High-Precision 3D Coarse Registration Using RANSAC and Randomly-Picked Rejections

Jong-Hee Back, Sunho Kim, and Yo-Sung Ho(✉)

Gwangju Institute of Science and Technology, 123 Cheomdangwagi-ro, Buk-gu, Gwangju 61005, Republic of Korea
{jongheeback, sunhokim, hoyo}@gist.ac.kr

Abstract. A point cloud registration is an essential process of finding a spatial transformation between two point clouds in computer vision. The Iterative Closest Point (ICP) algorithm is one of the most widely used registration methods. Since the ICP algorithm is a locally optimal registration method, it is not guaranteed to converge to an exact solution because of local-minimum problem. In addition, the ICP algorithm is a time-consuming task. Because the ICP algorithm is performed repeatedly to find the best transformation, it tends to be slow. For those reasons, a coarse registration, which helps point clouds align fast and exactly, is needed before fine alignment. This paper provides a 3D coarse registration method to solve the local-minimum problem in the ICP algorithm. First of all, an initial matching is computed by performing feature extraction using Fast Point Feature Histogram (FPFH) feature which establishes good initial correspondences. Since these correspondences are not accurate yet, we need to reject outlier correspondences. Inlier correspondences are picked out through two rejection methods, RANSAC rejection and Randomly-picked rejection we propose. With these organized correspondences, a transformation matrix between point clouds is obtained. As a result, it is helpful to avoid the local-minimum problem in the ICP algorithm. Moreover, it is quite efficient to register point clouds with noise and large transformations.

Keywords: Point cloud registration · 3D coarse registration
Initial correspondence matching · Outlier rejection method

1 Introduction

A point cloud registration is an important process to find a spatial transformation between two point clouds. It is being utilized to a wide range of fields in computer vision or robotics such as simultaneous localization and mapping (SLAM) [1–3], 3D reconstruction [6–8, 10], etc.

The Iterative Closest Point (ICP) algorithm [13–15] is one of the most widely used registration methods in computer vision. In the algorithm, a transformation is updated iteratively in the direction of minimizing an error metric between one cloud and the other transformed cloud. Therefore, we can compute a proper transformation matrix which is 3-by-3 rotation matrix and 3-by-1 translation vector. However, the ICP

K. Schoeffmann et al. (Eds.): MMM 2018, Part I, LNCS 10704, pp. 254–266, 2018.
https://doi.org/10.1007/978-3-319-73603-7_21

algorithm has two kinds of problems we should deal with. Since the ICP algorithms is a locally optimal registration method, it is not guaranteed to converge to an exact solution without an initial transformation that is close to the exact solution. In other words, it will be difficult to find an exact transformation if there are two point clouds with large transformation. The second problem is that the ICP algorithm is a time-consuming task. Since the ICP algorithm is performed repeatedly to find the best transformation matrix, it tends to be slow. For those reasons, a coarse registration, which helps point clouds align fast and exactly, is needed. Thanks to a coarse registration, a local-minimum problem can be fixed and two point clouds can be aligned fast and exactly through the low iteration of the ICP.

In this paper, we propose a 3D coarse registration method to solve the local-minimum problem in the ICP algorithm. In order to compute an initial matching, we use Fast Point Feature Histogram (FPFH) [5] features. FPFH is a feature which provides quite good initial correspondences. Nevertheless, these correspondences we obtain are still limited to find an accurate transformation. Through RANSAC [4] rejection and a proposed mechanism comparing a correlation between three correspondences randomly, inlier correspondences are picked out. The proposed outlier rejection mechanism, which is called Randomly-picked rejection method, is a method to find highly-correlated three pairs of correspondences repeatedly. RANSAC rejection is a strong rejection method that makes our algorithm more efficient. With these organized correspondences, a transformation matrix between two point clouds can be computed. As a result, it is helpful to solve local-minimum problem in the ICP algorithm. It also saves much time and trouble before fine registration such as the ICP algorithm. Even though there is some noise in point clouds, these point clouds are almost aligned. Moreover, our algorithm has quite good performance in the case of point clouds with large transformation.

2 Related Works

An extensive study of the point cloud registration has been made. Generally, there are two types of methods to register point clouds, local method and global method. The global method is a method to find the globally optimal alignment, and local method is a method to calculate the transformation iteratively in the direction of minimizing an error metric by making use of optimization theory.

The Iterative Closest Point (ICP) algorithm [13–15], which is used widely, is one of the local registration methods. The most typical ICP algorithm is point-to-plane ICP [15]. This method is a popular algorithm employed to register, but it is still limited to find an accurate transformation since incorrect pairs of correspondences have a large effect on the result and a local-minimum problem exists. Recently, several good ICP methods such as Generalized ICP [13] and EM-ICP [14] have been proposed. Besides, there are many approaches to perform robust registration based on Gaussian Mixture Model (GMM) [17].

There are a variety of global methods in order to solve the local-minimum problem. The feature-based methods, which set up highly-accurate correspondences making use of 3D local descriptors such as Fast Point Feature Histograms (FPFH) [5] and Intrinsic

Shape Signatures (ISS) [16] and estimate a transformation matrix, have been proposed. Zhou [6] proposed a fast registration method that initial matching using FPFH was performed and optimization based on Geman-McClure estimator was done. Yang [7] introduced Go-ICP which was a global registration method based on BnB searching scheme. Recently, correspondence propagation method [9] to find exact correspondences globally was introduced.

3 Proposed Approach

Figure 1 presents the flowchart of the proposed coarse registration method. After uniform down-sampling of point cloud P and Q, an initial matching using FPFH is computed. The role of uniform down-sampling is to reduce the computational complexity of several processes such as feature detection, RANSAC rejection, etc. Next, two outlier rejection algorithms, which are RANSAC rejection and Randomly-picked rejection, are performed. A transformation matrix can be computed by using several pairs of the inlier correspondences we obtain through two rejection methods. This is the whole algorithm of coarse registration and more accurate transformation can be found by the process of fine alignment. We use point-to-plane ICP [15] as the fine alignment. We focus on three main processes of the proposed method in detail.

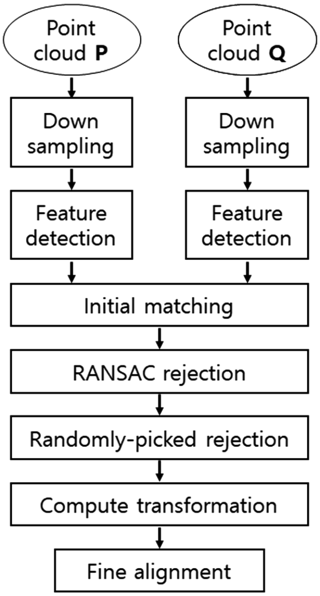

Fig. 1. Flowchart of the proposed registration method.

3.1 Uniform Down-Sampling

There are a lot of points in point cloud **P** and **Q**. If we perform a registration method using all points, it might be time-consuming. That's the advantage of uniform down-sampling. Let $\mathbf{P}_s = \{p_1, p_2, \cdots, p_m\}$ be the points of sampled point cloud **P** and $\mathbf{Q}_s = \{q_1, q_2, \cdots, q_n\}$ be the points of sampled point cloud **Q**. The important thing is that proper sampling rate should be set. If a lot of points in a point cloud are removed, it can cause bad result due to a lack of information. On the contrary, the algorithm might be slow if the points in a point cloud are hardly sampled. Figure 2 is the result of uniform down-sampling of a point cloud. We use a library function called UniformSampling which is included in Point Cloud Library (PCL) [18].

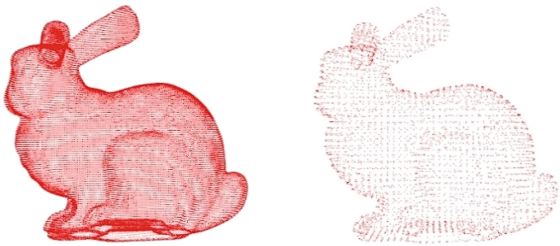

Fig. 2. Uniform down-sampling

3.2 Feature Detection

An initial matching using FPFH feature [5] is performed. FPFH, which reduces the computational complexity and retains highly efficient performance, provides quite good initial correspondences. In order to get FPFH features of points in point clouds, surface normals are required. After obtaining FPFH features of each point cloud based on the surface normals, we can establish initial correspondences. Let $M = \{(p_k, q_t), \ldots, (p_r, q_s)\}$ be the initial correspondences using FPFH features. Figure 3 represents a part of the initial correspondences. There are a lot of good correspondences in Fig. 3, however bad pairs of correspondences can be found.

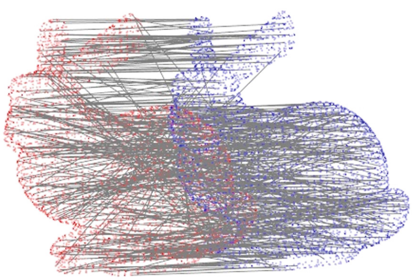

Fig. 3. Initial correspondences M using FPFH

3.3 Correspondence Rejection

As shown in Fig. 3, inaccurate correspondences exist in the initial correspondences M. By rejecting outlier correspondences, it is possible to find exact transformation matrix. That's the reason why the correspondence rejection method is needed. We use two rejection methods, RANSAC rejection [4] and Randomly-picked rejection that we propose.

Before the process of Randomly-picked rejection, RANSAC rejection method plays the primary role of eliminating bad correspondences. RANSAC is widely used because of its high performance.

Randomly-picked rejection we propose is an outlier rejection method to find three highly-correlated correspondences repeatedly. Figure 4 represents a principle of Randomly-picked rejection method. The right picture in Fig. 4 is the example of unselected correspondences due to the unsatisfied condition.

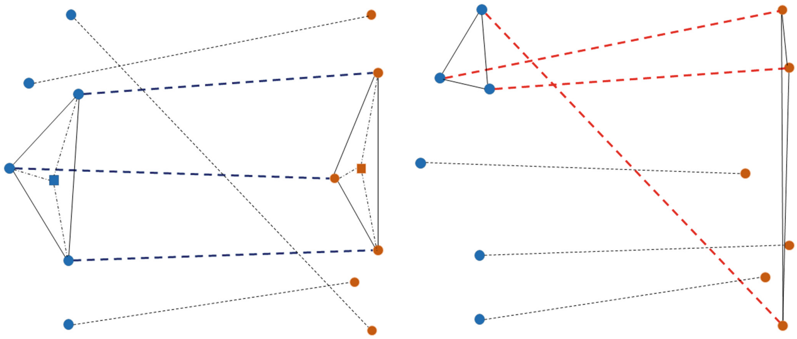

Fig. 4. A principle of randomly-picked rejection method.

First of all, three correspondences in the initial correspondence set M are selected randomly and two matrices are formed as below.

$$V = [P_a, P_b, P_c], U = [Q_a, Q_b, Q_c] \tag{1}$$

where matrix V and U are 3×3 matrices which consist of three column vectors. The P_k is a 3-by-1 coordinate column vector of point p_a in point cloud **P**s. The Q_k is the same type as the P_k. Next, the average of three points in each matrix is computed and matrix $V1$ and $U1$ are calculated as below.

$$P_{avg} = \frac{P_a + P_b + P_c}{3}, Q_{avg} = \frac{Q_a + Q_b + Q_c}{3} \tag{2}$$

$$V_1 = \left[P_a - P_{avg}, P_b - P_{avg}, P_c - P_{avg}\right], U_1 = \left[Q_a - Q_{avg}, Q_b - Q_{avg}, Q_c - Q_{avg}\right] \tag{3}$$

With these matrices, we can compute the matrix V_2 and U_2 which mean the correlation information of three points in each matrix.

$$V_2 = V_1^T V_1, U_2 = U_1^T U_1 \tag{4}$$

We decide whether those correspondences are proper or not by comparing the matrix V_2 and U_2. Given the complexity, we only compare the sign of each corresponding element by using bit operation as shown in Fig. 5 below. The simple idea to filter bad correspondences realizes the fast algorithm without using special cost function.

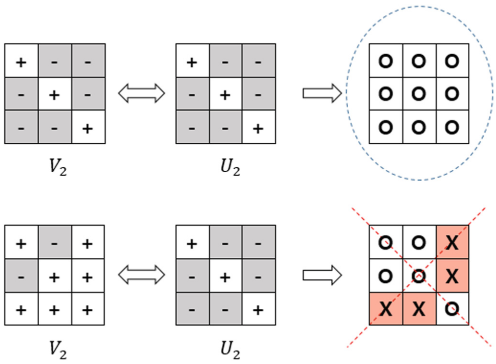

Fig. 5. A process of bad correspondences filtering

Finally, three correspondences are selected if the condition is satisfied and go back to the first step. There are a few things to be aware of. Duplicated correspondence is not allowed and the minimum number of correspondence should be decided. Additionally, it is important to repeat this mechanism properly. If the number of repetition is large, it takes several times. If the number of repetition is small, biased information tends to be obtained.

Figure 6 represents the performance of outlier rejection methods. With these organized correspondences, the accurate transformation matrix can be obtained.

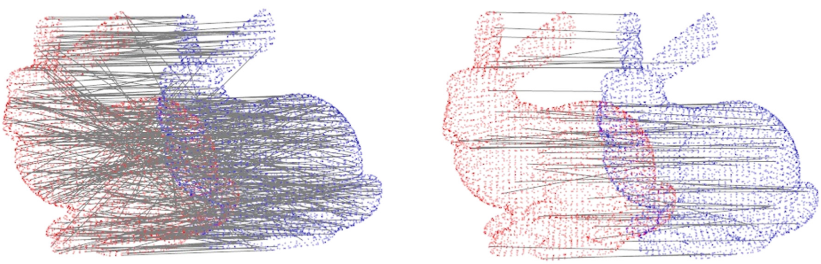

Fig. 6. The result of two rejection algorithms

Since the number of inlier correspondences is more than the number of outlier correspondences, a probability to select three bad correspondences is relatively low. Even though three bad correspondences are chosen, the majority of the picked correspondences are good correspondences, so it does not have a big influence on the result. Therefore, a globally optimal transformation can be computed.

4 Experimental Results

We explain a variety of experimental results in order to verify the performance of our proposed method. The algorithm has been implemented using Point Cloud Library (PCL) which is C/C++ based [18] in Microsoft Visual C++ 2013. All experiments were performed using a PC with Intel Xeon E5630 CPU clocked at 2.53 GHz.

4.1 Robustness to Noise

In order to verify robustness to noise, we test our method on Aim@shape repository (Bimba, Dancing Children, and Chinese dragon), Stanford bunny[1], and the Berkeley angel [11] which are experimented in [6]. We made use of the results of other methods which are tested in [6] for an accurate comparison of performance. There are 25 partially overlapping point clouds with $\sigma = 0.0025$ and 0.005 respectively. σ is the standard deviation of the Gaussian distribution which means noise.

Table 1 shows average root mean square error (RMSE) values of point clouds with $\sigma = 0.0025$ and 0.005 which represents a widely-used measure to check how accurate two point clouds are aligned. The lower RMSE value is, the better the performance is.

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N} \left(Rp_i - \hat{p}_i\right)^2} \tag{5}$$

In our method, the sampling rate is set to 0.03 and the number of iterations is fixed to 500. RANSAC threshold is set to 0.2.

Table 1. Average of 25 RMSE values in the case of $\sigma = 0.0025$ and 0.005

Method	$\sigma = 0.0025$	$\sigma = 0.005$
GoICP [7]	0.06513	0.07624
GoICP-Trimming [7]	0.07624	0.08659
Super4PCS [10]	0.02191	0.02730
CZK [8]	0.01326	0.07319
Fast Global Registration [6]	0.00742	0.01407
Proposed method	**0.00394**	**0.00771**

[1] https://graphics.stanford.edu/data/3Dscanrep/.

In Table 1, two average RMSE values of the proposed method are lower than other methods. Despite the presence of quite strong noise such as σ = 0.005, the proposed method has a good performance.

Figure 7 represents the visualized results of the proposed method. The right-hand column in Fig. 7 means input point clouds before alignment. After performing coarse registration, two point clouds are almost converged as shown in the center column of the picture in Fig. 7. Thanks to coarse registration, fine alignment such as point-to-plane ICP algorithm, is done fast. The right-hand column in Fig. 7 is the results of the final alignment is performed.

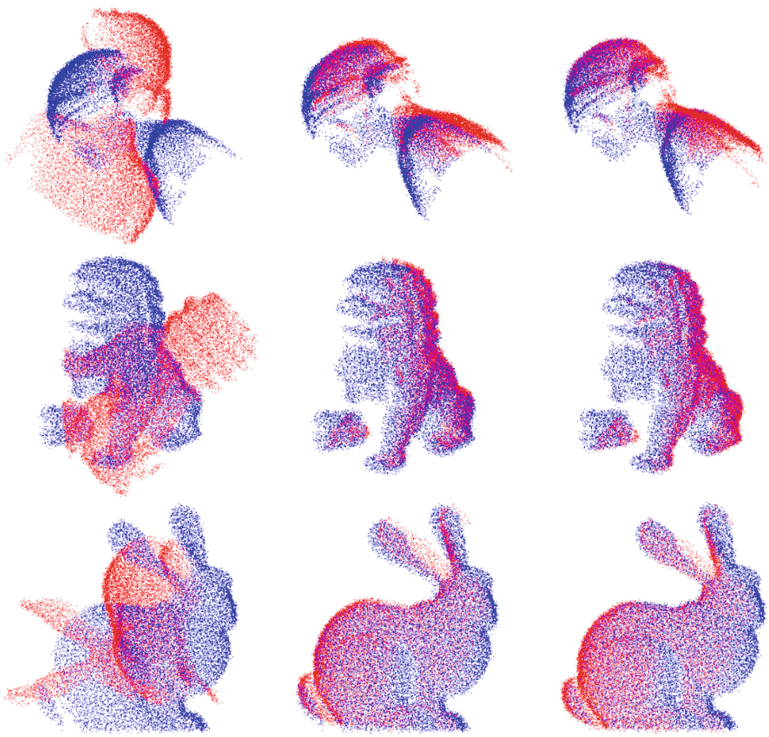

Fig. 7. The results of proposed registration method in the case of σ = 0.005

Table 2 represents performance comparison between using only RANSAC and using RANSAC and Randomly-picked rejection method. For greater accuracy, a coarse alignment process is excluded and experiment is performed according to the RANSAC threshold. As shown in Table 2, outliers RANSAC cannot reject are removed through Randomly-picked rejection. Only Randomly-picked rejection spends less time compared to RANSAC. In Table 2, RS means RANSAC and RS + RP represents RANSAC and Randomly-picked rejection method.

Table 2. Performance comparison between RANSAC and RANSAC + Randomly-picked

RANSAC threshold	σ = 0.0025				σ = 0.005			
	RS		RS + RP		RS		RS + RP	
	RMSE	Time	RMSE	Time	RMSE	Time	RMSE	Time
0.2	0.01618	0.144	**0.01500**	0.156	0.02790	0.587	**0.02641**	0.597
0.4	0.05279	0.046	**0.04341**	0.056	0.12913	0.132	**0.12653**	0.143
0.6	0.08134	0.025	**0.07882**	0.034	0.15086	0.048	**0.13451**	0.061
0.8	0.07693	0.017	**0.06831**	0.027	0.18512	0.027	**0.15828**	0.039

4.2 Execution Time

Table 3 shows the running time of proposed method and Fast Global Registration [6] method. In [6], Fast Global Registration is overwhelmingly faster than the other point cloud registration methods such as Go-ICP [7], Super 4PCS [10], etc. Therefore, we compare the execution time of our method with Fast Global Registration. The measured time unit is seconds. The time of feature detection process is not included in the measured time of Fast Global Registration in Table 3. However, it does not seem to have a significant effect on the results.

Table 3. Comparison with running time of Fast Global Registration

Method	σ = 0.0025	σ = 0.005
Fast Global Registration [6]	1.1369	**1.1500**
Proposed method	**1.0753**	2.7798

In the case of σ = 0.0025, our method is faster than [6]. However, since the speed of our method depends on the number of initial correspondences, our method is slower than [6] even considering the time of feature detection process in [6].

Actually, rejection method we propose takes so little time that it does not have a large effect on total running time of registration method. Figure 8 represents execution time of each process in the proposed method. The blue part occupying the widest area in Fig. 8 means RANSAC rejection, and the purple part means feature detection process. The black part which looks black line above blue part is the rejection method that accounts for about 1% of the total running time. Other processes such as normal estimation represent the mint color part. The speed of our method depends on the number of initial correspondences. Especially, RANSAC rejection method is largely affected by the number of initial correspondences. Additionally, the number of initial correspondences depends on the number of down-sampled points. To sum up, sampling rate affects the running time and performance like RMSE. That's why it is important to set the sampling rate properly.

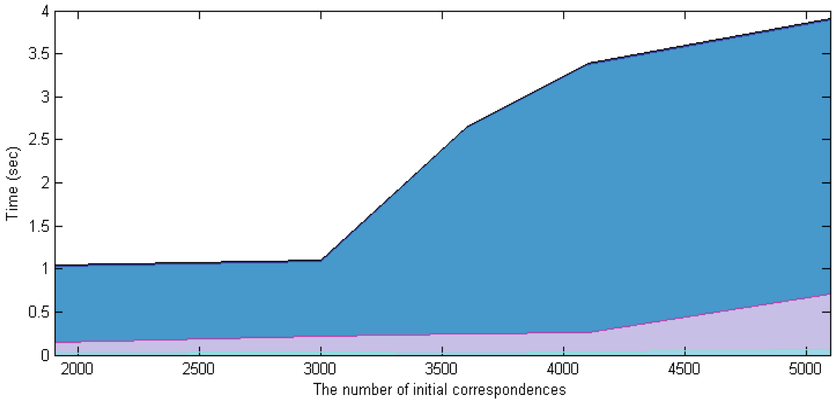

Fig. 8. Execution time of each process in proposed method (Color figure online)

4.3 Ability to Solve Local-Minimum Problem in the Case of RGB-D Data

As mentioned above, the ICP algorithm has a local-minimum problem. In addition, it is easy to converge to a strange place without the accurate pairs of correspondences. We test whether to solve the local-minimum problem using RGB-D data. Figure 9 Represents two frames of ICL-NUIM dataset [12].

For the experiment, the sampling rate is set to 0.04 and the number of iterations is fixed to 500. RANSAC threshold is set to 0.3. One image in Fig. 9 is largely transformed to the other. Without coarse registration, a local-minimum problem such as the left side of the picture in Fig. 10 is encountered. With wrong pairs of correspondences, this problem cannot be solved. By using our method making use of globally-picked correspondences, two point clouds from Fig. 9 can be registered clearly as shown in the right side of the picture in Fig. 10 below. Even though one image is transformed largely, a local-minimum problem can be solved easily. Figure 11 is the result of reconstruction using only eight frames of ICL-NUIM dataset.

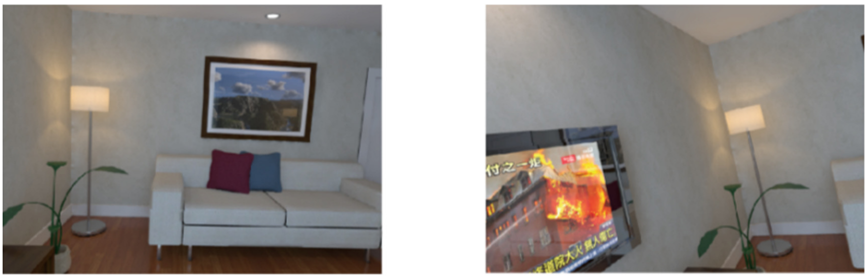

Fig. 9. Two images for testing large transformation

Fig. 10. The result of proposed method solving local-minimum problem

Fig. 11. 3D Reconstruction using the eight RGB-D data

4.4 Discussion

Through experiments, as shown above, we present that our method has quite good performance while maintaining fast execution time. Unfortunately, there are some limitations to our algorithm. In order to achieve good performance and fast running time, the sampling rate should be decided properly. Second, RANSAC rejection method is a highly-efficient algorithm, but it is a time-consuming task. The proposed rejection method must be more efficient if a fast rejection method with comparatively good performance is involved. If two things are dealt with, our method will get better performance.

5 Conclusion

In this paper, we have presented 3D coarse registration method which uses two outlier rejection methods, RANSAC based method, and Randomly-picked rejection method. In order to speed up, uniform down-sampling is performed. Initial matching is computed using FPFH feature. Through two outlier rejection methods, we obtain quite accurate pairs of correspondences. By using organized correspondences, a transformation matrix is computed. The point-to-plane ICP which is widely used ICP algorithm is utilized as a fine registration.

We present that our method has good performance through various experiments. Our method works rather efficiently in the case of point clouds with noise compared with other registration methods. In addition, we observe that local-minimum problem is solved fast in RGB-D data. We also discuss some drawbacks that need to be addressed. Nevertheless, our algorithm can be applied to various fields that require point cloud registration like SLAM and 3D reconstruction. Specifically, our method can be used with other fine registration methods. If those fine registration methods have superior performance, it might be better than before.

Acknowledgements. This research was partially supported by the 'Brain Korea 21 Plus Project' of the Ministry of Education & Human Resources Development, Republic of Korea (ROK) [F16SN26T2205], and partially supported by the 'Cross-Ministry Giga Korea Project' of Ministry of Science, ICT and Future Planning, Republic of Korea (ROK). [GK17C0100, Development of Interactive and Realistic Massive Giga – Content Technology].

References

1. Kerl, C., Sturm, J., Cremers, D.: Dense visual SLAM for RGB-D cameras. In: Proceedings of the International Conference on Intelligent Robot Systems (IROS) (2013)
2. Izadi, S., Kim, D., Hilliges, O., Molyneaux, D., Newcombe, R., Kohli, P., Shotton, J., Hodeges, S., Freeman, D., Davison, A., Fitzgibbon, A.: KinectFusion: real-time 3D reconstruction and interaction using a moving depth camera. In: Proceedings of ACM Symposium on User Interface Software and Technology (2011)
3. Endres, F., Hess, J., Engelhard, N., Sturm, J., Cremers, D., Burgard, W.: An evaluation of the RGB-D SLAM system. In: ICRA (2012)
4. Fischler, M.A., Bolles, R.C.: Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Commun. ACM **24**(6), 381–395 (1981)
5. Rusu, R.B., Blodow, N., Beetz, M.: Fast point feature histograms (FPFH) for 3D registration. In: ICRA, pp. 3212–3217 (2009)
6. Zhou, Q.-Y., Park, J., Koltun, V.: Fast global registration. In: Leibe, B., Matas, J., Sebe, N., Welling, M. (eds.) ECCV 2016. LNCS, vol. 9906, pp. 766–782. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-46475-6_47
7. Yang, J., Li, H., Campbell, D., Jia, Y.: Go-ICP: a globally optimal solution to 3D ICP point-set registration. IEEE TPAMI **38**(11), 2241–2254 (2016)
8. Choi, S., Zhou, Q.Y., Koltun, V.: Robust reconstruction of indoor scenes. In: CVPR (2015)
9. Lei, H., Jiang, G., Quan, L.: Fast descriptors and correspondence propagation for robust global point cloud registration. IEEE Trans. Image Process. **26**(8), 3614–3623 (2017)
10. Mellado, N., Aiger, D., Mitra, N.J.: Super4PCS: fast global pointcloud registration via smart indexing. In: Computer Graphics Forum. 33(5), pp. 205–215. Wiley Online Library (2014)
11. Kolluri, R., Shewchuk, J.R., O'Brien, J.F.: Spectral surface reconstruction from noisy point clouds. In: Proceedings of the 2004 Eurographics/ACM SIGGRAPH Symposium on Geometry processing, pp. 11–21 (2004)

12. Handa, A., Whelan, T., McDonald, J., Davison, A.J.: A benchmark for RGB-D visual odometry, 3D reconstruction and SLAM. In: ICRA, pp. 1524–1531 (2014)
13. Segal, A.V., Haehnel, D., Thrun, S.: Generalized-ICP. In: Proceedings of Robotics: Science and Systems, pp. 26–27 (2009)
14. Granger, S., Pennec, X.: Multi-scale EM-ICP: a fast and robust approach for surface registration. In: Heyden, A., Sparr, G., Nielsen, M., Johansen, P. (eds.) ECCV 2002. LNCS, vol. 2353, pp. 418–432. Springer, Heidelberg (2002). https://doi.org/10.1007/3-540-47979-1_28
15. Low, K.L.: Linear least-squares optimization for point-to-plane ICP surface registration. Technical report, TR-04-004. University of North Carolina (2004)
16. Zhong, Y.: Intrinsic shape signatures: a shape descriptor for 3D object recognition. In: ICCV Workshops, pp. 689–696 (2009)
17. Jian, B., Vemuri, B.C.: Robust point set registration using Gaussian mixture models. IEEE TPAMI **33**(8), 1633–1645 (2011)
18. Rusu, R.B., Cousins, S.: 3D is here: point cloud library (PCL). In: ICRA, pp. 1–4 (2011)