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Dynamic Differential Evolution Algorithm Applied in Point Cloud Registration

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Abstract. Aiming at the problem of point cloud registration, a registration method based on dynamic differential evolution algorithm (DDE) is proposed. The voxel grid method is used to uniformly sample the point cloud to reduce the time complexity of DDE. The individuals of DDE are coded by rotation angle and the translation distance. The kd-tree is used to search for corresponding point pairs, and the root mean square error is defined as the objective function of DDE. Experiments show that the proposed method can register point clouds with a large difference in position, and has better registration accuracy than iterative closest point (ICP).

1. Introduction

With the rapid development of 3D scanning technology, 3D reconstruction of objects based on point cloud has been widely used in agriculture, medicine, and reverse engineering [1-3], which has important research value. Due to the object's size and the linear propagation characteristics of light, to obtain the complete point cloud on the object surface, point cloud collection of multiple views is required. And the point cloud registration refers to transform the data collected in multiple views into a common coordinate system by seeking an appropriate coordinate transformation. The accuracy of point cloud registration will directly affect the accuracy of subsequent 3D reconstruction.

At present, the ICP registration algorithm proposed by Besl [4] is the most influential, and many improved algorithms have emerged [5-9]. However, the algorithm needs a good initial position, or it may fall into a local optimum, which result in registration failure. Therefore, it is very necessary to study the coarse registration algorithm to transform the position of point cloud to convergence domain of ICP. The common method is to use point cloud's normal vector [10-13] and curvature [14] and other feature information to establish the correspondence between point cloud data to achieve coarse registration, or use PCA [15-16] method and genetic algorithm [17]. For the above methods, feature histograms and curvature maps generally need to be established, which are time-consuming. The application of PCA needs to meet the extremely high similarity between point clouds to be registered. Therefore, it is of great significance to continue the research on the coarse registration of point clouds.

Because the differential evolution (DE) algorithm has powerful global search capability and fast convergence performance [18-19], this paper applies a dynamic differential evolution algorithm to point cloud coarse registration. Then, the ICP algorithm is used to the fine registration of the point cloud.

2. Dynamic differential evolution algorithm

Some typical test functions have shown that DDE has a faster convergence rate than original DE [20]. So, DDE is used to the coarse registration rather than DE.

2.1. The principle of dynamic differential evolution algorithm

The main steps of the DDE algorithm based on optimal ordering mutation operation [20] are shown as follows:

a) Set the population size NP, evolutionary generation D, scaling factor F and crossover rate CR.

b) Randomly initialize the population X in the search space. The i-th individual is shown as:

$$X_i = \left\{x_{i1}, \cdots, x_{ij}\right\} \tag{1}$$

Where $i \in [1, \mathrm{NP}]$. j represents the dimension of the individual population.

c) Perform mutation operation to generate mutant individuals:

$$V_i = X_1 + F \cdot (X_2 - X_3) \tag{2}$$

Where X_1, X_2 and X_3 are three different individuals randomly selected from the current generation population, but they satisfy the following relationship of objective function value:

$$f(X_1) \le f(X_2) \le f(X_3) \tag{3}$$

That is, the best individual X_1 among the three individuals is taken as the base vector, and the search is performed along the direction $(X_2 - X_3)$ in which the individual objective function value is better. In this way, the random selection of three individuals can guarantee the global search performance, and the optimal sorting mutation strategy can improve the convergence rate of the algorithm.

d) Perform crossover operation to generate trial individuals.

$$Q_i = \left\{q_{i1}, \cdots, q_{ij}\right\} \tag{4}$$

$$q_{ij} = \begin{cases} v_{ij}, & rand_{ij} \le CR \quad or\ j = j_{rand} \\ x_{ij}, & otherwise \end{cases} \tag{5}$$

Where, $rand_{ij}$ represents a random number between [0,1]. j_{rand} represents a random integer between [0, j].

e) Individuals with better objective function values are selected to enter current population.

$$X_i = \begin{cases} Q_i, & if \quad f(Q_i) \le f(X_i) \\ X_i, & otherwise \end{cases} \tag{6}$$

2.2. Registration parameter calculation

Given a source point cloud S and a target point cloud M, the goal of 3D registration is to find the six parameters for point cloud position transformations that can minimize the distance between two point clouds. These six parameters are rotation angle $\alpha_x, \alpha_y, \alpha_z$ around xyz axis and translation distance t_x, t_y, t_z along xyz axis, which are defined as the individual X of DDE expressed as follows:

$$X = [\alpha_x \quad \alpha_y \quad \alpha_z \quad t_x \quad t_y \quad t_z] \tag{7}$$

Then, rotation matrix R and translation vector T can be calculated based on X:

$$R = \begin{bmatrix} \cos\alpha_z & -\sin\alpha_z & 0 \\ \sin\alpha_z & \cos\alpha_z & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\alpha_y & 0 & \sin\alpha_y \\ 0 & 1 & 0 \\ -\sin\alpha_y & 0 & \cos\alpha_y \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\alpha_x & -\sin\alpha_x \\ 0 & \sin\alpha_x & \cos\alpha_x \end{bmatrix} \tag{8}$$

$$T = \begin{bmatrix} t_x & t_y & t_z \end{bmatrix}^{\mathrm{T}} \tag{9}$$

The root mean squared error (RMSE) of the registration is used as the objective function of DDE:

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$$f_{\mathrm{RMSE}}(R,T)=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\| m_i - s_i' \|^2}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\| m_i-(T+Rs_i)\|^2} \tag{10}$$

Where n indicates the number of corresponding points. s_i represents the point in the source cloud and s_i' represents the point after coordinate transformation of s_i. In order to speed up the search, the kd-tree [21] algorithm is used, and m_i, searched from M, represents the closest point to s_i'. R and T can be calculated by DDE minimizing $f_{\mathrm{RMSE}}(R,T)$, and finally coarse registration result can be obtained based on R and T.

3. Experimental results

The experimental dataset contains “bunny” and “dragon” obtained from Stanford University Graphics Lab [22]. Our algorithm is implemented in MATLAB 2015a, while all the experiments are conducted on a 3.2GHz Intel(R) core i5-4460 processor with 8GB RAM.

Firstly, the voxel grid method is used to down sample the point cloud. Figure 1 (a) and Figure 2 (a) show original point clouds, where blue and red represent two perspectives. After sampling, bunny data was reduced from 40256 to 2067 for blue and from 40097 to 2004 for red, while dragon data was reduced from 41841 to 2156 for blue and from 22092 to 1499 for red. In order to verify the validity of DDE for point cloud registration with a large difference in position, the down sampling point cloud is arbitrarily transformed as (11) to increase its position distance. The point clouds after sampling and transformation are shown in Figure 1 (b) and Figure 2 (b).

$$[\alpha_x,\alpha_y,\alpha_z,t_x,t_y,t_z]=[50,-20,30,0.5,-0.2,0.1] \tag{11}$$

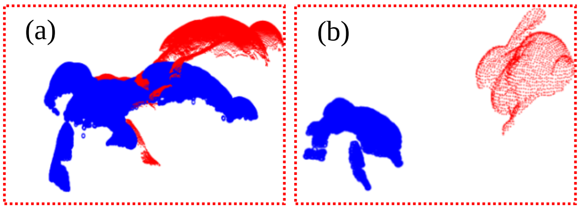

Figure 1. Point cloud sampling and transformation of bunny. (a)Original point clouds; (b) The point clouds after sampling and transformation

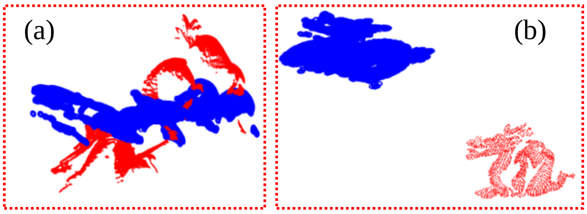

Figure 2. Point cloud sampling and transformation of dragon. (a)Original point clouds; (b) The point clouds after sampling and transformation

Considering that if the search space of DDE is too large, it will affect the registration speed, so it is necessary to choose a suitable search space. According to the position of sampled and transformed point cloud in Figure 1 (b), the search space roughly is set as shown in (12). The parameters of DDE are set to: $\mathrm{NP}=30$, $D=80$, $F=0.4$ and $\mathrm{CR}=0.8$.

$$\left(\alpha_x,\alpha_y,\alpha_z,t_x,t_y,t_z \mid \alpha_x,\alpha_y\in[-\frac{\pi}{2},\frac{\pi}{2}],\alpha_z\in[-\frac{\pi}{4},\frac{\pi}{4}],t_x,t_y,t_z\in[-0.6,0.6]\right) \tag{12}$$

Considering that for a point cloud that does not have any predictable information, it is difficult to determine the registration error because a strict corresponding point pair cannot be determined. To solve this problem, this paper uses the method of [9] to define the registration error parameter e as follows:

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$$\begin{cases} e = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} J(M_i, S_i) \\ J(M_i, S_i) = \begin{cases} 1 & Dist(M_i, S_i) > \delta \\ 0 & otherwise \end{cases} \end{cases} \tag{13}$$

Where $Dist(M_i, S_i)$ indicates euclidean distance of point pair (M_i, S_i). δ represents registration accuracy and N is the number of point. $J(M_i, S_i)$ is used to measure whether the current point pair meets the registration accuracy. Obviously, e represents the proportion of data point pairs that do not meet the accuracy in the point cloud.

Figure 3 shows the registration results for the bunny and Figure 4 shows the registration results for the dragon. In the two figures, (a) is ICP registration. (b) is DDE registration, and (c) is DDE-ICP registration which represents a fine registration using ICP [5] based on the DDE coarse registration. Table 1 shows the registration error comparison for the above registration algorithms.

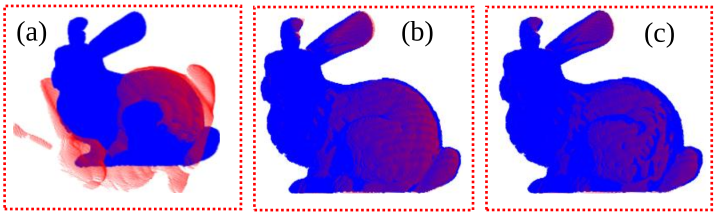

Figure 3. Registration results of bunny. (a) ICP registration; (b) DDE registration; (c) DDE-ICP registration

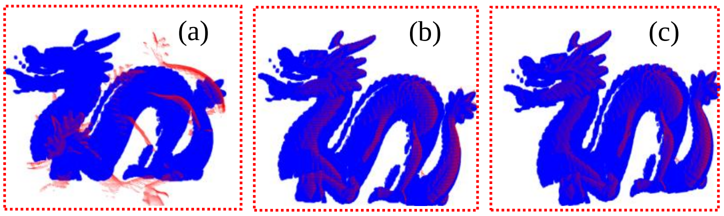

Figure 4. Registration results of dragon. (a) ICP registration; (b) DDE registration; (c) DDE-ICP registration

Table 1. Registration error of different algorithms

Model	ICP	DDE	DDE-ICP
	e	e	e
Bunny	0.9384	0.6777	0.3677
Dragon	0.9316	0.6785	0.6707

From the above experimental results, we can see:

For point cloud registration, the original ICP is likely to fall into a local extreme for point cloud with a large distance in position, which causes registration failure. DDE has strong global search performance, and successfully register the point cloud. Based on the coarse registration of DDE, the ICP algorithm is used again to perform fine registration of point clouds. For the bunny model, the DDE-ICP registration error is significantly smaller than that of the DDE, but for the dragon model, the change is not obvious, indicating that the DDE registration accuracy can basically reach the ICP registration accuracy for some models, which verifies that the DDE coarse registration has a good registration effect.

4. Conclusions

Although ICP is widely used in point cloud registration, it requires a proper initial position and it is easy to fall into a local extreme. Because differential evolution algorithm has strong global search performance, so in order to solve this problem, a point cloud registration algorithm based on DDE was proposed. By using the voxel grid method to down sample the point cloud, the time complexity of the DDE is greatly reduced. Compared with the traditional ICP algorithm, DDE can effectively deal with the problem of point cloud registration with large distance, and it can be used as an effective coarse registration algorithm.

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