

# Imaging Beyond Consumer Cameras – Proseminar (911.422)

## Exercise sheet D

### Exercise 1.

8 P.

In the ICP algorithm from the lecture, we used the *point-to-point* error metric. Here, we are going to use the *point-to-plane* error metric and aim to register (wrt. rotation and translation only) two point clouds following a least-squares approach. In particular, we have two sets of points in  $\mathbb{R}^3$ , i.e., a source point cloud  $\{p_i\}_{i=1}^N$  and a target point cloud  $\{q_i\}_{i=1}^N$ . The **error function** (without scaling) is given by

$$\sum_{i=1}^N ((\mathbf{R}p_i + \mathbf{t} - q_i)^\top \mathbf{n}_i)^2$$

and we want to minimize this sum wrt.  $\mathbf{R}$  (rotation) and  $\mathbf{t}$  (translation). In this setting, the normal vectors  $\{\mathbf{n}_i\}_{i=1}^N$  in the *target* point cloud are also given. Assuming we have only *incremental rotations*, we can *linearize* the rotation matrix. For instance, in case of rotation in  $x$ , we linearize via

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos \alpha & -\sin \alpha \\ 0 & \sin \alpha & \cos \alpha \end{pmatrix} \approx \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & -\alpha \\ 0 & \alpha & 1 \end{pmatrix}$$

This means, we approximate  $\cos \alpha$  by 1 and  $\sin \alpha$  by  $\alpha$ . The overall rotation matrix thus becomes (approximately)

$$\mathbf{R} \approx \begin{pmatrix} 1 & -\gamma & \beta \\ \gamma & 1 & -\alpha \\ -\beta & \alpha & 1 \end{pmatrix}.$$

The **linearized error function** thus simplifies to

$$\sum_{i=1}^N [((p_i - q_i)^\top \mathbf{n}_i) + \mathbf{r}^\top (p_i \times \mathbf{n}_i) + \mathbf{t}^\top \mathbf{n}_i]^2 \quad (1)$$

with  $\mathbf{r} = (\alpha, \beta, \gamma)^\top$  and  $\mathbf{t} = (t_x, t_y, t_z)^\top$  denoting the translation vector.

Your task is find a **least-squares** solution to the problem of minimizing the **linearized error function** wrt.  $\mathbf{R}$  and  $\mathbf{t}$ . The idea is to formulate Eq. (1) as

$$\|\mathbf{Ax} - \mathbf{b}\|^2$$

and use, e.g., numpy's least squares solver `np.linalg.lstsq`. In particular, this requires to appropriately construct the matrix  $\mathbf{A} \in \mathbb{R}^{N \times 6}$  and the vector  $\mathbf{b} \in \mathbb{R}^N$ . Calling `np.linalg.lstsq` will then give you the least-squares solution  $\mathbf{x} \in \mathbb{R}^6$  holding  $(\alpha, \beta, \gamma, t_x, t_y, t_z)$  (the order depends on how you set up the matrices).

Once you have found the least-squares solution, transform the source point cloud according to the found  $\mathbf{R}$  and  $\mathbf{t}$  and visualize the result.

The provided Jupyter notebook, `Exercise-Sheet-D-Notebook-2021.ipynb` contains additional details and helper code, e.g., code to obtain  $\mathbf{R}$  from the found  $\alpha, \beta, \gamma$ .

### Exercise 2.

2 P.

Consider the following list of set of seven points:  $\{(12, 8), (18, 11), (15, 15), (8, 12), (3, 18), (10, 1), (17, 5)\}$ . Create a *median k-D tree* using *coordinate cycling* as the cutting dimension per level. Draw the *k-D tree*.

### Exercise 3.

2 P.

Consider the point set from the previous question. Given a query point  $\mathbf{q} = (4, 5)$ , (1) what is the closest point and (2) which subtrees of the *k-D tree* are not explored? Mark the *not-explored subtrees* in your drawing from the previous question.