ACCURATE CO-REGISTRATION OF MULTI-TEMPORAL TERRESTRIAL LIDAR DATA FOR ROAD MANAGEMENT

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ABSTRACT: In this paper, we present a method that achieves accurate co-registration of multi-temporal point clouds even though the data are occluded. One of the most widely known algorithms for co-registration of multi-temporal point clouds is Iterative Closest Point (ICP) method. However, the ICP method has disadvantages that it requests initial parameter values of relative rotation angles and transition close to actual ones. In addition, it is not robust against the occlusion caused by pedestrians or vehicles. The proposed method composes of two processing. The first processing realizes a rough co-registration, and the latter one implements the ICP-based accurate co-registration. In the first processing, we assume that the three-dimensional space of interest may have common and dominant normals, and that they are robustly estimated even though parts of the space are lacking in the point clouds due to occlusion. In the experiments, we used the point clouds observed by using terrestrial light detection and ranging (LiDAR) data, and the parts of the point clouds were intentionally excluded, representing the occlusion by objects. The proposed method generated acceptable root mean square error (RMSE) for both non-occluded and occluded data sets, respectively. As a result, it was demonstrated that the proposed method is robust against the data lacking, and is capable of co-registration of point clouds for road maintenance.

1. INTRODUCTION

Mobile mapping system (MMS) rapidly generating huge amount of point clouds is expected to be used for maintaining infrastructure by comparing the point clouds observed at different times. MMS measures the three coordinate values of objects, but when the objects of interest are occluded, the generated point clouds become incomplete. For example, the observation of roads using MSS are conducted twice or several times within a limited time for compensating the occluded data. However, because of the positional errors caused by global navigation satellite system (GNSS) or other factors, the point clouds may have geolocational errors. In operational processing, these errors are corrected by manually selecting ground control points (GCPs).

One of the most widely known algorithms for co-registration of multi-temporal point clouds is Iterative Closest Point (ICP) method (Besl and McKay, 1992). Given a point of a point cloud, the ICP method automatically selects the corresponding point from another point cloud. However, the ICP method requests initial parameter values of relative rotation angles and transition should be close to actual ones. In addition, it is not robust against the occlusion caused by pedestrians or vehicles. In terms of application to road surface monitoring, such occlusion can easily occur. Our preliminary examination revealed that the ICP method fails in co-registration of partly occluded point clouds.

In this paper, we present a method that achieves accurate co-registration of multi-temporal point clouds even though the data are occluded. The proposed method composes of two processing. The first processing realizes a rough co-registration without selecting GCPs common to the two sets of point clouds. In the first processing, we assume that the three-dimensional space of interest may have common and dominant normals, and that they are robustly estimated even though parts of the space are lacking in the point clouds due to occlusion. The latter processing of the proposed method implements the ICP-based accurate co-registration, assuming that the data are almost co-registered by the first processing. In Section 2, we describe the proposed method, and we explain the data used in this research in Section 3. After we report the results in Section 4, we discuss them in Section 5. Finally, we conclude this paper in Section 6.

2. PROPOSED ALGORITHM

In this paper, we assume to co-register a set of point cloud, e.g. Point Cloud 2, to another set of point cloud, e.g. Point Cloud 1, and they are observed in an environment that has ground and vertical planes, e.g. walls of buildings. The novelty of the proposed method is that it does not utilize point-based matching in the first processing to improve the robustness against the occlusion. Instead, it utilizes normals aggregated from plane-type objects including walls and roads. Figure 1 shows the flowchart of the proposed algorithm.

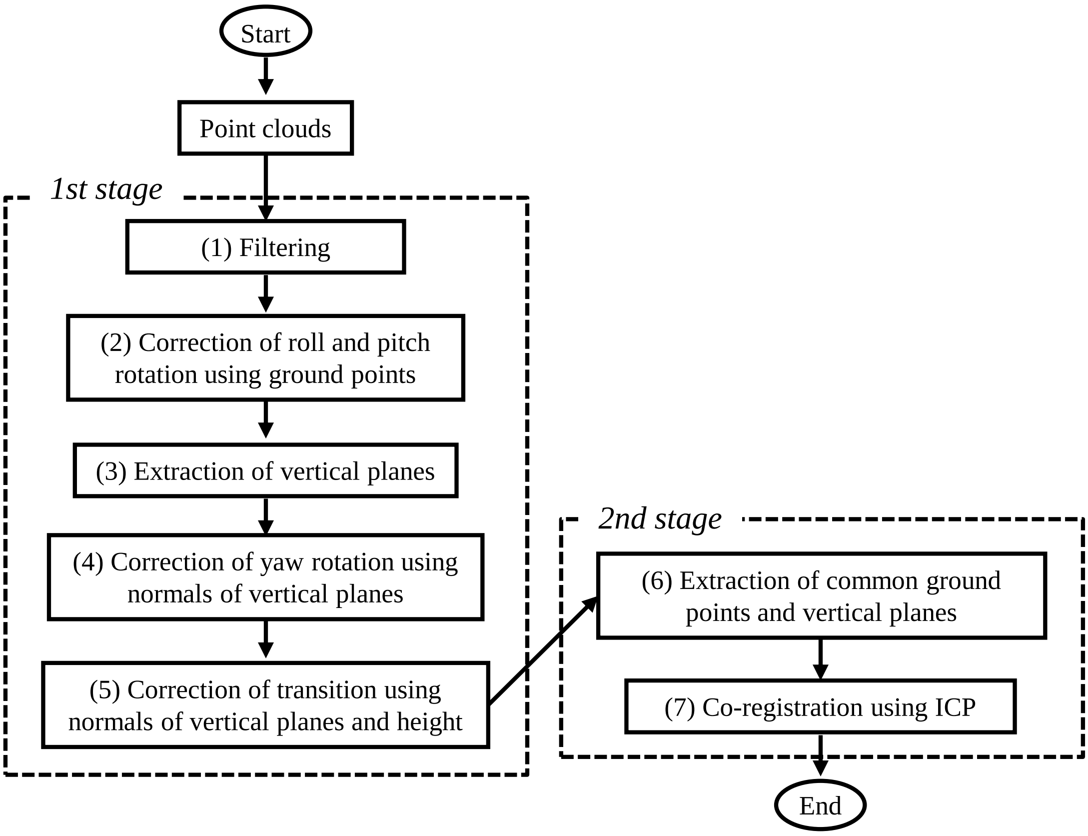


Figure 1 Flowchart of the proposed algorithm

The proposed algorithm first filters point clouds and extracts ground points. This procedure is applied for respective point clouds. Then, two normals of ground are estimated. Here, we define a normal that is perpendicular to the two normals as $(n_x, n_y, n_z)^t$. We also define an interior angle between the two normals as θ. The correction of roll and pitch rotation is implemented using this normal and angle:

$$\boldsymbol{R}_\theta = \boldsymbol{I} + \sin\theta \cdot \boldsymbol{A} + (1-\cos\theta)\cdot \boldsymbol{A}^2 . \tag{1}$$

$$\boldsymbol{A} = \begin{pmatrix} 0 & -n_z & n_y \\ n_z & 0 & -n_x \\ -n_y & n_x & 0 \end{pmatrix}. \tag{2}$$

Then, the proposed algorithm extracts the vertical planes, e.g. building walls, and the normals of the planes are examined. The dominant normal is selected. The relative azimuth angle between the extracted two normals is determined. Using this angle, the proposed algorithm corrects yaw rotation. At this stage, the rotation of Point Clouds 2 is roughly corrected.

The proposed algorithm uses the normals of vertical planes extracted to determine the transition term. First, normal distribution along x-axis, and the several peaks of the distributions are extracted. Utility of a peak for determining x component of transition term is not robust against the occlusion. Therefore, examination of several peaks performs robust determination. Then, similarly, y component of transition term is determined. After transition along x and y-axes are corrected, the transition along z-axis is finally corrected. The transition value is determined by calculating the difference of height within a grid corresponding to ground. This is the end of the first stage.

In the second stage, we extract ground points and vertical planes common to both point clouds. The extracted point clouds are used for co-registration using the ICP method. Finally, the co-registered point cloud is generated.

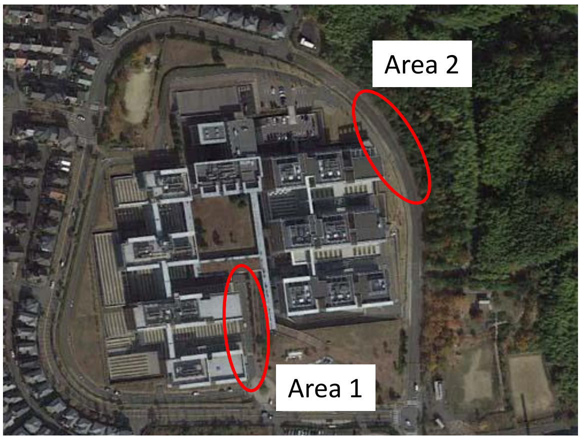
3. DATA USED

We did measurement using Riegl LMS-400, a terrestrial LiDAR, in two areas of Katsura campus, Kyoto University in the morning of November 3, 2015. The study areas are shown in Figure 2. The interval angle for the measurement was set to 0.04º, and the measurement range was from -40º to 60º of elevation angle and 360º of azimuth angle. In each area, we set up the LiDAR at different two points. The distances between two points were approximately several meters, and relative yaw angles of the two coordinates were approximately 40º to 50º. The data sets are shown in Figure 3. Nine reflective targets were set and measured for validating the co-registration errors.

In this research, we aimed to investigate the performance of co-registration when the data are partly occluded. We removed parts of points to artificially represent the occlusion. We implemented two types of removal, "Occlusion 1" and "Occlusion 2". The first one represents a large occlusion, while the latter one represents a few small occlusions. Table 1 shows number of points for each data set.

4. RESULTS

We used the filtering algorithm presented by Susaki (2012). We calculated two normals from filtered ground points at each area, and obtained $\boldsymbol{R}_{\theta}$ in Equation (1). Then, we corrected roll and pitch rotation of Data 2. Figure 4 shows the extracted vertical planes. In this processing, we set several thresholds: maximum RMSE for estimating planes 0.01 m, minimum number of points for estimating planes 6, voxel size for counting points 0.1 m. Figure 5 shows the histograms of yaw rotation derived from normals of vertical planes. Figure 6 shows the histograms of points of vertical planes along X and Y axis. We selected the maximum peaks of the two data sets, and determine X and Y transition values. After correcting X and Y transition, we determined the Z transition value and corrected it.



(a)

(b)

(c)

Figure 2. Study areas. (a) from nadir view (GoogleEarth), (b) Study area 1 and (c) Study area 2

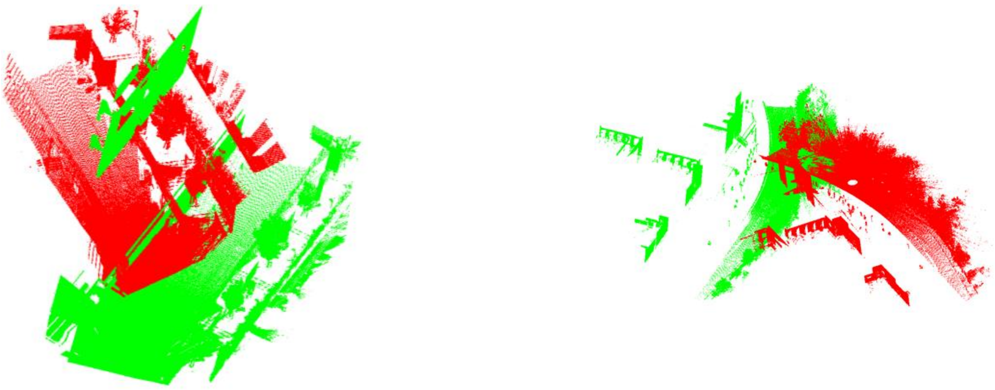


Figure 3. Measured data. Each area has two data sets, Data 1 shown by red and Data 2 shown by green.

Table 1. Number of points used. "Occlusion 1" represents a large occlusion, while "Occlusion 2" represents a few small occlusions.

Status	Area 1		Area 2	
	Data 1	Data 2	Data 1	Data 2
Before sampling	1,449,929	4,210,109	16,299,986	16,160,834
After sampling	90,498	105,701	782,573	790,284
Occlusion 1	67,295	89,890	685,941	633,729
Occlusion 2	73,109	82,932	630,752	653,423

Finally, the co-registered point clouds are shown in Figure 7. It compares the results obtained by direct application of the ICP method and the proposed method. Accuracy assessment results are shown in Table 2.

5. DISCUSSION

Table 2 shows that the proposed method achieved the high accuracies of co-registration for the data of Areas 1 and 2. It is confirmed in both cases of occluded and non-occluded data sets. For example, the result of "Occlusion 1" of Data 1 and "Occlusion 2" of Data 2 in Area 2 shows the first processing accuracy was not acceptable, an RMSE of 209.8 mm. However, the final accuracy was an RMSE of 4.9 mm. Even though rough co-registration was conducted in the first processing, the ICP method can achieve the acceptable accuracy. It indicates that the proposed method may be robust against the occlusion in point clouds.

We conducted investigation to the data measured at the areas those include vertical walls. In reality, it is possible that the area of interest has no such vertical wall, or the area has vertical walls far away from the LiDAR. In the latter case, the point density may not be so high. As a result, the percentage of the walls extracted as "vertical planes" during the processing will be low. When the walls available for the analysis are limited, the proposed method may fail in determining the yaw rotation angle and transition values. In near future, we will investigate this issue, and improve the proposed method.

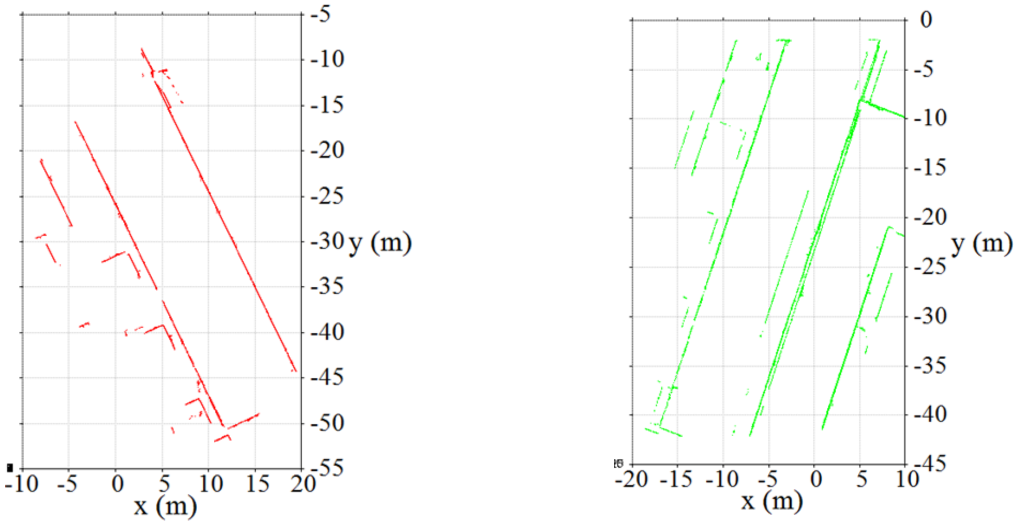


Figure 4. Extracted vertical planes of Area 1. (a) Data 1 and (b) Data 2.

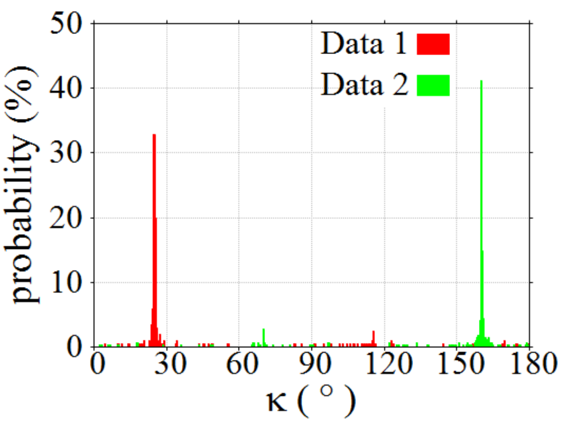


Figure 5. Histograms of yaw rotation by using normals of vertical planes of Area 1

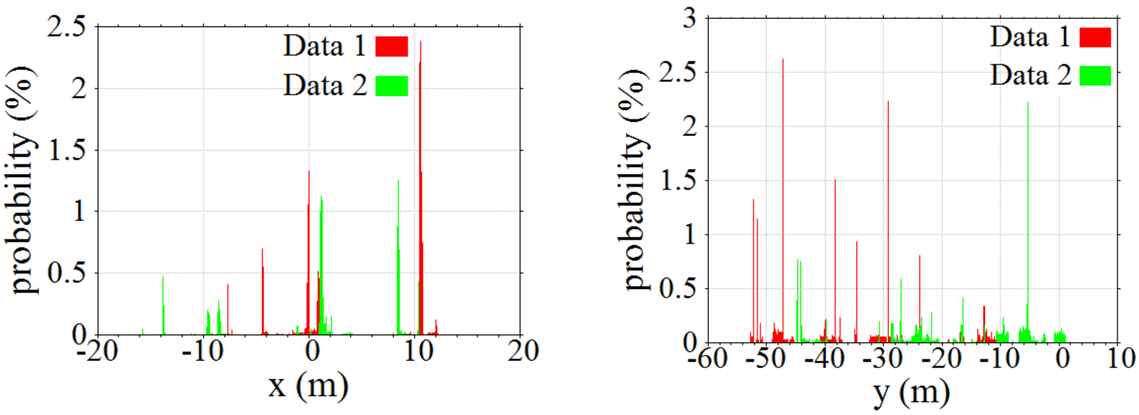
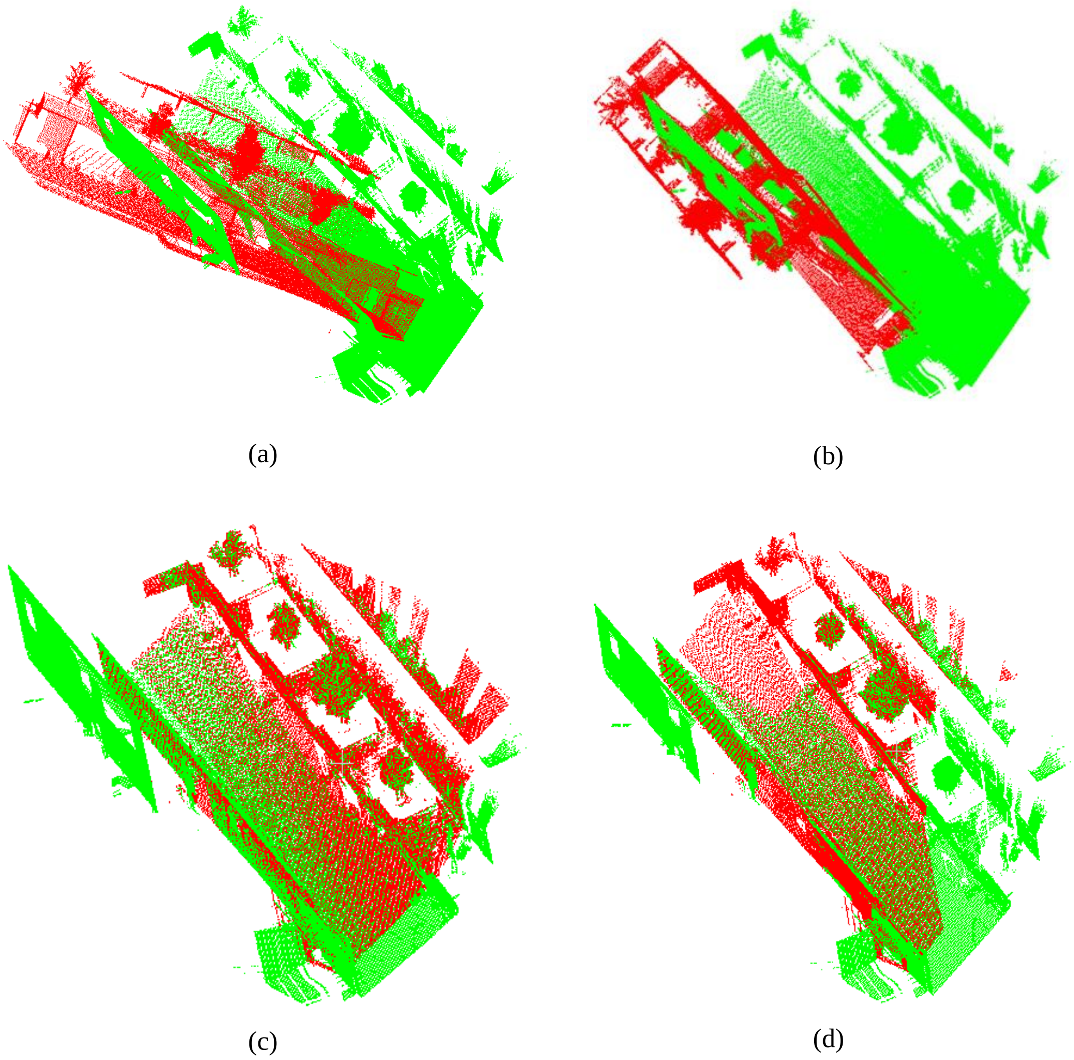


Figure 6. Histograms of points of vertical planes of Area 1. (a) Histograms along X-axis, and (b) histograms along Y-axis.



(a) (b) (c) (d)

Figure 7. Results of co-registration of Area 1. (a) Direct application of ICP in a point-to-point mode, (b) direct application of ICP in a point-to-plane mode, (c) after the first processing of the proposed method for the non-occluded data, and (d) the first processing of the proposed method (“Occlusion 1” of Data 1 and “Occlusion 1” of Data 2)

6. CONCLUSIONS

In this paper, we presented a novel method that achieves accurate co-registration of multi-temporal point clouds even though the data are occluded. In the proposed method, the first processing realizes a rough co-registration, and the latter one implements the ICP-based accurate co-registration. The first processing does not extract GCPs, and utilizes the normals obtained from the ground and vertical walls. In the experiments, we used the LiDAR data, and the parts of the point clouds were intentionally excluded. The proposed method generated acceptable RMSEs for both non-occluded and occluded data sets, respectively. As a result, it was demonstrated that the proposed method is robust against the data lacking, and is capable of co-registration of point clouds for road maintenance.

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Table 2. Accuracy assessment of co-registration

(a) Area 1

		RMSE (mm)	component		
			x	*y*	*z*
Data 1 and Data 2	Before co-registration	10,745	5,931	8,344	3,263
	Direct application of ICP (point-to-point)	15,269	9,655	581	11,814
	Direct application of ICP (point-to-plane)	18,379	15,609	4,057	8,813
	The first processing of the proposed method	73.5	16.6	28.9	65.5
	The second processing of the proposed method	4.1	2.9	2.4	1.6
"Occlusion 1" of Data 1 and "Occlusion 1" of Data 2	The first processing of the proposed method	98.6	96.1	21.3	6.1
	The second processing of the proposed method	3.6	2.9	1.4	1.3
"Occlusion 2" of Data 1 and "Occlusion 2" of Data 2	The first processing of the proposed method	89.6	78.6	35.9	23.6
	The second processing of the proposed method	8.1	3.3	7.2	1.7

(b) Area 2

		RMSE (mm)	component		
			x	*y*	*z*
Data 1 and Data 2	Before co-registration	41,373	34,586	21,100	8,370
	Direct application of ICP (point-to-point)	29,581	26,667	12,148	4,041
	Direct application of ICP (point-to-plane)	37,431	34,119	15,147	2,745
	The first processing of the proposed method	79.5	62.4	48.6	8.6
	The second processing of the proposed method	2.0	0.6	1.6	1.1
"Occlusion 1" of Data 1 and "Occlusion 1" of Data 2	The first processing of the proposed method	111.5	90.3	62.7	18.04
	The second processing of the proposed method	2.2	0.7	1.5	1.4
"Occlusion 2" of Data 1 and "Occlusion 2" of Data 2	The first processing of the proposed method	209.8	155.3	135.1	40.9
	The second processing of the proposed method	4.9	3.2	2.7	2.6