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An Acceleration Method to Iterative Closet Point Registration Algorithm

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Abstract. To solve the problem of low registration efficiency of the classical ICP algorithm in point cloud data registration, a point cloud registration method to improve the ICP algorithm is proposed. By considering the similarity of the point cloud data, our algorithm find a more reasonable point pair to compare with the classical ICP. In addition, we used a new distance error measure in the ICP framework, which considers the similarity instead of the Euclidean distance. By observing the experimental results, we find that the proposed scheme speeded up the registration convergence and eliminated the mispairing of data points. The running time of the algorithm is significantly improved to meet the requirements of the registration, and the Registration efficiency is improved to 8 times the original.

Keywords: point cloud, registration, iterative closet point, distance error function, optimization, overlap, similarity

1. Introduction

For two 3D point clouds models of rigid objects acquired under different lighting and angle, the purpose of registrating the two models is to establish the spatial correspondence between the two models, and find the optimal transformations between them to align the two-point clouds in space. The 3D point cloud rigid body registration is widely used in intelligent robotics, uncrewed vehicles, medicine, and heritage conservation.

Besl and Mckay proposed the iterative closest point (ICP) algorithm in 1992 [1], which is one of the mainstream algorithms for point cloud registration. And its essence is based on the principle of least squares to solve the rigid body transformation parameters, including rotation matrix and translation vector. Given two corresponding point sets, P (source point cloud) and Q (target point cloud), the coordinate system of the target point cloud is assumed as a fixed reference system for rotating and translating the source point set P during the point cloud registration. The traditional ICP algorithm had the problems of low computational efficiency and high requirement for the initial position of the registration, and it is easy to fall into local optimality. Therefore, most related scholars use the initial registration method to obtain a good initial position and conduct a lot of research on the improvement algorithm based on the traditional ICP method. Some scholars find point-to-point correspondence based on local geometric features on the surface of two-point clouds through improved point pairs [2-11], such as Spin Images (SI), Signature of Histograms of Orientations (SHOT), Point Feature Histograms (PFH) and the improved Fast Point Feature Histogram (FPFH) , etc. However, for dense point clouds, calculating the features of each point affects the alignment efficiency of the point cloud. Literature [13] An improved ICP algorithm based on k-d trees to improve the efficiency and accuracy of tree point cloud data registration. In this paper, the ICP algorithm for point cloud registration is improved by normalizing the point cloud to get a good point pair at each iteration, and the registration efficiency of the improved Algorithm is increased.

2. Related STUDIES

The ICP algorithm is currently one of the leading algorithms for point cloud alignment. Given two corresponding point sets $P=\{p_i,i=1,,,n\}$(source point cloud) and $Q=\{q_i,i=1...m\}$ (target point cloud).When performing point cloud alignment, the coordinate system of the target point cloud is assumed to be the fixed reference system and the source point set P is rotated and translated.

The steps of the ICP algorithm are:

Step 1: Using Euclidean distance to find the nearest points of two point clouds for point pair matching

Step 2: The Singular Value Decomposition (SVD) [15] is used to decompose the identified point pair relationship to find the optimal R and T:

$$f(R,t)=\sum_{pi\in P}(Rpi+t-qi)^2 \tag{1}$$

where R is the rotation matrix and t is the translation vector.

Step 3: Update the coordinate information of the source point cloud P using the rotation parameter R and translation parameter T, and then determine whether it converges. Iteration convergence conditions are: f (R,t) is small enough, ΔR_k, Δt_k is small enough or the maximum number of iterations is reached. If it does not converge, steps 1-3 are reexecuted.

The ICP algorithm using Eqn. (1) has an analytical solution, but its convergence speed is slow. Therefore, many works have been proposed to improve speed and Reasonableness of point pair matching [2-11].

Generalized-ICP [12] is based on MLE (maximum likelihood estimation) as a nonlinear optimization step and used K-D tree [14] to compute discrete correspondences. It is unique in that the incorrect correspondences can be removed by symmetry. A k-d tree is a binary search tree in which each node represents a partition of a k-dimensional space. It can store, manage and search data efficiently and has been used to reduce the runtime cost of ICP. An improved ICP algorithm which based on k-d tree was used in decreasing the runtime expense of point registration. For convenience, we refer to an improved ICP algorithm based on k-d trees [13] as Kd-tree_ ICP in this paper. Compared with classical ICP, these two algorithms are faster than original ICP. but this paper proposed a better method to find matching correspondence points. (5)

3. IMPROVED ICP

The ICP algorithm uses Euclidean distance to find the nearest points of two point clouds for point pair matching, this method may lead to the following problems:

(1) As shown in Figure 1, the point pair connected by a dashed line is reasonable from the perspective of the outline of two shapes. But point pair matching according to original ICP, the point pair connect by a solid line as the matched points, which is aparrently unreasonable, and neccessarily lead to many iterations to correct this unreasonable point maching.

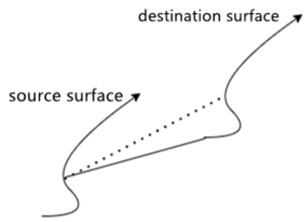
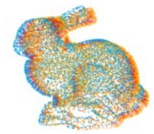


Fig. 1. Schematic diagram of unreasonable point to point match.

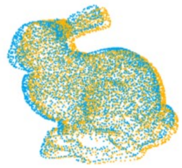
The ICP algorithm uses Euclidean distance to find the correspondence points between the two point clouds. We propose an idea. The source point cloud P and the target point cloud Q are normalised to the source point cloud P_n and the target point cloud Q_n. As shown in Figure 2 (a) is the point pair matching between the source point cloud P and the target point cloud Q. (b) is the point pair matching of the source point cloud P_n and the target point cloud Q_n. Point pairs are connected with red lines. To optimise the point pair matching in(a), we replace the point pair matching of (a) with the point pair matching of (b) to obtain the point pair matching effect of (c). Then, the optimal transformation matrix is calculated based on the matched point pairs of (c), and the source point cloud P is transformed to obtain the result in (d). Doing so achieves that the intermediate process can be eliminated, greatly improving efficiency.

(a)point pair matching of Initial point cloud



(b)point pair matching of matching normalised point cloud

(c)Improved point pair matching



(d)Results of point cloud alignment

Fig. 2. Schematic of the effect of location on point-to-match.

Based on this idea, this paper introduce the similarity of normalized matrix point cloud coordinate vectors to establish a more accurate correspondence between two point-clouds. Table I shows the pseudo-code of the improved algorithm.

Table I. Pseudo-code to improve the algorithm

Improved algorithm pseudo-code
Input:Source Point Cloud $P = \{pi\}, 0 \le i \le N$.Target point cloud $Q = \{q_i\}, 0 \le i \le M$.
Output:Best Registration Results
Step1:Set $K = 0$ and give a threshold value δ
Step 2:The target and source point clouds are normalized to obtain the normalization matrices P_n and Q_n
Step 3:Read pi in P_n as the query point and search for the most similar point in Q_n as the corresponding point
Step 4:According to the corresponding P and Q point sets, the rigid transformation matrices R and T are obtained by the quadratic method or SVD algorithm;
Step 5:After rotation, find the new source point of the source cloud, translate P;
Step 6:If the iteration error of two iterations satisfies f_k - f_k+1 < δ, the iteration terminates. Otherwise, k=k+1 and execute steps 2 to 6

A. Point Cloud Normalization

Image normalization resists translations, rotations, scaling, and other transformations. The normalized target and source point clouds are similar ,which helps to match good point pairs. We normalize the point cloud data P. The normalization operation was performed.

Step 1:Find the maximum values in x,y,z coordinates of the point cloud matrix as x_{max},y_{max},z_{max} and the minimum values in x,y,z coordinates of the point cloud matrix as x_{min},y_{min},z_{min} respectively.

Step 2: Calculate $d_x=x_{max}-x_{min}, d_y=y_{max}-y_{min}, d_z=z_{max}-z_{min}$

Step3: $P_n = \{\frac{pi_x - x_{min}}{|d_x|}, \frac{pi_y - y_{min}}{|d_y|}, \frac{pi_z - z_{min}}{|d_z|}\} pi \in P$

where pi is a point in P,pi_x,pi_y,pi_z are the x,y,z dimensional coordinate values of the point pi respectively. P_n is the set of points normalized by the point cloud P.

We normalize the source point cloud P and the target point cloud Q of rabbits in Stanford by the above method to obtain the normalized source point P_n and the normalized target point Q_n. Figure 3 shows the state of the source and target point clouds before and after normalization.

(a)Initial state

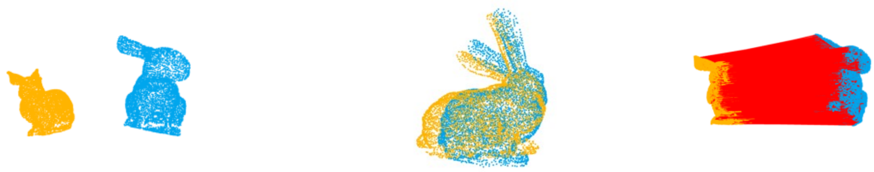
(b)Point cloud after normalization

Fig. 3. Point cloud normalization operation diagram.

The pair of source and target point clouds on the left (a) of Fig. 3 is without normalization, and the pair on the right (b) is after both of the above normalization operations have been performed. After normalization, the source point cloud P_n and the target point cloud Q_n can get an excellent relative position.An excellent relative position can match a more reasonable point pair, improve the convergence speed, and improve the model accuracy to some extent.

B. Matching of Correspondence Points

In practical applications, shape features need to be used to select the corresponding point pairs quickly. However, point pairs matching of the original ICP only consider the Euclidean distance of two point-clouds. We propose to use the similarity of normalized matrix point cloud for matching point pairs, thus utilizing more local information of the point cloud. Figure 4 shows the process of improved algorithm point pair matching. The source point cloud P and the target point cloud Q in (a) figure are normalized into (b) figure source point cloud P_n and target point cloud Q_n. The point cloud P_n and the point cloud Q_n is similar. Read pi in P_n as the query point and search the one point qi in Qn as the corresponding point by the min sum of the absolute differences [16] that is $|pi_x-qi_x|+|pi_y-qi_y|+|pi_z-qi_z|$, pi_x,pi_y,pi_z are the x,y,z dimensional coordinates of the point pi, qi_x,qi_y,qi_z are the x,y,z dimensional coordinates of the point qi, respectively. The point connected by the red line in figure c is the corresponding point.



(a) Initial state (b)Point cloud normalization (c)Point-to-match situation

Fig. 4.Point cloud normalization operation diagram.

C. Improved Error Function

We use the framework of the ICP algorithm to compute the rotation matrix R and the translation matrix T to transform the point cloud P to coincide as much as possible with the point cloud Q. We use the sum of the absolute differences to determine the degree of overlap between the two point clouds., the loss function of the absolute difference sum is introduced into the 3D point cloud rigid body registration optimization model. The new distance function is defined as:

$$f(R,t) = \sum_{pi\in Pn}(|Rp_i + t - q_i|)$$

where R is the rotation matrix, T is the translation vector, $pi\in P_n$,$qi\in Q_n$。

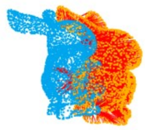
4. Experimental results and discussion

To further verify the efficiency of our algorithm, this paper use the point cloud data from the Stanford 3D model library for registration comparison experiments.

Compared with ICP considering only Euclidean, our algorithm match more reasonable point pairs. We experimented with the point cloud model of the Stanforth rabbit to compare the reasonableness of the corresponding point matching of the four algorithms. We obtained point-to-match states from the improved ICP algorithm, the k-d sequence algorithm, the classical IC algorithm and the generalised ICP algorithm.

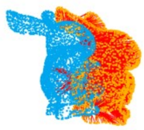
(a) First iteration (b) Second iteration

(1) ICP point pair matching case



(a)First iteration (b) second iteration

(2) Generalized-ICP point pair matching case



(a)First iteration (b) second iteration

(3) k-d-tress-ICP point pair matching case

(a)First iteration (b) Second iteration

(4) ImprovedICP point pair matching case

Fig. 5.Comparison of matching point pairs schematic.

The above figure show the corresponding points of the first two iterations of the four algorithms. As can be seen from the figure, in each iteration of the improved algorithm each point in the source point cloud matches a reasonable point in the target point cloud., which is mainly due to the adoption of the matching corresponding points approach based on the similarity of normalized point cloud. The other three algorithms use the Euclidean distance to find the corresponding point. In the first iteration, a small number of points in the source point cloud are matched to a reasonable number of points in the target point cloud. In the second iteration, the number of reasonable point pairs becomes larger. Our algorithm can shorten the iteration times and improve the registration efficiency. In order to prove the effectiveness of our algorithm, we use Stanford point cloud data model to compare these four algorithms from three aspects of accuracy, time and iteration times. Accuracy evaluation adopts the mean value of Euclidean distance between all corresponding points. The smaller the mean value is, the more accurate the registration result will be. The analysis of the experimental results is shown in Table I.

TABLE I. STATISTICS OF EXPERIMENTAL DATA

Attribution		**Value**			
Data name		***Bunny***	***Dragon***	***Horse***	***Hand***
Point cloud number		***11200***	***6700***	***6200***	***7400***
ICP	Calculation time	128s	20s	12.7s	15.4s
	Number of iterations	29	24	15	15
	RMS	1.195e-04	1.99e-05	1.020e-05	8.96e-04
Improve_ICP	Calculation time	36s	7.9s	1.07s	1.12s
	Number of iterations	11	6	6	8
	RMS	1.195e-04	1.99e-05	1.020e-05	8.96e-04
Generalized_ICP	Calculation time	66.3s	18.6s	11.5s	14.4s
	Number of iterations	20	19	15	15
	RMS	1.183e-04	1.909e-05	1.01975e-05	8.96e-04
Improve_Generalized_ICP	Calculation time	32s	9.4s	0.92s	1.5s
	Number of iterations	9	13	7	8
	RMS	1.192e-04	1.91e-05	1.019e-05	8.939e-04
Kd-tree_ICP	Calculation time	29s	8.7s	0.92s	1.14s
	Number of iterations	29	24	15	15
	RMS	1.195e-04	1.956e-05	1.020e-05	8.96e-04

Attribution		Value			
Data name		***Bunny***	***Dragon***	***Horse***	***Hand***
Improve_kd-tree_ICP	Calculation time	26s	8.2s	0.8s	1.07s
	Number of iterations	9	6	7	7
	RMS	1.195e-04	1.998e-05	1.020e-05	8.94e-04

It can be seen from Table I that compared with traditional ICP and Generalized_ICP, the iteration times and time of the improved algorithm have been greatly improved, which is higher than KD-Tree_ICP.

5. Conclusion

This paper analyzes the shortcomings of the existing algorithms and puts forward the corresponding improvement measures a new strategy for selecting corresponding points. The improved algorithm can effectively avoid the many-to-one uncertainty and make full use of the similarity of normalized point cloud for accurate point-pair matching information.we observe that new point-pair matching method can improve the efficiency of traditional ICP algorithm and its variants and this accelerating registration method will benefits applications in a variety of fields.

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