



Advanced Computer Vision

Week 08

Oct. 25, 2022

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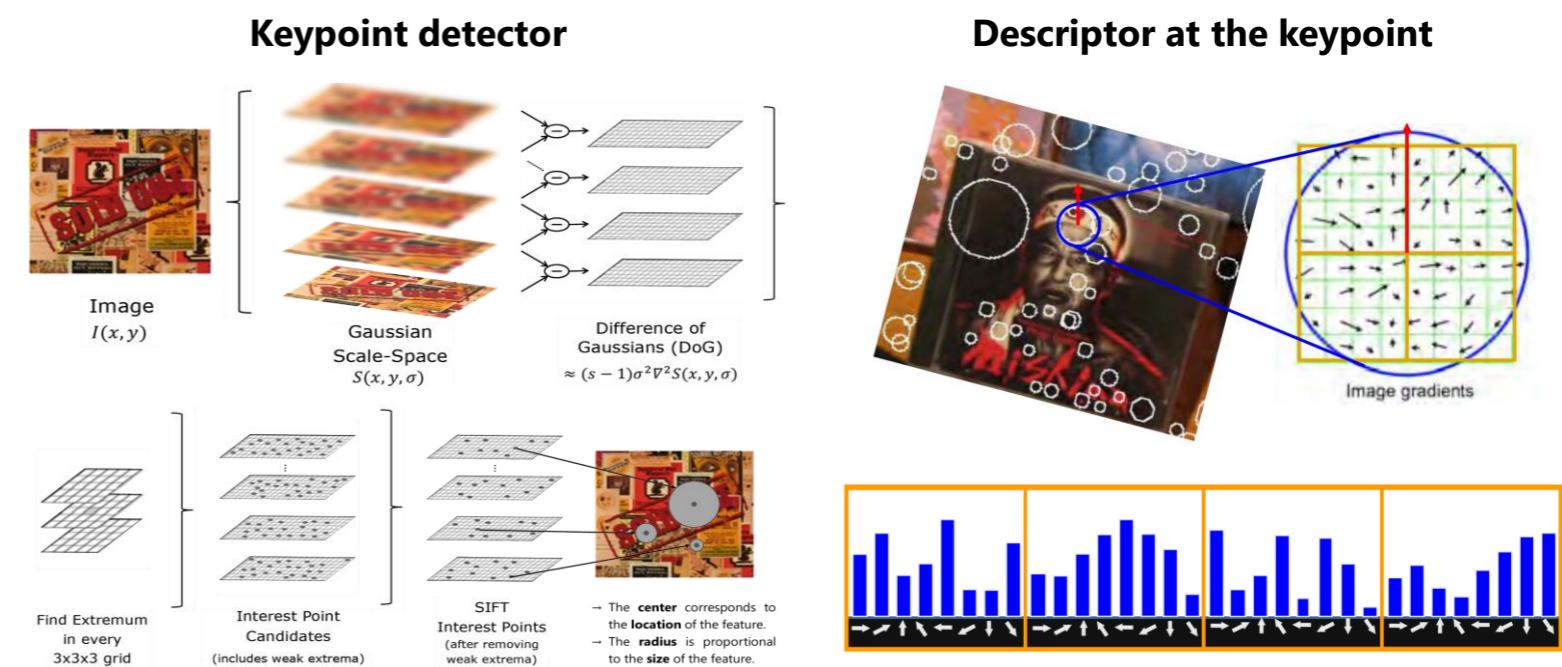
SIFT Algorithm

Scale Invariant Feature Transform (SIFT)

and its applications for image alignment and 2D object recognition.

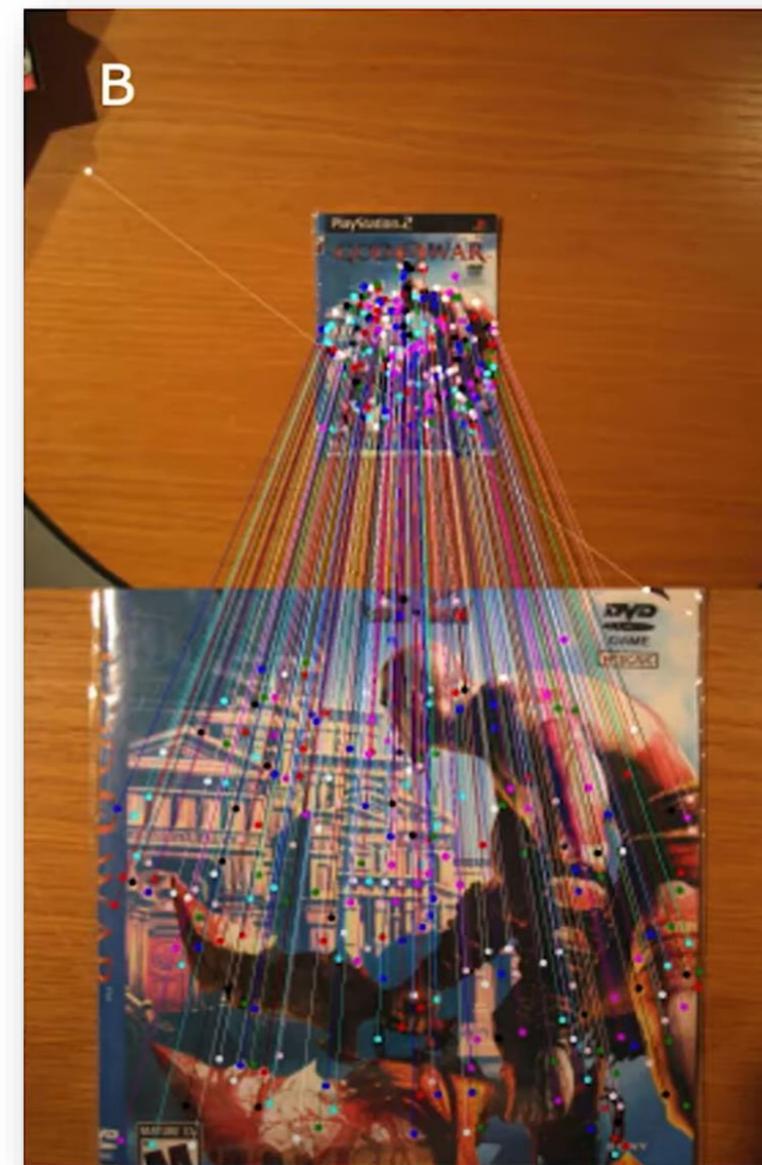
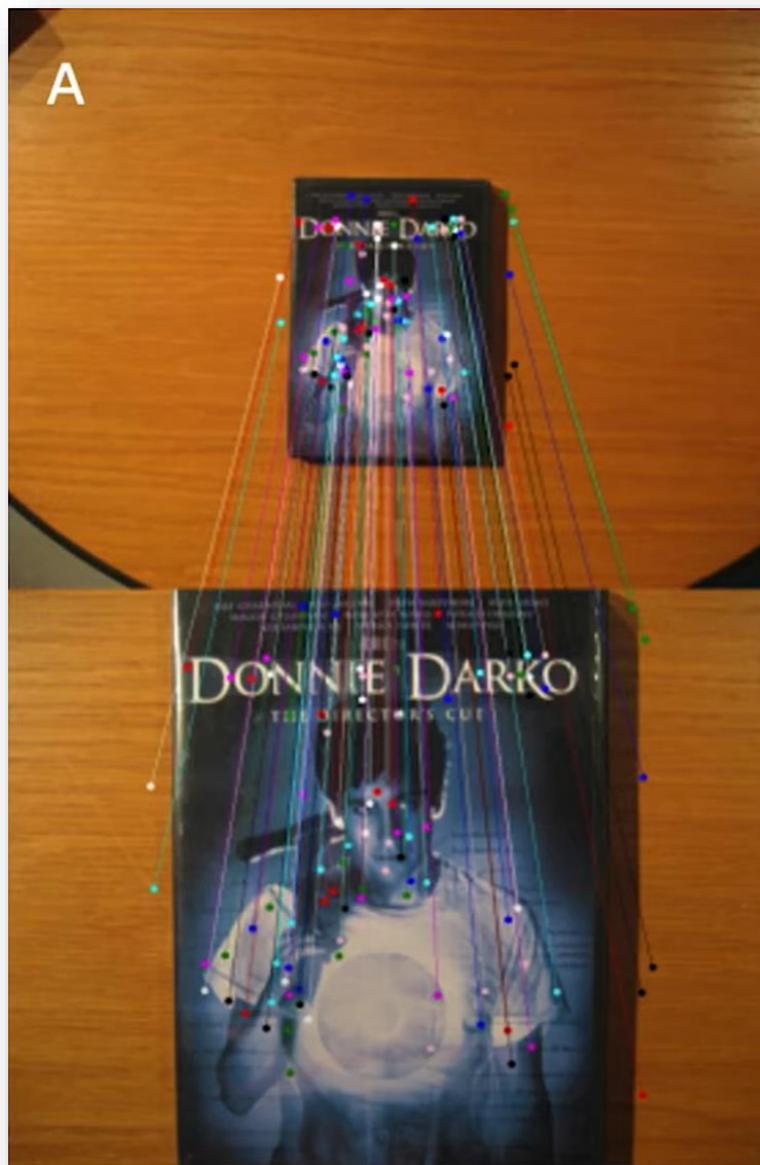
Topics:

- (1) What is an Interest Point?
- (2) Detecting Blobs
- (3) SIFT Detector
- (4) SIFT Descriptor

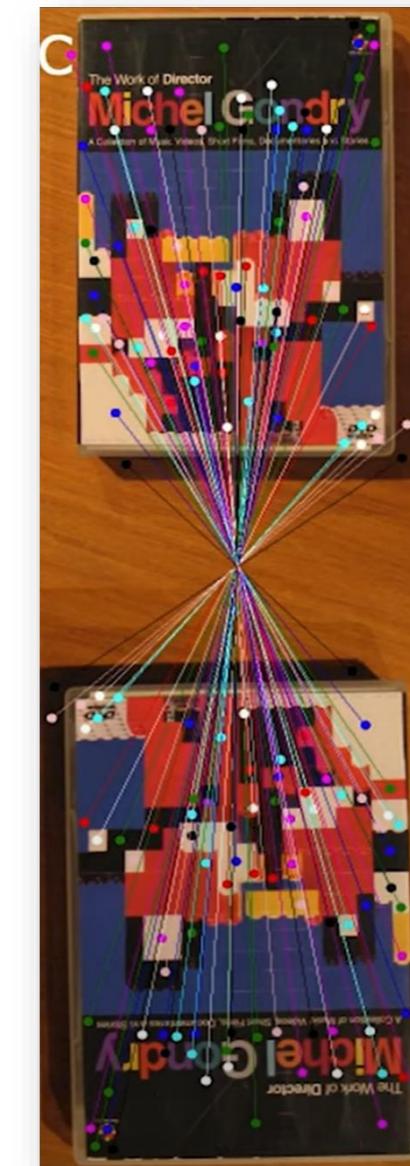
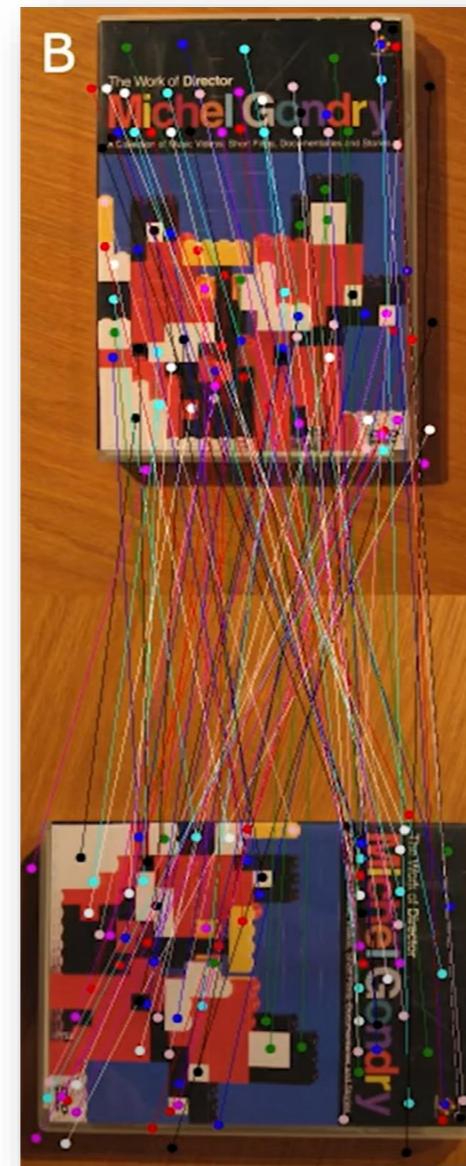
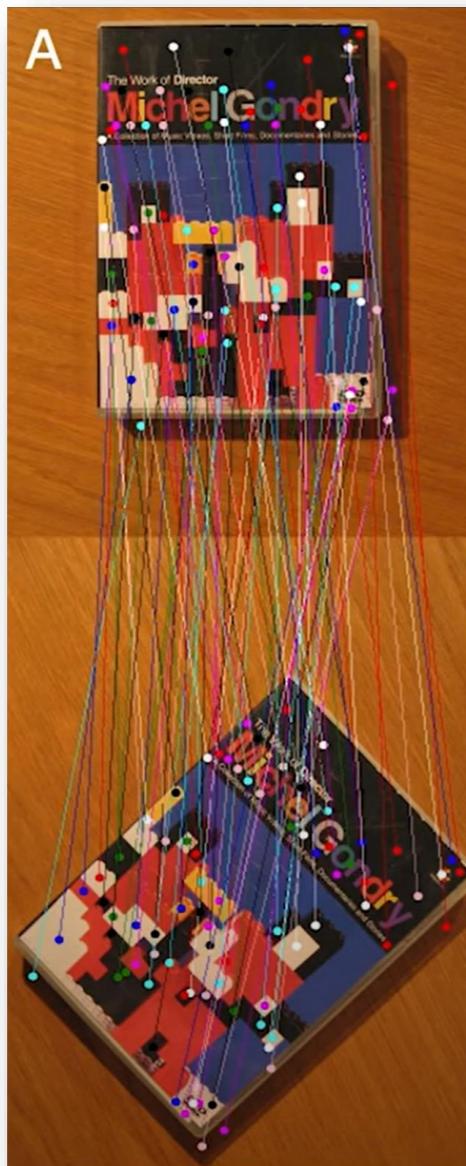


Experiment 1: SIFT Matching

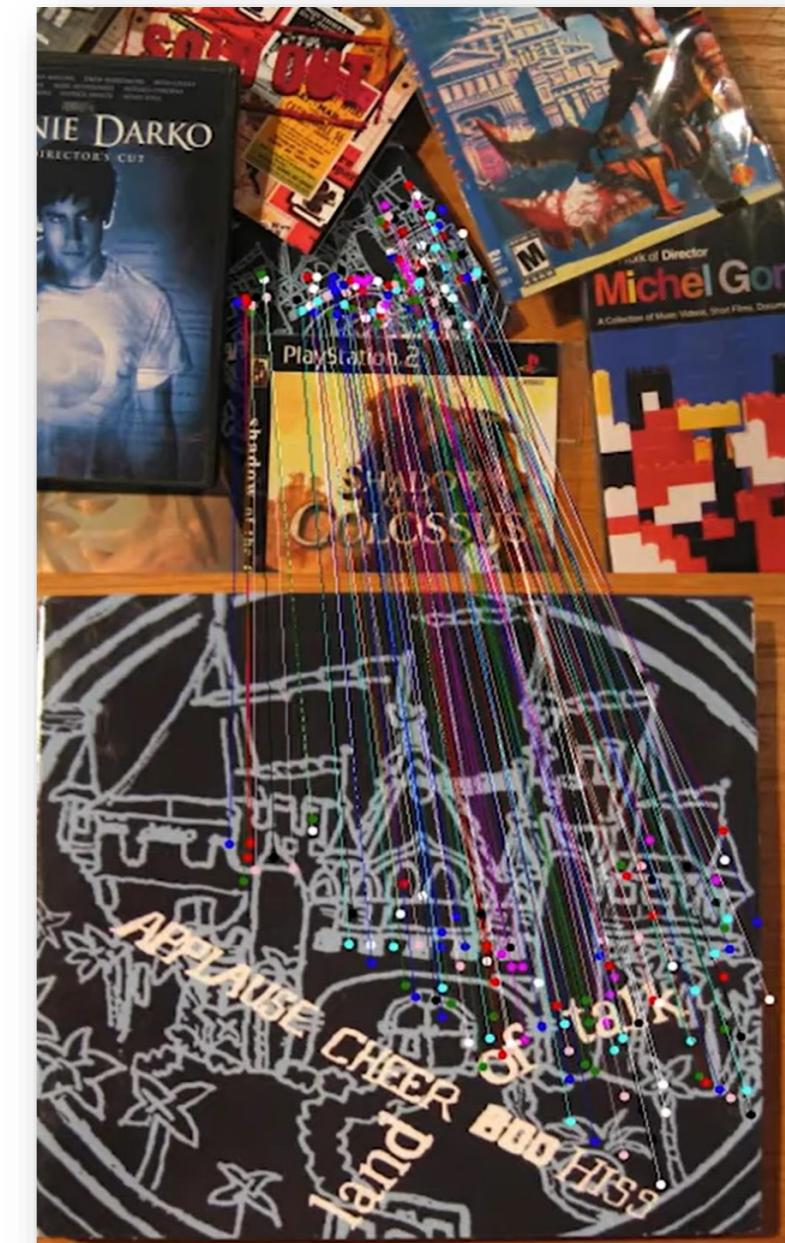
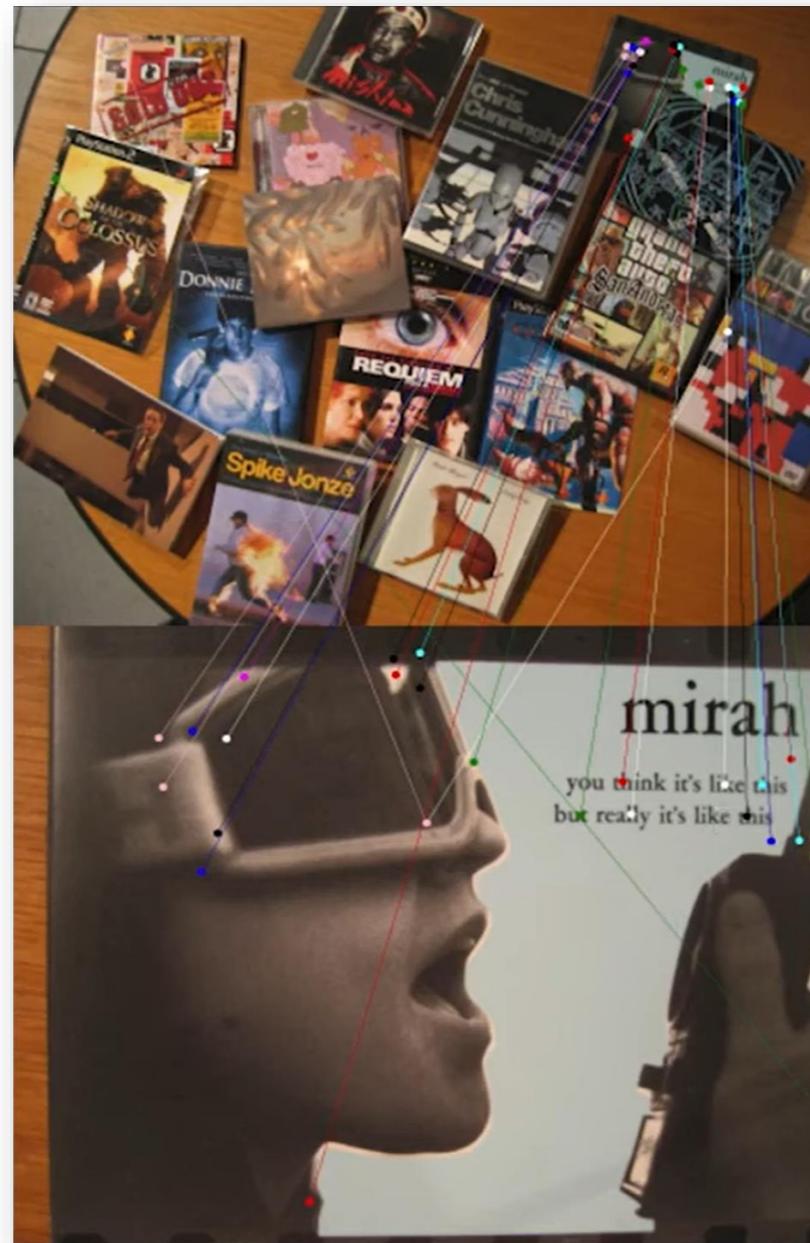
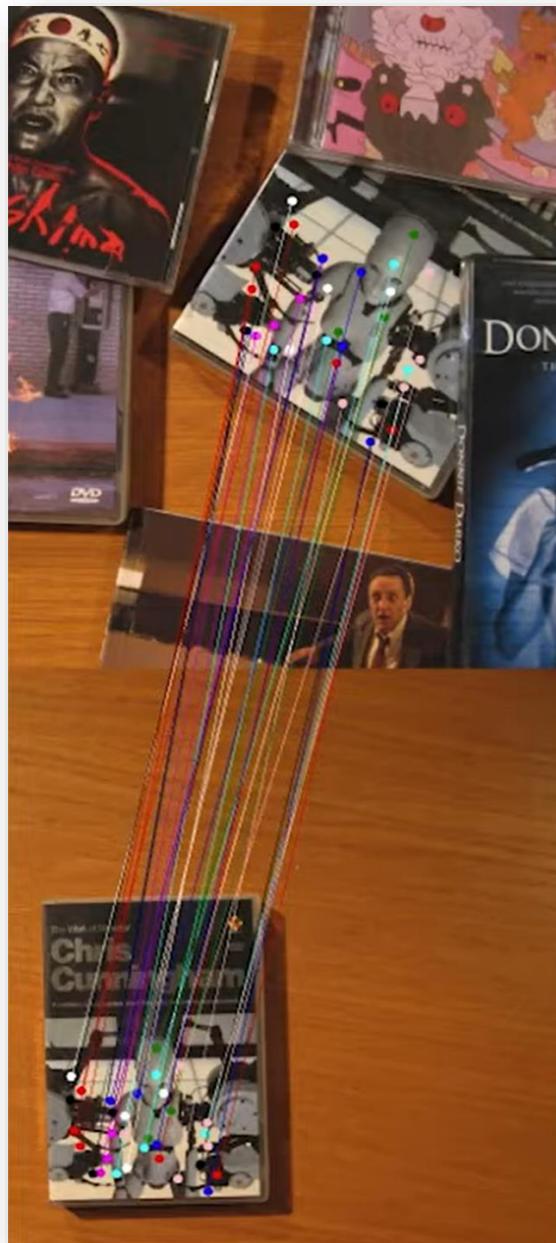
SIFT Results: Scale Invariance



SIFT Results: Rotation Invariance

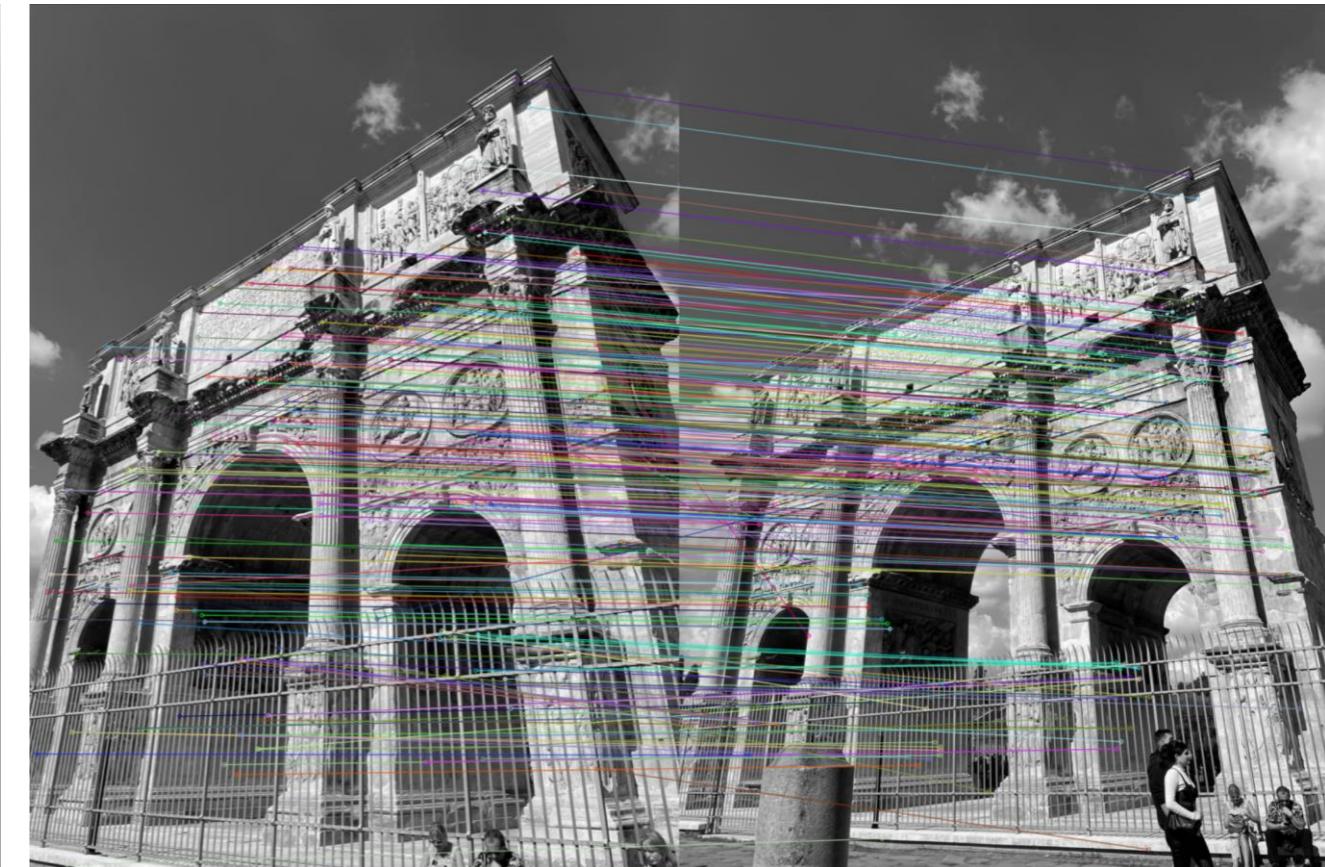


SIFT Results: Robust to Clutter



Experiment 1: SIFT Matching with Different Motions and Image Transformations

<https://view.kentech.ac.kr/f088fa7f-874e-44bc-bd6d-6084b42dfdf7>



How to Handle Outliers?





RANSAC

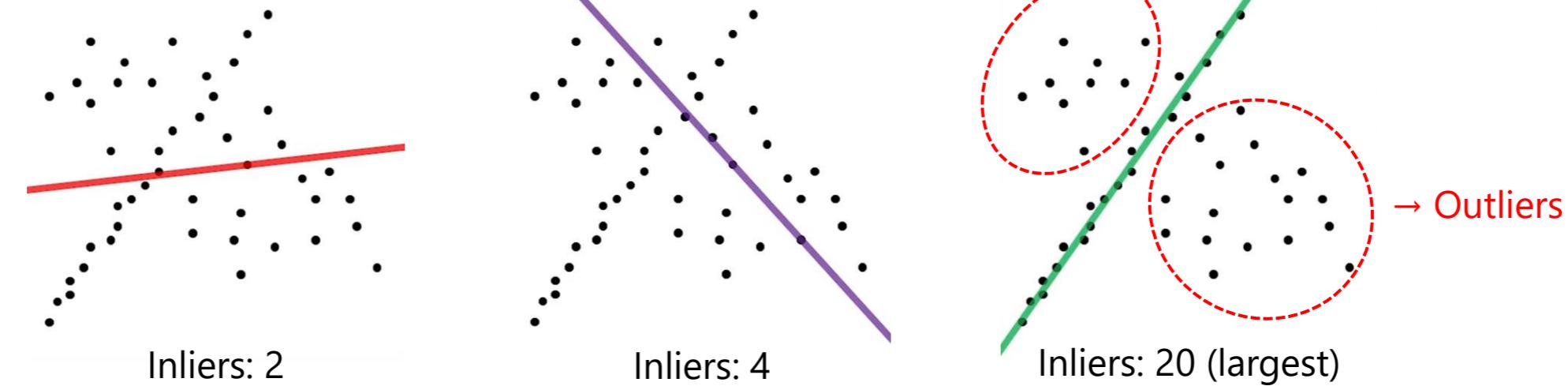


RANdom SAmple Consensus

General RANSAC Algorithm :

1. Randomly choose s samples. Typically s is the minimum samples to fit a model.
2. Fit the model to the randomly chosen samples.
3. Count the number M of data points (inliers) that fit the model within a measure of error ϵ .
4. Repeat Steps 1-3 N times.
5. Choose the model that has the largest number M of inliers.

ex) Line fitting :



Experiment 2: Image Stitching

Experiment 2: Panorama Stitching Using SIFT + RANSAC



Image 1



Image 2



Match SIFT interest points.

Experiment 2: Panorama Stitching Using SIFT + RANSAC

Warp and combine images to create a larger image.

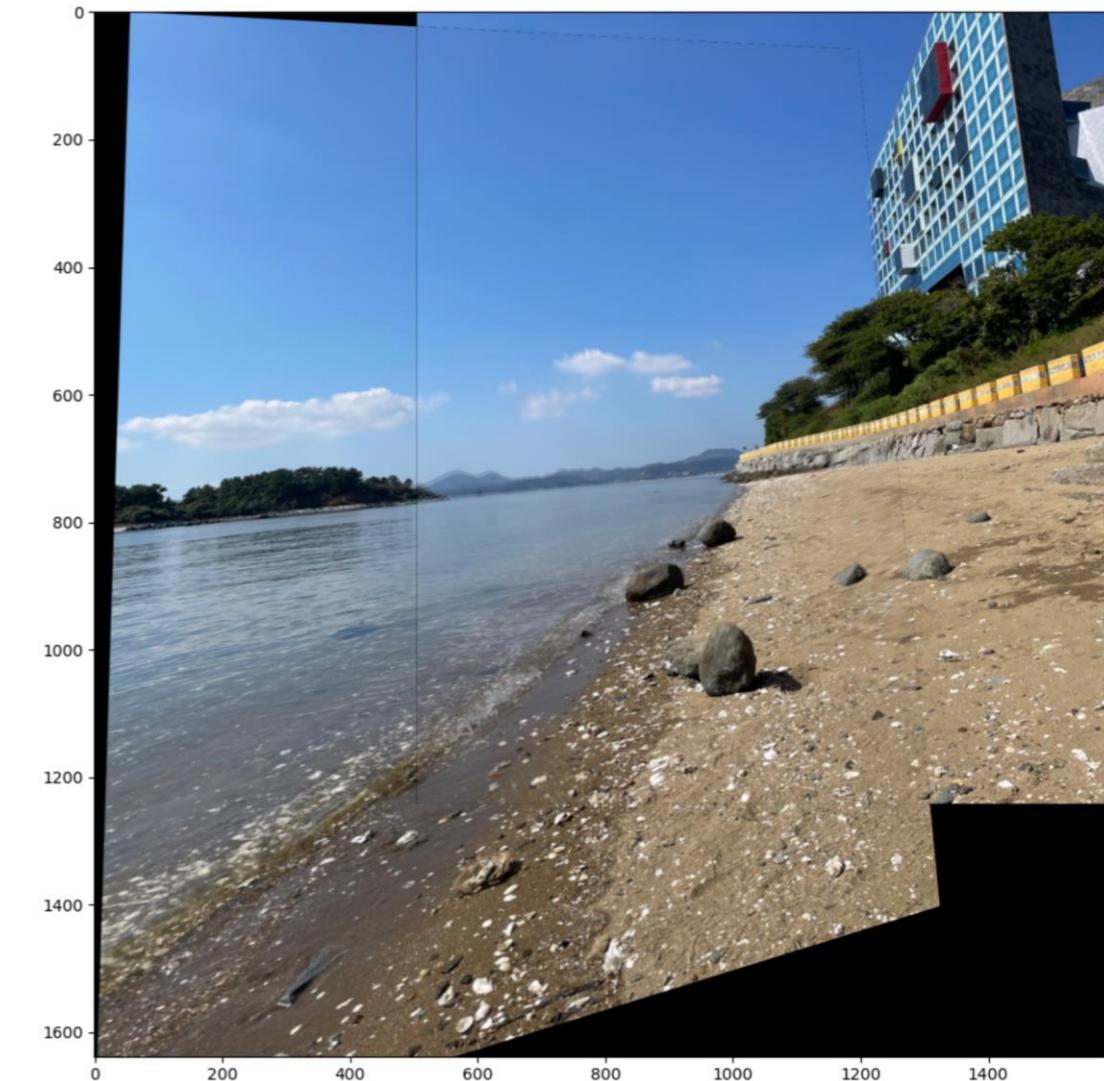


Experiment 2: Panorama Stitching Using SIFT + RANSAC

→ Output results

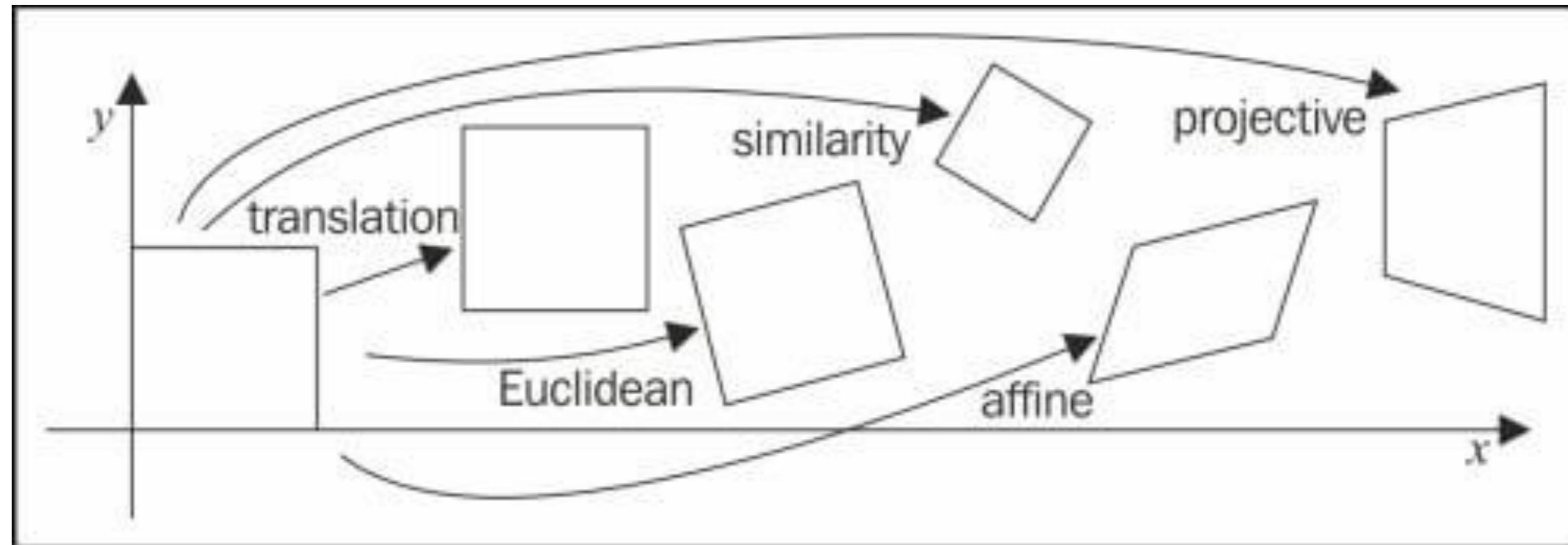


Matching result after SIFT matching + RANSAC



Warping result

Review: Homography



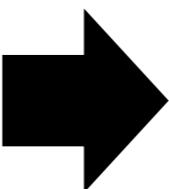
Review: Homography

- Any projective transformation of the form:

$$\begin{bmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \tilde{z}_1 \end{bmatrix}$$

Also called **Homography**

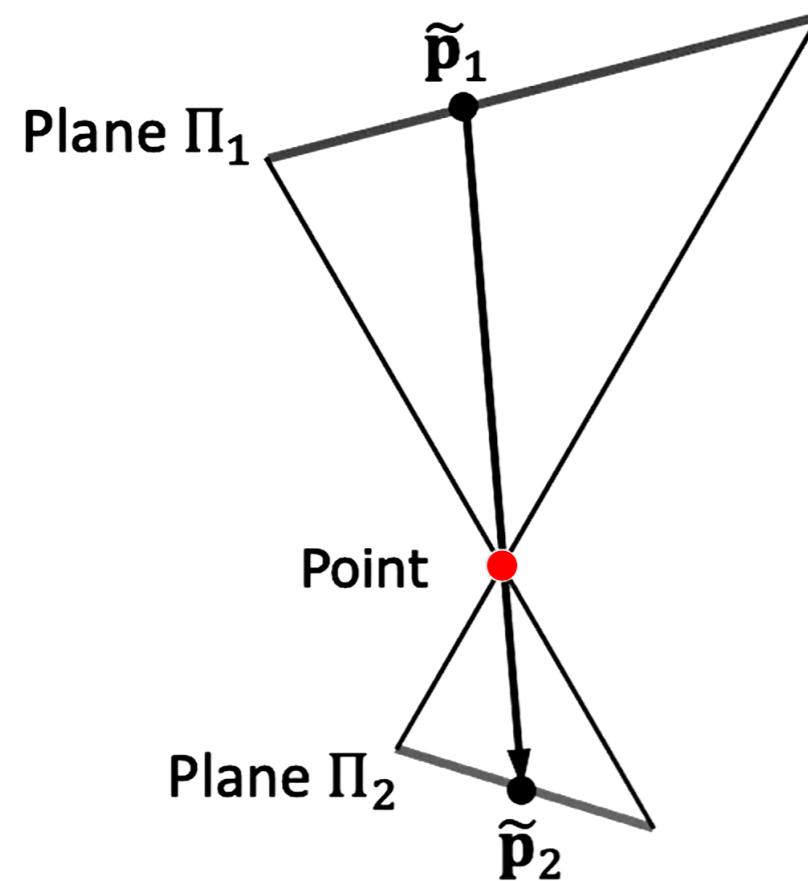
$$\tilde{\mathbf{p}}_2 = H\tilde{\mathbf{p}}_1$$



Review: Homography

- Mapping of one plane to another through a point.

$$\tilde{\mathbf{p}}_2 = H\tilde{\mathbf{p}}_1$$

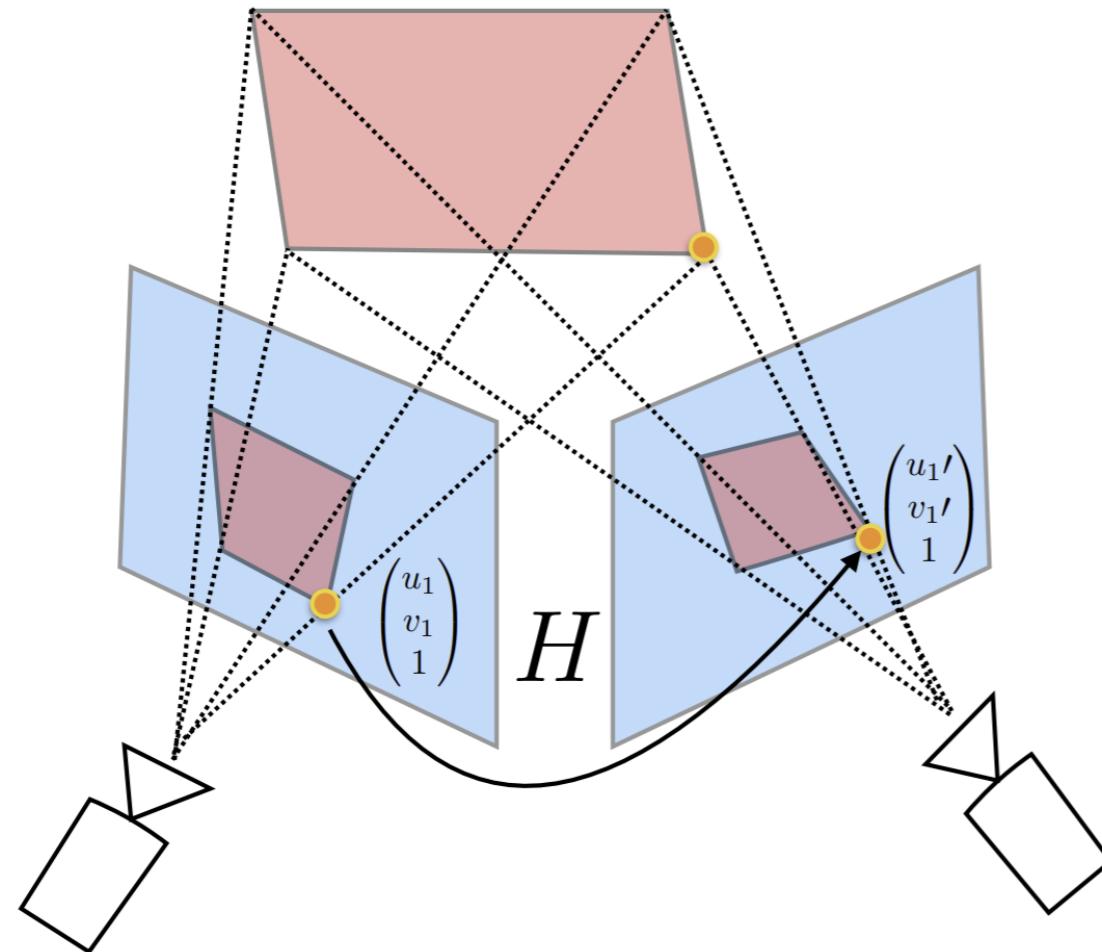


$$\begin{bmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \tilde{z}_1 \end{bmatrix}$$

Same as **imaging** a **plane** through a **pinhole**

- Origin does not necessarily map to the origin
- Lines map to lines
- Parallel lines do not necessarily remain parallel
- Closed under composition

Finding Homography with Given 4 points Correspondence



$$H_{4point} = \begin{pmatrix} \Delta u_1 & \Delta v_1 \\ \Delta u_2 & \Delta v_2 \\ \Delta u_3 & \Delta v_3 \\ \Delta u_4 & \Delta v_4 \end{pmatrix}$$

↑
1-to-1 mapping
↓

$$H_{matrix} = \begin{pmatrix} H_{11} & H_{12} & H_{13} \\ H_{21} & H_{22} & H_{23} \\ H_{31} & H_{32} & H_{33} \end{pmatrix}$$

Finding Homography with Given 4 points Correspondence

$$H_{projective} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & 1 \end{bmatrix} \rightarrow \begin{bmatrix} x'_i \\ y'_i \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & 1 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} \rightarrow \begin{cases} x'_i = \frac{ax_i + by_i + c}{gx_i + hy_i + 1} \\ y'_i = \frac{dx_i + ey_i + f}{gx_i + hy_i + 1} \end{cases}$$

→ Solve for \mathbf{p} , if $A\mathbf{p} = 0$ → Least square method (**LSM**) or singular value decomposition (**SVD**)

$$\begin{array}{l} \xrightarrow{\quad} \begin{cases} x'_i(gx_i + hy_i + 1) = ax_i + by_i + c \\ y'_i(gx_i + hy_i + 1) = dx_i + ey_i + f \end{cases} \xrightarrow{\quad} \begin{bmatrix} x_i & y_i & 1 & 0 & 0 & 0 & -x'_i x_i & -x'_i y_i & -x'_i \\ 0 & 0 & 0 & x_i & y_i & 1 & -y'_i x_i & -y'_i y_i & -y'_i \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\ \left[\begin{array}{c} a \\ b \\ c \\ d \\ e \\ f \\ g \\ h \\ 1 \end{array} \right] \end{array}$$

$$\begin{array}{l} \xrightarrow{\quad} \begin{cases} x'_i(gx_i + hy_i + 1) = ax_i + by_i + c \\ y'_i(gx_i + hy_i + 1) = dx_i + ey_i + f \end{cases} \end{array}$$

→ In $H_{projective}$, the **last** entry is defined only up to scales (**8-DoF**) → A 2D point has **2-DoF** to (x, y) components and each point-to-point **correspondence** accounts for **two constraints**. This is the reason why we need **4 points correspondences** for finding the homography.

[1] D. DeTone, et al., "Deep Image Homography Estimation", 2016.

[2] <https://ai.stackexchange.com/questions/21042/how-do-you-find-the-homography-matrix-given-4-points-in-both-images>

Python Codes

<https://view.kentech.ac.kr/f088fa7f-874e-44bc-bd6d-6084b42dfdf7>

- Homography

```
def homography(pairs):  
    rows = []  
    for i in range(pairs.shape[0]):  
        p1 = np.append(pairs[i][0:2], 1)  
        p2 = np.append(pairs[i][2:4], 1)  
        row1 = [0, 0, 0, p1[0], p1[1], p1[2],  
                -p2[1]*p1[0], -p2[1]*p1[1], -p2[1]*p1[2]]  
        row2 = [p1[0], p1[1], p1[2], 0, 0, 0,  
                -p2[0]*p1[0], -p2[0]*p1[1], -p2[0]*p1[2]]  
        rows.append(row1)  
        rows.append(row2)  
    rows = np.array(rows)  
    U, s, V = np.linalg.svd(rows)  
  
    H = V[-1].reshape(3, 3)  
    H = H/H[2, 2]  
    return H
```

- RANSAC

```
def ransac(matches, threshold, iters):  
    num_best_inliers = 0  
  
    for i in range(iters):  
        points = random_point(matches)  
        H = homography(points) # candidate  
  
        if np.linalg.matrix_rank(H) < 3:  
            continue # Avoid dividing by zero.  
  
        errors = get_error(matches, H)  
        idx = np.where(errors < threshold)[0]  
        inliers = matches[idx]  
  
        num_inliers = len(inliers)  
        if num_inliers > num_best_inliers:  
            best_inliers = inliers.copy()  
            num_best_inliers = num_inliers  
            best_H = H.copy()  
  
    return best_inliers, best_H
```