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A Point Cloud Registration Method Using Sample Consensus Pre-Rejective Algorithm and Iterative Closest Point Algorithm

Khoo Xin Ping, Lim Chot Hun, Ong Lee Yeng and Koo Voon Chet
Center for Remote Sensing and Surveillance Technologies (CRSST),
University Centre of Excellence, Multimedia University, Cyberjaya, Malaysia

Abstract: A point cloud registration method using sample consensus pre-rejective algorithm and iterative closest point algorithm incorporate with rotation matrix is described in this study. The performance of the presented algorithm was quantitatively analyzed by a series of experiments. The registration qualities of the proposed algorithm were studied through the experiments. Results obtained from the experiments showed significant improvement in point cloud registration quality through the application of proposed algorithm as compare to the individual point cloud registration algorithm.

Key words: Point cloud, registration, sample consensus pre-rejective, iterative closest point, RGB-D, significant

INTRODUCTION

Point cloud can be defined as a collection of data points commonly presented in three-dimensional Cartesian coordinate system. Basically, point clouds are utilized to represent the external surface of an object or an area of interest. The point cloud raw data have been further analyzed in different field of researches in order to obtain meaningful information which can be utilized in various applications. For example, in a study by Wi *et al*. (2016) the point cloud data of rooster beak is collected and analyzed to aid the design of a roller structure, aimed to simplify the discretization process and lower the damage caused during kernel dispersal.

Although, point cloud can be generated and analyzed directly, the raw point cloud will mostly be reconstructed and converted into meshes forms in order to be used in three-dimensional applications. In recent years, research utilizing three-dimensional properties of objects and elements have been boosted through the development of technology in reconstructing out the three-dimensional model. For example, in a study by Woodall and Bevly (2012) the acquired point cloud served as the raw data in forming a three-dimensional map that can be used for teleoperation. While in a study by Alexiadis *et al*. (2013) a three-dimensional body reconstruction method is presented to be applied in tele-immersive environments. This method provided a higher degree sense of interactions between the physically separated users during tele-conferencing. Meanwhile, Shamgholi *et al*. (2014) discussed about the restoration of images from documents by analyzing the three-dimensional shape which is estimated from the generated three-dimensional models. The applications mentioned above showed the wide possibility of utilizing the reconstructed three-dimensional model in providing solutions for various problems faced in different fields.

Processes in forming three-dimensional model and problems occurred in registration: A three-dimensional model is formed through a series of steps. The first step is known as the acquisition whereby the sensor is used to acquire the information of the navigated environment or the targeted object either in still images, video or depth information. After the acquisition step, the acquired three-dimensional images, being converted into point cloud will be pre-processed for down sample and filter purposes. After this stage, the preprocessed point cloud is registered to align in common coordinate frame (Majdi *et al*., 2013). Registration process can be divided into 2 forms. The first registration method is founded on feature description while the second registration method is based on iterative approach (Majdi *et al*., 2013). Upon the completion of registration process, merging is carried out to combine the point cloud into a three-dimensional model. Lastly, the merged point cloud will undergo post-processing stage to further enhance the quality of the three-dimensional model formed.

Note that there are two common problems affecting the registration quality during the registration process. The first problem arose due to the imperfection in visual

Corresponding Author: Khoo Xin Ping, Center for Remote Sensing and Surveillance Technologies (CRSST), University Centre of Excellence, Multimedia University, Cyberjaya, Malaysia

odometry while aligning two consecutive point clouds that having small relative movement (Ren *et al*., 2013), mainly caused by the low quality of alignment between consecutive clouds. The second problem is known as the loop closure problem, arose due to the lack of quality on the alignment of the last point cloud with the initial point cloud once overlapped. In another words, loop closure problem is caused by the accumulation of alignment errors in the registration process of previous pairs of clouds.

Reviews of point cloud registration: In this study, the discussion is focused on the point cloud registration process targeting on the two problems mentioned above. The reason of focusing on registration process is due to the fact that an accurate three-dimensional model can only be formed with the combination of individual point cloud data from different observation angles. In addition, due to the limitation of field of view and observation range of the sensor, registration process is a must in order to form a larger three-dimensional model or a three-dimensional map.

The registration problems were analyzed in a few papers with different solutions proposed. In the RGB-D mapping system developed by Henry *et al*. (2010) using Kinect, the registration process is carried out by considering both the sparse feature matching and the dense Iterative Closest Point (ICP) matching. The Random Sample Consensus (RANSAC) algorithm is executed to align the Scale Invariant feature Transform (SIFT) features obtained from the RGB frame (Henry *et al*., 2010). Next, the feature matching is combined with the dense ICP matching obtained from depth frame to align the frame in common coordinate frame (Henry *et al*., 2010). In a study by Wang *et al*. (2014) a three-dimensional reconstruction method is presented using an RGB-D camera. In order to support for robust registration that work in challenging cases, the study proposed a method utilizing both geometry and visual features with the combination of Structure From Motion (SFM) technique to enhance the quality of the feature matching and the camera pose estimation (Wang *et al*., 2014). Furthermore, this study introduced a prior based multicandidate RANSAC to enhance the speed of the camera pose estimation and improving the efficiency in estimating the model parameters, thus, improved the registration quality (Wang *et al*., 2014). On the other hand, the estimation of alignment pose in registration process between two three-dimensional model surfaces have been addressed by Buch *et al*. (2013). A set of semi-local descriptors consists of rich appearance and shape information are generated utilizing the combination of three-dimensional shape information and two-dimensional image information (Buch *et al*., 2013). In addition, a modification of RANSAC is introduced in the pose estimation step to reduce the operation time required through enforcing a low-level geometric constraint after the first step of each iteration Buch *et al*., 2013). This modified RANSAC had significantly increased the operating speed of RANSAC algorithm, thus improved the efficiency of registration process.

Proposed algorithm: In this study, an enhanced point cloud registration algorithm using Sample Consensus Pre-rejective (SCP) algorithm and ICP incorporated with rotation matrix is introduced to enhance the registration process quality. This algorithm also served as the solutions in answering the two problems raised.

The main framework of this algorithm is inspired by Henry *et al*. (2010) and the algorithm is enhanced by incorporating in the modified RANSAC developed by Buch *et al*. (2013). It should be noted that in the proposed system, the movement of the data acquired sensor is known and limited only to rotation motion. Therefore, the highlight in our proposed algorithm is that a rotation matrix is applied to transform the source point cloud data as a rough position estimation before executing the initial alignment step using SCP and ICP. This step significantly reduces the computational requirement for point cloud alignments, thus resulting in a smaller size of the resultant point cloud after registration process. This advantageous feature made the proposed algorithm different from others. Without the rotation matrix, the number of acquired point clouds increased significantly due to the high overlapping region required in applying the ICP algorithm. In short, the proposed algorithm combined two main registration branches, namely the feature based approach and the iterative approach, to enhance the quality of registration process while the incorporated rotation matrix reduced the amount of required input point cloud.

MATERIALS AND METHODS

In our system, the used sensor is an RGB-D camera (Kinect sensor developed by Microsoft). This sensor is able to capture color information and depth information of the targeted region between the ranges of 0.5-6 m. The internal accurate alignment of the acquired color frame and depth frame in the common coordinate frame resulted in the formation of point cloud. Note that, the point cloud data is the input to the proposed algorithm.

This study introduced an enhanced point cloud registration algorithm based on SCP initial alignment and ICP, incorporate with the rotation matrix. Note that, the

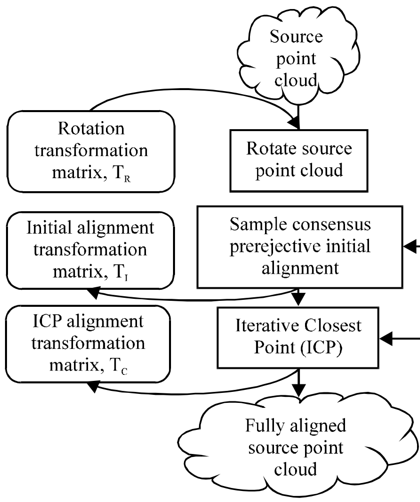

Fig. 1: Flow of proposed registration algorithm

registration of point cloud can be divided into two types, namely the pairwise registration and the simultaneous registration. Pairwise registration brings the meaning of registering the current point cloud with the previous point cloud. On the other hand, simultaneous registration aligned all the point clouds at once. Note that pairwise registration is selected in the proposed algorithm, since, it is less computational expensive as compare to the simultaneous registration.

Figure 1 depicted the complete flow of the proposed algorithm. To start a pairwise registration process, the source point cloud, P_S and the target point cloud, P_T need to be identified. Source point cloud is defined as the newly acquired point cloud while target point cloud is defined as the former point cloud. The aim of this proposed algorithm is to improve the alignment accuracy of the source point cloud to the target point cloud. The alignment started by transforming the source point cloud using a rotation matrix based on the rotation movement of the sensor. After that, the features of the source point cloud and the target point cloud are served as the input to perform another alignment known as the SCP initial alignment. After this alignment is made, the pairwise registration is further refine through ICP. The detail of the algorithm is outlined and explained in the following sub sections.

Rotation matrix: In this system, the movement of the sensor is known and fixed as a rotation motion in clockwise direction. Ideally, a successful registration of source point cloud and target point cloud will return a predicted rotation transformation matrix corresponded to the sensor's degree of rotation, T_R. However, error might happen during the rotation process due to the imperfections of the rotation mechanism. Equation 1 depicts the rotation matrix based on the predicted rotation angle θ in clockwise direction. Note that R (θ) is multiplied with the source point cloud to achieve the first transformation as described in Fig. 1:

$$R(\theta)=\begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix} \quad (1)$$

It should be noted that despite the fact that the predicted rotation matrix is served as a pre-guess transformation in the registration process, it is important to reduce the total number of input point clouds required to form the three-dimensional model. This is due to the fact that image based registration required high percentage of similar features to be found between two point clouds. Thus, without the predicted rotation matrix, the movement of the sensor will be limited to a small scale, resulting in the requirement of large number of point cloud to cover the whole area of interest with extra processing power requirement. Upon the completion of this stage, a rotated source point cloud P_S^R will be generated.

Sample Consensus Pre-rejective (SCP) initial alignment: Ideally, the source point cloud undergo the rotation transformation matrix is aligned to the target point cloud. However, there may have alignment errors due to the imperfection in point cloud acquisition process. To tackle this issue, the SCP initial alignment algorithm is used to ensure the alignment accuracy between the source point cloud and target point cloud after the rotation. The algorithm required the computation of both the features of the source point cloud and the target point cloud. In our algorithm, the features were computed using the Fast Point Feature Histograms (FPFH) due to its lower computation complexity as compare to Point Feature Histograms (PFH) while maintaining the discriminative power of PFH. After the features of both source point cloud and target point cloud are computed, these features will be set as the input to the SCP alignment class for initial alignment pose estimation. Note that SCP is an alignment class modified from RANSAC routine. As its name implies, a pre-rejection step is added into the RANSAC pose estimation loop to reduce the need of verification for the pose hypotheses that might be wrong. Local pose-invariant geometric constraints are used to achieve the pre-rejection target. At the end of this process, a transformation matrix which shows the alignment transformation between the rotated source point cloud and the target point cloud, T_I is obtained and an aligned source point cloud P_S^I is thus, produced.

Iterative Closest Point (ICP): After the alignment between the rotated source point cloud and the target point cloud is done, the overlapping area between the aligned source point cloud and the target point cloud is now large enough to satisfy the criteria of performing ICP. To initiate the ICP algorithm, the aligned source point cloud is now served as the input to the ICP algorithm with the aim to refine the registration between both point clouds.

The idea of ICP is to transform all the subsequent point cloud data into the very first point cloud's frame. This step is done by accumulating the best transforms between each pair of point clouds. To better elaborate the operations of ICP, consider two point clouds, P^1 and P^2 with i number of points in Cartesian coordinates as elaborated in Eq. 2 and 3:

$$P^1 = \left\{p_i^1\left(x_i^1, y_i^1, z_i^1\right)\right\} \tag{2}$$

$$P^2 = \left\{p_i^2\left(x_i^2, y_i^2, z_i^2\right)\right\} \tag{3}$$

The point cloud pair P^1 and P^2 are iteratively matched to find the optimal relative rigid transformation matrix T_C, as shown in Eq. 4 where T_K is the updated incremental transformation obtained through searching the correspondence in source point cloud and target point cloud by minimizing the distance between them. By completing ICP operation an iteratively aligned source point P_S^C will be produced:

$$T_C = T_K \times T_C \tag{4}$$

Complete algorithm: The complete pseudo-code of the proposed registration algorithm is shown below. A transformation matrix and a transformed source point cloud is generated by each of the three main alignment routines. The source point cloud, P_S is aligned to the target point cloud, P_T by applying the final transformation matrix T_F which is equal to the multiplication of the three transformation matrix generated in the 3 routines as shown in Eq. 5 (Algorithm 1).

Algorithm 1; Proposed registration algorithm flow:

1. BEGIN
2. defined P_S and P_T
3. rotate P_S with $T_R \rightarrow P_S^R$
4. SCP align to $P_T \rightarrow T_I$ and
5. ICP align to $P_T \rightarrow T_C$ and
6. END

$$T_F = T_R \times T_I \times T_C \tag{5}$$

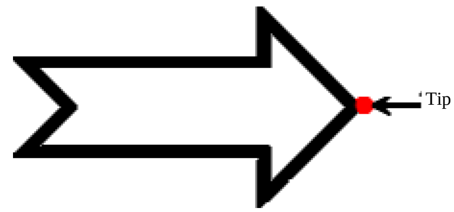

Fig. 2: Marking used in experiment

Experiment setup: An experiment is designed and carried out to verify the performance of the proposed registration algorithm. The steps of this experiment are outlined as follows:

A total of eight specially designed 2D symbols are placed in a confined room. The RGB-D sensor is placed at the center of the room. The sensor is instructed to collect only eight point clouds data in one complete rotation where each point cloud data should contain one of the 2D symbol. Figure 2 illustrated the symbols used in the experiment.

The actual distance, d_{Ac}^n between the consequent marks (distance between the tips of consequent marks) is manually measured and confirmed with a laser rangefinder where n is the sequence of point cloud acquired from 1-8 with each sequence differ by 45°.

A turn table is located at the center of location of interest with the RGB-D sensor placed on top of it and directed to 0°. The RGB-D sensor is rotated with 45° interval from 0-315° (8 times in total) as shown in Fig. 3. Such rotation is enough to provide coverage over the area of interest.

A single point cloud data is recorded for each rotation and the pairwise registration algorithm will be executed with the new input point cloud until the last point cloud is taken in. The Euclidean distance, d_{Eu}^n between the marks in the consecutively registered point clouds is measured using Eq. 6.

The actual distance measured between the consequent pair of markings are compared with the Euclidean distance obtained and the values are average up to obtain the average Root Mean Square Error (RMSE), Err_{RMS}^{Avg} based on Eq. 7:

$$d_{Eu}^n = \sqrt{\left(x_2^n - x_1^n\right)^2 + \left(y_2^n - y_1^n\right)^2 + \left(z_2^n - z_1^n\right)^2} \tag{6}$$

$$Err_{RMS}^{Avg} = \frac{\sum_1^n \left|d_{Ac}^n - d_{Eu}^n\right|}{n} \tag{7}$$

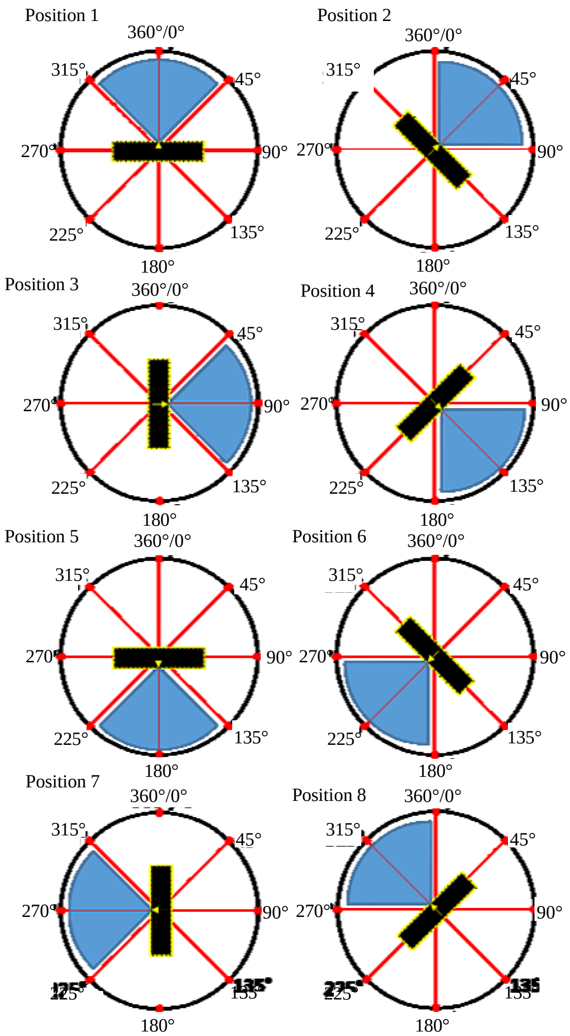

Fig. 3: Position of sensor in experiment

RESULTS AND DISCUSSION

Based on the setup, experiment had been carried out to test the proposed algorithm. To verify the performance of the proposed algorithm, another three different registration methods had been performed on the same setup to compare with the performance of the proposed algorithm. These three registration methods are existing techniques used in point cloud registration process incorporate with the rotation matrix.

Among the three methods, the first method (rotated registration) considered only rotation transformation matrix applied to each of the incoming source point cloud. No image based registration method involved in this method. On the other hand, the second method (rotated

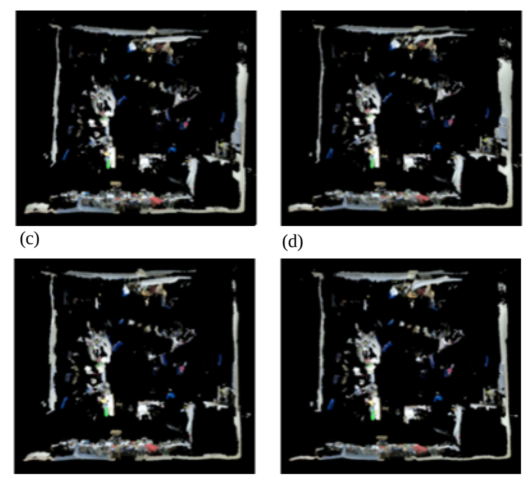

Fig. 4: Registered point clouds of 4 different registration methods: a) Rotated registration; b) Rotated ICP registeration; c) Rotated prerejective registration and d) Rotated prerejective ICP registration

Table 1: Average RMSE of four registration methods

Registration methods	Err_{RMS}^{Avg} (m)
Rotated registration	0.050949
Rotated ICP registration	0.053527
Rotated pre-rejective registration	0.053687
Rotated pre-rejective ICP registration	0.037247

ICP registration) considered the source point cloud will be rotated with the rotation transformation matrix before being registered using ICP algorithm. Lastly in the third method (rotated pre-rejective registration), the source point cloud undergo same steps as first method while the computed output is fed into the SCP algorithm for initial alignment. Meanwhile in our proposed method (Rotated pre-rejective ICP registration), the rotated source point cloud first being aligned to the target point cloud before going through the ICP to further refine the registration process.

The registered point cloud results from the four different methods are shown in Fig. 4 with the average RMSE of the four registration methods featured in Table 1. Based on the registered point cloud images shown in Fig. 4, it is found that through visual inspection, the registration quality of all four registration method are similar whereby all four generated point clouds are well registered. It is also observed that there is no obvious loop closure problem found in the registered point cloud. This result can be explained as all four methods are having one similarity whereby among the four methods, all source point clouds have been transformed by the rotation matrix. Therefore, if there is no large deviation of the sensor movement during point cloud acquiring process, the pre-guessing rotation matrix which transformed the source point cloud in each of the pairwise registration should produce similar result.

Table 1 illustrated the average RMSE computed from the four different methods. As show in Table 1, the proposed method achieved the lowest RMSE error as compare to other existing registration method with the average RMSE improved by 26.89% over method 1, 30.41% over method 2 and 30.62% over method 3. Such results verified that the proposed point cloud registration algorithm had improved the registration quality indicating that the proposed algorithm has a lower visual odometry problem as compare to the other three point cloud registration methods.

CONCLUSION

An enhanced, a point cloud registration algorithm utilizing SCP algorithm and ICP algorithm with the aid of rotation matrix is proposed. Experiments were carried out to analyze the performance of the designed algorithm. Results from the experiments showed that the proposed algorithm had improved the registration quality in point cloud registration process as compare with three other existing point cloud registration algorithms. The improvement in registration can be seen from the lower average RMSE from the quantitative analysis. In addition, based on visual inspection, there was no significant loop closure problem observed in the registered point cloud . This implied that the proposed algorithm had improved the performance of the overall system by reducing the effect of the two main problems (visual odometry and loop closure) during point cloud registration process.

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REFERENCES

Alexiadis, D.S., D. Zarpalas and P. Daras, 2013. Real-time, realistic full-body 3D reconstruction and texture mapping from multiple Kinects. Proceedings of the 2013 IEEE 11th Workshop on IVMSP, June 10-12, 2013, IEEE, Seoul, South Korea, ISBN:978-1-4673-5857-6, pp: 1-4.

Buch, A.G., D. Kraft, J.K. Kamarainen, H.G. Petersen and N. Kruger, 2013. Pose estimation using local structure-specific shape and appearance context. Proceedings of the 2013 IEEE International Conference on Robotics and Automation (ICRA), May 6-10, 2013, IEEE, Karlsruhe, Germany, ISBN:978-1-4673-5641-1, pp: 2080-2087.

Henry, P., M. Krainin, E. Herbst, X. Ren and D. Fox, 2010. RGB-D mapping: Using depth cameras for dense 3D modeling of indoor environments. Proceedings of the 12th International Symposium on Experimental Robotics (ISER), December 18-21, 2010, Springer, New Dehli, India, ISBN:9783642285721, pp: 1-15.

Majdi, A., M.C. Bakkay and E. Zagrouba, 2013. 3D modeling of indoor environments using Kinect sensor. Proceedings of the 2013 IEEE Second International Conference on Image Information Processing (ICIIP), December 9-11, 2013, IEEE, Shimla, India, ISBN:978-1-4673-6099-9, pp: 67-72.

Ren, X., D. Fox and K. Konolige, 2013. Change their perception: RGB-D for 3-D modeling and recognition. IEEE. Rob. Autom. Mag., 20: 49-59.

Shamgholi, M., H. Khosravi and S.M. Riazi, 2014. Document image dewarping based on text line detection and surface modeling (research note). Intl. J. Eng. Trans. C. Aspects, 27: 1855-1862.

Wang, K., G. Zhang and H. Bao, 2014. Robust 3D reconstruction with an RGB-D camera. IEEE. Trans. Image Process., 23: 4893-4906.

Wi, K., X. Li and Y. Ma, 2016. Microscopic structures analysis and experimental research of beak. Intl. J. Eng.Trans. A. Basics, 29: 942-947.

Woodall, W.J. and D. Bevly, 2012. Using the microsoft kinect for 3D map building and teleoperation. Proceedings of the 2012 IEEE/ION Symposium on Position Location and Navigation (PLANS), April 23-26, 2012, IEEE, Myrtle Beach, South Carolina, USA., ISBN:978-1-4673-0385-9, pp: 1054-1061.