Research on the Multi-view Point 3-D Clouds Splicing Algorithm based on Local Registration

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Abstract

The paper proposed a new 3-D measurement point cloud splicing algorithm. The algorithm utilizes registration ideal in model identification technology to realize unbound and accurate splicing of 3-D data. First, sample the overlapping areas in the two 3-D point clouds which need to be spliced. Carry out pre-processing over the sampled point cloud with principal analysis method based on the statistic theory. Through extracting the feature vector that could best indicate the point cloud information, it realizes the dimension reduction for data. Then, apply improved iterate corresponding point algorithm to the sampled point cloud data which has realized pre-registration to achieve accurate registration. In the process, the set of progressive decrease of iterate condition by different levels reduced the iterate times. The utilization of new comprehensive distance measurement function effectively increases the accuracy and robustness of overall iterated convergence. Finally, apply the transformation parameter based on local sampled point cloud calculation to the entire point cloud splicing and achieve the accurate registration of multiple sampled point cloud. In the end, the actual test proved that the algorithm boasts high splicing accuracy with high overall convergence robustness, few convergence iterate times and strong anti-noise capacity.

Keywords: *3-D scanning, registration, free view point, iterate closest point method.*

1. Introduction

With the development of non-contact optical 3D scanning technology and the application expansion in the field of medical care, entertainment, manufacturing, testing and reverse engineering, panoramic holistic measurement becomes more and more important [1]. However, optical scanning system based on the characteristics of WYSIWYG, limits the use when it could not obtain the entire information of an object surface caused by obscuration or blind spots. So, in order to obtain full information of the measured object, all-round ad multi-angle scan measurements for local measurement data splicing has been the focus of the study, which is also a difficulty.

For some special applications, such as the human oral teeth three-dimensional information direct collection, three-dimensional scanning of the human body, tiny objects measurement and multi-angle measurements which do not support marked point pasting or shaft fixation, it is very difficult to splice and using traditional methods could not be very satisfactory. In this paper, based on analyzing the special nature of problems, it proposed a free camera-oriented unconstrained "two-step" point cloud splicing algorithm. The method does not require any auxiliary signs pasted on the surface. It stitches multiple point cloud data for free angle scanning and uses N side method for pre-splicing. The obtained conversion parameters provides subsequent fine splicing with a good initial value, and then it uses improved ICP algorithm to ensure global splicing convergence accuracy. Finally, the algorithm is validated by actual tests that the algorithm boasts reliability and splicing accuracy for free angle scanning point cloud and situations without distinct feature information

2. Relevant Algorithm Study and Analysis

Current splicing techniques can be broadly divided into mechanical shaft splicing paste the identified splicing and splicing algorithm based on closet point convergence algorithm. These three methods have their own advantages and application conditions.

Iterative closest point (ICP) splicing algorithm is proposed by Besl and McKay [7]. It is a geometric structure-based splicing and registration algorithm. The algorithm first identifies the correspondence between the point clouds that need splicing. It then uses repeated iterate method to reduce the distance between two groups of point clouds and gradually reduces errors. It then finds a group of geometric transformation matrix with minimum square variance soas to make the two point cloud to be spliced after geometric conversion [8]. The method does not require the additional features and it could achieve two objects splicing. However, ICP algorithm still has its own shortcomings: (A) in order to avoid falling into the local minimum mis-registration, the algorithm needs to have a good initial estimate for conversion parameters (B) when the two curve surfaces(which need registration) data are large, there would be large calculation for searching the closest point, leading to time-consuming consequence; (C) on noise-free data, it could not guarantee to obtain the correct results, to converge to the global (or even local) minimum, so it has poor robustness.

3. Algorithm Descriptions

This paper presents a highly efficient, high-quality splicing algorithm. The algorithm generally requires two steps. First, carry out N side pre-splicing for sampling point cloud and largely overlap the two point clouds to achieve the rough splicing. Then use ICPP(iterative closest plane and point algorithm) for pre-splicing model to ensure global convergence, reduce iterate times, realize accurate splicing and make the two point clouds fully overlap. Finally, convert the two splicing into parameter and use it to the entire data to realize the highly accurate seamless splicing.

3.1 Improved principal component analysis to extract feature vector

The idea of principal component analysis originates from the Karhunen-Loeve transform. The purpose is to find the optimal set of unit orthogonal vector base (that is the principal element) by the linear transformation. Use their linear combination to reconstruct the original sample, and to minimize difference between rebuild samples and the original sample. The principal component analysis is based on the training sample set second-order statistics. In fact, it refers to the de-correlation on second-order statistics.

PCA (principal components analysis) is based on the Euclidean distance metric unsupervised learning methods. As the most commonly used data dimensionality reduction method, PCA is widely used in pattern recognition [1, 2], face recognition, which is an effective statistic technique i image understanding field. It is also used for low-dimensional data to indicate features of high-dimensional data. It is used to distinguish the characteristics of data and highlight similarities and differences of the data. Therefore, for high-dimensional data, which is not easily distinguishable from the intuitive way, PCA is a powerful tool to analyze these data. With PCA calculation, you can find out about the spindle distribution of the point cloud model distribution.

The whole calculation process of PCA is presented as follows: If R is the correlation matrix of a n-dimensional input vector X, i.e., $R = E[xx^T]$, the eigenvalues $\lambda_i \geq \lambda_{i+1}$ are in descending order. The corresponding feature vectors are $\omega_1, \omega_2, \ldots, \omega_n$ respectively. We wish to find an orthogonal matrix W so that W is the diagonal matrix of the transformed matrix of X:

$$W = [\omega_1, \omega_2, \ldots, \omega_n]^T, \quad \omega_i \omega_j^T = \{1\ i{=}j; 0\ i|{=}j\}$$

Then $y_j = \omega_j^T x$, j=1,2,…,n, in which y_j is the projection of vector X in the principle direction represented by ω_1, namely, the principal component. By selecting m feature vectors corresponding with larger eigenvalues, we transform the low-dimensional vector y<Rm into a high-dimensional x<Rn, m<n.

Step 1: get the data.
Take samples of two three-dimensional point sets and make one of them the targeted point set $Pt1(x_i,y_i,z_i)$, another the reference point set $Pt2(x_j,y_j,z_j)$, the number of point in the two point sets are N_i and N_j respectively.

Step 2: calculate the barycenter of the targeted point set $Pt1$ and the reference point set $Pt2$.

$$W_{pt1} = \frac{1}{N_i} \sum_{i=1}^{N_i} Pt1_i$$

$$W_{pt2} = \frac{1}{N_j} \sum_{j=1}^{N_j} Pt1_j$$

Step 3: calculate the covariance matrix C_{pt1} and C_{pt2} of the targeted point set $Pt1$ and the reference point set $Pt2$.

$$C_{Pt1} = \frac{1}{N_i} \sum_{i=1}^{N_i} (Pt1_i - W_{pt1})(Pt1_i - W_{pt1})^T$$

$$C_{Pt2} = \frac{1}{N_j} \sum_{j=1}^{N_j} (Pt1_j - W_{pt2})(Pt1_j - W_{pt2})^T$$

Step 4: calculate the eigenvalues and feature vectors of the covariance matrix of the two point sets.

$$Evu \cdot C = Evr \cdot C$$

Sort the eigenvalues in descending order $Evu_i \geq Evu_{i+1}$. As this system deals with three dimensional point set, we choose feature vectors $Pt1\_Evr_m$, $Pt2\_Evr_m$(m=1,2,3) that corresponds with the top 3 non-zero eigenvalues as pivots. Then we can use low-dimensional subspace of principal component to describe the former space.

Step 5: create two transformed matrix TR1 and TR2 in three-dimensional vector direction

$$TR_1 = \begin{bmatrix} Pt1\_Evr_1.x, Pt1\_Evr_1.y, Pt1\_Evr_1.z \\ Pt1\_Evr_2.x, Pt1\_Evr_2.y, Pt1\_Evr_2.z \\ Pt1\_Evr_3.x, Pt1\_Evr_3.y, Pt1\_Evr_3.z \end{bmatrix}$$

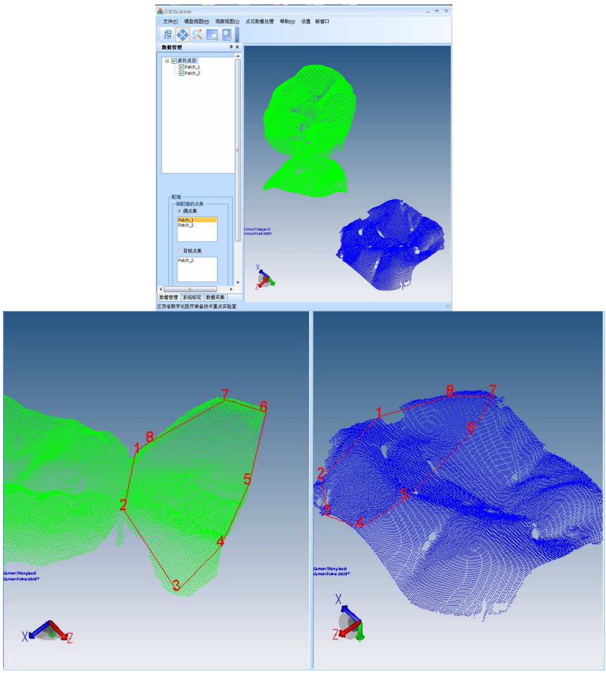
$$TR_2 = \begin{bmatrix} Pt2\_Evr_1.x, Pt2\_Evr_1.y, Pt2\_Evr_1.z \\ Pt2\_Evr_2.x, Pt2\_Evr_2.y, Pt2\_Evr_2.z \\ Pt2\_Evr_3.x, Pt2\_Evr_3.y, Pt2\_Evr_3.z \end{bmatrix}$$

Step 6: describe targeted point set Pt1 and reference point set Pt2 in space of principal component by Pt1' and Pt2' _temp:

$$Pt1' = TR_1 \cdot Pt1, \quad Pt2'\_temp = TR_2 \cdot Pt2$$

Calculate the translation matrix T1=Wpt2- Wpt1 between the two point sets and we can get the needed point set by coinciding the two bary-centers in the pivotal coordinate system.

Based on this principle, this system interactively selects two parts which point clouds overlap as targeted point set and reference point set. As picture 1 demonstrates, the two pictures are parts of the point clouds. Image a.b is the sample data stored in targeted point set Pt1(xi,yi,zi) and reference point set Pt2(xj,yj,zj)



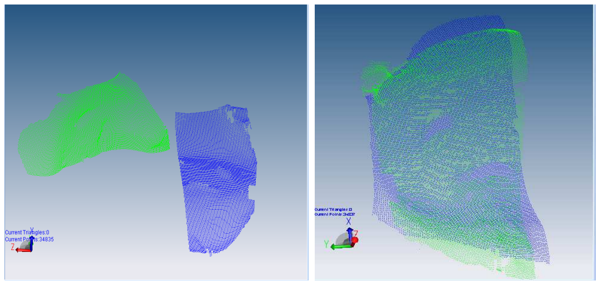


Figure 1 image of samples in data system of those needing registration

Given the statistics of the proportion and calculative proportion of principal components in total variance, we can see that the dominant accumulated contribution are made by the top 3 pivotal components, providing enough pre-splicing conditions for follow-up Iterative closest point splicing.

After primary location registration, we compare the two point clouds generally. Due to the complexity of three-dimensional geometric model and the accuracy of registration, fine-tuning is required after general registration.

3.2 Improved ICP Algorithm Used for Accurate Splicing

Traditional ICP (iterative closest point) algorithm [7] is highly restrictive, with the limitations of the initial positions. It is not applicable to two point cloud with large distance. In addition, it is slow in convergence, with poor efficiency. Therefore, many scholars have proposed improved ICP algorithm. Document [10] proposed an ICL (iterative closest line) algorithm. The registration is performed through a direct connection and finding of the corresponding segment of the two points clouds. But it could not guarantee to the correspondence relationship between the line segments; Document [11] uses the normal plane of the point in the first surface as the distance metric function, due to the contradictions among different corresponding control points, the convergence rate is relatively slow; document [12] uses the cut plane of the point to approximate the point cloud. The target distance metric function is simplified to the least squares distance from the point to the tangent plan. In this case, through the small angle approximation rotation, it could achieve the conversion. When the initial positions of two points set are very close, with some relatively low noise, the pint-to-plane error distance measure can achieve the second convergence. However, if the distance of the initial positions of the two point clouds are distant, or point cloud noise is large, the algorithm will lead to the error convergence of the ICP algorithm; document [13] proposed to regard the distance from the point to a local triangle food point of another curve surface as the distance metric function; document [14] proposed the mixed local curve rate and weighting distance among points, the two distance measuring methods. It obtains a second-order approximated square distance function. The distance is from point pi to the curve surface Q the distance. It is able to obtain quadratic convergence when two point clouds are close. It could also realize relative fine linear convergence for point clouds with distant initial positions, but it could not guarantee the global optimum.

According to the study, ICP algorithm relies heavily on selection of corresponding point and setting of target distance measurement function to effectively converge and achieve global optimum minimum of objective function. Therefore, we propose the point-to-point distance metrics and point-to-plane and point overall distance metrics. By setting iterative termination condition through different levels, it reduces the iterative termination times. It uses kd tree-based search algorithm [15] to repeatedly sample corresponding point set to reduce the search time of the corresponding point, ensuring the correctness of the corresponding point selection and ultimately achieving correct global minimum convergence acquisition.

(1) The Initial Level Convergence

As for $P_{1,}$ N the local point cloud data of N deformation sampling, Q1 gets the proper amount of point set based on geometric curvature s and regards P_2,*Q2* as set pair of corresponding points. First, it sets a relatively large termination threshold 0.1mm in order to reduce the number of iterations and further narrow the distance between the point clouds.

Suppose pi, Qi (i = 1, ..., N) are points in point clouds P2 and Q2. Theoretically, it is believed there exists such rigid body transformation between (p_i,q_i) when two surfaces splicing is completed.

$$\left\| Tp_i - q_j \right\| = 0$$

However, the equation ca not be established because the actual measurement data obtained can be influenced by calibration error, system accuracy, and noise data. Therefore, we need to first set an infinitesimal value accepted by the precision so that the equation can hold water. Set the limit value e and you can easily obtain the transformation matrix space by minimizing the following value:

$$e = \sum_{i=1}^{N} \left\| Tp_i - q_i) \right\|^2$$

However, the seeking of corresponding point pairs is difficult and time consuming, especially for non-regular curved surface. The paper first fixes the curved surface P_2. Deploy the k-d tree search algorithm [15] to find the nearest point of the minimum distance in P2 to Q2:

$$q_i = q \mid \min_{q \in Q} \left\| Tp_i - q \right\|$$

Assume that TR0 is the obtained position after the initial N-gon method. With the increase of iteration times, you should substitute the obtained data from last iteration T (k-1) into the iterative formula so as to seek q_j^k:

$$e^k = \sum_{i=1}^{N} \left\| T^k p_i - q_j^k) \right\|^2 ,$$

In the above formula, $q_j^k = q \mid \min_{q \in Q} \left\| T^{k-1} p_i - q \right\|$. From the above analysis, we can see that the point set obtained through minimization is a digitalized surface model. If we approximately replace the curved surface with a point, then the problem will be greatly simplified. During the initial iteration cycle, if distance between the point clouds is unknown or relatively big, we can deploy the point-to-plane distance metric function [12] in that it can renders better linear convergence in the case of far distance to point cloud position. As shown in the following Diagram 4, we can achieve conversion through the small-angle approximation rotation. Assume that the tangent plane at point q_i is represented by s_i , then the distance metric function ca be expressed as follows:

$$e = \sum_{i=1}^{N} \left\| Tp_i - q_j^{'}) \right\|^2 \text{ Wherein, } q_j^{'} = q \mid \min_{q \in S_J} \left\| Tp_i - q \right\|$$

The distance between the point and the surface can be expressed by a linear function:

$$e^k = \sum_{i=1}^{N} d_s^2 (T^k p_i, S_j^k),$$

$$S_j^k = \{ s \mid n_{qj}^k \cdot (q_j^{'k} - s) = 0 \}, \quad q_j^{'k} = (T^{k-1} l_i) \cap Q$$

In the above formula, d_s is the distance between the point and the plane; n_{qj}^{k} stands for the normal vector of surface Q_2 at the point q'^{k}_{j} ; $l = a \mid (p_i - a) \times n_{pi} = 0$ refers to the linear tangent vector at the point p_i, n_{pi} represents the normal vector of the surface *P* at the point p_i; $(Tl_i) \cap Q_2$ is the insertion point of the line *l on the* surface of Q2.

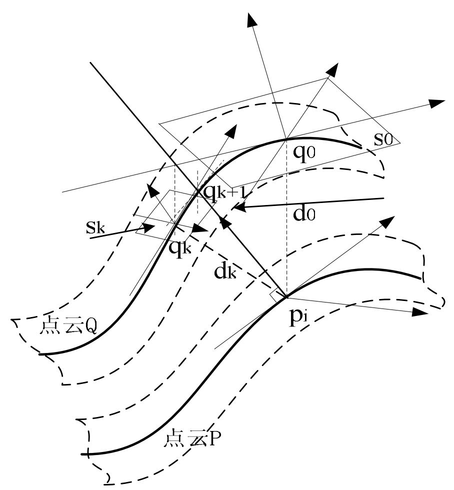


Figure 2 Analog Figure of the Convergence Approximation of Metric Function

This algorithm gives no brooding to special corresponding points, thus eliminating the problem of slow convergence. Besides, the system has set a relatively relax condition for convergence termination: 0.1 mm, which greatly reduces the number of iterations. After the step-by-step iterative approximation, we can obtain the final conversion matrix parameters. In order to verify the efficiency of the algorithm, we compare the algorithm of this system and the metric function algorithm based on point-to-plane distance as well as the traditional ICP algorithm.

(2) Second-hierarchy Convergence

Establish corresponding relation between the corresponding points seeking and the corresponding transformation parameters. If the correspondence relationship parameters $\{c_1,\ldots,c_k\}$ are known, we can easily find the nearest corresponding point of each point with these parameters. On the contrary, if the cloud data of the two point clouds are in the best conversion splicing state, the conversion relation of the two point clouds is to find the splicing conversion parameters. Therefore, based on the established splicing conversion relation TR_1, this system re-samples corresponding point sets P3 and Q3. Then it searches for the corresponding nearest points of these sampling points among the local parts around the reference sampling set. After these steps, we can reduce the search time to less than the O(LogNx)of the global search by k-d tree. The detailed implementation is as follows:

Points $p'_i=(x_1,y_1,z_1)$ and $q'_j=(x_2,y_2,z_2)$, $(i=1,\ldots N_q)$ are respectively two corresponding point set pair based on the approximate conversion re-sampling. The Euclidean distance between the two points between the is $d(p_i',q_i')$, $d(p_i,q_i)=\|p_i-q_i\|=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2+(z_2-z_1)^2}$,. The initial iterative is set as $T_0=[1,0,0,0,0,0,0]^T$; the number of iterations, k = 0; the spliced vector obtained in the iterative splicing process is defined as a sequence: $t_1,t_2,t_3,\ldots t_k$. The specific implementation steps can be expressed as:

1) Obtain the target point cloud P_3(p_i<P,(i=1…Np))and the reference point cloud Q_3(qi<Q,(i=1,…Nq))
2) Based on the initial transformation parameters TR_1, resample N_p points of P_3 in Q3 and mark the corresponding point set Q4;
3) Initialize the data: X0=P3, $T_0=[1,0,0,0,0,0,0]^T$,k=0;
4) Around the local area of corresponding point set Q_4, use k-d tree to search for the nearest point *Y of each point of* P_3.. The k-th iteration is defined as: $Y_k=T(X_k,Q_4)$;
5) Calculate the spliced vector: $(t_k,d_k)=T(X_0,Y_k)$;
6) Apply the k-th splicing vector to the initial point set X_0 : $X_{k+1}=t_k(X_0)$;
7) Simplify the point-to-point quadratic distance function to the multiple unconstrained minimization based on the linear search. The angle between iteration vectors in the splicing space determines the direction of convergence the. In the formula, $\Delta q_k = q_k - q_{k-1}$
8) Determine whether the error converges. If the dk-dk +1 < δ , converge. Otherwise, come to step 4. The termination of this iteration renders us the splicing conversion parameters TR2. The termination condition δ is set as 0.02mm.

The efficiency of the traditional ICP algorithm based on the point-to-point distance function is low, and, in the worst case, the cost time can reach $O(N_pN_q)$. In addition, it itself can not guarantee the global minimum convergence. This paper obtains the optimum initial position through the preliminary steps. After several re-sampling, the number of corresponding point is significantly reduced. k-d tree is adopted here to search in the neighboring filed, which successfully solves the slowness of the traditional algorithm and brings the advantages, for example precision, of this proposed algorithm into full play. In this way, we can reduce the difficulty of solving complex nonlinear problems.

The proposed splicing algorithm consists of two steps: initial pre-splicing and fine splicing. The purpose of the pre-splicing is to minimize positional relationship between two point cloud data so that two data can have the same accuracy alignment splicing conditions; the purpose of fine splicing is to minimize the distance and error of two point cloud sampling data to be spliced. The pre-splicing guarantees that the two depending approximate conversion parameters are known. Through the ICPP procedures to search the nearest point so as to obtain the approximate conversion parameter matrix space, which provides the premise for the point-to -surface ICP search. Thus, we can reduce the difficulty in solving complex nonlinear problem and facilitate the search of global minimum distance d (P, Q). The proposed algorithm not only has good splicing precision but also has good convergence efficiency. Compared with the original point-to-point-distance-based ICP algorithm and point-to-surface-distance-based ICP algorithm, the improved multi-sampling point algorithm deploys the k-d tree global search to reduce the number of iterations in local area, improve the convergence efficiency, and guarantee the splicing accuracy. The following Table 1 shows the comparison of data of various algorithms:

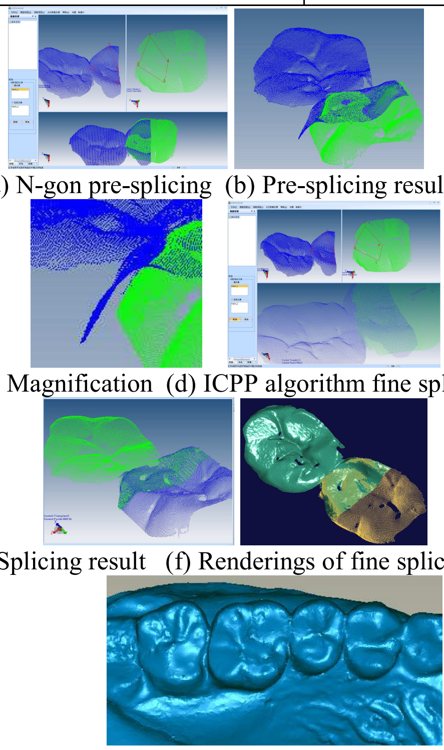
Table 1 Comparison of Convergence Efficiency and Accuracy between Various Algorithms

	Amount of Point Cloud Data	Point-to-point-distance-based ICP Algorithm	Point-to-surface-distance-based ICP Algorithm	The Proposed ICPP Algorithm
Number of Iteration	99022	23	18	13
	111385	35	32	16
Splicing Accuracy (mm)	99022	0.018	0.026	0.02
	111385	0.019	0.028	0.019

This paper takes the photos of tooth and head, whose point cloud data is respectively 99,022 and 111,385 points, for example. Three algorithms are applied and compared in terms of the number of iterations and splicing accuracy, which are specifically shown in Table 1. We can learn that the proposed algorithm is better than the other two algorithms in terms of convergence speed and the overall splicing precision. It is notable that the point-to-point algorithm can result in local convergence and splicing errors in the case of head photo.

4. Algorithm Example Verification and Splicing Assessment

In order to realize the unconstrained multi-cloud 3-D splicing based on free-view angle scanning, this paper develops a 3-D point cloud collection and splicing system according to VC++.NET20003. We developed the measurement system based on the structured light viewing angle measuring system D3Dscanner. The tooth in Prosthodontics is taken as the measurement object for multi-view point cloud scanning. The proposed algorithm is applied to splice multi-chip point cloud and display the process. Figure 4 is the software interface using this system for the pre-splicing; Figure 3a shows the polygon sampling pre-splicing of two point clouds to be spliced. Figure 3b shows the pre-splicing results. From the magnified partial view of the splicing gap 4c, we can see that precise splicing is needed. On the basis of the pre-splicing, the photo after the ICPP fine splicing in this paper is displayed in Figure 6d. Figure 3e shows the high-precise splicing. From the renderings of Figure 3f, we can know that the splicing precision can meet the system requirements. Figure 3g demonstrates the splicing of multiple point clouds by using the proposed algorithm.



(a) N-gon pre-splicing (b) Pre-splicing result

(c) Magnification (d) ICPP algorithm fine splicing

(e) Splicing result (f) Renderings of fine splicing

(g) Rendering of multiple teeth point cloud

Figure 3 System splicing process of software interface

In terms of splicing results, we can assess the splicing result from the point cloud direct display. However, we can not judge the splicing precision. Therefore, we use the similarity assessment function S mentioned by the reference [16] to quantify precision. The mathematical function of the degree of similarity S is expressed as:

$$S = (e^{-\frac{SSD_{D,M}}{(L_D + L_M)^{1/2}}}) \times 100\%,$$

Where, $SSD = \left| x_b - T(x_a) \right|^2$,XP = (XP, YP, ZP), Xq = (xq, YQ, ZQ) are respectively the corresponding coordinates of point sets P and Q; $SSD_{D,M}$ is the quadric sum of the smallest difference between two point cloud models; L_D is quadratic sum of the distance between vertex value and the original point of the point cloud P model; L_M is the square of the distance between the vertex value and origin point of cloud Q model. The following table shows the similarity assessment of the proposed algorithm on randomly chosen multiple cloud points of corresponding point.

Table 2 Similarity of Point Cloud Splicing

Corresponding two point clouds	Similarity
The 1st pair	94.523%
The 2nd pair	95.146%
The 3rd pair	93.259%
The 4th pair	94.842%
The 5th pair	95.024%

5. Conclusion

This paper introduces a point cloud splicing method oriented for scanning point clouds with special needs. It solves such problems with global measurement in terms of no obvious characteristics, no use of shaft measuring and paste mark point. As splicing is a problem of local matching, this paper, according to ideas about matching, realizes local splicing. Firstly, we broadly sample the overlapping parts of the two point clouds. Then, it employs the proposed method of N-gon to minimize the distance between each other and proposes necessary initial position for fine splicing. Through the setting of hierarchy conditions for iteration termination and the improved iterative closest point fusion algorithm, we can reduce the number of iterations and ensure the obtaining global minimum convergence. Examples prove that the proposed method has better splicing accuracy and convergence efficiency with simple operation. Finally, the three-dimensional splicing technology and our self-developed three-dimensional measurement system are jointly deployed to realize accurate information acquisition from complex objects. In a word, the proposed method boasts pretty high practical value.

References

[1] Michael Zimba, Sun Xingming, "Digital Image Splicing Detection Based on Local Complexity of Local Maximum Partial Gradient of DWT Coefficients.", JDCTA, Vol. 6, No. 5, pp. 1 ~ 9, 2012

[2] Bo Wang, Xiangwei Kong, Lanying Wu, "Different-quality Re-demosaicing in Digital Image Forensics", JCIT, Vol. 7, No. 17, pp. 492 ~ 505, 2012

[3] Li Yao, Dong-Xiao Li, , Ming Zhang, "A Temporally Streamlined Optimization Method for Stereo Video Correspondence", IJACT, Vol. 4, No. 2, pp. 238 ~ 246, 2012

[4] HE Huaiqing , , YANG Lei , XU Qing , "Multidimensional Uncertainty Visualization with Parallel Coordinate and Star Glyph", JDCTA, Vol. 5, No. 6, pp. 412 ~ 420, 2011

[5] Kwangmu Shin, Sunghwan Chun, Kidong Chung, "An Efficient Mode Selection Exploiting Property of Region in Multi-view Video Coding", IJIPM, Vol. 2, No. 3, pp. 44 ~ 51, 2011

[6] Zhi Liu, Hongjun Wang, Hui Xu, Shangling Song, "3D Tongue Reconstruction Based on Multi-view Images and Finite Element", AISS, Vol. 3, No. 11, pp. 60 ~ 66, 2011

[7] Xin Wang, Guofang Lv, Huibin Wang, "Multi-View Tracking of Occluded Targets by Scenic Feature Modeling", AISS, Vol. 4, No. 22, pp. 312 ~ 319, 2012

[1] [8] Guifang Duan, Shuci Wu, Yen-Wei Chen, "Robust Facial Feature Point Extraction via Viewpoint-Specific Active Appearance Model", JNIT, Vol. 3, No. 3, pp. 10 ~ 18, 2012