Tooth segmentation on dental meshes using morphologic skeleton

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1. Introduction

Numerous dental clinics world-wide use orthodontic computer-aided-design (CAD) systems to prepare for treatments. These CAD systems exploit hardware-supported computer graphics technology to effectively and efficiently plan treatments traditionally done manually. These systems free clinical dentists from repeated work and facilitate accurate treatment planning. Orthodontic CAD systems have an important part in modern dentistry [1–3]. In computer-aided orthodontics, for example, after acquiring a dental model by scanning the teeth of the patient, the dentist often needs to extract all teeth separately from the model. After tooth segmentation, the dentist analyzes tooth positions and arrangements on a computer screen and runs simulations to work out an applicable treatment plan. During a treatment planning procedure, tooth segmentation is a critical part that produces segmented teeth with precision that significantly influences the accuracy of the following work. The efficiency of tooth segmentation is also critical because most dentists do not like spending hours just segmenting teeth.

However, tooth segmentation on dental meshes remains a difficult task. Dental meshes from patients often have teeth crowding problems when adjacent teeth crowd, thus making the interstices between them irregular and difficult to distinguish. Various tooth shapes make outlining tooth contours difficult. Artifacts resulting from scanning or model-making errors on commonly obtained clinical meshes make teeth segmentation more challenging. Normal mesh segmentation approaches are not directly suited for segmenting dental meshes because they lack adjustments to handle complex tooth shapes and teeth arrangements. Other segmentation approaches proposed to handle dental meshes have shortcomings, such as being either labor-intensive or not sufficiently accurate. Although several commercial products in this field are available, such as “3Shape”, their user interactions are intensive and significantly influence the accuracy of results.

In this study, we propose a novel tooth segmentation approach based on morphologic skeleton techniques. Our approach requires less user interaction and manual parameter tuning. It is robust to various tooth shapes, complex tooth arrangements, and various levels of tooth-crowding problems. Furthermore, based on morphologic skeleton techniques, the proposed approach eliminates the need for a complex, precise estimation of mesh features, which is often critical in other works. The present approach only requires an efficient rough initial guess of mesh features.

Overall, our approach has three major benefits:

1. User interactions are significantly reduced to obtain high-quality tooth segmentation results, with minimal parameter tuning.
2. The morphologic skeleton based-techniques proposed in this study are both easy to implement and efficient.
3. The techniques presented in this study are robust to various tooth shapes, irregular teeth arrangements, and common teeth crowding problems.

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2. Related work

In this section, we briefly review several related works on general mesh segmentation approaches in computer graphics as well as approaches specifically designed for dental meshes.

2.1. General mesh segmentation approaches

Numerous mesh segmentation approaches have been proposed in computer graphics. The most recent works include K-means [4], clustering or decomposition [5,6], fitting primitives [7], graph cut [8], normalized and randomized cut [9], watersheds [10], random walks [11], core extraction [12], shape diameter function [13], active contours or scissoring [14,15], fast marching [16]. Surveys have been conducted in [17,18]. These approaches can be briefly classified as region-classifying approaches [4–7,10,11,16] and boundary-outlining approaches [8,9,12–15]. Region-classifying approaches aim to find different regions based on similarity measures. These approaches regard segmentation by finding mesh regions or grouping different mesh regions. Boundary-outlining approaches attempt to find optimal curves that split two adjacent parts, often by maximizing differences among separated parts. These approaches regard segmentation as a task for finding cutting boundaries that clearly bound the segmented area. Non-supervised or semi-supervised machine learning approaches have also been proposed for mesh segmentation [19,20]. These approaches learn from databases that contain various mesh segmentation results to gain information that can guide them in segmenting meshes automatically.

However, when dealing with complex tooth shapes and segmentation arrangements, we need a more specific approach that fully exploits dental characteristics.

2.2. Dental mesh segmentation approaches

Both automatic and interactive approaches have been proposed for dental mesh segmentation.

Given that tooth boundaries are clear in projected 2D images, Yamany et al. [21] used a specifically designed mesh representation that maps 3D vertices onto 2D vertices and exploits 2D image segmentation techniques to segment teeth. Similarly, Kondo et al. [22] proposed an automatic approach by extracting interstice points on planar and panoramic range images, i.e., the projection of model vertices onto the occlusal plane and the side view along the dental arc, respectively. Their approach is highly automatic, with only an interaction of the occlusal plane specification. However, when the information provided by the two projected range maps is restricted, the aforementioned approach may not be able to extract several complex interstices. Using simple rectangular spokes along the dental arc to separate teeth may also miss some irregular interstices or lead to inaccurate cuttings. This problem is particularly critical when dealing with adjacent teeth with interstices with complex shapes. Another approach using range map images was presented in the work of Grzegorzek et al. [23]. These researchers used multiple parallel-range map images to obtain 2D contours and to cut adjacent teeth by connecting significant non-convex points on them. The contours are then refined with active contours and mapped back into 3D space. This approach produces precise 2D contours to use multiple range map images instead of single ones. However, restricting range map images from a single view leads to inaccurate tooth contours, and some of their critical non-convex points may be difficult to find on contours with complex shapes.

Given that image-based segmentation lacks information in 3D space, focusing on segmenting teeth directly on 3D meshes is reasonable. Zhao et al. [24] proposed an interactive approach based on user-specified separating points between adjacent teeth. The contour of each tooth is then selected by automatically connecting user-specified interstice points through tooth contours. However, the interactions of their approach are intensive for clicking at least two points for each tooth. The contours of their segmented teeth are also not guaranteed to be smooth enough. Kumar et al. [25] automatically identified interstices between teeth by connecting significant points on tooth boundaries that connect the lingual and labial sides and used them to cut adjacent teeth. Their approach works well on regular teeth but may not work on teeth with complex contours by misleading both sharp point extraction and cutting curve approximation. The commonly encountered crowding problem may also decrease the effectiveness of this approach.

Given that each tooth on a dental model can be supposed to have a closed contour around its bottom area, active contour techniques have also been exploited. Kronfeld et al. [26] proposed a snake-based approach that starts with an initial contour on the gingiva and evolves through a GVF-like feature attraction field. The cusps of each tooth are then selected to start a local tooth contour and to evolve until each tooth bottom is reached. Their approach is highly automatic but may not produce good results when the model has boundary noises that interrupt feature attraction fields.

Several commercial orthodontic CAD systems are also available, such as Insignia, SureSmile, and 3Shape. Among these products, only 3Shape provides teeth segmentation functionalities to end-users. However, the segmentation operation of 3Shape is interaction-intensive and may not produce good results if the required interactions are not sufficiently accurate.

In general, published approaches for teeth segmentation on dental meshes have at least one of the following problems:

1. easily affected by boundary corruption,
2. incapable of accurately finding interstices, and
3. interaction-intensive.

We argue that a practical teeth segmentation approach should accomplish the following objectives:

1. locate teeth on meshes automatically,
2. separate adjacent teeth accurately with regard to various levels of crowding problems,
3. acquire smoothed and well-fitted boundaries for teeth, and
4. robust to mesh noises and less dependent on a complex and precise estimation of mesh features.

2.3. Mesh skeleton techniques

Mesh skeleton is used to represent the basic topological relations among different parts of a mesh. To put it simply, a mesh skeleton is a space curve to which the maximum distances of all vertices are the same. Skeletonization is a useful technique to obtain inherent geometric information within meshes and is used in various scenarios, such as in smoothing, simplification, segmentation, and animation. Typically, a mesh skeleton refers to the interior curve inside enclosed mesh surfaces; this skeleton is extracted by using either volumetric or geometric approaches [27]. Volumetric approaches use regularized volume representation to enclose all mesh vertices and faces to facilitate the process of peering outside parts iteratively [28–30], whereas geometric approaches directly work on mesh vertices and faces through techniques such as Voronoi graph [31], Reeb graph [32], deformable models [33], mesh decomposition [12], and mesh contraction [27].

In the present work, we aim to extract the skeleton on the surface for areas composed of connected triangulated faces; thus, the aforementioned approaches are unsuitable. We use a morphologic skeleton...
technique. The morphologic skeleton technique is originally proposed by Rossl et al. [34]. The process starts with classifying all featured vertices into three groups by analyzing their neighborhood vertices and iteratively peering off vertices on the outermost layer. Their approach is simple and efficient for extracting skeleton on surface areas. Morphologic operations also do not require a precise mesh feature estimation to obtain good results. In our work, using an improved version of a morphologic skeleton technique based on the version of Rossl et al. [34] provides more benefits, which are discussed in the following sections.

3. Segmentation pipeline

We use a series of strategies to accomplish the four objectives mentioned in the previous section. Scanned dental meshes, which are the focus of our approach, often contain gingiva around the base parts of the models. Those gingiva parts should thus be eliminated before extracting teeth. First, we locate teeth on the dental meshes through region-growing starting from the bottom parts of the model. We propose an automatic base cutting plane estimation method using a specially designed energy function. The cutting plane intersects the bottom area of the model and produces seed points for region-growing. The teeth–gingiva and teeth–teeth boundaries are extracted simply by mean curvature thresholding with regard to the “minimal rule” [35]. We then use an improved morphologic skeleton technique to extract single-vertex width boundaries, which describe the topology of different potential dental parts on meshes. The use of morphologic skeleton techniques also allows roughly estimated mesh features to be the initial guess rather than a complex and precise mesh feature estimation. To separate teeth based on the extracted skeleton, we propose a highly automatic technique that selects the most likely plane which clearly separates gingiva and tooth parts. The entire process is depicted in Fig. 1.

4. Identifying teeth

Identifying tooth parts is unavoidable in every dental mesh segmentation approach. Other approaches require manual selection of an enclosed area containing tooth parts. This process is, however, labor-intensive and inconvenient. The precision of eliminating gingiva parts is also crucial in tooth segmentation; thus, dependence on interaction accuracy is unreliable. To address this issue, we propose a highly automatic technique to eliminate gingiva parts and to leave all teeth for further use.

4.1. Identifying potential tooth boundary

The location of teeth boundaries on dental models is the key. In this study, we classify useful tooth boundaries on dental meshes as teeth–teeth boundaries and teeth–gingiva boundaries. We simply follow the “minimal rule” proposed by Hoffman et al. [35], which states that different visual parts on a mesh are often separated by concave areas with relatively large negative curvatures. Through mean curvature thresholding and connectivity filtering, we can acquire potential boundaries by selecting vertices with large negative mean curvatures and better connectivity (i.e., more feature vertices are connected). These vertices are called boundary vertices in this paper. This step only approximately estimates boundary vertices, which are refined in the following operations.

4.2. Automatic cutting of gingiva

We use a region-growing technique to eliminate gingiva on dental meshes. To obtain seed points, we devise a plane-estimating technique based on Principal Component Analysis (PCA) that produces a cutting plane which clearly separates gingiva and tooth parts.

We first employ the same plane estimation operation used in [26], that is

\[
M_{\text{covariance}} = \frac{1}{\|F_k\|} \sum_{v \in F_k} (v - \bar{v}) \otimes (v - \bar{v})
\]

where \(F_k\) is the set of vertices extracted by mean curvature thresholding, and \(\otimes\) is a Cartesian product operator. \(\bar{v}\) is the barycentric coordinate of the vertices in \(F_k\).

The estimated plane is determined by \(\bar{v}\) and the normal vector calculated as \(\vec{n} = \frac{\bar{e}_0}{\|\bar{e}_0\|}\), where \(\bar{e}_0\) is the eigenvector corresponding to the smallest eigenvalue for \(M_{\text{covariance}}\) in Eq. (1). The estimated plane holds the property such that the total distance from the boundary vertices to the cutting plane is minimized. However, the plane can also intersect with tooth parts, as shown in Fig. 2(a). To address this issue, we adjust the initial estimated plane to intersect only with gingiva parts. Thus we...
propose the following energy function as

\[ E_{\text{penalty}}(s) = \frac{1}{\|F_k\|} \sum_{v \in F_k} w(v)p(v,s) \]  \hspace{1cm} (2)

where \( p(v,s) \) is the penalty value contributed by each potential vertex \( v \) regarding its distance to the cutting plane \( s \), and \( w(v) \) denotes the correspondent penalty weight determined as

\[ w(v) = \frac{\|R_v\|}{\|F_k\|} G_{\sigma_{R_v}}(\kappa(v) - \mu_{R_v}) \]  \hspace{1cm} (3)

where \( R_v \) is the set of boundary vertices connected to vertex \( v \), \( G(\cdot) \) is a Gaussian function, and \( \sigma_{R_v} \) and \( \mu_{R_v} \) denote the standard deviation and the mean of the mean curvature values of the vertices in \( R_v \), respectively. The weight is designed based on the fact that all dental model features corresponding to high geometric surface changes are concentrated around the boundaries between the teeth and gingiva, thus increasing the connectivity of these boundaries. The \( p(v,s) \) is mainly determined by the distance from a certain vertex \( v \) to the cutting plane \( s \), that is

\[ p(v,s) = (d(v,s) - \mu)^2 \]  \hspace{1cm} (4)

where \( d(v,s) \) is the distance from vertex \( v \) to plane \( s \), and \( \mu \) indicates the optimal distance to the cutting plane, which is an initial guess of how far the optimal plane should be from the bottom of the teeth. The penalty potential is estimated, in which penalty increases when a certain vertex \( v \) is either too close to or too far from a certain plane \( s \). In our implementation the specific value of \( \mu \) does not influence the results significantly, and thus, is set to be 8.0.

Based on the previous PCA-estimated plane, an optimization is applied to fit a least energy in Eq. (2). Given that we do not need to find a precise position with an exact minimal energy, we simply move the plane along its normal tracks in large steps and check the penalty in each step until the penalty stops decreasing. The penalty energy field and the optimal cutting plane are depicted in Fig. 2. The vertices intersected with the estimated cutting plane \( s' \) are then marked as seed points on gingiva parts. The estimated plane cuts the dental model into half, with all the teeth on the same side, thus leaving the other side with only gingiva parts. This result guarantees that during a region-growing operation that starts from these seed points, tooth parts are never eliminated. In several extreme cases where tooth positions vary significantly, the estimated cutting plane may intersect with several teeth. To address this problem, we provide an interface for users to manually rectify the position of cutting planes, but this function is rarely used in our experiments.

Fig. 2. (a) Cutting plane produced using PCA-based techniques. (b) Penalty energy field for different cutting plane positions (energy increases as color changes from blue to red). (c) Cutting plane estimated by our approach [curvature range \( = (-\infty, -0.7) \), \( \mu = 8.0 \)]. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

Fig. 3. A typical “disk eliminating” problem on two-vertex width features using the approach in [34].

4.3. Boundary skeleton extraction

In our approach, smaller regions around boundary vertices are filtered out, and disconnected boundaries or small non-boundary holes are connected or filled using morphologic inflation as proposed in [34]. We then propose an improved morphologic skeleton extraction technique to refine coarse boundaries into strict single-vertex-width boundaries. The “improved morphologic skeleton” techniques are critical during our entire segmentation process. First, by using morphologic skeleton techniques, we can obtain precise boundaries without a more complex and precise initial boundary guess which is often required in other mesh segmentation approaches. In our work we simply use efficient mean curvature filtering and connectivity filtering. Second, the morphologic skeleton on dental meshes describes the topological relationship among different potential dental parts, which we can further refine into precise teeth separating lines. Third, the single-vertex width boundaries make the teeth separation operation easier, which will be discussed later.

We improve the morphologic skeleton extraction technique originally proposed by Rossil et al. [34]. All boundary vertices can be classified into three groups [34]:

1. “Complex vertices” are single-vertex width boundaries.
2. “Disk vertices” are outside layers.
3. “Center vertices” are surrounded by other boundary vertices.

During each iteration, the outermost “disk vertices” are eliminated, followed by a new vertex classification. After several iterations, all “disk vertices” and “center vertices” are eliminated, thus leaving only “complex vertices” as thin boundaries. However, the approach used in [34] has a problem, as shown in Fig. 3. “Disk eliminating” becomes difficult because, in this case, the remaining vertices will be disconnected. Given that [34] did not provide a clear solution to this issue, we propose a technique to solve this problem.

Our technique is based on labeling “disk” vertices. To avoid the problem in Fig. 3, connected “disk” vertices that separate disjoint
non-boundary regions must not be removed simultaneously during an iteration. Given that any “disk” vertex connects to only one “non-boundary” region, we can label each “disk” vertex with the region tag it connects to. Then, “disk” elimination on these connected “disk” vertices needs to remove vertices connected to only one of the two “non-boundary” regions at a time.

Based on the topological composition of the two-vertex width boundaries on the mesh, any two-vertex width boundary can be regarded as two single-vertex width boundaries connected to different regions. In order to avoid connecting adjacent regions, only one of either such single-vertex width boundary can be eliminated. In this way we can guarantee that adjacent regions will not join after the iteration. In our approach, when a two-vertex width boundary exists, the single-vertex width boundary that constitutes it, and which has more vertices, is removed. An illustration of our improved skeleton technique is shown in Fig. 4. A result on a dental mesh is depicted in Fig. 5.

Our improved morphologic skeleton extraction approach guarantees that only strict single-vertex width skeletons exist after the iteration stops. This is helpful in our remaining operations for eliminating gingiva parts precisely and splitting adjacent teeth.

4.4. Region growing

When single-vertex width skeletons are obtained, all gingiva parts are marked using a region-growing operation. The extracted seed points produced during cutting-plane estimation propagate to nearby regions until the skeleton boundaries are reached. The teeth are then unmarked.

5. Teeth separation

After previous region-growing operation, the gingiva are removed, with only the connected teeth left. The fact that a single concave area should be found between any two adjacent teeth is considered. An automatic approach is proposed to find those separating lines. Each separating line is used for adjacent teeth separation, as Fig. 6 illustrates. Our teeth separation operation is divided into three operations.

5.1. Finding cutting points

Boundaries extracted after morphologic skeleton extraction operation contain two types of useful boundaries: teeth–gingiva boundaries and teeth–teeth boundaries, as shown in Fig. 6. After previous “region-growing” operation, teeth–gingiva boundaries are marked, thus leaving the remaining boundaries as teeth–teeth boundaries. We then select points where teeth–teeth and teeth–gingiva boundaries join (Fig. 6) as candidate cutting points.

Given that our improved morphologic skeleton technique guarantees that only single-vertex width boundaries exist, then only one joining point for two different boundary lines is found. In other extreme cases the solution is trivial.

5.2. Pairing cutting points

In our work, cutting lines that separate adjacent teeth are generated by connecting cutting points through teeth–teeth
boundaries. Several misleading interstice boundaries are presented, as depicted in Fig. 7; such boundaries introduce unnecessary cutting points. These interferences are attributed to the extracted boundary lines in central fosses on tooth crowns, and are unavoidable in previous boundary extraction operation. To address this problem, we provide a solution to eliminate unnecessary cutting points and to connect useful cutting points.

Two kinds of abnormal problems should be handled:

1. Unnecessary cutting points and cutting points that are misconnected through.

Our technique is based on the principle that each interstice between two adjacent teeth can only be made by connecting two different cutting points, or one cutting point with a joint point. The cutting points that satisfy certain rules are paired, thus leaving unpaired cutting points and joint points to be discarded. The remaining cutting points that cannot be paired are then discarded. The pairing rules are as follows:

1. A cutting point cannot be paired more than once, whereas a joint point can.
2. A pair of two cutting points can be paired only if they are not too close to each other through a teeth–gingiva boundary, and a long enough path along the teeth–teeth boundary exists between them.
3. A joint point and a cutting point can be paired if their distance along the teeth–teeth boundaries is not too large or too small compared with the same kind of distance of other cutting points to the joint point.
4. The remaining cutting points that cannot be paired are then discarded.

All possible situations and their solutions are illustrated in Fig. 7.

5.3. Teeth separation

Separating lines can then be generated by connecting each cutting point pair through a geodesic path on the mesh. Through our approach even adjacent teeth with severe crowding problems are separated correctly, as in Fig. 8. Besides, the proposed teeth separation technique is completely interaction-free.

6. Refining tooth boundary

The separated teeth have rough boundaries. Such teeth are unacceptable for precise clinical dental treatment planing. The boundary of each tooth should be both smooth and precise. To refine those boundaries, we propose a contour refining technique based on the characteristics of dental models.

For each segmented tooth, we first extract its closed boundary line using a depth-first searching technique among its boundary points. This closed boundary is then sampled to produce controlling points of an approximated contour. We first project all the contour points onto a 2D plane, sample them to produce 2D contours, and then map them back to 3D contours. We use three constraints to sample 2D contours.

The first two constraints are measurements of geometric changes along the projected 2D contour. The first constraint is calculated by

$$
\sum_{v_i \in \text{PATH}(p,p')} \arccos \left( \frac{\langle v_i, v_{i+1} \rangle \cdot \overrightarrow{\mathbf{t}}}{\| v_i, v_{i+1} \| \cdot \| \overrightarrow{\mathbf{t}} \|} \right) \phi(v_i) > \lambda
$$

where \( \langle v_i, v_{i+1} \rangle \) is a vector from \( v_i \) to \( v_{i+1} \), \( \text{PATH}(p,p') \) denotes the consequent points on the projected contour \( C' \) between last sampled point \( p \) and current candidate sample point \( p' \). For each point \( v_i \) on \( C' \), \( v_{i-1} \) and \( v_{i+1} \) are its immediate predecessor and successor, respectively. Eq. (5) measures the direction change around vertex \( v_i \) by calculating the angle between next edge and a vector \( \overrightarrow{\mathbf{t}} \) perpendicular to the current edge. \( \overrightarrow{\mathbf{t}} \) is defined as

$$
\overrightarrow{\mathbf{t}} = \langle v_{i-1}, v_i \rangle \cdot \frac{(v_{i+1}, v_i) \cdot (v_{i-1}, v_{i+1})}{\| (v_{i-1}, v_i) \|} \| (v_{i+1}, v_i) \|
$$

where \( c' \) is the barycentric point of projected 2D contour \( C' \). In Eq. (5), a direction function is also used to specify whether the current point is moving forward or backward and to compensate for geometric
changes when moving in the opposite direction:

$$\phi(v_i) = \text{sign} \left( \frac{(v_{i-1} - v_i) \cdot (v_i - v_{i+1})}{\|v_{i-1} - v_i\| \cdot \|v_i - v_{i+1}\|} \right)$$

where $\text{sign}(x)$ is equal to 1 if $x > 0$, otherwise it is equal to $-1$.

The second geometric constraint is defined as

$$\sum_{v_i \in \text{PATH}(p,p')} \frac{(v_{i-1} - v_i) \cdot \vec{s}}{\|\vec{s}\|} > \tau$$

where the significance of the contour length is measured by calculating the projected length of the current edge onto the direction vertical to the direction from the midpoint $m$ of the current edge to the contour center $c'$. $\vec{s}$ is defined as

$$\vec{s} = (v_{i-1} - v_i) - \frac{(v_{i-1} - v_i) \cdot (m - c')}{\|v_{i-1} - v_i\| \cdot \|m - c'\|} (m - c')$$

In Eqs. (5) and (8), $\lambda$ and $\tau$ are respective thresholding parameters. Our sampling technique is based on the understanding that each tooth contour can be roughly approximated using a circle. The significance of geometric change along the contour is shown in Fig. 9.

The constraint in Eq. (5) restricts the next sample point to be placed on the position with a large accumulated direction change,
whereas the constraint in Eq. (8) allows placement of sample points when the accumulated projected distance is long enough. In our implementation, $\lambda$ and $\tau$ are set to be 0.25, 0.75, respectively. The third constraint restricts the point sampling rate around the “cutting points” extracted in previous “teeth separation” operation, because in cases with tooth crowding problems the contours where adjacent teeth come in contact are easily disrupted by soft tissue and scanning difficulties. Through this constraint we can obtain smooth contours around the cutting points. In our implementation we avoid sampling points with distances to nearby “cutting points” that are less than 1.0.

Sampling projects 2D controlling points and maps them back to 3D contour points. The tooth contours are approximated using controlling points and interpolating schemes. In this study, we use a fourth-order polynomial interpolation technique. An example of our sampling approach is shown in Fig. 10.

7. Results

We conducted experiments on clinically acquired dental meshes.

7.1. Segmentation experiments

Three kinds of experiments were devised:

(1) Experiments on dental meshes with different levels of crowding problems.

(2) Experiments on dental meshes of the same patient with different modeling qualities.

(3) Comparative experiments conducted using a commercial software “3Shape”, active-contour model, “closest-pair” approach, and our approach.

7.1.1. Different levels of crowding problems

First, we demonstrate our segmentation results on clinical dental meshes with various levels of teeth crowding problems. According to the levels of crowding, the dental models are classified into three types: “mild crowding”, “moderate crowding” and “severe crowding”. Three typical cases are selected. For each case we segment teeth on both the maxilla and mandible models. The results are shown in Fig. 11. Given the restriction on paper length, we can only display the segmentation operations of six typical cases (12 models) of our numerous successful results.

All teeth in six cases, including the case with severe crowding problem (Case C in Fig. 11.), are clearly segmented and labeled into different colors (Fig. 11(d)).

7.1.2. Different model qualities

The models used in Fig. 11 are obtained by intraoral-scanning devices that produce dental models with relatively high quality. However, other modeling techniques are still used. For example alginate or polyvinyl silicon (PVS) dental models are still employed in clinics. To test our approach on meshes with relatively low quality, three different modeling techniques including alginate, PVS and intraoral-scanning are used to produce three pairs of dental meshes for three patients. The meshes derived from intraoral-scanning often have higher quality and less noise than those obtained from the other two techniques. In addition, PVS models are better than alginate models. The results are depicted in Fig. 12.

The dental meshes derived from alginate or PVS have more noises on boundaries. However, these noises only affect the boundary extraction operation and can be compensated by a small quantity of manual boundary completing operations. In such cases, our approach still obtains acceptable results with a certain degree of robustness against noises (Fig. 12).

7.1.3. Comparison with other approaches

We compare our results with those produced by other approaches. Fig. 13 shows the comparison of the results produced by the active-contour model in [26], the “closest-pair” proposed in [25] and our results. The approach presented in [26] fails to extract the true boundary when several feature lines cross each other, whereas the approach proposed in [25] fails to separate teeth with severe crowding problems because of information limited only from the lingual and labial sides. Our approach is capable of handling these two difficult cases. We also use a popular commercial software, i.e., “3Shape” to segment the same models. The precision of teeth segmentation provided by “3Shape” relies significantly on the manual marking of the mesial and distal points of each tooth. If user interactions are not sufficiently accurate, then the results produced by “3Shape” are poor, whereas our approach produces good results with few interactions, as shown in Fig. 14.

7.2. Evaluation

In this section, we provide time consumption, error and user interaction evaluations.
Fig. 11. The segmentation results of our approach on multiple dental meshes with crowding problem varying from "mild crowding" to "severe crowding". (a), (b), (c), and (d) show the consecutive segmentation operations.
7.2.1. Time consumption

We recorded the time consumed by our approach during experiments on 56 models, including the cases shown in Fig. 11. The time consumption of all cases is displayed in Fig. 15. For convenience, we classify all operations in our implementation into four groups. Group “Skeleton Generation” consists of “boundary point extraction” and “skeleton generation”. “Teeth Segmentation” is composed of “region growing” and “teeth separation”. Our program is tested on a desktop configured with: Intel Core i7 @ 2.93 GHz, 4 GB RAM, and Microsoft Windows 7 32bits.

The most time-consuming operations are boundary extraction, teeth separation and contour modeling, each of which takes approximately 2–4 s. Boundary extraction takes time in calculating curvatures on each vertex and region-growing. Teeth separation consumes a relatively more time because of its geodesic path calculation. The average execution cost in each segmentation experiment is less than 10 s.

7.2.2. Error

Given that no dental segmentation benchmark provides ground truth for evaluation, we asked three dentists to mark the boundary of each tooth manually on all experimental models. For each tooth, all its marked contours from three dentists were averaged to produce its ground truth. The boundaries of our segmented teeth were then compared with “ground truth” using mean errors, as shown in Fig. 16.

Fig. 12. The segmented results of our approach on dental meshes involving crowding problems and mesh quality. (Cases A, B, and C in Fig. 11 are obtained using three different modeling techniques).
The mean errors of our approach are below 0.16 mm, which is acceptable by clinical standards (i.e., less than 1.0 mm). We also analyzed the distribution of errors across all segmented boundary vertices. In most cases more than 98% of the errors are below 0.5 mm.

7.2.3. User interaction

We recorded the time consumed by user interactions. The only user interactions required in our experiments are “boundary completion” and “seed point addition”. As shown in Fig. 17, only one or both of these interactions were needed occasionally in each model. The time consumption in each model for “boundary completion” is less than 30 s for marking or unmarking a few missing or unwanted boundaries. “Seed point addition” consumes approximately 10 s in each model. Although we have devised a “cutting plane readjustment” for users to rectify the cutting plane position manually, we only apply this process to one model (among the 56) because it is an extreme case wherein a single tooth is located near the bottom and far from the other teeth. Our results can only be rectified by these two interactions which are both simple and efficient. Along with the program execution time of less than 10 s, we can easily segment a model within 1 min or 2 min. By contrast, the popular commercial software “3Shape” often takes minutes of interaction to segment one model.
Fig. 16. (a) denotes the mean errors that compare our results to manually labeled ground truth. (b) is the distribution of particular error values across all segmented boundary vertices. The blue, yellow, red lines indicate the ranges of $[0, 0.25]$, $[0.25, 0.5]$, $[0.5, 1.5]$, respectively. The unit is mm. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

Fig. 17. Time consumed (s) by user interactions. The blue and yellow lines indicate manual boundary completion and additional seed addition, respectively. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)
8. Conclusion

Tooth segmentation is an important part of computer-aided orthodontics. In this study we propose a novel tooth segmentation approach for dental meshes. Our approach is simple, effective and involves fewer user interactions compared with published approaches. As shown in the experiments, our approach is capable of producing good results with regard to different levels of crowding problems and noises. Meanwhile, the time cost of segmenting a model is reduced by using our approach.

The limitation of our approach is that in cases with a significant amount of noise, our method may require more user interactions to guarantee accurate results. However, given that the required interactions (“boundary completion” and “additional seed addition”) are both simple and time-saving, the time consumed by user interactions is only 1–2 min.

Our future work will involve developing our platform into a dental mesh segmentation benchmark, given that we have conducted much work in building ground truth for numerous models that cover different tooth shapes and crowding problems. Determining how to avoid user interactions completely is also important.

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References