## Exercise May 19: Geometric Transform of Image

Align multiple images. Then, Generate a "stitched" image from the aligned multiple images.

- 1. Take a series of interesting overlapping photos. (more than 3 images, >3)
- 2. Detect feature points from the images and match the feature points. You can use a library function, such as AKAZE, SIFT, ORB, supergru, etc.
- 3. Assign a unique index i to each track. Then you can have  $\{x_i, y_i\}$  for N feature points for the series of input images.
- 4. Estimate a transform for each image **using the linear solution**. **Try every transform: translation, similarity, and affine** as the motion model.
- 4'. For perspective transform (homography), use OpenCV function, or other ways. example: cv2.getPerspectiveTransform
- 5. Compute the size of the resulting composite canvas.
- 6. Warp each image into its final position on the canvas. cv2.warpPerspective
- 7. Average all of the images.

# 1. Take a series of interesting overlapping photos































# 2. Detect feature points from the images and match the feature points.

You can use a library function, such as AKAZE, SIFT, ORB, etc.

**AKAZE** <a href="https://docs.opencv.org/3.4/db/d70/tutorial\_akaze\_matching.html">https://docs.opencv.org/3.4/db/d70/tutorial\_akaze\_matching.html</a>

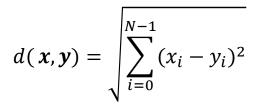
ORB <a href="https://docs.opencv.org/4.x/d1/d89/tutorial\_py\_orb.html">https://docs.opencv.org/4.x/d1/d89/tutorial\_py\_orb.html</a>

**SUPERPOINT** https://github.com/rpautrat/SuperPoint

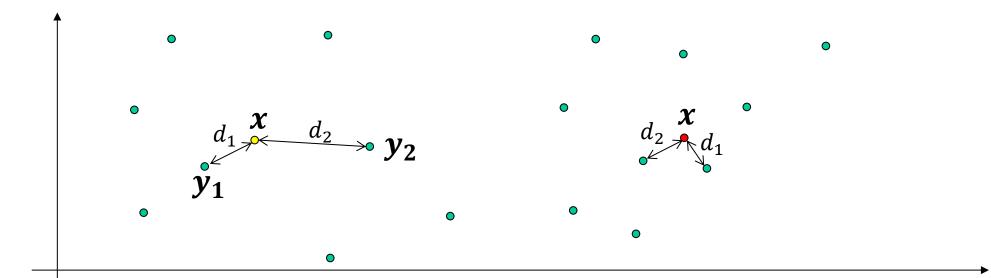
https://github.com/magicleap/SuperPointPretrainedNetwork



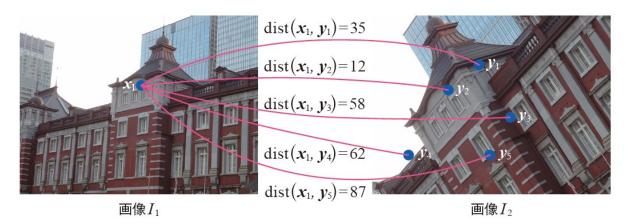
## Matching strategy and error rates



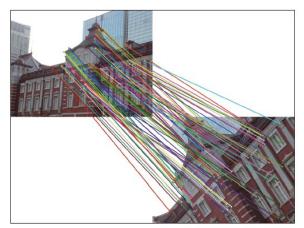
the feature descriptor space (*N* dim)



Nearest Neighbor Distances Ratio NNDR= $\frac{d_1}{d_2} < k$ 

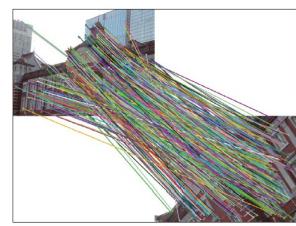


#### ■図11.21――対応点の探索



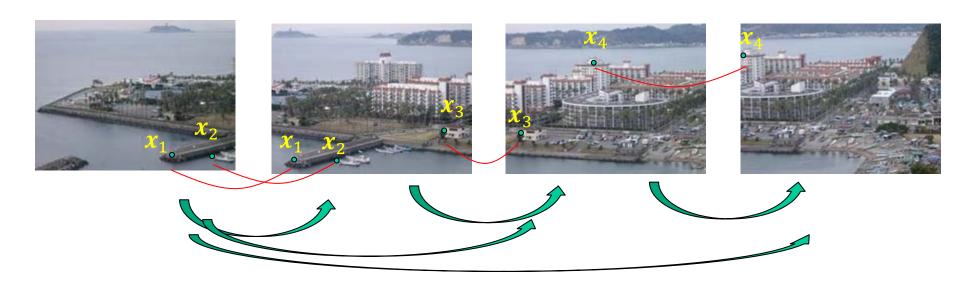
[a] k=0.25 の場合の対応づけ結果

■図 11.22 ----2 画像間の対応点とマッチング



[b] k=0.8の場合の対応づけ結果

3. Assign a unique index i to each track. Then you can have  $\{x_i, y_i\}$  for N feature points for the series of input images.

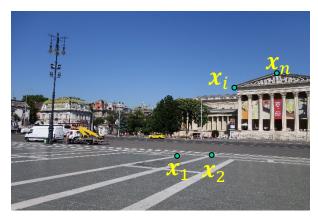


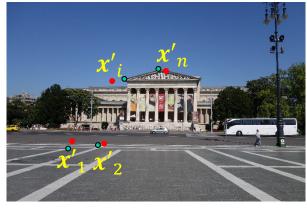
4. Estimate a transform for each image using the linear solution.

Transform	Matrix <b>V</b>
translation	$\begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \end{bmatrix}$
Euclidean	$\begin{bmatrix} c_{\theta} & -s_{\theta} & t_x \\ s_{\theta} & c_{\theta} & t_y \end{bmatrix}$
similarity	$\begin{bmatrix} 1+a & -b & t_x \\ b & 1+a & t_y \end{bmatrix}$
affine	$\begin{bmatrix} 1 + a_{00} & a_{01} & t_x \\ a_{10} & 1 + a_{11} & t_y \end{bmatrix}$
Homography projective	$\begin{bmatrix} 1 + h_{00} & h_{01} & h_{02} \\ h_{10} & 1 + h_{11} & h_{12} \\ h_{20} & h_{21} & 1 \end{bmatrix}$

## 2D alignment using least squares (LS)

Given a set of matched feature points  $\{(\boldsymbol{x}_i, \boldsymbol{x}_i')\}$ 





$$oldsymbol{x}' = oldsymbol{f}(oldsymbol{x}; oldsymbol{p})$$

$$\mathbf{x}' = f(\mathbf{x}; \mathbf{p})$$

Estimate p by minimizing the sum of squared residuals:  $E_{LS}$ 

$$E_{LS} = \sum_{i} ||r_{i}||^{2} = \sum_{i} ||f(x_{i}; p) - x_{i}'||^{2}$$

Predicted location by transformation model p

measurement

## Matched Feature Points $\{(x_i, x'_i)\}_1^N$

If we can assume a linear relationship between the amount of motion  $\Delta x = x' - x$  and the unknown parameters p

$$x' = f(x; p) = \left(\frac{\partial f(x; p)}{\partial p}\right) p + x = J(x) p + x$$
Jacobian

$$x' - x = \Delta x = J(x)p$$

$$\sum_{i} \|J(x_i)\mathbf{p} - \Delta x_i\|^2 \to 0$$

$$E_{LLS} = \sum_{i} ||J(x_i)p - \Delta x_i||^2$$

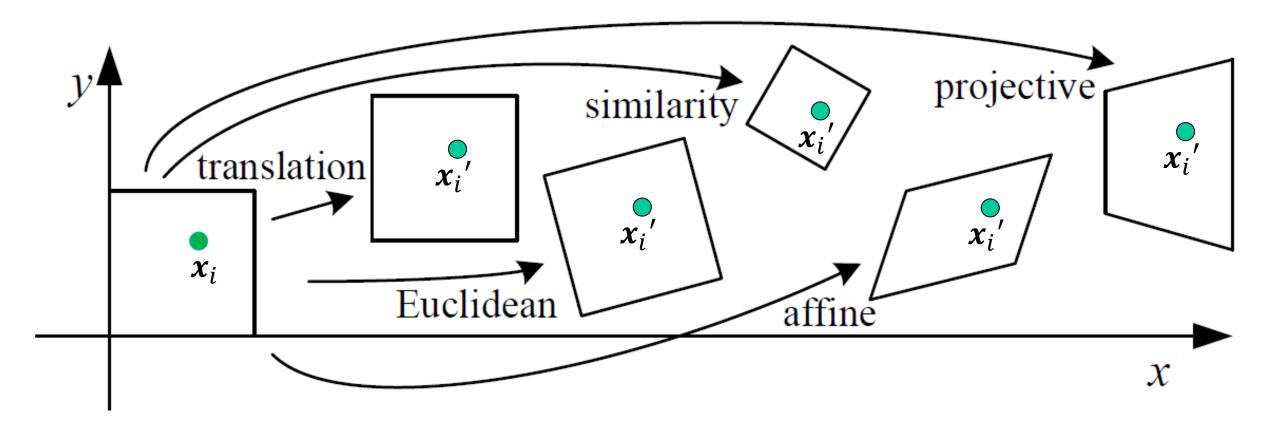
$$= p^T \left[ \sum_{i} J^T(x_i) J(x_i) \right] p - 2p^T \left[ \sum_{i} J^T(x_i) \Delta x_i \right] + \sum_{i} ||\Delta x_i||^2$$

$$= p^T Ap - 2p^T b + c$$
LLS: linear least squares

Minimum  $E_{LLS}$  can be found by solving symmetric positive definite (SPD) system :

$$A\mathbf{p} = \mathbf{b}$$
  $A = \sum_{i} J^{T}(x_{i})J(x_{i})$   $\mathbf{b} = \sum_{i} J^{T}(x_{i})\Delta x_{i}$ 

## Matched Feature Points $\{(x_i, x'_i)\}_1^N$



## Jacobians of the 2D coordinate transformations

Transform	Matrix	Parameters p	Jacobian J
translation	$\begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \end{bmatrix}$	$(t_x,t_y)$	$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$
Euclidean	$\begin{bmatrix} c_{\theta} & -s_{\theta} & t_x \\ s_{\theta} & c_{\theta} & t_y \end{bmatrix}$	$(t_x,t_y,\theta)$	$\begin{bmatrix} 1 & 0 & -s_{\theta}x - c_{\theta}y \\ 0 & 1 & c_{\theta}x - s_{\theta}y \end{bmatrix}$
similarity	$\begin{bmatrix} 1+a & -b & t_x \\ b & 1+a & t_y \end{bmatrix}$	$(t_x, t_y, a, b)$	$\begin{bmatrix} 1 & 0 & x & -y \\ 0 & 1 & y & x \end{bmatrix}$
affine	$\begin{bmatrix} 1 + a_{00} & a_{01} & t_x \\ a_{10} & 1 + a_{11} & t_y \end{bmatrix}$	$(t_x, t_y, a_{00}, a_{01}, a_{10}, a_{11})$	$\begin{bmatrix} 1 & 0 & x & y & 0 & 0 \\ 0 & 1 & 0 & 0 & x & y \end{bmatrix}$
projective	$\begin{bmatrix} 1 + h_{00} & h_{01} & h_{02} \\ h_{10} & 1 + h_{11} & h_{12} \\ h_{20} & h_{21} & 1 \end{bmatrix}$	$(h_{00}, h_{01}, \dots, h_{21})$	(see Section 8.1.3)

re-parameterized the motions so that they are identity I for p = 0.

### Jacobians of the 2D coordinate transformations

#### **Translation**

$$f(x; \mathbf{p}) = f\left(\begin{bmatrix} x \\ y \end{bmatrix}; \begin{bmatrix} t_x \\ t_y \end{bmatrix}\right) = \begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}, \qquad J = \frac{\partial f}{\partial \mathbf{p}} = \begin{bmatrix} \frac{\partial x}{\partial \mathbf{p}} \\ \frac{\partial y'}{\partial \mathbf{p}} \end{bmatrix} = \begin{bmatrix} \frac{\partial x}{\partial t_x} & \frac{\partial x}{\partial t_y} \\ \frac{\partial y'}{\partial t_x} & \frac{\partial y'}{\partial t_y} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

### **Similarity**

$$f(x; \mathbf{p}) = f\left(\begin{bmatrix} x \\ y \end{bmatrix}; \begin{bmatrix} t_x \\ t_y \\ a \\ b \end{bmatrix}\right) = \begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1+a & -b & t_x \\ b & 1+a & t_y \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}, \qquad J = \frac{\partial f}{\partial \mathbf{p}} = \begin{bmatrix} \frac{\partial x'}{\partial \mathbf{p}} \\ \frac{\partial y'}{\partial \mathbf{p}} \end{bmatrix} = \begin{bmatrix} \frac{\partial x'}{\partial t_x} & \frac{\partial x'}{\partial t_y} & \frac{\partial x'}{\partial a} & \frac{\partial x'}{\partial b} \\ \frac{\partial y'}{\partial t_x} & \frac{\partial y'}{\partial t_y} & \frac{\partial y'}{\partial a} & \frac{\partial y'}{\partial b} \end{bmatrix} = \begin{bmatrix} 1 & 0 & x & -y \\ 0 & 1 & y & x \end{bmatrix}$$

### **Affine**

$$f(x; \mathbf{p}) = f\left(\begin{bmatrix} x \\ y \end{bmatrix}; \begin{bmatrix} t_x \\ t_y \\ a_{00} \\ a_{01} \\ a_{10} \end{bmatrix}\right) = \begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 + a_{00} & a_{01} & t_x \\ a_{10} & 1 + a_{11} & t_y \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \mathbf{J} = \frac{\partial f}{\partial \mathbf{p}} = \begin{bmatrix} \frac{\partial x'}{\partial \mathbf{p}} \\ \frac{\partial y'}{\partial \mathbf{p}} \end{bmatrix} = \begin{bmatrix} \frac{\partial x'}{\partial t_y} & \frac{\partial x'}{\partial a_{00}} & \frac{\partial x'}{\partial a_{01}} & \frac{\partial x'}{\partial a_{10}} & \frac{\partial x'}{\partial a_{11}} \\ \frac{\partial y'}{\partial t_x} & \frac{\partial y'}{\partial t_y} & \frac{\partial y'}{\partial a_{00}} & \frac{\partial y'}{\partial a_{01}} & \frac{\partial y'}{\partial a_{10}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & x & y & 0 & 0 \\ 0 & 1 & 0 & 0 & x & y \end{bmatrix}$$

## Motion Alignment in Translation Case

Matched Feature Points 
$$\{(\boldsymbol{x}_i, \boldsymbol{x'}_i)\}_1^N = \left\{ \begin{pmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix}, \begin{bmatrix} x_i' \\ y_i' \end{bmatrix} \right\}_1^N$$
  $\{\Delta \boldsymbol{x}_i\}_1^N = \left\{ \begin{bmatrix} x_i' - x_i \\ y_i' - y_i \end{bmatrix} \right\}_1^N$ 

$$A = \sum_{i} J^{T}(x_{i})J(x_{i})$$

$$A = \sum_{i=1}^{N} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} N & 0 \\ 0 & N \end{bmatrix}$$

$$\boldsymbol{b} = \sum_{i} \boldsymbol{J}^{T}(\boldsymbol{x}_{i}) \Delta \boldsymbol{x}_{i}$$

$$\boldsymbol{b} = \sum_{i=1}^{N} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_i' - x_i \\ y_i' - y_i \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{N} (x_i' - x_i) \\ \sum_{i=1}^{N} (y_i' - y_i) \end{bmatrix}$$

$$Ap = b$$

$$\begin{bmatrix} N & 0 \\ 0 & N \end{bmatrix} \begin{bmatrix} t_x \\ t_y \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{N} (x_i' - x_i) \\ \sum_{i=1}^{N} (y_i' - y_i) \end{bmatrix}$$

## Motion Alignment in similarity transform

Matched Feature Points 
$$\{(\boldsymbol{x}_i, \boldsymbol{x'}_i)\}_1^N = \left\{ \begin{pmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix}, \begin{bmatrix} x_i' \\ y_i' \end{bmatrix} \right\}_1^N$$
  $\{\Delta \boldsymbol{x}_i\}_1^N = \left\{ \begin{bmatrix} \Delta x_i \\ \Delta y_i \end{bmatrix} \right\}_1^N = \left\{ \begin{bmatrix} x_i' - x_i \\ y_i' - y_i \end{bmatrix} \right\}_1^N$ 

$$\mathbf{A} = \sum_{i=1}^{N} \begin{bmatrix} 1 & 0 & x_i & -y_i \\ 0 & 1 & y_i & x_i \\ x_i & y_i & x_i^2 + y_i^2 & 0 \\ -y_i & x_i & 0 & x_i^2 + y_i^2 \end{bmatrix}$$

$$A = \sum_{i=1}^{N} \begin{bmatrix} 1 & 0 & x_{i} & -y_{i} \\ 0 & 1 & y_{i} & x_{i} \\ x_{i} & y_{i} & x_{i}^{2} + y_{i}^{2} & 0 \\ -y_{i} & x_{i} & 0 & x_{i}^{2} + y_{i}^{2} \end{bmatrix}$$

$$b = \sum_{i=1}^{N} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ x_{i} & -y_{i} \\ y_{i} & x_{i} \end{bmatrix} \begin{bmatrix} \Delta x_{i} \\ \Delta y_{i} \end{bmatrix} = \sum_{i=1}^{N} \begin{bmatrix} \Delta x_{i} \\ \Delta y_{i} \\ y_{i} \Delta x_{i} - y_{i} \Delta y_{i} \end{bmatrix}$$

赤のところの符号が逆?

$$Ap = b$$

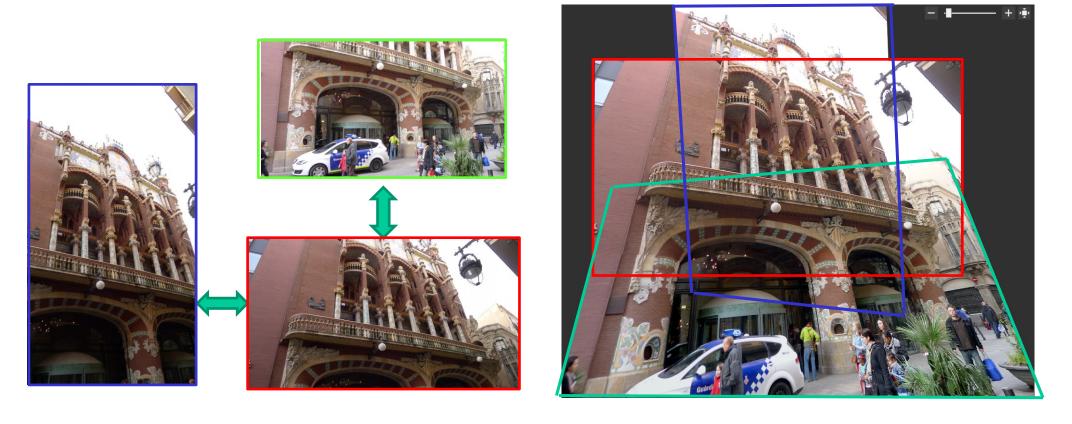
$$\begin{bmatrix} \sum_{i=1}^{N} x_i & -\sum_{i=1}^{N} y_i \\ \sum_{i=1}^{N} x_i & \sum_{i=1}^{N} y_i \\ \sum_{i=1}^{N} x_i & \sum_{i=1}^{N} y_i & \sum_{i=1}^{N} x_i^2 + y_i^2 & 0 \\ -\sum_{i=1}^{N} y_i & \sum_{i=1}^{N} x_i & 0 & \sum_{i=1}^{N} x_i^2 + y_i^2 \end{bmatrix} \begin{bmatrix} t_x \\ t_y \\ a \\ b \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{N} \Delta x_i \\ \sum_{i=1}^{N} \Delta y_i \\ \sum_{i=1}^{N} \Delta x_i - y_i \Delta y_i \\ \sum_{i=1}^{N} x_i \Delta x_i - y_i \Delta y_i \end{bmatrix}$$

# 4'. Use OpenCV function for estimating homography. cv2.getPerspectiveTransform

https://www.devdoc.net/linux/OpenCV-3.2.0/da/d6e/tutorial\_py\_geometric\_transformations.html

```
pts1 = np.float32([[176,187],[465,94],[98, 411],[572,356]])
pts2 = np.float32([[100,200],[500,200],[100,700],[500, 700]])
M = cv2.getPerspectiveTransform(pts1,pts2)
```

## 5. Compute the size of the resulting composite canvas.



6. Warp each image into its final position on the canvas. cv2.warpPerspective

dst = cv2.warpPerspective(img, M, (600, 800))

# Stitching and Panograph

This exercise is a similar as Ex 8.2: Panography in the reference book p.549.

**Panograph** and **stitching** are both methods of combining multiple photographs to create a larger image, but with different objectives and results.

A panograph (https://edelberto-cabrera.pixels.com/featured/panograph-of-a-beach-edelberto-cabrera.html)

- an artistic technique where overlapping photos are arranged in a non-linear, mosaic-like fashion,
   emphasizing their individual perspectives and angles, resulting in a creative, fragmented appearance.
- celebrates the differences between individual photos

#### **stitching** (or photo stitching)

- aims to produce a seamless, cohesive image.
- aligns and blends photos carefully to ensure continuity in perspective, scale, and lighting, commonly
  used for panoramic images in landscape and architectural photography.
- seeks to make these differences invisible.

## Report submission

• Deadline: June 2

Language: English or Japanese

Content: Goal, Method, Results, Discussion, Conclusion

#### Discussion

- Comparison of different geometric transforms
- Comparison with recent applications for stitching
  - https://paperswithcode.com/task/image-stitching
  - https://mattabrown.github.io/autostitch.html
  - https://www.microsoft.com/en-us/research/project/image-composite-editor/
  - https://paperswithcode.com/task/image-stitching