ES 637: Mathematical Foundations for Computer Vision and Graphics Programming Assignment-2

Pansetty Karthik 15110082

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Question:

Given two 3D point clouds (RGB-D), design a technique using Iterative Closest Point (ICP) to jointly estimate the point correspondences as well as the global rotation matrix and the translation vector.

Iterative Closest Point (ICP)

Iterative Closest Point is used to find the corespondences of two point clouds. We iteratively perform the transformation of rotation and translation of source first point cloud to get the target point cloud.

ICP Algorithm

- 1. Find the intial point corespondences by using a feature descriptor and matching.
- 2. We find the 3D point by taking the column index, the row index of the RGB image as X and Y coordinates and use the corresponding value of the depth map to get the 3rd coordinate.
- 3. Find the weights by taking gaussian of the norm of corresponding feature descriptors. (We can also use the inverse of the distance of corresponding feature descriptors to be the weights)

$$w_{\rm i} = e^{-\left(des(\vec{p_{\rm i}}) - des(\vec{q_{\rm i}})\right)^2/2\sigma^2}$$

- 4. We create a weight matrix W by keeping all the weights as diagonal entries.
- 5. p_i is the souce image points and qi is the target image points.
- 6. Subtract the mean vector from p_i to the mean p vector. Similarly, find the mean q vector.

$$\widehat{p} = \frac{\sum_{i=1}^{n} w_i \vec{p_i}}{\sum_{i=1}^{n} w_i}$$

$$\widehat{q} = \frac{\sum_{i=1}^{n} w_i \vec{q_i}}{\sum_{i=1}^{n} w_i}$$

7. We get \vec{X}_i and \vec{Y}_i by the following

$$\vec{X}_{\mathrm{i}} = \vec{p}_{\mathrm{i}} - \widehat{p}$$

$$\vec{Y}_{\mathrm{i}} = \vec{q}_{\mathrm{i}} - \hat{q}$$

8. We get the X and Y matrices by the following

$$X = \begin{bmatrix} \vec{x_1} & \vec{x_2} & \dots & \vec{x_n} \end{bmatrix}$$

$$Y = [\vec{y_1} \quad \vec{y_2} \quad \dots \quad \vec{y_n}]$$

9. We get S matrix by the following

$$S = XWY^{\mathrm{T}}$$

10. Then we perform Eigen Value Decomposition on S.

$$S = UDV^{\mathrm{T}}$$

11. We get the optimal Rotation matrix R by

$$R^* = VU^{\mathrm{T}}$$

12. We get the optimal translation vector t by

$$\vec{t}^* = \hat{q} - R^* \hat{p}$$

13. Then we remap the point correspondences and iterate over this algorithm.

Implementation Details

- The dataset I have used is the one posted in the classroom of ES 637.
- ORB feature descriptor is used to find the initial point correspondences.
- We get the weight matrix by taking gaussian of the norm of corresponding feature descriptors. (We get distance/norm from the matches object itself).
- $\bullet\,$ The transformed image should have the same shape of the source image.
- The sigma(σ) value is taken to be 1.5
- The rotation matrix has dimensions 3x3 and the translation vector has dimensions 3x1.

Results

• Transforming 467.png to 472.png



(a) Transformed Image



(b) Reference image

Figure 1: Comparison of the transformed image and the reference image

 \bullet Transforming 472.png to 480.png



(a) Transformed Image



(b) Reference image

Figure 2: Comparison of the transformed image and the reference image

 \bullet Transforming 467.png to 480.png



(a) Transformed Image



(b) Reference image

Figure 3: Comparison of the transformed image and the reference image

References

- Besl, Paul J.; N.D. McKay (1992). "A Method for Registration of 3-D Shapes". IEEE Trans. on Pattern Analysis and Machine Intelligence. Los Alamitos, CA, USA: IEEE Computer Society. 14 (2): 239–256.
- [2] Bruteforce feature matching using ORB feature descriptor from "https://docs.opencv.org/3.0-beta/doc/py_tutorials/py_feature2d/py_matcher/py_matcher.html".
- [3] Stéfan van der Walt, S. Chris Colbert and Gaël Varoquaux. The NumPy Array: A Structure for Efficient Numerical Computation, Computing in Science & Engineering, 13, 22-30 (2011), DOI:10.1109/MCSE.2011.37.
- [4] John D. Hunter. Matplotlib: A 2D Graphics Environment, Computing in Science & Engineering, 9, 90-95 (2007), DOI:10.1109/MCSE.2007.55.