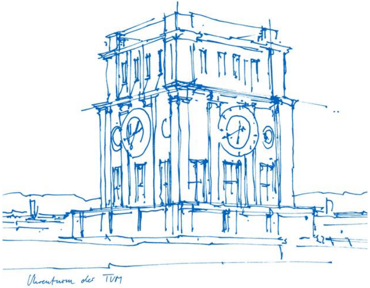
Computer Vision II: Multiple View Geometry (IN2228)

Chapter 05 Correspondence Estimation
(Part 2 Large Motion)

Dr. Haoang Li

17 May 2023 12:00-13:30



Announcement

➢ Updated Lecture Schedule

For updates, slides, and additional materials:
https://cvg.cit.tum.de/teaching/ss2023/cv2

90-minute course; 45-minute course

Foundation

Wed 19.04.2023 Chapter 00: Introduction
Thu 20.04.2023 Chapter 01: Mathematical Backgrounds

Wed 26.04.2023 Chapter 02: Motion and Scene Representation (Part 1)
Thu 27.04.2023 Chapter 02: Motion and Scene Representation (Part 2)

Wed 03.05.2023 Chapter 03: Image Formation (Part 1)
Thu 04.05.2023 Chapter 03: Image Formation (Part 2)

Wed 10.05.2023 Chapter 04: Camera Calibration
Thu 11.05.2023 Chapter 05: Correspondence Estimation (Part 1)

Wed 17.05.2023 Chapter 05: Correspondence Estimation (Part 2)
Thu 18.05.2023 No lecture (Public Holiday)

Wed 24.05.2023 No lecture (Conference)
Thu 25.05.2023 No lecture (Conference)
Videos and reading materials about the combination of deep learning and multi-view geometry

Core part

Wed 31.05.2023 Chapter 06: 2D-2D Geometry (Part 1)
Thu 01.06.2023 Chapter 06: 2D-2D Geometry (Part 2)

Wed 07.06.2023 Chapter 06: 2D-2D Geometry (Part 3)
Thu 08.06.2023 No lecture (Public Holiday)

Wed 14.06.2023 Chapter 07: 3D-2D Geometry (Part 1)
Thu 15.06.2023 Chapter 07: 3D-2D Geometry (Part 2)

Wed 21.06.2023 Chapter 08: 3D-3D Geometry (Part 1)
Thu 22.06.2023 Chapter 08: 3D-3D Geometry (Part 2)

Wed 28.06.2023 Chapter 09: Single-view Geometry (Part 1)
Thu 29.06.2023 Chapter 09: Single-view Geometry (Part 2)

Advanced topics and high-level task

Wed 05.07.2023 Chapter 10: Photometric Error (Direct Method)
Thu 06.07.2023 Chapter 11: Bundle Adjustment and Optimization

Wed 12.07.2023 Chapter 12: Robot Estimation
Thu 13.07.2023 Knowledge Review

Wed 19.07.2023 Chapter 13: SLAM and SFM (Part 2)
Thu 20.07.2023 Chapter 13: SLAM and SFM (Part 1)

Announcement

- ➢ Updated Lecture Schedule

Though we do not have lectures on 24 and 25 May, the **exercise session will still be held normally on 24 May**.

Wed 24.05.2023 No lecture (Conference)
Thu 25.05.2023 No lecture (Conference)

} Videos and reading materials about the combination of deep learning and multi-view geometry

Tentative Exercise Schedule

Wed 26.04.2023 Exercise 1: Introduction

Wed 03.05.2023 Exercise 2: Mathematical Background

Wed 10.05.2023 Exercise 3: Representing a Moving Scene

Wed 24.05.2023 Exercise 4: Perspective Projection

Wed 31.05.2023 Exercise 5: Lucas-Kanade Method

Wed 14.06.2023 Exercise 6: Reconstruction from two views

Wed 21.06.2023 Exercise 7: Reconstruction from multiple views

Wed 05.07.2023 Exercise 8: Direct Image Alignment

Wed 12.07.2023 Exercise 9: Direct Image Alignment

Explanations for Previous Knowledge

➢ Which Points Should We Track?

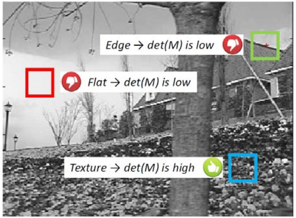
✓ Theoretical strategy

Eigenvalues

$$M = \begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

I_x and I_y:
Directional derivatives

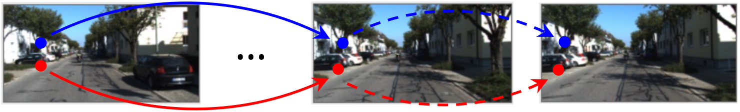
Eigenvectors



Problem: relatively low efficiency due to judgement on **all the pixels** in an image

✓ Practical solution

Only first image: judge **each** pixel



Subsequent images: only consider the **tracked** points

Explanations for Previous Knowledge

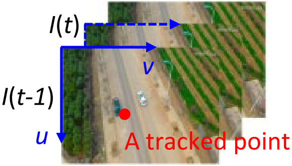
➢ Brightness Consistency

✓ Video *I* (sequential images) is w.r.t. the time *t*. A tracked point's position *x* is also w.r.t. the time *t*.

✓ We use the pixel coordinate system whose origin is located at the top-left of image.

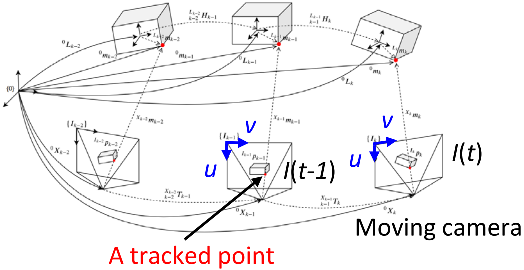
$$I(x(t), t) = \text{const.} \quad \forall t,$$

Frames obtained by a static camera



Sequential images

Moving object



Explanations for Previous Knowledge

➢ Chicken-and-egg Problem

✓ Definition

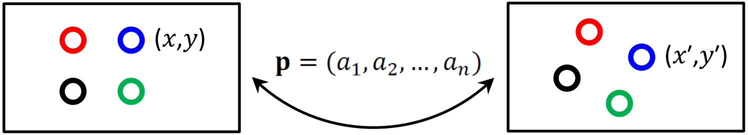
A problem has two sets of unknown parameters. Parameters are mutually determined.

✓ Examples

$$x' = x cos(a_3) - y sin(a_3) + a_1$$
$$y' = x sin(a_3) + y cos(a_3) + a_2$$

(x,y) and (x',y') constitute a pair of unknown-but-sought correspondences

$\mathbf{p} = (a_1, a_2, \ldots, a_n)$ are warping parameters to estimate



Explanations for Previous Knowledge

- Chicken-and-egg Problem

✓ Solution

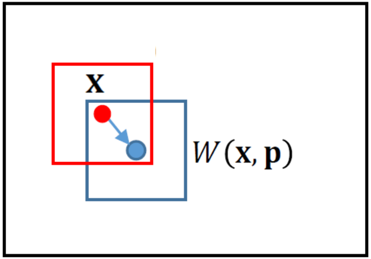
Find **additional constraint** to solve parameters.

2nd image
(current image)

$$SSD = \sum_{\mathbf{x} \in \mathbf{T}} \left[I\left(\boxed{W(\mathbf{x}, \mathbf{p})}\right) - T(\boxed{\mathbf{x}}) \right]^2$$

1st image
(template image)

Additional constraint:
Brightness consistency



Brightness consistency

Today’s Outline

- Overview of Indirect Method
- Feature Detector
- Feature Descriptor

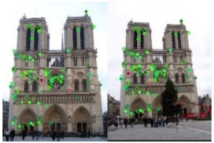
Overview of Indirect Method

- Recap on Problem Formulation

- ✓ Core idea: To compute the transformation between two images, we resort to detecting and matching features (points or lines).
- ✓ Pros: They can cope with **large** frame-to-frame **motions** and strong illumination changes.
- ✓ Cons: They are slow due to costly feature extraction, matching, and outlier removal (e.g., RANSAC).

Direct method (KLT):

A one-step strategy

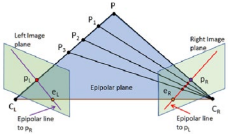


Feature detection

Inliers

Outliers

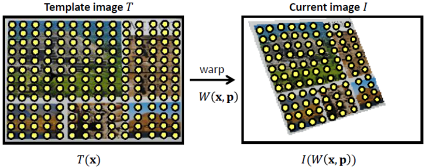
Feature matching



Transformation estimation

Indirect method: A two-step strategy

Overview of Indirect Method



➢ Recap on Problem Formulation

✓ Pipeline for alignment between template and current images

1. Detect and match features that are invariant to scale, rotation, view point changes (e.g., SIFT)

2. Transformation computation and Geometric verification (e.g., 4 point RANSAC for planar objects, or 5 or 8 point RANSAC for 3D objects)

3. Refine the initial estimation by minimizing the sum of squared reprojection errors between the observed feature $\boldsymbol{f}^i$ in the current image and the warped corresponding feature $W(\mathbf{x}^i, \mathbf{p})$ from the template

$$\mathbf{p} = argmin_{\mathbf{p}} \sum_{i=1}^{N} \left\| W(\mathbf{x}^i, \mathbf{p}) - \boldsymbol{f}^i \right\|^2$$

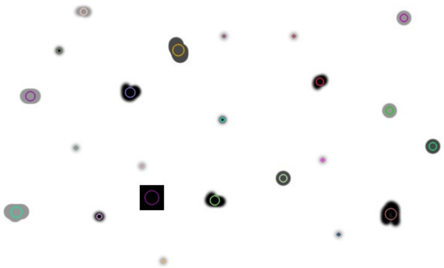
Geometric feature (point) distance

2D coordinates of points

Feature Detector

- ➢ Definition of Blob

- ✓ A blob is a group of **connected pixels** in an image that share some common property (e.g, grayscale value).
- ✓ In the image below, the colored regions are blobs, and **blob detection** aims to identify and mark these regions.



Feature Detector

➢ Comparison between Corner and Blob

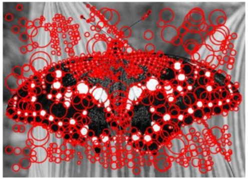
✓ A **corner** is defined as the intersection of two or more edges

- Corners have **high localization** accuracy
- Corners are **less distinctive than blobs**
- E.g., Moravec, Harris, Shi-Tomasi, SUSAN, FAST

Corners

✓ **Blob** introduced before

- Blobs have less localization accuracy than corners
- Blobs are more distinctive than corners
- E.g., MSER, LOG, DOG (SIFT), SURF, CenSurE, etc.



Blobs

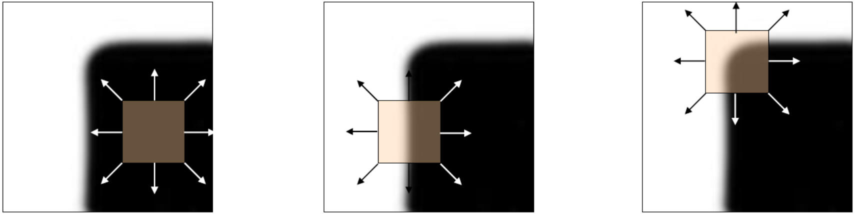
Methods shown in blue will be mainly discussed

Feature Detector

➢ Corner Detection

✓ Key observation: in the region around a corner, the image gradient has multiple dominant directions (e.g., vertical, horizontal, and diagonal).

✓ Shifting a window in any direction should cause large intensity changes around a corner.



"flat" region:
no intensity change
(i.e., $SSD \approx 0$ in all directions)

"edge":
no change along the edge direction
(i.e., $SSD \approx 0$ along edge but $\gg 0$ in other directions)

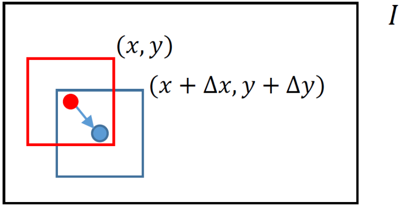
"corner":
significant change in all directions
(i.e., $SSD \gg 0$ in all directions)

Feature Detector

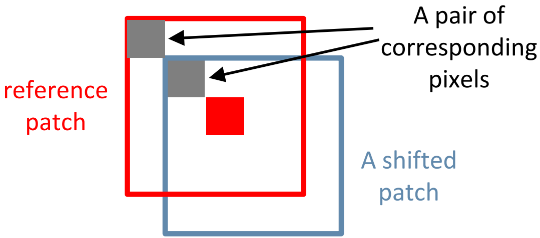
➢ Corner Detection

- ✓ We use Sum of Squared Differences (SSD) to measure the brightness change.
- ✓ Consider the reference patch and a patch **shifted by** $(\Delta x, \Delta y)$. The Sum of Squared Differences between them is

$$SSD(\Delta x, \Delta y) = \sum_{x,y \in \Omega} \left(I(x,y) - I(x + \Delta x, y + \Delta y) \right)^2$$



SSD along the direction along the diagonal



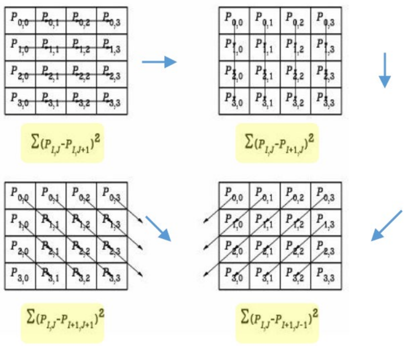
Feature Detector

➢ Corner Detection

✓ Moravec's method

- For two patches, compute the **sum of squared differences** (SSD) between all pairs of corresponding pixels.
- A lower SSD indicates higher similarity between two patches.
- Consider SSD along multiple directions. The **interest measurement** of a patch is defined as the smallest SSD.
- If a patch's interest measurement is higher than a threshold, the patch center is a corner.

✓ We have to physically shift the window. Can we make it more efficient?



Horizontal, vertical, and two diagonals

Feature Detector

➢ Corner Detection

$$f(a) + \frac{f'(a)}{1!}(x-a)$$

The first-order Taylor polynomial

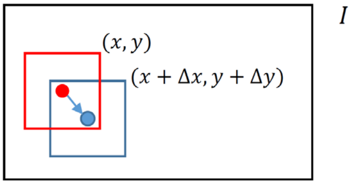
✓ Approximating with a 1st order Taylor expansion (introduced before):

$$SSD(\Delta x, \Delta y) = \sum_{x,y \in \Omega} \left(I(x,y) - I(x+\Delta x, y+\Delta y) \right)^2$$

We no longer minimize SSD but just measure SSD here!

$$I(x+\Delta x, y+\Delta y) \approx I(x,y) + I_x(x,y)\Delta x + I_y(x,y)\Delta y$$

$$\Rightarrow \quad SSD(\Delta x, \Delta y) \approx \sum_{x,y \in \Omega} \left(I_x(x,y)\Delta x + I_y(x,y)\Delta y \right)^2$$



This is a quadratic function in two variables $(\Delta x, \Delta y)$

Feature Detector

➢ Corner Detection

✓ Matrix form of approximation result

$$SSD(\Delta x, \Delta y) \approx \sum_{x,y\in\Omega} \left(I_x(x,y)\Delta x + I_y(x,y)\Delta y \right)^2$$

$$SSD(\Delta x, \Delta y) \approx \sum_{x,y\in\Omega} \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} \begin{bmatrix} I_x{}^2 & I_x I_y \\ I_x I_y & I_y{}^2 \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

$$= \begin{bmatrix} \Delta x & \Delta y \end{bmatrix} \boxed{\begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix}} \begin{bmatrix} \Delta x \\ \Delta y \end{bmatrix}$$

Manually selected

This matrix encodes the SSD change

⇨

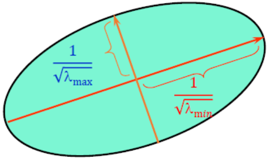
Eigenvalues

$$M = \begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

Eigenvectors

I_x and I_y: Directional derivatives

direction of quickest change of SSD



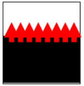
direction of the slowest change of SSD

Feature Detector

➢ Corner Detection

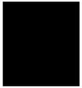
✓ Conclusion

If both eigenvalues are much larger than 0 then we have a corner.



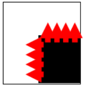
Edge

$$M = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & \lambda_2 \end{bmatrix}$$



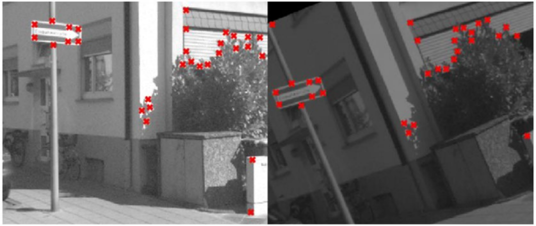
Flat region

$$M = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$



Corner

$$M = \begin{bmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{bmatrix} = \begin{bmatrix} \cos\frac{\pi}{4} & -\sin\frac{\pi}{4} \\ \sin\frac{\pi}{4} & \cos\frac{\pi}{4} \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \begin{bmatrix} \cos\frac{\pi}{4} & \sin\frac{\pi}{4} \\ -\sin\frac{\pi}{4} & \cos\frac{\pi}{4} \end{bmatrix}$$



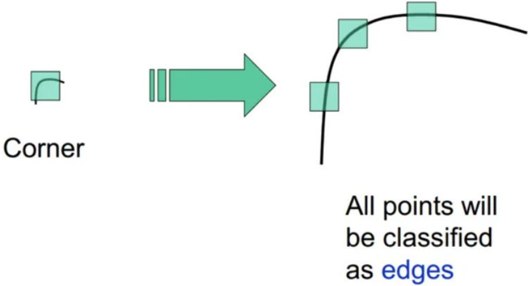
Representative results

Feature Detector

➢ Corner Detection

✓ The above method **without explicitly shifting patch** is called **Harris detector**
✓ The Harris detector is not scale invariant (same patch size is not applicable to different scales of images)

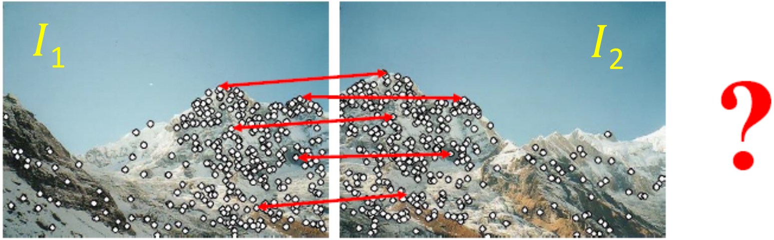
An example: we apply the same window/patch size to two images with different scales



Feature Descriptor

➢ Feature Matching Based on Descriptor

✓ Given a detected point in I_1, how to find the best match in I_2?



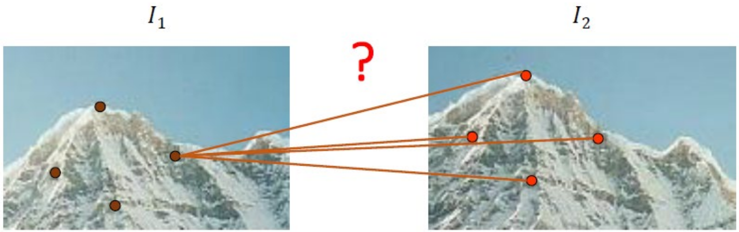
- Define point descriptors, e.g., Census, HOG, ORB , BRIEF , BRISK, FREAK.
- Define distance function that compares two descriptors, e.g., SSD , SAD , NCC or Hamming distance.

Feature Descriptor

➢ Feature Matching Based on Descriptor

✓ A naive matching strategy: Brute force matching

- Here, we assume that detected points, point descriptions are both known.
- Compare each feature in I_1 against all the features in I_2 (N^2 comparisons, where N is the number of features in each image).
- Select the point pair with the minimum distance, i.e., the closest description.



Feature Descriptor

➢ Feature Matching Based on Descriptor

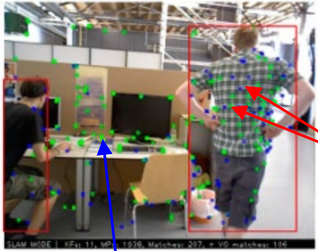
✓ Issue with closest descriptor:

Algorithm can occasionally return good scores for false matches

A solution: compute ratio of distances to 1st to 2nd closest descriptor

$$\frac{d_1}{d_2} < Threshold\ (usually\ 0.8)$$

Distinctive enough



Unreliable points due to repetitive pattern

Distinctive points

where:

d_1 is the distance from the closest descriptor

d_2 is the distance of the 2nd closest descriptor

Feature Descriptor

➢ Distance Function Definition

✓ Similarity measurement (applicable to both 2D and 1D)

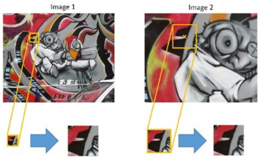
- **Sum of Squared Differences (SSD):** always ≥ 0. It's exactly 0 only if H and F are identical

$$SSD = \sum_{u=-k}^{k} \sum_{v=-k}^{k} \left(H(u,v) - F(u,v) \right)^2$$

H and F denote left and right patches/descriptors respectively

- Sum of Absolute Differences (SAD): always ≥ 0. It's 0 only if H and F are identical

$$SAD = \sum_{u=-k}^{k} \sum_{v=-k}^{k} \left| H(u,v) - F(u,v) \right|$$



2D patches

1D descriptors

Feature Descriptor

➢ Distance Function Definition

✓ Similarity measurement

- Normalized Cross Correlation (NCC): ranges between -1 and +1 and is exactly 1 if H and F are identical

(1,1) and (1,1):
NCC = 1

$$NCC = \frac{\sum_{u=-k}^{k}\sum_{v=-k}^{k} H(u,v)F(u,v)}{\sqrt{\sum_{u=-k}^{k}\sum_{v=-k}^{k} H(u,v)^2}\sqrt{\sum_{u=-k}^{k}\sum_{v=-k}^{k} F(u,v)^2}}$$

(1,1) and (-1,-1):
NCC = -1

- To account for the difference in the average intensity of two images (typically caused by additive illumination changes), we subtract the mean value of each image:

$$\mu_H = \frac{1}{n}\sum_{u=-k}^{k}\sum_{v=-k}^{k} H(u,v) \qquad \mu_F = \frac{1}{n}\sum_{u=-k}^{k}\sum_{v=-k}^{k} F(u,v)$$

$$\Rightarrow \quad ZSSD = \sum_{u=-k}^{k}\sum_{v=-k}^{k}\left(\left(H(u,v)-\boxed{\mu_H}\right)-\left(F(u,v)-\boxed{\mu_F}\right)\right)^2$$

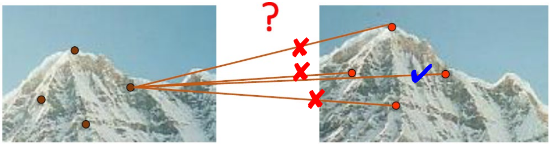
Zero-mean

Feature Descriptor

➢ Properties of Descriptor

✓ Distinctiveness of a feature descriptor

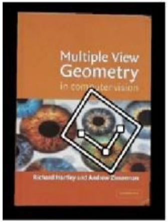
- A descriptor is a “description” of the pixel information **around** a feature.
- “Distinctiveness” means that the descriptor can uniquely distinguish a feature from the other features **without ambiguity**.



Distinctiveness

✓ Robustness to geometric changes

- Scale-invariant (for zooming)
- Rotation-invariant
- View point-invariant (for perspective changes)



Geometric changes

Feature Descriptor

➢ Properties of Descriptor

✓ Robustness to illumination changes

- Small illumination changes are modelled with an affine transformation (so called affine illumination changes) changes:

Intensities

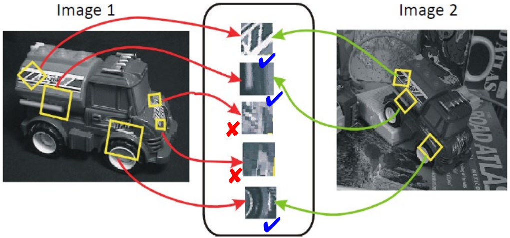
$$I'(x,y) = \alpha I(x,y) + \beta$$

Feature Descriptor

➢ Traditional Method based on Patch Feature

✓ General pipeline

- Determine the scale, rotation and viewpoint change of each patch (introduced later).
- Warp each patch into a canonical patch.
- Establish patch correspondences based on similarity of the warped patch.



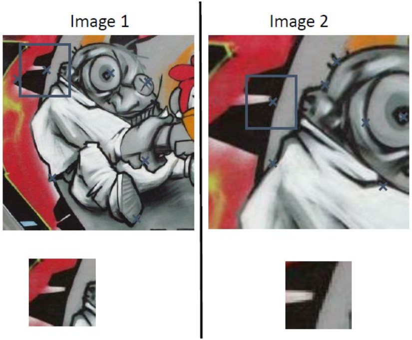
Canonical space

Feature Descriptor

➢ Scale of Descriptor

✓ Problem formulation

Two image patches have the same size, but are in the **images with different scales**. How can we match these patches?



Images with **different scales**

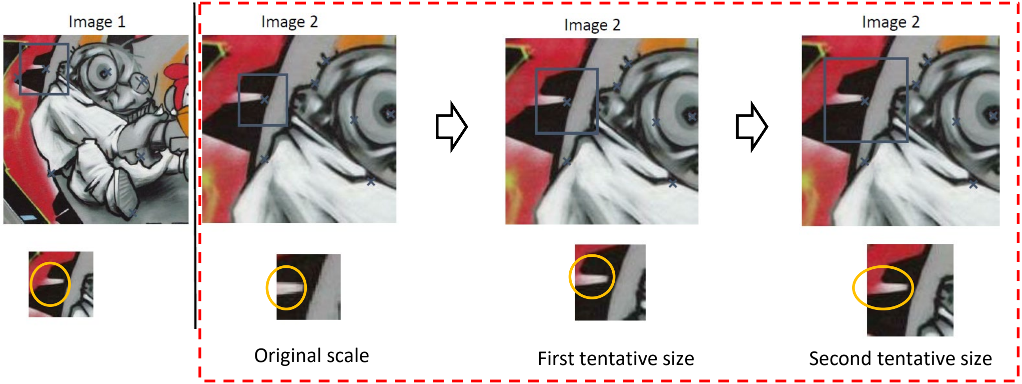
Two patches with **the same size**

Feature Descriptor

➤ Scale of Descriptor

✓ A possible solution

Keep the **left patch unchanged, and resize** the **right patch** with different tentative sizes.

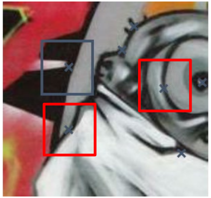


Feature Descriptor

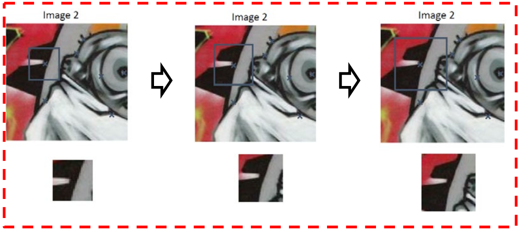
➢ Scale of Descriptor

✓ Patch size search is time-consuming

- We need to individually re-size **all the patches** in the right image.
- Algorithm complexity is N^2S assuming N features per image and S tentative sizes per feature.



N patches



S sizes

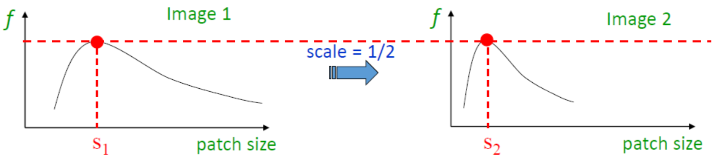
- A better solution of automatic size selection: We aim to "**automatically" assign each patch (both left and right) its own size**.

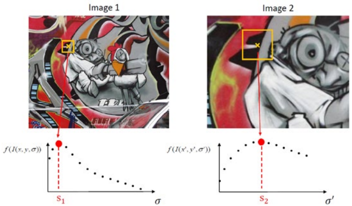
Feature Descriptor

➢ Scale of Descriptor

✓ Overview of automatic size selection

- Core idea: Assign a **function** to the image patch. The **function extremum** is scale invariant.
- Try candidate scales in each image **independently**





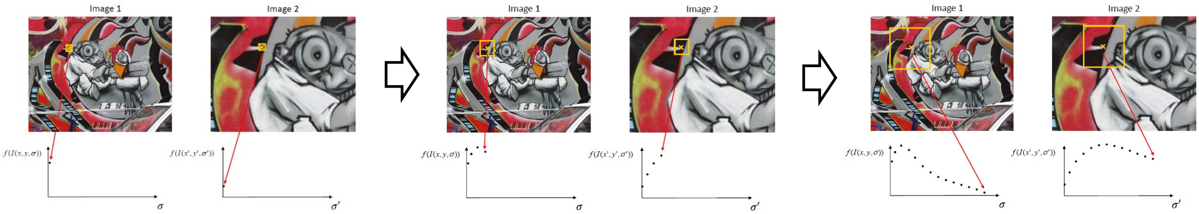
- When the left patch is resized by s_1, and the right patch is resized by s_2, their associated functions both achieve (the same) extremum. s_1 and s_2 are our automatically determined sizes of patches.
- We care about which scale leads to the extremum. The value of extremum is not important.

Feature Descriptor

➢ Scale of Descriptor

✓ An example of automatic scale selection

- Patches with **the same size** correspond to **different function values**.



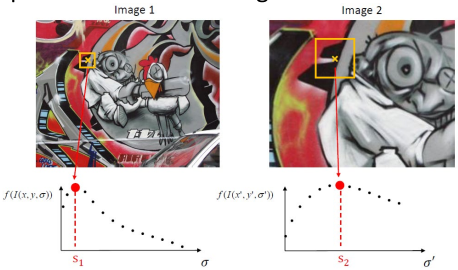
- Intuitively, only if two patches correspond to **the same 3D area**, their associated extreme values of function are the same.

Feature Descriptor

➢ Scale of Descriptor

✓ An example of automatic scale selection

- Two patches with different sizes correspond to the same 3D areas. These two patches lead to the same extreme value of function.
- Note: We determine the scale of a patch in each image **independently**. We try a set of candidate scales for a patch. The scale leading to extremum is the optimal scale.



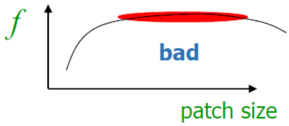
What scale-invariant function should we assign to patch?

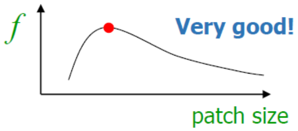
Feature Descriptor

- Scale of Descriptor

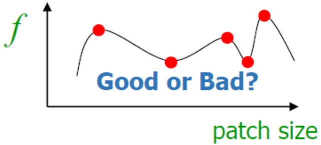
✓ Function properties

- A "good" function for scale detection should have a single & sharp peak
- **Sharp intensity changes** are good regions to monitor in order to identify the scale





- In our context, for ease of understanding, we do not consider a more complex case (multiple extrema)



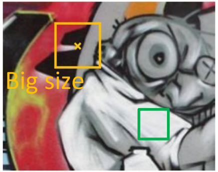
Feature Descriptor

➢ Scale of Descriptor

Image 1

Discontinuity

Image 2



Smoothness

✓ Function selection

- Intuitively, a human can identify the scale (patch sizes) by comparing the areas with sharp brightness discontinuities. (we can easily identify the same 3D area at different scales)
- Therefore, the ideal **function** for determining the scale should be able to highlight sharp discontinuities.
- Solution: convolve image patch with a kernel that highlights edges

$$f = \text{Kernel} * \text{Image}$$

Scale invariant Function

A patch

Feature Descriptor

➢ Scale of Descriptor

✓ Function selection

- Recap on Laplace operator

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$
$$= [f(x+1,y) + f(x-1,y)$$
$$+ f(x,y+1) + f(x,y-1)] - 4f(x,y)$$

Laplace operator

200	200	200
200	50	200
200	200	200

$*$

0	1	0
1	-4	1
0	1	0

$=$

	600	

Convolution

Apply **Laplace operator** to a pixel

Laplace operator highlights the pixels with sharp intensity discontinuity (e.g., edge pixels)

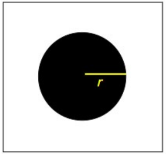
Feature Descriptor

➢ Scale of Descriptor

✓ Function selection

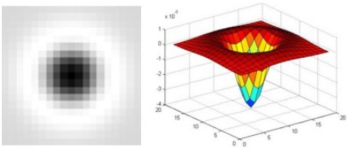
- Extension to the blob

It has been shown that the Laplacian of Gaussian kernel is optimal under certain assumptions [1]



image

A circular blob



Laplacian

- The Laplacian of Gaussian is a circularly symmetric filter defined as:

$$LoG(x,y,\sigma)=\nabla^2 G_\sigma(x,y)=\frac{\partial^2 G_\sigma(x,y)}{\partial x^2}+\frac{\partial^2 G_\sigma(x,y)}{\partial y^2}$$

∇^2 is the Laplacian operator: $\nabla^2=\frac{\partial^2}{\partial x^2}+\frac{\partial^2}{\partial y^2}$

[1] Lindeberg, Scale-space theory: A basic tool for analysing structures at different scales, Journal of Applied Statistics, 1994

Feature Descriptor

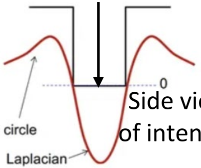
➢ Scale of Descriptor

✓ Function selection

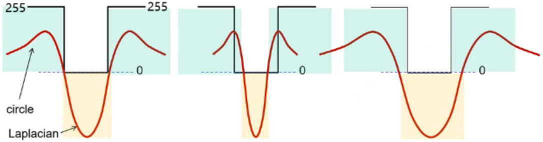
At **what scale** does the **Laplacian** achieve a maximum response (extremum) to **a binary circle of radius r**?

- To get the maximum response, the Laplacian has to be aligned to the circle.
- The maximum response occurs at $\sigma = r / \sqrt{2}.$
- A simplified but not general case with known circle. Generally, we have to test a set of candidate scales.

Circle pixels with low intensity (fixed)



Laplacian of Gaussian (LoG)
with **adjustable** "width" (scale) σ



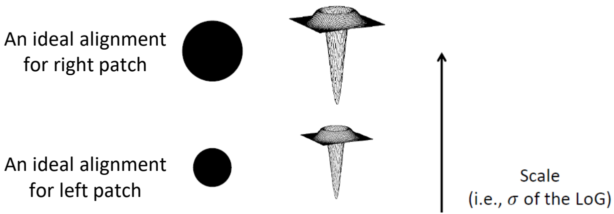
Largest response

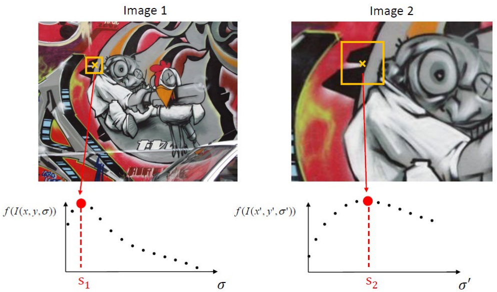
Feature Descriptor

➢ Scale of Descriptor

✓ Scale determination

- An ideal alignment between blob and LoG leads to a extrema
- The correct scale is found at the local extremum



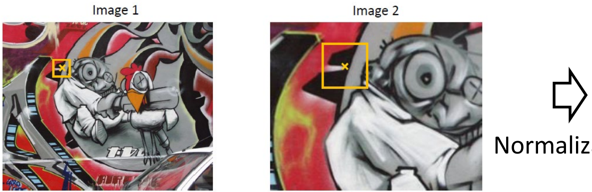


Feature Descriptor

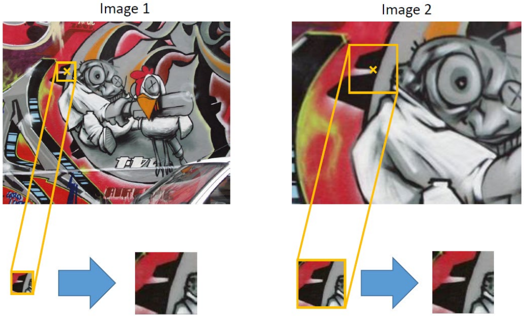
➢ Scale of Descriptor

✓ Post-processing

When the right scale is found, the patches must be normalized to a canonical size so that they can be compared by SSD. Patch normalization is done via warping.



Normalization



Feature Descriptor

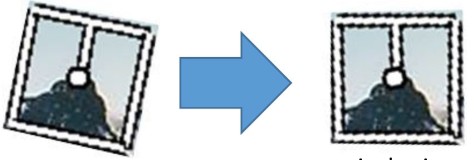
➢ Rotation of Descriptor

✓ Determining patch orientation

Eigenvectors of M matrix of Harris (introduced before) or dominant gradient direction (see next slide)

✓ Back-rotating patch through “patch warping”

This step puts the patches back into a **canonical orientation**



canonical orientation

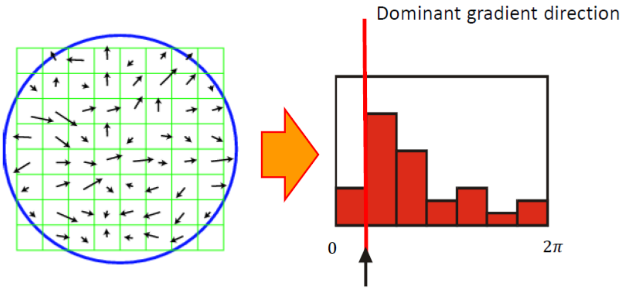
Feature Descriptor

➢ Rotation of Descriptor

✓ A general pipeline to express patch orientation

- Compute gradients vectors **at each pixel** within a patch
- Build a histogram of gradient orientations, weighted by the gradient magnitudes (norm of vector).
- Extract all local maxima in the histogram: each local maximum above a threshold is a candidate dominant orientation.

One patch with multiple pixels



Feature Descriptor

➢ Viewpoint of Descriptor

✓ Affine warping provides invariance to small view-point changes

- The second moment **matrix M** of the Harris detector can be used to identify the two directions of fastest and slowest change of SSD around the feature
- Out of these two directions, an ellipse-shaped patch is extracted
- The region inside the ellipse is **normalized** to a canonical **circular patch**

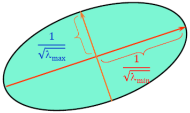
Eigenvalues

$$M = \begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

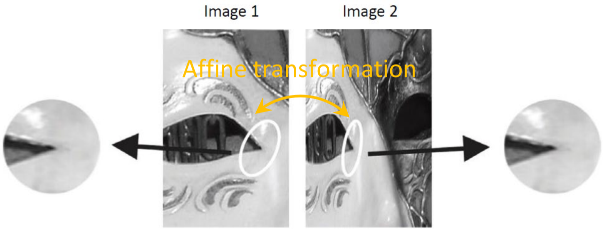
Eigenvectors

I_x and I_y: Directional derivatives

direction of quickest change of SSD



direction of the slowest change of SSD

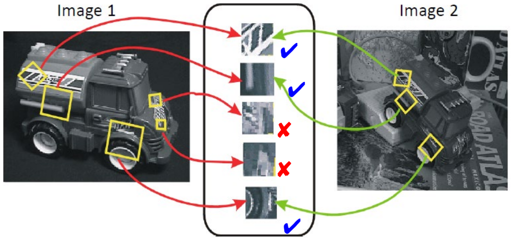


Feature Descriptor

➢ Summary

✓ Scale, rotation, and affine-invariant patch matching

1. Scale assignment: compute the scale using the LoG operator. (scale-invariant)
2. Rotation assignment: use Harris or gradient histogram to find dominant orientation. (rotation-invariant)
3. View point transformation: use Harris eigenvectors to extract affine transformation parameters. (view point-invariant)
4. Warp the patch into a canonical patch



Feature Descriptor

➢ Disadvantages of Patch Feature-based Method

✓ If the warping is not estimated accurately, very small errors in rotation, scale, and view point will affect matching score (e.g., SSD of patch features).

Is there a better strategy without directly using patch feature? Census feature (introduced in the next class).

Summary

- Overview of Indirect Method
- Point Detector
- Point Descriptor

Thank you for your listening!

If you have any questions, please come to me :-)