

Problem 5

This question requests an algorithm to find the best/optimal rigid body transformation between two point sets, $\mathcal{P} = \{p_1, p_2, \dots, p_n\}$ and $\mathcal{Q} = \{q_1, q_2, \dots, q_n\}$ which can be formalized as [1][2]:

$$F = (\mathbf{R}, \mathbf{t}) = \underset{\mathbf{R}, \mathbf{t}}{\operatorname{argmin}} \sum_{i=1}^n \|(Rp_i + t) - q_i\|^2 \quad (1)$$

We can find the optimal translation between the two points by taking the derivative w.r.t \mathbf{t} , equating the derivative to 0, and finding \mathbf{t} .

$$\begin{aligned} \frac{\partial F}{\partial t} &= \sum_{i=1}^n 2((Rp_i + t) - q_i) \\ &= 2R \sum_{i=1}^n p_i + 2t \cdot n + 2 \sum_{i=1}^n q_i \\ \implies t &= \frac{1}{n} \sum_{i=1}^n q_i - R \frac{1}{n} \sum_{i=1}^n p_i \\ t &= \bar{q} - R \cdot \bar{p} \end{aligned}$$

where $\bar{p} = \frac{1}{n} \sum_{i=1}^n p_i$ and $\bar{q} = \frac{1}{n} \sum_{i=1}^n q_i$

Replacing the value of \mathbf{t} in equation 1, we now obtain the minimization as:

$$\begin{aligned} R &= \underset{R}{\operatorname{argmin}} \sum_{i=1}^n \|R(p_i - \bar{p}) - (q_i - \bar{q})\|^2 \\ &= \underset{R}{\operatorname{argmin}} \sum_{i=1}^n \|Rx_i - y_i\|^2 \end{aligned} \quad (2)$$

Now, we aim to find the optimal rotation, we can show from [1] after simplifying the terms that minimizing R can be shown as maximizing the trace of the diagonal matrix $\operatorname{tr}(Y^\top RX)$

We compute the SVD decomposition of the covariance matrix \mathbf{XY}^\top to obtain the orthogonal decomposition, i.e.,

$$\mathbf{XY}^\top = \mathbf{U} \cdot \mathbf{\Sigma} \cdot \mathbf{V}^\top \quad (3)$$

We know that for matrices, $\operatorname{tr}(AB) = \operatorname{tr}(BA)$, therefore we can write

$$\operatorname{tr}(\mathbf{Y}^\top \mathbf{R} \mathbf{X}) = \operatorname{tr}(\mathbf{R} \mathbf{X} \mathbf{Y}^\top)$$

We need to now maximize $tr(\mathbf{RXY}^\top) = tr(\mathbf{RS}) = tr(\mathbf{RU} \cdot \mathbf{\Sigma} \cdot \mathbf{V}^\top) = tr(\mathbf{\Sigma V}^\top \mathbf{RU})$. Note that $\mathbf{V}^\top, \mathbf{R}, \mathbf{U}$ are orthogonal matrices, which implies that the columns of each of these matrices are required to be orthonormal. Therefore, $\mathbf{M} = \mathbf{V}^\top \mathbf{RU}$ also has orthonormal matrices, further now since we need to find $\text{argmax}(tr(\mathbf{\Sigma M}))$, we note that, we require \mathbf{M} to be an identity matrix.

Therefore, we can conclude that

$$\mathbf{M} = \mathbf{I} = \mathbf{V}^\top \mathbf{RU} \implies \mathbf{R} = \mathbf{V} \cdot \mathbf{U}^\top \quad (4)$$

It may be possible that the $\det(R) = -1$ which means that the Rotation could also contain reflections. Any reflection matrix can be constructed by inverting the sign of a row of the rotation matrix [1], it follows that we are optimizing for the convex hull of the points $(\pm 1, \dots, \pm 1)$, with an odd number of -1 's. Expressing this as a linear function we have:

$$tr(\Sigma M) = \sigma_1 m_{11} + \sigma_2 m_{12} + \dots + \sigma_d m_{dd} \quad (5)$$

$$tr(\Sigma M) = \sigma_1 + \sigma_2 + \sigma_3 + \dots - \sigma_d \quad (6)$$

This linear function attains its maxima at its vertices, since our domain is a convex polyhedron. Therefore we have 6. Finally we have a formula for \mathbf{R} with reflection as follows:

$$\mathbf{R} = \mathbf{V} \begin{pmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 \\ & & & & -1 \end{pmatrix} \mathbf{U}^\top \quad (7)$$

and now the general formula for \mathbf{R} is:

$$\mathbf{R} = \mathbf{V} \begin{pmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 \\ & & & & \det(VU^\top) \end{pmatrix} \mathbf{U}^\top \quad (8)$$

The algorithm is given as below

- Compute the centroid of the point sets through the formula as below

$$\bar{p} = \frac{1}{N} \sum_{i=1}^N p_i, \quad \bar{q} = \frac{1}{N} \sum_{i=1}^N q_i$$

- Compute the centered vectors as:

$$x_i = p_i - \bar{p}, \quad y_i = q_i - \bar{q}$$

- Compute the co-variance matrix between $\mathbf{x} = \{x_1, x_2, \dots, x_n\}$ and $\mathbf{y} = \{y_1, y_2, \dots, y_n\}$ as

$$\mathbf{H} = \mathbf{xy}^\top \quad \text{where } \mathbf{H} \text{ forms a } 3 \times 3 \text{ matrix}$$

- Compute the SVD of \mathbf{H} as $\mathbf{U}\Sigma\mathbf{V}^\top$, now the required optimal rotation in the least squared sense for the point set is

$$\mathbf{R} = \mathbf{VU}^\top$$

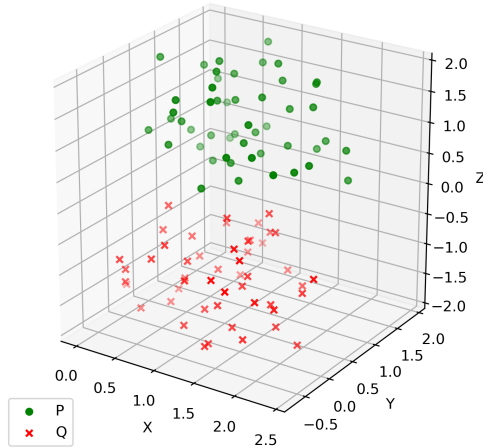
- Finally compute the optimal translation for the rigid body as:

$$\mathbf{t} = -\mathbf{R}\bar{\mathbf{p}} + \bar{\mathbf{q}}$$

Code

The solution to this problem is implemented in `q5.py`. The python code generates a random 3d point set, and transforms it with a known random \mathbf{R} and \mathbf{t} to generate \mathbf{Q} . These two point sets are then used as the data for the algorithm. Example 3d point sets, transformed by \mathbf{R} and \mathbf{t} and the estimated \mathbf{R} and \mathbf{t} in Figure 1

3d points P and Q = transformed by original R and t



3d points P and Q transformed by estimated R and t

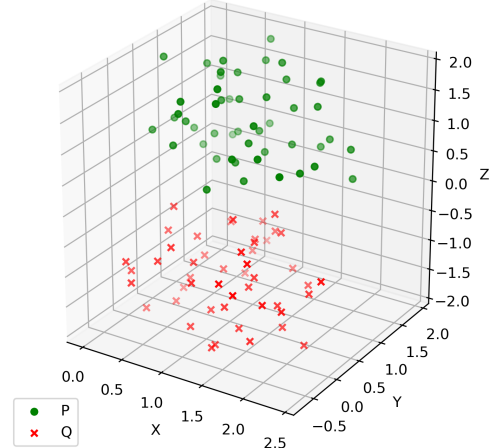


Figure 1: 3D point set P and transformed point set Q ([left] transformed by original \mathbf{R} and \mathbf{t} , and [right] estimated \mathbf{R} and \mathbf{t})

Thought

The above problem can also be thought of in a different way:

We know that SVD decomposes the matrices as orthogonal matrices. In the problem given we are trying to find the least squares closest orthogonal matrix \mathbf{R} which approximates \mathbf{A} an over-constrained system of point transformations from \mathcal{P} to \mathcal{Q} .

Intuitively to obtain a rigid body transformation we require that there is no shearing of the object in any of the axes/bases, which effectively amounts to $\Sigma = I$, therefore, we could compute as $\mathbf{R} = \mathbf{U} \cdot \Sigma \cdot \mathbf{V}^\top = \mathbf{U} \cdot \mathbf{I} \cdot \mathbf{V}^\top$.

Further looking at the previous proof, it seems that this solution gives us the inverse transform from \mathcal{Q} to \mathcal{P} !

Discussion citation

For this problem, I have discussed with *Tarasha Khurana* andrewID: `tkhurana@andrew.cmu.edu`, and *Rohit Jena* andrewID: `rjena@andrew.cmu.edu`

References

- [1] Sorkine-Hornung, Olga and Rabinovich, Michael, *Least-squares rigid motion using svd* Computing, 1, 2017
- [2] Arun, K. Somani, Thomas S. Huang, and Steven D. Blostein. *Least-squares fitting of two 3-D point sets* IEEE Transactions on pattern analysis and machine intelligence 5 (1987): 698-700.