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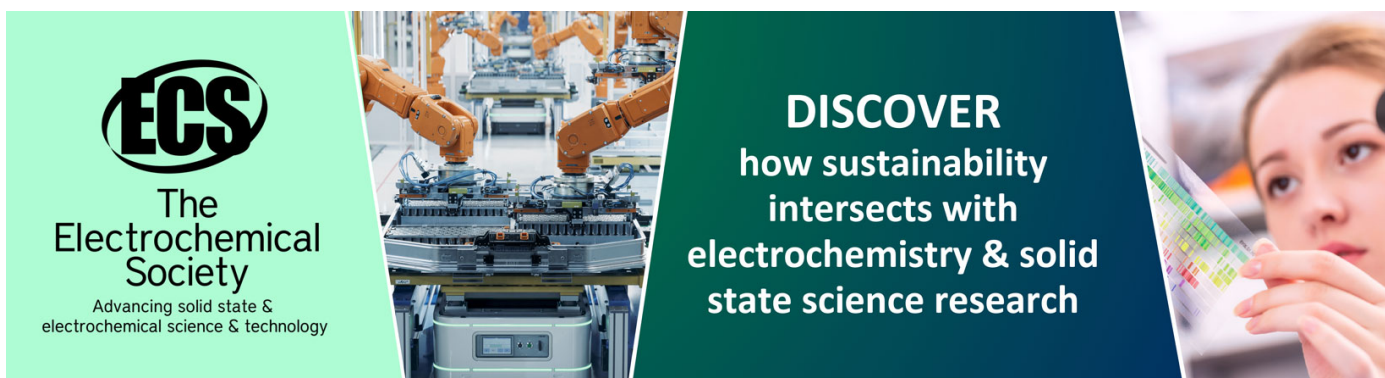
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Research on point cloud registration of industrial parts based on FGR-ICP algorithm

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Abstract. In the industrial application environment, there are some challenges to point cloud registration caused by disordered and occluded industrial parts. A point cloud registration method combining fast global alignment (FGR) and improved ICP is proposed for the problem that the traditional Iterative Closest Point (ICP) needs to rely on good initialization quality and easily falls into local optimal solutions. The method can optimize the different components of the objective function alternately by FGR to obtain the optimal initial transformation matrix. An improved ICP algorithm was used for exact matching of the initial transformation results. The experimental results showed that the method in this paper had greatly improved the matching accuracy, and the speed had been improved by an order of magnitude compared with the traditional method.

1. Introduction

As the depth sensor gradually becomes cheaper, 3D point cloud processing technology has begun to be widely used in three-dimensional reconstruction [1], robot grasping [2], target recognition [3] and other fields. Point cloud registration [4] is a critical technology in point cloud processing. Machine vision guided Bin-picking has attracted widespread attention and has gradually become a research hotspot. One of the Bin-picking difficulties lies in the problem of target recognition caused by the disorderly placement of parts and mutual occlusion. This paper studies this problem. The point cloud of the part is quickly obtained through the line laser scanning system and matched with the standard template point cloud model, and then the accurate 6D pose parameters are received and transferred to the robot hand for target grasping.

The ICP algorithm [5] is a widely used classic registration method. The nearest point information estimates the rigid transformation matrix, and the transformation matrix is optimized by local iteration. When the noise is slight and the initial position is close, the ICP algorithm can achieve higher registration accuracy and better algorithm convergence. Still, its performance depends heavily on the initial registration state, and it is easy to form a locally optimal solution. The SAC-IA algorithm in Literature [6] first performs a rough registration on the point cloud, provides a better initialization state, and then uses the ICP algorithm to match the rough registration results finely. Literature [7] proposes the global optimal solution registration method Go-ICP, which searches the branch and bound (BnB) of the entire 3D space Euclidean transformation ($SE(3)$). The minimum value of the registration objective function



is obtained by the geometric characteristics of $SE(3)$. The fusion of ICP into BnB calculates the global optimal solution and speeds up the registration.

This paper proposes a point cloud registration method combining FGR [8] and an improved ICP algorithm, which can better solve slow recognition speed and low recognition accuracy caused by overlapping and disorder of parts.

2. Initial registration

2.1. Objective function

For the given point cloud set $P = \{P_i\}$ to be registered and $Q = \{Q_i\}$ of the part template point cloud, look for the rigid transformation matrix T , and align P and Q to minimize the Euclidean distance between the matching point pairs. Assuming that the set of matching point pairs established between P and Q is $\mathcal{K} = \{(\mathbf{p}, \mathbf{q}) | \mathbf{p} \in P, \mathbf{q} \in Q\}$, the objective function form is as follows:

$$E(\mathbf{T}) = \frac{1}{|\mathcal{K}|} \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2 \quad (1)$$

The robust penalty function Geman-McCure is used to deform it, as shown in formula (2).

$$E(\mathbf{T}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \rho(\|\mathbf{p} - \mathbf{T}\mathbf{q}\|) \quad (2)$$

Where $\rho(x) = \frac{\mu x^2}{\mu + x^2}$. The parameter μ controls the weight of the residual in the objective function. When μ is large, $\rho(x)$ is severely affected by a larger value of x . When the parameter μ gradually decreases, $\rho(x)$ is affected by a smaller value of x . Therefore, the corresponding point at a larger distance is invalidated as an error point.

This paper uses the Robust Statistics method combined with Line Process to solve it. First, calculate the line process weight $\mathbb{L} = \{l_{\mathbf{p}, \mathbf{q}}\}$ on the correspondence relationship $\mathcal{K}$ between the point pairs, and construct joint objective function:

$$E(\mathbf{T}, \mathbb{L}) = \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} l_{\mathbf{p}, \mathbf{q}} \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2 + \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}} \Psi(l_{\mathbf{p}, \mathbf{q}}) \quad (3)$$

Among them, $\Psi(l_{\mathbf{p}, \mathbf{q}})$ is expressed as a priori function:

$$\Psi(l_{\mathbf{p}, \mathbf{q}}) = \mu(\sqrt{l_{\mathbf{p}, \mathbf{q}}} - 1)^2 \quad (4)$$

To minimize $E(\mathbf{T}, \mathbb{L})$, let the partial derivative of $l_{\mathbf{p}, \mathbf{q}}$ be zero:

$$\frac{\partial E}{\partial l_{\mathbf{p}, \mathbf{q}}} = \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2 + \mu \frac{\sqrt{l_{\mathbf{p}, \mathbf{q}}} - 1}{l_{\mathbf{p}, \mathbf{q}}} = 0 \quad (5)$$

Solve for $l_{\mathbf{p}, \mathbf{q}}$:

$$l_{\mathbf{p}, \mathbf{q}} = \left(\frac{\mu}{\mu + \|\mathbf{p} - \mathbf{T}\mathbf{q}\|^2} \right)^2 \quad (6)$$

At this time, the minimum solution of optimizing the joint objective function is also the optimal solution of formula (2).

The advantage of formula (3) is to optimize the same global goal, $\mathbf{T}$ and $\mathbb{L}$ can be alternately optimized by fixing the value of $l_{\mathbf{p}, \mathbf{q}}$ to ensure the convergence of the algorithm. When $\mathbb{L}$ is fixed, the joint objective function becomes the weighted sum of the L^2 penalty of the distance between the points

and the corresponding relationship. When $l_{p,q}$ satisfies formula (6), the standard objective function value is the smallest.

2.2. Use local features to find the corresponding relationship $\mathcal{K}$

To generate the initial corresponding set $\mathcal{K}$, this paper uses FPFH to extract the regional characteristics of the point cloud. Calculate the feature histograms of the point cloud set P and the reference part point cloud set Q , respectively expressed as $F(P) = \{F(\mathbf{p}) : \mathbf{p} \in P\}$ and $F(Q) = \{F(\mathbf{q}) : \mathbf{q} \in Q\}$.

The corresponding estimation method of ‘mutual’ is adopted. When $F(\mathbf{p})$ is the nearest neighbor of $F(\mathbf{q})$ in $F(P)$ and $F(\mathbf{q})$ is the nearest neighbor of $F(\mathbf{p})$ in $F(Q)$, add all $(\mathbf{p}, \mathbf{q})$ that satisfy this relationship to the corresponding set $\mathcal{K}_1$. Randomly select three pairs of points from $\mathcal{K}_1$, expressed as (p_1, q_1) , (p_2, q_2) , (p_3, q_3) , construct $\{p_1, p_2, p_3\}$ and $\{q_1, q_2, q_3\}$ into triangles respectively, Denoted as S_p and S_q , use the following formula to check the similarity between:

$$\forall i \neq j, \quad \tau < \frac{\|p_i - p_j\|}{\|q_i - q_j\|} < \frac{1}{\tau} \quad (7)$$

Here τ is the set unified threshold, and the value is 0.9. When the above formula is satisfied, three pairs of points are added to the corresponding set $\mathcal{K}$, and the objective function is constructed to optimize it to obtain the optimal initial transformation state.

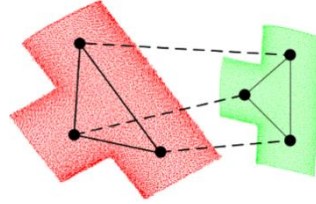


Figure 1. Determine point-to-correspondence based on the principle of similarity.

3. Improved ICP

FGR provides a better initial registration position, but there is still a deviation inaccuracy, and further fine registration is required to obtain a high-precision registration effect. In this paper, the ICP algorithm is used to iteratively solve the spatial point cloud stiffness change matrix, and each iteration is solved by solving a nonlinear least-squares equation.

3.1. The linear solution of a transformation matrix

Because the previously used FGR method has aligned the surfaces for the two models of the target point cloud and the template point cloud, the relative distance is no longer large. Based on this understanding, this paper selects the definition of the distance function from the point to the plane to solve the ICP nonlinear problem. The approximation is transformed into the solution of linear problems so as to obtain a faster convergence rate.

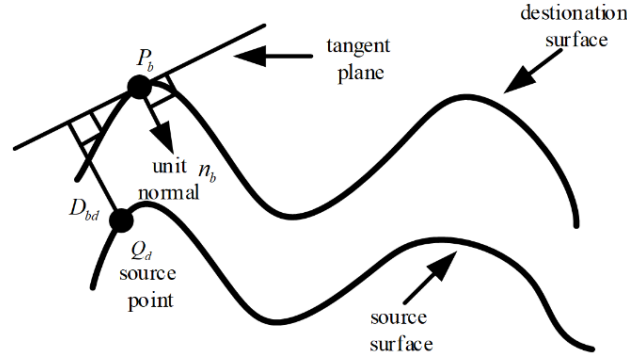


Figure 2. The point-to-plane error between two surfaces

$$D_{bd} = |(Q_b - P_d)^T V_n|^2 \quad (8)$$

D_{bd} is the distance formula from point to the plane, $\mathbf{T}_{opt}$ is the best posture change matrix.

$$\mathbf{T}_{opt} = \operatorname{argmin}_{\mathbf{T}} \sum_i ((\mathbf{T} \cdot Q_i - P_i) \cdot n_i)^2 \quad (9)$$

Construct the matrices $\mathbf{A}$ and $\mathbf{b}$ so that the matrices $\mathbf{A}$ and $\mathbf{b}$ satisfy the following relationship, where ξ is still a 6-dimensional vector of the local linearization of $\mathbf{T}_{opt}$.

$$\min_{\mathbf{T}} \sum_i ((\mathbf{T} \cdot Q_i - P_i) \cdot n_i)^2 = \min_{\xi} |\mathbf{A}\xi - \mathbf{b}|^2 \quad (10)$$

Convert the solution of $\mathbf{T}_{opt}$ to the solution of the local linear vector ξ :

$$\xi_{opt} = \operatorname{argmin}_{\xi} |\mathbf{A}\xi - \mathbf{b}|^2 \quad (11)$$

3.2. BBF optimized k-d tree search

Best Bin First (BBF) is an improved approximate search method based on the k -d tree. This method searches the target point cloud for the closest point from the reference point cloud by establishing a prioritized backtracking search method. Simultaneously, it uses a timeout response Mechanism when all nodes in the queue are traversed, or the search exceeds the set time threshold, the current optimal result is used as the closest point. BBF can ensure priority search for the nearest point with high possibility and has high operating efficiency.

3.3. Eliminate wrong point pairs

In the process of matching keypoints between point clouds, there may be a specific ratio of wrong corresponding points in the initial registration relationship, which will seriously affect the registration quality, so these wrong corresponding point sets need to be eliminated.

This paper uses the method of combining the K-means algorithm and the splitting method to eliminate the wrong point pairs. The initial matching point pairs are clustered through the K-means algorithm, and the largest cluster is retained so that part of the wrong corresponding points are eliminated, and a rough elimination effect is achieved. Finally, the splitting method is used, and the wrong point pair is finely eliminated by adopting the judgment method of combining Euclidean distance and standard deviation.

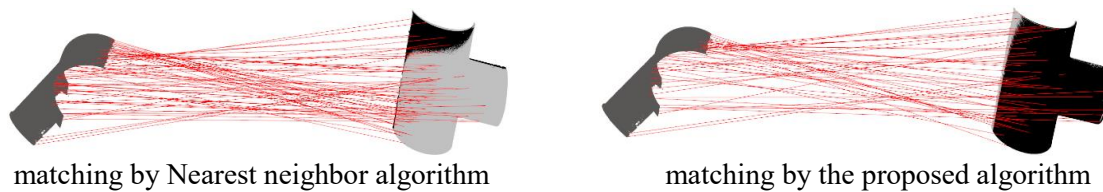


Figure 3. Matching diagram of two parts.

4. Experimental results and analysis

This article uses a 6-axis ABB industrial robot fixed AT high-speed 3D line scan camera (25k/sec) for depth image acquisition. The experiment is performed under the Win10 system with a CPU frequency of 3.6 GHz and a memory of 8 G. The experimental platform is Visual Studio 2017.

In an industrial application environment, the disorderly placement of workpieces causes a large area of occlusion in the collected point cloud model, and some features are obviously lost, resulting in low matching accuracy. In order to test the processing effect of the proposed algorithm in dealing with this situation, experimental verification is carried out on the model with 20% missing point clouds and 40% missing point clouds. The experiment uses real workpiece three-way pipe and the Brick and Gear parts in the open data set Siléane [9] to conduct experimental tests to demonstrate the algorithm's effectiveness. Because the line laser collects high-density point cloud data (point cloud scale is greater than 1 million), in order to improve the speed, this paper first uses the voxel method to downsample the point cloud data.

Figure 4 is the point cloud registration results under 20% missing and 40% missing, respectively. In the face of most point cloud missing, the algorithm in this paper still maintains a good registration performance and achieves a high-precision registration effect.

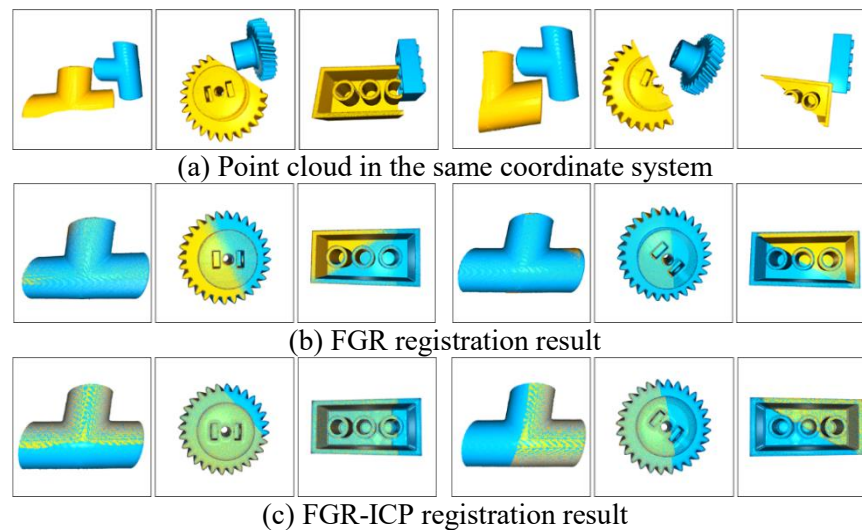


Figure 4. 20% and 50% point cloud occlusion registration.

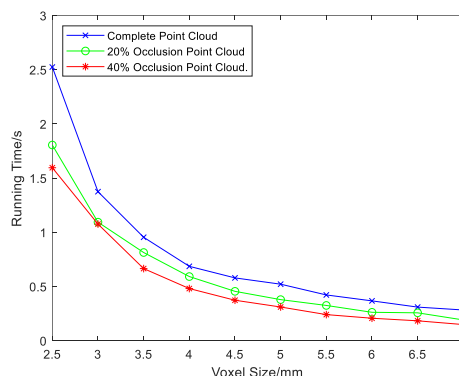


Figure 5. The registration time.

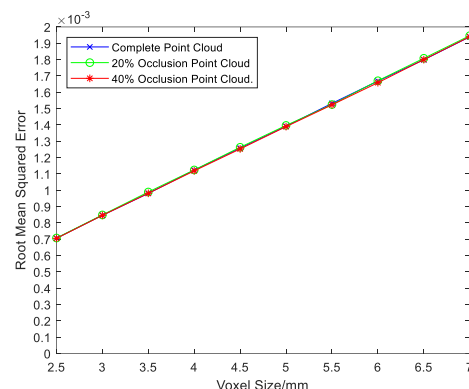


Figure 6. Root mean square error.

Figure 5 and 6 are the experimental results of the three-way pipe under different Voxel size sampling and occlusion. The time is the sum of FGR registration and ICP registration, and the root mean square error is selected for evaluation. As shown in Figure 5 and 6, the registration time of the FGR-ICP algorithm decreases steadily as the size of the Voxel increases. The root mean square error of different

degrees of point cloud missing is basically the same, and good registration results have been achieved in both visual and root mean square errors.

Table 1. Comparison of running time and root mean square error.

Point cloud name	Number of point clouds	method	Coarse registration		Fine registration		Total time/s
			Running time /s	Root mean square error /10 ⁻³	Running time /s	Root mean square error /10 ⁻³	
Three-way pipe	37209	SAC-IA and ICP	17.553	16.651	13.143	13.560	29.676
		GO-ICP	—	—	20.455	11.603	20.455
		RANSAC and ICP	0.686	2.693	0.463	0.993	1.149
		Our algorithm	0.445	1.382	0.368	0.981	0.813
		SAC-IA and ICP	34.344	16.431	29.027	10.400	63.371
Brick	80831	GO-ICP	—	—	56.489	5.396	56.489
		RANSAC and ICP	2.503	1.756	0.820	0.792	3.323
		Our algorithm	1.994	1.463	0.790	0.785	2.784

In this table, the point cloud sampled at 3.5mm voxel size is used to compare different algorithms because the point cloud at this sampling rate has both computational cost and accuracy. Three-way pipe and Brick parts are selected for algorithm comparison. It can be seen from Table 2 that due to the accuracy deviation of the SAC-IA algorithm, the calculation time of the ICP algorithm is increased, and at the same time, better accuracy cannot be achieved. GO-ICP still cannot meet the speed requirements for rapid identification in the industry in terms of time cost. The algorithm of the combination of RANSAC and ICP has greatly improved the running time and error, but the efficiency is still not up to the ideal speed (within 1 second) required by industrial applications. Compared with the above three methods, the calculation time of the method in this paper is significantly improved, and the error is greatly reduced.

5. Conclusions

A point cloud registration method combining FGR and improved ICP algorithm was proposed for the problem that the traditional ICP algorithm has good initialization quality and is easy to fall into local optimal solutions. First, FGR was used to alternately and quantitatively optimize the different components of the objective function to obtain the optimal initial transformation. Secondly, the distance from the point to the surface was the closest point calculation method to linearly solve the accurate transformation matrix. In this process, a combination of the K-means algorithm and splitting method was used to eliminate error point pairs. BBF can be used to optimize the search method of the k-d tree to improve the efficiency of the search operation. The experimental results showed that the method in this paper has improved the efficiency of the search operation, reduced the possibility of falling into the local optimal solution, achieved accurate matching and speeded up the convergence speed.

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