3D Point Cloud Registration and Segmentation of Reflective Metal Objects Using Go-ICP and Improved RANSAC

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Abstract

Registration and segmentation of 3D data are necessary in many fields, such as factory automation, automated driving, or even in the medical field. However, the technique is generally applied to non-metal objects. One of the problems of registration of a metal object is that the point clouds representing a metal object contain many outliers and missing points because of its reflective nature. This makes the accuracy of the registration and segmentation degrade. In this paper, we propose registration and segmentation techniques that are robust to outliers. For registration, we use the globally optimal Go-ICP (Global optimal - Iterative Closest Point) algorithm considering the goodness of a combination of point cloud sets to escape from convergence to a local solution. In segmentation, we address the problem of RANSAC generating false segments consisting of nearly identical multiple planar points and introduce an improved RANSAC. We use three kinds of the metal tray to show the effectiveness of the proposed technique.

Keywords: Registration, Segmentation, Reflective Metal objects, Go-ICP, RANSAC

1. Introduction

Registration and segmentation are important techniques in various fields, such as factory automation, automated driving, and the medical field. However, no effective method has been proposed for objects such as metals, which are strongly affected by reflections. The problem with metallic objects is that reflections cause a lot of noise and missing points in the point cloud, which reduces the accuracy of registration. Another problem is that segmentation generates many spurious surfaces. In this study, we investigate effective registration and segmentation techniques for trays made of metal. In Chapter 2, we describe a proposed registration technique using a threshold value. In Chapter 3, we describe a proposed segmentation technique using normals and RANSAC, and in Chapter 4, we conduct experiments to verify the effectiveness of the proposed technique.

2. Registration

Let $X = \{x_i\}$ ($i = 1, \dots, M$) and $Y = \{y_j\}$ ($j = 1, \dots, N$) be two point groups. Here, $x_i, y_j \in \mathbb{R}^3$ are points in a 3-dimensional space. To perform 3-dimensional registration, we find a rotation matrix $\mathbf{R} \in SO(3)$ and a translation vector $\mathbf{t} \in \mathbb{R}^3$ that minimize the distance between corresponding points in the two point groups.

The evaluation function is given by

$$E(\mathbf{R}, \mathbf{t}) = \sum_{i=1}^{M} e_i(\mathbf{R}, \mathbf{t})^2 \qquad (1)$$

$$= \sum_{i=1}^{M} \left\| \mathbf{R}x_i + \mathbf{t} - y_{j^*} \right\|^2$$

where $e_i(\mathbf{R}, \mathbf{t})$ is the pointwise residual of x_i. The point $y_{j^*} \in Y$ is represented as the optimal correspondence of x_i. j^* is then

$$j^* = \underset{j\in\{1,\ldots N\}}{\operatorname{argmin}} \left\| \mathbf{R}x_i + \mathbf{t} - y_j \right\| \qquad (2)$$

In this study, the Go-ICP algorithm is used to find the optimal $\mathbf{R}, \mathbf{t}$ that minimize the evaluation function $E(\mathbf{R}, \mathbf{t})$.

2.1. *Go-ICP algorithm*

The Go-ICP algorithm [1] is a combination of the branch-and-bound method and the ICP algorithm. It is a globally optimal ICP algorithm that uses the branch-and-bound method to reduce the possibility of convergence to a local solution.

2.2. *Proposed Method*

The proposed method adds a threshold to the Go-ICP algorithm to improve the accuracy of registration of multiple point clouds. three thresholds th_1, th_2, andth_3 are set, and the process is performed in five steps. The steps are shown below. Let p_k $(k = 1, \ldots, K)$ be the point clouds. r_{before} is the distance between the point clouds before registration, and r_{after} is the distance between the point clouds after registration.

1. Align p_k and p_{k+1}
   If $k = 0$ and $r_{after_k} < th_1$, then $p_k$and p_{k+1} are integrated to make P_l $(l = 1)$.
   Also, let $k = k + 1$.
   If $k \geq 1$ and $r_{after_k} < th_1$, then integrate p_{k+1} into P_l. Also, assume $k = k + 1$.
   If $k \geq 1$ and $r_{after_k} > th_1$ then $l = k$, $k = k + 1$ and go to step 2.
2. Repeat 1 for all point groups. Multiple point clouds $P_l, P_{l+k}, \ldots, P_L$ are created. If $l_i \neq l_{i+1} - 1$ and $l_i \neq l_{i-1} + 1$ for subscript l of P, go to Step 3.
3. Calculate the RMSE of P_l and P_{l+n} $(n = 1)$ before alignment.
   Align P_l and P_{l+n} if $r_{before_l} < th_2$. Go to Step 4.
   If $r_{before_l} > th_2$, do not align, $n = n + 1$ (until $n \leq 2$, $l = l + 1$ if $n > 2$) and $l = l + 1$, then go to Step 5.
4. Calculate RMSE after alignment.
   If $r_{after_l} < th_3$, merge $P_l$and P_{l+n}. $l = l + 1$ and go to step 5.
   If $r_{after_l} > th_3$, do not integrate, $n = n + 1$ (until $n \leq 3$, $l = l + 1$ if $n > 3$) and $l = l + 1$, then go to Step 5.
5. Repeat step 3.
6. Output the point cloud.

Since point clouds contain noise and outliers, they significantly impact the accuracy of registration. By using a threshold value, point clouds whose registration results are below the threshold value can be excluded, and, as a result, point clouds containing noise and outliers can be excluded. By performing step 3 and subsequent steps, this method can exclude point clouds that are above the threshold value and improve the accuracy of 3D reconstruction. Therefore, if the registration results are good, the process terminates at step 2, and the result is the same as the original Go-ICP.

3. Segmentation

The point cloud of the metal tray obtained by registration is segmented to determine its shape. For this purpose, the four sides and the bottom of the point cloud tray are segmented. After segmentation, the plane equation of the bottom surface is used to obtain the top surface of the tray, and the vertices of the tray are obtained from the plane equations of each plane. The dimensions of the point cloud tray are then determined by measuring the height, width, and depth of the tray from the vertices.

3.1. *RANSAC-based Segmentation*

RANSAC is used to obtain the planes of metal trays. However, metal objects are often noisy and deficient, and if RANSAC is applied to metal trays, the problem is estimating spurious planes, as shown in Figure 1. Therefore, we propose a method of dividing the point cloud by the normal vector of the surface and the normal vector of the point, and then performing RANSAC. This method can solve the problem of spurious surfaces.

The search radius is used to calculate the normals. Let $\boldsymbol{P}_i$ be a point and r be a radius. using a KD tree, points within radius r from the point of interest are used and principal component analysis is performed to obtain the normal vector $\boldsymbol{n}_i$. This is done for all points.

RANSAC consists of the following four steps:

1. Select 3 points at random from the input points.
2. Estimate the plane from the three points.
3. Set a threshold and measure the number of inliers.
4. Repeat steps 1-3 a specified number of times to find the plane with the maximum number of inliers.

The final decision plane $\widehat{M}$ can be expressed by the following equation [2];

$$\widehat{M} = \underset{M}{\operatorname{argmax}} \left\{ \sum_{P_i \in U} T(P_i, M) \right\} \quad (3)$$

where U is the set of remaining points, P_i is a point, M is a plane, and $T(P_i, M)$ is an inlier index defined by

$$T(P_i, M) = \begin{cases} 1 & L_i < L_t \\ 0 & otherwise \end{cases} \quad (4)$$

Here L_i is the point-to-surface distance and L_t is the corresponding threshold value.

3.2. *Proposed Method*

In the proposed method, initially, only a single plane of the metal tray is estimated using RANSAC. Then, normal vector $\vec{n} = (\mathrm{a}, \mathrm{b}, \mathrm{c})$ of the estimated plane is obtained. Similarly, normal vector $\overrightarrow{n_{P_i}} = (a_i, b_i, c_i)$ is found for each point in the point group, the point-plane angle θ is calculated, and the point group is divided into three parts as follows;

$$S_k(P_i) = \begin{cases} S_1(P_i) & \theta_i < \theta_1 \\ S_2(P_i) & \theta_1 < \theta_i < \theta_2 \\ S_3(P_i) & \theta_2 < \theta_i \end{cases} \quad (5)$$

where $S_k(P_i)$is the set of segmented points and $\theta_k(\mathrm{k} = 1,2,3)$ is the threshold value.

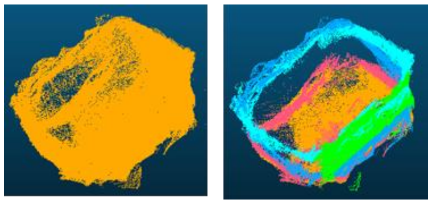
The threshold value θ_i is calculated by

$$\theta_i = \frac{(a \cdot a_i + b \cdot b_i + c \cdot c_i)}{\sqrt{a^2 + b^2 + c^2} \cdot \sqrt{{a_i}^2 + {b_i}^2 + {c_i}^2}} \times \frac{360°}{\pi} \quad (6)$$

For each point cloud that is divided, all planes of the metal tray can be estimated using RANSAC. The top surface of the tray is then determined by varying the intercept of the plane equation for the bottom surface.

$$T(P_i, M) = \begin{cases} 1 & a_i x + b_i y + c_i z + d' > 0 \\ 0 & otherwise \end{cases} \quad (7)$$

The top surface is determined by varying d' until the total number of points counted satisfies $T(P_i, M) < T_{th}$. Here, T_{th} is the threshold value for the number of points counted. Once the required sides, bottom and top surfaces are estimated, the 8 vertices are determined and the tray's height, depth and width are calculated.



(a) (b)

Figure 1. Examples of spurious surface detection. (a) Point cloud of a metal tray viewed from an angle; (b) results of applying RANSAC five times to (a) and coloring the estimated planes; the bottom of the tray (orange) and one side (green) are estimated, but the rest planes are estimated as spurious planes.

4. Experiment

4.1. *Multiple Registration*

In this section, we register multiple point clouds of metal trays from different viewpoints. We compare the registration results of the proposed method with those of the original Go-ICP to demonstrate the effectiveness of the proposed method. The three types of trays used in the experiments are shown in Figure 2. The point cloud dataset was obtained by photographing the metal trays rotated on a rotating table with a fixed realsenseD455 (Figure 3). Only the metal tray is extracted by background differencing, and the point cloud of the tray is generated from the resulting depth image. The detailed conditions of the experiment are listed in Table 1. Stainless steel (SUS304) has noise, outliers, and defects most, so registration is performed over a 360° range. The registration results using the conventional and proposed methods are shown in Figure 4 and Figure 5, respectively. The registration results of the conventional method differ from those of the proposed method only for the stainless steel (SUS304) tray, indicating that the accuracy of 3D reconstruction is improved by the threshold value. The results for the aluminum tray and the stainless steel (SUS340) tray were the same as those of the conventional method because they did not proceed beyond step 3 of the proposed method.

4.2. *Segmentation*

In this section, we segment the point cloud after registration, measure the dimensions, and determine the difference from the original dimensions. The experimental results show a point cloud with only the trays enlarged. The result of segmenting the point cloud into three parts using the proposed method is shown in Figure 6. The pink point cloud is the first plane estimated, and it was divided into three point clouds, pink, orange, and green, based on the angle between the normal vector of the pink plane and the normal vector of each point. Applying RANSAC to each of the three divided point groups, all sides of the tray can be estimated as shown in Figure 6. RANSAC was applied multiple times for each point group, and the one that estimated the sides correctly was manually selected. The dimensions are measured from the planes estimated in Figure 7 as shown in Figure 8, and as given in Table 2,3, and 4.

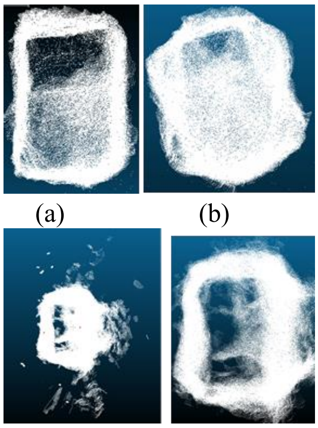
(a) (b) (c)

Figure 2. Metal trays for experiments: (a) Aluminum tray; Width: 156[mm], Depth: 227[mm], Height: 85[mm] ; (b) Stainless steel (SUS340) tray; Width: 169[mm], Depth: 227[mm], Height: 78[mm] ; (c) Stainless steel (SUS304) tray; Width: 170[mm], Depth: 225[mm], Height: 78[mm]

Figure 3. Experimental environment: (Left) A camera fixed on the robot and the metal tray on the rotating stand; (Right) a metal tray viewed from the camera; the metal tray is rotated clockwise and photographed.

Table 1. Registration details for each point cloud

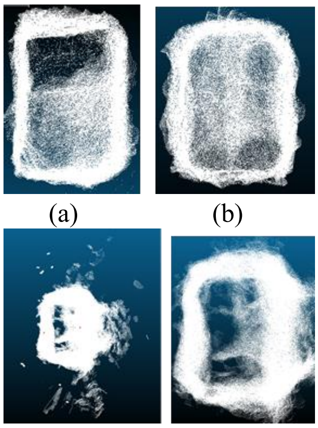
Metal Types	Aluminum	Stainless steel (SUS340)	Stainless steel (SUS304)
Registration range(°)	180	180	360
Point cloud set	28	28	110
Parallax of 1 set (°)	6.42	6.42	3.27



(a) (b)

(c)

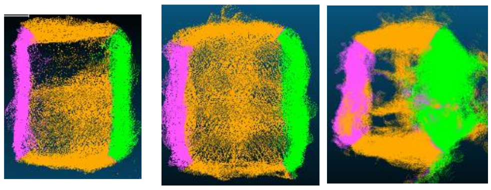
Figure 4. Registration results of conventional methods: (a) Aluminum tray; (b) Stainless steel (SUS340) tray; (c) Stainless steel (SUS304) tray: (Left) original result; (Right) enlarged tray.



(a) (b)

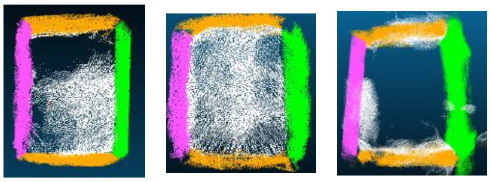
(c)

Figure 5. Registration results of the proposed method: (a) Aluminum tray, (b) stainless steel (SUS340) tray;
(c) stainless steel (SUS304) tray: (Left) original result; (Right) enlarged tray.



(a) (b) (c)

Figure 6. Result of dividing the point cloud into three regions based on the normal vector of the pink side and the angle of each point: (a) aluminum tray;



(a) (b) (c)

Figure 7. Results of applying RANSAC to each point cloud in the three regions: (a) Aluminum tray; (b) Stainless steel (SUS340) tray; (c) Stainless steel

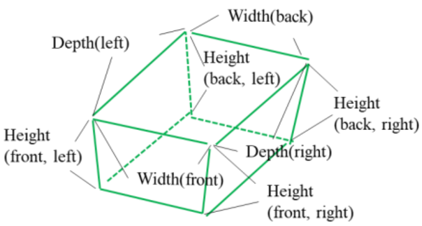


Figure 8. Dimensional measurement

Table 2. The result of dimensional measurement with an aluminum tray

	Actual size	Measurement Results		Error	
Width[mm]	156	143(front)	139(back)	-13	-17
Depth[mm]	227	218(left)	222(right)	-9	-5
Height(right)[mm]	85	97(front)	95(back)	+12	+10
Height(Left)[mm]	85	99(front)	98(back)	+14	+13

Table 3. The result of dimensional measurement with a stainless steel (SUS340) tray

	Actual size	Measurement Results		Error	
Width[mm]	169	165(front)	169(back)	-4	±0
Depth[mm]	227	214(left)	232(right)	-13	+5
Height(right)[mm]	78	81(front)	83(back)	+3	+5
Height(Left)[mm]	78	82(front)	84(back)	+4	+6

Table 4. The result of dimensional measurement with a stainless steel (SUS304) tray

	Actual size	Measurement Results		Error	
Width[mm]	170	180(front)	146(back)	+10	-24
Depth[mm]	225	208(left)	236(right)	-17	+11
Height(right)[mm]	78	101(front)	100(back)	+23	+22
Height(Left)[mm]	78	98(front)	97(back)	+20	+19

5. Conclusion

In this study, we investigated effective registration and segmentation methods for metal trays with high noise, outliers, and missing values. A threshold was introduced for registration of point clouds of metal trays viewed from multiple directions. The normal information and RANSAC were used to segment the sides and bottom of the trays.

Several improvements can be considered for future work. In registration, the threshold is set manually, and, in segmentation, the correct plane is selected manually. Therefore, it is thought that automating the process will increase its versatility. In this study, we applied RANSAC multiple times and manually selected the one that correctly estimated the sides. It is, however, possible to automatically estimate the sides and bottom by using the normal vector of the plane in which the tray is placed. Then, variants of RANSAC could be used for plane estimation.

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