3D Reconstruction Based on Model Registration Using RANSAC-ICP Algorithm

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Abstract. The development of image preprocessing has provided new opportunities in the field of three-dimensional reconstruction. One of the most important areas of three-dimensional reconstruction is focused on model registration by means of matching algorithm. This is mainly due to the great increase of registration algorithm in the pattern recognition system such as image acquisition, image preprocessing, 3D reconstruction. This paper presents an analysis of model registration algorithm of three-dimensional reconstruction by comparison common registration algorithm such as RANSAC (Random Sample Consensus) and ICP (Iterative Closest Point). Then, in order to elevate registration precision and robustness affecting the 3D reconstruction results, CTF (Coarse to Fine) registration strategy based on RANSAC-ICP Algorithm is proposed. Finally, by using three-dimensional reconstruction experiment based on RANSAC-ICP Algorithm, the performance of CTF registration strategy has been analyzed, and some problems and design solutions have been identified and registration precision and robustness have also been validated by experimental results.

Keywords: 3D reconstruction · RANSAC algorithm · ICP algorithm · Model registration · CTF strategy

1 Introduction

In order to get the three-dimensional data information of object, image acquisition is taken at each angle to acquire three-dimensional cloud point model of each part. Three dimensional point cloud model is constructed at differential coordinate system. All pieces of the point cloud rigid bodies [1] that describe a complete model of object are transformed to the same coordinate system to acquire the integral model. Figure 1 shows the procedure of multi-angle reconstruction. Registration strategy based on RANSAC-ICP Algorithm is proposed to acquire complete point cloud data to match parts of the model.

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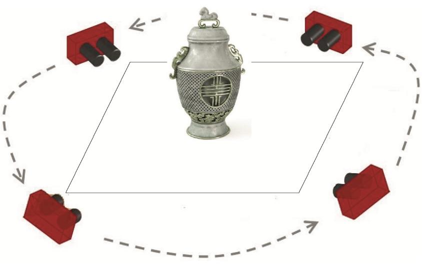

Fig. 1. Diagram of multi-angle reconstruction

2 Model Registration

Model registration that matches point cloud model in different views is a key step in 3D reconstruction and surface acquisition. The purpose of model registration which makes a point cloud model coincide with another point cloud model part is to find a rigid transformation between the two parts of the point cloud model [2–4].

2.1 Rigid Transformation Matrix

In different coordinate systems, three-dimensional points of the same object generate two sets of three-dimensional coordinate data. K can be expressed as follows:

$$K = \begin{pmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{1}$$

where K is the rigid transformation matrix of two different sets of three-dimensional coordinate data. Rotation matrix is defined as:

$$R = \begin{pmatrix} \cos\beta\cos\gamma & \cos\beta\sin\gamma & \sin\beta \\ -\cos\alpha\sin\gamma - \sin\alpha\sin\beta\cos\gamma & \cos\alpha\cos\gamma - \sin\alpha\sin\beta\sin\gamma & \sin\alpha\cos\beta \\ \sin\alpha\sin\gamma - \cos\alpha\sin\beta\cos\gamma & -\sin\alpha\cos\gamma - \cos\alpha\sin\beta\sin\gamma & \cos\alpha\cos\beta \end{pmatrix} \tag{2}$$

In the process of model registration, $\alpha, \beta, \gamma, t_x, t_y, t_z$ are computed.

2.2 Acquisition of Corresponding Points

Rigid transformation constraint equation of three-dimensional points in different coordinate system for the same object is defined as follow:

$$X_2 = KX_1 = \begin{pmatrix} R & t \\ 0 & 1 \end{pmatrix} X_1 \tag{3}$$

It requires a minimum of three pairs of control points to uniquely identify the Euclidean transformation matrix and three control points are not collinear [5]. The acquisition of three-dimensional data at different angles is calculating three pairs control points to complete parameter estimation of Euclidean transformation matrix and achieving the three-dimensional data registration.

2.3 Rigid Transformation Matrix

In order to avoid the non-linear equation solving function (3), rotation matrix R is expressed as follow:

$$R = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \tag{4}$$

$$X_2 = RX_1 + t \tag{5}$$

$$X_2 = RX_1 + T = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} X_1 + \begin{pmatrix} t_x \\ t_y \\ t_z \end{pmatrix} \tag{6}$$

Using four control points, twelve linear constraint equations are computed to achieve translation vector T and rotation matrix R [6].

3 CTF Registration Strategy Based on RANSAC-ICP Algorithm

RANSAC (Random Sample Consensus) Algorithm [7] used in three-dimensional model registration requires a low level of the initial position of the model that contains overlap data with high robustness and relevant parameters have a relatively large impact on the final results.

ICP (Iterative Closest Point) Algorithm [8] is considered the best performance of the algorithm used in three-dimensional model registration based on geometric model. ICP algorithm is an essentially optimal registration algorithm determining the cycle “Define correspondence between point sets-Compute the optimal rigid transformation-Update the target point set” with Least squares method.

Factor M is the number of iteration which is the key parameter related to the speed and accuracy of the registration [9]. The registration rate is relatively slow with large Value of M and more iterations and a bad sample is extracted with small value of M. The number of iteration M is defined as follow:

$$M = \frac{1 + 3\sqrt{1 - \omega^h}}{\omega^h} \tag{7}$$

Where is the ω^h expectation of the samples. Below the error threshold, the probability of points being accepted is α. Error threshold δ is expressed as follow:

$$\delta = \sigma_{\eta}\sqrt{F^{-1}_{\chi^2_n}(\alpha)} \tag{8}$$

CTF (Coarse to Fine) registration strategy [10] which is comprised of RANSAC model and ICP model is proposed in the paper. The first step of registration strategy with RANSAC registration with high robustness is coarse registration. ICP registration with high precision which is implemented in the second step is fine registration.

4 Result Analysis

Registration experiments are implemented between RANSAC Algorithm and RANSAC-ICP Algorithm with eight same registrations. Registration error curves are showed in Fig. 2. Blue line is RANSAC Algorithm. Red line is RANSAC-ICP Algorithm [11]. Figure 2 shows that RANSAC-ICP Algorithm has higher precision than RANSAC Algorithm.

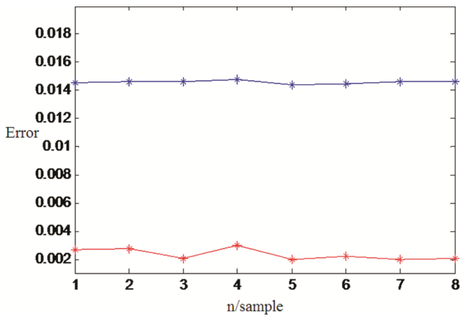

Fig. 2. The curve of registration error

Figure 3(a) and (b) are two parts of a cup. Figure 3(c) is the result of registration with RANSAC-ICP Algorithm.

Part I (b) Part II (c) Registration result

Fig. 3. The result of model registration experiment

The model of the whole cup is accomplished with integrity of registration on varying at each angle. It shows in Fig. 4.

Fig. 4. The overall model diagram

Contrasting the true cup and the model of cup, the deviation of the height and width is in the range of 3 %. It shows in Fig. 5.

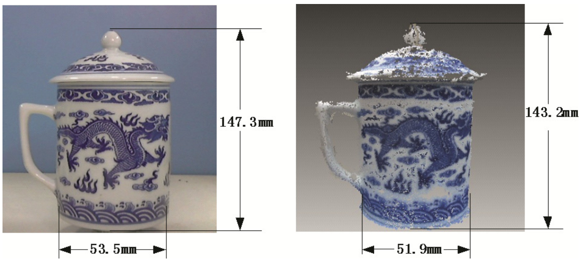

Fig. 5. Model size error

5 Conclusion

Registration precision and robustness affect the 3D reconstruction results. In order to elevate precision and to implement a robust algorithm, CTF registration strategy based on RANSAC-ICP Algorithm is proposed in this paper. The experimental results illustrate that the CTF registration strategy using RANSAC-ICP algorithm makes a powerful tool for model registration to better understand and guide the development of future 3D reconstruction.

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