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Point Cloud Simplification Algorithm Based on Hausdorff Distance and Local Entropy of Average Projection Distance

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Abstract:

The high precision digital dental model obtained by intraoral optical scanner poses great challenges to processing speed and storage space of computers when performing tasks such as data storage, transmission and management. A simplification algorithm based on Hausdorff distance and local entropy of average projection distance is proposed to meet the practical application requirements of digital impression technology. After the edge points are extracted and the interdental points are sampled, the proposed algorithm used octree structure to segment the remaining points. According to the average Hausdorff distance of all points in each subcube and the average Hausdorff distance of the remaining points, the corresponding obtained evaluation ratio is compared with different thresholds of the multi-level simplification criterion, so as to determine the feature degree of the subcube. The point cloud simplification factor and the local entropy of average projection distance are used to preserve the corresponding number of feature points in the feature subcube. According to the local point cloud distribution, all points in the non-feature subcube can be replaced by a certain number of points closest to the center of all points. The experimental results show that the proposed algorithm can well preserve many detail features of the dental model and effectively avoid the appearance of holes in non-feature regions. The proposed algorithm is superior to other comparison algorithm in terms of simplification effect and simplification error.

Keywords*: Intraoral optical scanner, Digital dental model, Point cloud simplification, Information entropy, Multi-level simplification criteria.*

I. INTRODUCTION

With the continuous expansion and application of reverse engineering technology, 3D printing technology and computer-aided design and manufacturing technology in the field of stomatology, the emerging dental treatment and repair technology is gradually replacing traditional manual molding, which means that dental restoration has officially entered the era of digitization and modeless. Compared with the extraoral acquisition method, the emerging intraoral optical scanning technology can save many tedious modeling steps, reduce material consumption and manual labor, and effectively minimize modeling errors [1]. The intraoral optical scanning technology has been recognized by the industry as the mainstream development technology in the field of dental restoration in the future. Although intraoral optical scanning technology can quickly obtain the digital dental model with complex tissue structure [2, 3], it needs to consume a lot of processing time and memory resources when performing tasks such as data storage, transmission and display [4-6]. Point cloud simplification is the key step in 3D model reconstruction, and the simplified result will directly determine the reconstruction result of the 3D model. Therefore, how to efficiently and accurately simplify the massive points of the 3D model has become the current research hotspot of reverse engineering.

Bao et al. [7] used k-means clustering method to adaptively simplify 3D points. Yuan et al [8] mapped the point clusters obtained by the k-means clustering method to the Gaussian sphere, and then used the adaptive mean shift method to classify the points, but it is easy to lose the boundary features and is not suitable for non-closed 3D models. Compared with non-edge points, edge points with more significant features should be retained. However, the simplification method in literature [7, 8] did not extract the edge points, which resulted in partial loss of the edge contour features of the model. Chen et al. [9] retained the edge contour features of the 3D model through the x-y boundary extraction, and achieved iterative simplification of model points through fuzzy entropy. Han et al. [10] effectively extracted edge points and realized iterative simplification of model points by calculating the importance of each point, but it is easy to generate holes in non-feature regions. Based on the work contributions made by Kim [11], Zhu et al. [12] used the Hausdorff distance of the principal curvature of points to determine the extraction of feature points. When the simplification rate is high, holes are likely to appear in the non-feature region of the 3D model. Yang et al. [13] extracted feature points by using Hausdorff distance. Although the simplification efficiency has been significantly improved, the simplification results are not uniform. Zhang et al. [14] can better retain the detail features and the boundary features of the 3D model, but the feature point detection requires a lot of calculation. Zhang et al. [15] used the average value of the normal vector and the distance weight of the normal vector to extract the feature points. When the simplification rate is high, holes are easily generated in non-feature regions. Ji et al. [16] proposed a simplified algorithm for importance assessment of point cloud. Dong et al. [17] judged whether the cluster was a characteristic cluster by comparing the estimated curvature difference values within the k-means cluster with the set threshold, and classified points whose local entropy of the weight product is greater than the average local entropy within the cluster as feature points. For 3D models with lots of complex features, the detail features of strong feature regions are seriously lost.

Aiming at the problems existing in the above algorithms, we propose a simplification algorithm based on Hausdorff distance and local entropy of average projection distance. After extracting the edge points and down sampling the extracted interdental points, the corresponding evaluation ratio obtained from the average Hausdorff distance of all points in each subcube and the average Hausdorff distance of remaining points are compared with the threshold set by the multi-level simplification criterion to determine the feature degree of each subcube. The local entropy of average projection distance of each point in the subcube are calculated and sorted according to the entropy value. According to the feature degree of the

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feature subcube, the simplification factor can be determined, and the corresponding number of non-feature points in the feature subcube can be simplified. For the non-feature subcube, some points closest to the center of all points are used to approximately replace all points in the non-feature subcube.

II. METHODOLOGY

2.1 Calculation of Point Cloud Geometric Feature Information

2.1.1 Principal curvature

According to the characteristics of three-dimensional points, the spatial topological relation of point cloud is constructed by using K-D tree. After conducting a large number of studies on the selection of k-neighboring points, scholars have concluded that the appropriate value range of k is 15~30[18]. In this paper, k is chose as 15. The main methods for calculating the normal vector are MLS and PCA. MLS method can accurately calculate the normal vector while greatly reducing the calculation efficiency. Considering the stability and efficiency of normal vector estimation [19], we choose the classical PCA method. We can get the sample p and its neighborhood $q_i\left(i=1,2,\cdots,k\right)$. N_q is the k-neighboring points set, and $\overline{p}$ is the geometric center of N_q. The normal vector is n and the spatial distance from the fitted plane to the ordinate origin is d. The fitted plane F is shown in (1). Then, it is simplified to eigenvalue decomposition of the matrix C in (2).

$$F(n,d)=\arg\min_{(n,d)}\sum_{i=1}^{k}(n\overline{p}-d)^2,\ \overline{p}=\frac{1}{k}\sum_{i\in N_q}q_i \tag{1}$$

$$C=\frac{1}{k}\sum_{i=1}^{k}\left(q_i-\overline{p}\right)\left(q_i-\overline{p}\right)^T \tag{2}$$

We can get the eigenvalues $\gamma_j\left(j=1,2,3\right)$ and eigenvectors $\upsilon_j\left(j=1,2,3\right)$ through the covariance matrix C. Set point p as the origin of coordinates, take the direction of its unit normal vector n_p as the direction of w axis, establish the right-handed coordinate system, and select any two perpendicular points on the fitting plane as the coordinate axis u and v. The local quadric surface equation can be expressed as:

$$r(u,v)=F(u,v,f(u,v)) \tag{3}$$

$$f(u,v)=au^2+buv+cv^2 \tag{4}$$

Gaussian curvature, mean curvature and principal curvature can be calculated by (5) ~ (7) respectively.

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$$K = \frac{f_{uu} f_{vv} - f_{uv}^{\ 2}}{\left(1 + f_u^{\ 2} + f_v^{\ 2}\right)^2} \tag{5}$$

$$H = \frac{f_{uu}(1 + f_v^{\ 2}) + f_{vv}(1 + f_u^{\ 2}) - 2 f_u f_v f_{uv}}{(1 + f_u^{\ 2} + f_v^{\ 2})^{3/2}} \tag{6}$$

$$\begin{cases} k_1 = H + \sqrt{H^2 - K} \\ k_2 = H - \sqrt{H^2 - K} \end{cases} \tag{7}$$

2.1.2 Hausdorff distance

$H\left(A,B\right) = \max\left(d\left(A,B\right), d\left(B,A\right)\right)$ can reflect the similarity degree between point sets A and B [20], so we used the Hausdorff distance to determine the feature degree in the local region where the point is located. The principal curvature of target point p are k_1 and k_2. The principal curvature of any k-neighboring points q are $k_1^{'}$ and $k_2^{'}$. The Hausdorff distance between $\left\{k_1, k_2\right\}$ and $\left\{k_1^{'}, k_2^{'}\right\}$ can be solved as the difference in curvature between the point p and its k-neighboring points q [21]. The Hausdorff distance of the principal curvature of each point is calculated by (8), and the maximum value of all the Hausdorff distances is taken as the Hausdorff distance of point p. The Hausdorff distance of point p [12] can be defined as (8) and (9).

$$H = max\left(\max_{i=1,2} \min_{j=1,2}\left(\frac{\|k_i - k_j'\|}{\|k_i\| + \|k_j'\|}\right), \max_{j=1,2} \min_{i=1,2}\left(\frac{\|k_i - k_j'\|}{\|k_i\| + \|k_j'\|}\right)\right) \tag{8}$$

$$H_p = max(H_1, H_2, H_3, \cdots, H_k) \tag{9}$$

Where, $H_1, H_2, \cdots, H_k$ are the Hausdorff distance corresponding to sample p and its k neighborhood points.

The Hausdorff distance can effectively reflect the feature degree of the local region where the sample p is located. The small Hausdorff distance indicates that the point p is located in the region where the local geometry changes less. On the contrary, when the Hausdorff distance value is large, it indicates that point p is located in the region where the local geometry changes significantly.

2.1.3 Average projection distance

For the sample p, we can obtain the normal vector corresponding to its k-neighboring points $q_i\left(i = 1, 2, \cdots, k\right)$, and unitized as $n_i\left(i = 1, 2, \cdots, k\right)$. Fig 1 shows the projection distance from sample p to

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the estimated tangent plane at any point of its k-neighboring points q_i. The average projection distance can reflect the change degree of the geometric shape of the local surface where the point is located [10, 22]. The average projection distance [10] is calculated by (10). When the average projection distance is large, it means that p is located in a region where the geometric shape changes significantly.

$$i(p)=\frac{\sum_{i=1}^{k}\left|n_i\left(p-q_i\right)\right|}{k} \tag{10}$$

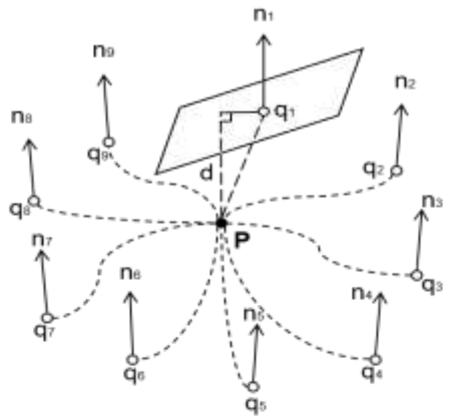

Fig 1: projection distance from sample p to the estimated tangent plane of point q_1

2.1.4 Local entropy of average projection distance

As a state function of the system, information entropy can be used to measure the uncertainty and information in communication [23]. Shannon gave the quantitative expression of information entropy:

$$H(X)=-K\sum_{i=1}^{n}P_i logP_i \tag{11}$$

Where, K is a fixed normal number, P_i is the probability of event, and it satisfies the conditions $0\le P_i\left(i=1,2,\cdots,n\right)$ and $\sum_{i=1}^{n}P_i=1$.

In this paper, the membership degree in a certain type of feature can be expressed by information entropy. The average projection distance and information entropy are combined to express the feature degree of 3D model points. The average projection distance of point p is calculated by (10) and the local entropy of average projection distance is calculated by (12). w and w_i are the average projection distance of the point p and its k neighborhood, while p_w and p_{w_i} are the probabilities corresponding to

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the average projection distance of the point p and its k neighborhood.

$$I(P) = -P_w \log P_w - \sum_{i=1}^{k} P_{w_i} \log P_{w_i} \tag{12}$$

$$P_w = \frac{w}{w + \sum_{i=1}^{k} w_i}, P_{w_i} = \frac{w_i}{w + \sum_{i=1}^{k} w_i} \tag{13}$$

To some extent, the local entropy of average projection distance can reflect the geometric features of 3D model surface. The high local entropy indicates that the local region of point p is closer to the feature region. On the contrary, it indicates that the local region of p is more likely to be the flat region. Therefore, we save the points with high local entropy of average projection distance as feature points, and reasonably simplify the corresponding number of points with low local entropy of average projection distance according to the feature degree.

2.2 Extraction of Edge Points

For a non-closed 3D model, the edge contour is a direct description of its geometric features. In order to avoid loss of geometric features due to the simplification of boundary points, a certain number of model edge points need to be extracted. The edge points have the characteristics of uneven distribution. Most of the existing methods classify the points larger than the threshold as edge points by comparing the Euclidean distance between the sample p and the center of its k neighborhood points with the threshold. We extract the edge points by comparing the coordinate values of the corresponding projection points of the k-neighboring points projected on the fitting plane [10]. Taking point p as the center of the coordinate system, three reference planes xpy, xpz, and ypz can be obtained, corresponding to xpy, xpz, and ypz respectively. The ratio is formed by the difference of the projection points on both sides of a reference plane and the k-neighboring points. When the ratio is larger than the set threshold, p can be regarded as an edge point. As shown in Fig 2, there are 3 projection points below the plane xpy and 12 projection points above the plane xpy, so the ratio is $\frac{3}{5}$.

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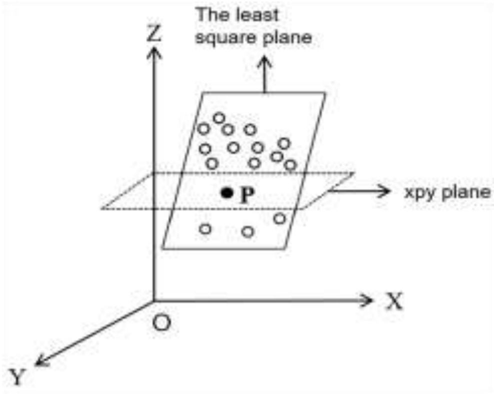

Fig 2: projection of k-neighboring points

2.3 Down Sampling of Interdental Points

The key of simplified algorithm is to retain the detail features of the original 3D model while eliminating as many redundant points as possible. The detail features such as tooth contour and occlusal structure should be efficiently preserved. We can know from some previous experiments that interdental points have large curvature values and they are extremely densely distributed. The interdental points occupy a part of the original points of the dental model. Therefore, under the premise of ensuring the integrity of the reconstructed dental model, the extracted interdental points should be appropriately simplified to meet the needs of patients for rapid restoration of teeth and dentition. A feature measurement factor of local distribution density is introduced to extract interdental points. We take the point p as the center and obtain a minimum surrounding sphere containing k-neighboring points. The radius of the surrounding sphere is r. The local distribution density ρ_p [24] can be calculated by (14).

$$\rho_p = \frac{k}{\pi \cdot r^2} \tag{14}$$

The specific steps of extraction of interdental points are as follows:
Step 1 Calculate the local distribution density of each point and set the threshold.

Step 2 Extracted the points larger than the set threshold, save as the interdental points set.

Step 3 Performed non-uniform simplification.

2.4 Simplifying Non-feature Points

The threshold of multi-level simplification criterion can be set flexibly to meet the requirements of point cloud simplification. After analyzing the feature degree of each subcube, the simplification factor is used to simplify the non-feature points in the feature subcube, so as to realize the extraction and retention

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of feature points. For the non-feature subcube, all points in the subcube are approximately replaced by a certain number of points closest to the center of all points, so as to achieve efficient simplification of non-feature points. The local distribution density can be calculated by (14). The number of reserved points is determined by the point cloud distribution in non-feature subcube, which can effectively simplify the non-feature points.

Set the total number of points in all non-feature subcubes is num_0, and the total number of simplified points obtained in all non-feature subcubes is num_1. The simplification ratio α can be estimated by (15). Suppose a subcube is judged to be a non-feature subcube, and the number of points it contains is n. The number of simplified points obtained by the non-feature subcube n' is calculated by (16). $\lceil \cdot \rceil$ means that the value of n' is rounded upward.

$$\alpha = \frac{num_1}{num_0} \tag{15}$$

$$n' = \lceil n \times \alpha \rceil \tag{16}$$

III. THE OVERALL PROCESS OF THE PROPOSED ALGORITHM

Fig 3 illustrates the process of our algorithm. The algorithm steps are as follows:

Step 1 Construct point cloud space topological relationship with k-d tree and search for k neighborhood points of each point.

Step 2 Calculate the normal vector, principal curvature and other feature measurement factors of each point.

Step 3 Extract edge points as the edge points set, save the result of the extracted interdental points after down sampling as the interdental points set, and classify the remaining points as the remaining points set.

Step 4 Calculate the Hausdorff distance of each point in the remaining points set, build octree structure to divide the remaining points, set multi-level simplification criterion and multiple thresholds.

Step 5 Calculate the average Hausdorff distance of the remaining points H_{dis} and the average Hausdorff distance of all points contained in each subcube h_{dis}.

Step 6 Compared the evaluation ratio λ constituted by H_{dis} and h_{dis} to multiple thresholds. If the ratio λ is greater than the multi-threshold $\lambda_j \left(j = 1, 2, \cdots k \right)$, the simplification factor is obtained.

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Calculate the loacl entropy of average projection distance of each point in the feature subcube, and sort all points according to the entropy value. According to the multiple simplification criterion, the corresponding number of points with low entropy are simplified. On the contrary, if the ratio λ is less than the multi-threshold $\lambda_j\left(j=1,2,\cdots k\right)$, all points in the non-feature subcube will be replaced by some points closest to the center of all points in the non-feature subcube.

Step 7 Repeat Step 6 until all subcubes are traversed, and save the simplified points of all subcubes as simplified points set.

Step 8 Merge and splice the edge points set, interdental points set, and simplified points set, output all processed points as the simplified results of dental model.

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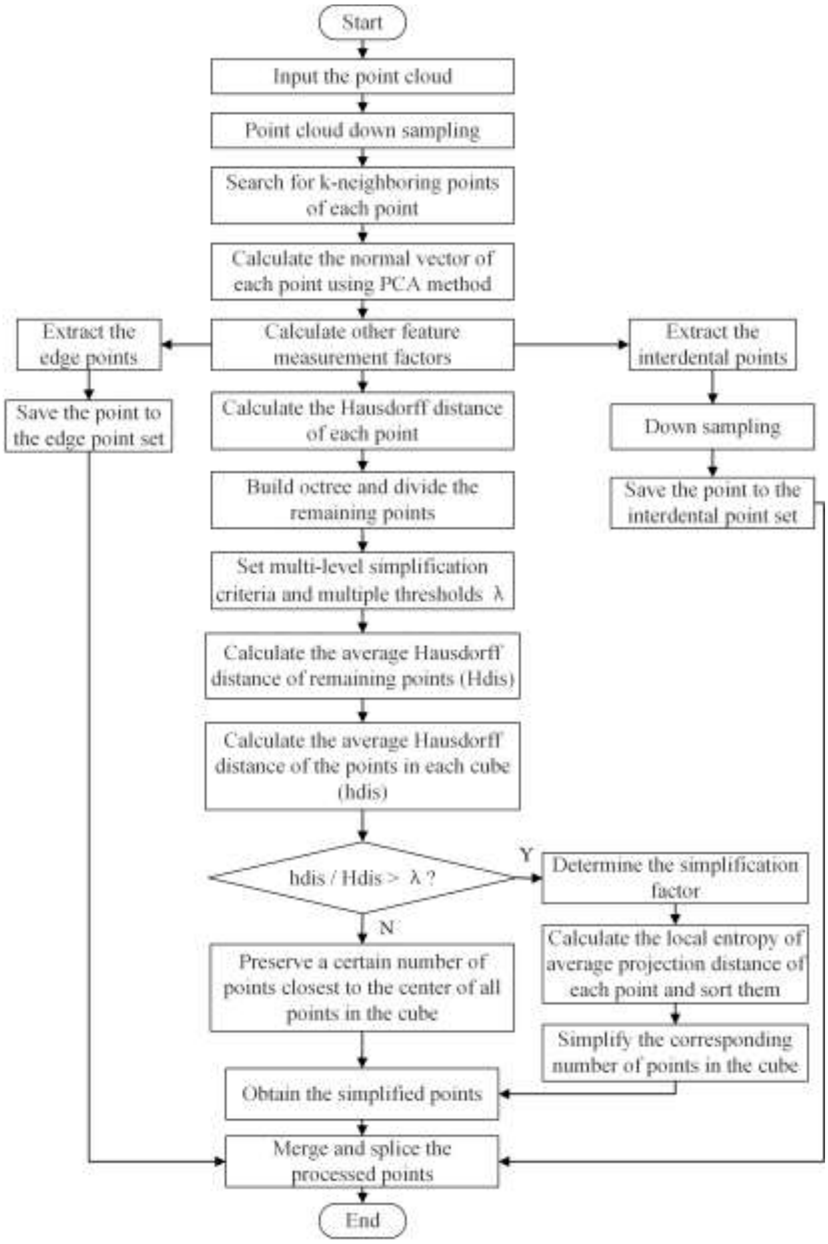

Fig 3: Flowchart of our algorithm

IV. EXPERIMENT AND ANALYSIS

4.1 Simplified Result of Our Algorithm

The digital dental model with many complex features is obtained by 3Shape intraoral optical scanner, and the initial number of point clouds are 159433. The down sampling parameter is set as 9 and there are 28358 points after down sampling. After the initial simplification of the original points by down sampling, the simplified points can still have a high retention degree for the detail features of the original dental model [25]. The k of k-neighboring is chose as 15. The tooth contour and the occlusal structure are

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regarded as the detail features of the dental model, while tooth smooth surfaces and gums are non-feature regions. Interdental points are classified as non-feature points. All experiments were carried out on a PC with Intel Core i7-6700k, CPU 3.40 GHz and 8 GB RAM, and the programming environment was MATLAB R2018b.

In order to analyze the point cloud simplification results of the dental model of the proposed algorithm, the point cloud simplification rates are respectively set to be about 58.7%, 54.1%, 48.2%, 45.6%, and 39.6%. Fig 4 shows the simplified results of the dental model with different point cloud simplification rates. Among them, Fig 4a is the points of the dental model after down sampling, and Fig 4b to Fig 4f are the simplified points corresponding to different simplification rates.

(a) points after down sampling (b) group 1 (c) group 2

(d) group 3

(e) group 4 (f) group 5

Fig 4: simplified results of dental model with different simplification rates

It can be seen from Fig 4 that the proposed algorithm can maintain a large number of points in areas with more detailed features of the dental model, such as tooth contours and occlusal structure. A proper number of points are reserved in relatively flat areas such as tooth smooth surfaces and gums, which can avoid the appearance of larger holes. In addition, the reasonable simplification of the interdental points can effectively reduce the appearance of holes in the tooth gap and curb the expansion of holes.

To provide a quantitative analysis of the reconstructed dental model, Geomagic Studio was used to fit

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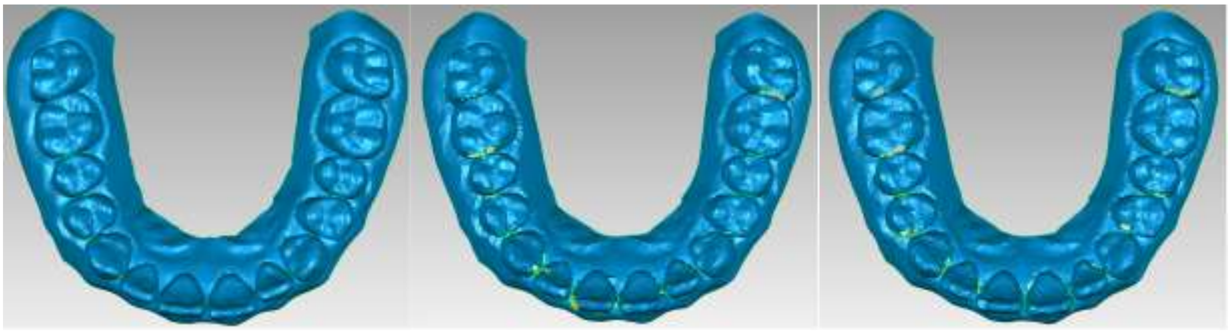
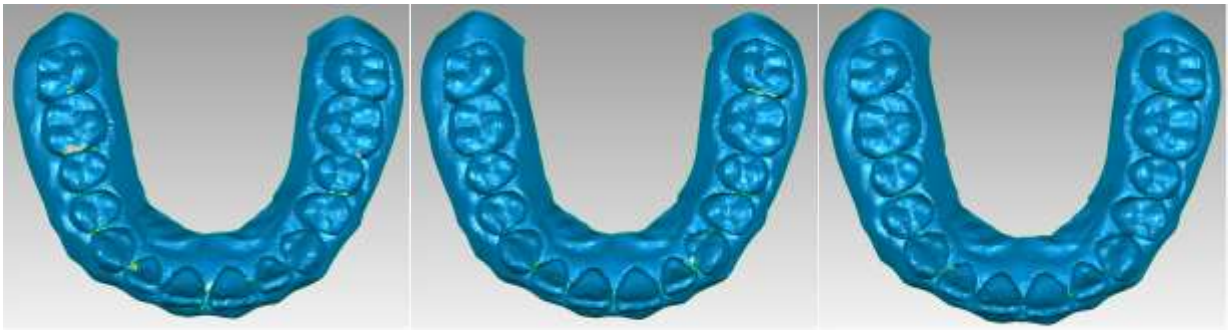
the simplified points. Fig 5 shows the reconstruction results of dental model and TABLE I shows the accuracy comparison under different point cloud simplification rates.

The reconstruction results of dental model with different simplification rates are shown in Fig 5. In Fig 5b and Fig 5c, the points of the dental model is oversimplified, resulting in the serious loss of some detail features. Some areas of the reconstructed dental model, such as the tips of the incisors and the occlusal structure of the molars, are extremely blurred. There are more and larger holes in the gaps between the teeth. Fig 5d shows that the occlusal structure of the molars has a better reconstruction result, and there are fewer and smaller holes in the gaps between the teeth. Compared with Fig 5b, Fig 5c and Fig 5d, Fig 5e and Fig 5f can better retain the detail features of the dental model such as tooth contour and occlusal structure, and there are almost no holes in the gaps between the teeth.



(a) points after down sampling (b) group 1 (c) group 2



(d) group 3 (e) group 4 (f) group 5

Fig 5: reconstruction results of dental model with different simplification rate

It can be seen from TABLE I that the standard deviation of the reconstructed dental model decreases as the number of simplified points increases, indicating that the reconstructed dental model obtained by the proposed algorithm can obtain a better accuracy evaluation as the number of simplified points increases. It can be seen from Fig 5 and TABLE I that when the point cloud simplification rate is less than 50%, our algorithm can effectively retain the detail features of the dental model such as the tooth contour and

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occlusal structure.

TABLE I. Accuracy comparison under different simplification rates

Group	Number of simplified points				Mean deviation		Standard deviation	RMS Estimate
	Edge points	Feature points	Non-feature points	Total point (simplification rate/%)	Positive	Negative		
1	2757	5891	3072	11720(58.67%)	0.0094	-0.0060	0.0103	0.0115
2	2784	6922	3321	13027(54.06%)	0.0089	-0.0046	0.0096	0.0108
3	2807	8293	3589	14689(48.20%)	0.0078	-0.0045	0.0092	0.0105
4	2788	8930	3702	15420(45.62%)	0.0069	-0.0038	0.0086	0.0095
5	2810	10352	3974	17136(39.57%)	0.0063	-0.0033	0.0079	0.0089

4.2 Comparison with Other Algorithm

In order to prove the effectiveness and superiority of our algorithm, we selected octree coding simplified method, Hausdorff distance simplified method [12], and weight product local entropy simplified method [17] as comparison algorithms. Fig 6 shows the simplified results of dental model and TABLE II shows the simplification rate of different algorithms.

As can be seen from TABLE II, the simplification rate of different algorithms is close to 43%, and the number of simplified points is about 16K. Fig 6a shows the simplified results of dental model after down sampling. As shown in Fig 6a, there are some regions without point clouds in the gap between the teeth, and a large number of relatively dense points are distributed near the areas without point clouds. In Fig 6b, fewer interdental points are retained than those in Fig 6c and Fig 6d. The proposed algorithm retains more points in feature areas such as tooth contour and occlusal structure, and simplifies points in non-feature areas to an appropriate extent. In Fig 6c, excessive retention of interdental points results in less retention of points in feature areas such as tooth contour and occlusal structure. As shown in Fig 6d, the points located in the tooth gap are extremely dense, while the retention of feature points is obviously insufficient and the distribution of points in non-feature areas is extremely sparse. Fig 6e shows that the retention of feature points in areas such as overall contour and occlusal structure of molars and premolars is insufficiently, and the retention of detail features is not obvious. In Fig 6c, Fig 6d and Fig 6e, they all have the problem of excessive retention of interdental points. Compared with Fig 6c, Fig 6d and Fig 6e, feature points extraction and non-feature points simplification in Fig 6b are more reasonable. The running time of the proposed algorithm is slightly lower than Weight product local entropy simplified method, but higher than Octree coding simplified method and Hausdorff distance simplified method.

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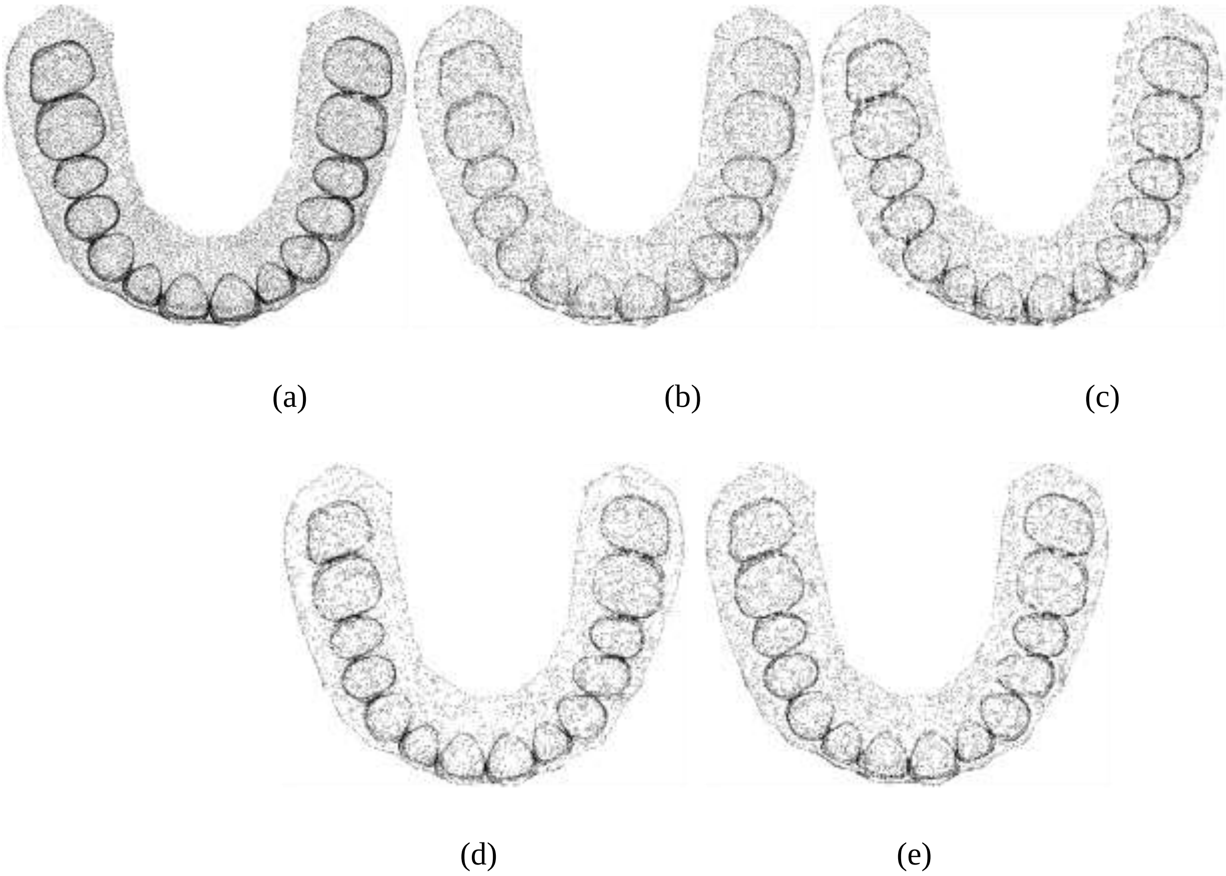

Fig 6: simplified results of dental model (a) Points after down sampling, (b) Our algorithm, (c) Octree coding simplified method, (d) Hausdorff distance simplified method, (e) Weight product local entropy simplified method

TABLE II. Simplification rate of different algorithms

Experimental algorithm	**Points after down sampling**				**Original data**	**Running time/s**
	Edge points	**Feature points**	**Non-feature points**	**Total points (Simplification rate/%)**	**Simplification rate /%**	
Our algorithm	2803	9456	3798	16057(43.38%)	89.93%	12.2
Octree coding simplified method	16241			16241(42.73%)	89.81%	6.5
Hausdorff distance simplified method	2877	13099		15976(43.66%)	89.98%	7.1
Weight product local entropy simplified method	2717	9626	3713	16056(43.38%)	89.93%	13.4

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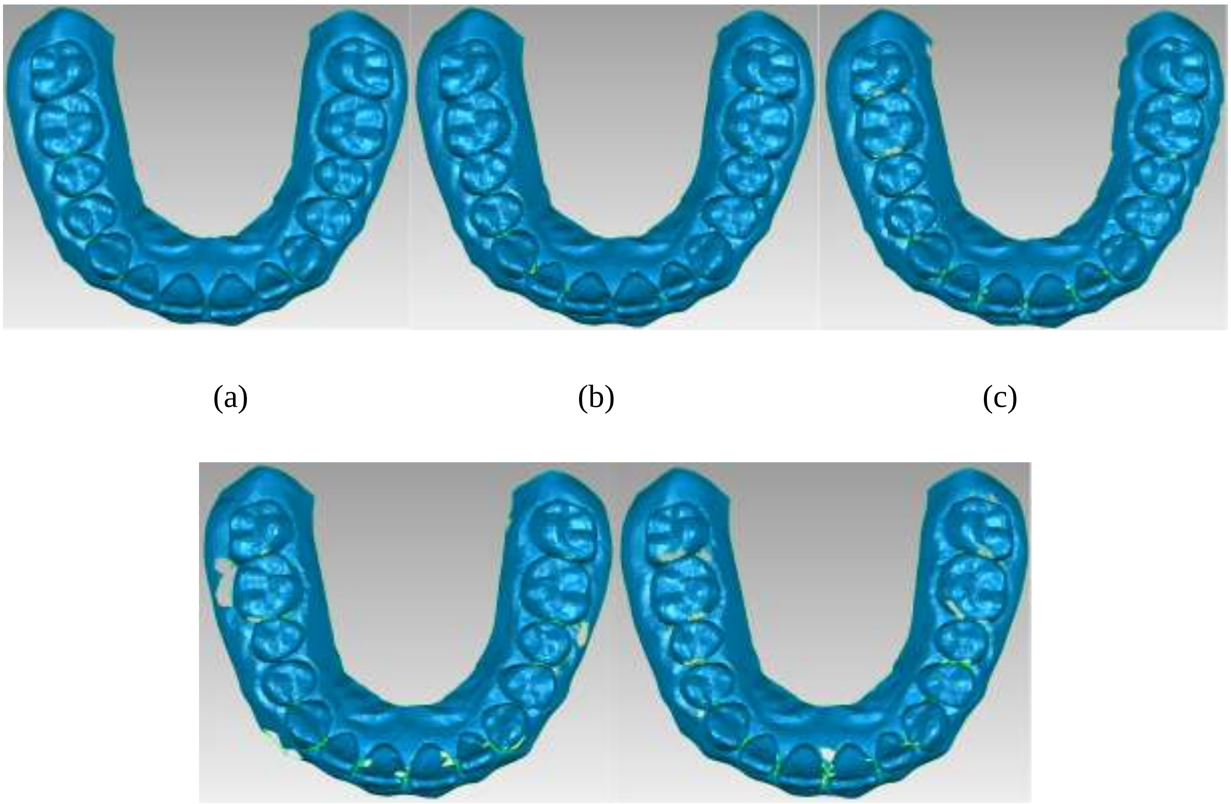
To provide a quantitative analysis of the reconstructed dental model, Geomagic Studio was used to fit the simplified points. Fig 7 shows the reconstruction results of the dental model and TABLE III shows the accuracy comparison of the reconstructed model.



(a) (b) (c)

(d) (e)

Fig 7: Reconstruction results of dental model (a) Points after down sampling, (b) Our algorithm, (c) Octree coding simplified method, (d) Hausdorff distance simplified method, (e) Weight product local entropy simplified method

TABLE III. Accuracy comparison of the reconstructed model

Experimental algorithm	**Mean deviation**		**Standard deviation**	**RMS Estimate**
	Positive	**Negative**		
Our algorithm	0.0064	-0.0033	0.0081	0.0092
Octree coding simplified method	0.0075	-0.0035	0.0086	0.0102

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Hausdorff distance simplified method	0.0116	-0.0051	0.0114	0.0139
Weight product local entropy simplified method	0.0067	-0.0032	0.0083	0.0095

Fig 7 shows the reconstruction results of the dental model. In Fig 7b, the proposed algorithm has a good preservation effect on the detail features of the dental model, such as the tooth contour and the occlusal structure, and there are only a few small holes in the gaps between the teeth. The reconstructed result is almost same as the result after down sampling in Fig 7a. In Fig 7c, there are a lot of large holes in the gap between the teeth, resulting in partial loss of the edge contour of incisors, canines, and premolars. In addition, the reconstructed surfaces of molars and premolars are blurred, and the detail features are not obvious. As shown in Fig 7d, large holes occur in non-feature regions such as gums and smooth surface of incisors and canines, and there are some large holes in the gap between incisors and canines. In Fig 7e, the detail features of molars and premolars, such as tooth contour and occlusal structure, are not sufficiently preserved, and the reconstructed surface is relatively fuzzy. There are some large holes in the gap between the teeth, resulting in seriously loss of the reconstruction area of the central incisors. According to TABLE III, our algorithm has a smaller mean deviation range and a smaller standard deviation, and our algorithm is better than other simplified algorithms in terms of accuracy evaluation.

The proposed algorithm can accurately extract feature points such as tooth contour and occlusal structure to better preserve the detail features of the 3D dental model. At the same time, reasonable simplification of points in non-feature regions can effectively avoid the occurrence of holes. The simplified points have better reconstruction results in the following 3D reconstruction task.

The excessive preservation of interdental points by Octree coding simplified method leads to the occurrence of large holes, resulting in the seriously loss of the reconstruction area of the tooth contour. Octree coding simplified method cannot obtain a more complete reconstruction result of the dental model. According to a series of previous experiments, interdental points have relatively large curvature values and Hausdorff distance values. Therefore, Hausdorff distance simplified method excessively extracts interdental points. To some extent, it affects the retention of detail features such as tooth contour and occlusal structure. When the simplification rate is high, excessive simplification of points may lead to insufficient retention of detail features and the appearance of holes in non-feature areas. Weight product local entropy simplified method also has the situation of excessive extraction interdental points. In addition, the feature points located in the tooth tip area of the incisors are insufficient preserved, which leads to the appearance of large holes. This method has a very poor evaluation of the reconstruction result of the dental model with complex surfaces. Weight product local entropy simplified method is inferior to our algorithm and Hausdorff distance simplified method in evaluating the reconstruction results of molars and premolars, and it is inferior to our algorithm in evaluating the reconstruction results of incisors and canines.

Generally, Octree coding simplified method, Hausdorff distance simplified method and Weight product local entropy simplified method are not well applicable to the dental model with many complex detail features. The proposed algorithm can better simplify the original points of the dental model and

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provide high-quality simplified points for subsequent 3D reconstruction tasks. The simplified points obtained by our algorithm are superior to other comparison algorithms in the accuracy evaluation of the reconstructed dental model.

V. CONCLUSION

In view of the characteristics of dental model with complex surface features, large number of points and uneven sampling, this study presents a simplification algorithm based on Hausdorff distance and local entropy of average projection distance. We conducted a series of experiments with the dental model to prove the effectiveness and superiority of the proposed algorithm.

According to the characteristics of the points of the dental model, the proposed algorithm is designed for the steps of edge points extraction, interdental points down sampling, analysis of feature degree and multi-level simplification of point clouds. Based on the Hausdorff distance, the proposed algorithm analyzes the feature degree of each subcube of the dental model. By setting different simplified thresholds and simplification factors, the average projection distance is combined with the information entropy to accurately and reasonably extracting the feature points with high entropy in the feature subcube. A certain number of points closest to the center of all points are used to replace all points in the non-feature subcube to achieve efficient simplification of non-feature points. Experimental results show that when the simplification rate of the original point clouds of the dental model is as high as about 90%, the proposed algorithm can still accurately extract the feature points such as the tooth contour and the occlusal structure, and better retain the complex detail features of the dental model. At the same time, it can effectively avoid the appearance of holes in non-feature areas such as gums and tooth smooth surface, and prevent the holes in the gaps between teeth from expanding. Compared with the other three comparison algorithms, the proposed algorithm can obtain better point cloud simplification results of dental model with smaller simplification error. The proposed algorithm can effectively solve the obstacles of digital impression technology in practical application, such as data storage, transmission, management and other tasks, so it has high practical application value.

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