GEOS 639 – INSAR AND ITS APPLICATIONS

GEODETIC IMAGING AND ITS APPLICATIONS IN THE GEOSCIENCES

Lecturer:

Franz J Meyer, Geophysical Institute, University of Alaska Fairbanks, Fairbanks; fjmeyer@alaska.edu

Lecture 5: Stereo Photogrammetry – Processing Details and Transition to Structure-from-Motion

Stereo-Photogrammetry: Image Matching Techniques

Part 1: Normalized Cross Correlation

Feature Extraction and Correspondence Matching

- When generating DEMs from stereo pairs, we are applying **automatic procedures** during the **Relative Orientation** and the final **3-D Coordinate Estimation steps**:
  - Identification of clearly recognizable features with clearly defined position → **interest point detection**
  - Finding the corresponding feature in image 2 based on a feature found in image 1 → **feature matching**
- **Today, we will discuss traditional and advanced techniques for these tasks**
- **Selected Methods:**
  - **Correlation**
  - Moravec Operator
  - Harris Operator
  - **SIFT**
  - SURF

We will focus on these (one traditional and one advanced technique)

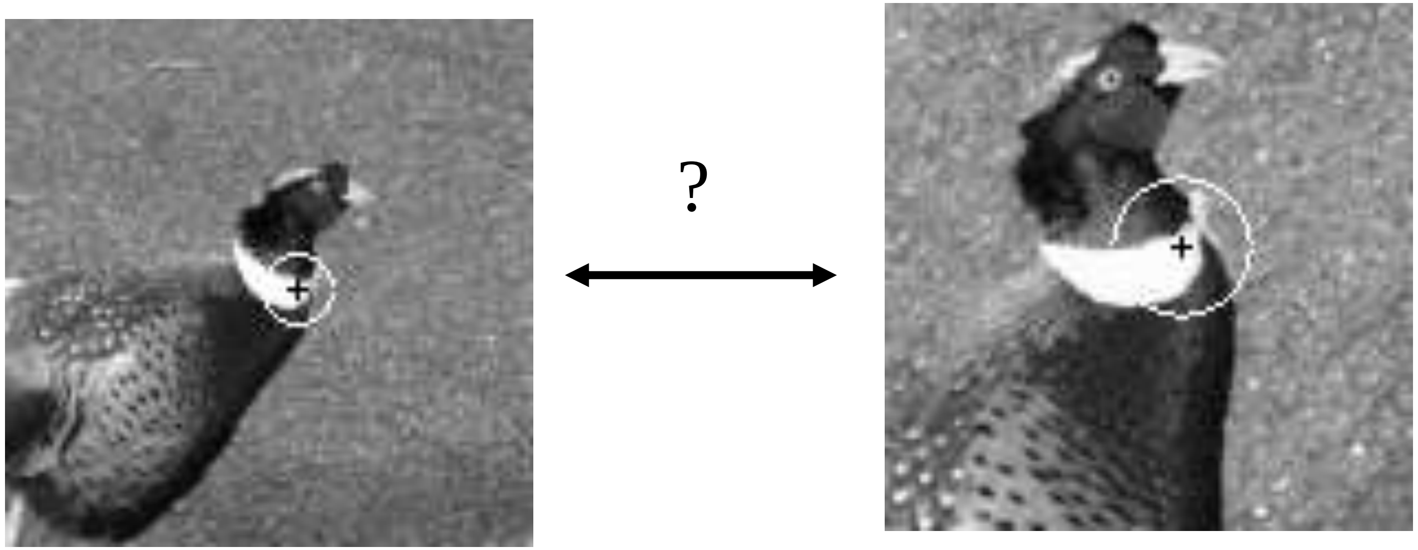
- **In the next lectures, we will discuss one more method that will increase the robustness of image matching (RANSAC)**

Relevant Work on Interest Point Detection and Image Matching

- **Corner-based local interest points**
  - Moravec (1981), Harris (1992)
- **Descriptors**
  - **Correlation window around each corner**
    - Zhang (1995)
  - **Local, rotationally invariant**
    - Schmid & Mohr (1997)
  - **Scale-invariance:**
    - Crowley & Parker (1984),
    - Shokoufandeh et. al. (1999),
    - Lindeberg (1993,1994),
    - Mikolakczyk & Schmid (2002).
- **Maximally-Stable Extremal Regions (MSER)**
  - Matas (2002)
- **Scale Invariant Feature Transform (SIFT)**
  - Lowe (1999, 2004)
- **Speeded Up Robust Features (SURF)**
  - Bay,Tuytelaars, Van Gool (2006)

The Feature Matching Problem

- Given we identified an area of interest in an image, what information should we use for finding (matching) corresponding regions in different images?



Feature Matching Methods

Simplest Approach: Cross Correlation

- Directly compare intensities using “sum of squared differences” or “normalized cross-correlation”

Feature Matching Methods

Simplest Approach: Normalized Cross Correlation

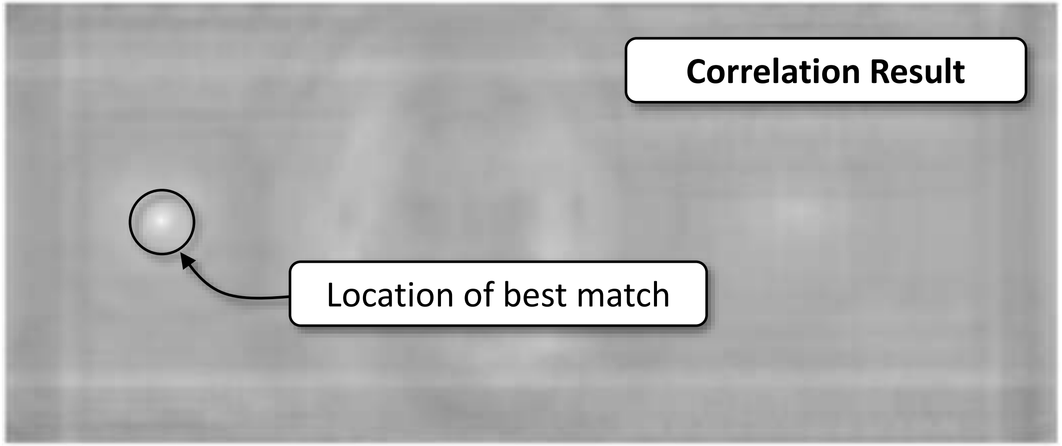
- Correlation is oldest technique for finding correspondence between image pixels
- Normalized Cross Correlation is a pattern matching techniques that uses an image template to find corresponding gray value patterns in a second image (see example below)

- Assumptions:
  - **Scene point must have same intensity in each image**
  - **Cross-correlation is not rotation invariant – so images should not be rotated relative to each other**

Cross-Correlation matching example:

- Find Federal Reserve stamp on $100 bill

Template for correlation matching



Feature Matching Methods

Simplest Approach: Normalized Cross Correlation

- **Input information needed for cross-correlation:**
  - Pair of input images (u_1 and u_2)
  - Define window of size W to be used for cross correlation analysis (how large do you want your search template to be?)
  - Define a search region $R(P_1)$ in image 2 associated with a pixel P_1 in image 1

- For each image location at distance $d = [d_i \quad d_k]^T$ from pixel P_1, **calculate correlation coefficient**

$$cc(d) = \frac{\left|\sum_W u_1[i,k] \cdot u_2[i,k]\right|}{\sqrt{\sum_W |u_1[i,k]|^2 \cdot \sum_W |u_2[i,k]|^2}}$$

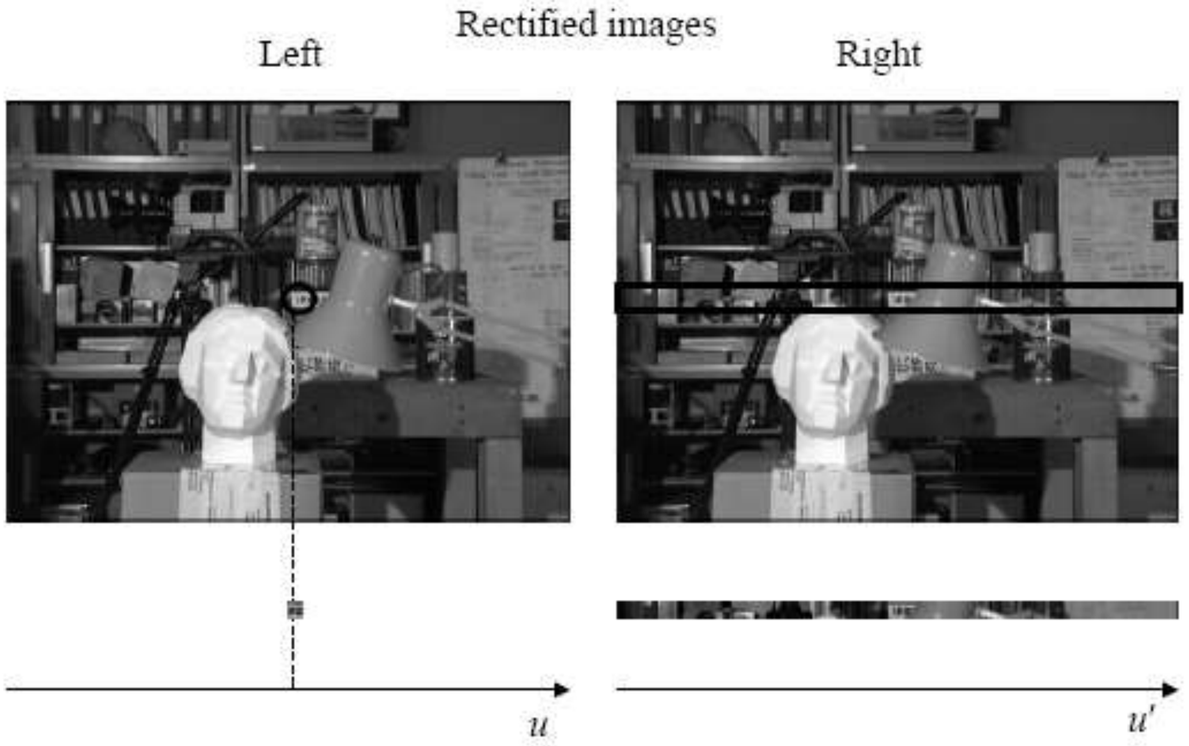
- **The disparity** for P_r is the vector $\bar{d} = [\bar{d}_i \quad \bar{d}_k]^T$ that maximizes $cc(d)$ within $R(P_1)$

$$\bar{d} = argmax_{d \in R(P_1)}\{cc(d)\}$$

Feature Matching Methods

Simplest Approach: Cross Correlation

- Works satisfactorily when we matching corresponding regions related mostly by translation.
  - e.g., stereo pairs, video sequence assuming small camera motion



Feature Matching Methods

Simplest Approach: Normalized Cross Correlation

- **Problems – Part 1:**
  - **What if image contrast and image noise levels differ between images**
    - → Different maximum and minimum intensities
    - → **Simple intensity matching degrades quickly**
  - **What if Images were acquired from different directions and scatter differently in these directions?**
    - → Scene objects are not perfect Lambertian scatterers
    - → **Matching quality reduced**

- **Solution to Problems – Part 1:**
  - **Do not use image intensity values but use intensity gradients instead!**
  - **Possible approach:**
    - Compute the gradient magnitude at each pixel in the two images without smoothing
    - Map the gradient magnitude values into three values: -1, 0, 1 (by thresholding the gradient magnitude)
    - → **Amplitude independent and more sensitive correlations**

Feature Matching Methods

Simplest Approach: Cross Correlation

- **Problems – Part 2:**
  - **Cross-correlation does not allow for the following variations between images:**
    - Relative image rotations
    - Variation of pose (due to different image locations)
    - Variations in image scale
  - **Matching success strongly depends on image structure relative to search window size.**
    - too small a window → may not capture enough image structure and → many false matches
    - too large a window → matching less sensitive to noise (desired) but also decreases precision (blurs disparity map)
- Hence, we will discuss a more powerful descriptor called **SIFT**

Stereo-Photogrammetry: Image Matching Techniques

Part 2: Scale Invariant Feature Transform (SIFT)

SIFT – A Powerful Feature Extraction and Matching Method

- **SIFT** = **S**cale **I**nvariant **F**eature **T**ransform
- **Properties**:
  - Extracts & describes large amount of features to recognize objects in images
  - Robust identification of objects even among clutter and under partial occlusion,
  - **Invariant** to uniform scaling, changing orientation, and partially invariant to affine distortion and illumination changes.
- **An Image matching approach based on SIFT includes the following steps:**
  1. **Scale-space feature extraction and formulating a descriptor for these features**
     - Extract scale and rotation invariant interest points (i.e., keypoints).
  2. **Matching features in one image to the same features in other images**
     - Find features in other images.
  3. **Combine features to identify the location of objects**
     - This is done using an algorithm called the Hough transform.
  4. **Model verification and outlier removal**
     - Use least squares methods to verify solutions and remove outliers.

Almost all of SIFT is hidden here!

D. Lowe, "Distinctive Image Features from Scale-Invariant Keypoints", **International Journal of Computer Vision**, 60(2): 91-110, 2004. **Cited 45,696 times (3/2018) – 55,920 times (3/2020)**

Think – Pair – Share

Feature identification and matching

Q1: In Stereo photogrammetry we use automatic methods such as **cross-correlation** to detect and match-up interest points in the two images of a stereo pair.

What is the goal of automatically finding and matching many points in the two images? What is the product we are trying to create?

Q2: Cross-correlation has limitations for feature detection and matching.

What are the main limitations of cross-correlation and for which stereo constellations (1) do we and (2) do we not care about these limitations

SIFT – A Powerful Feature Extraction and Matching Method

- **Let's reiterate the main problems in feature matching:**
  - Find most robust features that describe a scene the best and can be easily recognized in other images
  - Formulate a descriptor that can robustly describe what your feature looks like
  - Make sure your descriptors are robust even if (1) image scale, (2) image orientation, (3) image illumination, and (4) image noise are changing

- **Hence: SIFT performance goal check list**
  - Scale Invariance
  - Rotation Invariance
  - Illumination invariance
  - Viewpoint invariance

The SIFT Algorithm

Overview of the Approach

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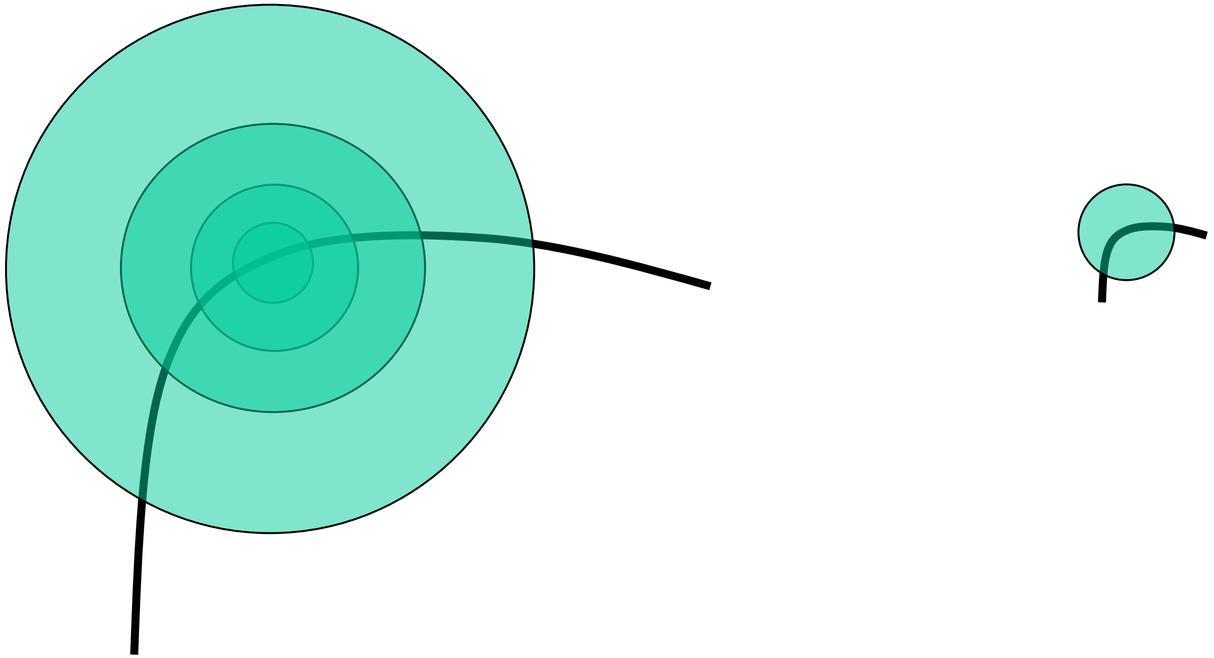
Match Keypoints found in different images

SIFT – Scale Invariant Feature Detection

Step 1: Construct Scale Space

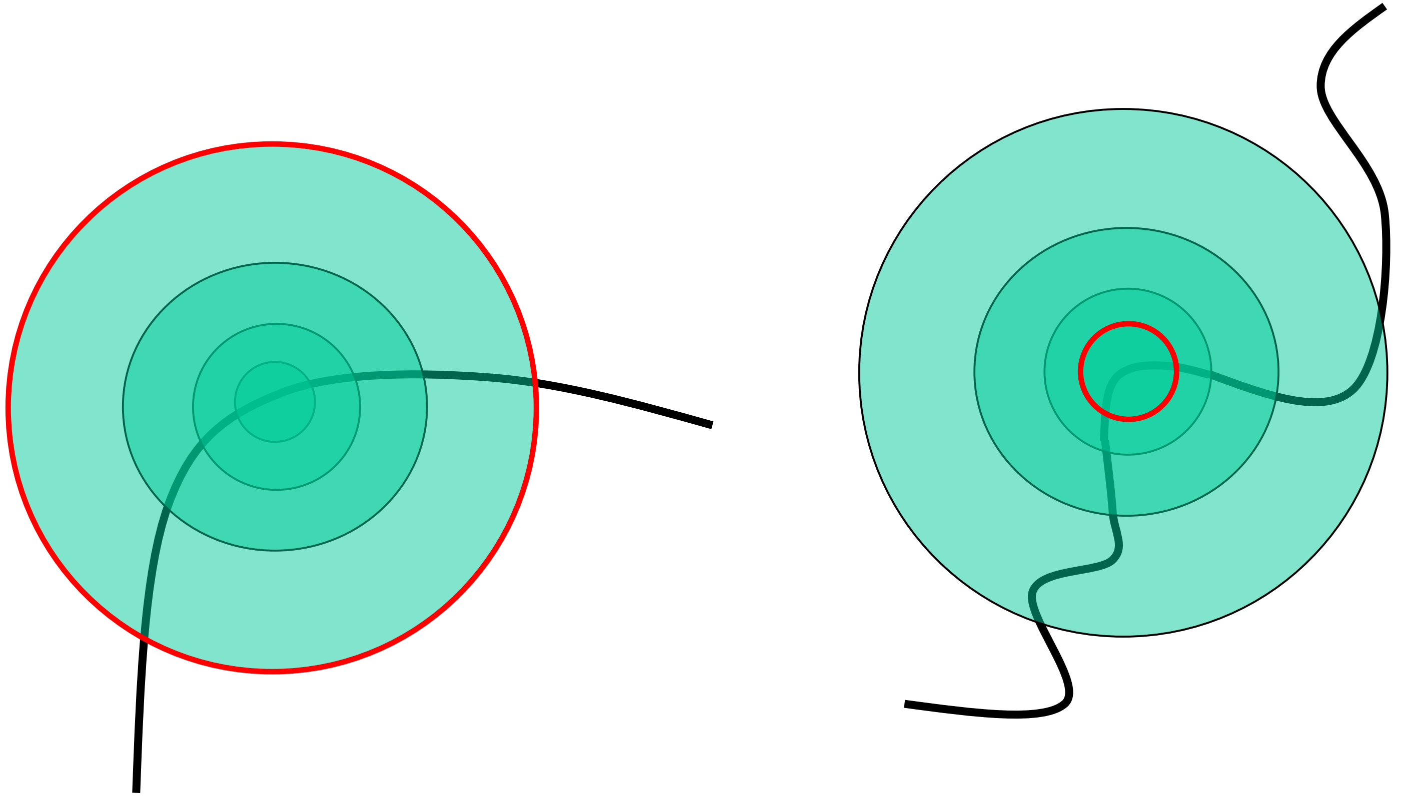
- **Why use various scales?**
  - Consider regions (e.g. circles) of different sizes around a point
  - Regions of corresponding **relative** sizes will look the same in both images



SIFT – Scale Invariant Feature Detection

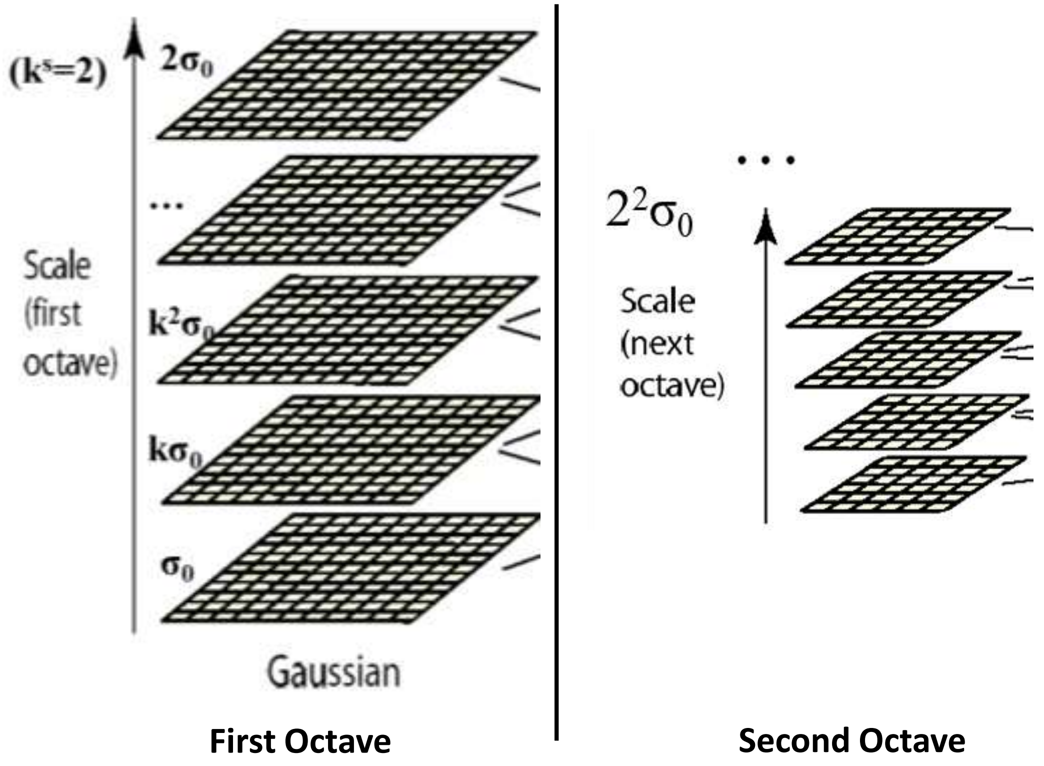
Step 1: Construct Scale Space

- **Why use various scales?**
  - Consider regions (e.g. circles) of different sizes around a point
  - Regions of corresponding **relative** sizes will look the same in both images
  - **Problem**: How to choose corresponding circle sizes **automatically and independently** in each image?



SIFT – Scale Invariant Feature Detection
Step 1: Construct Scale Space

- **Solution**: We construct multiple resolution scales for each image using Gaussian Scale Space Processing



Gaussian Scale Space Concept

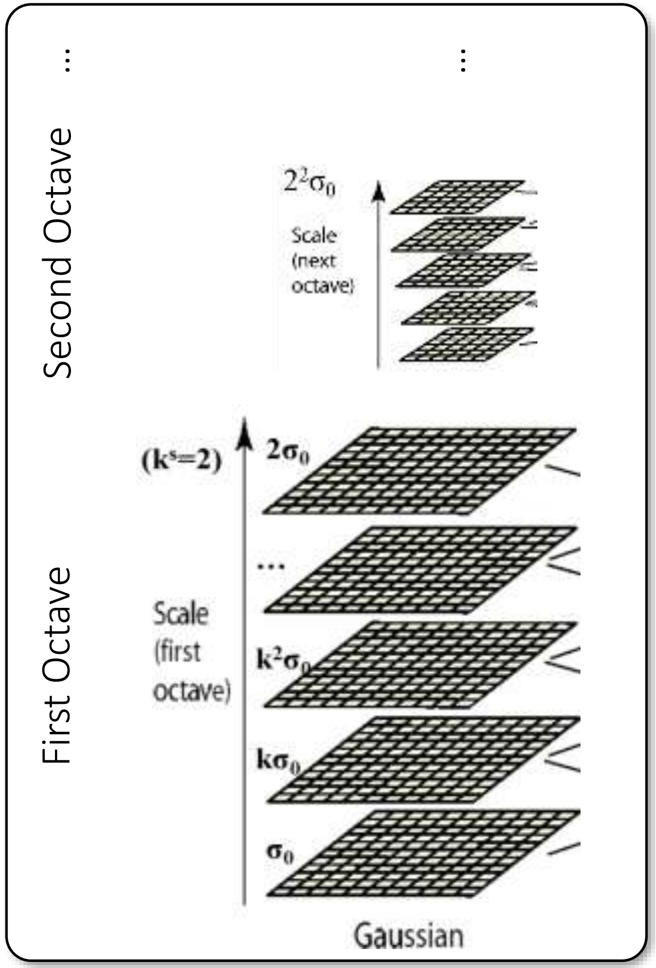
- **Gaussian Scale Space:**
  - **Created by convolving image u with Gaussian smoothing kernels of progressively larger standard deviation σ**
  - **An image pyramid is created**,
    - each pyramid level is called octave o and contains a total of s sublevels
    - Each sublevel is separated by constant factor k such that the standard deviation scales as

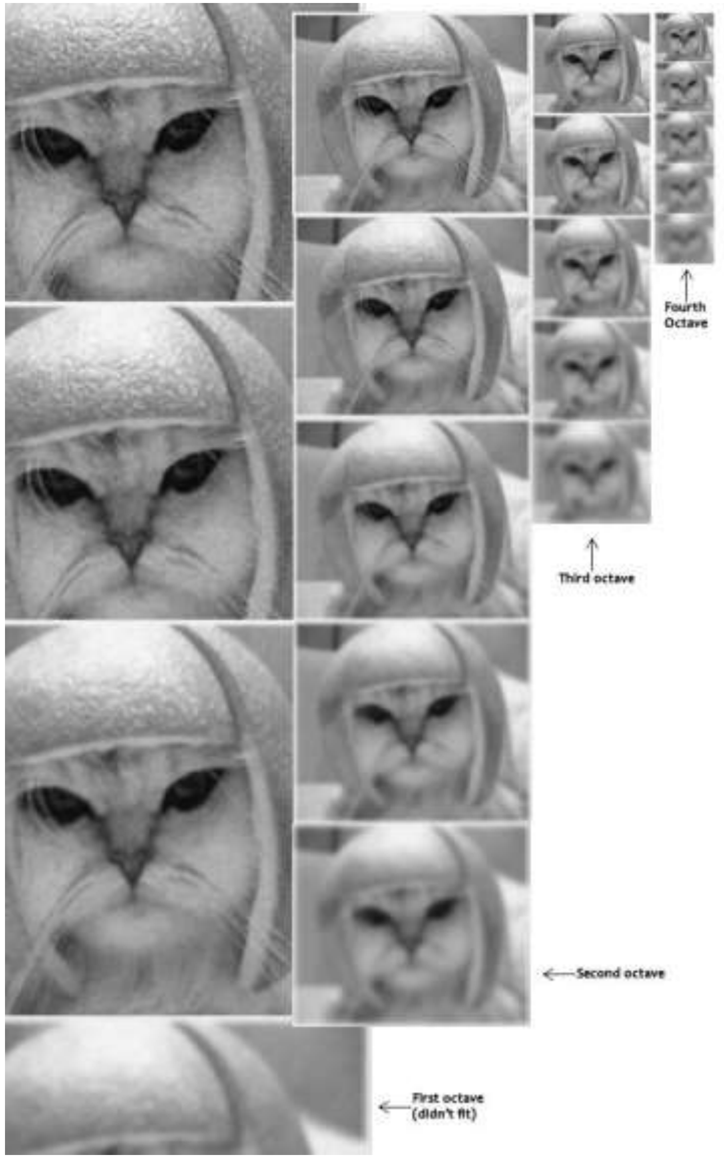
$$\sigma(s, o) = \sigma_0 2^{(o+(k/s))}$$

SIFT – Scale Invariant Feature Detection

Step 1: Construct Scale Space

- Example of a Gaussian Scale Space composed of four octaves





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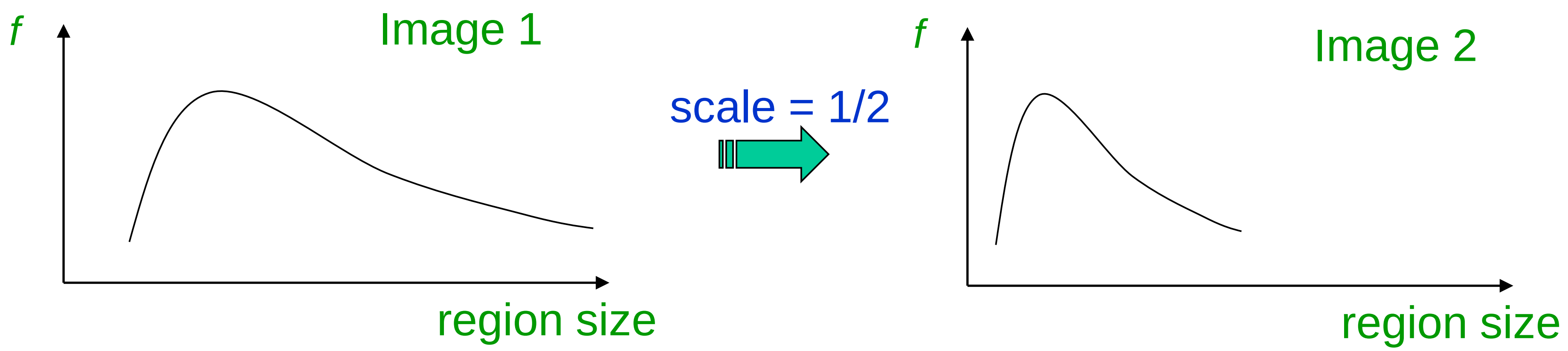
Match Keypoints found in different images

SIFT – Scale Invariant Feature Detection

Step 2: Take Difference of Gaussians

- **Problem 2:** Now that we have developed a scale space, **we need to identify a descriptor that can help us identify scale invariant features**
- **Solution:**
  - Find a function within a region (circle), which is “scale invariant” (the same for corresponding regions, even if they are at different scales)
  - **Example**: average intensity [for corresponding regions (even of different sizes) it will be the same]

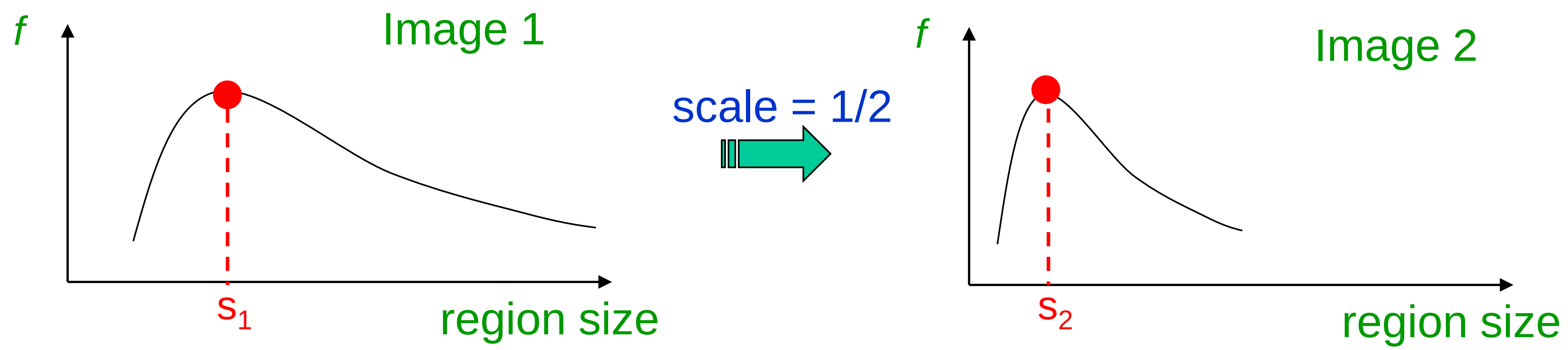


Example of an image function that looks the same at different scales (scale invariant)

SIFT – Scale Invariant Feature Detection

Step 2: Take Difference of Gaussians

- **Problem 2:** Now that we have developed a scale space, **we need to identify a descriptor that can help us identify scale invariant features**
- **Solution:**
  - To make detection of invariant features robust we usually **take a local maximum of this function**
  - **Observation**: region size, for which the maximum is achieved, should be invariant to image scale

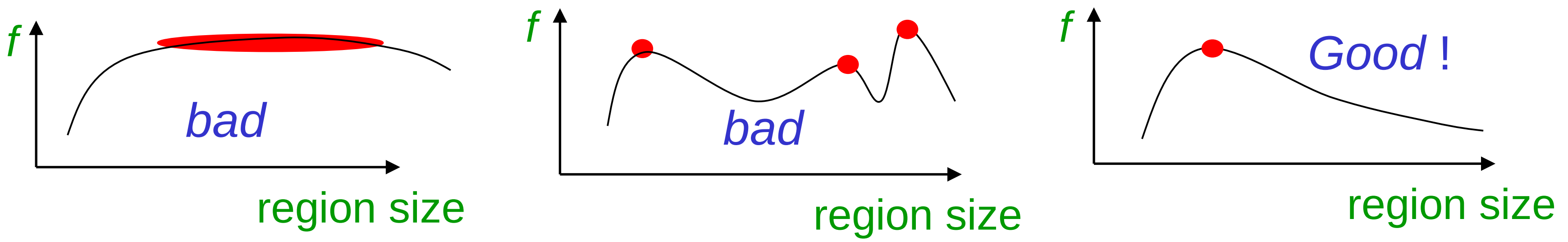


Example of an image function that looks the same at different scales (scale invariant)

SIFT – Scale Invariant Feature Detection

Step 2: Take Difference of Gaussians

- **Problem 2:** Now that we have developed a scale space, **we need to identify a descriptor that can help us identify scale invariant features**
- **Solution:**
  - **Finally**, To identify scale accurately, we want a function that has one sharp peak



Examples of image functions with varying peak quality

→ A good function would be one which responds to local contrast (sharp local intensity change)

SIFT – Scale Invariant Feature Detection

Step 2: Take Difference of Gaussians

- **Difference of Gaussians** is a good scale invariant feature producing a clear peak at a feature's spatial scale

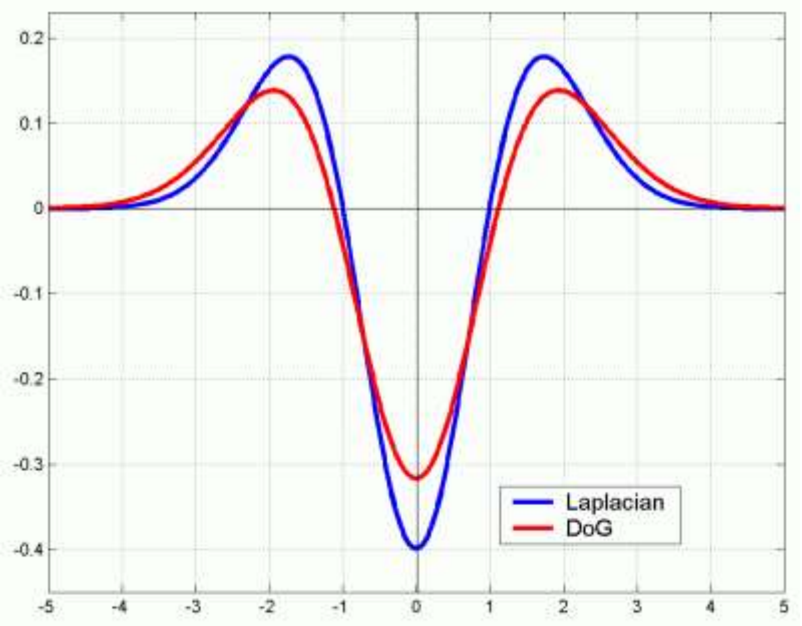
$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

  - With Gaussian

$$G(x, y, \sigma) = \frac{1}{\sqrt{2\pi} \cdot \sigma} exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

- DoG is related to the Laplacian L that some of you may know from digital image processing
  - Advantage of DoG is that it is faster to calculate

$$L = \sigma^2 \left(G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma)\right)$$

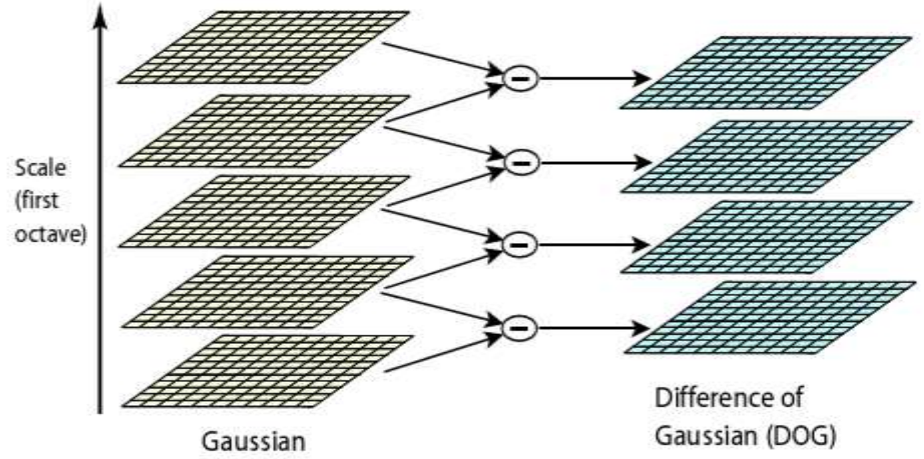


L or DoG kernel is a matching filter. It finds blob-like structure. It turns out to be also successful in getting characteristic scale of other structures, such as corner regions.

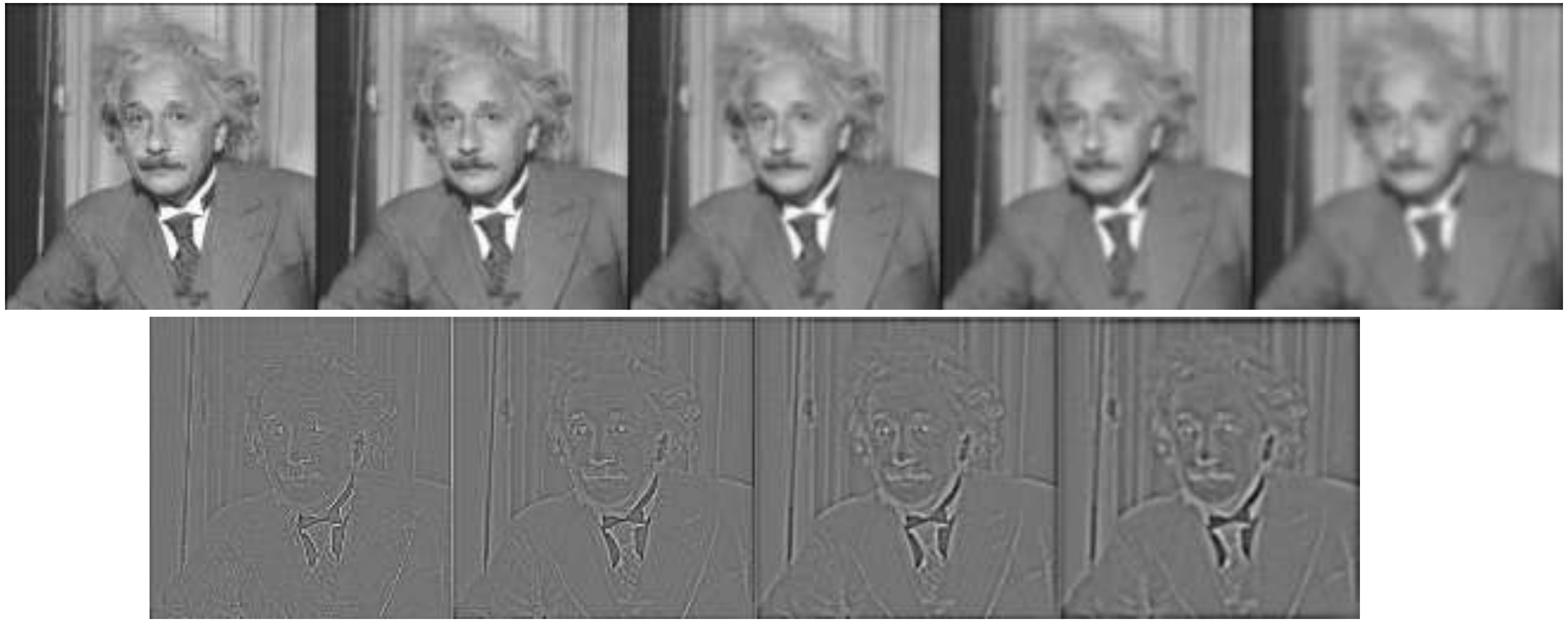
SIFT – Scale Invariant Feature Detection
Step 2: Take Difference of Gaussians

- **Example of DoG images through a Gaussian Scale Space**

Concept



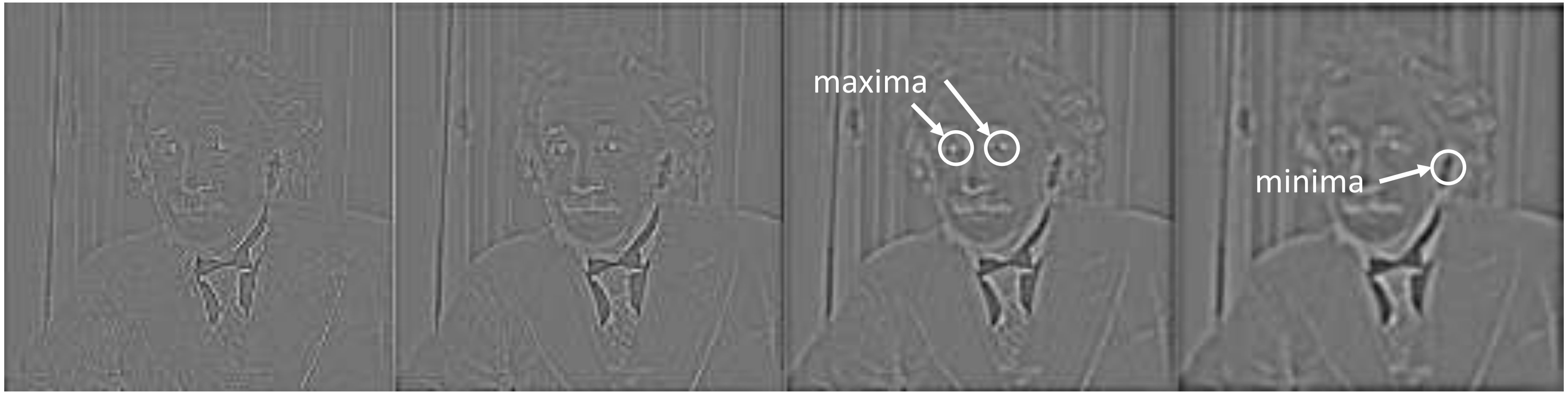
Example



Why the Difference of Gaussian is Useful

- Difference of Gaussian extrema identify and locate “blobs” in images → blob-type features are great for measuring the location of that feature in the image
  - Maxima = dark blobs on light background
  - Minima = light blobs on dark background

- The sigma parameter of the DoG filter can help determining the scale of a detected blob feature



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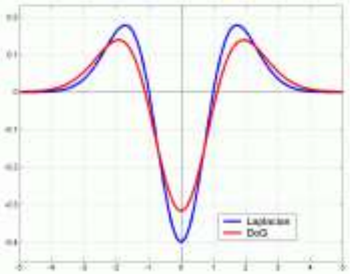
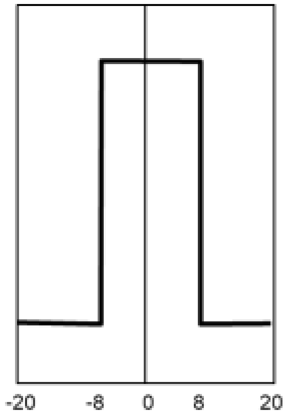
SIFT – Scale Invariant Feature Detection

Step 3 & 4: Automatic Scale Selection

- Automatic Scale Selection

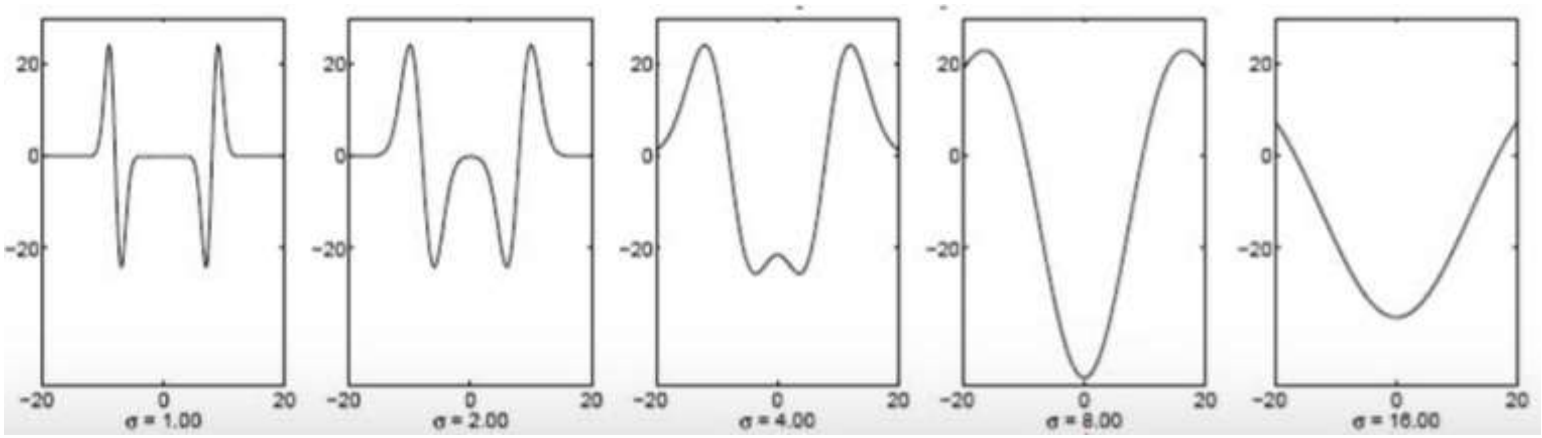


Original Signal



Radius = 8

DoG Responses



Increasing sigma parameter

Extremum

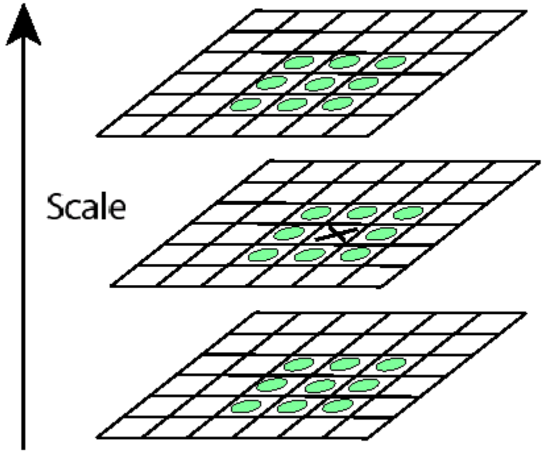
→ optimal scale at which feature can be detected in the image

→ location of feature in the image

SIFT – Scale Invariant Feature Detection

Step 3 & 4: Sub-pixel Local Spatial DoG Maximum

- **Detect DoG Extrema in the scale space by 3D Curve Fitting to DoG shape**



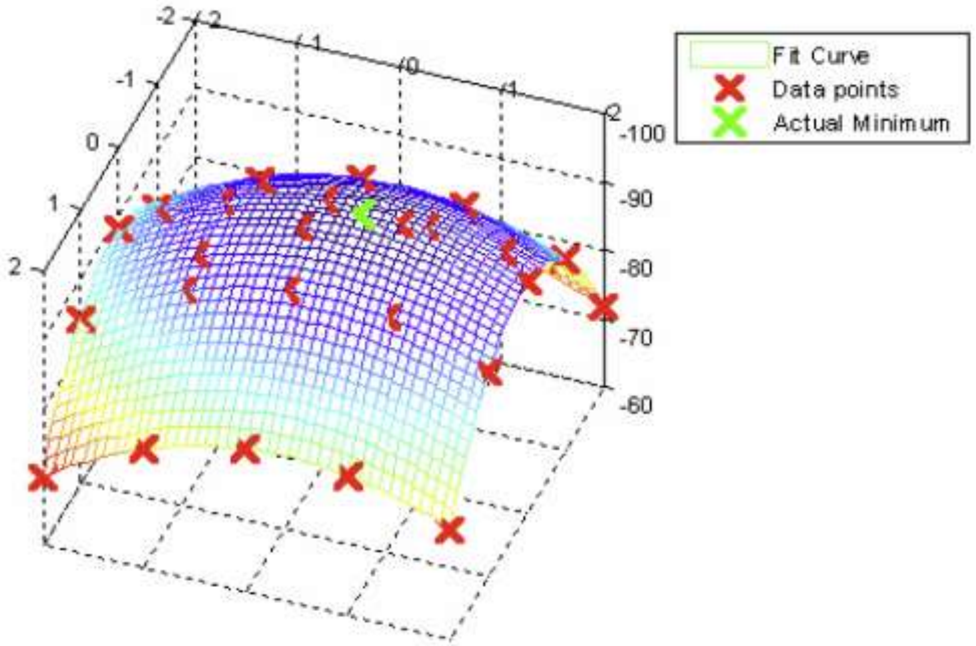
- **Then, Taylor Series expansion of fitted curve:**

$$D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x$$

  – Differentiate and set to 0

$$\hat{x} = -\frac{\partial^2 D}{\partial x^2}^{-1} \frac{\partial D}{\partial x}$$

  to get subpixel maximum locations.



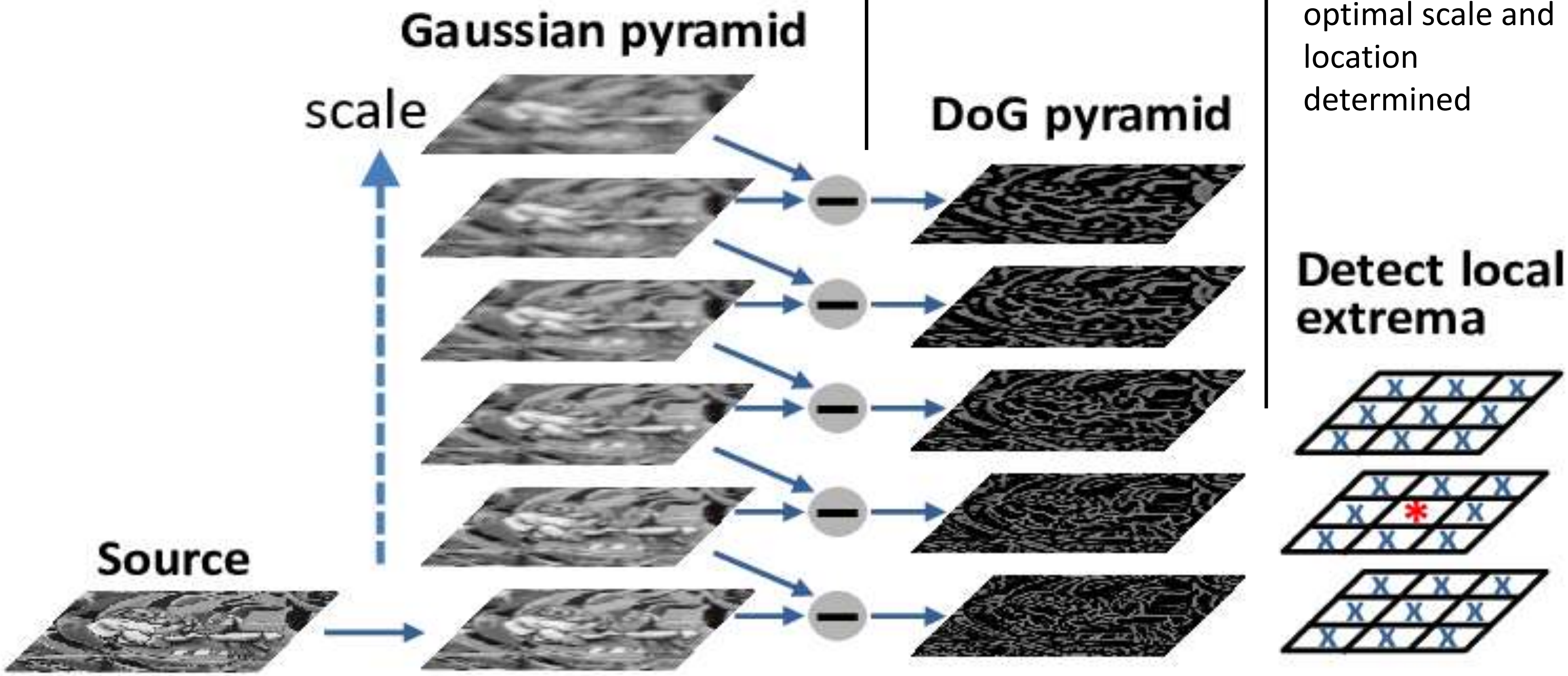
We achieved scale invariance !!
We achieved accurate feature location !!

SIFT Workflow so Far

Step 1: Image Pyramid
Facilitate scale invariance

Step 2: DoG Pyramids
Finds blob-like features (keypoints)

Step 3: Scale Selection
Keypoints detected at optimal scale and location determined



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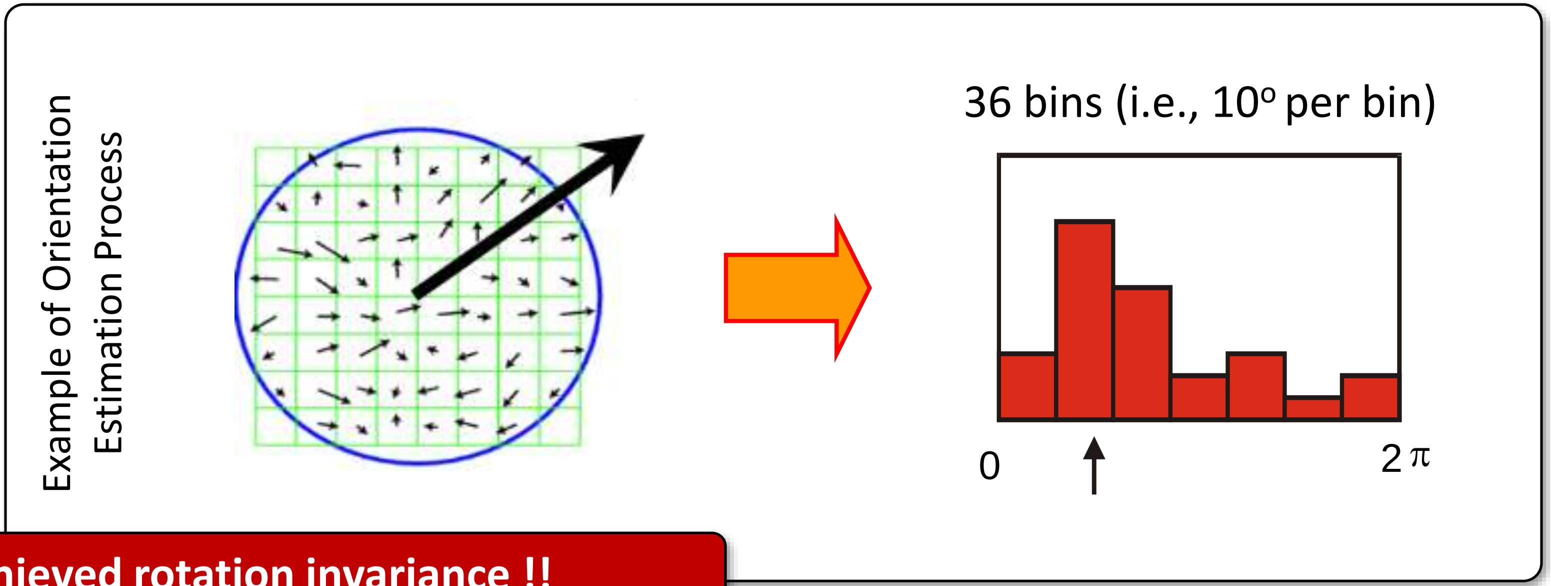
Match Keypoints found in different images

SIFT – Scale Invariant Feature Detection

Step 5: Assign Keypoint Orientations

- **Knowing the orientation of identified features makes matching more robust**
- **Compute gradients** for at the optimal scale of the detected keypoint
- **For 8x8 region around keypoint**
  - Calculate $8 \cdot 8 = 36$ gradients and create directional histogram
  - Weight each point by distance from keypoint with Gaussian window of 1.5σ
  - **Maximum of directional histogram is keypoint orientation**



We achieved rotation invariance !!

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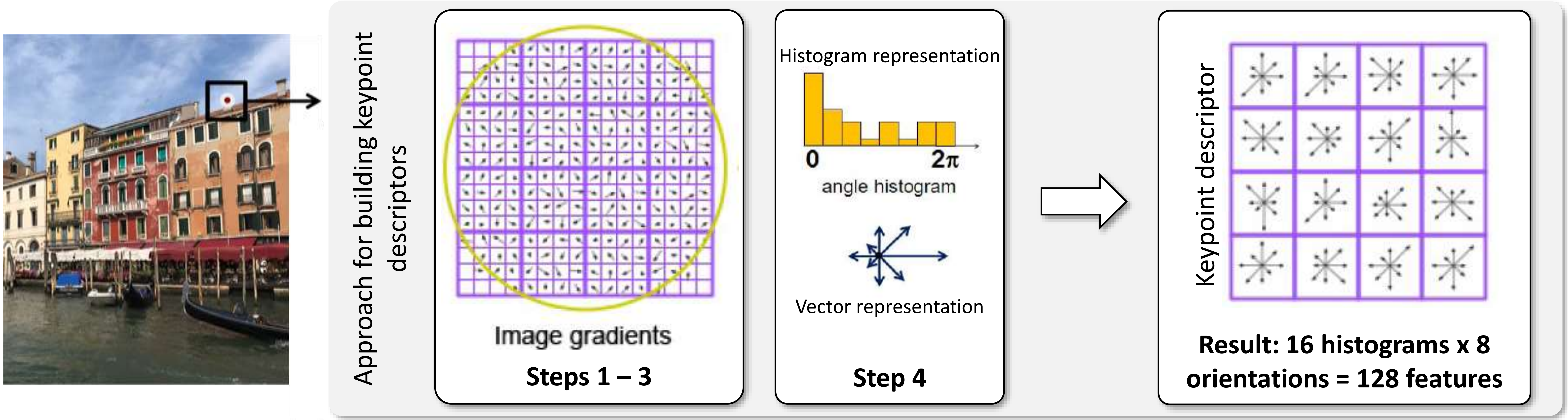
Match Keypoints found in different images

SIFT – Scale Invariant Feature Detection

Step 6: Build Keypoint descriptors

- **Goal:** Extract as much information as possible for each keypoint to improve matching quality and reduce amount of mis-matches between images – **we use local image gradients as a descriptor**
- **Approach per keypoint:**
  1. Find the blurred image of closest scale
  2. Take a 16 x16 window around detected keypoint
  3. Divide into a 4x4 grid of cells.
  4. Compute histogram in each cell [typically 8 bin histogram]



SIFT – Scale Invariant Feature Detection

Back to Performance Check

- **Criterion 1:** Scale Invariance ✓
  - Scale Space usage
- **Criterion 2:** Rotation Invariance ✓
  - Align with largest gradient
- **Criterion 3:** Illumination Invariance ✓
  - Gradient based rather than illumination based
- **Criterion 4:** Viewpoint Invariance (✓)
  - For small viewpoint changes –Check (mostly)

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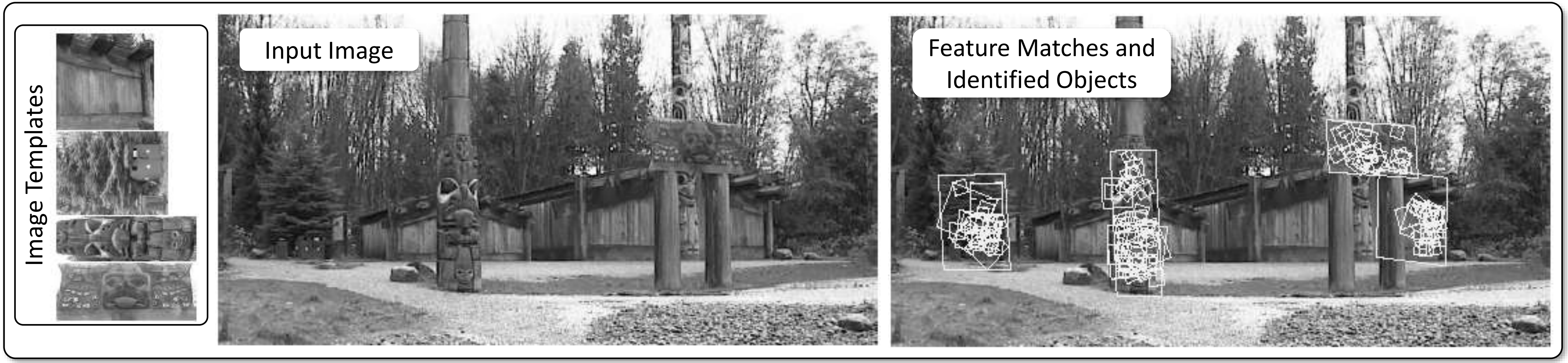
SIFT – Scale Invariant Feature Detection

Identifying and Matching Objects Based on SIFT Features

- **Can be done with as few as 3 SIFT features.**
- **Use Hough transform to cluster features belonging to one object**
- Clusters can be identified in Hough space after 3 entries
- More details in the next slide (hidden in this presentation but available in the online slide deck)

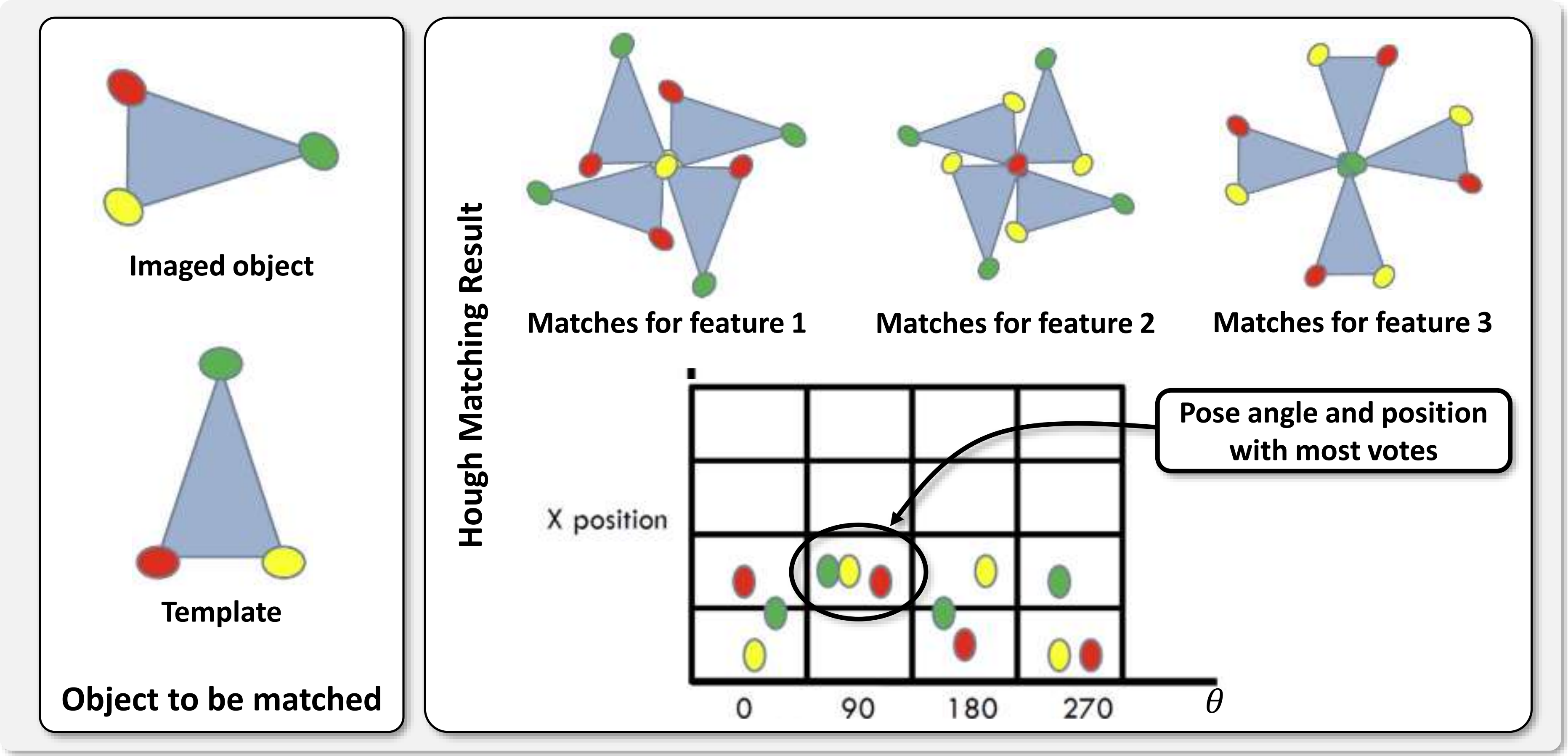
- **Example problem to solve:** Identifying Objects (templates) in this outdoor scene



SIFT – Scale Invariant Feature Detection

Hough Transform Matching Concept

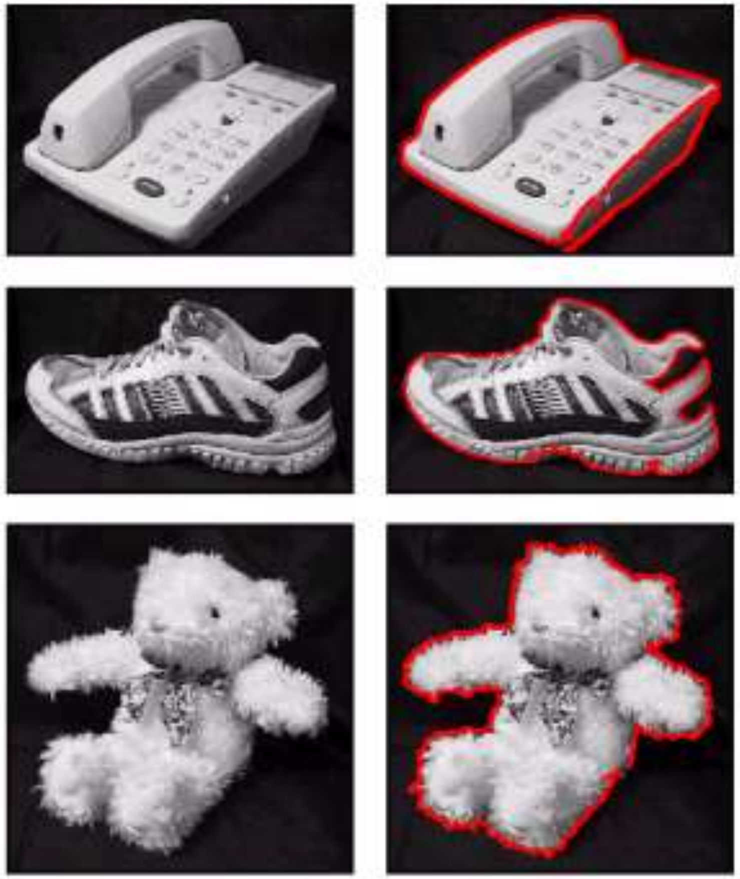
- For the Current View, color feature match with template image
- Take each feature and align template image at that feature → vote for the x position of the object center and the θ of the object based on all aligning poses



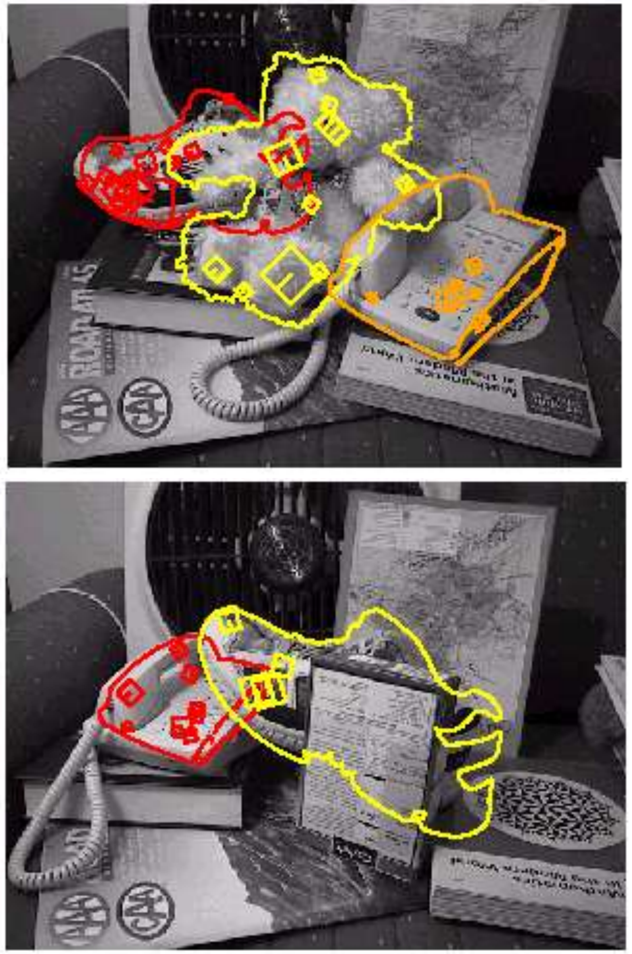
SIFT – Scale Invariant Feature Detection
Matching Examples

- **Identifying objects (even if partially obstructed)**

Object Models

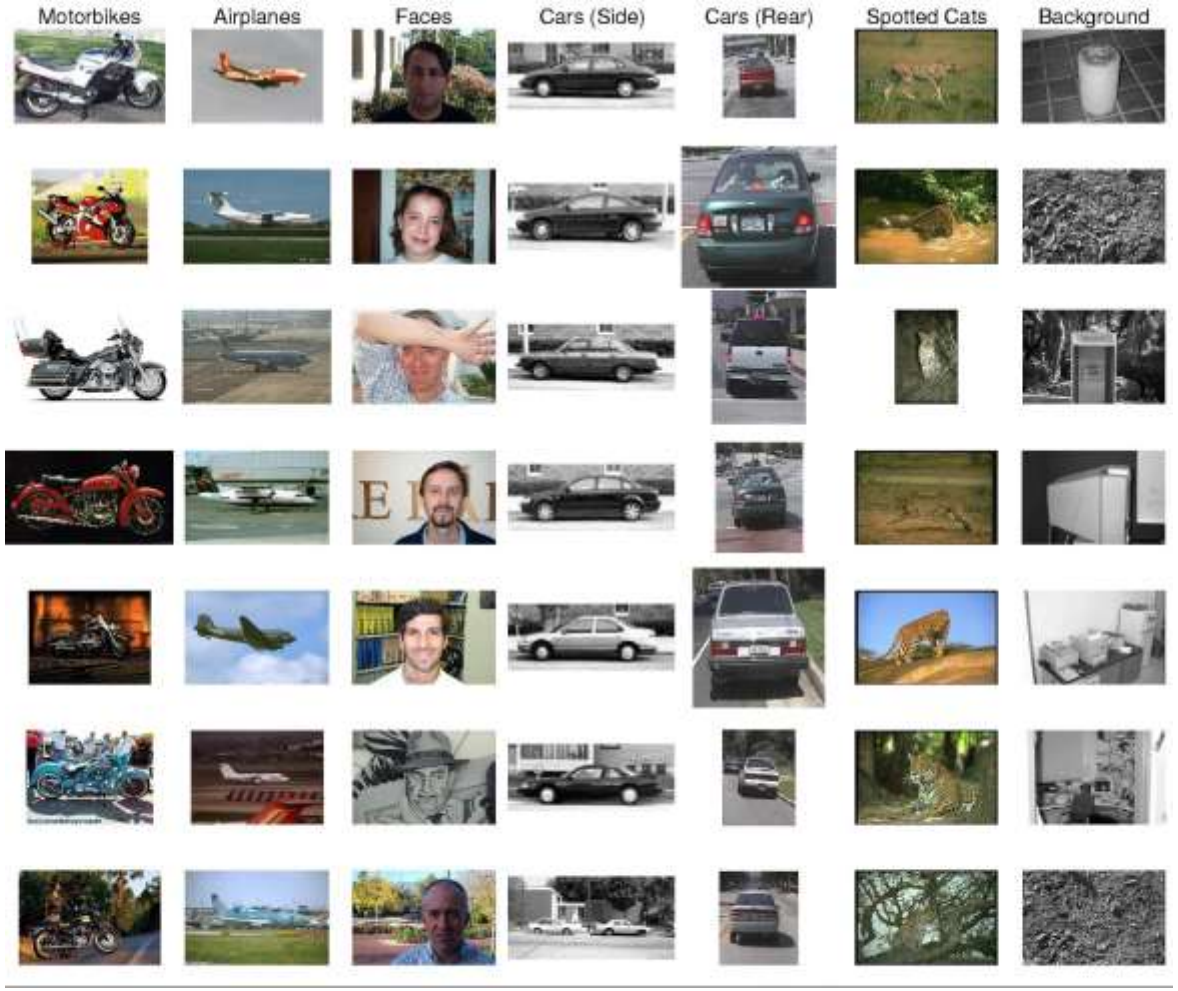


Recognition under occlusion



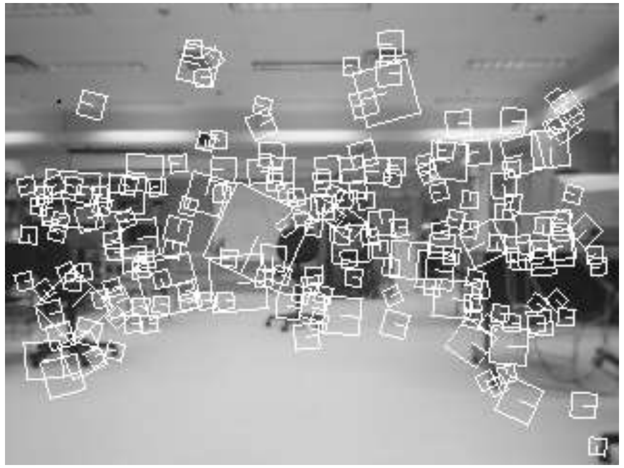
SIFT – Scale Invariant Feature Detection
Other SIFT Applications: Automatic Image Categorization

- **Flickr images automatically categorized based on SIFT features**



SIFT – Scale Invariant Feature Detection
Other SIFT Applications: Robot Trajectory Estimation

- **Automatic tracking of trajectory of robot in a room based on matched SIFT features**



SIFT – Scale Invariant Feature Detection

Other SIFT Applications: Automatic Image Retrieval from Data Bases

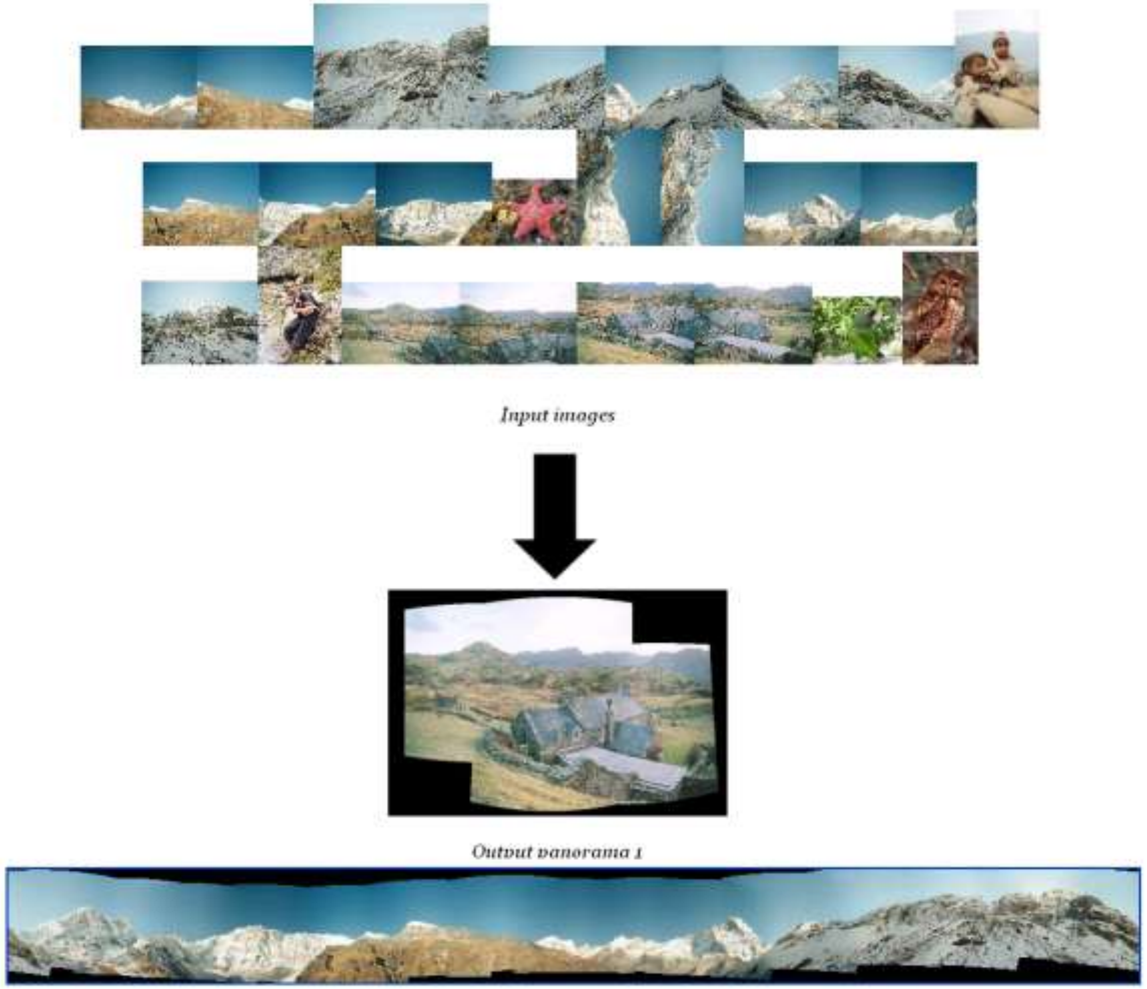
- **Automatic retrieval of matching images from the Flickr data base**

Template image

SIFT – Scale Invariant Feature Detection

Other SIFT Applications: Image panoramas from an unordered image set

- **Automatic mosaicking of unsorted image sets**



Cool Stuff Powered by SIFT

What's Next

- **Next Lecture:**
  - Structure-from-Motion Processing to generate Digital Elevation Models

- **After that:**
  - **Lab:** Structure-from-Motion for DEM processing