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Accurate Registration of Point Clouds Based on ADF and ICS

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Abstract

The registration of point cloud is a key problem for model acquisition and 3D reconstruction, it was Put forward that a kind of automatic registration method from multi-views depth image to complete geometric models. First, According to the invariant characteristics of the relative position of the space points in the condition of rigid body transformation, the effective initial matching points array was construct with curvature invariant features and ZNCC, and the coordinate transformation of the matching feature points was solved based on the Unit quaternion, thus the data coarse registration was completed; Then by using fine matching technology based on adaptive distance function and the improved iterative closest surface, the different perspectives of clouds were optimally matched in 3D space; Finally registration error was calculated according to the matching results, and the registration accuracy and speed were analyzed. The results show that, the method can effectively improve the efficiency of registration in the guarantee of the accuracy of registration.

Keywords: *Free curved surface; accurate registration; Curvature features; ADF (Adaptive distance function); ICS (iterative closest surface)*

1. Introduction

Registration of 3-D point cloud data [1] is a heated research question in the field of surface modeling and object recognition. In the complex free-form surfaces in three-dimensional scanning of objects, under the influence of numerous factors such as the range of measuring instruments affected by physical constraints or the measured surface itself obscured and many others ,making the scan much more difficult to get a complete 3D surface geometry. Therefore it needs to be measured in a multi-perspective partial surface measurements, which based on the point cloud data to obtain their own coordinate system, then stitching registration, the establishment of a global object surface shape of an accurate description of point cloud registration or so.

Currently the widely used registration algorithm is proposed by Besl [3], such as ICP algorithm and various modifications [4-6]. So far, these algorithms have been greatly improved, but because of the error measure is defined in point - the point, the point - the aspect or point - the distance above the surface, so there is not correspond exactly with the corresponding point on the issue, making such algorithm greatly affected by the deviation point. The literature [7] by extracting geometric feature points, and then matching feature points (FM) to achieve coarse stitching, but the method accuracy is not high, and the feature point extraction is time-consuming; BASDOGAN method put forward using Adjacent method estimate local neighborhood point in the literature [8], while using the Euclidean distance between the points to select the matching dotted pairs, which is comparatively sensitive to noise. China, Gao Pengdong presents an accurate registration algorithm [9] by using the spatial volume of depth image between the overlapping area as an error metric, this algorithm is not sensitive to the initial motion parameters, the speed of convergence is comparatively fast in this algorithm which has a

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stronger robustness and high registration accuracy and good ability to overcome the noise, but in massive data the efficiency of this algorithm is not high enough.

In this paper, aiming at the complex three-dimensional objects, it was proposed that an accurate registration method based on ADF and ICS for laser point cloud. First, invariant under rigid transformation, with the curvature invariant features and ZNCC construct a valid point based on the relative position of the space on the initial match dotted pairs array unit quaternion based on matching feature points on the coordinate transformation to solve the complete data coarse registration; On this basis, the use of adaptive distance function and improved iterative closest patch of fine matching techniques, the different perspectives of the point cloud in three-dimensional space to optimize matching to achieve a precise point cloud data registration. This paper combined with complex three-dimensional curved objects for algorithm verification, experimental results show that the fine registration algorithm proposed in the registration accuracy and speed has been significantly improved, a higher application value.

2. Rough Registration

2.1. Curvature Invariant Feature

In the three-dimensional space R^3, typical discrete surface is curved Monge, its parametric equation can be described [10] by using equation (1):

$$\boldsymbol{r}(u,v) = \begin{bmatrix} u & v & h(u,v) \end{bmatrix}^T,\ u = 1,2,\ldots,m,\ v = 1,2,\ldots,n \tag{1}$$

Then the unit surface $\boldsymbol{r}(u,v)$ normal direction vector is:

$$\boldsymbol{n} = \frac{1}{\sqrt{h_u^2 + h_v^2 + 1}}(-h_u, -h_v, 1)^T \tag{2}$$

$\boldsymbol{r}(u,v)$ Can be expressed as two basic amount, the first describes the basic amount of the intrinsic properties [11] of the surface:

$$\begin{aligned} I(d_u, d_v) &= d\boldsymbol{r} \bullet d\boldsymbol{r} = (\boldsymbol{r}_u d_u + \boldsymbol{r}_v d_v) \bullet (\boldsymbol{r}_u d_u + \boldsymbol{r}_v d_v) \\ &= E d_u^2 + 2F d_u d_v + G d_v^2 \end{aligned} \tag{3}$$

Among them, E, F, G are the first basic parameters, and there:

$$E = 1 + h_u^2,\ F = h_u h_v,\ G = 1 + h_v^2 \tag{4}$$

The second basic parameters represent the degree of bending surfaces [10]:

$$II(d_u, d_v) = (\mathbf{r}_{uu} d_u^2 + 2\mathbf{r}_{uv} d_u d_v + \mathbf{r}_{vv} d_v^2) \bullet \mathbf{n} = L d_u^2 + 2M d_u d_v + N d_v^2 \tag{5}$$

Among them, L, M, N are the second basic parameters, and there:

$$L = \frac{1}{\sqrt{h_u^2 + h_v^2 + 1}} h_{uu},\ M = \frac{1}{\sqrt{h_u^2 + h_v^2 + 1}} h_{uv},\ N = \frac{1}{\sqrt{h_u^2 + h_v^2 + 1}} h_{vv} \tag{6}$$

Visibly, by E, F, G, L, M, N and other six parameters uniquely identified two basic amount of surface, Gaussian curvature K, mean curvature H, and the principal curvatures k_1, k_2 can be also expressed by these parameters [12]:

$$K = \frac{h_{uu}h_{vv} - h_{uv}^2}{(h_u^2 + h_v^2 + 1)^2}, H = \frac{EN + GL - 2FM}{2(EG - F^2)} \tag{7}$$

$$k_1 = H + \sqrt{H^2 - K}, k_2 = H - \sqrt{H^2 - K} \tag{8}$$

Thus, Gaussian curvature K , mean curvature H and the maximum and minimum principal curvatures k_1, k_2 contains information about surface shape as well.

Mean curvature H can be expressed by derivative of a function of the surface:

$$H = \frac{1}{2}\frac{\left(1+h_v^2\right)h_{uu}+\left(1+h_u^2\right)h_{vv}-2h_u h_v h_{uv}}{\left(1+h_u^2+h_u^2\right)^{3/2}} \tag{9}$$

Their respective units were the main direction vector:

$$\begin{aligned} \boldsymbol{u} &= \pm \frac{(k_1\times G - N)\boldsymbol{r}_u + (M - k_1\times F)\boldsymbol{r}_v}{\left|(k_1\times G - N)\boldsymbol{r}_u + (M - k_1\times F)\boldsymbol{r}_v\right|}, \\ \boldsymbol{v} &= \pm \frac{(k_2\times G - N)\boldsymbol{r}_u + (M - k_2\times F)\boldsymbol{r}_v}{\left|(k_2\times G - N)\boldsymbol{r}_u + (M - k_2\times F)\boldsymbol{r}_v\right|} \end{aligned} \tag{10}$$

2.2. Acquisition of the Initial Match Points Array

Two adjacent alignment angle to be set to scan point cloud data were $P = \{\mathbf{p}_i | \mathbf{p}_i \in \mathrm{R}^3\}$ And $Q = \{\mathbf{q}_i | \mathbf{q}_i \in \mathrm{R}^3\}$ (Q is reference point cloud). In order to get the correct match point right, inherent in this paper, differential invariant feature point cloud data. Firstly calculate the normal vector, the principal curvatures and the corresponding principal direction vector according to 2.1, and select the normal vector $\boldsymbol{n}$ direction so that all the normal volume point to point cloud surfaces on the same side, while selecting the main direction of the vector $\boldsymbol{u},\boldsymbol{v}$ direction $\boldsymbol{u},\boldsymbol{v},\boldsymbol{n}$ constitute a right-handed coordinate system. Then the literature cited herein proposed method to determine $\mathbf{p}_i$ and $\mathbf{q}_j$ correspond to neighborhood groups in order to gain initial match points.

2.3. Initial Registration Parameter Estimation

The use of discrete feature points corresponding roughly to estimate the initial registration pose. Corresponding feature points based registration method is selected group $N\,(N \geq 3)$ feature points in the point cloud model Ps effective two adjacent views and Qs (reference point cloud model) to (otherwise known as the corresponding feature points), each set of features corresponds to the same point on the actual object feature points. Ps using point cloud model of feature ($\mathbf{p}_1, \mathbf{p}_2, \mathrm{L}\ , \mathbf{p}_N$) and point cloud models in the N feature QS ($\mathbf{q}_1, \mathbf{q}_2, \mathrm{L}\ \mathbf{q}_N$) transform the relationship $\mathbf{q}_i = \mathbf{R}_0 * \mathbf{p}_i + \mathbf{t}_0 (i = 1, 2, \mathrm{L}\ , N)$ .And the four elements of literature and linear least squares method to solve the initial value of the rigid transformation ($\mathbf{R}_0\ \mathbf{t}_0$), will transform ($\mathbf{R}_0, \mathbf{t}_0$,) on the application of the point cloud model Ps has been transformed its rigid point cloud model $P\mathrm{s}' = \mathbf{R}_0 P\mathrm{s} + \mathbf{t}_0$, so that the two point clouds model Ps and Qs rough alignment to the same coordinate system (Qs as a reference point cloud model), to achieve a rough alignment.

3. Accurate Registration with ADF and ICS

3.1. Adaptive distance function (ADF)

As given in Figure 1,For mobile measurement data $\mathbf{p}_i \in \mathbf{P}s$,Measurement data points in the target set $\mathbf{Q}_s = \{\mathbf{q}_1, \mathbf{q}_2, \ldots\ldots, \mathbf{q}_n\}$,Searching the nearest point $\mathbf{q}_j$,on condition that $\mathbf{n}_j$ is the represented of the Units outside the normal vector in $\mathbf{q}_j$,and its Tangent plane $\mathbf{T}_P = \{\mathbf{x} \,|\mathbf{n}_j^T(\mathbf{x} - \mathbf{q}_j) = 0\}$ $\mathbf{T}_P$ is on the motion parameters $\mathbf{g} = (\mathbf{t}, \mathbf{R})$ .if $\mathbf{p}_i$ can be shown as $\mathbf{p}_{i+}$ the new coordinates of points in 3D space, then $\mathbf{p}_{i+}$ and $\mathbf{q}_j$ as the Update Point Connection ,whose Curvature center $\mathbf{o}_j$,then $\mathbf{q}_{j+}$ can be worked out as the data on the intersection of the target. As such, its definition based on Adaptive distance function of a surface point closest distance can be given as:

$$d_{ADF}{}^2(g, Q) = \left\|\mathbf{p}_{i+}\mathbf{c}\right\|^2 + \mu \left\|\mathbf{t}_j^T(\mathbf{p}_{i+} - \mathbf{q}_j)\right\|^2, \mu \in [0,1] \quad (11)$$

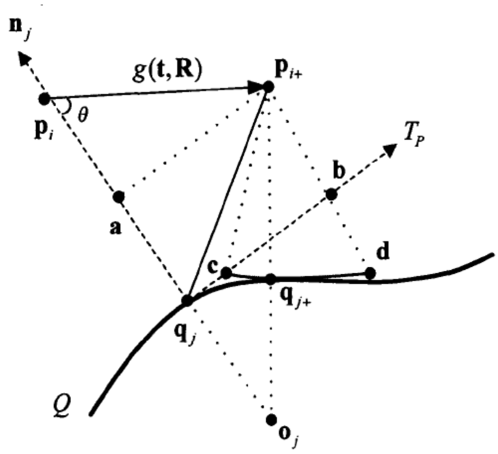


Figure 1. Adaptive Distance $\mathbf{p}_{i+}\mathbf{c}$ between $\mathbf{p}_i$ and the Target Surface $\mathbf{Q}_s$' Represented by Discrete Points

(1) On the condition that $\mu = 0$, its Adaptive distance function $d_{ADF}{}^2(g, Q)$ turn to be the Error metrics $d_{TDF}{}^2(g, Q) = \left\|\mathbf{n}_j^T(\mathbf{p}_{i+1} - \mathbf{q}_j)\right\|^2$ .Then for $d_{TDF}{}^2(g, Q)$ in Figure.1, its Section distance function $\left\|(\mathbf{p}_{i+1}\mathbf{b})\right\|^2$ applied in the distance function in Pottmann's TDM Algorithm [14] as metrics.

(2) On the condition that $\mu = 1$,its Adaptive distance function $d_{ADF}{}^2(g, Q)$ turn to be the Error metrics $d_{PDF}{}^2(g, Q) = \left\|(\mathbf{p}_{i+1} - \mathbf{q}_j)\right\|^2$,Then for

$d_{PDF}{}^2(g,Q)=\left\|(\mathbf{p}_{i+1}-\mathbf{q}_j)\right\|^2$ in Figure 1, its Section distance function $\left\|(\mathbf{p}_{i+1}q_j)\right\|^2$,which is used in Besl and Mckar's ICP Algorithm[3] as metrics.

(3) On the condition that $\mathbf{q}_j$ is in the Low curvature region(such as in the plane),then $d_{TDF}{}^2(g,Q)$ could be one of the metrics of the description of the distance between point &point ,but for $d_{PDF}{}^2(g,Q)$,it would be the distance deviation $\varepsilon_{PDF}=\left(\left\|\mathbf{p}_{i+1}\mathbf{q}_j\right\|-\left\|\mathbf{p}_{i+1}\mathbf{q}_{j+1}\right\|\right)^2$ .To the contrary, suppose that $\mathbf{q}_j$ is in the high curvature region, its function $d_{TDF}{}^2(g,Q)$ turn out to be the distance deviation $\varepsilon_{TDF}=\left\|\mathbf{b}\,\mathbf{d}\right\|^2=\left(\left\|\mathbf{p}_{i+1}\mathbf{q}_{j+}\right\|-\left\|\mathbf{p}_{i+1}\mathbf{b}\right\|\right)^2$,which is accurately related to the Curvature of $\mathbf{q}_j$.

$d_{TDF}{}^2(g,Q)$ And $d_{PDF}{}^2(g,Q)$ are two kinds of the Adaptive distance function $d_{ADF}{}^2(g,Q)$'s particular form. In the description of different characters of Curvature error in the distance between point-point and point-plane: ε_{PDF} and ε_{TDF} .In the Adaptive distance function, by adopting proper correction factor μ , reflecting the influence of the character of Curvature in distance deviation. For surface with Low curvature, by using a even Smaller coefficient $\mu\approx 0$, showing the nearest distance in point-plane; On the contrary, for high curvature, the Larger coefficient ($\mu\approx 1$) should be adopted. Compared with traditional method, $d_{PDF}{}^2(g,Q)$, the closest distance between point-point and $d_{TDF}{}^2(g,Q)$,the closest distance between point-plane; $d_{ADF}{}^2(g,Q)$ can't be more accurate.

3.2. ICS Fine Registration

Set the function f for mapping $R^3\to R$ .Using f the zero level set approximately that it expresses a point $\mathbf{p}$ of neighborhood $NB_r(\mathbf{p})$ of the curved surface $\mathbf{P}s$, denoted by:

$$f_{\mathbf{p},r}(\mathbf{x})=0 \tag{12}$$

In formula (12), $NB_r(\mathbf{p})$ is the r closed ball domain for curved surface Ps at the point $\mathbf{p}$. To the target data Qs of any point $\mathbf{q}_i$ and $NB_r(\mathbf{q}_i)$, all can construct surface patches $f_{\mathbf{m}_i,r}(\mathbf{x})=0$, which $NB_r(\mathbf{m}_i)$ is defined on the point set Qs on the ball closure. Putting the curved surface Ps approximately that it expresses as a group of surface patches $f_{\mathbf{m}_i,r}(\mathbf{x})=0(i=1,2,\cdots,N)$.

According to the corresponding surface patches registration, it is proposed the ICS registration algorithm that is iterative registration algorithm of the corresponding surface patches. ICS registration algorithm using local quadratic surface patches instead of discrete points as the registration of target geometry, reducing the impact of sampling density on registration accuracy. And moving data corresponding to a point $\mathbf{p}$ in the surface patches, it should be all surface patches to the point $\mathbf{p}$ of the nearest distance in the surface patches, which is approximated in the formula (11).

Define objective function of ICS algorithm is:

$$F = \frac{1}{2}\sum_{i=1}^{m} d_{ADF}{}^{2}(g, Q) \tag{13}$$

Using $\mathbf{Y} = C(P\mathrm{s}, Q\mathrm{s})$ express moving point set $P\mathrm{s}$ in the target point set $Q\mathrm{s}$ in the collection of the corresponding surface patches, $(\mathbf{g}, \varepsilon) = \mathbf{P}\mathrm{s}(\mathbf{P}\mathrm{s}, \mathbf{Y})$ express point set $\mathbf{P}\mathrm{s}$ the calculation of coordinate transformation to the corresponding surface patches set $\mathbf{Y}$. Which ε is the error of the corresponding points and surface matching. Initialization $\mathbf{P}\mathrm{s}_0 = \mathbf{P}\mathrm{s}$, the number of iterations $k = 0$. The state vector $\mathbf{g}$ of the initial value is estimated according to section 2.3. The k iteration process of ICS algorithm is as follows:

(1) Calculate the nearest surface patches set $\mathbf{Y}_k = C(\mathbf{P}\mathrm{s}_k, Q\mathrm{s})$, which is $\mathbf{P}\mathrm{s}_k$ after the $k-1$ iteration ,get the coordinate transformation $\mathbf{a}_{k-1}$ acting on the moving point set $\mathbf{P}\mathrm{s}_0$ to generate point set;

(2) Construct the objective function:

$$F_k = \frac{1}{2}\sum_{i=1}^{m} d_{ADF}{}^{2}(g_k, Q_s)$$

(3) determine the correction coefficient μ , and establish nonlinear optimization model;

(4) The computation of transformation $(\mathbf{g}_k, \varepsilon_k) = \mathbf{P}\mathrm{s}(\mathbf{P}\mathrm{s}_0, \mathbf{Y}_k)$, which

$$\varepsilon_k = \varepsilon(\mathbf{g}_k) = \frac{1}{N}\sum_{i=1}^{N} f_i(\mathbf{p}_i(\mathbf{g}_k))^2[\nabla f_i(\mathbf{p}_i(\mathbf{g}_k))^T \nabla f_i(\mathbf{p}_i(\mathbf{g}_k))]^{-1}$$

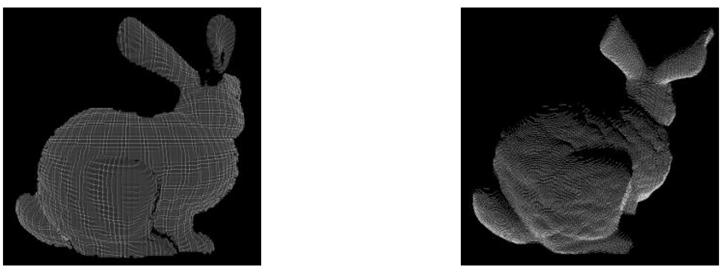
$\mathbf{p}_i(\mathbf{g}_k)$ For point $\mathbf{p}_i \in \mathbf{P}\mathrm{s}$ shape and position of a coordinate $\mathbf{g}_k$, f_i for $\mathbf{Y}_k$ in $\mathbf{p}_i(\mathbf{g}_{k-1})$ for the corresponding surface patches. The time complexity of this step is $O(NT_{LM})$, which is T_{LM} for the literature [15] in the average number of iterations in the LM algorithm.

(5) Making coordinate transformation $\mathbf{g}_k$ for moving points set $\mathbf{P}\mathrm{s}_0$, then obtain $\mathbf{P}\mathrm{s}_{k+1}$.

(6) For a given error value $\tau > 0$ or $N_k > 0$, when desired $\varepsilon_k - \varepsilon_{k-1} < \tau$ or $k > N_k$, terminate the iteration and outputs the optimal transformation $\mathbf{g}_* = \mathbf{g}_0 \bullet \mathbf{g}_1 \bullet \mathrm{L}\ \mathbf{g}_k$. Otherwise, let $k = k+1$ return to step (1).

4. Analysis of Experimental Results

In this paper, the registration was made with the 12 perspective of Bunny laser scanning data provided by Stanford University, limited space, only two the perspective (shows in Figure 2). In this experiment, the optimal correction coefficient $\mu = 0.05$.

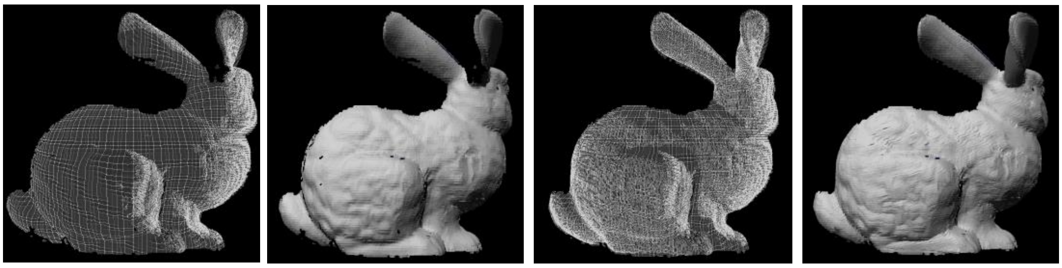


a) b)

Figure 2. a. Point Data of Bunny from View1
b. Point Data of Bunny from View2

Figure 2 (a) as shown in the point cloud contains 40279 data points, Figure 2 (b) as shown in the point cloud contains 38220 data points

Figure 3(a) was the initial registration results by using this algorithm for the first, second perspective cloud showed in Figure 2 (a), 2 (b), its corresponding initial registration error is $4.8e-07$. Figure 3 (b) was shown to be 3 (a) by Delaunay triangulation of illumination model; from Figure 3 (a) and 3 (b) can be seen, the initial registration effect is good, basically realize the correct registration two pieces of point cloud data. But in some areas, such as Bunny tail, chest, mouth, registration of point cloud slight loophole. After fine registration algorithm based on ADF and ICS become roughly complete, as shown in Figure 3 (c), corresponding to the fine registration error is $3.2e-07$; Figure 3 (d) was shown to be 3 (c) by Delaunay triangulation of illumination model;

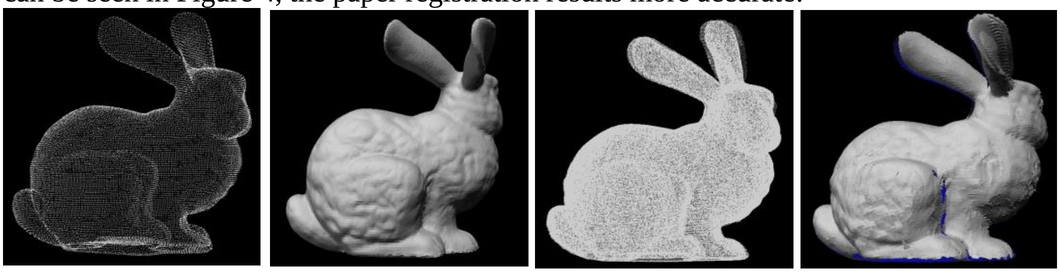


a) b) c) d)

Figure 3 a. Initial Registration Result of Point Cloud from View1 and View2 in Figure 2

b. Initial Registration Model of point cloud from view1 and view2 in figure 2
c. Fine Registration Result of point cloud from view1 and view2 in figure 2
d. Fine Registration Model of point cloud from view1 and view2 in figure 2

The multi perspective point cloud data registration can be transformed into two perspective point cloud data registration sequentially. Figure 4 (a) shows the whole registration point cloud data with the algorithm described in this paper for the 12 perspective of Bunny point cloud data; Figure 4 (b) is illumination model of Figure 4(a) by Delaunay triangulation; Figure 4(c) shows the overall registration of point cloud data with the literature [16] algorithm to get the perspective of 12 bunny point cloud data; Figure 4 (d) is illumination model of Figure 4 (c) by Delaunay triangulation. Comparison can be seen in Figure 4, the paper registration results more accurate.



a) b) c) d)

Figure 4 a. Whole registration Result with This Paper

b. Whole registration Model with This Paper
c. Whole registration Result with literature [16]
d. Whole registration Model with literature [16]

A quantitative comparison of Table 1 shows in Figure 3 registration results, these results are in Pentium IV, 3.10 GHz CPU, 8GB memory PC machine on the calculated, the development platform is VC++6.0 and MA TLAB7.0. Table 1 lists the two kinds of algorithm iteration number and registration error, as can be seen, this algorithm is more efficient and precise.

Table 1. Quantitative comparison of the registration result in figure 4 $\tau = 10^{-6} mm$

	iterations	Running time (s)	Average error	Standard deviation
Figure 4 (a)	63	401	$0.28\ \tau$	$0.09\ \tau$
Figure 4 (c)	128	753	$0.43\ \tau$	$0.97\ \tau$

5. Conclusion

Based on an analysis of the existing point cloud data registration method, introducing a new adaptive distance function ADF and the iterative closest patches ICS algorithm, proposed a new laser point cloud data of fine registration method. Compared with the existing iterative registration method under the framework of ICP, the proposed algorithm has two contributions: one is according to the point to point distance function and point tangent distance function, the introduction of a new point - surface distance function, to construct a more accurate point -surface distance error metric index; two is based on the traditional ICP algorithm on the registration of, put forward the ICS registration algorithm, using the local two patches instead of discrete points as the target geometry registration, reduce the effect of sampling density on the accuracy of registration, to ensure the accuracy and efficiency of the algorithm.

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