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Research on Registration Algorithm of Point Clouds

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Abstract

With the rapid development of computer vision, intelligent control and other technologies, mobile robots are moving towards various fields.Due to the diversified application range of mobile robots, new requirements are put forward for automatic scene perception and mapping.Among them, registration of point clouds is one of the key steps of environment awareness and mapping.This paper introduces four types of algorithms that had been widely used in the registration of point cloud, namely ICP-like methods, model-based registration methods, local feature registration methods, and global optimization methods.Then the principles and disadvantages of the classical registration algorithms are introduced. Finally, the research status of these four types of algorithms is listed.

Keywords

Point Cloud, Registration, Mapping.

1. Introduction

With the emergence of 3D data acquisition devices, such as 3D laser and Kinect, point cloud registration technology has been widely used in many fields. By comparing scanned point clouds with standard point clouds, we can know the patient's condition, the content of the text, whether the quality inspection is qualified and how the cultural relics are repaired.Target detection, 3D reconstruction and map matching are also used to obtain scene data through mobile devices, register key points, and complete scene reconstruction and map drawing in real time. However, due to the shortcomings of existing registration algorithms in application scope and operational efficiency, the study of point cloud registration algorithm has a great contribution to computer vision and graphics graphics.

A 3D point cloud is a set of data points in a 3D coordinate system, usually defined by x, Y, and Z coordinates, designed to represent the outer surface of an object. In addition to simple coordinate information, point cloud data can also contain color information, distance between points in the point cloud, and other geometric information. Point cloud registration is to combine point clouds from multiple perspectives into a complete point cloud by solving the rotation and translation matrix of the obtained 3D point cloud data from different perspectives.

Point cloud registration is divided into rigid registration and non-rigid registration. In the rigid transformation,the purpose is to find the rotation matrix R and the translation vector t that meet the constraints. For two points with overlapping parts, P and Q are gathered to satisfy $q_i=Rp_i+t$. Where, p_i is any point on point clustered P, and is also the corresponding point of q_i in point set Q. Non-rigid registration involves deformation and other factors, so more reliable consistent corresponding information needs to be defined for registration, which is different from rigid body transformation in expression form. Non-rigid registration algorithms can be divided into two types: one based on physical deformation model using partial differential equation theory and the other based on function fitting model using interpolation theory. This paper mainly introduces the correlation algorithm of rigid point cloud registration.

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2. Point cloud registration

2.1 ICP-like methods

ICP-like methods[1,2,3,4] are all variants of Iterative Closest Point algorithm. In 1992, Besl presented Iterative Closest Point algorithm (ICP), the algorithm is based on the distance between the point set to minimize the iterative process, can obtain more accurate 3D pose estimation within a small space transform or based on good initial estimates.

ICP algorithm principle, set $P = \{Pi\}_{i=1}^{N}, Q = \{Qi\}_{i=1}^{N}$ as the data set of two point clouds to be registered. According to certain constraints, find the corresponding point Qi in source point cloud Q for each point Pi in target point cloud P.Then the optimal matching parameters R and T are calculated to minimize the error function E(R,t).Where n is the number of nearest point pairs.

$$E(R,t) = \frac{1}{n}\sum_{i=1}^{n} ||q_i - (Rp_i + t)||^2 \tag{1}$$

ICP algorithm makes registration effect more accurate through continuous iteration. The most important step for ICP algorithm is to find the initial corresponding relationship between two point clouds. A good initial corresponding relationship can reduce the number of iterations as well as the running time of the program, while improving the accuracy of registration.Since the algorithm does not contain local shape information, the registration accuracy is limited, and the nearest point is searched in each iteration, the calculation efficiency on the common CPU is low.

Chen[5] et al. proposed a method to find the least square distance from the point to the tangent plane, but this method would not converge when the curvature of the target surface changes obviously.Blais G[6] et al. combined the reverse calibration method and the random search method to improve the speed, but it would affect the registration accuracy. In addition, with the increase of noise data, the decrease of data measurement accuracy and the increase of the proportion of non-overlapping matching areas, ICP algorithm tends to fall into the local optimal. An improved approach to 3D scene reconstruction based on fast point feature histograms (FPFH) and iterative closest point (ICP) method was proposed by Peng Wu[7]. The improved FPFH is combined with ICP to improve the speed of ICP iteration. ICP-like methods generally alternate between estimating the point correspondence and the transformation matrix. However,these methods rely on the assumption that all points have pairwise counterparts between two sets.

2.2 Model-based registration methods

RANSAC-like methods adopt the similar idea of model registration. As a popular method, RANSAC[8] randomly selected the minimum subset of data points and attempted to estimate the parameters of the model. RANSAC could not guarantee global operation, and randomness determined the time. Many modifications to the RANSAC developed random sampling and acceleration strategies to enhance the original RANSAC. In particular, Chum et al[9]. proposed a method to guide the minimum subset of sampling.Although its performance is superior to RANSAC, consistent and easily processed fitting results cannot be obtained.

Aiger and Mitra[10] proposed a robust four-point matching algorithm based on RANSAC. Affine transformation of point matching algorithm follows the following rule. Given three collinear points a,b, and c, then the ratio $r = ||\frac{a-b}{a-c}||$ is unchanged.

The algorithm flow of four-point registration is shown in Figure 1.Given two point sets P, Q, uncertainty δ, and the estimated degree f of overlap between point set P and point set Q . First, 3 points are randomly selected from the point cloud data to form a surface, and the fourth point is selected on this surface to form a surface, forming a wide-area basis B⊂P. Under the restriction of δ, all four-point subsets of Q that may be congruent with B are extracted to form the corresponding basis U={U_1, U_2,...,Us}.T_i is the rigid transformation matrix between each U_i.S_i is a set that satisfies

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$d(T_i(p),S_i)$, $S_i \subset Q$, d are distances.Our goal is to find a rigid transformation so that as many of the points in point set P are less than delta from some of the points in point set Q.

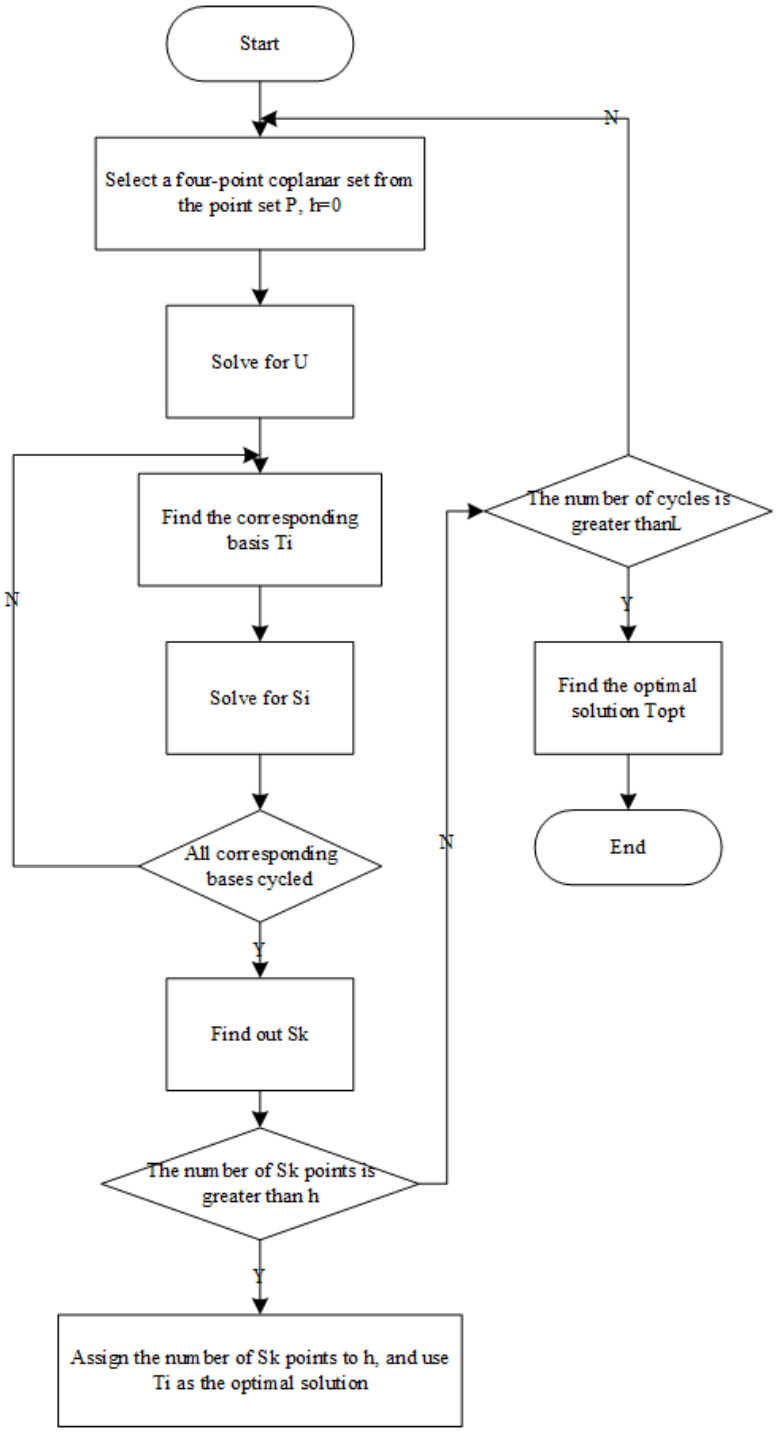

Figure 1. 4PCS algorithm flow chart

Super 4PCS is an acceleration scheme for 4PCS proposed by Nicolas Mellado, Dror Aiger, Niloy J. Mitra et al in 2014[11].The G-4PCS is an extension of the 4PCS proposed by M Mohamad, D Rappaport, and M Greenspan[12], so that the 4-point method is not limited to coplanar 4-point pairs.

2.3 Local feature registration methods

Rusu et al.[13]proposed the point feature histogram (PFH) to code local surfaces and further constructed the fast point feature histogram (FPFH)[14], which reduces computational complexity

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while retaining most of the distinguishing capabilities of PFH.However, their approach is sensitive to outliers and noise.Tombari et al. [15] proposed the azimuth histogram feature (SHOT), which is very robust to noise but sensitive to changes in grid resolution.

Jiayi Ma et al.[16] designed an effective local hold-matching method. The basic principle of the method is to maintain local neighborhood structures with potential true matches by deriving closed solutions with linear time and linear space complexity. Junming et al.[17] proposes a general model for partial point clouds analysis, each local point set constructs a vote that corresponds to a distribution in the latent space, and the optimal latent feature is the one with the highest probability.

With the advent of deep learning, for example, Zeng et al. [18] proposed a 3DMatch that USES millions of corresponding tags found in existing RGB-D reconstructs to learn local descriptors.However, 3DMatch ignores the essence of input: sparsity and unstructure.Deng et al. [19] proposed a PPFNet that is highly aware of the global context of pure geometry.However, PPFNet is not completely rotation-invariant.Gojcic et al. [20] provided 3DSmoothNet with full convolution for 3D point cloud matching, and its performance is more than 20% higher than PPFNet.

2.4 Global optimization methods

Many global optimization algorithms have been proposed. Salhi et al[21] proposed the BnB algorithm in 1994, but BnB's running time increases exponentially with the size of the input.Enqvist[22], Olsson[23], Parra[24] et al. optimized SO (3) and SE (3), but the running time efficiency was still low.

The methods of Game Theory(GT)[25,26], which consider the relationship between correspondences, have been proposed for point cloud registration. This method first defines the payoff matrix of the strategy and then tries to find the corresponding inner subset by maximizing the average psionic consistency.Therefore, the solution is optimized according to the evolutionary stable state.However, in practical application, outliers are scattered in the initial key point correspondence, which makes it difficult to suppress mismatches directly.

3. Conclusion

This paper introduces the ICP-like methods, model-based registration methods, local feature registration methods, and global optimization methods. Many methods have been able to achieve point cloud registration, but its efficiency and accuracy need to be improved. Especially for the abnormal point processing of the point cloud registration, the point cloud registration can be made more accurate and efficient to a certain extent. With the development of deep learning, not only static point cloud registration must be considered, but dynamic point cloud registration is also an important research direction

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