# Feature Detection and Matching

**Chul Min Yeum** 

**Assistant Professor** 

Civil and Environmental Engineering

University of Waterloo, Canada

**CIVE 497 – CIVE 700: Smart Structure Technology** 



Last updated: 2020-02-26

## **Two Major Challenges in Computer Vision**

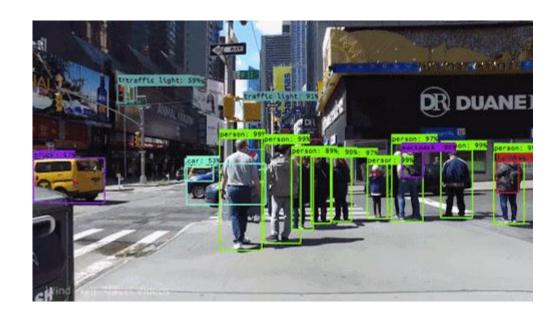
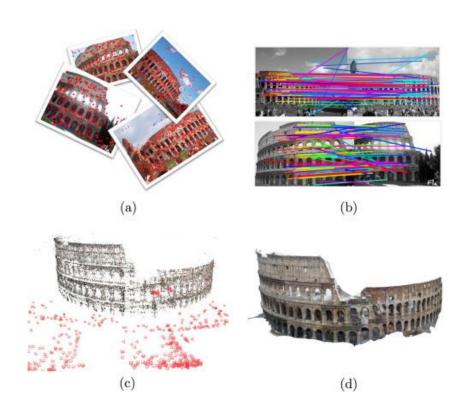


Image recognition



Feature matching

## Why We Extract Features? Extracting Features

## Motivation: panorama stitching

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

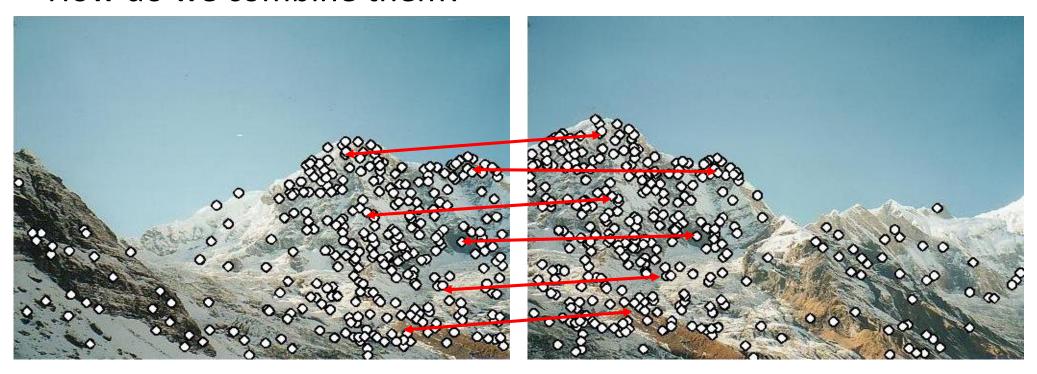




## Why We Extract Features? Extracting Features (Continue)

## Motivation: panorama stitching

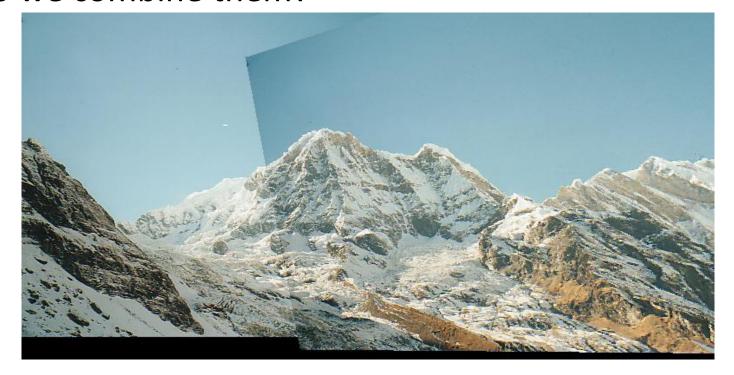
- We have two images
- How do we combine them?



## Why We Extract Features? Extracting Features (Continue)

## Motivation: panorama stitching

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



## **Example: Automatic Panoramas**

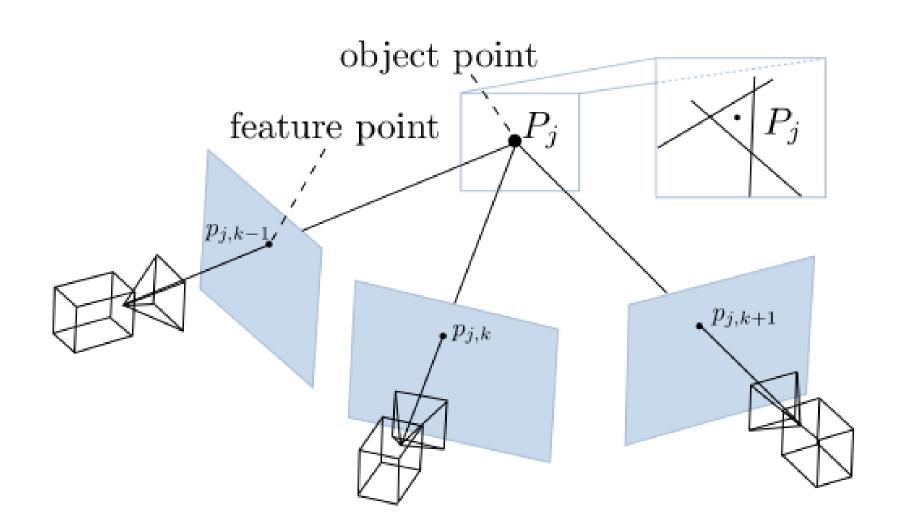


A large volume collected images from drone



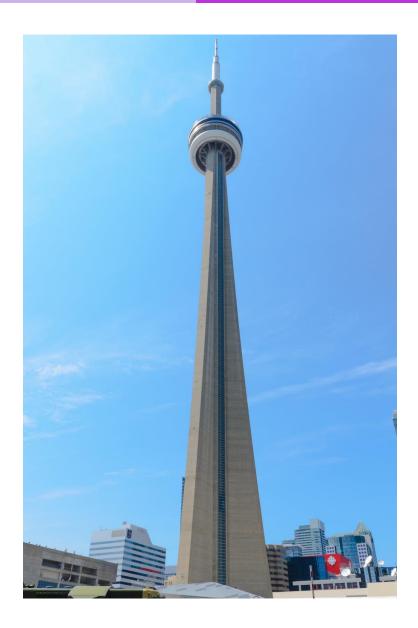
Orthophoto(10,000 × 3,656) geometrically connected to each collected images

## **Example: Multi-view Geometry**



Streo-camera

# Image Matching





## What are Features (Keypoints)?

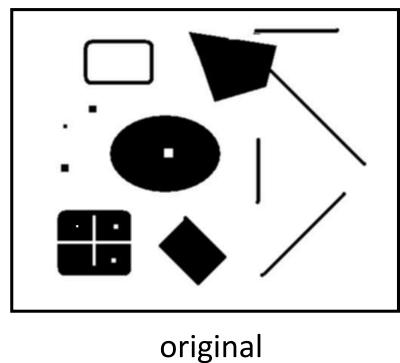
- A feature is an prominent point that is selected based on a certain criteria, such as edge, corner, or blob.
- This is represented in terms of the coordinates of the image points by pixel or sub-pixel.
- The feature likely contain and preserve the distinctive local regional information.
- Note: "interest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

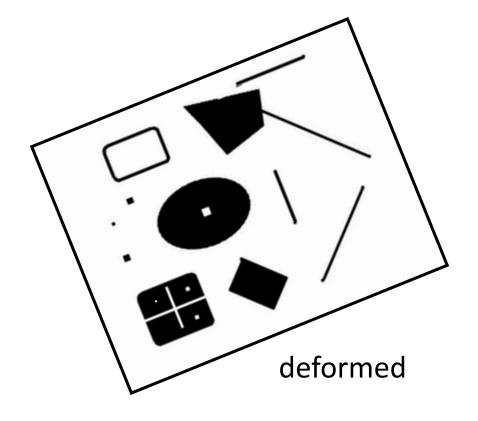
#### Many applications:

- 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

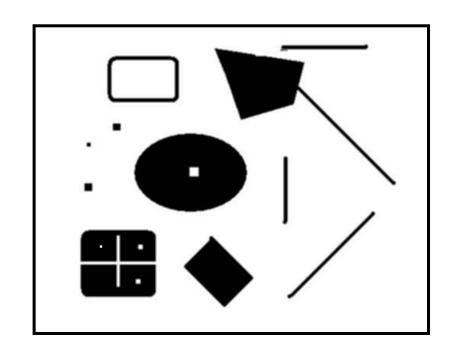
## **Example: Keypoints/Features**

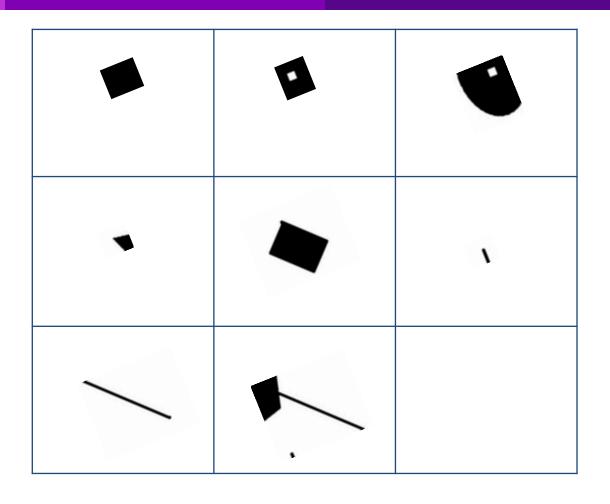
Suppose you have to click on some point, go away and come back after I deform the image, and click on the same points again. Which points would you choose?





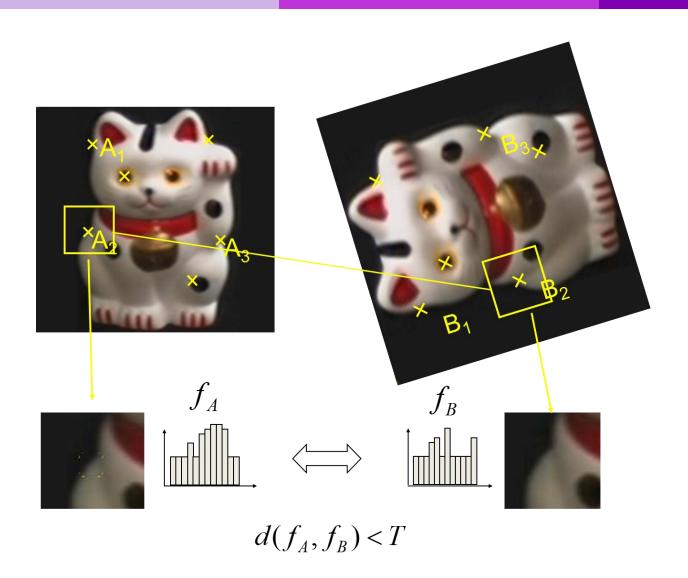
## **Example: Keypoints/Features (Continue)**





- A feature is an prominent point that is selected based on a certain criteria, such as edge, corner, or blob.
- The feature likely contain and preserve the distinctive local regional information.

## **Overview of Feature Matching**



- Find a set of distinctive keypoints
- 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



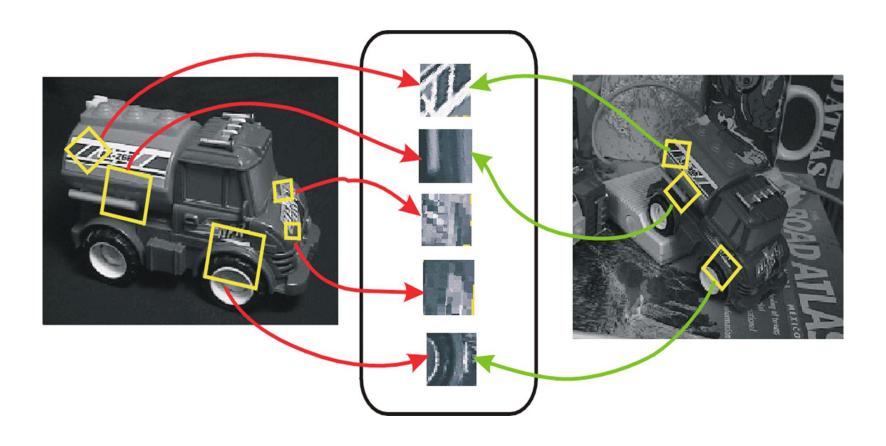




Detect points that are repeatable and distinctive

#### **Invariant Local Features**

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



#### **Characteristic of Good Features**

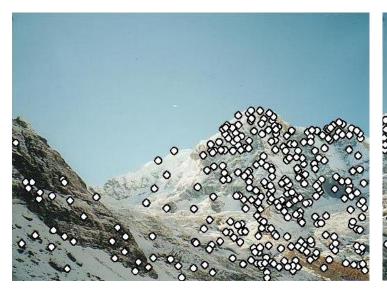
Repeatability: The same feature can be found in several images despite geometric and photometric

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





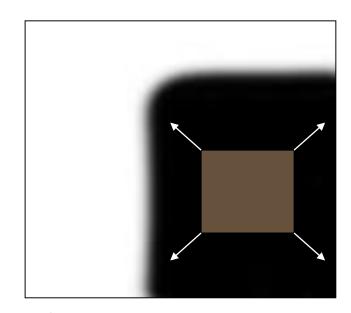
## What Points would You Choose?



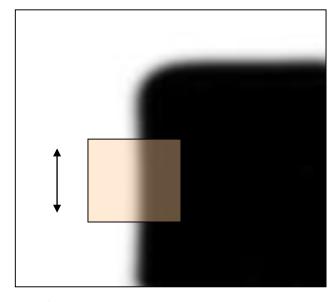


#### **Corner Detection: Basic Idea**

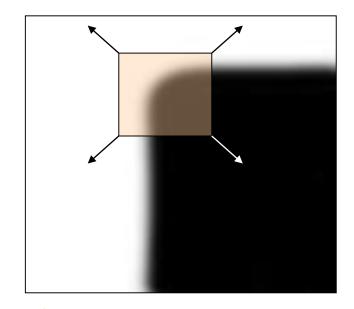
- We should easily recognize the point by looking through a small window
- Shifting a window in any direction should give a large change in intensity



Flat region no change in all directions



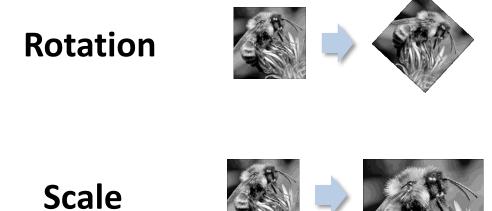
Edge no change along the edge direction



Corner significant change in all directions

## **Image Transformations**

Geometric



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,

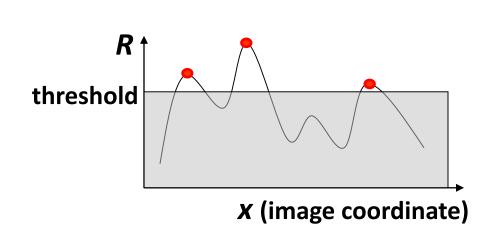
features should be detected in corresponding locations

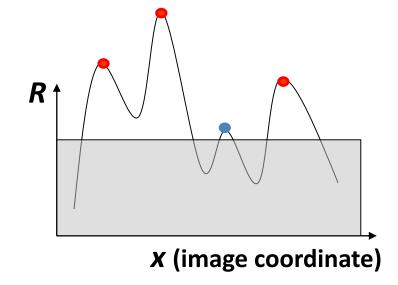
## **Intensity Change**



$$I \rightarrow a I + b$$

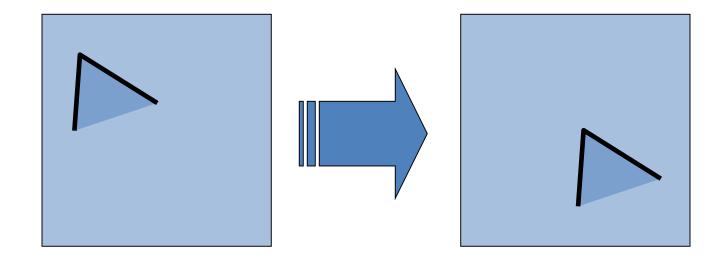
- Only derivatives are used => invariance to intensity shift  $I \rightarrow I + b$
- Intensity scaling:  $I \rightarrow a I$





Partially invariant to intensity change

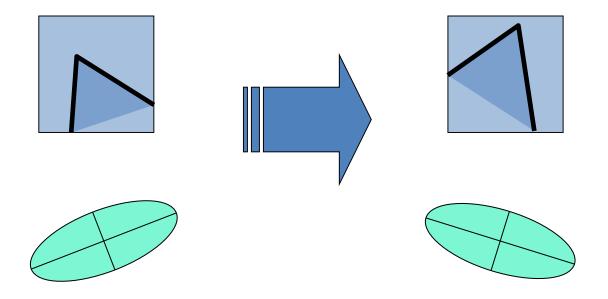
## **Image Translation**



Derivatives and window function are shift-invariant

**Corner location is covariant to image translation** 

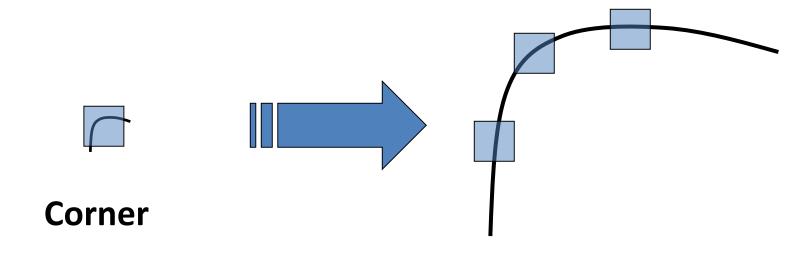
## **Image Rotation**



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

**Corner location is covariant to image rotation** 

## Scaling

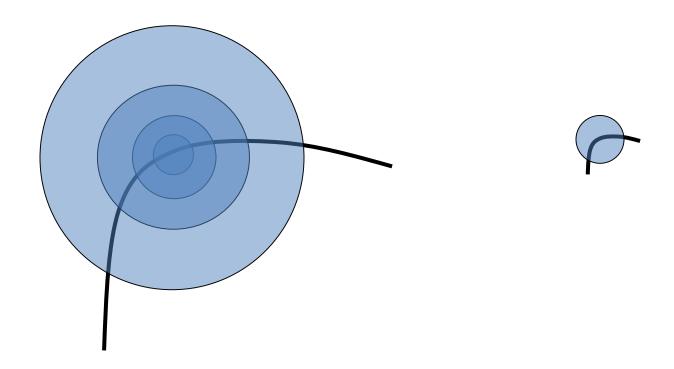


All points will be classified as edges

Corner location is **not** invariant to image scale!

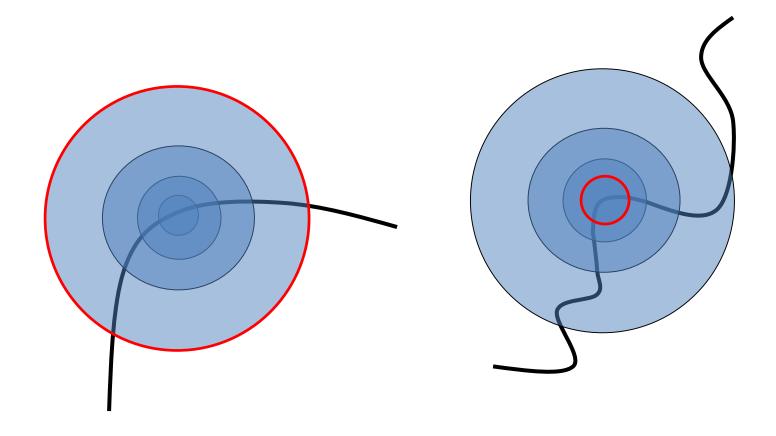
#### **Scale Invariant Detection**

- 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