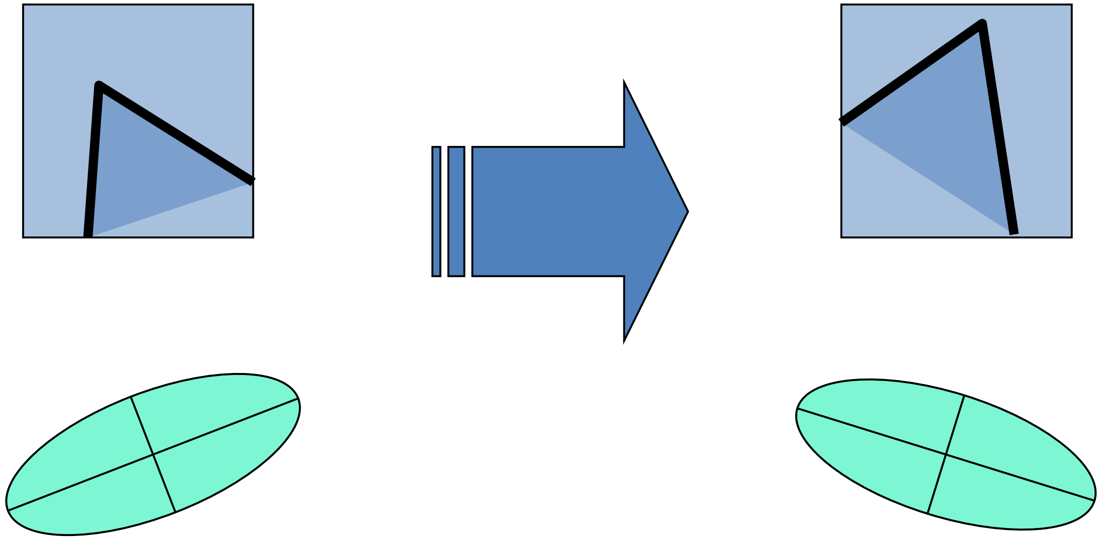
Image Translation



- **Derivatives and window function are shift-invariant**

Corner location is covariant to image translation

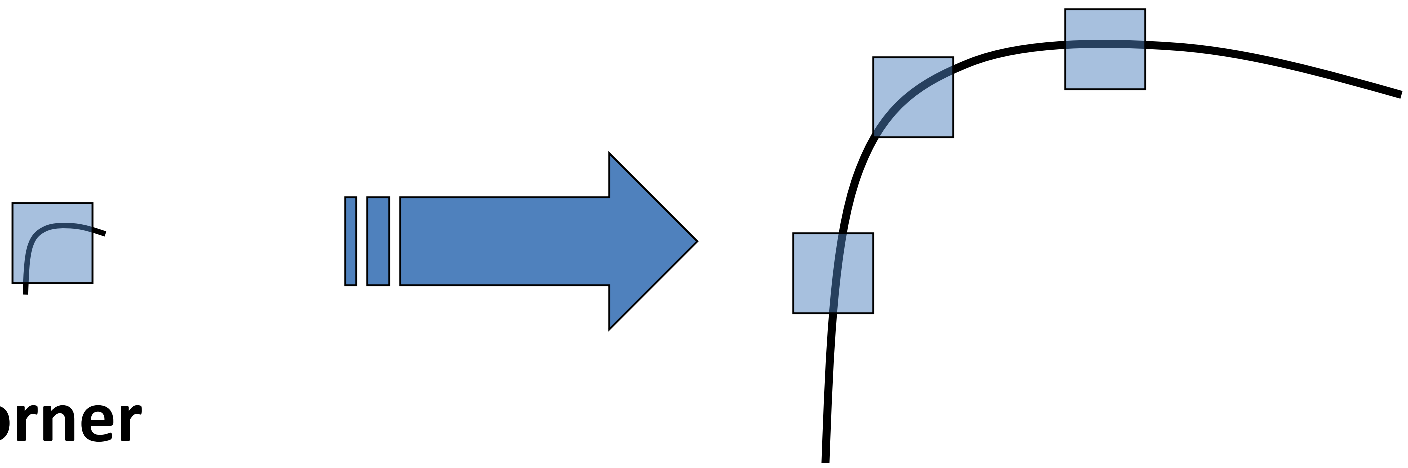
Image Rotation



Second moment ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner location is covariant to image rotation

Scaling



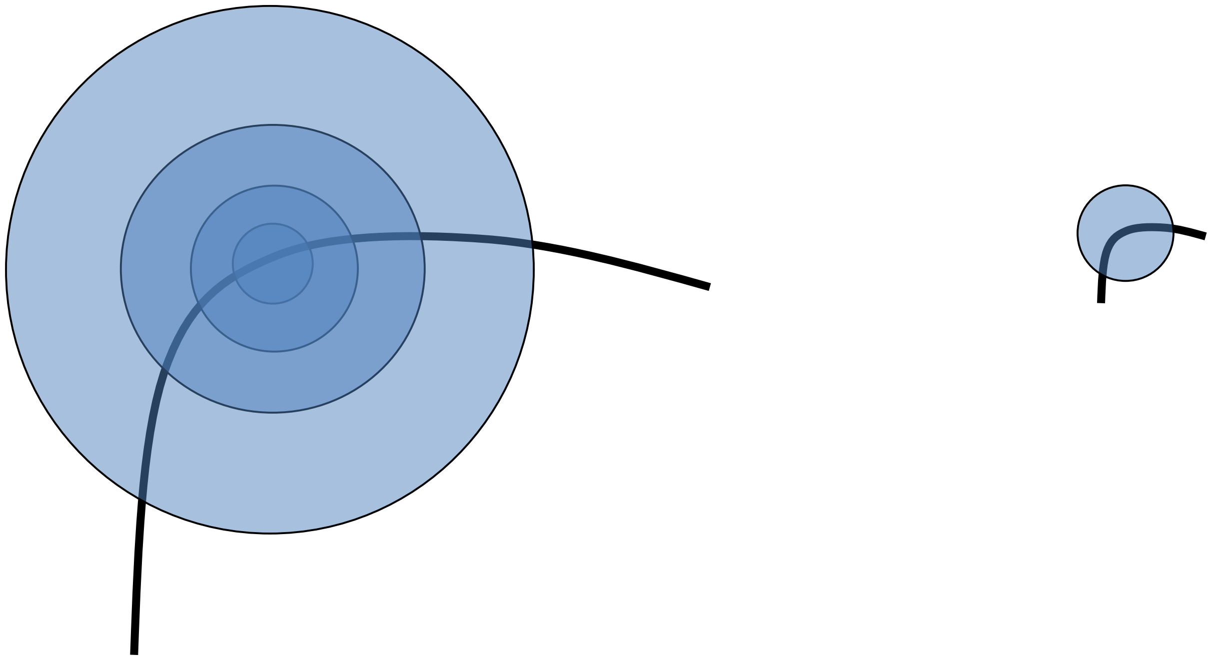
Corner

All points will be classified as edges

Corner location is not invariant to image scale!

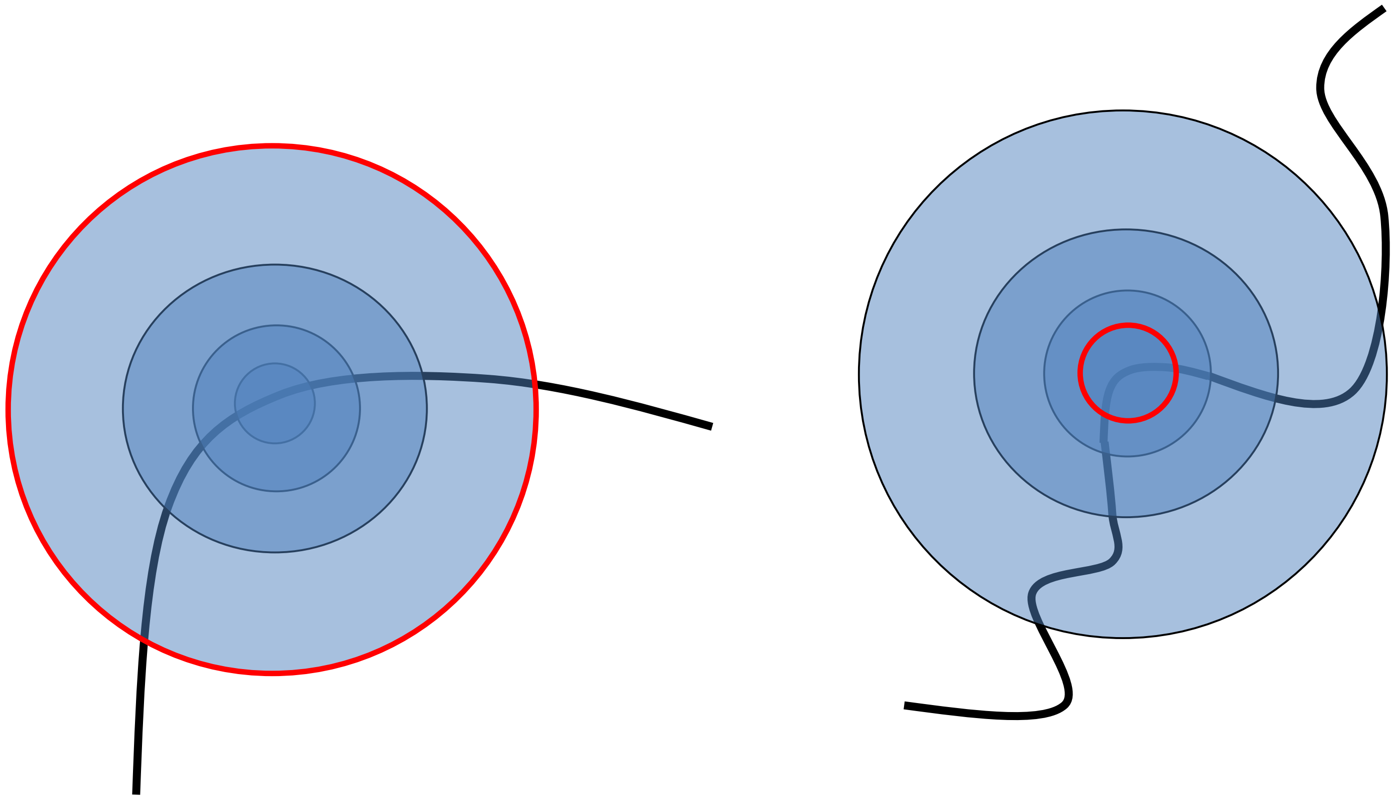
Scale Invariant Detection

- Consider regions (e.g. circles) of different sizes around a point
- Regions of corresponding sizes will look the same in both images



Scale Invariant Detection (Continue)

- The problem: how do we choose corresponding circles ***independently*** in each image?
- Choose the scale of the "best" corner



Example: Scale Invariance

Slide Credits and References

- Lecture notes: S. Narasimhan
- Lecture notes: Gordon Wetzstein
- Lecture notes: Mohammad Jahanshahi
- Lecture notes: Noah Snavely
- Lecture notes: L. Fei-Fei
- Lecture notes: D. Frosyth
- Lecture notes: James Hayes
- Lecture notes: Yacov Hel-Or
- Lecture notes: K. Grauman, B. Leibe