

# Lecture 6 & 7

## Matching, Alignment, and Mosaicing

Yonghao Lee

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# 1 Part I: Feature Detection and Matching

## 1.1 The Matching Pipeline

To align images (e.g., for panoramas) or recognize objects, we follow a standard pipeline:

1. **Detection:** Find interesting points (keypoints) in the image.
2. **Description:** Build a descriptor (fingerprint) for each point.
3. **Matching:** Find corresponding pairs between images.
4. **Alignment:** Use these pairs to align images (e.g., compute Homography).

A good descriptor must be **Invariant** (to rotation, scale, lighting) and **Distinctive** (unique enough to match correctly).

## 1.2 Feature Descriptors

### 1.2.1 MOPS (Multi-Scale Oriented Patches)

MOPS is a simpler descriptor that uses raw pixel intensities.

- **Detection:** Uses Multi-scale Harris Corners.
- **Scale Invariance:** Extracts regions from a blurred image pyramid at scale  $s$ .
- **Rotation Invariance:** Detects the dominant orientation ( $\theta$ ) and rotates the patch to align with it.
- **The Descriptor:**
  1. Extract a  $40 \times 40$  pixel patch centered at the keypoint.
  2. Downsample it to a tiny  $8 \times 8$  patch (low resolution).
  3. **Intensity Normalization:** Normalize pixels ( $I' = \frac{I - \mu}{\sigma}$ ) to handle lighting changes.

### 1.2.2 SIFT (Scale-Invariant Feature Transform)

SIFT is a robust descriptor based on gradient statistics.

- **Detection:** Uses Difference of Gaussians (DoG) extrema to find  $(x, y, s)$ .
- **Canonical Orientation:** Computes a gradient direction histogram. The peak determines orientation.
- **The Descriptor:**
  1. Take a  $16 \times 16$  region around the keypoint.
  2. Divide into a  $4 \times 4$  grid of sub-regions.
  3. Compute a histogram of gradients with **8 bins** for each sub-region.
  4. **Dimensionality:**  $4 \times 4 \times 8 = 128$  dimensions.
- **Illumination:** Normalized to unit length; values  $> 0.2$  are clipped to handle glare.

### 1.3 Matching Strategy

**The Ratio Test (Lowe's Ratio):** To reject ambiguous matches, compare the distance to the nearest neighbor (1-NN) vs. the second nearest neighbor (2-NN).

$$\text{Ratio} = \frac{\text{Distance}(1\text{-NN})}{\text{Distance}(2\text{-NN})} < \text{Threshold} \quad (1)$$

### 1.4 RANSAC (Robust Model Fitting)

Standard Least Squares fails when outliers (wrong matches) are present. RANSAC is an iterative method to ignore outliers.

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**Algorithm 1** RANSAC Algorithm

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- 1: **repeat**
  - 2:   **Sample:** Randomly select  $s$  points (min required for model).
  - 3:   **Model:** Solve for parameters using these  $s$  points.
  - 4:   **Score:** Count Inliers (points fitting this model within threshold  $\delta$ ).
  - 5: **until** Max Iterations reached
  - 6: **Refine:** Re-compute model using Least Squares on **all inliers** of the best model.
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## 2 Part II: Image Alignment and Mosaicing

### 2.1 Motion Models

To stitch images, we must define the mathematical relationship between them.

- **Translation (2 DOF):** Shifting coordinates ( $x' = x + t_x$ ). Only valid for flat scenes perpendicular to the camera.
- **Affine (6 DOF):** Includes translation, rotation, scale, and shear. Preserves parallelism.
- **Homography (8 DOF):** The most general planar transformation. Maps straight lines to straight lines but does not preserve parallelism (creates perspective convergence).

### 2.2 Homography on Points vs. Lines

A Homography  $H$  maps points from one view to another.

- **Points:** A point  $x$  transforms via matrix multiplication:

$$x' = Hx \quad (2)$$

- **Lines:** A line  $l$  is defined such that  $l^T x = 0$ . If points transform by  $H$ , the line must transform differently to maintain orthogonality. The transformation is the **Inverse Transpose**:

$$l' = H^{-T} l \quad (3)$$

### 2.3 Building Panoramas

To build a panorama, we rotate a camera around its optical center.

- **Pure Rotation:** If the camera center does not move, there is no parallax. The relationship between any two images is a Homography.
- **Planar Projection:** Warping images onto a flat plane works for small angles but causes massive distortion ("explosion") as the Field of View (FOV) approaches 90°.
- **Cylindrical Projection:** For 360° panoramas, we project images onto a cylinder.
  - Straight lines in the world become curved (conic sections) on the cylinder.
  - Alignment becomes a simple translation in the cylindrical coordinate space (images just slide sideways).

### 2.4 Video Mosaicing (Strip Mosaicing)

Instead of stitching full photos, we can use video to create panoramas.

- **Method:** Cut a narrow vertical strip from the center of each video frame and paste them together.
- **Why center strips?** The center of the lens has the least distortion.
- **Manifold Projection:** This effectively creates a "pushbroom" camera view.
- **Stereo Mosaicing:** If the camera rotates off-axis (not around the center), parallax is introduced. We can create two panoramas:
  - Left-looking strips → Left eye view.
  - Right-looking strips → Right eye view.

### 3 Part III: Compositing and Seam Finding

Once images are aligned, they must be blended to hide the transition.

#### 3.1 The Problems

- **Exposure Differences:** One image is brighter than the other.
- **Misalignment:** Slight errors in Homography calculation.
- **Ghosting:** Moving objects (e.g., a person walking) appear in both images, creating semi-transparent ghosts.

#### 3.2 Approach A: Blending (Smoothing)

Blending attempts to smooth the transition region.

1. **Alpha Blending (Feathering):** A weighted average where the weight  $\alpha$  transitions linearly from 1 to 0 across the overlap.

$$I_{final} = \alpha I_{left} + (1 - \alpha) I_{right} \quad (4)$$

*Drawback:* Can cause blurring if alignment is imperfect.

2. **Pyramid Blending:** Decomposes the image into frequency bands (Laplacian Pyramid).

- **Low Frequencies (Color/Lighting):** Blended over a wide range.
- **High Frequencies (Details/Edges):** Blended over a very narrow range.

This preserves sharp details while smoothing out exposure differences.

#### 3.3 Approach B: Optimal Seam Finding (Cutting)

For moving objects, blending causes ghosting. The solution is to find a jagged **cut** that avoids the moving object entirely. Ideally, the cut passes through regions where the two images are identical.

##### 3.3.1 Dynamic Programming

Finds a seam from top to bottom by minimizing a cumulative cost function.

- **Cost Calculation:**  $E(i, j) = (I_1(i, j) - I_2(i, j))^2 + \min(\text{neighbors from row above})$ .
- **Process:** Forward pass to calculate costs, Backward pass to trace the optimal path.
- **Limitation:** Can only handle simple paths (cannot loop back or handle complex shapes).

##### 3.3.2 Graph Cuts (Min-Cut / Max-Flow)

A more robust method that treats the image as a graph.

- **Nodes:** Pixels in the overlap region.
- **Terminals:** Source ( $S$ ) represents Image A; Sink ( $T$ ) represents Image B.
- **Edge Weights:** Represent the "cost" of cutting between pixels.
  - High difference ( $|I_A - I_B|$  is large)  $\rightarrow$  High weight (Hard to cut).

- Low difference (Identical pixels) → Low weight (Easy to cut).
- **Min-Cut Theorem:** The minimum cut in the graph corresponds to the optimal seam that separates Image A from Image B while passing through the pixels with the least visual difference. This effectively routes the seam *around* moving objects.