Nuages de Points et Modélisation 3D (NPM3D) TP2

Zhe HUANG, from IASD

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1 Question1

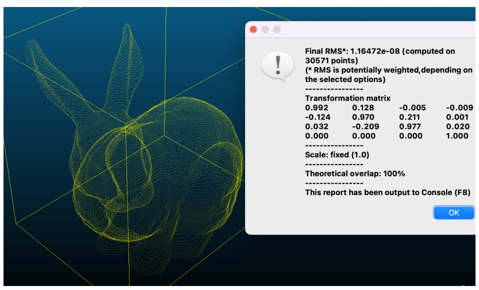

Figure 1: ICP on original bunny and perturbed bunny

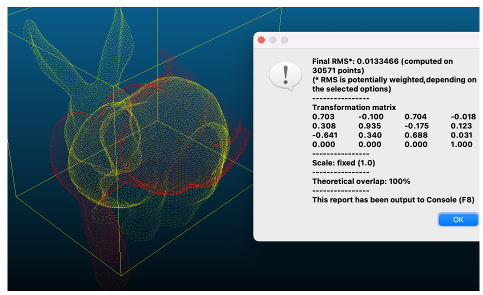

Figure 2: ICP on original bunny and returned bunny

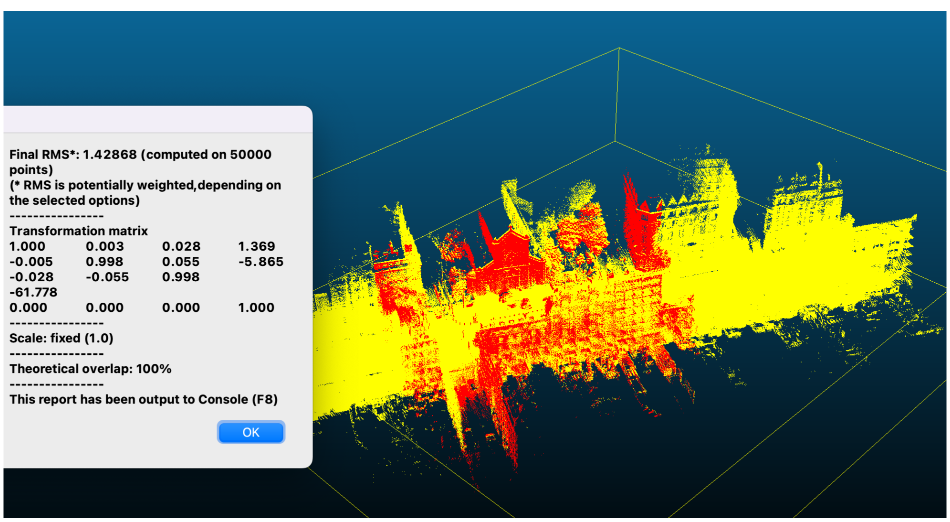

Figure 3: The two Notre Dame Des Champs

The figures above illustrate the performance of ICP(Iterative Closest Points algorithm) in three different examples. In the first example, ICP successfully aligns all points, resulting in a perfect overlap. However, in the second example, ICP can be described as a complete failure, as it fails to achieve any meaningful alignment. Finally, in the third example, ICP succeeds as well. the aligned cloud of Notre_Dame_Des_Champs_2.ply is observed to be a subset of Notre_Dame_Des_Champs_1.ply.

The aligned cloud(red part in the figures) is the result of applying the transformation to the source cloud to bring it into alignment with the reference cloud. The reference cloud(yellow part) remains fixed and serves as the target for alignment.

Aligning the smaller subset to the larger, more detailed reference cloud would likely yield a more accurate alignment result. Thus Notre_Dame_Des_Champs_1.ply should be the reference cloud because it represents the more comprehensive and detailed data.

2 Question2

	Before	**After**
Root Mean Square Error	0.161	0.000

Table 1: the RMS error between the points of each cloud before and after applying the best rigid transform.

The best_rigid_transform function does not require an initial guess, as it computes the optimal transformation in a single step based on the SVD(Singular Value Decomposition). Conversely, ICP's performance is highly dependent on the initial position of the point clouds. If the initial guess in CloudCompare was poor, it might have led to suboptimal alignment.

Also, the SVD approach used in the best_rigid_transform function assumes that point correspondences are known and fixed. CloudCompare's ICP, however, dynamically determines correspondences during its iterations, which can be error-prone and might not converge if the initial alignment is too far off.

The best_rigid_transform function cannot align the 3D scans of "Notre Dame des Champs" because this function assumes that each point in the data set has a corresponding point in the ref set. However, when the point clouds have different numbers of points, as is the case with Notre_Dame_Des_Champs_2.ply and Notre_Dame_Des_Champs_1.ply, there is no one-to-one point correspondence. The SVD method is then not directly applicable because it cannot handle the situation where the subset does not have a pre-established correspondence with the larger set.

3 Question3

In applying our own ICP on the two examples above(2D_data left and bunny right), we track and plot below the the RMS error at each iteration during ICP convergence.

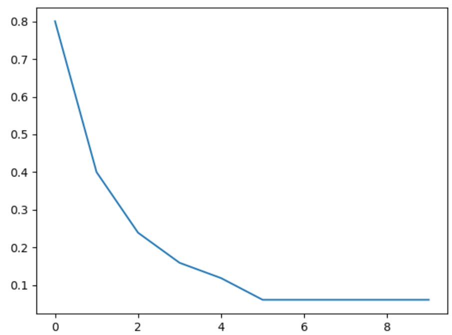

Figure 4: RMS during ICP convergence for 2D_data

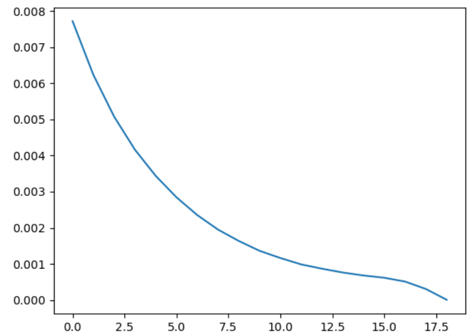

Figure 5: RMS during ICP convergence for bunny

4 Question4

Figure 4 exhibits a rapid decline in RMS error for the 2D data, quickly stabilizing as the algorithm reaches optimal alignment around iteration 5, due to the RMS dropping below the threshold.

Figure 5 shows a consistent reduction in RMS error for the 3D bunny data, continuing to improve up to the final iteration, indicating that the convergence threshold was not met within the given iterations.

Both plots demonstrate the ICP algorithm's capability to progressively refine the alignment of point clouds, with the 2D data converging faster than the 3D data.

5 Question Bonus

We now plot the RMS (computed on all points) during ICP convergence for the "Notre Dame Des Champs" clouds with 1000 and 10000 sampled points used at each iteration.

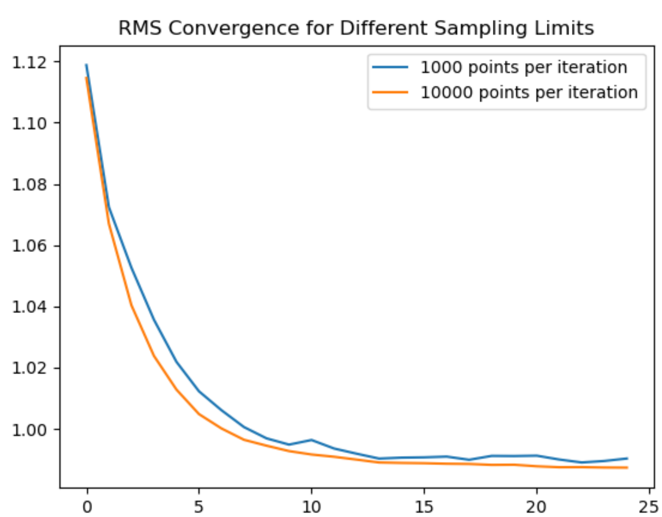

Figure 6: RMS during ICP convergence for "Notre Dame Des Champs" clouds

Considering that the aligned cloud of Notre_Dame_Des_Champs_2.ply is observed to be a subset of Notre_Dame_Des_Champs_1.ply, both RMS curves in the figure above converge to an value close to 1.0, which is relatively high. This is indicative of a partial alignment, constrained by the extent of overlap between the point clouds.

Furthermore, the sampling limit—1000 and 10000 points per iteration—affects the convergence behavior. The curve with 10000 points demonstrates greater stability and a smoother convergence profile, suggesting that a larger sample size provides a more reliable estimate of the RMS at each step, thereby leading to a steadier decrease in error.

In contrast, the curve with 1000 points not only converges more slowly but also exhibits oscillations. This is likely due to the smaller sample size providing a less accurate representation of the entire data set, which may introduce variability into the calculation of R and T, and consequently, into the RMS values from one iteration to the next.